Optimizing train station inspection operations in the region of Magdeburg.

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MANAGEMENT SUMMARY

This study was conducted at the Train Station Management (TM) department of Deutsche Bahn AG (DB) in Magdeburg. The TMs, managed by DB's subsidiary DB Station&Service AG (since 01.01.2024 fusion with DB Netze AG to DB InfraGo AG), monitor the operation of train stations in Germany, provide equipment, facilitate communication between customers and the company, and ensure safety during travel to enhance the overall experience for passengers. The safety and quality of physical train stations are maintained through regular safety inspections and proactive maintenance efforts. Currently, TMs with train stations spread across different geographical areas, such as the one in Magdeburg, face lengthy commutes to service stations in the peripheral regions of their responsibility. These long travel distances reduce productive work time, prompting TM Magdeburg to contemplate restructuring its operational strategy. Inspectors follow a manually constructed schedule, while repair personnel get tasks assigned on demand, starting their work from the office in Magdeburg. The proposed solution involves locating service teams at field offices, if applicable, to minimize travel time and distance, conserve fuel, reduce emissions, and enhance work quality by shortening commute times. DB owns properties at train stations with available space that can be outfitted to accommodate these field offices.

Given the complexity and interrelation between location and routing problems, as evidenced by existing research, the analysis of office locations alongside effective tour planning can be framed as the Location-Routing Problem (LRP). Considering the periodic nature of station inspections and variations in inspection frequencies across stations, this problem is extended to the Periodic LRP (PLRP). Balancing conflicting objectives, such as minimizing total travel distance and cost per planning horizon while also minimizing the maximum duration of individual tours, further complicates the optimization problem. This study aims to design an optimization approach that locates service teams to field offices, assigns the train stations to the teams respectively, and provides a periodic tour schedule. To address this, a Mixed-Integer Linear Program (MILP) was formulated to accommodate all relevant constraints. However, MILP struggles to simultaneously address all objectives without prior knowledge of decision makers' preferences and cannot efficiently handle large problem instances within acceptable time frames. Consequently, a metaheuristic approach called Multi-objective Adaptive Large Neighborhood Search (MO-ALNS) was devised, incorporating customized operators to tackle this problem.

MO-ALNS operates by exploring the solution space using destroy and repair operators. Instead of seeking a single solution, it identifies non-dominated solutions to construct a Pareto front representing trade-off solutions across multiple objectives. Additionally, it employs the Roulette wheel method to dynamically adjust the probability of selecting operators based on their past performance. It evaluates solutions using the Metropolis criterion, occasionally accepting worse solutions to encourage diversification.

Moreover, the algorithm underwent fine-tuning, focusing on optimizing improvement operators, termination criteria, and other parameters. Ten scenarios were created using the Magdeburg dataset to achieve this. These scenarios were generated by randomly selecting subsets from the train station set and adjusting the number of service teams based on the subset's size. Following the optimization process, the effectiveness of the solutions was assessed by comparing them to results obtained through the optimization of each objective independently. This was

done using single-objective equivalents to the MO-ALNS approach and incorporating the proposed MILP method for smaller instances. The results indicate that, for smaller instances (up to 100 stations), single-objective approaches excel by minimizing Key Performance Indicators (KPIs) individually. Conversely, MO-ALNS is effective with larger datasets (more than 100 stations), offering the advantage of generating a comprehensive set of non-dominated solutions in a single run.

Subsequently, a series of numerical experiments for the deterministic solution evaluation were conducted, considering other four scenarios. These scenarios included variations such as an additional service team, a reduced number of service teams, and an additional field office with a favorable location, albeit at an additional rental cost. Alongside analyzing the Magdeburg dataset, the TM region in Halle was also examined, encompassing scenarios with similar resource allocations. The model showcased versatility across TM regions and provided valuable insights into team capacity management.

A more detailed analysis of the Magdeburg case was conducted, employing an extended run of the MO-ALNS method, followed by a stochastic examination of a subset of the Pareto front. The solutions adhered to a constraint of a maximum tour duration of 15 hours and required a minimum improvement of 3% over the existing situation. The analysis revealed that the Stendal field office was utilized in 78% of the resultant non-dominated set, indicating its explicit utilization for reducing the total distance traveled by approximately 17% ($\sim$ 1,100-1,900 km) and achieving modest cost savings. Aschersleben and Dessau were selected in 39% and 35% of solutions, respectively. Additional inclusion of one of these field offices showed a further reduction in total distance traveled, albeit with a slight cost increase. Furthermore, setting a maximum tour duration estimate below 12.5 hours is feasible for constructing tour schedules and improves workload balance by approximately 20%. Doing so will provide the least exposure to overtime occurrences, which is supported by the results of the stochastic evaluation.

Examining the results for different numbers of open offices revealed that additional offices correlated positively with distance reduction but showed diminishing cost savings. Considering fixed office installation costs, the profitability of adding a third or fourth office may be questionable when keeping the current team structure. In scenarios where a cross-disciplinary team structure covers at least 60% of maintenance trips during the scheduled tours, simultaneous operation of all three field offices could lead to a substantial decrease in travel distances by approximately 50% (around 5,800 km) and a monthly cost reduction of 11% (around €450) in travel and operational expenses.

In conclusion, the MO-ALNS metaheuristic offers valuable insights into the complex interplay between location and routing issues. While conclusions can be drawn regarding team-office allocation, the tour schedules generated by each solution are not necessarily optimal. This is attributed to the vast solution space, inadequately specific operators for tour optimization, and insufficient runtime to obtain the true Pareto front. Nonetheless, this solution approach holds promise for application across different regions, providing Deutsche Bahn with a versatile tool to analyze strategies for managing train station operations and potential field office placements.

In addition to measurable factors, such as cost and time savings from reduced travel, the impact on employee well-being, particularly the reduced time spent sitting in vehicles, should be considered. Moreover, the implications for interconnected departments must be considered when employees and materials are outsourced to external offices.

PREFACE

Completing this master's thesis marks the end of an academic pursuit and the peak of a personal journey filled with growth, challenges, and cherished experiences. As I look back on the paths I have taken, I am reminded that this milestone represents more than just an accumulation of knowledge; it embodies the transformation of my character and the acquisition of invaluable life lessons. During my time in the Industrial Engineering and Management program at the University of Twente, I have been immersed in the complexity of industrial systems, organizational behavior, and strategic management. However, it is the connections developed and the resilience refined that have truly shaped my development.

This thesis is not only a product of research and analysis but a testament to the persistent support and encouragement of professors, peers, and loved ones. Their guidance has been a constant source of inspiration, propelling me forward even in the most challenging moments. In particular, I extend my deepest gratitude to Eduardo Lalla-Ruiz and Leo van der Wegen, whose insightful feedback and guidance have been invaluable throughout this journey. I would also like to express my sincere thanks to Danny Derbe, whose belief in my abilities from the moment we met gave me the confidence and motivation to tackle this project.

As I say goodbye to this academic chapter, I carry a profound sense of resilience, adaptability, and determination. The skills refined and the insights gained will certainly guide me as I explore the complexities of the professional world. I extend my genuine appreciation to all those who have played a part in this journey. As I embark on the next chapter of my life, I do so with a heart full of optimism and excitement for the adventures that lie ahead.

I hope you enjoy reading my thesis!

Maike Höner
March 2024

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1 INTRODUCTION

The first chapter of this research report provides essential background information about the company and describes the problem context, as well as the methodology employed to conduct this research. Section 1.1 introduces the company, while Section 1.2 provides a detailed description of the identified problem. Following this, Section 1.3 explains the research goal. Finally, Section 1.4 formulates the research questions, and Section 1.5 presents the research design.

1.1 Introduction of Deutsche Bahn

Deutsche Bahn AG (DB) is Germany's state-owned infrastructure and mobility service provider for freight and public transportation. Their subsidiary, DB Netze AG, owns the longest railway network in Europe with 33,400km (Statista, 2023). They oversee the transfer stations crucial for commercial transport, while DB Station&Service AG (DB S&S), another wholly owned subsidiary, manages most public transport train stations. DB envisions climate-friendly transportation and a sustainable transport system through their strategic initiative "Starke Schiene" (meaning 'strong rail' in English), aiming to create future-proof and livable cities (Deutsche Bahn AG, 2023). This initiative is integral to Germany's transition to greener transportation (Verkehrswende), a priority for the federal government. Promoting public transportation over private vehicles and prioritizing freight transportation on railways are vital strategies. DB's vision aligns with the United Nations' Sustainable Development Goals, facilitating Germany's compliance with European climate standards, including a commitment to total climate neutrality and the exclusive use of renewable energies (Mamedova, 2022). To incentivize the public to choose public transportation, enhancing its attractiveness and reliability is imperative. This involves not only optimizing train connections but also ensuring high-quality service at train stations.

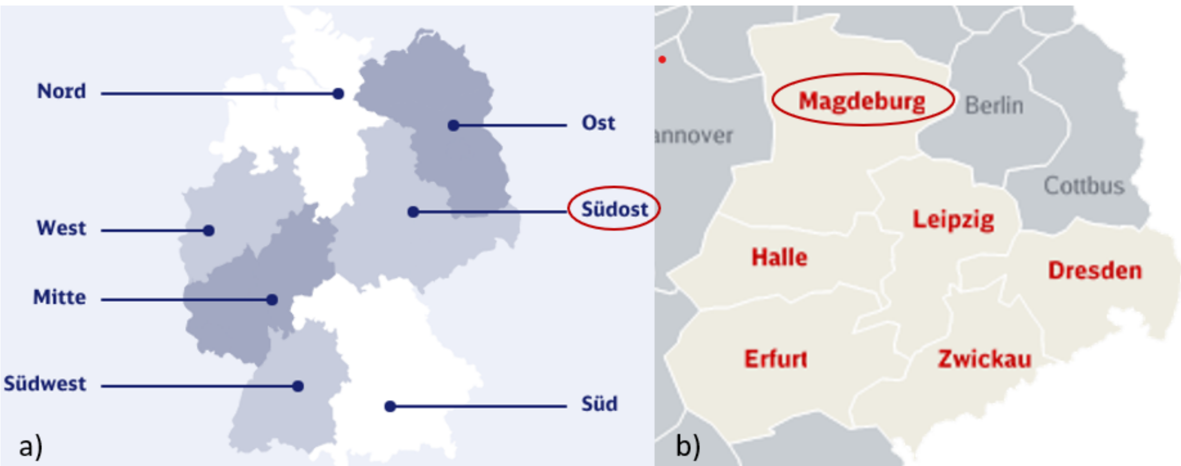

Figure 1.1: a) The Federal Republic of Germany divided into seven regions b) Region Southeast (Südost) divided into six subregions, which form each a train station management ©DB Station&Service

DB S&S is tasked with operating and maintaining the train stations for passenger transportation (DB Station&Service AG, 2023). They aim to offer a comfortable and secure experience of departures, transitions, and arrivals. This includes providing information through personnel at service points, signage, and posters as well as ensuring the physical facilities undergo regular inspection and maintenance. Within Germany, the DB S&S is divided into seven regions, each containing smaller subregions (see Figure 1.1), where they observe station operations (Janicki, 2016). The department responsible for managing the train station conditions within a subregion is known as train station management (TM). Stations of all sizes undergo routine inspections to address safety concerns, vandalism, graffiti, technical issues, and other forms of damage. Additionally, showcases are equipped with various information, including timetables and relevant updates.

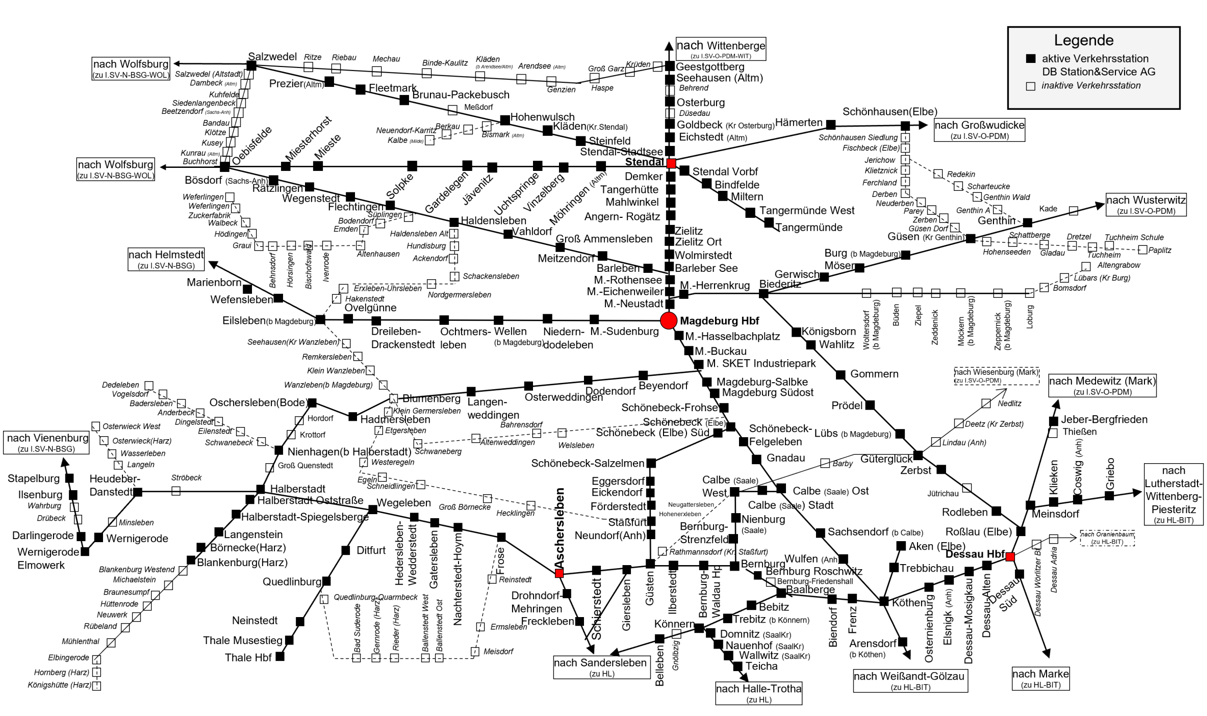

Figure 1.2: Station Network of Subregion Magdeburg in the Region South-East ©DB S&S

The project explored by this thesis has been launched by the leader of the TM in Magdeburg in the region South-East. They oversee an area of over 11,500 km^2, accounting for more than a quarter of the entire land area of the Netherlands. Their purview includes the management of 160 active and 38 inactive stations (SDB, 2023), as illustrated in Figure 1.2. Station inspectors and repairmen travel by car from the central office in Magdeburg to conduct inspections and maintenance across all stations. Inspectors adhere to prescribed tour schedules, where each tour must be completed within a specific time window, termed the validity period. The stations also have designated inspection frequencies, ranging from 2 to 12 weeks.

A tour is a sequence of stations that must be visited within the stipulated validity period. A schedule is a set of small periods or slots within a planning horizon, dictating when a tour should be concluded. Once a tour is allocated to a period in the schedule, it is routinely conducted during that timeframe. A baseline tour schedule was constructed for the inspectors, which gets adjusted on short notice based on immediate workload and pending tasks. The tours are not only assigned to a certain period but also to employees. Inspectors are tasked with examining technical features, eliminating minor damages, and reporting more significant damages at each station. Repair personnel subsequently receive directives to address the reported issues, operating on an on-demand basis.

1.2 Problem description

Based on a couple of observations, a need to reassess the operational procedures of station supervision arose. Firstly, it was noted that many trips were being duplicated, with separate teams conducting inspections and repairs. This practice stems from inspection crews following designated routes to assess quality and safety while documenting any deficiencies encountered. Subsequently, the repair team responds to reported issues at the respective stations. Given the prevalent incidents of vandalism at train stations (Bahnblogstelle, 2023), inspectors frequently report damages of varying severity.

Consequently, the repair teams often traverse similar routes to those previously covered by the inspection teams. Moreover, addressing particular repair tasks at distant outlying stations requires extensive travel. In urgent cases, these trips cannot be delayed until other tasks closer to that station arise. Additionally, many employees do not live in the surrounding area of the starting point in Magdeburg. They travel far to reach the main office, only to commence tours that might be in the surroundings of their private residences. DB S&S possesses several facilities in other locations within the region that could serve as field offices, mitigating the need for extensive travel and associated costs and carbon emissions. Notably, carbon emissions are of concern in the first place, given the reliance on combustion engine vehicles within the fleet.

Furthermore, the current manual construction of the baseline tour schedule for TM Magdeburg relies on estimations without a defined strategy. This leads to considerable variation in the number of stations covered per tour, which lacks a discernible underlying logic. While accounting for differing station sizes is essential, a closer examination reveals that the tours have been primarily structured based on the geographical layout of the train routes.

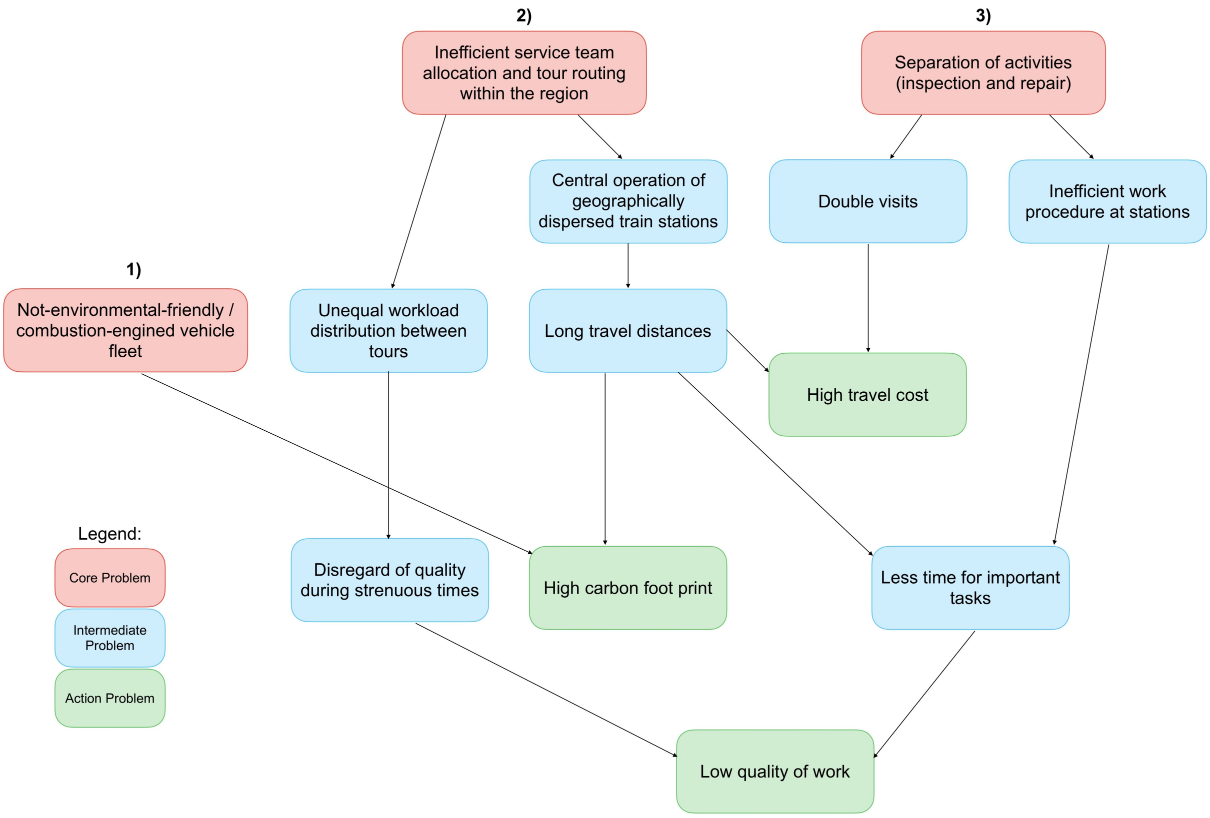

Figure 1.3: Problem cluster for DB S&S

The TM Magdeburg team is considering a strategic, operational shift based on identified issues such as lengthy travel distances, redundant visits, lack of station-to-tour allocation logic, and uneven workload distribution. To visualize the connections between the problems in a structured way, the issues are organized in a problem cluster, shown in Figure 1.3. This project focuses on the action problems at the end of the causal chain, highlighted in green. High travel costs, the concern about CO_2 emissions, and a decline in work quality stem from several core problems, as displayed in red. The intermediary blue boxes outline the causal chain, providing a comprehensive understanding of the TM Magdeburg scenario. Each core problem is elaborated on:

1. The use of a combustion-engine vehicle fleet, rather than one powered by eco-friendly energy sources, primarily contributes to carbon footprint significantly. However, since this issue directly leads to only one action problem, it is not the primary focus. Moreover, transitioning to electric vehicles and establishing battery-charging stations primarily depends on budget considerations. Factors such as limited battery capacity and extended charging times may not align with other efficiency-related goals.
2. The next core problem concerns the inefficiency of tour routing logic. The absence of a systematic approach to tour construction and reliance on a single starting point results in extensive travel distances to remote stations. The lack of balance in tour plans regarding station coverage hinders short-term planning flexibility. It creates an irregular work environment, which causes a neglection of quality during busy times.
3. Lastly, the practice of separating inspection and maintenance tasks leads to duplicated efforts and redundant station visits. Specifically, inspectors invest time in documenting damages, only for a separate repair team to subsequently travel to the station for rectification.

The third core problem can be mitigated by merging inspection and maintenance into teams of two, each possessing cross-disciplinary expertise. This approach would accelerate inspections, enable immediate basic maintenance, save time on damage reporting, and ensure a second person is on-site for assistance. Consequently, most issues can be addressed immediately, obviating the need for a subsequent station visit. This combined touring approach would be implemented Monday to Thursday, reserving Fridays for special maintenance. In cases where large damages necessitate specific materials or tools, it would be duly reported and scheduled for handling during available time slots.

The project owner (responsible for TM Magdeburg) has endorsed the proposed team configuration and workday arrangement upon request. While it may not align with every TM's preference due to considerations of flexibility or staffing constraints, the subsequent section will define the project's scope and limits.

Hence, the core problem of this project is defined as follows:

"Inefficient office allocation and tour routing within the region."

1.3 Research goal

The DB S&S train station supervision department in Magdeburg wants to improve its operating strategy, focusing on planning inspection and repair tours by installing field offices. Therefore, this research aims to develop an optimization approach for decision support that encompasses determining tour starting points from potential field offices, allocating service teams to offices, assigning stations to teams, and optimizing tour routes based on available resources and service frequencies. Additionally, it aims to ensure a balanced workload for employees. While retaining the original starting point with at least one team, using field offices is optional and can be utilized by one or more teams. This optimization approach will be applied to one region at a time but will be adaptable to all DB S&S management regions. Therefore, the research goal is formulated as follows:

"Design an optimization approach that locates service teams to field offices, assigns the train stations to the teams respectively, and provides a periodic tour schedule."

Given the complexity of location and routing problems and the time constraints of a master thesis, it is imperative to define the study's scope and limitations:

Scope:

- Selecting regional field offices and constructing a new routing plan aligned with the resources and periodic schedule.
- Conducting a historical data analysis for comparison with the current situation.
- Designing a model applicable in different regions, serving as a foundation for a nationwide rollout.
- Assuming homogeneity in cross-disciplinary teams as a management decision does not limit the results if a TM decides against such a team structure.
- Adopting a four-day week for the tour schedule to allow flexibility for the schedule and the short-term planning.

Limitations:

- Excluding short-notice adjustments of the tour schedule from the research.
- Relying on available data that documents the system's performance, such as driver's logbooks since April 2021, the train station database (TSD), and the digital excellence platform documenting the completed tasks at the train stations. Some TSD information may require manual verification, updating, or supplementation.
- Omitting the consideration of vehicle equipment and employee qualification requirements since these will be considered prerequisites for implementing the newly developed structure. With homogenous teams, the vehicle fleet is also anticipated to be homogeneous.

1.4 Research questions

The goal of this research is to answer the main research question. The goal will be reached by systematically obtaining information to answer the sub-research questions. The main research question is formulated as follows:

"How can a solution approach be designed to locate service teams to field offices, assign the train stations to the teams respectively, and provide a periodic tour schedule?"

The following sub-research questions have been defined to solve the core problem and answer the main research question. The first part concentrates on the current situation at DB Service&Station. The problem context, including the requirements, assumptions, and limitations, is investigated hereby.

1. How does DB S&S currently operate its tour routing?

- Which logic/methods are applied for the tour schedule?
- What are the most relevant key performance indicators (KPIs) for measuring the efficiency of the routing schedule?
- How well does the current method perform according to certain KPIs?
- What are the circumstances and constraints given by DB S&S concerning the restructuring of their operating strategy?

Afterward, the literature is studied for existing information and solution approaches that could be useful for this problem. The methodology that seems to be fitting must be analyzed in greater detail to obtain an explicit overview and baseline for further decisions.

2. In the literature, what solution approaches are suggested to solve the problem?

- What literature is available about methods to solve the problem of DB S&S?
- What are the differences between the researched methods?
- Which methodology is most suitable for the problem?

With the gained knowledge about the potential models, the problem-specific details need to be addressed. This will be processed in the third step of the research.

3. What should the design of the solution approach look like?

- What are the requirements and assumptions to be considered in the model?
- What input data is needed?
- What is the expected output?

When the solution approach is developed, it must be validated and tested for accuracy. Since the company is looking for a concept that is applicable to all regions of Germany, the translation to other scenarios must be tested.

4. How does the solution approach perform for the experiments and compared to the current situation?

- Which experimental setups and scenarios should be considered?
- Is the model valid and generally applicable to different regions?
- How does the developed approach perform for different DB S&S train station management regions?

Lastly, the research needs to be interpreted and finalized with conclusions and recommendations for the routing operations at DB S&S.

5. What can be concluded and recommended following the observations of the result analysis?

- Which advantages and disadvantages are implicated by the solution approach?
- Which recommendations and conclusions can be formulated for DB S&S?
- Which aspects could be included in further research?

1.5 Research design

The research will be divided into multiple sections framing the design concept. Step by step, the sub-research questions and, eventually, the main research question will be answered. The stages are constructed as follows:

- Problem identification and analysis
- Solution generation
- Solution experimentation and model validation
- Evaluation, implementation, and interpretation

Including the required input and the necessary output, the phases of the research design are schematically displayed in Figure 1.4.

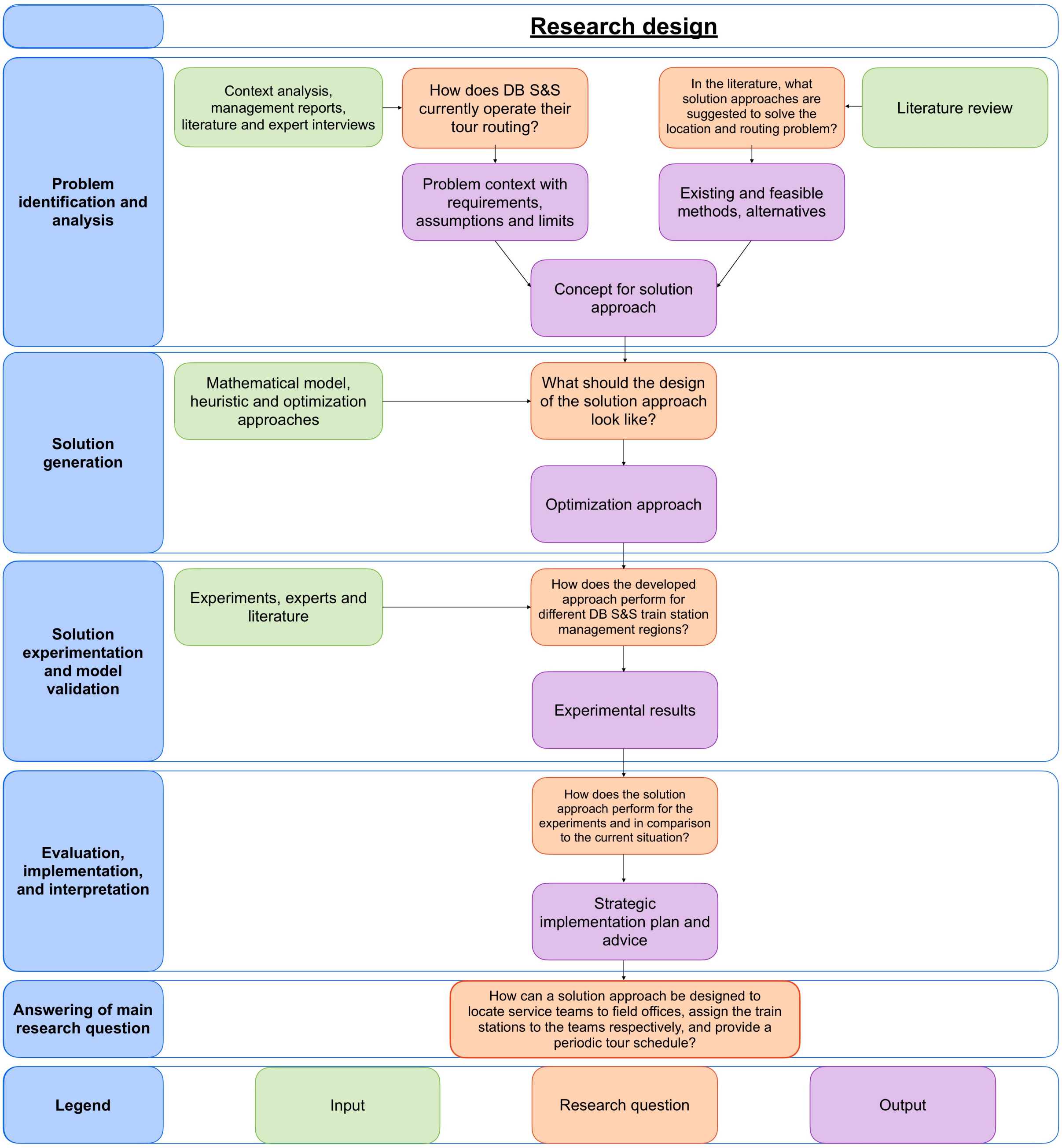

Figure 1.4: Graphical representation of the research design for the problem of DB S&S

2 CONTEXT ANALYSIS

This chapter presents a comprehensive context overview and addresses the first research question: How does DB S&S currently manage its tour routing? Within the domain of train station management (TM), roles overseeing station supervision encompass the leader, coordinating and administrative staff, assistants, station inspectors, and repair personnel.

The latter two, crucial for on-site tasks, have tours scheduled as outlined in Section 2.1. Section 2.2 provides an overview of relevant KPIs, while Section 2.3 focuses on parameter estimations for these indicators. The analysis of the current tour schedule results is presented in Section 2.4, and Section 2.5 outlines considerations for the proposed change in operational strategy.

2.1 Tour scheduling

The employees are assigned specific tours that they need to complete. A tour is a sequence of train station visits where designated tasks are carried out. Inspection and repair teams travel to stations by car, transporting necessary tools and materials. The vehicle fleet is stationed at the main office within each subregion, serving as the starting point for every tour. These vehicles are equipped with all the tools and materials required for the job. The supervisor manually plans the work schedules for inspectors and repair personnel. Here, we have three different types of scheduling.

Inspection baseline schedule:

The baseline schedule for the safety inspection is constructed with tours based on past inspections and the mandated check-up frequencies, ensuring they occur within the corresponding validity periods. The tours mainly comprise the train routes connecting these stations despite their far distances to travel.

The task of safety inspection covers all safety aspects on platforms, walkways, and station buildings, including checking for missing or illegible safety signs, broken showcases, or any irregularities in platform surfaces or edges. Any potential direct dangers or malfunctions must be identified and addressed. If immediate resolution is not possible, temporary fixes or warnings must be implemented, and a request for reinstatement work should be filed. Additionally, unauthorized graffiti or stickers must be removed or obscured. This is the most critical task, with prioritizing total safety, especially during staff shortages. While theoretically, almost any TM employee can perform this task, it primarily falls to station inspectors and, secondarily, craftsmen. Each inspector is assigned specific tours, fostering continuity in station service and allowing employees to be familiar with their designated area. This territorial expertise facilitates an efficient work routine, a key aspect to uphold.

Maintenance schedule:

The repair personnel's schedule is determined based on registered orders. This task includes addressing damages such as graffiti, damaged trash cans, signs, or dodger shelters. Urgent or general reinstatement work is primarily the responsibility of repair personnel, provided it is within their capability. Such tasks are conducted on-demand following reported damages, which can be identified by inspectors or observers like passengers, fellow DB employees, or the police. If specialized tools or skills are required, or if outsourcing proves more economical, the task may be delegated to a suitable company. Some tasks, for instance, those necessitating a ladder, also require the presence of two individuals for mutual safety. Non-urgent tasks are postponed until they can be incorporated into a comprehensive tour, preventing unnecessary travel time. Downtime is utilized for preventative maintenance or facility restoration.

Short-term planning:

Lastly, the planning team refines the inspection baseline schedule on a weekly and daily basis and tasks the repair personnel with upcoming tasks besides their planned reinstatement work. Ad-hoc tasks like placing posters in showcases or reviewing the work of cleaning and gardening companies may be added to the tour schedules of inspection and repair personnel when feasible. Also, if an inspection tour from the previous day was not completed, it must be finished within the designated time frame. In cases of employee absence due to vacation or illness, priority is given to safety inspections to meet regulatory deadlines and address urgent safety repairs. Only essential work is undertaken to achieve this. A missed inspection could result in station closure, which has never occurred. In extreme circumstances, the head of train station supervision, a qualified colleague, or even a neighboring TM may step in to complete the inspection. While safety inspections are the main focus for inspectors, repair personnel primarily handle reinstatement work. However, both roles are qualified for almost all types of work.

2.2 Key Performance Indicators

The documentation and measurement of the system's performance lack comprehensiveness. The primary emphasis is completing prioritized tasks within specified deadlines or according to urgency. Challenges arise from an exceptionally high number of absent employees due to sickness or vacation, hindering the execution of planned tours. The tour-planning team prioritizes safety and meeting quality-check deadlines above all else. All available resources, including the planning team, will be mobilized if required. Many employees are qualified to serve as train station inspectors, providing a contingency to prevent closures. Notably, the number of late inspections is not a valuable indicator for this research, which focuses solely on baseline scheduling rather than short-term adjustments. The focus remains on analyzing travel distances and the associated cost savings from reduced fuel consumption, alongside consideration of potential costs for field offices.

Travel distance:

In the vehicle, a logbook records the distance traveled daily and monthly. The distance traveled can be used as an indicator and measured in kilometers. While this data includes all distances traveled, not just originally scheduled routes, it complicates direct historical comparisons. Estimating travel distances will yield more accurate values for direct comparison.

Cost:

Operating from the main office in Magdeburg incurs no additional costs. However, for potential field offices, it is essential to account for fixed and operational expenses associated with employee placement. Fixed costs include necessary furniture and materials for the new offices. Operational costs pertain to leased equipment such as printer systems and Wi-Fi access. Material like sanitary articles, which are universally required regardless of the team's location, are not factored into the cost assessments.

To standardize Key Performance Indicators (KPIs), the travel distance can be translated into gas and wear cost based on the average mileage and prevailing gas price. According to TradingEconomics (2023), the diesel price in Germany is projected to rise to approximately 2.30$ in the first half of 2024. Since 2024 is the earliest time this project could be implemented, we decided to use the forecasted diesel price for further calculations. In Euros, the gas price will be around €2.15. For instance, assuming the cars consume about 9 Liters of gas per 100km, and the projected gas (diesel) price is €2.15 per liter, the cost per kilometer driven is:

$$\frac{9L}{100km} \cdot \frac{2.15€}{L} = 0.194\frac{€}{L}$$

Including some value for wear and tear of a car, the cost can be rounded up to 0.35€/km. This aligns with Germany's general kilometer allowance, which is up to 0.38€/km (Deutscher Bundestag, 2022). These traveling costs also need to be considered for the repair team since they gain the same decrease in travel distance when placed in a field office. In summary, cost is the most relevant KPI, categorized into three components:

- Travelling cost: €0.25 per km driven
- Operational cost: €500 per month per field office (when in use)
- Fixed cost: €1,000 one-time payment for field office installation

Workload balance:

Another crucial factor is workload balance. Ensuring each service team operates at approximately equal capacity necessitates measuring equity in tour scheduling. While estimating service time and assigning stations to teams accordingly helps balance workload, it overlooks potential disparities in travel distances to reach these stations. Consequently, considering expected service times at stations and anticipated travel times associated with assigned tours, the total tour time offers a more effective indicator for balancing the baseline schedule. The difference between the maximal and minimal total tour times is calculated to measure the work balance. While in the case of optimization, minimizing the maximal tour time would also encourage the reduction of the travel time, this measure is more universal. Since the maximal tour time can differentiate with different numbers of teams and stations by much, it is unclear when the workload balance is good (enough).

2.3 Estimation of parameter

Measures need to be gathered and estimated to make the KPIs tangible and comparable. It is important to acknowledge that travel time and service duration are subject to uncertainty. While stochastic variations are primarily relevant for short-term planning, accurate service and travel time estimations are essential for a realistic approach to the problem. This section outlines the methodology for deriving these estimations.

2.3.1 Travel distance

We need to know the distances between the train stations to calculate the total distance covered during a tour or the entire planning horizon. With 198 locations, this translates to 39,204 entries in a distance matrix. While tools like Google Maps or other navigation systems can provide precise point-to-point distances, it is hindering that Google's Distance Matrix API has a daily request limitation of 2,500 daily requests (Google, 2023). Generating the distance matrix for TM Magdeburg alone would take approximately 15.7 days. Therefore, we explored estimations of travel distances.

We calculated straight-line distances using the coordinates (longitude and latitude) provided by the train station database. We employed the Haversine formula to account for the Earth's curvature, a method widely recognized for determining great circle distances (Ballou, Rahardja, Sakai, 2002). This formula is represented as follows:

$$D_{A-B} = 6378\{arccos(sin\ LAT_A *\ sin\ LAT_B \\ +\ cos\ LAT_A *\ cos\ LAT_B * cos\ |LONG_A - LONG_B\ |)\}$$

Here D_{A-B} denotes the great circle distance between the points A and B, 6378 (km) is the radius of the earth, and LAT and LONG represent the latitude and longitude coordinates of the point in the subscript in radians (Ballou et al., 2002).

While the straight-line distance offers an initial measure, it does not directly represent the actual road distance. Further adjustments are needed. Ballou et al. (2002) introduced circuit factors (a ratio of the straight-line distance to the actual road distance) to approach a more realistic distance value. As the straight line represents the shortest distance between two points, the factor must be greater than 1. Their research led to a circuit factor of 1.32 for Germany.

$$TD_{AB} \approx D_{A-B} * 1.32$$

Where TD_{AB} is the travel distance on the actual road, D_{A-B} is the straight-line distance as calculated above, and 1.32 is the chosen circuit factor.

We followed a similar procedure, calculating circuit factors for a sample of distances between stations. The average circuit factor was 1.33, with a standard deviation of 0.11. We also conducted a regression analysis. The regression coefficients enabled the construction of a linear regression equation with a y-intercept of 2.439 and a variable coefficient of 1.261:

$$RegTD_{AB} = 2.439 + 1.261 * D_{A-B}$$

Subsequently, we assessed the accuracy of travel distance estimation using measures like Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The results are displayed in Table 2.1.

Table 2.1: Measures of accuracy of travel distance estimation

	Regression	***Circuit factor***
MSE	17.996	19.169
MAPE	6.9%	6.7%
MAD	-5.62E-16	-7.31E-03

It is evident from the results that the circuit factor formula, with a MAPE of 6.7%, provides a reliable estimation of road distances compared to the regression approach (MAPE of 6.9%). Both methods' MSE values are close, demonstrating their comparable accuracy. Additionally, the MAD values, though small, indicate minimal discrepancies. Importantly, the circuit factor represents a more universal method since the regression analysis is based on real data specific to our context. Given its remarkably close performance to the regression approach, the circuit factor is a highly practical and efficient tool for estimating road distances.

The approach presented by Berens and Körling (1985) further supports this conclusion. Years prior, they conducted a similar study, proposing a formula incorporating additional factors (up to three) for various geographical conditions, such as terrain and road system development. While their primary focus was U.S. roads, they also applied their model to the German road system. However, they found only marginal improvements in accuracy compared to using a single factor. Moreover, their results corroborated the effectiveness of the factor 1.32. Even though some areas might be more rural, urban, or mountainous, the effort to determine additional factors outweighs its effect. Given that Germany does not exhibit extraordinary geographical circumstances or an irregular road system, we can confidently affirm the appropriateness of using the circuit factor 1.32 to estimate road distance from a straight-line distance.

2.3.2 Travel time

The travel time varies based on the traffic conditions. Most vehicles in the Magdeburg fleet display an average speed that was driven. These velocities lay around 50 km/h. This implies that a driver requires approximately 1.2 minutes for each kilometer. We collected travel distance data and estimated travel times using a routing application like Google Maps for 100 trips to validate this. Dividing travel time by distance yielded a ratio denoting speed in minutes per kilometer, termed the speed factor (SF). The relationship between travel speed (in min/km) and travel distance (km) is illustrated in Figure 2.1.

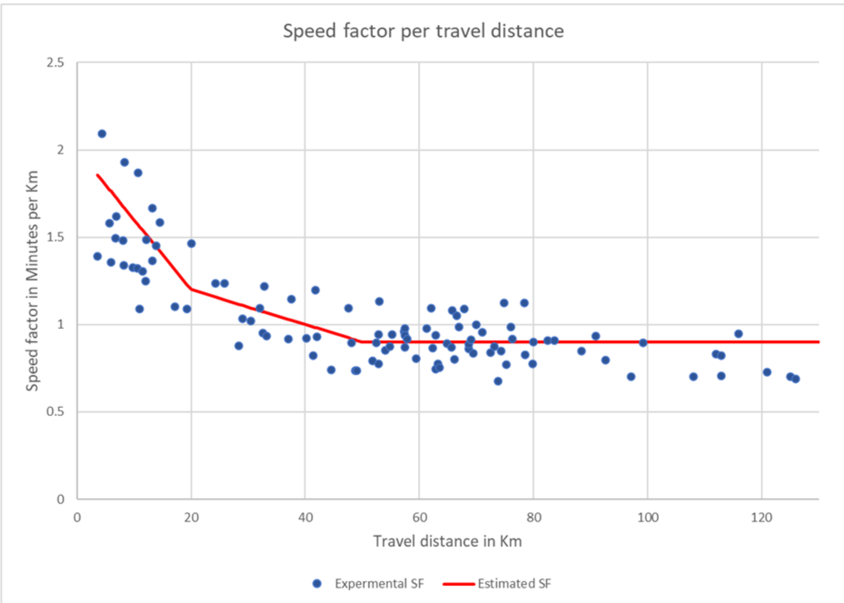

Figure 2.1: Experimental and estimated speed factors based on area of TM Magdeburg

From our data, we derived an average speed of 1.03 min/km across all distances. This average is also reflected in the range of 20km to 50km, with a mean of 0.99. For longer distances (>50km), the average speed drops to 0.88 min/km. This discrepancy is attributed to the use of country roads and highways, where speed limits are considerably higher (mostly >70km/h) compared to urban and village areas (≤ 50 km/h). Such longer distances typically occur when an employee travels to or from a remote station. For distances below 20km, the speed factor consistently exceeds 1 min/km, with the ratio increasing as distance decreases. This is due to employees frequently covering shorter distances between stations, resulting in the car screen's average speed displaying below 60km/h (≙ 1 min/km).

To estimate the travel time (TT) we introduced a speed factor (SF) based on the travel distance (TD):

$$SF_{AB} = \begin{cases} 2 - 0.04 * TD_{AB}, & \text{for } 0 \leq TD_{AB} < 20 \\ 1.4 - 0.01 * TD_{AB}, & \text{for } 20 \leq TD_{AB} < 50 \\ 0.9, & \text{for } TD_{AB} \geq 50 \end{cases}$$

Here, SF_{AB} and TD_{AB} represent the speed factor and travel distance for the journey from point A to B, respectively. This function is defined by the red line in Figure 2.1. For distances less than 20km, between 20km and 40km, and between 40km and 60km, the speed factor is defined by three linear functions depending on travel distance. For TD ≥ 50km, SF is a constant numerical factor with a value of 0.9.

Table 2.2: Accuracy measures of sped factor estimation

	SF
MSE	0.027
MAPE	-8.2%
MAD	-4.4E-02

Analyzing the accuracy measures (see Table 2.2), we observe low MSE and MAD values, indicating that the estimation closely aligns with the actual data mean. The MAPE is approximately 17%, signifying that, on average, the estimation deviates about 17% from the actual mean. Given the fluctuating nature of traffic flow and employee driving speeds between stations, we conclude that the derived speed factor function is an effective estimator for converting travel distance into travel time.

As employees are required to park and reverse their cars at each station, an additional 3 minutes will be incorporated for each trip. Therefore, the following piece-wise-defined function will be employed to estimate travel time in minutes.

$$\begin{aligned} TT_{AB} &= 3 + SF_{AB} * TD_{AB} \\ &= \begin{cases} 3 + (2 - 0.04 * TD_{AB}) * TD_{AB}, & \text{for } 0_{AB} < 20 \\ 3 + (1.4 - 0.01 * TD_{AB}) * TD_{AB}, & \text{for } 20 \leq TD_{AB} < 50 \\ 3 + 0.9 * TD_{AB}, & \text{for } TD_{AB} \geq 50 \end{cases} \end{aligned}$$

2.3.3 Train station characteristics

The first intention to estimate the service time at each station was to assume that the "bigger" the station, the more time needed to execute the safety inspection. However, interviewing employees about this presumption manifested that, to some extent, it may be applicable, but it is not that simple. Therefore, here the train station classifications with their limits are investigated, especially since they also play an important role in the inspection frequencies.

DB AG employs a detailed classification system to gauge the scale or significance of a station (Janicki, 2016). Stations are broadly categorized into active and inactive. Active stations are those regularly serviced with scheduled train stops, requiring a quality and safety check every four weeks. On the other hand, inactive stations have no regular scheduled train stops and consequently require inspections at longer intervals, specifically every twelve weeks. Regardless of classification, both types have a maximum five-day time frame for inspection completion.

Table 2.3: Distribution of train station categories in TM Magdeburg

	Category	Frequency
inactive:	0	38
active:	1	0
	2	1
	3	5
	4	6
	5	20
	6	79
	7	50
Total:		198

Active stations are further graded based on their importance, ranging from classes 1 to 7, as detailed in the specialized DB publication by Janicki (2016). These classes are determined by weighted criteria such as platform edge count and length, daily passenger and train stop volume, as well as provisions for disabled access (DB Station&Service AG, 2021). Class 1 stations hold the highest importance, offering top-tier services, often acting as hubs for numerous long-distance train connections. Generally, it is observed that as importance and size increase, the class numbers ascend to class 7. Class 7 stations serve the fewest passengers and are predominantly in remote rural areas. They see such infrequent use that upgrading accessibility may not be deemed necessary. The most common classification is class 6, typically found in sparsely populated rural regions, providing fundamental services for public railway transportation. Table 2.3 presents the distribution of stations across these categories, while inactive stations are designated as category 0 for simplicity and clear attribution.

Additionally, some stations have not been updated to accommodate the longer trains introduced over the years. As a makeshift solution, platforms were extended, with markers indicating the minimal safety distance to the platform edge. However, these markers are exposed to natural elements. To ensure continuous safety with visible barrier lines, these stations require more frequent checks every two weeks. TM Magdeburg oversees six such stations, classified under either category 6 or 7.

Active, inactive, and special attention classifications play a crucial role in determining inspection frequency. The classification scale offers insights into the time and effort required for inspections. The lower the class (excluding 0), the more comprehensive the service, and the greater the number of elements to be assessed. Given that most stations fall into higher classes (6 or 7), which offer basic services, workload estimation needs to be extended.

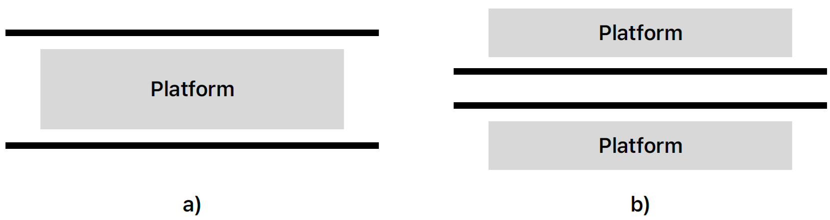

Figure 2.2: Platform variations a) intermediate platform b) side-boarding platform

However, these classifications are not decisive enough for the service time estimation at each station. The foundational work for the baseline schedule centers on safety inspections, involving thoroughly examining every platform edge and other elements on the platform. This task is one of the job's most time-consuming yet predictable aspects. Consequently, the number of departure platforms should be considered when estimating workload. For instance, a station with two tracks for train stops and passenger boarding/disembarking presents two potential layouts (as depicted in Figure 2.2, Janicki, 2016). In scenario a), the platform is placed between the train tracks, allowing the inspector to traverse one side and return on the other, all while assessing the edges. In scenario b), two platforms accommodate an equal number of train tracks. Here, the inspector walks along an edge for examination and back, doubling the time required for walking. This aspect will be factored into workload and service time estimations. Furthermore, more distance to walk occurs when the inspection of an entry building is included, which can also not be deduced by the classification.

2.3.4 Service time

We consider various station characteristics to estimate the service time (ST). As outlined in the previous subsection, relying solely on classification yields inadequate estimates. Therefore, we incorporate the following attributes to model task times exclusively for active stations. Inactive stations receive a fixed service time of 15 minutes.

- Station classification
- Number of platforms
- Number of elevators
- Entry building (yes: 1 or no: 0)

Platforms are a useful factor as they house similar equipment requiring inspection and maintenance. Apart from walking along the edge, platforms entail additional checks for items like trashcans, showcases, weather protection shelters, and grit containers for vandalism, safety, cleanliness, or functionality. Tasks such as hanging up train schedules in showcases may also be required. Based on estimations provided by the leader of train station supervision, the total time for platform-related tasks is approximately 20 minutes per platform.

The number of elevators serves as an indicator of other technical equipment, such as digital timetables or train indicator boards. This entails ensuring the functionality of technical devices and emergency buttons in the elevators, a task estimated to take 15 minutes per elevator.

DB S&S typically does not own many entry buildings due to economic reasons; private owners operate most. However, at six stations managed by TM Magdeburg, overseeing the safety and quality of entry buildings is within their purview, necessitating extra time. This task is assigned 20 minutes per entry building.

Considering these characteristics, we estimate the working time for predictable tasks. The station classification enables a more precise assessment of station size. Although vandalism does not necessarily increase with station size, larger stations have longer walkways, more areas where small debris may need to be addressed, and higher foot traffic, which can impact work efficiency.

Each station will get an additional 20 minutes multiplied by its reverse classification. With reverse classification, it means that the classification number increases with the size of a station so that 7 denotes the largest station type and 1 represents the smallest. However, to express this mathematically, the classifications for active stations need to be reversed. Therefore, the classification is manipulated by the following expression: $(7 - classification_{i+1})$ for station i. As a result, larger stations with typically lower classification numbers receive the highest additional time. This adjustment accounts for inspectors' challenges due to the station's size. Therefore, the service time for station i is estimated as follows:

If $classification_i = 0$ then $ST_i = 15$.

Else,

$$ST_i = 20 + (7 - classification_{i+1})^2 + 18 * numPlatforms_i \\ + 8 * numElevators_i + 20 * entryBuilding_i$$

While this formula estimates the time spent at a station, it does not account for unusual extreme circumstances. Additionally, the estimated times may exceed the actual times in cases where damage surveys are not needed.

2.3.5 Stochasticity

Each phase of the employees' tasks is subject to varying degrees of uncertainty. This includes unpredictable factors such as travel durations between points and the time required to complete tasks at the stations.

Travel Time: Factors like rush hour, construction, and accidents significantly influence travel time. Even with a predetermined route, anticipating rush hour traffic remains challenging, as service times at stations are also unpredictable. However, it is possible to model an estimated travel time based on the corresponding travel distance, which is most relevant for constructing the baseline schedule.

Service Time: The time spent on tasks at the stations also fluctuates. Inspectors may encounter varying documentation needs or engage in minor tasks like updating timetables for altered departure times. Conversely, there may be instances where no issues require attention, allowing for swift completion. Similar irregularities apply to maintenance teams, who may find tasks larger or smaller than anticipated upon arrival. Consequently, tour schedules are adjusted accordingly in both scenarios.

Acts of vandalism are not contingent on station size. Smaller rural stations may be targeted by young individuals seeking an uninhibited environment. Meanwhile, larger stations may witness groups passing through, some of whom may be predisposed to disruptive behavior, like football fans leaving club stickers or venting frustration on showcases. However, larger stations are more public-facing and undergo more frequent restoration efforts to maintain high standards. As a result, an estimation of service time is determined by the classification and the specific physical attributes overseen by DB S&S.

2.4 Analysis of current tour schedule

The current tour schedule comprises 33 individual tours conducted by six station inspectors. From these six inspectors, one inspector is employed with reduced hours (by 25%), and another one is also dedicated to executing reinstatement work. Tours 1 to 28 occur on a four-week cycle, with some including one or two inactive stations that are only visited based on their respective frequencies. Tours 26 to 28 cover the three central stations; each assigned its own tour. Tours 29 to 34 solely consist of inactive stations and are conducted every twelve weeks. We estimated the travel time per tour based on the distance traveled, assuming each tour is completed without interruption. Additionally, understanding the time spent at each station is crucial for accurately estimating the tour duration. To this end, we derived an estimate of the service time by considering the station's classification and other specific information, such as the number of platforms and elevators to be inspected, as well as whether the entry building falls under the responsibility of DB S&S.

Figure 2.3: Travel time and service time per tour in TM Magdeburg (minimum and maximum of tours 1 to 25 are marked)

Figure 2.3 illustrates the estimated travel and service times for each tour outlined in the baseline schedule for TM Magdeburg. Excluding tours 26 to 33, we observe differences in travel time and service time of up to 5 hours and 12.5 hours, respectively. Tour 28, centered around the main station in Magdeburg (where the current office is located), necessitates no additional travel time. Inactive stations, requiring minimal servicing, are allotted a flat-rate time of 15 minutes.

Figure 2.4 provides an overview of the total time estimates for each tour in TM Magdeburg. Notably, these estimates exhibit significant variations across the tours, ranging from 7.5 hours for Tour 18 to over 15 hours for Tour 10. While major shifts in traffic volume or tasks may lead to longer total times, these estimates underscore the imbalanced nature of the tour structure. Especially considering the reduced hourly capacity by the inspector covering tours 1 to 3, this results in an estimate that would exceed three days. This gives little space for short-term adjustment and increases the pressure on the employee to finish the tour, leading to rushed work with low quality and doing what is absolutely necessary.

Combining the travel time, service time, and total time for all tours, we arrive at the following estimates:

- Total travel + service time: 322 hours
- Total travel time: 95 hours (30%)
- Total service time: 227 hours (70%)

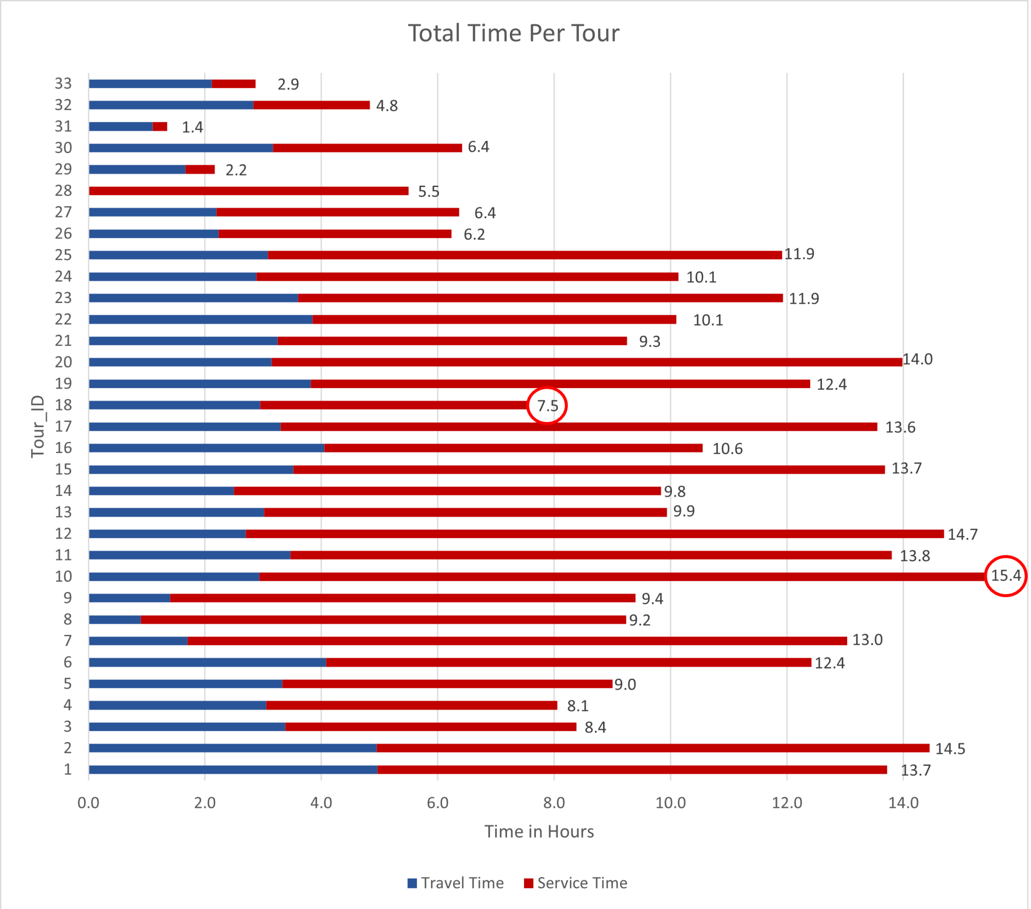

Figure 2.4: Total time estimation per Tour in TM Magdeburg (minimum and maximum of tours 1 to 25 are marked)

Considering a standard work week of eight hours per day, one full day is reserved for special tasks and meetings. Additionally, 25% of the daily hours are dedicated to material preparation, paperwork handling, and documentation. Thus, within a four-week period ($4\frac{\text{weeks}}{\text{horizon}} \cdot 4\frac{\text{days}}{\text{week}} \cdot 6\frac{\text{hours}}{\text{day}} = 96\frac{\text{hours}}{\text{horizon}}$), each inspector has approximately 96 hours available for actual travel and station service (72 hours with 25% reduced work hours). Looking at the distribution of total tour times among the inspectors in TM Magdeburg showed that each employee that is only designated for the safety inspection has tours assigned that fulfill about 59%-67% of their available time. This indicates that the distribution between employees is relatively fair and that the estimated durations leave considerable flexibility and spare time for short-term planning. Furthermore, the hourly capacity of an employee must be considered to maintain a fair working environment. Concluding the analysis of the current tour schedule, the values of the KPI measures are displayed in Table 2.4.

Table 2.4: KPIs of current Tour schedule

KPI	Current value
Total travel distance	4,500 km
Total cost	2,250 €
Max. tour duration	925 min

2.5 Consideration of adjusted operation strategy

This section explains the considerations made to make the change in operation strategy feasible and as realistic as possible.

2.5.1 Office location

Currently, the main office in Magdeburg serves as the central hub for all operations within the subregion. However, given its relatively distant location from certain stations, there is a notable expenditure of time and fuel when employees travel to stations further away. To mitigate this, the concept of establishing field offices has been proposed. The DB company already possesses suitable buildings at various train stations, making the implementation of offices and storage units a straightforward process. Specifically, in the TM Magdeburg region, DB holds properties at the Dessau, Stendal, and Aschersleben stations. While Magdeburg must remain designated as the main office, the other three locations can be utilized as field offices. This implies that, for the purposes of this thesis, at least one inspector or inspection team must be stationed at the main office in Magdeburg. Similarly, for any additional location to function as an office, it must accommodate at least one inspector or inspection team. To ensure that employees do not drive to a field office that is even further away from their private stay, each team has a set of possible offices that they can be located at.

2.5.2 Applying the cross-disciplinary team structure

Adopting the combined team structure or not, reducing tour distances due to installing field offices has a positive effect on each case. When the repair personnel are located in a decentralized manner, they also experience shorter travels to outside laying stations. This can be already captured by accounting for twice the distance when calculating the travel cost in the monetary objective.

The effect will be more noticeable when the new team structure is applied. This results in the reduction of double tours of inspection and repair separately and can improve the work routine at the station by saving documentation time and assisting one another. As the aphorism ”time is money” indicates, time has a value that can be used to make a profit. Therefore, not wasting time driving and documenting, using it instead for completing tasks and more qualitative work, can be worth the money. However, since this system is just theoretically developed, there is no indication of how big of an effect it has. Therefore, this aspect remains for the solution interpretation and recommendations.

TM Magdeburg currently employs six individuals for the inspection tours and has three employees exclusively for maintenance duties. They aim to implement the combined team structure consisting of four teams and one additional reserve employee. To facilitate this transition, the development of the baseline schedule for Magdeburg, irrespective of the team configuration, accommodates four inspectors or service teams.

2.5.3 Comparison of tour estimates to reality

The estimates applied to the current tour schedule in Section 2.4 are helpful for directly comparing with the newly developed tour schedule resulting from the solution approach. However, looking at the drivers’ logbooks reveals the actual distances driven. The inspectors drive an average of 7,500 km per month, and the repair personnel 5,300km per month. Table 2.5 shows the ratios to the estimated total tour distance.

Table 2.5: Distance ratios of real distance to tour distance estimate

	Real km	Ratio to estimate	Used ratio	Manipulated KPI
Inspection	7,500	1.667	1.5	6,750
Repair	5,300	1.178	1.1	4,950

Based on information from employees, it is proper to assume that some distance is due to trips unrelated to the tour schedule or task-related activities. Therefore, a slightly reduced ratio will be used for the objective manipulation and interpretation approach. To manipulate the distance and cost KPI, the kilometers obtained by estimators ($distance_{est}$) are one time multiplied by 1.5 and added together with another time multiplied by 1.1 to account for the inspection and repair trips separately. This total tour distance will also be used to calculate the travel cost. The formulas for both KPIs are presented below.

$$\begin{aligned} TotalTourDistance &= distance_{est}(1.5 + 1.1) \\ &= 2.6 * distance_{est} \\ TotalTravelCost &= TotalTourDistance * travelCost_{per\,km} \end{aligned}$$

Since each train station management will be confronted with fluctuating travel and service times and tasks outside the baseline schedule, it is a justifiable assumption to apply manipulation factors on a general basis. With these manipulation factors, the KPIs of travel distance and costs are estimated to be 11,700km travel distance and €4,095 in total costs.

2.6 Conclusion

Inspectors and repair personnel responsible for train station inspections and maintenance follow a defined set of tasks, encompassing safety inspections, reinstatement work, technical activities, cleaning examination, and other station-related tasks. Emphasis is consistently placed on prioritizing safety inspections and addressing situations proposing safety risks. While repair personnel respond to maintenance tasks as they arise, inspectors adhere to a pre-determined tour schedule, which is manually constructed based on the train routes. Both groups receive tasks on short notice.

An analysis of the current situation at TM Magdeburg identifies operational inefficiencies within their train station department's manual schedule. There exists an opportunity for cost savings, reduced environmental impact, and a more evenly distributed workload over the planning horizon. To address these objectives, a new tour schedule needs to be constructed. Additionally, the implementation of field offices, where employees and their equipment can be stationed, is being explored. The project owner also desires a team structure that assigns schedules to pairs of employees. While short-term adjustments will not be prioritized, the schedule should allow flexibility for task inclusion, provide a time buffer, and accommodate employee shortages.

Even though travel and service times contain uncertainties, our focus lies on establishing a new baseline schedule, and variations in time are of secondary concern. We employed estimations for analysis to gain a clear understanding of travel distance, travel time, and service times. Based on the current tour schedule and these estimates, we identified imbalances in workload distribution among tours. Regular tours exhibit varying total estimated travel and service times, ranging from 7.5 to over 15 hours. We plan to utilize the maximal tour duration as a key performance indicator for efficient tour routing and a balanced schedule. Furthermore, the total travel distance and total cost will be examined. Under these measures, the current tour schedule has a total travel distance of 4,500km (11,700km manipulated), the associated costs are €4,095, and the maximal tour duration lies at 15.4 hours.

3 LITERATURE REVIEW

This chapter presents a comprehensive review of relevant literature pertinent to this research while answering the second research question: In the literature, what solution approaches are suggested to solve the location and routing problem? It begins with exploring literature related to train operations and providing contextual information. Subsequently, it contextualizes the planning levels associated with the maintenance problem of DB S&S in Section 3.2. Sections 3.3 and 3.4 introduce and elaborate on the two distinct subproblems: facility location and vehicle routing. An explanation and literature review of the integrated Location-Routing Problem follows this. Sections 3.6 and 3.7 deal with multi-objective approaches and the selected metaheuristic Adaptive Large Neighborhood Search, respectively. Section 3.8 reflects on a stochastic evaluation method. Finally, Section 3.9 summarizes the chapter with concluding remarks.

3.1 Railway operations

The maintenance operations of railway infrastructure cover various components, reflecting the diversity of related literature and research. A crucial aspect of a reliable train system is the functionality of the train tracks. Sedghi et al. (2021) recently reviewed railway track maintenance planning and scheduling. In addition to national budgets, the European Union (EU27) allocated €41.8 billion for the maintenance, upgrade, renewal, and expansion of European rail infrastructure in 2020 (European Commission, 2023). Given the capital-intensive nature of the rail sector, even minor operational improvements can significantly impact overall expenditures and system efficiency (Sedghi et al., 2021).

In the context of train track maintenance, such improvements can be achieved through various means, including optimizing maintenance policies (Gerum et al., 2019), crew scheduling and routing (Peng & Ouyang, 2014), the strategic location of maintenance facilities (Xie et al., 2016), and the application of sensor technologies for condition monitoring (Castillo-Mingorance et al., 2020). Additionally, proper scheduling and maintenance of rolling stock and locomotives are essential for ensuring safety, comfort, and punctuality in train services (Anderegg et al., 2003). Tönissen and Arts (2020) introduced the Stochastic Maintenance Location Routing Allocation Problem for Rolling Stock (SMLRAP), optimizing the locations of maintenance facilities and allocating rolling stock accordingly.

In the context of this thesis, the focus shifts to maintenance activities outside the train tracks. While the trains themselves are not directly involved, the maintenance of train stations is equally critical. Non-performance can lead to the decommissioning of stations, subsequently affecting train operations. Addressing this challenge involves solving location and routing problems. Locating employees, along with their vehicles and equipment, in field offices for efficient coverage of geographically dispersed stations constitutes a location problem. Constructing a new tour plan for employees represents a routing problem. Notably, the tour plan is designed as a periodic schedule to meet legally required station inspection frequencies. Moreover, ensuring an equitable workload distribution among employees or teams, both within each tour and over the planning horizon, is imperative. Given the equal importance of both location and routing components in achieving the most efficient solution for DB S&S, this research centers on Location-Routing Problems (LRPs).

To explore the LRP application in the context of railway operation, we conducted a search using the Elsevier search engine Scopus to acquire unbiased information. Using the search query ("location routing problem" OR location-routing) AND (train OR railway) AND (maintenance OR inspection), we obtained four relevant results. Among these, three are contributions by Tönissen and Arts (2018, 2020) and Tönissen et al. (2019), all centered on maintenance location routing for rolling stock. Jamali (2019) delves into multimodal multi-vehicle hazardous materials transport, considering costs dependent on the quantity of materials loaded. Since these initial results provided limited insight, we broadened the search term to ("location routing problem" OR location-routing) AND (train OR railway). This refinement yielded four additional articles focusing on multimodal LRP models optimizing transportation on highways and high-speed railways (Yu et al., 2023), the Euro-China expressway and its connection points (Lu et al., 2019b), as well as the catering logistics for high-speed railway trains (Wu et al., 2017). Lu et al. (2019a) concentrate on the refueling of locomotives.

While these papers are considered in the context of railway operations, it is essential to note that there is limited overlap with our specific research attributes. Therefore, we will place more emphasis on analyzing problem characteristics rather than relying on contextual relevance. This approach will involve breaking down the problem and evaluating existing research that shares pertinent characteristics.

3.2 Planning levels

The problem of this project addresses challenges across different planning levels. The first subproblem involves determining the location for inspection teams at (field) offices. This falls into the scope of network design or location theory, constructing a strategic problem (Farahani & Hekmatfar, 2020). These decisions are expected to endure longer due to the substantial time and financial investments required for potential changes. Since establishing a field office involves significant costs, deciding on the placement of employees within existing facilities is a long-term commitment.

The second subproblem pertains to the routing of the vehicles, a task that can be adjusted with shorter notice and less effort. Constructing a recurrent skeleton plan constitutes tactical planning (Prodhon & Prins, 2008). The final adjustments made on the day prior, or the actual tour days, are referred to as offline and online operational planning, respectively. Offline planning incorporates pre-known events into the tour, while online planning involves last-minute adaptions, such as emergencies that demand immediate attention.

Traditionally, these two subproblems have been tackled separately due to the differing levels of decision-making involved. The complexity significantly escalates when attempting to integrate both steps. Facility location and vehicle routing are classified as NP-hard combinatorial optimization problems (Nagy & Salhi, 2006). This implies that even finding optimal solutions for each individual can only be achieved in exponential time due to their inherent complexity. Nonetheless, Salhi and Rand (1989) demonstrated, through experimentation, that there exists a substantial interdependence between vehicle routing and location allocation. This realization, coupled with the growing international significance of logistics in the 1970s and 1980s, spurred research into the Location-Routing Problem (Farahani & Hekmatfar, 2020).

3.3 Location problem

The first subproblem can be outlined as follows: Within a defined network of arcs (representing streets), nodes (representing demand points, in this case, train stations), and potential facilities (a subset of nodes), it is aimed to select a subset of potential facilities as service team locations. This selection is made with the objective of minimizing the total costs or travel distances to all demand points. It is important to note that the train stations and the connecting streets are pre-existing and cannot be altered. Thus, the network is considered fixed. The currently established facility remains unchanged; however, additional field offices can be selected for employee placement. The capacity of these facilities, indicating how many demand points they can serve, depends on the number of service teams assigned to each facility. If a field office is utilized, it must host at least one team. Similarly, the existing facility must host at least one team as well. Consequently, when addressing a challenge of this nature, the following decisions need to be made:

1. Which facility location will be utilized?
2. How many service teams will be stationed at each facility?
3. Who will be responsible for each train station?

This decision-making process is a core component of Facility Location Problems (FLPs), a specific subset within the broader category of Network Design Problems (NDPs). FLPs concentrate on strategically placing facilities, such as warehouses, factories, or service centers, within a network to efficiently serve a set of demand points (Marianov & Serra, 2002). This process involves careful consideration of factors such as demand distribution, transportation costs, and capacity constraints. In FLPs, the goal is to determine the optimal locations for facilities to minimize costs or maximize benefits (Farahani & Hekmatfar, 2020). This optimization process holds significance across various domains, including logistics, supply chain management, urban planning, and public services (Melo, Nickel, & Saldanha-da-Gama, 2009). In the context of railway operations, facility location problems find broad applicability when finding locations, for example, for infrastructure maintenance depots for all kinds of rail vehicles (Kim & Kim, 2021) or resting facilities for trains of Railway Rapid Transit Systems (Canca & Barrena, 2018).

3.4 Routing problem

The second subproblem involves the routing and scheduling special field services for periodic inspections and maintenance of demand points (train stations). They have different inspection frequencies and validity periods for their required service. Service teams are tasked with conducting on-site inspections and maintenance activities to fulfill these requirements. Therefore, establishing a fixed schedule with defined tours that allocate specific work locations is crucial in efficiently organizing these repetitive operations. Each service team operates from designated starting and ending points for their assigned tour to distribute workload and ensure tours have similar durations and time commitments. The key decisions to be made are:

1. Which station is covered by each tour?
2. Who is responsible for each tour?
3. In what period is each tour happening?

The unique characteristics that distinguish the DB S&S problem include the need for routing with a balanced workload and adherence to a periodic schedule. Consequently, our investigation involves an examination of the Vehicle Routing Problem (VRP), incorporating both balance constraints and objectives, along with a periodic extension of the VRP.

In general, VRP is recognized as an NP-hard problem that determines optimal routes for a vehicle fleet to satisfy demand points (Oyola, Arntzen, & Woodruff, 2016). The pioneering work of Dantzig and Ramser in 1959 applied VRP to a fleet of gasoline delivery trucks. Since then, numerous variations of VRP have been explored in diverse logistical contexts. In consumer goods logistics, depots and vehicles are typically constrained by limited storage space and carrying capacity, respectively. Additionally, route lengths may be restricted, particularly with electric vehicles, due to battery limitations. These scenarios give rise to the Capacitated VRP (CVRP), for which various exact and heuristic approaches have been developed. An example of the railway operations context is the route planning of maintenance agents through the railway network without disrupting the active train traffic by Buriuly, Vachani, Sinha, Ravitharan, and Chaunhan (2022). Furthermore, Müller, Ehlers, and Gollnick (2019) proposed a drone routing optimization to monitor the railway infrastructure.

3.5 Location-Routing Problem

The Location-Routing Problem (LRP) is a branch of locational analysis research distinguished by its consideration of the fundamental problem of vehicle routing (Nagy & Salhi, 2006). A thorough examination of LRP literature reveals many different variations for a wide range of applications, including the distribution of goods (e.g., food or mail), waste collection, health-care (mobile healthcare services), and stationing of military equipment (Farahani & Hekmatfar, 2020). Defining the problem comprehensively requires consideration of various aspects, which existing research combines in diverse ways. However, due to the complexity of the two subproblems, only a few exact formulations have been devised, with a greater emphasis on heuristic approaches.

Breaking down the classical LRP involves three decisions based on a set of potential facility locations, including their opening costs, a homogenous vehicle fleet, and a set of demand points with known requests. Drexl and Schneider (2015) define three interdependent decisions that are crucial for LRPs:

1. Which of the potential facilities should be utilized?
2. Which customer clusters should be formed?
3. Within each cluster, which sequence of demand points should be served by a vehicle?

The primary objective is to minimize the overall cost, encompassing facility opening costs, fixed vehicle expenses, and route-related costs. As logistic costs represent a significant portion of companies' expenditures, the research on this topic has expanded rapidly over the years (Prodhon & Prins, 2014). Mathematical formulations and heuristics exist for various extensions of the classical LRP.

To clearly understand LRP models and their alignment with our specific problem attributes, Figure 10 presents the taxonomy proposed by Mara, Kuo, and Sri Asih (2021). Notably, the scenario characteristics include deterministic data, a periodic planning period, and single-trip vehicle usage. Further scenario characteristics are not considered or, due to irrelevance, marked as not allowed. The physical features of our problem concentrate on a single echelon with a direct approach from a discrete number of facility locations to the demand points. Additionally, we address single-service operations at train stations, denoted by vertices, hence adopting a vertex-routing approach. The vehicle fleet is assumed to be homogeneous, and no capacity constraints are applied for facilities or vehicles. Our objective function emphasizes cost reduction while ensuring an equitable distribution of workload. Consequently, models addressing multiple objectives, particularly those related to cost reduction and workload balance, are relevant to our investigation.

Author	Model	Objective	Context	WL balancing	Multi-objective	Periodic	Data		Solution approach
							D	S	
Lin & Kwok (2006)	MOLRP	Min. total cost , load imbalance & working time imbalance	Distribution logistics	X	X			X	TS & SA
Pirkwieser & Raidl (2010)	PLRP	Min. total cost	Distribution system			X	X		VNS with VLNSs
Martínez-Salazar et al. (2014)	TLRP	Min. distribution cost & maximal tour difference	Distribution system	X	X		X		SSPMO & NSGA-II
Golmohammadi et al. (2016)	LRP	Min. total cost & difference of distance traveled	Warehouse logistics	X	X		X		MOICA
Hemmelmayr (2016)	PLRP	Min. total cost	Collaborative Recycling			X	X		ALNS
Koc (2016)	PLRPs	Min. total cost	Network design			X	X		U-ALNS
Tunalioglu et al. (2016)	MPLRP	Min. total cost	Olive oil mill wastewater			X	X		ALNS
Hadian et al. (2018)	MOLRP	Min. total cost & difference between distances traveled	Distribution system	X	X		X		MOICA & NSGA-II
Vahdani et al. (2018)	MOMPLRP	Min. maximum travel time & total cost; Max. minimal reliability	Relief distribution with roadway repair	X	X	X	X		NSGA-II & MOPSO
Zhang et al. (2018)	MOLRP	Min. maximum vehicle route travel time, emergency relief cost & emissions	Emergency logistics	X	X			X	GA
Rabbani et al. (2019)	PLRP	Min. total cost & transport risk	Industrial hazadous waste		X	X		X	MINLP; NSGA-II with MC
Mamaghini & Davari (2020)	MOPLRP	Min. total cost & violation of time windows	Reverse supply chain		X	X	X		NSGA-II & NRGA
Tönissen et al. (2020)	SMLRAP	Min. facility opening cost & transportation cost	Maintenance for railway rolling stock		X	X		X	MIP
Li & Tang (2021)	PLRP	Min. total cost	Recycling logistics			X	X		SOS
Long et al. (2021)	MMRLRP	Min. total travel time & the total cost ; Max. fairness of relief allocation	Epidemic logistics system		X	X		X	PICEA-g-td
Gläser (2022)	PLRP	Min. weighted combination of costs	Waste Collection			X	X		ALNS
Savaser & Kara (2022)	PLRP	Min. total travel distance	Mobile healthcare services	X		X	X		Cluster first-route second
Kordi et al. (2023)	LRP	Min. total costs, environmental pollution, risk, total expected arrival time violation	Dental waste management		X	X		X	RMCGP
Garlindres et al. (2023)	S-CLRP	Min. total cost, emission & maximum route length	Sustainable supply chain management	X	X		X		ILS
Shi et al. (2023)	SLVRP-SPD	Min. total cost & maximal working time	Express packaging	X	X		X		MO-HH based on NSGA-II
This Study	**MOPLRP**	**Min. total cost, total route length & maximal tour duration**	**Train station maintenance**	X	X	X	X		**ALNS**

Figure 3.1: Summary of relevant literature addressing Location-Routing Problems

These selected articles' characteristics are summarized in Figure 3.1, with a specific emphasis on vertex-routing, single-echelon, and single-modal environments. The data sets used are categorized as either deterministic (D) or stochastic (S). Additionally, when an equity function is incorporated into an objective or constraint, we focus only on workload balance (WL). A more detailed and broader review has been done by Prodhon and Prins (2014), Drexl and Schneider (2015), Mara et al. (2021), and Tadaros and Migdalas (2022).

3.5.1 Periodic LRP

The periodic dimension of the LRP was initially introduced by Prodhon (2008) and has gained increasing attention in recent years. Drexl and Schneider (2015) describe the Periodic Location-Routing Problem (PLRP) as a combination of the classical LRP and the Periodic Vehicle-Routing Problem. Existing research relevant to our study has primarily focused on waste management contexts (e.g., Kordi, Hasanzadeh-Moghimi, Paydar, and Asadi-Gangraj, 2023; Gläser, 2022; Tunalioglu, Koc & Bektas, 2016), distribution logistics (e.g., Pirkwieser & Raidl, 2010; Li a& Tang, 2021; Hemmelmayr, 2015), mobile healthcare (Savaser & Kara, 2022), and maintenance of railway rolling stock (Tönissen & Arts, 2020).

Examining various solution methodologies, we first explore single-objective applications. Pirkwieser and Raidl (2010) introduced a metaheuristic combining a Variable Neighborhood Search (VNS) with three Integer Linear Programming (ILP)-based Very Large Neighborhood Searches (VLNS), utilizing diverse shaking neighborhoods for diversification and local search for intensification of the solution space. Hemmelmayr (2015) and Gläser (2022) developed Adaptive Large Neighborhood Search (ALNS) techniques that effectively handle both small and large instances by destroying and repairing the current solution. Koc (2016) proposed the Unified-Adaptive Large Neighborhood Search (U-ALNS) metaheuristic for various PLRP configurations, employing Simulated Annealing (SA) within an outer local search framework. Tunalioglu et al.(2016) addressed the multi-period LRP in the context of olive oil mill wastewater collection, adapting three versions of the ALNS algorithm, differing primarily in their selection of operators. Savaser and Kara (2022) presented a heuristic based on a cluster first–route second approach, capable of finding (near) optimal solutions within appropriate computational time, emphasizing continuity in the assigned service, evenly distributed periodic visits, and balanced workload within constraints.

Subsequently, we delve into papers focusing on multi-objective PLRP solution approaches. Vahdani, Veysmoradi, Shekari, and Mousavi (2018) present two population-based multi-objective optimization evolutionary algorithms, namely Non-dominated Sorting Genetic Algorithm-II (NS-GAII) and Multi-Objective Particle Swarm Optimization (MOPSO), demonstrating favorable Pareto solutions with NSGA-II excelling in the ideal answer criterion and MOPSO performing better in generating diverse solutions. Rabbani, Heidari, and Yazdanparast (2019) enhance NSGA-II with Monte Carlo simulation, yielding superior solutions for waste management challenges compared to other simulation-optimization approaches. Mamaghani and Davari (2020) proposed the Non-dominated Ranked Genetic Algorithm (NRGA) for a PLRP with simultaneous pickups and deliveries. NRGA is NSGA-II-based with a modified selection strategy, outperforming NSGA-II regarding the diversity of solutions, while NSGA-II demonstrated better spacing and runtime. Long, Zhang, Liang, Li, and Chen (2021) solve the multi-objective PLRP with a Preference-Inspired Co-Evolutionary Algorithm with Tchebycheff decomposition (PICEA-g-td), showing superior performance compared to three other algorithms, namely NSGA-II, MOEA/D and PICEA-g. Tönissen and Arts (2020) present a Mixed-Integer Problem (MIP) for railway rolling stock maintenance allocation, providing insights into facility number dependence on allocation restrictions. Li and Tang (2021) proposed a Symbiotic Organisms Search (SOS) algorithm for recycling logistics, considering route reliability across different problem instances and effective and consistent solution generation.

In the realm of solution approach, a notable distinction arises between single- and multi-objective models. Single-objective PLRPs are predominantly solved using neighborhood search techniques, particularly ALNS, to explore solution spaces efficiently. In contrast, multi-objective PLRPs are mainly solved with evolutionary algorithms like NSGA-II, manifesting in their ability to optimize conflicting objectives in diverse scenarios concurrently. Such distinct methodologies underscore the need for specialized approaches in navigating the complexities of different LRP problem formulations to achieve optimal solutions effectively. Neglecting the type of objective, ALNS and NSGA-II represent two powerful metaheuristic approaches, each with distinct characteristics and strategies for solving optimization problems. ALNS and NSGA-II differ significantly in their methodologies, exploration of solution spaces, and handling of periodic LRPs.

3.5.2 LRP with workload balance

The workload balance is a critical aspect of our LRP formulation, impacting schedule equality, flexibility, and employee satisfaction. Despite its significance, the integration of workload balance into LRPs remains infrequent.

Notably, Savaser and Kara (2022) stand out in implementing workload balance with constraints setting a maximal acceptable value. They focused on minimizing total travel distance as a single objective, incorporating constraints for workload balance, and solving their mobile healthcare problem using a cluster-first, route-second algorithm. However, a few studies have transformed the multi-objective model into a single objective using different methodologies. Martinez-Salazar, Molina, Angelo-Bello, Gomez, and Caballero (2014) addressed an extended LRP known as Transportation LRP (TLRP), employing metaheuristics such as Scatter Tabu Search Procedure for Non-Linear Multi-objective Optimization (SSPMO) and NSGA-II strategies. Their objectives aimed at minimizing economic costs and the difference between maximal and minimal tour length. They applied the weighted sum method and epsilon constraint method to obtain the exact frontier. While SSPMO generated high-quality solutions for small instances, the NSGA-II-based heuristic performed better for large ones. Zhang, Li, Li, and Peng (2018) proposed a hybrid intelligent algorithm integrating uncertain simulation and a genetic algorithm. The objectives are described in one main objective (minimization of the maximum travel time) and two goal constraints (minimization of relief cost and minimization of CO2 emissions). Numerical experiments highlighted the efficiency and robustness of their designed heuristic.

As mentioned in the previous subsection, Vahdani et al. (2018) used NSGA-II and MOPSO to address their multi-objective PLRP. Their approach to workload balance involved minimizing the maximal vehicle route while minimizing the total costs, and maximizing the minimal route reliability. Shi et al. (2023) propose a bi-objective MILP for the simultaneous facility location and vehicle routing problem. Their objectives focused on minimizing maximum vehicle working time and total cost. They were solved using an NSGA-II-based hybrid heuristic with a VNS procedure, yielding promising solution exploration and generation results. Lin and Kwok (2006) applied Tabu Search (TS) and Simulated Annealing (SA) as metaheuristics in their multi-objective LRP. They implemented workload balance by measuring the load imbalance and working time imbalance per vehicle. TS outperforms SA on average within computation time limits. Golmohammadi, Bonab, and Parishani (2016) proposed an Imperialist Competitive Algorithm (ICA) for the multi-objective LRP, aiming to minimize total cost and difference in vehicle travel distance. ICAs perform better than NSGA-II and PAES regarding quality and spacing metrics across various problem sizes. Similarly, Hadian, Golmohammadi, Hemmati, and Mashkani (2019) introduce a Multi-Objective ICA (MOICA) for LRP with a capacitated and homogeneous vehicle fleet, focusing on minimizing total costs and differences in distance traveled. MOICA outperforms NSGA-II, especially for large problem instances. Lastly, Garlindres et al. (2023) proposed a Mixed-Integer Linear Programming (MILP) model and an Iterated Local Search (ILS) and decomposition (ILS/D) for capacitated LRP, emphasizing workload balance among drivers by minimizing the maximal route length, total cost minimization, and environmental impact reduction. Comparing Pareto fronts obtained from exact and approximate methods revealed the favorable dispersion and convergence characteristics of ILS/D.

In conclusion, while workload balance remains a crucial aspect in Location Routing Problems (LRP), it often takes a subsidiary role compared to other primary objectives. Consequently, multi-objective models have predominantly been favored in addressing LRP concerns, allowing for simultaneous consideration of workload balance besides monetary improvements. However, even though multi-objective models seem to be preferred, practical methods exist to transform these into single-objective frameworks. Techniques such as the weighted sum or epsilon constraint methods offer pathways to merge multiple objectives into a singular optimization goal, providing an alternative approach for addressing workload balance within a more focused framework (Deb, Sindhya, & Hakanen, 2016).

3.6 Multi-objective approaches

Multi-objective optimization problems (MOPs), as defined by Schüzte and Hernández (2021), involve optimizing multiple conflicting objectives while adhering to certain constraints. The complexity inherent in these problems necessitates specialized techniques, particularly (meta) heuristic methods, which primarily focus on the concept of Pareto dominance (Schüzte & Hernández, 2021). These techniques fall into two categories: single-solution-based and population-based, depending on whether they manipulate a single solution or a set of solutions to explore the search space diversely (Sharma & Kumar, 2022). Additionally, they can also be classified into single- and multi-objective approaches. Single-objective techniques use a single fitness function based on predetermined preferences, yielding a unique solution. In contrast, multi-objective approaches consider conflicting objectives, generating a set of non-dominating solutions.

Mara et al. (2021) provide an updated classification: commonly used techniques for single-objective LRPs include Simulated Annealing, Genetic Algorithms, Tabu Search, (Variable) Neighborhood Search, and Particle Swarm Optimization. Conversely, for multi-objective LRP models, widely used techniques are the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO). In our specific literature review, NSGA-II in the population-based category and neighborhood search heuristics (particularly ALNS) in the single-solution-based category were most frequently employed. ALNS was primarily used to address the periodic aspect, while NSGA-II stood out for multi-objective criteria. However, techniques were also applied to simplify multi-objective problems. Ehrgott (2005) and Deb et al. (2016) provide comprehensive overviews. Some commonly used methods include:

- The **Pareto method** collects all trade-off solutions dominant in different objectives, forming the Pareto front.
- **Scalarization**, or weighted-sum method, merges multi-objective function into a scalar fitness function using pre-assigning weights and normalization. However, difficulties in weight selection and non-convexity led to the development of the epsilon constraint method.
- The **epsilon constraint method** optimizes one objective while treating others as constraints, demanding careful selection of epsilon.
- The **lexicographic method** considers single objectives in sorted order, starting with the most important one, solving the optimization problem multiple times.
- **Goal programming** assigns goals to each objective, aiming to minimize deviations from these goals.

This flexibility in modeling methods tailors approaches to specific problem needs. For our study, we use the Pareto method to optimize all objectives simultaneously. This postpones preference decisions until after the generation of a set of trade-off solutions. Selecting parameters a priori heavily depends on the decision-maker's favorability regarding the different criteria. Furthermore, transforming multiple objectives into one limits the exploration of the Pareto front and does not guarantee Pareto optimality (Deb et al., 2016).

Metaheuristics employing Pareto-optimality concepts are predominantly population-based multi-objective optimization techniques since they can search for many efficient solutions simultaneously, e.g., NSGA-II or MOPSO (Ehrgott & Gandibleux, 2000). Furthermore, single-solution approaches have been adapted by maintaining an archive of non-dominated solutions and updating it with each iteration of the algorithm. This way, multi-objective versions of, e.g., Genetic Algorithm (MOGA) or Simulated Annealing (MOSA) have been developed (Ngatchou et al., 2005). Furthermore, Schaus and Hartert (2013) propose the multi-objective large neighborhood search (MOLNS).

Our literature review indicates that Adaptive Large Neighborhood Search is an intriguing solution approach for Periodic Location-Routing Problems, especially in its multi-objective extension. Rifai, Nguyen, and Dawal (2016) developed Multi-Objective Adaptive Large Neighborhood Search (MOALNS) for flow shop scheduling, showing superior results compared to LNS, ALNS, and NSGA-II applications, supporting the effectiveness of MOALNS. Although MOALNS with the Pareto method has not been applied to location-routing problems, Ke and Zhai (2014) proposed a similar population-based algorithm (MALNS) for a vehicle routing problem with efficient results. This underlines the lack of practice and research of ALNS in the multi-objective environment of different contexts.

We focus on the Pareto method because it precisely represents trade-off solutions. Additionally, we will solve each single-objective instance for reference. Comparing these results ensures Pareto-optimality and evaluates ALNS compatibility with strictly multi-objective solutions, an area still relatively unexplored (Mara, Norcahyo, Jodiawan, Lusiatoro, & Rifai, 2022). In summary, our strategy involves leveraging the efficacy of ALNS in addressing periodic LRPs and harnessing the power of the Pareto method to address multiple objectives. This approach promises a robust solution for our specific problem and contributes significantly to exploring Multi-Objective Adaptive Large Neighborhood Search, particularly within the context of LRPs.

3.7 Adaptive Large Neighborhood Search

Adaptive Large Neighborhood Search (ALNS) is a widely employed metaheuristic belonging to the family of Local Search algorithms, extensively utilized in diverse problem domains like routing, scheduling, and location problems (Mara et al., 2022). Originating as an extension of the Large Neighborhood Search (LNS) developed by Ropke and Pisinger in 2006, ALNS functions by iteratively exploring expansive neighborhoods of solutions and dynamically adapting its search strategy based on past performance (Ropke & Pisinger, 2007). The fundamental concept involves cyclically destroying and repairing parts of the solution to avoid local optima, thereby exploring a broader solution space (Mara et al., 2022). When applying the algorithm, key considerations include determining the adaptive mechanism, acceptance and termination criteria, and selecting destroy and repair operators. Mara et al. (2022) conducted a comprehensive survey on ALNS, revealing the prevalent use of the Roulette Wheel adaptive mechanism, the Metropolis acceptance criterion (also known as the Simulated Annealing criterion), and the iteration count as a termination criterion. These parameters form the standard structure of ALNS, as outlined in Figure 3.2. On average, six destroy and four repair heuristics are utilized, although some practitioners also employ combined heuristics.

The standard algorithm is structured as follows: The ALNS algorithm starts with initializing the parameters. A feasible initial solution S needs to be generated, which starts to be the newly obtained solution S' and the best-known solution so far S^* (line 2). The initial temperature T_0 and the cooling factor α are given as input (line 1), where the current temperature T gets initialized with T_0 (line 2). The weights (w_i^-, w_i^+) and probabilities (p^-, p^+) to the selected set of destroy and repair heuristics must be initialized (line 3). Afterward, a while-loop starts, which runs until the stopping criterion is met. Within the loop, first, the destroy and repair heuristics get selected according to the Roulette Wheel method (line 5) and applied (line 6). Now, the performance of the obtained solution is evaluated. If the solution is better than the current solution, it will be accepted (lines 7-8). If it is better than the current best solution S^*, the solution will be the new S^* (lines 9-10). Otherwise, a probability is generated with which the solution will be

1: **input**: a feasible solution S, Ω^-, Ω^+, η_s, α, T_0
2: $S^* \leftarrow S$, $S^{'} \leftarrow S$, $i \leftarrow 1$, $T \leftarrow T_0$
3: Initialize w_i^-, w_i^+, p^-, and p^+
4: **repeat**
5: Select a destroy and a repair operator from Ω^- and Ω^+ using roulette wheel selection
6: $S^{'} \leftarrow repair(destroy(S))$
7: **if** $accept(S^{'}, S)$ **then**
8: $S \leftarrow S^{'}$
9: **If** $(f(S)\langle f(S^*))$ **then**
10: $S^* \leftarrow S$
11: **end if**
12: **else**
13: **if** $rand[0,1]\langle e^{-(f(S^{'})-f(S))/T}$ **then**
14: $S \leftarrow S^{'}$
15: **end if**
16: **end if**
17: **if** $i = \eta_s$ **then**
18: Update w_i^-, w_i^+, p^-, and p^+
19: $i = 0$
20: **end if**
21: $T = \alpha T$, $i = i + 1$
22: **until** stop-criterion met
23: **return** S^*

Figure 3.2: Pseudocode for ALNS algorithm proposed by Mara et al. (2022)

accepted as the current solution to continue the algorithm (lines 12-15: single-objective variation). Afterward, whether the operator probabilities and weights need to be updated is checked. Every $_s$ iteration, the algorithm subsequently calculates probabilities for each heuristic i relative to the sum of all heuristic weights ($\frac{w_i}{\sum_{j=1}^{|\Omega|} w_j}$). These iterations are counted by i, incremented by $i = i + 1$ (line 21), and after the update, reset to 0 (line 19). The temperature for the Metropolis acceptance probability gets updated in line 21. Finally, when the stopping criterion is reached, the best solution gets returned (line 23).

Despite being a single-solution-based heuristic, ALNS can be extended to address multi-objective problems by maintaining an archive of non-dominated solutions. Multi-objective ALNS (MOALNS), incorporating the Pareto method introduced by Rifai et al. (2016), has shown promising results. In MOALNS, akin to ALNS, the algorithm utilizes the Metropolis acceptance method but instead identifies non-dominated solutions in each iteration to construct the Pareto frontier. This mechanism draws inspiration from the Archived Multi-Objective Simulated Annealing (AMOSA) algorithm proposed by Bandyopadhyay, Saha, Maulik, and Deb (2008). Although MOALNS has not explicitly been applied to Location-Routing Problems, related algorithms such as MALNS by Ke and Zhai (2014) Vehicle Routing Problem, modifications proposed by Labdiad, Nasri, Hafidi, and Khhalif (2021) for VRPs, and the extension by Wang, Wang, Fan, Wang, and Zhen (2023) for VRPs with a split algorithm exist. Additionally, Cota et al. (2019) developed a MOALNS with decomposition for a machine scheduling problem, indicating the algorithm's applicability across diverse contexts with promising results. Given its versatility and favorable performance, MOALNS appears to hold promise as a practical algorithm for solving our periodic Location-Routing Problem (PLRP).

3.8 Stochastic evaluation

Simulation is a complex process involving creating a model to imitate a real-world system, allowing experimentation to comprehend its behavior and assess operation strategies (Shannon, 1975). Therefore, these are frequently used to analyze stochastic systems or risk in financial processes. Simulation methods provide a means to explore and predict outcomes without actual implementation, offering valuable insights and aiding decision-making (Hillier & Lieberman, 2021). Due to the progress in computational processing power and pseudo-random number generators, techniques like the Monte Carlo simulation have been incorporated into the spectrum of solving stochastic combinatorial problems (Rabbani et al., 2019). In this context, stochastic variables are treated as deterministic with their expected values, and the solution space is searched for appropriate feasible solutions. Subsequently, for the most promising solutions identified based on predetermined performance indicators, simulation is employed to generate estimates for the corresponding stochastic problem instances (Juan, Faulin, Grasman, Rabe, & Figueira, 2015). These results can then be used to reevaluate the solutions based on their variability, robustness, or expected value rather than their objective function (de León, Lalla-Ruiz, Melian-Batista, & Monero-Vega, 2021). While Monte Carlo simulation provides a valuable means to incorporate uncertainty, the results are not anticipated to be optimal. Instead, a trade-off between different solution variations can be determined by considering preferences such as risk aversion.

In Location-Routing Problems, Monte Carlo simulation has proven instrumental in evaluating and optimizing complex systems affected by stochastic factors. For instance, Rabbani et al. (2019) utilized Monte Carlo simulation to address a stochastic multi-period industrial hazardous waste LRP, integrating it with NSGA-II. Their study introduced stochasticity in factors such as transportation costs, demand fluctuations, and service times, allowing for a comprehensive analysis of the robustness and efficiency of hazardous waste management strategies over multiple time periods. Integrating Monte Carlo simulation with NSGA-II facilitated the exploration of diverse solution alternatives under uncertain conditions, providing decision-makers with valuable insights into the trade-offs between cost, risk, and service quality in hazardous waste logistics. This instance demonstrates the practicality of Monte Carlo simulation in addressing stochasticity within logistical and operational contexts, facilitating informed decision-making, and enhancing system performance.

3.9 Conclusion

The DB S&S problem addresses two complex combinatorial optimization challenges: the Facility Location Problem (FLP) and the Vehicle Routing Problem (VRP). Location-Routing Problems (LRPs) are a crucial link between the strategic planning of FLPs and the tactical optimization of VRPs. In an LRP, the objective is to simultaneously determine the optimal locations for facilities and the corresponding routes for vehicles. This approach considers facility location and vehicle routing decisions, providing a comprehensive solution for efficient logistics operations.

Research in LRPs covers various topics and methodologies, exploring various problem variants. These variants, whose characters can be recognized in the problem context of this project, focus on single- and multi-objective formulations, periodic models, and considerations of equity regarding workload. In the context of railway operations, LRPs have found applications primarily in multimodal transportation and rolling stock management. When examining LRP models independently of context while considering our problem attributes, we noted that simultaneously addressing monetary and workload objectives is commonly achieved through multi-objective models but not necessarily. However, the relevant periodic LRPs employ Adaptive

Large Neighborhood Search (ALNS) as the most frequent solution approach. Although these papers concentrate on single objectives, there are efficient methods to apply a metaheuristic to multi-objective problems. Among these is the Pareto method, which we use to approach the problem, considering all objectives simultaneously. Additionally, we will solve each mono-objective problem as a comparison to ensure Pareto-optimality and fill the gap of applying ALNS to LRP in a multi-objective environment.

By selecting ALNS as the solution approach and applying both the Pareto method and single-objective solution to evaluate the multiple solution criteria, we aim to gain insight into employing ALNS in a multi-objective setting and compare the quality of solutions obtained between the single-objective instances and the ones obtained with the Pareto method. Furthermore, we aim to investigate the outcomes using stochastic evaluation methods like the Monte Carlo simulation. They provide insight into the robustness of constructed solutions for the general stochastic properties of service and travel time in real-world applications.

4 SOLUTION DESIGN

This chapter addresses the third research question: What should the design of the solution approach look like? Firstly, the problem of DB Station&Service is defined as a multi-objective optimization problem in Section 4.1, followed by the description of assumptions in Section 4.2. Section 4.3 presents the mathematical formulation of the model, elucidating the notation, objective functions, and constraints. Subsequently, Section 4.4 delves into describing the employed metaheuristic and its components. An algorithm for stochastic evaluation of promising solutions is presented in Section 4.5. The chapter concludes with a summary in Section 4.6.

4.1 Formal problem definition

The multi-objective periodic location-routing problem with workload balance combines several complex components. The problem is defined on an undirected graph $G = (N, A)$, where $N = D \cup M$ is the set of nodes. D is the set of demand points representing the train stations that must be visited according to their specific inspection frequency $freq_i$. ST_i shows the estimated service time at station $i \in D$. M is the set of offices from which the main office $(m = 1)$ must be used while the others are potential field offices. The graph's arcs are represented by the set A, defined as $(i, j) : i, j \in N$. The distance and travel time between location $i \in N$ and $j \in N$ are shown by $dist_{ij}$ and TT_{ij}, respectively, while the travel cost per kilometer driven is given by TC. S represents the set of service teams that complete the service at the stations, where service means the completion of required tasks described in Section 2.3. T is the set of time slots that account for the planning horizon, which complies with the four-week frequency of the most important active stations. Each week is split into two time-slots, which divide the horizon into slots indexed as $T = 1, 2, ..., 8$. Each team $s \in S$ must complete one tour in each time slot $t \in T$. Furthermore, each team $s \in S$ gets an office assigned from which they depart and finish each tour. The possible office assignments per team $s \in S$ are given by pos_i^s with 1 if possible and 0 if not. The monthly running cost per field office is given OC. We assume homogeneity for the service teams with their vehicles since they have the same education and equipment.

For the problem formulation, the following decision variables are defined. Let z_i^s be a binary variable equal to 1 if team $s \in S$ is located at office $i \in M$, and 0 otherwise. Following, y_i represents the decision that office $i \in M$ gets utilized with 1, 0 otherwise. A third set of binary variables indicates when and from which team a station is served, namely w_i^{st} is equal to 1 if station $i \in D$ is being served by team $s \in S$ in period $t \in T$, and 0 otherwise. The last set of binary variables x_{ij}^{st} indicates the traveled arcs. The variable equals 1 if team $s \in S$ travels in time slot $t \in T$ on arc $(i, j) \in A$, 0 otherwise.

The problem consists of choosing the best team-to-office assignment and constructing a periodical tour schedule serving all stations in a particular geographical area according to their frequencies. The literature review shows that a Location-Routing model is an appropriate model to approach the given problem of DB S&S. The location and routing decisions should be made under the objectives of balancing the workload between tours and teams by minimizing the maximal estimated time needed for a tour while minimizing the total costs and total travel distance.

4.2 Assumptions

To streamline the complexity of the process, the following assumptions have been made:

- Validity Periods: The time windows for task completion are disregarded, as tours are already planned within a two-day timeframe, allowing sufficient flexibility. Any deviations will be addressed during short-term scheduling.
- Distance Calculation: The distance matrix is computed using the Haversine Formula to determine straight-line distance, supplemented by a distance factor (refer to Section 2.3.1). Subsequently, travel time is estimated based on speed factors outlined in Section 2.3.2.
- Accounting for Travel Distance Fluctuation: The difference in travel distance between theoretical schedule and reality is included through a distance factor as elaborated in Section 2.5.3.
- Service Time Estimation: The service time at each train station is estimated based on its physical attributes and classification, detailed in Sections 2.3.3 and 2.3.4.
- Station Information: Details regarding stations, such as coordinates and physical attributes, as well as resource information, like the number of teams and offices, are provided through individual inputs from the TM.
- Workload Balancing: Assuming an equal number of tours assigned to each service team, workload balancing is achieved by minimizing the disparity in total tour times across teams.
- Treatment of Inactive Stations: Inactive stations, which occur every 12 weeks, are treated as if they occur every four weeks to simplify planning. However, service is only required for every third planning horizon, so the workload calculation is adjusted accordingly using a workload manipulation factor (act_i). This factor distinguishes between active and inactive stations, taking a value of 1 for active stations and 1/3 for inactive stations.

The required input includes station information such as coordinates, classification, and frequency and infrastructure details like the number of platforms, elevators, and DB-owned entry buildings. Frequency data is essential for accurately constructing the tour schedule, while the remaining information informs estimations for travel distance, travel time, and service time.

4.3 Mixed-Integer Linear Program

This subsection presents the proposed mathematical formulation starting with the notations followed by the mathematical formulation, divided into objective function and constraints together with explanations, respectively.

4.3.1 Notations and definitions

For better understanding and guidance in the solution design, the problem has been formulated as a mathematical model. Due to the complexity of location-routing problems and the size of this specific problem instance, it is impossible to obtain a solution. A heuristic algorithm to solve the problem is formulated in Section 4.4.

Sets

D	Set of demand points (stations) $\{0, \ldots.., \lvert D\rvert - 1\}$
D'	Set of $i \in D$ with $freq_i = 2$
M	Set of (potential) offices $\{\lvert D\rvert, \ldots.., \lvert D\rvert + \lvert M\rvert - 1\}, \lvert D\rvert:$ already existing office
N	Set of nodes, $N = D \cup M$
S	Set of service teams $\{1, \ldots.., s\}$
T	Set of time slots $\{1, \ldots, t\}$
i, j	Indices to nodes $i, j \in N$
s	Indices to service teams
t	Indices to time slots

Parameters

$freq_i$	frequency of service at station $i \in D$
ST_i	estimated service time at station $i \in D$
TT_{ij}	estimated travel time from location $i \in N$ to location $j \in N$
$dist_{ij}$	distance from location $i \in N$ to location $j \in N$
TC	cost for gas and wearing per 1km distance traveled
OC_i	monthly cost per utilized (field) office i
pos_i^s	indication whether team $s \in S$ can be assigned to $i \in M$
act_i	workload manipulation factor for station $i \in D$
cap_s	service capacity of team $s \in S$ (fraction of usual work hours)
F_{dist}	distance factor to overcome the reality gap (see Section 2.5.3)
WL	time limit of a tour restricted by the size of the time slots
M	large positive number

Decision variables

$$w_i^{st} = \begin{cases} 1 & \text{if station } i \in D \text{ is served by team } s \in S \text{ in time slot } t \in T \\ 0 & \text{otherwise} \end{cases}$$

$$x_{ij}^{st} = \begin{cases} 1 & \text{if team } s \in S \text{ drives in time slot } t \in T \text{ from location } i \in N \text{ to location } j \in N \\ 0 & \text{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1 & \text{if office } i \in M \text{ gets utilized} \\ 0 & \text{otherwise} \end{cases}$$

$$z_i^s = \begin{cases} 1 & \text{if team } s \in S \text{ is located at office } i \in M \\ 0 & \text{otherwise} \end{cases}$$

u_i^{st}	arrival time from team $s \in S$ in time slot $t \in T$ at location $i \in N$
R_{max}	maximal tour duration (travel and service times) of all tours
R^{st}	total tour time for tour traveled by team $s \in S$ at time $t \in T$

4.3.2 Mathematical model

Objective functions

$$\text{Minimize } L_1 = \sum_{t\in T}\sum_{s\in S}\sum_{i\in N}\sum_{j\in N} x_{ij}^{st} * dist_{ij} \tag{4.1}$$

$$\text{Minimize } L_2 = \sum_{i\in M} y_i * OC_i + \sum_{t\in T}\sum_{s\in S}\sum_{i\in N}\sum_{j\in N} x_{ij}^{st} * dist_{ij} * F_{dist} * TC \tag{4.2}$$

$$\text{Minimize } L_3 = R_{max} \tag{4.3}$$

Constraints
Subject to:

$$z_i^s \leq y_i \qquad \forall i \in M, s \in S \tag{4.4}$$

$$\sum_{s\in S} z_1^s \geq 1 \tag{4.5}$$

$$\sum_{i\in D} z_i^s = 1 \qquad \forall s \in S \tag{4.6}$$

$$pos_1^s \geq z_i^s \qquad \forall i \in M, s \in S \tag{4.7}$$

$$\sum_{i\in N} x_{ij}^{st} = w_j^{st} \qquad \forall j \in N, s \in S, t \in T \tag{4.8}$$

$$\sum_{i\in D} w_i^{st} \geq 1 \qquad \forall s \in S, t \in T \tag{4.9}$$

$$\sum_{t\in T}\sum_{s\in S} w_i^{st} = freq_i \qquad \forall i \in D \tag{4.10}$$

$$w_i^{st} = w_i^{s((t+\frac{|T|}{freq_i})\, mod\, |T|)} \qquad \forall i \in D', s \in S, t \in T \tag{4.11}$$

$$\sum_{i\in N} x_{ih}^{st} - \sum_{j\in N} x_{hj}^{st} = 0 \qquad \forall h \in N, s \in S, t \in T \tag{4.12}$$

$$\sum_{j\in D} x_{ij}^{st} = z_i^s \qquad \forall i \in M, s \in S, t \in T \tag{4.13}$$

$$u_i^{st} + TT_{ij} - u_j^{st} \leq (1 - x_{ij}^{st})M \qquad \forall i,j \in D, s \in S, t \in T \tag{4.14}$$

$$\sum_{j\in D} x_{ij}^{st} = 0 \qquad \forall i \in M, s \in S, t \in T \tag{4.15}$$

$$R^{st} = \frac{\sum\limits_{i\in D}(w_i^{st} * ST_i) + \sum\limits_{i\in N}\sum\limits_{j\in N}(x_{ij}^{st} * TT_{ij})}{cap_s} \qquad \forall s \in S, t \in T \tag{4.16}$$

$$R_{max} \geq R^{st} \qquad \forall s \in S, t \in T \tag{4.17}$$

$$R_{max} \leq WL \tag{4.18}$$

$$w_i^{st} \in \{0,1\} \qquad \forall i \in D, s \in S, t \in T \tag{4.19}$$

$$x_{ij}^{st} \in \{0,1\} \qquad \forall i,j \in N, s \in S, t \in T \tag{4.20}$$

$$y_i \in \{0,1\} \qquad \forall i \in M \tag{4.21}$$

$$z_i^s \in \{0,1\} \qquad \forall i \in M, s \in S \tag{4.22}$$

$$u_i^{st} \in R^+ \qquad \forall i \in N, s \in S, t \in T \tag{4.23}$$

$$R^{st} \in R^+ \qquad \forall s \in S, t \in T \tag{4.24}$$

$$R_{max} \in R^+ \tag{4.25}$$

The first objective (4.1) deals with minimizing the total distance of all tours. The total monthly cost is minimized in the second objective (4.2). The first component contains the monthly cost of running the utilized field offices. The second component comprises the traveling costs that arise with the tour schedule of one planning horizon. In the third objective (4.3), the maximal tour duration of the individual tours over the whole planning horizon is minimized. This aims for equally long tours while lowering each tour duration.

Constraint (4.4) and (4.5) ensures that a team can only be assigned to an open office but must be assigned to exactly one office. Constraint (4.6) ensures that at least one service team will still use the original office. Constraint (4.7) ensures that each team can only be located at one of their possible offices. Constraint (4.8) ensures that each station is served by only one team when they are being served, while constraint (4.9) ensures that each slot for each team contains a tour consisting of at least 1 station. Constraint (4.10) ensures that each station is served in the amount according to their frequency. Constraint (4.11) ensures the time difference is assigned correctly according to the frequency. To do so, it uses the modulo operation mod. This constraint can be modified depending on given frequencies. Constraint (4.12) secures route continuity, while constraint (4.13) ensures that a team can only travel from an assigned office. Constraint (4.14) deals with subtour elimination within an assigned tour per team per time-slot as proposed by Lalla-Ruiz and Voß (2020). Constraint (4.15) ensures that no trips between two offices are occurring. Constraint (4.16) calculates the duration estimation for a tour assigned to service team s in period t with respect to a service team's capacity. Following, constraint (4.17) establishes the maximum estimated tour duration of all tours. Constraints (4.19) to (4.22) are integrality constraints that guarantee that these decision variables are binary integers. Constraints (4.23) to (4.25) define u_i^{st}, R^{st}, and R_{max} as positive continuous variables.

4.4 Metaheuristic solution approach

For large instances of the problem, obtaining a feasible solution utilizing the MILP within an acceptable time is difficult. Hence, as the literature also suggested, a heuristic is necessary. It has been decided to apply the Adaptive Large Neighborhood Search (ALNS) as it has been used in similar LRPs in literature. In addition, given the multi-objective nature of this problem, we propose to enhance it by implementing a multi-objective variant utilizing the Pareto method, a strategy commonly employed in addressing complex problems such as vehicle routing. This section outlines the methodology of the Multi-Objective Adaptive Large Neighborhood Search (MO-ALNS) metaheuristic used to solve the problem described above.

4.4.1 Algorithm definition

The ALNS algorithm's standard framework, outlined in Section 3.7, necessitates the selection of various components. Research by Mara et al. (2022) identifies the Roulette Wheel adaptive mechanism and the Metropolis acceptance criterion as popular choices due to their simplicity and effectiveness. Consequently, we incorporate these elements into our adaptation. Determining the termination criterion will occur during the algorithmic adjustments detailed in Chapter 5.

Its adaptability is at the core of ALNS, particularly evident in its treatment of destroy and repair operators. These operators, denoted as Ω^- and Ω^+, respectively, are pivotal to ALNS's efficacy. The Roulette Wheel selection principle assigns probabilities, represented by p_i^- and p_i^+ for destroy and repair operators, based on their respective weights, w_i^- and w_i^+. These weights are reassessed after every η_s iteration, ensuring that operators with a significant impact on solution improvement are more likely to be chosen. Additionally, to enhance the diversification and intensification of the solution space, a diminishing degree of destruction is applied, optimizing

Algorithm 1 MO-ALNS-1

Input: feasible solution S, $\Omega^-, \Omega^+, \eta_{max}, \alpha, T_0, LB, UB$

initialize ND by adding S
set $S' \leftarrow S, i \leftarrow 1, \eta_s \leftarrow 0.1\eta_{max}, T \leftarrow T_0$
initialize w^-, w^+, p^-, p^+
while stopping criterion not reached **do**
    select a destroy and repair heuristic from Ω^- and Ω^+ using the Roulette wheel selection
    set $S' \leftarrow repair(destroy(S))$
    ND and $S \leftarrow MO\_Metropolis(S')$
    if $i = \eta_s$ **then**
        update w^-, w^+, p^-, p^+
        update degree of destruction LB and UB
        $i = 0$
    end if
    $T = T_0 * (\frac{T_N}{T_0})^{\frac{i}{\eta_{max}}}, i = i + 1$
end while

Output: ND

the operators' effectiveness.

We integrate improvement operators into our methodology to further enhance exploration within the solution space. Specifically, three variants of the Multi-Objective Adaptive Large Neighborhood Search (MO-ALNS) have been devised, each incorporating these operators differently. The operators directly manipulate solutions to refine them without reliance on destroy or repair heuristics. The features of these three versions are delineated as follows:

1. **MO-ALNS-1:** In this approach, the improvement methods will be integrated into the set of destroy heuristics. However, unlike other instances, no subsequent repair heuristic will be applied.

2. **MO-ALNS-2:** Upon applying a series of neighborhood operators, the improvement methods from a predefined set Ω^* will be chosen using the roulette wheel mechanism. Subsequently, their selection probabilities (p_i^*) and weights (w_i^*) will be updated like the destroy and repair heuristics.

3. **MO-ALNS-3:** In this version, improvement strategies are selected after neighborhood operators have been applied based on the potential of the current solution. The assessment of whether a solution is promising or not is done in comparison to the existing Pareto front. When a solution shows promise, a second roulette wheel mechanism chooses an improvement operator from a predefined set Ω^*. This process involves updating associated probabilities (p_i^*) and weights (w_i^*). Subsequently, the chosen enhancement operator is applied.

The MO-ALNS-2 algorithm draws inspiration from Gläser's (2022) ALNS algorithm, structured in two main phases: shaking and local search. Conversely, the development of MO-ALNS-3 is influenced by the sequential large neighborhood search (LNS-S) method proposed by Hemmelmayr (2015) and further refined by Cota et al. (2019). Following the generation of a solution, whether it is accepted must be decided. Unlike greedy approaches that only accept solutions with improved objective values, the Metropolis criterion employed here evaluates worse solutions based on a calculated acceptance probability, considering both the obtained solution's performance and the temperature. This strategy helps prevent the algorithm from becoming trapped in local optima. Further elaboration on this approach, due to its differentiation between single-objective and multi-objective contexts, is provided in Section 4.4.5 for clarity and depth

Algorithm 2 MO-ALNS 2 & 3

Replacements of Line 5 and 6 of Algorithm 1 to obtain MO-ALNS-2 and MO-ALNS-3

Additional Input: Ω^*

Version 2:
select a destroy, repair and improvement heuristic from Ω^-, Ω^+ and Ω^* using the Roulette wheel selection
$S' \leftarrow improvement(repair(destroy(S)))$

Version 3:
select a destroy and repair heuristic from Ω^- and Ω^+ using the Roulette wheel selection
set $S' \leftarrow repair(destroy(S))$
if S' is a promising solution **then**
select an improvement heuristic from Ω^* using the Roulette wheel selection
$setS' \leftarrow improvement(S')$
end if

of understanding.

Utilizing these methodologies, Algorithm 1 displays the structure of the applied algorithm. The modifications leading to versions MO-ALNS-2 and -3 are presented in the combined Algorithm 2. These algorithms deviate from the standard ALNS algorithm outlined in Section 3.7 by the following key steps:

- Implementation of a decreasing degree of destruction, with the updating procedure occurring every η_s iterations.
- Establishment of termination criteria based on empirical observations, either after a maximal number of iterations or a number of non-improving iterations.
- Development of tailored operators to yield high-quality solutions within a reasonable computational time frame.
- Integration of improvement methodologies in three distinct versions.
- Introduction of a mechanism for analyzing multiple objectives facilitated by creating an archive containing non-dominating solutions.
- Adaptation of the cooling schedule to a less iteration-sensitive variant.

4.4.2 Initial solution

The ALNS algorithm relies on an initial solution to initiate its search among neighboring solutions. This initial solution is constructed randomly in three phases. Firstly, offices are randomly selected from available options for each team. If the main office is not selected, a random team is chosen to occupy it. The next phase involves systematically iterating through team tours and time slots, randomly assigning a station to the tour schedule. If a station is already assigned, the algorithm proceeds to the next tour unless the current tour length is shorter than a calculated threshold (=rounddown($|N|/(|S| * |T|)$)). To ensure feasibility, stations are immediately assigned based on their frequency. Subsequently, each tour undergoes a check to determine if a 'nearest neighbor' tour construction improves its distance. If an improvement is found, the tour is updated; otherwise, the nearest neighbor tour is discarded.

Since the initial solution significantly influences ALNS outcomes, we opted for random initialization to explore a broader solution space. We aim to establish a slightly more efficient upper bound for objectives by setting a minimum tour length and considering nearest neighbor improvements. Nevertheless, maintaining feasibility remains paramount. The pseudocode for the initial solution is presented in Algorithm 3.

Algorithm 3 Initial solution: pseudo-random approach

Input: Information about stations, offices, teams, and preferences

```
for k ← 0 to (numTeams − 1) do
    assign random office to team k from its preference
end for
if main office is not assigned then
    locate random team in main office
end if
while unassigned stations > 0 do
    for t ← 0 to (slots − 1) do
        for s ← 0 to (numTeams − 1) do
            set station ← randint(0, numStations − 1)
            if len(Tour[t][s]) < 4 then
                while station already assigned do
                    set station ← randint(0, numStations − 1)
                end while
            end if
            Tour[t][s] append station
            insert station in Tour according to frequency
        end for
    end for
end while
```

Output: $Tour$, $Allocation$

4.4.3 Solution representation

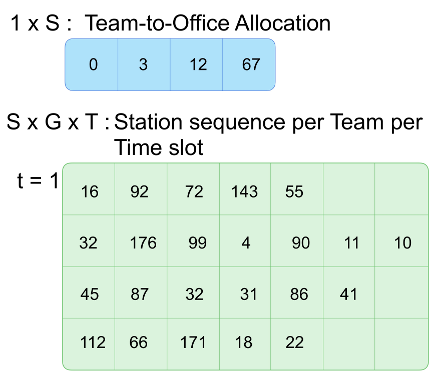

Figure 4.1: Display of Solution

The representation in this context defines how solutions are encoded for the problem at hand. Each station is assigned a unique identification number (ID), with the main office typically designated ID-0. A feasible chromosome, representing a potential solution, comprises two distinct matrices. The first matrix is a $1×S$ array, where S represents the total number of teams involved. This matrix outlines each team (denoted by index s) and its corresponding assigned office, identified by its unique number. The second matrix is three-dimensional, depicting the periodic tour schedule. Each row of this matrix illustrates the sequence of stations to be served by each team s during each time slot t. Here, G denotes the maximum number of stations permissible in a tour. None-values denote any blank spots within this matrix and do not impact the tour schedule. Combined, these matrices form a feasible solution for the problem under consideration.

Figure 4.1 provides an illustrative example of such a representation for a small-scale instance. The output of the entire algorithm is the Pareto front obtained, which comprises a set of trade-off solutions. The objectives and the complete solution representation are outputted for each solution within this set that is not dominated by any other solution.

4.4.4 Adaptive weight adjustment procedure

Following Section 3.7, the Roulette-wheel technique stands out as the most effective method for selecting destroy and repair heuristics and is also applied for choosing improvement operators. This technique assigns weights to each heuristic, which are calculated individually for the destroy heuristics, repair heuristics, and improvement procedures. The weight calculation for each method i is derived as $(\frac{w_i}{\sum_{j=1}^{|\Omega|} w_j})$, where Ω represents the set of available heuristics. Every η_s iteration, these weights are updated for the new segment considering the weights from the previous segment. Here, η_s is defined as $\eta_s = 0.05 * \eta_{max}$, ensuring updates occur relative to the maximum number of iterations (η_{max}). For the upcoming segment $j+1$ the weight update is computed as $w_{i,j+1} = w_{i,j}(1-r_w)+r_w\Phi_i/\xi_i$, where r_w represents the roulette wheel parameter, Φ_i signifies the score assigned to heuristic i in the past segment, and ξ_i denotes the number of selections during the past segment (Ropke & Prisinger, 2006). Note that after the updating procedure, scores and selection counts are reset to 0.

The scores are updated based on performance. For the single-objective ALNS, if the obtained solution results in the best solution so far ($S' < S$ and $S' < S^*$), then the scores for the applied to destroy and repair heuristics are increased by σ_1. Similarly, if the new solution is better than the current one ($S' < S$), the scores for the applied operators are increased by σ_2. Conversely, if the new solution is inferior but accepted per the Metropolis criterion, the scores for the employed heuristics are increased by σ_3.

4.4.5 Acceptance criteria

Acceptance of a solution within the Metropolis criterion, also known as the Simulated Annealing criterion, is contingent upon its performance compared to the current solution and best solution(s) so far. A new solution, denoted as S', is accepted if it yields superior results to the current solution S. Conversely, if it performs worse, an acceptance probability is computed to determine whether it should be adopted as the new current solution. The calculation of acceptance probability varies between single- and multi-objective contexts, both of which involve using a temperature parameter. In each iteration i, the temperature T is determined using a cooling schedule proposed by Bandyopadhyay et al. (2008), given by the formula $T = T_0 * (\frac{T_N}{T_0})^{\frac{i}{\eta_{max}}}$, where T_0 is the initial temperature and T_N is the final temperature. This cooling schedule considers the number of iterations to ensure a controlled temperature adjustment. Consequently, the algorithm initiates with more diversification, like a random search, and progresses towards intensification resembling a local search.

For the single-objective version, the acceptance criterion assigns a probability of acceptance, expressed as $e^{-f(S')-f(S)/T}$, to the new solution S', where T denotes the current temperature. This version is depicted in the standard ALNS algorithm (Figure 3.2). In contrast, the multi-objective variant involves a more intricate acceptance criterion and solution update mechanism. Drawing inspiration from Archived Multi-Objective Simulated Annealing (AMOSA), proposed by Bandyopadhyay et al. (2008), this variant stores Pareto-optimal solutions. To achieve this, a procedure is introduced to quantify domination between two solutions a and b, denoted as $\Delta dom_{a,b}$ and calculated as follows:

$$\Delta dom_{a,b} = \frac{\prod_{o=1, f_o(a)\neq f_o(b)}^{O} |f_o(a) - f_o(b)|}{R1_o - R2_o}$$

This calculation involves the number of objectives M, as well as the maximum ($R1_o$) and minimum ($R2_o$) values of each objective o in the approximated Pareto front. Since the true Pareto front is inaccessible, the approximated front comprises mutually non-dominated solutions identified during the search process (Heilig, Lalla-Ruiz, & Voß, 2017). The complete procedure is presented in Algorithm 4, as detailed by Rifai et al. (2021).

Algorithm 4 Procedure for the acceptance criteria and Archive update

Input: S, S', ND, T

check the domination status of the newly obtained solution S' with respect to the current solution S and the non-dominated set ND

```
if S ≻ S' then
    Δ̄ = ((∑_{i=1}^{k} Δ_{i,S'}) + Δ_{S,S'})/(k + 1)
    P = 1/(1 + exp^(Δ̄·T))
    if rand[0, 1] ≤ P then
        set S ← S'; Score = σ_3
    end if
else if S and S' are non-dominating each other then
    if A_k ≻ S', k ≥ 1 then
        Δ̄ = (∑_{i=1}^{k} Δ_{i,S'})/k
        P = 1/(1 + exp^(Δ̄·T))
        if rand[0, 1] ≤ P then
            set S ← S'; Score = σ_3
        end if
    else if all A ∈ ND and S' are non-dominating each other then
        set S ← S'; Score = σ_2
        insert S' to ND
    else if S' ≻ A_k, k ≥ 1 then
        set S ← S'; Score = σ_2
        insert S' to ND
        ND = ND \ A_k
    end if
else if S' ≻ S then
    if A_k ≻ S', k ≥ 1 then
        Δ_min = min_{i∈k} Δ_{i,S'}
        P = 1/(1 + exp^(−Δ_min))
        if rand(0, 1) ≤ P then
            set S ← S'; Score = σ_3
        else
            set S ← A_k with Δ_min
        end if
    else if all A ∈ ND and S' are non-dominating each other then
        set S ← S'; Score = σ_2
        insert S' to ND
    else if S' ≻ A_k, k ≥ 1 then
        set S ← S'; Score = σ_2
        insert S' to ND
        ND = ND \ A_k
    end if
end if
```

Output: S, ND, $Score$

4.4.6 Operators

The operators are selected based on the Roulette Wheel method. The operator weights and probabilities, as well as the degree of destruction, are updated after η_s iterations.

Destroy heuristics

By applying destroy heuristics, several variables are eliminated from the current solution. The magnitude of this elimination, termed the "degree of destruction", profoundly influences the performance of the ALNS algorithm. If the degree is too small, the algorithm lacks diversity and fails to explore the full breadth of potential solutions within the neighborhood. Conversely, an overly large degree leads to diminished intensification, resulting in suboptimal solutions and increased computational time. Drawing inspiration from Koc's work (2016), we adopt a strategy of gradually reducing the degree of destruction as the algorithm processes, thereby concentrating efforts on promising solution areas. This adaptive adjustment is governed by an updating procedure defined as follows:

$LB_{j+1} = LB_j - \frac{\eta_s(UB_{max}-UB_{min})}{\eta_{max}}; UB_{j+1} = UB_j - \frac{\eta_s(UB_{max}-UB_{min})}{\eta_{max}}$

Here, LB_{j+1} and UB_{j+1} represent the updated lower and upper bounds of the degree of destruction for segment j+1, respectively. LB_j and UB_j denote the previous lower and upper bounds, while LB_{max} and LB_{min} (likewise for UB_{max} and UB_{min}) represent the maximum and minimum limits for the degree of destruction. η_s and η_{max} operate as scaling parameters.

In our implementation, several destroy heuristics have been integrated. The degree of destruction is dynamically determined within predefined lower and upper bounds at each iteration segment. Specifically, a random integer k, uniformly distributed between $|D| * LB$ and $|D| * UB$, is used to determine the number of stations to be removed from the tour schedule, where $|D|$ represents the total number of train stations.

Random removal (RR): This heuristic randomly removes k stations from the given solution and saves them in a removal list. In the case of multiple occurrences in the tour schedule due to a station's frequency, all duplicates will be removed.

Worst removal – distance (WD): This heuristic removes k stations that add the most distance value to the total tour distance sequentially.

Worst removal – workload (WW): This heuristic looks for the tour with the longest total tour time and removes the station with the worst distance within that tour. This is repeated k times.

No-related removal (NR): This heuristic is inspired by the commonly used related removal, where related demand points get removed. However, stations that do not have any related stations in their tour are removed. The attribute "related" refers to the areal closeness determined by the distance radius to other stations. The closeness variables with the quality of the given solution. Starting with a large radius, it might be the case that every station has a related station in its tour, and the removal list remains empty. In that case, the closeness value will be reduced until stations can be removed. Since this heuristic is newly developed, the pseudocode is displayed in Algorithm 5.

In addition to classical destroy and repair heuristics, an operator that manipulates the team-office allocation has been implemented. This can be selected with the roulette wheel procedure as a destroy heuristic, but no repair heuristic will be needed afterward. The following office operator has been implemented:

Change random office (CO): Here, the office of a random team is changed to a random office out of its preferences. When the team only has one possible office, another team is chosen. Also, it is guaranteed that the main office will remain in use.

Algorithm 5 Destroy heuristic: No-related removal

Input: Tour

```
Initialize removed and Dist = 75
while removed is empty and Dist > 10 do
    for t ← 0 to (slots − 1) do
        for s ← 0 to (numTeams − 1) do
            if len(Tour[t][s]) > 1 then
                for n ← 0 to len(Tour[t][s]) do
                    Check if there is a station in Tour[t][s] with distance < Dist
                end for
                if no station in Tour[t][s] with distance < Dist then
                    add Tour[t][s][n] to removed
                    remove Tour[t][s][n] and all its duplicates
                end if
            end if
        end for
    end for
    Dist− = 10
end while
```

Output: $Tour$, $removed$

Change all offices (AO): This operator changes the office of all teams if possible. When it happens that no team would be located at the main office, a random team is chosen to be located there.

Only main office (OMO): This operator locates all teams in the main office to also allow exploring the case when no field offices will be used.

Open all offices (OO): Since closing offices will always lead to lower costs, we decided to force the algorithm to open all offices. However, since this will mainly lead to high costs, this operator is not used individually but during the improvement of operator WO, as explained below.

Repair heuristics

Given a removal list, repair heuristics insert the removed stations into the destroyed tour plan. The heuristics insert stations according to their frequency and maintain feasibility.
The following repair heuristics have been implemented:

Greedy repair distance (GD): This heuristic searches the partially constructed tour for the best position to insert each removed station sequentially. Here, the best position is determined by the least increase in distance to the total tour length value.

Insert shortest tour (ST): This heuristic works like the distance greedy repair. The difference is that now it looks first for the shortest tour and then determines which of the removed stations fits best and in what position determined by the least increase of distance to the total tour length value.

Insert nearest neighbor – short tour (NN-ST): This heuristic is an extended version of the previous nearest neighbor heuristic. It places a station only next to its nearest neighbor if it is on a tour shorter than ‘the average tour time plus one hour’.

Greedy repair workload – distance (WL-D): This heuristic looks for tours that are not worsening the workload balance. If there are multiple, from these tours, the logic of the GD heuristic is used to select the position that adds the least to the total distance.

Insert to best office (BO): For each removed station, the heuristic determines which currently used office is the closest and which tours begin there. Afterward, from these tours, the logic of the GD heuristic is used to select the position that adds the least to the total distance.

Improvement heuristics

Furthermore, improvement methods that reconstruct a given solution are applied to obtain more quality solutions within a shorter time. These are the following:

Workload balance (WB): This operator looks for the longest tour and removes the station that contributed the most amount to its tour length, as well as all frequency-related duplicates. Afterward, this removed station is inserted with the NNST repair heuristic. This gets repeated until no improvement is obtained.

Workload balance with office (WO): This local search operator is an extension to WB. It is constructed by combining the opening of all offices or changing one office to get the stations more clustered by region. With a probability of 0.5, the operator OO is accessed to open all offices; else, operator CO is used. Afterwards, the regular WB local search is used. The two workload balance local search procedures are addressed separately, so the performance of changing an office or not can be evaluated during the roulette wheel method.

Rearrange per Team (RT): This operator searches the tours of each team individually to improve the tour structure of one team without changing the general clustering of stations between the teams. Systematically, cycling through the tours of team s, the best position in those tours for each station gets checked by looking at the improvement of the sum of the lengths of each tour.

Swap (SW): This method swaps a station with another station and determines which swap results in the best distance improvement. This is repeated systematically until no improvement is made.

Leveling Tours (LT): This operator looks for tours whose total tour time is lower than the maximal service time of all stations. Then the best fitting station from tours with a total tour time higher than the average is selected and added to that short tour.

4.5 Stochastic evaluation

Service teams often encounter travel and service time variations during train station operations, as explained in Section 2.3.5. Understanding how the stochastic factors impact the quality of tour scheduling is crucial. Therefore, we integrate these parameters into our evaluation process. This entails conducting numerous stochastic scenarios through Monte Carlo simulation and analyzing the results. To realize this, we introduce Algorithm 6.

Algorithm 6 Stochastic simulation

$Det_{Problem}$ = deterministic problem
$Stoch_{Problem}$ = stochastic problem
ND = MO-ALNS1$(Det_{Problem})$
$ND^* \leftarrow$systematically selected solutions of ND with $s_i \in ND^*$
for $(s \in ND^*)$ **do**
    for $(j = 1; j \leq 1000; j++)$ **do**
        $values[j]$ = Evaluate$(s, Stoch_{Problem})$
    end for
end for
Analysis$(values)$

Initially, the algorithm applies the MO-ALNS metaheuristic once, generating a set of non-dominated solutions, which are subsequently utilized in a Monte Carlo simulation. Finally, the outcomes are examined using box plots for clear visualization.

The selection of solutions from the non-dominated set is based on weighted scores derived from normalized objectives, scaled against their respective minimum and maximum values. These weighted scores are computed using the weights outlined in Table 4.1. The first three weights prioritize performance in individual objectives, whereas the fourth weight combination aims for a balanced approach. The remaining six weight combinations emphasize one or two objectives more heavily. If a solution achieves the minimum weighted score in one weight combination but has already been selected by a previous combination, the following weight combination is considered. This process continues until an as-yet-unselected solution is eligible for inclusion in the solution set for stochastic analysis so that a total of ten solutions will be considered. The order for applying the objective weight configurations follows the order shown in Table 4.1.

Table 4.1: Selection scheme for stochastic analysis

Solution	Dist. weight	Cost weight	WL weight
1	1	0	0
2	0	1	0
3	0	0	1
4	1/3	1/3	1/3
5	0.5	0.25	0.25
6	0.25	0.5	0.25
7	0.25	0.25	0.5
8	0.4	0.2	0.4
9	0.2	0.4	0.4
10	0.4	0.4	0.2

4.6 Conclusion

This chapter answers the research question "What should the design of the solution approach look like?" and its respective sub-questions. After a formal problem definition of the Location-Routing Problem in Section 4.1, the assumptions and requirements are stated upon which the implementations of the problem as Adaptive Large Neighborhood Search (ALNS) and Mixed-Integer Linear Program (MILP) are based. The solution approach focuses on optimizing the total distance of the periodic tour schedule while minimizing the travel and office operation costs as well as the maximal tour duration by locating the service teams to (field) offices considering the possible periodic tour schedule.

The mathematical model is described, including the notation of the used sets, parameters, and decision variables, as well as the objective functions and constraints. Afterward, the metaheuristic Multi-Objective ALNS (MO-ALNS) is adapted to suit our problem. Each component of the algorithm is described. Information about the train stations, offices, and service teams is needed for input. A solution will then be output as a list indicating the office locations per team and a three-dimensional matrix containing the tours per team and time slot. While the MILP can only generate one solution for one objective for only a small scenario within a reasonable time, the MO-ALNS heuristic will use destroy, repair, and improvement operators to assess all objectives simultaneously and collect non-dominated solutions. Starting with a pseudo-random-generated initial solution, the metaheuristic manipulates solutions with operators selected by the Roulette Wheel method. This method evaluates and chooses the operators based on their past performance, providing the heuristic with its adaptability. Furthermore, the Metropolis criterion is applied to accept not only better solutions but also worse solutions to foster diversification.

The selection of improvement operators is carried out in three different ways: in the first version, they are chosen concurrently with destroy operators; in the second version, one improvement operator is selected and applied in each iteration following the destroy and repair operators; and in the third version, an improvement operator is applied after the destroy and repair operators, but exclusively to promising solutions. The most effective implementation of improvement operators, the termination criteria, and other parameters will be determined during the experimental phase outlined in the following chapter. Additionally, a stochastic evaluation algorithm utilizing Monte Carlo simulation has been proposed to understand the impact of stochastic factors on the quality of tour scheduling.

5 EVALUATION

In this chapter, the fourth research question is answered: How does the solution approach perform for the experiments in comparison to the current situation? Firstly, the experimental design is determined in Section 5.1. Afterward, we present the different scenarios that will be used to approach the experiments. The execution of the experiments is sequentially explained, and results are displayed. The insights gained and required for the following experiments are interpreted and summarized for each experiment. The first set of experiments addressing the algorithmic of the proposed model is presented in Section 5.3, while the second set of experiments is designed to gain specific insight into the company's problem and is presented in Section 5.4. As displayed in Section 5.5, the third set of experiments focuses on analyzing the robustness of proposed solutions stochastically.

5.1 Experimental design

In this section, we define experiments to improve and evaluate the performance of the proposed solution approach. They are distinguished into six categories, which are explained below. The first three experiments deal with tuning the algorithm, the fourth one with validating the models, and the last two with practical insights. The experiments are conducted on a Windows computer with an Intel Core i5 processor of 2.5GHz and 16GB RAM. All codes have been implemented in Python (3.11.3) with Spyder 5.4.3 IDE.

1. Operator selection: This study compares the three proposed variations of improvement operator implementation into the Multi-Objective Adaptive Large Neighborhood Search (MO-ALNS) algorithm in terms of their efficacy in refining initial solutions within a limited number of iterations. Evaluation criteria include running time, hypervolume, and the size of the resulting non-dominated front.

2. Termination criterion: This experiment evaluates the stopping criteria for the algorithm. It investigates whether the algorithm converges to a satisfactory solution within a predetermined runtime, thus determining an appropriate benchmark for the number of iterations required for convergence.

3. Parameter selection: During parameter selection, various values for the roulette wheel parameter and performance scores are tested to enhance the algorithm's efficiency in evaluating operator performance.

4. Algorithm performance analysis: This experiment compares the results obtained from the MO-ALNS algorithm with those from the single-objective equivalent ALNS and, if available, with results from the mathematical Mixed Integer Linear Programming (MILP) model.

5. Deterministic solution evaluation: This experiment evaluates the current state of two train station management regions to understand resource allocation and demonstrate the model's applicability to other regions.

6. Stochastic solution evaluation: The final experiment incorporates stochasticity in travel and service times. A subset of potentially good solutions from the Pareto front is evaluated using Monte Carlo simulation to assess the fitness of tour schedules to given time frames and resources, providing robust decision support.

The temperature parameters ($T_0 = 100, T_N = 1$) were chosen beforehand to allow for the acceptance of suboptimal solutions at the outset of the algorithm, with their likelihood of acceptance diminishing as the algorithm progresses. The performance scores ($\sigma_1, \sigma_2, \sigma_3 = 33, 9, 13$) and roulette wheel parameter ($r_w = 0.1$) have been proposed by Ropke and Prisinger (2005) and favorably applied in other studies, e.g., the one by Gläser (2022). These will be used for experiments 1 and 2 and addressed in experiment 3.

5.2 Scenarios

For the parameter tuning, data sets of different sizes and components are needed. The original set of TM Magdeburg has 198 stations, four offices, and four teams (MDB-7). From this, multiple sets of different numbers of stations, offices, and teams are randomly generated. Also, to create larger scenarios, fictive stations are used as fillers. A total of 10 scenarios will be used to assess the algorithm's quality for different instances. The number of stations, possible offices, and teams of each scenario are presented in Table 5.1.

Table 5.1: Overview of scenarios for parameter tuning

Data instance	Stations	Offices	Teams
MDB-1	50	3	2
MDB-2	50	4	2
MDB-3	100	3	3
MDB-4	100	4	3
MDB-5	150	4	3
MDB-6	150	4	4
MDB-7	198	4	4
MDB-8	198	4	5
MDB-9	250	4	5
MDB-10	250	5	5

Looking at the research question regarding the model validity and applicability in different regions, we are interested in data sets of different TMs besides the one in Magdeburg. Because of its close relation to this TM and good data accessibility, we use data instances from TM Halle (HAL) in the southeast region. Besides their original data (-A), additional instances are created for MDB and HAL. The second set (-B) has an extra team, while the third set (-C) contains an additional field office option outside of DB property, which means a higher cost (€1500) due to rent but in a favorable location. The last set (-D) has the property to have one less service team than the current situation. The number of stations, possible offices, and teams of these scenarios are presented in Table 5.2.

Table 5.2: Overview of scenarios for numerical experiments

Data instance	Stations	Offices	Teams
MDB-A	198	4	4
MDB-B	198	4	5
MDB-C	198	5	4
MDB-D	198	4	3
HAL-A	159	3	3
HAL-B	159	3	4
HAL-C	159	4	3
HAL-D	159	3	2

Parameter tuning necessitates scenarios of varying scales, whereas obtaining company-specific numerical insights solely requires using real-world settings. For this reason, these two distinct sets of scenarios are employed. To connect the utilization of the scenarios with the execution of experiments, Table 5.3 provides a concise overview of the order of actions, goals, and the respective scenarios employed for each experiment.

Table 5.3: Overview of experiments and their goal

Order	Experiment	Goal	Scenarios
1	Operator selection	Selecting the most efficient implementation of improvement operators.	MDB-4, -7, -9
2	Termination criterion	Selecting a fitting termination criterion.	MDB-4, -7, -9
3	Parameter selection	Finding algorithm- and model-specific parameter settings to archive the best solving performance regarding the remaining experiments.	MDB-1 to MDB-10
4	Algorithm performance analysis	Analyzing the model behavior when dealing with scenarios of different sizes and resource parameters.	MDB-1 to MDB-10
5	Deterministic solution evaluation for two TMs	Gaining insight into the regional applicability of the solution approach combined with first insights into solution interpretation.	MDB-A to -D, HAL-A to -D
6	Stochastic solution evaluation	Executing stochastic scenarios to conclude the best decision-making strategy.	MDB-A

5.3 Parameter tuning

In this section, the subsequently executed experiments to improve the algorithmic are explained, and their results and conclusions are presented.

5.3.1 Operator selection

OperatorSel The most efficient MO-ALNS version of the three proposed ones must be selected. For a selected data instance, all three versions are executed with a termination criterion of 500 iterations to obtain the improvement from the initial solution with the same number of iterations. Next to the percentage improvement from the initial solution to the minimal obtained value of each objective, the hypervolume, number of obtained non-dominated solutions, and runtime are considered as additional performance metrics for each version.

The hypervolume (HV) is a metric used to assess the quality of a Pareto front in multi-objective optimization. It measures the volume of the space dominated by the Pareto front in the objective space, considering a reference point outside the front or the nadir point (While, Bradstreet, & Barone, 2012). A higher hypervolume indicates a better Pareto front, representing a more extensive diversity and convergence of the objective space by the non-dominated solutions (Rifai et al., 2021). The Python pymoo package presented by Blank and Deb (2020) is used for the calculation.

This study examines the effectiveness of three different approaches for implementing improvement heuristics. The results from scenarios MDB-4, -7, and -9 are presented in Table 5.4. The percentage improvement of the three objectives from the initial solution, the hypervolume, the size of the obtained solution set, and the running time are documented. The best values for each criterion of the heuristic versions per scenario are colored in blue. MO-ALNS-1 demonstrates significantly lower running times than the other methods and consistently achieves the

Table 5.4: Results to operator selection experiment

Scenario	Version	Dist.	Cost	WL	HV	Size ND	Run time
MDB-4	MO-ALNS-1	51%	34%	64%	0.7773	23	293.846
	MO-ALNS-2	50%	37%	65%	0.5313	27	657.714
	MO-ALNS-3	47%	53%	63%	0.6539	31	423.493
MDB-7	MO-ALNS-1	57%	53%	82%	0.7737	23	1380.151
	MO-ALNS-2	57%	51%	76%	0.744	27	3227.035
	MO-ALNS-3	43%	41%	84%	0.7733	30	1803.921
MDB-9	MO-ALNS-1	60%	55%	80%	0.8671	36	2689.164
	MO-ALNS-2	57%	41%	77%	0.705	17	9422.695
	MO-ALNS-3	48%	47%	79%	0.802	26	3462.118

highest hypervolume across all instances. Moreover, the improvement from the initial solution to the minimum achieved values per objective is most pronounced in six out of nine cases. Particularly noteworthy is the substantial improvement across all three objectives for the largest instance (MDB-9), which indicates that MO-ALNS-1 holds the most promise among the algorithm variants. In contrast, MO-ALNS-2 yields unfavorable long running times across all instances, ranging from 2 to 3.5 times longer than MO-ALNS-1. Meanwhile, MO-ALNS-3 exhibits only a modest increase in running time, ranging from 25% to 45% longer than MO-ALNS-1. Based on these observations, we decided to proceed with version MO-ALNS-1.

5.3.2 Termination criterion

In the context of optimizing performance, the decision on when to terminate the algorithm is crucial. Using the best-performing version MO-ALNS-1, this decision is based on analyzing variations in the Pareto fronts obtained through two termination conditions: after a maximal number of iterations, denoted as η_{max}, or after $0.1 * \eta_{max}$ iterations without improvement. Furthermore, various η_{max} values have been explored to ascertain their impact on the algorithm's performance. The assessment of outcomes involves considering key metrics such as hypervolume (HV), the quantity of non-dominated solutions obtained, and the algorithm's running time. We also document instances where the algorithm faces $0.1 * \eta_{max}$ iterations without any improvement and terminates before reaching η_{max}. This analysis sheds light on the potential efficiency of utilizing non-improvement iterations as termination criteria, especially if the algorithm recurrently converges early.

The results of the termination criterion experiment are tabulated in Table 5.5. We conducted three scenarios of different sizes for each selected η_{max} value to obtain the metrics as mentioned above. The best-performing values of HV and ND size within each scenario are highlighted in blue. Instances of early termination are documented with the respective iteration number, while scenarios without early termination are marked with an X.

Notably, the algorithm terminated early only once before reaching the maximum number of iterations. Observing the runtime, it is evident that for iteration thresholds up to $\eta_{max} = 1,000$, all executions were completed within two hours, which was deemed acceptable. Additionally, a recognizable trend of the non-dominated solution set expanding in size with increased iterations suggests the potential benefit of further iterations. Moreover, the hypervolume metric demonstrates its peak average (0.81), with runs comprising 2,000 iterations, followed by those with 500 iterations (0.72) and 1,000 iterations (0.72). The similarity in the sizes of non-dominated sets for 500 and 1,000 iterations elucidates the comparable hypervolume averages between them, while the averages for 1,000 iterations display greater consistency across the three instances.

Table 5.5: Results for runs with different η_{max} values

η_{max}	Instance	Run time	HV	Size ND	Early term.
100	MDB-4	74.279	0.4801	14	X
	MDB-7	409.665	0.5195	17	X
	MDB-9	601.388	0.2351	8	at iteration 31
500	MDB-4	326.482	0.4966	26	X
	MDB-7	1637.872	0.73	32	X
	MDB-9	4532.923	0.946	20	X
1000	MDB-4	622.268	0.5907	25	X
	MDB-7	3240.04	0.8744	38	X
	MDB-9	6019.769	0.6856	17	X
2000	MDB-4	1484.818	0.722	43	X
	MDB-7	6608.428	0.8235	34	X
	MDB-9	15682.963	0.8704	39	X
5000	MDB-4	6056.04	0.4574	43	X
	MDB-7	17370.867	0.8011	63	X
	MDB-9	33753.954	0.775	50	X

Furthermore, it becomes evident that opting for a lower percentage of η_{max} as the maximal number of non-improvement iterations might not be advisable. This choice could potentially hinder the algorithm's ability to escape from local optima. Considering the dynamics of optimization processes, it is plausible that certain iterations are necessary to explore alternative solutions and navigate away from suboptimal local regions. Considering this, the rationale for choosing a maximal number of 1,000 iterations as the termination criterion seems a sufficient choice. This threshold strikes a balance between computational efficiency and exploration of the solution space. It allows the algorithm sufficient time to converge towards promising solutions while avoiding excessive computational costs. Therefore, based on the observed trends and the need to balance computational resources with solution quality, a maximal number of 1,000 iterations emerges as the most prudent choice for terminating the algorithm in this study concerning executing several experiments.

5.3.3 Parameter selection

This experiment investigates the impact of the roulette wheel parameter r_w and various combinations of performance scores σ_i. Ropke and Prisinger (2006) proposed a strategy where a 'worse but accepted' solution (σ_3) is rewarded more than a 'better than current' solution (σ_2), intending to promote diversification. They suggested using higher integer values (33, 9, 13) for these scores, a suggestion also supported by other researchers such as Gläser (2022). Following this, we adopted these score values but varied the ranges experimentally. We selected four different combinations to observe how they influence the promotion of diversification and the spacing between the scores. Additionally, we will assess the impact of the roulette wheel parameter by considering three different values (0.1, 0.2, 0.3). The results are documented in Tables 5.6 and 5.7 for the roulette wheel parameter and performance score analysis, respectively. For each scenario, the best obtained objective values over all parameter selections are highlighted in blue as 0.0(%). The other values present the percentage increase from these best values per scenario.

Concluded from the results presented in Table 5.6, the roulette wheel parameter $r_w = 0.2$ consistently yields favorable outcomes. In 9 out of 10 scenarios, at least one of the objectives archives the minimum across the three experiments. Consequently, this value is selected, and the process proceeds to evaluate the optimal performance scores.

Table 5.6: Results roulette wheel parameter tuning (in %)

	$r_w = 0.1$			$r_w = 0.2$			$r_w = 0.3$		
Scenario	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**
MDB-1	4.1	0.9	0.0	0.0	0.0	6.3	23.0	2.5	2.8
MDB-2	0.0	0.6	1.4	2.1	0.0	0.0	0.6	3.7	2.8
MDB-3	9.8	5.4	0.0	0.0	0.0	3.2	14.3	11.6	3.4
MDB-4	6.5	0.0	7.0	0.0	11.5	0.0	0.4	0.2	2.1
MDB-5	5.6	12.6	0.0	12.1	0.0	3.2	0.0	13.9	1.7
MDB-6	0.0	3.5	0.0	7.6	0.0	6.6	1.6	2.7	4.7
MDB-7	6.8	4.7	5.6	0.0	0.0	0.0	13.9	15.6	2.4
MDB-8	7.1	5.8	5.1	0.0	6.9	0.0	8.0	0.0	2.7
MDB-9	0.0	0.1	0.0	3.9	0.3	1.3	8.6	0.0	0.3
MDB-10	10.4	9.9	0.0	0.0	4.8	4.0	11.3	0.0	10.1
AVG	5.0	4.3	1.9	2.6	2.3	2.5	8.2	5.0	3.3

In evaluating various scores, our objective is to ascertain the extent to which diversification, characterized by accepting suboptimal solutions, should be prioritized over enhancing the current solution. Additionally, we aim to determine the relative decrease in scores when accepting suboptimal solutions compared to attaining a new addition to the non-dominated set.

Table 5.7: Results performance scores (in %)

	S1: (33,9,13)			S2: (33,13,9)			S3: (33,11,22)			S4: (33,22,11)		
Scenario	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**
MDB-1	3.0	1.7	5.8	12.3	0.0	4.1	3.4	9.4	2.2	0.0	7.0	0.0
MDB-2	2.1	3.5	3.1	4.4	3.3	0.0	0.0	1.6	6.2	0.3	0.0	6.4
MDB-3	8.7	0.0	3.9	0.0	12.1	0.0	11.7	7.5	0.6	8.4	0.7	3.6
MDB-4	18.2	12.7	0.0	15.6	0.0	4.3	11.4	10.6	1.6	0.0	1.9	1.6
MDB-5	15.2	1.0	3.2	7.1	10.0	3.0	2.9	16.6	0.0	0.0	0.0	1.2
MDB-6	6.8	5.2	4.3	3.2	0.0	2.2	1.6	0.2	2.2	0.0	3.1	0.0
MDB-7	0.0	9.8	2.3	14.3	0.0	0.0	6.3	23.9	2.3	13.2	11.9	2.3
MDB-8	0.0	6.4	0.0	10.9	7.2	1.0	5.9	5.1	2.6	11.3	0.0	1.7
MDB-9	9.8	1.6	0.0	3.4	1.4	0.4	9.2	0.0	6.3	0.0	1.8	1.0
MDB-10	0.0	4.3	0.0	10.3	9.4	4.5	17.4	6.8	4.8	11.9	0.0	0.7
AVG	6.4	4.6	2.3	8.2	4.3	1.9	7.0	8.2	2.9	4.5	2.6	1.9

Table 5.7 shows the results of the performance score assessment. The score combination denoted as S4 exhibits the highest frequency of scenarios where at least one objective performs optimally in eight scenarios. In six out of the ten scenarios, both S1 and S2 demonstrate optimal performance in at least one objective, whereas S3 achieves this in only three scenarios. On average, S4 displays a deviation of 3.0%, whereas S1 and S2 exhibit deviations of 4.4% and 4.8%, respectively, and S3 displays a deviation of 6.0%. Given the consistent attainment of low objective values by S4, potentially indicating a superior Pareto front, we have selected these performance scores for proceeding with our solution approach.

Concluding, the parameter settings as displayed in Table 5.8 have been selected.

5.3.4 Algorithm performance analysis

First, the models need to be validated to assess the solution quality of the MO-ALNS based on the single-objective equivalent ALNS and the MILP. For both ALNS metaheuristics, a function

Table 5.8: Parameter settings used in (MO-)ALNS

Description	Selected values
Total number of iterations η_{max}	1,000
Number of iterations for roulette wheel η_s	0.05η_{max}
Initial temperature T_0	100
Final temperature T_N	1
Roulette wheel parameter r_w	0.2
New global/ Pareto solution σ_1	44
Better than /dominating current solutionσ_2	22
Worse but accepted solution σ_3	11
Lower limit of degree of destruction	3-13% of $\|D\|$
Lower limit of degree of destruction	10-30% of $\|D\|$

is programmed to check and guarantee the feasibility of the solutions. For the MILP, very small instances were generated, which can be solved in a reasonable time to optimality. The results were manually checked for incongruities of office allocation, tour construction, and frequency assignments as well as calculations of the objectives. The absence of discrepancies confirms the mathematical model's validity in addressing the given problem. Since the validity of the models is guaranteed, the effectiveness of the MO-ALNS method is evaluated by comparing the results to both MILP for smaller instances and the ALNS algorithm when optimizing each objective separately.

Table 5.9: Comparison of results generated by MO-ALNS, ALNS, and MILP for small instances

		MO-ALNS			ALNS			MILP			
Scenario	**Focus**	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**	**Gap(%)**
MDB-1	Dist.	1644.12	1996.15	596	1531.63	1893.78	698	1726.0	2070.66	575	23.56
	Cost	1879.75	1710.57	597	1655.62	1506.61	705	1941.63	1766.88	582	34.94
	WL	2004.87	2324.43	449	1930.27	2256.55	449	3378.48	3074.42	482	28.75
MDB-2	Dist.	1813.86	2150.61	614	1773.16	2113.58	696	1813.34	2150.14	662	39.11
	Cost	2092.1	1903.81	695	2061.44	1875.91	684	2022.85	1840.79	682	21.32
	WL	2576.26	2844.4	483	2524.47	2797.27	479	2978.08	3210.05	487	24.64
MDB-75.1	Dist.	2480.16	2756.95	666	2334.42	2124.32	790	2345.83	2634.71	687	34.92
	Cost	2529.25	2301.62	615	2519.71	2292.94	713	2505.9	2280.37	708	29.01
	WL	3317.43	3018.86	452	3077.37	3300.41	422	4467.31	4565.25	451	26.83
MDB-75.2	Dist.	2090.48	1902.34	774	1983.45	2304.94	897	2197.23	2499.48	861	43.18
	Cost	2090.48	1902.34	774	2301.7	2094.55	786	2319.2	2110.47	826	45.23
	WL	2869.23	2611.0	600	2820.02	3066.22	622	3702.98	3369.71	625	25.12

Due to computational constraints, we can only comprehensively compare all three methods for MDB-1 and MDB-2 instances. Therefore, two additional scenarios (MDB-75.1 and MDB-75.2) with each 75 stations were constructed to gain a clearer result. ALNS and MILP are executed three times, each focusing on a specific objective, whereas MO-ALNS is executed once, targeting the minimum value for each objective. The results include values for three key performance indicators (KPIs), presented in two tables: Table 5.9 displaying MILP-permissible scenarios and Table 5.10 showing scenarios without MILP. The "focus" column in these tables indicates the optimization target in the single-objective approaches. Conversely, for the MO-ALNS method, the focus indicates the objective for which the minimal value was sought from the Pareto front, along with its complete solution. The best value per focus for each scenario is colored in blue.

Notably, MILP performs sub-optimally in both scenarios across all objective focuses. While MILP is time-limited to 60 minutes, MO-ALNS and ALNS achieve results in under 15 minutes.

The complexity of the Location-Routing Problem (LRP), comprising Facility Location and Vehicle Routing subproblems with numerous decision variables, demands substantial memory and time resources for solution evaluation, hindering MILP's performance against heuristics. Even though the running time was already 1 hour for the MILP, the gaps are undesirably high, averaging 31%. Considering Table 5.9 and 5.10 results, MO-ALNS outperforms ALNS in reaching minimum values for at least one objective for the larger scenario instances, while ALNS is archiving superior results with the smaller instances. In general, all methods at one point yield solutions that either dominate or are dominated by others, but with the majority of solutions across the focuses being non-dominant to each other.

Table 5.10: Comparison of results generated by MO-ALNS and ALNS for large instances

		MO-ALNS			ALNS		
Scenario	**Focus**	**Dist.**	**Cost**	**WL**	**Dist.**	**Cost**	**WL**
MDB-3	Dist.	2471.51	3249.07	577	2360.32	3147.89	689
	Cost	3350.69	3049.13	600	3055.75	2780.73	673
	WL	3225.4	3935.11	520	2623.64	3387.51	548
MDB-4	Dist.	2248.17	3545.83	699	2513.78	2787.54	777
	Cost	2770.51	3021.16	653	2917.52	2654.94	723
	WL	3447.11	4136.87	528	3379.41	3575.26	540
MDB-5	Dist.	2415.08	3197.72	759	3022.5	3750.48	792
	Cost	2787.19	3036.34	791	3639.19	3311.66	782
	WL	3488.65	4174.67	657	3486.68	3672.88	679
MDB-6	Dist.	2732.79	3986.84	695	2896.95	4136.22	729
	Cost	3377.58	3573.6	799	3791.44	3450.21	799
	WL	3409.44	4602.59	599	2935.56	4171.36	589
MDB-7	Dist.	2981.05	4212.76	881	3291.95	4495.67	832
	Cost	3511.78	3695.72	845	4305.51	3918.01	843
	WL	4583.31	4670.81	705	3512.4	4696.28	708
MDB-8	Dist.	3447.2	4136.95	745	3869.93	4521.64	827
	Cost	4347.37	3956.11	880	3997.96	4138.14	880
	WL	4845.76	5409.64	621	4436.93	5537.61	569
MDB-9	Dist.	4188.33	5311.08	872	4209.55	4830.69	861
	Cost	5088.33	4630.38	860	5154.3	4792.22	854
	WL	7286.62	7130.82	694	4691.95	5769.67	678
MDB-10	Dist.	4262.81	4879.16	864	4475.08	5072.32	889
	Cost	4262.81	4879.16	864	4693.4	4771.0	879
	WL	4791.38	5360.16	741	5987.19	6948.34	676

This discrepancy may stem from the choice of operators in ALNS to simultaneously improve all KPIs. Although the Roulette wheel procedure encourages operators to lead to improvement, conflicting KPIs can hinder exploration and exploitation. In contrast, MO-ALNS gathers trade-off solutions, enabling reentry into solution space using the AMOSA criterion for further exploration and exploitation. Thus, MO-ALNS emerges as a valuable heuristic, capable of achieving satisfactory solutions within reasonable timeframes compared to its single-objective counterpart, ALNS, and the mathematical model MILP.

Nevertheless, when examining the KPIs, the inherent trade-offs become evident. Opting for low cost often entails refusing the use of field offices, resulting in longer distances traveled compared to scenarios where some field offices are utilized. Conversely, aiming for minimal distance involves maximizing tour lengths, which may lead to unbalanced schedules for employees. On the other hand, imposing a strict limit on tour duration can help achieve a more balanced schedule, but it also does not guarantee optimal tour construction in every case. It is apparent that pursuing either extreme solution comes with significant drawbacks. Hence, neither extreme represents the optimal or even a satisfactory solution. This underscores the importance of considering trade-offs, as captured by the MO-ALNS algorithm. Analyzing a comprehensive set of non-dominated solutions can give a deeper understanding of feasible and beneficial approaches for the given problem instance.

5.4 Deterministic solution evaluation

The metaheuristic method and its predefined parameters are applied to analyze the proposed problem in-depth, providing significant insights pertinent to the company's objectives. We evaluate the case of TM Magdeburg and its neighboring TM Halle, demonstrating the model's adaptability to diverse management regions. Subsequently, we present a comprehensive conclusion derived from the collective assessments of both regions.

5.4.1 Magdeburg insights

In addition to the current situation in Magdeburg (referred to as scenario MDB-A), three alternative scenarios were examined theoretically. In scenario MDB-B, an extra service team was considered, while in scenario MDB-C, the feasibility of adding another rental field office was explored due to its potentially advantageous location. To see the feasibility of long-term personnel shortage, the case of one less service team is examined as scenario MDB-D. The findings following the obtained Pareto front per scenario are summarized in Table 5.11. The first entries illustrate the range of the KPIs from their minimum to maximum values. Below, the complete set of objective values and the number of utilized offices are provided for these solutions, which achieve a minimum objective value. Furthermore, the table presents the percentage of solutions where each field office is utilized and the percentage of utilized offices overall.

From the results, it can be observed that the range of the objective values varies in the obtained Pareto fronts. Even though not all offices are utilized, the lowest maximal tour duration results in the highest cost. This supports the statement from the last subsection that the balance of the tours results in longer distances, which are more expensive than having some shorter and a few very long tours.

Furthermore, we see that the fluctuation in the objectives is the highest in the case of MDB-B since we have more human resources, which gives more flexibility for creating the schedule. The total tour distance will be longer since we now have more tours which means more drives from an office to stations and back. The maximal tour duration should be shorter since there are more service teams to spread the work on. A lower minimal WL-objective value notices this.

The office selection also gives a clear result. The office in Stendal (SDL) is used in every solution obtained in cases MDB-A, -B, and -C, which makes it the first choice of field office to install. In all three cases, the second most selected office is the one in Aschersleben (ASL). In case A, a total number of 3 offices appears the most often in the solution set, but those cases do not have the overall majority. Therefore, depending on the decision-maker's preferences, it is a considerable choice. Similarly, opening even more offices can be advantageous when focusing on providing the most comfort for the service teams without expecting a saving to the current situation. Case C reveals that the rental office in Oebisfelde (OBF) would not be efficient, which was expected since the other possible offices already provide good coverage of the region at a much lower cost. Case D shows a different field office choice than the other three cases. Now ASL is selected more often than SDL. This indicates a shift in strategy when the workforce is reduced. Also, the minimal WL value is much higher than in the other cases, which reflects a loss of flexibility in the possible tour schedules.

Table 5.11: Results of numerical experiments for Magdeburg

Scenario: MDB-A	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	3002.93	3821.31	689	
Max	4179.94	4721.59	863	
Min. Dist.	3002.93	4232.67	815	4
Min. Cost	3649.79	3821.31	863	2
Min. WL	4089.66	4721.59	689	3
Field office	**ASL**	**DSS**	**SDL**	
Percentage of ND	64.7%	47.1%	100%	
Number of Offices	**1**	**2**	**3**	**4**
Percentage of ND	0%	23.5%	41.2%	35.3%
Scenario: MDB-B	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	3292.26	4018.77	603	
Max	5288.6	5312.63	869	
Min. Dist.	3292.26	4495.96	755	4
Min. Cost	3866.78	4018.77	832	2
Min. WL	5288.6	5312.63	603	3
Field office	**ASL**	**DSS**	**SDL**	
Percentage of ND	55%	35%	100%	
Number of Offices	**1**	**2**	**3**	**4**
Percentage of ND	0%	30%	50%	20%
Scenario: MDB-C	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	3085.65	3558.43	712	
Max	3702.34	4311.19	881	
Min. Dist.	3085.65	3807.94	881	3
Min. Cost	3360.91	3558.43	837	2
Min. WL	3638.67	4311.19	712	3
Field office	**ASL**	**DSS**	**SDL**	**OBF**
Percentage of ND	66.67%	0%	100%	0%
Number of Offices	**1**	**2**	**3**	**4/5**
Percentage of ND	0%	33.33%	66.67%	0%
Scenario: MDB-D	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	3457.61	3408.77	826	
Max	4310.54	4733.25	900	
Min. Dist.	3457.61	3646.43	875	2
Min. Cost	3745.9	3408.77	900	1
Min. WL	4102.47	4733.25	826	3
Field office	**ASL**	**DSS**	**SDL**	
Percentage of ND	61.54%	0%	15.38%	
Number of Offices	**1**	**2**	**3**	**4**
Percentage of ND	38.46%	46.15%	15.38%	0%

5.4.2 Regional applicability: Halle

In a parallel manner to the examination conducted for Magdeburg, the present experiment investigates the scheduling dynamics in Halle to evaluate the feasibility of implementing the proposed solution approach to different management regions of DB S&S. Halle, being comparatively smaller in scale than Magdeburg, operates with three service teams. Moreover, the management team in Halle also oversees geographically dispersed stations, utilizing a single central office for operational coordination. The results summarizing the Pareto fronts of each scenario are displayed in Table 5.12.

Table 5.12: Results of numerical experiments for Halle

Scenario: HAL-A	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	2186.76	2515.26	711	
Max	3398.01	3729.18	883	
Min. Dist.	2186.76	2989.95	853	3
Min. Cost	2764.02	2515.26	883	1
Min. WL	3398.01	3092.19	711	1
Field office	**BIT**	**NMB**		
Percentage of ND	44.44%	38.89%		
Number of Offices	**1**	**2**	**3**	
Percentage of ND	44.44%	27.78%	27.78%	

Scenario: HAL-B	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	2534.26	2762.38	555	
Max	4093.28	4240.61	860	
Min. Dist.	2534.26	2806.18	840	2
Min. Cost	3035.58	2762.38	860	1
Min. WL	4093.28	4224.88	555	2
Field office	**BIT**	**NMB**		
Percentage of ND	85.19%	14.81%		
Number of Offices	**1**	**2**	**3**	
Percentage of ND	29.63%	55.56%	14.81%	

Scenario: HAL-C	**Dist.**	**Cost**	**WL**	**Num. Offices**
Min	2251.52	2341.38	691	
Max	3071.61	4234.5	879	
Min. Dist.	2251.52	4048.88	853	3
Min. Cost	2572.94	2341.38	835	1
Min. WL	3071.61	2795.17	691	1
Field office	**BIT**	**NMB**	**LWB**	
Percentage of ND	0%	12.5%	50%	
Number of Offices	**1**	**2**	**3**	**4**
Percentage of ND	50%	37.5%	12.5%	0%

Testing the solution approach on the Halle (HAL) dataset demonstrates its applicability to other management regions of DB S&S. The model is designed with flexibility in mind, allowing for customizable data inputs. Similar trends in results to those observed in the MDB dataset are evident. In scenarios where additional teams are available (Case B), there is a tendency to open more offices, resulting in a minimal increase in the total distance traveled compared to Case A. Case C suggests that the rental office in Lutherstadt Wittenberg (LWB) may offer a more advantageous location than the other potential field offices in Bitterfeld (BIT) and Naumburg (NMB). However, the higher cost associated with LWB must be carefully considered when evaluating the solution set. The observation that half of the solutions do not utilize any field office supports the notion that the high rental cost of LWB may render it an unprofitable choice for a field office location. Conversely, Case D, which considers fewer available teams, leads to an empty solution set. This implies that the feasible solution space is too constrained to be found within the given iteration or no feasible solution exists. Such findings suggest that a long-term shortage of employees could pose challenges in meeting inspection deadlines without resorting to minimal efforts.

5.4.3 Insight summary

Insights gained from studying various train station management cases in Magdeburg and Halle reveal several critical points about the proposed solution approach. Firstly, the model exhibits adaptability across different regions and generates valuable feedback through a non-dominated solution set. Analyzing the Pareto front obtained from this process sheds light on optimal team-to-office configurations. Decision-makers can gather pertinent information by examining the distribution of objective values and the prevalence of specific office utilization within the solution set. Furthermore, the feasibility or necessity of adjusting resources like teams or vehicles can be predicted, providing valuable insights into team capacity management.

In Experiment 2, when examining the termination criterion, it was realized that the more often the algorithm is executed, the better the solution. In Experiment 3, the quality assessment revealed that the quality of the solution decreases with increasing scenario set. Combining that insight with the current experiment implies that the adequacy of available resources significantly influences the quality of solutions obtained within a predefined number of iterations. Introducing additional offices or service teams expands the solution space but necessitates more algorithmic iterations to maintain comparable validity. Conversely, insufficient resources, particularly inadequate personnel for station inspections, result in an empty solution set. Moreover, tours exceeding a maximum duration of 900 minutes (equivalent to 15 hours) become impractical for teams to manage within two days. Here, the algorithm would also need more time to find the smaller feasible solution space if it exists.

Therefore, short running durations of the algorithm can provide a good impression of the solution space but remain potential for improvement in the resulting tours of each solution and identification of gaps within the true Pareto front. To enhance understanding of the train station management in Magdeburg, the forthcoming experiment will increase the number of iterations to expand the Pareto front, followed by a stochastic analysis.

5.5 Extended analysis with stochastic solution evaluation

To delve deeper into the problem identified by the leader of train station management in Magdeburg, an extensive analysis of the problem is undertaken. This analysis involves the utilization of a proposed algorithm outlined in Section 5.5, which employs a long Monte Carlo simulation to provide statistical insights. The Pareto front obtained from the extended MO-ALNS run is examined in the first subsection to offer educated recommendations. Given the problem owner's interest in exploring changes to operational strategy, specifically the incorporation of cross-disciplinary service teams for inspection and maintenance alongside the establishment of field offices, both variations are thoroughly evaluated. Subsequently, attention is directed towards a chosen subset of solutions that exhibit promise across multiple objectives, focusing on the details of the stochastic evaluation and its outcomes.

5.5.1 Analysis of Pareto front

The MO-ALNS was applied over 5,000 iterations, yielding a non-dominated set of solutions, depicted in Figure 5.1. The complete output, referenced herein, is detailed in Appendix A, including improvement calculations. The visualization of the non-dominated set illustrates the wide spread within the solution space, necessitating substantial computational resources for exploration. Despite the considerable iteration count, achieving a densely packed front was unattainable. Nevertheless, Table 5.13, summarizing the non-dominating solutions, provides enough information to draw conclusions. The first two rows illustrate the utilization percentage of each field office within the obtained non-dominated set. Notably, the Standal field office was selected in 78% of solutions, whereas Aschersleben and Dessau were selected in only 39% and 35% of the obtained solutions, respectively. Statistics concerning the solutions with varying numbers of open offices are provided below. This includes the proportion of non-dominated solutions relative to the number of active offices, along with their cumulative representation. For example, 26% of solutions incorporated two offices, contributing to a cumulative utilization of at least two offices in 78% of cases. Additionally, the table presents average distance and cost improvements compared to the current scenario, considering both the existing team structure and a hypothetical combined team structure. To recall from Chapter 2, the KPIs for the current tour schedule are a total travel distance of 11,700 km (4,500km not manipulated), a monthly cost of €4,095, and a maximum tour duration of 15.4 hours.

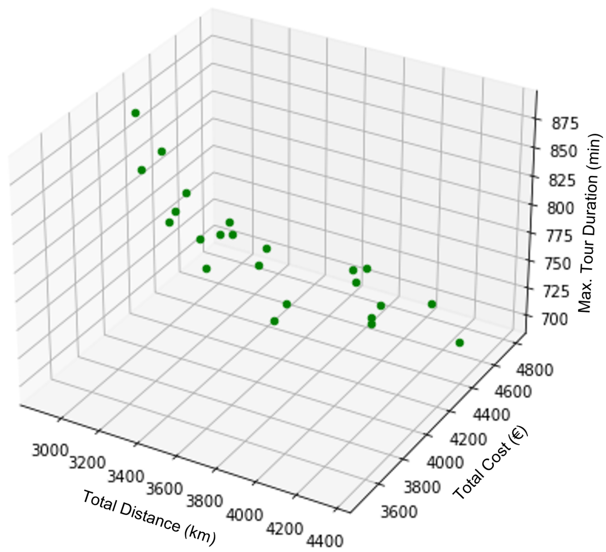

Figure 5.1: Three-dimensional Pareto front of scenario MDB-A

Table 5.13 presents that the model found solutions that use a single central office (1 open office) which result in modest yet noticeable savings in both distance traveled and associated costs. This underscores the potential for optimizing the current tour scheduling approach for greater efficiency. Furthermore, when considering solutions with field offices, the decision to establish such an office hinges on installation costs, which have not been factored in yet. Nonetheless, the data suggests that establishing an office in Stendal would yield significant reductions in travel distances and prove, even if just slightly, financially advantageous. The anticipated long-term savings from decreased monthly expenditures are expected to outweigh the initial investment. The projected distance savings of 17% equate to approximately 1,100km to 1,900km, depending on whether the repair personnel also benefit from the presence of this field office. Converting this into time, the entire train station inspection crew is expected to save at least 18 hours during each planning horizon.

The next viable location for a field office could be Aschersleben or Dessau. Adding another office to the Magdeburg and Stendal locations would further minimize travel distances by an additional 5% on average. However, its profitability remains questionable and contingent upon the efficiency of the tour schedule. Notably, solutions with longer maximum tour durations appear to yield profitability in the Pareto front, while those with shorter maximum tour durations may not offer significant cost savings. This underlines the importance of the trade-off between

Table 5.13: Results of extended execution for TM Magdeburg

Field Office:	**Aschersleben**	**Dessau**	**Stendal**	
%age of use:	39%	35%	78%	
Open offices:	**1**	**2**	**3**	**4**
%age of use	22%	26%	30%	22%
Cumulative %age	100%	78%	52%	22%
Current team structure:				
Avg. Dist. improvement	7.77%	16.71%	21.69%	30.16%
Avg. Cost improvement	7.77%	4.50%	-2.73%	-6.47%
Combined team structure:				
Avg. Dist. improvement	31.18%	37.86%	41.57%	47.89%
Avg. Cost improvement	31.18%	25.65%	17.15%	11.26%

cost savings and a balanced schedule. Moreover, the fixed costs of furnishing the office must be considered. However, opening a third field office does not lead to cost improvement in any of the non-dominated solutions obtained but an additional 8% distance saving.

These improvements are magnified when considering a cross-disciplinary team approach. Assuming that only 60% of maintenance trips can be integrated into the combined team structure, even greater reductions in distance and costs can be achieved, with all solutions providing cost savings. This underscores the efficiency of installing all three field offices. Nevertheless, careful planning is required for the combined team structure, ensuring compatibility among employees and locations, as well as effective management of materials, equipment, and transportation. Since the combined team structure was not analyzed during this study, the effect and possible implementation results are based on assumptions. It is important to note that while the combined team structure was not the primary focus of this study, this recommendation is founded on a theoretical assumption of achieving a 60% reduction in the distance through combined trips.

The maximum tour duration was selected as the key performance indicator (KPI) regarding workload balance. Setting an upper limit of 900 minutes for the maximum tour duration, which is lower than the longest estimates in the current tour schedule, ensures improvement in this aspect across all tours in the Pareto front. However, the average maximum tour duration across the Pareto front (793 minutes, indicating a 14% improvement) suggests that a more balanced schedule is achievable and advisable. Therefore, aiming for a solution around this average value is recommended to ensure a balanced workload without compromising tour quality. Additionally, the more travel distance saved, the more significant the reduction in maximum tour duration, further emphasizing the benefits of optimizing travel routes.

5.5.2 Stochastic evaluation

Given the absence of reliable service time records in any Deutsche Bahn (DB) database, we introduce uniformly distributed factors to adjust the estimated service and travel times. Our approach involves the introduction of two distinct factor distributions, one representing a realistic scenario and the other a pessimistic outlook, allowing for an examination of extreme conditions. The selected distributions for these factors are displayed in Table 5.14

Table 5.14: Distributions for travel and service time factors

	Realistic	Pessimistic
Travel time factor	U(0.8, 1.5)	U(0.95, 1.5)
Service time factor	U(0.75, 1.25)	U(0.95, 1.25)

Due to the unpredictable nature of traffic fluctuations and their impact on travel times, adjustments are made conservatively. Travel time estimates may decrease by up to 30% or increase by up to 70%, with a maximum multiplier of 1.5 applied to the original estimate. Conversely, service times are less likely to be significantly extended, as the primary focus is completing the entire service tour, with any extra work potentially deferred. However, it is also possible that the estimated service time exceeds the actual requirement, resulting in unnecessary buffer time. Therefore, adjustments to service times are equally likely to decrease or increase by up to 25%. These were selected for the realistic case, while for the pessimistic case, the probability of decreased travel and/or service time is reduced.

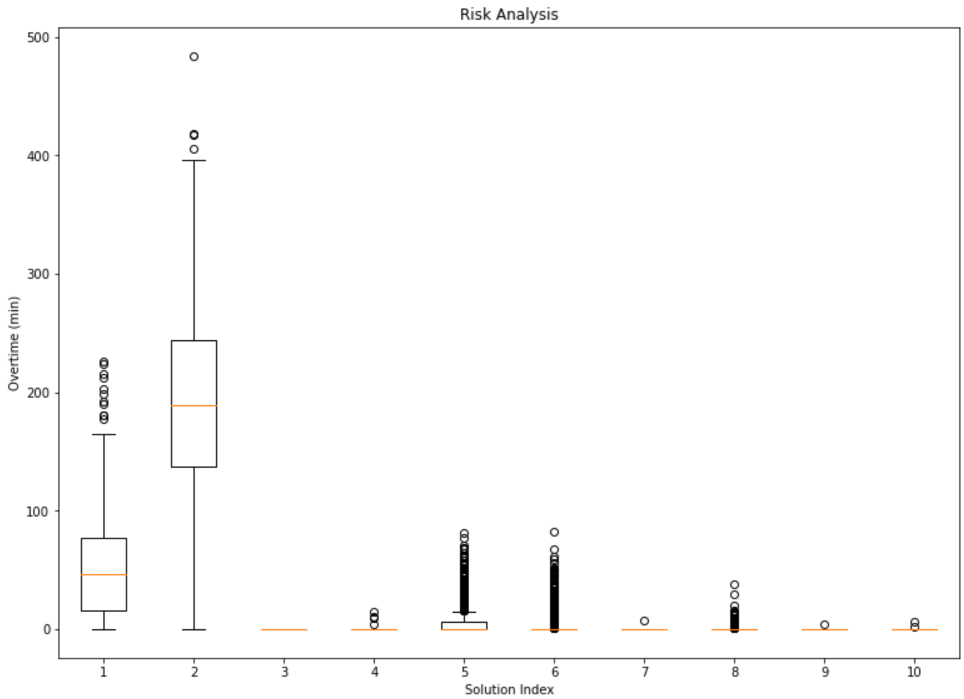

Figure 5.2: Box plot representation of overtime fluctuation for realistic case

The selected measure for evaluating the selected solutions is the average total overtime. This means every time a tour exceeds 900 minutes, overtime will be counted. During the Monte Carlo simulation, each solution gets evaluated 1,000 times. In each run, new stochastic travel and service times are calculated, and the overtime for each tour is summed up. The outcome of each solution for the realistic case is represented in box plots in Figure 5.2, while the box plot for the pessimistic case is presented in Figure 5.3.

The initial three box plots provide significant yet straightforward insights for both cases. These plots depict solutions derived from greedy algorithms, each targeting a specific optimization goal: minimizing distance (solution 1), cost (solution 2), or the maximal tour duration (solution 3). The first two solutions exhibit notable variance, with average overtime of approximately 50 and 190 minutes, respectively, escalating to 340 and 1,000 minutes under a pessimistic perspective. This indicates that prioritizing singular aspects such as distance or cost reduction may lead to inefficient schedules, albeit compliant with given constraints. Notably, schedules with shorter maximal tour durations display smaller fluctuations.

Further analysis of the realistic case reveals instances of overtime across all solutions except for solution 2, identifiable through box plots or outlier points. Solution 5 notably displays frequent overtime instances along with outliers. In contrast, solutions 4, 7, 9, and 10 display minimal mean overtime, suggesting reliability in accommodating fluctuations. However, occasional in-

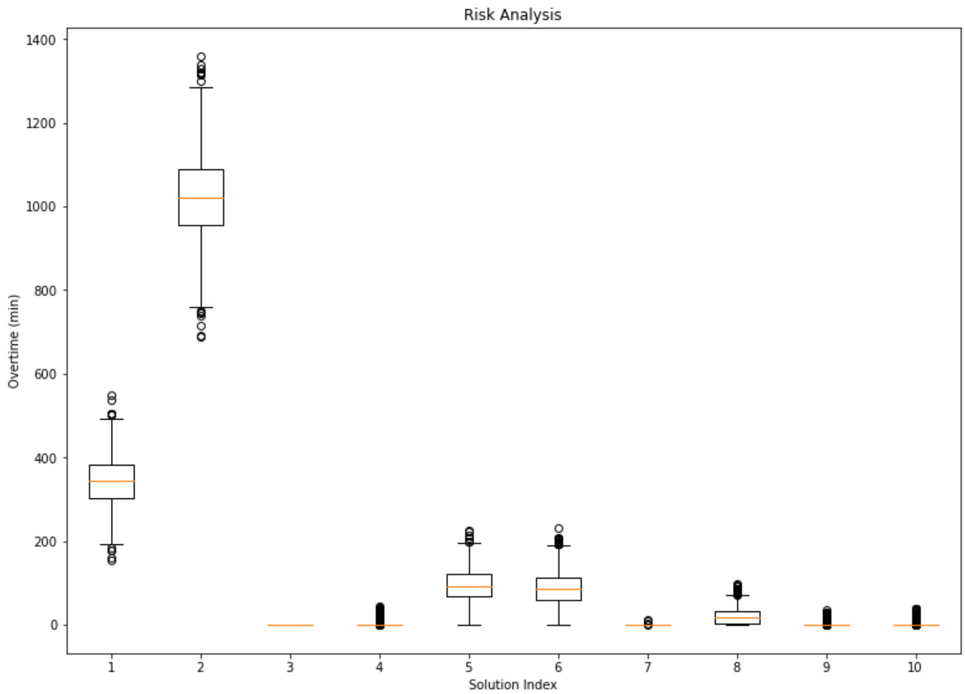

Figure 5.3: Box plot representation of overtime fluctuation for pessimistic case

stances of overtime remain possible. From these solutions, only solution 7 remains with minimal overtime for the pessimistic case, while the other three solutions have overtime occurrences in 12% to 20% of the simulation runs. The preference for solutions 2 and 7, emphasizing minimal tour duration, particularly superior in the face of adverse travel and service time fluctuations, underscores the necessity of a balanced tour schedule for continuous service provision.

Solutions 3, 4, 7, 9, and 10 have an overtime occurrence of under 1% and an average overtime of less than one minute for the realistic case and at most 20% overtime occurrence and an average overtime of fewer than three minutes for the pessimistic case. These solutions are constructed to minimize the risk of overtime based on this Monte Carlo simulation, albeit under the assumption of uniformly distributed travel and service times, which may not fully align with real-world scenarios. Despite this simplification, their resilience to broad estimates suggests a favorable condition. A comprehensive examination of these solutions, detailed in Appendix A, reveals an average maximal tour duration ranging from 740 minutes for solutions 3, 4, 7, 9, and 10. This value appears reasonable, given the conflicting objectives at play.

5.6 Conclusion

This chapter answers the research question “How does the solution approach perform for the experiments and compared to the current situation?” First, the experimental methodology employed in this study was outlined. The first experiments were designed to fine-tune the algorithmic parameters of the proposed solution approach. Initially, twelve distinct scenarios were constructed using data from the Magdeburg dataset. These scenarios varied in size, encompassing scenarios smaller, equal in size, and larger than real-world instances. Subsequently, the performance of the Multi-Objective Adaptive Large Neighborhood Search (MO-ALNS) was compared against both its single-objective counterpart, ALNS, and the mathematical formulation represented by the Mixed Integer Linear Program (for smaller instances). The findings underscored the superior efficiency of the MO-ALNS approach as the size of the data instances increases while the single-objective methods are superior to the small scenarios.

In the following experimental phase, valuable insights pertinent to the company were gained. Real-world scenarios derived from train station management departments in both Magdeburg and Halle were utilized. The model's applicability to the Halle scenario yielded promising results, affirming the model's generalizability. In the case of Magdeburg, which holds particular significance for the project owner, it was realized that utilizing field offices is an effective strategy. Notably, establishing a field office in Stendal seems most efficient, resulting in substantial savings in travel distance ($\sim$ 17% $\widehat{=}$ 1,100-1,900km) and, consequently, time while keeping the cost reasonable. The addition of further field offices showed potential for further reduction in total travel distance. However, the profitability of each decision necessitates a detailed evaluation of the entire non-dominated set. Generally, as the utilization of offices increased, the total distance traveled decreased, though cost improvements diminished. This is equivalent when considering the cross-disciplinary team structure, but the distance improvement is up to 48% ($\sim$ 5,600km) and cost savings of 11% ($\sim$ €450) even when utilizing all three field offices.

Lastly, the stochastic nature of the problem was addressed by incorporating variability in travel and service times into the evaluation process. Potential solutions were assessed using Monte Carlo simulations, providing insights into their flexibility in adapting to fluctuating conditions. Analysis of the box plots presented in Section 5.5 elucidates that a tour schedule with a maximal tour duration of around 730 or lower should guarantee flexibility to adjust to unexpected occurrences. A further look into the provided tour schedules revealed that the baseline schedules obtained do not present optimal routings. Therefore, the schedule can be constructed even more efficiently than the metaheuristic can compile.

Therefore, the resume from the experimental phase shows that the use of field offices, especially Stendal, can reduce traveling distance and time for TM Magdeburg. Applying the combined team structure will additionally be profitable in the long run. Furthermore, the proposed model offers good decision support for locating teams to possible offices due to its exploration and provision of a wide range of possible solutions. However, the tours for specific solutions still have room for improvement. This can be solved by running the model for much more time or solving the isolated subproblem, the Periodic Vehicle Routing Problem, to get the best tour schedule for the chosen team-to-office allocation.

6 CONCLUSION AND RECOMMENDATIONS

This chapter summarizes the conducted research and its outcomes in Section 6.1. Subsequently, in Section 6.2, recommendations for DB S&S stemming from these findings are presented. Section 6.3 discusses limitations and the potential of future research, while Section 6.4 addresses the contributions made to both theoretical frameworks and practical applications.

6.1 Conclusion

This research commenced by describing the problem faced by the head of the train station management in Magdeburg, leading to the main research goal. This is the design of an optimization approach that locates service teams to field offices, assigns the train stations to the teams respectively, and provides a periodic tour schedule. Given the crucial role of DB in Germany's transition to sustainable transportation, by contributing to the reduction of emissions as well as making traveling by train as pleasant as possible, such a model holds significant potential for each management region to reassess its operational approach. Guided by research questions answered throughout each chapter, this research is concluded by answering the following main research question:

"How can a solution approach be designed to locate service teams to field offices, assign the train stations to the teams respectively, and provide a periodic tour schedule?"

To tackle this problem, the operating strategy of the inspections and maintenance tours has been explored concerning the employee's office location. The aim was to find a team-to-office allocation and a periodic baseline tour schedule to reduce the distance traveled by the employees as well as total costs while keeping the tours balanced throughout the planning horizon. Therefore, a Mixed Integer Linear Program (MILP) and a multi-objective Adaptive Large Neighborhood Search (MO-ALNS) have been developed to optimize the location-routing problem. Given the conflicting nature of our objectives, we employed the MO-ALNS to generate a set of non-dominated solutions efficiently, providing insights into the optimal strategy for train station inspection and maintenance. To ensure generality and applicability in other regions, we fine-tuned the MO-ALNS algorithm and parameters, testing them against both single-objective ALNS and MILP approaches. Using various scenarios and resources based on the Magdeburg and Halle datasets, we conducted numerical experiments to validate the effectiveness of our methodology.

Our results demonstrate that adjusting the operating strategy, such as opening a field office in Stendal while maintaining separate team structures, can reduce travel distances by 17% without increasing monthly costs. Additional offices contribute to further distance reductions, albeit without cost benefits, especially due to initial installation expenses. However, by adopting a combined team structure, travel distance savings can reach nearly 50%, justifying the monthly office costs even with all possible field offices open. Although the tours generated by MO-ALNS are not optimal, further improvements to the tour schedule are feasible. Through stochastic simulations of travel and service times, we determined that a maximum tour duration of 12.5 hours is achievable and sufficient to accommodate unplanned services without compromising work quality.

6.2 Recommendations

Based on the analysis conducted of the MO-ALNS results, the recommendation for Deutsche Bahn (DB) regarding the establishment of field offices is as follows: Firstly, it is advised to prioritize the opening of a field office in Stendal due to its potential to significantly reduce travel distances and generate monthly cost savings, despite the initial installation costs. Additionally, considering the potential profitability, the next viable locations for field offices could be Aschersleben or Dessau. The addition of another office could further minimize travel distances, although its profitability remains uncertain and contingent upon efficient tour scheduling. However, the fixed costs associated with furnishing the office should be carefully evaluated but also the time saving for the employees should be considered. Emphasizing the time aspect is substantial, as it ensures high-quality work, leading to improved customer satisfaction overall.

Moreover, implementing a cross-disciplinary team approach could lead to even greater reductions in distance and costs, potentially justifying the installation of all three field offices. Nonetheless, careful planning is required to ensure compatibility among employees and locations, as well as effective management of materials, equipment, and transportation. It is crucial to aim for a balanced workload by setting an upper limit for the maximum tour duration, ensuring improvement across all tours without compromising quality. Considering the broader impact of field office installations on other work processes, both within and outside of train station inspection and maintenance, is also recommended to weigh the overall benefits and drawbacks of this transformation thoroughly. The appreciation of values coming with distance, cost, and time savings, as well as providing a consistent work schedule, remains to the project owner.

6.3 Limitations and further research

The study encounters several limitations that warrant consideration. Firstly, the computational time requirements of the metaheuristic pose a significant constraint, particularly when dealing with large instances, thereby restricting the full exploration of its potential. Addressing this limitation could involve optimizing the programming efficiency and leveraging relevant packages, alongside exploring alternative operators and heuristics to enhance performance. Additionally, the non-optimality of tour schedules derived from the Pareto front highlights a need for further investigation, such as integrating periodic vehicle routing analysis for the selected office allocation.

Moreover, data availability proves to be a challenge due to inadequate documentation of operations and inefficient administration of databanks. Ambiguous information within working steps documentation hampers the derivation of valuable insights, while outdated information within the train station databank necessitates manual retrieval of related data. Incorporating additional details, such as train line routes through each station, could further refine the analysis. Furthermore, the study's scope does not encompass the cross-disciplinary team structure, yet exploring its impact on service time and station management dynamics could yield valuable insights for future extensions. Initiating a pilot project to observe and document these effects could offer a path forward in addressing this limitation.

6.4 Contribution

The research presented in this study significantly contributes to theoretical understanding and practical application within the domain of train station inspection and maintenance and beyond.

Contribution to theory

Research in train station inspection and maintenance has been relatively limited. While there has been some investigation into the maintenance of rolling stock and other related areas, these studies often lacked the necessity of establishing a baseline schedule and primarily focused on addressing stochastic demand. Although periodic Location-Routing Problems have been encountered in other contexts, considerations of workload balance were seldom integrated. Furthermore, this study introduces a novel approach by combining Adaptive Large Neighborhood Search (ALNS) with multi-objective analysis using the Pareto method, specifically tailored to address periodic Location-Routing Problems. This unique methodology, customized for the infrastructure of Deutsche Bahn (DB), presents a fresh perspective on optimizing inspection processes. Moreover, the study synthesizes insights from various sources, incorporating improvement operators, degree of destruction, and other parameters to enhance the algorithm's efficiency.

Contribution to practice

In practical terms, the research provides DB with a valuable decision support tool to enhance the efficiency of their train station inspection departments across all regions. By offering a robust framework for optimizing inspection schedules, the study enables DB to streamline maintenance operations effectively. Additionally, the study offers educated recommendations to the Train Station Management of Magdeburg regarding the selection and management of field offices. These recommendations, based on thorough analysis and empirical evidence, provide actionable insights to stakeholders, enabling a more strategic and efficient allocation of resources within the realm of inspection and maintenance. Overall, the study's contributions extend beyond theoretical advancements to directly impact and improve real-world practices within the railway infrastructure management sector.

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APPENDICES

A Solution set for Magdeburg

Presentation of the obtained Pareto front with analysis of distance and cost improvements considering the current team structure and the combined team structure.

											Current Team Structure			Combined Team Structure	
	Total Distance	Total Cost	WL		Team 1	Team 2	Team 3	Team 4	# open offices	Improvement:	Distance	Cost		Distance	Cost
0	3899.75	4548.77	714		MDB	MDB	DSS	SDL	3		13.3%	-11.1%		35.3%	10.9%
1	4075.25	4708.48	709		MDB	MDB	DSS	SDL	3		9.4%	-15.0%		32.4%	8.0%
2	3287.89	4491.98	726		MDB	ASL	DSS	SDL	4		26.9%	-9.7%		45.5%	8.9%
3	3323.9	4024.75	769		MDB	ASL	MDB	SDL	3		26.1%	1.7%		44.9%	20.5%
4	4193.77	3816.33	832		MDB	MDB	MDB	MDB	1		6.8%	6.8%		30.5%	30.5%
5	2902.48	4141.26	825		MDB	ASL	DSS	SDL	4		35.5%	-1.1%		51.9%	15.2%
6	3391.94	4086.67	757		MDB	ASL	MDB	SDL	3		24.6%	0.2%		43.8%	19.3%
7	3013.43	4242.22	785		MDB	ASL	DSS	SDL	4		33.0%	-3.6%		50.0%	13.4%
8	3720.1	3885.29	820		MDB	MDB	MDB	SDL	2		17.3%	5.1%		38.3%	26.1%
9	3184.48	3897.88	876		MDB	ASL	MDB	SDL	3		29.2%	4.8%		47.2%	22.8%
10	3620.67	4794.81	697		MDB	ASL	DSS	SDL	4		19.5%	-17.1%		40.0%	3.3%
11	3814.32	3471.03	885		MDB	MDB	MDB	MDB	1		15.2%	15.2%		36.8%	36.8%
12	3205.06	3916.6	814		MDB	MDB	DSS	SDL	3		28.8%	4.4%		46.9%	22.4%
13	3586.71	4263.91	728		MDB	ASL	MDB	SDL	3		20.3%	-4.1%		40.5%	16.1%
14	3575.42	3753.63	837		MDB	MDB	MDB	SDL	2		20.5%	8.3%		40.7%	28.5%
15	4358.02	4465.8	713		MDB	MDB	MDB	SDL	2		3.2%	-9.1%		27.7%	15.5%
16	3474.25	3661.57	876		MDB	MDB	MDB	SDL	2		22.8%	10.6%		42.4%	30.2%
17	3746.06	3908.91	756		MDB	MDB	MDB	SDL	2		16.8%	4.5%		37.9%	25.7%
18	4236.97	3855.64	831		MDB	MDB	MDB	MDB	1		5.8%	5.8%		29.7%	29.7%
19	2889.88	4129.79	876		MDB	ASL	DSS	SDL	4		35.8%	-0.8%		52.1%	15.5%
20	3613.63	3788.4	835		MDB	MDB	MDB	SDL	2		19.7%	7.5%		40.1%	27.9%
21	4252.9	3870.14	788		MDB	MDB	MDB	MDB	1		5.5%	5.5%		29.5%	29.5%
22	4254.22	3871.34	783		MDB	MDB	MDB	MDB	1		5.5%	5.5%		29.5%	29.5%
								AVG:	2.52	AVG:	19.2%	0.6%		39.7%	21.1%
MIN	2889.88	3471.03	697							Equates min:	1296.45	14.79		4646.742	865.49
MAX	4358.02	4794.81	885							Equates max:	2247.18	25.64			
Current:	4500	4095	925												
Manipulated:	11700														
Average per number of open offices:															
	1	2	3	4											
Dist.	4150.44	3747.91	3523.87	3142.87											
Cost	3776.90	3910.60	4206.72	4360.01											
WL	823.80	806.17	766.71	781.80											

Figure 1: Excel output: Solution set for MDB-A

The conversion of the average distance and cost improvement is aligned with the amount of influence on the maintenance crew. If the existing team structure is maintained and the improvements are only factored in for the inspectors, we observe a distance and cost improvement of 1,296km and €15, denoted as "Equates min". However, if we assume that the repair team also benefits proportionately from the operational change, then the enhancements increase to 2,247km and €26, labeled as "Equates max."

Presentation of the selected solutions for the stochastic evaluation and the average result of the executed Monte Carlo (MC) simulation.

										MC realistic		MC pessimistic	
	Total Distance	Total Cost	Workload balance		Team-to-office Allocations				# open offices	Avg. Overtime (min)	OT occurence	Avg. Overtime (min)	OT occurence
1	2889.88	4129.79	876		MDB	ASL	DSS	SDL	4	51.65	896	343.14	1000
2	3814.32	3471.03	885		MDB	MDB	MDB	MDB	1	193.47	999	1023.59	1000
3	3620.67	4794.81	697		MDB	ASL	DSS	SDL	4	0	0	0	0
4	3091.94	4313.67	757		MDB	ASL	DSS	SDL	4	0.04	4	2.29	204
5	2902.48	4141.26	825		MDB	ASL	DSS	SDL	4	6.24	312	95.39	999
6	3205.06	3916.6	814		MDB	MDB	DSS	SDL	3	4.15	224	87.48	998
7	3287.89	4491.98	726		MDB	ASL	DSS	SDL	4	0.01	1	0.02	4
8	3013.43	4242.22	785		MDB	ASL	DSS	SDL	4	0.27	33	20.82	825
9	3746.06	3908.91	756		MDB	MDB	MDB	SDL	2	0	1	1.04	118
10	3323.9	4024.75	769		MDB	ASL	MDB	SDL	3	0.01	2	1.62	137
AVG:	3289.563	4143.502	789										

Figure 2: Excel output: Results of stochastic simulation