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Implementation of Optimization Techniques in SMEs with imperfect information
A traveling e-bike repairman example

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Abstract

Small and medium-sized enterprises (SMEs) with labour-intensive operations often underutilize contemporary digitalization and optimization technologies, which limits the efficiency and scalability of services. Drawing from direct practical experience, this study identifies a clear need for overcoming technical and financial barriers through accessible and practical optimization solutions and highlights a scalable approach. The aim of this work is to develop and assess a low barrier and easy to implement routing framework specifically designed for SMEs that employ field service mechanics. The main focus is on minimizing complexity, costs and entry barriers to optimization practices. Two historically simple and well-established heuristics were customized for a capacitated, stochastic repair context: (i) a Nearest Neighbor (NN) algorithm including a 2-opt local search procedure, and (ii) a cheapest insertion based Sequential Adaptive Insertion (SAI) algorithm. The implementation was done in C# and was evaluated by a simulation consisting of 4000 randomly generated instances representing potential workdays. The simulations spanned four different operational scales (10-61 customer locations) and incorporated log-normally distributed random repair times to reflect realistic uncertainties. Both heuristic methods produced feasible and cost-effective routes across all tested scenarios, confirming that simple algorithms can offer meaningful solutions for SMEs. The Nearest Neighbor heuristic was particularly effective in smaller, stable settings, resulting in shorter respective travel times and allowing ease of implementation. Sequential Adaptive Insertion, while more complex, consistently outperformed NN in large and more variable scenarios, repairing 6-10% more e-bikes and visiting more hubs on average. SAI also exhibited lower shift time variability and better mechanic workload balance. These findings demonstrate that both heuristics offer viable, low-barrier routing solutions for SMEs. Their respective trade-offs allow for alignment with different operational scales, variability levels, and digital capabilities, enabling a shift from intuition based planning to structured, data driven operations. Moreover, these lightweight methods provide a foundation for future enhancements, such as real-time task updates, adaptive traffic routing and other hybrid frameworks.

Kleine und mittlere Unternehmen (KMU) mit arbeitsintensiven Tätigkeiten setzen moderne Digitalisierungs- und Optimierungstechnologien oft nicht ausreichend ein, was die Effizienz und Skalierbarkeit von Services einschränkt. Auf der Grundlage direkter praktischer Erfahrungen zeigt diese Studie einen klaren Bedarf für die Überwindung technischer und finanzieller Barrieren durch zugängliche und praktische Lösungen zur Optimierung auf und hebt einen skalierbaren Ansatz hervor. Ziel dieser Arbeit ist die Entwicklung und Bewertung eines einfach zu implementierenden und niedrigschwellige Routing-Frameworks speziell für KMU, die Außendienstmechaniker beschäftigen. Das Schwerpunkt liegt auf der Minimierung von Komplexität, Kosten und Eintrittsbarrieren für Optimierungspraktiken. Zwei historisch einfache und etablierte Heuristiken wurden an einen kapazitären, stochastischen Reparaturkontext angepasst: (i) ein Nearest Neighbor (NN)-Algorithmus, der ein 2-optiges lokales Suchverfahren beinhaltet, und (ii) ein auf billigster Insertion basierender Sequential Adaptive Insertion (SAI)-Algorithmus. Die Implementierung erfolgte in C# und wurde durch eine Simulation mit 4000 zufällig erzeugten Instanzen bewertet, die potenzielle Arbeitstage repräsentieren. Die Simulationen umfassten vier verschiedene Skalen (10-61 Standorte) und beinhalteten lognormalverteilte zufällige Reparaturzeiten, um realistische Unsicherheiten widerzuspiegeln. Beide heuristischen Methoden ergaben für alle getesteten Szenarien machbare und kosteneffiziente Routen, was bestätigt, dass einfache Algorithmen sinnvolle Lösungen für KMU bieten können. Die Nearest Neighbor-Heuristik war besonders effektiv in kleineren, stabilen Umgebungen, was zu kürzeren jeweiligen Fahrzeiten führte und eine einfache Implementierung ermöglichte. Sequential Adaptive Insertion (SAI) ist zwar komplexer, übertraf aber in größeren und variableren Szenarien durchweg NN, indem es im Durchschnitt 6-10 % mehr E-Bikes reparierte und mehr Knotenpunkte besuchte. SAI zeigte auch eine geringere Variabilität der Schichtzeiten und eine bessere Verteilung der Arbeitslast der Mechaniker. Diese Ergebnisse zeigen, dass beide Heuristiken praktikable, niedrigschwellige Routing-Lösungen für KMU bieten. Ihre jeweiligen Kompromisse ermöglichen die Anpassung an unterschiedliche betriebliche Größenordnungen, Variabilitätsniveaus und digitale Fähigkeiten, wodurch ein Übergang von der intuitiven Planung zu strukturierten, datengesteuerten Abläufen ermöglicht wird. Darüber hinaus bieten diese leichtgewichtigen Methoden eine Grundlage für künftige Erweiterungen, wie Aufgabenaktualisierungen in Echtzeit, adaptive Verkehrslenkung und andere hybride Systeme.

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List of abbreviations

API	=	Application Programming Interface
B2B	=	Business-to-business
CVRP	=	Capacitated Vehicle Routing Problem
ERP	=	Enterprise Resource Planning
IT	=	Information Technology
JIT	=	Just-In-Time
MRP	=	Material Requirements Planning
NN	=	Nearest Neighbor
NP-hard	=	non-deterministic polynomial-time hardness
SAI	=	Sequential Adaptive Insertion
SLAs	=	Service Level Agreements
SMEs	=	Small and medium-sized enterprises
TSP	=	Travelling Salesman Problem
VRP	=	Vehicle Routing Problem

1. Introduction

1.1 Problem Statement

The efficient management of vehicle routing is a critical operational challenge for all logistics and maintenance operations which has a significant impact on the quality of service, operational cost and the overall competitiveness of an enterprise. Small and medium-sized enterprises (SMEs) that provide field maintenance services such as e-bike repairs face challenges in routing that are only aggravated by manual planning. Manual planning not only creates inefficient routes with excess travel times, unbalanced workloads and unused capacities but is also a significant cost factor in administrative overhead. This increases exponentially with increased growth and scaling, making it a significant hindrance to growth (Toth & Vigo, 2002, pp. 1-5) .

From personal observation in my role within the operations department, operations managers often dedicate significant time and effort to daily route creation and assignment. This effort is driven by intuition, client demands, knowledge of the environment and informal communication with field mechanics. As a result, resource utilization of managers is suboptimal and diverts attention away from strategic tasks of a much higher value. Therefore, a critical need can be identified for optimization methods which are designed for improving route efficiency but also reducing administrative cost associated with route management.

1.2 Motivation & Context

The motivation for this research is explicitly derived from personal experience as an operations manager at an SME operating in the Business-to-business (B2B) e-bike rental and maintenance branch. During the time, it became evident that manual routing processes were operationally inefficient and consumed a high level of resources. Planning required high administrative effort involving manual adjustments, client negotiations, mechanic coordination, all resulting in high overhead and inefficiencies.

These observations further emphasize the existing broader context for SMEs where there is an ever present issue in resource constraints. This can be looked at from different levels with each level revealing unique challenges. The superficial level can be easily seen with the lack of digitalization. Under 20% of European SMEs are highly digitalized, whereas large corporations reach almost 50% (European Investment Bank, n.d.). Looking a level deeper where digitalization is undertaken, we see that there are existing tools that can be used to increase efficiency and move towards optimizing operations. Examples range from Just-In-Time (JIT) manufacturing principles to material requirements planning (MRP) which are assisted by the implementation of Enterprise Resource Planning (ERP) systems. We see the main reason for not implementing these tools is that there is a lack of expertise on the ground to implement or control these systems. Finally, even in the cases where we do see exploration of these solutions, due to the lack of digital literacy, the implementations become costly and inflexible (Moeuf et al., 2018, pp. 1-2).

1.3 Research Objectives

This thesis aims to address the outlined inefficiencies by developing, implementing and evaluating two of the simplest heuristic route-optimization methods which are changed and tailored to the specific B2B e-bike rental and maintenance branch but also suited for a broader SME context. The methods are based on well known concepts of Nearest Neighbor and a Cheapest Insertion in this paper referred to as Nearest Neighbor (NN) and Sequential Adaptive Insertion (SAI) respectively. For more details on the concepts explained, see also Rosenkrantz et al. (1977). Both heuristic methods are very easily implemented suited to be applied as a Capacitated Vehicle Routing Problem (CVRP) which is a version of what the specific environment requires, almost without changing any logic other than specific case constraints (Laporte, 1992b, p. 355).

The heuristic methods have been explicitly implemented from scratch in the C# programming language, explicitly being tailored to specific constraints and realities of the operating environments including stochastic repair times, mechanic shift times and mechanic travel durations. Specifically, these seek to solve the following issues:

- **Operations Efficiency**: Specifically developing simple heuristics algorithms (NN & SAI) targets the improvement of performance relative to status quo in terms of total mechanic time, productivity and general service reliability under realistic stochastic repair conditions with limited shifts. In terms of the heuristic approaches, this is to be understood as maximizing total bikes repaired within an allocated shift time of 450 minutes per mechanic.
- **Administrative Cost Reduction:** Automating route creation process through the explicitly developed heuristic models based on simple existing knowledge aims for a significant reduction in managerial and administrative effort in daily route planning.

By targeting an approach that addresses route efficiency and administrative workload, this research aims to demonstrate that even simple well known heuristic models offer significant advantages in the specific B2B e-bike rental and maintenance example but also for a broader SME environment.

1.4 Structure of the Thesis

This thesis systematically addresses the problem by introducing heuristic methods, detailing their implementation, analyzing comparative results and discussing relevant implications. Chapter 2 “Current Operational Environment” defines the B2B e-bike rental and maintenance scenario. Chapter 3 “Algorithmic Approach & Rationale (Conceptual)” presents the heuristic approaches NN and SAI. Chapter 4 “Methodology & Implementation” explicitly details methodology used, outlines theoretical assumptions, the implementation in C# and the simulations framework to evaluate performance. Chapter 5 “Simulation & Results” presents the empirical results of the simulation which measure efficiency in travel time, repair count, total time and locations visited. Chapter 6 “Interpreting the Results in the SME Context” discusses the findings and the practical implications for SMEs such as feasibility, adoption challenges and benefits. Finally, Chapter 7 “Conclusion and Outlook” concludes with insights from the benefit of increased operational efficiency and administrative cost reduction as well as suggesting future potential expansions for further improvements.

2. Current Operational Environment

2.1 Overview of the Operational Environment

The operational environment described and researched here is based on a real world, urban centered B2B e-bike rental and maintenance service operating in Berlin, Germany. This consists of a centralized depot and a network of 61 client hubs that are distributed in the city. Within this environment, there is a significant set of operational challenges which significantly undermine operational efficiency, service reliability and managerial overhead. Most of the issues can be traced to difficult to predict repair times, manual routing of mechanics through a working day and the constraints imposed by the business aspect and the service level agreements (SLAs) with clients.

When examining the operational environment and the core elements, it becomes evident that there is a necessity for an optimized routing solution in order to efficiently manage the operation. These core elements include spatial distribution of locations, the mechanics' operational constraints, travel time, repair time variance, and targeted service levels.

2.2 Key Operational Constraints and Their Algorithmic Implications

2.2.1 Locations and Fleet Distribution

The company operates by servicing a network of fixed client hubs, each of which can host between 5 and 25 e-bikes. These e-bikes are rented by corporate clients that rely on the availability for daily operations.

Due to high usage, breakdowns occur regularly and require timely interventions. Clients update the status of each e-bike as either operational or down (requiring repair) in a shared platform. Maintenance is therefore reactive, although an agreed buffer period between reporting and repair allows some pre planning. Nevertheless, this still results in significant fluctuations which adds a further layer of complexity.

Algorithm Implications

These real-world conditions get incorporated into the heuristic optimization network as datasets.

- The set **L** represents all locations, including hubs and the depot.
- Locations/Hubs that have more than 20% of e-bikes down are considered candidate locations for visiting and are represented by **C.**
- A precomputed **travel time matrix** is created to map out all travel times between all locations efficiently.

These aspects are integrated into the heuristic model to prioritize repairs based on the actual business impact and enhance service efficiency.

2.2.2 Mechanics and Shift Constraints

The company employs a number of mechanics, usually scaled to the operations requirements of the specific area. In the current scenario, each mechanic has a shift length of 7.5 hours or 450 minutes. This shift length needs to include all travel and repair times.

Mechanics start their working day and end their working day at the central depot. There they collect their cargo e-bike by which they travel and all the tools and spare parts necessary for the day.

Algorithm Implications

These real-world conditions get incorporated into the heuristic model by defining the set of mechanics and the various constraints.

- The set **M** represents all mechanics with the individual mechanics as $\mathbf{m} \in \mathbf{M}$**.**
- Constraints of 450 minutes as **Total Time per Mechanic.**
- **Depot Constraint:** where all mechanics **must start and end at the depot.**

2.2.3 Travel Time and Routing

The travel times between hubs are pre-computed using data from Google Maps Application Programming Interface (API), specifically using the standard bicycle travel mode, assuming consistent traffic conditions (Google, n.d.). Each specific travel duration is stored in a **L x L** travel time matrix which provides travel times for all possible locations **L** within the operational environment.

In the current approach, real time fluctuations in traffic conditions are not explicitly taken into consideration. The model assumes that average travel time durations are sufficiently stable to allow for reliable routing decisions, particularly as the models inherently handle travel time variance in mechanic shift time utilization.

Algorithm Implications

- The **travel time matrix T** is used to provide the values for every pair combination of locations.
- The **Nearest Neighbor** heuristic makes routing decisions based on the nearest feasible location in terms of **travel time.**
- The **Sequential Adaptive Insertion** heuristic considers the cheapest insertion based on the same travel time plus the theoretical repair time per e-bike down per location.

2.2.4 Repair Time and Stochasticity

One of the most critical aspects and sources of uncertainty is the actual repair time per e-bike. Based on historical operational data collected within the company, the average duration of an e-bike repair is around 15 minutes, but real world conditions make this value vary substantially.

Some repairs have very simple solutions such as plugging in a cable, while others can have complex mechanical issues. This introduces the randomness factor in the predicted repair times. To account for this in the simulation stages of this problem, stochastic repair times are necessary.

Algorithm Implications

- For **initial route construction,** a **fixed repair time of 15 minutes** is taken as the presumed duration of a repair. It allows for simple modeling and is the maximum accuracy possible pre-repair.
- For the **execution of the simulation**, the repair times are modeled using a lognormal distribution with a **mean of 15 minutes** and a **standard deviation of 5 minutes** which reflects the real world uncertainty. This choice is supported by empirical studies that demonstrate that repair durations are typically right-skewed and well approximated by a lognormal distribution (Kline, 1984).

2.2.5 Business Logic and Service Level Agreements

The company operates under various SLAs with different clients. Based on these agreements the target operational percentage is set. For simplicity and modeling comparability, a single level of 80% was chosen. A failure to meet these thresholds results in financial penalties.

To ensure SLA compliance, any routing algorithm undertaken in this business scenario must prioritize these locations strategically and optimize accordingly.

Algorithm Implications

- Locations, where more than 20% of e-bikes are down, are flagged as needing repair.
- Routing algorithms filter out locations that do not meet the threshold thus reducing unnecessary travel and repair time and optimizing indirectly mechanics' efficiency.

2.3 Summary of Operational Challenges and Computational Design

The assumptions along with the constraints outlined in this section establish the realities of the operational environment and allow for it to be defined as a problem. These real-world limitations get incorporated into a framework which targets achieving operational optimization by implementing heuristic models which have two primary targets:

1. Maximize Repair Efficiency: To ensure that the maximum number of e-bikes are serviced within each mechanic shift.
2. Minimize Total Travel Time: By optimally ordering the repair visits, the solutions both aim to reduce unnecessary travel.

The motivation behind the proposed heuristics is in the balance between efficiency, feasibility and ease of implementation. The primary purpose is to improve performance under realistic constraints and to address an overlooked component of operational cost: administrative and managerial burden. As scaling occurs, manual planning becomes impractical and resource intensive. In this context, adopting an effective and easy to implement automating tool as presented in these models, offers a scalable and viable solution.

The transition from manual to automated decision making has been shown to offer improvements in operational efficiency even when relying on relatively simple heuristic models. Automated routing consistently outperform manual planning particularly in dynamic logistics environments where timely and scalable solutions are essential. These advantages highlight the value of algorithmic approaches over subjective human planning (Mes & van Heeswijk, 2020).

3. Algorithmic Approach & Rationale

3.1 Algorithm Selection Rationale

Given operational and administrative realities and the NP-hard nature of the Travelling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) (Toth & Vigo, 2002, p. 8), it is common practice to choose heuristic approaches to routing. The nature of resource limitation specifically in SMEs almost makes the simplicity and ease of implementation of heuristic optimization methods a clear choice. One sees a clear balance between robust empirical performance and simplicity. All leading to easy administration and automation within the operational environment (Laporte, 1992a, pp. 241-245).

In this research, two of the most well known and accessible TSP heuristics were intentionally selected. Both are applicable to VRP and in this case, a Capacitated VRP (CVRP), and are used to demonstrate a tangible value that even the simplest approaches can deliver great results in a resource limited SME setting (Laporte, 1992b, p. 351).

- **Nearest Neighbor:** explicitly chosen as a low complexity option that is straightforward and simple. This option is paired with a 2-opt route improvement for optimizing results as well as a built in recourse action to account for random repair times.
- **Sequential Adaptive Insertion:** a self developed heuristic based on the cheapest insertion. The development of this heuristic is based on the principles of creating complete planned routes that change based on time of repair deviation from plan for

all mechanics. This provides a more dynamic and better suited solution to handle randomness but with increased complexity.

Both of these solutions however are targeting a reduction in managerial overhead and increased operational efficiency (Laporte, 1992a, pp. 241-245).

3.2 Nearest Neighbor Conceptual Overview

The NN heuristic is a classic greedy approach applied to routing problems and lends itself well to simplicity and speed. In this case it constructs mechanic routes iteratively. Starting from the depot, for each mechanic it selects the next closest feasible location based on the minimum travel time. The travel time is added with the average 15 minute assumed repair time per e-bike for each e-bike down in that specific location to the total time per mechanic. The iteration continues until the mechanics shift time constraint of 450 minutes is reached. When all routes for the explicitly stated number of mechanics have been created, each route is enhanced by the incorporated 2-opt to find local improvements (Rosenkrantz et al., 1977).

In order to deal with the issue of random repair times which causes the most difficulty in this environment, a recourse action that the mechanics can take was used. If the duration of the repair times was longer than expected (average 15 minutes per e-bike) and the mechanic reaches the end of the strict shift time limit before the planned route and repairs are complete, the route can be abandoned and the mechanic can head to the depot early. If the repair times were shorter than expected and the mechanic has reached the end of the route faster than planned, a new nearest neighbor can be further requested if travel time plus theoretical total repair time for all e-bikes is under maximum shift time.

3.3 Sequential Adaptive Insertion Conceptual Overview

The SAI heuristic is more complex than the NN variant. It requires a more in depth implementation and has more moving parts. It begins by constructing the routes from all mechanics starting with and ending with the depot. It then constructs complete (hidden) theoretical routes for all mechanics. This is done as mentioned by the cheapest insertion logic which loops through all locations and finds the cheapest insertion and adds it to the route. The same presumptions apply here as in the NN variant, the 15 minute theoretical repair time per e-bike and 450 minute maximum total time per mechanic (Rosenkrantz et al., 1977).

At any given time there are two versions of each route for each mechanic. The mechanics see only the final route, which will include all visited locations including their current location, but start off by only displaying the depot at the beginning of the day. The second (hidden) route, which is a helper route, includes everything the mechanic sees plus the rest of the locations that create the complete theoretical route.

A key strength of the SAI heuristic lies in the ability it has to adapt to the randomness in repair times and the fluctuations through its dynamic iterative approach. The core of the method uses two distinct structures for each mechanic.

- The final route which includes the already visited locations and accounts for the actual realised repair and travel times;
- The hidden route which is a theoretical construction used internally to plan ahead based on estimated repair durations;

During the execution, whenever a mechanic requests a new location, the hidden routes get recalculated in the background. These dynamic reconstructions consider remaining shift times and the current position of mechanics. Although the hidden routes are based on the fixed 15-minute assumptions, it consistently updates during a working day's progression as mechanics consume their time differently. This ongoing rebuilding is what helps with balancing route distribution and improving performance.

Key Differences

Aspect	**Nearest Neighbor**	**Sequential Adaptive Insertion**
Approach	Greedy, local choice	Global Cheapest Insertion, iterative rebuilding
Complexity	Lower, fast to implement	Higher, more resource-intensive
Adaptability	Limited (2-opt)	Rebuild routes dynamically
Suitability	Good for smaller/stable operational environments	Better for unpredictable or larger operational environments

4. Methodology & Implementation

4.1 Problem Formulation

This problem is modeled as a CVRP with stochastic repair times. The goal is to maximize total bikes repaired and minimize total travel time while being subject to mechanic shift constraints.

4.1.1 Set Definitions - The Problem Space

Set	Definition
L	*Set of all **locations** (hubs + depot) where **l** $\in$ **L**.*
M	*Set of **mechanics**, where **m** $\in$ **M.***
B_l	*Set of **e-bikes at location l**, where **l** $\in$ **L**.*
B_l^{down}	*Set of **down e-bikes** at location **l**.*

4.1.2 Variables - Dynamic Values Used in Optimization

Variable	Definition
T_m	*Mechanic shift time limit = **450 minutes***
$T_{travel}(l_1, l_2)$	*Travel time matrix between any locations l_1 and l_2, obtained from Google Maps API.*
T_{repair}	***Repair time per e-bike**, modeled as:*

*- **Fixed** (for heuristic construction):*

$$T_{repair\_fixed} = 15min/e - bike$$

*- **Stochastic** (for sim only):*

$$T_{repair\_stochastic} \sim LogNormal(15, 4.95)$$

$X_{m,l} \in \{0, 1\}$ *Binary **decision variable**:*

*- 1 if mechanic **m** visits location **l***

- 0 otherwise

4.1.3 Constraints - Rules for governing the Models

- **Mechanic Shift Time Constraint**

$$\sum_{l \in L} (T_{travel}(l_{prev}, l) + B_l^{down} \times T_{repair}) \leq T_m$$

  - *Ensures total mechanic shift time (travel + repair) does not exceed 450 minutes*

- **Depot Start & End Constraint**

$$X_{m,0} = X_{m,L} = 1, \quad \forall m \in M$$

  - *Ensures each mechanic starts and ends at the depot.*

- **SLA-Based Location Filtering (Pre-Processing Step)**

$$C = \{l \in L \mid \frac{B_l^{down}}{B_l} > 0.2\}$$

  - *Only locations where more than 20% of e-bikes are down are considered as candidate locations for repair.*
  - *This is not a routing constraint, but a filter applied before route construction.*
  - *Where C is the set of candidate locations that must be visited.*

4.1.4 Objective Function

We aim to minimize total travel time while maximizing e-bike repairs.

- **Minimizing Total Travel Time**

$$\min \sum_{m \in M} \sum_{l \in C} X_{m,l} \cdot T_{travel}(l_{prev}, l)$$

- **Maximizing Total Repairs**

$$\max \sum_{l \in C} B_l^{down} \cdot X_{m,l}$$

4.2 Algorithmic Implementation

The following sections describe the implementation of Nearest Neighbor and Sequential Adaptive Insertion in C#.

4.2.1 Nearest Neighbor Algorithm

Input: Set of candidate locations (C), travel time matrix (T), repair time per e-bike
Output: Optimized route for each mechanic

1. **Sort** candidate locations by **percent down** in descending order.
2. **Initialize** Route[m] = **[Depot]** for each mechanic.
3. **Initialize** Total_Time[m] = 0 for each mechanic.
4. **While** Total_Time[m] ≤ **Mechanic_Shift_Limit**, do:
    1. **Find** the **nearest unvisited location** l from **C**.
    2. **Compute** New_Total_Time:
        - New_Total_Time = Total_Time[m] + **T_travel(Depot, l)** + **(B_down** × **T_repair_fixed)**
    3. **If** New_Total_Time > **Mechanic_Shift_Limit**:
        - **Break** (mechanic **returns to depot early**).
    4. **Else**:
        - **Add** l to Route[m].
        - **Remove** l from **C**.
5. **Append** depot to Route[m] to **close the route**.
6. **Apply 2-Opt Optimization** for route improvement.
7. **Return** final route.

Real-World Recourse Actions (Applied After Algorithm Execution)

8. **If** Total_Time[m] > **Mechanic_Shift_Limit** before completing the planned route:
    - **Mechanic abandons remaining stops** and **returns to the depot**.
9. **If** Total_Time[m] < **Mechanic_Shift_Limit** after completing all planned stops:
    - **Mechanic requests a new nearest neighbor** from **C** if feasible.
    - **If a valid location exists**, add it to Route[m]; otherwise, **return to depot**.
10. **If no further visits are possible**:
    - **Mechanic returns to the depot early**.

4.2.2 Sequential Adaptive Insertion Algorithm

SAI is a dynamic heuristic that continuously rebuilds routes based on the cheapest insertion logic.

Input: Set of candidate locations (C), travel time matrix (T), repair time per bike
Output: Optimized route for each mechanic

1. **Initialize** FinalRoute[m] = **[Depot, Depot]** for each mechanic.
2. **Initialize** HiddenRoute[m] as an empty list for preliminary route construction.
3. **Initialize** Total_Time[m] = 0 for each mechanic.
4. **Determine the last fixed location** for each mechanic (this is the last committed stop before the depot).
5. **While valid candidate locations remain in C**:
    1. **Mechanic requests a new location**.
    2. **Rebuild** HiddenRoute[m] using **Cheapest Insertion**, ensuring:
        - **Preserve all fixed locations** from FinalRoute[m]; no insertions occur before the last fixed node.
        - **Consider only possible insertions after the last fixed location**, never modifying past stops.
        - **Find the insertion with the lowest additional travel cost**.
        - **Ensure feasibility**:
            - Total_Time[m] + **T_travel** + **(B_down** × **T_repair_fixed)** ≤ **Mechanic_Shift_Limit**.
    3. **If no valid insertion exists, stop inserting new locations**.
    4. **Otherwise, commit the next best location** from HiddenRoute[m] to FinalRoute[m].
    5. **Update last fixed location** to reflect the new committed stop.
    6. **Remove committed location** from **C**.
6. **Depot remains the final stop in FinalRoute[m]**, ensuring shift compliance.
7. **Return final optimized routes**.

5. Simulation & Results

This chapter presents the empirical results which have been derived from the stochastic simulation. The simulation systematically creates stochastic repair times and goes through a process of route building and analysis in order to be able to evaluate the operational and administrative performance of the two heuristic algorithms developed in this thesis: Nearest Neighbor and Sequential Adaptive Insertion.

The simulation assesses each algorithm in terms of route efficiency, workload distribution and repair performance under realistic operational constraints. This simulation framework does not directly model or quantify the administrative aspects, but the one central motivation behind implementing these heuristics is to reduce the managerial time and automated route generation.

5.1 Simulation Design and Execution Framework

The created simulation environment was structured in such a way to ensure robust evaluation and allow for testing realistic operational conditions encountered in this specific operational environment. The experiments replicate the explicit scenario by using stochastic repair times and varying instance size and “down” status of e-bikes. This creates an environment that has scaled dynamic mechanics based on the required number of locations to be visited.

5.1.1 Scenario Configuration

- **Small Scenario:** 10 Locations Requiring Service, 1 Mechanic(s)
- **Medium Scenario:** 20 Locations Requiring Service, 2 Mechanic(s)
- **Large Scenario:** 30 Locations Requiring Service, 3 Mechanic(s)
- **Complete Scenario:** 61 Locations Requiring Service, 2 Mechanic(s)

The rationale of creating an ever expanding number of locations that are in need of service was to see how scaling operations complexity and pure business scaling could affect the efficiency of the respective heuristics. For each scenario, there was an initial step to actually create the instances. This setup followed a random number approach to create 10 separate randomly generated instances for each scenario. This means that for the testing run there were 40 total separate instances created. Each instance was separately simulated 100 times for both algorithms. In a conceptual sense, this means that one instance was a certain stat of a beginning of the day and it being simulated 100 different times means that there were 100 separate sets of generated repair times with which the respective heuristics built the routes and from which data was collected. This is to be understood as 100 possible scenarios of played out days of repairs for one theoretical day down e-bikes. This created a total of 4000 days simulated and the total data gathered from these was used to compare both heuristics performance.

5.1.2 Simulation Procedure

The logic of the simulation follows the structured construction and where applicable recourse application as would be applied in the field. This happens across all scenarios, and instances with a set of generated stochastic repair times being used for both the NN and the SAI with the same instance as to allow for direct comparison and unbiased simulation.

```
Initialize mechanics and Location data
---------------------------------------------------------------
For each scenario (10, 20, 30, 61 hubs):
  For each heuristic method (NN, SAI):
    Repeat simulation 100 times:
      Sample stochastic repair durations from lognormal distribution
      Apply heuristic (NN or SAI):
        - Construct and optimize routes
        - Apply real-time recourse handling (for time overruns or spare capacity)
      Log performance metrics per mechanic:
        - Total Route Time
        - E-bikes Repaired
        - Number of Hubs Visited
        - Total Travel Time
    Compute means and standard deviations across all runs
```

5.2 Evaluation Criteria and Key Metrics

In order to quantify and fairly compare the performance of the NN and SAI heuristic approaches, the following metrics were chosen as they represent the most realistic and relevant aspects of the operational environment:

- **Total Route Time (min):** Total minutes spent by mechanic on travel and repairs, indicating overall time efficiency and mechanic utilization.
- **E-bikes Repaired per Shift:** Measures the service productivity under the existing shift constraints and is in the research and real operations environment the main objective to be maximized.
- **Number of Locations Visited:** Is the measure that best reflects the operational coverage and the allocation efficiency.
- **Total travel Time (min):** A component of route time being isolated as transport related used to judge the second objective to minimize total travel time.

5.3 Comparative Results and Analysis

To analyze the effectiveness of the two proposed heuristics, NN and SAI, this section presents a multi layered evaluation. The results are presented at three different levels: a comparative overview for all simulated scenarios, a breakdown along mechanics performance within one selected scenario and an in depth examination of a single instance in both initial deterministic construction presumptions and under stochastic conditions.

5.3.1 Scenario-Level Performance Comparison

The first layer compares average performance across the four operational scenarios: 10, 20, 30 and 61 locations. For each scenario, 10 instances were simulated 100 times with stochastic repair durations. The key metrics were gathered and averaged to reflect efficiency and coverage.

Findings:

- **Spatial Coverage:** SAI offers up better performance when it comes to the total amount of hubs visited. This shows a better utilization of capacity specifically as the problem increases. In the 61-location scenario, SAI visits an average of **7.19** locations while NN only **6.72**.

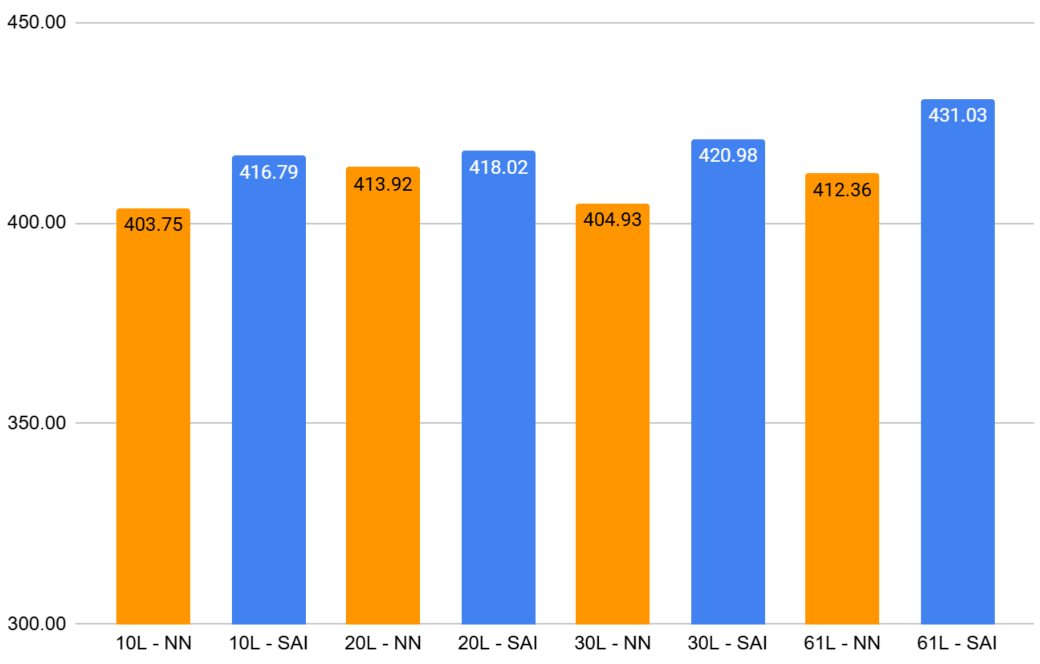
- **Repair Throughput:** SAI consistently achieves a higher number of repairs (except for the 20-location scenario). In the largest scenario (61-locations) SAI completes an average of **25.97** repairs compared to **24.47** for the NN. This improvement can be attributed to the SAI ability to dynamically update based on available shift time and the global insertion logic which enables better assignment especially as scale increases.

- **Travel Time Efficiency:** NN produces shorter travel times, often 5-10 minutes per mechanic. For example, in the 30-location scenario, the average travel time for the NN is **74.27** minutes while SAI is **79.14**. However, this travel efficiency comes at the cost of leaving more available shift time unused and completing fewer repairs.

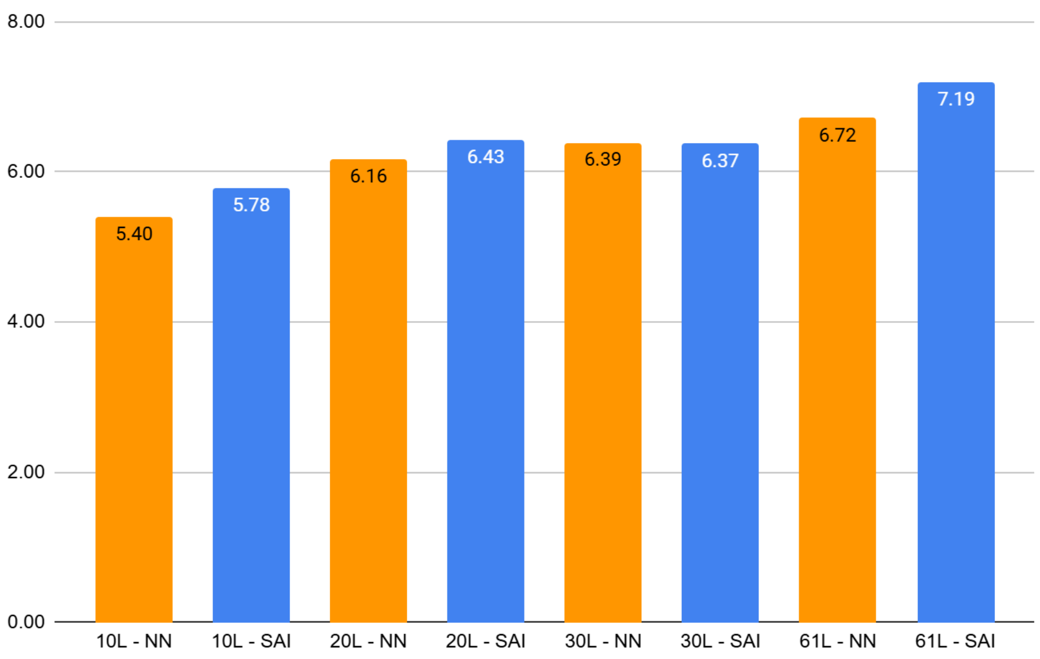
- **Scalability:** The gap widens between SAI and NN as the instance size increases and the number of mechanics increase. The NN shows deteriorating performance due to limited foresight and simple route construction. This is in contrast to the SAI that scales robustly and adapts well to repair distribution and balances travel and productivity. The differences between the two at larger scales can also be seen as larger opportunity cost of suboptimal assignments for the NN as scale increases.

All of these findings taken together highlight that NN can be a sufficient solution in a low-complexity, more static environment, whereas SAI's adaptive framework is better capable to exploit capacities and to meet service targets in a larger, more demanding context.

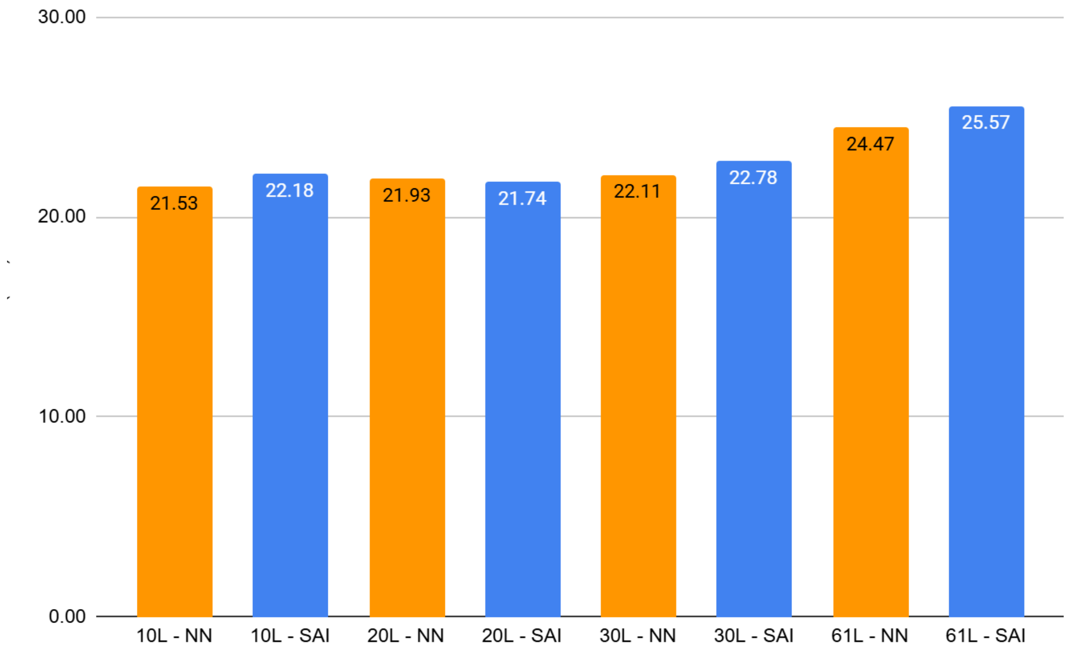
Infographic 1: Total Time (min) - High Level



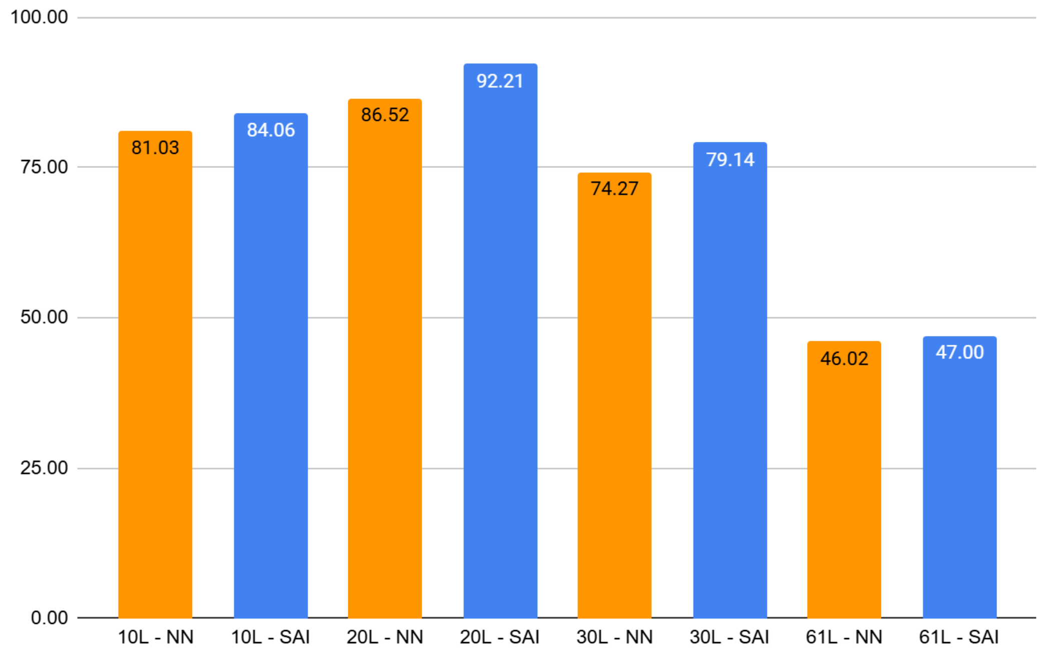
Infographic 2: Locations Visited - High Level



Infographic 3: Bikes Repaired - High Level



Infographic 4: Travel Time (min) - High Level



5.3.2 Mechanic-Level Workload Distribution (30 Hubs, 3 Mechanics)

The next level of analysis will look deeper at how each heuristic distributes tasks across individual mechanics. This will be looked at in detail for the 30-location, 3-mechanic scenario. The previously displayed high level aggregate performance looks at overall efficiency, the mechanic-level reveals how these approaches perform in terms of fairness, shift utilization differences and general route balancing. Those are factors against which a solution can be judged for reliability and labor sustainability.

Findings:

- **Time Allocation:** The NN heuristic shows uneven total time distribution across the mechanics, ranging from **~398 to 415 minutes**. The NN significantly overloads the first mechanic (M1). The SAI heuristic in contrast shows a tightly grouped distribution ranging from **~419 to 421 minutes**, highlighting consistent and balanced allocation across the team.

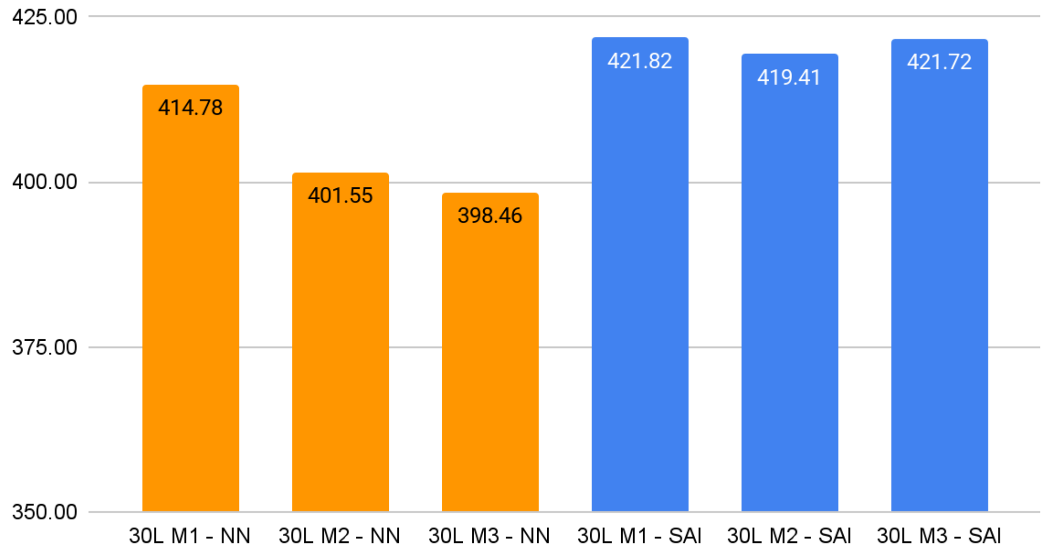
- **Locations Visited:** Here again NN shows a significant gap with M1 visiting **6.8** Locations and M2 **5.7**. This in contrast with SAI even distribution ranging from **5.9** to **6.5** locations visited. This points to a better spatial spread of responsibilities.

- **Repairs Completed:** The imbalance is further confirmed by the number of repairs. M1 with NN completes **23.9** repairs, while M3 only **20.3**. In SAI, all three complete between **22.6** and **22.9** repairs.

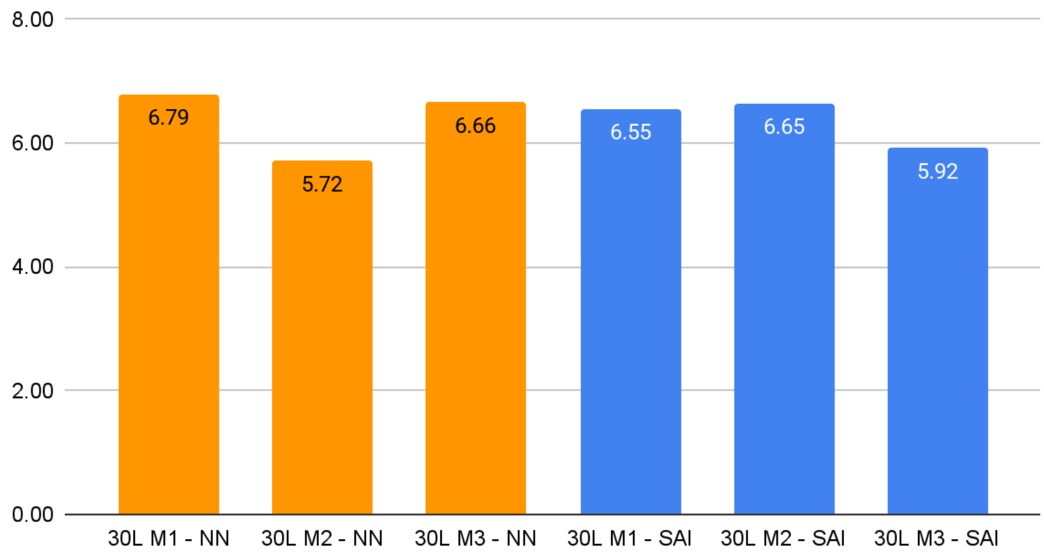
- **Travel Time Disparities:** The highest skewed variable is the travel time. M3 travels on average over **95** minutes whereas M1 under **57** minutes. This highlights inefficient routing balancing. SAI shows at this level again consistent results from **77** to **81** minutes.

All patterns show that even if overall performance is acceptable, NN disproportionally assigns work to certain mechanics. This can lead to bottle necks and certain personnel issues. SAI produces consistently fairer and more predictable workloads. This consistency becomes valuable as scale becomes a factor where these discrepancies can have long term consequences.

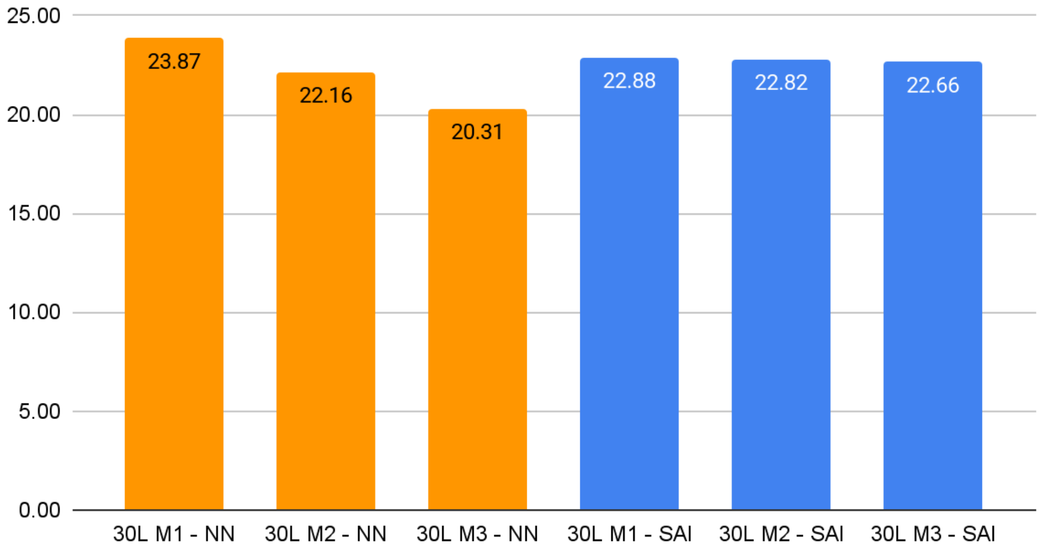
Infographic 5: Total Time (min) - Mechanic Level



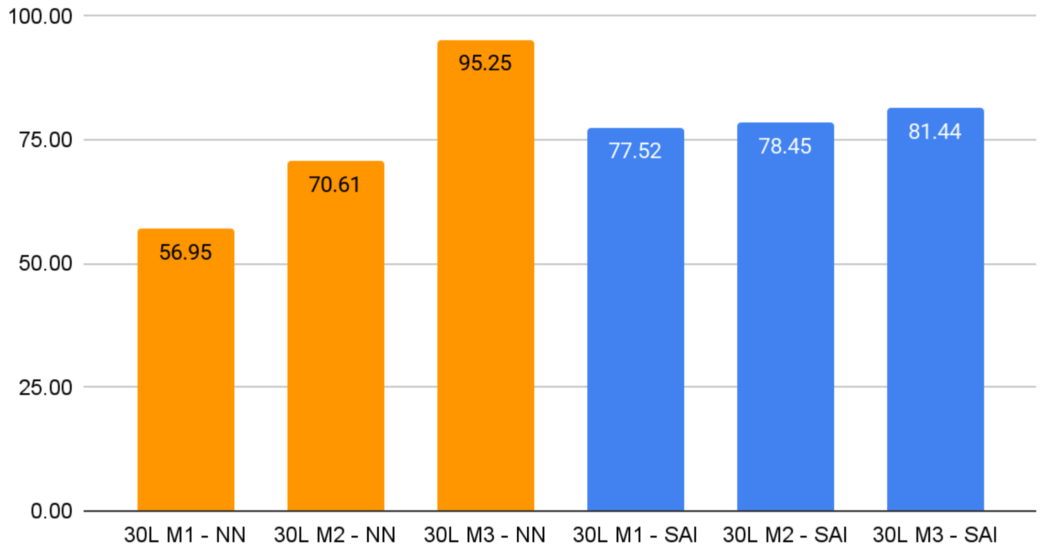
Infographic 6: Locations Visited - Mechanic Level



Infographic 7: Bikes Repaired - Mechanic Level



Infographic 8: Travel Time (min) - Mechanic Level



5.3.3 Response to Random Variability in a Single Instance (20 Hubs, 2 Mechanics)

The final layer of evaluation looks at a single instance from the 20-location, 2-mechanic scenario. The initial heuristic output based on the deterministic 15-min repair time is compared with the behavior after 100 stochastic simulations.

Initial Planning Outcomes

In the initial deterministic setup, both heuristics produce feasible routes within the given set of constraints. The NN completes more repairs overall, though we can see here again that it happens at the cost of workload imbalance. Mechanic 2 in the NN solution travels twice as much as Mechanic 1. This highlights the heuristics lack of global workload considerations. SAI in contrast creates an initial construction that is more balanced in terms of total travel time, however it does have slightly less repairs for one mechanic and in total. Overall both results are quite close to each other.

Post Simulation Behavior

Once the two heuristics are exposed to stochasticity in repairs, differences emerge in reliability and efficiency.

- **Consistency and Predictability:** SAI has a lower variance in total time across both mechanics. For NN, Mechanic 1 shows high relative variability which indicates that it is more sensitive to stochasticity.
- **Utilization of Time:** Again SAI has higher travel times but completes more repairs. It also shows an ability to maintain location coverage and even increases the number of repairs compared to initial planning, showing better adaptation.
- **Balance Under Stochasticity:** SAI shows evenness in workload and travel time in the simulation results despite stochasticity. NN in contrast shows imbalances specifically in comparing mechanics.

Interpretation

This instance demonstrates that NN could perform quite well under ideal conditions and can come to a similar result as SAI in a deterministic environment. However when introducing dynamic uncertainty, SAI rebalances even better than the initial planning would indicate.

Table 1: Single Instance - Initial Construction

Initial 15 min Construction		
NN	**M1**	**M2**
Total Time (min)	439.72	460.27
Locations Visited	3.00	5.00
Bikes Repaired	26.00	24.00
Travel Time (min)	49.72	100.27
SAI	**M1**	**M2**
Total Time (min)	435.15	408.28
Locations Visited	4.00	4.00
Bikes Repaired	26.00	22.00
Travel Time (min)	45.15	78.28

Table 2: Single Instance - Simulation Results

After 100 Simulations				
NN	**Mean M1**	**Std M1**	**Mean M2**	**Std M2**
Total Time (min)	372.40	68.85	418.86	36.32
Locations Visited	3.61	0.49	4.37	0.58
Bikes Repaired	22.10	4.90	22.34	2.58
Travel Time (min)	43.28	8.09	87.46	11.54
SAI	**Mean M1**	**Std M1**	**Mean M2**	**Std M2**
Total Time (min)	429.13	23.11	422.10	22.59
Locations Visited	4.00	0.60	5.11	0.92
Bikes Repaired	24.66	2.00	22.24	1.63
Travel Time (min)	56.89	12.89	89.84	22.44

6. Interpreting the Results in the SME Context

6.1 Operational Insights and Trade-Offs

The simulation results reveal relevant differences between the Nearest Neighbor and the Sequential Adaptive Insertion heuristics and the potential support they can offer SMEs in routing operations. The NN heuristic has the benefit of simplicity while still retaining the ability to produce efficient routes in a stable, small scale environment. The SAI heuristic increases complexity and demonstrates significantly improved performance in larger and less predictable environments by balancing workloads and adapting to random repair times.

The trade-offs go beyond the simple performance metrics, the whole operational context for this particular scenario and all other similar SME environments become relevant when trying to apply solutions to the real world. The simple NN approach allows for a quick and lower effort implementation whereas the implementation effort increases for the SAI requiring greater technical input and more defined computing structures.

More importantly, the results explored here underline that there can be many factors which become relevant to field operations and a problem cannot be reduced to a simple approach of maximizing or minimizing an objective. The longer term value comes from strategically implementing the specific tool in field operations and considering all relevant individual circumstances in the environment where it is applied.

6.2 Conditions for Adoption: Technical and Organizational

For any SME considering route optimization, the success is tied to technical capacity and organizational readiness. In this instance the choice between NN and SAI makes possible certain implementations at different operations scales. There is however a minimum requirement of data reliability, staff capability and to a lesser extent digital infrastructure.

SMEs with a small number of hubs and relative stability in demands of daily rerouting are definitely well positioned to adopt the NN, even when confronted with limited technical resources. NN can be implemented using spreadsheets or simple scripts and is more flexible when it comes to incomplete or static data. SMEs that deal with fluctuating demand, high number of locations or multiple mechanics are more likely to notice significant outperforming of the SAI in contrast to the simple NN. Based on professional observations within operations roles, these organizations already operate in a more digitally advanced environment such as an ERP or other digital platforms. These conditions are favorable to the implementation and use of more advanced tools such as the SAI solution.

6.3 Strategic Implications for SME Practice

The principal motivation for this thesis is an attempt to bridge the gap between the academic theoretical environment and the operational environment of SMEs. While large corporations have in place the structures and Information Technology (IT) tools necessary to undertake such implementations organically, SMEs often struggle, which is why these implementations go beyond routing improvements. These heuristics allow organizations to move away from intuition based routing and operations to a more structured and repeatable approach that is grounded in data.

The use of these automated route generation tools introduces an operations environment to planning discipline, reduces subjectivity and provides operational visibility. It allows SMEs to codify and benchmark operational processes which previously relied on individual input. This lays the groundwork for a mature approach to operations and over time these tools can evolve with other integrated components and platforms to increase mechanic efficiency, coverage and service level. In this way, these heuristics can be a first step towards structured and scalable operational growth.

7. Conclusion and Outlook

This thesis sought to explore how simple heuristic algorithms could improve operational efficiency and reduce administrative burden in SMEs managing decentralized field services. The context specifically focused on a traveling e-bike repairman concept and the development, implementation and simulation of the Nearest Neighbor and Sequential Adaptive Insertion.

The key findings demonstrate the ability of even lightweight heuristics to deliver significant improvements over manual planning. NN specifically excels in ease of deployment in small scale predictable environments whereas SAI offers superior adaptability and performance under dynamic conditions particularly when it comes to balancing workloads across assigned mechanics and handling random repair time durations at the cost of being more technically demanding in implementation.

The findings reinforce the view that simple heuristic optimizations, if appropriately matched to the operations context, still are a viable option and can deliver real value to SMEs without heavy investment or advanced analytics. NN is a low barrier to entry point for organizations looking to introduce structure and efficiency to planning. SAI, while more demanding in implementation, is well suited to scalíling where adaptability and dynamic resource assignment is critical. Essential for both methods is reliable input data and willingness to integrate automated planning into existing operations.

Looking ahead, there are further promising research and development directions that could be explored. These can be an incorporation of real time data such as traffic and changing repair needs, or hybrid models that use features from NN and SAI to create better performing heuristics. The general exploration of more advanced techniques which may provide even better route optimization can also be a possible option. Further exploration on the direct user and operations level could be achieved by providing expanding usability and interface integration to support adoption and ease of use.

In conclusion, the thesis has shown that practical, scalable optimization is within reach for SMEs. Through alignment of tool complexity, operations needs and digital readiness, even organizations with resource constraints can enhance quality and streamline operations, setting a foundation for optimized scalable digital operations.

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Appendix

Experimental Results for 10-Locations & 20-Locations

Instance	NN			
10L M1	Total Time	Location	Bikes Rep	Travel T
10_1	409.91	6.64	18.92	125.74
10_2	419.15	6.99	22.07	86.13
10_3	423.18	6.98	22.62	86.49
10_4	397.91	4.84	20.40	95.13
10_5	393.54	4.95	21.50	73.72
10_6	429.88	4.57	24.71	50.13
10_7	389.79	3.30	22.50	57.84
10_8	416.04	4.01	23.03	71.79
10_9	337.63	3.06	20.60	27.28
10_10	420.50	8.64	18.93	136.05
Average				
	403.75	5.40	21.53	81.03
M1	403.75	5.40	21.53	81.03
M2				
M3				

Instance	SAI			
10L M1	Total Time	Location	Bikes Rep	Travel T
10_1	421.64	7.60	20.03	122.50
10_2	416.20	6.93	21.83	85.59
10_3	413.25	7.03	21.11	97.67
10_4	417.58	6.79	20.37	112.70
10_5	417.44	3.55	23.65	64.41
10_6	424.53	4.75	24.57	54.42
10_7	413.93	4.02	23.72	59.54
10_8	415.81	4.07	23.11	69.35
10_9	416.30	3.91	23.77	59.04
10_10	411.25	9.18	19.65	115.35
Average				
	416.79	5.78	22.18	84.06
M1	416.79	5.78	22.18	84.06
M2				
M3				

Instance	NN			
20L M1	Total Time	Location	Bikes Rep	Travel T
20_1	425.85	7.34	25.62	38.77
20_2	419.93	6.08	23.16	73.99
20_3	417.78	9.45	21.80	92.67
20_4	373.73	3.62	22.20	43.45
20_5	401.78	6.26	22.30	68.07
20_6	413.13	4.46	24.38	50.63
20_7	428.57	9.38	22.64	94.06
20_8	427.26	5.79	24.57	59.80
20_9	415.69	6.20	22.36	83.09
20_10	405.31	6.78	19.88	112.84
20L M2	Total Time	Location	Bikes Rep	Travel T
20_1	419.90	3.49	22.70	80.41
20_2	407.46	4.99	18.94	122.79
20_3	415.39	5.91	19.48	121.24
20_4	419.00	4.27	22.38	84.71
20_5	409.43	7.01	19.02	127.34
20_6	400.28	6.43	20.15	101.85
20_7	429.33	7.88	21.74	104.54
20_8	418.97	4.89	23.79	58.56
20_9	407.71	5.29	21.16	90.02
20_10	421.89	7.77	20.31	121.61
Average				
	413.92	6.16	21.93	86.52
M1	412.90	6.54	22.89	71.74
M2	414.94	5.79	20.97	101.31
M3				

Instance	SAI			
20L M1	Total Time	Location	Bikes Rep	Travel T
20_1	422.25	6.70	22.57	83.15
20_2	418.65	6.17	22.80	79.71
20_3	415.96	7.87	19.95	117.08
20_4	425.83	3.88	24.48	57.97
20_5	408.52	7.85	18.93	123.27
20_6	415.76	6.03	22.40	86.72
20_7	415.95	8.00	20.91	102.53
20_8	422.15	5.95	23.47	70.38
20_9	416.87	5.85	21.97	89.10
20_10	410.20	7.12	20.44	105.78
20L M2	Total Time	Location	Bikes Rep	Travel T
20_1	424.81	5.32	23.98	61.99
20_2	422.66	6.70	20.99	109.36
20_3	418.68	7.82	20.36	111.15
20_4	418.06	5.13	22.19	85.92
20_5	421.88	6.10	21.92	92.68
20_6	419.28	5.37	22.40	81.76
20_7	419.32	9.32	22.03	90.68
20_8	417.88	4.45	23.12	66.31
20_9	415.32	5.63	21.57	91.44
20_10	410.44	7.29	18.41	137.22
Average				
	418.02	6.43	21.74	92.21
M1	417.21	6.54	21.79	91.57
M2	418.83	6.31	21.70	92.85
M3				

Experimental Results for 30-Locations & 61-Locations

Instance	NN			
30L M1	Total Time	Location	Bikes Rep	Travel T
30_1	419.54	7.26	24.80	50.83
30_2	414.99	5.00	25.94	24.15
30_3	403.00	7.33	22.98	55.55
30_4	425.39	7.31	23.49	75.29
30_5	406.77	6.46	23.84	48.11
30_6	417.05	7.10	21.35	96.22
30_7	428.12	6.12	25.02	49.80
30_8	400.89	7.00	23.09	57.08
30_9	421.49	8.35	25.30	45.35
30_10	410.59	5.95	22.87	67.15
30L M2	Total Time	Location	Bikes Rep	Travel T
30_1	430.09	6.69	22.38	93.29
30_2	414.82	6.18	22.94	74.52
30_3	406.69	4.38	22.50	67.48
30_4	347.00	5.32	20.20	49.00
30_5	431.37	6.40	24.80	64.27
30_6	409.40	6.96	20.68	103.10
30_7	416.59	4.36	23.41	65.79
30_8	391.97	4.99	22.90	48.05
30_9	350.09	5.00	18.00	80.36
30_10	417.45	6.92	23.76	60.25
30L M3	Total Time	Location	Bikes Rep	Travel T
30_1	420.40	7.15	22.50	85.76
30_2	424.89	7.20	22.40	89.74
30_3	414.71	4.83	21.32	95.82
30_4	414.03	7.21	19.57	123.37
30_5	399.77	5.75	19.00	118.54
30_6	410.84	6.99	21.99	75.92
30_7	347.62	7.02	18.18	77.26
30_8	328.78	6.11	16.10	83.34
30_9	412.09	7.50	20.50	105.18
30_10	411.49	6.79	21.58	97.58
Average				
	404.93	6.39	22.11	74.27
M1	414.78	6.79	23.87	56.95
M2	401.55	5.72	22.16	70.61
M3	398.46	6.66	20.31	95.25

Instance	SAI			
30L M1	Total Time	Location	Bikes Rep	Travel T
30_1	422.47	5.35	22.78	78.75
30_2	422.91	6.03	24.04	59.56
30_3	424.66	6.64	22.34	91.86
30_4	416.07	6.73	23.04	71.68
30_5	421.53	6.61	22.58	81.38
30_6	419.64	8.09	22.09	90.67
30_7	432.72	6.06	23.94	66.07
30_8	416.05	5.88	23.19	70.61
30_9	423.44	7.20	23.72	66.52
30_10	418.70	6.93	21.09	98.05
30L M2	Total Time	Location	Bikes Rep	Travel T
30_1	416.96	7.73	22.14	89.15
30_2	417.16	6.06	23.17	71.79
30_3	422.20	5.91	23.44	68.36
30_4	417.23	7.65	22.30	86.69
30_5	427.50	5.56	24.32	61.05
30_6	414.58	7.08	21.62	87.00
30_7	424.49	7.50	23.40	77.91
30_8	410.24	5.32	23.30	61.60
30_9	424.46	6.34	21.97	96.17
30_10	419.31	7.30	22.52	84.81
30L M3	Total Time	Location	Bikes Rep	Travel T
30_1	420.15	6.83	22.72	78.93
30_2	423.97	5.82	22.66	83.73
30_3	423.08	5.01	22.83	78.64
30_4	416.93	5.90	22.84	73.84
30_5	425.76	7.37	23.45	77.08
30_6	417.67	6.01	21.22	96.39
30_7	428.85	4.58	23.79	69.75
30_8	413.37	7.43	21.67	84.92
30_9	427.70	5.72	23.01	86.68
30_10	419.73	4.53	22.36	84.42
Average				
	420.98	6.37	22.78	79.14
M1	421.82	6.55	22.88	77.52
M2	419.41	6.65	22.82	78.45
M3	421.72	5.92	22.66	81.44

Instance	NN			
61L M1	Total Time	Location	Bikes Rep	Travel T
61_1	425.10	5.61	26.97	25.67
61_2	421.88	6.29	26.18	29.46
61_3	403.60	8.06	24.34	38.74
61_4	424.00	6.93	24.82	52.04
61_5	424.49	7.17	26.00	34.74
61_6	424.15	7.70	25.39	43.05
61_7	416.55	4.82	25.46	38.87
61_8	427.64	6.42	25.86	42.46
61_9	406.24	4.92	25.44	22.61
61_10	403.20	6.41	25.02	30.01
61L M2	Total Time	Location	Bikes Rep	Travel T
61_1	418.23	7.42	24.64	48.93
61_2	429.01	6.53	24.06	66.71
61_3	406.27	7.60	22.00	75.94
61_4	415.80	7.43	24.54	45.50
61_5	412.71	8.29	22.22	79.03
61_6	396.85	5.61	24.27	33.78
61_7	389.37	6.36	23.52	36.08
61_8	396.94	6.98	22.01	64.50
61_9	394.54	5.70	24.30	34.02
61_10	410.56	8.07	22.31	78.27
Average				
	412.36	6.72	24.47	46.02
M1	417.69	6.43	25.55	35.77
M2	407.03	7.00	23.39	56.28
M3				

Instance	SAI			
61L M1	Total Time	Location	Bikes Rep	Travel T
61_1	431.17	7.37	26.12	41.88
61_2	429.86	6.64	25.46	45.46
61_3	431.67	9.26	24.89	59.19
61_4	434.60	8.88	25.86	44.31
61_5	427.42	8.58	25.09	55.13
61_6	427.63	9.01	25.05	53.69
61_7	433.04	5.49	26.50	35.69
61_8	430.18	6.99	25.31	49.72
61_9	434.85	4.31	27.10	29.37
61_10	429.75	8.12	25.36	47.73
61L M2	Total Time	Location	Bikes Rep	Travel T
61_1	433.97	7.77	25.44	51.52
61_2	432.17	7.60	25.30	48.41
61_3	429.51	7.07	24.83	54.87
61_4	432.28	6.70	25.85	45.92
61_5	433.50	6.50	25.56	47.54
61_6	428.97	5.67	25.92	38.85
61_7	431.06	6.07	26.04	40.80
61_8	428.97	7.25	25.30	49.09
61_9	430.20	7.62	25.12	50.98
61_10	429.82	6.96	25.28	49.88
Average				
	431.03	7.19	25.57	47.00
M1	431.02	7.47	25.67	46.22
M2	431.05	6.92	25.46	47.79
M3				