DOI: 10.2195/lj_proc_gehl_en_202510_01

# A Novel Approach to Transform Theoretical Vehicle Routing Problems to Practical Applications

**Alexander Gehl[1], Niklas Jost[1], Jan Endendyk[1], Jérôme Rutinowski[1], Alice Kirchheim[1, 2]**

[1] Chair of Material Handling and Warehousing, TU Dortmund University, Germany
[2] Fraunhofer Institute for Material Flow and Logistics IML, Germany

**In procurement logistics, manual route planning often leads to inefficiencies such as high costs, congestion, and unbalanced truck arrivals. This paper presents a framework for applying Vehicle Routing Problem (VRP) heuristics to inbound logistics, formulated as an Open VRP with real-world constraints such as vehicle capacities, time windows, and maximum tour duration. Two classical construction heuristics, the Nearest Neighbor Heuristic and the Insertion Heuristic, are adapted and implemented in a configurable tool that enables scenario definition and reproducible evaluation. The approach is motivated by a case from a German manufacturing company, whose situation served as a reference point for designing fictitious but realistic datasets. The evaluation across 18 scenarios shows that both heuristics generate feasible solutions suitable as baselines for routing decisions. On average, the Insertion Heuristic achieves 13 % higher loading meter utilization (83 % compared to 69 % for the Nearest Neighbor Heuristic) and requires fewer tours, while overall travel times remain nearly identical between the two methods. Overall, the study demonstrates that heuristic methods provide systematic and time-efficient support for inbound routing in procurement logistics, offering a foundation for practical decision-making and further methodological refinements.**

*[Keywords: Vehicle Routing Problem, Procurement Logistics, Inbound Logistics, Heuristics]*

## 1 Introduction

In the context of inbound logistics, companies encounter the challenge of optimizing route planning for inbound deliveries in a manner that reduces transportation costs and minimizes environmental impact. This planning is often carried out manually, based on experience and operational data such as transport times, handling times, and shipment characteristics as weight, size or quantity. This process is time-consuming and often results in inefficient routing and an uneven distribution of truck arrivals throughout the day. The resulting peak loads cause congestion and inefficient utilization of internal resources. While theoretical approaches and vehicle routing algorithms already exist to optimize such processes, their practical application in procurement logistics remains limited due to the complexity of real-world operations.

This study addresses that gap by presenting a configurable tool that operationalizes established vehicle routing heuristics for inbound logistics. The tool ingests procurement-related data, maps practical constraints such as time windows, loading meters, weight limits, and maximum tour duration, and generates feasible tour plans together with transparent key performance indicators. The implementation applies classical construction heuristics that can be executed with limited computational effort and provides interfaces for parameterization, scenario definition, and reproducible evaluation.

The approach is motivated by a real industrial challenge observed at a large German manufacturing company, where the problem of inbound routing arises in practice. For this study, the company's situation served as a reference point to design fictitious datasets that replicate typical procurement conditions. While the datasets are entirely fictitious and independent from the company, their structure and parameters reflect realistic shipment patterns, geographical distributions, and operational constraints. In line with practical procurement settings, the tours are assumed to be carried out by external logistics service providers, implying flexible fleet availability. This ensures that the scenarios used in the evaluation remain close to practical requirements, while the developed tool is designed to be applicable across different companies and not limited to a single case. Moreover, the shown algorithm is successfully in use in that company.

The paper is structured as follows: Section 2 reviews related work on routing problems and heuristics in logistics. Section 3 presents the problem formulation used in this


*Article is protected by German copyright law*

DOI: 10.2195/lj_proc_gehl_en_202510_01

study. Section 4 describes the heuristic methods and the implementation details, including the output structure used for evaluation. Section 5 outlines the application setup, including the datasets and constraint variants used for testing. Section 6 reports the results and discusses their implications for procurement logistics. Section 7 concludes the paper and provides an outlook on future research.

## 2 Related Work

In the scientific literature, route planning is typically described using a depot-customer relationship, where customers are supplied from a central depot (see [1, 2, 3, 4]). This basic model serves to illustrate routing problems and solution approaches and is adapted in this study to the scenario of multiple suppliers delivering to a central industrial site. The foundation of routing problems is the well-known Traveling Salesperson Problem (TSP), where a single tour driver must visit a set of customers exactly once while minimizing total distance or cost (see [3, 4, 5], [6]). The TSP is one of the most studied combinatorial optimization problems, with its first formalization published by Dantzig et al. in 1954 [7].

The TSP is extended by the Vehicle Routing Problem (VRP), where multiple vehicles depart from a depot to serve several customers. The Capacitated Vehicle Routing Problem (CVRP) represents a variant that results in a set of tours corresponding to multiple vehicles. The capacitated variant considers vehicle capacity constraints [8, 9]. Further practical extensions include the Vehicle Routing Problem with Time Windows (VRPTW), which incorporates time restrictions for deliveries [4, 8], and the Open Vehicle Routing Problem (OVRP), where the start and end points of the tours may differ [4, 8].

These routing problems can be decomposed into an assignment problem, determining the allocation of customers to tours, and a sequencing problem, defining the optimal order of customer visits [10]. Both subproblems are NP-hard, implying that computational complexity increases exponentially with problem size [5, 11] unless $P = NP$. For small problem sizes, exact methods such as branch-and-bound algorithms can be applied [5, 12], but these quickly become impractical as the number of customers increases. Therefore, heuristic approaches are commonly used in real-world applications, offering feasible but not necessarily optimal solutions within reasonable computational time [13].

This study focuses on classical construction heuristics, which are particularly useful in industrial practice for generating fast initial solutions [5]. Specifically, the Nearest Neighbor Heuristic, first introduced by Karg and Thompson [14], iteratively selects the nearest unvisited customer [15, 16, 17], and the Cheapest Insertion Heuristic, originally developed for the Traveling Salesman Problem by Solomon [18], are applied and evaluated in the context of inbound logistics [1, 2].

## 3 Preliminaries

To address a practical application in procurement logistics, we model the problem as a mathematical optimization task. Specifically, we formulate it as an *Open Vehicle Routing Problem (OVRP)* with additional real-world constraints such as vehicle capacity and scheduling restrictions. We follow the standard formulation introduced by [19].

Let a graph $G = (V, E)$ be given, where $V = \{v_0, v_1, \ldots, v_n\}$ denotes a set of locations. The node $v_0$ represents the central customer location, while each node $v_i$ with $i > 0$ represents the $i$th supplier location. Each edge $(i, j) \in E$ is associated with a cost $c_{ij}$, representing the time required to travel from node $i$ to node $j$.

The solution consists of a set of tours. Let $x_{ijt}$ be a binary decision variable indicating whether edge $(i, j)$ is traversed in tour $t$. The number of available tours is upper bounded by a parameter $K$, which is assumed to be large enough to ensure feasibility.

Each tour is executed by one truck, which is subject to the following real-world constraints:

- The maximum *loading meters* it can carry.
- The maximum *loading weight* it can carry.
- *Time windows* for pickups and deliveries.
- The *maximum duration* of a tour.

These limits depend on the truck type and the associated contract. We denote the maximum allowed loading meters by $\lambda$, and the maximum allowed weight by $\mu$. Each location $v \in V$ is associated with a fixed time window $[\alpha_v, \beta_v]$ during which service must occur. The maximum duration of a tour is denoted by $\Delta$.

For the nodes we considered $d_i^\lambda$ as the required loading meters at node $i$, $d_i^\mu$ as the weight of the goods at $i$ and $s_i$ as the necessary service time at $i$. The parameters and variables are summarized in Table 1.

### Mathematical Model

Based on the parameters, we present the mathematical model we consider:


Article is protected by German copyright law

DOI: 10.2195/lj_proc_gehl_en_202510_01

*Table 1: Model parameters and decision variables.*

| Symbol | Type | Description |
|---|---|---|
| $V$ | Set | Set of all locations (nodes) |
| $E \subseteq V \times V$ | Set | Set of edges between locations |
| $c_{ij}$ | Parameter | Cost (travel time) of edge $(i, j)$ |
| $K$ | Parameter | Maximum number of tours (assumed large enough) |
| $\lambda$ | Parameter | Maximum loading meters for truck |
| $\mu$ | Parameter | Maximum loading weight for truck |
| $[\alpha_v, \beta_v]$ | Parameter | Time window during which location $v$ must be served |
| $\Delta$ | Parameter | Maximum duration of a tour |
| $d_i^\lambda$ | Parameter | Loading meters required at node $i$ |
| $d_i^\mu$ | Parameter | Loading weight required at node $i$ |
| $s_i$ | Parameter | Service time at node $i$ |
| $x_{ijt} \in \{0, 1\}$ | Binary Variable | 1 if edge $(i, j)$ is used in tour $t$, 0 otherwise |
| $a_i$ | Variable | Arrival time at node $i$ |

$$\min \sum_{i \in V} \sum_{j \in V} \sum_{t=1}^{K} c_{ij} x_{ijt} \tag{1}$$

$$\sum_{i \in V} \sum_{t=1}^{K} x_{ijt} = 1 \quad \forall j \in V \setminus \{0\} \tag{2}$$

$$\sum_{j \in V} \sum_{t=1}^{K} x_{ijt} = 1 \quad \forall i \in V \setminus \{0\} \tag{3}$$

$$\sum_{i \notin S} \sum_{j \in S} x_{ijt} \geq \tau(S) \quad \forall S \subseteq V \setminus \{0\}, S \neq \emptyset \tag{4}$$

$$\sum_{i \in V} \sum_{j \in V} d_i^\lambda x_{ijt} \leq \lambda \quad \forall t = 1, \ldots, K \tag{5}$$

$$\sum_{i \in V} \sum_{j \in V} d_i^\mu x_{ijt} \leq \mu \quad \forall t = 1, \ldots, K \tag{6}$$

$$\alpha_i \leq a_i \leq \beta_i \quad \forall i \in V \tag{7}$$

$$a_j \geq a_i + s_i + c_{ij} - M(1 - x_{ijt}) \qquad \substack{\forall i, j \in V, \\ \forall t = 1, \ldots, K} \tag{8}$$

The objective function (1) minimizes the total travel cost over all used edges in all tours. Each location (excluding the depot) must be visited exactly once, enforced by constraints (2) and (3), which ensure a one-to-one assignment of visits across tours.

Constraint (4) is a subtour elimination constraint ensuring connectivity and preventing disconnected cycles. Constraints (5) and (6) enforce the vehicle capacity limits in terms of loading meters and weight, respectively, for each tour.

Time windows for servicing each location are enforced via (7), ensuring that the arrival time at each node lies within its permissible time interval. Finally, constraint (8) ensures correct time progression between visits. Here, $M$ is a sufficiently large constant used in the time propagation constraint (Big-M method).

## 4 Methods

To solve the inbound vehicle routing problem formulated in Section 3, we apply two classical but adaptable heuristics: the *Nearest Neighbor Heuristic* (NNH) and the *Insertion Heuristic* (IH). These methods are selected for their computational efficiency and their flexibility in accommodating operational constraints such as vehicle capacities, time windows, and tour duration limits. The heuristics are designed to rapidly produce high-quality, feasible solutions that reflect real-world logistics planning requirements.

### 4.1 Input Data and Parameter Configuration

The model requires three categories of input data:

- **Location data:** includes travel times, distances, and time windows for all suppliers and the customer, extracted from internal systems.
- **Shipment data:** derived from procurement requirements, including quantities, weights, and volume dimensions per supplier.
- **Constraint parameters:** such as vehicle capacity limits, maximum tour duration, and service times, defined from operational experience and internal guidelines.

Table 2 provides an overview of the main parameters and their practical values used in the heuristics.

*Table 2: Heuristic parameter configuration (representative values).*

| Parameter | Value | Description |
|---|---:|---|
| $\lambda$ | 13.6 m | Max. loading meters per truck |
| $\mu$ | 24,000 kg | Max. loading weight per truck |
| $\Delta$ | 8 h | Max. tour duration |
| $s_i$ | 20 min | Service time at each supplier |
| $[\alpha_v, \beta_v]$ | 6:00–16:00 | Time windows at suppliers (standard) |
| $M$ | 1000 min | Big-M constant for time constraints |

The chosen parameter values reflect typical constraints observed in European procurement logistics. For example, 13.6 meters and 24,000 kg correspond to standard trailer capacity limits, while the 8-hour duration aligns with labor regulations and scheduling practices. Service times and


Article is protected by German copyright law

time windows are based on average handling durations and supplier availability. Throughout the analysis, each tour is assigned the smallest feasible truck type. In addition, the model incorporates both qualitative and quantitative requirements. Qualitatively, it is assumed that all considered suppliers can generally be served within a milk-run concept, whereas direct deliveries are treated separately. From a cost perspective, fixed transportation costs are incurred regardless of tour length, making both the minimization of total distance and the number of tours relevant objectives. These requirements provide the basis for the subsequent tour construction heuristics.

### 4.2 Nearest Neighbor Heuristic (NNH)

The Nearest Neighbor Heuristic builds tours incrementally by selecting the unassigned supplier that is geographically closest (in terms of travel time) to the current endpoint of a tour. To reduce long detours, the first supplier of a new tour is always the one furthest from the customer. Time feasibility, capacity limits, and maximum duration are continuously monitored.

Algorithm 1: Nearest Neighbor Heuristic

Initialize all suppliers as unassigned
**while** unassigned suppliers remain **do**
  Start new tour $T_i$ with the unassigned supplier $v_f$ furthest from customer and next index $i > 0$
  Initialize $T_i$: $\text{load}_{T_i} \leftarrow 0$, $\text{length}_{T_i} \leftarrow 0$, $\text{time}_{T_i} \leftarrow 0$
  **while** feasible insertion exists **do**
    Find nearest unassigned supplier $v_n$ to last node in $T_i$
    Compute arrival and departure times at $v_n$
    **if** capacity and time constraints satisfied **then**
      Add $v_n$ to $T_i$; mark $v_n$ as assigned
      Update load, weight, and time of $T_i$
    **else**
      Remove $v_n$ from candidate set and continue
    **end if**
  **end while**
  Close tour $T_i$
**end while**

**return** tours $T_1, \ldots, T_K$

### 4.3 Insertion Heuristic (IH)

The Insertion Heuristic constructs tours by evaluating all possible positions for inserting each unassigned supplier into existing tours. The position yielding the smallest additional cost (typically travel time) is selected, provided it results in a feasible tour.

Algorithm 2: Insertion Heuristic

Initialize empty tours $T_1, T_2, \ldots, T_K$ with depot node 0 ln
Set of unassigned customers $U \leftarrow V \setminus \{0\}$
**while** $U \neq \emptyset$ **do**
  **for** each customer $j \in U$ **do**
    **for** each tour $T_t$ **do**
      **for** each feasible insertion position in $T_t$ **do**
        **if** insertion of $j$ in $T_t$ is feasible w.r.t. capacity and time **then**
          Compute cost increase $\theta$
          Store insertion $(j, t, \text{position}, \theta)$
        **end if**
      **end for**
    **end for**
  **end for**
  Select the insertion with the smallest $\theta$
  Insert customer $j$ into tour $T_t$ at best position
  Update arrival times and loads in $T_t$
  Remove $j$ from $U$
**end while**

**return** tours $T_1, \ldots, T_K$

### 4.4 Output Structure and Evaluation

Both heuristics output a set of feasible tours that:

- Cover all suppliers exactly once.
- End at the customer location.
- Satisfy all vehicle and scheduling constraints.

Each tour includes:

- An ordered list of supplier locations.
- Arrival, departure, and waiting times at each stop.
- Total driving time, waiting time, and service time.
- Total loading meters and weight.

This structured output supports not only fast planning but also enables comprehensive evaluation in terms of efficiency, feasibility, and resource utilization. In the next section, we evaluate and compare them across 18 test scenarios.

## 5 Experimental Setup

To evaluate the applicability of the presented heuristics to real-world procurement logistics, we apply the Nearest Neighbor Heuristic (NNH) and the Insertion Heuristic (IH) to a fictitious data set. The data set was constructed on the basis of data provided by a large German industrial com-


Article is protected by German copyright law

pany, which served as a template for designing a realistic scenario. This approach ensures that the resulting data remains close to actual procurement conditions while not representing any real company. The structure and parameterization of the data reflect typical delivery patterns, geographical distributions, and capacity requirements observed in industrial logistics networks.

The test scenario consists of a central production site located in Dortmund and 20 supplier locations distributed across a plausible delivery area. Travel times between all locations were generated using the OpenRouteService API based on realistic geographic coordinates and actual road networks. This ensures that spatial relationships and travel durations mirror those found in practice.

Each supplier is associated with shipment-specific attributes including loading meters, shipment weight, time windows, and service times. These parameters were defined to capture the heterogeneity of inbound flows typically observed in manufacturing industries. An overview of the parameter ranges is provided in Table 3.

*Table 3: Supplier data – key characteristics (20 suppliers).*

| Parameter | Range | Mean (SD) |
|---|---:|---:|
| Travel time [min] | 7–220 | – |
| Loading meters [m] | 1.2–12.8 | 6.4 (3.8) |
| Shipment weight [t] | 0.6–17.5 | 4.3 t (4.1) |
| Service time [min] | 30–90 | - |
| Time window start | 6:00–10:00 | – |
| Time window end | 14:00–21:00 | – |

To further examine the robustness of the heuristics, three dataset variants were created from this scenario. While all share the same network structure with 20 suppliers and one central production site, the datasets differ in shipment characteristics and travel times. This design enables systematic evaluation across a range of representative procurement logistics situations, from baseline cases to more challenging environments.

- **Dataset I**: Represents a realistic base case with heterogeneous shipment sizes and weights as well as realistic travel times, with loading meters ranging from 1.2 m to 12.0 m (average 6.29 m) and loading weights from 0.525 t to 17.0 t (average 5.57 t).

- **Dataset II**: Maintains the travel times and time windows of Dataset I but replaces the shipment data with smaller and more balanced consignments, with loading meters ranging from 1.1 m to 6.0 m (average 3.60 m) and loading weights from 0.8 t to 10.0 t (average 2.95 t). This enables a higher consolidation of shipments into fewer tours, thereby testing the adaptability of the heuristics to structural changes in shipment composition.

- **Dataset III**: Retains the shipment data of Dataset II but doubles all travel times. This creates an artificially larger geographical distribution and longer tours without altering shipment characteristics. The design allows to examine how the heuristics perform under significantly increased travel times, reflecting scenarios such as wider supply regions or persistent congestion effects.

This structure isolates the effects of shipment composition and travel times, allowing a targeted analysis of the robustness of both heuristics.

### 5.1 Constraint Variants

To further evaluate the heuristics under diverse operational settings, three variants of constraint parameters are defined. These variants represent different levels of planning realism and flexibility, ranging from conservative assumptions to idealized conditions.

- **Variant A** simulates standard operating conditions with conservative planning buffers. Maximum vehicle capacities are set to 13.6 meters and 24 tons, while a buffer of 0.5 meters and 2 tons is subtracted to account for planning uncertainties. The maximum tour duration is limited to 8 hours, reflecting standard daily driver availability. For the Nearest Neighbor Heuristic, a maximum waiting time of 1 hour is allowed.

- **Variant B** assumes extended planning flexibility, e.g., through handover between drivers or the use of relay concepts. The maximum tour duration is increased to 16 hours, while all other parameters remain as in Variant A.

- **Variant C** assumes the absence of planning buffers. Vehicle capacities are fully utilized without safety margins, and the maximum tour duration is kept at 8 hours, identical to Variant A. The variant represents a scenario without operational uncertainties, for example when loading procedures and shipment characteristics are standardized and predictable, so that additional safety margins are not required in the planning.

The combination of three fictitious datasets with two heuristics (NNH and IH) and three constraint variants (A–C) results in a total of 18 test scenarios. This experimental design systematically explores how changes in shipment structure, travel times, and operational constraints affect solution quality. The results provide insights into the sensitivity, robustness, and practical applicability of the heuristic approaches in procurement logistics.


Article is protected by German copyright law

*Table 4: Detailed results across datasets (I–III) and constraint variants (A–C).*

| Dataset | I | | | | | | II | | | | | | III | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Constraint Variants | A | | B | | C | | A | | B | | C | | A | | B | | C | |
| max. driving time [hh:mm] | 08:00 | | 16:00 | | 08:00 | | 08:00 | | 16:00 | | 08:00 | | 08:00 | | 16:00 | | 08:00 | |
| max. waiting time [hh:mm] | | 01:00 | | 01:00 | | 02:00 | | 01:00 | | 01:00 | | 02:00 | | 01:00 | | 01:00 | | 02:00 |
| loading meters (jumbo trailer) [m] | 15.5 | | | | | | 15.5 | | | | | | 15.5 | | | | | |
| buffer [m] | 0.5 | | 0.5 | | 0 | | 0.5 | | 0.5 | | 0 | | 0.5 | | 0.5 | | 0 | |
| loading meters (mega trailer) [m] | 13.5 | | | | | | 13.5 | | | | | | 13.5 | | | | | |
| buffer [m] | 0.5 | | 0.5 | | 0 | | 0.5 | | 0.5 | | 0 | | 0.5 | | 0.5 | | 0 | |
| loading weight [t] | 24 | | | | | | 24 | | | | | | 24 | | | | | |
| buffer [t] | 2 | | 2 | | 0 | | 2 | | 2 | | 0 | | 2 | | 2 | | 0 | |
| **Algorithm** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** | **INS** | **NN** |
| time before optimization [hh:mm] | 55:25 | 58:22 | 58:14 | 57:13 | 56:13 | 57:52 | 47:17 | 48:56 | 46:51 | 44:56 | 47:17 | 44:57 | 66:50 | 67:38 | 62:47 | 62:19 | 66:50 | 67:38 |
| time after optimization [hh:mm] | 55:25 | 56:04 | 56:56 | 55:55 | 54:57 | 55:14 | 47:17 | 46:56 | 46:51 | 44:56 | 47:17 | 44:57 | 66:50 | 66:51 | 62:47 | 62:19 | 66:50 | 66:51 |
| number of tours | 12 | 13 | 12 | 13 | 12 | 13 | 7 | 8 | 7 | 7 | 7 | 7 | 10 | 10 | 7 | 7 | 10 | 10 |
| loading meter utilization before buffer [%] | 90.79 | 81.61 | 89.64 | 81.63 | 92.78 | 83.53 | 84.05 | 66.24 | 79.67 | 72.73 | 85.80 | 73.86 | 60.16 | 51.79 | 84.31 | 72.10 | 60.16 | 25.99 |
| loading meter utilization after buffer [%] | 94.05 | 84.57 | 92.82 | 84.59 | 92.78 | 83.53 | 87.08 | 68.77 | 82.41 | 74.73 | 85.80 | 73.86 | 62.41 | 53.72 | 87.21 | 74.73 | 60.16 | 25.99 |
| weight utilization before buffer [%] | 33.83 | 31.23 | 33.83 | 31.23 | 33.83 | 31.23 | 35.29 | 30.87 | 35.29 | 35.28 | 35.29 | 35.28 | 24.70 | 24.70 | 35.29 | 35.28 | 24.70 | 24.70 |
| weight utilization after buffer [%] | 36.91 | 34.07 | 36.91 | 34.07 | 33.83 | 31.23 | 38.50 | 33.68 | 38.50 | 38.49 | 35.29 | 35.28 | 26.95 | 26.94 | 38.50 | 38.49 | 24.70 | 24.70 |

## 6 Results and Discussion

The evaluation of the two heuristics reveals differences in their performance with respect to the objective of minimizing total travel cost. Both approaches generate feasible tour plans that ensure each supplier is visited exactly once. A central finding is that the Insertion Heuristic (IH) produces fewer tours in almost all scenarios compared to the Nearest Neighbor Heuristic (NNH). On average, IH requires around half a tour less, which is a side effect of its construction logic: by inserting suppliers at positions of lowest additional cost, some routes can be combined more efficiently, leading to fewer overall tours. Travel times after optimization differ only marginally between the two heuristics, with average deviations of less than one percent. This indicates that the main differences stem from their construction logic.

Notable differences arise in vehicle utilization. It is assumed that each tour is carried out with the smallest feasible truck type, with an unlimited fleet available. Utilization values are therefore not optimized directly but serve as comparative indicators of tour efficiency. Across all scenarios, IH achieves higher loading meter utilization, averaging 83% compared to 69% for the NNH. Weight utilization, in contrast, remains low in both approaches (25–39%), reflecting that loading meters, rather than weight, are the binding capacity constraint in procurement logistics. However, these observations are strongly influenced by the characteristics of the available data and thus also depend on the specific industry under consideration.

The constraint variants further influence the outcomes. Extending maximum driving time (Variant B) allows longer routes and in some cases reduces the number of tours, while removing buffers (Variant C) slightly improves utilization values but has limited effect on tour numbers. Overall, IH achieved on average 13% higher loading meter utilization and required fewer tours in 14 out of 18 scenarios, while travel times remained nearly identical between the two methods. For instance, in Dataset II, Variant A, IH reduced the number of tours from 8 to 7 and increased utilization from 69% to 87%, whereas the corresponding travel times differed by less than one minute. This underlines that the observed advantages of IH are consistent across datasets and not driven by isolated cases. A detailed overview of all results is provided in Table 4.

## 7 Conclusion and Outlook

The objective of this study was to develop a tool that can be applied in practice to optimize inbound routing in procurement logistics. The Nearest Neighbor Heuristic and the Insertion Heuristic were successfully adapted to the constructed Open Vehicle Routing Problem and proved capable of generating feasible solutions across different scenarios. By testing different datasets and constraint variants, it was demonstrated that the framework is not limited to a single industry but can be applied to various companies with a broad range of operational requirements. While the approach does not guarantee optimality, the results indicate that the Insertion Heuristic often provides more favorable outcomes in terms of loading meter utilization and tour construction. Both heuristics therefore offer valid solutions that can serve as a robust baseline for decision-making in practice. They provide an initial planning baseline which, in op-


Article is protected by German copyright law

erational use, can be reviewed and adjusted by planners, for example in light of company-specific requirements, to incorporate experience-based considerations and short-term constraints.

The results also highlight that solution quality depends strongly on the characteristics of the available data and the specific industry context. In particular, the vehicle utilization outcomes are shaped by the assumption of an unlimited fleet of different truck sizes, which simplifies the model but may not reflect real operational conditions. Future research could address this limitation by introducing constraints on fleet availability and by comparing different allocation strategies. Moreover, automated data extraction from enterprise resource planning or transportation management systems would be a promising step to support applicability in practice.

Overall, the study shows that heuristic approaches can support cost-efficient and feasible inbound routing in procurement logistics. They enable structured use of planning data and allow integration into operational processes, particularly when supported by buffer-based scheduling mechanisms. While the solutions are designed to be applied directly, a manual review can complement the results to account for specific operational insights or situational adjustments.

Future research should explore refinements of the heuristics to improve solution quality, for example by adapting termination criteria or by varying starting conditions. The consideration of multiple objectives such as balancing distance and vehicle utilization could further enhance the flexibility of the approach. A relevant extension is the integration of company-specific fleet structures and limitations, since the availability of vehicles is often restricted in practice. In addition, dynamic aspects including order timing, shipment sizes, and inventory considerations could be incorporated to align routing with procurement planning. Finally, the approach may be extended towards multi-day planning, recurring time windows, and the integration of regulatory driving and rest times to better reflect real-world requirements.

## REFERENCES

[1] D. Arnold, H. Isermann, A. Kuhn, H. Tempelmeier, and K. Furmans, Eds., *Handbuch Logistik*, ser. VDI-Buch. Berlin, Heidelberg: Springer Berlin Heidelberg, 2008. [Online]. Available: http://link.springer.com/10.1007/978-3-540-72929-7

[2] D. C. Mattfeld and R. Vahrenkamp, *Logistiknetzwerke: Modelle für Standortwahl und Tourenplanung*, 2nd ed., ser. SpringerLink Bücher. Wiesbaden: Springer Gabler, 2014.

[3] Domschke, Wolfgang; Scholl, Armin, *Logistik: Rundreisen und Touren*, 5th ed. München: Oldenbourg, 2010, num Pages: 282.

[4] R. Lasch, *Strategisches und operatives Logistikmanagement: Distribution*. Wiesbaden: Springer Fachmedien Wiesbaden, 2023. [Online]. Available: https://link.springer.com/10.1007/978-3-658-42901-0

[5] W. Domschke, A. Drexl, R. Klein, and A. Scholl, *Einführung in Operations Research*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015. [Online]. Available: https://link.springer.com/10.1007/978-3-662-48216-2

[6] P. Toth and D. Vigo, Eds., *Vehicle routing: problems, methods, and applications*, second edition ed., ser. MOS-SIAM series on optimization. Philadelphia: Society for Industrial and Applied Mathematics : Mathematical Optimization Society, 2014.

[7] G. Dantzig, R. Fulkerson, and S. Johnson, “Solution of a Large-Scale Traveling-Salesman Problem,” *Journal of the Operations Research Society of America*, vol. 2, no. 4, pp. 393–410, 1954, publisher: INFORMS. [Online]. Available: http://www.jstor.org/stable/166695

[8] C. Ohrt, Ed., *Tourenplanung im Straßengüterverkehr*, ser. SpringerLink Bücher. Wiesbaden: Betriebswirtschaftlicher Verlag Dr. Th. Gabler / GWV Fachverlage GmbH, Wiesbaden, 2008.

[9] G. B. Dantzig and J. H. Ramser, “The Truck Dispatching Problem,” *Management Science*, vol. 6, no. 1, pp. 80–91, 1959, publisher: INFORMS. [Online]. Available: http://www.jstor.org/stable/2627477

[10] H. Beckmann, *Grundkurs Beschaffungsmanagement*, 1st ed. Wiesbaden: Springer Fachmedien Wiesbaden, 2023.

[11] U. Bankhofer, *Quantitative Unternehmensplanung: Mathematische Methoden und betriebliche Anwendungsbeispiele*, ser. Studienbücher Wirtschaftsmathematik. Wiesbaden: Springer Fachmedien Wiesbaden, 2022, iSSN: 2627-2032, 2627-2040. [Online]. Available: https://link.springer.com/10.1007/978-3-8348-2466-0

[12] H.-J. Zimmermann, *Operations Research: Methoden und Modelle. Für Wirtschaftsingenieure, Betriebswirte, Informatiker*, ser. SpringerLink Bücher. Wiesbaden: Vieweg+Teubner Verlag, 2005.

[13] D. Scholz, *Optimierung interaktiv: Grundlagen verstehen, Modelle erforschen und Verfahren anwenden*, 1st ed. Berlin, Heidelberg: Springer Berlin Heidelberg, 2018.

[14] R. L. Karg and G. L. Thompson, “A Heuristic Approach to Solving Travelling Salesman Problems,” *Management Science*, vol. 10, no. 2, pp. 225–248, Jan. 1964.

[15] M. Bellmore and G. L. Nemhauser, “The Traveling Salesman Problem: A Survey,” *Operations Research*,


Article is protected by German copyright law

vol. 16, no. 3, pp. 538–558, 1968, publisher: INFORMS. [Online]. Available: http://www.jstor.org/stable/168581

[16] J. W. Gavett, "Three Heuristic Rules for Sequencing Jobs to a Single Production Facility," *Management Science*, vol. 11, no. 8, pp. B–166–B–176, Jun. 1965, publisher: Institute for Operations Research and the Management Sciences (INFORMS). [Online]. Available: https://pubsonline.informs.org/doi/10.1287/mnsc.11.8.B166

[17] D. J. Rosenkrantz, R. E. Stearns, and P. M. Lewis, "An analysis of several heuristics for the traveling salesman problem," in *Fundamental Problems in Computing: Essays in Honor of Professor Daniel J. Rosenkrantz*, S. S. Ravi and S. K. Shukla, Eds. Dordrecht: Springer Netherlands, 2009, pp. 45–69. [Online]. Available: https://doi.org/10.1007/978-1-4020-9688-4_3

[18] M. M. Solomon, "Algorithms for the Vehicle Routing and Scheduling Problems with Time Window Constraints," *Operations Research*, vol. 35, no. 2, pp. 254–265, Apr. 1987.

[19] P. Toth and D. Vigo, *The Vehicle Routing Problem*, P. Toth and D. Vigo, Eds. Society for Industrial and Applied Mathematics, 2002. [Online]. Available: https://epubs.siam.org/doi/abs/10.1137/1.9780898718515

---

**Alexander Gehl, B.Sc.**, Research Assistant at the Chair of Material Handling and Warehousing (FLW), TU Dortmund University.

**Niklas Jost, M.Sc.**, Research Associate at the Chair of Material Handling and Warehousing (FLW), TU Dortmund University.

**Jan Endendyk, M.Sc.**, Research Assistant at the Chair of Material Handling and Warehousing (FLW), TU Dortmund University.

**Dr.-Ing. Jérôme Rutinowski**, Head of Research and Operations at the Chair of Material Handling and Warehousing (FLW), TU Dortmund University.

**Prof. Dr.-Ing. Alice Kirchheim**, Director of Fraunhofer Institute for Material Flow and Logistics IML and Head of the Chair of Material Handling and Warehousing (FLW), TU Dortmund University.

Address: Chair of Material Handling and Warehousing (FLW), LogistikCampus, Joseph-von-Fraunhofer-Str. 2-4, 44227 Dortmund, Germany
E-Mail: alexander.gehl@tu-dortmund.de


*Article is protected by German copyright law*