Minimizing earliness-tardiness costs in supplier networks – A Just-in-time Truck Routing Problem

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We consider a routing problem where orders are transported just-in-time from several suppliers to an original equipment manufacturer (OEM). This implies that shipments cannot be picked up before their release date when they are ready at the supplier and should be delivered as close as possible to their due date to the OEM. Every shipment may have a distinct due date but all shipments loaded onto the same truck arrive at the same time. The performance of the transportation network is optimized by finding an allocation of shipments to trucks and routes for each truck that minimizes the total earliness-tardiness cost. These penalties are caused by deviations between the truck arrival times at the OEM and the due dates of the loaded shipments. To solve the problem, we introduce a metaheuristic approach based on large neighborhood search, which we combine with an efficient local search scheme that allows the evaluation of neighborhood solutions in worst-case logarithmic time despite the nonlinear objective function. Our algorithm can find high-quality solutions to large instances with 200 shipments in less than 12 minutes of CPU time. From a practical perspective, our computational tests indicate that a too small truck fleet or very limited time differences between release and due date can dramatically affect the punctuality of the deliveries.

Keywords: Logistics, Just-in-time, Vehicle Routing, Large Neighborhood Search, Local Search

1. Introduction

Just-in-time (JIT) is a fundamental concept for original equipment manufacturers (OEM) in the automotive industry (Boysen et al., 2015). Applying JIT principles affects different optimization problems in production and logistics. In this paper, we investigate an optimization problem in a JIT context which, to the best of our knowledge, has not been researched yet in the OR literature, in spite of its practical relevance. We consider the problem where an OEM gets the inputs (parts and subassemblies) into its production processes delivered from multiple suppliers. Shipments from different suppliers are consolidated on trucks. Each shipment in the JIT production system is needed at a specific time, its *due date*. Moreover, a shipment becomes available for pickup after its *release date*, and there are given travel times between all locations, including the depot and the

Routing Problem	Requirements to model a TRP-JIT a pickup location for each shipment	one delivery location with one arrival time per route	hard time windows for pickups	soft time windows for deliveries
VRPTW **VRPTWSPD**	✓	✓	✓	✗
VRPSTW **VRPSTWSPD**	✓	✓	✓, by setting prohibitive cost factors	✗, no shipment-specific time-windows
PDVRPTW	✓	✗, several arrival times, one for each shipment	✓	✗, no consideration of earliness and tardiness costs
PDVRPSTW	✓	✗, several arrival times, one for each shipment	✓	✓

VRPTW: Vehicle Routing Problem with Time Windows, VRPSTW: Vehicle Routing Problem with Soft Time Windows,
VRPTWSPD: VRPTW with Simultaneous Pickup and Delivery, VRPSTWSPD: VRPSTW with Simultaneous Pickup and Delivery,
PDVRPTW: Pickup and Delivery VRPTW, PDVRPSTW: Pickup and Delivery VRPSTW

Table 1: Properties of well-known routing problems compared to the requirements to model a TRP-JIT

OEM. If a shipment is late, the logistics provider incurs the costs (tardiness costs) of delaying production. If a shipment arrives early, on the other hand, there are inventory holding and storage costs. The difference between the due date and the actual arrival time of a shipment at the OEM determines the earliness-tardiness costs, and these costs are to be minimized. We call the problem the *just-in-time truck routing problem (TRP-JIT)*. It can be difficult to achieve low earliness and tardiness costs, as 1) shipments with different due dates are consolidated on trucks; and 2) there are release dates and travel times that make it difficult to reach the appropriate due dates.

We consider the earliness-tardiness costs as the only objective because, in JIT systems, they usually dominate other concerns (like travel distance) due to steep contractual penalties for unpunctual deliveries (Boysen et al., 2015). For instance, Boysen et al. (2015) report that sometimes parts that otherwise do not arrive on time are flown in by helicopter.

A typical use case of TRP-JIT occurs in the automotive industry. A third-party logistics (3PL) provider organizes the transportation system between several suppliers and one OEM. The task of the 3PL is to transfer the shipments from the suppliers to the OEM for a certain day. It can become prohibitively expensive to collect each shipment on a separate transport haul. Therefore, shipments are collected on vehicles, a situation known in the literature as a *milk-run* JIT system (Boysen et al., 2015). While the tardiness and earliness of shipments form an important objective in JIT environments in general (Jozefowska, 2007), they have so far rarely been considered in the context of routing problems, despite the prevalence of such problems in practice.

To contextualize TRP-JIT in the large family of vehicle routing problems (VRP), we briefly review the most relevant VRP variants that include time windows to manage the release and due dates, and a *many-to-one* network structure, i.e., the transportation from several sources (suppliers) to a common sink (OEM). An overview of the closest variants and how they (do not) comply with the requirements for representing TRP-JIT is given in Table 1. In a nutshell, the models derived from the VRP with (soft or hard) time windows (VRPTW or VRPSTW) consider one time window per node, not per shipment. In TRP-JIT, however, the due date at the OEM depends on which suppliers have previously been visited, i.e., which shipments have been picked up. On the other hand, models based on pickup-and-delivery VRPTW do not have the prerequisite many-to-one structure. While it is possible to clone the OEM and assign the same destination to every pickup, this does not ensure that all shipments loaded onto the same truck arrive at the same time. In TRP-JIT, the punctuality of a shipment depends not on when a supplier is visited but on the delivery time at the OEM at the end of the route, which is common for all shipments on a truck.

To summarize, the TRP-JIT has not been considered in the JIT literature and is not covered by any classic

VRP variant. Therefore, we develop approaches to solve the TRP-JRP in this paper. First, we define a Mixed Integer Program (MIP) formulation for obtaining exact solutions. However, we find that such an approach takes reasonable time only for small instances. Therefore, we develop a Large Neighborhood Search (LNS) metaheuristic, which we combine with an efficient local search scheme that allows to evaluate neighborhood solutions quickly despite the nonlinear objective function. To summarize, our contributions are:

- The introduction and the formulation of the TRP-JIT,
- the development of an LNS metaheuristic method, which includes an efficient Local Search (LS) component, and
- gaining managerial insights into how to achieve reductions in earliness and tardiness costs.

The article is structured as follows: We present the literature related to the TRP-JIT in Section 2 and show the relevance of our work in this context. In Section 3, we introduce a formal definition of the TRP-JIT and formulate the problem as a MIP. Subsequently, we provide a metaheuristic framework, which is based on large neighborhood search (LNS) and local search (LS) and its application to the TRP-JIT in Section 4. The design and results of the experiments are reported in Section 5, as well as the managerial insights derived from the results. Finally, the overall outcomes and conclusions of our article are summarized in Section 6.

2. Literature review

While research into vehicle routing problems (VRP) has a long history dating back to Dantzig and Ramser (1959) (Toth and Vigo, 2014), its consideration in the context of just-in-time logistics is more recent. For an overview of different VRP variants, see Braekers et al. (2016). We discuss related problems in more details below. For an overview on (JIT) part logistics, we refer to Boysen et al. (2015).

The minimization of earliness-tardiness costs is characteristic for JIT scheduling problems, e.g., considered by Hall and Posner (1991), Lee and Kim (1995), and Rolim and Nagano (2020), but it is also relevant in the context of JIT routing. We can find this in the VRP with release and due dates of Shelbourne et al. (2017). They consider a problem where orders are released from the depot and delivered to one of the customers. They solve the problem by applying a path relinking algorithm and an iterated local search. Both travel costs and tardiness of deliveries contribute with specific weights to the objective function. Kang et al. (2008) consider a very similar problem but without release dates. They apply a tabu search algorithm. Mu and Eglese (2013) include release dates in their modified VRP and minimize the travel and tardiness costs as well as the labor costs for the drivers, which depend on the release date. They also propose a tabu search heuristic. Furthermore, the articles of Lee and Prabhu (2016) and Ganji et al. (2020) consider aspects of both JIT and green routing, i.e., routing problems in which the objective is to minimize carbon emissions or fuel consumption. Soman and Patil (2020) assume a heterogeneous fleet. In summary, there are several problems that consider the distribution of goods from a depot to customers (one-to-many) by applying JIT principles but not the delivery of goods from a supplier network to a production facility (many-to-one) for further processing at a single OEM.

In Section 1, we noted several VRP variants that are related to the TRP-JIT. The VRPTW is proposed as starting point by Boysen et al. (2015) to develop solution procedures for specific JIT milk-run routing problems. Constructive heuristics, LS procedures, and metaheuristics are reviewed by Bräysy and Gendreau (2005a,b). Initial work for the VRPTW has been done in the 1980s by Solomon (1986) presenting constructive heuristics, and by Solomon (1987) evaluating these heuristics in a computational study. The hybrid genetic algorithm by Vidal et al. (2013), the penalty-based edge assembly memetic algorithm by Nagata et al. (2010), the path relinking approach by Hashimoto and Yagiura (2008), or LNS by Shaw (1998) are some state-of-the-art heuristics for the VRPTW.

Concerning the VRPSTW, Fu et al. (2008) consider different types of soft time windows, either only causing penalty costs in case of a violation, which is also the case for our due dates, or combined with hard or one-sided time windows. Vidal et al. (2015) review soft time windows as a case of allowing infeasible solutions in a VRPTW, where the violation of time windows causes penalties. Similar to Fu et al. (2008), Taillard et al. (1997) and Chiang and Russell (2004) propose tabu search-based solution procedures for the VRPSTW. Koskosidis et al. (1992) propose an optimization-based heuristic, and Balakrishnan (1993) focuses on constructive heuristics. Ibaraki et al. (2008) assume convex penalty functions for the time windows and apply an iterated local search. Fachini and Armentano (2020) consider a traveling salesman problem with flexible time windows, which means a combination of soft and hard time windows.

Pickup and delivery problems generalize the standard VRP such that both pickups and deliveries can be considered along the routes. Different variants have been studied in literature. An overview is given by Battarra et al. (2014), Berbeglia et al. (2007, 2010), and Parragh et al. (2008a,b). The VRP variants with pickups and deliveries are distinguished by their network and transportation structure, i.e., a *one-to-many-to-one*, *one-to-one*, or *many-to-many* structure. The first is represented by the *vehicle routing problem with time windows and simultaneous pickup and derlivery* (VRPTWSPD) and VRPSTWSPD, the two latter structures by the PDVRPTW and PDVRPSTW according to Battarra et al. (2014). In a one-to-one structure, the goods are transported from a certain pickup location to one delivery location, whereas in the many-to-many case the shipments can be composed from different pickup locations and split to be delivered to several locations.

Koç et al. (2020) review the VRP with simultaneous pickup and deliveries. Dethloff (2001) propose a MIP model and heuristic solution procedures for the VRP with simultaneous pickups and deliveries. Bhusiri et al. (2014) survey a JIT use case in urban freight transportation with simultaneous pickups and deliveries at several convenient stores serviced by a single depot. The earliness-tardiness objective refers to the convenient stores, which are not at the end of the routes like the OEM in the TRP-JIT. Deng et al. (2009) propose a simulated annealing heuristic for the VRPSTWSPD. Kafle et al. (2017) model a subproblem of the so-called crowdsource-enabled urban parcel relay and delivery system by the VRPSTWSPD. They apply a solution procedure based on tabu search.

Initial work on the PDVRPTW and other closely related problems to the standard VRP is provided by Solomon and Desrosiers (1988). Jung and Haghani (2000) present a genetic algorithm for the PDVRPTW. Nanry and Wesley Barnes (2000) solve the problem by a reactive tabu search algorithm. Fagerholt (2001) presents the PDPSTW considering also different slopes for the penalty functions. Mourdjis et al. (2016) propose a variable neighborhood descent-based metaheuristic approach for the dynamic PDPSTW. Bettinelli et al. (2014) study a branch-and-price algorithm for the PDVRPSTW with heterogeneous fleet and multiple depots. De Giovanni et al. (2019) focus on an application in express fright trucking, where they solve the PDVRPSTW by a local search based heuristic. All of these models, however, either do not consider the many-to-one structure of the TRP-JIT or the truckload-specific time windows at the OEM.

LNS is a successful method for solving routing problems with time windows (e.g., Schneider et al., 2014) and in the context of JIT, e.g., for in-house feeding to assembly lines (Emde and Schneider, 2018). An overview of different principles and operators for LNS and other metaheuristics is given by Shaw (1998), Pisinger and Ropke (2007, 2019), Zäpfel et al. (2010), Gendreau et al. (2019). Generally, local search is a metaheuristic framework that can be applied on the different VRP variants, e.g., to the PDVRPSTW by De Giovanni et al. (2019). Regarding the VRPTW, Hashimoto and Yagiura (2008) and Nagata et al. (2010) apply local search phases together with other metaheuristic principles, similar to our solution approach. The neighborhood operators often applied to VRPTWs are presented by Bräysy and Gendreau (2005a). In addition to neighborhood operators, the definition of slacks for time windows are reviewed by Savelsbergh (1992), Kindervater and Savelsbergh (2018). Vidal et al. (2014) provide an overview of slacks commonly used in routing problems. Ibaraki et al. (2005, 2008), Hashimoto et al. (2010, 2013) survey more general definitions of soft and hard time windows and how to efficiently evaluate them. These papers, however, do not consider earliness-tardiness penalties at the end of the routes (i.e., at the OEM).

3. Problem description

The scope of this section is to formally describe the TRP-JIT. At first we introduce a formal definition of the problem in Section 3.1. Based on this, we illustrate the TRP-JIT by introducing an example in Section 3.2. We use the formal definitions in Section 3.3 to provide a MIP model including considerations of valid inequalities.

To model the problem concisely, we make the following assumptions:

- The 3PL operates with a homogeneous fleet, i.e., a fixed number of trucks with the same capacity.
- Minimizing the earliness and tardiness of the shipments is the dominant objective. It may safely be assumed that drivers and trucks are available at the 3PL.
- For the driving time matrix, the triangle inequality holds.
- Capacities are measured one-dimensionally, e.g., as weight of volume.
- All parameters are integers. Note that this can always be imposed to arbitrary precision by rescaling the inputs.
- Earliness and tardiness penalties can be expressed by piecewise linear convex semi-continuous functions. Note that this allows quite some flexibility, e.g., to encode one-sided hard time windows (by setting a prohibitively steep slope for either earliness or tardiness) or flexible time windows, where some violation is possible at a penalty cost but excessive violation is prohibitively expensive.

3.1. Formal description

Given is a set $N = \{1, \ldots, n\}$ of shipments to be picked up from specific locations. Note that some shipments may originate from the same physical location (i.e., supplier plant). Moreover, there is a truck depot with index 0, which is operated by the logistics provider. Finally, all shipments must be transported to the OEM denoted by index $\eta = n+1$. The shipments are delivered by a given fleet of homogeneous trucks. There are m trucks, each with a given capacity of Q, yielding the set of trucks $M = \{1, \ldots, m\}$. Each shipment $i \in N$ is associated with a capacity requirement $q_i \in \mathbb{N}_{\leq Q}$, a release date $r_i \in \mathbb{N}$, i.e., the earliest time when it can be picked up from the supplier location, and a due date $p_i \in \mathbb{N}_{>r_i}$ at the OEM. Note that due date p_i does not refer to the latest time when the shipment must be picked up but to the time when it should be dropped off at the OEM facility η. The TRP-JIT is defined on a directed graph $G = [V, A, t]$, where $V = \{0, \eta\} \cup N$ is the set of vertices representing the depot, the shipments and the OEM's location, $A = \{[i, j] \mid i \in V \setminus \{\eta\}, j \in V \setminus \{0\}, i \neq j\}$ is the set of arcs, and $t : A \to \mathbb{N}$ denotes the travel times. We use the index notation t_{ij} to denote the travel time on the arc $[i,\ j] \in A$. Note that t_{ij} may also include the service time at location i if applicable.

If a shipment $i \in N$ that is assigned to a truck $k \in M$ arrives at the OEM facility at time τ_k, a JIT penalty of $\rho_i(\tau_k)$ is incurred, where $\rho_i : \mathbb{R}_0^+ \to \mathbb{R}_0^+$ is a penalty function that punishes both earliness and tardiness, i.e., ideally, each shipment $i \in N$ should be delivered exactly at due date p_i. For the sake of simplicity, we assume in the following that ρ_i consist only of two linear segments, i.e., each time unit of earliness is penalized by α_i and tardiness by β_i dependent on the shipment $i \in N$. Hence, the penalty function $\rho_i(\tau)$ for the earliness-tardiness costs of a shipment $i \in N$ at an arbitrary arrival time τ is given by the lower semi-continuous, piecewise-linear and convex function

$$\rho_i(\tau) = \begin{cases} \alpha_i\,(p_i - \tau) & \text{if } \tau \le p_i, \\ \beta_i\,(\tau - p_i) & \text{if } \tau > p_i. \end{cases} \tag{1}$$

Note, however, that our solution method can handle any penalty function ρ_i of the arrival time that is piecewise linear convex. We elaborate on this further in Section 4.1.2.

A solution to the TRP-JIT consists of a partition $\{R_1, \ldots, R_m\}$ of set N, permutations π_k of R_k, $\forall k \in M$, and times $\tau_k \in \mathbb{N}$, $\forall k \in M$. Variable τ_k stands for the arrival time of truck k at the OEM facility η, and π_k is the sequence in which truck k picks up the shipments in set R_k. Note that each truck's route starts at the depot (node 0) and ends at the OEM facility (node η), which is not explicitly encoded in π_k.

In terms of objective, we aim to minimize the total earliness-tardiness cost of all shipments, i.e., we minimize

$$\sum_{k \in M} \sum_{i \in R_k} \rho_i(\tau_k), \tag{2}$$

where the arrival time of a shipment i depends on the time τ_k the truck it is loaded on arrives at the OEM.

We include the sequence of shipments on a route in the solution, but not explicitly their pickup times. Given a solution for the TRP-JIT as defined before, we can consider two approaches for the pickup times: forward and backward planning. Given a partition $\{R_1, \ldots, R_m\}$ and permutations π_k, $\forall k \in M$, the earliest pickup time for any shipment $i \in N$ is formally defined by $\vec{t_i}$. Let $\pi_k(l)$ denote the lth shipment on truck k's tour, and $\vec{t}_{\pi_k(l)} \in \mathbb{N}$ the earliest time when truck $k \in M$ can pick up its lth shipment. We get $\vec{t_i}$ by scheduling the arrivals on route π_k as early as possible:

$$\vec{t}_{\pi_k(l)} = \begin{cases} \max\{r_{\pi_k(1)}, t_{0,\pi_k(1)}\} & \text{if } l = 1, \\ \max\{r_{\pi_k(l)}, \vec{t}_{\pi_k(l-1)} + t_{\pi_k(l-1),\pi_k(l)}\} & \text{else.} \end{cases}$$

Time $\vec{t}_{\pi_k(l)}$ for the lth shipment of truck k therefore represents a feasible pickup time. The arrival time at the OEM τ_k can then be any arbitrary value $\tau_k \ge \vec{t}_{\pi_k(|R_k|)} + t_{\pi_k(|R_k|),\eta}$.

A solution is feasible if and only if, for each truck $k \in M$, the capacity of the truck is not exceeded, i.e., $\sum_{i \in R_k} q_i \le Q$, and the arrival time at the OEM is not sooner than the last pickup time plus driving time, i.e., $\tau_k \ge \vec{t}_{\pi_k(|R_k|)} + t_{\pi_k(|R_k|),\eta}$.

3.2. Example

We illustrate the formal definitions by considering a small example for the TRP-JIT. Its setup and optimal solution are illustrated in Figure 1. The relevant variables and parameters are defined in Table 2. The travel times between two consecutive shipments on a route are mentioned in the figure. Additionally, all travel times can be found in Table 5 in the appendix. Note that the example is based on the R107 instance of Solomon (1987) for the VRPTW including the first 12 of 25 customers. We assume the fleet to consist of $m = 3$ trucks, each of which possesses a capacity of $Q = 100$ weight units (WU). The costs per time unit (TU) for the earliness $\alpha_i \in (0.7; 1.0]$, $\forall i \in N$, are chosen such that they are always smaller than any of the costs of tardiness per TU $\beta_i \in (1.0; 1.3]$, $\forall i \in N$, which is realistic, albeit not a requirement for our modeling approach. For some shipments, the release dates are set to $r_i = 0$. This means that the cargo is already available at the beginning of the planning period.

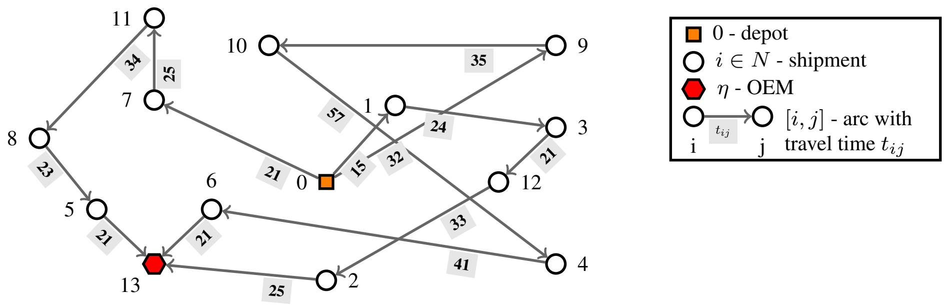


Figure 1: Graph of the optimal routes of a TRP-JIT including the relevant travel times.

route k (τ_k: arrival time)	**route 1** ($\tau_1 = 118$)				**route 2** ($\tau_2 = 135$)				**route 3** ($\tau_3 = 241$)			
shipment i	1	2	3	12	5	7	8	11	4	6	9	10
α_i: earliness cost p. TU	0.71	0.83	0.89	0.97	0.72	0.78	0.9	0.75	0.75	0.83	0.71	0.75
β_i: tardiness cost p. TU	1.26	1.04	1.19	1.2	1.14	1.24	1.15	1.25	1.02	1.01	1.15	1.26
r_i: release date	0	0	0	0	0	0	85	57	139	89	87	114
p_i: due date	97	46	101	60	41	91	122	137	252	189	195	177
q_i: capacity demand	10	7	13	19	26	5	9	12	19	3	16	16
ρ_i (τ_k): penalty cost	26.46	74.88	20.23	69.6	107.16	54.56	14.95	1.5	8.25	52.52	52.9	80.64
e_i: earliness in TU	0	0	0	0	0	0	0	2	11	0	0	0
d_i: tardiness in TU	21	72	17	58	94	44	13	0	0	52	46	64
$\vec{t}_i$: pickup time	15	93	39	60	114	32	91	57	179	220	87	122

Table 2: Relevant parameters to define an example of a TRP-JIT and its solution in Figure 1 except the travel times. These can be found in Table 5.

The (optimal) solution of the TRP-JIT, visible in the figure, consists of the partitions $R_1 = \{1, 2, 3, 12\}$, $R_2 = \{5, 7, 8, 11\}$, and $R_3 = \{4, 6, 9, 10\}$. Optimal routes are given by $\pi_1 = \langle 1, 3, 12, 2 \rangle$, $\pi_2 = \langle 7, 11, 8, 5 \rangle$, and $\pi_3 = \langle 9, 10, 4, 6 \rangle$. The optimal arrival times τ_k, $\forall k \in M$, are in Table 2, including some information about the earliness e_i and tardiness d_i in TU, and the related penalty costs ρ_i for each shipment $i \in N$ according to Eq. (1). Specifically, note that the earliness and tardiness cost of a shipment i does not depend on the pick-up time $\vec{t}_i$ but on the arrival time τ_k of the corresponding truck k at the OEM.

3.3. Mixed-integer programming model

The MIP model for the TRP-JIT is developed based on the one for the VRPTW in Toth and Vigo (2014). Before defining the objective function and constraints for the MIP model, we give an overview of the relevant sets, parameters, and variables:

- **Sets:**
  - M: set of m trucks, $M = \{1, \ldots, m\}$,
  - N: set of n shipments, $N = \{1, \ldots, n\}$,
  - V: set of the depot, n shipments, and OEM, $V = N \cup \{0, \eta\}$,
  - A: set of arcs between the depot, shipments and the OEM, $A = \{[i, j] \mid i \in V \setminus \{\eta\}, j \in V \setminus \{0\}, i \neq j\}$.
- **Parameters:**

- Q: capacity of the vehicles $k \in M$,
- q_i: capacity demand of shipment $i \in N$,
- r_i: release date of shipment $i \in N$ at the supplier,
- p_i: due date of shipment $i \in N$ at the OEM,
- α_i: costs of earliness per TU of shipment $i \in N$,
- β_i: costs of tardiness per TU of shipment $i \in N$,
- t_{ij}: travel time from the depot or shipment $i \in N \cup \{0\}$ to shipment or the OEM $j \in N \cup \{\eta\}$,
- P: big integer, we propose and set $P = \max_{i \in N} \{\max \{r_i, p_i, t_{0i}\}\} + \sum_{i \in N} \max_{j \in N \cup \{\eta\}} \{t_{ij}\}$.

- **Variables:**
  - x_{ijk}: binary variable: 1 if truck k travels directly from depot or shipment $i \in N \cup \{0\}$ to shipment or OEM $j \in N \cup \{\eta\}$ on its route, 0 otherwise,
  - y_{ik}: binary variable: 1 if shipment $i \in N$ is assigned to the route of truck $k \in M$, 0 otherwise,
  - e_i: continuous variable for the earliness of shipment i's arrival at the OEM ($i \in N$),
  - d_i: continuous variable for the tardiness of shipment i's arrival at the OEM ($i \in N$),
  - $\bar{t}_i$: continuous variable for shipment i's pickup time at the supplier ($i \in N$),
  - τ_k: continuous variable for truck k's arrival time at the OEM ($k \in M$).

Including these definitions, the objective function and constraint set are then expressed by the following MIP model.

$$\text{Minimize:} \quad \sum_{i \in N} (\alpha_i e_i + \beta_i d_i), \tag{3}$$

subject to:

$$\sum_{k \in M} y_{ik} = 1 \qquad \forall i \in N, \tag{3a}$$

$$\sum_{j \in N} x_{0jk} = 1 \qquad \forall k \in M, \tag{3b}$$

$$\sum_{i \in V \setminus \{j, \eta\}} x_{ijk} - \sum_{i \in V \setminus \{0, j\}} x_{jik} = 0 \qquad \forall j \in N, k \in M, \tag{3c}$$

$$\sum_{j \in V \setminus \{0, i\}} x_{ijk} = y_{ik} \qquad \forall i \in N, k \in M, \tag{3d}$$

$$\sum_{i \in N} q_i y_{ik} \leq Q \qquad \forall k \in M, \tag{3e}$$

$$r_i \leq \bar{t}_i \qquad \forall i \in N, \tag{3f}$$

$$t_{0i} x_{0ik} \leq \bar{t}_i \qquad \forall i \in N, k \in M, \tag{3g}$$

$$t_{ij} + P x_{ijk} \leq \bar{t}_j - \bar{t}_i + P \qquad \forall i, j \in N, i \neq j, k \in M, \tag{3h}$$

$$\bar{t}_i + t_{i\eta} + P x_{i\eta k} \leq \tau_k + P \qquad \forall i \in N, k \in M, \tag{3i}$$

$$\tau_k - p_i + P y_{ik} \leq d_i + P \qquad \forall i \in N, k \in M, \tag{3j}$$

$$y_{ik} p_i - \tau_k \leq e_i \qquad \forall i \in N, k \in M, \tag{3k}$$

$$0 \leq d_i, 0 \leq e_i \qquad \forall i \in N, \tag{3l}$$

$$0 \leq \tau_k \qquad \forall k \in M, \tag{3m}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall [i, j] \in A, k \in M, \tag{3n}$$

$$y_{ik} \in \{0, 1\} \qquad \forall i \in N, k \in M, \tag{3o}$$

Algorithm 1 Large Neighborhood Search for the TRP-JIT

$s \leftarrow 0$; $s_{\text{imp}} \leftarrow 0$; $s_{\text{DR}} \leftarrow 0$
// initial solution
$S^{\text{DR},0} \leftarrow$ insertionHeuristic (); $S^{\text{DR,ref}} \leftarrow S^{\text{DR},0}$
$S^{\text{LS},0} \leftarrow$ localSearch $\left(S^{\text{DR},0}\right)$; $S^{\text{best}} \leftarrow S^{\text{LS},0}$
// stopping criterion
while $s_{\max} > s$ **and** $s_{\text{imp,max}} > s_{\text{imp}}$ **and** computationTime < timeLimit **do**
    $S^{\text{D},s} \leftarrow$ destroy $\left(S^{\text{LS},s}\right)$
    $S^{\text{DR},s} \leftarrow$ repair $\left(S^{\text{D},s}\right)$
    // acceptance criterion
    if eval $\left(S^{\text{DR},s}\right) <$ eval $\left(S^{\text{DR,ref}}\right)$ **or** $s_{\text{DR}} \geq s_{\text{DR,max}}$ **then**
        $S^{\text{DR,ref}} \leftarrow S^{\text{DR},s}$
        $S^{\text{LS},s} \leftarrow$ localSearch $\left(S^{\text{DR},s}\right)$
        if eval $\left(S^{\text{LS},s}\right) <$ eval $\left(S^{\text{best}}\right)$ **and** $S^{\text{LS},s}$ is feasible **then**
            $S^{\text{best}} \leftarrow S^{\text{LS},s}$
            $s_{\text{imp}} \leftarrow 0$
        else
            $s_{\text{imp}} \leftarrow s_{\text{imp}} + 1$
        end if
        $s_{\text{DR}} \leftarrow 0$
    else
        $s_{\text{DR}} \leftarrow s_{\text{DR}} + 1$
    end if
    $s \leftarrow s + 1$
end while

The objective function in (3) is equivalent to the nonlinear expression in (2). The constraints in (3a)-(3c) ensure that each shipment is assigned to uniquely one vehicle, that all vehicles are leaving the depot, and that there is exactly one truck entering and leaving a shipment node. This also implies that all vehicles arrive at the OEM by the end of their route. We ensure by the constraints in (3d) that only if a shipment $i \in N$ is assigned to a truck $k \in M$ is it part of its route. The capacity limit is included by the constraints in (3e). The pickup time of a shipment cannot be before its release date, which is ensured by (3f). According to the constraints in (3g) and (3h), the pickup time of the first shipment and the difference between the pickup times of two consecutive shipments on a route must be larger than the respective travel times. With the constraints in (3h), we ensure that the solution does not contain subcycles. The relationship between the pickup times of the shipments and the arrival time at the OEM is established by (3i). The arrival time at the OEM defines the earliness and tardiness of the shipment, which is implied by (3j) and (3k) in the constraint set. Finally, the domain of the variables is defined by (3l) through (3o).

It is well known that the LP relaxation of vehicle-flow models of routing problems with time windows tends to provide weak bounds (Toth and Vigo, 2014). Therefore, valid inequalities are sometimes considered in literature, e.g., for the VRP by Desrochers and Laporte (1991), Kara et al. (2004), for the multi-period VRP with due dates by Archetti et al. (2015), and for the PDP with time windows by Ropke et al. (2007). We describe how we adapt some of these valid inequalities to the TRP-JIT in B.

4. Solution method

It has long been recognized that the VRP is computationally demanding (e.g., Lenstra and Kan, 1981). As the TRP-JIT is closely related to the VRP, we can also assume this for the TRP-JIT. Hence, we present a heuristic solution method for the TRP-JIT which is mainly based on the large neighborhood search (LNS) framework initially developed by Shaw (1998) and extend by Pisinger and Ropke (2007, 2019). In this framework, we embed a local search (LS) procedure for a stronger intensification of the search. The LNS, especially the destroy and repair operator, ensure a diversification. The general structure of the procedure is outlined in Algorithm 1.

The main components of the metaheuristic are the insertion heuristic to construct the initial solution, the stopping criterion, the destroy and repair operators, the acceptance criterion, and the local search characterized by neighborhood operators. The destroy and repair operator and the local search are repeated until a stopping criterion is met. In the acceptance step, we decide whether the local search is performed in the current iteration, where $s_{\text{DR,max}}$ is the number of iterations until any solution is accepted. The stopping criterion is determined by a fixed number of iterations s_{max}, the maximum number of iterations without finding a new global best solution $s_{\text{imp,max}}$, and a time limit for the computations.

The tuple

$$S = (\{R_k,\ \forall k \in M\}, \{\pi_k,\ \forall k \in M\}, \{\tau_k,\ \forall k \in M\})$$

represents a solution of the TRP-JIT including a partitioning $\{R_1, \ldots, R_m\}$, permutations $\pi_1, \ldots, \pi_m$, and arrival times $\tau_1, \ldots, \tau_m$ as introduced in Section 3.1. The function eval (S) describes the quality of a solution S based on the earliness-tardiness costs and earliest arrival times. Feasible solutions are obtained after each step in the procedure except the destroy operation. They are denoted by $S^{\text{DR},s}$ after applying the destroy and repair operator in iteration $s > 0$ and the initial solution for iteration $s = 0$, the output solutions $S^{\text{LS},s}$ of the local search for $s \geq 0$, the reference solution for the acceptance criterion $S^{\text{DR,ref}}$, and the best known solution (after the local search) S^{best}. Additionally, the procedure contains infeasible solutions $S^{\text{D},s}$ in iteration $s > 0$ after applying a destroy operator. Note that we make the local search step dependent on the quality of the repaired solution. Before explaining the structural components of the LNS, the relevant criteria and slacks to efficiently evaluate modifications of a TRP-JIT solution are surveyed.

4.1. Evaluation criteria and slacks

The core principles of the LNS and the LS are to modify solutions of the TRP-JIT and to evaluate these modified solutions. For the classic VRP with time windows, slacks are discussed by Savelsbergh (1992), Kindervater and Savelsbergh (2018). Vidal et al. (2014) provide an overview of slacks often applied in routing problems. Slacks depend on certain properties of the current solution. They can be used to derive evaluation criteria for modifications of the current solution quickly. Hence, because we need to evaluate a lot of different modifications, they are crucial for the performance of our solution procedure. Each modification of a solution is characterized by removing single shipments or subsequences of shipments from one route and inserting them in another route or the same route at a different position. We start by considering a single route with set R_k and permutation π_k for some $k \in M$. To simplify the notation of the following calculations, we define the subsets $\vec{R}_i$ and $\overleftarrow{R}_i$ for each shipment $i \in N$. Subset $\vec{R}_i$ includes all shipments on the same route up to and including shipment $i \in N$ in sequence π_k. Subset $\overleftarrow{R}_i$ contains all shipments on the same route after shipment $i \in N$, excluding shipment i.

4.1.1. Demands along the routes

Modifications of a solution affect the load of the vehicles. The accumulated load on a route $\vec{q}_i$ up to and including the pick-up of shipment $i \in N$ and the total load on the routes $u_k, \forall k \in M$, are formally defined by:

$$\vec{q}_i = \sum_{j \in \vec{R}_i} q_j \qquad \forall i \in N, \qquad u_k = \sum_{i \in R_k} q_i \qquad \forall k \in M.$$

If a route $k \in M$ is modified by inserting or removing a subsequence $\langle \pi_k(l), \ldots, \pi_k(l') \rangle$ of shipments, we define Δu_k as the change of the load, where $\pm \Delta u_k = \vec{q}_{\pi_k(l')} - \vec{q}_{\pi_k(l-1)}$. If $\pi_k(l) = \pi_k(1)$ is the first shipment on the route, we set $\vec{q}_{\pi_k(l-1)} = 0$. In case of an insertion, the load of route k increases by Δu_k, and in case of a removal, it drops by Δu_k. We hence store $\vec{q}_i, \forall i \in N$, and $u_k, \forall k \in M$, as the load slacks, which allows us to evaluate Δu_k in constant time.

4.1.2. Partition-optimal arrival time

Given a set of shipments R_k, we define the *partition-optimal arrival time* τ_k^{opt} at the OEM as the time when the total earliness and tardiness penalty of the shipments in set R_k is minimal. Note that the actual arrival time τ_k of truck k at the OEM depends on the route π_k and may or may not coincide with the ideal arrival time τ_k^{opt}. The partition-optimal arrival time τ_k^{opt} can be determined for each route $k \in M$ with set of shipments R_k by evaluating its earliness-tardiness cost function $\rho_{R_k}(\tau) := \sum_{i \in R_k} \rho_i(\tau)$. The value of τ_k^{opt} corresponds to the $\arg\min$ of the function $\rho_{R_k}(\tau)$. According to the definition in (1), the penalty cost function for a single shipment $i \in N$ is a piecewise-linear, convex function with a single minimum and discontinuity at the due date p_i. Consequently, $\rho_{R_k}(\tau)$ is also a piecewise-linear convex function with discontinuities at the due dates $p_i, \forall i \in R_k$. The arrival time with minimal cost τ_k^{opt} is at (at least) one of these discontinuities, i.e., $\tau_k^{\text{opt}} \in \{p_i : i \in R_k\}$. The number of possible candidates for τ_k^{opt} is limited by the number of shipments in the problem n or, more specifically, on the route $|R_k|$.

We define the earliness-tardiness cost functions for each shipment to be lower semi-continuous. Hence, we can use the left derivative of the earliness-tardiness costs for route $k \in M$, i.e., $\rho'_{R_k}(\tau) := \sum_{i \in R_k} \rho'_i(\tau)$, to determine τ_k^{opt}. It is defined for an arrival time τ of a shipment i by

$$\rho'_i(\tau) = \begin{cases} -\alpha_i & \text{if } \tau \leq p_i, \\ \beta_i & \text{if } \tau > p_i, \end{cases} \qquad \forall i \in N,\ \tau \in \mathbb{N}.$$

The slope of $\rho_{R_k}(\tau)$ and the value of $\rho'_{R_k}(\tau)$ only change at the discontinuities of the respective function, which are the due dates, i.e., for $\tau = p_i, \forall i \in R_k$. Hence, it is sufficient to consider the values of $\rho_{R_k}(\tau)$ only at arrival times τ equal to due dates $p_i, \forall i \in R_k$, for finding partition-minimal penalty costs. Note that we also account for a value $p_{\text{max}} > \max_{i \in N} \{p_i\}$ that is larger than any due date in case arrival time τ_k is greater than any shipment's due date, such that we capture all possible values of the left derivative.

For a given solution, we store $\rho_{R_k}(\tau)$ and $\rho'_{R_k}(\tau)$ for each distinct due date $p_i, \forall i \in N$, as slacks. Then, the partition-optimal arrival time τ_k^{opt} and the corresponding costs $\rho_{R_k}(\tau_k^{\text{opt}})$ can be found by a binary search on all sorted and distinct due dates with a computational complexity of $\mathcal{O}(\log n)$ as follows.

Assume that we want to calculate the partition-optimal arrival time of some shipment set $R_k \subseteq N$, where $\theta = |R_k|$. We define the $\theta \leq n$ distinct due dates and the late time p_{max} to be sorted in ascending order by $p_{i_1} < \cdots < p_{i_\gamma} < p_{i_{\gamma+1}} < \cdots < p_{i_\theta} < p_{i_{\theta+1}} = p_{\text{max}}$ with $\{i_1, \ldots, i_\gamma, i_{\gamma+1}, \ldots, i_\theta\} \subseteq N$. Note that sorting can be done in preprocessing. We consider the shipment $i_\gamma \in N$ with $\gamma \leq \theta \leq n$. The value of $\rho'_{R_k}(p_{i_\gamma})$

indicates the slope of the penalty function on the left-side of the due date p_{i_γ}. The partition-optimal arrival time τ_k^{opt} is the due date p_{i_γ} where the sign changes from negative to non-negative between $\rho'_{R_k}(p_{i_\gamma}) < 0$ and $\rho'_{R_k}(p_{i_{\gamma+1}}) \geq 0$ with the corresponding costs $\rho_{R_k}(\tau_k^{\text{opt}})$.

It is crucial for the LNS and LS to quickly evaluate the impact of the routes' modifications on the objective function in (2). Additionally to $\rho_i(\tau)$ and its left derivative $\rho'_i(\tau)$, we store earliness-tardiness penalty functions for the segment of a route $\vec{\rho}_i(\tau)$ and its left derivative $\vec{\rho'}_i(\tau)$ up to and including each shipment $i \in N$:

$$\vec{\rho}_i(\tau) = \sum_{j \in \vec{R}_i} \rho_j(\tau) \qquad \forall \tau \in \{p_i \mid i \in N\},$$

$$\vec{\rho'}_i(\tau) = \sum_{j \in \vec{R}_i} \rho'_j(\tau) \qquad \forall \tau \in \{p_i \mid i \in N\} \cup \{p_{\max}\}.$$

For the first shipment $\pi_k(1)$ on a route $k \in M$, the functions are equal to the penalty of the single shipment, i.e., $\vec{\rho}_{\pi_k(1)}(\tau) = \rho_{\pi_k(1)}(\tau)$ and $\vec{\rho'}_{\pi_k(1)}(\tau) = \rho'_{\pi_k(1)}(\tau)$ hold. Contrarily, for the last shipment $\pi_k(|R_k|)$ on a route $k \in M$, the functions are equivalent to the total earliness-tardiness penalty for all shipments on the same route $k \in M$, i.e., $\vec{\rho}_{\pi_k(|R_k|)}(\tau) = \rho_{R_k}(\tau)$ and $\vec{\rho'}_{\pi_k(|R_k|)}(\tau) = \rho'_{R_k}(\tau)$ hold.

Similarly to the load slack, we can define the change of the earliness-tardiness cost function, when adding or removing a subsequence $\langle \pi_k(l), \ldots, \pi_k(l') \rangle$ of a route $k \in R_k$ by $\pm\Delta\rho_{R_k}(\tau) = \vec{\rho}_{\pi_k(l')}(\tau) - \vec{\rho}_{\pi_k(l-1)}(\tau)$, where $\vec{\rho}_{\pi_k(l-1)}(\tau) = 0$, if $\pi_k(l) = \pi_k(1)$. The same applies for the left derivative, i.e., $\pm\Delta\rho'_{R_k}(\tau) = \vec{\rho'}_{\pi_k(l')}(\tau) - \vec{\rho'}_{\pi_k(l-1)}(\tau)$.

Note that these slacks and the binary search method to calculate penalties also work for more involved piecewise linear convex functions. Instead of only evaluating the penalty function and the left derivative at the distinct due dates, we must consider also each of the other discontinuities of the piecewise functions. If the number of discontinuities remains constant for each of the n shipments, the asymptotic complexity of the binary search step does not increase.

4.1.3. Earliest arrival time

As the release dates and the travel times are not considered in the computation of the partition-optimal arrival time τ_k^{opt}, $\forall k \in M$, τ_k^{opt} may not be a feasible. Hence, the *earliest arrival times* τ_k^{e} depending on sets R_k and the permutations π_k for each $k \in M$ have to be considered because they define the feasible range of arrival times $\tau_k \in [\tau_k^{\text{e}}, \infty)$. It follows from the forward planning approach for the pickup times in Section 3.1 that the earliest arrival time is $\tau_k^{\text{e}} = \vec{t}_{\pi_k(|R_k|)} + t_{\pi_k(|R_k|),\eta}$.

The partition-optimal arrival time τ_k^{opt} is also optimal for the arrival time τ_k if it is feasible, i.e., if $\tau_k^{\text{e}} \leq \tau_k^{\text{opt}}$ holds. In the other case, $\tau_k^{\text{e}} > \tau_k^{\text{opt}}$, the earliest arrival time τ_k^{e} is the best feasible arrival time for a truck $k \in M$, i.e., $\tau_k := \tau_k^{\text{e}}$. For $\tau > \tau_k^{\text{opt}}$ the earliness-tardiness cost $\rho_{R_k}(\tau)$ of route k are non-decreasing. Consequently, the smallest feasible arrival time should be chosen to minimize the earliness-tardiness costs. Hence, $\tau_k = \max\{\tau_k^{\text{opt}}, \tau_k^{\text{e}}\}$.

To efficiently evaluate the effect of the solutions' modification on the earliest arrival time, we introduce the waiting times w_i of a truck at any shipment $i \in N$. Let $i^- \in N \cup \{0\}$ be the predecessor of shipment i on i's route. Then,

$$w_i = \begin{cases} r_i - \left(\vec{t}_{i^-} + t_{i^-,i}\right) & \text{if } i^- \neq 0, \\ r_i - t_{0i} & \text{else.} \end{cases}$$

If shipment $i \in N$ is the first on a route, the depot ($i^- = 0$) is the predecessor and $\vec{t}_0 = 0$ is assumed. The waiting time w_i is negative if a shipment $i \in N$ can only be picked up later than its release date r_i and positive if the sum of the pickup time $\vec{t}_{i^-}$ of the predecessor i^- and the travel time from i^- to i is smaller than the release date r_i. The waiting times w_i, $\forall i \in N$, inform the forward $\vec{w}_{ij}$ and the backward slacks $\overleftarrow{w}_{ij}$ for $i \in R_k$ and $j \in \overleftarrow{R}_i \cup \{\eta\}$ on each route $k \in M$. With these slacks, the effects of changing the earliest pickup time $\vec{t}_i$ of shipment i on the earliest pickup time $\bar{t}_j$ of shipment $j \in \overleftarrow{R}_i$ after i on the same route or the earliest arrival time at the OEM τ_k^{e} for $j = \eta$ can be evaluated. The forward and backward slacks are defined by:

$$\vec{w}_{ij} = \sum_{i' \in \vec{R}_j \setminus \vec{R}_i} \max\{0,\ w_{i'}\}, \qquad \vec{w}_{i\eta} = \vec{w}_{i,\pi_k(|R_k|)},$$

$$\overleftarrow{w}_{ij} = \max_{i' \in \vec{R}_j \setminus \vec{R}_i} \{\min\{0,\ w_{i'}\}\}, \qquad \overleftarrow{w}_{i\eta} = \overleftarrow{w}_{i,\pi_k(|R_k|)} \qquad \forall k \in M, i \in R_k, j \in \overleftarrow{R}_i.$$

For a subsequence $\langle \pi_k(l), \ldots, \pi_k(l') \rangle$ of route $k \in R_k$ with start $i = \pi_k(l)$ and end $j = \pi_k(l')$ this implies:

- for an earlier start $\Delta\vec{t}_i \leq 0$ that shipment j can be picked up not more than $\overleftarrow{w}_{ij}$ time units earlier, i.e., $\Delta\vec{t}_j = \max\left\{\Delta\vec{t}_i, \overleftarrow{w}_{ij}\right\}$, and
- for a delayed start $\Delta\vec{t}_i > 0$ that the earliest pickup time $\vec{t}_j$ for shipment j is only affected by delays at shipment i longer than $\vec{w}_{ij}$, i.e., $\Delta\vec{t}_j = \max\left\{0,\ \vec{t}_i - \vec{w}_{ij}\right\}$.

Inserting or removing a subsequence from a route shifts the pickup times in the subsequence itself and in the other subsequences of the route. The effect on the earliest arrival time is determined by evaluating the shifts of the subsequences along the route.

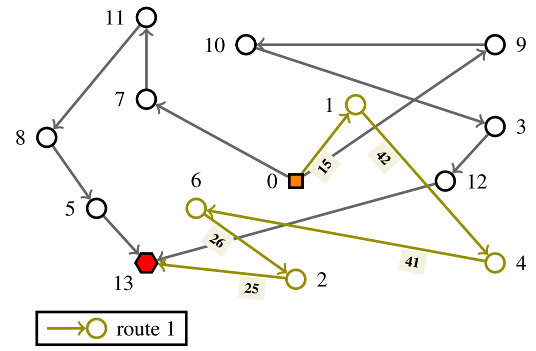
In addition to the penalty cost $\rho(S)$ of a solution S as the primary objective, the sum of the earliest arrival times $\tau^{\mathrm{e}}(S) = \sum_{k \in M} \tau_k^{\mathrm{e}}$ is evaluated in a lexicographic order as the secondary auxiliary objective in the LNS. In Algorithm 1, both objectives are considered in this manner by the function $\mathrm{eval}(S)$. There may be several solutions with the same penalty costs that differ in the sum of the earliest arrival times. Minimizing this secondary objective, the sum of earliest arrival times, is especially helpful in the local search so that the procedure finds a better local optimum before terminating.

4.1.4. Example

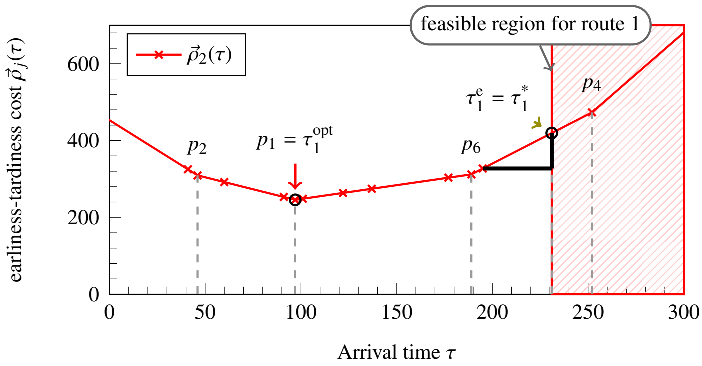
Based on the example problem in Section 3.2, we consider the feasible solution illustrated in Figure 2a. The load slacks of route 1 can be found in the Gantt chart in Figure 2c. The accumulated load for the last shipment on the route, $i = 2$, is equivalent to the total load on the route, i.e., $\vec{q}_2 = u_1$.

The partition-optimal arrival time can be evaluated based on the function depicted in Figure 2b. The function $\vec{\rho}_i(\tau)$ for shipment $i = 2$ corresponds to the earliness-tardiness penalty of the whole route, i.e., $\vec{\rho}_2(\tau) = \rho_{R_1}(\tau)$. Consequently, we can determine the partition-optimal arrival time for route 1 by $\tau_1^{\mathrm{opt}} = p_1 = 97$. The figure also includes the feasible region for the arrival time of route 1. It depends on the earliest arrival time, which is calculated based on the travel times and the release dates. The partition-optimal arrival time for route 1 is not feasible. In the figure, we can see that the earliest arrival time is also the optimal arrival time $\tau_1^* = 231$ for route 1.

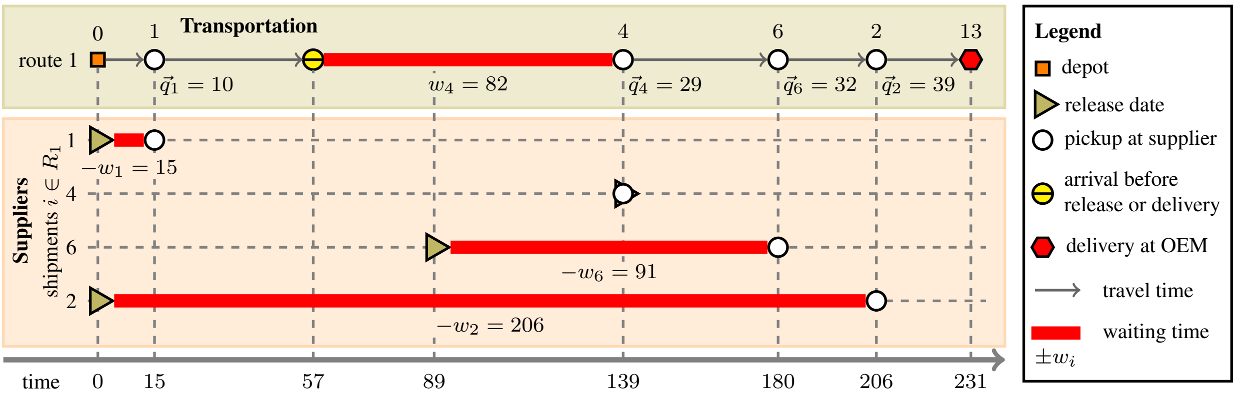
To illustrate the waiting times, we need to consider the Gantt chart in Figure 2c again. In the forward planning, waiting times of the truck appear if the release date of a shipment is after the earliest possible arrival time of the truck. If the opposite is the case, the shipments must wait at the suppliers from their release until they are picked up. The first case applies for shipment $i = 4$ and the latter for shipments $i = 1, 2, 6$. We can see that it is possible to pick up shipment $i = 1$ 82 time units later without increasing the earliest arrival time at the OEM. On the other hand, we could decrease the pickup times by up to 15, 206 or 91 time units for shipments $i = 1, 2, 6$ if it were possible to pick them up earlier with respect to their release dates. This would eventually



(a) Route 1 in the solution graph,



(b) Earliness-tardiness costs of route 1,



(c) Forward planning Gantt-Chart of route 1 including the waiting time and load slacks.

Figure 2: Evaluation criteria and slacks for a feasible solution of the example from Section 3.2.

reduce the earliest arrival time. In the second case, the pickup times are limited by the travel times among the preceding shipments. Hence, evaluating different sequences of precedent shipments is a starting point to reduce the earliest arrival time and to potentially improve the solution quality. Note that waiting times can also appear if the partition-optimal arrival time is after the earliest arrival time, i.e., $\tau_k^e < \tau_k^{opt}$, $k \in M$.

4.2. Insertion heuristic

We use the principles of the parallel insertion heuristic by Potvin and Rousseau (1993) to construct the initial solution for the TRP-JIT. The constructive heuristic is called parallel because the m routes are built simultaneously, instead of one route after another in a serial manner. We define the set U to contain all unassigned shipments. As no shipment is assigned at the beginning of the procedure, set U is initialized by the set of all shipments N, i.e., $U \leftarrow N$.

The shipment to be inserted next is determined by a regret criterion instead of choosing the shipment simply by the minimal impact on the objective function. For all unassigned shipments $i \in U$, we determine the best and second best position for insertion, where we consider only strictly inferior positions for the second best position. If empty routes exist in the solution, they are prioritized over the other routes for the best insertion position.

The heuristic is outlined in Algorithm 2. We formally define $\Delta S_{\text{in},i} = (S, i, k, l)$ to be the modification of solution S to insert shipment $i \in U$ on the lth position of route $k \in M$. Moreover, $\Delta S_{\text{in},i}^{*,\nu}$ is the insertion of shipment $i \in U$ with the νth best objective value. The expressions $\Delta\rho\,(\Delta S)$ and $\Delta\tau^{e}\,(\Delta S)$ denote the change in the earliness-tardiness costs and the sum of earliest arrival times by ΔS. Hence, the regrets for the earliness-tardiness penalty and for the sum of earliest arrival times are then given by $\text{regret}_{\delta,\rho}\,(S, i) =$

Algorithm 2 Parallel Insertion Heuristic for the TRP-JIT

$U \leftarrow N$; $Q_{\text{allowed}} \leftarrow Q$;
$R_k \leftarrow \emptyset\, \forall k \in M$; $\pi_k \leftarrow \langle\rangle\, \forall k \in M$; $\tau_k \leftarrow t_{0\eta} \forall k \in M$;
$S = (\{R_k,\, \forall k \in M\}, \{\pi_k,\, \forall k \in M\}, \{\tau_k,\, \forall k \in M\})$;
while $U \neq \emptyset$ **do**
  Determine empty routes $M_0 \leftarrow \{k \in M \mid R_k = \emptyset\}$; $M_1 \leftarrow M \backslash M_0$;
  if $M_0 = \emptyset$ **then**
    $M_0 \leftarrow M$; $M_1 \leftarrow M$;
  end if
  for all $i \in U$ **do**
    Determine best insertion $\Delta S^{*,1}_{\text{in},i}$ on routes $k \in M_0$ with truck capacity Q_{allowed};
    Determine second best insertion $\Delta S^{*,2}_{\text{in},i}$ on routes $k \in M_1$ with truck capacity Q_{allowed};
    while $S^{*,1}_{\text{in},i}$ not found **do**
      $Q_{\text{allowed}} \leftarrow Q_{\text{allowed}} + Q$;
      Determine $\Delta S^{*,1}_{\text{in},i}$ on M_0 and $\Delta S^{*,2}_{\text{in},i}$ on M_1 with truck capacity Q_{allowed} again;
    end while
    Calculate $\text{regret}_{2,\rho}(S,i)$ and $\text{regret}_{2,\tau^{\text{e}}}(S,i)$ based on $\Delta S^{*,1}_{\text{in},i}$ and $\Delta S^{*,2}_{\text{in},i}$;
  end for
  Choose
    $i^* = \arg\max_{i \in U} \left\{\text{regret}_{2,\rho}(S,i) \succ \text{regret}_{2,\tau^{\text{e}}}(S,i)\right\}$
  Update R_{k^*}, π_{k^*} according to $\Delta S^{*,1}_{\text{in},i^*} = (S, i^*, k^*, l^*)$;
  $U \leftarrow U \backslash \{i^*\}$;
end while

$\sum_{\nu=2}^{\delta}\left(\Delta\rho\left(\Delta S^{*,\nu}_{\text{in},i}\right) - \Delta\rho\left(\Delta S^{*,1}_{\text{in},i}\right)\right)$ and $\text{regret}_{\delta,\tau^{\text{e}}}(S,i) = \sum_{\nu=2}^{\delta}\left(\Delta\tau^{\text{e}}\left(\Delta S^{*,\nu}_{\text{in},i}\right) - \Delta\tau^{\text{e}}\left(\Delta S^{*,1}_{\text{in},i}\right)\right)$. The δ-regret is similarly defined by Potvin and Rousseau (1993), Ropke and Pisinger (2006). In the following, the parameter $\delta := 2$ is assumed to be constant. If the νth best solution of insertion does not exist, a sufficiently large value is assumed for the objectives, which results in a high regret.

All routes are empty at the start of the insertion heuristic. Thus, for each shipment $i \in U$, the possible insertions have the same earliness-tardiness penalty $\Delta\rho\left(\Delta S^{*,1}_{\text{in},i}\right)$, no second best solution exists for this criterion, and $\Delta\rho\left(\Delta S^{*,2}_{\text{in},i}\right)$ and $\Delta\tau^{\text{e}}\left(\Delta S^{*,2}_{\text{in},i}\right)$ are respectively equal to a large value. Hence, the heuristic starts by inserting the shipment $i \in U$ with the minimal $\Delta\tau^{\text{e}}\left(\Delta S^{*,1}_{\text{in},i}\right)$, which is usually the minimal travel time from the depot and to the OEM for any shipment $i \in U$. As long as empty routes exist, $\Delta S^{*,1}_{\text{in},i}$ must be an insertion in such a route and $\Delta S^{*,2}_{\text{in},i}$ can be the best among the remaining routes. This ensures that the final solution includes no empty routes.

We allow the procedure to create infeasible solutions if at some point the assigned shipments are allocated to the trucks such that there is not enough capacity remaining to insert any unassigned item into any route. If no feasible insertion position is found for a shipment $i \in U$, the allowed capacity Q_{allowed} is increased by an excess of Q capacity units for each vehicle. The load beyond the capacity is penalized by a cost per weight unit in the objective. The cost factor must be larger than the earliness-tardiness cost in any relevant scenario. Even if the solution is infeasible, it is suitable to start the local search to eventually find a feasible solution. The tolerated excess is set to zero again as soon as a feasible solution is found.

Computing the two best insertion positions demands a complexity of $\mathcal{O}\left(n^2 \log n\right)$ for each shipment $i \in N$, also including the recalculations in case the capacity limit is lifted. As the allowed capacity of each vehicle is increased by Q and $q_i \leq Q, \forall i \in N$, a shipment $i \in N$ can be assigned after increasing the overcapacity once. Hence, if the capacity limit had to be adapted for each unassigned shipment, in the worst case, the number of computations would be twice as high, i.e., increased by a constant factor.

The evaluation of an insertion $\Delta S_{\text{in},i}$ requires $\mathcal{O}(\log n)$ because of the binary search to determine the new optimal arrival time for the route, as discussed in Section 4.1. Selecting the unassigned shipment with the highest regret leads to a computational complexity of $\mathcal{O}(n)$. Consequently, the overall computational complexity for the insertion of one shipment is $\mathcal{O}\left(n^2 \log n\right)$, and $\mathcal{O}\left(n^3 \log n\right)$ for the insertion heuristic because all n shipments have to be inserted.

4.3. Destroy operator

Ropke and Pisinger (2006) discuss different destroy operators for the adaptive LNS. For our LNS metaheuristic, the so-called random destroy operator is relevant. From a current solution $S^{\text{LS},s}$ in iteration s, it removes a random number of $n_{\text{rem}} \sim \mathcal{U}\left(n_{\text{rem}}^{-}, n_{\text{rem}}^{+}\right)$ shipments, where n_{rem} is uniformly distributed between n_{rem}^{-} and n_{rem}^{+}. The removed shipments define the set of unassigned shipments U in the destroy operator.

4.4. Repair operator

The repair operator is based on the same regret-principle as the parallel insertion heuristic in Section 4.2. It is also applied in the adaptive LNS by Ropke and Pisinger (2006). The two main differences between the repair operator and the insertion heuristic are:

- The set of unassigned shipments U is defined by the outcome of the destroy operator instead of all shipments N.
- We choose the vth best insertion according to

$$\max_{i \in U} \left\{\text{regret}_{2,\rho}(S,i) \succ \text{regret}_{2,\tau^{\text{e}}}(S,i)\right\},$$

  instead of simply selecting the best. The value of $v \sim \mathcal{U}(1, v_{\max})$ is randomly drawn from a uniform distribution between 1 and $v_{\max}$ in each insertion step.

Besides diversification, the first aspect accounts for intensification because not all shipments are removed from the solution. The second aspect only aims at diversification. The overall complexity of the repair operator is $\mathcal{O}\left(n^2 \log n\right)$ if the number of removed shipments has a constant limit and $\mathcal{O}\left(n^3 \log n\right)$ if the limit depends on the number of shipments n.

4.5. Local search with acceptance criterion

After the destroy and repair operation, an acceptance criterion decides whether to perform a local search. The intention is to avoid applying a local search on solutions that are strongly inferior to the reference solution. We either accept a solution to perform the local search if it is better than the reference solution from the destroy-repair procedure to intensify the search or if no solution has been accepted for more than $s_{\text{DR,max}}$ iterations. The reference solution $S^{\text{DR,ref}}$ from the procedure is updated in case of acceptance.

The local search procedure explores the solution space by evaluating solutions that are similar to a current solution. The procedure starts with a given initial solution or a solution after the destroy and repair operation, which we formally define by $S^{\text{DR},s}$ with $s \geq 0$. Similar solutions are generated by applying neighborhood operators. The best solution regarding the objective value is chosen from all neighborhoods in each iteration until no better solution is found. The criteria and slacks defined in Section 4.1 are evaluated to efficiently find the optimal neighbor. This also includes the sum of earliest arrival times as a secondary objective.

We consider VRP neighborhood operators from the literature. Especially, the concepts of Bräysy and Gendreau (2005a), Gendreau et al. (1992), Irnich et al. (2006), Toth and Vigo (2002, 2014) are relevant. The neighborhood operators (or moves) implemented in the local search are:

- the *exchange operator*, where two subsequences of shipments $\langle i_1, \ldots, j_1 \rangle$ and $\langle i_2, \ldots, j_2 \rangle$ from two different routes (inter-route) $k_1, k_2 \in M$ or the same route (intra-route) $k \in M$ are swapped,
- the *relocation operator*, where a subsequence of shipments $\langle i_1, \ldots, j_1 \rangle$ from one route $k_1 \in M$ is removed and inserted in another position of a different route $k_2 \in M$ or the same route $k_1 \in M$,
- and the *2-opt* operator*, where two arcs $[i_1, j_1]$ and $[i_2, j_2]$ are replaced by two others, so that the sequence of the routes is preserved and the head and tail of two routes are swapped, i.e., we get the routes $\langle \ldots, i_1, j_2, \ldots \rangle$ and $\langle \ldots, i_2, j_1, \ldots \rangle$.

In the exchange and relocate operator, we swap only a subsequence of between 1 and n_{seq} shipments. The neighborhood operators are similar to those in the local search of Hoogeboom et al. (2020). But instead of considering only one of the neighborhoods in an iteration and adapting the neighborhood to a more complex one if no improving solution is found, we evaluate all five neighborhoods in each iteration and select the best neighbor to determine the new solution. We only consider moves that do not empty any of the routes.

Searching through a neighborhood means evaluating all of its possible moves. We apply the slacks and evaluation criteria introduced in Section 4.1 for this purpose. We need to define the new total truck load, partition-optimal arrival time and earliest arrival times for the routes. The latter criterion changes in both the inter-route and intra-route neighborhood operators, whereas the first two evaluation criteria are only affected by an inter-route neighborhood operator. Let i^- be the predecessor and i^+ be the successor of any arbitrary shipment node $i \in N$. Then we can determine the truck load u_{new,k_1} and u_{new,k_2}, the earliness-tardiness cost functions ρ_{new,k_1} and ρ_{new,k_2}, and their left derivatives ρ'_{new,k_1} and ρ'_{new,k_2} for routes $k_1,\ k_2 \in M$ for an inter-route exchange by

$$
\begin{aligned}
u_{\text{new},k_1} &= u_{k_1} - \vec{q}_{j_1} + \vec{q}_{i_1^-} + \vec{q}_{j_2} - \vec{q}_{i_2^-}, & u_{\text{new},k_2} &= u_{k_2} - \vec{q}_{j_2} + \vec{q}_{i_2^-} + \vec{q}_{j_1} - \vec{q}_{i_1^-},\\
\rho_{\text{new},k_1} &= \rho_{k_1} - \vec{\rho}_{j_1} + \vec{\rho}_{i_1^-} + \vec{\rho}_{j_2} - \vec{\rho}_{i_2^-}, & \rho_{\text{new},k_2} &= \rho_{k_2} - \vec{\rho}_{j_2} + \vec{\rho}_{i_2^-} + \vec{\rho}_{j_1} - \vec{\rho}_{i_1^-},\\
\rho'_{\text{new},k_1} &= \rho'_{k_1} - \vec{\rho'}_{j_1} + \vec{\rho'}_{i_1^-} + \vec{\rho'}_{j_2} - \vec{\rho'}_{i_2^-}, & \rho'_{\text{new},k_2} &= \rho'_{k_2} - \vec{\rho'}_{j_2} + \vec{\rho'}_{i_2^-} + \vec{\rho'}_{j_1} - \vec{\rho'}_{i_1^-}.
\end{aligned}
$$

For the sake of readability, we leave out the variable $\tau \in \{p_i \mid i \in N\}$ for the arrival time in $\rho_{\text{new},k}(\tau)$, $\rho_k(\tau)$, $\rho'_{\text{new},k}(\tau)$ and $\rho'_k(\tau)$ with $k = k_1, k_2$. We can see that the evaluation criteria for the truck load, the earliness-tardiness costs and its left derivative follow the same structure of terms to add and subtract. Therefore, we only state the new truck loads for the inter-route relocate operator by $u_{\text{new},k_1} = u_{k_1} - \vec{q}_{j_1} + \vec{q}_{i_1^-}$ and $u_{\text{new},k_2} = u_{k_2} + \vec{q}_{j_1} - \vec{q}_{i_1^-}$, and for the 2-opt* move by $u_{\text{new},k_1} = u_{k_1} - \vec{q}_{i_1} + \vec{q}_{i_2}$ and $u_{\text{new},k_2} = u_{k_2} - \vec{q}_{i_2} + \vec{q}_{i_1}$. If in a specific move, the node in the index of a slack does not refer to a shipment node, we consider the respective term to be zero. For example in the inter-route exchange, if for node $i \in N$ the predecessor $i_1^- = 0$ is the depot, we consider $\vec{q}_{i_1^-} := 0$.

Evaluating the new truck load for a move requires constant computational time, i.e, $\mathcal{O}(1)$. To find the new partition-optimal arrival time $\tau^{\text{opt}}_{\text{new},k}$, we need to consider the values of $\rho'_{\text{new},R_{k_1}}$ and $\rho'_{\text{new},R_{k_2}}$ for several arrival times $\tau \in \{p_i \mid i \in N\}$ until we find the change of the sign. This operation can be done by a binary search on the due dates, which results in a computational complexity of $\mathcal{O}(\log n)$. To further reduce the computational effort, note that in the inter-route relocate neighborhood, the partition-optimal arrival time $\tau^{\text{opt}}_{\text{new},k_2}$ only needs to be calculated once for the sequence of shipments to be relocated and each route $k_2 \in M$ it can be inserted into. However, the new partition-optimal arrival time $\tau^{\text{opt}}_{\text{new},k_2}$ is independent of the insertion position within the route. Contrarily, for the inter-route exchange and 2-opt* operators, each move can have unique partition-optimal arrival time.

The earliest arrival times are determined by evaluating the pickup times of the shipments at the changed arcs along the routes. We evaluate the effect of an earlier or later pickup by using the backward and forward slacks $\overleftarrow{w}_{ij}$ and $\vec{w}_{ij}$ with $i \in N$, $j \in \overleftarrow{R}_i$. The backward slack $\overleftarrow{w}_{ij}$ indicates the maximum change of the earliest pickup time of shipment j when shipment i is picked up earlier. If $\Delta\vec{t}_i$ defines the change in the earliest pickup time of shipment i, then this means for shipment j that $\Delta\vec{t}_j = \max\left\{\overleftarrow{w}_{ij}, \Delta\vec{t}_i\right\}$ if $\Delta\vec{t}_i \leq 0$. The forward slack $\vec{w}_{ij}$, on the other hand, indicates for a delayed earliest pickup time $\vec{t}_i$ of shipment i, the maximum change $\Delta\vec{t}_i > 0$ so that the earliest arrival time $\vec{t}_j$ of shipment j is not affected. This is expressed by $\Delta\vec{t}_j = \max\left\{0, \Delta\vec{t}_i - \vec{w}_{ij}\right\}$ if $\Delta\vec{t}_i > 0$. The same applies for the earliest arrival time at the OEM τ^{e}_k, $k \in M$, with $\vec{w}_{i\eta}$, $i \in R_k$. Hence, the effect on the truck's earliest arrival time at the OEM when inserting or removing a subsequence of shipments are evaluated in $\mathcal{O}(1)$ time.

Finally, we need to evaluate whether the new partition-optimal arrival time of a route $k \in M$ can be attained, i.e., $\tau^{\mathrm{e}}_{\mathrm{new},k} \leq \tau^{\mathrm{opt}}_{\mathrm{new},k}$. Then, the earliness-tardiness cost $\rho_{\mathrm{new},k}\left(\tau^{\mathrm{opt}}_{\mathrm{new},k}\right)$ corresponds to a specific due date and can be determined in constant time $\mathcal{O}(1)$. Otherwise, $\rho_{\mathrm{new},k}\left(\tau^{\mathrm{e}}_{\mathrm{new},k}\right)$ must be calculated because the earliest is the optimal arrival time, i.e., $\tau^{*}_{\mathrm{new},k} = \tau^{\mathrm{e}}_{\mathrm{new},k}$. This arrival time may not correspond to a certain due date. Hence, we have to find the latest due date p_{bef} before and the earliest due date p_{aft} after $\tau^{\mathrm{e}}_{\mathrm{new},k}$ by applying a binary search, which demands $\mathcal{O}(\log n)$ time, on the due dates and $p_{\max}$, i.e., $\{p_i \mid i \in N\} \cup \{p_{\max}\}$. Then, we can determine the earliness-tardiness costs of route k by

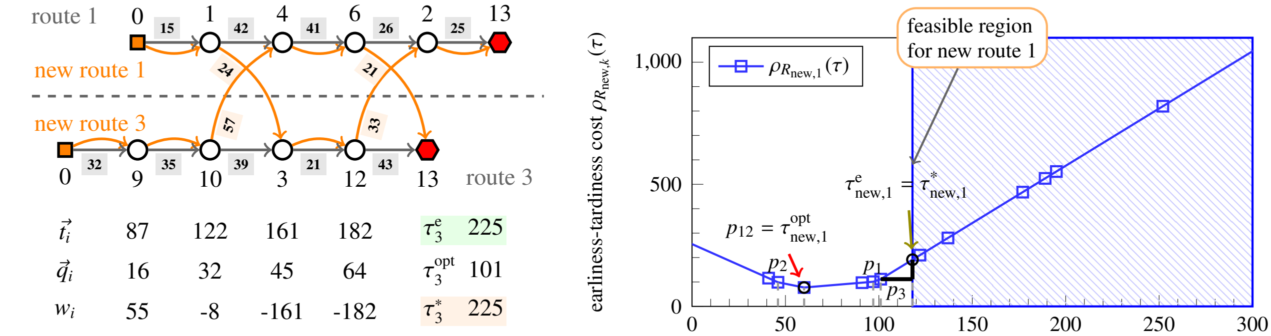
$$\rho_{\mathrm{new},k}\left(\tau^{\mathrm{e}}_{\mathrm{new},k}\right) = \rho_{\mathrm{new},k}\left(p_{\mathrm{bef}}\right) + \left(\tau^{\mathrm{e}}_{\mathrm{new},k} - p_{\mathrm{bef}}\right)\rho'_{\mathrm{new},k}\left(p_{\mathrm{aft}}\right).$$

Finally, the computational complexity of evaluating a single move results in $\mathcal{O}(\log n)$. The number of possible moves in each of the five neighborhoods relates to n^2 for n shipments. This leads to a complexity of $\mathcal{O}\left(n^2 \log n\right)$ for an initial local search iteration when setting n_{seq} to a constant. The sequence length n_{seq} increases the computational complexity by n^2_{seq}. We also store the best moves for each neighborhood and pair of routes (inter-route) or route (intra-route) in the local search. As the slacks are dependent on the routes and shipments but a neighborhood move only affects a single route or pair of routes, the slacks depending on these routes change in an iteration. If we perform a move on the pair of routes k_1 and k_2, then for the next iteration, we only have to update the best moves between route k_1 and all the other routes in $M\setminus\{k_1\}$, and k_2 and all the other routes in $M\setminus\{k_1, k_2\}$. Hence, we do not need to update the moves of all routes or pair of routes in each iteration. The computational complexity of further local search iterations reduces to $\mathcal{O}\left(n^2\right)$.

4.6. Example

We demonstrate the application of the slacks and evaluation criteria in the neighborhood operators with the example introduced in Sections 3.2 and 4.1.4. We start with the feasible solution in Figure 2a. By exchanging the subsequence of shipments $\langle 4, 6\rangle$ with $\langle 3, 12\rangle$ between routes 1 and 3, we get to the optimal solution depicted in Figure 1. The move is illustrated in Figure 3a. The relevant slacks are included in Figure 2 for route 1 and in Figure 3 for route 3. In the following, we describe how to evaluate the new route 1:

- The new *total load* of route 1 is defined by $u_{\mathrm{new},1} = \vec{q}_2 - \vec{q}_6 + \vec{q}_1 + \vec{q}_{12} - \vec{q}_{10} = 49 \leq 100 = Q$, which is feasible.
- From Figure 2b, we can see that $\tau^{\mathrm{opt}}_1 = 97$ is the *partition-optimal arrival time* in the current route 1 by using that $\rho_{R_1}(\tau) = \vec{\rho}_2(\tau)$. For the new route 1, the earliness-tardiness penalties and its left derivative



(a) Exchange move: slacks, pickup and arrival times for route 3 (current routes: straight grey arcs, new (optimal) routes: sloped orange arcs).

(b) Earliness-tardiness costs of new (optimal) route 1.

Figure 3: An inter-route exchange move to transform the solution in Figure 2a to the optimal one in Figure 1.

are given by $\rho_{\text{new},1}(\tau) = \vec{\rho}_2(\tau) - \vec{\rho}_6(\tau) + \vec{\rho}_1(\tau) + \vec{\rho}_{12}(\tau) - \vec{\rho}_{10}(\tau)$ and $\rho'_{\text{new},1}(\tau) = \vec{\rho}'_2(\tau) - \vec{\rho}'_6(\tau) + \vec{\rho}'_1(\tau) + \vec{\rho}'_{12}(\tau) - \vec{\rho}'_{10}(\tau)$. The graph of $\rho_{\text{new},1}(\tau)$ is plotted in Figure 3b. The partition-optimal arrival times of the new route 1 results in $\tau^{\text{opt}}_{\text{new},1} = 60$.

- The *earliest arrival time* of the new route 1 is determined by considering the earliest pickup times and the slacks $\vec{w}_{ij}$ and $\overleftarrow{w}_{ij}$ for $i \in R_1$, $j \in \overleftarrow{R}_i$ based on the waiting times w_i for $i \in R_1$. The earliest pickup time of shipment 3 changes to $\vec{t}_{\text{new},3} = \max\left\{r_3, \vec{t}_1 + t_{1,3}\right\} = 39$, i.e., by $\Delta\vec{t}_3 = \vec{t}_{\text{new},3} - \vec{t}_3 = -122$. The effect on shipment 12 is then given by $\Delta\vec{t}_{12} = \max\left\{\Delta\vec{t}_3, \overleftarrow{w}_{3,12}\right\} = -122$ with $\overleftarrow{w}_{3,12} = \max\left\{\min\left\{0, w_{12}\right\}\right\} = -182$ and shipment 12 can be picked up at $\vec{t}_{\text{new},12} = \vec{t}_{12} + \Delta\vec{t}_{12}$ at earliest and shipment 2 at $\vec{t}_{\text{new},2} = \max\left\{r_2, \vec{t}_{\text{new},12} + t_{12,2}\right\} = 93$. Hence, the earliest arrival time shifts by $\Delta\tau^{\text{e}}_1 = \Delta\vec{t}_2 = \vec{t}_{\text{new},2} - \vec{t}_2 = -113$ to $\tau^{\text{e}}_{\text{new},1} = \tau^{\text{e}}_1 + \Delta\tau^{\text{e}}_1 = 118$.
- The earliest arrival time for route 1 is again larger than the partition-optimal, i.e., $\tau^{\text{opt}}_{\text{new},1} = 60 \leq 118 = \tau^{\text{e}}_{\text{new},1}$. It follows that the *optimal arrival time* for the new route 1 is $\tau^{*}_{\text{new},1} = 118$. This complies with the arrival time stated in Table 2.
- To calculate the *earliness-tardiness costs* of new route 1 at the earliest arrival time $\tau^{\text{e}}_{\text{new},1}$, we have to determine the latest due date in the set of shipments N before $p_{\text{bef}} = p_3$ and the earliest due date after the arrival $p_{\text{aft}} = p_8$. Then, we determine the earliness-tardiness costs of the new route by $\rho_{\text{new},1}(\tau^{*}_{\text{new},1}) = \rho_{\text{new},1}(p_3) + \left(\tau^{*}_{\text{new},1} - p_3\right)\rho'_{\text{new},1}(p_8) = 197.17$.

For route 3, we can apply the same procedure to find the new optimal arrival time and the corresponding earliness-tardiness costs. If we do so, the total earliness-tardiness costs decrease from $\rho = 1038.12$ to $\rho^{*} = 563.65$.

5. Computational study

We start by explaining the definition of the benchmark instances, the algorithmic parameters of the LNS, and the computational environment in Section 5.1. In Section 5.2, we tune the parameters of our LNS. We analyze the contribution of the components of the LNS algorithm in Section 5.3 and evaluate the overall performance in Section 5.4. Finally, we derive managerial insights by investigating the interplay between time window tightness, fleet size, and punctuality in Section 5.5.

5.1. Benchmark instances and computational environment

The instances for the TRP-JIT used in the computations are based on those of Solomon (1987) with up to 100 suppliers and Gehring and Homberger (1999) with 200 suppliers for the VRPTW. The original instances are publicly available online (link: `https://www.sintef.no/vrptw/`). They are grouped by the way the locations of the shipments are generated in the original instances. In the C instances, the locations are clustered, in the R instances they are uniformly distributed and in the RC instances, it is a mix of both.

The locations of the shipments and the depot are the same as in the original instances. The location of the OEM is defined by the mean of the x- and y-coordinates of all locations of a certain instance. The capacity demands q_i, $\forall i \in N$, are adopted from the original instances. The travel times are determined by Euclidean distances plus a random service time for picking up each shipment $i \in N$ drawn from a uniform distribution such that they are in the interval $[15, 30]$.

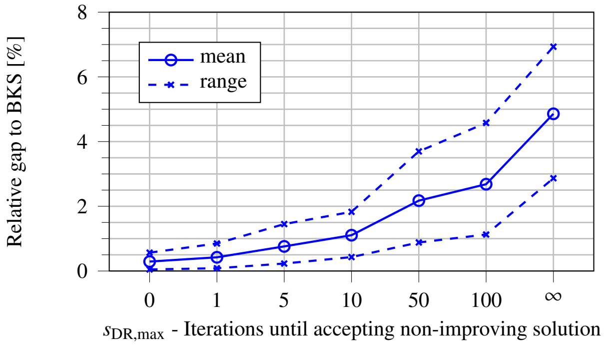
The parameters relevant for JIT routing, i.e., the release dates, due dates, earliness, and tardiness cost factors, the fleet size and the load capacity are defined the following way: The release dates r_i and due dates p_i take place within a planning horizon $t_{\text{plan}} = 480$. Then we draw the release dates r_i from a uniform distribution within the interval $r_i \in \left[0, t_{\text{plan}} - t_{i\eta}\right]$ and the due dates p_i within the interval $p_i \in \left[\max\left\{\max\left\{r_i, t_{0i}\right\} + t_{i\eta}\right\}, t_{\text{plan}}\right]$. The earliness and tardiness costs per time unit are drawn from a uniform distribution rounded to two decimal places such that $\alpha_i \in [0.70, 0.99]$ and $\beta_i \in [1.00, 1.29]$, $\forall i \in N$. The definition of the number of vehicles m and their load Q is different depending on the considered set of instances. We set $m = 4$ and $Q = 100$ for the instances with 15 shipments, $m = 6$ and $Q = 200$ for the instances with 50 shipments, $m = 10$ and $Q = 200$ for the instances with 100 shipments, and $m = 20$ and $Q = 200$ for the instances with 200 shipments. The fleet sizes of the instances are chosen such that the ratio between the number of shipments n and the fleet size m is around the same. Consequently, the average number of shipments per truck and the fleet size increase proportionally to the number of shipments. This applies except for the instances with 15 shipments, where this principle would have led to a relatively small fleet size with only $m = 1$ or $m = 2$ trucks. Therefore, we considered a lower truck capacity here. In the instances with $n = 50$ shipments we also deviate from this definition by allowing $m = 6$ instead of $m = 5$ trucks to account for feasibility. The truck capacity is set to the same value $Q = 200$ for the larger instances with $n = 50,\ 100,\ 200$ shipments. The instances with 15 shipments are created by removing the last ten shipments from the instances of Solomon (1987) with 25 suppliers.

The algorithms are implemented in C# 8.0, targeting the .NET Core 3.1 framework. All computations were performed on an x64 PC with an Intel Core i9-10900K CPU, 128 GB RAM and Microsoft Windows 10. As benchmarks, we use an exact solver (Gurobi 9.1.1) and a heuristic solver (Google OR Tools 9.3.10497). Gurobi uses all 10 cores and remains in its standard configuration. Beside tuning the constructive heuristics and metaheuristics, we keep the heuristic solver in its standard configuration, too. From our experience, OR Tools only use one core. The computations on our heuristics are limited to one single core to make it easier to compare them to further research in this field.

5.2. Definition of the algorithmic parameters

We set the parameters of our LNS in a series of preliminary experiments based on the instances of Solomon (1987) with $n = 50$ suppliers. We repeat the computations 5 times for each instance because of the stochastic components in the solution procedure, taking the average, minimum, and maximum objective value or computation time of the repetitions over the considered instances.

For example, the parameter $s_{\text{DR,max}}$ of the acceptance criterion is set by repeating the computations for the



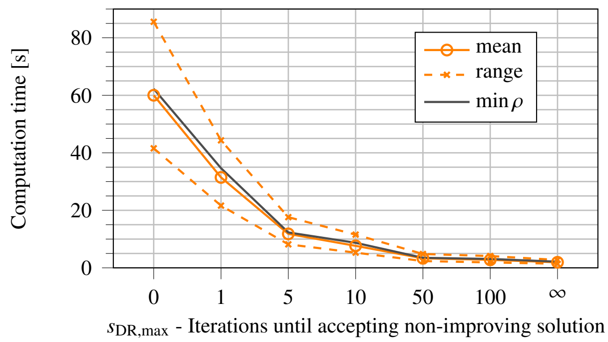


Figure 4: Average relative gap to BKS and computation time over all instances of Solomon (1987) with $n = 50$ shipments for different values of parameter $s_{\text{DR,max}}$.

parameter values $s_{\text{DR,max}} = 0, 1, 5, 10, 50, 100, \infty$. The result for the objective value and the computation time are depicted in Figure 4. It can be seen that setting the parameter to $s_{\text{DR,max}} = 5$ gives an appropriate trade-off between the objective value and computation time including considerations on their ranges. The plot also shows the average of the computation time for the solution with the minimal objective value out of the 5 repetitions for each instance. As this value lies between the minimum and the maximum value, we can conclude that a longer search and hence a larger computation time does not guarantee a better solution.

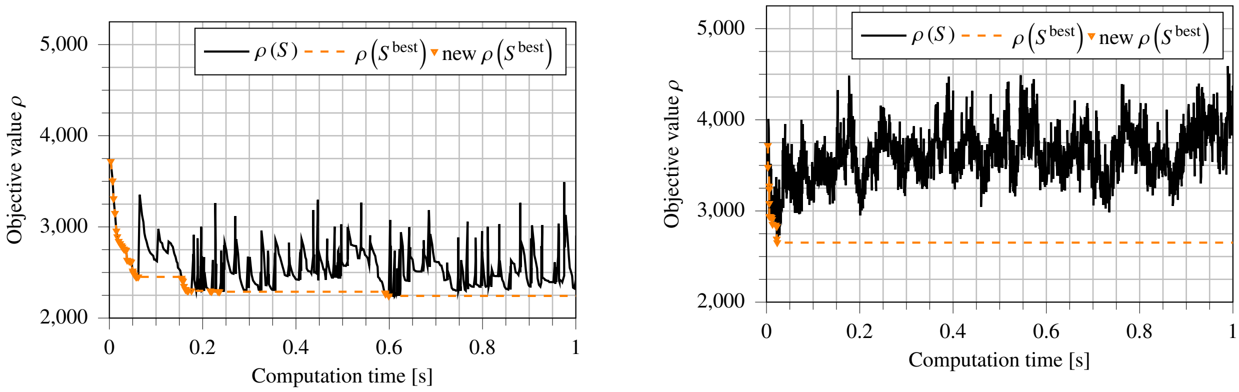
Overall, we find the following parameter settings to yield the best compromise between runtime and solution quality. The number of iterations is limited by $s_{\text{max}} = 50000$ (overall) and $s_{\text{imp,max}} = 2500$ (iterations without new best solution). In the destroy operator between $n^{-}_{\text{rem}} = 5$ and $n^{+}_{\text{rem}} = \max\{5, \lceil 0.4n \rceil\}$ shipments are randomly removed from the routes. The repair operator selects one of the $v_{\text{max}} = 5$ best shipments to be reinserted randomly in each step. A solution that is not better than the reference solution $S^{\text{DR,ref}}$ is accepted after $s_{\text{DR,max}} = 5$ repetitions of the destroy-repair operation. In the LS, we consider subsequences of up to $n_{\text{seq}} = 3$ shipments.

Additionally, we also need to define parameters for our benchmark, Google OR Tools, i.e., we choose a constructive heuristic, a metaheuristic, and a time limit for the procedure. We tuned the two former parameters based on the instances of Solomon (1987) with $n = 15$ shipments. The results are summarized in Table 6 in the appendix. It turns out that choosing the Parallel Cheapest Insertion Heuristic (PCI) combined with Tabu Search (TS) among six constructive heuristics and six metaheuristics (including the case of not applying any metaheuristic) is the most promising. Hence, we consider the solutions from OR Tools after initial solution by PCI and after applying TS. The time limit for OR Tools is chosen in dependence on the size of the instances, i.e., 30s for the instances with $n = 15$ shipments, 300s for $n = 50$, 600s for $n = 100$, and 1800s for $n = 200$, which is significantly more time than what our LNS takes on the same instances.

5.3. Analysis of the components of the LNS algorithm

The main components of the solution procedure presented in Section 4 are the constructive parallel insertion heuristic, the LS, the destroy and repair operator, and the acceptance criterion. We investigate the impact of these components by considering the instance C101 by Solomon (1987) with $n = 50$ shipments.

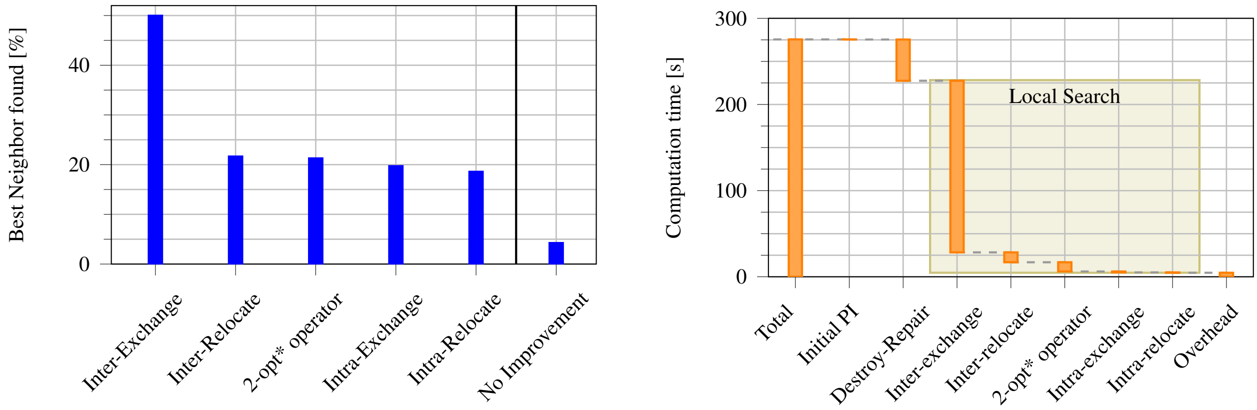
Figure 4 shows the effect of parameter $s_{\text{DR,max}}$ for the acceptance criterion. The case of $s_{\text{DR,max}} = 0$ is equivalent to neglecting the acceptance criterion in the solution procedure because we accept any (even non-improving) solution after rejecting 0 inferior solutions. Compared to the chosen value $s_{\text{DR,max}} = 5$, we can see that the decision of introducing the acceptance criterion or not is again a trade-off between computation time and solution quality.



(a) Large neighborhood search with local search (LNS).

(b) Large neighborhood search without local search (LNS-noLS).

Figure 5: Plot of the objective value for the first second of CPU time in the large neighborhood search with and without LS for the instance C101 by Solomon (1987) with $n = 50$ shipments.



(a) Rate of finding the best neighbor in a local search iteration of each neighborhood operator.

(b) Analysis of the computation time of the algorithms' components.

Figure 6: Considerations on the components of the LNS algorithm, especially the neighborhood operators, based on the average of the instances of Gehring and Homberger (1999) with $n = 200$.

To evaluate the effect of the LS in the LNS algorithm, we refer to Figure 5. It shows how the objective value of the current and the best known solution develop over time in the LNS with and without LS; we refer to the latter as *LNS-noLS*. In the figure, the more systematic decline in the objective value of the LNS compared to the LNS-noLS is striking. This leads to a smaller objective value already in the beginning of the LNS whereas LNS-noLS appears to merely variate randomly over a certain interval. It can also be seen that applying the destroy and repair operators, which may increase the objective value again, supports the search for better solutions for both the LNS and LNS-noLS.

The contribution of the neighborhood operators in the search procedure is evaluated by how often the best neighbor comes from a specific neighborhood, as a percentage of all accepted neighbors. This is shown in Figure 6a for the average over all instances of Gehring and Homberger (1999) with $n = 200$ shipments. It shows that in most cases the inter-exchange operator leads to the most improving neighbor. The numbers add up to more than 100% because the different neighborhoods can overlap, i.e., contain the same moves to some degree, or the best moves from different neighborhoods lead to the same scale of improvement.

In case no improving neighbor is found, the LS stops and the solution procedure continues with the subsequent steps. We also track the time spent on searching the individual neighborhoods, the destroy and repair operation, and constructing the initial solution. The split of the total computation time is illustrated in Figure

Instances	Solver		PI	LS	LNS			OR Tools (PCI)		OR Tools (TS)
	objective value - ρ^*	comp. time [s]	rel. gap BKS [%]	rel. gap BKS [%]	computation time in [s] mean	min	max	rel. gap to BKS	comp. time [s]	rel. gap to BKS
C1xx	251.08	6.01	47.26	20.45	0.36	0.35	0.37	12.19	0.21	0.00
C2xx	320.46	16.41	18.20	6.49	0.38	0.37	0.39	7.54	0.14	0.00
R1xx	392.31	153.44	14.36	5.93	0.43	0.40	0.49	8.50	0.14	0.34
R2xx	342.12	34.38	44.20	7.60	0.39	0.38	0.40	9.97	0.14	1.30
RC1xx	435.27	57.21	19.70	9.06	0.35	0.33	0.37	5.15	0.12	1.46
RC2xx	382.47	23.06	34.90	8.18	0.32	0.31	0.35	15.10	0.11	0.51
All	354.22	54.41	29.76	9.44	0.38	0.36	0.40	9.71	0.14	0.61

Table 3: Results for the instances with $n = 15$ shipments.

Instances	PI		LS		LNS						OR Tools (PCI)		OR Tools (TS)
	rel. gap BKS [%]	c.t. [s]	rel. gap BKS [%]	c.t. [s]	rel. gap to BKS [%] mean	min	max	c.t. [s] mean	min	max	rel. gap BKS [%]	comp. time [s]	rel. gap BKS [%]
$n = 50$													
C1	66.54	0.01	11.47	0.06	0.92	0.34	1.75	11.20	8.19	16.96	18.70	3.21	10.15
C2	50.03	0.00	11.76	0.05	0.93	0.25	1.74	12.17	8.58	18.61	26.61	3.34	13.36
R1	52.26	0.00	12.99	0.06	0.74	0.17	1.44	13.86	9.85	20.26	18.50	3.25	12.00
R2	51.82	0.00	14.35	0.05	0.81	0.13	1.62	15.20	9.75	22.61	19.56	3.18	13.18
RC1	49.26	0.00	13.35	0.04	0.40	0.19	0.70	7.98	5.77	11.30	10.37	2.10	5.81
RC2	47.56	0.00	9.66	0.03	0.74	0.34	1.34	8.24	5.42	12.89	14.55	2.58	6.89
All	53.05	0.00	12.41	0.05	0.76	0.23	1.45	11.81	8.17	17.62	18.17	2.98	10.51
$n = 100$													
C1	69.72	0.03	17.63	0.19	1.77	0.00	3.17	62.22	42.47	90.53	25.39	13.36	16.39
C2	58.16	0.02	16.26	0.19	0.97	0.00	2.29	58.56	37.51	105.71	18.19	15.19	14.23
R1	55.32	0.02	12.83	0.28	0.86	0.00	1.79	94.75	59.23	134.21	19.39	19.44	14.49
R2	57.73	0.02	12.10	0.35	0.91	0.00	1.90	88.09	56.05	126.06	18.68	19.91	13.82
RC1	56.63	0.02	15.44	0.22	0.88	0.00	1.50	59.64	38.84	89.43	19.48	13.05	15.09
RC2	50.89	0.02	13.47	0.20	1.09	0.00	1.94	55.96	39.35	78.18	16.49	15.39	13.96
All	58.07	0.02	14.41	0.25	1.06	0.00	2.08	72.49	47.06	107.12	19.64	16.46	14.64
$n = 200$													
C1	77.06	0.13	13.49	1.27	0.98	0.00	1.77	276.29	186.65	413.98	17.39	86.03	14.45
C2	65.78	0.12	13.97	0.83	1.32	0.00	2.29	331.10	203.45	506.94	19.87	66.32	16.81
R1	65.46	0.12	14.27	1.03	1.02	0.00	1.90	286.35	176.03	420.12	15.83	84.42	14.13
R2	65.50	0.12	14.55	1.05	0.79	0.00	1.53	255.47	166.62	399.47	18.03	82.70	15.50
RC1	66.54	0.12	15.53	1.03	1.06	0.00	1.93	260.90	183.46	369.12	16.46	76.42	12.62
RC2	65.53	0.12	14.87	1.02	0.84	0.00	1.65	242.97	164.28	343.73	17.99	82.16	14.48
All	67.65	0.12	14.45	1.04	1.00	0.00	1.84	275.51	180.08	408.89	17.60	79.67	14.67

Table 4: Results for the different solution procedure on the aggregated by sets of instances.

6b. Most of the CPU time is spent on the LS and the destroy and repair operator, whereas the calculation of the initial solution by parallel insertion (PI) and the overhead, which is mostly caused by updating the slacks, are relatively small. When comparing both plots in Figure 6, we can see that although the rate of finding the best neighbor of the neighborhood operators other than the inter-exchange operator is significantly lower, their computation time is also much lower. Consequently, we draw the conclusion that the trade-off between computation time and solution quality is in balance for all neighborhood operators.

5.4. Comparison of the solution methods

The focus in the following is on comparing the proposed LNS-based solution procedure to the quality of the initial solution by PI and after applying the LS once. We also consider the performance of a commercial exact solver (Gurobi) solving the MIP in Section 3.3, and the heuristic solver OR Tools. The time limit of the (exact) solver is set to 7200 s, and for OR Tools depending on the size of the instances (see Section 5.2). The results of the MIP solver are only available for the instances with $n = 15$ shipments within the time limit. For the larger instances with $n = 50,\ 100,\ 200$, we report the computation time and solution quality of the LNS-noLS procedure in the appendix, too. The results are summarized in Table 3 and Table 4, providing information about the average of the objective value ρ, the computation time (c.t.) and the relative gap to the best known solution (relative gap to BKS or rel. gap BKS). The relative gap to the BKS for an instance solved with a certain solution method is calculated by the objective value ρ in reference to the best known solution for the instance with objective value ρ^*, i.e., we set

$$\text{rel. gap BKS} = \frac{\rho - \rho^*}{\rho^*}.$$

For solution procedures with stochastic components, i.e., the LNS and LNS-noLS, the computations for each instance are repeated 5 times. The min and max value indicate the average over respectively the minimum or maximum of the objective value, computation time or relative gap to BKS over these 5 repetitions for each instance in the (sub-)set of instances. The detailed results are presented in the appendix; for the instances with 15 shipments in Table 7 and for the instances with 50, 100, and 200 shipments in Tables 8 and 9 for the relative gaps to BKS, and in Tables 10, 11, 12, 13, and 14 for the objective values and computation times.

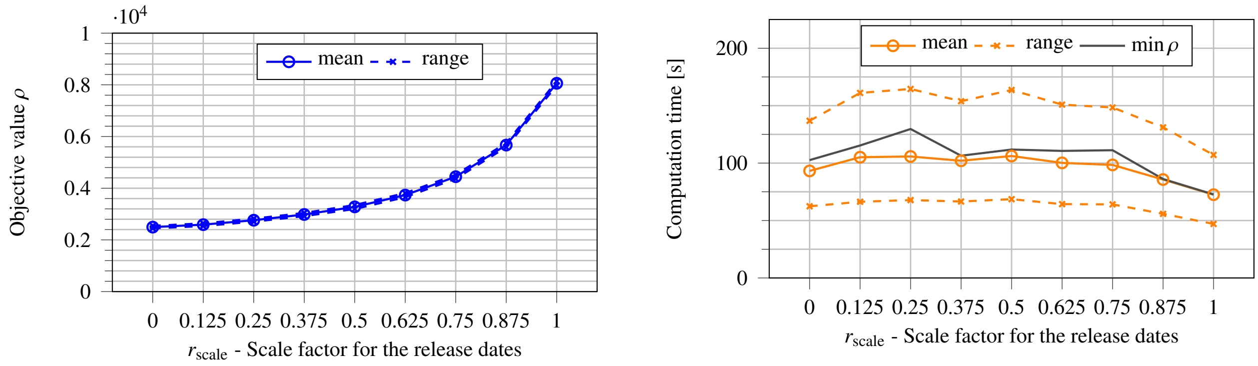
It can be seen that for all instances the application of the LS on the initial PI solution and the whole LNS procedure significantly improve the solution quality. We know the optimal solution for the smallest instances with $n = 15$ shipments. The results are summarized in Table 3. The LNS procedure always finds the optimal solution for these instances. The objective value found is the same in all of the 5 repetitions for each instance. Concerning the computation time, even for small instances, the LNS approach outperforms the solver by orders of magnitude. We can also state that the performance of OR Tools is good for the small instance with a small gap to the best known (optimal) solution of 0.61% after applying TS.

From the results for the larger instances summarized in Table 4, we can conclude that LNS scales quite well. Note that we gain the best known solution (BKS) from all test runs, including the tuning of $s_{\text{DR,max}}$ in the acceptance criterion, hence the minimum LNS gap to the BKS for the instance with $n = 50$ shipments in the table can sometimes be greater than 0%. Regarding the computation time, even for the instances with $n = 200$ shipments, computing the LNS solution takes about 3 minutes on average, and roughly 12 minutes in the single very worst case (for instance c2-2-9 with $n = 200$ shipments), which should be acceptable for most practical applications. The data also highlight that the LNS component is quite important for the large instances, as LS alone can produce quite significant gaps in some instances. We compare our LNS metaheuristic to OR Tools only. We can state that the LNS outperforms OR tools significantly with a relative gap around 10% for the instances with $n = 50$ shipments, and roughly 14% on average for the larger instances with $n = 100,\ 200$ shipments. The detailed results for all instances can be found in C.

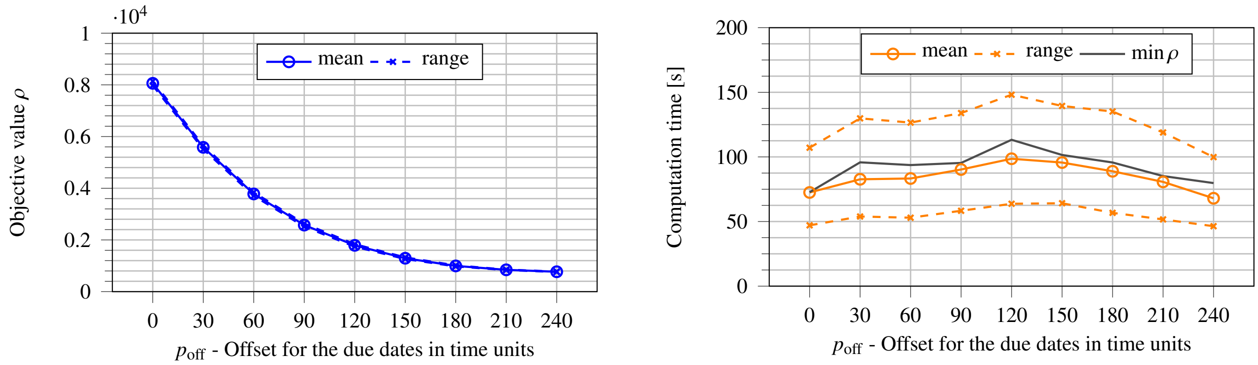
5.5. Effect of time window tightness and fleet size

So far, we have assumed that the release dates and due dates can take place on the same planning horizon between 0 TU and 480 TU. This may imply relatively tight planned lead times, i.e., the difference between the release and due dates is so small that we can only avoid delays by direct shipments. Hence, the shipments are more likely to arrive delayed than early. In practice, managers may have some flexibility regarding the time windows. While due dates may often be given because of the production sequence, it may be possible to release some shipments earlier (possibly at a cost), effectively extending the lead time. Similarly, increasing the truck fleet size may presumably make it easier to achieve punctual deliveries, but entails additional cost for vehicles and drivers.

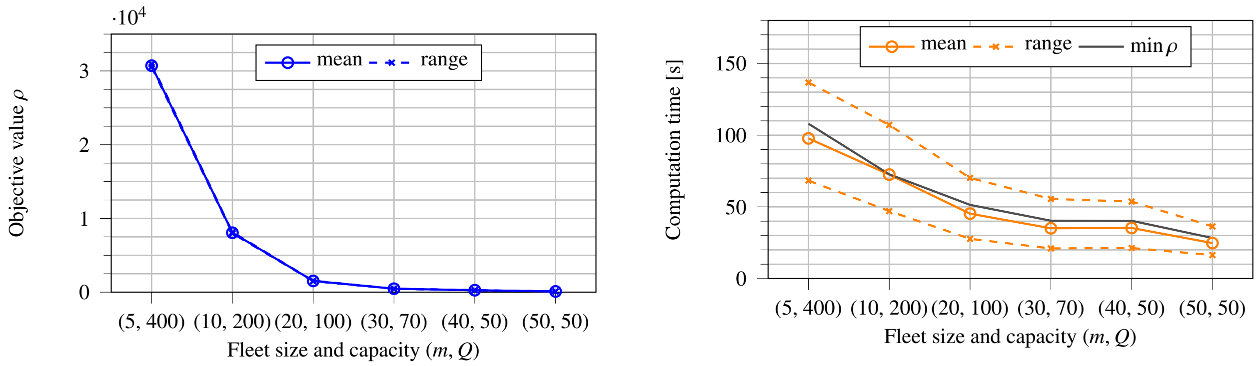
To investigate the effect on the earliness-tardiness cost, we vary the time span between the release date and the due date as well as the truck count and capacity. This means that we apply the LNS on the instances with $n = 100$ shipments and repeat the computations 5 times, but we vary over some parameters instead of using



(a) The effect of earlier release dates.



(b) The effect of delaying the due dates.



(c) The effect of increasing the fleet size and reducing the trucks' capacities.

Figure 7: Managerial insights about the TRP-JIT based on the instances with $n = 100$ shipments.

the fixed values in Section 5.1:

- We bring forward the release dates, i.e., the new release dates $r_{\text{new},i}$, $\forall i \in N$, are set to $r_{\text{new},i} := r_i \cdot r_{\text{scale}}$ rounded to the nearest integer, where $r_{\text{scale}} = 0, 0.125, \ldots, 0.875, 1$ is the factor to be multiplied with the original release dates. Hence, we ensure that the shipments are available before time $0, 60, 120, \ldots, 480$ [TU]. The case $r_{\text{scale}} = 1$ corresponds to the original instances.
- We delay the due dates, i.e., the new due dates p_i, $\forall i \in N$, are set to $p_{\text{new},i} := p_i + p_{\text{off}}$ rounded to the nearest integer, where $p_{\text{off}} = 0, 30, \ldots, 120, 150$ [TU] is the constant to be added to the original due dates. The case $p_{\text{off}} = 0$ corresponds to the original instances.
- We evaluate the impact of the fleet size, i.e., the capacity and number of vehicles, by decreasing it to $m = 5$ vehicles with capacity $Q = 400$ and increasing it to $m \in \{20, 30, 40, 50\}$, respectively, while decreasing the load capacity $Q \in \{100, 70, 50\}$ ($Q = 50$ for both of the largest fleet sizes to keep the solutions feasible). In other words, we investigate how the punctuality of the deliveries is affected if a large fleet of small vehicles is used as opposed to a small fleet of large trucks.

5.5.1. Algorithmic implications

The results are depicted in Figure 7. We can see that the computation time remains rather stable when varying the planned lead time in Figure 7a and 7b. The computation time clearly shows a decreasing slope when varying the fleet size in Figure 7c. If the fleet size is increased, fewer shipments are loaded on the trucks on average. Hence, when updating the stored best moves for each neighborhood, and route or pair of routes that are affected by the previous move, normally fewer shipments have to be considered.

5.5.2. Managerial insights

Looking at TRP-JIT from a supply chain perspective, there is a need to coordinate collaboration between the suppliers, the OEM, and especially the 3PL in the transportation network. Three important questions arise:

- What is the impact of the *planned lead time* on the supplier network? What planned lead time is favorable for JIT production?
- What is the effect of increasing the planned lead time by negotiating with the suppliers (release dates) or the OEM (due dates)?
- How do the *fleet size and load capacity* affect the supplier network's performance? Should we use few heavy goods vehicles with high capacity or many small vans with low capacity?

Generally, increasing the planned lead time may imply larger storage costs either at the suppliers or the OEM. Contrarily, we can see in the results in Figure 7a and 7b that a longer planned lead time reduces the earliness-tardiness costs. By this, the 3PL can perform the deliveries earlier and tardiness is avoided. The curve of the objective value flattens for approximately $r_{\text{scale}} \leq 0.5$ and $p_{\text{off}} \geq 150$. A further increase of the planned lead time has a marginal effect on the earliness-tardiness costs. We conclude that this is a saturation point.

Consequently, the decision makers at the 3PL, suppliers, and OEM should agree on appropriate planned lead times: too small time spans cause additional earliness-tardiness costs. However, agreeing on too large planned lead times would imply additional storage costs for shipments waiting to be picked up at the suppliers and potentially leading to earlier deliveries at the OEM, where storage space is the most expensive. We can also see that the effect of bringing forward the release dates is smaller than delaying the due dates concerning the earliness-tardiness costs. The former is also limited by the beginning of the planning horizon. But the latter, delaying the due dates, may be harder to set in practice, because of the high contractual power of the OEM.

The properties of the fleet, namely the fleet size and the truck capacity, are another managerial issue, especially for the 3PL. A small fleet may be favorable with respect to the salary costs for the drivers and fixed costs for the vehicles. Increasing the fleet size while reducing the load capacity enables shorter routes. It also helps to address different due dates of the shipments in one truck load more accurately.

Figure 7c shows the results of our computations for this aspect. We can see that especially using a reduced number of vehicles with larger capacity strongly increases the earliness-tardiness costs. Contrarily, increasing the fleet size to $m = 20$ drastically reduces the earliness-tardiness costs. Enlarging the fleet size further does not have the same effect. Consequently, similar to the planned lead time, we state that a saturation point exists. Hence, we should find a trade-off between potential costs for increasing the fleet size and the corresponding reduction of the earliness-tardiness costs.

The managerial insights indicate that increasing the vehicle fleet or the lead time can lead to steep decreases, but up to a saturation point. However, these measures also increase cost. Our approach can aid in best trade-off between earliness and tardiness costs and the cost of the vehicle fleet and/or long lead times.

6. Conclusion

We define and solve the TRP-JIT in this article. Traditional routing problems typically deal with the distribution of goods from a depot to customers. Instead, our problem focuses on the supply side of an OEM's production facility, where parts and subassemblies are collected from suppliers to be taken to the OEM in a just-in-time manner. We propose a MIP and a metaheuristic approach based on LNS and LS. Our major outcomes are as follows:

- A commercial solver using our MIP model is only capable of solving instances up to $n = 15$ shipments, in spite of valid inequalities that improve the performance. For these instances, LNS finds the optimal solutions in much shorter time.
- In our computational study, LNS finds high-quality solutions for instances with up to $n = 200$ shipments in a reasonable computational time. All components of the LNS algorithm are balanced concerning the trade-off between their contribution to the solution quality and the computational time. Our LNS algorithm also outperforms the tabu search of the standard heuristic solver Google OR Tools on any instance size we tested.
- Increasing the fleet size and the time span between release and due date both can reduce the earliness-tardiness costs. When both of the parameters are small, the effect of increasing one of the parameters on the earliness-tardiness costs is stronger. The result is useful for managers who must balance earliness-tardiness costs on the one hand, and storage and fleet-related costs on the other hand.

We propose the following directions for future research. First, although we observe that our valid inequalities improve the performance of the solver significantly, only small instances can be solved. Improvements to the MIP formulation or exact methods like branch-and-price may lead to the solution of larger instances. Secondly, Lee and Prabhu (2016) and Ganji et al. (2020) evaluate the environmental impact of JIT principles in vehicle routing. Similar studies can be conducted for supplier networks by modifying and extending the TRP-JIT. Thirdly, since our problem formulation does not necessarily lead to the shortest routes, a direction for future research is to include travel time as an objective as well, possibly in a multi-objective approach.

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A. Example

i, j	1	2	3	4	5	6	7	8	9	10	11	12	13
0	15	18	22	25	20	11	21	26	32	25	33	15	21
1	-	42	24	42	42	34	31	41	27	25	36	26	45
2	42	-	44	30	33	26	46	46	57	53	60	33	25
3	24	44	-	35	52	43	45	55	25	39	50	21	53
4	42	30	35	-	51	41	56	60	50	57	67	25	45
5	42	33	52	51	-	20	30	23	60	43	45	45	21
6	34	26	43	41	20	-	30	29	52	40	45	35	21
7	31	46	45	56	30	30	-	22	46	24	25	43	40
8	41	46	55	60	23	29	22	-	58	36	34	50	35
9	27	57	25	50	60	52	46	58	-	35	45	35	63
10	25	53	39	57	43	40	24	36	35	-	21	42	51
11	36	60	50	67	45	45	25	34	45	21	-	52	55
12	26	33	21	25	45	35	43	50	35	42	52	-	43

Table 5: Travel times $t_{ij} \forall i, j \in V$ between the locations of the shipments, the depot and the OEM in the example.

B. Valid inequalities

In the MIP model in Section 3.3, we can enforce a backward planning for the pickup times by adding the constraints $\bar{t}_j - \bar{t}_i + Px_{ijk} \leq t_{ij} + P, \forall i, j \in N, i \neq j, k \in M$ and $\tau_k + Px_{i\eta k} \leq \bar{t}_i + t_{i\eta} + P, \forall i \in N, k \in M$. The upper limit of the tardiness variables d_i is $d_i \leq P$, $\forall i \in N$. Similarly, for the earliness variables, we add the constraints $e_i \leq p_i - r_i$, $\forall i \in N$, as the earliness can never be larger than the difference between the release and the due date.

The arrival times at the OEM is constrained for all $k \in M$ by

$$\max \left\{ \min_{j \in N} \left\{ \max \left\{ r_j, t_{0j} \right\} \right\} + \min_{i \in N} \left\{ t_{i\eta} \right\}, \min_{i \in N} \left\{ p_i \right\} \right\} \leq \tau_k,$$

and $\tau_k \leq P$. The constraints $\max \left\{ r_j, \min_{i \in V \setminus \{j, \eta\}} \left\{ t_{ij} \right\} \right\} y_{jk} \leq \tau_k, \forall j \in N, k \in M$ and $\sum_{j \in N} \max \left\{ r_j, t_{0j} \right\} x_{0jk} + \sum_{i \in N} \sum_{j \in N \cup \{\eta\}} t_{ij} x_{ijk} \leq \tau_k, \forall k \in K$ are also valid inequalities relating the binary variables to the arrival time at the OEM. For the pickup times of the shipments, a constant lower limit can be defined by $\max \left\{ r_j, \min_{i \in N \cup \{0\}} \left\{ t_{ij} \right\} \right\} \leq \bar{t}_j$, $\forall j \in N$ and an upper limit by $\bar{t}_i \leq P$, $\forall i \in N$. A lower limit for the pickup times is formulated using binary variables by

$$\sum_{k \in M} \sum_{i \in N} \max \left\{ r_i + t_{ij}, r_j \right\} x_{ijk} \leq \bar{t}_j, \ \forall j \in N$$

and an upper limit by $\bar{t}_i \leq \tau_k + (1 - y_{ik}) P, \forall i \in N, k \in M$. Finally, the constraints $\bar{t}_i \leq p_i + d_i - e_i, \forall i \in N$, are valid as the delivery of a shipment $i \in N$ at the OEM is defined by $p_i + d_i - e_i$ and must not be earlier than the pickup time.

C. Computational Study

Metaheuristics	Unset	GenericTabuSearch	GreedyDescent	GuidedLocalSearch	SimulatedAnnealing	TabuSearch
Constructive Heuristics						
LocalCheapestCostInsertion	7.15	7.15	7.15	5.81	7.15	1.48
LocalCheapestInsertion	9.93	9.93	9.93	6.78	9.87	1.99
ParallelCheapestInsertion	9.71	9.71	9.71	8.12	9.71	0.61
PathCheapestArc	11.55	11.55	11.55	7	11.55	1.29
PathMostConstrainedArc	11.19	10.96	11.19	6.71	10.96	1.09
SequentialCheapestInsertion	9.71	9.71	9.71	8.12	9.71	0.61

Table 6: Relative gaps to best known solution for the different constructive heuristics and metaheuristics of Google OR Tools for the instances of Solomon (1987) with $n = 15$ shipments.

Instances	PI		LS		LNS				Solver		OR Tools (PCI)			OR Tools (TS)	
	objective value- ρ	rel. gap to BKS [%]	objective value - ρ	rel. gap to BKS [%]	objective value - ρ^*	computation time in [s] mean	min	max	objective value - ρ^*	comp. time [s]	objective value - ρ	rel. gap to BKS [%]	comp. time [s]	objective value - ρ	rel. gap to BKS [%]
C101	472.93	62.54	472.93	62.54	290.97	0.33	0.32	0.36	290.97	2.7	290.97	0	0.24	290.97	0
C102	258.92	0	258.92	0	258.92	0.4	0.39	0.42	258.92	3.27	278.98	7.75	0.26	258.92	0
C103	278.67	16.34	239.54	0	239.54	0.33	0.32	0.35	239.54	30.07	264.47	10.41	0.15	239.54	0
C104	653.27	132.55	280.92	0	280.92	0.33	0.32	0.34	280.92	4.43	280.92	0	0.12	280.92	0
C105	554.87	82.36	304.27	0	304.27	0.35	0.34	0.37	304.27	3.1	304.27	0	0.24	304.27	0
C106	144.1	0	144.1	0	144.1	0.36	0.35	0.38	144.1	3.09	200.39	39.06	0.2	144.1	0
C107	295.69	7.14	295.69	7.14	275.98	0.37	0.36	0.38	275.98	1.53	275.98	0	0.16	275.98	0
C108	281.83	1.4	277.93	0	277.93	0.41	0.41	0.43	277.93	4.49	423.93	52.53	0.21	277.93	0
C109	417.25	123.04	401.09	114.41	187.07	0.35	0.35	0.35	187.07	1.41	187.07	0	0.28	187.07	0
C201	653.82	63.25	461.59	15.25	400.5	0.38	0.37	0.41	400.5	46.26	463.17	15.65	0.11	400.5	0
C202	286.17	10.73	286.17	10.73	258.43	0.37	0.37	0.38	258.43	5.71	294.13	13.81	0.11	258.43	0
C203	320.15	0.05	320	0	320	0.36	0.36	0.37	320	9.99	320	0	0.12	320	0
C204	494.16	15.41	494.16	15.41	428.17	0.37	0.36	0.38	428.17	30.14	549.85	28.42	0.08	428.17	0
C205	438.53	27.27	344.58	0	344.58	0.38	0.38	0.39	344.58	15.85	344.58	0	0.2	344.58	0
C206	383.43	14.71	369.46	10.53	334.25	0.37	0.36	0.38	334.25	11.07	334.25	0	0.13	334.25	0
C207	200.5	4.24	192.34	0	192.34	0.41	0.4	0.42	192.34	5.41	197.04	2.44	0.2	192.34	0
C208	313.69	9.9	285.42	0	285.42	0.37	0.37	0.38	285.42	6.88	285.42	0	0.18	285.42	0
R101	354.25	34.69	338.07	28.53	263.02	0.52	0.42	0.61	263.02	6.75	263.02	0	0.24	263.02	0
R102	384.43	8.69	384.43	8.69	353.69	0.43	0.39	0.48	353.69	5.84	353.69	0	0.13	353.69	0
R103	220.35	17.19	220.35	17.19	188.02	0.55	0.5	0.61	188.02	5.32	196.65	4.59	0.15	188.02	0
R104	541.4	0	541.4	0	541.4	0.44	0.41	0.49	541.4	164.79	602.33	11.25	0.14	541.4	0
R105	611.29	55.31	393.6	0	393.6	0.41	0.4	0.41	393.6	15.55	393.6	0	0.11	393.6	0
R106	1,166.7	43.9	844.59	4.17	810.75	0.39	0.37	0.41	810.75	1,014.61	855.01	5.46	0.14	844.29	4.14
R107	374.55	0	374.55	0	374.55	0.37	0.36	0.38	374.55	9.46	374.55	0	0.13	374.55	0
R108	282.52	0	282.52	0	282.52	0.4	0.39	0.4	282.52	7.03	362.32	28.25	0.2	282.52	0
R109	148.81	9.31	148.81	9.31	136.14	0.56	0.41	0.94	136.14	9.18	136.14	0	0.14	136.14	0
R110	549.69	0	549.69	0	549.69	0.38	0.36	0.39	549.69	110.78	604.23	9.92	0.09	549.69	0
R111	480.11	3.25	480.11	3.25	465.01	0.4	0.38	0.4	465.01	473.79	480.11	3.25	0.09	465.01	0
R112	349.37	0	349.37	0	349.37	0.37	0.36	0.38	349.37	18.2	486.72	39.31	0.13	349.37	0
R201	526.79	0	526.79	0	526.79	0.37	0.36	0.38	526.79	94.51	539.91	2.49	0.14	526.79	0
R202	340.84	68.98	201.71	0	201.71	0.37	0.37	0.38	201.71	6.5	201.71	0	0.12	201.71	0
R203	262.51	13.27	262.51	13.27	231.75	0.39	0.37	0.42	231.75	7.26	257.92	11.29	0.18	239.48	3.34
R204	500.74	35.99	404.44	9.84	368.22	0.43	0.41	0.45	368.22	25.11	423.38	14.98	0.15	368.22	0
R205	599.52	161.95	228.87	0	228.87	0.42	0.41	0.44	228.87	6.72	228.87	0	0.15	228.87	0
R206	419.21	61.35	329.26	26.73	259.81	0.38	0.37	0.39	259.81	14	259.81	0	0.16	259.81	0
R207	723.56	100.59	407.73	13.03	360.72	0.36	0.36	0.37	360.72	29.56	360.72	0	0.13	360.72	0
R208	601.83	6.4	585.81	3.57	565.61	0.38	0.37	0.39	565.61	49.08	565.61	0	0.11	565.61	0
R209	302.52	0	302.52	0	302.52	0.35	0.35	0.36	302.52	9.53	532.05	75.87	0.16	335.71	10.97
R210	720.37	33.63	631.31	17.11	539.06	0.42	0.4	0.44	539.06	124.89	566.08	5.01	0.09	539.06	0
R211	185.4	4.02	178.23	0	178.23	0.39	0.39	0.4	178.23	10.99	178.23	0	0.16	178.23	0
RC101	316.63	7.66	316.63	7.66	294.09	0.34	0.33	0.36	294.09	17.96	339.44	15.42	0.12	322.62	9.7
RC102	439.16	2.19	429.76	0	429.76	0.39	0.34	0.43	429.76	14.05	466	8.43	0.15	429.76	0
RC103	1,021	38.44	775.42	5.14	737.5	0.37	0.35	0.4	737.5	330.68	804.2	9.04	0.08	751.94	1.96
RC104	306.13	20.54	306.13	20.54	253.97	0.39	0.36	0.42	253.97	2.09	253.97	0	0.12	253.97	0
RC105	502.73	57.96	407.48	28.03	318.26	0.37	0.34	0.4	318.26	4.32	337.29	5.98	0.19	318.26	0
RC106	557.79	19.73	465.87	0	465.87	0.28	0.28	0.29	465.87	45.96	465.87	0	0.09	465.87	0
RC107	524.17	4.75	524.17	4.75	500.42	0.31	0.3	0.31	500.42	24.78	512.03	2.32	0.08	500.42	0
RC108	512.85	6.33	512.85	6.33	482.31	0.32	0.32	0.33	482.31	17.86	482.31	0	0.16	482.31	0
RC201	596.58	28.97	462.56	0	462.56	0.28	0.28	0.29	462.56	28.98	498.01	7.66	0.06	462.56	0
RC202	561.26	30.53	561.26	30.53	429.97	0.31	0.3	0.34	429.97	71.77	514.08	19.56	0.09	442.45	2.9
RC203	440.82	42.91	310.18	0.56	308.45	0.41	0.39	0.43	308.45	38.26	310.18	0.56	0.16	308.45	0
RC204	655.6	25.03	573.59	9.39	524.35	0.28	0.28	0.29	524.35	11.05	573.59	9.39	0.14	524.35	0
RC205	437.78	41.57	309.24	0	309.24	0.3	0.28	0.36	309.24	11.57	437.17	41.37	0.12	309.24	0
RC206	166.45	1.19	166.45	1.19	164.49	0.37	0.33	0.45	164.49	3.87	166.45	1.19	0.12	166.45	1.19
RC207	623.16	15.01	623.16	15.01	541.83	0.3	0.28	0.31	541.83	16.41	638.35	17.81	0.11	541.83	0
RC208	618.56	94	346.65	8.72	318.84	0.33	0.31	0.35	318.84	2.61	392.89	23.22	0.11	318.84	0
mean	453.13	27.92	383.7	8.32	354.22	0.38	0.36	0.4	354.22	54.41	387.68	9.71	0.14	356.58	0.61

Table 7: Detailed results for the instances of Solomon (1987) with $n = 15$ shipments.

Instance	PI	LS	LNS			LNS-noLS			OR Tools		acceptance criterion - LNS mean						acceptance criterion - LNS min						acceptance criterion - LNS max					
			mean	min	max	mean	min	max	PCI	TS	0	1	10	50	100	∞	0	1	10	50	100	∞	0	1	10	50	100	∞
C101	66.04	9.48	0.48	0	1.16	17.68	11.55	28.46	25.1	24.09	0.03	0.12	0.49	1.1	1.47	2.26	0	0	0	0.46	1.01	1.4	0.16	0.29	0.96	1.9	2.28	3.75
C102	51.2	5.87	1.49	1.1	1.87	12.07	7.93	16.28	12.14	8.76	0.7	0.65	1.38	2.08	2.5	2.72	0	0	1.1	1.66	1.73	1.1	1.1	1.1	1.86	2.47	3.85	4.27
C103	70.57	5.53	0.25	0.13	0.48	13.26	10.8	17.49	8.45	6.13	0.05	0.01	0.1	1.09	1.02	4.25	0	0	0	0.11	0.11	1.14	0.13	0.02	0.24	2.55	3.01	5.53
C104	48.57	7.17	1.81	1.45	2.47	19.45	13.8	27.12	26.46	6.81	0.69	1.02	1.92	2.94	2.75	5.26	0	0	1.23	1.45	1.57	2.42	1.45	1.57	2.81	3.43	4.59	7.08
C105	68.52	16.92	0.44	0	1.6	20.05	13.68	25.6	21.49	7.85	0	0.41	2.34	0.76	1.41	1.02	0	0	1.6	0	0	0	0	1.73	2.79	1.93	2.72	2.3
C106	47.45	13.47	2.14	0	3.94	20.73	17.11	27.76	25.8	9.16	1.99	2.37	3.42	3.58	5.66	4.15	1.28	0	2.14	2.01	4.14	3.82	2.61	3.27	4.41	4.78	7.43	5.03
C107	114.94	21.69	0.37	0	1.65	17.48	14.58	19.36	18.55	14.59	0.04	0.37	1.11	2.96	2.85	5.19	0	0	0.18	1.65	1.65	3.65	0.18	1.65	1.65	6.48	4.74	11.36
C108	60.24	12.21	0.64	0	1.37	15.18	8.67	18.14	11.59	5.29	0.06	0.32	0.64	2.13	3.1	7.52	0	0.03	0.03	0.49	0.03	3.91	0.28	0.69	2.28	3.62	5.99	9.22
C109	71.32	10.88	0.64	0.4	1.18	12.51	9.28	15.47	18.7	8.67	0.01	0.08	0.32	0.5	1.48	2.87	0	0	0.06	0.06	0.52	1.18	0.06	0.27	0.52	0.64	2.52	4.94
C201	55.78	7.45	1.29	0.57	2.02	17.14	11.05	20.36	23.46	13.14	0.16	0.69	1.52	1.96	3.83	5.49	0	0	0.31	0	2.3	2.19	0.66	1.49	2.54	4.55	4.53	7.45
C202	36.04	10.18	0.67	0.35	1.12	9.51	6.72	11.5	26.14	12.66	0.21	0.21	0.72	1.05	2.62	3.58	0	0	0.5	0.5	1.48	0.99	0.52	0.5	1.05	1.78	4.02	7
C203	52.45	13.55	0.16	0	0.3	22.59	20.04	28.57	29.75	15.48	0.12	0.07	0.26	3.24	5.1	6.55	0	0	0.13	0.18	3.79	5.26	0.17	0.17	0.65	7.04	7.54	8.02
C204	78.85	17.66	2.62	0	5.18	21.52	12.81	26.95	23.38	10.38	1.95	2.57	3.14	3.75	4.83	5.52	0	1.69	0	2.53	2.63	3.16	3.47	4.09	4.43	5.7	6.42	7.17
C205	48.17	21.91	0.48	0	1.49	18.3	14.91	22.08	31.98	22.1	0.05	0.28	0.93	1.86	3.61	9.14	0	0	0	0.64	0.87	4.9	0.12	0.42	1.79	3.3	7.69	14.39
C206	37.7	3.03	1.4	1.04	1.56	9.97	6.57	15.83	18.97	10.05	0.84	0.56	1.39	1.22	1.49	1.62	0.32	0	1.1	0.18	1.2	1.47	1.49	1.26	1.85	1.78	1.74	1.8
C207	55.01	9.91	0.76	0	1.81	15.13	10.54	19.58	27.48	8.55	0.09	0.2	0.42	0.65	1.91	2.95	0	0	0.27	0.44	0.44	0	0.44	0.44	0.64	1.48	4.92	5
C208	36.27	10.35	0.09	0	0.41	14.86	10.43	19.64	31.73	14.56	0	0	0.41	2.6	2.71	5.32	0	0	0	0	0	4.33	0	0	1.97	5.89	5.4	6.54
R101	63.37	21.06	0.46	0.17	0.82	25.97	16.13	31.24	23.15	23.15	0.36	0.33	1.37	2.25	2.17	9.49	0.17	0.02	1	0.98	0	5.37	0.65	0.76	2.07	2.67	4.53	13.49
R102	37.4	17.37	0.04	0	0.18	17.83	15.04	20.56	30.46	3.81	0	0	0	0.75	2.36	5.19	0	0	0	0	0.35	0.05	0	0	0	1.83	5.19	10
R103	64.84	24.93	1.15	0.51	2.1	21.45	8.75	32.51	5.95	5.95	0	0.01	0.72	2.2	2.39	2.88	0	0	0	1.37	0	0.3	0.02	0.04	1.67	3.13	5.22	5.29
R104	45.81	10.77	1.04	0	2.4	12.77	8.77	17.77	15.76	9.32	0.84	0.76	1.9	2.61	2.74	8.13	0.24	0.24	1.22	1.44	2	5.05	1.84	1.05	2.59	3.67	3.72	10.77
R105	37.77	5.08	0.76	0	1.82	13.91	11.11	15.63	12.32	9.72	0	0.06	1.21	2.87	1.87	2.97	0	0	0.01	1.83	0	2.18	0.01	0.28	2.53	3.39	3.68	3.68
R106	57.5	16.74	1.48	0	2.89	20.42	15.1	22.8	21.59	18.77	2.08	2.46	3.79	4.54	3.65	10.25	0	1.86	2.52	3.53	2.95	7.68	2.74	3.12	4.47	5.37	4.71	11.55
R107	31.44	7.11	0	0	0.01	11.61	7.54	13.83	19.68	15.82	0	0	0	0.76	1.05	4.77	0	0	0	0	0	4.19	0	0	0	1.69	3.49	5.73
R108	79.13	13.49	0.97	0.22	1.54	20.31	14.92	24.11	15.71	9.38	0.06	0.59	1.19	2.02	2.61	3.5	0	0	0.3	0.48	1.66	1.41	0.22	0.9	2.16	4.91	3.27	6.58
R109	59.74	6.04	0.48	0	1.41	15.2	11.49	18.9	29.57	11.82	0	0.03	0.81	1.76	1.79	4.24	0	0	0.14	0.79	0.28	2.74	0	0.14	1.67	2.64	3.48	6.04
R110	33.56	7.67	1.22	0.59	1.87	12.35	10.03	13.71	8.41	6.85	0.33	0.67	1.56	2.98	3.88	5.25	0	0.23	0.38	1.87	2.08	4.12	0.58	1.21	2.71	5.77	5.82	6.06
R111	57.76	16.25	0.7	0.54	1.14	15.08	12.11	17.19	20.68	19.38	0.26	0.44	1.25	1.33	2.72	4.99	0	0.01	0.54	0.01	0	3.41	0.75	0.75	2.49	2.59	5.44	7.83
R112	58.81	9.42	0.64	0	1.09	13.03	10.33	14.8	18.71	10.04	0.3	0.4	0.79	1.21	1.11	1.08	0	0	0	0.6	0.1	0.5	0.89	0.89	1.05	1.72	1.75	2.09
R201	42.21	10.11	0.83	0	1.43	16.29	12.99	19.89	10.31	4.69	0.3	0.5	1.57	1.99	2.5	3.82	0	0	1.14	1.14	1.38	0.98	1.08	1.35	1.92	3.27	4.26	7.61
R202	49.88	14.51	1.1	0.58	1.94	16.33	12.78	20.72	21.99	20.62	0.92	1.05	1.91	5.06	4.71	6.64	0.09	0	0.92	2.95	2.79	4.48	1.27	1.68	2.93	7.12	7.29	8.17
R203	57.09	10.6	0.79	0.01	1.64	21.3	14.49	30.22	25.77	11.36	0.46	0.52	1.96	2.71	2.88	2.91	0	0	1.24	2.01	1.06	1.13	0.96	1.69	2.72	3.37	4.02	4.17
R204	45.4	7.75	1.38	0.1	2.09	12.66	10.33	16.02	16.06	13.94	0.25	0.47	1.7	3.11	3.2	3.47	0	0	0.1	1.97	2.45	2.06	0.62	1.96	3.07	4.35	3.92	4.35
R205	74.85	24.4	0.61	0	2.39	14.6	12.22	17.29	14.94	12.05	0.1	0.07	2.04	3.4	7.57	14.97	0	0	0.08	0.13	3.87	12.63	0.25	0.23	4.64	7.03	13.63	18.83
R206	41.99	17.81	0.58	0	1.54	18.97	11.8	25.58	22.39	19.91	0.12	0.09	1	2.26	2.53	5.32	0	0	0	0.2	0.2	2.98	0.2	0.43	1.98	5.67	6.22	7.8
R207	35.33	8.33	0.41	0.01	0.94	11.92	10.21	14.14	29.65	10.37	0.01	0.08	1.4	1.17	0.97	1.45	0	0	0.27	0.56	0.55	0.69	0.01	0.28	2.05	2.44	1.56	2.68
R208	66.79	13.46	1.59	0.13	3.59	26.23	22.5	32.38	18.51	17.79	0.2	0.2	1.87	4.89	5.49	10.16	0	0	0	3.31	3.17	8.92	0.72	0.71	4.67	6.23	6.73	11.52
R209	51.69	16.61	0.69	0.63	0.9	20.05	13.43	23.6	24.23	14.97	0.37	0.38	0.68	3.6	2.16	6.59	0	0	0.59	0.9	0.9	3.86	0.63	0.63	0.9	7.1	4.43	7.38
R210	61.26	15.77	0.26	0	0.53	21.87	16.2	27.54	20.58	8.53	0	0.07	0.85	3	2.93	10.69	0	0	0	0	0.92	5.96	0	0.34	1.77	5.37	7.69	13.49
R211	43.51	18.54	0.61	0	0.88	16.25	8.22	20.58	10.7	10.7	0.1	0.26	0.61	1.55	3.17	6.68	0	0	0	0.76	0.76	1.65	0.5	0.81	1.25	2.53	6.22	13.28
RC101	36.41	2.85	0.59	0.21	0.74	6.3	5.37	7.41	5.83	1.76	0.18	0.4	0.59	1.6	0.88	1.49	0	0.21	0.21	0	0	0.21	0.5	0.68	0.93	2.85	2.27	2.39
RC102	63.49	17.84	0.07	0	0.34	7.18	5.07	13.16	4.86	3.36	0	0	0.19	2.34	1.53	4.8	0	0	0	0	0.76	2.84	0	0	0.49	4.58	2.33	9.15
RC103	49.37	16.82	0.82	0.09	1.33	5.66	4.65	7.1	5.31	3.76	0.31	0.46	1.15	2.18	1.75	2.86	0	0.09	0.93	0.88	0.59	1.28	0.88	0.81	1.5	4.07	3.26	4.58
RC104	61.19	16.9	0.28	0.14	0.48	7.89	2.95	10.9	18.12	2.38	0.13	0.1	0.44	3.12	3.22	7.54	0.12	0	0.14	0.47	0.56	6.98	0.15	0.15	0.79	7.01	7.01	7.78
RC105	41.61	7.82	0	0	0	8.81	4.61	13.06	12.48	9.88	0	0	0	0.13	4.11	7.14	0	0	0	0	0	6.85	0	0	0	0.63	6.85	7.77
RC106	58.69	26.6	0.21	0	1.07	9.07	4.27	14.66	21.77	15.38	0	0	0.16	1.99	4.72	8.5	0	0	0	0	0.82	7.5	0	0	0.67	4.02	7.32	10
RC107	46.93	9.05	0	0	0	7.82	6.83	8.93	6.88	4.16	0	0	0.63	1.34	1.36	1.62	0	0	0	0	0	0	0	0	1.67	1.86	1.86	2.31
RC108	36.4	8.9	1.25	1.1	1.64	10.94	5.39	13.96	7.67	5.76	0.67	0.92	2.06	2.19	2.64	3.46	0	0	1.64	2.07	2.23	2.07	1.14	1.22	2.42	2.68	3.27	8.22
RC201	40.09	9.06	1.09	0.43	2.09	11.69	7.62	16.49	14.25	5.23	0.05	0.51	0.92	2.13	2.8	2.8	0	0	0	0.43	1.86	2.22	0.23	1.48	2.09	2.89	3.92	3.27
RC202	60.96	10.15	0.52	0	1.54	12.69	8.53	17.59	5.21	4.61	0.26	0.58	1.08	1.67	0.92	1.5	0	0.35	0	0.15	0	0	0.61	1.23	1.62	3.97	2.1	3.49
RC203	47.67	12.57	0	0	0	9.45	7.55	11.93	31.86	15.17	0	0.17	0	1.01	2.13	4.71	0	0	0	0	0	0	0	0.87	0	4.16	5.39	9.64
RC204	58.13	8.14	0.86	0.45	1.72	10.99	7.26	14.43	12.59	9.49	0.45	0.27	0.71	3.71	2.47	4.14	0.45	0	0.45	2.86	1.72	1.9	0.45	0.45	1.72	5.4	3.95	5.4
RC205	58.59	14.3	2.51	1.85	2.76	8.88	6.39	11.89	13.43	4.22	0.16	0.71	2.54	3.26	3.64	6.28	0	0	1.6	2.49	2.8	1.84	0.75	1.84	3.3	4.21	5.04	8.44
RC206	44.7	13.64	0.33	0	1.66	10.61	6.33	12.71	13.17	6.55	0	0	0.04	1.06	1.14	0.32	0	0	0	0	0	0	0	0	0.13	1.94	1.97	1.58
RC207	25.95	8.02	0.57	0	0.94	4.72	3.37	6.16	17.97	1.87	0.04	0.19	0.76	2.61	1.97	3.92	0	0	0	0.84	0.84	3.62	0.22	0.73	1.29	3.62	3.62	4.36
RC208	44.4	1.36	0	0	0	8.94	5.23	13.67	7.95	7.95	0	0	0	0	0.1	0.13	0	0	0	0	0	0	0	0	0	0	0.47	0.62
mean	53.05	12.41	0.76	0.23	1.45	14.56	10.33	18.66	18.17	10.51	0.29	0.42	1.11	2.17	2.68	4.86	0.05	0.08	0.43	0.88	1.13	2.87	0.57	0.85	1.83	3.7	4.58	6.93

Table 8: Gaps to BKS in percent % for the instances based on Solomon (1987) with $n = 50$ shipments.

			LNS			LNS-noLS			OR Tools	
Instance	PI	LS	mean	min	max	mean	min	max	PCI	TS
C101	54.78	17.41	2.24	0	4.1	34.27	30.86	36.56	29.43	22.62
C102	85.47	16.23	3.03	0	4.5	49.5	46.53	52.5	17.17	16.31
C103	68.93	11.58	0.53	0	0.98	32.83	26.66	38.34	10.64	10.64
C104	81.92	9.82	1.54	0	3.14	39.11	34.52	42.71	41.4	25.33
C105	69.53	25.21	1.3	0	2.15	38.78	35.57	46.73	28.38	12.37
C106	69.46	26.98	1.71	0	3.19	40.53	37.57	44.67	24.45	13.21
C107	69.71	21.8	1.83	0	2.73	40.6	34.97	45.06	26.19	16.38
C108	69.5	16.01	1.7	0	3.82	36.51	34.83	37.33	26.55	14.43
C109	58.14	13.63	2.01	0	3.89	35.89	33.12	39.2	24.28	16.23
C201	63.06	17.7	0.83	0	3.14	41.12	37.2	47.78	17.45	16.71
C202	56.34	30.37	1.82	0	3.48	34.18	32.34	36.17	27.92	20.38
C203	53.15	14.16	1.17	0	3.28	23.65	20.46	25.9	9.3	7.53
C204	73.11	17.54	0.65	0	1.54	26.08	23.89	27.78	12.64	8.06
C205	60.64	10.12	0.72	0	1.07	25.51	22.2	27.94	18.61	9.72
C206	61.57	15.15	1	0	2.12	31.62	26.95	34.55	15.64	15.16
C207	41.83	17.76	0.76	0	2.13	22.63	20.16	26.14	17.64	16.96
C208	55.59	7.28	0.8	0	1.57	28.77	25.87	32.31	26.33	19.35
R101	34.67	8.4	0.92	0	1.28	20	16.43	24.4	13.28	13.28
R102	44.64	10.12	0.78	0	1.66	22.94	20.44	24.51	13.53	9.94
R103	46.13	12.45	0.86	0	1.91	34.05	32.32	36.89	21.32	16.08
R104	65.26	14.81	0.83	0	1.92	28.81	23.44	34.71	20.43	12.52
R105	53.38	8.12	0.48	0	1.15	23.19	21.78	24.73	16.99	14.1
R106	85.5	11.2	0.97	0	2.59	42.76	38.68	46.62	25.33	23.2
R107	52.08	22.67	2.29	0	3.53	34.42	25.29	41.81	30.91	21.69
R108	53	7.94	0.67	0	1.31	29.86	23.57	32.96	18.99	14.66
R109	57	13.02	0.84	0	2.58	27.8	24.35	29.61	26.12	12.16
R110	68.3	17.36	0.8	0	1.44	25.08	20.97	28.23	18.61	11.63
R111	62.04	14.89	0.51	0	0.94	31.06	28.22	34.42	16.37	14.98
R112	41.79	12.94	0.35	0	1.14	25.52	19.73	29.45	10.75	9.67
R201	50.04	16.18	2.06	0	4.49	34.47	29.91	37.17	25.61	22.81
R202	53.93	15.31	0.58	0	2.09	26.82	24.6	28.06	19.68	10.94
R203	68.75	12.33	1.5	0	2.43	35.09	30.26	41.8	19.88	15.71
R204	52.27	12.57	0.65	0	2	26.5	18.02	31.34	21.91	17.22
R205	55.31	11.68	1.15	0	1.78	26.88	23.58	30.44	17.08	10.48
R206	60.67	8.79	0.54	0	1.06	38.04	32.46	40.31	23.88	7.52
R207	72.9	14.7	0.81	0	1.32	33.32	28.43	36.46	15.38	14.15
R208	56.84	12.31	0.82	0	1.54	26.4	22.35	29.72	11.61	11.42
R209	61.42	4.71	0.65	0	1.71	32.91	27.51	37.89	17.9	17.9
R210	45.3	6.81	0.58	0	1.47	16.83	15.03	18.65	12.58	4.06
R211	57.61	17.67	0.61	0	1.03	26.53	21.3	30.95	20	19.83
RC101	52.16	11.45	0.78	0	1.59	24.68	19.93	28.35	16.7	9.01
RC102	46.06	17.83	0.49	0	0.84	34.09	30.44	38.08	28.56	25.86
RC103	70.12	13.06	0.76	0	1.34	22.37	18.21	27.42	18.8	17.93
RC104	63.99	24.78	0.67	0	1.27	29.77	26.09	33.04	14.5	14.5
RC105	77.5	9.92	2.23	0	3.38	38.61	35.06	42.67	20.54	14.61
RC106	57.28	16.11	0.46	0	0.85	32.79	28.98	35.8	10.59	9.99
RC107	41.97	9.81	1.3	0	1.97	24.7	23.08	26.62	22.71	16.86
RC108	43.94	20.56	0.31	0	0.73	21.07	13.22	27.06	23.4	11.93
RC201	42	20.69	0.51	0	1.04	21.16	19.2	23.52	16.06	15.5
RC202	44.48	19.14	1.5	0	2.41	24.66	19	28.29	20.68	17.07
RC203	47.52	13.65	2.05	0	3.15	21.73	19.87	25.1	12.76	12.76
RC204	71.47	15.2	0.95	0	1.88	37.18	31.22	41.38	15.72	13.11
RC205	54.78	13.74	0.35	0	0.78	28.39	25.14	33.87	15.73	15.73
RC206	45.58	10.15	1.32	0	2	27.46	22.87	30.39	10.2	10.2
RC207	46.11	6.09	0.86	0	1.88	28.88	21.87	33.08	23.75	11.8
RC208	55.2	9.1	1.17	0	2.4	28.71	23.47	34.13	17.01	15.47
mean	58.07	14.41	1.06	0	2.08	30.31	26.25	33.96	19.64	14.64

(a) based on Solomon (1987) with $n = 100$ shipments.

			LNS			LNS-noLS			OR Tools	
Instance	PI	LS	mean	min	max	mean	min	max	PCI	TS
c1-2-1	83.61	13.39	1.5	0	2.1	48.83	45.14	50.67	21.55	21.55
c1-2-2	76.67	16.09	0.47	0	1.28	37.76	34.62	42.12	15.86	13.11
c1-2-3	78.05	12.18	0.75	0	1.67	33.98	32.28	36.91	19.25	19.25
c1-2-4	74.9	8.65	1.38	0	2.28	40.92	32.99	49.85	18.01	11.69
c1-2-5	73.16	9.15	0.27	0	0.75	37.28	32.16	42.46	16.39	11.99
c1-2-6	88.32	14.5	1.53	0	2.72	43.25	37.87	46.98	15.87	9
c1-2-7	78.84	15.76	0.7	0	1.2	36.16	33.68	38.5	15.45	15.45
c1-2-8	66.67	14.06	0.77	0	1.59	40.41	33.04	47.96	17.09	13.38
c1-2-9	59.09	13.58	0.56	0	0.89	41.89	31.34	50.02	19.4	14.11
c1-2-10	91.32	17.54	1.86	0	3.24	40.25	37.25	44.73	15.08	15.01
c2-2-1	77.17	20	2.32	0	3.51	49.51	47.04	51.73	20.33	19.84
c2-2-2	65.98	14.15	0.87	0	1.98	42.86	37.47	47.18	22.58	16.95
c2-2-3	47.69	10.7	1.25	0	2.33	37.95	36.59	39.95	27.17	27.17
c2-2-4	58.1	11.52	0.61	0	1.32	40.48	38.35	43.68	16.41	14.66
c2-2-5	91.55	11.29	0.65	0	1.28	44.63	42.62	48.42	26.24	26.24
c2-2-6	61.45	11.01	1.65	0	2.8	41.89	34.66	49.69	17.59	13.17
c2-2-7	71	17.54	2.12	0	3.4	45.92	43.1	48.37	21.07	15.07
c2-2-8	57.95	13	1.57	0	2.58	36.67	33.5	39.94	19.64	15.97
c2-2-9	54.66	14.37	0.59	0	1.1	32.55	29.42	39.66	10.64	5.44
c2-2-10	72.26	16.13	1.54	0	2.64	47.55	46.03	49.45	17	13.64
r1-2-1	74.82	17.34	0.78	0	1.69	41.09	38.94	42.83	13.52	11.67
r1-2-2	70.53	16.33	1.6	0	3.41	39.86	35.27	42.65	19.92	18.33
r1-2-3	60.3	8.54	0.85	0	1.52	32	30.03	35.55	12.7	10.61
r1-2-4	74.95	15.47	0.69	0	1.42	39.93	37.62	42.91	14.84	13.27
r1-2-5	71.02	13.87	1.09	0	2.02	35.51	30.19	39.55	12.07	12.02
r1-2-6	58.41	12.15	1.38	0	2.11	32.29	29.39	35.89	21.11	21.11
r1-2-7	73.54	20.11	1.35	0	1.96	40.7	38.45	42.36	15.98	14.85
r1-2-8	57.68	9.13	0.15	0	0.47	37.11	34.46	41.93	19.64	11.5
r1-2-9	44.87	13.96	0.66	0	1.3	34.28	31.46	36.55	18.01	17.36
r1-2-10	68.46	15.77	1.62	0	3.06	36.5	31.73	39.32	10.53	10.53
r2-2-1	59.52	16.53	0.83	0	1.96	29.34	27	31.57	18.34	16.39
r2-2-2	52.79	9.55	1.14	0	1.75	36.47	30	40.62	17.01	14.78
r2-2-3	73.01	13.59	0.32	0	0.71	31.02	26.37	38.43	17.12	17.12
r2-2-4	71.98	12.21	1.26	0	2.44	37	33.91	39.26	19.92	17.21
r2-2-5	48.11	10.29	0.36	0	0.79	32.23	29.95	35.2	13.63	5.7
r2-2-6	74.58	14.19	0.53	0	1.69	38.17	33.56	42.55	14.04	13.72
r2-2-7	72.86	13.32	0.85	0	1.76	39.97	37.21	42.85	20.52	20.3
r2-2-8	70.8	16.43	1.01	0	1.75	37.59	34.15	40.75	15.25	12.88
r2-2-9	58.76	13.32	0.72	0	1.18	35.39	30.5	38.47	19.27	19.27
r2-2-10	72.55	26.07	0.84	0	1.29	36.9	34.72	38.44	25.21	17.64
rc1-2-1	81.25	19.34	1.98	0	3.32	46.7	43.32	52.5	12.89	11.14
rc1-2-2	74.44	21.04	1.23	0	2.01	37.62	35.24	39.9	20.12	11.44
rc1-2-3	57.44	11.05	0.66	0	0.96	34.19	27.22	37.37	15.58	15.58
rc1-2-4	64.45	12.32	1.06	0	2.63	36.51	32.73	39.59	10.33	8.97
rc1-2-5	54.51	13	0.33	0	0.71	33.81	30.07	38.48	20.87	14.92
rc1-2-6	64.79	12.64	0.26	0	0.63	35.45	26.29	40.16	12.75	9.95
rc1-2-7	63.2	19.97	1	0	1.94	36.83	30.74	39.96	19.62	11.9
rc1-2-8	80.14	11.08	1.34	0	2.31	42.18	36.31	51.06	21.06	18.21
rc1-2-9	54.27	16.85	0.96	0	1.85	39.17	31.77	42.5	15.61	11.33
rc1-2-10	70.92	18.05	1.82	0	2.93	51.05	49.99	53.49	15.78	12.73
rc2-2-1	70.04	18.87	0.47	0	1.17	41.44	31.68	47.28	14.54	14.54
rc2-2-2	56.99	17.92	0.98	0	1.6	33.97	29.91	37.42	17.87	14.82
rc2-2-3	50.2	15.67	1.11	0	2.18	31.78	27.61	36.13	20.19	15.98
rc2-2-4	56.57	15.39	0.75	0	1.1	29.46	27.89	31.38	23.5	16.86
rc2-2-5	79.47	19.17	1.36	0	2.92	44.41	40.23	49.67	14.41	14.41
rc2-2-6	67.42	9.24	0.66	0	1.27	38.91	36.84	41.08	17.93	10.09
rc2-2-7	67.81	10.23	0.32	0	0.8	39.66	36.1	41.1	16.2	13.03
rc2-2-8	82.06	15.41	1.46	0	2.84	53.24	48.03	58.59	23.25	22.77
rc2-2-9	63.49	16.58	0.77	0	1.31	45.96	39.51	49.58	15.49	9.49
rc2-2-10	61.27	10.22	0.53	0	1.29	33.73	31.85	36.13	16.5	12.86
mean	67.65	14.45	1	0	1.84	38.84	34.79	42.66	17.6	14.67

(b) based on Gehring and Homberger (1999) with $n = 200$ shipments.

Table 9: Gaps to BKS in percent %.

Instance	Parallel Insertion (PI) objective value - ρ	Parallel Insertion (PI) comp. time [s]	Local Search (LS) objective value - ρ	Local Search (LS) comp. time [s]	LNS objective value - ρ mean	LNS objective value - ρ min	LNS c.t. of min [s]	LNS objective value - ρ max	LNS computation time in [s] mean	LNS computation time in [s] min	LNS computation time in [s] max	LNS-noLS objective value - ρ mean	LNS-noLS objective value - ρ min	LNS-noLS c.t. of min [s]	LNS-noLS objective value - ρ max	LNS-noLS computation time in [s] mean	LNS-noLS computation time in [s] min	LNS-noLS computation time in [s] max	OR Tools (PCI) objective value - ρ	OR Tools (PCI) comp. time [s]	OR Tools (TS) objective value - ρ
C101	3,718.36	0.05	2,451.76	0.07	2,250.17	2,239.41	12.4	2,265.42	9.66	7.92	12.4	2,635.34	2,498.11	1.24	2,876.71	1.39	1.24	1.77	2,801.47	2.74	2,778.85
C102	5,067.29	0	3,548.19	0.09	3,401.36	3,388.29	13.91	3,413.92	11.21	8.12	15.2	3,755.88	3,617.26	1.83	3,896.8	1.62	1.24	2.54	3,758.15	3.02	3,644.82
C103	4,070.48	0	2,518.38	0.06	2,392.42	2,389.4	14.17	2,397.77	11.96	8.27	14.17	2,702.71	2,643.98	3.39	2,803.85	2.05	1.27	3.39	2,588.11	3.12	2,532.68
C104	3,191.29	0	2,302.08	0.05	2,186.85	2,179.08	9.98	2,201.16	11.2	9.38	13.49	2,565.74	2,444.46	1.25	2,730.53	1.45	1.18	2.33	2,716.43	2.58	2,294.32
C105	4,002.81	0	2,777.18	0.04	2,385.62	2,375.28	7.81	2,413.17	13.98	7.17	34.33	2,851.63	2,700.21	1.5	2,983.25	1.45	1.24	2	2,885.81	4.06	2,561.85
C106	3,736.69	0	2,875.55	0.05	2,588.34	2,534.15	15.71	2,634.11	10.63	8.01	15.71	3,059.6	2,967.63	1.98	3,237.71	2.16	1.31	3.15	3,187.84	2.9	2,766.18
C107	4,530.83	0	2,565.16	0.06	2,115.7	2,108	17.72	2,142.79	11.71	8.88	17.72	2,476.52	2,415.42	2.59	2,516.09	1.94	1.32	2.59	2,498.94	3.79	2,415.63
C108	5,207.96	0	3,646.9	0.06	3,271	3,250.1	8.31	3,294.48	9.8	8.31	14.89	3,743.4	3,532.02	4.02	3,839.62	2.16	1.24	4.02	3,626.63	3.32	3,421.96
C109	5,046.96	0	3,266.38	0.05	2,964.64	2,957.79	10.41	2,980.57	10.6	7.68	14.71	3,314.36	3,219.09	1.31	3,401.57	1.32	1.22	1.47	3,496.64	3.36	3,201.29
C201	4,500.33	0	3,104.28	0.05	2,926.17	2,905.5	8.03	2,947.41	10.74	7.89	16.19	3,384.06	3,208.04	1.99	3,477.18	1.77	1.26	2.56	3,566.71	2.73	3,268.53
C202	4,913.45	0	3,979.33	0.04	3,635.99	3,624.55	13.12	3,652.26	13.32	9.91	19.24	3,955.41	3,854.32	1.61	4,027.08	1.78	1.28	2.41	4,556.05	3.16	4,068.98
C203	3,783.99	0	2,818.48	0.05	2,486.11	2,482.1	11.7	2,489.48	11.87	8.61	15.43	3,042.91	2,979.63	1.28	3,191.34	1.34	1.28	1.44	3,220.59	3.5	2,866.44
C204	4,649.12	0	3,058.59	0.06	2,667.44	2,599.42	9.02	2,734.1	14.69	9.02	23.6	3,158.81	2,932.38	1.61	3,299.95	1.95	1.38	2.65	3,207.26	4.38	2,869.19
C205	3,953.95	0	3,253.08	0.04	2,681.18	2,668.49	8.74	2,708.18	14.51	7.94	30.87	3,156.7	3,066.32	1.99	3,257.68	1.79	1.34	2.17	3,521.75	3.93	3,258.27
C206	4,374.4	0	3,272.9	0.05	3,221.07	3,209.85	11.1	3,226.2	9.35	7.33	11.84	3,493.35	3,385.27	1.27	3,679.57	1.26	1.25	1.27	3,779.13	3.37	3,495.83
C207	4,893.82	0	3,470.11	0.06	3,181.02	3,157.15	14.72	3,214.14	11.99	9.47	14.72	3,634.97	3,490.03	1.28	3,775.33	1.53	1.28	1.85	4,024.77	2.53	3,427.06
C208	4,552.96	0	3,686.91	0.04	3,344.04	3,341.09	10.42	3,354.88	10.86	8.45	17.03	3,837.55	3,689.64	2.68	3,997.35	1.53	1.21	2.68	4,401.12	3.08	3,827.43
R101	4,807.96	0	3,562.61	0.05	2,956.53	2,947.99	20.57	2,967.07	18.91	10.51	29.66	3,707.29	3,417.62	1.62	3,862.21	1.68	1.28	2.15	3,624.14	3.13	3,624.14
R102	5,710.49	0	4,877.97	0.05	4,157.64	4,156.17	13.45	4,163.53	12.01	9.3	15.46	4,897.06	4,781.33	1.44	5,010.51	1.68	1.24	3.24	5,422.12	2.62	4,314.52
R103	4,307.12	0	3,264.26	0.04	2,642.93	2,626.22	13.3	2,667.81	14.46	10.98	20.31	3,173.3	2,841.59	1.48	3,462.34	1.7	1.31	2.35	2,768.48	4.21	2,768.48
R104	5,895.99	0	4,478.92	0.06	4,085.68	4,043.55	15.86	4,140.47	13.61	9.6	17.63	4,560.1	4,398.21	1.73	4,762.03	1.58	1.35	1.88	4,680.74	2.93	4,420.56
R105	6,026.61	0	4,596.48	0.07	4,407.4	4,374.29	9.81	4,453.91	13.13	9.81	19.6	4,982.56	4,860.17	1.32	5,057.89	1.4	1.31	1.65	4,913.22	3.73	4,799.65
R106	5,838.71	0	4,327.67	0.07	3,761.87	3,707.1	10.76	3,814.38	16.13	9.83	29.07	4,464.06	4,266.77	3.25	4,552.3	2.27	1.27	3.25	4,507.34	3.05	4,403.1
R107	4,734.1	0	3,857.93	0.05	3,601.87	3,601.81	9.47	3,602.09	12.98	9.47	16.72	4,019.86	3,873.32	2	4,100.04	1.86	1.25	2.65	4,310.73	3.29	4,171.79
R108	4,560.88	0	2,889.67	0.07	2,570.83	2,551.66	21.16	2,585.28	13.57	9.95	21.16	3,063.19	2,926.08	1.52	3,160.1	1.39	1.27	1.52	2,946.13	2.8	2,784.83
R109	4,567.11	0	3,031.74	0.06	2,872.89	2,859.15	9.41	2,899.33	11.11	9.41	13.54	3,293.87	3,187.6	1.54	3,399.42	1.5	1.25	2.16	3,704.62	2.52	3,196.96
R110	5,950.39	0	4,797.04	0.06	4,509.6	4,481.33	15.8	4,538.66	14.98	11.77	21.39	5,005.39	4,901.91	1.29	5,065.75	1.32	1.23	1.42	4,829.82	3.79	4,760.53
R111	5,558.97	0	4,096.28	0.04	3,548.36	3,542.63	10.57	3,563.92	10.92	8.56	12.94	4,054.99	3,950.44	1.27	4,129.33	1.47	1.27	1.8	4,252.56	3.92	4,206.52
R112	6,829.97	0	4,705.68	0.06	4,328.05	4,300.64	25.64	4,347.52	14.53	9.02	25.64	4,860.95	4,744.69	2.14	4,937.29	1.58	1.33	2.14	5,105.34	2.98	4,732.39
R201	6,147.3	0	4,759.7	0.04	4,358.62	4,322.62	20.84	4,384.54	14.86	9.18	20.84	5,026.69	4,883.92	1.38	5,182.58	1.78	1.38	2.29	4,768.38	2.48	4,525.32
R202	5,489.29	0	4,193.87	0.05	3,702.85	3,683.55	13.17	3,733.39	17.26	13.17	23.16	4,260.57	4,130.43	1.78	4,421.21	1.52	1.25	1.78	4,467.73	2.63	4,417.63
R203	5,022.7	0	3,536.22	0.06	3,222.78	3,197.81	9.44	3,249.73	14.44	8.09	22.48	3,878.57	3,660.75	1.32	4,163.72	1.77	1.32	2.49	4,021.29	3.13	3,560.56
R204	6,355.22	0	4,709.62	0.06	4,430.88	4,375.03	25.73	4,462.21	16.84	8.02	25.73	4,924.14	4,822.39	1.54	5,070.97	1.39	1.25	1.59	5,072.68	3.48	4,980.26
R205	6,270.6	0	4,461.38	0.07	3,608	3,586.23	14.14	3,672.05	13	9.78	17.41	4,109.93	4,024.57	1.8	4,206.39	2.62	1.64	5.93	4,122.1	3.35	4,018.41
R206	4,903.35	0.01	4,068.46	0.03	3,473.47	3,453.36	18.75	3,506.46	17.4	9.81	26.53	4,108.48	3,860.77	1.32	4,336.65	1.89	1.29	2.57	4,226.46	3.19	4,140.91
R207	6,078.86	0	4,865.86	0.05	4,510.42	4,492.41	17.61	4,534.04	15.17	8.43	21.45	5,027.47	4,950.6	2.04	5,126.93	1.65	1.31	2.07	5,823.75	2.75	4,957.76
R208	4,660.47	0	3,170.2	0.07	2,838.52	2,798	14.06	2,894.59	20.52	13.56	39.58	3,527.06	3,423.07	1.34	3,699.06	1.46	1.27	2.01	3,311.56	3.16	3,291.35
R209	5,554.4	0	4,269.82	0.05	3,686.85	3,684.86	10.62	3,694.79	10.5	9.52	11.21	4,395.78	4,153.51	1.88	4,525.86	1.45	1.26	1.88	4,549.01	4.43	4,209.85
R210	4,349.19	0	3,122.25	0.08	2,704.14	2,697.05	8.6	2,711.26	14.03	8.6	22.03	3,286.96	3,133.94	1.25	3,439.7	1.52	1.25	2.22	3,252	3.51	2,927.18
R211	5,061.37	0	4,180.69	0.05	3,548.58	3,526.96	18.29	3,558.05	13.2	9.13	18.29	4,099.95	3,816.83	1.31	4,252.71	1.49	1.27	2.16	3,904.2	2.85	3,904.2
RC101	5,042.75	0	3,802.04	0.04	3,718.47	3,704.36	6.91	3,724.01	8.06	6.26	10.47	3,929.62	3,895.33	1.28	3,970.64	1.27	1.21	1.33	3,912.23	1.97	3,761.73
RC102	6,802.46	0	4,903.04	0.06	4,163.53	4,160.7	6.85	4,174.84	8.89	6.85	12.8	4,459.24	4,371.84	2.41	4,708.05	2.11	1.26	2.94	4,363.05	2.31	4,300.54
RC103	5,807.63	0	4,542.03	0.03	3,919.97	3,891.66	14.72	3,939.61	9.3	5.31	14.72	4,108.17	4,068.86	1.33	4,164.32	1.41	1.27	1.67	4,094.66	2.72	4,034.45
RC104	6,143.64	0	4,455.68	0.04	3,822.06	3,817	12.32	3,829.65	7.94	5.32	12.32	4,112.44	3,924.01	2.16	4,227.04	2.07	1.33	3.16	4,502.27	1.92	3,902.36
RC105	5,930.17	0	4,515.32	0.03	4,187.82	4,187.82	5.95	4,187.82	6.03	5.38	6.61	4,556.95	4,381.08	2.42	4,734.73	1.7	1.4	2.42	4,710.5	2.07	4,601.43
RC106	6,403.27	0	5,108.66	0.04	4,043.81	4,035.2	10.25	4,078.27	7.94	5.73	11.7	4,401.17	4,207.57	1.5	4,626.93	1.68	1.36	2.27	4,913.69	1.4	4,655.89
RC107	7,442.17	0	5,523.38	0.04	5,065.02	5,065.02	11.79	5,065.02	8.52	5.43	11.79	5,460.87	5,411.2	1.2	5,517.44	1.76	1.2	2.53	5,413.59	1.83	5,275.48
RC108	4,448.28	0	3,551.55	0.02	3,301.99	3,297.16	6.43	3,314.9	7.12	5.91	9.99	3,618.12	3,437.05	1.25	3,716.5	1.75	1.25	2.28	3,511.38	2.58	3,449.15
RC201	5,127.61	0	3,991.98	0.04	3,700.33	3,676.21	8.72	3,736.95	9.69	5.6	14.74	4,088.12	3,939.29	1.21	4,263.77	1.74	1.21	2.97	4,181.88	2.89	3,851.8
RC202	5,745	0	3,931.67	0.03	3,587.93	3,569.29	5.51	3,624.25	6.41	5.2	7.32	4,022.24	3,873.79	1.22	4,196.97	1.49	1.22	2.24	3,755.41	2.6	3,733.77
RC203	6,309.34	0	4,809.89	0.03	4,272.64	4,272.64	7.7	4,272.64	6.82	4.7	9.14	4,676.57	4,595.31	1.63	4,782.45	1.44	1.26	1.63	5,633.75	2.79	4,920.99
RC204	6,703.31	0	4,583.96	0.05	4,275.38	4,258.29	10.74	4,311.81	8.42	5.81	10.74	4,704.95	4,546.68	2.46	4,850.95	1.87	1.22	3.11	4,772.69	2.71	4,641.17
RC205	6,395.05	0	4,609.16	0.02	4,133.67	4,107.28	7.21	4,143.87	7.86	5.5	10.55	4,390.56	4,290.01	2.19	4,512.14	2.08	1.46	3.31	4,574.14	2.66	4,202.58
RC206	5,931.22	0	4,658.16	0.03	4,112.64	4,099.06	5.59	4,166.98	5.7	5.13	7.12	4,534.02	4,358.65	1.2	4,619.93	1.47	1.19	1.94	4,638.82	2.36	4,367.46
RC207	5,228.76	0	4,484.44	0.03	4,175.09	4,151.4	12.06	4,190.55	13.57	5.81	31.33	4,347.16	4,291.4	1.26	4,406.97	1.39	1.26	1.66	4,897.24	2.17	4,229.06
RC208	6,847.38	0	4,806.68	0.04	4,742.24	4,742.1	12.16	4,742.33	7.46	5.62	12.16	5,166.24	4,989.94	1.28	5,390.18	1.63	1.22	2.58	5,118.98	2.48	5,118.98
mean	5,271.14	0	3,905.31	0.05	3,508.04	3,490.27	12.31	3,530.69	11.81	8.17	17.62	3,965.6	3,825.65	1.72	4,100.1	1.67	1.28	2.35	4,096.72	2.98	3,836.84

Table 10: Detailed results of the objective value and computation time for the instances of Solomon (1987) with $n = 50$ shipments.

Instance	acceptance criterion - LNS mean						acceptance criterion - LNS min						acceptance criterion - LNS max					
	0	1	10	50	100	∞	0	1	10	50	100	∞	0	1	10	50	100	∞
C101	2,240.11	2,241.99	2,250.44	2,264.09	2,272.33	2,289.92	2,239.41	2,239.41	2,239.41	2,249.66	2,262.07	2,270.76	2,242.92	2,245.86	2,260.83	2,282.04	2,290.48	2,323.47
C102	3,374.79	3,373.28	3,397.55	3,421.16	3,435.12	3,442.46	3,351.34	3,351.34	3,388.29	3,407.11	3,409.2	3,388.29	3,388.29	3,388.29	3,413.67	3,434.02	3,480.24	3,494.54
C103	2,387.58	2,386.55	2,388.74	2,412.27	2,410.59	2,487.88	2,386.37	2,386.37	2,386.37	2,388.9	2,388.9	2,413.46	2,389.4	2,386.82	2,392.07	2,447.3	2,458.11	2,518.38
C104	2,162.79	2,169.92	2,189.32	2,211.22	2,207.1	2,261.09	2,148.01	2,148.01	2,174.44	2,179.08	2,181.65	2,200.06	2,179.08	2,181.65	2,208.29	2,221.67	2,246.56	2,300.1
C105	2,375.28	2,384.91	2,430.76	2,393.4	2,408.69	2,399.5	2,375.28	2,375.28	2,413.17	2,375.28	2,375.28	2,375.28	2,375.28	2,416.32	2,441.57	2,421.08	2,439.87	2,430.02
C106	2,584.47	2,594.23	2,620.77	2,624.83	2,677.53	2,639.22	2,566.56	2,534.15	2,588.34	2,584.96	2,639.18	2,630.86	2,600.37	2,617.11	2,645.92	2,655.3	2,722.47	2,661.53
C107	2,108.74	2,115.7	2,131.42	2,170.45	2,168.07	2,217.41	2,108	2,108	2,111.69	2,142.79	2,142.79	2,184.91	2,111.69	2,142.79	2,142.79	2,244.61	2,208.02	2,347.4
C108	3,251.94	3,260.48	3,270.97	3,319.29	3,350.92	3,494.54	3,250.1	3,251.15	3,251.15	3,265.96	3,251.15	3,377.17	3,259.31	3,272.56	3,324.2	3,367.85	3,444.85	3,549.67
C109	2,946.29	2,948.07	2,955.33	2,960.6	2,989.52	3,030.3	2,945.86	2,945.86	2,947.7	2,947.7	2,961.3	2,980.57	2,947.7	2,953.7	2,961.3	2,964.8	3,020.1	3,091.45
C201	2,893.65	2,908.96	2,932.73	2,945.5	2,999.67	3,047.62	2,888.95	2,888.95	2,898.04	2,888.95	2,955.52	2,952.22	2,908.01	2,932	2,962.34	3,020.3	3,019.85	3,104.28
C202	3,619.5	3,619.45	3,637.96	3,649.74	3,706.23	3,741.04	3,611.78	3,611.78	3,629.75	3,629.75	3,665.16	3,647.39	3,630.74	3,629.75	3,649.63	3,676.13	3,756.93	3,864.59
C203	2,485.05	2,483.79	2,488.48	2,562.47	2,608.64	2,644.72	2,482.1	2,482.1	2,485.25	2,486.6	2,576.24	2,612.67	2,486.33	2,486.33	2,498.17	2,656.94	2,669.22	2,681.19
C204	2,650.11	2,666.26	2,681.1	2,696.8	2,725	2,742.91	2,599.42	2,643.44	2,599.42	2,665.12	2,667.73	2,681.44	2,689.67	2,705.83	2,714.46	2,747.59	2,766.34	2,785.81
C205	2,669.74	2,675.87	2,693.27	2,718.04	2,764.88	2,912.39	2,668.49	2,668.49	2,668.49	2,685.44	2,691.72	2,799.21	2,671.61	2,679.78	2,716.28	2,756.43	2,873.69	3,052.53
C206	3,203.21	3,194.58	3,220.84	3,215.58	3,224.03	3,228.1	3,186.9	3,176.67	3,211.59	3,182.42	3,214.68	3,223.32	3,223.89	3,216.58	3,235.52	3,233.14	3,231.85	3,233.95
C207	3,159.91	3,163.38	3,170.42	3,177.54	3,217.41	3,250.27	3,157.15	3,157.15	3,165.82	3,170.95	3,170.95	3,157.15	3,170.95	3,170.95	3,177.5	3,203.91	3,312.58	3,314.91
C208	3,341.09	3,341.09	3,354.65	3,427.84	3,431.65	3,518.94	3,341.09	3,341.09	3,341.09	3,341.09	3,341.09	3,485.9	3,341.09	3,341.09	3,406.99	3,537.89	3,521.56	3,559.53
R101	2,953.66	2,952.74	2,983.11	3,009.06	3,006.69	3,222.24	2,947.99	2,943.66	2,972.27	2,971.76	2,942.93	3,101.01	2,962.12	2,965.22	3,003.91	3,021.4	3,076.3	3,339.79
R102	4,156.17	4,156.17	4,156.17	4,187.31	4,254.33	4,371.83	4,156.17	4,156.17	4,156.17	4,156.17	4,170.53	4,158.25	4,156.17	4,156.17	4,156.17	4,232.11	4,371.86	4,571.9
R103	2,613.04	2,613.25	2,631.68	2,670.31	2,675.33	2,688.17	2,612.94	2,612.94	2,612.94	2,648.7	2,612.94	2,620.67	2,613.44	2,614.01	2,656.52	2,694.66	2,749.42	2,751.26
R104	4,077.35	4,074.45	4,120.35	4,149.29	4,154.45	4,372.16	4,053.36	4,053.36	4,092.74	4,101.78	4,124.27	4,247.71	4,117.86	4,085.95	4,148.32	4,192.02	4,194.16	4,478.92
R105	4,374.43	4,376.79	4,427.28	4,499.7	4,455.93	4,504.13	4,374.29	4,374.29	4,374.65	4,454.16	4,374.29	4,469.6	4,374.65	4,386.45	4,484.89	4,522.4	4,535.25	4,535.22
R106	3,784.34	3,798.14	3,847.63	3,875.33	3,842.5	4,087.19	3,707.1	3,776.23	3,800.65	3,837.86	3,816.41	3,991.97	3,808.66	3,822.64	3,872.91	3,906.03	3,881.72	4,135.45
R107	3,601.81	3,601.81	3,601.81	3,629.17	3,639.71	3,773.62	3,601.81	3,601.81	3,601.81	3,601.81	3,601.81	3,752.74	3,601.81	3,601.81	3,601.81	3,662.79	3,727.47	3,808.36
R108	2,547.68	2,561.19	2,576.33	2,597.65	2,612.67	2,635.21	2,546.12	2,546.12	2,553.7	2,558.25	2,588.51	2,581.9	2,551.66	2,568.93	2,601.11	2,671.07	2,629.27	2,713.56
R109	2,859.15	2,859.93	2,882.23	2,909.36	2,910.19	2,980.32	2,859.15	2,859.15	2,863.05	2,881.62	2,867.27	2,937.6	2,859.15	2,863.05	2,906.8	2,934.66	2,958.62	3,031.74
R110	4,469.88	4,485.16	4,524.48	4,587.81	4,628.21	4,689.25	4,455.16	4,465.3	4,472.06	4,538.66	4,547.85	4,638.68	4,481.08	4,508.92	4,576.08	4,712.18	4,714.35	4,725.1
R111	3,532.76	3,539.34	3,567.68	3,570.62	3,619.73	3,699.66	3,523.73	3,523.96	3,542.63	3,523.96	3,523.73	3,643.83	3,550	3,550	3,611.6	3,615.04	3,715.39	3,799.76
R112	4,313.72	4,317.76	4,334.7	4,352.73	4,348.53	4,346.87	4,300.64	4,300.64	4,300.64	4,326.39	4,304.95	4,322.22	4,338.89	4,338.77	4,345.86	4,374.59	4,375.91	4,390.31
R201	4,335.57	4,344.37	4,390.61	4,408.7	4,430.89	4,487.82	4,322.62	4,322.62	4,371.92	4,371.92	4,382.17	4,365.04	4,369.42	4,380.92	4,405.53	4,463.86	4,506.79	4,651.45
R202	3,695.97	3,700.68	3,732.47	3,847.69	3,835.06	3,905.74	3,665.72	3,662.39	3,696.21	3,770.38	3,764.69	3,826.35	3,709.03	3,723.75	3,769.83	3,922.97	3,929.38	3,961.67
R203	3,212.29	3,213.96	3,260.01	3,283.99	3,289.48	3,290.47	3,197.42	3,197.42	3,237.15	3,261.78	3,231.22	3,233.64	3,228.19	3,251.4	3,284.33	3,305.09	3,325.94	3,330.66
R204	4,381.56	4,391.3	4,445.26	4,506.86	4,510.79	4,522.53	4,370.77	4,370.77	4,375.03	4,457	4,477.68	4,460.84	4,397.91	4,456.58	4,504.77	4,561.07	4,542.14	4,560.91
R205	3,589.69	3,588.75	3,659.37	3,708.1	3,857.68	4,123.23	3,586.23	3,586.23	3,588.94	3,590.78	3,725.08	4,039.06	3,595.09	3,594.55	3,752.81	3,838.44	4,074.98	4,261.53
R206	3,457.46	3,456.32	3,487.83	3,531.54	3,540.89	3,637.1	3,453.36	3,453.36	3,453.36	3,460.2	3,460.2	3,556.3	3,460.2	3,468.15	3,521.9	3,649.2	3,668	3,722.67
R207	4,492.21	4,495.52	4,554.81	4,544.27	4,535.3	4,556.84	4,491.9	4,491.9	4,504.17	4,517.25	4,516.55	4,523.11	4,492.41	4,504.29	4,584.13	4,601.36	4,561.89	4,612.15
R208	2,799.76	2,799.85	2,846.6	2,930.8	2,947.7	3,078.09	2,794.23	2,794.23	2,794.23	2,886.63	2,882.71	3,043.52	2,814.35	2,814.12	2,924.8	2,968.3	2,982.17	3,116.08
R209	3,675.27	3,675.59	3,686.52	3,793.63	3,740.71	3,903.01	3,661.69	3,661.69	3,683.24	3,694.79	3,694.79	3,803.21	3,684.86	3,684.86	3,694.79	3,921.54	3,823.86	3,931.87
R210	2,697.05	2,698.89	2,719.85	2,777.87	2,776	2,985.27	2,697.05	2,697.05	2,697.05	2,697.05	2,721.9	2,857.79	2,697.05	2,706.27	2,744.86	2,841.92	2,904.52	3,060.88
R211	3,530.5	3,536.18	3,548.51	3,581.5	3,638.8	3,762.67	3,526.96	3,526.96	3,526.96	3,553.73	3,553.73	3,585.05	3,544.65	3,555.38	3,571.21	3,616.2	3,746.44	3,995.25
RC101	3,703.45	3,711.38	3,718.46	3,755.73	3,729.22	3,751.83	3,696.65	3,704.36	3,704.36	3,696.65	3,696.65	3,704.36	3,715.24	3,721.92	3,731.03	3,802.04	3,780.5	3,785.07
RC102	4,160.7	4,160.7	4,168.44	4,257.95	4,224.34	4,360.53	4,160.7	4,160.7	4,160.7	4,160.7	4,192.14	4,278.87	4,160.7	4,160.7	4,181	4,351.13	4,257.52	4,541.25
RC103	3,900.19	3,906.16	3,932.9	3,972.84	3,956.22	3,999.16	3,888.09	3,891.66	3,924.11	3,922.23	3,910.9	3,937.9	3,922.23	3,919.56	3,946.49	4,046.37	4,014.71	4,066.15
RC104	3,816.6	3,815.52	3,828.13	3,930.39	3,934.31	4,099.1	3,815.92	3,811.53	3,817	3,829.59	3,833.01	4,077.42	3,817.15	3,817.15	3,841.82	4,078.56	4,078.56	4,107.99
RC105	4,187.82	4,187.82	4,187.82	4,193.09	4,360.02	4,486.81	4,187.82	4,187.82	4,187.82	4,187.82	4,187.82	4,474.82	4,187.82	4,187.82	4,187.82	4,214.18	4,474.82	4,513.13
RC106	4,035.2	4,035.2	4,041.71	4,115.39	4,225.83	4,378.23	4,035.2	4,035.2	4,035.2	4,035.2	4,068.48	4,337.89	4,035.2	4,035.2	4,062.11	4,197.49	4,330.62	4,438.75
RC107	5,065.02	5,065.02	5,097	5,132.92	5,134.12	5,147.19	5,065.02	5,065.02	5,065.02	5,065.02	5,065.02	5,065.02	5,065.02	5,065.02	5,149.48	5,159.03	5,159.1	5,181.96
RC108	3,283.07	3,291.26	3,328.29	3,332.76	3,347.27	3,374.22	3,261.26	3,261.26	3,314.9	3,328.83	3,333.94	3,328.83	3,298.49	3,300.89	3,340.07	3,348.5	3,367.79	3,529.45
RC201	3,662	3,679.14	3,694.11	3,738.08	3,762.92	3,762.65	3,660.29	3,660.29	3,660.29	3,676.21	3,728.55	3,741.57	3,668.82	3,714.6	3,736.8	3,765.96	3,803.94	3,780.07
RC202	3,578.59	3,589.82	3,607.85	3,628.74	3,602.11	3,622.73	3,569.29	3,581.68	3,569.29	3,574.8	3,569.29	3,569.29	3,591.03	3,613.05	3,627.22	3,710.98	3,644.21	3,693.69
RC203	4,272.64	4,280.04	4,272.64	4,315.59	4,363.74	4,474.09	4,272.64	4,272.64	4,272.64	4,272.64	4,272.64	4,272.64	4,272.64	4,309.63	4,272.64	4,450.39	4,502.89	4,684.5
RC204	4,258.29	4,250.6	4,268.99	4,396.49	4,343.65	4,414.39	4,258.29	4,239.07	4,258.29	4,360.44	4,311.81	4,319.41	4,258.29	4,258.29	4,311.81	4,468.02	4,406.33	4,468.02
RC205	4,039.09	4,061.27	4,134.87	4,163.75	4,179.23	4,285.71	4,032.49	4,032.49	4,096.84	4,132.77	4,145.33	4,106.53	4,062.71	4,106.53	4,165.54	4,202.24	4,235.57	4,372.88
RC206	4,099.06	4,099.06	4,100.75	4,142.41	4,145.78	4,112.04	4,099.06	4,099.06	4,099.06	4,099.06	4,099.06	4,099.06	4,099.06	4,099.06	4,104.53	4,178.74	4,179.78	4,163.98
RC207	4,153.24	4,159.3	4,183.01	4,259.71	4,233.32	4,314.21	4,151.4	4,151.4	4,151.4	4,186.45	4,186.45	4,301.58	4,160.62	4,181.68	4,204.98	4,301.58	4,301.58	4,332.31
RC208	4,742.1	4,742.1	4,742.15	4,742.24	4,746.64	4,748.16	4,742.1	4,742.1	4,742.1	4,742.1	4,742.1	4,742.1	4,742.1	4,742.1	4,742.33	4,742.33	4,764.33	4,771.73
mean	3,492.19	3,496.45	3,519.77	3,557.18	3,573.89	3,648.26	3,484.1	3,485.42	3,496.98	3,512.94	3,520.07	3,580.32	3,501.47	3,510.76	3,544.32	3,609.24	3,638.59	3,718.41

Table 11: Detailed results of the objective value when varying the acceptance criterion for the instances of Solomon (1987) with $n = 50$ shipments.

	acceptance criterion - LNS mean						acceptance criterion - LNS min						acceptance criterion - LNS max					
Instance	**0**	**1**	**10**	**50**	**100**	∞	**0**	**1**	**10**	**50**	**100**	∞	**0**	**1**	**10**	**50**	**100**	∞
C101	61.52	36.71	8.38	3.61	3.05	1.47	40.06	24.52	5.18	2.46	2.14	1.43	90.66	45.83	11.72	4.84	3.79	1.54
C102	50.25	37.08	8.13	3	2.98	1.95	40.89	22.69	5.02	2.3	1.83	1.4	60.19	51.36	16.14	4.09	4.97	3.86
C103	53.05	27.99	9.1	3.13	2.64	2.1	35.95	19.47	5.19	2.44	1.96	1.27	75.11	38.13	17.45	4.1	3.01	4.27
C104	72.57	37.19	6.69	2.95	2.19	1.59	34.15	23.94	4.42	2.12	1.68	1.28	159.45	54	11.25	4.65	3.39	2.39
C105	72.63	24.97	5.48	2.76	1.95	1.84	51.69	21.19	4.52	2.42	1.66	1.5	84.72	32.06	8.31	3.3	2.57	2.06
C106	57.8	26.52	7.83	4.57	2.86	2.06	40.91	19.05	6.07	2.06	1.62	1.63	90.94	45.2	12.77	7.48	4.58	3.11
C107	54.11	32.21	7.32	2.41	2.88	1.97	40.52	19.35	5.96	2.04	2.09	1.4	83.85	42.94	8.58	2.85	3.62	2.6
C108	72.26	28.72	9.83	4.57	3.15	2.05	43.37	21.5	5.31	2.86	1.89	1.57	102.05	34.71	14.86	6.69	4.37	3.38
C109	59.26	25.41	7.23	3.46	2.59	2	40.65	18.78	4.38	2.44	1.74	1.45	78.77	34.89	10.23	5.61	3.38	2.38
C201	94.27	28.46	6.27	2.62	2.08	1.44	38.95	21	4.63	1.95	1.58	1.28	149.96	36.98	7.74	4	2.92	1.65
C202	53.28	32.2	7.97	3.27	2.34	2.28	36.94	19.4	7.15	2.25	1.68	1.44	89.68	51.31	9.13	5.04	3.6	2.89
C203	53.88	37.04	8.04	3.44	2.86	1.93	42.54	26.96	6.82	2.87	1.73	1.44	77.77	49.91	9.18	4.33	4.4	2.58
C204	90.82	29.57	8.56	2.91	2.76	2.99	54.41	22.39	5.37	2.11	1.9	1.38	153.9	50.75	13.06	3.71	4.42	6.01
C205	101.21	33.91	7.41	4.29	3.77	2.31	49.75	18.46	5.72	2.28	1.94	1.41	159.48	64.41	10.15	6.21	5.81	3.25
C206	50.31	28.9	5.56	2.24	2.21	1.56	37.28	19.81	4.48	1.83	1.75	1.43	68.74	41.79	9.28	2.54	3.52	1.71
C207	61.04	31.91	9.26	3.77	2.67	2.57	41.63	21.92	5.28	3.09	2.05	1.97	87.81	42.78	12.74	5.03	3.66	3.09
C208	39.57	25.54	9.79	4.45	3.07	2.09	37.4	19.34	6.39	3.06	2.73	1.4	42.39	36.97	17.78	8.41	3.26	3.43
R101	101.31	55.01	14.8	4.37	4.72	2.16	57.36	35.33	7.85	2.68	2.44	1.5	165.6	65.78	32.88	5.73	8.24	3.14
R102	52.25	31.6	13.09	4.67	3.29	2.37	42.72	23.78	6.89	3.03	1.97	1.63	60.96	36.53	18.66	7.07	5.86	3.11
R103	58.5	50.43	8.38	3.15	2.68	2.17	49.02	30.84	5.77	2.39	1.83	1.41	68.41	70.77	10.98	4.17	3.83	3.51
R104	63.8	52.12	7.45	3.59	3.23	1.66	48.31	25.42	6.97	2.65	1.77	1.36	94	82.27	8.08	4.69	4.57	2.53
R105	72.73	35.62	10.1	3.15	2.6	2.07	54.53	24.53	6.08	2.25	1.72	1.55	85.97	49.87	17.01	3.91	3.46	2.77
R106	87.93	50.5	10.99	4.24	4.67	2.26	53.96	38.01	6.79	2.88	3.65	1.55	114.63	79.11	17.96	7.91	5.89	3.27
R107	45.43	30.15	6.22	3.52	3.98	1.67	39.64	24.74	4.81	2.8	1.85	1.27	57.6	37.31	9.49	5.02	5.62	2.73
R108	68.05	33.4	8.15	2.95	3.33	2.17	46.65	24.58	5.67	2.17	2.27	1.51	87.72	43.5	12.36	4.44	5.05	3.01
R109	75.65	32.85	8.1	3.84	3.49	1.71	50.84	24.99	5.96	2.76	2.09	1.3	122.15	38.27	13.77	5.03	4.92	2.11
R110	81.37	33.18	9.54	5.78	2.34	1.56	45.17	25.05	6.37	3.54	1.65	1.28	133.48	49.89	13.92	10.08	3.49	2.32
R111	69.5	35.96	9.72	4.88	2.38	1.74	49.14	23.84	6.43	4.35	1.86	1.4	110.82	57.36	13.52	5.36	3.18	2.19
R112	97.53	35.13	8.31	2.6	2.48	2.08	71.69	22.67	7.41	2.12	1.73	1.34	124.17	46.87	9.34	3.39	3.55	3.03
R201	77.14	44.44	8.93	3.92	2.78	2.29	52.23	27.24	5.65	2.66	1.76	1.34	120.39	67.7	17.91	5.2	5.11	3.1
R202	79.29	47.97	11.54	3.62	3.65	2.04	58.33	35.02	5.44	2.43	2.18	1.48	93.48	62.31	21.63	7	6.39	3.22
R203	93.41	37.02	5.95	3.83	2.7	2.22	60.88	26.69	4.94	2.13	2.17	1.51	166.44	51.4	7.51	7.14	3.85	3.47
R204	67.93	38.18	7.45	3.13	2.58	1.44	45.42	24.47	5.44	2.3	1.69	1.3	99.64	55.65	12.58	4.18	4.04	1.78
R205	61.51	47.03	9.93	5.1	3.06	2.05	47.28	30.44	7.07	3.45	2.61	1.43	82.89	65.14	13.76	6.01	4.04	3.53
R206	64.46	41.34	6.98	3.21	2.34	2.07	49.23	24.92	6.06	2.23	1.87	1.66	87.06	67.24	8.74	4.51	2.9	2.8
R207	57.34	29.82	6.11	2.58	2.17	1.92	52.25	20.52	4.76	2.15	1.92	1.47	60.03	45.61	9.43	3.65	2.46	3.02
R208	67.95	35.15	7.62	4.62	3.32	2.31	50.85	28.33	5.66	2.77	2.14	1.68	91.34	43.89	9.05	7.85	4.17	3.06
R209	62.75	34.26	9.12	3.14	4.05	2.45	44.25	28.15	6.04	2.45	3.28	2.28	82.45	43.15	13.38	4.01	4.91	2.59
R210	84.46	28.37	7.28	3.3	4.31	1.76	56.58	21.49	5.7	2.46	2.17	1.35	107.95	36.14	10.44	5.35	7.04	2.7
R211	87.64	34.06	8.97	3.07	2.89	2.36	51.99	24.37	5.61	2.44	1.77	1.59	130.09	59.39	12.49	4.22	4.38	2.86
RC101	39.78	19.58	5.97	2.67	1.73	1.61	25.76	13.53	4.23	1.68	1.48	1.36	62	26.97	8.29	4.97	2.28	1.95
RC102	32.38	18.38	9.1	3.08	2.51	1.99	30.49	14.77	5.16	2.38	1.56	1.36	33.62	28.22	18.36	3.79	3.56	2.99
RC103	46.82	26.46	6.11	2.34	2.7	1.47	32.84	19.23	3.74	1.67	1.78	1.28	58.01	35.39	11.72	3.05	3.63	1.97
RC104	39.14	24.95	6.51	3.61	3.54	1.49	30.84	14.17	3.89	1.86	1.62	1.29	55.21	36.98	8.16	7.46	5.51	1.72
RC105	24.99	13.73	4.65	2.87	2.26	1.33	24.36	13.12	4.14	2.1	1.47	1.17	25.51	15.18	5.11	3.63	2.77	1.69
RC106	30.08	20.05	5.63	2.86	2.69	1.92	27.95	15.18	4.31	2.45	1.53	1.52	33.14	25.86	7.18	3.35	5.46	2.28
RC107	28.82	23.28	5.33	2.84	2.28	1.65	25.68	14.63	3.87	2.4	1.5	1.23	32.93	40.95	6.86	3.18	3.25	2.96
RC108	46.63	21.8	3.96	2.2	1.95	1.48	33.06	14.35	3.43	1.79	1.51	1.29	72.97	31.15	4.47	3.13	2.59	1.93
RC201	61.06	21.11	6.17	2.81	2.08	2.19	27.47	16.44	3.51	1.82	1.59	1.37	92.92	25.68	9.63	3.77	2.98	3.21
RC202	39.87	18.96	3.94	2.22	2.19	1.51	30.1	13.03	3.52	1.71	1.44	1.19	55.24	25.95	4.73	3.12	4.25	2.26
RC203	22.69	15.34	5.03	2.5	2.07	1.76	19.74	10.29	4.32	1.74	1.56	1.26	25.21	19.76	5.84	3.07	2.57	2.51
RC204	30.75	24.41	6.45	2.61	1.81	1.99	26.92	14.36	4.64	1.83	1.41	1.41	35.68	32.34	8.13	3.52	2.85	3.03
RC205	38.39	29.91	6.22	2.85	3.01	1.72	28.53	13.65	4.71	1.75	2.17	1.37	68.31	47.87	8.53	3.59	4.11	2.11
RC206	29.75	17.68	4.33	2.46	2.05	1.57	24.18	12.78	3.43	1.65	1.45	1.32	37.87	24.44	6.44	4.84	3.51	2.18
RC207	43.97	31.18	6.41	2.7	2.49	1.98	28.33	23.02	4.66	1.84	1.52	1.29	67.85	39.94	8.44	3.5	5.42	2.63
RC208	29.79	15.82	5.25	1.97	1.88	1.58	25.78	13.85	3.38	1.69	1.48	1.23	32.42	16.98	9.58	2.77	2.9	2.27
mean	60.01	31.44	7.65	3.33	2.79	1.93	41.56	21.63	5.29	2.36	1.88	1.42	85.56	44.34	11.55	4.81	4.11	2.75

Table 12: Detailed results of the computation time when varying the acceptance criterion for the instances of Solomon (1987) with $n = 50$ shipments.

Instance	Parallel Insertion (PI) objective value - ρ	Parallel Insertion (PI) comp. time [s]	Local Search (LS) objective value - ρ	Local Search (LS) comp. time [s]	Large Neighborhood Search with Local Search (LNS) objective value - ρ mean	min	c.t. of min [s]	max	LNS computation time in [s] mean	min	max	Large Neighborhood Search without Local Search (LNS-noLS) objective value - ρ mean	min	c.t. of min [s]	max	LNS-noLS computation time in [s] mean	min	max	OR Tools (PCI) objective value - ρ	OR Tools (PCI) comp. time [s]	OR Tools (TS) objective value - ρ
C101	12,286.9	0.07	9,320.09	0.18	8,115.89	7,938.25	34.75	8,263.43	38.92	33.06	47.78	10,658.84	10,388.03	11.56	10,840.42	6.5	5.15	11.56	10,274.79	10.08	9,733.5
C102	11,601.16	0.02	7,270.16	0.21	6,444.95	6,255.15	104.62	6,536.35	64.77	46.79	104.62	9,351.52	9,165.66	5.56	9,538.85	6.32	5.02	9.14	7,329.16	21.01	7,275.45
C103	14,183.07	0.02	9,367.81	0.22	8,440.47	8,395.62	53.2	8,478.28	55.88	50.51	65.8	11,151.5	10,633.67	6.58	11,614.43	7.64	5.95	9.56	9,289.25	16.01	9,289.25
C104	13,782.38	0.02	8,320.19	0.2	7,692.56	7,576.13	50.75	7,813.82	52.9	44.35	63.36	10,539.41	10,191.59	5.23	10,812.25	6.77	5.12	9.34	10,712.32	12.82	9,495.2
C105	11,759.94	0.02	8,685.64	0.16	7,027.23	6,936.74	40.75	7,085.87	65.97	40.75	83.52	9,626.92	9,404	5.08	10,178.53	5.58	5.07	6.97	8,905.65	12.91	7,795.1
C106	12,530.46	0.02	9,389.84	0.17	7,521.36	7,394.55	131.02	7,630.22	73.69	43.81	131.02	10,391.84	10,172.87	5.11	10,697.58	6.67	5.11	10.44	9,202.24	12.1	8,371.33
C107	11,615.9	0.02	8,336.78	0.2	6,969.99	6,844.7	79.06	7,031.26	61.64	35.89	93.62	9,623.58	9,237.97	8.42	9,929.21	6.62	5.19	8.42	8,637.49	13.34	7,965.99
C108	12,048.16	0.02	8,245.76	0.15	7,228.92	7,108.02	107.64	7,379.6	62.39	38.81	107.64	9,702.91	9,583.55	10.09	9,761.36	6.54	5.09	10.09	8,995.26	10.64	8,134
C109	13,173.87	0.02	9,465.66	0.21	8,497.51	8,330.28	117.46	8,654.42	83.83	48.29	117.46	11,319.6	11,089.49	6.53	11,595.53	5.72	5.14	6.53	10,352.94	11.37	9,682.52
C201	10,227.74	0.02	7,382.89	0.19	6,324.33	6,272.39	75.96	6,469.12	106.37	46.31	296.66	8,851.74	8,605.73	5.08	9,269.37	5.31	5.04	5.8	7,367.23	18.45	7,320.54
C202	12,246.63	0.02	10,211.96	0.13	7,975.59	7,833.21	44.57	8,105.75	63.91	44.57	114.58	10,510.31	10,366.21	6.75	10,666.47	7.56	5.52	10.49	10,020.42	10.71	9,429.46
C203	14,481.67	0.02	10,795.37	0.18	9,567.06	9,456.06	32.78	9,765.99	44.84	32.52	65.09	11,692.35	11,390.71	5.7	11,905.22	6.26	5.05	10.33	10,335.83	21.37	10,168.37
C204	15,204.28	0.02	10,323.57	0.2	8,840.52	8,783.15	43.77	8,918.18	52.91	36.06	97.69	11,073.77	10,881.41	5.96	11,222.78	6.45	5.23	7.57	9,893.01	13.68	9,491.01
C205	12,077.69	0.02	8,279.38	0.24	7,572.51	7,518.6	68.22	7,599.3	46.24	31.43	68.22	9,436.49	9,187.8	9.02	9,619.17	6.42	5.09	9.02	8,917.84	15.97	8,249.65
C206	13,605.3	0.02	9,696.3	0.18	8,505.48	8,420.92	81.03	8,599.03	57.73	34.46	81.03	11,083.66	10,690.5	6.1	11,330.73	6.09	5.43	6.83	9,737.62	17.27	9,697.76
C207	13,535.78	0.02	11,238.5	0.19	9,616.06	9,543.84	35.1	9,747.52	39.53	30.06	52.42	11,703.35	11,468.23	5.73	12,038.99	7.63	5.14	11.74	11,227.59	12.85	11,162.34
C208	13,270.44	0.02	9,150.09	0.25	8,597.24	8,528.94	70.02	8,663.19	56.96	44.67	70.02	10,982.35	10,735.45	10.76	11,284.31	9.45	5.45	10.89	10,774.26	11.27	10,179.3
R101	11,249.71	0.02	9,055.15	0.22	8,430.11	8,353.29	63.61	8,459.9	78.52	47.3	130.71	10,023.87	9,725.51	5.55	10,391.19	5.78	5.19	7.14	9,462.98	21.08	9,462.98
R102	12,007.38	0.02	9,142.1	0.29	8,366.47	8,301.61	82.8	8,439.48	83.19	60.58	113.31	10,206	9,998.7	5.53	10,336.14	7.58	5.53	13.86	9,425.2	22.64	9,126.62
R103	10,167.78	0.02	7,824.4	0.23	7,017.33	6,957.82	83.63	7,090.97	80.02	56.24	106.41	9,326.75	9,206.6	5.35	9,524.23	6.36	5.35	10.25	8,440.96	17.72	8,076.97
R104	12,156.66	0.02	8,445.64	0.29	7,417.09	7,356.27	58.92	7,497.69	83.41	58.92	99.19	9,475.8	9,080.83	9.12	9,909.75	6.69	5.7	9.12	8,858.82	20.93	8,277.26
R105	13,130.15	0.02	9,255.68	0.28	8,601.41	8,560.35	118.25	8,658.63	95.85	65.21	118.25	10,545.66	10,425.16	5.69	10,676.94	7.07	5.53	10.11	10,014.86	16.45	9,767.16
R106	10,564.44	0.02	6,332.88	0.31	5,750.58	5,695.15	87.77	5,842.38	83.22	57.23	99.18	8,130.41	7,897.88	6.76	8,350.48	7	5.54	8.81	7,137.59	20.61	7,016.55
R107	10,493.07	0.02	8,464.04	0.18	7,057.41	6,899.72	133.74	7,143.11	115.61	62.63	182.56	9,274.28	8,644.45	5.52	9,784.43	5.54	5.39	5.64	9,032.66	16.56	8,396.38
R108	11,881.15	0.02	8,382.4	0.25	7,817.41	7,765.61	121.75	7,867.61	92.94	51.32	121.75	10,084.09	9,595.96	11.77	10,325	8.9	5.59	11.77	9,240.36	20.84	8,903.7
R109	11,950.03	0.02	8,602.61	0.33	7,675.05	7,611.3	162.46	7,807.4	124.03	55.69	167.54	9,727.5	9,464.65	6.11	9,864.64	6.1	5.57	7.43	9,599.66	17.36	8,536.71
R110	14,626.53	0.02	10,199.48	0.31	8,760.23	8,690.87	62.1	8,816.03	101.9	57.25	157.72	10,870.87	10,513.31	8.04	11,143.98	6.45	5.6	8.04	10,308.15	21.75	9,701.59
R111	11,100.79	0.02	7,870.8	0.35	6,885.49	6,850.76	76.52	6,915.15	107.24	71.92	177.18	8,978.87	8,784.16	5.5	9,208.83	6.14	5.33	7.59	7,972.36	19.48	7,876.84
R112	11,562.83	0.02	9,209.81	0.29	8,183.28	8,154.81	66.51	8,247.46	91.12	66.51	136.68	10,235.75	9,763.76	11.35	10,556.4	7.91	5.53	11.35	9,031.14	17.9	8,943.45
R201	10,845.82	0.02	8,397.94	0.29	7,377.11	7,228.44	70.68	7,553.22	93.1	50.32	122.8	9,720.3	9,390.35	5.76	9,915.34	6.57	5.57	9.62	9,079.75	21.98	8,877.43
R202	11,159.17	0.02	8,359.68	0.27	7,291.43	7,249.43	68.03	7,401.07	76.38	57.04	133.48	9,194.08	9,032.94	6.71	9,283.97	6.35	5.59	7.03	8,676.19	17.68	8,042.67
R203	9,930.56	0.02	6,610.5	0.25	5,973.24	5,884.74	102.22	6,027.82	87.36	51.83	122.75	7,949.45	7,665.27	5.66	8,344.69	6.43	5.66	7.44	7,054.46	17.56	6,809.23
R204	12,662.01	0.02	9,360.09	0.36	8,369.34	8,315.25	115.53	8,481.71	94.97	57.45	115.53	10,518.83	9,813.39	6.28	10,921.36	6.84	5.66	8.46	10,137.03	19.35	9,747.42
R205	12,128.11	0.02	8,721.23	0.31	7,898.43	7,808.94	94.11	7,947.75	85.7	52.6	124.24	9,907.9	9,650.63	5.54	10,185.73	9.15	5.54	11.55	9,143.05	18.51	8,627.68
R206	11,104.41	0.02	7,518.63	0.38	6,948.77	6,911.21	61.34	6,984.71	76.77	58.96	103.06	9,540.1	9,154.43	7.5	9,696.96	6.05	5.55	7.5	8,561.82	17.51	7,430.85
R207	12,530.95	0.02	8,312.88	0.45	7,306.02	7,247.36	66.16	7,343.22	109.25	66.16	178.47	9,661.82	9,307.48	10.16	9,889.57	8.03	5.67	11.14	8,362.04	16.88	8,272.76
R208	12,868.63	0.02	9,215.14	0.41	8,272.65	8,205.07	52.97	8,331.79	88.67	52.97	111.62	10,371.17	10,039.07	5.57	10,643.55	6.94	5.57	8.34	9,157.84	28.03	9,141.92
R209	12,057.59	0.02	7,820.98	0.44	7,518.32	7,469.52	87.87	7,597	86.76	54.52	139.25	9,927.92	9,524.32	10.83	10,299.83	9.38	5.56	17.72	8,806.38	19.94	8,806.38
R210	13,039.01	0.02	9,585.09	0.43	9,026.25	8,973.84	49.79	9,105.49	53.05	45.9	62.57	10,483.91	10,322.23	12.61	10,647.48	9.3	6.06	12.61	10,102.49	19.64	9,337.81
R211	11,316.09	0.02	8,448.27	0.24	7,223.51	7,179.81	68.8	7,253.57	117.01	68.8	172.9	9,084.33	8,709.21	5.92	9,402.13	8.09	5.92	11.17	8,615.67	21.98	8,603.58
RC101	13,482.06	0.02	9,874.56	0.21	8,929.76	8,860.29	83.52	9,001.53	65.28	48.08	83.52	11,047.4	10,625.79	6.03	11,372.53	5.71	5.27	6.55	10,339.78	13.2	9,658.6
RC102	12,488.65	0.02	10,075.31	0.14	8,592.19	8,550.6	58.08	8,622.33	46.79	34.65	60.05	11,465.26	11,153	5.29	11,806.48	5.43	5.26	5.86	10,992.95	10.63	10,761.8
RC103	15,276.27	0.02	10,152.64	0.25	9,048.32	8,979.8	45.6	9,099.79	53.26	42.04	75.84	10,988.31	10,614.58	5.36	11,442.04	7.79	5.27	15.38	10,667.92	17.86	10,590.18
RC104	13,290.66	0.02	10,113.01	0.24	8,158.78	8,104.36	62.02	8,207.43	73.53	40.89	128.52	10,517.42	10,219.19	10.33	10,782	6.67	5.19	10.33	9,279.18	13.14	9,279.18
RC105	13,200.7	0.02	8,174.65	0.3	7,603.16	7,437.21	39.02	7,688.6	56.23	39.02	93.27	10,308.42	10,044.55	5.67	10,610.92	6.42	5.19	9.42	8,965.09	15.32	8,523.6
RC106	13,709.84	0.02	10,120.95	0.23	8,757.07	8,716.62	38.14	8,791.02	63.35	38.14	84.53	11,574.65	11,242.66	9.5	11,837.27	6.88	5.27	9.5	9,640.07	12.66	9,587.38
RC107	14,053.5	0.02	10,869.53	0.2	10,027.41	9,898.88	44.07	10,093.86	44.78	33.03	59.8	12,343.5	12,183.61	5.24	12,534.32	5.98	5.24	7.22	12,146.85	11.77	11,567.61
RC108	14,036.29	0.02	11,756.33	0.17	9,782.06	9,751.59	123.3	9,822.4	73.9	34.9	129.91	11,806.54	11,040.97	5.56	12,389.89	5.7	5.22	7.05	12,033.7	9.81	10,914.58
RC201	14,065.67	0.02	11,954.14	0.14	9,955.38	9,905.1	48.12	10,008.15	51.53	35.91	94.55	12,001.08	11,806.53	6.21	12,234.32	8.37	6.21	15.3	11,495.92	16.33	11,440.55
RC202	12,614.38	0.02	10,401.89	0.15	8,861.79	8,730.76	44.67	8,941.21	56.88	44.67	64.43	10,883.37	10,389.42	8.74	11,200.54	7.23	5.22	11.39	10,536.08	12.42	10,221.34
RC203	14,083.3	0.02	10,850.27	0.18	9,742.73	9,546.74	102.84	9,847.76	68.82	36.18	102.84	11,621.71	11,443.89	5.42	11,942.84	6	5.25	7.11	10,764.59	20.34	10,764.59
RC204	12,219.54	0.02	8,209.41	0.21	7,194.35	7,126.3	49.64	7,260.35	66.99	46.64	106.74	9,776	9,351.14	5.36	10,075.46	6.33	5.2	9.22	8,246.66	13.06	8,060.52
RC205	13,340.35	0.02	9,802.9	0.23	8,649.26	8,618.75	43.42	8,686.36	52.39	43.42	64.56	11,065.62	10,785.15	5.2	11,538.06	5.38	5.2	5.65	9,974.65	16.8	9,974.65
RC206	12,621.98	0.02	9,549.77	0.19	8,784.61	8,670.09	67.08	8,843.29	53.62	36.92	67.08	11,050.82	10,653.13	5.22	11,304.84	6.13	5.15	9.74	9,554.27	13.52	9,554.27
RC207	11,534.09	0.02	8,374.79	0.26	7,962.35	7,894.11	51.02	8,042.57	45.89	32.59	56.5	10,174.13	9,620.73	7.85	10,505.64	6.34	5.12	7.89	9,769.23	15.99	8,825.86
RC208	14,043.28	0.02	9,871.72	0.26	9,154.47	9,048.3	44.47	9,265.68	51.55	38.47	68.71	11,645.92	11,171.7	5.49	12,136.72	5.42	5.31	5.49	10,587.69	14.65	10,447.98
mean	12,539.73	0.02	9,120.84	0.25	8,059.08	7,975.84	72.7	8,138.87	72.49	47.06	107.12	10,343.03	10,022.31	6.97	10,630.74	6.79	5.38	9.31	9,521.23	16.46	9,132.1

Table 13: Detailed results of the objective value and computation time for the instances of Solomon (1987) with $n = 100$ shipments.

Instance	Parallel Insertion (PI)		Local Search (LS)		Large Neighborhood Search with Local Search (LNS)							Large Neighborhood Search without Local Search (LNS-noLS)							OR Tools (PCI)		OR Tools (TS)
	objective value - ρ	comp. time [s]	objective value - ρ	comp. time [s]	objective value - ρ mean	objective value - ρ min	objective value - ρ c.t. of min [s]	objective value - ρ max	computation time in [s] mean	computation time in [s] min	computation time in [s] max	objective value - ρ mean	objective value - ρ min	objective value - ρ c.t. of min [s]	objective value - ρ max	computation time in [s] mean	computation time in [s] min	computation time in [s] max	objective value - ρ	comp. time [s]	objective value - ρ
c1-2-1	27,955.89	0.14	17,264.89	1.23	15,455.11	15,225.97	223.67	15,546.21	301.31	189.68	586.35	22,660.69	22,098.68	28.43	22,940.96	38.21	28.43	71.28	18,507.68	81.99	18,507.68
c1-2-2	26,160.1	0.13	17,190.41	1.34	14,877.74	14,807.66	314.13	14,997.17	294.32	169.76	485.3	20,399.18	19,934.41	31.1	21,045.04	35.89	28.53	51.02	17,155.58	107.36	16,749.36
c1-2-3	28,033.83	0.12	17,662.66	1.47	15,862.58	15,744.69	210.99	16,007.14	227.04	179.61	296.05	21,095.49	20,827.05	51.57	21,555.92	40.71	29.01	54.98	18,776.16	79.28	18,776
c1-2-4	25,583.92	0.12	15,892.56	1.28	14,828.7	14,627.43	167.37	14,961.22	299.95	167.37	427.83	20,613.31	19,452.96	32.66	21,919.43	30.11	27.49	33.1	17,261.81	79.71	16,336.85
c1-2-5	26,339.18	0.12	16,602.68	1.35	15,251.23	15,210.81	368.38	15,325.55	265.15	162.35	368.38	20,881.05	20,102.75	47.09	21,669.39	32.57	28.17	47.09	17,703.51	81.53	17,034.72
c1-2-6	29,469.6	0.12	17,916.9	1.04	15,887.64	15,648.57	250.04	16,073.86	183.81	149.51	250.04	22,416.58	21,574.16	28.92	22,999.79	32.76	28.1	42.43	18,132.57	110.69	17,057.14
c1-2-7	31,656.07	0.12	20,490.04	1.62	17,823.74	17,700.36	503.41	17,912.49	289.33	201.53	503.41	24,100.73	23,662.27	27.92	24,515.18	47.36	27.92	54.93	20,434.63	61.52	20,434.63
c1-2-8	25,192.25	0.12	17,240.45	1.08	15,231.27	15,114.78	194.66	15,355.24	233.36	174.14	282.13	21,222.07	20,108.52	58.45	22,363.96	35.15	28.67	58.45	17,697.68	82.87	17,137.32
c1-2-9	21,893.55	0.11	15,630.94	0.96	13,838.71	13,762.16	232.44	13,884.65	309.54	222.3	441.74	19,526.81	18,075.48	29.32	20,645.97	33.31	27.74	51.74	16,431.35	81.26	15,703.62
c1-2-10	27,387.17	0.18	16,826.02	1.32	14,581.47	14,314.71	280.02	14,778.02	359.04	250.27	498.55	20,076.46	19,646.72	55.3	20,717.64	42.23	28.71	55.86	16,473.3	94.06	16,463.76
c2-2-1	29,800.2	0.11	20,184.4	0.92	17,210.15	16,819.82	284.05	17,409.54	265.2	156.8	384.5	25,146.59	24,732.62	42.82	25,519.92	35.96	26.43	42.82	20,238.9	83.58	20,156.79
c2-2-2	27,913.37	0.12	19,197.41	0.75	16,963.3	16,817.02	570.5	17,150.47	349.11	199.17	570.5	24,024.38	23,118.59	27.79	24,750.89	34.86	27.79	46.77	20,613.75	77.31	19,667.11
c2-2-3	27,180.2	0.11	20,372.38	0.76	18,632.99	18,402.95	462.95	18,831.54	313.6	176.31	545.89	25,387.64	25,136.59	27.84	25,755.73	28.61	27.59	30.07	23,403.15	60.14	23,403.15
c2-2-4	27,931.09	0.12	19,703.15	0.96	17,774.36	17,667.05	150.44	17,900.88	298.23	150.44	441.41	24,819.55	24,441.56	53.8	25,383.3	59.22	29.76	84.23	20,565.99	82.06	20,256.66
c2-2-5	30,325.85	0.12	17,619.59	1	15,935.13	15,832.1	248.88	16,034.54	342.58	248.88	409.14	22,897.43	22,579.07	28.43	23,498.73	38.01	26.68	54.61	19,985.96	40.34	19,985.96
c2-2-6	26,915.09	0.12	18,506.27	0.73	16,946.79	16,671.04	407.54	17,138.29	408.31	253.82	626.04	23,655.2	22,449.03	29.91	24,955.09	29.25	28.15	31.15	19,603.68	69.73	18,866.52
c2-2-7	29,592.17	0.12	20,340.24	0.78	17,671.55	17,305.38	261.32	17,894.16	323.6	261.32	408.28	25,252.11	24,763.38	29.21	25,676.65	30.97	29.21	33.13	20,950.89	49.22	19,913.4
c2-2-8	29,162.96	0.12	20,863.46	1.02	18,753.02	18,463.36	279.76	18,940.51	414.19	170.42	648.6	25,234.17	24,648.59	51.33	25,838.4	40.62	26.89	57.24	22,088.94	65.32	21,411.24
c2-2-9	30,101.92	0.12	22,260.85	0.67	19,578.9	19,463.69	214.56	19,677.07	339.76	214.56	678.72	25,798.92	25,189.66	59.86	27,182.35	39.67	28.34	59.86	21,534.89	59.98	20,522.06
c2-2-10	30,120.17	0.12	20,305.82	0.7	17,753.93	17,485.52	356.29	17,946.72	256.42	202.77	356.29	25,799.04	25,534.36	27.33	26,132.83	29.22	27.33	30.25	20,457.48	75.47	19,869.76
r1-2-1	32,551.49	0.12	21,848.09	1.05	18,764.92	18,620.24	372.99	18,934.57	284.86	196.97	372.99	26,270.43	25,871.63	29.53	26,594.92	29.06	28.44	29.97	21,137.38	89.44	20,794.13
r1-2-2	30,019.51	0.12	20,477.8	0.98	17,884.68	17,603.73	253.37	18,204.61	270.11	196.62	412.32	24,620.8	23,812.63	28.07	25,112.58	34.67	28.07	47.27	21,110.87	86.54	20,830.61
r1-2-3	34,244.32	0.12	23,186.41	0.96	21,543.23	21,362.33	243.54	21,687.1	231.14	164.59	307.94	28,198.96	27,778.46	34.85	28,957.59	34.35	28.15	41.47	24,075.79	74.98	23,629.24
r1-2-4	31,178.07	0.12	20,577.05	1.08	17,944.36	17,820.83	482.34	18,074.21	333.16	141.69	536.2	24,936.9	24,525.9	30.43	25,468.53	35.8	29.69	49.93	20,465.8	79.56	20,186.51
r1-2-5	34,219.16	0.12	22,783.47	1.24	20,226.83	20,008.84	216.44	20,412.79	385.81	216.44	482.61	27,114.59	26,049.72	34.51	27,922.13	31.9	27.6	38.01	22,423.28	123.39	22,413.52
r1-2-6	30,905.64	0.12	21,879.28	1.13	19,779.28	19,509.42	221.46	19,921.36	229.45	191.09	270.02	25,808.55	25,242.55	47.89	26,511.38	35.09	29.26	47.89	23,627.46	73.87	23,627.46
r1-2-7	31,961.13	0.12	22,121.1	1.04	18,666.7	18,417.24	448.03	18,777.7	264.71	163.4	448.03	25,912.78	25,498.69	28.88	26,218.44	35.08	27.59	48.84	21,360.13	75.72	21,151.7
r1-2-8	31,801.6	0.12	22,008.54	0.93	20,198.26	20,167.93	311.79	20,262.92	311.83	159.48	557.61	27,651.68	27,118.01	28.2	28,623.89	30.27	27.8	38.84	24,128.72	80.21	22,486.26
r1-2-9	30,721.48	0.12	24,166.88	0.82	21,344.99	21,205.95	280.75	21,481.56	263.3	170.08	351.28	28,474.67	27,878.13	27.88	28,956.47	30.84	27.38	42.32	25,025.99	63.71	24,888.08
r1-2-10	32,160.87	0.12	22,101.45	1.12	19,400.35	19,090.86	462.16	19,674.44	289.17	159.95	462.16	26,058.35	25,149.31	30.9	26,596.73	30.88	28.74	34.45	21,101.55	96.81	21,101.55
r2-2-1	34,145.65	0.12	24,943.31	0.98	21,582.31	21,404.69	254.38	21,823.49	217.31	160.9	256.49	27,684.1	27,184.66	27.76	28,162.42	29.48	27.64	35.09	25,330.72	68.96	24,912.52
r2-2-2	28,403.22	0.12	20,365.37	1.16	18,801.61	18,590.12	196.81	18,915.71	198.59	146.37	307.88	25,369.7	24,167.19	32.54	26,140.98	35.51	28.25	46.65	21,752.65	78.18	21,336.94
r2-2-3	34,006.2	0.12	22,326.87	1.25	19,718.49	19,655.38	156.02	19,794.07	246.4	156.02	495.75	25,752.23	24,839.11	58.47	27,208.88	39.38	30.66	58.47	23,021.27	74.68	23,020.13
r2-2-4	31,114.72	0.12	20,300.94	1.2	18,320.45	18,091.67	246.76	18,533.43	274.3	187.25	450.49	24,785.86	24,226.94	27.81	25,195.14	29.71	27.81	32.73	21,694.8	81.76	21,204.89
r2-2-5	30,420.38	0.12	22,652.27	0.73	20,612.47	20,539.07	279.58	20,700.65	284.84	184.3	374.1	27,158.21	26,690.09	28.94	27,768.45	31.79	27.89	37.07	23,339.19	76.03	21,710.08
r2-2-6	35,953.48	0.12	23,516.53	1.15	20,702.93	20,594.31	479.42	20,943.08	291.13	161.97	479.42	28,455.84	27,506.67	41.33	29,356.62	30.99	27.92	41.33	23,485.27	101.15	23,420.71
r2-2-7	31,301.6	0.12	20,519.94	1.13	18,260.66	18,107.61	374.23	18,425.91	247.22	159.67	374.23	25,345.79	24,846.1	49.66	25,867.48	41.73	27.97	60.49	21,824.07	95.24	21,782.9
r2-2-8	32,973.47	0.13	22,477.14	0.97	19,500.65	19,305.8	173.1	19,644.24	277.93	173.1	393.1	26,563.49	25,899.33	28.72	27,173.46	35.55	28.6	57.29	22,249.31	92.78	21,792.76
r2-2-9	29,504.64	0.12	21,061.08	1.03	18,718.16	18,584.75	373.39	18,803.5	255.43	162.81	373.39	25,161.01	24,253.64	28.3	25,734.42	33.89	27.83	54.21	22,165.52	81.91	22,165.52
r2-2-10	30,322.68	0.12	22,155.26	0.92	17,721.54	17,573.68	197.75	17,800.62	261.52	173.85	489.86	24,059.24	23,674.85	35.76	24,328.57	35.29	27.98	47.4	22,004.07	76.34	20,673.29
rc1-2-1	30,086.89	0.12	19,810.78	1.08	16,928.96	16,599.83	279.5	17,151.09	276.41	183.53	329.21	24,351.65	23,790.17	28.11	25,315.14	28.32	26.72	32.04	18,739.73	78.8	18,448.93
rc1-2-2	31,926.16	0.12	22,152.87	1.01	18,528.22	18,302.28	290.16	18,669.44	263.48	198.04	387.88	25,187.53	24,752.02	34.54	25,605.47	31.92	27.84	39.68	21,985.59	81.38	20,395.94
rc1-2-3	30,352.53	0.12	21,409.38	1.05	19,405.84	19,279.21	444.74	19,464.36	288.79	163.54	444.74	25,870.34	24,526.55	27.23	26,483.69	34.21	27.23	53.66	22,283.33	69.96	22,283.33
rc1-2-4	31,374.15	0.12	21,428.25	1.12	19,279.83	19,077.86	163.89	19,580.17	259.01	163.89	450	26,042.91	25,321.28	44.08	26,630.07	32.49	27.81	44.08	21,048.39	70.71	20,789.02
rc1-2-5	29,392.24	0.12	21,495.6	0.84	19,086.03	19,022.76	261.96	19,157.61	277.77	214.19	350.15	25,453.77	24,743.6	35.04	26,343.46	34.73	27.01	55.83	22,993.54	72.57	21,861.26
rc1-2-6	30,960.79	0.12	21,162.09	1.17	18,836.87	18,787.71	193.78	18,905.85	200.22	178.96	233.48	25,448.14	23,726.29	33.96	26,332.27	35.45	28.55	46.99	21,183.33	73.38	20,656.52
rc1-2-7	29,324.49	0.11	21,556.5	0.87	18,148.55	17,968.29	276.42	18,316.52	272.87	186.5	329.99	24,586.18	23,491.96	27.9	25,147.62	30.58	27.66	34.55	21,494.09	73.98	20,107.41
rc1-2-8	30,383.94	0.12	18,734.54	1.37	17,092.51	16,866.42	156.92	17,255.67	193.57	156.92	288.42	23,980.84	22,989.96	32.85	25,478.32	33.55	27.96	45.77	20,418.47	82.12	19,938.28
rc1-2-9	30,900.32	0.12	23,405.39	0.89	20,221.74	20,029.81	284.93	20,400.45	236.1	165.98	289.72	27,874.86	26,393.34	28.47	28,542.28	32.33	27.58	46.71	23,156.7	72.13	22,299.91
rc1-2-10	28,334.45	0.12	19,570.21	0.86	16,879.73	16,577.91	587.64	17,063.01	340.77	223.03	587.64	25,041.43	24,865.53	28.52	25,444.77	36.12	28.52	49.88	19,194.18	89.15	18,689.07
rc2-2-1	27,691.7	0.12	19,358.13	0.97	16,361.67	16,285.15	243.55	16,476.15	259.91	171.91	410.29	23,033.11	21,444.95	28.79	23,985.23	29.55	27.47	32.71	18,652.85	73.75	18,652.85
rc2-2-2	30,268.7	0.13	22,734.4	0.96	19,470.09	19,280.2	158.89	19,588.55	195.8	158.89	248.69	25,830.25	25,046.29	28.15	26,494.58	29.23	27.91	31.98	22,724.69	73.44	22,136.69
rc2-2-3	28,637.35	0.13	22,052.97	0.87	19,277.87	19,065.67	205.67	19,481.98	248.12	151.81	348.46	25,124.34	24,329.85	28.24	25,954.33	28.72	27.41	32.08	22,914.89	77.95	22,111.95
rc2-2-4	30,076.02	0.12	22,165.01	0.87	19,353.94	19,209.51	175.44	19,421.34	204.89	157.76	289.84	24,867.71	24,566.25	43.02	25,236.74	45.3	28.37	54.04	23,722.96	73.44	22,447.28
rc2-2-5	29,557.17	0.13	19,625.58	1.07	16,691.96	16,468.77	371.45	16,949.45	295.12	162.04	392.89	23,782.69	23,094.19	37.22	24,649.35	31.34	28.54	37.22	18,842.3	93.91	18,842.3
rc2-2-6	30,510.28	0.12	19,907.29	1.24	18,345.32	18,224.24	274.64	18,454.81	196.7	152.39	274.64	25,315.83	24,938.59	52.4	25,709.97	37.83	27.48	52.99	21,491.72	95.9	20,063.62
rc2-2-7	29,858.07	0.12	19,613.14	1.06	17,850.45	17,793.08	254.34	17,935.35	226.92	196.87	254.34	24,850.41	24,217.18	29.68	25,106.78	32.24	28.55	43.85	20,675.17	87.69	20,112.38
rc2-2-8	28,227.56	0.12	17,893.04	1.24	15,730.44	15,504.26	234.35	15,944.37	260.9	180.33	390.55	23,758.61	22,951.64	33.72	24,587.92	30.7	27.25	35.82	19,108.34	74.72	19,034.22
rc2-2-9	28,395.86	0.12	20,248.41	0.93	17,501.47	17,368.54	394.09	17,595.96	284.41	161.75	394.09	25,351.7	24,230.99	34.3	25,979.93	29.8	27.76	34.3	20,059.45	83.74	19,017.02
rc2-2-10	29,976.67	0.12	20,488.65	1.01	18,687.35	18,588.21	183.53	18,827.44	256.92	149.05	433.5	24,858.72	24,509.27	37.6	25,304.86	33.76	28.27	45.31	21,655.87	87.08	20,978.97
mean	29,880.99	0.12	20,472.54	1.04	18,070.5	17,893.99	290.69	18,220.35	275.51	180.08	408.89	24,783.36	24,070.33	35.39	25,454.98	34.4	28.03	45.5	21,028.12	79.67	20,504.16

Table 14: Detailed results of the objective value and computation time for the instances of Gehring and Homberger (1999) with $n = 200$ shipments.