Strategic planning of electric logistics fleet networks: A robust location routing approach

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Abstract

We present a robust location routing approach that considers simultaneous decisions on routing vehicles and locating charging stations for strategic network design of electric logistics fleets. In this approach, we consider uncertain customer patterns with respect to the spatial customer distribution, demand, and service time windows. To solve large sized instances as well as instances considering a high number of scenarios, a (parallelized) adaptive large neighbourhood search is presented. We derive new benchmark instances for the proposed problem class with different degrees of uncertainty and evaluate the performance of our algorithm. Results are presented for a real-world application case and are compared to results of different deterministic modeling approaches. Based on these results, the benefit of a robust planning approach with regard to operational feasibility and savings in overall costs is analyzed for the underlying planning problem, and managerial insights are derived.

Keywords: electric logistics fleets, robust location routing, green logistics

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1. Introduction

The transportation sector contributes with 20% to the total European greenhouse gas (GHG)-emissions, and is one of the main sources for hazardous emissions and noise in cities (European Environment Agency 2014). Against this background, electric commercial vehicles (ECVs) are seen as sustainable and environmentally friendly means of transportation, since they have zero tank-to-wheel emissions and even zero well-to-wheel emissions if fueled by renewable energy sources. Thus, local hazardous emissions as well as global GHG-emissions caused by transportation can be reduced to a large extend using ECVs. Nevertheless, high acquisition costs, limited driving range and lack of charging infrastructure currently slow down the market diffusion of ECVs.

Logistics fleets provide an opportunity to speed up the market penetration of ECVs. The high utilization of vehicles in logistics fleets favors the usage of ECVs, since acquisition costs for ECVs are higher, but operational costs are lower than for internal combustion engine vehicles (ICEVs). Thus, the higher the utilization of ECVs is, the higher are the savings from operational costs (see, e.g., Feng and Figliozzi 2013, Schiffer et al. 2016) that can substitute higher acquisition costs. For short-haul logistics, limited driving range and lack of infrastructure play a minor role, since it is sufficient to recharge ECVs once a day (i.e., at the depot over night). Accordingly, first pilot projects on electric logistics fleets within short-haul logistics launched by UPS (UPS 2013) and DPDHL (DPDHL 2014) show promising results regarding the competitiveness of ECVs. However, within mid-haul logistics, time-consuming recharging en-route and the need to install charging infrastructure to keep vehicles operational still provide challenges (cf. Stütz et al. 2016). First results of pilot projects for mid-haul logistics show that ECVs are on the verge of breaking even, but optimal decisions have to be taken with regard to the location of charging stations and the operation of vehicles (cf. Schiffer et al. 2016). Herein, interdependencies between these decisions have to be regarded, as routing decisions depend on the location of charging infrastructure and locating charging infrastructure depends on the expected routes (cf. Schiffer and Walther 2017).

Additionally, results of real-world cases show that the network design and operation is highly sensitive with regard to the underlying customer patterns (i.e., spatial customer distribution, demand patterns and service time windows). This is for instance shown in Schiffer et al. (2016), where the design and operation of a distribution network of a German retail company is analyzed for an ECV logistics fleet. In this paper, 12 scenarios with varying vicinities around a central warehouse were analyzed covering 144 to 302 customers. While the number of required vehicles and the overall traveled distance increased monotonously with increasing vicinities, the number of charging stations was strongly fluctuating. This effect appeared despite the fact that the customers were rather equally distributed within the analyzed region, and time windows were very large and did not affect the route patterns substantially. Thus, slight variations in customer demand resulted in highly sensitive results with regard to the number of charging stations. As a consequence, even higher fluctuation in results can be expected for networks with stronger changing customer patterns and smaller time windows. Since the decision on charging station locations is taken at strategic level, future customer demand, spatial customer distribution, and time windows might be uncertain. However, these uncertainties have to be regarded when taking the decision on the location of charging stations, in order to built operationally feasible distribution networks.

Since logistics fleet operators usually decide on both, buying and operating of ECVs as well as building charging infrastructure, the present situation holds a unique planning situation to design sustainable and efficient transportation networks for ECVs. Optimization models can substantially contribute to support these concurrent decisions under uncertainty. However, current optimization models for electric fleets aim either at (i) the operation of ECVs applying vehicle routing problems (VRPs) with special emphasize on range limitations and recharging times, or at (ii) the location of charging stations applying facility location problems (FLPs) for locating charging infrastructure. Integrated location routing problems (LRPs) approaches for ECVs that are deriving optimal solutions for both decisions simultaneously are still sparse. The few approaches that exist focus on a single deterministic scenario and are only suitable to design electric logistics fleet networks for milk-runs (cf. Yang and Sun 2015, Schiffer and Walther 2017). Uncertainty has not been considered within the discussed approaches for ECVs up to now, and even for classical LRPs for ICEVs only few approaches consider uncertainty.

Against this background, the aim of this paper is to present an approach for simultaneous decisions on vehicle routing and locating charging stations for electric logistics fleets with uncertain customer patterns (i.e., spatial customer distribution, demand and service time windows). To do so, we develop the robust electric LRP with time windows and partial recharging (RELRP-TWPR) as the first model that considers all of the above mentioned aspects. We present an adaptive large neighbourhood search (ALNS) framework using computational parallelization techniques to solve large sized instances with several scenarios in reasonable time. Additionally, we derive several deterministic approaches (e.g., deterministic, median, worst case) in order to evaluate the competitiveness of the robust planning approach. We create new benchmark instances by mapping data from a real-world case study (Schiffer et al. 2016) to the Solomon instances (Solomon 1987) and incorporate different degrees of uncertainty. In this course, we analyze variations of customer patterns with respect to the spatial distribution of customers, the width of service time windows and the demand patterns in order to show the significance of the proposed planning approach for different degrees of uncertainty. Results are discussed with respect to overall costs and feasibility aspects allowing for a comparison of the robust planning approach with deterministic planning approaches. Based on these results, we analyze the advantages and importance of a robust planning approach for the design of logistics networks with electric fleets and derive managerial insights.

The remainder of this paper is structured as follows: A brief overview on related literature is given in Section 2 with a focus on existing planning approaches for ECVs and on approaches for optimization under uncertainty. In Section 3, a short introduction into robust modeling approaches is provided, and the RELRP-TWPR is presented as a new planning approach. A parallelized hybrid of ALNS and dynamic programming (DP) is presented in Section 4 in order to solve large-sized instances. In Section 5, we describe the instance generation and the experimental design as well as the deterministic and robust modeling approaches. Section 6 details results on the proposed planning approaches. In this course, the benefit of the proposed planning approach is discussed and managerial insights for the robust design of electric logistics fleets are derived. Section 7 summarizes the main findings of this paper.

2. Literature Review

In this section, a brief overview of recent research on ECVs within logistics fleets is given. Besides focusing on VRP and LRP approaches for ECVs, we give a short overview on considering uncertainty within optimization models.

So far, literature on electric logistics fleets either focuses on operational planning by adopting VRP approaches to the specific characteristics of ECVs, or on strategic design by applying FLPs for siting of charging infrastructure.

ECVs within logistics fleets have widely been discussed from a VRP perspective. The first model focusing on ECVs considering range limitations and recharging at customer vertices has been proposed by Conrad and Figliozzi (2011). Erdoğan and Miller-Hooks (2012) proposed the green VRP (GVRP), which is the first model considering charging facilities on routes. Barco et al. (2013) provided an electric VRP (EVRP) minimizing the overall consumed energy instead of the overall traveled distance. To the best of our knowledge, Schneider et al. (2014) were the first focusing explicitly on electric logistics fleets with time dependent charging options on routes by introducing the EVRP with time windows (EVRP-TW). Based on the EVRP-TW, several EVRP variations have been proposed focusing on heterogeneous fleets (Hiermann et al. 2016, Goeke and Schneider 2015) as well as partial recharging (Felipe et al. 2014, Sassi et al. 2015a,b, Keskin and Çatay 2016, Montoya et al. 2017) and different charging technologies (Felipe et al. (2014)). A branch-price-and-cut algorithm for different EVRP-TW variants has been proposed by Desaulniers et al. (2016). Recent research on hybrid electric vehicles was presented by Mancini (2015) and Doppstadt et al. (2016). Pelletier et al. (2016) gave an extensive overview on recent research in the field of goods distribution with ECVs. The behavior and characteristics of batteries have been analyzed in Pelletier et al. (2017) in this context. However, charging infrastructure is assumed to be already fixed in these approaches, which might result in unrealized improvement potentials if these decision can still be taken.

FLPs to determine charging station locations can be separated into tow problem classes; vertex-based and flow-based planning approaches. To keep this paper concise, we refer to Schiffer and Walther (2017) for a profound overview of these approaches. Although a lot of research has been done in this field for public charging infrastructure, these approaches consider either charging demand being aggregated in single vertices (vertex-based) or predetermined traffic flows (flow-based). Thus, all of these approaches lack of considering the interdependencies between routing of vehicles and charging station location decisions.

Since EVRPs as well as FLPs neglect the interdependencies between siting decisions for charging infrastructure and routing decisions for ECVs, first integrated modeling approaches have been provided from a LRP perspective by Yang and Sun (2015) and Schiffer and Walther (2017). While Yang and Sun (2015) presented the battery swap station electric vehicle LRP (BSS-EV-LRP) focusing on battery swapping stations (BSSs), Schiffer and Walther (2017) introduced the electric LRP with time windows and partial recharging (ELRP-TWPR) taking time windows as well as the complete range of recharging options into consideration. In addition, Schiffer and Walther (2016) introduced the LRP with intra-route facilities (LRPIF) as a generic model addressing simultaneous routing and siting decisions for intra-route facilities, herein covering the location of charging stations as well as freight replenishing facilities. The LRPIF was extended for multiple resources and different types of intra-route facilities by Schiffer et al. (2017b). A real-world case study, highlighting the benefit of integrated planning of charging station location and vehicle routing decisions for electric logistics networks has been presented by Schiffer et al. (2016). Concluding, all of these LRPIFs represent a first step into solving simultaneous ECV routing and charging station location decisions. However, these models are so far limited to a single customer scenario. A modeling approach that allows to consider uncertain customer patterns is still missing. To the best of our knowledge, no approach that considers simultaneous routing and charging station location decisions for ECVs as well as uncertain customer patterns has been developed so far.

Approaches that integrate uncertainty into optimization models are mainly separated into two research streams: stochastic optimization and robust optimization. Within stochastic optimization, the uncertainty of parameters is described by probability distributions. Thus, stochastic models can only be applied if a probability function is given. Furthermore, the stochastic reformulation of the discrete model has to remain computationally tractable to allow for stochastic optimization. Within robust optimization, no probability distribution is needed to model uncertainty. Instead, an uncertainty set that defines discrete states of the uncertain parameters is used. Due to its computational tractability, robust optimization has been applied to many application cases and has become increasingly popular in recent years.

While research on integrating uncertainty into VRPs has been widely discussed, research on integrating uncertain information into LRP approaches is still sparse. To the best of our knowledge, only five publications exist in this field. The first publication on stochastic LRPs was provided by Albareda-Sambola et al. (2007) focusing on stochastic demand. Ahmadi-Javid and Seddighi (2013) studied a stochastic LRP with disruption risk, while Hassan-Pour et al. (2009), Zhang et al. (2008), and Ahmadi-Javid and Azad (2010) focused on stochastic LRPs with inventory routing components. The RELRP-TWPR that is developed within this paper differs from those planning approaches for two main reasons: First, the RELRP-TWPR does not site depots as done in classical LRP approaches, but intra-route facilities (charging stations) on routes in order to keep vehicles operational while providing service. Second, uncertainty is not only considered to derive good solutions for worst case scenarios as it is done in classical approaches, but the aim is to obtain (at least) feasible solutions for all scenarios. Concluding, the proposed planning problem focusing on simultaneous ECV routing and charging station location decisions for electric logistics fleets with uncertain demand, time windows and service times has not been addressed in literature yet.

3. The robust electric location routing problem with time windows and partial recharging

In this section, we introduce the RELRP-TWPR as a robust mixed integer linear problem. In order to show how the RELRP-TWPR can be classified as a general robust modeling approach, we first give a very brief overview on robust optimization techniques in Section 3.1. For further studies on robust optimization we refer to Ben-Tal and Nemirovski (2002), Ben-Tal et al. (2004, 2009, 2015) and Gorissen et al. (2015). Then, we present a mixed integer problem formulation for the RELRP-TWPR in Section 3.2

3.1. Robust optimization techniques

Remember from Section 2 that in robust optimization uncertainty is considered by an uncertainty set $\mathcal{U}$, defining a range of possible discrete states of the uncertain parameters. Then, a general linear optimization problem characterizing uncertainty by set based discrete values can be written as follows:

$$\begin{aligned} \min_{\boldsymbol{x}} \ & \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} \\ s.t. \quad & \boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{d} \\ & (\boldsymbol{c}, \boldsymbol{A}, \boldsymbol{d}) \in \mathcal{U}, \quad \boldsymbol{c} \in \mathbb{R}^{n}, \quad \boldsymbol{A} \in \mathbb{R}^{m \times n}, \quad \boldsymbol{d} \in \mathbb{R}^{m}, \end{aligned} \tag{3.1}$$

considering a vector with objective function coefficients $\boldsymbol{c}$, a right hand side (RHS) vector $\boldsymbol{d}$, a left hand side (LHS) $\boldsymbol{A}$ and a solution vector $\boldsymbol{x}$. Without loss of generality Model (3.1) can be transformed into a formulation in which $\boldsymbol{c} \in \mathbb{R}^{n}$ and $\boldsymbol{d} \in \mathbb{R}^{m}$ are certain and the uncertainty is limited to $\boldsymbol{A}$ (cf. Ben-Tal et al. 2009, Gorissen et al. 2015). This formulation, referred to as the robust counterpart (RC) model of (3.1) is given as follows:

$$\begin{aligned} \min \ & \boldsymbol{c}^{\mathrm{T}}\boldsymbol{x} \\ s.t. \quad & \boldsymbol{A}(\boldsymbol{\zeta})\, \boldsymbol{x} \leq \boldsymbol{d} \qquad \boldsymbol{\zeta} \in \mathcal{Z} \\ & \boldsymbol{c} \in \mathbb{R}^{n}, \quad \boldsymbol{A} \in \mathbb{R}^{m \times n}, \quad \boldsymbol{d} \in \mathbb{R}^{m}, \end{aligned} \tag{3.2}$$

considering a primitive uncertainty set $\mathcal{Z}$. Within those conservative robust optimization models, all decisions on $\boldsymbol{x} \in \mathbb{R}^{n}$ have to be made before the realization of the uncertainty is known.

A strategic real world decision often consists of several decisions that can be separated in two classes. While some decisions have to be taken before the realization of the uncertainty is known, other decisions can be adjusted afterwards. Therefore, decision variables can be separated into two sets. The non-adjustable set contains all decision variables whose values have to be determined before the realization $\boldsymbol{\zeta}$ of the uncertainty is known. Those decisions are often referred to as here and now decisions. The adjustable set contains wait and see variables, which can be adjusted after $\boldsymbol{\zeta}$ is known. Thus, a less conservative robust optimization model containing such a two-stage decision can be derived by integrating $\boldsymbol{x} = (\boldsymbol{u}^{\mathrm{T}}, \boldsymbol{v}^{\mathrm{T}}(\boldsymbol{\zeta}))$ with a vector of non-adjustable decision variables $\boldsymbol{u}$ and a vector of adjustable decision variables $\boldsymbol{v}(\boldsymbol{\zeta})$ into model (3.1). Based on this, an adjustable RC (ARC) model (3.3) is defined as derived in Ben-Tal et al. (2004).

$$\begin{aligned} \min \ & \boldsymbol{c}^{\mathrm{T}}(\boldsymbol{u}^{\mathrm{T}}, \boldsymbol{v}^{\mathrm{T}}(\boldsymbol{\zeta})) \\ s.t. \quad & \boldsymbol{A}(\boldsymbol{\zeta})\,(\boldsymbol{u}^{\mathrm{T}}, \boldsymbol{v}^{\mathrm{T}}(\boldsymbol{\zeta})) \leq \boldsymbol{d} \qquad \boldsymbol{\zeta} \in \mathcal{Z} \\ & \boldsymbol{c} \in \mathbb{R}^{n}, \quad \boldsymbol{A} \in \mathbb{R}^{m \times n}, \quad \boldsymbol{d} \in \mathbb{R}^{m} \end{aligned} \tag{3.3}$$

In the following, we show how the integrated decision on locating charging infrastructure and routing ECVs while considering uncertain customer patters can be modeled as an ARC. Herein, the siting of charging stations is modeled by non-adjustable decision variables (which are equal over all scenarios), as these variables have to be determined before the realization $\boldsymbol{\zeta}$ of the uncertainty is known. The routing decisions however, are modeled by adjustable variables as these depend on uncertain customer patterns.

3.2. Mixed integer problem formulation

The RELRP-TWPR can be stated as a robust mixed integer linear problem based on the following assumptions: The vehicle speed is assumed to be constant and differences in altitude are neglected. In addition, energy consumption is linear dependent on the traveled distance, while the recharging time depends linearly on the amount of energy recharged. It should be noted that these assumptions are used for the formal description of the problem, but can be easily relaxed and extended to consider real-world data. Charging stations are allowed to be sited at any vertex, and an unlimited number of vehicles is allowed to charge simultaneously. One charging station is sited at the depot to ensure feasibility of tours for a multi-period planning horizon. Partial recharging is allowed, and recharging and service at a customer can take place simultaneously (cf. Schiffer et al. 2016). Additionally, vehicles are allowed to charge at a customer's site, even if they are not serving this specific customer. Time windows are considered, since time dependent recharging strongly affects the overall route duration and has a significant influence on route feasibility (cf. Schiffer and Walther 2017). It is even more important to consider time windows for the RELRP-TWPR than for the ELRP-TWPR, since the target is to determine a solution that is feasible for any scenario out of the uncertainty set. Thus, all customer demands have to be fulfilled in order to ensure operational competitiveness between ECVs and ICEVs. Within the objective function, acquisition costs for charging stations and vehicles as well as operational costs depending on the driven distance are considered. All costs are accounted as costs per day in order to keep costs comparable.

Our model formulation holds as follows: Given a set of arcs $(i, j) \in \mathcal{A}$ and a set of vertices $\mathcal{V}_{0,n+1}$ including vertices 0 and $n+1$ for the start-depot and the end-depot vertex, the RELRP-TWPR is defined on a complete, directed graph $G = (\mathcal{V}_{0,n+1}, \mathcal{A})$. While $\mathcal{V}$ is the set of all vertices excluding depot vertices, a set of customer vertices is given by $\mathcal{C}$ and a set of potential recharging vertices is given by $\mathcal{F}$. Since we use dummy vertices as it has been done in Schiffer and Walther (2017) to allow multiple visits to charging stations, $\mathcal{S}_\kappa$ denotes a set of dummy vertices for vertex κ and thus, the set of all dummy vertices is given by $\mathcal{S} = \bigcup_{\kappa \in \{\mathcal{C} \cup \mathcal{F}\}} \mathcal{S}_\kappa$. Sets subscripted with 0 or $n+1$ contain the respective depot vertices. To keep the model notation short, we use the cut sets $\delta^-(i) = \{j \in \mathcal{V}_{0,n+1} : (i,j) \in \mathcal{A}\}$ and $\delta^+(i) = \{j \in \mathcal{V}_{0,n+1} : (j,i) \in \mathcal{A}\}$ to identify all vertices that are successors or predecessors of vertex i.

To consider uncertainty, several parameters depend on the realization ζ out of the uncertainty set $\mathcal{Z}$. Thus, the earliest arrival time e_i^ζ, the latest arrival time l_i^ζ, the service time s_i^ζ and the customer demand p_i^ζ at a vertex i are vertex-based parameters that have to be differentiated according to ζ. We assume that the distance d_{ij} of an arc (i, j), the driving time t_{ij}, the recharging rate r and the consumption rate h as well as the battery capacity Q and the freight capacity F are discrete and independent of the underlying scenario.

Table 1: Decision variables and parameter definitions.

Sets	
$\mathcal{C}$	set of customer vertices
$\mathcal{F}$	set of potential recharging vertices
$\mathcal{S}_\kappa$	set of dummy vertices for vertex $\kappa \in \{\mathcal{C} \cup \mathcal{F}\}$
$\mathcal{S}$	set of all dummy vertices $(\bigcup_{\kappa \in \{\mathcal{C} \cup \mathcal{F}\}} \mathcal{S}_\kappa)$
$\mathcal{V}$	set of all vertices without depot vertices $(\mathcal{C} \cup \mathcal{F} \cup \mathcal{S})$
$\mathcal{Z}$	uncertainty set
Decision variables	
x_{ij}^ζ	binary: arc (i,j) is traveled
y_i	binary: recharging station is sited at vertex i
τ_i^ζ	arrival time at vertex i
w_i^ζ	amount of energy charged at vertex i
q_i^ζ	battery load at vertex i
f_i^ζ	freight load at vertex i
Parameters	
e_i^ζ	earliest time of arrival allowed at vertex i
l_i^ζ	latest time of arrival allowed at vertex i
s_i^ζ	service-time at vertex i
p_i^ζ	demand at vertex i
t_{ij}	driving time from vertex i to vertex j
d_{ij}	distance between vertex i and vertex j
r	recharging rate
h	consumption rate
Q	battery capacity
F	freight capacity

The decision variables of the RELRP-TWPR are divided in adjustable and non-adjustable decision variables. While the location decision for charging stations, modeled by binary variables y_i, is non-adjustable, decision variables affecting the routing decision are adjustable with respect to ζ. Thus, the binary variables x_{ij}^ζ indicating if arc (i,j) is traversed, as well as the arrival time τ_i^ζ, and the amount of energy recharged w_i^ζ at a vertex i are indexed by ζ and are allowed to be adjusted with respect to the finally holding ζ. This also holds for a vehicle's state of charge q_i^ζ and the residual freight f_i^ζ at a vertex i. In addition, k is used to track the fleet size in order to estimate vehicle acquisition costs. Table 1 gives an overview of the used notation.

The Objective (3.4) of the RELRP-TWPR considers cost terms for driving costs c_{ij}, fixed costs for the installation of charging stations c^{s}, and fixed costs for the acquisition of vehicles c^{v}. The necessary fleet size is determined by obtaining constraints 3.5, considering the maximum number of vehicles out of all ζ.

$$\min \quad Z = c^{\mathrm{v}} k + \sum_{i \in \{\mathcal{V} \setminus \mathcal{S}\}} c^{\mathrm{s}} y_i + \sum_{(i,j) \in \mathcal{A}, \zeta \in \mathcal{Z}} c_{ij} x_{ij}^\zeta \tag{3.4}$$

$$\sum_{j\in\delta^+(0)} x_{0j}^{\zeta} \leq k \qquad \zeta \in \mathcal{Z} \quad (3.5)$$

Constraints (3.6)–(3.8) extend state of the art constraints to a robust model formulation. While (3.6) secures that all customer demand is served, (3.7) extends the single-assignment constraint for charging station vertices. By allowing arcs to be assigned only if a charging station is sited at the outgoing vertex i, we strengthen the formulation and reduce the computational time significantly (cf. Schiffer and Walther 2017). Flow conservation for any scenario is enforced by (3.8). Time window constraints are given by (3.9)–(3.11). While (3.9) holds for customer vertices, (3.10) holds for charging stations. If a charging station is built at a customer vertex, the tighter one of these two constraints holds. Constraints (3.11) obtain time window feasibility to any vertex. The charging station location decision is linked to the routing and recharging decisions by constraint (3.12) and (3.13). Constraints (3.12) allow for recharging at vertex i only if a charging station is built at vertex i. Constraints (3.13) mirror the location decision to dummy vertices. Constraints (3.14) and (3.15) extend state of the art freight balance constraints to ζ. Range limitations due to battery capacity and recharging are modeled by constraints (3.16)–(3.19). Constraints (3.16) and (3.17) obtain the energy balance for the underlying problem considering energy consumption and recharging. The initial state of charge of a vehicle is limited by (3.18) to the battery capacity. Constraints (3.19) enforce the amount of recharged energy to be within the capacity limit of the batteries. The entity of these constraints prevents vehicles from running out of energy on routes. Binary variables are defined in (3.20) and (3.21).

$$\sum_{j\in\delta^+(i)} x_{ij}^{\zeta} F \geq p_i^{\zeta} \qquad i \in \mathcal{C},\ \zeta \in \mathcal{Z} \quad (3.6)$$

$$\sum_{i\in\delta^-(j)} x_{ij}^{\zeta} \leq y_j \qquad j \in \{\mathcal{V} \setminus \mathcal{C}\},\ \zeta \in \mathcal{Z} \quad (3.7)$$

$$\sum_{j\in\delta^-(i)} x_{ji}^{\zeta} - \sum_{j\in\delta^+(i)} x_{ij}^{\zeta} = 0 \qquad i \in \mathcal{V},\ \zeta \in \mathcal{Z} \quad (3.8)$$

$$\tau_j^{\zeta} \geq \tau_i^{\zeta} + \left(t_{ij} + s_i^{\zeta}\right) x_{ij}^{\zeta} - l_0^{\zeta}\left(1 - x_{ij}^{\zeta}\right) \qquad i \in \mathcal{C}_0,\ j \in \delta^+(i),\ \zeta \in \mathcal{Z} \quad (3.9)$$

$$\tau_j^{\zeta} \geq \tau_i^{\zeta} + t_{ij}x_{ij}^{\zeta} + r\ w_i^{\zeta} - \left(l_0^{\zeta} + rQ\right)\left(1 - x_{ij}^{\zeta}\right) \qquad i \in \mathcal{V},\ j \in \delta^+(i),\ \zeta \in \mathcal{Z} \quad (3.10)$$

$$e_i^{\zeta} \leq \tau_i^{\zeta} \leq l_i^{\zeta} \qquad i \in \mathcal{V}_{0,n+1},\ \zeta \in \mathcal{Z} \quad (3.11)$$

$$w_i^{\zeta} \leq Qy_i \qquad i \in \mathcal{V},\ \zeta \in \mathcal{Z} \quad (3.12)$$

$$y_i \geq y_j \qquad i \in \{\mathcal{V} \setminus \mathcal{S}\},\ j \in \mathcal{S}_i \tag{3.13}$$

$$0 \leq f_j^\zeta \leq f_i^\zeta - p_i^\zeta x_{ij}^\zeta + F\left(1 - x_{ij}^\zeta\right) \qquad (i,j) \in \delta\left(V_{0n+1}\right),\ \zeta \in \mathcal{Z} \tag{3.14}$$

$$0 \leq f_0^\zeta \leq F \qquad \zeta \in \mathcal{Z} \tag{3.15}$$

$$q_j^\zeta \leq q_0^\zeta - h\ d_{0j} x_{0j}^\zeta + Q\left(1 - x_{0j}^\zeta\right) \qquad j \in \delta^+(0),\ \zeta \in \mathcal{Z} \tag{3.16}$$

$$0 \leq q_j^\zeta \leq q_i^\zeta + w_i^\zeta - h\ d_{ij} x_{ij}^\zeta + Q\left(1 - x_{ij}^\zeta\right) \qquad (i,j) \in \delta\left(V_{0n+1}\right),\ \zeta \in \mathcal{Z} \tag{3.17}$$

$$0 \leq q_0^\zeta \leq Q \qquad \zeta \in \mathcal{Z} \tag{3.18}$$

$$0 \leq q_i^\zeta + w_i^\zeta \leq Q \qquad i \in \mathcal{V},\ \zeta \in \mathcal{Z} \tag{3.19}$$

$$x_{ij}^\zeta \in \{0;1\} \qquad (i,j) \in \delta\left(V_{0n+1}\right),\ \zeta \in \mathcal{Z} \tag{3.20}$$

$$y_i \in \{0;1\} \qquad i \in \mathcal{V} \tag{3.21}$$

4. Solution Method

Focusing on RC formulations in general, even a single constraint may get computationally intractable if e.g., an ellipsoidal or polyhedral uncertainty set is used. To achieve a computationally tractable model for a RC, two different approaches can be used: Within the first approach, robust reformulation techniques are used to eliminate any $\forall \zeta \in \mathcal{Z}$ in each constraint. For an overview of robust reformulation techniques, we refer to Ben-Tal et al. (2009) for linear problems, and to Ben-Tal et al. (2015) for nonlinear problems. The second approach, which is often used if robust reformulation techniques are not sufficient, is called the adversarial approach. Within this approach, a finite set of scenarios out of $\mathcal{Z}$ is used to solve the model. Afterwards, the derived solution is evaluated for all scenarios. If there is an infeasible scenario left, this scenario is added to the subset of considered scenarios and the problem is solved again. For a detailed description of this method, we refer to Bienstock and Özbay (2008). Often, using robust reformulation techniques is the state of the art to solve RCs. However, if the RC cannot be stated as a tractable reformulation, the adversarial approach provides a good alternative to solve the RC.

Within the application case of this paper, the uncertainty is covered within scenarios that consider different customer patterns representing daily delivery scenarios. No complex uncertainty set is used and thus, the respective RC can be solved by a single iteration of the adversarial approach. For a fixed ζ, the proposed problem is a special case of the LRPIF, which has been proposed in Schiffer and Walther (2016). The proposed problem is NP-hard and even the deterministic problem variant cannot be solved by commercial solvers in acceptable time for real-world data set sizes (cf. Schiffer and Walther 2016, Schiffer et al. 2016). Therefore, a metaheuristic solution approach is needed to solve large sized instances. Since the algorithm that was developed in Schiffer and Walther (2016) proved to be very competitive and able to provide high quality solutions for different variants of the LRPIF, we extend this algorithm to solve the RELRP-TWPR. This method can also be used for variants of the model, e.g., regarding complex uncertainty sets, if the adversarial approach is chosen.

In the following, a concise description of the algorithm, which is a hybrid of ALNS and DP, is given: ALNS, as introduced by Ropke and Pisinger (2006), is a metaheuristic that extends the large neighborhood search (LNS) that has been introduced by Shaw (1998) by an adaptive learning mechanism. In a LNS, a destroy and repair mechanism is used to explore large neighborhoods. Within every search step, a destroy operator is used to remove vertices from the current solution in a specific fashion. Afterwards, the removed vertices are inserted by a repair operator to create a new solution. With this mechanism, larger neighborhoods are explored and thus, the search procedure is capable of overcoming local optima. ALNS enhances LNS in that destroy and repair operators are no longer chosen randomly but based on probabilities that reflect the success of each operator during former search steps.

We use ALNS as the basic part of our hybrid solution method, which is extended by a dynamic programming component in order to intensify the search in promising facility configurations. To derive an efficient location component, we separate the destroy operators into two sets: Large destroy operators out of set $\mathcal{D}_{\text{l}}$ change the facility configuration and remove customer vertices, while small destroy operators out of set $\mathcal{D}_{\text{s}}$ remove only customer vertices. A repair operator out of set $\mathcal{R}$ is used after each destroy operator to create a new solution. In addition, a generalized cost function with penalty terms and adaptive penalty weights as it was first proposed by Cordeau et al. (2001) in order to explore larger parts of the search space is used (cf. Schiffer and Walther 2016).

Figure 1 shows the pseudo code of the proposed algorithm: Each search step starts with a destroy and repair phase. Every η^{lrg} iterations, a large destroy operator is used to change the facility configuration before removing customers. After a large destroy operator, the temporal solution σ' is passed on to the current solution σ. A local search as well as dynamic programming elements are then used to improve the solution. Even if the previous solution could not be enhanced, the temporal solution is passed on to the current solution to allow for further search steps on the respective facility configuration. In between these large destroy iterations, a small destroy operator is used to prevent the algorithm from running into local optima for the current

$\sigma \leftarrow InitialSolution()$, $InitializeParameters()$, $\iota \leftarrow 0$
while $(\iota < \eta^{\max})$ **and** $(\iota - \iota_{\text{imp}} < \eta^{\max}_{\text{noi}})$ **do**
  if $\left(\textbf{modulo}\left(\iota, \eta^{\text{lrg}}\right) = 0\right)$ **then**
    $\sigma' \leftarrow destroyAndRepair(\mathcal{D}_{\text{l}}, \mathcal{R}, \sigma)$
  else
    $\sigma' \leftarrow destroyAndRepair(\mathcal{D}_{\text{s}}, \mathcal{R}, \sigma)$
  if $\left(\lambda(\sigma') < \lambda(\sigma^*)\left(1 + \delta^{\text{l}}\right)\right)$ **then**
    $\sigma' \leftarrow localSearch(\sigma')$
    if $\left(\lambda(\sigma') < \lambda(\sigma^*)\left(1 + \delta^{\text{d}}\right)\right)$ **then**
      $\sigma' \leftarrow dynamicProgramming(\sigma')$
  if $(\lambda(\sigma) < \lambda(\sigma'))$ **then**
    $\sigma \leftarrow \sigma'$
    if $(\lambda(\sigma') < \lambda(\sigma^*))$ **then**
      $\sigma^* \leftarrow \sigma'$
      $\sigma'_{\text{f}} \leftarrow generateFeasibleSolution(\sigma')$
      if $feasible(\sigma'_{\text{f}})$ **and** $(\lambda(\sigma'_{\text{f}}) < \lambda(\sigma^*_{\text{f}}))$ **then**
        $\sigma^*_{\text{f}} \leftarrow \sigma'_{\text{f}}$
        $\iota_{\text{imp}} \leftarrow \iota$
  if $(\textbf{modulo}(\iota, \eta^{\text{res}}) = 0)$ **then**
    $\sigma \leftarrow \sigma^*_{\text{f}}$
  $\iota \leftarrow \iota + 1$

Figure 1: Adaptive large neighborhood search.

facility configuration. To intensify the search in promising parts of the search space, a corridor based approach is used to guide the local search and the dynamic programming component. If the deviation of the temporal solution σ' from the so far best solution σ^* is lower than δ^{l} after a destroy and repair phase, a local search (cf. Schiffer and Walther 2016) is carried out to intensify the search. If the deviation is lower than δ^{d}, an additional dynamic programming component is used on a limited search tree to obtain the optimal facility positions on each route (cf. Schiffer and Walther 2016). The best solution σ^* as well as the best feasible solution σ^*_{f} are stored separately in order to evaluate infeasible regions of the search space and to overcome local optima (cf. Cordeau et al. 2001). If the current solution is improved, the temporal solution σ' is forwarded to the current solution σ after a search step. If σ' further improves the best solution σ^*, it is forwarded to σ^*. Additionally, a feasible solution σ'_{f} is generated using the method described in Vidal et al. (2014). If a feasible solution σ'_{f} is obtained that improves the so far best feasible solution σ^*_{f}, σ'_{f} is forwarded to σ^*_{f}. After η^{res} iterations, the current solution is reset to the so far best feasible solution in order to restart the algorithm and to prevent a too deep evaluation of infeasible parts of the search space. For a detailed explanation of the individual components of the algorithm, we refer to Schiffer and Walther (2016). The proposed algorithm is implemented in C++, and parallelization techniques are used for solving multiple scenarios with lower computational time based on the OpenMP API. The destroy and repair step as well as the local search and the dynamic programming component are all parallelized as they can be applied for each scenario separately as long as the facility configuration is fixed. Thus, only the large destroy step and the adaptive evaluations of the respective step as well as the stopping criterion check are executed within a critical section of the code.

5. Design of experiments

In order to show the benefit of the RELRP-TWPR for the design of logistics networks operated with ECV fleets, we design benchmark instances by mapping real-world data presented in Schiffer et al. (2016) to the Solomon instances. These benchmark instances are modified with regard to varying spatial customer patterns, variability in demand as well as in time window variations (cf. Section 5.1). Additionally, we derive several deterministic modeling approaches (deterministic, worst case, median) that can alternatively be used to solve the addressed problem (cf. Section 5.2). We use these approaches to analyze the benefit of the robust location routing approach.

5.1. Benchmark instances

In the following we derive benchmark sets that allow for carrying out a comprehensive analysis of the impact of variations in customer patterns on the design of electric logistics fleet networks. As a result of these analysis, we aim at a twofold contribution by (i) determining the benefit of our robust approach compared to deterministic approaches, and by (ii) deriving real-world managerial insights with regard to the design of logistics networks for ECV fleets. Thus, the benchmark instances must reflect the complete variety in spatially and temporally varying customer patterns and must also resemble real-world data.

To derive benchmark instances that meet these requirements, we use the data that is provided within Schiffer et al. (2016) to consider real-world energy consumption and charging time values. However, the customer distribution of the instances derived in Schiffer et al. (2016) does not match our requirements, since there are no variations in customer distribution and time windows. Thus, we additionally use the Solomon instances (cf. Solomon 1987) that have been adjusted for electric logistics fleets by Schneider et al. (2014). These instances consist of 6 different benchmark sets with clustered (c), randomly distributed (r) and randomly clustered (rc) customer locations. In addition, these categories are further separated into two classes of instances that contain either short time windows and small vehicle capacities (c100, r100, rc100) or wide time windows and large vehicle capacities (c200, r200, rc200). We map the real-world information of the vehicle battery capacity and charging as well as consumption profiles from Schiffer et al. (2016) to the Solomon instances and thus create instances that consider the real-world data as well as varying customer patterns. The instances are mapped to the real-world case described in Schiffer et al. (2016) as follows:

1. The distance between the depot and the customer with the highest distance to the depot within the modified Solomon instances is set to 120 km. All other distances of the modified Solomon instances are converted proportionally and transfered to kilometers.
2. To regard realistic consumption and recharging rates of vehicles, these parameters are estimated from the real-world case study data and are transfered to the modified Solomon instances.
3. The overall planning horizon of the Solomon instances is set to the case study planning horizon, and all time windows of the modified Solomon instances are scaled proportionally.
4. Time windows are adjusted once more, taking the real-world ratio between the arc length and the travel speed into consideration, since fictitious travel speeds and distances are used within the modified Solomon instances. Thus, the average traveling speed of the real-world case study is used within the derived instances.

For each of those categories, we create five instances, assuming a weekly customer profile with five working days, so that each instance contains five scenarios. After arbitrarily choosing a deterministic instance, scenarios for these instances are created considering three different degrees of uncertainty within the customer patterns, obtaining 90 instances in total, as follows:

1. **Customer variation (deg1):** For the first degree of uncertainty, regular and sporadic customers are modeled by randomly assigning the majority of the customers to selected scenarios, with only a small subset of customers being assigned to all scenarios. Thus, 75% of (randomly chosen) customers are distributed equally over the five scenarios (sporadic customers), while 25% of all customers are fixed within all scenarios (regular customers).
2. **Demand variation (deg2):** To extend the degree of uncertainty, varying demands are considered for both regular and sporadic customers within the second degree of uncertainty. Doing so, the demand of each customer is varied within the range of the minimum and maximum demand of the instance set. In addition, the demand of each regular customer is forced to differ between the scenarios.
3. **Delivery pattern variation (deg3):** The third degree of uncertainty represents the maximum degree of uncertainty for the generated instances. Besides customer and demand variation, also time windows are now shifted randomly for all customers. Herein, the time windows of a regular customer are forced to differ for varying scenarios.

Doing so, benchmark instances are derived that on the one hand account for different network structures and customer patterns, but on the other hand also reflect the real-world planning characteristics of electric logistics fleets.

5.2. Modeling approaches

To evaluate the benefit of the robust modeling approach, we compare the robust results to three deterministic approaches that consider the uncertain information to a certain degree. First, a deterministic model is derived, which allows for a comparison of the robust solution with results for single deterministic scenarios. Second, a median modeling approach is derived, which allows for a comparison of robust results with results for median demands and time windows. Third, a worst case modeling approach is derived in order to allow for a comparison of robust results with the results derived based on a worst case estimation of customer demand and time windows.

For all approaches, the locations of charging stations are determined first using an integrated location-routing approach. Based on the determined charging station infrastructure, an additional VRP solution (cf. Schiffer et al. 2017a) is obtained at a second stage, aiming at a minimization of vehicle acquisition and operational costs. Thus, comparable solution quality is ensured for the different approaches. Concluding, four different planning approaches result:

Deterministic model (D-model): For the deterministic modeling approach, one customer pattern is chosen out of the uncertainty set. Thus, the simultaneous vehicle routing and charging station location decision is based on one specific scenario. Based on the resulting charging stations infrastructure, the VRP approach (cf. Schiffer et al. 2017a) is used within a second step to derive optimal routing decisions for all customer patterns (respective scenarios).

Median model (M-model): Within the median modeling approach, one average customer pattern representation is derived out of all given customer patterns using average demand $\overline{p}_i$ as well as average time windows $\left[\overline{e}_i, \overline{l}_i\right]$ for each vertex i as defined in (5.1). The integrated vehicle routing and charging station location decision is then determined for this average scenario. Afterwards, all scenarios are solved for the predetermined charging station configuration using the VRP approach.

$$\overline{p}_i = \sum_{\zeta \in \mathcal{Z}} \frac{p_i^\zeta}{|\mathcal{Z}|}; \qquad \overline{e}_i = \sum_{\zeta \in \mathcal{Z}} \frac{e_i^\zeta}{|\mathcal{Z}|}; \qquad \overline{l}_i = \sum_{\zeta \in \mathcal{Z}} \frac{l_i^\zeta}{|\mathcal{Z}|} \qquad \forall i \in \mathcal{V} \tag{5.1}$$

Worst case model (W-model): Within the worst case modeling approach, a worst case customer pattern representation is derived from the uncertainty set $\mathcal{Z}$, i.e. worst case demand $\hat{p}_i$ and worst case time window values $[\hat{e}_i, \hat{l}_i]$ are determined for each vertex i. Therefore, the highest demand as well as the tightest time window out of $\mathcal{Z}$ are considered for any vertex as stated in (5.2). Analogously to the median and deterministic approach, a VRP approach is used afterwards to solve all customer patterns with the obtained charging station configuration.

$$\hat{p}_i = \max_{\zeta \in \mathcal{Z}} p_i^{\zeta}; \qquad \hat{e}_i = \max_{\zeta \in \mathcal{Z}} e_i^{\zeta}; \qquad \hat{l}_i = \min_{\zeta \in \mathcal{Z}} l_i^{\zeta} \qquad \forall i \in \mathcal{V} \tag{5.2}$$

Robust model (R-model): Within the robust modeling approach, all scenarios of a single instance are considered as depicted in Section 3. Although a postponed VRP approach is not necessary to derive a feasible solution, the same two-step approach as for the other modeling approaches is used in order to keep the solution quality of all approaches comparable.

6. Results

Within this section, we present results for the deterministic and the robust planning approaches introduced in Section 5.2 on all benchmark instances. Herein, we analyze to which extend a robust planing approach for the network design affects the operational feasibility at a later decision making stage, and if the benefit of a robust planning approach at a strategic level also results in further cost savings at an operational level. In this course, we discuss if alternative deterministic planing approaches, like the D-, M- and W-model, are sufficient to derive the charging station locations for an ECV distribution network. We also discuss the impact of the different degrees of uncertainty. Additionally, we derive managerial insights for practitioners that design logistics networks for ECVs.

For all modeling approaches (D-, M-, W-, R-model), we apply a two-stage solution approach. First, we identify the best facility configuration for each instance and modeling approach using a LRP, applying the parallelized ALNS described in Section 4 for the R-model, respectively the same ALNS without parallelization techniques for the deterministic models (D-, M-, W-model). Second, we solve a VRP for each scenario of each instance fixing the charging station locations that have been identified in the LRP step. For the VRP step, the algorithm described in Schiffer et al. (2017a) is used. For both planning stages, driving costs as well as investment costs for vehicles and charging stations are regarded at a daily basis within the objective function. Cost terms are used as provided in Schiffer et al. (2016). To secure a sufficient solution quality, we use the best solution out of ten runs for each experiment. To keep the paper concise, we present only aggregated results in this chapter, while detailed results on the LRP and the VRP calculations are given in Appendix A in Table 4 – Table 19.

First, we analyze the applicability of the four modeling approaches at the LRP planning stage, since the derivation of aggregated deterministic instances (as done for the M-model and the W-model) might lead to infeasible instance representations. If one of the instances is infeasible within the LRP stage when solving the M-model or the W-model, the feasibility of the instance is tested with an external routine. Herein, the accessibility of each customer is tested with respect to time windows and charging station positions. Table 2 presents the feasibility for all modeling approaches with respect to the instance sets and the degrees of uncertainty (deg1, deg2, deg3). As can be seen, for the W-model approach a number of instances is already infeasible at the LRP planning stage. Herein, the number of infeasible instances is increasing with increasing degree of uncertainty. This is because worst case representations for customer patterns are chosen that lead to over-proportional conservative estimations of time windows and demand for the W-model.

Although the D-model and the M-model are feasible at the LRP planning stage, the derived charging station locations affect the feasibility on the successive VRP planning stage. Table 3 shows the feasibility of each instance, solving the single scenarios of each instance in the VRP planning step. In this course, an instance is defined to be infeasible if one or more of the underlying scenarios are infeasible for the underlying charging station configuration. Again, feasibility is checked by an external routine. As can be seen, all deterministic planning approaches lack operational feasibility at the VRP planning step, since the uncertainty is not

Table 2: Instance feasibility on the LRP planning stage.

	D-model			M-model			W-model			R-model		
Set	deg1	deg2	deg3	deg1	deg2	deg3	deg1	deg2	deg3	deg1	deg2	deg3
c100	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	3 / 5	3 / 5	2 / 5	5 / 5	5 / 5	5 / 5
c200	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5
r100	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	2 / 5	2 / 5	2 / 5	5 / 5	5 / 5	5 / 5
r200	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	4 / 5	5 / 5	5 / 5	5 / 5
rc100	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	3 / 5	3 / 5	1 / 5	5 / 5	5 / 5	5 / 5
rc200	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5	5 / 5
Feasible	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	76.67%	76.67%	63.33%	100.00%	100.00%	100.00%

For each instance set, n / m shows the number n of feasible instances out of the number m of instances included in the instance set.

Table 3: Instance feasibility on the VRP planning stage.

	D-model			M-model			W-model			R-model		
Set	deg1	deg2	deg3	deg1	deg2	deg3	deg1	deg2	deg3	deg1	deg2	deg3
c100	3 / 5	5 / 5	3/5	2 / 5	5 / 5	4 / 5	1 / 5	3 / 5	1 / 5	5 / 5	5 / 5	5 / 5
c200	5 / 5	5 / 5	3/5	4 / 5	3 / 5	4 / 5	5 / 5	5 / 5	4 / 5	5 / 5	5 / 5	5 / 5
r100	4 / 5	4 / 5	2 / 5	4 / 5	3 / 5	3 / 5	2 / 5	2 / 5	2 / 5	5 / 5	5 / 5	5 / 5
r200	5 / 5	5 / 5	4 / 5	4 / 5	4 / 5	4 / 5	4 / 5	2 / 5	3 / 5	5 / 5	5 / 5	5 / 5
rc100	3 / 5	3 / 5	3 / 5	5 / 5	2 / 5	4 / 5	1 / 5	2 / 5	1 / 5	5 / 5	5 / 5	5 / 5
rc200	4 / 5	3 / 5	5 / 5	5 / 5	4 / 5	4 / 5	4 / 5	4 / 5	4 / 5	5 / 5	5 / 5	5 / 5
Feasible	80.00%	83.33%	66.67%	80.00%	70.00%	76.67%	56.67%	60.00%	50.00%	100.00%	100.00%	100.00%

For each instance set, n / m shows the number n of feasible instances out of the number m of instances included in the instance set.

sufficiently considered at the LRP planning stage. No conclusion can be drawn regarding the interrelation between the share of infeasible instances and the degree of uncertainty. However, the lowest share of feasible instances is again obtained with the W-model.

Concluding, the applied deterministic modeling approaches do not prove to be sufficient to obtain appropriate locations for charging stations regarding operational feasibility for routing of ECV within logistics networks. This already holds for slight uncertainties (deg1) in customer patterns. Furthermore, the chosen locations for charging stations might be even worse, if uncertain information is regarded within a deterministic instance (compared to neglecting uncertainties), since aggregated representations of uncertainty might affect the obtained solution in an over-proportional fashion as is the case for the W-model.

To analyze the benefit of the R-model planning approach with respect to overall costs, we compare the overall costs for each instance that result from the VRP solutions of each scenario, including costs for vehicles and charging stations. The box-whisker-plots in Figure 2 – Figure 4 show the cost increases (Δ *cost*) of the remaining feasible instances for each deterministic planning approach with respect to the solution of the robust planning approach. These distributions confirm that the R-model is superior to all deterministic modeling approaches, since (in addition of the advantages in obtaining operational feasibility) the R-model results in lower or equal costs for any instance that can be compared at this stage. However, the box-whisker-plots do not show a specific relation between the cost increases with respect to the modeling approach over the degrees of uncertainty. This shows that the effect of uncertainty in this planning task cannot be generalized, but is case sensitive. In this course, high additional costs can result even for low degrees of uncertainty.

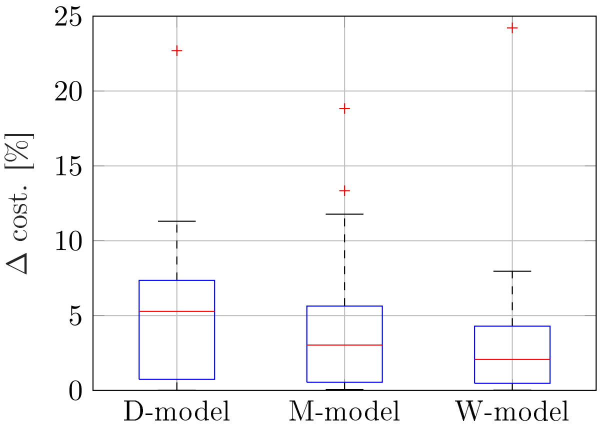

Figure 2: Cost increase for the deterministic approaches compared to the robust approach for uncertainty deg1.

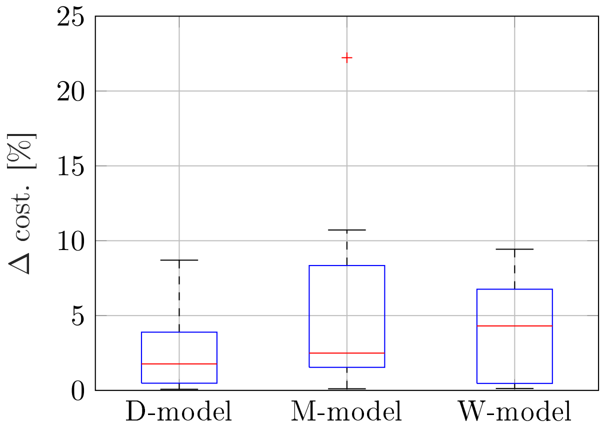

Figure 3: Cost increase for the deterministic approaches compared to the robust approach for uncertainty deg2.

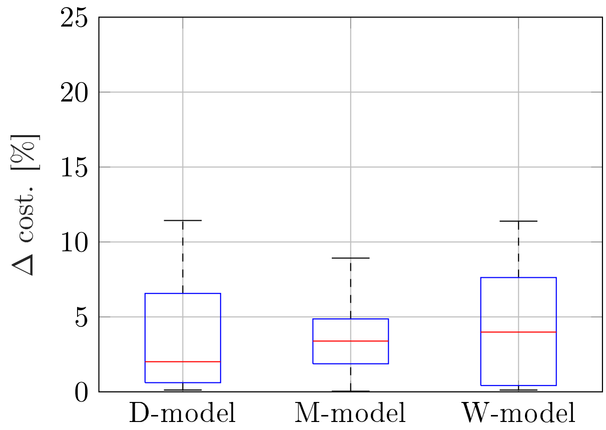

Figure 4: Cost increase for the deterministic approaches compared to the robust approach for uncertainty deg3.

To analyze if robust solutions can be derived with respect to costs independent of the degree of uncertainty, we analyze the results of the R-model. To do so, we first calculate the average total cost value $\overline{C}$ over all three degrees of uncertainty for each instance. Afterwards, we calculate the percentage difference $\Delta C_x = \frac{\overline{C}-C_x}{\overline{C}} \cdot 100$ between the average total cost value $\overline{C}$ and the total costs C_x for each uncertainty degree $x \in \{1, 2, 3\}$. The box-whisker-plots in figures 5–7 show these deviations for each degree of uncertainty. As can be seen, nearly equal cost values can be realized independent of the degree of uncertainty for all instance sets of type 200. This holds for all types of spatial customer distributions, although the deviations increase slightly with a higher number of randomly distributed customers. For type 100 instances, large deviations in costs arise, being negative for small degrees of uncertainty (cf. Figure 5) and positive for higher degrees of uncertainty (cf. Figure 6 and Figure 7). As can be seen from

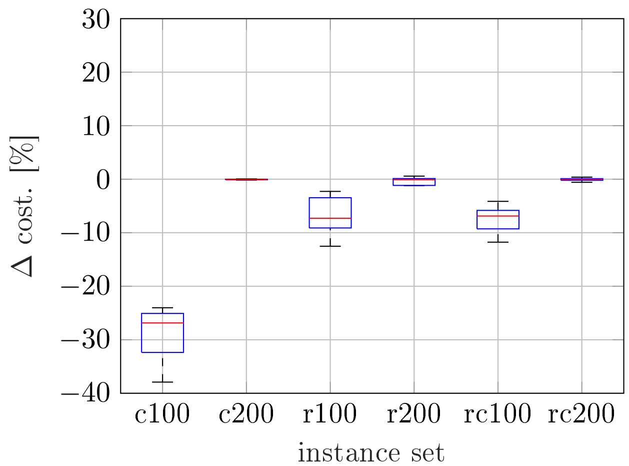

Figure 5: Cost deviations for each instance set for deg1 uncertainty.

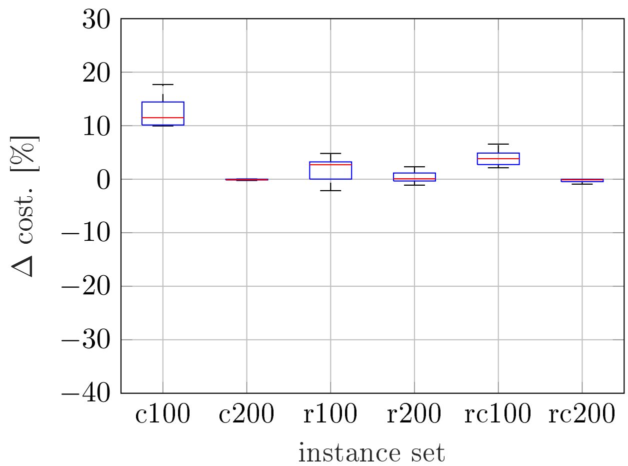

Figure 6: Cost deviations for each instance set for deg2 uncertainty.

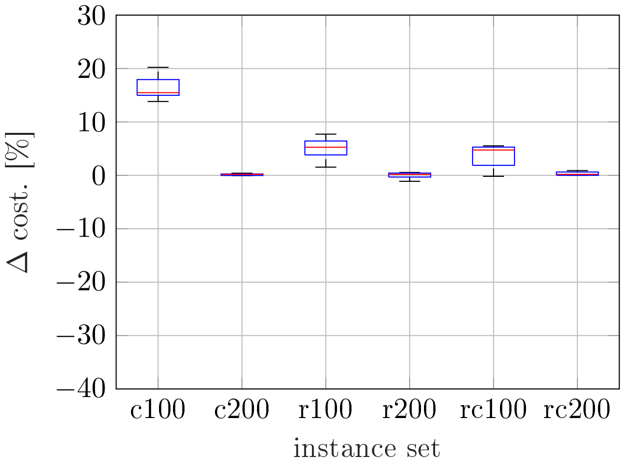

Figure 7: Cost deviations for each instance set for deg3 uncertainty.

these results, the total costs increase significantly with an increasing degree of uncertainty for instance sets of type 100. Contrary to type 200 instances, deviations appear to be the highest for clustered customer distributions. Analyzing this effect in detail, this difference in deviations between type 100 and type 200 instances is due to different vehicle freight volumes. Since the vehicle freight volume is higher for type 200 instances, changes in demand can be compensated. Thus, only changes in time-windows affect the solution, which can be considered sufficiently within the robust planning approach. As a result, operational costs can be kept nearly constant. The opposite effect occurs for type 100 instances with smaller freight volumes, since changes in customer patterns (spatial customer distribution, demand) cannot be compensated by higher freight volumes of vehicles. Therefore, higher demand uncertainty results in more vehicles needed to cover demand, which also influences operational costs. This effect is even higher if the customer distribution is clustered, since certain clusters cannot be supplied efficiently for specific demand and time window combinations.

7. Conclusion

In this paper, we presented the RELRP-TWPR, a robust location routing approach for the design of electric logistics fleet networks. To solve large sized instances, we developed a parallelized hybrid of ALNS and DP. To assess the advantages of the robust planning approach, we derived three deterministic planning approaches that (partially) aggregate the uncertainty of customer patterns in a deterministic instance representation. We created new benchmark instances by adopting the Solomon instances to real-world case data. The presented results focus on operational feasibility, total costs and robustness of solutions. Three main findings can be drawn out of these experiments. First, a robust modeling approach proves to be necessary to obtain operational feasibility, since none of the deterministic approaches is capable of determining feasible network configurations for all analyzed instances. Second, overall costs can be reduced significantly by applying the robust planning approach. Third, fluctuating degrees of uncertainty can be compensated by oversizing the vehicles' freight volumes to keep solutions robust with respect to overall costs, if the network configuration is derived with the robust planning approach that compensates further uncertainties on time windows.

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A. Detailed results

A.1. First planning stage (LRP results)

Table 4: LRP results for the D-model.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
c11	1040.12	1091.66	27.06	1346.44	1418.37	177.58	1616.31	1673.68	409.63
c12	1024.57	1057.56	74.86	1335.50	1397.16	254.44	1705.40	1775.77	872.08
c13	1021.14	1047.25	32.97	1277.22	1322.02	138.87	1334.83	1416.71	576.69
c14	892.93	959.37	35.33	1549.20	1655.49	851.56	1335.71	1404.57	409.83
c15	995.67	1058.42	42.36	1457.87	1477.86	536.52	1395.83	1448.65	306.42
c21	863.18	929.29	49.82	879.05	939.72	43.32	854.04	939.54	39.75
c22	902.02	917.36	32.52	846.76	923.77	37.97	842.72	916.37	30.68
c23	910.22	990.06	37.67	907.51	938.56	30.84	908.33	950.15	36.00
c24	906.52	960.59	40.19	896.65	933.11	38.91	905.73	940.46	44.62
c25	842.91	915.47	40.89	879.49	955.85	39.03	845.71	915.38	37.05
r11	1186.79	1321.65	162.72	1322.34	1405.65	130.94	1325.40	1440.34	350.34
r12	1180.87	1277.80	42.67	1177.15	1441.23	78.18	1341.22	1389.25	285.93
r13	1124.13	1196.37	93.03	1094.52	1155.78	97.29	1113.95	1168.79	124.61
r14	1049.15	1087.59	39.80	1049.81	1120.05	223.10	1105.56	1146.52	177.10
r15	1111.63	1165.34	66.01	1172.04	1241.40	101.10	1114.66	1211.05	73.40
r21	1051.21	1140.98	51.74	987.25	1104.42	63.54	1046.76	1104.46	49.77
r22	989.21	1078.25	39.90	993.36	1062.91	38.98	1050.56	1108.78	39.90
r23	984.92	1026.25	33.58	985.22	1047.58	36.08	982.50	1016.20	34.43
r24	990.76	1073.04	37.71	979.20	1025.66	37.89	984.42	1046.95	33.26
r25	1083.77	1142.81	47.64	1060.07	1131.18	44.38	1051.92	1132.35	42.35
rc11	1111.56	1309.01	54.36	1121.91	1205.49	151.19	1194.29	1310.06	508.68
rc12	1051.13	1117.69	62.82	1182.86	1274.19	317.60	1182.96	1264.31	158.12
rc13	1313.92	1380.23	49.46	1378.48	1501.62	418.00	1507.52	1577.85	283.48
rc14	1111.28	1181.11	61.95	1255.59	1335.34	283.92	1182.94	1256.60	77.35
rc15	1119.27	1212.16	117.26	1178.26	1276.03	376.65	1170.47	1237.71	140.81
rc21	1036.72	1115.24	65.05	1044.97	1083.89	42.41	985.04	1062.92	63.29
rc22	977.93	1028.96	46.85	987.95	1055.75	37.69	1035.25	1066.62	40.01
rc23	1052.87	1145.06	71.67	1058.08	1153.15	136.90	1049.22	1086.68	42.02
rc24	1044.70	1127.09	41.54	1062.89	1136.37	39.84	1058.38	1142.25	38.53
rc25	992.44	1066.84	54.86	988.57	1084.23	64.02	981.21	1056.66	41.22

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 5: LRP results for the M-model.

Instance	deg1			deg2			deg3		
	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}
c11	1046.10	1155.58	19.62	1260.28	1348.37	232.88	1348.55	1407.03	228.75
c12	968.42	1098.56	31.58	1202.43	1263.13	168.36	1270.63	1321.38	148.09
c13	958.97	1027.59	55.94	1146.32	1229.43	169.74	1206.44	1270.16	228.31
c14	818.55	853.72	30.05	1322.25	1402.23	1290.85	1365.28	1461.86	814.13
c15	899.92	956.34	38.33	1209.47	1283.11	410.89	1206.82	1251.91	272.67
c21	909.02	981.16	36.50	957.31	1007.97	35.13	967.71	1035.43	38.20
c22	905.99	954.11	30.33	890.90	947.79	36.48	902.83	964.58	32.82
c23	910.92	977.41	35.69	908.23	981.33	39.14	909.07	974.85	34.61
c24	894.48	956.28	31.99	905.35	946.13	33.97	905.12	952.53	33.84
c25	900.87	903.58	31.45	889.16	943.08	45.79	900.66	936.94	34.95
r11	1324.33	1388.02	73.23	1316.68	1407.85	108.66	1368.63	1420.08	100.43
r12	1432.99	1469.33	43.79	1435.54	1509.63	91.34	1411.60	1544.73	196.54
r13	1111.79	1190.91	71.49	1160.21	1183.16	61.55	1195.52	1272.89	82.41
r14	1036.92	1089.99	43.42	1050.70	1122.45	88.32	1048.24	1096.62	80.05
r15	1178.02	1203.51	61.28	1120.64	1226.46	90.91	1174.32	1411.49	66.55
r21	1051.03	1140.38	46.98	1099.35	1155.66	53.45	1049.54	1135.12	54.51
r22	1059.81	1146.24	47.15	1140.14	1186.34	43.29	1063.22	1142.28	44.57
r23	1047.18	1081.53	41.35	1042.69	1057.97	50.47	1047.30	1105.63	40.48
r24	983.36	1081.87	43.12	967.76	1025.00	37.39	991.10	1074.07	42.98
r25	1061.21	1160.94	53.70	1060.23	1172.72	50.98	1059.95	1146.48	47.53
rc11	1038.06	1151.65	53.68	1117.11	1180.44	97.66	1109.95	1177.38	55.94
rc12	1055.27	1146.93	52.10	1125.07	1218.97	410.62	1114.74	1222.39	297.99
rc13	1566.34	1605.32	69.30	1580.28	1634.50	96.87	1650.47	1692.24	186.91
rc14	1181.74	1231.23	53.24	1121.50	1269.17	63.74	1198.14	1278.33	38.03
rc15	1186.54	1421.12	71.55	1244.92	1312.97	105.13	1277.09	1332.76	82.74
rc21	1048.49	1127.30	46.45	1062.73	1155.17	54.40	1039.46	1153.40	44.84
rc22	976.83	1005.81	32.74	1017.00	1048.34	49.66	978.16	1048.75	41.79
rc23	1121.58	1180.48	83.71	1122.38	1204.94	73.75	1115.24	1149.63	46.07
rc24	1122.32	1205.95	42.22	1123.57	1169.09	46.59	1111.21	1160.22	42.69
rc25	1023.81	1077.82	45.41	985.41	1067.81	43.73	1039.89	1092.25	48.16

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^{a} [s] - average computational time out of ten runs.

Table 6: LRP results for the W-model.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}
c11	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
c12	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
c13	1028.48	1113.24	64.64	1819.01	1896.13	533.24	n.f.	n.f.	n.f.
c14	911.81	990.20	31.98	2144.40	2213.03	1512.93	2082.96	2188.75	1917.13
c15	1027.14	1091.46	47.00	1912.75	1955.61	591.08	1797.97	1889.53	451.94
c21	903.55	966.86	54.60	904.67	978.33	63.19	1024.31	1066.50	66.04
c22	903.51	933.30	51.81	902.74	936.21	41.83	845.81	927.72	36.40
c23	910.20	965.58	52.19	897.65	978.89	41.69	910.49	975.31	36.15
c24	903.36	926.18	54.26	906.58	940.87	35.75	905.25	929.42	38.99
c25	842.23	916.75	35.99	830.55	908.44	35.75	888.99	921.97	37.46
r11	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
r12	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
r13	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
r14	1049.23	1122.01	43.63	1565.58	1631.19	255.84	1563.59	1631.41	267.35
r15	1180.52	1235.98	156.80	1445.95	1586.10	281.72	1557.35	1634.71	307.08
r21	1047.10	1122.44	59.36	1048.53	1103.74	114.52	n.f.	n.f.	n.f.
r22	1058.33	1122.39	47.73	1058.82	1103.03	38.74	1058.21	1112.69	39.90
r23	987.68	1076.20	39.78	987.77	1054.80	34.66	983.791	1061.27	36.39
r24	980.04	1019.15	35.56	980.09	1011.39	43.47	982.71	1027.90	44.34
r25	1122.39	1159.61	50.14	1055.30	1108.00	38.84	1057.43	1131.44	43.50
rc11	1120.9	1190.94	76.9642	1505.52	1597.62	443.419	n.f.	n.f.	n.f.
rc12	1115.47	1160.51	74.2562	1624.35	1702.96	591.575	n.f.	n.f.	n.f.
rc13	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
rc14	1241.69	1297.57	92.7074	1570.24	1644.9	296.192	1581.59	1650.54	291.609
rc15	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.	n.f.
rc21	1053.55	1121.67	63.6279	1051.59	1155.01	71.4115	1116.76	1364.43	150.692
rc22	976.691	1007.87	35.7024	962.059	1011.46	40.7207	963.908	999.096	35.4398
rc23	1161.06	1262.17	72.4759	1174.73	1252.37	88.8245	1253.13	1303	98.9376
rc24	1120.54	1174.16	44.0812	1130.08	1168.61	36.5397	1060.35	1147.66	46.902
rc25	975.864	1046.33	86.4931	982.653	1079.9	70.0626	1043.34	1094.23	60.6008

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^{a} [s] - average computational time out of ten runs.

Table 7: LRP results for the R-model.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}
c11	4613.99	4721.38	177.34	6694.25	6765.93	249.93	7013.32	7127.53	338.11
c12	4550.06	4593.52	190.25	6418.52	6456.27	276.25	6548.54	6612.17	261.41
c13	4114.98	4203.58	161.94	6231.74	6269.80	345.74	6372.19	6433.25	432.99
c14	3976.19	4068.59	226.44	7397.08	7451.31	513.10	7445.00	7519.98	594.00
c15	4167.81	4224.01	219.36	6583.42	6684.34	384.14	6485.89	6569.52	421.16
c21	4000.68	4105.07	205.25	4003.08	4100.32	234.78	4096.76	4236.91	215.04
c22	3978.75	4046.23	160.69	3914.40	4034.44	149.35	3897.71	3997.67	220.01
c23	4046.51	4110.29	151.97	3959.92	4069.70	176.44	4060.79	4119.96	138.03
c24	3956.88	4022.55	209.95	3935.16	4035.87	205.05	3976.85	4070.64	156.63
c25	3893.03	3979.14	194.08	3845.13	3966.54	197.24	3906.23	3980.52	135.79
r11	5606.23	5710.64	256.27	5777.93	5941.34	273.28	5885.68	6028.94	301.05
r12	5397.58	5622.62	231.12	5672.06	5801.12	275.03	6127.31	6247.46	287.90
r13	5027.93	5078.71	213.48	5199.78	5307.01	271.05	5312.98	5477.30	307.91
r14	4478.34	4576.27	179.60	5016.45	5065.87	221.64	5079.42	5152.49	248.33
r15	5079.08	5190.73	280.03	5289.76	5439.39	337.72	5394.01	5497.76	277.40
r21	4733.36	4821.65	302.61	4707.26	4817.60	302.94	4723.52	4808.59	260.81
r22	4679.92	4783.97	198.51	4712.16	4828.06	169.09	4681.81	4817.49	188.05
r23	4504.30	4600.67	211.42	4563.69	4620.33	205.85	4430.38	4571.63	191.74
r24	4483.26	4597.61	222.36	4396.84	4535.53	307.58	4446.84	4620.80	193.61
r25	4865.06	4990.98	268.59	4843.35	4957.49	251.86	4802.83	4928.01	303.00
rc11	4865.74	5041.03	189.85	5202.40	5257.22	288.62	5105.27	5220.45	274.18
rc12	4847.63	4905.24	201.29	5578.29	5653.49	275.37	5559.66	5659.95	235.80
rc13	5902.03	5980.81	235.77	6310.81	6455.79	264.23	6534.12	6733.02	239.73
rc14	5211.77	5280.96	240.31	5435.92	5542.50	254.87	5244.73	5398.51	213.10
rc15	5081.84	5161.98	253.15	5516.74	5601.57	315.30	5491.86	5609.85	237.59
rc21	4550.51	4707.38	155.26	4588.99	4665.02	136.99	4639.18	4717.38	163.96
rc22	4383.18	4523.87	137.72	4389.97	4481.64	185.02	4380.03	4498.78	177.19
rc23	4818.63	4926.87	202.73	4843.47	4914.38	255.76	4769.59	4859.02	169.61
rc24	4663.79	4811.84	165.83	4748.29	4813.16	159.14	4763.62	4825.92	149.87
rc25	4569.47	4741.35	213.73	4573.45	4708.99	200.48	4647.03	4716.60	207.59

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^{a} [s] - average computational time out of ten runs.

A.2. Second planning stage (VRP results)

Table 8: VRP results for the D-model for clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
c11_1	833.06	886.28	102.55	1202.68	1258.84	106.04	1261.28	1276.28	130.37
c11_2	824.03	865.47	122.60	1196.91	1252.53	126.67	1267.40	1317.24	114.52
c11_3	890.87	892.38	81.97	1195.71	1215.13	105.37	1319.87	1342.19	109.03
c11_4	884.37	886.54	98.63	1257.33	1265.61	124.58	1265.20	1325.04	98.47
c11_5	894.32	921.14	122.29	1259.44	1260.35	111.33	1268.24	1316.51	117.00
c12_1	761.44	812.37	112.81	1186.87	1195.34	82.33	n.f.	n.f.	-
c12_2	750.91	786.44	151.21	1176.89	1178.60	96.18	n.f.	n.f.	-
c12_3	754.89	779.69	162.91	1068.59	1119.61	106.81	n.f.	n.f.	-
c12_4	821.89	829.65	131.43	1251.45	1269.37	120.91	n.f.	n.f.	-
c12_5	744.38	753.03	114.53	1137.76	1199.62	122.50	n.f.	n.f.	-
c13_1	n.f.	n.f.	-	1174.15	1174.85	154.17	1117.22	1125.16	149.09
c13_2	n.f.	n.f.	-	1183.36	1223.78	120.71	1180.00	1205.94	157.57
c13_3	n.f.	n.f.	-	1182.13	1191.47	158.10	1123.24	1149.76	161.58
c13_4	n.f.	n.f.	-	1117.44	1150.07	170.85	1183.13	1197.56	166.08
c13_5	n.f.	n.f.	-	994.37	1047.50	141.53	1178.13	1187.77	137.38
c14_1	n.f.	n.f.	-	1382.91	1457.52	143.66	1374.49	1424.07	135.12
c14_2	n.f.	n.f.	-	1363.35	1408.28	129.99	1365.46	1417.73	106.37
c14_3	n.f.	n.f.	-	1374.87	1413.89	136.56	1430.32	1434.09	195.52
c14_4	n.f.	n.f.	-	1356.25	1359.23	135.62	1368.70	1404.00	159.80
c14_5	n.f.	n.f.	-	1437.00	1485.85	146.98	1376.83	1406.38	130.98
c15_1	735.76	736.75	87.32	1177.47	1203.10	130.54	1180.01	1225.60	183.48
c15_2	684.50	731.87	101.38	1185.87	1214.80	146.19	n.f.	n.f.	-
c15_3	749.61	780.72	98.58	1244.72	1280.38	135.32	1177.69	1201.26	142.01
c15_4	744.88	747.24	156.73	1187.90	3648.44	128.52	1245.92	1246.42	133.27
c15_5	740.84	749.55	79.96	1176.30	1222.48	140.72	1234.74	1258.19	116.54
c21_1	763.71	770.59	118.52	628.92	647.98	133.88	n.f.	n.f.	-
c21_2	777.58	794.57	178.73	629.10	648.38	131.95	n.f.	n.f.	-
c21_3	766.32	772.83	154.82	626.06	626.52	171.47	n.f.	n.f.	-
c21_4	771.38	790.34	196.28	627.94	628.25	154.88	n.f.	n.f.	-
c21_5	763.80	766.02	207.88	624.39	624.44	131.94	n.f.	n.f.	-
c22_1	699.94	701.23	140.89	635.72	680.53	107.67	632.62	651.19	138.48
c22_2	635.44	669.63	123.57	625.16	626.25	104.29	624.91	625.88	107.81
c22_3	696.57	710.20	118.63	622.78	623.57	144.57	622.78	624.24	142.73
c22_4	694.30	695.34	133.54	627.20	628.17	121.15	n.f.	n.f.	-
c22_5	697.21	698.30	166.94	624.42	625.20	114.33	624.35	624.94	138.37
c23_1	632.19	644.30	109.27	629.70	630.32	112.04	629.95	630.63	109.60
c23_2	630.24	631.14	140.26	630.50	642.39	117.13	630.20	636.65	111.06
c23_3	694.47	3154.36	108.10	694.39	696.20	120.57	696.28	703.42	142.70
c23_4	632.54	650.78	135.15	633.15	662.75	138.62	631.95	633.11	145.25
c23_5	632.19	649.92	148.37	630.26	631.54	114.91	630.11	636.54	145.43
c24_1	628.37	635.19	121.86	691.66	692.37	124.45	701.04	719.29	161.66
c24_2	624.10	630.43	122.98	626.54	627.26	91.90	695.78	696.75	159.44
c24_3	634.20	670.77	139.27	700.42	700.82	123.11	698.04	704.61	150.98
c24_4	628.95	652.95	117.04	694.52	695.08	121.13	699.33	729.12	149.09
c24_5	625.40	626.02	116.47	630.78	659.64	136.16	696.74	697.65	176.31
c25_1	695.12	695.38	170.76	628.26	629.15	140.00	699.63	700.72	189.20
c25_2	700.54	702.31	181.87	631.47	637.92	135.42	637.22	689.76	186.22
c25_3	634.84	663.63	172.30	624.88	625.63	103.55	697.67	698.10	176.91
c25_4	629.02	630.04	191.51	625.21	625.69	97.71	630.23	630.46	149.92
c25_5	626.54	626.99	142.22	624.66	626.12	135.95	628.45	629.16	150.85

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 9: VRP results for the D-model for randomly distributed instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
r11_1	910.15	942.83	194.18	n.f.	n.f.	-	n.f.	n.f.	-
r11_2	913.75	957.04	204.97	n.f.	n.f.	-	n.f.	n.f.	-
r11_3	1043.39	1043.63	265.40	n.f.	n.f.	-	n.f.	n.f.	-
r11_4	980.35	1008.47	188.12	n.f.	n.f.	-	n.f.	n.f.	-
r11_5	915.82	965.40	128.56	n.f.	n.f.	-	n.f.	n.f.	-
r12_1	904.39	953.92	153.55	954.57	963.36	153.73	1022.07	1040.76	190.09
r12_2	902.41	938.27	159.77	955.37	970.19	127.48	1029.18	1066.46	161.14
r12_3	902.42	942.37	181.39	897.78	948.28	113.32	1019.63	1027.42	199.23
r12_4	915.03	961.06	143.14	960.74	996.84	118.72	1025.75	1028.34	177.70
r12_5	n.f.	n.f.	-	967.64	1021.69	143.14	1094.87	1137.07	146.69
r13_1	781.81	851.95	197.52	894.87	897.37	308.80	1042.08	1083.89	240.62
r13_2	770.08	800.47	166.17	829.02	872.03	251.96	965.97	991.78	169.26
r13_3	767.49	769.18	188.40	826.63	840.88	254.10	835.00	853.62	166.47
r13_4	775.35	800.14	216.58	895.59	910.55	299.94	901.87	922.30	217.07
r13_5	770.93	823.67	183.22	825.11	834.59	296.85	896.45	908.76	188.33
r14_1	771.62	773.25	157.90	832.02	833.03	175.81	897.03	920.42	217.86
r14_2	703.11	709.84	149.39	828.21	837.91	142.90	828.23	841.17	189.60
r14_3	705.03	717.72	158.72	888.72	897.39	150.28	829.42	870.55	174.69
r14_4	773.40	774.44	164.65	900.39	908.93	187.56	n.f.	n.f.	-
r14_5	768.35	769.59	154.31	841.33	890.14	158.82	894.71	895.44	214.27
r15_1	838.62	847.10	156.88	832.94	858.40	197.33	n.f.	n.f.	-
r15_2	841.83	842.54	164.14	901.35	950.82	195.50	n.f.	n.f.	-
r15_3	847.25	902.68	177.91	843.00	895.80	226.47	n.f.	n.f.	-
r15_4	848.85	901.87	195.69	901.97	950.10	188.08	n.f.	n.f.	-
r15_5	844.12	876.42	201.89	896.61	898.41	179.98	n.f.	n.f.	-
r21_1	779.97	799.17	188.06	775.82	782.69	228.80	777.43	785.20	223.38
r21_2	769.86	770.89	259.47	767.73	768.34	136.54	708.65	751.65	145.69
r21_3	708.52	732.86	210.62	767.59	769.44	177.42	708.52	739.36	182.42
r21_4	771.80	786.20	179.02	713.09	761.82	184.86	770.83	777.63	189.48
r21_5	769.58	771.63	153.19	712.32	762.23	189.19	770.07	778.71	194.60
r22_1	709.22	721.41	161.16	770.31	778.33	162.34	711.67	735.98	211.70
r22_2	708.83	709.45	138.56	770.23	771.68	175.35	709.57	734.31	182.97
r22_3	775.18	775.88	152.61	773.48	781.18	152.15	773.38	773.89	166.50
r22_4	774.11	774.91	188.59	774.31	775.35	163.82	773.72	774.76	194.64
r22_5	777.10	784.41	170.39	779.44	793.15	168.32	782.63	832.41	197.62
r23_1	768.01	769.44	170.61	710.11	728.42	197.59	706.34	720.05	192.89
r23_2	769.89	771.01	149.57	709.18	758.36	197.37	706.95	720.45	206.08
r23_3	706.91	707.73	169.82	707.25	714.04	192.66	702.16	709.01	180.76
r23_4	775.66	776.01	143.23	771.19	775.77	155.88	774.19	775.57	211.63
r23_5	771.73	773.88	182.57	710.05	710.67	156.98	767.74	768.20	166.93
r24_1	773.49	788.43	195.84	771.76	773.15	172.16	926.54	982.10	160.56
r24_2	710.75	764.68	160.68	766.81	767.64	141.20	913.41	914.70	230.08
r24_3	704.21	722.87	190.53	700.64	713.11	152.95	844.90	857.30	175.41
r24_4	770.75	773.78	177.54	705.86	712.39	182.56	848.10	872.92	182.47
r24_5	771.50	787.47	121.20	700.99	701.07	160.02	n.f.	n.f.	-
r25_1	779.73	786.37	204.13	781.18	781.84	201.42	780.34	798.91	166.06
r25_2	781.41	799.85	196.20	778.94	779.33	201.07	780.33	780.82	194.62
r25_3	784.33	820.18	225.71	781.89	789.16	200.23	780.36	799.06	167.71
r25_4	781.88	813.04	218.07	779.28	779.68	174.37	779.18	779.36	151.39
r25_5	778.58	785.93	209.93	778.98	786.38	180.66	781.09	828.38	169.58

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 10: VRP results for the D-model for randomly clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
rc11_1	849.26	870.68	202.16	909.08	910.05	159.59	n.f.	n.f.	-
rc11_2	779.20	786.79	203.68	899.57	911.49	153.72	n.f.	n.f.	-
rc11_3	839.95	841.78	170.30	901.11	902.66	178.44	n.f.	n.f.	-
rc11_4	838.90	840.78	163.14	960.70	962.56	204.90	n.f.	n.f.	-
rc11_5	778.99	798.52	186.85	901.32	915.05	188.21	n.f.	n.f.	-
rc12_1	779.88	828.63	154.64	n.f.	n.f.	-	n.f.	n.f.	-
rc12_2	836.85	837.63	152.50	n.f.	n.f.	-	1031.35	1045.23	178.40
rc12_3	832.62	834.51	120.33	n.f.	n.f.	-	962.04	967.61	190.82
rc12_4	849.92	895.00	139.87	n.f.	n.f.	-	1026.34	1036.34	171.91
rc12_5	833.84	835.02	164.58	n.f.	n.f.	-	973.90	1025.63	165.75
rc13_1	n.f.	n.f.	-	1100.28	1131.23	103.91	1103.57	1155.60	84.15
rc13_2	n.f.	n.f.	-	1097.57	1132.24	112.90	1161.52	1197.11	111.03
rc13_3	n.f.	n.f.	-	1099.15	1156.68	126.31	1107.57	1160.36	119.35
rc13_4	n.f.	n.f.	-	1168.64	1226.18	95.81	1231.88	1241.63	96.35
rc13_5	n.f.	n.f.	-	1239.86	1254.38	127.57	1180.02	1210.13	140.67
rc14_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc14_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc14_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc14_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc14_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc15_1	900.64	940.65	168.45	904.08	963.46	135.03	904.00	954.72	132.42
rc15_2	903.17	950.80	186.13	961.79	969.36	164.72	971.39	990.60	191.25
rc15_3	899.40	946.07	156.53	957.08	958.03	165.14	965.44	990.95	152.34
rc15_4	901.81	916.34	176.81	961.43	981.07	164.78	969.94	1015.20	166.95
rc15_5	914.03	961.43	185.10	967.15	1005.82	131.00	1032.03	1059.19	213.93
rc21_1	766.78	766.99	110.31	n.f.	n.f.	-	762.43	762.64	123.79
rc21_2	763.58	764.97	122.12	n.f.	n.f.	-	761.60	761.83	115.96
rc21_3	766.56	766.79	106.52	n.f.	n.f.	-	765.34	766.29	123.89
rc21_4	765.73	766.07	94.49	n.f.	n.f.	-	763.41	763.94	111.86
rc21_5	769.68	770.25	124.11	n.f.	n.f.	-	771.64	802.34	136.34
rc22_1	778.81	778.88	163.52	709.32	743.45	165.62	709.05	751.92	115.24
rc22_2	781.72	801.10	174.68	773.52	786.49	131.93	706.36	706.72	127.79
rc22_3	767.40	768.59	155.58	703.45	703.71	126.18	697.98	698.32	115.87
rc22_4	834.88	835.35	108.22	768.28	768.38	110.20	764.13	764.44	107.19
rc22_5	766.56	766.82	134.63	699.64	700.81	130.98	697.45	697.85	110.96
rc23_1	839.10	848.25	148.66	773.92	774.44	145.98	780.49	822.00	154.92
rc23_2	773.46	786.62	152.08	772.25	780.06	139.31	777.17	822.32	174.17
rc23_3	770.07	771.06	150.28	770.74	771.80	151.54	776.46	783.75	189.52
rc23_4	769.21	776.47	101.73	771.74	772.63	111.67	771.19	771.79	152.15
rc23_5	775.96	812.71	124.69	777.59	819.20	148.05	781.26	821.38	189.95
rc24_1	n.f.	n.f.	-	783.26	783.26	146.08	844.51	845.63	141.57
rc24_2	n.f.	n.f.	-	780.20	780.20	178.30	845.08	845.44	171.66
rc24_3	n.f.	n.f.	-	782.79	782.79	159.61	846.78	847.48	144.90
rc24_4	n.f.	n.f.	-	779.47	779.47	164.62	841.95	842.46	132.52
rc24_5	n.f.	n.f.	-	843.54	843.54	186.93	853.54	881.63	199.67
rc25_1	714.28	763.86	156.29	n.f.	n.f.	-	780.85	815.19	212.20
rc25_2	766.96	767.24	112.79	n.f.	n.f.	-	835.79	837.17	181.84
rc25_3	768.46	769.97	130.15	n.f.	n.f.	-	779.10	822.71	145.46
rc25_4	765.98	767.86	152.07	n.f.	n.f.	-	838.78	839.48	171.05
rc25_5	702.93	703.19	161.59	n.f.	n.f.	-	767.93	769.34	178.32

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 11: VRP results for the M-model for clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}
c11_1	824.97	857.69	72.00	1329.75	1385.40	134.02	1265.40	1318.81	115.48
c11_2	825.99	857.81	85.24	1323.63	1333.29	127.79	1316.42	1319.44	128.80
c11_3	823.59	836.78	73.75	1255.50	1265.86	101.34	1317.53	1324.72	152.42
c11_4	818.82	826.86	82.36	1381.91	1384.28	98.19	1323.07	1330.58	127.39
c11_5	827.11	885.03	76.24	1335.14	1384.80	111.78	1326.29	1334.97	115.53
c12_1	814.23	815.42	86.03	1188.06	1191.65	127.17	1189.10	1204.14	109.29
c12_2	755.25	791.26	113.64	1186.77	1233.79	110.83	1180.97	3607.70	102.82
c12_3	823.22	831.30	97.30	1066.89	1096.45	119.80	1247.48	1251.46	122.76
c12_4	823.02	831.84	86.52	1256.88	1265.17	126.74	1186.70	1206.07	147.56
c12_5	753.02	788.11	84.03	1197.30	1221.22	85.46	1184.19	1217.55	119.97
c13_1	n.f.	n.f.	-	1118.12	1120.53	139.60	1107.89	1109.50	240.90
c13_2	n.f.	n.f.	-	1179.30	1186.79	120.21	1178.69	1210.43	223.72
c13_3	n.f.	n.f.	-	1131.43	1180.04	147.81	1116.52	1120.16	236.59
c13_4	n.f.	n.f.	-	1120.36	1144.44	133.78	1182.00	3602.79	189.22
c13_5	n.f.	n.f.	-	989.63	1008.65	143.62	1179.61	1183.38	183.35
c14_1	n.f.	n.f.	-	1441.41	1450.16	140.06	1365.89	1399.95	165.53
c14_2	n.f.	n.f.	-	1430.33	1477.07	101.16	1417.68	1418.99	144.75
c14_3	n.f.	n.f.	-	1447.65	1507.23	124.83	1426.55	1445.57	119.68
c14_4	n.f.	n.f.	-	1361.23	1363.09	106.50	1374.03	1422.88	148.10
c14_5	n.f.	n.f.	-	1500.77	1549.57	146.40	1369.69	1414.45	118.93
c15_1	n.f.	n.f.	-	1176.04	1200.97	128.96	n.f.	n.f.	-
c15_2	n.f.	n.f.	-	1180.12	1207.81	140.49	1128.06	1201.08	116.76
c15_3	n.f.	n.f.	-	1241.01	1242.21	138.47	1174.35	1175.09	104.13
c15_4	n.f.	n.f.	-	1191.74	1239.36	138.37	1185.74	1238.09	121.50
c15_5	n.f.	n.f.	-	1183.59	1240.55	142.20	1235.86	1240.18	114.49
c21_1	628.67	635.70	140.42	630.63	654.44	110.66	n.f.	n.f.	-
c21_2	629.17	635.94	112.75	629.49	635.89	110.03	n.f.	n.f.	-
c21_3	626.54	662.66	124.20	629.84	631.24	115.27	n.f.	n.f.	-
c21_4	627.81	628.74	151.22	631.56	638.27	137.58	n.f.	n.f.	-
c21_5	625.24	626.21	130.08	628.52	634.56	147.76	n.f.	n.f.	-
c22_1	632.80	640.47	118.91	636.01	675.07	149.02	692.84	695.38	125.42
c22_2	625.24	626.58	116.18	624.71	626.24	104.84	628.54	635.66	112.99
c22_3	622.78	623.97	111.48	623.51	624.28	108.18	631.71	667.89	125.12
c22_4	627.68	634.69	103.62	627.07	628.32	140.14	633.95	673.85	127.12
c22_5	624.36	625.38	99.90	623.15	624.46	136.36	631.47	637.52	168.93
c23_1	632.12	668.63	149.73	770.09	771.13	149.08	629.70	630.39	115.34
c23_2	629.62	636.95	110.04	841.51	865.07	163.31	630.27	631.31	123.37
c23_3	696.43	710.57	173.51	773.39	779.94	179.97	693.50	695.24	111.38
c23_4	638.19	702.38	144.11	773.77	787.31	161.95	633.15	645.44	165.40
c23_5	630.88	631.90	152.30	771.43	784.14	137.74	630.26	642.49	127.89
c24_1	701.45	707.61	143.48	n.f.	n.f.	-	629.69	642.31	105.85
c24_2	697.61	698.02	149.19	n.f.	n.f.	-	624.08	624.68	124.91
c24_3	700.71	707.73	171.73	n.f.	n.f.	-	627.48	627.80	91.37
c24_4	701.16	713.75	129.29	n.f.	n.f.	-	627.73	634.14	122.17
c24_5	700.77	706.87	158.85	n.f.	n.f.	-	625.16	626.27	109.31
c25_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c25_2	761.37	764.12	167.65	n.f.	n.f.	-	n.f.	n.f.	-
c25_3	691.34	692.38	191.08	n.f.	n.f.	-	n.f.	n.f.	-
c25_4	634.13	686.23	169.64	n.f.	n.f.	-	n.f.	n.f.	-
c25_5	689.58	690.34	156.81	n.f.	n.f.	-	n.f.	n.f.	-

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^{a} [s] - average computational time out of ten runs.

Table 12: VRP results for the M-model for randomly distributed instances.

Instance	deg1 λ^b	deg1 λ^a	deg1 t^a	deg2 λ^b	deg2 λ^a	deg2 t^a	deg3 λ^b	deg3 λ^a	deg3 t^a
r11_1	908.17	944.64	186.79	904.20	929.30	149.15	959.88	964.49	162.20
r11_2	912.06	979.97	195.26	964.77	967.81	199.04	1026.37	1029.41	203.01
r11_3	912.61	963.99	213.61	962.88	971.23	176.69	1030.62	1041.16	177.23
r11_4	1036.66	1039.78	216.80	976.70	1016.39	186.71	972.83	1040.98	186.06
r11_5	916.62	969.46	193.72	965.20	973.36	177.56	963.80	979.71	180.70
r12_1	900.74	957.66	152.12	n.f.	n.f.	-	1019.47	1022.62	205.57
r12_2	897.64	906.84	115.00	n.f.	n.f.	-	1025.04	1045.84	200.59
r12_3	892.55	895.53	141.36	n.f.	n.f.	-	959.85	1004.95	178.40
r12_4	899.33	919.08	118.96	n.f.	n.f.	-	968.85	1005.36	213.46
r12_5	905.12	938.14	160.27	n.f.	n.f.	-	1089.45	1096.99	183.58
r13_1	907.73	956.46	190.25	1043.13	1063.81	186.42	n.f.	n.f.	-
r13_2	836.17	855.08	208.16	896.79	933.81	185.02	897.73	946.43	231.90
r13_3	775.11	842.90	193.24	895.26	897.79	173.32	833.85	870.37	217.95
r13_4	841.72	856.74	206.25	962.00	971.09	171.92	836.58	886.95	272.20
r13_5	836.84	867.74	217.58	837.01	879.19	202.94	893.81	895.18	267.35
r14_1	n.f.	n.f.	-	837.68	844.83	203.58	n.f.	n.f.	-
r14_2	n.f.	n.f.	-	831.20	845.35	194.48	n.f.	n.f.	-
r14_3	n.f.	n.f.	-	891.37	892.67	142.63	n.f.	n.f.	-
r14_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r14_5	n.f.	n.f.	-	896.60	899.22	127.20	n.f.	n.f.	-
r15_1	834.60	837.04	207.26	892.47	893.39	231.05	897.00	936.30	297.68
r15_2	778.56	809.67	187.44	955.59	956.75	151.25	961.48	969.19	241.76
r15_3	844.35	885.80	165.16	901.74	909.37	187.44	906.32	960.45	216.07
r15_4	843.20	851.35	211.81	901.22	921.65	172.00	963.19	983.10	248.06
r15_5	779.93	824.81	172.11	894.60	909.19	177.03	896.16	943.48	201.85
r21_1	n.f.	n.f.	-	847.51	855.23	235.54	777.18	778.10	211.39
r21_2	n.f.	n.f.	-	775.36	801.66	197.32	770.56	771.83	288.54
r21_3	n.f.	n.f.	-	777.44	803.04	197.04	768.22	769.22	204.10
r21_4	n.f.	n.f.	-	777.12	778.31	176.65	770.96	771.71	179.06
r21_5	n.f.	n.f.	-	776.46	796.85	199.17	769.84	771.36	233.79
r22_1	711.17	758.73	178.43	n.f.	n.f.	-	771.44	772.79	252.07
r22_2	711.22	765.10	146.44	n.f.	n.f.	-	712.37	730.59	261.34
r22_3	774.08	775.56	183.80	n.f.	n.f.	-	775.04	782.56	260.64
r22_4	773.47	774.84	214.15	n.f.	n.f.	-	775.13	781.89	260.52
r22_5	778.51	779.47	202.39	n.f.	n.f.	-	779.61	779.93	284.06
r23_1	767.16	768.20	242.77	705.69	712.74	195.12	780.16	798.51	299.74
r23_2	768.05	768.94	196.24	706.02	706.48	178.27	781.07	788.12	266.83
r23_3	708.69	710.22	205.48	704.60	705.30	186.03	779.18	792.34	278.68
r23_4	773.22	773.29	236.60	771.88	773.20	185.02	n.f.	n.f.	-
r23_5	709.59	733.21	191.45	707.06	726.22	143.55	781.40	824.18	294.49
r24_1	771.19	777.88	182.59	772.05	774.21	185.30	777.32	791.23	259.45
r24_2	707.34	731.87	168.69	710.21	757.43	147.67	711.39	760.57	198.43
r24_3	700.87	713.82	181.76	699.38	701.17	182.60	705.82	724.52	270.26
r24_4	705.35	752.43	187.30	765.12	766.57	160.67	768.44	769.51	272.61
r24_5	703.92	710.46	185.12	702.19	702.57	156.05	707.50	714.16	245.96
r25_1	776.53	776.89	149.26	781.21	812.46	174.31	846.44	847.01	293.83
r25_2	777.62	778.06	188.32	779.55	799.89	195.05	843.52	851.80	292.26
r25_3	781.69	819.26	174.31	782.66	818.87	200.32	846.05	859.44	294.21
r25_4	776.98	778.72	198.49	779.63	786.13	152.73	844.59	845.77	345.17
r25_5	777.37	778.59	202.48	780.29	786.97	217.88	845.99	846.67	396.06

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 13: VRP results for the M-model for randomly clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
rc11_1	844.23	857.24	155.87	n.f.	n.f.	-	n.f.	n.f.	-
rc11_2	775.93	811.17	144.00	n.f.	n.f.	-	n.f.	n.f.	-
rc11_3	782.25	831.17	169.43	n.f.	n.f.	-	n.f.	n.f.	-
rc11_4	843.34	844.52	196.43	n.f.	n.f.	-	n.f.	n.f.	-
rc11_5	782.62	839.68	156.96	n.f.	n.f.	-	n.f.	n.f.	-
rc12_1	775.01	788.58	132.73	n.f.	n.f.	-	963.26	970.18	127.05
rc12_2	834.67	835.33	118.64	n.f.	n.f.	-	971.14	1018.06	156.62
rc12_3	772.13	806.23	109.46	n.f.	n.f.	-	903.36	949.26	146.34
rc12_4	842.16	843.14	139.88	n.f.	n.f.	-	970.56	1025.51	126.90
rc12_5	775.16	804.72	143.06	n.f.	n.f.	-	964.39	1003.63	150.80
rc13_1	977.77	1026.81	141.06	n.f.	n.f.	-	1102.72	1114.67	119.72
rc13_2	976.03	998.40	101.25	n.f.	n.f.	-	1162.73	1186.29	105.19
rc13_3	980.25	1012.59	141.23	n.f.	n.f.	-	1093.86	1126.74	122.56
rc13_4	986.04	1049.95	151.85	n.f.	n.f.	-	1167.28	1183.89	118.74
rc13_5	1046.01	1067.57	157.58	n.f.	n.f.	-	1115.82	1181.54	130.02
rc14_1	914.39	960.43	152.70	911.71	959.20	149.04	911.71	952.48	188.12
rc14_2	910.91	928.43	150.39	977.06	1029.08	163.37	907.12	956.50	175.91
rc14_3	853.89	910.42	134.31	975.60	1007.35	161.78	969.90	972.34	135.08
rc14_4	912.36	941.81	194.24	976.05	998.55	128.58	912.49	973.73	120.88
rc14_5	904.12	910.44	121.97	903.57	952.47	138.48	901.18	927.09	148.98
rc15_1	835.12	864.84	171.90	964.71	991.95	148.40	961.37	1015.62	125.13
rc15_2	902.80	941.54	134.32	969.76	1008.80	141.85	970.83	1026.18	135.64
rc15_3	897.60	905.45	142.67	1021.02	1037.58	87.55	969.63	1009.56	134.46
rc15_4	833.67	851.68	174.50	965.01	998.28	156.07	969.30	1035.27	125.44
rc15_5	908.41	952.75	153.80	968.87	1011.22	144.84	1024.94	1026.89	131.66
rc21_1	834.08	834.24	155.59	767.32	767.94	171.79	766.51	767.32	145.75
rc21_2	777.65	822.33	188.12	767.57	768.56	152.36	766.44	766.90	143.66
rc21_3	906.81	906.98	178.50	770.49	771.23	151.44	769.35	769.66	146.76
rc21_4	905.08	911.68	154.90	772.95	774.54	176.97	767.48	768.07	126.56
rc21_5	840.96	841.46	129.94	772.83	773.28	132.38	770.62	771.47	126.45
rc22_1	707.19	724.96	136.95	770.46	772.20	100.60	765.89	766.32	108.26
rc22_2	706.59	720.37	142.98	n.f.	n.f.	-	711.53	730.62	159.32
rc22_3	697.63	697.96	107.93	701.53	701.69	117.25	697.57	698.22	118.52
rc22_4	763.35	763.69	118.49	771.43	771.56	118.66	764.32	764.60	114.69
rc22_5	696.60	697.10	117.51	700.86	707.29	121.95	697.23	698.23	122.26
rc23_1	843.93	858.57	221.89	845.00	863.20	172.00	n.f.	n.f.	-
rc23_2	776.75	784.79	128.16	786.51	821.41	172.48	n.f.	n.f.	-
rc23_3	776.87	777.69	155.53	840.79	841.50	136.10	n.f.	n.f.	-
rc23_4	774.14	775.34	169.51	841.15	842.15	167.37	n.f.	n.f.	-
rc23_5	777.49	790.21	202.25	845.29	845.56	152.50	n.f.	n.f.	-
rc24_1	922.09	922.49	175.01	778.56	779.45	144.41	778.65	779.12	144.09
rc24_2	926.46	928.24	160.23	780.10	787.48	132.71	782.89	832.53	157.99
rc24_3	922.37	922.61	178.24	780.01	787.61	118.54	780.81	781.49	119.87
rc24_4	922.66	923.95	172.01	776.50	777.00	135.12	777.28	779.47	111.95
rc24_5	925.61	925.74	170.55	842.97	844.04	111.57	784.81	809.61	169.12
rc25_1	706.97	719.65	178.51	769.53	769.92	135.34	770.86	777.70	158.79
rc25_2	711.56	739.34	151.99	773.33	773.86	149.04	778.09	821.64	155.70
rc25_3	711.29	742.28	155.85	838.02	838.65	130.60	781.50	830.77	143.49
rc25_4	766.67	767.99	172.33	771.33	771.89	133.41	777.83	795.33	183.65
rc25_5	703.35	704.52	152.61	769.53	770.43	147.00	771.30	783.64	156.46

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 14: VRP results for the W-model for clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
c11_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c11_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c11_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c11_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c11_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c12_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c12_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c12_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c12_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c12_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
c13_1	n.f.	n.f.	-	1189.60	1233.38	128.15	n.f.	n.f.	-
c13_2	n.f.	n.f.	-	1186.49	1246.20	152.99	n.f.	n.f.	-
c13_3	n.f.	n.f.	-	1186.45	1198.75	155.04	n.f.	n.f.	-
c13_4	n.f.	n.f.	-	1183.28	1192.48	153.09	n.f.	n.f.	-
c13_5	n.f.	n.f.	-	1058.49	1071.83	141.54	n.f.	n.f.	-
c14_1	n.f.	n.f.	-	1440.59	1454.78	135.37	1365.62	1395.14	128.64
c14_2	n.f.	n.f.	-	1421.67	1422.91	108.13	1359.46	1388.82	160.70
c14_3	n.f.	n.f.	-	1441.76	1479.57	159.25	1374.56	1420.96	158.38
c14_4	n.f.	n.f.	-	1356.57	1358.47	143.82	1360.53	1362.83	180.29
c14_5	n.f.	n.f.	-	1435.31	1468.87	173.55	1315.99	1363.21	135.44
c15_1	680.99	731.40	129.75	n.f.	n.f.	-	n.f.	n.f.	-
c15_2	741.49	743.41	130.04	n.f.	n.f.	-	n.f.	n.f.	-
c15_3	752.97	807.65	117.16	n.f.	n.f.	-	n.f.	n.f.	-
c15_4	748.19	760.18	152.73	n.f.	n.f.	-	n.f.	n.f.	-
c15_5	741.95	748.89	140.51	n.f.	n.f.	-	n.f.	n.f.	-
c21_1	627.46	658.28	149.75	627.84	646.96	149.52	629.60	653.46	181.23
c21_2	630.58	630.95	182.46	629.72	630.54	106.38	634.09	680.70	174.18
c21_3	626.43	627.86	126.78	625.94	633.87	158.98	631.15	683.30	126.36
c21_4	627.11	634.12	133.35	631.86	632.21	190.17	632.10	657.17	149.18
c21_5	625.12	626.17	172.85	625.08	626.46	166.25	627.96	628.84	156.58
c22_1	637.53	688.77	114.84	634.77	647.57	126.68	n.f.	n.f.	-
c22_2	627.22	628.01	117.07	627.30	628.00	118.00	n.f.	n.f.	-
c22_3	624.71	626.00	140.82	625.56	626.89	121.82	n.f.	n.f.	-
c22_4	628.28	628.59	131.07	628.38	629.96	89.59	n.f.	n.f.	-
c22_5	625.44	632.87	120.51	624.35	624.64	125.86	n.f.	n.f.	-
c23_1	n.f.	n.f.	-	695.40	703.71	138.74	630.19	630.64	134.34
c23_2	n.f.	n.f.	-	634.03	669.89	155.49	630.22	630.70	132.05
c23_3	n.f.	n.f.	-	693.99	701.92	126.74	694.61	701.47	139.79
c23_4	n.f.	n.f.	-	695.01	703.39	121.77	633.15	652.00	167.12
c23_5	n.f.	n.f.	-	694.14	3430.10	129.00	630.27	636.53	133.70
c24_1	628.28	629.50	137.40	628.31	630.30	112.96	629.53	630.07	118.40
c24_2	624.14	642.74	113.50	624.11	624.65	137.11	625.36	625.77	121.16
c24_3	627.73	628.10	112.04	633.44	668.31	129.61	634.18	684.65	159.26
c24_4	627.98	634.12	155.65	627.91	629.41	143.98	631.53	643.50	151.60
c24_5	625.19	625.59	118.49	625.24	632.16	95.71	625.17	631.65	122.70
c25_1	776.73	791.44	166.08	623.31	623.91	137.65	696.44	697.81	142.78
c25_2	784.89	837.23	174.84	638.32	691.85	144.65	702.60	703.10	145.61
c25_3	769.19	776.27	174.56	623.08	623.58	138.80	697.12	697.55	118.82
c25_4	772.91	775.02	166.26	624.62	625.62	129.09	631.42	631.61	187.02
c25_5	768.57	769.20	167.97	624.04	624.26	132.53	630.05	630.56	162.55

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 15: VRP results for the W-model for randomly distributed instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}
r11_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r11_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r11_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r11_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r11_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r12_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r12_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r12_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r12_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r12_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r13_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r13_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r13_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r13_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r13_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
r14_1	772.52	780.43	215.01	829.12	832.66	206.64	960.43	962.49	179.30
r14_2	708.87	751.55	172.19	828.56	829.60	228.05	889.60	892.95	219.12
r14_3	768.00	770.72	178.80	891.17	892.54	174.70	893.40	895.14	234.66
r14_4	777.21	797.88	205.53	897.54	922.88	212.94	962.40	996.22	187.38
r14_5	772.10	774.46	190.16	893.07	894.25	169.03	960.57	968.70	209.11
r15_1	777.92	827.41	156.07	836.27	877.72	187.92	964.96	973.37	171.55
r15_2	773.39	780.40	182.70	956.18	965.00	198.58	972.79	1018.17	211.53
r15_3	842.53	877.91	188.78	901.86	904.08	225.13	972.96	975.00	233.54
r15_4	837.64	840.21	170.76	900.69	925.92	229.09	1044.70	1084.72	221.49
r15_5	778.81	830.44	198.39	897.13	921.44	139.11	961.02	964.32	202.24
r21_1	777.71	785.11	230.94	842.04	843.80	187.76	n.f.	n.f.	-
r21_2	707.60	752.25	139.01	773.04	779.92	177.57	n.f.	n.f.	-
r21_3	710.05	757.31	174.28	772.94	785.54	180.54	n.f.	n.f.	-
r21_4	709.63	722.17	177.98	776.95	777.75	210.42	n.f.	n.f.	-
r21_5	707.14	739.74	139.93	772.04	772.87	166.97	n.f.	n.f.	-
r22_1	n.f.	n.f.	-	n.f.	n.f.	-	773.29	774.17	177.49
r22_2	n.f.	n.f.	-	n.f.	n.f.	-	773.64	774.01	176.90
r22_3	n.f.	n.f.	-	n.f.	n.f.	-	777.32	784.00	236.84
r22_4	n.f.	n.f.	-	n.f.	n.f.	-	777.11	807.82	161.23
r22_5	n.f.	n.f.	-	n.f.	n.f.	-	779.85	793.18	176.28
r23_1	709.46	733.45	172.16	709.75	716.45	142.87	778.67	798.12	222.50
r23_2	709.13	745.62	176.08	773.45	774.20	190.13	779.25	780.51	193.25
r23_3	705.17	705.62	175.40	709.26	751.20	166.02	776.06	777.12	238.28
r23_4	776.24	777.09	206.23	n.f.	n.f.	-	n.f.	n.f.	-
r23_5	770.20	772.29	216.51	713.02	718.58	145.28	838.50	840.36	162.74
r24_1	768.54	781.35	174.59	n.f.	n.f.	-	772.88	774.96	218.77
r24_2	707.14	755.44	172.10	n.f.	n.f.	-	772.35	773.42	185.05
r24_3	698.65	705.39	194.37	n.f.	n.f.	-	700.96	702.00	201.88
r24_4	704.11	729.07	183.24	n.f.	n.f.	-	706.63	712.75	170.68
r24_5	702.29	703.17	166.66	n.f.	n.f.	-	703.91	704.27	176.17
r25_1	847.95	861.62	183.99	776.08	783.66	135.81	848.12	849.85	245.26
r25_2	787.87	834.51	238.77	775.50	776.38	178.37	847.54	855.45	219.47
r25_3	848.29	849.23	226.38	777.57	777.84	182.29	849.45	851.27	233.41
r25_4	786.68	829.39	220.45	775.90	776.68	150.28	849.52	856.44	238.75
r25_5	787.11	853.85	190.20	776.59	777.82	151.19	846.57	847.25	227.44

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^{a} [s] - average computational time out of ten runs.

Table 16: VRP results for the W-model for randomly clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
rc11_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc11_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc11_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc11_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc11_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc12_1	n.f.	n.f.	-	1030.53	1033.85	183.08	n.f.	n.f.	-
rc12_2	844.31	863.03	153.27	897.91	912.15	135.72	n.f.	n.f.	-
rc12_3	842.06	855.76	179.54	1084.04	1094.15	179.71	n.f.	n.f.	-
rc12_4	910.32	912.25	155.42	974.93	1000.64	185.71	n.f.	n.f.	-
rc12_5	843.44	856.27	165.89	962.54	998.09	164.85	n.f.	n.f.	-
rc13_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc13_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc13_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc13_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc13_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc14_1	907.13	939.42	167.42	918.19	953.01	166.22	911.27	962.86	176.55
rc14_2	904.24	905.59	154.03	1037.56	1059.03	159.66	965.20	969.46	170.89
rc14_3	905.40	920.79	188.38	982.15	1028.72	160.75	971.27	981.13	122.34
rc14_4	912.09	945.94	144.10	981.08	1003.50	146.25	972.21	974.24	166.56
rc14_5	843.94	897.65	137.99	968.75	970.63	167.57	897.64	912.51	152.14
rc15_1	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc15_2	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc15_3	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc15_4	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc15_5	n.f.	n.f.	-	n.f.	n.f.	-	n.f.	n.f.	-
rc21_1	763.15	763.42	106.65	766.96	767.17	112.93	773.51	774.33	164.01
rc21_2	762.22	763.01	84.81	766.57	767.44	115.98	771.72	771.95	152.90
rc21_3	767.79	768.37	122.11	770.15	770.40	135.54	836.15	836.59	121.76
rc21_4	763.74	764.15	92.41	769.45	769.60	134.70	842.33	843.56	161.19
rc21_5	773.07	803.78	127.22	772.38	772.80	133.55	837.49	838.12	174.85
rc22_1	712.61	762.67	152.15	n.f.	n.f.	-	709.45	744.49	126.73
rc22_2	710.95	750.94	180.61	n.f.	n.f.	-	711.16	758.65	137.85
rc22_3	701.86	702.49	149.44	n.f.	n.f.	-	698.99	699.89	119.60
rc22_4	767.30	767.71	125.16	n.f.	n.f.	-	765.88	766.36	103.46
rc22_5	700.45	701.37	157.16	n.f.	n.f.	-	697.32	698.45	120.34
rc23_1	844.36	872.81	172.91	845.54	866.69	208.45	777.07	784.10	140.71
rc23_2	773.87	774.60	205.38	838.86	840.65	257.33	771.15	786.17	171.07
rc23_3	773.33	773.93	186.50	840.61	840.94	242.20	772.77	779.76	183.90
rc23_4	773.04	774.06	186.26	839.62	840.67	250.45	771.30	778.00	141.36
rc23_5	777.46	825.07	172.09	841.46	842.18	199.39	773.98	774.82	181.35
rc24_1	n.f.	n.f.	-	844.26	849.16	157.85	n.f.	n.f.	-
rc24_2	n.f.	n.f.	-	847.34	861.85	166.63	n.f.	n.f.	-
rc24_3	n.f.	n.f.	-	850.52	859.26	156.60	n.f.	n.f.	-
rc24_4	n.f.	n.f.	-	842.55	847.54	189.95	n.f.	n.f.	-
rc24_5	n.f.	n.f.	-	849.54	880.67	148.69	n.f.	n.f.	-
rc25_1	706.83	730.36	172.74	707.36	725.24	148.38	776.23	777.55	169.59
rc25_2	768.38	768.63	188.14	767.93	768.63	142.05	776.01	793.91	190.59
rc25_3	711.95	754.60	162.55	712.56	743.73	136.15	779.71	818.49	159.09
rc25_4	768.09	768.47	153.93	709.11	751.60	143.54	836.40	839.20	197.74
rc25_5	703.81	704.50	157.41	702.02	703.61	154.81	704.38	710.86	173.08

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 17: VRP results for the R-model for clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
c11_1	763.50	836.03	111.11	1193.49	1195.81	165.43	1254.39	1264.44	137.97
c11_2	759.01	789.69	138.61	1196.25	1240.13	142.91	1258.91	1306.52	152.37
c11_3	821.69	829.09	118.43	1188.51	1202.27	148.90	1259.57	1303.26	126.56
c11_4	817.22	830.20	100.03	1247.17	1262.60	144.47	1255.68	1257.00	155.60
c11_5	825.78	868.92	108.80	1252.55	1253.69	133.62	1260.52	1282.31	143.02
c12_1	758.482	796.886	142.724	1124.72	1164.97	141.53	1119.64	1142.93	150.84
c12_2	805.537	806.247	119.45	1118.44	1156.14	148.45	1124.09	1154.63	158.21
c12_3	757.055	808.258	99.0913	1055.99	1057.87	170.95	1246.23	1255.14	118.77
c12_4	751.088	752.057	109.621	1179.73	1216.81	174.05	1120.85	1142.72	153.89
c12_5	744.327	751.341	110.255	1130.23	1171.88	177.65	1183.41	1190.07	154.52
c13_1	687.764	706.465	182.187	1108.43	1119.08	190.34	1111.79	1135.24	132.54
c13_2	748.516	756.378	123.825	1116.13	1172.99	167.35	1186.74	1238.05	189.94
c13_3	756.707	794.249	119.147	1122.49	1176.51	194.56	1119.70	1136.05	207.01
c13_4	750.665	782.181	136.555	1111.39	1133.96	136.99	1179.77	1182.75	203.57
c13_5	695.893	750.298	150.812	984.18	993.47	145.32	1118.17	1180.44	203.93
c14_1	744.33	745.40	135.96	1366.34	1367.26	180.33	1301.92	1337.93	194.84
c14_2	669.12	676.41	127.65	1291.12	6652.75	150.96	1359.91	1405.66	176.83
c14_3	692.24	737.42	149.32	1300.10	1328.68	166.91	1362.72	1414.45	205.64
c14_4	670.58	677.21	148.66	1228.97	1253.84	133.24	1361.54	1369.98	171.62
c14_5	681.44	700.09	176.29	1367.50	1404.85	174.46	1308.95	1361.38	162.68
c15_1	736.25	736.56	130.91	1173.14	3865.26	149.786	1247.14	1247.79	151.541
c15_2	684.41	726.12	148.50	1181.34	1189.32	127.357	1181.55	1182.61	117.716
c15_3	748.84	781.69	143.23	1238.5	1239.23	177.645	1242.53	1242.92	142.303
c15_4	744.64	745.27	172.86	1190.41	1257.15	140.678	1251.44	1302.63	108.427
c15_5	741.33	748.48	143.69	1177.75	1228.99	136.374	1241.27	1258.89	119.646
c21_1	626.29	627.14	171.27	626.29	626.87	172.32	628.12	675.14	215.23
c21_2	628.36	629.16	164.81	628.28	635.01	202.96	631.03	679.30	185.99
c21_3	625.99	627.34	169.91	625.99	632.59	193.22	629.24	674.58	190.46
c21_4	627.16	628.05	192.41	626.99	633.65	206.21	628.34	651.93	218.06
c21_5	624.14	625.27	157.47	624.33	625.19	185.76	624.23	630.91	201.26
c22_1	633.754	664.736	138.696	632.63	646.27	148.23	632.71	675.78	159.60
c22_2	624.737	626.033	129.472	624.89	626.22	138.65	629.31	642.71	161.99
c22_3	623.512	638.385	122.833	622.78	623.82	131.68	627.29	628.35	182.82
c22_4	627.204	628.153	105.311	627.20	628.10	129.43	632.16	645.27	124.77
c22_5	566.672	618.966	171.295	623.49	624.66	155.19	629.71	641.66	156.52
c23_1	629.79	636.55	153.83	630.20	642.88	130.19	629.69	631.38	171.50
c23_2	629.62	630.47	152.66	629.62	630.51	148.40	629.62	630.58	130.96
c23_3	694.16	700.86	163.60	694.48	695.18	150.73	693.93	700.74	178.37
c23_4	634.22	675.17	173.69	631.49	661.82	141.18	631.51	632.83	163.17
c23_5	629.77	630.28	170.81	629.77	636.57	158.56	629.77	630.12	189.64
c24_1	627.74	629.20	177.29	628.60	635.45	182.36	628.259	629.539	136.271
c24_2	624.07	630.55	169.93	624.45	631.08	151.67	624.046	624.592	131.888
c24_3	627.44	627.88	157.75	627.71	628.33	161.58	627.449	628.036	97.101
c24_4	628.44	652.57	159.24	628.65	634.88	157.43	627.866	640.379	114.746
c24_5	625.20	625.93	182.25	625.56	626.48	173.26	625.162	625.99	124.145
c25_1	621.97	623.25	126.50	622.16	623.22	145.08	623.71	625.61	151.46
c25_2	627.84	634.53	112.16	627.92	628.28	145.81	629.57	630.16	153.59
c25_3	621.97	622.83	151.61	621.83	622.60	145.17	625.02	625.53	158.41
c25_4	623.21	623.57	180.28	623.03	624.18	148.70	623.41	3087.47	179.57
c25_5	622.34	623.25	130.45	622.13	622.76	162.96	624.99	625.45	196.87

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 18: VRP results for the R-model for randomly distributed instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^a	λ^b	λ^a	t^a	λ^b	λ^a	t^a
r11_1	900.17	902.47	229.43	905.29	954.30	215.76	899.86	936.35	244.01
r11_2	901.76	910.19	284.05	966.50	975.39	229.60	904.66	959.10	198.42
r11_3	903.12	922.26	243.39	908.45	952.00	279.64	960.12	980.34	222.92
r11_4	907.48	939.89	267.11	972.33	1037.97	215.44	968.47	993.45	237.95
r11_5	905.48	941.74	218.77	905.06	954.21	215.75	961.05	1002.83	212.14
r12_1	892.79	900.84	225.02	896.06	921.57	233.23	957.79	995.09	192.07
r12_2	892.25	893.89	198.99	896.43	927.58	213.82	1025.50	1051.90	233.70
r12_3	889.91	891.26	187.58	893.87	929.08	178.89	956.64	997.20	218.07
r12_4	894.78	896.32	189.87	901.70	952.78	185.21	962.22	975.69	188.11
r12_5	901.91	949.56	155.94	963.50	999.51	200.24	1028.14	1066.42	164.28
r13_1	775.22	825.08	285.39	892.33	898.82	265.93	958.60	986.04	303.38
r13_2	765.70	781.50	245.61	828.21	846.58	261.02	887.61	890.38	239.71
r13_3	765.38	766.95	276.77	824.67	833.70	314.12	828.62	843.47	236.58
r13_4	770.99	790.05	283.27	889.88	899.43	231.74	832.01	881.79	205.54
r13_5	768.56	810.87	278.60	825.35	827.84	246.87	831.71	890.22	246.14
r14_1	703.98	716.82	189.56	830.09	840.11	196.16	895.99	932.25	180.11
r14_2	700.68	708.24	145.94	826.09	828.38	175.69	824.20	838.60	162.94
r14_3	698.09	708.49	160.34	883.14	888.07	182.08	826.40	851.26	196.41
r14_4	709.32	740.11	153.96	837.57	882.39	239.60	893.47	894.74	216.55
r14_5	706.54	731.90	172.42	839.10	890.92	200.02	892.46	901.98	228.65
r15_1	767.98	768.59	240.56	833.75	858.51	250.06	889.40	892.58	269.48
r15_2	770.10	783.47	185.56	900.79	945.15	201.14	894.19	937.79	263.77
r15_3	777.68	831.77	222.14	842.47	888.88	230.46	838.96	873.94	218.45
r15_4	774.15	817.77	191.19	896.65	911.94	211.94	901.56	947.54	244.93
r15_5	768.93	788.91	233.06	832.93	894.40	234.15	889.65	905.08	230.12
r21_1	774.13	789.40	213.59	774.58	775.49	165.22	770.22	786.83	215.76
r21_2	707.68	749.95	198.96	709.77	752.61	153.88	705.99	731.48	183.28
r21_3	706.13	725.22	206.87	711.22	764.33	200.81	707.55	738.29	185.69
r21_4	709.57	764.63	179.82	768.92	770.42	210.22	767.28	768.63	176.19
r21_5	708.55	750.98	255.57	711.39	740.50	257.71	710.84	762.64	189.86
r22_1	710.53	762.90	146.58	711.59	759.21	233.67	709.58	746.12	231.38
r22_2	709.25	745.85	184.55	712.05	771.31	227.17	709.17	745.10	232.90
r22_3	770.82	771.66	178.62	771.92	773.17	186.25	771.05	771.91	205.92
r22_4	770.80	771.57	163.57	770.28	773.35	229.67	770.81	771.58	152.16
r22_5	776.10	777.16	207.02	775.88	784.06	188.71	775.91	788.89	214.11
r23_1	703.94	705.37	195.06	704.38	711.64	146.83	705.25	705.88	201.07
r23_2	704.43	711.42	179.26	704.53	711.88	202.00	704.67	712.01	210.10
r23_3	701.74	703.05	173.14	699.91	700.79	118.92	700.76	702.34	166.70
r23_4	772.10	773.82	158.04	711.70	765.10	153.91	768.57	771.03	152.02
r23_5	704.50	712.58	205.00	706.05	712.52	185.83	706.05	706.77	254.24
r24_1	709.30	750.24	152.20	767.76	775.67	164.46	709.38	757.92	195.94
r24_2	705.38	724.29	200.49	704.77	723.75	172.48	706.54	746.32	205.79
r24_3	697.68	699.20	184.51	697.56	698.87	157.04	698.11	699.13	178.18
r24_4	701.64	720.55	235.86	703.74	722.66	237.43	702.51	703.35	212.50
r24_5	699.37	699.74	173.07	765.11	766.55	150.03	699.95	700.18	201.42
r25_1	774.33	775.34	158.41	773.49	774.51	200.07	776.48	791.35	134.61
r25_2	772.22	772.43	141.80	772.52	773.03	192.38	775.21	775.49	195.12
r25_3	775.33	775.52	194.23	775.36	775.88	165.93	775.89	776.06	208.92
r25_4	773.56	774.74	172.66	774.63	775.80	182.72	776.47	777.88	198.46
r25_5	773.30	774.07	159.99	774.01	774.84	208.36	776.24	776.62	183.09

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^a [s] - average computational time out of ten runs.

Table 19: VRP results for the R-model for randomly clustered instances.

	deg1			deg2			deg3		
Instance	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}	λ^b	λ^a	t^{a}
rc11_1	841.39	845.74	185.44	904.31	912.42	228.55	901.05	911.32	235.01
rc11_2	773.44	787.63	203.43	837.00	856.54	242.51	842.34	867.24	185.90
rc11_3	776.16	829.95	215.45	839.84	878.85	261.31	839.45	879.30	271.24
rc11_4	777.05	822.11	218.51	895.32	899.02	288.79	908.89	950.80	228.72
rc11_5	776.36	808.10	157.65	898.72	907.59	254.39	829.56	831.16	205.28
rc12_1	773.74	787.36	225.73	964.13	989.64	231.91	901.89	937.04	228.52
rc12_2	774.59	820.98	194.73	891.21	894.34	188.60	962.37	984.20	231.07
rc12_3	768.97	776.33	190.93	1021.71	1028.95	224.79	894.27	898.50	201.74
rc12_4	840.34	842.38	216.59	969.63	971.48	229.62	967.14	992.54	221.76
rc12_5	771.65	773.29	235.23	898.60	936.79	209.64	959.30	962.64	209.25
rc13_1	904.10	935.98	212.58	1029.55	1047.03	220.58	1035.50	1055.75	203.20
rc13_2	911.77	971.05	177.15	977.72	1058.36	186.42	1094.40	1121.76	172.22
rc13_3	965.80	976.38	187.61	1037.51	1085.04	196.37	1038.75	1120.74	167.53
rc13_4	909.96	966.14	211.98	1096.25	1110.58	179.86	1105.93	1161.73	137.07
rc13_5	976.83	1035.54	204.12	1107.77	1154.61	229.35	1106.00	1110.27	185.90
rc14_1	850.65	900.77	202.19	902.83	913.29	208.82	902.37	910.90	291.44
rc14_2	899.67	903.70	199.28	968.57	976.62	185.67	900.38	902.55	204.50
rc14_3	840.79	849.42	200.28	969.53	978.18	234.90	906.61	913.60	239.74
rc14_4	844.14	897.91	204.67	907.94	938.55	218.20	906.23	913.41	293.11
rc14_5	838.46	847.08	202.84	902.13	918.84	223.92	834.43	848.38	273.65
rc15_1	821.71	823.90	155.94	897.81	959.13	156.38	890.37	906.51	207.05
rc15_2	833.50	876.00	219.80	899.54	947.14	172.09	963.03	965.17	184.27
rc15_3	829.32	831.01	216.12	952.55	961.11	172.81	894.07	920.58	227.57
rc15_4	828.77	843.09	207.31	897.51	948.55	234.21	955.82	958.34	225.79
rc15_5	835.32	853.86	238.23	902.77	959.45	226.58	962.53	975.67	168.94
rc21_1	762.67	762.90	151.50	763.60	763.76	162.06	762.12	762.53	154.40
rc21_2	702.99	745.10	132.13	705.08	740.16	155.09	761.45	762.22	158.99
rc21_3	765.92	766.64	136.82	768.65	769.26	177.26	764.01	764.88	130.52
rc21_4	763.09	763.60	132.50	765.75	766.32	152.42	763.17	763.80	155.17
rc21_5	767.94	768.31	153.26	769.85	770.68	158.95	767.34	767.71	144.15
rc22_1	706.32	713.01	141.28	706.11	717.97	138.59	706.24	718.10	160.78
rc22_2	705.84	706.23	164.63	705.92	706.59	142.57	705.84	706.47	121.09
rc22_3	697.41	698.07	106.49	697.41	697.85	140.51	697.61	697.87	132.66
rc22_4	763.38	763.87	125.59	763.27	763.87	125.23	763.38	763.89	101.40
rc22_5	696.27	696.87	122.02	696.27	696.81	145.94	696.27	696.94	136.38
rc23_1	769.79	789.78	179.32	769.52	770.07	173.51	771.95	772.90	213.73
rc23_2	767.00	781.46	162.85	766.51	767.84	185.26	769.20	769.72	159.80
rc23_3	769.41	771.18	151.23	769.29	769.99	185.32	772.18	773.13	225.78
rc23_4	766.48	767.76	171.73	766.30	768.84	148.25	768.12	769.37	187.05
rc23_5	772.03	772.38	183.40	771.97	772.60	205.30	773.34	780.77	228.64
rc24_1	776.34	776.64	157.44	776.34	777.07	130.81	776.36	776.87	160.95
rc24_2	776.52	778.03	159.04	776.73	778.37	145.23	776.94	777.37	161.74
rc24_3	777.86	778.45	141.34	777.20	778.39	143.85	777.14	785.00	157.13
rc24_4	774.36	774.63	172.40	774.36	774.64	190.34	774.57	775.63	147.14
rc24_5	782.14	800.24	154.24	781.68	800.29	179.86	781.73	812.42	196.97
rc25_1	705.73	705.87	215.80	706.03	706.33	198.69	707.62	713.31	158.64
rc25_2	765.06	765.53	145.88	710.92	743.79	155.93	711.05	760.48	148.94
rc25_3	709.71	723.05	210.32	711.46	736.47	167.55	765.97	794.55	115.14
rc25_4	708.34	750.35	177.24	712.26	761.76	151.80	708.15	749.29	199.69
rc25_5	700.08	702.17	139.45	701.49	702.50	142.51	701.39	709.08	161.45

Abbreviations hold as follows: λ^b - best solution out of ten runs, λ^a - average solution out of ten runs, t^{a} [s] - average computational time out of ten runs.