



Invited Review

A survey of variants and extensions of the location-routing problem

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ABSTRACT

This is a review of the literature on variants and extensions of the standard location-routing problem published since the last survey, by Nagy and Salhi, appeared in 2006. We propose a classification of problem variants, provide concise paper excerpts that convey the central ideas of each work, discuss recent developments in the field, and list promising topics for further research.

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1. Introduction

Location-Routing Problems (LRPs) combine two basic planning tasks in logistics. In LRPs, as their name implies, decisions on the location of arbitrary types of facilities (plants, depots, warehouses, hubs, cross-docks, etc.) are jointly taken with decisions on the routing of vehicles. It is well-known that making these types of decisions independently of one another may lead to highly suboptimal planning results (Salhi & Rand, 1989), even if the location decisions must be made for the long term (Salhi & Nagy, 1999). We define the term *location-routing problem* (LRP) as a mathematical optimization problem where at least the following two types of decisions must be made interdependently:

- (i) Which facilities out of a finite or infinite set of potential ones should be used (for a certain purpose)?
- (ii) Which vehicle routes should be built, i.e., which customer clusters should be formed and in which sequence should the customers in each cluster be visited by a vehicle from a given fleet (to perform a certain service)?

We further define a *standard* LRP as a deterministic, static, discrete, single-echelon, single-objective problem where each customer (vertex) must be visited exactly once for the delivery of a good from a facility, and where no inventory decisions are relevant. We give a survey of newer works on the standard LRP in a

separate paper (Drexler & Schneider, 2014). The present paper discusses variants and extensions of the standard LRP, which include problems with stochastic and fuzzy data, multi-period planning horizons, continuous location in the plane, multiple objectives, more complex requests or route structures, such as pickup-and-delivery requests or routes with load transfers, and inventory decisions.

We consider only problems where the selection of the facilities to use is not implicitly determined by the routing decisions, and where routes for vehicles must be determined, not only assignments of customers or flows of goods. In particular, the selection of facilities will not be implicitly determined by the routing decisions if

- (i) there are fixed costs for opening and/or variable (volume-dependent) costs for using a facility or
- (ii) (exactly or at most) a given number of facilities must be selected out of a larger set or
- (iii) the facilities have some kind of capacity limitation.

We use these criteria as a general guideline for limiting the material discussed in this review. Thus, problems not studied here are pure facility location problems (FLPs, Daskin, 1995), and (service) network design problems (Crainic & Kim, 2007; Wieberneit, 2008). In these problems, no vehicle routing is performed. Moreover, we exclude vehicle routing-allocation/median cycle problems (Nagy & Salhi, 2007), as for these problems, none of the three criteria listed above applies. Hamiltonian p -median problems (Branco & Coelho, 1990) are also omitted; we do not consider this problem type an LRP because it actually requires no locational decision. Finally, we do not cover the following problems because

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in all of them, the location decisions are implicitly determined by the routing: multi-depot vehicle routing problems (MDVRPs, Cordeau, Gendreau, & Laporte, 1997), VRPs with intermediate depots or re-fill points (Ghiani, Improta, & Laporte, 2001; Tarantilis, Zachariadis, & Kiranoudis, 2008), pickup-and-delivery problems with transshipments, vehicle and driver routing and scheduling problems with driver changes at relay stations en route, and VRPs with trailers and transshipments (see Drexler (2012a) for a survey of the last three problems).

LRPs have been studied for decades. Earlier surveys were published by Balakrishnan, Ward, and Wong (1987); Laporte (1988); Laporte (1989); Berman, Jaillet, and Simchi-Levi (1995); Min, Jayaraman, and Srivastava (1998); Nagy and Salhi (2007), and very recently by Prodhon and Prins (2014). The present survey is based on the technical report of Drexler and Schneider (2013), which is parallel and independent work to the review of Prodhon and Prins (2014). It differs from the paper of Prodhon and Prins (2014) in several aspects:

- (i) The definition of what constitutes an LRP differs between the two papers.
- (ii) The present paper specializes on variants and extensions of the standard LRP, while Prodhon and Prins (2014) also review the standard LRP.
- (iii) While there is clearly an overlap, the set of discussed papers in both works is not identical.
- (iv) Prodhon and Prins (2014) essentially offer rather brief and compact overviews of the reviewed papers, whereas our aim is to provide more detailed excerpts that make the central ideas and unique features of each work clear without the reader having to consult the original reference.

Thus, both surveys are complementary.

In the last years, the LRP research community has been very active. In particular, the newer literature on LRPs follows a rather general trend in logistics planning towards studying ‘richer’, more comprehensive and integrated models (Hartl, Hasle, & Janssens, 2006; Drexler, 2012b). Thus, we considered it worthwhile to compile a new literature review, focusing on the recent literature on variants and extensions of the standard LRP. The survey is not intended to cover the complete literature. Instead, we provide a literature update and restrict ourselves to papers that (i) were published between 2006 and the first half of 2014 and (ii) were not already discussed in the survey of Nagy and Salhi (2007).

We have included journal articles, conference proceedings, technical reports, and Ph.D. dissertations written in English. We do not claim to have collected all the literature from 2006 onwards, but we think we have identified a representative subset of the work carried out by the research community since then. Our aim is to provide excerpts on a level of detail that makes the central ideas and unique features of each work clear. Nevertheless, excerpt lengths vary and depend on several factors such as the complexity of the conveyed ideas, the length of the original paper, the similarity of the original paper to previously discussed works and concepts, and, to some extent, also on our own subjective opinion on the importance of an article.

The rest of this paper is structured as follows. In Section 2, different types and characteristics of LRPs are described. Section 3 describes widely used sets of benchmark instances. Sections 4–10 review literature on different variants of LRPs. In these sections, excerpts of relevant papers are presented. Papers are mostly listed in chronological order, but closely related works by the same researchers are sometimes described together. Section 11 summarizes the key insights we gained during our study, concerning problems, models, applications, and algorithms. To conclude, Section 12 suggests promising topics for further research. All abbreviations

and acronyms used in the text are listed in the Appendix. We use the term *facility* to denote the objects to be located, no matter what these objects are in an actual or potential application context.

2. LRP variants

As mentioned, there are numerous types or variants of LRPs. In this section, we identify the most important criteria for categorizing the existing literature by problem type. We differentiate between so-called main characteristics that fundamentally change the nature of the problem, thus defining a new problem variant, and so-called subcharacteristics, for which this is not the case.

2.1. Main characteristics defining new problem variants

Deterministic vs. stochastic vs. fuzzy data. In a deterministic planning situation, all problem data are known in advance. Stochastic data means that some information (in most cases, customer demands or travel times) is given in the form of probability distributions. Fuzzy data means that some problem parameters are available in the form of fuzzy numbers. Most papers in this review assume deterministic data. We found four papers dealing with stochastic and five concerned with fuzzy data, see Section 7.

Static vs. dynamic vs. periodic problems. Static problems consider one single planning period. The term dynamic refers to problems with multiple planning periods where some information (usually customer demands) is initially unknown and becomes available over time. Periodic LRPs (PLRPs) comprise multiple planning periods and assume complete information on all relevant data. The aim of periodic problems is to determine visiting patterns for customers, i.e., to decide on the periods in which to visit each customer. We have reviewed several papers on PLRPs and one paper on a multi-period LRP, but we have not found any work on a dynamic LRP (Section 5).

Discrete vs. continuous vs. network locations. In discrete problems, the potential locations for opening facilities are given as a (sub)set of vertices of a graph. In continuous or planar problems, the choice of facility locations is not restricted to a discrete set, but facilities may be located freely in the plane. In network location problems, a facility may be opened at any vertex of a graph/network or anywhere on a link (edge, arc). The large majority of papers considers discrete problems. The planar problem was first studied by Schwardt and Dethloff (2005) for locating a single facility. To the best of our knowledge, the only work dealing with the case of multiple facilities is (Salhi & Nagy, 2009), which is already included in the review of Nagy and Salhi (2007). Other than that, we found only two papers on planar location, which are reviewed in Section 10. We found no paper considering network location.

Single vs. multiple echelons. The basic idea of Multi- or N-Echelon Vehicle Routing Problems and LRPs (NE-VRPs/LRPs) is that customers are not served directly from a central depot but via N legs in an N -stage distribution network. An N -stage distribution network contains $N + 1$ levels of locations. Echelon $n \in \{1, \dots, N\}$ considers transports from location level $n - 1$ to n , see Fig. 1. For each echelon n , there are dedicated vehicles that can only visit the facilities defining echelon n . Load transfers are required between vehicles of different echelons. As can be seen in Section 4, many papers on multi-echelon LRPs have appeared in the last few years.

Single vs. multiple objective. Most papers consider a single objective such as minimization of the sum of fixed facility location costs and fixed and variable vehicle routing costs. Some works, though, deal with several objective functions simultaneously. Mostly, qualitative measures such as service levels are considered along with monetary objectives (see Section 8).

Vertex routing vs. arc routing. While in vertex-routing problems service is performed at vertices, Location Arc-Routing

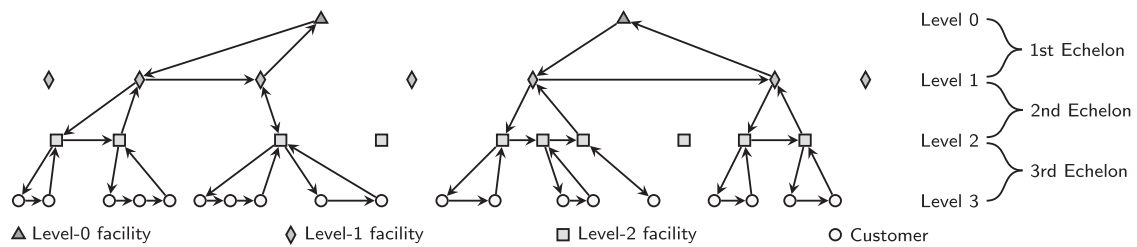


Fig. 1. Example of a three-echelon routing problem.

Problems (LARPs) consider service requirements along the links of a network. Ghiani and Laporte (2001) present a survey on the topic. We have found only two papers that have appeared since then (Section 10).

Generalized LRPs (GLRPs). Similar to the well-known generalized traveling salesman problem (TSP) (Fischetti, Salazar-González, & Toth, 2002), in GLRPs, the customers are clustered into disjoint groups. The requirement in the GLRP is to find routes, starting and ending at a facility, so that exactly one customer from each group is visited exactly once. Obviously, the LRP variants discussed above can be regarded as GLRPs of the type where each group contains exactly one customer. We found only two papers on GLRPs, reviewed in Section 10.

Prize-Collecting LRPs (PCLRPs). PCLRPs allow that some customers are not visited by any tour. For these customers, a per-customer penalty (e.g., an outsourcing cost) is incurred. The sum of fixed facility opening, variable tour and outsourcing costs is to be minimized. Here, we found only two papers, and these are reviewed in Section 10.

Split delivery LRPs (SDLRPs). The option of split delivery allows that a customer can be visited more than once and by more than one vehicle in order to fulfill his demand. There is quite a number of papers on VRPs with split delivery (see the survey by Archetti & Speranza, 2008), whereas we found only one paper considering split delivery LRPs (Section 10).

Pickup-and-delivery LRPs. The tasks to be performed in LRPs may consist in delivering goods to customers from one of several potential facilities, in picking up goods at customers and delivering these goods to one of several potential facilities, or both. In this last case, it is possible that goods must be picked up at one customer and delivered to another. Such problems are called pickup-and-delivery LRPs. It is also possible that a single customer requires both a pickup and a delivery of goods, and that pickup and delivery at a customer have to be done during the same visit. This is called simultaneous pickup and delivery (LRSPD). Many-to-many LRPs are pickup-and-delivery problems where the planning goal is to locate a network of intermediate facilities or hubs for the transshipment of goods. Pickups and deliveries are performed on local, multi-stop routes starting and ending at a hub; inter-hub transports are usually direct. Such problems arise, e.g., in postal or parcel delivery applications. Papers on pickup-and-delivery and many-to-many LRPs are reviewed in Section 6.

Inventory LRPs (ILRPs). ILRPs integrate inventory management decisions at the facilities, i.e., how much of a good to keep in stock and when and how much to order from the manufacturer. Several papers have integrated such a component into an LRP (see Section 9).

Reviews of papers that do not fit any of the introduced problem variants are included in Section 10.

2.2. Subcharacteristics not defining new variants

Besides the above characteristics, LRPs may differ with respect to the following aspects:

- (i) (Un)directed network.
- (ii) (Un)capacitated facilities.
- (iii) (No) fixed costs for opening a facility.
- (iv) (Un)limited/(un)capacitated fleet.
- (v) Homo-/heterogeneous fleet.

In our opinion, these aspects do not change the nature of a problem so much as to constitute a new LRP variant. The majority of the reviewed papers consider capacitated facilities with fixed costs for opening and with capacitated vehicles. Therefore, in the review sections, we only indicate exceptions from this 'rule'.

3. Benchmark instances

The recent LRP literature has made extensive use of standardized benchmark instances to evaluate the quality of the developed solution procedures by comparing their performance with that of other algorithms. We list the benchmark sets by problem variant and in chronological order in Table 1. Benchmarks for the standard LRP are also included in the table because many papers on LRP variants use these instances to assess the performance of the proposed solution method.

The following sections discuss the problem variants introduced above, starting with multi-echelon LRPs.

4. Multi-echelon LRPs

Multi-echelon LRPs have only very recently attracted the interest of researchers: In the last survey on LRPs by Nagy and Salhi (2007), just three references are mentioned. However, judging from the number of publications that have appeared since then, multi-echelon LRPs are the most important LRP modeling extension of the last decade. Although the literature on the topic dates back to Jacobsen and Madsen (1980), the terms multi-echelon or N -echelon VRP/LRP are, in fact, first used in Gonzalez Feliu, Perboli, Tadei, and Vigo (2008) and Perboli, Tadei, and Vigo (2008) (of which an extended version with new results was later published as Perboli, Tadei, and Vigo (2011)).

This development starts to reflect the practical importance of multi-echelon LRPs. Applications include strategic or tactical design of national or international consumer goods distribution networks, postal and parcel delivery distribution systems, press distribution, grocery distribution, home delivery services, e-commerce, and multimodal transportation (see Gonzalez Feliu, 2009). In particular, city logistics concepts for operational planning of goods distribution on the local level, which have been discussed in practice for decades, have finally been investigated by several researchers (see below).

Most papers studying multi-echelon LRPs are concerned with the two-echelon case and ignore temporal aspects such as time windows or the synchronization of transshipments at intermediate levels. These papers are reviewed in the following subsection. After that, a subsection is devoted to works on two echelon LRPs

Table 1
Benchmark instances.

Acronym	First reference	Number of instances	Size (min–max number of facilities/customers)	Link
<i>LRP</i>				
Perl	Introduced in the unpublished Ph.D. dissertation of Perl (1983)	5	2–15/12–318	sweet.ua.pt/sbarreto/_private/SergioBarretoHomePage.htm
TB	Tuzun and Burke (1999)	36	10–20/100–200	prodhonc.free.fr/homepage
B	Introduced in the unpublished Ph.D. dissertation of Barreto (2003). Used in (Barreto et al., 2007)	13	5–14/21–150	sweet.ua.pt/sbarreto/_private/SergioBarretoHomePage.htm
ADF	Albareda-Sambola et al. (2005)	15	5–10/10–30	Not on the Internet
PPW	Prins et al. (2006a)	30	5–10/20–200	prodhonc.free.fr/homepage
ABR	Akca et al. (2009)	12	5/30–40	claudio.contardo.org/instances
BMW	Baldacci et al. (2011)	4	14/150–199	claudio.contardo.org/instances
HKM	Harks et al. (2013)	27	100–1000/ 1000–10,000	www.coga.tu-berlin.de/v-menue/download_media/clrlib
<i>Two-Echelon LRP (2E-LRP)</i>				
GPTV	Gonzalez Feliu et al. (2008)	105	1/2–4/12–50	people.brunel.ac.uk/~mastijb-jeb/orlib/vrp2einfo.html
CPMT	Crainic et al. (2010) . Instances with 50, 100, 150, and 250 customers. Strictly speaking, these are no LRP instances according to our criteria specified above because the selection of the potential facilities is unrestricted and implicitly determined by the routing decisions. The instances are, however, used in papers on 2E-LRPs	132	1/2–10/50–250	people.brunel.ac.uk/~mastijb-jeb/orlib/vrp2einfo.html (only the instances with 50 customers)
NPP-N	Nguyen et al. (2010)	24	1/5–10/20–200	prodhonc.free.fr/homepage
NPP-P	Nguyen et al. (2010) . PPW instances modified by adding one level-0 facility	30	1/5–10/20–200	prodhonc.free.fr/homepage
S	Sterle (2010)	93	2–5/3–20/8–200	Not on the Internet
<i>Others</i>				
Prodhon	PLRP, Prodhon (2008)	30	5–10/20–200	prodhonc.free.fr/homepage
KAKD	LRSPD, Karaoglan et al. (2011) . Modified B and PPW instances (those with up to 100 customers)	37	2–10/8–100	Not on the Internet
LPFS	LARP, Lopes et al. (2014)	30	11–140	lore.web.ua.pt

(2E-LRPs) with temporal aspects. Finally, SubSection 4.3 deals with N -echelon problems for $N > 2$.

4.1. Two-echelon LRPs

This section first described the proposed approaches and later provides a comparison of the methods for which tests were conducted on the same benchmark instances.

[Perboli, Tadei, and Vigo \(2011\)](#) present an arc-variable based Mixed Integer Program(ing) (MIP) formulation for the 2E-LRP with one level-0 facility and capacitated level-1 facilities without fixed opening costs, but with variable, facility-specific costs that depend on the amount of load transhipped at a facility. The formulation was introduced in [Gonzalez Feliu et al. \(2008\)](#). The authors derive additional valid inequalities and develop two matheuristics based on the formulation. Both heuristics exploit the fact that, once the assignment of customers to level-1 facilities is fixed, the problem decomposes into one VRP for the level-0 facility and one VRP for each level-1 facility. Given an optimal solution to the Linear Programming (LP) relaxation, the first heuristic performs a diving procedure (branch-and-bound without backtracking). It successively fixes to zero the binary customer-to-facility assignment variables with smallest positive value and highest pseudocost (see [Linderroth & Savelsbergh, 1999](#)) and then solves the resulting LP relaxation again. Once all assignment variables are integral, the resulting CVRP instances are solved by means of the heuristic introduced in [Perboli, Tadei, and Masoero \(2008\)](#). A repair routine is included to ensure that the capacity constraints of the level-1 facilities are satisfied. The second heuristic relaxes the integrality requirements on the arc variables (but not on the assignment variables). A small set of constraints is added to make sure that level-1 capacities are maintained. A standard solver is run on the resulting simplified MIP for a given time limit, and the k best feasible solutions found are stored. For each of these solutions, the resulting CVRPs are solved with the heuristic of [Perboli et al. \(2008\)](#).

Computational experiments are performed with the GPTV instances and the 50-customer CPMT instances. The results show that, even when the valid inequalities are added, the MIP formulations of the GPTV instances can be consistently solved to optimality with a commercial solver only for instances with up to 21 customers. Only one instance with 32 customers is solved to optimality. For larger instances, gaps of between 0.7% and 42% remain after three hours of computation time. For the CPMT instances, no optimal solutions are found, and the gap averages 11%. The results of the heuristics show that the second one outperforms the first one on the CPMT instances, whereas on the GPTV instances, no heuristic dominates the other. Although computation times are generally below 30 seconds, both heuristics find better solutions than the best upper bounds provided by the exact method for many of the larger instances.

[Perboli, Tadei, and Masoero \(2009\)](#) and [Perboli, Tadei, and Tadei \(2010\)](#) develop valid inequalities for the formulation introduced in [Gonzalez Feliu et al. \(2008\)](#) and show the effectiveness of these cuts by performing computational experiments with the GPTV and the 50-customer CPMT instances. Using the new cuts, all GPTV instances with 32 customers or less are solved to optimality, and for the remaining instances of both sets, the gaps are significantly reduced.

[Crainic, Mancini, Perboli, and Tadei \(2008\)](#) and [Crainic, Perboli, Mancini, and Tadei \(2010\)](#) study heuristics for a 2E-VRP with one level-0 facility and limited fleet. However, the potential facilities neither incur fixed costs for opening, nor is the number of facilities to be opened smaller than the number of available facilities, nor are the facilities capacitated. Thus, according to our LRP criteria given in the Introduction, their problem is not an LRP. Nevertheless, the papers are described here because they provide approaches and insights as well as benchmark instances that the authors use in subsequent publications on 2E-LRPs.

[Crainic et al. \(2008\)](#) separate the problem into two subproblems, one for each echelon. The second-echelon problem is solved

first, and from its solution, a problem instance for the first echelon is constructed, where the level-1 facilities act as customers with a demand equal to the sum of the demands of the customers assigned to each facility in the second-echelon problem. Two constructive and three Local Search (LS) improvement heuristics are presented. The first constructive heuristic performs an initial clustering of customers by assigning each customer to its nearest level-1 facility, taking into account the limited number of available vehicles. Then, the resulting VRPs on the second and first echelon are solved by means of a commercial heuristic VRP solver. After that, the authors try to improve the solution by moving one customer from its assigned facility to the next closest one. If such a move is feasible (with respect to the limited fleet), the resulting VRPs for the two affected level-2 facilities and the first echelon are solved again. This is repeated until no improved solution is found or a stopping criterion is met. The second constructive heuristic uses the commercial heuristic solver to solve a Multi-Depot VRP (MDVRP) with limited fleet for the second echelon and then for the first echelon. The three LS improvement heuristics are to (i) split a route into two routes if it contains a pair of successive customers whose distance lies above a threshold, (ii) move one customer from one route to another, and (iii) swap two customers between two routes. If necessary, the level-1 subproblem is re-solved.

Despite the chronological inversion, computational experiments are performed with the GPTV and the CPMT instances with 50, 100, and 150 customers. For the GPTV instances, the clustering heuristic clearly outperforms the MDVRP-based one. On the larger GPTV instances, the clustering heuristic, in combination with the improvement procedures, yields better solutions than the exact procedure used in [Perboli et al. \(2011\)](#). Computation times are a few seconds for instances with 32 customers. The clustering heuristic with improvement is then employed to perform analyses on the impact of the geographical distribution of level-1 facilities and customers, using the CPMT instances.

[Crainic et al. \(2010\)](#) continue this research, again using the clustering heuristic with improvement. Extensive studies are performed with different configurations regarding the locations of facilities and customers. Both [Crainic et al. \(2008, 2010\)](#) conclude that, if the facilities are adequately located, a two-echelon system can significantly reduce the total distribution costs compared to a one-echelon system with one central facility. They state that their results emphasize the potential benefit of two-echelon systems for city logistics in large urban areas but point out the need for further research, especially on extensions of the 2E-VRP model used.

[Crainic, Mancini, Perboli, and Tadei \(2010\)](#) present a multi-start heuristic to solve the 2E-LRP with one level-0 facility and capacitated level-1 facilities. Perturbed solutions for the multi-start component are constructed by two stochastic rules specifying probabilities for the assignment of a customer to a facility and performing roulette-wheel selection. To compute an initial solution and to perform an LS on the perturbed solutions, the authors use the clustering heuristic and the improvement procedures from [Crainic et al. \(2008\)](#). To account for facility capacities, the authors introduce a repair procedure that tries to move customers one by one from overloaded facilities to others with free capacity.

Computational experiments are performed with the GPTV and the CPMT instances with 50 customers. The results show that the heuristic outperforms the two matheuristics described in [Perboli et al. \(2011\)](#), yielding a better solution quality in less computation time.

[Sterle \(2010\)](#), [Boccia, Crainic, Sforza, and Sterle \(2011\)](#) and [Crainic, Sforza, and Sterle \(2011b\)](#) present MIP formulations for a problem version with several level-0 facilities, where both level-0 and level-1 facilities are capacitated and incur fixed opening costs. The latter two papers are technical reports that summarize the

results described in the first one, which is the author's Ph.D. thesis. Four different formulations are presented. The first one is a three-index arc-variable formulation based on the one introduced in [Ambrosino and Scutellà \(2005\)](#) for the three-echelon case. The second one is a two-index arc-variable formulation based on the MDVRP formulation described in [Dondo and Cerdá \(2007\)](#), the third one extends the two-index arc-variable standard LRP formulation by [Prins, Prodhon, and Wolfler Calvo \(2006a\)](#), and the fourth one is a path variable formulation.

Computational experiments are performed with the first and second formulation using a commercial solver on the smaller *S* instances with up to 4 level-0 facilities, 10 level-2 facilities, and 25 customers. The largest instances solved to optimality have 3 level-0 facilities, 8 level-2 facilities, and 10 customers. The objective function value of the root node LP relaxation is always much higher in the three-index formulation, and in all but two cases, the three-index formulation finds solutions as good as or better than those found with the two-index formulation. For the larger *S* instances, which have up to 5 level-0 facilities, 20 level-2 facilities, and 200 customers, a heuristic sequential decomposition is performed: First, a two-echelon Capacitated Facility Location Problem (CFLP) is solved, and then two MDVRPs, one for each echelon. The three subproblems are solved (to optimality or until a prespecified maximum gap) with the commercial solver. Using this decomposition approach, feasible solutions are computed for all instances.

[Sterle \(2010\)](#), [Boccia, Crainic, Sforza, and Sterle \(2010\)](#) and [Crainic, Sforza, and Sterle \(2011a\)](#) present a Tabu Search (TS) heuristic for the 2E-LRP version just described. Again, the latter two papers are technical reports that summarize the results described in the first one. Also in these works, the problem is decomposed by echelon, and both subproblems are further decomposed into a CFLP and an MDVRP. Essentially, the TS algorithm used by [Tuzun and Burke \(1999\)](#) for the single-echelon LRP is extended to the two-echelon case. In a first step, a solution to the two-echelon CFLP is determined by means of a greedy heuristic. Given the initial CFLP solution, a route plan is computed for each facility with the savings heuristic and 2- and 3-opt improvements. Then, shift and swap moves are performed (shift a customer from a route to another one and swap two customers between two routes). These moves are executed first only between routes belonging to the same facility, and then between routes from different facilities. In the TS, on both echelons, besides the shift and swap routing moves, two move types affecting location decisions are performed (swap: close an opened and open a closed facility; add: open a closed facility).

Two move evaluation criteria are used, similar to the nested approach first proposed in [Nagy and Salhi \(1996\)](#) and applied in [Tuzun and Burke \(1999\)](#). To evaluate the first feasible solution and the location moves, only the fixed facility opening costs and the direct distance between a customer and the assigned facility (or the direct distance between a level-1 facility and the assigned level-0 facility) are considered. To evaluate routing moves, the fixed opening costs and the exact costs of the routes are used. Moreover, a feedback loop between the two levels is included: When a new solution for the second echelon is determined that improves the best one found so far or violates the capacity of a level-1 facility, the subproblem for the first echelon is re-solved.

Computational experiments are performed with the *S* instances. For the smaller instances, the performance of the TS algorithm is compared to the results obtained with the branch-and-cut approach described in [Sterle \(2010\)](#) (see above). For those smaller instances for which an optimal solution could be found with the branch-and-cut algorithm, the TS always finds an optimal solution, too. For those instances where branch-and-cut failed to find an optimal solution, the TS always finds a better solution than the best feasible one found with branch-and-cut. For the larger instances,

the TS with feedback loop clearly outperforms the one without in the large majority of cases.

Jin, Zhu, Shen, and Ku (2010) study a 2E-LRP with several uncapacitated level-0 facilities, capacitated level-1 facilities, fixed opening costs for facilities on both levels, direct transports on the first echelon, and routing decisions with a heterogeneous fleet on the second. The authors present a three-index arc-variable formulation for the problem and develop a Genetic Algorithm (GA) to solve it.

A solution is encoded in a fixed-length chromosome, using a scheme containing binary and general integer genes. A proportional selection scheme is used to choose individuals for reproduction, which is performed with a two-point crossover, and a random mutation operator is applied. A fixed-length first-in-first-out tabu list is maintained that stores parts of the chromosomes/solutions selected for reproduction. Computational experiments are performed with two self-generated random instances with 5 level-0 facilities, 10 level-1 facilities and 20 and 40 customers respectively.

Nguyen, Prins, and Prodhon (2010) present a multi-start heuristic for the 2E-LRP with one level-0 facility and capacitated level-1 facilities with fixed opening costs. Using a vehicle incurs fixed costs, and it is allowed to visit customers on tours starting at the level-0 facility. The heuristic consists of two components: A Greedy randomized adaptive search procedure (GRASP) and an embedded Evolutionary LS (ELS)/Iterated LS (ILS). In both the GRASP and the ELS/ILS, a tabu list is maintained. The GRASP uses three construction heuristics followed by a Variable Neighborhood Descent (VND). In the ELS/ILS, a prespecified total number of child solutions is created. The ELS/ILS first creates a giant tour consisting of all customers. The giant tour is initialized with the customers of a second-echelon tour. Then, the other second-echelon tours are successively inserted into the giant tour. After that, a mutation operator changes the sequence of customers on the giant tour. Then, the currently opened level-1 facilities plus one currently closed facility are used to form a set of potential facilities. With this set, a split procedure generalizing the one presented in Prins (2004) is called that builds second-echelon tours from the giant tour. The second-echelon tours originate at a facility from the current set of potential facilities. If facility capacities are violated, a repair procedure is called. Finally, a VND scheme that only works on the routing part of a solution is executed. The whole process is iterated until a stop criterion applies.

The procedure is quite complex and contains a number of parameters that have to be set. It is noteworthy that, to find good parameter values, the performance of different setups is compared by sophisticated statistical tests. This goes beyond what is usually done in the literature for this purpose. Computational experiments are performed with the NPP-N, NPP-P and PPW instances. On the first two instance classes, the heuristic is compared with two unpublished procedures by the same authors and achieves very convincing results. On the third class, which consists of standard LRP instances, the heuristic is compared with existing, specialized procedures for the standard LRP (Prins et al., 2006a, Prins, Prodhon, & Wolfier Calvo, 2006b, 2007; Duhamel, Lacomme, Prins, & Prodhon, 2010). The results show that the heuristic is competitive with the other approaches both with respect to solution quality and computation time.

Nguyen, Prins, and Prodhon (2012b) study the same variant as Nguyen et al. (2010) and present a multi-start ILS with a tabu list and Path Relinking (PR). The authors give a three-index arc-variable formulation for the problem. The ILS cyclically uses the three heuristics described in Nguyen et al. (2010) to provide a good initial solution. The search then operates on two search spaces, namely, valid 2E-LRP solutions and TSP-like giant tours over the level-0 facility and all customers: After an LS on the 2E-LRP solutions obtained by the constructive heuristics, a giant tour is formed. A kick operator selected randomly out of three possible

ones is then applied to perturb the giant tour. This kind of indirect search avoids having to handle facility and vehicle capacity violations resulting from the perturbation. The modified giant tour is split into a 2E-LRP solution by means of a heuristic version of the procedure introduced in Prins (2004) (heuristic to keep running times acceptable), and LS is again performed on this solution. Deteriorating solutions are allowed; a child solution is accepted when the gap to the best solution found so far does not exceed a given percentage. Otherwise, the search is restarted from another initial solution.

The LS is performed via two VND improvement procedures. The first is applied to each new solution, whereas the second, which contains more complex neighborhoods, is applied only to solutions with a given maximum gap to the best one found so far. The tabu list stores recent solutions and is supposed to shorten the current ILS iteration when a tabu solution is created again. PR is embedded in the procedure as an intensification step, as a post-optimization step, or both. A fixed-size pool of solutions is created, into which locally optimal solutions are inserted if their objective function value is below a certain threshold. If the pool is full, a new solution replaces the oldest one. PR uses the notion of a 'big tour', which is a sequence of customers into which level-0 facilities are inserted but the tours on the first echelon are not. According to the authors, this is because generating path trajectories between two 2E-LRP solutions or between two giant tours did not work well; the first yielded too many infeasible intermediate solutions, the other was too time-consuming. Like the one described in Nguyen et al. (2010), this procedure requires a number of parameters to be set. Again, the authors perform thorough statistical tests to determine good setups. Computational experiments are performed with the NPP-N, NPP-P, and PPW instances as well as with the larger S instances (those with at least 50 customers). On the NPP-N and NPP-P instances, the heuristic is compared with two unpublished algorithms by the same authors and clearly outperforms these simpler procedures. On the PPW instances, which are standard LRP s, the heuristic is again compared with the procedures described in Prins et al. (2006a, 2006b, 2007) and Duhamel et al. (2010). It achieves competitive results, albeit at slightly higher computation times.

Nguyen, Prins, and Prodhon (2012a) solve the variant studied in the previous two papers and describe a GRASP reinforced by a learning process and PR. A two-index arc-variable formulation is presented. Four constructive heuristics are used: the three heuristics described in Nguyen et al. (2010) and a heuristic consisting in the construction of giant tours and applying a splitting procedure generalizing the one presented in Prins (2004). The two VND improvement procedures described in Nguyen et al. (2012b) are applied. The GRASP contains a diversification and an intensification mode that are iteratively executed, similar to the procedure used in Prins et al. (2006a). The intensification procedure constitutes the learning process. The PR step follows the same ideas as in Nguyen et al. (2012b). PR is used within the GRASP each time a solution is accepted in the pool, after the GRASP is completed, or in both situations.

As in the previous two works, extensive parameter testing and evaluation with statistical methods is done. Computational experiments are performed with the NPP-N, NPP-P, and PPW instances. On the NPP-N and NPP-P instances, the complete heuristic is compared with several partial versions that comprise only one of the constructive heuristics and one of the VND searches. Not surprisingly, the complete version yields by far the best results. On the NPP-P instances (which are constructed from standard LRP instances), the results are additionally compared to an extended version of the procedure proposed in Prins et al. (2007) for the standard LRP. Here, results are mixed: The complete heuristic finds fewer best solutions than the extended Prins et al. (2007)

procedure, but it performs more stable and has a significantly smaller average gap.

Hemmelmayr, Cordeau, and Crainic (2012) present an Adaptive Large Neighborhood Search (ALNS) heuristic for the 2E-VRP (facilities have no fixed opening costs and are uncapacitated) with one level-0 facility. The paper is included in this survey because the authors show how standard LRP's can be modeled and solved as a 2E-VRP. This works as follows: A dummy vertex is created for the single level-0 facility. The potential facilities of the LRP are used as level-1 facilities. The fixed costs for opening the LRP facilities are put on the links from the dummy vertex to the level-1 facilities in the 2E-VRP. No links are introduced between level-1 facilities. For each level-1 facility, there is a dedicated vehicle that can visit only its assigned facility and the dummy vertex and has a capacity equal to that of the corresponding LRP facility.

The ALNS first constructs a feasible solution by assigning each customer to its closest level-1 facility and then solving the resulting VRPs on the second and first echelon with the savings heuristic. Eight different destroy operators are used, some of which change only the assignment of customers, whereas others also allow to open or close one or more facilities. As repair operators, variants of greedy and regret insertion are used. LS is applied on the routes of both echelons with several standard move types. No LS moves affecting location decisions are performed. Infeasible solutions (violating vehicle and, for the LRP, facility capacities) are allowed and penalized in the objective function.

Extensive computational experiments are performed with the larger GPTV instances (with at least 21 customers) and the 50-customer CPMT instances for the 2E-VRP, and the TB, B, and PPW instances for the standard LRP. In addition, a set of 2E-VRP instances is created by appropriately modifying 17 PPW instances with more than 50 customers. The ALNS performs very well on the 2E-VRP and the LRP instances: In comparison with several solution approaches from the literature (Perboli et al., 2010; Perboli et al., 2011; Crainic, Mancini, et al., 2010 for the 2E-VRP, Tuzun & Burke, 1999; Prins et al., 2006a, 2006b, 2007; Duhamel et al., 2010; Pirkwieser & Raidl, 2010; Yu, Lin, Lee, & Ting, 2010 for the standard LRP), it provides the best average solution quality. Contardo, Hemmelmayr, and Crainic (2012) study the 2E-LRP with several capacitated level-0 and level-1 facilities and fixed opening costs for facilities on both levels, where routes must be computed on both echelons. They describe a branch-and-cut algorithm and an ALNS. The central observation made by the authors, exploited in both solution approaches, is that the 2E-LRP can be decomposed into two standard LRPs (one for each echelon) that are connected via the level-1 facilities.

The branch-and-cut algorithm is based on a two-index arc-variable formulation. Besides the binary arc variables, the formulation has continuous variables indicating the amount of load passing through a level-1 facility. These variables are used to connect the two LRPs at each echelon: For the first echelon, the variable values correspond to demands at the level-1 facilities, for the second echelon, the values correspond to facility capacities. This relationship allows to use most of the valid inequalities for standard LRP's introduced in the papers discussed in (Contardo, Cordeau, & Gendron, 2013). The authors introduce several new types of inequalities and describe separation procedures.

The ALNS heuristic recursively calls a modification of the ALNS described in Hemmelmayr et al. (2012). An initial solution is constructed for the second echelon in a manner similar to the one described in the latter paper. Then, a solution for the first echelon is built by opening randomly one level-0 facility and serving all level-1 facilities from it. This may violate facility capacities, but, as in Hemmelmayr et al. (2012), infeasible solutions are allowed and penalized. Given a solution, a destroy-repair iteration is first performed on the second-echelon problem. Then, the resulting

first-echelon problem undergoes a destroy-repair step. LS is performed only on the second echelon. The destroy and repair operators as well as the LS moves are similar to those used in Hemmelmayr et al. (2012).

Computational experiments are performed with the NPP-N, NPP-P, and S instances. The ALNS clearly outperforms the approaches described in Nguyen et al. (2012a, 2012b) on the tested instances. The branch-and-cut algorithm is compared to the three-index arc-variable formulation described in Boccia et al. (2011) (which was re-implemented by Contardo et al. (2012)). The results show that the two-index formulation by Contardo et al. (2012) solves more and larger instances and provides tighter gaps for those instances that cannot be solved to optimality. A comparison of the results of the ALNS and the branch-and-cut algorithm shows an average gap of only about 3% between the upper and lower bounds provided by these procedures. This demonstrates the quality of both algorithms.

Schwengerer, Pirkwieser, and Raidl (2012) present a Variable Neighborhood Search (VNS) approach for the 2E-LRP. They extend the VNS of Pirkwieser and Raidl (2010), which was originally designed for the (P)LRP. The authors determine an initial, not necessarily feasible solution as follows. Level-1 facilities are opened randomly one by one until the capacity is sufficient to accommodate the complete customer demand. Each customer is assigned to its closest open facility. Then, routes are computed for each level-1 facility with the Clarke and Wright savings algorithm. The fleet size is limited, therefore, if the number of created routes exceeds the number of available vehicles, this number is reduced by greedily re-assigning customers from least-customer routes to other routes. The same steps are repeated for the first echelon, taking the opened level-1 facilities as customers with demands equal to their associated cumulated customer demands. Contrary to the approach used in Pirkwieser and Raidl (2010), penalties for infeasible solutions are varied in the course of the algorithm.

In the shaking phase, six different neighborhood structures are used, and 21 shaking neighborhoods are applied overall. The basic neighborhoods are (i) exchange two segments of variable length between the routes of the same facility, (ii) as before, but between different facilities on the same echelon, (iii) close one level-1 facility and open another one, (iv) open or close one level-1 facility, (v) close one level-0 facility and open another one, (vi) open or close one level-0 facility. A fixed shaking neighborhood order is applied. As intensification, 3-opt as intra-route and 2-opt* as inter-route neighborhood are used. Moreover, deteriorating solutions are accepted according to a Simulated Annealing (SA) criterion.

Computational experiments are performed with the NPP-P, NPP-N, and S instances. The results show that the VNS is competitive with existing approaches (Nguyen et al., 2012a, 2012b; Contardo et al., 2012). Although the VNS exhibits slightly higher average gaps than the ALNS of Contardo et al. (2012), it is able to identify or improve the Best Known Solutions (BKS) for a significantly larger number of instances.

Ambrosino, Sciomachen, and Scutellà (2009) study a very special case of a 2E-LRP. In their problem, the set of customers is partitioned into given clusters (regions). There is one given central facility and, for each region, one local facility must be established at one of the customer locations. Each customer's demand consists of two parts. One part must be delivered from the central facility, the other from the local facility. Therefore, routes must start at the central facility and go directly to a local facility before visiting customers of the corresponding region and returning to the central facility. A fixed fleet of heterogeneous vehicles is available to this end. The authors describe a two-stage matheuristic. In the first stage, it computes a feasible solution by solving, for each region, an Integer Program (IP) for clustering customers into groups to be visited by one particular vehicle and for determining the facility

to open in the region. For each such cluster, an asymmetric TSP is then solved with a branch-and-bound code to determine the visit sequence. In the second stage, the given solution is improved by first trying to replace a local facility with a different one. Then, the routes within each region are improved using a neighborhood based on cyclic exchanges of customers between routes. This neighborhood can be represented by a suitably defined digraph, where a cyclic exchange corresponds to a special negative cost cycle. Finding such cycles is NP-hard, but the authors use an efficient heuristic search method.

Computational experiments are performed with random self-generated instances with up to 420 customers in 6 regions and one real-world instance with 200 customers in 5 regions. For the large instances, a commercial solver fails to compute a feasible solution within 25 hours. The heuristic finds feasible solutions for all instances and optimal solutions for instances with up to 40 customers. For the large instances, the gap between the heuristic solution and a lower bound is 10% on average.

Martínez-Salazar, Molina, Ángel-Bello, Gómez, and Caballero (2014) and Govindan, Jafarian, Khodaverdi, and Devika (2014) also study 2E-LRPs. However, these authors consider multi-objective settings, and the focus of their work is on the multi-objective nature of the respective problems. Thus, these papers are discussed in Section 8.

Comparative analysis of algorithms for 2E-LRPs. The following tables report the solution quality of the described approaches on the benchmark sets GPTV and CPMT (Table 2), and on NPP-P, NPP-N and S (Table 3). In the tables, we refrain from a direct comparison of run-times of the approaches, because the methods are partly coded in different programming languages, and tests are run on different platforms with different hardware and operating systems installed.

In Table 2, we report the best result of 5 runs for the ALNS of Hemmelmayr et al. (2012) (HCC), the result of the branch-and-cut algorithm by Perboli et al. (2009) (PTM) with a time limit of 10000 s and the best results found by any of the other heuristic methods (Other) discussed above (Perboli et al., 2011; Crainic et al., 2008, 2010). We selected PTM as it is the best exact method proposed for these instances. Solution quality is assessed as gap to the BKS of the respective instance and the reported results are given as averages over the defined instance groups. For each instance group, we further report the percentage of instances for which the respective method was able to find the BKS. Finally, we provide average results for the separate benchmark sets and overall averages. Instance groups to which PTM was not applied are indicated by a dash.

Table 2
Comparison of 2E-LRP solution methods on benchmark sets GPTV and CPMT.

	Avg. gap to BKS (%)			BKS found (%)		
	HCC	Other	PTM	HCC	Other	PTM
<i>GPTV</i>						
Class 2, 22 customers	0.00	0.00	0.00	100.00	100.00	100.00
Class 2, 33 customers	0.00	0.00	0.00	50.00	100.00	100.00
Class 2, 51 customers	0.00	0.07	4.47	88.89	88.89	11.11
Class 3, 22 customers	0.00	0.00	0.00	83.33	100.00	100.00
Class 3, 33 customers	0.00	0.03	5.99	83.33	50.00	0.00
Class 3, 51 customers	0.00	0.58	19.26	100.00	0.00	0.00
Avg. GPTV	0.00	0.11	4.91	86.84	76.32	50.00
<i>CPMT</i>						
50–2	0.00	1.85	–	94.44	5.56	–
50–3	0.04	2.89	–	88.89	11.11	–
50–5	0.01	2.06	9.35	100.00	5.56	0.00
Avg. CPMT	0.01	2.07	9.35	94.44	7.41	0.00
Total Avg.	0.01	1.24	90.32	35.48		

On the GPTV and CPMT instances, HCC performs best. The procedure consistently outperforms all others on all tested instances, irrespective of instances' characteristics. As far as exact algorithms are concerned, the largest instance solved to optimality has 51 customers. PTM found only one better solution than HCC (with an improvement of 0.0099%), and performed worse for 44% of the GPTV and 100% of the CPMT instances.

Table 3 reports results in analogous fashion to Table 2. We provide the best result of 10 runs for the ALNS of Contardo et al. (2012) (CHC-A), the best result of 20 runs for the VNS of Schwengerer et al. (2012) (SPR), the results of the best exact method on these instances, the branch-and-cut algorithm of Contardo et al. (2012) (CHC-B) run with a time limit of two hours, and the best result found by any of the other heuristics discussed above (Nguyen et al., 2010, 2012a, 2012b).

The best approaches for the NPP-P, NPP-N and S instances are CHC-A, which is based on the ALNS by Hemmelmayr et al. (2012), and SPR. These procedures consistently outperform all others on all tested instances, irrespective of instances' characteristics. The performance differences between the two approaches are negligible. The run-times of the discussed heuristics, as reported by the respective authors, are of the same order of magnitude. As far as exact algorithms are concerned, the largest instance solved to optimality has 50 customers. The branch-and-cut method CHC-B could not improve any of the feasible solutions determined by CHC-A. For all test instance types, the gaps between the global lower bound and the best upper bound increase significantly with increasing instance sizes, and, except for some of the smallest instances, the run-times are significantly higher than those of the heuristics.

4.2. Two-echelon LRPs with temporal aspects

None of the previous papers considered temporal aspects of synchronization at the intermediate facilities, but several of them mention this as an important topic for further research. The papers in this section treat problems containing such aspects.

Burks (2006) studies the so-called theater distribution problem, which is a 2E-LRP with multiple commodities, time windows, a limited, heterogeneous fleet, and capacitated facilities. In addition to the location and assignment decisions regarding the facilities, vehicle depots have to be selected out of a discrete set of potential depots, and the available vehicles must be assigned to a depot. Direct transports from level-0 facilities to customers are allowed. In contrast to all other NE-LRPs reviewed here, the fleet is not partitioned into vehicle classes that are restricted to operate on one particular echelon. The vehicles differ with respect to costs, capacities, temporal availability and the commodities they can transport. The objective is to minimize the fixed depot and facility opening and vehicle usage costs, and the variable facility operating and distance-dependent vehicle routing costs.

The author presents an arc-variable based MIP model for the problem and a solution approach based on Adaptive TS (ATS). For the description of the solution representation and the neighborhood and move definitions, concepts and terms from algebraic group theory are used. To construct an initial solution, a simple greedy heuristic and a sequential insertion procedure are used. Three levels of solution (in)feasibility are considered: Infeasible solutions violating hard constraints such as vehicle-request compatibilities, near-feasible solutions violating time window constraints, and feasible solutions fulfilling all constraints. All infeasibilities are penalized in the objective function, and the penalties are adjusted during the solution process. The ATS uses four different insert and two different swap neighborhoods, some of which allow opening or closing depots or facilities. A dynamic move- and solution-based tabu list is maintained. Also, an elite list

Table 3

Comparison of 2E-LRP solution methods on benchmark sets NPP-N, NPP-P and S.

	Avg. gap to BKS (%)				BKS found (%)			
	CHC-A	SPR	Other	CHC-B	CHC-A	SPR	Other	CHC-B
<i>NPP-N</i>								
20 customers	0.00	0.00	0.00	0.00	100.00	100.00	100.00	100.00
50 customers	0.00	0.00	0.20	0.05	100.00	100.00	100.00	87.50
100 customers	0.03	0.58	1.15	4.21	87.50	75.00	0.00	0.00
200 customers	0.17	0.46	2.32	9.89	50.00	0.00	0.00	0.00
Avg. NPP-N	0.04	0.27	0.84	3.07	87.50	75.00	33.33	45.83
<i>NPP-P</i>								
25 customers	0.00	0.00	0.24	0.00	100.00	100.00	75.00	100.00
50 customers	0.00	0.00	0.45	2.19	100.00	100.00	37.50	50.00
100 customers	0.49	0.19	1.03	4.20	33.33	8.33	0.00	0.00
200 customers	0.54	0.04	1.62	6.44	0.00	50.00	0.00	0.00
Avg. NPP-P	0.30	0.08	0.89	3.55	53.33	53.33	20.00	26.67
<i>S</i>								
I1	0.23	0.12	3.37	2.96	80.65	72.73	0.00	54.84
I2	0.24	0.73	2.25	2.47	90.32	40.00	10.00	61.29
I3	0.05	0.13	1.85	1.85	83.87	63.64	0.00	64.52
Avg. S	0.17	0.31	2.49	2.43	84.95	59.38	3.33	60.22
Total Avg.	0.18	0.22	1.45	2.76	78.91	61.63	17.86	51.37

of the best found feasible and near-feasible solutions is kept. After a predefined number of iterations without improvement, a restart is performed with an elite solution as the new incumbent.

The computational experiments are an outstanding feature of the work. To determine suitable values for the ATS parameters, the author conducts an extensive and sophisticated statistical analysis. The assessment of the algorithm's performance is based on problem characteristics. Eleven evaluation questions are formulated (e.g., 'How do instance characteristics such as time window width affect the number of TS iterations necessary to achieve a certain solution quality?' or 'Does the use of elite lists affect the solution process?'). Overall, 16 factors in three categories concerning problem (scheduling, e.g., time window width, and routing, e.g., number of potential facilities) as well as algorithmic aspects (e.g., tabu tenure) are considered. To determine the significance of these factors with regard to the questions posed, an advanced Design Of Experiments (DOE) approach is taken.

To conduct the experiments, random instances are generated. The two most important results are that the time window width has a significant effect on the solution structure (number of open facilities and used vehicles), and that the use of elite lists considerably improves solution quality. Furthermore, the quality of the heuristic solutions (obtained with the settings determined in the DOE experiment) is evaluated by comparing the objective function values to optimal solutions and lower bounds. Optimal solutions are obtained for small instances by solving the proposed formulation with a commercial solver. Lower bounds are computed by decomposing the problem into a location and a routing subproblem, solving the subproblems to optimality, and adding the two objective function values. For the 25 instances that could be solved to optimality, the ATS finds the optimal solution in 22 cases, and in the other three, the gap is below 2.5%. The optimal number of depots, facilities, and vehicles is determined in all cases. For the instances for which a lower bound is computed, the ATS has an average gap of 2.6%. Finally, the ATS is compared with an existing, partly manual planning software system on two large random and three real-world instances. The results show that the ATS yields significantly better results in shorter time.

Aksen and Altinkemer (2008) study a variant of the 2E-LRP with given uncapacitated level-0 facilities and two different types of

capacitated level-1 facilities. The authors assume existing level-1 facilities of one type, which may be closed or transformed into the other type. In addition, new facilities of either type may be opened at a fixed cost. On the first echelon, direct goods flows are determined. Routes are computed only for the second echelon. The customers have single-sided time windows (latest arrival). Not all customers need to be served: Customers have a certain maximum distance to the nearest open level-1 facility. If no facility is open within this distance, the customer demand is lost at a penalty.

The authors provide an MIP formulation for their problem. Essentially, the formulation represents the problem as a Two-Echelon Uncapacitated FLP (2E-UCFLP) and an MDVRP with time windows and links the two subproblems by means of appropriate constraints. The problem is solved by nested Lagrangian Relaxation (LR) and subgradient optimization. Upper bounds are provided and improved by heuristics. In the LR, the constraints linking the two subproblems are relaxed. The relaxed problem then decomposes into a 2E-UCFLP and a capacitated minimum spanning forest problem with single-sided time windows. The former is solved to optimality in each subgradient iteration by a commercial solver. The latter is again solved by LR.

Computational experiments are performed with self-generated random instances with one level-0 facility and up to five level-1 facilities and 300 customers. The results show that, although most instances cannot be solved to optimality (i.e., a gap of more than 0.1% between the upper bound provided by the heuristics and the lower bound provided by LR remains), the method clearly outperforms a direct solution of the formulation with a standard solver.

Crainic, Ricciardi, and Storch (2007, 2009) deal with an extended version of the 2E-LRP in the context of city logistics. A multi-commodity setting is considered, i.e., the demand of each customer consists of a particular, non-substitutable consignment that must be picked up at a designated level-0 facility and delivered to the customer through a two-echelon transport network. The authors study models where an exact synchronization in space and time of the vehicles of the two echelons is required. A first-echelon vehicle may only arrive at a level-1 facility when there are enough second-echelon vehicles to receive the complete load

of the first-echelon vehicle. Vehicles must not wait, and load cannot be stored at the level-1 facilities.

The authors develop a model using path variables, based on a time-discrete network where there is one vertex for each pair (level-1 facility, time period). There are three types of path variables: One each for the paths/routes of the first- and second-echelon vehicles, and one for the path each customer request takes. This is necessary because the goods to be transported are not substitutable.

The work is essentially a modeling paper, so no detailed algorithmic developments are described, and no computational experiments are performed. Nevertheless, the authors propose a heuristic hierarchical decomposition by echelon.

[Nikbaksh and Zegordi \(2010\)](#) study a problem version with capacitated level-0 and level-1 facilities and fixed costs for opening level-1 facilities. On the first echelon, only direct transports are considered. Routing decisions are made on the second echelon. Customers have time windows (a, b, c) with $a \leq b \leq c$. Visiting a customer before time a is impossible and requires waiting. Visiting a customer after time a and not later than time b is allowed at no penalty. Visiting a customer after time b and not later than time c is allowed at a fixed penalty. Visiting a customer after time c is infeasible. An upper bound on the number of vehicles that may be used at each level-1 facility and a maximum route duration are specified.

The authors present a three-index arc-variable MIP formulation, compute a lower bound for the problem based on this formulation, and develop a heuristic solution procedure. The lower bound is determined by relaxing a set of constraints that link the location with the routing aspects.

The heuristic is an extension of the two-stage LRP heuristic by [Albareda-Sambola, Fernández, and Laporte \(2007\)](#). First, an initial feasible solution for the second-echelon subproblem is constructed by opening level-1 facilities one by one based on the ratio of fixed costs to capacity. Customers are assigned to the newly opened facility and routes are built as long as the constraints on the maximum number of allowed vehicles at the facility, the vehicle capacities, and the time windows are maintained. Then, an LS is executed using 3-opt moves and the neighborhoods defined in [Albareda-Sambola et al. \(2007\)](#) as well as two new ones. These neighborhoods are applied iteratively in a fixed sequence and until a stop criterion is met.

Computational experiments are performed on self-generated random instances with up to 10 level-0 facilities, 50 level-1 facilities and 100 customers. The gap of the heuristic to the computed lower bound is 8.55% on average. For small instances, where optimal solutions could be computed with a standard solver, the gap is below 1.9%.

4.3. Multi-echelon LRPs with more than two echelons

There are only a few papers on systems with more than two echelons. Given the practical relevance and scientific challenge of such problems, this comes as a surprise. Prior to 2006, there is only one paper, the seminal work by [Ambrosino and Scutellà \(2005\)](#), which was already reviewed in [Nagy and Salhi \(2007\)](#). [Gonzalez Feliu \(2009\)](#) presents a path-based MIP model for the general N -echelon LRP but performs no computational experiments.

[Lee, Moon, and Park \(2010\)](#) study a three-echelon LRP with routing decisions on the first and third echelon. They consider capacitated facilities on levels 1–3 and fixed costs for opening facilities on levels 1 and 2. Two MIP models are developed. The first one considers only direct transports on each echelon, the second one is a three-index arc-variable based formulation for the 3E-LRP. A heuristic is presented that repeats the following three steps for a given

number of iterations: First, the sets of level-1 and level-2 facilities to open are determined, then, the routing problems on echelons 1 and 3 are solved, and finally, a solution to the resulting transportation problem on echelon 2 is computed. The authors do not specify how the three subproblems are solved.

Computational experiments are performed with five small self-generated random instances with up to eight customers. All instances can be solved to optimality with both models using a commercial solver, with the second one leading to better solutions because of the larger feasible region (multi-stop routes on two echelons besides direct transports). The heuristic is able to find the optimal solutions in all cases. In addition, four larger test instances with 30, 10, and 10 facilities on levels 0, 1, and 2 respectively, and 30 customers are constructed. On these instances, the heuristic is compared with a simplified procedure that solves the three subproblems just described only once, using the LRP heuristic by [Wu, Low, and Bai \(2002\)](#) for the routing problems and LP to solve the transportation problem. The heuristic clearly outperforms the simplified procedure.

[Hamidi, Farahmand, and Reza Sajjadi \(2012a, 2012b, 2014\)](#) study a three-echelon LRP with multiple commodities, capacitated facilities on levels 0–2, existing facilities on level 0, fixed costs for opening facilities on levels 1 and 2, and a limited number of capacitated, homogeneous vehicles with fixed as well as variable costs and a limit on the route length. Transports are allowed from any level- n location to any location on level $n' > n$, and horizontal transports on the same level are possible on levels 0 and 1. Moreover, customers may be served from a facility on any level. Routes are only allowed for deliveries to customers; transports between facilities must be direct. [Hamidi et al. \(2012a\)](#) present a three-index arc-variable based MIP model for this problem, and [Hamidi et al. \(2012b\)](#) describe a metaheuristic. The procedure decomposes the problem into two subproblems, a location-allocation-transshipment problem, and a routing problem. GRASP and TS are combined to solve the first subproblem in which the routing cost is considered through an approximation. The second subproblem is solved with a combination of the savings heuristic and a node ejection chain procedure. [Hamidi et al. \(2014\)](#) present an extended and improved version of the heuristic. Computational experiments are performed with self-generated random instances with 3, 20, and 30 potential facilities on levels 0, 1, and 2, 380 customers, and 5 commodities.

5. Periodic and multi-period LRPs

This section first describes the works on Periodic LRPs (PLRPs) and then one reference we found on a multi-period LRP that does not fall into the latter category. PLRPs combine the standard LRP with the Periodic VRP (PVRP, see, e.g., [Francis, Smilowitz, & Tzur, 2008](#)), in which trips have to be planned over a multi-period horizon. The periods of visit for each customer can be selected from a set of allowed visiting patterns. PLRPs aim to determine (i) the facility configuration used over all periods, (ii) the assignment of visiting patterns to customers, (iii) the assignment of customers to facilities for each period of the planning horizon (a customer is not necessarily assigned to the same facility in each period), and (iv) the vehicle routes of all facilities for all periods. The objective is to minimize the sum of facility opening costs, fixed vehicle costs, and routing costs. Note that in the PLRP, vehicles are assumed to be stationed at facilities over all periods. Therefore, the vehicle fixed costs for each facility are based on the maximal number of vehicle routes that are performed from this facility in any period of the horizon. All available PLRP approaches use the set of PLRP instances introduced in [Prodron \(2008\)](#) for benchmarking purposes, from now on denoted as Prodron PLRP instances. After the description of the approaches, we provide a table and discussion comparing the proposed methods on this instance set.

If additional tests are conducted on benchmark instances of the related problems LRP and PVRP, which both represent special cases of the PLRP, the discussion of the results is included in the description of the respective approach.

Prodhon (2008) presents an iterative three-stage heuristic for the PLRP. In the first stage, the PLRP is transformed into a single-period LRP, where all customers of the multi-period horizon have to be served in one period, with their demands and facility capacities adjusted accordingly. A set of solutions to the resulting problem is generated with several iterations of the Randomized Extended Clarke and Wright Algorithm (RECWA) of Prins et al. (2006a) run in diversification mode. The best facility configuration found is used for the current global iteration of the algorithm. In the second stage, a parallel insertion heuristic assigns visiting patterns to customers based on the frequency of edges in the set of solutions generated in the first stage. The procedure is based on the idea that customers that are consecutive in many LRP solutions of the first stage are also likely to be consecutive customers in a PLRP solution, if this is compatible with the visiting patterns. Therefore, the edges are sorted in decreasing order of their frequency and are then selected with a given probability starting from the most frequent edge. The visiting pattern is selected in a way that inserts the edge at minimum cost in a maximum number of periods (the details of the procedure are not described in the paper). Afterwards, the obtained solution is improved separately for each period by the LS of Prins et al. (2006a).

In the third stage, for each period, an MDVRP is solved with the RECWA run in intensification mode, followed by LS. In addition, two LS steps that consider the entire planning horizon are applied. The first one tries to find assignments of patterns to customers that lead to reduced routing costs by exchanging the visiting patterns of customers, and the second one aims at reducing the number of vehicles assigned to a facility over the periods. The algorithm finishes after a given number of global iterations of the three stages. Tests are conducted on the PPW instances for the standard LRP, and the PVRP instances of Cordeau et al. (1997) (besides the Prodhon instances for the PLRP). On the PPW instances, a decent solution quality is obtained with approximately 2% gaps to the BKS at the time, whereas on the PVRP instances rather significant gaps to the BKS (around 6%) are observed.

Prodhon and Prins (2008) adapt the Memetic Algorithm with Population Management (MA|PM), originally proposed by Prins et al. (2006b) for the standard LRP, to the PLRP. All individuals in the population of one generation are assumed to have the same assignment of visiting patterns to customers, and these patterns are not changed in the genetic process. As a consequence, chromosomes of the same length can be generated by representing a PLRP solution as a concatenation of LRP solutions for each period of the planning horizon, where the single-period solutions are encoded as described in Prins et al. (2006b). Note that the facility configuration of all parts of the chromosome must be identical since the same facilities are open during all periods of the planning horizon. Decoding of a chromosome works as proposed in Prins et al. (2006b), with the one difference that the splitting of the giant tours of the facilities must be performed for each period.

The algorithm uses binary tournament to select parents and performs the crossover described in Prins et al. (2006b) separately for each chromosome part corresponding to a single period. The crossover is followed by an extended version of the repair procedure described in Prins et al. (2006b) and an LS that is similar to the one described in Prins et al. (2006a) and executed with a certain probability. Contrary to the original work, the distance measure used in the population management step is not based on structural properties of the solutions but on their fitness values. After the crossover and LS, an additional LS step on the visiting patterns is performed. If the resulting solution is superior to all

solutions in the current population, its assignment of visiting patterns is recorded to diversify the search in later generations. Note that the solution found in this LS step is not included in the population because all individuals must have the same visiting patterns. The algorithm stops as soon as a prespecified number of generations is reached.

In computational experiments on the PPW instances for the standard LRP and the PVRP instances of Cordeau et al. (1997), the MA|PM is not able to match the solution quality and run-time of Prodhon (2008). Pirkwieser and Raidl (2010) present a matheuristic based on VNS coupled with IP-based very large-scale neighborhoods for the standard LRP and the PLRP. The VNS uses a greedy randomized construction heuristic (choose random visiting patterns and facilities to be opened, greedily assign customers) and allows and penalizes intermediate infeasible solutions violating vehicle and facility capacity constraints during the search. In the shaking phase, five different neighborhood structures are used, each with several moves of increasing perturbation size, and 18 shaking neighborhoods are applied overall. Solution acceptance is based on an SA criterion.

Three MIP-based Very Large-scale Neighborhood Searches (VLNS, see Ahuja, Ergun, Orlin, & Punnen, 2002) are performed, using a standard MIP solver. The first one, V1, operates on the routes of a given VNS solution and consists in solving a path-variable based (P)LRP with one variable for each route of the current VNS solution, where it is possible to open and/or close facilities and assign routes to different facilities. The second one, V2, is a set-covering model based on the model for V1 and introduces additional binary variables indicating for each customer whether or not a certain visiting pattern is chosen. The third one, V3, operates on the customer level and extracts sequences of customers from existing routes, reconnects the disconnected route parts, and then finds an optimal allocation of the extracted sequences to the possible insertion points, i.e., between any two (remaining) consecutive customers. The customers to be extracted are selected by randomly grouping customers into equal-sized subsets. V3 is performed for each such subset.

Computational experiments are performed with the PPW instances for the standard LRP and the Prodhon instances for the PLRP. For the standard LRP, the more VLNS neighborhoods are used, the better the solution is, whereas for the PLRP, adding V3 to the set {V1,V2} deteriorates solution quality and run-time. The proposed method shows a convincing performance on the PPW instances, finding 15 (out of 30) new best solutions compared to the results reported in (Duhamel et al., 2010) and on Prodhon's website (prodhonc.free.fr/homepage). As mentioned above, results on the Prodhon PLRP instances are reported below in a comparative table.

Prodhon (2011) presents an MIP formulation for the PLRP and proposes a hybrid of ELS and the RECWA of Prins et al. (2006b). An individual is represented as a list of visiting patterns for the customers, i.e., no information about the facility configuration, the assignment of customers to facilities and the routes is encoded. The fitness of an individual is evaluated by creating a PLRP solution for the list of visiting patterns using the RECWA and LS of Prins et al. (2006b). More precisely, the RECWA is first run in diversification mode for each single period of the planning horizon. As different facilities may be opened for each period, a straightforward adoption of the single-period solutions is likely to lead to a low-quality facility configuration over the planning horizon because potentially far too many facilities are open. Therefore, the overall facility configuration is derived as a subset of all facilities opened for the single periods based on (i) the maximal utilization of a facility in any period and (ii) the contribution of the facility to satisfying the total customer demand. Next, the RECWA is run in its intensification mode using the determined overall facility

configuration. The results are improved by the LS of Prins et al. (2006b) on the routing, executed for each period of the planning horizon.

The overall algorithm starts with a randomly generated solution that is evaluated in the described manner and is further improved by an LS on the visiting patterns. The resulting solution becomes the starting solution for the ELS component. The latter generates a number of children by randomly mutating the visiting patterns of a given percentage of customers. The algorithm evaluates the fitness of the children, again performs the LS on visiting patterns, and the best child becomes the starting solution of the next ELS iteration if it improves on the previous starting solution. After a certain number of ELS iterations is reached, a new individual is randomly generated for the next global iteration of the algorithm. The overall algorithm stops after a fixed number of total solution evaluations.

On the PPW benchmark for the standard LRP, the solution quality is decent with a gap to the BKS of 2.23%. The required run-time is on a level with that of MA|PM but clearly slower than the dedicated methods described in Prins et al. (2006a, 2006b, 2007). Finally, an average gap of 2.6% to the current BKS of the PVRP instances of Cordeau et al. (1997) is obtained.

Prodhon (2009) presents a preliminary version of the ELS-RECWA hybrid of Prodhon (2011) that features a PR component. Contrary to Prins et al. (2006a), where PR is used as post-optimization step, PR is applied as intensification step between the best solution found at the end of an ELS iteration and the most distant solution in an elite set composed of the best solutions at the end of previous ELS steps. Here, the distance is defined as the number of customers with different visiting patterns in the two solutions. Transformation takes place by replacing the visiting patterns of the original solution with those of the guiding solution and is followed by the evaluation step with RECWA and the LS on visiting patterns described above.

Comparative analysis of algorithms for PLRPs. Table 4 provides a comparison of the methods P11 (Prodhon, 2011), P09 (Prodhon, 2009), PP08 (Prodhon & Prins, 2008), P08 (Prodhon, 2008), and PR10 (Pirkwieser & Raidl, 2010) on the Prodhon PLRP instances. Solution quality is measured as gap to the current BKS, which are provided by Pirkwieser and Raidl (2010) for 29 of the 30 instances and by Prodhon (2011) for the instance named P20-5-0b. The table reports gaps averaged over the instance groups defined by the number of customers n and potential locations m . In the table, the gap of the best solution found in the given number of runs to the BKS is denoted as Δ_{best} , the gap of the average result as Δ_{avg} , and the gap of the best solution found during the overall testing of a method as Δ_{best}^* . Average gaps calculated over all instances are given at the bottom of the table as Avg. Δ . Although, in general, the comparison of the run-times of different methods is critical as explained in Section 4, Table 4 reports run times for two reasons: (i) all tests of the Prodhon methods were conducted on the same platform, which renders results comparable and (ii) interesting results concerning the scaling behavior of the discussed

methods can be derived. More precisely, we report the average of the run-times of a single run for all methods in row Avg. t (seconds). For the two best performing methods of Prodhon, P09 and P11, and for PR10, we additionally provide the average run-times for the instance groups in columns t (seconds).

Technically speaking, a direct comparison of all methods is not valid because the given results are based on different numbers of runs and different measurements (Δ_{best} vs. Δ_{best}^* vs. Δ_{avg}). However, we believe that a meaningful comparison is possible due to relatively profound differences in the quality of the methods. P08 and PP08 are not competitive with the other methods, exposing by far the largest gaps while requiring the same or even more time than P11. Although results are not directly comparable between P09 and P11 due to a different number of test runs, it seems that P09 is not able to match the solution quality of P11, but it has lower run-times. Concerning solution quality, PR10 performs best overall. For all instance groups but the smallest one with 20 customers, the average result reported for PR10 is superior to the best result of the other methods, with a noticeable difference especially for the larger instances. While a direct comparison of the run-times of PR10 and the approaches of Prodhon and coauthors is critical, it should be pointed out that the scaling behavior of PR10 with regard to instance size is superior.

Albareda-Sambola, Fernández, and Nickel (2012) study a multi-period LRP with uncapacitated facilities and vehicles and different time scales for the location and for the routing decisions. This means that routing decisions are made in each period, whereas decisions on opening of facilities are made only in certain prespecified periods. The problem is not a periodic LRP because the customer demand in each period is specified in advance, so that there is only one visiting pattern per customer.

The authors provide an arc-variable based MIP model. To solve the problem, a relaxation is considered where routing decisions are approximated by forests rooted at available facilities. This relaxation is considerably easier to solve with standard software than the original problem. After solving the approximation, solutions to the original problem are obtained by optimally solving a series of TSPs for each time period.

Computational experiments are performed with self-generated random instances with up to 20 facilities, 70 customers, 12 time periods for routing, and 4 time periods for location decisions. The results show that, for instances that could be solved to optimality, the solution to the relaxation usually provides excellent approximations to the original problem, both in terms of the facilities to open at the different time periods and the customers to be served by each of the available facilities.

6. LRPs with pickup and delivery

In this section, we first describe two articles on the LRP with Simultaneous Pickup and Delivery (LRPSPD) and subsequently two articles on the many-to-many LRP (MMLRP).

Table 4
Comparison of the methods P11 (Prodhon, 2011), P09 (Prodhon, 2009), PP08 (Prodhon & Prins, 2008), P08 (Prodhon, 2008), and PR10 (Pirkwieser & Raidl, 2010) on the Prodhon PLRP instances.

Inst. group	P11		P09			PP08		P08		PR10		
	Δ_{best} (%)	t (seconds)	Δ_{best} (%)	Δ_{avg} (%)	t (seconds)	Δ_{best} (%)	Δ_{best} (%)	Δ_{avg} (%)	t (seconds)	Δ_{best}^* (%)		
$n = 20, m = 5$	1.34	2.08	1.41	3.50	1.15	5.98	7.48	2.04	1.83	0.18		
$n = 50, m = 5$	4.75	11.28	6.30	7.49	7.46	16.90	26.68	3.71	4.20	0.00		
$n = 100, m = 5$	6.09	59.22	8.47	9.71	41.00	16.73	25.65	4.82	7.88	0.00		
$n = 100, m = 10$	7.63	111.25	8.89	10.32	75.73	21.36	19.75	4.26	14.97	0.00		
$n = 200, m = 10$	7.28	665.02	7.25	9.32	454.67	19.51	13.76	4.66	23.75	0.00		
Avg. Δ	5.65		6.79	8.33		16.82	19.95	4.01		0.02		
Avg. t (seconds)	165.3		116.4			166.7	226	10.7				
#Runs	10		5	5		1	1	30				

Karaoglan, Altıparmak, Kara, and Dengiz (2011) present a branch-and-cut algorithm for the LRSPD. They consider a directed graph with homogeneous fleet and develop a formulation with five types of variables: Binary variables indicate whether or not an arc is traversed, whether or not a facility is opened, and whether or not a customer is assigned to a facility. Continuous variables indicate the demand to be delivered to customers routed after vertex i and transported over arc (i,j) if a vehicle uses that arc, and the demand to be picked up from customers routed up to i and transported over (i,j) . The authors describe several types of valid inequalities. Upper bounds are computed in two ways: (i) A feasible initial solution is computed with the RECWA by Prins et al. (2006a). (ii) In the course of the algorithm, further feasible solutions are determined from fractional solutions by a greedy rounding heuristic. The solutions are improved by an SA metaheuristic using four different LS neighborhoods.

Computational experiments are performed with the KAKD instances, which are introduced in this paper. The algorithm is compared to its simplified version without upper bounding and to the direct solution of the instances with an MIP solver; it clearly outperforms these two alternatives.

Karaoglan, Altıparmak, Kara, and Dengiz (2012) present an alternative LRSPD formulation without the continuous flow variables. Instead, variables indicating the delivery and the pickup load just before and just after having served a customer are used. Computational experiments are performed with the KAKD instances described in Karaoglan et al. (2011). The two formulations are compared with respect to which instances are solved to optimality and with respect to the quality of the lower bounds obtained. The result is that no formulation strictly outperforms the other. Moreover, an iterative heuristic is proposed. First, a feasible initial solution is computed with one of two approaches: either with the RECWA, as in Karaoglan et al. (2011), or by solving the location subproblem as a Single-Source CFLP (SS-CFLP) with a standard solver and then the routing subproblem with the routing part of the RECWA. In both cases, the result is improved with SA as in Karaoglan et al. (2011). A location phase follows where three move types are considered (add, drop, swap). The procedures for routing and location improvement are repeated until a stopping criterion is met. Computational experiments show that better results are obtained with the heuristic if the second approach is used.

Çetiner, Sepil, and Süral (2010) consider an MMLRP application arising in postal logistics and make the following assumptions: For each pair of customers, a required flow of goods in either direction is specified. Hubs are uncapacitated, and vehicles have no loading constraints, but a maximum route length is specified. The pickup and the delivery at a customer are performed simultaneously. Each customer may be assigned to more than one hub, i.e., may send its outgoing goods to several hubs and receive its incoming goods from several hubs. The objective is hierarchical: First, minimize the number of vehicles used subject to a specified maximal direct distance between a customer and any of its assigned hubs, and then minimize overall transport costs. There are no fixed hub or vehicle costs, but a prespecified number p of hubs must be used.

To solve the problem, a nested iterative two-stage matheuristic is used. In the first stage, a multiple allocation p -hub median problem is solved, while in the second stage, multiple TSPs with restricted tour length are tackled for each hub opened in the first stage. The second-stage problems are first solved for a given upper bound on the number of vehicles at each hub, and then repeatedly solved with a decreasing number of vehicles until no feasible solution is found, thus minimizing the number of vehicles. For both problems, an exact solution is computed using MIP models from the literature and a standard MIP solver. After each iteration, the distances between customers and hubs in the first-stage problem are updated using the results of the second stage. The process is repeated until the solution no longer changes between iterations.

Computational experiments are performed with seven modified benchmark instances taken from four different sources belonging to the facility location literature and one real-world instance, with up to 81 customers. The results obtained with the solution procedure are compared to those obtained when only one iteration of the procedure is performed, and savings of more than 20% are reported.

de Camargo, de Miranda, and Løkketangen (2013) also study an MMLRP. The assumptions underlying their problem are similar to those of Çetiner et al. (2010), but de Camargo et al. (2013) assume that (i) each customer is assigned to exactly one hub (single assignment), so that each customer is visited exactly once and (ii) each customer location is considered a potential hub location. The objective is to minimize the sum of fixed costs of installing hubs, handling costs incurred for transferring goods at hubs, fixed costs for assigning vehicles to open hubs and distance-dependent costs for the local vehicle routes and the inter-hub transports. The authors propose an arc-variable based MIP model combining the model of Skorin-Kapov, Skorin-Kapov, and O'Kelly (1996) for the single allocation hub location problem with the model of Claus (1984) for the TSP. These models are used because of the strength of the respective linear relaxation.

The problem is solved to optimality by Benders decomposition embedded in a branch-and-cut framework. The Benders subproblem is further decomposed into two different problems, the first one a transportation problem, the second one a pure feasibility problem. These two sub-subproblems can again be decomposed: The first one into transportation problems between single pairs of customers; the second one into feasibility problems to decide whether the current master problem solution contains a feasible routing for a certain vehicle assigned to a certain hub. By this decomposition of the subproblem, it is possible to generate both optimality and feasibility cuts simultaneously in one iteration of the Benders decomposition algorithm. The authors refine the algorithm and accelerate its convergence by adding only Pareto-optimal cuts (Magnanti & Wong, 1981; Papadakos, 2008) and by using a special cut selection technique (Fischetti, Salvagnin, & Zanette, 2010) for choosing the feasibility cuts to add.

For computational experiments, test instances with 10–100 customers are generated from a data set for hub location problems. For instances with up to 30 customers, the authors compare their algorithm with a direct solution of the formulation by a standard MIP solver and observe an acceleration factor of between 2 and 100. The largest instance solved to optimality with the Benders decomposition algorithm has 100 customers. This is remarkable, as a 100-customer-instance corresponds to 10,000 commodities and contains more than four million integer variables.

Rodríguez-Martín, Salazar-González, and Yaman (2014) study an MMLRP in which each customer location in the network is a potential hub, and exactly p hubs must be installed. There are no fixed costs for using a location as a hub, and inter-hub transports are direct. At most q customers can be assigned to a hub, and at each hub, there is exactly one vehicle for visiting the assigned customers on one multi-stop route.

The authors present an MIP model based on an undirected graph with five types of decision variables. An exact branch-and-cut algorithm is introduced for solving the model. To strengthen the LP relaxation, a number of valid inequalities and proofs of their validity are presented. These additional valid inequalities and the sub-tour elimination constraints are separated dynamically. The separation routines used are described in detail. Computational experiments are performed with modified instances taken from the hub location literature. The algorithm is able to solve instances with up to 50 locations to optimality within two hours on a modern PC. The authors observe that the instances become more

difficult to solve when q , the hub capacity measured in number of assigned customers, decreases.

Rieck, Ehrenberg, and Zimmermann (2014) study a generalized MMLRP with multiple products and the possibility of direct transports between pickup and delivery locations. In parcel or mail delivery applications, as described above, each origin–destination pair constitutes a unique commodity/product. The problem studied by Rieck et al. (2014) generalizes this situation: There are several different products, each of which is produced at one or several locations and demanded at one or several other locations. At a location, zero or more products are produced, and zero or more products are demanded.

A limited fleet of homogeneous vehicles is stationed at the hubs and allowed to perform three different types of routes: (i) multi-stop pickup routes starting empty at a hub, visiting one or more pickup locations before zero or more delivery locations, and returning empty or partially loaded to the hub, (ii) direct inter-hub routes from one hub to another and back, and (iii) multi-stop delivery routes starting partially loaded at a hub, visiting zero or more pickup locations before visiting one or more delivery locations, and returning empty to the hub. Each vehicle may perform at most one route of each type and must perform the routes in this sequence to ensure flow conservation at hubs.

Rieck et al. (2014) present an MIP model using binary variables for opening decisions on hubs, binary arc variables for the routing, and 36 types of constraints. In addition, they propose several types of valid inequalities. The authors present a multi-start Fix-and-Optimize Procedure (FOP) and a GA. The FOP generates an initial feasible solution in two steps. First, an adapted version of the savings heuristic is applied to determine the type-1 and type-3 routes. Second, a multi-commodity fixed-charge network flow problem is solved to determine the inter-hub routes. In each iteration of the procedure, a subset of hub opening and/or routing variables is fixed, and a lower bound is computed. If this lower bound is worse than the current global upper bound, the current fixation is pruned, and a new iteration begins. Otherwise, an MIP solver tries to find a feasible or optimal solution to the partially fixed problem within a given time limit. The overall FOP terminates when a global time limit is reached.

The GA codes a solution in two parts: a binary vector indicating the hub configuration, and a matrix with two rows for each vehicle and one column per location, indicating for each vehicle a priority number for visiting any of the locations on its type-1 and type-3 route. A decoder transforms this coding into a feasible solution by sequentially assigning the locations, in the order indicated by the priorities, to feasible routes. For the hub opening vector, a one-point crossover is used, for the vehicle–location–matrix, the order crossover by Prins (2004) is used.

Computational experiments are performed on 2880 random instances with between 12 and 146 locations, ranging from 2 to 40 pickup, 8 to 100 delivery, and 2 to 6 hub locations. The locations are chosen from actual geographical positions of sawmills and wood-manufacturers across Central Europe. Instances with clustered and instances with purely randomly selected locations are created. The largest instances solved to optimality with the MIP solver within a time limit of one hour have 17 locations. In general, the clustered instances are harder for the MIP solver. The FOP is faster than the MIP solver and returns the same or better solutions in most cases. The GA consistently outperforms the FOP. Instances with more than 44 locations can only be solved by the GA. The authors also compare their GA with a pure random search where each generation of individuals is created randomly. For all instances, the GA finds better solutions than the random search; the average improvement in solution quality ranges from 28% to 45% for the different instance sizes.

7. Stochastic and fuzzy LRPs

The papers in this section consider nondeterministic data for one or more problem aspects, such as customer demands or travel times. First, stochastic LRPs assuming a known probability distribution are discussed, then fuzzy LRPs where the uncertain data is given in the form of fuzzy numbers.

Ahmadi-Javid and Seddighi (2013) study the following stochastic LRP: During a planning horizon, customers should be visited several times, and each visit should be performed by the same vehicle along the same route starting at the same facility. The capacity of a facility and the number of times a vehicle can perform its assigned route during the horizon are modeled as discrete random variables with finite support. The stochastic objective is to minimize the sum of (i) fixed facility opening costs, (ii) variable routing costs, and penalty costs if (iii) the realization of a facility capacity is below the sum of demands of the assigned customers, or (iv) the realization of a random variable modeling the number of times a vehicle can perform its route is below a desired value.

The authors develop a three-index arc-variable MIP for the problem and use a simplified version of the metaheuristic described in Ahmadi-Javid and Azad (2010) (see Section 9). To deal with the stochastic objective, they propose a moderate, a cautious, and a pessimistic risk-management policy to scalarize its stochastic components. The authors provide a discussion of risk measurements and policies as well as theoretical analyses on the potential impact of the different policies on solution quality.

Computational experiments are performed with self-generated random instances with 2–30 facilities and 4–200 customers. Instances with up to 4 facilities and 9 customers can be solved to optimality with a commercial solver. Using a relaxation of the MIP model, lower bounds are computed for medium-sized instances with 8–17 facilities and 20–60 customers. The heuristic computes solutions that are at most 7% above the lower bounds. Scenario analyses shows that for any risk measure, the obtained results improve significantly compared to the case where the stochastic components of the objective function are ignored. Other authors that study stochastic aspects are Hassan-Pour, Mosadegh-Khah, and Tavakkoli-Moghaddam (2009), who consider a multi-objective problem where the availability of facilities and transport links is stochastic, and Zhang, Ma, and Jiang (2008) and Ahmadi-Javid and Azad (2010), who consider stochastic inventory LRPs. These works are reviewed in the sections on multi-objective and on inventory LRPs (Sections 8 and 9) respectively.

Zarandi, Hemmati, and Davari (2011) address an LRP with capacitated facilities and vehicles and time window constraints. Travel times are uncertain and represented as triangular fuzzy variables. The problem is modeled according to the credibility theory of Liu (2004), and the authors present an SA algorithm. Time windows are not treated explicitly in the algorithm and the time windows of the one test instance investigated in the numerical experiment are the same for all customers and all facilities. To assess the quality of the algorithm, it is run on one 20-customer instance of the PPW benchmark set for the standard LRP and is able to find the BKS for this instance.

Zarandi, Hemmati, Davari, and Turksen (2013) study an extension of the problem with fuzzy customer demands. The proposed SA algorithm uses a different initialization procedure and treats the time window aspect by discarding initial solutions that violate time windows. The generated test instances again have identical time windows for all customers. Numerical studies investigate the influence of different problem parameters on self-generated instances with 100 customers and 5 potential facilities. Moreover, a random selection of 9 small instances of the B and PPW sets for

the standard LRP are solved. The proposed approach shows deviations between 0% and 4.4% to the BKS.

Zare Mehrjerdi and Nadizadeh (2013) study an LRP with capacitated facilities and vehicles and uncertain demands given as triangular fuzzy variables, and which is modeled based on the credibility theory of Liu (2004). To solve the problem, the clustering heuristic of Sahraeian and Nadizadeh (2009) is adapted to the fuzzy problem and stochastic simulation is used to determine the actual demands of the customers. Numerical experiments are carried out on three self-generated problem instances. The authors investigate the optimal risk attitude of a vehicle dispatcher who has to decide whether to use the entire vehicle capacity and risk a so-called route failure, i.e., the vehicle has to return to its assigned facility for a refill in order to be able to serve the actual demand of the next customer. The results of the proposed method are compared to the solution obtained by a commercial solver on the relaxed problem without facility and vehicle capacities. Here, gaps between 40% and 95% are witnessed. The run-times of the proposed algorithm are rather high.

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Golozari, Jafari, and Amiri (2013) present an LRP with maximum route duration constraints, where customer demands, traveling times and service times are fuzzy. The resulting model is converted into an LP by means of a fuzzy ranking function. The authors present an SA method enhanced by a mutation operator for stronger diversification to solve the problem and conduct numerical tests on small self-generated random instances.

8. Multi-objective LRPs

This section reviews papers that simultaneously deal with more than a single objective. The presented works consider a wide range of monetary and non-monetary objectives.

Lin and Kwok (2006) study an LRP with three objectives: minimize (i) the fixed facility setup costs and the variable vehicle routing costs, (ii) the workload imbalance with respect to time, and (iii) the workload imbalance with respect to load. An iterative three-stage procedure is developed and alternatively embedded in a TS and an SA metaheuristic. The first stage deals with the location aspect: The minimal number n of necessary facilities is determined by dividing total demand by facility capacity. The facilities are sorted in nondecreasing order of total distance to all customers. In each iteration of the three-stage procedure, n facilities are selected systematically from the sorted list of facilities using a tree search. The second stage is concerned with the routing aspect: A multi-depot VRP (with heterogeneous fleet, where the vehicles differ with respect to their depot and thus with respect to the

distances from their depot to the customers) is solved using two versions of a savings and a nearest neighbor heuristic, followed by LS. Intra- as well as inter-route improvement steps are performed. To allow multiple use of vehicles, the third stage solves a bin-packing problem (exactly or heuristically, depending on the instance size) for each facility, where the bins are the vehicles, the bin capacity is the maximal working time of the vehicle's driver, the items are the routes, and the item size is the route duration. Two approaches are used for the routing. Either the second and third stage are performed sequentially as described or in a simultaneous fashion (no detailed description of this variant is given in the work). The routing stage takes into account only the cost objective. The values of the other two objectives are stored for each feasible solution. The solutions are then evaluated with regard to all three objectives, and efficient ones are stored to gradually build an approximation to the efficient frontier, which is steadily updated and refined in the course of the algorithm.

Computational experiments are performed with self-generated and real-world instances with 10–20 facilities and 100–200 customers. On average, the TS approach yields better results than the SA version, and the simultaneous execution of the second and third stage is superior to the sequential one on both instance types. To compare the two heuristics based on the multi-objective solutions obtained, a new and nontrivial statistical procedure, the so-called coverage measure, is proposed: 'Coverage ... refers to the ability of an algorithm to generate efficient solutions spanning a wider range of values than another algorithm for each separate objective. The more wide-spread the solutions are, the more flexibility is offered to the decision-maker' (p. 1840).

Caballero, González, Guerrero, Molina, and Paralera (2007) consider a five-objective LRP with uncapacitated facilities and describe an application concerning the installation of waste incineration facilities in southern Spain. The objectives are the minimization of (i) the fixed facility setup costs, (ii) the vehicle routing costs, (iii) the degree of rejection of a facility by towns that vehicles pass through when traveling to or from the facility, (iv) the maximal degree of social rejection corresponding to the town most affected by waste transportation, and (v) the degree of social rejection by towns close to open facilities. An upper bound on the number of facilities to be opened and route duration constraints are specified.

To solve the problem, a multi-objective metaheuristic using an Adaptive Memory Procedure (AMP) is used. The heuristic exploits the well-known fact that within a certain neighborhood of an efficient solution, another efficient solution can be found. The heuristic first generates an initial subset of the set of efficient solutions and then tries to obtain a good approximation of the complete efficient set by means of an intensification process. To generate the initial subset, a first solution is obtained with a greedy procedure that considers only the routing costs. Then, neighboring solutions are determined by performing a fixed number of AMP iterations using auxiliary objective functions and six LS neighborhoods, three of which consider only the routing aspect, whereas the others allow opening and closing facilities. All solutions found during the AMP are checked for inclusion in the initial set of efficient solutions. The intensification consists in trying to find additional efficient solutions by applying the AMP to each solution in the initial efficient set.

The quality of the approximation of the efficient set is assessed with three different measures widely used in the literature on multi-objective combinatorial optimization. A real-world instance is solved with the algorithm, but no information is given on the implementation of the solution in practice. Lacking benchmark instances for the problem type studied, computational experiments are also performed with the ADF instances (which are single-objective problems). Compared to the results reported in Albareda-Sambola, Díaz, and Fernández (2005), where these

instances are originally introduced, for nine out of 15 instances, a better solution is found, and the computation times are generally shorter.

Tavakkoli-Moghaddam, Makui, and Mazloomi (2010) study a bi-objective LRP with optional customers. The first objective is to minimize the sum of fixed facility setup costs, variable facility throughput costs, and vehicle routing costs. The second is to maximize the total customer demand served. The authors present an arc-variable based MIP model and describe two metaheuristics, a Multi-Objective Scatter Search (MOSS) and an Elite TS (ETS).

The MOSS works as follows: First, a lower bound on the number of facilities, n_f , is determined by dividing the overall customer demand by the capacity of a facility. For this number, all potential facility combinations are enumerated. For each of these facility combinations, a VRP that considers only the cost objective function is solved by first assigning customers to their closest open facilities and then using the savings algorithm and considering only the cost objective function. The solution is improved by 2-opt. Next, the Scatter Search (SS) is performed as described below. After all these combinations have been examined, the algorithm tests whether the cost of the best solution is less than or equal to the cost of opening $n_f + 1$ facilities. If this is the case, the algorithm terminates; otherwise, the procedure is repeated with sets of $n_f + 1$ facilities. Efficient solutions are stored in an archive set of limited size. To avoid having to remove solutions that are important for approximating the set of efficient solutions, a solution is only added if it is sufficiently different from the solutions in the archive set.

The SS maintains a reference set (the current population from which new solutions are generated) that consists of the archive set and a set containing diverse solutions. New solutions are added to the latter set if they satisfy a distance/diversity measure. In the SS, solutions from the reference set are combined by the so-called freak path algorithm, which is similar to PR and uses a crossover procedure (that is not described in detail in the paper) to combine two solutions. An ideal point in the solution space (optimum of both objective functions) is determined and updated dynamically in the course of the algorithm. The solution from the reference set with the minimal difference to the ideal point is used as starting solution, and all other solutions in the reference set are used as target solutions. Each new solution is locally optimized with respect to the cost objective by a swap move of two customers between two routes and a relocate move. The ETS uses the same iterative concept as the MOSS and the same facility selection procedure. A random routing solution is created and improved by the swap and relocate moves described above. An aspiration criterion is defined using a special distance measure. Overall, the ETS approach appears to be less sophisticated than the MOSS.

Computational experiments are performed with self-generated random instances. The solutions produced by the two heuristics are compared via three quality measures from the literature. The results show that the MOSS clearly outperforms the ETS.

Hassan-Pour et al. (2009) study a bi-objective LRP with uncapacitated facilities where the availability of facilities and transport links is stochastic. In other words, open facilities may fail to provide service and transport links may be unusable with a given probability. The objectives are to (i) minimize the total costs, consisting of fixed facility opening and variable vehicle routing costs and (ii) maximize the number of customers served.

The problem is solved with a two-stage metaheuristic. In the first stage, a single-objective (cost minimization) chance-constrained SSCFLP is solved exactly with a standard solver. The chance constraint is that the probability that a customer is served must be greater than or equal to a specified value. In the second stage, a bi-objective MDVRP is solved, where the depots are the facilities opened in the solution to the SSCFLP. The first objective is cost minimization, the second is minimization of the probability that

a customer is not served. To solve the MDVRP, the two objective functions are scalarized, i.e., aggregated into a single objective by a weighted sum of the normalized values of each objective (normalization is necessary as the objectives have different units). The resulting single-objective MDVRP is solved with an SA that uses a shift (one customer from one route to another) operator and 2-opt in the LS.

Computational experiments are performed on self-generated random instances with up to 16 facilities and 100 customers. For small instances, a lower bound is computed by solving a relaxation of an MIP formulation for the MDVRP with a standard solver, and summing up the optimal objective function values of this relaxation and the SSCFLP. The heuristic is capable of determining solutions with an average gap of 20% to the lower bound of the cost objective within a few seconds.

Martínez-Salazar et al. (2014) study a bi-objective 2E-LRP with several capacitated level-0 facilities, capacitated level-1 facilities, fixed opening costs for facilities on both levels, direct transports on the first echelon, and routing decisions with a homogeneous fleet on the second. The first objective is to minimize the sum of fixed facility opening and variable vehicle routing costs. The second is to balance route duration, i.e., to minimize the difference between the duration of the longest and the shortest route. The authors present a three-index arc-variable formulation and two metaheuristics for solving the problem: a Scatter tabu Search Procedure for non-linear Multi-objective Optimization (SSPMO), originally developed by Molina, Laguna, Martí, and Caballero (2007), and a Non-dominated Sorting GA II (NSGA-II), originally proposed by Deb, Agrawal, Pratab, and Meyunivan (2002).

Both metaheuristics allow infeasible solutions. Constraint violations are handled by a penalty function to be minimized as a third objective. SSPMO uses TS as a seeding and solution improvement method. First, a randomly generated initial solution is used to generate a first approximation of the set of efficient solutions. Second, new trial solutions are created from each pair of solutions in the reference set. Each new solution is formed by the random combination of characteristics from both reference solutions and is improved by TS. Third, the new trial solutions are used to update the current set of efficient solutions and the current reference set. The described steps are iterated until a convergence criterion is fulfilled.

To approximate the efficient set in the second step, four linked tabu searches considering different objectives are performed. The first one uses the initial solution as input, the subsequent ones take the solution resulting from the respective previous TS. The first TS considers cost minimization, the second one route balance, the third one penalty minimization, and the fourth one again cost minimization. In the TSs, eight different local neighborhoods and a first improvement acceptance criterion are applied. The reference set in the SS is composed of five solutions: For each of the three objectives, the best solution in the current efficient set approximation is selected, and two further solutions are added which maximize a pre-defined diversity measure with respect to the three already selected ones.

The NSGA-II essentially applies a fast sorting procedure to Pareto-rank the solutions prior to selection. The authors make several modifications to the basic NSGA-II: An initial solution is randomly constructed in the same manner as for the SSPMO, a TS procedure similar to the one in the SS is used instead of the classical mutation operator, and the crossover operator is the same as the method for combining solutions in the SS. Computational experiments are performed with 144 self-generated random instances ranging from 3 to 5 level-0 facilities, 4 to 10 level-1 facilities and 12 to 50 customers. The results show that SSPMO is the better solution algorithm for small instances, but with increasing instance size, NSGA-II offers a better approximation of the efficient frontier.

[Govindan et al. \(2014\)](#) study a 2E-LRP with soft time windows in the context of optimizing the supply chain of a producer of perishable food. They consider multiple potential level-0 and level-1 facilities with fixed opening costs and limited capacities. Routes are computed on both echelons. Two objectives are pursued: (i) the minimization of the sum of fixed facility opening and variable vehicle routing costs and (ii) the total environmental impact of the system, measured by GHG emissions. The authors present an MIP model based on arc variables with 40 types of constraints. To solve the problem, they develop a new hybrid multi-objective metaheuristic called MHPV, which is a combination of two known multi-objective algorithms, the Multi-Objective Particle Swarm Optimization (MOPSO) and Adapted Multi-Objective VNS (AMOVNS).

Computational experiments are performed with 12 randomly generated instances with 4–12 level-0 facilities, 8–18 level-1 facilities, and 12–30 customers. The MHPV is compared, with respect to four different performance measures, to three multi-objective GAs from the literature, among them the NSGA-II described above. The results show that the MHPV clearly outperforms the GAs according to three of the four measures and yields comparable results with regard to the fourth one.

[Rath and Gutjahr \(2014\)](#) address the problem of locating intermediate distribution depots to provide people with necessary goods in a disaster relief setting. The problem resembles a warehouse LRP, where goods have to be transported from plants (supply points such as harbors or airports) to warehouses (intermediate depots) in full truckloads and then be distributed to the customers (demand nodes) on vehicle routes. However, demand may be higher than supply, potentially leading to a selection of customers to serve and only partial demand fulfillment at the last customers on routes from the intermediate depots. Routing operations are only limited by the available driving time, i.e., multiple trips with capacitated vehicles are possible, resulting in a multi-depot multi-trip capacitated team orienteering problem (MDMT-COP) to be solved as subproblem.

The model considers the following three objectives: (i) minimize medium-term costs (fixed costs for opening depots, including the acquisition and operation costs of vehicles), (ii) minimize short-term costs (transport from plants to depots and warehousing costs proportional to the throughput of the depots), and (iii) maximize covered demand, which conflicts with the first two objectives. No routing costs are considered and the routing decision is solely driven by the third objective. To deal with the multi-objective nature of the problem, the adaptive epsilon-constraint algorithm of [Laumanns, Thiele, and Zitzler \(2006\)](#), which is based on solving a sequence of single-objective problems, is applied. The single-objective problems consider the third objective and objectives one and two are constrained by appropriate upper bounds.

To solve the single-objective problems, the authors propose an exact algorithm based on an MIP model and the iterative adding of constraints. Without changing the structure of the algorithm, the exact method can be transformed into a matheuristic that uses a VNS for solving MDMT-COP to generate the constraints. In extensive numerical tests on artificially generated instances, the proposed matheuristic shows a very convincing performance when compared to the exact method on smaller instances. On larger instances, the matheuristic outperforms a combination of NSGA-II with a greedy heuristic, which was implemented as comparison method, and a simplified MIP model.

9. Inventory LRPs

This section discusses works that consider the integration of inventory, location, and routing decisions into one problem.

[Zhang et al. \(2008\)](#) study a single-product, multi-period, stochastic Inventory LRP (ILRP). The objective is to minimize the sum of facility opening, inventory and vehicle routing costs. The customer demands for the product follow a Poisson distribution. Inventory decisions must be taken at the facilities. Customers have to be assigned to one facility for the complete planning horizon and must place an order at that facility once every period. The facilities, in turn, have a facility-specific lead time and plan their stock levels taking into account fixed ordering and variable holding and shortage costs.

The authors present an arc-variable based MIP model and a GA. The GA uses a fixed-length binary encoding specifying which facilities are open. The fitness value of an individual equals the total cost of a solution. The facility opening costs are obvious given the encoding scheme. To compute the inventory costs, it is assumed that the demand of each customer in each period equals the expected value and that each customer is assigned to the closest open facility. Under these assumptions, the authors develop a formula for the total inventory costs in each period. Vehicle routes for each opened facility are determined with the savings algorithm. Individuals are selected for reproduction with a roulette-wheel procedure. A two-point crossover operator and a mutation operator that randomly exchanges two values in the encoding bit-string are used. The algorithm is verified using one random test instance.

[Ahmadi-Javid and Azad \(2010\)](#) extend the inventory-location model of [Shen and Qi \(2007\)](#) by transportation decisions, resulting in a static ILRP with stochastic, normally distributed customer demands and capacitated facilities with a choice of different capacity levels. Note that the problem addressed by [Shen and Qi \(2007\)](#) is not an LRP according to our definition because no vehicle routes are determined. [Ahmadi-Javid and Azad \(2010\)](#) assume a homogeneous vehicle fleet, an order size/reorder point (Q, r) inventory policy, and safety stocks at facilities. The optimal inventory policy, i.e., how often to reorder and what safety stock to keep at the facilities, considering fixed costs for placing orders and inventory holding costs at facilities, must be determined in addition to the classical LRP objectives of finding the optimal facility configuration and routing solution. The precise objective is a weighted function of location costs, costs for ordering and holding inventory and safety stocks plus transportation costs from a supplier to the facilities and from the facilities to customers. The problem is modeled as a mixed integer convex program. No stochastic optimization technique is applied. Instead, the expected value and the standard deviation of demand are used to determine expected inventory and safety stock costs.

The authors propose a metaheuristic hybrid to solve the problem. Starting from a randomly generated initial solution, location/allocation and routing decisions are iteratively tackled in two separate stages by means of a hybrid of SA and TS that is adapted to each stage by using different search neighborhoods. Vehicle routes after moves are determined by a nearest neighbor algorithm.

Studies on randomly generated instances of small to medium size show that the heuristic yields better solution quality than a commercial solver. For instances of all sizes, the method shows a stable and moderate gap to the exact solution of the relaxed problem without subtour elimination constraints. Finally, the authors show that their integrated approach is able to clearly improve on a sequential approach based on the work of [Shen and Qi \(2007\)](#).

[Ahmadi-Javid and Seddighi \(2012\)](#) consider a similar model with deterministic demands and multiple suppliers. The authors present a three-stage metaheuristic. It starts with an initial solution generated by a greedy heuristic similar to the one described in [Yu et al. \(2010\)](#). In the first two stages, an SA algorithm similar to the hybrid in [Ahmadi-Javid and Azad \(2010\)](#) is used to improve location/allocation and routing decisions. In the third stage, the routing is

improved by a savings-based ACO. The algorithm is tested on a selection of the B instances for the standard LRP and compared to known lower bounds; however, no comparison to the results of other heuristics is made. On randomly-generated instances of the investigated problem, a strong improvement in comparison to an extended version of the method proposed in [Ahmadi-Javid and Azad \(2010\)](#) is found. Finally, significant cost savings in comparison to a sequential approach considering separately (i) location and routing and (ii) inventory are reported.

[Guerrero, Prodhon, Velasco, and Amaya \(2013\)](#) study a deterministic, multi-period ILRP considering inventory decisions at both facilities and customers (retailers). The authors assume a single supplier, storage-capacitated facilities and customers, and a homogeneous, unlimited fleet of capacitated vehicles with fixed costs. In addition to the standard LRP decisions on facility configuration, customer assignment and vehicle routing, the product quantities to ship (i) from the supplier to facilities and (ii) from facilities to retailers have to be determined. The goal is to minimize the sum of facility opening costs, transportation costs, ordering costs and inventory costs at facilities and customers. The authors present an MIP model and two sets of valid inequalities to strengthen it.

An iterative matheuristic is presented, whose general idea is to address subproblems of the ILRP and exchange information between the different solution components. In a first step, facility configuration, customer assignment, and inventory decisions are addressed by solving a Supply Chain Design Problem (SCDP) based on estimated distribution costs that is solved by means of a commercial solver. The estimates of the distribution costs are updated every time feasible routes are computed in later stages. In this way, information between the routing solution and the supply chain design is exchanged. In the next step, customer assignment and routing decisions are considered. Based on the LRP solutions for all periods, determined separately for each period by means of the RECWA of [Prins et al. \(2006a\)](#), each customer is assigned to a facility, and then routes for each period and facility are built with the RECWA. With some probability, the resulting solution is improved by a VND-embedded LS component addressing routing, inventory and customer assignment decisions.

The authors further propose an intensification phase to investigate the inventory and routing decision. Based on fixed locations and customer assignments, they iteratively solve a Dynamic Lot-Sizing Problem with an MIP solver and determine corresponding routes with the RECWA and the described LS. Finally, the algorithm uses a post-optimization procedure that aims at improving customer assignment and routing decisions with an ILS that perturbs the solution by randomly modifying the assignment of a given percentage of customers and then improves the perturbed solution by means of the LS.

For the computational experiments, the authors present 20 randomly generated instances with up to 5 facilities, 15 customers and 7 periods. Results are compared to a commercial solver and a sequential heuristic solving the SCDP and using the ILS to make inventory and routing decisions. On the small and medium-sized instances, the proposed method is able to improve the best solution found by the commercial solver within a time limit of 8200 seconds by 0.5% on average, while using significantly lower computational effort. The method is also able to clearly improve the solution quality of the sequential heuristic, however, with higher run-times. On the large instances with 15 customers, a considerable improvement on the best solution found by the solver in 9 hours can be observed. Here, the solution quality is again superior to that of the sequential method, but run-times are higher. Moreover, the method shows good performance on the PPW standard LRP instances and acceptable performance on the Inventory Routing Problem instances of [Bertazzi, Paletta, and Speranza \(2002\)](#).

10. Other LRP variants

In this section, papers on rarely-studied LRP variants or problems that could not be subsumed under one of the above section headings are discussed. We have two papers that deal with planar LRPs ([Schwardt & Fischer, 2009](#); [Manzour-al-Ajdad, Torabi, & Salhi, 2012](#)), one paper on location arc-routing ([Hashemi Doulabi & Seifi, 2013](#)), one that considers an LRP with outsourcing options ([Stenger, Schneider, Schwind, & Vigo, 2012](#)), one that studies a prize-collecting LRP ([Ahn, de Weck, Geng, & Klabjan, 2012](#)), one concerned with generalized LRPs ([Glicksman & Penn, 2008](#)), one that examines generalized, prize-collecting, and split delivery LRPs ([Harks, König, & Matuschke, 2013](#)), and a case study ([Schittekat & Sörensen, 2009](#)).

[Schwardt and Fischer \(2009\)](#) study a planar LRP with Euclidean distances where a single, uncapacitated facility is to be located in order to minimize transportation costs. Vehicles are limited, capacitated and homogeneous and do not incur fixed costs. The authors extend the preliminary results published in [Schwardt and Dethloff \(2005\)](#) and propose a neural network approach based on a self-organizing map as heuristic construction procedure. For each vehicle, a neuron ring is defined and the rings are connected in a central point, which is the neuron representing the unique open facility. The number of neuron rings (vehicles) must be predefined and is initially set to the minimal possible value. It is increased in the next runs if no feasible solution can be found. The algorithm's allocation of customers to neurons determines the resulting tours, and the weight vector associated with the central point defines the location of the facility.

In order to avoid tours that are infeasible with respect to vehicle capacity, the algorithm (i) integrates vehicle capacity utilization in the distance computation for the input and weight vector, (ii) removes customers from neuron rings violating the capacity constraints, and (iii) uses a tabu counter to ensure that the removed customers are allocated to different neuron rings and are not removed from their new rings in the next iterations. However, this does not guarantee the feasibility of the final solution of a run. As a consequence, the authors conduct multiple runs for each instance. Finally, the location of the facility is improved by using the end-points of the generated tours as input to a Weber problem and solving it by means of the Weiszfeld method ([Weiszfeld, 1937](#)).

Numerical tests are conducted on the VRP instances of [Christofides and Eilon \(1969\)](#), [Gillett and Johnson \(1976\)](#), [Christofides, Mingozzi, and Toth \(1979\)](#), [Fisher \(1994\)](#), which feature between 21 and 249 customers. To assess the quality of the algorithm, a set of sequential methods based on weighted and unweighted Weber problems and different savings algorithms are used for comparison. The authors show that their self-organizing map approach outperforms all comparison methods. They further point out that the parameter setting of the method is not trivial and strongly influences the success on each instance.

[Manzour-al-Ajdad et al. \(2012\)](#) study the same problem and also propose a heuristic solution method. The initial location of the facility is determined by means of the Weiszfeld algorithm, and new candidate facility locations are generated within an ellipsoid using the initial location as center. For each candidate, routes are built using a savings algorithm and are then further improved by an LS with intra- and inter-route insertion, intra-route string insertion, 2-opt and swap. Neighborhoods are applied in a cyclic fashion until no improvement is found in one complete cycle. Finally, for each candidate location, the end-points of the routes are used as input for the Weiszfeld algorithm, thus further reducing the total traveled distance. To intensify the search, the best found location becomes the center of the next ellipsoid and the size of the ellipsoid gradually decreases in each iteration. The

procedure stops if no improvement can be found in two successive ellipsoids.

The same test data as in [Schwardt and Fischer \(2009\)](#) is used. The proposed heuristic shows a smaller average gap to the BKS compared to the methods of [Schwardt and Dethloff \(2005\)](#), [Schwardt and Fischer \(2009\)](#), [Salhi and Nagy \(2009\)](#) and is able to produce nine new best solutions of 15 instances. Moreover, the authors conduct studies that confirm the benefit of all components of their algorithm.

[Hashemi Doulabi and Seifi \(2013\)](#) study a location arc-routing problem (LARP) with uncapacitated facilities on a mixed graph. The objective is to minimize the sum of fixed facility setup and fixed and variable vehicle routing costs. There is an upper bound on the number of facilities to be opened and on the number of routes assigned to each opened facility. Based on previous work by [Gouveia, Mourão, and Pinto \(2010\)](#) for the mixed Capacitated Arc Routing Problem (CARP), the authors present two arc-variable based formulations, one for the case where one facility is to be opened and one for the case where several facilities may be opened. They also develop an aggregated formulation with fewer variables that can be solved faster. This aggregated formulation is not valid for their problem, but it provides a valid lower bound.

To solve the problem heuristically, an iterative procedure combining an arc-routing and a location-allocation heuristic is proposed. As initial solution, routes visiting only one required link are created and assigned to the closest facility. In each iteration, the arc-routing heuristic receives as input a complete route plan that may violate the upper bound on the number of routes per facility and merges routes one by one. Merging two routes works as follows: One route is selected, and the path from the first to the last required link on the route, say, (l_1^1, \dots, l_1^k) , is inserted between two consecutive required links l_2^1, l_2^2 of another route (consecutive means that no other required link appears between l_2^1 and l_2^2 in the route, but there may be non-required links in between). The insertion is performed by linking the end vertex of l_2^1 to the start vertex of l_1^1 and the end vertex of l_1^k to the start vertex of l_2^2 by means of a shortest path. The location-allocation heuristic iteratively opens and closes facilities and re-assigns existing routes to different facilities. Routing and location-allocation are performed alternately until no improvement is found. The new solution is accepted according to an SA criterion. Then, a neighborhood generator splits up routes, thus forming smaller routes that provide opportunities for merging, and the process is repeated until a stop criterion is met.

Computational experiments are performed with two sets of mixed CARP instances introduced by [Belenguer, Benavent, Lacomme, and Prins \(2006\)](#). These instances are interpreted as LARPs by allowing that each vertex be a potential facility. The quality of the lower bound provided by the aggregated formulation is demonstrated by the fact that, for 22 instances with 24–50 vertices and 44–138 links, the lower bound is always equal to the optimal solution value. The heuristic solutions, in turn, are on average 10% above the lower bounds for larger instances with up to 401 vertices and 1056 links.

[Lopes, Plastria, Ferreira, and Santos \(2014\)](#) propose several heuristics for the capacitated LARP: two construction algorithms, the extended augment merge (EAM) and the extended merge (EM), which are similar to the RECWA of [Prins et al. \(2006a\)](#) for the standard LRP, and two improvement heuristics, intra-route reverse, the arc routing equivalent of 2-opt, and intra- and inter-route relocate. The proposed heuristics are integrated into the following three metaheuristics: a TS-VNS hybrid (TS for the location decision, VNS for the routing), a pure GRASP based on the randomization of the EAM and EM heuristics and using some concepts of the GRASP of [Prins et al. \(2006a\)](#), and a TS-GRASP hybrid (TS for the location phase, GRASP for the routing).

The authors propose a new set of test instances for the capacitated LARP based on existing test instances for the CARP. On these instances, EM performs better than EAM, but the difference between the two construction methods becomes very small if an LS is performed on the constructed solution. Concerning the metaheuristics, the best results and run-times are provided by the TS-GRASP, followed by GRASP based on EM, GRASP based on EAM, and finally the TS-VNS hybrid.

[Stenger et al. \(2012\)](#) present an extension of the standard LRP, where subcontracted facilities are available that serve assigned customers at a route-independent cost given by the subcontractor. As solution method, the authors present a metaheuristic hybrid of SA and VNS. To generate an initial solution, facilities are opened in a random fashion, customers are assigned to the closest facility with free capacity, and routes for the self-owned facilities are determined by a savings algorithm. In the subsequent location phase, SA uses facility add, drop, and swap moves to improve the facility configuration.

The evaluation of a location move, i.e., the reassignment of customers and the generation of new tours (in case of self-owned facilities), is restricted to a so-called Adjustable Area of Influence (AAI) in order to reduce the computational effort (cp. [Nagy & Salhi, 1996](#)). The AAI is increased in the course of the SA in order to evaluate the moves in later phases of the SA (when basically only improving solutions are accepted) more precisely. After a location move, customers within the AAI are assigned to their closest facility, and tours for self-owned facilities are generated by the savings algorithm followed by an LS step and two VNS iterations. The shaking step of the VNS is defined on a set of CROSS-exchange neighborhoods ([Taillard, Badeau, Gendreau, Guertin, & Potvin, 1997](#)), and the embedded LS uses 2-opt and relocate moves. If the SA accepts a move, an MDVRP involving all facilities within the AAI is addressed by a complete VNS run. The final solution returned by the SA undergoes another VNS improvement step that is not restricted to the AAI. Infeasible solutions concerning facility and vehicle capacities are allowed and are handled by means of a dynamic penalty mechanism.

Tests on the B instances for the standard LRP show that the presented algorithm is capable of providing good solution quality in short time. Based on the B set, the authors generate test instances with subcontracting options and show that their method is able to exploit this option by producing clearly better solutions compared to a situation where no subcontracting is possible. Finally, the authors address a practice-inspired test case, where the planning starts from the currently established facility configuration and the subcontracting option is given.

[Ahn et al. \(2012\)](#) study a Prize-Collecting LRP (PCLRP). Their problem is motivated by a planning task in space exploration and has several other applications in military operations, sports, and logistics. When viewed from a logistics perspective, the novel feature of the problem, in addition to the location-routing and the prize-collecting aspects, is that for each opened facility, one out of several potential modes of transportation must be selected. Each mode incurs certain costs, induces resource constraints on the routes originating at the facility, such as the vehicle capacity or the maximum route length, and determines which customers can be visited from a facility. The objective is to maximize profit, which consists only of selecting an appropriate subset of customers to be visited; costs are not part of the objective but are bounded from above by a budget constraint.

The problem is solved by heuristic branch and price and by a three-stage heuristic. The heuristic branch-and-price identifies negative reduced cost columns via a modification of an algorithm by [Butt and Ryan \(1999\)](#) and performs incomplete branching by diving along a single branch of the tree (no backtracking). The three-stage heuristic first divides the vertices into groups, each

containing one or more facilities, by computing connected components in an auxiliary graph. Second, it determines a set of facilities and transportation modes for every group and solves an MDVRP with Profits (MDVRPP) for each group and its assigned set of facilities and transportation modes. If the number of facilities in a group is small enough, all facility/mode pairs are enumerated. Otherwise, they are selected randomly based on greedy estimates. The MDVRPP is tackled by solving its LP relaxation with column generation and solving an IP over the resulting set of columns. Third, using a standard solver, it solves an IP that assigns one transportation mode to each group so that the total profit for the overall problem is maximized while ensuring that the selected transportation modes satisfy the budget constraint.

Computational experiments are performed with a set of self-generated random instances and a real-world instance from space exploration. The results show that the heuristic branch-and-price performs better than the three-stage method, finding better or equal solutions for 75% of the instances.

Glicksman and Penn (2008) study the Generalized LRP (GLRP) with uncapacitated facilities and vehicles. The authors develop a $(2 - (1/(|V| - 1)))g_{\max}$ -approximate algorithm, where g_{\max} is the cardinality of the largest group. The algorithm first determines the customers to be visited by solving the LP relaxation of a relaxed arc-variable formulation for the GLRP. With these customers, an instance of a prize-collecting Steiner tree problem is constructed and solved using the algorithm of Goemans and Williamson (1995). The resulting tree is then transformed into a GLRP solution. No computational experiments are performed.

Harks et al. (2013) develop approximation algorithms for several types of LRPs with uncapacitated facilities and homogeneous capacitated vehicles. Besides the split delivery LRP (SDLRP), the authors study the PCLRP, the GLRP, and the corresponding variants of these problems with the possibility of load transshipments at customer locations. Approximation algorithms for the SDLRP, the GLRP, and the PCLRP with approximation factors of 4.38, $4.38g_{\max}$, and 6 respectively are presented. For the corresponding problem variants with load transfers, approximation factors of 3.5, $3.5g_{\max}$, and 6 are obtained. Note that the algorithms for the non-generalized versions provide a constant-factor approximation.

To solve the SDLRP, the authors compute an approximate solution to a special Uncapacitated FLP (UFLP) and a minimum spanning tree on a modified graph. Then, to obtain an SDLRP solution, the spanning tree is decomposed into subtrees with the property that the sum of the demands of the customers in each subtree is between 50% and 100% of the vehicle capacity. These subtrees are turned into routes by duplicating the tree edges, and the routes are assigned to facilities opened in the UFLP solution or the spanning tree.

This algorithm is modified and used to solve the PCLRP and the GLRP. For the PCLRP, the difficulties are that, for the subtree decomposition to work, the solutions to the UFLP and to the spanning tree must serve the same set of customers, and that the sum of the costs of the solutions to these two subproblems must remain a lower bound for the original problem. The authors resolve these issues by using an approximation algorithm for the prize-collecting UFLP and an LP-based approximation algorithm for the prize-collecting Steiner tree problem to obtain two sets of visited customers. The customers in the intersection of both sets are selected to be visited in the PCLRP solution. To solve the GLRP, the authors describe how a solution of the GLRP can be interpreted as a two-commodity flow on a directed graph. They construct an LP representing such a flow and show how a solution to this LP can be used to select a customer from each group. To handle the possibility of transshipments, the authors modify the subtree decomposition procedure. Any solution returned by one of the algorithms has

the property that each customer is visited by vehicles from only one facility. If all customer demands are less than or equal to the vehicle capacity, each customer is visited by exactly one vehicle exactly once. As this latter assumption is usual in the LRP literature, the presented algorithms are suitable for the unsplit delivery, single assignment LRPs commonly studied in the literature. Computational experiments are performed with the Perl, TB, B, and HKM benchmark instances. The latter are introduced in this paper and contain up to 1000 facilities and 10,000 customers. For the experiments, each single tour of a solution returned by the approximation algorithm is improved by the Lin–Kernighan–Helsgaun heuristic. For those Perl, B, and TB instances for which optimal solutions are known from the literature, the average gap is 10%. For the HKM instances, the average gap to lower bounds obtained from the solution of the spanning tree and facility location subproblems is about 60%, a value far better than the theoretical quality guarantee. For the TB and B instances, the run-times are at most 0.02 seconds, and for the HKM instances with 1000 facilities and 10,000 customers, they range between 5 and 23 min.

Schittekat and Sörensen (2009) present a case study in the context of spare parts delivery for a major automobile manufacturer, for which a decision support tool based on the solution of an LRP has been developed. Third-Party Logistics (3PL) providers make bids on delivery regions of the considered company, whose task is to select the set of 3PL providers to operate the intermediate hubs in its distribution network. Thus, the company does not directly have to solve an LRP as the 3PL partners are responsible for the last-mile delivery by vehicle routes. However, the information gained from investigating the LRP allow the company to better estimate the distribution costs of potential 3PL providers, thus enhancing the company's negotiation power in the provider selection process.

The addressed problem considers capacitated facilities and a rich multi-depot VRP featuring heterogeneous vehicles and several constraints such as vehicle capacity, vehicle-dependent site accessibility constraints, time windows, and maximum driving time. The authors propose a TS based on the one described in Nagy and Salhi (1996) to solve the problem of finding a high-quality facility configuration. The routing solutions are determined by integrating a commercial vehicle routing solver into the decision support tool. A solution (a facility configuration) is encoded as sequence of zeros (facility is closed) and ones (facility is open).

The starting solution corresponds to the current configuration used by the company. The TS uses the neighborhoods facility add, drop, and swap. Due to the long run-times of the routing solver, the concept of area of influence proposed by Nagy and Salhi (1996) is used (see Stenger et al., 2012, above). To diversify the search, a frequency memory stores how often each facility is open in previous iterations, and after a number of unsuccessful iterations, the most frequently used facility is deselected, the least used facility is selected, and the inverse moves are included in the tabu list.

The key feature of the tool is the generation of a set of diverse, high-quality solutions instead of only one single best solution. This is achieved by keeping a set of elite solutions during the course of the algorithm. The quality of the solutions in the set is guaranteed by only adding solutions whose cost is within a certain percentage of the cost of the best solution found so far. The diversity of the set is ensured by fixing a minimal Hamming distance of a new candidate configuration to any solution in the set. The authors state that this feature is especially useful to analyze alternatives, which increases the negotiation power of the company. Experiments on company data show that the tool is able to provide a set of high-quality solutions with lower cost than the current setting, assessed based on the LRP objective and the routing cost evaluation of the

solver. Run-times of the tool are considerable but are deemed adequate by the company due to the strategic importance of the problem.

11. Summary

This section sums up the key insights we gained during our study, concerning problem aspects, practical applications, and algorithmic issues.

Problem aspects. A significant amount of the recent research still deals with the standard LRP (see Prodhon & Prins, 2014; Drexler & Schneider, 2014). However, the present paper demonstrates that there is a clear trend towards considering more complex and integrated problems: Besides multi-echelon LRPs, multi-objective LRPs and problems incorporating inventory decisions are receiving increased interest from the research community.

Practical applications. Table 5 lists the most important LRP applications and case studies published in the last few years. The table demonstrates the wide applicability of location-routing models in practice. Moreover, it shows that the facilities to locate in an abstract LRP can be rather diverse objects.

Algorithmic issues. The crux in solving LRPs, in heuristic as well as exact algorithms, is how to handle the subproblems of location, allocation, and routing. Many different approaches are possible, some of which appear to be particularly attractive as they are successfully used by several authors. These recurrent solution methods are:

- Exact methods exploit that an optimal solution to an LRP can be computed by minimizing, over all subsets of the set of potential facilities, the opening costs of the facilities in a subset and the costs of an optimal solution to a multi-depot VRP where the depots correspond to the facilities in the subset and have the respective capacities.
- Heuristic approaches often decompose the problem into a location-allocation stage, where the facilities to be opened and assignments of customers to facilities are determined, and a

routing stage, where a VRP is solved for each opened facility. Sometimes, allocation decisions are also allowed during the routing stage. In many cases, the two stages are solved iteratively in a feedback loop. It should be noted that both single-solution as well as population-based metaheuristics have been successfully applied to LRPs. For many LRP variants, it has been found that the quality of a solution strongly depends on the opened facilities (see, e.g. Prins et al., 2006a). Therefore, the most successful heuristics intensively search the space of potential facility configurations, often using diversification and intensification phases. GRASP is a very frequently used approach in this context. Determining high-quality routing solutions is not only important for the final solution quality but also for an accurate evaluation of the quality of facility configurations (see, e.g., Stenger, Schneider, & Enz, 2011). In principle, any fast (MD)VRP heuristic with good solution quality is adequate here.

- Approximation algorithms exploit the relationship between (minimum) spanning or Steiner trees and closed tours (cycles) in graphs to estimate route lengths.

Researchers who intend to work on variants of LRPs might consider the above ideas first. As far as the different problem variants addressed in this paper are concerned, the following observations can be made: With the exception of the 2E-LRP and the PLRP, a comparison of solution approaches is impossible, because the different papers study rather different problems and, consequently, use different instances in their computational experiments. The consolidation in this respect, i.e., the use of standardized benchmark instances to obtain comparable results, has not yet reached variants of the LRP other than the 2E-LRP and the PLRP. This lack has already been pointed out by Nagy and Salhi (2007), and, for the standard LRP, a consolidation has now taken place to a large extent.

As described above, for the 2E-LRP, the ALNS by Contardo et al. (2012) and the VNS by Schwengerer et al. (2012) show the best performance, and no recommendation in the direction of one particular metaheuristic can be made. Exact solution approaches are suitable for small and medium-sized instances only and, compared to heuristics, have long and unpredictable running times. On the PLRP, the matheuristic approach of Pirkwieser and Raidl (2010)

Table 5
Applications of LRPs and case studies.

Paper	Problem type	Application
Chan and Baker (2005)	Standard LRP	Depot location and vehicle routing for delivery of classified documents for armed forces in the USA
Lin and Kwok (2006)	Multi-objective LRP	Vehicle depot location and routing of delivery vehicles for document dispatching in Hong Kong
Burks (2006)	Two-echelon LRP	Theater distribution problem for military operations: Location of supply bases and vehicle depots, routing of supply vehicles
Caballero et al. (2007)	Multi-objective LRP	Installation of waste incineration facilities considering non-monetary factors such as social rejection by towns close to open facilities, routing of waste collection vehicles
Lopes et al. (2008)	Standard LRP	Description of a professional decision support tool for LRP applications
Marinakis and Marinaki (2008)	Standard LRP	Location of local delivery facilities for wood distribution in Greece, routing of delivery vehicles
Crainic et al. (2009)	2E-LRP	City logistics with spatio-temporal vehicle synchronization constraints
Ambrosino et al. (2009)	Special LRP variant	Location of local delivery facilities for food distribution for a supermarket chain in Italy, routing of delivery vehicles
Schittkat and Sörensen (2009)	Standard LRP	Location of hubs and routing of small delivery vehicles in automobile spare parts distribution
Çetiner et al. (2010)	Many-to-many LRP	Hub location and routing in a real-world mail delivery network
Ahn et al. (2012)	Prize-collecting LRP	Mission planning in space exploration: Plan which missions (routes) to perform with which exploration vehicles from which landing points (potential bases/facilities) on a planet to maximize the scientific value of the information gathered while maintaining a budget constraint
Stenger et al. (2012)	Special LRP variant	Location of parcel delivery self-owned and subcontracted depots, where the latter serve customers at route-independent cost, routing of own fleet
Govindan et al. (2014)	2E-LRP with time windows	Distribution of perishable food products
Rieck et al. (2014)	Generalization of many-to-many LRP	Hub location and routing of multiple product pickup-and-delivery requests in the timber-trade industry in Central Europe

outperforms the metaheuristic approaches of Prodhon (2008, 2009, 2011) and Prodhon and Prins (2008) and may be better suited for this problem type.

12. Suggestions for further research

Before presenting our research suggestions, we briefly summarize to what extent the scientific community has taken on the topics proposed by Nagy and Salhi (2007). These authors suggest nine topics for future research:

Use of route length formulae instead of vehicle routing algorithms to speed up the routing part of a heuristic: The approximation algorithms described in the papers of Glicksman and Penn (2008), Chen and Chen (2009) and Harks et al. (2013) rely on this principle. Apart from that, only Albareda-Sambola et al. (2012) exploit the idea.

Dynamic and stochastic problems. We found four papers on stochastic and five on fuzzy LRPs (see Section 7). Compared to the number of papers on deterministic problems, this is clearly expandable, all the more so as only a small share of real-world applications is of deterministic nature. Six papers in this review consider periodic and multi-period problems (see Section 5).

Planar location. Literature on problems where the potential facilities may be located anywhere in the plane is still scarce: Only two new papers (Schwardt & Fischer, 2009; Manzour-al-Ajdad et al., 2012) treat such problems since the last review (see Section 10). From our point of view, the variant with multiple facilities to locate, or extensions such as considering forbidden regions deserve the attention of the research community.

Integrated methods in logistics. Nagy and Salhi state that it would be interesting to combine location-routing with other aspects of logistics, and mention inventory and packing aspects in particular. As Section 9 shows, the former type of problems has indeed been studied more often in recent years, but we think that the topic still needs further research. We found no papers dealing with LRPs incorporating packing aspects.

Multi-objective LRPs. This problem variant has received quite some attention, see Section 8, but in our opinion is also far from being exhausted.

Competitive LRPs. Nagy and Salhi point out that competitive location theory is a well-established field but that there is no work on competitive LRPs. As far as we know, this is still the case.

Eulerian location/location arc-routing. The only two papers on LARPs we found are Hashemi Doulabi and Seifi (2013) and Lopes et al. (2014), see Section 10.

Hybrid methodologies. Nagy and Salhi point out the fragmentation of LRP research into various strands and request to unite different methodologies. In particular, they advocate the combination of exact and heuristic methods. The widespread use of benchmarking in the recent literature is a major step to better connecting different research strands, and the numerous matheuristic approaches described in this review provide evidence that exact and heuristic methods have started to unite in the field of LRPs.

Modeling complex situations. Nagy and Salhi request that more complex and realistic problems be studied. As can be seen in Section 10, there is actually a trend to considering more comprehensive and integrated models.

This short discussion shows that several of the research gaps listed by Nagy and Salhi have not yet been filled.

In addition to the topics just mentioned, we propose the following potential areas for future research, dealing with methodological as well as modeling aspects. From a methodological point of view, these are:

Systematic techniques for parameter optimization and design of experiments: To find suitable values for the parameters

of an algorithm, it is still common to perform what most authors call ‘preliminary testing’. Systematic and documented approaches, as proposed by Johnson (2002), Bartz-Beielstein et al. (2010) or Montgomery (2012), are rare in the field of LRPs. By performing sophisticated statistical tests and reporting on the results, the papers of Burks (2006) and Nguyen et al. (2010, 2012a, 2012b) constitute the notable exceptions.

Algorithm evaluation criteria: It is surely a valuable and non-trivial task to devise and fine-tune an algorithm so that it performs well (with respect to solution quality and run-time) on a given set of benchmark instances. As mentioned, this is what has increasingly been done in the last few years. The general scientific and practical value of a solution approach, though, is affected by additional criteria, such as simplicity (How easy is it to understand the algorithmic principle?), flexibility (How easy is it to include additional constraints?), and robustness (Does the algorithm compute high-quality solutions for different instances?) (see Cordeau, Gendreau, Laporte, Potvin, & Semet, 2002; Bräysy & Gendreau, 2005). The only reference we are aware of that conducts a thorough study of these criteria is (Burks, 2006), who uses a design of experiments (DOE) approach. For future works, similar analyses are recommended to obtain deeper insights on the usefulness of algorithms under different conditions (see Ahuja & Orlin, 1996; Cordeau et al., 2002; Bräysy & Gendreau, 2005; Silberholz & Golden, 2010).

Causal performance analysis of metaheuristic approaches: In the LRP literature, absolutely no light is shed on the important question why a certain metaheuristic performs better than other approaches with a comparable degree of sophistication. There is not a single paper that elaborates on this issue, although techniques such as fitness landscape analysis have attracted interest in many other fields (see Watson, 2010; Quiroz Castellanos et al., 2011). Moreover, this is in marked contrast to discussions on reasons for the strength of MIP formulations and corresponding exact algorithms. Progress in this area would be very valuable.

From a modeling point of view, we propose the following research topics:

Important but rarely-studied variants. Despite their theoretical and practical relevance, pickup-and-delivery LRPs, generalized LRPs, split delivery LRPs, and LRPs with time windows have been rarely considered until now. With the exception of generalized problems, this is in contrast to the literature on vehicle routing, where the respective problem variants have received a considerable amount of attention (see, e.g., Parragh, Doerner, & Hartl, 2008a; Parragh, Doerner, & Hartl, 2008b; Archetti & Speranza, 2008; Bräysy & Gendreau, 2005; Baldacci, Mingozzi, & Roberti, 2012).

Multi-echelon LRPs with space–time synchronization. It is noteworthy that most papers on multi-echelon LRPs ignore the temporal aspect of the load transfers that occur in such situations. This may be justified for strategic or tactical applications. In an operative setting, though, the temporal aspect of transshipments must be taken into account and requires synchronization of operations in space and time (Drexler, 2012a). There is hardly any work on this admittedly very difficult topic.

Integration of location, routing, and revenue management. Although there is a trend to more integrated and complex models, as mentioned above, and although the revenue aspect of long-, medium-, and short-term economic activities is studied by an entire branch of operations research (Phillips, 2005), the usual objective in LRPs is still cost minimization. We are unaware of any papers on the integration of revenue management aspects into location-routing models. In our opinion, contributions to this field would be very valuable, as revenue management is meanwhile successfully employed in many other logistics areas (Talluri & Van Ryzin, 2008). We are convinced that integrating revenue

management into LRP models will provide highly interesting and challenging research questions.

All in all, we hope that the present survey provides useful information for researchers and will motivate further work in the field of location-routing.

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Appendix A. Summary of abbreviations

2E-LRP	Two-echelon LRP
2E-UCFLP	Two-echelon UCFLP
3PL	Third-party logistics
AAI	Adjustable area of influence
ALNS	Adaptive large neighborhood search
AMP	Adaptive memory procedure
ATS	Adaptive TS
BKS	Best known solution
CARP	Capacitated arc routing problem
CFLP	Capacitated FLP
DOE	Design of experiments
ELS	Evolutionary LS
ETS	Elite TS
FLP	Facility location problem
FOP	Fix-and-optimize procedure
GA	Genetic algorithm
GLRP	Generalized LRP
GRASP	Greedy randomized adaptive search procedure
ILS	Iterated LS
ILRP	Inventory LRP
IP	Integer program(ming)
LARP	Location arc-routing problem
LP	Linear program(ming)
LR	Lagrangian relaxation
LRP	Location-routing problem
LRSPD	LRP with simultaneous pickup and delivery
LS	Local search
MDMT-COP	Multi-depot multi-trip capacitated team orienteering problem
MDVRP	Multi-depot VRP
MDVRPP	Multi-depot VRP with profits
MIP	Mixed integer program(ming)
MMLRP	Many-to-many LRP
MOSS	Multi-objective SS
NE-LRP	N-echelon LRP
PCLRP	Prize-collecting LRP
PLRP	Periodic LRP
PR	Path relinking
RECWA	Randomized extended Clarke and Wright algorithm
SA	Simulated annealing
SCDP	Supply chain design problem
SDLRP	Split delivery LRP
SS	Scatter search
SSCFLP	Single-source CFLP
TS	Tabu search
TSP	Traveling salesman problem
UFLP	Uncapacitated FLP

VLNS	Very large-scale neighborhood search
VND	Variable neighborhood descent
VNS	Variable neighborhood search
VRP	Vehicle routing problem

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