



Bi- and multi-objective location routing problems: classification and literature review

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Abstract

The facility location problem and the vehicle routing problem are highly interdependent and critical parts of any efficient and cost-effective supply chain. The location of facilities heavily affects the design of distribution routes between the facilities and various demand nodes. Within locational analysis, the location-routing problem is a mathematical optimization problem that considers the underlying issues of vehicle routing and simultaneously optimizes the location of facilities and the design of distribution routes. Since, in real-life applications, it is common that decision-makers encounter more than one, often conflicting objectives, the problem can be stated in term of multi-objective optimization. This paper reviews 80 journal articles published in the field of bi- and multi-objective location-routing problems between 2014 and 2020. Included papers are classified based on several factors covering model assumptions and characteristics, objectives, solution approaches, and application area. For each application area, individual papers are presented and discussed. The paper concludes with remarks and suggestions for future research.

Keywords Multi-objective location-routing · Waste management · Disaster relief · Perishable supply chain · Inventory

1 Introduction

Efficient and cost-effective distributions are a critical part of any supply chain. Location decisions and vehicle routing are two problems that highly influence the efficiency of the distribution and emerge in many real-life situations. In addition, location and distribution are closely dependent. The location of various facilities, such as plants, warehouses, depots, cross-dockings, etc., heavily affects the design

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of distribution routes, and the establishment of a new facility in an existing distribution network disrupts the previous conditions and requires a re-optimization of distribution routes between facilities and demand nodes. As a research area within locational analysis location-routing problems (LRP) is a mathematical optimization problem that considers the underlying issues of vehicle routing and simultaneously optimizes the location of facilities and the design of distribution routes. Typically, decisions such as the number, size, and location of facilities and the allocation of demand points to facilities in the combination of the design of routes are combined in LRPs. The simultaneous optimization means that the decision on facilities is not an implicit result of the routing but that both decisions are made inter-dependently. Drexler and Schneider (2015) lists three different situations when that is the case; if opening a facility is associated with a fixed cost or a variable cost for using that facility, there is either a given number or an upper limit on the number of facilities that must be selected from a larger set, and lastly, if the facilities are subject to any capacity limitation.

Supply chain optimization problems can be strategic, tactical, or operational. Strategic problems regards decisions which require significant capital investments and which can be hard to change after a decision has been implemented. They thus typically address questions regarding the characteristics of facilities such as number, size, type, capacity, type of technology, quality, and location (Farahani et al. 2014). Decisions regarding and problems considering transportation, inventory, procurement policy, or information technology are seen as tactical while operational decisions could for example concern which service level or prices should be offered. Location-routing problems have been studied for a long time, and scholars have over the years used different definitions of what constitutes an LRP. Bruns (1998) considers LRPs as “location planning with tour planning aspects taken into account.” Nagy and Salhi (2007) defines the LRP with a hierarchical point of view. In order to solve the master problem (facility location), one has to solve the sub-problem simultaneously, which is the vehicle routing problem. Such a definition thus also entails an integrated solution approach. The authors also point out the important aspect of including tour planning in LRP models; routes should consist of multiple stops and is necessary when demand is less than a full truckload for any given demand node. Considering the two components of the problem, the facility location problem and the vehicle routing problem, they can be seen as special cases of the LRP (Nagy and Salhi 2007). If all demand nodes were directly linked to a facility, the LRP reduces to an FLP. On the contrary, if the location of the facilities were to be fixed, the problem would transform into an ordinary VRP.

It is a known fact that LRPs are NP-hard since they incorporate two NP-hard problems (Prodhon and Prins 2014). Traditionally, the approach of treating these two problems separately by deciding the location first and then designing routes has been challenged by scholars and gradually replaced by the integrated approach (Lopes et al. 2013). Salhi and Rand (1989) argues that they should not be optimized separately since they are so strongly linked. However, even if the inter-dependency is a known fact, it is often ignored by researchers and practitioners (Lopes et al. 2013). Nagy and Salhi (2007) highlights three possible reasons for this; the first one is that it might not be required to consider routing aspects in practical situations,

researchers object to an integrated approach based on the different levels of decisions (where facility location being strategic decisions and thereby have a longer planning horizon than the tactical decisions of routing). Lastly, the LRP is harder to solve conceptually, making the location problem easier. Several of such arguments have been impugned previously in the literature. Especially that FLP being a strategic problem and the VRP a tactical where routes can be re-designed and recalculated and that it is therefore inappropriate to combine these was challenged by Salhi and Nagy (1999) who showed that a separated approach could lead to sub-optimal decisions compared to LRP for long planning horizons. In addition, Lopes et al. (2013) argues that in some situations, it is even more critical to utilize an LRP approach rather than a separate approach. In situations where the cost or characteristics of the transported products have a significant impact, the authors exemplify a situation where hazardous material is being transported. Another instance could, for example, be when planning a disaster relief network where the routing has a considerable impact on the evaluation of the system.

The capacitated LRP is by Prodhon and Prins (2014) described as a complete, weighted, and undirected network consisting of potential facilities to be located and customers to be served. Furthermore, the facilities share a homogeneous vehicle fleet, and the traveling cost for using an edge satisfies the triangle inequality. A solution is obtained by determining which facilities should be opened, from which depot each customer should be served, and by designing routes for servicing all customers. At the same time, several constraints must be upheld; facilities and vehicles are capacitated, which means that the total demand of the customers assigned to a facility cannot exceed the capacity of the facility, and the total demand of the customers serviced by a vehicle cannot exceed the capacity of the vehicle. Each vehicle performs at most one route, no split deliveries are allowed, and each vehicle starts and ends their route at the same facility. Now, consider the multi-objective version of the problem; $\min (f_1(x), \dots, f_p(x))$ are the objectives to be minimized subject to $x \in X$. There is in total p objective functions and a Pareto optimal solution is a feasible solution $\hat{x} \in X$ if there exist no solution $x \in X$ such that $f_k(x) \leq f_k(\hat{x})$ for $k \in \{1, \dots, p\}$ and $f_i(x) < f_i(\hat{x})$ for any $i \in \{1, \dots, p\}$. A Pareto optimal solution is sometimes referred to as a non-dominated solution, whereas a Pareto optimal set is formed by all Pareto optimal alternatives and their corresponding objective values.

In real-life practical optimization problems, it is seldom that only one objective is preferable by the decision-makers. Therefore, to more accurately mimic real-life decision-making in routing problems, multiple objectives can be optimized (Zajac and Huber 2021). Due to the nature of multi-objective optimization, objectives are often conflicting; there is typically no single solution that simultaneously optimizes each objective. Instead, decision-makers, based on their preferences, have to choose a solution from a Pareto optimal set. Naturally, due to the increased complexity, these problems are more complicated than the single-objective version.

This paper presents an overview of multi-objective LRPs and reviews 80 journal articles. Other surveys covering the location-routing problem in recent years include Nagy and Salhi (2007) who presented a comprehensive review on location-routing papers published until 2006. Lopes et al. (2013) presented a taxonomical analysis on methods and objectives for papers published in 2013 and earlier. An updated review

of Nagy and Salhi (2007) was presented by Prodhon and Prins (2014) which covered the standard version and variants of the LRP as well as compact overviews of the reviewed papers spanning from 2006 to 2014. Drexl and Schneider (2015) focus on extensions and variants of the LRP, and Schneider and Drexl (2017) surveys the standard LRP while the focus in the paper by Cuda et al. (2015) is on multi-echelon VRPs and LRPs. However, the increasing number of publications in the field and the practical relevance makes it necessary for a review focusing on multi-objective LRPs.

2 Research design

The purpose of this paper is to present an overview of the main contributions to the field of multi-objective LRPs. We limit our study to journal articles published between 2014 and 2020 written in English, thus omitting conference proceedings, technical reports, books, and PhD-dissertations. We do not claim to cover all contributions made in the field but rather a representative sample of the work presented in recent years. Furthermore, we define the multi-objective location routing problem similar to Nagy and Salhi (2007) and Prodhon and Prins (2014) as the integrated approach to solve the two inherent problems based on at least two objectives and where the aspect of tour-planning has a central part of the problem. This means that any two-stage models, where the location of facilities is first determined and routes designed afterward, are not included in the survey. The same applies to problems not considering tour-planning aspects, for example, when the tour-planning can be reduced to the transportation problem rather than multi-stop routes.

The databases Web of Science and Scopus were used to retrieve published articles using both “location-routing” and “location-routing” combined with multi-objective, multi-criteria, bi-objective, and bi-criteria. Table 1 depicts the combination of searched keywords and their unique hits, as well as the number of papers excluded for not meeting the inclusion criteria mentioned above. The papers were first screened based on the abstract, problem description, and model formulation. If there still were doubts about whether they would be included or not, the entire paper was read in order to make that decision.

3 Classification and terminology used

LRPs can be classified on a large variety of characteristics. However, in this survey, we have limited ourselves to characteristics that essentially change the basic properties of the problem. A brief description of these characteristics is presented below for which the included papers were read and classified according to.

Number of objectives Papers included could either be bi-objective, exactly two objectives, or multi-objective, more than two objectives.

Data assumption Data, in most cases the customer demand or travel times, can be deterministic or stochastic. In deterministic models, all the data is known beforehand. On the contrary, for stochastic models, the data is uncertain and given by a

Table 1 Screening and selection of papers

Item	Description
Keywords	Location-routing OR "location routing" AND (multi-objective OR multiobjective OR "multi objective") Location-routing OR "location routing" AND (multi-criteria OR multicriteria OR "multi criteria") Location-routing OR "location routing" AND (bi-objective OR biobjective OR "bi objective") Location-routing OR "location routing" AND (bi-criteria OR bicriteria OR "bi criteria")
Databases	ISI Web of Science, Scopus
Search fields	Title, Abstract, Keywords
Publication type	Journal articles
Time window	2014–2020
Unique hits	116
Exclusion criterias	Papers not considering an integrated solution approach Papers not considering tour planning aspects
Excluded based on abstract	25
Excluded based on entire paper	11
Final sample	80

probability distribution. Some researchers even differentiate between fuzzy data, i.e., in the form of fuzzy numbers. Our view is that fuzzy data is also stochastic data, and hence papers included in this survey are classified as either deterministic or stochastic models.

Planning horizon Models can be classified as either static or dynamic. In static models, only a single planning period is considered, whereas, for dynamic models, multiple planning periods are considered. Dynamic models aim to determine a visiting pattern or how to design a supply chain over time, i.e., the sequence of which each customer should be visited in each time-period or in which period various facilities should be used. Previous classifications differ between dynamic and periodic models. That is, while both include multiple periods, in dynamic models, some information is initially unknown and becomes available over time as opposed to periodic models in which all relevant data is known beforehand (Drexl and Schneider 2015). However, if the data involves more than one time period, whether it is known beforehand or not, the problem is classified as dynamic in this paper.

Solution method Both exact i.e. optimizing and heuristic solution methods occurs in the literature. By heuristic we mean solution methods which produce an approximate solution of good quality or an optimal solution, however, without proof of its optimality. Due to the NP-hard nature of the LRP, only small examples can be solved using exact methods. Naturally, most of the surveyed papers utilize some heuristic method to solve the problem.

Papers can also be classified as discrete or continuous problems. The difference between continuous and discrete models is linked to their respective decision space, wherein discrete models' possible locations that could be selected are restricted to

a finite set of candidates. These candidates have previously been determined eligible within the decision space. For continuous models, it is possible to locate facilities at every single point within the decision space. However, all papers included in the survey were classified as discrete, and no continuous model could be identified. Furthermore, LRPs may be differentiated based on aspects that do not necessarily change the basic properties of the problem, such as capacitated or incapacitated facilities or vehicles, fixed costs or no fixed costs for opening facilities, or if the vehicle fleet is assumed heterogeneous or homogeneous. Figure 1 provides an overview of the classified papers based on the characteristics mentioned above.

By analyzing objectives commonly used, one can identify combinations of objectives that have not been studied or received much attention. To that end, objectives have been categorized and grouped based on their characteristics. Based on the included papers, we have identified six different groups of objectives, that is, costs, profit, coverage, environmental, risks, and social objectives.

Table 2 shows the grouping and classification scheme of the objectives identified, while Table 3 describe the use of different objective category combinations for bi- and multi-objective models, Table 3a, b respectively.

Operations research as a discipline can be described as application-based. Typically, the aim of a paper and its contribution is to make recommendations based on some analysis; the data may be randomly generated or originating from a real-world case study. Therefore, the practical applications of LRPs should not be ignored. Table 4 provides the classification of surveyed papers according to their application area. Note that most of these concerns are the distribution of goods; however, applications such as disaster relief or hazardous waste management have received some attention in the literature. Models do share similarities across these areas. However, factors such as objectives are commonly shared within each area. To facilitate an overview of each area, the individual papers will be presented and discussed based on this classification. Furthermore, Table 5 depicts the different solution approaches and in which paper the individual approaches have been used

4 Applications

Papers have been classified based on application area. In this section individual papers are reviewed and discussed according to such a classification. Some papers could fit several application areas, however, they are presented within the application area judged best fitted.

4.1 Waste management

Waste management supply chains incorporate activities such as collection and transportation, storage, transfer, and processing. Furthermore, different waste types require different treatment and processing, while waste management systems become more complex as volumes increase and processes differentiate. Industrial waste has a significant impact on the environment and human health.

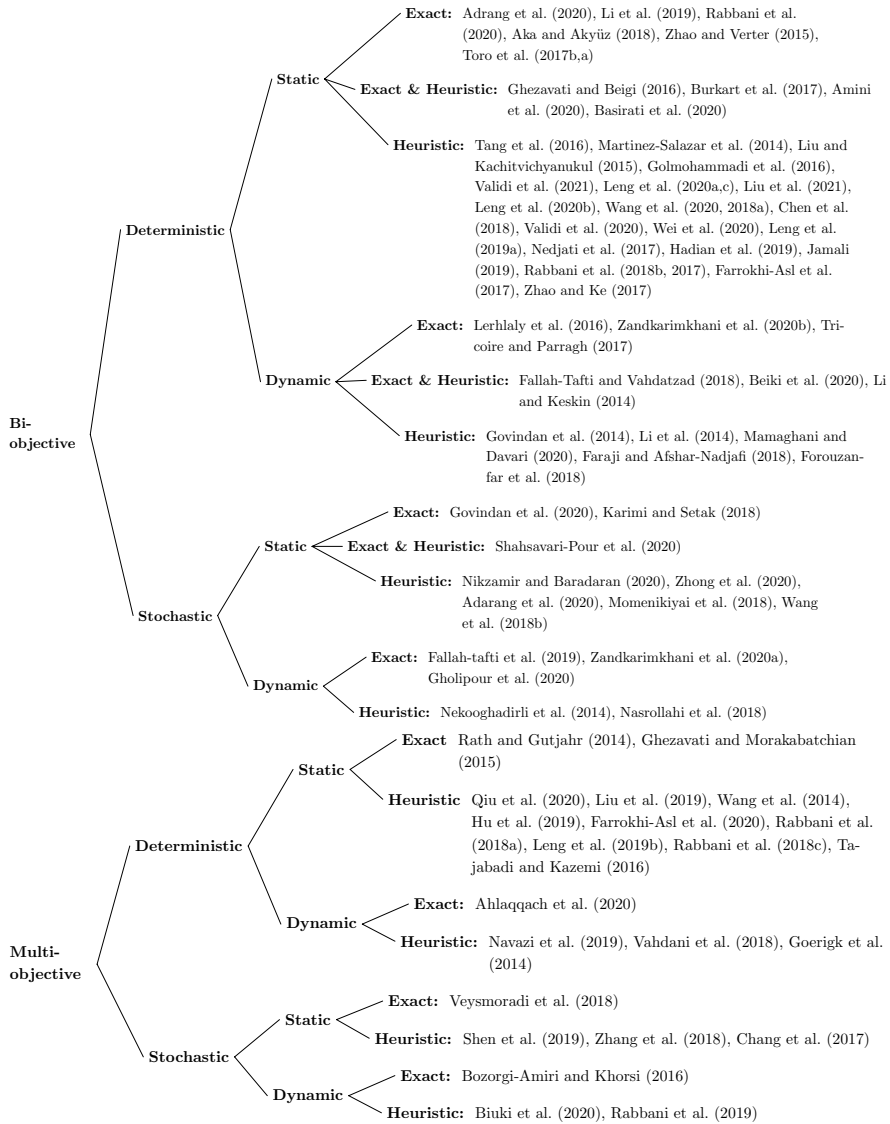


Fig. 1 Classification of included papers

Consequently, a large number of published works are concerned with modelling such risk aspects, particularly in connection to transportation and site location and management. Almost all papers reviewed handle risks in addition to cost.

Zhao and Verter (2015) presented a bi-objective model to minimize the total cost and total environmental risk when simultaneously locating storage facilities for used oil and routing it from generation nodes to the storage facilities. Their model combined two parts; risk assessment and a two-commodity flow vehicle

Table 2 Identified groups of objectives**Cost**

Difference between min and max costs of vehicle allocated to each route	Basirati et al. (2020)
Min cost	Adrang et al. (2020), Beiki et al. (2020), Fallah-Tafti and Vahdatzad (2018), Farrokhi-Asl et al. (2017), Forouzanfar et al. (2018), Jamali (2019), Li and Keskin (2014), Nikzamir and Baradaran (2020), Qiu et al. (2020), Rabbani et al. (2017, 2018), Shahsavari-Pour et al. (2020) and Wang et al. (2018)
Min CVaR-R Cost	Zhong et al. (2020)
Min facility cost	Rath and Gutjahr (2014)
Min operational cost	Rath and Gutjahr (2014) and Toro et al. (2017b, 2017a)
Min relief cost	Zhang et al. (2018)
Min total cost	Martinez-Salazar et al. (2014), Adarang et al. (2020), Amini et al. (2020), Asgari et al. (2017), Basirati et al. (2020), Biuki et al. (2020), Bozorgi-Amiri and Khorsi (2016), Burkart et al. (2017), Chen et al. (2018), Fallah-tafti et al. (2019), Faraji and Afshar-Nadjafi (2018), Farrokhi-Asl et al. (2020), Ghezavati and Morakabatchian (2015), Ghezavati and Beigi (2016), Gholipour et al. (2020), Golmohammadi et al. (2016), Govindan et al. (2014, 2020), Hadian et al. (2019), Hu et al. (2019), Karimi and Setak (2018), Leng et al. (2019, 2019, 2020, 2020, 2020), Lerhlaly et al. (2016), Li et al. (2014, 2019), Liu and Kachitvichyanukul (2015), Liu et al. (2021), Mamaghani and Davari (2020), Momenikiyai et al. (2018), Nasrollahi et al. (2018), Navazi et al. (2019), Nekooghadirli et al. (2014), Rabbani et al. (2018, 2018, 2019, 2020), Shen et al. (2019), Tajabadi and Kazemi (2016), Tang et al. (2016), Tricoire and Parragh (2017), Vahdani et al. (2018), Validi et al. (2020, 2021), Veysmoradi et al. (2018), Wang et al. (2014, 2018, 2020), Wei et al. (2020), Zandkarimkhani et al. (2020, 2020), Zhao and Verter (2015) and Zhao and Ke (2017)
Min total distribution cost	Chang et al. (2017)
Coverage	
Maintain workload balance	Martinez-Salazar et al. (2014)
Max coverage	Li and Keskin (2014) and Tajabadi and Kazemi (2016)
Max covered demand	Rath and Gutjahr (2014)
Max customer satisfaction	Wang et al. (2018)
Max customer satisfaction (vehicle punctuality)	Wang et al. (2018)
Max delivery flow by LAT	Karimi and Setak (2018)
Max demand served	Aka and Akyüz (2018) and Liu and Kachitvichyanukul (2015)
Max of worst path satisfaction	Chang et al. (2017)

Table 2 (continued)

Max path transport capacity	Chang et al. (2017)
Max reliability	Vahdani et al. (2018) and Wang et al. (2014)
Max satisfaction level for customers	Hu et al. (2019)
Maxmin route reliability	Veysmoradi et al. (2018)
Min avg waiting time	Qiu et al. (2020)
Min client waiting time	Leng et al. (2019)
Min CVaR-R waiting time	Zhong et al. (2020)
Min delivery time	Shen et al. (2019)
Min difference traveling distance	Hadian et al. (2019)
Min distance	Aka and Akyüz (2018)
Min distribution time	Wang et al. (2020)
Min earliness/lateness	Momenikiyai et al. (2018)
Min evacuation time	Goerigk et al. (2014)
Min expected cost failure	Shahsavari-Pour et al. (2020)
Min imbalanced distance traveled	Golmohammadi et al. (2016)
Min makespan	Amini et al. (2020)
Min max loss of demand nodes	Liu et al. (2019)
Min max time required for nodes to receive relief	Liu et al. (2019)
Min number of injured not transferred to hospitals	Mansoori et al. (2020)
Min relief time	Adarang et al. (2020)
Min service duration	Leng et al. (2019)
Min shortage	Gholipour et al. (2020) and Govindan et al. (2020)
Min time	Adrang et al. (2020)
Min time between two stages	Forouzanfar et al. (2018)
Min time win violation	Wei et al. (2020) and Mamaghani and Davari (2020)
Min total delivery time	Li et al. (2019)
Min total loss of all nodes	Liu et al. (2019)
Min total time	Ghezavati and Beigi (2016) and Li et al. (2014)
Min total unmet relief commodity needs	Mansoori et al. (2020)
Min total waiting time	Leng et al. (2020)
Min travel time	Bozorgi-Amiri and Khorsi (2016), Vahdani et al. (2018) and Wang et al. (2014)
Min unserved demand	Burkart et al. (2017), Nedjati et al. (2017) and Zandkarimkhani et al. (2020)
Min vehicle waiting time	Leng et al. (2019)
MinMax delivery time	Nekooghadirli et al. (2014)
Minmax shortage	Bozorgi-Amiri and Khorsi (2016)
Minmax travel time	Veysmoradi et al. (2018) and Zhang et al. (2018)
Minmax unserved demand	Beiki et al. (2020)
Number of shelters used	Goerigk et al. (2014)
Total weightet waiting time	Nedjati et al. (2017)
Workload balance	Rabbani et al. (2018)

Table 2 (continued)

Environmental	
Min co2	Chen et al. (2018), Lerhlaly et al. (2016), Shen et al. (2019), Tang et al. (2016), Tricoire and Parragh (2017), Validi et al. (2020, 2021) and Zhang et al. (2018)
Min emissions	Faraji and Afshar-Nadjafi (2018), Nikzamir and Baradaran (2020) and Qiu et al. (2020)
Min environmental impact	Biuki et al. (2020), Govindan et al. (2014), Liu et al. (2021), Navazi et al. (2019) and Rabbani et al. (2018)
Min fuel consumption	Nasrollahi et al. (2018), Rabbani et al. (2018) and Toro et al. (2017b, 2017a)
Min total pollution	Tajabadi and Kazemi (2016)
Risk	
Min damage of prod	Leng et al. (2020)
Min damage of quality	Leng et al. (2020)
Min pollution risk	Rabbani et al. (2020)
Min risk	Ahlaqqach et al. (2020), Asgari et al. (2017) and Jamali (2019)
Min risk exposure	Goerigk et al. (2014)
Min site risk	Farrokhi-Asl et al. (2020), Ghezavati and Morakabatchian (2015) and Rabbani et al. (2018, 2019)
Min total environmental risk	Zhao and Verter (2015)
Min total Risk	Fallah-tafti et al. (2019), Hu et al. (2019) and Zhao and Ke (2017)
Min transportation risk	Ghezavati and Morakabatchian (2015), Fallah-Tafti and Vahdatzad (2018), Farrokhi-Asl et al. (2020) and Rabbani et al. (2018, 2019)
Social	
Max job creation	Ahlaqqach et al. (2020) and Biuki et al. (2020)
Max social effects	Farrokhi-Asl et al. (2017), Rabbani et al. (2017) and Zandkarimkhani et al. (2020)
Utility of personnel and customers	Navazi et al. (2019)
Profit	
Max profit	Ahlaqqach et al. (2020)

routing formulation. The weighted goal programming method was proposed using a percentage normalization technique to solve it as a mixed-integer programming (MIP) problem. Applied to a real-world case study, the presented model outperformed the traditional VRP formulation obtaining both lower cost and lower environmental risk with a smaller optimality gap and shorter CPU time.

A fuzzy goal programming method was used by Aka and Akyüz (2018) to determine the location of waste containers and the routing between those. They proposed a covering model to maximize the demand served and minimize the routing distance. It was developed for a specific region, the Siteler district in

Table 3 Objective combinations used

(a) Bi-objective papers						
	Cost	Coverage	Environmental	Risk	Social	Total
Cost	1	29	14	8	3	55
Coverage		3				3
Total	1	32	14	8	3	58
(b) Multi-objective papers						
	Cost	Coverage	Environmental	Risk		Total
Cost						
Coverage	1	6	1	1		9
Environmental		4				4
Risk				4		4
Social			2			2
Coverage						
Coverage		1		1		2
Profit						
Social				1		1
Total	1	11	3	7		22

Table 4 Classification based on application area

Application area	References	Multi-objective
	Bi-objective	
<i>Waste management</i>	Aka and Akyüz (2018), Farrokhi-Asl et al. (2017), Jamali (2019), Nikzamir and Baradaran (2020), Rabbani et al. (2017, 2018, 2020), Zhao and Verter (2015) and Zhao and Ke (2017)	Farrokhi-Asl et al. (2020), Ghezavati and Morakabatchian (2015), Hu et al. (2019) and Rabbani et al. (2018, 2019)
<i>Disaster relief</i>	Adarang et al. (2020), Adrang et al. (2020), Beiiki et al. (2020), Burkart et al. (2017), Li et al. (2014), Mansoori et al. (2020), Nedjati et al. (2017), Wei et al. (2020) and Zhong et al. (2020)	Bozorgi-Amiri and Khorsi (2016), Chang et al. (2017), Goerigk et al. (2014), Liu et al. (2019), Rath and Gutjahr (2014), Shen et al. (2019), Vahdani et al. (2018), Veysmoradi et al. (2018), Wang et al. (2014) and Zhang et al. (2018)
<i>Perishable supply chain</i>	Govindan et al. (2014), Leng et al. (2020, 2020, 2020), Li et al. (2019), Liu et al. (2021), Nasrollahi et al. (2018), Validi et al. (2020, 2021), Wang et al. (2020) and Zandkarimkhani et al. (2020)	Ahlaqqaeh et al. (2020), Biuki et al. (2020), Navazi et al. (2019) and Qiu et al. (2020)
<i>Inventory</i>	Fallah-Tafti and Vahdatzad (2018), Fallah-tafti et al. (2019), Forouzanfar et al. (2018), Gholipour et al. (2020), Govindan et al. (2020), Lerhaly et al. (2016), Momenkiyayi et al. (2018), Nekooghadrli et al. (2014) and Tang et al. (2016)	
<i>Other applications</i>	Martinez-Salazar et al. (2014), Amini et al. (2020), Basirati et al. (2020), Chen et al. (2018), Faraji and Afshar-Nadjafi (2018), Ghezavati and Beigi (2016), Golmohammadi et al. (2016), Hadian et al. (2019), Karimi and Setak (2018), Leng et al. (2019), Li and Keskin (2014), Liu and Kachitvichyanukul (2015), Mamaghani and Davari (2020), Shahsavari-Pour et al. (2020), Toro et al. (2017, 2017), Tri-coire and Parragh (2017), Wang et al. (2018, 2018) and Zandkarimkhani et al. (2020)	Leng et al. (2019), Rabbani et al. (2018) and Tajabadi and Kazemi (2016)

Table 5 Solution approaches

Exact	Used in (including modifications)
<i>AUGMECON2</i> : Augmented ϵ -constraint method 2	Amini et al. (2020), Basirati et al. (2020) and Fallah-Tafti and Vahdatzad (2018)
<i>Chance constrained fuzzy goal programming</i> :	Zandkarimkhani et al. (2020a)
<i>Decomposition method</i> :	Tricoire and Parragh (2017)
<i>ϵ-Constraint</i> :	Adrang et al. (2020), Bozorgi-Amiri and Khorsi (2016), Burkart et al. (2017), Fallah-tafti et al. (2019), Ghezavati and Beigi (2016), Karimi and Setak (2018), Li and Keskin (2014b), Rabbani et al. (2020), Rath and Gutjahr (2014), Shahsavari-Pour et al. (2020) and Toro et al. (2017b, 2017a)
<i>Fuzzy goal programming</i> :	Aka and Akyüz (2018) and Veysmoradi et al. (2018)
<i>Weighted goal programming</i> :	Zhao and Verter (2015)
<i>Weighted method</i> :	Karimi and Setak (2018), Lerhlaly et al. (2016), Li et al. (2019), Mansoori et al. (2020) and Zandkarimkhani et al. (2020b)
<i>Commercial solver</i> :	Beiki et al. (2020), Gholipour et al. (2020) and Govindan et al. (2020)
<i>Conversion to single objective</i> :	Ahlaqqach et al. (2020) and Ghezavati and Morakabatchian (2015)
<i>Complete enumeration</i> :	Burkart et al. (2017)
Heuristics and Meta-heuristics	
<i>AWGA</i> : Adaptive weight genetic algorithm	Hu et al. (2019)
<i>Decomposition heuristic</i> :	Li and Keskin (2014b)
<i>(H)-GA</i> : (Hybrid) genetic algorithm	Li et al. (2014a), Zhang et al. (2018), Zhong et al. (2020), Biuki et al. (2020), Faraji and Afshar-Nadjafi (2018), Chang et al. (2017) and Goerigk et al. (2014)
<i>(MO)HH</i> : (Multi-objective) hyper heuristic	Qiu et al. (2020), Leng et al. (2019b, 2020b, 2020c), Wang et al. (2020) and Leng et al. (2019a)
<i>Hybrid heuristic algorithm</i> :	Liu et al. (2019)
<i>H-IA</i> : Hybrid immune algorithm	Liu et al. (2021)
<i>NRGA</i> : Non dominated ranked genetic algorithm	Nasrollahi et al. (2018), Mamaghani and Davari (2020) and Tajabadi and Kazemi (2016)
<i>MHPV</i> : Multi objective hybrid approach	Govindan et al. (2014)
<i>MOICA</i> : Multi-objective imperialist competitive algorithm	Basirati et al. (2020), Golmohammadi et al. (2016), Nekooghadirli et al. (2014) and Hadian et al. (2019)
<i>MOFA</i> : Multi-objective firefly algorithm	Shahsavari-Pour et al. (2020)
<i>MOGA-II</i> : Multi-objective genetic algorithm of kind II	Validi et al. (2020, 2021)
<i>MOHCGA</i> : Multi objective hybrid cultural and genetic algorithm	Farrokhi-Asl et al. (2020)
<i>MOLAHC</i> : Multi-objective late acceptance hill climbing	Amini et al. (2020)
<i>MOPSA</i> : Multi-objective parallel simulated annealing	Nekooghadirli et al. (2014)

Table 5 (continued)

<i>(MO)PSO</i> : (Multi-objective) Particle swarm optimization	Beiki et al. (2020), Farrokhi-Asl et al. (2017), Forouzanfar et al. (2018), Liu and Kachitvichyanukul (2015), Momenikiyai et al. (2018), Navazi et al. (2019), Rabbani et al. (2018c, 2018a), Tang et al. (2016), Vahdani et al. (2018), Validi et al. (2021) and Shen et al. (2019)
<i>MOSFLA</i> : (Multi-objective) Shuffled frog leaping algorithm	Adarang et al. (2020)
<i>MOWFA</i> : Multi-objective water-glow like algorithm	Nikzamid and Baradaran (2020)
<i>NSDE</i> : Non sorting differential evaluation algorithm	Wang et al. (2014)
<i>NSGA-II</i> : Non sorting genetic algorithm II	Martinez-Salazar et al. (2014), Amini et al. (2020), Basirati et al. (2020), Beiki et al. (2020), Burkart et al. (2017), Farrokhi-Asl et al. (2017), Forouzanfar et al. (2018), Ghezavati and Beigi (2016), Hadian et al. (2019), Jamali (2019), Mamaghani and Davari (2020), Momenikiyai et al. (2018), Navazi et al. (2019), Nekooghadirli et al. (2014), Rabbani et al. (2017, 2018b, 2018c, 2018a), Shahsavari-Pour et al. (2020), Tajabadi and Kazemi (2016), Vahdani et al. (2018), Validi et al. (2021), Wang et al. (2014), Zhong et al. (2020), Nedjati et al. (2017), Chen et al. (2018), Wang et al. (2018b) and Rabbani et al. (2019)
<i>ACO</i> : Ant colony optimization	Wei et al. (2020)
<i>PAES</i> : Pareto archived evolution strategy	Nekooghadirli et al. (2014)
<i>PESA-II</i> : Pareto envelope-based selection algorithm II	Momenikiyai et al. (2018)
<i>PROMETHEE-II</i> : Preference ranking organization method for enrichment of evaluations II	Nasrollahi et al. (2018)
<i>SSPMO</i> : Scatter tabu search procedure for non-linear multi-objective optimization	Martinez-Salazar et al. (2014)
<i>TOPSIS</i> : Technique for order of preference by similarity to ideal solution	Zhao and Ke (2017)
<i>TS</i> : Tabu search	Wang et al. (2018a)

Antalya, Turkey. By applying different tolerance ranges, it could be concluded that the model could obtain optimal solutions through fuzzy goals and tolerance ranges.

Rabbani et al. (2020) studied the industrial waste transportation system in the automotive industry and presented a MIP model for the capacitated location routing problem with a heterogeneous fleet of vehicles. The objectives were to minimize the total cost and the population risk in transportation. Their model aims to determine the optimal set of routes for waste collection and the location of a single collection center. The authors also considered that the waste collection was performed in a separated form, either from multi-compartment vehicles or waste-vehicle compatibility. An epsilon-constraint (ϵ -constraint) method was used to

solve the problem, and numerical experiments proved that the proposed MIP model considering heterogeneous transport fleet and waste collection separately was the best solution to reduce logistics costs in the presence of transportation risk criteria.

Jamali (2019) considered multimodal transportations and presented a bi-objective mathematical model, which determined the location of multimodal terminals and optimizes total cost and the risk associated with transportation. Both exact methods, such as the ϵ -constraint method and the metaheuristic NSGA-II, were used to solve the problem. Numerical experiments showed that the NSGA-II algorithm outperformed the ϵ -constraint method, based on the evaluation of Mean Ideal Distance indicator (MID), CPU time, a space metric (SM), a quality metric (QM), and a diversification metric (DM). In addition, sensitivity analysis was conducted, which confirmed the structural performance of the model.

Hu et al. (2019) considered the influence of traffic restrictions on a hazardous waste management system. A multi-objective model with soft time windows was formulated while considering alternative paths between every origin-destination pair. The aim was to determine, based on a set of warehouses, which warehouses should be used, assigning customers to those warehouses, and determining a route for each group of warehouses and customers. By fulfilling the aim, three objectives were optimized, total cost minimization, total risk minimization, and maximizing satisfaction level for customers, i.e., the ability to meet the time windows. An adaptive algorithm and an adaptive weight genetic algorithm were proposed to solve the problem. It was concluded that further research is required to improve the efficiency of running the algorithms in order to solve problems of larger scale.

In a two-layer supply chain, Farrokhi-Asl et al. (2017) presented a bi-objective model for the location of vehicle depots and disposal facilities while minimizing total cost and maximizing the distance of the disposal facilities from customer areas. Multi-compartment vehicles start their route at the depot to collect other wastes from customers. When all customers are served, the vehicles visit the corresponding disposal center to the collected waste before returning to the depot. An NSGA-II and a MOPSO algorithm were proposed, and the two algorithms were tested on various instances and then compared with respect to the number of Pareto solutions, a spacing metric of the uniformity of the distribution of solutions, one spacing uniformity metric for how the items in the approximation set are distributed in the objective space, and a diversification metric. The NSGA-II algorithm outperformed the MOPSO algorithm for the test problems in all aspects, except for the running time. Considering that the NSGA-II could find more Pareto solutions and search more regions of the solution space, the authors conclude that its higher computational time is rational.

Rabbani et al. (2017) extended the model proposed by Farrokhi-Asl et al. (2017) to include capacitated depots and the fact that some customers are delegated to contractors resulting, thus, in both open and closed routes since a contract vehicle does not have to return to the depot after completing the tour. An NSGA-II algorithm was proposed and compared to weighted sum, goal programming, and goal attainment

methods. Results showed that the NSGA-II was superior to the other methods in both large and small-sized problems in all aspects, however, with higher computational time since it searches more regions of the solution space.

Rabbani et al. (2018b) sought to determine the location of collection and processing centers as well as the number of vehicles needed and developed a bi-objective model to minimize cost and environmental impact. They were able to achieve approximate optimum solutions within an acceptable time by using an NSGA-II, which included an augmented epsilon constraint. The Taguchi method was used in parameter tuning, while the best worst method (BWM) was used to determine the optimal combination of parameters.

Zhao and Ke (2017) developed a bi-objective model for the combined optimization of facility location and vehicle routing, which incorporates inventory risk when dealing with explosive waste management. The aim was to minimize both total cost and total risk. They simultaneously designed three routes; tours, direct routes, and return trips. Tours can be described as ordinary routes where the vehicles return to the origin node. Direct routes are open in the sense that vehicle do not need to return to the same collection center while return trips can be described as direct full truck load shipments between collection centers and recycling facilities. Furthermore, the vehicle routing formulation was a modification of the capacitated vehicle routing problem based on a two-commodity network flow approach, to which location, inventory, and routing decisions from different levels are incorporated. A case study showed that the model improved cost savings and risk reduction.

Rabbani et al. (2018a) extended the model of Samanlioglu (2013) in a three echelon supply chain consisting of a central depot, demand nodes, treatment, recycling, and disposal facilities. The aim was to determine the collection routes from demand nodes, locate the various facilities, determine which technologies that should be adopted at treatment centers, and to route the waste residues generated at different facilities. Three objectives were considered: transportation risk, site risk, and total cost. The authors proposed an NSGA-II and a MOPSO algorithm to solve the model. A three-level Taguchi design was applied to analyze the effect of essential NSGA-II and MOPSO parameters. The algorithms were evaluated based on CPU time, the number of Pareto solutions, spacing, and a diversity metric. The results indicated that the NSGA-II algorithm performed better than the MOPSO in terms of CPU time, Pareto optimal solutions, and the spacing metric, while the MOPSO algorithm had better results in terms of the diversity metric.

Farrokhi-Asl et al. (2020) considered the same objectives as (Rabbani et al. 2018a) in a similar supply chain. However, their model also evaluated fuel consumption, carbon dioxide emissions, and their environmental impact. The authors proposed a hybrid meta-heuristic algorithm called multi-objective hybrid cultural and genetic algorithm (MOHCGA), compared to NSGA-II, SPEA-II, MOSA, and MOPSO. Results showed that the MOHCGA could produce competitive solutions, although the SPEA-II algorithm could generate more Pareto solutions distributed uniformly in the Pareto front.

In an attempt to minimize total cost, transportation- and site risk Ghezavati and Morakabatchian (2015) developed a MIP model with fuzzy time windows which were solved with data retrieved from the Petrochemical Special Economic Zone in

south-west Iran. The model sought to optimize the waste collection from generation nodes to warehouses, the location of warehouses and various treatment centers, and the routing of hazardous waste to compatible treatment centers. By converting the risk objectives into economic objectives, i.e., the cost of the transportation risk and the site risk, respectively, the model could be optimized as a single objective function, and the Pareto optimal solutions could be found automatically.

Rabbani et al. (2019) presented a stochastic mixed-integer nonlinear programming model where uncertainty was incorporated in the model by the amount of waste generated and the number of people at risk as a consequence of the waste management activities. The model covered the integrated location, vehicle routing, and inventory control decisions. Furthermore, the model was converted to a MIP using an exact linearization method. A simulation-optimization approach was developed based on a multi-objective evolutionary algorithm, integrating NSGA-II and Monte Carlo simulation to overcome stochastic combinatorial optimization. Results showed that the proposed approach could find high-quality solutions in a relatively reasonable computational time.

Nikzamir and Baradaran (2020) studied the health waste location routing problem and emphasized the stochastic emissions caused by infectious and non-infectious waste transported between healthcare and disposal centers. The authors presented a bi-objective non-linear mixed-integer programming (NL-MIP) model minimizing total cost and emissions caused considering stochastic travel times. A Multi-Objective Water-Flow-like Algorithm (MOWFA) with two neighborhood operators for the local search and an analytic hierarchy process (AHP) to rank non-dominated solutions. In addition to a real-world case study, the algorithm was compared to the meta-heuristics MOICA and MOSA based on error rate (ER), spacing metric (SM), and maximum spread (MS). The evaluation of the results showed that the MOWFA performed better than the other two meta-heuristics. An overview of the waste management papers is presented in Table 6.

4.2 Disaster relief

Pre- and post-disaster decisions are mainly concerned with designing a relief network and determining efficient routes to deliver relief supplies or the evacuation of injured people or people at risk. Disasters cause severe disruptions to infrastructure, safety stocks of necessary supplies, and the availability of rescue and relief personnel. Furthermore, any relief response must be rapid as the likelihood of survival decreases significantly after 72 hours in case of a severe disaster (Zhong et al. 2020). In addition, often, the occurrence of disasters and their severity can not be determined to an exact certainty. Several of such factors are considered when modelling these decision problems in the papers reviewed.

In studying disaster relief, Rath and Gutjahr (2014) developed a three-objective warehouse location-routing model which minimizes strategic costs such as facility costs and operational costs as well as it maximizes covered demand. The ϵ -constraint

Table 6 Classification of waste management papers

Paper	Objective function	Environment	Time horizon	Model	Solution approach	Validation method
Ghezvati and Morakabatchian (2015)	Multi-objective	Deterministic	Static	MIP	Conversion to one objective	Case study
Zhao and Verter (2015)	Bi-objective	Deterministic	Static	MIP	Weighted goal programming	Case study
Rabbani et al. (2017)	Bi-objective	Deterministic	Static	MIP	NSGA-II	Numerical experiment
Farrokhi-Asl et al. (2017)	Bi-objective	Deterministic	Static	MIP	NSGA-II, MOPSO	Case study
Zhao and Ke (2017)	Bi-objective	Deterministic	Static	MIP	TOPSIS	Case study, Numerical experiment
Farrokhi-Asl et al. (2020)	Multi-objective	Deterministic	Static	MIP	MOHCGA	Numerical experiment
Rabbani et al. (2018a)	Multi-objective	Deterministic	Static	MIP	NSGA-II, MOPSO	Numerical experiment
Aka and Akyüz (2018)	Bi-objective	Deterministic	Static	MIP	Fuzzy goal programming	Case study
Rabbani et al. (2018b)	Bi-objective	Deterministic	Static	MIP	NSGA-II	Numerical experiment
Rabbani et al. (2019)	Multi-objective	Stochastic	Multi-period	NL-MIP	Simheuristic (NSGA-II + Monte Carlo)	Numerical experiment
Hu et al. (2019)	Multi-objective	Deterministic	Static	MIP	AWGA	Case study
Jamali (2019)	Bi-objective	Deterministic	Static	MIP	NSGA-II	Case study
Nikzamid and Baradaran (2020)	Bi-objective	Stochastic	Static	NL-MIP	MOWFA	Case study, Numerical experiment
Rabbani et al. (2020)	Bi-objective	Deterministic	Static	MIP	ϵ -constraint	Case study

method was proposed as well as a metaheuristic approach, based on the MIP formulation of the problem with a heuristically generated constraint pool.

With the aim to present an integrated logistics system in order to support an optimal pre-disaster plan and at the same time consider post-disaster decisions, Bozorgi-Amiri and Khorsi (2016) proposed a multi-objective dynamic stochastic programming model. Three objectives were minimized; unsatisfied demand, travel time, and total cost. Their aim was to determine the location of distribution centers and their respective required inventory and the routes and amount of supplies from distribution centers to affected areas. The model was solved as a single-objective, linear programming problem using the ϵ -constraint method. A specific case study is used to test the model.

Burkart et al. (2017), in contrast to the regular distance-based model, proposed a choice-based location model and introduced the element of beneficiary's choice. The authors reason that while modeling approaches to the covering tour problem are usually based on a hypothetical assignment of demand for relief goods to the nearest DC; beneficiaries need not necessarily follow that assumed assignment. Moreover, Competitive Location Models provide the tools to model choices in terms of competition between facilities. A bi-objective location-routing model to minimize total cost and unserved demand for opening distribution centers and deciding the routing of relief goods was proposed. The model's focus is the optimal location for distribution centers and relief delivery tours in drought disasters. Three different solution approaches were applied; the ϵ -constraint method, a brute-force complete enumeration procedure, and NSGA-II. The algorithms were evaluated based on real-world instances from Mozambique. While the Pareto front could be determined exactly for small instances by the ϵ -constraint method, the NSGA-II was implemented for larger and more realistic instances.

Genetic algorithms compose the overwhelming majority of solution methods used in papers concerning disaster relief. In an attempt to increase efficiency in a post-earthquake logistics system Li et al. (2014a) formulated a bi-objective dynamic location-routing model to determine the location of emergency service facilities and efficient routes to affected areas. The aim was to minimize total cost and total time. A meta-heuristic that incorporates a hybrid multi-objective genetic algorithm was proposed to solve the model. A numerical example indicated that the proposed model and its heuristic solution method were computationally affordable.

An integrated model which considered shelter location and routing, both for public and individual traffic simultaneously, in case of evacuation, was proposed by Goerigk et al. (2014). The authors present a multi-criteria MIP problem that minimizes total time, risk exposure of evacuees, and the number of shelters used. Private traffic was modeled as a dynamic network flow, while public traffic as a dynamic multi-commodity network flow. NSGA-II was used to solve the problem, and real-world evacuation instances to evaluate its performance. The first instance regarded a bomb threat in Kaiserslautern, Germany, and consisted of a graph of 13,284 nodes and 32,463 arcs. The other instance concerned the evacuation after an earthquake in the city of Nice with a graph consisting of 6237 nodes and 13,209 arcs. The authors discussed the impact of the data aggregation on the solution and the trade-off between finer granulation and smaller computations times.

Wang et al. (2014) presented a non-linear integer open tour location-routing problem which minimized total cost and travel time while maximized the reliability of the routes in post-earthquake situations. Two algorithms were tested and compared, NSGA-II and NSDE, based on a case study of the Great Sichuan Earthquake in China and five generated test instances. The NSDE algorithm obtained solutions with larger diversity than the NSGA-II. On the other hand, the approximate Pareto optimal solutions generated by the NSGA-II dominated almost all solutions produced by the NSDE. Furthermore, the results of the NSGA-II algorithm for the generated test instances were obtained faster and significantly outperformed the NSDE with respect to quality.

Nedjati et al. (2017) also considered post-earthquake situations and focused on service time restrictions, replenishment at intermediate depots, as well as customer mobility in predefined walking distance when stating the covering tour location routing problem. They formulated a bi-objective MIP model which minimizes the unserved demand and the total waiting time. A distinction was made between routes and trips, where routes connect two depots, while a trip is the sequence of the routes belonging to a vehicle. Vehicles do also remain in service up to a time limit and can, during that time, reload at any established depot. Furthermore, nodes were grouped to form in-tour, out-tour, and lost demand nodes. In-tour nodes are served within the tour, while out-tours are those nodes that are not included in the route but have an in-tour node within their walking distance and must thus be allocated to the nearest in-tour node. The NSGA-II algorithm with two distinct improvements, 2n Improvement, and First Front Improvement, was proposed as solution procedures. The results for 36 randomly generated test instances were analyzed in terms of QM, quantity, DM, CPU time, and spread of Pareto front solutions. The authors conclude that the NSGA-II-FFI performed better than the NSGA-II-2NI except for the computational time.

Further examples of post-disaster relief include Beiki et al. (2020) who presented a bi-objective MIP model minimizing cost and the maximum unserved demand. They emphasized issues associated with post-disaster decisions such as the location of relief facilities, allocation of resources, distribution of goods, and the transfer of survivors to treatment facilities. A real-life case study in Iran was solved. The ϵ -constraint method was used to solve the problem and NSGA-II and MOPSO. The two metaheuristics were evaluated based on DM, spread of non-dominated solutions (SNS), data envelopment analysis (DEA), percentage of domination (POD), and CPU time. The authors concluded that the NSGA-II was the most efficient of the two, highly outperforming the MOPSO.

Adrang et al. (2020) studied support efforts after a disaster in urban areas. Their model, a bi-objective MIP, optimizing cost and time, took into consideration both ambulances and helicopters as well as two groups of patients based on the severity of the injury. The model was solved using the ϵ -constraint method based on randomly generated instances. The authors also discussed sensitivity analysis based on the demand parameter, i.e., changes in injured people in each group and its effect on the objectives.

Vahdani et al. (2018) considered emergency roadway repair and developed a multi-objective, multi-commodity, and multi-period model for the distribution of

relief after earthquakes. It is an open tour model, i.e. vehicles do not need to return to their origin after the proposed route, with split deliveries. A non-linear integer program (NL-IP) seeks to minimize both total cost and travel time and maximize the reliability of the routes. Two meta-heuristic algorithms, NSGA-II and MOPSO, were proposed to solve the problem. The two algorithms were compared on several test instances with respect to the number of POS, DM, SM, MID, and CPU time. The NSGA-II algorithm was superior with respect to the SM, while MOPSO performed better in terms of DM, MID, and POS.

Zhong et al. (2020) presented a bi-objective NL-MIP risk-averse optimization model with stochastic demand. It included conditional value at risk with regret (CVaR-R), defined as the expected regret of the worst-case scenario. The proposed objectives are the CVaR-R of the waiting time and the CVaR-R of the system cost. The model was linearized using the big-M method. NSGA-II was used to find the Pareto front, while the Nash bargaining solution guides the decision-maker to select the final solution from the Pareto front based on a distance function. Numerical examples were designed based on Solomon's VRPTW benchmark instance RC208. The results demonstrated the trade-off between the waiting time and system cost and the effects of various parameters, including the confidence level and distance parameter, on the solution.

Chang et al. (2017) presented a three-objective NL-MIP model in which half-time windows are considered. The goal was to minimize total cost and maximize the minimum material satisfaction rates of affected areas and transport capacities of the worst path. In addition, uncertain demand and transportation velocities were assumed, and robust optimization was used to deal with these uncertainties. A genetic algorithm was used to solve the problem, and experimental results confirmed the efficiency and stability of the algorithm.

Zhang et al. (2018) presented a multi-objective MIP model for emergency response considering uncertainty and the minimization of the maximum travel time, emergency relief costs, and CO₂ emissions. The authors utilized the main-objective method, taking the maximum travel time as the main objective and using chance constraint on the other two objectives. A hybrid algorithm that integrates uncertainty simulation and a genetic algorithm was designed. Uncertainty simulation was first applied to simulate the inverse uncertainty distribution and uncertainty measure with uncertainty variables. Then, uncertainty simulation was integrated into the GA to produce a hybrid intelligent algorithm. The robustness and efficiency of the model are investigated through numerical examples.

Mansoori et al. (2020) presented a rescue-relief bi-objective MIP model minimizing the number of injured and homeless people not being transferred to a hospital and the total shortages of three different relief commodities. They considered demand and travel times as uncertain parameters and developed approaches to deal with such uncertainty. Robust optimization with ellipsoidal uncertainty and robust optimization with box and polyhedral uncertainty sets. A case study in Iran was conducted and a sensitivity analysis of both deterministic and robust models. The authors concluded that robust models resulted in more conservative solutions in all cases and that the box and polyhedral sets outperformed the ellipsoidal.

Adarang et al. (2020) focused on demand uncertainty in relief planning for urban disasters. Injured people can be relieved either by helicopter or ambulance based on the severity of their injury. A robust LRP was proposed where decisions in the first phase were made regarding the optimal location of facilities and in the second phase the optimal routes for transferring patients. Two objectives were considered total cost and relief time. An SFLA algorithm was developed to solve the problem. The solution was compared to the ϵ -constraint method for small and medium-sized test instances and to an NSGA-II algorithm for larger instances. Even if the NSGA-II was faster, the SFLA performed better; it covered a wider range of solutions with better quality and generated a more uniform front.

Wei et al. (2020) aimed to design a system to delivery supplies to affected areas after disasters. Every affected area had a corresponding soft time window, and two objectives were optimized; total operational cost and the penalty for not meeting the time window. The authors developed a hybrid ant colony optimization (ACO) algorithm using particles as operators. This allowed for a more comprehensive search in finding the optimal locations of depots and assigning areas to them; the ants could then find effective and balanced vehicle routes. The algorithm was compared to PAO, ACO, and an H-GA. The results showed that the proposed algorithm outperformed the others with respect to both computational efficiency and solution quality.

Considering the fairness perspective Liu et al. (2019) presented an overall plan for fair allocation and distribution of relief. The lexicographic order object method was used to develop a three objective MIP problem considering urgent time windows. The objectives were to minimize the maximum loss of demand nodes, minimize the total loss of all nodes, and minimize the maximum time required for demand nodes to receive relief. A hybrid heuristic algorithm (HHA) was developed, which combined a greedy algorithm with an ACO algorithm using a hierarchical sequence method. The feasibility and validity of the HHA algorithm was demonstrated by the study of camp distribution on the first day after the Wenchuan earthquake in China.

Shen et al. (2019) proposed a fuzzy low-carbon open tour MIP problem for emergency logistics that sought to minimize delivery time, total cost, and CO_2 emissions. A triangular fuzzy function was used to deal with the unpredictability of demand of the affected areas, and a hybrid two-stage particle swarm-tabu search algorithm was proposed. In the first stage, PSO is used to find a partial solution, while in the second stage, tabu search is applied to obtain a global solution. An example of a post-earthquake rescue was used to validate the established problem.

Veysmoradi et al. (2018) present a NL-MIP open tour location routing model which considered both terrestrial and aerial transportation networks simultaneously for the relief from distribution centers to affected areas. The model minimizes the total cost, maximum travel time, and maximizes the minimum reliability of the routes. The robust optimization method provided by Ben-Tal and El Ghaoui (2009) was applied to deal with uncertainties in some model parameters, and the fuzzy multi-objective programming proposed by Torabi and Hassini (2008) was used to solve the multi-objective problem. A case study of the East Azarbaijan earthquake in

Iran was presented, and the certainty and uncertainty results were compared to each other. Table 7 presents an overview of the classified disaster relief papers.

4.3 Perishable supply chains

Food supply chains and supply chains for perishable products are, to a large extent, part of the class of cold supply chains, i.e. chains that utilize low-temperature transportations. A perishable product can be described as one that during its handling, its quality or quantity decrease considerably, its value decreases as a function of time or if its reduced functionality results in dangerous consequences. Food, medicine, and chemicals are thus typical perishable products. As a consequence of these special characteristics, supply chains for perishable products are complicated, time-sensitive, and dynamic. In its simplest form, the bi- and multi-objective location-routing problem included in this review aim to locate various distribution centers (DCs) and design efficient routes to customers from these locations. In some cases, the supply chain is extended with another echelon, including plants or suppliers. Only one of the reviewed papers considers a three-echelon supply chain. All papers consider cost as one of the objectives. A second objective is set up to minimize some kind of undesirability. As cold chain logistics use low-temperature transportations in order to preserve the quality of the products, these vehicles consume more fuel and thereby emit more greenhouse gases (Leng et al. 2020b). Many papers focus on minimizing the environmental impact while others focus on the quality of the product itself and minimize the undesirability in terms of waiting time or distribution time or the damage that may occur to the products. Only two papers did also consider the maximization of certain social factors such as the utilization of personnel and customers or job creation.

Govindan et al. (2014) considered soft time-windows and sustainability aspects in a two-echelon supply chain. A MIP model was presented to minimize total cost and environmental impact. The authors propose a hybrid heuristic algorithm combining adapted multi-objective PSO and adapted variable neighborhood search (VNS) to solve the problem. The algorithm was compared to NREGA, MOGA, and NSDA-II based on 12 different test instances. It was concluded that the proposed algorithm outperformed the others in terms of DM, SNS, POD, whereas no conclusion could be made based on MID.

Validi et al. (2020) introduced a bi-objective AHP-integrated MIP model with a design of experiments-guided (DoE) meta-heuristic solution approach for a two-echelon dairy supply chain. To minimize total cost and CO₂, a two-phase solution method was used. Phase-1 finds the optimal set of open/closed plants and DCs as well as the optimal routing pattern connecting plants and DCs, and DCs to retailers. In the second phase, using the result from the first phase as input, the optimal routing in-between retailers was determined. DoE guided MOGA-II was used in the second phase while the TOPSIS method was used to analyze the feasible optimal solutions sets from the first and second phases.

Table 7 Classification of disaster relief papers

Paper	Objective function	Environment	Time horizon	Model	Solution approach	Validation method
Goerigk et al. (2014)	Multi-objective	Deterministic	Dynamic	MIP	Genetic Algorithm	Case study
Li et al. (2014a)	Bi-objective	Deterministic	Dynamic	MIP	H-GA	Numerical experiment
Rath and Gujjar (2014)	Multi-objective	Deterministic	Static	MIP	ϵ -constraint	Case study, Numerical experiment
Wang et al. (2014)	Multi-objective	Deterministic	Static	NL-IP	NSGA-II, NSDE	Case study, Numerical experiment
Bozorgi-Amiri and Khorsi (2016)	Multi-objective	Stochastic	Dynamic	MIP	ϵ -constraint	Case study
Burkart et al. (2017)	Bi-objective	Deterministic	Static	MIP	ϵ -constraint, brute force complete enumeration, NSGA-II	Case study, Numerical experiment
Chang et al. (2017)	Multi-objective	Stochastic	Static	NL-MIP	Genetic Algorithm	Numerical experiment
Nedjati et al. (2017)	Bi-objective	Deterministic	Static	MIP	NSGA-II, NSGA-II ₂ NI, NSGA-II-FFI	Numerical experiment
Vahdani et al. (2018)	Multi-objective	Deterministic	Dynamic	NL-MIP	NSGA-II, MOPSO	Numerical experiment
Veysmoradi et al. (2018)	Multi-objective	Stochastic	Static	NL-MIP	Fuzzy Programming	Case study, Numerical experiment
Zhang et al. (2018)	Multi-objective	Stochastic	Static	MIP	H-GA	Numerical experiment
Liu et al. (2019)	Multi-objective	Deterministic	Static	MIP	Hybrid heuristic	Case study
Shen et al. (2019)	Multi-objective	Stochastic	Static	Fuzzy MIP	Hybrid PSO-TS	Numerical experiment
Adarang et al. (2020)	Bi-objective	Stochastic	Static	MIP	MOSFLA	Numerical experiment
Adrang et al. (2020)	Bi-objective	Deterministic	Static	MIP	ϵ -constraint	Numerical experiment
Beiki et al. (2020)	Bi-objective	Deterministic	Dynamic	MIP	GAMS, NSGA-II, MOPSO	Case study
Mansoori et al. (2020)	Bi-objective	Stochastic	Dynamic	MIP	Weighted method	Case study
Wei et al. (2020)	Bi-objective	Deterministic	Static	MIP	PA-ACO	Case study
Zhong et al. (2020)	Bi-objective	Stochastic	Static	NL-MIP	H-GA, NSGA-II	Numerical experiment

The same model was considered by Validi et al. (2021) which employed two GA-based and one PS-based metaheuristic, namely NSGA-II, MOGA-II, and MOPSO. These algorithms were also two-phased and DoE-guided. It was found that the NSGA-II algorithm was the more efficient when compared to MOGA-II and MOPSO. In addition, scenario analysis was performed on the results. Different scenarios showed the amount of CO₂ emitted and the total costs from a closed route if forced to be open.

Navazi et al. (2019) considered simultaneous pick-up and delivery in a three echelon supply chain minimizing the total cost, environmental impact, and maximizing the utility of personnel and customers. NSGA-II and MOPSO were proposed to solve the model, and were compared and evaluated based on ten moderate and large-scale instances. It was concluded that even if the MOPSO was faster than the NSGA-II algorithm, NSGA-II achieved more Pareto solutions of higher quality.

Economic, ecologic, and social aspects were also considered by Biuki et al. (2020) which integrated inventory decisions in their model aiming to minimize total cost and environmental impact caused by greenhouse gas emissions while maximizing job creation. The authors emphasized several real-life aspects such as allowing backlogging, discount offers in procurement, demand uncertainty and multi-period, and a multi-product setting for a three echelon supply chain. A two-phase solution strategy was proposed in which supplier selection is performed in the first phase applying the PROMETHEE method. The model was then converted to a crisp single objective version. Two-hybrid metaheuristic algorithms based on parallel and serial combinations of GA and PSO were constructed to solve the problem. Results obtained from a set of small, medium and large size test instances showed the superiority of the parallel hybridization over the serial.

Liu et al. (2021) sought to minimize total cost and environmental impact for mixed fleets and mixed satellites for a sustainable E-grocery distribution network consisting of vans, robots, and parcel lockers. The authors proposed a hybrid immune algorithm (HIA) combining an immune algorithm with a genetic search technique. Furthermore, the algorithm incorporated two improvement steps, vaccination, and immunization, where vaccination aims to improve fitness while immunization aims to prevent population degradation. Based on 12 generated test instances, the algorithm was compared to NSGA-II and MHPV. The results showed that even if no priority could be established between the algorithms based on MID, the HIA significantly outperformed NSGA-II and MHPV considering SNS, DM, and rate of achievement (RAS).

Turning to other factors such as time and quality of the products, Li et al. (2019) focused on big event logistics and the minimization total delivery time in addition to the total cost. They considered several aspects of the supply chain, such as multi-commodity, combined storage strategy, multi-vehicle, and multi-point distribution in a single echelon supply chain. As part of the solution method, the objective coefficients were weighted according to the sensitivity of different perishable commodities to time and cost. Furthermore, the model was strengthened by reducing the number of binary variables, increasing the search space limitation, and performing clustering analysis. The resulting problem was solved with the CPLEX solver with data from a real-life case study based on the Beijing 2022 Winter Olympics.

Leng et al. (2020b) proposed a bi-objective model with the aim to minimize total costs, including fuel and carbon emissions cost, and product damage for a cold chain logistic system. Several types of commodities were considered, such as general, refrigerated, and frozen. They proposed and evaluated a multi-objective hyper-heuristic (MOHH) combining seven different multi-objective evolutionary algorithms (MOEA). Furthermore, they examined the efficiency of a proposed delivery strategy and performed an extensive analysis of problem parameters such as depot capacity, hard time windows, and fleet composition. Leng et al. (2020a) proposed a bi-objective MIP model for cold chain and low carbon supply chain and employed six well-known MOEAs to solve the problem. Total cost and total waiting time was considered as well as simultaneously pick-up and delivery, heterogeneous vehicle fleet, several types of cargo, and hard time windows. Moreover, the first improvement and best improvement search mechanisms were developed. Experiments were conducted to analyze factors such as depot capacity and cost, crowding distance, and traveling speed and their effects on the solution quality. The authors concluded that MOEAs using the first improvement performed better than the best improvement. A strategy that mixes original and refrigerated cargo outperformed the strategy in which cargos must be delivered separately.

Wang et al. (2020) developed a bi-objective mathematical model for cold chain logistics distribution optimizing total cost, including time window penalty cost and distribution time. A hyper-heuristic (HH) optimization framework is proposed, which can be described as a heuristic used to choose a suitable solution heuristic. Four different selection strategies and acceptance criteria were used for this purpose. Comparison to NSGA-II validated the efficiency of the hyper-heuristic and solving cold chain instances validated the practicality of the algorithm.

Leng et al. (2020c) presented a model very similar to that of Leng et al. (2020a) in which they considered hard time windows, simultaneous pick-up and delivery, and a mixed delivery strategy to satisfy customer demand in general, as well as refrigerated and frozen products. The model aims to minimize total cost and the total quality decay of the perishable food. Considering decomposition, the authors propose a MOHH framework to solve the model. Extensive experiments were carried out to test the effect of parameters and different features. Comparative results were also performed in which the MOHH was compared to NSGA-II, SPEA2, GrEA, and IBEA. The authors concluded that the proposed algorithm was efficient and that it provided sufficiently good Pareto fronts.

Qiu et al. (2020) proposed a multi-objective MIP model to minimize total cost, greenhouse gas emission, waiting time, and quality degradation for a cold supply chain considering mixed cargos, heterogeneous vehicle fleet, time-windows, and simultaneous pick-up and deliveries. They presented a framework that combines the evolutionary algorithms NSGA-II, SPEA2, and IBEA. Furthermore, they developed a large composite neighborhood formed by 16 operators and grouped them into three modules. Extensive tests were performed, and the authors discussed the implications of the results related to delivery strategies, depots cost, time windows, and fleet composition.

Another side of perishable supply chains is related to health care services such as blood collection and pharmaceutical distribution. Not many papers have been

published on this particular subject which also fall within the scope of the review. However, the remaining papers presented in this section considered distribution of pharmaceutical products. Nasrollahi et al. (2018) studied a two-echelon pharmaceutical distribution network and provided a computational method to measure transport-related carbon emissions. The aim was to minimize the total costs and fuel consumption of a heterogeneous fleet of vehicles. The demand for each product was assumed to be a trapezoidal fuzzy number. Multi-objective NPGA was used to solve the MIP model, while PROMETHEE-II determined the best solution on the Pareto front. M-NPGA was compared to both NSGA-II and MOPSO based on test instances, and the authors concluded that the proposed approach performed better than NSGA-II and MOPSO even if the NSGA-II needed lesser time.

Zandkarimkhani et al. (2020a) presented a bi-objective MIP model, which in addition to location-routing, also considered inventory decisions, soft- and hard time windows, and stochastic demand. The objectives were to minimize total cost and lost demand in a two-echelon supply chain. A novel chance-constrained fuzzy goal programming approach was developed to solve the problem with probabilistic constraints. This allows for the decision-makers to incorporate their preferences in the model. Data from an MS disease drug distribution network in Tehran was used to validate the model. A significant contribution of the study was the realization of a humanitarian supply chain, where the lost demand is zero, can be designed even if this is more costly. The proposed model does also calculate that extra cost. Therefore, decision makers can estimate the required budget for designing a humanitarian supply chain.

Lastly, Ahlaqqach et al. (2020) presented a MIP model for a closed-loop supply chain network for supply and recovery of end-of-life pharmaceutical products. The authors considered time windows and inventory decisions in the multi-product, multi-echelon, and multi-period supply chain. The aim was to maximize profits, i.e., sales minus total costs, maximize job creation while minimizing the risk along the routes. A real-world case was presented and solved optimally for small-sized instances as three separate single-objective problems. The authors conclude that the experimentation with small instances gave a good result in a reasonable time. Table 8 presents the classified papers for perishable supply chains.

4.4 Inventory

This section discusses contributions that focus on location considering inventory and routing decisions. Although applications of this type have gained increased attention by the research community in recent years the number of publications still remains low. In the papers reviewed, in addition to cost, objectives modelled include coverage, risks, and environmental impact. Most of these works are concerned with stochastic and dynamic versions of the problem.

Tang et al. (2016) introduced the concept of consumer environmental behaviors (CEBs) in sustainable supply chain and location-routing inventory decisions. The assumption was that consumers are willing to pay a premium for low carbon

Table 8 Classification of papers in perishable supply chain

Paper	Objective function	Environment	Time horizon	Model	Solution approach	Validation method
Govindan et al. (2014)	Bi-objective	Deterministic	Dynamic	MIP	MHPV	Numerical experiment
Nasrollahi et al. (2018)	Bi-objective	Stochastic	Dynamic	MIP	M-NRGA, PROMETHEE-II	Case study
Validi et al. (2020)	Bi-objective	Deterministic	Static	MIP	MOGA-II	Case study
Li et al. (2019)	Bi-objective	Deterministic	Static	MIP	Weighting method	Case study
Navazi et al. (2019)	Multi-objective	Deterministic	Dynamic	MIP	NSGA-II, MOPSO	Numerical experiment
Ahlaqqach et al. (2020)	Multi-objective	Deterministic	Dynamic	MIP	Conversion to single objectives	Case study
Biuki et al. (2020)	Multi-objective	Stochastic	Dynamic	MIP	H-GA-PSO	Numerical experiment
Leng et al. (2020b)	Bi-objective	Deterministic	Static	MIP	MOHH	Numerical experiment
Leng et al. (2020c)	Bi-objective	Deterministic	Static	MIP	MOHH	Numerical experiment
Leng et al. (2020a)	Bi-objective	Deterministic	Static	MIP	MOHH	Numerical experiment
Liu et al. (2021)	Bi-objective	Deterministic	Static	MIP	Hybrid immune algorithm	Numerical experiment
Qiu et al. (2020)	Multi-objective	Deterministic	Static	MIP	MOHH	Numerical experiment
Validi et al. (2021)	Bi-objective	Deterministic	Static	MIP	NSGA-II, MOGA-II, MOPSO	Case study
Wang et al. (2020)	Bi-objective	Deterministic	Static	MIP	MOHH	Case study
Zandkarimkhani et al. (2020a)	Bi-objective	Stochastic	Dynamic	MIP	Chance constrained fuzzy goal programming	Case study

emission products. A MIP model minimizing total cost and CO_2 was presented and solved using a MOPSO algorithm for real-world data. The same technique was used to derive revenue curves from different carbon emissions. In analyzing the sensitivity of the case study, the author could conclude that more positive CEBs result in higher demand and revenue. In addition, the pricing of low carbon operations is critical, and companies, therefore, should make marketing efforts to strengthen consumers' environmental preferences.

Lerhlaly et al. (2016) do also minimize total cost and CO_2 emissions and consider a heterogeneous fleet of vehicles and multi-period decisions for an location routing inventory model for Hazmat. An LP model is presented and solved using the lexicographic weighting method with predefined priority orders, in which four weights are compared to determine the best CO_2 emissions objective.

Fallah-Tafti and Vahdatzad (2018) studied the "cash in transit" sector in Iran, more specifically, cash delivered from the central bank to ATMs routed through logistics centers. They presented a bi-objective MIP model minimizing total cost and transportation risk considering multiple time periods and time windows. The model is solved using the AUGMECON2 method and validated with real-world data. A similar problem was studied by Fallah-tafti et al. (2019) who proposed a crisp bi-objective MIP, minimizing risk and total cost, for refilling ATMs in "cash in transit" sector. Several real-life assumptions were considered, such as multiple periods, capacitated facilities and vehicles, time windows, and uncertain demand. The model was validated in a real-world case utilizing the AUGMECON2 method.

For a closed-loop supply chain, Govindan et al. (2020) presented a two-stage model, whereas, in the first stage, suppliers are evaluated using a decision support system based on fuzzy analysis network process and fuzzy decision making trial and evaluation laboratory. In the second stage, a fuzzy bi-objective MIP model was presented for a closed five-level supply chain where routing was performed between distribution centers and customers. The model minimized the system's total costs, including greenhouse gas emissions and inventory shortage. The fuzzy approach proposed by Zimmermann (1978) and Lin (2012) was used to solve the model by GAMS/CPLEX, and the solution obtained for a real-world case was within a relative optimality gap of less than 5 percent. Similar work is also presented by Gholipour et al. (2020), in which total cost, including fuel costs, and shortages were minimized by utilizing the fuzzy membership function of Govindan et al. (2020) in order to deal with demand uncertainty. GAMS/CPLEX was used to validate the model, and sensitivity analysis was performed with respect to demand reduction and demand increase.

Papers presented so far in this group all focus on minimizing an undesirability objective and costs related to environmental or social factors, either explicitly or implicitly, as a part of the cost function. The rest of the papers are concerned with inventory decisions with focus on the time dimensions in addition to cost.

Momenikiyai et al. (2018) proposed a bi-objective MIP model considering heterogeneous vehicle fleet, soft time windows, and risk pooling, i.e., inventory aggregation to deal with demand uncertainty. The model aims to minimize total cost and the earliness and lateness of vehicles. 30 random test instances were generated and the metaheuristic algorithms NSGA-II, MOPSO, and PESA-II were proposed. The

Taguchi method was used, and the evaluation of the different algorithms was based on QM, SM, DM, and MID. Obtained results showed that the NSGA-II algorithm outperformed the other heuristics. Compared to the optimal solution of a small instance with two vehicles and distribution centers and six customers, the solution by the NSGA-II had a 6 percent optimality gap only for one objective.

Forouzanfar et al. (2018) presented a bi-objective, non-linear, multi-period integer program to minimize the system costs and the sum of maximum difference in arrival and departure time between plants and DCs. The ϵ -constraint method, NSGA-II, and MOPSO were all proposed to solve the problem. Solutions of the ϵ -constraint method were used to validate the results of NSGA-II and MOPSO for small instances, while for medium- and large-sized problems, the NSGA-II and MOPSO were compared with respect to NPS, MID, SM, and QM. Furthermore, to increase the efficiency of the algorithms, the Taguchi method was utilized to set some of the input parameters. Results on 27 randomly generated test instances demonstrated that MOPSO was superior with respect NPS and QM while NSGA-II outperformed MOPSO with respect to MID and SM.

Nekooghadrli et al. (2014) considered a multi-period and multi-product supply chain with stochastic demand and presented a bi-objective MIP model. In addition, probabilistic traveling times between customers were considered. The uncertain demand of the customers followed a normal distribution, and each distribution center held a particular safety stock. Total cost and the maximum delivery time were optimized, and MOICA was proposed to solve the problem. In order to validate the proposed algorithm, it was compared to NSGA-II, PAES, and MOPSA based on QM, SM, DM, and MID. The authors concluded that the proposed MOICA outperformed the other three algorithms. An overview of the surveyed inventory papers is presented in Table 9.

4.5 Other applications

This section reviews and discusses papers that did not fit exactly into one of the discussed application areas or that the sample was deemed too small to be reviewed of their own. In addition to ordinary product distribution, this section includes applications related to soft drink distribution, reverse logistics, postal services, and patrol coverage.

A bi-objective MIP model is proposed by Ghezavati and Beigi (2016) for a three echelon reverse supply chain minimizing total cost and total time. Furthermore, capacitated and heterogeneous vehicle fleets and soft time windows with associated penalty costs were considered. On several random test instances, the ϵ -constraint method is proposed for small and medium-sized problems. In contrast, the NSGA-II is proposed for larger problem instances to find the Pareto front.

To optimize an inter-province postal delivery system, Karimi and Setak (2018) introduced a bi-objective flow shipment scheduling hub LRP. The network is not fully interconnected, and the objectives were to minimize total cost, incorporate fixed establishing and variable routing costs, and maximize the delivery flow by the

Table 9 Classification of Inventory papers

Paper	Objective function	Environment	Time horizon	Model	Solution approach	Validation method
Nekooghadiri et al. (2014)	Bi-objective	Stochastic	Multi-period	MIP	MOICA, MOPSA, NSGA-II, PAES	Numerical experiment
Lerhlaly et al. (2016)	Bi-objective	Deterministic	Multi-period	MIP	Lexicographic weighting method	Numerical experiment
Tang et al. (2016)	Bi-objective	Deterministic	Static	MIP	MOPSO	Case study
Fallah-Tafti and Vahdatzad (2018)	Bi-objective	Deterministic	Multi-period	MIP	Augmecon2	Case study
Forouzanfar et al. (2018)	Bi-objective	Deterministic	Multi-period	NL-IP	NSGA-II, MOPSO	Numerical experiment
Momenikiyar et al. (2018)	Bi-objective	Stochastic	Static	MIP	NSGA-II, MOPSO, PESA-II	Numerical experiment
Fallah-tafti et al. (2019)	Bi-objective	Stochastic	Multi-period	Crisp MIP	Augmecon2	Case study
Gholipour et al. (2020)	Bi-objective	Stochastic	Multi-period	MIP	Gams,Cplex	Case study
Govindan et al. (2020)	Bi-objective	Stochastic	Static	MIP	Gams,Cplex	Case study

latest arrival time. Integer programming models are presented in which time is first assumed to be uncertain and modeled by the chance constraint method, and the flow is then considered uncertain. A number of valid inequalities and preprocessing were used together with both the ϵ -constraint and normalized weighted sum method to solve the problem. The authors state that using all preprocessing and valid inequalities, the computation time could be reduced to 89.34 percent compared to the base model.

Mamaghani and Davari (2020) considered a set of homogeneous vehicles for an LRP with simultaneous pick-up and delivery and time windows. A bi-objective MIP model was presented to minimize the total cost and time-windows violations. NSGA-II and NPGA were proposed to solve the problem, while the Taguchi method was applied for parameter tuning. Based on 45 benchmark instances, the algorithms were compared based on SM, DM, NPS, CPU-time, and MID. The result showed that while the NPGA outperformed NSGA-II based on DM, the NSGA-II was superior based on SM and CPU-time. However, the results were inconclusive and not statistically significant regarding NPS and MID.

A many-to-many hub LRP with hard time windows and simultaneous pick-up and delivery was studied by Basirati et al. (2020). A bi-objective MIP model was proposed to minimize the total costs of the system and the difference between the minimum and the maximum costs of vehicles allocated to each route, i.e., minimizing the imbalance in the distance traveled. The model was validated by solving small-sized instances based on data of road freight transport in Iran using the AUGMECON2 method and comparing those to a proposed MOICA algorithm. The results showed that the MOICA performed satisfactorily. Furthermore, the MOICA algorithm was compared to an NSGA-II algorithm for large instances based on QM, SM, DM, and MID metrics. The results showed that the MOICA performance was superior in finding high quality solutions in an acceptable computational time.

Leng et al. (2019a) studied the regional low-carbon LRP (RLCLRP) and accounted for simultaneous pick-ups and deliveries, hard time windows, and a heterogeneous vehicle fleet. In the RLCLRP, goods are to be picked up and delivered to customers from depots in a city located in nested zones with their speed limits. A bi-objective MIP model was presented to minimize the costs of the system, including depot and vehicle costs and travel costs which have been defined as fuel consumption and carbon emissions. The second objective was to minimize the vehicle waiting time. A HH is presented to solve the model, which utilizes a quantum-based approach for selecting the high-level strategy. Leng et al. (2019b) study the same problem but with the objectives to minimize the service duration time, client waiting time, and the total costs, including fuel consumption and carbon emissions. A MOHH was proposed to solve the problem with four selection strategies for the higher-level heuristics, three acceptance criteria, and three MOEAs as the pool for the lower-level heuristics. The results showed that the proposed algorithm could produce high-quality solutions for most instances.

Emphasizing distance minimization, Golmohammadi et al. (2016) utilized a MOICA to optimize storage location and vehicle routing, with the objectives to minimize total cost and the imbalanced distance traveled. For small, medium-sized, and large test instances, the MOICA was compared to NSGA-II and PAES based

on a QM and SM. The authors state that MOICA outperformed the other two algorithms in both matrices. Hadian et al. (2019) did also compare the MOICA algorithm to NSGA-II but in terms of QM and MID for a two-stage supply chain with a capacitated and homogeneous vehicle fleet. A bi-objective MIP model aims to minimize the system's total costs, and the difference in vehicle traveling distance was presented. In addition, several crossover and mutation strategies were adjusted using the response surface methodology. Based on 56 generated instances of small, medium, and large scales, the superiority of the MOICA algorithm over the NSGA-II, especially for large-sized instances, was demonstrated.

In recent years environmental objectives have gained increased attention from scholars. Even if not always explicitly, such objectives have been implicitly included in the cost functions, as, for instance by Leng et al. (2019a, 2019b) who have included fuel consumption and carbon emissions in their total cost function. Papers on multi-objective location-routing problems focusing explicitly on the environmental factors could be divided in two groups: minimizing fuel consumption and minimizing greenhouse gas emissions respectively. In most cases, however, these groups overlap.

Toro et al. (2017b) considered the green capacitated LRP with operational costs and total emissions, explicitly minimizing fuel consumption in the proposed bi-objective MIP. Furthermore, they presented a new set of constraints that maintain the connectivity requirements of the problem. Their work is extended by Toro et al. (2017a) which presents a Green Open tour LRP optimizing the same objectives as Toro et al. (2017b) and utilizing an emission factor model to calculate the fuel consumption assuming constant speed. Test instances adapted from Prins et al. (2007) were used in both studies to validate the models using the ϵ -constraint method. An interesting conclusion from both studies was that better fuel economy in the long term, and thus less emissions, can be achieved by using more vehicles. More vehicles that carry lesser loads and prioritize customers with higher demand first can perform shorter routes and are thus preferable from an environmental point of view in the long run.

Tajabadi and Kazemi (2016) presented a NL-IP model with three objectives; minimizing the total cost, maximizing demand served, and minimizing the pollution rate caused by transportation for a two-echelon supply chain. Two meta-heuristic algorithms, NSGA-II and NPGA, are developed to solve the problem, and the Taguchi method is used to set the values of the parameters. For six randomly generated test instances, the two algorithms are compared based on SM, DM, NPS, and CPU-time. The result showed that the NSGA-II outperformed the NPGA in DM and NPS, while NPGA was superior in CPU-time. However, no superiority between the algorithms could be established based on SM.

Rabbani et al. (2018c) compared the NSGA-II and MOPSO algorithms based on NPS, SM, DM, and CPU-time for the transportation LRP (TLRP), which could be described as an extension of a two-echelon location routing problem. For a set of homogeneous vehicles and soft time windows, the presented MIP model aims to minimize total costs, fuel consumption, and CO₂ emissions, as well as the workload balance of the drivers. Based on randomly generated test instances, the result

showed that the MOPSO algorithm was outperformed by the NSGA-II in all metrics but CPU time.

NSGA-II was compared to an NSGA-II algorithm combining tabu search based on MID and DM in Chen et al. (2018). The authors presented a bi-objective MIP model that minimizes the total costs and the CO₂ emissions caused. Full truckloads and split deliveries were allowed as well as that a truck can visit the same supplier logistic centers and plants multiple times. 36 randomly generated instances were used in the comparison. The result showed that the NSGA-II-TS was superior in both evaluation metrics on 34 out of 36 test instances and got a better value in at least one metric of the remaining two instances.

Tricoire and Parragh (2017) and Faraji and Afshar-Nadjafi (2018) both considered multi-period models. Tricoire and Parragh (2017) introduced the green city hub location routing problem (GCHLRP) in which, in addition to facility location decisions, fleet size and mixture were considered. The model aims to investigate the trade-off strategic cost and future operational emissions, and therefore the objectives of the bi-objective model were to minimize cost and CO₂ emissions. However, the cost does not include operational routing costs but only strategic costs incurred when establishing the infrastructure. A MIP model was presented, and a decomposition method was developed in which routes were first generated and then aggregated using a set covering model. Based on small instances, the approach was almost always able to find the Pareto-front, and in cases when it was not, the solutions were very close to the Pareto set.

Faraji and Afshar-Nadjafi (2018) proposed a bi-objective model minimizing total cost and greenhouse gas emissions. In addition to multiple time periods, the authors considered multiple depots, products, constraints of hard and soft time windows, and a heterogeneous set of vehicles. In addition, the fuzzy approach by Lei (2008) was applied to the model. A hybrid genetic algorithm integrating simulated annealing was proposed to solve the problem. The results on randomly generated small and medium-sized problems were compared to the optimal solutions obtained by GAMS with respect to computational time and quality. For small-sized problems, the solutions by the H-GA-SA algorithm had an optimality gap of 2 percent. The algorithm was able to find four of eight optimal solutions, with a runtime within 32 percent of that needed by the GAMS software. For medium-sized problems, the algorithm achieved an optimality gap of 8 percent within 23 percent of the GAMS runtime.

It can be argued that being eco-friendly in today's society is a necessity for organizations rather than a competitive advantage (Govindan et al. 2020). As the awareness of sustainable development increases, some scholars focus on other aspects of the triple bottom line, such as social factors. For instance, Zandkarimkhani et al. (2020b) proposed a two-phase approach that utilizes FAHP and FTOPSIS in the first phase to order location of facilities after social factors. The second phase consists of a bi-objective MIP model that considers heterogeneous and capacitated vehicles, split-delivery in a multi-echelon and multi-period supply chain. The aim was to minimize the total costs while maximizing social effects, and the model was validated through a case of a producer in the PET industry using CPLEX.

The total cost and workload balance of the routes was considered by Martinez-Salazar et al. (2014). They proposed a representation of the TLRP based on priorities, making it suitable for local search procedures and evolutionary algorithms and reducing the computational effort. Two solution approaches are developed based on local search, SSPMO and an evolutionary NSGA-II. Based on computational evaluations and by comparing to exact methods, the authors conclude that SSPMO achieved high-quality solutions while reducing CPU-time and by outperforming the NSGA-II on small instances. However, as the sizes of the instances increased, NSGA-II achieved better estimations of the Pareto front.

Similar work has been performed by Amini et al. (2020) who study the transportation location arc routing problem (TLARP) and presented a bi-objective MIP model which sought to minimize the total costs and the makespan. To solve the problem, the AUGMECON2 method was used. However, due to the problem's NP-hardness, NSGA-II in combination with multi-objective late acceptance hill-climbing algorithm (MOLAHC) and a local search procedure was also used, resulting in four meta-heuristics; NSGA-II, NSGA-II-LS, hybrid, and hybrid-LS. A response surface methodology was used to find suitable parameters for the metaheuristics. Based on 40 randomly generated test instances, it could be shown that the NSGA-II-LS performed better than the others while the hybrid-LS was the second-best. However, the hybrid-LS required significantly less computational time.

A large part of the papers addressing MO-LRP focus on minimizing undesirable objectives that can be conceived as interrelated, such are, for instance, cost and distance or cost and fuel consumption. However, some works focus on maximizing desirable objectives in which case the conflict of the objectives is intuitively more clear, for instance, cost and demand served or, in more general terms, cost and customer satisfaction. In such a work, Liu and Kachitvichyanukul (2015) presented a bi-objective MIP problem minimizing total cost and maximizing demand served. To solve the problem, an MOPSO was utilized on data sets from Prodhon (2010), modified to include capacity and number of vehicles. Furthermore, the authors proposed and utilized two different decoding methods of which the first one starts by first selecting the depot location and then the customer assignment and the route construction, while the second one first clusters the customers around one depot and subsequently performs the assignment. The authors conclude that the MOPSO framework could produce high-quality Pareto fronts for most instances, independently of decoding method, although the quality may differ between the two methods.

Li and Keskin (2014b) aimed towards an effective coverage of highway patrol and dynamic patrol routing. They proposed a multi-period dynamic LRP, and assumed that troopers start their routes at temporary stations, patrol specific locations with previous high crash frequencies, and return to the same or another temporary station; it is a open tour routing in that sense. A MIP model was presented, which determines the number of troopers, routes, location of stations, and where to start and end the routes. The objectives were to minimize total cost while maximizing the coverage. In order to solve the problem, the ϵ -constraint method was used in addition to a custom-built heuristic algorithm that utilizes the hierarchical structure of the problem based on neighborhood searches embedded within simulated annealing. The authors concluded

that by allowing routes to start from multiple locations, the coverage was improved up to 12 percent compared to the single depot coverage model.

Wang et al. (2018a) presented a bi-objective LRP model with simultaneous pick-up and delivery as well as fuzzy time windows for an urban distribution network. In addition, two delivery modes were considered as home delivery and customer pick-up. They proposed an MIP minimizing total cost and maximizing customer satisfaction by a trapezoidal fuzzy membership function for customers served within a specific time. A tabu search heuristic of three phases, initialization, location, and routing, was used to solve the presented problem and compared to a simulated annealing algorithm based on a set of 15 generated test instances. By evaluating the service mode and the effects of time windows, the authors concluded that the tabu search heuristic showed significant improvement for most test instances compared to the simulated annealing algorithm with better non-dominated solutions.

Wang et al. (2018b) considered hard time windows, and presented a bi-objective MIP model to minimize total cost and maximize customer satisfaction measured as vehicle punctuality. The authors use data mining to group customers in similar clusters and utilize the K-mean clustering algorithm to provide initial populations. These populations are used in a modified NSGA-II algorithm that includes scanning the nodes' position in the initial population generation and a partially mapped crossover operator. The model and solution approach was validated by comparison to MOGA and MOPSO on a real-world instance of a beverage distribution network in Chongqing, China.

Lastly, Shahsavari-Pour et al. (2020) proposed a fuzzy bi-objective MIP minimizing the total cost and maximizing reliability, whereas the reliability was considered as the probability of failure in either depot, vehicles, or routes. The second objective is thus, expressed as the minimization of such probability. Small instances are solved using the ϵ -constraint method. In contrast, larger instances were solved utilizing the NSGA-II and a developed firefly meta heuristic with non dominated sorting method in combination with a new method for calculating distances between fireflies (NSDFA). The authors concluded that the NSDFA performed better than the NSGA-II in small to medium-sized instances, while the NSGA-II is better suited for larger instances. Table 10 presents an overview of the papers discussed above.

5 Conclusions

In this paper, an extensive overview is provided of the field of bi- and multi-objective location routing problems. The paper reviews 80 journal articles published between 2014 and 2020. Included papers are classified based on several different factors covering model assumptions and characteristics, objectives, and solution approaches and a literature review is provided based on the contributions various application areas.

Although the present survey considers only multi-objective problems some of the research suggestions proposed by previous surveys on LRPs do apply. Referring in particular to the suggestions proposed by Nagy and Salhi (2007) and subsequent

Table 10 Classification of papers in other applications

Paper	Objective function	Environment	Time horizon	Model	Solution approach	Validation method
Martinez-Salazar et al. (2014)	Bi-objective	Deterministic	Static	MIP	SPPMO, NSGA-II	Numerical experiment
Li and Keskin (2014b)	Bi-objective	Deterministic	Dynamic	MIP	ϵ -constraint, developed heuristic	Case study
Liu and Kachitvichyanukul (2015)	Bi-objective	Deterministic	Static	MIP	MOPSO	Numerical experiment
Ghezavati and Beigi (2016)	Bi-objective	Deterministic	Static	MIP	NSGA-II, ϵ -constraint	Numerical experiment
Golmohammadi et al. (2016)	Bi-objective	Deterministic	Static	MIP	MOICA	Numerical experiment
Tajabadi and Kazemi (2016)	Multi-objective	Deterministic	Static	NL-MIP	NSGA-II, NPGA	Numerical experiment
Toro et al. (2017b)	Bi-objective	Deterministic	Static	MIP	ϵ -constraint	Numerical experiment
Toro et al. (2017a)	Bi-objective	Deterministic	Static	MIP	ϵ -constraint	Numerical experiment
Tricoire and Parragh (2017)	Bi-objective	Deterministic	Dynamic	MIP	Decomposition set covering	Case study
Chen et al. (2018)	Bi-objective	Deterministic	Static	MIP	NSGA-II-TS	Numerical experiment
Faraji and Afshar-Nadjafi (2018)	Bi-objective	Deterministic	Dynamic	MIP	H-GA-SA	Numerical experiment
Karimi and Setak (2018)	Bi-objective	Stochastic	Static	MIP	ϵ -constraint, Normalized weighted sum	Numerical experiment
Rabbani et al. (2018c)	Multi-objective	Deterministic	Static	MIP	NSGA-II, MOPSO	Numerical experiment
Wang et al. (2018b)	Bi-objective	Stochastic	Static	MIP	M-NSGA-II	Case study
Wang et al. (2018a)	Bi-objective	Deterministic	Static	MIP	Tabu Search	Numerical experiment
Amini et al. (2020)	Bi-objective	Deterministic	Static	MIP	AUMECON2, NSGA-II, MOLAHIC	Numerical experiment
Basirati et al. (2020)	Bi-objective	Deterministic	Static	MIP	AUGMECON2, MOICA, NSGA-II	Case study, Numerical experiment
Hadian et al. (2019)	Bi-objective	Deterministic	Static	MIP	MOCIA, NSGA-II	Numerical experiment
Leng et al. (2019a)	Bi-objective	Deterministic	Static	MIP	QS-MOHH	Numerical experiment
Leng et al. (2019b)	Multi-objective	Deterministic	Static	MIP	MOHH	Numerical experiment
Mamaghani and Davari (2020)	Bi-objective	Deterministic	Dynamic	MIP	NSGA-II, NPGA	Numerical experiment
Shahsavari-Pour et al. (2020)	Bi-objective	Stochastic	Static	MIP	ϵ -constraint, NSGA-II, MOFA	Numerical experiment
Zandkarimkhani et al. (2020b)	Bi-objective	Deterministic	Dynamic	MIP	FAHP, FTOPSIS, CPLEX	Case study

discussions on these by Drexl and Schneider (2015) and Prodhon and Prins (2014) we can conclude that some progress has been made with regard to several aspects:

- *Dynamic and stochastic problems* have previously been scarce among the contributions to the field. However, although the majority of the works are still deterministic and static, such problems are gaining increased attention.
- *Integrated problems in logistics* where other aspects of logistics are considered in combination with location-routing have also been suggested as an interesting research avenue. Drexl and Schneider (2015) concluded that integrated problems did attract more attention however, that the topic still required further research. In the case of multi-objective LRPs we can conclude that this topic has received considerable attention since applications such as disaster relief, waste management, or perishable supply chains compose a sizable part of the contributions of this survey.

However, there are research topics suggested in previous reviews that attracted less attention. The design of exact methods which exploit the problem structure, and the development of unified heuristics to avoid the proliferation of very similar variants are two suggestions by Prodhon and Prins (2014) which are still very much valid.

With regard to the present survey several conclusions can be drawn. The fact that many of the included papers are case studies, using real-world data to validate the model, demonstrate the practical importance of the problem. Yet, the field is somewhat unexplored and most papers deal with basic variants of the problem. Although, some real-life aspects such as time windows and capacitated facilities are considered in many contributions, there are only few papers which present innovative modeling approaches. Furthermore, in case of multiple echelons, routing is mostly conducted only in the last stage. A possible direction for future research is therefore on multi-level LRPs.

A large number of the papers have been focused on the application of nature-inspired algorithmic approaches where the NSGA-II is the most popular followed by PSO. The focus of algorithmic development and the limited scope of exact solution methods used in cited papers underline the complexity of the presented problems. Thus, the development of exact methods and the unification of heuristics, as previously indicated, still constitutes an interesting area for future research.

Furthermore, as there is a lack of generally available benchmark instances it is hard to draw any comparative and general conclusions regarding different solution approaches. Instead, instances used are usually randomly generated to fit the specific problem discussed. This means that various solution methods are hard to compare and evaluate. Thus, deriving such a benchmark library of instances is sought.

Regarding the objectives used, almost all cited papers consider some type of cost and very few did not include a cost. The most used combination of objectives were cost and coverage. These can be considered as traditional objectives from a business perspective. Even if objectives regarding environmental factors has attracted some attention lately it is reasonable to assume that decision makers have to consider such factors to a larger extent in the future due to increased customer awareness

and imposed regulations. Thus, incorporating environmental factors in the modeling process should be considered as a research opportunity.

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Declarations

Conflict of interest The authors have no competing interests to declare that could have appeared to influence the work reported in this paper.

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