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Invited Review

Multi-objective vehicle routing problems

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Abstract

Routing problems, such as the traveling salesman problem and the vehicle routing problem, are widely studied both because of their classic academic appeal and their numerous real-life applications. Similarly, the field of multi-objective optimization is attracting more and more attention, notably because it offers new opportunities for defining problems. This article surveys the existing research related to multi-objective optimization in routing problems. It examines routing problems in terms of their definitions, their objectives, and the multi-objective algorithms proposed for solving them.

Keywords: Combinatorial optimization; Routing; Multi-objective programming

1. Introduction

This article provides an overview of the research into routing problems with several objectives. By routing problems, we mean any problem that involves of generating a tour, or a collection of tours, on a network, or a subset of a network, given a set of constraints and the need to optimize one or several fixed objective(s). Together, routing problems form a highly-studied family of problems that includes the well-known traveling salesman problem. Although such problems are frequently used to model real cases, they are often set up with the single objective of minimizing the cost of the solution, despite the fact that the majority of the problems encountered in industry, particularly in logistics, are multi-objective in nature. In real-life, for instance, there may be several costs associated with a single tour. Moreover, the objectives may not always be limited to cost. In fact, numerous other aspects, such as balancing of workloads (time, distance ...), can be taken into account simply by adding new objectives.

A routing problem can be defined in terms of the following components: the network, the demand(s), the fleet, the cost(s), and the objective(s).

- The *network* can be symmetrical, asymmetrical or mixed. It is represented as a graph on which the nodes stand for towns, customers and/or depots, while arcs stand for real links (e.g., roads, pipelines) or symbolic connections. On valuated graphs, a value generally represents the cost of traversing an arc. Time windows associated with

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nodes or arcs may also be defined in some problems.

- The *demands* can be fixed or stochastic, can be associated with both nodes and arcs, and can be given for one or several product(s). Generally, demands appear in distribution problems, in which a certain amount of a given product must be delivered to certain nodes (i.e., customers) or must travel along a certain arc (i.e., delivery route). Demands are also a part of pick-up and delivery problems, in which demanded goods must first be picked up at a specific location and then be delivered elsewhere.
- The *fleet* generates constraints that affect the tours. A fleet can be heterogeneous or homogeneous. It can be composed of a single vehicle or several vehicles, whose use may, or may not, be limited by capacity, time or distance, for example. In addition, there may be dependencies between vehicles, drivers, products, nodes, and/or arcs. The term *fleet* does not always refer to a group of vehicles. In fact, in some problems, there are no vehicles at all. However, in this text, the terms *vehicle* and *fleet* are used systematically in order to avoid confusion.
- The *costs* are generally fixed for the vehicle and variable for its use, in terms of distance traveled or time used. Costs can also include the service penalties incurred when a customer receives a late or incomplete delivery. Related to costs, profit can also be associated to given nodes and/or arcs with the profit being collected when the node is visited and/or the arc is chosen.
- The *objectives* can be multiple and diverse. The objective function can be computed for a single period or for several periods, though in the latter case, both vehicles and visits must be assigned to the different periods. The most common objectives include minimizing the total distance traveled, the total time required, the total tour cost, and/or the fleet size, and maximizing the quality of the service and/or the profit collected. However, when multiple objectives are identified, the different objectives frequently conflict. For this reason adopting a multi-objective point of view can be advantageous.

A multi-objective problem (MOP) can be stated as follows:

$$(\text{MOP}) = \begin{cases} \min\ F(x) = (f_1(x), f_2(x), \ldots, f_n(x)) \\ s.t.\ x \in D, \end{cases}$$

where $n \geqslant 2$ is the number of objective functions; $x = (x_1, x_2, \ldots, x_r)$, the decision variable vector; D, the feasible solution space; and $F(x)$, the objective vector. The set $O = F(D)$ corresponds to the feasible solutions in the objective space, and $y = (y_1, y_2, \ldots, y_n)$, where $y_i = f_i(x)$, is a solution of the objective space. The solution to a multi-objective problem (MOP) is the set of non-dominated solutions called the Pareto set (PS), where dominance is defined as:

Definition 1.1. A solution $y = (y_1, y_2, \ldots, y_n)$ dominates (denoted $\prec$) a solution $z = (z_1, z_2, \ldots, z_n)$ if and only if $\forall i \in \{1 \ldots n\}$, $y_i \leqslant z_i$ and $\exists\, i \in \{1 \ldots n\}$, $y_i < z_i$.

A solution y found by an algorithm A is said to be potentially Pareto optimal (PPS), relative to A, if A does not find a solution z so that z dominates y. However, the Pareto dominance does not establish a complete order of the solutions of a problem. There are three approaches to solve a multi-objective problem: *a priori* approaches, *interactive* approaches, and *a posteriori* approaches. In *a priori* approaches, a decision-maker provides preferences for the different objectives. In *interactive* approaches, the decision-maker's choices are made during the problem solving process. In *a posteriori* approaches, a set of potentially non-dominated solutions is first generated, and then the decision-maker chooses among those solutions.

This paper presents an overview of the most recent multi-objective routing problems and solutions found in the scientific literature. The rest of the paper is organized as follows. Section 2 describes the different ways that multi-objective optimization can be applied to routing problems. Section 3 classifies the different types of objectives, and Section 4 reports on the different approaches to multi-objective optimization used in the literature to deal with routing problems. Section 5 presents our conclusions. The papers referenced in this survey are listed in Tables 1 to 7.

2. From single-objective to multi-objective routing problems

Multi-objective routing problems are mainly used in three ways: to extend classic academic problems in order to improve their practical application (while never losing sight of the initial objective), to generalize classic problems, and to study

Table 1
Multi-objective routing problems extended from single-objective problems (I)

Authors	Problem	Method	Tour	Nodes/Arcs	Resources
Park and Koelling (1986, 1989) [54,55]	Vehicle routing problem	Goal programming Heuristic	Min. the traveled distance	Max. the realization of urgent queries Max. the station conditional dependence	Min. the merchandise deterioration
Sutcliffe and Board (1990) [63]	Vehicle routing problem	Linear programming	Min. the traveled distance Max. the equalization of the vehicle travel times		Max. the capacity utilization
Current and Schilling. (1994) [12]	Median tour problem Maximal covering tour problem	Heuristics	Min. the total length	Max. access to the tour for the nodes not directly on it	
Lee and Ueng (1998) [45]	Vehicle routing problem	Aggregation Heuristic	Min. the traveled distance Optimize the balance of the load (length)		
Sessomboon et al. (1998) [61]	Vehicle routing problem with time windows	Pareto approach Hybrid genetic algorithm	Min. the traveled distance	Max. the customer satisfaction	Min. the number of vehicles Min. the vehicle waiting times
Hansen (2000) [28]	Multi-objective traveling salesman problem	Scalarizing function Local search	Min. the total lengths		

Table 2
Multi-objective routing problems extended from single-objective problems (II)

Authors	Problem	Method	Tour	Nodes/arcs	Resources
Ribeiro and Lourenço (2001) [58]	Multi-period vehicle routing problem	Aggregation Iterated local search	Min. the traveled distance Optimize the balance (number of visited customers)	Marketing: driver/customer relationship	
Jozefowiez et al. (2002, 2004, 2005, 2006) [34,33,37,38]	Vehicle routing problem with route balancing	Pareto approaches/multi-objective evolutionary algorithms Goal programming/Tabu search	Min. the traveled distance Optimize the balance of the tours (length)		
Borges and Hansen (2002) [6]	Multi-objective traveling salesman problem	Weighted sum program	Min. the total lengths		
Paquete and Stützle (2003) [53]	Multi-objective traveling salesman problem	Aggregation Local search	Min. the total lengths		
Zhenyu et al. (2003) [69]	Multi-objective traveling salesman problem	Pareto approach Genetic algorithm	Min. the total lengths		

real-life cases in which the objectives have been clearly identified by the decision-maker and are dedicated to a specific real-life problem or application.

Table 3
Multi-objective routing problems extended from single-objective problems (III)

Authors	Problem	Method	Tour	Nodes/arcs	Resources
Angel et al. (2004) [1]	Multi-objective traveling salesman problem	Local search	Min. the total lengths		
Chitty and Hernandez (2004) [9]	Dynamic vehicle routing problem	Ant colony optimization system	Min. the total mean transit time Min. the total variance in transit time		
Li (2005) [46]	Bi-objective traveling salesman problem	Attractor Heuristic	Min. the total lengths		
Murata and Itai (2005, 2007) [48,49]	Multi-objective vehicle routing problem	Pareto approach Genetic algorithm Local search	Optimize makespan		Min. the number of vehicles

Table 4
Multi-objective routing problems generalizing single-objective problems (I)

Authors	Problem	Method	Tour	Nodes/Arcs	Resources
Keller (1985) [40], Keller and Goodchild (1988) [41]	Traveling salesman problem with profit	Lexicographic method Heuristic	Min. the tour length Max. the profit		
Hong and Park (1999) [30]	Vehicle routing problem with time windows	Goal programming Heuristic	Min. the total travel time	Min. the total customer waiting times	
Geiger (2001, 2003) [21,22]	Vehicle routing problem with time windows	Pareto approach Genetic algorithm	Min. the total distance	Min. the total deviations from the time window bounds Min. the number of violations	Min. the number of vehicles
Rahoual et al. (2001) [57], Rahoual and Djoukhdjoukh (2003) [56]	Vehicle routing problem with time windows	Pareto approach	Min. the traveled distance	Min. the number of violated constraints	Min. the number of vehicles

2.1. Extending classic academic problems

Multi-objective optimization is one possible way to study other objectives other than the one initially defined, which is often related to solution cost. In this context, the problem definition remains unchanged, and new objectives are added. The purpose of such extensions is often to enhance the practical applications of the model by recognizing that logistics problems are not only cost driven. Some of the different extensions found in the literature are listed below.

2.1.1. Driver workload

Lee and Ueng [45] proposed an extension of a vehicle routing problem in which the balance of the tour lengths is considered. This balance objective was added to increase the fairness of the solution produced. The authors were motivated to complete this study by the fact that, in Taiwan, tasks are assigned by a decision-maker who may be influenced by personal preferences, incomplete information and/or other human factors. When drivers compare their schedules and discover disparities, they complain. Lee and Ueng argue that, since drivers can make the difference for a company, their welfare is important. This objective has also been taken into account by Jozefowiez et al. [34,33,37].

2.1.2. Customer satisfaction

Sessomboon et al. [61] added objectives to a vehicle routing problem with time windows in order to improve customer satisfaction with regard to delivery dates.

2.1.3. Commercial distribution

Ribeiro and Lourenço [58] proposed an extension of the periodic vehicle routing problem.

Table 5
Multi-objective routing problems generalizing single-objective problems (II)

Authors	Problem	Method	Tour	Nodes/Arcs	Resources
Baràn and Schaerer (2003) [4]	Vehicle routing problem with time windows	Ant colony system	Min. the total time	Min. the total delivery times	Min. the number of vehicles
Tan et al. (2003, 2006) [65,64]	Vehicle routing problem with time windows	Pareto approach Hybrid genetic algorithm	Min. the total length		Min. the number of vehicles
Jozefowiez et al. (2004, 2005) [33,35,36]	Covering tour problem	Pareto approach/Multi-objective genetic algorithm Cooperative approach: genetic algorithm/branch and cut algorithm ϵ-Constraint method/branch-and-cut algorithm	Min. the length	Min. the cover	
Riera-Ledesma and Salazar-Gonzalez (2005) [59]	Traveling purchaser problem	Aggregation Branch and cut algorithm	Min. the length Min. the purchasing cost		
Ombuki et al. (2006) [50]	Vehicle routing problem with time windows	Pareto approach Weighted sum Genetic algorithm	Min. the total length		Min. the number of vehicles

Table 6
Real-life multi-objective routing problems (I)

Authors	Problem	Method	Tour	Nodes/arcs	Resources
Bowerman et al. (1995) [7]	Urban schoolbus routing	Aggregation Heuristics	Min. the total length Optimize the balance of the load	Min. the student walking distance	
Giannikos (1998) [25]	Location and routing for hazardous waste transportation and treatment	Goal programming	Min. of the total cost Min. of the total perceived risk	Min. of the individual perceived risk Min. of the individual disutility	
El-Sherbeny (2001) [19]	Vehicle routing problem adapted to the case of a Belgian transportation company	Pareto approach Simulated annealing	Min. the total time Optimize the balance (length) Max. the flexibility	Min. the waiting times	Min. the number of trucks Min. the number of covered trucks Min. the number of uncovered trucks Min. the unused working hours
Corboran et al. (2002) [11]	Rural schoolbus routing problem	ϵ-Constraint approach Scatter search	Min. the makespan		Min. the number of vehicles
Lacomme et al. (2006) [42]	Capacitated arc routing problem	Pareto approach Genetic algorithm	Min. the total length Min. the makespan		

Through this extension was motivated by issues that can arise in the food and beverage industry, no practical case has been solved or studied by the authors. The extension takes into account diverse

Table 7
Real-life multi-objective routing problems (II)

Authors	Problem	Method	Tour	Nodes/arcs	Resources
Pacheco and Marti (2006) [51]	Rural schoolbus routing problem	ϵ-Constraint method Tabu search	Min. the makespan		Min. the number of vehicles
Zografros and Androustsopoulos (2004) [70]	Vehicle routing problem with time windows for hazardous product transportation	Aggregation Heuristic	Min. the length Min. the risk		
Tan et al. (2006) [66]	Truck and trailer vehicle routing problem	Pareto approach Hybrid genetic algorithm	Min. the total length		Min. the number of vehicles
Mourgaya (2004) [47]	Multi-period vehicle routing problem	Heuristics	Optimize the regionalization (clustering) of the customers Optimize the balance of the load		
Doerner et al. (2006) [15]	Mobile healthcare facility tour planning	P-ACO (ant colony optimization) MOEA VEGA	Min. the ineffectiveness of the personnel	Min. the average distance for an inhabitant to walk Max. the size of the population covered	

objectives, including cost, balancing, and marketing issues. Like Lee and Ueng [45], they add a balance objective to incorporate the notion of fairness into the task allocation. In the food and beverage industry, driver schedules are produced weekly, and the relationship between the customer and the driver is very important for improving sales and the reputation of the company.

2.1.4. Multi-objective traveling salesman problem and variants

Several researchers have studied the multi-objective traveling salesman problem (MOTSP) [18,53,69,52,46], in which several costs are associated to each arc. This kind of TSP is used to model networks for which two or more objectives must be computed simultaneously (e.g., the cost of the solution and the time required). In addition, because MOTSP extend a well-known problem, they can be used as a benchmark to validate theoretical or methodological research [28,31,6,1].

Current and Schilling [12] defined two bi-objective variants of the traveling salesman problem: the median tour problem (MTP) and the maximal covering tour problem (MCTP). In both problems, one of the objectives is the minimization of the total tour length. The second objective maximizes access to the tour from the nodes that are not directly visited. Such TSP can be applied in the design of mobile service delivery systems (e.g., health care delivery in the rural areas of developing countries), bi-modal transportation systems (e.g., overnight mail delivery), and distributed computer networks, among others.

2.1.5. Other multi-objective routing problems

Some multi-objective routing problems do not share common objectives with classic routing problems at all. For example, Chitty and Hernandez [9] define a dynamic vehicle routing problem in which the total mean transit time and the total variance in transit time are minimized simultaneously. Likewise, Murata and Itai [48,49] define a bi-objective vehicle routing problem which seeks to minimize both the number of vehicles and the maximum routing time of those vehicles (makespan).

2.2. Generalizing classic problems

Another way to use multi-objective optimization is to generalize a problem by adding objectives instead of one or several constraints and/or parameters. In the literature, this strategy has notably been applied to the vehicle routing problem with time window constraints where the time windows are replaced by one or several objectives [4,21,22,30,50,56,57,64].

Boffey [5] provides a list of routing problems that he classified as problems which are implicitly multi-objective. In those problems, a constraint and/or parameter or a set of constraints and/or parameters is used instead of what can be naturally modeled as an objective. Feillet et al. [20] have described a class of problems, called traveling salesman problems with profits (TSPP), which belong to this category. In these problems, a profit, associated with each customer, can be collected when the customer is visited, but it is not necessary to visit all customers. The two conflicting objectives in such problems can be clearly identified:

(1) Maximize the profit by visiting the maximum number of customers, thus increasing the length of the solution.
(2) Minimize the length of the solution by visiting fewer customers, thus decreasing the profit generated by the solution.

From the perspective of single-objective optimization, three associated problems have been addressed in the literature:

(1) Problems in which both objectives are combined in the objective function, with the goal being to find a solution that minimizes the tour length minus the collected profit. Dell'Amico et al. [14] refer to this version of the TSPP as the profitable tour problem (PTP).
(2) Problems in which a maximum allowed tour length $c_{\max}$ is imposed as a bound, with the goal being to find a tour that maximizes the total collected profit while satisfying this bound. This problem is called the orienteering problem (OP). The OP has also been referred to as the selective traveling salesman problem (STSP) [43] and the maximum collection problem [39].
(3) Problems in which a minimum allowed profit $p_{\min}$ is imposed as a bound, with the goal being to find a minimal length tour whose total collected profit is not smaller than this bound. This problem is also called the prize-collection traveling salesman problem (PCTSP) [3] or the quota traveling salesman problem (QTSP) [2].

An attempt to address the traveling salesman problem with profits in its explicitly multi-objective form was made by Keller [40], and later by Keller and Goodchild [41], who referred to the problem as the multi-objective vending problem. However, from a bi-objective point of view, there are not three problems but a single one.

Boffey also mentioned another example of routing problem generalization: the bi-objective covering tour problem (CTP) [33,35,36], which generalizes the covering tour problem [23]. In the CTP, the goal is to find a tour on a network subset, such that certain nodes are a given distance c from visited nodes. In the bi-objective generalization, the parameter c is removed and replaced by an objective to optimize the cover. The cover of the solutions is then computed according to the visited nodes.

Riera-Ledesma and Salazar-González [59] have defined a bi-objective travelling purchaser problem, which consists of determining a route through a subset of markets in order to collect a set of products, while simultaneously minimizing the travelling distance and the purchasing cost. The problem is usually solved as a single-objective problem in which the two objective functions are replaced by a single composite function obtained by adding the travelling distance and the purchasing cost. These authors formulated the problem as a bi-objective mixed-integer linear program.

2.3. Studying real-life cases

Multi-objective routing problems are also studied for a specific real-life situation, in which decision-makers define several clear objectives that they would like to see optimized. Several examples of these real-life studies are presented below:

2.3.1. Transport delivery routing

El-Sherbeny [19] worked on a vehicle routing problem for a Belgian transportation company. The problem involved delivering a given amount of goods to a set of customers, starting from a location which is not the fleet depot, and the solution had to meet eight objectives defined by the company. The fleet was heterogeneous, consisting of both covered and uncovered trucks. There was no capacity constraint, which allowed the query to be split if necessary. Deliveries were accomplished in two phases: first, the vehicle picked up the goods at a given location, and then delivered them to the final customer. Since the set of customers varied from day to day, the delivery schedule had to be planned on a daily basis.

2.3.2. Urban schoolbus route planning

Bowerman et al. [7] looked at schoolbus route planning for urban areas, specifically in the county of Wellington, Ontario. According to the authors, the schoolbus routing problem is more complex than the classic vehicle routing problem. The problem was specified as follows: a set of students located in different areas must have access to a public schoolbus to take them from their residence to their school and vice versa. The problem is to find a collection of schoolbus routes that will ensure fair distribution of services to all eligible students. The authors proposed a multi-objective mathematical model with four objectives: the minimization of the total route length, the minimization of the total student walking distance, the fair distribution of the load (i.e., the number of students transported), and the fair division between the buses of the total distance traveled.

The authors chose a two-phase approach to the problem, which did not consider the route length balancing objective. In the first phase, the students were clustered so that all the students in a given cluster could be served by a single bus. The optimized objectives in phase 1 were route length, student walking distance (as demonstrated by the compactness of the cluster), and load distribution. In the second phase, the bus route associated with each cluster was calculated, with the solution for one cluster being independent of the other solutions. The bus stops were also selected during this phase to insure that student walking distances would be minimal. The optimized objectives in phase 2 were the minimization of the tour length for each cluster and the minimization of the student walking distance.

2.3.3. Rural schoolbus routing

Both Corberan et al. [11] and Pacheco and Marti [51] examined methods for transporting students from home to school, and back again. The transportation had to be accomplished as safely as possible, while still considering economics and comfort. The studies focused on Spanish rural areas where the distances between two pick-up points and from pick-up points to the schools tend to be large. The number of passengers per bus was excluded from the study, because buses were generally not filled before the prespecified time limit was reached. The time constraint insured that students would not spend too much time on the bus and that there would be no glaring inequities between the first student picked up on the tour and the last one.

2.3.4. Urban trash collection

In Lacomme et al. [42], trash had to be collected in the streets of the town of Troyes (France) and delivered to a waste treatment facility. This problem was modeled as an arc-routing problem. The trucks left the factory at 6 a.m. and had to return to the factory before a given hour since the workers had to sort the waste afterwards. The authors considered two objectives: the minimization of the total route length and the minimization of the longest route.

2.3.5. Merchandise transport routing

Tan et al. [66] investigated a bi-objective problem based on a *vehicle capacity planning system* for a Singapore logistics company, originally described by Lee et al. [44]. The model used was a truck and trailer vehicle routing problem (TTVRP) [8]. In a TTVRP, the vehicles are composed of two elements, the truck and the trailer, which can be separated to allow truck alone to be used to reach locations that are not accessible by the entire vehicle. In this study, the size of the fleet was not fixed, and time windows were associated to the different customers.

2.3.6. Hazardous product distribution

Giannikos [25] considered a hazardous product distribution where the goal is the location of the treatment facilities and the selection of the routes for hazardous waste shipments. His method is driven by four considerations modeled as objectives: (i) minimization of the total operating cost, (ii) minimization of the total perceived risk, (iii) equitable distribution of the risk among population centers, (iv) equitable distribution of the disutility caused by the operation of the treatment facilities.

Zografos and Androustsopoulos [70] proposed modeling hazardous product distribution as a bi-objective routing problem in which the objectives of minimizing route length and minimizing risk are considered simultaneously. The problem was modeled as a vehicle routing problem with time windows, and the proposed heuristic was incorporated into a GIS for hazardous product logistic operations.

2.3.7. Multi-periodic vehicle routing

Mourgaya [47] studied a real-life multi-period vehicle routing problem involving up to 6000 customers over a 20-day period. She tried to optimize the solutions to produce a balanced workload and compact customer clusters that would allow *regionalization* (i.e., geographical clusters of the customers) to be achieved.

2.3.8. Tour planning for mobile healthcare facilities

In this study, Doerner et al. [15] attempt to deal with the fact that developing countries frequently face the dilemma engendered by a growing population and very restrictive budget limitations for healthcare expenditures. The purpose of the study is to propose cost-effective routing for mobile healthcare facilities, thus providing *access* to health services for a large proportion of the population. The proposed strategy is thought to be more efficient for developing countries, particularly in terms of accessibility, than building a great number of fixed-site hospitals, which such countries cannot afford.

To model the problem, the authors extend the problem presented in Hodgson et al. [29] and Hachicha et al. [27], which itself is based on the covering tour problem [23]. The problem involves selecting the stops and the routing for the mobile facility, while also considering the three following objectives: (i) *efficiency of workforce deployment*, as measured by the ratio between the time spent on medical procedures and total time spent, including travel time and facility setup time; (ii) *average accessibility*, as measured by the average distance that the inhabitants need to walk to reach the nearest stop on the tour; and (iii) *coverage*, as measured by the percentage of inhabitants living within a given maximum walking distance to a tour stop. The problem is solved for real data for the Thiès region in Senegal.

3. Most common objectives

In this section, the different objectives studied in the literature are presented and classified according to the component of the problem with which they are associated: the tour, the node/arc activity, or the resources.

3.1. Objectives related to the tour

3.1.1. Cost

Minimizing the cost of the solutions generated is the most common objective. Cost can be expressed in many ways, such as the distance traveled, the time required, or the number of customers visited. Generally speaking, minimizing cost is linked to an economic criterion. In the multi-objective traveling salesman problem, the different objectives correspond to the different arc costs. However, other motivations are possible. For instance, in studies by Park and Koelling [54,55], the distance traveled must be minimized to avoid damaging the product being transported.

Giannikos [25] defined cost as the sum of the cost of opening the treatment facilities and the length of the tours generated to pick-up the waste and deliver it to the treatment facilities. In Riera-Ledesma and Salazar-González's bi-objective traveling purchaser problem [59], the cost is due to travel. In such problems, the purpose is to visit enough markets to allow a certain quantity of different products to be bought. Each product cannot be bought in every market, and each market has a limited quantity of products and a different product price. Thus, the cost objective can be expressed as $\min \sum_{p_k \in K} \sum_{v_i \in M_k} b_{ki} z_{ki}$, where K is the set of products; M_k is the subset of markets where the product p_k is available; b_{ki} is the unit price of product p_k at market v_i; and z_{ki} is the number of units of product p_k bought at the market v_i.

Doerner et al. [15] define *cost* by considering the ratio of the work time compared to the total time needed to accomplish the task (i.e., working time, traveling time, and setup time at each of the different stops). They talk about efficiency of the workforce deployment. Their goal can also be seen as minimizing of the inefficiency of the mobile facility workforce, as determined by the formula:

$$\frac{\mu k(x) + t(x)}{T},$$

where T is the total work of a member of the mobile facility workforce, μ is the time for the setup of the mobile facility at a stop, $k(x)$ the number of stops on the tour, and $t(x)$ the total driving time during the tour.

3.1.2. Makespan

Although cost minimization is the most common objective, this objective is sometimes ignored, as is the case in the studies by Corberan et al. [11] and Pacheco and Marti [51]. These authors chose instead to minimize the makespan (i.e., to minimize the length of the longest tour). This choice was motivated by the environment: a rural area in Spain where, due to the large distances between pick-up locations, the bus routes tend to be long and the bus never full. Minimizing the makespan ensures some fairness in terms of time spent on the bus by the first student picked up compared to the time spent by the last one.

Minimizing the makespan was also an objective for Lacomme et al. [42], because the trash collection had to be finished as soon as possible so that the workers would have time to sort the trash. Murata and Itai [48,49] also worked to optimize this objective.

3.1.3. Balance

Some objectives are designed to even out disparities between the tours. Such objectives are often introduced in order to bring an element of *fairness* into play. To define a balancing objective, it is necessary to define a tour's workload, which can be expressed as the number of customers visited, the quantity of goods delivered, the time required or the tour length, for example.

Sutcliffe and Board [63] studied a problem in which mentally handicapped people had to be transferred, with an attempt made to establish parity in terms of traveling time. Lee and Ueng [45] incorporated balance to enhance fairness between drivers' assignments. The tour workload incorporates the travel time needed and the time needed to load and unload the truck. The objective is modeled as the minimization of the sum of the differences between the workload of each tour and the smallest workload. Balance was also an issue for Ribeiro and Lourenço [58]. In their study, the tour workload was equal to the volume transported during the period. According to the authors, this definition of workload is advantageous for the food and beverage industries, since a percentage of the remuneration is often related to the quantity of products sold and distributed.

In the case of the Belgian transportation company considered by El-Sherbeny [19], the tour workload corresponds to the time needed to travel between the different pick-up and delivery locations, plus the time required to load and unload the trucks. The waiting time of vehicles arriving earlier than the lowest bound of the customer time windows, and thus being forced to wait to be unloaded, is also added to the workload of the tour. The objective is to minimize the difference between the workload of the longest tour and the one of the shortest tour. The same objective is used by Jozefowiez et al. [34,33]. However, in this study, the tour workload is equal to the length of the tour.

In the multi-period vehicle routing problem studied by Mourgaya [47], load balancing is taken into account because it is not acceptable for the workload to be heavy one day and light the next. According to the author, industrial decision-makers wanted to spread deliveries out over the entire week. Thus, balance can be obtained either between the workloads over a series of days or between the workloads of each vehicle. The first solution allows an homogeneous schedule for the period, whereas, the second approach allows a homogeneous use of the fleet over the complete time horizon.

3.1.4. Specific objectives

Some objectives are defined by the nature of the problem or the context in which the problem occurs. In the problem studied by Keller and Goodchild [40,41], a profit value is associated with each node. Since it is not necessary to visit every node, the objective is to maximize the profit while minimizing the total length of the tour.

When transporting hazardous products, there is a risk associated with the path taken by a vehicle. Due to the drastic consequences of an accident on the people and the environment near an accident site, the risk of accidents must be minimized on the roads selected. Giannikos [25] minimizes the total perceived risk which is expressed as the weighted sum of the individual perceived risk. Each population has a weight and an individual perceived risk computed according to the amount of waste passing through the population location.

For Zografos and Androutstsopoulos [70], the calculated risk is expressed as the sum of $p_s \times C_s$ on the segments of the tour, where p_s is the probability of an accident and C_s is the total population within a given distance from the segment s.

In the study by Mourgaya [47], the classic objective of minimizing the total tour length is set aside. Instead, a *regionalization* objective is used in order to create geographical clusters for the tours. This regionalization objective is modelled by minimizing the sum of the costs for each cluster, where each cluster corresponds to a set of customers who are close to one another, with each customer belonging to a single cluster. It appears that the solutions identified when optimizing the minimization of the total tour length are typically composed of tours that have few or no customer clusters. However, grouping the customers creates areas that a driver can become familiar with, which can in turn reduce the time required to complete the entire tour. Thus, the minimization of the total tour length is accomplished at the operational level.

3.2. Objectives related to node/arc activity

Most of the studies dealing with objectives related to node/arc activity involve time windows [30,19,21,57,56,4,22]. In such studies, the time windows are replaced by an objective that minimizes either the number of violated constraints [57,56], the total customer and/or driver's wait time due to earliness or lateness [30,19,4], or both objectives at the same time [21,22].

Other objectives related to the node/arc activity both assign a priority to the nodes or the arcs and create a dependence between the nodes and/or the arcs [54,55]. It is also possible to define economic or marketing objectives, such as increasing customer satisfaction [61] or improving the customer-driver relationship [58].

In the study of schoolbus routing by Bowerman et al. [7], the sum of the distances between some nodes on the graph associated with the residential clusters and those corresponding to the bus stops must be minimized, meaning that the distance the pupils must walk to take the bus has to be minimized.

Doerner et al. [15] also define a similar objective, denoted the *average accessibility* objective, which corresponds to the classic p-median formulation of location problems. This formulation is equal to the average distance an inhabitant has to walk in order to reach the nearest stop of the mobile facility. In the model, the following objective is minimized: $\frac{1}{N}\sum_{v_i \in W} p_i d_i$ where N is the total number of inhabitants, W is the set of the settlements to be covered, p_i is the population of the settlement $v_i \in W$, and d_i is the minimum distance of v_i to a node contained in the tour.

This objective is close to the notion of *coverage*. Coverage occurs when there is still a connection between the visited nodes and the unvisited ones, even though all the nodes do not have to be visited by the tour. In the median tour problem (MTP), Current and Schilling introduce an access objective whose goal is to minimize the weighted sums of the distances between each unvisited node and its nearest node on the tour. The maximal covering tour problem (MCTP), also defined by Current and Schilling, is a special case of the MTP, in which the second objective is to maximize the total demand within some prespecified maximal travel distance from a tour stop. This is mathematically expressed as the minimization of the total sum of uncovered demands.

The covering tour problem (CTP) proposed by Gendreau et al. [23] is related to both the MTP and the MCTP. In the CTP, a distance c is specified and every node from a specified set must be within a distance less than c from a visited node. Jozefowiez et al. [35,36] have generalized this problem by removing the covering constraints and replacing them with an objective that minimizes the maximal distance between a node to be covered and the nearest visited node.

Another objective related to the idea of covering is used in the study of Doerner et al. [15]. Here, the cover is a parameter and the objective is to select the stops so as to maximize the percentage of the population that is covered. This objective aims to provide an idea of equity or fairness: no inhabitants should be excluded at all from medical services due to a prohibitive distance between them and the nearest facility.

3.3. Objectives related to resources

The main resources encountered in the literature are vehicles and goods. One objective that often appears is the minimization of the number of vehicles, which can be interpreted economically, in that fewer vehicles means less monetary investment (e.g., for vehicle purchases, gas, and/or drivers' salaries) [11,19,48–51,64,66].

This kind of objective is also considered in the vehicle routing problem with time windows. The classic model of the problem has two objectives that are treated lexicographically. This means that first the number of vehicles is minimized, and then the length of the solution is minimized for that given number of vehicles. Apart from the study by Hong and Park [30], the existing research on multi-objective vehicle routing problems with time windows assigns the same level of priority to both objectives, rather than considering them lexicographically.

Other vehicle-related objectives can be used to maximize vehicle cost-effectiveness in terms of time [61,19] or capacity [63], while goods-related objectives can be introduced to take the nature of the goods into account. For instance, the latter can be used to consider the fact that the merchandise is *perishable* in order to avoid its deterioration [54,55].

Giannikos [25] computes an individual perceived risk for each node corresponding to a population center, equal to the sum of the amount of hazardous waste transported through that center. The objective is to minimize of the greatest perceived risk. It is done in order to ensure that no population centre is unfairly treated. Giannikos also minimizes the disutility of the nodes that provide waste as well as nodes that do not provide waste. It is assumed that the disutility caused by a treatment facility on a population center i is an increasing function of the facility size and a decreasing function of the distance between the population center and the facilities. The individual disutility for i is the sum of all open treatment facilities j of the disutility caused by j to i. Thus, the objective is to minimize of the maximum disutility among the population center.

4. Multi-objective optimization algorithms

Over the last several years, many techniques have been proposed for solving multi-objective problems. These strategies can be divided into three general categories: scalar methods, Pareto methods, and methods that belong to neither the first nor second category. Scalar methods use mathematical transformations, like weighted linear aggregation. Pareto methods, which apply the notion of Pareto dominance to evaluate the quality of a solution or to compare solutions, are mainly used with evolutionary algorithms and are becoming more and more popular [13,10]. The last category includes the techniques that consider the different objectives separately.

4.1. Scalar techniques

The most popular scalar method is, as mentioned above, weighted linear aggregation. However, this method has several disadvantages. First, weights must be set according to the importance of the objectives, which can be a difficult task. In addition, this method is unable to find all the Pareto optimal solutions, i.e., it only finds the solutions on the convex hull of the optimal Pareto set [24]. Still, this technique is relatively simple to implement and can be used with any of the single-objective heuristics or meta-heuristics described in the literature.

For multi-objective routing problems, weighted linear aggregation has been used with specific heuristics [7,45,70], local search algorithms [58,53], and genetic algorithms [50]. Specifically, Bowerman et al. [7] use five different sets of weights chosen by a decision-maker. Their heuristic is an allocation-routing-location strategy which first groups the nodes into clusters that can be served by a vehicle, and then determines a tour for each cluster and the specific stops along the tour. Lee and Ueng [45] set the weights to 0.5 and use an insertion algorithm that iteratively adds one node to the vehicle with the shortest work time using a saving criterion. Zografos and Androutsopoulos [70] use an insertion heuristic based on a method proposed by Solomon [62]. Their heuristic differs from Solomon's algorithm in the selection of the customers to be inserted, allowing both routed and unrouted demand points to be inserted. Paquete and Stützle [53] use a two-phase method, which first generates an initial solution by optimizing a single objective, and then initiates a search for non-dominated solutions starting from the initial solutions, exploiting a sequence of different aggregations of the objectives. Ombuki et al. [50] transform the problem into a single-objective one by using a couple of weights established empirically.

Riera-Ledesma and Salazar-González [59] use a weighting method with additional constraints. First, they compute the initial solutions by optimizing both objectives hierarchically, using a branch-and-cut algorithm. The solutions thus produced constitute the extremities of an optimal Pareto set. Then, they build the weighted problem by adding the following two constraints: $f_1(x) < f_1^*$ and $f_2(x) < f_2^*$ where f_i^* is the best value for the objective f_i obtained during the first phase. The weight is computed using these values. The resulting problem is solved by a branch-and-cut algorithm, which finds the optimal Pareto solution associated to the point (f_1', f_2') of the objective space. Two new problems can then be defined using the couples (f_1^*, f_2') and (f_1', f_2^*) to build the two additional constraints and computing the associated weight. The process is iterated for each subproblem until no new solution is found. This method is similar to the first phase of the two-phase method proposed by Ulungu and Teghem [67]. Although this strategy is able to solve bi-objective problems exactly, it should be noted that these methods can be quickly limited in terms of problem size, especially if there are a great number of optimal Pareto solutions. Although it is not necessary to solve for every solution in the Pareto set, the need to iterate an exact method limits the size of the problems that can be solved in a reasonable time.

Another scalar approach uses goal programming methods. In this approach, a goal (i.e., a point in the objective space) is chosen, and then a search is conducted to minimize the *distance* between the current solution and the goal. The main difficulty with this method comes from defining the goal. This technique has been used with specific heuristics by Park and Koelling [54,55], and as part of a two-phase heuristic by Hong and Park [30]. In the first phase of the latter study, a parallel insertion procedure clusters the customers into different groups according to the given constraints and the decision-maker preferences for the two objectives. The second phase does the routing for each cluster. This cluster-by-cluster routing is advantageous because the problems associated with each cluster are easier to solve than the complete problem and can be expressed as linear programs, which are then solved using a LINGO program. Giannikos [25] has also used this approach, in which the goals are fixed according to the data by formulas proposed arbitrarily by the author. Jozefowiez et al. [33] have proposed a technique to dynamically define goal points. In this method, several Tabu searches are performed, each one starting from the solution of a previously-found approximation. For each search, a goal is computed based on the starting solution's neighbor solutions in the objective space. During the search process, the complete area dominating the current approximation is explored, and the searches do not overlap. When all the Tabu searches are completed, the whole process is iterated.

The last scalar approach found in this survey of the literature is the ϵ-constraint method [51,35,33]. In this strategy, only one objective is optimized and the others are considered as constraints, expressed as $f_i(x) \leqslant \epsilon_i$. Changing the ϵ_i values yields several solutions. Corberàn et al. [11] optimize the makespan objective for every possible value of the second objective (in this study, the number of buses) and then use a scatter search approach to solve each problem. The same strategy has been applied by Pacheco and Marti [51], but, instead of the scatter search, they use a Tabu search algorithm. Jozefowiez et al. [35,36] also use an ϵ-constraint approach. Since the problem is a generalization, considering the new objective as an additional constraint produces a problem similar to the original single-objective problem, which can then be solved using a branch-and-cut algorithm developed for the single-objective problem [23].

4.2. Pareto methods

Pareto methods use the notion of Pareto dominance directly. This approach was mainly introduced by Goldberg [26] for genetic algorithms. Though it does not allow one compromise to be favored over another, it can be a useful aid for the decision-makers. In multi-objective vehicle routing problems, the Pareto concept is frequently used within an evolutionary framework. Many authors [61,21,57,34,56,42,69,65,66,35,33,36,37,48,64,50,22,15,49] have used evolutionary algorithms with Pareto methods to solve multi-objective routing problems. Some among them have proposed hybrids based on evolutionary algorithms and local searches, heuristics, and/or exact methods for the considered problem [61,34,42,65,66,33,36–38,64,15].

Pareto dominance has also been used by El-Sherbeny [19] in a simulated annealing technique called Multi-Objective Simulated Annealing (MOSA) [68], while Paquete et al. [52] have called upon *Pareto Local Search* techniques. These techniques are based on the principle that the next current solution is chosen from the non-dominated solutions of the neighborhood.

4.3. Non-scalar and non-Pareto algorithms

Some studies employ neither scalar nor Pareto methods to solve multi-objective routing problems. In this case, these non-scalar and non-Pareto methods are based on genetic algorithms, lexicographic strategies, ant colony mechanisms, or specific heuristics.

4.3.1. Vector Evaluated Genetic Algorithm (VEGA)

Doerner et al. [15] proposed using VEGA to solve their problem. VEGA was originally proposed by Schaffer [60] and was the first use of a genetic algorithm to solve multi-objective problems. In VEGA, at each iteration, the population is divided into n subpopulations, where n is the number of objectives, which are mixed together to obtain a smaller population on which genetic operators are applied. As with MOGA, Doerner et al. only use VEGA to generate the sets of visited nodes. The tour on this set is computed by means of the Nearest Neighbor heuristic [32] post-optimized by a 2-opt local search.

4.3.2. Lexicographic methods

In lexicographic methods, the objectives are each assigned a priority value, and the problems are solved in order of decreasing priority. When one objective has been optimized, its value cannot be changed and it becomes a new constraint for the problem. Such a lexicographic approach has been used by Keller and Goodchild [40,41]. Current and Schilling [12] have also used a variant of this method. Their method works as follows. First, a solution is generated and becomes the *incumbent*. Then, a neighborhood is generated and the angle between each neighbor and the incumbent is calculated. The neighbor with the maximum angle that is not dominated by the incumbent becomes the new incumbent, and the process is iterated.

4.3.3. Ant colony systems

Baràn and Schaerer [4] do not use a standard multi-objective approach, but rather consider the multi-objective nature of the problem via mechanisms in the ant colony system they propose. Chitty and Hernandez [9] also use an ant colony system. The ant colony paradigm is adapted to the bi-objective situation by using two types of pheromones, one for the total mean transit time and one for the variance in the transit time. Alternatively, to solve their problem, Doerner et al. [15] treat the location and routing aspects simultaneously by means of P-ACO (Pareto Ant Colony Optimization). P-ACO is a multi-objective meta-heuristic that generalizes the Ant Colony Optimization (ACO) meta-heuristic to the case of several objective functions, determining approximations to the set of optimal Pareto solutions. (P-ACO was introduced by Doerner et al. in an earlier article [16,17]).

4.3.4. Specific heuristics

Mourgaya [47] uses specific heuristics to optimize one objective at a time, varying the objective in terms of the current solution. Specifically, the customers are first grouped according to four criteria. The criterion groups and the order in which they are examined are based on the different objectives. Once the ranking has been done, the solutions are built by inserting the customers. Li [46] proposes the following heuristic method. First, for each objective, a solution attractor is built by means of a heuristic for the single-objective TSP. This attractor is composed of the best-found solution set for the objective. Li assumes that each solution in an attractor consists of a large proportion of low-cost edges for the corresponding objective and combines these attractors in order to mix the edges. Based on these mixed edges, the potentially Pareto optimal solutions are built.

4.4. Designing multi-objective methods for multi-objective vehicle routing problems

Although any of methods and approaches listed above could be applied to any multi-objective vehicle routing problem, some choices appear to be more relevant than others. First, Pareto-based methods within a population strategy, such as multi-objective evolutionary algorithms, are able to deal with any kind of problem with any number of objectives. They are particularly interesting for obtaining preliminary information about the characteristics of the optimal Pareto sets. Such information can be useful notably for real-life problems, which may not be directly linked to a well-known academic problem.

However, other approaches can also be very useful. When extending academic problems, adding new objectives usually does not modify the parameters and constraints of the initial problems. Therefore, combining the objectives by means of an aggregation or a goal programming strategy allows the problem to be brought back to a single-objective problem, to which any good quality, efficient method used in the literature for the original problem can be applied. When generalizing academic problems, the ϵ-constraint method seems to be helpful in that it allows certain methods designed for the initial problems to be used to provide information for the multi-objective problems. An easy way to use this method is to identify the ϵ-constraints with the new objectives, which brings the problem back to its initial form, and then to employ the techniques in the literature to solve for initial objective and to properly set the ϵ values to obtain values for the other objectives.

Nonetheless, using the different methods in cooperation appears to be the key to a successful multi-objective method. For instance, in the extension of the capacitated vehicle routing problem presented by Jozefowiez et al. [38], the fact that genetic algorithms are not the most effective method for the initial problem somewhat limits the quality of the results, although the use of a multi-objective evolutionary algorithm does allow a first approximation of the Pareto set. One way to resolve this difficulty is to devise a goal programming strategy. Using such a strategy allows one of the best Tabu search methods for the capacitated vehicle routing problem to be used as a post-optimization method, which significantly improves the quality of the approximations. Another example of cooperation between methods is seen in the solution to the bi-objective covering tour problem [36], in which the solutions of a multi-objective evolutionary algorithm are used to build subproblems that can be solved exactly by a previously developed branch-and-cut algorithm [23].

5. Conclusions

This survey describes the multi-objective methods used to deal with several kinds of objectives. The existing multi-objective problems are classified according to their application (extension, generalization, or real-case study), and the objectives are classified according to the components of the problems to which they are related (tour, node/arc, or resources). Although it has attracted more and more interest in recent years, the relatively moderate number of publications would seem to indicate that the domain of multi-objective routing problems is still young. In fact, apart from three studies done before 1990, all the others appeared after 1995, with more than half of the papers surveyed being published after 2000.

Despite this recent increase in the number of studies on multi-objective vehicle routing problems, almost every study appears to have been undertaken independently of all the others. Cleraly, some of these studies could have been linked together. In some cases, the different studies deal with the same or almost the same multi-objective problem; when the entire problem is not exactly the same, at least several objectives are shared. Based on this observation, it would seem that there is a need to define some *general* multi-objective vehicle routing problems that could be used as the starting points for more complex problems. For instance, in analogy with single-objective vehicle routing problems, both the traveling salesman problem and the capacitated vehicle routing problem have been the focus of many academic studies and have many real-life applications, particularly in the definition of variants. However, the methods used to solve these variants are usually simple modifications and/or adaptations of single-objective methods for academic single-objective vehicle routing problems.

Based on this survey, two main strategies seem to be the most widely used for solving multi-objective problems. The first relies on scalar methods, notably weighted aggregation, and the second relies on multi-objective evolutionary algorithms. The widespread use of scalar methods is no doubt linked to the fact that aggregations allow single-objective methods to be used without the need to adapt them for the multi-objective nature of the problems. However, these scalar methods require setting the weights and the quality of the approximations can be limited. The growing interest in multi-objective evolutionary algorithms, on the other hand, is directly linked to the focus on these methods. However, many implementations of multi-objective evolutionary algorithms are too simple: used genetic operators were not designed to consider a number of different objectives. The studies employing multi-objective evolutionary algorithm usually limit themselves to operators from the literature, which were designed to solve for an objective associated to the single-objective problem underlying the studied multi-objective problems. There is a real need for future studies to develop operators for the other objectives, as well as operators that can deal with several objectives simultaneously. The need to define general multi-objective vehicle routing problems is closely connected to this need to develop new operators.

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References

[1] E. Angel, E. Bampis, L. Gourvès, Approximating the Pareto curve with local search for the bicriteria TSP (1, 2) problem, Theoretical Computer Science 310 (2004) 135–146.
[2] B. Awerbuch, Y. Azar, A. Blum, S. Vempala, New approximation guarantees for minimum-weight k-trees and prize-collection salesmen, SIAM Journal on Computing 28 (1998) 254–262.
[3] E. Balas, The prize-collecting traveling salesman problem, Networks 19 (1989) 621–636.
[4] B. Baràn, M. Schaerer, A multiobjective ant colony system for vehicle routing problem with time windows, in: Proceedings of the Twenty-first IASTED International Conference on Applied Informatics, pp. 97–102, 2003.
[5] B. Boffey, Multiobjective routing problems, Top 3 (1995) 167–220.
[6] P.C. Borges, M.P. Hansen, Essays and surveys in metaheuristics, chapter A study of Global Convexity for a Multiple

Objective Traveling Salesman Problem, Kluwer Academic Publishers, Norwell, 2002, pp. 129–150.
[7] R. Bowerman, B. Hall, P. Calamai, A multi-objective optimization approach to urban school bus routing: Formulation and solution method, Transportation Research Part A 29 (1995) 123–197.
[8] I-M. Chao, A tabu search method for the truck and trailer problem, Computers and Operations Research 29 (2002) 22–51.
[9] D.M. Chitty, M.L. Hernandez, A hybrid ant colony optimisation technique for dynamic vehicle routing, in: K. Deb et al. (Eds.), GECCO 2004, Lecture Notes in Computer Science, vol. 3102, Springer-Verlag, 2004, pp. 48–59.
[10] C.A. Coello Coello, D.A. Van Veldhuizen, G.B. Lamont (Eds.), Evolutionary Algorithms for Solving Multi-objective Problems, Kluwer Academic Press, 2002.
[11] A. Corberan, E. Fernandez, M. Laguna, R. Marti, Heuristic solutions to the problem of routing school buses with multiple objectives, Journal of the Operational Research Society 53 (2002) 427–435.
[12] J.R. Current, D.A. Schilling, The median tour and maximal covering tour problems: Formulations and heuristics, European Journal of Operational Research 73 (1994) 114–126.
[13] K. Deb, Multi-objective Optimization using Evolutionary Algorithms, John Wiley and Sons, 2001.
[14] M. Dell'Amico, F. Maffioli, P. Värbrand, On prize-collecting tours and the asymmetric travelling salesman problem, International Transactions in Operational Research 2 (1995) 297–308.
[15] K. Doerner, A. Focke, W.J. Gutjahr, Multicriteria tour planning for mobile healthcare facilities in a developing country, European Journal of Operational Research (2006).
[16] K. Doerner, W.J. Gutjahr, R. Hartl, C. Strauss, C. Stummer, Ant colony optimization in multiobjective portfolio selection, in: Fourth Metaheuristics International Conference 2001, (MIC'2001), pp. 243–248, 2001.
[17] K. Doerner, W.J. Gutjahr, R. Hartl, C. Strauss, C. Stummer, Pareto Ant Colony Optimization: A metaheuristic approach to multiobjective portfolio selection, Annals of Operations Research 131 (2004) 79–99.
[18] M. Ehrgott, Approximation algorithms for combinatorial multi-criteria problems, International Transactions in Operations Research 7 (2000) 5–31.
[19] N. El-Sherbeny, Resolution of a vehicle routing problem with multi-objective simulated annealing method. Ph.D. thesis, Faculté Polytechnique de Mons, Mons, Belgique, 2001.
[20] D. Feillet, P. Dejax, M. Gendreau, Traveling salesman problems with profits, Transportation Science 36 (2005) 188–205.
[21] M.J. Geiger, Genetic algorithms for multiple objective vehicle routing, in: Metaheuristic International Conference 2001 (MIC'2001), pp. 348–353, 2001.
[22] M.J. Geiger, Multi-criteria und Fuzzy Systeme in Theorie und Praxis chapter A Computational Study of Genetic Crossover Operators for Multi-objective Vehicle Routing Problem with Soft Time Windows, Deutscher Universitats-Verlag, 2003, pp. 191–207.
[23] M. Gendreau, G. Laporte, F. Semet, The covering tour problem, Operations Research 45 (1997) 568–576.
[24] A. Geoffrion, Proper efficiency and theory of vector maximization, Journal of Mathematical Analysis and Applications 22 (1968) 618–630.
[25] I. Giannikos, A multiobjective goal programming model for locating treatment sites and routing hazardous wastes, European Journal of Operational Research 104 (1998) 333–342.
[26] D.E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, Reading, Massachussett, USA, 1989.
[27] M. Hachicha, M.J. Hodgson, G. Laporte, F. Semet, Heuristics for the multi-vehicle covering tour problem, Computers and Operations Research 27 (2000) 29–42.
[28] M.P. Hansen, Use of substitute scalarizing functions to guide local search based heuristic: The case of the moTSP, Journal of Heuristics 6 (2000) 419–431.
[29] M.J. Hodgson, G. Laporte, F. Semet, A covering tour model for planning mobile health care facilities in Suhum district, Ghana, Journal of Regional Science 38 (1998) 621–639.
[30] S-C. Hong, Y-B. Park, A heuristic for a bi-objective vehicle routing with time window constraints, International Journal of Production Economics 62 (1999) 249–258.
[31] A. Jaszkiewicz, Genetic local search for multi-objective combinatorial optimization, European Journal of Operational Reseach 137 (2002) 50–71.
[32] D.S. Johnson, J.A. McGeoch, The traveling salesman problem and its variationschapter Experimental analysis of heuristics for the TSP, Kluwer Academic Publishers, 2002, pp. 369–443.
[33] N. Jozefowiez, Modélisation et résolution approchées de problèmes de tournées multi-objectif. Ph.D. thesis, Laboratoire d'Informatique Fondamentale de Lille, Université des Sciences et Technologies de Lille, Villeneuve d'Ascq, France, December 2004.
[34] N. Jozefowiez, F. Semet, E-G. Talbi, Parallel and hybrid models for multi-objective optimization: Application to the vehicle routing problem, in: J.J. Merelo Guervos et al. (Eds.), Parallel Problem Solving from Nature VII, Lecture Notes in Computer Science, vol. 2439, Springer-Verlag, 2002, pp. 271–280.
[35] N. Jozefowiez, F. Semet, and E-G. Talbi, Applications of multi-objective evolutionary algorithm, Advance in Natural Computation, chapter A multi-objective evolutionary algorithm for the covering tour problem, vol. 1, World Scientific, 2004, (pp. 247–267).
[36] N. Jozefowiez, F. Semet, E-G. Talbi, The bi-objective covering tour problem, Computers and Operations Research 34 (2007) 1929–1942.
[37] N. Jozefowiez, F. Semet, E-G. Talbi, Enhancements of NSGA II and its application to the vehicle routing problem with route balancing, in: E-G. Talbi, P. Liardet, P. Collet, E. Lutton, M. Schoenauer (Eds.), Artificial Evolution 2005, 7th International Conference (EA'2005), Lecture Notes in Computer Science, vol. 3871, Springer, 2006, pp. 131–142.
[38] N. Jozefowiez, F. Semet, E-G. Talbi, Target Aiming Pareto Search and its application to the vehicle routing problem with route balancing, Journal of Heuristics (2006).
[39] S. Kataoka, S. Morito, An algorithm for the single constraint maximum collection problem, Journal of the Operational Research Society of Japan 31 (1988) 515–530.
[40] C.P. Keller, Multiobjective routing through space and time: The MVP and TDVRP problems, Ph.D. thesis, Department of Geography, University of Western Ontario, London, Ontario, Canada, 1985.

[41] C.P. Keller, M. Goodchild, The multiobjective vending problem: A generalization of the traveling salesman problem, Environment and Planning B: Planning and Design 15 (1988) 447–460.

[42] P. Lacomme, C. Prins, M. Sevaux, A genetic algorithm for a bi-objective capacitated arc routing problem, Computers and Operations Research 33 (2006) 3473–3493.

[43] G. Laporte, S. Martello, The selective traveling salesman problem, Discrete Applied Mathematics 26 (1990) 193–207.

[44] L.H. Lee, K.C. Tan, K. Ou, Y.H. Chew, Vehicle capacity planning system (VCPS): A case study on vehicle routing problem with time windows, IEEE Transaction on Systems, Man and Cybernetics: Part A 33 (2003) 169–178.

[45] T-R. Lee, J-H. Ueng, A study of vehicle routing problem with load balancing, International Journal of Physical Distribution and Logistics Management 29 (1998) 646–648.

[46] W. Li, Finding pareto-optimal set by merging attractors for a bi-objective traveling salesman problem, in: C.A. Coello Coello, A.H. Aguirre, E. Zitzler (Eds.), Evolutionary Multi-Criterion Optimization, Third International Conference, EMO 2005, Lecture Notes in Computer Science, vol. 3410, Springer, Guanajanto, Mexico, 2005, pp. 797–810.

[47] M. Mourgaya, The periodic vehicle routing problem: planning before routing. PhD thesis, Laboratoire de Mathématiques Appliquées de Bordeaux, Université de Bordeaux 1, Bordeaux, France, July 2004.

[48] T. Murata, R. Itai, Multi-objective vehicle routing problems using two-fold EMO algorithm to enhance solution similiraty on non-dominated set, in: C.A. Coello Coello, A.H. Aguirre, E. Zitzler (Eds.), Evolutionary Multi-Criterion Optimization. Third International Conference, EMO 2005, Lecture Notes in Computer Science, vol. 3410, Springer, Guanajanto, Mexico, 2005, pp. 885–896.

[49] T. Murata, R. Itai, Local search in two-fold EMO algorithm to enhance solution similarity for multi-objective vehicle routing problems, in: S. Obayashi, K. Deb, C. Poloni, T. Hiroyasu, T. Murata (Eds.), EMO 2007, vol. 4403, Springer, 2007, pp. 201–215.

[50] B. Ombuki, B.J. Ross, F. Hanshar, Multi-objective genetic algorithm for vehicle routing problem with time windows, Applied Intelligence 24 (2006) 17–30.

[51] J. Pacheco, R. Marti, Tabu search for a multi-objective routing problem, Journal of the Operational Research Society 57 (2006) 29–37.

[52] L. Paquete, L. Chiarandini, T. Stützle, Pareto local optimum sets in the bi-objective traveling salesman problem: An experimental study, in: X. Gandibleux, M. Sevaux, K. Sörensen, V. T'Kindt (Eds.), Metaheuristics for Multiobjective Optimization, Lecture Notes in Economics and Mathematical Systems, vol. 535, Springer, 2004, pp. 177–199.

[53] L. Paquete, T. Stützle, A two-phase local search for the bi-objective traveling salesman problem, in: C.M. Fonseca et al. (Eds.), Evolutionary Multi-criterion Optimization, Lecture Notes in Computer Science, vol. 2632, Springer-Verlag, 2003, pp. 479–493.

[54] Y. Park, C. Koelling, A solution of vehicle routing problems in multiple objective environment, Engineering Costs and Production Economics 10 (1986) 121–132.

[55] Y. Park, C. Koelling, An interactive computerized algorithm for multicriteria vehicle routing problems, Computers and Industrial Engineering 16 (1989) 477–490.

[56] M. Rahoual, W. Djoukhdjoukh, Métaheuristique hybride Pareto pour le problème de tournées de véhicules avec fenêtres horaires. in: Evolution Artificielle 2003, pp. 380–395, 2003.

[57] M. Rahoual, B. Kitoun, M. Mabed, V. Bachelet, F. Benameur, Multicriteria genetic algorithms for the vehicle routing problem with time windows, in: Metaheuristic International Conference (MIC'2001), pp. 527–532, 2001.

[58] R. Ribeiro and H.R. Lourenço, A multi-objective model for a multi-period distribution management problem, in: Metaheuristic International Conference 2001 (MIC'2001), pp. 91–102, 2001.

[59] J. Riera-Ledesma, J.J. Salazar-González, The biobjective travelling purchaser problem, European Journal of Operational Research 160 (2005) 599–613.

[60] J.D. Schaffer, Multiple objective optimization with vector evaluated genetic algorithms, in: Genetic Algorithms and their ApplicationsProceedings of the First International Conference on Genetic Algorithms, vch, 1985, pp. 93–100.

[61] W. Sessomboon, K. Watanabe, T. Irohara, K. Yoshimoto, A study on multi-objective vehicle routing problem considering customer satisfaction with due-time (the creation of Pareto optimal solutions by hybrid genetic algorithm), Transaction of the Japan Society of Mechanical Engineering (1998).

[62] M. Solomon, Algorithms for the vehicle routing and scheduling problems with time window constraints, Operations Research 35 (1987) 254–265.

[63] C. Sutcliffe, J. Board, Optimal solution of a vehicle routing problem: Transporting mentally handicapped adults to an adult training centre, Journal of the Operational Research Society 41 (1990) 61–67.

[64] K.C. Tan, Y.H. Chew, L.H. Lee, A hybrid multi-objective evolutionary algorithm for solving vehicle routing problem with time windows, European Journal of Operational Research 34 (2006) 115–151.

[65] K.C. Tan, T.H. Lee, Y.H. Chew, L.H. Lee, A multiobjective evolutionary algorithm for solving vehicle routing problem with time windows, in: IEEE International Conference on Systems, Man, and Cybernetics, IEEE Service Center, 2003, pp. 361–366.

[66] K.C. Tan, Y.H. Chew, L.H. Lee, A hybrid multi-objective evolutionary algorithm for solving truck and trailer vehicle routing problems, European Journal of Operational Research 172 (2006) 855–885.

[67] E. Ulungu, J. Teghem, The two-phase method: An efficient procedure to solve bi-objective combinatorial optimization problems, Foundations of Computing and Decision Sciences 20 (1995) 149–165.

[68] E.L. Ulungu, J. Teghem, P. Fortemps, D. Tuyttens, MOSA method: A tool for solving MOCO problems, Journal of Multi-Criteria Decision Analysis 8 (1999) 221–236.

[69] Y. Zhenyu, L. Zhang, K. Lishan, L. Guangming, A new MOEA for multi-objective TSP and its convergence property analysis, in: C.M. Fonseca et al. (Eds.), Evolutionary multi-criterion optimization, Lecture Notes in Computer Science, vol. 2632, Springer-Verlag, 2003, pp. 342–354.

[70] K.G. Zografos, K.N. Androustsopoulos, A heuristic algorithm for solving hazardous material distribution problems, European Journal of Operational Research 152 (2004) 507–519.