Review

Operations research in solid waste management: A survey of strategic and tactical issues

G. Ghiani, D. Laganà, E. Manni, R. Musmanno, D. Vigo

Abstract

Solid waste management (SWM) is an increasingly complex task, absorbing a huge amount of resources and having a major environmental impact. Computerized systems based on operations research techniques can help decision makers to achieve remarkable cost savings as well as to improve waste recovery. Nevertheless, the literature is quite scattered and disorganized. The objective of this paper is to present an updated survey of the most relevant operations research literature on SWM, mainly focusing on strategic and tactical issues. In addition to providing an extensive bibliographic coverage, we describe the relationships between the various problems, and outline future research.

1. Introduction

The large and increasing amount of solid waste generated each year in both industrialized and developing countries, along with the public concern for environmental preservation, is making solid waste management one of modern society’s most relevant issues. The Municipal Solid Waste (MSW) is defined by the United States Environmental Protection Agency (U.S. EPA) to include waste from residential, multifamily, commercial, and institutional (e.g., schools, government offices) sources [1]. This definition excludes many materials that are frequently disposed with MSW in landfills, including combustion ash, water and wastewater treatment residuals, construction and demolition waste, and nonhazardous industrial process waste. Each year in the European Union about 3 billion tonnes of waste are generated, and some 90 million
tonnes of it are hazardous [2]. Moreover, the amount of waste generated is rapidly increasing, with values close to 20% over a period of 11 years (1995–2006) in North America and the EU [3]. The last U.S. EPA document on MSW generation in the U.S. reports a production of about 250 million tonnes of waste in 2009, and about 85 million tonnes of recycled and composted material, leading to approximately 34% of recycling rate [1].

In this context, an integrated Solid Waste Management (SWM) represents a real request and a big challenge at the same time. A recent description of modern and integrated waste management systems can be found in Tchobanogous [4], whereas decision support models and their practical impact on the Integrated Urban Waste Management Framework are reviewed in the recent book of Vigo et al. [5]. Studying a SWM system from an operations research point of view implies modeling it through a multi-echelon supply chain in which the following processes take place: waste generation in regional districts; waste collection in transfer stations; waste separation performed at the sources or in separation plants; waste treatment through incinerators, waste-to-energy plants, reclamations, or composite plants; waste disposal by land filling or land spreading.

SWM involves a number of strategic, tactical and operational decisions, such as the selection of SW treatment technologies, the location of treatment sites and landfills, the future capacity expansion strategies of the sites, waste flow allocation to processing facilities and landfills, service territory partitioning into districts, collection days’ selection for each district and for each waste type, fleet composition determination, and routing and scheduling of collection vehicles. Given that dealing with each of these aspects leads to solving several combinatorial optimization problems, computerized systems based on Operations Research (OR) techniques can help decision makers to achieve remarkable cost savings. Several successful applications of OR methods have been described in the last 40 years. Most of the models presented in the literature aim at guiding the decision maker toward the choice of the best strategy, selected among a set of options. Such methods evaluate all the suitable alternatives at every stage of the decision process. In some cases, the goal of the model is simple (e.g., optimize waste collection routes for vehicles), while in others it is more complex (e.g., evaluate alternative waste management strategies). However, because SWM involves also institutional, social, financial, economic, technical, and environmental factors, no model described in the literature is able to capture all different aspects to be considered. On the other hand, general models have so many variables and constraints that solving them through general-purpose solvers can be very hard and time consuming. In general, the literature is still scattered and disorganized. Given that a survey of all OR models in this area would require a very long article, the focus of this paper is to concentrate on some of the most important methodological contributions and the most meaningful applications originating from the application of OR techniques to strategic and tactical problems arising in SWM, as well as to indicate future research directions.

The remainder of the paper is organized as follows. Section 2 describes strategic planning issues (mostly arising at a regional level), whereas Section 3 is devoted to tactical decisions. Finally, Section 4 concludes the paper and outlines future research directions.

### 2. Strategic issues

For planning purposes, a SWM system can be decoupled into two major subsystems: a regional management system, and a collection system. Each town is in charge of its own curbside garbage collection, using either its own workforce from a municipal or regional agency, or a contracted service. On the other hand, the regional administration is responsible for the treatment and disposal of the collected waste. The primary reason for this is the existence of relevant economies of scale in waste transportation and disposal (see [6]). In the current literature, these two subsystems are usually considered as separate, although remarkable cost savings might result from an integrated approach. Given a set of potential processing facilities and landfills (each characterized by a location and a number of additional technological and economic features), the most relevant regional planning decision amounts to determining which facilities should be built or used, and how waste should be routed, processed and disposed so as to minimize the total waste disposal cost, net of any revenue for reclaimed material and generated energy. Building a new treatment or disposal facility may take 1–4 years, while the operating life of a facility is estimated to be around 15–30 years (similar considerations hold for landfills). After this period, certain replacements are required. Consequently, designing or re-designing a regional SWM system is a strategic decision having long-lasting effects. The main features to take into account are:

- **Time**: Decisions related to building a new facility or closing an existing one affect a long-term planning horizon.
- **Network structure**: A multi-echelon logistic network is needed to model all the strategic decisions.
- **Commodities**: The cost of transporting and disposing waste depends heavily on the type of waste (municipal refuse, industrial waste, farm refuse, demolition and construction debris, etc.). Moreover, each waste type can be processed in a limited number of ways (e.g., inert refuse cannot be composted).
- **Facility cumulative capacity**: Landfills have an overall cumulative capacity for waste disposal, which progressively reduces as long as refuse are stored (see, e.g., [7]).
- **Economies of scale**: The operating cost of a facility is a concave function of its activity level because of economies of scale that may be achieved.
- **Transshipment with waste transformation**: Once a waste type is processed in a facility, its own characteristics change (e.g., its volume reduces). This peculiar feature can be modeled through a network flow with gains (see, e.g., [8]).
- **Objectives**: Decision makers often pursue conflicting goals, such as to locate facilities as close as possible to sources (to minimize transportation costs), and to locate facilities as far as possible from urban centers. In addition, SWM often gives rise to sociopolitical issues that are difficult to model (see, e.g., [9,10]).

We now present a Mixed Integer Programming (MIP) model that is a generalization of models from the literature [11] and puts together all the previous aspects, and then categorize the literature with respect to it.

#### 2.1. A MIP model for the strategic planning of a SWM system

The possible configurations of a SWM system to be designed at the strategic level can be represented by a directed graph $G = (V, A)$ in which the vertex set $V$ may be partitioned into four subsets: $V_S$ representing sources, $V_L$ modeling potential transfer stations, $V_F$ describing processing facilities (incinerators, waste-to-energy plants, etc.), and $V_L$ representing landfills, disposal facilities and markets for recycled products and energy. Arcs in set $A$ correspond to feasible shipments between sites (Fig. 1).

Decisions have to be made over a long-term horizon defined over a set $T$ of periods. Each period $t \in T$ may represent, for instance, one year or several years. Moreover, in order to take into account the possibility to manage different types of waste, we
A mathematical formulation of the problem is represented by \( G_{0w} \). Observe that uncertainty may affect the value of \( G_{0w} \). Finally, let \( b_{ijw} \) denote the reduction coefficient per unit weight (or volume) of the waste commodity \( w \in W \) into the waste commodity \( w' \in W' \) at facility \( j \in V_j \). This coefficient is used to describe how the waste flows are converted when they reach a processing facility. The costs involved in these processes are: a non-negative transportation cost per unit weight (or volume) of waste \( c_{ijw} \) that is associated with each arc \((i,j) \in A\), an initial cost \( f_{ijw}^l \) for opening a new facility \( j \in V_j \) into \( W' \) in period \( t \) (\( t = 1, \ldots, T \)), a fixed cost \( f_{ijw}^l \) for operating facility \( j \in V_j \) into \( W' \) in period \( t \) (\( t = 1, \ldots, T \)), and a cost \( p_{ijw}^l \) when processing a unit of waste of type \( w \in W \) at facility \( j \in V_j \) in period \( t \) (\( t = 1, \ldots, T \)). These costs are time-dependent to account for possible variations over time. Decision variables \( z_{ijw} \) are binary variables taking the value 1 if and only if a facility \( j \in V_j \) is open in period \( t \) (\( t = 1, \ldots, T \)), 0 otherwise. Variables \( y_{ijw} \) are also binary variables taking the value 1 if another facility \( j \in V_j \) is open in period \( t \) (\( t = 1, \ldots, T \)), and 0 otherwise. Finally, variables \( x_{ijw} \) represent the flow of waste commodity \( w \in W \) traversing arc \((i,j) \in A\) in period \( t \) (\( t = 1, \ldots, T \)).

A mathematical formulation of the problem is

\[
\begin{align*}
\text{min} & \quad \sum_{t=1}^{T} \sum_{w} \sum_{(i,j) \in A} c_{ijw} x_{ijw} + \sum_{t=1}^{T} \sum_{w} \sum_{i} p_{ijw} + \sum_{i} x_{ijw} \\
& + \sum_{t=1}^{T} \sum_{w} \sum_{i} p_{ijw} + \sum_{t=1}^{T} \sum_{w} \sum_{i} \sum_{j} f_{ijw} \sum_{i} y_{ijw} \\
& + \sum_{t=1}^{T} \sum_{i} \sum_{w} \sum_{(i,j) \in A} (f_{ijw} z_{ijw} + f_{ijw} y_{ijw}) \\
\text{subject to} & \quad \sum_{j \in V_j} x_{ijw} = G_{0w} \quad t = 1, \ldots, T, \quad i \in V_i, \quad w \in W
\end{align*}
\]

In this formulation, the objective function aims at minimizing the sum of all the costs incurred over the entire planning horizon. Eqs. (2) impose that all the waste generated at each source is collected. Eqs. (3) is flow balance conditions taking into account volume reduction, inequalities (4) do not allow using a facility which was not previously opened, imposing, at the same time, that the amount of waste treated is no greater than the capacity of the facility. Moreover, inequalities (5) impose that the total volume of waste treated over the horizon cannot exceed the overall landfill capacity, and inequalities (6) guarantee that each intermediate facility cannot be opened more than once over the time horizon. Finally, inequalities (7) and (8) ensure that the values of \( y_{ijw} \) and \( z_{ijw} \) (\( j \in V_j \) and \( w \in W \)) are consistent. We observe that some variables \( y_{ijw} \) may be fixed.

2.2. Literature classification

A large class of waste management facility location–allocation problems is characterized by multiple, often conflicting objectives such that the solutions provided by computerized systems based on OR techniques are not effective for real SWM systems. Therefore, considerable local oppositions are induced by the site selection of waste facilities, leading to arguments like BANANA (Built Absolutely Nothing Anywhere Near Anyone), LULU (Locally Unwanted Land Use), NIMBY (Not In My Back Yard), NOPE (Not On Planet Earth), or NOTE (Not Over There Either). Location models taking into account either economical and social aspects or conflicting objectives are developed in the papers we describe in the following.

Given the large variety of characteristics that are incorporated into the strategic models proposed in the literature, we introduce a classification scheme for this problem family that will be used in the paper to identify the specific variant at hand.

The classification is based on four fields p/s/c/o, each associated with a significant component of the problem. The first field “\( p \)” corresponds to the problem periodicity: it takes value 1 if a single period occurs and 0 if multiple periods are considered. The second field “\( s \)” is associated with the network structure and may contain multiple subfields separated by commas:

- C, if the optimal location of new collection sites is taken into account,
- S, if the presence of existing or new transfer stations is considered,
- P, if either the opening of new processing facilities or optimizing the operating of existing processing facilities is evaluated,
- L, if existing or new landfill, disposal or market facilities are considered.
The third field “c” describes additional constraints and characteristics of the problem, again possibly separated by commas:

“multiwaste”, if several types of waste are considered, “uncert”, if uncertainty in waste generation takes place.

Finally, field “o” is associated with the optimization objectives:

TC, if transportation costs are minimized, PC, if processing costs at the facilities are considered, FC, if fixed costs either for existing facility operations or new facility opening are included, “multiobj”, if multi-objective optimization is explicitly considered.

Whenever the model does not include specific assumptions for one of the above fields, the corresponding value is set “-“.

An example of the use of this classification scheme is 1/S,P/-/TC,FC that stands for a single period problem that considers possible opening of transfer stations and plants and minimizes transportation and facility setup costs. Table 1 reports a summary of the main characteristics of some of the most representative papers on regional planning.

<table>
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<tr>
<th>Article</th>
<th>Collection site location</th>
<th>Transfer station location</th>
<th>Waste processing facility location</th>
<th>Landfill location</th>
<th>Economies of scale</th>
<th>Multi-period capacity expansion</th>
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2.2.1. Single-period location models

The first group of papers we describe emphasize the strategic aspects of the SWM problem related to the location of the logistic facilities in order to minimize the total SWM cost. They do not consider the integration of these characteristics with other crucial strategic aspects that have a strong impact on the performance of the system, like the time-dependency, multi-commodity, and uncertainty on the waste generation.

Bloemhof-Ruwaard et al. [12] consider a two-level location problem described through a 1/P/L/multiwaste/TC,FC model, in which the objective is to minimize the sum of the total fixed cost for opening plants and waste disposal units, the total cost for shipping flow from the plants to the customers, and from the plants to the waste disposal units. They provide two alternative formulations, valid inequalities, a Lagrangean lower bound, as well as a rounding heuristic and a decomposition procedure. A number of researchers have used similar models. Jenkins [13] utilizes a 1/S,P/-/PC,FC large scale fixed-charge model, including shipments of recycled materials to markets, to locate resource recovery plants in Southeastern Ontario. He also performs a parametric analysis on both the objective function coefficients and the constraints’ right-hand-side. Kulcar [14] describes a case study dealing with the optimization of the solid waste collection in Brussels (Belgium). A two-phase approach based on the combination of a branch-and-bound method with systems engineering is developed to minimize waste transportation costs in a major urban area. A 1/S,P/-/TC,FC capacitated location model is used to determine the receiving terminal site and assess the need of a new intermediate site between the collection routes and the incinerator. A pure integer capacitated location model is also used to evaluate the impact on the collection process of a possible reduction in the number of depots.

Antunes [15] studies the MSW system of Central Portugal and develops a 1/S,L/-/TC,FC MIP model, combining elements of a p-median model and of a capacitated facility location model with...
transshipments, in which a maximum distance between sources and transfer stations, and between transfer stations and landfills is imposed. The model is solved through a general purpose solver, evaluating the decrease in the costs related to transfer stations and waste transportation. Badran and ElHaggar [16] present a model for municipal solid waste management in Port Said (Egypt). The proposed model aims at minimizing the municipal waste management cost, determining the best location for collection sites among a given set of candidate locations. A 1/S,P,L/TC,PC,FC MIP model is used to describe the SWM system. Such a model provides consistently better solutions than that previously implemented.

Mitropoulos et al. [17] study a three-echelon network design problem with central treatment facilities, transfer stations and landfills, where the goal is to minimize the total cost of the SWM system. A 1/S,P,L/TC,FC MIP model is presented. Valid inequalities based on those developed for the capacitated distribution and waste disposal problem studied by Bloemhof-Ruwaard et al. [12] and the two level network for recycling sand proposed by Barros et al. [18] are illustrated to improve the proposed formulation. Some of these inequalities are added to the root node of the search tree to strengthen the lower bound and reduce computation time significantly. Small instances are solved to optimality through the presented model, while an interchange heuristic is designed to find feasible solutions for large instances of the problem. The effectiveness of this approach is tested within a research project for the development of a SWM system for a specific region in Greece.

Eiselt [19] evaluates how far the observed locations of landfills and transfer stations deviate from the optimized (i.e., cost-minimizing) solution. The location problem is modeled through a path-based garbage transfer problem, in which the decision to locate landfills and transfer stations at some sites is made by means of binary variables. He develops a 1/S,L/TC MIP model, in which the proportion of the garbage shipped directly from the customers to the landfills and via transfer stations is represented by flow allocation variables. Similar to hub location problems, a discount is charged into the objective function whenever the garbage is processed and via transfer stations is represented by

The time dimension in the context of the location problem of disposal sites and processing facilities is analyzed by Shekdar et al. [21], who propose a T/S,P,L/TC,FC MIP model aimed at minimizing solid waste handling costs over several development phases of an urban area. This model faces a location problem of the disposal sites and allocates the collection areas to the sites and processing facilities in the long time horizon. The model is applied to a real case to show its usefulness for long range planning in cities.

### 2.2.3. Multi-objective location models

The following papers study the SWM system as location and multi-commodity flow models where multiple objectives must be optimized. Caruso et al. [22] present a T/P,L/multiwaste/TC,FC, multiobj model, in which multiple commodities and three different objectives (the overall cost, the waste of recyclable resources, and the environmental impact) are considered. The three objectives are then combined into a parametric single objective according to the weighting method. A set of approximate Pareto solutions is then searched through an add-drop heuristic. Finally, the reference point method [23] is used to help the decision-maker in identifying the final solution. Rahman and Kuby [24] propose a 1/S–/TC,FC,multiobj model locating transfer stations, where the focus is the compromise between minimizing transportation costs and maximizing the distance of the facilities from the residential zones. Only transfer station facilities are considered, in which refuse is transferred from collection trucks to long-haul trucks for more economical shipping to distant landfills. The public opposition to the location of facilities near to the inhabitants areas is measured by a decreasing function of distance from facilities. A comparison study of the regional and prefectural SWM planning in Central Macedonia is described in Erkut et al. [25]. The prefectural plan is designed by locating waste facilities in each preference. The regional plan allows cooperation between preferences, so that waste facilities are located to serve the entire region. A 1/S,P,L/TC,FC,multiobj MIP model is developed for the location–allocation SWM municipal problem at the regional level. The multiobjective problem is formulated as a lexicographic minimax problem aiming at finding a nondominated solution with all normalized objectives as close as possible. A solution provided by such model consists of locations and technologies for transfer stations, material recovery facilities, incinerators and sanitary landfills, and waste flow between the locations.

Tralhão et al. [26] propose a T/P/multiwaste/TC,FC,multiobj MIP approach to identify the locations and capacities of multi-compartment sorted waste containers. The model aims at determining the number of facilities to be opened, as well as the respective container capacities, their locations, and the dwellings assigned to each facility. The solution approach integrates an optimization model in a Geographical Information System-based interactive decision support system with the aim of minimizing the following four objectives: (1) the total investment cost; (2) the average distance from dwellings to the respective multi-compartment container; (3) the number of individuals too close to any containers; (4) the number of dwellings too far from the respective multi-compartment container. The proposed approach is tested on a case study raised the city of Coimbra (Portugal).
2.2.4. Location models integrating economical and social components

All the already cited papers typically use a general purpose solver to solve a MIP model for the location problem related to the transfer stations, processing facilities and landfills of a SWM system. They are focused typically on the application of classical location models to a subnetwork of the more complex SWM network depicted in Fig. 1, and do not take into account the integration of the solutions obtained through the location models with economical and social components. The following papers represent a significant step to integrate location strategic decisions within a more general SWM optimization problem as described by the model illustrated in Section 2.1.

Integrated optimizer tools, or Decision Support Systems (DSS), supporting the decision maker in order to assume solid waste strategic decisions are frequently used in the real world context. Fiorucci et al. [27] describe a DSS tested in the city of Genoa (Italy), allowing to plan the optimal number of landfills and treatment plants, and to determine the optimal quantities and the characteristics of the refuse that must be sent to treatment plants, to landfills and to recycling. The core of the DSS optimization process is based on a constrained non-linear 1/P,L/multiwaste/TC,PC,FC optimization problem, in which an objective function including recycling, transportation and material costs is minimized over various constraints. A 1/S/–/TC,PC,FC,multiobj optimization model integrating economical and environmental aspects for a solid waste management system is proposed by Noche et al. [28]. They develop a mixed-integer linear programming model for municipal solid waste management of the city of Duisburg (Germany) including different scenarios. The proposed model aims at minimizing the total solid waste management system costs by considering different restrictions such as logistic, technical, environmental, and social constraints.

Antunes et al. [29] illustrate a three stage 1/S/–/TC MIP-based approach helping the company responsible for the municipal SWM system in the Litoral Centro area of Portugal to find the best way to redevelop the existing SWM system. This study aims at identifying the best possible location for a new generation of incinerators with energy recovery, as well as the best locations, capacities, and coverage areas for possible new transfer stations. A three-stage solution approach is presented. The first stage consists in finding the best municipalities to locate the incinerator and the new transfer stations. The second stage reduces to the problem of finding the best communities where to locate the incinerator within the municipalities identified in the first stage. The third stage consists in solving the classification problem of the industrial sites located within the communities identified in the second stage according to the relevant criteria. A MIP model is proposed to solve the problems related to the first and second stage.

Recently, Galante et al. [30] have studied the localization and dimensioning of transfer stations in the logistic chain of the solid waste stream. A 1/S/–/TC,FC,multiobj integrated optimization approach aiming at defining the number and type of vehicles is also carried out. Two conflicting objectives consisting in the minimization of both the total cost and the environmental impact are considered in an integrated multi-objective optimization approach. The methodology is applied in the context of the waste management of the city of Palermo (Italy).

Ghiani et al. [10] study the problem of minimizing the total number of collection sites to be located in a SWM system, chosen among a set of candidate locations. Such an objective ensures not only the reduction of the impact due to the presence of the collection bins close to the residential sites, but also the reduction of the overall cost related to the collection phase. The proposed model determines also the optimal allocation of citizens to collection sites by ensuring that each citizen is serviced by a collection site which is within a threshold distance from his/her home. Such a condition is achieved through peculiar constraints added to the 1/C/–/– model.

2.2.5. Models with uncertainty

Very few papers deal with the uncertainty on the waste generation. Such papers typically address the waste-management planning problem to minimize the associated treatment costs through interval analysis, chance-constrained, stochastic, and fuzzy programming approaches, where dynamic aspects and economies of scale are modeled.

A 1/P,L/uncert/TC,PC Two-stage Interval Stochastic Programming (TISP) model for the planning of SWM systems under uncertainty is developed in Maqsood and Huang [31]. The proposed approach is applied to a case wherein a solid-waste manager is responsible for allocating waste from cities to disposal facilities over a planning horizon. The uncertainty affects the amount of waste generation in each of the cities at the time when the planning decisions must be made. The objective function of the TISP model minimizes the expected value of the SWM system cost in the region. The uncertainty is expressed through intervals and probability distributions of random variables, while penalties come into play when policies represented by allowable waste-loading levels are violated. The solution approach reduces the TISP model into two deterministic submodels, which correspond to the lower and upper bounds for the desired objective-function value.

A 1/P,L/uncert/TC,PC Interval-parameter Two-stage Mixed Integer Linear Programming (ITMILP) model is proposed by Li and Huang [32] with the aim of supporting long-term planning of waste management activities in the city of Regina, Canada. The proposed model integrates both two-stage stochastic programming and interval linear programming into a general MIP model. The uncertainty is modeled through probability density functions and discrete intervals related to random variables. The model captures dynamic, interactive and uncertain aspects of the SWM system in the city. The decision variables are both discrete and continuous random variables. The discrete variables represent the expansion options for waste management facilities in different periods, while the continuous ones represent the optimized waste flows from the city’s residences to the waste management facilities. The objective minimizes the total expected system cost by achieving optimal plans for facility expansion/development and waste flow allocation over the entire planning horizon. The solution approach solves the presented model over three scenarios based on different waste management policies.

An Interval MiniMax Regret Programming (IMMRP) method is designed by Yong and Huang [33] for the planning of municipal SWM system under uncertainty. Such method improves on the existing interval programming and minimax regret analysis methods by allowing uncertainties, presented as both intervals and random variables of the optimization process. The IMMRP takes into account the economic impacts of all possible scenarios without any assumption on their probabilities. The developed method is applied to a case study of long-term SWM planning under uncertainty. The uncertainty arises in waste-generation rate, and it is modeled by means of random variables; on the other hand, some random events can only be quantified as discrete intervals, leading to the concept of Interval Random Variable (IRV). The decision maker does not know the probabilistic distribution of the IRV. Based on this method, if the waste-flow level equals the waste-generation rate, the system pays regular costs, leading to minimum cost and regret levels, otherwise an excess regret is generated due to the violation of the available resources. A computational analysis is performed with multiple scenarios associated with different cost and risk levels. The results show that
the proposed approach is helpful for planning policies in the context of waste management under a variety of uncertainties.

Uncertainty in both left- and right-hand-side parameters of probabilistic constraints is tackled by means of intervals and probability distributions by Guo et al. [34], who combine stochastic programming, integer programming, and interval semi-infinite programming approach for a SWM system. To address the uncertainties affecting coefficients in both hand-sides of probabilistic constraints through probabilistic distributions, robust optimization model are proposed. In particular, Cai et al. [35] develop an Interval-Valued Fuzzy Robust Programming (I-VFRP) model for a municipal SWM system under uncertainty.

3. Tactical issues

At the tactical (or mid-term) level, several decisions must be taken. Among them, the most representative are: allocating waste flow among the facilities selected at the strategic level, partitioning the service territories into districts, choosing collection days for each district and for each waste type, determining the composition of the fleet and the crew.

A summary of the main characteristics of the papers concerning tactical issues that are described in the following, is reported in Table 2, at the end of this section.

3.1. Waste flow allocation

When waste generation is deterministic, the waste flow allocation problem is usually solved as a part of the more general strategic planning models (see Section 2). Examples of such papers, already described in the previous section, are those by Bloemhof-Ruwaard et al. [12], Erkut et al. [25], Mitropoulos et al. [17], and Ghiani et al. [10].

On the other hand, when uncertainty comes into play, the waste flow allocation problem becomes much more complicated. However, despite its importance and practical relevance, still very few papers deal with it. Aspects which can be treated as uncertain are: the processing cost of waste processed at the different facilities, the cost of transporting waste among the facilities, the waste generation at each district, the fraction of waste generated at each district which is recyclable. As pointed out in Section 2, typical solution approaches make use of stochastic programming based algorithms.

Huang et al. [36] solve the problem of allocating municipal waste flow under uncertainty using a case study from the Municipality of Hamilton-Wentworth in the Province of Ontario. They propose an approach based on Grey Linear Programming (GLP), a method that is able to deal with interval input data, in which problems containing interval parameters are transformed into a pair of deterministic submodels. When solved in tandem, such models guarantee stable upper and lower limits for the solution. This transformation is executed in a prescribed order using the output from the first submodel as direct input into the second submodel. The final output of the method is a set of stable interval values for the objective function and for all decision variables related to uncertainty, such as the quantity of waste generated at each district. Using GLP, Huang et al. [36] are able to determine a solution for the case study, in which the existing system cost could be consistently reduced with only minor changes to the existing waste management scheme.

Yeomans et al. [37] combine a genetic algorithm with simulation to solve the problem of municipal waste flow allocation under uncertainty, improving the work in Huang et al. [36]. In particular, each candidate solution of the population set, which contains uncertain elements such as the quantity of waste generated at each district, is simulated to be evaluated. Then, based on the results of the simulation phase, the genetic algorithm allows the system to evolve toward better solutions, generating a new set of candidates to be evaluated again by simulation. After termination, the algorithm provides, in addition to the best solution, a number of “good” solutions. In this way, the method could be used even for policy comparisons purposes. The procedure is tested on real data from the same case study as in Huang et al. [36]. When compared to the results of such study, the proposed approach is able to improve over them, with gains ranging from 4% to 6%.

Table 2

Selected papers on tactical issues in SWM.

<table>
<thead>
<tr>
<th>Article</th>
<th>Waste flow allocation</th>
<th>Zoning</th>
<th>Collection decisions</th>
<th>Fleet and crew composition</th>
<th>Uncertainty</th>
<th>Exact method</th>
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Yeomans [38] further extends the work by Yeomans et al. [37] combining the use of penalty functions with GLP into an Evolutionary Simulation-Optimization (ESO) procedure. The computationally efficient GLP procedure [36] is used to quickly generate a starting population to initialize the evolutionary algorithm. Then, in order to allow ESO to explore regions beyond its feasible boundaries, infeasible solutions are considered in a penalty-based fashion, transforming the MSW model into an unconstrained stochastic minimization problem.

More recently, Yeomans [39] studies the possibility to use a co-evolutionary simulation-optimization approach to generate multiple solution alternatives in a municipal SWM system. Each alternative solution generated is such that it is sufficiently different from the others, so that it can provide quite different planning perspectives. The approach is tested on the same case study as in Yeomans et al. [37].

3.2. Districting

The purpose of the districting (or zoning) phase is to determine collection districts. The districts must be such that the sum of solid waste loads within each district does not exceed the capacity of the vehicles that will perform the operations. The problem of districting, especially in the context of location and (arc) routing, is not widely addressed in the literature, or in many cases it is assumed to be solved a priori, de facto neglecting the positive impact it could have on the subsequent routing phase, or included in the strategic issues.

Male and Liebman [40] propose a districting heuristic based on the construction of an auxiliary graph, called cyclenode graph, in which nodes represent trips and edges represent feasible trips aggregations. The approach is based on the partition of an Eulerian graph into cycles using a “checkerboard pattern”. This partition is characterized by a large number of small cycles where every edge of the graph belongs to exactly one of them. Such cycles are then used to determine the districts.

Eisenstein and Iyer [41] approach this problem by devising flexible schedules for garbage trucks in the city of Chicago. The weight and time required to collect garbage from a single block are modeled as random variables, whose parameters are estimated from real data. They introduce a dynamic scheduling scheme that uses flexible truck routes, with the flexibility deriving from the possibility to visit the dumpsite once or twice a day. The choice of a truck route is modeled as a Markov Decision Process (MDP), that adjusts the number of dumpsite visits throughout the week to maximize the service level. Given a sequence of \( n \) blocks to be collected by a single truck over a work week, plus an additional dummy block \( n+1 \) with no weight and time requirements, the state of the MDP is said to be \( i \) at day \( t \) if at the beginning of day \( t \) the truck is starting to collect block \( i \). At the beginning of each morning, a decision \( a \) must be taken \((a \in A = \{1, 2\})\), concerning whether to use a route which visits the dumpsite once \((a = 1)\), or twice a day \((a = 2)\). Given the probabilities \( p_{ij}(a) \) to transition to state \( j \) following decision \( a \) in state \( i \), the value function \( v_t(i) \) is defined as the maximum probability that a truck will complete all assigned blocks by the last day of the week, given that it starts in state \( i \) on day \( t \). Since the system always begins in state 1 on day 1, the objective is to determine a policy, i.e., a sequence of deterministic Markov decision rules, that maximizes \( v_T(1) \). This is achieved through backward induction. Empirical results of the impact on data collected from sample wards show the possibility to obtain a reduction in the number of truck routes required to perform the garbage collection operations, ranging between 12% and 16%, leading to over $9 million overall cost savings.

Hanafi et al. [42] study the weekly sectorization problem regarding household waste collection, with the aim of determining a fixed number of sectors which should be balanced with respect to daily total time for collection tasks. For this problem, they propose an optimization model that is not easily solvable for large-sized instances. Thus, a local search heuristic that is based on the definition of a new effective data structure (sectorization matrix) is described. The proposed methods are tested on three real-world instances (related to Quito in Ecuador and Echirolles and Saint-Martin d’Hères in France) and 28 randomly generated instances.

Labelle et al. [43] present models and heuristics for partitioning a city into sectors, with respect to snow disposal operations, and for assigning the sectors to disposal sites. Even though this paper is not directly related to SWM, it is worth citing it, because, as pointed out by the authors, it is similar to the problem encountered in garbage collection operations. The sector design process provides a set of sectors, each of which is assigned to a disposal site. For this purpose, a districting problem needs to be solved first, to define the boundaries of each sector, and an assignment problem must be solved later, to associate sectors with disposal sites. The goal is to minimize the overall cost for performing operations, made up of operational costs, and fixed costs for equipment. As a proxy for trucks fixed costs, the number of trucks required for performing the operations is considered. Given that the mathematical model may be very hard to solve because of nonlinearities in the objective function, the authors develop a heuristic procedure. The overall problem of sector design is decomposed into two sequential sub-problems. First, they determine for each disposal site its area of influence; second, they partition the area of influence for each site into sectors. The objective of the first phase is to minimize relevant operational costs; the objective for the second phase is to minimize the number of trucks for the given zone assignments. These algorithms are incorporated in a DSS built on a geographical information system, and tested on the city of Montréal.

Sahoo et al. [44] discuss how to divide the area from which waste is to be collected into districts in order to subdivide the problem and make it more manageable. In particular, they propose a mathematical model, as well as a two phase insertion algorithm, in which a feasible solution is first generated, and then improved. The first phase of the solution approach utilizes a \( k \)-means-variant-balanced-clustering algorithm [45], that randomly selects initial centroids, and then clusters the stops according to the distances between the stops and the centroids. The second phase makes use of an extended version of the insertion algorithm by Solomon [46], and a simulated-annealing metaheuristic combined with the CROSS exchange local-search method of Taillard et al. [47] for further improvements.

Nuortio et al. [48] describe the zoning of a service territory in Eastern Finland by determining vehicle routes and schedules for the collection of municipal solid waste. The problem is modeled as a Stochastic Periodic Vehicle Routing Problem with Time Windows and a limited number of vehicles, which is solved by the Guided Variable Neighborhood Thresholding (GVNT) metaheuristic [49]. The stochasticity lies in the accumulation rate of waste in each container type, and in the travel times. The proposed approach is made up of two phases. In the first phase, a feasible solution is created with a hybrid insertion heuristic. Then, in the subsequent phase, the GVNT metaheuristic is used to try to improve the initial solution. GVNT is based on three well known metaheuristic principles, namely guided local search [50], variable neighborhood search [51], and threshold accepting [52]. When compared to the current solution of the waste management company, it is shown that significant improvements (up to 46%) can be obtained.

More recently, Mourão et al. [53] study the sectoring arc routing problem, which has a natural application in waste collection. The aim is to partition the service territory into a number of sectors, so that each sector can be covered by a set of vehicle trips.
The authors propose three heuristics to face this problem. The first two heuristics are made up of two phases. In the first phase the sectors are determined, whereas in the second phase vehicle routes are obtained by solving a mixed capacitated arc routing problem (MCARP). The two variants differ by the heuristic used for the sectoring phase. In particular, the first sectoring heuristic, called Circuit of Tasks Heuristic, adds to the selected sector the tasks of a small demand circuit computed in a balanced graph. On the other hand, the second sector heuristic, Single Task Heuristic, adds one task at a time. Finally, the third heuristic, namely the Best Insertion Heuristic, builds sectors and trips simultaneously. In particular, each sector is initialized with a different seed-task, and, in order to ensure that the different sectors are balanced, at each iteration it is chosen to expand the sector with the least workload. Then, to limit the increase in workload and to keep the sectors as compact as possible, one task close to such a sector is added to it. The three heuristics are tested on three groups with five MCARP instances each, resembling waste collection operations in modern towns, old historical town centers, and low-traffic suburban areas.

3.3. Collection patterns

Collection decisions mainly involve the choice of the collection days when the different operations must be performed. In particular, important decisions concern the maximum number of accumulation days (that is, the maximum number of days between two consecutive removals), and the service frequency (for instance, once or twice a week). In fact, if such decisions are not taken properly (for instance, there are too many accumulation days, or the service frequency is not adequate) the risk is that the refuse removal is not uniform during the week and the trucks are fully exploited only in some peak days, while they are only partially filled in the other days. This would lead to increased costs for the subsequent operational collection phase. Thus, a minimization of the service costs can be obtained through a minimization of the maximum quantity removed in a day (peak quantity). This is the objective pursued by Mansini and Speranza [54]. In this paper, the problem of the efficient management of municipal household refuse collection at a tactical level is tackled, aiming at deciding the collection days for a single city district. In particular, municipal refuse generation is assumed to occur at a constant rate and collection is supposed to be periodic. At each collection site, the number of consecutive accumulation days must be contained into a user-defined set. Mansini and Speranza [54] consider the problem of minimizing the maximum amount (peak) of refuse collected in a day. This choice is roughly equivalent to minimizing the number of vehicles and crews required to collect waste. By solving their model on data from the city of Brescia, the authors are able to obtain a peak reduction ranging between 10% and 16% (depending on the collection frequency), compared to the peak values without using the proposed model.

The main limit of the above formulation is the absence of differentiation between different waste commodities. Mansini and Speranza [54] overcome such a limit by generalising it to the case of separate collection of different types of refuse (organic waste, glass, paper, etc.). As recyclable materials (such as glass and paper) may have a longer accumulation period, the authors are able to reduce peak by 18.5% in the considered case study.

A similar problem is tackled by Angelelli and Speranza [55]. In this paper, the authors consider a problem in which a fixed number of vehicles is available for collecting waste. A number of collection points is spread over the collection area, and each point must be served at a given frequency. For instance, if the frequency is twice a week, the manager in charge of the collection operations can choose to serve that point on Monday–Thursday, or Tuesday–Friday, or on Wednesday–Saturdays. In this case, (M-Th), (Tu-F), (W-S) make up a list of feasible visiting schedules for such a point. Finding a good visiting schedule is not trivial, because two conflicting objectives must be optimized. First of all, the service at each collection point must be frequent enough to prevent any inconvenience to citizens. On the other hand, a very frequent service would contribute in increasing the costs of the collection operations. Angelelli and Speranza devise a model for such a problem in which a number of days, the duration of the daily shift, a fleet of vehicles, and a set of collection points (each of them with an associated set of feasible collection schedules, where a collection schedule is a visiting schedule with additional information on the demand for each day) are given. The goal is to find a set of routes assigned to each vehicle on each day of the planning horizon, so that every collection point is visited according to a feasible collection schedule, no more than once on the same day. The solution approach consists in a tabu search. First, a visiting schedule is randomly chosen for every macro-point. Then, an initial solution is built, and the algorithm starts to repeatedly move from one solution to another by means of moves which induce “small” changes in the current solution. After a fixed number of iterations, the best feasible solution is returned. The method is tested on two real cases, namely Val Trompia (in the province of Brescia), and Antwerp (Belgium).

Bommisetty et al. [56] consider the problem of collecting recyclable materials in a large university campus with many buildings. Such problem involves a hierarchical decision process to determine: (1) the weekly collection frequency as well as the specific collection days in the week for each building (weekly collection schedule); (2) the number of runs per day and the buildings to be visited in each run; (3) the route in each run. The problem is modeled as a Periodic Vehicle Routing Problem, which is solved by means of a two-phase algorithm. In phase 1, the buildings to be inserted on each day of the week are selected, depending on their collection frequencies, ensuring that the maximum available driving time for the day is not exceeded. Phase 2 defines a set of routes for the assigned buildings, for each day of collection, minimizing both travel and collection times. In both phases, a Nearest Insertion Heuristic is used.

Another contribution is due to Chu et al. [57]. In this paper, the authors study the Periodic Capacitated Arc Routing Problem, a periodic version of the Capacitated Arc Routing Problem (CARP), used to model municipal waste collection. They present both a best-insertion greedy heuristic and a scatter search method. In the latter, a small set of solutions, called reference set, is combined to obtain new solutions. The approach is tested on instances derived for 23 classical CARP instances, resembling waste collection operations.

3.4. Fleet and crew composition

A large percentage of total solid waste management cost related to waste collection (about 75% according to [58]), is due to the equipment and the workforce. Therefore, optimizing such aspects could result in significant cost savings. However, regardless of its importance, the problem of optimizing the fleet composition and the crew assignment has not been much studied in the literature with respect to solid waste management.

Seminal contributions are due to [59,60]. Altman et al. [59] present a non-linear model for calculating manpower requirements for refuse collection. This model is used for matching work shifts to curbside refuse demand so as to minimize weekly missed collections, subject to union regulations and manpower and truck constraints. The algorithm used for solving the non-linear model is a modification of the gradient method, in which constraints are handled in the objective function by means of penalty terms.
Numerical computations were carried out on data related to some districts in New York City. Ignall et al. [60] formulate linear programs to model the assignment of sanitation crews to shifts and days of the week on a single district basis. The goal is to balance payroll cost and missed refuse collection, while satisfying constraints due to available equipment and policies for granting rest days. The models are solved by means of standard linear programming routines, and extensions of the model to planning for several districts simultaneously are pointed out.

More recently, Hansmann and Zimmermann [61] and Baudach et al. [62] propose a three-phase approach to determine the route plans and the crew schedules in a waste management system. In particular, in Phase 1 they generate the daily crew tasks, including the routes and the assignment to days, with minimum number of crews required for the disposal process. Then, in Phase 2 they generate the daily crew tasks (including routes and assignment to days) with respect to the minimum number of crews from the previous phase, ensuring a good “similarity” between the routes in a daily crew task, and minimizing the maximum duration of a daily crew task. Finally, Phase 3 amounts to assigning the employees to the daily crew tasks (from Phase 2) for all working days over a year, optimizing the goals from the crew scheduling perspective.

The contribution by List et al. [63] is mainly focused on radioactive waste disposal. However, the authors underline that the model is also applicable to other types of waste disposal problems where there are specific shipment requirements to be met in particular markets (perhaps through contracts), there is uncertainty in the actual set of shipments that will be offered over time, and the acquisition of equipment requires significant lead times. List et al. [63] develop a two-stage stochastic optimization problem, to take into account the stochasticity of some of the problem characteristics, such as the total quantity of waste to be moved in specific situations, or the processing rates at the sites. The problem is modeled as a two-stage stochastic optimization problem, in which decision variables are separated into first-stage variables, and second-stage, or recourse variables. In this case, the truck and package acquisition variables are the first-stage variables, because they must be decided before values for the uncertain parameters are revealed. The second-stage variables are represented by flow variables for packages and trucks, which are scenario-dependent. Another contribution of the paper is the extension of previous work on robust optimization for fleet planning List et al. [64] to include two distinct “risk” variables related to monetary and “political” risk, respectively. Computational experiments show that considering these risk terms is important in determining the overall level of equipment acquisition.

Ghiani et al. [65] study the problem of simultaneously scheduling crews and vehicles shifts. In particular, given a set of waste management tasks to be performed by a single company in an integrated urban waste management context, they propose both an optimization model, and a fast constructive heuristic. As a minor contribution, they also select, for each task, the best optimization model, and a fast constructive heuristic. As a result, the authors underline that considering these risk terms is important in determining the overall level of equipment acquisition.

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4. Conclusions

In this paper we reviewed the most significant literature on the use of OR methodologies to improve SWM. In particular, we focused on strategic and tactical issues. As can be easily seen from the tables summarizing the papers described throughout the review, many research directions would require additional work. In fact, the existing literature focused on strategic SWM issues is extremely rich of sectorial contributions aimed at finding the optimal solution for reduced problems of the more complex and general problem described in Section 2.1. More precisely, the literature appears poor as far as aspects like time dimension, multi-commodity, economies of scale, and uncertainty affecting the waste generation rates and the transportation costs over a long time horizon. On the other hand, a huge amount of research exists about location problems occurring in SWM systems. More efforts are required in order to develop efficient approaches devoted to rich SWM strategic models, in which all the aforementioned characteristics are carefully integrated. A new challenge is represented by studying and modeling a unified framework in which decisions related to the collection sites, transfer stations, processing facilities and landfills location are combined with decisions on shipping multi-commodity waste flows on the basis of how much profitable is to convert fractions of the waste into recycling materials and alternative energies. Recent advances in exact and matheuristic methodology for solving large scale MIPs represent new powerful tools to find quickly good quality solutions of more complex optimization problems, as those occurring in SWM systems. More precisely, branch-and-price guided search methodology for integer programming, and “a priori” reformulations of the problem to be embedded into a commercial MIP solver (a similar approach has been shown to be able to solve a nontrivial fraction of practical lot-sizing problems by Wolsey [66] and Gicquel et al. [67]) represent suitable approaches. Tractability of mathematical models like those devoted to SWM systems may be dealt with by decoupling the problem into partial subproblems to be optimized. In such a fashion, strategic aspects may be considered over a long-term planning horizon, while modeling the impact of tactical decisions on the strategic solution through tactical constraints modifying the solution obtained at each iteration.

As to purely tactical issues, one aspect which is evident from the tables, is that the literature integrating an important aspect like uncertainty in tactical decisions is still scarce. In fact, very few papers address the use of stochastic parameters such as waste generation, or travel times. In addition to these findings, we note that the a great part of tactical models related to SWM is mostly oriented at minimizing costs. Of course, this makes sense, because SWM decisions usually involve large monetary sums. However, the socio-political aspects related to SWM are important issues that should be taken into account more carefully, given the growing public concern for environmental preservation, as also pointed out in Section 1.

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