A Stochastic Programming Model for a Tactical Solid Waste Management Problem

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Abstract

Solid waste management poses a rich variety of interesting and challenging optimization problems. Waste managers are required to take short-, medium-, and long-term planning decisions, while taking into account the articulated multi-echelon supply chain of waste generation, treatment and disposal. In all such situations, neglecting the uncertainty of the waste generation rates can lead to unreliable decision plans.
In this paper we address a tactical problem of waste flow allocation from a waste operator point of view with the aim of minimizing the total management cost, net of possible profits obtained by special subproducts. We propose a two-stage multi-period stochastic programming formulation. The first-stage decisions take into account the facility activation and a pre-allocation of waste flow, while the recourse action considers the excess waste. We then benchmark the formulation by solving an instance derived from historical data provided by a large Italian waste treatment company. Scenario trees are generated from predictive models of unsorted waste. Finally, the impact of the stochastic waste generation on the problem solution is examined, showing the benefit of the stochastic methodology when compared with the deterministic formulation.

Keywords: OR in Service Industries, Waste Management, Network Flow, Stochastic Programming

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1. Introduction

Nowadays, Solid Waste Management (SWM) is a major concern for urban communities. The problem involves a wide variety of factors, such as environmental, technical, political, institutional, financial and economical issues (see Tchobanoglous [52]). In addition, waste logistic networks evolved from a straightforward source-to-landfill scheme to a multi-echelon network in which waste generally goes through several operations before reaching a destination site. SWM involves waste collection (see Rogge and Jaeger [45], Huang and Lin [27], López-Sánchez et al. [32]), waste treatment (see Münster et al. [40]), waste routing (see Sahoo et al. [47], Inghels et al. [28]) and waste disposal (see Pérez-López et al. [42]).

In such a complex context, Operations Research techniques can help the waste operator to take cost-effective decision plans (see de Souza Melaré et al. [17]). Strategical, tactical, or operational issues can be taken in a SWM problem, depending on the length of the period affected by the decision. Integrated approaches to tackle several levels of time planning are receiving increasing attention (see Samanlioglu [48], Das and Bhattacharyya [16], Bruecker et al. [7]). For an extended discussion on the optimization problems arising in solid waste management, the reader is referred to Ghiani et al. [23].

A large part of the SWM literature considers deterministic formulations (see Bloemhof-Ruwaard et al. [6], Erkut et al. [19], Ghiani et al. [21], Inghels et al. [28]), namely where all problem parameters are known at the moment of planning. This assumption is not practical in all cases. Uncertainty can affect parameters such as processing and transportation costs, waste transformation coefficients in the treatment facilities and the amount of waste generated in the sources of the network.
In this paper, we consider tactical waste flow allocation under uncertainty during a yearly planning horizon. The waste operator is required to take monthly decisions on which facilities are active, and on which is the amount of waste shipped in each arc of the network, processed or disposed of in facilities. Modifications of the waste network, such as increasing facilities capacity, location and opening plants (see Eiselt and Marianov [18]), are strategic prerogatives, hence are not considered here. The aim of the planning for the waste operator is to minimize the management costs, minus the possible profits obtained by special subproducts, such as electric energy or raw materials from recycling processes. The work is motivated by the avail-

ability of: (i) historical data on waste generation rates, obtained from the largest Italian waste treatment company, HERAmbiente SpA, (ii) features of the waste network managed by HERAmbiente, provided by the consulting company Optit Srl. The industrial partners highlighted the relevance of the estimation of the waste generation amounts before making tactical decisions. Indeed, inaccurate estimations or forecasts (see Jiang and Liu [29], Ghiani et al. [22]) can force to make expensive adjustments after the waste is allocated. Hence, we consider the uncertainty affecting the waste generation rates by a using stochastic programming approach.

A two-stage multi-period stochastic mixed-integer formulation for the waste flow allocation problem is introduced in this paper. The operational schedule of the facilities and a pre-allocation of waste are planned for the year ahead, then the waste in excess is treated via recourse actions (e.g., shipment outside the network). This is in line with the actual planning operation of waste operators, in which the pre-allocation of waste can be used to stipulate contracts with carriers or facility managers.

The proposed stochastic formulation is tested on a realistic instance based on the data provided by our industrial partners in the Italian region of Emilia-Romagna. In order to validate the stochastic optimization model, we test it on scenario trees, describing the problem uncertainty, derived by econometric models. In order to tune the right number of scenarios to include in the scenario tree, we compute *in-sample stability* (see Kaut and Wallace [30]). The stochastic formulation is further investigated in terms of the impact of stochasticity in comparison with expected value solution by means of some stochastic measures.

The contributions of the paper can be summarized as follows:

- Introduction of a two-stage multi-period stochastic formulation for a tactical waste flow allocation problem.
- Scenario trees generation for unsorted waste evolution based on Autoregressive econometric models derived from real data of 124 Italian towns.
- Validation of the stochastic formulation in terms of in-sample stability.
- Analysis of the impact of uncertainty through the computation of measures of the quality of the deterministic solution in a stochastic environment.

The paper is organized as follows. Section 2 provides an overview of the literature on SWM problems with uncertain parameters and related problems. In Section 3, the specific tactical planning problem is described, while Section 4 presents the stochastic model we formulate. In Section 5, the scenario generation method is described. In Section 6, numerical results on a realistic instance are discussed. Finally, conclusions and future research directions are drawn in Section 7.

2. Literature Review

A wide line of research in SWM under uncertainty adopts modelling paradigms such as: interval-parameter programming, chance-constrained programming, fuzzy programming, inexact programming and two-stage stochastic programming, as documented by Sun et al. [51]. A common claim is that the lack of accurate information on the uncertainties makes impossible to compute statical properties, such as probability distributions. Especially in large-scale problems, obtaining an accurate description of the planning data is particularly laborious (see Maqsood and Huang [39]), and the uncertainties vary between known bounds. As a results, such formulations provide a range of solution alternatives to the waste managers, which are required to evaluate the trade-offs among the different solutions. In this direction, a weekly waste flow allocation problem is considered in Huang et al. [26]. The authors develop a gray linear programming model for addressing the regional municipality of Hamilton-Wentworth in Ontario. Stable interval solutions are provided for three scenarios of facility operativeness. Yeomans et al. [54] and Yeomans [55] improve the results of [26] on the same case study by proposing Evolutionary Simulation-Optimization (ESO) procedures. Cheng et al. [12] and Cheng et al. [11] discuss a hierarchical framework to formulate the SWM supply chain. A solution approach integrating fuzzy programming and mixed-integer programming provides several waste treatment policies, even for strategical decisions. Sun et al. [50] formulate a joint chance-constrained programming model to express the uncertainties on the waste network parameters and waste generation rates.
As for inventory problems, Chen et al. [9] address multiple sources of uncertainties in a modeling paradigm for long-term planning, which combines inventory model, inexact chance-constrained programming, interval-valued fuzzy programming, and mixed-integer linear programming. On the same case study, Chen et al. [10] propose stochastic fractional inventory-theory-based approach to consider various constraint-violation risks. Several modeling paradigms have been proposed for related uncertain problems. Corato and Montinari [13] use stochastic dynamic programming to decide on the

design of landfills, while considering the uncertainty in the price of recyclables. Nematian [41] considers a interval-parameter two-stage stochastic programming approach in water resources management. The uncertainty affecting the seasonal water flow is expressed via fuzzy variables. Water resources management is also addressed in Wang and Huang [53] by means of multi-level Taguchi-factorial two-stage stochastic programming.
In this work, we validate a two-stage multi-period stochastic programming formulation on a set of representative scenarios obtained from an econometric model. The scenario generation approach is viable thanks to the availability of an historical database of unsorted waste generation values.

3. Waste flow allocation at a tactical level

In this section we introduce the main characteristics of the waste flow allocation problem. The waste management network is represented as a graph $G = (V, A)$, where V is the set of network nodes and A is the set of feasible waste shipments between nodes. A small waste network is displayed in Figure 1. The network is composed of: waste generation sources V_O, a set V_S of separation and transfer stations (i.e., plants in which waste is temporarily stocked and then loaded into larger vehicles), a set V_P of processing facilities (e.g., incinerators, inerting systems), a set $V_R \subset V_P$ where a revenue is obtained from the waste treatment (e.g., waste-to-energy plants, composting facilities), a set V_L of destination sites for waste, such as landfills and disposal facilities, and markets $V_M \subset V_L$ for recycled products and energy. The waste flow is divided in several commodities W and subproducts $W_R \subset W$ give a revenue to the waste manager.

For each period $t \in \{1, \dots, T\}$ of the planning horizon, the waste manager needs to determine which facilities should be used, and how waste should be routed, processed and disposed of in each period in order to minimize the total cost, net of any revenue for recycled material and generated energy. The total planning cost is made up by unitary transportation costs c_{ij}^w associated with arc (i, j) and commodity w, fixed costs f_j^t for each operating facility $j \in V_S \cup V_P$ in period t, processing costs p_{jw}^t per unit of waste w treated at facility j in period t, and a revenue r_{jw}^t obtained from waste flow $w \in W_R$ produced in facility $j \in V_R$ in period $t = 1, \dots, T$.
The planning needs to respect the facility limitations, such as the capacity q_{jw}^t of facility $j \in V_S \cup V_P \cup V_L$ for commodity $w \in W$ in period t, and the minimum threshold m_{jw}^t of incoming waste commodity w in period $t = 1, \dots, T$ in plant $j \in V_S \cup V_P$. The treatment and separation operations

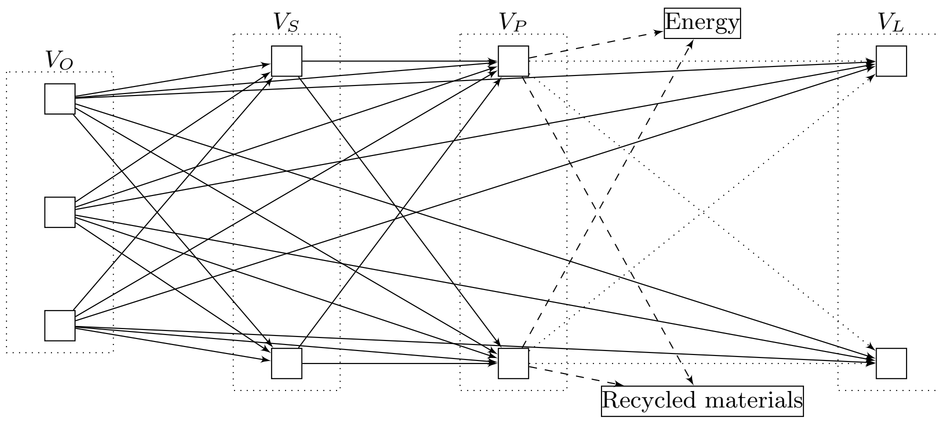

Figure 1: The SWM network

are expressed by transformation coefficients $b_{jww'}$ per unit weight (or volume) of the waste commodity $w \in W$ into the waste commodity $w' \in W$ at facility $j \in V_S \cup V_P$. The structure of the network is fixed, i.e., we cannot build new facilities and landfills or close them permanently. This assumption is appropriate in the medium-short level of planning.

The waste flow allocation problem is modeled as a multicommodity flow problem (see Shevchik [49]) with multiple sources and sinks. This is common also in other related service network problems, such as hub network design problems (see Rothenbächer et al. [46], Alibeyg et al. [2]). The tactical waste flow allocation problem requires also to select which facilities (nodes) are operative in the waste network during each period of the planning horizon. We note that node selection is devised also in other routing problems in supply chain management, such as supplier selection problems (see Qin et al. [43]), orienteering problems (see Gunawan et al. [25]), traveling purchaser problems (see Bianchessi et al. [4], Manerba et al. [38]) and fixed charged transportation problems (see Bertazzi and Maggioni [3]).
The stochastic model of this paper can be considered as a stochastic reformulation of the deterministic model presented in [23] for strategic waste flow allocation. Given that strategic decisions are out of the scope of this paper, in our model the decisions on the facilities regard their operational state, rather than the possibility of opening/closing them.

As already mentioned, several SWM parameters are not known at the moment in which the planning has to be made. In this study, we focus on the stochasticity in waste generation quantities, given the practical interest of their uncertainty for waste managers. In the next section we propose the stochastic programming model for the solid waste management planning problem just described.

4. A Stochastic Programming Model for the Waste Flow Allocation Problem

To include the random nature of the waste production in the problem we consider a two-stage stochastic programming with multi-period model (see, e.g., Birge and Louveaux [5]) which reflects the way in which the uncertainty in waste generation is expressed and revealed during the planning horizon. In the two-stage stochastic multi-period paradigm, the actual realization of the waste generation values in each period (i.e., a month) of the planning horizon becomes known as soon as the facility activation decisions for the first period take place.

We now describe in detail the two-stage stochastic programming with multi-period model. As explained in the introduction, it is common for waste managers to decide for a pre-allocation of the waste flow in each period of the planning horizon. The model goes in this direction and introduces first-stage decision variables to represent the facility activation and pre-allocations of waste flow. The *recourse action* is the treatment of unexpected waste produced in generation sources. In order to describe the stochasticity of the problem, we approximate the distribution of the uncertain parameters by a discrete distribution with a finite number of outcomes, also called *scenarios*. We denote with $\mathcal{S}$ the set of scenarios, with $|\mathcal{S}|$ its cardinality and with ρ_s, the probability of realization of scenario $s \in \mathcal{S}$. Let then $g_{iw}^{t,s}$ be the uncertain amount of waste commodity $w \in W$ generated in source $i \in V_O$ in period t according to scenario s.
The decision variables are:

y_j^t	binary variables assuming the value 1 if facility $j \in V_S \cup V_P$ is operating in period $t = 1, \ldots, T$ and 0 otherwise;
x_{ijw}^t	planned waste flow of commodity $w \in W$ shipped in arc $(i, j) \in A$ in period $t = 1, \ldots, T$;
$\xi_{iw}^{t,s}$	excess waste of commodity $w \in W$ present in source $i \in V_O$ in period $t = 2, \ldots, T + 1$ in scenario $s \in \mathcal{S}$.

The stochastic recourse decision is given by the corrective waste flow $\xi_{iw}^{t,s}$, which is non-negative if in period $t - 1$ and scenario s the waste generation of commodity w present in source i has turned out to be lower than expected. Such waste can be treated in several ways in practical applications. We assume that the unexpected waste is collected in waste generation sources incurring in C^t_{iw} costs, higher than network transportation costs, and shipped outside the network. In this situation, the excess flow affects only the waste collection constraints in sources sites. Another possibility of treatment of the unforeseen waste could be that of routing it inside the network, at the price of additional transportation costs, because of possible vehicle overloading or usage of extra vehicles.

A mathematical formulation of the two-stage stochastic multi-period mixed-integer problem with waste flow pre-allocation is given by Model $\mathcal{M}$:

$$
\begin{aligned}
\mathcal{M}: \min \quad & \sum_{t=1}^{T} \sum_{j \in V_S \cup V_P} f_j^t y_j^t + \sum_{t=1}^{T} \sum_{w \in W} \sum_{(i,j) \in A} c_{ij} x_{ijw}^t + \\
& + \sum_{t=1}^{T} \sum_{w \in W} \sum_{j \in V_S} p_{jw}^t \sum_{i \in V_O} x_{ijw}^t \\
& + \sum_{t=1}^{T} \sum_{w \in W} \sum_{j \in V_P} p_{jw}^t \sum_{i \in V_O \cup V_S \cup V_P} x_{ijw}^t \\
& + \sum_{t=1}^{T} \sum_{w \in W} \sum_{j \in V_L} p_{jw}^t \sum_{i \in V_O \cup V_S \cup V_P} x_{ijw}^t \\
& - \sum_{t=1}^{T} \sum_{w \in W_R} \sum_{i \in V_R} r_{iw}^t \sum_{j \in V_M} x_{ijw}^t \\
& + \sum_{s=1}^{\mathcal{S}} \rho_s \Big(\sum_{t=2}^{T+1} \sum_{i \in V_O} \sum_{w \in W} C_{iw}^t \xi_{iw}^{t,s} \Big) \qquad (1)
\end{aligned}
$$

$$
\text{s.t.} \sum_{j \in V_S \cup V_P \cup V_L} x_{ijw}^t + \xi_{iw}^{t+1,s} = g_{iw}^{t,s} \qquad \forall\, i \in V_O,\ w \in W, \quad t = 1, \ldots, T,\ s \in \mathcal{S}, \qquad (2)
$$

$$
\sum_{w \in W} b_{jww'} \sum_{i \in V : (i,j) \in A} x_{ijw}^t = \sum_{i \in V : (j,i) \in A} x_{jiw'}^t \qquad \forall\, j \in V_S \cup V_P,\ w' \in W, \quad t = 1, \ldots, T, \qquad (3)
$$

$$
\sum_{i \in V : (i,j) \in A} x_{ijw}^t \le q_{jw}^t y_j^t \qquad \forall\, j \in V_S \cup V_P,\ w \in W, \quad t = 1, \ldots, T, \qquad (4)
$$

$$\sum_{i \in V:(i,j) \in A} x^t_{ijw} \geq m^t_{jw} y^t_j \qquad \forall\, j \in V_S \cup V_P,\ w \in W,\ t = 1, \dots, T, \quad (5)$$

$$y^t_j \in \{0, 1\} \qquad \forall\, j \in V_S \cup V_P,\ t = 1, \dots T, \quad (6)$$

$$x^t_{ijw} \geq 0 \qquad \forall\, w \in W, (i, j) \in A,\ t = 1, \dots T, \quad (7)$$

$$\xi^{t,s}_{iw} \geq 0 \qquad \forall\, w \in W, i \in V_O,\ t = 2, \dots T + 1,\ s \in \mathcal{S}. \quad (8)$$

The objective function (1) is composed by the following terms: (i) the operational costs for active facilities; (ii) the waste transportation costs in every arc of the network; (iii) the processing costs in transfer stations due to the waste collected in sources; (iv) the costs incurred to process the waste coming either directly from generation sources, or re-organized in transfer station, or preliminarily treated in other processing plants; (v) the processing costs in destination facilities; (vi) profits associated with special waste subproducts and (vii) recourse costs, given by the penalties for treating the excess flow waste outside the network. Indeed, all the levels of the waste management supply chain are taken into account.
Constraints (2) ensure that the stochastic waste generated in each source is collected and shipped either inside the network or outside the network. Equations (3) impose the reduced flow balance in each transfer or processing facility. Constraints (4) represent capacity limitations for active plants, while inequalities (5) model the requirement for operating facilities to receive a minimum amount of incoming waste flow. Finally, constraints (6),(7), (8) define the decision variables of the problem.
In Figure 2, the scenario tree which describes the situation represented by the model (1)-(8) over 12 months with $|\mathcal{S}| = 3$ is presented, for the sake of visualization. The sequence of decisions over stages is reported to the right of the scenario tree.

4.1. Possible model extensions

Further constraints can be added to the mathematical formulation so as to express additional practical features of the waste network.

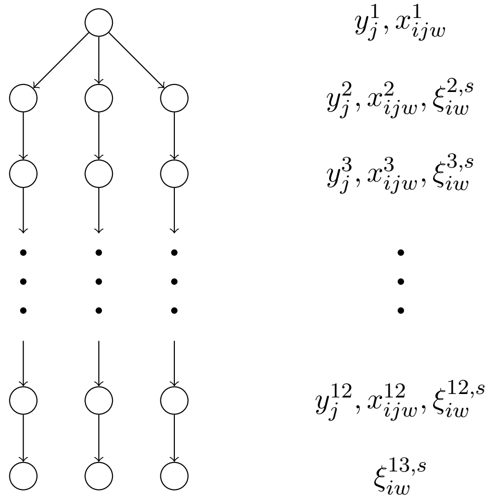

Figure 2: Two-stage multi-period scenario tree structure related to formulation $\mathcal{M}$. For the sake of visualization, the tree has $|\mathcal{S}| = 3$ and $T = 12$. Decision variables are indicated to the right of the scenario tree.

Let a_j be the capacity for landfill $j \in V_L$ valid on the whole planning horizon (i.e., an overall capacity). Then model $\mathcal{M}$ can be added with:

$$\sum_{t=1}^{T} \sum_{w \in W} \sum_{i \in V:(i,j) \in A} x_{ijw}^t \leq a_j \qquad \forall\ j \in V_L. \tag{9}$$

In case maintenance operations need to be taken for a subset V_D of facilities, a deactivation term of duration D_j^t for facility j starting at period t is required. The waste manager decision on the selection of the starting period for the deactivation is expressed by binary variables z_j^t, $\forall\ j \in V_D$, $t = 1, \ldots, T$, which are active on the first deactivation period t. The actual number of periods τ_j^t of temporary deactivation of facility j within the planning horizon is computed as $\tau_j^t = \min\{D_j^t - 1, T - t\}$. If the non-operativeness term does not end within T, the remaining deactivation periods are imposed by setting the binary variables y_j^t accordingly in the first periods of the next planning year. The temporary deactivation decisions can then be formulated in $\mathcal{M}$ as:

$$\sum_{i=0}^{\tau_j^t} y_j^{t+i} \leq (\tau_j^t + 1)(1 - z_j^t) \qquad \forall j \in V_D,\ t = 1, \ldots, T, \tag{10}$$

$$\sum_{t=1}^{T} z_j^t \geq 1 \qquad \forall\, j \in V_D, \tag{11}$$

$$z_j^t \in \{0,1\} \qquad \forall\, j \in V_D,\ t = 1,\dots,T. \tag{12}$$

Based on the data received by the industrial partners, we observed that overall capacity constraints for landfills are not particularly tight. This is because we avail of the waste generation data for a subset of the waste commodities dealt by the network. In addition, no compulsory deactivation periods were imposed by the partners. In the present paper the modeling extensions are not considered in the computational results, since the calibration of the related parameters requires further discussions with the industrial partners.

5. Scenario Trees Generation for Waste Production

In this section we describe how to generate the scenario tree of unsorted waste (UW) parameter. The process which discretizes the distributions of the stochastic parameters with a limited number of outcomes is usually called *scenario tree generation*.

We have analyzed the *unsorted waste* database composed of $i = 1,\dots,124$ individual towns of Emilia-Romagna expressed in tons normalized by the number of inhabitants observed for $t = 1,\dots,36$ periods (months) provided by our industrial partner HERAmbiente SpA. The considered towns are in the region of Emilia-Romagna, which is located on the Adriatic coast, one of the most touristic areas of northern Italy. Hence, the towns population is subject to strong seasonal fluctuations. During the summer, in internal towns people migrate, while, during the same period, coastal towns receive tourists. The UW produced in towns is clearly dependent on the number of actual inhabitants, therefore the historical data are characterized by seasonality as well. For each town the level of demand for the waste disposal in 36 consecutive months is revealed.

We considered available historical data g_{iw}^t for the single commodity w corresponding to unsorted waste. For this reason from now on we will denote g_{iw}^t with g_i^t. In order to generate scenario trees which describe the uncertainty of the problem, we investigate an econometric model (see [44]) which fits the time series with a good approximation. Since our goal is to test the goodness of the forecast of the econometric model, in the remainder of this section, we suppose to have been given only the data for $t = 1,\dots,24$ and to use the data in $t = 25,\dots,36$ only for evaluation purposes. For each town $i = 1, \dots, 124$, we select the best Autoregressive model ($AR(p)$)

$$Y_{i,t} = c_i + \beta_{i,1} Y_{i,t-1} + \ldots + \beta_{i,p} Y_{i,t-p} + \epsilon_{i,t}, \ i = 1, \dots, 124, \ t = 24, \dots, 36, \quad (13)$$

where:

- c_i is a constant of town i;
- p is the number of considered lags;
- $Y_{i,t}$ stands for the dependent variable representing the demand of town i at month t;
- $\beta_{i,j}$ is the estimator for each town i with $j = 1, \dots, p$;
- $Y_{i,t-j}$ is the regressor, representing the level of demand of town i at month $t - j$ with $j = 1, \dots, p$;
- $\epsilon_{i,t}$ is the error term of town i at month t.

The best $AR(p)$ model is obtained by choosing the number $p = 1, \dots, 15$ of lags which minimizes the Akaike Information Criterion (AIC) (see [1]) independently for each town i using maximum likelihood estimation. Results are reported in Table 1. Notice that Model (13) is also evaluated including a first order difference in $Y_{i,t}$ for potential unit roots. The symbol † on a order indicates that Model (13) without unit roots has been selected for the town considered. The AIC is one of the most common Information Criteria (IC), which are of the following form:

$$IC = \text{goodness of fit} + \text{penalty for model complexity},$$

where model complexity is typically the number of model parameters scaled by some factor to make it comparable to the goodness of fit metric. In particular AIC takes the form:

$$AIC = 2k + n \ln(MSE),$$

where k is the number of model parameters, "ln" is the natural logarithm and MSE is the Mean Squared Error. According to Akaike's theory, the most accurate model has the smallest AIC: a model that fits well will have small MSE. In addition, in case the model needs a lot of parameters (i.e., has a greater complexity) then the term $2k$ will be large, thus making AIC larger. The model with the smallest AIC will be the model that fits best

town i	p	town i	p	town i	p	town i	p	town i	p
1	$15^\dagger$	26	15	51	14	76	15	101	15
2	$7^\dagger$	27	15	52	15	77	15	102	15
3	15	28	2	53	12	78	15	103	15
4	15	29	15	54	15	79	7	104	12
5	14	30	2	55	15	80	14	105	15
6	7	31	4	56	15	81	15	106	15
7	15	32	15	57	15	82	11	107	15
8	15	33	13	58	15	83	15	108	14
9	15	34	15	59	14	84	14	109	15
10	15	35	14	60	15	85	15	110	14
11	1	36	15	61	14	86	15	111	15
12	14	37	15	62	15	87	11	112	14
13	15	38	15	63	12	88	15	113	15
14	14	39	13	64	15	89	15	114	14
15	13	40	15	65	14	90	11	115	14
16	15	41	15	66	15	91	15	116	13
17	15	42	3	67	15	92	15	117	15
18	14	43	14	68	15	93	15	118	15
19	14	44	15	69	11	94	15	119	15
20	15	45	15	70	15	95	15	120	15
21	14	46	15	71	15	96	13	121	14
22	15	47	15	72	15	97	14	122	15
23	15	48	15	73	15	98	15	123	15
24	15	49	15	74	15	99	11	124	14
25	13	50	15	75	14	100	13		

Table 1: Number $p = 1, \dots, 15$ of lags which minimizes AIC [1] calculated independently for each Town $i = 1, \dots, 124$.

to the data, with the smallest complexity and therefore will have a smaller chance of over-fitting.

Figure 3 reports a comparison between the actual 2013 data and the forecasted models for 6 of the major towns of the region. Similar results are obtained for all the 124 towns included in the dataset. Interestingly, the seasonal component in coastal towns which receive tourists during summer is well described by the econometric models obtained (see Towns 5 and 6 in the figure).

Scenarios of forecasted waste are then generated by a Monte Carlo simulation on the error terms $\epsilon_{i,t}$ of the $AR(p)$ models (see (13)) which are uncorrelated normally distributed random variables; thus, they can be described by the Brownian motion:

$$\epsilon_{i,t} := Y_{i,t} - Y^*_{i,t} = \mathrm{d}Y_{i,t} = \mu_i \mathrm{d}t + \sigma_i \mathrm{d}W_{i,t} \ , \qquad i = 1, \ldots, 124 \ , \qquad (14)$$

where $Y^*_{i,t}$ are the observed values, μ_i and σ_i are respectively the mean and the variance of the errors series and $W_{i,t}$ is the Wiener process (see Gong et al. [24]). The process to generate scenario trees is outlined in Pseudo Code 1.

Pseudo Code 1 Scenario trees generation for waste production

for $i = 1, \ldots, 124$ **do**
  for $t = 1, \ldots, 24$ **do**
    $Y_{i,t} := g_i^t$
  end for
  for $t = 25, \ldots, 36$ **do**
    $Y^*_{i,t} := g_i^t$
    Minimize Akaike Information Criterion (AIC)
    Evaluate potential unit roots s.t.
    $Y_{i,t} := c_i + \beta_{i,1} Y_{i,t-1} + \ldots + \beta_{i,p} Y_{i,t-p} + \epsilon_{i,t}$
    $\epsilon_{i,t} := Y_{i,t} - Y^*_{i,t}$
  end for
  for $s \in \mathcal{S}$ **do**
    Obtain $\epsilon^s_{i,t}$ from Monte Carlo simulation on $\epsilon_{i,t}$
    $Y^s_{i,t} = c_i + \beta_{i,1} Y_{i,t-1} + \ldots + \beta_{i,p} Y_{i,t-p} + \epsilon^s_{i,t}$,
    return $g_i^{ts} = Y^s_{i,t}$
  end for
end for

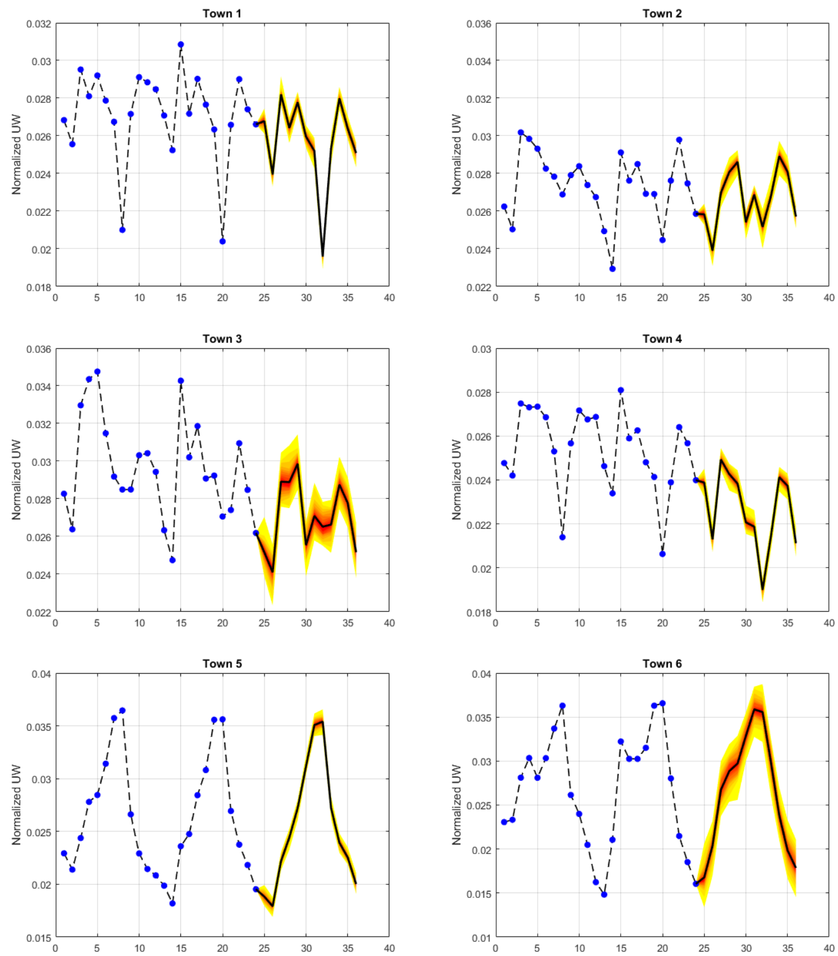

Figure 3: Fan charts of normalized unsorted waste including a simple line chart for observed past data (dashed line connecting blue points in the years 2011-2012 and black line in the year 2013). 60 possible scenarios of 2013 forecasts obtained using model (13) are shown in orange.

6. Computational Results

In this section, we present and analyze the results of the computational experiments. The goal is to evaluate the effectiveness of the methodology proposed on a realistic instance based on an existing waste management network provided by the consulting company Optit Srl, an accredited spinoff company of the University of Bologna, which has a long-lasting collaboration with HERAmbiente SpA on waste logistics. Privacy issues of the considered

data do not allow us to explicitly give their values which were slightly altered with respect to the original data.
Our industrial partners provided the actual values of UW generated in 124 towns of Emilia-Romagna and some relevant information of the waste management network associated with such waste generation sources. In the real-world situation, the network is meant for treating every commodity of municipal waste. Hence, by considering only the production of UW in urban sites, an oversize of the set of facilities is implied, overestimating parameters like capacity limitations. This motivated the extraction of a smaller instance, which considers only a subset of plants with respect to those treating all types of waste in the existing network. The instance we considered has the following features. The original set of 124 waste generation sources is treated by 28 plants, divided in: 7 separation facilities, 6 Waste-to-Energy (WtE) facilities, 6 other processing plants, 8 landfills and 1 market for the Electric Energy (EE) produced by WtEs. Besides UW, the network nodes can accept other 13 waste commodities, obtained as results of the various operations taking place in facilities. As a consequence of the "shrinking" of the real network, some of its original parameters were changed accordingly. In order to limit an excessive impact of the revenue for EE in the objective function, a capacity restriction for incoming UW in WtEs was set. Minimum flow threshold were set for validation purposes. The transportation costs c_{ij} are proportional to the distance between nodes i and j; because unit transportation costs are set by medium-term contracts, for the sake of simplicity, we neglected economies of scale in the transportation costs (see Callan and Thomas [8]). In our tactical horizon of planning, there is no possibility of closing permanently a facility or building a new one; hence, in the objective function (1), we only required to make the facilities operate as less as possible by setting all activation costs f_j^t to 1.

For the Recourse Problem $\mathcal{M}$, we compute its total cost denoted with RP, we analyze the loss in terms of quality of the solution due to the use of the Expected Value approaches (EV) by computing standard measures in stochastic programming like the *Value of Stochastic Solution at stage t* (VSS^t) and the *Expected Value of Perfect Information* ($EVPI$) (see Birge and Louveaux [5], Maggioni and Wallace [34], Maggioni et al. [35, 37, 36], Maggioni and Pflug [33]).
The stochastic model $\mathcal{M}$ has been implemented in AMPL and solved with CPLEX 12.7.0.0 on a Intel Core $i5-4440$ machine with 3.10 Ghz CPU and 8 GB RAM (see Fourer et al. [20], CPLEX Manual [14]).

Subsection 6.1 discusses the size of the scenario tree through in-sample stability, while a validation of model $\mathcal{M}$ with standard measures is presented in Subsection 6.2. A deeper understanding of the quality of the expected value solution is analyzed in Subsection 6.3 through the computation of the *Multistage Expected Skeleton Solution Value* (see Maggioni et al. [36]) and the extension of the *Loss of Reduced Cost-based Variable Fixing* defined in Crainic et al. [15] in a multi-stage setting.

6.1. Determining the size of the scenario tree

In this section we perform an in-sample stability (see Kaut et al. [31]) of model $\mathcal{M}$ which allow us to qualify its results. In sample-stability consists in performing a sensitivity analysis of the objective function in terms of the number of scenarios needed in the tree to obtain stable results. This is obtained by comparing the optimal objective function values using scenario trees of increasing size. Box-plots of in-sample values over 5 runs on scenario trees with increasing sizes are shown in Figure 4. The results confirm the robustness of the scenario generation method on model $\mathcal{M}$ and that the in-sample stability is reached for the scenario tree of size 420.

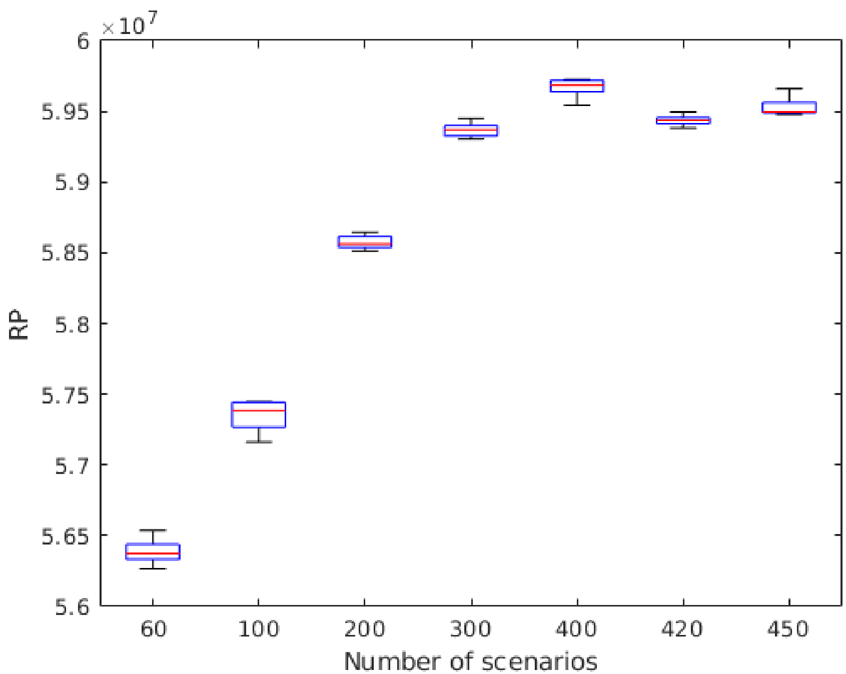

Figure 4: Box-plot of objective function values (RP) of model $\mathcal{M}$ over scenario trees of cardinality $60, 100, 200, 300, 400, 420$ and 450 respectively.

The computational time required for solving model $\mathcal{M}$ for increasing number of scenarios is reported in Figure 5. The results indicate a linear growth of the computational effort with the scenario tree size.

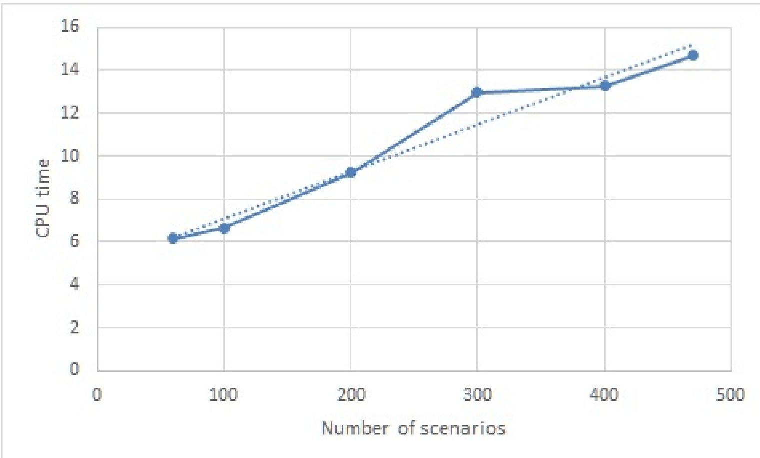

Figure 5: CPU time in seconds to obtain the RP value of $\mathcal{M}$ for scenario trees of cardinality 60, 100, 200, 300, 400, 470. The dashed line represents the trend line of the data, having an R-squared value of 0.9578.

In the remainder of the section, we report the results obtained on a scenario tree of size 470, called $\mathcal{S}_{470}$.

6.2. Analyzing the impact of uncertainty via standard stochastic measures

This subsection is devoted to qualify the model $\mathcal{M}$ by showing:

- the benefits of using the stochastic formulation versus the *Expected Value one, (EV)*, where the decision maker replaces all random variables by their expected values and solve a deterministic program;
- the importance of the stochasticity by comparing the stochastic formulation with the perfect information case (the so-called *Wait and see* approach, (WS)), where the realization of all random parameters are known already at the first stage.

This is done by considering respectively the *Value of Stochastic Solution at stage t* (VSS^t) and the *Expected Value of Perfect Information* ($EVPI$) measures. The Value of Stochastic Solution indicates the expected gain from solving the stochastic model rather than its deterministic counterpart, in which the random parameters are replaced with their expected values and is defined as follows:

$$VSS^t := EEV^t - RP, \quad t = 1, \ldots, T \tag{15}$$

where EEV^t denotes the solution value of the RP model, having the decision variables up to stage t fixed at the optimal values obtained by using the expected value solution. Note that model $\mathcal{M}$ is defined over $T + 1$ stages. Furthermore, the Expected Value of Perfect Information is defined by the difference between the objective values of the stochastic (RP) and wait-and-see (WS) solutions, given by:

$$EVPI := RP - WS. \tag{16}$$

For the scenario tree $\mathcal{S}_{470}$, results are summarized in Table 2 showing the percentage gap (in %) relative to the optimal value of the stochastic formulation (the RP) for different solution methods and standard measures.

We note that in the deterministic counterpart of Model $\mathcal{M}$, the waste manger will never require the treatment of excess waste flow, since the perfect knowledge of the future allows an exact determination of the waste-flow variables x. This explains why the EV and WS are approximately 26% less than RP and why the $EVPI$ of $\mathcal{M}$, obtained by solving a sequence of independent deterministic problems, represents a high percentage (i.e., 25.51%) of the stochastic solution RP. These results mean that the stochasticity of the waste generation plays an important role in the decision making process. Besides, the EEV^t problems are infeasible already at the first stage $t = 1$. The reason of the infeasibility can be explained as follows: being the corrective flows $\xi_{iw}^{t,s}$ non-negative, constraint (2) of $\mathcal{M}$ cannot be satisfied whenever the deterministic waste flow x_{ijw}^t obtained by the EV collects more than the actual waste generated in a source. The infeasibility of such deterministic models justifies the adoption of the stochastic model $\mathcal{M}$ and shows the inappropriateness of a deterministic model for such a problem.

6.3. Measuring the quality of the expected value solution

In the previous sections, the infinite values of VSS^t showed that the deterministic solutions obtained by $\mathcal{M}$ are highly inappropriate in a stochastic framework. However the reason of the badness of such a deterministic solution is still not clear. In the next section we further investigate it by means of measures of the quality of expected value solution in stochastic programming like *The Loss of Using the Skeleton Solution* and *The Loss of Reduced Cost-based Variable Fixing.*

6.3.1. The Loss of Using the Skeleton Solution

In order to make progresses in this direction, Maggioni and Wallace [34] introduced the *Loss Using the Skeleton Solution (LUSS)* for two-stage formulations. The $LUSS$ helps to determine if the stochastic solution can partially inherit properties from the deterministic one. To this end, the *Expected Skeleton Solution Value* ($ESSV$) is computed by fixing to zero (or to the lower bound) all first stage variables that are equal to zero (or to the lower bound) in the expected value solution, and then solving the stochastic program. The $LUSS$ then compares $ESSV$ and RP as follows:

$$LUSS = ESSV - RP.$$

The $LUSS$ measure is extended to multistage formulations in Maggioni et al. [36], with the name of *Multistage Expected Skeleton Solution Value at stage t* ($MESSV^t$), $t = 1, \dots, T$ and *Multistage Loss Using the Skeleton Solution until stage t* ($MLUSS^t$), $t = 1, \dots, T$, respectively. Each $MESSV^t$ is the optimal solution of the stochastic model in which all the variables that are at zero (or at the lower bound) in the deterministic solution until stage t are fixed at zero (or at the lower bound). The $MLUSS^t$ is then defined as

$$MLUSS^t = MESSV^t - RP, \quad t = 1, \dots, T.$$

We analyzed $MLUSS^t$ on $\mathcal{M}$ and reported the results in Table 2. On $\mathcal{S}_{470}$, $MLUSS^1 = 10\,413.43 = 0.0174\%\ RP$ suggests that the main reason of the infeasibility obtained by EEV^1 described in Section 6.2, was due to the wrong values of the non-zero variables. Furthermore, the relatively small value of $MLUSS^1$ indicates that the choice of out-of-basis first-stage variables of the expected value solution provides good information on the choice of out-of-basis first-stage variables of the stochastic solution. The information given by $MLUSS^1$ can be better understood by comparing the RP and $MESSV^1$ solutions. The $MESSV^1$ solution does not modify the schedule y_j^t of activation of the plants and the excess flows ξ_{iw}^{ts} of the RP solution. Only 273 out of the $424\,032$ x_{ijw}^t variables have an optimal value that differs from that of the RP solution. This shows that, by choosing the out-of-basis first-stage variables of the expected-value solution, the waste manager is not required to treat any additional excess flow ξ_{iw}^{ts}, which is paid at unfavorable unitary cost C_{iw}^t. In addition, it should be observed that $MLUSS^1$ enables to obtain information on the quality of some components of the deterministic solution, while $VSS = +\infty$ could not provide any indications of goodness of the deterministic solution. Finally, $MLUSS^t = +\infty$, $t > 1$. This further demonstrates the bad behavior of the deterministic solution for stages $t > 1$ in the stochastic framework.

EV	$EVPI$	$VSS^t, 1 \leq t \leq T$	$MLUSS^1$	$MLUSS^t, 1 < t \leq T$
-25.5134	25.5176	∞	0.0174	∞

Table 2: Results of standard stochastic measures expressed in percentage gap (%) to the RP problem, for model $\mathcal{M}$ based on scenario tree $\mathcal{S}_{470}$.

6.3.2. The Loss of Reduced Cost-based Variable Fixing

As additional effort in understanding of the structure of the deterministic solution, Crainic et al. [15] introduced a new measure of quality of the deterministic solution in the Two-Stage Stochastic setting, namely the *Loss of Reduced Cost-based Variable Fixing (LRCVF)*. The *LRCVF* helps to identify, even in case of large *VSS* and $LUSS$, if some components of the deterministic solution can be inherited in the stochastic counterpart, by considering the reduced costs of the out-of-basis variables in the first stage expected value solution.
Due to the multi-period nature of the problem analyzed, we will apply $LRCVF$ measure by considering the reduced costs of only the first-stage decision variables in direct analogy with two-stage case definition given in [15]. The aim of this measure is to identify the wrong variables from the expected value solution that led to an extra-cost, when adopted in a stochastic environment, quantified by the positive value of $MLUSS^1$ (see Section 6.3.1). After sorting and grouping the set of reduced costs into N homogeneous classes, the *Reduced Cost-based Variable Fixing*, $RCVF(p, N)$, is obtained by fixing at their lower bound only the first-stage variables with reduced cost in the expected value solution belonging to the last $N - p + 1$ classes with higher reduced cost. The *Loss of Reduced Cost-based Variable Fixing* is then defined as:

$$LRCVF(p, N) = RCVF(p, N) - RP,\ p = 1, \dots, N.$$

We next report the $LRCVF$ for $\mathcal{M}$ obtained in our computational experience. We considered the scenario tree $\mathcal{S}_{470}$, in which there are 35 194 out-of-basis first-stage variables. Given the large width of the reduced costs interval $[r_{min} = -110, r_{max} = 1\,000\,233]$, we divided it into $N = 3, 10, 100, 1\,000$ and 10 000 classes of constant width respectively, in order to identify with high precision the good and bad variables to use in the stochastic setting. Results are reported in Table 3.
We observe that $LRCVF(p, N)$ is able to find the optimal solution of $\mathcal{M}$ when a subset of variables are fixed at zero. In the case of $N = 3$, the values $LRCVF(2, 3) = LRCVF(3, 3) = 0$ indicate that the variables in the deterministic solution included in the last two classes can be inherited in the

stochastic solution with null error. Clearly, fixing at zero all the first-stage out-of-basis variables yields $LRCVF(1,3) = MLUSS^1 = 0.0174\%\ RP$.
Further information on the structure of the deterministic solution at the first stage can be obtained by a finer partition of the set of reduced costs. Setting $N = 10, 100, 1\,000, 10\,000$, one can obtain more detailed information on the variables to inherit by examining the values of $LRCVF(p,N)$, $p = 1,\ldots,N$. Results show that with $N = 10\,000$, the variables in classes $p = 4,\ldots,10\,000$ are at zero also in the stochastic solution. Therefore, we can conclude that a large portion of expected value solution, i.e., all the variables belonging to the interval $[r_{min} + \frac{3(r_{max}-r_{min})}{10\,000}, r_{max}]$, can be inherited in the stochastic solution. Finally, a nearly optimal solution with $LRCVF(3, 10\,000) = 10.29 = 0.0000172\%\ RP$ is obtained by fixing the variables in class $p = 3$.

N	$LRCVF(p,N)$		
3	$p = 1 : 0.00174$	$p \geq 2 : 0$	
10	$p = 1 : 0.00174$	$p \geq 2 : 0$	
100	$p = 1 : 0.00174$	$p \geq 2 : 0$	
1 000	$p = 1 : 0.00174$	$p \geq 2 : 0$	
10 000	$p \leq 2 : 0.00174$	$p = 3 : 0.0000172$	$p \geq 4 : 0$

Table 3: Results of $LRCVF(p,N)$ for increasing values of N on $\mathcal{M}$ as % from RP. Scenario $\mathcal{S}_{470}$.

7. Conclusions and Future Works

In this paper a Two-Stage Multi-period Stochastic Programming formulation for tactical problems arising in Solid Waste Management has been proposed. The formulation considers a pre-allocation of waste flow at the moment of planning and introduces corrective actions to treat excess waste flows. The solution methods have been tested by solving model instances derived from historical data provided by a large Italian waste treatment company. Scenario trees of uncertain waste production have been generated from predictive models of unsorted waste and validated in terms of in-sample stability.
The impact of the stochastic waste generation on the problem solution has been examined, showing the benefit of the stochastic methodology when compared to solving the deterministic formulation which can lead to an unreliable decision plan. We computed stochastic measures that analyze the

impact of the data randomness and the quality of the expected value solution. The inappropriateness of the deterministic solution in the stochastic framework has been shown and additional information on the first-stage solution has been derived by identifying the variables which can be inherited from the expected value solution. Furthermore, numerical results show that good estimation of the waste generation could yield important cost savings for the waste manager. We note that, even in the cases of limited percentages of expected savings, the waste manager would consider the stochastic solution a favorable alternative to the deterministic one, given the large monetary value of waste management processes.
Future works will consider a proper multistage stochastic formulation, with uncertain parameters revealed at the end of every period of the planning horizon. In addition, a different stochastic formulation could be obtained without allocating the waste flow during the planning phase: all the waste would then be treated via recourse actions. This massive introduction of recourse variables would make the formulation very challenging computationally. Approximated solution approaches such as those based on Benders' decomposition and progressive hedging would be very useful to validate the model.

Acknowledgements

Research activities of Claudio Gambella related to this paper were entirely performed at DEI, University of Bologna. Research activities of Daniele Vigo were supported by MIUR, Italy. Francesca Maggioni has been supported by Bergamo University grant, years 2015-2016. The authors gratefully thank Adriano Guarnieri, Fabrizio Salieri and Alessandro Testi of HER-Ambiente SpA and Fabio Lombardi and Lorenzo Ravaglia of Optit srl for providing the data on waste generation and the waste-treatment network. Finally, the authors would like to thank Prof. Georg Pflug and Juan Ramon Trapero Arenas for useful discussions on a preliminary version of the paper.

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