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A multi-objective approach to solid waste management

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ABSTRACT

The issue addressed in this paper consists in the localization and dimensioning of transfer stations, which constitute a necessary intermediate level in the logistic chain of the solid waste stream, from municipalities to the incinerator. Contextually, the determination of the number and type of vehicles involved is carried out in an integrated optimization approach. The model considers both initial investment and operative costs related to transportation and transfer stations. Two conflicting objectives are evaluated, the minimization of total cost and the minimization of environmental impact, measured by pollution. The design of the integrated waste management system is hence approached in a multi-objective optimization framework. To determine the best means of compromise, goal programming, weighted sum and fuzzy multi-objective techniques have been employed. The proposed analysis highlights how different attitudes of the decision maker towards the logic and structure of the problem result in the employment of different methodologies and the obtaining of different results. The novel aspect of the paper lies in the proposal of an effective decision support system for operative waste management, rather than a further contribution to the transportation problem. The model was applied to the waste management of optimal territorial ambit (OTA) of Palermo (Italy).

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1. Introduction

Waste management is a complex issue implicating several different aspects including social responsibility, global economics, production processes, material technology, environmental impact, etc.

Waste management systems are assigned by the Public Administration to specific geographic areas on the basis of the administrative subdivision of the region. These geographic areas are known as optimal territorial ambits (OTAs).

The central Public Administration is obliged to take into account the needs of both the local administration and the population and their awareness of environmental problems. In the recent past the "NIMBY" (not in my backyard) syndrome led to the failure of waste management projects and the resulting loss of resources, limiting the approach to waste management to an emergency/contingency response rather than a true management approach. This confirms the importance of hidden social, ethical and political issues together with technical and economical variables in the design of waste management systems.

Thus, a high number of decision variables is accounted for, rising exponentially with problem dimensions. In this context the decision maker should be assisted in identifying different alternatives and selecting the one best suited to achieve stakeholder consensus by means of transparent, scientific means.

The present paper contributes to the above approach. Although recent trends in waste management are largely oriented towards recycling, a residual fraction of waste remains which must be disposed of or incinerated. This paper refers to an incineration plant serving an OTA in Sicily (Italy), in particular to problems in location of the treatment plants and vehicle fleet dimensioning.

Waste management issues have been addressed in the past by numerous authors proposing both linear and non-linear models. In particular, Chang and Chang (1998) developed a non-linear model taking into account waste streams from facilities, landfills, transfer stations and incinerators. Non-linearity in the model is provided by the presence of pre-treatment plants and technical specifications of the incinerator.

Fiorucci et al. (2003) also developed a non-linear model characterizing waste streams according to their merceological class (paper, plastic, wood, metal, etc.), selecting potential location for waste-treatment plants in order to minimize total annual cost. The main limitation of this model is represented by computational difficulty in solving the quadratic model for practical applications.

All authors however refer to a single-objective function (cost), thus neglecting other important social and environmental objectives.

It is a well-known fact that optimization methodology cannot be restricted to economic implications alone. Indeed, landfill frequently represents the most convenient solution according to cost criterion (Daskalopoulos et al., 1998), but is nevertheless often the least desirable solution from an environmental point of view. In addition, different conflicting objectives are generally involved,

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hence dictating the need to apply multi-objective optimization methods taking into account the decision maker's preferences.

Zimmermann (1978, 1985) reports the use of two main methodologies: multi-attribute decision making (MADM) and multi-objective decision making (MODM). The former method is applied to discrete decision making variables while the latter is applied to continuous decision making variables. The most common techniques employed in MADM are AHP (Saaty, 1980) and ELECTRE (Roy, 1968; Roy and Vanderpooten, 1996).

Literature articles referring to the above method include papers by Hokkanen and Salminem (1997) who developed a MADM model for the selection of a waste management system to be employed in the region of Oulu (Finland). This paper dealt with selection of the most adequate technologies (landfill, incineration, composting, refuse-derived fuel production) and corresponding centralized/decentralized management model. The solutions identified were evaluated according to eight different criteria, including economic parameters, technical considerations, environmental and social issues, such as initial investment and operating cost, reliability, greenhouse effect, manpower increase and air pollution. The model was solved by means of ELCTRE III method.

Chambal et al. (2003) applied MADM to the USAF base of Eareckson in Alaska, referring to the new environmental directives issued by US Air Force (USAF). The best alternative was selected by means of the value focused thinking method.

Referring to MODM, Sudhir et al. (1996) tackled the problem of implementing a waste collection system in India, taking into account economic considerations (budgetary constraint), environmental issues (maximum amount of waste for landfill), vehicle and plants technical parameters and social aspects related to the presence of abusive waste collectors. The approach is based upon multi-objective lexicographic goal programming taking into account several possible scenarios.

Chang and Wang (1996) focused their research on waste treatment systems for the city of Kahosinung in Taiwan. The study aimed to analyze optimal management policies for use in the in the long-term, identifying the most suitable types of plants to be constructed over an established period. A dynamic multi-objective model was applied which evaluated cost as well as traffic, noise and air pollution. The model was solved by means of the compromise programming technique considering different scenarios.

The above literature review leads to conclude that when a multi-objective methodology is employed, the decision maker is initially interested in determining a set of candidate solutions and subsequently selects the one best fitted for use with specific strategies.

In this paper Pareto-optimal solutions (i.e., solutions that are not outperformed by other solutions according to all criteria considered) were determined by means of three different methods corresponding to different attitudes of the decision maker.

The issue addressed here referred to a multi-objective mathematical programming model which took into account both economical and environmental issues, considering the total annual cost and air pollution caused by vehicles.

2. Model formulation

The waste management system considered was constituted by a set of production points (municipalities), each characterized by a daily production rate and a known geographic location. Waste production sites were connected by different routes having different average speeds for each type of vehicle available. A single incinerator located in a fixed known position with a sufficient capacity to enable treatment of all waste collected in the OTA was used.

Collection was performed by small capacity vehicles incapable of traveling long distances, hence the need for the presence of waste transfer stations. In a similar framework each municipality will use its own vehicles to collect waste and transport it to the transfer stations, then bigger vehicles (trucks) with higher capacities will transfer the waste to the incinerator.

Decision variables were as follows:

- the number and type of transfer stations and their location;
- the cities served by each transfer station;
- the number and type of vehicles employed.

The objective was to determine a set of values for the decision variables in order to minimize both costs and environmental impact.

2.1. Selection of potential locations for transfer stations

Transfer stations should be located at several different potential locations within an OTA, in proximity of road access. The number of potential locations was finite but large; hence the mathematical model described in the following paragraph might be computationally unsolvable if all potential locations were taken into consideration. Therefore, to reduce the dimensions of the problem and computation effort, a preliminary selection of potential locations for transfer stations was performed on the basis of a heuristic optimality method. In a second phase, among the selected potential locations, the most convenient locations were determined.

In particular, a fuzzy clustering procedure was applied to determine the set of potential locations by means of a clustering criterion based upon fuzzy relationships.

In general two types of fuzzy clustering relations can be employed (Klir and Yuan, 1995):

- based upon c-mean;
- based upon fuzzy equivalence relations.

In this paper the second method was preferred as it did not require the number of clusters to be specified at the beginning, but rather the number was obtained as a result of the procedure according to the aggregation level established.

A crisp relation represents a link, interaction or interconnection among the elements of two or more different sets. This concept can be generalized to take into consideration different levels of strength of the interaction among elements, with the strength being represented by a fuzzy membership function. A binary relation can be defined among elements belonging to the same set X also and can be indicated as $R(X, X)$. Fuzzy binary relations can be defined on the basis of three characteristic properties: reflexivity, symmetry and transitivity. A binary relation is:

reflexive if and only if $R(x_i, x_i) = 1$;
symmetric if and only if $R(x_i, x_j) = R(x_j, x_i)$;
max–min transitive if and only if:

$$R(x_i, x_j) \geqslant \max_{\forall x_k \in X} \min\lfloor R(x_i, x_k),\ R(x_k, x_j)\rfloor \quad \forall x_i, x_j \in X \tag{1}$$

A fuzzy relation meeting the three conditions provided above is defined as similar. Similar relations allow elements to be clustered into crisp equivalent classes, each one constituted by similar elements according to a pre-specified level of membership α. When a fuzzy relation satisfies symmetry and reflexivity conditions it is termed as "compatible".

Generally speaking, given a set of elements (data, points, objects, etc.) $X = \{x_1, x_2, x_n\}$ defined in a space of p dimensions, so that each element is a vector of p components (attributes), the elements of the vector can be indicated by $x_{i,j}$, $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, p$. Therefore, a fuzzy relation R can be defined on X once a proper distance function, such as Minkowsky (Klir and Yuan, 1995), has been defined by means of the following equation:

$$R(x_i, x_k) = 1 - \delta\left(\sum_{j=1}^{p} \left|x_{ij} - x_{kj}\right|^q\right)^{1/q} \quad \forall (x_i, x_k) \in X \tag{2}$$

where $q \in \mathscr{R}^+$ and δ is a constant such that $R(x_i, x_k) \in [0, 1]$. Clearly δ can be the inverse of the maximum Minkowsky distance among all couples belonging to X. The fuzzy relation derived is symmetric and reflexive, hence a fuzzy compatible relation, although not necessarily equivalent. Therefore, in order to define different aggregation levels, it must be turned transitive according to Eq. (1), by means of an operation named "transitive closure". A possible algorithm to obtain the transitive closure is based upon an iterative procedure in which the following relations are calculated.

$$\begin{aligned} R^{(2)} &= R \circ R \\ R^{(4)} &= R^{(2)} \circ R^{(2)} \\ R^{(8)} &= R^{(4)} \circ R^{(4)} \\ &\vdots \\ R^{(2^k)} &= R^{(2^{k-1})} \circ R^{(2^{k-1})} \end{aligned} \tag{3}$$

where $\circ$ represents the max–min operator and the procedure ends when $R^{(2k)} = R^{(2k-1)}$.

In our case, by defining as $t_{i,j}$ the time required to drive from municipalities i and j, in function of the kilometric distance and viability (highways, interstates, roads), the elements of the fuzzy relations are defined by the following equations:

$$\begin{aligned} R(x_i, x_j) &= \frac{60 - t_{i,j}}{60} \quad \text{if } t_{i,j} \leqslant 60 \\ R(x_i, x_j) &= 0 \quad \text{if } t_{i,j} \geqslant 60 \end{aligned} \tag{4}$$

The constant 60 indicates that the interaction is considered null when travel time exceeds 60 min. In any case this hypothesis can be discarded by substituting the maximum travel time among two municipalities to the constant 60. The transitive closure of such fuzzy compatible relations was carried out by means of Eqs. (3) and (4). Different partitions of its α-cut ($\alpha = 0.5$, $\alpha = 0.58$, $\alpha = 0.62$ and $\alpha = 0.65$) were calculated. As an example, the results obtained for $\alpha = 0.5$ are given in Fig. 1, representing the OTA subdivided into the sub-areas where transfer stations may be potentially located. In addition, C_k^α being the kth sub-area belonging to the territorial aggregation with a membership function α, for each sub-area C_k^α, the municipality j where the transfer station must be located, has been determined on the basis of the following equations:

$$\sum_{i \in C_k^\alpha} t_{i,j} \cdot p(i) = \min_{\forall l \in C_k^\alpha} \sum_{i \in C_k^\alpha} t_{i,l} \cdot p(i) \tag{5}$$

where $p(i)$ is the waste production of ith municipality belonging to the subset C_k^α and $t_{i,j}$ is the travel time between municipality i and j.

Fig. 1 shows the potential locations of transfer stations related to the subset obtained for $\alpha = 0.5$.

The potential locations of transfer stations are assumed to be the positions determined by Eq. (5) for the entire sub-area corresponding to the different α-cuts considered, discarding the sub-area having a single municipality.

Table 1 illustrates the municipalities individuated as potential locations on the basis of different clusters corresponding to $\alpha = 0.5$, $\alpha = 0.58$, $\alpha = 0.62$ and $\alpha = 0.65$. In the last row the potential locations of the transfer stations obtained merging the sets corresponding to cited α-cuts are reported. The city of Palermo, the capital of the region, confers directly to the incinerator on the basis of a pre-established waste management policy, hence its fluxes have not been considered in the model.

2.2. Cost model

Eight different types of plant were considered for the transfer stations; each was characterized by a different storage capacity and different loading system. Initial cost and structures and equipment used was evaluated by means of the annual equivalent (AE) method and shown in Table 2. The underlying assumptions were:

interest rate 3%;
service life: 30 years and 10 years for structures and equipment, respectively;
null residual values.

Operative and maintenance costs, energy, manpower and general expenditures are reported in Table 3. In the last column of this table the total annual cost, sum of the annual equivalent cost and operative cost, is given.

Three different types of vehicle were considered for the transportation of waste from transfer stations to the incinerator:

- 30 ton capacity tractor with compactor trailer;
- 30 ton capacity tractor and trailer;
- 15 ton capacity telehoist.

The fixed cost evaluated for each type of vehicle was obtained taking into account purchase price, insurance, taxation and driver salary and expressed as AE, considering a service life of 5 years

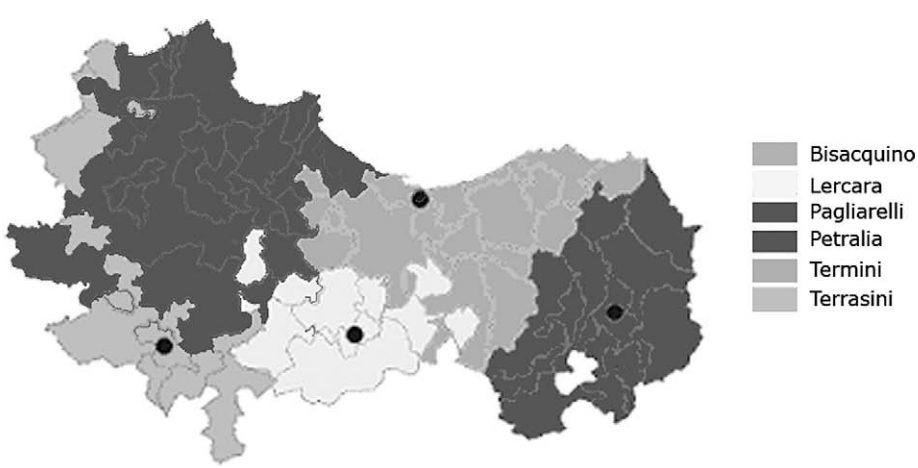

Fig. 1. Sub-areas obtained for $\alpha = 0.5$: Lercara, Palermo-Pagliarelli, Petralia, Bisaquino, Termini, Terrasini.

Table 1
Potential locations of transfer stations.

$\alpha = 0.50$	Lercara, Palermo-Pagliarelli, Petralia, Bisaquino, Termini, Terrasini
$\alpha = 0.58$	Cefalù, Petralia, Palermo-Pagliarelli, Prizzi, Bisaquino, Camporeale, Terrasini
$\alpha = 0.62$	Cefalù, Petralia, Palermo-Pagliarelli, Prizzi, Lercara, Bisaquino, Camporeale, Terrasini
$\alpha = 0.65$	Cefalù, Petralia, Caltavuturo, Alimena, Cerda, Palermo-Pagliarelli, Baucina, Piana degli Albanesi, Partinico, Monreale
Overall potential locations	Cefalù, Petralia, Caltavuturo, Alimena, Cerda, Prizzi, Lercara, Bisaquino, Palermo-Pagliarelli, Baucina, Piana degli Albanesi, Partinico, Terrasini, Camporeale, Monreale, Partitico, Termini

Table 2
Initial investment cost per plant typology.

Plant type	Capacity (ton/day)	Structures × 10^3€	Equipments × 10^3€	Annual equivalent × 10^3€/year
1	110	384	109	29.6
2	140	384	114	30.2
3	120	384	173	37.1
4	200	643	384	73.6
5	400	1055	726	131.0
6	600	1465	1038	187.0
7	800	1816	1349	240.0
8	1000	1816	1349	273.0

Table 3
Annual cost per plant typology.

Plant type	Capacity (ton/day)	Annual equivalent × 10^3€/year	Maintenance × 10^3€/year	Energy × 10^3€/year	Manpower × 10^3€/year	General cost × 10^3€/year	Total cost × 10^3€/year
1	110	29.6	5.8	1.9	70.0	7.8	115.2
2	140	30.2	6.0	1.9	93.4	10.1	141.6
3	120	37.1	6.6	4.7	93.4	10.5	152.5
4	200	73.6	15.7	7.8	93.4	11.7	202.3
5	400	131.3	28.9	13.6	163.4	20.6	358.0
6	600	186.8	40.8	19.2	233.5	29.4	509.5
7	800	239.7	52.7	23.6	280.2	35.6	632.0
8	1000	273.4	62.3	30.5	420.3	51.3	837.9

and residual values of 20% of the purchase price. The total annual fixed cost is reported in the 7th column of Table 5. Finally, variable fuel cost, proportional to the kilometers driven each year, is provided in the last column of the same table.

To evaluate the cost of collection and transportation from production sites to transfer stations, it was assumed that each municipality possesses its own vehicles, hence only operative cost was considered. A constraint had been enforced whereby for administrative reasons, municipalities may only transport their waste to a single transfer station.

The total cost of the system, also expressed in terms of AE, was obtained by adding the cost of all active transfer stations, collection costs towards transfer stations and transportation costs from stations to the incinerator.

The problem was formulated as a mixed integer linear programming model (MILP). Boolean decision variables $x_{i,j}$ take value 1 if the ith municipality confers to the jth station, 0 otherwise. Since each municipality can confer to a single transfer station, the following constraint is enforced:

$$\sum_j x_{i,j} = 1 \quad \forall i \tag{6}$$

Conversely, variables $y_{k,j}$ are related to the transfer stations, hence $y_{k,j} = 1$ means that a transfer station of type k is activated at position j. Since in each location only a single type of plant can be active, the following constraint is also enforced:

$$\sum_k y_{k,j} \leqslant 1 \quad \forall j \tag{7}$$

Municipality i can confer to station j only if it has been activated, and the total amount of waste conferred must be less than or equal to the capacity of the transfer station. Hence the following constraints are enforced:

$$\sum_k y_{k,j} \geqslant x_{i,j} \quad \forall i,j \tag{8}$$

$$\sum_k y_{k,j} q_{k,j} \geqslant \sum_i x_{i,j} p_i \quad \forall j \tag{9}$$

The variable $q_{k,j}$ identifies the capacity of the type of plant activated (see Table 2), while vector p_i identifies the amount of waste produced and transferred from the ith municipality to the collection plant in tons per day.

As stated previously, the following cost categories were considered: initial cost and fixed operating cost for each transfer station expressed by the variable *cti*, transportation costs from each municipality to the transfer station (*cts*) and the cost related to the transportation of waste collected in the transfer station to

Table 4
Purchase price of vehicles for transportation between transfer stations and incinerator.

Plant type	Tractor × 10^3€	Trailer × 10^3€	Telehoist body × 10^3€
1	83.0	–	60.2
2	67.4	77.8	–
3–8	67.4	51.9	–

Table 5
Fixed annual costs and operative cost of the vehicles.

Plant type	Annual equivalent of tractor × 10^3€/year	Annual equivalent of trailer × 10^3€/year	Annual equivalent of telehoist body × 10^3€/year	Taxes × 10^3€/year	Driver × 10^3€/year	Total fixed annual cost × 10^3€/year	Fuel consumption (€/km)
1	15.0	–	10.9	2.1	25.9	53.9	0.51
2	12.2	14.1	–	2.1	25.9	54.3	0.67
3–8	12.2	9.4	–	2.1	25.9	49.6	0.67

the incinerator (*ctt*), including fixed annual equivalent cost of the vehicles. According to this model, total cost ($Cost^{TOT}$) is given by:

$$cti = \sum_{k,j} y_{k,j} \cdot c_{k,j} \tag{10}$$

$$cts = \sum_{i,j} c_0 t_{i,j} \cdot x_{i,j} \cdot 312 \cdot 2 + P \tag{11}$$

$$ctt = \sum_{j} K_j^{na} + K_j^a + K_j^c + T_j^{FF} + T_j^F \tag{12}$$

$$Cost^{TOT} = cti + ctt + cts \tag{13}$$

where the term $c_{k,j}$ expresses the annual equivalent cost for each plant according to type, as provided in Table 3.

Eq. (11) expresses the cost of transportation of waste from municipalities towards potential transfer stations. This cost was assumed to be proportional to travel time, which depends upon distance and route. The daily transportation cost from municipalities to transfer stations was obtained as $c_0 \cdot t_{i,\,j}$, being c_0 the cost per hour of vehicles, as reported in Table 6.

The cost was doubled (taking into account the return trip) and multiplied by 312 working days per year to obtain the annual cost. The variable *P* in Eq. (11) refers to the transportation cost related to the city of Palermo which, as stated above, confers waste directly to the incinerator located close to the city. Variables K_j^{na}, K_j^a, K_j^c are related to the total annual cost of a 30 ton-tractor with compactor trailer, a second 30 ton-tractor and trailer and a 15 ton telehoist operating in the transfer stations. Vehicle operation is authorized to the extent of a single vehicle for each type of station, as reported in Table 4. This further constraint is expressed by Eqs. (23)–(25). The type of transfer stations and vehicles depends upon several factors: the amount of waste collected at each station, the distance to the incinerator, average speed (considering that the round-trip to the incinerator must be completed over one work-shift). Finally, T_j^{FF} and T_j^F variables represent variable transportation cost of 15 and 30 ton vehicles, respectively.

The above-described variables are required to satisfy the following equations:

$$K_j^{na} \geqslant (KK_j^{30} - I_j \cdot M_1) \cdot L_{na} + A - II_j M_1 L_{na} \quad \forall j \tag{14}$$

$$K_j^a \geqslant (KK_j^{30} - I_j \cdot M_1) \cdot L_a + B - (1 - II_j) M_1 L_a \quad \forall j \tag{15}$$

$$K_j^c \geqslant [KK_j^{15} - (1 - I_j) \cdot M_1] L_c + C \quad \forall j \tag{16}$$

$$T_j^{FF} \geqslant KV_j^{15} \cdot D_j \cdot 0.61 \cdot 312 \cdot 2 - (1 - I_j) \cdot M_2 \quad \forall j \tag{17}$$

$$T_j^F \geqslant KV_j^{30} \cdot D_j \cdot 0.77 \cdot 312 \cdot 2 - I_j \cdot M_3 \quad \forall j \tag{18}$$

where

I_j, II_j are auxiliary Boolean variables introduced to represent a unique link between the type of station and the related type of transportation vehicles;
M, M_1, M_2 and M_3 are arbitrary large positive numbers (Big *Ms*);
L_{na} is the fixed annual cost of a tractor and trailer;
A, B and C represent the annual equivalent of an additional trailer, compactor trailer and body, respectively, required to ensure continuity of service.
L_a is the fixed annual cost of a tractor with compactor trailer;
L_c is the fixed annual cost of the telehoist;
D_j is the distance between station *j* and the incinerator;
0.61 and 0.77 are costs per kilometer (€/km) for fuel and maintenance for the 15 and 30 ton trucks, respectively;
312 is the number of working days per year.

The number of 30 and 15 ton vehicles and the number of runs per day must fulfill the following constraints

$$KK_j^{30} \geqslant \frac{T_j \sum_i x_{i,j} \cdot p_i}{30 T_{max}} \quad \forall j \tag{19}$$

$$KK_j^{15} \geqslant \frac{T_j \sum_i x_{i,j} \cdot p_i}{15 T_{max}} \quad \forall j \tag{20}$$

$$KV_j^{30} \geqslant \frac{\sum_i x_{i,j} \cdot p_i}{30} \quad \forall j \tag{21}$$

$$KV_j^{15} \geqslant \frac{\sum_i x_{i,j} \cdot p_i}{15} \quad \forall j \tag{22}$$

where variables KK_j^{30} and KK_j^{15} are integer variables representing the number of 30 and 15 ton vehicles required to transport waste from a station *j* to the incinerator within a work-shift. In fact T_j is the time required to travel from the generic transfer station *j* to the incinerator, determined assuming a speed of 40 km/h on highways, 20 km/h on speedways and 15 km/h on all other roads. T_{max} is half a time shift, i.e., 4 h.

KV_j^{30} and KV_j^{15} indicate the number of trips per day to be performed by 30 and 15 ton vehicles, respectively. Finally, the following constraints are enforced to ensure logical coherence among the variables introduced:

$$y_{1,j} \cdot M \geqslant K_j^c \quad \forall j \tag{23}$$

$$y_{2,j} \cdot M \geqslant K_j^a \quad \forall j \tag{24}$$

$$(y_{3,j} + y_{4a,j} + y_{4b,j} + y_{4c,j} + y_{4d,j} + y_{4e,j}) \cdot M \geqslant K_j^{na} \quad \forall j \tag{25}$$

2.3. Environmental impact and multi-objective approach

The model described previously is a single-objective model that can be solved through application of standard mathematical programming methods. In addition to the minimum cost objective, environmental impact of the system has been considered and

Table 6
Cost per hour of the municipality collector vehicles.

Capacity (ton)	Purchase price × 10^3€	Annual equivalent × 10^3€/year	Taxes × 10^3€/year	Driver × 10^3€/year	Total cost × 10^3€/year	Cost per hour (€/h)
6	93.4	16.9	1.3	25.9	44.1	26.7

evaluated on the basis of daily fuel consumption, responsible for air pollution, during waste transportation. To consider these additional optimality criteria the following equations have been introduced:

$$Fuel^{con} = \sum_{i,j} x_{i,j} \cdot d_{i,j} \cdot 0.32 \quad (26)$$

$$Fuel_j^{ST15} \geqslant KV_j^{15} \cdot D_j \cdot 0.54 - (1 - I_j)M_1 \quad \forall j \quad (27)$$

$$Fuel_j^{ST30} \geqslant KV_j^{30} \cdot D_j \cdot 0.71 - I_j \cdot M_1 \quad \forall j \quad (28)$$

$$Fuel^{tot} \geqslant Fuel^{con} + \sum_j \left(Fuel_j^{ST15} + Fuel_j^{ST30}\right) \quad (29)$$

where

$Fuel^{con}$ represents total daily fuel consumption for the transportation of waste from municipalities to transfer stations, $d_{i,j}$ being the distance from municipality i to transfer station j;
$Fuel_j^{ST15}$ and $Fuel_j^{ST30}$ represent fuel consumption related to 15 and 30 ton vehicles;
$Fuel^{tot}$ represents total amount of daily fuel consumption and the coefficients 0.32, 0.54, and 0.71 represent average fuel consumption in l/km for each type of vehicle.

Eqs. (13) and (29) represent the two objectives considered in the optimization model.

An set of effective solutions should be determined from which, in a subsequent phase, the decision maker will select the most appropriate. This approach is justified when considering that by reducing the number of alternatives, and increasing awareness of the problem, the expectations of stakeholders can be better ascertained. The most significant approaches to multi-objective optimization are based on utility function (Keeney and Raiffa, 1976), goal programming (Ignizio, 1976) and compromise programming (Zeleny, 1982). The technique based on rank order goal programming, also known as lexicographic and preemptive goal programming, requires the drawing up of a list of priority objectives: the solution technique subsequently consists in a sequential single-objective optimization, according to the rank assigned to objectives. As the optimal solution according to the first objective was determined, the value obtained becomes a constraint and the second objective is pursued and so on according to the pre-established ranking. In the second case, the weighted method, once the objective functions have been properly normalized, the decision maker assigns to each a coefficient expressing the relative importance of the corresponding objective.

A multi-objective technique alternative to classical methodologies is the fuzzy multi-objective programming method (Zimmermann, 1985). Assuming that the model is crisp and the decision maker is interested in a crisp solution, a multi-objective fuzzy model can be formulated in which a membership function representing the degree of satisfaction is assigned to each objective.

In the following section the solutions obtained by means of the techniques described are discussed.

3. Identification of the set of alternatives

The model described was implemented by means of the GAMS modeling language while the solver employed was the mixed integer programming (MIP) of CPLEX 8.0. A graphical rendering of the solution was obtained by means of a commercial geographic information system (Arcmap 8.1). Solutions are therefore represented by a geographic map of the OTA considered. Each transfer station activated is identified on the map by means of proper indicators, and municipalities conferring to the same transfer station are indicated by the same color (see Figs. 2 and 3).

3.1. Goal programming

3.1.1. Solution with ranking: cost, fuel consumption

The solution obtained by means of the method discussed in Section 2 featured a total annual cost of 2.65M€ while fuel consumption per day amounted to 1486 l. The solution was characterized by the activation of three transfer stations (Fig. 2): one in Palermo-Pagliarelli with a capacity of 400 ton/day and two others, with capacities of 200 and 140 ton/day, located in Termini Imerese and Terrasini, respectively. The total capacity of transfer stations corresponds to 740 ton/day, currently meeting a demand of 664 ton/day.

3.1.2. Solution with ranking fuel consumption, cost

This solution consists of eight transfer stations: the largest located in Palermo-Pagliarelli, two mid-sized stations located in Petralia and Terrasini, and five smaller ones located in Cefalù, Scillato, Termini Imererse, Lercara and Bisacquino (Fig. 3). Total fuel consumption amounted to 1020 l/day for a total annual cost of 3.48M€. Fuel consumption was reduced by 48% with a cost increase of 31%.

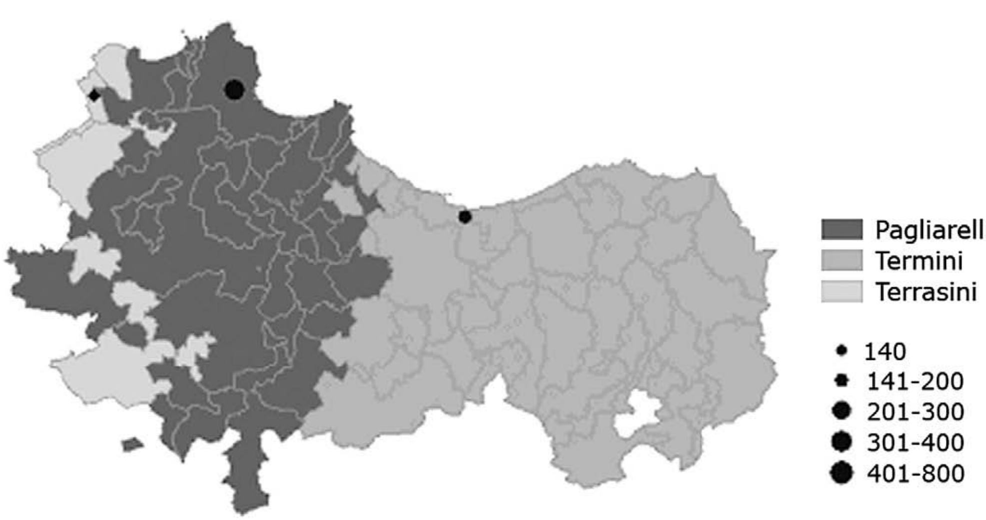

Fig. 2. Solution obtained with ranking cost, fuel consumption.

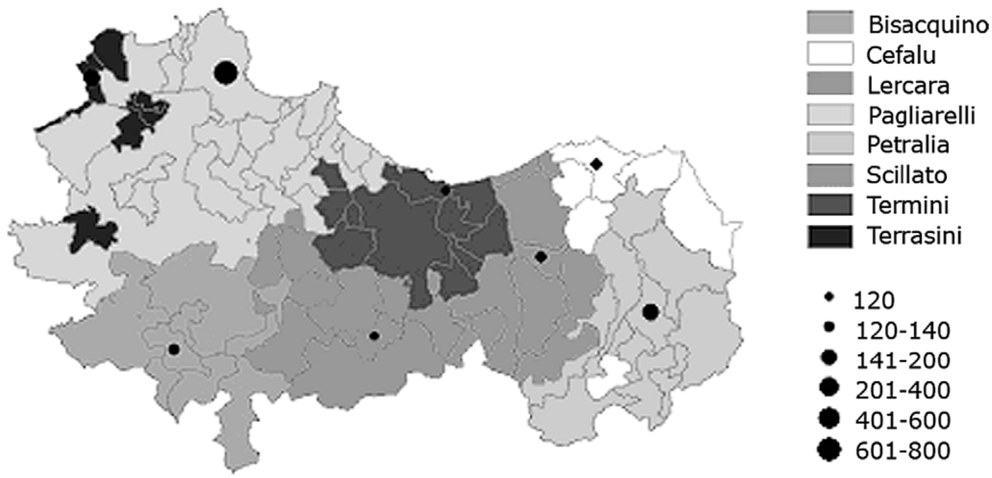

Fig. 3. Solution obtained with ranking fuel consumption, cost.

3.2. Weighted method

The solution of a multi-objective optimization problem involving k criteria is a vector of k-coordinates x_i. If objective functions are to be minimized, the solution $\mathbf{x} = (x_1, x_2, \ldots, x_k)$ is said to "dominate" the solution

$$\begin{aligned}&\mathbf{y} = (y_1, y_2, \ldots, y_k) \text{ if :}\\&x_i \leqslant y_i \quad \forall i = 1, \ldots, k\\&\text{and}\\&x_i < y_i \quad \text{for at least one } i\end{aligned}$$

A solution which is not dominated by any other feasible solution is defined as Pareto-optimal. If a solution is Pareto-optimal, there is no other feasible solution that improves any criterion without worsening the value of at least another one.

One of the most common procedures used in determining Pareto-optimal solutions is the weighted method. When considering an optimization problem defined by two objective functions $F_1(\mathbf{x})$ and $F_2(\mathbf{x})$ to be minimized, the first step in the application of the weighted method approach consists in the normalization of the given functions. This operation is aimed at rendering the two objectives comparable. Once normalized, the two objective functions will be defined by the following equation:

$$f_i(\mathbf{x}) = \frac{F(\mathbf{x}) - F^{min}(\mathbf{x})}{F^{max}(\mathbf{x}) - F^{min}(\mathbf{x})} \tag{30}$$

where $F_i^{min}(\mathbf{x})$ and $F_i^{max}(\mathbf{x})$ are the extreme values of the objective functions determined by means of the goal programming technique described in the previous paragraph.

The weighted method approach consists in determining $\forall w_i > 0 | \sum w_i = 1$ the solution of the optimization problem. For a two-dimensional case the following equation is applied:

$$\min f(x) = \min[w_1 \cdot f_1(x) + w_2 \cdot f_2(x)] \tag{31}$$

or

$$\min f(\mathbf{x}) = \min \frac{f(\mathbf{x})}{w_1} = \min \left[f_1(\mathbf{x}) + \frac{w_2}{w_1} \cdot f_2(\mathbf{x}) \right] \tag{32}$$

indicating identification in the space $f_1(\mathbf{x}), f_2(\mathbf{x})$ the feasible solution having the minimum distance from the generic line:

$$f_1(x) + \frac{1 - w_1}{w_1} \cdot f_2(x) = c \quad c \in R. \tag{33}$$

As w_1 varies, the slope of the generic line varies sweeping from 0, which corresponds to the $f_1(\mathbf{x})$ axis, to ∞ which corresponds to $f_2(\mathbf{x})$ axis. Clearly this technique can be employed for a finite set of weights, thus obtaining a linear approximation of the Pareto-frontier.

Since the linear envelope is convex, it will not be possible to find solutions (if they indeed exist) that violate the convexity of the frontier. Accordingly, similar solutions cannot be identified by means of this technique.

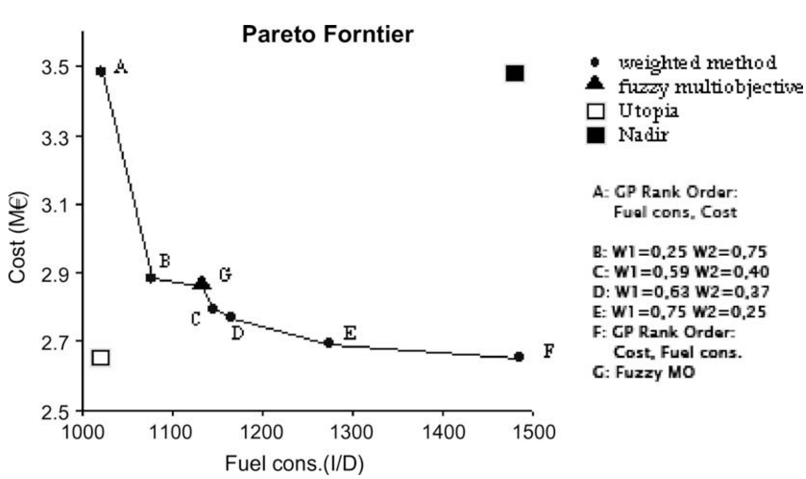

Fig. 4. Pareto-frontier.

Table 7
Solution set.

Solution	w_1	w_2	Fuel use (l/day)	Cost (€)	f_1 (fuel use)	f_2 (cost)
A	*GP rank order: fuel use, cost*		1020.8	3,484,352	0.00	1.00
B	0.25	0.75	1076.7	2,881,837	0.12	0.28
G	*Fuzzy MO*		1133.6	2,862,638	0.24	0.26
C	0.59	0.41	1145.8	2,793,904	0.27	0.17
D	0.63	0.37	1165.9	2,770,198	0.31	0.15
E	0.75	0.25	1274.6	2,687,856	0.55	0.47
F	*GP rank order: cost, fuel use*		1486.1	2,648,397	1.00	0.00
Nadir			1486.1	3,484,352	1.00	1.00
Utopia			1020.8	2,648,397	0.00	0.00

The solutions obtained correspond to the maximum satisfaction of the decision maker, provided global satisfaction can be expressed as the sum of the partial scores obtained for each objective function. The additive property of the satisfaction scores is hence a fundamental assumption for application of this method.

In the case illustrated here, the weighted method approach was applied to determine four new solutions situated between the solutions previously obtained by means of rank-based goal programming (Fig. 4 and Table 7).

3.3. Fuzzy multi-objective linear programming

A membership function $\mu_i(\mathbf{x}) \in [0, 1]$ is assigned to each objective, representing the degree of satisfaction of the solution $\mathbf{x}$ according to objective i. Once the $\mu_i(\mathbf{x})$ have been defined, the overall satisfaction level must be determined. Zimmermann (1985) suggests the employment of a standard T-norm operator (i.e., intersection) identifying $\mu_x(\mathbf{x})$ as the minimum of the $\mu_i(\mathbf{x})$. This way, the maximization of $\mu_x(\mathbf{x})$ corresponds to the attitude of the decision maker of obtaining the same satisfaction level for all objectives considered or, in other words, the best compromise solution. In particular, this solution maximizes the global satisfaction of the decision maker measured as the minimum of the partial satisfaction scores. Considering a multi-objective problem and assuming all objective functions to be minimized:

$$\begin{aligned} &\min Z(\mathbf{x}) = C\mathbf{x} \\ &\text{subject to :} \\ &\quad A\mathbf{x} \leqslant b \\ &\quad \mathbf{x} \geqslant 0 \end{aligned} \tag{34}$$

For each objective i a fuzzy set is defined with a linear membership function $\mu_i(\mathbf{x})$, establishing a minimum and a maximum level of satisfaction, expressed as values d_i and $(d_i + p_i)$ of the objective function:

$$\mu_i(x) = \begin{cases} 1 & \text{if} \quad C_i\mathbf{x} \leqslant d_i \\ 1 - \frac{C_i\mathbf{x} - d_i}{p_i} & \text{if} \quad d_i < C_i\mathbf{x} \leqslant d_i + p_i \\ 0 & \text{if} \quad C_i\mathbf{x} > d_i + p_i \end{cases} \tag{35}$$

Since the degree of membership $\mu_x(\mathbf{x})$ of solution $\mathbf{x}$, according to all the objectives, is defined as:

$$\mu_x(x) = \min_i \{\mu_i(x)\} \tag{36}$$

in order to maximize $\mu_x(\mathbf{x})$, the following operation should be performed:

$$\max_x \mu_x(\mathbf{x}) = \max_x \min_i \mu_i(\mathbf{x}) \tag{37}$$

By defining a new variable $\lambda(\mathbf{x})$:

$$\lambda(\mathbf{x}) = \min_i \left(1 - \frac{C_i\mathbf{x} - d_i}{p_i}\right) \tag{38}$$

the multi-objective formulation becomes a single-objective linear programming model, transforming all the original objective functions into constraints:

$$\begin{aligned} &\max \lambda(\mathbf{x}) \\ &\text{subject to :} \quad \lambda p_i + C_i x \leqslant d_i + p_i \\ &\qquad\qquad\quad A\mathbf{x} \leqslant b \\ &\qquad\qquad\quad \mathbf{x} \geqslant 0 \end{aligned} \tag{39}$$

Assigning to d_i and $(d_i + p_i)$ the values of the ith objective function obtained by means of the rank-based goal programming approach, an additional Pareto-optimal solution has been determined (point G in Fig. 4).

4. Discussion

In order to clarify the meaning and differences between the weighted method and the multi-objective fuzzy procedure, the compromise programming (CP) multi-objective optimization method formalized by Zeleny (1982) may be referred to for convenience. The fundamental concept is the "compromise", indicating the determination of the solution closest to the "ideal" solution. In a multi-objective optimization problem two extreme points can be defined: Utopia and Nadir (see Fig. 4). These two points represent the ideal and the least desirable solution, respectively. Once a pay-off matrix has been determined and a proper normalization has been carried out, it is possible to establish a suitable measure function in the space of solutions and evaluate the alternatives in terms of their distance from the ideal point. A class of distance functions can be expressed by the following relation:

$$d_p = \left(\sum_{i=1}^{n} w_i^p \cdot |x_i - x_i^*|^p\right)^{1/p} \tag{40}$$

where x_i^* represents the value of the ith objective function in the Utopia point, x_i is the value of the generic objective function i, w_i is a constant and p, ranging from 1 to ∞, is a parameter which defines the metric employed.

For $p = 1$, the CP approach becomes the weighted method:

$$\min d_1 = \min \sum_{i=1}^{n} w_i |x_i - x_i^*| \tag{41}$$

For $p = 2$, the Euclidean distance is employed, and CP approach results in:

$$\min d_2 = \min \left(\sum_{i=1}^{n} w_i^2 \cdot |x_i - x_i^*|^2\right)^{1/2} \tag{42}$$

For $p = \infty$, the CP formulation results in:

$$\min d_\infty = \min\{\max(w_i \cdot |x_i - x_i^*|)\} \tag{43}$$

To conclude, it is clear that the different solution techniques employed are strictly linked to the decision makers preferences. In particular, application of the weighted method (i.e., CP with

$p = 1$) leads to determination of the global level of satisfaction of the decision maker as the sum of the partial satisfaction functions. By means of the fuzzy approach, or CP with $p = \infty$, the resulting global satisfaction represents the minimum of the partial satisfaction functions. Consequently, different attitudes of the decision maker towards the logic and the structure of the preferences will result in the application of different techniques and obtaining of different results.

5. Conclusions

In the design of complex systems involving several stakeholders, the traditional single-objective approach shows all its limitations and the concept itself of optimality must be properly revisited. The approach described configures as a valid tool for decision making, in view of the fact that the generation of a set of Pareto-optimal solutions may assist the decision maker in selecting the most effective alternative. The choice should in fact take into account the expectations of all involved stakeholders and must achieve the best compromise to be accepted by all. In such a complex problem, reducing the number of solutions to only seven possible configurations, as illustrated in Fig. 4, facilitates the convergence toward a shared compromise solution.

The present paper highlights how the different attitudes of the decision maker towards the logic and the structure of the preferences, implies the choice of a suitable solution procedure aimed at obtaining appropriate results. The results obtained show how according to the choice of the decision maker variations in fuel use and total cost are about 45% and 32%, respectively. The attitude of the decision maker, hence, significantly influences the performance of the system on the basis of the objectives considered.

Furthermore, it should be pointed out that the solution obtained by considering cost as the main optimization objective, corresponds to a "centralized" system design consisting of only two plants. On the contrary, by inverting the ranking of objectives a better distributed configuration is obtained consisting in seven small plants. The centralized solution achieves high economies of scale, thus minimizing total costs and representing a traditional approach to plant management and design. However, on taking into account environmental impact as the main objective, a more decentralized solution is obtained, which minimizes fuel consumption. Nowadays, the trade-off between economical efficiency and environmental impact is gaining considerable interest: as an example, the issue of CO_2 emissions was one of the main topics discussed during the recent United Nations climate conference in Copenhagen in December 2009. Indeed, the results obtained show that the maximum pulverization level aimed at ensuring optimum conditions to the system amounts to seven stations, corresponding to solution A; thus, further decentralization is of little use even when fuel consumption is of major concern to the decision maker.

Finally, the proposed model could be extended to consider other procedures of waste treatment, which in a modern integrated perspective, should match the incineration. Although not taking into account the fluxes deriving from the source separated collection, which constitutes a separate problem, we refer to the plant that subdivides the waste according to final destination: recycling, composting, landfill and incineration. In this case, in addition to the transfer stations, the location and dimensioning of the pretreatment stations should also be taken into due consideration.

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