Optimization model of integrated MSW management

Lubomir Nondek

Integra Consulting Services Ltd., Praha, Czech Republic

Abstract

The communication presents a conceptual model proposed for optimal municipal solid waste allocation. The current version of model optimizes cumulative emission of greenhouse gases. Model takes advantages of algebraic modelling languages, which enables to develop models in a scalable manner independent of the database used. Continuous flows of four municipal solid waste components (bio-waste, materials, refuse derived fuel and inert fraction), which take place between sets of sources and installations are quantified and converted to the greenhouse gases emission. Uncertainties of inputs, especially varying composition of MSW, have been modelled by Monte-Carlo experiments.

Key words

Integrated waste management, allocation model, greenhouse gas emissions, linear programming

1 Introduction

Since beginning of 90s, various municipal solid waste (MSW) management models have been designed mostly utilizing life cycle analysis (LCA). Majority of such models are static and deterministic ones which means that uncertainty of inputs (e.g. quantities and composition o MSW or emission factors) is not taken into account. The static LCA models also do not enable to optimise the allocation of MSW between spatially distributed sources (municipalities) and installations (separators, composting facilities, incinerators, landfills etc.). The limitations of LCA for waste management planning and policy making has been discussed by EKVALL ET AL. (2004). However LCA is a basic method to assess alternative scenarios as demonstrated by DE FEO AND MALVANO (2009). In this respect further modifications of LCA such as economic input-output life-cycle assessment (EIO-LCA) results in valuable modelling tools applicable at national level as shown recently (HENDRICKSON, LAVE AND MATTHEWS, 2006; DISTEFANO AND BELENKY, 2009).

Major drawback of regional- or local-scale LCA relates to its inability to characterise spatial distribution of impacts. Local impacts like transport noise, groundwater pollution or PM10 emitted by transport vehicles are more important in local decision making processes such as EIA than acidification or global warming. In such cases LCA should be combined with other techniques such as noise or dispersion modelling. Especially impact of increasing waste transport draws attention to logistic models which are combined with LCA (SALHOFER, SCHNEIDER AND OBERSTEINER, 2007). However the goal of transport modelling is not only to assess traffic impacts but to look for optimal allocation of MSW or other wastes between sources and installations, which may have individual spectrum of emission factors or material/energy efficiencies. One may look at the system composed of MSW sources and receiving installations in a holistic view and look for various allocation optima (minimum emissions, maximum energy efficiency etc.).

Several different allocation models using linear programming, integer programming, mixed-integer programming or non-linear programming had been reported. COSTI ET AL. have designated a mixed integer non-linear programming decision support model for optimization of integrated waste management (IWM) system composed of separators, refuse derived fuel (RDF) production plants, incinerators with energy recovery, processing of biodegradable wastes and sanitary landfills. Genova region (Italy) has been used for their case study. The same area has been modelled by FIORUCCI ET AL. using an integer non-linear programming model. Goal of the modelling experiments has been to estimate optimal structure of landfills and treatment plans in respect to the composition of MSW.

We have used the technique of linear programming (LP) to design an optimization model for minimization of greenhouse gas emissions (carbon dioxide, methane and nitrous oxide) related to a set of spatially distributed MSW sources (municipalities) and installations with various disposal capacities and emission factors. Because of the LP solver used the model is scalable enough to be used on a regional/national scale and the set of installation categories can be expanded. Uncertainties of inputs, especially varying composition of MSW, have been modelled by Monte-Carlo experiments. The model is relatively simple and currently optimizes the allocation of four MSW components: biodegradable waste, recyclable materials, RDF and inert fraction.

2 Optimization problem and basic model characteristics

In this case, minimum aggregated emission of GHGs (expressed as CO_2 eq) in a system composed of MSW sources and receiving installations such as separators, composting facilities, bioreactors, material reprocessing facilities, energy sources and landfills are looked for. Sources and facilities are located in a 2-dimensional map where MSW and materials derived from (separated biodegradable fraction, recyclable materials, refuse derived fuel and inert waste) are transported between individual objects (municipalities, installations) defined by x, y - coordinates, generation rates and capacities.

Basic characteristics of the model can be summarized:

1. Single parameter optimization (e.g. cumulative emissions, overall energy consumption or efficiency, transport intensity, overall costs) by a commercially available LP solver,

2. Model is based upon a rational behaviour of collectors and waste transporters to minimize the transport distances/costs. It does not apply to extreme cases of MSW transport referred by SALHOFER, SCHNEIDER AND OBERSTEINER (2007) when wastes were transported e.g. from south Italy to foreign incinerators.

3. Flow of MSW and material components during the time period considered (e.g. year) is continuous, no accumulation occurs,

4. Model is scalable to encompass large number of sources and installations. Its practical size is limited by data availability and the programming environment used (MS Excel and an available version of commercial LP solver LINGO),

5. Sources are characterised by data sets including GPS coordinates, population size, prevailing character of municipality (apartment houses, family houses or villages), MSW composition and generation rates, efficiency of MSW separation at source etc. Emissions related to collection of MSW and its transport are related to the character of municipality and capacity of the collection cars used,

6. Installations are characterised by technology used, emission factors and disposal capacities,

7. As a first approximation, Euclid distances calculated from GPS coordinates are modified by an average tortuosity estimated for the geographic area studied. Euclid distance can be substituted by road distance if necessary.

8. All adjustable parameters are either available (measurements, literature) or substitutable by expert judgment.

9. Propagation of uncertainty related to inputs (e.g. generation rates, compositions, emission factors and collection distances) is modelled using a Monte-Carlo technique. At this stage, normal distribution functions are assumed for inputs. Stochastic independence between inputs is assumed at this stage of model development, which means that the value taken by one input parameter does not influence the probability of occurrence of the other input parameters.

10. Testing procedures have been set down during the development of the LP model.

3 Concise description of the model

The optimization model consists of six sets:

i MSW sources

j waste separators

k bioreactors and/or composting facilities

l material processing units

m energy recovery units

n landfills

Overall material flows between individual parts of the IWM system are demonstrated in Figure 1.

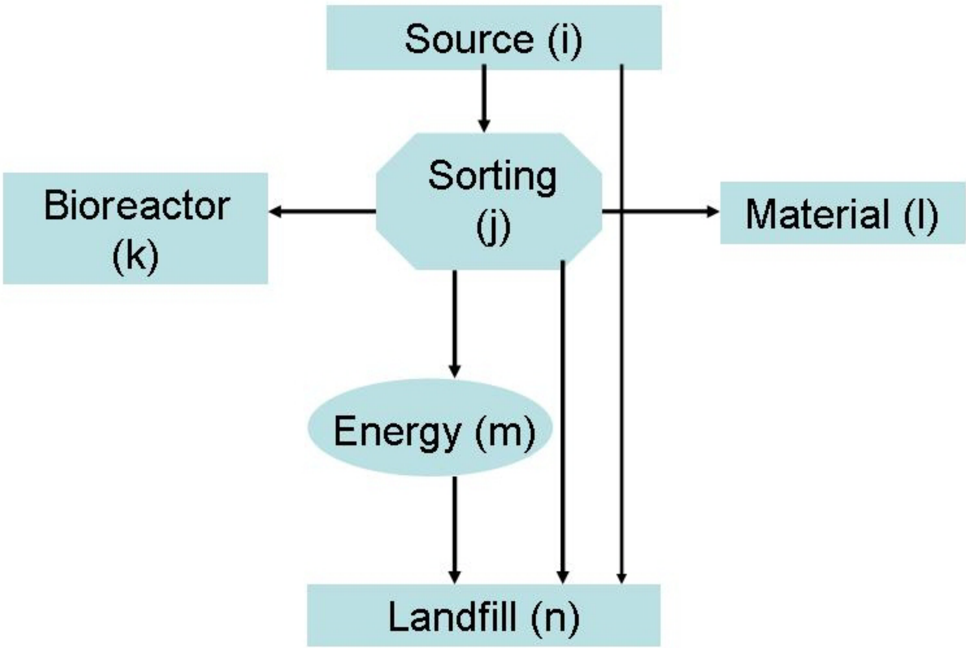

Figure 1 Overall diagram of material flows modelled

In this case, MSW consists of four components: biodegradable wastes (B), recyclable materials (M), refuse derived fuel (F) and inert waste (I). The individual waste components flow from set of sources into the set of waste separators and installations or they are directed to set of landfills (Figure 1). Arrows represent direction of flows along the allocation routes. Flows of individual components (B, M, F and I) have been derived from the overall flow diagram (Figure 1).

Emissions of GHGs (expressed as CO_2 eq) occur during transport and processing of wastes in individual installations as they depend upon technology and processed quantities of B, M, F and I. For example emissions, *e*, related to transport and separation of input quantity, *q,* of waste in a separator can be expressed as

$$e = q(\varepsilon_t l / C_{veh} + \varepsilon_p)$$

where ε_t is a transport emission factor (as CO_2 emissions per km), *l* is transport distance, C_{veh} is the capacity of transport vehicle and ε_p is an overall process emission factor for the given separator. For all *j* separators one can therefore calculate aggregated emissions as

$$E_{separ} = \sum_j q_{i,j}(\varepsilon_t l_{ij} / C_{veh(i,j)} + \varepsilon_p) \qquad \forall routes, separators$$

Similar expressions are derived for other installations. Objective function, ***E (min),*** is a sum of aggregated emissions related to all installations, routes and allocated quantities MSW including its individual components (B, M, F and I):

E (min) = $E_{separ} + E_{mat} + E_{bio} + E_{fuel} + E_{land}$

Installed annual capacities C_{separ}, C_{bio}, C_{mat}, C_{energ}, C_{land} are used as constraints. For example, for all *j* separators the following constraint holds:

$$C_{separ} \leq \sum_i q_{Bi} + \sum_i q_{Mi} + \sum_i q_{Fi} + \sum_i q_{Ii} \qquad \forall sources$$

Analogically, input/output mass balances of individual installations represent another set of constraints, e.g. for component B treated in composting facilities or disposed at landfills

$$\sum_i q_{Bi} = \sum_j q_{Bj} + \sum_n q_{Bn}$$

$$\sum_j (\sigma_B . q_{Bj}) = \sum_k q_{Bk}$$

$$\sum_j ((1 - \sigma_B) . q_{Bj}) = \sum_k q_{Bn}$$

Separation efficiencies, σ, are adjusted for the separated component and given installation in interval (0, 1). Constraining mass balances are set down for other components in the same way.

4 Implementation of the model

Model has been implemented in LINGO algebraic modelling language and solved by means of a linear programming LINGO solver (Lindo Systems Inc., USA). As a comprehensive modelling language LINGO allows the transcription of the above balance equations and constraints closer to their mathematical forms than other programming languages. LINGO enables to programme algebraic operations over basic and derived sets (sources, installations, routes) which make the code comprehensive and condensed. For example, a series of similar constraints can be expressed as a single statement. The advantages of algebraic modelling languages (e.g. GAMS, AMPL, LINGO, NOP or Numerica) have been described by Schichl (2003).

After drawing flow diagrams (Figure 1) for individual waste components, a pseudo-code has been drafted to describe the content of basic blocks of the model (objective function, mass balances, constraints, sets and derived sets, data transfer). LINGO allows relatively long names for variables, which makes code building followed by inspections is easier. For example the set of capacity constraint for *j* separators (over B, M, F and I) is written as:

```
@FOR(MBT (J):
     @SUM(ROUTE_SOURCE_MBT(I,J):    SF_MBT_COMP*XB(I)*Q_SOURCE_MBT(I,J)) =
     @SUM(ROUTE_MBT_COMP(J,K):      Q_MBT_COMP(J,K)));

  @FOR(MBT (J):
     @SUM(ROUTE_SOURCE_MBT(I,J):    SF_MBT_MAT*XM(I)*Q_SOURCE_MBT(I,J)) =
     @SUM(ROUTE_MBT_MAT(J,L):       Q_MBT_MAT(J,L)));

  @FOR(MBT(J):
     @SUM(ROUTE_SOURCE_MBT(I,J):    SF_MBT_ENERG*XF(I)*Q_SOURCE_MBT(I,J))=
     @SUM(ROUTE_MBT_ENERG(J,M):     Q_MBT_ENERG(J,M)));

  @FOR(MBT(J):
     @SUM(ROUTE_SOURCE_MBT(I,J):   (1-SF_MBT_MAT)*XM(I)*Q_SOURCE_MBT(I,J) +
                                   (1-SF_MBT_COMP)*XB(I)*Q_SOURCE_MBT(I,J) +
                                   (1-SF_MBT_ENERG)*XF(I)*Q_SOURCE_MBT(I,J) +
                                    XI(I)*Q_SOURCE_MBT(I,J))  =
     @SUM(ROUTE_MBT_LAND(J,L):      Q_MBT_LAND(J,L)));
```

The model consists of two modules:

1. Optimization program in LINGO and
2. MS Excel database with quantities Q of MSW and amounts of B, M, F and I generated by individual sources, installation capacities, emission factors and separation factors of the installations. Sets of transport matrices contain distances *l*.

The transfer of data from the MS Excel database uses OLE (Object Linking and Embedding), which is a Microsoft's standard. OLE is used to transfer results of optimization into the MS Excel file (separate sheet or file). Besides value of the objective function, the set of allocation matrices is generated. The matrices indicate the quantities of waste allocated along the individual routes from sources to separators/landfills and between installations (separators, bioreactors, material processing units, energy units and landfills), see Figure 1. The optimization model is independent of the size and content of the database (number of sources and installations). It is therefore possible to model scenarios prepared as individual MS Excel files, which makes the archiving of input data and modelling results quite easy.

4.1 Model testing

Testing is an integral part of software development that needs to be carried out in parallel with computer program building (McConnell, 2004). Testing datasets have been therefore prepared during design and coding. Tests are based upon mass balance for individual components (B, M, F and I). A simple testing database (6 sources, 4 separators, 4 landfills, 2 bioreactors, 2 material processing units, 2 incinerators) has been used as a first testing tool. Simple allocation problems ("toy problems", see Schichl, 2003) such as allocation of several mass units have been recalculated manually.

Next database has been prepared for "real life" district MSW disposal (real map, 110 municipalities, 4 landfills). The set of municipalities and installations has been taken from a regional MSW management plan. At present, the system is being currently modified and new installations are introduced into the system (anaerobic digester, composting facility, separator with RDF production and incinerator) as several scenarios. Emission factors and MSW composition are taken from a literature review.

Matrix of transport distances as an input is constructed in the first step as Euclidean distances multiplied with tortuosity (1.25 +/- 0.10), which has been estimated from a sample of 3 x 25 roads (distances from 10 to 50 km) located in 3 different regions (South Bohemia, lowlands of Elbe River and mountainous landscape of Česko-Moravská Vysočina). Than allocation matrices (mass flows between objects) are compared with the real routes and the Euclidean distances are substituted in second modelling step by real distances (road map) for the routes used by the major sources. Unused or marginal routes can be characterised by Euclidean approximation.

An advanced testing database with 110 sources contains a random number generator (normal or rectangular distributions) which allows a random modelling of the proportions of B, M, F and I in MSW generated and therefore also random modelling of the total quantity of MSW generated by individual sources. Those experiments give information on cumulative distribution function of modelled output: total GHGs emissions (means and standard deviations estimated from series of modelling experiments) related to various uncertainty of MSW input. This gives at least a rough idea on propagation of uncertainty. More sophisticated approach has been proposed by BACCOU ET AL. (2008).

5 Results

For a real-life testing of the model, a rural district of the Czech Republic has been chosen. The district has following characteristics: 102,8 thous. inhab., 1326 km^2, 8 towns, largest town has 35,6 thous. inhab., 60,6% inhabitants live in settlements > 5 thous. inhab., 22,9% of inhabitants live in villages < 1000 inhabitants. There are 4 landfills receiving MSW with total capacity of 66 500 t/yr (MSW and non-toxic business waste). Two largest landfills are equipped with collection systems and co-generation units exploiting landfill gas. One landfill is equipped with collection system and bio-oxidation of landfill gas, the smallest landfill (1500 t/yr) has no treatment of landfill gas. Using information from publicly available integrated permits (IPPC), we have estimated methane emissions (collection efficiency, oxidation to CO_2).

Several scenarios of advanced MSW disposal have been modelled including a new mechanical biological treatment (MBT) of MSW, production of refuse derived fuel (RDF), composting and material recovery. MBT unit is located at the largest landfill, RDF produced is transported to the largest town to be used in the centralized heating system incl. cogeneration. Material recovered at MBT is transported to the same town. Other landfills have been closed or equipped with more efficient collection systems. In parallel, Monte-Carlo modelling of output (GHGs emissions) uncertainty related to the uncertainty of input MSW composition has been carried out. Difference between MSW composition generated by rural settlements (home composting and coal/wood stoves) and apartment buildings (no home composting, central heating) has been modelled based upon housing statistics. MSW municipal statistics have been used to calculate annual generated amount of MSW per capita. Transport and collection emissions have been estimated by means of population density in settlements, road map (table of transport distances) and collection cars used (20 or 10 t capacity).

The scenarios modelled have been compared with a worst-case scenario derived from the Czech national GHGs emission inventory (MINISTRY OF THE ENVIRONMENT, 2009), which estimates that landfill gas emissions contribute by ca 2,5 mil. t/yr of CO_2 eq to the national GHGs emission budget. This equals approx. to 0,25 t/inhab. of CO_2 eq at annual MSW generation rate of 400 kg/inhab. The above estimates do not take into account oxidation of emitted methane in the upper layer of the landfill cover and/or flaring or energy use of landfill gas. In our modelled district, the worst-case CO_2 eq emissions per capita are 0,183 t/yr and annual average MSW production is 283 kg/inhab., which gives the worst-case emissions (0,26 t/yr CO_2 eq) corrected for higher MSW generation rate close to the above national estimate. Collection and transport emissions are negligible for the worst-case scenario contributing by ca 0,5 % to the total emission budget.

For “business-as-usual“ scenario (present situation) when the estimates take into account the landfill gas treatment at the landfills the total emissions are ca 3200 t CO_2 eq/yr due to the collection and oxidation of landfill methane at the two largest landfills. The contribution of collection and transport is ca 3% of the total GHGs emissions. In more advanced Scenario 1, including MBT, material recovery and composting, the total GHGs emissions are 2500 t of CO_2 eq/yr in which the contribution of transport is ca 4-5%. Scenario 2, which takes into account production of RDF from plastics and 50% of paper present in MSW, the total GHGs emissions are about 6000 t CO_2 eq/yr due to the CO_2 emissions from the combustion of RDF. At this stage of modelling, we have not carried out any calculations of emissions avoided by a substitution of natural gas or coal by landfill gas and RDF. It is however evident that more precise emission factors and technical characteristics of the installations are needed.

In case of Scenario 2, the propagation of uncertainty related to the composition of the MSW has been modelled. MSW composition depends upon municipality character (DEN BOER ET AL., 2010), e.g. types of houses, prevailing mode of heating, average family income, lifestyle etc. It is therefore difficult to estimate a single probability distribution function related to amounts of individual MSW components. Moreover, it is possible that some types of packaging waste are substituted by others, e.g. glass containers may be substituted by plastic ones. Alternatively biodegradable textiles (cotton, wool etc.) can be substituted by synthetic ones, which mean that some inputs are not stochastically independent. Also information on landfill gas emissions are varying among published studies. Modelling, which ignores the above uncertainties in input data, may lead to biased conclusions. The Monte Carlo calculations are the only way to study propagation of the input uncertainties.

In Figure 2, the dependence of uncertainty related to the output (aggregate GHGs emissions) upon uncertainty of MSW composition is shown. Due to stochastic compensations between bio-waste production of the largest sources of MSW and the landfill and combustion (RDF) emissions, the output uncertainty (expressed as S.D.) is even lower than the input one. It means that for similar scenarios the standard deviation between 10 and 20 % rel. related to content of the major MSW components does lead to acceptable standard deviations related to the aggregated GHGs emissions (5-10% rel.). Statistical analysis of output values resulting from Monte-Carlo experiments (n=100) indicate normal distribution function.

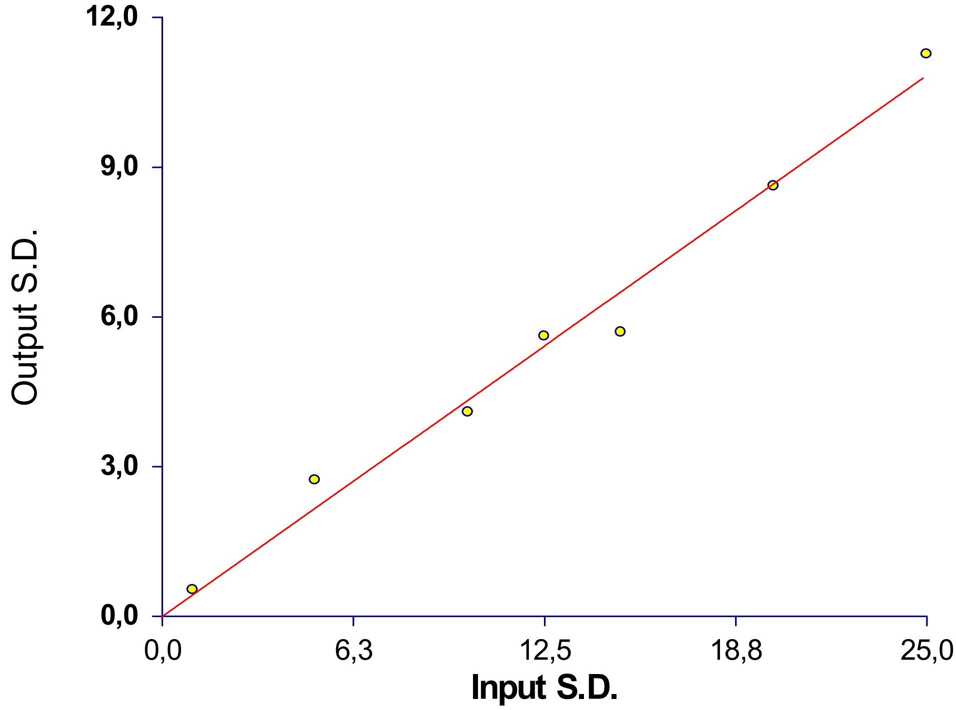

Figure 2: Linear dependence of the output standard deviation (S.D.) upon the uncertainty related to the MSW composition (slope = 0,434).

6 Conclusions

Algebraic modelling languages like LINGO allow easy building of integrated waste management models based upon mass or energy balance. The conceptual model described in this communication optimizes aggregated GHGs emissions resulting from MSW transport, utilization (mass or energy) and disposal. Optimal allocation of four basic components of MSW (bio-waste, recyclable materials, refuse derived fuel and inert waste) into set of installations (separators, bioreactors or composting facilities, material recovery units, energy sources fired by refuse derived fuel or methane and landfills) is modelled. Transport emissions of carbon dioxide are included.

The aggregated emissions depend upon inputs (quantity and composition of MSW) and adjustable parameters (emission factors, separation efficiencies, unit consumption of energy in installations etc.) which are known with substantial uncertainties. Due to the complexity of the model, application of Monte Carlo simulation seems to be a suitable method to estimate propagation of the uncertainties. Besides optimization of existing MSW management systems (regional or multiregional scale), optimal sitting of new installations (in combination with EIA) could be a practical application of the model.

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Author's address

Ing. Dipl.-Chem. Lubomir Nondek, PhD.
Integra Consulting Ltd.
Pobřežní 18/16
CZ-18600 Praha 8
Telefon + 420 728732165
E-mail: lubomir.nondek@integranet.cz

Website: www.integranet.cz