Description of the optimisation tool

Contents

i. Introduction

The purpose of the optimization tool is to develop a mathematical programming model that will describe the Municipal Solid Waste (MSW) system and then solve it. All the available technologies and paths of the MSW system are expressed in the model with proper relationships (equalities and inequalities). The model consists of the decision variables (the unkowns of the problem), the parameters (the known data), the constraints (the relationships that describe the system) and one or more objective functions (the drivers of the optimization). Once the model is created, then the optimization of the model takes place. By optimization of the model we mean looking for the optimal values for the decision variables using mathematical programming methods.

Borrowing ideas from the field of **process synthesis** in chemical engineering, the problem can be formulated as a multi-period structure, design and operational optimization problem (Iyer and Grossmann, 1998). All the available MSW options and their interdependencies can be considered in the **superstructure** of the system (topology of all the available MSW options) and the Mathematical Programming model proposes the best solution. A simultaneous, **structural, design and operational** optimization of the MSW system is achieved i.e. the outputs of the created model are which technology units will be used and which paths are followed for the MSW system (structure), what is the capacity of these units (design) and what are the flows and operating loads to and from the units in annual base (operational optimization). In the case that multiple criteria are considered we have more than one objective functions and the set of Pareto optimal solutions is obtained. Mathematical Programming has already be used for the optimization of MSW systems in various cases (see e.g. Abou Najm and El-Fadel, 2004; Louis and Shih, 2007; Jing et al. 2009).

The model will be multiperiod which means that it will have a dynamic evolving element over time following the scenario for the quantity of produced MSW. The results of the optimization will refer to each period of time and there will be inter-period constraints quantifying the relevant linking relationships. The model will be developed and solved using the widely known modeling language GAMS (General Algebraic Modeling System, Brooke et al. 1998).

ii. Multi-objective Mathematical programming

Nowadays environmental concern is growing more and more, questioning the “dictatorship” of the economic criterion as the unique criterion in various decision making contexts. As the environmental benefits cannot be easily monetized in order to be embedded in one economic objective function, the integrated MSW planning requires the use of **Multi-Objective Optimization**. During the last two decades, relevant **Multi-Objective** models have been applied for optimization in fields like energy systems, process synthesis, project selection, environmental management, water management etc (Belton and Stewart, 2002; Figueira et al. 2005). Today, the integrated planning also in MSW becomes mandatory (Abou Najm and El-Fadel, 2004). The term “**integrated**” is used to emphasize a broader view of the system, where beyond the **economic objectives** (the investor’s point of view) also the **environmental objectives** (the sustainability’s point of view) and **societal objectives** (the society’s point of view) are pursued.

As the name suggests, multi-objective optimization (or multi-criteria optimization) involves optimization in the presence of more than one (usually conflicting) objective functions (crieteria). Multi-objective optimization problems arise in a variety of real word applications and the need for efficient and reliable methods is increasing. The main difference between single and multi-objective optimization is that in the case of latter, there is usually no single optimal solution, but a set of equally good alternatives with different trade offs, also known as **Pareto-optimal** (or non-dominated or efficient) solutions. The Pareto optimal solutions are the feasible solutions that cannot be improved in one objective function without deteriorating their performance in at least one of the rest. In the absence of any other information, none of these solutions can be said to be better than the other. Usually a decision maker is needed to provide additional preference information and to identify the "most preferred" solution ("optimal" according to his/her subjective preferences). Depending on the paradigm used, such knowledge may be introduced before, during or after the optimization process. Multi-objective optimization thus has to combine two aspects: optimization and decision support.

In the context of Mathematical Programming (MP), the multi-objective optimization is performed through **Multi-Objective Mathematical Programming** (MOMP). In MOMP models more than one objective functions are present. The solution of MOMP problems is a twofold task: First, the generation of the Pareto optimal solutions and then the selection among them. The first part is a purely computational task while the second involves the decision maker that expresses his/her preferences (Steuer, 1986).

According to Hwang and Masud (1979) the methods for solving MOMP problems can be classified into three categories according to the phase in which the decision maker involves in the decision making process expressing his/her preferences: The a priori methods, the interactive methods and the generation or a posteriori methods. In a priori methods, the decision maker expresses his/her preferences before the solution process by e.g. setting goals (Goal Programming) or weights for the objective functions. The criticism about the a priori methods is that it is very difficult for the decision maker to know beforehand and to be able to accurately quantify (either by means of goals or weights) his/her preferences. Moreover, no tradeoff information is produced in order to be exploited by the decision maker. In the interactive methods, phases of dialogue with the decision maker are interchanged with phases of calculation and the process usually converges after a few iterations to the most preferred solution. The decision maker progressively drives the search with his answers towards the most preferred solution. The drawback is that he never sees the whole picture (the set of efficient solutions) or an approximation of it. Hence, the most preferred solution is "most preferred" in relation to what he/she has seen and compare so far. In a posteriori methods (or generation methods) the efficient solutions of the problem (all of them or a sufficient representation) are generated and then the decision maker involves, in order to select among them, the most preferred one. Although the generation methods are the less popular (mainly due to their computational effort and the lack of widely available software), they have some significant advantages as the solution process is divided into two discrete phases: First, the generation of the efficient solutions and subsequently the involvement of the decision maker when all the information is on the table. Therefore, he/she can explore the characteristics of the Pareto optimal solutions, discard unattractive solutions, compare tradeoffs and eventually selects his/her more preferred solution. Besides, the fact that none of the potential solutions has been left undiscovered reinforces the decision maker's confidence on the final decision. In the present study, the generation of the Pareto optimal solutions will be done using a version of the popular epsilon constraint method (Mavrotas, 2009).

iii. Model building

The mathematical model will describe the MSW system as a directed graph. There are nodes that represent the processes and arcs that represent the flows between the processes. The boundaries of the system are defined from the collection phase till the final disposal. The model will represent the superstructure of the system, i.e. all the available options with their interconnections as shown in Figure 1.

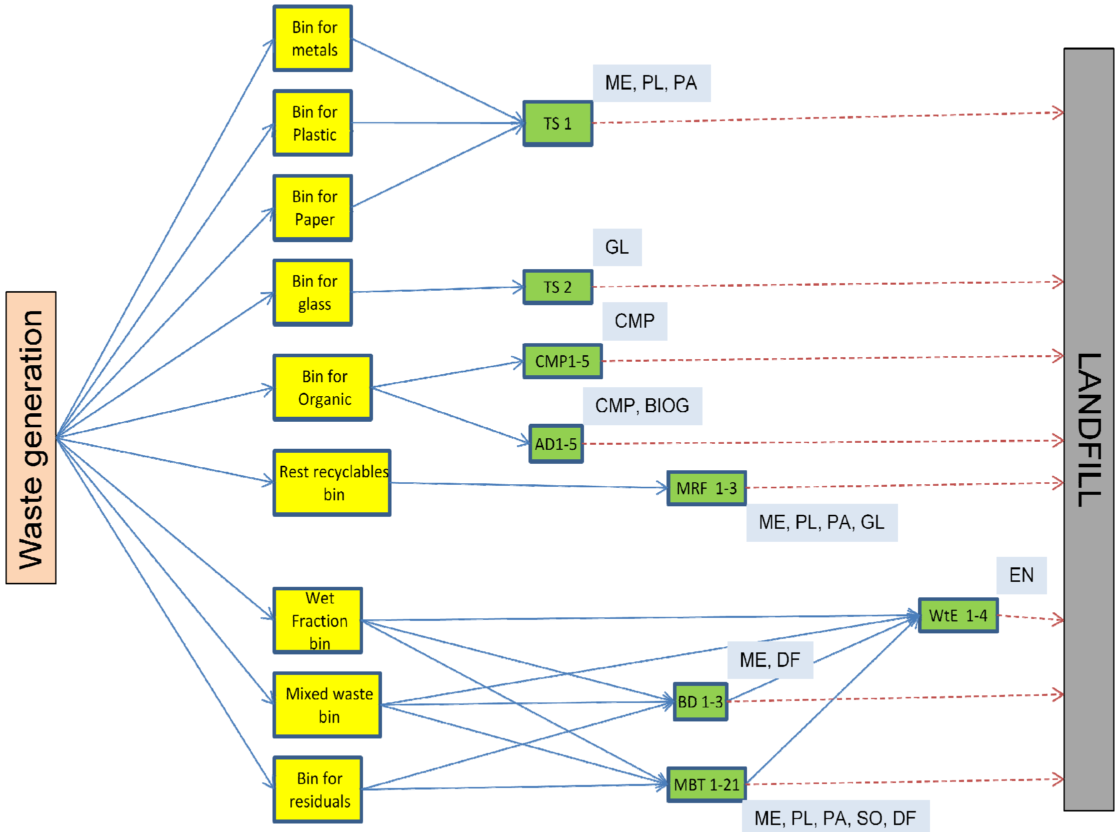

Figure 1: Graphical representation of the superstructure of the MSW system (Acronyms for Processes TS: Temporary Storage, CMP: Composting, AD: Anaerobic Digestion, MRF: Material Recycle Facility, WtE: Waste to Energy, BD: Biodrying, MBT: Mechanical and Biological Treatment. Acronyms for products ME: Metals, PL: Plastic, PA:paper, GL: Glass, CMP: Compost, BIOG: Biogas, DF: Derived Fuel, SO: Stabilized Organic, EN: Energy

In Figure 1 we can see how the bins are connected with the processes, how the processes are interconnected and which the main products of each process are. The dashed arrows are the flows to the landfill from each process. It must be noted that for each generic technology we have more than one specific type of units that can be utilized which are mutually exclusive. For example for Composting we have 5 types of units while for Mechanical and Biological treatment we have 21 types of units. The optimal type of unit for each technology will be selected by the model.

The model will be properly formulated in order to perform structural, design and operational optimization. In other words the major questions that will be answered with the optimization process are: which processes (structure), what will be there capacity (design) and what will be there annual operational load (operation). All these figures will be computed in period-wise basis. In technical terms the model is a Mixed Integer Linear Programming (MILP) model, which means it contains continuous and integer (mostly binary) variables. More than one objective functions can be incorporated in the model: the economic objective function quantified as the minimization of the discounted cost of the system and the environmental objective function quantified as the minimization of the associated CO_2 - equivalent emissions.

There are four elements for each Mathematical programming model: The decision variables, the constraints, the objective function(s) and the parameters.

Decision variables

The decision variables of the model are actually the unkowns of the problems, i.e. those variables for which we are trying to find their optimal values. In our case we have discrete (binary or integer) and continuous decision variables. The discrete variables are mostly associated with the structural characteristics (is i-th technology present in the optimized MSW system? how many units will be needed?). The continuous variables are mostly associated with the design and operational characteristics (what is the capacity of i-th unit in period t? which is the amount of waste transported from i-th unit to j-th unit?).

Constraints

The main constraints of the model are the mass balances that have to be satisfied between nodes (equality constraints) and the capacity constraints that have to be satisfied ("less than" constraints. There can be also policy constraints (e.g. "the recycling rate for glass must be at least α%" or "no more than β % of the initial waste may go to landfill"). Logical constraints are also present in order to apply conditions for mutually exclusive alternatives. Auxiliary constraints may also be present (e.g. linearization of non-linear terms).

Objective functions

Two are the main objective functions of the problem: (1) the minimization of the Net Present Cost (NPC) of the MSW system over a period of twenty years which represents the economic objective and (2) the minimization of total CO2-eq emissions of the MSW system which represents the environmental objective.

Parameters

The parameters of the model are the known data. These data are the economic and technological characteristics of the processes, the prices of the recycled materials and produced energy, the conversion factor of every ingredient in each one of the candidate technologies. The original waste is classified in more or less twenty ingredients and its composition is considered known for the model based on representative past data. The scheme of the bin configuration is also considered as given (which types of bins are used) in the model with the capability of examining different scenarios regarding the bin configuration.

iv. Modes of operation

The model can be used as an optimization tool or just as a simple calculation tool. The user can adjust the extent of optimization by controlling the degrees of freedom of the model. Instead of performing the optimization from scratch (with all the degrees of freedom), he/she can consider some technologies as given and the system will be optimized based on this information. In this case the corresponding decision variables will have fixed values in the optimization and will not be altered. If all the required technologies and their expansion planning are fixed by the user (zero degrees of freedom) then the model is used as a simple calculation tool providing the required capacities and flows between the nodes.

v. Expected results

The problem of MSW system optimization can be solved either as single objective or multi-objective. In the former case the result will be a unique optimal solution while in the latter case a representative set of the Pareto optimal solutions. With the term solution we mean the structural characteristics (which units will be constructed in each period) the design characteristics (what will be the capacity of the units, what capacity expansions will be required) and the operational characteristics (what will be the annual waste flows between the units). All these amounts are expressed with appropriate decision variables and their values will be the main output of the system, of course along with the value of the objective function(s).