CHEMICAL ENGINEERING TRANSACTIONS

VOL. 29, 2012

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at: www.aidic.it/cet

Guest Editors: Petar Sabev Varbanov, Hon Loong Lam, Jiří Jaromír Klemeš
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ISBN 978-88-95608-20-4; **ISSN** 1974-9791

DOI: 10.3303/CET1229124

Waste-to-Energy Facility Planning Supported by Stochastic Programming - Part II Model Development and Application

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This paper deals with the development and presentation of the use of computational optimization tool for the conceptual planning of facilities in the field of waste-to-energy (WTE).
Decision about individual facility parameters includes in particular the determination of suitable capacity and selection of appropriate heat recovery system according to heat released utilization strategy (i.e. either only electricity production or combined heat and power if feasible). The main goal is to ensure the economic feasibility of the project. An optimization tool that was created in the system GAMS (General Algebraic Modelling System) was developed for this purpose and is introduced in this paper.
Realization of a new plant from the initial considerations to its full operation is a long-term process with duration at minimum 5 to 7 years. The erection is then followed by operational phase exceeding 20 years. At the beginning of the project (preparation of implementation phase) when important decisions related to the technology selection are made, the future development of many parameters affecting project sustainability are not clear. The developed tool takes these aspects into account by implementing elements of stochastic programming that allow this uncertainty and randomness to be reflected in optimization problems and, hence, proposed solution.
In the article, a brief theory related to uncertainties (approach wait and see and/or here and now, definitions and use of scenarios), is given by first, followed by a description of a mathematical problem and demonstration of using tools through the case study.

1. Advanced computational approaches – basic theory

The paper follows Šomplák et al. (2012), in which the motivation for the development of a tool for design and operation planning of WTE plant was described. Necessary mathematical methods, which are used for the evaluation of strategic investments in erection of a new WTE plant, are described in this part. The real-world optimization problem to be solved also involves uncertain parameters (e.g. low heating value of waste, trend of energy prices, heating demand, lifetime of a plant, etc.). Therefore, stochastic programming seems to be a suitable tool to deal with the uncertainty in the considered problem. As the research result, the proper approach to tackle the problem has been identified as two-stage stochastic programming and the original scenario-based two-stage stochastic programming model has been built.

Please cite this article as: Šomplák R., Touš M., Ferdan T., Pavlas M. and Popela P., (2012), Waste-to-energy facility planning supported by stochastic programming - part II model development and application, Chemical Engineering Transactions, 29, 739-744

1.1 Two stage stochastic programming

This approach deals with problems which are time-discrete and in which the decisions are made in different time points. From the decision maker point of view, the decisions may be classified as follows:

1. Decisions which are made at the beginning when no information on realization of uncertain parameters are available. In other words, the decisions have to be made before values of uncertain parameters are known. Such decisions are called first-stage decisions.
2. Decisions which are made after values of uncertain parameters are known. These decisions are called second-stage decisions.

An uncertain parameter is further denoted as ξ, the first-stage decision as $\boldsymbol{x}$ and the second-stage decision as $\boldsymbol{y(\xi)}$. In the case of discrete probability distribution, a lower index is used to make a difference among the individual decisions made for individual realizations of ξ (see Figure 1).

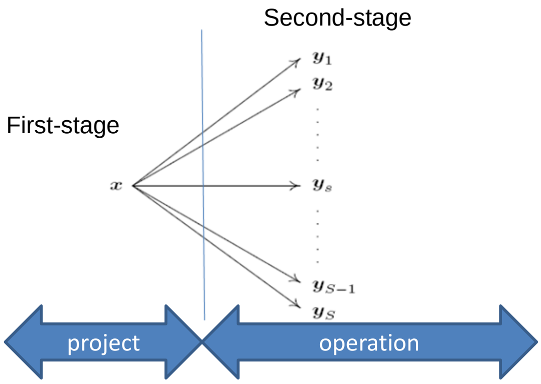

Figure 1: Decisions in two-stage stochastic programming.

IN our case study we can be more specific about the interpretation of random elements and variables. Thus, **x** is related to decisions on waste treatment capacity, steam turbine choice (backpressure or extraction condensing turbine) and **y(ξ)** is related to decisions on operation of a plant (heat-oriented operation or power-oriented operation) according to the trend of the key uncertain parameters influencing plant economics (e.g., prices of heat and power).

Next, it is necessary to decide how to model possible realizations of uncertain parameters. Instead of statistical inference and identification of parameters of some multivariate continuous probability distribution we prefer to use empirical data and related discrete probability distributions. This directly leads to so called scenario-based approach that is frequently used in industrial applications of stochastic programming, see, e.g. Birge and Louveaux (1997).

1.2 Scenario-based approach

Scenarios create a set of realizations of uncertain parameter ξ, which can be enumerated by index *s,* and denoted as ξ_s. In literature, the realizations or often called scenarios, some authors identify scenarios with indices. We will use the common sense reasoning and will unify both ideas using the concept scenarios for indices and realizations as well. Therefore, a set of indices is denoted as $S = \{s_i, i = 1, 2, \ldots, L\}$, where L is a number of different indices and so scenarios. So, realization of scenario s has the probability $p_s \geq 0$, $\forall\, s \in S$ and $\sum_{s \in S} p_s = 1$. If the set S is a set with large number of elements then the optimization problem can be difficult to solve as its number of variables and constraints exponentially grows with the increase of cardinality of the scenario set. Therefore, it is recommended to initially include only those scenarios, which are mostly relevant. Advanced computational studies may follow for the large problem instances and will be realized in the future. Following the previous study (Šomplák, 2012), we prefer that the selection of scenarios is based on experts' opinions. In fact, this approach leads to the case of the set S with small number of elements and so all developed scenarios are included in the model. We further assume that we want to minimize total expected costs involving chosen scenarios. Then, the nonlinear program can be at the general level defined as follows:

minimize $f(\boldsymbol{x}) + \sum_{s \in S} \mathrm{ps} Q(\boldsymbol{x}, \xi s)$, subject to $\boldsymbol{g}_1(\boldsymbol{x}) \le \boldsymbol{0}$, $\boldsymbol{h}_1(\boldsymbol{x}) = \boldsymbol{0}$, where $Q(\boldsymbol{x}, \boldsymbol{\xi} s) = \min_{y(\xi s)}\{q(\boldsymbol{y}(\boldsymbol{\xi} s), \boldsymbol{\xi} s)\}$ subject to $\boldsymbol{g}_2(\boldsymbol{x}, \boldsymbol{y}(\xi s), \xi s) \le \boldsymbol{0}$, $\boldsymbol{h}_2(\boldsymbol{x}, \boldsymbol{y}(\xi s), \xi s) = \boldsymbol{0}$, $\forall s \in S$.

The first stage strategic decision x about the WTE plant capacity is related to the direct investment costs included in the first stage objective function f(x). The constraints applied to the first stage decision are in the form of inequality and equality constraints as it is common in nonlinear programming and can be defined by multivariate vector functions g1 and h1. The weighted average in the objective function represents the expected future operational costs. The particular cost Q(x, ξs) for the given first stage decision x and scenario s is obtained as the optimal result of the future operational control i.e. by the optimal second stage decision that is wait-see-decision with respect to scenario s. The second stage objective function q is a cost of the operational action $\boldsymbol{y}(\boldsymbol{\xi})$ in the second stage. It can be also seen as a reduction of negative effects caused by the first-stage decision, which arise due to difference between assumed and observed realization of uncertain parameters. Functions $\boldsymbol{g}_2$ and $\boldsymbol{h}_2$ are dependent on first-stage and second-stage decisions and realizations. They specify the feasible region for the second stage variables under the restrictions given by the first stage decision and realization. The subject of the first-stage model is to optimally decide about the waste treatment capacity of the WTE plant and individual apparatus (their designed throughputs) with respect to maximum operating profit. The approach "Here and now" (Birge and Louveaux, 1997) is used to make an optimal decision. The second-stage problem deals with an optimal response to the realizations of uncertain parameters (i.e. scenarios) with respect to decisions made in first-stage problem. This approach is called "Wait and see" (Birge and Louveaux, 1997).

Both problems can be put together by the substitution of the second stage objective function into the first stage objective. The new composed objective function is minimized subject to constraints for both stages.

2. WTE plant model

The analyses described in Pavlas et al. (2011) is used to build a mathematical model of the WTE plant. The flow sheet of the considered technology with the key components is presented in Figure 2.

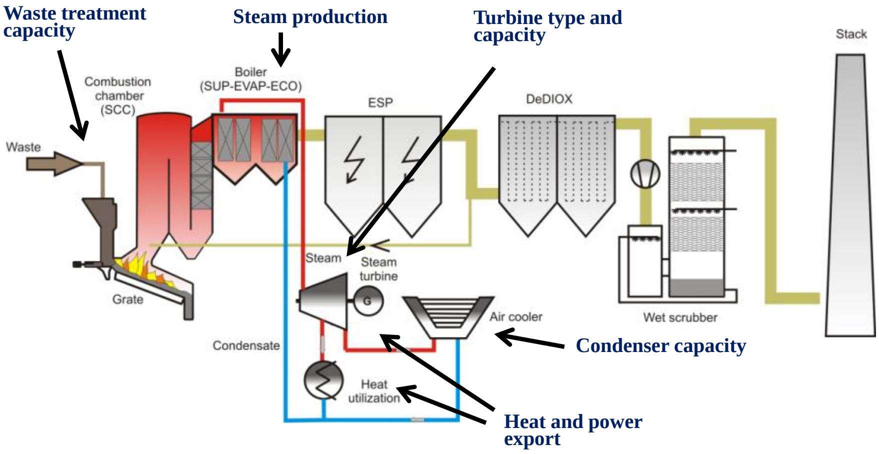

Figure 2:The flowsheet of technology

The WTE plant model considers steam production with parameters of 400 °C and 4 MPa. The further general model of an extraction condensing turbine with one extraction is considered. It is possible to replace it with a backpressure turbine model alternatively. The extraction pressure (or pressure at the output of a backpressure turbine) is 0.8 MPa (subsequent hot water heating for a district heating system).

The steam turbine represents a key part of the heat recovery system. An operating mode has a significant effect on environmental benefits of the technology (discussed in Pavlas et al. (2010)). The turbine model consists of two stages divided by steam extraction for heating purposes – the backpressure stage and condensing stage. About 10 % of steam produced is used in the condensing stage in the case of a high heat demand (technology constraints). When there is no heat demand, all the steam produced is used in the condensing stage. The turbine electrical efficiency is dependent on the operating mode since the steam flow rate through a condensing stage influences its isentropic efficiency. The complex models for turbine modelling including its part-load operation can be found in Varbanov et al. (2005). In this paper, a simple model addressing constant isentropic efficiency for a specific turbine capacity (in correlation with waste throughput) was used for simplicity. The linear dependence of isentropic efficiency on turbine (WTE plant) size was obtained consulting the turbine manufacturer. The isentropic efficiency in ranges from 75 to 80 % and from 80 to 85 % can be expected for throughputs 100 kt/a and 300 kt/a, respectively. The relation between electricity production and heat production for heat recovery system in Figure 2 was considered (Pavlas et al., 2011). A mathematical model was implemented in GAMS (General Algebraic Modelling System) and used in the following case study.

3. Case study

A new WTE facility providing its service for a region of 98 thousands inhabitants is designed. Its full operation is planned in 2020. The objective is to find the optimal values of key parameters (Figure 1):

- waste treatment capacity of WTE plant
- turbine type (backpressure, extraction condensing, condensing) and its capacity
- capacity of condenser for heat rejection after condensing stage.

To perform optimization, it was necessary to determine real input parameters and their future trends as well as to describe uncertainties and their future trends.

Only a few of the parameters are discussed in more details and only one (heat demand) is included in this study to demonstrate the approach based on stochastic programming (SP). The role of capital cost in WTE is discussed in Šomplák et al. (2012). Operational costs were determined as a result of complex balance calculation, price forecasting, and comparison with real operation experience. Details are not provided in this paper because of the restricted number of pages. The energy prices (heat and power) and the gate fee (so called *initial prices* in the following text) are estimated by using real prices in the Czech Republic in 2011. Following prices are the most important for the project feasibility:

- initial selling price of heat: 6.8 €/GJ (based on historical data in considered region, district heating available)
- initial redemption price of power: 45.6 €/MW (experts' opinion).

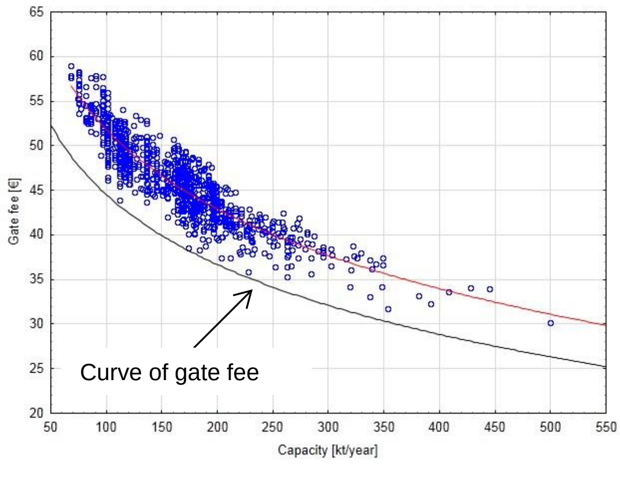

Figure 3: The gate fee curve used in the model

Future trend of energy prices (their growth) is taken into account. The gate fee is determined with respect to competitive strength of the WTE plant regarding landfills, other potential WTE plants and facilities producing refuse-derived fuel. The gate fee depends on the annual throughput. An example of its evaluation based on competition modelling in waste management using sophisticated tool is in

Figure 3. A trend of increasing of the gate fee for a lifetime period of the WTE plant is taken into account.
In addition to the heat price, a possibility of the heat supply to district heating system is important from the plant economics point of view. The initial distribution of heat demand over a year for the case study is depicted in Table 1.

Table 1: Initial heat demand over a year

Month	1	2	3	4	5	6	7	8	9	10	11	12
Demand [TJ]	322	252	250	123	16	81	79	73	43	153	248	319

The heat demand is the only uncertain parameter, which is modelled by using a larger number of scenarios. This parameter has a crucial effect on the decision about initial investments since it determines the amount of heat supplies. Moreover, it influences the choice of a turbine type (backpressure or more often extraction condensing turbine). Especially, the utilization of condensing stage depends on the heat demand. The high demand for heat means a large amount of steam to extraction and a small amount of steam to condensing stage. Three scenarios for the heat demand for lifetime period of WTE plant were chosen in the case study. The initial values of a heat demand in every single month are determined by using real operation data (Table 1). Individual scenarios are depicted in Table 2.

Table 2: Scenarios for trend of heat demand.

Scenario	1	2	3
Decrease of heat demand per year	0 %	1 %	5 %

It is assumed that all scenarios can occur with equal probability $p_1 = p_2 = p_3 = {}^1/_3$.
Different methods for economic evaluation can be implemented (Brown, 2007). Our objective was to optimize crucial parameters of key components providing maximum internal rate of return (IRR) of the project (erection and operation of the WTE plant).

Table 3: Optimization results.

IRR [%]	8.98
Payback period [years]	13
Net present value (NPV) [M€]	243
Waste treatment capacity [kt/year]	239
Extraction condensing turbine capacity [MW]	24.3
Backpressure stage capacity [MW]	10.3
Condensing stage capacity [MW]	14
Condenser capacity [MW]	37.7

IRR is very sensitive to the first-stage decisions. To have an idea, IRR sensitivity to waste treatment capacity is shown in Figure 4. IRR is above 8.5 % for capacities from 150 to 350 kt/y. It indicates considerable stability of the solution.

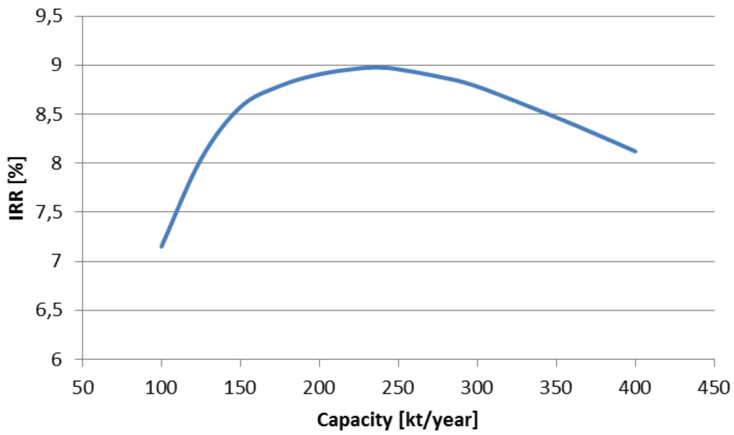

Figure 4: Sensitivity of IRR to waste treatment capacity

4. Conclusion

The presented tool enables the evaluation of optimum values of the key parameters of WTE plant with respect to maximum IRR. The technology model used in this case study represents one of available lay-out of an up-to-date plant. It has to be modified if different technology is considered (e.g. flue gas cleaning system). The evaluation of annual financial balance and information on allocation of costs and incomes are included. The presented model is able to help us to evaluate optimal plant operations with respect to uncertain input parameters (energy prices, heat demand, steam parameters, etc.). In addition, it is possible to react with optimal reinvestments (e.g. in steam turbine) when input parameters are significantly changed.

Acknowledgement

We gratefully acknowledge financial support of the OPVK 2.3 Science for practice - System for Enhancement of Research Teams in Mechanical Engineering and Border Studies, reg. no. OPVK 2.3 CZ.1.07/2.3.00/20.0020.

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