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ECONOMIC OPTIMIZATION OF SUSTAINABLE COMPLEX PROCESSES UNDER UNCERTAIN COST PARAMETERS

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ABSTRACT

One of the major difficulties of the computer aided process optimization is that the cost parameters determining the economic goal functions are not constant, but are uncertain variables themselves. Accordingly, the minimal cost or maximal profit has to be calculated from widely varying specific costs, prices, demand and supply. In the course of optimal process design, we have to choose the possibly "best" solution from the alternative solutions of various structures and parameters. The usual paradox situation is, that the technological data are better known than the economic parameters. To solve this problem in the recently developed new solution all of the candidate alternatives generated by the optimization tool, are tested with another algorithm which selects those "good enough" solutions that are insensive for the uncertain economic data. The methodology will be illustrated by the example of the economic optimization of sustainable recycling between agricultural and food industrial processes.
Keywords: simulation model, optimization, economic uncertainty, sustainable processes

INTRODUCTION

In the course of optimal process design, we have to choose the possibly "best" from the alternative solutions of various structures and parameters. Accordingly, the minimal cost or maximal profit has to be calculated from widely varying specific costs, prices, demand and supply, while the paradox situation is that the technological data are better known than the economic parameters.

In a recent paper Marquardt reviewed that in the past decades many methodologies and tools have been proceeded to support process modelling, simulation and optimization (*Marquardt*, 2008). He also noted that these tools became indispensable in today's industrial practice.

One of the major difficulties of the computer aided process optimization is that the cost parameters determining the economic goal functions are not constants, but are uncertain variables themselves. The literature of uncertainty in economical decisions is wide and diversified. Galbraigth defines the uncertainty in the most general way (*Galbraight*, 1973). Accordingly, uncertainty is the difference between the amount of information required to perform a task and the amount of the information already possessed.

There are many forms of uncertainty in the course of production, but as a general rule we can divide it into two groups. First is the environmental uncertainty of the prices, costs, demand or supply. Second is the system uncertainty that involves the uncertainty within the production process, such as production time, yield, quality of the product, failure of the system and many other changing characteristics of the processes.

In a review paper Diwekar arranged the uncertainty problems in three groups, based on the management of the randomness (*Diwekar*, 2002). These three groups are the following: ”wait and see”, ”here and now” and ”chance constrained”.

In ”wait and see” method we wait until an observation of the random element and then solve the stochastic problem as deterministic. The basic principle of “here and now” algorithm is that in the decision making we have to answer the questions immediately, therefore the random elements are substituted with an expected value. In case of the third approach we use constrains for decreasing the uncertainty of problem solving.

The optimization under uncertainties found widespread applications in the study of physical and chemical systems, in engineering design, in production planning and scheduling processes and in resource allocation on financial systems (*Sahinidis*, 2004).

There are three general methodologies to solve the optimization under uncertainty. First, there are the stochastic versions of conventional mathematical programming techniques (LP, NLP, IP, MILP, MINLP), second there is the fuzzy logic, and finally the genetic algorithm. The basic idea of the genetic algorithm is the crossover, the selection and the mutation of combinations, resulting in better and better solutions (*Holland*, 1975).

Nowadays it is a big challenge to develop the (e.g. food) industrial processes in a sustainable and environmentally sound way, which exploits also the positive externalities.

A key element of sustainability is the utilization of organic wastes. The anaerobic digestion process is the most important process for treating various organic wastes because it combines energy production with decreasing pollution. There are many papers about the detailed model based investigation of the anaerobic processes (e.g. *Batstone et al.*, 2000; *Boubaker*, 2008).

In the following, the developed new optimization under uncertainty methodology will be illustrated by an example of the economic optimization of sustainable recycling between agricultural and food industrial processes.

MATERIALS AND METHODS

Our objective is to elaborate a general algorithm which helps to manage the economic optimization of complex processes under environmental uncertainty. It has been solved by the extension of the formerly developed *generic/genetic* simulation program. The structure of the complex process has been represented with the *Graphviz*, an open source code visualization tool.

The main characteristic of the generic simulation methodology is that the translation of the problem to the executable computer program follows a simplified procedure (*Csukás*, 1998). In the conventional case we need to build a complicated mathematical construction, and then decompose it for solving in numerical way. On the contrary, the direct computer mapping starts from the building blocks of the conservational and informational processes and describe them by two prototypes of the "active" and "passive" elements. The balance elements and the signs, as well as the elementary transitions and the rules can be described by brief uniform programs, executed by the kernel algorithm. The execution consists of four (practically two) cyclically repeated consecutive steps, as follows:

1. active elements read the content of the associated passive elements;
2. brief programs, associated with active elements calculate the changes;
3. passive elements are modified according to the changes coming from the active elements;
4. brief programs, associated with passive elements calculate the new state.

The recently developed version of generic simulator is a platform independent software tool, consisting of a general kernel, communicating with expert and user interfaces.

We currently used the Graphviz program tool as a temporary graphical interface. It makes possible the access to the input/output data or to the parts of the program easier. With the use of the graphical editor of Graphviz we can build the structure of the investigated process. Moreover, the program maps the structure into an XML-like language, in dot format. This file, extended with the brief programs of the elements, can generate the user and expert programs of the generic simulator automatically.

In optimization, the generic simulator can be combined effectively with the genetic algorithm. The new multi-criteria discrete/continuous genetic algorithm (*Csukás and Balogh*, 1998) provides an effective and robust optimization tool.

In the collaboration of the generic simulator with the genetic algorithm, first the user must define the so-called possibility space of the given problem. The possibilities can be declared either directly by a full set of the possible active and passive generic elements, or indirectly, by the alternative features and variables. Next, the objective(s) have to be declared that can be formulated by an aggregated goal function or by a number of various evaluations. The genetic algorithm prepares an initial population. Next the kernel generates and simulates the variants, one after the other, followed by the evaluation of the prescribed objectives. With the knowledge of these evaluations, the genetic algorithm proposes a new population to be studied, while the new variants will be tendentiously better and better.

The optimization methodology was tried for the example of a general, complex food industrial and agricultural recycle process. The idea of the studied complex process came from the literature. One of the most important elements of these complex processes is the anaerobic digestion. It is an environmental friendly way of the treatment and utilization of the different wastes, from the municipal waste water (*Forster-Carneiro et al.*, 2007) to the various food industrial (*Boubaker*, 2008), commercial, slaughterhouse, etc. wastes. Besides the decomposition of harmful wastes it produces energy. In the course of the study an instructive example was the local food industrial biogas plant (*Csima et al.*, 2007) built in Kaposvár Sugar Factory.

RESULTS AND DISCUSSION

In this proposed solution the candidate alternatives, generated by the optimization tool, are tested with another algorithm which selects those “good enough” solutions that are insensitive for the uncertain economic data.

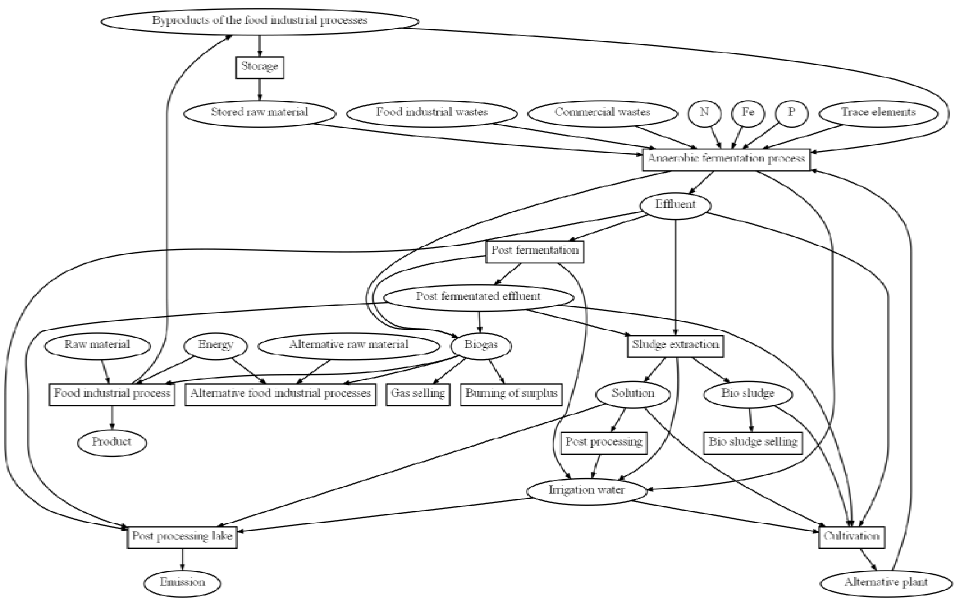
First the possible structures and parameters are analyzed, and the so-called possibility space is to be determined for the detailed computation.

On the basis of the literature and of the previous works we substantiated the superstructure of a sustainable food industrial and agricultural complex process, which contains all of the possible steps and technologies. The structure was described by the Graphviz tool (*Figure 1*).

The special digraph structure consists of two types of nodes which represent the active (ellipse) and passive (box) elements distinguished in the course of simulation. The direction of the edges determines two types of the connections. Reading channels start from passive elements and go to active ones, while modifying channels are directed reversely.

Figure 1

Graph of the investigated process superstructure



In *Figures 2 and 3* actual examples for the brief program codes associated with the nodes and edges are illustrated. The upper level global model of the complex process is based on simplified stoichiometries, which can be derived from the detailed models of the respective partprocesses (e. g. anaerobic digestion).

Figure 2

Example for passive and active node programs

```
"effluens" [
                label = "Effluens"
                fontsize = "14"
                fontname = "Times-Roman"
                fontcolor = "black"
                shape = "ellipse"
                style = "bold"
                model = "measures"
                yn = "y"
                comment =
"[M,Msorg,Msinorg,Mlorg,Mlinorg,Mw]"
                initial = "[1000,200,100,200,100,400]"
]
"iszapkinyeres" [
label = "Iszapkinyeres"
shape = "box"
style = "bold"
yn = "y"
prototype = "iszapkinyeres"
param = "[d(ktg,l,[Uzktg],nd),d(param,l,[Alfa],nd)]"
data = "[d(ktg,l,[30],nd),d(param,l,[0.2],nd)]"
input = "[i(effluens,l,[Ms,Msorg,Msinorg,Mlorg,Mlinorg,Mw],kg_t)]"
inp = "[i(effluens,l,[],kg_t)]"
output = "[o(effluens,l,[IM,IMsorg,IMsinorg,IMlorg,IMlinorg,IMw],t),
o(bioiszap,l,[Bm,Sorg,Sinorg,W1],t), o(oldat,l,[Om,Osorg,Osinorg,Lorg,Linorg,W2],t)]"
out = "[o(effluens,l,[],t),o(bioiszap,l,[],t), o(oldat,l,[],t)]"
program = "g(dt,DT), factor(F), Q is Ms*F*DT, W1 is Alfa*Mw*Q,
                W2 is (1-Alfa)*Mw*Q, Sorg is Msorg*Q, Sinorg is Msinorg*Q,
                Bm is Sorg+Sinorg+W1, Lorg is Mlorg*Q, Linorg is Mlinorg*Q,
                Om is Lorg+Linorg+W2,IM is (-1)*Q,Osorg is 0, Osinorg is 0,
                IMsorg is (-1)*Msorg*Q, IMsinorg is (-1)*Msinorg*Q, IMlorg is (-1)*Mlorg*Q,
                IMlinorg is (-1)*Mlinorg*Q,IMw is (-1)*Mw*Q,
                Tol is 0.5*Uzktg, Ig is 1.5*Uzktg, random(Tol,Ig,RUzktg),
                Profit is ((-1)*250-RUzktg)*F*DT, novel(Profit)"
]
```

Figure 3

Example for an edge program

```
"effluens" -> "iszapkinyeres" [
                fontsize = "14"
                fontname = "Times-Roman"
                fontcolor = "black"
                style = "bold"
                yn = "y"
                inpop = "read"
                inpnev = "konc"
                outop = "write"
                outnev = "effluens"
                idozit = "[t(0,120,[],0,300)]"
]
```

Decision points of the superstructure determine the possibility space which can be discrete property equivalency classes, or variable continuous design parameters. According to *Figure 1* the discrete property equivalency classes (signed with P) are the following (the numbers represent the code of the possible properties):

- *P1* (food industrial principal activity): *1* only main raw material is processed; *2* main and alternative raw materials
- *P2* (fermentation): *1* byproduct; *2* byproduct and stored byproduct; *3* byproduct and other food industrial wastes; *4* byproduct and commercial wastes; *5* not involved
- *P3* (post-fermentation): *1* involved; *2* not involved
- *P4* (sludge separation): *1* involved; *2* not involved
- *P5* (wastewater emission): *1* into digestion lakes; *2* for agricultural utilization; *3* into digestion lake and for agricultural utilization.

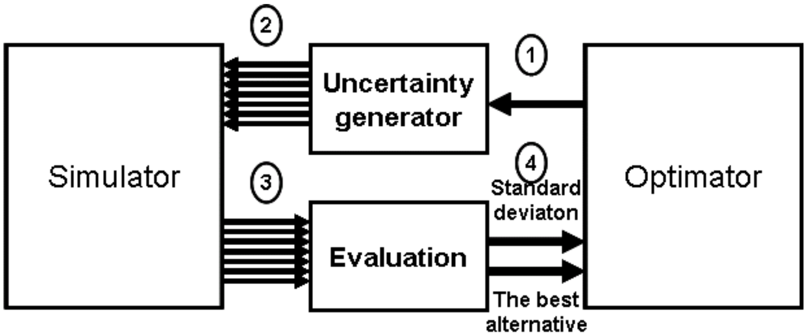
The combination of these possibilities results in 120 potential structural alternatives in the design of the complex process.

One part of variable continuous design parameters is associated with the connection points of the investigated system and its environment (e.g. the quantity of the main and alternative raw materials, the required energy, etc.). Another part of the design variables is associated with the process units.

The recently developed new solution of the uncertainty problem is shown in *Figure 4*. The optimator (genetic algorithm) generates alternatives from the possibility space in step 1. The uncertainty generator extends the alternatives with randomly or consciously selected discrete values from the wide ranges of the uncertain economic parameters in step 2. The simulation tool (generic simulator) calculates all of the alternatives, and in step 3 gives the results to the evaluator that calculates the best alternative of maximal profit, as well as the standard deviation of the simulated solutions. Finally, these evaluations in step 4 are passed to the genetic algorithm, which selects those "good enough" solutions that are insensitive for the uncertain economic data.

Figure 4

Flowsheet of the developed method



CONCLUSIONS

Based on the literature we found that the technological data are usually better known than the economic parameters. To solve this problem in the recently developed new methodology all of the candidate alternatives generated by the optimization tool are tested with another algorithm, which selects those "good enough" solutions that are insensitive for the uncertain economic data. The methodology has been tried for the example of the economic analysis of sustainable recycling between agricultural and food industrial processes.

According to the preliminary studies the new method can be successfully applied to handle the uncertain economic parameters in the course of the optimization of a typical complex sustainable process. The detailed case study will be described in the next paper.

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