



## **Multiobjective multiproduct batch plant design under uncertainty: Application to protein production**

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# Multiobjective multiproduct batch plant design under uncertainty: Application to protein production

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## Abstract

The design of batch plants necessary involves how equipment may be utilized, which means that plant scheduling and production must form an integral part of the design problem. The market demand for such products is usually changeable, and at the stage of conceptual design of a batch plant, it is almost impossible to obtain the precise information on the future product demand over the lifetime of the plant. This paper addresses the problem of the optimal design of batch plants with imprecise demands and proposes an alternative treatment of the imprecision by using concepts of fuzzy logic. For this purpose, we extended a Multi-Objective Genetic Algorithm (MOGA) developed in previous works, taking into account simultaneously three criteria, i.e. minimization of the investment cost, the operation cost and the total production time. The case of study is a multiproduct batch plant for the production of proteins taken from the literature. The methodology provides a set of scenarios that are helpful to the decision's maker and constitutes a very promising framework for taken imprecision into account in new product development stage.

**Keywords:** Multi-objective optimization, genetic algorithm, fuzzy arithmetic.

## 1. Introduction

In recent years, there has been an increased interest in the design of batch processes due to the growth of specialty chemical, pharmaceutical, and related industries, because they are a preferred operating method for manufacturing small volumes of high-value products. The market demand for such products is usually changeable, and at the stage of conceptual design of a batch plant, it is almost impossible to obtain the precise information on the future product demand over the lifetime of the plant. However, decisions must be made on the plant capacity. This capacity should be able to balance the product demand satisfaction and extra plant capacity in order to reduce the loss on the excessive investment cost or that on market share due to the varying demands on products. Consequently, the mission of the designer, assisted by traditional tools, may prove to be hazardous and makes essential the resort to a more robust approach.

The design of multiproduct batch plants has been an active area of research over the past decade. Most of the work has been yet limited to deterministic approaches, wherein the problem parameters are assumed to be known with certainty. However, in reality

there can be uncertainty in a number of factors such as processing times, costs, demands, and not all the requirements placed by the technology of the process and the properties of the substances are defined. To cope with this, there has been increased interest in the development of different types of probabilistic models that explicitly take into account the various uncertainties (Sahinidis, 2003). For instance, Wellons and Reklaitis proposed an MINLP model for the design of batch plants under uncertainty with staged capacity expansions. Based on the structure of multiproduct batch plants, Straub and Grossmann (1992) developed an efficient procedure to evaluate the expected stochastic flexibility, embedded within an optimization framework for selecting the design (size and number of parallel equipment). Two-stage stochastic programming approaches have also been applied for design under uncertainty (Ierapetritou and Pistikopoulos (1996); Harding and Floudas (1997); Petkov and Maranas (1998); Cao and Yuan (2002).

The key point in the optimal design of batch plants under imprecision concerns modeling of demand variations. The most common approaches treated in the dedicated literature represent the demand uncertainty with a probabilistic frame by means of Gaussian distributions. Yet, this assumption does not seem to be a reliable representation of the reality, since in practice the parameters are interdependent, leading to very hard computations of conditional probabilities, and do not follow symmetric distribution rules. In this work, fuzzy concepts and arithmetic constitute an alternative to describe the imprecise nature on product demands.

For this purpose, we extended a multi-objective genetic algorithm, developed in previous works (Dietz et al. 2005). For instance, the optimal design of a multiproduct batch chemical plant is not only to minimize the investment, but also to minimize the operation cost and to minimize the total production time, simultaneously. The paper is organized as follows. Section 2 is devoted to process description and problem formulation. Section 3 presents a brief overview of fuzzy set theory involved in the fuzzy framework within a multi-objective genetic algorithm. The presentation is then illustrated by some typical results in Section 4.

## **2. Process description and problem formulation**

In previous works (Dietz et al., 2005, 2006), batch plant design was carried out minimizing the investment cost and the production system was represented using discrete event simulation techniques in order to take into account different production policies. Two strategies for campaign policies were tested, either monoproduct or multiproduct. In this work, only the monoproduct campaign policy was considered, so that the computation of cycle time can be easily implemented using the classical formulation proposed in (Montagna et al., 2000), involving size and time equations as well as constraints. The model uses the formulation presented in (Modi and Karimi, 1989), then modified in (Xu et al., 1993), for multiproduct batch plant design formulation. It considers not only treatment in batch stages, which usually appears in all kinds of formulation, but also represents semi-continuous units that are part of the whole process (pumps, heat exchangers...). Let us recall that a semi-continuous unit is defined as a continuous unit working by alternating low-activity and normal activity periods. Besides, this formulation takes into account short-term or mid-term intermediate storage tanks. They are used to divide the whole process into subprocesses, in order to store materials corresponding to the difference of each subprocess productivity. This representation mode confers to the plant a major flexibility for numerical resolution, by preventing the whole process production from being

paralysed by one bottleneck stage. Therefore, a batch plant is finally represented by series of batch stages (B), semi-continuous stages (SC) and storage tanks (T).

The model considers the synthesis of  $I$  products treated in  $J$  batch stages and  $K$  semi-continuous stages. Each batch stage consists of  $m_j$  out-of-phase parallel items of same size  $V_j$ . Each semi-continuous stage consists of  $n_k$  out-of-phase parallel items of same processing rate  $R_k$ . The item size (continuous variables) and equipment number per stage (discrete variables) are bounded. The  $S$ - $I$  storage tanks, of size  $V_s^*$ , divide the whole process into  $S$  sub-processes.

For instance, the optimal design of a multiproduct batch chemical plant is not only to minimize the investment, but also to minimize the operation cost and to minimize the total production time, simultaneously. Then, an optimal design problem becomes a MOOP as following:

$$\text{Min (Cost)} = \sum_{j=1}^J (m_j a_j V_j^{\alpha_j}) + \sum_{k=1}^K (n_k b_k R_k^{\beta_k}) + \sum_{s=1}^S (c_s V_s^{\gamma_s}) \quad (1)$$

$$\text{Min (D}_p) = \sum_{i=1}^N \sum_{j=1}^M C_{E_j} \frac{Q_i}{B_{is}} + C_{O_i} Q_i \quad (2)$$

$$\text{Min (H)} = \sum_{i=1}^I \frac{Q_i}{B_{is}} T_{is} \quad (3)$$

The problem statement involves four forms of different constraints as reported in literature: (i) Dimension constraints: every units has to restrict to its allowable range. (ii) Time constraint: the summation of available production time for all products is inferior to the total production time. (iii) Limiting cycle time for product  $i$ . (iv) Volume constraints: the volume  $V_j$  has to be able to process all the products  $i$ .

### 3. Overview of fuzzy multiobjective genetic algorithm approach

#### 3.1. Representation of fuzzy demands and time horizon due-date

In the context of engineering design, an imprecise variable is a variable that may potentially assume any value within a possible range because the designer does not know *a priori* the final value that will emerge from the design process. The fuzzy set theory was introduced by Zadeh to deal with problems in which a source of vagueness is involved. The proposed approach involves arithmetic operations on fuzzy numbers and quantifies the imprecision of the demand by means of fuzzy sets (trapezoidal). In this case, the flat line over the interval  $(q_2, q_3)$  represents the precise demands with an interval of confidence at level  $\alpha=1$ , while the intervals  $(q_1, q_2)$  and  $(q_3, q_4)$  represent the “more or less possible values” of the demand. The result of the *total production time*  $\tilde{H}_i$  and the operation cost are treated and analyzed through fuzzy numbers. The time horizon  $\tilde{H}$  represented by a fuzzy expression (rectangle) and the production time  $\tilde{H}_i$  (trapezoidal) are fuzzy quantities, three different cases for determination of the criterion may occur, as shown in figure 1. The temporal criterion selected is called “common surface”, representing the intersection between the sum of the production time (trapezoid) and the horizon of time to respect (rectangle). The calculation of the criterion depends on each case: for instance, case1 illustrate the solutions which arrive just in time.

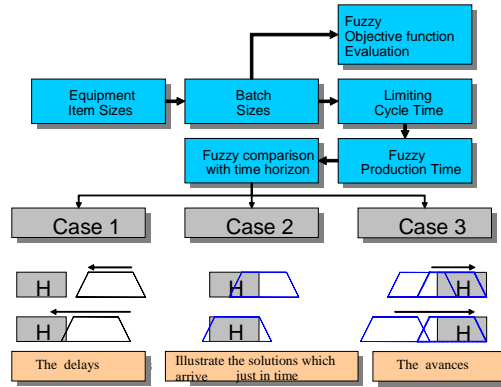


Figure 1 – Fuzzy evaluation procedure in the GA

### 3.2. Overview of multi-objective genetic algorithm approach

The multi-objective genetic algorithm presented elsewhere (Dietz et al., 2005) was then extended to take into account the fuzzy nature of both demand and horizon time. Let us mention that the same encoding procedure was adopted since no fuzzy parameter is involved at that stage. The originality of this proposed research is that fuzziness is maintained throughout the computation procedure and no defuzzification is operated so that fuzzy results are proposed to the decision's maker. The tunable parameters of the GA will also not be discussed here. More detail can be found in (Dietz et al., 2006). They involve addition, subtraction, taking the maximum of two fuzzy numbers (mainly at the selection stage and at the Pareto sort procedure), through the extension principle of (Zadeh, 1975). Although there is a large body of literature that deals with the comparison of fuzzy numbers, the approach proposed by (Liou and Wang, 1992) was finally adopted here.

### 3.3. Treatment of an illustrative example

The case of study is a multiproduct batch plant for the production of proteins taken from the literature (Montagna et al., 2000), (Pinto et al., 2001). The batch plant involves eight stages for producing three recombinant proteins, on one hand two therapeutic proteins, Human insulin (I) and Vaccine for Hepatitis B (V) and, on the other hand, a food grade protein, Chymosin (C). This example is used as a benchmark since short-cut models describing the unit operations involved in the process are available.

The GA parameters are the following ones: Population size 200 individuals, number of generations 400 iterations, crossover probability 40%, mutation probability 30% and the stop criterion considered in this study concerns a maximum number of generations to reach. For the considered example, table 1 shows the values for processing times, size factor for the units, cost data, and the production requirement for each product quantifying the imprecision of the demand by means of fuzzy numbers representing the "more or less possible values".

## 4. Typical results

The method proposes a sufficiently large range of compromise solutions making it possible to the decision's maker to tackle the problem of the final choice, with relevant

information for his final choice. The result obtained of the multi-objective optimization problem involves 200 non-dominated solutions: among them, 4 represent the case 2, where the production time  $H_i$  (trapezoidal) is within of time horizon  $H$  (rectangle), 2 represent the first case (the delay) and 194 represent the case 3(the advance). This study leads to three different scenarios as a fuzzy decision-making approach to preliminary design. Table 2 shows the solution that minimizes the investment cost for case 2. Tables 3 and 4 present the results that minimize the total production time and minimize the investment cost (cases 1 and 3), respectively.

	Processing time $\tau_{ij}$ (h)						Size factors (l/kg)						
	B1	B2	B3	B4	B5	B6	B1	B2	B3	B4	B5	B6	
Human Insulin (I)	1.15	3.98	9.86	5.28	1.2	3.57	8.28	6.92	9.7	2.95	6.57	10.6	
Chymosin (C)	5.95	7.52	7.01	7	1.08	5.78	5.58	8.03	8.09	3.27	6.17	6.57	
Vaccine for Hepatitis B (V)	3.96	5.07	6.01	5.13	0.66	4.37	2.34	9.19	10.3	5.7	5.98	3.14	
$\gamma_i$	0.4	0.29	0.33	0.3	0.2	0.35							
							I=(428260, 432630, 441370, 445740) C=(317520, 320760, 327240, 330480) V=(252840, 255420, 260580, 263160) $\tilde{H}$ =(5950, 5950,6240,6240) Rectangle						
Unit price for product $i$ (\$/Kg)		Coefficients $c_{ij}$											
$C_P$	$C_O$	B1	B2	B3	B4	B5	B6	Cost of Fermenter=\$250V <sup>0.6</sup>					
I	0.70	0.08	0.2	0.36	0.24	0.4	0.5	0.4	Cost of Micro Filter=\$250V <sup>0.6</sup>				
C	0.74	0.1	0.15	0.5	0.35	0.7	0.42	0.38	Cost of Homogenizer=\$250V <sup>0.6</sup>				
V	0.80	0.07	0.34	0.64	0.5	0.85	0.3	0.22	Cost of Ultra filter=\$250V <sup>0.6</sup>				
							Cost of Extractor=\$250V <sup>0.6</sup>						
							Cost of Chromatographic=\$250V <sup>0.6</sup>						
Minimum size =250 l Maximum size = 10 000 l							Operating cost factors						
							B1	B2	B3	B4	B5	B6	
							$C_E$	20	30	15	35	37	18

Table 1 – Data used in example

Product	$B_i$ kg	$T_{ij}$ h	Optimal objective function value				Storage Tanks
I	639.6	3.9	Cost = 595,266.56 [\$]				$V_s = 1737.22$ [l]
C	808.6	5.6	$\tilde{D}_p = [302914.3 \ 306005.3 \ 312187.2 \ 315278.2]$ [\$]				
V	576.4	4.8	$\sum \tilde{H}_i = [5998.05 \ 6059.25 \ 6181.66 \ 6242.8]$ [h]				

Table 2 – Fuzzy optimal design of batch plant for case 1 (delay)

Product	$B_i$ kg	$T_{ij}$ h	Optimal objective function value				Storage Tanks
I	636.4	3.9	Cost = 601269.4 [\$]				$V_s = 1736.2$ [l]
C	831.8	5.6	$\tilde{D}_p = [299022.5 \ 302073.81 \ 308176.3 \ 311227.5]$ [\$]				
V	621.4	4.8	$\sum \tilde{H}_i = [5962 \ 6022.8 \ 6144.5 \ 6205.3]$ [h]				

Table 3 – Fuzzy optimal design of batch plant for case 2

Product	$B_i$ kg	$T_{ij}$ h	Optimal objective function value				Storage Tanks
I	642.9	3.9	Cost = 598996.9 [\$]				$V_s = 1730.6$ [l]
C	808.2	5.6	$\tilde{D}_p = [300165.7 \ 303228.6 \ 309354.4 \ 312417.3]$ [\$]				
V	602.1	4.8	$\sum \tilde{H}_i = [5937.3 \ 5998.3 \ 6119.4 \ 6180.08]$ [h]				

Table 4 – Fuzzy optimal design of batch plant for case 3 (advance)

## 5. Conclusions

In this paper, we have proposed a fuzzy approach to the treatment of imprecise demands in the batch design problem. In real application, designers not only require to minimize

investment, but also to minimize the operation cost and horizon time, simultaneously. An example was used to show the significance of the proposed approach. The results show that a set of compromise solutions is generated to the decision's maker, with an acceptable degree of imprecision affecting the defined criteria, which seems more realistic than a classical crisp approach. This approach will reduce the risk of making design decisions incorrectly. The results obtained on the treated example have shown that three different scenarios were obtained as a fuzzy decision-making approach. Finally, this framework provides an interesting decision-making approach to design multiproduct batch plants under conflicting goals.

## References

- D.M. Cao, X.G. Yuan, 2002, Optimal design of batch plants with uncertain demands considering switch over of operating modes of parallel units. *Industrial Engineering and Chemistry Research*, 41, 4616.
- A. Dietz, C. Azzaro-Pantel, L. Pibouleau, and S. Domenech, 2005, A Framework for Multiproduct Batch Plant Design with Environmental Consideration: Application To Protein Production, *Industrial Engineering and Chemistry Research*, 44, pp. 2191-2206
- A. Dietz, A. Aguilar-Lasserre, C. Azzaro-Pantel, L. Pibouleau, S. Domenech, 2006, Multiobjective multiproduct batch plant design under uncertainty, *Computer Aided Chemical Engineering*, Volume 21, Part 2, 2006, pp. 2249-2254
- S.T. Harding, CA. Floudas, 1997, Global optimization in multiproduct and multipurposebatch design under uncertainty. *Industrial Engineering and Chemistry Research*, 36, 1644.
- T.S. Liou, M.J. Wang, 1992, Ranking fuzzy numbers with integral value, *Fuzzy Sets System*, vol. 50, 247.
- A. K. Modi, I.A. Karimi, 1989, Design of multiproduct batch processes with finite intermediate storage, *Computer and Chemical Engineering*, 13, pp 127-138
- J.M. Montagna A.R. Vecchiatti, O.A. Iribarren, J.M. Pinto J.A. Asenjo, 2000, Optimal design of protein production plants with time and size factor process models. *Biotechnol. Prog.* 16, 228-237
- M.G. Ierapetritou, E.N. Pistikopolous, 1996, Batch plant design and operations under demand uncertainty. *Industrial Engineering and Chemistry Research*, 35, 772.
- S.V. Petkov, C.D. Maranas, 1998, Design of single-product campaign batch plants under demand uncertainty. *AIChE Journal*, 44, 896.
- J.M. Pinto, J.M. Montagna, A.R. Vecchiatti, O. A. Iribarren, J. A. Asenjo, 2001, Process performance models in the optimisation of multiproduct protein production plants. *Biotechnology and bioengineering*, 74 (6), 451- 465
- N.V. Sahinidis, 2003, Optimization under uncertainty: state-of-the-art and opportunities. In *Proceedings of the Conference on Foundations of Computer Aided Process Operations FOCAPO 2003*, Coral Springs, USA, 153.
- D.A. Straub, I.E., Grossmann, 1992, Evaluation and optimization of stochastic flexibility in multiproduct batch plants. *Computers and Chemical Engineering*, 16, 69.
- H.S. Wellons, G.V. Reklaitis, 1989, The design of multiproduct batch plants under uncertainty with staged expansion. *Computers and Chemical Engineering*, 13, 115.
- X. Xu., G. Zheng S. Cheng S., 1993, Optimal design of multiproduct batch chemical process – Mixed simulated annealing. *Journal of Chemical Engineering*, 44, pp. 442-459
- L.A. Zadeh, 1975, The concept of a linguistic variable and its application to approximate reasoning, *Inform. Sci.*, 8, 199.