Enhanced Genetic Algorithm-Based Fuzzy Multiobjective Strategy to Multiproduct Batch Plant Design

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Abstract. The design of such plants necessary involves how equipment may be utilized, which means that plant scheduling and production must form an integral part of the design problem. This work proposes an alternative treatment of the imprecision (demands) by using fuzzy concepts. In this study, we introduce a new approach to the design problem based on a multi-objective genetic algorithm, taking into account simultaneously maximization of the net present value $\widetilde{NPV}$ and two other performance criteria, i.e. the production delay/advance and a flexibility criterion. 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. Besides, a hybrid selection method Pareto rank-tournament was proposed and showed a better performance than the classical Goldberg's wheel, systematically leading to a higher number of non-dominated solutions.

Keywords: Multiobjective Optimization, Genetic Algorithm, Fuzzy Arithmetic, Batch Plant Design.

1 Introduction

In recent years, there has been an increased interest in the design of batch plant due to the growth of specialty chemical, biochemical, pharmaceutical and food industries. The most common form of batch plant design formulation considered in the literature is a deterministic one, in which fixed production requirements of each product must be fulfilled. However, it is often the case that no precise product demand predictions are available at the design stage (Shah and Pantelides, 1992).

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. Nevertheless, decisions must be taken on the plant capacity. This capacity should be able to balance

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the product demand satisfaction and extra plant capacity in order to reduce the loss on the excessive investment cost or than on market share due to the varying product demands (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 multiobjective genetic algorithm, developed in previous works (Aguilar et al. 2005), taking into account simultaneously the maximization of the net present value $N\tilde{P}V$ and two other performance criteria, i.e. the production delay/advance and a flexibility criterion. 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 multiobjective genetic algorithm. The presentation is then illustrated by some typical results in Section 4.

2 Process Description and Problem Formulation

2.1 Problem Statement

In conventional optimal design of a multiproduct batch chemical plant, a designer specifies the production requirements for each product and total production time for all products. The number, required volume and size of parallel equipment units in each stage are to be determined in order to minimize the investment cost (Huang and Wang 2002).

The designers must not only satisfy technico-economic criteria, but also respect some due dates. In this framework, this study introduces a new design approach to maximize the net present value $N\tilde{P}V$ and two other performance criteria, i.e. the production delay/advance and a flexibility criterion. Such an optimal design problem becomes a multi-objective optimization problem (MOOP).

In order to specify the production requirements for each product and total production time for all products, it is almost impossible to obtain some precise information. Indeed, the ability of batch plants to deal with irregular product demand patterns reflecting market uncertainties or seasonal variations is one of the main reasons for the recently renewed interest in batch operations. In this paper, we consider an alternative treatment of the imprecision of the demand by using fuzzy concepts. A genetic algorithm was implemented for solving this problem, since it has demonstrated to be efficient in multi-objective optimization problems.

2.2 Assumptions

The model formulation for batch plant design problems adopted in this paper is based on Modi's approach (Modi and Karimi 1989). It considers not only treatment in batch stages, which usually appears in all types of formulation, but also represents semi-continuous units that are part of the whole process (pumps, heat exchangers,...). Besides, this formulation takes into account mid-term intermediate storage tanks. So, a batch plant is finally represented by series of batch stages (B), semi-continuous stages (SC) and storage tanks (ST). The model is based on the following assumptions:

1. The devices used in a same production line cannot be used twice by one same batch.
2. The production is achieved through a series of single product campaigns.
3. The units of the same batch or semi-continuous stage have the same type and size.
4. All intermediate tank sizes are finite.
5. If a storage tank exists between two stages, the operation mode is "Finite Intermediate Storage". If not, the "Zero-Wait" policy is adopted.
6. There is no limitation for utility.
7. The cleaning time of the batch items is included into the processing time.
8. The item sizes are continuous bounded variables.

2.3 Model Formulation

The model considers the synthesis of *I* products treated in *J* batch stages and *K* semi-continuous stages. Each batch stage consists of *mj* out-of-phase parallel items with same size *Vj*. Each semi-continuous stage consists of *nk* out-of-phase parallel items with same processing rate *Rk* (i.e. treatment capacity, measured in volume unit per time unit). The item sizes (continuous variables) and equipment numbers per stage (discrete variables) are bounded. The *S-1* storage tanks, with size *Vs**, divide the whole process into *S* sub-processes.

a) Economic criterion evaluation: The net present value method ($N\tilde{P}V$) of evaluating a major project allows to consider the time value of money (1). Essentially, it helps find the present value in "today's value money" of the future net cash flow of a project. Then, this amount can be compared with the amount of money needed to implement the project. When using this formula, the values of the number of periods (n), *d*iscount rate (r) and tax rate (a) take respectively the following classical values 5, 10% and 0 (computation before tax). In order to calculate investment cost *(Cost)* (2), the working capital *(f)*, revenue ($\tilde{V}_p$), operation cost ($\tilde{D}_p$) and depreciation (A_P) are introduced.

$$Max\left(N\tilde{P}V\right) = -Cost - f + \sum_{p=1}^{n} \frac{(\tilde{V}_p - \tilde{D}_p - A_p)(1-a) + A_p}{(1+r)^n} \tag{1}$$

$$Cost = \sum_{j=1}^{J} (m_j a_j V_j^{\alpha_j}) + \sum_{k=1}^{K} (n_k b_k R_k^{\beta_k}) + \sum_{s=1}^{S} (c_s V_s^{\gamma_s}) \tag{2}$$

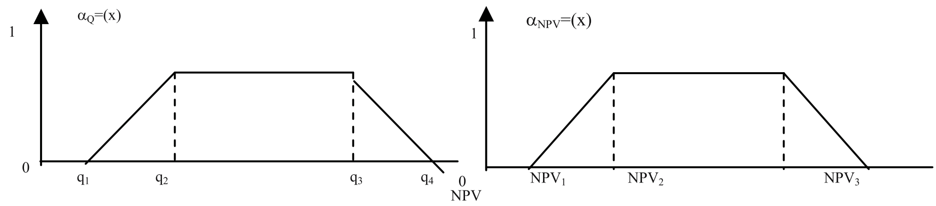

Fig. 1. Two trapezoidal fuzzy numbers, $\tilde{Q} = (q_1,q_2,q_3,q_4)$, $N\tilde{P}V$ =(NPV_1,NPV_2,NPV_3,NPV_4)

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 α=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 *net present value* ($N\tilde{P}V$) is treated and analyzed through fuzzy numbers. The demand and the net present value are fuzzy quantities as shown in figure 1.

b) Computation of the criterion penalizing the delays and advances of the production time necessary for the synthesis of all the products: for this purpose, we must compare the time horizon $\tilde{H}$ represented by a fuzzy expression (rectangle) and the production time $\tilde{H}_i$ (trapezoidal). For the comparison of fuzzy numbers, Liou and Wang's method (Liou and Wang 1992) was adopted.

The production time necessary to satisfy each product demand must be less than a given time horizon, but due to the nature of the fuzzy numbers, eight different cases for determination of the second criterion may occur. The different cases are reported in figure 2.

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 example, case1 illustrate the solutions which arrive just in time.

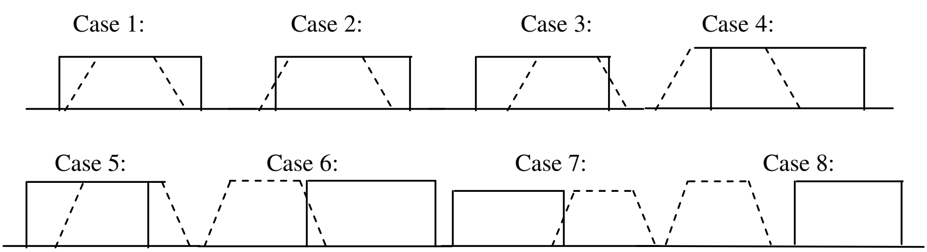

Fig. 2. Eight cases for the minimization of a criterion that penalizes the delays and advances of the time horizon necessary for the synthesis of all the products

The criterion relative to the advances (2, 4, 6 and 8) or to the delays (3, 5 and 7) is calculated by the formulas 3 and 4 respectively. The corresponding mathematical expressions of the objective functions are proposed as follows:

$$Max\ (Criterion\ of\ advance) = Common\ surface\ \ x\ \ \ \omega \tag{3}$$

$$Max\ (Criterion\ of\ delay) = Common\ surface\ \ x\ \ \ 1/\ \omega \tag{4}$$

The penalization term is equal to an arbitrary value of ω for an advance and $1/\omega$ for a delay in order to penalize more delays than advances. A sensitivity analysis leads to adopt a value of 3 for ω.

c) Flexibility index: Finally, an additional criterion was computed in case of an advance (respectively a delay), representing the additional production (the demand not produced) that the batch plant is able to produce. Without going further in the detailed presentation of the computation procedure, it can be simply said that a flexibility index is computed by dividing the potential capacity of the plant by its actual value.

The problem statement involves four forms of different constraints as reported in literature (Modi and Karimi 1989): Dimension constraints, time constraint, constraint on productivities and the size of intermediate storage tanks.

3 A Fuzzy Decision-Making Approach for Multiproduct Batch Plant Design

3.1 Overview of Multiobjetive Genetic Algorithm Approach

The GA implemented in this study uses quite common genetic operators. The proposed GA procedure implies the following steps:

1) *Encoding of solution.* The encoding of the solutions was carried out dividing the chromosome, i.e. a complete set of coded variables, into two parts. The first one deals with the items volumes, which are continuous in the initial formulation. Nevertheless, they were discretized here with a 50 unit range, while their upper and lower bounds were preserved. The second part of the chromosome handles the number of equipment items per stage: the value of these discrete variables is coded directly in the chromosome.

2) *Initial population creation.* The procedure of creating the initial population corresponds to random sampling of each decision variable within its specific range of variation. This strategy guarantees a population various enough to explore large zones of the search space.

3) *Fitness Evaluation.* The optimization criterion considered for fitness evaluation involves the *net present value* (NPV) and two other performance criteria, i.e. the production delay/advance and a flexibility criterion. Traditionally, a GA uses a fitness function, which must be maximized. The fitness for these criteria is equal to their directly calculated values.

4) *Selection Procedure.* The multi-objective aspects are taken into account in the selection procedure. A hybrid selection method Pareto rank-tournament was proposed and showed a better performance than the classical Goldberg's wheel, systematically leading to a higher number of non-dominated solutions.

The method of tournament preferentially selects the non-dominated individuals of case 1, thus successively and in a consecutive way the procedure selects then if need be cases 2, 3, 4, 5, 6 and 7 (preference for the solutions with greatest common surfaces between the sum of the horizons of time “trapezoid” and the horizon of time to respect “rectangle”) until arriving at case 8 (without common surface).

The procedure of selection of the hybrid selection method Pareto rank-tournament into account a Pareto set following the criteria of Pareto dominance are then implemented on the population of individuals and makes it possible to extract the set of the non-dominated Pareto’s optimal solutions.

5) ***Crossover.*** Two selected parents are submitted to the crossover operator to produce two children. The crossover is carried out with an assigned probability, which is generally rather high. If a randomly generated number is superior to the probability, the crossover is performed. Otherwise, the children are copies of the parents.

6) ***Mutation.*** The genetic mutation introduces diversity in the population by an occasional random replacement of the individuals. The mutation is performed on the basis of an assigned probability. A random number is used to determine if a new individual will be produced to substitute the one generated by crossover. The mutation procedure consists of replacing one of the decision variable values of an individual, while keeping the remaining variables unchanged. The replaced variable is randomly chosen, and its new value is calculated by randomly sampling within its specific range.

7) ***Registration of all non-dominated individuals in Pareto set.*** Pareto’s sort procedure is carried out at the end of the algorithm over all the evaluated solutions; at the end of the procedure, the whole set of the non dominated Pareto’s optimal solutions, are obtained.

3.2 Treatment of an Illustrative Example

We consider an example to illustrate the approach fuzzy-AG based on arithmetic operations on fuzzy numbers and quantifying the imprecision of the demand. The example was initially presented by Ponsich and al. (2004): the plant, divided into two sub-processes, consists of six batch stages to manufacture three products.

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”.

For the construction of the trapezoid which represents the request for each product, the original values of the demand were used as a reference. To determine the support and the core, one calculated a percentage of opening taking as reference the demand of the original data is computed.

Table 1. Data used in example

		Processing time $\tau_{i,j}$ (h)						***Size factors (1/kg)***					
		B1	*B2*	*B3*	*B4*	*B5*	*B6*	*B1*	*B2*	*B3*	*B4*	*B5*	*B6*
Minimum size =250 l	**A**	1.15	3.98	9.86	5.28	1.2	3.57	8.28	6.92	9.7	2.95	6.57	10.6
Maximum size = 10 000 l	**B**	5.95	7.52	7.01	7	1.08	5.78	5.58	8.03	8.09	3.27	6.17	6.57
	C	3.96	5.07	6.01	5.13	0.66	4.37	2.34	9.19	10.3	5.7	5.98	3.14
	γ_i	0.4	0.29	0.33	0.3	0.2	0.35						

Unit price for product i ($/Kg)			***Coefficients $c_{i,j}$***						Q_1=(419520. 428260, 441370, 445740) Q_2=(311040, 319140, 330480, 336960) Q_3=(247680, 258000, 263160,268320) H = (5760, 5760, 6240, 6240)
	C_P	*C_O*	*B1*	*B2*	*B3*	*B4*	*B5*	*B6*	Cost of mixer=$250V^{0.6}$
A	0.70	0.08	0.2	0.36	0.24	0.4	0.5	0.4	Cost of reactor=$250V^{0.6}$
B	0.74	0.1	0.15	0.5	0.35	0.7	0.42	0.38	Cost of extractor=$250V^{0.6}$
C	0.80	0.07	0.34	0.64	0.5	0.85	0.3	0.22	Cost of centrifuge=$250V^{0.6}$
									(Volume V in liter)

	Operating cost factors					
	B1	*B2*	*B3*	*B4*	*B5*	*B6*
C_E	20	30	15	35	37	18

4 Typical Results

4.1 Monocriterion Case

For the monocriterion case, the best individuals, that are the surviving ones, are chosen with the Goldberg's roulette. Each individual is represented by a slice of the roulette wheel, proportional to its fitness value. Since the criteria are represented by fuzzy numbers, they were defuzzified (the defuzzified value was calculated with the Liou and Wang's method) in the roulette wheel.

GA typical results obtained with $N\tilde{P}V$ as the only criterion to consider are presented in Table 2 (ten runs were performed to guarantee the stochastic nature of the GA). In particular, the value of the best individual of each generation and the average value of the function objective of the population take a traditional form of regular increase, to stabilize itself finally at the end of the research.

4.2 Multi-objective Optimization

The multi-objective resolution strategy for multiproduct batch plant design uses two genetic algorithms (bicriteria and tricriteria optimizations are considered).

4.2.1 Bicriteria Case: NPV- The Delays and Advances of the Time Horizon

The first bicriteria analysis takes into account the NPV and the criterion which represents the advances or delays of the time horizon with the hybrid selection method Pareto rank-tournament.

Table 2. Monocriterion ($N\tilde{P}V$): Fuzzy optimal design of batch plant

Product	B_{is} kg	T_{Li} h	*Criterion: The net present value ($)*	*Information Complémentaire*
A	943.3	4.8	$\tilde{N}PV$ =[722225.3 803765.7 892941.6 969060.6]	$\tilde{V}_p$ =[721977.6 742345.6 764042.2 782142.4] [$]
B	1145.5	7.3		$\tilde{D}_p$ = [232095.9 238513.7 245540.9 251437.2] [$]
C	899.7	6.6		I = 698877.8 [$] A_p= 139775.5 [$]
				f= 104831.6 [$] V_s = 1505.2 [l]
				$\sum\tilde{H}_i$ = [5759.9 5925.4 6097.3 6239.9] [h]

To treat the bicriteria optimization, the analysis is performed on the solution of case 2 with the best NPV and on those for case 3 having, on the one hand, larger common surfaces and, on the other hand, the best NPV. The example did not provide any solution of case 1, because the rectangle which represents the horizon of time to respect is larger than the trapezoids obtained for the sum of times of production. Table 3 shows the results of the chosen solutions.

Table 3. Fuzzy optimal design of batch plant for case 2 (advance) and cases 3 (delays)

	NPV (Mean Value)	Common surface	$N\tilde{P}V$ ($) and production time $\Sigma\tilde{H}$ (h)
Cas 2	860358	653	$N\tilde{P}V$ = [736120, 817367, 906144, 981801] $\Sigma\tilde{H}$ = [5758, 5916, 6089, 6238]
Cas 3a	860550	163	$N\tilde{P}V$ = [736327, 817565, 906332, 981976] $\Sigma\tilde{H}$ = [5772, 5930, 6104, 6253]
Cas 3b	861823	129	$N\tilde{P}V$ = [737489, 818728, 907495, 983139] $\Sigma\tilde{H}$ = [5883, 6045, 6222, 6374]

4.2.2 Bicriteria Case: NPV- Flexibility Index

The second bicriteria analysis takes into account the NPV and the criterion which represents the flexibility index of the configuration chosen to produce a possible additional demand. Figure 3 exhibits 277 non dominated solutions of the advance cases “(2, 4, 6 and 8) and of the delay cases (3, 5 and 7).

Two solutions of case 2: the first is the solution with the best benefit and the second configuration has the best index of flexibility. The third corresponds to case 3 with the best index of flexibility.

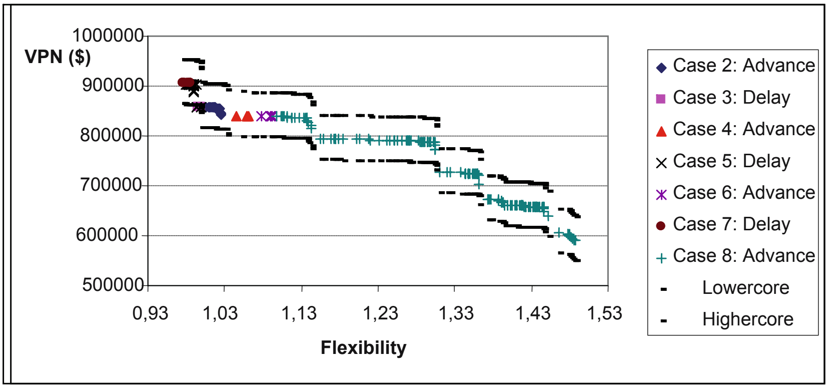

Fig. 3. Bicriteria results: NPV- Flexibility Index

4.2.3 Comparison Between a Hybrid Selection Method (Pareto Rank-Tournament) and the Classical Goldberg's Wheel for the Bicriteria Optimization Case

To evaluate the performance of the selection method of the fuzzy genetic algorithm (combination of Pareto set and tournament), it is proposed to test the algorithm modified with the classical Goldberg's wheel. The same number of surviving individuals is chosen for each criterion (two roulettes). The same parameters for AG with the procedure of Pareto rank-tournament, are used with Goldberg's wheel.

A higher number of non dominated individuals are obtained with the hybrid method because the selection provides compromise solutions between the two criteria and the values of their criteria are better than those obtained with the Goldberg's wheel.

4.2.4 Tricriteria Case: NPV- Delays/Advances- Flexibility Index

Lastly, the fuzzy optimal design of batch plant takes into account simultaneously the three criteria, i.e., NPV, criteria of the advances or delays (common surface) and index of flexibility. 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.

To analyse the results obtained with the tricriteria case, 6 non dominated solutions are adopted: 3 of case 2, 2 of case 4 and 1 of case 6. These solutions were selected by considering the same policy as for the bicriteria case.

5 Conclusions

For the most common form of design of a multiproduct batch chemical plant, the designers specify the production requirement of each product and the total production time. However, no precise product demand predictions are generally available. For this reason, an alternative treatment of the imprecision by using fuzzy concepts is introduced in this paper.

In this study, we have introduced a fuzzy-AGs approach to solve the problem of multi-objective optimal design of a multiproduct batch chemical plant. The results obtained on the treated example have shown that three different scenarios were obtained as a fuzzy decision-making approach. The analysis tended to be helpful for decision making.

Its benefits can be summarized as follows:

- Fuzzy concepts allow us to model imprecision in cases where historical data are not readily available, i.e. for demand representation;
- The models do not suffer from the combinatorial explosion of scenarios that discrete probabilistic uncertainty representation exhibit;
- Another significant advantage is that heuristic search algorithms, namely genetic algorithms for combinatorial optimization can be easily extended to the fuzzy case;
- The hybrid selection method Pareto rank-tournament was proposed and showed a better performance than the classical Goldberg's wheel, systematically leading to a higher number of non-dominated solutions.
- Multiobjective concepts can also be taken into account.
- The proposed approach thus constitutes an efficient and robust support to assist the mission of the designer, leading to a quite large set of compromise solutions.

Finally, this framework provides an interesting decision-making approach to design multiproduct batch plants under conflicting goals.

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