

MULTIOBJECTIVE OPTIMIZATION OF AN UPFLOW ANAEROBIC SLUDGE BLANKET REACTOR

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Abstract

The purpose of this paper is to optimize the operation of an upflow anaerobic sludge blanket (UASB) reactor. In this kind of processes, besides to maximize organic matter removal, it is attractive to capture the biogas and to use it to provide energy services. For this purpose, the biogas has to be produced in large quantities. Thus, we have two clear objectives to be achieved: to maximize both the organic matter removal and the biogas production. Three multiobjective optimization techniques are used to solve this problem. The first optimization approach is multiplex, which is based on the simplex method for single objective optimization. Other used approach is an interior point method, which is proved to be an efficient linear programming technique. Finally, it is applied an evolutionary algorithm, namely the elitist non-dominated sorting genetic algorithm (NSGA II), which is considered a very attractive heuristic method. Formulation of the multiobjective optimization problem is based on a multivariate regression model, which is built using experimental data from a full-scale UASB reactor, at CETESB, in São Paulo City, Brazil. Obtained optimization solutions are compared and discussed.

Keywords: UASB reactor, Wastewater treatment, Multiobjective optimization, Multiplex, Interior-point methods, Genetic algorithms, Multivariate modelling.

I. INTRODUCTION

The development of new types of non-conventional bioreactors, has led anaerobic processes to be more and more attractive (Kalogo and Verstraete, 1999). Such reactors make possible a reasonable efficient treatment of domestic and industrial wastewaters associated with a low investment and operational costs and the low sludge production and space required by the system. With this improvement, the anaerobic digestion has been used as a pre-treatment, mainly in effluents with high organic matter concentration. Among the non-conventional reactors highlights the upflow anaerobic sludge blanket (UASB) reactor, developed in The Netherlands for treatment of industrial wastewater (Lettinga et al., 1980). In Brazil, the adaptation of UASB technology to treat domestic wastewater has been studied at CETESB by Vieira and Garcia (1992) and Vieira et al. (1994). Today, UASB reactors are widely

used in Europe, the US and Japan for the pre-treatment of wastewater predominantly derived from processing industries.

In an UASB reactor, it is interesting to implement a biogas recovery system and to utilize it as a supplementary energy source for thermal energy loads and the electricity generation. As it is known, biogas is mainly composed of methane (CH_4) and carbon dioxide (CO_2) and trace levels of other gases such as hydrogen (H_2), carbon monoxide (CO), nitrogen (N_2), oxygen (O_2) and hydrogen sulfide (H_2S). Despite the studies emphasized on energy management, the energetic potential of methane is little utilized. Inside of this context, the ENERBIOG Project aims to analyze the use of biogas to electricity generation in Brazil (Coelho et al., 2005). For this purpose, the biogas has to be produced in considerable quantity, but without compromising the organic matter removal, so that the biogas recovery is feasible. To get a better compromise between both objectives,

i.e. organic matter removal and biogas production, multiobjective optimization techniques have to be applied.

As the present case, many real-life problems involve multiple objectives that are often conflicting and non-comparable. Using single objective function optimization techniques do not adequately solve such problems. Non-comparable objectives are associated to multiobjective optimization problems that represent a trade-off among objectives and whose solutions are named as Pareto optimal solutions (Bhaskar et al, 2000). For instance, Videla et al. (1990) used multiobjective optimization to find a Pareto optimal solution to design operational parameters of anaerobic digesters to treat leachates. In this case, the optimization problem consists in maximizing net biogas production, maximizing chemical oxygen demand (COD) removal and minimizing costs. Another example is given in Ciric et al. (1994). They presented an approach for determining the sensitivity of maximum net profits to uncertainty in the waste treatment costs in a chemical process.

There are several multiobjective optimization techniques. Interesting surveys are provided by Andersson (2000) and Marler and Arora (2004). Ignizio and Cavalier (1994) introduced linear programming (LP) models to deal with multiobjective optimization and to find an optimal solution. This method named multiplex is derived from the simplex method for the optimization of a single objective function. In contrast to the simplex method, which moves toward a solution on the vertices of the constraint polytope, interior-point (IP) methods move toward the solution through the interior of the polytope (Potra and Wright, 2000). Karmarkar (1984) demonstrated the computational efficiency of IP methods for LP, reporting solution times up 50 times faster than the simplex method. While activity in IP methods for single objective linear optimization problems has reported thousands of research papers, very little has been done to apply this algorithm to multiobjective linear programming (MOLP) problems. Some attempts related to this topic are the works of Arbel (1997) and Trafalis and Alkahtani (1999).

On the other hand, evolutionary algorithm are becoming an alternative approach to the

classical optimization methods because they permit to work with great search spaces, can generate the best compromise solution among several objectives in a unique run and they do not need extra information, as the function derivative. Evolutionary algorithms refer to a class of optimization methods that simulate the natural evolution principle to drive the search in direction to an optimal solution. Among the several multiobjective evolutionary algorithms have been reported in the literature, it can be mentioned the multiobjective genetic algorithm (MOGA) by Fonseca and Fleming (1993) and the non-dominated sorting genetic algorithm (NSGA) by Srinivas and Deb (1994). Deb et al (2002) proposed the elitist non-dominated sorting genetic algorithm (NSGA II) with the purpose to alleviate three principal criticisms of the NSGA: computational complexity, non-elitist approach and the need of specifying a sharing parameter.

In this paper, three optimization algorithms, namely multiplex, IP method and NSGA II are used aiming to solve the multiobjective operation of a full-scale UASB reactor, i.e. to maximize both biogas production and organic matter removal. Multiobjective optimization applied to UASB reactors is rare in the literature. In the present case, formulation of the optimization problem is based on a multivariate regression model, which is developed using experimental data from the reactor. This multivariate regression approach is appropriate to deal with highly correlated data, as it is the case of this wastewater treatment process. The paper is organized as follows. Section 2 describes the UASB reactor. In section 3, the multiobjective optimization problem is formulated. Section 4 presents the problem solution using multiplex. Section 5 discusses the optimization solution by IP method meanwhile optimal solution through the NSGA II algorithm is presented in section 6. Finally, conclusions are explained in section 7.

II. THE UASB REACTOR

This paper considers the process studied by Vieira and Garcia (1992) and Vieira et al. (1994). It is a 120 m³ UASB reactor to treat raw domestic wastewater, which was designed and installed at CETESB, located

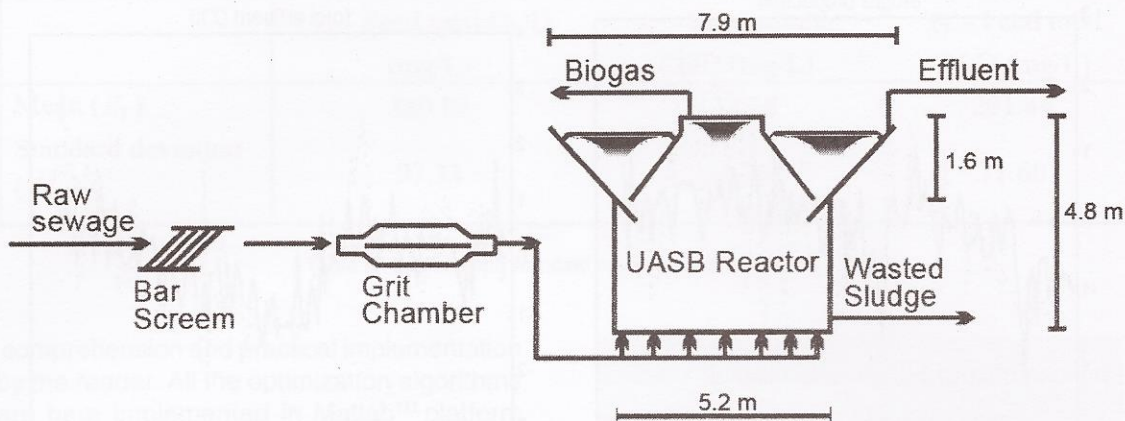


Figure N° 1. Layout of the UASB reactor

in São Paulo, SP, Brazil. This reactor was fed with sewage collected by the Pinheiros wastewater treatment plant of SABESP (Basic Sanitation Company of São Paulo State), and it is capable to attend a population of about 4000 habitants. A simplified schematic diagram of the UASB reactor and its main dimensions are shown in figure N° 1.

The reactor is built of carbon steel, internally lined with epoxy paint. It consists of a cylindrical tank with a frustum conical settler at its top to separate solids, and a gas deflector to carry the gas to the central cover of the digester. In this system, sewage passes through a sieve and a grit chamber before entering the UASB reactor. At the top of the digester there is a chamber to receive the sewage and distribute it through 12 tubes to the bottom of the reactor. Of this way the sewage is uniformly distributed at the bottom and travels upward through the digester and sludge bed that is formed within. The treated effluent is collected in channels at the top of the reactor.

The sludge is periodically removed from the bottom by means of pipes, which reach the center of the reactor. There are six sludge sampling points vertically distributed along the reactor. The gases produced are carried to the central dome and then through tubes to the burner after first passing through a gas flow meter.

In this process, for a hydraulic retention time (HRT) range of 4 to 15 hours, it was found that the organic removal efficiency did not vary appreciably, having maintained a value of

about 60% for chemical oxygen demand (COD), 70% for biochemical oxygen demand (BOD) and 70% for total suspended solids (TSS), with effluent quality varying between 20 to 300 mg COD/l and 10 to 200 mg BOD/l, with 50 mg TSS/l on average and biogas production varying from 0.008 to 1 Nm³/m³.d, which is approximately composed of 70%, 9%, 20% and 1%.

Table N° 1. Variables used for PLS modelling

Variable	Tag
Biogas producción (Nm ³ /m ³ .d)	y ₁
Total effluent COD (mg/l)	y ₃
Hydraulic retention time (h)	x ₂
Ambient temperature (°C)	x ₄
Feed total COD (mg/l)	X ₅
Feed soluble COD (mg/l)	X ₆
Feed total BOD (mg/l)	X ₇
Feed TSS (mg/l)	X ₈

III. FORMULATION OF THE OPTIMIZATION PROBLEM

In this work, the operation of the UASB reactor aims to maximize both biogas production and organic matter removal (COD). The first step to formulate this multiobjective problem is to obtain a mathematical model of the process. Here, experimental data from the UASB reactor is used to identify a process model based on multivariate statistical methods. Partial least squares (PLS) and principal component analysis (PCA) were applied by

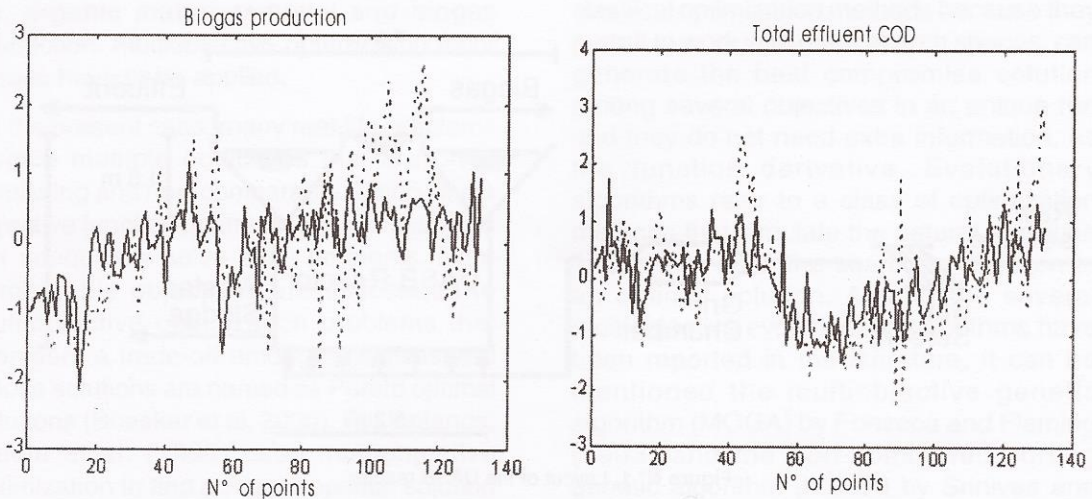


Figure N° 2. UASB identification results: experimental data (-----), PLS model (—)

Teppola et al. (1997) and Tomita et al. (2002) in activated sludge processes, respectively. In the present case, it is used PLS regression modelling technique. The variables used for PLS modelling of the UASB reactor are listed in Table 1.

For a better process identification, the raw data set is normalized by subtracting the mean and by dividing by the standard deviation. Using the Matlab Chemometrics toolbox (Kramer, 1993), linear PLS models with six latent structures for the UASB reactor are obtained as follows:

$$y_1 = -0.5659x_2 + 0.2772x_4 + 0.0657x_5 + 0.1999x_6 + 0.1257x_7 - 0.0853x_8 \quad (1)$$

$$y_3 = -0.2853x_2 - 0.2435x_4 + 0.3964x_5 + 0.2836x_6 - 0.1146x_7 + 0.0467x_8 \quad (2)$$

The mean squared error of estimation (MSEE) is used as performance index to evaluate the adequacy of the identified models. The MSEE index for models (1) and (2) is 0.6906 and 0.5770, respectively. Figure N° 2 shows the outputs generated by the PLS models. As it can be observed, these models are able to reproduce reasonably well the process and, therefore, they are well suited for optimization applications.

Using the PLS models, the multiobjective optimization problem can be formulated as maximization of biogas production (y_1) and minimization of total effluent COD (y_3), which

can be mathematically expressed of the following form (Tomita, 2004):

$$\begin{aligned} \max \quad & y_1 \\ \min \quad & y_3 \end{aligned} \quad (3)$$

subject to:

$$-1.4 \leq x_2 \leq 1.7$$

$$-2.5 \leq x_4 \leq 2$$

$$-2.2 \leq x_5 \leq 1.8$$

$$-2 \leq x_6 \leq \frac{(x_5 d_{x_5}^{1/2} + \bar{x}_5) - \bar{x}_6}{d_{x_6}^{1/2}}$$

$$-2 \leq x_7 \leq \frac{(x_5 d_{x_5}^{1/2} + \bar{x}_5) - \bar{x}_7}{d_{x_7}^{1/2}}$$

$$-1.3 \leq x_8 \leq 2.4$$

Constraints (4) are derived from minimum and maximum operational conditions of the reactor, where \bar{x}_i and $d_{x_i}^{1/2}$ are the mean and the standard deviation of the raw data set, respectively, as shown in Table 2.

The solution of the above multiobjective problem (3) subject to constraints (4) is solved by using multiplex (Ignizio and Cavalier, 1994), IP method (Arbel, 1997) and NSGA II algorithm (Deb et al., 2002). In the next sections, these optimization algorithms are briefly summarized, in order to facilitate its

	x_5 - Feed total COD (mg/L)	x_6 - Feed soluble COD (mg/L)	x_7 - Feed total BOD (mg/L)
Mean (\bar{x}_i)	330.80	132.96	201.44
Standard deviation ($d_{x_i}^{1/2}$)	97.33	34.76	71.60

Table N° 2. Mean and standard deviation of the data set

comprehension and practical implementation by the reader. All the optimization algorithms are here implemented in Matlab™ platform (MathWorks Inc., 2002).

IV. MULTIOBJECTIVE OPTIMIZATION USING MULTIPLEX

The multiplex algorithm of Ignizio and Cavalier (1994) solves a MOLP problem given by:

$$\text{lexmin } u = \{c^{(1)}v, c^{(2)}v, \dots, c^{(k)}v\}$$

Subject to:

$$\begin{aligned} Av &= b \\ v &\geq 0 \end{aligned} \tag{5}$$

$c^{(k)}$: vector of coefficients, or weights, of k -th term of the achievement vector.

$$v = \begin{bmatrix} x \\ \eta \\ \rho \end{bmatrix} \text{ :vector of all structural and deviation variables.}$$

A: matrix of coefficients for the goal set (priority order in the rows and coefficients x, η and ρ in the columns)

b: right-hand side vector of the goal set

The multiplex considers that the first term of vector u is minimized. After, the second term is minimized without alter the result obtained to the first term, and so on. The multiplex algorithm is summarized to follow:

step 1: Initialization. Assume that basic variables are negative deviation variables.

$$\begin{aligned} v_B &= \eta \\ B^{-1} &= I \\ \beta &= B^{-1}b = b \end{aligned}$$

Initially, all variables are unchecked.

Set $k = 1$ (counter)

step 2: Develop the pricing vector for level k . Determine: $\pi^{(k)} = c_B^{(k)} B^{-1}$

step 3: Price out all unchecked, nonbasic variables at level k . Calculate:

$$d_j^{(k)} = \pi^{(k)} a_j - c_j^{(k)}$$

where j belongs to unchecked and nonbasic variable set. Therefore, the coefficients a_j belong to matrix N and c_j belong to vector c_N .

step 4: Selection of the entering nonbasic variables. Examine the values of d computed in step 3.

If none is positive, go to step 8.

Otherwise, select the nonbasic variable with the most positive value of d as entering variable.

Designate this entering variable as v_q .

step 5: Update the entering column:
 $\alpha_q = B^{-1}a_q$

step 6: Determine the leaving basic variable. Designate the row associated with the leaving basic variable as row p . Choose the leaving basic variable by the following way:

$$\begin{aligned} \beta_p / \alpha_{p,q} &= \min \{ \beta_i / \alpha_{i,q} \} \\ \alpha_{i,q} &> 0 \end{aligned}$$

If $\alpha_{i,q} \leq 0$, for all i , the problem is unbounded and the algorithm may be ended.

Otherwise, the basic variable associated with row p to leave the base is that with lower $\beta_i/\alpha_{i,q}$. This variable is designated as $v_{B,p}$.

step 7: Pivot. Replace a_p in B by a_q and compute the new basis inverse B^{-1} . return to step 2.

step 8: Convergence check. If either (or both) of the following conditions holds, terminate the program as the solution has been found:

- a) if all d_j^k 's as computed in step 3 are negative, or
- b) if $k = K$, in other words, if all elements of achievement are determined.

Otherwise, check all nonbasic variables associated with negative values of d_j^k , set $k = K + 1$, and return to step 2.

To apply the multiplex algorithm to the problem (3)-(4), the decision variable vector \mathbf{x} must be positive, then firstly, let \mathbf{x} to be a new variable \mathbf{x}' . For example:

$$x_2 \geq -1.4 \Rightarrow \underbrace{x_2 + 1.4}_{x_2'} \geq 0 \Rightarrow x_2' \geq 0$$

$$x_2 \geq -1.7 \Rightarrow x_2' - 1.4 \geq 1.7 \Rightarrow x_2' \geq 3.1$$

Now, considering that minimization of variable y_3 can be transformed in maximization of $-y_3$, the problem (3)-(4) can be reformulated as:

$$\max \begin{cases} y_1 = -0.5659(x_2' - 1.4) + 0.2772(x_4' - 2.5) + 0.0657(x_6' - 2.2) \\ \quad + 0.1999(x_8' - 2) + 0.1257(x_7' - 2) - 0.0853(x_8' - 1.3) \\ -y_3 = 0.2853(x_2' - 1.4) + 0.2435(x_4' - 2.5) - 0.3964(x_5' - 2.2) \\ \quad - 0.2836(x_6' - 2) + 0.1146(x_7' - 2) - 0.0467(x_8' - 1.3) \end{cases} \quad (6)$$

subject to:

$$x_2' \leq 3.1$$

$$x_4' \leq 4.5$$

$$x_5' \leq 4$$

$$x_6' - 2.8004x_5' \leq 1.5315 \quad (7)$$

$$x_7' - 1.3593x_5' \leq 0.8162$$

$$x_8' \leq 3.7$$

$$x \geq 0$$

Finally, the objective functions (6) can be converted into a type II (\geq) inequality constraints by means of the aspiration level value establishment (level that is desired and/or acceptable); In this case, it is considered $y_1 \geq 3$ and $y_3 = -y_3 \geq 3$. Writing problem (6)-(7) in the general form of equation (5), we have that:

$$\text{lexmin } u = \{(\rho_1 + \rho_2 + \rho_3 + \rho_4 + \rho_5 + \rho_6), (\eta_7), (\eta_8)\}$$

subject to:

$$\eta_1 - \rho_1 = 3.1$$

$$x_4' + \eta_2 - \rho_2 = 4.5$$

$$x_5' + \eta_3 - \rho_3 = 4$$

$$x_6' - 2.8004x_5' + \eta_4 - \rho_4 = 1.5315 \quad (8)$$

$$x_7' - 1.3593x_5' + \eta_5 - \rho_5 = 0.8162$$

$$x_8' + \eta_6 - \rho_6 = 3.7$$

$$\begin{aligned} y_1 &= -0.5659x_2' + 0.2772x_4' + 0.0657x_5' + 0.1999x_6' + 0.1257x_7' \\ &\quad - 0.0853x_8' + \eta_2 - \rho_2 = 3.5856 \\ -y_3 &= 0.2853x_2' + 0.2435x_4' - 0.3964x_5' - 0.2836x_6' + 0.1146x_7' \\ &\quad - 0.0467x_8' + \eta_7 - \rho_7 = 3.7374 \end{aligned}$$

The solution of problem (8) by multiplex, after 6-iterations, is given by:

$$x^{opt} = [1.7 \quad 2 \quad 2.2 \quad -2 \quad -1.1838 \quad -1.3]^T$$

which corresponds to the point $A = (-0.9898, 2.3361)$ of the objective space in figure N° 3

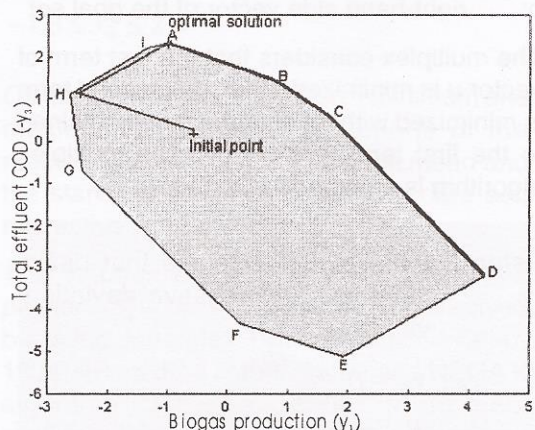


Figure N° 3. UASB optimization using multiplex method

V. MULTIOBJECTIVE OPTIMIZATION USING INTERIOR-POINT METHOD

Considers the following MOLP problem:

$$\left. \begin{array}{l} \max c_1^T x \\ \max c_2^T x \\ \vdots \\ \max c_q^T x \end{array} \right\}, 1 \leq i \leq q \Rightarrow \max C^T x \quad (9)$$

subject to:

$$Ax = b$$

$$x \geq 0$$

To solve this problem, Arbel (1997) proposed the self-scaling path-following primal IP algorithm, which is summarized below:

step 0: Find the initial set of efficient anchor point $\{x_{end_i}\}$ by solving a set of q single-objective LP problems, by using the weighting method.

step 1: $k = 0$. Initialize $x(k) = x_0$; $\rho(k) = \rho_0$ where x_0 is the initial feasible solution and ρ_0 is the initial step-size factor.

step 2: $k = k + 1$. Evaluate:

$$dx_{end_i}(k) = x_{end_i}(k) - x(k).$$

Find the i -th step direction vector:

$$dx_i(k) = D^2 [c_i - A^T y_i(k)],$$

where

$$(AD^2(k)A^T)y_i = AD^2(k)c_i$$

and the scaling matrix

$$D(k) = \text{diag}(x(k))$$

step 3: Find the set of q new iterates $\{x_i\}$:
 $x_i(k+1) = x(k) + \rho(k+1)\alpha_i(k)dx_i(k)$,
 where $\rho(k+1) = \gamma\rho(k)$,
 $0 < \gamma < 1$, and the step-size $\alpha_i(k)$ is found through the ratio test. Evaluate the value vectors $\{v_i\}$:
 $v_i = C^T x_i$.

Step 4: Use the AHP (analytic hierarchy process) to compare the individual

value vectors of the end points and the anchor points, and determine their relative preference through a comparison matrix, in order to construct the combined step direction vector, dx . In this case, it is used an utility function as DM (decision-maker). Normalizing these utility values and using the normalized utilities (λ) to form a convex combination of the step direction vectors, the combined step vector is given by:

$$dx(k) = \begin{cases} \sum_{i=1}^q \lambda_i dx_i, & \text{for } k=1 \text{ and } \sum_{i=1}^q \lambda_i = 1 \\ \sum_{i=1}^q \lambda_i dx_i + \sum_{i=1}^q \lambda_{end_i} dx_{end_i}, & \text{for } k>1 \text{ and } \sum_{i=1}^q \lambda_i + \sum_{i=1}^q \lambda_{end_i} = 1 \end{cases}$$

step 5: Find the new boundary point along the direction dx , by taking a full step ($\rho = 1$): $x_{new} = x(k) + dx(k)$

Evaluate the utility function for $\{x_{new}\}$.

step 6: If the value of the utility function for $\{x_{new}\}$ is preferred to any corresponding to $\{x_{end_i}\}$, remove the least preferred anchor point and replace it with $\{x_{new}\}$.

step 7: If termination conditions are met, set the solution at $x = \sum_{i=1}^q \lambda_i x_{end_i}$ and Stop; otherwise go to step 2.

In problem (3)-(4), we start the solution process by transforming the variables x to x' and by obtaining two (efficient) anchor points. For this purpose, it is constructed the weighted objective functions $J_1 = 0.96y_1 - 0.04y_3$ and $J_2 = 0.04y_1 - 0.96y_3$. The solution of these single-objective LP problems is given the anchor points $x_{end_1} = [0 \ 4.5 \ 4.0 \ 12.73 \ 6.25 \ 0]^T$ and $x_{end_2} = [3.1 \ 4.5 \ 0 \ 0 \ 0.8162 \ 0]^T$, which represent the points $D=(4.2560, -3.1217)$ and $A=(-0.9898, 2.3361)$ in non-dominated set of the objective space, respectively, as shown in figure N° 4.

For only two objectives we prefer to use an utility function rather than using the AHP as DM. Assuming an utility function $u = x_1 \cdot x_2 / x_3$ and the initial inferior feasible solution point $x^0 = [1 \ 1 \ 1 \ 1 \ 1 \ 1]^T$, $\rho_0 = 0.95$ and $\gamma = 0.75$, the

optimal solution, after 13-iterations, is given by $x_{opt} = [3.1 \ 4.5 \ 0 \ 0 \ 0.8162 \ 0]^T$ with $u = 17.0893$, this solution also can be expressed by

$x^{opt} = [1.7 \ 2 \ 2.2 \ -2 \ -1.1838 \ -1.3]^T$ with $u = 2.8721$. As it can be observed in figure N° 4, this result corresponds to the point A (in this case the optimal solution represents a vertices in the constraint polytope), which is the same as obtained by the multiplex method.

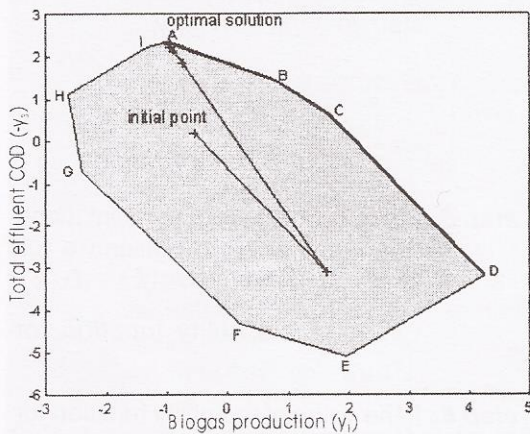


Figure N° 4. UASB optimization using IP method

VI. MULTIOBJECTIVE OPTIMIZATION USING GENETIC ALGORITHMS

Consider the following multiobjective nonlinear programming:

$$\left. \begin{array}{l} \max f_1(x) \\ \max f_2(x) \\ \vdots \\ \max f_q(x) \end{array} \right\}, \quad 1 \leq i \leq q \quad (10)$$

subject to:

$$g(x) \geq 0$$

$$h(x) = 0$$

$$x^l \leq x \leq x^h$$

Problem (10) can be solved by using the NSGA II algorithm proposed by Deb et al. (2002). The steps of this algorithm is summarized as follows:

step 1: Initialize the NSGA II parameters – number of decision variables, number of objective functions, number of constraints, population size, generation number, crossover probability, mutation probability, seed for random number, upper and lower limits for decision variables.

step 2: Initialize the generation number counter.

step 3: Initialize the random number generator.

step 4: Create a initial population P_0 of N_p random solutions.

step 5: Evaluate the objective functions and constraints. And classify the solutions into different fronts, by comparing the solutions in pairs. In this comparison, firstly, the constraints are considered. If a solution i violates the constraints and solution j does not violates, solution j will enter in the front (P') and it is removed of P_0 . If both solutions are feasible, i and j enter in the front (P') and they are removed of P_0 . Otherwise, if both solutions are infeasible, the fitness values of these solutions are compared based on non domination. The non-dominated solution will enter in the front (P'). Repeat this procedure for all solutions in P_0 . P' constitutes the first front of non-dominated solutions and it is assigned with $rank = 1$. Create subsequent fronts using the solutions remaining in P_0 .

step 6: Evaluate the crowding distance, d_{ii} that is a measure of the search space around solution i which is not occupied by any other solution in the population. For each objective function m , rearrange all solutions in front F in ascending order of their fitness functions values. Assign a large distance to the boundary (minimum and maximum) solutions,

and for all other solutions $i = 2, \dots, (l-1)$ (l is the number of solutions in the front), assign:

$$d_{li} = d_{li} + \frac{f_m^{li+1} - f_m^{li-1}}{f_m^{\max} - f_m^{\min}}$$

This helps maintain diversity in the Pareto set.

step 7: Selection of the solutions to form offspring population. Select any pair of solutions, i and j , randomly, irrespective of fronts. Identify the better of these two solutions by using the crowded tournament selection. The first comparison is in terms of dominance (belong or not to the same non-dominated front). If solution i has a better (lower) rank than j , i is chosen to enter in the offspring population. If solutions i and j belong to the same rank (non-dominated front), the solution that has better (higher) crowding distance is chosen. In other words, solution i wins a tournament with another solution j if any of the following conditions are true: (i) if solution i has a better rank, $r_i < r_j$ (ii) if they have the same rank but solution i has a better crowding distance than solution j , that is, $r_i = r_j$ and $d_i > d_j$.

step 8: Crossover. Carry out crossover of the solutions in Q . In our implementation, we use the simulated binary crossover (SBX) (Deb, 2000) for real-coded variables.

step 9: Mutation. Carry out mutation of the solutions in Q . In our implementation, we use the polynomial mutation (Deb, 2000) for real-coded variables.

step 10: Evaluate the objective functions and constraints for offspring population Q .

step 11: The parent and offspring populations are combined to form

a global population of size $2N_p$. The solutions of global population are ranked in different fronts as explained in step 5. Select the best N_p solutions. If the size of first front F_1 is smaller than N_p , all member of this front is chosen to form the next population P_{t+1} . The remaining members of P_{t+1} are chosen from subsequent non-dominated fronts in the order of their ranking. This procedure is continued until no more sets can be accommodated. In general, the count of solutions in all sets from the first front F_1 to last front F_l to be accommodated would be larger than the population size. To choose exactly N_p solutions, the last front is sorted using the crowding distance comparison operator (as shown in step 6 and 7) and the best solutions needed to fill the population P_{t+1} is chosen.

step 12: Increment the generation counter.

step 13: Stop if criteria are met. Otherwise, go to step 7.

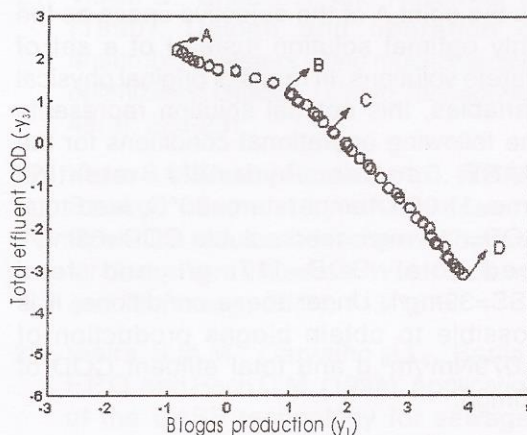


Figure N° 5. UASB optimization using NSGA II method

In the application of the NSGA II to the problem (3)-(4), it is considered a population size of 50 solutions and the final solution should be obtained at the end of 60 generations. Are used a crossover probability of $P_c = 0.9$ and a mutation probability of

$P_m = 0.1$. The distribution index to crossover and mutation are set as $\eta_c = 100$ and $\eta_m = 1$, respectively.

In this case it is obtained a set of Pareto solutions as shown in figure N° 5. Once a set of trade-off solutions is found, the DM can make a choice of the "best" solution by using high-level qualitative information. If the DM gives more importance to COD removal, the point A is chosen, as in previous results presented in sections 4 and 5; otherwise, if biogas production is more important than COD removal, then point D is chosen. On the other hand, if both objectives are equally important, any point among points B and C can be selected.

VII. CONCLUSIONS

In this paper we are interested in testing different optimization methods for the multiobjective operation of a full-scale UASB reactor. The problem formulation is based on a PLS regression model, which was able to represent reasonably well the process.

The multiplex method is relatively easy to handle, but it presents limitations when we need to automate the procedures. In the IP method, the calculation procedure is more automated than the first one. Also, it is promising to be used when we have to solve problems with major numbers of objectives. Both methods, multiplex and IP method, give us the point A of the objective space as the only optimal solution instead of a set of Pareto solutions. In terms of original physical variables, this optimal solution represents the following operational conditions for the UASB reactor: hydraulic retention time=11.05h, temperature=30°C, feed total COD=117 mg/l, feed soluble COD=63mg/l, feed total BOD=117mg/l and feed TSS=39mg/l. Under these conditions, it is possible to obtain biogas production of 0.079Nm³/m³.d and total effluent COD of 25mg/l.

On the other hand, if we want to obtain a set of n non-dominated solutions, it is necessary to run multiplex or IP method n times by using different user-defined parameters. The solution obtained of this manner is not the optimal solution of each individual objective. It is a better compromise solution, which is influenced by weights that

express the relative importance of each goal. In the case of the NSGA II, it give us the set of trade-off solutions (point A included) in one single simulation run, which makes this algorithm to be an ideal candidate for solving multiobjective optimization problems. The results obtained demonstrated that by selecting any operation point among points B and C of the objective space, the UASB reactor can be effectively used to accomplish appropriate biogas production and organic matter removal. For instance, choosing point B represents the following setting for the UASB reactor: hydraulic retention time=4.13h, temperature=30°C, feed total COD=117mg/l, feed soluble COD=63 mg/l, feed total BOD=117mg/l and feed TSS=39mg/l. Thus, are obtained biogas production of 0.1629Nm³/m³.d and total effluent COD of 38mg/l.

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