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Multiobjective optimization and multivariable control of the beer fermentation process with the use of evolutionary algorithms

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Abstract: This paper describes empirical research on the model, optimization and supervisory control of beer fermentation. Conditions in the laboratory were made as similar as possible to brewery industry conditions. Since mathematical models that consider realistic industrial conditions were not available, a new mathematical model design involving industrial conditions was first developed. Batch fermentations are multiobjective dynamic processes that must be guided along optimal paths to obtain good results. The paper describes a direct way to apply a Pareto set approach with multiobjective evolutionary algorithms (MOEAs). Successful finding of optimal ways to drive these processes were reported. Once obtained, the mathematical fermentation model was used to optimize the fermentation process by using an intelligent control based on certain rules.

Key words: Multiobjective optimization, Genetic algorithms, Industrial control, Multivariable control systems, Fermentation processes

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INTRODUCTION

The fermentation process has great scientific and practical importance. For several reasons, quality control, for example, it is important to include all kinds of technological advances in the industrial processes. This is the main aim of our research, which is very complex due to the non-linearity of the studied phenomena.

The mathematical models found in literature include only laboratoy conditions. A mathematical model has been developed for the beer fermentation process because of the advantages that it provides. It allows simulating what can happen when one or other strategies are applied; and allows study on how different initial factors can affect the evolution in a process. Also, a good model predicts the future evolution of the process and during the same production, the model makes it possible to develop "software sensors", which enable real-time indirect measurement of important variables, and in this way, improve process monitoring and supervision.

At present, the most important problem for large industrial companies is the optimization of resources. Obtaining a good product must be compatible with other objectives: minimize costs and maximize profits. This is why in the case of beer production, we studied how to obtain control action at the moment when production has reached the required maximum quality (good smell and taste) alcohol level while minimizing contamination risks, energy costs, temperature variations in the tanks, and fermentation time. Industry controls the process by modifying the temperature in the tanks.

This considers a problem which multiple objectives: obtaining optimal production temperature trajectory for a dynamic system and, simultaneously, defining the dynamic factors driving the system along this optimal trajectory with good properties. This is a multivariable problem requiring achievement of eight different objectives as the fermentation is a batch process controlled by the heat added or extracted to the system. In order to get the optimal temperature profile, sometimes heat must be added to or subtrated from the system. The final goal of this research was to find ways obtaining the best beer in the minimum possible time. But the control methods to make the process follow the required temperature profile must be feasible. Satisfying minimum conditions that make it applicable to the real process in an industrial fermentation plant must be another objective to achieve. Also, aside from the ethanol level of the beer, its quality must be ensured and, in this sense, the byproducts (diacetyl, acetates, ...) must satisfy some constraints.

As an alternative to conventional optimization methods, an Artificial Intelligence system (AI) was been applied: Genetic Algorithms (GAs) satisfactory results, reduce computational costs and simplifies programming (Goldberg, 1989). Their multiobjective variants, including the Multiobjective Evolutionary Algorithms (MOEAs) (Michalewicz, 1999) based on Pareto sets of solutions (Coello, 2000) can be used to deal with the multiobjective nature of many real-life problems that can be mutually contradictory (Knowles and Corne, 2000). During the investigation, a MOEA that was implemented included a new special chromosome representation which provided specific knowledge of the optimizing process. Also, this algorithm allows that the time interval to which each GA gene is assigned could be variable in size; and in this way the numbers of genes will be different for each chromosome, and will change continuously from one generation to another. In this case, the added/extracted heat profiles obtained are smoother.

Once we obtained the mathematical model of the industrial beer fermentation process, identified its parameters and optimized the process, an intelligent advanced control, AI, based on "rules" will be implemented. It will be also able to identify problems, report on the possible causes and take remedial actions. For this supervisory function we use a simulation that runs simultaneously with the control of the process.

EXPERIMENTATION PLANT

For the research, we designed an experimental plant at the laboratory. The process has been implemented in compliance with industrial conditions to obtain the most realistic results. The implementation criteria and experimental design are described in Andrés *et al*.(1997).

In order to obtain real practical scope knowledge and to establish a good model for the industry, our research was developed by reproducing, at appropriate scale the industrial process with industrial wort and yeast, and without mechanical stirring.

Also, from the observations and experience acquired during the experimental phase, and with the use of the model, an Artificial Intelligence system (AI) was implemented to monitor and supervise the process. To carry out the research, experimental devices were designed and prepared. The fermentation plant included the required electronic measures and programming to use the computer to process data obtained by sensors, and to control the fermentation temperature. The plant is composed of the following parts: water tank, fermenter, water cooling system, water heating system, sensors, electronic interface, computer. In the sections below, we briefly describe each part.

A 1 m hight 0.35 m diameter tank (approximately 1/10 the size of the one used in the industry) with 0.15 m high, 100 liter lower receptor cone to ferment 80 liters of wort; and is surrounded by a 0.45 m diameter insulator.

Temperature control system able to supply the desired temperature to the tank by means of a dual circuit (cooling and heating). The cooling loop pumps water via a coil into a freezer, at 0.05 L/s of constant flow. Control is designed in such a way that this circuit never stops. The heating loop also pumps water at 0.05 L/s of constant flow into a metallic tube rounded by an electric resistance coil (1000 W, 220 V). This heating loop regulates the tank temperature.

A computer, including a data register circuit board with an analogical/digital converter board with some inputs and some digital outputs that by means of the data register board and the corresponding electronic interface enables control of the process, updating of variable values, their storage, and presentation of the corresponding graphic representations. The digital outputs control the switching on and off of the warm water pump and the resistance heater coil are also measures of the fermentation temperature and pH, and the water tank temperature. For this task, the required sensors and electronic interface are used and the analogical inputs to the data register board are inserted. We implemented the necessary programs to carry out all the jobs mentioned above.

Sensors, the fermenter includes some sensors for the real-time fermentation process control: a temperature sensor measures the wort temperature, a pH sensor that will indicate if the fermentation could be contaminated, a CO_2 sensor that will indicate the presence of carbonic gas in the suspension and a pressure sensor, at the bottom of the fermenter that will obtain the instantaneous wort density. To calibrate them, all these sensors were employed in some of the 250 fermentations carried out.

The system has a device able to adjust the heat to control the water temperature. The suspended biomass concentration could be deduced from the measured cloudiness in the fermenter. Light sensors were placed in each frontal window at the tank to measure the cloudiness in two important places (the geometrical middle of the tank and the top of the vessel where froth is formed during the process). These photocells allow us to know the different fermentation phases. There is an interior cone for the storage of the wort.

During the experiments, the computer is responsible for keeping the required temperature as indicated by the operator at the beginning of each experiment, the data registered for the biomass, alcohol, pH, etc. are shown graphically on the screen. These data are stored in a disk file for later study. The computer can also detect, during the experiments, the differences among the measured values for the cloudiness, temperature and pH and alarm the operator.

Some temperatures (8 °C, 12 °C, 16 °C, 20 °C and 24 ºC) in this plant were measured in order to establish a mathematical model. The sugars evolution, ethanol, etc. were measured for comparison with the results reported by Andrés *et al.*(1997); for fitting them to a variable temperature profile indicated by the optimization of the process for the fermentation to follow it.

We obtained the curve of the relation between the value indicated by the pressure sensor and the density value measured in the fermenter, and from these values we calculated the ethanol concentration inside the fermenter. The ethanol production rate could be deduced if the fermentation followed the model correctly.

MATHEMATICAL MODEL DETERMINATION

There are available literature on scientific studies on *Saccharomyces Cerevisiae* on its general aspects (Hough *et al.*, 1971; Tenney, 1985), on its biological process (Sonnleitner and Kappeli, 1986), on its breathing and growth (Steinmeyer and Shuler, 1989) including its structured model, on its mathematical model (Gee and Ramirez, 1988; 1994; Engasser *et al.*, 1981), on its control and "software sensors" (Johnson, 1987; Bastin and Dochain, 1986; 1990; Dochain and Bastin, 1984; Gauthier *et al.*, 1992), estimation of its growth rates (Park and Ramirez, 1988), on application of artificial intelligence techniques on fermentation processes (Steyer *et al.*, 1993).

The great number of published models which can help us as reference, such as Engasser *et al.* (1981)'s model describing the dependency of the evolution of the sugars and ethanol on the total biomass. However, our model does not use the total biomass as the most important variable but use the suspended active biomass. This means modifications in the values of some parameters, taking into account the ones that are mentioned in the references, and a change in the study of the phenomena to be modulated, introducing the effect of the biomass sedimentation.

For the model, we distinguish two consecutive periods during the fermentation: lag and active fermentation. It is important to take into account that in the yeast that is inoculated in the wort there are three types of cells: lag, active and dead, the number of lag cells being smaller than the other two types.

During the lag phase not too much ethanol is produced, lag cells are transformed into active cells and the biomass is settled down to the bottom. We used differential Eqs.(1)−(19) to describe these main processes.

We considered other factors during the fermentation phase. Suspended active yeast concentration increases and decreases as shown in Fig.1. Our increase of the temperature steepened the gradient of the trajectory. Although sedimentation still occurred, Eqs.(14)−(17), it was counteracted by the carbonic activity. Total yeast in the fermenter showed increasing rate. The evolution of the sugars concentration is described by Eqs.(7)−(10). Alcohol concentration showed increasing rate and depended on the temperature: increasing the temperature resulted in faster growth. Ethanol production rate was limited by the initial total sugars concentration.

The active yeast concentration, Eqs.(5) and (6), and ethanol production rates are inhibited, Eq.(11) due to the increase of the ethanol concentration.

Our model also includes the ethyl acetate, Eq.(18) and diacetyl production, Eq.(19), as important by-products whose concentrations are not desirable to be more than certain determined limits. We are interested in knowing their evolution during the fermentation in order to optimize the process without degrading the results quality.

To determine the characteristics and parameters of the model, we carried out more than 250 fermentations (Andrés *et al*., 1997) according to the following criteria:

The fermentations were run isothermally at 8 °C, 12 °C, 16 °C, 20 °C and 24 °C to cover all the possible operation limits of the process. The parameters values are the mean values.

Yeast, maltotriose, maltose, glucose, sucrose, fructose and ethanol concentration were measured. Each fermentation focused on 35 points, often at the most critical moments considered.

We propose the following model for industrial beer fermentation. All the terms and constants are explained in (Andrés *et al*., 1998a):

Lag phase:

$$x_{\text{active}} + x_{\text{lat}} = cons\tan t = 0.48x_{\text{initial}} \quad (1)$$

$$\mathrm{d}x_{\text{active}} / \mathrm{d}t + \mathrm{d}x_{\text{lat}} / \mathrm{d}t = 0 \quad (2)$$

$$\mathrm{d}x_{\text{active}} / \mathrm{d}t = \mu_{\text{Lat}}(0.48x_{\text{initial}} - x_{\text{active}}) \quad (3)$$

$$\mathrm{d}x_{\text{lat}} / \mathrm{d}t = -\mathrm{d}x_{\text{active}} / \mathrm{d}t = -\mu_{\text{Lat}} x_{\text{lat}} \quad (4)$$

Fermentation phase:

$$\mathrm{d}x_{\text{active}} / \mathrm{d}t = \mu_x x_{\text{active}} - k_+ x_{\text{active}} + \mu_{\text{L}} x_{\text{lat}} \quad (5)$$

$$\mu_x = \mu_{xo} s / \left(0.5 s_{\text{initial}} + e\right) \quad (6)$$

$$\mathrm{d}s_{\text{cons}} / \mathrm{d}t = \mu_s x_{\text{active}} \quad (7)$$

$$\mu_s = \mu_{so} s / \left(ks + s\right) \quad (8)$$

$$\mathrm{d}s / \mathrm{d}t = -\mathrm{d}s_{\text{cons}} / \mathrm{d}t \quad (9)$$

$$s = s_{\text{initial}} - s_{\text{cons}} \quad (10)$$

$$\mathrm{d}e / \mathrm{d}t = \mu_{\text{a}} f\, x_{\text{active}} \quad (11)$$

$$f = 1 - e / 0.5 s_{\text{initial}} \quad (12)$$

$$\mu_a = \mu_{ao} s / \left(ka + s\right) \quad (13)$$

$$\mathrm{d}x_+ / \mathrm{d}t = k_+ x_{\text{active}} - \mu_{\text{d}} x_+ \quad (14)$$

$$\mu_{\text{D}} = 0.5 s_{\text{initial}} \mu_{\text{D0}} / \left(0.5 s_{\text{initial}} + e\right) \quad (15)$$

$$\mathrm{d}x_{\text{bottom}} / \mathrm{d}t = \mu_{\text{D}} x_+ \quad (16)$$

$$x_{\text{susp}} = x_{\text{active}} + x_{\text{lat}} + x_+ \quad (17)$$

$$\mathrm{d}(ea) / \mathrm{d}t = \mu_{\text{eas}} \mathrm{d}s / \mathrm{d}t = \mu_{\text{eas}} \mu_x x_{\text{active}} \quad (18)$$

$$\mathrm{d}(v\mathrm{d}k) / \mathrm{d}t = k_{\text{DC}} s x_{\text{active}} - k_{\text{DM}} (v\mathrm{d}k) e \quad (19)$$

In these equations, parameters are affected by the temperature as described by the Arrhenius equations. This way to describe how much temperature (the control variable) and the other variables to affect the process, causes the model to be non-linear.

This model was used referenced by several authors (Titica *et al*., 2000; Trelea *et al*., 2001a; 2001b; 2002; Carrillo, 1999; Cheruy, 2000). The model was validated experimentally through more than 200 fermentations carried out during three years. Its agreement with real data is very good, according to the industrial conditions applied for our work (Figs.1, 2, 3, 4, 5 and 6).

BEER FERMENTATION AS A MULTIOBJECTIVE AND MULTIVARIABLE OPTIMIZATION PROBLEM

The final goal of this work is to obtain an optimal temperature profile easy to be implemented. For its industrial application, the total external calorific energy profile should be smooth. Also, the process duration and contamination risk must be minimized to achieve the required concentrations of ethanol while fulfilling the desired quality for taste and aroma (diacetyl and ethyl acetate). Taking into account all of these goals, eight different optimization objectives are used in the MOEA. Three of them are considered constraints, high priority objectives, which must be satisfied before optimizing the five remaining objectives (low priority objectives).

Table 1 shows the specifications of the objec-

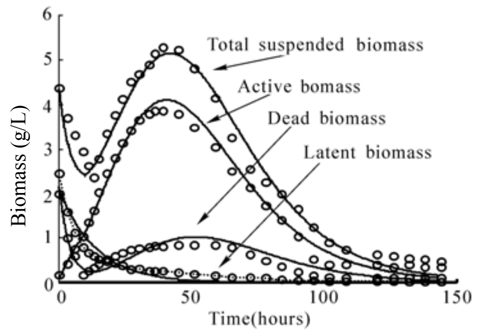

Fig.1 Total suspended latent, active, dead biomass

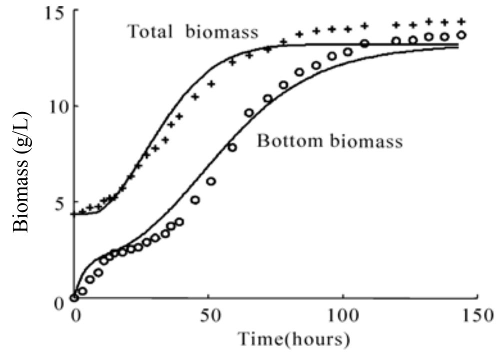

Fig.2 Total and bottom biomass (latent, active and dead)

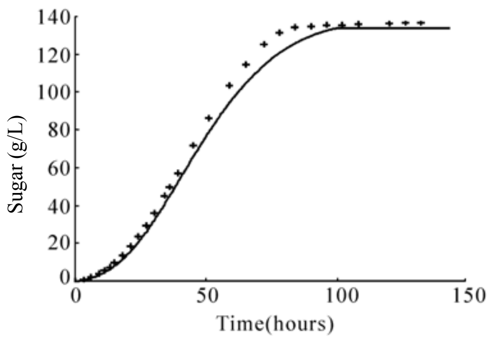

Fig.3 Consumed sugar evolution

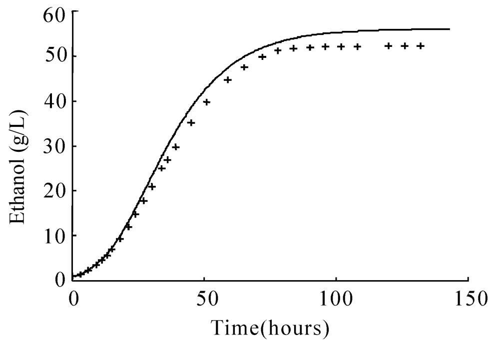

Fig.4 Ethanol evolution

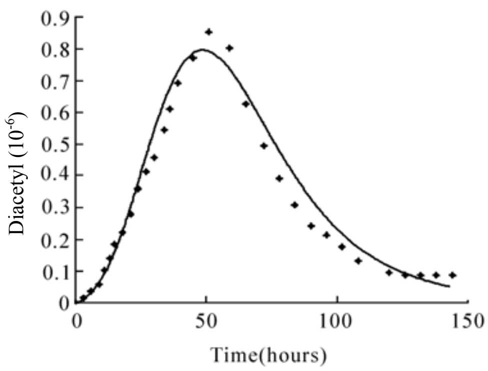

Fig.5 Diacetyl evolution

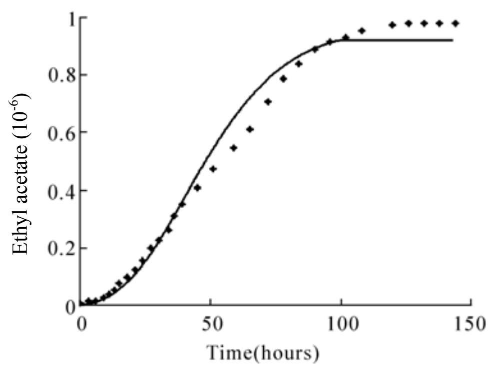

Fig.6 Ethyl acetate evolution

Table 1 Objectives of the problem

Obj	Function	Meaning	T_1	T_2	T_3
J_1	$ethanol_{end}$	Ethanol final concentration	H0	o	Q
J_2	$diacetyl_{end}$	Diacetyl final concentration	H0	u	Q
J_3	$acetate_{end}$	Acetate final concentration	H0	u	Q
J_4	$\int_0^t \mu_{LB} dt$	Spoiling Risk	S0	m	R
J_5	$\sum_{i=1}^{time} abs(T_{i+1} - T_i)$	Temperature Smoothness	S0	m	C
J_6	$\sum_{i=1}^{time} Q_i^2$	Total and Instant Heat	S0	m	C
J_7	$\max\lvert Q_{i+1} - Q_i\rvert$	Heat Smoothness	S0	m	C
J_8	*Time*	Process Time	S0	m	T

T_1 shows if the objective is considered a constraint (high priority objective H0) or a function to be optimized (low priority objective S0); T_2 if the value should be over (o) or under (u) a threshold, or minimized (m); and T_3 if it is related with the quality (Q) of the beer, the spoiling risk (R), the control (C) or the time (T)

tives and constraints. The constraint J_1 is the final ethanol concentration. Ethanol in beer must be below 0.06 kg/L. The other two constraints are the final concentrations of diacetyl (J_2) and ethyl acetate (J_3) for the final good taste and aroma. More constraints can be added (Meilgaard *et al.*, 1982); however, we considered only these ones, following the criteria of the brewery company that collaborated in this investigation project.

The first low priority objective (J_4) indicates the risk of beer spoiling by *Lactobacillus Plantarum* (one of the most important bacteria posing danger of spoilage) which increases much with temperatures over 16 ºC. Obviously, it must be minimized. This objective should be included in the above mentioned constraints although industrial conditions make it almost always satisfied.

The temperature profiles obtained based only on these four objectives were too "jagged" so industry cannot implement them. So, a new objective (J_5) for minimizing abrupt changes of temperature was added; so that, the GA was transformed into a memetic or hybrid algorithm by including hill climbing procedures to improve the smoothness of the temperature profile (Andrés *et al.*, 1998b) and (Titica *et al.*, 2000), and better profiles were obtained.

Improving the smoothness of the temperature profile (less jagged) was not the best criteria because what we were interested in was that the energy cost (heat/cold) be minimal and applicable. This condition required a smoother profile. Therefore, new low priority objectives were incorporated to improve the control, reducing the total and instant heat as much as possible (J_6) and improving its smoothness (J_7). J_6 is a square value (sum of heat, calories-frigories consumed every 0.1 hour) as it allows inclusion of the minimization of both the total and instant heat cost of the process. J_7 is the minimization of the maximum difference of heat between two successive intervals. It is used to assume uniform consumption and so to smooth the energy cost.

The last objective was that the total time of the process (J_8) must be minimized as it is important to maximise the productivity of the process.

The second column of Table 1 shows the value for the different objectives, with the last three columns indicating how the different objectives are considered during the optimization process.

MULTIOBJECTIVE EVOLUTIONARY ALGORITHM

Genetic algorithm description

Genetic Algorithms involve Artificial Intelligence technique that had been used for 30 years (Goldberg, 1989). Since then, a great number of variants have been developed for different problems (Michalewicz, 1999). For this problem, a tight linkage GA was implemented which included selection, crossover and mutation operators whose probabilities were chosen based on results obtained in previous research (Andrés *et al*., 1999a; 1999b). It was a hybrid algorithm (Moscato, 1989) that included a local search operator to improve the solutions cyclically. The population size was variable as immigrants (some new individuals created randomly every generation) are admitted. Therefore, the problem was multiobjective with several constraints (Fonseca and Fleming, 1998).

Each individual of the population represents a temperature profile as a sequence of temperature values. The simplest way to represent it was using a piecewise approximation of the temperature profile. Usually, the profile was divided into equal intervals of one hour and the temperature values at the breakpoints were registered. The sequence of numbers obtained was considered an individual and each gene represented the temperatures after an hour. In this case, every gene was a real number from 10 °C to 18 °C. An example (I) can be seen in Fig.7a.

The algorithm was developed in such a way that the size of the intervals could be used as another variable of the problem. Therefore, it was named VIM (Variable Interval Multiobjective) Algorithm. Each individual stored the information of the temperature at the breakpoints. The VIM will determine all the values and the interval size. An example (II) can be seen in Fig.7b. This special representation, very easy to implement with the Matlab tool EVOCOM (Besada *et al*., 2002), has some advantages in optimizing the beer fermentation process. Individuals created randomly are smoother than previous ones (for equal intervals of one hour). Besides, the VIM could modify the interval size and the final temperature. When the intervals are big enough, these changes smoothly modify the profile during some hours. Consequently, the VIM obtains usually smooth temperature profiles and, therefore, it is easier for the rest of the variables to be optimized.

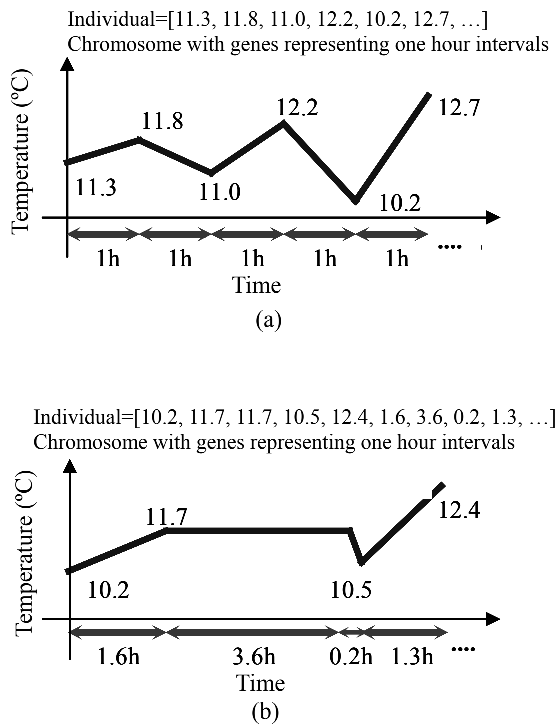

Fig.7 Individuals representations of the problem
(a) Example (I); (b) Example (II)

Multiobjective evolutionary algorithm

In multiobjective problems, all the components of the vector which stores the different objectives should be optimized simultaneously. These types of problems usually have no unique solutions. The different objectives offer a set of solutions that are equally good and applicable. This type of solution is named Pareto set of solutions, or Pareto set, in honors of Vilfredo Pareto, 19th century mathematic, who studied this kind of problem (Miettinen, 1999).

The different MOEAs presented in the literature (Coello, 2000) can be classified in two groups: aggregating functions (all the objectives are included in only one function) and non-aggregating functions. They can be classified as using or not using the Pareto set. Our problem was solved using three different MOEAs which implement non-aggregating functions based on the Pareto set, as introduced by Goldberg (1989). This technique made it easier to increase the number of objectives and avoid better the local optima. The main advantage was that the solution of the problem could be a set of several solutions considered equally good, so that the user could choose the best one for each case.

Many researchers developed different MOEAs according to Goldberg (1989)'s idea. Fonseca and Fleming (1998) proposed a multiobjective method based on goals (constraints and optimizations), priorities and Pareto sets. The objectives were ordered in different priority levels and constraints each of which could be applied. The main advantage of this method was that it could see a concave trade-off surface as convex in some cases, thus avoiding local optima. Its main drawback was that it favoured some objectives over others and so made the population converge to a particular part of the Pareto set, rather than cover it totally.

In line with the approach by Fleming and Fonseca, our MOEA considered different priority levels (Fig.8). The method had been modified, so that all the constraints that were set to the maximum priority were considered optimized once they had been achieved; and the values of the rest of the objectives were discretized into intervals. This caused two different individuals to have the same objective values and sped up the MOEA.

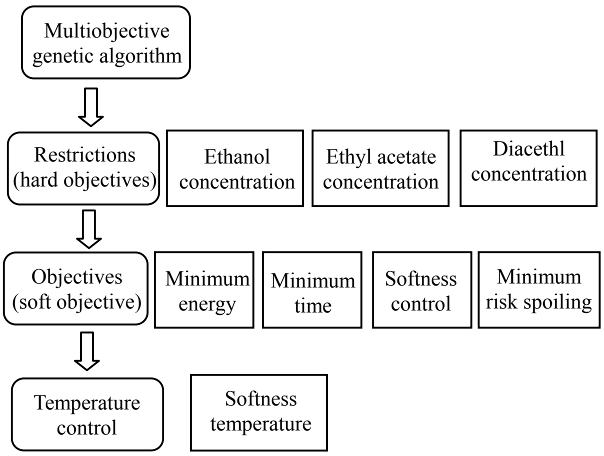

Fig.8 Beer fermentation multiobjective problem objectives

As above mentioned, in the VIM, the size of each interval was also variable for each individual. For this reason, new crossover, mutation and initialisation operators, which include knowledge about the problem, were implemented. The inclusion of different constraints could limit the feasible space of solutions. The values of the different parameters of the algorithm were selected from values in experiments developed previously (Andres *et al*., 1998b).

EXPERIMENTAL RESULTS

Fig.9 of some experimental results obtained

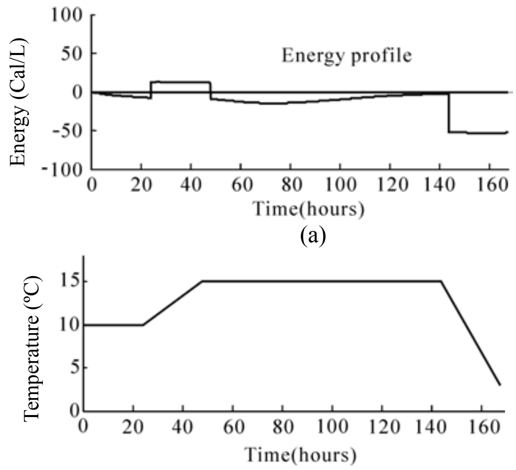

Fig.9 Industrial beer fermentation profile
(a) Energy profile; (b) Temp. profile

with the VIM shows the temperature profile that an important Spanish brewery is applying and includes the control that with our model should be applied on the energy (external heat) to obtain this energy profile. So that, we could compare the industrial profile with the obtained results for the different algorithms.

We show below the results obtained with the VIM algorithm. It is worthy note that for the three cases, all the solutions satisfied all the constraints for the problem due to the characteristics of the chosen Pareto set.

A large set of solutions was obtained, all of them were included in the Pareto set obtained with the VIM algorithm. As operators have been designed again to include knowledge acquired with the algorithms used in previous experiments, the individuals created randomly were better and easily improved by the MOEA. Therefore, the immigrants had more possibilities to be selected and included; in this way, new MOEA schemes could be designed for each generation in order to speed up the MOEA.

This algorithm vielded a set of 90 equally, good solutions from which to choose the best one for the control. Besides, depending on the requirements, the solution that optimizes only one desired objective could be selected. Another advantage of this method, which cannot be seen in the graphics, is that the number of variables for each individual is less than that if we use the conventional chromosome representation with constant intervals. For example, the best individual of a conventional MOEA could have 150 genes (one per hour), while each individual of the Pareto set which represents 150 hours, could have 60 genes (30 for temperatures and 30 for the intervals sizes).

Table 2 shows the profiles of the Pareto set with less spoiling risk, smoothest temperature profile, best control (less energy consumed and smootheer energy profile) and shorter process duration. In the last line of Table 2, industrial profile values are given. In each case, the value obtained by the VIM was better than the industrial one. However, some of these profiles made some of the rest of the values worse. Instead of choosing the best profile of each value to optimize, we can look in the Pareto set for the profile that, although not being the best optimum for one of the values, optimizes all the values of the industrial profile. In this case, it was observed that the profile with less risk optimizes also the rest of the variables. Figs.10, 11, 12 and 13 are the profiles obtained for four cases displayed in Table 2. The main difference with the industrial profile was that the energy input initially (until the 30−40 hours) was weakly heating, and only later cooling (the main part). In the industry the temperature increase is caused by the yeast metabolism, and the major energy input is initially cooling. The temperature rise is delayed until the yeast is largely converted from the lag phase into the growth phase. Fig.12 shows the profile with the best control as it simultaneously minimizes the consumption and optimizes the smoothness of the energy profile. Total fermentation time was 150 hours, Temperature and energy profiles are very smooth, so that it is easily applicable in industry. Compared with Fig.9, the energy profile is smoother than the industrial one and the total time necessary for the fermentation has been reduced and this will increase the production and reduce the energy cost.

It is possible to calculate profiles with conditions different from those in industry; for example, the profile that minimizes the total time of the process (115 hours) is shown in Fig.13. This means an improvement of 55 hours with respect to the industrial time. However, the temperature and ener-

Table 2 Experimental and industrial results for the MOEA with variable intervals

J_4	J_5	J_6	J_7	J_8	Profile
5	10.2	4.3846 e+5	20	130	Less risk
85	6.7	1.5910 e+5	10	140	Smoother temp.
45	6.8	1.4051 e+5	10	150	Better control
40	15.1	9.4131 e+5	50	115	Less hours
15	17.0	8.2238 e+5	50	170	Industrial

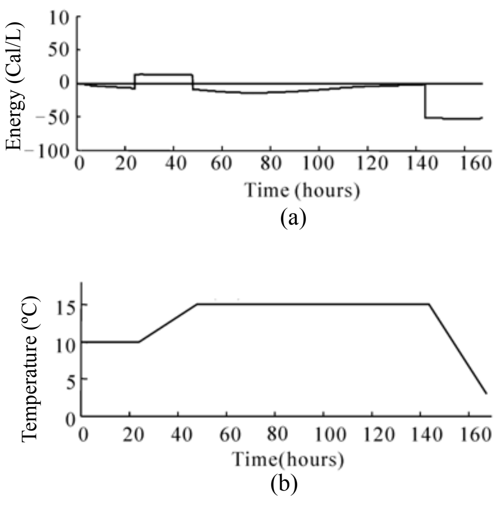

Fig.10 Energy (a) and temperature (b) profiles obtained by the VIM algorithm (less contamination risk)

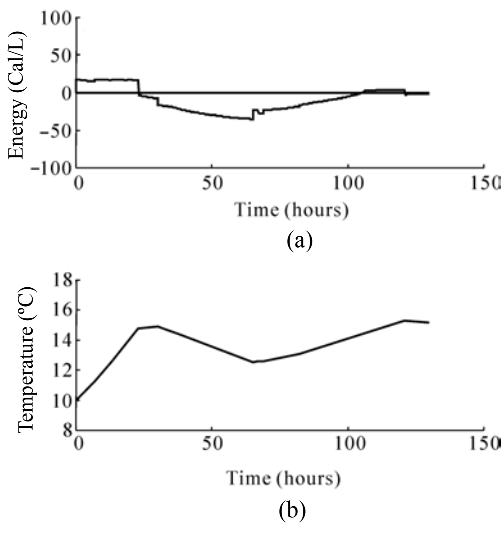

Fig.11 Energy (a) and temperature (b) profiles obtained by the VIM algorithm (smoother temperature profile)

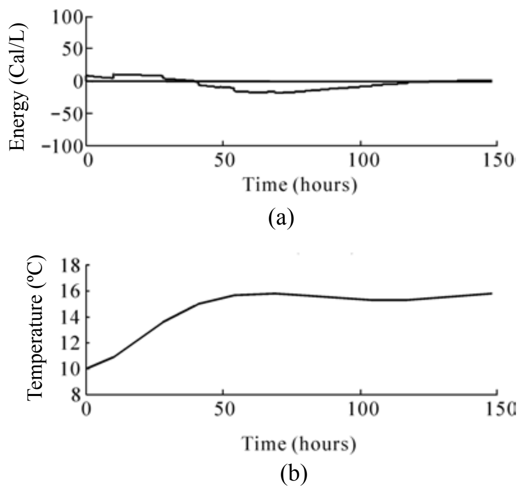

Fig.12 Energy (a) and temperature (b) profiles obtained by the VIM algorithm (better control)

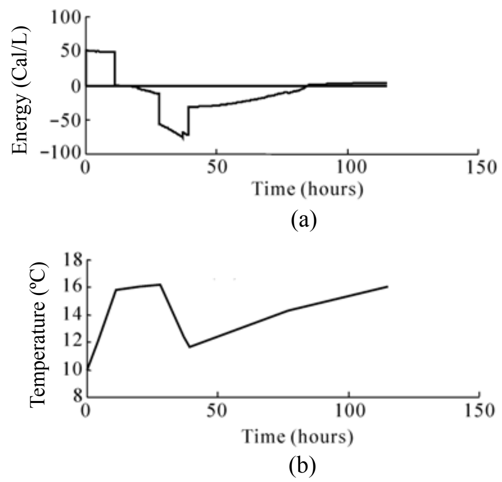

Fig.13 Energy (a) and temperature (b) profiles obtained by the VIM algorithm (less time)

gy profiles are more jagged, which will make its application more difficult. Besides, in industry, wort heating is achieved by exothermic fermentation reaction only, and this profile should require fast external temperature increase at the beginning of the fermentation.

REAL-TIME SUPERVISED CONTROL

Once we have obtained the mathematical model which represents the industrial beer fermentation process, identified its parameters and optimized the process, we can then deal with the main aim of an intelligent advanced control, AI, based on "rules" which can also identify problems, report on the possible causes and take the corresponding actions. For this supervisory function, we used a simulation that ran simultaneously with the control of the process. More detailed description can be found in (Andrés, 1996) and (Andrés *et al*., 1999a).

The control of the bioprocess: By means of an interactive dialog that we implemented, the optimal temperature profile was introduced into the computer and a real fermentation starts. The computer will manage to apply this profile on the fermentation process with the programs, we had also implemented, and to supervise that it runs just as planned.

The simulation of the bioprocess: Simultaneously with the run of the control programme, a fermentation simulation was also run and each time the actual and simulated results were compared. Therefore, there are two programmes that run at the same time: the actual control and the simulation of the process.

Correction actions: The computer or the user has to make some corrections actions depending on the deviation of the actual data from the planned data by the simulation (for example when a contamination or a device failure in the plant happens).

Programming with objects (PPO) is a method that allows creating programmes with a clear and intuitive structure. For example, by means of the objects, the same elements that take part in the processes-products and micro-organisms and even the subjects that take part in a determinate activity could be represented as units "ad hoc". We use the conventional terminology: classes and objects, messages, answers and inheritance.

Based on the "fermenter" and "tank" objects, with their thermodynamic equations, the thermal behaviour of the plant can be simulated. These objects use the properties of these other objects "water", "wort", "mass" (biomass). The object "control" runs the desired temperature profile, activating the heating simulated circuit. The object "coordinator" is responsible for the interrelation among the objects at the same pace of the actual process which is being supervised.

All the objects are included as a unit that interacts with other units. The object "judge" is very important, because with its knowledge of the rules, it can judge if the trajectory follows that of the actual fermentation, comparing it with the simulated fermentation (which is the reference); and judge if the fermentation is running well or has problems. In the case of problems, the "judge" uses other models to simulate and check which one is the most similar to the actual one (for example, contamination risk and failures in the plant are foreseen). According to this analysis task, the "judge" issues warnings to the operator or intervenes in the case it is necessary.

Each knowledge rule has an IF that activates a CAUSE which explains the reason why it has done it and an ACTION which runs the control action or notifies the operator of the system. An example, using pseudo-code:

If any sensor does not indicate values inside the established limits (pH, pressure, T, etc.)

CAUSE they fail, they are not switched on, data register card fails, electronic interface is switched off or fails, or other causes.

ACTION repairs them, switch them on, review cards, review auxiliary electronic interface, look for the cause and introduce it in the rules tree.

The rules can be divided in two main types: rules concerning failures in the plant, sensors, etc. (total of 39) and rules concerning failures in the fermentation process (total of 152). By means of an alarms display, the user can know the causes of the failures and correct them as soon as possible.

For example, if a failure in the cooling circuit will increase the temperature, then the system will detect this problem, and this session will appear independently of the place of the environment in which is the user, and it will indicate graphically a message with the actions that are taken or should be taken. Failure correction in real-time is only possible in some cases. Obviously, there are cases, as the breakdown of the pump, where the only possibility is to notify the user to repair it as soon as possible.

CONCLUSION

In this paper, a research based on experiments is described for the modulation, optimization and supervisory control of beer fermentation under industrial conditions. The work includes several practical tasks such as the design and implementation of laboratory systems, the development of programmes, and the theoretica aspects of the modulation and of the multiobjective optimization. All the items used for this work are in service and can be used for other later researches. Particularly, we are now interested in considering energy and automation technology matters to be applied in the fermentation industry.

It was very interesting and positive to join an interdisciplinary team of researchers to carry out this work.

Taking into account how important is the optimization of the process for the beer industry, in this paper we describe a method based on Evolutionary AI to deal with the multiobjective optimization dynamic problem of the fermentation. The proposed solution is based on the optimal Pareto set of solutions approach. Besides, it uses a representation of the chromosome in which each gene can represent a variable interval of time. For this reason, it has been named VIM (Variable Interval Multiobjective) algorithm. By applying this concept, the temperature profiles obtained have achieved the objectives proposed at the beginning of the research. We were not interested in being too obsessed with the number and importance of these profiles. It is only an example of what can be done. Each industry establishes its conditions and priorities. The process we studied was the beer fermentation although this method can be applied to many other control problems.

The main advantage of the MOEAs is their versatility for including a variety of objectives and constraints. The VIM optimal set lets users select among different solutions, all equally good for VIM, according to some final requirements. In this particular case, several solutions were obtained that improve the heat waste, reduce the total processing time for the fermentation and smooth the temperature profile and control.

References

Andrés Toro, B. De, 1996. Modelización, Optimizacióny Control de Un Proceso Cervecero Industrial. PhD., Univ. Complutense de Madrid, Spain.

Andrés Toro, B. De, Cámara Hurtado, M., Díez Marqués, C., Fernández Conde, C., Girón Sierra, J.M., Torija Isasa,

M.T., 1997. Evolución del contenido de azúcares durante la fermentación cervecera industrial. *Alimentación, equiposy tecnología*, **4**:59-71.
Andrés Toro, B. De, Girón-Sierra, J.M., López Orozco, J.A., Peinado, J.M., García Ochoa, F., 1998a. A kinetic model for beer fermentation under industrial operational conditions. *Mathematics and Computer Simulation*, **48**:65-74.
Andrés Toro, B. De, Girón-Sierra, J.M., López Orozco, J.A., Fernández Conde, C., Fernández Blanco, P., 1998b. A Fast Genetic Optimization for Batch Fermentation Processes. Proc. 7th Intl. Conf. on Computer Applications in Biotechnology CAB7, IFAC, Osaka, Japan, p.61-66.
Andrés Toro, B. De, Girón-Sierra, J.M., Torija Isasa, M.T. and Cámara Hurtado, M., 1999a. Modelizacióny Control de la fermentación industrial de la Cerveza. Estudio experimental. *Alimentación, Equiposy Tecnología*, **4**:93-99.
Andrés Toro, B. De, Girón-Sierra, J.M., López Orozco, J.A., Fernández Blanco, P., 1999b. A Genetic Optimization Method for Dynamic Processes. The 14th World Congress IFAC, Pergamon Ed., Beijing, China.
Bastin, G., Dochain, D., 1986. On-line Estimation of microbial specific growth rates. *Automatica*, **22**(6): 705-709.
Bastin, G., Dochain, D., 1990. On-line Estimation and Adaptative Control of Bioreactors. Elsevier, Amsterdam.
Besada Portas, E., López Orozco, J.A., Andrés Toro, B. De, 2002. A Versatile Toolbox for Solving Industrial Problems with Several Evolutionary Techniques. *In*: Evolutionary Methods for Design, Optimization and Control, Ed. International Centre for Numerical Methods in Engineering (CIMNE), Barcelona, Spain.
Carrillo, G.E., 1999. Optimal Control of Fermentation Process. PhD, Control Engineering Research Centre, London.
Cheruy, A., 2000. Control du Profil Arôme de la Bière Lors de la Fermentation Alcoolique. PhD, Laboratoire d'Automatique de Grenoble.
Coello, C.A., 2000. An updated survey of GA-based multiobjective optimization techniques. *ACM Computing Surveys*, **32**:109-143.
Dochain, D., Bastin, G., 1984. Adaptive identification and control algorithms for nonlinear bacterial growth systems. *Automatica*, **20**(5):621-634.
Engasser, J.M., Marc, I., Moll, M., Duteurtre, B., 1981. Proceedings EBC Congress, p.579-583.
Fonseca, C.M., Fleming, P.J., 1998. Multiobjective Optimization and Multiple Constraint Handling with Evolutionary Algorithm−Part I: Unified Formulation. *In*: IEEE Transactions on Systems, Man, and Cybernetics. Part A: Systems and Humans, **28**(1):3-18.
Gauthier, J.P., Hammouri, H., Othman, S., 1992. A simple observer for nonlinear systems: applications to Bioreactors. *IEEE T. Autom. Control*, **37**(6):875-880.
Gee, D.A., Ramírez, F.W., 1988. Optimal temperature control for batch beer fermentation. *Biotech. and Bioeng.*, **31**:224-234.
Gee, D.A., Ramírez, F.W., 1994. A flavour model for beer fermentation. *J. Ins. Brewing*, **100**:321-329.
Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley Publishing Co., Inc., Redwood City, Ca.
Hough, J.S., Briggs, D.E., Stevens, R., 1971. Malting and Brewing Science. Chapman & Hall.
Johnson, A., 1987. The control of fed-batch fermentation processes−a survey. *Automatica*, **23**(6):691-705.
Knowles, J.D., Corne, D.W., 2000. Approximating the nondominated front using the pareto archived evolution strategy. *IEEE Evolutionary Computation*, **8**(2):149-172.
Meilgaard, M.C., Reid, D.S., Wyborski, K.A., 1982. Reference Standards for beer flavor terminology systems. *Journal of American Society of Brewing Chemist*, **40**: 119-128.
Michalewicz, Z., 1999. Genetic Algoritm + Data Structures = Evolution Programs. Springer-Verlag, Berlin.
Miettinen, K.M., 1999. Nonlinear Multiobjective Optimization. Academic Publishers, Kluwer.
Moscato, P., 1989. On Evolution, Search, Optimization, Genetic Algorithms and Material Arts: towards Memetic Algorithms. *In*: Technical Report Computation Program. Californian Institute of Technology, U.S.A.
Park, S., Ramirez, W.F., 1988. Optimal production of secreted protein in fed-batch reactors. *AIChE Journal*, **34**:1550-1558.
Sonnleitner, B., Kappeli, O., 1986. Growth of saccharomyces cerevisiae is controlled by its limited respiratory capacity: formulation and verification of a hypothesis. *Biotech. Bioeng.*, **28**:927-937.
Steinmeyer, D.E., Shuler, M.L., 1989. Structured model for saccharomyces cerevisiae. *Chem. Eng. Sci.*, **44**(9): 2017-2030.
Steyer, J.P., Queinnec, I., Simoes, D., 1993. Biotech: a real-time application of artificial intelligence for fermentation processes. *Control Eng. Practice*, **1**(2): 315-321.
Tenney, R.I., 1985. Rationale of the brewery fermentation. *J. Am. Soc. Brew. Chem.*, **43**:57-60.
Titica, M., Landau, S., Trelea, I.C., Latrille, E., Corrieu, G., Cheruy, A., 2000. Kinetics of aroma production in beer batch fermentation: Simulation and sensitivity to the operating conditions. *J. Am. Soc. Brew. Chem.*, **58**(4): 167-174.
Trelea, I.C., Latrille, E., Landau, S., Corrieu, G., 2001a. Reliable estimation of the key variables. *Bioprocess Biosystems Engineering*, **24**:227-237.
Trelea, I.C., Titica, M., Landau, S., Latrille, E., Corrieu G., Cheruy, A., 2001b. A predictive modelling of brewing fermentation: from knowledge-based to black-box models. *Mathematics and Computers in Simulation*, **56**: 405-424.
Trelea, I.C., Latrille, E., Landau S., Corrieu, G., 2002. Prediction of confidence limits for diacetyl concentration during beer fermentation. *J. Am. Soc. Brew. Chem.*, **60**:77-87.