USING GENETIC ALGORITHMS FOR DYNAMIC OPTIMIZATION: AN INDUSTRIAL FERMENTATION CASE

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ABSTRACT

The research deals with the dynamic optimization of the beer batch fermentation, getting a temperature profile to drive the process along an optimal trajectory. We discretize the temperature profiles in form of chromosomes, and genetic algorithms are applied to search for the best solution. An objective function is established, and employed as fitting function along the evolutionary optimization. Satisfactory results are obtained, requiring not much computation effort, and getting a fine discretization of the solution.

THE BATCH FERMENTATION PROCESS

Batch fermentation processes play a fundamental role in many and important industrial activities. Frequently these processes exhibit complex characteristics that ask for the application of control advanced techniques. We selected beer fermentation [1] because it is a representative case, that we can study, experimentally, in our laboratory. Our objective is the optimization of the process, on the basis of real-time computer control. Due to evident economic reasons, the industrial desire is to accelerate the process, without sacrificing quality.

During fermentation, sugars are converted to ethanol. The only intervention on the batch fermentation process permitted by law is the temperature control. Temperature has an important effect: at 8 ºC. the fermentation takes 12 days, but at 24 ºC it takes 3 days (loosing some ethanol efficiency). Experts say that above 15 ºC there is a serious risk of spoilage; risk that multiplies by ten for each 1 ºC increase. In addition to ethanol, and depending of temperature, some byproducts are originated: in particular, diacetyl and ethyl acetate. They must have concentrations no surpassing certain limits, for they have undesirable effects on flavor and aroma. The brewery uses a specific temperature profile to drive the process.

RESEARCH OBJECTIVES AND PHASES

We want to find a temperature profile that accelerates the fermentation and obtains good ethanol efficiency, with no spoilage risks, and without breaking concentration limits of diacetyl and ethyl acetate. This is a multiobjective (time and production) dynamic optimization problem, that requires a solution in terms of an optimal process trajectory, imposed by a certain temperature profile.

After an extensive experimental study, we got an adequate mathematical model of the process: a set of differential equations, with coefficients that depend exponentially on temperature [2]. The equations describe the evolution, during the fermentation process, of sugars, yeast, ethanol, diacetyl, and ethyl acetate concentrations.

Then, we specified the optimization problem and studied how to solve it. After several trials, we found a feasible way by using genetic algorithms. We devised a simple scheme: taking the time invested by industry for the fermentation (about 150 hours), we get a temperature profile that obtains a maximum ethanol production and obeys to the byproducts and spoilage risk constraints. Then, fermentation time is shortened, and we find a new optimal temperature profile. This is repeated, until the optimal profile fails to offer satisfactory beer quality. The key of this strategy is a quick calculation of the optimal profiles.

OBTAINING THE OPTIMAL PROFILES

To apply genetic algorithms [3][4], we need to establish the optimization problem in terms of chromosomes. We consider a piecewise approximation of the temperature profiles, by a series of breakpoints and straight segments (figure 1). With this approach, we can describe any profile by a string of numbers (temperatures at the breakpoints), forming a chromosome. We use integer numbers between 8 ºC and 18 ºC (note that we do not use a binary representation, but directly integer numbers). The breakpoints are regularly spaced, every 1 hour.

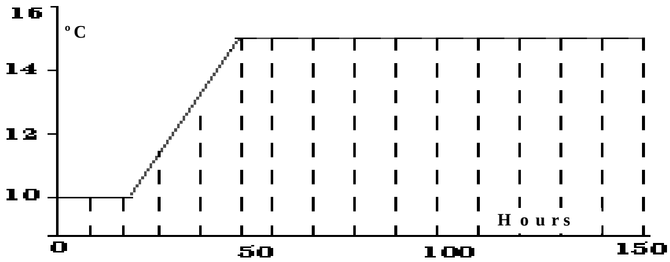

Figure 1: Discretization of a temperature profile

Cromosome = {10, 10, 11, 12, 13, ...}

During the evolution process, the chromosomes are evaluated with a fitting function, to select the individuals to be substituted by the new generations. We employ as fitting function, the value of the objective function to be optimized. This function (to be maximized) is specified as the addition of four terms. The first corresponds to the ethanol concentration obtained at the end of fermentation, and is positive. The others are negative, and correspond to diacetyl and ethyl acetate final concentrations, and to a measure of the spoilage risk along the trajectory followed by the process. We employed exponentials to penalize limit surpassings. Weighting factors are included to make the four terms comparable.

$$J = +10 \cdot \text{ethanol}_{\text{end}} - \int_0^t \mu_{LB}.dt -$$
$$-1'16..e^{(460 \cdot \text{acetate} - 66.77)} - 5.73.e^{(95 \cdot \text{diacetyl} - 11.51)}$$

An initial population of 1200 chromosomes was created at random. Each new generation originates 400 new chromosomes, and substitutes the worst 400 old ones. Parent selection is made by roulette-wheel. The crossover probability is 0.8, and the mutation probability is 0.008 (as recommended by literature). Taking the best chromosome of each new generation, and plotting the value of its fitting function, we obtain the figure 2, that shows how the evolution tends to an optimal value.

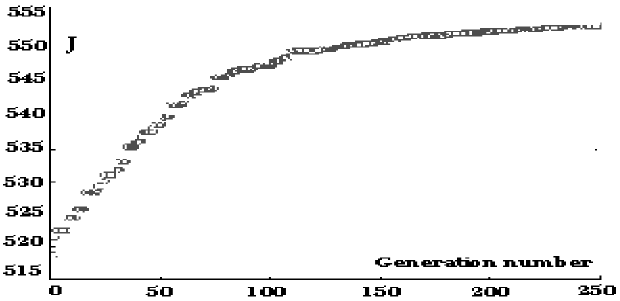

Figure 2: Evolution of J (best chromosomes)

The evaluation of each chromosome is made by running a complete simulation of the fermentation process, to see the effects of the temperature profile described by the chromosome. The simulation must be fast, because many chromosomes need to be evaluated. Figure 3 shows an optimal profile (after 250 generations) that can shorten the process, from 150 hours to 130 hours.

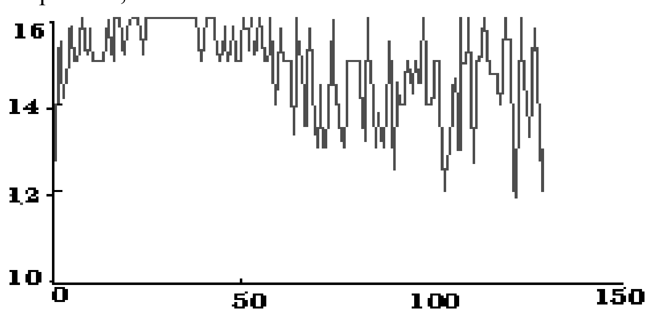

Figure 3: Optimal temperature profile obtained by GA

FURTHER REFINEMENTS

Clearly, a smoother solution is needed for real application, so we add to the objective function a new factor that penalizes brisk changes of temperature:

$$-\sum_{i=1}^{130} \frac{T_{i+1} - T_i}{\Delta t}$$

In addition, we systematically studied different algorithm changes, to obtain a faster version. The conclusion is that is better to start with an initial population of 600 individuals, and to substitute 350 in each generation. Also, it is better to use double-point crossover. With the new objective function, and the changes in the algorithm, we obtain the optimal profile of figure 4, that can easily be smoothed by a simple local optimization algorithm:

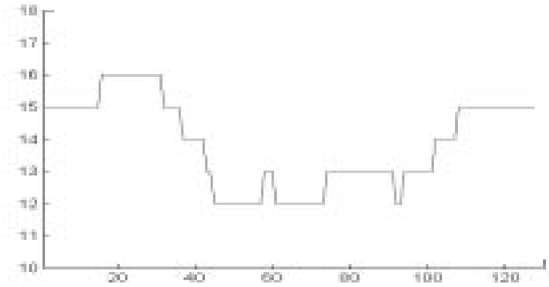

Figure 4: Optimal temperature profile with the new J

CONCLUSIONS

The application of genetic algorithms to our optimization problem showed quick and satisfactory results. With MATLAB it is easy to develop the code. We think that it is interesting a fast calculation of the optimal profile, to cope with changes in the initial conditions of wort and yeast: taking advantage of the MATLAB facilities, we parallelized the code, to obtain results in less than 2 hours on a 100 Mz. Pentium PC. Our research continues considering other relevant aspects for the industrial implant (economic and energetic factors, experimental tests, instrumentation, etc.) of a new temperature profile.

Acknowledgment: The authors wish to acknowledge support of this work by the Multidisciplinar Research Projects of the University Complutense of Madrid, ref. PR160/93#. We also thank the Cruzcampo's brewery for its collaboration.

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