Temperature Profile in Fermenting Process using Differential Evolution

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Abstract: It is regularly to optimization of temperature and feeding profiles in batch process for several objectives and constraints. A temperature profile is applied to drive the process so as to obey certain constraints during the beer fermentation. The design of this temperature profile is an optimization problem where the objective is to minimize the operation time and optimize the quality of beer. In this paper, differential evolutionary computation is exploited to efficiency handle such problems. The proposed approach has been implemented and practical to design temperature profile for beer fermentation process. The results show that differential evolution is a proficient and at ease method to incorporate the prior knowledge of the user into the temperature profile optimization of batch processes.

Key-Words: Optimization, Fermentation, Brewery, Differential Evolution

1 Introduction
We are interested in applied control problems, requiring the use of advanced computer-based methods. Beer fermentations are good candidates for two reasons: the complexity of the biological phenomena taking place, and the dynamic nature of the process. Fermentations are the basis of many important industrial activities. Both for modeling and testing purposes, we selected the conventional beer fermentation, as a representative example that can be experimentally studied at laboratory scale with a moderate equipment effort. The results obtained in this way, can be useful for many other fermentation processes.

In order to decide a suitable parameter of the extrusion process, optimum design methods that combine the optimization algorithm with the computer simulation have been reported [1-2]. By the way, Evolutionary Algorithms (EAs) such as Genetic Algorithm (GA) are practical optimization algorithms and applied to various optimum design problems effectively. Therefore, GAs have been also applied to the optimum design problem of extrusion process. In some previous paper, a recent EA called Differential Evolution (DE) was applied to the optimum design problem of a balanced SAW filters [3-4].

2. Differential Evolution
DE is a very simple population based, stochastic function minimizer which is very powerful at the same time. DE managed to finish 3rd at the First International Contest on Evolutionary Computation (1stICEO) which was held in Nagoya, may 1996. DE turned out to be the best genetic type of algorithm for solving the real-valued test function suite of the 1st ICEO (the first two places were given to non-GA type algorithms which are not universally applicable but solved the test-problems faster than DE). The crucial idea behind DE is a scheme for generating trial parameter vectors. Basically, DE adds the weighted difference between two population vectors to a third vector. This way no separate probability distribution has to be used which makes the scheme completely self-organizing.
3. Description of the process

Batch processes play an important role in brewery industry (fig. 2). During batch-and fed-batch operation of bioreactors the system states change considerably. As a consequence of the varying process states, the best operation results can be realized by varying the input variables along optimal trajectories during the operation time. This explains why searching for efficient methods for calculating the optimal trajectories has been an important issue for bioreactor control. Several methods have been discussed in literature: e.g. first-order gradient method and dynamic programming [5]. During the beer fermentation a temperature profile is applied to drive the process so as to obey to certain constraints. The design of this temperature profile is an optimization problem where the objective is to minimize the operation time and optimize the quality of the beer. These objectives are frequently in conflict with one another. Trade-offs exist between some objectives, where advantage in one objective will cause deterioration in another. These multi-objective optimization problems involve the simultaneous consideration of multiple performance criteria that should be defined prior to the optimization procedure. This requires in-depth information concerning the various trade-offs and valuation of each individual objective. Such detailed model-based multi-criteria optimization of the temperature profile of beer fermentation is discussed in several articles [5, 7-8].
4. Mathematical Model
In fermentation, an accurate mathematical model is indispensable for the control, optimization and the simulation of a process. Models used for on-line control and those used for simulation will not generally be the same (even if they pertain to the same process) because they are used for different purposes; no model could be a reconstruction of the process rather it is intended to serve as a set of operators on the identified set of inputs, producing similar outputs as expected from the process.

The problem is that the process output is usually contaminated with noise and other disturbances, whereas ideally the model should follow the true output of the underlying representative process, which is unknown. Genetic algorithms, if properly chosen, yield the parameter values after processing of data coming from measurements on the system. Application to Model based Optimization of Beer Fermentation

The performance of the proposed differential evolution technique is illustrated in the model-based temperature profile optimization of beer fermentation.

4.1 Process Description
In this paper a kinetic model [6] has been used to estimate the effect of the temperature profiles. This model has been developed from experimental data and shows good results in the aspect of a realistic view of the fermentation process. The model takes into account seven components: three components of the biomass (latent, active, dead), ethanol and sugar, and two important byproducts: ethyl acetate and diacetyl. The model equations and parameters are taken [7]. Most of the process parameters vary as arrhenius function of temperature, expect diacetyl appearance and disappearance rate which are constant values.

\[
\frac{dx_{\text{lag}}}{dt} = -\mu_{\text{lag}} x_{\text{lag}} \\
\frac{dx_{\text{active}}}{dt} = -\mu_{s} x_{\text{active}} - k_{m} x_{\text{active}} + \mu_{\text{lag}} x_{\text{lag}} \\
\frac{dx_{\text{bottom}}}{dt} = k_{m} x_{\text{active}} - \mu_{s} x_{\text{bottom}} \\
\frac{ds}{dt} = -\mu_{s} x_{\text{active}}
\]

Fig.2 Brewery process description.
(www.tewsbrewery.com/images/the-brewing-process.jpg)
The reaction rates:

\[ \mu_x = \frac{\mu_{a0} s}{0.5s_x + e}, \quad \mu_D = \frac{0.5s_x}{0.5s_x + e} \]

\[ \mu_s = \frac{\mu_{a0} s}{ks + s}, \quad \mu_a = \frac{\mu_{a0} s}{ks + s} \]

\[ f = 1 - \frac{e}{0.5s_x} \]

The parameters:

\[ \mu_{x0} = e^{-11654.64 T + 273.15}, \quad \mu_{s0} = e^{-41.92 T + 273.15} \]

\[ \mu_{DO} = e^{1267.24 T + 273.15}, \quad \mu_{a0} = e^{3.27 T + 273.15} \]

\[ \mu_{tas} = e^{-9501.54 T + 273.15}, \quad \mu_{lag} = e^{-30.72 T + 273.15} \]

\[ k_m = e^{-34203.95 T + 273.15}, \quad k_s = e^{-119.63 T + 273.15} \]

\[ k_{dc} = 0.000127672, \quad k_{dm} = 0.00113864 \]

The initial values:

\[ x_{lag,j} = 0.08, \quad x_{bottom,j} = 2, \quad s_i = 130, \quad e_i = 0, \]

\[ (acet)_i = 0, \quad (diac)_i = 0. \]

When the parameters used as the following:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_a )</td>
<td>Ethanol production rate</td>
<td>( h^{-1} )</td>
</tr>
<tr>
<td>( \mu_D )</td>
<td>Specific yeast setting rate</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( \mu_{tas} )</td>
<td>Ethyl acetate coefficient rate</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( \mu_{lag} )</td>
<td>Specific rate of latent formation</td>
<td>( h^{-1} )</td>
</tr>
<tr>
<td>( \mu_s )</td>
<td>Substrate consumption rate</td>
<td>( h^{-1} )</td>
</tr>
<tr>
<td>( \mu_x )</td>
<td>Specific yeast growth rate</td>
<td>( h^{-1} )</td>
</tr>
<tr>
<td>( acs )</td>
<td>Ethyl acetate concentration</td>
<td>( ppm )</td>
</tr>
<tr>
<td>( diac )</td>
<td>Diacetyl concentration</td>
<td>( ppm )</td>
</tr>
<tr>
<td>( f )</td>
<td>Fermentation inhibition factor</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( k_{dc} )</td>
<td>Diacetyl appearance rate</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( k_{dm} )</td>
<td>Diacetyl reduction rate</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( k_{vy} )</td>
<td>Yeast growth inhibition</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( k_s )</td>
<td>Sugar inhibition parameter</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( s )</td>
<td>Concentration of sugar</td>
<td>( g/l )</td>
</tr>
<tr>
<td>( s_0 )</td>
<td>Initial concentration of sugar</td>
<td>( g/l )</td>
</tr>
</tbody>
</table>

5. Result and Discussion

The multi-objective optimization problem and task is to find a good temperature profile which result in a high ethanol, low sugar and ethyl acetate concentrations, a very low diacetyl and biomass concentrations, and a smooth temperature profile, and short operation time. In this case study, from applying the differential evolution, the results demonstrate that the final ethanol level is smaller, the ethyl acetate and diacetye concentrations are lower, and the biomass and sugar concentration has been decreased also (fig 3-6).
Fig. 5 Byproducts behavior.

Fig. 6 Ethanol and sugar concentration.

6. Conclusion
This paper illustrates the differential evolution to be suitable in optimization of batch fermentation process. The differential evolution applied here appears to be a flexible representation of the model that was easy to interface with the differential evolution algorithm. In addition, a cost-value function has been obtained by means of the differential evolution algorithm for the optimization of the beer process. Also a softer profile by parameterising and calculating average temperatures made results suitable for implementation.

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References: