Differential Evolution Application in Temperature Profile of Fermenting Process

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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.
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Key-Words: Optimization, Fermentation, Brewery, Differential Evolution, Temperature profile

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, a**s** 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 has been also applied to the optimum design problem of extrusion process. B. Andres-Toro,and others [3] illustrated that batch fermentations are dynamic processes that must be guided along convenient paths to obtain the desired results. Their research deals with the application of computers for advanced control of such processes and selected beer fermentation, and started to investigate whether it is possible to optimize the process, taking as reference to be improved a real industrial fermentation. In their paper they describe the process, the new model, the optimization problem, and the solution by Genetic Algorithms.

Conor and others (2002) integrated fuzzy logic into the fermentation process in a brewery involving a local commercial brewery, Beamish and Crawford Brewery plc in Cork, Ireland. Their approach consists of developing a control system for a fermentation process using fuzzy logic in two stages. In the first stage the software package *fuzzy*Tech from Inform provided the fuzzy logic controller, and in the second stage In touch from wonder ware provided the user front-end. The results of the new controller and the fault detection system show a clear alternative over the conventional controller (PID). Optimization of the fermentation vessel is run simultaneously with this project. The main idea is based on examining the various input parameters that influence the fermentation process. These parameters include temperature, pressure, fermentation duration and yeast count. Then the quality or output parameters are identified. These include alcohol content, present gravity, pH, colors and bitters. A model based on fuzzy logic was developed to establish the inter-relationships between these factors and how they affect the output quality factors. The ultimate objective is to integrate this fuzzy logic model into the fermentation process control system [4, 20-25].

Most of ester compounds found in beer are produced by yeast during fermentation. They contribute significantly to beer flavour. Therefore, the control of their formation is very important to maintain consistent quality of the product. Riverol and Cooney (2007) analyzed the influences of fermentation temperature and dissolved oxygen content in the production of ethyl acetate and isoamyl acetate using a comparative studied between kinetic methods and neural networks. The results confirmed that the production of ester and isoamyl acetate can be expressed as a function of the ethanol formation, however the isoamyl acetate production is independent of the temperature of the fermenter. The neural networks allowed obtaining a good prediction of ester's production without to use complex model (kinetic analysis) [5, 17-19].

In some previous paper, a recent EA called Differential Evolution (DE) was applied to the optimum design problem of a balanced SAW filters [6-7].

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.

DE is an improved version of Genetic Algorithms (GA) [Deb, (1996)] for faster optimization. DE uses real coding of floating point numbers. Among the DE is advantages are its simple structure, ease of use, speed and robustness. Price and Storn [8] gave the working principle of DE with single strategy. Later on, they suggested ten different strategies of DE. The strategy to be adopted for a problem is to be determined by trial and error. The key parameters of control are: NP - the population size, CR - the cross over constant, F - the weight applied to random differential (scaling factor).

Evolutionary Algorithm

Differential evolution (DE) is the stochastic, population-based optimization algorithm. It was introduced by Storn and Price in 1996 [1,2]. It was developed to optimize real (float) parameters of a real valued function. The general problem formulation is: for an objective function

$$f(\bar{x}) = f(x_1, ..., x_D) \tag{1}$$

defined in the region

$$L_n \leq x_n \leq U_n \tag{2}$$

the minimization problem is to find $\vec{x}^*$ such that

$$f(\vec{x}^*) \leq f(\vec{x}) \tag{3}$$

for any $\vec{x}$ in the region (2).

Evolutionary Algorithms

DE is an Evolutionary Algorithm (EA) or Genetic Algorithm (GA) [3, 4]. The parameter vector $\vec{x}$ is called an individual (or chromosome, or genome). The objective function is also called the fitness function. The general scheme is the same for all EAs:

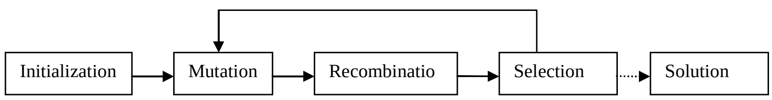

Fig. 1 Differential Evolution Scheme.

- Initialization - creation of a population of individuals
- Mutation (and migration in multi-population

versions) - random change of the vector $\vec{x}$ components (genes). It can be a single-point mutation, inversion, translocation, deletion, etc.

- Recombination (Crossover) - merging the genetic information of two or more parent individuals for producing one or more descendants
- Selection - choice of the best individuals for the next cycle.

One cycle in the above scheme is called a generation. The solution is found if some stopping criterion is met.

Differential evolution

The canonical EA-GA work with the strings of bits or integers (letters). Evolution strategy (ES) and Differential evolution both work with vectors of real numbers as representations of solutions. The ES typically uses adaptive mutation rates for the vectors themselves, but DE uses mutations of the differences of the parameter vectors.

Algorithm

Definition: x_i^{-g} are the parameters for the individual i (i = 1, . . . , P) in the generation g (g = 1, . . . , G max)

Mutation:

i, a,b, c are mutually different indexes of individuals

x_i^{-g} is the target vector

$\vec{d}_i = \vec{x}_a^{g} + F(\vec{x}_b^{g} - \vec{x}_c^{g})$ is the donor vector

F is the scaling (weighting) factor

Recombination:

construct a trial vector

$$t_{n,i} = \begin{cases} d_{n,i} \\ X_{n,i}^{g} \end{cases}$$

rand < CR or n = rand (D) + 1

otherwise

C_r is the crossover

Here rand generates the random numbers in the interval [0, 1) and rand (D) generates integer numbers in the interval 0, 1, . . ., D -1.

Selection:

$$\vec{x}_i^{g+1} = \begin{cases} \vec{t}_i \\ \vec{x}_i^{g} & f(\vec{t}_i)\langle \vec{x}_i^{g} \end{cases}$$

Otherwise

Variants of mutation:

$$\vec{d}_i = \vec{x}_a^{g} + F(\vec{x}_b^{g} - \vec{x}_c^{g}) \tag{4}$$

$$\vec{d}_i = \vec{x}_a^{g} + K(\vec{x}_{best}^{g} - \vec{x}_i^{g}) + F(\vec{x}_b^{g} - \vec{x}_c^{g}) \tag{5}$$

$$\vec{d}_i = \vec{x}_i^{g} + K(\vec{x}_a^{g} - \vec{x}_i^{g}) + F(\vec{x}_b^{g} - \vec{x}_c^{g}) \tag{6}$$

Here K is the combination factor. For K = 1 Eq. (6) reduces to Eq. (4). Eq.(5) has the following limits:

$$\vec{d}_i = \vec{x}_{best}^{g} + F(\vec{x}_b^{g} - \vec{x}_c^{g}) K = 1 \tag{7A}$$

$$\vec{d}_i = \vec{x}_i^{g} + F(\vec{x}_b^{g} - \vec{x}_c^{g}) K = 0 \tag{7B}$$

Acceleration

In the case when the mutation and crossover operations do not further improve the best fitness a steepest descent method is applied to push the best individual towards a better point:

$$\vec{x}_{best}^{new} = x_{best} - \rho \vec{\nabla} f(\vec{x})\Big|_{x_{best}}$$

The gradient can be estimated numerically.

Recommendations

All control constants are problem-specific. According to [1], typical values for the weighting factor F = 0.8 and for the crossover constant CR = 0.9. In general, they both should be chosen from the interval [0.5,1]. In [6] it is recommended to choose CF from the interval [0,1] with typical value CR = 0.8. The value for K should be chosen around 0.5. It is also reported that the random choice of F from the interval [0,2] gives a good result.

The overall structure of the DE algorithm resembles that of most other population based searches. The parallel version of DE maintains two arrays, each of which holds a population of NP, D-dimensional, real valued vectors. The primary array holds the current vector population, while the secondary array accumulates vectors that are selected for the next generation. In each generation, NP competitions are held to determine the composition of the next generation. Every pair of vectors (X_a, X_b) defines a vector differential: X_a - X_b. When X_a and X_b are chosen randomly, their weighted differential is used to perturb another randomly chosen vector X_c. This process can be mathematically written as $X_{ic} = X_c + F (X_a - X_b)$. The scaling factor F is a user supplied constant in the range ($0 < F \leq 1.2$). The optimal value of F for most of the functions lies in the range of 0.4 to 1.0 (Price and Storn, 1997). Then in every generation, each primary array vector, X_i is targeted for crossover with a vector like X'_c to produce a trial vector X_t. Thus the trial vector is the child of two parents, a noisy random vector and the target vector against which it must complete. The non-uniform crossover is used with a crossover constant CR, in the range $0 \leq CR \leq 1$. CR actually represents the probability that the child vector inherits the parameter values from the noisy random vector. When CR = 1 for example every trial vector parameter is certain to come from X' c. If, on the other hand, CR=0, all but one trial vector parameter comes from the target vector. To ensure that X_t differs from Xi by at least one parameter, the final trial vector parameter always comes from the noisy random vector, even when CR=0. Then the cost of the trial vector is compared with that of the target vector, and the vector that has the lowest cost of the two would survive for the next generation. In, all just three factors control evolution under DE, the population size, NP; the weight applied to the random differential, F; and the crossover constant, CR. The pseudo-code for DE is given in the fourth section.

Choosing NP, F, and CR is seldom difficult and some general guidelines are available. Normally, NP ought to be about 5 to 10 times the number of parameters in a vector. As for F, it lies in the range 0.4 to 1.0. Initially F = 0.5 can be tried then F and/or NP is increased if the population converges prematurely. A good first choice for CR is 0.1, but in general CR should be as large a possible (Price and Storn, 1997). Among DE is advantages are its simple structure, ease of use, speed and robustness. Babu and Angira [2001] presented the application of Differential Evolution (DE), an Evolutionary Computation method, for the optimization of Thermal Cracking operation. The objective in this research was the estimation of optimal flow rates of different feeds to the cracking furnace under the

Already, DE has been successfully applied for solving several complex problems and is now being identified as a potential source for accurate and faster optimization.

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. Price and Storn [8] have given some simple rules for choosing key parameters of DE for any given application. DE has been successfully applied in various fields. The various applications of DE are: digital filter design, fuzzy decision making problems of fuel ethanol production, design of fuzzy logic controller, batch fermentation process, multi sensor fusion, dynamic optimization of continuous polymer reactor, estimation of heat transfer parameters in trickle bed reactor, optimal design of heat exchangers, synthesis and optimization of heat integrated distillation system optimization of non-linear functions, optimization of thermal cracker operation, etc [9].

Babu and Monava [10] presented the application of Differential Evolution (DE) for the optimal design of shell-and-tube heat exchangers. The main objective in any heat exchanger design is the estimation of the minimum heat transfer area required for a given heat duty, as it governs the overall cost of the heat exchanger. Lacks of configurations are possible with various design variables such as outer diameter, pitch, and length of the tubes; tube passes; baffle spacing; baffle cut etc. Hence the design engineer needs an efficient strategy in searching for the global minimum. In the present study for the first time DE, an improved version of Genetic Algorithms (GAs), has been successfully applied with different strategies for 1,61,280 design configurations using Bellís method to find the heat transfer area. In the application of DE 9680 combinations of the key parameters are considered. For comparison, GAs are also applied for the same case study with 1080 combinations of its parameters. For this optimal design problem, it is found that DE, an exceptionally simple evolution strategy, is significantly faster compared to GA and yields the global optimum for a wide range of the key parameters [10].

restriction on ethylene and propylene production. Thousands of combinations of feeds are possible. Hence an efficient optimization strategy is essential in searching for the global optimum. In this study LP Simplex method and DE, an improved version of Genetic Algorithms (GA), have been successfully applied with different strategies to find the optimum flow rates of different feeds. In the application of DE, various combinations of the key parameters are considered. It is found that DE, an exceptionally simple evolution strategy, is significantly faster and yields the global optimum for a wide range of the key parameters. The results obtained from DE are compared with that of LP Simplex method [11].

Babu and Munawar [200] presented the application of Differential Evolution (DE) for the optimal design of shell-and-tube heat exchangers. A primary objective in the heat exchanger (HE) design is the estimation of the minimum heat transfer area required for a given heat duty, as it governs the overall cost of the heat exchanger. However, many numbers of discrete combinations of the design variables are possible. Hence the design engineer needs an efficient strategy in searching for the global minimum heat exchanger cost. In this study, for the first time DE, an length, number of tube passes, baffle spacing and baffle cut. Bellís method is used to find the heat transfer area for a given design configuration. For a case study taken up, it is observed that DE, an exceptionally simple evolution strategy, is significantly faster compared to GA and is also much more likely to find a function was true global optimum[12].
improved version of Genetic Algorithms (GA), had been successfully applied with 1,61,280 design configurations obtained by varying the design variables: tube outer diameter, tube pitch, tube

Babu and Sastry [1999] proposed a new non-sequential technique for the estimation of *effective* heat transfer parameters using radial temperature profile measurements in a gas–liquid co-current down flow through packed bed reactors (often referred to as trickle bed reactors). Orthogonal collocation method combined with a new optimization technique, differential evolution (DE) is employed for estimation. DE is an exceptionally simple, fast and robust, population based search algorithm that is able to locate near-optimal solutions to difficult problems. The results obtained from this new technique are compared with that of radial temperature profile (RTP) method. Results indicate that orthogonal collocation augmented with DE offer a powerful alternative to other methods reported in the literature. The proposed technique takes less computational time to converge when compared to the existing techniques without compromising with the accuracy of the parameter estimates. This new technique takes on an average 10 s on a 90 MHz Pentium processor as compared to 30 s by the RTP method. This new technique also assures of convergence from any starting point and requires less number of function evaluations [13].

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 [14].

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 exists 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 [14, 16-18].

4. Mathematical Model

In fermentation, an accurate mathematical is dispensable 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.

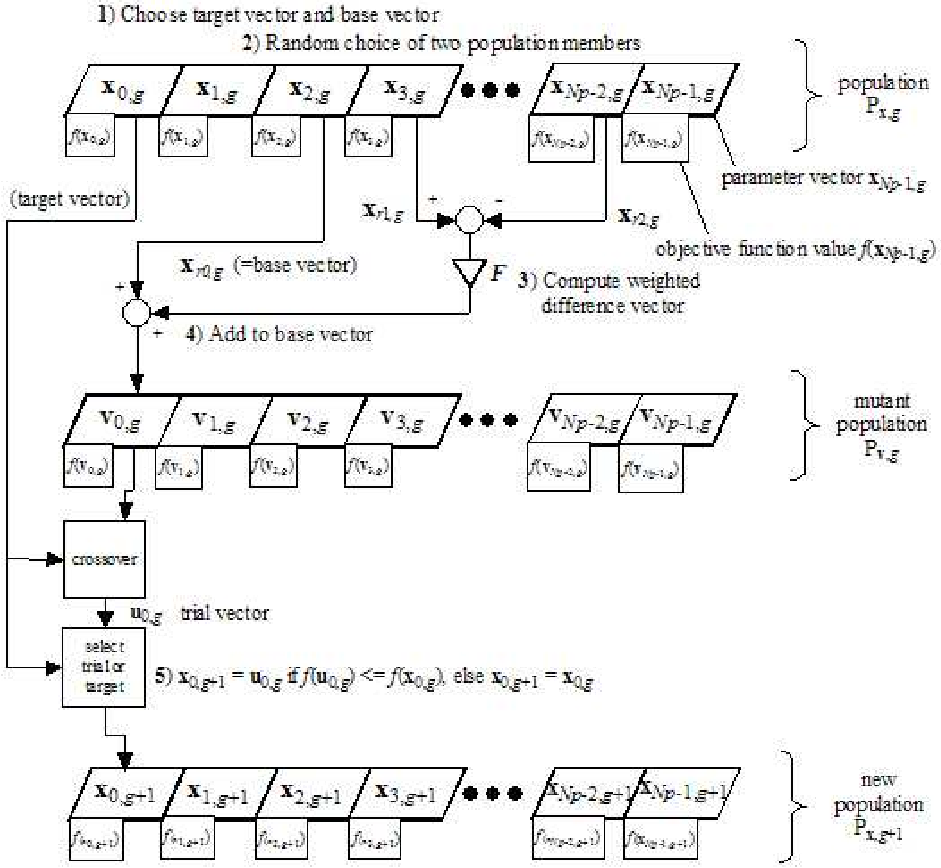

Fig 1. a scheme for generating trial parameter vectors

(http://www.icsi.berkeley.edu/~storn/code.html#basi)

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 [16]. Most of the process parameters vary as Arrhenius function of temperature, expect diacetyl appearance and disappearance rate which are constant values.

$$\frac{dx_{lag}}{dt} = -\mu_{lag} x_{lag}$$

$$\frac{dx_{active}}{dt} = -\mu_x x_{active} - k_m x_{active} + \mu_{lag} x_{lag}$$

$$\frac{dx_{bottom}}{dt} = k_m x_{active} - \mu_D x_{bottom}$$

$$\frac{ds}{dt} = -mu_s x_{active}$$

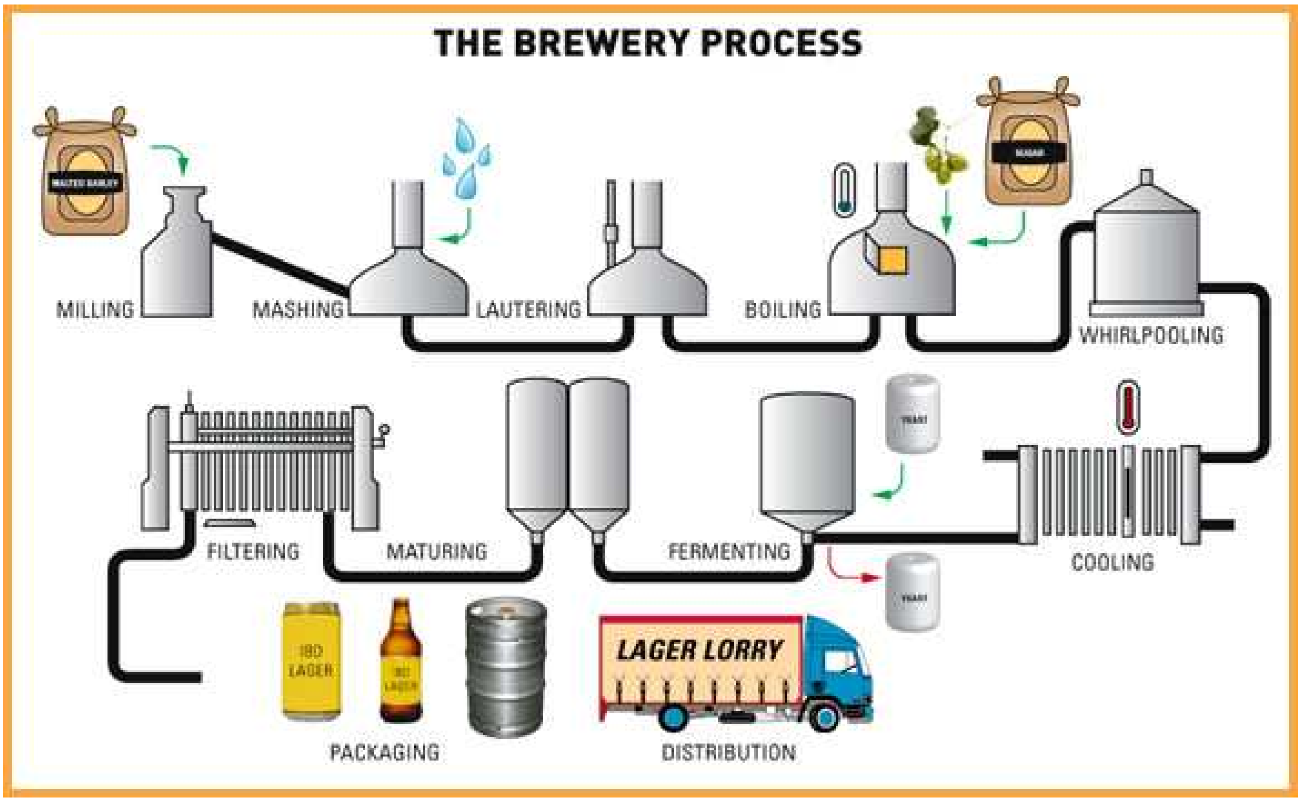

Fig.2 Brewery process description.
(www.tewsbrewery.com/images/the-brewing-process.jpg)

The reaction rates:

$$\mu_x = \frac{\mu_{x0} s}{0.5 s_i + e}, \quad \mu D = \frac{0.5 s_i \mu_{D0}}{0.5 s_i + e}$$

$$\mu_s = \frac{\mu_{s0} s}{ks + s}, \quad \mu_a = \frac{\mu_{a0} s}{ks + s}$$

$$f = 1 - \frac{e}{0.5 s_i}$$

The parameters:

$$\mu_{x0} = e^{108.31 - \frac{31934.09}{T+273.15}}, \quad \mu_{s0} = e^{-41.92 - \frac{11654.64}{T+273.15}}$$

$$\mu_{DO} = e^{33.82 - \frac{10033.28}{T+273.15}}, \quad \mu_{a0} = e^{3.27 - \frac{1267.24}{T+273.15}}$$

$$\mu_{eas} = e^{89.92 - \frac{26589}{T+273.15}}, \quad \mu_{lag} = e^{30.72 - \frac{9501.54}{T+273.15}}$$

$$k_m = e^{130.16 - \frac{38313}{T+273.15}}, \quad k_s = e^{-119.63 - \frac{34203.95}{T+273.15}}$$

$$k_{dc} = 0.000127672, \quad k_{dm} = 0.00113864$$

The initial values:

$$x_{lag,i} = 0.08,\ x_{bottom,i} = 2,\ s_i = 130,\ e_i = 0,$$
$$(acet)_i = 0,\ (diac)_i = 0.$$

When the parameters used as the following:

Table 2 Categorization used.

Parameter	Description	Unit
μ_a	Ethanol production rate	h^{-1}
μ_D	Specific yeast setting down rate	g/l
μ_{eas}	Ethyl acetate coefficient rate	g/l
μ_{log}	Specific rate of latent formation	h^{-1}
μ_s	Substrate consumption rate	h^{-1}
μ_x	Specific yeast growth rate	h^{-1}
acet	Ethyl acetate concentration	ppm
diac	Diacetyl concentration	ppm
e	Ethanol concentration	g/l

Parameter	Description	Unit
f	Fermentation inhibition factor	g/l
k_{dc}	Diacetyl appearance rate	
k_{dm}	Diacetyl reduction rate	
k_m	Yeast growth inhibition parameter	g/l
k_s	Sugar inhibition parameter	g/l
s	Concentration of sugar	g/l
s_o	Initial concentration of sugar	g/l
t	Time	H
T	Temperature	^oC
x_{active}	Suspended active biomass	g/l
x_{dead}	Suspended dead biomass	g/l
x_{log}	Suspended latent biomass	g/l

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 the ethyl acetate and diacetyle concentrations are applying the differential evolution, the results demonstrated that the final ethanol level is smaller, lower, and the biomass and sugar concentration has been decreased also (fig 3-6).

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 parameter rising and calculating average temperatures made results suitable for implementation.

7. Acknowledgement

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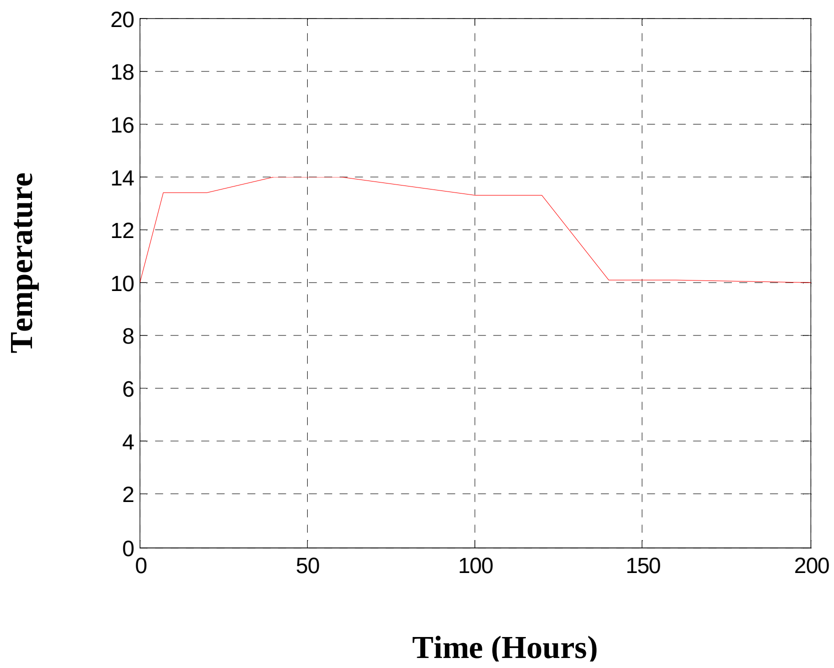

Fig. 3 Temperature profile of fermenting process by differential evolution.

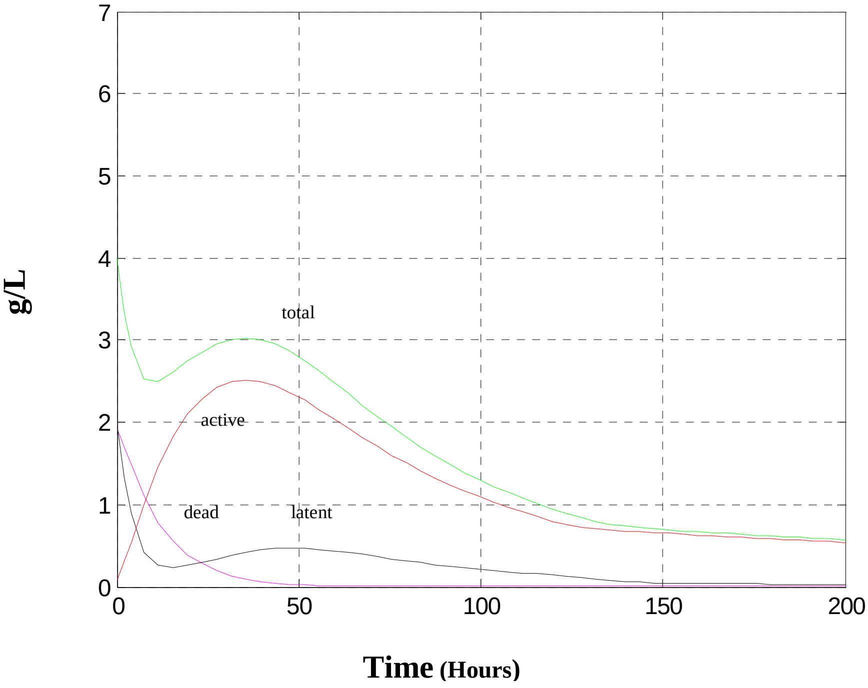

Fig. 4. Suspended biomass behavior results as following :
total biomass (-); active microbial (-); dead microbial (-); latent heat (-).

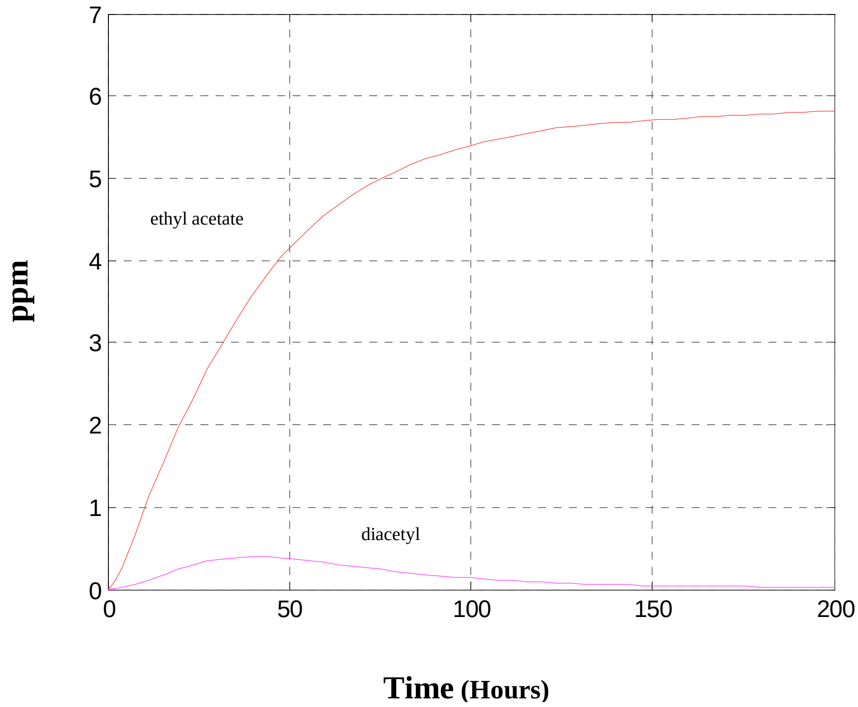

Fig. 5 Byproducts behavior results as following: ethyl acetate (-); diacetyl acetate (-).

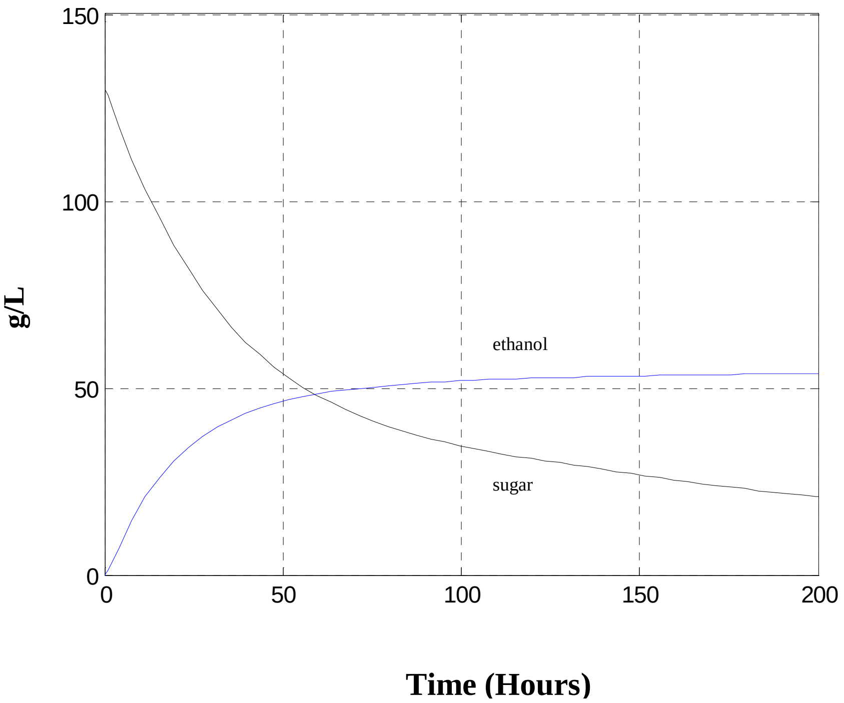

Fig. 6 Ethanol and sugar concentration as following: ethanol (-); suagar (-).

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