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Fitness partition-based multi-objective differential evolutionary algorithm and its application to the sodium gluconate fermentation process

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ABSTRACT

The operating conditions of the fermentation process of sodium gluconate play a key role in the quality and quantity of its production. The fermentation process is highly nonlinear and dynamic, and several objects must be considered. To implement a global and efficient optimization for the fermentation process, a fitness partition-based multi-objective differential evolutionary algorithm (FPMDE) is proposed. In the FPMDE algorithm, the information in the target space, which expresses some superiority message, is used to guide the evolutionary process. Namely, according to the fitness values, the target space is divided into some sub-region, and then some optimal directions are extracted for individuals to search for the optimal region and finally approximate the Pareto front. Experimental results on 20 benchmark functions show its advantage in convergence and diversity compared with 5 other state-of-art algorithms. Further, three objective functions for the fermentation process of sodium gluconate are proposed, and the FPMDE algorithm is applied to obtain its Pareto front; the conversion rates and utilization rate of equipment has been improved. It is shown that the FPMDE can optimize the conditions of the production of sodium gluconate effectively and efficiently.

1. Introduction

Sodium gluconate is an important derivative of gluconic and acid polyhydroxy organic salt. It has the advantages of non-toxic character, having a broad variety of sources of raw materials, good thermal stability and non-corrosive character that allow it to be widely used in chemistry, food, medicine, light industry and so on. In the concrete admixture [1], sodium gluconate, as an important water reducing agent and retarder, has gained a good effect. Four production methods are typically used to produce sodium gluconate: the biological fermentation process [2], homogeneous catalytic oxidization, the electrolytic oxidation method and heterogeneous catalytic oxidation. Batch fermentation by *Aspergillus niger* is an effective method to generate sodium and this method has been modeled in many forms: e.g., mathematical models [3] and kinetic models [4] and hybrid neural network models [5], etc. Conditions in this fermentation process play an important role, as different conditions will obtain different amounts of sodium gluconate. Thus, it is meaningful to study the balance between bacteria growth, yield of production and glucose consumption. Selecting a suitable condition will help to improve the production efficiency and reduce the production cost.

The multi-objective problem [6] appears in all areas of life. Most of the time, the objectives are conflicting, and the solutions are not unique. Under the different requirements, Pareto optimal solutions can enable the different objective functions to obtain good results. Years of research on the meta-heuristics algorithm has revealed outstanding advantages for finding the Pareto-optimal solutions. In early studies, researchers proposed vector evaluated genetic algorithm(VEGA) [7], multiple objective genetic algorithms(MOGAs) [8], non-dominated sorting in genetic algorithms(NSGAs) [9], etc. Those methods are almost exclusively based on non-dominated sorting and fitness sharing. Subsequently, many modified algorithms that are based on classic algorithms, such as the particle swarm optimization algorithm, the estimation of distribution algorithm and the differential evolutionary algorithm were proposed. Multi-objective particle swarm optimization [10] (MOPSO) adopted an adaptive grid to sort the external population and determined the selection probability of a solution based on the grid. Regularity model-based, multi-objective estimation of the distribution algorithm [11] (RM-MEDA) combined evolutionary algorithms with statistical learning to build a probability model of individual distribution. The non-dominated sorting genetic algorithm [12] (NSGA II) introduced the elite reserves mechanism that makes parents and offspring compete with each other to generate the next generations. Those algorithms are all

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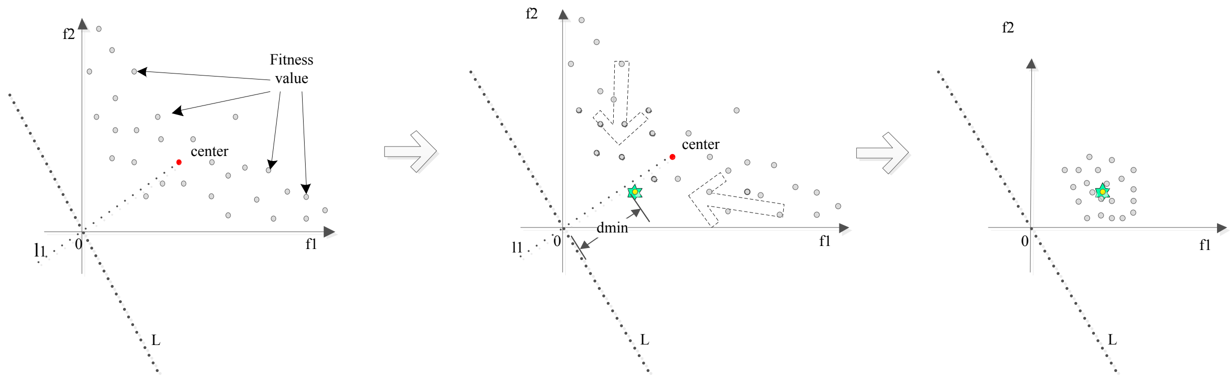

Fig. 1. The situation of one global optimal solution.

improving the evolutionary level of the whole population.

Generally, the solution of a multi-objective problem is a Pareto set. It is difficult to utilize the information of the global optimal solution and the locally optimal solution to guide the evaluation. Some researchers have proposed the reference point or reference vector as a form of preference. NSGA-III [13] was adopted as a predefined reference point set to ensure the diversity of the obtained solutions. A reference vector-guide evolutionary algorithm [14] was used an adaptive reference vector to decompose the multi-objective problem into a single objective problem and to target a preferred subset in the Pareto front according to user preference. An indicator based algorithm [15] was developed that utilized a set of reference points to select the candidate solutions and adapt via the external archive. Some researchers had extracted the useful information in the decision space. Wang et al. [16] proposed a parallel cell coordinate system to estimate the density and evaluate the evolutionary environment for selecting the global optimal solution. Considering the convergence of the algorithm is influenced by the distribution of individuals, DSPEA [17] was developed based on the decision space partition; in this method, the decision space is divided into several hyperspheres, and then, NSGA II combines with PSO to implement the evolution.

Although MOPs are complex, in addition to the use of the decision space to help to guide evolution, information in the target space is also very valuable; thus, adopting a suitable method to extract such information to guide the search approximate to the Pareto front is significant. The target space has a close connection to the decision space, and the superior individual in the target space includes much useful information. The superior individual can provide a superior direction to help the population evolve to the ideal place. MOPs are different from single optimization, and the superior individual is not unique; meanwhile, the solutions should not only have good convergence but also should have good diversity. In this article, a fitness partition-based multi-objective differential evolutionary algorithm (FPMDE) is proposed. The target space is divided into several blocks such that the solutions in each of the blocks has its own superior individual, and an adaptive mutation strategy is used to implement the evolve process. Furthermore, the conversion rates, the remaining glucose, and the utilization rate of equipment are proposed as the fitness function of the sodium gluconate fermentation process; using FPMDE to optimize the operation condition, the result are found to be advantageous.

The remainder of this article is structured as follows. Section 2 presents the related techniques: the basic concept of multi-objective optimization problems and the differential evolutionary algorithm. Section 3 introduces the novel FPMDE algorithm in detail. The experimental results and discussion are shown in Section 4. Section 5 presents the optimization of the sodium gluconate fermentation process. Finally, the conclusion is drawn in Section 6.

2. Related techniques

2.1. Multi-objective optimization problems (MOPs)

MOPs always include two or three optimization functions; these functions are usually optimized at the same time (maximum or minimum) with constraint conditions. The mathematical representation is described as follows [18]:

$$\begin{array}{ll} \min & \boldsymbol{F}(\boldsymbol{x}) = \{f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x})\} \\ s.t. & g_i(\boldsymbol{x}) \le 0, i = 1, 2, \ldots, q \\ & h_j(\boldsymbol{x}) = 0, j = 1, 2, \ldots, p \end{array} \tag{1}$$

where $F(\boldsymbol{x})$ are the objective functions; m is the number of objective functions; $g(\boldsymbol{x}), h(\boldsymbol{x})$ represent the inequality constraints and equality constraints, respectively; and q, p represent the number of constraints.

In the situation where all the functions are minimized, several definitions are as follows:

Definition 1. (Pareto Dominance). In a decision space of n-dimension, two feasible solutions $\boldsymbol{x}_1$, $\boldsymbol{x}_2 \in \boldsymbol{\Omega}$, if and only if $\forall i \in \{1, 2, \ldots, m\}$, $f_i(\boldsymbol{x}_1) \le f_i(\boldsymbol{x}_2)$, $\exists j \in \{1, 2, \ldots, m\}$, $f_j(\boldsymbol{x}_1) < f_j(\boldsymbol{x}_2)$, defined $\boldsymbol{x}_1$ dominates $\boldsymbol{x}_2$ (denoted as $\boldsymbol{x}_2 \prec \boldsymbol{x}_1$).

Definition 2. (Pareto Optimal Set). All of the Pareto-optimal solutions constitute the Pareto-optimal set (PS) defined as $\boldsymbol{PS} = \{\boldsymbol{x}^* | \neg\exists \boldsymbol{x} \in \boldsymbol{\Omega} : \boldsymbol{x} \succ \boldsymbol{x}^*\}$.

Definition 3. (Pareto Front). The area where all the Pareto-optimal solutions corresponding to the objective function value are formed as $\boldsymbol{PF} = \{\boldsymbol{F}(\boldsymbol{x}^*) | \boldsymbol{x}^* \in \boldsymbol{PS}\}$.

2.2. Differential evolutionary algorithm

DE algorithm is a heuristic global search based on the differences among the population [19]. It has the advantages of simple principle, less controlled parameters and strong robustness, etc. By adopting real number code programming, the theory of DE and genetic algorithms are quite similar: using the difference vector among individuals to realize the mutation of individual, this mutation mode utilizes the distribution characteristics of the population to effectively develop the search capability.

In the DE algorithm, there are seven mutation strategies. The form is DE/x/y/z, x is a basis vector which can be selected in the population randomly or the best individual in the population or the current individual in the population; y is the number of difference vector; z is the pattern of crossover. The last symbol (1, 2, bin) is the crossover pattern, bin represent the binomial crossover. DE/rand/1 and DE/rand/2 are easy to implement and widely used. These strategies use the difference vector between two individuals or more multiplied by mutation coefficients added to the third individual to generate a new vector. DE/best/1 and