

# Production Scheduling of Batch Processes Based on Adaptive DE Algorithm

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**Abstract**—Production scheduling problems and traditional differential evolution (DE) are analyzed in this paper. Taking the minimum of total completion time as the objective function of production scheduling, a production scheduling model is established for batch processes in process industry. Considering that the performance of the traditional DE algorithm is sensitive to the parameter settings, an adaptive control evolution strategy is used to control the parameter scale factor  $F$  and crossover probability  $CR$  to solve the problem of parameter settings. Taking a practical production problem as a scheduling example, the established model and adaptive DE algorithm are applied to implement the production scheduling simulation. The simulation results show that compared with the ant colony system (ACS) algorithm, the adaptive DE algorithm is effective and feasible.

**Index Terms**—batch processes, adaptive differential evolution algorithm, production scheduling, ant colony system algorithm

## I. INTRODUCTION

Batch processes in industrial production are a kind of production forms of organizing production by batch mode. As an important branch of industrial production processes, the batch processes are widely used in the industry of fine chemicals, biological productions, pharmaceutical production and dyeing technology, and so on [1]. As a typical and complex production process, the batch processes have the characteristics of complexity, randomness, multi-constraint and multi-objective. It involves both discrete and continuous operation and owns a lot of internal restrictions and restraints, which bring great difficulties in modeling and solving. With the greatly increasing in the aspect of complexity of production scheduling, the discrete and continuous production scheduling methods cannot be applied to the production scheduling of batch processes directly [2]. At present, researchers in domestic and overseas have achieved a number of research achievements in the field of batch processes production scheduling. According to the scheduling problems of batch processes production, a scheduling model for multi-product batch processes with maximum profit was established, and a modified genetic

algorithm with mixed coding was used to solve the scheduling model [3]. A set of heuristic scheduling rules was proposed to solve scheduling problems of intermediate transfer policies in multiproduct chemical batch processes [4]. An adaptive hybrid ant colony optimization algorithm was established to solve the scheduling problems of dual resource constrained job shop [5].

Differential evolution (DE) algorithm is a heuristic evolution algorithm which was proposed by Rainer Storn and Kenneth [6]. The DE algorithm is a simple and efficient parallel search algorithm, which has better robustness and faster convergence capability than other evolution algorithms [7]. In recent years, the basic DE algorithm and some of its improved algorithms have been used to solve and optimize the production scheduling problems effectively [8-10]. In view of the problems that traditional DE algorithm is sensitive to the parameters of scale factor  $F$  and crossover probability  $CR$ , an adaptive control evolution strategy is used to make parameter  $F$  and  $CR$  change dynamically to improve the optimization performance of the traditional DE algorithm [11]. And the adaptive DE algorithm was applied to production scheduling of batch processes. And the simulation results of production scheduling are satisfactory.

## II. DESCRIPTION OF SCHEDULING PROBLEMS FOR BATCH PROCESSES PRODUCTION

Batch processes production can be divided into two categories according to the similar degree of productions in production technology, which are multi-product batch processes production and multi-purpose batch processes production [12]. Multi-product batch processes production scheduling problem is similar to the flow-shop scheduling problem, which includes the problems of the amount and size of batch production and process time. Whereas, multi-purpose batch processes production scheduling has the sequencing problem, which is similar to job-shop scheduling problem. This paper mainly takes the multi-purpose batch processes scheduling problem as the research object and makes an assumption as follows [13]: 1) Each equipment can only carry out a

certain process step of one production in each time, and the next step can be started until the previous process step is completed;2)The process time for each process step is certain,and the equipment preparation time is included in the process time;3)There is no binding of priority between the processing steps of different productions;4)All of the process batches of materials are certain, and the material balance problems are not considered;5)There are no other resource constraints except of equipments;6)The materiel shift time between equipments is ignored;7)The unlimited intermediate store policy is used for storing materials.

According to the above assumption model, some assumptions are made as follows:1) $J_i$  is the number of process steps of production  $i$ ;2) $P_{ij}$  is the  $j$ -process step of production  $i$ ;3) $T_{ijk}$  is the process time of the  $j$ -process step for production  $i$ , which is on equipment  $k$ ;4) $S_{ijk}$  is the starting time of the  $j$ -process step for production  $i$ , which is on equipment  $k$ ;5) $E_{ijk}$  is the finishing time of the  $j$ -process step for production  $i$ , which is on equipment  $k$ . The following three conditions should be met in batch processes production scheduling:1)Order constraint:the order constraint is the process order constraints between adjacent processing steps in the same production, it means that the  $j$  step cannot start unless the  $j-1$  step has stopped in production  $i$ . Order constraint can be described as follows, $E_{ijk}-E_{i(j-1)k} \geq T_{ijk}$ ;2)Occupancy constraint:the occupancy constraint is that each equipment can only be processed one production at one time, which means that any two different productions or any two different process steps cannot be processed on equipment  $k$  at the same time. Occupancy constraint can be listed as follows, $E_{efk}-E_{ijk} \geq T_{efk}$ ;3)Time constraint:the difference time of any processing step between completion time and the starting time can't be shorter than its processing time.Time constraint can be described as follows, $E_{ijk}-S_{ijk} \geq T_{ijk}$ .

### III. ADAPTIVE DE ALGORITHM FOR BATCH PROCESSES PRODUCTION SCHEDULING

#### A. Adaptive DE Algorithm

##### 1)Basic DE Algorithm

If there are  $D$ -dimension independent variable to the solving problem, then the  $i$ th individual  $X_i$  among the population  $NP$  can be described as

$$X_i = \{x_i(j), x_i(j), \dots, x_i(j)\} \quad (1)$$

Where  $x_i(j) \in [l_j, u_j]$ ;  $i = 1, \dots, NP$ ;  $j = 1, \dots, D$ ;  $x_i(j)$  is a real number, which is generated uniformly and randomly by initialization within the range of  $[l_j, u_j]$ .

The differential mutation operator is the important operator of DE algorithm. Two differential individual vectors  $X_{r2}$  and  $X_{r3}$  execute difference operation and scale operation by that operator. A mutant individual vector  $V_i$  can be obtained by adding the optimal individual vector  $X_{best}$  in the population and the

combination individual vector of  $X_{r2}$  and  $X_{r3}$ .The individual vector  $V_i$  is described by the following equation

$$V_i = X_{best} + F \times (X_{r2} - X_{r3}) \quad (2)$$

Where  $X_{best}$  is the optimal vector in current population;  $r2, r3 (r2 \neq r3 \neq i)$  are two individual vectors which are randomly selected among the population  $NP$ ;  $V_i$  is the mutant individual vector;  $X_{r2} - X_{r3}$  is the difference vector;  $F \in [0, 1]$  is the scale factor.

Then the experiment individual vector  $U_i$  can be generated by crossing over the mutant individual vector  $V_i$  and father individual vector  $X_i$ , as in

$$U_i(j) = \begin{cases} V_i(j) & \text{randreal}_j[0,1] < CR \text{ or } j = j_{rand} \\ X_i(j) & \text{otherwise} \end{cases} \quad (3)$$

Where  $j = 1, \dots, D$ ;  $CR$  is the crossover probability;  $j_{rand}$  is a random integer of  $[0,1]$ ,which can ensure that there is an individual vector of  $U_i$  coming from the mutant individual vector  $V_i$ .

Finally, compared the fitness value of experimental individual vector  $U_i$  with father individual vector  $X_i$ , the better individual vector will be preserved in the next generation, as in

$$X_i(\text{next generation}) = \begin{cases} U_i & f(U_i) \leq f(X_i) \\ X_i & \text{otherwise} \end{cases} \quad (4)$$

Where  $f(X_i)$  is the fitness value of individual vector  $X_i$ .

##### 2)Adaptive DE Algorithm

The searching performance and convergence speed of the DE algorithm are sensitive to the setting of control parameter  $F$  and  $CR$ . Concerning the disadvantage of the basic DE algorithm,many researchers have proposed many adaptive control strategies to control the parameter settings of DE algorithm[11]. In this paper, a new mutation strategy named DE/current-to-pbest is used to control parameter  $F$  and  $CR$  to adapt the population environment in period of solving and optimization[11][14]. It can be described as

$$V_i = x_{r1} + F_i \times (x_{best}^p - x_{r1}) + F_i \times (x_{r2} - \bar{x}_{r3}) \quad (5)$$

Where  $x_{best}^p$  is an arbitrary individual vector of 100p% individuals in current population;  $p \in (0,1]$ ;  $x_{r1}$  and  $x_{r2}$  are two different individual vectors randomly selected from population  $P$ ;  $\bar{x}_{r3}$  is an individual vector randomly chosen from the union  $P \cup A$ .

The parameter  $CR$  affects the crossover operation of each dimension of every vector. With  $CR$  diminishing, the difference between the individual and its father individual becomes smaller.With the convergence speed becoming slower, in the same time,the performance of global search and optimizing efficiency are weakening. In

reverse, with the difference becoming larger, the convergence speed will become faster and the corresponding performance will be improved than before. The crossover probability  $CR_i$  of each individual  $X_i$  is independently generated according to the following equations[11]:

$$\begin{cases} CR_i = rndn_i(\mu_{CR}, 0.1) \\ \mu_{CR} = (1-c) \times \mu_{CR} + c \times mean_i(S_{CR}) \end{cases} \quad (6)$$

Where  $CR_i$  is truncated to the range of [0,1],if it isn't at the range of [0,1].  $rndn_i(\mu_{CR}, 0.1)$  is a random number generated according to the parameter  $\mu_{CR}$  and 0.1.  $mean_i(S_{CR})$  is the arithmetic mean of the set of all successful crossover probability;  $c$  is a constant, which is  $c \in (0,1)$ . The initial value of  $\mu_{CR}$  can be selected as 0.5.

Scale factor  $F$  controls the convergence speed and diversity of population. When  $F$  becomes smaller, convergence speed of the algorithm will become faster and DE algorithm is easy to fall into local optimum. On the contrary, the convergence speed will become lower and algorithm can search the optimal solutions, but the convergence speed is slower. The parameter  $F$  of the adaptive DE algorithm is independently generated according to the following equation.

$$\begin{cases} F_i = rndc_i(\mu_F, 0.1) \\ \mu_F = (1-c) \times \mu_F + c \times mean_L(S_F) \end{cases} \quad (7)$$

If  $F_i > 1.0$ , then  $F_i = 1.0$ . When  $F_i < 0$ , generate it again.  $rndc_i(\mu_F, 0.1)$  is a Cauchy random number generated according to the parameter  $\mu_F$  and scale parameter 0.1. The initial value of  $\mu_{CR}$  can be selected as 0.5, and then it can be updated at the end of each generation.  $S_F$  is the set of all successful mutation individual vectors  $F_i$  in generation  $G$ .  $mean_L(\cdot)$  is the Lehmer average value operation, and it can be expressed as follows.

$$mean_L(S_F) = \frac{\sum_{i=1}^{|S_F|} F_i^2}{\sum_{i=1}^{|S_F|} F_i} \quad (8)$$

### B. Design of Adaptive DE Algorithm for Batch processes Production Scheduling

#### 1) Method of Encoding and Decoding

In this paper, methods of encoding and decoding can be described as follows. Each individual in current population represents a process task and the length of the individual represents the steps of process task. Each dimension of independent variables(individual) is rounded, which respectively represents each process step corresponding to the process equipment. For example, the number one means the equipment whose serial number is one and number two means the equipment whose serial number is two. Each dimension value range of individual is defined as the number of using equipment corresponding to its process task. For example, there are

two equipments can be used for a process step, which are named equipment A and equipment B. According to the above method, the dimension value range of that individual is [1,2,3]. In other words, number three means that the two equipments have three kinds of combination modes, which are A or B or A & B.

#### 2) Realization of Adaptive DE Algorithm for Batch Processes Production Scheduling

The realization steps of the adaptive DE algorithm for batch processes production scheduling are as follows.

Step 1: Initialize the population  $P_G$ , and set each dimension value range of individual at the corresponding range.

Step 2: Compute the fitness value of each individual of the population  $P_G$ . The fitness value of each individual is the completion time of process task. Decoding the individual, and the equipment serial number can be got corresponding to its process step. Determine equipment and compute the completion time of task, and the completion time is the fitness value.

Step 3: Generate parameter  $F$  and  $CR$  according to (6) and (7).

Step 4: Select different individuals from an initial population  $P_G$  randomly and carry out a difference mutant operation, so as to get a mutant individual vector  $V_i$ .

Step 5: Make crossover operation between the mutant vector  $V_i$  and its father vector  $X_i$  according to (5), so as to generate the experiment individual vector  $U_i$ .

Step 6: Compare the fitness value of  $U_i$  with its father vector  $X_i$ , and select the optimal individual vector which is used to evolve in the next generation  $P_{G+1}$ .

Step 7: If  $G > G_{max}$ , stop the scheduling task and output the non inferior solution. Otherwise,  $G=G+1$ , and go to step 3 to carry out the evolution operation continually.

### IV. SIMULATION OF BATCH PROCESSES PRODUCTION SCHEDULING BASED ON ADAPTIVE DE ALGORITHM

#### A). Description of Batch processes Production Scheduling Example

A production scheduling example of batch processes production enterprise is used to verify the validity of the adaptive DE algorithm. The production process of production 1 and production 2 are shown in Figure 1[13]. In the production process, production 1 and production 2 are both processed by two raw materials. Material 1 of production 1 is a solid material which occupies 85% of all raw materials. Material 2 of production 1 is a liquid material which occupies 15%. Production 1 is composed of five processes that are mixture, ageing, cooling and filtering. Material 1 of production 2 is a solid material which occupies 80% of all raw materials. Material 2 of production 2 is also a liquid material which occupies 20% of all raw materials.

Production 2 is composed of five processes that are mixture , dilution, ageing, filtering and toning.

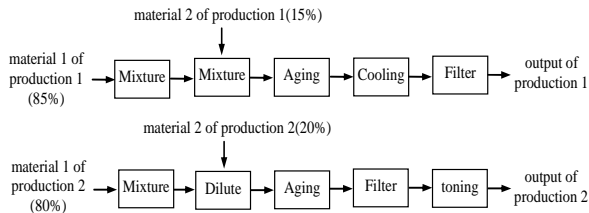


Figure 1. An example of batch processes production scheduling

The basic characteristic of production process is described as table I .The serial numbers of three preparing mixture caldron are named as {R11,R12,R13}, the preparation caldron is {R2}, the two aging pots are {R31,R32}, the cooling pot is {R4}, the two filter pots are {R51,R52}, and the adjustable caldron is {R6}.There is an assumption that production enterprise will process four tasks of production 1 and production 2 ,whose responding amount of tasks are {production 1(7), production 2(15), production 2(18), production 1(18)}.

TABLE I. BASIC CHARACTERISTIC OF PRODUCTION PROCESS

Production name	Process steps	Process requirement	Process equipment	Serial number	Process time	Process capacity
Production 1	1	Mixture	Preparing mixture caldron	R11	5	8
	2	Mixture	Preparation caldron	R2	5	5
	3	Ageing	Aging pot	R31	10	10
	4	Cooling	Cooling pot	R4	3	5
	5	Filter	Filter pot	R51	5	5
Production 2	1	Mixture	Preparing mixture caldron	R12	5	10
	2	Dilute	Preparing mixture caldron	R13	5	5
	3	Ageing	Aging spot	R32	10	8
	4	Filter	Filter spot	R52	5	8
	5	Toning	Adjustable caldron	R6	6	10

B)Simulation Results and Its Analysis

There are many criteria to evaluate the scheduling performance, such as the minimum of total completion time (Makespan), the highest ratio of equipments using, the lowest energy consuming and the least cycle period of production manufacture, and so on. Makespan is the most common performance index in production scheduling problem, and it has a more practical significance[12]. So Makespan is selected as the scheduling performance in this paper. According to the scheduling example, the selected parameters are described as follows: circle factor Ncmax is selected as 200,and number of population NP is selected as 20,and length of individual n is selected as 4,and parameter F and CR are generated by (6) and (7).

Results of production scheduling based on the adaptive DE algorithm are shown as table II .

TABLE II. RESULTS OF PRODUCTION SCHEDULING BASE ON ADAPTIVE DE ALGORITHM

Processes		Steps				
		Step 1	Step 2	Step 3	Step 4	Step 5
Task 1	Start time	0	5	15	25	31
	Ending time	5	15	25	31	36
	Using equipment	R11+ R12	R2	R31	R4	R52
Task 2	Start time	5	10	15	36	46
	Ending time	10	15	35	46	58
	Using equipment	R11+ R12	R11+ R12	R32	R52	R6
Task 3	Start time	15	20	25	46	61
	Ending time	20	25	45	61	73
	Using equipment	R11+ R12+ R13	R11+ R12+ R13	R31	R52	R6
Task 4	Start time	25	35	45	55	61
	Ending time	35	45	55	61	71
	Using equipment	R13	R2	R31	R4	R51

In order to show the superiority of designed algorithm, the scheduling results between ant colony system(ACS) algorithm and adaptive DE algorithm are compared. The specific parameters of the ACS algorithm are described as follows[15]: the number of ants m is selected as 60, and initial value of pheromone  $\tau_0$  is selected as 2.5, and the heuristic factor of information  $\alpha$  is selected as 0.2, and expectation heuristic factor  $\beta$  is selected as 0.5, and balanceable factor q0 is selected as 0.1,and total pheromone Q is selected as 100, and volatility of pheromone  $\rho$  is selected as 0.4,and circle factor Ncmax is selected as 200.The scheduling results of two algorithms are shown as table III. The simulation results show that the adaptive DE algorithm is feasible, and has a better scheduling performance than the ACS algorithm.

TABLE III. SCHEDULING RESULTS COMPARISON OF ADAPTIVE DE ALGORITHM AND ACS ALGORITHM

Indexes	ACS algorithm	Adaptive DE algorithm
Makespan(time equivalent)	77	73
Average utilization ratio of equipments	59.867%	62.221%
Average time of program running(ten times)	5.9s	3.953s

V. CONCLUSIONS

Aiming at the production scheduling of batch processes and the disadvantage of the basic DE algorithm, an adaptive DE algorithm was designed and used to realize production scheduling of batch processes. The simulation results indicate that the adaptive DE algorithm can improve the scheduling performance of equipment utilization ratio, minimum makespan time and solving

time. It also shows that the adaptive DE algorithm has more advantage in solving batch processes production scheduling problems and has a certain practical reference value.

#### ACKNOWLEDGMENT

This research was supported by Guangxi Natural Science Foundation (No.0991252).

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