

# Between the Two Parallel Computing Genetic Algorithms

## – An Example of Scheduling

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**Abstract.** This study will compare two different ideas for parallel computing genetic algorithm (GA). We will try to improve the efficiency of optimization for production planning and scheduling. It will fit the real-time requirement of smart manufacturing. In the first step, we will develop the basic genetic algorithm module. Since the chromosomes in GA are independent, parallel computing should be applied in GA. In the second step, we will develop the two parallel computing GA. One GA will solve each generation by parallel computing, and another GA will solve at least two populations by multi-population strategy. Finally, we will solve the practical problems of Taiwan's high-tech industry as a basis for developing advanced intelligent manufacturing systems. We will focus on the production planning and scheduling problem. We will use the practical problem as the empirical study to verify the applicability and validity.

**Keywords:** Parallel computing genetic algorithm, Production planning and scheduling, Industry 4.0

## 1. INTRODUCTION

This study develops the model for chemicals production planning and scheduling. In the first step, we will develop the basic genetic algorithm module. Since the chromosomes in GA are independent, parallel computing should be applied in GA. In the second step, we will develop the two parallel computing GA. One GA will solve each generation by parallel computing, and another GA will solve at least two populations by multi-population strategy. Finally, we will solve the practical problems of Taiwan's high-tech industry as the empirical study to verify the applicability and validity.

## 2. PROBLEM DEFINITION

The flexible scheduling problem in this case is defined in the following:

1.  $n$  jobs and  $m$  stage and each stage has multiple machines. Each job is processed on a series of  $m$  stage sequentially by one machine at every stage. There are 3 stages containing “mixing”, “filling” and “final quality control” in the electronic chemical industry. But some jobs don't need to work in the “mixing” stage and they are only to be processed on the latter two stages sequentially.
2. For mixing stage, we need to consider the constraint

of raw material. Each job can be processed only when we already get the raw material of job.

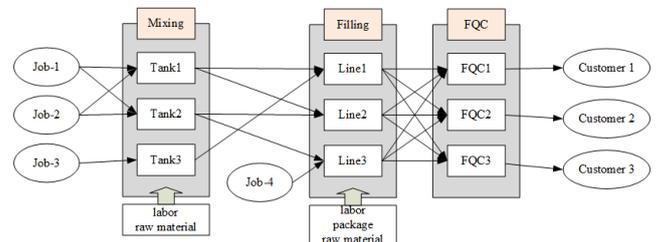


Figure 1: The framework of problem.

3. For filling stage, we need to consider the constraint of raw material and packaging. If job don't need to mix, it can be processed only when we already get the raw material and packaging of job. If job need to mix, it can be processed only when we get the packaging of job ready.

4. In mixing stage, we have a set  $M_i$  eligible mixing tank that can process the job  $i$  where  $M_i \geq 1$ . Also, we have a set  $F_i$  eligible filling line which can process the job  $i$  where  $L_i \geq 1$ .

5. A machine can process few kinds of jobs is possible.

6. Each machine in every stage has capacity constraint . Each machine can process only one operation at a time and each job can be processed by one machine at a time. We can consider the job be processed in batch in the “mixing” stage, so that the machine in the “mixing” stage can mix several jobs at a time and it can be deemed as one operation.

7. If two jobs be filled by the same line, the two periods of time of jobs be processed cannot overlap. Because the jobs can be processed in batch in mixing, the periods of time of the operations in the same mixing tank cannot overlap.

8. When a job finish mixed in a mixing tank, the tank would be storage to store the job and the job would wait for filling. If the mixing tank stores the job, it cannot start to mix the new job. The tank can only process the new job after the storing job finish filled by the filling line.

9. For mixing and filling stage, we need sufficient labor to start and process the job. In the “mixing” stage, the labor only work when the process starting. In the “filling” stage, if the packaging materials of job are small-batch, the labor has to work until the filling processing complete. Otherwise, if the packaging materials of job is chemical tank car, the labor has to work when the filling start and finish. And chemical tank car will deliver product to customer and come back to company after delivery.

10. Once a job is processed on a machine, it cannot be terminated before completion.

11. We consider setup time in some mixing tank and all of the filling line. It can maintain product in the high quality.

### 3. METHODOLOGY

#### 3.1 Basic genetic algorithm

In this problem, we have four objective functions and use weighted average method to find the fitness value. Since the jobs are delivered on time is important for the electronics industry, the weights of “the numbers” and “overdue hours” of overdue jobs are larger than the others.

We develop the genetic algorithm with uniform crossover, insertion mutation and elitism strategy. The chromosomes stand for the priorities of the jobs. Elitism strategy means that we retained the best individuals in a

generation unchanged in the next generation.

Parent1	0.55	0.51	0.24	0.67	0.14	0.38	0.97	0.85
Parent2	0.77	0.64	0.63	0.11	0.48	0.72	0.12	0.07
Rand() $<$ 0.5	0.41	0.48	0.93	0.71	0.58	0.02	0.82	0.75
Child1	0.77	0.64	0.24	0.67	0.14	0.72	0.12	0.85
Child2	0.55	0.51	0.63	0.11	0.48	0.38	0.97	0.07

Figure 2: Uniform crossover

Parent1	0.43	0.72	0.08	0.45	0.73	0.51	0.44	0.64
Child1	0.43	0.72	0.51	0.08	0.45	0.73	0.44	0.64

Figure 3: Insertion mutation

The figure 4 is the flowchart of decoding. It considers production capacity, pipelines, manpower, raw materials, packaging materials and other constraints.

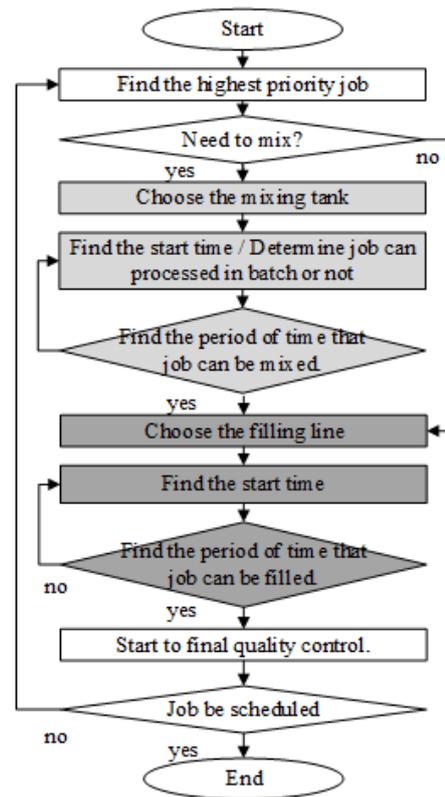


Figure 4: The flowchart of decoding.

### 3.2 Parallel computing strategy

Since the chromosomes in GA are independent, parallel computing should be applied in GA. This study develops the parallel computing GA solve each generation by parallel computing.

For example, we have  $n$  parallel computing threads (thread, core, or machine). There are  $N$  chromosomes which need to be decoded in one population. This strategy splits chromosomes to each thread.

### 3.3 Multi-population strategy

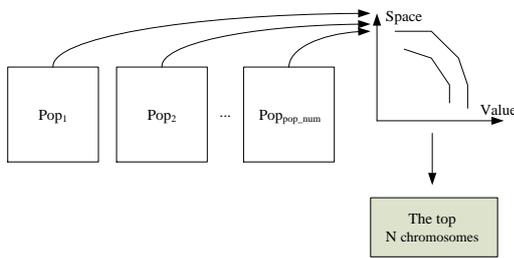


Figure5: Multi-population strategy

In the multi-population strategy used in this paper, several populations are evolved independently in parallel. After a pre-determined number of generations, all the chromosomes in each population are ranked by fitness. Then the overall top chromosomes added into each population. Some studies observed that exchanging too many chromosomes, or exchanging them too frequently, often leads to the disruption of the evolutionary process (Gonçalves and Resende, 2012).

## 4. RESULT

The electronics industry is the core of Taiwan's economic. Its process requires a huge number of various chemicals that are small-batch, high degree of purity, and less-particle. The electronics industry is a highly competitive market. To improve international competitiveness in enterprises, the products should be delivered on time. In the electronic chemicals industry, we must consider four resources: machine, packaging (container), material and labor.

In this case, there are 556 jobs, 44 mixing tanks, 35 filling lines and 157 jobs with due day. In the Gantt chart of mixing process (in Figure 6), we can find some jobs be processed in batch.

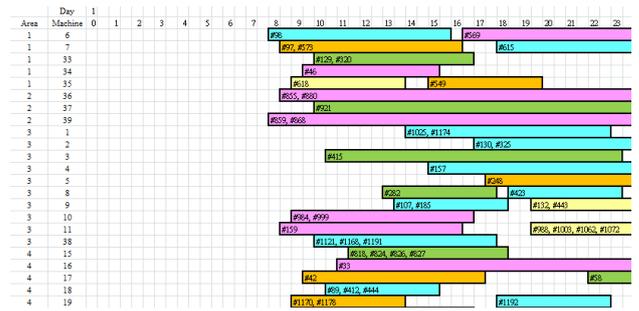


Figure 6: The Gantt chart of mixing process.

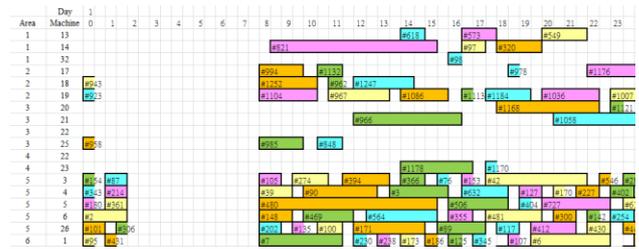


Figure 7: The Gantt chart of filling process.

In this problem, we have four objective functions and use weighted average method to find the fitness value. Since the jobs are delivered on time is important for the electronics industry, the weights of “the numbers” and “overdue hours” of overdue jobs are larger than the others.

Table 1: Summary of result

157 jobs with due day	proposed model	Case data	Improved rate
Makespan	26 days	30 days	12.8%
# of overdue jobs	25	83	69.9%
Total time of overdue jobs	133 days	306 days	56.5%

## 5. CONCLUSION

This study develops the model for chemicals production planning and scheduling. In the first step, we will develop the basic genetic algorithm module. In the second step, we will develop the two parallel computing GA. One GA will solve each generation by parallel computing, and another GA will solve at least two populations by multi-population strategy.

Finally, we will solve the practical problems of Taiwan's high-tech industry as the empirical study to verify the applicability and validity. We can improve the 56.5% of total time of overdue jobs and the 69.9% of the number of overdue jobs.

However, this study can be improved in the future. The two parallel computing approaches need some overhead time to split/merge the chromosomes, collect the information, and change the chromosomes. We can use more cases in different scale and complexity to evaluate the efficiency.

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