PS-NC Genetic Algorithm Based Multi Objective Process Routing

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요약 이 논문은 다목적 공정순서계획 알고리즘을 소개한다. 공정순서계획이란 가용한 기계들을 이용하여 원재료를 가공 완료된 부품으로 변형해주는 최적 공정순서들을 결정하는 일이다. 어느 컴퓨터 지원 공정계획 시스템에서나, 가공작업 순서의 결정은 부품 가공이나 부품 도면상의 기술적인 요구사항들을 충족시켜주기 위한 가장 중요한 활동 중의 하나이다. 여기서, 목표는 생산시간, 생산비용, 기계가동률 또는 이들을 복합적으로 만족시켜주는 최적 가공순서를 생성하는 일일 것이다. 파레토 스트라튬 니치 큐비클 (PS NC) 유전 알고리즘이 두 가지 상호 배타적인 기준인 생산비용과 생산품질을 동시에 최적화 시켜주는 가공순서들을 찾는데 이용되었다. 예제에 의한 검증은 제안된 PS NC 유전자 알고리즘이 공정계획문제에 있어서 효과적이며 효율적인 결과를 가져오는 것을 보여준다.

핵심주제어 : 공정순서계획, 공정계획, 다목적 유전 알고리즘, 파레토 스트라튬 니치 큐비클

Abstract This paper presents a process routing (PR) algorithm with multiple objectives. PR determines the optimum sequence of operations for transforming a raw material into a completed part within the available machining resources. In any computer aided process planning (CAPP) system, selection of the machining operation sequence is one of the most critical activities for manufacturing a part and for the technical specification in the part drawing. Here, the goal could be to generate the sequence that optimizes production time, production cost, machine utilization or with multiple these criteria. The Pareto Stratum Niche Cubicle (PS NC) GA has been adopted to find the optimum sequence of operations that optimize two conflicting criteria; production cost and production quality. The numerical analysis shows that the proposed PS NC GA is both effective and efficient to the PR problem.

Key Words : Process Routing, Process Planning, Multi Objective Genetic Algorithm, Pareto Stratum Niche Cubicle.

1. INTRODUCTION

The Process Routing (PR) refers to activities to determine the optimum production sequence which converts a raw material into a completed part through multi stage process. In other words, it is to find the best process routing among numerous alternatives given a certain criteria such as minimum cost, minimum time, maximum quality, maximum machine utilization, or with multiple these criteria. The implicit enumeration of all these alternatives can be formulated using flow networks. Flow network formulation has been widely used to find the best process routing under single objective criterion where the problem is equivalent to solving the Shortest Path Problem (SPP). Figure 1 shows a simple PR problem by the means of network flow. In the case of single objective criterion, the problem can be efficiently dealt with by some algorithms such as Dijkstra's and Floyed's. However, in the

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case of multiple objective criteria, a weighted sum approach based on the dynamic programming or goal programming is usually adopted. In this case, a priori the knowledge of the relevant weights is assumed.

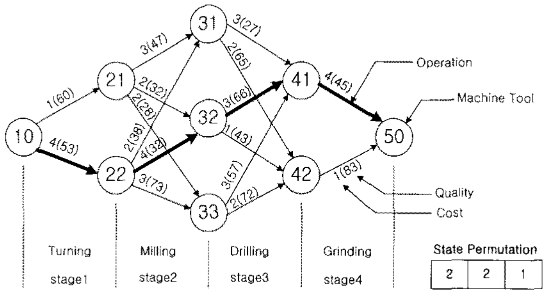

Figure 1. Flow network for a simple PR problem.

Recently, several GA based approaches for the PR problem have been reported [1],[5],[8],[12]. There are several multi-objective solution approaches which have been successfully applied in various application areas. [2]-[6],[8],[9],[12] The Pareto Stratum Niche Cubicle (PS NC) GA which is proposed by Hyun *et al* [3] is adopted in this research. They proposed the PS NC GA for determining sequences for three goals in mixed model assembly line balancing problem and reported successful achievements.

In a Pareto optimal solution set, there cannot be another single solution which is better in the two objectives. There may exist a solution which is better in one objective, and another solution which is better in another objective, but no single solution exists which is better in two objectives. [6] The PS-NC GA may be one of the best solution approach for the multi-objective problem to be solved within a Pareto solution domain. It is because it simultaneously provides the ability to find good solution quickly in terms of Pareto optimality, and to maintain a set of diverse individuals in a solution population.

Therefore, major issue of this study is to adopt the PS NC GA in the PR problem and to report the findings and corresponding modifications.

2. PR PROBLEM DESCRIPTION

The PR usually consists of a series of machining operations, such as turning, drilling, grinding and so on, to transform a raw material into its final shape. The whole process can be divided into several stages. At each stage, there can be a set of manufacturing alternatives. The PR problem is to find the optimal process routing among all possible alternatives given a certain criteria such as minimum cost, minimum time, maximum quality, maximum machine utilization, or under multiple of these criteria which are defined on the operations to be chosen. In this study, two conflicting objectives are considered to be achieved; *i.e.*, minimizing production cost and maximizing production quality.

The bicriterion PR problem can be defined as follows:

$$\begin{aligned} &\min \mathrm{C}(x_1, x_2, \ldots, x_n) = \textstyle\sum_{k=1}^{n} v_k(s_k, x_k) \\ &\max \mathrm{Q}(x_1, x_2, \ldots, x_n) = \textstyle\sum_{k=1}^{n} v_k(s_k, x_k) \\ &s.t. \quad x_k \in D_k(s_k) \end{aligned} \tag{1}$$

where s_k is the some state at stage k, $D_k(s_k)$ is the set of possible states to be chosen at stage k, k=1, 2, ⋯, n, and let x_k be the decision variable to determine which state to choose at stage k, obviously $x_k \in D_k(s_k)$, k=1, 2, ⋯, n. $v_k(s_k, x_k)$ represents the criterion to determine x_k under state s_k at stage k, usually defined as real number such as cost, time or quality, and so on.

3. PS NC GENETIC ALGORITHM

Two important issues in designing multiple objective genetic algorithms are the capabilities of efficient exploitation and wide exploration of the search space. Exploitation is the ability to find good solutions quickly in terms of Pareto optimality, and exploration is that to maintain a set of diverse individuals in a population. These two are primarily controlled by the selection scheme used.

The PS NC scheme basically combines the Pareto GA and the niched GA. The selection method used by Pareto GA only focuses on improving solution quality, while the niched GA can only improve the diversity of solutions in a population. Therefore, the PS NC GA combines the two methods to round off the weakness of each other, so that it simultaneously meets the two issues of exploitation and exploration.

3.1 Genetic Representation and Initial Population

In the network flow representation shown in Figure 1, the PR can be naturally identified by indicating which node or state is chosen for a particular operation at each stage. The alternative states at each stage can be expressed by a series of integers to indicate the node or state. If a state for an operation is chosen at some stage for the PR, then its corresponding integer for that node or state can be assigned whereas the integer is within the number of possible states at that stage. Therefore, the PR solution can be concisely encoded in a state permutation format [12] by concatenating all the set states of the stages as shown in Figure 1.

As there is always only one state to be chosen at the last stage, it need not be indicated in the encoding. This state permutation encoding is one to one mapping for the PR problem. As to the initial population for an n stage PR problem, each individual is a permutation with n 1 integers whereas the each integer is generated randomly within the number of all possible states at the corresponding stage. In the Figure, the dark black arrow line indicates a possible PR path which is represented by (2 2 1) in state permutation format.

3.2 Genetic Operation

Two points crossover operation has been adopted. Since each individual position in a chromosome on the state permutation encoding has its own value range, the crossover operation will not generate any illegal offsprings. In addition, one point mutation operation has also been adopted in this study. The randomly chosen one mutation position in an individual can be changed within any other possible values in that stage.

3.3 Evaluation

Since the two objectives (minimum production cost and maximum production quality) usually conflict with each other in practice, we can only calculate each objective value of the problem but can not simply evaluate its fitness value. In addition, these two factors are non commensurate because they can not be measured on the same scale or unit. In other words, we can not obtain the absolute optimal solution, but we can only get the Pareto optimal solutions.

3.4 Selection

The uniqueness of PS NC is the selection method which associates every individual with a rank. The rank is determined by the sparseness of individuals and Pareto optimality. The algorithm use the concepts of niche cubicle and Pareto strata.

Niche cubicles are first constructed for every individual of a generation. A niche cubicle of an individual is a rectangular region whose center is the individual. Let MAX_{lt} and MIN_{lt} be the maximum and the minimum of the lth objective function at generation t, respectively. Then, the size of the niche cubicle, σ_{lt} is computed using equation (2); where pop_size is the size of population.

$$\sigma_{lt} = \frac{MAX_{lt} - MIN_{lt}}{\sqrt[n]{pop\_size}}, \quad l = 1,2,\ldots,n \qquad (2)$$

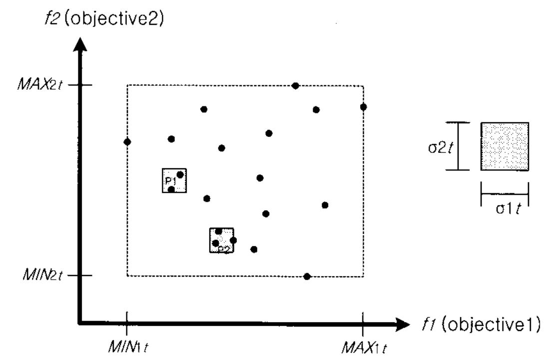

Figure 2. Niche cubicles (source: [2]).

The niche size is calculated at every generation. Since the size of every niche cubicle is same, the solution density of a niche cubicle can be simply measured by the number of individuals included in the cubicle. A solution located in a less dense cubicle is allowed to have a higher probability to survive in the next generation.

Pareto strata (or Pareto frontier) are then identified for a population. Among the solutions generated, non dominated solutions which form a Pareto stratum are filtered. Removing the stratum from the population of solutions uncovers the next Pareto stratum. This can be repeated until all the solutions are checked out. A higher probability will be assigned to a solution contained in a stratum found earlier. The fitness evaluation is carried out using these two indirect measures; *i.e.*, Pareto strata and sparseness. Individuals dominated by an individual p can never be more highly ranked than p. Solution density is considered secondarily for individuals in same Pareto stratum. This contributes to maintaining a distribution of diverse solutions in a population.

3.5 PS NC GA Procedure

The overall PS NC GA is as follows:

[Step 1] Randomly generate the initial population using the state permutation encoding within the number of all possible states at the corresponding stage.

[Step 2] Calculate the two fitness values individually.

[Step 3] Calculate the selection probability for each solution in present population:

(step 3 1) Construct the niche cubicle and calculate the density of the cubicle.

(step 3 2) Find the Pareto stratum. If the Pareto stratum is the first one in current generation, save the solutions separately as the current Pareto stratum.

(step 3 3) Sort the Pareto stratum solutions in ascending order and then assign the rank correspondingly.

(step 3 4) If all solutions used up, go to [Step 4]; otherwise, delete the current Pareto stratum and go to (step 3 2).

[Step 4] Check and keep Pareto optimality between the current Pareto stratum and the previous one.

[Step 5] Determine the probability of survival using a rank based selection scheme wherein the following geometric distribution is used

$Prob[p(\upsilon)]=q(1 \quad q)^{\upsilon \ -1}$, υ =1, 2, 3, ⋯, *pop_size*,

where v is a rank and q is the selection parameter ($0 < q < 1$).

[Step 6] Select (pop_size - R) different chromosomes based on the survival probability

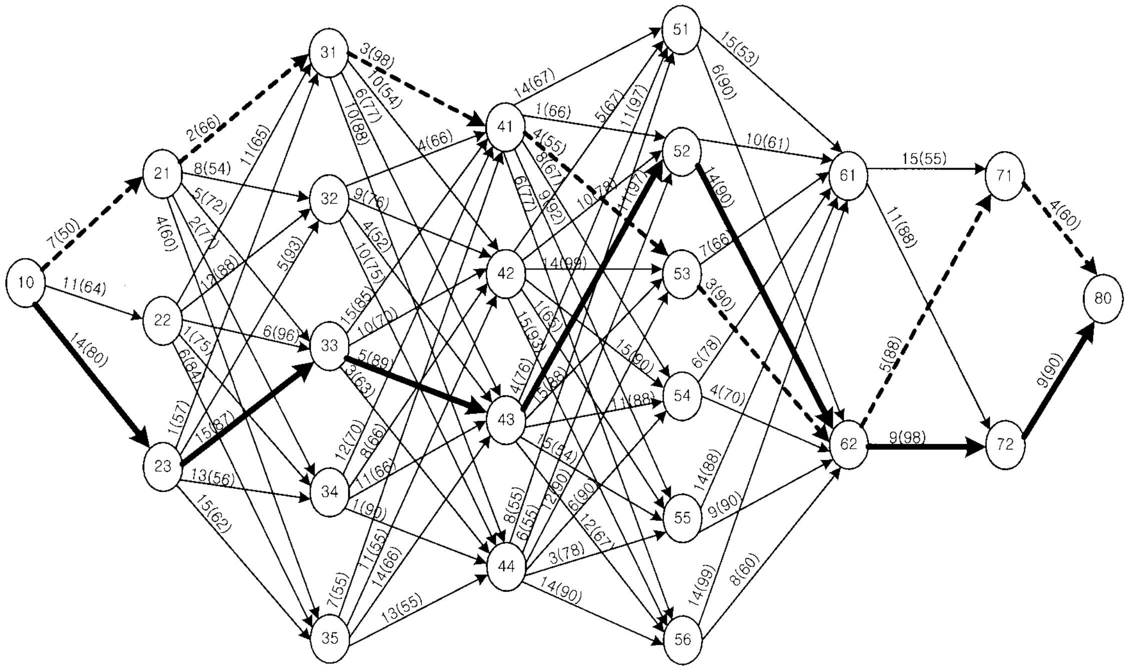

Figure 3. The example network flow with two attribute values; cost and quality in bracket.

from the current population and then copy these into the new population. Here, the R is the some random number between 1 and pop_size [7].

[Step 7] Select R chromosomes based on the survival probability from the current population.

[Step 8] Apply genetic operators crossover and mutation to the R chromosomes to generate new population. If the same solutions are found, keep one and substitute the rest with some random possible solutions so that the population keeps all different solutions.

[Step 9] Calculate the two fitness values individually.

[Step 10] If the number of current generation is equal to the number of maximum generation, stop. Otherwise, increase the current generation number by 1 and go to [Step 3].

4. NUMERICAL ANALYSIS

The numerical example with single objective reported by B. Awadh *et al.*[1] has been adopted in this study. Some random values have been added to the example in order to serve as a second objective. The problem consists of 7 stages, 24 nodes, 80 arcs, and the total number of 1440 possible process routings. The algorithm was programmed using Matlab software and operated at the Pentium 233 and 40 MB RAM PC. The average run time took 46 seconds for this specific example.

Figure 3 shows the example network and the corresponding two objective values.

In the network, optimum path for each objective is marked for comparison purpose. The dotted line stands for the least cost routing path (1 >1 >1 >3 >2 >1). The thick line stands for the maximum quality routing path (3 >3 >3 >2 >2 >2). The first objective, F1 was to find the least cost and the second, F2 to find the maximum quality process routing among all possible paths in the network. Here, the F1 is modified to be maximization problem as F1=U – f1. Where the U is the some big number greater or equal to the maximum cost value (in this specific example, 105) and f1 is the total cost for a specific routing path. Thus, the two objectives F1 and F2 now become both maximization problem. The experiment is repeated 20 times each for the various parameters set and a representative solution set is reported. Figure 4 shows a sample plot of the final results obtained at the end of 50th generations for the given parameters set in Table 1. Most of experiments have shown similar results like the one in Figure 4. The ideal point (77, 631) was calculated using a SPP for each of the two objectives individually. The figure clearly indicates that the Pareto frontier converges near to the ideal points as close as possible and also relatively enough number of solutions are generated. This means that the proposed system has the capabilities to provide a good amounts of and diverse set of Pareto solutions as well within a satisfactory CPU time.

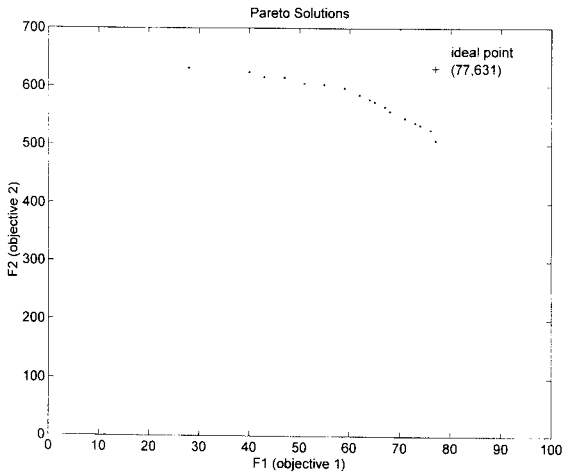

Figure 4. Pareto optimal solution plot for the two objectives, F1 and F2.

Table 1 shows 19 different Pareto solutions including two different routings with the same objective values. The two extreme points are (28, 631) and (77, 507), which equal the ideal point value in one of two objectives.

Table 1. Pareto optimal solutions obtained at the end of 50th generations for the given parameters set

F1	F2	Pareto sol'n	Parameters
28	631	3 3 3 2 2 2	
40	624	2 3 3 2 2 2	
43	616	3 2 4 3 2 2	
47	615	2 3 3 3 2 2	
51	605	3 1 1 5 2 2	
55	603	2 3 3 1 2 2	Popsize=50
59	597	2 4 4 3 2 2	R=40
62	585	1 4 4 3 2 2, 2 4 4 5 2 2	Maxgen=50
64	577	2 4 4 4 2 2	q=3/popsize
65	573	1 4 4 5 2 2	P_c=0.8
67	565	1 4 4 4 2 2	P_m=0.1
68	557	2 4 4 3 2 1	
71	545	1 4 4 3 2 1, 2 4 4 5 2 1	
73	537	2 4 4 4 2 1	
74	533	1 4 4 5 2 1	
76	525	1 4 4 4 2 1	
77	507	1 1 1 3 2 1	

5. CONCLUSIONS

In this study, an efficient PS NC GA algorithm was adopted to obtain diverse optimum process routings with conflicting two objectives; *i.e.*, minimizing production cost and maximizing production quality. Since the two objectives may conflict each other, there may not exist a sequence that can optimize both objectives simultaneously. Thus the PS NC GA which seeks a set of diverse non dominated solutions has been proposed to solve the PR problem. The numerical results show that the proposed system is promising approach to find Pareto optimal set of solutions in PR problem in terms of efficient exploitation and wide exploration of the search space in a short time. The performance comparison with other methods may be a further research issue.

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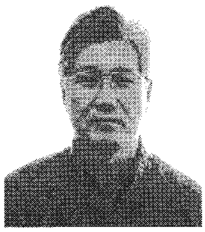

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