Application of Genetic Algorithms to Optimal Selection of Cutting Length of Bars

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Abstract

The optimal selection method of cutting length of bars by genetic algorithms is explained. When the raw bars of various length are cut to finished products of predetermined various length, the combination of cutting length in a raw bar is determined by genetic algorithms to achieve the minimum length of a scrap produced, at the same time, keeping the amount of each size of products in accordance with the order of customers at the end of production.
key words: *genetic algorithms, optimizing problem , optimal cutting control*

1 Introduction

Genetic algorithms (GAs) have been studied enthusiastically for various applications for more than twenty years, since Professor Holland proposed them first in 1975[1]. Even though they are simple algorithms, many successful results have been reported, especially, to the problems which are difficult to introduce mathematical model. This report describes a method using GAs for the optimal selection of cutting length of each of bars, when a series of raw bars are cut to finished bars of various predetermined length. This is required at the production of steel bars in steel plants, but similar situation will exist at other processes. The problem is of NP complete , thus it will take a lot of time to get results by means of ordinary methods.

Several years ago, we reported a similar method by the neural networks which are of mutual connected Hopfield type. This time, we have succeeded in solving the same problem by GAs.

2 Problem statements

The problem treated here is how to select the optimal combination of various cutting length of finished bars for each of raw bars. Fig.1 shows a example for steel bar cutting plant, where a seies of raw bars are cut to finished bars of various length requested by customers. Since the length of each raw bars differs due to losses at the previous processes, the first problem to solve is to determine the combination of cutting length in each bar so that the length of a scrap produced becomes minimum. This is the first optimal problem.

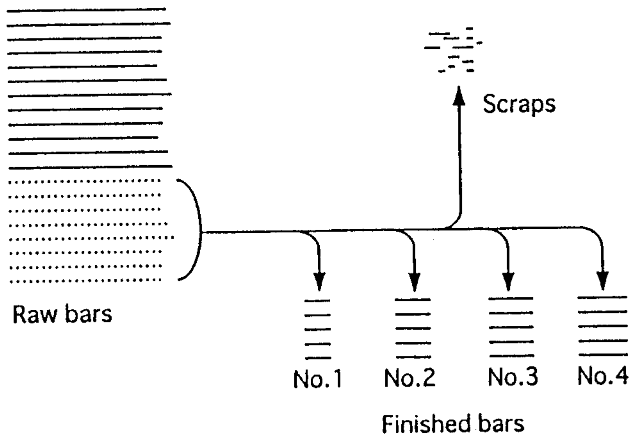

Figure 1: Production of finished bars from raw bars

If the production proceeds by this method only, the imbalance will occur between the amount ordered from customers and those actually produced for each length of finished bars. For example, a finished bar of some length may be produced more or fewer than needed and then this will bring about losses of production. Therefore, keeping the balance of amounts among the finished bars of each size at the end of production is the second optimal problem.

As the result, the optimal selection method of cutting length should satisfy these two requirements.

3 Genetic algorithms

Several matters related GAs, which consern to the later discussions will be briefly explained here. GAs are computer software which takes in the evolution mechanism in the nature, that is, the servival of the fittest, including crossover between two genes and mutation of genes at the transfer of genetic information between generations, and have been applied to various problems including optimal problems. In GAs, a generation consisting of fixed number of individuals is tranfered to the next generation, by applying evolutionary operations, which are made up of selection, crossover and mutation. Starting from a group of individuals which have random characteristics, those consisting of excellent individuals are obtained by repeating those operations, and thus the optimal problem is solved. Fig.2 shows these operations. The following describes the items to be considered when GAs are applied.

1) The representation of genes for each of individuals : According to the problems to be treated, various representation methods of bit, integer, and floating points can be possible. In our system, we adopted the bit-representation and represented various parameters related to the optimal selection with binary figures. Fitness values are calculated from these figures for selection.

2) Selection : Selection is a operation which choses superior individuals to tranfer from the present generation to the next. The adopted method of selection is a roulette wheel method, in which a pair of mates are picked up from a group of individuls at the probability proportional to the fitness value of each individual. This method is based on the assumption that by letting two individuals having superior characters mate(crossover), much more superior individuals will be produced.

3) Crossover : The purpose of crossover operation is to poduce superior individuals(children) inher-

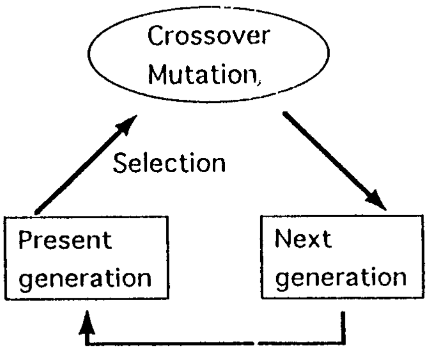

Figure 2: Genetic algorithms

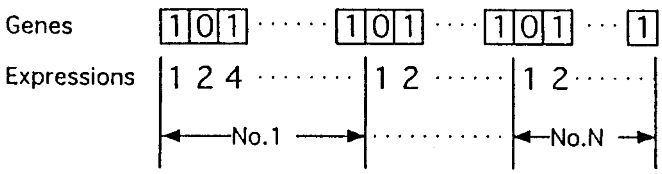

Figure 3: Representation of genes

iting the excellent characters of their parents by exchanging a part of their genes between the pair of mates. This operation is based on so called " Building block hypothesis theorem " [2]. From the various methods of crossover, we adopted one point crossover from simple point of view and it shows enough performance.

4)**Mutation** : As seen in the nature, mutation operator is also necessary for the evolution. If GA operation proceeds without this operation, sooner or later the group will drop into the state of local minimum or maximum, where almost all the individuals become identical and no more advancement can be expected, and will not get to the optimal state. To save the group from this situation the mutation is introduced. In case of bit expressions for the genes, the mutation is done by reversing the each value of genes to the oposit : from 0 to 1 or 1 to 0, at the predetermined probability.

4 Details of system

1)Expression of genes : The purpose of the system is to determine the combination of cutting length in a raw bar, hence the chromosome of each individual which corresponds to a raw bar consists of genes expressing the number of cuts to each finished bar length. Fig.3 shows the composition of the genes.

2)Fitness function : The fitness function of each individual consists of following two functions :

1. Fitness function $F_1(k)$ which aims to make the length of scrap minimum.
2. Fitness function $F_2(k)$ whose purpose is to keep balance among the numbers of produced finished bars.

By taking weighting factors $a(k)$ and $b(k)$ into consideration, a summarized fitness function $F(k)$ is expressed as follows :

$$F(k) = a(k)F_1(k) + b(k)F_2(k) \tag{1}$$

where, k stands for k-th raw bar.

Then the function $F_1(k)$ is reduced as follows :

$$F_1(k) = f_1(\Delta L(k)) \tag{2}$$

$$\Delta L(k) = L(k) - \sum_{i=1}^{N} L_i n_i(k) \tag{3}$$

where, $L(k)$ is the length of each raw bar, N is the number of kind of finished bar lengths, L_i and $n_i(k)$ are the length and the number of cuts for i-th finished bar length. Hence $\Delta L(k)$ stands for the length of each scrap and should be non-negative. In order to make the scrap length minimum, we determined the function $f_1(x)$ as a non-negative decreasing function whose value becomes maximum at $x = 0$ and is always non-negative in the operating range. As a function to satisfy these requirements, we adopted $f_1(x) = \exp(-c_1 x^2)$.

Next, since the function $F_2(k)$ should express how well the amounts of finished bars for each length match those of order from customers, it was determined as follows :

$$F_2(k) = \sum_{i=1}^{N} f_2(\Delta r_i(k)) \tag{4}$$

$$\Delta r_i(k) = \frac{r_i}{\sum_{j=1}^{N} r_j} - \frac{p_i(k) + n_i(k)}{\sum_{j=1}^{N}(p_j(k) + n_j(k))} \tag{5}$$

where, r_i stands for the target of production ratios among the finished bars and p_i is the summarized number of the finished bars produced until now for each size. Hence $\Delta r_i(k)$ is the deviation of production ratios from the object values.

The function $f_2(*)$ is also a non-negative decreasing one to make the deviation of the ratios minimum, by the same reason as in $f_1(*)$.

Next, both the coefficients $a(k)$ and $b(k)$ indicate the weight of $F_1(k)$ and $F_2(k)$ in the function $F(k)$. We assume that the length of raw bars are not known beforehand except for the latest several bars, this will happen at most plants, then the conbination of cutting length for each bar can not help being determined by the limitted information of these latest raw bars, therefore we assume here that the combination is determined only by the data of the latest bar just to be cut. On the other hand, we should take the request that the amount of finished bars for each length should match the object value at least at the end of production into consideration. From these two requirements, we adopted a inclining coefficient method so that at the early stage of production the conbination of length is determined to make the scrap length of each raw bar minimum, while at the final stage to keep the balance of production, and in the intermediate stage both requirements are taken into by changing the degree of weight as the production proceeds. To realize the above conditions, the coefficient $a(k)$ is set large at the initial stage and is gradually decreased as the production proceeds, on the other hand, $b(k)$ is changed in opposite way, that is, from small to large. The actual patterns of change are decided from the results of simulation, because it is difficult to determines these theoretically. At the moment, linear characteristics as to the number of raw bars produced are adopted, and they give good results as explained later in the results of simulation.

3) Genetic operation : We adopted simple genetic algoritms(SGA), which consist of the following :

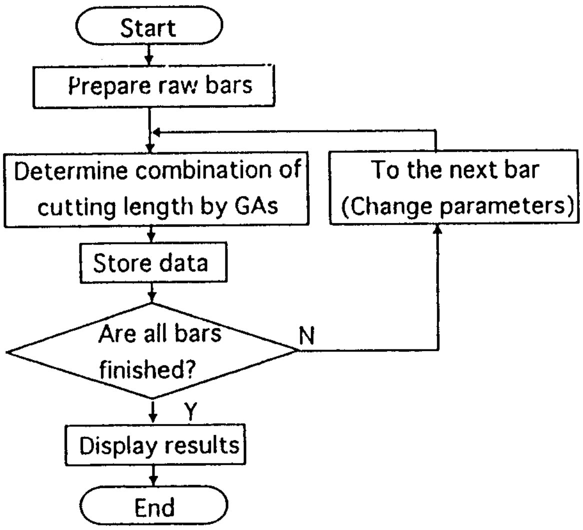

Figure 4: Flow chart for simulation

1. Selection by roulette wheel method

2. One point crossover

3. Mutation by fixed probability

Fig.4 shows the flow chart for simulation. The combination of cutting lengths for each raw bar is determined by GAs. Before transition to the next bar, the parameters such as p_i, $a(k)$ and $b(k)$ are reset to the new values calculated by the data taken in until now. After the repeat of this cycle until the last raw bars, the final results are calculated to check if the requirements are satisfied.

5 Results of simulation and discussion

To investigate the optimizing characteristics of the proposed method, we conducted simulation studies. Especially to clarify the relation between two requirements of the minimum length of a scrap for each raw bar and the balance among the amounts of finished bars, we carried out the following test :

1. Optimization for each bar, that is, only the minimum length of a scrap for each bar is considered. In this simulation, the coefficient $b(k)$ is set zero.

2. Optimization as a whole, that is, both the minimum scrap length and the balance of products to be satisfied. With various values of the production ratio, the results of simulation have been collected.

Table1 shows the specifications of raw and finished bars, while Table2 are the setting values of various parameters. Fig.5 shows the patterns of variation for the parameters $a(k)$ and $b(k)$ as to the variable k (the number of raw bars to be processed).

Table3 shows the results of the simulation for Case 1, that is, the optimization of each bar. From the table we can see that the total length of scrap is zero, that is, perfect optimization is attained. Both

Table 1: Specifications of raw and finished bars

Raw bars	finished bars			
Length[m]	Length[m]	Target of ratio[%]		
		Case-1	Case-2	Case-3
123	11	-	25.0	33.3
131	13	-	25.0	33.3
137	17	-	25.0	16.7
145	21	-	25.0	16.7
151				

Table 2: Parameter values for optimal cutting

Number of population	50
Probability of crossover	0.1
Probability of mutation	0.1

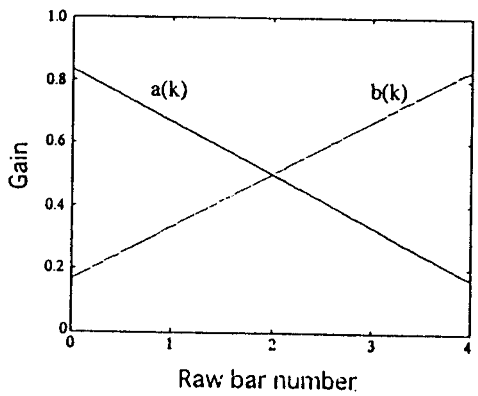

Figure 5: Patterns of weighting coefficent $a(k)$ and $b(k)$

Table 3: Optimal cut for each bar

		No.1	No.2	No.3	No.4	No.5	Total	Ratio[%]	
Length of raw bars[m]		123	131	137	145	151	687	Targets	Results
Number of finished bars	11m	5	0	2	2	1	10	-	23.3
	13m	1	1	3	1	3	9	-	20.9
	17m	2	2	2	4	1	11	-	25.6
	21m	1	4	2	2	4	13	-	30.2
Length of scraps[m]		0	0	0	0	0	0	-	100.0

Table 4: Optimal cut for all of bars : case-1

		No.1	No.2	No.3	No.4	No.5	Total	Ratio[%]	
Length of raw bars[m]		123	131	137	145	151	687	Targets	Results
Number of finished bars	11m	3	1	2	3	2	11	25.0	25.0
	13m	1	2	3	4	1	11	25.0	25.0
	17m	2	3	2	1	3	11	25.0	25.0
	21m	2	2	2	2	3	11	25.0	25.0
Length of scraps[m]		1	1	0	1	2	5	100.0	100.0

Table4 and Table5 show the results for the optimization as the total system at various target values of production ratios. In the both cases the production ratios obtained by GAs are kept nearly equal to the taget values, and at the same time the total length of the scraps produced is kept quite small. The reason why the total length of the scraps is not zero as in the first case is that it is defficult to achieve the optimization of all the objectives at the same time and some trade-off among the optimized values of those objectives is indispensable, in a multi-objective optimal problem as this.

Several years ago, we had studied to realize the same system using neural networks of cross connected Hopfield type. In the neural networks method, a energy function is defined to attained same optimal conditions as GAs, and the networks are brought to the optimal state by adjusting the weight of each network connection so as to make the energy function minimum, through applying the gradient method to the energy function. From the theoretical point of view, the neural networks method is expected to show the superior performance of optimalization than GAs, the actual performance,

Table 5: Optimal cut for all of bars : case-2

		No.1	No.2	No.3	No.4	No.5	Total	Ratio[%]	
Length of raw bars[m]		123	131	137	145	151	687	Targets	Results
Number of finished bars	11m	3	3	2	5	4	17	33.3	35.4
	13m	4	2	3	4	2	15	33.3	31.2
	17m	1	3	2	1	1	8	16.7	16.7
	21m	1	1	2	1	3	8	16.7	16.7
Length of scraps[m]		0	0	0	0	1	1	100.0	100.0

however, suggests that the GA method is much better than the neural networks method. In addition, at the neural networks we are suffered from a local minimum phenomenon, even though we added proper annealing operation to get rid of this problem. From these experiences the GAs method would be suitable to the problems having many local minimum points such as those treated here.

6 Conclusions

We have demonstrated genetic algorithms can be applied effectively to the multi-object problems having a lot of local minimum points, taking the optimal selection of cutting length of bars as an example. The genetic algorithms can solve two optimal requirements at the same time, which consist of to make the length of scraps minimum and to keep balance among the quantities of finished bars in order to match the produced quantities with those ordered from customers as nearly as possible. We confirmed these characteristics by simulation studies.

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