Second International Conference on Construction in the 21st Century (CITC-II)
"Sustainability and Innovation in Management and Technology"
10-12 December, 2003, Hong Kong

Using Adaptive Genetic Algorithms for Construction Time-Cost Optimization

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Abstract:

Time-Cost Optimization (TCO) is one of the greatest challenges in construction project planning and control, since the optimization of either time or cost would usually be at the expense of the other. Despite that, difficulties are still being encountered in construction TCO; as there is a lack of unique solutions for integrated constraints associated with the time and cost requirements. In this paper, adaptive genetic algorithms are proposed to automatically balance the weights of time and cost, finally achieving a compromise between population diversity and searching efficiency. In addition, a computer program called MAWA was developed as an add-on tool of MS project to automate the calculating and analyzing processes. Applications of MAWA were presented as a benchmark project and the results were compared with those from existing time-cost approaches.

Keywords
Adaptive Weight, Genetic Algorithms, Scheduling, Time-Cost Optimization

1. Introduction

In today's market-driven economy, the ability to minimize the time and/or cost of a project could determine the profitability and even the survival of a construction company. In fact, project time and cost are intricately related. Classical time-cost estimation concepts construe an inverse relationship between direct cost and activity duration, implying an increase in labor and plant costs when project duration is shortened (Adrian, 1979). Indirect cost, as characterized by the project overhead, however, increases with the project duration. Therefore, it is quite difficult to tell whether the total cost (direct cost + indirect cost) will increase or decrease with the compression or extension of project duration.

Over the last few decades, various approaches have been proposed to minimize total cost given that the construction durations are normally predetermined and stipulated in tender documents.

They can be broadly classified as those relating to heuristics or mathematical derivations such as Fondahl's (1961) method--hybrid LP/IP (Liu et al, 1995). The weaknesses of the heuristics and mathematical methods are widely documented (e.g. Zheng *et al*, 2002), but the major deficiency of those methods is their inability to handle more than one objective, and it is questionable as to whether the solution is a 'global', optimal one, because some valuable TCO alternatives might have been ignored.

The increasing acceptance of alternative tenders and different project delivery systems such as design and build, management contracting, build-operate-transfer, partnering, etc., allows greater flexibility in construction duration--to the mutual benefits of both client and contractor. This also means that both construction time and cost should be considered concomitantly at the estimation and planning stages. And from time-cost tradeoff relationship, it is evident that there exists a great possibility that the lowest cost and shortest time can be located synchronically.

In this paper, adaptive genetic algorithms (GAs) are proposed to efficiently deal with time and cost simultaneously, and to solve some deficiencies of simple genetic algorithms. Here, a self-balancing ability was introduced to the mechanism of GAs by modifying the Adaptive Weight Approach (AWA) originally proposed by Gen and Cheng (2000). Furthermore, some innovative techniques (including Pareto ranking, niche formation) are introduced to avoid 'genetic drift' in the processing of GAs. A computer system called MAWA was developed into an add-on tool for the MS Project™, so it takes the least effort for construction professionals to optimize time and cost while conducting their day-to-day practice.

2. Adaptive Genetic Algorithms

2.1 The Mechanism of GAs

GAs are general-purpose search methods that combine the essences of directed and stochastic searches to achieve a better balance between exploration and exploitation during the search process. GAs employ random choice as a means to guide a highly explorative search through an initially unknown space. After randomly selecting the initial population, the engine would evaluate each chromosome in the population according to the fitness functions and assign a value to represent its fitness. The fitness value is then exploited by subsequent selection mechanisms to form a candidate pool for genetic operation: i.e. crossover and mutation. The detailed operation is shown in Figure 1 below.

2.2 Modified Adaptive Weight to Fitness Functions in GA's

Obviously, the fitness function is very important in controlling the survival chance of each chromosome. Therefore, a proper assignment of weights to time and cost induces difficulties, because the likely output would normally be affected by the selected weight approach. More recently, Gen and Cheng (2000) adopted the Adaptive Weight Approach (AWA) to automatically balance the weights of multiple objectives in candidates' fitness function shown in figure 2. This approach utilizes some useful information from the current population to generate an adaptive weight for each objective, thereby, exerting a search pressure towards the ideal point.

$$w_c = 1/(z_c^{\max} - z_c^{\min}) \qquad w_t = 1/(z_t^{\max} - z_t^{\min}) \tag{1}$$

w_c is the adaptive weight for the criteria of cost; w_t is the adaptive weight for the criteria of time

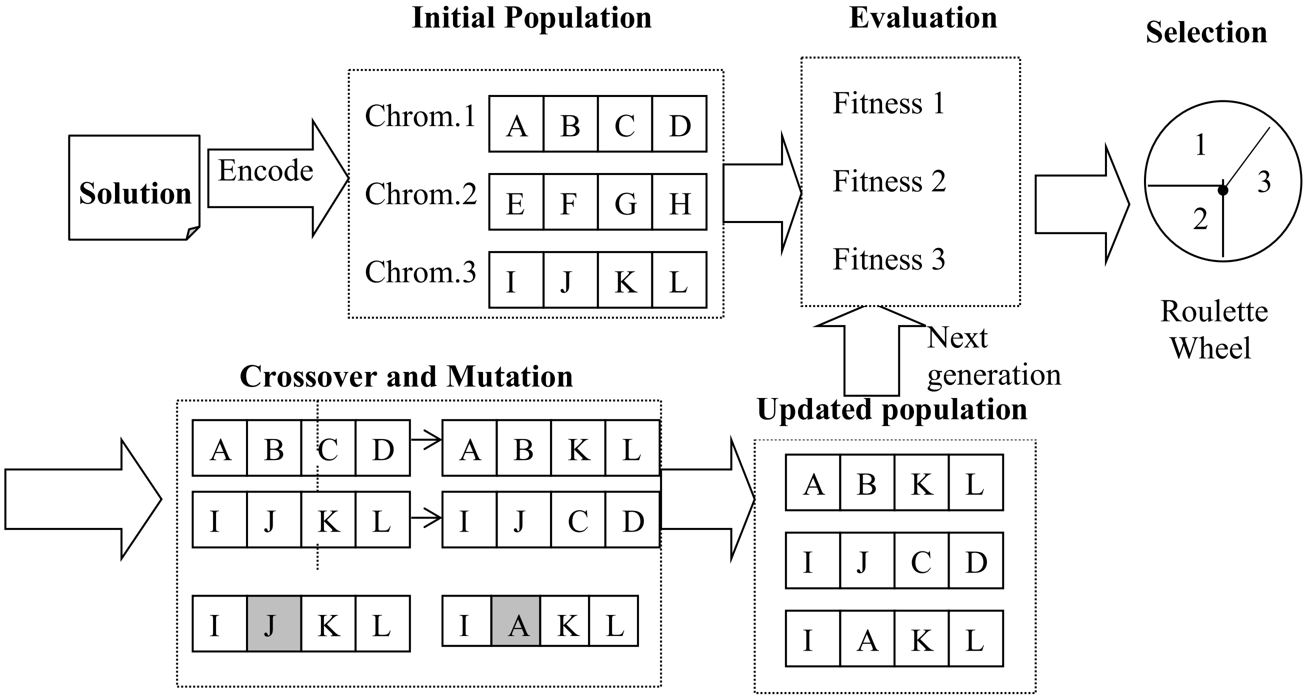


Figure 1: The operations of genetic algorithms

The above formula illustrates the principle meaning of adaptive weights, which address that the inferior objective with narrower exploration extent should be given more attention in the next generation. And the adaptive moving line in figure 2 will gradually approach the ideal point with the evolution of Z^+ and Z^-. Based on the same idea, the weights are further improved by the authors by proposing different weight formulation under four detailed conditions (see the formula by Zheng, 2003). In doing so, there is no worry about scaling difference between time, cost, and zero division any more. And the weights can actually represent the importance of each criterion in the fitness function since the sum of weights is always equal to 1, subjective to the restriction of weights in theory.

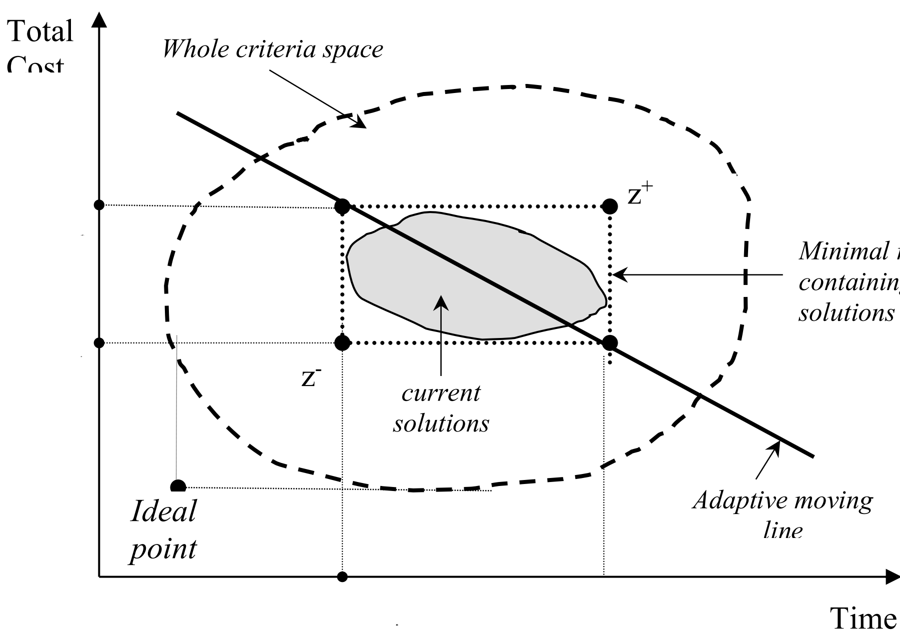


Figure 2: Concept of adaptive weight approach (adapted from Gen and Cheng, 2000)

2.3 Pareto Ranking

In the traditional GA models, researchers utilized proportional selection (also referred to as 'roulette wheel' selection shown in figure 1) as the selection mechanism, in which the chances of survival of each individual is in accordance with their relative fitness value. This method has the ability to ensure that the lesser-fitted individuals will be rejected while the better-fitted ones will be copied to replace them. However, the main disadvantages of proportional selection include: (i) it can only be applied to maximization problems with positive values of the objective function over the domain (Osyczka, 2002), (ii) the Pareto solutions are treated separately in terms of their fitness values, and this could introduce biases into the non-dominated individuals which are equally good or having the same reproductive potential according to the rational of PF.

Therefore, the model proposed by the authors utilizes the combined idea of proportional selection and non-dominated sorting mechanism originated by Goldberg (1989). All non-dominated solutions in current population are identified and flagged. They are labeled Rank 1 and then removed from the population. The next set of non-dominated individuals is identified and assigned Rank 2. This process continues until the entire population is ranked. Thereafter, the fitness value of elements in each rank-set are summed up and then divided by the set size. The average fitness value represents the respective rank. Therefore, as top ranks will have larger fitness value, the elements in those ranks will have more chance to survive, according to the rationale of proportional selection. Once a rank is selected with the "roulette wheel", the algorithms will randomly select an element from the set into further evolution. The new selection mechanism overcomes the deficiency of traditional proportional selection, for not only does better Pareto optimal have greater chances for survival, it could also ensure equal reproductive probability among non-dominated solutions on the same level.

2.4 Niche formation by fitness sharing

In a multi-objective optimization problem, decision-makers might be interested in finding as many optimal solutions as possible. It is understandable that each optimum will work with an adequate sub-population of solutions, which is defined as a "niche". However, due to stochastic errors in evolution, "genetic drift" usually occurs to mislead GAs to converge toward a single peak of a multi-objective optimization (a problem with multiple peaks). The population cannot be distributed over a number of different peaks and each peak cannot receive a fraction of population in proportion to the height of that peak. To promote uniform sampling and maintain population diversity, the model developed in this research utilized a simple niche formation technique shown below based on the suggestion from Goldberg (1989).

Step 1 The user should define a niche size of a solution (d_n).

Step 2 The distance ($d(x_i, x_j)$) between the target solution (x_i) and any other solution (x_j) is calculated (j=1, 2, … n; n is the population size).

Step 3 Compare the distance $d(x_i, x_j)$ with the niche size d_n.

Step 4 If the distance d (x_i, x_j) is equal to or less than the niche size (d_n), the sharing function of x_i ($sh(x_i)$) will be added by 1. Otherwise, $sh(x_i)$ will remain unchanged.

Step 5 If all elements in the population have been considered, the sharing fitness value $f_s(x_i)$ is equal to unshared original fitness value $f(x_i)$ divided by sharing function of x_i $sh(x_i)$. Otherwise return to *Step 2*.

Therefore, when there are many individuals in the same neighborhood, they contribute to each other's sharing functions, thereby degrading one another's fitness. This promotes diversity and helps in limiting the uncontrolled dominance of individuals with 'high' fitness.

3. Case study

The above concepts were programmed into model MAWA using VBA as an add-on tool of MS Project. An 18-activity project found in Feng *et al* (1997) and Hegazy (1999) was fitted into the prototype model for testing. The data on the activities' names, precedence relationships, and time-cost options were input into Microsoft Project™ shown in figure 3.

Tasks	Pred.	Duration	Cost	D1	C1	D2	C2	D3	C3	D4	C4	D5	C5
1		16 d	$1,900.00	14	2400	15	2150	16	1900	21	1500	24	1200
2		23 d	$1,500.00	15	3000	18	2400	20	1800	23	1500	25	1000
3		15 d	$4,500.00	15	4500	22	4000	33	3200				
4		16 d	$35,000.00	12	45000	16	35000	20	30000				
5	1	30 d	$10,000.00	22	20000	24	17500	28	15000	30	10000		
6	1	24 d	$18,000.00	14	40000	18	32000	24	18000				
7	5	18 d	$22,000.00	9	30000	15	24000	18	22000				
8	6	14 d	$220.00	14	220	15	215	16	200	21	208	24	120
9	6	15 d	$300.00	15	300	18	240	20	180	23	150	25	100
10	2,6	15 d	$450.00	15	450	22	400	33	320				
11	7,8	16 d	$350.00	12	450	16	350	20	300				
12	5,9,10	24 d	$1,750.00	22	2000	24	1750	28	1500	30	1000		
13	3	18 d	$3,200.00	14	4000	18	3200	24	1800				
14	4,10	15 d	$2,400.00	9	3000	15	2400	18	2200				
15	12	12 d	$4,500.00	12	4500	16	3500						
16	13,14	22 d	$2,000.00	20	3000	22	2000	24	1750	28	1500	30	1000
17	11,14,15	14 d	$4,000.00	14	4000	18	3200	24	1800				
18	16,17	9 d	$3,000.00	9	3000	15	2400	18	2200				

Key: *Pred. – predecessor*

D1, D2…D5- project duration days for option 1,2…5

C1, C2…C5-project direct cost for option 1,2…5

Duration – the project duration for selected option

Cost – the project total cost

Figure 3 Test data of an 18 activities project

With indirect cost being $1500/day, population size being 50, generation size being 500, crossover rate being 0.8, mutation rate being 0.04, the program gave out the following computing results.

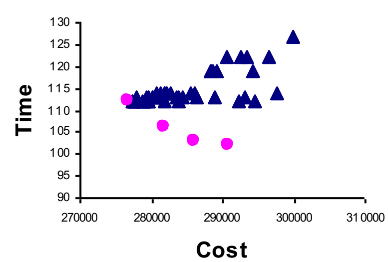
Table 1. The test results of best solutions with different combinations

Generation No. (1)		*(1)* Time (2)	Cost (3)	*(1)+(2)* Time (4)	Cost (5)	*(1)+(2)+(3)* Time (6)	Cost (7)
100	1	108	300820	106	283508	100	293720
	2	111	298120	112	276708	101	290520
	3	117	282420	NA	NA	110	280320
300	1	108	300820	103	292308	100	293720
	2	111	298120	105	288208	101	290220
	3	117	282420	106	281708	104	286720
	4	NA	NA	112	276708	110	275720
500	1	108	300820	102	290870	100	287720
	2	111	298120	103	286070	101	284020
	3	117	282420	106	281708	104	280020
	4	NA	NA	112	276708	110	273720

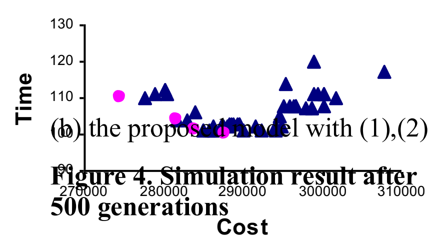
Note : (1) adaptive weights (2) Pareto ranking (3) niche formation

● *represent best points on Pareto front*

▲ *represent individual solution in the population*



(a) Gen & Cheng's approach



(b) the proposed model with (1),(2) & (3)

Figure 4. Simulation result after 500 generations

From the above table, it is obvious that modules with (2) and (3) are better than others, since the solutions in the last two modules can dominate most of the points in the first module. In addition, after 500 generations, any solution in the last module can dominate at least one solution from the second module. And from the figure on the right, we can clearly see that the individuals after 500 generations are distributed evenly along the points on Pareto front rather than converging prematurely to peaks shown in figure 4(a).

4.Conclusion

This paper developed an innovative computer model with adaptive GAs to optimize construction time and cost simultaneously. By modifying Gen's & Cheng's adaptive weight approach, the new model was endorsed with a self-learning ability to balance the priority of each objective judging from historical performance. And the "genetic drift" reported by many GA developers or users are overcome in this research by the introduction of Pareto ranking and niche formation. The case study conducted in this research further demonstrated the robustness of the proposed model since no existing GAs models can optimize construction time and cost in one step. Therefore, this new model has the potentials to ensure the project is completed within the shortest time at the lowest cost, for the mutual benefit of both client and contractor.

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