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Decision Support Tool for Excavation Operation using Genetic Algorithms

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Abstract

The appropriate fleet estimation of the excavation equipment is a major factor in the determination of the cost and time requirements of a project. But the decision of what kind of equipment selected is often based on heuristic methods or trial and error in Korea. Thus, this study proposes a prototype model that uses genetic algorithms to select fleet estimation of loaders (backhoe) and trucks used in excavation work. To verify the applicability of this model, the case study was performed. And the result of the genetic model was compared with that of the trial & error method. The use of the genetic model suggested this study required 44days, 2 units of backhoes, 7 units of trucks, and a total cost of 171,839,756 won. With the estimated fleet number of equipment, the minimum cost of excavation work can be calculated, taking account of the time-cost trade-off. By utilizing this prototype model, the efficiency of excavation work can be improved.

Keywords : Excavation Works, Genetic Algorithms, Optimal Solution

1. INTRODUCTION

The primary role of a construction manager is to achieve the largest profit, through coordination of various factors such as time, cost, quality, safety, and environment of a project. These elements aim to reduce time, save cost, improve quality, and prevent accidents and pollutions in the construction field. However, some aims have to be sacrificed for others. But because diverse uncertainties exist in a construction process (Yau, 1998), construction managers have difficulty in .making appropriate selections among these aims.

In relation, earthmoving operations, in particular excavation work, require absolute coordination, since they have more uncertain factors than other types of operations. Because of the large number of variables, some of which are virtually uncontrollable, excavation work must be considered as one of the financially riskier construction trades (building construction, 1995). In addition, the excavation work is exposed to unforeseen subsurface, although tests such as digging pits or boring, finding water table, etc., do not provide correct information of the subsurface. During excavation, for example, rock was uncovered where no rock was indicated in the boring on each side of the rock formation. And obscure under surface situation can be lead to unexpected claims. Therefore, this paper is to improve the accuracy of prediction during execution of an underground construction project about diverse uncertainties.

2. BACKGROUNDS

Traditionally, many researchers have pursued the same objectives in construction management , namely, saving cost and productivity improvement To this end, mathematical formulas, statistical techniques, artificial intelligent techniques, and so on have been used. Recently, artificial intelligence , including expert systems, rule-based systems, artificial neural networks, genetic algorithms, and so on, have been frequently used to perform optimizations (Hegagy, 1999), predictions (Kim et al., 2004), classifications, estimations, and etc. Furthermore, accurate prediction methods of the construction costs, and other important factors affecting the success of a construction project have been studied. Especially, cost estimations in the early stage of a construction project are important for facilitating project cash flow, preventing cost overruns, and so on. These aims also apply in earthmoving operations, and they affect the selection and assignment of the earthwork equipment, which is a major resource of an earthmoving operation (Elazouni & Basha, 1996). and equipment selection and assignment need to be determined carefully. However, the selection and assignment of equipment has always been a challenge for the project manager for achieving overall optimization of a project. The equipment selected and assigned must minimize the production cost, and/or maximize the fleet productivity.

Many selection and assignment methods of equipment used in earthmoving operations had been developed. The equipment selected by these methods can not only can reduce the total cost but also improve productivity. Smith (1999) developed regression techniques to estimate earthmoving productivity. Karshenas (1989) developed mathematical formulation to select truck capacity for

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earthmoving. Farid and Koning (1994) suggested multiloader-truck assignment systems using MicroCYCLONE, which is a computer simulation package. Smith et al. (1995) developed discrete-event modeling for simulation of an earthmoving system. Expert systems were studied for assisting in the selection of earthmoving equipment (Amirkhanian & Baker, 1992). Shi (1999) developed for construction practitioners a simple tool for predicting earthmoving operations, which are modeled by back propagation neural networks. Most of these methods are deterministic, and cannot address the random and dynamic nature of earthmoving operations. Although computer simulation and artificial neural network can overcome these limitations, the difficulty in implementing simulations has greatly restricted these methods from being applied widely in the industry.

Genetic algorithms (GAs) have been used as a powerful tool for optimization (Li et al., 1998). In the construction industry, GAs have been utilized for: (1) estimating optimum markup (Moselhi et al., 1993); (2) resource scheduling optimization (Chan et al., 1996; Feng et al., 1997; Li and Love, 1997; Hegazy 1999a,b); (3) site layout optimization (Philip et al., 1997); and (4) maintenance budget allocation and pavement rehabilitation decisions (Chan et al., 1994; Fwa et al., 1994). Thus, in this study, the decision support model is developed by using GAs to determine optimal earthmoving equipment operation. To achieve this aim, operating and leasing cost of a number of trucks and hoes were analyzed. And genetic algorithms were applied to optimize cost and productivity. The result by model is compared with case study by manual, then, appropriate methods for equipment assignment are discussed.

3. GENETIC ALGORITHMS

Genetic algorithms are recently developed artificial intelligence techniques inspired by the theory of evolution and biogenesis (Holland, 1992). GAs use random techniques but exploit information from past experience to evolve solutions to real-world problems, once real-world problems are appropriately encoded. This adaptive search technique, which has powerful non-linear processing capabilities, can be used to solve multi-dimensional optimization problems with discrete variables and discontinuous functions. GAs can treat discrete variables and complex functions without derivatives (most real planning, design and construction problems include discrete variables and quite complex and ambiguous evaluation functions). Furthermore, GAs are less susceptible to becoming stuck at local optima than the gradient search methods. However, GAs are computationally expensive and will usually be outperformed when specialized algorithms for problems exist (Al-tabtabai, 1999).

(1) Fitness (or objective) function

A fitness function must be devised for each problem to be solved.

(2) Selection

The nature of this model is the 'survival-of-the-fittest' mechanism. Fitter solutions survive, while weaker ones perish. Through selection, a chromosome survives to the next generation and produces an offspring according to chromosome's relative fitness (Mawdesley et al., 2002).

(3) Crossover

This is the operation for searching the solution space. Pairs of chromosomes are picked at random from a population to be parents and are subjected to crossover. Crossover is a procedure of exchanging the information of both parent chromosomes to produce an offspring with mixed genes (Mawdesley et al., 2002).

(4) Mutation

After crossover is continuously applied for some generations, some genetic information may be lost. The mutation operation is used to restore the lost information. In many applications, mutation is only treated as a secondary operator after the crossover operator (Mawdesley et al., 2002).

(5) Termination Criterion

Equipped with all the components, genetic algorithms can operate continuously until pre(-)specified termination conditions are satisfied. Some of the most widely used termination criteria are maximum number of generations, maximum non(-)improvement generation numbers, and convergence rate of the population. In practice, other termination criteria are also possible (Mawdesley et al., 2002).

4. DECISION SUPPORT MODEL

4.1 General process

The process of building and evolving a population of individuals is simple:

1. Build a population of individuals and chromosomes.
2. Specify the evolutionary parameters (crossover rate, mutation, etc.)
3. For each individual in the population:
4. If the best fitness computed (maximum or minimum) is better than the best fitness so far, then the user's display is updated with the best so far and the chromosomes are saved.
5. If either of the following is true, then stop:
6. Reproduce the population (make a new generation)
7. Go to step 3.

4.2. Computation procedure

The computing process in this paper is shown Fig. 1. First, the quantity of excavation, required cycle time, and daily costs of each unit are defined as user input items. Second, in the genetic program, GENE-HUNTER, which is EXCEL Add-in software, the population size, genetic operators, and termination criteria are selected by the user. Third, the genetic process is started and each variation is computed as follows:

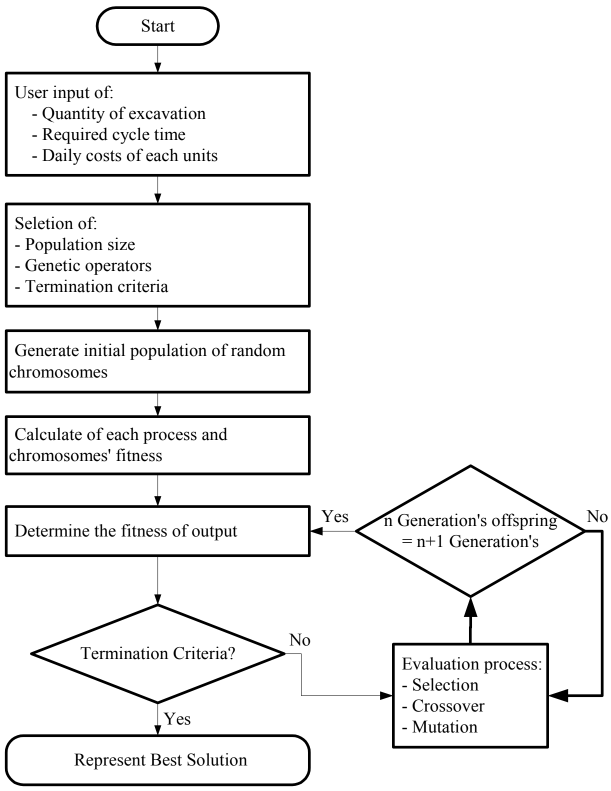

Figure 1. Model computation process

(1) Hoe's duration and production rate

The excavation cycle time- dig, swing, dump, swing- can be determined, respectively.

$$t_s = dig + swing + dump + swing\ \ time$$

$$t_s = \sum_{j=1}^{n(s)} t_{sj}$$

t_s; total cycle time of a system

t_{sj}; the load time of hoe s performing action j

$n(s)$; total number of actions or segments in activity s

The actual capacity of the trucks and hoe is determined by the swell factor. When solid earth materials are loosened by digging they usually occupy more volume than before. This phenomenon is call swelling and it could calculate as multiply by swell factor. The swell factor is shown in table 1.

Table 1. Swell factor

Rock type	Swell factor	Mean
Broken_rock	1.5~2.0	1.75
Gravel	1.0~1.1	1.05
Clay	1.25~1.4	1.325
Sand	1.0~1.3	1.15
Common_earth	1.1~1.3	1.2

$$C_t = \frac{capacity\ \ of\ \ truck}{swell\ \ factor} \times number\ \ of\ \ trucks$$

$$C_h = \frac{capacity\ \ of\ \ hoe}{swell\ \ factor}$$

The time to load truck is determined by,

$$T_s = \frac{C_t}{C_h} \times t_s$$

The reciprocal of the hoe's cycle time becomes the service rate μ.

$$\mu = \frac{60s/\min}{T_s}$$

The production rate and required duration to excavate of hoe can be expressed as;

$$N_s = C_t \mu$$

$$T_{dh} = \frac{Q}{N_s}$$

(2) truck's duration and productivity

The cycle time of truck unit can be expressed as (total duration)

$$T_t = \sum_{j=1}^{n(t)} t_{tj}$$

t_{tj}; the separate action durations needed to conduct activity j

$n(t)$; total number of actions of segments in activity t

This time involves the queuing time

The arrival rate per hour is

$$\lambda = \frac{60\min/h}{T_t}$$

The production rate and required duration to haul of truck (customer being serviced)

$$N_t = \theta C_t \lambda$$

$$T_{dt} = \frac{Q}{N_t}$$

θ; portion of an hour that is productive.

(3) Calculation of optimum cost

Then, the duration of the excavation is determined, and excavation equipments (hoe and truck) and labor(operator) costs(i.e. foreman, hoe operator, truck driver, hoe cost, truck cost) are selected. The prices or costs are shown Tables 1 and 2. Total daily cost = working hour per day * (foreman cost + hoe and operator's cost * number of hoe + truck and driver's cost * number of trucks).

$$Min\{Total \;\; daily \;\; cost\}$$

Ideally, from a deterministic point of view, the operation should be balanced, or

$$N_s = N_t$$

Therefore, the number of haul units needed to balance the operation is

$$k = \frac{\mu}{\lambda}$$

,but the system cannot be balanced, unless there is a haul unit in line, waiting to be loaded or if the loader is idle for any part of the time period. This will cause the production rate to be less than the maximum.

4.3 Decision-Support Tool

To provide simple access to the developed GAs, a spreadsheet interface was developed to facilitate data input and automate performance assignment. The interface was developed on Microsoft Excel using its macro programming tools. The type of equipment for digging and excavation, hauling capacity, loading time, and soil type can be selected. The quantity of soil, cycle time of truck operation, and target duration should be input manually, as shown Fig. 2.

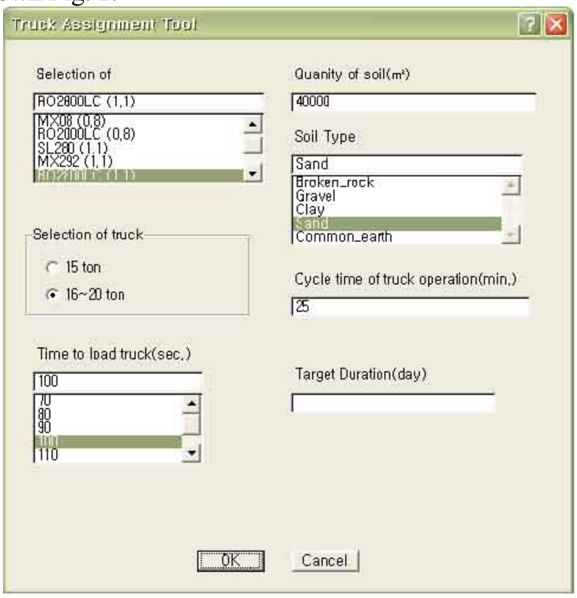

Figure 2. Decision support tool

Then, the genetic process is computed by Gene-Hunter developed by the Ward System Co. It is connected to the spread sheet program. Thus, the fitness function and chromosomes should be designated on the sheet. The genetic software is shown by Figure 3.

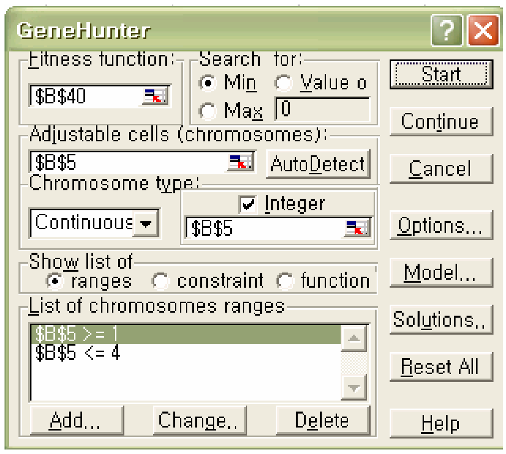

Figure 3. Genetic algorithms software

5. CASE STUDY & RESULT

The proposed decision-support tool was applied to this case study by use of macro programming, and genetic algorithms software was applied in the computation procedure to calculate the optimum solution. The case study is presented in Table 2. And Table 3 & 4 is shown by each unit cost. The costs are used for calculating and optimizing the total cost. The model was verified by comparing it with the trial & error method by manual.

Table 2. Case study description

Item	Quantity and type	Unit
Quantity of excavation work (m^3)	20,000	-
Type of soil	Common_earth	Swell factor 1.2
Backhoe type	MX292	bucket $1.1m^3$
Truck type	15ton	Capacity $10m^3$
Hire cost of backhoe	350,000	won/day
Hire cost of truck	360,000	won/day
Foreman	85,318	won/day
Backhoe operator	78,015	won/day
Truck driver	63,443	won/day

Table 3. Labor cost

Work man type	$(cost/day)
Foreman	72.65
Hoe operator	66.43
Truck driver	298.02

Table 4. Equipment cost

Equipment type	bucket	$(cost/day)
SL200LC	$0.8m^3$	255.45
MX08	$0.8m^3$	255.45
RO2000LC	$0.8m^3$	255.45
SL280	$1.1m^3$	298.02
MX292	$1.1m^3$	298.02
RO2800LC	$1.1m^3$	298.02
SL360	$1.4m^3$	340.60
MX352	$1.4m^3$	340.60
R3600	$1.4m^3$	340.60

The genetic model suggested this study required a duration of 44days, 2 backhoe units, 7 truck units, and total cost of 171,839,756 won, as shown figure 4. In addition, we can calculate same results by the trial & error method. It shows that the genetic model can be used for equipment optimization successfully. Thus, the genetic model would not only increase the accuracy of estimation for equipment selection but also decrease human error. However, if the desired aim is minimum duration, the model gave results of 31days, 4 backhoe units, 10 truck units, and total cost of 186,986,048 won by controlling the fittest function.

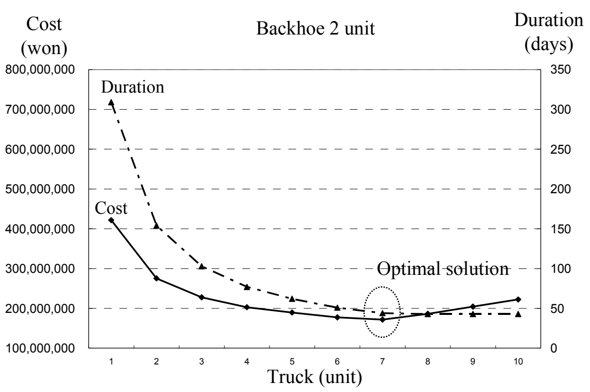

Figure 4. Optimal solution

6. CONCLUSION AND FUTURE WORK

In this study, to support construction engineers or managers in their task of proper coordination, a decision support model for earthmoving operation using genetic-algorithms was suggested. To verify this model, a case study was performed. The proposed model presented appropriate optimal solutions, when compared to those obtained by trial & error method. Therefore, genetic algorithms could the means by which optimal solutions can be obtained in an excavation fleet optimization process. However, an advanced model, not a prototype, should be established and should include quantity factors as well as quality ones and consider the indirect costs.

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APPENDIX: NOTATION

t_s; total cycle time of a system
t_{sj}; the load time of hoe s performing action j
$n(s)$; total number of actions or segments in activity s
C_t : capacity of the trucks
C_h : capacity of the hoes
T_s : the hoe's cycle time for one truck
μ :the reciprocal of Ts
N_s : productivity of the hoes
T_{dt} : expected total time
Q : quantity of excavated work
T_t : a cycle time of truck
T_{tj} : the time of truck performing action j
λ : service rate of truck
N_t : productivity of truck
T_{dt} : expected total time of truck
T_c : (total daily cost)
T_{wd} : daily working time

(Data of Submission : 2006. 8.19)