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OPTIMAL FLEET SELECTION FOR EARTHMOVING OPERATIONS

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Earthmoving operations often involve a large number of specially designed equipment with significant purchasing/leasing prices, high operating and maintenance costs. Hence, choosing the right fleet is a major concern from the construction planners' point of view. This paper presents a methodology that combines discrete-event simulation and optimization to solve the optimal fleet selection problem for earthmoving operations. Two optimization objectives are formulated and solved using the proposed framework and a genetic algorithm: minimization of Total Cost of Ownership (TCO) and maximization of productivity. Further, a two-stage rating scheme is introduced to arrange the fleet configurations so that the optimization algorithm converges to a fleet with better second-stage performance while the first-stage performance remains at the same level. The case study shows that the proposed mechanism can effectively allocate an optimal equipment combination for earthmoving operations and hence serve as an efficient tool for construction management.

Keywords: earthmoving operations, equipment selection, simulation optimization, discrete-event simulation, genetic algorithm.

1 Introduction

Earthmoving operations are a fundamental part of construction engineering and are regularly impacted with uncertainty. Accurate productivity estimation and cost analysis are necessary before and during a construction project to ensure that the project is completed within the targeted timetable and budget. Equipment selection is one of the most important decisions to guarantee the success of a construction project. Normally, this is done using rules of thumb and engineering experience.

In recent years, simulation and optimization methods have been used to enhance the study of construction engineering. AbouRizk and Shi (1994) developed an optimization method which utilizes the delay statistics of resources and reasonable matching among resources to guide the simulation system to search for the most appropriate resource allocation. Minimizing unit cost, maximizing production rate and optimizing resource utilization were the objectives studied. Marzouk and Moselhi (2000) presented an automated system that integrates a simulation module and a genetic algorithm for optimizing earthmoving operations. Total project cost, overall project duration and idle time for specific piece of equipment are estimated using simulation and fed into the genetic optimization algorithm to select an optimal fleet. Zhang (2008) formulated a multi-objective problem and incorporated simulation within a particle swarm optimization algorithm to look for potential equipment configurations. The performance of different fleet combinations was evaluated with respect to a multiple attribute objective function and statistical methods for variance reduction were introduced to handle stochasticity in the performance. Cheng and Yan (2009) created a mechanism that incorporates a so-called messy genetic algorithm and a simulation engine to optimize resource utilization with respect to the production rate or unit cost. This mechanism could generate various working schemes of the earthmoving operations and build the necessary components for conducting simulation in each scheme.

However, the above studies solve the optimal fleet selection problem from a pre-determined equipment configuration, i.e. they optimize the decision variables given that the loading unit of a specific model is consistent with a hauling unit model. Decision variables refer to the number of equipment units while variables capturing the properties of equipment, such as model and capacity, are important as well. It is time-consuming to pre-calculate the "good match" between equipment types as the numbers of variables increase.

In this paper, we formulate an optimal fleet selection problem where the performance of earthmoving operations is measured using the Total Cost of Ownership concept (TCO) or productivity. The earthmoving operations are modeled and simulated using a developed simulation platform (Fu 2012a). In earlier work (Fu 2012b) we designed and used a genetic algorithm (GA) to interact with the simulation platform to search for an optimal fleet configuration in terms of TCO, considering a set of qualitative and quantitative variables. In this study, we extend the GA with a two-stage ranking procedure which could further improve its performance. Numerical examples of TCO minimization and productivity maximization are given to demonstrate the effectiveness of the proposed optimization algorithm.

The remainder of this paper is organized as follows. Section 2 formulates the optimal fleet selection problem while considering two different objectives. Section 3 describes the essential features of the proposed simulation-based optimization approach to solve the problem of interest. Numerical examples of the optimization problems are shown in Section 4. Section 5 concludes the paper.

2 Optimization Problem Formulation

Two optimization problems are formulated and studied in this paper:

- TCO minimization
- productivity maximization

These two conflicting objectives are the most commonly used in the construction business.

TCO is originally a management accounting term designed to estimate the direct and indirect costs of an investment. A TCO analysis takes into account the acquisition cost, the operating cost and the productivity, and provides a clear picture of profitability. TCO is defined as the cost per production unit, and is calculated as the quotient of the total cost per operating hour and the production per operating hour. TCO consists of the capital cost (purchasing cost, residual value, depreciation, interest, insurance, and taxes) and the operating cost (operator cost, fuel consumption, wear parts, preventive maintenance and repair cost). The operating cost is subjected to the uncertainties of the operating environment.

Productivity is defined as the output per unit time from the entire fleet, and is normally measured in ton per operating hour.

2.1 *TCO minimization*

Eq. (1) formulates the TCO minimization problem:

$$\begin{aligned}
\min \quad & \mathrm{TCO} \\
\text{subject to} \quad & P \geq P_{\min} \\
& \sum_{l=1}^{L} \sum_{b=1}^{B_l} x_{l,b} \leq N_{\max}^{\mathrm{LU}} \\
& \sum_{h=1}^{H} y_h \leq N_{\max}^{\mathrm{HU}} \\
& x_{l,b} \in \left\{0,1,2,\ldots,N_{\max}^{\mathrm{LU}}\right\} \\
& y_h \in \left\{0,1,2,\ldots,N_{\max}^{\mathrm{HU}}\right\}
\end{aligned} \tag{1}$$

where P is the production rate (ton/h), $P_{\min}$ the minimum production rate defined by the user, $N_{\max}^{\mathrm{LU}}$ and $N_{\max}^{\mathrm{HU}}$ the maximum number of loading and hauling units respectively, $x_{l,b}$ the integer variable representing the loading unit of model *l* with bucket size *b*, y_h the integer variable referring to the number of hauling units of model *h*. The first three constraints in Eq. (1) ensure that the production rate is not lower than the required minimum value and the numbers of loading and hauling units are within the given maximum quantities. The last two constraints define the integer ranges of the variables $x_{l,b}$ and y_h .

2.2 *Productivity maximization*

The productivity maximization problem is given in Eq. (2).

$$\begin{array}{ll} \max & P \\ \text{subject to} & P \le Cap_{\text{crusher}} \\ & \sum_{l=1}^{L}\sum_{b=1}^{B_l} x_{l,b} \le N_{\max}^{\text{LU}} \\ & \sum_{h=1}^{H} y_h \le N_{\max}^{\text{HU}} \\ & x_{l,b} \in \left\{0,1,2,...,N_{\max}^{\text{LU}}\right\} \\ & y_h \in \left\{0,1,2,...,N_{\max}^{\text{HU}}\right\} \end{array} \tag{2}$$

The first constraint in Eq. (2) ensures that the productivity is not above the capacity of the crusher, Cap_{crusher} . The crusher capacity is an important factor that affects the entire fleet's productivity. As shown in Fu (2012b), overcapacity of equipment can lead to the productivity exceeding the crusher capacity by crushing material during breaks in a work shift. However, this situation is not always allowed by labor regulation since some operators will be forced to work overtime while others are on lunch break. Thus, fleet combinations with overcapacity will be eliminated from the search space in the optimization process using this constraint.

3 Simulation-based Optimization using Genetic Algorithm

Simulation is a widely used tool in operations research due to its ability to model complex systems at the desired level of detail. In recent years, simulation techniques have been used to model the processes in construction engineering. A discrete-event simulation platform (Fu 2012a) is utilized in this study to model earthmoving operations. This platform was developed based on the well-known CYCLONE modeling method (Halpin and Riggs 1992) and captures the interactions between resources at a very detailed level. The duration of earthmoving activities can be modeled as deterministic or stochastic. Through the simulation, TCO, productivity, queue statistics etc. can be observed in order to evaluate the performance of alternative fleet configuration.

A genetic algorithm is designed in this study to search for potential optimal fleet configurations without exhaustively testing all combinations. Genetic algorithms belong to the class of evolutionary computation algorithms which imitate the process of natural selection (Gen and Cheng 2000). Figure 1 demonstrates the chromosome structure designed in the GA implementation. The genes in the first part of the chromosome are the integer variables $x_{l,b}$ representing the number of loader type *l* with bucket size *b*. The second part of genes with dash-dot line refers to the quantity of hauling unit *h*.

This GA mechanism then carries on the standard procedure until the fitness value of the optimal solution does not improve for a certain number of iterations or the GA reaches its maximum number of iterations. The basic steps are outlined below:

(i) Simulate earthmoving operations and calculate the fitness values of the current population.

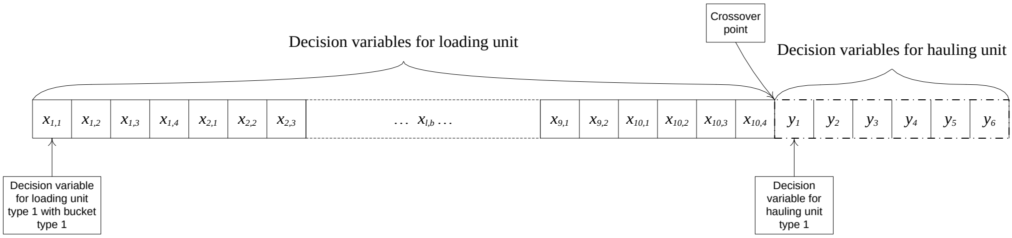

Figure 1 The chromosome structure in genetic algorithm

(ii) Rank the population according to the fitness (the value of the objective function) of chromosomes and select a pair of parent chromosomes for reproduction from the current generation.

(iii) Perform crossover with probability p_c of selected parent chromosomes at the pre-determined point to form offspring. In this GA method, the crossover point is chosen between variables for loading and hauling units, as shown in Figure 1.

(iv) Mutate the chromosomes with mutation rate p_m for preservation of diversity.

(v) Go to step (ii).

The required user inputs for implementing GA are population size *N*, crossover probability p_c and mutation rate p_m.

3.1 *A two-stage ranking process in GA*

A two-stage ranking scheme in step (ii) of the GA procedure is introduced in this study so that fleet combinations that have the same objective value are rated again using another secondary objective. Taking the TCO minimization problem as an example, a fleet with the same unit cost and higher productivity is preferred over one with lower productivity. Hence, the productivity is considered as the second aspect in the ranking process. The fitness of chromosomes is first arranged according to the objective value (TCO), and then ranked again by their productivity. In this way, for fleet combinations with the same TCO values, the one with higher production rate will have higher rank and hence higher probability to be selected to produce offspring. For the productivity maximization problem, the TCO value is chosen as the criterion in the second ranking procedure. Intuitively, lower TCO for the same production rate indicates lower production cost.

In contrast to using a multi-objective formulation of the problem, this two-stage ranking procedure allows the user to define the objectives of a project on two levels of priority. First of all, the users do not need to test different weight parameters of each objective before obtaining a satisfactory result. Secondly, this method can find fleets with better overall performance compared to single objective optimization. This two-stage method is thus more straightforward and less computationally demanding for construction management applications.

4 Case Study

A real-world numerical example of quarry site operations is given here to demonstrate the proposed GA. The quarry site is situated in the north of Stockholm, Sweden and produces gravel, aggregate, and sand all year round. The uncrushed material is either obtained on site or purchased from other construction sites. In this example, the uncrushed material is first loaded by the loading equipment into the hauling units, which travel to the dumping station to empty the load into the crusher. The hauling units then return to the loading station to begin another load-haul cycle, and the material is crushed in several processing units until it reaches the desire size. Details of the operation can be found in Fu (2012b). The average density of the uncrushed rock is 1.60 ton/m^3 and the crusher has a capacity of 500

m^3/h with a hopper of 50 m^3 connected on top. The type and capacity of available equipment employed in this operation are given in Table 1. The duration and fuel consumption of earthmoving activities of the machines are provided by the equipment manufacturer, Volvo Construction Equipment. The activity durations are considered to be deterministic in this case study.

Table 1 Available equipment types and capacities

Equipment	Type	Capacity (m^3)
Loader	Volvo L60G	2.1, 2.3
	Volvo L70G	2.3, 2.4
	Volvo L90G	2.5, 2.8
	Volvo L110G	3.0, 3.4
	Volvo L120G	3.3, 3.6
	Volvo L150G	4.0, 4.4, 4.5
	Volvo L180G	4.4, 4.6, 4.8
	Volvo L220G	4.9, 5.2, 5.6
	Volvo L250G	5.7, 6.4
	Volvo L350G	6.6, 6.8, 6.9, 7.7
Hauler	Volvo A25F	15.0
	Volvo A30F	17.5
	Volvo A35F	20.5
	Volvo A35FS	20.5
	Volvo A40F	24.0
	Volvo A40FS	24.0

Due to the spatial limitations of the site, only one loading unit and at most five hauling units can be employed in the earthmoving process. The total number of equipment combinations for this operation is thus

$$25 \cdot \sum_{k=1}^{5} \binom{6+k-1}{k} = 11525 \qquad (3)$$

where 25 is the number of combinations for the loading unit with different bucket capacities given in Table 1, and 6 is the number of hauling unit models.

In the application of the GA, the population size, maximum number of generations, crossover rate, and mutation rate are set to 40, 100, 0.5 and 0.3, respectively after a few trials with the algorithm. Further, the GA terminates the simulation-optimization process if the optimal fleet does not change in 20 generations.

4.1 *TCO minimization*

Using the proposed simulation optimization algorithm, the result for TCO minimization (Eq. (1)) is shown in Figure 2. The upper plot displays the TCO value of the optimal fleet in GA iteration, and the lower plot depicts the production rate for the corresponding fleet. The GA successfully finds an optimal solution already at iteration 4 and computes $4 \cdot 40 / 11525 \approx 1.4\%$ of total possible solutions. In this case, there are no configurations with the same TCO value and the second stage of our two-stage ranking technique does not come into action.

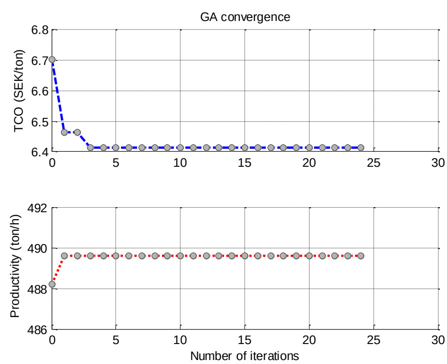

Figure 2. TCO minimization - GA convergence

4.2 *Productivity maximization*

Figure 3 shows the GA convergence of the productivity maximization problem (Eq. (2)). We observe that the objective function (production rate) already converges to its optimum in the first iteration shown in the upper plot, but the TCO value in the lower plot continues to decline until iteration 40 since there are several alternatives with the same production rate. With deeper examination of the optimal fleet in each iteration, we observe that the crusher capacity restrains the productivity and the GA selects the “cheaper and slower” equipment so that the hauling units wait less at the dumping station. Hence, we can conclude that the two-stage ranking process can guide the GA further to better solutions when there are multiple combinations with the same first-stage objective value. In this problem, the two-stage GA searches through $7 \cdot 40 / 11525 \approx 2.4\%$ of all possible solutions before finding the optimum at iteration 7.

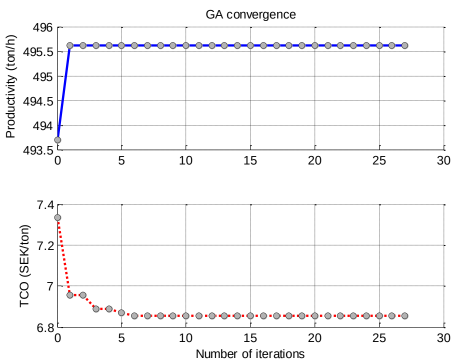

Figure 3. Productivity maximization - GA convergence

The optimal fleet configurations for the two optimization problems formulated in this earthmoving operation are summarized in Table 2.

Table 2 Optimal fleet configurations

	TCO minimization	Productivity maximization
Optimal fleet	L60G 2.3m^3 2 haulers of A25F	L150G 4.4m^3 2 haulers of A35F
TCO (SEK/ton)	6.41	6.85
Productivity (ton/h)	489.60	495.62

5 Conclusion

In this paper, we present a framework which integrates a discrete-event simulation platform with a genetic algorithm to solve the optimal fleet configuration problem for earthmoving operations. Two different objectives, TCO minimization and productivity maximization are formulated and demonstrated with a case study. The case study shows that the proposed method can efficiently find an optimal combination of construction machinery while each stage of the two-stage ranking method has its own objective function. Hence, it is an efficient, effective technique that can assist the project management in fleet selection.

Here we only study the deterministic duration of earthmoving activities. It will be interesting in future work to compare the performance of the proposed simulation optimization system while taking the stochasticity into account, and to analyze the impact of activity duration variability on the optimal fleet configuration.

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