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OPTIMUM CONSTRUCTION EQUIPMENT FLEETS FOR ROAD SURFACE OPERATIONS

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The optimum selection of equipment fleets in surface work operations is a key element to the success of any road construction project. For years, computer simulations have been used to predict the performance of construction operations based on process flows and resources utilized. However, simulations in essence are not a resource optimization platform, since all possible resource combinations should be examined within the simulation process itself. This paper proposes a hybrid mechanism that integrates discrete event simulation and genetic algorithms to efficiently determine the best resource combination for the surface work operations in road construction. The paper employs genetic algorithms (GAs) for minimizing the total cost of surface work operations examined. A dynamic link utilizes a simulation engine, which models a road's surface work operations, to calculate the fitness of the generated chromosomes. An actual case study is further utilized to illustrate the effectiveness and performance of this hybrid mechanism.

Keywords: Road construction, Simulation, Equipment selection, Optimization, Genetic algorithms.

1 INTRODUCTION

Road construction is an equipment-intensive process, where equipment fleets play a vital role in performing the work. Most contractors tend to rely upon historical data and experience in similar projects to assist in selecting the optimum fleet and estimating the production rate of surface work operations. However, this approach proved inadequate because of the complexities, great variability, and numerous uncertainties associated with road construction operations (Castro and Dawood 2005).

Since the early 1990s, discrete-event simulation has been used to predict the performance of many construction operations, especially those with a repetitive nature. When properly utilized, discrete-event simulation can help contractors to: (1) understand how resources influence the overall performance of a given construction system, (2) compare all possible strategies for job execution, and (3) determine which resource combinations provide the greatest production and/or least construction costs.

However, discrete-event simulation, on its own, lacks the means to optimize a construction operation. One has to examine all possible combinations of resources to arrive at the optimum process configuration. In more complex construction systems, intuition or heuristics are employed to decide which combinations to examine, but there is no guarantee of reaching optimum or near-optimum solutions.

The advent of intelligent optimization techniques brings a new capacity to planning construction operations. Evolutionary algorithms, such as genetic algorithms (GAs), have been recognized as capable optimizers in various problems in engineering and construction management. GAs can smoothly incorporate information from a previous stage to create a better new search in next stage, as per the principle of survival of the fittest and adaptation (Limsisi 2011). Interestingly, McHaney (1999) reported that GAs are relatively adaptable for the discrete-event computer simulation environment.

This paper presents a hybrid method that integrates simulation and GAs to optimize equipment fleets used for surface work operations in road construction projects. Following a brief literature review of resource management in construction operations, this paper explains the developed GA and its interaction with the simulation engine. A brief case study is later presented to illustrate its effectiveness.

2 SIMULATION AND RESOURCE OPTIMIZATION IN THE LITERATURE

Discrete event simulation has been shown to be effective in experimenting with alternative construction scenarios while accounting for the uncertainties of the construction process (Abraham and Halpin 1998, Zayed and Halpin 2001, Marzouk and Moselhi 2004). Despite these studies and many others, reaching an optimum or near-optimum resource configuration is by no means a straightforward process.

The search for better means to optimize the resource configuration within the simulation environment dates back to the 1990's. AbouRizk and Shi (1994) proposed a heuristic algorithm to efficiently identify the most appropriate resource configuration of a simulated construction system. The main drawback is that this approach is problem-dependent. Use of evolutionary algorithms followed in the last decade. For instance Hegazy and Kassab (2003) utilized GA for resource optimization during planning.

An exhaustive literature search indicated that, unlike earthmoving and concreting works, there are few studies addressing the proper selection of equipment fleets for road-surface operations. This partially instigated this study along with the need to improve on the GA optimization process and linkage with the simulation environment as detailed later in the paper.

3 ROAD-SURFACE WORKS SIMULATOR

During the simulator design stage, CYCLONE network diagramming was utilized to depict the various elements and logical relationships between road-surface work activities. Two primary construction processes were modeled (Figure 1). They are (1) aggregate works and (2) paving works. The former uses fleets of aggregate trucks, water distributors, and graders, whereas the latter employs hot-mixed asphalt (HMA) trucks, bitumen distributors, and pavers. A CAD model, whose details are not part of this paper, is used to model spatial locations and truck cycles. The purpose is to properly estimate the out-of-site fleet activities while accounting for road conditions, road network, speed limits, and other factors.

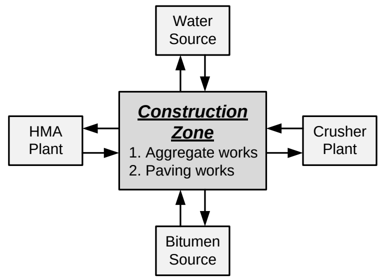

Figure 1. Surface Work Operations – A Schematic.

During the simulator implementation stage, object-oriented (OO) concepts were utilized to replicate a predefined set of resources/fleets. A built-in algorithm allows the incremental change in construction system resources so multiple configurations can be examined throughout the optimization process.

4 GA OPTIMIZER

GA capabilities are utilized to search for the optimum fleet configuration. In this context, the optimum configuration associates with the operation's minimum cost while accounting for all project requirements and constraints, e.g., desired production, work conditions, resource availability, etc. The available equipment fleet, with well-defined types, models, and numbers, is necessary for the creation of feasible scenarios for the optimization process.

4.1 Chromosome Structure

According to GA terminology, the optimum fleet combination would correspond to the genes with the best fitness. The chromosome structure (Figure 2) is designed in such a way that the length of the chromosome (i.e., the number of genes) reflects the number of equipment types used in both aggregate and paving works; the genes in that chromosome represent the number/count of each equipment type used. Such design allows the entire solution space to be examined by varying the values of genes throughout their entire ranges.

4.2 Optimization Function

To perform the optimization process a minimization function is utilized, as follows.

$$\text{Minimize } F_c = (SHD*(\Sigma_i\Sigma_j\, EHC_{ij} * N_{ij} * (QA_g / DA_{gProd}))) + (SHD*(\Sigma_k\Sigma_l\, EHC_{kl} * N_{kl} * (Q_p / D_{PProd}))) + (TR_{IC} / D_m * ((QA_g / DA_{gProd}) + (Q_p / D_{PProd}))) + TI_{IC} \quad (1)$$

where Fc is the estimated fitness (in US$); SHD is the scheduled hours per day (in hours); EHC_{ij} is the hourly owning and operating costs (including operator wage) of equipment type i, model j (in US$//hour); N_{ij} is the number of equipment pieces of types i model j; N_{kl} is the number of equipment pieces of types k model l; QA_g is the total quantity of aggregate material (in tons); DA_{gProd} is the estimated daily production of aggregate (in tons/hour); Q_P is the total quantity of asphalt material (in tons); D_{PProd}

is the estimated daily production of asphalt (in tons/hour); D_m is the scheduled workdays per month (in days); TR_{IC} is the time-related indirect cost (in US$/month); TI_{IC} is the time-independent indirect cost (in US$).

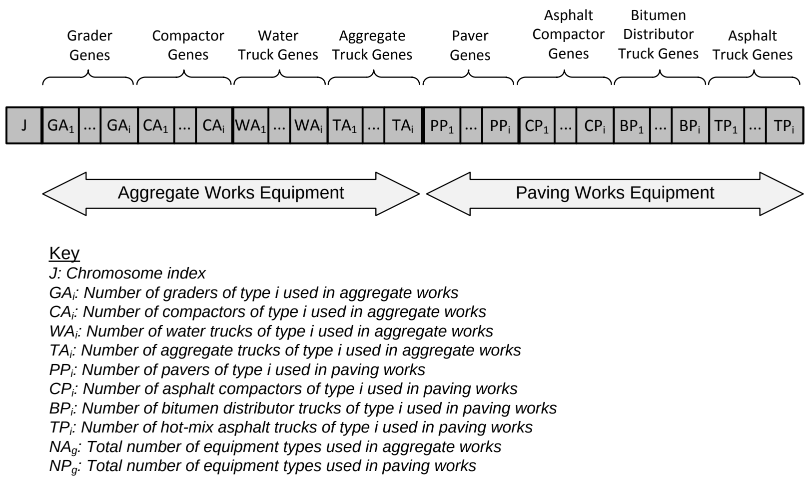

Figure 2. Chromosome Representation for Road Surface Work Operations.

4.3 Optimization Process and Operators

During the reproductive phase of the GA, genetic operators such as selection, crossover, and mutation should be used. In this research, a roulette wheel selection procedure (Holland 1992, Goldberg 1989, Coley 1999) was utilized to carry out the selection process. Since the traditional roulette wheel procedure is biased towards maximum fitness, a modification was adopted to direct the selection towards chromosomes that have minimum fitness (i.e., seeking minimum project total cost). This can be simply achieved by converting $F(C_i)$ to $1/F(C_i)$.

To ensure that genes contents receive new values in the new generations, an arithmetic crossover is used. To avoid local minima, a mutation process takes place for all genes of the generated chromosomes except for the chromosome index.

The computational rigor of the GA is further enhanced via two utilities, namely, matching chromosome and elitism. Matching chromosome is a function that has been developed to check if a chromosome was ever present in a previous population. If true, the fitness is simply copied to avoid duplicate computations. To overcome the problem of losing the best chromosome in each population, due to randomization, an elitism function was employed to retain the top fitness chromosomes.

5 INTEGRATED SIMULATOR-OPTIMIZER FOR SURFACE WORKS OPERATIONS

A computerized mechanism (Figure 3) was developed to integrate the GA optimizer with the discrete event simulator in search of the optimal fleet configuration for road surface works. The GA attempts to select the alternatives with less cost and removes those producing high costs based on the results of the simulation engine.

First, a population of chromosomes is randomly produced as per the structure in Figure 2. The simulation engine estimates the daily production, which is then utilized to compute the fitness of each chromosome. New offspring is generated using GA common operators: selection, crossover, and mutation. The process continues by reevaluating each chromosome's fitness and applying genetic operators for hundreds of evolution cycles until a termination condition is reached.

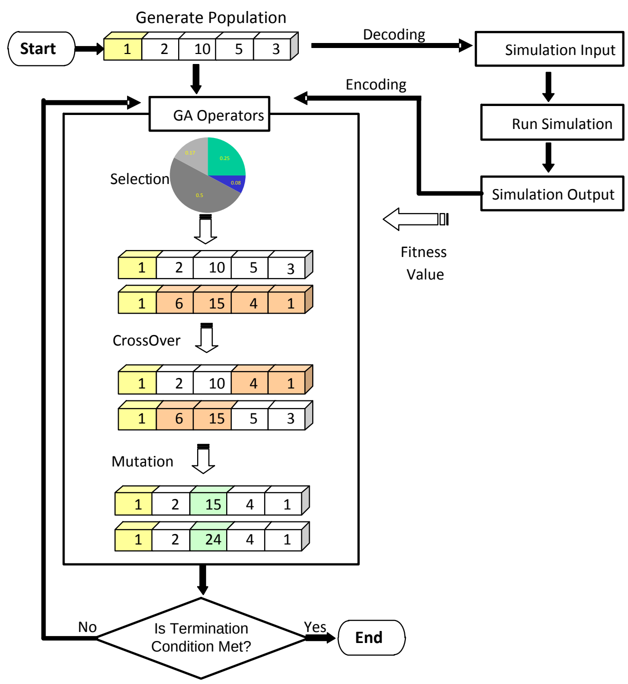

Figure 3. Hybrid Optimizer-Simulator for Surface Road Works.

6 EXAMPLE APPLICATION

To illustrate the capabilities of the integrated mechanism in selecting optimum or near-optimum configuration in road surface operations, an example project drawn from Farrar *et al.* (2004) was used. The project was a road stretch that was 14 meters wide and 8.79 kilometers long. The actual case configuration was considered as a benchmark for results comparison. The integrated mechanism was used for optimizing the road construction operation into account. Outcomes of the analysis are illustrated in Table 1 in comparison to their counterparts in the original case. As can be noted, there was a reduction in the number of trucks needed, e.g., 19 aggregate trucks instead of 23. Further, the cost difference between the benchmarked and optimum configuration was $457,635, which translated into an 18.3% saving.

7 SUMMARY AND CONCLUSIONS

Optimizing equipment fleets in surface work operations is a critical element in the success of road construction projects. The paper introduced an integrated scheme that utilizes both computer simulation and GAs for such purpose. Both the simulator and optimizer developed were dynamically linked to enhance the selection process of equipment fleets used in the construction zone. Besides the basic concepts presented in this paper, the simulator made use of layouts and CAD for modeling the construction process and the out-of-site movements. Complete CYCLONE models of both aggregate and paving works were built in the simulator. These different aspects have been presented in other publications by the authors. This paper primarily focused on the optimization aspect and its link with the simulator.

Table 1. GA-Optimized Configuration vs. Base Case for Example Project.

Parameter	Cost ($)	Graders	Agg. Trucks	Agg. Comp.	Pavers	Asph. Trucks	Asph. Comp.
Reference	$ 2,501,422.5	1	23	2	2	18	2
GA Configuration	$ 2,043,787.5	1	19	2	2	10	2

To demonstrate the practical use of the simulator-optimizer scheme, an example project was used. Results showed the potential for optimizing the equipment fleet in road-construction operations. With such a computerized mechanism, construction planners will have the means to better understand, analyze, and optimize construction operations.

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