SIMULATION OF CONSTRUCTION OPERATION WITH DIRECT INPUTS OF PHYSICAL FACTORS

Simulation with first-order factors

L.C. CHAO
School of Building and Real Estate, National University of Singapore, Singapore

Durability of Building Materials and Components 8. (1999) *Edited by M.A. Lacasse and D.J. Vanier*. Institute for Research in Construction, Ottawa ON, K1A 0R6, Canada, pp. 2287-2295.

Abstract

The deterministic approach to estimating the production rate of a construction operation assumes constant midpoint physical attributes without addressing the effect of randomness of job conditions. On the other hand, most simulation models bypass physical factors and rely on second-order inputs of probability distributions of task times, the judgements of which have been cited as difficult for users to make. This paper presents an alternative approach to production estimation, based on simulating directly the effects of changing job factors on task times, while addressing the probabilistic nature of construction. The neural network model is used as the computing mechanism for determining the cycle times of the equipment in given conditions and provides the basis for estimation. The obtained times are then fed directly into a discrete-event simulation model to simulate the process and establish the production capacity of the system as constrained by first-order factors. The approach is illustrated using a hypothetical excavating and hauling operation while the object-oriented programming technique is used to implement the computing procedure.

Keywords: construction productivity, excavation operation, neural network, discrete event simulation, object oriented programming

1 Introduction

The maximum production rate that can be achieved for an on-site mechanised construction operation is dependent on the production capacity of the set-up of the employed equipment resources working in the given physical environment. The estimate of this capacity will be the basis for the expected speed of the operation which is obtained by applying further a percentage efficiency factor to reduce the maximum rate. The result is then used in cost and time estimation for the involved project.

The scope of the current paper is to study methods for estimating the above-mentioned maximum capacity as constrained by physical job factors only, without considering non-physical or management factors that influence operation efficiency. Existing estimating methods are reviewed and commented before a proposed method is presented, which is based on neural network models for computing task times from physical factors while embedded in discrete event simulation. The common excavation and hauling operation is used throughout the discussion and comparison of the methods.

2 Existing estimating methods: deterministic vs. stochastic

The traditional deterministic method is most commonly used for production estimation for construction operations. With this method, fixed average job conditions are assumed even though the conditions encountered are changeable. The production capacity of the leading resource of a system is usually first estimated according to such assumptions to determine the output rate of the set-up which includes other resources that work together.

For example, in an excavation and hauling operation which employs an excavator and a fleet of trucks, the excavator is the leading resource whose digging capacity determines the number of truck loads that can be produced at most. Since the excavator's maximum hourly production depends on the number of digging cycles achievable per hour, its average cycle time for the job needs to be estimated first. With the deterministic method, midpoint values of work dimensions and conditions, i.e. average depth of cut, average swing angle, average soil properties are assumed and used in estimating the average cycle time and thus the production rate. Similarly, fixed haul conditions are assumed in estimating the average truck travel time for determining the system production for a given number of trucks.

If considering the overhead time spent by the excavator repositioning itself after each truck load, the deterministic estimates of the production capacity of the operation can be obtained as follows:

$$X_{\max} = \frac{60}{T_l + T_r} \times V_t \qquad \text{(when } N > N_b\text{)} \tag{1}$$

or

$$X_{\max} = \frac{60}{T_l + T_r} \times V_t \times \frac{N}{N_b} \qquad \text{(when } N < N_b\text{)} \tag{2}$$

where X_{max} = operation production (m^3 per hour)
T_l = loading time per truck (minutes)
T_r = excavator reposition time after each truck load (minutes)
V_t = volume per truck load (m^3)
N = number of trucks
N_b = balanced number of trucks

Further, T_l and N_b can be obtained as follows:

$$T_l = \frac{t_c}{60} \times \frac{V_t}{V_b} \tag{3}$$

$$N_b = \frac{T_t + T_l}{T_l + T_r} \tag{4}$$

where t_c = average digging cycle time (seconds)
V_b = bucket volume (m^3)
T_t = average truck cycle time (including spot time, hauling time, dump time, and return time but excluding loading time, minutes)

More details on the deterministic method can be found in many publications such as Nunnally (1987), Caterpillar (1988), and Gransberg (1996). Despite its wide use, one acknowledged important problem with the above method is that it ignores the effects of changing job conditions and random task times, which are prevalent in real situations, and at times this might lead to inaccurate results.

To better model the randomness existing in construction operations, many researches have suggested stochastic simulation based methods and programs, which often are intended for general uses instead of a particular type of operation. Using such packages to estimate an operation's production will require inputs of probability distributions of task times, relations among tasks, and types and numbers of resources. During a simulation run, task times are sampled from the inputted distributions and events are generated through the period of the operation to accumulate productions and compute various statistics. For more about such discrete event simulation models, see McCahill and Bernold (1993).

The critical information needed for using the above general purpose simulation method is the probabilistic task times which are determined by the user based on past data. The model itself is not concerned with the influence of physical job conditions (or first order factors) such as work dimension and soil type on task times (or second order factors). Its ability to deal with closely the relation between first and second order factors for a particular operation has to be sacrificed in order for it to be general, but the user will in the same time lose the feel of the impact of first order factors on the final results. This problem has been cited as hindrance to wider use of simulation models (Schexnayder 1997).

3 Proposed method: simulation with physical factors

As an alternative approach to estimating an operation's production capacity, the proposed method is based on computing directly the effects of physical factors on task times meanwhile simulating the work flows of the employed resources to establish the production rate. Since the exact job conditions change constantly in a random manner and the speeds of equipment resources will vary accordingly, the probabilistic nature of production in the construction environment is addressed.

To cater for the special attributes of each task involved in a particular type of operation, certain computing mechanisms will have to be developed as the basis for estimating task times. They will be embedded in the discrete event simulation program as modules to be called by the main procedure when tasks are enacted. For reasons of computing efficiency and complex mapping ability, it is suggested to use the neural network model as the common mechanism to provide task times in given conditions for the simulation process. Each task will require a neural network pre-trained on observed performance data for the employed equipment to perform the following mapping function:

$$(x_1, x_2, \ldots, x_N) \Rightarrow T \qquad \textbf{(5)}$$

where $x_1, x_2, \ldots, x_N$ = parameters for physical job conditions
T = task time

For example, the neural network model's input parameters for an excavator will be depth of cut, angle of swing, and type of soil, while its output will be excavator digging cycle time. The neural network model's input parameters for a truck will be gross weight, total resistance (grade plus rolling), and travel distance, while its output will be truck travel time.

Training data for a neural network can be obtained from site observations of equipment performance or from the manual prepared by the manufacturer for that particular model of excavator or truck. Details of developing a neural network model for estimating productivity of construction equipment can be found in Chao and Skibniewski (1994).

For reasons of system modularity and flexibility, it is suggested to use the object oriented technique to implement the system design and develop the simulation programs. In such programs, each task and resource of an operation is represented by an object which is a combination of relevant data and functions. In the case of typical excavation and hauling operations, the simulation system developed in C++ will include the following components:

- a main function that initiates the attributes of a job, creates the objects for the job, contains the simulation algorithms, and outputs the results
- an excavator object that includes the excavator's characteristics and a function for estimating its digging cycle time for given digging parameters
- a series of truck objects that each include a truck's characteristics and a function for estimating its travel time for given haul parameters
- truck-loading task objects that each include the excavator and truck objects concerned, the excavation attributes, and a loading time estimating function

The structure and weights of a neural network trained for an excavator or truck for cycle time estimating will be imported from an external file by the excavator or truck object concerned. For more about developing an object oriented application for estimating task times in construction, see Chao (1998).

Due to the randomness introduced in the simulation process, each independent run of an operation will result in a somewhat different production rate achievable, and hence a large sample of, say, 100 runs should be obtained to find out the average production level as the estimated operation capacity. The method presented above is illustrated using a numerical example of the excavating and hauling operation in the following.

4 Illustrative example

Assume the scenario of an excavation and hauling operation with a medium size hydraulic excavator digging in medium job conditions and loading a fleet of off-highway trucks one by one which will then travel individually to a dump to dump the load and travel back for another load. The model of the trucks used has an empty weight of 31 ton and a maximum gross weight of 67 ton. The excavator's features and a summary of the job conditions are shown in Table 1 and Table 2, respectively.

Table 1: Features of excavator

Heaped bucket capacity	1.7 m3
Maximum depth of cut	5.8 m
Width of undercarriage	3.0 m
Optimum horizontal reach	5.5 m
Maximum horizontal reach	8.0 m
Effective reposition speed	0.15 m/sec
Set-up time per reposition	10 sec

Table 2: Job conditions of example excavation and hauling operation

Depth of excavation (m)	3.6
Type of soil	II (common earth)
Unit weight of soil (kg/m3 in bank measure)	1840
Load factor of soil	0.80
Bucket fill factor of soil	0.80 - 1.10
Haul distance (m)	1600
Total resistance of haul road to dump (%)	12
Total resistance of haul road to excavation (%)	3

The excavator will finish the excavation in strips of equal width while being positioned on the bench with bench height equal to the depth of the excavation. During digging and loading it will have its front facing the work zone, the width of which equal to its undercarriage width in order to minimise the swing angles from cut locations to the truck positioned on one side of the excavator. After each truck load the excavator will move backward to reposition itself and start another truck load.

The cut location for each digging cycle will be set randomly within the work zone so that all locations have equal chance to be reached. The swing angle and depth of cut that defines a cut location will vary accordingly to the effect of changing digging cycle times and truck-loading times.

Since exactly how much material contained in each bucket load is uncertain, the bucket fill factor is assumed to vary randomly within the range shown in Table 2. The work volume (m3, bank measure) completed in a digging cycle will be calculated as heaped bucket capacity times bucket fill factor times load factor, with an average of 1.29 m3.

Consequently, the volume of a truck load, which needs 15 buckets to fill it, will not be a definite number but vary accordingly. The changing gross vehicle weight will lead to a different truck travel time to the dump.

Based on the considerations described above and the concepts presented in the previous section, the required modules of a simulation program can be developed to solve the production estimation problem for the given job conditions as well as other similar operation scenarios. The common back propagation algorithm can be used to train the two neural networks embedded in the program.

Training data for the neural networks in this example was obtained from Nunnally (1987) and Caterpillar (1988), for excavator cycle times and truck travel times, respectively. A summary of the characteristics of the two neural networks developed is shown in Table 3.

Table 3: Summary of neural networks used

Network Attributes	Excavator cycle time estimating network	Truck cycle time estimating network
No. of training sets	72	52
No. of hidden layer nodes	8	11
No. of training cycles	12000	18000
System error	0.000012	0.000012
Average error	0.67%	0.94%
Maximum error	2.31%	2.81%

For the given job conditions (work zone width of 3 m, maximum depth of cut of 3.6 m, and type II soil), the frequency distribution of the excavator's digging cycle times produced by the neural network model is shown in Fig. 1. For cut locations throughout the excavation, the cycle times range from 16.5 to 20.5 seconds, with a mean of t_c = 18.3 seconds and standard deviation of σ = 0.81 seconds. The average loading time per truck calculated using (3) will then be T_l = 4.6 minutes.

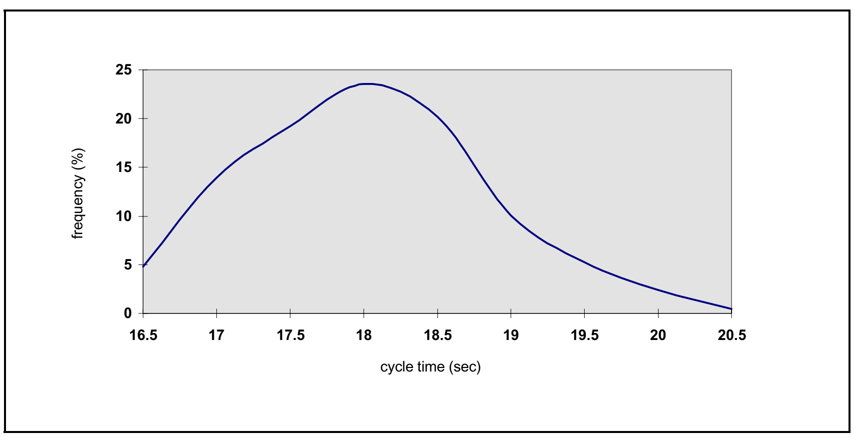

Fig. 1: Frequency distribution of digging cycle times

Assume that each truck load requires the truck to spend a fixed time of 1.8 minutes in manoeuvring and dumping and that the operation runs continuously for 210 minutes (3.5 hours). The average hourly production from 100 independent simulation runs is taken as the estimated capacity of the system that employs a certain number of trucks. As shown in Fig. 2, where the results are plotted against the numbers of trucks used ranging from 1 to 10, the production level achieved when a sufficient number of trucks (more than 3) are employed is around 236 m3 per hour.

A comparison of simulation versus deterministic estimates is also shown in Fig. 2. While the former is based on all cut locations and a changing bucket fill factor, the latter is based on the midpoint of the work zone and excavation depth and a fixed bucket fill factor, which result in a digging cycle time of 17.8 seconds, a truck loading time of 4.45 minutes, a truck cycle time of 11.1 minutes, and a system capacity of 241.3 m3 per hour. For this example, the deterministic method over-estimates the productions consistently because it under-estimates the task times needed.

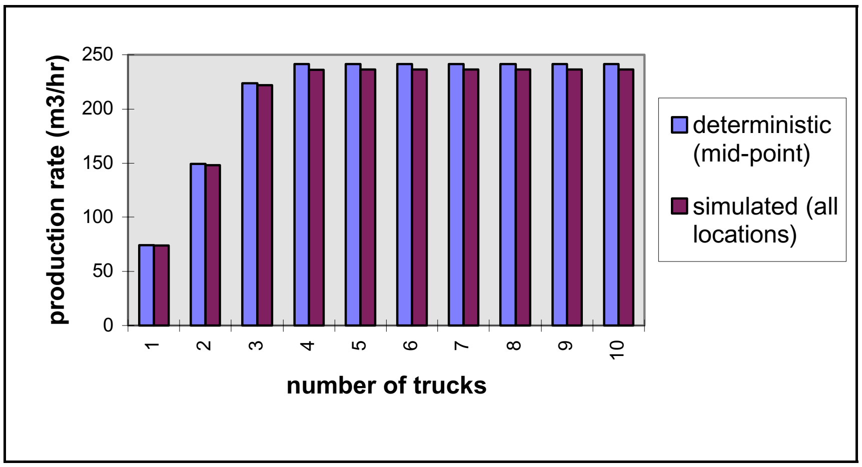

Fig. 2: System production estimates

5 Conclusions

A neural network based simulation method for estimating the production of a construction operation is presented. The objective is to establish the system capacity as constrained by first-order factors. Because of the tedious and complex calculations involved, the traditional deterministic method uses simplifications for a short cut to the solution which sometimes will lead to inaccuracy. A more realistic estimation is made possible with the use of neural network computing within the framework of discrete event simulation while developed using the object oriented technique. As shown in the illustrative example, a complex real world problem involving many variables becomes tractable. However, such programs will have to be built specially for a particular type of operation, because the performance of various types and models of equipment in construction is influenced by a variety of physical parameters in unique ways.

6 References

Caterpillar Performance Handbook, Edition 19. (1988) Caterpillar Inc., Peoria, IL.

Chao, L.-C. (1998) Estimating excavation duration: OOP plus NN approach. *Computing in Civil Engineering, Proceedings of the International Computing Congress*, ASCE.

Chao, L.-C. and Skibniewski, M. J. (1994) Estimating construction productivity: neural-network-based approach. *Journal of Computing in Civil Engineering,* ASCE, 8(2), 234-251.

Gransberg, D. D. (1996) "Optimizing haul unit size and number based on loading facility characteristics." *Journal of Construction Engineering and Management,* ASCE, 122(3), 248-253.

McCahill, D. F. and Bernold, L. E. (1993) "Resource-oriented modeling and simulation in construction." *Journal of Construction Engineering and Management*, ASCE, 119(3), 590-606.

Nunnally, S. W. (1987) *Construction Methods and Management.* Prentice-Hall, Inc., Englewood Cliffs, N.J.

Schexnayder, C. J. (1997) Discussions on "Analysis of earth-moving systems using discrete-event simulation." *Journal of Construction Engineering and Management,* ASCE, 123(2), 199-199.