STOCHASTIC ANALYSIS OF CYCLIC CONSTRUCTION PROCESSES

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Many construction processes are stochastic systems. A deterministic analysis of these systems may not allow for the random distribution of system events, resulting in poor or unrealistic system attributes. Two examples of such systems are the cyclic processes of earthmoving and concrete placing. While both processes have different objectives, their execution has much in common; in particular both can be modelled as queuing systems. Analysis of such models allows the construction engineer to firstly achieve improved estimates of the overall productivity and thus schedule operations better, and secondly, determine the effect of non-anticipated events such as excessive delivery or cycle times.

Outlined are results obtained from studies of both earthmoving and concreting operations; both studies are based on data obtained from actual UK construction projects. Results have been encouraging and have been used by a major UK civil engineering contractor in the management of earthmoving operations. Preliminary results have indicated initially that a numerical model of earthmoving and concreting operations can be analysed using simulation techniques. Secondly, it has been shown that the estimation of construction operations using such techniques can be more accurate and realistic than when more traditional or deterministic methods are used.

Keywords: Concreting, earthmoving, estimating, planning, stochastic systems.

INTRODUCTION

Many construction processes are cyclic. For example, earthmoving, concreting, pavement laying, steel erection, pipelaying and even bricklaying consist of base activities which are repeated continually until the operation is complete. In this respect, they are similar to manufacturing processes or 'production' lines; work is being undertaken by many workers to apply manufacturing techniques to construction to increase its productivity and effectiveness. Construction processes are also highly random or stochastic - therefore, by representing the processes as queuing systems, they can be analysed by a myriad of techniques that are available to the systems analyst, for example queuing theory, regression analysis and simulation.

This paper reports on the findings of work undertaken on by the University of Edinburgh in collaboration with Tarmac Civil Engineering. Initially, earthmoving was the construction process chosen for study but this has more recently been extended to concreting operations. The same technique of simulation has been applied to both processes.

The findings are fundamental: the stochastic nature of these processes prohibits accurate analysis by deterministic methods. By using simulation, more accurate estimations of the operating characteristics of these processes can be established thus providing a useful tool for both planning and estimation.

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This paper will look, briefly, at queuing systems in general as well as reporting the some of the main findings from the investigations into the earthmoving and concreting processes. Future research areas will also be discussed.

QUEUING SYSTEMS

Figure 1 shows a typical queuing system model that can be applied to most of the above systems.

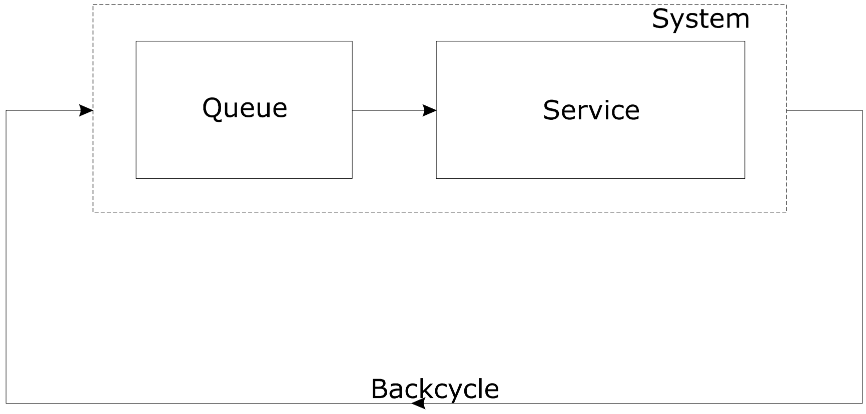

Figure 1 Schematic diagram of a general finite source queuing process

A queuing system consists of both *customers* and *servers*. For each server, customers will queue until they are served and then leave. Customers within finite source systems will continue on their *back-cycle* until they rejoin the system - again queuing if the server is busy. The time at which they rejoin the system is therefore dependent on the characteristics of the back-cycle. Customers within an infinite source system will leave once served but do not undertake a back-cycle. They may rejoin the system later, but the time at which this happens is not dependent on any characteristics of the system and is usually considered to be random. Many common queuing systems, such as supermarket checkouts or banks, consist of a series of infinite source queues.

The characteristics of a queuing system, the main one being the length of time a customer spends within the system, can be determined in a number of ways. If every service and back-cycle time (for finite source) or inter-arrival time (for infinite source) is always the same then the system is non-stochastic and the characteristics can be calculated deterministically. It is normally the case, however, that these times are highly variable, thus making the system stochastic. If the system is analysed using the average times deterministically errors may result due to the interactions of the customers. For example, the variable back-cycle times of a finite source system (e.g. buses on a bus route) cause the customers (i.e. buses in this case; the server is the bus stop) to ‘bunch’. This is the exact cause of the expression “no buses for *x* minutes then *y* turn up at once”. Bunching reduces the productivity of the system by an amount which cannot be derived deterministically.

It is normal to analyse queuing systems in a non-deterministic way. Three examples are:

- Queuing theory. An operations research technique used in many applications. Its application to construction has been extensively researched by Carmichael (1986, 1987) who applied the theory to earthmoving and mining operations.

- Regression analysis. This is a statistical tool which provides equations for outputs derived from real operation data. These equations can then be used to deterministically analyse further operations.
- Simulation. By synthesising input data based on the probability distributions of actual operations, each step of an operation can be recreated. A computer can recreate each step very quickly thus allowing the simulation of lengthy, real operations. Many workers have used simulation (e.g. Farid and Aziz 1993, Halpin 1977, Smith *et al.* 1995, 1996) to model construction processes, and it is the tool which will be discussed within the remainder of this paper.

EARTHMOVING

Earthmoving is a classic, finite-source queuing system and as such can be analysed using simulation. Such analysis is important as it will allow for variations of plant cycle times and interaction and interference of various items of plant which will cause inefficiencies in the operation.

To develop a mathematical model of the earthmoving system it is first necessary to understand the logical and quantitative relationships which will be manipulated. With reference to Figure 1, the earthmoving system can be broken down into its component parts, or *cycle component times.* These are:

- Service time:
  - Manoeuvre (spot) time.
  - Load time. This is built up from individual bucket swing times.
- Back-cycle Time:
  - Haul and return time. Collectively travel time.
  - Dump time.

The simulation model requires mathematical representations of actual time distributions. The best way to achieve this is to observe actual operations over a period of time and for different site conditions and for this project, data was collected from four different projects over the period 1992 to 1996. These sites are shown in Table 1.

The data collected was essentially a series of the above identified component times catalogued under various headings such as soil types and plant types. In addition the volumes of earth per load as well as information such as fleet sizes, weather, haul length and duration of operation was taken.

This data was collated and analysed in order to determine the underlying probability distributions. It is these distributions which are synthesised in order to provide input to the simulation model.

Table 1: Road projects from which earthmoving data obtained

	M1/A1 Contracts 2 & 3	**M£ Bar End to Compton**	**A52 Ashbourne**	**M65 Blackburn Southern By-pass**
Period	1992-3	1993-4	1993	1994-6
Principle soil type	Clay	Chalk	Sand/gravel	Glacial till
Principal truck fleet	Cat D400	Volvo A35	Volvo A25	Cat D400
Principal loader fleet	Cat 245	Cat 245	Cat 235	Cat 350
Approx earthworks volume	2,500,000 m³	3,000,000 m³	100,000 m³	3,000,000 m³
Approx construction cost	£35m	£45m	£3m	£66m

Discrete - Event Simulation

This type of simulation models the state of the system as it develops over time. The *state* is defined as 'the collection of variables necessary to describe the status of the system at any given time' (Carmichael 1986). The state of the system changes when an event occurs; in the earthmoving system, there are two main events and these are *arrival* and *departure* events, i.e. when the trucks arrive into or depart from the system.

Simulation works by recreating the occurrence of these events. As the system evolves over time, the trucks depart and arrive at the queue and the time when these events occur will determine the cycle time of the trucks and the number of cycles completed. From a knowledge of the number of cycles completed per hour and the volume of earth carried per cycle (which is dependent on the size of the loaders bucket and the number of bucket passes per load) the productivity of the earthmoving operation can be calculated. To achieve this within a computer, cycle component times must be generated which agree with the pre-determined and observed distribution. This is done using a *random variate generator* which is used to draw up an event list from which the simulation program is run. This event list is an array in the computers memory which shows, in chronological order, the type, time and to which truck the next event will occur. For example, if truck *a* departs then the time of the next arrival of this truck can be determined by generating a random *travel* time and a *dump* time and adding these to the time at which the truck departed. This time is then added to the event list along with times for all the other trucks in the system.

Trucksim

A simulation program, called *Trucksim*, has been developed at the University of Edinburgh, and works using the discrete-event method described above. The probability distribution on which it is based is an Erlang distribution which is a modified gamma distribution. Goodness-of-fit exercises indicated that the fit between the observed data and the generated data with this distribution was in some cases excellent and in all other cases adequate.

The program allowed the rapid simulation of earthmoving operations at many different configurations and as such allowed a series of 'experiments' to be carried out on the earthmoving system.

Experimental Analysis and Results

A real earthmoving system is far too large and expensive to experiment with - but experimentation would allow construction engineers to establish how the system responds to various changes in its configuration. By using the model of the earthmoving system as a platform for quasi-experimentation we can get a good idea as to which of the system factors are important and influence its output.

Essentially, the earthmoving system can be represented by the following function:

$$Y = f(k_1, k_2, k_3, \ldots k_n) \qquad (1)$$

where *Y* is a *response* of the system to certain values of $k_1, k_2, k_3, \ldots k_n$ which are called *factors*. For example, the dumptruck specification and the volume of earth per truckload are factors; productivity and plant utilisation are responses. It can be shown that the earthmoving system has at least 11 factors, all of which will have some effect on at least 6 responses (Smith et al. 1995). Which factors are the most important and over which ranges shall they be studied?

Box, Hunter and Hunter (1978: 303) indicated a paradoxical situation: the best time to design an experiment and therefore know the best factors to use is when it has been completed. Experimentation is iterative; after each successive experiment, more will be known about the system and future experiments will be more useful. In this respect *factorial designs* are useful in that they can give a ‘broad picture’ of the overall system and will help eliminate factors that have little effect on responses. For further information on factorial design experimentation, the author recommends the text by Box, Hunter and Hunter (1978).

After carrying out initial experiments in order to remove non-significant factors, a 2^4 experiment for the four most important factors of the earthmoving system, together with the productivity response was carried out. Such a factorial design means that an experiment must be carried out for every combination of the 4 factors at two different levels, thus giving 16 separate simulation runs. The factors, together with their two levels are shown in Table 2; the ‘+level’ is intended to promote a positive effect on productivity. In actual operation on which the experiment was based, the number of trucks was initially too high and thus a decrease in trucks was deemed to be beneficial. It was decided that there should be 11 replications, or separate simulations, for each run in order to reduce the variance of the results.

Table 2: Factors and their levels used in 2^4 experiment

Factor	- level	+ level
No of trucks	7	6
Passes per load	6	7
Pass time mean	17 s	14 s
Travel time mean	492 s	405 s

A factorial experiment allows the effect of changing a factor (from one level to another) on a response to be demonstrated. Such effects are known as main effects and, together with interaction effects (i.e. the effect of two or more factors acting together in a way they do not separately) the nature of the response to changes in system configuration can be determined.

The results from the 2^4 experiment can be seen in Figure 2.

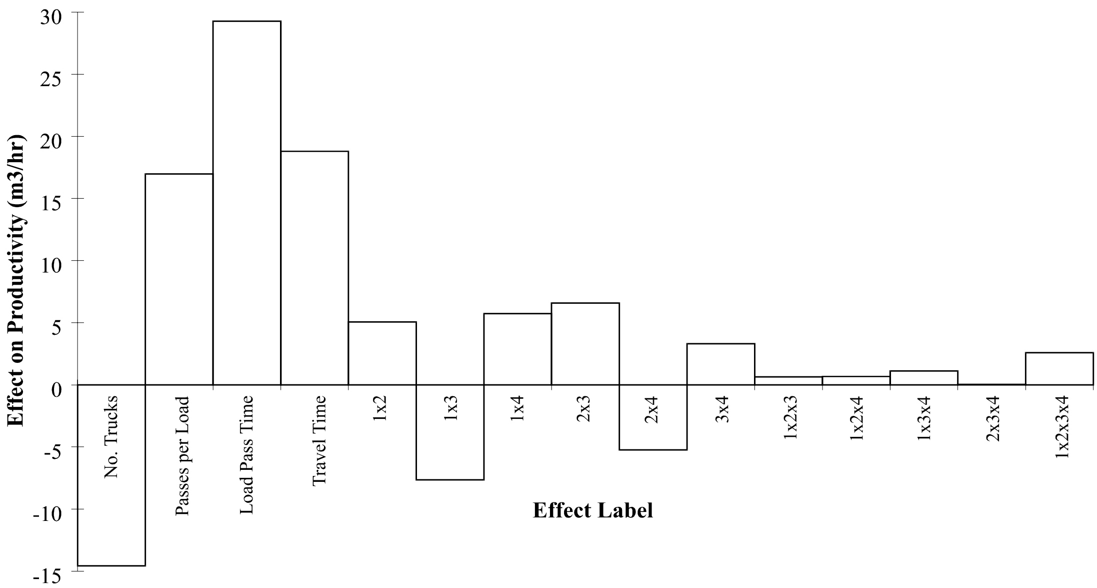

Figure 2: Main effects and two-, three- and four-factor interactions for 2^4 factorial design

Note that actual values of production have been coded for reasons of confidentiality. Several observations can be made from these results:

- The factor with the greatest effect is the load pass time (i.e. the time to load one bucket). In this example, a reduction from 17 seconds per pass to 14 seconds will, on average increase the productivity by 11 percent.
- Of the interactions, three and four-factor interactions are virtually negligible but the two-factor interactions are significant. Surprisingly, although most factors have an improving effect on the responses, two interactions (number of trucks / load pass time and passes per load / travel time) have a negative effect which may seem at first to be difficult to explain. The reason is that by combining an decrease in the number of trucks and a decrease in the load time (i.e. two positive effects singly) the operation becomes under-resourced with trucks and thus inefficient. Conversely, by increasing the number of loads and reducing the mean travel time (again both separately positive actions) the ‘service’ time increases and the ‘back-cycle’ decreases thus lengthening the queue, over-resourcing the operation and reducing efficiency.
- The effect of reducing the number of trucks by one did not bring about the anticipated increase in production. On its own, reducing the number of trucks would bring the operation to an ideal resource level. However, the changes in the other factors also did this and so a reduced fleet size made the operation under-resourced - with a consequent reduction in queue length and loader utilisation. In conclusion, the number of trucks should have been kept at seven although another experiment would have to be done to find out the exact effect.

CONCRETING

The pumping of concrete into formwork or other areas can also be considered a queuing system. With reference to Figure 1, a concrete truck will be batch and travels to site. It then enters the concreting system, queues, positions itself at the pump and then the concrete is discharged via the pump into the works. When empty, the truck is washed out and it returns to the batching plant. The truck actually then enters another queuing system and technically the whole system is a finite source, multiple queuing system.

Initial studies have simplified the analysis by considering an infinite source queuing system by ignoring the back-cycle. If the assumption is made that trucks randomly arrive on the site and are not considered once they leave there are only three times which have to be evaluated: inter-arrival time, truck positioning time (at the pump) and concrete pumping time. For this initial study, the Thelwall viaduct project on the M6 in Cheshire was chosen as it provided a vast range of pour types and sizes. The overall volume of the sampled operations ranged from 51m^3 to 470m^3 with an average of 210m^3. From these operations, a series of the above times were recorded for 29 separate operations.

Like the earthmoving studies, discrete-event simulation analysis was undertaken on the above model of the concreting process (i.e. an infinite source queuing system) but unlike the earthmoving system, the probability distribution shown to provide the best fit with the observed data was the gamma distribution. Again, the simulation analysis, this time undertaken on Microsoft Excel rather than a bespoke program, allowed a series of experiments to be undertaken.

Experimental analysis and results

The first two experiments involved investigating the effect of changing the interarrival time and the pump time while all other factors remained constant.

Experiment 1 varied the interarrival time distribution, with a mean ranging from 200 seconds to 1500 seconds. The position time was kept at 276 seconds while the pump time was maintained at 482 seconds. The operation that was modelled involved the delivery of 46 trucks at 6m^3 each giving a total of 276m^3. The main result of this experiment confirmed that the minimum operation completion time is around 9.9 hours (which may be predicted deterministically). However, as this time is mainly dependent on the rate at which the concrete pump actually provides concrete to the formwork, it can be achieved only if the concrete pump is not at any time idle. Unfortunately, as this is a stochastic situation, to ensure the pump is not idle, the interarrival time needs to be very low to ensure a constant supply of concrete. Analysis indicates that this results in excessive truck wait times: more than 1.5 hours on average per truck (see Figure 3).

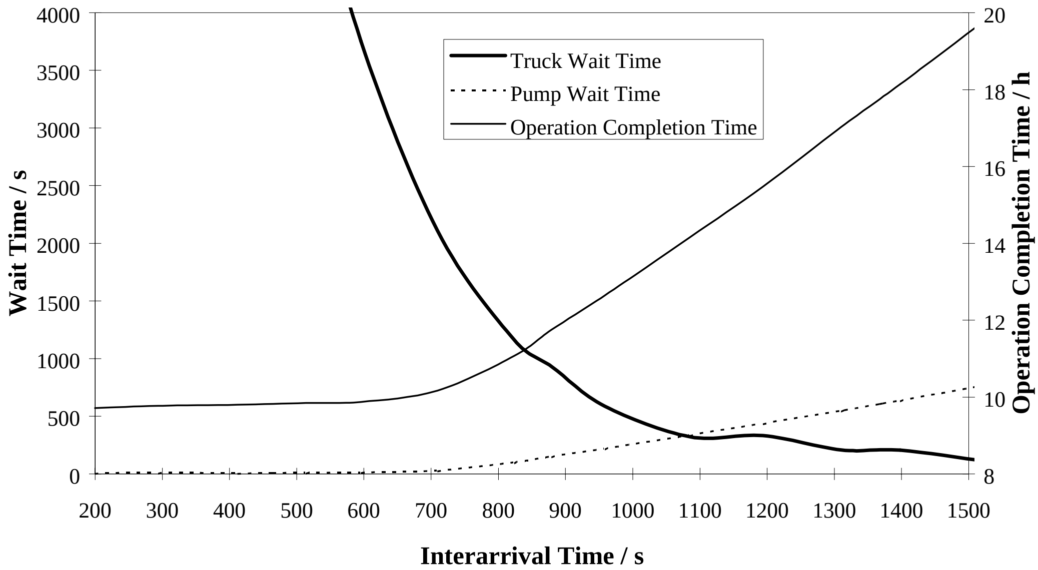

Figure 3: Results of experiment 1: varied inter-arrival time

The second experiment kept inter-arrival time (718s) and position time (276s) constant but changed the pump time from 50 to 1000 seconds. Such a large range of times is reasonable as the rate of pumping is dependent on the type of pour: large mass concrete pours ideally pump the concrete as fast as possible; smaller tall columns need a slower controlled rate of pour to prevent bursting of the formwork. In this experiment all other factors were the same as experiment one, that is total quantity = $276m^3$, trucks = 46, runs = 15 per result. The analysis indicates that when the truck pump time increases, the wait time of the trucks also increases. The rate of this increase may not have been expected: increasing pump time by only 50 seconds can increase the average truck wait time by up to 8 minutes. It is also to be expected that if pump time is increased then average pump wait time reduces to a minimum but operation completion time significantly increases.

It can be derived from both experiments that there are two indicators to what may constitute an efficient operation: minimum operation completion time and minimum queue wait time. It is proposed that the optimal operating conditions are achieved when the utilisation of the two types of plant, truck and pump, are minimised. On the basis of this proposal, the final experiment was conducted.

If the ideal operating conditions for a concrete pumping activity occur when truck wait time and pump wait time are minimised then it would be useful to determine this point for a range of times. Referring to Figure 3, it can be seen that this point occurs at an interarrival time of approximately 1080 seconds for a pump time of 482 seconds. Again, assuming that average position time remains constant at 276 seconds, the optimal times for pump and interarrival times were established by a series of simulation runs such as the ones conducted for experiments one and two. Twelve points were determined over the range of 450s to 1750s for interarrival time and 50s to 900s for pump time. The result can be seen in Figure 4. The optimum operating conditions provide a straight line (best fit provided) which can be compared to the deterministic situation derived assuming that all times are constant and not stochastic. The deterministic line is a result of the fact that if all times were constant, the interarrival time needs to be the sum of the position time plus the pump time for zero waiting.

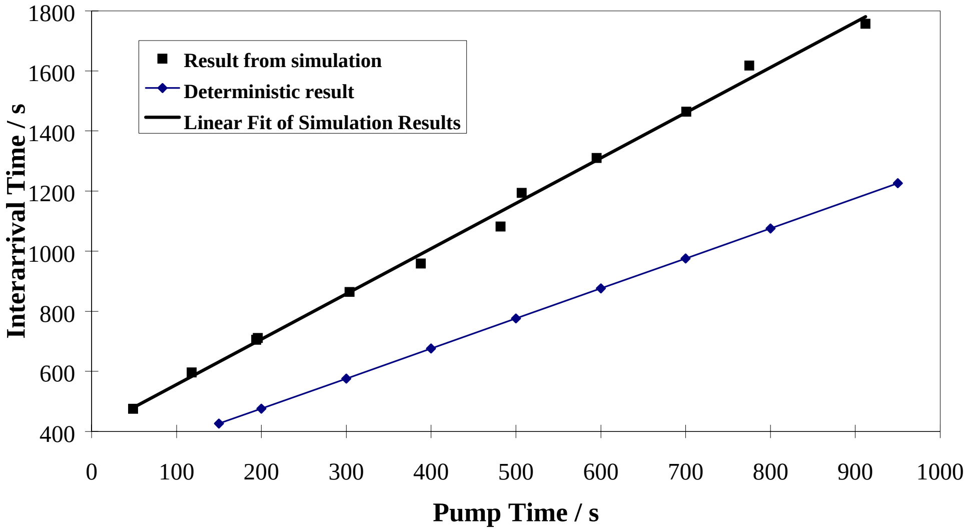

Figure 3: Comparison of optimum operating conditions for both simulation and deterministically derived results

As can be seen for any pump time the ideal interarrival time is greater than may be expected from the deterministic situation: if an operation used the deterministically derived interarrival time then in a stochastic situation excessive truck waiting would occur.

CONCLUSIONS

- It can be seen that stochastically analysing the two cyclic operations detailed in this paper produces results more consistent with actual operations. It has been shown that cyclic operations are generally highly variable and are stochastic in nature; as such they cannot be analysed accurately using deterministic measures.
- The earthmoving process, when modelled and analysed using simulation techniques, can provide increased accuracy for estimation and planning tasks. This paper has shown, through a factorial experiment, that the factor with the most influence on the output of the system is the speed at which the excavator can load bucketfuls of earth into a truck.
- The concreting process also has been shown to be stochastic. The main conclusion in this paper is that ideal operating conditions occur when the pump and truck waiting times are minimised. The pump and inter-arrival times for this situation are different when analysed stochastically than when analysed deterministically: planning on a deterministic basis would result in excessive truck wait times.

FUTURE WORK

It is intended that future work will follow the following two paths:

1. To investigate and apply the above techniques to other cyclic processes, the main one being pavement laying. Whether pavements consist of concrete or asphalt the operation involves servers (paving machine, concrete train) and customers (asphalt lorries, concrete trucks). It is a common sight on many road projects to see a long line of asphalt lorries queuing; this is a massive under-utilisation of resources.

2. To take forward the initial studies carried out on the concreting system. As indicated, the model used simplifies the actual process by ignoring the batching stage and the back-cycle. Potential savings can be made and increases in productivity are possible for both contractors and concrete suppliers. Further concrete studies would also need to determine the effects of different operating conditions, sites, contractors, batching plants and suppliers. The example shown above is based on just one site.

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