A HYBRID MODEL TO IMPROVE THE ESTIMATION OF CONCRETING OPERATIONS

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Stochastic construction operations, such as concreting, have been estimated effectively in the past using simulation. However, this effective estimation is only possible if the input (frequently probability distributions) to a simulation model is accurate. This accuracy is difficult to attain, and has prevented the widespread application of simulation in industry. An artificial intelligence technique, Case-Based Reasoning (CBR) is proposed as a method of improving the accuracy of input to a simulation model, allowing better estimates of concreting operations to be made. A simulation model, MatSim and a hybrid CBR-simulation model, CBRSim, have been developed (based on real construction data), validated, and compared to measure any improvements in output as a consequence of using a CBR-based input. CBRSim produced results that were more accurate and consistent than those of MatSim, indicating the potential advantage of using a CBR-based input in a simulation model of concreting operations. CBRSim is useful for the planning of concreting operations and may increase the industrial use of simulation as an effective estimation tool of stochastic construction operations.

Keywords: case based reasoning, concreting operations, simulation modelling, planning.

INTRODUCTION

The concrete supply, delivery and placement process (concreting operations) is stochastic in nature and is often inefficiently managed. Concreting operations require analysis using non-deterministic techniques (Smith, 1998a) such as discrete-event simulation, which has been used to estimate the output of construction operations for over three decades (Martinez and Ioannou, 1999). Simulation has been proven as an effective tool for improving construction process planning (Halpin, 1993), but unfortunately the wide application of the technology in industry has been prevented by usage difficulties (Shi and Abourizk, 1997). One such difficulty is: in constructing and using a simulation model an understanding is required of the stochastic nature of the process concerned (Zhang *et al.*, 2002). This nature is frequently represented by probability distributions and the importance of their effect on the accuracy of simulation output cannot be overemphasised (Abourizk *et al.* (1994), Banks and Carson (1984)). Therefore, to achieve an accurate simulation output, the probability distributions must describe the stochastic nature of construction operations as closely as possible, and therein lies the difficulty: How does a planning engineer with little statistical knowledge determine the correct probability distributions and parameters that represent a particular construction operation? This paper presents an artificial intelligence technique, Case-Based Reasoning (CBR) as a possible solution to this problem. It is proposed that CBR could be used to: reduce the level of statistical

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knowledge required to use simulation; and to improve the input to, and consequently the output of, a simulation model.

Two models of the concreting system are presented and validated: a discrete-event simulation model, MatSim; and a hybrid CBR-simulation model, CBRSim. Both models: are based on probability distributions that have been derived from real construction project data; and, model the overall duration of a concrete pour. Before outlining the models, this paper will look briefly at the process of concrete supply, delivery and placement.

THE CONCRETING SYSTEM

In previous research, concreting operations have been separated into two processes: batching and delivery (for example, Sawhney *et al.*, 1999); and pumping and placing (Dunlop and Smith (2000 and 2002)). In this study, the concrete supply, delivery and placing process is considered in its entirety. In an ideal situation, a truck mixer is filled with concrete at the batching plant and travels to the construction site. On arrival, the truck mixer moves into position at the pump and discharges its load. Finally, the empty truck mixer is cleaned in the washout area and proceeds back to the batching plant, completing the cycle. In reality, the events that occur within the system (e.g. truck arrival times and pump start times) take place at irregular intervals (Smith, 1998b). Queuing of trucks at the batching plant, pump and washout areas can be expected, as it is often unlikely that a truck will arrive simultaneous to the previous truck departing. If trucks arrive late, there will be a lengthening of the process and under-utilization of the pump- resulting in an inefficiently managed pour of the concrete. The stochastic nature of the concreting system can be recreated by using probability distributions to represent the following times of interest: travel time from batching plant to construction site (travel to site time); positioning time at pump (position time); discharge time (pump time); time to clean the truck mixer (washout time); travel time from site to batching plant (travel to batcher time); and load time (batch time). The probability distributions can produce times that are used to recreate a typical cycle of the process. Through the simulation of multiple cycles, the attributes of a particular operation’s set-up can be provided, such as pour duration (from which productivity can be derived) or pump utilization rates. To ensure that the model is realistic and accurate, it must be based on data collected from real construction sites.

DATA COLLECTION

The data used to build both MatSim and CBRSim were collected during a time study of four construction projects, which are detailed in Table 1. In total, 225 concrete pours were observed and the variables of interest were recorded. These variables were: pour date and type, weather, target and actual slump, batch time, arrival on site time, position time, start and completion of pumping times, washout time, batch quantity, total pour volume, truck wait times (at batcher and pump), batcher and pump idle times, and the number of trucks involved in the pour. From the observed data, the times of interest mentioned previously were extracted. The data that were used in validation were collected from a construction project independent from those used to build the models (See Table 1). In total, 63 pours were observed and from this data set, 20 pours were selected at random for use in the validation process.

Table 1: Details of studied projects

Project	Use in Study	Year of Completion	Type of Project	Location	No. of Observed Pours
1	Build Model	2000	Wastewater Treatment Plant Construction	Aberdeen, UK	152
2	Build Model	2000	Wastewater Treatment Plant Construction	Peterhead, UK	10
3	Build Model	2000	Wastewater Treatment Plant Construction	Fraserburgh, UK	18
4	Build Model	2000	Wastewater Treatment Plant Construction	Dundee, UK	45
5	Model Validation	1994	Motorway Viaduct Strengthening and Widening	Cheshire, UK	63

DISCRETE-EVENT SIMULATION MODEL, MATSIM

MatSim is a computer model written in the Matlab programming language and is based upon the discrete-event simulation methodologies described fully in Smith (1998a and 1999) and Law and Kelton (2000). To summarise the steps involved in the developing the model were:

- Fitting probability distributions. The theoretical probability distributions that best represent the previously mentioned times of interest were identified using a commercial package, BestFit. The fit of the distributions to the data was assessed using the K-S test and visual assessment. Generally, the data sets were best represented by the lognormal, gamma and beta distributions and only they will be considered further in MatSim.
- Generation of random variates. A random variate is a value (in this case a time of interest, e.g. position time) generated at random from the chosen probability distribution. Assuming a good fit between the data and the probability distribution, the random variate is a true representation of an actual value (Dunlop and Smith, 2000). A full discussion on the methods of generating random variates can be found in Law and Kelton (2000).
- Use random variates to synthesise ‘events’. An event is something that changes the state of the concreting system. It could be an arrival or departure at the batching plant, pump or washout area.
- Model operations. A real operation is a series of events, the timing of which determine its attributes (Dunlop and Smith, 2000) (for example, pour duration). These attributes can be determined for a simulated operation and to reduce variance, many replications are performed.

HYBRID CBR-SIMULATION MODEL, CBRSIM

CBR is the process of reasoning and learning by storing cases- records of specific prior reasoning episodes- and retrieving and adapting them to aid new problem solving or interpretation in similar situations (Kolodner, 1993). Aamodt and Plaza (1994) described the CBR process as cyclical, comprising of the following:

- Retrieval of the most similar case(s) from the case base

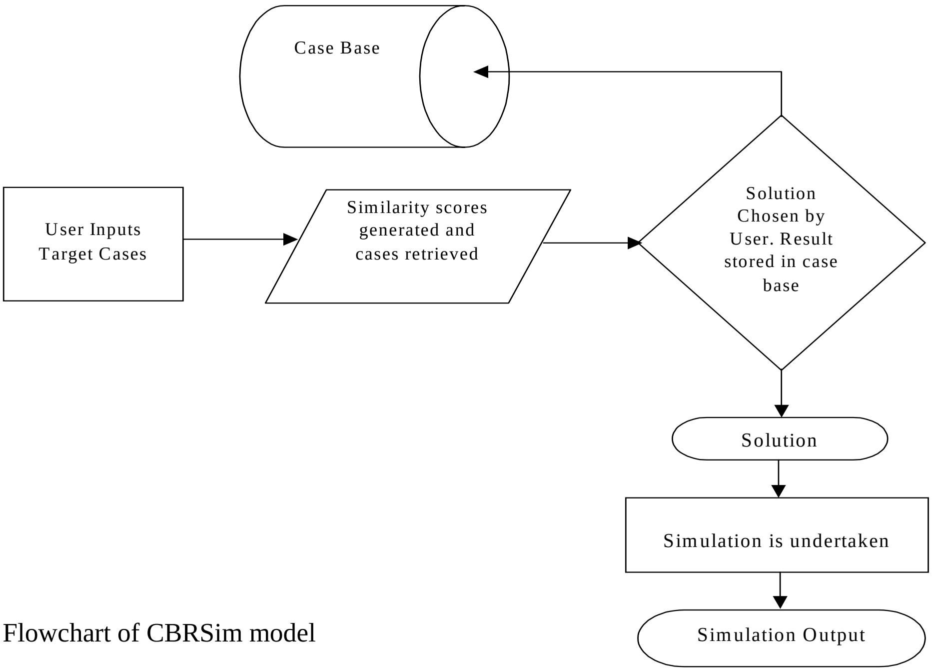

Figure 1: Flowchart of CBRSim model

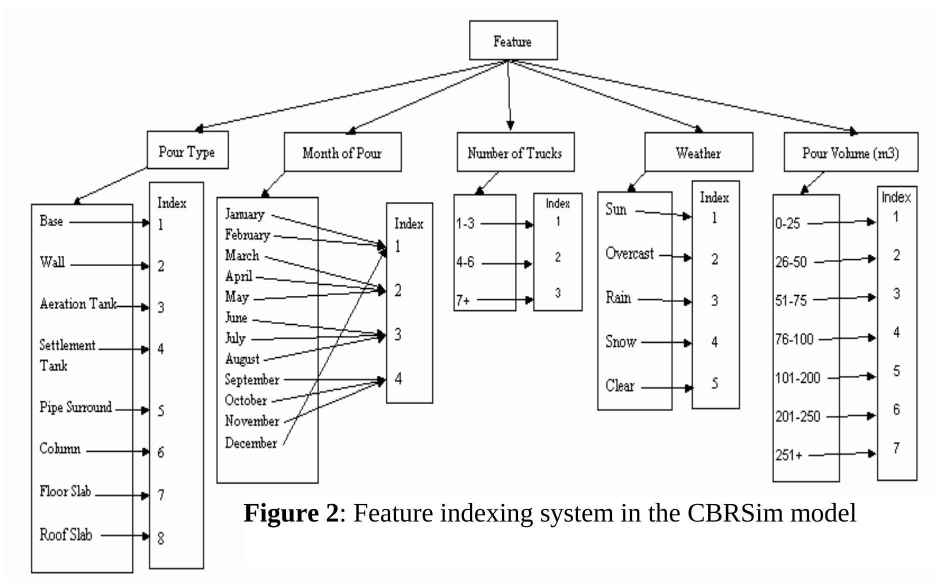

Figure 2: Feature indexing system in the CBRSim model

- Reuse of the case(s) to attempt to solve the problem
- Revision of the proposed solution, if necessary, to solve the problem
- Retention of the modified solution as a new case

The construction domain is a growing area for applications of CBR and it has been used successfully in solving prediction and estimating problems (Morcous *et al.*, 2002). This study intends to utilise CBR to predict the probability distributions and parameters that best represent a particular concreting operation. The predicted distributions will subsequently be used in a simulation model, forming the hybrid CBRSim model. CBRSim is based upon the cyclical process described by Aamodt and Plaza and its methodology is shown in Figure 1. In developing CBRSim the stages were:

1. Case base design
2. Case retrieval

3. Simulation using CBRSim

Case Base Design
The case base is the storage area for prior cases. Cases must be parameterised, typically by being divided into a series of distinct features by means of which their similarity to other cases can be judged. In CBRSim, the case base initially stored 225 cases, with all the cases sharing the same record structure of 5 input and 5 output features. The input features are: the number of trucks, pour volume, pour type, month of pour and weather. Each feature is assigned an index to aid the retrieval process (See Figure 2). The output features are the probability distributions and parameters that best represent each concreting operation, identified using BestFit. Seven distributions provided suitable representations of the concreting process, they were: uniform, normal, lognormal, exponential, weibull, gamma and beta. The next stage of the CBR process is case retrieval.

Case Retrieval
A CBR model derives its power from its ability to retrieve relevant cases quickly and accurately from its case base (Arditi and Tokdemir, 1999). To perform the retrieval process, CBRSim measures the similarity between a user specified target case and the indices of each case stored in the case base. This similarity measurement is in percentage form and is based upon Euclidean distance measurements, as detailed in Hand *et al.* (2001). If the similarity between the target case and a stored case is greater than 75%, the stored case is retrieved from the case base and is placed in a temporary storage area. Once all the relevant stored cases have been placed in the temporary storage area, the user is permitted to view them. The user is then required to select a case based only on the similarity measurements, removing the need for a user to have statistical knowledge of the process. If the target case features are not identical to the features of the selected case, CBRSim retains the target case features and the probability distribution information as a new case. Thus providing the learning ability of the model and completion of the CBR cycle. Finally, the case base should be updated over time with the details of new construction projects, improving the knowledge of the model.

Simulation using CBRSim
The determination of the most representative probability distributions for a given concreting operation ends the CBR side of the hybrid model. The methodology used by CBRSim to undertake simulation of the concreting process is the same as in MatSim. However, the computing methods used in the two models differ. CBRSim was developed using a spreadsheet package, Microsoft Excel, allowing the user to fully understand each step in the modelling process. This study must now validate both MatSim and CBRSim. The validation process shall also be used to compare the accuracy of the two models.

VALIDATION OF MODELS

Validation is the process of determining whether a simulation model is an accurate representation of the system. The concreting operation models, MatSim and CBRSim are intended to represent the existing system, not replace it, in order to allow estimations of the system output to be produced. Therefore, the model output (overall duration of a concrete pour) and data from the existing system can be compared to ascertain if the model is valid. In this study, a correlated inspection approach was used to indicate the validity of both models. Correlated inspection at its most extreme requires that a model be driven by exactly the same observations as the real system, but it is unclear if this indicates the predictive powers of a model (Smith *et al.*, 1995). Therefore, the model will be driven with random variates generated from probability distributions.

20 concrete pours (validation observations) were randomly selected from the validation data set discussed earlier. MatSim was investigated when random variates were generated from the lognormal, gamma and beta probability distributions. The parameters of these distributions were tailored to each individual pour, using knowledge of the stochastic nature of the process. The performance parameter of interest in this study is the pour duration and the results are shown in Figure 3. To overcome the variance in simulation output the model's results were replicated 100 times, and an average result was taken.

Table 2: Correlated inspection results for pour duration

		Percentage difference from observed value			
Validation Observation	Overall Pour Duration (mins)	CBRSim	MatSim Lognormal	MatSim Gamma	MatSim Beta
1	230	-1.5	-16.4	-6.3	-2.5
2	316	3.0	10.8	21.3	22.4
3	244	0.7	-9.3	0.4	5.7
4	351	-0.8	-22.1	-19.9	-17.8
5	396	-0.9	-2.5	8.3	15.4
6	318	1.0	-23.3	-18.9	-22.1
7	272	-3.5	-10.0	-7.6	-5.7
8	303	-2.4	-18.5	-15.8	-13.5
9	273	-1.7	-23.4	-21.3	-17.0
10	331	0.6	-19.3	-14.4	-12.6
11	409	-1.7	-18.0	-15.3	-12.6
12	288	-0.3	-8.8	-10.3	-6.3
13	235	2.8	-12.5	-8.6	-5.0
14	223	2.0	-7.8	-4.9	1.5
15	294	-1.0	-9.9	-4.0	-0.9
16	199	2.4	2.7	1.3	6.7
17	280	0.0	-7.0	-8.9	-3.9
18	225	-1.0	-22.5	-18.9	-14.8
19	255	1.2	19.3	-12.7	-11.9
20	477	0.2	16.5	11.9	14.2

Comparison of Results

It was the aim of this study to determine if a CBR derived input could improve the output of a simulation model. This improvement should be measured in terms of accuracy and reliability of the model. An examination of the results presented in Figure 3 shows that CBRSim has the ability to provide better estimates, generally, than MatSim. CBRSim achieved pour duration estimates to within a range of +/- 3% of the observed values, compared with a range of +/- 20% produced by MatSim. In terms of reliability, CBRSim estimated to within 10% of the observed value in 20 out of 20 validation observations (Table 2). In contrast, MatSim had a poor reliability record for pour duration estimating less than 50% of validation observations within 10% of the observed values (Table 2). In summary, both models provide reasonable estimates of the pour duration and can be affirmed as valid.

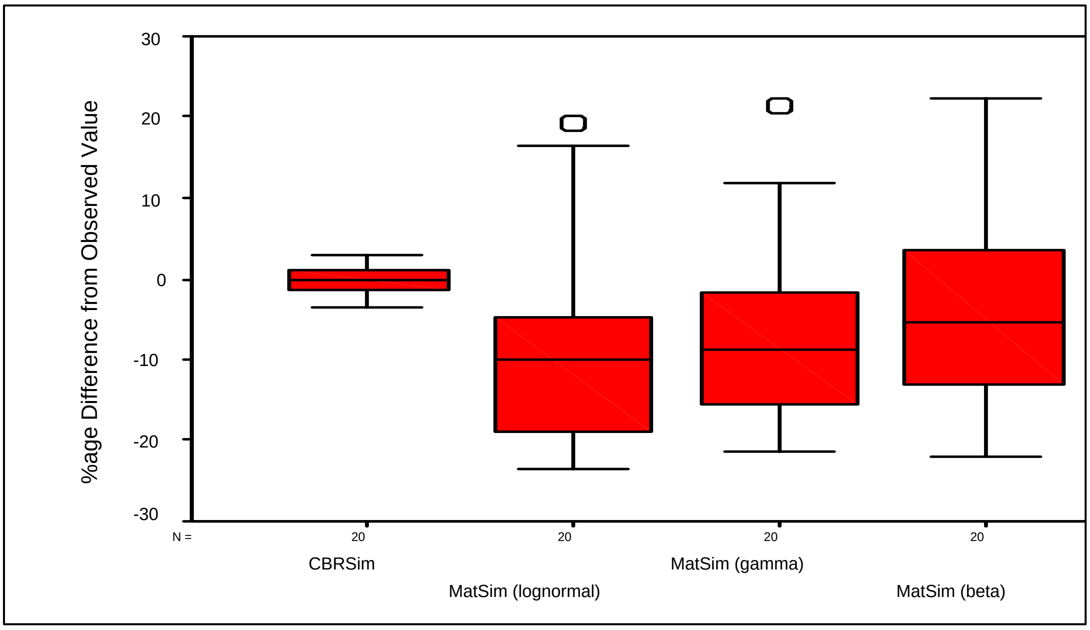

Figure 3: Box plots of percentage difference between model and observed values

CONCLUSIONS

In the past, simulation has been used to estimate the output of construction operations and has proven to be an effective tool for planning random construction processes, such as concreting. However, simulation is a difficult tool to use, as the output of a simulation model will be inaccurate if the input is unrepresentative of the environment. When probability distributions are the input to simulation models, their characteristics can be estimated using CBR. This removes the need for the user to have statistical knowledge of these distributions. A simulation model, MatSim and a hybrid CBR-simulation model, CBRSim were developed based on real construction project data. They were validated using data from a construction project independent to those on which the models were built. The pour duration estimates from both models were compared to determine the effect of using CBR in this study. It was found that CBRSim was able to estimate pour durations to within +/- 3% of the observed pours, compared with +/- 20% from MatSim. In terms of reliability, CBRSim estimated to within +/- 10% of the observed values in 100% of the validation observations. MatSim was unable to match this reliability record. It may be concluded that a case-based reasoning input simplifies the use of simulation, whilst improving its accuracy-making CBRSim a useful tool for the planning of concreting operations. The simplification of simulation modelling may increase the industrial application of simulation as an effective estimation tool of stochastic construction operations.

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