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ESTIMATING EXPECTED COMPLETION TIMES WITH PROBABILISTIC JOB ROUTING

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ABSTRACT

A common problem in production environments is the need to estimate the remaining time in system for work-in-progress jobs. Simulation can be used to obtain the estimates. However, when the future path of a job is uncertain (due to stochastic events such as rework), using simulation to estimate the remaining cycle time of a job at step *k* can be imprecise; traditional confidence intervals on the estimated remaining cycle times may be too large to be of practical significance. We propose a response surface methodology-based approach to estimating conditional confidence intervals on the remaining cycle times as jobs progress through the system and more information is obtained on them. This method will provide more useful and accurate estimates of remaining cycle times at various stages of the process flow. Further, we outline two different simulation approaches for estimating the response surfaces used to generate the confidence intervals.

1 INTRODUCTION

In production environments, it is often important to predict when a particular job will complete processing while the job is in the system. The prediction process becomes difficult if there are one or more seminal steps that lead to significant changes in the subsequent route of the job; this leads to large variability in the expected completion times. In Figure 1 below, for example, jobs that complete step k move to step ($k+1$) with probability p (which depends on the outcome of step k, O_k), and to step (k+1)' with probability 1-p. Jobs going to step ($k+1$) have a total of m more processing steps after step k, whereas jobs going to ($k+1$)' have m' more steps after step k. It is possible (and likely) that $m \neq m'$. Moreover, the expected processing times at steps on these two paths can be significantly different. Having a single confidence interval at step i, $i<k$, on the expected time to completion is not very useful from a practical standpoint since it will either:

1. be too large to be of value (as it contains two or more subpopulations); or
2. will not be a true (1-α) confidence interval. That is, for lower and upper bounds l and u and expected remaining cycle time after step i T_i, $P\left\{l \le E\left[T_i\right] \le u\right\} \neq 1-\alpha$.

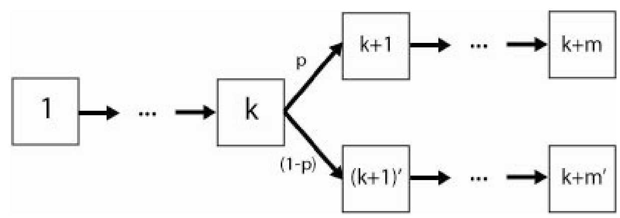

Figure 1: Process Flow Schematic

In this paper, we address two issues. The first is the need for more precise bounds on estimates of the remaining cycle time at each step as jobs progress through the system. That is, rather than returning a single confidence interval on T_i, we propose returning a set of conditional confidence intervals (CCIs): confidence intervals that depend on the outcome of step i. The second problem we address is the computational one of obtaining these confidence intervals. It can become resource-intensive to track all the information required to generate the conditional confidence intervals for all stages of interest. We propose using a response surface methodology (RSM)-based approach to find the conditional confidence intervals

The paper is organized as follows. Section 2 contains a brief literature survey. In Section 3, we introduce the new methodology, which is illustrated in an example in Section 4. Section 5 summarizes our conclusions and directions for future research.

2 BACKGROUND

The literature survey in this section is divided roughly by the main topics relevant to this paper.

2.1 Response Surface Methodology

RSM is a set of statistical and mathematical techniques first introduced by (Box and Wilson 1951) for characterizing the relationship between a response Y and a set of independent variables or factors $\mathbf{x}$. RSM is used extensively in industry to improve or optimize a process or product by determining values of factors that result in desirable response values. Using sequential experimentation, RSM builds empirical models of the response in terms of the factors. The assumption here is that the response can usually be expressed as a polynomial of some degree in the x's (a truncated Taylor series expansion). Let β_0 be the intercept, $\boldsymbol{\beta}$ be a vector of coefficients for linear effects in the factors $\mathbf{x}$, $\mathbf{B}$ be a matrix that contains the quadratic effects in the factors, and ε be the experimental error term that accounts for the inability of the model to explain the real physical phenomenon. Then the polynomial is given by the general formula

$$y(\mathbf{x}) = \beta_0 + \mathbf{x}'\boldsymbol{\beta} + \mathbf{x}'\mathbf{B}\mathbf{x} + \varepsilon, \qquad (1)$$

The degree of the polynomial depends on the desired accuracy of the model. For example, if the starting point of the investigation is far away from the optimum, a model involving first-order terms in the factors may approximate the response well. If a first-order model does not approximate the response well, a higher-order polynomial, in particular a second-order polynomial, may be required.

Hung et al. (2003) propose an RSM approach for estimating performance measures of queueing systems. They seek to reduce computational costs by partitioning the sample space into homogenous regions and creating a "local" model for each region. This is an interesting approach to make the experiment less costly. We propose addressing the expense by changing the type of simulation model. The RSM-based approach to estimation of remaining cycle times is outlined in Section 3.3.

2.2 Expected Sojourn Times in Generic Job Shops

There is a vast literature dealing with determining the expected sojourn time for job shops (or, similarly, scheduling job due dates). The approaches taken can be broadly classified as analytical or experimental. While analytic results, if available, have the advantage of being exact, they are often difficult to obtain. Buzacott and Shanthikumar (1993) give a detailed overview of different analytic approaches for estimating expected flow times in generic job shops.

The two main analytic techniques used are aggregation (where multiple job types are aggregated to a single one) and analysis using Jackson networks. Aggregation is also used in the well-known Queueing Network Analyzer by Whitt (1983). The disadvantage of aggregation in the context of this paper is that we would explicitly combine the different populations of jobs together, and would obtain only one estimate for T_i. Aggregation and reporting back single-valued estimates for the mean time in the system are useful when comparing different system configurations. In the context of this paper, however, we are interested in the expected time in the system for individual jobs, not for "the average" job (which may not even exist). This point is also implicitly made in Backus et al. (2006), where the tree regression shows clearly the different "populations" of jobs. By partitioning jobs based on certain predictors (for example, the type of job), they can find relatively accurate cycle time predictions using similar recent jobs.

Shanthikumar and Sumita (1998) provide an Exponential approximation for the time a job spends in a dynamic job shop. The biggest disadvantage of their model is that they assume that there is only one machine at each station in the system. A queueing network approach to a multi-product, multi-machine job shop is developed in (Vandaele et al. 2002); its chief disadvantage for the purposes of our research is that it assumes deterministic job routings.

Sabuncuoglu and Comlekci (2002) provide a nice review of the literature on flow-time estimation. Their proposed method works well in predicting the time-in-system. In contrast to our problem, however, they assume that a job's routing is known at the outset; this additional information makes a crucial difference in being able to provide accurate predictions. (A job's population is known at the beginning of its sojourn in the facility, rather than determined over the course of its progression through the factory.) We will assume for the rest of the paper that the job's routing is not known at the outset.

Hasan and Spearman (1995) derive a computational method for finding the completion time distribution of jobs. Unfortunately, the assumptions are very limiting (for example, single-server stations with no reentrant flow).

Typical predictors for a job's cycle time include the job type (where applicable) along with its theoretical processing time, the system load/congestion, and the loading of the stations on the job's route. Recently, there has been work done using data mining or neural network approaches to estimate job completion times (Liao and Wang 2004; Sha and Liu 2005; Backus et al. 2006).

The main difference between our work and the existing literature is that we are trying to predict the expected remaining time for individual jobs whose routing is not fully known until they have completed their processing in the system. Existing approaches either assume the routing is known (though it may differ from job to job), or that a single estimate (confidence interval) for all jobs will suffice. The closest work we found to ours are the data mining approaches. Our goal here is to be less tied to large amounts of historical data, but to be able to provide the user with a compact representation for predictions based on current data. Moreover, for a new system configuration, our simulation approach provides a means to generate predictions when historical data are not available.

2.3 Confidence Intervals

Most work we found on confidence intervals look at constructing traditional confidence intervals, possibly in highly-variable environments, for example (Cheng and Kleijnen 1999). However, the variability is different from the type of variability that concerns us in this paper. In this paper, the variability is not necessarily due to congestion or variabilities in processing times. Rather, it is because jobs are effectively from different populations, depending on the outcomes of the processing steps.

Cheng (2005) provides a nice overview on (computing) confidence intervals. Other methods have been proposed to address some of the difficulties associated with obtaining valid confidence intervals from simulation output. Strelen (2004) introduces a method for finding median confidence intervals. Its advantage is that it does not require the variance of the estimator (which can be very difficult to find). Johnson et al. (2004) propose a method for obtaining consistently-sized confidence intervals for cycle time-throughput curves. This is done by focusing the computational effort on more variable areas of the experimental region. Fleming and Simon (1991) derive a method for finding confidence intervals based on light- and heavy-traffic limits. This method can be applied in all cases where these limits exist, and is therefore quite general.

2.4 Simulation Approaches

We outline the methodology for using different types of simulation models for developing the RSM-based models. (The implementation of these approaches is beyond the scope of this paper.) To reduce the amount of computation required, a less detailed simulation known as a resource-driven model can be used. In the cases where more detail is needed, a job-driven simulation is used.

Broadly, job-driven simulations can be thought of as simulations where detailed information on each job in the system is maintained during the simulation; this job information is the information that drives the model. In contrast, resource-driven simulations look at the system from the perspective of resources, and very little information is stored for individual jobs. Rather, resource-driven simulations use general information like the number of jobs in queue. Job-driven simulations focus on the differences between jobs (and resources), resource-driven simulations focus on the similarities. For a more detailed discussion of the two approaches, see (Roeder 2004). For applications of this methodology, see (Roeder et al. 2004; Govind and Fronckowiak 2003).

In (Roeder et al. 2004), the authors illustrate the importance of types of information to simulation models. Information is classified as global or local based on whether it is relevant to the system as a whole, or only to certain parts. In Section 2.2, we discussed the important difference between knowing a job's probabilistic routing before the job begins service in a facility versus the routing being determined as the job progresses. This is a difference between local and global information.

3 METHODOLOGY

Traditionally, users of simulation models are either given single cycle time estimates for a system (regardless of the number of job types or the system characteristics); or are given individual cycle time estimates for each job type. The latter assumes that a job's type is known at the outset. In the former scenario, the resulting estimate may be of little value. For example, if a job's cycle time is either exactly 10 time units or exactly 20 time units, the prediction of 15 time units is infeasible. Our solution to this problem is outlined in Section 3.2.

3.1 Notation and Assumptions

In this section, we define the notation for the remainder of the paper. We also state our assumptions.

- n number of jobs
- j job index, $j = 1,\ldots,n$
- K_j number of steps for job j
- K^* total number of steps possible in system
- $i^j_{[l]}$ l^{th} step for job j, $l = 1,\ldots,K_j$
- i, k step indices, $i, k = 1,\ldots,K^*$
- r route, $r = 1,\ldots,R$
- O_k random variable for outcome at step k; realizations $o_k, o_k' \in \mathcal{O}_k$.
- O_k^j outcome for job j at step k
- p_{ok} probability of outcome o_k, $\sum_{o_k} p_{o_k} = 1$
- T_i^j remaining processing time for job j after step i
- T_0^j expected cycle time for job j when it enters the system
- $R = \prod_{k=1}^{K} |\mathcal{O}_k|$ number of possible job routes, assuming all steps are independent
- $I(E)$ indicator variable; $I(E) = 1$ if event E occurs, 0 otherwise
- γ_0, δ_0 intercept terms for RSM models
- $\boldsymbol{\gamma}, \boldsymbol{\delta}$ vectors of linear coefficients for RSM models
- $\boldsymbol{\Gamma}, \boldsymbol{\Delta}$ matrices of quadratic coefficients for RSM models

Assumptions:

- K_j, the number of possible steps in a job's route, is finite.
- Each step has a unique number. That is, if a job must repeat step 3, the repeat would have a different number, say, 4. (A job's routing will never contain the same step number more than once, even if the same step is repeated from an operational perspective.) The total number of possible "unique" steps is K^*. This assumption is for ease of computation and analysis.

3.2 Conditional Confidence Intervals

As a job enters the system, it is unknown what path it will follow. For example, it may require rework after step *i*, which will lead to a different routing than if it did not require rework. Assume we have obtained cycle times for *n* jobs (through either observation or simulation). Rather than predicting an expected remaining cycle time (and associated confidence interval) of

$$E[T_0] = \frac{\sum_{j=1}^{n} T_0^j}{n}, \tag{2}$$

we provide the user with a set of confidence intervals around the expected remaining time *given* possible outcomes at steps *k*, *k* > *i*, centered around

$$E[T_0 \mid o_k, \forall k] = \frac{\sum_{j=1}^{n} T_i^j \cdot I\left(O_k^j = o_k, \forall k\right)}{\sum_{j=1}^{n} I\left(O_k^j = o_k, \forall k\right)}. \tag{3}$$

After the job has begun processing, traditional estimates are centered around

$$E[T_i \mid o_k, k \le i] = \frac{\sum_{j=1}^{n} T_i^j \cdot I\left(O_k^j = o_k, k \le i\right)}{\sum_{j=1}^{n} I\left(O_k^j = o_k, k \le i\right)}. \tag{4}$$

Our estimates are centered on

$$E[T_i \mid o_k, k \le i; O_k, k > i] = \frac{\sum_{j=1}^{n} T_i^j \cdot I\left(O_k^j = o_k, k \le i; O_k^j = o_k^{'}, k > i\right)}{\sum_{j=1}^{n} I\left(O_k^j = o_k, k \le i; O_k^j = o_k^{'}, k > i\right)} \tag{5}$$

Rather than a single confidence interval, the user receives multiple confidence intervals at each step. Each confidence interval has an associated probability: the probability of the route associated with it. As the job progresses through the system, there are fewer confidence intervals as there are fewer candidate routes.

To find the expected values, we create a linear model for T_i, where the predictor variables are the outcomes O_k. This approach is outlined below.

3.3 RSM-based Estimation

The model in (1) can be used to derive response surfaces for the mean and variance of the response. However, we opt to use ideas from Myers and Carter (1973) who propose a dual response surface approach where a primary and a secondary response of interest are modeled using RSM. Using data from a designed experiment, we propose using the dual response surface approach to obtain fitted response surface models for mean and variance of the remaining cycle times at a given step:

$$E[y(\mathbf{x})] = \gamma_0 + \mathbf{x}'\boldsymbol{\gamma} + \mathbf{x}'\boldsymbol{\Gamma}\mathbf{x}\text{, and} \tag{6}$$

$$\text{Var}[y(\mathbf{x})] = \delta_0 + \mathbf{x}'\boldsymbol{\delta} + \mathbf{x}'\boldsymbol{\Delta}\mathbf{x}. \tag{7}$$

The data used to fit the two models is obtained from simulation replications. The factors $\mathbf{x}$ represent the outcomes at each of the steps where there is more than one future path for a job. Based on the response surface models for mean and variance, we can estimate the CCIs for the remaining cycle times after a step (for each subpopulation) by generating estimates of the mean and variance from these models after the known components of $\mathbf{x}$ are substituted with the values of the outcomes.

3.4 Simulation Models

It is well-known that the time and processor resources required for simulations in the semiconductor industry can be exorbitant, see (Roeder 2004) for references. A typical simulation requires detailed information on each job in the system to be stored in the simulation. This, in part, creates the computational burden associated with most simulation studies.

We outline two different resource-driven simulations. The first is similar in spirit to the approach taken in (Backus et al. 2006), in that we use current queue counts to estimate job waiting times at different resources. The second uses the additional "free" information gained from event time stamps.

3.4.1 Resource-Driven Model 1: Sums of Averages

In this model, rather than estimating expected remaining cycle times based on actual job cycle times, we estimate them based on expected processing times at future steps, plus expected waiting times estimated from Little's Law (Little 1961). The expected processing times are known, having been used as inputs to the simulation model. The expected waiting times can be derived based on the number of jobs in queue at a specific resource. The arrival rate can be estimated as the merging of the arrivals from all predecessor steps.

The variances of the estimates are slightly more complex to calculate, as the variance of the waiting times must be estimated in addition to the covariances between all the steps, as they cannot be assumed to be independent.

3.4.2 Resource-Driven Model 2: Time Stamps

The second resource-driven model requires less computational effort during the simulation run. We maintain counters of the number of jobs that have gone down each route, as well as the number that have completed each route or route segment. In addition, we output the associated event time stamps. From these, we can get rough estimates of the time it took jobs to go down unique paths (i.e., paths where all $p_{ok} = 1$). The estimated remaining processing times are the sums of the relevant path segments.

This method is similar to one introduced in (Roeder 2004). There, it was shown that the quality of the approximation can depend greatly on system parameters. Specifically, when job overtaking is possible and there is much variability present, the approximation can be rather poor.

4 EXAMPLE

We illustrate our methodology using a simple system where $K^* = 11$. The system is illustrated in Figure 2, where the probabilities of going along different routes are given (italics) along with the mean processing times. There are two steps at which routes diverge, steps 2 and 6.

For ease of experimentation, we assume Poisson arrivals (with a rate of 1/250) and Exponential service times. The expected theoretical processing times and the route probabilities for the four possible routes are given in Table 1. (Note that the weighted average processing time when a job enters the system is 469, which corresponds to none of the route times.) The routes are

- R1: 1-2-3-5-6-7-9-10-11
- R2: 1-2-3-5-6-8-11
- R3: 1-2-4-6-7-9-10-11
- R4: 1-2-4-6-8-11.

There are a total of 10 confidence intervals of interest: 4 when a job enters the system; 2 each if the job goes to step 3 or step 4 after completing step 2; and 1 each once it is determined whether a job will go to step 7 or 8 after completing step 6. In contrast, traditional models would report exactly one confidence interval at each stage.

Table 1: Route Processing Times and Probabilities After Outcomes of Steps 2 and 6 Are Known

Route	Time	Initial Prob.	Prob. past Step 3 (4)	Prob. past Step 7 (8)
1	535	0.48	0.6 (0)	1 (0)
2	420	0.32	0.4 (0)	0 (1)
3	435	0.12	0 (0.6)	1 (0)
4	320	0.08	0 (0.4)	0 (1)

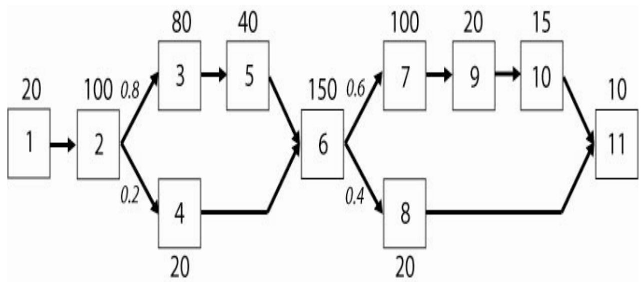

Figure 2: Example System

The system was simulated (using a job-driven approach) for 150,000 job completions using SIGMA, an event scheduling-based simulation package (Schruben and Schruben 2001). The first 5000 jobs were removed to account for initialization bias. For independence, every 10th job was sampled, for a total of $n = 14{,}500$. The confidence intervals obtained through our method as well as the conventional confidence intervals are shown in Figures 3-5. They illustrate how misleading conventional intervals are. The conventional confidence interval does not overlap with the other intervals in any of the three figures. In our example, they become increasingly inaccurate after each "branching" step has occurred when compared to the actual route confidence intervals.

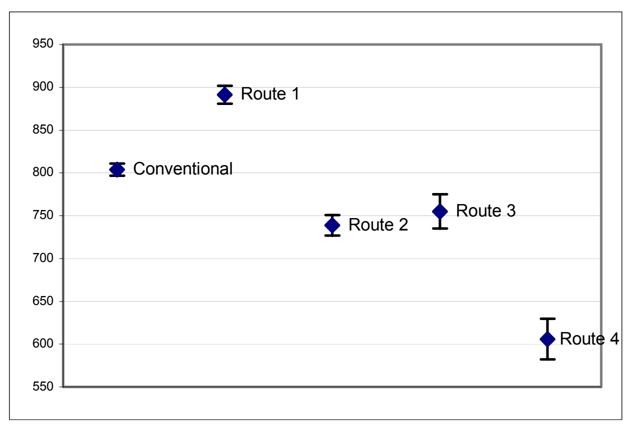

Figure 3: Confidence Intervals for Expected Cycle Times When a Job Enters the System

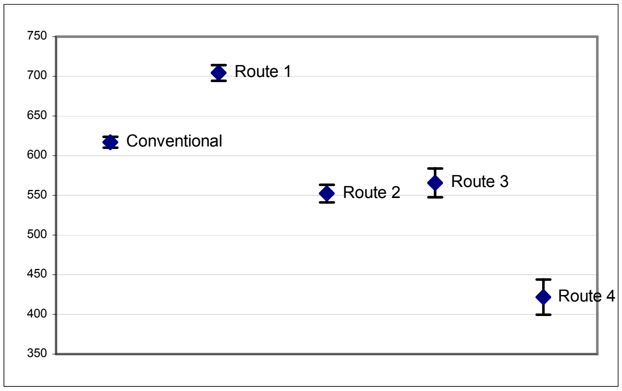

Figure 4: Confidence Intervals for Remaining Cycle Times After the Outcome of Step 2 Is Known

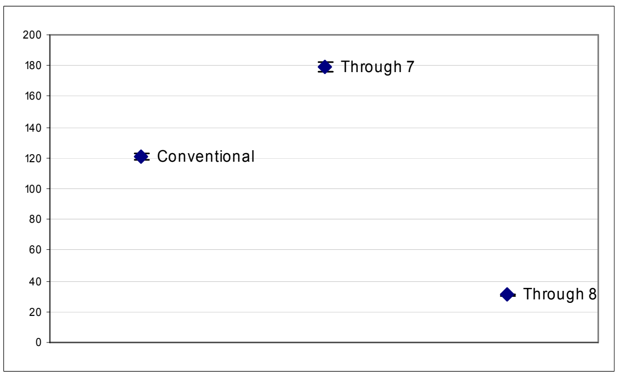

Figure 5: Confidence Intervals for Remaining Cycle Times After the Outcome of Step 6 is Known

We now illustrate the RSM-based estimation approach for this example. We fit linear models for the mean and variance of Y_0, the remaining cycle time when a job enters the system, and Y_2, the remaining cycle time after step 2. The predictors or factors used to fit the responses are the outcome of the probabilistic split at step 2 ($X_2 \in \{3,4\}$) and the outcome of the probabilistic split at step 6 ($X_6 \in \{7,8\}$). The models for the mean are given below. Both have adjusted R^2 values of 0.99.

$$\mathrm{E}(Y_0) = 2307.9 - 132.1X_1 - 145.4X_2 \quad (8)$$

$$\mathrm{E}(Y_2) = 2121.9 - 132.4X_1 - 145.6X_2 \quad (9)$$

The models for the variance are given below. Both have adjusted R^2 values of 0.57.

$$\mathrm{Var}(Y_0) = 341190 - 13010X_1 - 14677X_2 \quad (10)$$

$$\mathrm{Var}(Y_2) = 306131 - 11661X_1 - 14489X_2 \quad (11)$$

The models for the mean fit well whereas the models for the variance do not fit as well. This is to be expected given the variability in the system. However, the linear model estimation for the variance models can be improved by increasing the number of jobs used for estimation. The models above can be used to generate estimates for the confidence intervals for the remaining cycle times for a job entering the system as well as for a job after it completes step 2. Similar models can be estimated for the mean and variance of remaining cycle times after any step in the system, and the corresponding confidence intervals computed.

5 CONCLUSIONS AND FUTURE RESEARCH

We have proposed an RSM-based estimation approach for obtaining more accurate predictions of remaining job cycle times in systems where the path of a job is determined as the job progresses through the system. Rather than reporting a single confidence interval, we provide the user with a set of intervals (along with their associated probabilities) based on the potential paths the job can take. With the help of an example, we have illustrated both the problem with traditional confidence interval estimates for the remaining cycle times in such a system, and the RSM-based approach for estimating models for mean and variance of the remaining cycle times. In addition to the job-driven simulation approach, we have outlined two methods for less detailed simulation modeling to estimate the parameters for the linear model. A future publication will address the RSM-based estimation and the resource-driven approaches to estimating the parameters of the RSM models in detail.

Various extensions to the work proposed in this paper are possible:

- Use of non-Exponential service times
- Larger model with more steps and more branching
- Dependent routing probabilities
- Include other factors in the model, e.g., system loading.

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