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<th>A Gibbs-sampler approach to estimate the number of faults in a system using capture-recapture sampling</th>
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<tr>
<td>Author(s)</td>
<td>Hayakawa, Y; Yip, PSF</td>
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A Gibbs-Sampler Approach to Estimate the Number of Faults in a System Using Capture-Recapture Sampling

Yu Hayakawa and Paul S. F. Yip

Abstract—A new recapture debugging model is suggested to estimate the number of faults in a system, $\nu$, and the failure intensity of each fault, $\phi$. The Gibbs sampler and the Metropolis algorithm are used in this inference procedure. A numerical illustration suggests a notable improvement on the estimation of $\nu$ and $\phi$ compared with that of a removal debugging model.

Index Terms—Capture-recapture sampling, credible interval, Gibbs sampler, metropolis algorithm.

I. INTRODUCTION

A. Acronyms

CODA Convergence Diagnosis and Output Analysis software for Gibbs sampling output
HPP homogeneous Poisson process
H-Y Hayakawa-Yip model (developed in this paper)
J-M Jelinski-Moranda model
L-V Littlewood-Verrall model
MLE maximum likelihood estimate
PCPO prequential conditional predictive ordinate
TTT total time on test

B. Notation

$\phi$ failure intensity for each fault
$\nu$ number of faults in a system
$\{N_i(t); \ t \geq 0\}$ counting process of failure occurrences caused by fault $i$
$Y_i(t)$ indicator function of the event that fault $i$ is undetected or its counter is not removed on $[0,t]$
$\mathcal{F}_t$ $\sigma$-algebra generated by $\{N_i(s); \ s \in [0,t], i = 1, \cdots, \nu\}$
$S_{ij}$ encounter-time #j caused by fault i
$X_i$ $S_{i+1}$
$N(t)$: $t \geq 0$ \{encounter times caused by all faults in a system: $N(t) = \sum_{i=1}^{\nu} N_i(t)$
$\text{TTT}_i(t)$ TTT with respect to fault $i$

Probability densities (conditionals)

$\pi(\cdot|\nu)$ conditional distribution, given $\nu$
$\alpha, \beta$ [shape, scale] parameter
$G(\alpha, \beta)$ Gamma distribution with parameters $\alpha, \beta$
$\lambda(t)$ intensity process for $N(t)$
$M(t)$ zero-mean martingale
$\text{poi}(\omega)$ Poisson distribution with mean $\omega$
$\delta_i(t)$ indicator function: at least 1 failure caused by fault $i$ occurs in $[0,t]$
$\zeta$ remaining number of faults in a system
$q$ quantile to be estimated
$r$ desired accuracy of an estimate of $q$
$s$ Pr{an estimate of $q$ within $\pm r$ is obtained}
k thinning interval of the Gibbs chain
$M$ number of initial iterations to be discarded
$N$ number of further iterations required to estimate $q$ to accuracy $r$ with probability $s$ (Not $N$)
$N_{\text{min}}$ minimum number of iterations needed to estimate $q$, when the samples in the Gibbs chain are $\mathcal{S}$-independent
$I$ $N/N_{\text{min}}$
$T_i$ $X_i - X_{i-1}$: interfailure time #i
$\lambda_i$ failure rate of $T_i$ under the L-V model
$\psi(i)$ scale parameter of the prior for $\lambda_i$
$c_i$ PCPO for $T_i$

In the early 1970s software reliability models began to appear in the literature, e.g., [1, J-M], [2], and various models for software reliability have been suggested since then. For a comprehensive study of software reliability models, see [3]–[5].

J-M is one of the most well-known and earliest models in which the interfailure times are distributed $\mathcal{S}$-independently as exponential with failure rate proportional to the remaining number of faults in the system, and the faults are removed permanently upon detection without introducing new faults. This model can be interpreted as an exponential order statistic model with a constant failure intensity [6].

Reference [7, Nayak] extends the J-M model [1]: a recapture debugging model; the assumptions are the same as those for the J-M model except that the number of times the “faults” are accessed after their removal is recorded by using of counters inserted into the location of detected faults. Therefore, the faults in a system are accessed according to $\mathcal{S}$-independent HPP with the same failure intensity $\phi$. The motivation for the recapture debugging model is to obtain extra information on $\phi$ and $\nu$, so that they can be estimated better. The MLE and moment estimators of $\nu$ and $\phi$ are based on the recapture sampling information along with the first failure detection times of individual faults.
Following the Nayak [7] suggestion, this paper constructs a recapture debugging model which includes the Nayak model as a special case. The distinguishing properties of the H-Y model from the Nayak model are:

1. The removal of counters is allowed.
2. $\nu$ and $\phi$ are treated as random quantities.

The H-Y model can be considered as an extension of any Bayes version of the J-M model, e.g., a model studied in Kuo & Yang [8]. H-Y is studied via the Gibbs sampler and is compared with a removal debugging model: a Bayes version of the J-M model. The L-V model is also used to validate H-Y.

Section II describes the H-Y assumptions in detail.

Section III explains briefly the Gibbs sampler and the Metropolis algorithm which are instrumental for our inference on the remaining number of faults.

Section IV provides a numerical illustration of H-Y: first the assumption of exponentiality of failure times is validated via the modified Anderson-Darling statistics; then another data set is simulated to compare recapture and removal debugging models; finally the posterior analysis on the parameters of interest is presented.

Section V compares the removal and recapture versions of the J-M model and a version of the L-V model based on the criterion of the prequential conditional predictive ordinate.

Section VI presents the results.

II. MODEL ASSUMPTIONS

Consider a system which contains an unknown number of faults, $\nu$: $\{N_i(t), t \geq 0\}$ is the counting process for fault $i$, $i = 1, \cdots, \nu$.

A. Assumptions

1. When a fault is detected for the first time, it is immediately removed without introducing new faults, and a counter is inserted so that the number of occurrences of failures caused by the fault can be counted as if it were still there.
2. The CPU-clock is stopped each time a new fault is detected. After this fault is removed, the CPU-clock is restarted when the testing resumes.
3. Each fault has the same $\phi$.
4. Given $\nu$ and $\phi$, the $N_i(t)$ are $s$-independent HPP with failure intensity $\phi$.

In practice, the assumptions of perfect repair, immediate correction, and identical fault-detection rate are unrealistic. These would likely lead to an optimistic estimate for the remaining number of faults in the system [5, pp. 32–33, 54–56]. However, [9] shows that some software reliability models can be derived from Bayes versions of the J-M model, and many models can be considered as generalizations of the J-M model. Hence, as in [7], the J-M model is used as a starting point to present the approach to estimation and prediction in software reliability. This approach can be extended to other models.

To account for removals of the counters, see the following stochastic processes: for $i = 1, \cdots, \nu$,

$$Y_i(t) = \begin{cases} 1 & \text{if fault } i \text{ is undetected or its counter is not removed in } [0, t), \\ 0 & \text{otherwise.} \end{cases}$$

In the Nayak model, $Y_i(t) = 1$ for any $t$. From the definition of $S_i, n$,

$$S_{i,1} < S_{i,2} < \cdots < S_{i,N_i(t)}, \quad i = 1, \cdots, \nu.$$  

Then the likelihood function is

$$L(\phi, \nu | \mathcal{F}_t) = \frac{n!}{\nu - \sum_{i=1}^{\nu} \delta_i(t)!} \cdot \prod_{i=1}^{\nu} \phi^{N_i(t)} \cdot \exp[-\phi \cdot S_{i,N_i(t)}] + Y_i(t) \cdot (t - S_{i,N_i(t)})$$

$$\delta_i(t) \equiv \begin{cases} 1 & \text{if } S_{i,1} \leq t, \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

$TT_t(t) = S_{i,N_i(t)} + Y_i(t) \cdot (t - S_{i,N_i(t)})$ is the total time on test with respect to fault $i$. If fault $i$ is detected and its counter is removed before $t$, say at time $s < t$, then $TT_t(t) = s$. Otherwise $TT_t(t) = t$ if fault $i$ is undetected on $[0, t]$ or its counter is never removed on $[0, t]$.

Now consider the counting process, $\mathcal{N} = \{N(t), t \geq 0\}$, of all faults in the system:

$$N(t) = \sum_{i=1}^{\nu} N_i(t), \quad t \geq 0.$$  

Assume that, given $\nu, \phi$ has the gamma distribution, a priori:

$$\pi(\phi | \mathcal{F}_0) \sim G(\alpha, \beta).$$

By Bayes theorem,

$$\pi(\phi | \mathcal{F}_t) \propto \pi(\phi | \mathcal{F}_0) \cdot L(\phi, \nu | \mathcal{F}_t)$$

$$\propto \phi^{\alpha+\sum_{i=1}^{\nu} N_i(t)-1} \cdot \exp[-\beta \cdot \phi] \cdot \prod_{i=1}^{\nu} \phi^{N_i(t)} \cdot \exp[-\phi \cdot TT_t(t)]$$

$$= \phi^{\alpha+\sum_{i=1}^{\nu} N_i(t)-1} \cdot \exp \left( \beta + \sum_{i=1}^{\nu} TT_t(t) \right).$$

Therefore,

$$\pi(\phi | \mathcal{F}_t) \sim G \left( \alpha + \sum_{i=1}^{\nu} N_i(t), \beta + \sum_{i=1}^{\nu} TT_t(t) \right).$$

$$dN(t) = N(t) dt = E[\{dN(t) | \mathcal{F}_t\}].$$  

$dN(t)$ is the increment of $\mathcal{N}$ over the interval $[t, t + dt]$. [10]. Given $\phi$ and $\nu$, then $N(t)$ is the sum of $s$-independent HPP; hence the failure intensity for $N(t)$ is:

$$\left\{ \sum_{i=1}^{\nu} Y_i(t) \right\} \cdot \phi.$$
The posterior mean of $\phi$ given $F_t$ is:

$$\alpha + \sum_{i=1}^{\nu} \frac{N_i(t)}{\beta + \sum_{i=1}^{\nu} TTT_i(t)}.$$

Therefore,

$$\lambda(t) = \sum_{i=1}^{\nu} Y_i(t) \frac{\alpha + \sum_{i=1}^{\nu} N_i(t)}{\beta + \sum_{i=1}^{\nu} TTT_i(t)}.$$

$$M(t) = N(t) - \int_0^t \lambda(s) ds. \quad (2)$$

The intensity processes of the J-M model and the Littlewood model [11] are in [10, pp. 133–134], which are relevant to (2). The intensity processes of some other models are in [12]–[16].

### III. Inference Procedures

Inference on the ‘remaining number of faults’ and the ‘failure intensity per fault’ is made from a Bayes perspective. Assign a distribution to $\nu$, and assume a hierarchical model for $\phi$. Estimates of $\phi$ and $\nu$ are obtained using the Gibbs sampler [17] along with the Metropolis algorithm [18]; these are Markov chain Monte Carlo methods. As explained in [19], the Gibbs sampler is a special case of the Metropolis algorithm which was generalized in [20]. The Gibbs sampler enables one to generate random samples from the target density, in our setting posterior densities of the parameters, by iteratively simulating values from the full conditionals. It was popularized in [17] and has had a great impact on some of the statistical literature. References on both practical and theoretical issues of the Gibbs sampler are abundant, e.g., [21]–[23]. Both algorithms are now briefly described.

#### A. Gibbs Sampler

We want to generate samples from the posterior density of $(\theta_1, \ldots, \theta_d)$ given information $F_t$. Begin with initial values $(\theta_1^{(0)}, \ldots, \theta_d^{(0)})$. Then sample iteratively as follows: For $i = 0, 1, \ldots, k - 1$.

- Sample $\theta_1^{(i+1)}$ from $f(\theta_1 | \theta_2^{(i)}, \ldots, \theta_d^{(i)}, F_t)$;
- Sample $\theta_2^{(i+1)}$ from $f(\theta_2 | \theta_1^{(i+1)}, \theta_3^{(i)}, \ldots, \theta_d^{(i)}, F_t)$;
- Sample $\theta_d^{(i+1)}$ from $f(\theta_d | \theta_1^{(i+1)}, \ldots, \theta_{d-1}^{(i+1)}, F_t)$;

... $j = 1, \ldots, d$.

Under certain conditions [22], as $k \to \infty$, $(\theta_1^{(k)}, \ldots, \theta_d^{(k)})$ converges to $(\theta_1, \ldots, \theta_d)$ in distribution, whose density is $f(\theta_1, \ldots, \theta_d | F_t)$. Likewise, for $k$ large enough, $\theta_j^{(k)}$ is effectively a sample from the posterior marginal of $\theta_j$, $f(\theta_j | F_t)$, $j = 1, \ldots, d$.

#### B. Metropolis Algorithm

Begin with initial values $\theta^{(0)} = (\theta_1^{(0)}, \ldots, \theta_d^{(0)})$.

Then the sampling proceeds as: for $i = 0, 1, \ldots, k - 1$, generate $y$ from the candidate generating density $q(\theta^{(i+1)}, y)$; accept $y$ as the value of $\theta^{(i+1)}$ with probability

$$\min \left[ 1, \frac{f(y | F_t)}{f(\theta^{(i)} | F_t)} \right],$$

otherwise the value of the chain remains unchanged; repeat this procedure to create a chain $\{\theta^{(1)}, \ldots, \theta^{(k)}\}$.

For $k$ large enough, $\theta^{(k)} = (\theta_1^{(k)}, \ldots, \theta_d^{(k)})$ is effectively a sample from the target density $f(\theta | F_t)$, the joint posterior density of $\theta = (\theta_1, \ldots, \theta_d)$.

Although one can never conclude with certainty when these 2 procedures should be terminated and the simulated values used for analyses of unobservables, it is advisable to perform convergence diagnostics on the simulated values. For a numerical illustration of this inference procedure in Section IV, the diagnostic method in [24] is chosen and is implemented by the CODA software (Convergence Diagnosis and Output Analysis Software for Gibbs sampling output) [25], [26] which is a set of S-Plus routines for ‘convergence diagnostics and output analysis’ for the Markov chain Monte Carlo methods. Reference [27] compares various convergence diagnostic methods.

For the example in Section IV, assume the following priors for the parameters.

$$(3) \quad \pi(\phi | \alpha, \beta) \sim G(\alpha, \beta)$$

$$(4) \quad \pi(\alpha | \lambda, \mu) \sim G(\lambda, \mu)$$

$$(5) \quad \pi(\beta | \gamma, \delta) \sim G(\gamma, \delta)$$

$$(6) \quad \pi(\omega) \sim \text{poi}(\omega)$$

The full posterior conditionals necessary to implement the Gibbs sampler are:

$$(7) \quad \pi(\psi | \alpha, \beta, F_t) \sim G \left( \alpha + \sum_{i=1}^{\nu} N_i(t), \beta + \sum_{i=1}^{\nu} TTT_i(t) \right)$$

$$(8) \quad \pi(\alpha | \psi, \beta, F_t) \sim G(\gamma + \alpha, \delta + \phi)$$

$$\pi(\beta | \psi, \alpha, F_t) \sim \text{poi} [ \omega \cdot \exp(-\phi \cdot t) ]$$

$$(9) \quad \zeta \equiv \nu - \sum_{i=1}^{\nu} \delta_i(t).$$

viz, the remaining number of faults in the system. As for $\alpha$, its full posterior conditional can be obtained up to a proportionality constant:

$$\frac{\pi(\alpha | F_t) \psi^\alpha \cdot \phi^{\alpha - 1}}{\Gamma(\alpha)}.$$

Following the studies [8], [28], use the Metropolis algorithm to generate samples from the full posterior conditional distribution of $\alpha$. 
TABLE I
FAILURE DATA FOR AN INFORMATION SYSTEM AND SIMULATED ENCOUNTER TIMES

<table>
<thead>
<tr>
<th>Fault #</th>
<th>1st Failure Time</th>
<th>Simulated Subsequent Failure Times</th>
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<td>1</td>
<td>880</td>
<td>64653</td>
</tr>
<tr>
<td>2</td>
<td>4310</td>
<td>305937</td>
</tr>
<tr>
<td>3</td>
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<td>186946</td>
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<tr>
<td>5</td>
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</tr>
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IV. A NUMERICAL EXAMPLE

To illustrate the proposed inference procedure, the data-set from [10, p. 43] (originally reported in [29]) is used. It has 43 occurrence times (in seconds CPU time) of first failures caused by 43 distinct faults of an information system for registering aircraft movements; these numbers are in column 2 of Table I.

Step 1. Anderson-Darling statistics are computed to check if failure times in this data-set are identically exponentially distributed.

Step 2. The data-set is augmented by simulating subsequent failure times of each detected fault by treating failure-time #43 as a stopping time.

Step 3. CODA is explained and the Gibbs sampler is used to conduct analyzes on $\nu$ and $\phi$ regarding both recapture and removal debugging models.

A modified version of Anderson-Darling statistics is used to test the exponentiality of failure times [30], [31, pp. 114–115, 141–145]. The Table I data-set is assumed to be right (type 2) censored. A test procedure [31] is given next.

$X_1, \ldots, X_\nu$ are failure times, and $X_{(1)}, \ldots, X_{(\nu)}$ are the corresponding order statistics. Observation is stopped at $X_{(\nu)}$.

1. Compute

$$\hat{\beta} = \frac{\sum_{i=1}^{\nu} X_{(i)}}{\nu} + (\nu - r) \cdot X_{(r)}$$

2. Calculate

$$Z_{(i)} = 1 - \exp \left( \frac{-X_{(i)}}{\hat{\beta}} \right), \quad i = 1, \ldots, r.$$
3. Calculate a modified version of Anderson-Darling statistics:

\[
2A^2_{\text{rn}} = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{2i - 1}{n} \cdot \left[ \log(Z_{(i)}) - \log(Z_{(i)}) \right] \right) - 2 \sum_{i=1}^{n} \left[ \log(Z_{(i)}) - \frac{1}{n} \left[ \log(Z_{(i)}) - \frac{1}{n} \log(Z_{(i)}) \right] \right] \cdot \left[ (r-n)^2 \cdot \log(Z_{(r)}) - r^2 \cdot \log(Z_{(r)}) + n^2 \cdot Z_{(r)} \right];
\]

\[
\bar{Z}_{(i)} = 1 - Z_{(i)}.
\]

Since \( \nu \) is unknown, compute \( 2A^2_{\text{rn}} \) for various values of \( \nu \geq 43 \); the results are in Table II.

Refer the \( 2A^2_{\text{rn}} \) values in Table II to the percentage points in [31, Table 4.16, pp. 143–144]; the hypothesis of exponentiality of \( \nu \), \( \text{ie} \), cannot be rejected at the 5% significance level for \( \nu \), nor at the 2.5% significance level for \( \nu = 59, 60 \), based on interpolated percentage points, which does not reject the assumption.

From column 2 of Table I, compute [10, pp. 418–419] the MLE for \( \mu \) of individual faults.

Now generate interfailure times for each fault from the exponential distribution with failure rate \( \dot{\phi} \). Column 3 of Table I contains the simulated failure encounter times between the first encounter time of individual faults and the stopping time, 576,570 seconds in CPU time.

If the removal of counters was allowed, the TTT\(_{i}(t)\) and/or \( N_{i}(t) \) would be changed. For example, consider fault 15; suppose that its counter is removed at 400,000 seconds in CPU time. Then,

\[
\text{TTT}_{15}(576,570) = 400,000, \quad N_{i}(576,570) = 5
\]

instead of 576,570 and 7, respectively. The only change in implementation of the Gibbs sampler in this case would be through the full posterior conditional of \( \phi \), because it depends on TTT\(_{i}(t)\)s and \( N_{i}(t)\)s (7).

For both recapture and removal debugging models, two sets of priors, (A) and (B), are used; see (3)–(6) for notation. To study the effect of prior means for \( \mu \), denoted by \( \omega \), the only difference between the (A) and (B) priors is the value of \( \omega \).

If there exist past data of similar software, then the parameters of the prior (referred to as hyperparameters) can be determined, based on such data. See [32, chapter 3] for various methods on elicitation of prior information. As an ad hoc approach, one could choose values for the hyperparameters using estimates of the parameters obtained by classical methods such as MLE.

The method in [24] is implemented by \texttt{CODA} to detect convergence to the stationary distribution, and is used to determine the number of iterations to achieve a prespecified accuracy of an estimate, the spacing between iterations, and the number of burn-in iterations.

Next is an analysis based on [24] regarding a Gibbs chain, a sequence of samples simulated by the Gibbs sampler, of the recapture model with prior choice (B).

This method requires a quantile, \( q \), to be estimated, a desired accuracy, \( r \), of the estimate of \( q \), and a probability, \( s \), of obtaining an estimate of \( q \) within \( \pm r \). \( N \) represents the number of further iterations required to estimate \( q \) within \( \pm r \). \( s \) represents the number of further iterations required to achieve the accuracy \( r \) with probability \( s \). \( N_{\text{min}} \) is the minimum number of iterations needed to estimate \( q \), assuming that the samples in the Gibbs chain are \( s \)-independent. \( I \) measures the increase in the number of iterations needed for estimation of \( q \) due to dependence in the Gibbs chain. An \( I > 1 \) often indicates a high level of correlation in the Gibbs chain. Reference [24] shows that \( I > 5 \) often indicates difficulties and suggests changes in the implementation such as starting values and reparameterization.

For example, from the results associated with \( \phi \) in Table IV, discard the initial 4 iterations and require 749 further iterations with the thinning interval of 1 to estimate 0.025 quantile of \( \phi \) to within \( \pm 0.0125 \), with 0.95 probability. The chain of \( \phi \) values converges to the stationary distribution very quickly. \( I \) is close to 1, hence the iterates of the chain do not show a high level of correlation.

For convergence diagnostics of all the Gibbs chains simulated to analyze this numerical example, choose \( q = 0.025 \), \( r = 0.0125 \), \( s = 0.95 \). In most cases, the number of burn-in iterations are less 5, and 2000 iterations are more than sufficient to achieve the accuracy in the previous paragraph.

Table V summarizes the results from \texttt{CODA}’s output analysis of the Gibbs chains, which contain estimates of the:

- posterior mean
- posterior standard deviation
TABLE V
ESTIMATES OF POSTERIOR MEANS, STANDARD DEVIATIONS AND PERCENTILES

<table>
<thead>
<tr>
<th>var</th>
<th>data</th>
<th>ω</th>
<th>post. mean</th>
<th>SD</th>
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<td>34</td>
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<td>12</td>
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<td>4.33·10⁻⁶</td>
<td>1.09·10⁻⁶</td>
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<td>6.57·10⁻⁶</td>
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<tr>
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<td>3.09·10⁻⁶</td>
<td>1.05·10⁻⁶</td>
<td>1.47·10⁻⁶</td>
<td>5.50·10⁻⁶</td>
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<tr>
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<td>4.61·10⁻⁶</td>
<td>4.70·10⁻⁷</td>
<td>3.73·10⁻⁶</td>
<td>5.57·10⁻⁶</td>
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<tr>
<td>φ</td>
<td>generated</td>
<td>73</td>
<td>4.47·10⁻⁶</td>
<td>4.77·10⁻⁷</td>
<td>3.59·10⁻⁶</td>
<td>5.45·10⁻⁶</td>
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The estimates of 95% credible intervals for ζ and φ can be obtained using the last 2 columns of Table II. In addition, the graphs of estimates of the posterior densities for ζ produced by CODA are in Figs. 1–4.

Under the quadratic loss function, the posterior mean is the Bayes point estimate; thus compare the posterior means of ζ and φ in regard to the choice of model and prior distribution. With respect to the recapture debugging model (denoted by “Generated” in Table V and Figs. 1–2), the point estimates of ζ are approximately 4.27 and 5.78 for the prior choices of (A) and (B), respectively.

For the removal model (denoted by ‘Original’ in Table V and Figs. 3–4), the prior distributions of ζ corresponding to (A) and (B) have more bearing on the posterior estimates of ζ than those for the recapture debugging model.

The posterior standard deviations for ζ of the recapture debugging model are noticeably reduced compared with those of the removal debugging model. The posterior estimates of φ for the recapture debugging model are 4.61·10⁻⁶ and 4.47·10⁻⁶ corresponding to the prior choices (A) and (B), and those for the removal debugging model are 4.33·10⁻⁶ and 3.00·10⁻⁶.
respectively. Similar to the posterior estimates of $\zeta$, the prior distributions of $\phi$ for the removal model have more effect on the posterior estimates of $\phi$ than those for the recapture model. The uncertainty about $\phi$ with respect to the recapture debugging model for both (A) and (B) is greatly reduced as opposed to those with respect to the removal debugging model. Consequently, the credible intervals of $\phi$ for the removal debugging model are wider than those for the recapture debugging model. The removal debugging model tends to give lower point estimates of $\phi$ than the recapture debugging model.

From these observations we conclude that the effect of ignoring subsequent encounter times of failures has a great impact on the estimation of $\nu$ and $\phi$. With the recapture model, the estimates are likely to be more robust to prior selection of hyperparameters (parameters of the prior) values and are more accurate in the sense that the posterior distributions of the parameters have smaller standard-deviations compared to those of the removal model. Hence, one should use the information obtained from re-encounter times in practice in pursuit of more robust and accurate estimates of the parameters of interest.

V. MODEL COMPARISON

In order to validate the approach in this paper, the removal and recapture versions of the J-M model and a version of the L-V model are compared, based on the criterion of PCPO (defined in this section).

The L-V model [2] assumes that:

1. The interfailure times, $T_i$, $i = 1, \ldots, n$, are $s$-independent and exponentially distributed with failure rates $\lambda_i$.
2. The $\lambda_i$ are $s$-independent; each $\lambda_i$ is gamma distributed with shape parameter $k \alpha$ and scale parameter $k \beta$.

Unlike the J-M model, the L-V model allows imperfect debugging. Because $\psi(i)$ is increasing in $i$, the $E[T_i]$ increases in $i$.

Reference [8] uses the PCPO for model selection. This paper follows that approach for comparison of the H-Y model two other models. The PCPO for observation $i$ is [8, p. 74] of the H-Y model with

$$c_i = p(t_i | t_1, \ldots, t_{i-1}), \quad i \geq 2$$

$$c_2 = p(t_1).$$

For the removal and recapture versions of the J-M model, the $c_i$ are approximated using the Gibbs chains by

$$\hat{c}_i = \bar{f}(t_i | t_1, \ldots, t_{i-1})$$

$$= \frac{1}{N} \cdot \sum_{j=1}^{N} \zeta^{(j)} \cdot \phi^{(j)} \cdot \exp[-\zeta^{(j)} \cdot \phi^{(j)}]$$

where $\zeta^{(j)}$ and $\phi^{(j)}$ denote the samples #j of the Gibbs chains of $\zeta$ and $\phi$ and assume $\{t_1, \ldots, t_{i-1}\}$ is given after a convergence diagnostic is conducted.

For the L-V model, the linear function for $\psi(i)$ is used:

$$\psi(i) = \beta_0 + \beta_1 \cdot i.$$  

To approximate $c_i$, first estimate $\hat{\beta}_0$, $\hat{\beta}_1$ using a least squares method. The estimates, $\hat{\beta}_0$, $\hat{\beta}_1$ can be obtained by minimizing

$$\sum_{j=1}^{i-1} \left( t_j - \frac{\psi(j)}{\alpha - 1} \right)^2 ;$$

$\psi(j)/(\alpha - 1)$ is the $s$-expected value of $T_j$ [3, pp. 107–108]. $c_i$ is approximated by substituting $\hat{\beta}_0$, $\hat{\beta}_1$ for $\beta_0$, $\beta_1$ respectively in (8).

Fig. 5 plots the PCPO of the J-M removal and recapture models with prior option of (A) and the L-V model. The PCPO of all models are larger for about the first 30 interfailure times, then they decrease for the remainder of the data points. The difference between the PCPO of the J-M recapture model and the removal model is plotted in Fig. 6. Fig. 7 plots the difference between those of the J-M recapture model and the removal model. In Fig. 6, the number of points above and below zero are
for the L-V model, compute (denoted by and are greatly appreciates the hospitality shown by the Department.

about the same, but the average magnitude of the ‘points above 0’ appears to be slightly bigger than that of the ‘points below 0.’ This suggests that the J-M recapture model is preferred for the data set. According to Fig. 7, the J-M removal and recapture models are analogous.

As a model selection criterion [8, p. 74], this paper maximizes the joint density of interfailure times of distinct faults,

\[
\pi(t_1, \ldots, t_{43}) = \prod_{i=1}^{43} c_i.
\]

Since there is no \(c_i\) for the L-V model, compute \(\prod_{i=2}^{43} c_i\) for all 3 models as well. These values are summarized in Table VI. Based on \(\prod_{i=2}^{43} c_i\), the J-M recapture model is the best. It again is slightly more desirable than the J-M removal model by comparing the values of \(\prod_{i=1}^{43} c_i\).

VI. RESULTS

The Nayak [7] recapture debugging model is generalized by allowing the removal of counters and treating the \(\nu\) and \(\phi\) as random quantities. The Gibbs sampler and the Metropolis algorithm are used to analyze a data set through both recapture and removal debugging models. Two prior means for \(\nu\) and \(\phi\) are greatly reduced in comparison with the removal model’s counterparts. Hence, the recapture debugging models offers more robust estimates for \(\nu\) and \(\phi\) with less posterior standard-deviation than those based on the removal model.

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TABLE VI

<table>
<thead>
<tr>
<th>Model Comparison</th>
<th>J-M Recapture</th>
<th>J-M Removal</th>
<th>L-V</th>
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<tr>
<td>(\prod_{i=1}^{43} c_i)</td>
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<td>3.453923 \cdot 10^{-189}</td>
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<td>(\prod_{i=2}^{43} c_i)</td>
<td>2.569416 \cdot 10^{-193}</td>
<td>1.425401 \cdot 10^{-193}</td>
<td>Not Applicable</td>
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</table>

REFERENCES


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