

Journal of Statistics Applications & Probability An International Journal

Calibrated Confidence Intervals for Intensities of a Two Stage Open Queueing Network

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Received: 29 Aug. 2013, Revised: 16 Nov. 2013, Accepted: 19 Dec. 2013 Published online: 1 Mar. 2014

Abstract: In this paper calibration technique is used to construct approximate $100(1 - \alpha)\%$ confidence intervals for intensity parameters ρ_1, ρ_2 of a two-stage open queueing network with distribution-free interval and service times. Numerical simulation study is conducted to demonstrate performances of the calibrated confidence intervals. Also a measure, named relative coverage, is used to compare different calibrated confidence intervals.

Keywords: Calibration technique, Confidence intervals, Coverage percentage, Relative coverage.

1 Introduction

Consider the two-stage open queueing network shown in Fig-1.



The system consists of two nodes with respective service rates μ_1 and μ_2 . The external arrival rate is λ . The output of the node-1 is the input to the node-2. Traffic intensities are defined as the ratios

$$\rho_1 = \frac{\lambda}{\mu_1}, \quad \rho_2 = \frac{\lambda}{\mu_2} \tag{1}$$

where $1/\lambda$ represent mean inter-arrival time and $1/\mu_1$, $1/\mu_2$ denotes mean service times at node-1 and node-2 respectively. The condition for stability of the system is that ρ_1 and ρ_2 must be less than unity.

Burke [2] has shown that the output of an M/M/1 queue is also Poisson with rate λ . Jackson [14] showed that the product form solution also applies to open network of Markovian queues with feedback, also Jackson's theorem states that each node behaves like an independent queue. Disney [3] introduces basic properties of queueing networks. Thiruvaiyaru, Basawa and Bhat [23] established maximum likelihood estimators of the parameters of an open Jackson network. Thiruvaiyaru and Basawa [22] considered the problem of estimation for the parameters in a Jackson's type queueing network. Ke and Chu [15] constructed various confidence intervals for intensity parameter of a queueing system.

Calibration technique is used for improving the coverage accuracy of any system of approximate confidence intervals. The idea of the bootstrap calibration technique is, first use bootstrap to estimate the true coverage of confidence intervals and the intervals is then adjusted by comparing with the target nominal level. In literature, there is no work regarding the

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calibration technique used in queueing networks. So it is tempting to use calibration technique to construct new confidence intervals called calibrated for intensity parameters of a two stage open queueing network whose true coverage probabilities come closer to desired value.

Nonparametric inference for estimating intensity parameters is discussed in Section 2. In Section 2.1, we have explained calibration technique. In Section 2.2 to 2.9 we have proposed calibrated consistent and asymptotically normal, exact *t*, standard bootstrap, bootstrap-*t*, variance-stabilized bootstrap-*t*, Bayesian bootstrap, percentile bootstrap, bias-corrected and accelerated bootstrap confidence interval for intensity parameters ρ_1, ρ_2 . In Section 3, numerical simulation study is conducted. All simulation results are given in appropriate tables for illustrating performances of all estimation approaches. Finally some conclusions are drawn in Section 4.

2 Nonparametric Statistical Inference for Estimating Intensity Parameters

Let $(X_i, Y_i, i = 1, 2)$ be nonnegative, independent random variables representing respectively inter-arrival times and service times at first and second node of a two stage queueing network. Consider $(X_{ij}, Y_{ij}, i = 1, 2, j = 1, 2, \dots, n)$ is a random sample drawn from $(X_i, Y_i, i = 1, 2)$ for j^{th} customer at i^{th} node. The intensities are defined as follows:

$$\rho_1 = \frac{\mu_{Y_1}}{\mu_{X_1}} \quad \text{and} \quad \rho_2 = \frac{\mu_{Y_2}}{\mu_{X_2}},$$
(1)

where μ_{X_1}, μ_{X_2} denote the mean inter-arrival times at two nodes, μ_{Y_1}, μ_{Y_2} denote the mean service times at two nodes respectively. Define $(\overline{X}_i, \overline{Y}_i, i = 1, 2)$ to be the sample means of $(X_{ij}, Y_{ij}, i = 1, 2, j = 1, 2, \dots, n)$ respectively. According to the Strong Law of Large Numbers (Rousses [20]), we know that $(\overline{X}_i, \overline{Y}_i, i = 1, 2)$ are strongly consistent estimator of $(\mu_{X_i}, \mu_{Y_i}, i = 1, 2)$ respectively. Thus a strongly consistent estimator of intensities are given by

$$\hat{\rho}_i = \frac{\overline{Y}_i}{\overline{X}_i}, \quad i = 1, 2. \tag{3}$$

The true distributions of $(X_i, Y_i, i = 1, 2)$ are not often known in practice so the exact distributions of $\hat{\rho}_i, i = 1, 2$ cannot be derived. But under the assumption that X_i and Y_i being independent, the asymptotical distributions of $\hat{\rho}_i, i = 1, 2$ can be developed. By Slutsky's theorem (Hogg & Craig, [13]), we have

$$\sqrt{n}(\hat{\rho}_i - \rho_i) \xrightarrow{D} N(0, \sigma_i^2), \ i = 1, 2$$

where $\sigma_i^2 = (\mu_{X_i}^2 \sigma_{Y_i}^2 + \mu_{Y_i}^2 \sigma_{X_i}^2) / \mu_{X_i}^4$, i = 1, 2 and $\stackrel{D}{\rightarrow}$ denotes convergence in distribution. Now we can estimate σ_i^2 as

$$\hat{\sigma}_i^2 = (\overline{X}_i^2 S_{Y_i}^2 + \overline{Y}_i^2 S_{X_i}^2) / \overline{X}_i^4, \ i = 1, 2$$

where

$$S_{x_i}^2 = \frac{1}{n} \sum_{j=1}^n (X_{ij} - \overline{X}_i)^2, \quad S_{Y_i}^2 = \frac{1}{n} \sum_{j=1}^n (Y_{ij} - Y_i)^2, \quad i = 1, 2$$

Then $\hat{\sigma}_i^2, i = 1, 2$ is a strongly consistent estimator of $\sigma_i^2, i = 1, 2$. Again applying the Slutsky's theorem we have, $\frac{\sqrt{n}(\hat{\rho}_i - \rho_i)}{\hat{\sigma}_i} \xrightarrow{D} N(0, 1), i = 1, 2$. Thus $\hat{\rho}_i, i = 1, 2$ is a strongly consistent and asymptotically normal (CAN) estimator with approximate variances $\hat{\sigma}_i^2/n, i = 1, 2$.

2.1 Calibration Technique

The general theory of calibration is reviewed in Efron and Tibshirani [6], following ideas of Loh [16], Beran [1], Hall [11] and Hall and Martin [12]. The bootstrap calibration technique was introduced by Loh [16,17]. A confidence limit $\hat{\rho}_i[\alpha]$ is supposed to have probability α of covering the true value ρ_i , that is $P_{F_i}\{\rho_i \leq \hat{\rho}_i[\alpha]\} = \alpha, i = 1, 2$ where F_i is unknown continuous probability distribution. For an approximate confidence limit there is true probability β_i that ρ_i is less than $\hat{\rho}_i[\alpha]$ say, $\beta_i(\alpha) = P_{F_i}\{\rho_i \leq \hat{\rho}_i[\alpha]\}$. The actual coverage of a confidence procedure is rarely equal to the desired coverage and often it is substantially different. If we knew the function $\beta_i(\alpha)$ then we could calibrate an approximate confidence interval to give exact coverage. Suppose we know that $\beta_i(0.03) = 0.05$ and $\beta_i(0.94) = 0.95$. Then instead of $(\hat{\rho}_i[0.05], \hat{\rho}_i[0.195])$ we would use $(\hat{\rho}_i[0.03], \hat{\rho}_i[0.94])$ to get a central 90% interval with correct coverage probabilities.

In practice usually we don't know the calibration function $\beta_i(\alpha)$. However we can use the bootstrap to estimate $\beta_i(\alpha)$. The bootstrap estimate of $\beta_i(\alpha)$ is $\hat{\beta}_i(\alpha) = P_{\hat{F}_i}\{\hat{\rho}_i \leq \hat{\rho}_i[\alpha]^*\}$ where \hat{F}_i and $\hat{\rho}_i$ are fixed while $\hat{\rho}_i[\alpha]^*$ is the α^{th} confidence limit based on bootstrap dataset from \hat{F}_i . The estimate $\hat{\beta}_i(\alpha)$ is obtained by taking B bootstrap data sets and seeing what proportion of them have $\hat{\rho}_i \leq \hat{\rho}_i[\alpha]^*$.

2.2 Consistent and Asymptotically Normal (CAN) Calibrated Confidence Interval

With the CAN estimators $\hat{\rho}_i$, i = 1, 2 and its associated approximate variances $\hat{\sigma}_i^2/n$, i = 1, 2, we construct calibrated confidence intervals for intensities ρ_i , i = 1, 2. Let z_α be the upper α^{th} quantile of the standard normal distribution. Compute $\hat{\beta}(\alpha_1) = P\{\rho_i \le (\hat{\rho}_i - z_{\alpha/2}\hat{\sigma}_i/\sqrt{n})\}$ and $\hat{\beta}(\alpha_2) = P\{\rho_i \le (\hat{\rho}_i + z_{\alpha/2}\hat{\sigma}_i/\sqrt{n})\}$ where $\alpha_2 = 1 - \alpha_1$ and $0 \le \alpha_1 \le 1$. Then approximate $100(1 - \alpha)\%$ calibrated confidence intervals for ρ_i , i = 1, 2 are given by,

$$\left(\hat{\rho}_{i}^{\prime}-z_{\hat{\beta}(\alpha_{1})/2}\hat{\sigma}_{i}^{\prime}/\sqrt{n}, \ \hat{\rho}_{i}^{\prime}+z_{\hat{\beta}(\alpha_{2})/2}\hat{\sigma}_{i}^{\prime}/\sqrt{n}\right), \ i=1,2.$$

$$\tag{4}$$

2.3 Exact- t Calibrated Confidence Intervals

Let t_{α} be the upper α^{th} quantile of the Student's *t*-distribution. Compute $\hat{\beta}(\alpha_3) = P\{\rho_i \leq (\hat{\rho}_i - t_{(n-1),\alpha/2}\hat{\sigma}_i/\sqrt{n}\}$ and $\hat{\beta}(\alpha_4) = P\{\rho_i \leq (\hat{\rho}_i + t_{(n-1),\alpha/2}\hat{\sigma}_i/\sqrt{n}\}$, where $\alpha_4 = 1 - \alpha_3$ and $0 \leq \alpha_3 \leq 1$. Then approximate $100(1 - \alpha)\%$ exact-*t* calibrated confidence intervals of ρ_i , i = 1, 2 are given by,

$$\left(\hat{\rho}'_{i} - t_{(n-1),\hat{\beta}(\alpha_{3})/2}\hat{\sigma}'_{i}/\sqrt{n}, \ \hat{\rho}'_{i} + t_{(n-1)\hat{\beta}(\alpha_{4})/2}\hat{\sigma}'_{i}/\sqrt{n}\right), \ i = 1, 2.$$
(5)

2.4 Standard Bootstrap (SB) Calibrated Confidence Intervals

Efron [7,8,9] originally developed and proposed the bootstrap, which is a resampling technique that can be effectively applied to estimate the sampling distribution of any statistic. According to the bootstrap procedure, a simple random sample $(X_{ij}^*, Y_{ij}^*, i = 1, 2, j = 1, 2, \dots, n)$ is taken from the empirical distribution function of $(X_{ij}, Y_{ij}, i = 1, 2; j = 1, 2, \dots, n)$. Thus bootstrap estimate for intensity $\rho_i, i = 1, 2$ can be calculated as $\hat{\rho}_i^* = \frac{\overline{y}_i^*}{\overline{x}_i^*}, i = 1, 2$. The resampling process is repeated *N* times and $\hat{\rho}_{i1}^*, \hat{\rho}_{i2}^*, \dots, \hat{\rho}_{iN}^*, i = 1, 2$ are computed from the bootstrap resample. Averaging the *N* bootstrap estimates we get bootstrap estimate of $\hat{\rho}_i, i = 1, 2$ as $\hat{\rho}_N(i) = \frac{1}{N} \sum_{j=1}^{N} \hat{\rho}_{ij}^*, i = 1, 2$ and standard deviation of $\hat{\rho}_i, i = 1, 2$ is estimated by

$$sd(\hat{\rho}_N(i)) = \left\{ \frac{1}{N-1} \sum_{j=1}^N (\hat{\rho}_{ij}^* - \hat{\rho}_N(i))^2 \right\}^{1/2}, \ i = 1, 2$$

For necessary background on bootstrap technique, we refer to Efron and Gong [4], Efron and Tibshirani [5], Guntur [10], Mooney and Duval [19], Young [24], Rubin [21], Miller [18].

By central limit theorem the distribution of $\hat{\rho}_i$, i = 1, 2 is approximately normal. After Computing $\hat{\beta}(\alpha_5) = P\{\rho_i \le (\hat{\rho}_i - z_{\alpha/2} sd(\hat{\rho}_N(i)))\}$ and $\hat{\beta}(\alpha_6) = P\{\rho_i \le (\hat{\rho}_i + z_{\alpha/2} sd(\hat{\rho}_N(i)))\}$ where $\alpha_6 = 1 - \alpha_5$ and $0 \le \alpha_5 \le 1$. We get $100(1 - \alpha)$ % SB calibrated confidence interval for ρ_i is

$$\left(\hat{\rho}'_{i} - z_{\hat{\beta}(\alpha_{5})/2} sd(\hat{\rho}_{N}(i))', \ \hat{\rho}'_{i} + z_{\hat{\beta}(\alpha_{6})/2} sd(\hat{\rho}_{N}(i))'\right)$$

$$\tag{6}$$

2.5 Bootstrap-t Calibrated Confidence Intervals

Consider *N* bootstrap estimate $\hat{\rho}_{i1}^*, \hat{\rho}_{i2}^*, \dots, \hat{\rho}_{iN}^*, i = 1, 2$ computed from the bootstrap resample. We compute $Z_{ij}^* = \frac{(\hat{\rho}_{ij}^* - \hat{\rho}_N(i))}{sd(\hat{\rho}_N(i))}, i = 1, 2, j = 1, 2, \dots, N$ and $Z_{ij}^*, i = 1, 2, j = 1, 2, \dots, N$ follow an approximate *t* distribution. Also

compute $\hat{\beta}(\alpha_7) = P\{\rho_i \le (\hat{\rho}_i - t_{\alpha/2}sd(\hat{\rho}_N(i)))\}$ and $\hat{\beta}(\alpha_8) = P\{\rho_i \le (\hat{\rho}_i + t_{\alpha/2}sd(\hat{\rho}_N(i)))\}$ where $\alpha_8 = 1 - \alpha_7$ and $0 \le \alpha_7 \le 1$. Then $100(1 - \alpha)$ % bootstrap-*t* calibrated confidence interval for ρ_i is

$$\left(\hat{\rho}_{i}' - \hat{t}_{\hat{\beta}(\alpha_{7})/2} sd(\hat{\rho}_{N}(i))', \ \hat{\rho}_{i}' + \hat{t}_{\hat{\beta}(\alpha_{8})/2} sd(\hat{\rho}_{N}(i))'\right), \ i = 1, 2$$
(7)

where $\hat{t}_{\hat{\beta}_7(\alpha)/2}$ and $\hat{t}_{\hat{\beta}_8(\alpha)/2}$ equals the $\alpha/2$ percentile of the random sample $Z_{i1}^*, Z_{i2}^*, \cdots, Z_{iN}^*$, i = 1, 2.

2.6 Variance-stabilized Bootstrap-t (VST) Calibrated Confidence Intervals

Let $\hat{\rho}_i$, i = 1, 2 be a strongly consistent and asymptotically normal estimator with approximate variances $\hat{\sigma}_i^2/n$, i = 1, 2. Let $\hat{\sigma}_i = \phi(\hat{\rho}_i)$. To find a transformation $f(\hat{\rho}_i)$ such that $Var(f(\hat{\rho}_i)) \approx \text{constant}$, we use the first order Taylor series expansion and taking expectations on both sides, we get

$$Var[f(\hat{\rho}_i)] \approx Var(\hat{\rho}_i)(f'(\rho_i))^2 = (\phi(\rho_i))^2(f'(\rho_i))^2, \ i = 1, 2.$$

Now consider $f(\hat{\rho}_i) = \sqrt{n} \log(\phi(\hat{\rho}_i)), i = 1, 2$ is the variance-stabilizing transformation. Then we have,

$$V[f(\hat{\rho}_i)] \approx \left(\frac{\sqrt{n}}{\phi(\hat{\rho}_i)}\right)^2 \quad Var[\hat{\rho}_i] = \left(\frac{\sqrt{n}}{\hat{\sigma}_i}\right)^2 \quad Var[\hat{\rho}_i] = \frac{n}{\hat{\sigma}_i^2} \frac{\hat{\sigma}_i^2}{n} = 1, i = 1, 2.$$

Here we consider N bootstrap estimates $\hat{\rho}_{i1}^*, \hat{\rho}_{i2}^*, \dots, \hat{\rho}_{iN}^*, i = 1, 2$ computed from the bootstrap resample. We obtain

$$\theta_{ij}^* = (\sqrt{n}\log(\hat{\rho}_{ij}^*) - \sqrt{n}\log(\hat{\rho}_i)), i = 1, 2, j = 1, 2, \cdots, N.$$

Also Compute $\hat{\beta}(\alpha_9) = P\{\rho_i \le e^{\log(\hat{\rho}_i) - \frac{1}{\sqrt{n}}\hat{v}_i t_{1-\alpha/2}}\}$ and $\hat{\beta}(\alpha_{10}) = P\{\rho_i \le e^{\log(\hat{\rho}_i) - \frac{1}{\sqrt{n}}\hat{v}_i t_{\alpha/2}}\}$ where $\alpha_{10} = 1 - \alpha_9$ and $0 \le \alpha_9 \le 1$. A 100(1 - α)% VST calibrated confidence interval for $\rho_i, i = 1, 2$ is

$$\left(e^{\log(\hat{\rho}_i) - \frac{1}{\sqrt{n}}\hat{v}_i t_{\hat{\beta}(\alpha_0)}}, e^{\log(\hat{\rho}_i) - \frac{1}{\sqrt{n}}\hat{v}_i t_{\hat{\beta}(\alpha_{10})}}\right)$$
(8)

where $\hat{v}_i t_{\hat{\beta}_9(\alpha)}$ and $\hat{v}_i t_{\hat{\beta}_{10}(\alpha)}$ are $(\alpha/2)^{th}$ and $(1 - \alpha/2)^{th}$ percentile of the random sample $\theta_{i1}^*, \theta_{i2}^*, \cdots, \theta_{iN}^*, i = 1, 2$.

2.7 Bayesian Bootstrap (BB) Calibrated Confidence Intervals

Each BB replication generates a posterior probability for each X_{ij} , $i = 1, 2, j = 1, 2, \dots, n$. One BB replication is generated by drawing n - 1 uniform (0, 1) random numbers r_1, r_2, \dots, r_{n-1} , ordering them, and calculating the gaps $w_j = r_{(j)} - r_{(j-1)}$, $j = 1, 2, \dots, n$, where $r_{(0)} = 0$ and $r_{(n)} = 1$. Then $w_i = (w_{i1}, w_{i2}, \dots, w_{in})$, i = 1, 2 is the vector of probabilities attached to the inter-arrival data X_{ij} , $i = 1, 2, j = 1, 2, \dots, n$. Considering all BB replications gives the BB distribution of the distribution of X_i . Hence for μ_{x_i} , i = 1, 2 (the mean of X_i) in each BB replication we calculate $\overline{X}_i^{**} = \sum_{j=1}^n w_{ij}x_{ij}$, i = 1, 2. The distribution of the values of \overline{X}_i^{**} over all BB replications is the BB distribution of μ_{X_i} . Also, generating a vector of probabilities $v_i = (v_{i1}, v_{i2}, \dots, v_{in})$, i = 1, 2 attached to the service time data values Y_{ij} , i = 1, 2. $j = 1, 2 \dots n$ in a BB replication, and we calculate $\overline{Y}_i^{**} = \sum_{j=1}^n v_{ij}y_{ij}$ for μ_{Y_j} (the mean of Y_i). An estimate of intensity ρ_i can be calculated from BB replications as $\hat{\rho}_i^{**} = \frac{\overline{Y}_i^{**}}{\overline{X}_i^{**}}$, i = 1, 2, where $\hat{\rho}_i^{**}$, i = 1, 2 is called a Bayesian bootstrap estimate of ρ_i , i = 1, 2. The above BB process can be repeated N times. The N BB estimates $\hat{\rho}_{i1}^{*}$, $\hat{\rho}_{i2}^{*}$, \dots , $\hat{\rho}_{iN}^{*}$, i = 1, 2 can be computed from the *BB* replications. Averaging the N BB estimates, we obtain that $\hat{\rho}'_{BB}(i) = \frac{1}{N} \sum_{j=1}^{N} \hat{\rho}_{ij}^{**}$, i = 1, 2 is the BB estimate of ρ_i , i = 1, 2. In the BB estimate of $\hat{\rho}_i$ can be estimate of ρ_i , i = 1, 2.

$$sd(\hat{\rho}'_{BB}(i)) = \left\{\frac{1}{N-1}\sum_{j=1}^{N}(\hat{\rho}^{**}_{ij} - \hat{\rho}'_{BB}(i))^2\right\}^{1/2}, \ i = 1, 2.$$

Also find $\hat{\beta}(\alpha_{11}) = P\{\rho_i \leq (\hat{\rho}_i - z_{\alpha/2}sd(\hat{\rho}'_{BB}(i)))\}$ and and $\hat{\beta}(\alpha_{12}) = P\{\rho_i \leq (\hat{\rho}_i - z_{\alpha/2}sd(\hat{\rho}'_{BB}(i)))\}$, where $\alpha_{12} = 1 - \alpha_{11}, 0 \leq \alpha_{11} \leq 1$. Applying the asymptotical normality of $\hat{\rho}_i, i = 1, 2, 100(1 - \alpha)\%BB$ calibrated confidence interval for $\rho_i, i = 1, 2$ is

$$\left(\hat{\rho}'_{i} - z_{\hat{\beta}(\alpha_{11})/2} sd(\hat{\rho}'_{BB}(i))', \hat{\rho}'_{i} + z_{\hat{\beta}(\alpha_{12})/2} sd(\hat{\rho}'_{BB}(i))'\right), \quad i = 1, 2.$$
(9)

2.8 Percentile Bootstrap (PB) Calibrated Confidence Intervals

Now call $\hat{\rho}_i^*, \hat{\rho}_{i2}^*, \dots, \hat{\rho}_{iN}^*, i = 1, 2$ the bootstrap distribution of $\hat{\rho}_i, i = 1, 2$. Let $\hat{\rho}_i^*(1), \hat{\rho}_i^*(2), \dots, \hat{\rho}_i^*(N), i = 1, 2$ be the order statistics of $\hat{\rho}_{i1}^*, \hat{\rho}_{i2}^*, \dots, \hat{\rho}_{iN}^*, i = 1, 2$. Compute $\hat{\beta}(\alpha_{13}) = P\{\rho_i \leq \hat{\rho}_i^*([N(\frac{\alpha}{2})]\}$ and $\hat{\beta}(\alpha_{14}) = P\{\rho_i \leq \hat{\rho}_i^*([N(1-\frac{\alpha}{2})]\}$. Then utilizing the $100(\alpha/2)^{th}$ and $100(1-\alpha/2)^{th}$ percentage points of the bootstrap distribution, Then $100(1-\alpha)$ % PB calibrated confidence interval for $\rho_i, i = 1, 2$ is given by,

$$\left(\hat{\rho}_{i}^{*}\left(\left[N\left(\frac{\hat{\beta}(\alpha_{13})}{2}\right)\right]\right), \ \hat{\rho}_{i}^{*}\left(\left[N\left(\frac{\hat{\beta}(\alpha_{14})}{2}\right)\right]\right)\right), \ i=1,2$$

$$(10)$$

where [x] denotes the greatest integer less than or equal to x.

2.9 Bias-Corrected and Accelerated Bootstrap(BCaB) Calibrated Confidence Intervals

The bootstrap distribution $\hat{\rho}_{i1}^*, \hat{\rho}_{i2}^*, \dots, \hat{\rho}_{iN}^*, i = 1, 2$ may be biased, consequently the PB calibrated confidence interval of intensity method is designed to correct this potential bias of the bootstrap designed. Set $p_i = \frac{1}{N} \sum_{j=1}^{N} I(\hat{\rho}_{ij}^* < \hat{\rho}_i), i = 1, 2$ where $I(\cdot)$ is the indicator function. Define $\hat{z}_i = \phi^{-1}(p_i), i = 1, 2$ where ϕ^{-1} denotes the inverse function of the standard normal distribution ϕ . Except for correcting the potential bias of the bootstrap distribution, we can accelerate convergence of bootstrap distribution. Let $(\tilde{X}_i(k), \tilde{Y}_i(k), i = 1, 2, k = 1, 2, \dots, n)$ denote the original samples with the k^{th} observation

 $(X_{ik}, Y_{ik}, i = 1, 2)$ deleted, also $\hat{\rho}_{ik}, i = 1, 2$ be the estimator of $\rho_i, i = 1, 2$ calculated by using $(\tilde{X}_i(k), \tilde{Y}_i(k), i = 1, 2)$. Define $\tilde{\rho}_i = \frac{1}{2} \sum_{i=1}^{n} \hat{\rho}_{ik}, i = 1, 2$ and

Define
$$\tilde{\rho}_i = \frac{1}{n} \sum_{k=1}^{\infty} \hat{\rho}_{ik}, i = 1, 2$$
 and

$$\hat{a}_{i} = \frac{\sum_{k=1}^{n} (\tilde{\rho}_{i} - \hat{\rho}_{ik})^{3}}{\left\{ 6 \left(\sum_{k=1}^{n} (\tilde{\rho}_{i} - \hat{\rho}_{ik})^{2} \right)^{\binom{3}{2}} \right\}}, i = 1, 2$$

 \hat{z}_i and $\hat{a}_i, i = 1, 2$ are named bias-correction and acceleration respectively.

Also compute $\hat{\beta}(\alpha_{15}) = P\{\rho_i \leq \hat{\rho}_i^*([N\alpha_{i1}])\}$ and $\hat{\beta}(\alpha_{16}) = P\{\rho_i \leq \hat{\rho}_i^*([N\alpha_{i2}])\}$, where

$$\alpha_{i1} = \phi \left\{ \hat{z}_i + \frac{(\hat{z}_i - z_{\alpha/2})}{1 - \hat{a}_i(\hat{z}_i - z_{\alpha/2})} \right\} \quad \alpha_{i2} = \phi \left\{ \hat{z}_i + \frac{(\hat{z}_i + z_{\alpha/2})}{1 - \hat{a}_i(\hat{z}_i + z_{\alpha/2})} \right\}, \quad i = 1, 2.$$

Thus 100(1 – α)% BCaB calibrated confidence interval of intensities ρ_i , i = 1, 2 is given by

$$(\hat{\rho}_{i}^{*}([N\alpha_{i1}']), \hat{\rho}_{i}^{*}([N\alpha_{i2}'])). \ i = 1, 2.$$

$$(11)$$

where,

$$\alpha_{i1}' = \phi \left\{ \hat{z}_i' + \frac{(\hat{z}_i' - z_{\hat{\beta}_{15}(\alpha)/2})}{1 - \hat{a}_i(\hat{z}_i' - z_{\hat{\beta}_{15}(\alpha)/2})} \right\} \quad \alpha_{i2}' = \phi \left\{ \hat{z}_i' + \frac{(\hat{z}_i' + z_{\hat{\beta}_{16}(\alpha)/2})}{1 - \hat{a}_i(\hat{z}_i' + z_{\hat{\beta}_{16}(\alpha)/2})} \right\}, \ i = 1, 2.$$

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3 Simulation Study

To evaluate performances of calibrated confidence intervals numerical simulation study was undertaken. It is observed that most statisticians assess performances of interval estimations in terms of coverage percentages or average lengths of confidence intervals. However, through simulation study in the research work, we find that larger coverage percentages of confidence interval may often be due to wider standard deviation of interval estimation methods. Moreover, narrower confidence intervals may often lead to smaller coverage percentages. Hence, both coverage percentage and average length are not efficient for appraising interval estimation methods. In order to overcome above two shortcomings, we consider a measure, named relative coverage, to evaluate performances of interval estimation methods.

Relative coverage is defined as the ratio of coverage percentage to average length of confidence interval. Larger relative coverage implies the better performances of the corresponding confidence intervals. Here we set a continuous distribution with mean $1/\lambda$ on inter-arrival time of X_1 and X_2 and a continuous distribution with mean $1/\mu_1$ on the service time Y_1 at node-1 and that of $1/\mu_2$ on Y_2 at node-2. Different levels of intensity parameters considered in the simulation study are shown in Table-1.

Table-1 : Different levels of intensity parameters considered in the simulation study

$ ho_1 < ho_2$	$ ho_1 > ho_2$
(1) Low=0.1 and Moderate=0.5	(1) Moderate=0.5 and Low=0.1
(2) Low=0.1 and High=0.9	(2) High=0.9 and Low=0.1
(3) Moderate=0.5 and High=0.9	(3) High=0.9 and Moderate=0.5

For each level of ρ_i , i = 1, 2 random samples of inter-arrival times and service times $(X_{ij}, Y_{ij}, i = 1, 2, j = 1, 2, \dots, n)$ are drawn from $(X_i, Y_i, i = 1, 2)$. Next N = 1000 bootstrap resamples each of size n = 10 and 29 are drawn from the original samples, as well as N=1000 BB replications are simulated for the original samples. According to equations (4) to (11) we obtain calibrated CAN, Exact-*t*, Boot-*t*, VST, SB, BB, PB and BCaB confidence intervals of intensities ρ_1 and ρ_2 with confidence level 90%. The above simulation process is replicated N = 1000 times and we compute coverage percentages, average lengths and relative coverage of the above mentioned confidence intervals. We utilize a PC Dual Core and apply Matlab 7.0.1 to accomplish all simulations.

Queueing	Models	C.V. of	C.V. of	C.V. of	C.V. of
Networks	simulated	inter-arrival	inter- arrival	service time	service time
type		time for node-1	time for node-2	for node-1	for node-2
M/G/1 to	$M/E_4/1$ to $E_4/M/1$	1	1/2	1/2	1
G/M/1	$M/H_4^{Pe}/1$ to $H_4^{Pe}/M/1$	1	>1	>1	1
G/G/1 to	$E_4/H_4^{Pe}/1$ to $H_4^{Pe}/E_4/1$	1/2	> 1	> 1	1/2
G/G/1	$E_4/H_4^{Po}/1$ to $H_4^{Po}/E_4/1$	1/2	< 1	< 1	1/2

Table-2 : Different queueing network models simulated for study

Here C.V. represents coefficient of variation corresponding to the inter-arrival/service time distribution, M represents an exponential distribution, E_4 a 4-stage Erlang distribution, H_4^{Pe} a 4-stage hyper-exponential distribution and H_4^{P0} a 4stage hypo-exponential distribution. The coverage percentages, average lengths and relative coverage's of intensities ρ_1 and ρ_2 based on simulation study for queuing network models (presented in Table 2) with short run for different calibrated interval estimation approaches are shown in Tables 3 to 6.



	Intensity	Estimation		. 10		. 20	Cov	/erage	Ave	erage	Re	lative
	Parameters	Approcnes	B(a)	i = 10 $\beta(1 - \alpha_i)$	B(a)	i = 29 $\beta(1 - \alpha_i)$	Perce	entages	Ler n = 10	igtns	n = 10	verage
ŀ		CAN1	$p(u_i) = 0.040$	$p(1-\alpha_i)$ 0.913	$p(u_i) = 0.030$	$p(1-u_i)$ 0.919	0.842	0.882	0.113	0.069	7 428	12 792
		CAN2	0.017	0.847	0.030	0.911	0.782	0.840	0.546	0.329	1.432	2.551
		tCAN1	0.018	0.950	0.022	0.936	0.941	0.921	0.194	0.082	4.858	11.239
		tCAN2	0.009	0.867	0.025	0.916	0.807	0.856	0.700	0.352	1.152	2.433
		Boott1	0.016	0.891	0.016	0.900	0.832	0.869	0.113	0.067	7.338	12.965
		Boott2	0.014	0.816	0.022	0.893	0.719	0.827	0.450	0.311	1.599	2.661
		VST1	0.083	0.934	0.052	0.937	0.797	0.864	0.101	0.066	7.902	13.052
	$\rho_1 = 0.1$	VS12	0.077	0.915	0.062	0.946	0.780	0.847	0.541	0.329	5.744	2.578
	$a_{02} = 0.5$	SB2	0.025	0.934	0.023	0.930	0.907	0.911	0.138	0.330	1 4 6 6	2 558
	$p_2 = 0.5$	BB1	0.039	0.915	0.020	0.918	0.849	0.882	0.118	0.069	7.221	12.762
		BB2	0.026	0.834	0.031	0.906	0.746	0.830	0.473	0.317	1.579	2.618
		PB1	0.129	0.963	0.076	0.955	0.779	0.842	0.138	0.070	5.658	12.011
		PB2	0.045	0.870	0.042	0.926	0.764	0.840	0.445	0.313	1.718	2.685
		BCaB1	0.118	0.956	0.076	0.953	0.773	0.841	0.126	0.068	6.148	12.310
- L		BCaB2	0.048	0.870	0.041	0.930	0.757	0.842	0.433	0.315	1.750	2.669
		CAN1	0.043	0.918	0.044	0.922	0.855	0.857	0.114	0.065	7.473	13.087
		CAN2 +CAN1	0.017	0.867	0.026	0.897	0.759	0.837	0.979	0.580	0.770	1.429
		tCAN2	0.018	0.948	0.029	0.901	0.930	0.910	1 205	0.616	0.648	1 370
		Boott1	0.019	0.895	0.027	0.898	0.843	0.856	0.115	0.064	7.337	13.454
		Boott2	0.017	0.845	0.019	0.869	0.739	0.828	0.812	0.539	0.910	1.537
	$\rho_1 = 01.$	VST1	0.081	0.932	0.069	0.937	0.794	0.846	0.102	0.062	7.783	13.578
	&	VST2	0.074	0.916	0.069	0.938	0.789	0.849	0.959	0.564	0.823	1.504
	$\rho_2 = 0.9$	SB1	0.028	0.935	0.032	0.933	0.912	0.898	0.155	0.074	5.875	12.065
		SB2	0.023	0.863	0.027	0.891	0.750	0.829	0.924	0.575	0.811	1.442
		BBI	0.041	0.924	0.041	0.923	0.868	0.861	0.120	0.066	7.210	12.999
		PB1	0.029	0.854	0.027	0.955	0.722	0.820	0.140	0.068	5 479	11 978
		PB2	0.046	0.881	0.045	0.908	0.740	0.829	0.793	0.530	0.933	1.564
		BCaB1	0.104	0.961	0.087	0.951	0.759	0.824	0.132	0.066	5.744	12.424
		BCaB2	0.047	0.878	0.049	0.907	0.732	0.825	0.771	0.518	0.950	1.593
- 1		CAN1	0.035	0.920	0.038	0.928	0.872	0.867	0.595	0.342	1.467	2.535
		CAN2	0.019	0.836	0.021	0.894	0.743	0.853	0.103	0.068	7.230	12.556
		tCAN1	0.013	0.953	0.026	0.938	0.955	0.911	1.034	0.406	0.924	2.247
		tCAN2	0.011	0.856	0.018	0.899	0.773	0.863	0.130	0.072	5.963	11.931
		Boott1 Roott2	0.014	0.894	0.023	0.908	0.855	0.857	0.585	0.554	9.202	2.503
	$a_1 = 0.5$	VST1	0.010	0.805	0.015	0.035	0.095	0.834	0.085	0.325	1 549	2 565
	&	VST2	0.070	0.915	0.043	0.930	0.798	0.881	0.108	0.071	7.397	12,484
	$\rho_2 = 0.1$	SB1	0.020	0.941	0.032	0.934	0.932	0.896	0.825	0.377	1.130	2.379
	. 2	SB2	0.021	0.835	0.021	0.893	0.736	0.847	0.100	0.068	7.348	12.543
		BB1	0.038	0.922	0.038	0.930	0.873	0.870	0.608	0.343	1.437	2.534
		BB2	0.029	0.823	0.023	0.888	0.720	0.839	0.089	0.065	8.123	12.919
		PB1	0.115	0.964	0.087	0.951	0.780	0.812	0.708	0.341	1.102	2.384
		PB2 PCoP1	0.045	0.865	0.032	0.910	0.745	0.861	0.085	0.065	8.///	2 422
		BCaB2	0.046	0.864	0.032	0.909	0.739	0.850	0.083	0.062	8.877	13.763
- h		CAN1	0.050	0.924	0.056	0.937	0.843	0.870	0.562	0.328	1.501	2.650
		CAN2	0.021	0.841	0.024	0.893	0.760	0.856	0.946	0.594	0.803	1.441
		tCAN1	0.018	0.948	0.040	0.950	0.936	0.926	0.964	0.393	0.971	2.359
		tCAN2	0.009	0.859	0.020	0.895	0.785	0.868	1.243	0.632	0.632	1.373
		Boott1	0.018	0.879	0.026	0.913	0.820	0.865	0.542	0.333	1.514	2.595
		Boott2	0.015	0.809	0.015	0.879	0.731	0.845	0.792	0.567	0.923	1.490
	$a_1 = 05$	VST2	0.094	0.932	0.008	0.947	0.794	0.853	0.487	0.520	0.846	1 4 9 0
	p ₁ = 05 &	SB1	0.031	0.940	0.045	0.945	0.914	0.905	0.772	0.367	1.184	2.463
	$\rho_2 = 09$	SB2	0.022	0.837	0.023	0.891	0.749	0.855	0.924	0.594	0.810	1.440
	. 2	BB1	0.050	0.919	0.057	0.934	0.852	0.868	0.574	0.324	1.484	2.679
		BB2	0.034	0.826	0.026	0.891	0.705	0.848	0.804	0.572	0.877	1.483
		PB1	0.129	0.967	0.095	0.960	0.759	0.834	0.706	0.351	1.075	2.378
		PB2	0.052	0.861	0.045	0.908	0.746	0.859	0.769	0.536	0.970	1.602
		BCaB1 BCaB2	0.119	0.958	0.090	0.959	0.746	0.850	0.651	0.545	0.980	2.440
- F		CANI	0.032	0.906	0.047	0.934	0.841	0.846	1.046	0.597	0.804	1.005
		CAN2	0.022	0.864	0.019	0.898	0.768	0.837	0.102	0.068	7.495	12.351
		tCAN1	0.008	0.944	0.035	0.945	0.947	0.912	1.913	0.715	0.495	1.276
		tCAN2	0.011	0.878	0.016	0.905	0.784	0.852	0.130	0.073	6.016	11.733
		Boott1	0.007	0.878	0.028	0.919	0.835	0.851	1.029	0.612	0.812	1.391
		Boott2	0.019	0.842	0.012	0.882	0.747	0.852	0.087	0.064	8.568	13.347
	$\rho_1 = 09$	VSTI	0.071	0.925	0.073	0.946	0.795	0.824	0.936	0.571	0.849	1.444
	$\alpha_{2} = 01$	V512 SB1	0.079	0.923	0.038	0.938	0.797	0.862	1.454	0.005	0.630	1 3 1 3
	$p_2 = 01$	SB2	0.025	0.861	0.023	0.895	0.761	0.830	0.099	0.066	7.691	12.666
		BB1	0.031	0.910	0.052	0.935	0.849	0.847	1.095	0.599	0.775	1.413
		BB2	0.031	0.849	0.025	0.893	0.742	0.823	0.089	0.063	8.349	13.002
		PB1	0.115	0.953	0.096	0.967	0.778	0.816	1.163	0.662	0.669	1.233
		PB2	0.043	0.882	0.042	0.917	0.760	0.848	0.087	0.061	8.729	13.991
		BCaB1	0.108	0.949	0.088	0.954	0.777	0.809	1.099	0.610	0.707	1.326
- F		BCaB2 CAN1	0.044	0.878	0.045	0.912	0.750	0.832	0.084	0.059	8.948 0.922	14.141
		CAN2	0.047	0.911	0.030	0.930	0.765	0.855	0.536	0.342	1.426	2 526
1		tCAN1	0.023	0.942	0.016	0.949	0.928	0.932	1.699	0.791	0.546	1.179
		tCAN2	0.014	0.878	0.022	0.923	0.800	0.881	0.650	0.369	1.232	2.391
1		Boott1	0.021	0.886	0.015	0.912	0.820	0.892	1.014	0.624	0.808	1.430
1		Boott2	0.018	0.830	0.022	0.905	0.755	0.861	0.441	0.323	1.713	2.666
1	- 00	VST1	0.085	0.927	0.050	0.949	0.793	0.883	0.915	0.614	0.867	1.438
1	$\rho_1 = 0.9$	V512 SB1	0.083	0.923	0.069	0.946	0.805	0.015	0.523	0.525	0.651	2.050
1	$a_{02} = 0.5$	SB2	0.033	0.858	0.024	0.945	0.761	0.915	0.519	0.337	1.467	2.549
1	r2 0.0	BB1	0.046	0.915	0.028	0.935	0.849	0.892	1.062	0.647	0.799	1.379
1		BB2	0.027	0.848	0.031	0.913	0.730	0.844	0.469	0.326	1.556	2.588
1		PB1	0.131	0.953	0.082	0.966	0.742	0.868	1.178	0.664	0.630	1.308
1		PB2	0.044	0.880	0.049	0.931	0.769	0.865	0.446	0.316	1.725	2.734
1		BCaB1	0.116	0.954	0.077	0.958	0.748	0.864	1.143	0.626	0.654	1.381
1		BCaB2	0.047	0.879	0.052	0.932	0.753	0.859	0.432	0.314	1.742	2.738

Intensity Parameters	Estimation	n = 10	n = 29	Coverage Percentages	Average	Relative
		$\beta(\alpha_i) = \beta(1 - \alpha_i)$	$\beta(\alpha_i) = \beta(1 - \alpha_i)$	n = 10 $n = 29$	n = 10 $n = 29$	n = 10 $n = 29$
	CAN1	0.034 0.881	0.029 0.907	0.844 0.885	0.118 0.071	7.153 12.388
	CAN2	0.019 0.852	0.037 0.902	0.773 0.852	0.554 0.331	1.395 2.578
	tCAN2	0.014 0.922	0.023 0.923	0.926 0.929	0.724 0.354	1.110 2.456
	Boott1	0.013 0.864	0.018 0.880	0.787 0.845	0.114 0.067	6.924 12.690
	Boott2	0.014 0.830	0.030 0.878	0.735 0.825	0.469 0.306	1.568 2.695
- 01	VST1	0.083 0.899	0.052 0.923	0.761 0.856	0.104 0.068	7.341 12.531
$p_1 = 0.1$	SB1	0.079 0.917	0.029 0.917	0.891 0.914	0.157 0.077	5.668 11.881
$\rho_2 = 0.5$	SB2	0.018 0.858	0.037 0.903	0.772 0.854	0.566 0.331	1.365 2.579
12	BB1	0.032 0.885	0.032 0.906	0.849 0.881	0.123 0.070	6.891 12.554
	BB2 PB1	0.030 0.845 0.114 0.933	0.038 0.897	0.746 0.836 0.754 0.849	0.484 0.319 0.123 0.071	1.541 2.618 6.135 12.031
	PB2	0.049 0.883	0.051 0.918	0.763 0.846	0.465 0.315	1.639 2.685
	BCaB1	0.108 0.925	0.076 0.944	0.742 0.848	0.116 0.069	6.386 12.217
	BCaB2	0.049 0.874	0.055 0.924	0.743 0.845	0.449 0.316	1.657 2.674
	CAN2	0.044 0.903	0.027 0.928	0.761 0.833	0.970 0.590	0.785 1.412
	tCAN1	0.022 0.940	0.017 0.940	0.930 0.925	0.191 0.089	4.864 10.415
	tCAN2	0.015 0.876	0.028 0.899	0.799 0.845	1.222 0.630	0.654 1.342
	Boott1 Boott2	0.019 0.874	0.011 0.914	0.814 0.883	0.112 0.074	7.296 11.885
	VST1	0.084 0.922	0.059 0.941	0.800 0.857	0.105 0.068	7.651 12.606
$\rho_1 = 0.1$	VST2	0.085 0.923	0.080 0.928	0.751 0.818	0.959 0.556	0.783 1.472
&	SB1	0.028 0.926	0.021 0.936	0.903 0.914	0.158 0.082	5.708 11.094
$\rho_2 = 0.9$	SB2 BB1	0.025 0.851	0.033 0.896	0.765 0.834 0.854 0.890	0.963 0.591	0.795 1.411 6.934 11.999
	BB2	0.036 0.834	0.039 0.892	0.726 0.817	0.832 0.560	0.873 1.460
	PB1	0.103 0.952	0.079 0.960	0.793 0.847	0.135 0.074	5.854 11.376
	PB2 PCaP1	0.056 0.885	0.064 0.910	0.739 0.813	0.829 0.532	0.891 1.529
	BCaB2	0.052 0.949	0.062 0.910	0.735 0.804	0.130 0.072	0.916 1.514
	CAN1	0.038 0.899	0.030 0.910	0.829 0.880	0.582 0.351	1.425 2.505
	CAN2	0.027 0.891	0.029 0.903	0.782 0.849	0.112 0.068	6.997 12.562
	tCAN1 tCAN2	0.008 0.931	0.021 0.924	0.913 0.918	0.150 0.074	5.509 11.839
	Boott1	0.009 0.872	0.012 0.895	0.816 0.888	0.574 0.350	1.420 2.536
	Boott2	0.014 0.861	0.020 0.887	0.774 0.858	0.099 0.064	7.802 13.379
$a_1 = 0.5$	VST1	0.084 0.918	0.064 0.930	0.785 0.863	0.516 0.326	1.521 2.648
$ \rho_1 = 0.3 $	SB1	0.022 0.918	0.023 0.921	0.889 0.911	0.797 0.392	1.116 2.321
	SB2	0.028 0.890	0.027 0.903	0.784 0.852	0.112 0.068	7.026 12.456
	BB1	0.039 0.901	0.030 0.913	0.836 0.884	0.601 0.353	1.391 2.503
	PB1	0.127 0.942	0.032 0.897	0.748 0.834 0.779 0.859	0.620 0.352	1.256 2.437
	PB2	0.071 0.918	0.044 0.921	0.789 0.870	0.098 0.064	8.037 13.650
	BCaB1	0.119 0.942	0.072 0.946	0.779 0.860	0.603 0.346	1.292 2.487
	CAN1	0.036 0.895	0.035 0.922	0.828 0.874	0.591 0.354	1.401 2.467
	CAN2	0.021 0.864	0.023 0.904	0.788 0.850	1.010 0.635	0.780 1.338
	tCAN1	0.012 0.934	0.024 0.936	0.908 0.920	1.029 0.422	0.883 2.180
	tCAN2 Roott1	0.014 0.883	0.021 0.908	0.832 0.863	1.260 0.673	0.660 1.282
	Boott2	0.012 0.834	0.021 0.880	0.753 0.826	0.849 0.571	0.887 1.446
	VST1	0.075 0.921	0.059 0.942	0.766 0.857	0.542 0.342	1.412 2.509
$\rho_1 = 0.5$	VST2	0.079 0.923	0.059 0.937	0.800 0.847	0.994 0.615	0.805 1.376
$a_{2} = 0.9$	SB1 SB2	0.020 0.921 0.024 0.868	0.028 0.932	0.877 0.907	0.817 0.395	0.792 1.337
$p_2 = 0.5$	BB1	0.035 0.897	0.037 0.922	0.831 0.871	0.611 0.351	1.360 2.480
	BB2	0.034 0.850	0.023 0.902	0.754 0.843	0.869 0.620	0.868 1.359
	PB1 PB2	0.134 0.949	0.080 0.956	0.726 0.840	0.648 0.365	1.120 2.304
	BCaB1	0.119 0.945	0.047 0.918	0.721 0.837	0.620 0.354	1.163 2.367
	BCaB2	0.057 0.886	0.048 0.918	0.778 0.830	0.823 0.565	0.946 1.468
	CAN1 CAN2	0.039 0.896	0.037 0.908	0.837 0.863	1.056 0.607	0.793 1.423
	tCAN1	0.011 0.800	0.022 0.917	0.932 0.910	1.835 0.735	0.508 1.238
	tCAN2	0.006 0.881	0.016 0.926	0.812 0.894	0.158 0.080	5.149 11.109
	Boott1	0.011 0.872	0.020 0.889	0.820 0.853	1.042 0.591	0.787 1.443
	VST1	0.008 0.827 0.073 0.910	0.015 0.901 0.055 0.934	0.750 0.888	0.097 0.069	0.811 1.420
$\rho_1 = 0.9$	VST2	0.079 0.926	0.066 0.951	0.792 0.891	0.111 0.069	7.161 12.986
&	SB1	0.021 0.913	0.029 0.924	0.903 0.898	1.464 0.684	0.617 1.312
$\rho_2 = 0.1$	SB2	0.010 0.859	0.023 0.920	0.773 0.880	0.122 0.073	6.340 12.042
	BB2	0.018 0.845	0.025 0.914	0.744 0.869	0.104 0.070	7.130 12.437
	PB1	0.115 0.939	0.070 0.956	0.773 0.861	1.134 0.656	0.681 1.312
	PB2	0.048 0.888	0.046 0.933	0.771 0.874	0.095 0.067	8.131 13.120
	BCaB1 BCaB2	0.107 0.937	0.067 0.951	0.780 0.854	1.102 0.636	0.708 1.342 8158 13.023
	CAN1	0.026 0.911	0.037 0.921	0.843 0.875	1.139 0.633	0.740 1.383
	CAN2	0.024 0.873	0.021 0.897	0.798 0.846	0.572 0.353	1.396 2.397
	tCAN1 tCAN2	0.010 0.937	0.024 0.934	0.922 0.921	1.907 0.757 0.722 0.382	0.483 1.217
	Boott1	0.009 0.885	0.017 0.895	0.830 0.843	1.083 0.618	0.766 1.364
	Boott2	0.016 0.846	0.016 0.884	0.743 0.843	0.491 0.328	1.514 2.568
	VST1	0.074 0.924	0.063 0.935	0.782 0.840	0.979 0.599	0.799 1.402
$p_1 = 0.9$ &	VS12 SB1	0.078 0.936 0.016 0.924	0.050 0.942 0.028 0.927	0.780 0.870	0.581 0.359 1.513 0.703	1.342 2.425 0.593 1.281
$\rho_2 = 0.5$	SB1 SB2	0.026 0.877	0.024 0.896	0.800 0.842	0.571 0.347	1.401 2.428
1	BB1	0.025 0.908	0.035 0.921	0.848 0.880	1.174 0.637	0.722 1.380
	BB2 PB1	0.029 0.864	0.026 0.893	0.773 0.837	0.516 0.334	1.49/ 2.510
	PB2	0.052 0.891	0.037 0.917	0.764 0.851	0.486 0.325	1.573 2.619
	BCaB1	0.111 0.945	0.083 0.949	0.771 0.827	1.117 0.624	0.690 1.326
	BCaB2	0.048 0.894	0.035 0.914	0.770 0.844	0.488 0.321	1.579 2.626

Table-4 : Simulation results: 90% calibrated confidence intervals of $M/H_4^{Pe}/1$ to $H_4^{Pe}/M/1$.



			_									
I	ntensity	Estimation					Co	verage	Ave	rage	Rel	ative
F	Parameters	Approches		n = 10		n = 29	Perc	entages	Len	oths	Cov	erage
-		· · · · · · · · · · · · · · · · · · ·	P(a)	$\hat{R}(1, \alpha)$	R(ar)	$\frac{\theta}{1}$ $\frac{\theta}{1}$. 10				. 10	
			$p(\alpha_i)$	$p(1-\alpha_i)$	$p(\alpha_i)$	$p(1-\alpha_i)$	n = 10	n = 29	n = 10	n = 29	n = 10	n = 29
		CAN1	0.029	0.888	0.030	0.910	0.830	0.857	0.076	0.047	10.891	18.421
		CAN2	0.028	0.902	0.057	0.935	0.837	0.874	0.389	0.223	2.151	3.925
		ACA NI	0.020	0.012	0.022	0.012	0.975	0.966	0.004	0.050	0.205	17 210
		ICAINI	0.020	0.912	0.025	0.912	0.875	0.800	0.094	0.050	9.293	17.510
		tCAN2	0.018	0.917	0.045	0.942	0.884	0.895	0.490	0.244	1.805	3.672
		Boott1	0.021	0.866	0.023	0.894	0.793	0.842	0.068	0.044	11.664	19.064
		Boott2	0.019	0.879	0.040	0.922	0.796	0.874	0.350	0.222	2 272	3 9 4 3
		DOULZ	0.019	0.879	0.040	0.922	0.790	0.074	0.350	0.222	2.272	3.943
		VST1	0.069	0.923	0.051	0.928	0.811	0.851	0.071	0.045	11.424	18.881
P	$p_1 = 0.1$	VST2	0.064	0.920	0.077	0.949	0.790	0.866	0.351	0.215	2.250	4.029
8	¢.	SB1	0.037	0.887	0.030	0.908	0.818	0.851	0.073	0.046	11.210	18.426
	~ 0.5	SD1	0.030	0.005	0.056	0.026	0.010	0.051	0.205	0.010	2 1 2 1	2 002
P	$b_2 = 0.5$	SB2	0.029	0.905	0.056	0.936	0.839	0.876	0.395	0.224	2.121	3.902
		BB1	0.041	0.873	0.034	0.906	0.778	0.836	0.066	0.044	11.804	18.897
		BB2	0.040	0.893	0.056	0.931	0.795	0.869	0.342	0.216	2.322	4.031
		PB1	0.068	0.920	0.054	0.921	0.809	0.835	0.068	0.042	11.851	19 670
		DDO	0.000	0.020	0.027	0.040	0.000	0.000	0.000	0.012	2,262	2.004
		PB2	0.065	0.928	0.077	0.948	0.802	0.860	0.354	0.221	2.205	3.894
		BCaB1	0.066	0.919	0.051	0.920	0.815	0.832	0.068	0.043	11.979	19.533
		BCaB2	0.070	0.925	0.076	0.947	0.786	0.853	0.347	0.219	2.267	3.888
		CANI	0.022	0.002	0.022	0.017	0.025	0.070	0.07/	0.046	11.002	10.017
		CANI	0.033	0.892	0.033	0.917	0.835	0.870	0.076	0.046	11.002	19.017
		CAN2	0.054	0.908	0.042	0.925	0.830	0.868	0.648	0.410	1.281	2.119
		tCAN1	0.024	0.909	0.027	0.921	0.876	0.891	0.092	0.049	9.565	18.166
		+CAN2	0.027	0.026	0.027	0.022	0.001	0.990	0.808	0.441	1.115	2.017
	$\begin{array}{c} \text{Intensity} \\ \text{Parameters} \\ \\ \hline \\ \rho_1 = 0.1 \\ \& \\ \rho_2 = 0.5 \\ \\ \hline \\ \rho_2 = 0.5 \\ \\ \hline \\ \rho_1 = 0.1 \\ \& \\ \rho_2 = 0.9 \\ \\ \hline \\ \rho_1 = 0.5 \\ \& \\ \rho_2 = 0.1 \\ \\ \hline \\ \rho_1 = 0.9 \\ \& \\ \rho_2 = 0.1 \\ \\ \hline \\ \rho_1 = 0.9 \\ \& \\ \rho_2 = 0.5 \\ \\ \hline \\ \hline \\ \rho_1 = 0.9 \\ \& \\ \rho_2 = 0.5 \\ \\ \hline \end{array}$	D	0.037	0.920	0.037	0.000	0.701	0.007	0.000	0.441	1.115	2.017
		Boott1	0.028	0.856	0.025	0.902	0.768	0.864	0.065	0.044	11.780	19.715
		Boott2	0.041	0.885	0.032	0.905	0.803	0.842	0.601	0.392	1.336	2.150
		VST1	0.074	0.910	0.058	0.932	0.788	0.857	0.069	0.044	11.428	19.683
	0.1	VET2	0.007	0.021	0.056	0.045	0.700	0.057	0.596	0.205	1 247	2 1 5 5
P	$\rho_1 = 0.1$ &	V312	0.097	0.951	0.000	0.945	0.790	0.852	0.580	0.393	1.547	2.133
δ		SB1	0.036	0.893	0.036	0.912	0.834	0.864	0.075	0.045	11.177	19.346
6	$p_2 = 0.9$	SB2	0.057	0.910	0.039	0.919	0.835	0.869	0.655	0.410	1.275	2.120
r	2	DD1	0.042	0.979	0.027	0.010	0.799	0.862	0.067	0.043	11.917	10.045
		DDI	0.042	0.878	0.037	0.910	0.788	0.802	0.007	0.045	11.017	19.945
		BB2	0.070	0.899	0.045	0.917	0.777	0.844	0.571	0.388	1.361	2.176
		PB1	0.071	0.912	0.059	0.930	0.792	0.852	0.067	0.042	11.860	20.091
		DD 2	0.100	0.027	0.070	0.050	0.807	0.845	0.621	0.405	1.270	2.084
		PG PI	0.100	0.937	0.070	0.930	0.807	0.040	0.051	0.405	1.279	2.084
		BCaB1	0.069	0.910	0.056	0.930	0.799	0.851	0.066	0.043	12.019	19.968
		BCaB2	0.097	0.934	0.070	0.951	0.801	0.846	0.622	0.406	1.289	2.086
		CAN1	0.029	0.900	0.031	0.921	0.837	0.891	0.386	0.237	2 171	3 7 5 8
		CAND	0.022	0.900	0.041	0.027	0.037	0.000	0.075	0.047	10.075	10 200
		CAN2	0.055	0.899	0.041	0.937	0.826	0.900	0.075	0.047	10.975	19.200
		tCAN1	0.016	0.917	0.025	0.929	0.890	0.910	0.488	0.257	1.824	3.544
		tCAN2	0.022	0.920	0.037	0.946	0.879	0.919	0.095	0.051	9.257	18.162
		Roott1	0.021	0.870	0.024	0.001	0.820	0.861	0.246	0.224	2 271	2 850
		BOOUL	0.021	0.879	0.024	0.901	0.820	0.801	0.540	0.224	2.371	5.850
		Boott2	0.027	0.870	0.034	0.919	0.785	0.878	0.066	0.045	11.817	19.686
		VST1	0.081	0.926	0.050	0.940	0.806	0.872	0.339	0.233	2.377	3.750
0	n = 0.5	VST2	0.079	0.916	0.061	0.954	0.782	0.886	0.066	0.046	11 848	19 466
P	- 0.5	CD1	0.072	0.910	0.001	0.021	0.000	0.000	0.000	0.010	2.106	2 776
0	x	SB1	0.032	0.899	0.032	0.921	0.829	0.889	0.378	0.235	2.196	3.775
P	$p_2 = 0.1$	SB2	0.037	0.897	0.040	0.935	0.819	0.899	0.075	0.047	10.945	19.137
	~	BB1	0.045	0.891	0.034	0.912	0 784	0.878	0.332	0.224	2 362	3 9 1 7
		DD1	0.040	0.004	0.031	0.022	0.770	0.000	0.055	0.044	12.000	10.036
		BB2	0.049	0.884	0.047	0.932	0.778	0.885	0.065	0.044	12.020	19.926
		PB1	0.067	0.924	0.054	0.939	0.813	0.872	0.343	0.225	2.368	3.882
		PB2	0.089	0.929	0.065	0.957	0.787	0.886	0.068	0.047	11.565	18.968
		BC ₂ B1	0.067	0.914	0.053	0.938	0.802	0.873	0.332	0.224	2 418	3 805
		DCaD1	0.007	0.014	0.055	0.052	0.002	0.075	0.052	0.224	11 (52	10 401
		DCaD2	0.079	0.924	0.069	0.935	0.790	0.880	0.008	0.045	11.032	19.401
		CAN1	0.037	0.885	0.028	0.912	0.803	0.878	0.360	0.232	2.231	3.778
		CAN2	0.035	0.904	0.044	0.938	0.861	0.889	0.678	0.421	1.270	2.112
		+CAN1	0.021	0.006	0.026	0.018	0.856	0.801	0.455	0.246	1 992	3 6 2 2
		ICAIVI	0.021	0.900	0.020	0.918	0.850	0.891	0.455	0.240	1.665	5.025
		tCAN2	0.026	0.923	0.039	0.944	0.902	0.915	0.837	0.452	1.078	2.025
		Boott1	0.029	0.860	0.021	0.890	0.753	0.873	0.321	0.218	2.348	4.000
		Poott2	0.027	0.979	0.025	0.024	0.700	0.802	0.606	0.408	1 219	2.186
		LIGTH	0.027	0.070	0.055	0.024	0.777	0.092	0.000	0.400	1.510	2.100
		VSTI	0.091	0.918	0.049	0.929	0.764	0.881	0.322	0.225	2.373	3.923
P	$p_1 = 0.5$	VST2	0.079	0.926	0.061	0.951	0.798	0.892	0.604	0.409	1.322	2.183
	e ¹	SB1	0.040	0.883	0.028	0.912	0 798	0.881	0.352	0.232	2 264	3 796
	~ 0.0	SDA	0.025	0.005	0.014	0.041	0.072	0.000	0.000	0.406	1.250	2.100
ŀ	$J_2 = 0.9$	362	0.055	0.900	0.044	0.941	0.862	0.898	0.090	0.420	1.230	2.109
		BB1	0.050	0.872	0.031	0.906	0.763	0.863	0.313	0.221	2.438	3.909
		BB2	0.046	0.890	0.049	0.933	0.814	0.876	0.597	0.399	1.365	2.197
		PB1	0.070	0.913	0.041	0.926	0.772	0.878	0.323	0.220	2 302	3 002
		TBI	0.079	0.913	0.041	0.920	0.772	0.878	0.323	0.220	2.392	3.992
		PB2	0.082	0.934	0.068	0.957	0.804	0.881	0.629	0.420	1.278	2.096
		BCaB1	0.072	0.907	0.043	0.923	0.769	0.875	0.320	0.216	2.405	4.042
		BCaB2	0.082	0.929	0.068	0.954	0.797	0.880	0.614	0.414	1.299	2.128
		CANI	0.010	0.800	0.022	0.010	0.925	0.802	0.727	0.422	1.1.49	2.1.16
		CAN	0.019	0.070	0.032	0.719	0.033	0.892	0.727	0.422	1.140	2.110
		CAN2	0.045	0.916	0.030	0.926	0.835	0.899	0.074	0.048	11.265	18.897
		tCAN1	0.013	0.906	0.026	0.923	0.877	0.905	0.896	0.452	0.979	2.001
		tCAN2	0.028	0.930	0.026	0.931	0.879	0.915	0.093	0.051	9.444	17.943
		Boott1	0.013	0.866	0.025	0.901	0.784	0.883	0.636	0.400	1 233	2 2 1 0
		Dootti	0.015	0.000	0.020	0.001	0.704	0.000	0.050	0.400	11.233	10 725
		Boott2	0.031	0.892	0.023	0.914	0.806	0.903	0.069	0.046	11.746	19.735
		VST1	0.070	0.915	0.055	0.937	0.789	0.889	0.628	0.406	1.257	2.187
	$p_1 = 0.9$	VST2	0.082	0.934	0.048	0.947	0.798	0.911	0.067	0.047	11.847	19 534
P	-1 — 0.2 R	SP1	0.002	0.999	0.021	0.019	0.222	0.911	0.727	0.422	1 1 4 4	2 1 1 2
6	x _	301	0.018	0.008	0.031	0.918	0.635	0.891	0.727	0.422	1.140	2.113
P	$D_2 = 0.1$	SB2	0.044	0.921	0.029	0.929	0.836	0.903	0.076	0.048	10.980	18.721
	-	BB1	0.032	0.881	0.036	0.914	0.798	0.871	0.624	0.401	1.280	2.175
		BB2	0.052	0.904	0.026	0.924	0.704	0.884	0.066	0.045	11 961	10 625
1		DD2	0.032	0.004	0.030	0.724	0.001	0.004	0.000	0.040	1,212	17.023
		PB1	0.058	0.911	0.052	0.939	0.801	0.895	0.611	0.405	1.312	2.211
		PB2	0.086	0.936	0.052	0.949	0.795	0.908	0.070	0.046	11.372	19.597
		BCaB1	0.058	0.906	0.057	0.932	0 793	0.875	0.600	0 301	1 321	2,236
1		DCaD1	0.000	0.200	0.037	0.734	0.173	0.073	0.000	0.371	11.041	20,202
		BCaB2	0.080	0.938	0.056	0.939	0.802	0.895	0.071	0.044	11.368	20,203
		CAN1	0.024	0.910	0.032	0.921	0.854	0.863	0.733	0.420	1.165	2.055
		CAN2	0.040	0.897	0.033	0.934	0.827	0.890	0.365	0.242	2.265	3.682
		+CAN1	0.014	0.027	0.020	0.025	0.001	0.993	0.004	0.442	0.004	1 002
1		ICANI	0.016	0.927	0.030	0.925	0.901	0.882	0.900	0.442	0.994	1.998
		tCAN2	0.024	0.918	0.030	0.942	0.882	0.910	0.467	0.260	1.887	3.497
		Boott1	0.020	0.891	0.026	0.894	0.839	0.833	0.649	0.389	1.294	2.144
1		Boott?	0.029	0.874	0.024	0.927	0.792	0.894	0.333	0.238	2,380	3,751
		NOT:	0.027	0.074	0.024	0.727	0.772	0.074	0.555	0.230	1,000	0.701
		V511	0.073	0.952	0.055	0.955	0.822	0.845	0.041	0.401	1.285	2.106
C	$p_1 = 0.9$	VST2	0.082	0.921	0.053	0.948	0.794	0.885	0.330	0.232	2.406	3.808
	¢.	SB1	0.024	0.913	0.034	0.917	0.850	0.856	0.733	0.412	1.160	2.078
	-05	SD2	0.042	0.001	0.024	0.029	0.827	0.800	0.360	0.244	2.240	2 651
P	$y_2 = 0.5$	302	0.043	0.901	0.034	0.938	0.827	0.892	0.309	0.244	2.240	5.051
		BB1	0.037	0.902	0.039	0.916	0.807	0.846	0.636	0.394	1.268	2.145
		BB2	0.053	0.889	0.036	0.931	0.783	0.882	0.323	0.231	2.426	3.819
		PB1	0.070	0.930	0.040	0.932	0.821	0.853	0.635	0.396	1 293	2 1 5 5
		DDD	0.070	0.024	0.047	0.050	0.021	0.000	0.240	0.221	2.274	2.100
		PB2	0.081	0.924	0.061	0.950	0.806	0.873	0.340	0.231	2.374	3.178
		BCaB1	0.063	0.928	0.051	0.931	0.823	0.848	0.637	0.392	1.291	2.163
		BCaB2	0.082	0.927	0.060	0.950	0.807	0.877	0.341	0.231	2.368	3.800

Table-5 : Simulation results: 90% calibrated confidence intervals of $E_4/H_4^{Pe}/1$ to $H_4^{Pe}/E_4/1$.

Intensity	Estimation			20		Coverage		Average		Relative	
Parameters	Approches	R(~)	n = 10	R(a)	n = 29	Pero	entages	Le	engths 20	Cov	/erage
	CANI	$p(\alpha_i)$	$p(1 - \alpha_i)$	$p(\alpha_i)$	$p(1-\alpha_i)$	n = 10 0.819	n = 29 0.860	n = 10 0.076	n = 29	n = 10 10.731	n = 29 18 524
	CAN2	0.040	0.896	0.029	0.948	0.808	0.890	0.367	0.246 2	.199	3.617
	tCAN1	0.012	0.904	0.023	0.916	0.851	0.881	0.099	0.050	8.564	17.580
	tCAN2	0.025	0.913	0.032	0.952	0.861	0.908	0.463	0.266	1.861	3.416
	Boott1	0.015	0.847	0.025	0.896	0.758	0.865	0.067	0.044	11.361	19.783
	Boott2 VST1	0.030	0.867	0.030	0.933	0.770	0.875	0.330	0.238	2.335	3.6/5
$a_1 = 0.1$	VST2	0.087	0.921	0.066	0.957	0.766	0.864	0.328	0.229	2.335	3.778
&	SB1	0.026	0.878	0.031	0.909	0.812	0.858	0.075	0.046	10.833	18.739
$\rho_2 = 0.5$	SB2	0.041	0.898	0.041	0.947	0.809	0.885	0.373	0.244	2.172	3.622
	BB1	0.036	0.862	0.034	0.907	0.774	0.848	0.065	0.044	11.845	19.235
	BB2 PB1	0.052	0.879	0.046	0.945	0.764	0.876	0.320	0.233	2.385	3.767
	PB2	0.089	0.928	0.067	0.954	0.777	0.855	0.343	0.233	2.268	3.676
	BCaB1	0.059	0.904	0.050	0.921	0.782	0.859	0.065	0.043	11.951	20.169
	BCaB2	0.085	0.921	0.066	0.957	0.774	0.855	0.335	0.235	2.307	3.643
	CAN1	0.030	0.894	0.033	0.913	0.836	0.863	0.076	0.046	10.972	18.734
	tCAN1	0.044	0.895	0.023	0.932	0.813	0.889	0.039	0.448	8 975	1.965
	tCAN2	0.031	0.921	0.023	0.938	0.885	0.904	0.803	0.475	1.102	1.904
	Boott1	0.021	0.875	0.028	0.903	0.777	0.851	0.069	0.044	11.267	19.351
	Boott2	0.035	0.870	0.020	0.914	0.778	0.873	0.576	0.417	1.351	2.092
$a_1 = 0.1$	VST1	0.064	0.921	0.054	0.930	0.785	0.853	0.072	0.045	10.930	19.105
$p_1 = 0.1$	SB1	0.033	0.893	0.043	0.915	0.828	0.864	0.075	0.046	11.102	18.654
$\rho_2 = 0.9$	SB2	0.046	0.895	0.027	0.934	0.817	0.888	0.643	0.444	1.271	2.001
	BB1	0.040	0.883	0.036	0.911	0.792	0.855	0.067	0.044	11.856	19.340
	BB2	0.064	0.881	0.028	0.924	0.767	0.869	0.549	0.419	1.398	2.073
	PB2	0.001	0.917	0.034	0.952	0.791	0.854	0.008	0.422	1 305	2 083
	BCaB1	0.056	0.914	0.059	0.932	0.803	0.837	0.068	0.043	11.799	19.377
	BCaB2	0.099	0.926	0.050	0.949	0.781	0.875	0.587	0.419	1.330	2.089
	CAN1	0.027	0.891	0.037	0.916	0.819	0.852	0.387	0.228	2.117	3.739
	CAN2 tCAN1	0.042	0.924	0.038	0.938	0.852	0.871	0.077	0.048	11.113	18.232
	tCAN1 tCAN2	0.016	0.915	0.029	0.922	0.862	0.872	0.492	0.247	9,447	5.534 17.323
	Boott1	0.019	0.856	0.028	0.902	0.772	0.862	0.336	0.219	2.297	3.930
	Boott2	0.027	0.903	0.028	0.921	0.833	0.863	0.072	0.046	11.564	18.742
	VST1	0.059	0.922	0.052	0.934	0.808	0.869	0.369	0.227	2.192	3.837
$\rho_1 = 0.5$	VS12 SB1	0.095	0.940	0.066	0.953	0.803	0.859	0.066	0.045	2 107	3 735
$\rho_2 = 0.1$	SB1 SB2	0.023	0.925	0.030	0.938	0.859	0.876	0.078	0.228	11.022	18.349
	BB1	0.030	0.872	0.038	0.912	0.791	0.844	0.346	0.219	2.289	3.850
	BB2	0.061	0.920	0.044	0.933	0.803	0.853	0.067	0.045	11.921	18.953
	PB1	0.054	0.914	0.050	0.928	0.802	0.863	0.345	0.218	2.323	3.955
	PB2 BCaB1	0.098	0.946	0.072	0.958	0.811	0.850	0.072	0.047	2.348	3.940
	BCaB2	0.095	0.942	0.072	0.954	0.811	0.840	0.071	0.046	11.483	18.445
	CAN1	0.031	0.896	0.037	0.931	0.830	0.875	0.382	0.236	2.171	3.706
	CAN2	0.034	0.904	0.040	0.911	0.843	0.863	0.697	0.401	1.209	2.153
	tCAN1 tCAN2	0.015	0.916	0.032	0.935	0.867	0.894	0.494	0.251	1.757	3.562
	Boott1	0.020	0.924	0.033	0.916	0.902	0.868	0.343	0.432	2.303	3.885
	Boott2	0.025	0.879	0.029	0.894	0.791	0.854	0.628	0.386	1.260	2.210
	VST1	0.060	0.934	0.054	0.947	0.818	0.879	0.373	0.231	2.191	3.797
$\rho_1 - 0.5$	VST2	0.076	0.924	0.056	0.925	0.794	0.859	0.621	0.392	1.278	2.192
$a_{2} = 0.9$	SB1 SB2	0.031	0.896	0.041	0.930	0.825	0.869	0.379	0.231	2.178	2.138
$p_2 = 0.9$	BB1	0.040	0.885	0.039	0.925	0.786	0.863	0.337	0.225	2.333	3.833
	BB2	0.044	0.896	0.042	0.905	0.790	0.845	0.620	0.383	1.274	2.207
	PB1	0.062	0.924	0.051	0.947	0.811	0.883	0.348	0.231	2.327	3.814
	PB2 PCoP1	0.079	0.932	0.057	0.930	0.799	0.854	0.643	0.389	1.242	2.194
	BCaB2	0.000	0.925	0.055	0.945	0.801	0.875	0.633	0.387	1.266	2.193
	CAN1	0.046	0.881	0.035	0.923	0.822	0.866	0.629	0.414	1.306	2.091
	CAN2	0.036	0.911	0.034	0.931	0.846	0.909	0.077	0.048	11.037	18.925
	tCAN1 tCAN2	0.028	0.898	0.031	0.930	0.872	0.886	0.780	0.442	1.118	2.004
	Boott1	0.025	0.861	0.027	0.906	0.788	0.928	0.581	0.396	1.356	2.210
	Boott2	0.025	0.883	0.024	0.919	0.810	0.894	0.069	0.047	11.700	19.070
	VST1	0.082	0.904	0.054	0.942	0.787	0.883	0.591	0.406	1.331	2.175
$\rho_1 = 0.9$	VST2	0.070	0.928	0.054	0.944	0.819	0.888	0.070	0.046	11.716	19.277
& 02 - 0 1	SB1 SB2	0.047	0.878	0.034	0.923	0.814	0.866	0.622	0.415	1.310	2.087
$p_2 = 0.1$	BB1	0.052	0.869	0.031	0.910	0.774	0.845	0.551	0.386	1.405	2.191
	BB2	0.041	0.901	0.037	0.929	0.808	0.895	0.069	0.046	11.660	19.414
	PB1	0.076	0.900	0.050	0.943	0.800	0.888	0.570	0.406	1.404	2.188
	PB2 PC-P1	0.072	0.935	0.056	0.950	0.813	0.893	0.072	0.047	11.288	19.065
	BCaB1 BCaB2	0.073	0.896	0.051	0.935	0.785	0.880	0.565	0.394	1.387	2.234
	CAN1	0.027	0.919	0.036	0.934	0.866	0.876	0.717	0.428	1.208	2.047
	CAN2	0.032	0.900	0.042	0.934	0.826	0.885	0.379	0.233	2.181	3.791
	tCAN1	0.018	0.932	0.029	0.936	0.901	0.890	0.880	0.458	1.024	1.944
	tCAN2 Boott1	0.020	0.924	0.038	0.937	0.899	0.896	0.487	0.248	1.847	3.615
	Boott?	0.021	0.875	0.023	0.924	0.806	0.870	0.340	0.229	2,368	2.088
	VST1	0.065	0.936	0.056	0.950	0.849	0.868	0.650	0.415	1.307	2.090
$\rho_1 = 0.9$	VST2	0.070	0.918	0.066	0.944	0.807	0.854	0.341	0.220	2.365	3.881
&	SB1	0.029	0.917	0.035	0.934	0.853	0.876	0.704	0.428	1.211	2.045
$p_2 = 0.5$	5B2 BB1	0.035	0.903	0.042	0.933	0.835	0.888	0.382	0.254	2.180	2.008
	BB1 BB2	0.030	0.888	0.049	0.932	0.779	0.873	0.331	0.221	2.350	3.947
	PB1	0.056	0.935	0.052	0.951	0.853	0.870	0.647	0.421	1.318	2.068
	PB2	0.071	0.931	0.068	0.946	0.817	0.850	0.353	0.224	2.314	3.796
	BCaB1 BCaB2	0.056	0.931	0.052	0.949	0.850	0.866	0.636	0.418	1.336	2.074
L	DCaD2	0.008	0.924	0.070	0.943	0.618	0.640	0.345	0.220	2.3/1	3.810

Table-6 : Simulation results: 90% calibrated confidence intervals of $E_4/H_4^{Po}/1$ to $H_4^{Po}/E_4/1$



Note that:

(1) boldface denotes the greatest relative coverage among estimation approaches.

(2) Calibrated confidence intervals of ρ_1 under different estimation approaches are denoted by CAN1, Exact-t1, Boot-t1, VST1, SB1, BB1, PB1, BCaB1 and that of ρ_2 are denoted by CAN2 Exact-t2, Boot-t2, VST2, SB2, BB2, PB2 and BCaB2.

According to the simulation results in Tables 3 to 6, we find that average lengths are decreasing with sample size n, but both coverage percentages and relative coverage are increasing with sample size n. From Tables 3 to 6, one can observe that the coverage percentage can approach to 90% when n increases to 29. Also some interesting results are summarized in Table 7, about queueing network models or estimation approaches give greater relative coverage.

Queueing	Queuing Network	Queueing Network	Intensity	Estimation approach		
Network	simulated	with greater	Parameters	with	greatest	
Туре		relative coverage		relative	e coverage	
				n = 10	n = 29	
			$\rho_1 = 0.1$	VST	VST	
			$\&\rho_2 = 0.5$	BCaB	PB	
			$\rho_1 = 0.1$	VST	VST	
			& $\rho_2 = 0.9$	BCaB	BCaB	
	$M/E_4/1$ to $E_4/M/1$		$\rho_1 = 0.5$	VST	VST	
			$\&\rho_2 = 0.1$	BCaB	BCaB	
M/G/1 to $G/M/1$	and	$M/E_4/1$ to $E_4/M/1$	$\rho_1 = 0.5$	VST	BB	
			$\&\rho_2 = 0.9$	BCaB	BCaB	
	$M/E_4^{Pe}/1$ to $H_4^{Pe}/M/1$		$\rho_1 = 0.9$	VST	VST	
			$\&\rho_2 = 0.1$	BCaB	BCaB	
			$\rho_1 = 0.9$	VST	VST	
			$\&\rho_2 = 0.5$	BCaB	BCaB	
			$\rho_1 = 0.1$	BCaB	PB	
			$\&\rho_2 = 0.5$	BB	BB	
			$\rho_1 = 0.1$	BCaB	PB	
			& $\rho_2 = 0.9$	BB	BB	
	$E_4/H_4^{pe}/1$ to $H_4^{Pe}/E_4/1$		$\rho_1 = 0.5$	BCaB	BB	
			$\&\rho_2 = 0.1$	BB	BB	
G/G/1 to $G/G/1$	and	$E_4/H_4^{Pe}/1$ to $H_4^{Pe}/E_4/1$	$\rho_1 = 0.5$	BB	BCaB	
			$\&\rho_2 = 0.9$	BB	BB	
	$E_4/H_4^{Po}/1$ to $H_4^{Po}/E_4/1$		$\rho_1 = 0.9$	BCaB	BCaB	
			$\&\rho_2 = 0.1$	BB	BCaB	
			$\rho_1 = 0.9$	Boott	BCaB	
			$\&\rho_2 = 0.5$	BB	BB	

Table-7 : Performances of the estimation approaches of intensities

Based on Table 7, we note that:

- (1) Under M/G/1 to G/M/1 queueing network models, the calibrated confidence intervals corresponding to queueing network models with inter-arrival/service time distribution of small CV (< 1) have greater relative coverage than those of large CV (> 1).
- (2) Among the simulated M/G/1 to G/M/1 queueing network models, estimation approaches VST or BCaB calibrated confidence interval have the greatest relative coverage.
- (3) Among the simulated M/G/1 to G/M/1 queueing network models, the calibrated confidence intervals of queueing network model $M/E_4/1$ to $E_4/M/1$ shows the greatest relative coverage.
- (4) Under G/G/1 to G/G/1 queueing network models, the calibrated confidence interval corresponding to queueing network models with inter-arrival distribution/ service time distribution of large CV(> 1) have greatest relative coverage than those of small CV (< 1).
- (5) Among G/G/1 to G/G/1 queueing network models, the estimation approach BCaB or BB calibrated confidence intervals has the greatest relative coverage.
- (6) Among G/G/1 to G/G/1 queueing network models, the calibrated confidence intervals of model $E_4/H_4^{Pe}/1$ to $H_4^{Pe}/E_4/1$ shows the greatest relative coverage.

Limitations of the Study:

- (1) This is a comparative numerical simulation study based on two-stage open queueing network systems as shown in Figure -1.
- (2) Parameters selected in simulation study are arbitrary as shown in Table-1.



4 Conclusions

This paper provides the calibrated confidence interval estimations of intensities ρ_1 and ρ_2 for two-stage open queueing network. Eight different calibrated estimation approaches CAN, Exact-t, Boot-t, VST, SB, BB, PB and BCaB are applied to produce confidence intervals for intensities ρ_1 and ρ_2 . The relative coverage is adopted to understand, compare and assess performance of the resulted confidence intervals. The simulation results imply that VST and BCaB method has the best performance on calibrated confidence interval estimations of intensities ρ_1 and ρ_2 for M/G/1 to G/M/1 queueing network type models with short run data. Under G/G/1 to G/G/1 queueing network type models with short run data, the estimation approach BCaB or BB out performs the other estimation approach in terms of the relative coverage. This approach is easily applied to practical queueing network models.

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