

# BAYESIAN ESTIMATES OF PARAMETERS IN SOME QUEUEING MODELS

M. V. MUDDAPUR

(Received Nov. 14, 1969; revised Nov. 2, 1970)

## 1. Introduction and summary

A maximum likelihood procedure for estimating  $\lambda$  and  $\mu$ , the input and service parameters, respectively, in a single channel Poisson input and exponential holding time, first come first served queue in equilibrium, has been derived by A. B. Clarke [1]. In general, to estimate  $\lambda$ , one can observe the operation for a time of length  $T$ ; if  $n$  persons arrive, then one has  $\hat{\lambda}=n/T$ . And if  $m$  persons are served and the total busy time of the service channel is  $\tau$ , then  $\hat{\mu}=m/\tau$ . If  $\rho$  is the traffic intensity and if  $\rho \geq 1$  then the above estimates are the best one can find; otherwise if  $\rho < 1$  it is possible to use the initial queue size to improve the above estimates for the queue in equilibrium.

Clarke's method can be outlined as follows. Let  $m > i$ ,  $i$  being the initial queue size, and suppose that the busy time of the channel is observed until a preassigned value is reached; let  $T$  be the time at which the  $m$ th departure occurs. Let the random variables  $X_j, Y_j, Z_j$ , give the  $j$ th arrival time, and  $j$ th departure time, and the busy time of the channel up to the  $j$ th departure (all vanishing for  $j \leq 0$ ), respectively. Then we have recursively

$$(1) \quad Y_j = \max(Y_{j-1}, X_{j-i}) + Z_j - Z_{j-1}.$$

Knowing the initial number  $i$  and the  $X_j$  and  $Z_j$  (independent of  $X_j$ ), and assuming the initial queue size  $i$  has a geometric distribution  $(1-\rho)\rho^i$  ( $i=0, 1, 2, \dots$ ) which is of course the equilibrium solution of the queue size, he got the likelihood as

$$(2) \quad L = K \left(1 - \frac{\lambda}{\mu}\right) \mu^{m-i} \lambda^{n+i} e^{-\mu\tau - \lambda T}$$

where  $K$  is a function which does not depend on  $\lambda$  or  $\mu$ . Differentiating the likelihood and solving, Clarke gets maximum likelihood estimate of  $\rho$  the traffic intensity as the roots of the quadratic equation in  $\rho$ ,

one being equal to unity and other as

$$(3) \quad \hat{\rho}_1 = \frac{n+i}{m-i} \frac{\tau}{T}$$

$$(4) \quad \hat{\lambda} = \frac{(n+m)\hat{\rho}}{\hat{\rho}T + \tau}$$

and

$$(5) \quad \hat{\mu} = \frac{n+m}{\hat{\rho}T + \tau}$$

whenever the approximation of  $\rho_1$  for  $\rho$  is valid simple approximations for  $\lambda$  and  $\mu$  are

$$(6) \quad \hat{\lambda} \approx \frac{n+i}{T}$$

$$(7) \quad \hat{\mu} \approx \frac{m-i}{\tau}.$$

Here in this paper we have found the Bayesian estimates of  $\lambda$ ,  $\mu$  and  $\rho$  using the same likelihood given by Clarke and assuming some prior distributions for the parameters  $\lambda$  and  $\mu$ .

## 2. Derivation of the results for $M/M/1$

### (i) Using natural-conjugate prior density

Now the likelihood is

$$L = \left(1 - \frac{\lambda}{\mu}\right) e^{-\mu\tau - \lambda T} \mu^{m-i} \lambda^{n+i} K.$$

Hence the kernel of the likelihood is (refer Raiffa and Schlaifer [2])

$$(8) \quad = \left(1 - \frac{\lambda}{\mu}\right) e^{-\mu\tau - \lambda T} \mu^{m-i} \lambda^{n+i}.$$

Then the natural conjugate prior density of  $\lambda$  and  $\mu$  may be taken as

$$(9) \quad D'(\lambda, \mu/\tau', T') \propto \left(1 - \frac{\lambda}{\mu}\right) e^{-\mu\tau' - \lambda T'} \mu^{m'} \lambda^{n'}.$$

Hence the posterior joint density of  $\lambda$  and  $\mu$  is

$$(10) \quad D''(\lambda, \mu/\tau_1, T_1) \propto \left(1 - \frac{\lambda}{\mu}\right)^2 e^{\mu\tau_1 - \lambda T_1} \mu^{m_1} \lambda^{n_1}.$$

Where

$$\tau_1 = \tau + \tau', \quad T_1 = T + T', \quad m_1 = m + m' - i, \quad n_1 = n + n' + i.$$

The normalising constant  $k$  for  $D''(\lambda, \mu/\tau_1, T_1)$  is given by

$$(11) \quad k \int_0^\infty \int_0^\infty D''(\lambda, \mu/\tau_1, T_1) d\lambda d\mu = 1$$

i.e., 
$$\frac{1}{k} = \frac{\Gamma(m_1 - 1)\Gamma(n_1 + 1)}{\tau_1^{m_1 + 1} T_1^{n_1 + 3}} [m_1(m_1 - 1)T_1^2 - 2(m_1 - 1)(n_1 + 1)\tau_1 T_1 + (n_1 + 1)(n_1 + 2)\tau_1^2].$$

*Bayesian estimates of  $\lambda$ ,  $\mu$  and  $\rho$*

Using the posterior density of  $\lambda$ ,  $\mu$  we can find the expected values of  $\lambda$ ,  $\mu$  and  $\rho$  which are ultimately Bayesian estimates of  $\lambda$ ,  $\mu$  and  $\rho$ . They are as follows.

$$(12) \quad E^*(\lambda) = \frac{n_1 + 1}{T_1} \cdot \left[ \frac{m_1(m_1 - 1)T_1^2 - 2(m_1 - 1)(n_1 + 2)\tau_1 T_1 + (n_1 + 2)(n_1 + 3)\tau_1^2}{m_1(m_1 - 1)T_1^2 - 2(m_1 - 1)(n_1 + 1)\tau_1 T_1 + (n_1 + 1)(n_1 + 2)\tau_1^2} \right]$$

$$(13) \quad E^*(\mu) = \frac{m_1 - 1}{\tau_1} \cdot \left[ \frac{m_1(m_1 + 1)T_1^2 - 2m_1(n_1 + 1)\tau_1 T_1 + (n_1 + 1)(n_1 + 2)\tau_1^2}{m_1(m_1 + 1)T_1^2 - 2(m_1 - 1)(n_1 + 1)\tau_1 T_1 + (n_1 + 1)(n_1 + 2)\tau_1^2} \right]$$

$$(14) \quad E^*(\lambda/\mu) = E^*(\rho) = \frac{n_1 + 1}{m_1 - 2} \frac{\tau_1}{T_1} \cdot \left[ \frac{(m_1 - 1)(m_1 - 2)T_1^2 - 2(m_1 - 1)(n_1 + 2)\tau_1 T_1 + (n_1 + 2)(n_1 + 3)\tau_1^2}{m_1(m_1 - 1)T_1^2 - 2(m_1 - 1)(n_1 + 1)\tau_1 T_1 + (n_1 + 1)(n_1 + 2)\tau_1^2} \right].$$

(ii) *Taking the prior density of  $\lambda$  and  $\mu$  as of Gamma type*

Instead of considering the natural conjugate prior density for the parameters based on the kernel of the likelihood we may consider the prior densities of  $\lambda$  and  $\mu$  as gamma variates with parameters  $(T', n')$ ,  $(\tau', m')$  and assuming  $\lambda$  and  $\mu$  as independently distributed variates, the kernel of their joint density is

$$(15) \quad = e^{-\mu' - \lambda T'} \lambda^{n'-1} \mu^{m'-1}.$$

Then the posterior joint density of  $\lambda$  and  $\mu$  is

$$(16) \quad D''(\lambda, \mu/\tau_1, T_1) \propto \left(1 - \frac{\lambda}{\mu}\right) e^{-\mu_1 - \lambda T_1} \mu^{m_1} \lambda^{n_1}$$

where

$$\begin{aligned}\tau_1 &= \tau + \tau', & T_1 &= T + T', \\ m_1 &= m + m' - i - 1, & n_1 &= n + n' + i - 1.\end{aligned}$$

The normalising constant  $k$  is given by the integral

$$(17) \quad k \int_0^\infty \int_0^\infty D''(\lambda, \mu/\tau_1, T_1) d\lambda d\mu = 1$$

i.e., 
$$\frac{1}{k} = \frac{\Gamma m_1 \Gamma(n_1 + 1)}{\tau_1^{m_1 + 1} T_1^{n_1 + 2}} [m_1 T_1 - (n_1 + 1)\tau_1].$$

*Bayesian estimates of  $\lambda$ ,  $\mu$  and  $\rho$*

Expected values of  $\lambda$ ,  $\mu$  and  $\rho$  can be found by using the posterior density of  $\lambda$  and  $\mu$ , and they are

$$(18) \quad E^*(\lambda) = \frac{n_1 + 1}{T_1} \left[ \frac{m_1 T_1 - (n_1 + 2)\tau_1}{m_1 T_1 - (n_1 + 1)\tau_1} \right]$$

$$(19) \quad E^*(\mu) = \frac{m_1}{\tau_1} \left[ \frac{(m_1 + 1)T_1 - (n_1 + 1)\tau_1}{m_1 T_1 - (n_1 + 1)\tau_1} \right]$$

$$(20) \quad E^*(\rho) = \frac{n_1 + 1}{m_1 - 1} \frac{\tau_1}{T_1} \left[ \frac{(m_1 - 1)T_1 - (n_1 + 2)\tau_1}{m_1 T_1 - (n_1 + 1)\tau_1} \right]$$

which are ultimately Bayesian estimates of  $\lambda$ ,  $\mu$  and  $\rho$ .

### 3. Derivation of the results for $M/M/\infty$

Following the same steps given by Clarke, and assuming the initial queue size  $i$  has a Poisson distribution  $e^{-\rho} \rho^i / i!$  ( $i = 0, 1, 2, \dots$ ) which is the equilibrium solution of the queue size in this system  $M/M/\infty$  one can write the likelihood equation for this case as

$$(21) \quad L = e^{-\rho - \mu\tau - \lambda T} \mu^{m-i} \lambda^{n+i} K.$$

Before going for the Bayesian estimates one can have the maximum likelihood estimates of  $\lambda$ ,  $\mu$  and  $\rho$  as follows.

$$(22) \quad \hat{\lambda} = \frac{n+i}{1/\hat{\mu} + T}$$

$$(23) \quad \hat{\mu} = \frac{\tau - T(m-i) \pm \sqrt{[\tau - T(m-i)]^2 + 4\tau T(n+m)}}{2\tau T}$$

and

$$(24) \quad \hat{\rho} = \frac{2(n+i)\tau}{2\tau - T(m-i) \pm \sqrt{[\tau - T(m-i)]^2 + 4\tau T(n+m)}}.$$

*Bayesian estimates of  $\lambda$ ,  $\mu$  and  $\rho$*

Now the kernel of the likelihood is

$$(25) \quad = e^{-\rho - \mu\tau - \lambda T} \mu^{m-i} \lambda^{n+i}.$$

The conjugate prior density is

$$(26) \quad D'(\lambda, \mu/\tau', T') \propto e^{-\rho - \mu\tau' - \lambda T'} \mu^{m'} \lambda^{n'}.$$

Hence the posterior density is

$$(27) \quad D''(\lambda, \mu/\tau_1, T_1) \propto e^{-2\rho - \mu\tau_1 - \lambda T_1} \mu^{m_1} \lambda^{n_1}$$

where

$$\tau_1 = \tau + \tau', \quad T_1 = T + T', \quad m_1 = m + m' - i, \quad n_1 = n + n' + i.$$

The normalising constant  $k$  for  $D''(\lambda, \mu/\tau_1, T_1)$  is given by the integral

$$(28) \quad k \int_0^\infty \int_0^\infty D''(\lambda, \mu/\tau_1, T_1) d\lambda d\mu = 1$$

i.e., 
$$\frac{1}{k} = \frac{\Gamma(n_1+1)}{\tau_1^{m_1+1} T_1^{n_1+1}} \sum_{r=0}^\infty \binom{n_1+r+1}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r+1).$$

Hence the Bayesian estimates are given by the following expectations,

$$(29) \quad E^*(\lambda) = \frac{n_1+1}{T_1} \frac{\sum_{r=0}^\infty \binom{n_1+r+2}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r+1)}{\sum_{r=0}^\infty \binom{n_1+r+1}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r+1)}$$

$$(30) \quad E^*(\mu) = \frac{1}{\tau_1} \frac{\sum_{r=0}^\infty \binom{n_1+r+1}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r+2)}{\sum_{r=0}^\infty \binom{n_1+r+1}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r+1)}$$

$$(31) \quad E^*(\rho) = (n_1+1) \frac{\tau_1}{T_1} \frac{\sum_{r=0}^\infty \binom{n_1+r+2}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r)}{\sum_{r=0}^\infty \binom{n_1+r+1}{r} \left(-\frac{2\tau_1}{T_1}\right)^r \Gamma(m_1-r+1)}.$$

KARNATAK UNIVERSITY, DHARWAR, INDIA

REFERENCES

[ 1 ] Clarke, A. B. (1957). Maximum likelihood estimates in a simple queue, *Ann. Math. Statist.*, 28, 1036-1040.  
 [ 2 ] Raiffa, H. and Schlaifer, R. (1961). *Applied Statistical Decision Theory*, Harvard University, Boston.