CHAPTER 5

EXPECTED TIME FOR RECRUITMENT IN A TWO-GRADED MANPOWER SYSTEM HAVING SAME RENEWAL PROCESS FOR INTER-DECISION TIMES AND SCBZ PROPERTY FOR THRESHOLD DISTRIBUTION

5.1 INTRODUCTION

For a single graded system Sathiyamoorthi and Elangovan (1998(a)) have determined the expected time to recruitment using the idea of shock model and cumulative damage process discussed by Esary, Marshall and Proschan (1973). In (2006) for a two graded manpower system Suresh Kumar et al have obtained the mean and variance for time to recruitment, by designing a new recruitment policy involving exponentials thresholds in which the threshold for the cumulative loss of manhours in the two grades is the sum of the threshold levels for the two grades.

In this chapter, an organization with two grades is considered and each grade has its own threshold level with Setting the Clock Back to Zero (SCBZ) property. Recruitment is made by the organization whenever the cumulative loss of manpower crosses
the sum of the thresholds for both the grades. It is assumed that
the policy decisions taken by the organization are governed by the
same renewal processes. The objective of this chapter is to obtain
the mean time for recruitment in the organization under the above
cited policy.

The rest of this chapter is organized as follows: In section
5.2, description of the model is given, analytical expression for
meantime to recruitment is obtained and special cases are
discussed by assuming specific distributions. In section 5.3,
the analytical results are numerically illustrated and relevant
conclusions are made.

5.2 DESCRIPTION AND ANALYSIS OF THE MODEL
Assumptions:

1. An organization consisting of two grades (grades A and B)
takes policy decisions each at k epochs in \([0, \infty]\) and at
every decision making epoch, a random number of persons
quit the organization.

2. Each grade has its own threshold level whose distribution
has SCBZ property.

3. The depletion of manpower in grade A and grade B are
independent, linear and cumulative
4. Thresholds for grades A and B are independent.

5. The inter-decision times are independent and identically distributed random variables which are governed by same renewal process.

6. Recruitment is made whenever the cumulative loss of manhours in both the grades crosses the sum of the thresholds of the two grades.

**Notations:**

\[ X_{iA} \] : continuous random variable denoting the amount of manpower depletion in grade A at the \( i^{th} \) decision epoch, \( i=1,2... \)

\[ X_{iB} \] : continuous random variable denoting the amount of manpower depletion in grade B at the \( i^{th} \) decision epoch, \( i=1,2... \)

\[ X_{iA} + X_{iB} \] : total loss of manhours to the organisation at the \( i^{th} \) epoch, \( i=1,2 ... \) in both the grades

\[ \sum_{i=1}^{k}(X_{iA} + X_{iB}) \] : cumulative loss of manhours after \( k \) decision epochs

\[ Y_A \] : a continuous random variable denoting the threshold level for grade A

\[ Y_B \] : a continuous random variable denoting the threshold level for grade B
\( f(.) \) : probability density function of inter-decision times

\( f_k(.) \) : \( k \)-fold convolution of \( f(.) \)

\( F_k(.) \) : \( k \)-fold convolution of \( F(.) \)-the cumulative distribution of \( f(.) \)

\( g(x) \) : probability density function of \( X_{IA} \)

\( h(x) \) : probability density function of \( X_{IB} \)

\( k_1(.) \) : probability density function of \( Y_A \)

\( K_1(.) \) : cumulative distribution function of \( Y_A \)

\( k_2(.) \) : probability density function of \( Y_B \)

\( K_2(.) \) : cumulative distribution function of \( Y_B \)

\( Y \) : \( Y = Y_A + Y_B \)

\( T \) : a continuous random variable denoting the time to breakdown for the organization

\( l(t) \) : probability density function of \( T \)

\( L(t) \) : cumulative density function of \( T \)

\( z_k(.) \) : probability density function of \( \sum_{i=1}^{k} (X_{ia} + X_{ib}) \)

\( Z_k(.) \) : cumulative distribution function of \( \sum_{i=1}^{k} (X_{ia} + X_{ib}) \)

\( q(.) \) : probability density function of \( Y = \int_{0}^{y} k_1(u)k_2(y-u)du \)

\( Q(.) \) : cumulative distribution function of \( Y \)
MAIN RESULTS

In this section, expressions for $L(t)$, $L^*(s)$ and $E(T)$ are obtained.

$$P(T > t) = \sum_{k=0}^{\infty} \{\text{probability that there are exactly } k \text{ policy decision in } (0,t)\} \text{ and } \{\text{probability that the cumulative damage in the manpower system does not cross the threshold level}\}.$$ (i.e)

$$P(T > t) = \sum_{k=0}^{\infty} V_k(t)P\left[\sum_{i=1}^{k} (X_{id} + X_{id}) < Y\right]$$

$$= \sum_{k=0}^{\infty} (F_k(t) - F_{k+1}(t))P\left[\sum_{i=1}^{k} (X_{id} + X_{id}) < Y\right] \quad (5.2.1)$$

$Y_A$ and $Y_B$ has SCBZ property with parameters $(\theta_1, \theta_2, \mu_1)$ and $(\theta_3, \theta_4, \mu_2)$ respectively.

From chapter 2, the probability density function of $Y_A$ is

$$k_1(y) = p_1(\theta_1 + \mu_1)e^{-(\theta_1 + \mu_1)y} + q_1(\theta_2)e^{-\theta_2y} \quad (5.2.2)$$

where

$$p_1 = \frac{(\theta_1 - \theta_2)}{\theta_1 - \theta_2 + \mu_1}; \text{ and } q_1 = \frac{\mu_1}{\theta_1 - \theta_2 + \mu_1}$$

and the probability density function of $Y_B$ is
where

\[ p_2 = \frac{(\theta_3 - \theta_1)}{\theta_3 - \theta_1 + \mu_2}; \quad \text{and} \quad q_2 = \frac{\mu_2}{\theta_3 - \theta_4 + \mu_2} \]

Now the probability density function of \( Y \) is given by

\[ q(y) = \int_0^y k_2(u) k_1(y-u) \, du \quad (5.2.4) \]

Using (5.2.2) and (5.2.3) in (5.2.4)

\[
q(y) = \int_0^y \left\{ p_1 (\theta_1 + \mu_4) e^{-\left(\theta_1 + \mu_4\right)u} + q_4 \theta_4 e^{-\theta_4 y} \right\} \left\{ p_2 (\theta_3 + \mu_2) e^{-\left(\theta_3 + \mu_2\right)(y-u)} + q_3 \theta_3 e^{-\theta_3 (y-u)} \right\} du
\]
\[
\begin{align*}
&= \frac{p_1p_2(\theta_1 + \mu_1)(\theta_3 + \mu_2)}{-(\theta_1 + \mu_1 - \theta_3 - \mu_2)} \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_3 + \mu_2)y} \right\} + \frac{p_1q_2(\theta_1 + \mu_1)(\theta_4)}{-(\theta_1 + \mu_1 - \theta_4)} \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_4)y} \right\} \\
&\quad + \frac{p_2q_1\theta_2(\theta_3 + \mu_2)}{-(\theta_2 - \theta_3 - \mu_2)} \left\{ e^{-(\theta_2)y} - e^{-(\theta_3 + \mu_2)y} \right\} + \frac{q_1q_2(\theta_2)(\theta_4)}{-(\theta_2 - \theta_4)} \left\{ e^{-(\theta_2)y} - e^{-(\theta_4)y} \right\} \\
&= \frac{p_1p_2(\theta_1 + \mu_1)(\theta_3 + \mu_2)}{(\theta_3 + \mu_2) - (\theta_1 + \mu_1)} \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_3 + \mu_2)y} \right\} + \frac{p_1q_2(\theta_1 + \mu_1)(\theta_4)}{\theta_4 - (\theta_1 + \mu_1)} \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_4)y} \right\} \\
&\quad + \frac{p_2q_1\theta_2(\theta_3 + \mu_2)}{(\theta_3 + \mu_2) - \theta_2} \left\{ e^{-(\theta_2)y} - e^{-(\theta_3 + \mu_2)y} \right\} + \frac{q_1q_2(\theta_2)(\theta_4)}{\theta_4 - \theta_2} \left\{ e^{-(\theta_2)y} - e^{-(\theta_4)y} \right\} \\
&= B_1 \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_3 + \mu_2)y} \right\} + B_2 \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_4)y} \right\} + B_3 \left\{ e^{-(\theta_2)y} - e^{-(\theta_3 + \mu_2)y} \right\} + B_4 \left\{ e^{-(\theta_2)y} - e^{-(\theta_4)y} \right\} \\
&\quad (5.2.5)
\end{align*}
\]

where
\[
\begin{align*}
B_1 &= \frac{p_1p_2(\theta_1 + \mu_1)(\theta_3 + \mu_2)}{(\theta_3 - \mu_2) - (\theta_1 + \mu_1)} ; \quad B_2 = \frac{p_1q_2(\theta_1 + \mu_1)(\theta_4)}{\theta_4 - (\theta_1 + \mu_1)} \\
B_3 &= \frac{p_2q_1\theta_2(\theta_3 + \mu_2)}{(\theta_3 + \mu_2) - \theta_2} ; \quad B_4 = \frac{q_1q_2(\theta_2)(\theta_4)}{\theta_4 - \theta_2} \\
&\quad (5.2.6)
\end{align*}
\]

Now
\[
P\left[ \sum_{i=1}^{k} (X_{it} + \dot{X}_{it}) < Y \right]
\]

\[
= B_1 \int_{0}^{\infty} z_k(y) \left\{ -e^{-(\theta_1 + \mu_1)y} \right\} dy + B_2 \int_{0}^{\infty} z_k(y) \left\{ e^{-(\theta_1 + \mu_1)y} - e^{-(\theta_1)y} \right\} dy
\]

\[
+ B_3 \int_{0}^{\infty} z_k(y) \left\{ e^{-(\theta_1)y} - e^{-(\theta_3 + \mu_3)y} \right\} dy + B_4 \int_{0}^{\infty} z_k(y) \left\{ e^{-(\theta_3)y} - e^{-(\theta_4)y} \right\} dy
\]

\[
= B_1 \left[ \frac{z_k*(\theta_1 + \mu_1) - z_k*(\theta_3 + \mu_3)}{(\theta_1 + \mu_1)} \right] + B_2 \left[ \frac{z_k*(\theta_1 + \mu_1) - z_k*(\theta_4)}{(\theta_1 + \mu_1)} \right]
\]

\[
+ B_3 \left[ \frac{z_k*(\theta_2)}{\theta_2} - \frac{z_k*(\theta_3 + \mu_3)}{(\theta_3 + \mu_3)} \right] + B_4 \left[ \frac{z_k*(\theta_2) - z_k*(\theta_4)}{\theta_4} \right] \quad (5.2.7)
\]

As in chapter 2, using (5.2.7) in (5.2.1)

\[
P(T>t) = \sum_{i=0}^{\infty} \left\{ (F_i(t) - F_{i+1}(t)) \right\}_x
\]

\[
\left\{ B_1 \left[ \frac{z_k*(\theta_1 + \mu_1) - z_k*(\theta_3 + \mu_3)}{(\theta_1 + \mu_1)} \right] + B_2 \left[ \frac{z_k*(\theta_1 + \mu_1) - z_k*(\theta_4)}{(\theta_1 + \mu_1)} \right]
\]

\[
+ B_3 \left[ \frac{z_k*(\theta_2)}{\theta_2} - \frac{z_k*(\theta_3 + \mu_3)}{(\theta_3 + \mu_3)} \right] + B_4 \left[ \frac{z_k*(\theta_2) - z_k*(\theta_4)}{\theta_4} \right] \right\} \quad (5.2.8)
\]

Since

\[
L(t) = 1 - P(T>t),
\]
From (5.2.8)

\[
L(t) = B_1 \left[ \frac{1}{(\theta_1 + \mu_1)} \sum_{k=1}^{\infty} \frac{F_k(t)(z^* (\theta_1 + \mu_1))}{1 - z^* (\theta_1 + \mu_1)} \right] + B_2 \left[ \frac{1}{(\theta_2 + \mu_2)} \sum_{k=1}^{\infty} \frac{F_k(t)(z^* (\theta_2 + \mu_2))}{1 - z^* (\theta_2 + \mu_2)} \right] + B_3 \left[ \frac{1}{(\theta_3 + \mu_3)} \sum_{k=1}^{\infty} \frac{F_k(t)(z^* (\theta_3 + \mu_3))}{1 - z^* (\theta_3 + \mu_3)} \right]
\]

Taking Laplace –Steiltje’s tranform on both sides of (5.2.9) we get

\[
L'(s) = B_1 \left[ \frac{1}{(\theta_1 + \mu_1)} \left( f^* (s)(1 - z^* (\theta_1 + \mu_1)) \right) \right] + B_2 \left[ \frac{1}{(\theta_2 + \mu_2)} \left( f^* (s)(1 - z^* (\theta_2 + \mu_2)) \right) \right] + B_3 \left[ \frac{1}{(\theta_3 + \mu_3)} \left( f^* (s)(1 - z^* (\theta_3 + \mu_3)) \right) \right]
\]
\[ +B_4 \left[ \frac{1}{\theta_1} \left( f^*(s) \left( 1-z^*(\theta_0) \right) \right) - B_5 \left( 1-z^*(\theta_0) f^*(s) \right) \right] \] 

(5.2.10)

Write

\[ B_5 = \frac{B_1 + B_2}{\theta_1 + \mu_1}; \quad B_6 = \frac{B_1 + B_3}{\theta_1 + \mu_2}; \quad B_7 = \frac{B_3 + B_4}{\theta_2}; \quad B_8 = \frac{B_2 + B_4}{\theta_4}; \] 

(5.2.11)

\[ \therefore \quad L'(s) = B_5 \frac{f^*(s)\left( 1-z^*(\theta_0 + \mu_1) \right)}{1-z^*(\theta_0 + \mu_1)f^*(s)} - B_6 \frac{\left( 1-z^*(\theta_1 + \mu_2) \right)f^*(s)}{1-z^*(\theta_1 + \mu_2)f^*(s)} \]

\[ +B_7 \frac{f^*(s)\left( 1-z^*(\theta_2) \right)}{1-z^*(\theta_2)f^*(s)} - B_8 \frac{f^*(s)\left( 1-z^*(\theta_4) \right)}{1-z^*(\theta_4)f^*(s)} \] 

(5.2.12)

where \( B_5, B_6, B_7, B_8 \) are calculated using the equations (5.2.6) and (5.2.11)

\[ E(T) = -\frac{d}{ds} \left[ L'(s) \right]_{s=0} \] 

(5.2.13)

Using (5.2.12) and (5.2.13) mean time for recruitment can be obtained.

**SPECIAL CASE:**

Suppose \( f(.), g(.), h(.) \) follows exponential distributions with parameters \( \mu, \lambda_1, \lambda_2 \) respectively.

\[ f^*(s) = \frac{\mu}{\mu + s}; \quad g^*(s) = \frac{\lambda_1}{\lambda_1 + s}; \quad h^*(s) = \frac{\lambda_2}{\lambda_2 + s}. \] 

(5.2.14)
Since

\[ z(x) = \int_0^x g(u)h(x-u)du \]  

(5.2.15)

by convolution theorem of Laplace transform

\[ z^*(\theta) = \frac{\lambda_1\lambda_2}{(\theta + \lambda_1)(\theta + \lambda_2)} \]  

(5.2.16)

Using (5.2.14) and (5.2.16) in (5.2.12) we get

\[ L^*(s) = B_3 \left\{ \frac{\mu(\theta_1 + \mu_1)^2 + (\theta_1 + \mu_1)(\lambda_1 + \lambda_2)}{\mu((\theta_1 + \mu_1)^2 + (\theta_1 + \mu_1)(\lambda_1 + \lambda_2)) + s[(\theta_1 + \mu_1 + \lambda_1)(\theta_1 + \mu_1 + \lambda_2)]} \right\} 

- B_5 \left\{ \frac{\mu(\theta_2 + \mu_2)^2 + (\theta_2 + \mu_2)(\lambda_1 + \lambda_2)}{\mu((\theta_2 + \mu_2)^2 + (\theta_2 + \mu_2)(\lambda_1 + \lambda_2)) + s[(\theta_2 + \mu_2 + \lambda_1)(\theta_2 + \mu_2 + \lambda_2)]} \right\} 

+ B_7 \left\{ \frac{\mu(\theta_3)^2 + (\theta_3)(\lambda_1 + \lambda_2)}{\mu((\theta_3)^2 + (\theta_3)(\lambda_1 + \lambda_2)) + s[(\theta_3 + \lambda_1)(\theta_3 + \lambda_2)]} \right\} 

- B_8 \left\{ \frac{\mu(\theta_4)^2 + (\theta_4)(\lambda_1 + \lambda_2)}{\mu((\theta_4)^2 + (\theta_4)(\lambda_1 + \lambda_2)) + s[(\theta_4 + \lambda_1)(\theta_4 + \lambda_2)]} \right\} \]  

(5.2.17)

Consider the first term of: (5.2.17)

\[ (i.e) \quad B_3 \left\{ \frac{\mu(\theta_1 + \mu_1)^2 + (\theta_1 + \mu_1)(\lambda_1 + \lambda_2)}{\mu((\theta_1 + \mu_1)^2 + (\theta_1 + \mu_1)(\lambda_1 + \lambda_2)) + s[(\theta_1 + \mu_1 + \lambda_1)(\theta_1 + \mu_1 + \lambda_2)]} \right\} \]

Now

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Making similar computation can be made for the other terms in (5.4.4) and we get

\[
\frac{d}{ds} \left[ B_s \left\{ \frac{\mu(\theta_1 + \mu)}{\mu(\theta_1 + \mu)^2 + (\theta_1 + \mu)(\lambda_1 + \lambda_2)} \right\} \right]_{s=0} = \frac{B_s}{\mu} \left\{ \frac{(\theta_1 + \mu)(\theta_1 + \mu + \lambda_2)}{(\theta_1 + \mu)^2 + (\theta_1 + \mu)(\lambda_1 + \lambda_2)} \right\} \tag{5.2.18}
\]

and

\[
\frac{d}{ds} \left[ -B_s \left\{ \frac{\mu(\theta_2 + \lambda_1)(\theta_2 + \mu)}{\mu((\theta_2 + \mu)^2 + (\theta_2 + \mu)(\lambda_1 + \lambda_2)) + s[(\theta_2 + \lambda_1)(\theta_2 + \lambda_2)]} \right\} \right]_{s=0} = \frac{B_s}{\mu} \left\{ \frac{(\theta_2 + \lambda_1)(\theta_2 + \lambda_2)}{(\theta_2)^2 + (\theta_2)(\lambda_1 + \lambda_2)} \right\} \tag{5.2.20}
\]

Using (5.2.18), (5.2.19), (5.2.20), (5.2.21), in (5.2.17), we get the mean time for recruitment for the special case as,
Suppose we write

\[ E(T) = \frac{B_5}{\mu} \left\{ \frac{(\theta_1 + \mu_1 + \lambda_1)(\theta_1 + \mu_1 + \lambda_2)}{(\theta_1 + \lambda_1)^2 + (\theta_1 + \lambda_2)(\lambda_1 + \lambda_2)} \right\} - \frac{B_5}{\mu} \left\{ \frac{(\theta_2 + \lambda_2)(\theta_2 + \lambda_3)}{(\theta_2 + \lambda_2)^2 + (\theta_2 + \lambda_3)(\lambda_2 + \lambda_3)} \right\} \]

(5.2.22)

Suppose we write

\[ A_1 = \frac{1}{\mu} \left\{ \frac{(\theta_1 + \mu_1 + \lambda_1)(\theta_1 + \mu_1 + \lambda_2)}{(\theta_1 + \mu_1)^2 + (\theta_1 + \mu_1)(\lambda_1 + \lambda_2)} \right\}; \]

\[ A_2 = \frac{1}{\mu} \left\{ \frac{(\theta_2 + \lambda_2)(\theta_2 + \lambda_3)}{(\theta_2 + \lambda_2)^2 + (\theta_2 + \lambda_3)(\lambda_2 + \lambda_3)} \right\}; \]

\[ A_3 = \frac{1}{\mu} \left\{ \frac{(\theta_3 + \lambda_3)(\theta_3 + \lambda_4)}{(\theta_3 + \lambda_3)^2 + (\theta_3 + \lambda_4)(\lambda_3 + \lambda_4)} \right\}; A_4 = \frac{1}{\mu} \left\{ \frac{(\theta_4 + \lambda_4)(\theta_4 + \lambda_5)}{(\theta_4 + \lambda_4)^2 + (\theta_4 + \lambda_5)(\lambda_4 + \lambda_5)} \right\} \]

(5.2.23)

\[ \therefore \text{from (5.2.22) and (5.2.23) we get} \]

\[ E(T) = [A_1 B_5 - A_2 B_6 + A_3 B_7 - A_4 B_8] \]

(5.2.24)

Equation (5.2.24) gives the meantime for recruitment for the special case.

5.3 Numerical Illustration

In this section the above model is numerically illustrated and relevant conclusions are made.

Case (i)

Fixing \( \theta_1 = 0.8; \theta_2 = 0.7; \theta_3 = 0.6; \theta_4 = 0.5; \mu_1 = 1; \mu_2 = 2; \mu = 0.3 \) and varying \( \lambda_1 \) and \( \lambda_2 \), the values of \( E(T) \) are computed and tabulated in Table 5.3.1
Table 5.3.1

\( E(T) \)

<table>
<thead>
<tr>
<th>( \lambda_1 )</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>4.0024</td>
<td>2.1466</td>
<td>1.4645</td>
<td>1.1109</td>
<td>0.8948</td>
</tr>
<tr>
<td>0.4</td>
<td>2.3540</td>
<td>1.2715</td>
<td>0.8687</td>
<td>0.6594</td>
<td>0.5312</td>
</tr>
<tr>
<td>0.6</td>
<td>1.6421</td>
<td>0.8988</td>
<td>0.6153</td>
<td>0.4673</td>
<td>0.3767</td>
</tr>
<tr>
<td>0.8</td>
<td>1.2273</td>
<td>0.692</td>
<td>0.4752</td>
<td>0.3613</td>
<td>0.2913</td>
</tr>
<tr>
<td>1.0</td>
<td>0.8935</td>
<td>0.5607</td>
<td>0.3864</td>
<td>0.2941</td>
<td>0.2372</td>
</tr>
</tbody>
</table>

CONCLUSION:

From the above table, we make the following observations.

(i) The meantime for recruitment decreases as \( \lambda_1 \) increases, keeping other parameters fixed. In other words, when the total loss of manhours increases on the average, the mean time for recruitment decreases.

(ii) The meantime for recruitment decreases as \( \lambda_2 \) increases, keeping other parameters fixed. In other words, when the average loss of manhours increases, the mean time for recruitment decreases.
(iii) The meantime for recruitment decreases as $\lambda_1$ and $\lambda_2$ increases simultaneously, keeping other parameters fixed. Thus the organization can make use of anyone of the above conclusions in order to postpone the time to recruitment.

**Case (ii)**

Fixing $\theta_1 = 0.8; \theta_2 = 0.7; \theta_3 = 0.6; \theta_4 = 0.5; \mu_1 = 1; \mu_2 = 2; \lambda_1 = 0.4$ and varying $\lambda_1$ and $\lambda_2$, the values of $E(T)$ are computed and tabulated in

**Table 5.3.2**

<table>
<thead>
<tr>
<th>$\lambda_1$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
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<td>$\mu$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.2</td>
<td>2.2356</td>
<td>1.2423</td>
<td>0.8558</td>
<td>0.6521</td>
<td>0.5266</td>
</tr>
<tr>
<td>0.4</td>
<td>2.4132</td>
<td>1.2862</td>
<td>0.8752</td>
<td>0.6630</td>
<td>0.5335</td>
</tr>
<tr>
<td>0.6</td>
<td>2.4724</td>
<td>1.3008</td>
<td>0.8816</td>
<td>0.6666</td>
<td>0.5359</td>
</tr>
<tr>
<td>0.8</td>
<td>2.5020</td>
<td>1.3081</td>
<td>0.8849</td>
<td>0.6684</td>
<td>0.5370</td>
</tr>
<tr>
<td>1.0</td>
<td>2.5198</td>
<td>1.3125</td>
<td>0.8868</td>
<td>0.6695</td>
<td>0.5377</td>
</tr>
</tbody>
</table>
CONCLUSION:

From the above table, we make the following observations.

(i) The meantime for recruitment decreases as \( \lambda \) increases, keeping other parameters fixed. In other words, when the total loss of manhours increases on the average, the mean time for recruitment decreases.

(ii) The meantime for recruitment increases as \( \mu \) increases, keeping other parameters fixed. In other words, when the average loss of manhours increases, the mean time for recruitment increases.

(iii) The meantime for recruitment decreases as \( \lambda \) and \( \mu \) increases simultaneously, keeping other parameters fixed.

Thus the organization can make use of anyone of the above conclusions in order to postpone the time to recruitment.

Case (iii)

Fixing \( \theta_1 = 0.8; \theta_2 = 0.7; \theta_3 = 0.6; \theta_4 = 0.5; \mu = 1; \mu_2 = 2; \lambda_1 = 0.4 \) and varying \( \lambda \) and \( \lambda_2 \), the values of \( E(T) \) are computed and tabulated in Table 5.3.3.
**Table 5.3.3**

\( E(T) \)

<table>
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<th>( \lambda_2 )</th>
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<th>2</th>
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<th>5</th>
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<td>0.2</td>
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<td>1.2085</td>
<td>0.8023</td>
<td>0.6012</td>
<td>0.4808</td>
</tr>
<tr>
<td>0.4</td>
<td>2.5202</td>
<td>1.2655</td>
<td>0.8490</td>
<td>0.6389</td>
<td>0.5123</td>
</tr>
<tr>
<td>0.6</td>
<td>2.5111</td>
<td>1.2845</td>
<td>0.8645</td>
<td>0.6515</td>
<td>0.5227</td>
</tr>
<tr>
<td>0.8</td>
<td>2.5066</td>
<td>1.2940</td>
<td>0.8723</td>
<td>0.6578</td>
<td>0.5280</td>
</tr>
<tr>
<td>1.0</td>
<td>2.5039</td>
<td>1.2997</td>
<td>0.8770</td>
<td>0.6616</td>
<td>0.5311</td>
</tr>
</tbody>
</table>

**CONCLUSION:**

From the above table, we make the following observations.

(i) The meantime for recruitment decreases as \( \lambda_2 \) increases, keeping other parameters fixed. In other words, when the total loss of manhours increases on the average, the mean time for recruitment decreases.

(ii) The meantime for recruitment decreases as \( \mu \) increases, keeping other parameters fixed. In other words, when the average loss of manhours increases, the mean time for recruitment increases.
(iii) The meantime for recruitment decreases as \( \mu \) and \( \lambda_2 \) increases simultaneously, keeping other parameters fixed.
Thus the organization can make use of anyone of the above conclusions in order to postpone the time to recruitment.