CHAPTER 2

CONFIDENCE LIMITS FOR THE STEADY-STATE AVAILABILITY OF A STOCHASTIC MODEL OF UREA DECOMPOSITION SYSTEM IN THE FERTILIZER INDUSTRY

2.1 INTRODUCTION:

The role and importance of reliability has been a core issue in any Engineering industry for the last three decades. Reliability is of importance to both manufacturers and consumers. From the consumers and manufacturers point of view reliability provides quality and vice versa. So, the reliability measure is very important, as the improvement in reliability is achieved through quality. While this measure of reliability assumes great importance in industry there are many situations where continuous failure free performance of the system, though desirable, may not be absolutely necessary.

In such situations it may be eminently reasonable to introduce another measure called 'availability', which denotes the probability that the system is functioning at any time point. In the process industry like the fertilizer industry, we come across many processes like synthesis decomposition, crystallization, prilling and recovery [see U.N. Fertiliser Manual (1967), Kumar et al. (1991)].

The gas liquid mixture (urea, NH_3, CO_2, Biuret) flows from the reactor at 126°C into the upper part of a high-pressure decomposer where the flushed gases are separated. The liquid falls through a sieve plate, which comes in contact with high temperature gas available from the boiler and the falling film heater. The process is repeated in a low-pressure absorber. The solution is further heated to 165°C in the falling film heater, which reduces the Biuret formation and hydrolysis of urea (see figure 1).

The overhead gases from the high-pressure decomposition go to the high-pressure absorber cooler. The liquid flows to the top of the low-pressure absorber and is cooled in a heat exchanger. Additional flushing of the solution takes place in the upper part of the low-pressure absorber to reduce the solution pressure from 17.5 to 2.5 kg/cm^2. The low-pressure absorber has four sieve trays and a packed bed. In the packed bed, the remaining ammonia is stripped off by CO_2 gas.

The overhead gases go to the low-pressure absorber cooler, in which the pressure is controlled at 2.2 kg/cm^2. Most of the excess ammonia and carbonate is separated from the solution flowing to the gas separator. The gas separator has two parts:

(i) the upper part is at 105°C and 0.3 kg/cm^2 and here the remaining small amounts of ammonia and CO_2 are recovered by reducing the pressure; the sensible heat of the solution is enough to vaporize these gases.

(ii) The lower part has a packed section at 110°C and atmospheric pressure.

Air containing a small amount of ammonia and CO_2 is fed off from the gas absorber by an on/off gas blower, to remove the remaining small amounts of ammonia and CO_2 present on the solution. Off gases from the lower and upper parts are mixed and led to the off-gas condenser. The urea solution concentrated to 70-75% is fed to a crystallizer.

It is well known that the steady state availability is a satisfactory measure for systems, which are operated continuously (e.g. a detection radar system).

A point estimator of steady state availability is usually the only statistic calculated, although decisions about the true steady state availability of the system should take uncertainty into account. Since

$$A_\infty = \frac{MTBF}{MTBF + MTTR},$$

the uncertainties in the values of the MTBF and MTTR reflect an uncertainty in the values of the point steady state availability (where MTBF stand for Mean Time Between Failures and MTTR for Mean Time To Repair).

By treating these uncertain parameters as random variables, we can obtain the distribution of point steady state availability by combining the distribution of operation and repair times. Hence we can construct estimators and confidence limits for the steady state availability, which are consistent with equivalent statements on the operating time and repair time parameters. Thomson (1966) has derived techniques for placing a lower confidence limit on the system's steady state availability that differ significantly from a specified value, when MTBF and MTTR are estimated from test data.

Gray and Lewis (1967) established the exact confidence interval for steady state availability of systems assuming that the time between failures is described by an exponential random variable and that the time to repair is described by a lognormal random variable.

Butterworth and Nikolaisen (1973) have obtained the bounds on the availability function for the general repair time distribution. Masters and Lewis (1987) have derived exact confidence limits for the system steady state availability with Gamma life time and lognormal repair time. Masters et al. (1992) have proposed a method of establishing exact confidence limits for steady state availability of systems when the time between failure and time to repair are independent Weibull and lognormal random variables respectively.

Abu-Salih et al. (1990) have derived $100(1-\alpha)\%$ confidence limits for the steady state availability of a two unit parallel system with the assumption that the failure time distribution is exponential and the repair time has a two stage Erlangian distribution. They have also assumed that an upstate unit will not fail when the other unit is in the second stage of repair.

Chandrasekhar and Natarajan (1994a, b) have considered and n-unit parallel system with the assumption that the failure time distribution is exponential and the repair time has a two stage Erlangian distribution. Further they have assumed that an operable unit can also fail while the other unit is in the second stage of repair. In particular they have derived a 100(1-α)% confidence limits for the steady state availability of a two unit parallel system. Yadavalli et al. (2001, 2002, 2005) have studied the 100(1- α)% confidence limits for different types of systems (parallel and standby) with the assumption that the repair facility is not available for a random time.

The organisation of this chapter is as follows: Section 2.1 is introductory in nature, the system description and notation is given in Section 2.2. The availability analysis of the system is studied in Section 2.3. In Section 2.4, the interval estimation for A_∞ is studied, and subsequently the numerical results for Sections 2.3 and 2.4 are shown in Section 2.5.

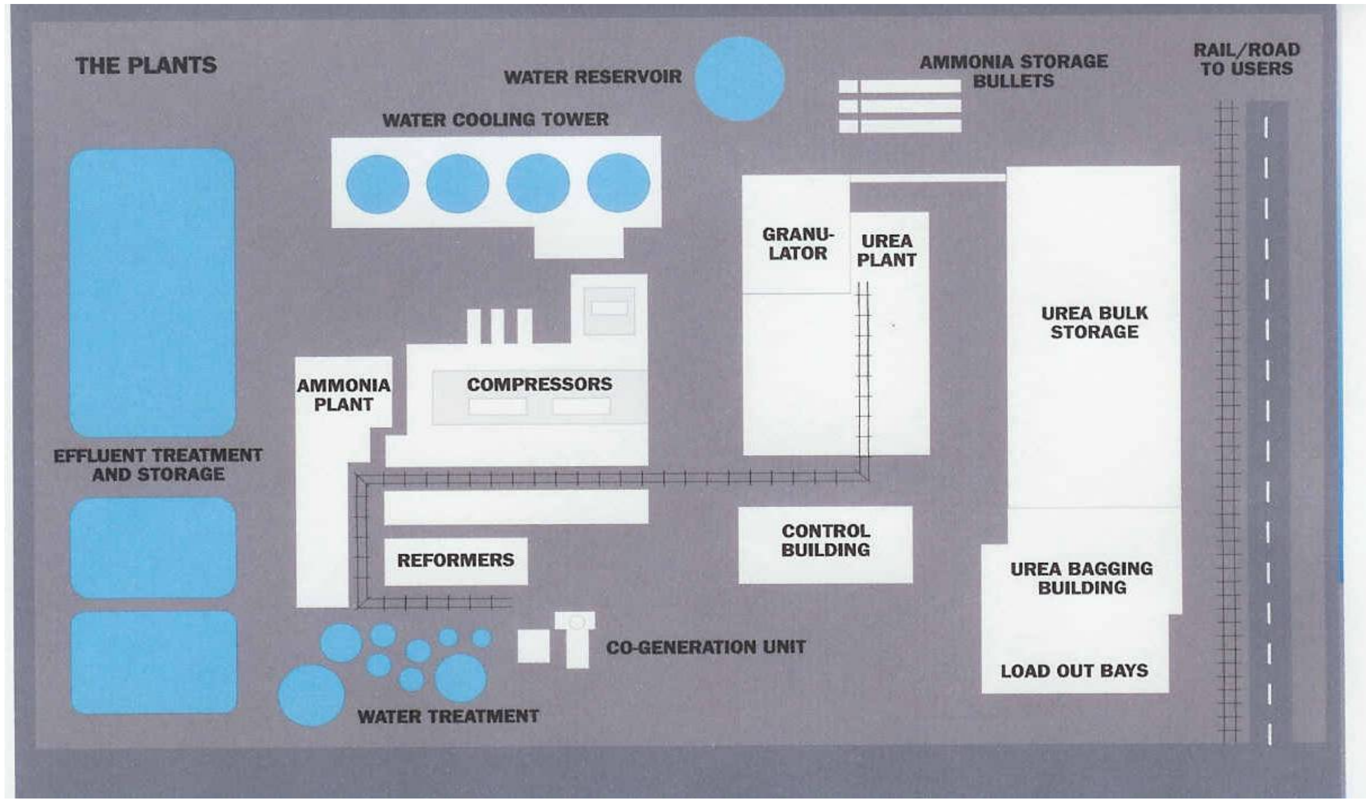

Figure 2.1 Urea plant (by courtesy of Balance Kapuni, South Taranaki, New Zealand)

2.2 SYSTEM DESCRIPTION AND NOTATION

The complex system described above consisting of four subsystems connected in series.

1. Subsystem (A_i) has two units. Unit A_1 is the boiler for the high-pressure absorber and A_2 is the falling filter heater for the low-pressure absorber. This subsystem (A_i) fails by failure of A_1 or A_2.
2. Subsystem B_i has two units in series. Unit B_1 is called the high-pressure absorber and unit B_2 is called the low-pressure absorber. Failure of either causes complete failure of the system.
3. Subsystem D, the gas separator, has one unit only, arranged in series with B_1 and B_2. Failure of unit D causes complete failure of the system.
4. Subsystem E_i the heat exchanger has one unit in standby. Failure occurs only when both units fail.
5. The life time of the units (A_i, B_i, D, E; i = 1,2) are exponentially distributed random variables with parameters λ_i; i=1,2,3,4,5,6.
6. The repair time of the units are exponentially distributed random variables with parameters $\mu_{j;}$ j = 1,2,3,4,5,6.
7. Each unit is as good as new after the repair.
8. Spare parts and the repair facility are always available.
9. The standby unit in E is of the same nature and capacity as the operating active unit.

10. The repair is done at regular time interval or at the time of failure. The repair includes the replacement as well.
11. There is no simultaneous failure among subsystems.
12. State O indicates the operating state without using standby unit and state 6 indicates the operating state using the standby state in subsystem E.
13. E_1 is the state of the system running at full capacity with a standby unit in subsystem E.

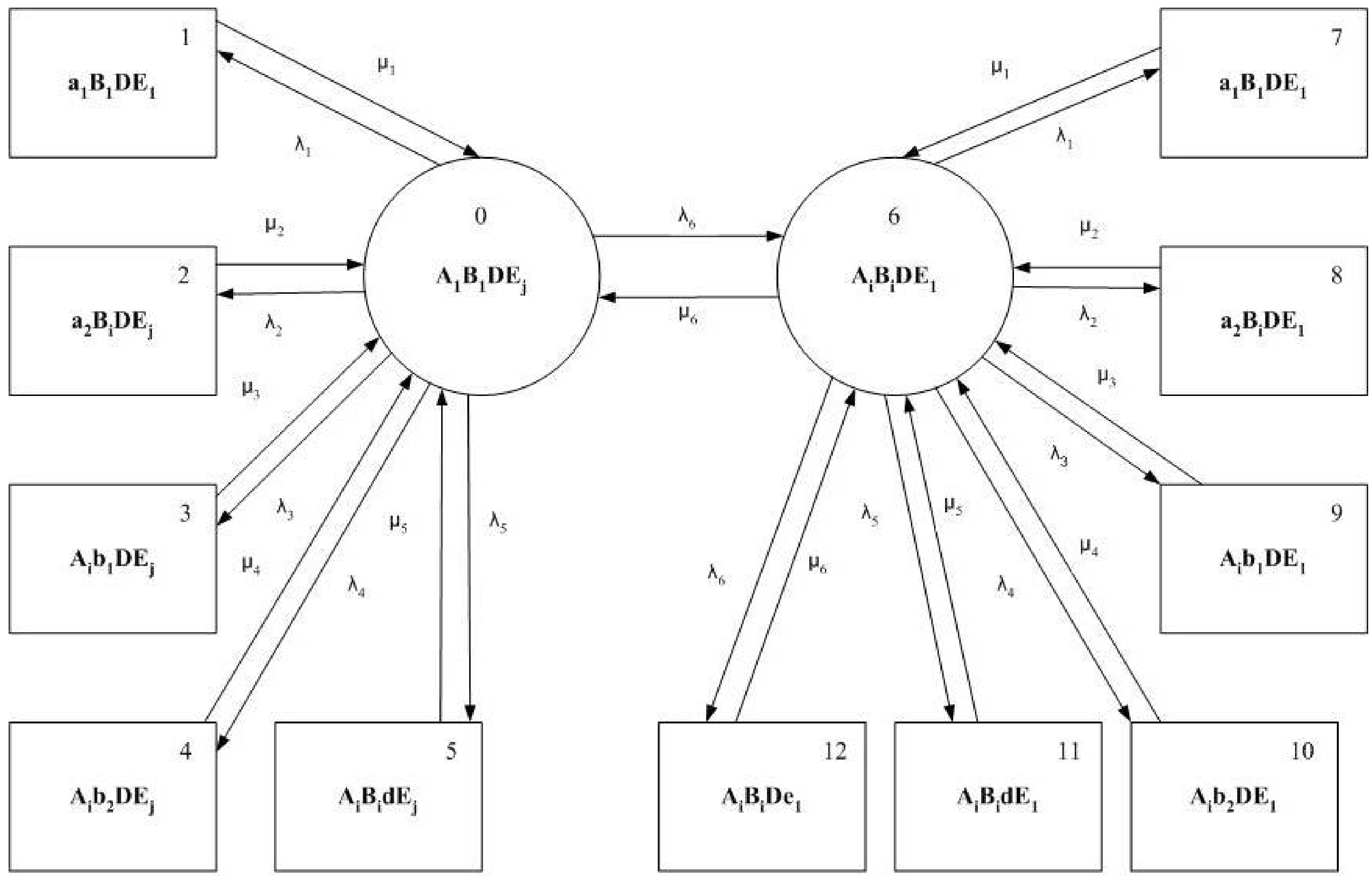
1
a1B1DE1
2
a2BiDEj
3
Aib1DEj
4
Aib2DEj
5
AiBidEj
0
A1B1DEj
6
AiBiDE1
7
a1B1DE1
8
a2BiDE1
9
Aib1DE1
10
Aib2DE1
11
AiBidE1
12
AiBiDe1
μ1
λ1
μ2
λ2
μ3
λ3
μ4
λ4
μ5
λ5
μ6
λ6

Figure 2.2

2.3 AVAILABILITY ANALYSIS OF THE SYSTEM

Let $P_i(t)$ = P[system is in state i, with only failure at time t]

$$P_i = \lim_{t \to \infty} P_i(t).$$

Writing the application of flow balance (Ravindran et al. (1982)), the steady state probability can be determined from the following equations:

With the help of Figure 2.2, we obtain the following differential equations describing the state probabilities:

$$P_0'(t) = -(\sum_{i=1}^{6} \lambda_i) P_0(t) + \sum_{i=1}^{6} \mu_i P_i(t) \tag{2.3.1}$$

$$P_6'(t) = -(\sum_{i=1}^{6} \lambda_i + \mu_6) P_6(t) + \sum_{i=1}^{6} \mu_i P_{i+6}(t) + \lambda_6 P_0(t) \tag{2.3.2}$$

$$\sum_{i=1}^{5} \mu_i P_i'(t) = -\sum_{i=1}^{5} \mu_i P_i(t) + \sum_{i=1}^{5} \mu_i P_0(t) \qquad i = 1, 2, \ldots, 5 \tag{2.3.3}$$

$$\sum_{i=1}^{6} \mu_i P_{i+6}'(t) = -\sum_{i=1}^{5} \mu_i P_{i+6}(t) + \sum_{i=1}^{6} \mu_i P_6(t) \qquad i = 1, 2, \ldots, 6 \tag{2.3.4}$$

$$\sum_{i=1}^{6} P_i(t) = 1 \tag{2.3.5}$$

In the steady state, the equations (2.3.1) – (2.3.5) become:

$$(\sum_{i=1}^{6}\lambda_i)\,p_0 = \sum_{i=1}^{6}\mu_i\,p_i \tag{2.3.6}$$

$$(\sum_{i=1}^{6}\lambda_i + \mu_6)\,p_6 = \sum_{i=1}^{6}\mu_i\,p_{i+6} + \lambda_6\,p_0 \tag{2.3.7}$$

$$\sum_{i=1}^{5}\mu_i\,p_i = \sum_{i=1}^{5}\lambda_i\,p_0\,;\,i = 1,2,\ldots,5 \tag{2.3.8}$$

$$\sum_{i=1}^{6}\mu_i\,p_{i+6} = \sum_{i=1}^{6}\lambda_i\,p_6\,;\,i = 1,2,\ldots,6 \tag{2.3.9}$$

$$\sum_{i=1}^{6}p_i = 1\,. \tag{2.3.10}$$

Solving the system of simultaneous equations (2.3.6) - (2.3.10), the steady state availability A_∞ can be obtained as

$$A_\infty = p_0 + p_6 = \frac{1+\frac{\lambda_6}{\mu_6}}{1+(1+\frac{\lambda_6}{\mu_6})\sum_{i=1}^{6}\frac{\lambda_i}{\mu_i}}\,.$$

For different parameters, Tables 2.3.1(a) – 2.3.1 (e) and the Figure 2.3 explain the availability function.

2.4. INTERVAL ESTIMATION FOR A_∞

Let $X_{i1}, X_{i2},\ldots, X_{in},;\ (i = 1, 2, \ldots, 6)$ be random samples of size n, each drawn from different exponential populations with failure rates λ_i, similarly $Y_{i1}, Y_{i2},\ldots, Y_{in},;\ (i = 1, 2, \ldots, 6)$ be random samples each drawn from exponential populations with parameters μ_i. Since λ_i 's are the parameters of the exponential distribution, then an estimate can be found for λ_i or for $1/\lambda_i = \alpha_i$ (say), which is equal to the mean value of the time of failure-free operation.

For the analysis, let

$$\alpha_i = \frac{1}{\lambda_i}, \beta_i = \frac{1}{\mu_i}.$$

Then the maximum likelihood estimates (MLE) of α_i and β_i are given by

$$\frac{1}{n}\sum_{j=1}^{n} X_{ij} = \overline{X}_i, \qquad \frac{1}{n}\sum_{j=1}^{n} Y_{ij} = \overline{Y}_i.$$

Hence

$$\hat{A}_\infty = \frac{1+\frac{\overline{y}_6}{\overline{x}_6}}{1+(1+\frac{\overline{y}_6}{\overline{x}_6})\sum_{i=1}^{6}\frac{\overline{y}_i}{\overline{x}_i}}.$$

By an application of the multivariate central limit theorem (Rao (1973)), it follows that

$\sqrt{n}(\overline{x}-\theta) \xrightarrow{D} N_6(0,\Sigma)$ as $n \to \infty$ where $\overline{X} = (\overline{X}_1, \overline{X}_2, \overline{X}_3, \overline{X}_4, \overline{X}_5, \overline{X}_6, \overline{Y}_1, \overline{Y}_2, \overline{Y}_3, \overline{Y}_4, \overline{Y}_5, \overline{Y}_6)$

We know that $\hat{A}_\infty$ is a real-valued function in $\overline{X}_i$ and $\overline{Y}_i$; i = 1, 2, ..., 6.

$$\theta = (\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6).$$

The dispersion matrix $\Sigma = (\sigma_{ij})_{12x12}$ is given by

$$\Sigma = diag(\alpha_1^2, \ldots, \alpha_6^2, \beta_1^2, \ldots, \beta_6^2).$$

From Rao (1973), as $n \to \infty$, i.e. using the multivariate central limit theorem,

$$\sqrt{n}(\hat{A}_\infty - A_\infty) \xrightarrow{D} N_6(0, \sigma^2(\theta)) \text{ where}$$

$$\sigma^2(\theta) = \sum_{i=1}^{6}\left(\frac{\partial A_\infty}{\partial \alpha_i}\right)^2 \sigma_{ii} + \sum_{i=1}^{6}\left(\frac{\partial A_\infty}{\partial \beta_i}\right)^2 \sigma_{ii}$$

Replacing by its consistent estimator

$\hat{\theta} = (\overline{X}_1, \overline{X}_2, \ldots, \overline{X}_6, \overline{Y}_1, \overline{Y}_2, \ldots, \overline{Y}_6)$, it follows that $\hat{\sigma}^2 = \sigma^2(\hat{\theta})$ is a consistent estimator of $\sigma^2(\theta)$. Since $\sigma^2(\theta)$ is a consistent estimator of θ, we know that $\sigma^2(\hat{\theta})$ is a consistent estimator of θ (see Wackerly et al. (2002)).

Then by Slutsky's theorem (Slutsky (1928))

$$\frac{\sqrt{n}\,(\hat{A}_\infty - A_\infty)}{\hat{\sigma}} \xrightarrow{D} N(0,1) \text{ as n} \to \infty.$$

This implies that

$$P\left[-k_{\frac{\alpha}{2}} \le \frac{\sqrt{n}\,(\hat{A}_\infty - A_\infty)}{\hat{\sigma}} \le k_{\frac{\alpha}{2}}\right] = 1 - \alpha,$$

where $k_{\alpha/2}$ is obtained from normal tables, i.e. 100(1 – α)% confidence interval is given by

$$\hat{A}_\infty \pm k_{\alpha/2}\hat{\sigma}(\theta).$$

2.5 NUMERICAL ILLUSTRATION

For different values of the parameters, the numerical computations for A_∞ are shown in Tables 2.5.1(a) – 2.5.1(e) and Figure 2.3.

The confidence limits for A_∞ were also obtained and shown Table 2.5.2.

		A_∞									
$A_1=\alpha_2$	$A_3=\alpha_4=\alpha_5$	$\alpha_6=$ 0.0	$\alpha_6=$ 0.001	$\alpha_6=$ 0.002	$\alpha_6=$ 0.003	$\alpha_6=$ 0.004	$\alpha_6=$ 0.005	$\alpha_6=$ 0.006	$\alpha_6=$ 0.007	$\alpha_6=$ 0.008	$\alpha_6=$ 0.009
0.0	0.0	1.00000	0.99998	0.99994	0.99985	0.99974	0.99961	0.99944	0.99924	0.99901	0.99875
	0.005	0.90909	0.90907	0.90903	0.90897	0.90888	0.90877	0.90863	0.90846	0.90827	0.90806
	0.010	0.83333	0.83332	0.83328	0.83323	0.83316	0.83306	0.83294	0.83280	0.83264	0.83247
0.001	0.0	0.99602	0.99600	0.99595	0.99587	0.99577	0.99563	0.99546	0.99526	0.99503	0.99478
	0.005	0.90578	0.90578	0.90574	0.90568	0.90559	0.90548	0.90534	0.90517	0.90498	0.90477
	0.010	0.83056	0.83055	0.83052	0.83046	0.83039	0.83029	0.83018	0.83004	0.82988	0.82970
0.005	0.0	0.98037	0.98037	0.98033	0.98025	0.98015	0.98002	0.97985	0.97966	0.97944	0.97919
	0.005	0.89284	0.89284	0.89280	0.89274	0.89266	0.89254	0.89241	0.89255	0.89207	0.89186
	0.010	0.81967	0.81966	0.81962	0.81957	0.81950	0.81941	0.81929	0.81916	0.81901	0.81883

Table 2.5.1 (a): Effect of Failure Rate (taking $\beta_1 = \beta_2 = 0.5$; $\beta_3 = \beta_4 = 0.2$; $\beta_5 = 0.1$; $\beta_6 = 0.25$)

		A_∞									
$\alpha_1=\alpha_2$	$A_3=\alpha_4=\alpha_5$	$\alpha_6=$ 0.0	$\alpha_6=$ 0.001	$\alpha_6=$ 0.002	$\alpha_6=$ 0.003	$\alpha_6=$ 0.004	$\alpha_6=$ 0.005	$\alpha_6=$ 0.006	$\alpha_6=$ 0.007	$\alpha_6=$ 0.008	$\alpha_6=$ 0.009
0.0	0.0	1	0.99998	0.99994	0.99986	0.99975	0.99961	0.99944	0.99924	0.99901	0.99875
	0.005	0.9090	0.90908	090904	0.90894	0.90888	0.90877	0.90863	0.90846	0.90827	0.90806
	0.010	0.83333	0.83332	0.83329	0.83323	0.83316	0.83316	0.83306	0.83294	0.83280	0.83247
0.001	0.0	0.99668	0.99666	0.99661	0.99654	0.99643	0.99629	0.99612	0.99592	0.99569	0.99544
	0.005	0.90634	0.90633	0.90629	0.90623	0.90614	0.90602	0.90588	0.90572	0.90553	0.90532
	0.010	0.83102	0.83101	0.83098	0.83093	0.83085	0.83075	0.83064	0.83050	0.83034	0.83016
0.005	0.0	0.98361	0.98359	0.98355	0.98347	0.98336	0.98323	0.98306	0.98287	0.98265	0.98240
	0.005	0.89552	0.89551	0.89547	0.89541	0.89532	0.89521	0.89507	0.89491	0.89473	0.89452
	0.010	0.82192	0.82191	0.82187	0.82182	0.82175	0.82165	0.82154	0.82140	0.82125	0.82107

Table 2.5.1 (b): Effect of Failure Rate (taking $\beta_1 = \beta_2 = 0.6$; $\beta_3 = \beta_4 = 0.2$; $\beta_5 = 0.1$; $\beta_6 = 0.25$)

		A_∞									
$\alpha_1=\alpha_2$	$A_3=\alpha_4=\alpha_5$	$\alpha_6=$ 0.0	$\alpha_6=$ 0.001	$\alpha_6=$ 0.002	$\alpha_6=$ 0.003	$\alpha_6=$ 0.004	$\alpha_6=$ 0.005	$\alpha_6=$ 0.006	$\alpha_6=$ 0.007	$\alpha_6=$ 0.008	$\alpha_6=$ 0.009
0.0	0.0	1	0.99998	0.99994	0.99986	0.99975	0.99961	0.99944	0.99924	0.99901	0.99875
	0.005	0.92308	0.92306	0.92302	0.92296	0.92286	0.92274	0.92260	0.92243	0.92223	0.92201
	0.010	0.85714	0.85713	0.85710	0.85704	0.85696	0.85685	0.92260	0.92243	0.92223	0.92201
0.001	0.0	0.99715	0.99714	0.99709	0.99701	0.99690	0.99676	0.99659	0.99639	0.99617	0.99591
	0.005	0.92065	0.92064	0.92060	0.92053	0.92044	0.92032	0.92017	0.92000	0.91981	0.91969
	0.010	0.85505	0.85504	0.85500	0.85494	0.85486	0.85476	0.84637	0.84623	0.84606	0.84588
0.005	0.0	0.98592	0.98590	0.98585	0.98578	0.98567	0.98553	0.98537	0.98517	0.98495	0.98470
	0.005	0.91106	0.91105	0.91101	0.91094	0.91085	0.91074	0.91060	0.91043	0.91024	0.91003
	0.010	0.84677	0.84676	0.84673	0.84667	0.84659	0.84649	0.84637	0.84623	0.84606	0.84588

Table 2.5.1 (c): Effect of Failure Rate (taking $\beta_1 = \beta_2 = 0.7$; $\beta_3 = \beta_4 = 0.3$; $\beta_5 = 0.1$; $\beta_6 = 0.25$)

		A_∞									
$\alpha_1=\alpha_2$	$\alpha_3=\alpha_4=\alpha_5$	$\alpha_6=$ 0.0	$\alpha_6=$ 0.001	$\alpha_6=$ 0.002	$\alpha_6=$ 0.003	$\alpha_6=$ 0.004	$\alpha_6=$ 0.005	$\alpha_6=$ 0.006	$\alpha_6=$ 0.007	$\alpha_6=$ 0.008	$\alpha_6=$ 0.009
0.0	0.0	0.99998	0.99994	0.99986	0.99975	0.99975	0.99961	0.99944	0.99924	0.99901	0.99875
	0.005	0.93023	0.93022	0.93018	0.93011	0.93001	0.92989	0.92975	0.92957	0.92937	0.92915
	0.010	0.86957	0.86955	0.86952	0.86946	086937	0.8627	0.86914	0.86899	0.86882	0.86862
0.001	0.0	0.99751	0.99749	0.99744	0.99736	0.99726	0.99712	0.99695	0.99675	0.99652	0.99626
	0.005	0.92807	0.92806	0.92802	0.92795	0.92786	0.92774	0.92759	0.92742	0.92722	0.92700
	0.010	0.86768	0.86767	0.86763	0.86757	0.86749	0.86738	0.86726	0.86711	0.86893	0.86674
0.005	0.0	0.98765	0.98764	0.98759	0.98752	0.98741	0.98727	0.98711	0.98691	0.98669	0.98644
	0.005	0.91954	0.91953	0.91949	0.91942	0.91933	0.91921	0.91906	0.91890	0.91870	0.91848
	0.010	0.86022	0.86020	0.86017	0.86011	0.86003	0.85992	0.85800	0.85970	0.85948	0.85929

Table 2.5.1 (d): Effect of Failure Rate (taking $\beta_1 = \beta_2 = 0.8$; $\beta_3 = \beta_4 = 0.4$; $\beta_5 = 0.1$; $\beta_6 = 0.25$)

		A_∞									
α_1=α_2	α_3=α_4=α_5	α_6= 0.0	α_6= 0.001	α_6= 0.002	α_6= 0.003	α_6= 0.004	α_6= 0.005	α_6= 0.006	α_6= 0.007	α_6= 0.008	α_6= 0.009
0.0	0.0	1	0.99998	0.99994	0.99986	0.99975	0.99961	0.99944	0.99924	0.99901	0.99875
	0.001	0.93458	0.93457	0.93452	0.93446	0.93436	0.93424	0.93409	0.93391	0.93371	0.93349
	0.005	0.87719	0.87718	0.87714	0.87708	0.87100	0.87689	0.87676	0.87661	0.87643	0.87623
0.001	0.0	0.99778	0.99777	0.99772	0.99764	0.99753	0.99739	0.99722	0.99702	0.99680	0.99654
	0.001	0.93264	0.93263	0.93259	0.93252	0.93242	0.93230	0.93215	0.93198	0.93178	0.93156
	0.005	0.87549	0.87547	0.87544	0.87538	0.87529	0.87519	0.87506	0.87490	0.87473	0.87453
0.005	0.0	0.98901	0.98900	0.98895	0.98887	0.98876	0.98863	0.98846	0.98827	0.98804	0.98779
	0.001	0.92497	0.92496	0.92492	0.92485	0.92476	0.92464	0.92449	0.92432	0.92413	0.92391
	0.005	0.86873	0.86871	0.86868	0.86862	0.86854	0.86843	0.86830	0.86815	0.86798	0.86778

Table 2.5.1 (e): Effect of Failure Rate (taking β_1 =β_2 = 0.9; β_3 = β_4 = 0.5; β_5 = 0.1; β_6 = 0.25)

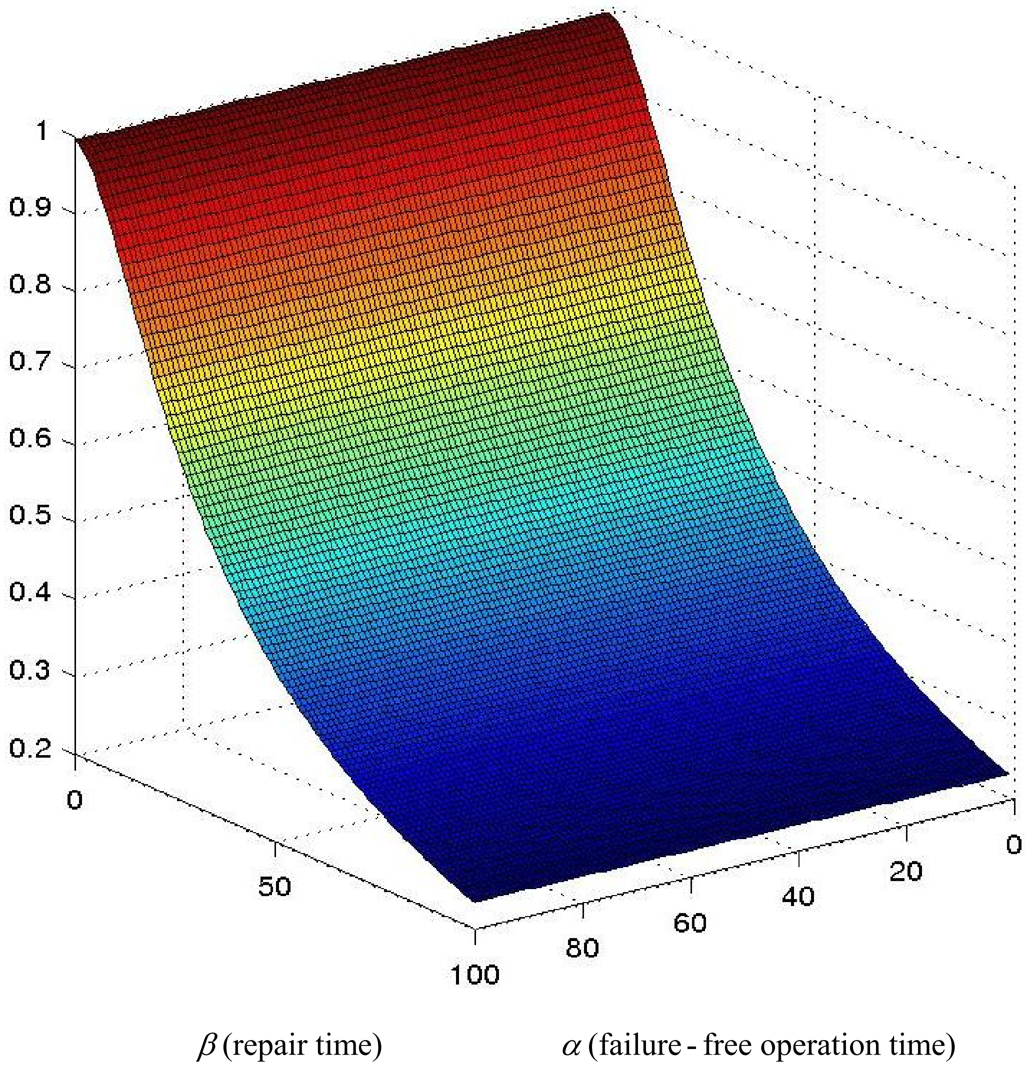

Figure 2.3: Availability for different α (failure-free operation time) and β (repair time) values

Table 2.5.2 presents the α = 95% and α = 99% confidence intervals for different simulated samples.

For $\alpha_1=\alpha_2=0;\ \alpha_3=\alpha_4=\alpha_5=0;\ \alpha_6=0.001$ $\beta_1=\beta_2=0.5;\ \beta_3=\beta_4=0.2;\ \beta_5=0.1;\ \beta_6=0.25$			
		α = 95%	**α = 99%**
n = 100	20	(0.79414; 0.96586)	(0.76702; 0.99298)
	40	(0.62674; 0.78366)	(0.60196; 0.80824)
	60	(0.54593 ; 0.68317)	(0.52533; 0.69537)
	80	(0.50775; 0.61515)	(0.48552; 0.62088)
	100	(0.47816; 0.56924)	(0.45556; 0.57544)
n = 200	20	(0.81928; 0.94072)	(0.80008; 0.95992)
	40	(0.64986; 0.76074)	(0.63234; 0.77826)
	60	(0.57289; 0.66421)	(0.55843; 0.67867)
	80	(0.52347; 0.59943)	(0.51147; 0.61143)
	100	(0.49148; 0.55592)	(0.48128; 0.56612)
n = 2000	20	(0.86080; 0.89920)	(0.85468; 0.90532)
	40	(0.68790; 0.72270)	(0.67998; 0.73062)
	60	(0.60409; 0.63301)	(0.59953; 0.63757)
	80	(0.54945; 0.57345)	(0.54567; 0.57723)
	100	(0.51356; 0.53384)	(0.51032; 0.53708)

Table 2.5.2

It can be observed that, as n increases, the steady state availability decreases.

2.6 CONCLUSION

The availability of equipment used for de-composition process in the urea production system is discussed. The system consisted of four subsystems, with a standby unit in one of the sub-systems. The failure and repair rates in each subsystem are taken to be constants. The log-run availability of the system is calculated, and the asymptotic confidence limits are obtained for the steady-state availability. The results are illustrated numerically for different measures. In tables 2.5.1(a) – (e), Figure 2.3 and table 2.5.2 shows that, as the repair time increases, the steady state availability decreases. This has been noticed in point availability and in the confidence limits.