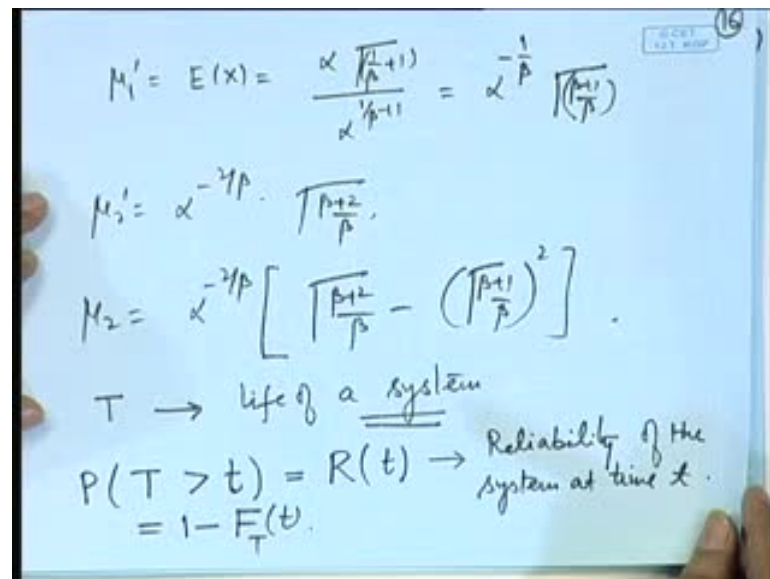


Probability and Statistics
Prof. Dr. Somesh Kumar
Department of Mathematics
Indian Institute of Technology, Kharagpur

Lecture No. #14
Special Distributions-V

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$$M_1' = E(x) = \frac{\alpha \Gamma(p+1)}{\alpha^{p+1}} = \alpha^{-\frac{1}{p}} \Gamma\left(\frac{p+1}{p}\right)$$

$$M_2' = \alpha^{-\frac{2}{p}} \cdot \Gamma\left(\frac{p+2}{p}\right)$$

$$M_2 = \alpha^{-\frac{2}{p}} \left[\Gamma\left(\frac{p+2}{p}\right) - \left(\Gamma\left(\frac{p+1}{p}\right)\right)^2 \right]$$

$T \rightarrow$ life of a system

$$P(T > t) = R(t) \rightarrow \text{Reliability of the system at time } t.$$

$$= 1 - F_T(t)$$

In the last lecture, I introduced the concept of reliability of a system at a given time t ; so, if T is a random variable which denotes the life of a system, then probability that the system is functioning at time T is equal to probability of T greater than small t , and we denoted by capital R_t , that is the survival function of the reliability function of the system at a given time t . So, by the definition of the cumulative distribution function, R_t is equal to $1 - F_T$, so this reliability function is quite important in the study of lives of mechanical systems in electronic system, that means, in engineering sciences wherever we are dealing with the various kinds of instruments equipments etcetera, we are interested in the survival probability.

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Instantaneous Failure Rate of System at time t (18)

$$\lim_{h \rightarrow 0} \frac{1}{h} P\left(\frac{t < T \leq t+h}{A} \mid \frac{T > t}{B}\right) = H(t)$$

hazard rate at time t

$$= \lim_{h \rightarrow 0} \frac{1}{h} \cdot \frac{P(A \cap B)}{P(B)} = \lim_{h \rightarrow 0} \frac{P(t < T \leq t+h)}{h \cdot P(T > t)}$$

$$= \lim_{h \rightarrow 0} \frac{F_T(t+h) - F_T(t)}{h \cdot R(t)} = \frac{f_T(t)}{R(t)}$$

$$H(t) = \frac{f_T(t)}{1 - F_T(t)} = - \frac{d}{dt} \log(1 - F_T(t))$$

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$$\log(1 - F_T(t)) = - \int H(t) dt + C$$

$$R(t) = 1 - F_T(t) = k e^{- \int H(t) dt}$$

So, we further introduced a concept called instantaneous failure rate of a system at time t which I called hazard rate at time t , which is the probability of the system failing within a short time immediately after time t , so the rate of failure, so we divided by h and we calculated the expression for that, and it turns out to be the density function divided by the reliability function or the density function divided by 1 minus cumulative distribution function of the system, and there is an inverse relationship also, which showed that the reliability of the system is equal to a constant times e to the power minus integral of $HTdt$, where the constant has to be determined from the initial condition.

So, now we will show that, this reliability function uniquely determines the distribution, the distribution uniquely determines the reliability function; the reliability function introduces **the**, or you can say uniquely determines the hazard rate; the hazard rate uniquely determines the reliability function etcetera.

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Lecture - 14

Let X be the Weibull distribution with parameters α, β

$$f(x) = \begin{cases} \alpha \beta x^{\beta-1} e^{-\alpha x^\beta}, & x > 0, \\ 0, & x \leq 0 \end{cases}$$

$\alpha > 0, \beta > 0$

F

Notice here one thing that we are dealing with the continuous distribution, because we are talking about the lives of the systems; although the reliability concept can be determined for probability of x greater than x can be determined for any discrete distribution also, but right now we are concentrating on this one. So, here let us consider say the distribution let x be the Weibull distribution with parameters α, β . So, we have the density function as $\alpha \beta x$ to the power β minus 1 e to the power minus αx to the power β , where x is positive and α and β are positive parameters, the density is 0 for x less than or equal to 0.

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Handwritten mathematical derivation on a whiteboard:

$$F(x) = \begin{cases} 1 - e^{-\alpha x^\beta} & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$M_k = E(X^k) = \int_0^\infty x^k \alpha \beta x^{\beta-1} e^{-\alpha x^\beta} dx$$

$$= \frac{\alpha \int_0^\infty x^{k+\beta-1} e^{-\alpha x^\beta} dx}{\alpha \int_0^\infty x^{\beta-1} e^{-\alpha x^\beta} dx}$$

Substitution: $x^\beta = y \Rightarrow x = y^{1/\beta} \Rightarrow dx = \frac{1}{\beta} y^{1/\beta-1} dy$

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Lecture - 14

Let X be the Weibull distribution with parameters α, β

$$f(x) = \begin{cases} \alpha \beta x^{\beta-1} e^{-\alpha x^\beta} & x > 0 \\ 0 & x \leq 0 \end{cases}, \quad \alpha > 0, \beta > 0$$

$$R(t) = \begin{cases} e^{-\alpha t^\beta} & t > 0 \\ 1 & t \leq 0 \end{cases}$$

$$H(t) = \frac{f(t)}{R(t)} = \alpha \beta t^{\beta-1}$$

Now, for this we calculated the reliability function to be, we firstly calculated the cumulative distribution function which was equal to 1 minus e to the power minus alpha x to the power beta; therefore, if we write down the reliability function, it is equal e to the power minus alpha t to the power beta, for t greater than 0 and it is 1 for t less than or equal to 0.

So, if we calculate the hazard rate for this, this is equal to f t divided by R t, so when we take the ratio, we are left with alpha beta t to the power beta minus 1; notice here, that

beta, if it is taking a positive integral value, then this is a polynomial function; on the other hand, if beta is a fraction, then suppose beta is a number less than 1, then it will become an increasing hazard rate as t increases.

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Given $h(t) = \alpha \beta t^{\beta-1}$

$$R(t) = k e^{-\int h(t) dt}$$

$$= k e^{-\int \alpha \beta t^{\beta-1} dt}$$

$$= k e^{-\alpha \beta t^{\beta}}$$

$R(0) = 1 \Rightarrow k = 1.$

So $F_T(t) = \begin{cases} 1 - e^{-\alpha \beta t^{\beta}} & t > 0 \\ 0 & t \leq 0 \end{cases}$

So $f_T(t) = \alpha \beta t^{\beta-1} e^{-\alpha \beta t^{\beta}}, t > 0$

If we are given $h(t)$ is equal to this, then we can use the formula for the calculation of reliability from here in the following way; given $h(t)$ is equal to $\alpha \beta t^{\beta-1}$, then $R(t)$ is equal to $k e^{-\int h(t) dt}$ that is equal to $k e^{-\int \alpha \beta t^{\beta-1} dt}$, that is equal to $k e^{-\alpha \beta t^{\beta}}$. So, if I could say $R(0)$ is equal to 1, then, this will give us k is equal to 1. So, $F_T(t)$ will become equal to $1 - e^{-\alpha \beta t^{\beta}}$ for $t > 0$ and 0 for $t \leq 0$. So, the density function is equal to $\alpha \beta t^{\beta-1} e^{-\alpha \beta t^{\beta}}$, which is nothing but the probability density function of the Weibull distribution.

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Lecture - 14

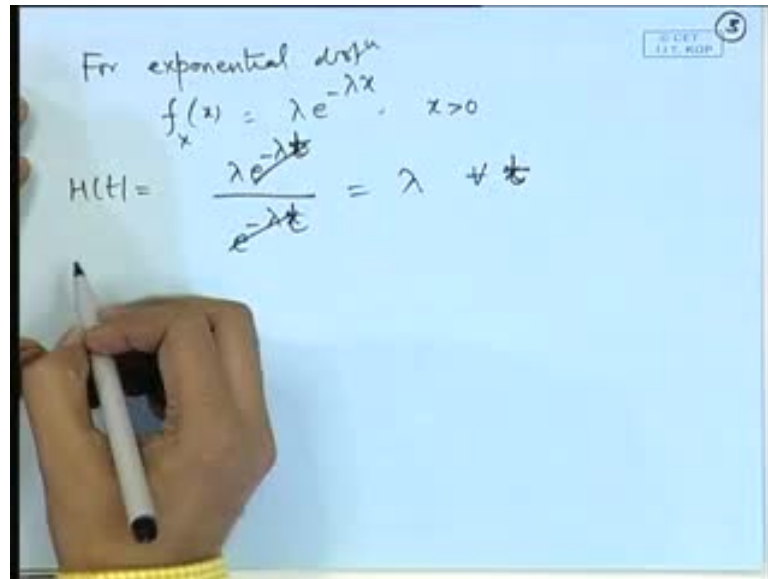
Let X be the Weibull distribution with parameters α, β

$$f(x) = \begin{cases} \alpha \beta x^{\beta-1} e^{-\alpha x^\beta}, & x > 0, \\ 0, & x \leq 0 \end{cases} \quad \alpha > 0, \beta > 0$$
$$R(t) = \begin{cases} e^{-\alpha t^\beta}, & t > 0 \\ 1, & t \leq 0 \end{cases}$$
$$h(t) = \frac{f(t)}{R(t)} = \alpha \beta t^{\beta-1}$$

So, this description shows that for Weibull distribution the form of the hazard rate is of a polynomial type of function $\alpha \beta t^{\beta-1}$, it will depend upon what are the values of β , whether β is a real value or it is a positive integral value etcetera, but one thing is clear if β is greater than 1, then this will be increasing with t and if β is less than 1, then this will be decreasing with t . So, you can have systems, where the hazard rate may be increasing with time or it may be decreasing with time.

For example, you consider **the** a very new system; now, that a very new system generally it is likely to fail more, but once it is in operation, for example, a new car or a new computer, but after certain time it will work, once it has stabilized, the life will be more, however after again a certain stage, the life may start decreasing.

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For exponential distn
 $f(x) = \lambda e^{-\lambda x} \quad x > 0$
 $H(t) = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda \quad \forall t$

Let us consider the special case here; beta is equal to 1 in the Weibull distribution which was corresponding to the exponential distribution. If we take beta is equal to 1 in the hazard rate, this becomes simply alpha that is a constant. Now, this is interesting, in the case of exponential distribution, that is if I am taking say $f(x)$ is equal to $\lambda e^{-\lambda x}$, the hazard rate is equal to $\lambda e^{-\lambda x}$, the reliability function was $e^{-\lambda x}$, that cancels all which is λ for all x .

That means, the hazard rate function, let us put t here in place of x , hazard rate function of the exponential distribution is independent of the time that means, constant failure rate. Now, this is the point, which I wanted to emphasize earlier, when we were talking about the memoryless property of an exponential distribution, that means, if a system is functioning it has not failed, then the failure rate remains the same; so that that is why the systems, which are having exponential life are more stable in nature and they are good basically for the users.

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Given $H(t) = \alpha \beta t^{\beta-1}$
 $R(t) = k e^{-\int H(t) dt}$
 $= k e^{-\int \alpha \beta t^{\beta-1} dt}$
 $= k e^{-\alpha t^\beta}$
 $R(0) = 1 \Rightarrow k = 1.$
So $F_T(t) = \begin{cases} 1 - e^{-\alpha t^\beta} \\ 0 \end{cases}$
 $f_T(t) = \alpha \beta t^{\beta-1} e^{-\alpha t^\beta}$

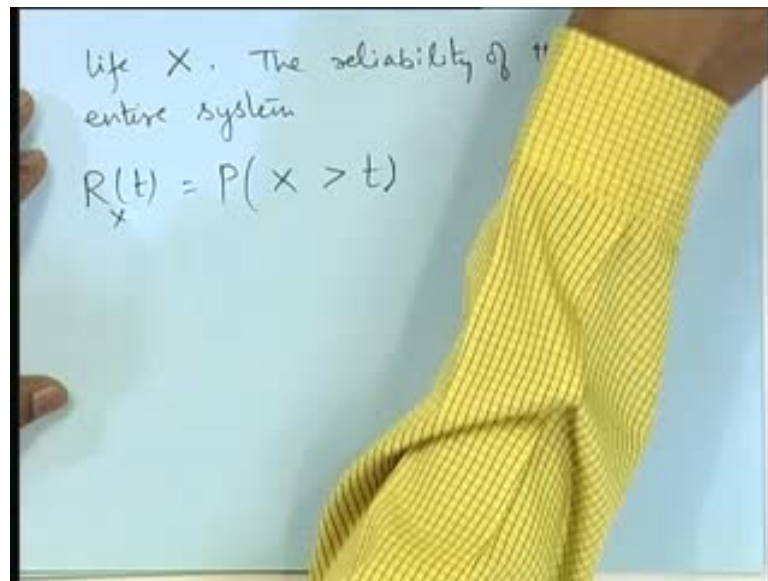
On the other hand, if the $H(t)$ is given to be λ , we can calculate using this formula; so we will get the $k e^{-\lambda t}$, and k will again become 1 by using the initial condition $R(0)$ is equal to 1, so it becomes $\lambda e^{-\lambda t}$ as the density function.

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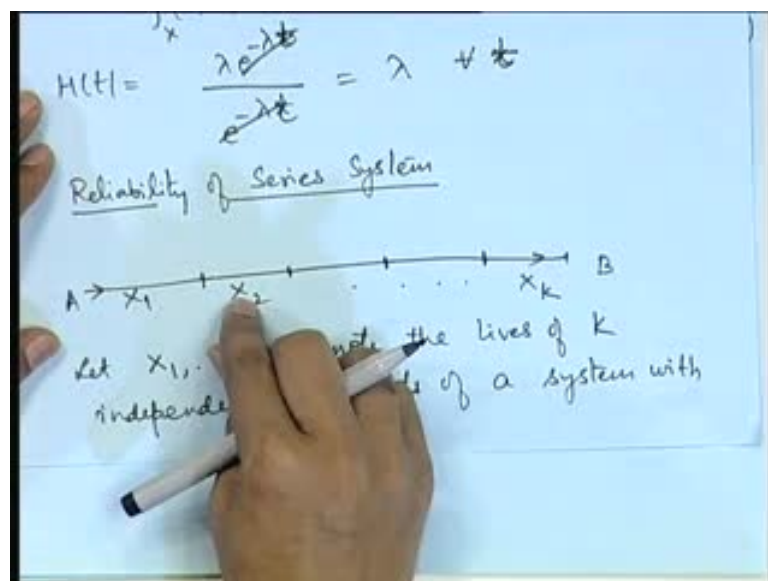
For exponential distn
 $f(x) = \lambda e^{-\lambda x} \quad x > 0$
 $H(t) = \frac{\lambda e^{-\lambda t}}{e^{-\lambda t}} = \lambda$
Reliability of Series System
A \rightarrow x_1 \mid x_2 \mid \dots \mid x_k \rightarrow B
Let x_1, \dots, x_k denote the lives of k independent components of a system with

We also discuss the reliability of complex systems, many times the entire system is made up of several components, which may be connected in parallel or in a series, so let us consider the reliability of such systems, let us consider the reliability of a series system.

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life X . The reliability of the entire system

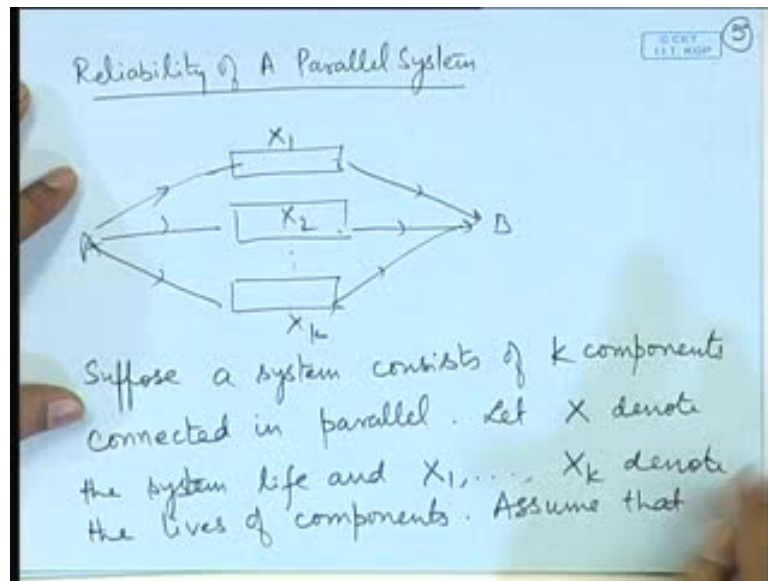
$$R_x(t) = P(X > t)$$
$$= P(X_1 > t, X_2 > t, \dots, X_k > t)$$
$$= \prod_{i=1}^k P(X_i > t) = \prod_{i=1}^k R_{X_i}(t)$$

SECRET (4)

So, suppose we have say k components which say lives x_1, x_2, x_k , and they are connected in a series, that means, the entire system will work, if and only if all the components are working; so, let x_1, x_2, x_k denote the lives of k independent components of a system with say life x ; so, the reliability of the entire system, that is R_t is equal to probability of X greater than t , however the system will be working if and only if, each of the components x_1, x_2, x_k are working at time t , that mean, this is equal to probability of x_1 greater than t, x_2 greater than t , and so on, x_k greater than t ; we are assuming that, the components are working independently, therefore the probability of the simultaneous occurrence will be equal to the product of the probabilities.

Now, this is nothing but the reliability of the R_x system x system; so, what we get here, is that, the reliability of a compound system, which consists of several components connected in a series is equal to the product of the reliabilities of the individual components. In a similar way, we may have systems which are connected in parallel.

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Let us look at reliability of a parallel system; so, there are several links from say A to B and the system will function, if any one of the components is functioning, let us call the lives as x_1, x_2, x_k etcetera.

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the component lives are independent

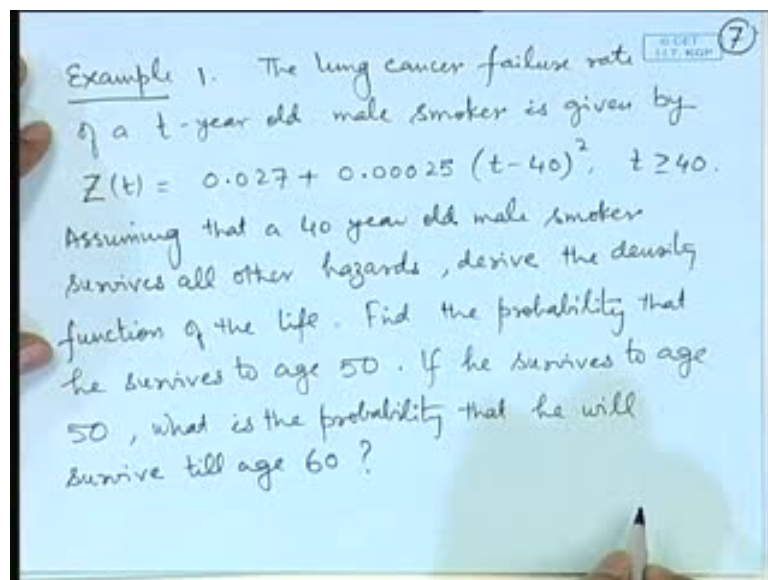
$$\begin{aligned} R_X(t) &= P(X > t) = 1 - P(X \leq t) \\ &= 1 - P(X_1 \leq t, X_2 \leq t, \dots, X_k \leq t) \\ &= 1 - \prod_{i=1}^k P(X_i \leq t) \\ &= 1 - \prod_{i=1}^k \{1 - P(X_i > t)\} \\ &= 1 - \prod_{i=1}^k R_i(t) [1 - R_i(t)] \end{aligned}$$

Suppose a system consists of k components connected in parallel; so, let x denote the system life and x_1, x_2, x_k denote the lives of components. Once again assume that the component lives are independent. Now, if we consider the reliability of the entire system at time t , now this will function if any of the systems is functioning, so we can write it as

1 minus probability of x less than or equal to t , that means, the system fails before time t . Now, the system will fail before time t , if each of the components fails, that means, it is equal to probability of x_1 less than or equal to t , x_2 less than or equal to t , and x_k less than or equal to t , this is equal to 1 minus..

Now, once again we can make use of the independence of the lives of the individual components, so it becomes product of the probabilities x_i less than or equal to t , which is nothing but 1 minus probability, 1 minus probability of x_i greater than t , now, this is nothing but the R_i ; therefore, the reliability of a system consisting of parallel components is expressed in terms of R x t is equal to 1 minus product of the reliabilities of the individual; this is 1 minus, so this is wrong expression 1 minus R_i .

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Let us look at one application; the lung cancer failure rate, that is, hazard rate of a t -year old male smoker is given by $Z(t)$ is equal to 0.027 plus 0.00025 $(t - 40)^2$, for t greater than or equal to 40. As you mean that, a 40 year old male smoker survives all other hazards, derive the density function of the life, find the probability that he survives to age 50. If he survives to age 50, what is the probability that he will survive till age 60.

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$$f(x) = \begin{cases} \alpha \beta x^{\beta-1} e^{-\alpha x^\beta} & , x > 0, \\ 0 & , x \leq 0 \end{cases}$$

$$R(t) = \begin{cases} e^{-\alpha t^\beta} & , t > 0 \\ 1 & , t \leq 0 \end{cases}$$

$$H(t) = \frac{f(t)}{R(t)} = \alpha \beta t^{\beta-1}$$

50, what is the probability that he will survive till age 60?

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Example 1. The lung cancer failure rate of a t -year old male smoker is given by
 $Z(t) = 0.027 + 0.00025 (t-40)^2, t \geq 40.$
Assuming that a 40 year old male smoker survives all other hazards, derive the density function of the life. Find the probability that he survives to age 50. If he survives to age 50, what is the probability that he will survive till age 60?

So, this is a shifted Weibull distribution kind of thing, because in the Weibull distribution, we have seen the hazard rate function is given by $\alpha \beta t^{\beta-1}$, that means, starting from time 0; now, if you compared with this, here it is shifted so $t - 40$, so we are assuming that the person is already 40 years old, after that the hazard rate function is given by this. So, from here you can make out that the distribution of the life of the t -year old male smoker is given by a Weibull distribution.

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$\log(1 - F_T(t)) = -\int H(t) dt + c$

$S(t) = 1 - F_T(t) = k e^{-\int H(t) dt}$

(Refer Slide Time: 19:11)

Example 1. The lung cancer failure rate of a t -year old male smoker is given by-

$$Z(t) = 0.027 + 0.00025 (t - 40)^2, \quad t \geq 40.$$

Assuming that a 40 year old male smoker survives all other hazards, derive the density function of the life. Find the probability that he survives to age 50. If he survives to age 50, what is the probability that he will survive till age 60?

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The image shows a hand writing the following equation on a whiteboard:

$$R(t) = e^{-\int_{40}^t Z(s) ds}$$
$$= e^{-\left[0.027(t-40) + \frac{0.00025}{3} \times (t-40)^3\right]}$$

A small logo in the top right corner of the whiteboard reads "ECCET 117 HGP".

So, we can make use of the relationship between the reliability function and the hazard function to calculate the reliability function; hence, the cumulative distribution function and hence the probability density function of the life, so, consider here $R(t)$ is equal to e to the power minus $\int_{40}^t z s ds$; now, here we have written indefinite integral there, but here since it is already given, so we can put the limit as 40 to t , that is equal to e to the power minus $0.027t$ minus 40 plus 0.000025 by 3 t minus 40 cube.

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The image shows a hand writing the following text and equation on a whiteboard:

of a t -year old male smoker is given by

$$Z(t) = 0.027 + 0.00025(t-40)^2, \quad t \geq 40$$

Assuming that a 40 year old male smoker survives all other hazards, derive the density function of the life. Find the probability that he survives to age 50. If he survives to age 50, what is the probability that he will survive till age 60?

(Refer Slide Time: 20:13)

The image shows a hand writing the following equations on a whiteboard:

$$R(t) = e^{-\int_{40}^t Z(s) ds}$$
$$= e^{-\left[0.027(t-40) + \frac{0.00025}{3} \times (t-40)^3\right]}$$
$$R(50) = e^{-0.3533} \approx 0.702342$$

So, one question was asked find the probability that he survives to age 50, that means, the reliability at t is equal to 50. So, once we have the reliability function, we can calculate R_{50} , which is obtained by substituting t is equal to 50 years; so, after evaluation, it turns out to be e to the power minus 0.3533, which is approximately 0.702343.

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The image shows a hand writing the following text on a whiteboard:

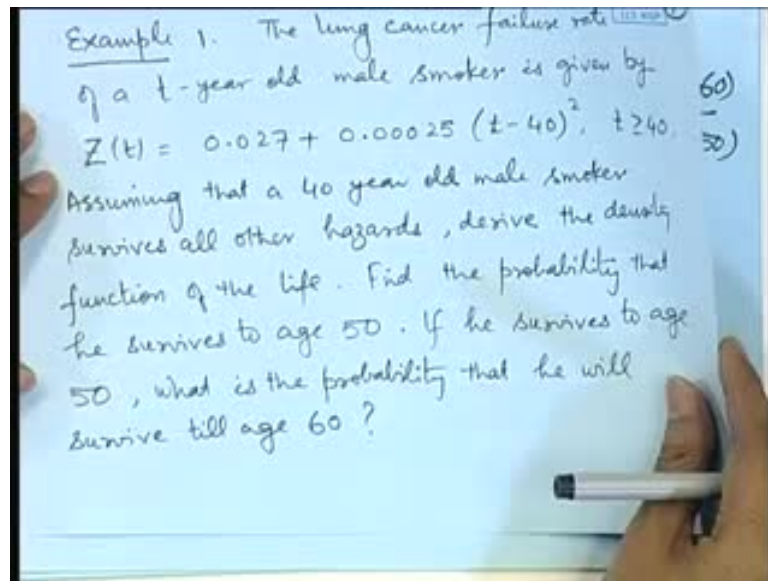
$Z(t) = 0.027 + 0.00025(t-40), t \geq 40.$
Assuming that a 40 year old male smoker survives all other hazards, derive the density function of the life. Find the probability that he survives to age 50. If he survives to age 50, what is the probability that he will survive till age 60?

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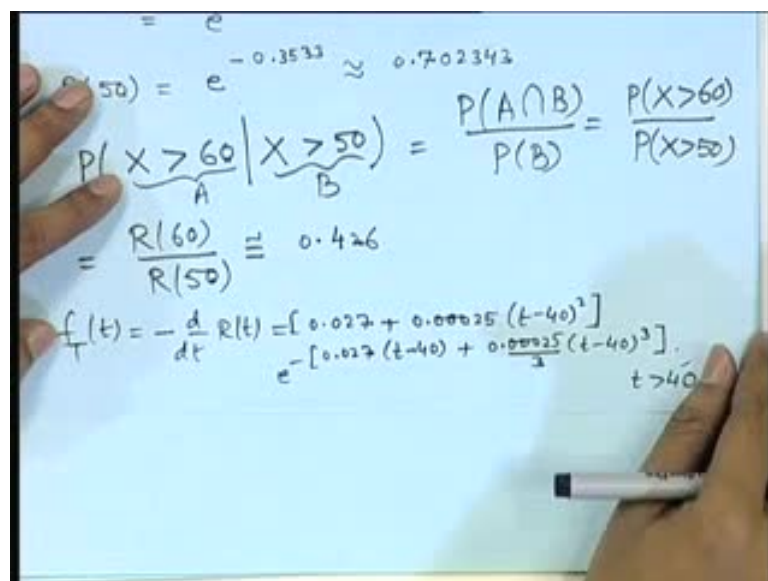
$$\begin{aligned} R(t) &= e^{-\int_{40}^t z(s) ds} \\ &= e^{-\left[0.027(t-40) + \frac{0.00025}{3} \times (t-40)^3\right]} \\ R(50) &= e^{-0.3533} \approx 0.702342 \\ P(\underbrace{X > 60}_A | \underbrace{X > 50}_B) &= \frac{P(A \cap B)}{P(B)} = \frac{P(X > 60)}{P(X > 50)} \\ &= \frac{R(60)}{R(50)} \approx 0.426 \end{aligned}$$

That means, if he is a smoker, and he is already 40 years old the probability of his surviving, beyond 50 is only 70 percent, that means 30 percent chance is that, he will not be able to survive. **If we are looking at**, if he survives to age 50, what is the probability that he will survive till age 60; this is conditional probability, that he is having life up to 60, at least up to 60 given that he has survived till 50. So, if we consider this event as A and this event as B, then it is probability of A intersection B divided by probability of B and that is equal to probability x greater than 60 divided by probability x greater than 50, which is the ratio of the reliabilities at t is equal to 60 and 50, and after some simple evaluation, this turns out to be 0.426, which means that, if he has survived till age 50, then the probability of his surviving till age 60 is 0.4; if you see here, the probability of surviving till age 50 is point 7, but if he has survived till 50, then probability of surviving till 60 is 0.42.

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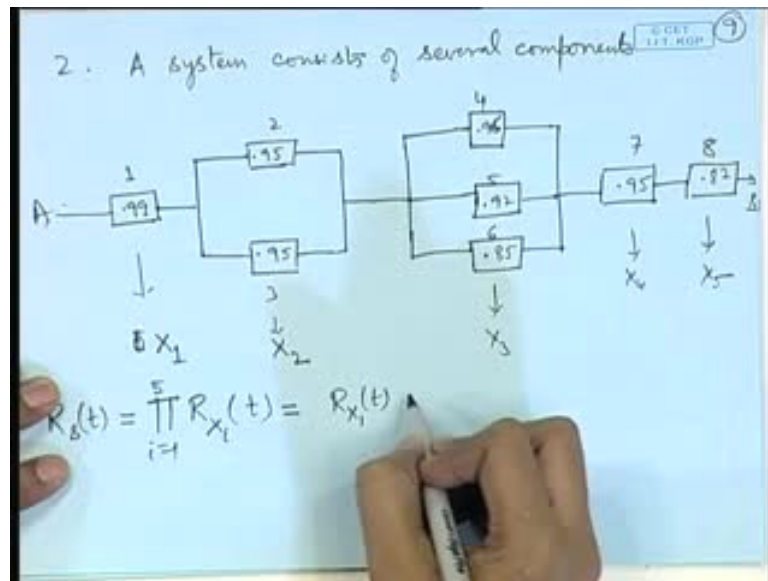


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The probability, the density function of the life can be obtained simply by looking at the derivative of the reliability function, because the reliability function is 1 minus the cumulative distribution function; so, the density function is obtained as minus d by dt of $R(t)$, which is equal to $0.027 + 0.00025(t-40)^2$ $e^{-0.027(t-40) - 0.00025(t-40)^3}$, that is t is greater than 40, which is nothing but the probability density function of a shifted Weibull distribution.

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Let us consider one more example here; a system consists of a several components as shown below, so the numbers, this represent the reliability of the component to be functioning, so 0.99 is the reliability of component 1 to be functioning; 0.95 for the second one, so the second assembly here is consisting of two components connected in parallel; so, the system this particular component will be working provided any of them is working, let us name it 2 and 3. The next part consists of three components connected in parallel with the reliabilities 0.96 for component 4, 0.92 for component 5, and 0.85 for component 6. The next one consist of a single component 0.95, and the next one consist of a single component, suppose this is A, this is B.

So, the entire assembly is consisting of A to B, 8 components, out of which some of them are connected in parallel, and some of them are connected in the series; let us name these systems, as say one let me call it system life as x_1 , this system life as x_2 ; this system life as x_3 , this as x_4 , this as x_5 .

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$$= 1 - \prod_{i=1}^k P(X_i \leq t)$$

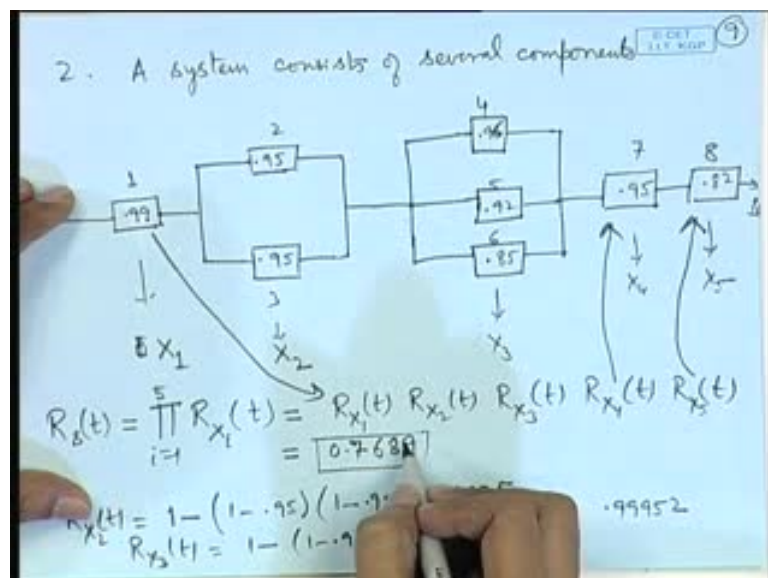
$$= 1 - \prod_{i=1}^k \{1 - P(X_i > t)\}$$

$$= 1 - \prod_{i=1}^k [1 - R_i(t)]$$

$R_{X_1}(t) = R_{X_1}(t)$

So, if we are interested to calculate the reliability of the entire system; now, this is a series, so it will be the reliability of the xith system, iis equal to 1 to 5; 1, 2, 3, 4, 5 systems which are connected in parallel, so this one will become equal to $R \times 1 t$; now $R \times 2 t$ is again a compound system, it consists of two parts connected in parallel, the probability that the system is functioning are the reliability of this is given by the formula for the reliability of a parallel system 1 minus product of 1 minus of the reliabilities.

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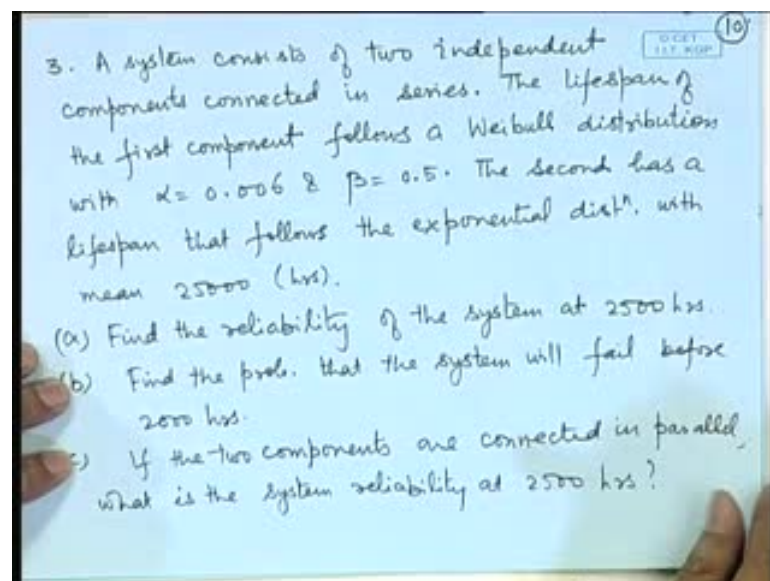


So, if we use this one, the reliability of the second system will be equal to 1 minus, let me firstly write R_{x2} , R_{x3} , R_{x4} and R_{x5} , where R_{x1} is given by this number R_{x4} is given by this number, R_{x5} is given by this number. If we look at R_{x2} , it is equal to $1 - (1 - 0.95)^2$, which is equal to 0.9975.

Similarly, if we consider the reliability of the third system, that is R_{x3} that is equal to $1 - (1 - 0.961 - 0.921 - 0.85)^2$ which is equal to 0.99952; if we substitute these values in this formula, we get 0.7689; this shows that the reliability of a complex system can be calculated by using the formula for the reliabilities of the individual systems, which are connected either in parallel or connected in a series form.

One more thing we should notice here, the reliabilities of the individual systems are quite high, for example, 0.99, 0.95, 0.95, 0.82 etcetera, but if we are looking at the reliability of the compound system, it is 0.7889, which is much smaller which shows that, when we multiply the probabilities, they become smaller, because each of the number is less than the 1, that is the effect; so, although individual systems may have high reliability, but when we connect them in a say series system, the reliability will become much smaller. If we connect them in a parallel, the reliability will increase, because any of them working will make ensure that the system is functioning.

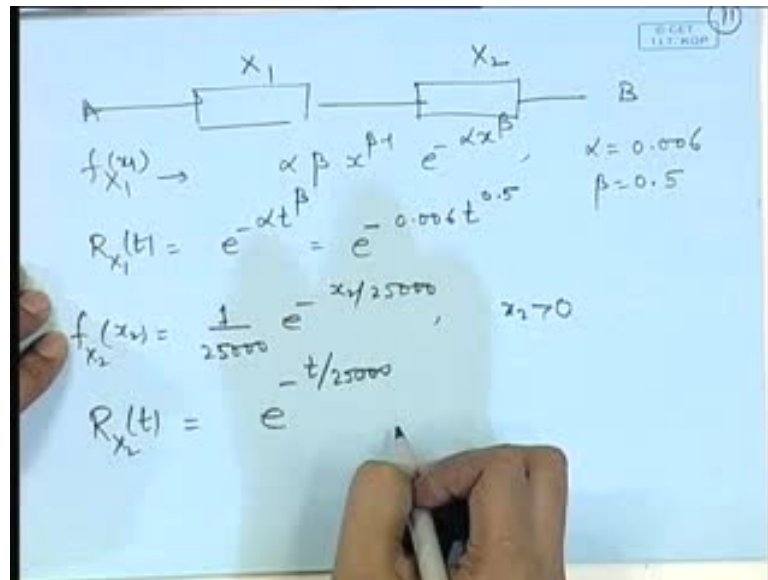
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A system consists of two independent components connected in series; the life span of the first component follows a Weibull distribution with alpha is equal to 0.006 and beta is

equal to 0.5; the second component has a life span that follows the exponential distribution with mean 25000, the measure is the unit is hours; find the reliability of the system at 2500 hours; find the probability that the system will fail before 2000 hours; if the two components are connected in parallel, what is the system reliability at 2500 hours.

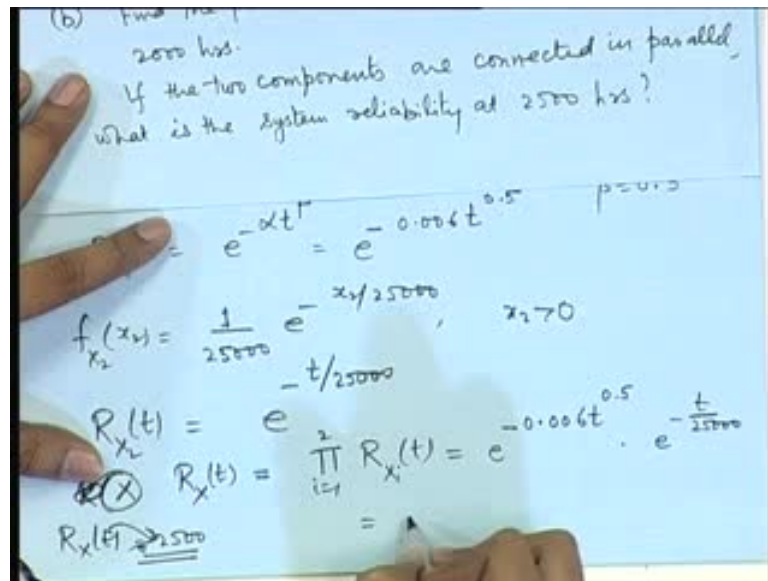
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So, here the two independent components are connected in the series; let us call this as x_1 and this as x_2 , the first one x_1 has Weibull distribution, so the density of is equal to $\alpha \beta x^{\beta-1} e^{-\alpha x^\beta}$, where α and β are given here. So, if we look at the reliability function of x_1 , that is equal to $e^{-\alpha t^\beta}$, that is, $e^{-0.006 t^{0.5}}$.

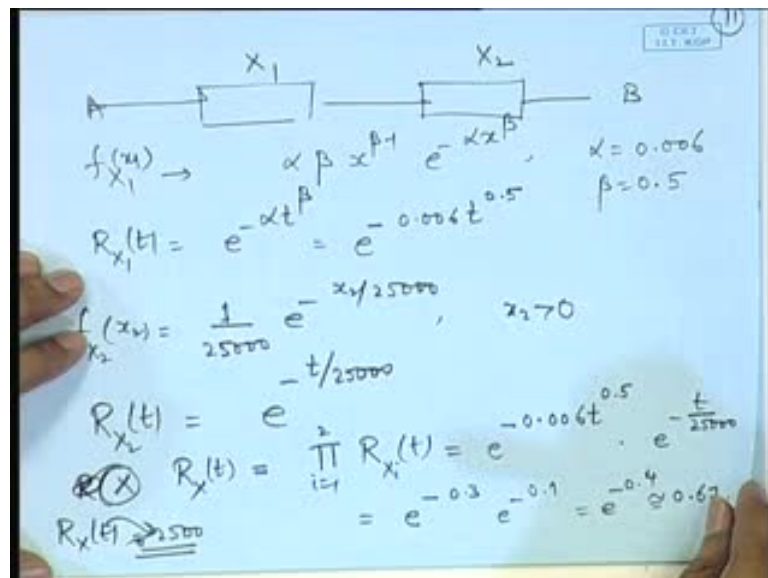
If we look at the second component, that is exponential distribution with mean 25000, so the density function will be, because mean of the exponential distribution with density $\lambda e^{-\lambda x}$ is $1/\lambda$. So, if you are saying mean is 1 by 25000, so the density function will become $1/25000 e^{-x/25000}$. So, the reliability of this is equal to $e^{-t/25000}$.

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Now, we are interested in the reliability of the system at 2500 hours, so **the system life**, suppose it is x , so the system reliability at time t , **that is equal to**, for a series system it is the product of the individual reliabilities, so, this is equal to e to the power minus $0.006 t$ to the power 0.5 into e to the power minus t by 25000 .

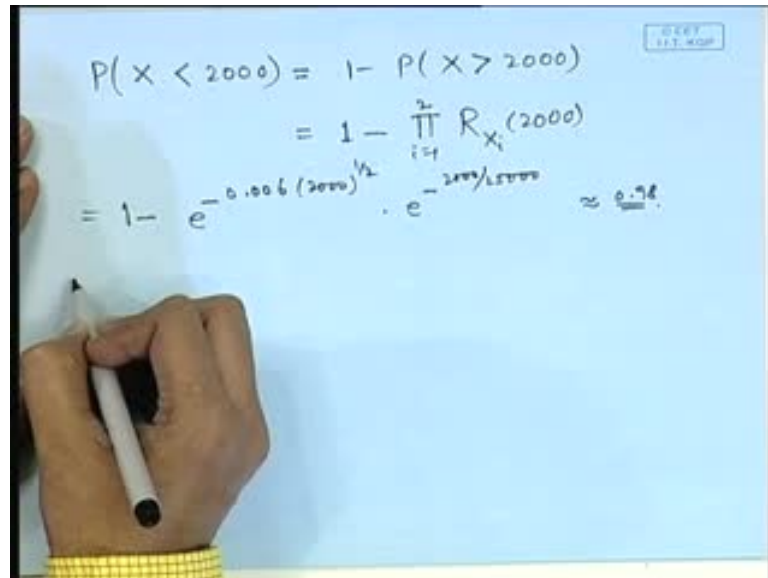
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So, if we are calculating the system reliability at 2500 hours at t is equal to 2500, then **this will be equal to**, after substitution this value is evaluated to be e to the power minus 0.3 and this one will become e to the power minus 0.1 , that is equal to e to the power

minus point 4 which is approximately 0.67. So, reliability of the compound system which **connected in a**, which consists of two components connected in a series can be evaluated by multiplying out the reliabilities of the individual components at the given time.

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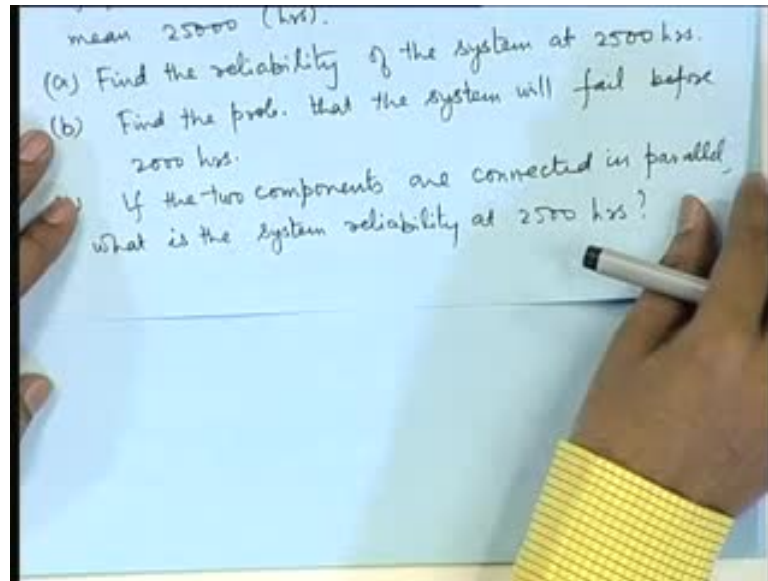


The image shows a hand holding a white marker writing on a whiteboard. The text on the whiteboard is as follows:

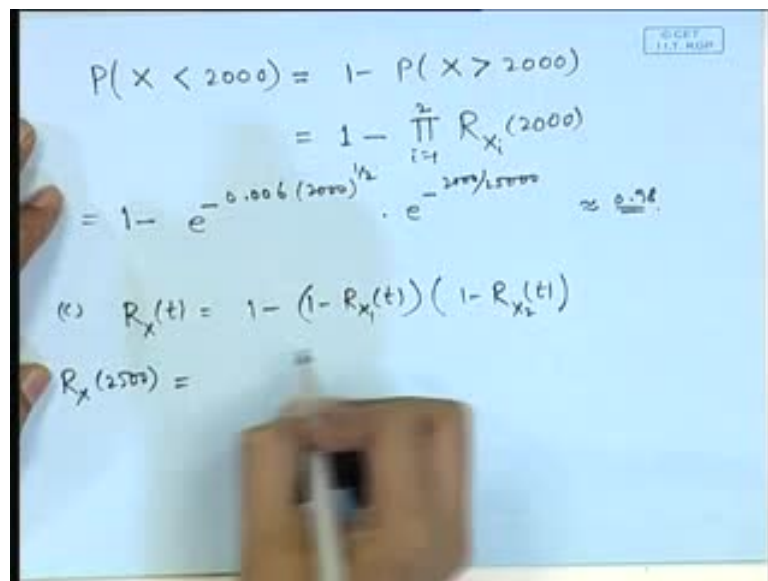
$$\begin{aligned} P(X < 2000) &= 1 - P(X > 2000) \\ &= 1 - \prod_{i=1}^2 R_{X_i}(2000) \\ &= 1 - e^{-0.006(2000)^{1/2}} \cdot e^{-2000/15000} \approx 0.98 \end{aligned}$$

Now, **the next part of, it is,** what is the probability that the system fails before time 2000 hours, that means, what is the probability that x is less than 2000; now, this can be written as 1 minus probability that x is working at 2000 hours, once again it is the product of the reliabilities at 2000 hours. So, this we can substitute the values 1 minus e to the power minus 0.0062000 to the power half e to the power minus 2000 divided by 25000; so, after some simplification this value turns out to be, well this value is approximately 0.98.

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$$R_{x_1}(t) = e^{-\alpha t^\beta} = e^{-0.006t^{0.5}} \quad \beta = 0.5$$

$$f_{x_2}(x_2) = \frac{1}{25000} e^{-x_2/25000}, \quad x_2 > 0$$

$$R_{x_2}(t) = e^{-t/25000}$$

$$\textcircled{X} R_x(t) = \prod_{i=1}^2 R_{x_i}(t) = e^{-0.006t^{0.5}} \cdot e^{-\frac{t}{25000}} = e^{-0.4} \approx 0.67$$

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$$P(X < 2000) = 1 - P(X > 2000)$$

$$= 1 - \prod_{i=1}^2 R_{x_i}(2000)$$

$$= 1 - e^{-0.006(2000)^{0.5}} \cdot e^{-2000/25000} \approx 0.98$$

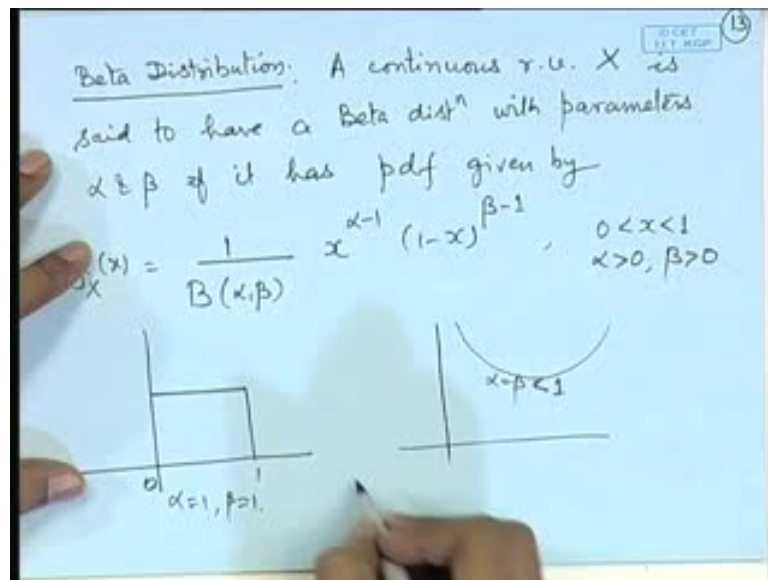
$$(*) R_x(t) = 1 - (1 - R_{x_1}(t))(1 - R_{x_2}(t))$$

$$R_x(2500) \approx 0.98$$

In the third part, if the two components are connected in parallel, what is the reliability; now, if the components are connected in parallel, then we have seen that the reliability of the system is given by **1 minus** 1 minus the reliability of x_1 into 1 minus reliability of x_2 . So, if we are calculating at 2500 hours, then after substitution of the values of R_{x_1} and R_{x_2} , which we have evaluated here; the R_{x_1} is this, and R_{x_2} is this, here if we put t is equal to 2500, and substitute in this one, it turns out to be approximately 0.98, compare the values which we calculated in the two parts.

If the components are connected in series, the system reliability is only 0.67 at time 2500 hours, whereas if they are connected in parallel, the system reliability is pretty high that is 0.98; so, this is the difference, because if we are insisting that each of the component should work, then the probability becomes smaller, when we are having the relaxation, that if any of the system is working, then the probability of system functioning will be much higher, that is why in the **industries, generally** there are systems kept as redundant; so, that is part of the reliability studies, when we study k out of n system that the system will function, if any k out of n systems are working. So, we find out the probabilities of that kind of events.

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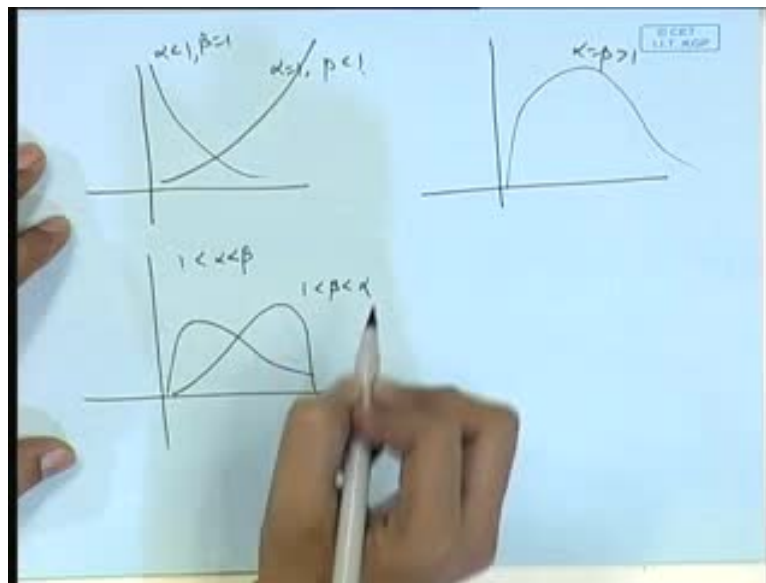
The next one is the discussion about a beta distribution; a continuous random variable x is said to have a beta distribution with parameters say α and β , if it has the probability density function given by $f(x) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1}$, where $B(\alpha, \beta)$ denotes the standard beta function $\int_0^1 x^{\alpha-1} (1-x)^{\beta-1} dx$, for $0 < x < 1$, α is positive, β is positive and 0 otherwise.

So, obviously this is called beta distribution, because, **the** it is consisting of a beta function, here the integral of this will give you $B(\alpha, \beta)$; therefore, the ratio will become 1. The distribution is quite useful in describing various kind of phenomena, where the range is bounded, and if range is bounded, we can limit it to the interval 0 to 1 ; in

fact, we can look at the shape of the curves, if I take alpha is equal to 1 and beta is equal to 1, it is reducing to uniform distribution; so, 0 to 1 if alpha is 1, beta is equal to 1.

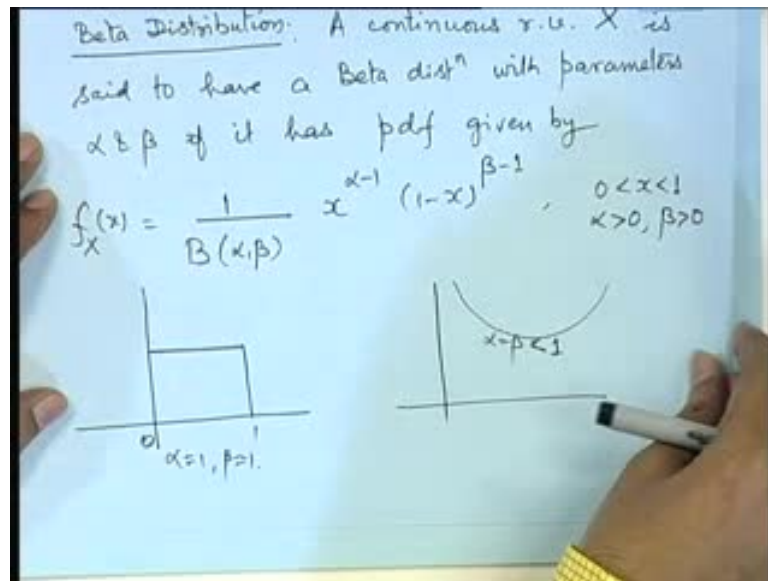
If we are having alpha, beta, both are less than 1, then it is becoming a function like this; suppose, I will take alpha and beta equal but less than 1. If we consider say beta is equal to 1, then this term will not be there, and suppose, if I take alpha to be less than 1, then this will be a decreasing function.

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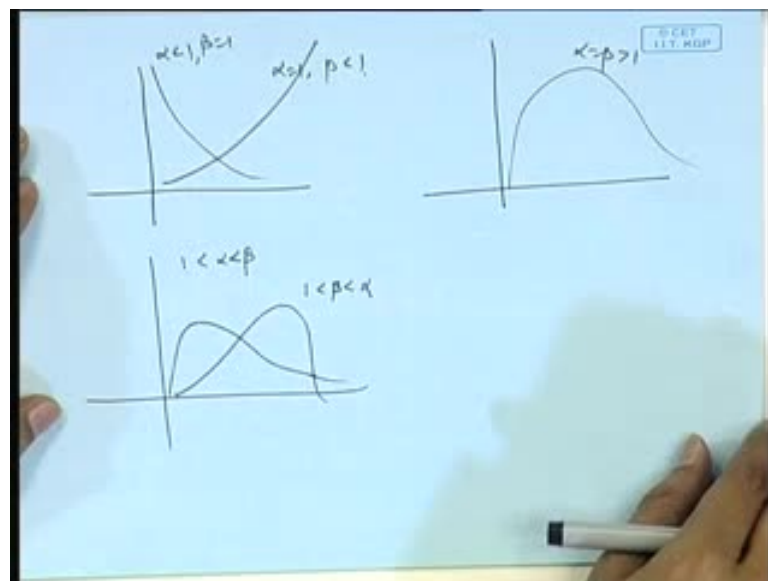


Suppose I consider alpha to be less than 1 and say beta equal to 1; on the other hand, if I take alpha is equal to 1 and beta to be less than 1, then it will become like this. If we take alpha is equal to beta but greater than 1, then the shape will become something like this; if we are having, say 1 less than alpha less than beta, then the shape will be something like this, **the shape will be something like this**, if we take 1 less than beta less than alpha

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So, here you can see, that since here two parameters alpha and beta are there, depending upon the values of alpha and beta, various kind of shapes are coming; if you are having alpha beta equal to 1 which is reducing it to uniform distribution, which is a symmetric distribution; if we have alpha is equal to beta but less than 1, then it is having a convex shape; if we are having alpha and beta equal but greater than 1, then it is having a concave shape, it may be positively skewed or negatively skewed depending upon various combination of alpha and beta values.

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Handwritten mathematical derivations for the moments of a Beta distribution:

$$\mu_k' = E(x^k) = \int_0^1 x^k \cdot \frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1} dx$$

$$= \frac{B(\alpha+k, \beta)}{B(\alpha, \beta)} = \frac{(\alpha+k-1)(\alpha+k-2)\dots(\alpha+1)\alpha}{(\alpha+\beta)(\alpha+\beta-1)\dots(\alpha+\beta-k+1)}$$

$$\mu_1' = E(x) = \frac{\alpha}{\alpha+\beta}, \quad \mu_2' = \frac{\alpha(\alpha+1)}{(\alpha+\beta)(\alpha+\beta+1)}$$

$$\mu_2 = V(x) = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

We can look at the moments of this distribution, since it is over a finite range, it is clear that the moments of all orders will exist, if we consider say expectation of x to the power k , this is equal to integral x to the power k multiplied by beta alpha beta x to the power alpha minus 1 $(1-x)$ to the power beta minus 1 dx from 0 to 1. So, this is nothing but the beta function $\alpha+k$ beta divided by beta alpha beta, so this can be simplified, and we get the expression as $\alpha+k-1$ $\alpha+k-2$ and so on upto $\alpha+1$ α divided by $\alpha+\beta$ $\alpha+\beta-1$ $\alpha+\beta-2$ and so on $\alpha+\beta$.

So, if we calculate the mean of this distribution, it is simply α by $\alpha+\beta$, the second moment will become equal to α into $\alpha+1$ divided by $\alpha+\beta$ into $\alpha+\beta+1$, and therefore variance of beta distribution will be equal to $\alpha\beta$ divided by $\alpha+\beta$ square into $\alpha+\beta+1$; the third and fourth moment will decide about the symmetry and the kurtosis of this distribution and we have already exhibited, that it will depend upon the values of α and β .

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Let X_1, \dots, X_n be independent $U(0,1)$ r.v.
 $Y_r \rightarrow r^{\text{th}}$ largest in X_1, \dots, X_n
 Want the distⁿ of Y_r .
 $A_i = \{X_i \leq t\}, i=1, \dots, n$
 $P(A_i) = t \quad 1 - P(A_i) = 1 - t$
 $P(Y_r > t) = P(\text{at most } (r-1) \text{ of } X_i \text{ is } \leq t)$

$$\sum_{k=0}^{r-1} \binom{n}{k} t^k (1-t)^{n-k}$$

 So c.d.f. of Y_r

$$F_{Y_r}(t) = 1 - \sum_{k=0}^{r-1} \binom{n}{k} t^k (1-t)^{n-k}$$

Here we give one derivation of beta distribution based on sampling from an uniform distribution; let x_1, x_2, \dots, x_n be independent uniform $[0,1]$ random variables; let us consider y_r the r th largest in x_1, x_2, \dots, x_n , what is the distribution of y_r .

Now, to consider this, we may consider some point t on the interval $[0, 1]$, then any x_i may be bigger than t , that means, it may be between t to 1 or it may be between 0 to t ; so, if we consider A_i to be the event that x_i is less than or equal to t , and if $x_i(s)$ are independent, then A_i are independent events.

So, observing of x_1, x_2, \dots, x_n denotes a sequence of Bernoulli trials, because each x_i may satisfy a $x_i \leq t$ or it may not satisfy, that means, A_i may happen or it may not happen and what is probability of A_i , that is t where t is a number between 0 to 1 , so, $1 - \text{probability of } A_i$ is $1 - t$; so, if we are looking at say probability of y_r is greater than t , it is equivalent to the event that at most $r - 1$ of $x_i(s)$ are greater than t , it is less than t .

So, this means, this event is equivalent to $\sum_{k=0}^{r-1} \binom{n}{k} t^k (1-t)^{n-k}$; so, let us analyze this, what I am saying is that, if the r th largest is bigger than t , then at most $r - 1$ of $x_i(s)$ will be less than or equal to t , because if they are bigger than, if r of them are less than or equal to t , then naturally, it may happen that the r th largest will also become less than or equal to t ; so, if we are

saying r th largest is greater than t , then at most $r - 1$ of the $x_i(s)$ will be less than or equal to t .

So, now let us consider k of the $x_i(s)$ are less than or equal to t , then for k of them there is a success and for the remaining $n - k$ is a failure; the success probability is t and the failure probability is $1 - t$, so it becomes like a binomial distribution out of n trials k success; so, the probability of the success is $\binom{n}{k} t^k (1 - t)^{n - k}$, and here we are saying, that k may be from 0 to $r - 1$. So, the cumulative distribution function of Y_r is then obtained as $1 - \sum_{k=0}^{r-1} \binom{n}{k} t^k (1 - t)^{n - k}$, k is equal to 0 to $r - 1$.

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The image shows a whiteboard with handwritten mathematical derivations. The top line is:
$$f_{Y_r}(t) = -\frac{d}{dt} \left[\binom{n}{0} t^0 (1-t)^n + \binom{n}{1} t^1 (1-t)^{n-1} + \binom{n}{2} t^2 (1-t)^{n-2} + \dots + \binom{n}{r-1} t^{r-1} (1-t)^{n-r+1} \right]$$
The next line is:
$$= n(1-t)^{n-1} - \left[\binom{n}{1} (1-t)^{n-1} + \binom{n}{1} (n-1) t (1-t)^{n-2} \right]$$
The third line is:
$$= \binom{n}{2} 2 t (1-t)^{n-2} + \binom{n}{2} (n-2) t^2 (1-t)^{n-3} + \dots$$
The fourth line is:
$$= \frac{n!}{(r-1)!(n-r)!} t^{r-1} (1-t)^{n-r}, \quad 0 < t < 1.$$
The final line is:
$$\underline{\underline{B(r, n-r+1)}}$$

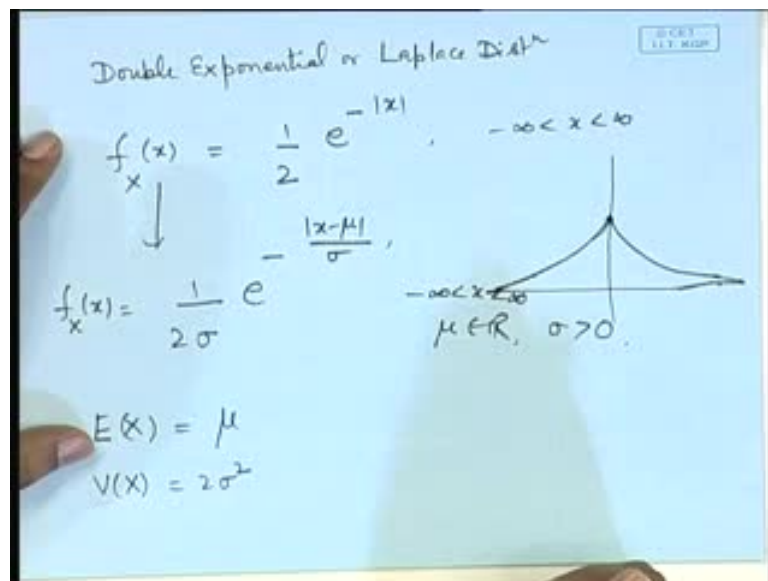
So, the density function of Y_r can be obtained by differentiation of this term, we will get $f_{Y_r}(t)$ is equal to minus $\frac{d}{dt}$, now here we have to write down the terms, so it is $\binom{n}{0} t^0 (1-t)^n + \binom{n}{1} t^1 (1-t)^{n-1} + \binom{n}{2} t^2 (1-t)^{n-2} + \dots + \binom{n}{r-1} t^{r-1} (1-t)^{n-r+1}$.

So, the derivative of this will give us, so if we consider the derivative the term by term differentiation will be there; each of the term is a product of two terms, except the first and the last. So, in the first one, we will get $1 - t$ to the power $n - 1$, there is a minus sign here, plus $\binom{n}{1}$, now derivative of this one will give simply $1 - t$ to the power $n - 1$, and there is a minus sign, so this will become minus and then you will have plus $\binom{n}{1}$ into $n - 1$ $t^1 (1 - t)^{n - 2}$ minus $\binom{n}{2}$ into $2 t^1 (1 - t)^{n - 3}$.

minus t to the power $n - 2$ plus $n - 2$ times $n - 2$ times t square $1 - t$ to the power $n - 3$ plus $n - 3$ times $n - 3$ times t to the power $n - 1$.

Again we can observe that the terms are telescopic in nature, that is the first term cancels with the second term; here, if we look at $n - 1$, that is n into $n - 1$, here it is n into $n - 1$ by 2 into 2 , so that is again ending to $n - 1$, so this again cancels out; so, likewise all the terms will cancel each other, and we will be left with, so here the last term was $n - 1$ times t to the power $n - 1$ minus t to the power $n - r$, so this we wrote wrongly, here the last term will give us $n - 1$ times t to the power $n - 1$ minus t to the power $n - r$, that is equal to n factorial divided by $(n - 1)$ factorial $n - r$ factorial t to the power $n - 1$ minus t to the power $n - r$, this is because of the cancellation of all the terms, after the $n - k$ into $n - k$, and that is same as $n - k + 1$ into $k + 1$; this is nothing but the beta distribution with parameters r and $n - r + 1$; so, this beta distribution arises in sampling from a uniform distribution with the distribution of the r th largest.

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Next, we introduce a double exponential or Laplace distribution, if we remember the exponential distribution, in the exponential distribution, the density was on the right side of the axis, if we consider the density on both the sides of the axis, say this is known as a double exponential distribution; we may introduce parameters here, we may consider $\frac{1}{2\sigma} e^{-|x - \mu|/\sigma}$, where μ is a positive, μ is a

real and σ is a positive parameter; so, this is known as a double exponential distribution.

The distribution is quite useful in various studies, where exponential is restricting to the positive side alone, but if we have some values on the left side also, we may use this distribution, find its use there. If we consider the mean, this is equal to μ which is obvious, because it is a symmetric distribution, if you look at the variance of this, this is $2\sigma^2$.

We may look at the measures of skewness which will be again 0, and the measures of kurtosis will be dependent on the value of the σ here. The moment function of this distribution will exist, because if you are looking at expectation of e^{tx} , then it is integral of this term into e^{tx} , so it will exist for all values of t .

In the next lecture, we will introduce one of the most important distributions in statistics, which is known as the normal distribution, and we will also show why it is important here. So, we stop here thank you.