

Structural Reliability
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Lecture –126
Component Reliability - Time Defined (Part - 05)

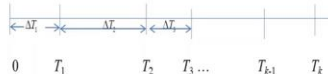
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Component reliability - time defined

Poisson occurrence of shocks

Shocks on a component occur according to a Poisson process until failure occurs at k^{th} shock.

The failure time is:

$$T_k = \Delta T_1 + \Delta T_2 + \dots + \Delta T_k$$


Now in a Poisson Process, the inter-arrival times are mutually independent and they are exponentially distributed with the same rate, λ .

$\Delta T_i \sim \exp(\lambda)$ for all i

ΔT_i is independent of ΔT_j for $i \neq j$

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Then, the failure time is Gamma distributed: $T_k \sim \text{gamma}(k, \lambda)$

Gamma is also known as Erlang when the parameter k is an integer. Its CDF is:

$$F_{T_k}(t) = P[\text{shock no. } k \text{ occurs at } t \text{ or earlier}]$$

$$= P[\text{at least } k \text{ shocks occur in } (0,t)]$$

$$= 1 - P[\text{up to } k-1 \text{ shocks occur in } (0,t)]$$

No. of shocks in $(0,t) = \text{Poisson RV}$


$$P[x \text{ shocks in } (0,t)] = \frac{(\lambda t)^x}{x!} e^{-\lambda t}$$

$$F_{T_k}(t) = 1 - \sum_{x=0}^{k-1} \frac{(\lambda t)^x}{x!} e^{-\lambda t}$$

$$\mu = \frac{k}{\lambda}$$

$$\sigma^2 = \frac{k}{\lambda^2}$$

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Let us look at random events occurring on the timeline leading to failure of an item in some detail. So, let us say that we have a component which has some reserve strength and it can withstand some shocks not fail at the first shock itself and these shocks occur according to a Poisson process. So, this component fails at shock number k we did look at the person process briefly when we discussed joint distributions.

So, this is a revisit to Poisson processes. The failure time would be the sum of all these inter arrival times. So, if failure occurs at shock number k the time is built up with increments $\Delta T_1, \Delta T_2, \dots, \Delta T_k$ each such increment is the inter arrival time between successive shocks. So, pictorially speaking this is what we have we start from 0 and then after ΔT_1 the first shock occurs. So, that is at random time T_1 then after random time ΔT_2 after random interval ΔT_2 the second shock occurs at random time T_2 and so, on until we reach the k^{th} shock occurring at a T_k .

So, we know that in a Poisson process the inter-arrival times are exponentially distributed with the rate λ and they are mutually independent. So, that is a very useful and very powerful property and to reiterate that. So, all the ΔT 's are exponential with the same constant λ which is the rate of the Poisson process and they are mutually independent in disjoint intervals. So, the failure time, so, the sum of these independent exponentials is a gamma random variable and T_k is gamma distributed the gamma distribution is defined by two parameters k and λ .

So, if k is an integer it is sometimes known as the Erlang distribution. Now let us derive the CDF of the gamma random variable. So, by definition the CDF of T_k evaluated at small t is that the shock number k occurs at time T or earlier. So, the probability of that that event which we can restate as the probability that at least k shocks occur in the interval 0 to T and if we take the complement it is 1 minus the probability that up to $k - 1$ shocks occur in interval zero to t .

So, zero shock or one shock or two all the way up to $k - 1$ shock can occur in the interval 0 to t . So, 1 minus the probability of that, would give us the CDF of the failure time t_k . Now this is also a very useful result comes out of the Poisson process is the number of events in a Poisson process over time 0 to t is actually a Poisson random variable. And we have seen the Poisson random variable extensively when we discussed the common distribution functions.

So we should be able to use the Poisson PMF and the person CDF. So, that x shocks occurs in interval 0 to t we know the PMF it is $\lambda^x t^x / x!$ times exponential of minus λt the λ is the same λ that defines the Poisson process. So we need to add x from 0 to $k - 1$ and subtract that sum from 1 that would give me the gamma or more specifically the Erlang CDF and its mean and variance could be defined in terms of k and λ and that is what we have here the mean is k / λ and the variance is k / λ^2 .

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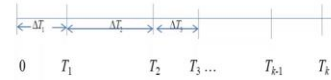
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$$F_k(t) = 1 - \sum_{x=0}^{k-1} \frac{(\lambda t)^x}{x!} e^{-\lambda t}$$

An important property of the gamma distribution is that the sum of independent gamma RVs is also gamma distributed (if rate remains the same):

If $X_1 \sim \text{Gamma}(k_1, \lambda)$, $X_2 \sim \text{Gamma}(k_2, \lambda)$
and $X_1 \perp X_2$
then, $Y = X_1 + X_2$ is $\text{Gamma}(k_1 + k_2, \lambda)$



Now continuing the gamma distribution is closed under addition the gamma family provided the rate does not change. So, if we continue adding gammas from the same underlying process defined by lambda gamma k 1 lambda and gamma k 2 lambda if they are independent then their sum would be a new gamma random variable with parameter k 1 + k 2 and the same lambda as before. So, now let us solve one or two examples with this sort of arrival on the time axis.