# Risk and Safety in

## Civil, Surveying and Environmental Engineering

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#### **Contents of Today's Lecture**

- Introduction to time variant reliability analysis
- The Poisson process
- The Normal process
- Assessment of the Mean Out-crossing rate
- Hierarchical modelling in time variant reliability analysis
- Simplifications

It is important to emphasize that probabilities are always somehow related to a "time measure"

Typically the "time measure" can be

- a particular number of experiments
- a time interval (e.g. a year)
- a spatial characteristic (e.g. length, area or volume)

In most cases we can formulate the reliability problems in a way that the "time measure" does not explicitly enter the probabilistic modelling of basic random variables

In order to understand "when to do what" we will consider some basic aspects of time variant reliability

As mentioned earlier we can often model reliability problems such that time does not enter the probabilistic modelling of the basic random variables.

This is e.g. the case when loads are ergodic – in which case reliability problems relating to extreme load events may be formulated using extreme value distributions for the extreme load realisations (corresponding to a certain time interval)

In such cases we may directly use FORM analysis for the assessment of the relevant probabilities.

In order to be able to introduce the basics of time variant reliability problems it is useful to introduce two special types of stochastic processes, namely the:

- Poisson process

Used extensively to describe statistical characteristics of events (usually rare)

- Normal process

Used extensively to describe the time variant behaviour of uncertain properties

The process N(t) denoting the number of points in the time interval (0; T] is called a simple Poisson process if it satisfies the following conditions

The simple Poisson process may be described completely by its density

For homogeneous Poisson processes, v(t) = constant

The probability of one event in the interval  $(t;t+\Delta t[$  is asympthotically proportional to  $\Delta t$ 

The probability of more than one event in the interval  $(t;t+\Delta t]$  is a function of a higher order term of  $\Delta t$  for  $\Delta t \rightarrow 0$ 

**Events in disjoint intervals are stochastically independent** 

$$\nu(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P(\text{one event in } (t; t + \Delta t[))$$

The probability of n events of a simple Poisson process in the interval (0;t[ can be shown to be given by:

From this, we can derive the probability of no events as:

and then we derive the probability distribution for the time till the first event as:

$$P_n(t) = \frac{\left(\int_0^t v(\tau)d\tau\right)^n}{n!} \exp\left(-\int_0^t v(\tau)d\tau\right)$$

$$P_0(t) = \exp(-\int_0^t v(\tau)d\tau)$$

$$F_{T_1}(t) = 1 - P_0(t) = 1 - \exp(-\int_0^t v(\tau) d\tau)$$

Filtered Poisson processes may be derived from the simple Poisson process

We assume that events are generated along the time axis – in accordance with a simple Poisson process

then we associate with all such events a response function

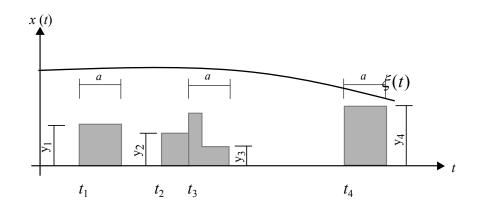
$$\omega(t,t_k,Y_k)$$

which is defined to be equal to 0 for  $t < t_k$ 

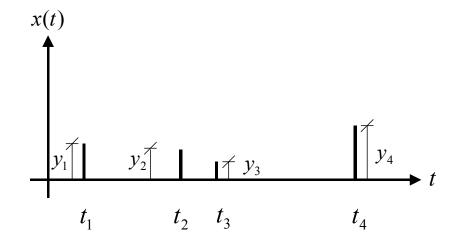
The filtered Poisson process is now established as:

$$X(t) = \sum_{k=1}^{N(t)} \omega(t, t_k, Y_k)$$

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If now we let the duration approach zero, we get the Poisson spike process

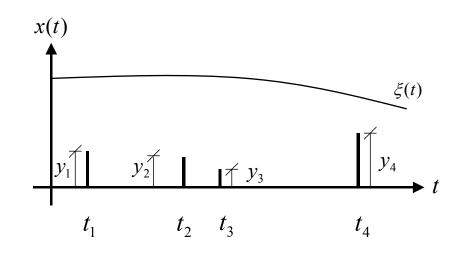


Here we consider the Poisson spike process with mutually independent random spikes  $Y_i$ 

If e.g. failure can be described as the event of a spike above the threshold x

It is recognised that these events are also events of a Poisson process with intensity

The probability distribution of the time till failure thus becomes exponentially distributed



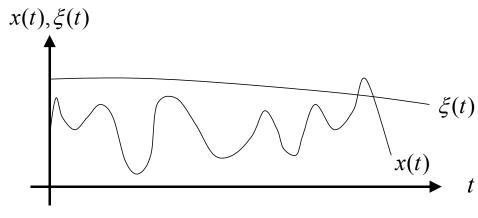
$$v^*(t) = v(t)(1 - F_{Y}(\xi(t)))$$

$$P_f(t) = 1 - \exp(-\int_0^t v(\tau)(1 - F_Y(\xi(\tau)))d\tau)$$

A random process X(t) is said to be Normal (Gaussian) if any set of random variables  $X(t_i)$ , i=1,2,...n is jointly Normal distributed

The mean number of out-crossings of a random process above the threshold  $\xi(t)$  can be derived as (Rice's formula)

The sample paths must be at least one time differentiable in respect to t



Realisation of Normal process

$$v^{+}(\xi(t)) = \int_{\dot{\xi}(t)}^{\infty} \varphi_{X,\dot{X}}(\xi,\dot{X})(\dot{X} - \dot{\xi})d\dot{X}$$

First order partial derivative of x

#### For random processes in general we have

#### where $f_{\theta}(t)$ is the first passage density function

Pensity function 
$$P_{f}(T) = \frac{N_{1} + \sum_{[0,T]} \Delta N_{0}}{N} = \frac{N_{1}}{N} + \frac{N_{0}}{N} \sum_{[0,T]} \frac{\Delta N_{0}}{N_{0}}$$

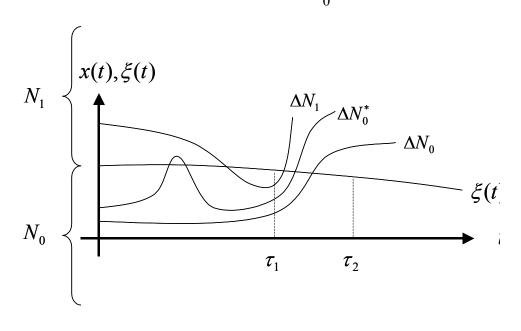
$$f_{0}(\tau) \Delta \tau = \frac{\Delta N_{0}}{N} + O(\Delta \tau)$$

$$f_0(\tau)\Delta\tau = \frac{\Delta N_0}{N_0} + O(\Delta\tau)$$

$$P_f(T) = P_f(0) + (1 - P_f(0)) \sum_{[0,T]} f_0(\tau) \Delta \tau + O(\Delta \tau)$$

$$P_{f}(T) \leq \frac{N_{1}}{N} + \frac{N_{0}}{N} \sum_{[0,T]} \frac{\Delta N_{0} + \Delta N_{0}^{*}}{N_{0}} = P_{f}(0) + (1 - P_{f}(0)) \int_{0}^{T} v_{X|S_{0}}^{+}(\xi(t)) d\tau$$

$$P_f(T) = P_f(0) + (1 - P_f(0)) \int_0^T f_0(\tau) d\tau$$



### For Normal processes two cases may be considered

- the stationary process and constant threshold case

- the in-stationary case and/or nonconstant threshold case

$$v^{+}(\xi) = \int_{0}^{\infty} \dot{x} \frac{1}{2\pi\sigma_{X}\sigma_{\dot{X}}} \exp(-\frac{1}{2}(\frac{\xi^{2}}{\sigma_{X}^{2}} + \frac{\dot{x}^{2}}{\sigma_{\dot{X}}^{2}}))d\dot{x}$$
$$= \frac{1}{2\pi} \frac{\sigma_{\dot{X}}}{\sigma_{X}} \exp(-\frac{1}{2}(\frac{\xi^{2}}{\sigma_{X}^{2}}))$$

$$v^{+}(\xi(t)) = \omega_{0}\varphi(\eta)(\varphi(\frac{\dot{\eta}}{\omega_{0}}) - \frac{\dot{\eta}}{\omega_{0}}\Phi(-\frac{\dot{\eta}}{\omega_{0}}))$$

$$\eta(t) = \frac{\xi(t) - \mu_X(t)}{\sigma_X(t)}$$

$$\omega_0(t)^2 = \frac{1}{\sigma_X(t)^2} \left[ \frac{\partial^2}{\partial t_1 \partial t_2} c(t_1, t_2) + \sigma_{\dot{X}}(t)^2 \right]$$

Approximations to time variant problems

Ultimately the first passage time is of interest in reliability applications – which is extremely hard to assess

$$P_f(T) = P_f(0) + (1 - P_f(0)) \int_0^T f_0(\tau) d\tau$$

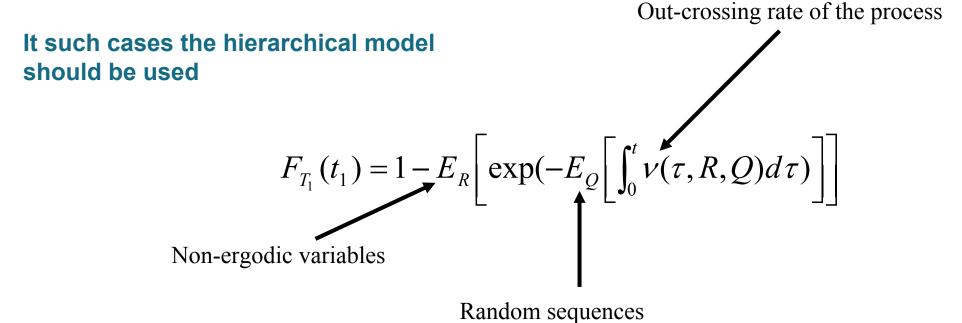
Whenever the reliability problem can be formulated in terms of a conditional probability of failure – given a certain event the Poisson spike model can be used to approximate the first passage probability

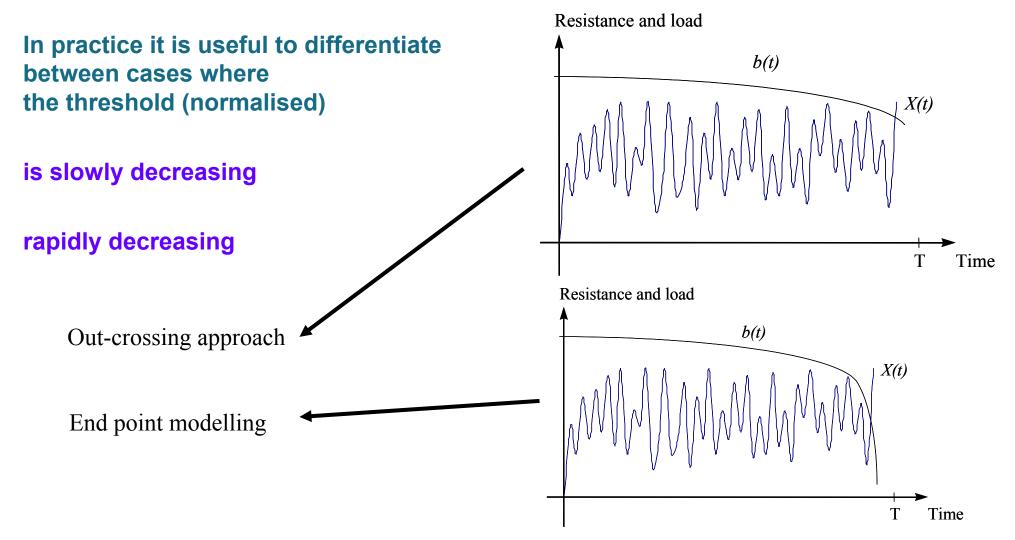
$$P_f(t) = 1 - \exp(-\int_0^t v(\tau)(1 - F_Y(\xi(\tau)))d\tau)$$

In cases where the probability of failure (e.g. per annum) may be calculated, the simple Poisson process may be used to approximate the first passage probability

$$F_{T_1}(t) = 1 - P_0(t) = 1 - \exp(-\int_0^t v(\tau) d\tau)$$

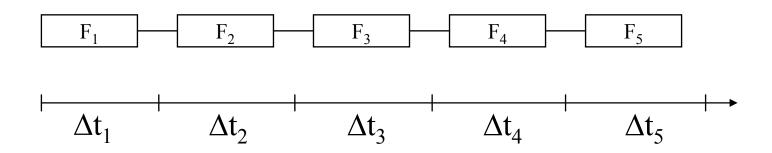
It is normally the case that the time variant includes not only random processes but also random sequences and random variables







Time variant reliability problems may also be addressed approximately by consideration of systems reliability analysis



$$P_f = P(F_1 \cup F_2 \cup F_3 \cup F_4 \cup F_5)$$
$$= 1 - P(\overline{F_1} \cap \overline{F_2} \cap \overline{F_3} \cap \overline{F_4} \cap \overline{F_5})$$

A final aspect of time variant reliability is the assessment of the annual probability of failure for components subject to accumulated deterioration

In these cases the reliability analysis provides the failure probability as a function of the experienced service life

If failures at consecutive times may be assumed to be fully dependent the annual failure probabilities may be established by subtraction

