

Stochastic Structural Dynamics
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Lecture No. # 24
Markov Vector Approach

We have been studying, how the Markov property of response vector of dynamical systems, driven by white noise excitations can be formulated, in terms of Fokker Planck equation; we continue with this discussion.

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Solution of FPK equations

$$M\ddot{X} + C\dot{X} + KX = \Gamma W(t); t \geq 0; X(0) = X_0; \dot{X}(0) = \dot{X}_0$$

$$X(t) \sim N \times 1; \Gamma \sim n \times m; W(t) \sim m \times 1$$

$$\langle W(t) \rangle = 0; \langle W(t)W^T(t+\tau) \rangle = [2D_{ij}]_{m \times m} \delta(\tau)$$

Transient & Steady state solutions

$$\dot{x} + \beta(x) = w(t); t \geq 0 \text{ \& } x(0) = x_0$$

$$\langle w(t) \rangle = 0; \langle w(t_1)w(t_2) \rangle = 2D\delta(t_1 - t_2)$$

Steady state solutions

$$\ddot{x} + \dot{x}f(H) + g(x) = w(t); t \geq 0; x(0) = x_0; \dot{x}(0) = \dot{x}_0$$

$$\langle w(t) \rangle = 0; \langle w(t)w(t+\tau) \rangle = 2D\delta(\tau)$$

$$m_j \ddot{X}_j + m_j \beta_j \dot{X}_j + \frac{\partial U}{\partial X_j} = W_j(t); t \geq 0; X_j(0) = x_{j0} \text{ \& } \dot{X}_j(0) = \dot{x}_{j0}$$

$$U = \frac{1}{2} X^T K X; \langle W_j(t) \rangle = 0; \langle W_j(t)W_k(t+\tau) \rangle = 2D_{jk} \delta(\tau)$$

$$\frac{m_j \beta_j}{2D_{jj}} = \gamma; j = 1, 2, \dots, n$$

So, what we did was, we formulated the governing equation for the time evolution of the transition probability density functions. And we showed that, for linear multi degree freedom systems under white noise excitations, we can obtain complete solution, that involves both steady state and transient regions; and the result that we obtain, agrees with what we got using **ample** integral approach earlier.

Similar solutions are also possible for first order non-linear and differential equations of this kind driven by white noise **and driven by white noise**. Here, steady state solutions

can be obtained quite easily, but the transient solutions need to be obtained using series expansion methods, by seeking a solution in every variables separable form.

But for more general class of problems, even single degree freedom systems or multi degree freedom systems, it is often not possible to exactly solve the governing Fokker Planck equation. Nevertheless, for certain class of problems, the steady state solutions can be obtained; and I showed that, for this class of systems, that is, where non-linearity is in damping as well as stiffness, but the non-linearity in damping is a function of the energy, **system** kinematic energy and potential energy. For this problem, we showed that, the steady state solution can be obtained exactly.

And similarly, for a class of multi degree freedom systems, I demonstrated that, such exact solution for steady state solutions can be obtained. There are broader class of dynamical systems, where exact solution to the governing Fokker Planck equations are possible, but I will not get in to that.

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Moment equations

$$dX(t) = f[t, X(t)]dt + G[t, X(t)]dB(t); t \geq 0; X(0) = X_0$$

$$\frac{\partial p}{\partial t} = - \sum_{j=1}^n \frac{\partial}{\partial x_j} [f_j(x, t)p] + \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial x_i \partial x_j} [(GDG^t)_{ij} p]$$

$$\frac{d}{dt} \langle h[X(t), t] \rangle = \left\langle \frac{\partial h}{\partial t} \right\rangle + \sum_{j=1}^n \left\langle f_j(X, t) \frac{\partial h}{\partial X_j} \right\rangle + \sum_{i=1}^n \sum_{j=1}^n \left\langle (GDG^t)_{ij} \frac{\partial^2 h}{\partial X_i \partial X_j} \right\rangle$$

$$\dot{X} + \beta X = w(t); t \geq 0; X(0) = X_0$$

$$\ddot{X} + 2\eta\omega\dot{X} + \omega^2 X = w(t); t \geq 0; X(0) \& \dot{X}(0) \text{ sp}$$



So, we will move on now with the next topic. We also considered the formulation of moment equations. So, for systems govern by these general stochastic differential equation, this is the Fokker Planck equation; and based on this, we can derive the time evolution of moments, where h is a function of X of t, and we derive this equation in terms of the left hand diffusion quotients. And I formulated these equations specifically

for a linear first order system and single degree freedom linear system driven by white noise.

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Example

$$\dot{X} + \beta X + \alpha X^3 = w(t); t \geq 0; X(0) = X_0$$

$$dX(t) = -\beta X dt - \alpha X^3 dt + dB(t) \quad m_k = \langle X^k(t) \rangle$$


$$f = -\beta X - \alpha X^3$$

$$\frac{d}{dt} \langle h[X(t), t] \rangle = \left\langle \frac{\partial h}{\partial t} \right\rangle + \left\langle -(\beta X + \alpha X^3) \frac{\partial h}{\partial X} \right\rangle + D \left\langle \frac{\partial^2 h}{\partial X^2} \right\rangle$$

$$\dot{m}_1 = \langle [-\beta X - \alpha X^3] \rangle = -\beta m_1 - \alpha m_3$$

$$\dot{m}_2 = \langle [-\beta X - \alpha X^3] 2X \rangle + 2D = -2\beta m_2 - 2\alpha m_4 + 2D$$

$$\dot{m}_3 = \langle [-\beta X - \alpha X^3] 3X^2 \rangle + 6Dm_1 = -3\beta m_3 - 3\alpha m_5 + 6Dm_1$$

$$\dot{m}_4 = \langle [-\beta X - \alpha X^3] 4X^3 \rangle + 12Dm_2 = -4\beta m_4 - 4\alpha m_6 + 12Dm_2$$


Now, let us continue, we consider now a first order non-linear system, $\dot{X} + \beta X + \alpha X^3 = w(t)$, where $w(t)$ as before as a white noise; and we write this in terms of stochastic differential equation as shown here, $dX(t) = -\beta X dt - \alpha X^3 dt + dB(t)$.

So, this drift term will be minus beta X minus alpha X cube, and the diffusion term will be $\sqrt{D} dB(t)$. So, the moment equation has this general form, $\frac{d}{dt} \langle h \rangle$ is given by this. And suppose if we now focus on expectations of the kind, $m_k = \langle X^k(t) \rangle$, so the equation, for \dot{m}_1 is shown here. You carefully look at the right hand side, the equation for \dot{m}_1 now has the term m_3 ; this m_3 is nothing but expected value of X^3 .


Now, we look at the expressions for \dot{m}_2 , that is expected value of X^2 , the mean square value. \dot{m}_2 if look at right hand side, I have m_4 which is expected value of X^4 . Similarly, you look at the equation for \dot{m}_3 , which is expected value of X^3 ; it has expected value of X^5 on its right hand side. So, these moment equations of this type here form an infinite hierarchy of equations, such that, at no stage, we get sufficient number of equations, so that we can solve the problem numerically. Suppose, you want to find \dot{m}_1 , you need to know m_3 . The moment you

write equation for m 3, you end up reading m 5; you write equation m 5, you need equation for m 7, and so on and so forth.

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Remarks

- Moment equations form an infinite hierarchy of equations which at no stage provide sufficient number of equations to solve for the moments: **CLOSURE PROBLEM**
- This is the characteristic feature of moment equations of non linear systems driven by random excitations
- Closure approximations
 - Assume that the higher order moments, beyond a given order, are related to the lower order ones as though they obey an adhocly specified pdf (Ex: Gaussian closure)
 - Neglect cumulants beyond a specified order



So, this problem is known as closure problem. So, moment equations form an infinite hierarchy of equations, which at no stage provides sufficient number of equations to solve for the moments; this is known as closure problem. This is the characteristic future of moment equations of non-linear systems driven by random excitation.

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Example

$$\dot{X} + \beta X + \alpha X^3 = w(t); t \geq 0; X(0) = X_0$$

$$dX(t) = -\beta X dt - \alpha X^3 dt + dB(t) \quad M_k = \langle X^k(t) \rangle$$



$$f = -\beta X - \alpha X^3$$

$$\frac{d}{dt} \langle h[X(t), t] \rangle = \left\langle \frac{\partial h}{\partial t} \right\rangle + \left\langle -(\beta X + \alpha X^3) \frac{\partial h}{\partial X} \right\rangle + D \left\langle \frac{\partial^2 h}{\partial X^2} \right\rangle$$

$$\dot{m}_1 = \langle [-\beta X - \alpha X^3] \rangle = -\beta m_1 - \alpha m_3$$

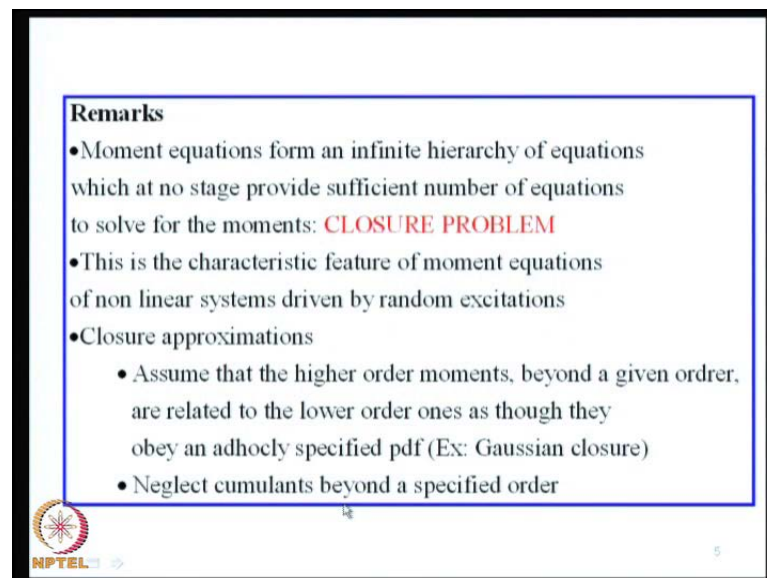
$$\dot{m}_2 = \langle [-\beta X - \alpha X^3] 2X \rangle + 2D = -2\beta m_2 - 2\alpha m_4 + 2D$$

$$\dot{m}_3 = \langle [-\beta X - \alpha X^3] 3X^2 \rangle + 6Dm_1 = -3\beta m_3 - 3\alpha m_5 + 6Dm_1$$

$$\dot{m}_4 = \langle [-\beta X - \alpha X^3] 4X^3 \rangle + 12Dm_2 = -4\beta m_4 - 4\alpha m_6 + 12Dm_2$$





Now, we can develop approximate methods to solve this infinite hierarchy of equations, if we adequately close this hierarchy by invoking some assumption. For example, after deriving an equation for m_1 and m_2 , I can assume that, all other higher order moments m_3 , m_4 , m_5 , etcetera are related to lower order moments, as if the X of t is a Gaussian random process. If you do that, it is known as Gaussian closure approximation. So, it is in some sense equivalent to linearizing the governing differential equation, because Gaussian responses are characteristics of linear systems under Gaussian random excitations. **Otherwise of doing it could be to...** you know, assume general form of probability density function of the response and we can close it an arbitrary level; we can go up to m_4 following this hierarchy equations, and equation for m_5 , m_6 , m_7 , etcetera can be assumed to be related to the first four order moments, again following certain positive related probability density functions.

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Remarks

- Moment equations form an infinite hierarchy of equations which at no stage provide sufficient number of equations to solve for the moments: **CLOSURE PROBLEM**
- This is the characteristic feature of moment equations of non linear systems driven by random excitations
- Closure approximations
 - Assume that the higher order moments, beyond a given order, are related to the lower order ones as though they obey an adhocly specified pdf (Ex: Gaussian closure)
 - Neglect cumulants beyond a specified order

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Other choice would be to neglect cumulants beyond a specific order; we can simply say that, fourth cumulants beyond third order are all 0, fourth order are all 0, that helps us to arise the hierarchy of equations and get sufficient number of equations to solve the low order moments. These are Adhoc procedures, but nevertheless, there widely discussed in the existing literature.

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Note : This problem occurs for non - white excitation also

$$m\ddot{x} + c\dot{x} + kx + \alpha x^3 = f(t); t \geq 0; x(0) \& \dot{x}(0) \text{ specified}$$

Taking expectations on both sides

$$m\langle \ddot{x}(t) \rangle + c\langle \dot{x}(t) \rangle + k\langle x(t) \rangle + \alpha\langle x^3(t) \rangle = \langle f(t) \rangle$$



Equation for mean response contains 3rd order expectations.

$$m\langle x(t_1)\ddot{x}(t) \rangle + c\langle x(t_1)\dot{x}(t) \rangle + k\langle x(t_1)x(t) \rangle + \alpha\langle x(t_1)x^3(t) \rangle = \langle x(t_1)f(t) \rangle$$

$$m\frac{\partial^2 R_{xx}(t, t_1)}{\partial t^2} + c\frac{\partial R_{xx}(t, t_1)}{\partial t} + kR_{xx}(t, t_1) + \alpha\langle x(t_1)x^3(t) \rangle = R_{xf}(t_1, t)$$

Equation for ACF of $x(t)$ contains $\alpha\langle x(t_1)x^3(t) \rangle$

Closure problem

The closure problem can occur, I mean, indeed occurs for non-white excitation also. We have been talking about white noise excitation, but suppose if you consider a duffing oscillator under a random excitation, this can be a band limited noise, stationary 0 mean random excitation. Suppose I am interested in mean of the response, I can take expectations on this equation; so, I get m into expected value of x double dot plus c into expected value of x dot, so on, so forth.

Here, I get α into expected value of x cube is equal to expected value of f . now, when you are writing equation for expected value of x , you are getting now expected value of x cube in your equation. Now, similarly, if you want to write now an equation for auto covariance or auto correlation between x of t and x of t_1 , I can multiply this equation by x of t_1 and take expectation. So, I get m into x of t_1 x double dot of t expected value plus all these; and here I get, α into expected value of x of t_1 x cube of t .

So, in terms of auto covariance auto correlation of x , I can write this double square R_{xx} double t square c double R_{xx} double t plus k $R_{xx}(t, t_1)$ plus the higher order moment, which at this stage I do not know; this actually you can call this a fourth order moment, which is not known. Suppose you want to now overcome this difficulty and multiply this equation by x cube of t , and try to get an equation for expected value of x of t and x cube of t_1 . When you multiply this with x cube of t , we get x cube of t_1 and x cube of t ; that means, a sixth order of moment will appear in your equation. So, again this forms an

infinite hierarchy, and this is a well-known problem known as closure problem. So, moment equations are difficult to deal with, in non-linear random vibration.

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Example

$$\ddot{X} + a_2 \dot{X} + [a_1 + w_1(t)] X = w_2(t);$$

$t \geq 0; X(0) \& \dot{X}(0)$ specified.

$$dX_1 = X_2 dt$$

$$dX_2 = -a_2 X_2 dt - a_1 X_1 dt - X_1 dB_1(t) + dB_2(t)$$

$$\begin{Bmatrix} dX_1 \\ dX_2 \end{Bmatrix} = \begin{Bmatrix} X_2 \\ -a_2 X_2 - a_1 X_1 \end{Bmatrix} dt + \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix} \begin{Bmatrix} dB_1(t) \\ dB_2(t) \end{Bmatrix}$$

$$\langle dB_i(t) dB_j(t + \tau) \rangle = 2D_{ij} \delta_j \delta(\tau); i, j = 1, 2$$

$$GDG^T = \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix} \begin{bmatrix} D_{11} & 0 \\ 0 & D_{22} \end{bmatrix} \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix}^T = \begin{bmatrix} 0 & 0 \\ 0 & D_{22} \end{bmatrix}$$

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Now, what happens if there is a parametric excitation? So, here, I consider X double dot plus $a_2 X$ dot plus $a_1 X$ plus another white noise w_2 of t . Now, here, we can assume initial conditions are specified and I can recast this into the stochastic differential equation form as shown here; and this matrix now, the so call G matrix has the term now minus X , so that means, one of the system states multiply the noise terms.

Now, we can write the moment equations for this. Now, it could be an interest to know, whether there will be a closure problem for this case. In fact, if you try to solve the governing Fokker Planck equation here, you will not able to solve this problem. There are no exact solutions to the evolution of probability density function for this class of problems. So, there is indeed a difficulty; but how about moment equations?

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$$\begin{cases} dX_1 \\ dX_2 \end{cases} = \begin{cases} X_2 \\ -a_2 X_2 - a_1 X_1 \end{cases} dt + \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix} \begin{cases} dB_1(t) \\ dB_2(t) \end{cases}$$

$$M_{rs} = \langle X_1^r X_2^s \rangle$$

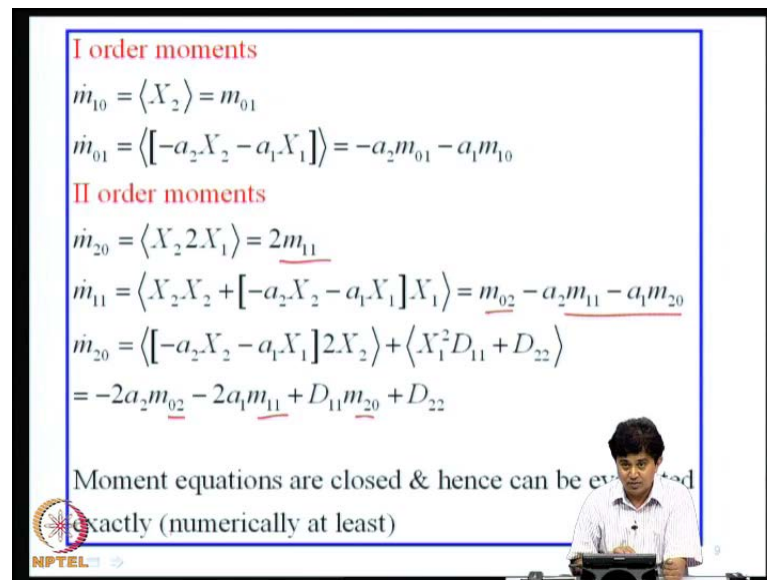
$$\begin{aligned} \dot{m}_{10} &= \langle \dot{X}_2 \rangle = m_{01} \\ \dot{m}_{01} &= \langle [-a_2 X_2 - a_1 X_1] \rangle = -a_2 m_{01} - a_1 m_{10} \\ \dot{m}_{20} &= \langle X_2 \dot{X}_1 \rangle = 2m_{11} \\ \dot{m}_{11} &= \langle X_2 \dot{X}_2 + [-a_2 X_2 - a_1 X_1] X_1 \rangle = m_{02} - a_2 m_{11} - a_1 m_{20} \\ \dot{m}_{20} &= \langle [-a_2 X_2 - a_1 X_1] 2X_2 \rangle + \langle X_1^2 D_{11} + D_{22} \rangle \\ &= -2a_2 m_{02} - 2a_1 m_{11} + D_{11} m_{20} + D_{22} \end{aligned}$$

Well, if you now write an equation for m_{10} , so the notation that I am following is, m_{rs} is expected value of X of t to the power of r X dot of t to the power of s . So, m_{10} nothing but expected value of X of t ; so, m_{10} , I get on the right hand side m_{01} .

So, similarly, if I write m_{01} , I get on the right hand side m_{01} as well as m_{10} . So, if you look at now the equation at the mean level, so this is the expected value of X , this is the expected value of X dot, we get a close set of equations; this is no problem here, because in the right hand side, I have nothing other than expected value of X and expected value of X dot. So, I can solve this problem and I can get exact solutions.

Although the governing Fokker Planck equation for the evolution of probability density function, I am unable to solve, but for the moments, I get exact equations which are solved. How about higher order moments? You now look at m_{20} , which is expected value of X square of t , you get on the right hand side $2 m_{11}$, which is auto correlation the correlation between X of t and X dot of t . Similarly, m_{11} dot if you write, on the other right hand side I get, you know, m_{02} , m_{20} , m_{11} , etcetera. How about m_{20} ? This is a m_{02} . I get here an equation which is again contains terms only up to second order; so, that could mean in this case, there is no closure problem.

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I order moments


$$\dot{m}_{10} = \langle X_2 \rangle = m_{01}$$
$$\dot{m}_{01} = \langle [-a_2 X_2 - a_1 X_1] \rangle = -a_2 m_{01} - a_1 m_{10}$$

II order moments

$$\dot{m}_{20} = \langle X_2 2X_1 \rangle = 2m_{11}$$
$$\dot{m}_{11} = \langle X_2 X_2 + [-a_2 X_2 - a_1 X_1] X_1 \rangle = m_{02} - a_2 m_{11} - a_1 m_{20}$$
$$\dot{m}_{20} = \langle [-a_2 X_2 - a_1 X_1] 2X_2 \rangle + \langle X_1^2 D_{11} + D_{22} \rangle$$
$$= -2a_2 m_{02} - 2a_1 m_{11} + D_{11} m_{20} + D_{22}$$

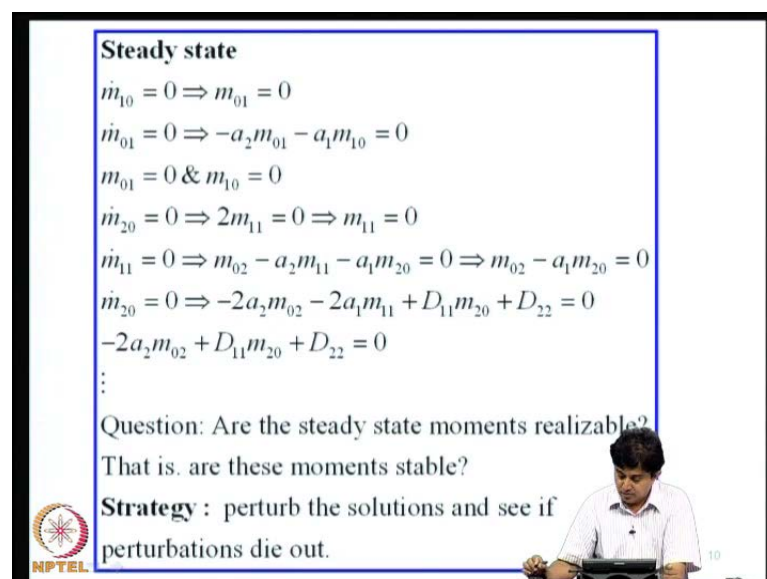
Moment equations are closed & hence can be evaluated exactly (numerically at least)

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So, you look at first order moments on the right hand side, I have only terms which are first order nature. You look at second order moments on the right hand side, I have terms which are basically the second order. See here, m_{02} m_{11} m_{20} ; so, that means moment equations are closed and hence can be evaluated exactly at least numerically. So, in this particular case, we get the approach that we are discussing forms source of an exact solution.

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Steady state


$$\dot{m}_{10} = 0 \Rightarrow m_{01} = 0$$
$$\dot{m}_{01} = 0 \Rightarrow -a_2 m_{01} - a_1 m_{10} = 0$$
$$m_{01} = 0 \ \& \ m_{10} = 0$$
$$\dot{m}_{20} = 0 \Rightarrow 2m_{11} = 0 \Rightarrow m_{11} = 0$$
$$\dot{m}_{11} = 0 \Rightarrow m_{02} - a_2 m_{11} - a_1 m_{20} = 0 \Rightarrow m_{02} - a_1 m_{20} = 0$$
$$\dot{m}_{20} = 0 \Rightarrow -2a_2 m_{02} - 2a_1 m_{11} + D_{11} m_{20} + D_{22} = 0$$
$$-2a_2 m_{02} + D_{11} m_{20} + D_{22} = 0$$

⋮

Question: Are the steady state moments realizable?
That is, are these moments stable?

Strategy : perturb the solutions and see if perturbations die out.

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Example

$$\ddot{X} + a_2 \dot{X} + [a_1 + w_1(t)]X = w_2(t);$$



$t \geq 0; X(0) \& \dot{X}(0)$ specified.

$$dX_1 = X_2 dt$$

$$dX_2 = -a_2 X_2 dt - a_1 X_1 dt - X_1 dB_1(t) + dB_2(t)$$

$$\begin{Bmatrix} dX_1 \\ dX_2 \end{Bmatrix} = \begin{Bmatrix} X_2 \\ -a_2 X_2 - a_1 X_1 \end{Bmatrix} dt + \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix} \begin{Bmatrix} dB_1(t) \\ dB_2(t) \end{Bmatrix}$$

$$\langle dB_i(t) dB_j(t + \tau) \rangle = 2D_{ij} \delta(\tau); i, j = 1, 2$$

$$GDG^T = \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix} \begin{bmatrix} D_{11} & 0 \\ 0 & D_{22} \end{bmatrix} \begin{bmatrix} 0 & 0 \\ -X_1 & 1 \end{bmatrix}^T = \begin{bmatrix} 0 & 0 \\ 0 & D_{22} \end{bmatrix}$$



Now, how about steady state here? So, for system driven by parametric excitations, as we know there is no guarantee that system is behavior could be stable, so **assume** vertically time becomes large; we do not know there is steady state is reached or not.

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Steady state

$$\dot{m}_{10} = 0 \Rightarrow m_{01} = 0$$

$$\dot{m}_{01} = 0 \Rightarrow -a_2 m_{01} - a_1 m_{10} = 0$$

$$m_{01} = 0 \& m_{10} = 0$$

$$\dot{m}_{20} = 0 \Rightarrow 2m_{11} = 0 \Rightarrow m_{11} = 0$$

$$\dot{m}_{11} = 0 \Rightarrow m_{02} - a_2 m_{11} - a_1 m_{20} = 0 \Rightarrow m_{02} - a_1 m_{20} = 0$$


$$\dot{m}_{20} = 0 \Rightarrow -2a_2 m_{02} - 2a_1 m_{11} + D_{11} m_{20} + D_{22} = 0$$

$$-2a_2 m_{02} + D_{11} m_{20} + D_{22} = 0$$

⋮

Question: Are the steady state moments realizable?
That is. are these moments stable?

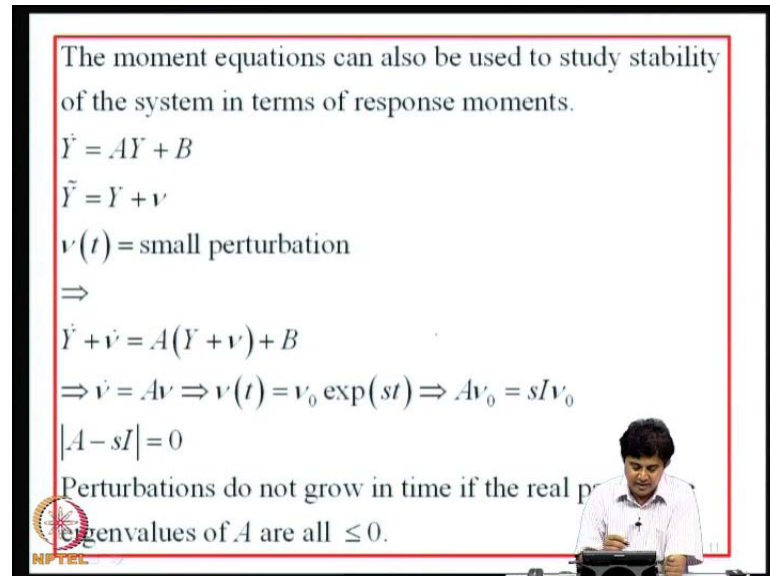
Strategy : perturb the solutions and see if perturbations die out.



But nevertheless, if we assume that a steady state indeed exist, we can get the solutions for m_{01} , m_{10} , etcetera. So, m_{01} , m_{10} are all 0; m_{20} , I get certain expressions. Now, the question are arises, whether these steady state solutions are realizable? They may not be realize, they may be on stable. So, what we do? We give a small perturbation to this

moments and see whether the perturbations decay in time or not; that means, I study now the stability of moment equations, which has set out the deterministic equations.

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The moment equations can also be used to study stability of the system in terms of response moments.

$$\dot{Y} = AY + B$$
$$\tilde{Y} = Y + v$$
$$v(t) = \text{small perturbation}$$
$$\Rightarrow$$
$$\dot{Y} + \dot{v} = A(Y + v) + B$$
$$\Rightarrow \dot{v} = Av \Rightarrow v(t) = v_0 \exp(st) \Rightarrow Av_0 = sIv_0$$
$$|A - sI| = 0$$

Perturbations do not grow in time if the real part of the Eigenvalues of A are all ≤ 0 .

So, that can easily be done; for example, if you have a set of equations, which is \dot{Y} is equal to AY plus B , and you give a perturbation Y plus nu , where nu is a small perturbation, I can get an equation for time evolution of nu , which is \dot{nu} is equal to $A nu$. So, if you now seek for the this set of equations and solution of this form, nu naught exponential st , again Eigenvalue problem governing nu naught and s , and we can show that the solutions are stable, provided the real parts of the Eigenvalues of a matrix are non-negative. Now, for stability, there non positive; if it is 0, the solution do not grow; but if it is negative, the solution decays.

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I order moments

$$\dot{m}_{10} = \langle X_2 \rangle = m_{01}$$

$$\dot{m}_{01} = \langle [-a_2 X_2 - a_1 X_1] \rangle = -a_2 m_{01} - a_1 m_{10}$$

II order moments


$$\dot{m}_{20} = \langle X_2 2X_1 \rangle = 2m_{11}$$

$$\dot{m}_{11} = \langle X_2 X_2 + [-a_2 X_2 - a_1 X_1] X_1 \rangle = m_{02} - a_2 m_{11} - a_1 m_{20}$$

$$\dot{m}_{20} = \langle [-a_2 X_2 - a_1 X_1] 2X_2 \rangle + \langle X_1^2 D_{11} + D_{22} \rangle$$

$$= -2a_2 m_{02} - 2a_1 m_{11} + D_{11} m_{20} + D_{22}$$

Moment equations are closed & hence can be evaluated exactly (numerically at least)



So, in any case, we can form this kind of equation \dot{Y} equal to AY plus B from the governing moment equations. And we are able to study now the stability of response moments; the stability of response moments need not guarantee the stability of sample process of the system. It only means, mean, standard deviation, variance, etcetera, co-variance whatever we are discussing are stable; it need not mean the samples of X of t need to be stable; so, that has to be core in mind. If you want to study stability of sample, there is an altogether different you know approach that we are not discussing in this course.

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Equations for two time moments

Consider $n = 2$


$$dX(t) = f[t, X(t)]dt + G[t, X(t)]dB(t); t \geq 0; X(0) = X_0$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^n \frac{\partial}{\partial x_j} [f_j(x, t) p] + \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial x_i \partial x_j} [(GDG')_{ij} p]$$

$$p = p(\tilde{x}, t | \tilde{x}_0; t_0) = p(x_1, x_2; t | x_{01}, x_{02}; t_0)$$

Consider

$$\langle X_1^m(t) X_1^m(t_0) \rangle = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1^m \eta_1^m p(x_1, \eta_1; t, t_0) dx_1 d\eta_1$$

$$p(x_1, \eta_1; t, t_0) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x_1, x_2, \eta_1, \eta_2; t, t, t_0, t_0) dx_2 d\eta_2$$


I have discussed till now equations for time evolution of moments, where I am considering only one time instant. Now, how about second order moments or equations for two time moments? So, for example, let us consider n equal to 2, it can be 3, 4, etcetera, but for the purpose of discussion will consider n equal to 2.

Now, this is an equation dX of t f of t X of t plus G dB t etcetera. Now, this is a governing Fokker Planck equation and this is a transition probability density function. Now, there are two time instance, t and t naught in the problem already; suppose, if I now consider expected value of X 1 to the power of m of t and X 1 to the power of n at t naught, so this can be written as X 1 to the power n n 1 to the power of n X 1 n 1 t comma t naught dx 1 d eta 1; this is a definition of expected value. For this joint density function, I will now write it as a marginal density of four-dimensional joint density function; that is, this density function I am writing it as a marginal of a fourth order density function.

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$$\begin{aligned} \langle X_1^m(t) X_1^n(t_0) \rangle &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1^m \eta_1^n p(x_1, \eta_1; t, t_0) dx_1 d\eta_1 \\ p(x_1, \eta_1; t, t_0) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x_1, x_2, \eta_1, \eta_2; t, t_0, t_0) dx_2 d\eta_2 \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x_1, x_2; t, t_0 | \eta_1, \eta_2; t, t_0) p(\eta_1, \eta_2; t, t_0) dx_2 d\eta_2 \\ \langle X_1^m(t) X_1^n(t_0) \rangle &= \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1^m \eta_1^n p(x_1, x_2; t, t_0 | \eta_1, \eta_2; t, t_0) p(\eta_1, \eta_2; t, t_0) dx_1 d\eta_1 dx_2 d\eta_2 \\ v(x_1, x_2; t, t_0) &= \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_1^n p(x_1, x_2; t, t_0 | \eta_1, \eta_2; t, t_0) p(\eta_1, \eta_2; t, t_0) d\eta_1 d\eta_2 \end{aligned}$$

Now, we can therefore look at this four-dimensional probability density function and use Markov property, and write that in terms of the transition probability density function and a second order density; actually, this is first order; eta 1 and eta 2 are elements of vector random process which is Markov. So, X 1 to the power of m X 1 to the power of n at t naught is given by this now. And if we now call the part of this integrant as a nu of X 1 comma X 2 t comma t naught, eta 1 to the power n and the only this term is retained; that

means, I retain look at only terms involving integration with respect to eta 1 and eta 2 and that integrant I will call it as v or nu.

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$$\langle X_1^m(t) X_1^m(t_0) \rangle = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1^m v(x_1, x_2; t, t_0) dx_1 dx_2$$

$$v(x_1, x_2; t, t_0) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_1^n p(x_1, x_2; t, t_0 | \eta_1, \eta_2; t, t_0) P(\eta_1, \eta_2; t, t_0) d\eta_1 d\eta_2$$

Consider the FPK equation

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^n \frac{\partial}{\partial x_j} [f_j(x, t) p] + \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial x_i \partial x_j} [(GDG^t)_{ij} p]$$

It follows that

$$\frac{\partial v}{\partial t} = -\sum_{j=1}^n \frac{\partial}{\partial x_j} [f_j(x, t) v] + \sum_{i=1}^n \sum_{j=1}^n \frac{\partial^2}{\partial x_i \partial x_j} [(GDG^t)_{ij} v]$$

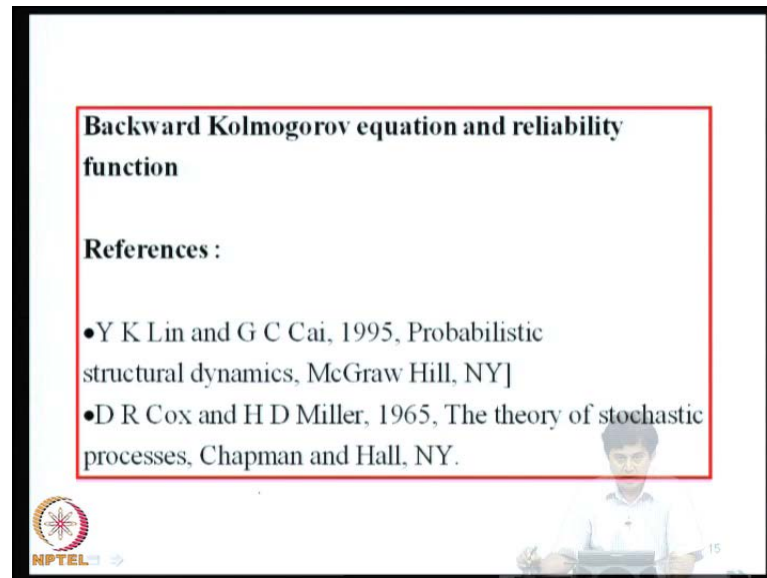
$$\lim_{t \rightarrow t_0} v(x_1, x_2; t, t_0) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \eta_1^n \delta(x_1 - \eta_1) \delta(x_2 - \eta_2) P(\eta_1, \eta_2; t_0, t_0) d\eta_1 d\eta_2$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(y_1, y_2; t_0, t_0) dy_1 dy_2$$

Now, the requisite moment can be written as, x_1 to the power of m ν $dx_1 dx_2$, now, where ν is given by this. Now, in the governing FPK equation, we can see that, the FPK equation is also satisfied by this function ν , because this involves $x_1 x_2 t$ and t naught; and if I substitute, if I carry out this integration with respective eta 1 and eta 2, this equation is not affected, because eta 1 and eta 2 are not the independent variables here. So, therefore, it is immediately follows that, the function ν is also satisfied by the same operator.

Now, how about initial conditions and bounded conditions? So, this now I have a Fokker Planck like, FPK like equation, where dependent variable is this function ν . I can establish the initial condition by considering the definition of ν at t equal to, as t goes to t naught, and I get this as, x_1 to the power of n $t y_1 y_2 t$ naught comma t naught; so, this is a fairly smooth function. So, it is good way to specify the initial condition. Then, I can actually solve this problem in principle; so, that would mean, using FPK equation, not only I can formulate a strategy to solve one time moments but also two time moments; and by the same token, higher order moments can also be, equations for higher order moments also can be set up.

(Refer Slide Time: 19:02)



Backward Kolmogorov equation and reliability function

References :

- Y K Lin and G C Cai, 1995, Probabilistic structural dynamics, McGraw Hill, NY]
- D R Cox and H D Miller, 1965, The theory of stochastic processes, Chapman and Hall, NY.

The slide features a red-bordered text box containing the title and references. In the bottom left corner, there is a circular logo with a star and the text 'NPTEL'. In the bottom right corner, there is a small inset image of a person sitting at a desk with a laptop, and the number '15' is visible in the bottom right corner of the slide frame.

I will not get into the details of this solutions etcetera, but we now move onto as related topic. What is known as backward Kolmogorov equation and reliability function? So far we have been looking at Fokker Planck equation, where the independent variable is t and X . And we assume the systems start from t equal to t_{naught} , and t is greater than t_{naught} ; so, the independent variable is greater than t_{naught} , and in that sense, it is a forward equation. Now, if we treat t_{naught} itself as an independent variable along with associated X_{naught} , then we get another equation known as backward Kolmogorov equation. In terms of that, backward Kolmogorov equation is useful for studying first passage times.

So far what we discussed was, the probability density function of the response and its moments. But this description does not helps us to solve the more important problem of first passage time, and extreme, and so on, so fourth, but the backward Kolmogorov equation assist us to you know tackle that problem. So, the two references: this one is a book by professors Lin and Cai, and other one is the book by professors Cox and Miller, which has certain useful background to this discussion.

(Refer Slide Time: 20:21)



Backward Kolmogorov equation and reliability function

Let $X(t)$ be a scalar Markov process. For $t_1 < t_2 < t_3$ we have

$$p(x_3; t_3 | x_1; t_1) = \int_{-\infty}^{\infty} p(x_3; t_3 | x_2; t_2) p(x_2; t_2 | x_1; t_1) dx_2$$

$$p(x_3; t_3 | x_2; t_2) = p(x_3; t_3 | \underline{x_1} + x_2 - \underline{x_1}; t_2)$$

$$= p(x_3; t_3 | x_1; t_2) + (x_2 - x_1) \left. \frac{\partial p}{\partial x_2} \right|_{x_2=x_1}$$

$$+ \frac{1}{2} (x_2 - x_1)^2 \left. \frac{\partial^2 p}{\partial x_2^2} \right|_{x_2=x_1} + o[(x_2 - x_1)^2]$$



Now, I will start the discussion on a scalar random process. Let X of t be a scalar Markov process, and I take three time instance, t_1 , t_2 , t_3 , and I have this equation which is the Jeff man Kolmogorov equation, which that transition probability density function must satisfied. So, what I will do now? I will consider this transition from t_2 to t_3 , and I will rewrite the argument x_2 as x_1 plus x_2 minus x_1 ; that is, I adding and subtracting x_1 , and I will now perform a Taylor's expansion of this function around x_1 . So, if I do Taylor's expansion around this and retain terms up to second order, I get this equation; that means, this is a function of x_2 , x_3 , t_2 , t_3 , I am performing Taylor's expansion only around x_2 ; x_2 written as x_1 plus x_2 minus x_1 . So, I am expanding this around x_1 .

(Refer Slide Time: 21:23)

$$\begin{aligned}
 p(x_3; t_3 | x_1; t_1) &= \int_{-\infty}^{\infty} p(x_3; t_3 | x_2; t_2) p(x_2; t_2 | x_1; t_1) dx_2 \\
 &= p(x_3; t_3 | x_1; t_2) + \left. \frac{\partial p}{\partial x_2} \right|_{x_2=x_1} \int_{-\infty}^{\infty} (x_2 - x_1) p(x_2; t_2 | x_1; t_1) dx_2 \\
 &\quad + \left. \frac{1}{2} \frac{\partial^2 p}{\partial x_2^2} \right|_{x_2=x_1} \int_{-\infty}^{\infty} (x_2 - x_1)^2 p(x_2; t_2 | x_1; t_1) dx_2 + o[(x_2 - x_1)^2] \\
 &\Rightarrow \frac{1}{\Delta} [p(x_3; t_3 | x_1; t_2) - p(x_3; t_3 | x_1; t_1)] \\
 &\quad + \frac{1}{\Delta} \left. \frac{\partial p}{\partial x_2} \right|_{x_2=x_1} \int_{-\infty}^{\infty} (x_2 - x_1) p(x_2; t_2 | x_1; t_1) dx_2 \\
 &\quad + \frac{1}{\Delta} \left. \frac{\partial^2 p}{\partial x_2^2} \right|_{x_2=x_1} \int_{-\infty}^{\infty} (x_2 - x_1)^2 p(x_2; t_2 | x_1; t_1) dx_2 + o[(x_2 - x_1)^2]
 \end{aligned}$$

After doing that, I will substitute that back into the Chapman-Kolmogorov equation and carry out the integration by parts. And if you do that, this is straightforward exercise, we can recast the equation as 1 by delta t; I can transpose some of the terms to the left hand side and divide both sides by delta t, and I can write this as the kind of 1 by delta t into transition from, I mean, $x_3, t_3 | x_1, t_2$, $x_3, t_3 | x_1, t_1$ plus these terms, which have displayed here.

(Refer Slide Time: 22:05)

Consider the $\lim t_2 \rightarrow t_1 \Rightarrow$

$$\frac{\partial p}{\partial t_1} + \alpha_1(x_1, t_1) \frac{\partial p}{\partial x_1} + \frac{1}{2} \alpha_2(x_1, t_1) \frac{\partial^2 p}{\partial x_1^2} = 0$$

$p \equiv p(x_3, t_3 | x_1, t_1)$

In the standard form the above equation written as

$$\frac{\partial p}{\partial t_0} = -\alpha_1(x_0, t_0) \frac{\partial p}{\partial x_0} - \frac{1}{2} \alpha_2(x_0, t_0) \frac{\partial^2 p}{\partial x_0^2}; p \equiv p(x, t | x_0, t_0)$$

is known as the backward Kolmogorov equation.

(Backward \because the independent variable $t_0 < t$)

ICS: $p(x, t_0 | x_0, t_0) = \delta(x - x_0)$

[Typical] BCS: $\lim_{x_0 \rightarrow \pm\infty} p(x, t | x_0, t_0) \rightarrow 0$

Now, if you allow delta t equal to 0, we get now the time derivative with respect to t; that is $\frac{\partial p}{\partial t} + \sum_{j=1}^n f_j \frac{\partial p}{\partial x_j} - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n [GDG' (t, \tilde{x}_0)]_{ij} \frac{\partial^2 p}{\partial x_i \partial x_j}$, where p is now the transition from t to t + delta t. So, this is known as backward Kolmogorov equation. In the standard form, the above equation is written as $\frac{\partial p}{\partial t} + \sum_{j=1}^n f_j \frac{\partial p}{\partial x_j} - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n [GDG' (t, \tilde{x}_0)]_{ij} \frac{\partial^2 p}{\partial x_i \partial x_j} = 0$, where p is probability density function of x at time t. This is called backward, as I said already, because the independent variable t is less than t_0. Initial conditions at t = t_0, as t goes to t_0, it is a direct delta function, and typical boundary conditions, as x goes to plus minus infinity, this goes to 0.

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Vector version of Backward Kolmogorov equation

$$dX(t) = f[t, X(t)]dt + G[t, X(t)]dB(t); t \geq 0; X(0) = X_0$$

$$\frac{\partial p}{\partial t_0} = - \sum_{j=1}^n f_j [t_0, \tilde{x}_0] \frac{\partial p}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG' (t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 p}{\partial x_{0i} \partial x_{0j}}$$

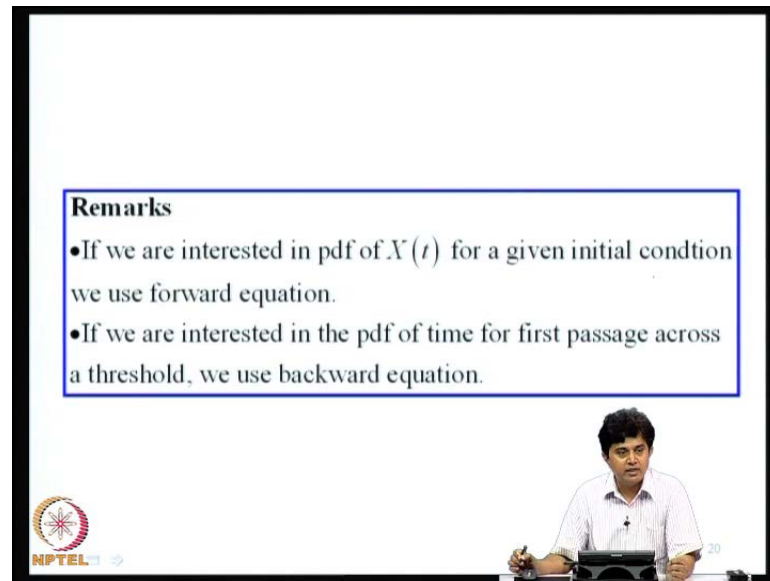
$$p \equiv p(\tilde{x}; t | \tilde{x}_0; t_0)$$

$$\text{ICS: } p(\tilde{x}; t_0 | \tilde{x}_0; t_0) = \prod_{i=1}^n \delta(x_i - x_{i0})$$

$$\text{BCS: } \forall j = 1, 2, \dots, n, \lim_{x_j \rightarrow \pm\infty} p(\tilde{x}; t | \tilde{x}_0; t_0) \rightarrow 0$$

Now, a vector version of this equation can also be set of... this is straightforward and we logic is same for this derivation and this is displayed here. So, you should notice that, now the independent variables are t, x and t_0 are the independent variables.

(Refer Slide Time: 23:35)

A video frame showing a slide with a blue border. The slide contains the following text:

Remarks

- If we are interested in pdf of $X(t)$ for a given initial condition we use forward equation.
- If we are interested in the pdf of time for first passage across a threshold, we use backward equation.

In the bottom right corner of the video frame, a lecturer is visible, sitting at a desk. In the bottom left corner of the video frame, there is a logo for NPTEL (National Programme on Technology Enhanced Learning) with the text 'NPTEL' and a small circular emblem.

Now, when to use forward equation and when to use backward equation? The same transition density function satisfied both the equations. So, when do we solve forward equation and when do we solve backward equation? If we are interested in probability density function of X of t for a given initial condition, we use forward equation; that means, start t equal to t naught to the given initial conditions, and you want to know what is known as probability density function after some time t , you use forward equation. But if you are interested in knowing if the trajectories originate, if you are interested in PDF of time purpose for passage across a threshold, we consider the backward equation; I will explain this further.

(Refer Slide Time: 24:17)

First passage times

Consider the scalar SDE

$$dX(t) = f(X)dt + G(X)dB(t) \text{ with } X(t_0) = x_0 < x_c$$



T = time at which $X(t)$ reaches the critical value x_c for the first time given that $X(t_0) = x_0 < x_c$.

Safe region: $X(t) \leq x_c$

Unsafe region: $X(t) > x_c$

$R(t, x_c; x_0; t_0)$ = Probability that $X(t)$ stays in the safe region during the interval t_0 to t .

$$R(t, x_c; x_0; t_0) = \int_{x_0}^{x_c} p(x, t | x_0; t_0) dx = P[T > t - t_0 | X(t_0) = x_0]$$

So, what that means? So, we talk about now first passage times. Now, let us consider the scalar SDE; now, I am considering a scalar function, $dX(t) = f(X)dt + G(X)dB(t)$, which is specified initial condition. And I defined a barrier x_c , which a critical barrier, and if $X(t)$ reaches that barrier, we say the system has failed; and what I am interested in is, if system start selecting from safe region, what is the time required for the first crossing of the critical barrier? That can be used as a descriptor of life time of the this structure.

So, t I defined as time at which $X(t)$ reaches the critical value of x_c for the first time, given that $X(t_0)$ is a X_0 , and X_0 itself less than a critical barrier; that means, $t = T$, where starting from the safe region. So, safe region is $X(t) \leq x_c$ and unsafe region $X(t) > x_c$.

So, I define R which is function of X_0 , t_0 and t , and x_c and X_0 ; that mean, trajectory originated t_0 from X_0 and reach a level x_c at time t . So, this is probability that $X(t)$ state in the safe region, during the interval t_0 to t . So this is nothing but integral of x_0 to x_c probability density of $X(t)$ condition $X(t_0) = X_0$ dx , which should be interpreted as probability of $T > t - t_0$; that means, first passage time is greater than t , if t_0 is 0 condition on the fact that $X(t_0) = X_0$.

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$$R(t, x_c; x_0; t_0) = \int_{x_l}^{x_c} p(x; t | x_0; t_0) dx = P[T > t - t_0 | X(t_0) = x_0]$$


Remark
The samples of $X(t)$ are such that the first time they reach the level x_c they get absorbed. That is, $X(t) = x_c$ is an absorbing barrier.

BK-equation
$$\frac{\partial p}{\partial t_0} + f(x_0) \frac{\partial p}{\partial x_0} + G(x_0) D \frac{\partial^2 p}{\partial x_0^2} = 0; p \equiv p(x; t | x_0; t_0)$$

ICS: $p(x, t_0 | x_0; t_0) = \delta(x - x_0)$

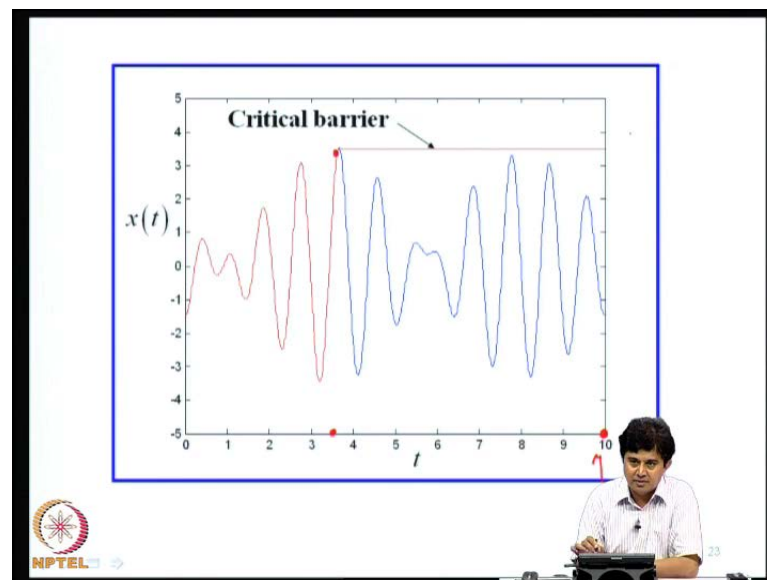
BCS: $p(x_c; t | x_0; t_0) = 0$ [Absorbing boundary]

We consider only those trajectories which have not yet reached the critical barrier.



Now, the samples of X of t are such that, the first time they reach the level x_c , they get absorbed; that is, X of t equal to x_c is an absorbing barrier.

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So, what that means is, suppose we are looking at sample of x of t , and imagine that this line as shown here is a sample of x of t , suppose at say x of t equal to is a 3.2 or whatever, I place a barrier. So, you see that, this time instant here, the trajectory reaches this level and it gets absorb. suppose I am interested in knowing what happens at this

time instant, what is the probability that first passage time is greater than 10 seconds, if I am interested?

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First passage times

Consider the scalar SDE
 $dX(t) = f(X)dt + G(X)dB(t)$ with $X(t_0) = x_0 < x_c$
 $T =$ time at which $X(t)$ reaches the critical value x_c for the first time given that $X(t_0) = x_0 < x_c$.

Safe region: $X(t) \leq x_c$
Unsafe region: $X(t) > x_c$

$R(t, x_c; x_0; t_0) =$ Probability that $X(t)$ stays in the safe region during the interval t_0 to t .

$R(t, x_c; x_0; t_0) = \int_{x_l}^{x_c} p(x; t | x_0; t_0) dx = P[T > t - t_0 | X(t_0) = x_0]$

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So, I have to look at only those trajectories, which have not yet been absorbed; and this integration that I am showing here is across only those trajectories, which have not yet been absorbed.

(Refer Slide Time: 27:08)




$R(t, x_c; x_0; t_0) = \int_{x_l}^{x_c} p(x; t | x_0; t_0) dx = P[T > t - t_0 | X(t_0) = x_0]$

Remark
 The samples of $X(t)$ are such that the first time they reach the level x_c they get absorbed. That is, $X(t) = x_c$ is an absorbing barrier.

BK-equation
 $\frac{\partial p}{\partial t_0} + f(x_0) \frac{\partial p}{\partial x_0} + G(x_0) D \frac{\partial^2 p}{\partial x_0^2} = 0; p \equiv p(x; t | x_0; t_0)$

ICS: $p(x, t_0 | x_0; t_0) = \delta(x - x_0)$
 BCS: $p(x_c; t | x_0; t_0) = 0$ [**Absorbing boundary**]

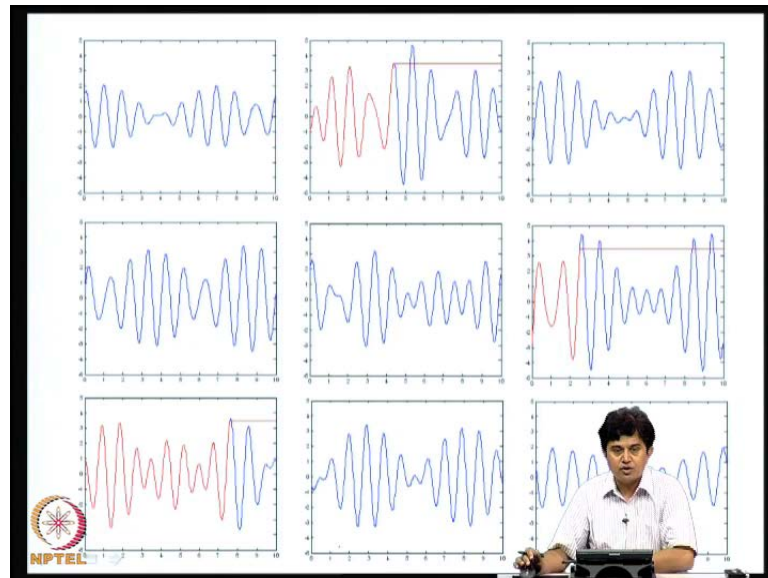
We consider only those trajectories which have not yet reached the critical barrier.

So, we have to now place an absorbing barrier for this equation; so, this is the backward Kolmogorov equation. And initial condition is that, t equal to t naught is a direct delta

function, and let the critical barrier we say that, probability density function is 0; that means, we consider only those trajectories, which have not yet reach the critical barrier.

(Refer Slide Time: 27:29)



So, I have shown here a few trajectories of a same random process. This is the trajectory, at equal to 10 second, it has not yet been absorbed. So, this stage in our reckoning, but whereas this goes out, because I am interested in what happens in 10 seconds, at the end of the time period. So, this trajectory is already been absorbed, this survives, this survives, this survive, this is absorbed, this is absorbed, this survives, this survives. So, among those trajectory which has survived, I will do the integration and find out what is a probability the first passage time is greater than 10 seconds.

(Refer Slide Time: 28:12)

$$R(t, x_c; x_0; t_0) = \int_{x_l}^{x_c} p(x; t | x_0; t_0) dx = P[T > t - t_0 | X(t_0) = x_0]$$

$$\frac{\partial p}{\partial t_0} + f(x_0) \frac{\partial p}{\partial x_0} + G(x_0) D \frac{\partial^2 p}{\partial x_0^2} = 0 \Rightarrow$$

$$\frac{\partial R}{\partial t_0} + f(x_0) \frac{\partial R}{\partial x_0} + G(x_0) D \frac{\partial^2 R}{\partial x_0^2} = 0$$

BCS

$$R(t_0, x_c; x_0; t_0) = 1$$


- [At $t = t_0$, no trajectory has reached the critical barrier]

$$R(t, x_c; x_c; t_0) = 0$$

- [If the trajectory originate from x_c the probability of failure=1]

$$0 \leq R(t, x; x_0; t_0) \leq 1$$

- [Because R is a probability]



So, how do we write that? Now, I have now got the backward Kolmogorov equation and I have got this expression for R , which is actually the probability that, first passage time is greater than t minus t_0 naught condition on the factor X of t_0 naught is x_0 naught.

Now, you can see that, the backward Kolmogorov equation is also satisfied by this function R ; that means, you perform this integration x_l to x_c on dx , which is not an dependent variable here; the form of the differential equation is will remain the same, because what you will do? Multiply by dx and integrate over x_l to x_c , and that first term will be $\frac{dR}{dt_0}$, second term will be $f(x_0) \frac{dR}{dx_0}$, and so on so forth. That means, the backward Kolmogorov operator is applicable even for R , which is the reliability function; R can be thought of us safety function or reliability function or survival function, because it means that, we are looking at a first passage time being greater than a specified time t .

So, what are the boundary conditions on it? $R(t_0, x_c; x_c; t_0) = 1$; that means, at t equal to t_0 , no trajectory has reached the critical barrier, that translates as one of the **Markov**. Then, $R(t, x_c; x_c; t_0) = 0$, that means, if the trajectory originate from x_c , the probability of failure is 1; therefore, survival is 0, and R be a probability is bounded between 0 and 1.

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Summary

$$R(t, x_c; x_0; t_0) = P[T > t - t_0 \mid X(t_0) = x_0]$$


$$\frac{\partial R}{\partial t_0} + f(x_0) \frac{\partial R}{\partial x_0} + DG(x_0) \frac{\partial^2 R}{\partial x_0^2} = 0$$

$$R(t_0, x_c; x_0; t_0) = 1$$

$$R(t, x_c; x_c; t_0) = 0$$

$$0 \leq R(t, x; x_0; t_0) \leq 1$$

Assume: $x_0 = z_l$ is reflective

$$\left[\frac{\partial p(x; t \mid x_0; t_0)}{\partial x_0} \right]_{x_0=y_l} = 0 \Rightarrow \left(\frac{\partial R}{\partial x_0} \right)_{x_0=y_l} = 0$$

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So, this actually constitutes an Eigenvalue problem; so, we to summarize that, this is a function that we are looking at, R is probability of t greater than t minus t naught condition X of t naught equal to x naught. This is the governing partial differential equation, these are the condition that has to be satisfied; and at the lower end, we are placing a non-critical barrier and we call it as a reflective barrier. Here, if trajectory reach x lower barrier, it is not absorbed, but it can return to the safe region subsequently.

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Let $\tau = t - t_0$


$$R(t, x_c; x_0; t_0) \equiv R(\tau, x_c; x_0) = P[T > \tau \mid X(t_0) = x_0]$$

$$-\frac{\partial R}{\partial \tau} + f(x_0) \frac{\partial R}{\partial x_0} + DG(x_0) \frac{\partial^2 R}{\partial x_0^2} = 0$$

$$R(\tau, x_c; x_0)|_{\tau=0} = 1$$

$$R(\tau, x_c; x_c) = 0$$

$$0 \leq R(\tau, x; x_0) \leq 1$$

$$\left(\frac{\partial R}{\partial x_0} \right)_{x_0=y_l} = 0$$

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Now, if we put tau as t minus t naught, I can make some simplification; this R can be written as tau of x c semicolon X naught; that means, probability of t greater than tau condition X of t naught is equal to x naught is what I am looking for. And I get the governing equation in terms of R, in terms of independent variables, which are tau and x naught. So, again the boundary condition following the similar logic can be written like this; this is the boundary condition on the absorbing barrier. And if we can solve this problem, this set of partial differential equation, I mean, this partial differential equation along this set of conditions, we have now as forced to derive in a probability of first passage times.

Now, the solution for the entire function, that is the probability distribution of first passage time would require solution of a partial differential equations. Suppose, if you are interested in moments of first passage times, situation be simpler.

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Moments of first passage time

$$P[T \leq \tau | X(t_0) = x_0] = 1 - P[T > \tau | X(t_0) = x_0]$$

$$P_T(\tau, x_c, x_0) = 1 - R(\tau, x_c; x_0)$$

$$p_T(\tau, x_c, x_0) = \frac{\partial}{\partial \tau} P_T(\tau, x_c, x_0) = -\frac{\partial}{\partial \tau} R(\tau, x_c; x_0)$$

We have

$$-\frac{\partial R}{\partial \tau} + f(x_0) \frac{\partial R}{\partial x_0} + DG(x_0) \frac{\partial^2 R}{\partial x_0^2} = 0$$

$$\Rightarrow p_T(\tau, x_c, x_0) = -f(x_0) \frac{\partial R}{\partial x_0} - DG(x_0) \frac{\partial^2 R}{\partial x_0^2}$$

$$\langle T^n \rangle = \int_0^{\infty} \tau^n p_T(\tau, x_c, x_0) d\tau = M_n(x_c, x_0)$$

So, if you look at that, now let us consider the probability distribution function of t, which is probability of t less than equal to tau condition on X t naught equal to x naught, which is 1 minus R, which is our survival function.

So, we see that, probability distribution function of first passage time is 1 minus a survival function. Now, the probability density function is derivative of this with respective tau, because tau is a state variable. So, that will be dou by dou tau this, and this is minus dou by dou tau R; that would mean that, we have this equation which

governs R and first term here is nothing but probability density function. So, I can tau as an independent variable now, I mean tau would no longer be an independent variable of this differential equation; this becomes an ordinary differential equation now. So, p_T can be written like this. From this, if I now find out the n th order moment - expected value of T^n - is will be 0 to infinity, tau n this density function $d\tau$, and I call it as M_n , with barrier x_c and x_{naught} .

(Refer Slide Time: 32:51)

$$M_n = \langle T^n \rangle = \int_0^{\infty} \tau^n p_T(\tau, x_c, x_0) d\tau = \int_0^{\infty} \tau^n \left(-\frac{\partial}{\partial \tau} R(\tau, x_c; x_0) \right) d\tau$$

$$= \left[\tau^n R(\tau, x_c; x_0) \right]_0^{\infty} + n \int_0^{\infty} \tau^{n-1} R(\tau, x_c; x_0) d\tau$$

$$= n \int_0^{\infty} \tau^{n-1} R(\tau, x_c; x_0) d\tau$$

We have

$$-\frac{\partial R}{\partial \tau} + f(x_0) \frac{\partial R}{\partial x_0} + DG(x_0) \frac{\partial^2 R}{\partial x_0^2} = 0$$

Multiply both sides of this equation by τ^n and integrate over 0 to $\infty \Rightarrow$

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So, if you look at M_n , this is the definition as I said just now, and we can now use the governing equation and integrate this by parts, and we can see that, we reach this equation M_n is n into tau n minus 1 $R d\tau$. Now, we can simplify by this by reverting back to the governing equation for R , what will do is, in this equation, we multiply both sides by tau to the power n and integrate on 0 to infinity.

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$$\int_0^{\infty} \tau^n \left(-\frac{\partial R}{\partial \tau} \right) d\tau + \int_0^{\infty} \tau^n f(x_0) \left(\frac{\partial R}{\partial x_0} \right) d\tau + D \int_0^{\infty} \tau^n G(x_0) \left(\frac{\partial^2 R}{\partial x_0^2} \right) d\tau = 0$$

$$M_n + \frac{1}{n+1} f(x_0) \frac{d}{dx_0} M_{n+1} + D \frac{G(x_0)}{n+1} \frac{d^2}{dx_0^2} M_{n+1} = 0$$

$$(n+1)M_n + f(x_0) \frac{d}{dx_0} M_{n+1} + DG(x_0) \frac{d^2}{dx_0^2} M_{n+1} = 0$$

$$M_n(x_c, x_0) \Big|_{x_0=x_c} = 0$$

$$M_n(x_c, x_0) \Big|_{x_0=x_l} < \infty$$

$$n = 1, 2, \dots$$

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If we do that and rearrange the terms slightly, I get a set of recursive relations for first passage times. So, the equation that I get is recursive relation for moments of first passage times. So, n plus 1 into M n plus f of x naught d by dx naught M n plus 1 plus DG of x naught d square M n plus 1 by dx naught square is equal to 0 and along with this stipulated boundary condition. So, we can solve this now sequentially.

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$$(n+1)M_n + f(x_0) \frac{d}{dx_0} M_{n+1} + DG(x_0) \frac{d^2}{dx_0^2} M_{n+1} = 0$$

$$n = 0 \Rightarrow M_0 = 1$$

$$1 + f(x_0) \frac{dM_1}{dx_0} + DG(x_0) \frac{d^2 M_1}{dx_0^2} = 0$$

$$M_1(x_c, x_0) \Big|_{x_0=x_c} = 0$$

$$M_1(x_c, x_0) \Big|_{x_0=x_l} < \infty$$

$$n = 1$$

$$f(x_0) \frac{dM_2}{dx_0} + DG(x_0) \frac{d^2 M_2}{dx_0^2} = -2M_1$$

$$M_2(x_c, x_0) \Big|_{x_0=x_c} = 0$$

$$M_2(x_c, x_0) \Big|_{x_0=x_l} < \infty$$

NPTEL

So, if you put n equal to 0, we know that M naught is 1, because that is a normalization condition on a probability density function; area under probability density function is 1,

therefore, M naught is 1. So, I get this simple equation and this can be solved; and if n equal to 1, what happens is, on the right hand side, I get M 1, which have already solved.

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Vif *GPV eqns*

Generalized Pontryagin Equations

$$f(x_0) \frac{d}{dx_0} M_{n+1} + DG(x_0) \frac{d^2}{dx_0^2} M_{n+1} = -(n+1)M_n$$

$$M_{n+1}(x_c, x_0)|_{x_0=x_c} = 0$$

$$M_{n+1}(x_c, x_0)|_{x_0=x_i} < \infty$$

$$n = 1, 2, \dots$$

NPTEL

So, I get a sequential set of equations, which I can tackle one by one and this set of equations are known as generalized Pontryagin equations. So, there are called GPV equation. **How about** This is for first one-dimensional random process - scalar random process. How about multi-dimensional case?

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Generalization to multi - dimensional problems

$$dX(t) = f[t, X(t)]dt + G[t, X(t)]dB(t); t \geq 0; X(0) = X_0$$

$$\frac{\partial p}{\partial t_0} = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial p}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG^t(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 p}{\partial x_{0i} \partial x_{0j}}$$

$$p \equiv p(\tilde{x}, t | \tilde{x}_0; t_0)$$

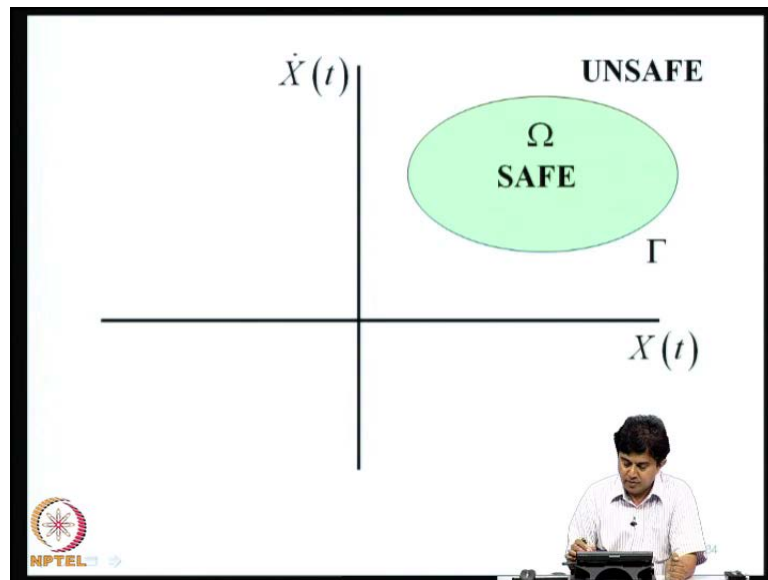
Safe region : $X(t) \in \Omega$, Γ = Limits of safe region

$$R(t, \Gamma; t_0, \Omega) = \int_{\Omega} p(\tilde{x}, t | \tilde{x}_0; t_0) d\tilde{x} = P[T > t - t_0 | X(t_0) = \tilde{x}_0]$$

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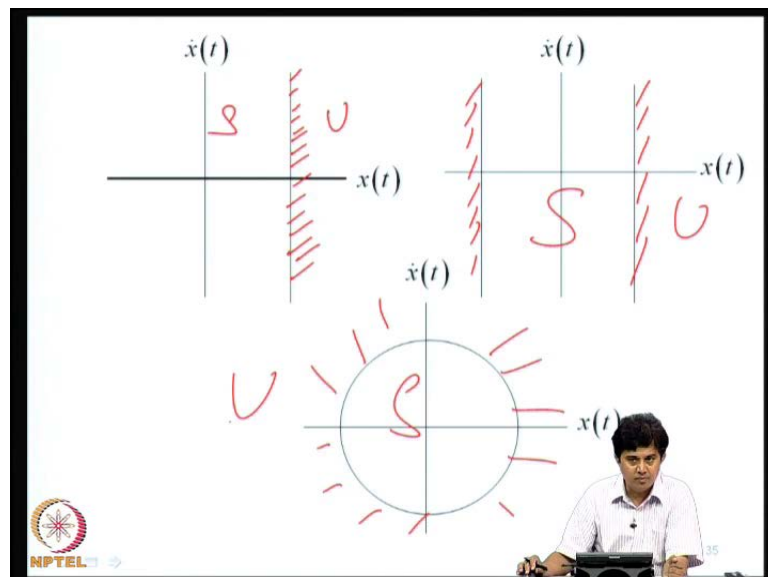
The same logic could work; the algebra is likely tedious. So, we look at now the vector version of the stochastic differential equation and associated backward equations; and we now define a safe region, it is no longer a barrier, now it is a region in safe face. So, X of t belongs to capital omega; we call it as a gamma is a limits of safe region.

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That means, **if you** in the phase plane, the two-dimensional problems, this can be safe and this boundary is gamma, and this is the answer. But this is the one proposed one possibility.

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But there could be other situation; for example, we can have a single barrier problem, this is unsafe, this is safe; or two barrier problems, this is safe, this is unsafe; and kind of region, so this is safe, this is unsafe. So, the boundary conditions for the associated governing partial differential equation have to be formulated, based on the physics of the failure criteria, that you are interested in studying; so, this can be fairly involved.

(Refer Slide Time: 36:12)



Generalization to multi - dimensional problems

$$dX(t) = f[t, X(t)]dt + G[t, X(t)]dB(t); t \geq 0; X(0) = X_0$$

$$\frac{\partial p}{\partial t_0} = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial p}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG'(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 p}{\partial x_{0i} \partial x_{0j}}$$

$$p \equiv p(\tilde{x}; t | \tilde{x}_0; t_0)$$

Safe region : $X(t) \in \Omega$, Γ = Limits of safe region

$$R(t, \Gamma; t_0, \Omega) = \int_{\Omega} p(\tilde{x}; t | \tilde{x}_0; t_0) d\tilde{x} = P[T > t - t_0 | X(t_0) = \tilde{x}_0]$$



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$$R(t, \Gamma; t_0, \Omega) = \int_{\Omega} p(\tilde{x}; t | \tilde{x}_0; t_0) d\tilde{x} = P[T > t - t_0 | X(t_0) = \tilde{x}_0]$$

$$\frac{\partial R}{\partial t_0} = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial R}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG'(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 R}{\partial x_{0i} \partial x_{0j}}$$

$$R(t_0, \Gamma; t_0, \Omega) = 1$$



- [At $t = t_0$, no trajectory has reached the critical barrier]

$$R(t, \Gamma; t_0, \Gamma) = 0$$

- [If the trajectory originate on Γ the probability of failure=1]

$$0 \leq R(t, \Gamma; t_0, \Omega) \leq 1$$

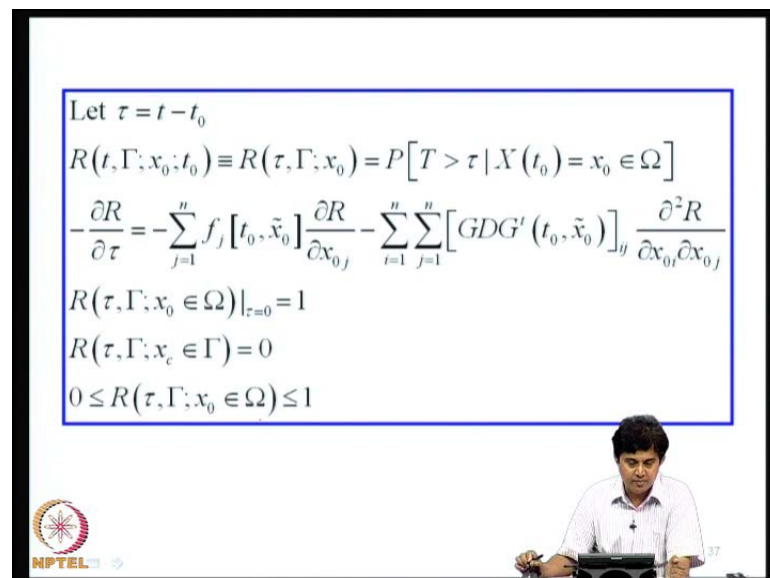
- [Because R is a probability]

So, in any case, we define R as the probability of $\tilde{x} : t$ condition on \tilde{x}_0 at t_0 over the safe region. So, again I place a boundary on Γ absorbing boundary

on gamma and this equation has to be solved in conjunction with absorbing boundary. So, if you look at that, again we can consider the governing backward Kolmogorov equation, and verify that the reliability function is again satisfied by the same operator and we have the governing partial differential equation for the survival of the system - probability of survival. And following the same argument that used for scalar random process, we can continue to use similar arguments and derive the associated boundary condition. In principle, therefore, we can formulate the required partial differential equation, which governs the first passage time. But now the first passage time in a region, it does not require barriers **in a** as in a scalar problem.

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Let $\tau = t - t_0$

$$R(t, \Gamma; x_0; t_0) \equiv R(\tau, \Gamma; x_0) = P[T > \tau | X(t_0) = x_0 \in \Omega]$$

$$-\frac{\partial R}{\partial \tau} = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial R}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG'(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 R}{\partial x_{0i} \partial x_{0j}}$$

$$R(\tau, \Gamma; x_0 \in \Omega)|_{\tau=0} = 1$$

$$R(\tau, \Gamma; x_c \in \Gamma) = 0$$

$$0 \leq R(\tau, \Gamma; x_0 \in \Omega) \leq 1$$

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Moments of first passage time

$$P[T \leq \tau | X(t_0) = x_0 \in \Omega] = 1 - P[T > \tau | X(t_0) = x_0 \in \Omega]$$

$$R(t, \Gamma; \tilde{x}_0 \in \Omega) = \int_{\Omega} p(\tilde{x}; t | \tilde{x}_0; t_0) d\tilde{x} = P[T > t - t_0 | X(t_0) = \tilde{x}_0 \in \Omega]$$

$$P_T(\tau, \Gamma, x_0 \in \Omega) = 1 - R(t, \Gamma; \tilde{x}_0 \in \Omega)$$

$$p_T(\tau, \Gamma, x_0 \in \Omega) = \frac{\partial}{\partial \tau} P_T(\tau, \Gamma, x_0 \in \Omega) = -\frac{\partial}{\partial \tau} R(t, \Gamma; \tilde{x}_0 \in \Omega)$$

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We have

$$-\frac{\partial R}{\partial \tau} = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial R}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG^t(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 R}{\partial x_{0i} \partial x_{0j}}$$

$$\Rightarrow p_T(\tau, \Gamma, x_0 \in \Omega) = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial R}{\partial x_{0j}} -$$


$$\sum_{i=1}^n \sum_{j=1}^n [GDG^t(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2 R}{\partial x_{0i} \partial x_{0j}}$$

$$\langle T^n \rangle = \int_0^{\infty} \tau^n p_T(\tau, \Gamma, x_0 \in \Omega) d\tau = M_n(\Gamma, x_0 \in \Omega)$$

$$\Rightarrow$$

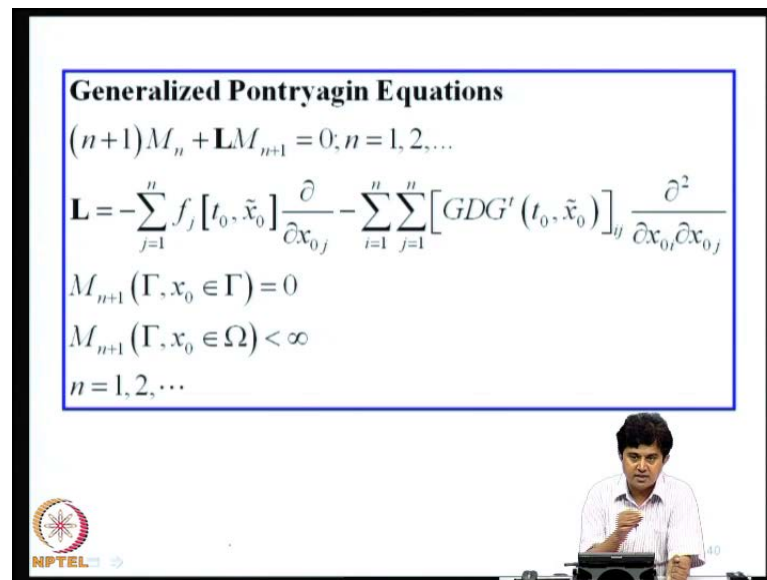
$$\mathbf{L} = -\sum_{j=1}^n f_j[t_0, \tilde{x}_0] \frac{\partial}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG^t(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2}{\partial x_{0i} \partial x_{0j}}$$

$(n+1)M_n + \mathbf{L}M_{n+1} = 0, n = 1, 2, \dots$ *GPV*



So, some of these can be simplified if you introduce tau is equal to t minus t naught and simplified version of this can be obtained; and from this, we can look at moments of first passage time; the logic is exactly the similar. We start with PDF of first passage time - probability distribution function of first passage time - and express in terms of express theta 1 minus R, and go back to the equation of R and derive the equation for the moments of first passage time as shown here. And we get this set of equation, that is, n plus 1 M n plus LM plus 1 is 0, for n equal to 1, 2, etcetera. So, these are the GPV equations for the system.

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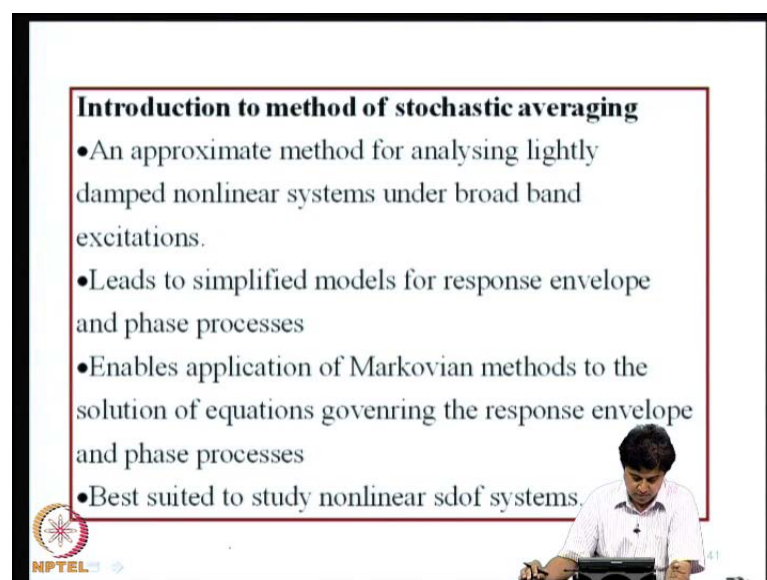
Generalized Pontryagin Equations

$$(n+1)M_n + \mathbf{L}M_{n+1} = 0; n = 1, 2, \dots$$
$$\mathbf{L} = -\sum_{j=1}^n f_j [t_0, \tilde{x}_0] \frac{\partial}{\partial x_{0j}} - \sum_{i=1}^n \sum_{j=1}^n [GDG^i(t_0, \tilde{x}_0)]_{ij} \frac{\partial^2}{\partial x_{0i} \partial x_{0j}}$$
$$M_{n+1}(\Gamma, x_0 \in \Gamma) = 0$$
$$M_{n+1}(\Gamma, x_0 \in \Omega) < \infty$$
$$n = 1, 2, \dots$$

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So, these are again recursive relation; you solve for n equal to 1, then you proceed to n equal to 2, and so on, so forth. In the existing literature, people have used various method of weighted residuals, finite element formulations, etcetera, to tackle these set of equations, and there are certain numerical approaches that exist, which can be used to solve these problems.

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Introduction to method of stochastic averaging

- An approximate method for analysing lightly damped nonlinear systems under broad band excitations.
- Leads to simplified models for response envelope and phase processes
- Enables application of Markovian methods to the solution of equations governing the response envelope and phase processes
- Best suited to study nonlinear sdof systems.

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Now, if you consider what we have been doing till now, based on Marcov property of response vector, we derive first the transition probability density function by solving the

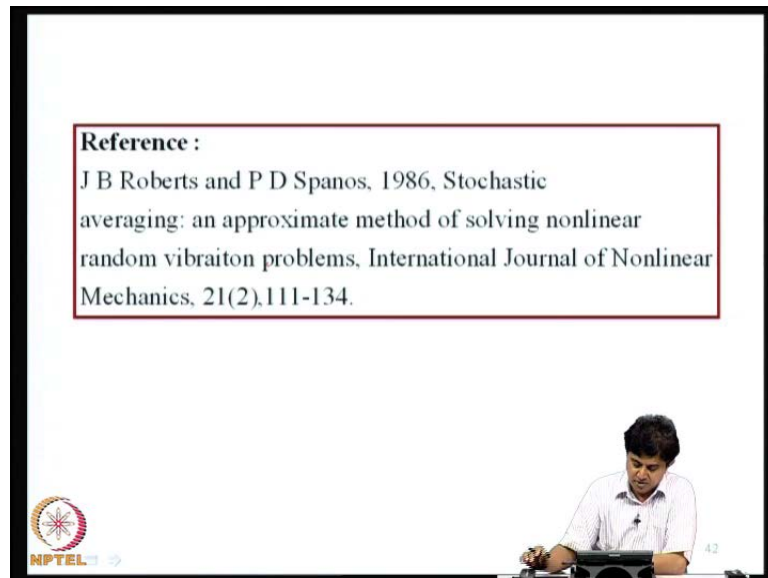
governing Fokker Planck equation, then we derive the equation for one time moments, derive the equation for two time moments, and so on, so forth. And using backward equation - backward Kolmogorov equation - we formulated the problem for first passage times.

If we recall the discussion that we had, when we study random vibration of a single degree freedom systems, we consider properties of envelope **source** - envelope and phase processes. So, how to study envelope and phase processes, when response process Markovian properties? So, that is a question that I would like to discuss now; and that is based on an approximate method of response analysis known as method of stochastic averaging.

So, what is method of stochastic averaging? It is an approximate method for analyzing lightly damped non-linear systems, under broadband excitations. So, it is applicable to weakly non-linear systems. Under broadband excitations, the excitations are not necessarily white to start with; they need to be broadband.

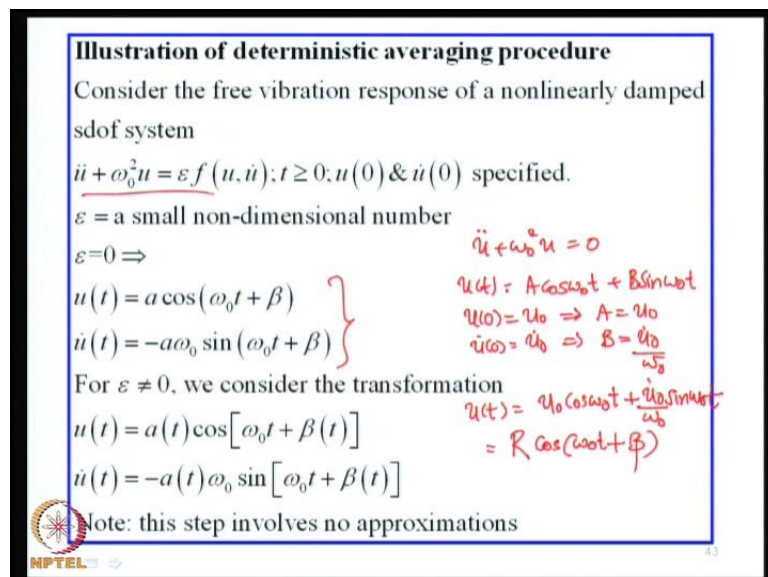
If use this method, you get simplified equation for the envelope and phase processes. So, it means simplified model for response envelope and phase processes. And once we get this simplified models, we can show that envelope and phase together constituted Markov vector; it can be shown that I will briefly demonstrate. And if moment you get the Markovian property we can applicable to envelope and phase, you can write the associated Fokker Planck equation, and get moment if you want or write the backward equation and solve first passage problems associated with envelopes. So, you can do lots of analysis. These methods are best suited for studying single degree freedom systems; they become unwieldy, if we look at multi degree freedom systems, but within the frame work of their own limitations, it still provide very powerful means to study envelope and phase of non-Gaussian random processes. So, that is the main advantage; so, what is this method of averaging?

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Before I get into that, I would like to cite a reference; this is a review paper written by Roberts and Spanos in 1986. It appeared in international journal of non-linear mechanics. So, this paper reviews various application of stochastic averaging, for solving a class of non-linear random vibration problems.

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Now, as a prelude to discussion of stochastic averaging, we will briefly look at, what is averaging in a deterministic context. Now, let us consider the free vibration response of a nonlinearly damped system, the system will u double dot plus ω naught square u is

equal to ϵ into $f(u, \dot{u})$, and time recon from 0 and initial conditions are specified. The parameter ϵ is a small non-dimensional number; if ϵ is 0, I have $u'' + \omega^2 u = 0$. So, $u(t)$ can be written as, $a \cos \omega t + B \sin \omega t$, and you can use initial conditions $u(0)$ is u_0 could imply $a = u_0$, $\dot{u}(0)$ is \dot{u}_0 implies $B = \dot{u}_0 / \omega$; and I can write $u(t)$ therefore as, $u_0 \cos \omega t + \dot{u}_0 / \omega \sin \omega t$ and this can be written as $R \cos(\omega t - \beta)$, where R and β are in terms of \dot{u}_0 and u_0 .

So, when ϵ is 0, I can always write this solution as $a \cos \omega t + \beta \sin \omega t$, where A and β are functions of specified initial conditions; and the velocity is $\dot{u}(t)$ is the derivative $-\omega a \sin \omega t + \omega \beta \cos \omega t$. So, when ϵ is 0, these two are exact, and a and β are constants; there not functions of time, there are only functions of initial conditions.

Now, what will do is, for ϵ not equal to 0, we will consider a transformation, which is fashioned after this exact solution. And we will write that, even when ϵ is not 0, I take $u(t)$ to be $a \cos \omega t + \beta \sin \omega t$ as before, except now that a and β are functions of time. And $\dot{u}(t)$, I again make the assume the same function of $\dot{u}(t) = -\omega a \sin \omega t + \omega \beta \cos \omega t$, but a and β as I said functions of time. So, if I can derive consistent set of equations for a and β , this satisfy these two equations and the governing equation; this will be an exact transformation; at this stage, there is no approximation in our discussion.

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Consider

$$u(t) = a(t) \cos[\omega_0 t + \beta(t)] = a(t) \cos \phi(t); \phi(t) = \omega_0 t + \beta(t)$$

$$\Rightarrow \dot{u}(t) = \dot{a}(t) \cos \phi(t) - a(t) [\omega_0 + \dot{\beta}(t)] \sin \phi(t)$$

Since we are taking $\dot{u}(t) = -a(t) \omega_0 \sin \phi(t)$, it follows

$$\dot{a}(t) \cos \phi(t) - a(t) \dot{\beta}(t) \sin \phi(t) = 0 \dots (A)$$


Consider $\dot{u}(t) = -a(t) \omega_0 \sin \phi(t)$

$$\Rightarrow \ddot{u}(t) = -\dot{a}(t) \omega_0 \sin \phi(t) - a(t) \omega_0 [\omega_0 + \dot{\beta}(t)] \cos \phi(t)$$

$$\Rightarrow -\dot{a}(t) \omega_0 \sin \phi(t) - a(t) \omega_0 [\omega_0 + \dot{\beta}(t)] \cos \phi(t) +$$

$$\omega_0^2 a(t) \cos \phi(t) = \varepsilon f [a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$$

$$\Rightarrow -\dot{a}(t) \omega_0 \sin \phi(t) - a(t) \omega_0 \cos \phi(t) =$$

$$f [a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)] \dots (B)$$


Now, I have u of t is a \cos $\omega_0 t + \beta$ of t and I will write ϕ of t as $\omega_0 t + \beta$ of t , and write u of t as a of t $\cos \phi$ of t . Now, if this is correct, then a time derivative of u of t would be $\dot{a} \cos \phi$ minus a as it is, and \cos becomes \sin , and derivative of ϕ is $\omega_0 + \dot{\beta}$. But we are taking \dot{u} of t as $-a \omega_0 \sin \phi$, therefore, the remaining terms in this equation must be equal to 0.

So, what are the remaining terms in these equation? $\dot{a} \cos \phi$ minus $a \dot{\beta} \sin \phi$, this must be equal to 0, fine. Now, you consider now, \dot{u} is equal to $-a \omega_0 \sin \phi$; that is, what would happen if this condition A is satisfied? From this, now you evaluate \ddot{u} ; \ddot{u} is what? $-\dot{a} \omega_0 \sin \phi$ minus $a \omega_0$, \sin becomes \cos , and ϕ dot becomes $\omega_0 + \dot{\beta}$. So, I get an expression for \ddot{u} and I have an expression for u , and I will substitute that into the governing differential equation and get this equation. A slight reordering of the terms, because two of the terms are going to get cancelled; I get an equation which is B. Now, A and B are the two equations which govern a and β , which are not known. So, I can solve for \dot{a} and $\dot{\beta}$ from these equations.

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$\dot{a}(t) \cos \phi(t) - a(t) \dot{\beta}(t) \sin \phi(t) = 0 \dots (A)$
 $-\dot{a}(t) \omega_0 \sin \phi(t) - a(t) \omega_0 \cos \phi(t) =$
 $\varepsilon f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)] \dots (B)$

Solving for $\dot{a}(t)$ and $\dot{\beta}(t)$ we get

$\dot{a}(t) = -\frac{\varepsilon}{\omega_0} \sin \phi(t) f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$
 $\dot{\beta}(t) = \frac{\varepsilon}{\omega_0 a(t)} \cos \phi(t) f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$

- Note: no approximations till now.
- If ε is small, $\dot{a}(t)$ and $\dot{\beta}(t)$ are small.

That is $a(t)$ and $\beta(t)$ do not change appreciably over the time duration t to $t + \frac{2\pi}{\omega_0}$.

So, the two equations are, this is A and this is B; and solving for a dot and beta dot, we get a dot as minus epsilon omega naught sine phi into some function of a cos phi and a omega naught sine phi; and beta dot is similarly shown here, minus epsilon omega naught a cos phi; and this function again let me emphasize, till now we have not made any approximation, this is exact.

Now, we can bring in some arguments based on epsilon being small. If epsilon is 0, a and beta are constant; if epsilon is small, you can expect a and beta will be functions of time, alright, but it could be slowly varying functions of time. So, they vary much slowly; a of t varying much slowly than sine phi of t itself, because when sine this function complete 1 cycle of oscillation, the change in amplitude could be quite small. Now, that is a and beta do not change appreciably over the time duration t to t plus 2 pi by omega naught, where t changes from t to t plus 2 pi by omega naught; this trigonometric functions undergo dramatic change; whereas the change in amplitude and phase will be quite small, if epsilon is small. If epsilon is 0, there would not be any change.

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$$\dot{a}(t) = -\frac{\varepsilon}{\omega_0} \sin \phi(t) f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$$

$$\dot{\beta}(t) = -\frac{\varepsilon}{\omega_0 a(t)} \cos \phi(t) f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$$

$$\dot{a}(t) \approx -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} \int_0^{2\pi} \sin \phi f[a \cos \phi, -a \omega_0 \sin \phi] d\phi$$

$$\dot{\beta}(t) \approx -\frac{\varepsilon}{\omega_0 a} \frac{1}{2\pi} \int_0^{2\pi} \cos \phi f[a \cos \phi, -a \omega_0 \sin \phi] d\phi$$

These are averaged equations.

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Based on that what we do is, we average over a cycle the right hand side of these equations by treating the functions a and beta in the procedural averaging as constants; over a cycle, they do not change as much as the function themselves. So, if I integrate from 0 to 2 pi and take the average 1 by 2 pi integrate pi, this integration can be performed by treating a and beta as constants. If I do that, I get here of approximate equations a dot and beta dot, and these who called as an averaged equations. At many times, we can solve for this a and beta or study the fixed point and their stability, and so on and so forth.

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Example

$$\ddot{u} + \omega_0^2 u = -2\varepsilon \mu \dot{u}$$

$$\dot{a}(t) \approx -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} \int_0^{2\pi} \sin \phi [2\mu a \omega_0 \sin \phi] d\phi$$

$$= -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} (2\mu a \omega_0) \int_0^{2\pi} \sin^2 \phi d\phi = -\varepsilon a \mu$$

$$\dot{\beta}(t) \approx -\frac{\varepsilon}{\omega_0 a} \frac{1}{2\pi} \int_0^{2\pi} \cos \phi [2\mu a \omega_0 \sin \phi] d\phi = 0$$

$$\Rightarrow u(t) \approx a_0 \exp(-\varepsilon \mu t) \cos[\omega_0 t + \beta_0]$$

Exercise: compare this with the known exact solution

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So, I will consider a few examples, so that this idea is established in your mind. So, you consider now the first example, $u \ddot{u} + \omega_0^2 u = -\varepsilon \dot{u} |\dot{u}|$; this is a damped free vibration of linear single freedom systems. So, here a dot, now this function is specified, so I can plug that function here and actually calculate a dot. And if I do that, I get a dot as, a dot I get as minus epsilon a mu and b dot as 0; and if I now solve this equations, I get u of t as a naught exponential minus epsilon mu t cos omega naught t plus beta naught. This is quite similar to the exact equation that you would get, if solve these equation by writing the correct complementary function and exposing the initial conditions. The changes would be in terms of frequency and slight changes in an amplitude, but by in law, this could be a reasonably good approximation to the given problem.

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Example

$$\ddot{u} + \omega_0^2 u = -\varepsilon \dot{u} |\dot{u}|$$

$$\dot{a}(t) \approx -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} \int_0^{2\pi} \sin \phi [a\omega_0 \sin \phi - a\omega_0 \sin \phi] d\phi$$

$$= -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} (a^2 \omega_0^2) \int_0^{2\pi} \sin^2 \phi |\sin \phi| d\phi = -\varepsilon \frac{4\omega_0 a^2}{3\pi}$$

$$\dot{\beta}(t) \approx -\frac{\varepsilon}{\omega_0 a} \frac{1}{2\pi} \int_0^{2\pi} \cos \phi [a\omega_0 \sin \phi - a\omega_0 \sin \phi] d\phi = 0$$

$$\Rightarrow u(t) \approx \left\{ \frac{a_0}{1 + \frac{4\varepsilon \omega_0 a_0}{3\pi} t} \right\} \cos[\omega_0 t + \beta_0]$$

Note: Rate of free vibration decay depends on

A slightly more complicated problem, $u \ddot{u} + \omega_0^2 u = -\varepsilon u \dot{u}$ into modulus of u dot.

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$$\dot{a}(t) = -\frac{\varepsilon}{\omega_0} \sin \phi(t) f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$$

$$\dot{\beta}(t) = -\frac{\varepsilon}{\omega_0 a(t)} \cos \phi(t) f[a(t) \cos \phi(t), -a(t) \omega_0 \sin \phi(t)]$$

$$\dot{a}(t) \approx -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} \int_0^{2\pi} \sin \phi f[a \cos \phi, -a \omega_0 \sin \phi] d\phi$$

$$\dot{\beta}(t) \approx -\frac{\varepsilon}{\omega_0 a} \frac{1}{2\pi} \int_0^{2\pi} \cos \phi f[a \cos \phi, -a \omega_0 \sin \phi] d\phi$$

These are averaged equations.



So, again, I go back now, look at these equations; I have now the simplified equation for a dot and beta dot, and f is given now.

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Example

$$\ddot{u} + \omega_0^2 u = -\varepsilon \dot{u} |\dot{u}|$$

$$\dot{a}(t) \approx -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} \int_0^{2\pi} \sin \phi [a \omega_0 \sin \phi | -a \omega_0 \sin \phi |] d\phi$$

$$= -\frac{\varepsilon}{\omega_0} \frac{1}{2\pi} (a^2 \omega_0^2) \int_0^{2\pi} \sin^2 \phi |\sin \phi| d\phi = -\varepsilon \frac{4\omega_0 a^2}{3\pi}$$


$$\dot{\beta}(t) \approx -\frac{\varepsilon}{\omega_0 a} \frac{1}{2\pi} \int_0^{2\pi} \cos \phi [a \omega_0 \sin \phi | -a \omega_0 \sin \phi |] d\phi = 0$$

$$\Rightarrow u(t) = \left\{ \frac{a_0}{1 + \frac{4\varepsilon \omega_0 a_0}{3\pi}} \right\} \cos[\omega_0 t + \beta_0]$$

$$\dot{a} = -\varepsilon \frac{4\omega_0^2 a^2}{3\pi}$$

$$\frac{da}{a^2} = -\frac{4\varepsilon \omega_0^2}{3\pi} dt$$

Note: Rate of free vibration decay depends on



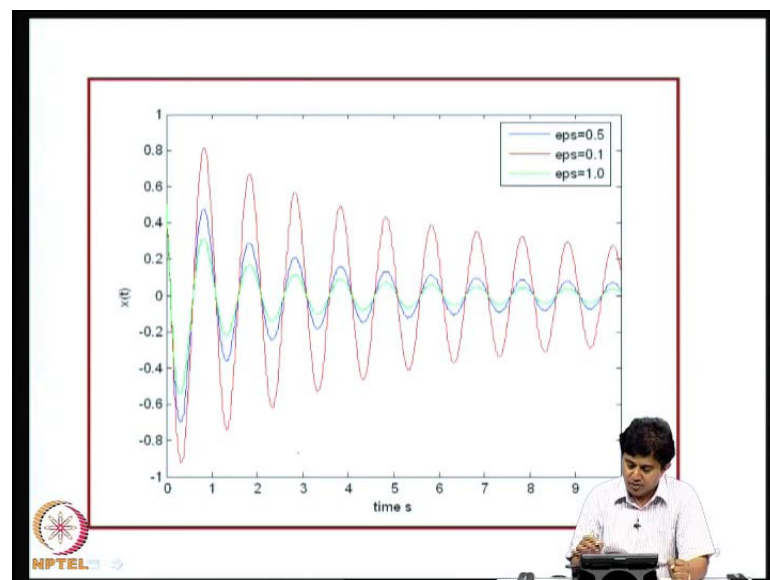
So, I substitute that, I get the equation for a dot and I have to integrate this; as I said, while integrating this, a and beta are written as constants; so, that means integration is done only with respect to phi and I get this equation. Similarly, beta dot if I do, in this case also, it turns out that beta dot is 0. Now, this equation a dot is equal to minus epsilon 4 omega naught square a square by 3 pi; we can solve this. This can be written as

da by a square is equal to minus epsilon dt 4 omega naught square by 3 pi etcetera, and I can integrate both side and solve for d of t.

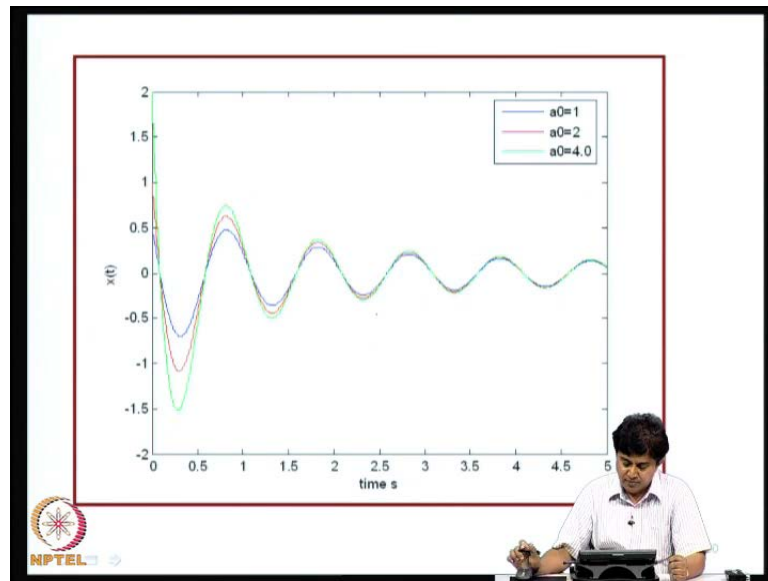
If I do this, I get this as the expression for the amplitude a of t; and **beta is** beta dot is 0, therefore, beta naught will be constant. Now, you look at now the nature of a of t; as t times to be infinity, you can see that the denominator here becomes increasingly large and the amplitude goes to 0. But the rate at which this amplitude goes to 0 depends on the multiplier here, which is a function of initial conditions; that means, for the same system starting with different initial conditions, you get different rates of decay.

So, if you work to compute the logarithmic decrement for this, it would mean the logarithmic decrement is a function of initial conditions; whereas in a linear system, where the concept of logarithmic decrement is basically applicable, logarithmic decrement is independent of initial conditions. The rate at which free vibration decays, in linear system, it is independent of initial conditions, but here, that the capability here, that principle no longer holds. So, the rate at which the oscillation decay depends how you start the system.

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So, here, I have shown different trajectories of the response using the approximate solution obtained using averaging, for different values of epsilon; and you can see that, as epsilon increases, the decay is rapid; and here I have shown for same epsilon, but with different initial conditions. So, if you compute the rate at decay is occurring, you can see that rate this actually dependent on the initial conditions, especially for small times. So, this is one of the complex feature associated with non-linear system behavior.

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Example

$$\ddot{u} + \omega_0^2 u = \varepsilon (u - u^3) \quad \ddot{u} + \omega_0^2 u - \varepsilon u(1 - u^2) = 0$$

$$\dot{a} = \frac{1}{2} \varepsilon a \left[1 - \frac{3}{4} \omega_0^2 a^2 \right] \quad \& \quad \dot{\beta} = 0$$

$$a(t) = \left\{ \frac{a_0^2}{\frac{3}{4} \omega_0^2 a_0^2 + \left[1 - \frac{3}{4} \omega_0^2 a^2 \right] \exp(-\varepsilon t)} \right\}^{\frac{1}{2}} \quad \& \quad \beta = \beta_0$$

$$\Rightarrow u(t) \approx \left\{ \frac{a_0^2}{\frac{3}{4} \omega_0^2 a_0^2 + \left[1 - \frac{3}{4} \omega_0^2 a^2 \right] \exp(-\varepsilon t)} \right\}^{\frac{1}{2}} \cos[\omega_0 t]$$

One more example, this is a system with limit cycles. So, here we are considering this equation; so, to understand this, we can write it this as $\omega_0^2 u - \ddot{u} = 1 - \dot{u}^2$. So, this is our dissipation term. Now, you can see here, there is a negative sign here and we have here $1 - \dot{u}^2$. So, if \dot{u} is small, $1 - \dot{u}^2$ will be greater than 0, and we will be dealing with a negative sign for the damping term; that means, motions in the neighborhood of origin tend to grow in few operations.



Whereas if we start with initial conditions, where $1 - \dot{u}^2$ is large, then the next sign of this term would be positive and the large oscillation is not decay. So, small oscillations grow and large oscillations decay, that could mean, in between them, there is a stable periodic solution - isolated periodic solution. And that is known as a limit cycle. So, we can go through the method of an averaging and we can get this equation; and I skip this details, you fill up the details, it is an exercise. So, I get a dot is this and we can solve this equation. And if you do that, we get β_0 as β_0 and a as this; the time is sitting here. So, as t becomes very large, this function becomes 0, and I am left with 4 by $3\omega_0^2$, square root of that as amplitude of a of t . So, that captures the qualitative feature of the response, that we expect even before solving the problem; so, this is a solution.

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$$u(t) \approx \left\{ \frac{a_0^2}{\frac{3}{4}\omega_0^2 a_0^2 + \left[1 - \frac{3}{4}\omega_0^2 a^2\right] \exp(-\epsilon t)} \right\}^{\frac{1}{2}} \cos[\omega_0 t + \beta_0]$$

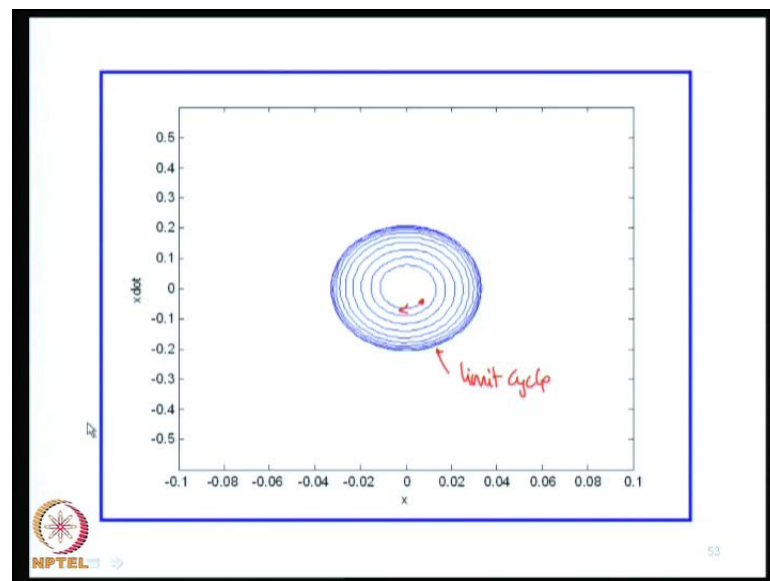
$$\lim_{t \rightarrow \infty} u(t) \rightarrow \left\{ \frac{4}{3\omega_0^2} \right\}^{\frac{1}{2}} \cos[\omega_0 t + \beta_0]$$

Note: the amplitude of steady state oscillations (in free vibrations) is independent of initial conditions. Contrast this with the response of undamped linear sdof system.

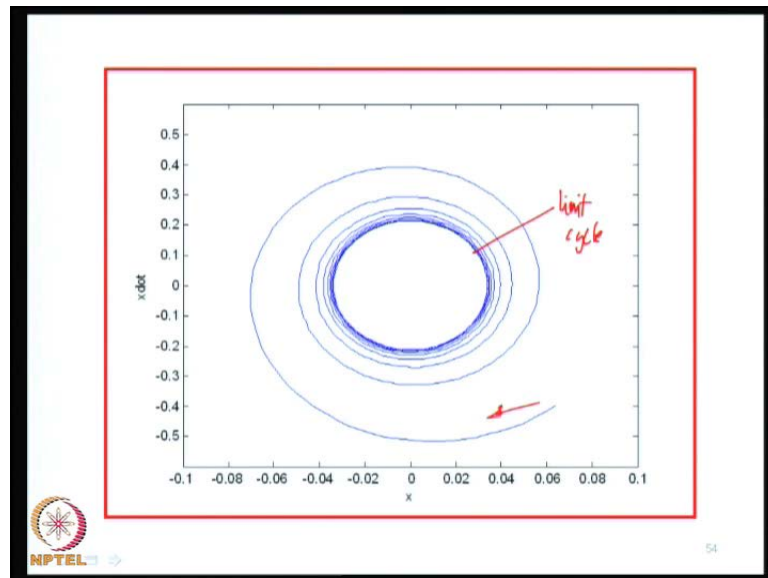
And as t tends to infinity, we get $4 \text{ by } 3 \omega \text{ naught square}$, square root of that into $\cos \omega \text{ naught } t \text{ plus } \beta \text{ naught}$. This is the amplitude of steady state oscillation in free vibration, is independent of initial conditions. Contrast this with the response of un-damped linear single degree freedom systems. You take un-damped linear single degree freedom system, the solution of that system is periodic, but amplitude is function of the initial conditions. So, here, there is no forcing, solution is periodic; so, in that sense, it is similar to un-damped free vibration, but the amplitude of free vibration in periodic state, it is independent of initial conditions; so, that is where the non-linearity comes in.

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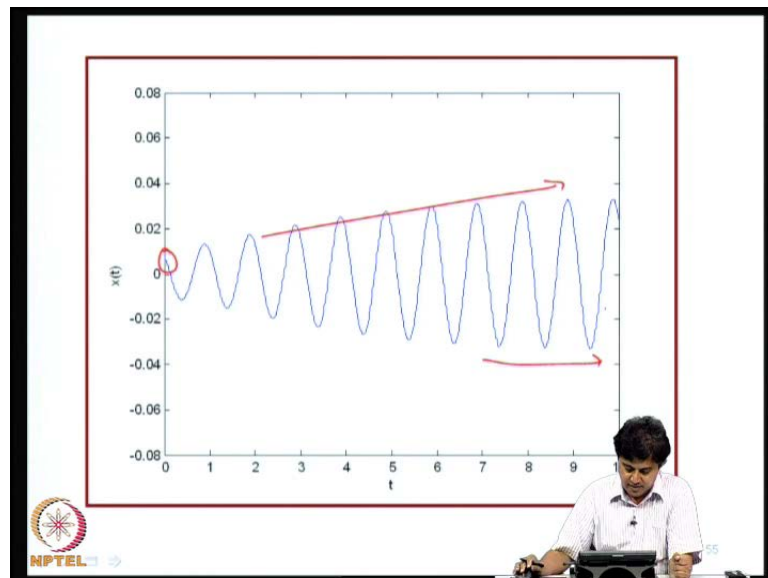
So, this is one trajectory, where the solutions have originated here, and they are growing and this is my limit cycle. So, this is phase plane plot, a velocity versus displacement; a small initial condition, the solution grows and reaches this outer circle.

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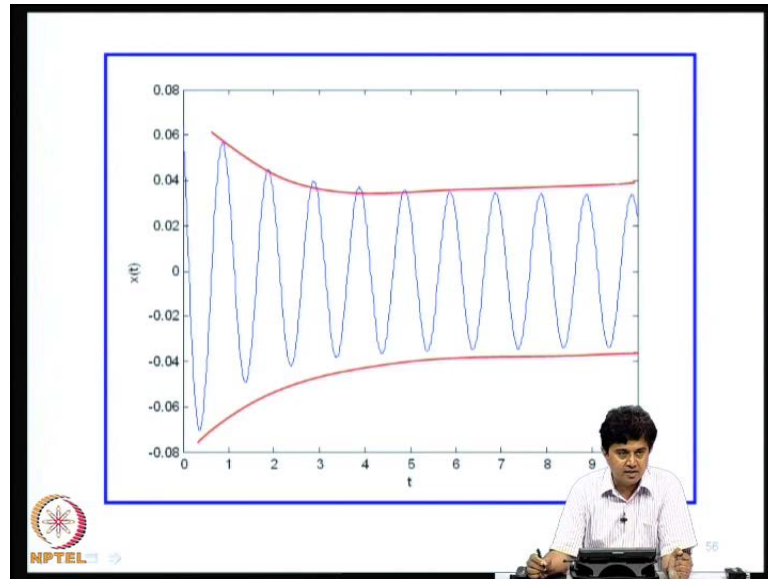
Here, the solution originates from this point, a large initial condition and decays; it moves in this direction, and it spirals down and I get the limit cycle; this is the limit cycle. So, that means, limit cycle here is approached from outside, large oscillations decays to that stable limit cycle.

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Now, this is time history of x of t , where in the first case, where motions started with a small value and it is now growing to reach the amplitude of limit cycle oscillations.

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In this case, the solution is starting in a large initial condition, it is now decaying to reach the limit cycle oscillations. So, it is moving towards the limit cycle from outside, whereas in the previous case, it was from inside. So, this is the behavior of non-linear systems without any random excitations, where we have used the concept of averaging.

So, in the next part of the lecture, we will consider how to implement this averaging principle, if there is noise present or the system is driven by random excitations. So, we will consider that in next lecture and we will close this lecture at this juncture.