

Stochastic Structural Dynamics

Lecture-22

Markov Vector Approach-2

Dr C S Manohar

Department of Civil Engineering

Professor of Structural Engineering

Indian Institute of Science

Bangalore 560 012 India

manohar@civil.iisc.ernet.in

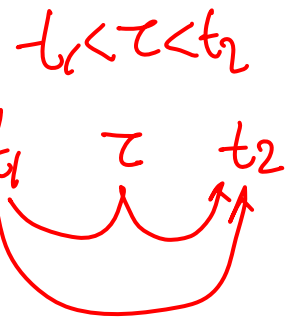


Recall

$$\underbrace{p(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)}_{\text{Multi-dimensional jpdf}} = \underbrace{p(x_1; t_1)}_{\text{Initial pdf}} \underbrace{\prod_{v=2}^n p(x_v; t_v | x_{v-1}; t_{v-1})}_{\text{Product of transitional pdfs}}$$

$$p(x_2, t_2 | x_1, t_1) = \int p(x_2, t_2 | x, \tau) p(x, \tau | x_1, t_1) dx$$

for all $t_1 < \tau < t_2$



Kinetic equation

$$\frac{\partial p}{\partial t} + \frac{\partial \lambda}{\partial x} = 0 \text{ \& \underline{BCS} and \underline{IC}}$$

$$\lambda(x, t) = - \sum_{n=1}^{\infty} \frac{(-1)^n}{n!} \frac{\partial^{n-1}}{\partial x^{n-1}} \left[\underline{\alpha_n(x, t)} \underline{p(x; t)} \right]$$

$$\underline{\alpha_n(x, t)} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[X(t + \Delta t) - X(t) \right]^n \mid X(t) = x \right\rangle; n = 1, 2, \dots$$

λ

Simple random walk

Let $\{X_i\}_{i=1}^{\infty}$ be an iid sequence of random variables
with

$$P(X = \Delta x) = p$$

$$P(X = -\Delta x) = q$$

such that $p + q = 1$.

$$\begin{aligned}\langle X \rangle &= P(X = \Delta x)(\Delta x) + P(X = -\Delta x)(-\Delta x) \\ &= \Delta x(p - q)\end{aligned}$$

$$\begin{aligned}\langle X^2 \rangle &= P(X = \Delta x)(\Delta x)^2 + P(X = -\Delta x)(-\Delta x)^2 \\ &= \Delta x^2(p + q)\end{aligned}$$

$$\begin{aligned}\text{Var}(X) &= \langle X^2 \rangle - \langle X \rangle^2 \\ &= \Delta x^2(p + q) - \Delta x^2(p - q)^2 \\ &= \Delta x^2(p + q)^2 - \Delta x^2(p - q)^2 \quad (\because p + q = 1) \\ &= \Delta x^2 \left[(p + q)^2 - (p - q)^2 \right] = 4pq\Delta x^2\end{aligned}$$

Let t be the time axis and let us divide the interval $(0, t)$ into n subintervals each of width Δt such that $n\Delta t = t$.

$$\text{Define } S(t) = \sum_{i=1}^n X_i$$

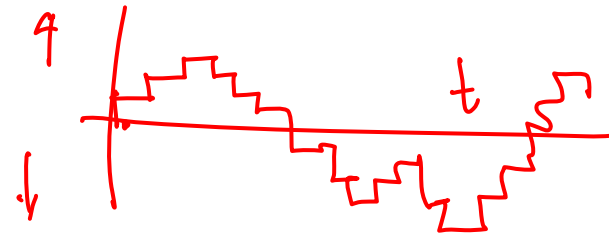
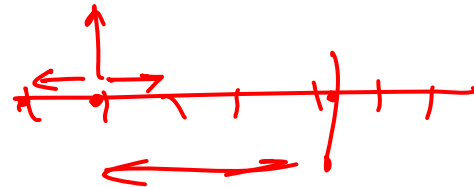
$$\Rightarrow \langle S(t) \rangle = \sum_{i=1}^n \langle X_i \rangle = \sum_{i=1}^n (p - q) \Delta x$$

$$= n(p - q) \Delta x //$$

$$= t(p - q) \frac{\Delta x}{\Delta t}$$

$$\text{Var}[S(t)] = t4pq\Delta x^2$$

$$= t4pq \frac{\Delta x^2}{\Delta t}$$



Remarks

- $S(t)$ is known as a simple random walk.
- $S(t)$ is a discrete state, discrete parameter random process.
- Consider the limit of $\Delta x \rightarrow 0$ as $\Delta t \rightarrow 0$

\Rightarrow

$$\lim_{\substack{\Delta x \rightarrow 0 \\ \Delta t \rightarrow 0}} \langle S \rangle = \lim_{\substack{\Delta x \rightarrow 0 \\ \Delta t \rightarrow 0}} t (p - q) \frac{\Delta x}{\Delta t}$$

and

$$\lim_{\substack{\Delta x \rightarrow 0 \\ \Delta t \rightarrow 0}} \text{Var} [S(t)] = \lim_{\substack{\Delta x \rightarrow 0 \\ \Delta t \rightarrow 0}} t 4pq \frac{\Delta x^2}{\Delta t} \rightarrow 0$$

\Rightarrow

In the limit of $\Delta x \rightarrow 0$ as $\Delta t \rightarrow 0$, $S(t)$ becomes a deterministic function. This is not an interesting limit from probabilistic point of view.

Wiener and Brownian motion Processes

Consider the following limit of the simple random walk

$$\Delta x^2 \rightarrow 0 \text{ as } \Delta t \rightarrow 0$$

with

$$\Delta x = \sigma \Delta t; \quad p = \frac{1}{2} \left[1 + \frac{\mu \sqrt{\Delta t}}{\sigma} \right]; \quad q = \frac{1}{2} \left[1 - \frac{\mu \sqrt{\Delta t}}{\sigma} \right]$$

\Rightarrow

$$\langle S(t) \rangle \rightarrow \mu t //$$

$$\text{Var}[S(t)] \rightarrow \sigma^2 t //$$

This is an interesting limit!

Remarks

- The resulting process is known as the Wiener process.
- This is a process with continuous state and continuous parameter.
- The process is a Gaussian process (central limit theorem).
- The process is nonstationary
- If $\mu = 0$, the process is known as a Brownian motion process.
- Without loss of generality we take $B(0) = 0$.

$$S(t) = \sum_{i=1}^n X_i$$

$$\Rightarrow S_n = X_n + \sum_{i=1}^{n-1} X_i$$

$$\Rightarrow S_n = S_{n-1} + X_n \checkmark$$

S_n is a process with independent increments.

S_n is Markov

\Rightarrow Wiener and Brownian motion processes are also Markov.

Autocovariance of $B(t)$

We have $\langle B(t) \rangle = 0$ & $\langle B^2(t) \rangle = \sigma^2 t$

Let $t > s$ & consider $[B(t) - B(s)]$ & $[B(s) - B(0)]$

$$\langle [B(t) - B(s)][B(s) - B(0)] \rangle = 0 //$$

$$\Rightarrow \langle [B(t) - B(s)]B(s) \rangle = 0$$

$$\langle B(t)B(s) \rangle = \langle B^2(s) \rangle = \sigma^2 s$$

Similarly, if $s > t$ we get

$$\langle B(t)B(s) \rangle = \langle B^2(t) \rangle = \sigma^2 t$$

$$\Rightarrow \langle B(t)B(s) \rangle = \sigma^2 \min(t, s)$$

$$\langle B(t)B(s) \rangle = \sigma^2 \min(t, s)$$

$$R_{BB}(t, s) = \sigma^2 \min(t, s)$$

Consider $s > t$

$$R_{BB}(t, s) = \sigma^2 t \text{ with } s > t$$

$$\frac{\partial R_{BB}(t, s)}{\partial t} = \sigma^2 U(s - t)$$


$$\frac{\partial^2 R_{BB}(t, s)}{\partial t \partial s} = \sigma^2 \delta(s - t)$$

Consider $t > s$

$$R_{BB}(t, s) = \sigma^2 s \text{ with } t > s$$

$$\frac{\partial R_{BB}(t, s)}{\partial s} = \sigma^2 U(t - s)$$

$$\frac{\partial^2 R_{BB}(t, s)}{\partial t \partial s} = \sigma^2 \delta(t - s)$$

Recall $\delta(ax) = \frac{1}{|a|} \delta(x)$. 

$$\Rightarrow \frac{\partial^2 R_{BB}(t, s)}{\partial t \partial s} = \sigma^2 \delta(t - s)$$

BMP and Gaussian white noise process

$$R_{BB}(t, s) = \sigma^2 \min(t, s) \quad \& \quad \frac{\partial^2 R_{BB}(t, s)}{\partial t \partial s} = \sigma^2 \delta(t - s)$$

Notice: $\sigma^2 \delta(t - s)$ is the autocovariance function of a white noise process.

\Rightarrow Gaussian white noise can be viewed as the formal derivative of a Brownian motion process.

• **Note:** BMP is not pathwise differentiable in the meansquare sense

because $\lim_{t \rightarrow s} \frac{\partial^2 R_{BB}(t, s)}{\partial t \partial s} \rightarrow \infty$.

$$\frac{dB}{dt} = W(t)$$

• $dB(t) = W(t) dt$

Increments of BMP

$$\Delta B(t) = B(t + \Delta t) - B(t)$$

$$\langle \Delta B(t) \rangle = \langle B(t + \Delta t) - B(t) \rangle = 0$$

$$\langle \Delta B^2(t) \rangle = \langle \{ B(t + \Delta t) - B(t) \}^2 \rangle$$

$$= \langle B^2(t + \Delta t) + B^2(t) - 2B(t + \Delta t)B(t) \rangle$$

$$= \sigma^2 [t + \Delta t + t - 2t]$$

$$= \sigma^2 \Delta t$$

Fokker Planck equation

Example

$$\frac{dx}{dt} = w(t); x(0) = x_0 \quad \checkmark$$

$$3\sigma^4 \quad \Delta t^2$$

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

$$\underline{dx(t) = dB(t); x(0) = x_0}$$

Recall

$$\rightarrow \frac{\partial p}{\partial t} = -\frac{\partial}{\partial x} [\alpha_1(x, t) p(x; t)] + \frac{1}{2} \frac{\partial^2}{\partial x^2} [\alpha_2(x, t) p(x; t)] //$$

$$\alpha_n(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)]^n \mid X(t) = x \right\rangle //$$

$$\alpha_1(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle dB(t) \mid X(t) = x \rangle = 0$$

$$\alpha_2(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [dB(t)]^2 \mid X(t) = x \right\rangle = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} 2D\Delta t = 2D$$

$$\frac{\partial p}{\partial t} = D \frac{\partial^2 p}{\partial x^2}; \underline{p(x; 0) = \delta(x)}; \underline{p(\pm\infty; t) = 0} //$$

FPK equation

$$\frac{\partial p}{\partial t} = D \frac{\partial^2 p}{\partial x^2}; p(x; 0) = \delta(x - x_0); p(\pm\infty; t) = 0$$

Solution

Consider the characteristic function

$$M(\theta, t) = \int_{-\infty}^{\infty} p(x; t) \exp(i\theta x) dx \quad \checkmark$$

$$p(x; t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} M(\theta, t) \exp(-i\theta x) d\theta \quad \checkmark$$

$$\frac{\partial p}{\partial t} = \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{\partial M(\theta, t)}{\partial t} \exp(-i\theta x) d\theta \quad \checkmark$$

$$\frac{\partial^2 p}{\partial x^2} = \frac{1}{2\pi} \int_{-\infty}^{\infty} -\theta^2 M(\theta, t) \exp(i\theta x) d\theta \quad \checkmark$$

$$\Rightarrow \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{\partial M(\theta, t)}{\partial t} \exp(i\theta x) d\theta = D \frac{1}{2\pi} \int_{-\infty}^{\infty} -\theta^2 M(\theta, t) \exp(i\theta x) d\theta$$

$$\frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{\partial M(\theta, t)}{\partial t} \exp(i\theta x) d\theta = D \frac{1}{2\pi} \int_{-\infty}^{\infty} -\theta^2 M(\theta, t) \exp(i\theta x) d\theta$$

$$\Rightarrow \frac{\partial M(\theta, t)}{\partial t} + D\theta^2 M(\theta, t) = 0$$

$$M(\theta, t) = M_0 \exp(-D\theta^2 t)$$

$$M(\theta, 0) = \int_{-\infty}^{\infty} \delta(x - x_0) \exp(i\theta x) dx = \exp(i\theta x_0)$$

$$\Rightarrow M(\theta, t) = M_0 \exp(i\theta x_0 - D\theta^2 t)$$

$$\Rightarrow p(x; t) \sim N(x_0, Dt)$$

$$p(x; t) = \frac{1}{\sqrt{2\pi Dt}} \exp\left[-\frac{1}{2} \left(\frac{x - x_0}{\sqrt{Dt}}\right)^2\right]; -\infty < x < \infty$$

$X(t)$ is a nonstationary, Gaussian, Markov random process

Alternative derivation of the FPK equation

Let $X(t)$ be a scalar Markov random process.

By virtue of CKS equation, the following is true.

$$p(x_2, t_2 | x_1, t_1) = \int p(x_2, t_2 | x, \tau) p(x, \tau | x_1, t_1) dx$$

for all $t_1 < \tau < t_2$.

This is an integral equation. The FPK equation is the associated PDE and can be derived as follows.

Consider

$$I = \int_{-\infty}^{\infty} R(y) \frac{\partial}{\partial t} p(y; t | x_0, t_0) dy$$

Here $R(y)$ is an arbitrary function that admits

Taylor's expansion and $R(\pm\infty) \rightarrow 0$ sufficiently fast.

$$\begin{aligned}
I &= \int_{-\infty}^{\infty} R(y) \frac{\partial}{\partial t} p(y; t | x_0; t_0) dy \\
&= \int_{-\infty}^{\infty} R(y) \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left[p(y; t + \Delta t | x_0, t_0) - p(y; t | x_0; t_0) \right] dy \\
&= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} R(y) \left[p(y; t + \Delta t | x_0; t_0) - p(y; t | x_0; t_0) \right] dy \\
&= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\{ \int_{-\infty}^{\infty} R(y) \left[\int_{-\infty}^{\infty} p(y; t + \Delta t | x; t) p(x; t | x_0, t_0) dx \right] dy \right. \\
&\quad \left. - \int_{-\infty}^{\infty} R(y) p(y; t | x_0, t_0) dy \right\} \dots (1)
\end{aligned}$$

$$R(y) = R(x + y - x) = R(x) + (y - x) R'(x) + \frac{(y - x)^2}{2!} R''(x) + \dots$$

The first of the integral reads

$$\int_{-\infty}^{\infty} R(y) \left[\int_{-\infty}^{\infty} p(y; t + \Delta t | x; t) p(x; t | x_0, t_0) dx \right] dy$$

$$= \int_{-\infty}^{\infty} \left[\underbrace{R(x)} + \underbrace{(y-x)R'(x) + \frac{(y-x)^2}{2!}R''(x) + \dots} \right]$$

$$\left[\int_{-\infty}^{\infty} p(y; t + \Delta t | x; t) p(x; t | x_0, t_0) dx \right] dy$$

Consider $\int_{-\infty}^{\infty} R(x) \left[\int_{-\infty}^{\infty} p(y; t + \Delta t | x; t) p(x; t | x_0, t_0) dx \right] dy$

$$= \int_{-\infty}^{\infty} R(x) p(x; t | x_0, t_0) \underbrace{\left[\int_{-\infty}^{\infty} p(y; t + \Delta t | x; t) dy \right]}_1 dx$$

$$= \int_{-\infty}^{\infty} R(x) p(x; t | x_0, t_0) dx \quad (\text{This cancels with the last term in equation 1})$$

$$\begin{aligned}
I &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} \left[(y-x) R'(x) + \frac{(y-x)^2}{2!} R''(x) + \dots \right] \\
&\quad \left[\int_{-\infty}^{\infty} p(y; t + \Delta t | x; t) p(x; t | x_0, t_0) dx \right] dy \\
&= \int_{-\infty}^{\infty} R'(x) p(x; t | x_0, t_0) \left[\lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} (y-x) p(y; t + \Delta t | x; t) dy \right] dx \\
&+ \int_{-\infty}^{\infty} \frac{R''(x)}{2} p(x; t | x_0, t_0) \left[\lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} (y-x)^2 p(y; t + \Delta t | x; t) dy \right] dx + \dots \\
I &= \int_{-\infty}^{\infty} \left[R'(x) A(x, t) + R''(x) B(x, t) + R'''(x) C(x, t) + \dots \right] p(x; t | x_0, t_0) dx
\end{aligned}$$

$$I = \int_{-\infty}^{\infty} \left[R'(x) A(x,t) + R''(x) \underbrace{B(x,t)} + R'''(x) C(x,t) + \dots \right] p(x;t | x_0, t_0) dx$$

$$A(x,t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} (y-x) p(y;t + \Delta t | x;t) dy$$

$$B(x,t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} (y-x)^2 p(y;t + \Delta t | x;t) dy$$

$$C(x,t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} (y-x)^3 p(y;t + \Delta t | x;t) dy \dots$$


Consider the first term

$$I = \int_{-\infty}^{\infty} R'(x) A(x,t) p(x;t | x_0, t_0) dx$$

$$= \underbrace{\left[A(x,t) p(x;t | x_0, t_0) R(x) \right]_{-\infty}^{\infty}}_0 - \int_{-\infty}^{\infty} R(x) \frac{\partial}{\partial x} \left[A(x,t) p(x;t | x_0, t_0) \right] dx$$

$$= - \int_{-\infty}^{\infty} R(x) \frac{\partial}{\partial x} \left[A(x,t) p(x;t | x_0, t_0) \right] dx$$

Consider the second term

$$\begin{aligned} I &= \int_{-\infty}^{\infty} R''(x) B(x, t) p(x; t | x_0, t_0) dx \\ &= \underbrace{\left[B(x, t) p(x; t | x_0, t_0) R'(x) \right]_{-\infty}^{\infty}}_0 - \int_{-\infty}^{\infty} R'(x) \frac{\partial}{\partial x} \left[B(x, t) p(x; t | x_0, t_0) \right] dx \\ &= - \underbrace{\left\{ \frac{\partial}{\partial x} \left[B(x, t) p(x; t | x_0, t_0) \right] R(x) \right\}_{-\infty}^{\infty}}_0 + \int_{-\infty}^{\infty} R(x) \frac{\partial^2}{\partial x^2} \left[B(x, t) p(x; t | x_0, t_0) \right] dx \\ &= \int_{-\infty}^{\infty} R(x) \frac{\partial^2}{\partial x^2} \left[B(x, t) p(x; t | x_0, t_0) \right] dx \end{aligned}$$


$$\begin{aligned}
I &= \int_{-\infty}^{\infty} R(y) \frac{\partial}{\partial t} p(y; t | x_0, t_0) dy \\
&= \int_{-\infty}^{\infty} R(x) \left\{ -\frac{\partial}{\partial x} [A(x, t) p(x; t | x_0, t_0)] + \frac{1}{2} \frac{\partial^2}{\partial x^2} [B(x, t) p(x; t | x_0, t_0)] \right\} dx \\
&\int_{-\infty}^{\infty} R(x) \left[\frac{\partial}{\partial t} p(y; t | x_0, t_0) + \frac{\partial}{\partial x} [A(x, t) p(x; t | x_0, t_0)] \right. \\
&\quad \left. - \frac{1}{2} \frac{\partial^2}{\partial x^2} [B(x, t) p(x; t | x_0, t_0)] + \dots \right] dx = 0
\end{aligned}$$

Since $R(x)$ is arbitrary, it follows that

$$\begin{aligned}
&\frac{\partial}{\partial t} p(y; t | x_0, t_0) + \frac{\partial}{\partial x} [A(x, t) p(x; t | x_0, t_0)] \\
&\quad - \frac{1}{2} \frac{\partial^2}{\partial x^2} [B(x, t) p(x; t | x_0, t_0)] + \dots = 0
\end{aligned}$$

This is the FPK equation.

$$\frac{\partial}{\partial t} p(y; t | x_0, t_0) + \frac{\partial}{\partial x} \left[A(x, t) p(x; t | x_0, t_0) \right] - \frac{1}{2} \frac{\partial^2}{\partial x^2} \left[B(x, t) p(x; t | x_0, t_0) \right] + \dots = 0$$

Remarks

- This equation is also known as the Kolmogorov forward equation

- "Forward" because $\frac{\partial}{\partial t} p(y; t | x_0, t_0)$ refers to time derivative

with respect to $t > t_0$.

- A, B, C, \dots are known as the derivative moments

$$A(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \int_{-\infty}^{\infty} (y - x) p(y; t + \Delta t | x; t) dy$$

$$= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)] \mid X(t) = x \right\rangle$$

$$B(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)]^2 \mid X(t) = x \right\rangle$$

$$C(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)]^3 \mid X(t) = x \right\rangle \dots$$

Models for systems driven by white noise

excitations : Ito's stochastic differential equations

Consider the differential equation governing the $n \times 1$ vector $x(t)$

$$\frac{dx}{dt} = F[t, x(t), f(t)]; t \geq t_0 \text{ \& } x(t_0) \text{ specified}$$

Here $f(t)$ is a $m \times 1$ vector random process and F is a $n \times 1$ nonlinear function. If $f(t)$ and F are such that the integral

$\int_{t_0}^t F[\tau, x(\tau), f(\tau)] d\tau$ exists in a mean square sense, then

$$x(t) - x(t_0) = \int_{t_0}^t F[\tau, x(\tau), f(\tau)] d\tau \cdots (A) \checkmark$$

is the solution.

If elements of $\underline{f(t)}$ are Gaussian white noises, then

$\int_{t_0}^t \underline{F[\tau, x(\tau), f(\tau)]} d\tau$ does not exist in mean square sense and

equation (A) loses its meaning.

For the sake of illustration, let us consider the scalar equation

$$\frac{dx}{dt} = f[t, x(t)] + G[t, x(t)]w(t); t \geq 0 \text{ \& } x(0) \text{ is specified.}$$

Here $w(t)$ is a zero mean Gaussian white noise.

Recall $w(t)$ is a formal derivative of Brownian motion process.

That is, $dw(t) = dB(t)$.

$$dx(t) = f[t, x(t)]dt + G[t, x(t)]dB(t); t \geq 0 \text{ \& } x(0) \text{ is specified.}$$

$$dx(t) = f[t, x(t)]dt + G[t, x(t)]dB(t); t \geq 0 \text{ \& } x(0) \text{ is specified } \dots (B)$$

$$\Rightarrow x(t) - x(0) = \int_0^t f[\tau, x(\tau)]d\tau + \int_0^t G[\tau, x(\tau)]dB(\tau)$$

$\int_0^t f[\tau, x(\tau)]d\tau$: This integral can be interpreted as the traditional

Riemann integral.

$\int_0^t G[\tau, x(\tau)]dB(\tau)$: This integral does not exist in a sample sense

but can be defined in a mean square sense.

(Ito's stochastic integral)

Equation (B) is called the Ito's stochastic differential equation.

References:

A H Jazwiniski, 1970, Stochastic processes and filtering theory, Academic Press, NY.

T T Soong, 1973, Random differential equations in science and engineering, Academic Press, NY.

$dx(t) = f[t, x(t)]dt + G[t, x(t)]dB(t); t \geq 0$ & $x(0)$ is specified

• $B(t)$ has independent increments from this it follows that $x(t)$ is Markov.

Intuitive explanation

Consider the time instants t , $t + \Delta t$ and $t + 2\Delta t$.

The change $x(t)$ to $x(t + \Delta t)$ is due to $[B(t + \Delta t) - B(t)]$.

The change $x(t + \Delta t)$ to $x(t + 2\Delta t)$ is due to $[B(t + 2\Delta t) - B(t + \Delta t)]$.

$[B(t + \Delta t) - B(t)]$ & $[B(t + 2\Delta t) - B(t + \Delta t)]$ are independent.

\Rightarrow The changes $[x(t) - x(t + \Delta t)]$ & $[x(t + \Delta t) - x(t + 2\Delta t)]$ are independent.

$\Rightarrow x(t)$ is Markov.

Question : Can we derive the governing FPK equation and solve it?

Example

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

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

$$dx = -\beta[x(t)]dt + dB(t)$$


Quantity of interest: $p(x; t | x_0; 0)$

Initial condition: $p(x; 0 | x_0; 0) = \delta(x - x_0)$

Boundary conditions: $\lim_{x \rightarrow \pm\infty} p(x; t | x_0; 0) \rightarrow 0$

$$\alpha_n(x, t) = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[X(t + \Delta t) - X(t) \right]^n \mid X(t) = x \right\rangle; n = 1, 2, \dots$$

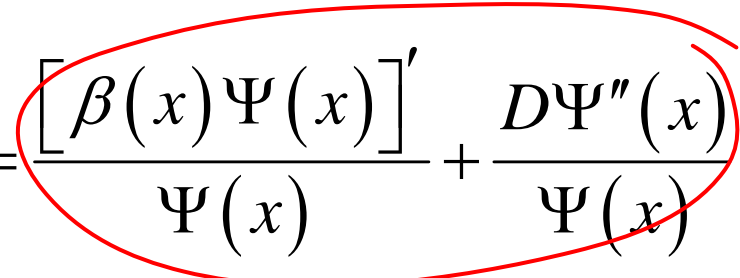
$$\begin{aligned}
\alpha_1(x, t) &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)] \mid X(t) = x \right\rangle \\
&= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle -\beta[x(t)] dt + dB(t) \right\rangle = -\beta(x) \\
\alpha_2(x, t) &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle [X(t + \Delta t) - X(t)]^2 \mid X(t) = x \right\rangle \\
&= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[-\beta[x(t)] dt + \overbrace{\beta[x(t)] dt}^{dB(t)} \right]^2 \right\rangle \\
&= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \underbrace{\beta^2(x) \Delta t^2} + [dB(t)]^2 - \underbrace{2\beta(x) dt \overbrace{\beta x(t) dt}^{dB(t)}} \right\rangle \\
&= \underline{\underline{2D}} \\
\Rightarrow \frac{\partial p}{\partial t} &= \frac{\partial [\beta(x) p]}{\partial x} + D \frac{\partial^2 p}{\partial x^2}; p \equiv p(x; t \mid x_0; 0)
\end{aligned}$$


$$\frac{\partial p}{\partial t} = \frac{\partial [\beta(x) p]}{\partial x} + D \frac{\partial^2 p}{\partial x^2}; p \equiv p(x; t | x_0; 0)$$

$$p(x; t | x_0; 0) = \Psi(x) T(t)$$

$$\Psi(x) \dot{T}(t) = [\beta(x) \Psi(x)]' T(t) + D \Psi''(x) T(t)$$

$$\Rightarrow \frac{\Psi(x) \dot{T}(t)}{\Psi(x) T(t)} = \frac{[\beta(x) \Psi(x)]' T(t)}{\Psi(x) T(t)} + \frac{D \Psi''(x) T(t)}{\Psi(x) T(t)}$$


$$\frac{\dot{T}(t)}{T(t)} = \frac{[\beta(x) \Psi(x)]'}{\Psi(x)} + \frac{D \Psi''(x)}{\Psi(x)} = \underline{\underline{\lambda}}$$

$$\dot{T} - \lambda T = 0 \quad \checkmark$$

$$D \Psi''(x) + [\beta(x) \Psi(x)]' - \lambda \Psi(x) = 0; \Psi(\pm\infty) = 0$$

$$D\Psi''(x) + [\beta(x)\Psi(x)]' - \lambda\Psi(x) = 0; \Psi(\pm\infty) = 0$$

This is an eigenvalue problem. Depending upon nature of $\beta(x)$, the solution can be obtained in the form

$$p(x; t | x_0; 0) = \sum_{i=1}^{\infty} a_i \exp(\lambda_i t) \Psi_i(x)$$

The constants a_i -s can be obtained using the condition

$$p(x; 0 | x_0; 0) = \delta(x - x_0)$$

Remark

$$\text{As } t \rightarrow \infty, \frac{\partial p}{\partial t} \rightarrow 0 \Rightarrow$$

$$\text{Stationary solution: } \frac{d[\beta(x)p]}{dx} + D \frac{d^2 p}{dx^2} = 0$$

Example

$$\ddot{x} + 2\eta\omega\dot{x} + \omega^2 x = w(t); t \geq 0; \underline{x(0) = x_0}; \underline{\dot{x}(0) = \dot{x}_0}$$

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

$$\underline{X(t)} = \begin{Bmatrix} \underline{X_1(t)} \\ \underline{X_2(t)} \end{Bmatrix} = \begin{Bmatrix} x(t) \\ \dot{x}(t) \end{Bmatrix}$$

$$dB(t) = dt w(t)$$

$$dX_1 = X_2 dt \checkmark$$

$$dX_2 = [-2\eta\omega X_2 - \omega^2 X_1] dt + \underline{dB(t)}$$

$$p \equiv \underline{p[\tilde{x}; t | \tilde{x}_0]} = p[x_1, x_2; t | X_1(0) = x_0, \dot{X}_1(0) = \dot{x}_0]$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^2 \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^2 \sum_{k=1}^2 \frac{\partial}{\partial x_j \partial x_k} [\alpha_{jk} p] \checkmark$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^2 \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^2 \sum_{k=1}^2 \frac{\partial}{\partial x_j \partial x_k} [\alpha_{jk} p]$$

$$\alpha_j = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle [X_j(t + \Delta t) - X_j(t)] | X(t) = \tilde{x} \rangle$$

$$\alpha_{ij} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle [X_i(t + \Delta t) - X_i(t)] [X_j(t + \Delta t) - X_j(t)] | X(t) = \tilde{x} \rangle$$

$$dX_1 = X_2 dt$$

$$dX_2 = [-2\eta\omega X_2 - \omega^2 X_1] dt + \underline{\underline{dB(t)}}$$

$$\alpha_1 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle \underline{X_2(t) dt} | X_1(t) = x_1, X_2(t) = x_2 \rangle = x_2$$

$$\alpha_2 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle [-2\eta\omega X_2 - \omega^2 X_1] dt + \underline{dB(t)} | X_1(t) = x_1, X_2(t) = x_2 \rangle$$

$$= -2\eta\omega x_2 - \omega^2 x_1$$

$$\alpha_{11} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle X_2^2 (dt)^2 | X_1(t) = x_1, X_2(t) = x_2 \rangle = 0$$

$$\text{Similarly, } \alpha_{12} = \alpha_{21} = 0 \text{ \& } \alpha_{22} = 2D$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^2 \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^2 \sum_{k=1}^2 \frac{\partial}{\partial x_j \partial x_k} [\alpha_{jk} p] //$$

$$\alpha_1 = x_2; \alpha_2 = -2\eta\omega x_2 - \omega^2 x_1; \alpha_{11} = \alpha_{12} = \alpha_{21} = 0 \text{ \& } \alpha_{22} = 2D$$

$$\frac{\partial p}{\partial t} = -x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\{2\eta\omega x_2 + \omega^2 x_1\} p \right] + D \frac{\partial^2 p}{\partial x_2^2}$$

$$p(x_1, x_2; t | X_1(0) = x_{10}, X_2(0) = x_{20}) = \delta(x_1 - x_{10}) \delta(x_2 - x_{20})$$

$$p(\pm\infty, x_2; t | X_1(0) = x_{10}, X_2(0) = x_{20}) = \underline{0}$$

$$p(x_2, \pm\infty; t | X_1(0) = x_{10}, X_2(0) = x_{20}) = \underline{0}$$

Remark

The FPK equation can be viewed as the equation of motion governing the evolution of pdf $p(\tilde{x}; t | \tilde{x}_0; 0)$

$$\frac{\partial \phi}{\partial t} \rightarrow 0$$

Equation in the steady state ($t \rightarrow \infty$)

$$-x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\left\{ 2\eta\omega x_2 + \omega^2 x_1 \right\} p \right] + \underline{\underline{D \frac{\partial^2 p}{\partial x_2^2}}} = 0$$

BCS

$$p(\pm\infty, x_2; t \mid X_1(0) = x_{10}, X_2(0) = x_{20}) = 0$$

$$p(x_2, \pm\infty; t \mid X_1(0) = x_{10}, X_2(0) = x_{20}) = 0$$

Example : nonstationary inputs

$$\ddot{x} + 2\eta\omega\dot{x} + \omega^2 x = e(t)w(t); t \geq 0; x(0) = x_0; \dot{x}(0) = \dot{x}_0$$

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

$e(t)$ = deterministic modulating function

$$X(t) = \begin{Bmatrix} X_1(t) \\ X_2(t) \end{Bmatrix} = \begin{Bmatrix} x(t) \\ \dot{x}(t) \end{Bmatrix}$$

$$dX_1 = X_2 dt$$

$$dX_2 = [-2\eta\omega X_2 - \omega^2 X_1] dt + e(t) dB(t)$$

$$p \equiv p[\tilde{x}; t | \tilde{x}_0] = p[x_1, x_2; t | X_1(0) = x_0, \dot{X}_1(0) = \dot{x}_0]$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^2 \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^2 \sum_{k=1}^2 \frac{\partial^2}{\partial x_j \partial x_k} [\alpha_{jk} p]$$

$$dX_1 = X_2 dt$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt + e(t) dB(t)$$

$$\alpha_1 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle X_2(t) dt \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle = x_2$$

$$\begin{aligned} \alpha_2 &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt + dB(t) \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle \\ &= -2\eta\omega x_2 - \omega^2 x_1 \end{aligned}$$

$$\alpha_{11} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle X_2^2 (dt)^2 \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle = 0$$

Similarly, $\alpha_{12} = \alpha_{21} = 0$ & $\alpha_{22} = 2De^2(t)$

$$\frac{\partial p}{\partial t} = -x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\left\{ 2\eta\omega x_2 + \omega^2 x_1 \right\} p \right] + \underline{\underline{De^2(t)}} \frac{\partial^2 p}{\partial x_2^2}$$

Note: no steady state solution exists.

Example : Nonlinear system

$$\ddot{x} + 2\eta\omega\dot{x} + \omega^2 x + \alpha x^3 = w(t); t \geq 0; x(0) = x_0; \dot{x}(0) = \dot{x}_0$$

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

$$X(t) = \begin{Bmatrix} X_1(t) \\ X_2(t) \end{Bmatrix} = \begin{Bmatrix} x(t) \\ \dot{x}(t) \end{Bmatrix}$$

$$dX_1 = X_2 dt \quad \checkmark$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 - \alpha X_1^3 \right] dt + dB(t)$$

$$p \equiv p[\tilde{x}; t | \tilde{x}_0] = p[x_1, x_2; t | X_1(0) = x_0, \dot{X}_1(0) = \dot{x}_0]$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^2 \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^2 \sum_{k=1}^2 \frac{\partial^2}{\partial x_j \partial x_k} [\alpha_{jk} p]$$

$$dX_1 = X_2 dt$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 - \alpha X_1^3 \right] dt + dB(t)$$

$$\alpha_1 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle X_2(t) dt \mid X_1(t) = x_1, X_2(t) = x_2 \rangle = x_2$$

$$\alpha_2 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle \left[-2\eta\omega X_2 - \omega^2 X_1 - \alpha X_1^3 \right] dt + dB(t) \mid X_1(t) = x_1, X_2(t) = x_2 \rangle$$

$$= -2\eta\omega x_2 - \omega^2 x_1 - \alpha x_1^3$$

$$\alpha_{11} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \langle X_2^2 (dt)^2 \mid X_1(t) = x_1, X_2(t) = x_2 \rangle = 0$$

Similarly, $\alpha_{12} = \alpha_{21} = 0$ & $\alpha_{22} = 2D$

$$\frac{\partial p}{\partial t} = -x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\left\{ 2\eta\omega x_2 + \omega^2 x_1 + \alpha x_1^3 \right\} p \right] + D \frac{\partial^2 p}{\partial x_2^2}$$

Steady state ($t \rightarrow \infty$)

$$-x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\left\{ 2\eta\omega x_2 + \omega^2 x_1 + \alpha x_1^3 \right\} p \right] + D \frac{\partial^2 p}{\partial x_2^2} = 0$$

Example : parametric random excitations

$$\ddot{x} + \dot{x} \left[2\eta\omega + \varepsilon W_1(t) \right] + x \left[\omega^2 + \alpha W_2(t) \right] = W_3(t);$$

$$t \geq 0; x(0) = x_0; \dot{x}(0) = \dot{x}_0$$

$$dB_i(t) = W_i(t) dt; \langle dB_i(t) dB_j(t + \tau) \rangle = 2D_{ij} \delta(\tau)$$

$$X(t) = \begin{Bmatrix} X_1(t) \\ X_2(t) \end{Bmatrix} = \begin{Bmatrix} x(t) \\ \dot{x}(t) \end{Bmatrix}$$

$$dX_1 = X_2 dt \quad \checkmark$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt - \varepsilon x_2 dB_1(t) - \alpha \dot{x}_1 dB_2(t) + dB_3(t)$$

$$p \equiv p[\tilde{x}; t | \tilde{x}_0] = p[x_1, x_2; t | X_1(0) = x_0, \dot{X}_1(0) = \dot{x}_0]$$

$$\frac{\partial p}{\partial t} = - \sum_{j=1}^2 \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^2 \sum_{k=1}^2 \frac{\partial}{\partial x_j \partial x_k} [\alpha_{jk} p]$$

$$dX_1 = X_2 dt \quad \checkmark$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt - \varepsilon x_2 dB_1(t) - \alpha x_1 dB_2(t) + dB_3(t)$$

$$\alpha_1 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle X_2(t) dt \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle = x_2 \quad \checkmark$$

$$\alpha_2 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt + dB(t) \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle$$

$- \varepsilon x_2 dB_1(t) - \alpha x_1 dB_2(t)$

$$= -2\eta\omega x_2 - \omega^2 x_1 \quad \checkmark$$

$$\alpha_{11} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle X_2^2 (dt)^2 \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle = 0$$

Similarly, $\alpha_{12} = \alpha_{21} = 0$

$$\alpha_{22} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left\{ \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt - \varepsilon x_2 dB_1(t) - \alpha x_1 dB_2(t) + dB_3(t) \right\}^2 \right\rangle$$

$$\mid X_1(t) = x_1, X_2(t) = x_2 \rangle$$

$$= 2\varepsilon^2 x_2^2 D_{11} + 2\alpha^2 x_1^2 D_{22} + 2D_{33} + 4\varepsilon\alpha x_1 x_2 D_{12} - 4\varepsilon x_2 D_{13} - 4\alpha x_1 D_{23}$$

$$dX_1 = X_2 dt$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt - \varepsilon x_2 dB_1(t) - \alpha x_1 dB_2(t) + dB_3(t)$$

$$\alpha_1 = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle X_2(t) dt \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle = x_2$$

$$\begin{aligned} \alpha_2 &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt + dB(t) \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle \\ &= -2\eta\omega x_2 - \omega^2 x_1 \end{aligned}$$

$$\alpha_{11} = \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle X_2^2(dt)^2 \mid X_1(t) = x_1, X_2(t) = x_2 \right\rangle = 0$$

Similarly, $\alpha_{12} = \alpha_{21} = 0$

$$\begin{aligned} \alpha_{22} &= \lim_{\Delta t \rightarrow 0} \frac{1}{\Delta t} \left\langle \left[-2\eta\omega X_2 - \omega^2 X_1 \right] dt - \varepsilon x_2 dB_1(t) - \alpha x_1 dB_2(t) + dB_3(t) \right\rangle^2 \\ &= 2\varepsilon^2 x_2^2 D_{11} + 2\alpha^2 x_1^2 D_{22} + 2D_{33} + 4\varepsilon\alpha x_1 x_2 D_{12} - 4\varepsilon x_2 D_{13} - 4\alpha x_1 D_{23} \end{aligned}$$

$$\frac{\partial p}{\partial t} = -x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\left\{ 2\eta\omega x_2 + \omega^2 x_1 \right\} p \right] +$$

$$\frac{\partial^2}{\partial x_2^2} \left[\left(2\varepsilon^2 x_2^2 D_{11} + 2\alpha^2 x_1^2 D_{22} + 2D_{33} + 4\varepsilon\alpha x_1 x_2 D_{12} - 4\varepsilon x_2 D_{13} - 4\alpha x_1 D_{23} \right) p \right]$$

$$p(x_1, x_2; t | X_1(0) = x_{10}, X_2(0) = x_{20}) = \delta(x_1 - x_{10}) \delta(x_2 - x_{20})$$

$$p(\pm\infty, x_2; t | X_1(0) = x_{10}, X_2(0) = x_{20}) = 0$$

$$p(x_2, \pm\infty; t | X_1(0) = x_{10}, X_2(0) = x_{20}) = 0$$

If stationary solution exist, it is governed by

$$-x_2 \frac{\partial p}{\partial x_1} + \frac{\partial}{\partial x_2} \left[\left\{ 2\eta\omega x_2 + \omega^2 x_1 \right\} p \right] +$$

$$\frac{\partial^2}{\partial x_2^2} \left[\left(2\varepsilon^2 x_2^2 D_{11} + 2\alpha^2 x_1^2 D_{22} + 2D_{33} + 4\varepsilon\alpha x_1 x_2 D_{12} - 4\varepsilon x_2 D_{13} - 4\alpha x_1 D_{23} \right) p \right] = 0$$

Example : Filtered white noise excitations

$$\ddot{x} + 2\eta\omega\dot{x} + \omega^2 x + \alpha x^3 = \underline{f(t)}; t \geq 0; x(0) = x_0; \dot{x}(0) = \dot{x}_0$$

$$\underline{\ddot{f} + 2\xi\lambda\dot{f} + \lambda^2 f = w(t)}; t \geq 0; f(0) = f_0; \dot{f}(0) = \dot{f}_0$$

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

$$\underline{X(t) = \left\{ x(t) \quad \dot{x}(t) \quad f(t) \quad \dot{f}(t) \right\}^t}$$

$$dX_1 = X_2 dt$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 - \alpha X_1^3 \right] dt + X_3 dt$$

$$dX_3 = X_4 dt$$

$$dX_4 = \left[-2\xi\lambda X_4 - \lambda^2 X_3 \right] dt + dB(t)$$

$$dX_1 = X_2 dt$$

$$dX_2 = \left[-2\eta\omega X_2 - \omega^2 X_1 - \alpha X_1^3 \right] dt + X_3 dt$$

$$dX_3 = X_4 dt$$

$$dX_4 = \left[-2\xi\lambda X_4 - \lambda^2 X_3 \right] dt + dB(t)$$

$$\alpha_1 = x_2$$

$$\alpha_2 = -2\eta\omega x_2 - \omega^2 x_1 - \alpha x_1^3 + x_3$$

$$\alpha_3 = x_4$$

$$\alpha_4 = -2\xi\lambda x_4 - \lambda^2 x_3$$

$$\alpha_{ij} = 0 \forall i, j = 1, 2, 3, 4 \text{ except } \alpha_{44} = 2D$$

$$\checkmark \frac{\partial p}{\partial t} = - \sum_{j=1}^4 \frac{\partial}{\partial x_j} [\alpha_j p] + D \frac{\partial^2 p}{\partial^2 x_4^2} \quad \curvearrowright$$

$$\frac{\partial p}{\partial t} = -\sum_{j=1}^4 \frac{\partial}{\partial x_j} [\alpha_j p] + D \frac{\partial^2 p}{\partial^2 x_4^2}$$

$$p(x_1, x_2; x_3, x_4; t | X(0) = \tilde{x}_0) = \prod_{i=1}^4 \delta(x_i - x_{i0})$$

$$p(\pm\infty, x_2, x_3, x_4; t | X(0) = \tilde{x}_0) = 0$$

$$p(x_1, \pm\infty, x_3, x_4; t | X(0) = \tilde{x}_0) = 0$$

$$p(x_1, x_2, \pm\infty, x_4; t | X(0) = \tilde{x}_0) = 0$$

$$p(x_1, x_2, x_3, \pm\infty; t | X(0) = \tilde{x}_0) = 0$$

If stationary solution exist, it is governed by

$$-\sum_{j=1}^4 \frac{\partial}{\partial x_j} [\alpha_j p] + D \frac{\partial^2 p}{\partial^2 x_4^2} = 0$$

Example : Linear MDOF systems

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

$$X(t) \sim N \times 1$$

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

$$\ddot{X} + M^{-1}C\dot{X} + M^{-1}KX = M^{-1}W(t)$$

$$Y = \begin{Bmatrix} Y_I \\ Y_{II} \end{Bmatrix} = \begin{Bmatrix} X \\ \dot{X} \end{Bmatrix}$$

$$dY_I = Y_{II} dt$$

$$dY_{II} = -M^{-1}CY_{II} - M^{-1}KY_I + M^{-1}dB(t)$$

$$dY(t) = PYdt + QdB(t) t \geq 0; Y(0) = Y_0$$

Example : Nonlinear MDOF systems

$$M\ddot{X} + F[X, \dot{X}] = W(t); t \geq 0; X(0) = X_0; \dot{X}(0) = \dot{X}_0$$

$$X(t) \sim N \times 1$$

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

$$\ddot{X} + M^{-1}F[X, \dot{X}] = M^{-1}W(t)$$

$$Y = \begin{Bmatrix} Y_I \\ Y_{II} \end{Bmatrix} = \begin{Bmatrix} X \\ \dot{X} \end{Bmatrix}$$

$$dY_I = Y_{II} dt$$

$$dY_{II} = -M^{-1}F(Y) dt + M^{-1}dB(t)$$

$$dY(t) = P(Y) dt + QdB(t) t \geq 0; Y(0) = Y_0$$

General: n - dimensional Ito SDE

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

$$X(t), f[t, X(t)] \sim n \times 1$$

$$G[t, X(t)] \sim n \times m$$

$$dB(t) \sim m \times 1$$

$$\langle dB(t) \rangle = 0; \langle \Delta B_i(t) \Delta B_j(t + \tau) \rangle = 2D_{ij} \delta(\tau)$$

$$\alpha_j = f_j[t, x]; j = 1, 2, \dots, n$$

$$\alpha_{ij} = 2[G D G^t]_{ij}; i, j = 1, 2, \dots, m$$

$$\frac{\partial p}{\partial t} = - \sum_{j=1}^n \frac{\partial}{\partial x_j} [\alpha_j p] + \frac{1}{2} \sum_{j=1}^m \sum_{k=1}^m \frac{\partial}{\partial x_j \partial x_k} [\alpha_{jk} p]$$

$$p(\tilde{x}; 0 | \tilde{x}_0; 0) = \prod_{i=1}^n \delta(x_i - x_{i0}) + \text{BCS}$$

Next Lecture

- Solutions of FPK equations
 - Transient solutions
 - Linear systems with additive noises
 - Steady state solutions
 - All scalar equations
 - All linear systems with additive noises
 - A class of nonlinear and parametrically excited systems
- Moment equations