



Stochastic Closure Schemes for bi-stable Energy Harvesters Excited by Colored Noise

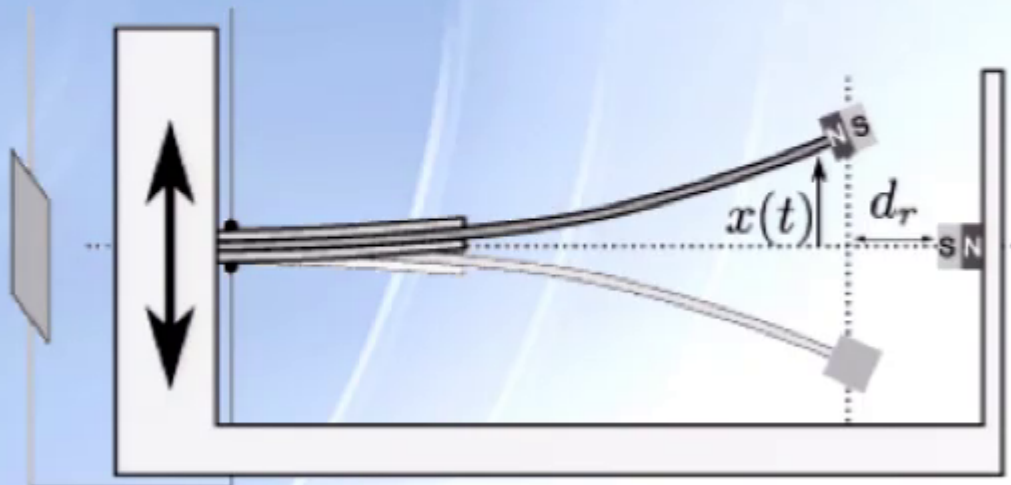
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Funding provided by MIT Energy Initiative

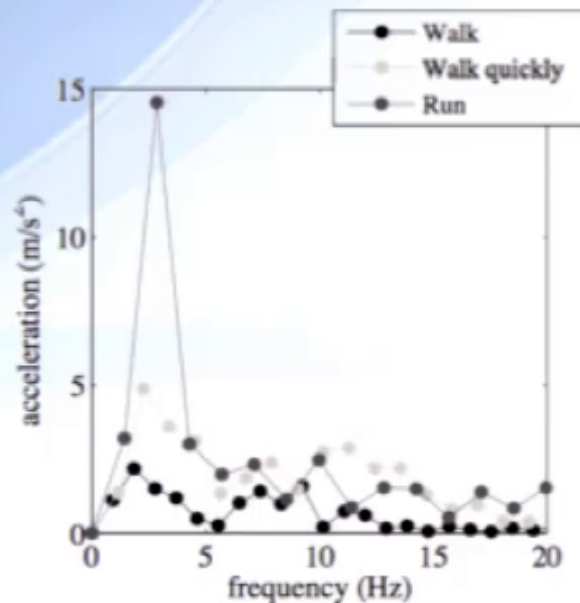


Bi-stable energy harvester subjected to random excitations

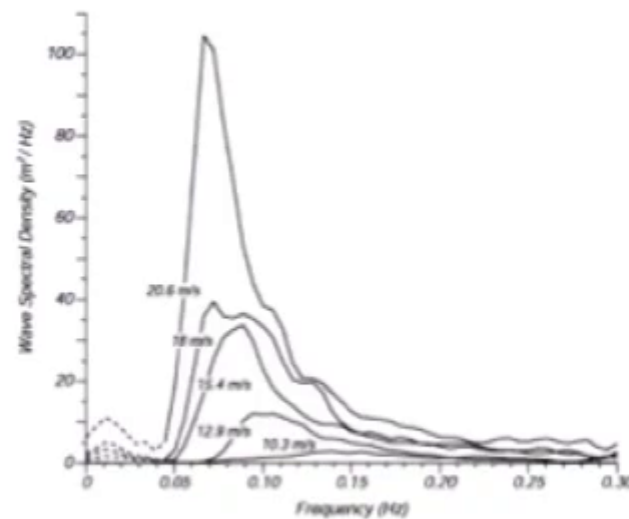


- Robustness under different loads
- Broadband operation
- Suitable for very weak loads
- Straightforward to implement

Walking vibrations



Ocean waves



Challenge: Most sources of energy are neither broadband nor monochromatic

Goal: Model the stochastic dynamics of a strongly nonlinear system involving multiple time scales and correlated excitations



Methods to analyze systems subjected to correlated noise

Computational cost

Fokker Planck Equation + Filters

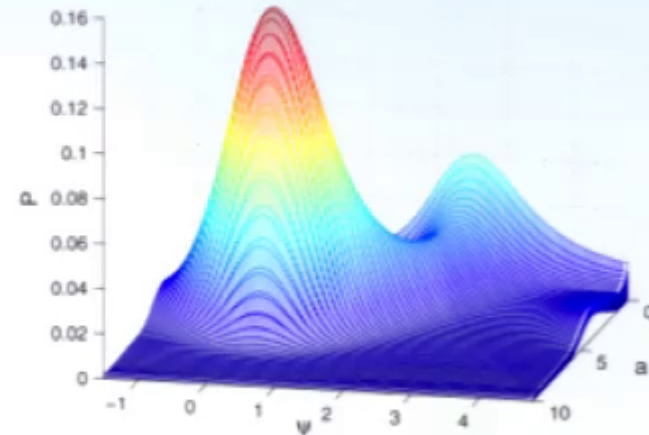
- Model the excitation as filtered white-noise
- Solve the coupled system+filter FP equation
- Very expensive and often unrealistic

Polynomial Chaos (Wiener, ...)

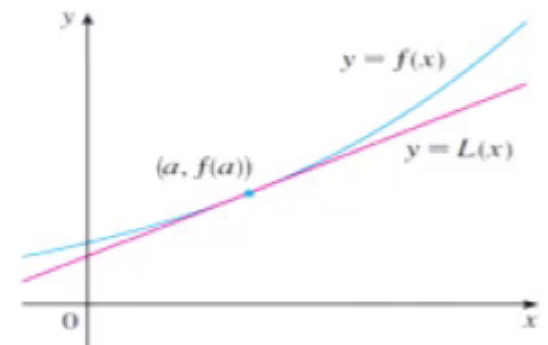
- Expand excitation and solution in a PC series
- Slow convergence for non-Gaussian responses...
- Little information about non-Gaussian statistics

Statistical (non) linearization (Boaton, Caughey, ...)

- Approximate dynamics by the closest linear system
- Very powerful method for vibrational systems
- Fails for bi-stable (bi-modal) systems



$$u = \sum_{J=0}^{N_{PC}} \hat{u}_J \Psi_J(\xi)$$



Plan of the presentation – overview of the method

- **Overview of statistical linearization methods and their limitations**
- **The moment-equation-closure minimization method**
 - *Moment equations expressing two-times statistics*
 - *Two-times pdf representations and induced closure schemes*
 - *Simultaneous error minimization for both the moments and the closure*
- **Representation of the full probability density function**
- **Application to bistable systems**
 - *Application to Duffing oscillator excited by correlated noise*
 - *Application to a bistable electromechanical energy harvester*
 - *Comparison with Gaussian closure methods*



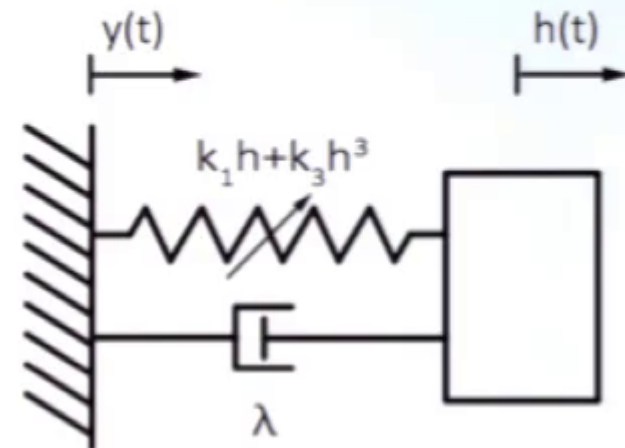
Overview of statistical linearization methods

Consider a nonlinear (SDOF) oscillator of the form:

$$\ddot{x} + \lambda \dot{x} + g(x) = \ddot{y}$$

$$g(x) = k_1 x + k_3 x^3$$

$y \rightarrow$ Correlated random excitation



Statistical linearization: *substitute the non-linear system by the "closest" linear*

$$\ddot{x} + \lambda \dot{x} + k_0 x = \ddot{y}$$

How to choose k_0 ?

$$E[\Delta^2] = E[(k_0 x - g(x))^2] = \min$$

$$\Rightarrow k_0 = \frac{E[xg(x)]}{E[x^2]}$$

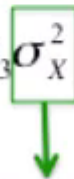


Overview of statistical linearization methods

Step 1: Adoption of a pdf representation (single-time statistics)

e.g. if Gaussian statistics for the response is assumed:

$$k_0 = \frac{E[xg(x)]}{E[x^2]} = \frac{E[k_1x^2 + k_3x^4]}{E[x^2]} = k_1 + 3k_3\sigma_x^2 \quad \text{Isserlis' Theorem}$$


unknown

Non-Gaussian pdf may also be utilized (statistical non-linearization)

Step 2: Two-times moment equation for the linear system

$$\ddot{x} + \lambda\dot{x} + k_0x = \ddot{y} \quad \xrightarrow{\text{WK Theorem}} \quad S_{XX}(\omega) = \frac{-\omega^2}{|-\omega^2 + \lambda i\omega + k_0|^2} S_{YY}(\omega) \quad \text{Two-time statistics}$$

$$\sigma_x^2 = \int_0^\infty \frac{-\omega^2}{|-\omega^2 + \lambda i\omega + k_1 + 3k_3\sigma_x^2|^2} S_{YY}(\omega) \quad \text{Algebraic equation for } \sigma_x^2$$



Limitations of statistical linearization methods

1. Moment equations express two-times statistics but adopted pdf representation is for a single-time statistics.

$$k_0 = \frac{E[xg(x)]}{E[x^2]}$$

Closure relies on single-time statistics...

Important for bi-stable system where we have rich correlation structure

2. Closure has to be exactly satisfied and all the mismatch is handled by the equation.

*Information obtained by the equation
under the condition*

$$\sigma_x^2 = \int_0^{\infty} \frac{-\omega^2}{|-\omega^2 + \lambda i\omega + k_1 + 3k_3\sigma_x^2|^2} S_{YY}(\omega)$$

$$k_0 = \frac{E[xg(x)]}{E[x^2]}$$

What if the closure condition is not exactly satisfied?

bi-stable systems have non-trivial pdf structure



The moment-equation-closure minimization method

Step 1: Develop a pdf representation for two-times statistics

We want this representation to:

- i. incorporate specific properties or information about the response pdf (single time statistics) in the statistical steady state*
- ii. incorporate a given correlation structure between the statistics of the response and the excitation, e.g. Gaussian*
- iii. have a consistent marginal with the excitation pdf (for the case of the joint response-excitation pdf),*
- iv. induce a non-Gaussian closure scheme that will be consistent with all the above properties.*



The moment-equation-closure minimization method

Step 1: Develop a pdf representation for two-times statistics

Single-time statistics:

$$f(x; \gamma) = \frac{1}{\mathcal{F}} \exp \left\{ -\frac{1}{\gamma} \left(\frac{1}{2} k_1 x^2 + \frac{1}{4} k_3 x^4 \right) \right\}$$

Shape that is consistent with the exact solution of the FP equation but with a free parameter

Two-times statistics:

response-excitation pdf $x(t)y(s)$	$q(x, y) = \frac{1}{\mathcal{M}} f(x)g(y)e^{cxy}$	} $f(x)$: marginal for $x(t)$ or $x(s)$ $g(y)$: marginal for $x(t)$
response-response pdf $x(t)x(s)$	$p(x, z) = \frac{1}{\mathcal{N}} f(x)f(z)e^{cxz}$	

Generic non-Gaussian marginals - Gaussian correlation structure



The moment-equation-closure minimization method

Two-times statistics:

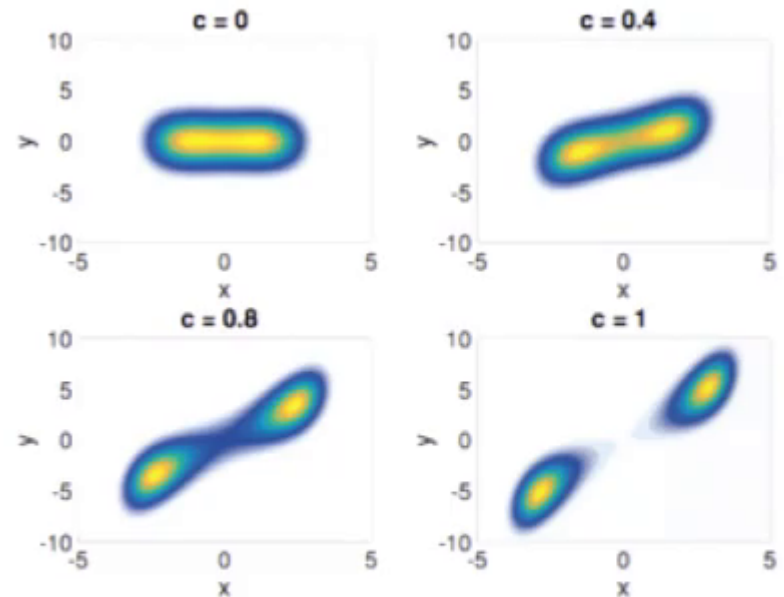
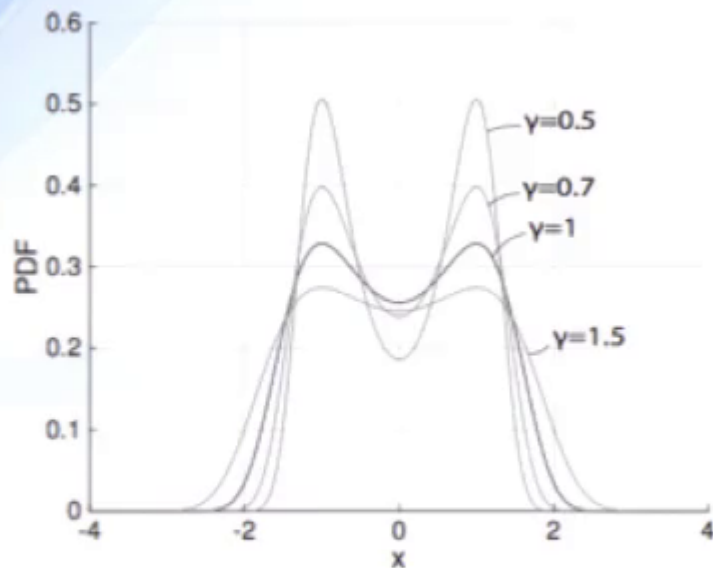
response-excitation pdf $q(x, y) = \frac{1}{\mathcal{M}} f(x)g(y)e^{cxy}$ $f(x)$: marginal for $x(t)$ or $x(s)$

$x(t)y(s)$

response-response pdf $p(x, z) = \frac{1}{\mathcal{N}} f(x)f(z)e^{cxz}$ $g(y)$: marginal for $x(t)$

$x(t)x(s)$

c : depends on $t-s$ & expresses degree of correlation



The moment-equation-closure minimization method

Step 2: Formulation of moment equations for the original system

$$\begin{aligned}\overline{\ddot{x}(t)y(s)} + \lambda \overline{\dot{x}(t)y(s)} + k_1 \overline{x(t)y(s)} + k_3 \overline{x(t)^3 y(s)} &= \overline{\ddot{y}(t)y(s)} \\ \overline{\ddot{x}(t)x(s)} + \lambda \overline{\dot{x}(t)x(s)} + k_1 \overline{x(t)x(s)} + k_3 \overline{x(t)^3 x(s)} &= \overline{\ddot{y}(t)x(s)}\end{aligned}$$

Assuming statistical stationarity: $\tau = t - s$

$$\begin{aligned}\frac{\partial^2}{\partial \tau^2} C_{xy}(\tau) + \lambda \frac{\partial}{\partial \tau} C_{xy}(\tau) + k_1 C_{xy}(\tau) + k_3 \overline{x(t)^3 y(s)} &= \frac{\partial^2}{\partial \tau^2} C_{yy}(\tau), \\ \frac{\partial^2}{\partial \tau^2} C_{xx}(\tau) + \lambda \frac{\partial}{\partial \tau} C_{xx}(\tau) + k_1 C_{xx}(\tau) + k_3 \overline{x(t)^3 x(s)} &= \frac{\partial^2}{\partial \tau^2} C_{xy}(-\tau)\end{aligned}$$

Different equations for $C_{xx}(\tau)$ and $C_{xy}(\tau)$

In statistical (non-) linearization closure is applied directly to the governing eq.

Here we apply closure to the exact two-times moment equations instead...



The moment-equation-closure minimization method

Step 3: Induced two-times closures for the terms $\overline{x(t)^3 y(s)}$ and $\overline{x(t)^3 x(s)}$

With some explicit computations using the two-times pdf representations we obtain

Closure constraint

$$\overline{x(t)^3 x(s)} = \rho_{x,x} \overline{x(t)x(s)} \quad \rho_{x,x} = \frac{\overline{x^4}}{\overline{x^2}} \quad \text{function of } \gamma$$

Using similar arguments we obtain a closure for $\overline{x(t)^3 y(s)}$

$$\rho_{x,y} = \frac{\overline{x^3 y}}{\overline{x y}} = \frac{\overline{x^4 y^2} c + \frac{1}{6} (\overline{x^6 y^4} - 3\overline{x^4 x^2 (y^2)^2}) c^3}{\overline{x^2 y^2} c + \frac{1}{6} (\overline{x^4 y^4} - 3(\overline{x^2})^2 (\overline{y^2})^2) c^3}$$



The moment-equation-closure minimization method

Substitute the induced two-times closures to the moment equations

$$\begin{aligned}\frac{\partial^2}{\partial \tau^2} C_{xy}(\tau) + \lambda \frac{\partial}{\partial \tau} C_{xy}(\tau) + (k_1 + \rho_{x,y} k_3) C_{xy}(\tau) &= \frac{\partial^2}{\partial \tau^2} C_{yy}(\tau), \\ \frac{\partial^2}{\partial \tau^2} C_{xx}(\tau) + \lambda \frac{\partial}{\partial \tau} C_{xx}(\tau) + (k_1 + \rho_{x,x} k_3) C_{xx}(\tau) &= \frac{\partial^2}{\partial \tau^2} C_{xy}(-\tau)\end{aligned}$$

We transform the two time equations to spectrum equations

$$S_{xx}(\omega) = \left| \frac{\omega^4}{\{k_1 + \rho_{x,y} k_3 - \omega^2 + j(\lambda\omega)\} \{k_1 + \rho_{x,x} k_3 - \omega^2 - j(\lambda\omega)\}} \right| S_{yy}(\omega)$$

From which we obtain the following constraint:

Dynamic constraint

$$\overline{x^2} = \int_0^\infty \left| \frac{\omega^4}{\{k_1 + \rho_{x,y} k_3 - \omega^2 + j(\lambda\omega)\} \{k_1 + \rho_{x,x} k_3 - \omega^2 - j(\lambda\omega)\}} \right| S_{yy}(\omega) d\omega$$



The moment-equation-closure minimization method

Step 4: Simultaneous minimization of the two constraints

$$\mathcal{J}(\gamma, \rho_{x,x}) = \underbrace{\left(\overline{x^2} - \int_0^\infty \left| \frac{\omega^4 S_{yy}(\omega)}{\{k_1 + \rho_{x,y}k_3 - \omega^2 + j(\lambda\omega)\}\{k_1 + \rho_{x,x}k_3 - \omega^2 - j(\lambda\omega)\}} \right| d\omega \right)^2}_{\text{Dynamics constraint}} + \underbrace{\left(\overline{x^2} - \frac{\overline{x^4}}{\rho_{x,x}} \right)^2}_{\text{Closure constraint}}$$

Notes:

- For the case where the closure constraint is exactly satisfied we recover the statistical (non-) linearization method.
- After we obtain the two unknowns we can go back and recover the correlation functions $C_{xx}(\tau)$ and $C_{xy}(\tau)$



The moment-equation-closure minimization method

- Using the values of the correlation functions we can find the constant c to obtain the full joint (two-times) pdf:

Full pdf representation

$$f_{x(t)x(t+\tau)y(t+\tau)}(x, z, y) = \frac{1}{\mathcal{R}} f(x; \gamma) f(z; \gamma) g(y) \exp(c_1 xz + c_2 xy + c_3 yz)$$

Correlation functions from the pdf...

$$C_{xx}(\tau) = \iiint xz f_{x(t)x(t+\tau)y(t+\tau)}(x, z, y) dx dy dz = c_1 (\bar{x}^2)^2 + \mathcal{O}(c_1^2)$$

$$C_{xy}(\tau) = \iiint xy f_{x(t)x(t+\tau)y(t+\tau)}(x, z, y) dx dy dz = c_2 \bar{x}^2 \bar{y}^2 + \mathcal{O}(c_2^2)$$

$$C_{xy}(0) = \iiint yz f_{x(t)x(t+\tau)y(t+\tau)}(x, z, y) dx dy dz = c_3 \bar{x}^2 \bar{y}^2 + \mathcal{O}(c_3^2)$$

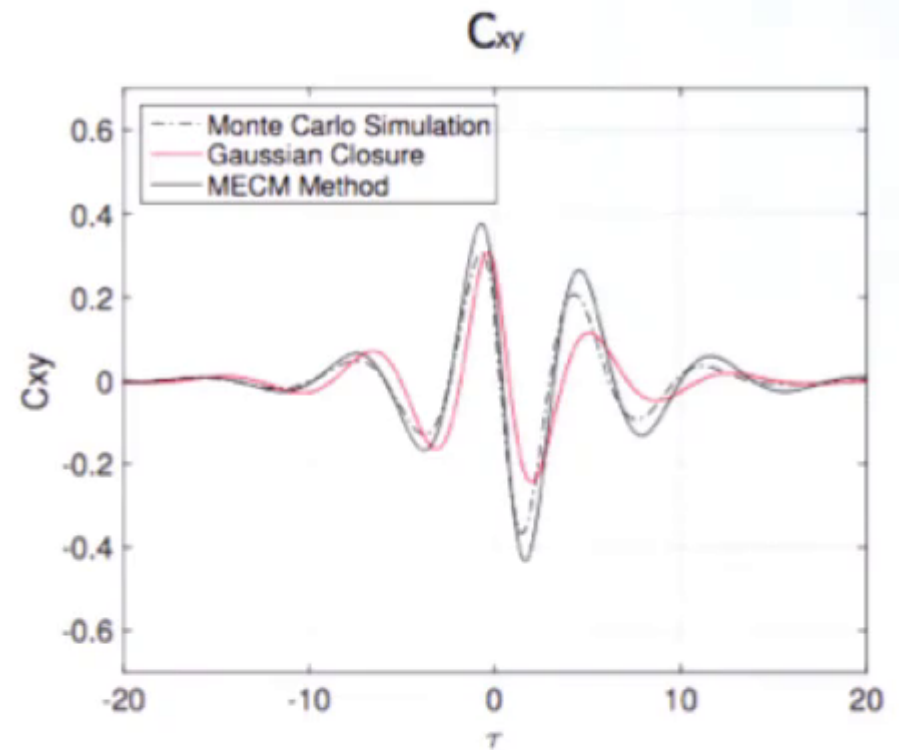
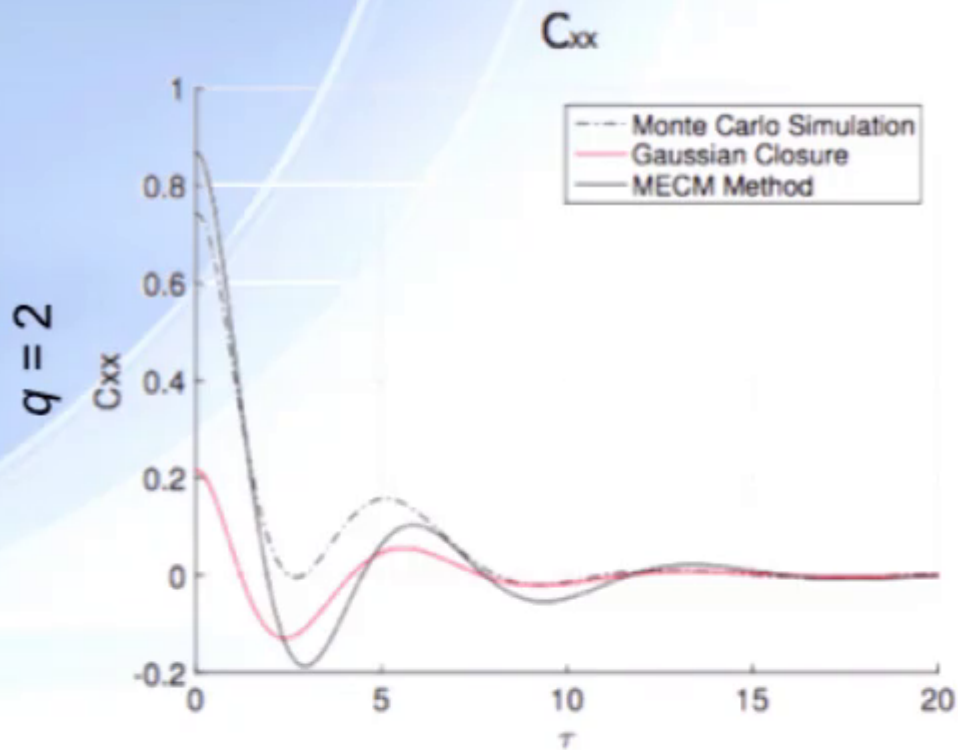


Application to the Duffing equation under correlated excitation

$$\ddot{x} + \lambda \dot{x} + k_1 x + k_3 x^3 = \ddot{y}$$

excitation is a Gaussian with spectrum

$$S(\omega) = q \frac{1}{\omega^5} \exp\left(-\frac{1}{\omega^4}\right)$$



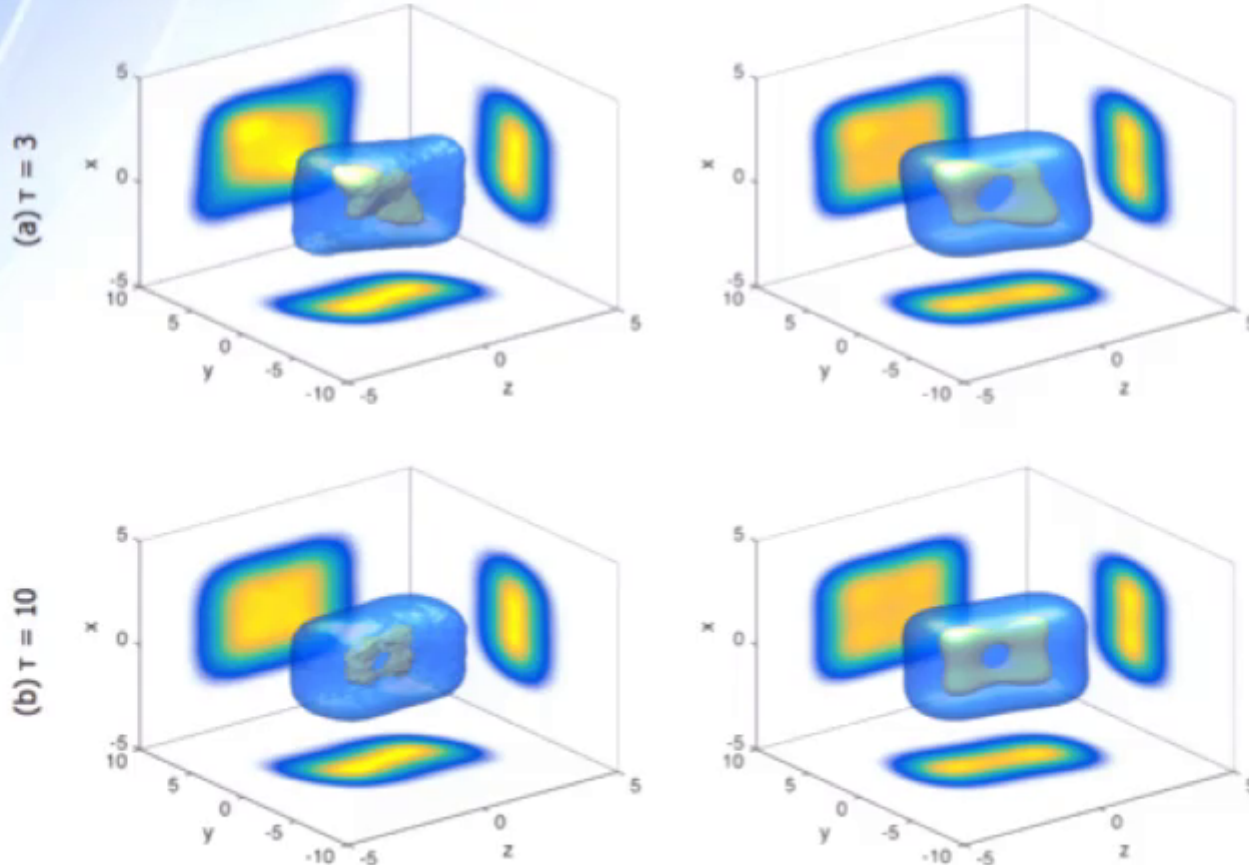
Application to the Duffing equation under correlated excitation

$$\ddot{x} + \lambda \dot{x} + k_1 x + k_3 x^3 = \ddot{y} \quad \text{excitation is a Gaussian with spectrum} \quad S(\omega) = q \frac{1}{\omega^5} \exp\left(-\frac{1}{\omega^4}\right)$$

$$f_{x(t)x(t+\tau)y(t+\tau)}(x, z, y)$$

Monte Carlo Simulation

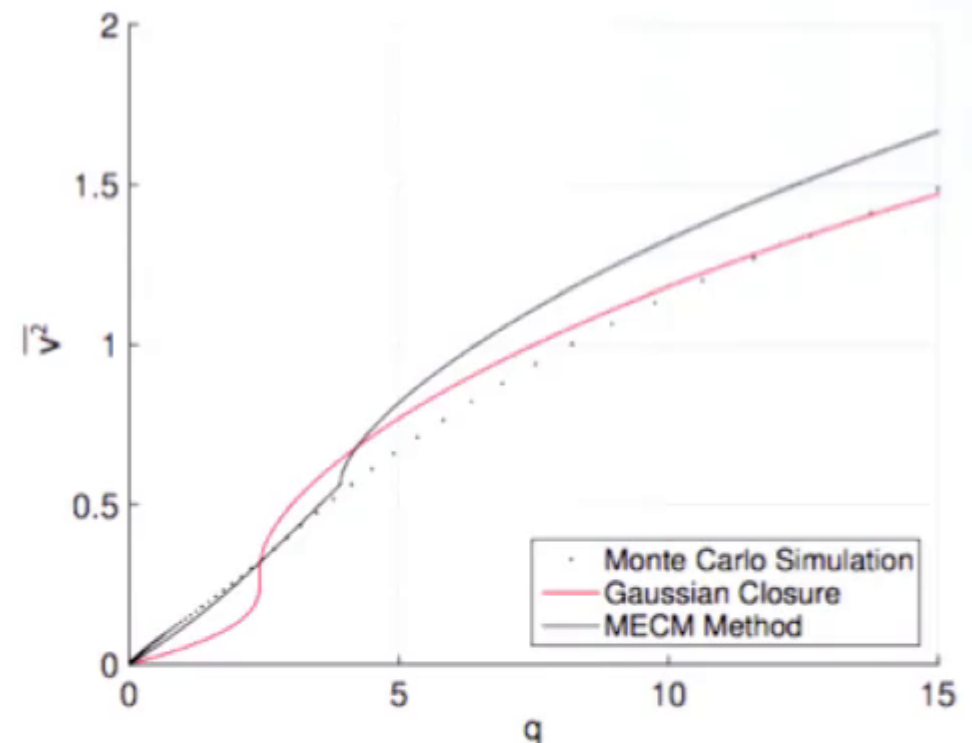
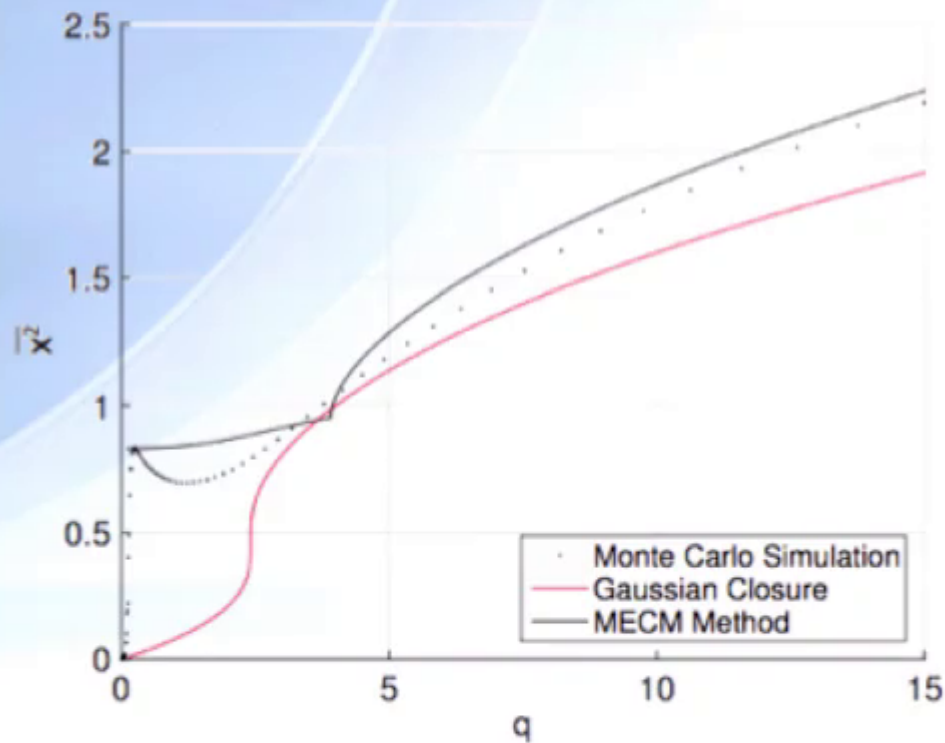
MECM Method



Bistable oscillator coupled to an electromechanical harvester

$$\ddot{x} + \lambda \dot{x} + k_1 x + k_3 x^3 + \alpha v = \ddot{y}, \quad \text{excitation is a Gaussian with spectrum } S(\omega) = q \frac{1}{\omega^5} \exp\left(-\frac{1}{\omega^4}\right)$$

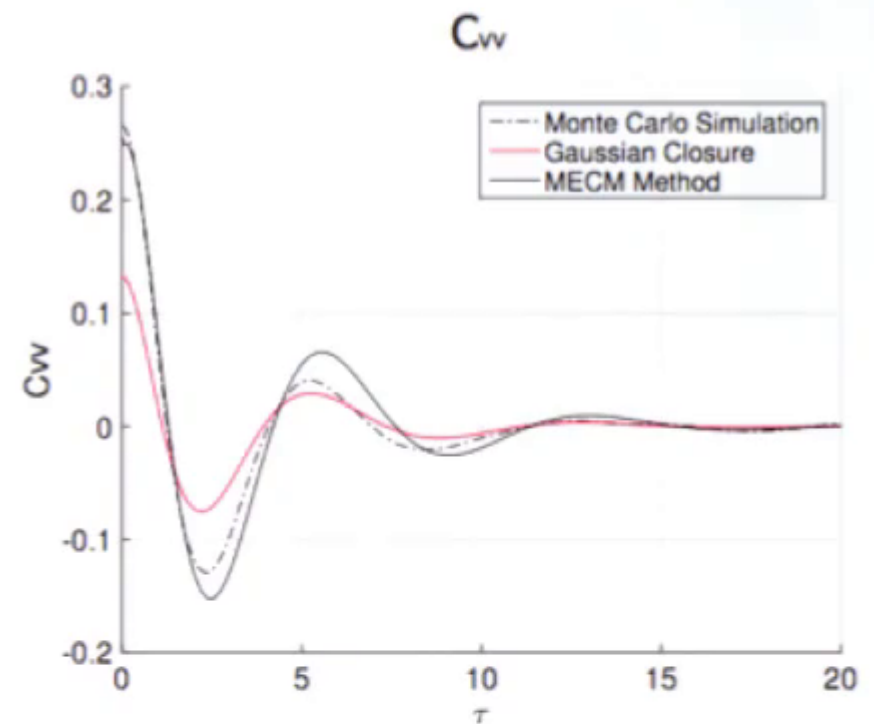
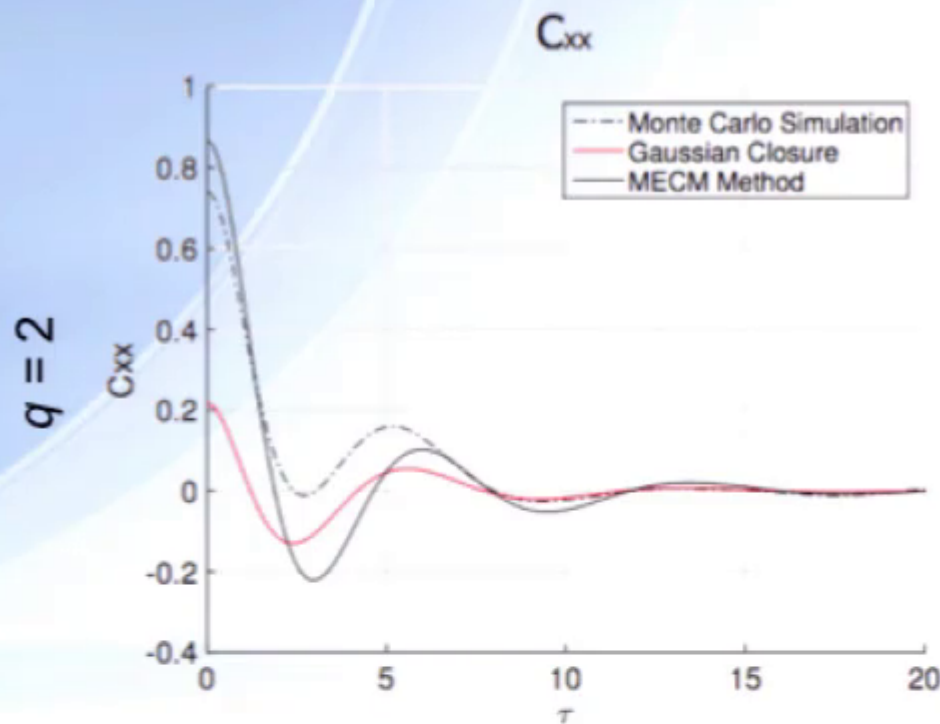
$$\dot{v} + \beta v = \delta \dot{x}$$



Bistable oscillator coupled to an electromechanical harvester

$\ddot{x} + \lambda\dot{x} + k_1x + k_3x^3 + \alpha v = \ddot{y}$, excitation is a Gaussian with spectrum
 $\dot{v} + \beta v = \delta\dot{x}$

$$S(\omega) = q \frac{1}{\omega^5} \exp\left(-\frac{1}{\omega^4}\right)$$



Bistable oscillator coupled to an electromechanical harvester

$$\ddot{x} + \lambda \dot{x} + k_1 x + k_3 x^3 + \alpha v = \ddot{y}, \text{ excitation is a Gaussian with spectrum } S(\omega) = q \frac{1}{\omega^5} \exp\left(-\frac{1}{\omega^4}\right)$$

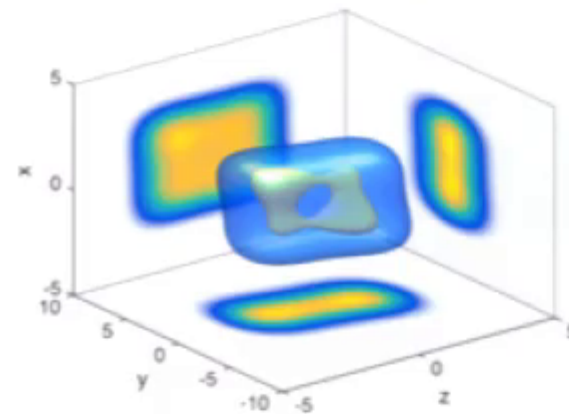
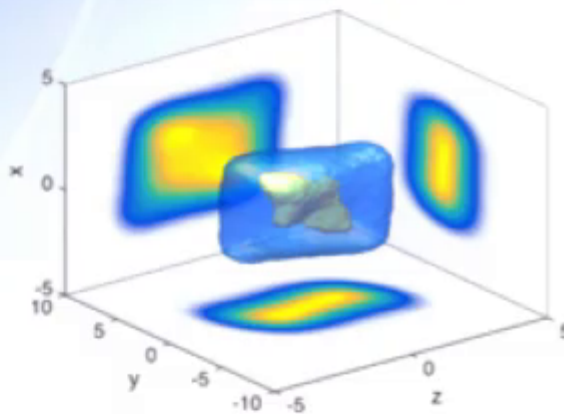
$$\dot{v} + \beta v = \delta \dot{x}$$

$$f_{x(t)x(t+\tau)y(t+\tau)}(x, z, y)$$

Monte Carlo Simulation

MECM Method

(a) $\tau = 3$



(b) $\tau = 10$

