



# *Distribution of Eigenvalues of Linear Stochastic Systems*

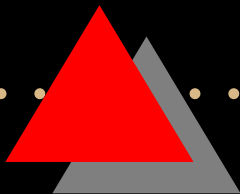
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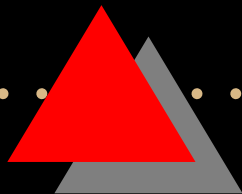
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# Outline of the talk

- Random eigenvalue problem
- Perturbation Methods
  - Mean-centered perturbation method
  - $\alpha$ -centered perturbation method
- Asymptotic analysis
- PDF of the eigenvalues
- Numerical Example
- Conclusions & Open Problems



# Random eigenvalue problem

The random eigenvalue problem of undamped or proportionally damped linear systems:

$$\mathbf{K}(\mathbf{x})\phi_j = \lambda_j\mathbf{M}(\mathbf{x})\phi_j \quad (1)$$

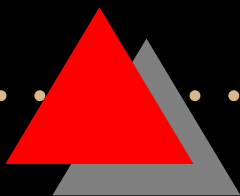
$\lambda_j$  eigenvalues;  $\phi_j$  eigenvectors;  $\mathbf{M}(\mathbf{x}) \in \mathbb{R}^{N \times N}$  mass matrix and  $\mathbf{K}(\mathbf{x}) \in \mathbb{R}^{N \times N}$  stiffness matrix.  $\mathbf{x} \in \mathbb{R}^m$  is random parameter vector with pdf

$$p(\mathbf{x}) = (2\pi)^{-m/2} e^{-\mathbf{x}^T \mathbf{x} / 2} \quad (2)$$



# *The fundamental aim*

- To obtain the joint probability density function of the eigenvalues and the eigenvectors.
- If the matrix  $\mathbf{M}^{-1}\mathbf{K}$  is GUE (Gaussian unitary ensemble) or GOE (Gaussian orthogonal ensemble) an exact closed-form expression can be obtained for the joint pdf of the eigenvalues.
- In general the system matrices for real structures are not GUE or GOE.



# Mean-centered perturbation

Assume that  $\mathbf{M}(\mathbf{0}) = \mathbf{M}_0$  and  $\mathbf{K}(\mathbf{0}) = \mathbf{K}_0$  are 'deterministic parts'. Deterministic eigenvalue problem:  $\mathbf{K}_0 \phi_{j_0} = \lambda_{j_0} \mathbf{M}_0 \phi_{j_0}$ . The eigenvalues  $\lambda_j(\mathbf{x}) : \mathbb{R}^m \rightarrow \mathbb{R}$  are non-linear functions of  $\mathbf{x}$ . Expanding  $\lambda_j(\mathbf{x})$  by Taylor series about  $\mathbf{x} = \mathbf{0}$ :

$$\lambda_j(\mathbf{x}) \approx \lambda_j(\mathbf{0}) + \mathbf{d}_{\lambda_j}^T(\mathbf{0})\mathbf{x} + \frac{1}{2}\mathbf{x}^T \mathbf{D}_{\lambda_j}(\mathbf{0})\mathbf{x} \quad (3)$$

$\mathbf{d}_{\lambda_j}(\mathbf{0}) \in \mathbb{R}^m$ : gradient vector,  $\mathbf{D}_{\lambda_j}(\mathbf{0}) \in \mathbb{R}^{m \times m}$  the Hessian matrix of  $\lambda_j(\mathbf{x})$  evaluated at  $\mathbf{x} = \mathbf{0}$ .

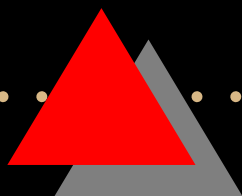


## *$\alpha$ -centered perturbation*

We are looking for a point  $\mathbf{x} = \boldsymbol{\alpha}$  in the  $\mathbf{x}$ -space such that the Taylor series expansion of  $\lambda_j(\mathbf{x})$  about this point

$$\lambda_j(\mathbf{x}) \approx \lambda_j(\boldsymbol{\alpha}) + \mathbf{d}_{\lambda_j}^T(\boldsymbol{\alpha}) (\mathbf{x} - \boldsymbol{\alpha}) + \frac{1}{2} (\mathbf{x} - \boldsymbol{\alpha})^T \mathbf{D}_{\lambda_j}(\boldsymbol{\alpha}) (\mathbf{x} - \boldsymbol{\alpha}) \quad (4)$$

is optimal in some sense. The optimal point  $\boldsymbol{\alpha}$  is selected such that the mean or the first moment of each eigenvalue is calculated most accurately.





## *$\alpha$ -centered perturbation*

The mean of  $\lambda_j(\mathbf{x})$  can be obtained as

$$\bar{\lambda}_j = \int_{\mathbb{R}^m} \lambda_j(\mathbf{x}) p(\mathbf{x}) d\mathbf{x} = (2\pi)^{-m/2} \int_{\mathbb{R}^m} e^{-h(\mathbf{x})} d\mathbf{x} \quad (5)$$

where  $h(\mathbf{x}) = \mathbf{x}^T \mathbf{x} / 2 - \ln \lambda_j(\mathbf{x})$  (6)

Expand the function  $h(\mathbf{x})$  in a Taylor series about a point where  $h(\mathbf{x})$  attains its global minimum. By doing so the error in evaluating the integral (5) would be minimized.



## *$\alpha$ -centered perturbation*

Therefore, the optimal point can be obtained as

$$\frac{\partial h(\mathbf{x})}{\partial x_k} = 0 \quad \text{or} \quad x_k = \frac{1}{\lambda_j(\mathbf{x})} \frac{\partial \lambda_j(\mathbf{x})}{\partial x_k}, \quad \forall k \quad (7)$$

Combining for all  $k$  we have  $\mathbf{d}_{\lambda_j}(\boldsymbol{\alpha}) = \lambda_j(\boldsymbol{\alpha})\boldsymbol{\alpha}$ .

Rearranging

$$\boldsymbol{\alpha} = \mathbf{d}_{\lambda_j}(\boldsymbol{\alpha}) / \lambda_j(\boldsymbol{\alpha}) \quad (8)$$

This equation immediately gives a recipe for an iterative algorithm to obtain  $\boldsymbol{\alpha}$ .





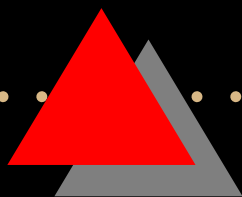


## *$\alpha$ -centered perturbation*

Substituting  $\mathbf{d}_{\lambda_j}(\boldsymbol{\alpha})$  in Eq. (4)

$$\begin{aligned} \lambda_j(\mathbf{x}) \approx & \lambda_j(\boldsymbol{\alpha}) (1 - |\boldsymbol{\alpha}|^2) + \frac{1}{2} \boldsymbol{\alpha}^T \mathbf{D}_{\lambda_j}(\boldsymbol{\alpha}) \boldsymbol{\alpha} \\ & + \boldsymbol{\alpha}^T (\lambda_j(\boldsymbol{\alpha}) \mathbf{I} - \mathbf{D}_{\lambda_j}(\boldsymbol{\alpha})) \mathbf{x} + \frac{1}{2} \mathbf{x}^T \mathbf{D}_{\lambda_j}(\boldsymbol{\alpha}) \mathbf{x} \quad (9) \end{aligned}$$

This, like the mean-centered approach, also results in a quadratic form in the random variable  $\mathbf{x}$ .



# *Eigenvalue statistics*

Both approximations yield a quadratic form in Gaussian random variable of the form

$$\lambda_j(\mathbf{x}) \approx c_j + \mathbf{a}_j^T \mathbf{x} + \frac{1}{2} \mathbf{x}^T \mathbf{A}_j \mathbf{x} \quad (10)$$

The moment generating function:

$$M_{\lambda_j}(s) = \mathbb{E} \left[ e^{s\lambda_j(\mathbf{x})} \right] \approx \frac{e^{sc_j + \frac{s^2}{2} \mathbf{a}_j^T [\mathbf{I} - s\mathbf{A}_j]^{-1} \mathbf{a}_j}}{\sqrt{\|\mathbf{I} - s\mathbf{A}_j\|}} \quad (11)$$

# Eigenvalue statistics

Cumulants:

$$\kappa_r = \begin{cases} c_j + \frac{1}{2} \text{Trace} (\mathbf{A}_j) & \text{if } r = 1, \\ \frac{r!}{2} \mathbf{a}_j^T \mathbf{A}_j^{r-2} \mathbf{a}_j + \frac{(r-1)!}{2} \text{Trace} (\mathbf{A}_j^r) & \text{if } r \geq 2 \end{cases} \quad (12)$$

Thus

$$\bar{\lambda}_j = \kappa_1 = c_j + \frac{1}{2} \text{Trace} (\mathbf{A}_j) \quad (13)$$

$$\text{Var} [\lambda_j] = \kappa_2 = \mathbf{a}_j^T \mathbf{a}_j + \frac{1}{2} \text{Trace} (\mathbf{A}_j^2) \quad (14)$$



# Asymptotic analysis

We want to evaluate an integral of the following form:

$$\mathcal{J} = \int_{\mathbb{R}^m} f(\mathbf{x}) p(\mathbf{x}) d\mathbf{x} = (2\pi)^{-m/2} \int_{\mathbb{R}^m} e^{\tilde{h}(\mathbf{x})} d\mathbf{x} \quad (15)$$

$$\text{where } \tilde{h}(\mathbf{x}) = \ln f(\mathbf{x}) - \mathbf{x}^T \mathbf{x} / 2 \quad (16)$$

Assume  $f(\mathbf{x}) : \mathbb{R}^m \rightarrow \mathbb{R}$  is smooth and at least twice differentiable and  $\tilde{h}(\mathbf{x})$  reaches its global maximum at an unique point  $\theta \in \mathbb{R}^m$ .

# Asymptotic analysis

Therefore, at  $\mathbf{x} = \boldsymbol{\theta}$

$$\frac{\partial \tilde{h}(\mathbf{x})}{\partial x_k} = 0 \text{ or } x_k = \frac{\partial}{\partial x_k} \ln f(\mathbf{x}), \forall k, \text{ or } \boldsymbol{\theta} = \frac{\partial}{\partial \mathbf{x}} \ln f(\boldsymbol{\theta}). \quad (17)$$

Further assume that  $\tilde{h}(\boldsymbol{\theta})$  is so large that

$$\left| \frac{1}{\tilde{h}(\boldsymbol{\theta})} \mathcal{D}^j(\tilde{h}(\boldsymbol{\theta})) \right| \rightarrow 0 \text{ for } j > 2 \quad (18)$$

$\mathcal{D}^j(\tilde{h}(\boldsymbol{\theta}))$ :  $j$ th order derivative of  $\tilde{h}(\mathbf{x})$  at  $\mathbf{x} = \boldsymbol{\theta}$ .



# Asymptotic analysis

Under previous assumptions, using second-order Taylor series of  $\tilde{h}(\mathbf{x})$  the integral (12) can be evaluated asymptotically as

$$\mathcal{J} \approx \frac{e^{\tilde{h}(\boldsymbol{\theta})}}{\sqrt{\|\tilde{\mathbf{H}}(\boldsymbol{\theta})\|}} = f(\boldsymbol{\theta})e^{-\left(\boldsymbol{\theta}^T \boldsymbol{\theta}/2\right)} \|\tilde{\mathbf{H}}(\boldsymbol{\theta})\|^{-1/2} \quad (19)$$

$\tilde{\mathbf{H}}(\boldsymbol{\theta})$  is the Hessian matrix of  $\tilde{h}(\mathbf{x})$  at  $\mathbf{x} = \boldsymbol{\theta}$ .

# Asymptotic analysis

An arbitrary  $r$ th order moment of the eigenvalues

$$\mu'_r = \int_{\mathbb{R}^m} \lambda_j^r(\mathbf{x}) p(\mathbf{x}) d\mathbf{x}, \quad r = 1, 2, 3 \dots \quad (20)$$

Comparing this with Eq. (12) it is clear that

$$f(\mathbf{x}) = \lambda_j^r(\mathbf{x}) \quad \text{and} \quad \tilde{h}(\mathbf{x}) = r \ln \lambda_j(\mathbf{x}) - \mathbf{x}^T \mathbf{x} / 2 \quad (21)$$

The optimal point  $\theta$  can be obtained from (14) as

$$\theta = r \mathbf{d}_{\lambda_j}(\theta) / \lambda_j(\theta) \quad (22)$$

# Asymptotic analysis

The  $r$ th moment:

$$\mu'_r = \lambda_j^r(\boldsymbol{\theta}) e^{-\frac{|\boldsymbol{\theta}|^2}{2}} \left\| \mathbf{I} + \frac{1}{r} \boldsymbol{\theta} \boldsymbol{\theta}^T - \frac{r}{\lambda_j(\boldsymbol{\theta})} \mathbf{D}_{\lambda_j}(\boldsymbol{\theta}) \right\|^{-1/2} \quad (23)$$

The mean of the eigenvalues (substitute  $r = 1$ ):

$$\bar{\lambda}_j = \lambda_j(\boldsymbol{\theta}) e^{-\frac{|\boldsymbol{\theta}|^2}{2}} \left\| \mathbf{I} + \boldsymbol{\theta} \boldsymbol{\theta}^T - \mathbf{D}_{\lambda_j}(\boldsymbol{\theta}) / \lambda_j(\boldsymbol{\theta}) \right\|^{-1/2} \quad (24)$$

Central moments:

$$\mathbb{E} [(\lambda_j - \bar{\lambda}_j)^r] = \sum_{k=0}^r \binom{r}{k} (-1)^{r-k} \mu'_k \bar{\lambda}_j^{r-k}.$$





# *Pdf of the eigenvalues*

**Theorem 1**  $\lambda_j(\mathbf{x})$  is distributed as a non-central  $\chi^2$  random variable with noncentrality parameter  $\delta^2$  and degrees-of-freedom  $m'$  if and only if (a)  $\mathbf{A}_j^2 = \mathbf{A}_j$ , (b)  $\text{Trace}(\mathbf{A}_j) = m'$  and (c)  $\mathbf{a}_j = \mathbf{A}_j \mathbf{a}_j$ ,  $\delta^2 = c_j = \mathbf{a}_j^T \mathbf{a}_j / 4$ .

This implies that the the Hessian matrix  $\mathbf{A}_j$  should be an idempotent matrix. In general this requirement is not expected to be satisfied for eigenvalues of real structural systems.



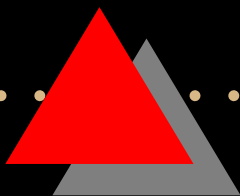
# Central $\chi^2$ approximation (Pearson's)

Pdf of the  $j$ th eigenvalue

$$p_{\lambda_j}(u) \approx \frac{1}{\tilde{\gamma}} p_{\chi^2_\nu} \left( \frac{u - \tilde{\eta}}{\tilde{\gamma}} \right) = \frac{(u - \tilde{\eta})^{\nu/2-1} e^{-(u-\tilde{\eta})/2\tilde{\gamma}}}{(2\tilde{\gamma})^{\nu/2} \Gamma(\nu/2)} \quad (25)$$

where

$$\tilde{\eta} = \frac{-2\kappa_2^2 + \kappa_1\kappa_3}{\kappa_3}, \quad \tilde{\gamma} = \frac{\kappa_3}{4\kappa_2}, \quad \text{and } \nu = 8 \frac{\kappa_2^3}{\kappa_3^2} \quad (26)$$



# Non-central $\chi^2$ approximation

Pdf of the  $j$ th eigenvalue

$$p_{\lambda_j}(u) \approx \frac{1}{\gamma_j} p_{Q_j} \left( \frac{u - \eta_j}{\gamma_j} \right) \quad (27)$$

where  $p_{Q_j}(u) = \frac{e^{-(\delta_j + u/2)} u^{m/2-1}}{2^{m/2}} \sum_{r=0}^{\infty} \frac{(\delta u)^r}{r! 2^r \Gamma(m/2+r)}$ ,

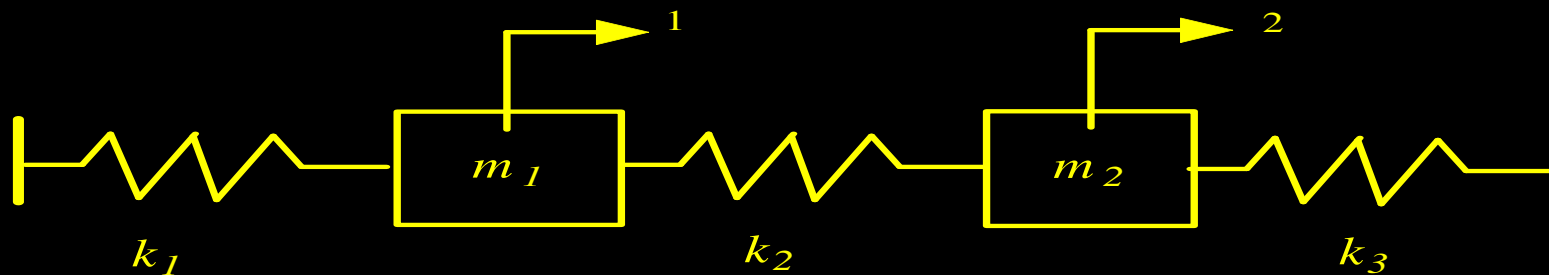
$\eta_j = c_j - \frac{1}{2} a_j^T \mathbf{A}_j^{-1} a_j$ ,  $\gamma_j = \frac{\text{Trace}(\mathbf{A}_j)}{2m}$ ,  $\delta_j^2 = \boldsymbol{\rho}_j^T \boldsymbol{\rho}_j$  and

$\boldsymbol{\rho}_j = \mathbf{A}_j^{-1} a_j$ .

# Numerical example

Undamped two degree-of-system system:

$m_1 = 1$  Kg,  $m_2 = 1.5$  Kg,  $\bar{k}_1 = 1000$  N/m,  $\bar{k}_2 = 1100$  N/m and  $k_3 = 100$  N/m.



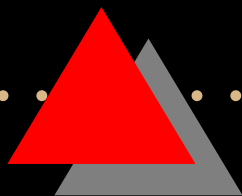
Only the stiffness parameters  $k_1$  and  $k_2$  are uncertain:  $k_i = \bar{k}_i(1 + \epsilon_i x_i)$ ,  $i = 1, 2$ .  $\mathbf{x} = \{x_1, x_2\}^T \in \mathbb{R}^2$  and the 'strength parameters'  $\epsilon_1 = \epsilon_2 = 0.25$ .



# Numerical example

Following six methods are compared

1. *Mean-centered first-order perturbation*
2. *Mean-centered second-order perturbation*
3.  *$\alpha$ -centered first-order perturbation*
4.  *$\alpha$ -centered second-order perturbation*
5. *Asymptotic method*
6. *Monte Carlo Simulation (10K samples) - can be considered as benchmark.*



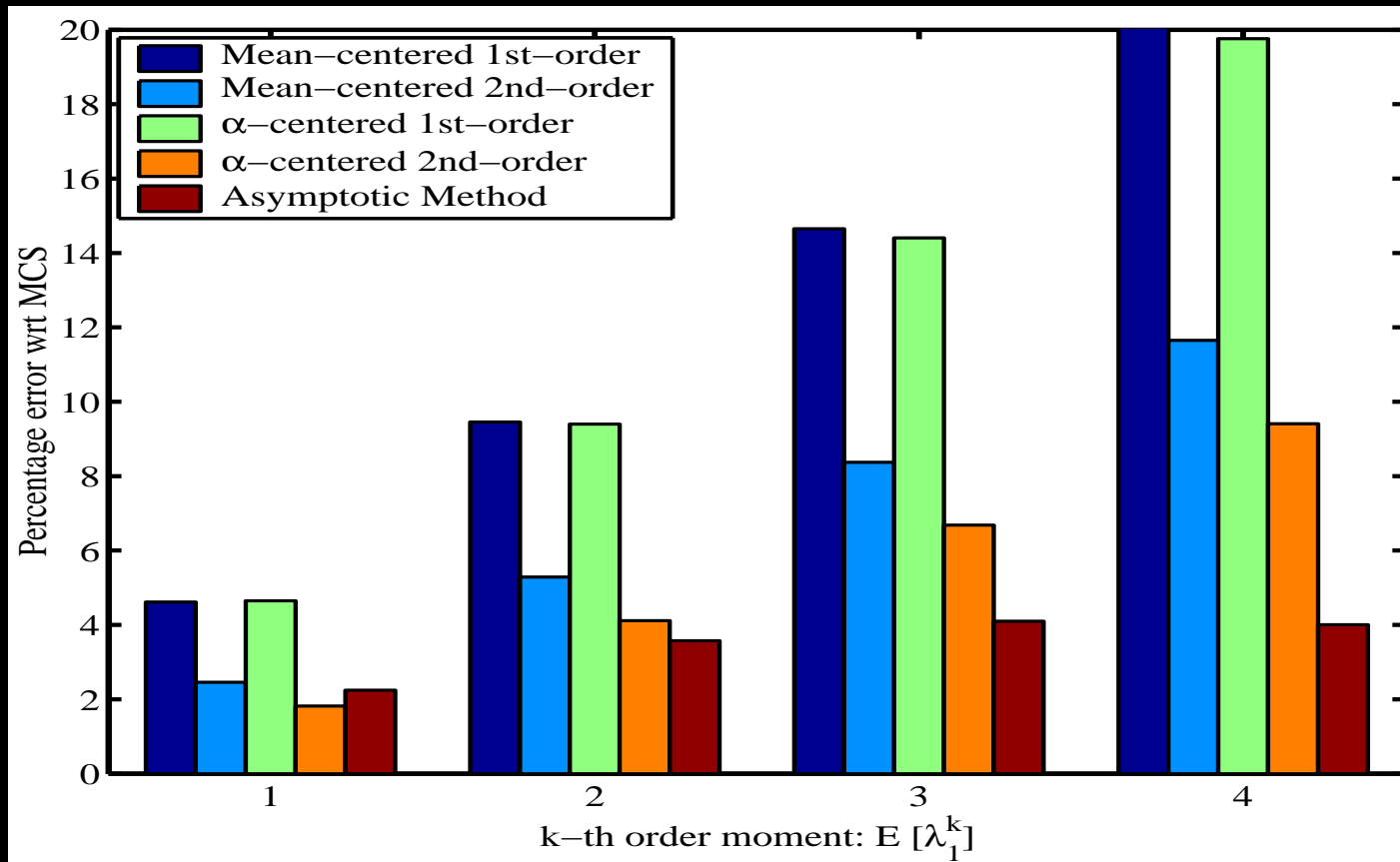
# Numerical example

The percentage error:

$$\text{Error}_{i\text{th method}} = \frac{\{\mu'_k\}_{i\text{th method}} - \{\mu'_k\}_{\text{MCS}}}{\{\mu'_k\}_{\text{MCS}}} \times 100$$

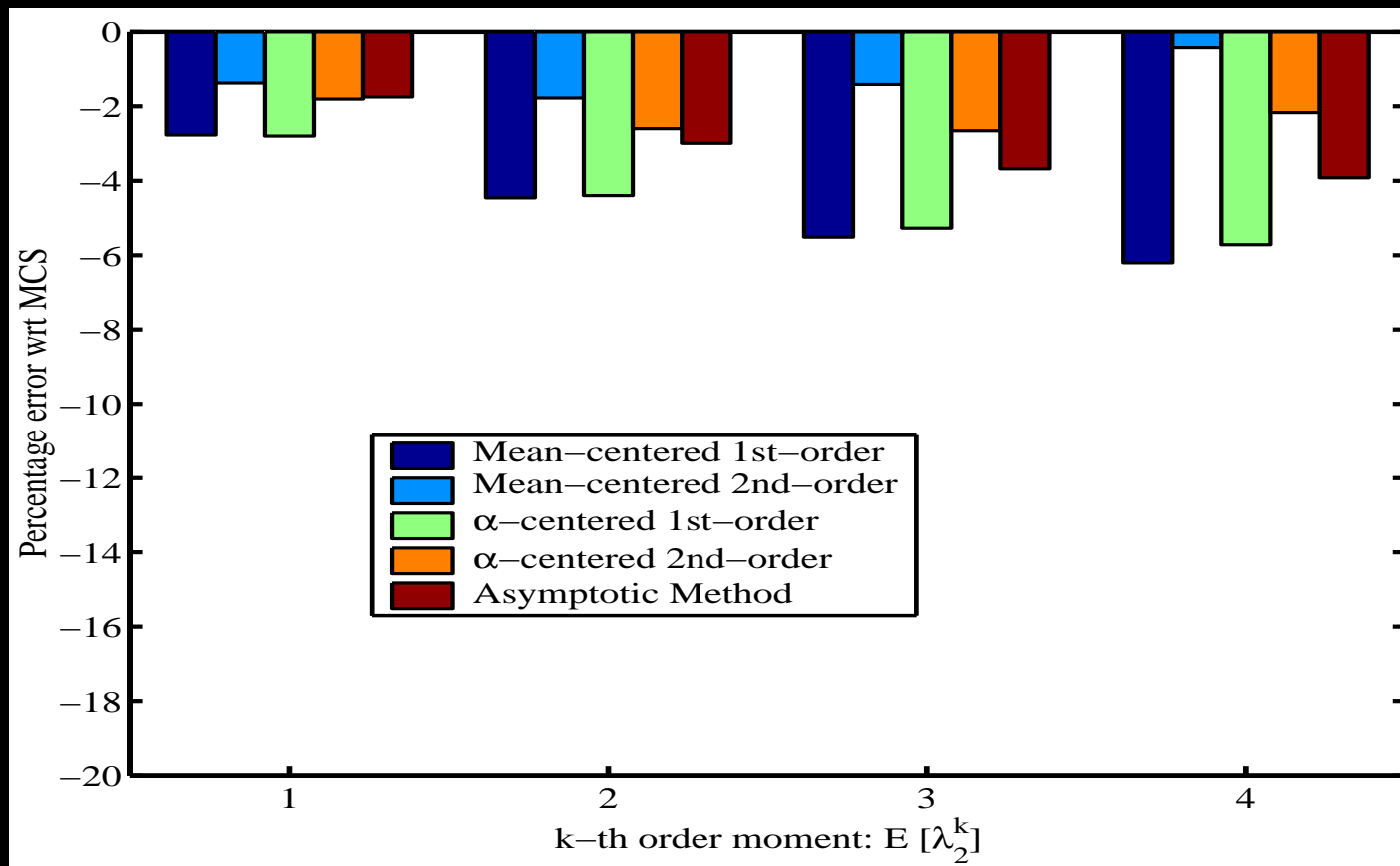
$$i = 1, \dots, 5.$$

# Numerical example



Percentage error for the first four raw moments of the first eigenvalue

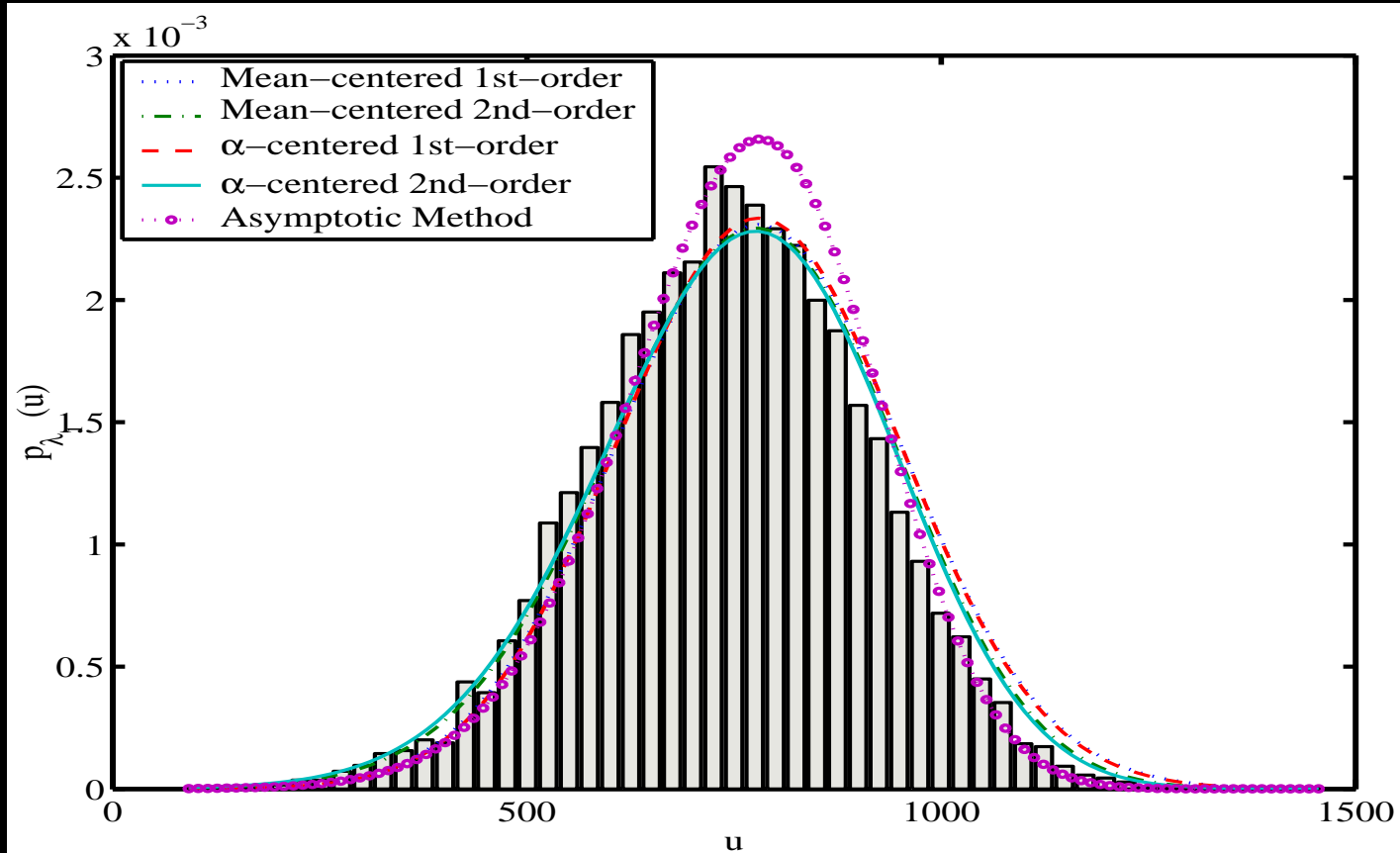
# Numerical example



Percentage error for the first four raw moments of the second eigenvalue

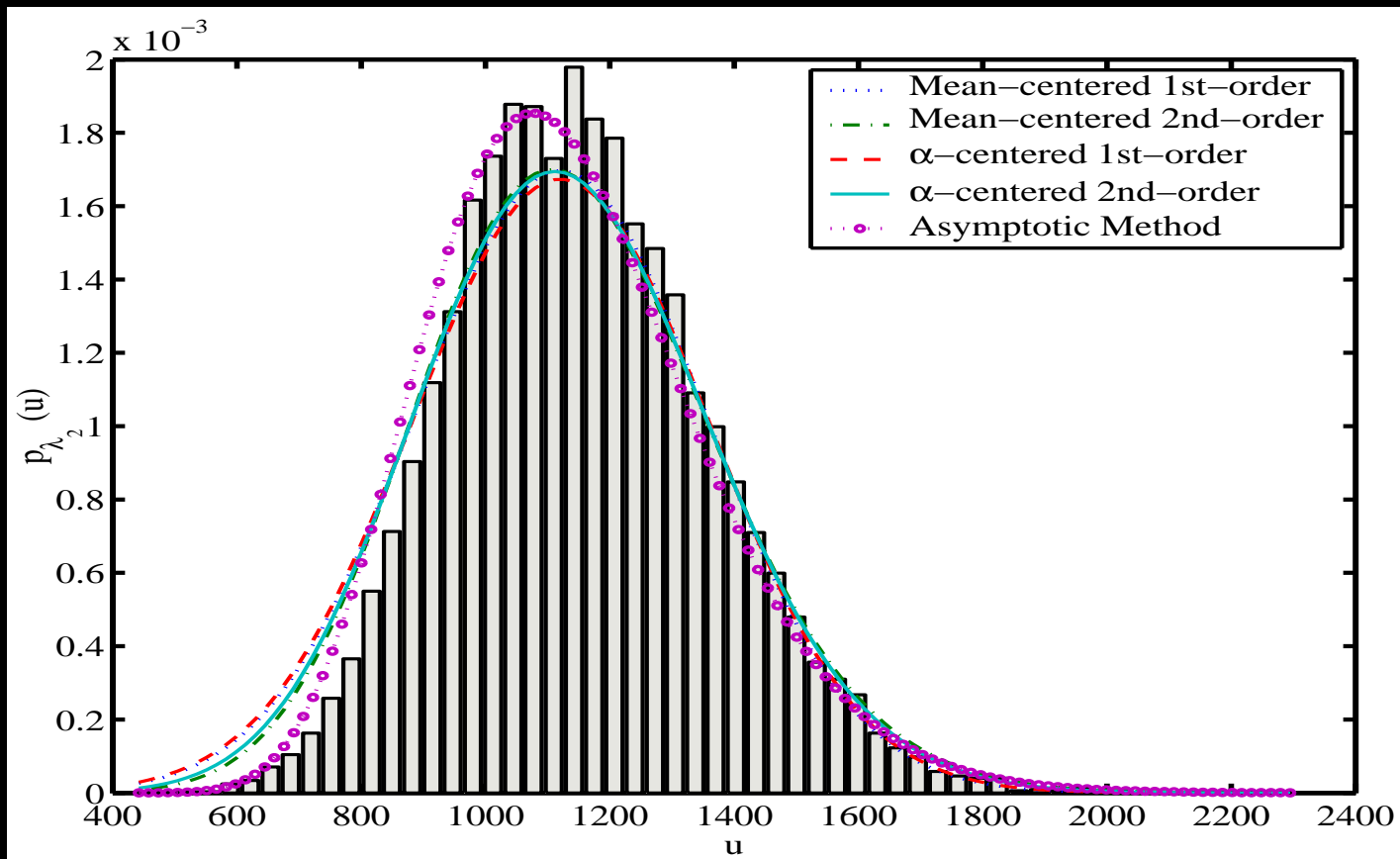


# Numerical example



Probability density function of the first eigenvalue

# Numerical example



Probability density function of the second eigenvalue



# Conclusions

- Two methods, namely (a) optimal point expansion method, and (b) asymptotic moment method, are proposed.
- The optimal point is obtained so that the mean of the eigenvalues are estimated most accurately.
- The asymptotic method assumes that the eigenvalues are large compared to their 3rd order or higher derivatives.
- Pdf of the eigenvalues are obtained in terms of central and non-central  $\chi^2$  densities.



# *Open problems*

- Joint statistics (moments/pdf/cumulants) of the eigenvalues with non-Gaussian system parameters.
- Statistics of the difference and ratio of the eigenvalues.
- Statistics of a single eigenvector (for GUE/GOE and general matrices).
- Joint statistics of the eigenvectors.
- Joint statistics of the eigenvalues and eigenvectors.

