Random Matrix Method for Stochastic Structural Mechanics

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Stochastic structural dynamics

- The equation of motion:

$$\mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}\dot{\mathbf{x}}(t) + \mathbf{K}\mathbf{x}(t) = \mathbf{p}(t)$$

- Due to the presence of uncertainty $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ become random matrices.
- The main objectives are:
  - to quantify uncertainties in the system matrices
  - to predict the variability in the response vector $\mathbf{x}$

Current Methods

Two different approaches are currently available

- Low frequency : Stochastic Finite Element Method (SFEM) - considers parametric uncertainties in details
- High frequency : Statistical Energy Analysis (SEA) - do not consider parametric uncertainties in details

Work needs to be done : Medium frequency vibration problems - some kind of ‘combination’ of the above two

Random Matrix Method (RMM)

- The objective: To have an unified method which will work across the frequency range.
- The methodology:
  - Derive the matrix variate probability density functions of $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$
  - Propagate the uncertainty (using Monte Carlo simulation or analytical methods) to obtain the response statistics (or pdf)

Outline of the presentation

In what follows next, I will discuss:

- Introduction to Matrix variate distributions
- Maximum entropy distribution
- Optimal Wishart distribution
- Numerical examples
- Open problems & discussions

Matrix variate distributions

- The probability density function of a random matrix can be defined in a manner similar to that of a random variable.
- If $\mathbf{A}$ is an $n \times m$ real random matrix, the matrix variate probability density function of $\mathbf{A} \in \mathbb{R}_{n,m}$, denoted as $p_{\mathbf{A}}(\mathbf{A})$, is a mapping from the space of $n \times m$ real matrices to the real line, i.e., $p_{\mathbf{A}}(\mathbf{A}) : \mathbb{R}_{n,m} \rightarrow \mathbb{R}$.

Gaussian random matrix

The random matrix $\mathbf{X} \in \mathbb{R}_{n,p}$ is said to have a matrix variate Gaussian distribution with mean matrix $\mathbf{M} \in \mathbb{R}_{n,p}$ and covariance matrix $\boldsymbol{\Sigma} \otimes \boldsymbol{\Psi}$, where $\boldsymbol{\Sigma} \in \mathbb{R}_n^+$ and $\boldsymbol{\Psi} \in \mathbb{R}_p^+$ provided the pdf of $\mathbf{X}$ is given by

$$p_{\mathbf{X}}(\mathbf{X}) = (2\pi)^{-np/2} |\boldsymbol{\Sigma}|^{-p/2} |\boldsymbol{\Psi}|^{-n/2} \operatorname{etr}\left\{-\frac{1}{2}\boldsymbol{\Sigma}^{-1}(\mathbf{X}-\mathbf{M})\boldsymbol{\Psi}^{-1}(\mathbf{X}-\mathbf{M})^T\right\} \quad (1)$$

This distribution is usually denoted as $\mathbf{X} \sim N_{n,p}(\mathbf{M}, \boldsymbol{\Sigma} \otimes \boldsymbol{\Psi})$.

Wishart matrix

A $n \times n$ symmetric positive definite random matrix $\mathbf{S}$ is said to have a Wishart distribution with parameters $p \geq n$ and $\mathbf{\Sigma} \in \mathbb{R}_n^+$, if its pdf is given by

$$p_{\mathbf{S}}\left(\mathbf{S}\right) = \left\{2^{\frac{1}{2}np}\,\Gamma_n\left(\frac{1}{2}p\right)|\mathbf{\Sigma}|^{\frac{1}{2}p}\right\}^{-1}|\mathbf{S}|^{\frac{1}{2}(p-n-1)}\mathrm{etr}\left\{-\frac{1}{2}\mathbf{\Sigma}^{-1}\mathbf{S}\right\} \tag{2}$$

This distribution is usually denoted as $\mathbf{S} \sim W_n(p, \mathbf{\Sigma})$.

Note: If $p = n + 1$, then the matrix is non-negative definite.

Matrix variate Gamma distribution

A $n \times n$ symmetric positive definite matrix random $\mathbf{W}$ is said to have a matrix variate gamma distribution with parameters a and $\mathbf{\Psi} \in \mathbb{R}_n^+$, if its pdf is given by

$$p_{\mathbf{W}}(\mathbf{W}) = \left\{\Gamma_n(a)\,|\mathbf{\Psi}|^{-a}\right\}^{-1} |\mathbf{W}|^{a-\frac{1}{2}(n+1)} \operatorname{etr}\{-\mathbf{\Psi}\mathbf{W}\}; \quad \Re(a) > \frac{1}{2}(n- \tag{3}$$

This distribution is usually denoted as $\mathbf{W} \sim G_n(a, \mathbf{\Psi})$. Here the multivariate gamma function:

$$\Gamma_n(a) = \pi^{\frac{1}{4}n(n-1)} \prod_{k=1}^{n} \Gamma\left[a - \frac{1}{2}(k-1)\right]; \text{ for } \Re(a) > (n-1)/2 \tag{4}$$

Inverted Wishart matrix

A $n \times n$ symmetric positive definite matrix random $\mathbf{V}$ is said to have an inverted Wishart distribution with parameters m and $\boldsymbol{\Psi} \in \mathbb{R}_n^+$, if its pdf is given by

$$p_{\mathbf{V}}(\mathbf{V}) = \frac{2^{-\frac{1}{2}(m-n-1)n} \left|\boldsymbol{\Psi}\right|^{\frac{1}{2}(m-n-1)}}{\Gamma_n\left(\frac{1}{2}(m-n-1)\right) \left|\mathbf{V}\right|^{m/2}} \mathrm{etr}\left\{-\mathbf{V}^{-1}\boldsymbol{\Psi}\right\}; \quad m > 2n,\ \boldsymbol{\Psi} > 0. \tag{5}$$

This distribution is usually denoted as $\mathbf{V} \sim IW_n(m, \boldsymbol{\Psi})$.

Distribution of the system matrices

The distribution of the random system matrices $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ should be such that they are

- symmetric
- positive-definite, and
- the moments (at least first two) of the inverse of the dynamic stiffness matrix $\mathbf{D}(\omega) = -\omega^2\mathbf{M} + i\omega\mathbf{C} + \mathbf{K}$ should exist $\forall\, \omega$

Distribution of the system matrices

- The exact application of the last constraint requires the derivation of the joint probability density function of $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$, which is quite difficult to obtain.
- We consider a simpler problem where it is required that the inverse moments of each of the system matrices $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ must exist.
- Provided the system is damped, this will guarantee the existence of the moments of the frequency response function matrix.

Maximum Entropy Distribution

Suppose that the mean values of $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ are given by $\overline{\mathbf{M}}$, $\overline{\mathbf{C}}$ and $\overline{\mathbf{K}}$ respectively. Using the notation $\mathbf{G}$ (which stands for any one the system matrices) the matrix variate density function of $\mathbf{G} \in \mathbb{R}_n^+$ is given by $p_{\mathbf{G}}\left(\mathbf{G}\right) : \mathbb{R}_n^+ \to \mathbb{R}$. We have the following constrains to obtain $p_{\mathbf{G}}\left(\mathbf{G}\right)$:

$$\int_{\mathbf{G}>0} p_{\mathbf{G}}\left(\mathbf{G}\right) d\mathbf{G} = 1 \quad \text{(normalization)} \tag{6}$$

and

$$\int_{\mathbf{G}>0} \mathbf{G}\, p_{\mathbf{G}}\left(\mathbf{G}\right) d\mathbf{G} = \overline{\mathbf{G}} \quad \text{(the mean matrix)} \tag{7}$$

Further constraints

- Suppose the inverse moments (say up to order ν) of the system matrix exist. This implies that $\mathrm{E}\left[\left\|\mathbf{G}^{-1}\right\|_{\mathrm{F}}^{\nu}\right]$ should be finite. Here the Frobenius norm of matrix $\mathbf{A}$ is given by $\|\mathbf{A}\|_{\mathrm{F}} = \left(\mathrm{Trace}\left(\mathbf{A}\mathbf{A}^T\right)\right)^{1/2}$.
- Taking the logarithm for convenience, the condition for the existence of the inverse moments can be expresses by

$$\mathrm{E}\left[\ln|\mathbf{G}|^{-\nu}\right] < \infty$$

MEnt Distribution - 1

The Lagrangian becomes:

$$\mathcal{L}\left(p_{\mathbf{G}}\right) = -\int_{\mathbf{G}>0} p_{\mathbf{G}}\left(\mathbf{G}\right)\ln\left\{p_{\mathbf{G}}\left(\mathbf{G}\right)\right\}\,d\mathbf{G} - \left(\lambda_0 - 1\right)\left(\int_{\mathbf{G}>0} p_{\mathbf{G}}\left(\mathbf{G}\right)\,d\mathbf{G} - 1\right) - \nu\int_{\mathbf{G}>0}\ln\left|\mathbf{G}\right| p_{\mathbf{G}}\,d\mathbf{G} + \mathrm{Trace}\left(\mathbf{\Lambda}_1\left[\int_{\mathbf{G}>0}\mathbf{G}\,p_{\mathbf{G}}\left(\mathbf{G}\right)\,d\mathbf{G} - \overline{\mathbf{G}}\right]\right) \quad (8)$$

Note: ν cannot be obtained uniquely!

MEnt Distribution - 2

Using the calculus of variation

$$\frac{\partial \mathcal{L}\left(p_{\mathbf{G}}\right)}{\partial p_{\mathbf{G}}} = 0$$

or $-\ln\left\{p_{\mathbf{G}}\left(\mathbf{G}\right)\right\} = \lambda_0 + \mathrm{Trace}\left(\mathbf{\Lambda}_1\mathbf{G}\right) - \ln\left|\mathbf{G}\right|^{\nu}$

or $p_{\mathbf{G}}\left(\mathbf{G}\right) = \exp\left\{-\lambda_0\right\}\left|\mathbf{G}\right|^{\nu}\mathrm{etr}\left\{-\mathbf{\Lambda}_1\mathbf{G}\right\}$

MEnt Distribution - 3

Using the matrix variate Laplace transform
$(\mathbf{T} \in \mathbb{R}_{n,n}, \mathbf{S} \in \mathbb{C}_{n,n}, a > (n+1)/2)$

$$\int_{\mathbf{T}>0} \operatorname{etr}\{-\mathbf{ST}\} |\mathbf{T}|^{a-(n+1)/2} \, d\mathbf{T} = \Gamma_n(a) \, |\mathbf{S}|^{-a}$$

and substituting $p_{\mathbf{G}}(\mathbf{G})$ into the constraint equations it can be shown that

$$p_{\mathbf{G}}(\mathbf{G}) = \frac{r^{nr} \left|\overline{\mathbf{G}}\right|^{-r}}{\Gamma_n(r)} |\mathbf{G}|^{\nu} \operatorname{etr}\left\{-r\overline{\mathbf{G}}^{-1}\mathbf{G}\right\} \qquad (9)$$

where $r = \nu + (n+1)/2$.

MEnt Distribution - 4

Comparing it with the Wishart distribution we have:

Theorem 1. *If* ν*-th order inverse-moment of a system matrix* $\mathbf{G} \equiv \{\mathbf{M}, \mathbf{C}, \mathbf{K}\}$ *exists and only the mean of* $\mathbf{G}$ *is available, say* $\overline{\mathbf{G}}$*, then the maximum-entropy pdf of* $\mathbf{G}$ *follows the Wishart distribution with parameters* $p = (2\nu + n + 1)$ *and* $\boldsymbol{\Sigma} = \overline{\mathbf{G}}/(2\nu + n + 1)$*, that is* $\mathbf{G} \sim W_n\left(2\nu + n + 1, \overline{\mathbf{G}}/(2\nu + n + 1)\right)$.

Properties of the Distribution

- Covariance tensor of $\mathbf{G}$:

$$\operatorname{cov}\left(G_{ij}, G_{kl}\right) = \frac{1}{2\nu + n + 1}\left(\overline{G}_{ik}\overline{G}_{jl} + \overline{G}_{il}\overline{G}_{jk}\right)$$

- Normalized standard deviation matrix

$$\delta^2_{\mathbf{G}} = \frac{\mathrm{E}\left[\|\mathbf{G} - \mathrm{E}\left[\mathbf{G}\right]\|^2_{\mathrm{F}}\right]}{\|\mathrm{E}\left[\mathbf{G}\right]\|^2_{\mathrm{F}}} = \frac{1}{2\nu + n + 1}\left\{1 + \frac{\{\mathrm{Trace}\left(\overline{\mathbf{G}}\right)\}^2}{\mathrm{Trace}\left(\overline{\mathbf{G}}^2\right)}\right\}$$

- $\delta^2_{\mathbf{G}} \leq \dfrac{1+n}{2\nu + n + 1}$ and $\nu \uparrow \Rightarrow \delta^2_{\mathbf{G}} \downarrow$.

Distribution of the inverse - 1

- If $\mathbf{G}$ is $W_n(p, \boldsymbol{\Sigma})$ then $\mathbf{V} = \mathbf{G}^{-1}$ has the inverted Wishart distribution:

$$P_{\mathbf{V}}(\mathbf{V}) = \frac{2^{m-n-1}n/2 \left|\boldsymbol{\Psi}\right|^{m-n-1}/2}{\Gamma_n[(m-n-1)/2] \left|\mathbf{V}\right|^{m/2}} \mathrm{etr}\left\{-\frac{1}{2}\mathbf{V}^{-1}\boldsymbol{\Psi}\right\}$$

where $m = n + p + 1$ and $\boldsymbol{\Psi} = \boldsymbol{\Sigma}^{-1}$ (recall that $p = 2\nu + n + 1$ and $\boldsymbol{\Sigma} = \overline{\mathbf{G}}/p$)

Distribution of the inverse - 2

- Mean: $\mathrm{E}\left[\mathbf{G}^{-1}\right] = \dfrac{p\overline{\mathbf{G}}^{-1}}{p-n-1}$
- $\operatorname{cov}\left(G_{ij}^{-1}, G_{kl}^{-1}\right) =$

$$\frac{\Big(2\nu+n+1)(\nu^{-1}\overline{G}_{ij}^{-1}\overline{G}_{kl}^{-1}+\overline{G}_{ik}^{-1}\overline{G}_{jl}^{-1}+\overline{G}^{-1}il\overline{G}_{kj}^{-1}\Big)}{2\nu(2\nu+1)(2\nu-2)}$$

Distribution of the inverse - 3

- Suppose $n = 101$ & $\nu = 2$. So $p = 2\nu + n + 1 = 106$ and $p - n - 1 = 4$. Therefore, $\mathrm{E}\left[\mathbf{G}\right] = \overline{\mathbf{G}}$ and $\mathrm{E}\left[\mathbf{G}^{-1}\right] = \frac{106}{4}\overline{\mathbf{G}}^{-1} = 26.5\overline{\mathbf{G}}^{-1}$!!!!!!!!!!
- From a practical point of view we do not expect them to be so far apart!
- One way to reduce the gap is to increase p. But this implies the reduction of variance.
- This discrepancy between the 'mean of the inverse' and the 'inverse of the mean' of the random matrices appears to be a fundamental limitation.

Optimal Wishart Distribution - 1

- My argument: The distribution of $\mathbf{G}$ must be such that $\mathrm{E}\left[\mathbf{G}\right]$ and $\mathrm{E}\left[\mathbf{G}^{-1}\right]$ should be closest to $\overline{\mathbf{G}}$ and $\overline{\mathbf{G}}^{-1}$ respectively.
- Suppose $\mathbf{G} \sim W_n\left(n+1+\theta, \overline{\mathbf{G}}/\alpha\right)$. We need to find α such that the above condition is satisfied.
- Therefore, define (and subsequently minimize) 'normalized errors':
$$\varepsilon_1 = \left\|\overline{\mathbf{G}} - \mathrm{E}\left[\mathbf{G}\right]\right\|_{\mathrm{F}} / \left\|\overline{\mathbf{G}}\right\|_{\mathrm{F}}$$
$$\varepsilon_2 = \left\|\overline{\mathbf{G}}^{-1} - \mathrm{E}\left[\mathbf{G}^{-1}\right]\right\|_{\mathrm{F}} / \left\|\overline{\mathbf{G}}^{-1}\right\|_{\mathrm{F}}$$

Optimal Wishart Distribution - 2

Because $\mathbf{G} \sim W_n\left(n+1+\theta, \overline{\mathbf{G}}/\alpha\right)$ we have

$$\mathrm{E}\left[\mathbf{G}\right] = \frac{n+1+\theta}{\alpha}\overline{\mathbf{G}}$$

and $$\mathrm{E}\left[\mathbf{G}^{-1}\right] = \frac{\alpha}{\theta}\overline{\mathbf{G}}^{-1}$$

We define the objective function to be minimized as

$$\chi^2 = {\boldsymbol{\varepsilon}_1}^2 + {\boldsymbol{\varepsilon}_2}^2 = \left(1 - \tfrac{n+1+\theta}{\alpha}\right)^2 + \left(1 - \tfrac{\alpha}{\theta}\right)^2$$

Optimal Wishart Distribution - 3

The optimal value of α can be obtained as by setting $\frac{\partial\chi^2}{\partial\alpha} = 0$ or
$\alpha^4 - \alpha^3\theta - \theta^4 + (-2\,n + \alpha - 2)\,\theta^3 + \big((n+1)\,\alpha - n^2 - 2\,n - 1\big)\,\theta^2 = 0.$
The only feasible value of α is

$$\alpha = \sqrt{\theta(n + 1 + \theta)}$$

Optimal Wishart Distribution - 4

From this discussion we have the following:

Theorem 2. *If ν-th order inverse-moment of a system matrix $\mathbf{G} \equiv \{\mathbf{M}, \mathbf{C}, \mathbf{K}\}$ exists and only the mean of $\mathbf{G}$ is available, say $\overline{\mathbf{G}}$, then the unbiased distribution of $\mathbf{G}$ follows the Wishart distribution with parameters $p = (2\nu + n + 1)$ and $\mathbf{\Sigma} = \overline{\mathbf{G}}/\sqrt{2\nu(2\nu + n + 1)}$, that is*

$$\mathbf{G} \sim W_n\left(2\nu + n + 1, \overline{\mathbf{G}}/\sqrt{2\nu(2\nu + n + 1)}\right).$$

Optimal Wishart Distribution - 5

- Again consider $n = 100$ and $\nu = 2$, so that $\theta = 2\nu = 4$.
- In the previous approach $\alpha = 2\nu + n + 1 = 105$. For the optimal distribution, $\alpha = \sqrt{\theta(\theta + n + 1)} = 2\sqrt{105} = 20.49$.
- We have $\mathrm{E}\left[\mathbf{G}\right] = \frac{105}{2\sqrt{105}}\overline{\mathbf{G}} = 5.12\overline{\mathbf{G}}$ and $\mathrm{E}\left[\mathbf{G}^{-1}\right] = \frac{2\sqrt{105}}{4}\overline{\mathbf{G}}^{-1} = 5.12\overline{\mathbf{G}}^{-1}$.
- The overall normalized difference for the previous case is $\chi^2 = 0 + (1 - 105/4)^2 = 637.56$. The same for the optimal distribution is $\chi^2 = 2(1 - \sqrt{105}/2)^2 = 34.01$, which is considerable smaller compared to the non-optimal distribution.

Response statistics - 1

- The equation of motion is $\mathbf{D}\mathbf{x} = \mathbf{p}$, $\mathbf{D}$ is in general $n \times n$ complex random matrix.
- The response is given by

$$\mathbf{x} = \mathbf{D}^{-1}\mathbf{p}$$

- Consider static problems so that all matrices/vectors are real.

Response statistics - 2

- We may want statistics of few elements or some linear combinations of the elements in $\mathbf{x}$. So the quantify of interest is

$$\mathbf{y} = \mathbf{R}\mathbf{x} = \mathbf{R}\mathbf{D}^{-1}\mathbf{p} \tag{10}$$

  Here $\mathbf{R}$ is in general $r \times n$ rectangular matrix. For the special case when $\mathbf{R} = \mathbf{I}_n$, we have $\mathbf{y} = \mathbf{x}$.

- Eq. (10) arises in SFEM. There are many papers on its solution. Mainly perturbation methods are used.

Response statistics - 3

Suppose $\mathrm{D} = \mathrm{D}_0 + \boldsymbol{\Delta}\mathrm{D}$, where D_0 is the deterministic part and $\boldsymbol{\Delta}\mathrm{D}$ is the (small) random part. It can be shown that

$$\mathbf{D}^{-1} = \mathbf{D}_0 - \mathbf{D}_0^{-1}\boldsymbol{\Delta}\mathbf{D}\mathbf{D}_0^{-1} + \mathbf{D}_0^{-1}\boldsymbol{\Delta}\mathbf{D}\mathbf{D}_0^{-1}\boldsymbol{\Delta}\mathbf{D}\mathbf{D}_0^{-1} + \cdots$$

From, this

$$\mathbf{y} = \mathbf{y}_0 - \mathbf{R}\mathbf{D}_0^{-1}\boldsymbol{\Delta}\mathbf{D}\mathbf{x}_0 + \mathbf{R}\mathbf{D}_0^{-1}\boldsymbol{\Delta}\mathbf{D}\mathbf{D}_0^{-1}\boldsymbol{\Delta}\mathbf{D}\mathbf{x}_0 + \cdots \tag{11}$$

where $\mathbf{x}_0 = \mathbf{D}_0^{-1}\mathbf{p}$ and $\mathbf{y}_0 = \mathbf{R}\mathbf{x}_0$.

Response statistics - 4

The statistics of $\mathbf{y}$ can be calculated from Eq. (11). However,

- The calculation is difficult if $\mathbf{\Delta D}$ is non-Gaussian.
- Even if $\mathbf{\Delta D}$ is Gaussian, inclusion of higher-order terms results very messy calculations (I have not seen any published work for more than second-order)
- For these reasons, the response statistics will be inaccurate for large randomness.

Response statistics - 5

I will propose an exact method using RMT. Suppose $\mathbf{D} \sim W_n(m, \boldsymbol{\Sigma})$.

$$\mathrm{E}[\mathbf{y}] = \mathrm{E}\left[\mathbf{R}\mathbf{D}^{-1}\mathbf{p}\right] = \mathbf{R}\,\mathrm{E}\left[\mathbf{D}^{-1}\right]\mathbf{p} = \mathbf{R}\boldsymbol{\Sigma}^{-1}\mathbf{p}/\theta \quad (12)$$

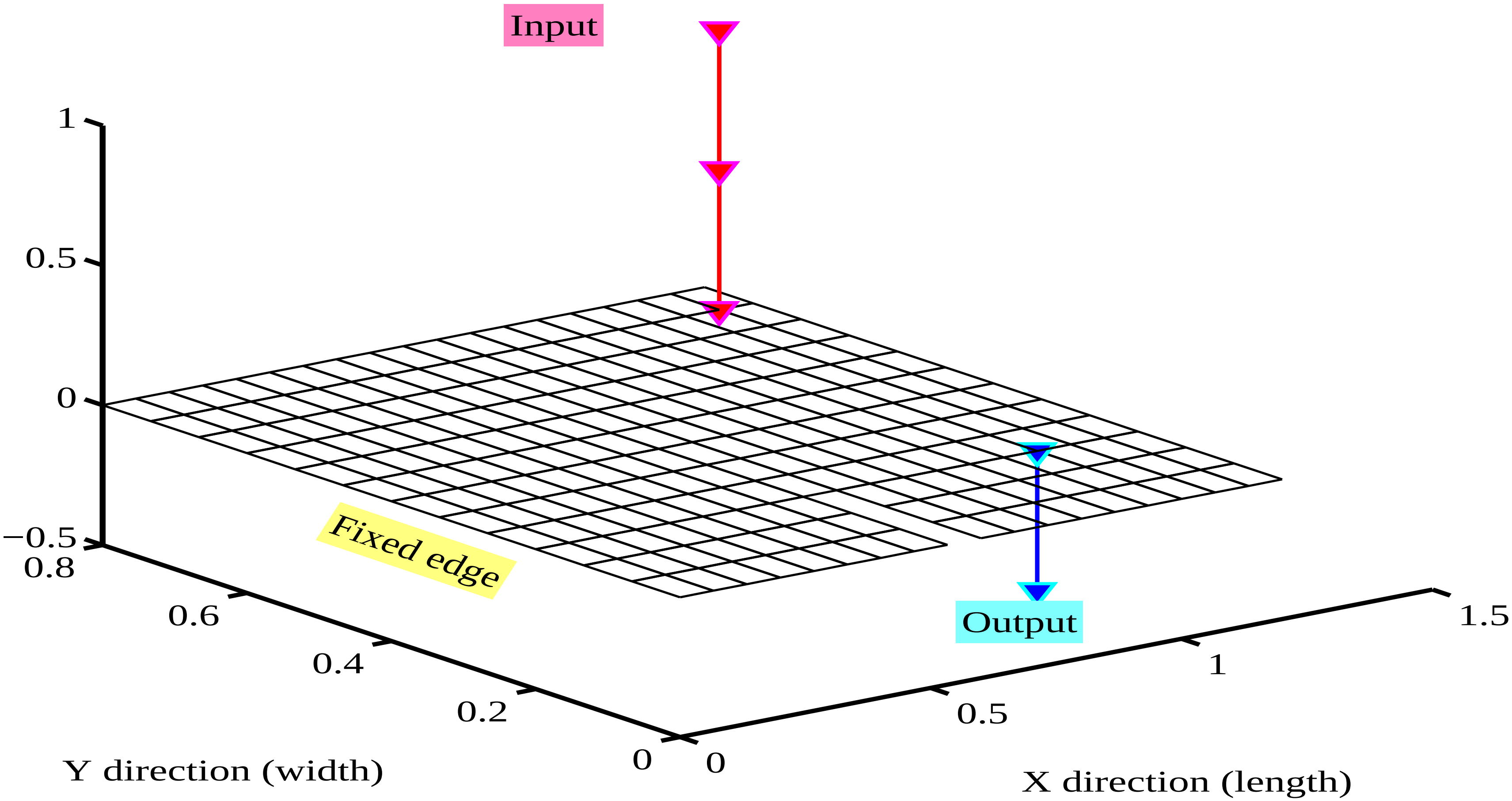
The complete covariance matrix of $\mathbf{y}$

$$\begin{aligned}
&\mathrm{E}\left[(\mathbf{y} - \mathrm{E}[\mathbf{y}])(\mathbf{y} - \mathrm{E}[\mathbf{y}])^T\right] \\
&= \mathbf{R}\,\mathrm{E}\left[\mathbf{D}^{-1}\mathbf{p}\mathbf{p}^T\mathbf{D}^{-1}\right]\mathbf{R}^T - \mathrm{E}[\mathbf{y}]\,(\mathrm{E}[\mathbf{y}])^T \\
&= \frac{\mathrm{Trace}\left(\boldsymbol{\Sigma}^{-1}\mathbf{p}\mathbf{p}^T\right)\mathbf{R}\boldsymbol{\Sigma}^{-1}\mathbf{R}^T}{\theta(\theta+1)(\theta-2)} + \frac{(\theta+2)\mathbf{R}\boldsymbol{\Sigma}^{-1}\mathbf{p}\mathbf{p}^T\boldsymbol{\Sigma}^{-1}\mathbf{R}^T}{\theta^2(\theta+1)(\theta-2)}
\end{aligned} \quad (13)$$

Simulation Algorithm: Dynamical Systems

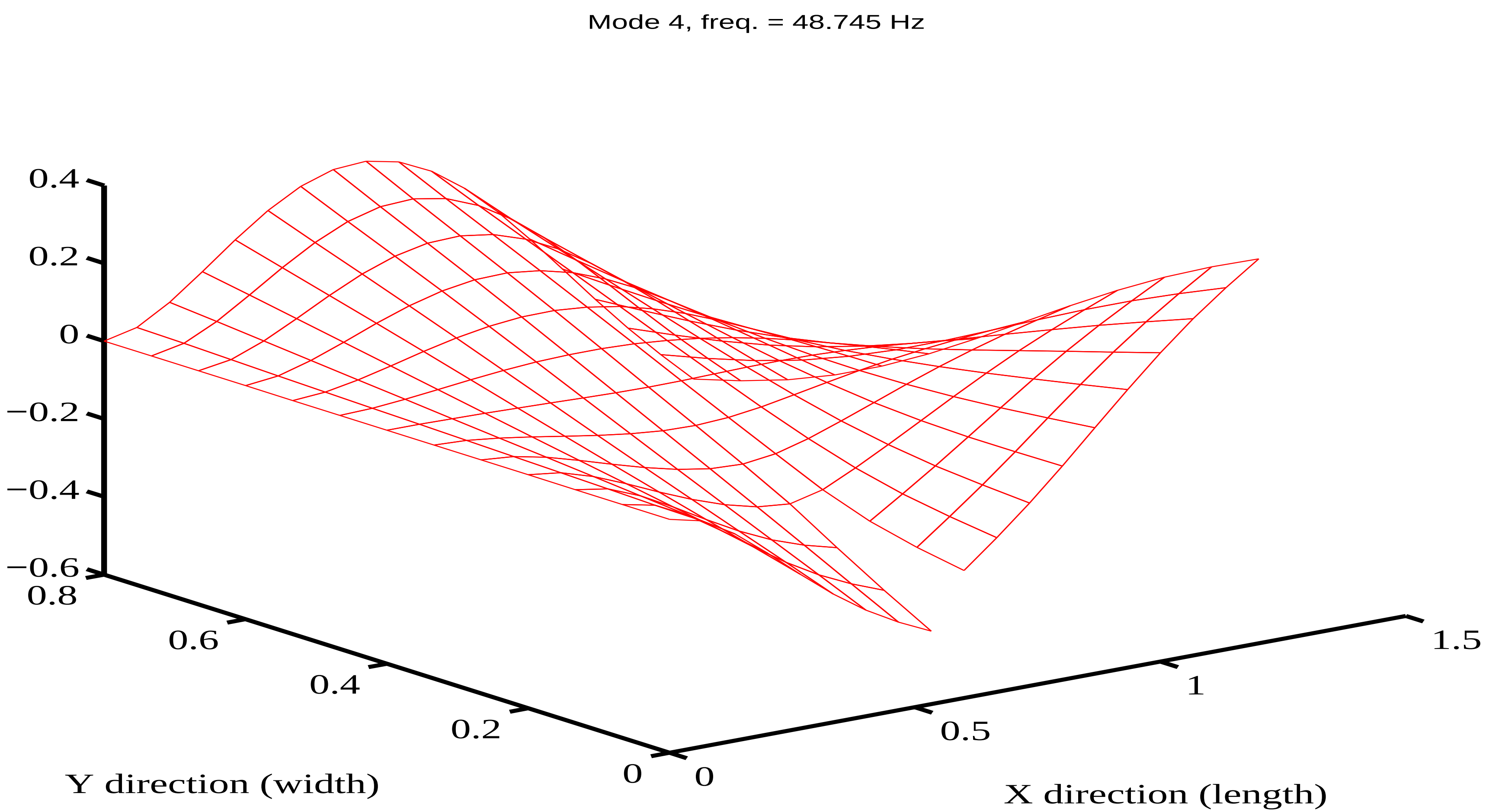
- Obtain $\theta = \frac{1}{\delta_{\mathbf{G}}^2}\left\{1 + \frac{\{\text{Trace}\left(\overline{\mathbf{G}}\right)\}^2}{\text{Trace}\left(\overline{\mathbf{G}}^2\right)}\right\} - (n+1)$
- If $\theta < 4$, then select $\theta = 4$.
- Calculate $\alpha = \sqrt{\theta(n+1+\theta)}$
- Generate samples of $\mathbf{G} \sim W_n\left(n+1+\theta, \overline{\mathbf{G}}/\alpha\right)$ (MATLAB® command `wishrnd` can be used to generate the samples)
- Repeat the above steps for all system matrices and solve for every samples

Example: A cantilever Plate



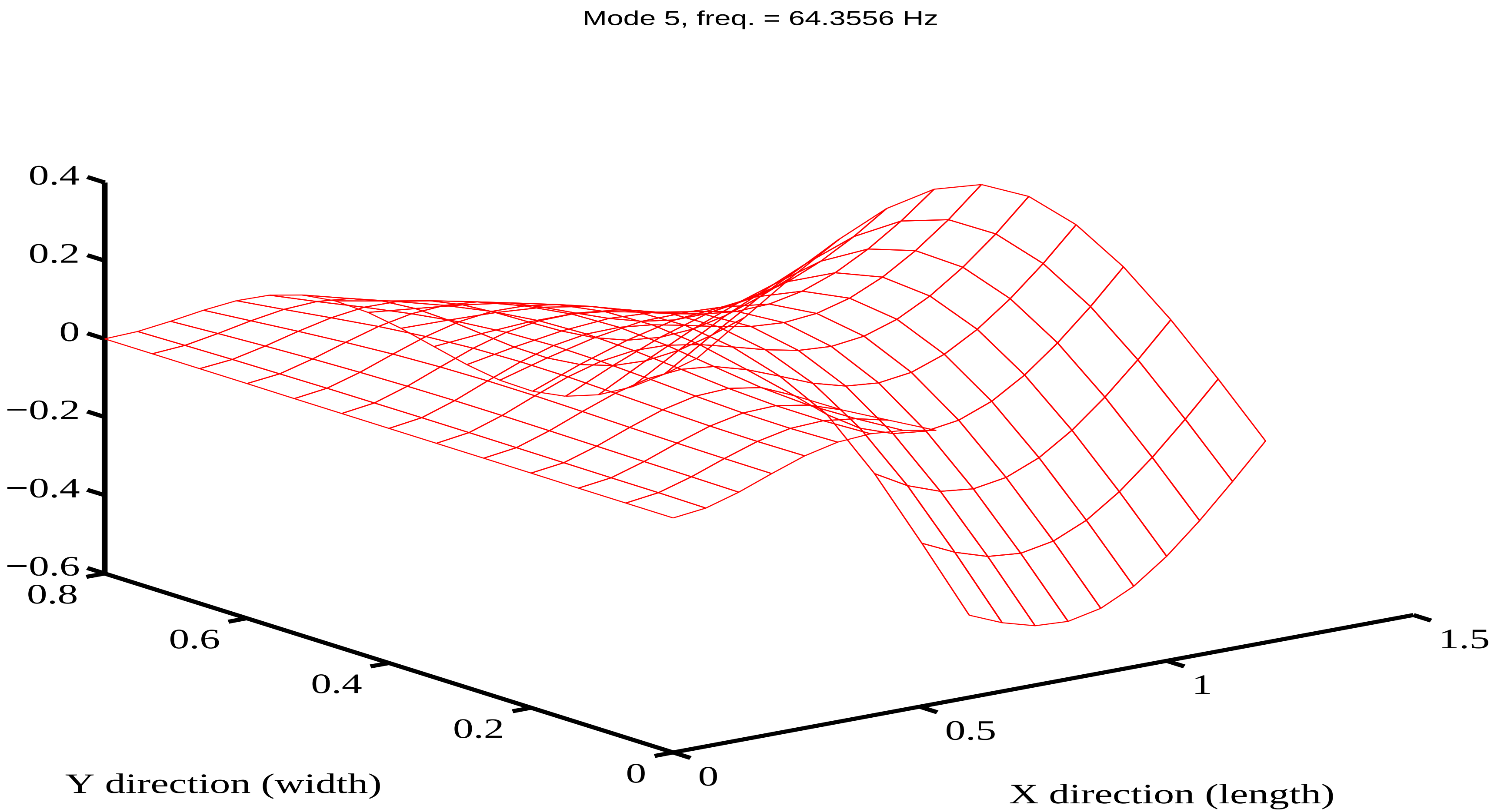
A Cantilever plate with a slot: $\bar{E} = 200 \times 10^9$N/m^2, $\bar{\mu} = 0.3$, $\bar{\rho} = 7860$kg/m^3, $\bar{t} = 7.5$mm, $L_x = 1.2$m, $L_y = 0.8$m.

Plate Mode 4



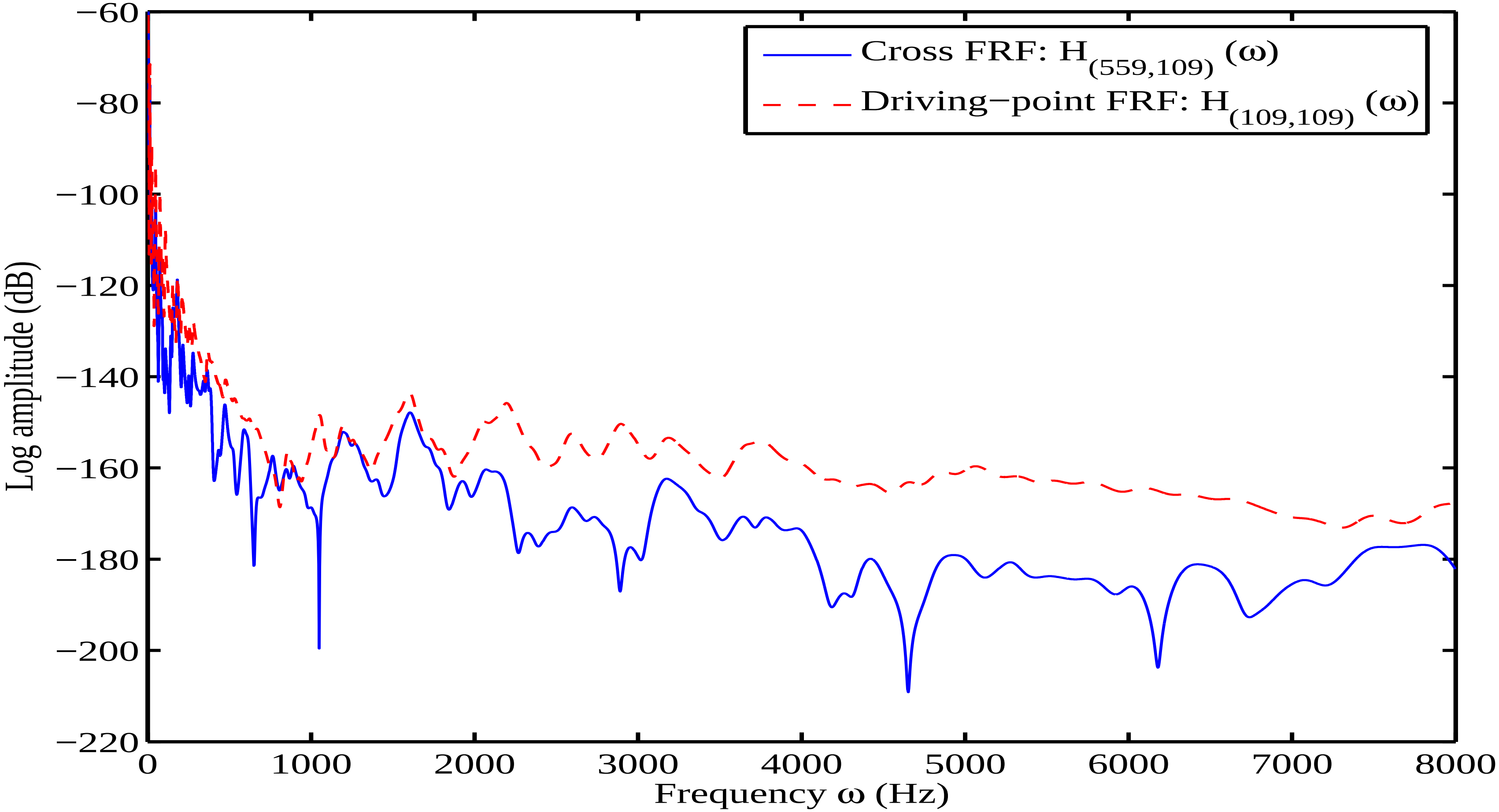
Fourth Mode shape

Plate Mode 5



Fifth Mode shape

Deterministic FRF



FRF of the deterministic plate

Stochastic Properties

The Young's modulus, Poissons ratio, mass density and thickness are random fields of the form

$$E(\mathbf{x}) = \bar{E}\left(1 + \epsilon_E f_1(\mathbf{x})\right) \quad (14)$$

$$\mu(\mathbf{x}) = \bar{\mu}\left(1 + \epsilon_\mu f_2(\mathbf{x})\right) \quad (15)$$

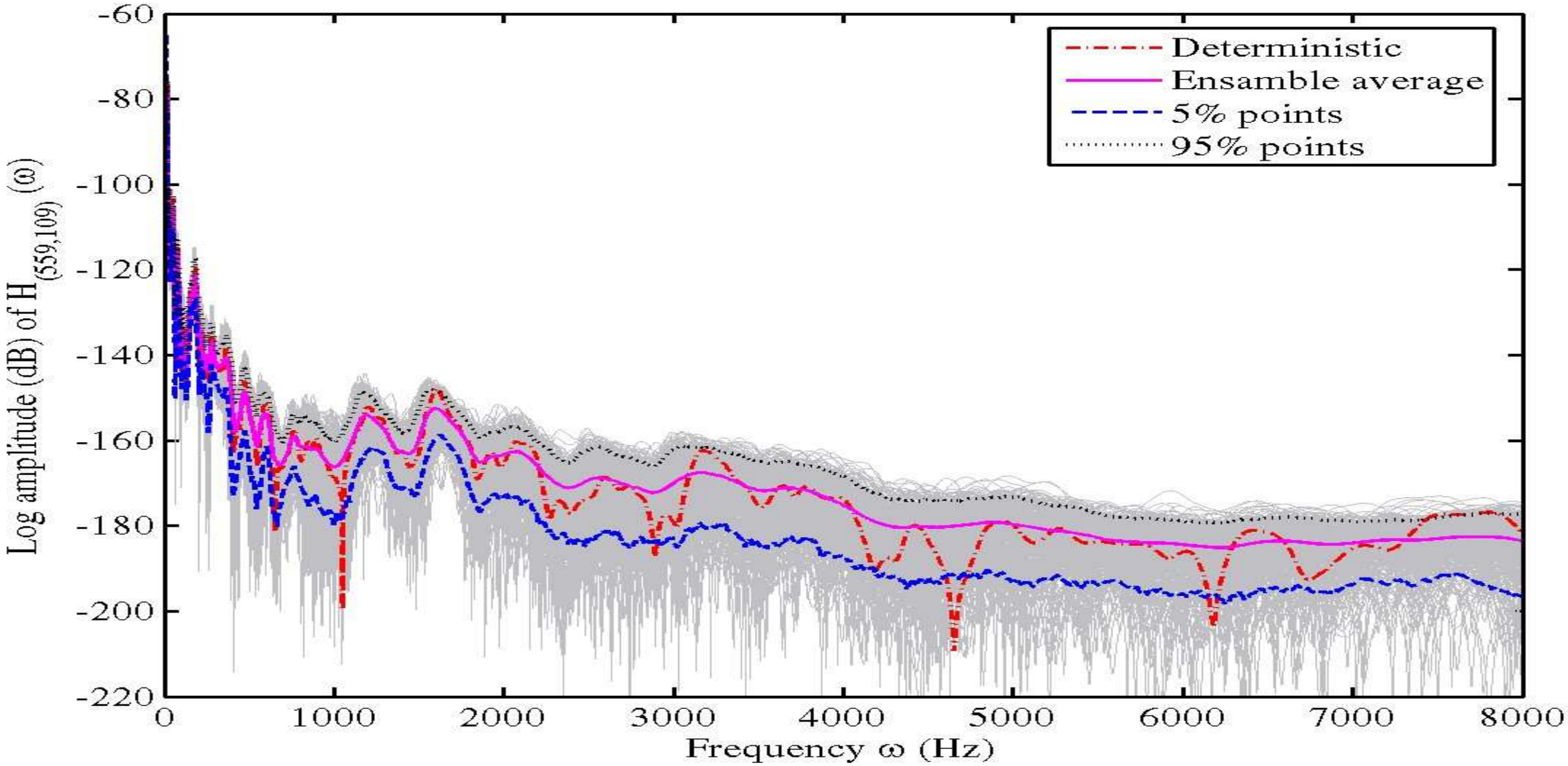
$$\rho(\mathbf{x}) = \bar{\rho}\left(1 + \epsilon_\rho f_3(\mathbf{x})\right) \quad (16)$$

and

$$t(\mathbf{x}) = \bar{t}\left(1 + \epsilon_t f_4(\mathbf{x})\right) \quad (17)$$

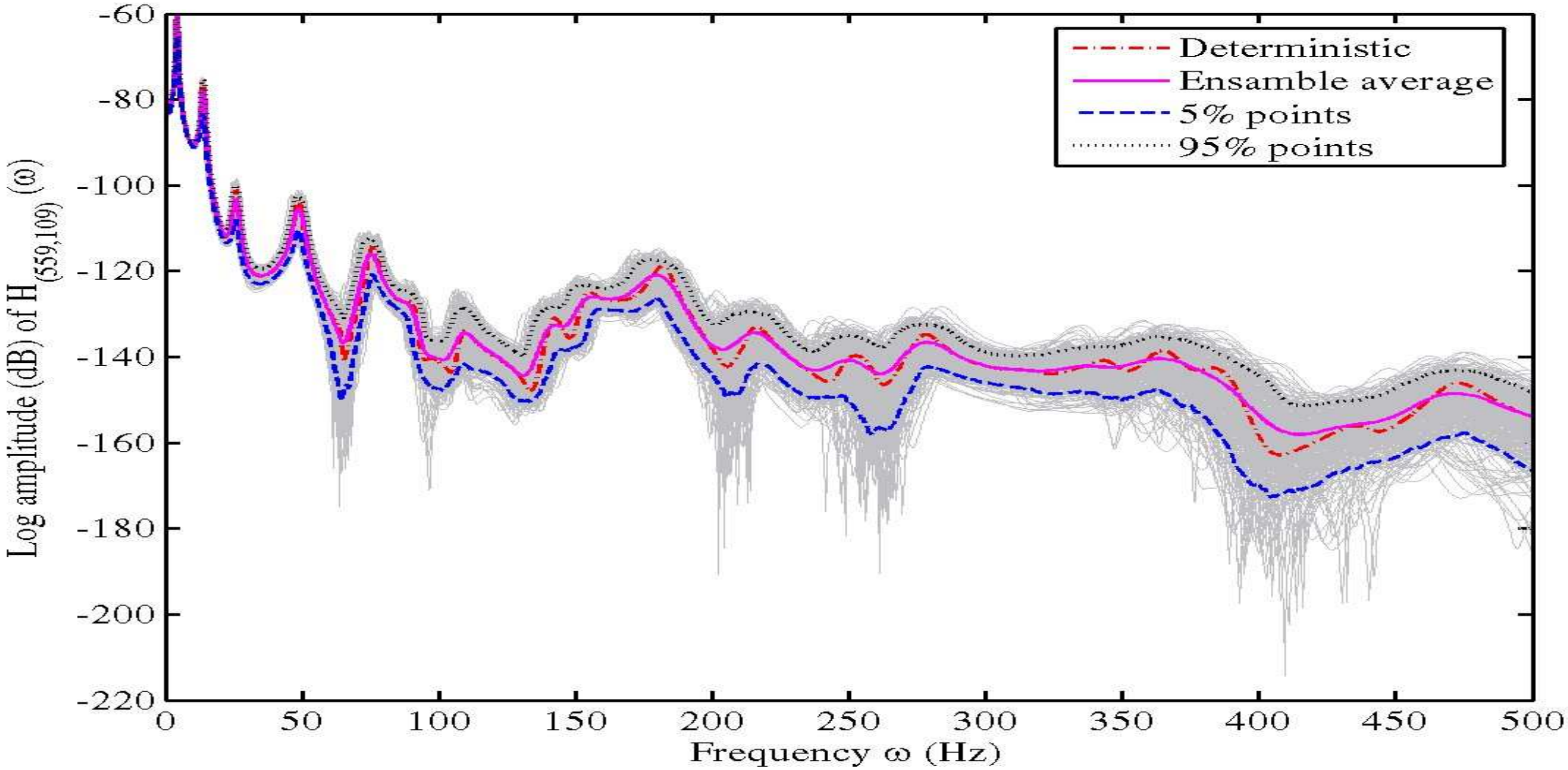
- The strength parameters: $\epsilon_E = 0.15$, $\epsilon_\mu = 0.15$, $\epsilon_\rho = 0.10$ and $\epsilon_t = 0.15$.
- The random fields $f_i(\mathbf{x}), i = 1, \cdots, 4$ are delta-correlated homogenous Gaussian random fields.

SFEM cross-FRF



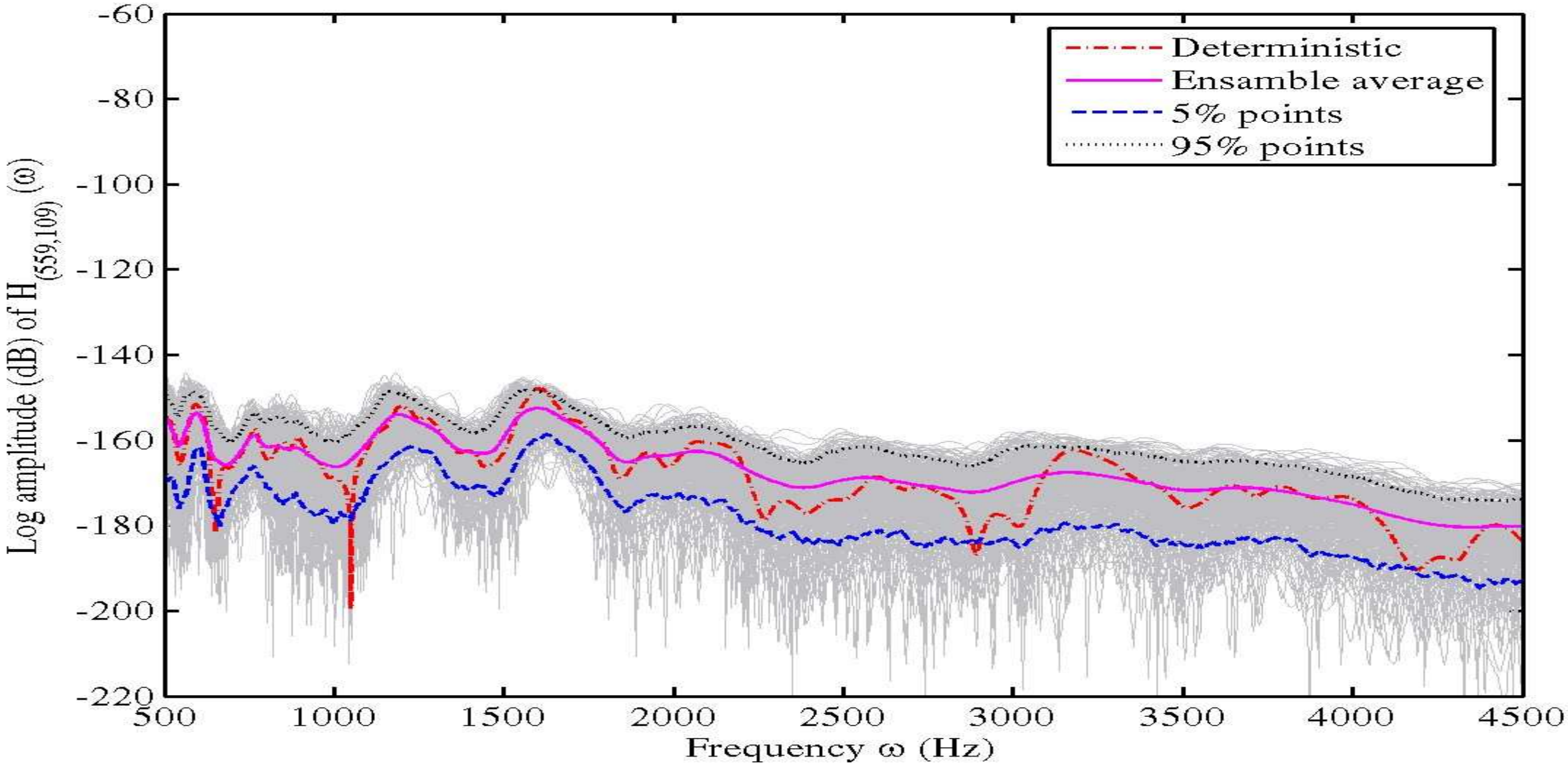
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the cross-FRF.

SFEM cross-FRF: Low Freq



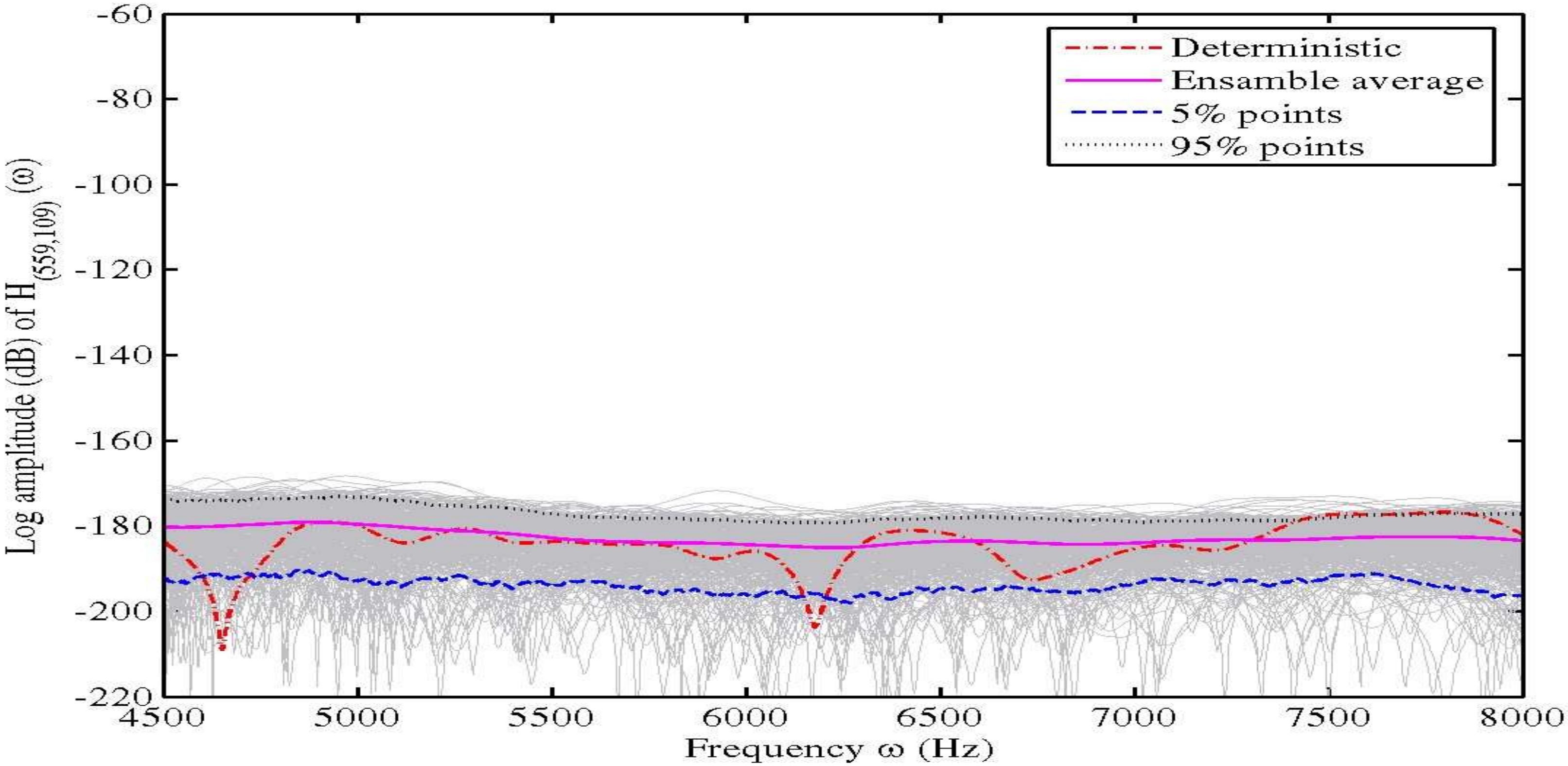
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the cross-FRF.

SFEM cross-FRF: Mid Freq



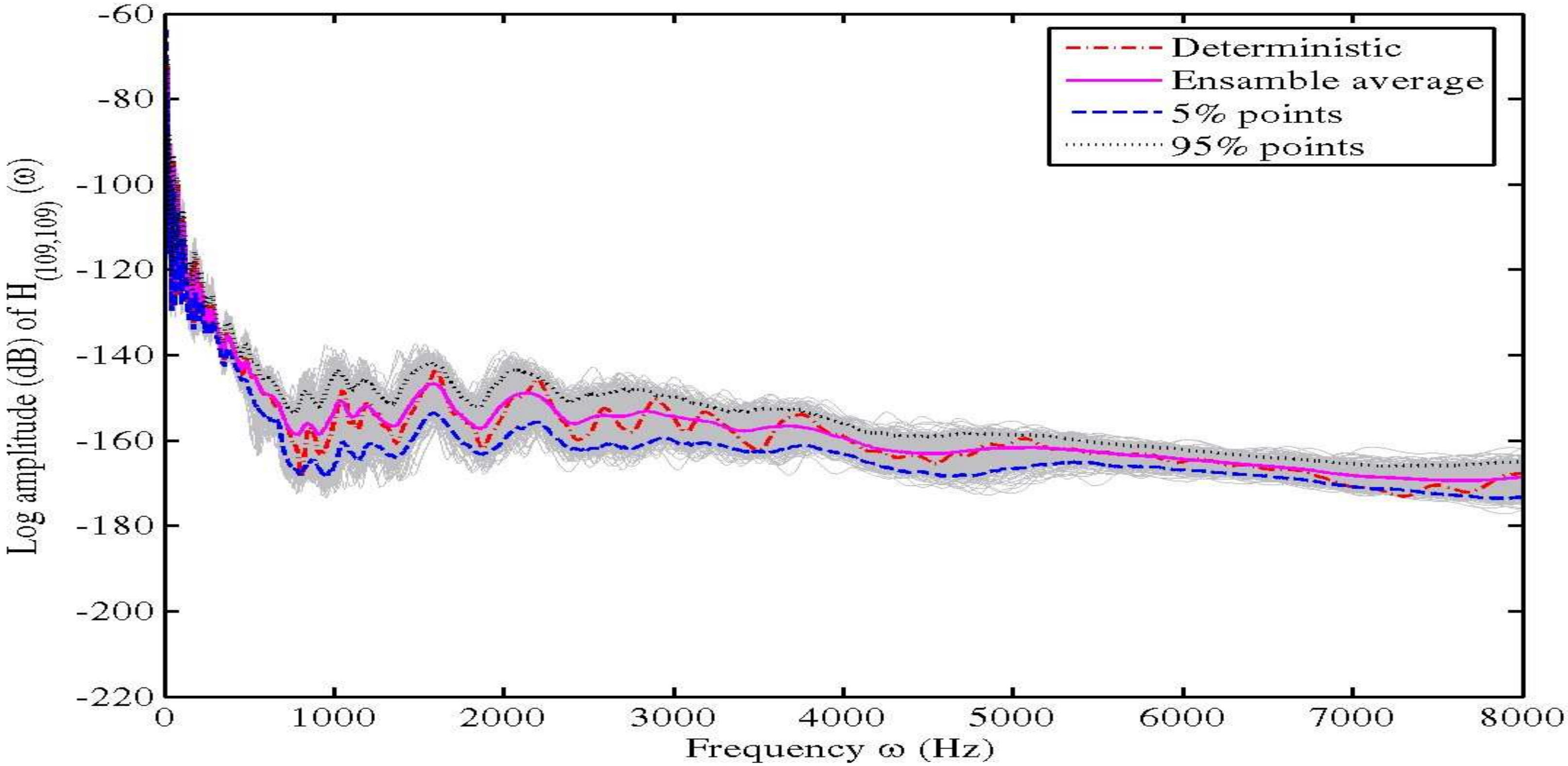
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the cross-FRF.

SFEM cross-FRF: High Freq



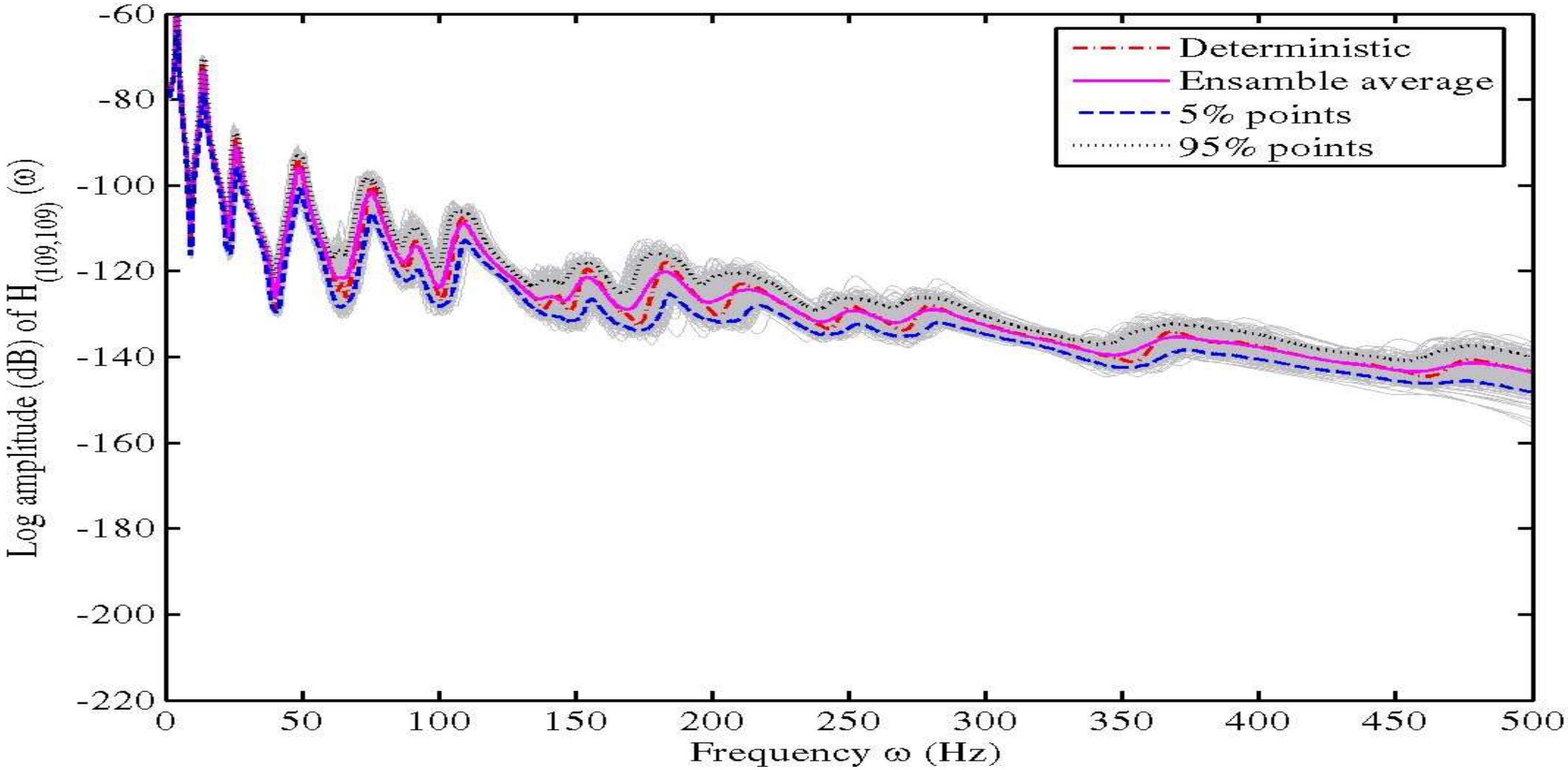
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the cross-FRF.

SFEM driving-point-FRF



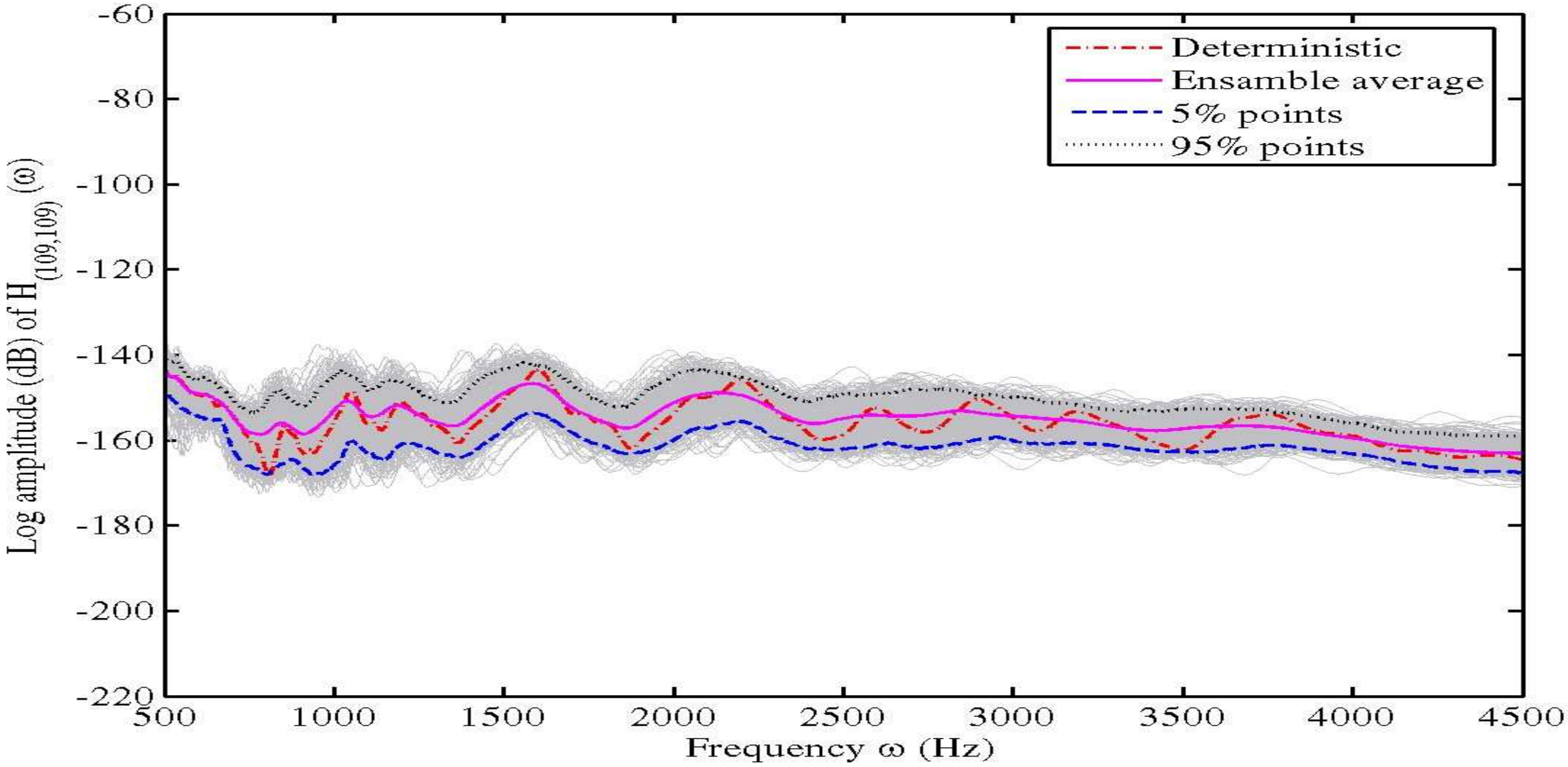
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the driving-point-FRF.

SFEM driving-point-FRF: Low Freq



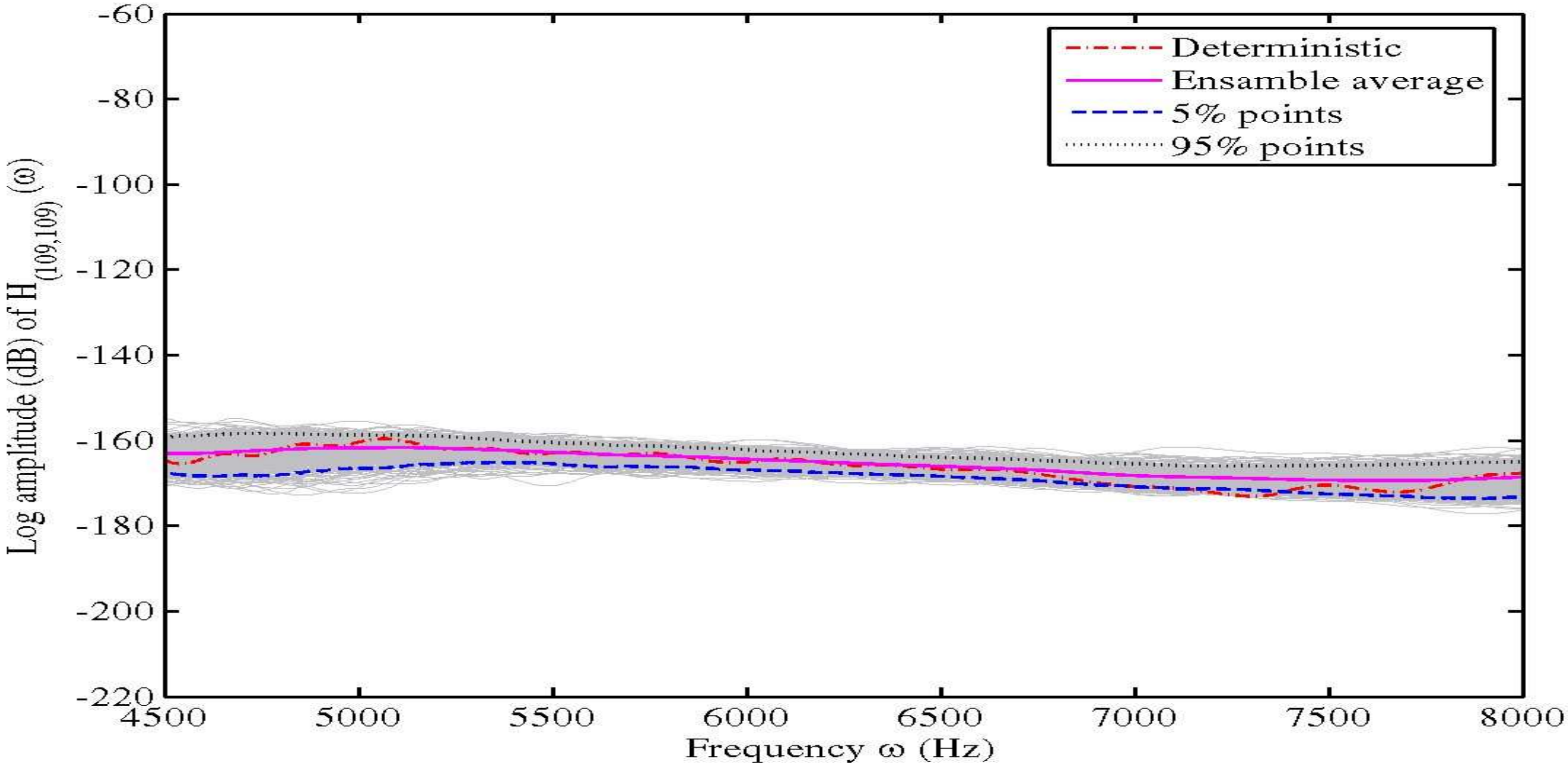
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the driving-point-FRF.

SFEM driving-point-FRF: Mid Freq



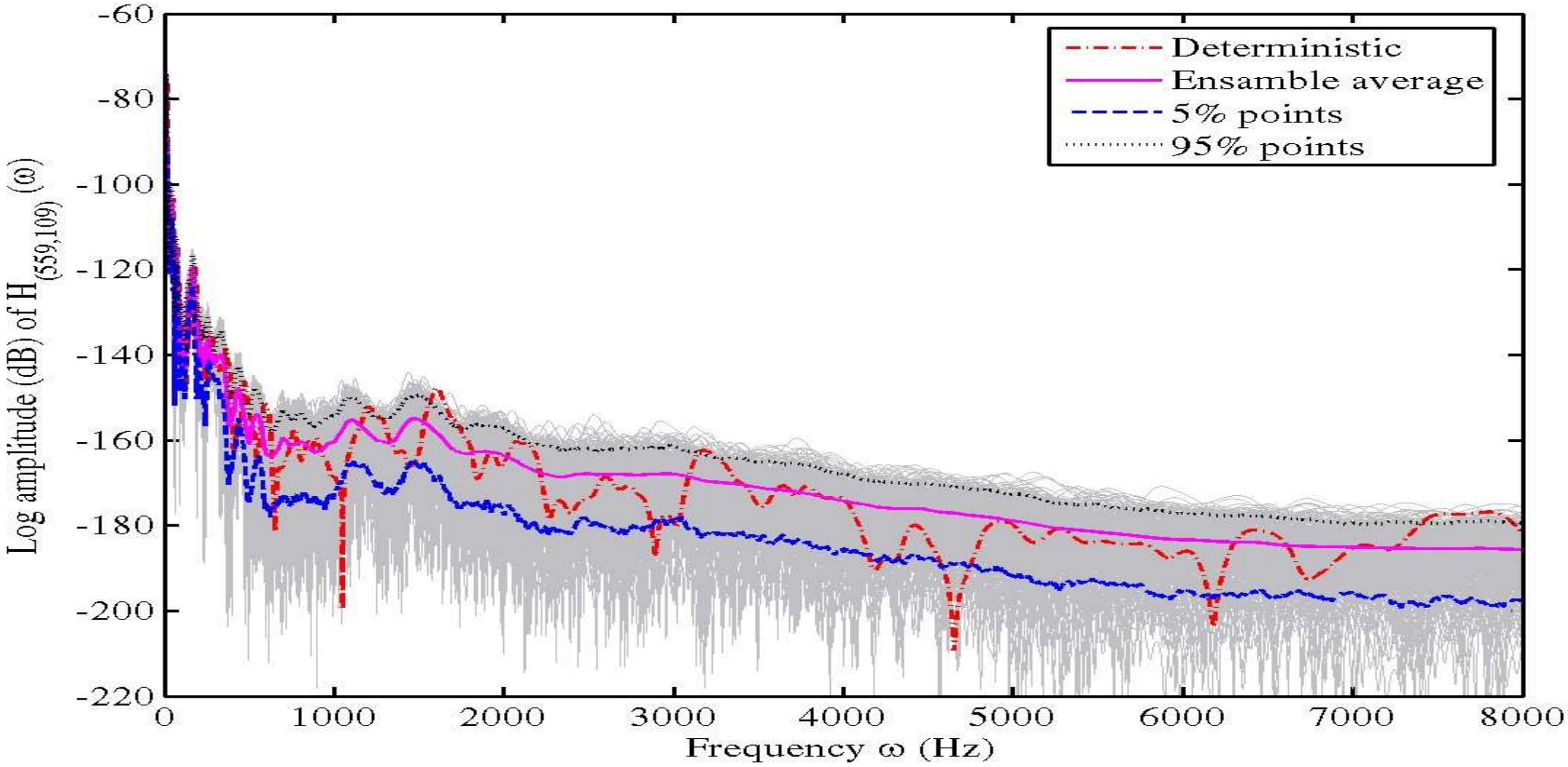
Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the driving-point-FRF.

SFEM driving-point-FRF: High Freq



Direct stochastic finite-element Monte Carlo Simulation of the amplitude of the driving-point-FRF.

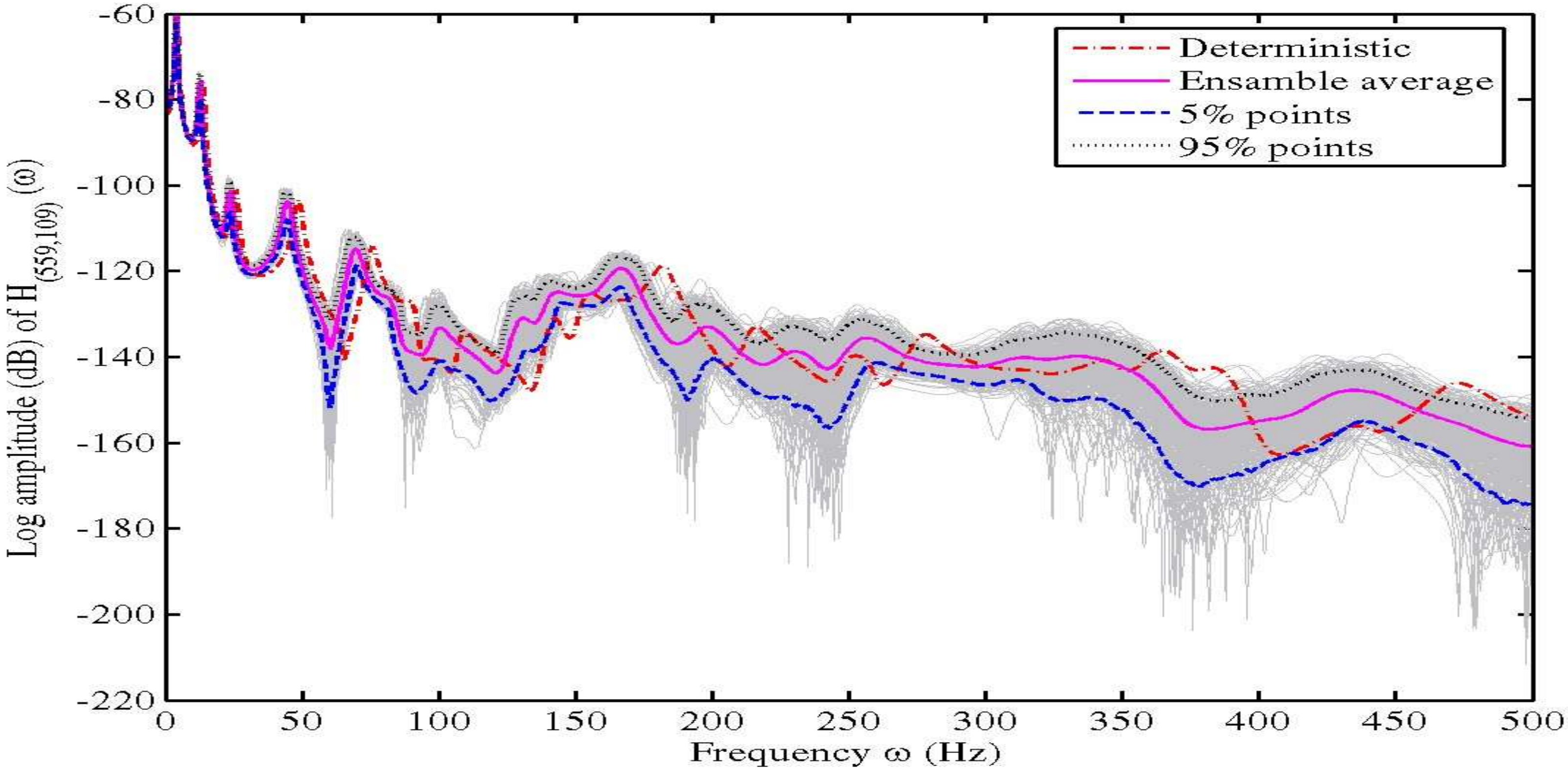
RMT cross-FRF



Amplitude of the cross-FRF of the plate using optimal Wishart mass and stiffness matrices,

$n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

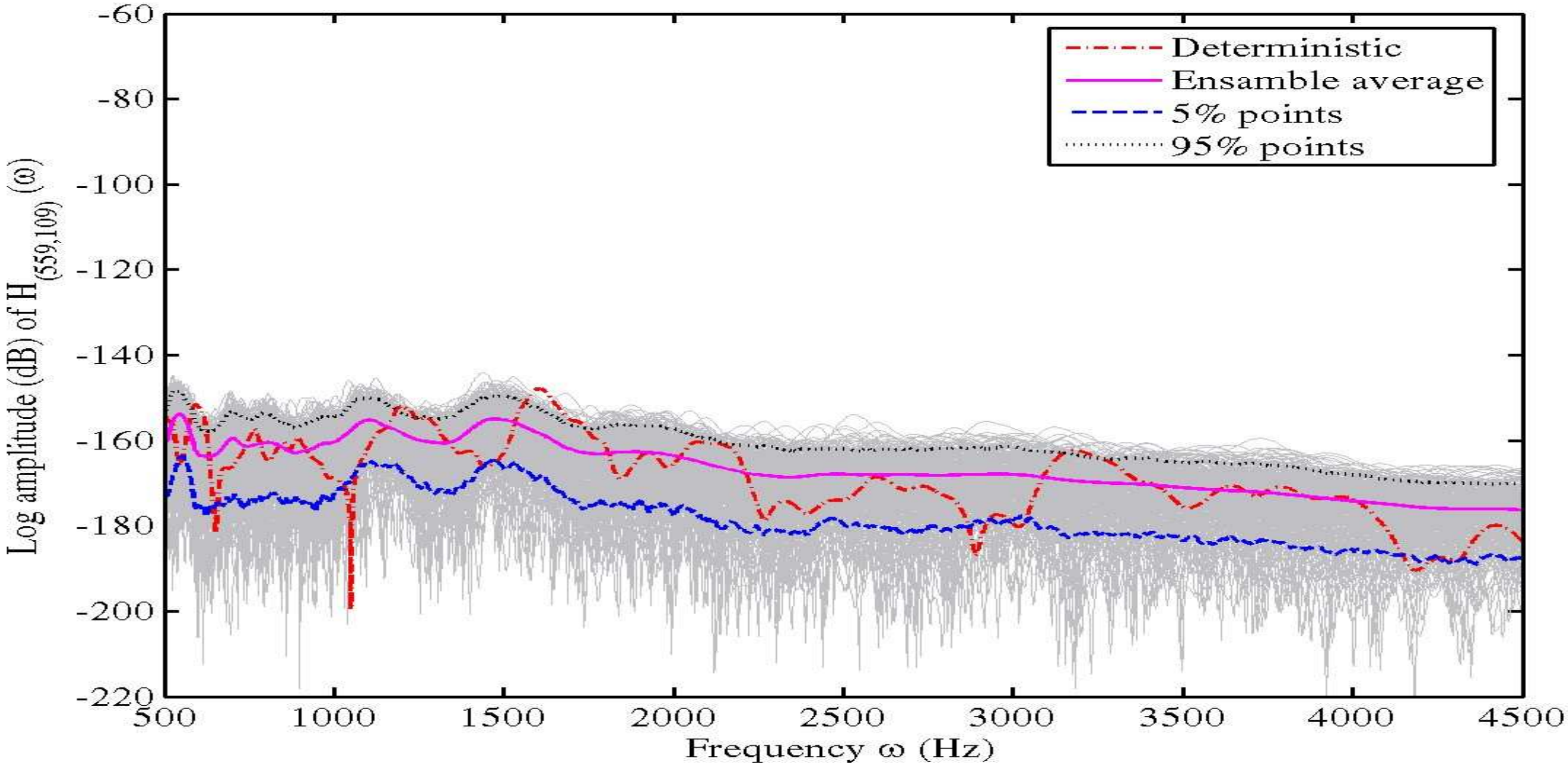
RMT cross-FRF: Low Freq



Amplitude of the cross-FRF of the plate using optimal Wishart mass and stiffness matrices,

$n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

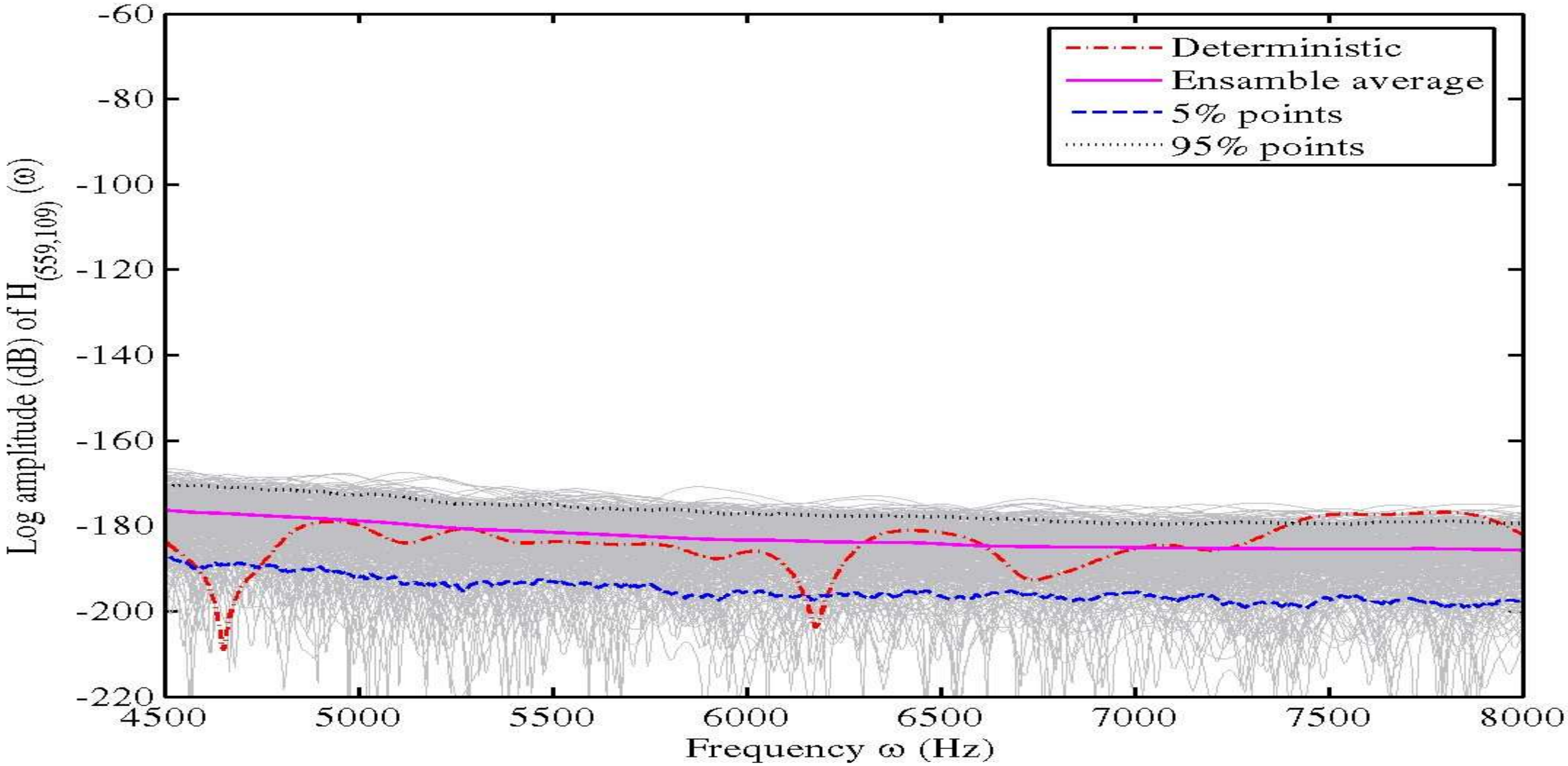
RMT cross-FRF: Mid Freq



Amplitude of the cross-FRF of the plate using optimal Wishart mass and stiffness matrices,

$n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

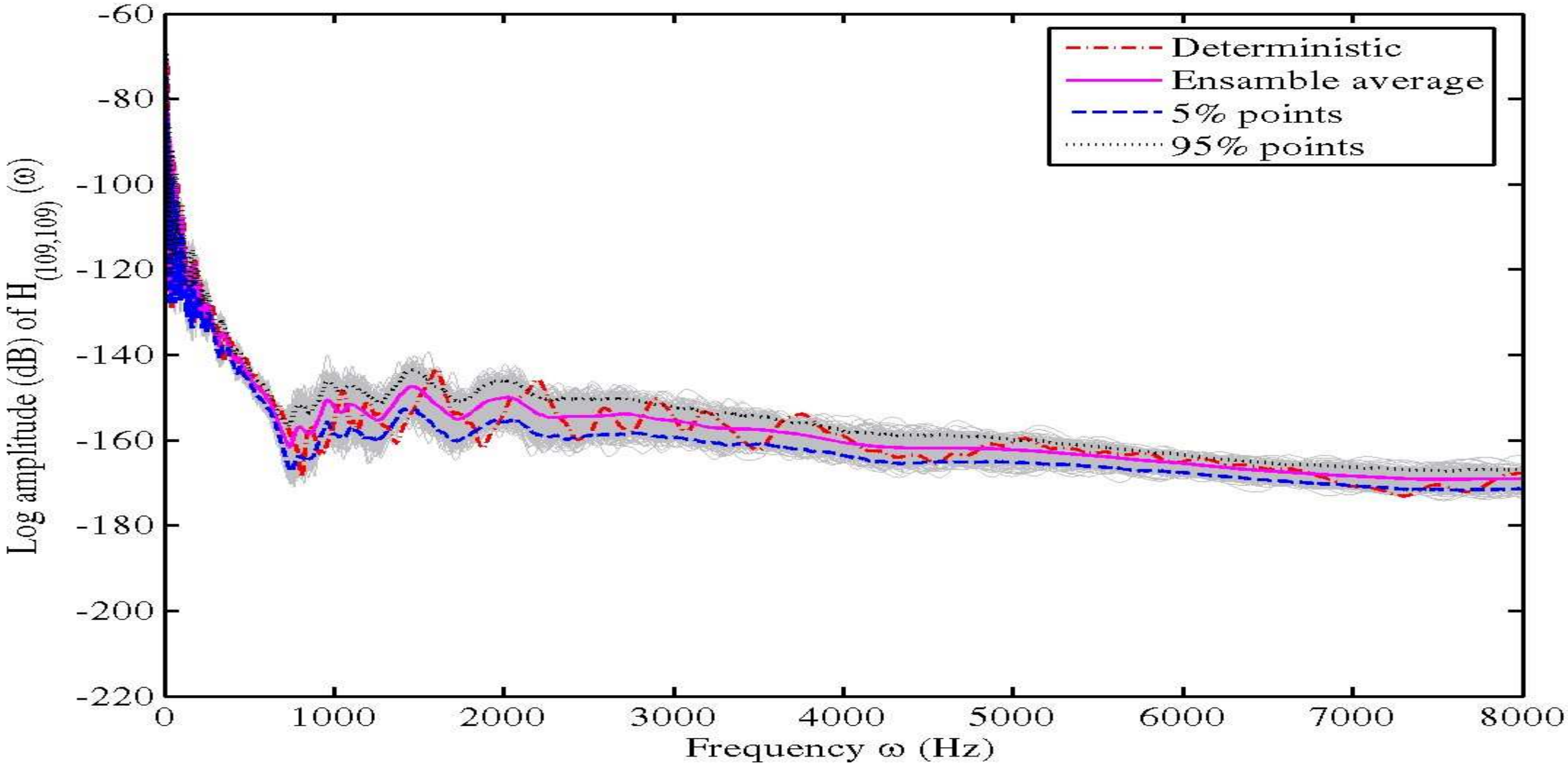
RMT cross-FRF: High Freq



Amplitude of the cross-FRF of the plate using optimal Wishart mass and stiffness matrices,

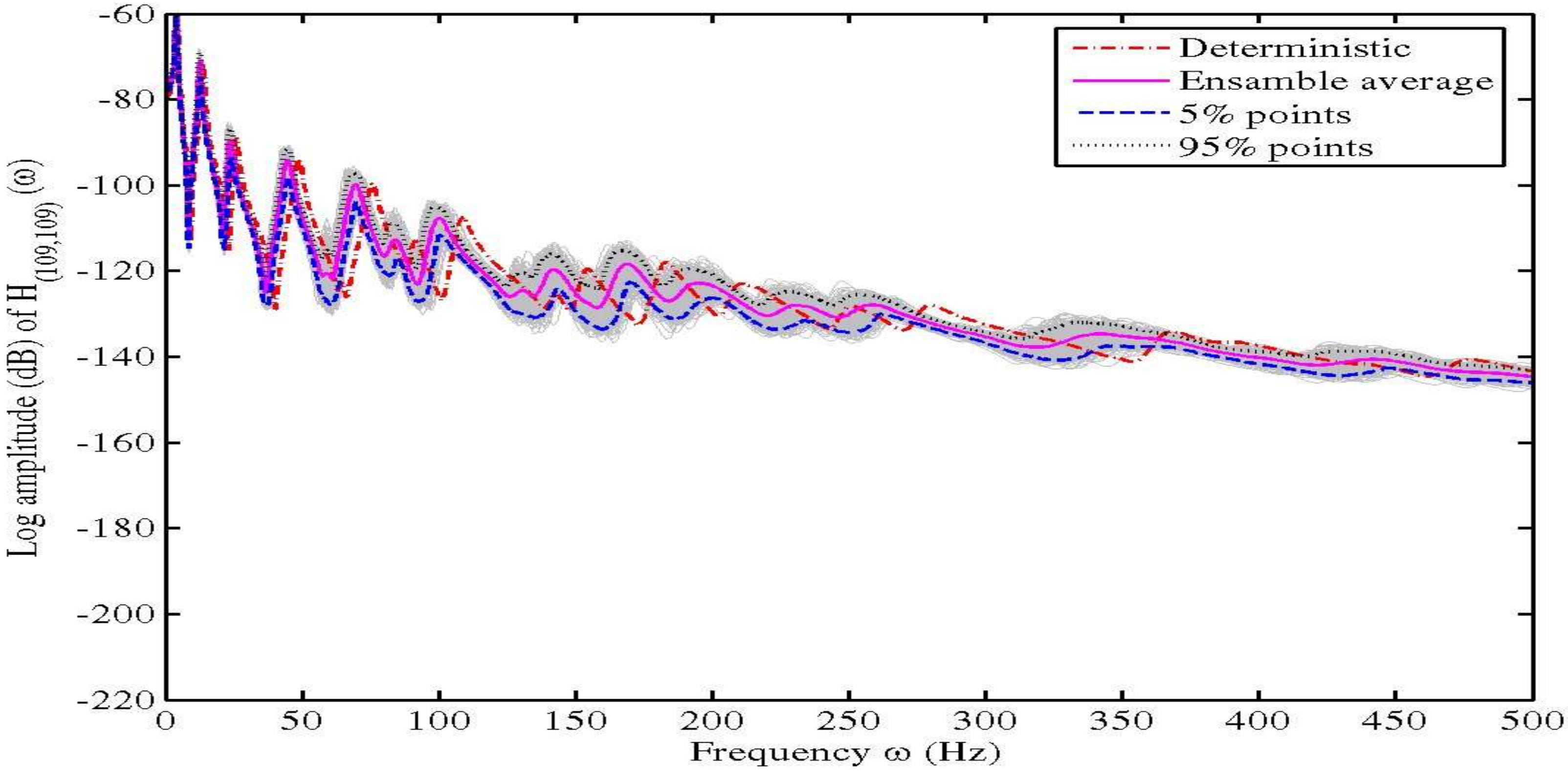
$n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

RMT driving-point-FRF



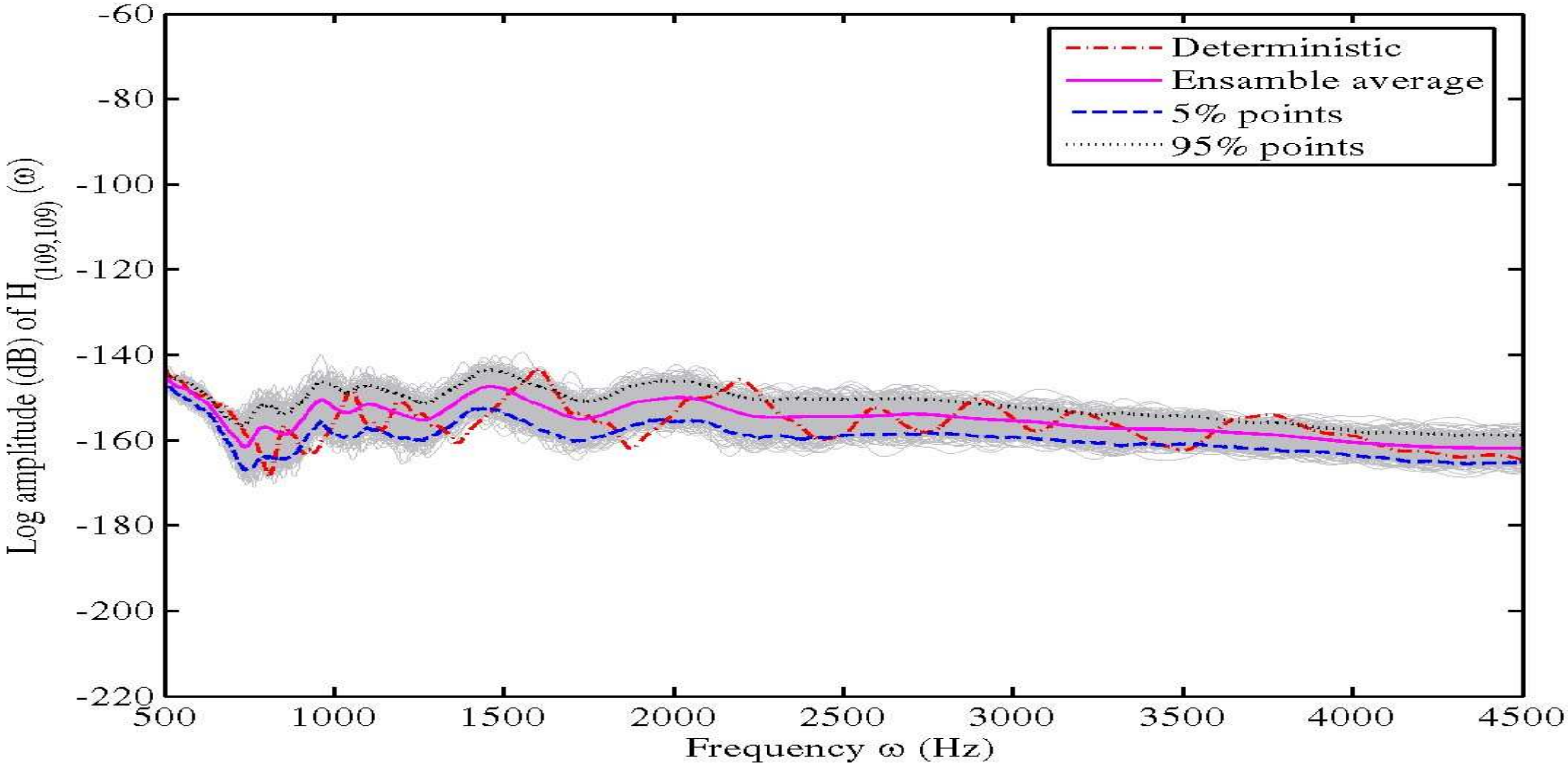
Amplitude of the driving-point-FRF of the plate using optimal Wishart mass and stiffness matrices, $n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

RMT driving-point-FRF: Low Freq



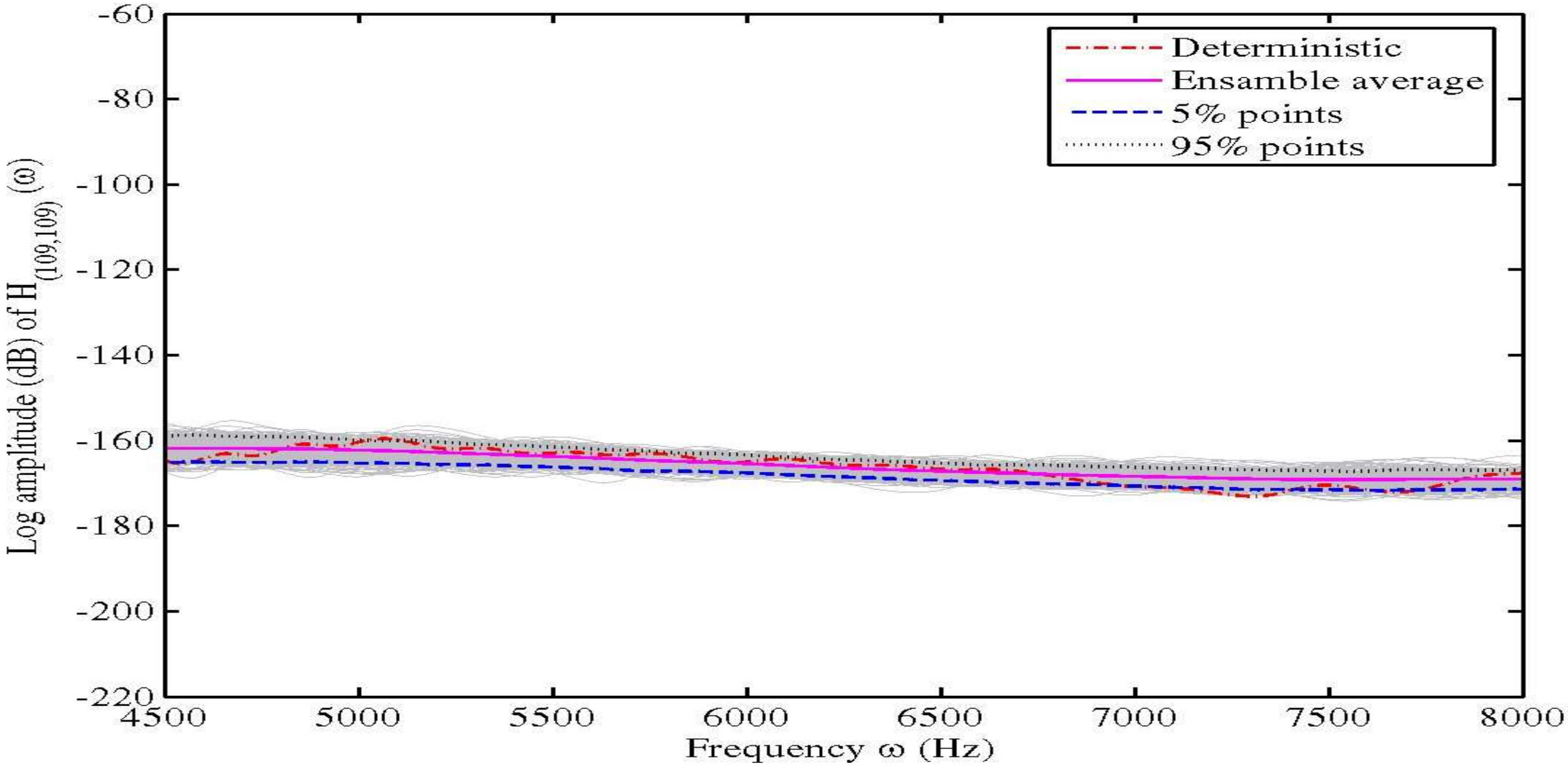
Amplitude of the driving-point-FRF of the plate using optimal Wishart mass and stiffness matrices, $n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

RMT driving-point-FRF: Mid Freq



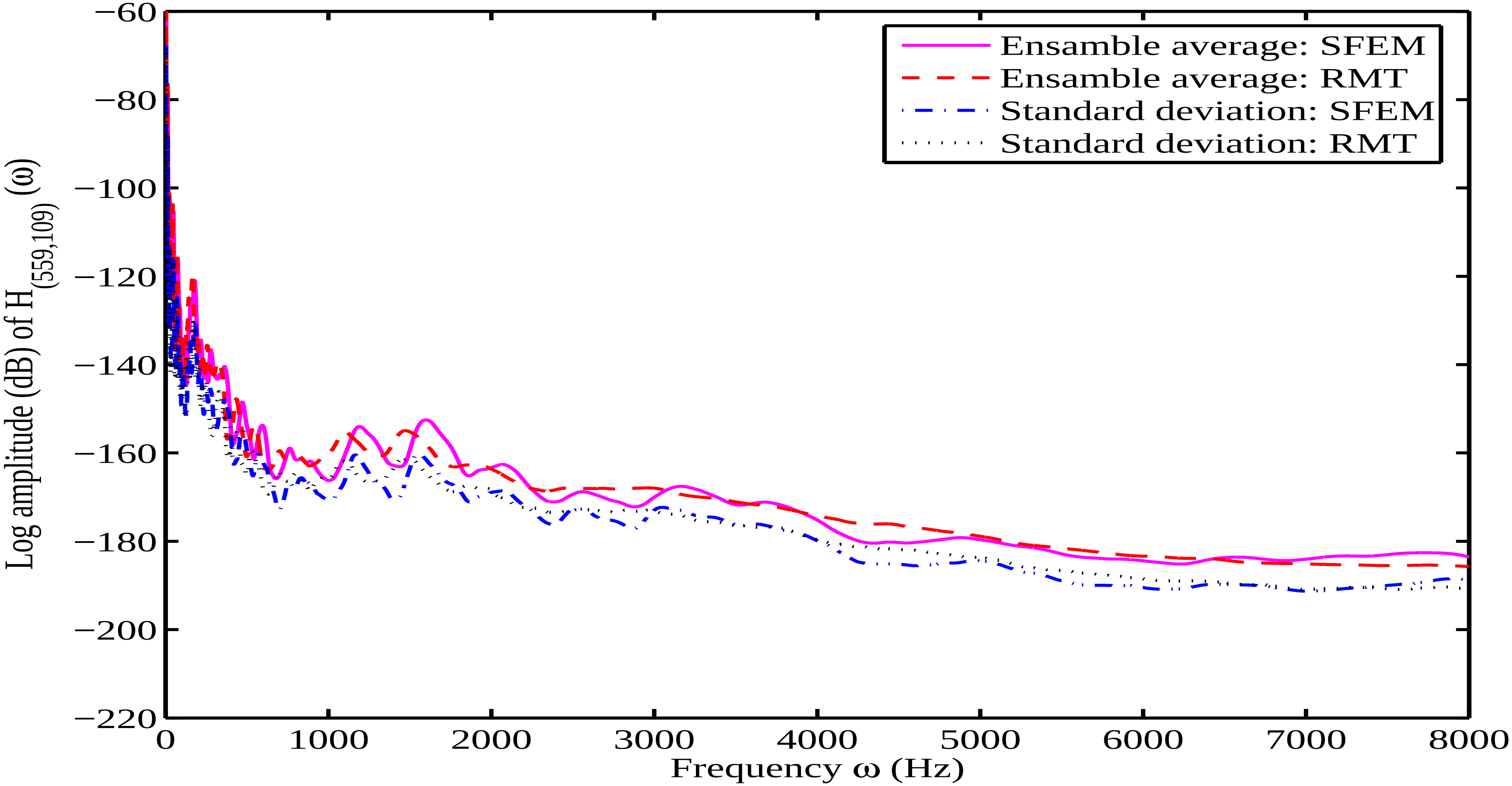
Amplitude of the driving-point-FRF of the plate using optimal Wishart mass and stiffness matrices, $n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

RMT driving-point-FRF: High Freq



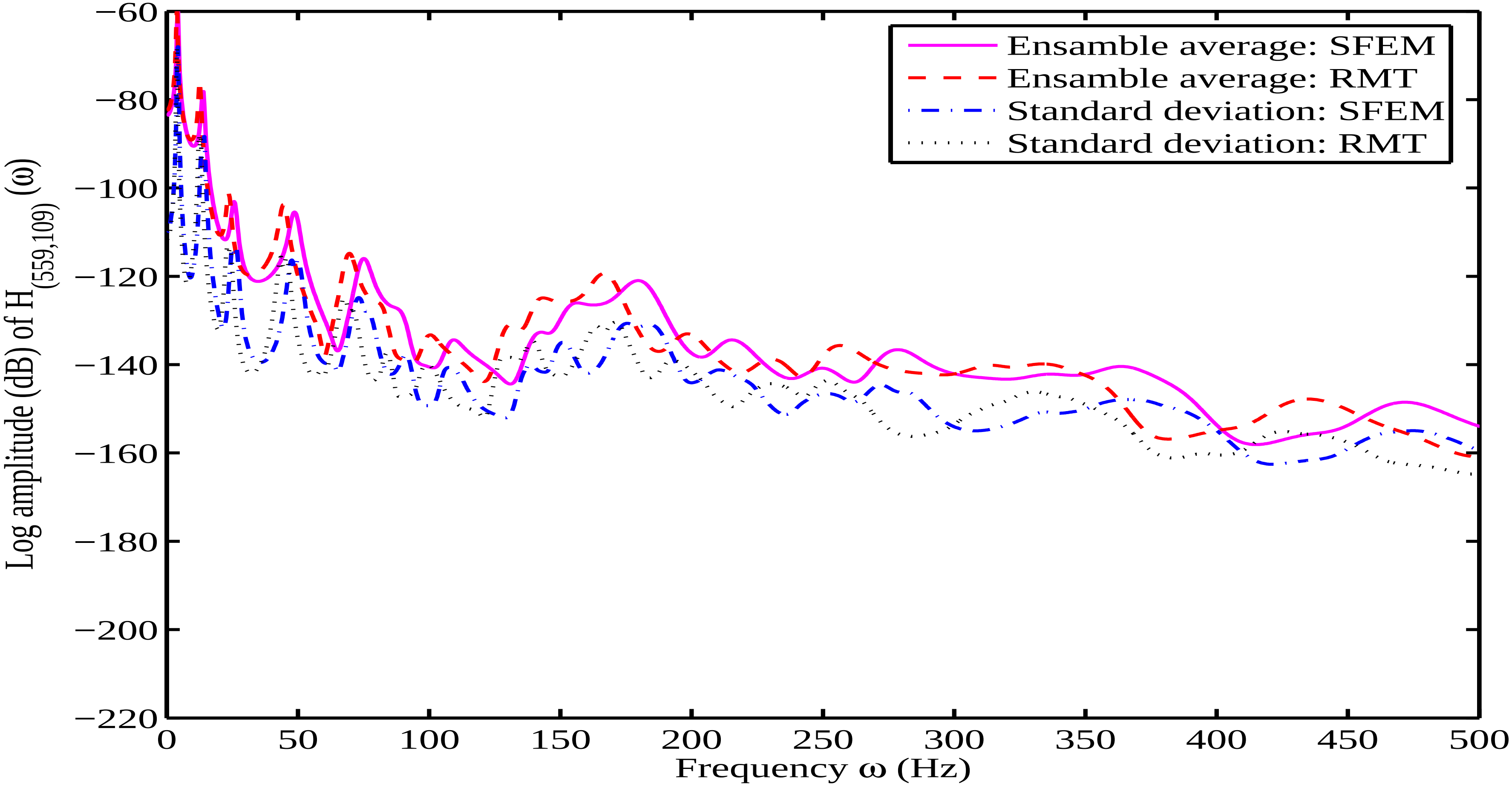
Amplitude of the driving-point-FRF of the plate using optimal Wishart mass and stiffness matrices, $n = 702$, $\delta_M = 0.1166$ and $\delta_K = 0.2622$

Comparison of cross-FRF



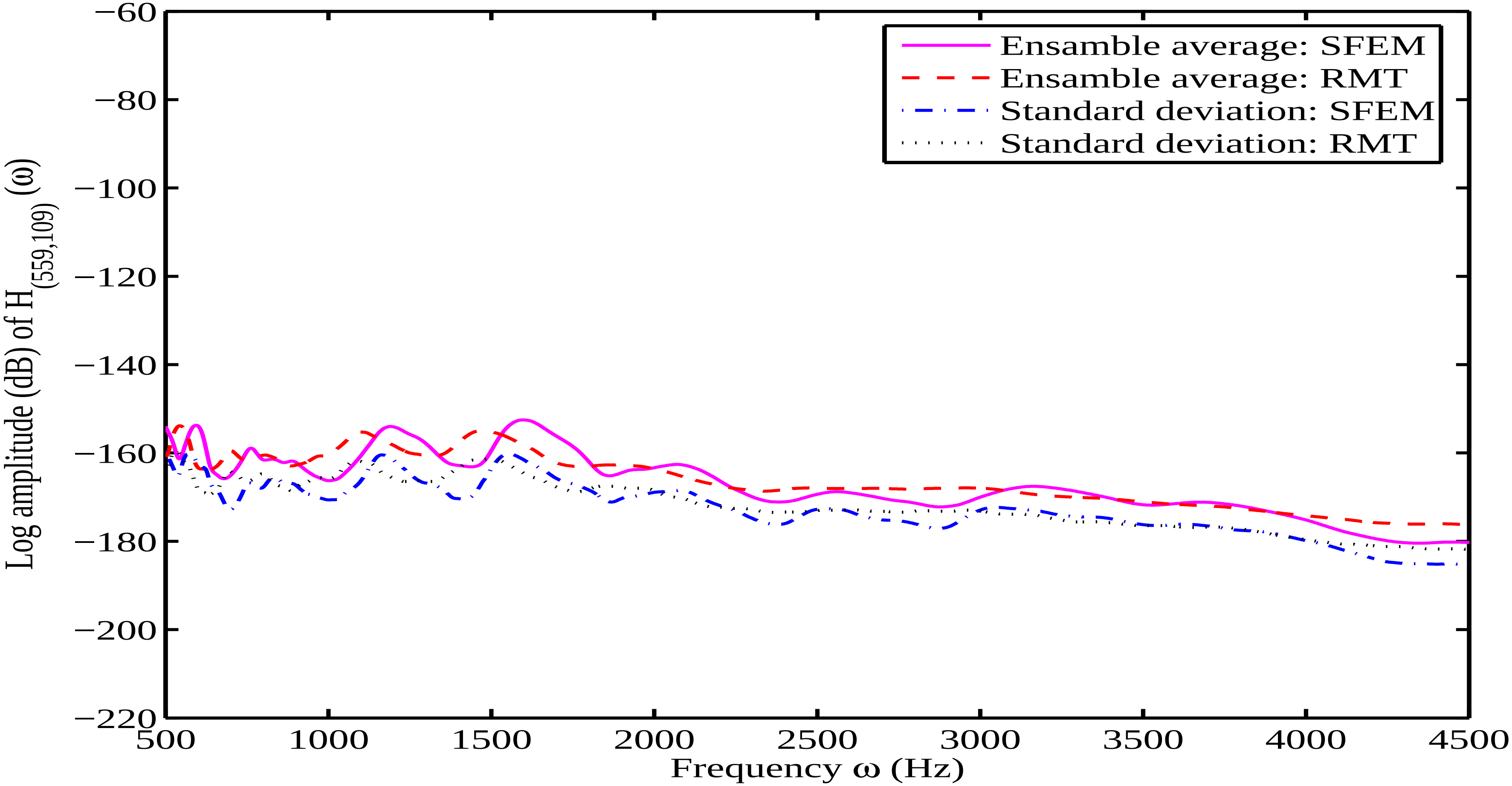
Comparison of the mean and standard deviation of the amplitude of the cross-FRF.

Comparison of cross-FRF: Low Freq



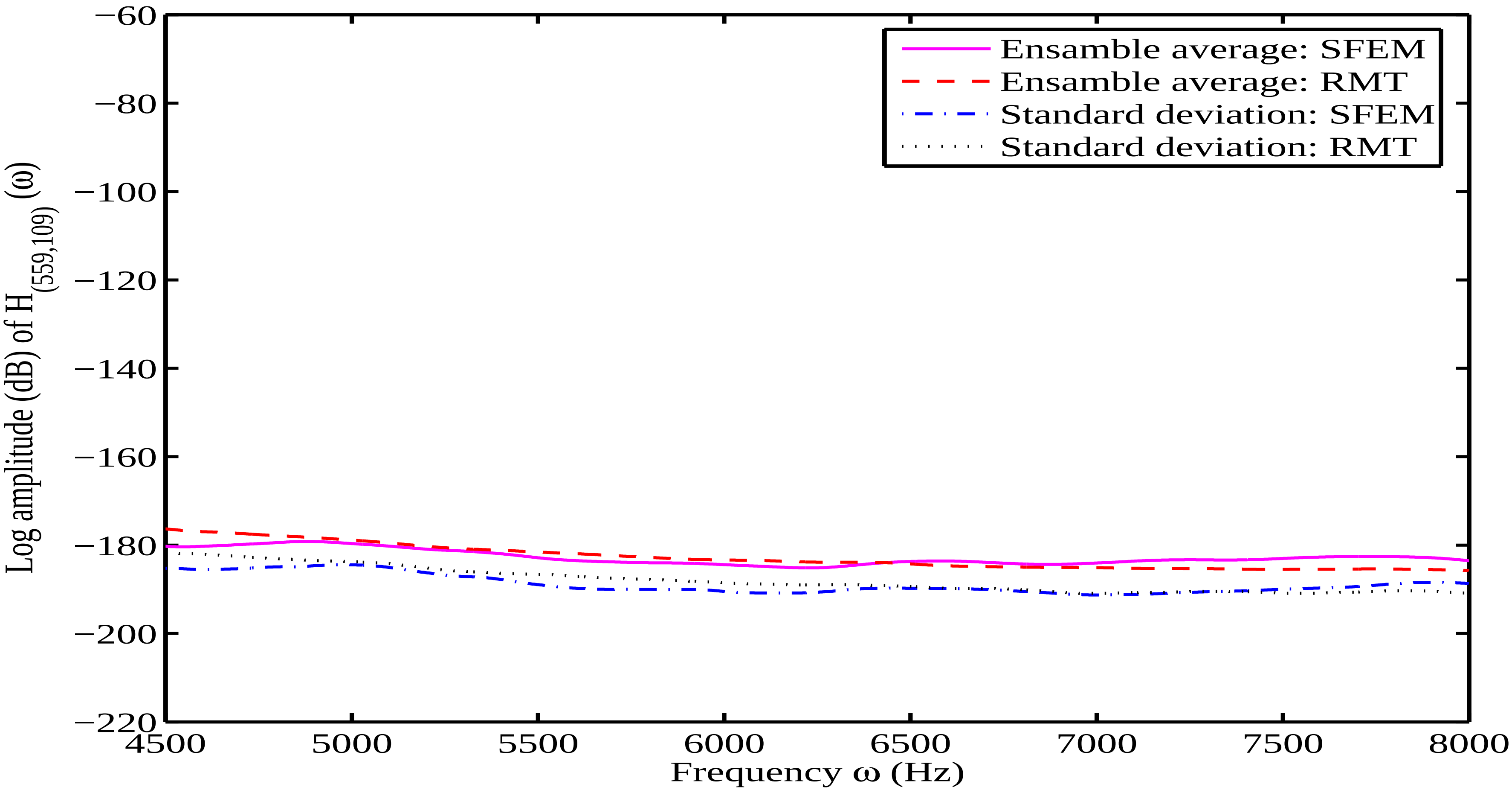
Comparison of the mean and standard deviation of the amplitude of the cross-FRF.

Comparison of cross-FRF: Mid Freq



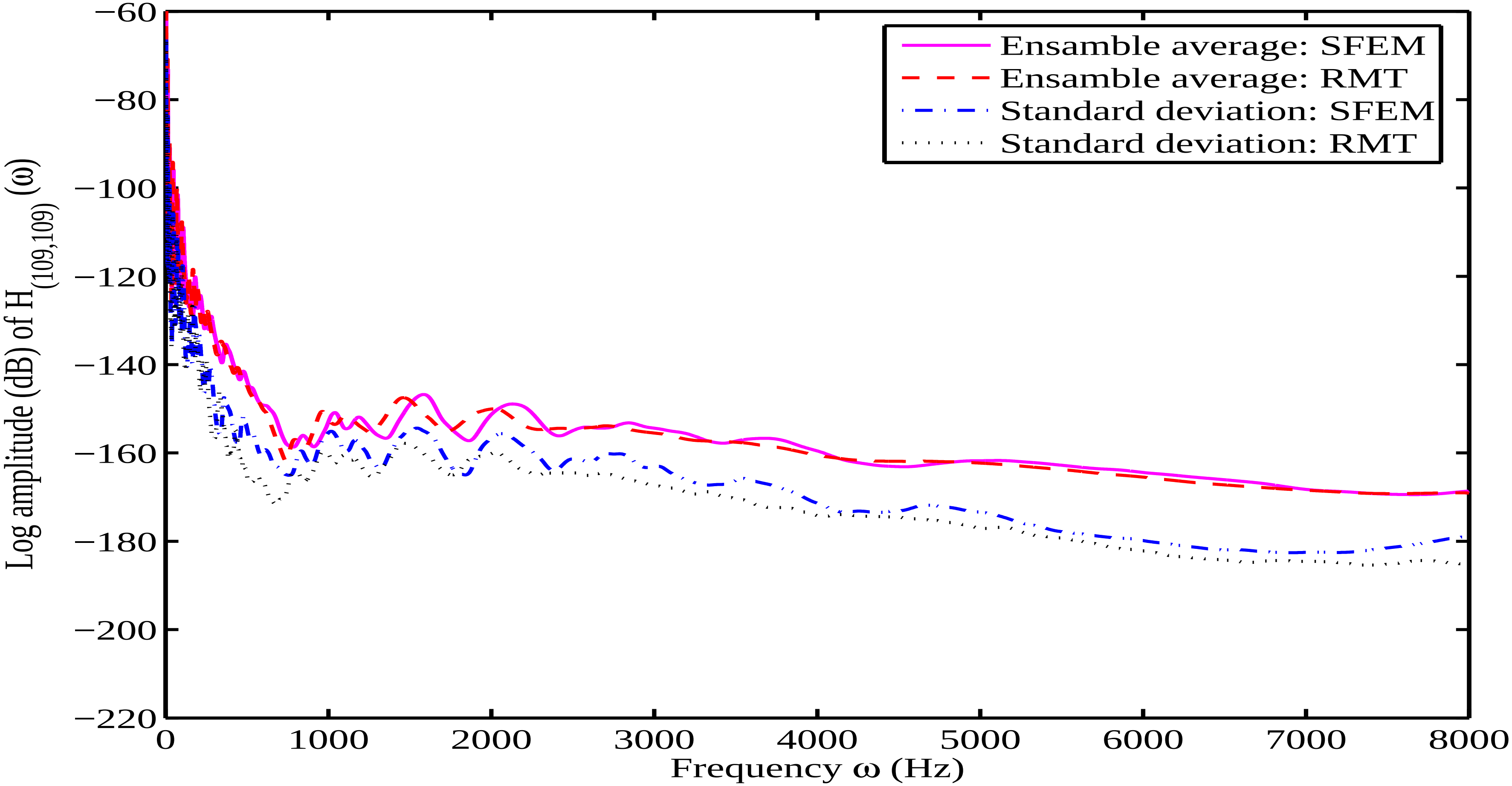
Comparison of the mean and standard deviation of the amplitude of the cross-FRF.

Comparison of cross-FRF: High Freq



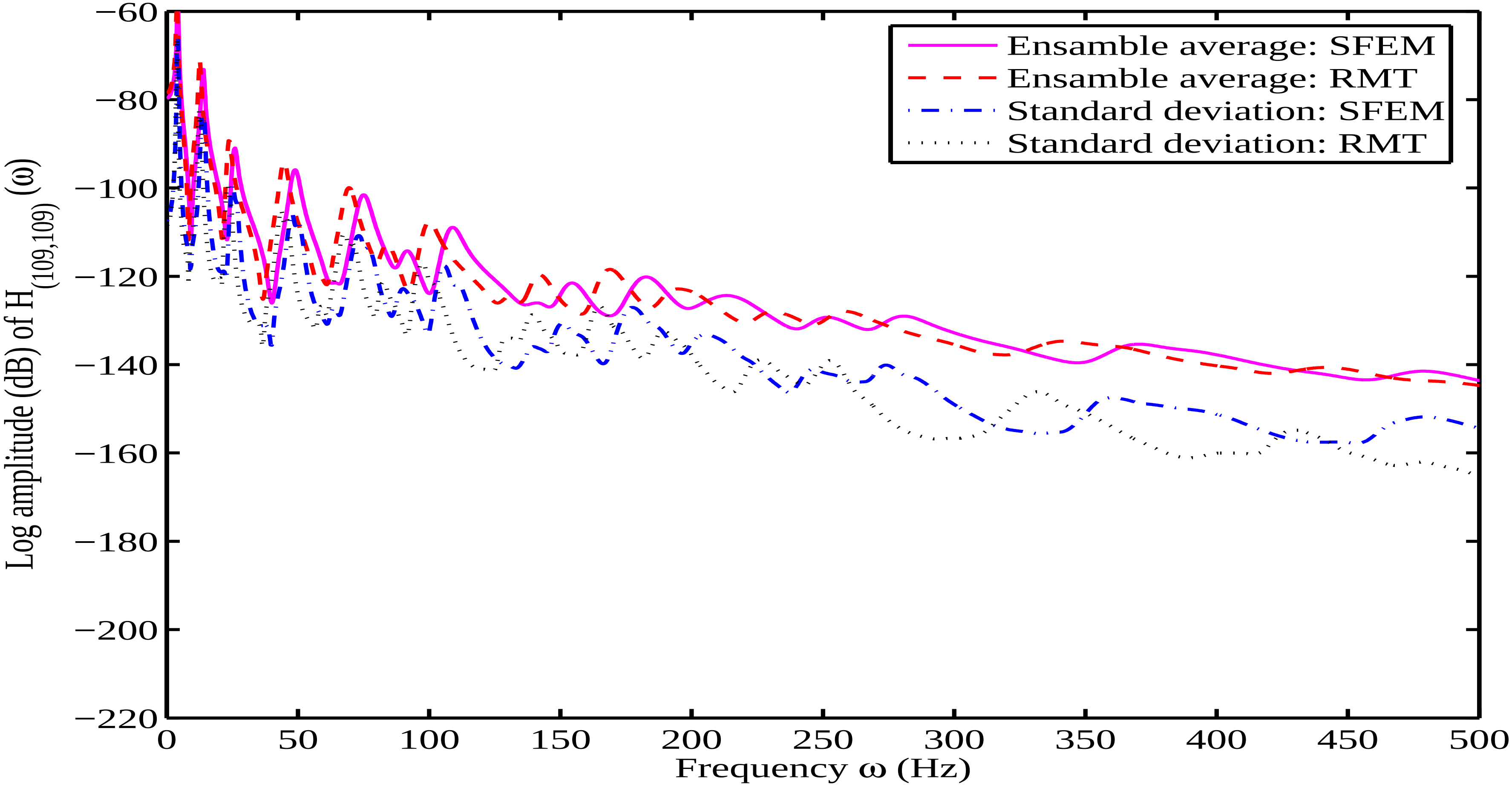
Comparison of the mean and standard deviation of the amplitude of the cross-FRF.

Comparison of driving-point-FRF



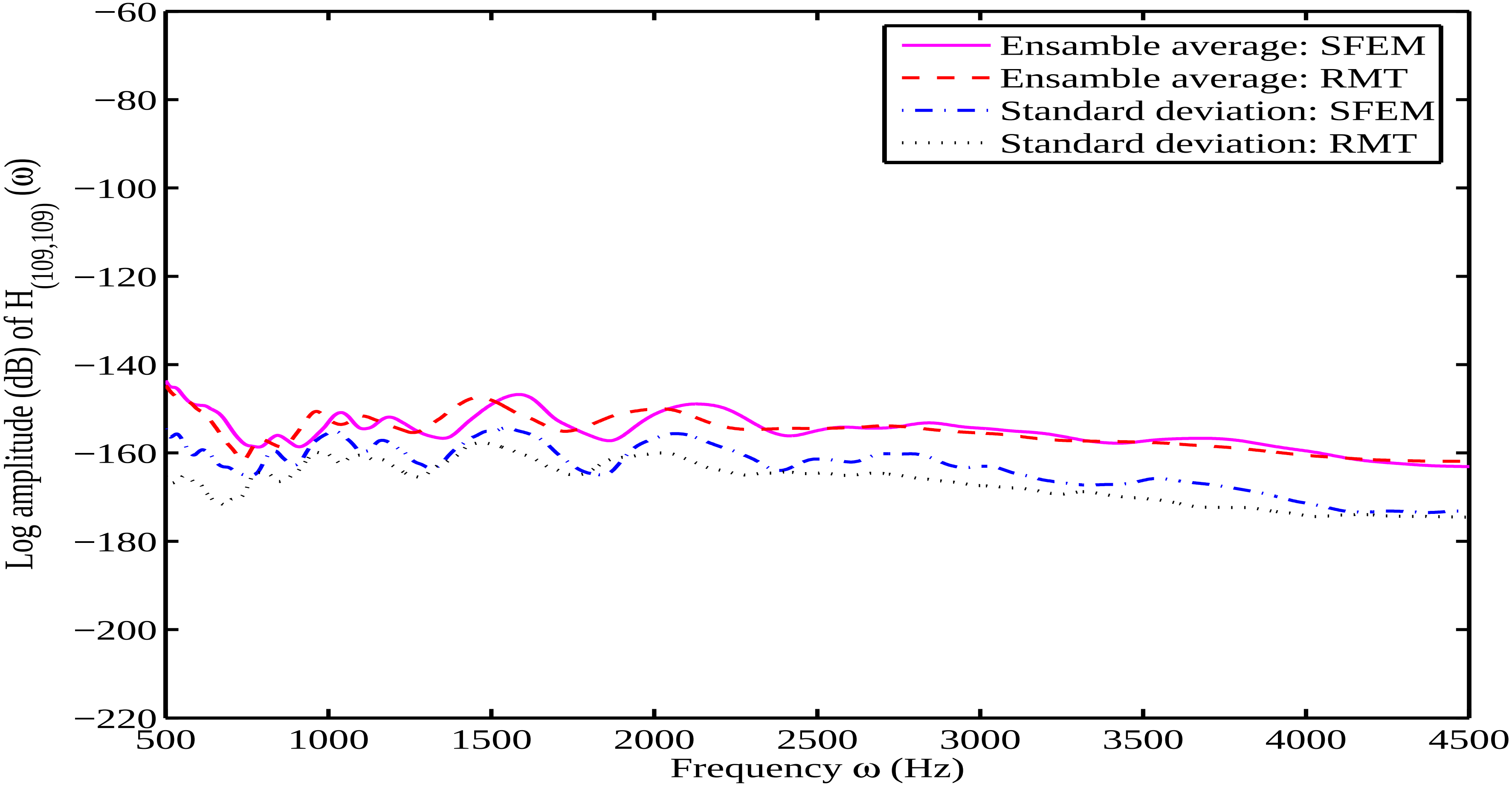
Comparison of the mean and standard deviation of the amplitude of the driving-point-FRF.

Comparison of driving-point-FRF: Low Freq



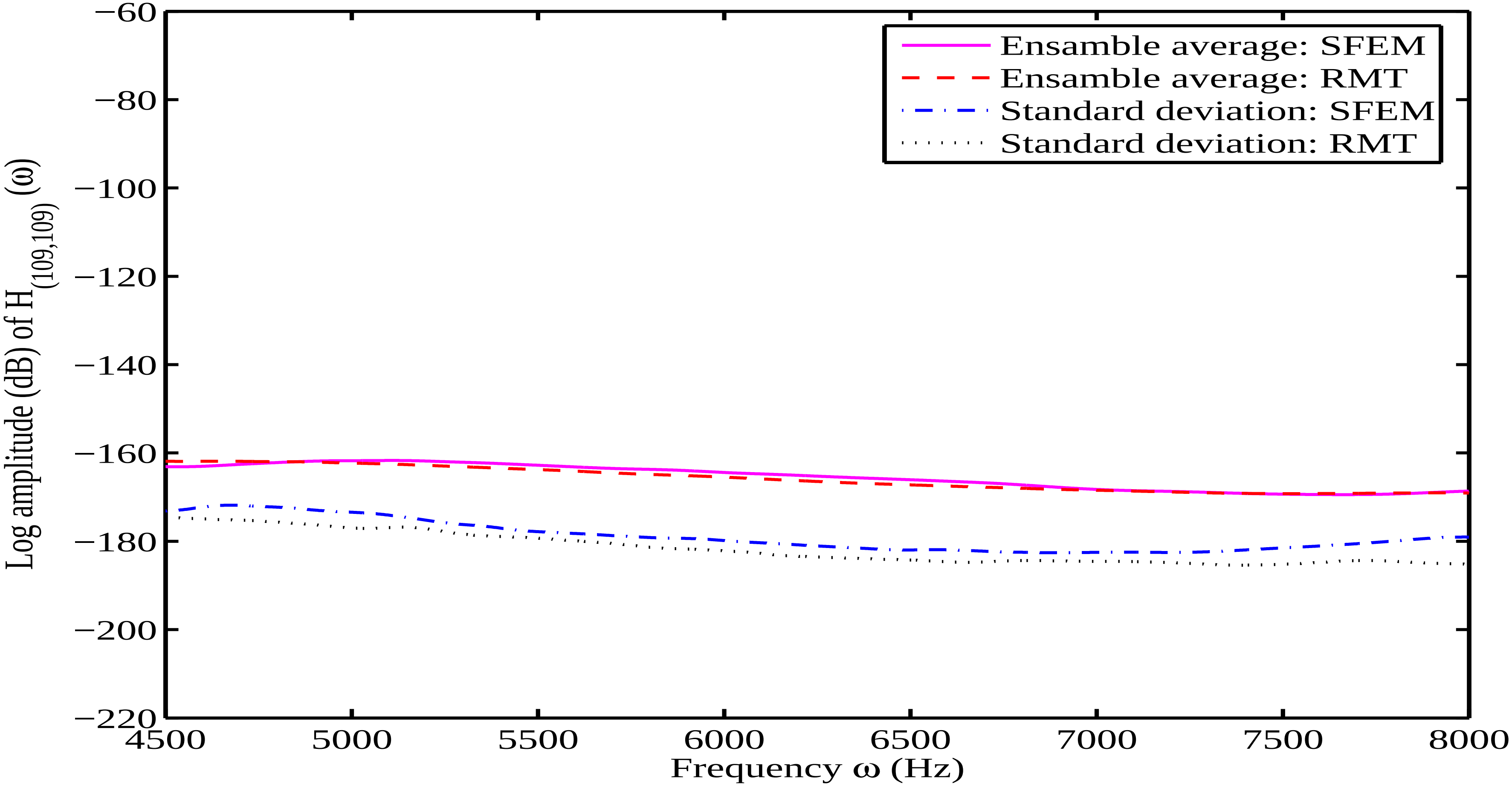
Comparison of the mean and standard deviation of the amplitude of the driving-point-FRF.

Comparison of driving-point-FRF: Mid Freq



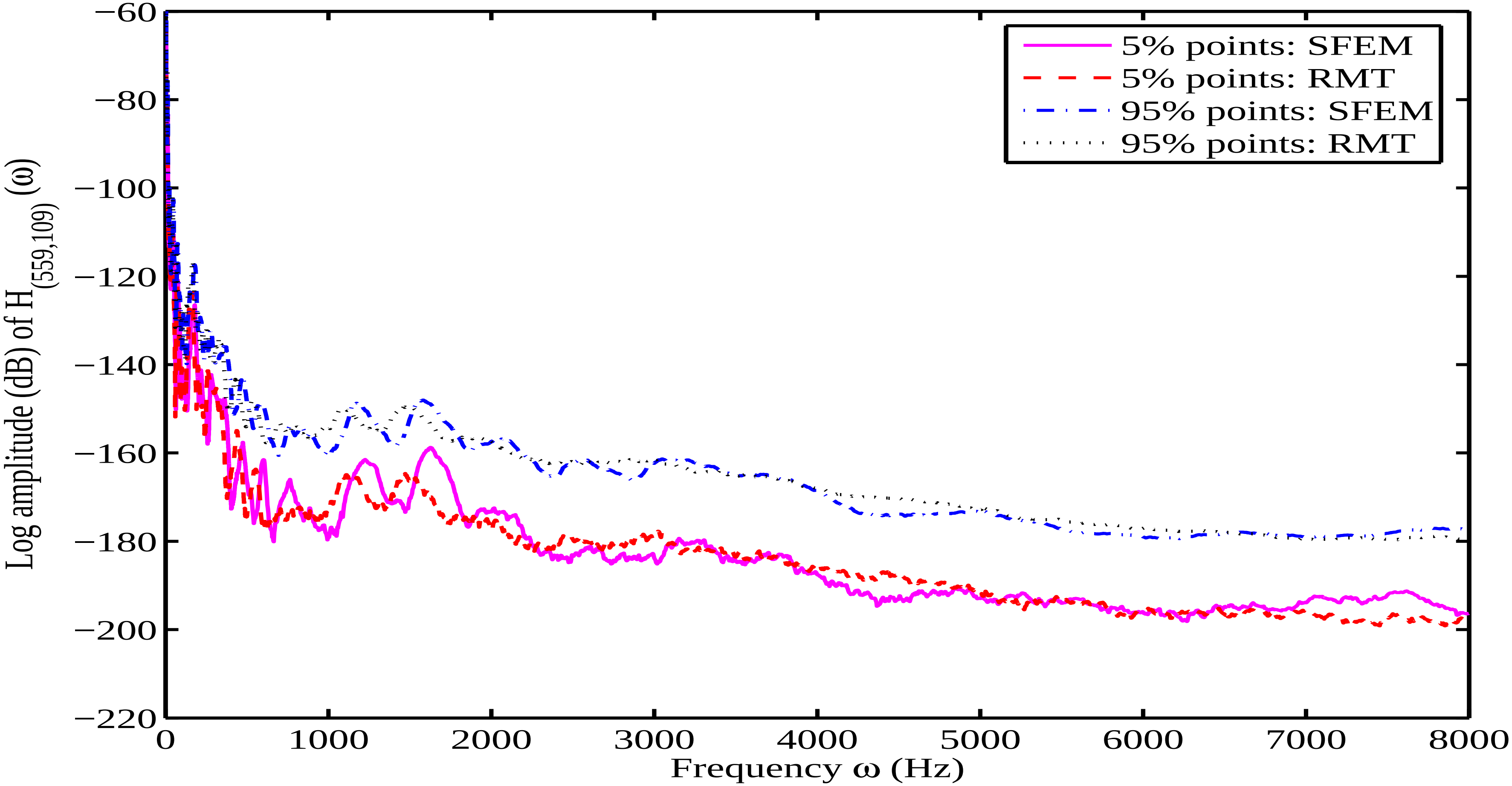
Comparison of the mean and standard deviation of the amplitude of the driving-point-FRF.

Comparison of driving-point-FRF: High Freq



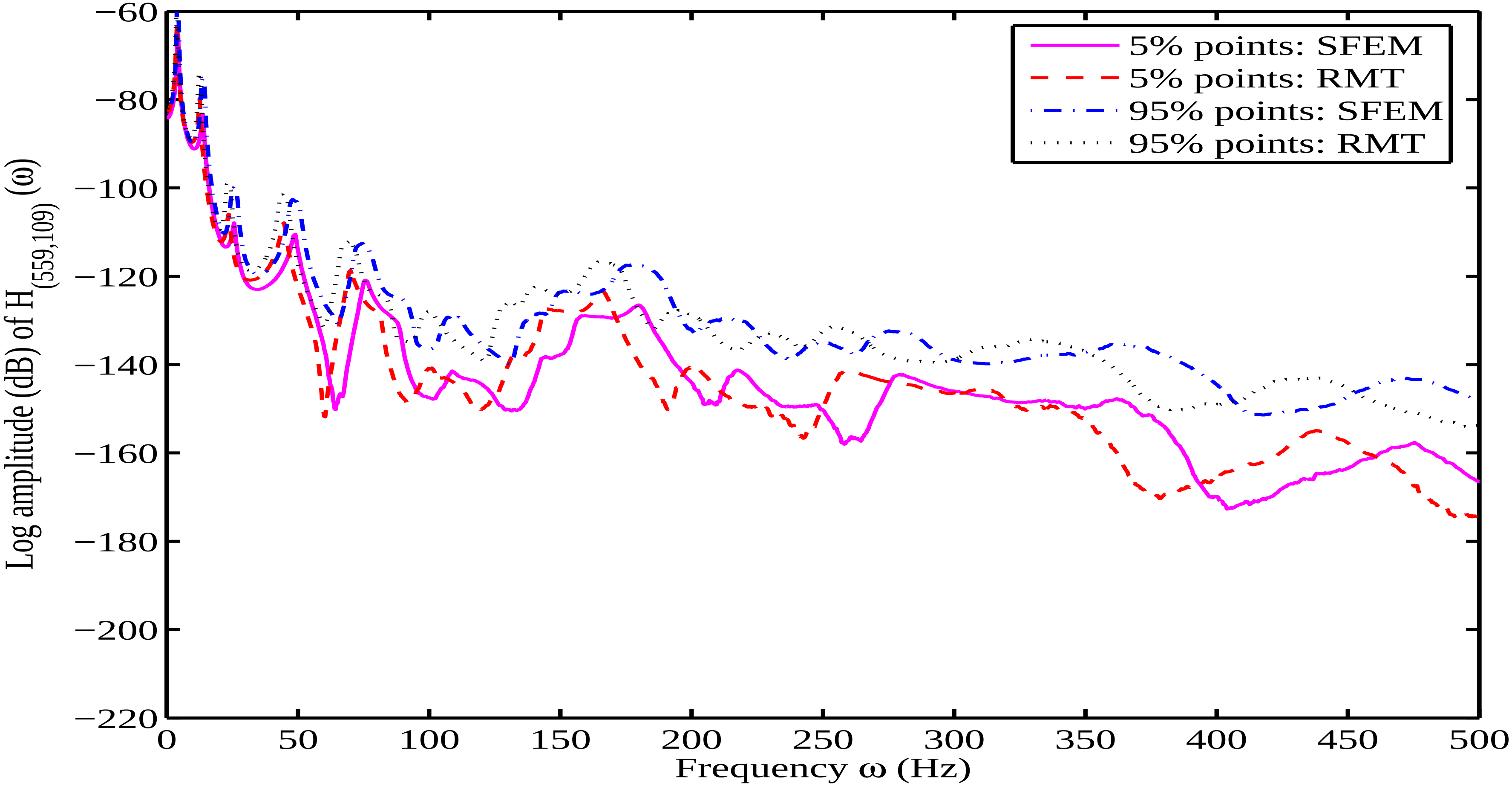
Comparison of the mean and standard deviation of the amplitude of the driving-point-FRF.

Comparison of cross-FRF



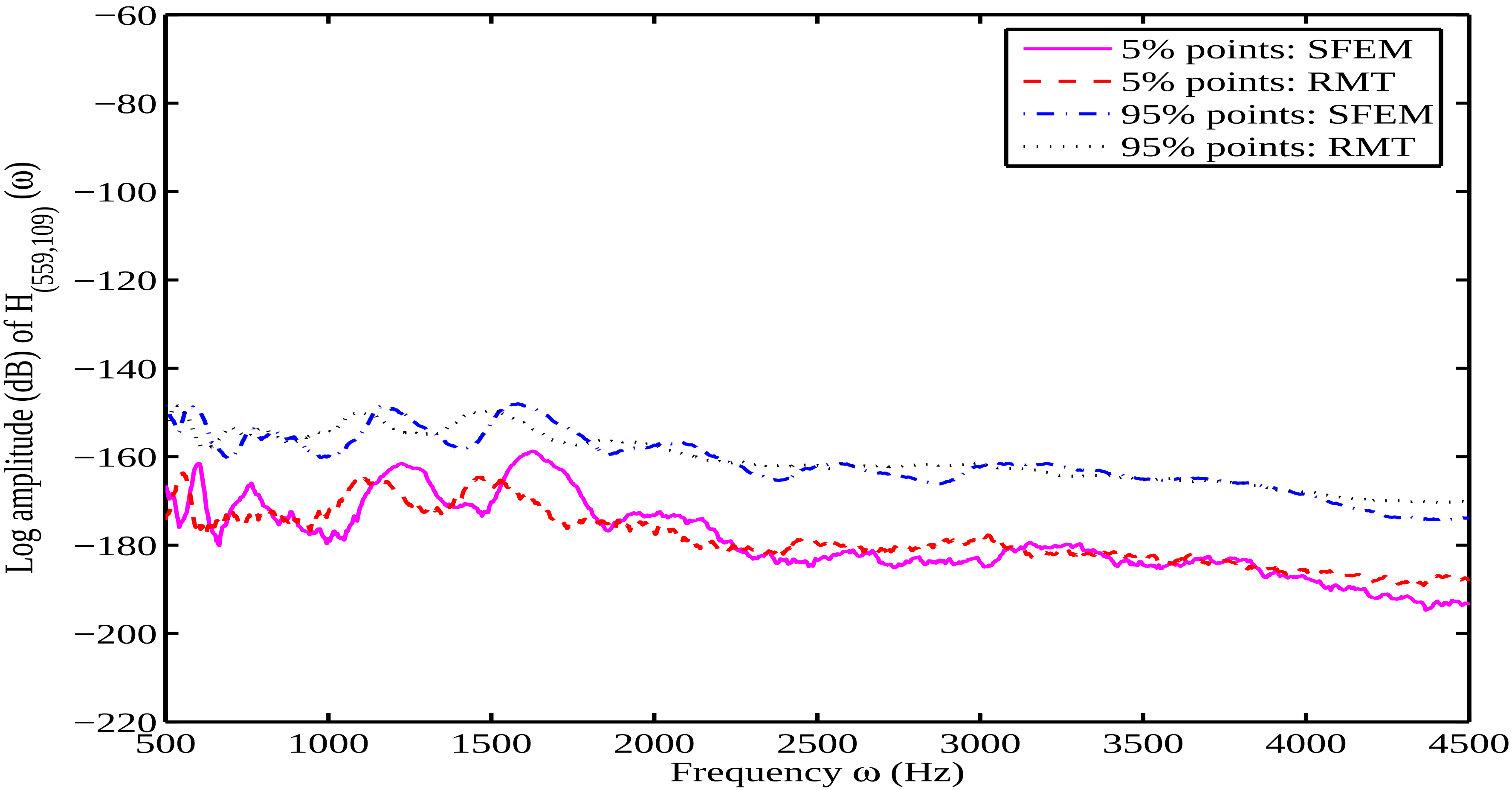
Comparison of the 5% and 95% probability points of the amplitude of the cross-FRF.

Comparison of cross-FRF: Low Freq



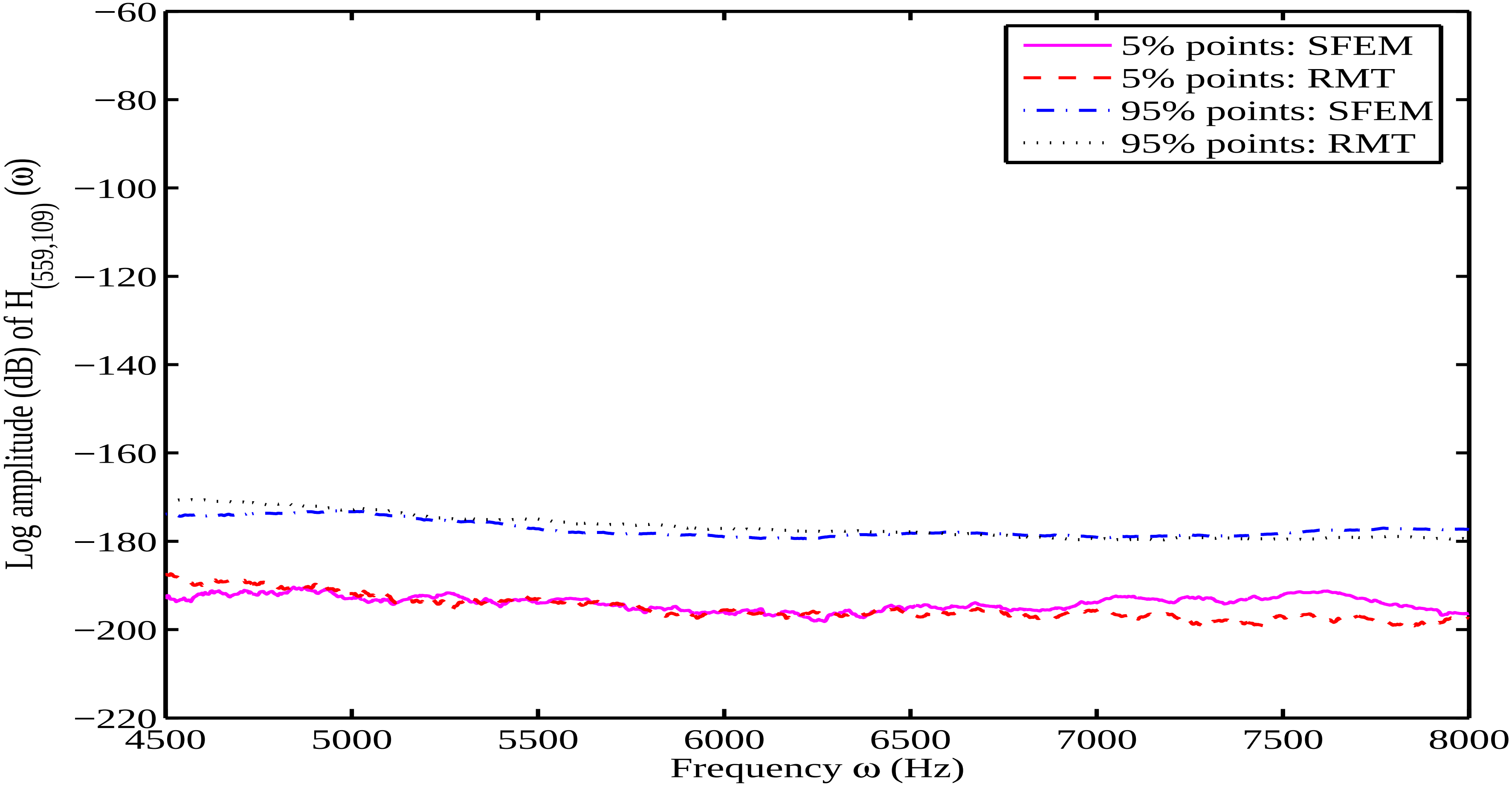
Comparison of the 5% and 95% probability points of the amplitude of the cross-FRF.

Comparison of cross-FRF: Mid Freq



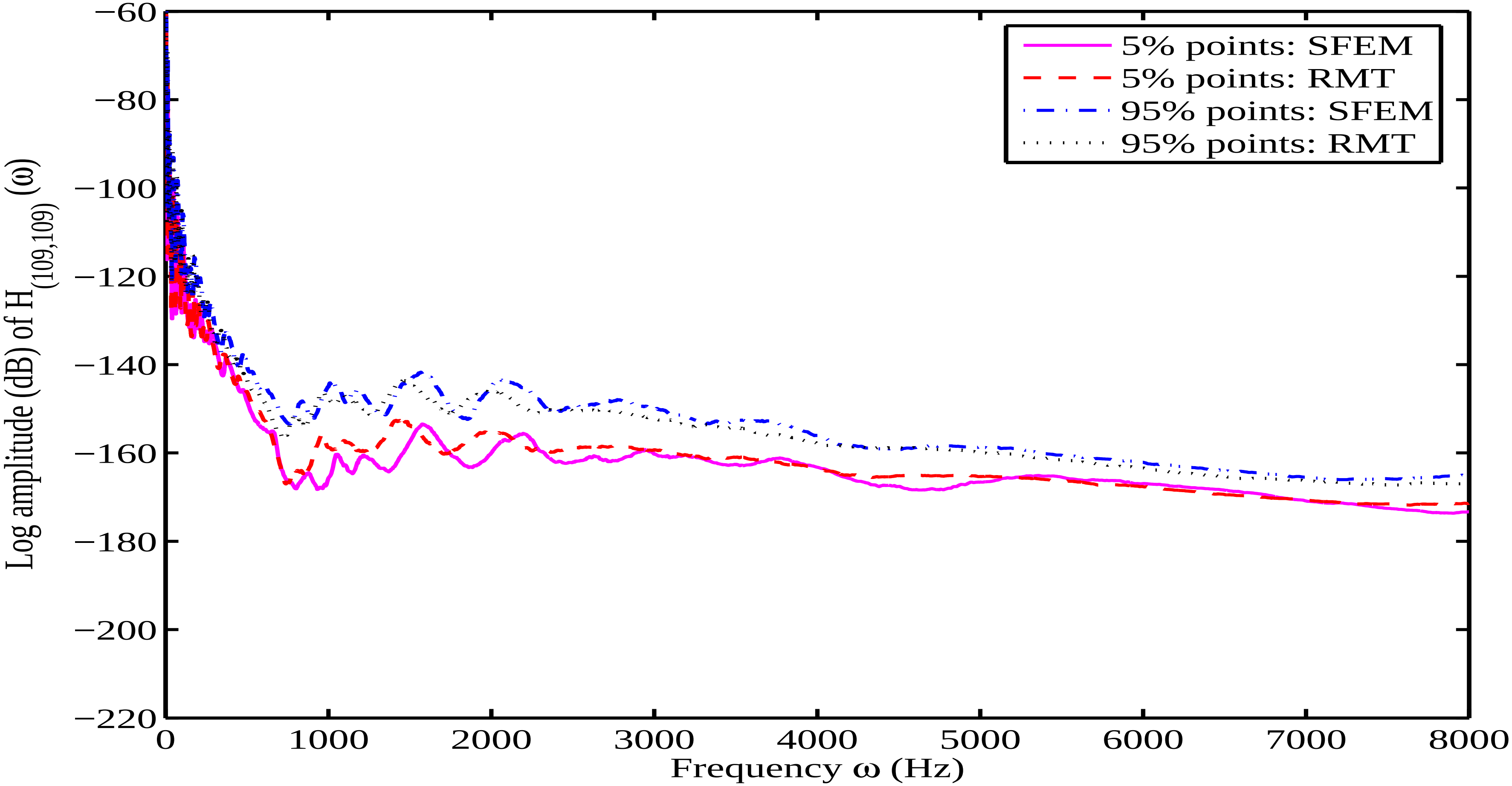
Comparison of the 5% and 95% probability points of the amplitude of the cross-FRF.

Comparison of cross-FRF: High Freq



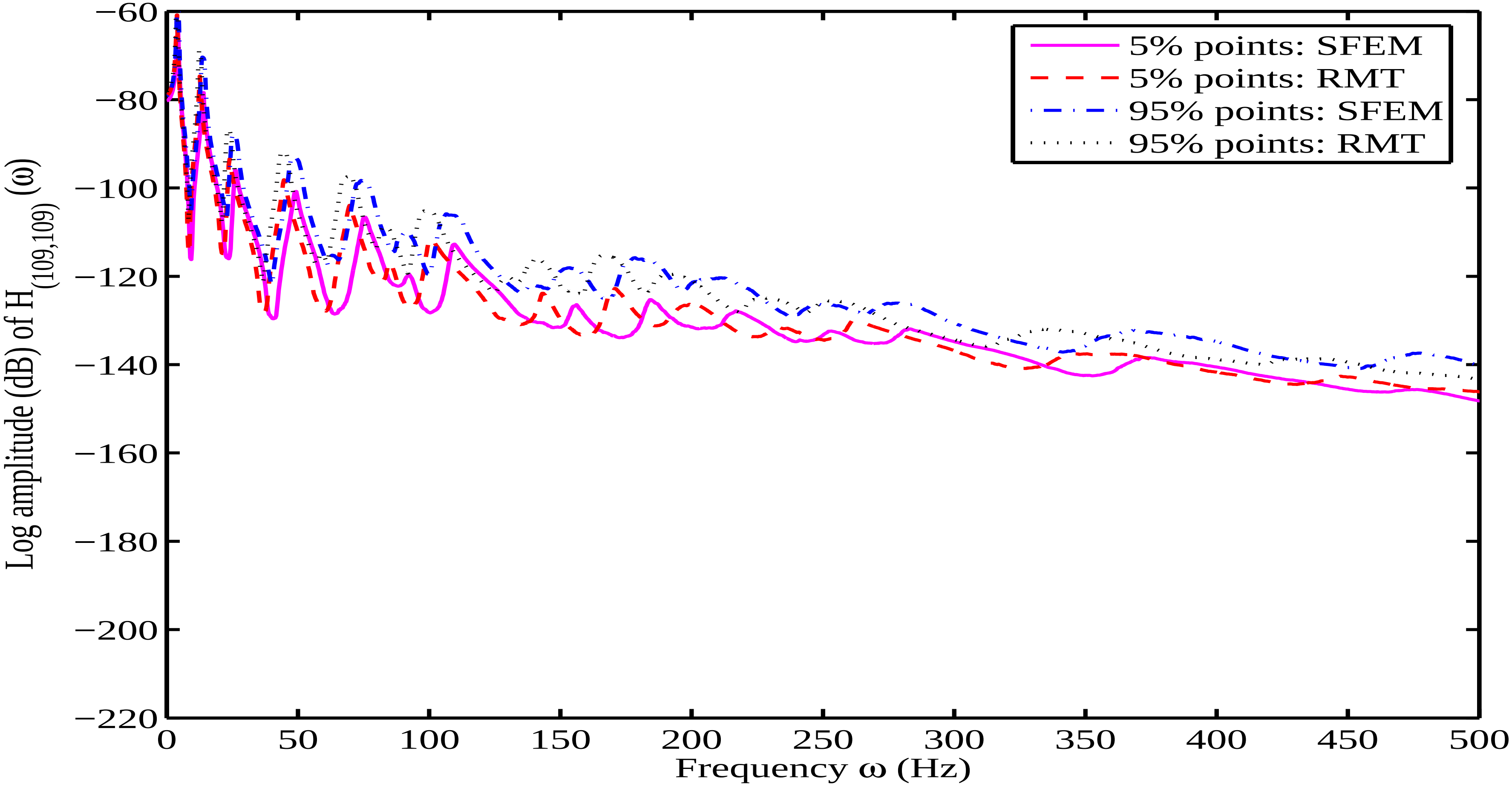
Comparison of the 5% and 95% probability points of the amplitude of the cross-FRF.

Comparison of driving-point-FRF



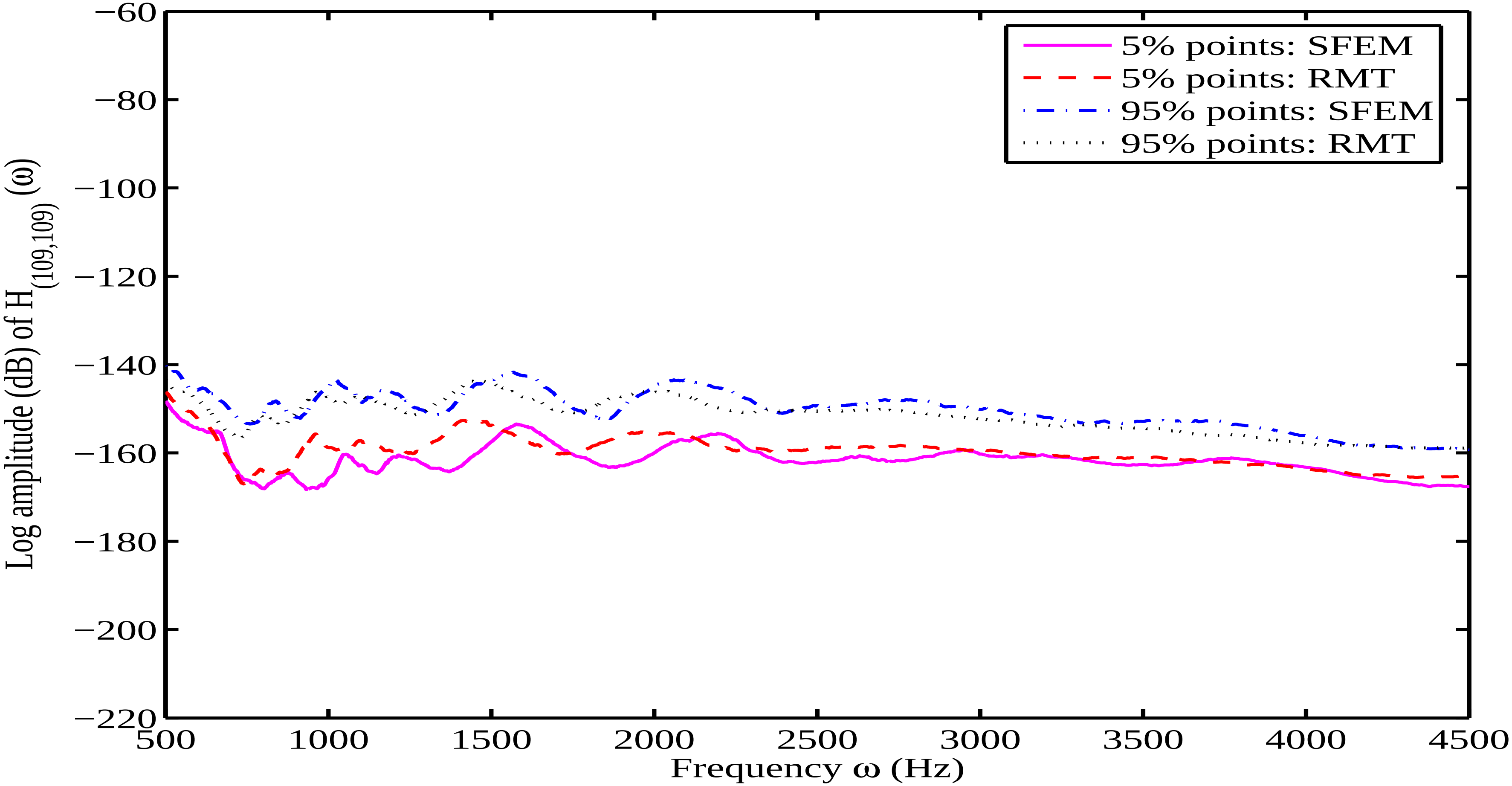
Comparison of the 5% and 95% probability points of the amplitude of the driving-point-FRF.

Comparison of driving-point-FRF: Low Freq



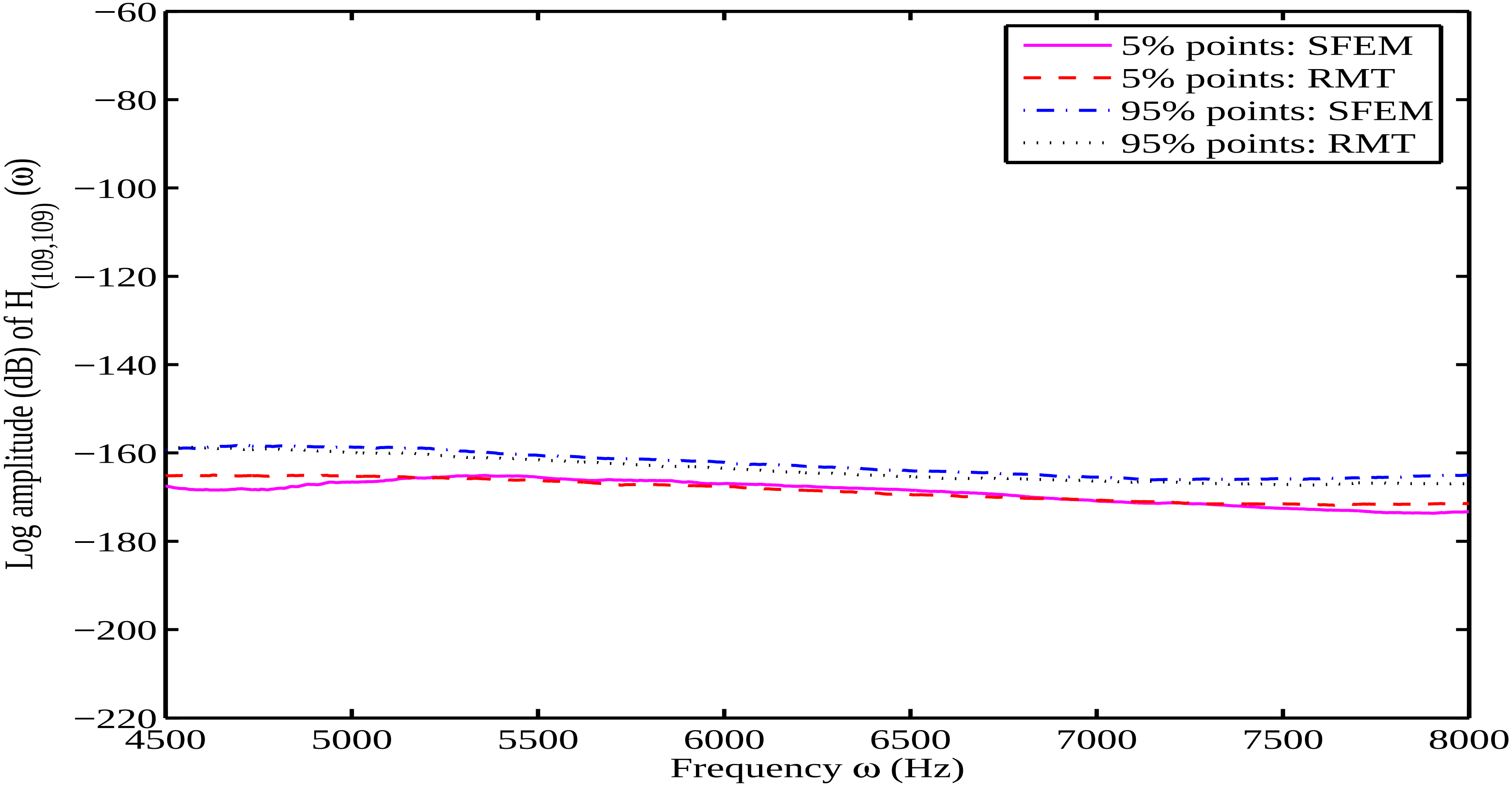
Comparison of the 5% and 95% probability points of the amplitude of the driving-point-FRF.

Comparison of driving-point-FRF: Mid Freq



Comparison of the 5% and 95% probability points of the amplitude of the driving-point-FRF.

Comparison of driving-point-FRF: High Freq



Comparison of the 5% and 95% probability points of the amplitude of the driving-point-FRF.

Summary & conclusions

- Wishart matrices may be used as the model for the system matrices in structural dynamics.
- The parameters of the distribution were obtained in closed-form by solving an optimisation problem.
- Only the mean matrix and normalized standard deviation is required to model the system.
- Numerical results show that SFEM and RMT results match well in the mid and high frequency region.

Next steps

- Eigenvalue and eigenvector statistics
- Steady-state and transient dynamic response statistics
- Distribution of the dynamic stiffness matrix (complex Wishart matrix?) and its inverse (FRF matrix)
- Cumulative distribution function of the response (reliability problem)

Open issues & discussions

- $\overline{\mathbf{G}}$ is just one 'observation' - not an ensemble mean.
- Are we taking account of model uncertainties ('unknown unknowns')?
- How to incorporate a given covariance tensor of $\mathbf{G}$ (e.g., obtained using the Stochastic Finite element Method)?
- What is the consequence of the zeros in $\mathbf{G}$ are not being preserved?