2026 International Conference on Green Aviation (ICGA 2026)
Track 3: Intelligent Structures and Manufacturing for Green Aviation

Decoupled Probability Density Evolution for Reliability-Based Design Optimization and Digital Twin Updating of Engineering Systems

Meng-Ze Lyu (律梦泽)

Institute for Risk & Reliability
Leibniz University Hannover, Germany
November 3, 2026 | Xi'an, China

Presentation overview

01 **Why green aviation needs full-probabilistic tools**
Lightweighting spends design margin — and margin is a probability, not a factor

02 **Decoupled multi-probability density evolution**
One decoupling principle; cost linear instead of exponential in the number of responses

03 **Application A — Reliability-based lightweight design**
Removing the double loop from reliability-based design optimisation

04 **Application B — Digital twin state reconstruction**
Conditional densities of responses that no sensor can reach

05 **Towards a real-time onboard twin**
Offline physics, online algebra — and what is still missing

Two very different engineering questions
— a design question and an operational one —
answered by re-weighting **the same batch of deterministic analyses**.

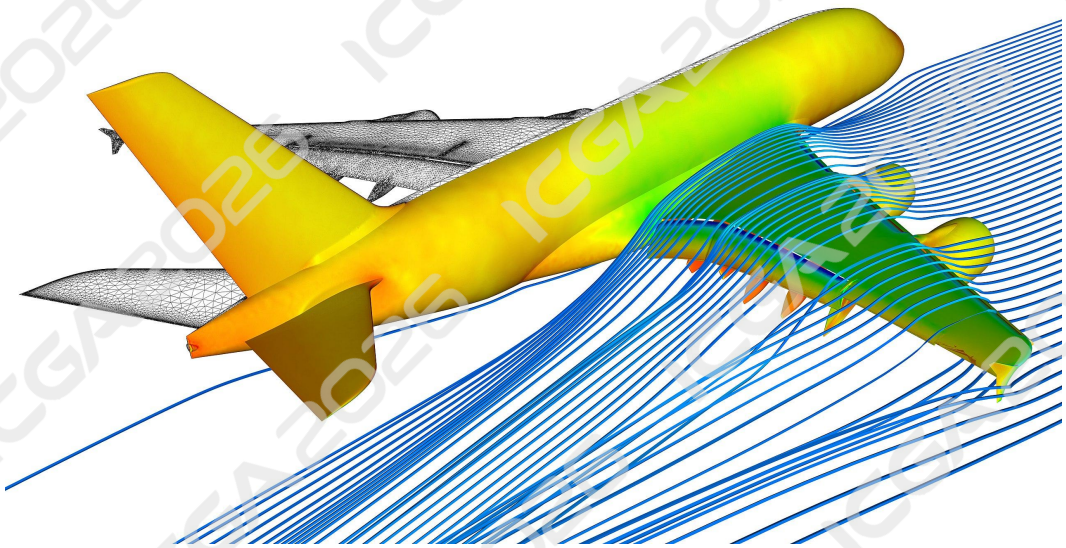
Part 1

Why green aviation needs full-probabilistic tools

Lightweighting spends design margin — and margin is a probability, not a factor

01. Why green aviation needs full-probabilistic tools

Lighter structures are the lever — and they spend the margin



Loads on a flexible airframe are themselves random processes

- Structural mass drives fuel burn and life-cycle emissions. Every kilogram removed compounds over the service life of the airframe.
- But mass is removed from the margin — the same margin that silently absorbs material scatter, process variability and load extremes.
- A deterministic safety factor cannot report how much of that margin is left. A probability can.

Lightweighting is an exercise in spending uncertainty deliberately rather than conservatively.

01. Why green aviation needs full-probabilistic tools

Where the uncertainty actually enters

Material

Composite ply and fibre-volume scatter, matrix properties, batch-to-batch variation

Manufacturing

Additive process parameters, porosity, residual stress, as-built vs as-designed geometry

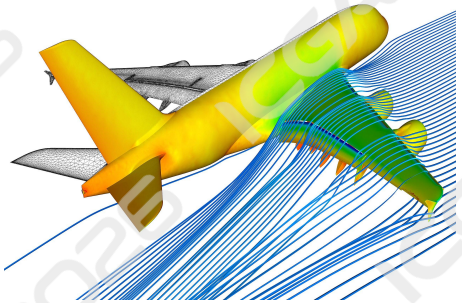


Assembly

Tolerances, joint stiffness, preload, uncertain boundary conditions

Operation

Gust and manoeuvre loads, thermal cycles, progressive damage and degradation



- High-dimensional — tens to hundreds of random variables once a process is resolved.
- Non-Gaussian, and interacting through a nonlinear structural response.
- Not reducible to a handful of load cases without discarding exactly the tails that matter.

01. Why green aviation needs full-probabilistic tools

Two questions — one computational obstacle

Before service — design

How light can this structure be and still meet a target reliability?

Reliability-based design optimisation

In service — operation

Given a handful of sensors, what is the state I cannot measure?

Probabilistic digital twin updating

Both reduce to the same object

full probability density of a nonlinear, high-dimensional response

- Monte Carlo: Accurate, but 10^5-10^6 high-fidelity analyses per design point.
- Explicit joint density grid: Storage and work grow exponentially with the number of responses.

Explicit joint grid

$$\mathcal{O}(N^m)$$

Decoupled M-PDEM

$$\mathcal{O}(m\,N)$$

Part 2

Decoupled multi-probability density evolution

Preservation of probability, the random-event description, and exact decoupling

02. Decoupled multi-probability density evolution

Stochastic system and random source

Equation of motion

$$\dot{\mathbf{X}}(t) = \mathbf{f}[\mathbf{X}(t), \boldsymbol{\Theta}, t], \qquad \mathbf{X}(0) = \mathbf{x}_0$$

Every response is a deterministic functional of $\boldsymbol{\Theta}$

$$Y(t) = h(\boldsymbol{\Theta}, t),$$

$$\boldsymbol{\Theta} = (\Theta_1, \ \ldots, \Theta_s)^{\mathrm{T}} \sim p_{\boldsymbol{\Theta}}(\boldsymbol{\theta})$$

Θ collects every source of uncertainty

Material	moduli, strengths, ply properties
Process	porosity, residual stress, geometry
Assembly	joint stiffness, preload, supports
Excitation	gust /manoeuvre /ground-motion randomness, via a finite set of random variables

Random-event description

Once $\boldsymbol{\Theta}$ is fixed at a realisation $\boldsymbol{\theta}$, the system is entirely deterministic. All randomness is carried by $\boldsymbol{\Theta}$ alone — and never re-enters the dynamics.

The dimension s of $\boldsymbol{\Theta}$ is the whole difficulty.

Lyu MZ, Chen JB*, 2022. ***Struct Saf***, 98: 102233.
Li J, Lyu MZ, 2026. ***Fundamentals of Structural Reliability Analysis***. Springer Nature (in publication).

02. Decoupled multi-probability density evolution

Preservation of probability gives a one-dimensional equation

Preservation of probability, random-event description

$$\frac{\mathrm{D}}{\mathrm{D}t}\int_{\Omega_t} p_{Y\Theta}(y,\boldsymbol{\theta},t)\,\mathrm{d}y\,\mathrm{d}\boldsymbol{\theta}=0$$

Generalised density evolution equation (Li-Chen equation)

$$\frac{\partial p_{Y\Theta}(y,\boldsymbol{\theta},t)}{\partial t}+\dot{h}(\boldsymbol{\theta},t)\frac{\partial p_{Y\Theta}(y,\boldsymbol{\theta},t)}{\partial y}=0$$

Initial condition and recovery of the response density

$$p_{Y\Theta}(y,\boldsymbol{\theta},0)=\delta(y-y_0)\,p_{\Theta}(\boldsymbol{\theta}),$$

$$p_Y(y,t)=\int_{\Omega_\Theta} p_{Y\Theta}(y,\boldsymbol{\theta},t)\,\mathrm{d}\boldsymbol{\theta}$$

Why this matters

- A single response coordinate y — whatever the system is.
- The order of PDE does not grow with the number of degrees of freedom n.
- Nor with the dimension s of the random source.

The curse of dimensionality is moved out of PDE and into the quadrature over $\boldsymbol{\Theta}$ — where point selection can handle it.

Li J, Chen JB, 2009. ***Stochastic Dynamics of Structures***. John Wiley & Sons.
Lyu MZ, Luo Y, Zhang SH*, Beer M, 2026. ***Reliab Eng Syst Saf***, 272: 112474.

02. Decoupled multi-probability density evolution

Decoupling dependent responses — exactly, not approximately

At a fixed realisation the responses are conditionally independent

$$p_{\mathbf{Y}|\boldsymbol{\Theta}}(\mathbf{y}\,|\,\boldsymbol{\theta},t)=\prod_{i=1}^{m}p_{Y_i|\boldsymbol{\Theta}}(y_i\,|\,\boldsymbol{\theta},t)$$

Integrating over the shared random source restores their dependence

$$p_{\mathbf{Y}}(\mathbf{y},t)=\int_{\Omega_{\boldsymbol{\Theta}}}\frac{1}{p_{\boldsymbol{\Theta}}^{m-1}(\boldsymbol{\theta})}\prod_{i=1}^{m}p_{Y_i\boldsymbol{\Theta}}(y_i,\boldsymbol{\theta},t)\,\mathrm{d}\boldsymbol{\theta}$$

One m-dimensional PDE

$$\mathcal{O}(N^{\,m})$$

m one-dimensional PDEs

$$\mathcal{O}(m\,N)$$

Cost grows linearly with the number of responses of interest — not exponentially.

No independence assumption is made.
The responses remain fully dependent after the integration — the product form holds only inside the conditional, where it is exact.

Lyu MZ, Feng DC*, Chen JB, Li J, 2024. ***Comput Meth Appl Mech Eng***, 418: 116443.
Lyu MZ, Feng DC*, Cao XY, Beer M, 2024. ***Earthq Eng Struct Dyn***, 53 (5): 1863-1881.

02. Decoupled multi-probability density evolution

Numerical implementation

1 Partition the probability space

GF-discrepancy point set over $\boldsymbol{\Theta}$;
Voronoi cells give the assigned probabilities

$$P_q = \int_{\Omega^{(q)}} p_{\boldsymbol{\Theta}}(\boldsymbol{\theta})\,\mathrm{d}\boldsymbol{\theta}, \qquad \sum_{q=1}^{n_{\mathrm{sel}}} P_q = 1$$

2 Run the deterministic analyses

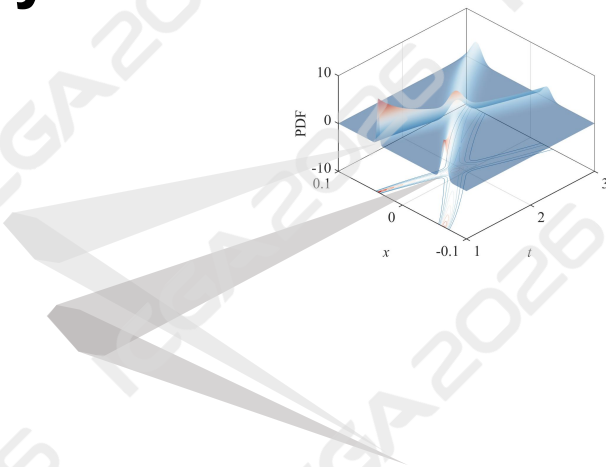
n_{sel} analyses with the full-fidelity model
— the only expensive step, and embarrassingly parallel

3 Solve one-dimensional Li-Chen equations

one per representative point and per response, by path integration /finite difference

4 Assemble the densities

sum the sub-densities weighted by the assigned probabilities



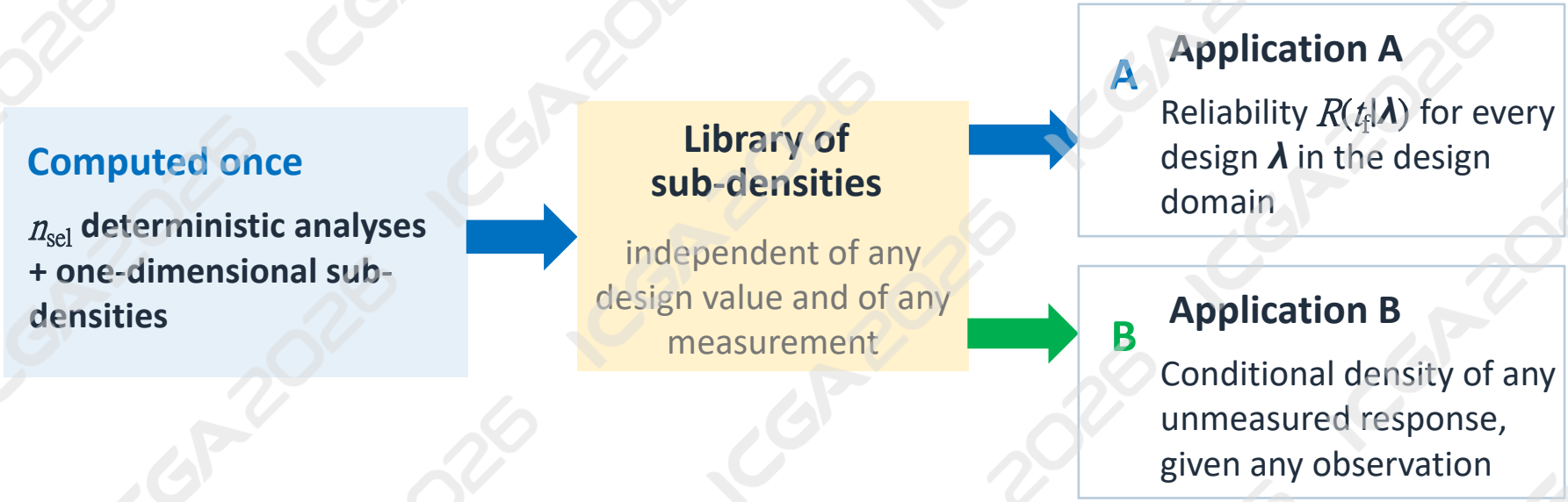
Representative points and their Voronoi cells over the random-source space

Typically $n_{\mathrm{sel}} \approx 10^2$-$10^3$ analyses, against 10^4-10^6 for Monte Carlo at comparable accuracy.

Lyu MZ, Feng DC*, Chen JB, Li J, 2024. ***Comput Meth Appl Mech Eng***, 418: 116443.
Zhou YF, Lyu MZ, Li J*, 2027. ***Reliab Eng Syst Saf***, 277: 113100.

02. Decoupled multi-probability density evolution

One batch of analyses — everything downstream is algebra



The expensive physics is evaluated once.

Design optimisation and state inference are then re-weightings of the same library — and a re-weighting is cheap enough to do inside an optimiser, or inside a monitoring loop while the event is still happening.

Lyu MZ, Feng DC*, Chen JB, Li J, 2024. ***Comput Meth Appl Mech Eng***, 418: 116443.
Luo Y, Lyu MZ*, Broggi M, Thiele M, Fragkoulis VC, Beer M, 2025. ***Reliab Eng Syst Saf***, 270: 112171.

Part 3

Application A — Reliability-based lightweight design

Removing the double loop from dynamic reliability-based design optimisation

03. Application A — Reliability-based lightweight design

Dynamic reliability-based design optimisation

Design problem

$$\min_{\boldsymbol{\lambda}} \ \psi(\boldsymbol{\lambda}) \quad \text{s.t.} \quad R(t_f|\boldsymbol{\lambda}) \geq p_r, \quad \varphi_j(\boldsymbol{\lambda}) \leq 0$$

with a first-passage dynamic reliability

$$R(t_f|\boldsymbol{\lambda}) = \Pr\{Z(t) \in \Omega_s, \ \forall t \in [0, t_f] \mid \boldsymbol{\lambda}\}$$

Conventional double loop

Outer: optimiser updates $\boldsymbol{\lambda}$

Inner: reliability at this $\boldsymbol{\lambda}$

n_{sel} dynamic analyses per iteration

Bottleneck

Reliability has no closed form, so it is evaluated numerically — inside the optimiser's loop. Every candidate design triggers a fresh batch of high-dimensional dynamic analyses.

$N_{iter} \times n_{sel}$ analyses — tens of thousands in practice

Lyu MZ, Yang JS*, Chen JB, Li J, 2025. *Reliab Eng Syst Saf*, 254: 110646.
Yang JS, Lyu MZ*, Chen JB, Xue JY, 2025. *Reliab Eng Syst Saf*, 264: 111378.

03. Application A — Reliability-based lightweight design

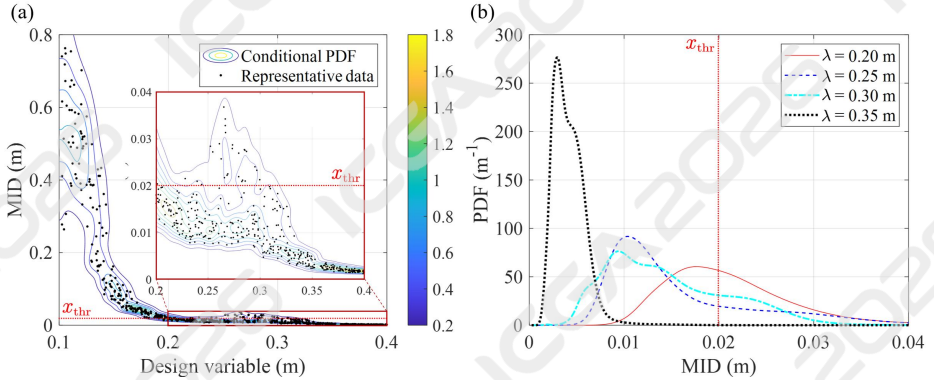
Virtually conditionalising the design variables

Treat the design vector as a uniform random vector

$$\tilde{\boldsymbol{\Theta}} = (\boldsymbol{\Theta}^{\mathrm{T}}, \boldsymbol{\Lambda}^{\mathrm{T}})^{\mathrm{T}}, \qquad \boldsymbol{\Lambda} \sim \mathcal{U}(\Omega_{\mathrm{D}})$$

Reliability becomes a conditional density

$$R(t_{\mathrm{f}}|\boldsymbol{\lambda}) = \int_{\Omega_{\mathrm{S}}} p_{Z|\Lambda}(z \,|\, \boldsymbol{\lambda}, t_{\mathrm{f}})\, \mathrm{d}z$$



(a) conditional density of the maximum inter-storey drift against the design variable
(b) its slices at four design values

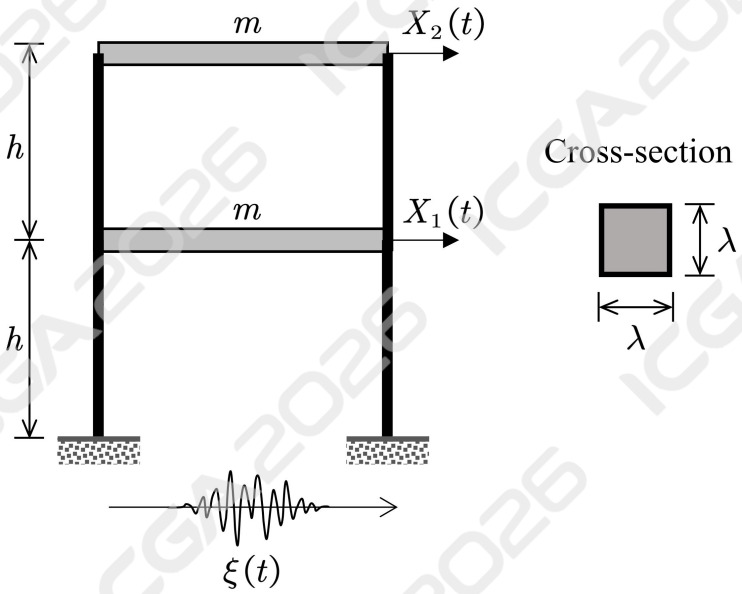
- One batch of analyses over the augmented source ($\boldsymbol{\Theta}$,$\boldsymbol{\Lambda}$) covers the entire design domain.
- The decoupled M-PDEM returns $p(z|\boldsymbol{\lambda})$ as a continuous function of $\boldsymbol{\lambda}$ — the whole reliability landscape at once.
- The optimiser then searches a cheap, surrogate-free function. No re-analysis, no inner loop.

Reliability at any $\boldsymbol{\lambda}$ is the area of the corresponding slice inside the threshold.

Lyu MZ, Feng DC*, Chen JB, Li J, 2024. ***Comput Meth Appl Mech Eng***, 418: 116443.
Lyu MZ, Yang JS*, Chen JB, Li J, 2025. ***Reliab Eng Syst Saf***, 254: 110646.

03. Application A — Reliability-based lightweight design

Example 1: 2-DOF system, one design variable



Linear frame under random harmonic excitation; design variable = column cross-section size λ

Method	Optimum	Re-analyses
Monte Carlo simulation	0.323 m	1,000,000
Iterative RBDO	0.322 m	5,400
Non-iterative (this work)	**0.322 m**	**600**

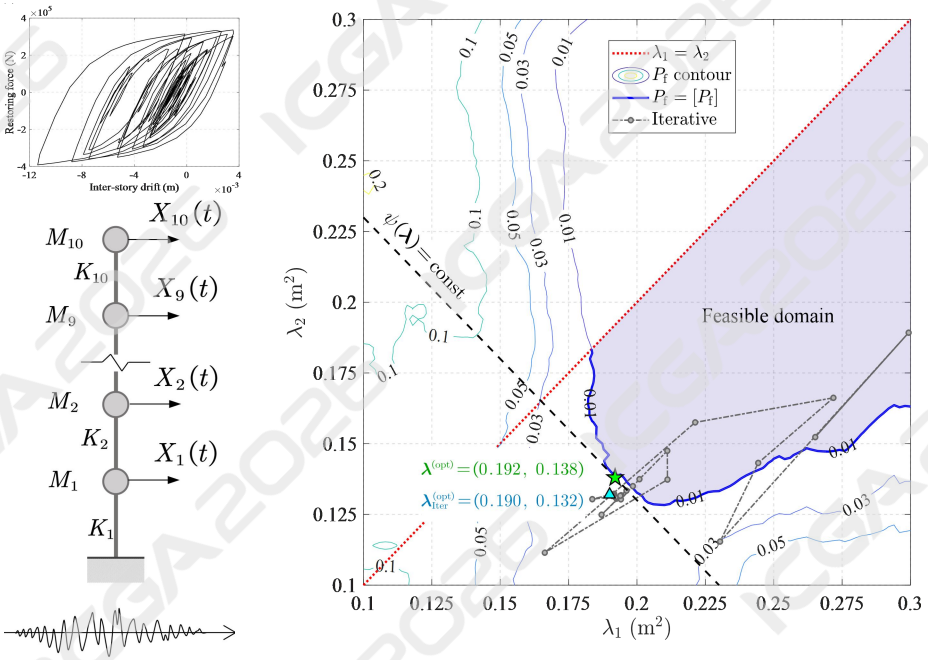
Same optimum —
9× fewer analyses than the iterative scheme,
≈1,700× fewer than Monte Carlo.

The optimum is reproduced to three significant figures. The saving is not accuracy traded for speed — it is the loop itself that has been removed.

Lyu MZ, Yang JS*, Chen JB, Li J, 2025. *Reliab Eng Syst Saf*, 254: 110646.
Yang JS, Lyu MZ*, Chen JB, Xue JY, 2025. *Reliab Eng Syst Saf*, 264: 111378.

03. Application A — Reliability-based lightweight design

Example 2: 10-DOF hysteretic system, two design variables



Bouc–Wen hysteresis at every storey; nonstationary stochastic ground-motion excitation

17× fewer analyses
— a strongly nonlinear, nonstationary, 2-design-variable problem.

- Hysteretic, degrading response — no linearisation anywhere in the formulation.
- The cost advantage grows with the number of design variables, because the optimizer's iteration count does.

Method	Optimum (λ_1, λ_2)	Re-analyses
Iterative RBDO	(0.190 m, 0.132 m²)	20,995
Non-iterative (this work)	**(0.192 m, 0.138 m²)**	**1,200**

The reference iterative scheme needs eight to ten outer iterations — each paying for a full probabilistic analysis. That multiplier is what disappears.

Lyu MZ, Yang JS*, Chen JB, Li J, 2025. *Reliab Eng Syst Saf*, 254: 110646.
Yang JS, Lyu MZ*, Chen JB, Xue JY, 2025. *Reliab Eng Syst Saf*, 264: 111378.

Part 4

Application B — Digital twin state reconstruction

Conditional densities of responses that no sensor can reach

04. Application B — Digital twin state reconstruction

What you can measure is not what you need to know

What a sensor gives you

- A few accelerations or strains
- At accessible, instrumentable points
- Sparse in space, dense in time

What a decision needs

- Internal loads at critical joints
- Damage and degradation state
- Remaining capacity, right now

There is no omniscient view

so the honest answer is a conditional density, not a point estimate

Three essential elements of full-probabilistic reconstruction

1 Computational model

a reliable physics-based dynamical model

2 Random-source model

a reasonable probabilistic characterisation of Θ

3 Monitoring data

valid measurements of the observed responses

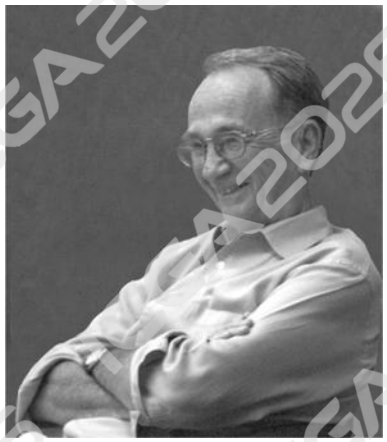
→ **Conditional density of the unmeasured response**

Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. *Mech Syst Signal Pr*, 241: 113452.
Ren T, Liu D*, Lyu MZ, 2026. *Probab Eng Mech*, 85: 103996.

04. Application B — Digital twin state reconstruction

Are the three elements ever exactly satisfied?

Computational model	Random-source model	Monitoring data	
Is it accurate?	Is it reasonable?	Is it exact?	**Never exactly.**



C. Allin Cornell

1938-2007

> *Maybe, in fact, we do not know as engineers how to deal with 'too much' realism in our models. Rather, perhaps progress is no more than a continuous refinement of operational procedures ('rules for a game') that capture just enough reality to protect the public and profession from low quality practice, on one hand, and, on the other, to be supportive of the competent engineering designer who wants to check himself or to roughly calibrate his new design relative to others where we have experience.*

So we state the three elements as assumptions, and study the baseline case first.

Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. ***Mech Syst Signal Pr***, 241: 113452.
Huang X, Lyu MZ, Chen JB*, Li J, 2025. ***Mech Syst Signal Pr***, 232: 112651.

04. Application B — Digital twin state reconstruction

Conditional density from observed-value slices

Quantity we want

$$p_{Y_{\mathrm{pr}}|\mathbf{Y}_{\mathrm{ob}}}(y_{\mathrm{pr}}, t \mid \tilde{\mathbf{y}}_{\mathrm{ob}}) = \ ?$$

Likelihood of each representative point

$$\lambda_q^{(i,k)} = \frac{p^{(q)}_{Y_{\mathrm{ob},i}}(\tilde{y}_{\mathrm{ob},i}(t_k), t_k)}{P_q}$$

Accumulate over the observation history, then normalise

$$W_q = P_q \prod_{k=1}^{j} \prod_{i=1}^{m_{\mathrm{ob}}} \lambda_q^{(i,k)}, \qquad \tilde{w}_q = \frac{W_q}{\sum_{r=1}^{n_{\mathrm{sel}}} W_r}$$

The conditional density is a re-weighted mixture

$$p_{Y_{\mathrm{pr}}|\mathbf{Y}_{\mathrm{ob}}}(y_{\mathrm{pr}}, t \mid \tilde{\mathbf{y}}_{\mathrm{ob}}) = \sum_{q=1}^{n_{\mathrm{sel}}} \tilde{w}_q \frac{p^{(q)}_{Y_{\mathrm{pr}}}(y_{\mathrm{pr}}, t)}{P_q}$$

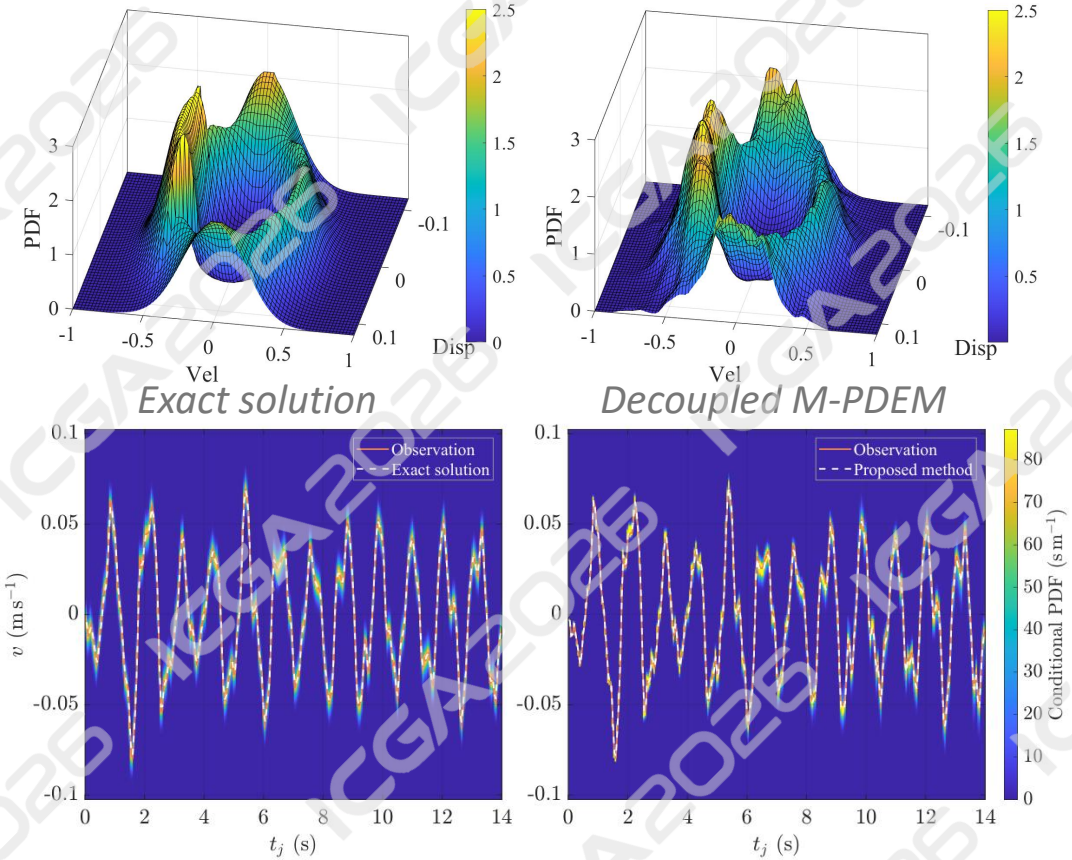
The observed value is simply substituted into the one-dimensional sub-density that was already computed. Nothing is re-run, and no measurement-noise model is required to define the likelihood.

No high-dimensional joint grid is ever assembled.
Each new observation multiplies one scalar per representative point — working storage is independent of the number of observations.

Lyu MZ, Feng DC*, Chen JB, Li J, 2024. *Comput Meth Appl Mech Eng*, 418: 116443.
Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. *Mech Syst Signal Pr*, 241: 113452.

04. Application B — Digital twin state reconstruction

Example 1: Verification on a case with an exact solution



Conditional density of the velocity given 280 displacement observations — exact (left) and proposed (right)

Damped oscillator, random base excitation

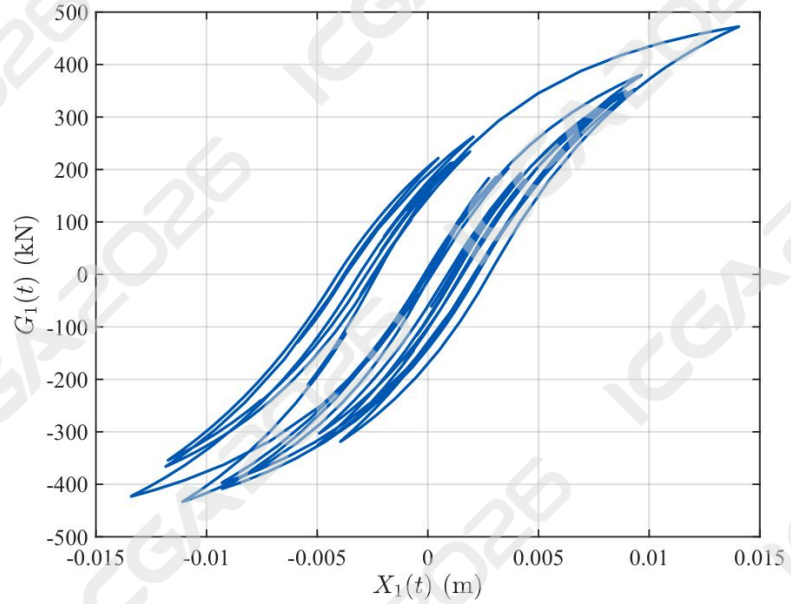
- Observed: the displacement history.
- Target: the velocity, never measured.
- The joint density of displacement and velocity is reproduced, including its multi-modal structure.

At every instant the output is a full density — not a mean and a standard deviation. Exact and proposed are visually indistinguishable.

Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. ***Mech Syst Signal Pr***, 241: 113452.
Huang X, Lyu MZ, Chen JB*, Li J, 2025. ***Mech Syst Signal Pr***, 232: 112651.

04. Application B — Digital twin state reconstruction

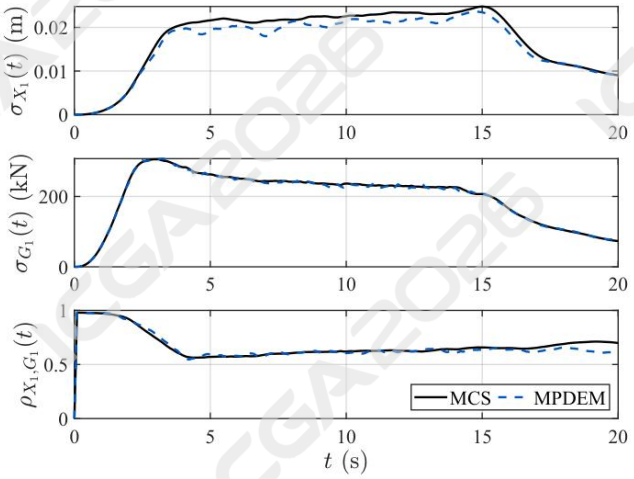
Example 2: 10-DOF hysteretic system — Structure from Application A



Bouc–Wen restoring force against inter-storey drift

Configuration

- Independent random elastic modulus at every storey; nonstationary ground motion via a stochastic harmonic representation.
- Observed: first-storey displacement. Target: first-storey restoring force — the quantity no sensor returns.
- 800 representative analyses against 10^4 Monte Carlo samples.

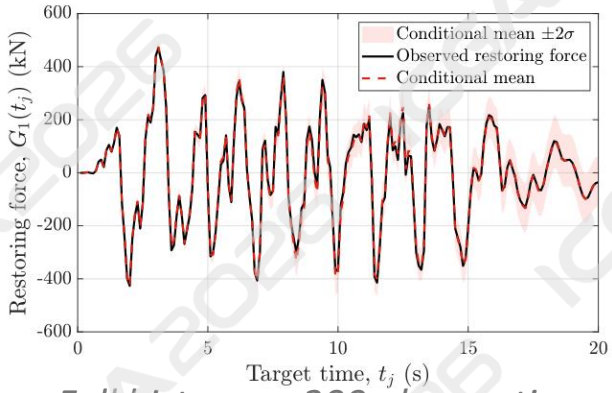


Unconditional check: standard deviations and correlation, Monte Carlo vs M-PDEM

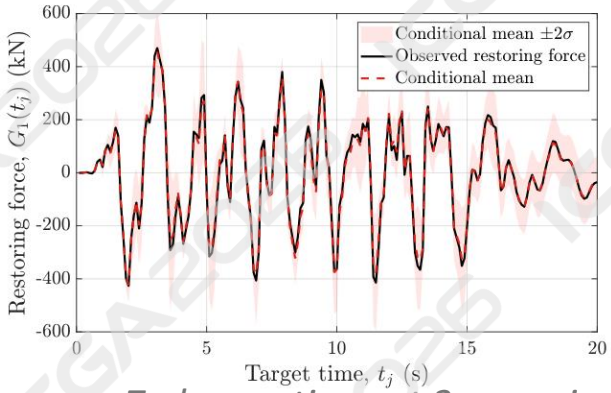
Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. ***Mech Syst Signal Pr***, 241: 113452.
Huang X, Lyu MZ, Chen JB*, Li J, 2025. ***Mech Syst Signal Pr***, 232: 112651.

04. Application B — Digital twin state reconstruction

Example 2: Reconstructing the unmeasured restoring force



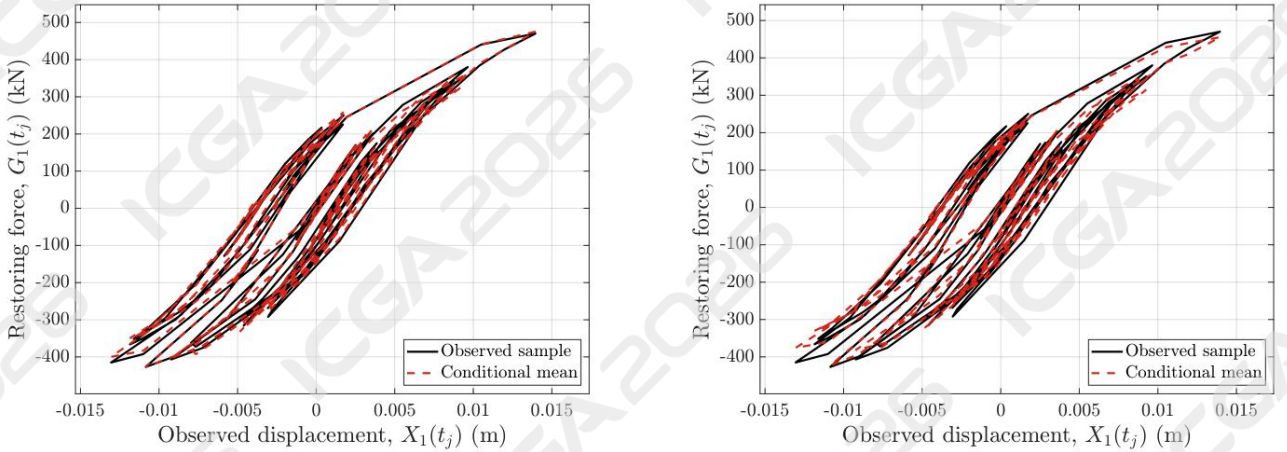
Full history — 200 observations



Sparse — 7 observations at 3 s spacing

The conditional band is the answer — not a by-product of it.

- With the full history the band is tight and the realised force sits inside it throughout.
- With seven observations the mean still tracks, and the band widens exactly where the history is unconstrained.
- A method that stayed confident between observations would be misreporting what it knows.

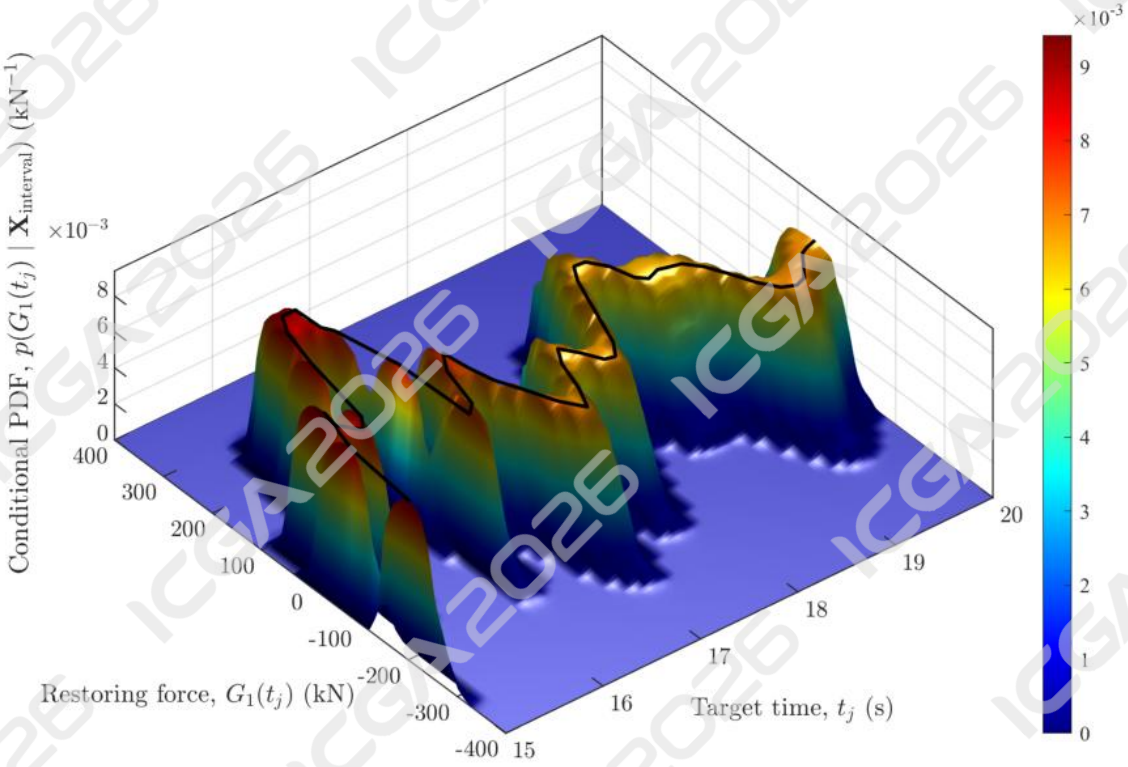


Restoring force against observed displacement — conditional mean vs realised sample

Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. ***Mech Syst Signal Pr***, 241: 113452.
Huang X, Lyu MZ, Chen JB*, Li J, 2025. ***Mech Syst Signal Pr***, 232: 112651.

04. Application B — Digital twin state reconstruction

Example 2: Full conditional density, not only a band



Conditional density of the first-storey restoring force over the target window, updated every second

- The complete conditional density of the unmeasured force, at every instant in the target window.
- Conditional quantiles, exceedance probabilities and any risk measure follow by integration.
- The mean ±2σ band of the previous slide is one projection of this surface.

This is the object a probabilistic digital twin should put in front of a decision-maker
— not a point estimate dressed with an error bar.

Lyu MZ, Zhang SH*, Chen JB, Li J, 2025. ***Mech Syst Signal Pr***, 241: 113452.
Huang X, Lyu MZ, Chen JB*, Li J, 2025. ***Mech Syst Signal Pr***, 232: 112651.

05. Towards a real-time onboard twin

Offline physics, online algebra

Offline — before the event

- Representative point selection and probability partition
- n_{sel} deterministic analyses at full fidelity
- One-dimensional Li-Chen equations → density library

unbounded compute, run once, on the ground

Online — while the event unfolds

$$\ell_q \leftarrow \ell_q + \sum_{i=1}^{m_{\mathrm{ob}}} \ln \lambda_q^{(i,j)}, \qquad \tilde{\mathbf{w}} = \mathrm{softmax}(\boldsymbol{\ell})$$

one multiply–accumulate per representative point, per channel, per sample

$$\mathcal{R} = \frac{\tau_{\mathrm{on}} + \tau_{\mathrm{tr}}}{\Delta t_{\mathrm{s}}} < 1, \qquad \tau_{\mathrm{on}} \sim \mathcal{O}(n_{\mathrm{sel}}\, m_{\mathrm{ob}})$$

The online cost is independent of the number of degrees of freedom and of the fidelity of the offline model. The physics can therefore stay in a high-fidelity model on the ground, while the inference runs on weight- and power-constrained avionics hardware.

Work in progress.

Concluding remarks

01 One decoupling principle - exact at a fixed realisation of the random source - turns an m-dimensional density evolution problem into m one-dimensional ones. Cost grows linearly, not exponentially.

02 In design, virtually conditionalising the design variables removes the double loop. Same optimum as iterative RBDO with 9-17× fewer analyses, and ~10^3× fewer than MCS - with no surrogate model.

03 In operation, the conditional density of an unmeasured response is a re-weighting of pre-computed one-dimensional densities. No joint grid; working storage independent of the observation count.

04 Both applications reuse one batch of deterministic analyses. That is what makes an offline/online split — and therefore a real-time twin — possible at all.

Further work

Model error, prior error and sensor error — and how the three interact. Validation against experimental SHM benchmarks. A diagnostic for when the offline library no longer covers the event being observed.

For this audience

The demonstrations are structural-dynamics benchmarks. What transfers is the engine: any system with a finite random source and a deterministic solver.

Key references

Lyu MZ, Feng DC, Chen JB, Li J, 2024. ***Comput Meth Appl Mech Eng***, 418: 116443.

Lyu MZ, Yang JS, Chen JB, Li J, 2025. ***Reliab Eng Syst Saf***, 254: 110646.

Lyu MZ, Zhang SH, Chen JB, Li J, 2025. ***Mech Syst Signal Pr***, 241: 113452.

Highly appreciate my supervisor and co-authors!



Prof. Jie Li
Tongji U



Prof. Jian-Bing Chen
Tongji U



Prof. Michael Beer
LU Hannover



Prof. De-Cheng Feng
SE.U



A/Prof. Shenghan Zhang
HKUST



A/Prof. Zhi-Qiang Wan
NW.PolyU



Dr. Jia-Shu Yang
Xi'an ATU



A/Prof. Li-Li Weng
Fujian AFU

LinkedIn

Meng-Ze Lyu (律梦泽)

LinkedIn public platform

ASCE-ASME Journal of Risk & Uncertainty in Engineering

Please feel free to contact me.

Call for Papers



ASCE-ASME Journal of Risk & Uncertainty in Engineering Systems Part B: Mechanical Engineering

Submission deadline: **Apr 30, 2027**

Special Issue

Advances in Reliability, Risk and Uncertainty Quantification through Global Collaboration

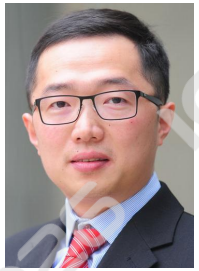
Guest Editors:



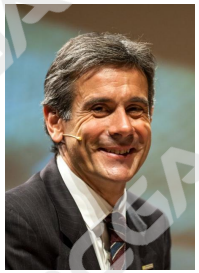
Jian-Bing Chen
Tongji U



Hong-Zhong Huang
UESTC



Yan-Fu Li
Tsinghua U



Enrico Zio
PoliMi



Michael Beer
LU Hannover



Meng-Ze Lyu
LU Hannover

National Chapter of ESRA in China

Welcome to your Contribution!

ASCE AMERICAN SOCIETY OF CIVIL ENGINEERS

ASME SETTING THE STANDARD

Thank you for your kind attention!

Meng-Ze Lyu (律梦泽), Ph.D.
Research Fellow & DFG-funed PI, LU Hannover
Secretary, TC R3, IASSAR
Secretary, Natl Chap China, ESRA
ECEB Member, *ASCE-ASME J Risk U A&B*
E-mail: mengze.lyu@irz.uni-hannover.de