Statistical characterisation of porous media from sound absorption and ultrasound transmission

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[5] KU Leuven, Department of Architecture, Campus Brussels and Ghent, Belgium

Question

More measurements

More uncertainty

?

More accuracy

?

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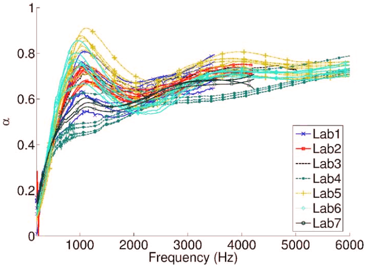
More uncertainty ?

More accuracy ?



Round robin tests, Horoshenkov et al. JASA 2007

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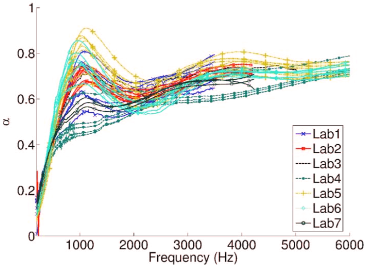

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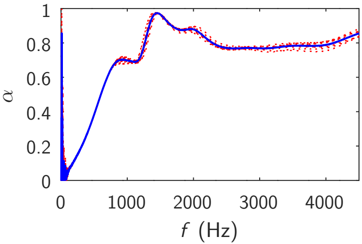

Repeatability test (1 material, 1 impedance tube)

Previous work

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

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Deterministic and statistical methods for the characterisation of poroelastic media from multi-observation sound absorption measurements

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ARTICLE INFO

Communicated by Annie Ross

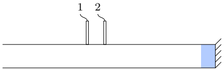
Keywords:
Poroelastic media
Parameter estimation
Coupled problems

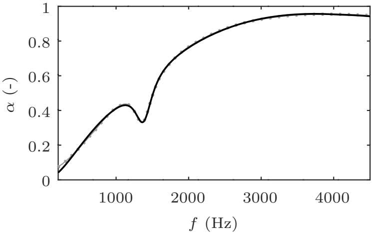
ABSTRACT

This paper proposes a framework for the estimation of the transport and elastic properties of open-cell poroelastic media based on sound absorption measurements. The sought properties are the Biot-Johnson-Champoux-Allard model parameters, namely five transport parameters, two elastic properties and the mass density, as well as the sample thickness. The methodology relies on a multi-observation approach, consisting in combining multiple independent measurements into a single dataset, with the aim of

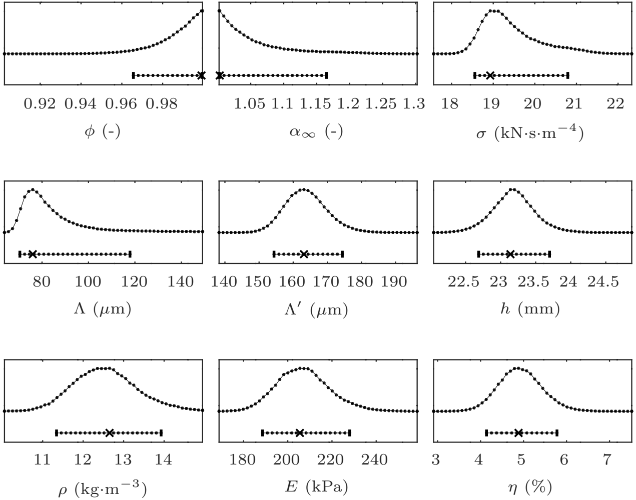
Previous work

Experimental data





Statistical inversion result



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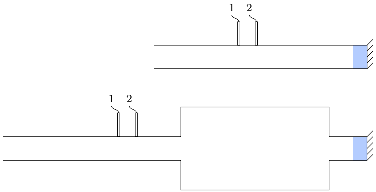

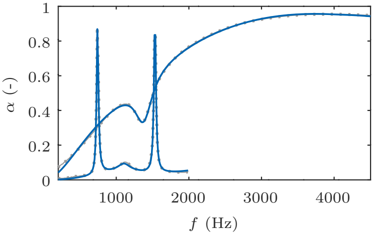

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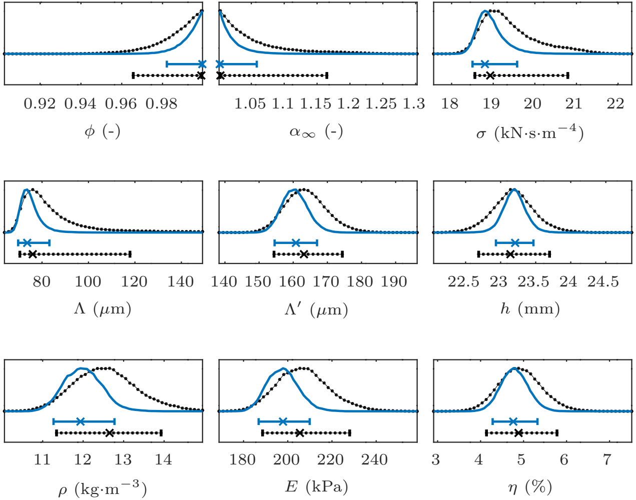


Motivation and goal

Motivation

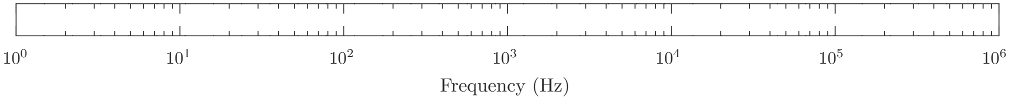
More equations for the same unknowns

↓

Less uncertainty

Idea

Combine measurement data from different frequency ranges



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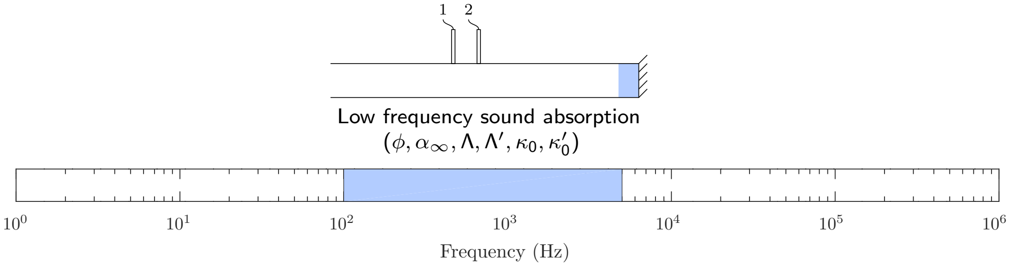

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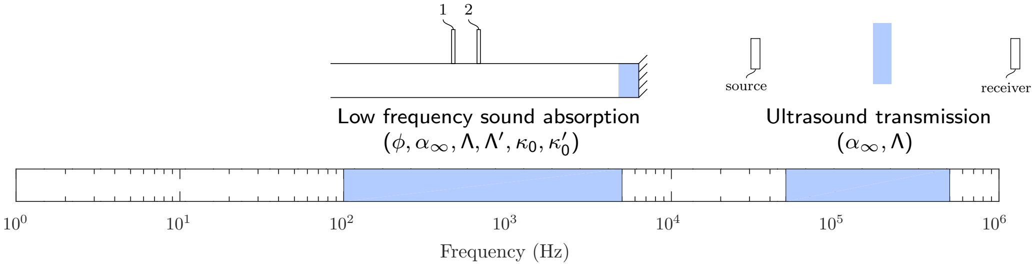

Model and setup

Inverse problem

Numerical tests

Experiments

Closing remarks

Model and setup

Porous material model

Johnson-Champoux-Allard-Lafarge model
e.g. with log-normal pore-size distribution parameterisation*

$\xi = e^{(\sigma_s \log 2)^2}$ $\quad \Lambda = \bar{s}\xi^{-5/2}$ $\quad \kappa_0 = \frac{\bar{s}^2\phi}{8\alpha_\infty}\xi^{-6}$

$\alpha_\infty = \xi^4$ $\quad \Lambda' = \bar{s}\xi^{3/2}$ $\quad \kappa_0' = \frac{\bar{s}^2\phi}{8\alpha_\infty}\xi^{6}$

Unknowns

$$\mathbf{x} = \{\phi, \bar{s}, \sigma_s\}$$

* Horoshenkov, Hurrell, Groby. JASA 145 (2019) 2512

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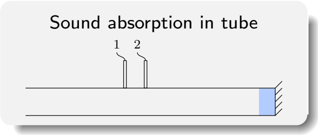
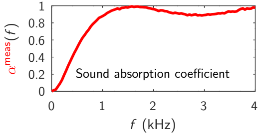
Experimental setups





Measurement data

$$\alpha^{\text{meas}}(\omega)$$

* Horoshenkov, Hurrell, Groby. JASA 145 (2019) 2512

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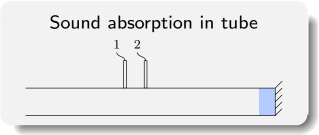
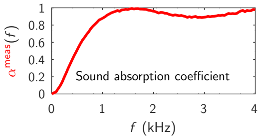
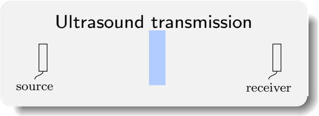
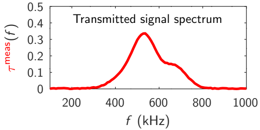








Measurement data

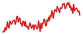
$$\alpha^{meas}(\omega)$$

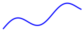
$$\tau^{meas}(\omega)$$

* Horoshenkov, Hurrell, Groby. JASA 145 (2019) 2512

Statistical model

$$\alpha^{\text{meas}}(\omega) = \alpha(\omega, \mathbf{x}) + \varepsilon(\sigma_\varepsilon)$$


measurement

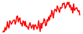

model


error

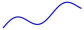
$\mathbf{x}$: unknown parameters
${\sigma_\varepsilon}^2$: unknown error variance

Statistical model

$$\alpha^{\mathrm{meas}}(\omega) - \alpha(\omega, \mathbf{x}) = \varepsilon(\sigma_\varepsilon)$$



measurement



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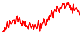
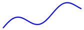


measurement



model

error

$\mathbf{x}$: unknown parameters

${\sigma_\varepsilon}^2$: unknown error variance

Likelihood:

$$P(\alpha^{\text{meas}}|\mathbf{x}) = P_\varepsilon$$

Statistical model

$$\alpha^{\text{meas}}(\omega) - \alpha(\omega, \mathbf{x}) = \varepsilon(\sigma_\varepsilon)$$

$$\tau^{\text{meas}}(\omega) - \tau(\omega, \mathbf{x}) = \mu(\sigma_\mu)$$

measurement — model — error

$\mathbf{x}$: unknown parameters
${\sigma_\varepsilon}^2$: unknown error variance
${\sigma_\mu}^2$: unknown error variance

Likelihood:

$$P(\alpha^{\text{meas}}|\mathbf{x}) = P_\varepsilon$$

$$P(\tau^{\text{meas}}|\mathbf{x}) = P_\mu$$

Statistical model

$$\alpha^{\text{meas}}(\omega) - \alpha(\omega, \mathbf{x}) = \varepsilon(\sigma_\varepsilon)$$

$$\tau^{\text{meas}}(\omega) - \tau(\omega, \mathbf{x}) = \mu(\sigma_\mu)$$

measurement model error

$\mathbf{x}$: unknown parameters
${\sigma_\varepsilon}^2$: unknown error variance
${\sigma_\mu}^2$: unknown error variance

Likelihood:

$$P(\alpha^{\text{meas}}|\mathbf{x}) = P_\varepsilon$$

$$P(\tau^{\text{meas}}|\mathbf{x}) = P_\mu$$

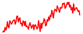
Posterior:

$$\Rightarrow \underbrace{P(\mathbf{x}|\alpha^{\text{meas}}, \tau^{\text{meas}})}_{\text{Posterior}} \propto \underbrace{P(\alpha^{\text{meas}}|\mathbf{x})P(\tau^{\text{meas}}|\mathbf{x})}_{\text{Likelihood}} \underbrace{P(\mathbf{x})}_{\text{Prior}}$$

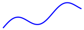
Statistical model

$$\alpha^{\text{meas}}(\omega) - \alpha(\omega, \mathbf{x}) = \varepsilon(\sigma_\varepsilon)$$

$$\tau^{\text{meas}}(\omega) - \tau(\omega, \mathbf{x}) = \mu(\sigma_\mu)$$



measurement



model

error (Gaussian)

$\mathbf{x}$: unknown parameters
${\sigma_\varepsilon}^2$: unknown error variance
${\sigma_\mu}^2$: unknown error variance

Likelihood:

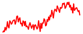
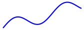
$$P(\alpha^{\text{meas}}|\mathbf{x}) = P_\varepsilon = \frac{\exp\left(-\frac{1}{2}\varepsilon^{\mathsf{T}}\boldsymbol{\Gamma}_\varepsilon^{-1}\varepsilon\right)}{\sqrt{(2\pi)^M \det(\boldsymbol{\Gamma}_\varepsilon)}}$$

$$P(\tau^{\text{meas}}|\mathbf{x}) = P_\mu = \frac{\exp\left(-\frac{1}{2}\mu^{\mathsf{T}}\boldsymbol{\Gamma}_\mu^{-1}\mu\right)}{\sqrt{(2\pi)^N \det(\boldsymbol{\Gamma}_\mu)}}$$

$\Rightarrow$ Posterior:

$$\underbrace{P(\mathbf{x}|\alpha^{\text{meas}}, \tau^{\text{meas}})}_{\text{Posterior}} \propto \underbrace{P(\alpha^{\text{meas}}|\mathbf{x})P(\tau^{\text{meas}}|\mathbf{x})}_{\text{Likelihood}}\ \underbrace{P(\mathbf{x})}_{\text{Prior}}$$

Statistical model

measurement		model		error (Gaussian)
$\alpha^{\text{meas}}(\omega)$	$-$	$\alpha(\omega, \mathbf{x})$	$=$	$\varepsilon(\sigma_\varepsilon)$
$\tau^{\text{meas}}(\omega)$	$-$	$\tau(\omega, \mathbf{x})$	$=$	$\mu(\sigma_\mu)$
				

$\mathbf{x}$: unknown parameters
${\sigma_\varepsilon}^2$: unknown error variance
${\sigma_\mu}^2$: unknown error variance

$P(\mathbf{x})$: uniform prior

Likelihood:

$$P(\alpha^{\text{meas}}|\mathbf{x}) = P_\varepsilon = \frac{\exp\left(-\frac{1}{2}\varepsilon^{\mathsf{T}}\boldsymbol{\Gamma}_\varepsilon^{-1}\varepsilon\right)}{\sqrt{(2\pi)^M \det(\boldsymbol{\Gamma}_\varepsilon)}}$$

$$P(\tau^{\text{meas}}|\mathbf{x}) = P_\mu = \frac{\exp\left(-\frac{1}{2}\mu^{\mathsf{T}}\boldsymbol{\Gamma}_\mu^{-1}\mu\right)}{\sqrt{(2\pi)^N \det(\boldsymbol{\Gamma}_\mu)}}$$

$\Rightarrow$

Posterior:

$$\underbrace{P(\mathbf{x}|\alpha^{\text{meas}}, \tau^{\text{meas}})}_{\text{Posterior}} \propto \underbrace{P(\alpha^{\text{meas}}|\mathbf{x})P(\tau^{\text{meas}}|\mathbf{x})}_{\text{Likelihood}} \underbrace{P(\mathbf{x})}_{\text{Prior}}$$

$$\propto \frac{\exp\left(-\frac{\sum_{m=1}^{M}|\alpha_m^{\text{meas}} - \alpha_m(\mathbf{x})|^2}{2\sigma_\varepsilon^2} - \frac{\sum_{n=1}^{N}|\tau_n^{\text{meas}} - \tau_n(\mathbf{x})|^2}{2\sigma_\mu^2}\right)}{\sqrt{(2\pi\sigma_\varepsilon^2\sigma_\mu^2)^{(M+N)}}} P(\mathbf{x})$$

Solution strategy

Posterior

$$P(\mathbf{x}|\alpha^{\text{meas}}, \tau^{\text{meas}}) = \frac{\exp\left(-\frac{\sum_{m=1}^{M}\left|\alpha_m^{\text{meas}} - \alpha_m(\mathbf{x})\right|^2}{2\sigma_\varepsilon^2} - \frac{\sum_{n=1}^{N}\left|\tau_n^{\text{meas}} - \tau_n(\mathbf{x})\right|^2}{2\sigma_\mu^2}\right)}{\sqrt{(2\pi\sigma_\varepsilon^2\sigma_\mu^2)^{(M+N)}}} P(\mathbf{x})$$

Unknowns

$$\mathbf{x} = \{\phi, \bar{s}, \sigma_s,\ \sigma_\varepsilon, \sigma_\mu\}$$

(Hyperparameters σ_ε and σ_μ have uniform hyperpriors)

Solution strategy

Posterior

$$P(\mathbf{x}|\alpha^{\text{meas}},\tau^{\text{meas}}) = \frac{\exp\left(-\frac{\sum_{m=1}^{M}\left|\alpha_m^{\text{meas}}-\alpha_m(\mathbf{x})\right|^2}{2\sigma_\varepsilon^2} - \frac{\sum_{n=1}^{N}\left|\tau_n^{\text{meas}}-\tau_n(\mathbf{x})\right|^2}{2\sigma_\mu^2}\right)}{\sqrt{(2\pi\sigma_\varepsilon^2\sigma_\mu^2)^{(M+N)}}} P(\mathbf{x})$$

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1. Sampling of the posterior

Metropolis-Hastings algorithm with adaptive proposal*

$\Rightarrow$ Markov chain = approximation of target distribution

* Haario, Saksman, Tamminen. Bernoulli 7 (2001) 223-242

Solution strategy

Posterior

$$P(\mathbf{x}|\alpha^{\text{meas}}, \tau^{\text{meas}}) = \frac{\exp\left(-\frac{\sum_{m=1}^{M}\left|\alpha_m^{\text{meas}} - \alpha_m(\mathbf{x})\right|^2}{2\sigma_\varepsilon^2} - \frac{\sum_{n=1}^{N}\left|\tau_n^{\text{meas}} - \tau_n(\mathbf{x})\right|^2}{2\sigma_\mu^2}\right)}{\sqrt{(2\pi\sigma_\varepsilon^2\sigma_\mu^2)^{(M+N)}}} P(\mathbf{x})$$

0. Initial estimate

Deterministic solution using differential evolution[†]

$$\mathbf{x}^{(\text{init})} = \underset{\mathbf{x}:P(\mathbf{x})}{\arg\min} \left(\sum_{m=1}^{M} \left|\alpha_m^{\text{meas}} - \alpha_m(\mathbf{x})\right|^2, \sum_{n=1}^{N} \left|\tau_n^{\text{meas}} - \tau_n(\mathbf{x})\right|^2 \right)$$

1. Sampling of the posterior

Metropolis-Hastings algorithm with adaptive proposal[*]

⇒ Markov chain = approximation of target distribution

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† Storn and Price. J Global Optim 11 (1997) 341-359
* Haario, Saksman, Tamminen. Bernoulli 7 (2001) 223-242

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$$P(\mathbf{x}|\alpha^{\text{meas}},\tau^{\text{meas}}) = \frac{\exp\left(-\frac{\sum_{m=1}^{M}\left|\alpha_m^{\text{meas}}-\alpha_m(\mathbf{x})\right|^2}{2\sigma_\varepsilon^2} - \frac{\sum_{n=1}^{N}\left|\tau_n^{\text{meas}}-\tau_n(\mathbf{x})\right|^2}{2\sigma_\mu^2}\right)}{\sqrt{(2\pi\sigma_\varepsilon^2\sigma_\mu^2)^{(M+N)}}} P(\mathbf{x})$$

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1. Sampling of the posterior

Metropolis-Hastings algorithm with adaptive proposal*

⇒ Markov chain = approximation of target distribution

2. Post-processing

Point estimates, e.g.:

- Maximum a posteriori estimate $\mathbf{x}^{(\text{MAP})}$
- Conditional mean estimate $\mathbf{x}^{(\text{CM})}$
- Median estimate $\mathbf{x}^{(\text{med})}$

Uncertainty ranges:

- Credible intervals (e.g. 95%)

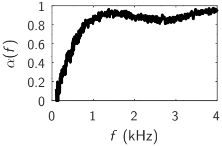
† Storn and Price. J Global Optim 11 (1997) 341-359
* Haario, Saksman, Tamminen. Bernoulli 7 (2001) 223-242

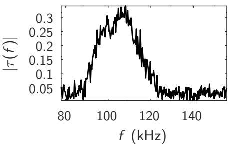
Numerical example 1: compatible model

Simulated material (thickness = 40 mm)

Johnson-Champoux-Allard-Lafarge equivalent fluid

ϕ	α_∞	Λ	Λ'/Λ	κ_0	κ'_0
0.95	2	100 μm	2	$0.5 \cdot 10^{-9}\text{m}^2$	$4 \cdot 10^{-9}\text{m}^2$





Unknowns

Pore-size distribution model parameters

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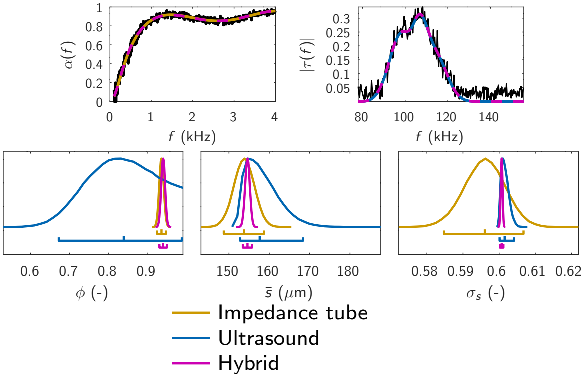
Results



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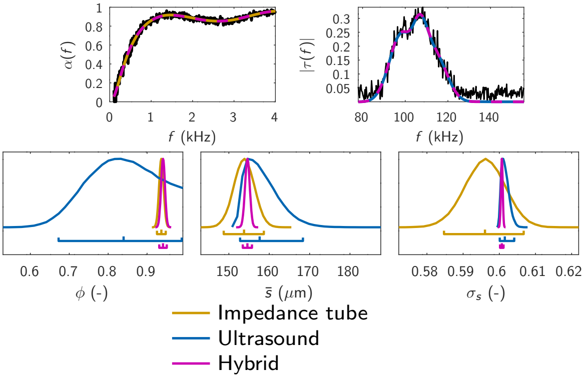
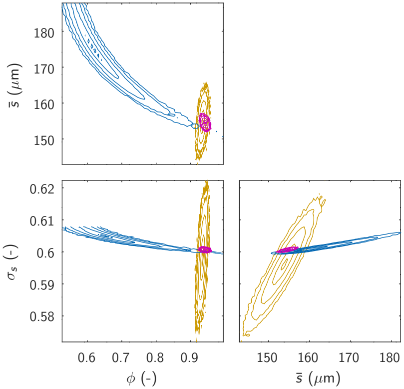


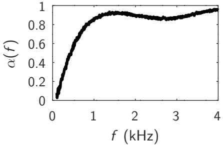


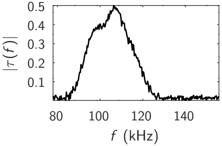
Numerical example 2: incompatible model

Simulated material (thickness = 40 mm)

Johnson-Champoux-Allard-Lafarge equivalent fluid

ϕ	α_∞	Λ	Λ'/Λ	κ_0	κ_0'
0.95	1.9	100 μm	2.1	$0.5 \cdot 10^{-9}$m^2	$4 \cdot 10^{-9}$m^2





Unknowns

Pore-size distribution model parameters

$$\mathbf{x} = \{\phi, \bar{s}, \sigma_s\}$$

Numerical example 2: incompatible model

Simulated material (thickness = 40 mm)

Johnson-Champoux-Allard-Lafarge equivalent fluid

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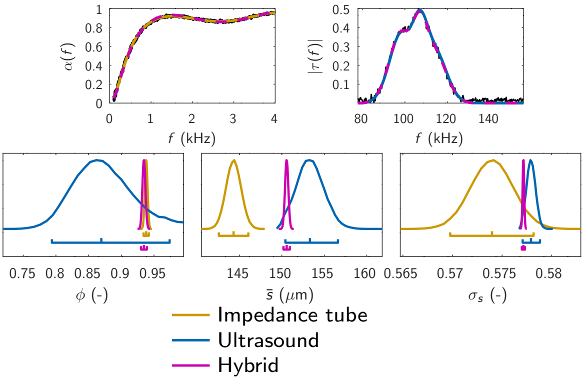
Results



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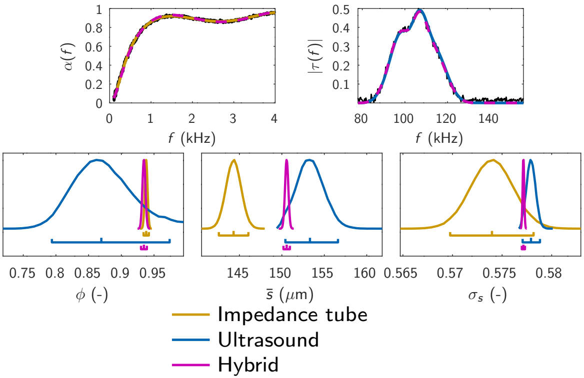
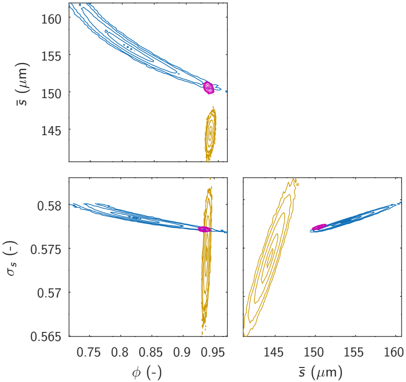
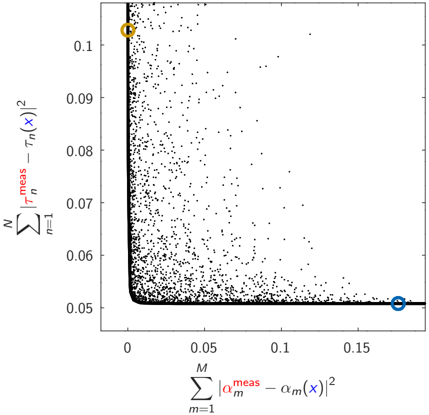




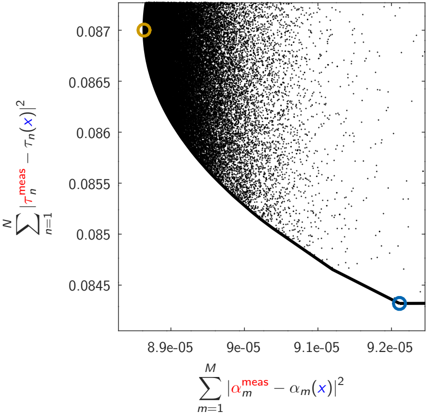
Pareto front

Example 1



Model is **compatible** with data

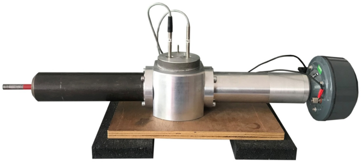
Example 2



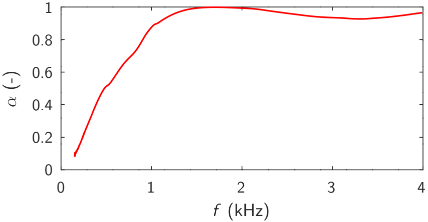
Model is **incompatible** with both datasets simultaneously

Setups

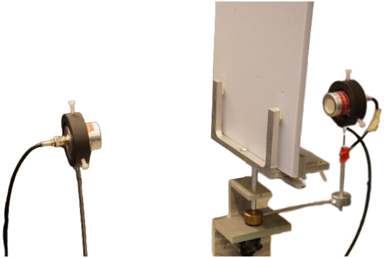
Sound absorption measurement

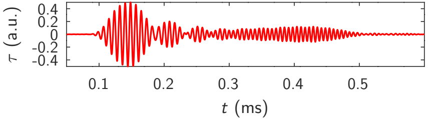


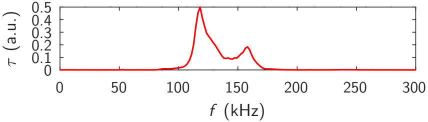
Measured data for a sample of melamine foam



Ultrasound transmission measurement



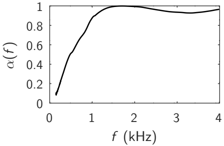


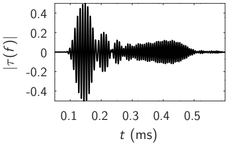


Preliminary experimental results

Tested material

Melamine foam
Thickness = 50 mm (impedance tube)
Thickness = 50 mm (ultrasound)





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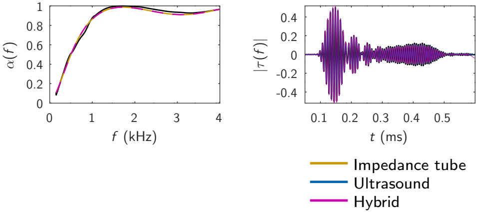

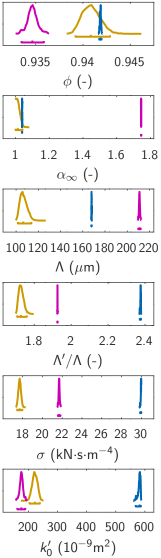

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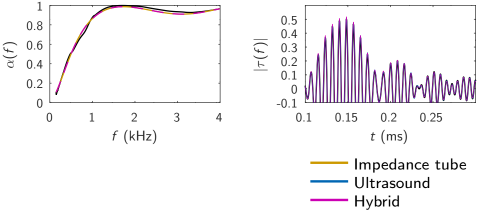

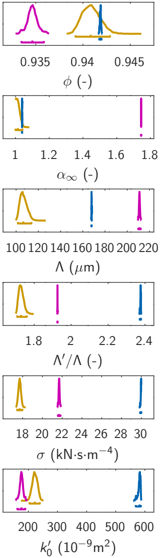

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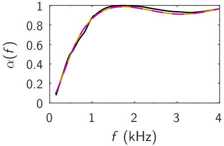

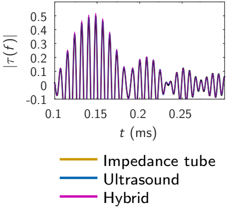

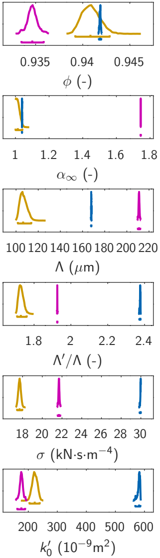

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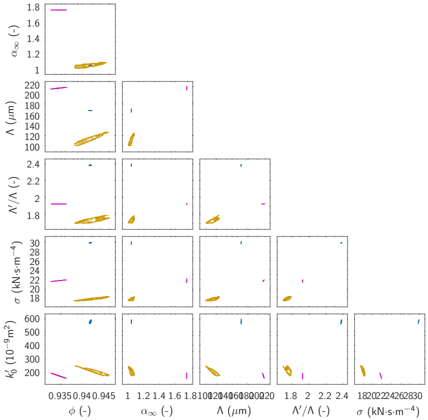

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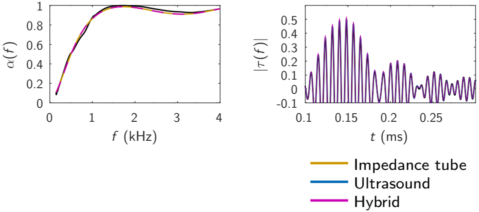
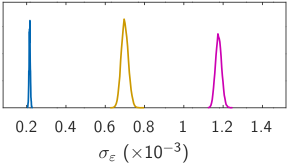
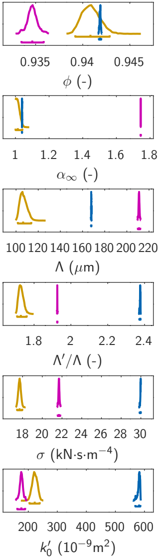


Reconstruction error





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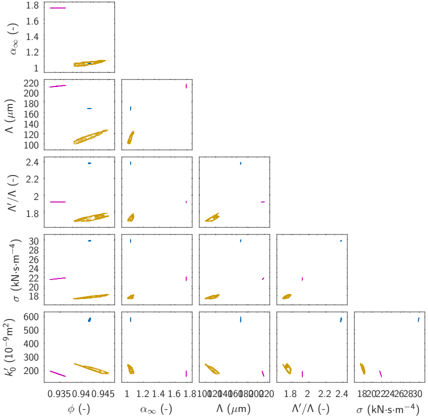


Model and setup

Inverse problem

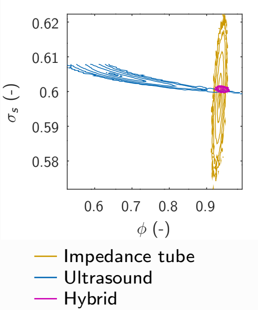
Numerical tests

Experiments

Closing remarks

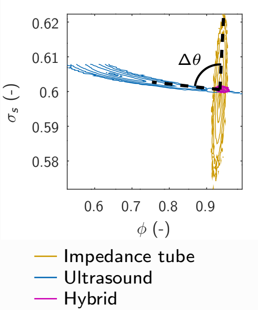
Closing remarks

Different datasets allow to look at the inverse problem from different angles



Closing remarks

Different datasets allow to look at the inverse problem from different angles
. . . literally



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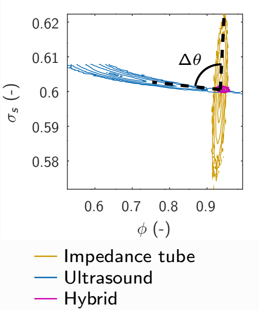
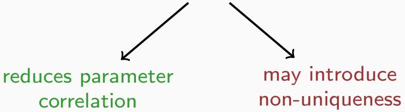


More experimental data



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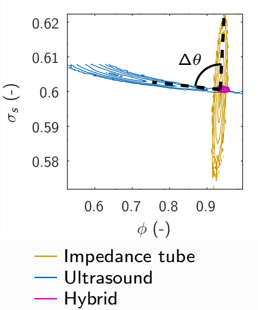

More experimental data

reduces parameter correlation

may introduce non-uniqueness

Future work

- Characterisation of individual samples
  ⇒ circumvent inhomogeneity
- Multi-objective Bayesian approach for the design of locally-resonant media:

  Objective vs. subjective criteria

Acknowledgements

Dr. Timo Lähivaara
University of Eastern Finland, Kuopio, Finland

Prof. Peter Göransson
KTH Royal Institute of Technology, Stockholm, Sweden

European Commission's Horizon Europe research and innovation programme
Grant agreement No. 101072415