ON THE SYNERGY OF DATA AND MODELS FOR VIRTUALIZING STRUCTURES & INFRASTRUCTURES

Prof. Dr. Eleni Chatzi

Chair of Structural Mechanics & Monitoring, ETH Zürich
Reality check: engineered systems...

- Experience motion
- Experience injury
- Experience accidents

- Are exposed to hazards
- Age & deteriorate
- Fail
Structural Health Monitoring

- **Low-cost and easily deployable sensors** for:
  - Recording & interpreting structural response
  - Diagnosing the system’s “health”
  - Optimally organize operation & maintenance actions
The SHM Chain

- Observations
- SHM Technology
- Simulation
- Performance
- Decision Support
- Time Series Analysis
- Network Level Populations
- Interpretability

SHM

Data-driven Models

Time Series Analysis

ML & Stochastic Indicators
The SHM Chain

Simulation

Performance

Decision Support

Interpretability

Network Level Populations

Multiscale FE

Data-driven Models

Nonlinear ROMs

SHM

Observations

SHM Technology

CIS Digital Twin Days
November 15-16th, 2021, EPFL
Prof. Dr. Eleni Chatzi
Inferring Models based on a purely data-driven approach
Learning from Data

Modelling Wake Effects

**Motivation**

- Obtain a representation of the data that is easier to manipulate and visualize
- Capture QoIs at the farm level, conditioned on operational variables

**Generative Modeling**

Visualization of wind deficits on individual WTs and at the farm level via Conditional Variational Autoencoders (CVAEs)

*Smyth and Elliott, 2014*

*Mylonas, Abdalla & Chatzi, Model Validation and Uncertainty Quantification, 2019*
Data is not enough

Physics-based Models

Hybrid Models
- Used for advanced SHM tasks or as Digital Twins
  - Detection, localization, quantification, prognosis
- Used on the fly for diagnostics & control
- Are explainable/interpretable

Purely data-driven representations

Simulation Paths

Hybrid

Computational toll should be low

Prognosis

Diagnosis
Reducing Uncertainty by Imposing Structure

Condition Monitoring
Challenge: Extracting robust data-driven indicators

**Challenge**
Non-stationary vibration response

**Time-periodic dynamics**
On short time intervals due to blade rotation and periodically varying excitation

**Time-dependency**
Over long time periods due to Environmental and Operational Variability (EOV)

Source: LPVS2019 presentation, L-D Avendano Valencia, E. Chatzi
Field Case Study

collaboration with
Repower Wind
Lübbenau GmbH
Bochum University

8 Wind Turbines
Vestas 90-2MW

Repower Wind Farm – Lübbenau Germany – Tower Monitoring
Wind Turbine Monitoring

Structural Response Data

Dertimanis, Spiridonakos, Bogoevska, Dumova, Höffer, & Chatzi

SCADA Data
Challenge: Extracting robust data-driven indicators

Hierarchical surrogate model

Coefficient model

Time-series model

Representation of short-term dynamics
- Non-parametric (PSD, FRF)
- Parametric (AR, ARMA, ARX, etc.)

Condition Assessment/Damage detection

Data – Driven Metamodels for Complex Dynamics

**Nonlinear System**

\[
y(t) = \sum_{i=1}^{n_d} \theta_i \cdot g_i(z(t)) + e(t), \quad e(t) \sim \text{NID}(0, \sigma^2_e[t])
\]

**Discrete Wavelet Transform (Multi-Resolution Analysis)**

\[
\begin{align*}
\theta_i(\xi) &= \sum_{j=1}^{p} \theta_{i,j} \phi_{d(j)}(\xi) \\
y(t) &= \begin{pmatrix} H(z) \\
G(z) \end{pmatrix} \Downarrow \rightarrow \begin{pmatrix} a^1 \\
H(z) \Downarrow \rightarrow \begin{pmatrix} a^2 \\
\vdots \Downarrow \rightarrow \begin{pmatrix} a^L \\
\end{pmatrix}
\end{pmatrix}
\end{align*}
\]

**Time Varying System**

\[
y(t) + a_1[t]y[t-1] + \ldots + a_n[t]y[t-n] = e[t] + c_1[t]e[t-1] + \ldots + c_n[t]e[t-n]
\]

\[
(1 - B)^\kappa a_i[t] = w_{a_i}[t], \quad w_{a_i}[t] \sim \text{NID}(0, \sigma^2_{w_{a_i}}[t])
\]

\[
(1 - B)^\kappa c_i[t] = w_{c_i}[t], \quad w_{c_i}[t] \sim \text{NID}(0, \sigma^2_{w_{c_i}}[t])
\]
K4 Vibration monitoring data
Dynamics of the WT under normal operation

TV-ARMA methods may be employed to model the non-stationary response

Model structure selection

<table>
<thead>
<tr>
<th>Method</th>
<th>BIC, stabilization (na = nc = 32)</th>
<th>BIC (na = nc = 32, v = 0.1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARMA</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SP-TARMA</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Challenge: Extracting robust data-driven indicators

Hierarchical surrogate model

Coefficient model

Time-series model
- Representation of short-term dynamics
  - Non-parametric (PSD, FRF)
  - Parametric (AR, ARMA, ARX, etc.)

Coefficient model
- Representation of long-term variations
  - Functional Series (FS) expansion
  - Polynomial Chaos Expansions (PCE)
  - Gaussian Process Regression (GPR)

Condition Assessment/Damage detection

Long-Term Monitoring – Diagnostic Index

<table>
<thead>
<tr>
<th>Random input variables</th>
<th>Output variables</th>
<th>Polynomial Chaos basis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Wind direction [deg]</td>
<td>1. Standard deviation of the SP-TARMA model residuals</td>
<td>Legendre polynomials (maximum total order = 5)</td>
</tr>
<tr>
<td>2. Power [kW]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. RPM [U/min]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Yaw [rad]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Operational WT in Lübbenau, Germany *(collaboration with Uni. Bochum, Bogoevska et al.)*

Bogoevska, Spiridonakos, Chatzi et al. (2017)
CIS Digital Twin Days
November 15-16th 2021, EPFL
Prof. Dr. Eleni Chatzi

- observe & train
- predict & track error

Robust outlier analysis

Diagnostic Plot
What can Data Driven Diagnosis Ensure?

Detection

Localization

Mode Shape Curvatures based Damage Index
(relying on the distribution of sensors within a structural system)
What can Data Driven Diagnosis Ensure?

Detection

- Healthy - Training
- Healthy - Validation
- Extreme weather
- Damage

Localization

Diagnosis

But not prognosis

Localization

Damage Index

- Baseline mean
- 27. Nov 11:35
- 27. Nov 12:24
- 27. Nov 17:5
- 28. Nov 8:12
- 28. Nov 14:2
Real-time estimation via Fusion of Data & Physics-based models

Part I: Reduction
Reduced Order Representations relying on First Principles
ML-driven ROMs for Nonlinear Dynamics

\[ \begin{bmatrix} X_1 & X_2 & \ldots & X_n \end{bmatrix} \]

*Simpson, Dervilis, Chatzi (2021), On the use of Nonlinear Normal Modes for Nonlinear Reduced Order Modelling*
Verification on a Nonlinear Benchmark

- 108 DOF frame structure featuring Bouc-Wen modelled hysteretic nonlinearities

Benchmark link (available in MATLAB & Python)
https://github.com/KosVla/BoucWenFrame

LSTM Tutorial for Nonlinear Sys ID
https://ethz.ch/content/dam/ethz/special-interest/baug/ibk/structural-mechanics-dam/Software/LSTM_demo_V2.html

Parametric Model Order Reduction

Problem statement

General nonlinear, parametric, dynamical structural system:

\[
M(p) \ddot{u}(t) + g(u(t), \dot{u}(t), p) = f(t, p)
\]

\[u(t) \in \mathbb{R}^n, M(p) \in \mathbb{R}^{n \times n}, f(t, p) \in \mathbb{R}^n, g(u(t), \dot{u}(t)) \in \mathbb{R}^n\]

Parametric dependency on \(k\) parameters denoted by:

\[p = [p_1, \ldots, p_k]^T \in \Omega \subset \mathbb{R}^k\]

Relevant notation:

- \(M\) is the system mass matrix
- \(u\) is the response time history
- \(f\) is the vector of external loads
- \(g\) are the nonlinear, state-dependent internal forces

The goal of parametric MOR is to generate a low-dimensional, equivalent system such that the underlying physics along with the parametric dependencies of interest are further retained.

\[
M_r(p_j) \ddot{u}_r(t) + g_r(u(t), \dot{u}(t), p_j) = f_r(t, p_j)
\]

\[
M_r(p_j) \in \mathbb{R}^{r \times r}, g_r(u(t), \dot{u}(t), p_j) \in \mathbb{R}^r, f_r(t, p_j) \in \mathbb{R}^r
\]

\[
u(t) = V(p_j)u_r(t)
\]

\[
f_r(p_j) = V(p_j)^T f(t, p_j)
\]

\[
M_r(p_j) = V(p_j)^T M(p_j) V(p_j)
\]

\[
g_r(p_j) = V(p_j)^T g(u(t), \dot{u}(t), p_j)
\]

\[r \ll n\]
Parametric Reduced Order Modelling
Handling Nonlinear Behaviour

Addressing Nonlinearities:
- Localized phenomena dominate response due to nonlinear terms
- Solutions span substantial different subspaces

⇒ Approximate local manifolds based on response and underlying dynamics similarity
⇒ Partitioning / Clustering strategies

Parametric Reduced Order Modelling
Handling Nonlinear Behaviour

**Addressing Nonlinearities:**
- Localized phenomena dominate response due to nonlinear terms
- Solutions span substantial different subspaces

$$\Rightarrow$$ Approximate local manifolds based on response and underlying dynamics similarity
$$\Rightarrow$$ Partitioning / Clustering strategies

3D Cantilever Beam

Localized nonlinear region:
Isotropic von Mises plasticity
Spanning 20% of global domain

Parametric context

Ground motion excitation:
=> Temporal & Spectral characteristics

System traits;
=> Yield Stress

Ground motion parametrization

- Gaussian noise signal (1000 components)
- Low-pass filter
  => Dependency on frequency
- Varying Amplitude coefficient

Response = Ideal + Deviatoric

Components are treated independently employing
POD projection-based reduction

→ Projection Basis $V_x$ for the external domains
→ Projection Basis $V_z$ for the isolated nonlinear region

Collab wth Dane Quinn (U Akron), Adam Brink (SNADIA)
ROM Performance

Example Response Approximation

Performance considerations

→ Response is reproduced accurately
→ Stress state is sufficiently captured
→ Speed-up
  ➢ Dependent on size of nonlinear domain
  ➢ Hyper-Reduction needed
→ Size of projection bases:
  ➢ Basis for external components: $r_x=4$
  ➢ Basis for internal component: $r_z=20$

Error metrics

<table>
<thead>
<tr>
<th></th>
<th>Error metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median (Displacements approx.)</td>
<td>$\leq 1%$</td>
</tr>
<tr>
<td>Maximum (Displacements approx.)</td>
<td>$\leq 1%$</td>
</tr>
<tr>
<td>Median (Nodal stress approx.)</td>
<td>$4.83%$</td>
</tr>
<tr>
<td>Maximum (Nodal stress approx.)</td>
<td>$14.75%$</td>
</tr>
</tbody>
</table>
ROM Performance

Stress visualization for the High Fidelity Model

Stress visualization for the pROM approximation
Real-time estimation via Fusion of Data & Physics-based models

Part II: Data Assimilation
Real-Time Virtual Sensing under unknown inputs
Joint Input-State estimation for Fatigue Assessment

Long, Tiso, Tatsis, Chatzi et al. (2018)
Virtual Sensing

1) Uncertainty
2) Nonlinearity
3) Limited Observations
4) Large Dimensionality

unknown states
unknown parameters
a-priori model
unknown inputs

Virtual Sensors
QoI (e.g. fatigue life)

Input-state-parameter estimation of structural systems from limited output information
Hybrid Schemes: Data coupled with Models

Consider the general dynamical system described by the following nonlinear continuous state-space (process) equation

$$\dot{x} = f(x(t), u(t), w(t))$$

and the nonlinear observation equation at time $t = k\Delta t$

$$y(t) = h(x(t), v(t))$$

or in discrete form:

$$x_{k+1} = F(x_k, u_k, w_k)$$

$$y_k = H(x_k, v_k)$$

where $w_k$ is the process noise vector with covariance matrix $Q_k$, $v_k$ is the observation noise vector with corresponding covariance matrix $R_k$, and function $F$ is obtained from $f$ via numerical integration.
Tackling Uncertainty - The Optimal Bayesian Solution

**Predict**

Assuming the prior $p(x_0)$ is known and that the required pdf $p(x_{k-1}|y_{1:k-1})$ at time $k-1$ is available, the prior probability $p(x_k|y_{1:k-1})$ can be obtained sequentially through prediction (**Chapman-Kolmogorov equation**):

$$p(x_k|y_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|y_{1:k-1})dx_{k-1}$$

**Update**

Consequently, the prior (or prediction) is updated using the measurement $y_k$ at time $k$, as follows (**Bayes Theorem**):

$$p(x_k|y_{1:k}) = p(x_k|y_k, y_{1:k-1}) = \frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p(y_k|y_{1:k-1})}$$
Approximation via Particles – the UKF & PF

**Predict Step**

\[ x_{k+1} = F(x_k, u_k, w_k) \]

**Update Step**

\[ y_k = H(x_k, v_k) \]

(measurement equation)
Real-time estimation via Fusion of Data & Physics-based models

Part III: Virtual Sensing for Damage Detection
Real-Time Vibration based Crack Detection using pROMs

Case Study: Crack Detection on Fuselage
**Parametric Model Order Reduction**

Projection based reduction

\[
\mathbf{M}(\theta)\ddot{\mathbf{u}}(t) + \mathbf{C}(\theta)\dot{\mathbf{u}}(t) + \mathbf{K}(\theta)\mathbf{u}(t) = \mathbf{S}_p \mathbf{p}(t), \quad \mathbf{u} \in \mathbb{R}^n
\]

\[
\tilde{\mathbf{M}}(\theta)\ddot{\mathbf{q}}(t) + \tilde{\mathbf{C}}(\theta)\dot{\mathbf{q}}(t) + \tilde{\mathbf{K}}(\theta)\mathbf{q}(t) = \mathbf{V}(\theta)^T \mathbf{S}_p \mathbf{p}(t) , \quad \mathbf{q} = \mathbf{V}(\theta)\mathbf{q}(t), \quad \mathbf{q} \in \mathbb{R}^k
\]

\(\mathbf{V}(\theta)\) Reduced basis, extracted via clustering over regions of the parameter space

\[
\mathbf{V}(p_4) \equiv ... \equiv \mathbf{V}(p_7)
\]

\[
\mathbf{V}(p_1) \equiv \mathbf{V}(p_2) \equiv \mathbf{V}(p_3)
\]
Parametric Model Order Reduction
Mesh Morphing

initial mesh → flat mesh

Discrete minimal surfaces

morphed flat mesh → morphed mesh

Agathos, Tatsis, Chatzi et al. (2021)
Hierarchical state-input-parameter estimation

Hierarchical Bayesian approach

\[ \hat{N}_{\text{eff}} \]

Hypothesis testing

\[ F_1(\theta_1^k) \]

\[ \tilde{y}_k, S_k \]

\[ \tilde{x}_k, P_k \]

\[ w_k^1 \]

\[ \theta_2^2 \]

\[ F_2(\theta_2^k) \]

\[ \tilde{y}_k, S_k \]

\[ \tilde{x}_k, P_k \]

\[ w_k^2 \]

\[ \vdots \]

\[ \vdots \]

\[ w_k^{n_0} \]

\[ F_{n_0}(\theta_1^{n_0}) \]

\[ \tilde{y}_k, S_k^{n_0} \]

\[ \tilde{x}_k^{n_0}, P_k^{n_0} \]

\[ w_k^{n_0} \]

\[ \sum \]

\[ \hat{x}_k, P_k \]

\[ \hat{\theta}_k \]

Resample parameter space

Update weights

Observations \( y_k \)

PF stage

Bank of adaptive AKFs

PF stage

Tatsis, Chatzi et al. (2021, MSSP)
Hierarchical state-input-parameter estimation

Results – Crack Localization

Parameter estimation results from five different runs depicted in red, blue, green orange and grey; actual values represented via black dashed lines.

Tatsis, Chatzi et al. (2021, MSSP)
Hierarchical state-input-parameter estimation

Results – Virtual Sensing

Response estimation at unmeasured points A, B, C and D; green line represents the actual noisy signal and black dashed line depicts the predicted response.

<table>
<thead>
<tr>
<th></th>
<th>FOM1</th>
<th>FOM2</th>
<th>ROM</th>
</tr>
</thead>
<tbody>
<tr>
<td>size</td>
<td>65,730</td>
<td>50</td>
<td>40</td>
</tr>
<tr>
<td>elements</td>
<td>10,402</td>
<td>10,402</td>
<td>258–270</td>
</tr>
<tr>
<td>number of clusters</td>
<td>–</td>
<td>–</td>
<td>8</td>
</tr>
<tr>
<td>maximum error %</td>
<td>–</td>
<td>0.0000</td>
<td>1.8279</td>
</tr>
<tr>
<td>mean error %</td>
<td>–</td>
<td>0.0000</td>
<td>0.6123</td>
</tr>
<tr>
<td>solution time (s)</td>
<td>71.5291</td>
<td>22.8316</td>
<td>0.1288</td>
</tr>
<tr>
<td>speedup</td>
<td>–</td>
<td>–</td>
<td>177.2420</td>
</tr>
</tbody>
</table>

Tatsis, Chatzi et al. (2021, MSSP)
Extensions

- **Dual Kalman Filter** for Joint Input-State estimation
- **Dual Unscented Kalman Filter** for Joint Input-Parameter-State estimation
- **Discontinous “D-KF”** for non-smooth systems
Extensions

- Discontinuous “D-KF” for non-smooth systems

To introduce the computational part of the $D-$ modification, a row switching transformation matrix $T_i$ is defined such that:

$$T_i \cdot v = \begin{cases} v^{oi} \\ v^{ui} \end{cases}$$

$$T_i \cdot A \cdot T_i^T = \begin{bmatrix} A^{oo} & (A^{uo})^T \\ A^{uo} & A^{uu} \end{bmatrix}$$
Extensions

- **Dual Kalman Filter** for Joint Input-State estimation
- **Dual Unscented Kalman Filter** for Joint Input-Parameter-State estimation
- **Discontinous “D-KF”** for non-smooth systems
- **Particle Filter with Mutation** for non-Gaussian states/noise sources

![Diagram](image_url)

Replace by the fit particles or by the prior estimate $\hat{x}_i$ with probability $p_e$

$w'_k = \frac{1}{N}$

Mutate the time invariant component of the previously unfit particles, using a mutation probability $p_m$.

Mutated weights:

$w'_k = \frac{1}{M} \frac{1}{\| \omega \|} $
Real-time estimation via Fusion of Data & Physics-based models
Part IV: Tackling Model Discrepancy
Structured Model Inference

Physic-based stream $z_{t-1}^{phy}$

Inference Network

Sensor data $(x_{1:T})$

Learning stream $z_{t-1}^{NN}$

Prior knowledge

Fusion of knowledge $\alpha z_{t}^{phy} + (1 - \alpha) z_{t}^{NN}$

$z_{t}^{phy}$

$z_{t}^{NN}$

$1 - \alpha$
Physics Informed Deep Markov Models
Coupling Model Structure with ML for Modeling Discrepancy

Bridge/road condition monitoring (drive-by monitoring)

physics-based model

$$\alpha \mathcal{M} + (1 - \alpha) \mathcal{N}\mathcal{N}_1$$

learning-based model

$\mathbb{Z}_t \xrightarrow{\mathcal{N}\mathcal{N}_2} \mathbb{X}_t \xrightarrow{\text{sensor data}} \mathbb{Z}_{t+1} \xrightarrow{\mathcal{N}\mathcal{N}_1} \mathbb{X}_{t+1} \xrightarrow{\text{sensor data}} \mathbb{Z}_{t+2} \xrightarrow{\mathcal{N}\mathcal{N}_1} \mathbb{X}_{t+2} \rightarrow \cdots \rightarrow \mathbb{Z}_T \rightarrow \mathbb{X}_T$
Mobile Sensing

\[ \alpha + (1 - \alpha) \mathcal{N}_1 \]

Collab with SMART @Create
The Silverbox Experimental Benchmark

Electronics Setup
- Models a non-linear damper
  - Linear damping
  - Nonlinear spring force
- Input – waveform representing an external force
- Output - displacement

\[ m \ddot{x}(t) + d \dot{x}(t) + ax(t) + bx^3(t) = u(t) + w(t) \]
\[ y(t) = x(t) + e(t) \]
The Silverbox Benchmark

Figure 14: Testing results of the Silverbox benchmark problem: (a) PgDMM; (b) DMM
Real-time estimation via Fusion of Data & Physics-based models

Part V: What Next?
Fusion of Models with Data (Hybrid approach)  
Vehicle – Track Simulation Models
Hybrid Performance Indicators

Measured axle box vibration

Simplified vehicle model

Kalman filter

Contact force

\[ F = k_{wf} \cdot r_f(t) \]

Forced displacement \( r_f(t) \)

Time (s)
Fractal Values as a Deterioration/Condition Indicator

- The DI decreases due to deterioration, until maintenance actions are taken.
- Actions taken in 2010 and 2011.
Identified Challenges

- Incorporate stochastic models and uncertain data, based on firm mathematical foundations
- Provide accurate assessment of system state at all times
- Optimize long-term objectives
- Uses near-real-time observations
- Allow for near-real-time optimal decision support
Sequential decision process with alternating Actions (A) & observations (Ω)

\[ T = P(s' | s, a) \]
Markov Decision process

**Fully Observable MDP**

- Decision depends on current state, no history
- Initial state is known
- Action’s consequences are known
- World is known
- The state is fully observable

**Partially Observable MDP**

(Smallwood and Sondik, 1973; Sondik, 1978)
Markov Decision process

Fully Observable MDP

- Decisions depend on current state and history
- Initial state is uncertain
- Actions are uncertain
- World is known
- Observations are uncertain
- Sequential process: action $\rightarrow$ observation $\rightarrow$ action . . .

(Partially Observable MDP)

- Decisions depend on current state and history
- Initial state is uncertain
- Actions are uncertain
- World is known
- Observations are uncertain
- Sequential process: action $\rightarrow$ observation $\rightarrow$ action . . .

(Smallwood and Sondik, 1973; Sondik, 1978)
The POMDP Framework

\[ O = P(o|s', a) \]

\[ T = P(s'|s, a) \]

\[ b(s) \]

\[ b(s') \]
Use of Reinforcement Learning for Model Inference

\[ O = P(o|s', a) \]

\[ T = P(s'|s, a) \]
Bayesian HMM to fit the fractal values DI

- Transition Matrices
  - Strongly informative Dirichlet priors, one per each action

- Hidden States
  - Categorical Distribution, Dependent on actions

- Observation Model
  - Informative priors
  - Sampling with HMC (NUTS)

- Observations (Fractal values)
Transition matrix results: action 0 Do-nothing
Transition matrix results

minor action 1 (tamping)

major action 2 (renewal)
Use of GPR Data for Ballast Assessment

Schöbi & Chatzi (2016); Andtiotis, Papokonstantinou & Chatzi (2021)
Goals

- **Intelligent Use** of Monitoring **Data for Understanding & Tracking Dynamics**

- **Optimally fuse data & models** for improved assessment and prediction capabilities for **systems beyond LTI**

- **Explainable/Interpretable Reduced Order Models**

- Identifying **suitable performance indicators** across local/global, system/network levels

- **Getting More** out of Engineered Systems (longer-lasting, safer, more serviceable systems)
Acknowledgments

- The European Research Council via the ERC Starting Grant WINDMIL (ERC-2015-StG #679843) on the topic of Smart Monitoring, Inspection and Life-Cycle Assessment of Wind Turbines.


- H2020-MSCA-IF-2017 Grant, SiMAero, Simulation-Driven and On-line Condition Monitoring with Applications to Aerospace Proposal

- SANDIA National Labs
We welcome questions/comments/collaboration:
chatzi@ibk.baug.ethz.ch