BUILD-IT2023 Workshop

19-20 October, Rome, Italy

DIGITAL TWINS OF CIVIL STRUCTURES USING NEURAL NETWORKS AND PROBABILISTIC GRAPHICAL MODELS

Matteo Torzoni

Dipartimento di Ingegneria Civile e Ambientale
Politecnico di Milano
matteo.torzoni@polimi.it

Joint work with
Marco Tezzele, Stefano Mariani, Andrea Manzoni, Karen E. Willcox

POLITECNICO MILANO 1863
DIPARTIMENTO DI INGEGNERIA CIVILE E AMBIENTALE

DIPARTIMENTO DI MATEMATICA

MOX MODELLISTICA E CALCOLO SCIENTIFICO
MODELING AND SCIENTIFIC COMPUTING

TEXAS

ODEN INSTITUTE FOR COMPUTATIONAL ENGINEERING & SCIENCES

The need of Structural Health Monitoring (SHM)

Aloha Airlines 1988, separation of the fuselage upper lobe – 1 fatality

Genoa 2018, partial collapse of the Morandi Bridge – 43 fatalities

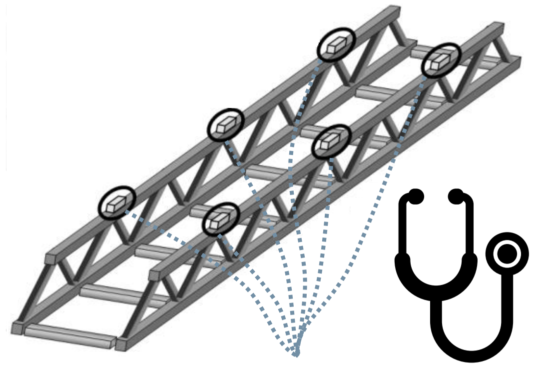
What is SHM?

The implementation of a damage detection strategy for deteriorating structures.

Why SHM?

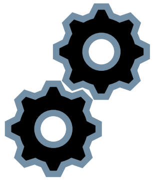
Optimal management: to reduce lifecycle costs and to increase the system safety and availability.

State-of-art: workflow & SHM hierarchical structure



Sensor observations
(multivariate time series,
e.g. accelerations meas.)

→



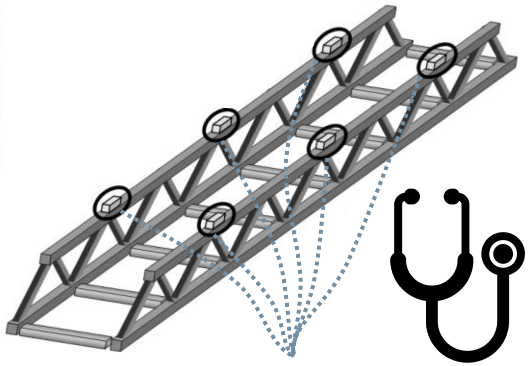
Vibration-based
SHM

→

Underlying
cause

Farrar, Worden. Structural Health Monitoring: A Machine Learning Perspective; John Wiley & Sons, 2013.
Rytter. Vibration Based Inspection of Civil Engineering Structures. Ph. D. dissertation. Aalborg University, Denmark, 1993.

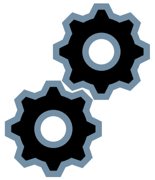
State-of-art: workflow & SHM hierarchical structure



Damage is any change in a structural property negatively affecting a mechanical system

Sensor observations
(multivariate time series, e.g. accelerations meas.)

→



Vibration-based SHM

→

Underlying cause

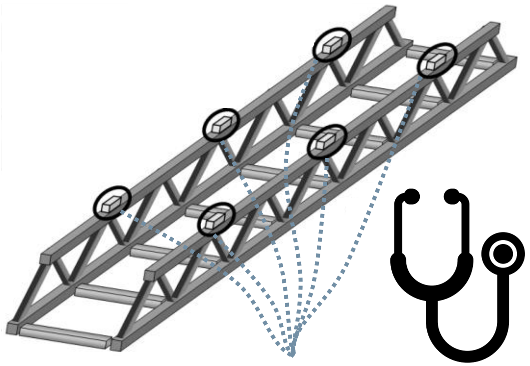
⇢

Levels of detail

- DETECTION
- LOCALIZATION
- QUANTIFICATION
- PROGNOSIS

Farrar, Worden. Structural Health Monitoring: A Machine Learning Perspective; John Wiley & Sons, 2013.
Rytter. Vibration Based Inspection of Civil Engineering Structures. Ph. D. dissertation. Aalborg University, Denmark, 1993.

State-of-art: workflow & SHM hierarchical structure



Damage is any change in a structural property negatively affecting a mechanical system

Sensor observations
(multivariate time series, e.g. accelerations meas.)
→
Vibration-based SHM
→
Underlying cause
- - - →
Levels of detail

- DETECTION
- LOCALIZATION
- QUANTIFICATION
- PROGNOSIS

Vibration-based SHM:

Data-driven
(need labeled training datasets)

Model-based
(need reduced-order or surrogate models)

Which data? → Physics-based models (localization, quantification)

Farrar, Worden. Structural Health Monitoring: A Machine Learning Perspective; John Wiley & Sons, 2013.
Rytter. Vibration Based Inspection of Civil Engineering Structures. Ph. D. dissertation. Aalborg University, Denmark, 1993.

SHM for optimal management of deteriorating structures

Maintenance paradigm shift

- CORRECTIVE (fault driven) — **yesterday**
- SCHEDULED (time based) — **today**
- CONDITION-BASED or PREDICTIVE — **sensor data systematic diagnoses**

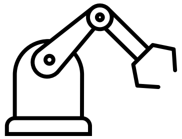
SHM for optimal management of deteriorating structures

Maintenance paradigm shift

- CORRECTIVE (fault driven) — **yesterday**
- SCHEDULED (time based) — **today**
- CONDITION-BASED or PREDICTIVE — **sensor data systematic diagnoses**

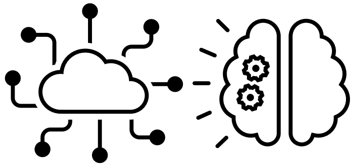
Goal: create a digital twin that adapts to the evolving structural health providing real-time health diagnostics that enable dynamic decision making about management and maintenance actions.

Digital twin



Physical object

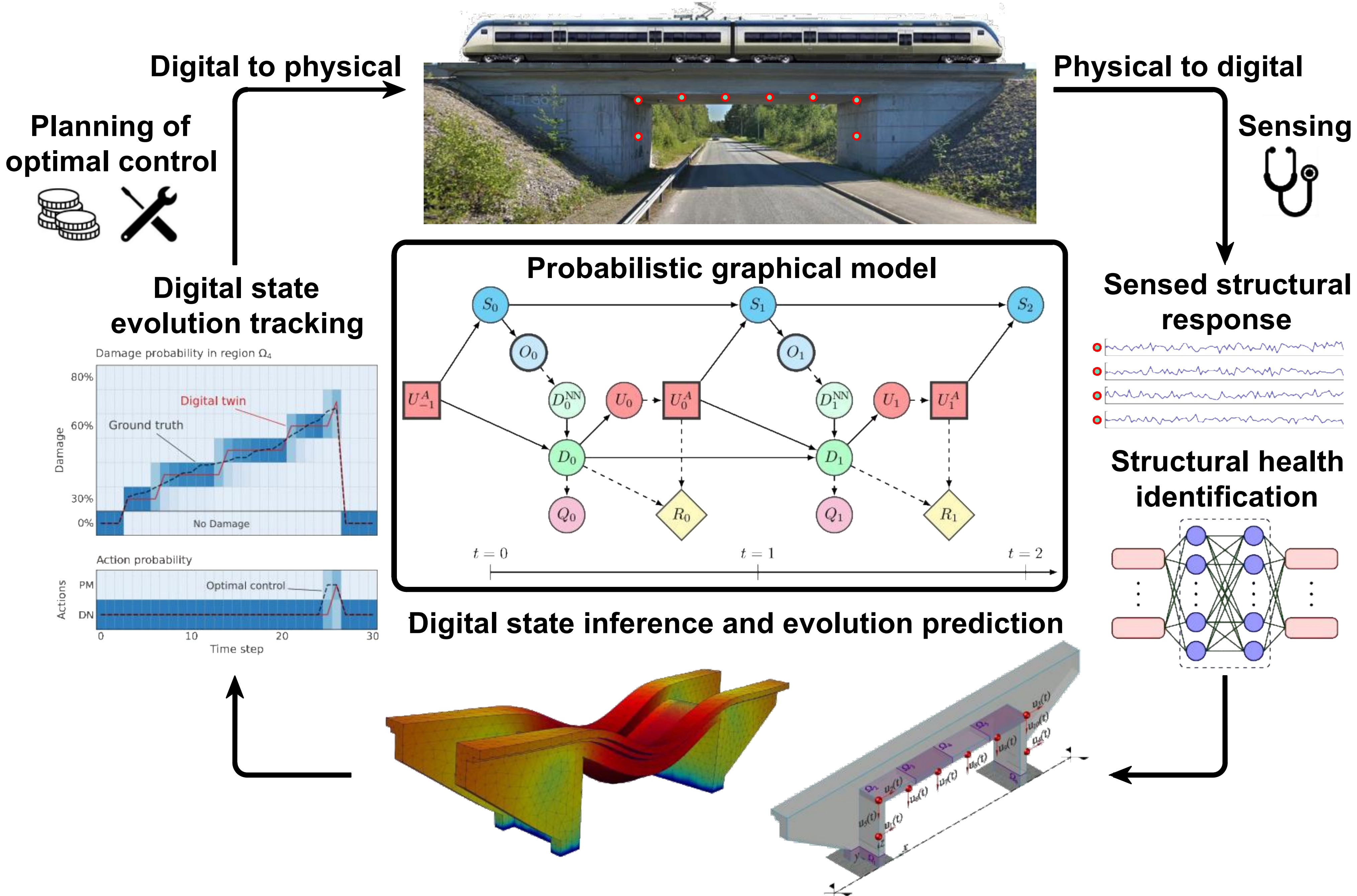
Virtual replica



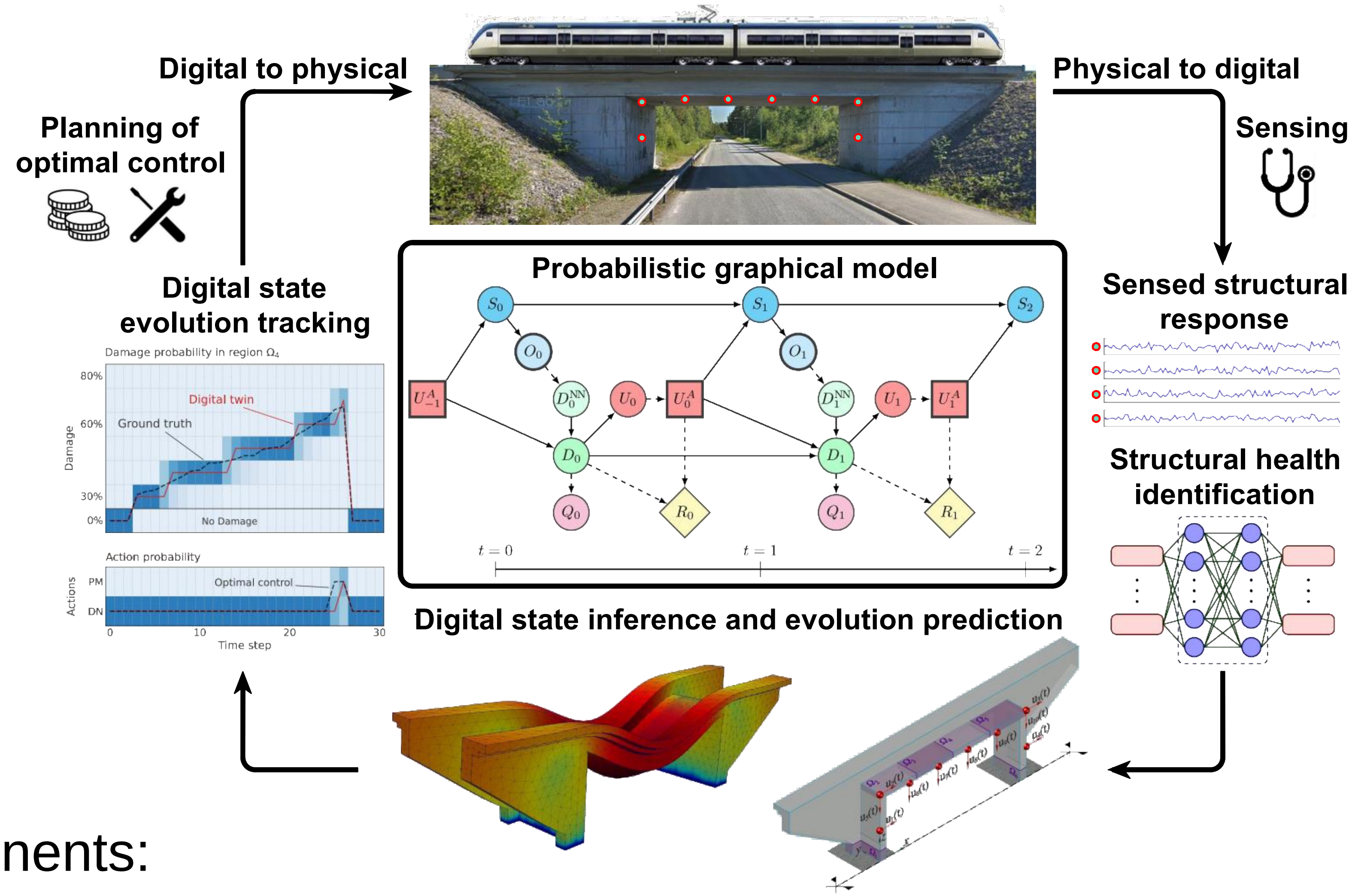
Data + models
Data assimilation
Prediction

Automatic information flow

Overview: end-to-end information flow



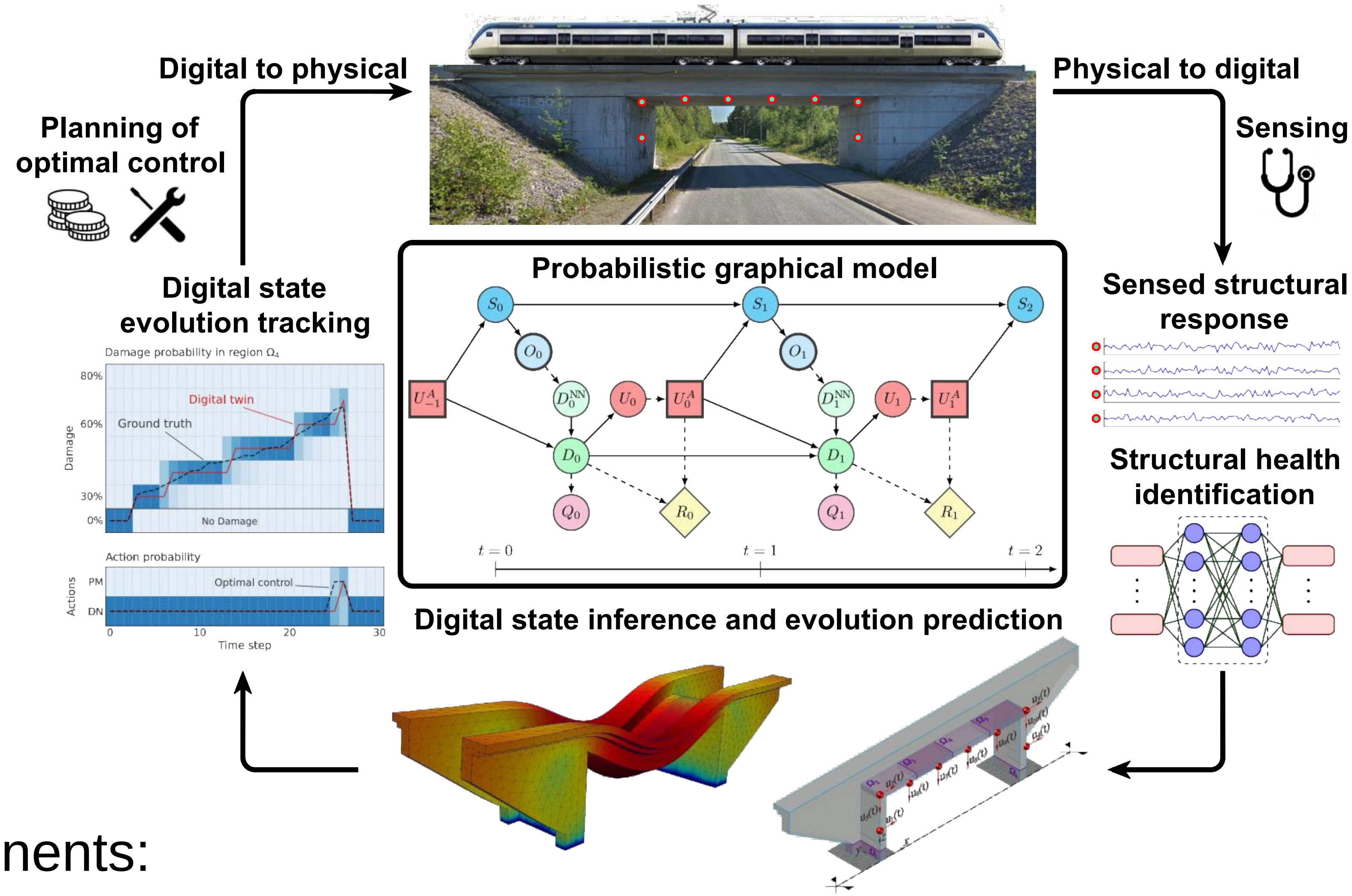
Overview: end-to-end information flow



Main components:

❖Simulation-based damage identification
❖Structural health identification using neural networks
❖Probabilistic graphical model for predictive digital twins

Overview: end-to-end information flow



Main components:

❖ <u>Simulation-based damage identification</u>

❖ Structural health identification using neural networks

❖ Probabilistic graphical model for predictive digital twins

Physics-based models to simulate the effect of damage

Governing equation of motion

$$\begin{cases} \rho \ddot{\boldsymbol{v}} + \eta \dot{\boldsymbol{v}} - \nabla \cdot \boldsymbol{\sigma}(\boldsymbol{v}, \boldsymbol{\mu}) = \boldsymbol{b}(\boldsymbol{x}, t, \boldsymbol{\mu}) & \text{in } \Omega \times (0, T) \\ \boldsymbol{v} = \boldsymbol{g}_D(\boldsymbol{x}, t, \boldsymbol{\mu}) & \text{on } \Gamma_D \times (0, T) \\ \boldsymbol{\sigma}(\boldsymbol{v}, \boldsymbol{\mu}) \cdot \boldsymbol{n} = \boldsymbol{g}_N(\boldsymbol{x}, t, \boldsymbol{\mu}) & \text{on } \Gamma_N \times (0, T) \\ \boldsymbol{v}(t = 0) = \boldsymbol{v}_0(\boldsymbol{x}) & \text{in } \Omega \\ \dot{\boldsymbol{v}}(t = 0) = \dot{\boldsymbol{v}}_0(\boldsymbol{x}) & \text{in } \Omega \end{cases}$$

Linearized kinematics

$$\boldsymbol{\varepsilon}(\boldsymbol{\mu}) = \frac{1}{2}[\nabla \boldsymbol{v}(\boldsymbol{\mu}) + (\nabla \boldsymbol{v}(\boldsymbol{\mu}))^\top]$$

Linear-elastic material

$$\boldsymbol{\sigma}(\boldsymbol{\mu}) = \boldsymbol{D}(\boldsymbol{\mu}) \boldsymbol{\varepsilon}(\boldsymbol{v}(\boldsymbol{\mu}))$$

Physics-based model describing the dynamic response of a structure to the applied loadings

Finite element space discretization

$$\begin{cases} \mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}(\boldsymbol{\mu})\dot{\mathbf{x}}(t) + \mathbf{K}(\boldsymbol{\mu})\mathbf{x}(t) = \mathbf{f}(t, \boldsymbol{\mu}), \quad t \in (0, T) \\ \mathbf{x}(0) = \mathbf{x}_0 \\ \dot{\mathbf{x}}(0) = \dot{\mathbf{x}}_0 \end{cases}$$

Physics-based models to simulate the effect of damage

Governing equation of motion

$$\begin{cases} \rho\ddot{\boldsymbol{v}} + \eta\dot{\boldsymbol{v}} - \nabla\cdot\boldsymbol{\sigma}(\boldsymbol{v},\boldsymbol{\mu}) = \boldsymbol{b}(\boldsymbol{x},t,\boldsymbol{\mu}) & \text{in } \Omega\times(0,T) \\ \boldsymbol{v} = \boldsymbol{g}_D(\boldsymbol{x},t,\boldsymbol{\mu}) & \text{on } \Gamma_D\times(0,T) \\ \boldsymbol{\sigma}(\boldsymbol{v},\boldsymbol{\mu})\cdot\boldsymbol{n} = \boldsymbol{g}_N(\boldsymbol{x},t,\boldsymbol{\mu}) & \text{on } \Gamma_N\times(0,T) \\ \boldsymbol{v}(t=0) = \boldsymbol{v}_0(\boldsymbol{x}) & \text{in } \Omega \\ \dot{\boldsymbol{v}}(t=0) = \dot{\boldsymbol{v}}_0(\boldsymbol{x}) & \text{in } \Omega \end{cases}$$

Linearized kinematics

$$\boldsymbol{\varepsilon}(\boldsymbol{\mu}) = \frac{1}{2}[\nabla\boldsymbol{v}(\boldsymbol{\mu}) + (\nabla\boldsymbol{v}(\boldsymbol{\mu}))^\top]$$

Linear-elastic material

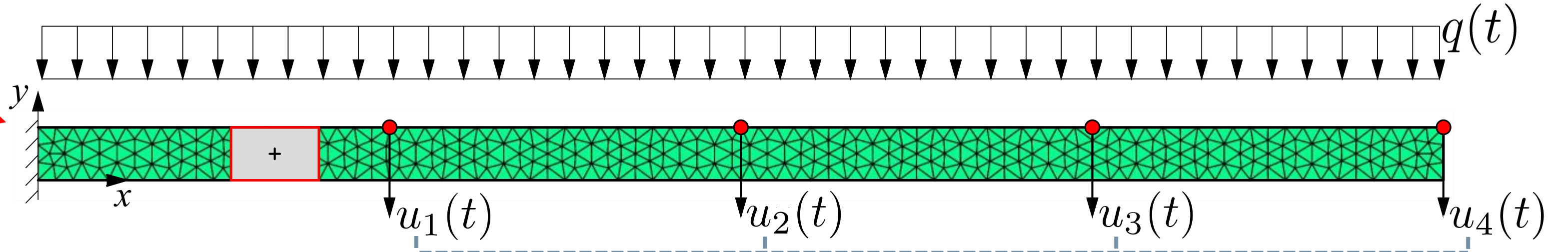
$$\boldsymbol{\sigma}(\boldsymbol{\mu}) = \boldsymbol{D}(\boldsymbol{\mu})\boldsymbol{\varepsilon}(\boldsymbol{v}(\boldsymbol{\mu}))$$

Physics-based model describing the dynamic response of a structure to the applied loadings

Finite element space discretization

$$\begin{cases} \mathbf{M}\ddot{\mathbf{x}}(t) + \mathbf{C}(\boldsymbol{\mu})\dot{\mathbf{x}}(t) + \mathbf{K}(\boldsymbol{\mu})\mathbf{x}(t) = \mathbf{f}(t,\boldsymbol{\mu}), \quad t\in(0,T) \\ \mathbf{x}(0) = \mathbf{x}_0 \\ \dot{\mathbf{x}}(0) = \dot{\mathbf{x}}_0 \end{cases}$$

Parameter vector $\boldsymbol{\mu}$: damage, loadings, environment, …



Given initial conditions, boundary conditions, and system parameters compute solution trajectories, **to be compared with sensor recordings**

The need of reduced-order modeling (ROM)

- The offline generation of synthetic training datasets, sufficiently representative of potential damage and operational conditions, may become prohibitive.
- We employ the reduced basis method for parametrized systems (not a restrictive choice).

The need of reduced-order modeling (ROM)

- The offline generation of synthetic training datasets, sufficiently representative of potential damage and operational conditions, may become prohibitive.
- We employ the reduced basis method for parametrized systems (not a restrictive choice).

FOM

↓

Low-dimensional subspace

$\mathbf{W}$ (POD/SVD or greedy)

best rank N approximation

↓

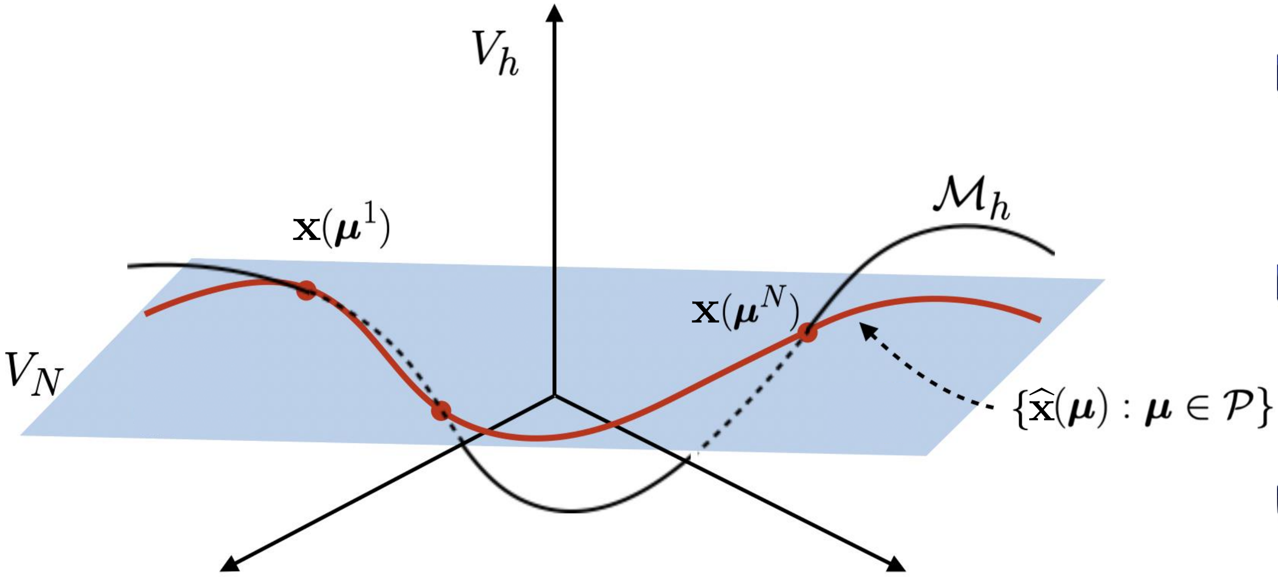
$$\mathbf{x}(t,\boldsymbol{\mu}) \approx \mathbf{W}\widehat{\mathbf{x}}(t,\boldsymbol{\mu})$$

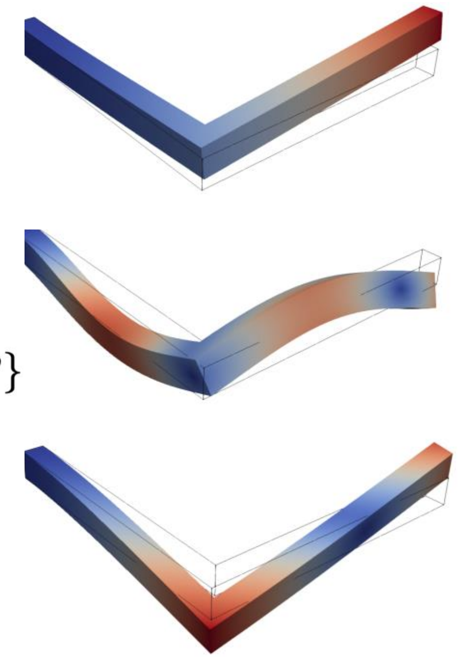
↓

(Petrov)-Galerkin projection

↓

ROM



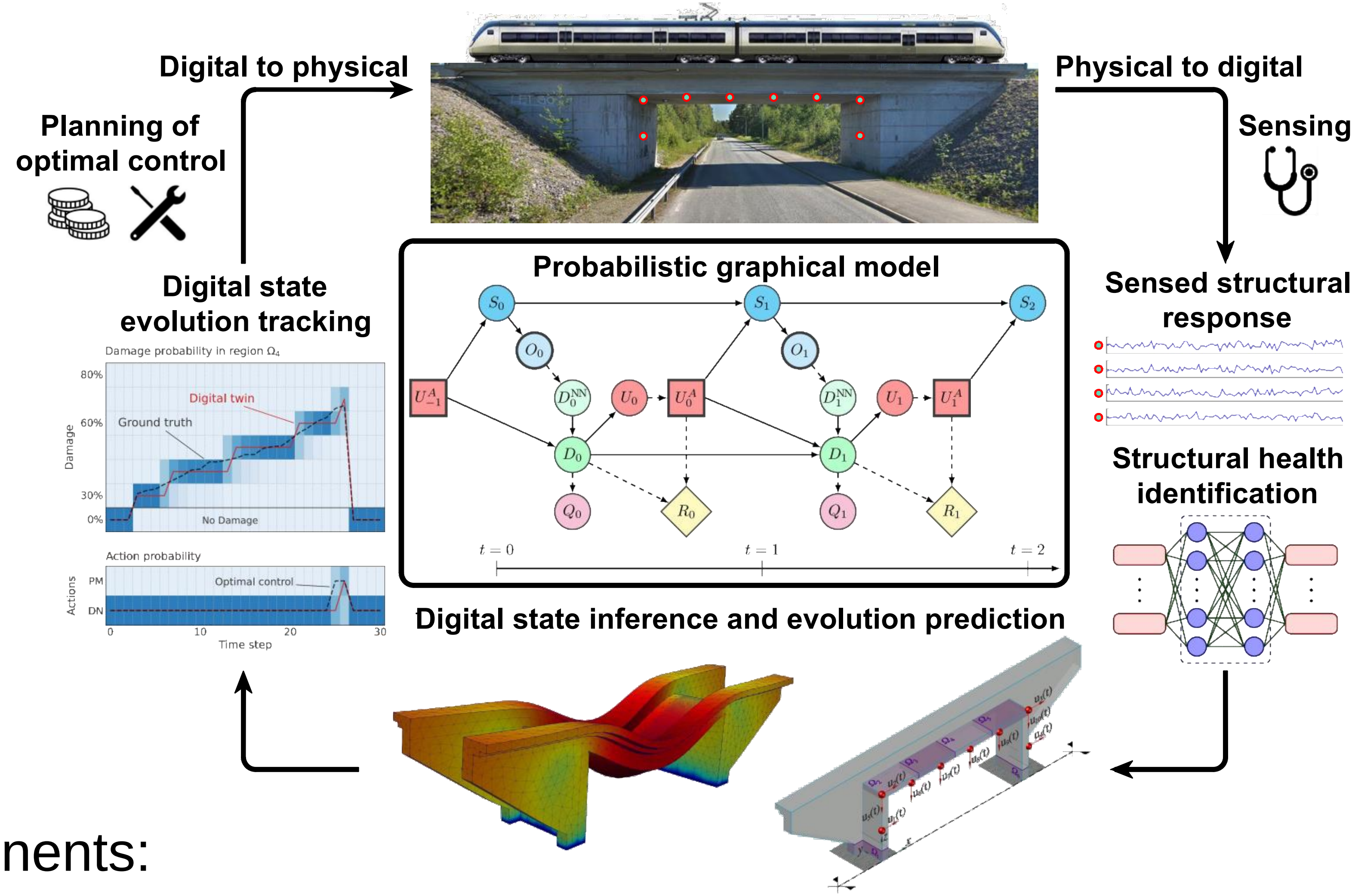


$$\mathbf{M}_r \equiv \mathbf{W}^\top\mathbf{M}\mathbf{W} \qquad \mathbf{C}_r(\boldsymbol{\mu}) \equiv \mathbf{W}^\top\mathbf{C}(\boldsymbol{\mu})\mathbf{W}$$
$$\mathbf{K}_r(\boldsymbol{\mu}) \equiv \mathbf{W}^\top\mathbf{K}(\boldsymbol{\mu})\mathbf{W} \qquad \mathbf{f}_r(t,\boldsymbol{\mu}) \equiv \mathbf{W}^\top\mathbf{f}(t,\boldsymbol{\mu})$$

$$\begin{cases} \mathbf{M}_r\ddot{\widehat{\mathbf{x}}}(t) + \mathbf{C}_r(\boldsymbol{\mu})\dot{\widehat{\mathbf{x}}}(t) + \mathbf{K}_r(\boldsymbol{\mu})\widehat{\mathbf{x}}(t) = \mathbf{f}_r(t,\boldsymbol{\mu}) \\ \widehat{\mathbf{x}}(0) = \mathbf{W}^\top\mathbf{x}_0 \\ \dot{\widehat{\mathbf{x}}}(0) = \mathbf{W}^\top\dot{\mathbf{x}}_0 \end{cases}$$

Low-dimensional dynamical system
(low-cost physics-based model)

Overview: end-to-end information flow



Main components:

- ❖ Simulation-based damage identification
- ❖ Structural health identification using neural networks
- ❖ Probabilistic graphical model for predictive digital twins

Data-driven approach to inverse problems – neural network case

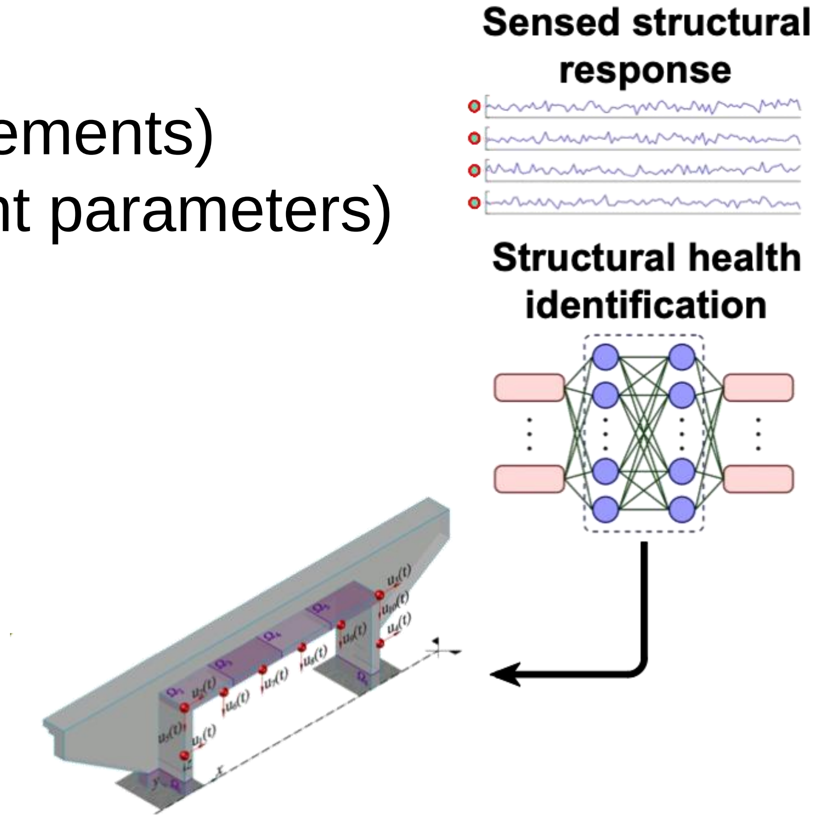
$\mathcal{F}$:= Forward operator (parameters $\rightarrow$ measurements)

$\mathcal{I}$:= Inverse problem (measurements $\rightarrow$ sought parameters)

$\mathcal{I}_{\theta*}$:= Neural network approximation to $\mathcal{I}$

Loss function prototype

$$= \arg\min_{\theta \in \Theta} \sum_j \|(\mathcal{I}_\theta \circ \mathcal{F})(\boldsymbol{\mu}_j) - \boldsymbol{\mu}_j\|$$



Data-driven approach to inverse problems – neural network case

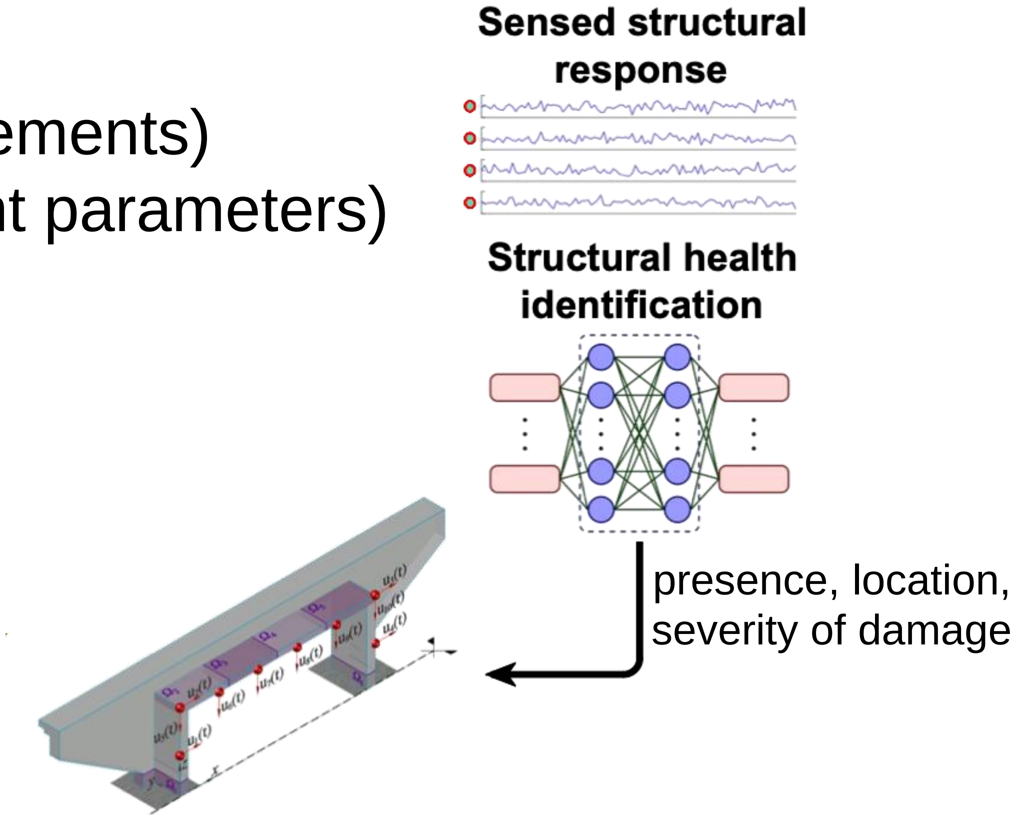
$\mathcal{F}$ $:=$ Forward operator (parameters $\rightarrow$ measurements)

$\mathcal{I}$ $:=$ Inverse problem (measurements $\rightarrow$ sought parameters)

$\mathcal{I}_{\theta*}$ $:=$ Neural network approximation to $\mathcal{I}$

Loss function prototype

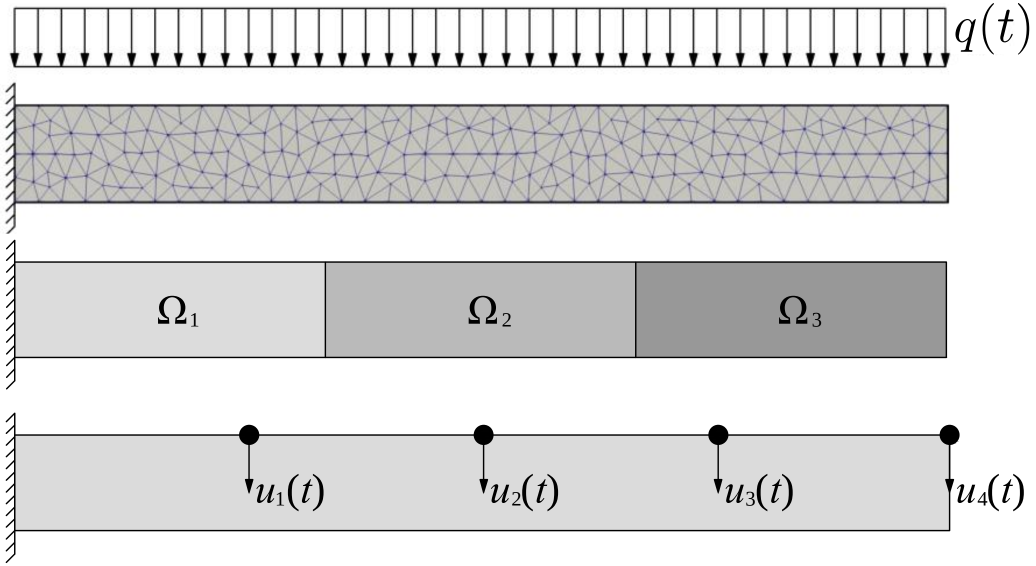
$$= \arg\min_{\theta \in \Theta} \sum_j \left\| (\mathcal{I}_\theta \circ \mathcal{F})(\boldsymbol{\mu}_j) - \boldsymbol{\mu}_j \right\|$$



The case of SHM:

- ❖ parameters $\boldsymbol{\mu}$: define an expressive representation of the structural health
  - stiffness reduction
  - loose knot bolts
  - crack pattern
  - delamination size
- ❖ measurements: experimental (sensors) vs simulated (reduced-order model)
- ❖ forward operator $\mathcal{F}$: real vs simulated structural response

Simulation-based damage detection/localization & quantification



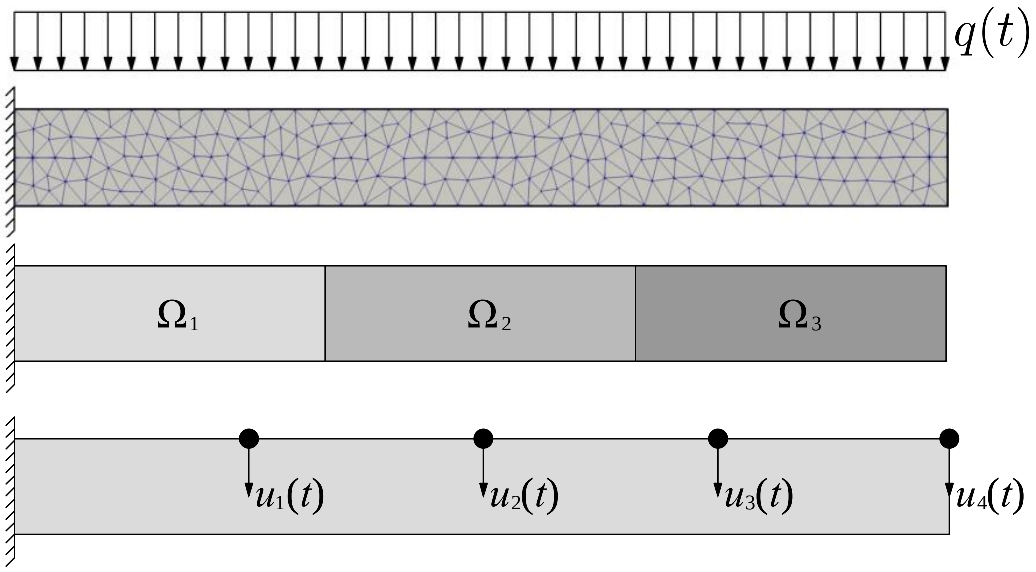
Simulation-based SHM: the problem is traced back to train machine learning models on simulated data.

Damage: introduce damageable regions distributed over the structure and model the effect of damage.

Processed data: vibration recordings shaped as multivariate time series, mimicking a sensor network.

Rosafalco, Torzoni, Manzoni, Mariani, Corigliano. Online structural health monitoring by model order reduction and deep learning algorithms, Computers & Structures, 255:106604, 2021.

Simulation-based damage detection/localization & quantification



Simulation-based SHM: the problem is traced back to train machine learning models on simulated data.

Damage: introduce damageable regions distributed over the structure and model the effect of damage.

Processed data: vibration recordings shaped as multivariate time series, mimicking a sensor network.

Evaluate forward models to generate training data and train inverse models (offline):

Damage detection/localization as a classification task:

$$\mathcal{D}_{\mathrm{CL}} = \{(\mathbf{U}_i, \boldsymbol{b}_i)\}_{i=1}^{I}$$

$$\mathcal{L}_{\mathrm{CL}}(\boldsymbol{\Theta}_{\mathrm{CL}}, \mathcal{D}_{\mathrm{CL}}) = -\frac{1}{I}\sum_{i=1}^{I}\sum_{m=0}^{N_y} b_i^m \log(\widehat{b}_i^m)$$

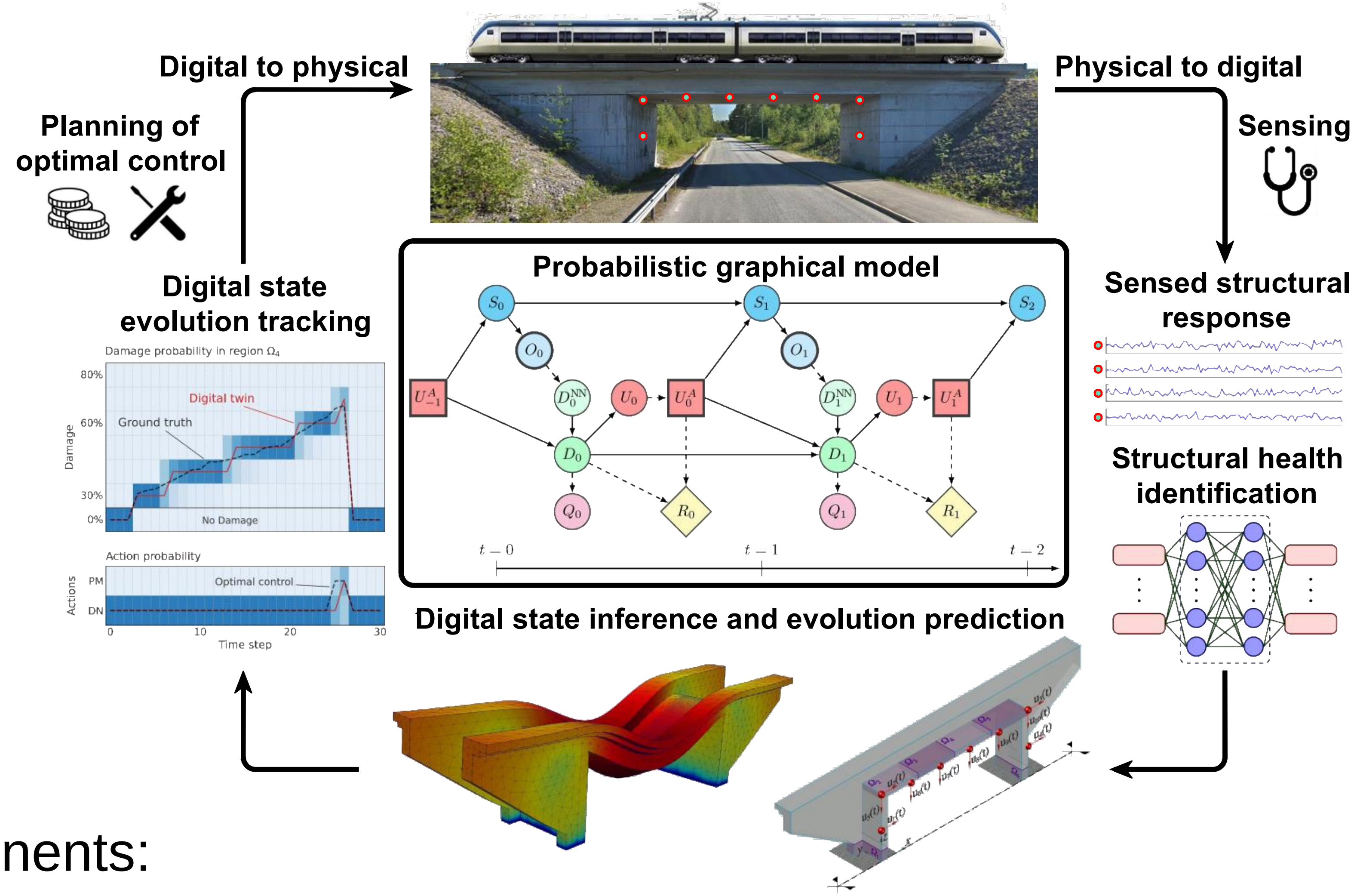
Damage quantification as a regression task:

$$\mathcal{D}_{\mathrm{RG}} = \{(\mathbf{U}_{i_{\mathrm{RG}}}, \delta_{i_{\mathrm{RG}}})\}_{i_{\mathrm{RG}}=1}^{I_{\mathrm{RG}}}$$

$$\mathcal{L}_{\mathrm{RG}}(\boldsymbol{\Theta}_{\mathrm{RG}}, \mathcal{D}_{\mathrm{RG}}) = \frac{1}{I_{\mathrm{RG}}}\sum_{i_{\mathrm{RG}}=1}^{I_{\mathrm{RG}}} (\delta_{i_{\mathrm{RG}}} - \widehat{\delta}_{i_{\mathrm{RG}}})^2$$

Rosafalco, Torzoni, Manzoni, Mariani, Corigliano. Online structural health monitoring by model order reduction and deep learning algorithms, Computers & Structures, 255:106604, 2021.

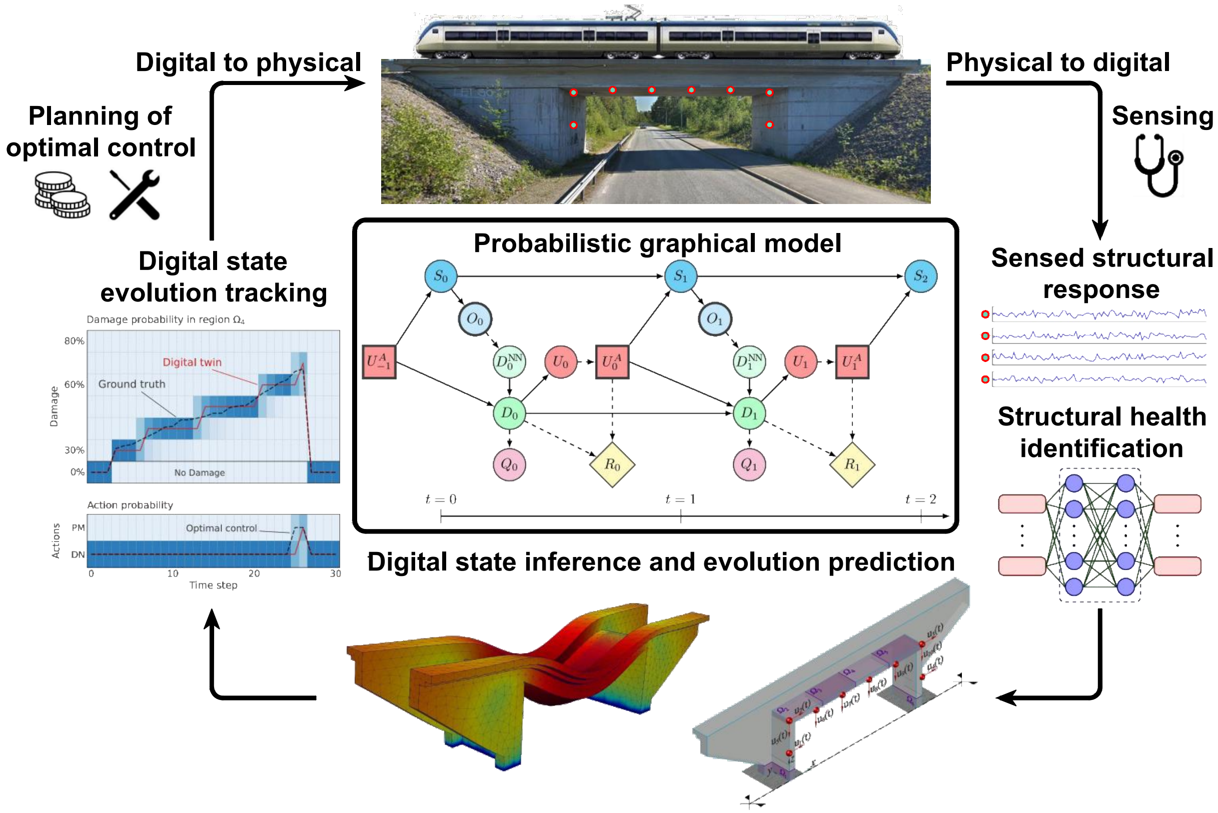
Overview: end-to-end information flow

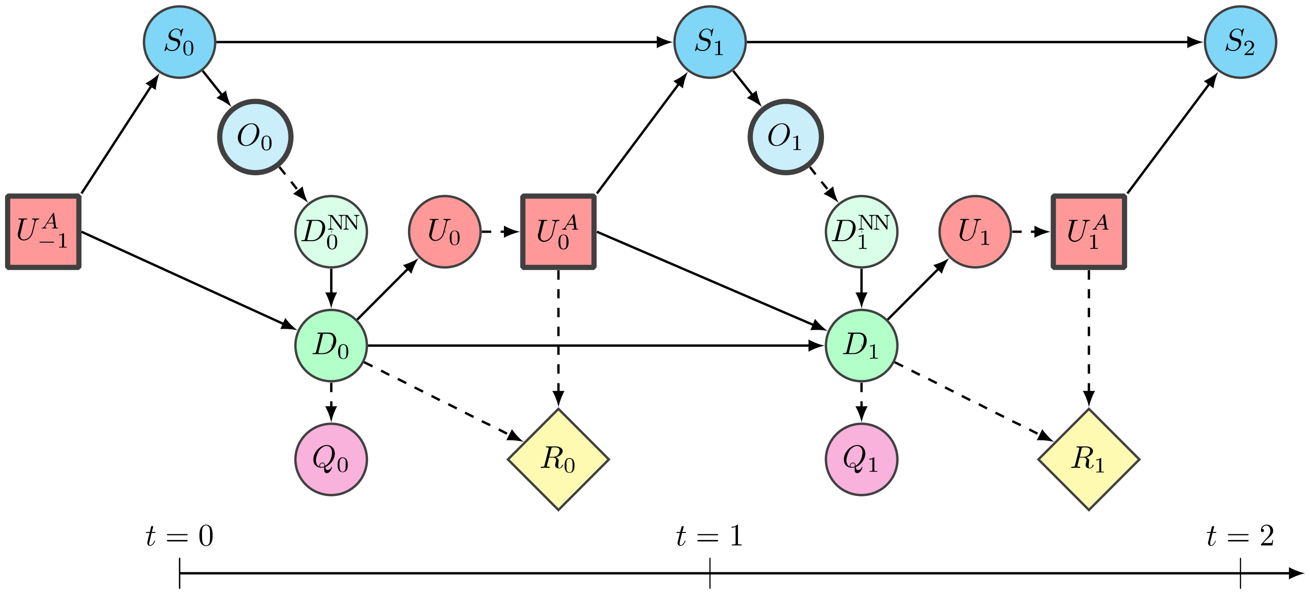


Main components:

- ❖ Simulation-based damage identification
- ❖ Structural health identification using neural networks
- ❖ Probabilistic graphical model for predictive digital twins

Probabilistic graphical model encoding the asset-twin system





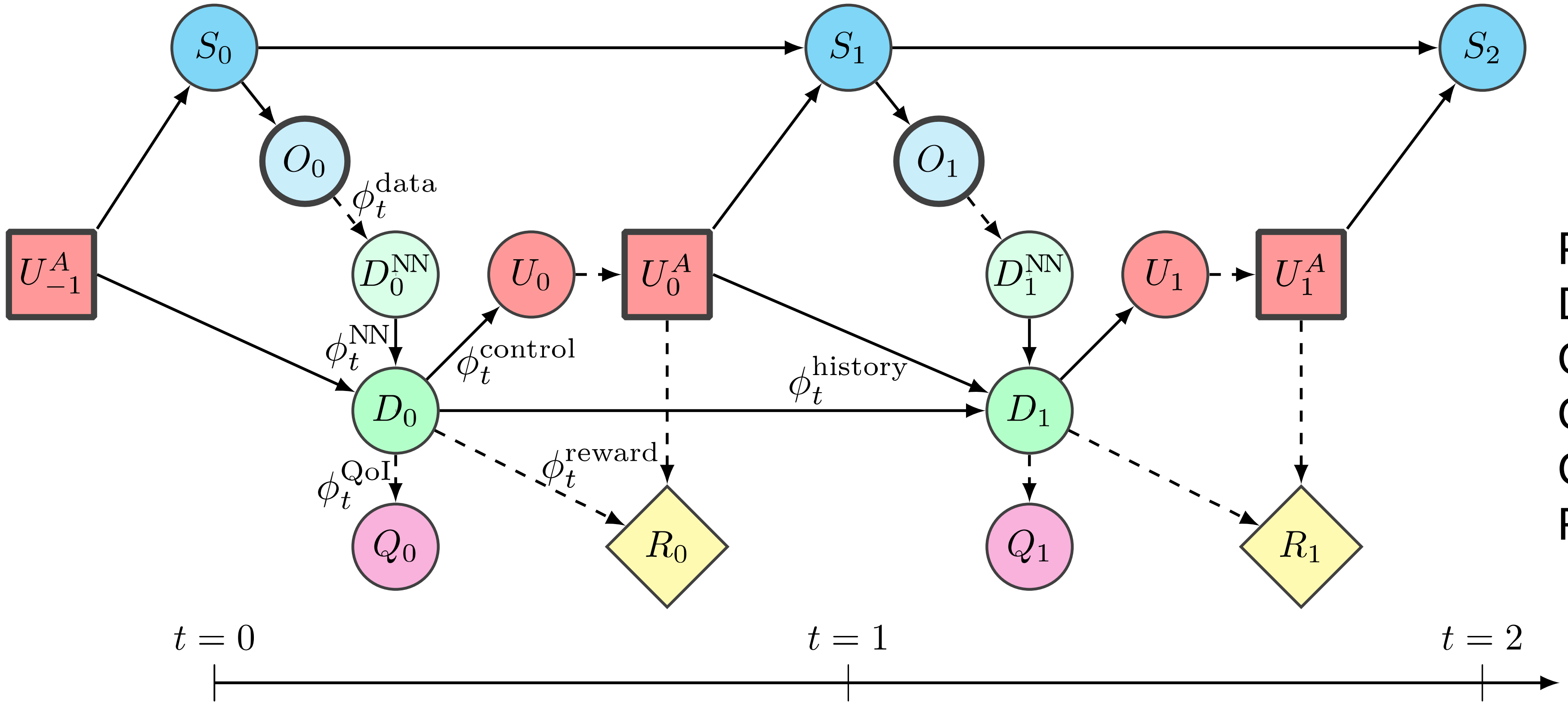
Physical state: $S_t \sim p(s_t)$ - variability of the asset
Digital state: $D_t \sim p(d_t)$ - capture the asset variability
Observations: $O_t \sim p(o_t)$ - from physical to digital flow
QoI: $Q_t \sim p(q_t)$ - estimated via model output
Control inputs: $U_t \sim p(u_t)$ - from digital to physical flow
Reward: $R_t \sim p(r_t)$ - asset-twin performance

Key assumptions:

- Physical state only observable indirectly via the sensed structural response.
- Markovianity of physical and digital states.

Torzoni, Tezzele, Mariani, Manzoni, Willcox. A digital twin framework for civil engineering structures, arXiv preprint, 2023.

Belief state factorization



Physical state: $S_t \sim p(s_t)$
Digital state: $D_t \sim p(d_t)$
Observations: $O_t \sim p(o_t)$
QoI: $Q_t \sim p(q_t)$
Control inputs: $U_t \sim p(u_t)$
Reward: $R_t \sim p(r_t)$

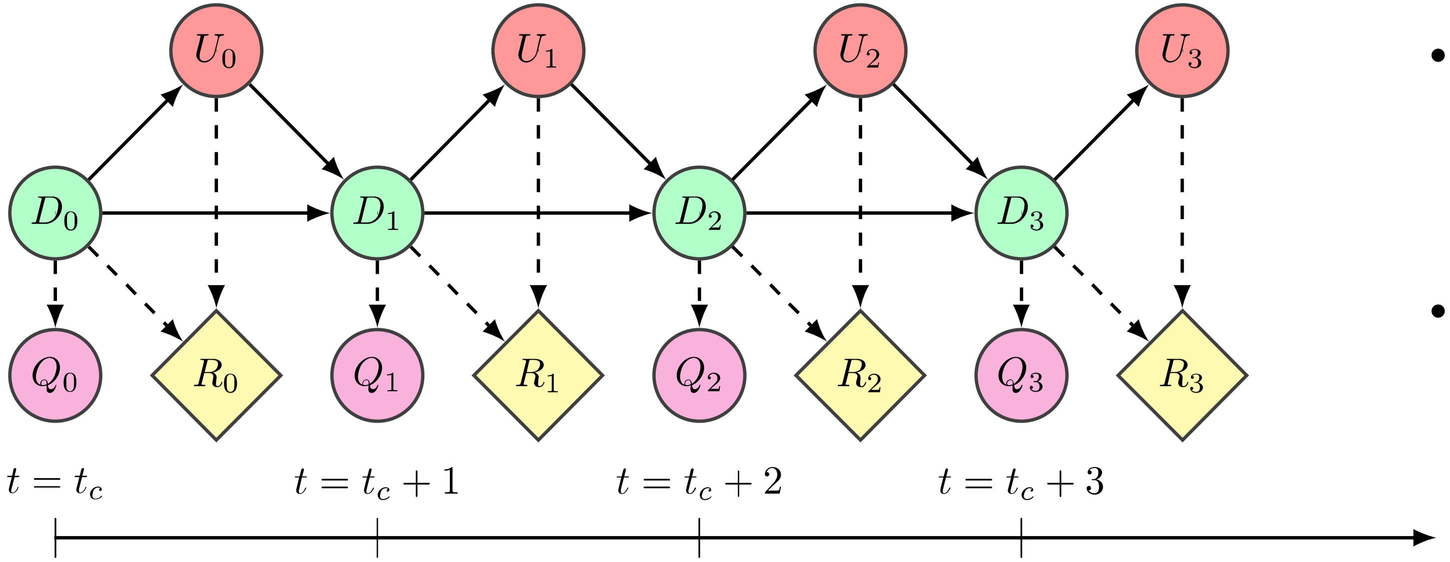
$$p(D_0^{\text{NN}}, \ldots, D_{t_c}^{\text{NN}}, D_0, \ldots, D_{t_c}, Q_0, \ldots, Q_{t_c}, R_0, \ldots, R_{t_c}, U_0, \ldots, U_{t_c} | o_0, \ldots, o_{t_c}, u_0^A, \ldots, u_{t_c}^A)$$

$$\propto \prod_{t=0}^{t_c} \left[\phi_t^{\text{data}} \phi_t^{\text{history}} \phi_t^{\text{NN}} \phi_t^{\text{QoI}} \phi_t^{\text{control}} \phi_t^{\text{reward}} \right],$$

$$\phi_t^{\text{data}} = p(O_t = o_t | D_t^{\text{NN}}), \qquad \phi_t^{\text{history}} = p(D_t | D_{t-1}, U_{t-1}^A = u_{t-1}^A), \qquad \phi_t^{\text{NN}} = p(D_t | D_t^{\text{NN}}),$$

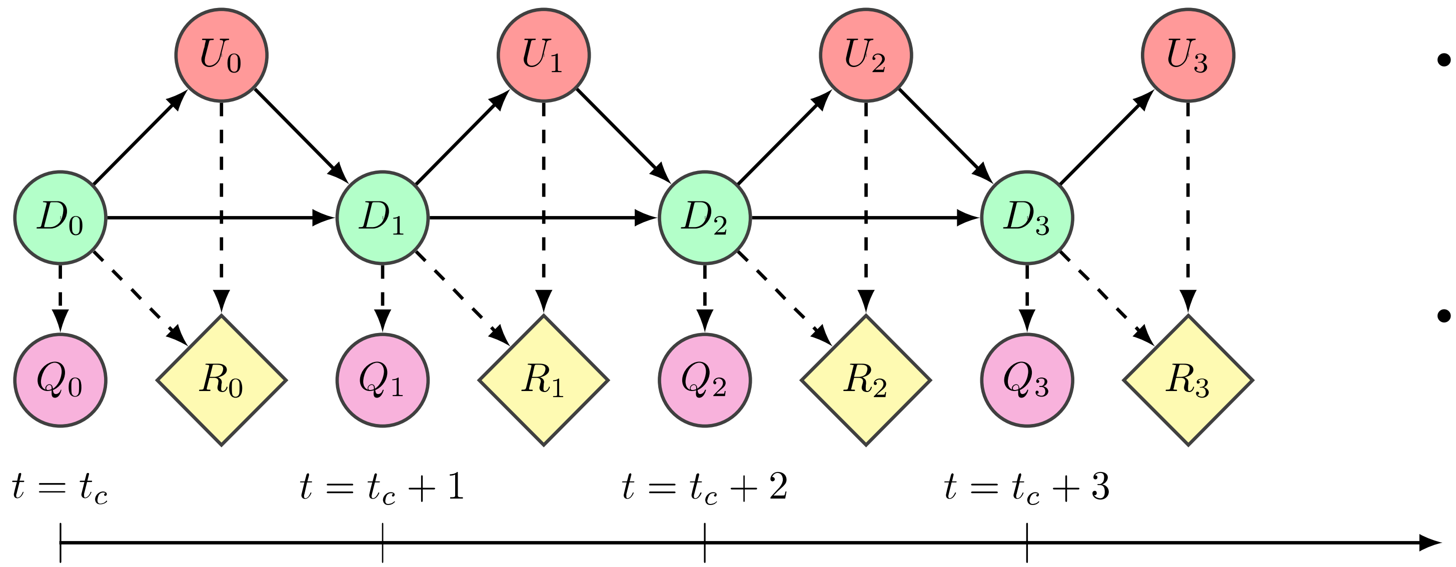
$$\phi_t^{\text{QoI}} = p(Q_t | D_t), \qquad \phi_t^{\text{reward}} = p(R_t | D_t, U_t^A = u_t^A), \qquad \phi_t^{\text{control}} = p(U_t | D_t).$$

Planning of optimal control & extension to prediction



- **Forecasting/maintenance planning** from the updated digital state at the current time step (no data assimilation).
- Unroll the portion of the graph relative to digital state, control inputs, reward and quantities of interest.

Planning of optimal control & extension to prediction



- **Forecasting/maintenance planning** from the updated digital state at the current time step (no data assimilation).
- Unroll the portion of the graph relative to digital state, control inputs, reward and quantities of interest.

Planning of optimal control

$$\pi(D_t) = \arg\max_{\pi} \sum_{t=0}^{+\infty} \gamma^t \mathbb{E}[R_t]$$

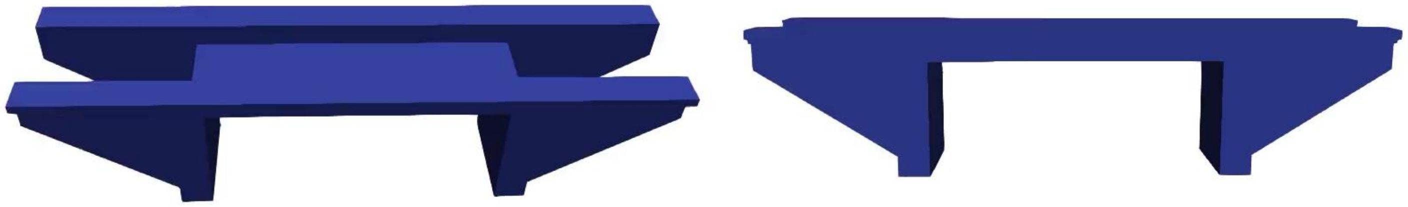
Multi-objective planning reward function

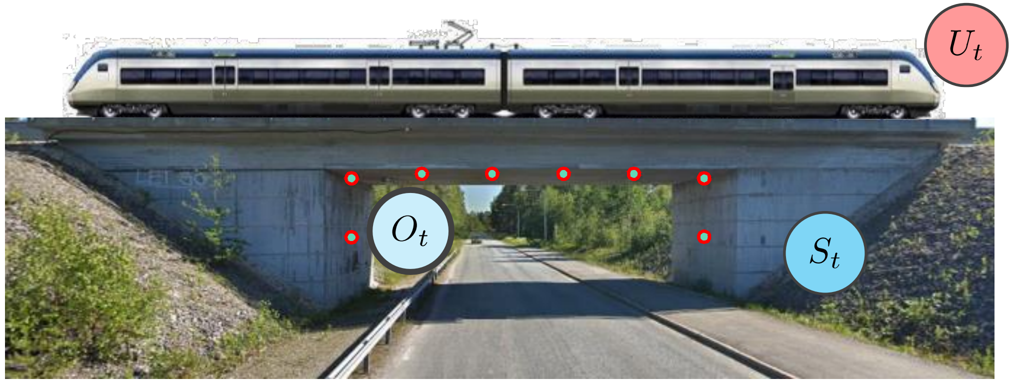
$$R_t(U_t, D_t) = R_t^{\text{control}}(U_t) + \alpha R_t^{\text{health}}(D_t)$$

$$\phi_t^{\text{control}} = p(U_t | D_t)$$ Control policy maps the digital state belief onto actions

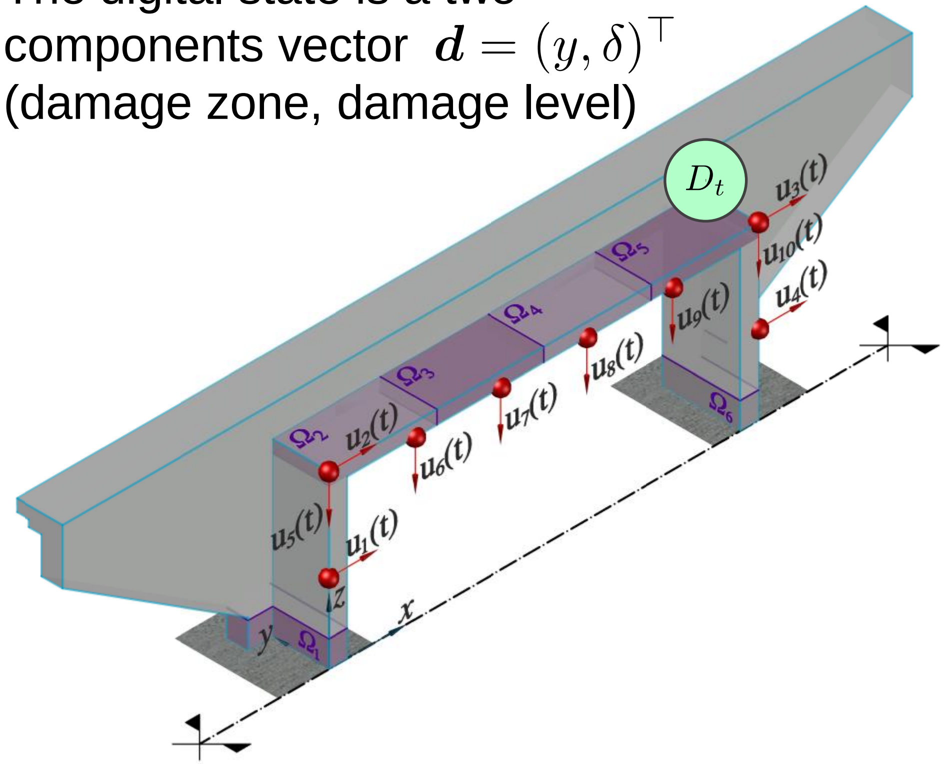
$$p(D_0^{\text{NN}}, \dots, D_{t_c}^{\text{NN}}, D_0, \dots, D_{t_p}, Q_0, \dots, Q_{t_p}, R_0, \dots, R_{t_p}, U_0, \dots, U_{t_p} | o_0, \dots, o_{t_c}, u_0^A, \dots, u_{t_c}^A)$$
$$\propto \prod_{t=0}^{t_p} \left[\phi_t^{\text{history}} \phi_t^{\text{QoI}} \phi_t^{\text{control}} \phi_t^{\text{reward}} \right] \prod_{t=0}^{t_c} \left[\phi_t^{\text{data}} \phi_t^{\text{NN}} \right]$$

Hörnefors railway bridge



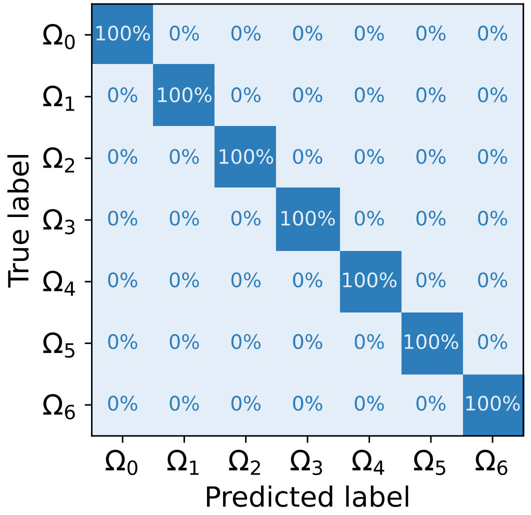


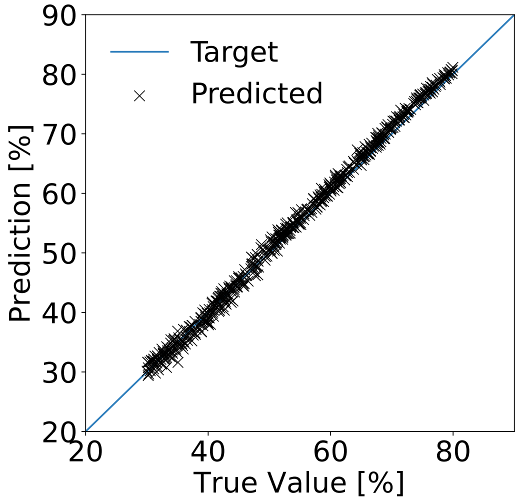
The digital state is a two components vector $\boldsymbol{d} = (y, \delta)^\top$ (damage zone, damage level)



Data assimilation:

$$\phi_t^{\text{data}} = p(O_t = o_t | D_t^{\text{NN}})$$



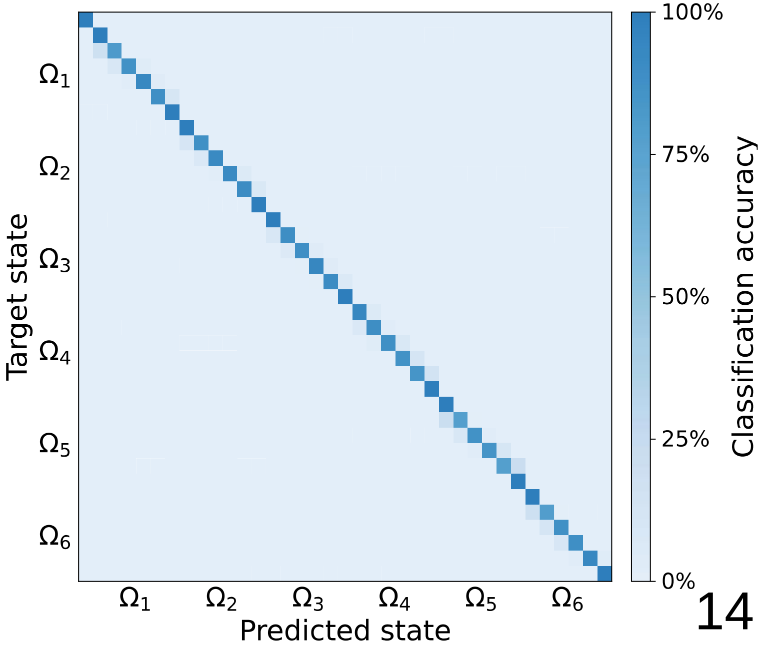


Damage modeling:

Undamaged case
+ 6 damageable zones

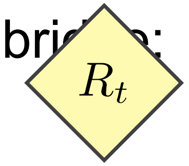
Stiffness reduction in the range (30%,80%), 6 intervals discretiz. (37 possible structural states)

$$\phi_t^{\text{NN}} = p(D_t | D_t^{\text{NN}})$$



Possible control inputs

- “**Do nothing**” (DN): the physical state evolves according to a stochastic deterioration process.
- “**Perfect maintenance**” (PM): A maintenance action is performed and the asset returns from its current condition to the damage-free state.
- “**Restrict operational conditions**” (RE): only light weight trains are allowed to cross the bridge; lower deterioration rate, but also lower revenue generated by the infrastructure.



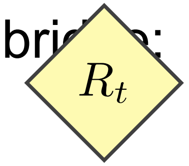
$$\phi_t^{\text{control}} = p(U_t|D_t)$$

$$\pi(D_t) = \arg\max_{\pi} \sum_{t=0}^{+\infty} \gamma^t \mathbb{E}[R_t],$$

solved offline via value iteration.

Possible control inputs

- "**Do nothing**" (DN): the physical state evolves according to a stochastic deterioration process.
- "**Perfect maintenance**" (PM): A maintenance action is performed and the asset returns from its current condition to the damage-free state.
- "**Restrict operational conditions**" (RE): only light weight trains are allowed to cross the bridge: lower deterioration rate, but also lower revenue generated by the infrastructure.



$$\phi_t^{\text{control}} = p(U_t | D_t) \qquad \pi(D_t) = \arg\max_{\pi} \sum_{t=0}^{+\infty} \gamma^t \mathbb{E}[R_t],$$

solved offline via value iteration.

Transition models

Each control input is provided with a conditional probability table describing the corresponding transition model.

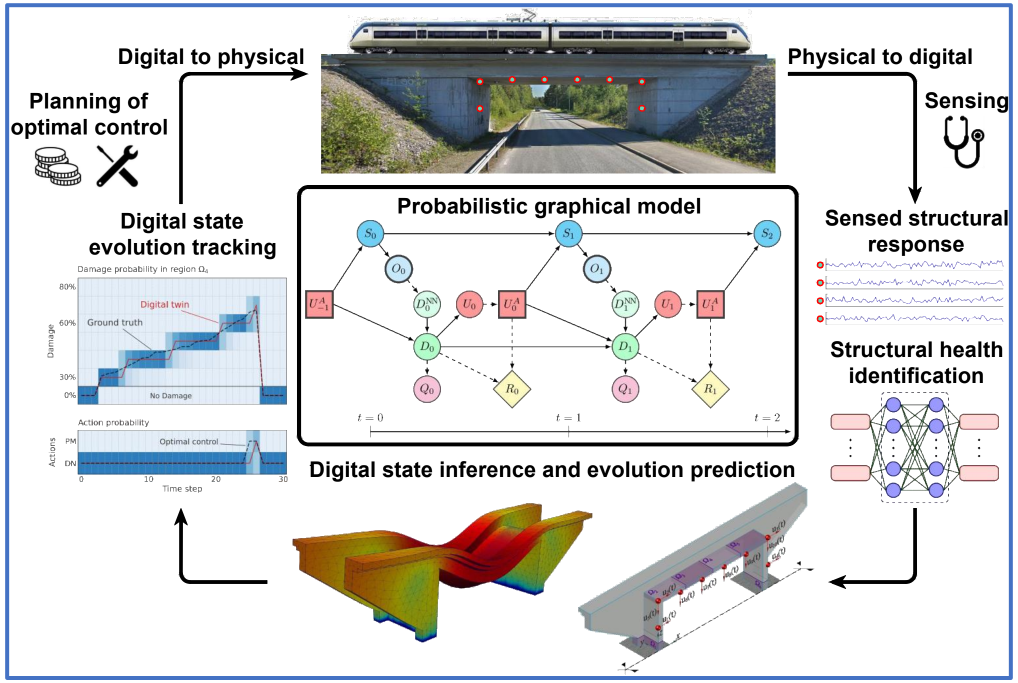
$$\phi_t^{\text{history}} = p(D_t | D_{t-1}, U_{t-1}^A = u_{t-1}^A)$$

- **DN**: damage may start in any subdomain with 0.1 probability, and then grow to the next δ interval with the same probability.
- **PM**: the belief about the digital state is mapped to the undamaged condition, independently of the current condition.
- **RE**: damage may start in any subdomain, with 0.03 probability, and then grow to the next δ interval with the same probability.

Ground-truth evolution model

To run a digital twin simulation we prescribe a (simulated) stochastic degradation process: the digital twin is dynamically updated and used to drive maintenance planning.

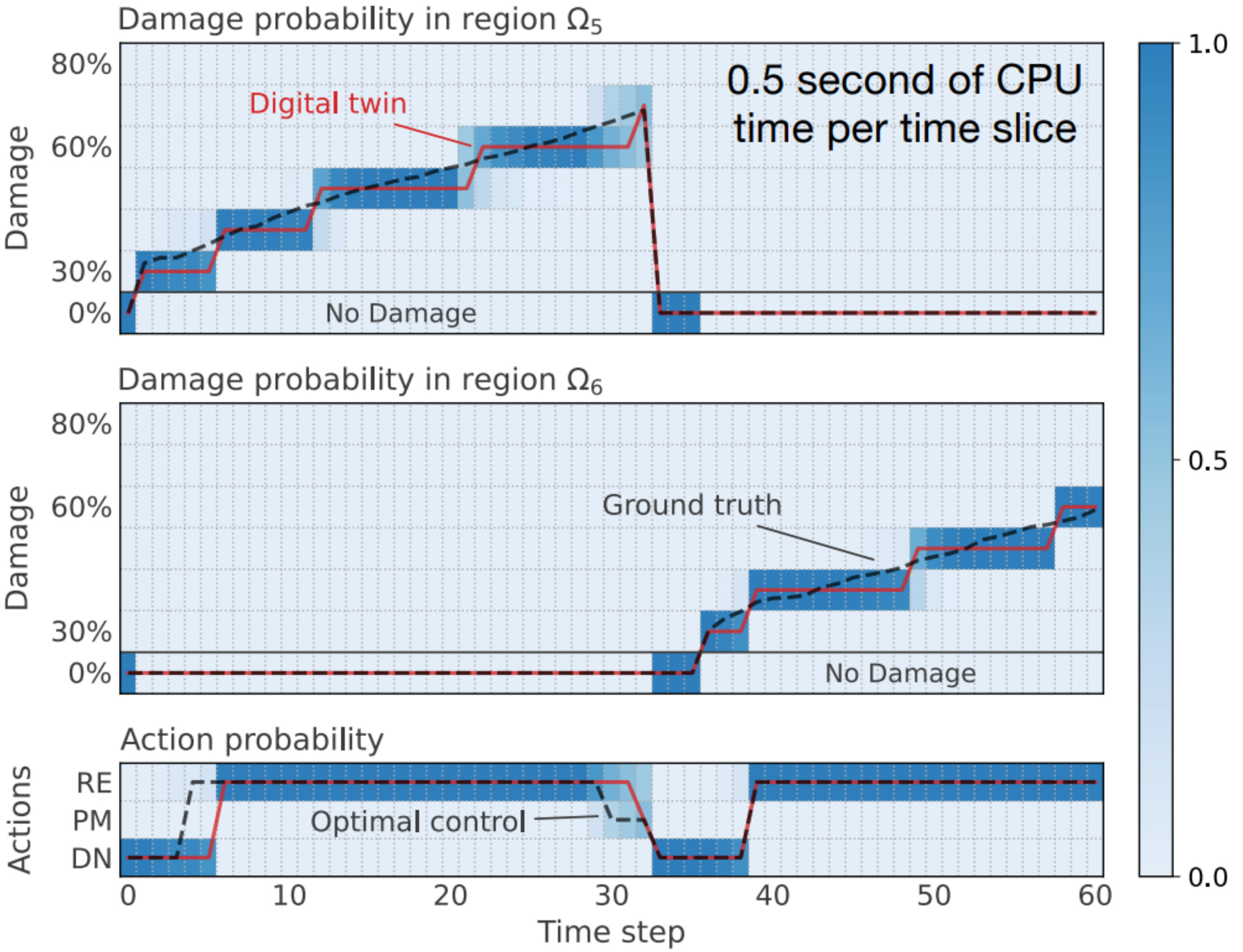
Damage may develop in any of the predefined regions and then propagate with δ increments sampled from a Gaussian pdf, chosen according to the last enacted control input.

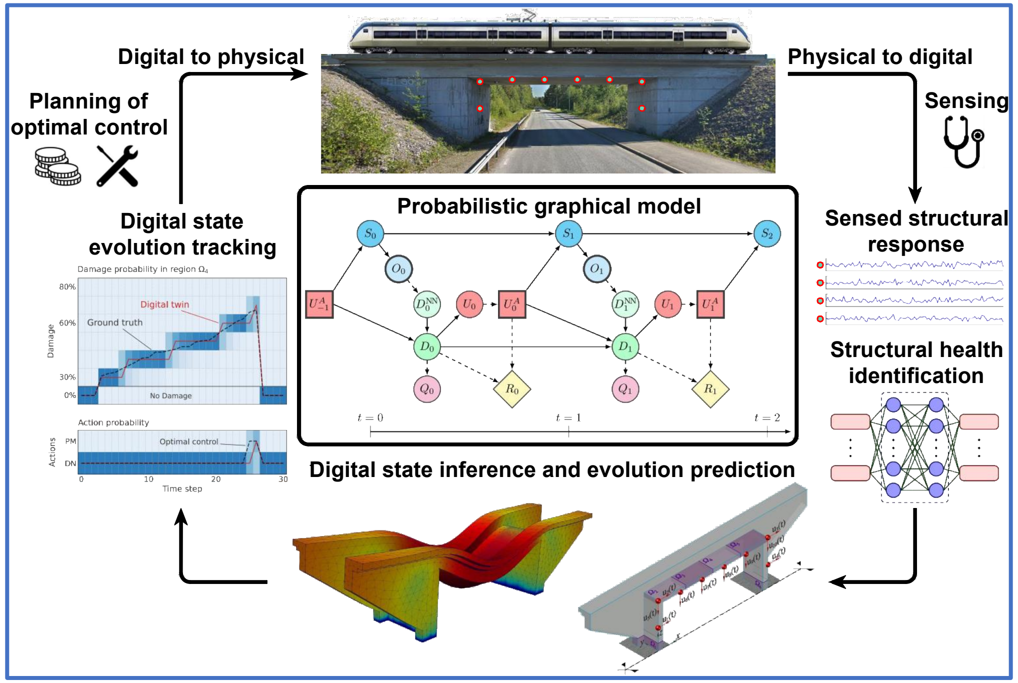


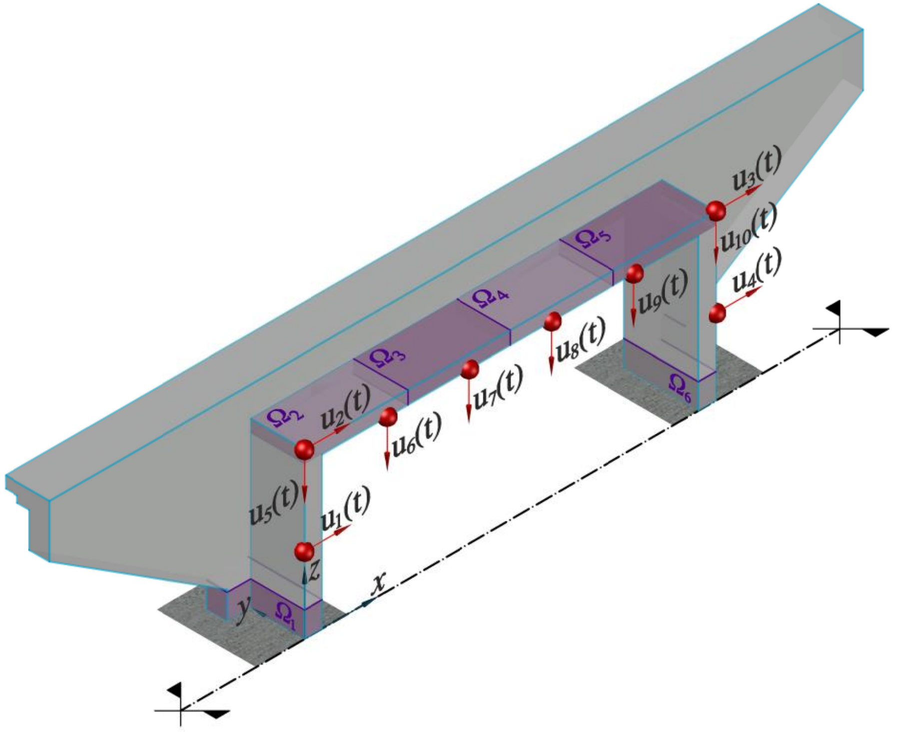
Ground-truth evolution model

To run a digital twin simulation we prescribe a (simulated) stochastic degradation process: the digital twin is dynamically updated and used to drive maintenance planning.

Damage may develop in any of the predefined regions and then propagate with δ increments sampled from a Gaussian pdf, chosen according to the last enacted control input.



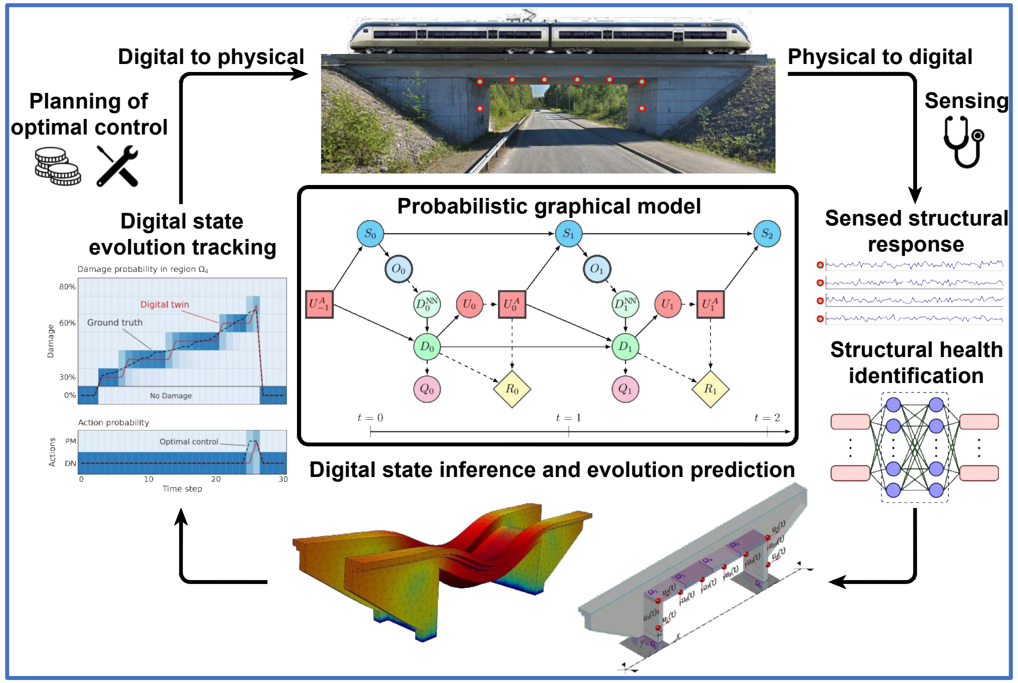


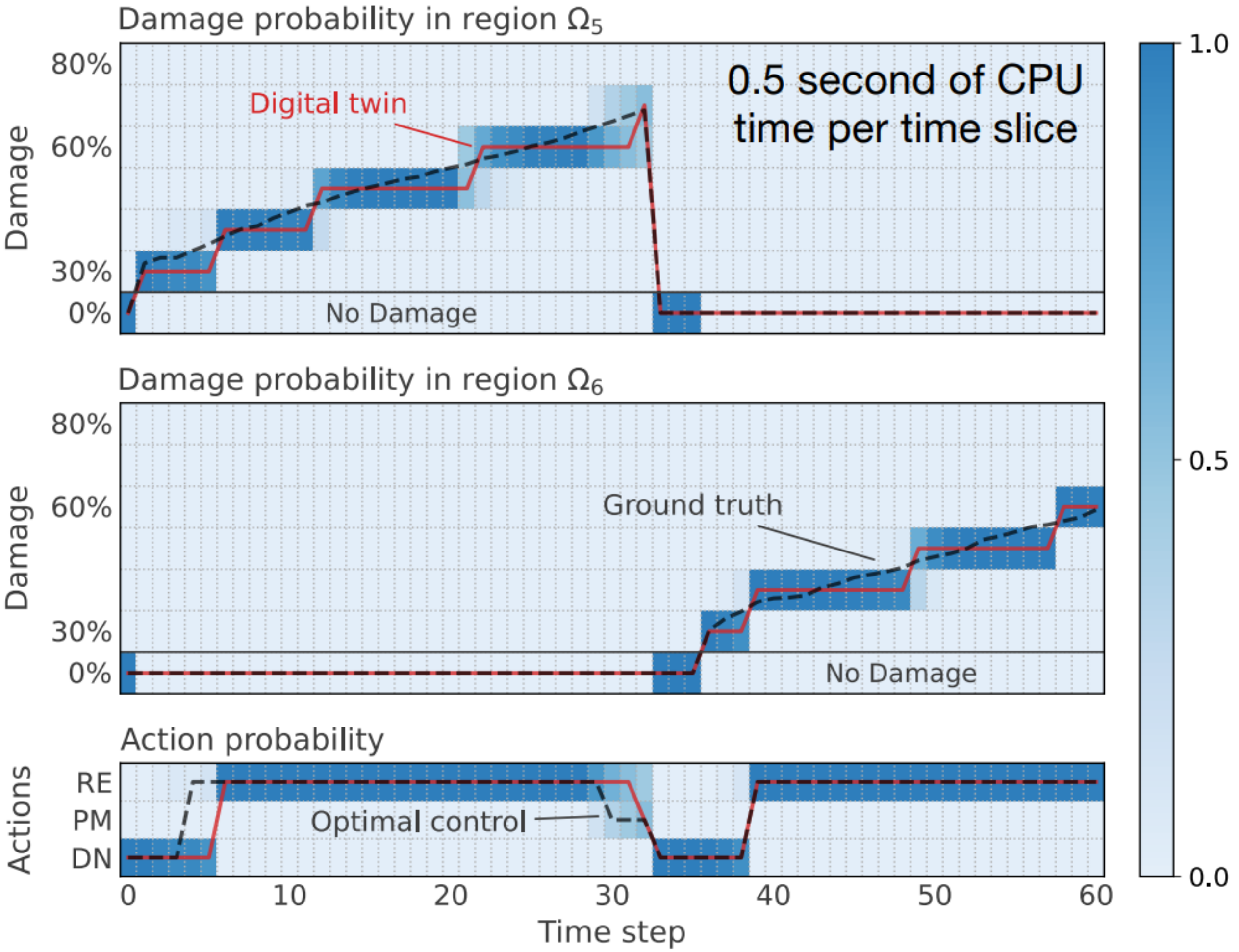


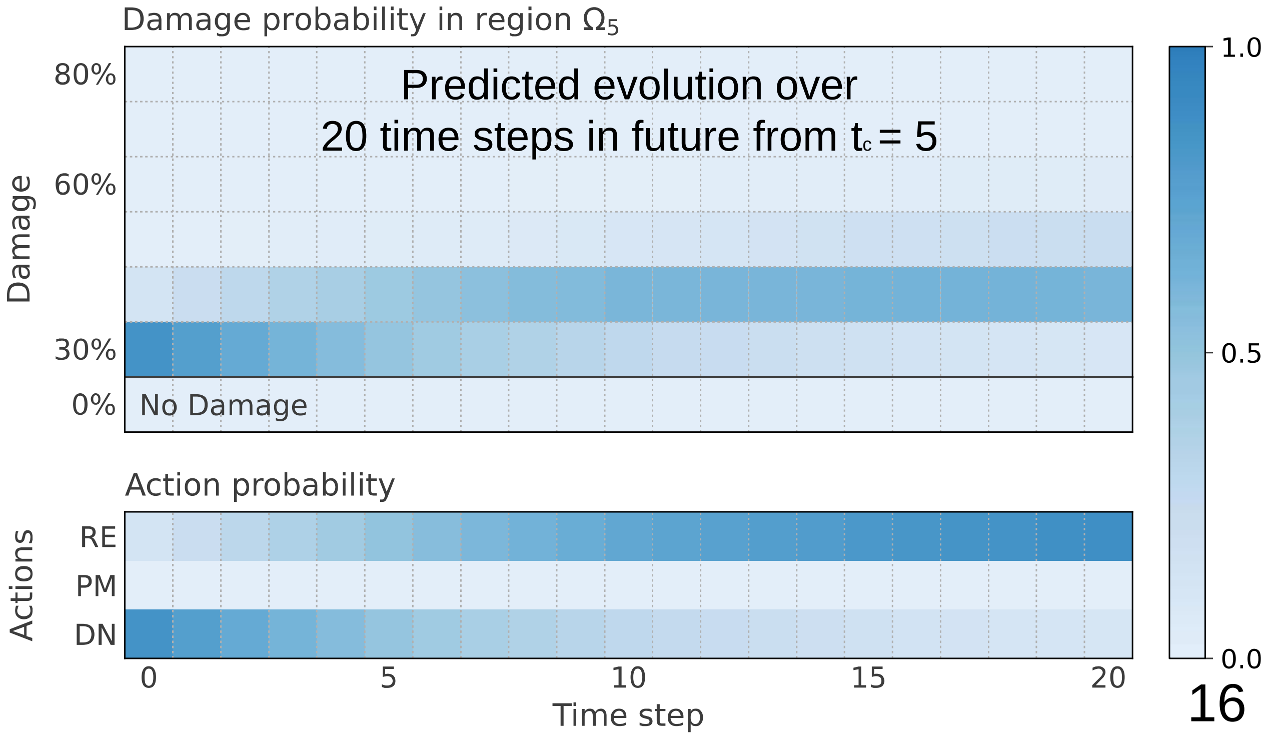
Ground-truth evolution model

To run a digital twin simulation we prescribe a (simulated) stochastic degradation process: the digital twin is dynamically updated and used to drive maintenance planning.

Damage may develop in any of the predefined regions and then propagate with δ increments sampled from a Gaussian pdf, chosen according to the last enacted control input.







Future developments

- The transition models are currently prescribed by the user. To better characterize them, it would be useful to **update the transition dynamic models from the online data stream**. This would result in a more calibrated prediction of the digital state expected evolution.

- The planning problem is currently solved by considering an infinite planning horizon, not realistic for civil structures. A more viable alternative would be **a finite planning horizon representing the design lifetime of the asset and, e.g., reinforcement learning.**

- **Quantities of interest** such as modal quantities or full response fields obtained through ROMs, currently not exploited, could be used **to perform posterior predictive checks on the tracking capabilities of the digital twin**, useful to evaluate how well it matches the reality.

BUILD-IT2023 Workshop

19-20 October, Rome, Italy

THANK YOU!

POLITECNICO MILANO 1863

DIPARTIMENTO DI INGEGNERIA CIVILE E AMBIENTALE

DIPARTIMENTO DI MATEMATICA

MODELLISTICA E CALCOLO SCIENTIFICO

MOX

MODELING AND SCIENTIFIC COMPUTING

TEXAS

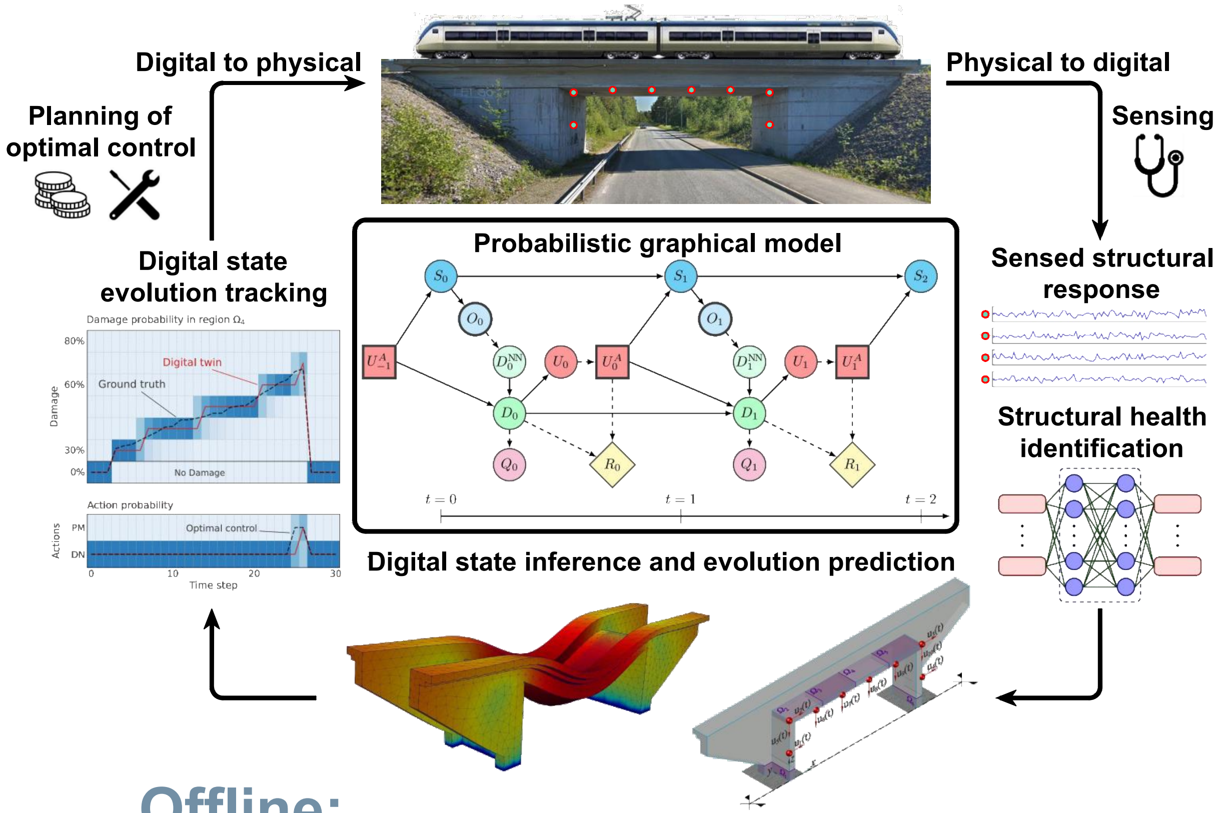
ODEN INSTITUTE FOR COMPUTATIONAL ENGINEERING & SCIENCES

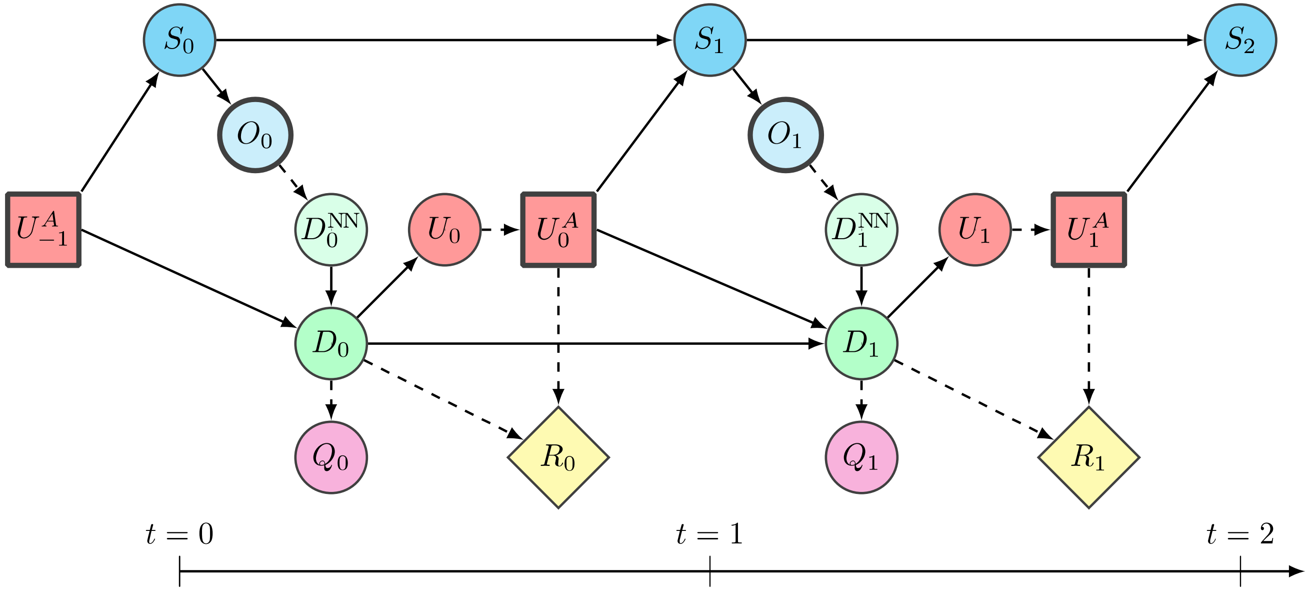
References

- Torzoni, Tezzele, Mariani, Manzoni, Willcox. **A digital twin framework for civil engineering structures**, arXiv preprint, 2023.
- Kapteyn, Pretorius, Willcox. **A probabilistic graphical model foundation for enabling predictive digital twins at scale**, Nature Computational Science,1(5):337–347, 2021.
- Torzoni, Rosafalco, Manzoni, Mariani, Corigliano. **SHM under varying environmental conditions: an approach based on model order reduction and deep learning**, Computers & Structures, 266:106790, 2022.
- Rosafalco, Torzoni, Manzoni, Mariani, Corigliano. **Online structural health monitoring by model order reduction and deep learning algorithms**, Computers & Structures, 255:106604, 2021.
- Torzoni, Manzoni, Mariani. **A multi-fidelity surrogate model for structural health monitoring exploiting model order reduction and artificial neural networks**, Mechanical Systems and Signal Processing, 197:110376, 2023.
- Torzoni, Manzoni, Mariani. **Structural health monitoring of civil structures: a diagnostic framework powered by deep metric learning**, Computers & Structures, 271:106858, 2022.

Dipartimento di Ingegneria Civile e Ambientale
Politecnico di Milano
matteo.torzoni@polimi.it

Probabilistic graphical model encoding the asset-twin system





Offline:

- Derive the reduced-order model
- Populate the training dataset
- Train the SHM deep learning models
- Estimate the transition models ϕ_t^{history} from historical data of similar structures
- Compute the control policy (planning)

Online (repeats indefinitely):

- Assimilate incoming observational data
- Inference of digital state and control inputs
- Update ϕ_t^{history} on the online data stream
- Compute quantities of interest
- Predict the digital state evolution
- Enact the suggested control action

Bonus