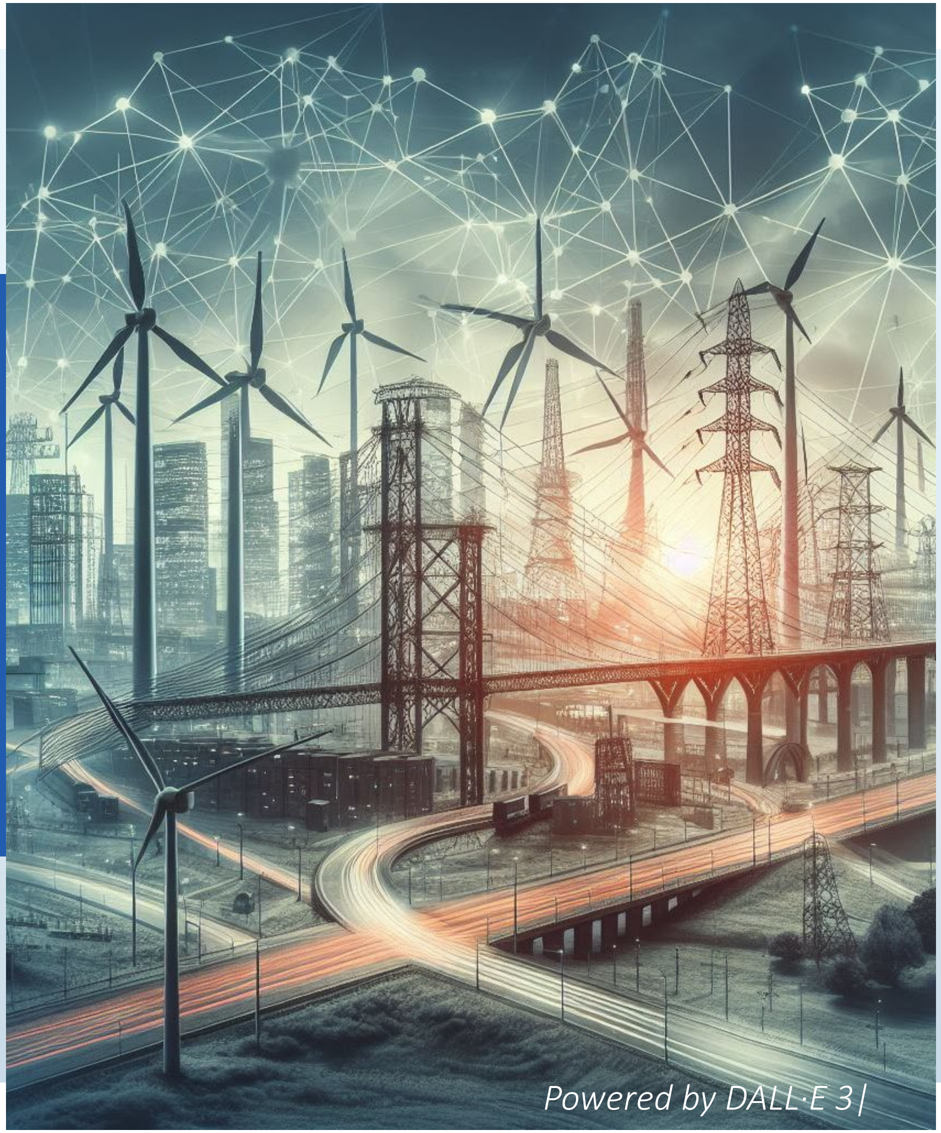
ETH zürich

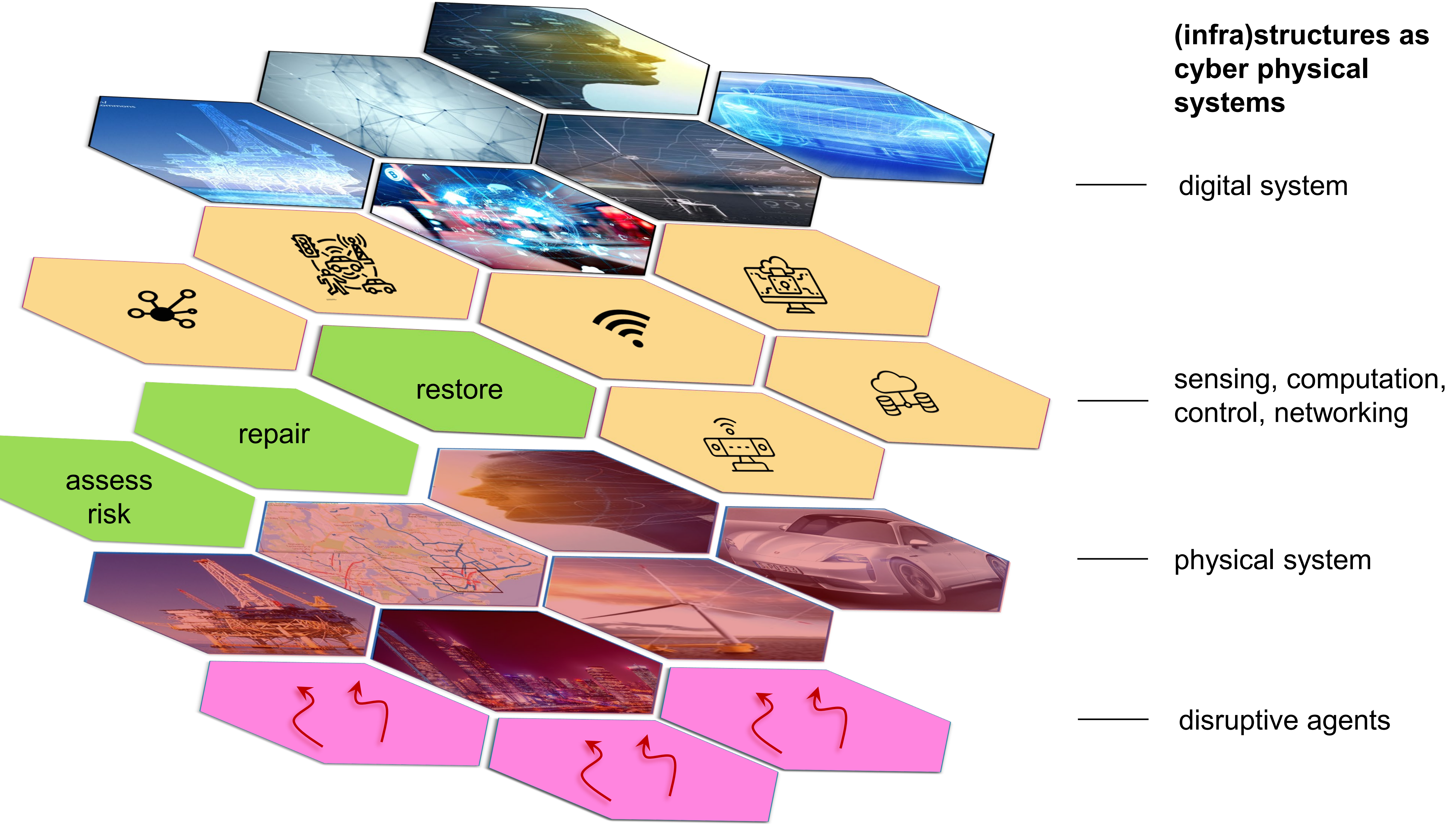
Chair of Structural Mechanics & Monitoring

Graph representations as a natural learner for monitoring and twinning, with applications to railway, wind energy, and bridge assets

Eleni Chatzi
ETH Zürich

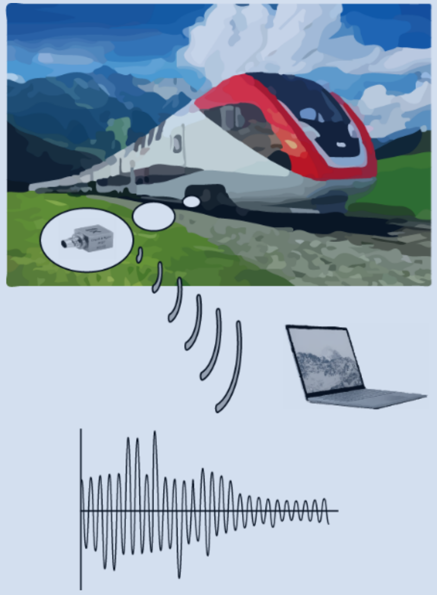


D BAUG



(infra)structures as cyber physical systems
digital system
sensing, computation, control, networking
physical system
disruptive agents
restore
repair
assess risk

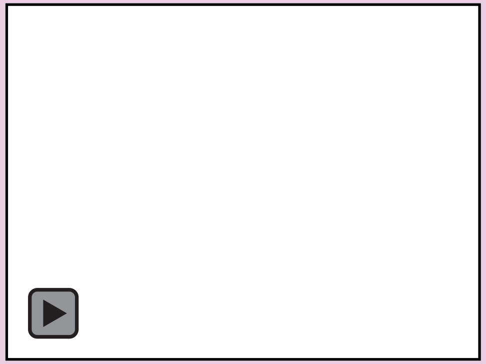
Data Sources at the SMM Group



on board
monitoring for
roadway/railway

Transport infrastructure

PTOON, Wind Farm Greece



SMM owned Aventa Turbine

Wind Energy Infrast.

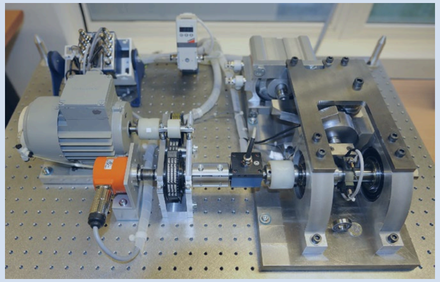
Monitoring under Demolition

Haus Du Pont, Zürich

SBB Bridge, Sempach

Steinavötn Bridge, Iceland

Built Environment



PRONOSTIA ball bearings

train seats

Industrial Assets

Data is not enough | Hybrid Modelling

"as-designed"

Physics-based representations

Hybrid Models
- Advanced SHM/twinning tasks Detection, localization, quantification, prognosis
- Used on the fly for diagnostics & control
- Are eXplainable/Interpreatable

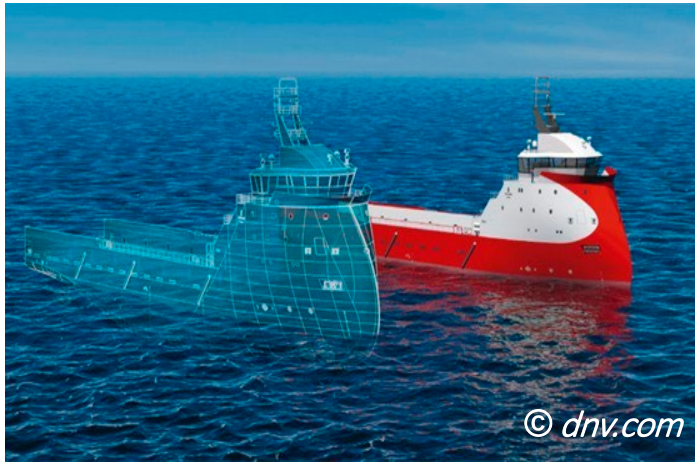
Interactive, closed loop DTs

Purely data-driven representations

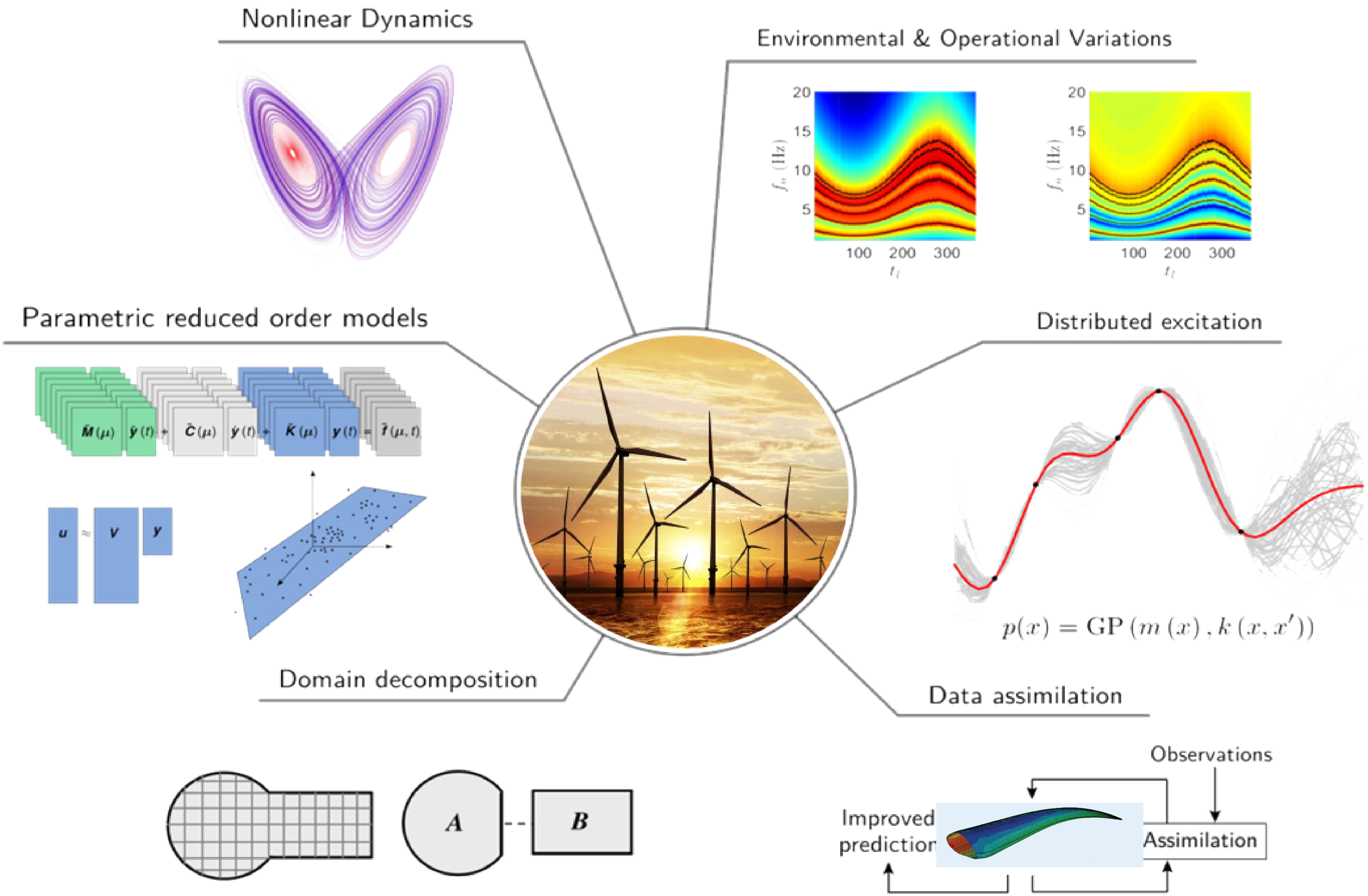
"as-is", diagnosis

Hybrid

Simulation Paths



Modelling Complex Systems under Operating Environments



Use Cases

– Reduced Order Modeling for Virtualization & Twinning

– Virtual sensing for real-time estimation & condition assessment

– Data driven Diagnosis & Prognosis

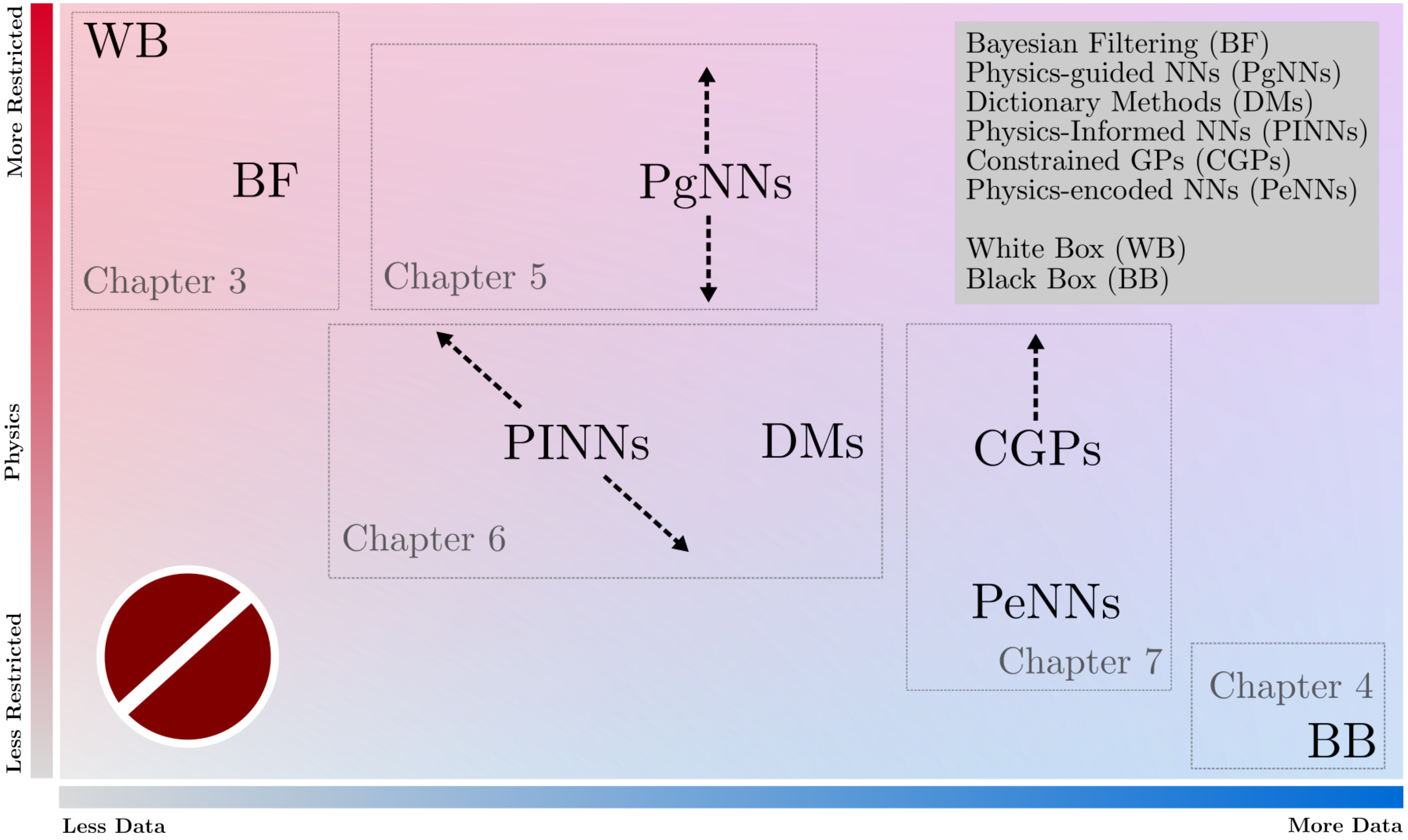
– Applications in Hybrid Simulation & Control

Photo Credit: Dr. K. Tatsis

At the Nexus of Models & Data → Physics - enhanced Machine Learning

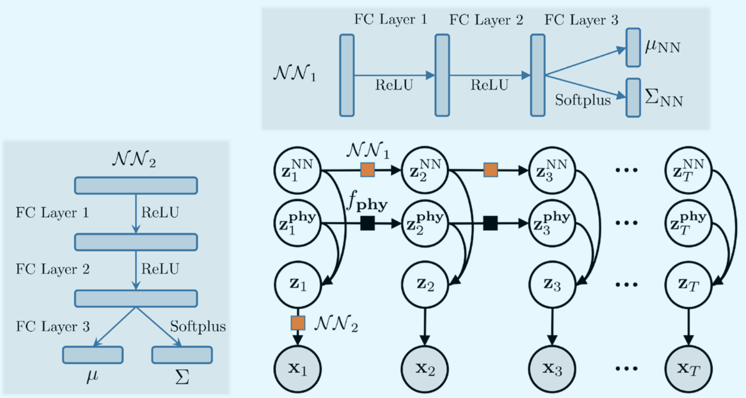
Paper

Code

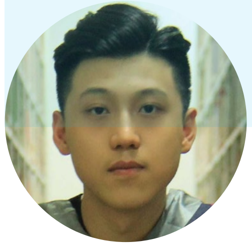


Physics-enhanced Machine Learning

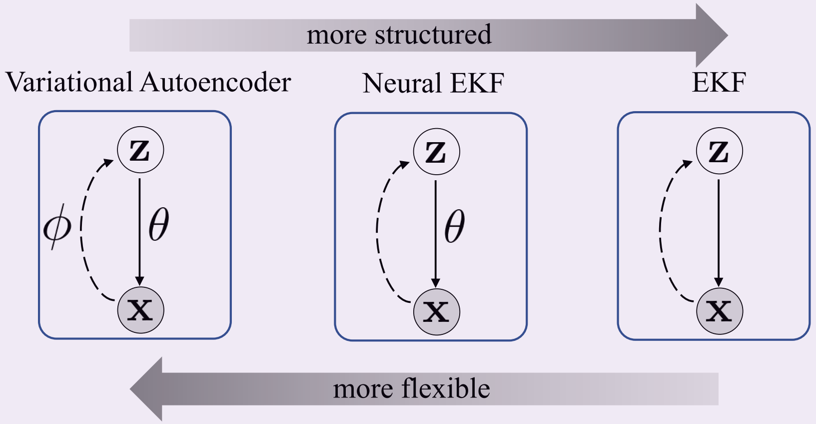
Physics-guided



Physics-guided Deep Markov Models



Physics-encoded

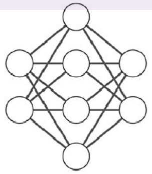


Neural Extended KFs

$$\frac{d\mathbf{h}(t)}{dt} = f(\mathbf{h}(t), t, \boldsymbol{\theta})$$

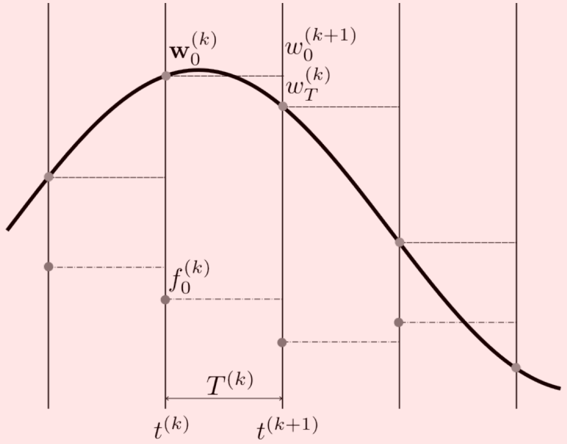
$$\downarrow$$

$$\frac{d\mathbf{h}(t)}{dt} = f_{phy}(\mathbf{h}(t), t) + NN(\mathbf{h}(t), t, \boldsymbol{\theta})$$



Physics-Informed Neural ODEs

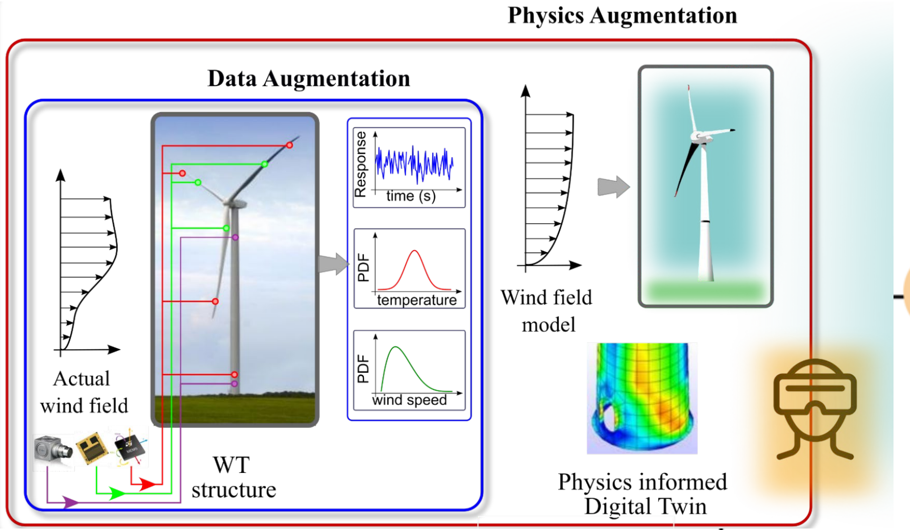
Physics-Informed



1-step ahead PINN predictors

(FRS) FUTURE RESILIENT SYSTEMS

Application: Interactive Digital Twins - Closing the loop

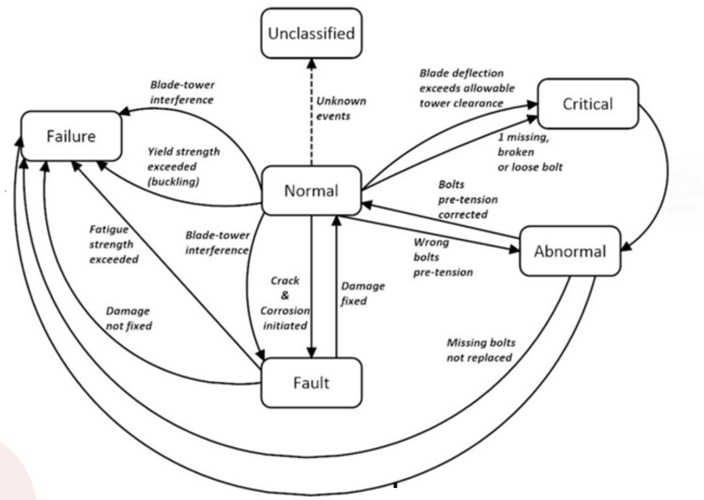


API

API

Courtesy of Dr. Silvia Vettori – ETHZ/Siemens DIS

Object-Oriented Real-Time Decision-Tree

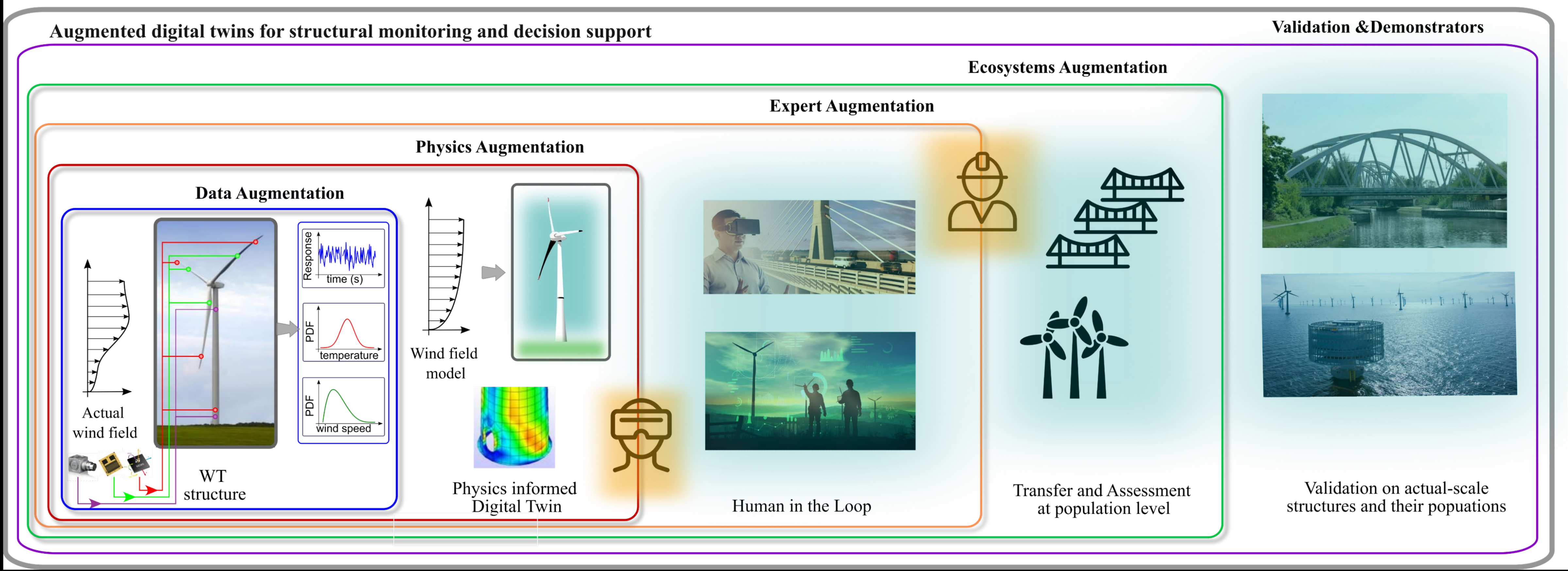


Courtesy of Dr. Silvia Vettori – ETHZ/Siemens DIS & SMM Chair

Cloud computing, storage & analytics

SIEMENS
Ingenuity for life

Augmented digital twins for structural monitoring & decision support



Graphs for Learning at the Ecosystem Level

Natural fit as representation of interconnected systems

Scalable from local to global
From individual assets to entire networks, graphs adapt seamlessly.

Support dynamic data integration
Capture evolving relationships, data flows, and temporal dynamics across systems.

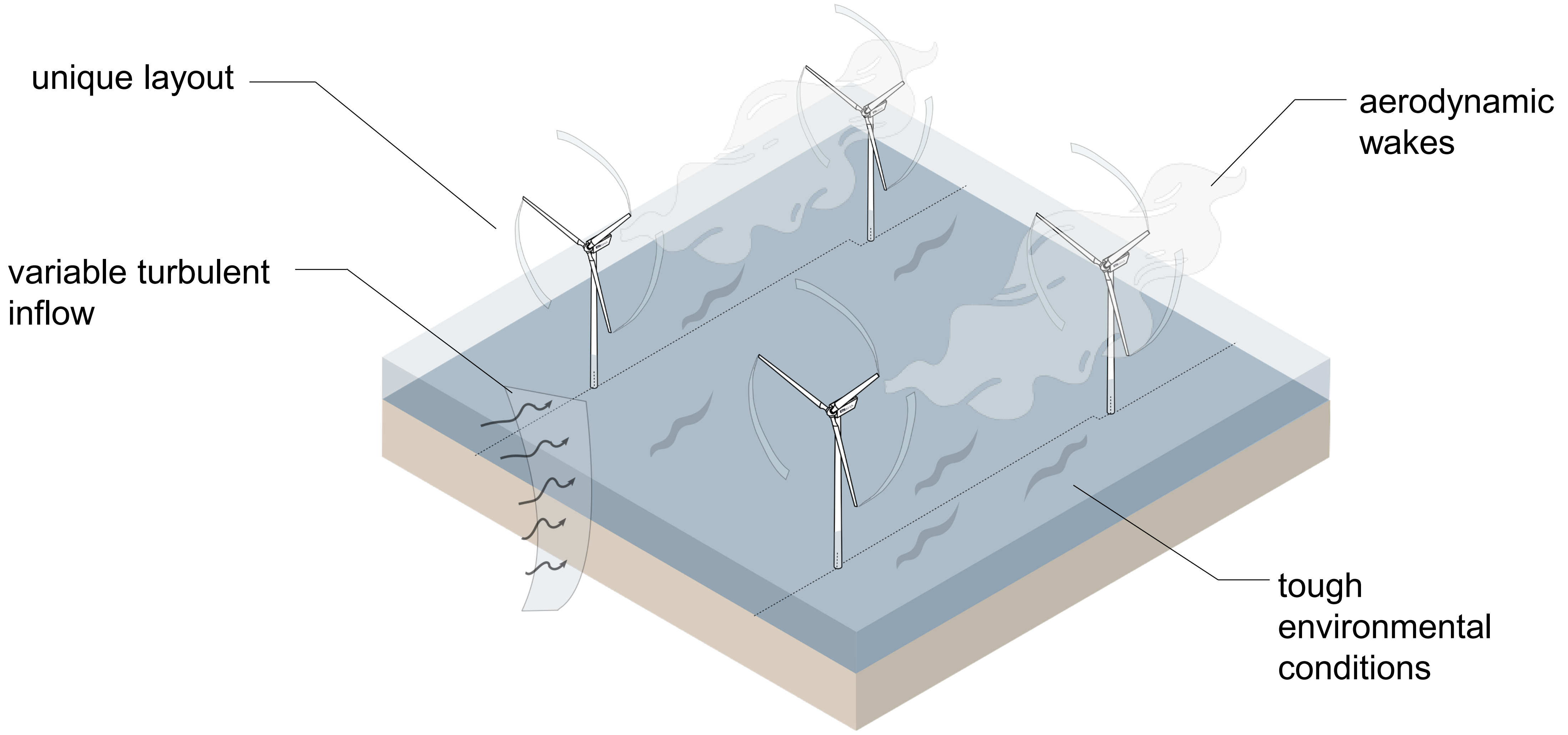
Enable transfer learning across assets
Shared topological and behavioral patterns allow knowledge to transfer between similar subsystems (e.g., across bridges, or wind turbines).

Foundation for digital twins
Serve as the structural layer of digital twins, supporting hybrid modeling & interpretability.

Fleet-level diagnostics & decision support
Enable population-level insights via network-based learning.

At the Fleet Level

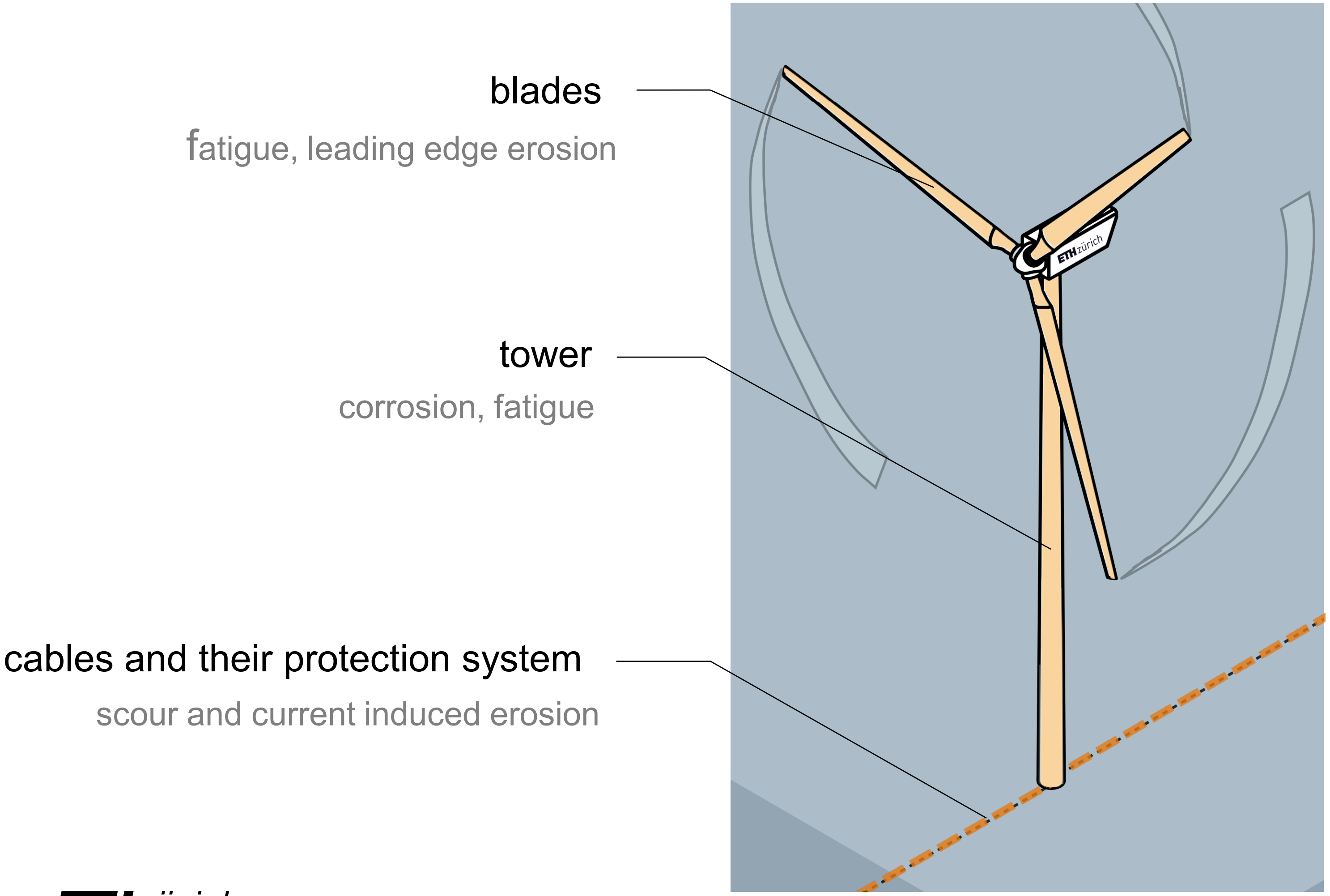
Wind farms are complex systems involving physical processes at multiple scales.



At he individual asset level

Turbines themselves are systems of individual components, each with its own unique behavior.

Some critical components are difficult to monitor and degrade over extended periods of time.

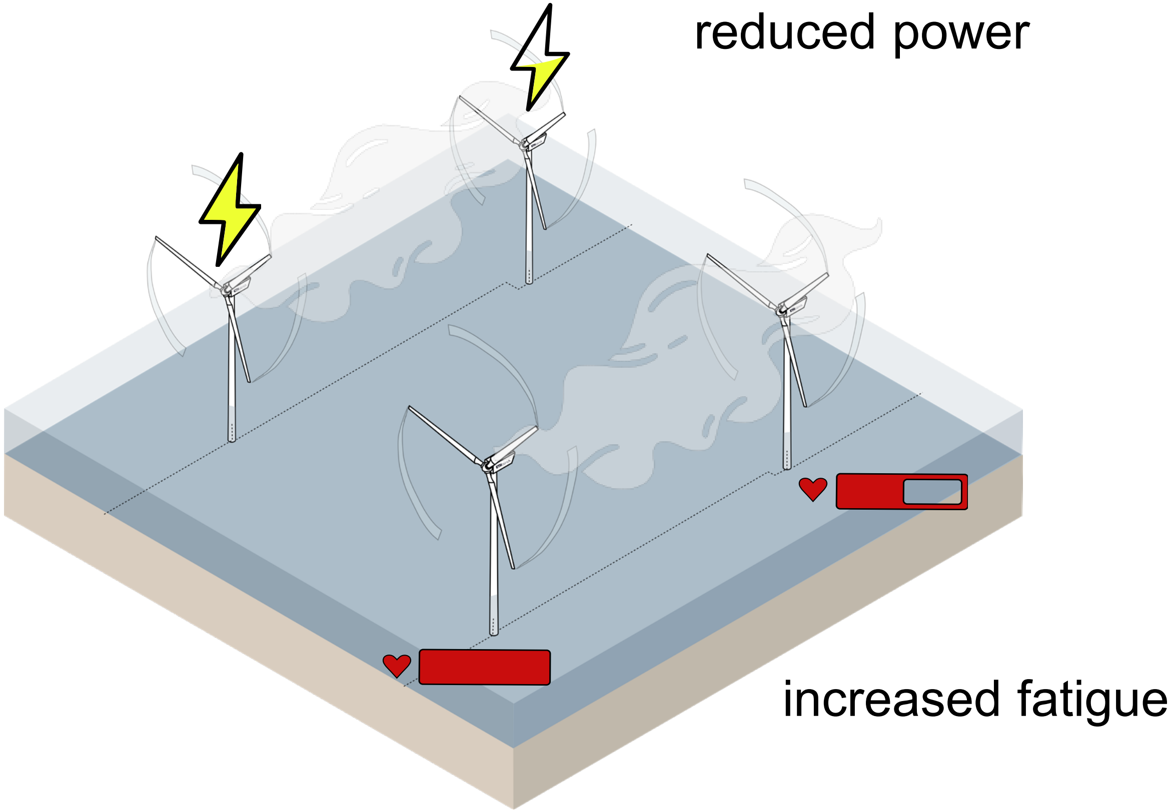


How can we design neural architectures that can deal with all of these challenges, leading to better generalization?

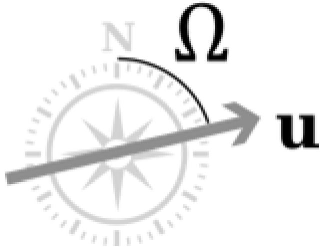
At the Farm Level: Wind turbine wake effects

Source: Vattenfall. Photographer: Christian Steiness.

Wind turbine wakes cause:



ML for wind farms



any wind farm (layout + turbine model)

any inflow condition

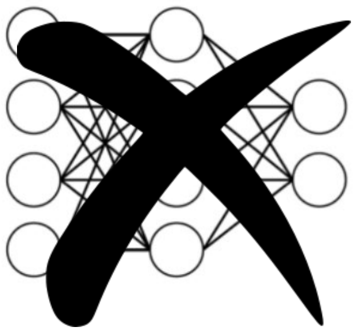
ML

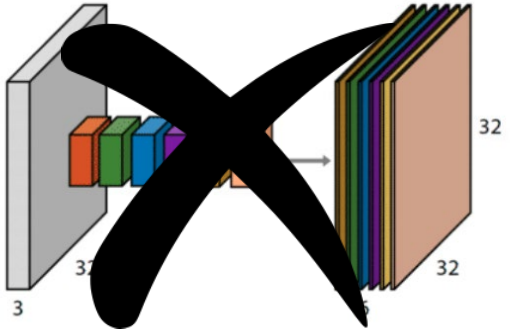
power, local flow, fatigue loads for each turbine

ML for wind farms

Traditional ML methods can’t deal with unordered sets of variable size

Graph neural networks are perfectly suited for this!

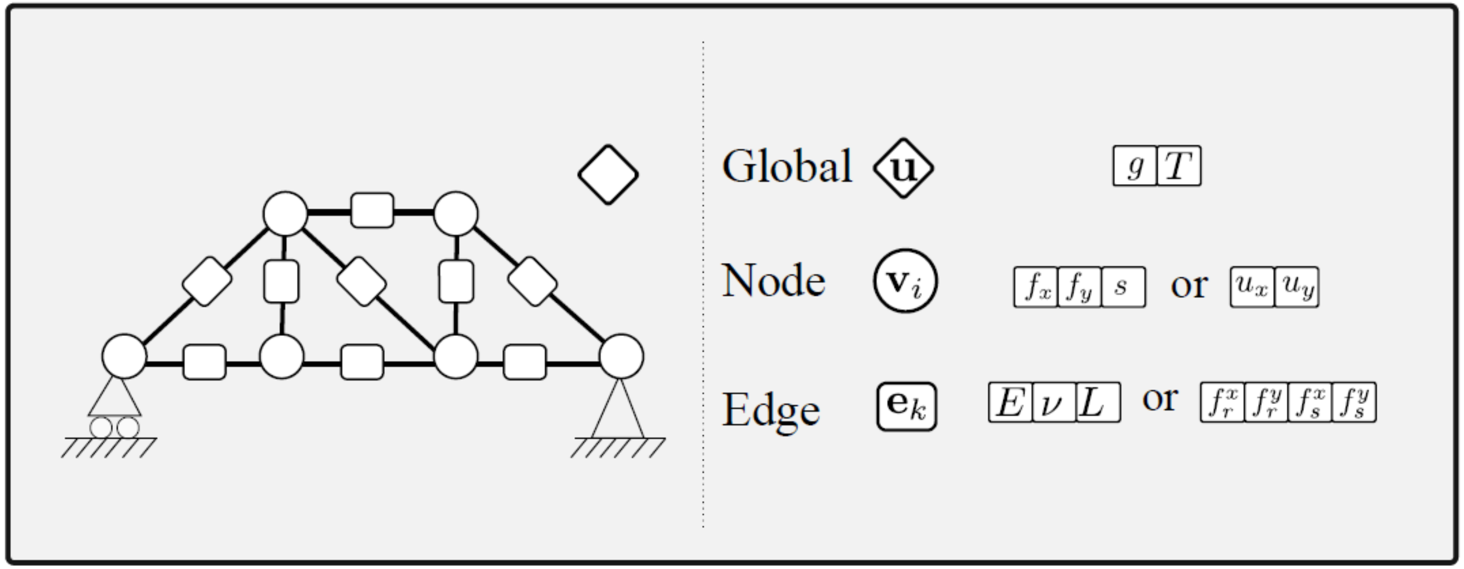




SMM Entry point:
Deep Learning Algorithms for attributed graph data

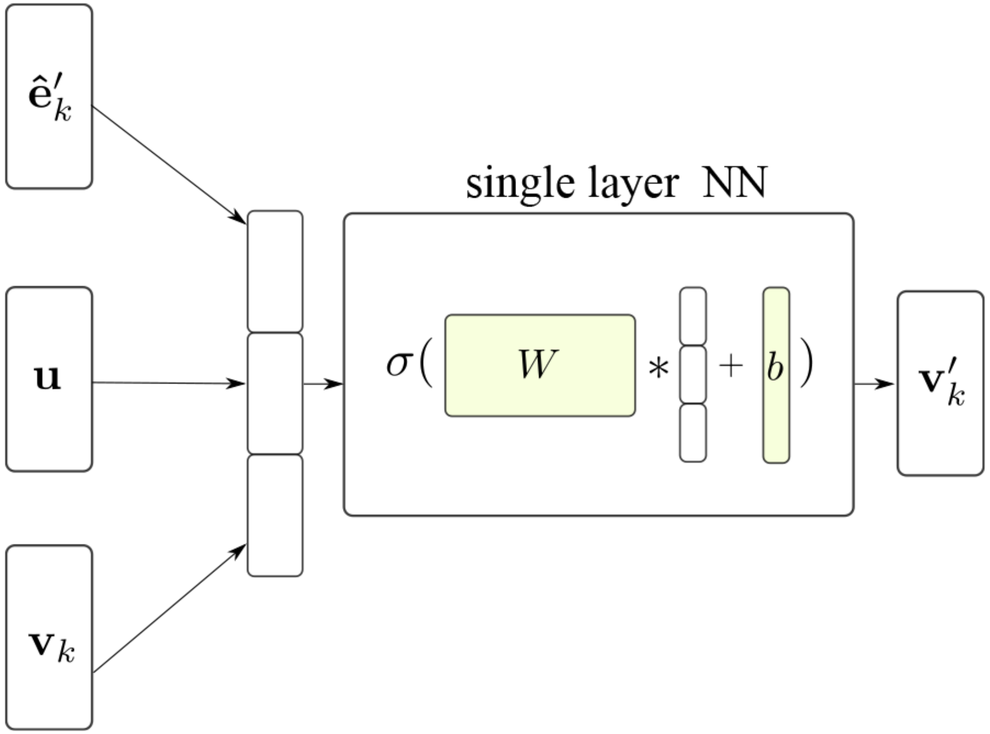
Doctoral Thesis of Charilaos Mylonas (2021)

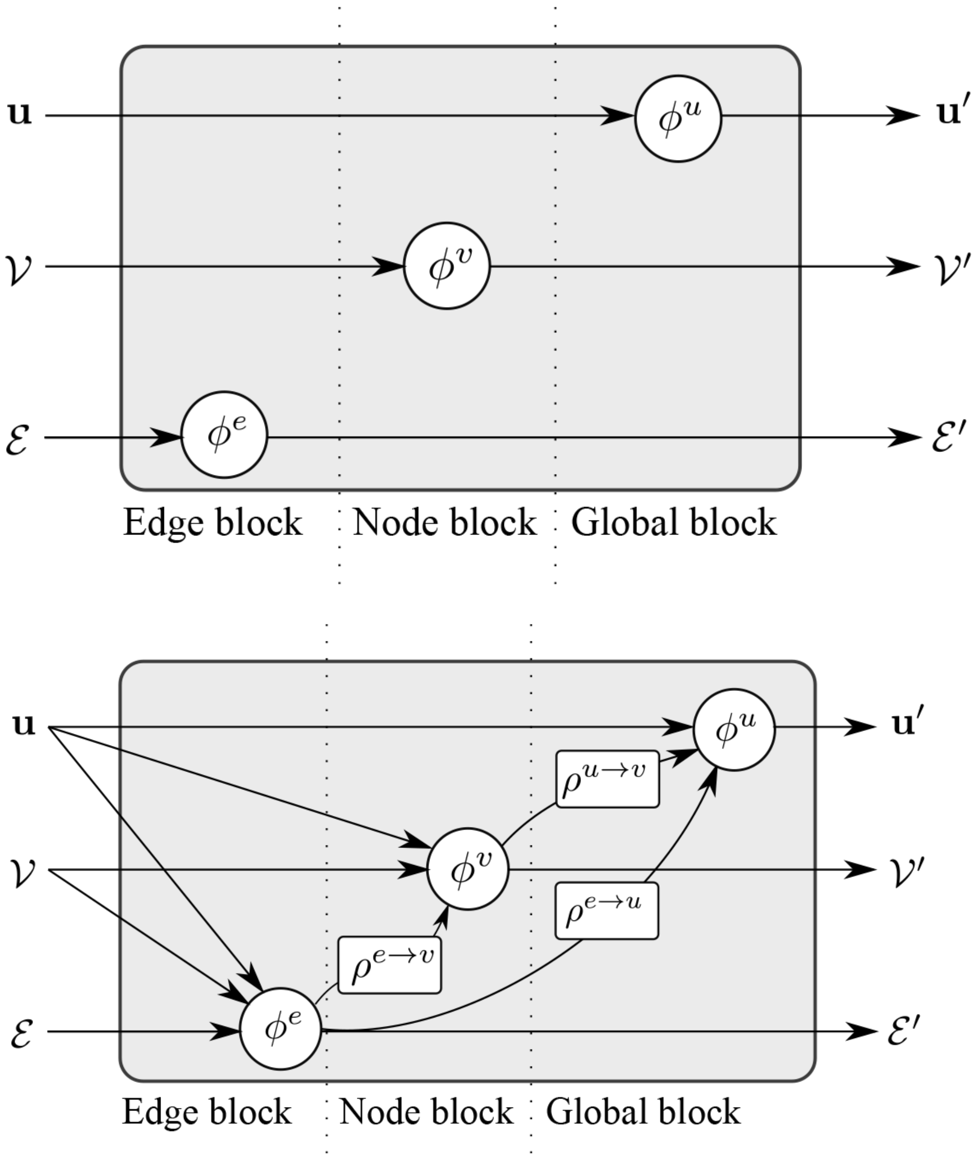
> *"...we reject the false choice between "hand-engineering" and "end-to-end" learning, and instead advocate for an approach which benefits from their complementary strengths."*
>
> (Battaglia et al, 2018)



Deep Learning Algorithms for attributed graph data

Encode-process-decode architecture





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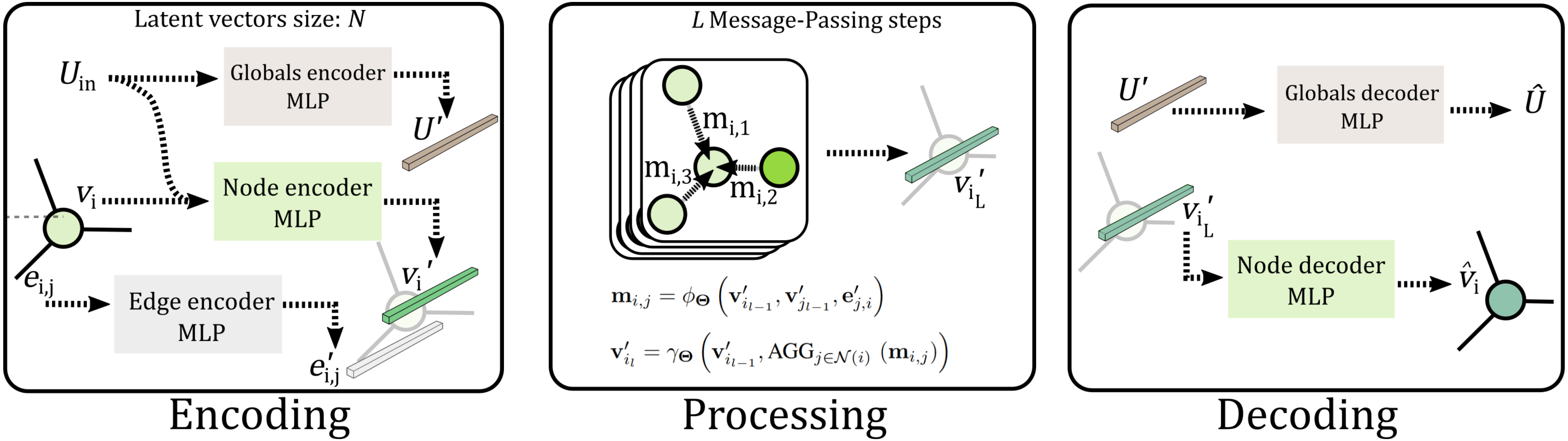
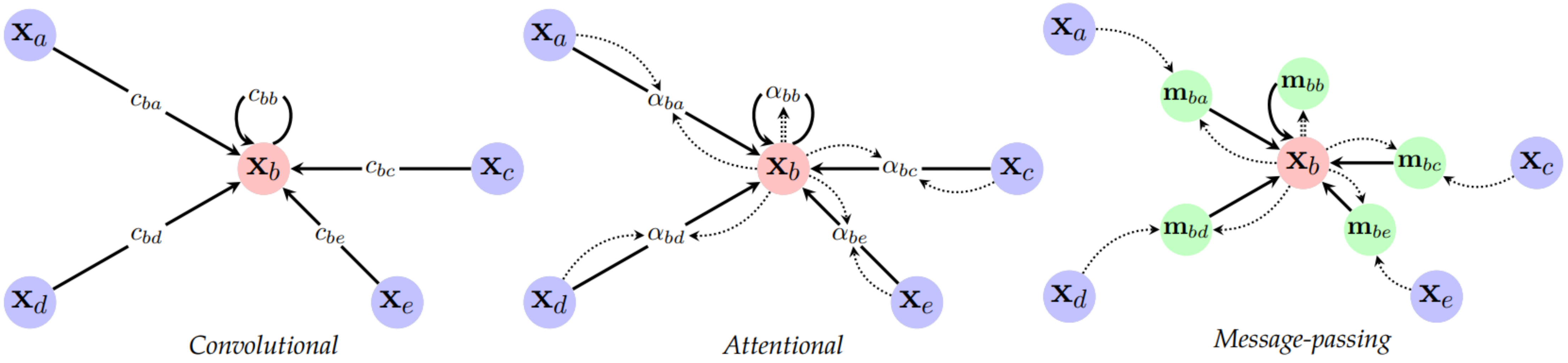
Charilaos Mylonas, Doctoral Thesis, ETH Zurich, 2021, LINK

Deep Learning Algorithms for attributed graph data

Encode-process-decode architecture

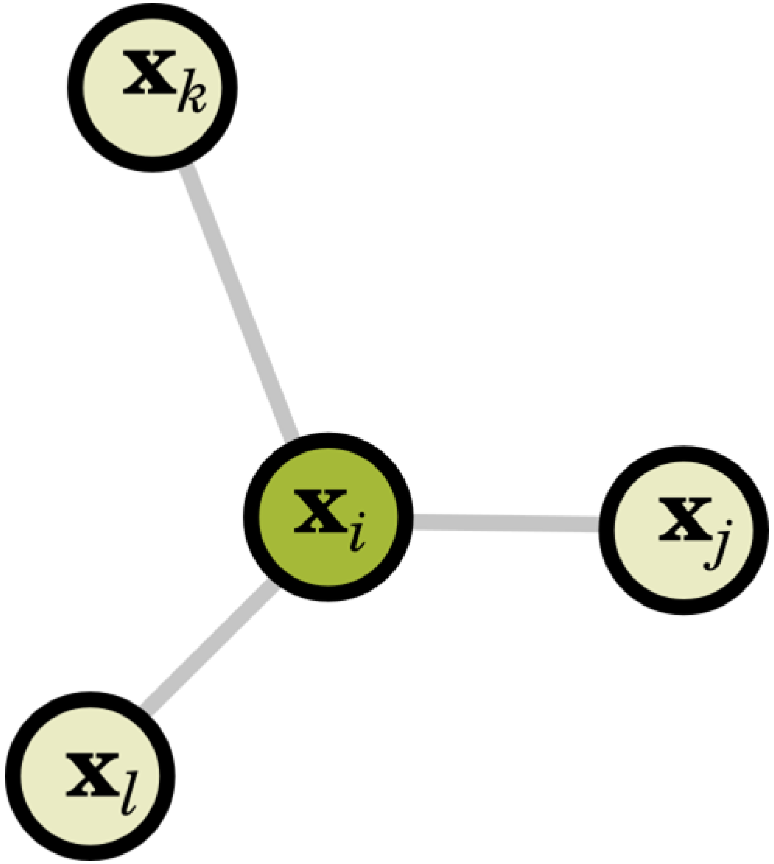


Different kinds of message-passing

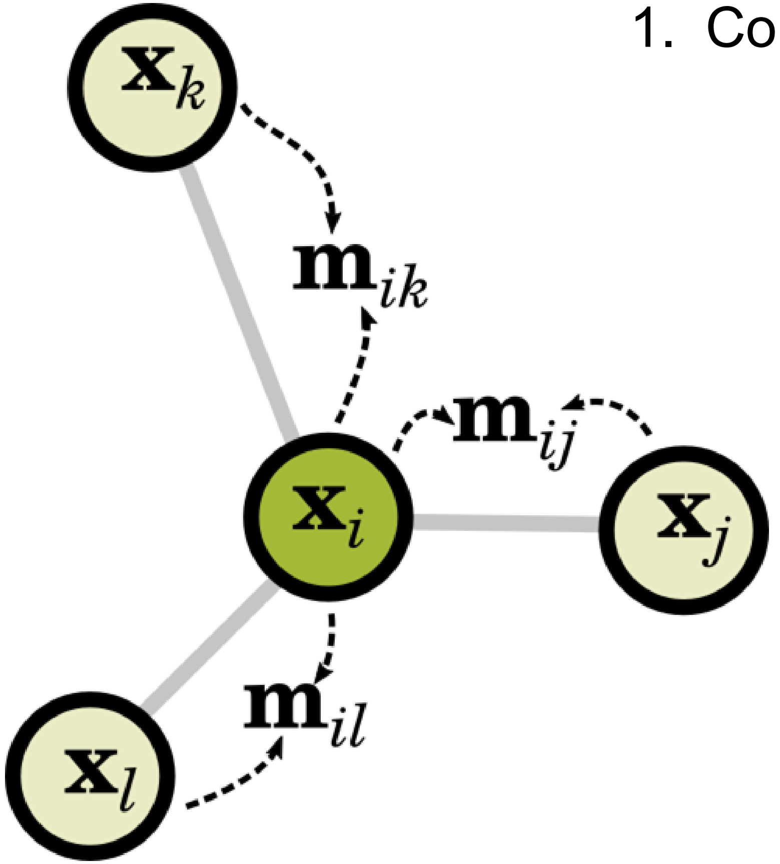


Source: Bronstein, Bruna, Cohen, Veličković (2021)

GNNs: propagation of information through message-passing



GNNs: propagation of information through message-passing

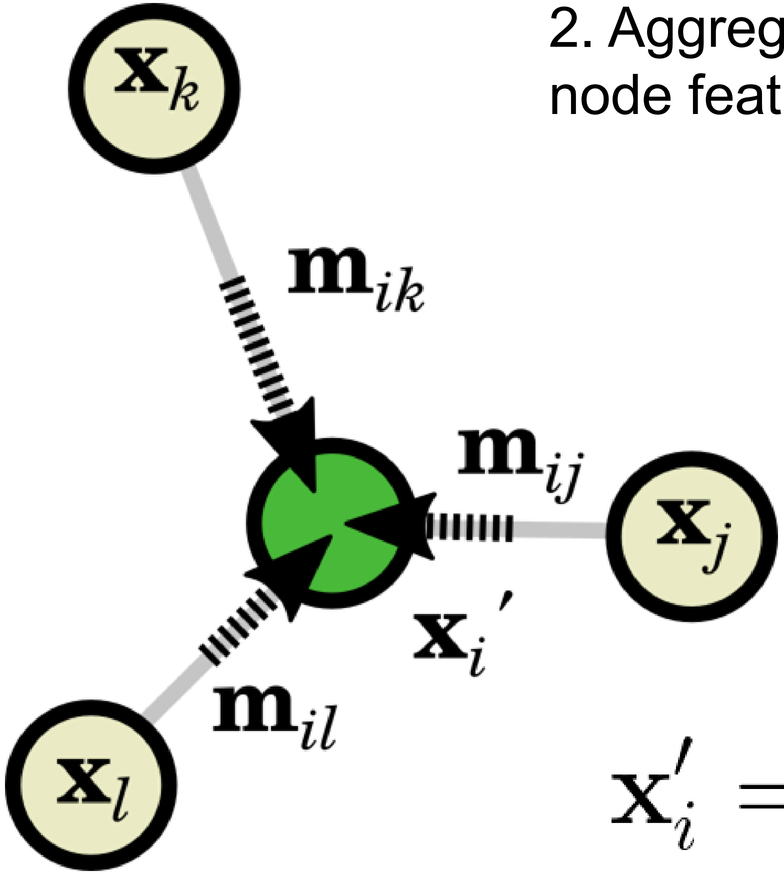


1. Compute messages for each edge

$$\mathbf{m}_{ij} = \phi(\mathbf{x}_i, \mathbf{x}_j)$$

often a NN

GNNs: propagation of information through message-passing



2. Aggregate incoming messages to update node features

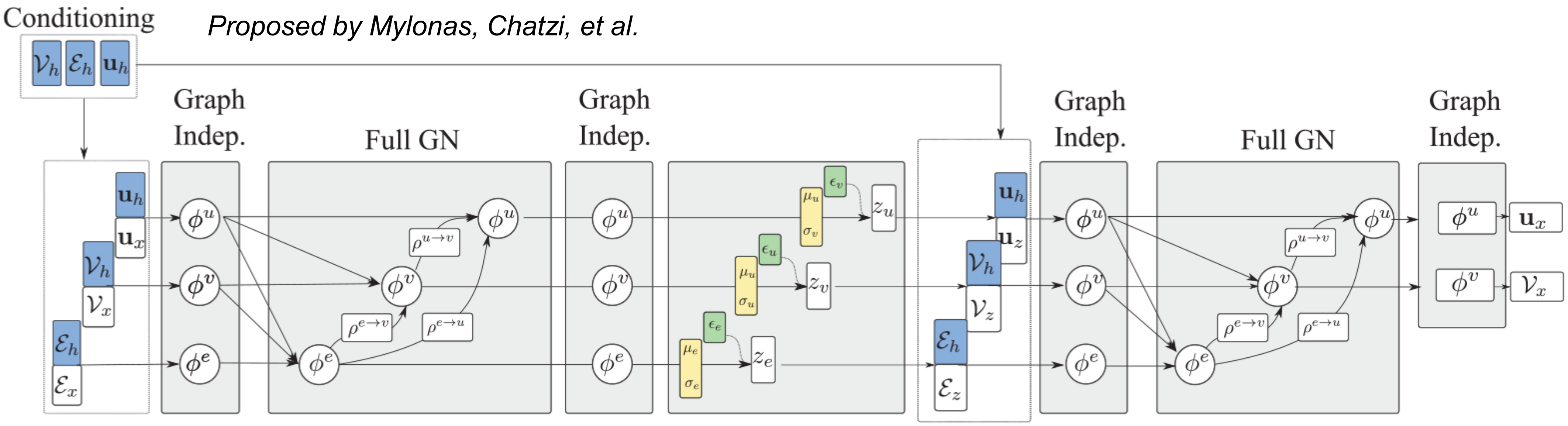
permutation invariant aggregation (sum, mean, etc.)

$$\mathbf{x}_i' = \gamma\left(\mathbf{x}_i, \square_{j \in \mathcal{N}(i)} \left(\mathbf{m}_{ij}\right)\right)$$

often a NN

Variational Bayesian GNNs

Proposed by Mylonas, Chatzi, et al.



Conditional Relational VAE

$$\mathcal{V}_z \sim q_{\phi}^{(\mathcal{V})}(G_z|G_x;G_h) = \mathcal{N}(f_{q_\phi}^{\mu(\mathcal{V})}(G_x;G_h), f_{q_\phi}^{\sigma^2(\mathcal{V})}(G_x;G_h))$$

$$\mathcal{E}_z \sim q_{\phi}^{(\mathcal{E})}(G_z|G_x;G_h) = \mathcal{N}(f_{q_\phi}^{\mu(\mathcal{E})}(G_x;G_h), f_{q_\phi}^{\sigma^2(\mathcal{E})}(G_x;G_h))$$

$$\mathbf{u}_z \sim q_{\phi}^{(\mathbf{u})}(G_z|G_x;G_h) = \mathcal{N}(f_{q_\phi}^{\mu(\mathbf{u})}(G_x;G_h), f_{q_\phi}^{\sigma^2(\mathbf{u})}(G_x;G_h)).$$

$$\hat{\mathcal{V}}_x \sim p_{\theta}^{(\mathcal{V})}(G_x|G_z;G_h) = \mathcal{N}(g_{p_\theta}^{\mu(\mathcal{V})}(G_z;G_h), g_{p_\theta}^{\sigma^2(\mathcal{V})}(G_z;G_h))$$

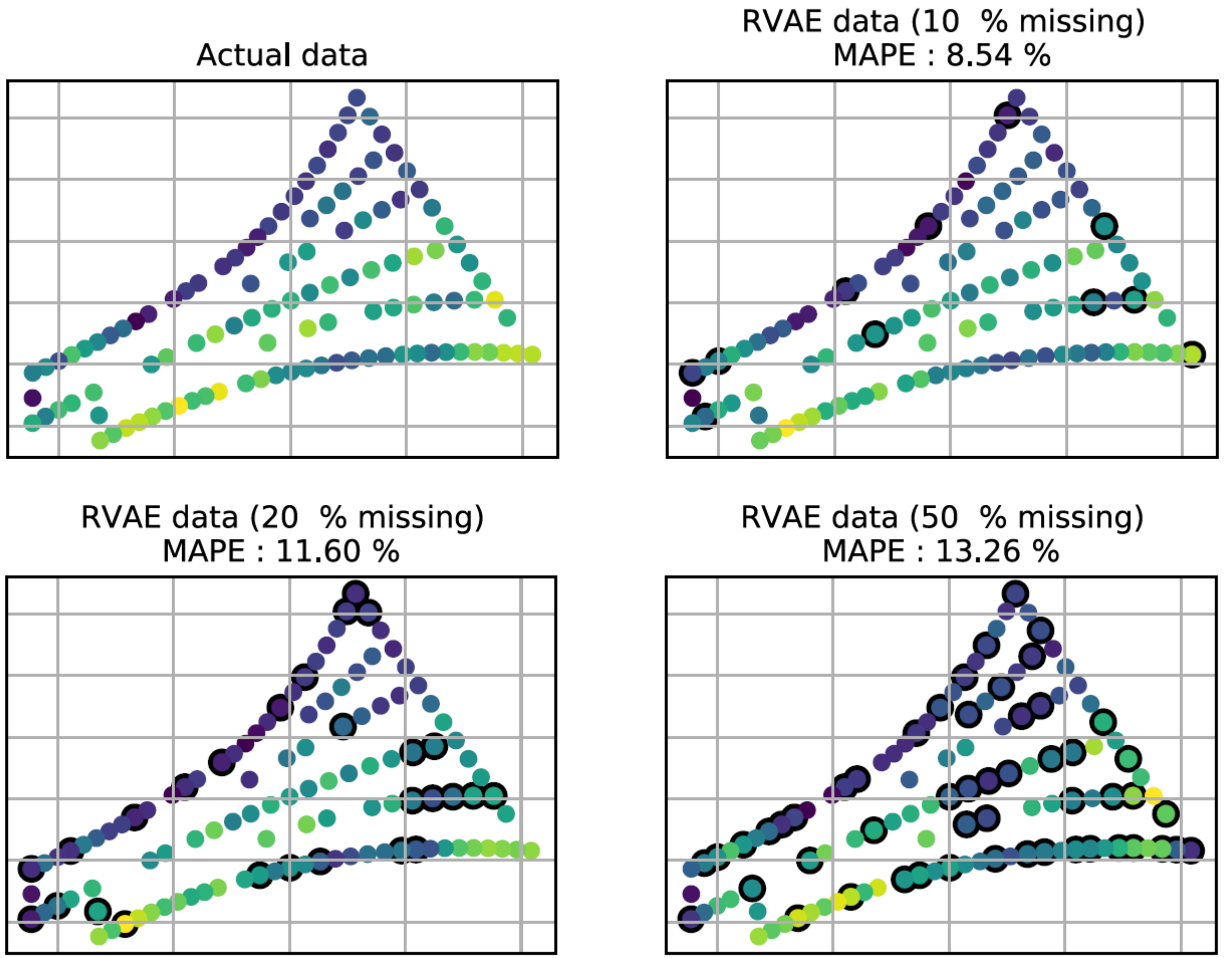
$$\hat{\mathbf{u}}_x \sim p_{\theta}^{(\mathbf{u})}(G_x|G_z;G_h) = \mathcal{N}(g_{p_\theta}^{\mu(\mathbf{u})}(G_z;G_h), g_{p_\theta}^{\sigma^2(\mathbf{u})}(G_z;G_h))$$

$$\begin{aligned}\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\phi}; G_x^{(i)}, G_h^{(i)}) =& \mathbb{E}_{q_{\boldsymbol{\theta}}(G_z|G_x^{(i)};G_h^{(i)})}\left[\log p_{\boldsymbol{\theta}}(G_x^{(i)}|G_z;G_h^{(i)})\right] \\ &- \beta_{\mathcal{V}} D_{KL}(q_{\boldsymbol{\phi}}^{(\mathcal{V})}(G_z|G_x^{(i)};G_h^{(i)})||p_{\boldsymbol{\theta}}^{(\mathcal{V})}(G_z;G_h^{(i)})) \\ &- \beta_{\mathcal{E}} D_{KL}(q_{\boldsymbol{\phi}}^{(\mathcal{E})}(G_z|G_x^{(i)};G_h^{(i)})||p_{\boldsymbol{\theta}}^{(\mathcal{E})}(G_z;G_h^{(i)})) \\ &- \beta_{\mathbf{u}} D_{KL}(q_{\boldsymbol{\phi}}^{(\mathbf{u})}(G_z|G_x^{(i)};G_h^{(i)})||p_{\boldsymbol{\theta}}^{(\mathbf{u})}(G_z;G_h^{(i)}))\end{aligned}$$

Prediction on the Anholt Wind Farm Data

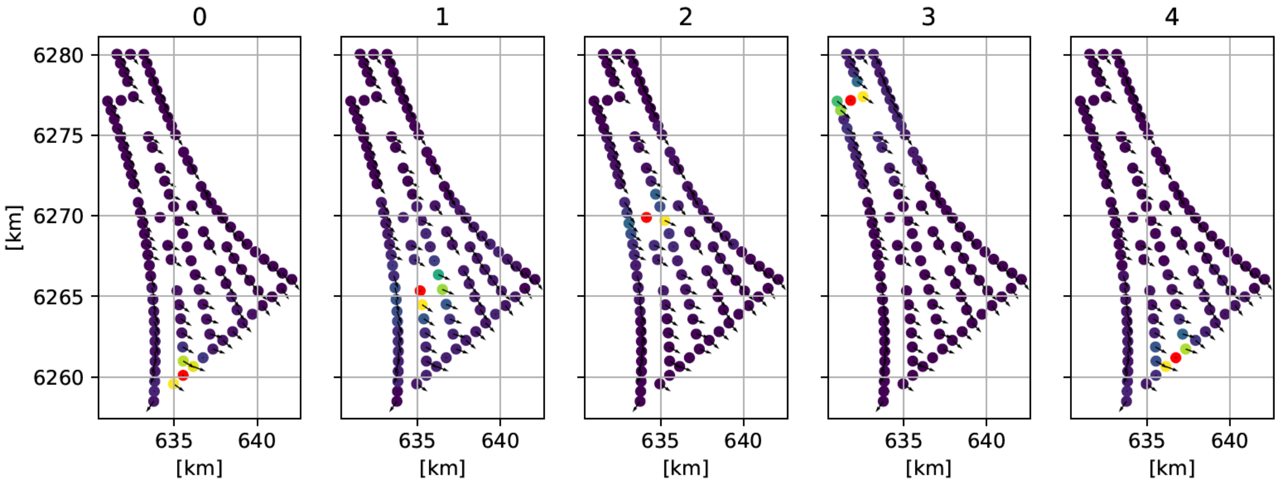
Imputation of wind speeds given neighboring Turbine Data

Quantity	Variable se
Turbine rotor size	$\mathcal{V}_h$
Turbine distance	$\mathcal{E}_h$
Turbine rel. orientation	$\mathcal{E}_h$
Farm mean wind orientation	$\mathbf{u}_h$
Farm mean wind speed	$\mathbf{u}_h$
Time of day	$\mathbf{u}_h$
Power (turbine)	$\mathcal{V}_x$
Wind mean (turbine)	$\mathcal{V}_x$
Wind std (turbine)	$\mathcal{V}_x$
Turb. Nacelle orientation	$\mathcal{V}_x$
Nacelle temperature	$\mathcal{V}_x$
Farm mean wind orientation	$\mathbf{u}_x$
Farm mean wind speed	$\mathbf{u}_x$
Node latent	$\mathcal{V}_z$
Edge latent	$\mathcal{E}_z$
Global latent	$\mathbf{u}_z$



Prediction on the Anholt Wind Farm

Imputation given neighboring Turbine Data

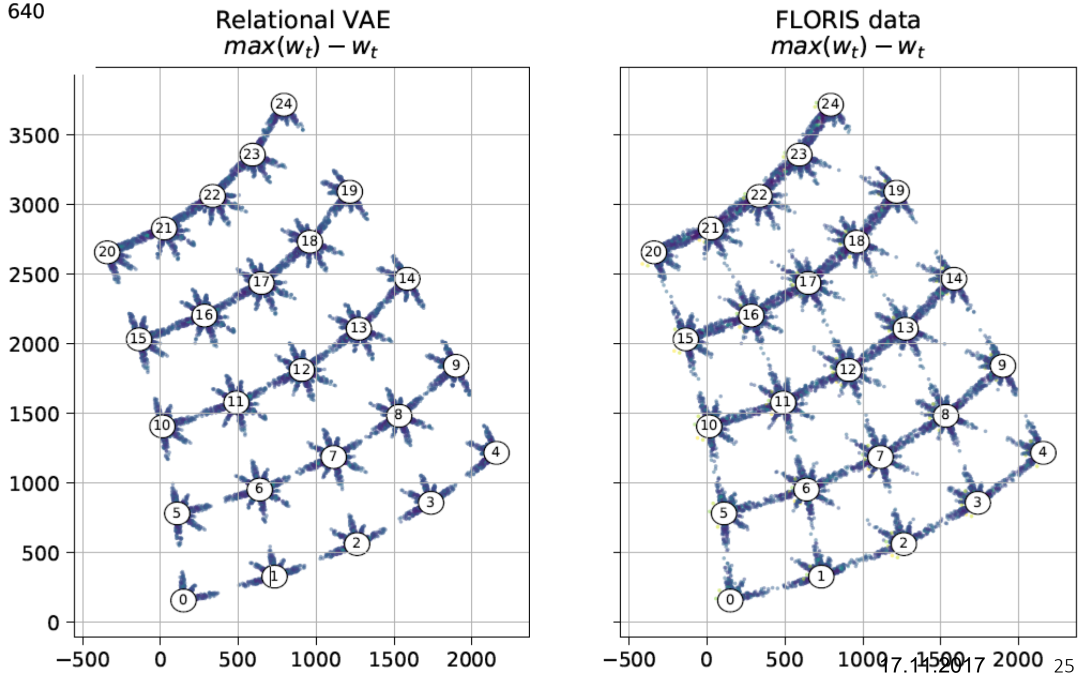


Interpretable diagnostics

The model is end-to-end differentiable → compute an absolute gradient sensitivity

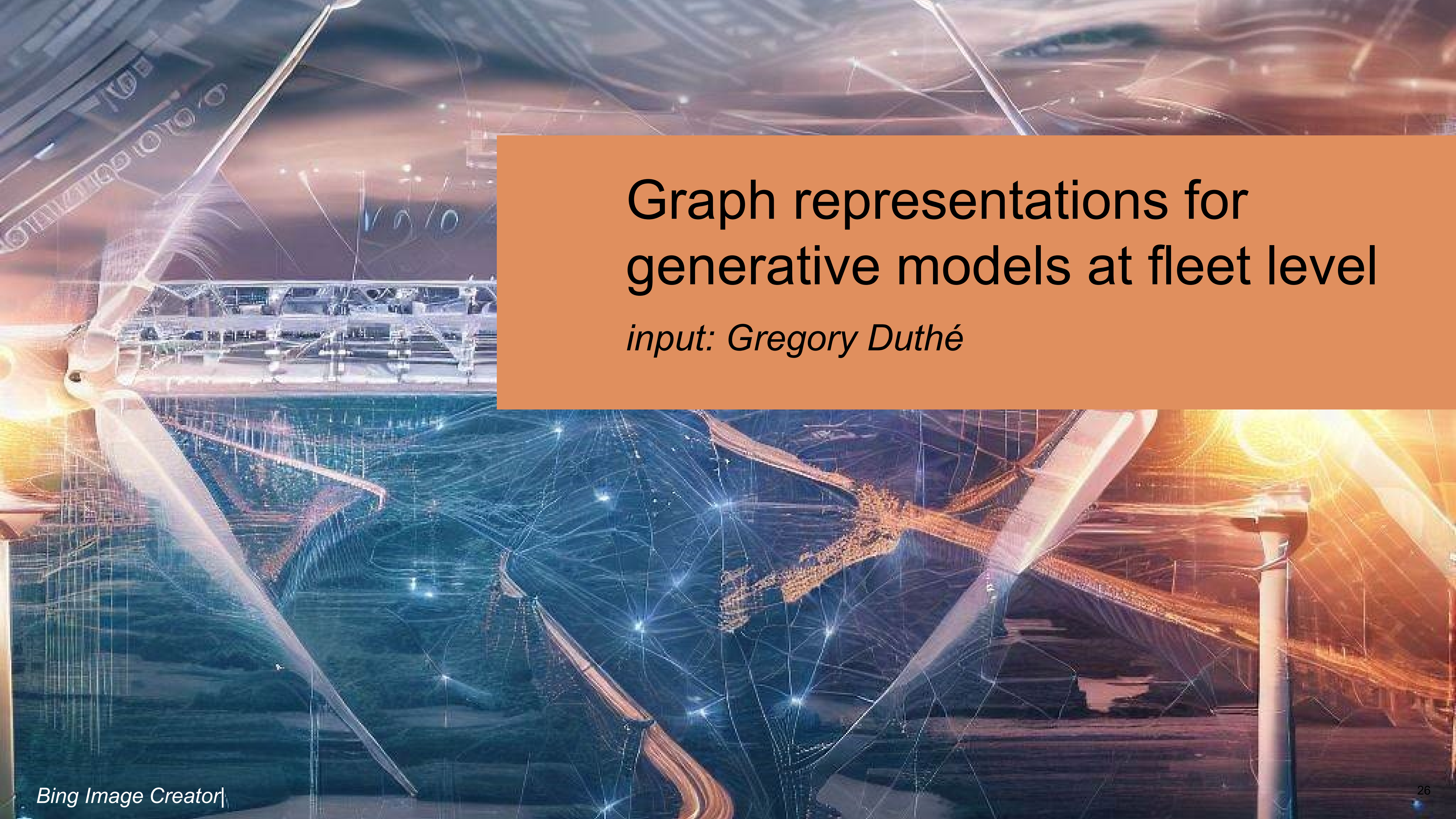
Inferring Engineering relevant Quantities & Transfer

- Generalization to an unseen simulated farm (FLORIS)
- Learnt spatial distribution of wake related wind speed deficit



Graph representations for generative models at fleet level

input: Gregory Duthé



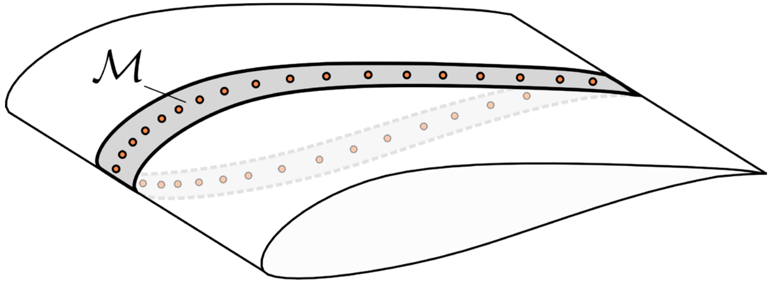
Bing Image Creator

Capitalizing on relational inductive biases for Transfer

To build ML models that have more potential to generalize, we need to leverage **inductive biases**.

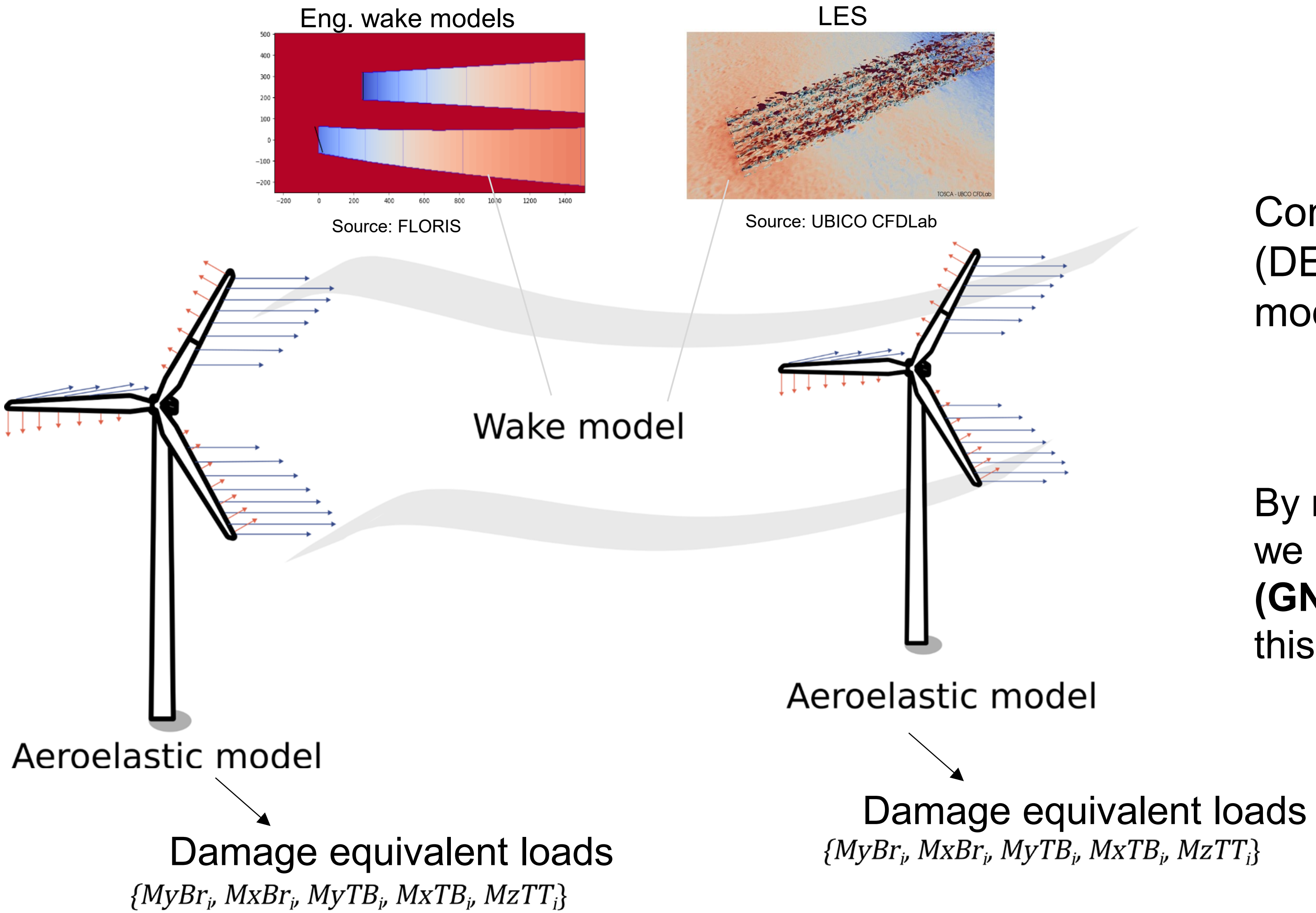
→ built in assumptions that guide the learning process.

In particular, **geometric and relational inductive biases** can be used to build neural architectures that are flexible and can operate on irregular, non-Euclidean structures.



This forms the basis of **Geometric Deep Learning (GDL)**
(Duthé, Doctoral Thesis, 2025)

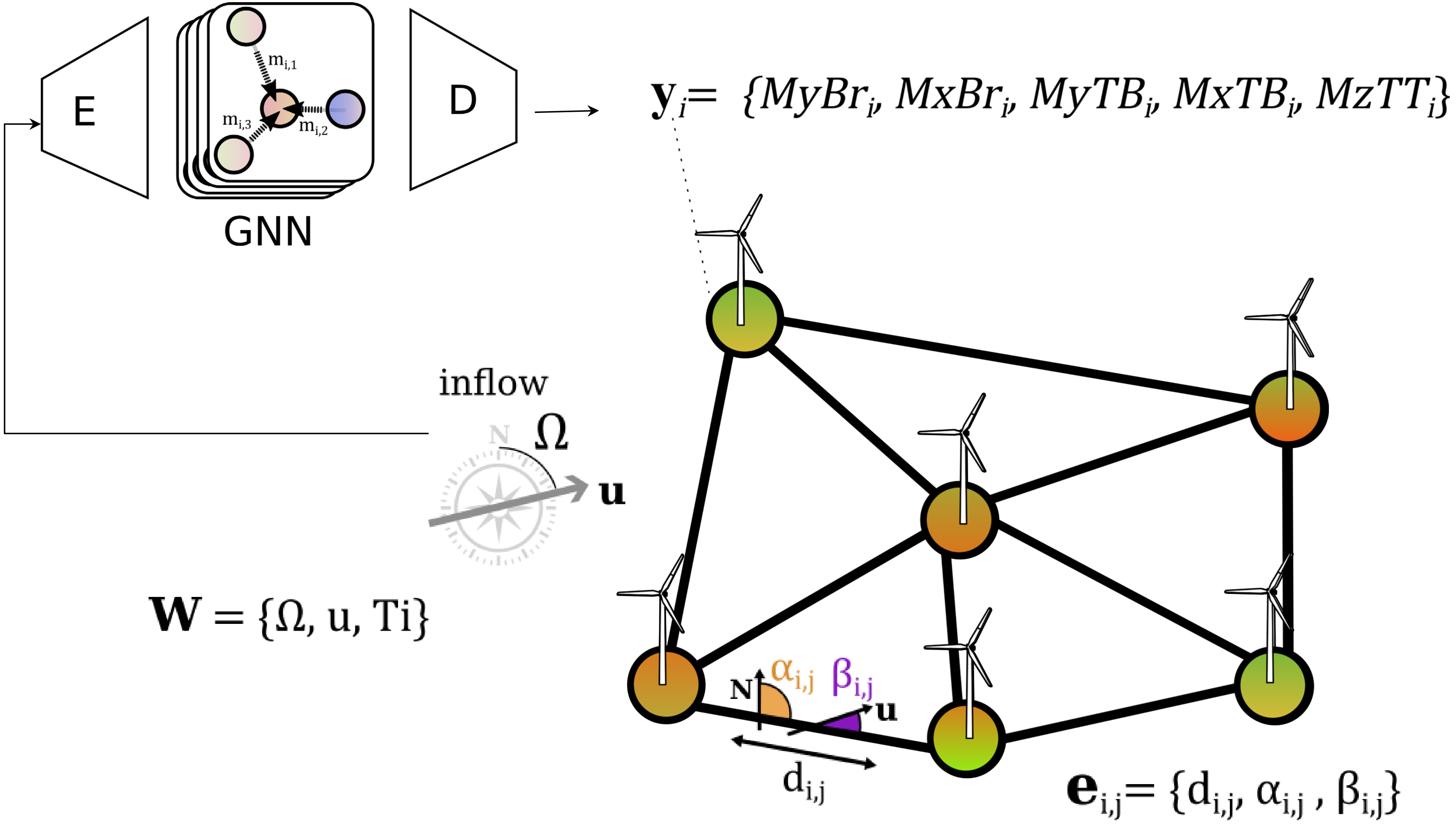
Challenges in wind turbine fatigue modelling



Computing damage equivalent loads (DELs) using coupled aeroelastic models is computationally costly.

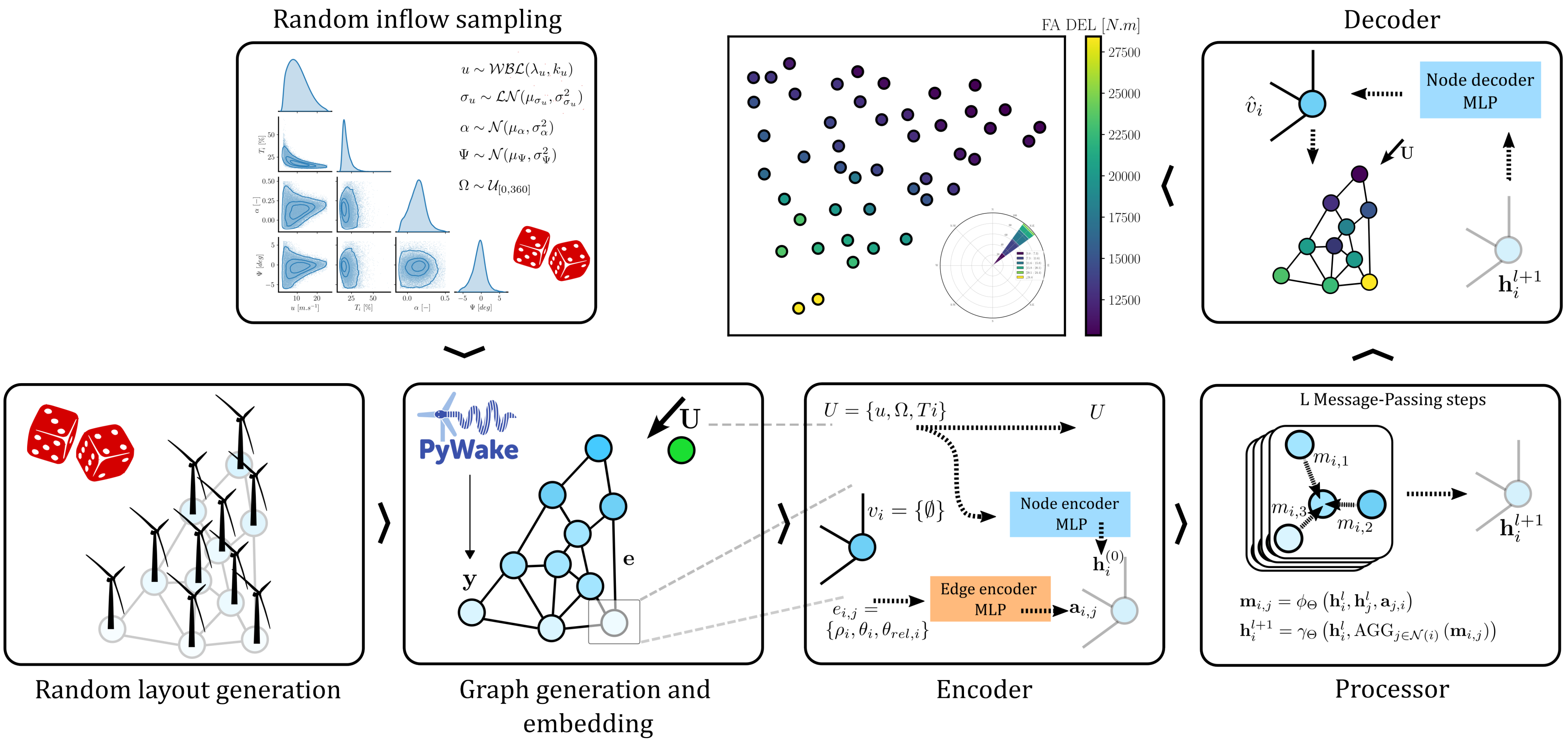
By representing wind farms as graphs, we can use **Graph Neural Networks (GNNs)** as efficient surrogate models of this process.

GNNs for fast wind farm simulations

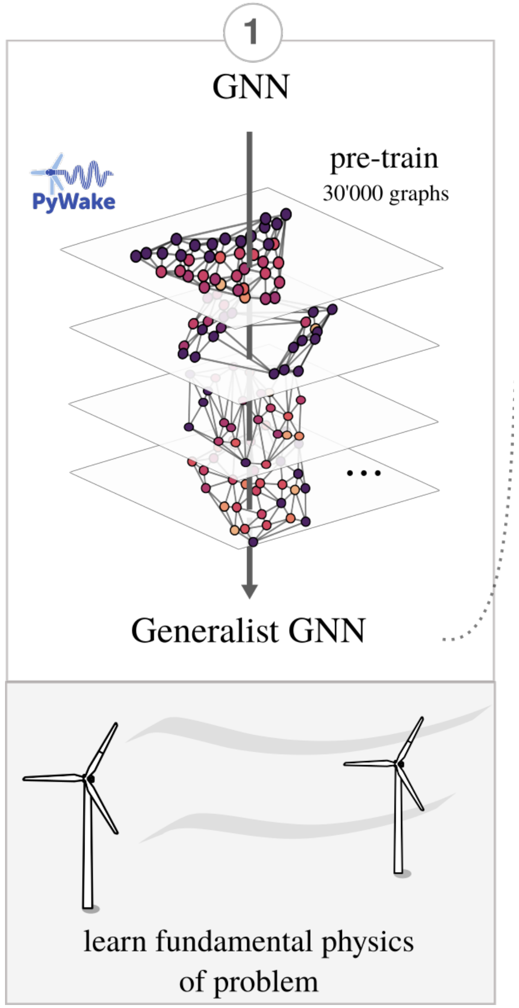


GNN Architecture

Harnessing the power of graph representations for learning across populations/fleets



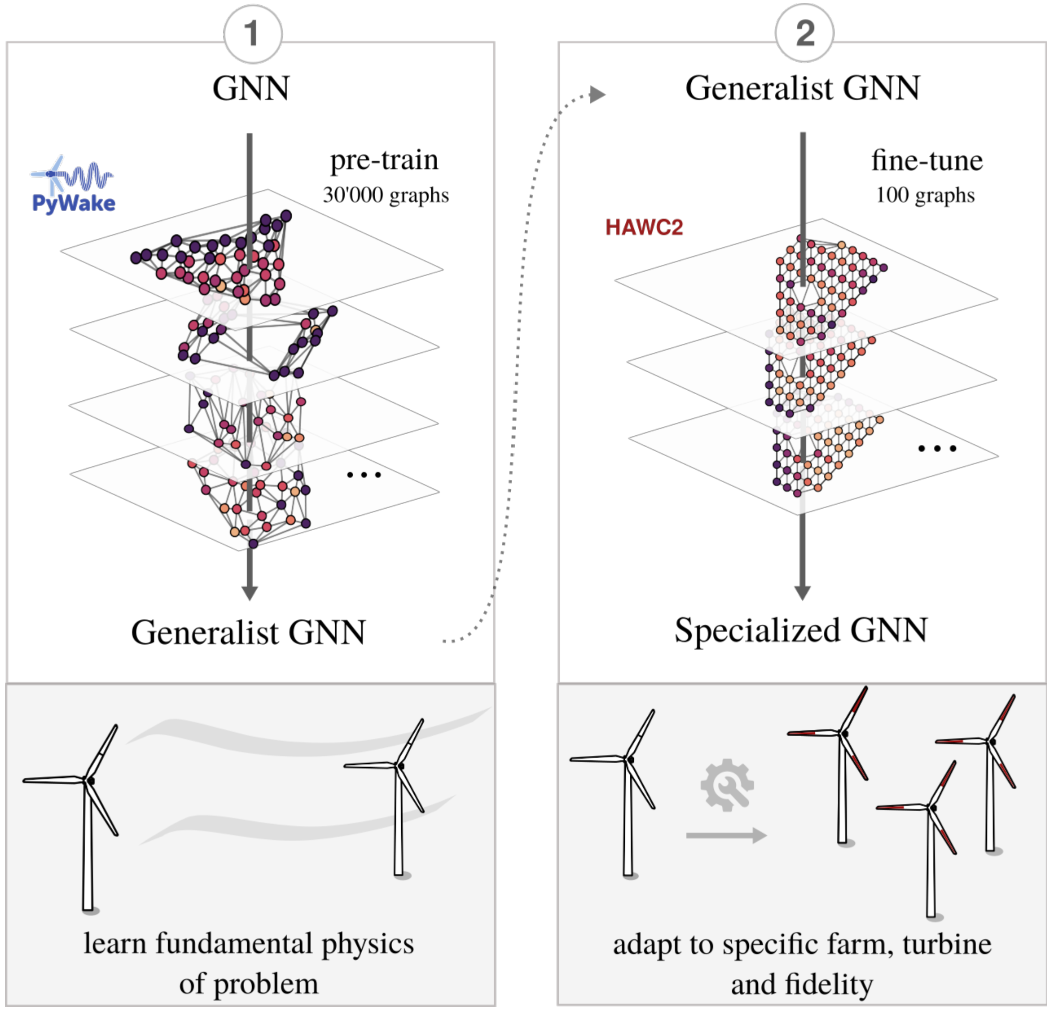
Training strategy



We can obtain a generalist GNN by training on thousands of random layouts simulated with PyWake, a low fidelity simulator.

Parameter	Value	Description
$\mathbb{E}(u)$	10	Mean wind speed $[m.s^{-1}]$
k_u	2.0	Shape factor of the Weibull distribution for wind speed
I_{ref}	0.16	Iref parameter
u_{min}	3	Minimum simulated wind speed $[m.s^{-1}]$
u_{max}	25	Maximum simulated wind speed $[m.s^{-1}]$
α_{min}	-0.099707	Minimum shear exponent (from PyWake)
α_{max}	0.499414	Maximum shear exponent (from PyWake)
Ψ_{min}	-6	lower limit of skewness distribution $[deg]$
Ψ_{max}	6	upper limit of skewness distribution $[deg]$
Ω_{min}	0	lower limit of wind direction distribution $[deg]$
Ω_{max}	360	upper limit of wind direction distribution $[deg]$

Training strategy



We can obtain a generalist GNN by training on thousands of random layouts simulated with PyWake, a low fidelity simulator.

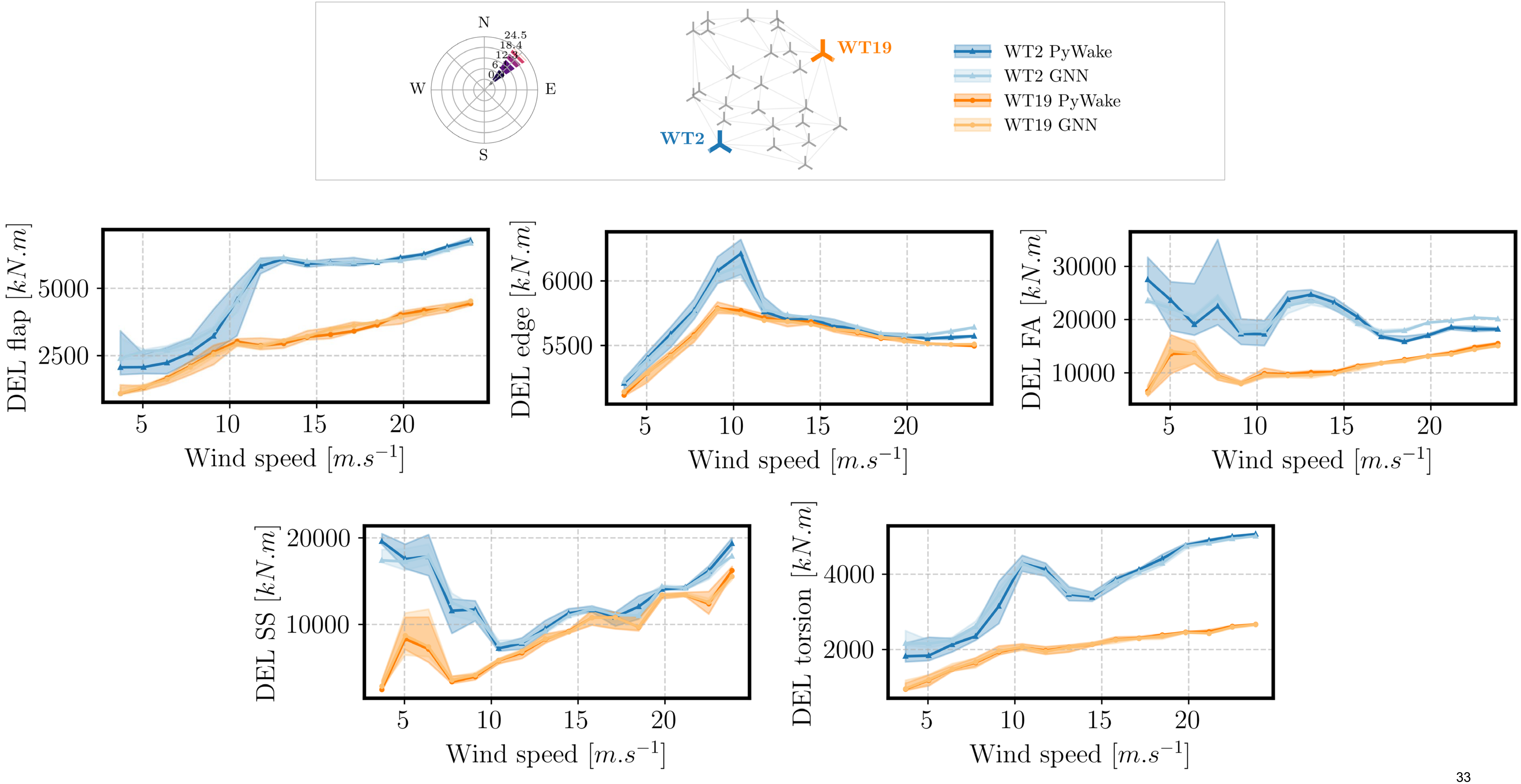
We can then finetune this generalist model to higher fidelities, different turbines, etc. with small amounts of new data, using Low Rank Adaptation[1] (LoRA).

Here we use HAWC2Farm as the higher fidelity model using 1000 1 hr long simulation of the Lillgrund farm, by Liew, Riva & Göcmen.

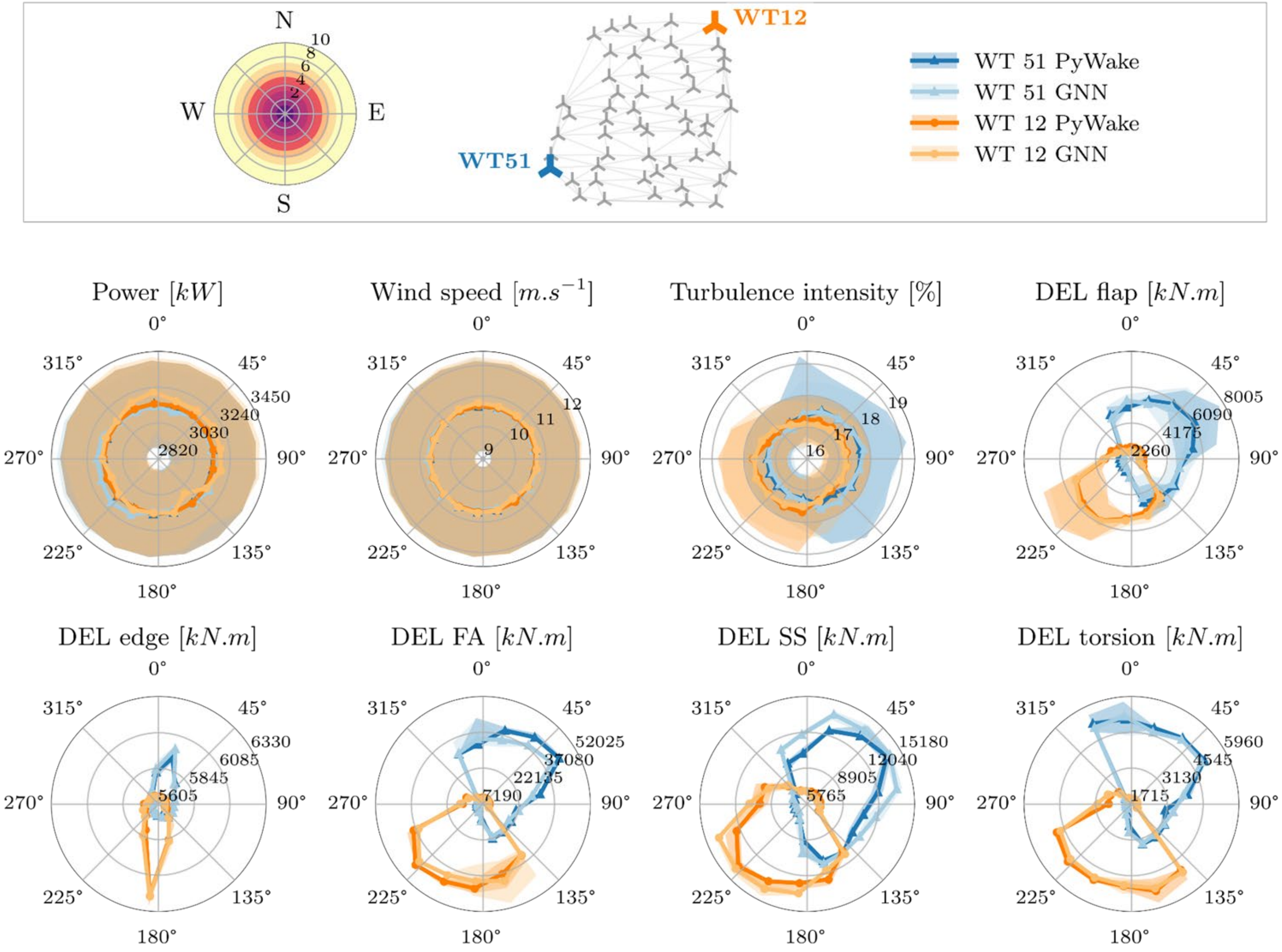
→ Specialized model, where training is 'bootstrapped'

[1]Hu, Edward J., et al. "Lora: Low-rank adaptation of large language models. arXiv 2021." *arXiv preprint arXiv:2106.09685* (2021).

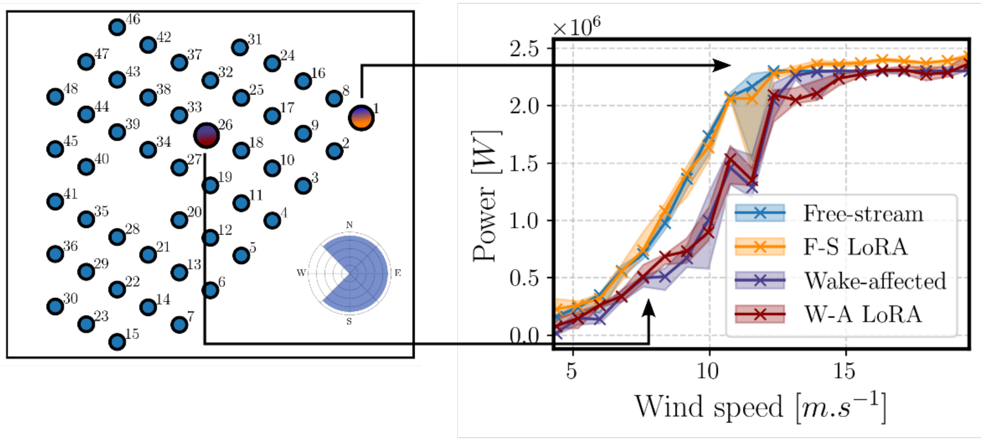
Generalist model results

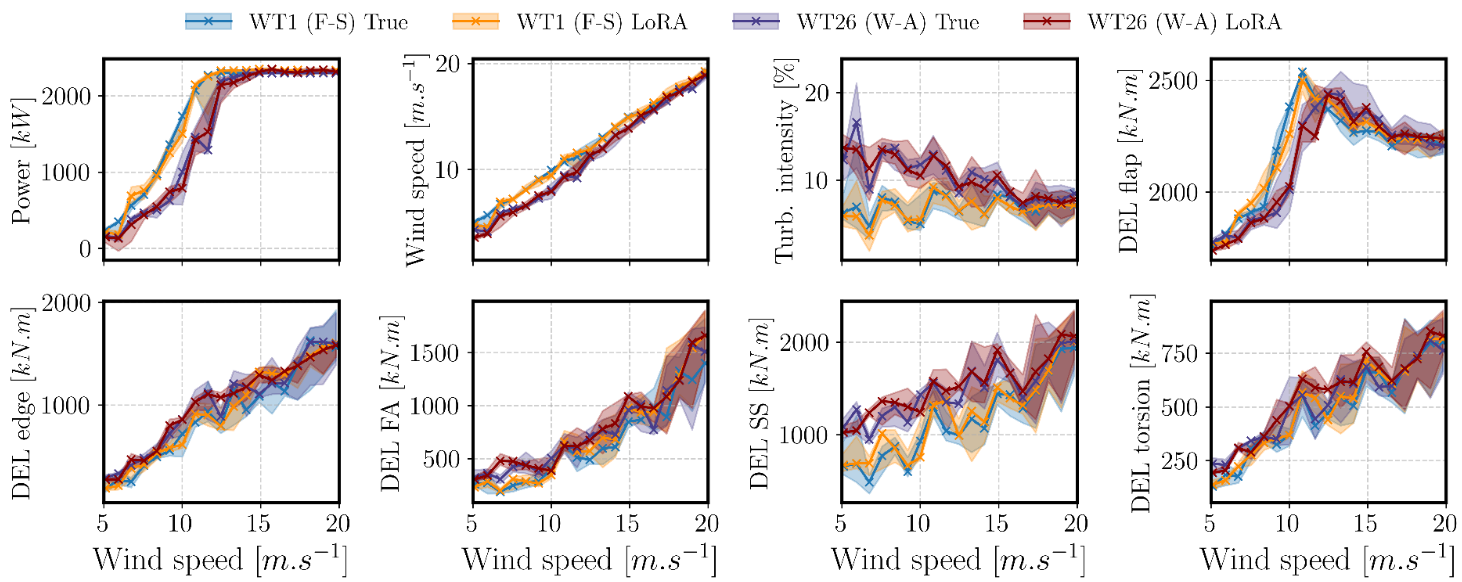


Generalist model results



Fine-tuned model performance



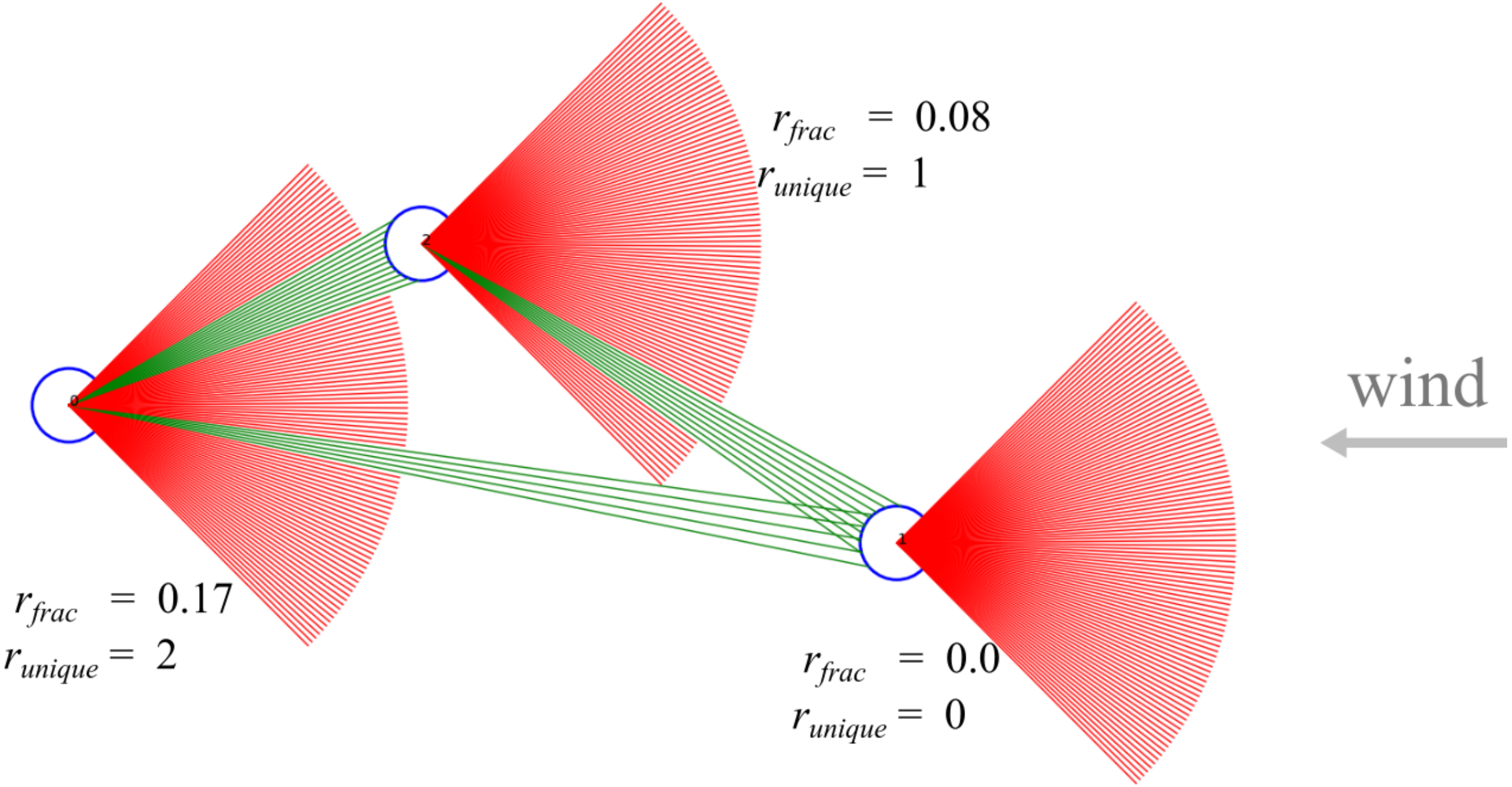


Fine-tuned on only ~100 samples of HAWC2Farm data

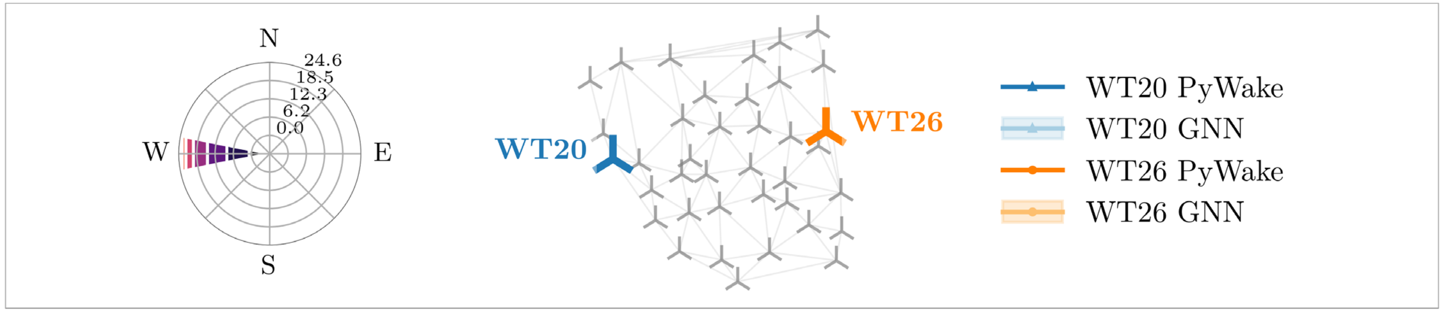
Uncertainty estimation extension

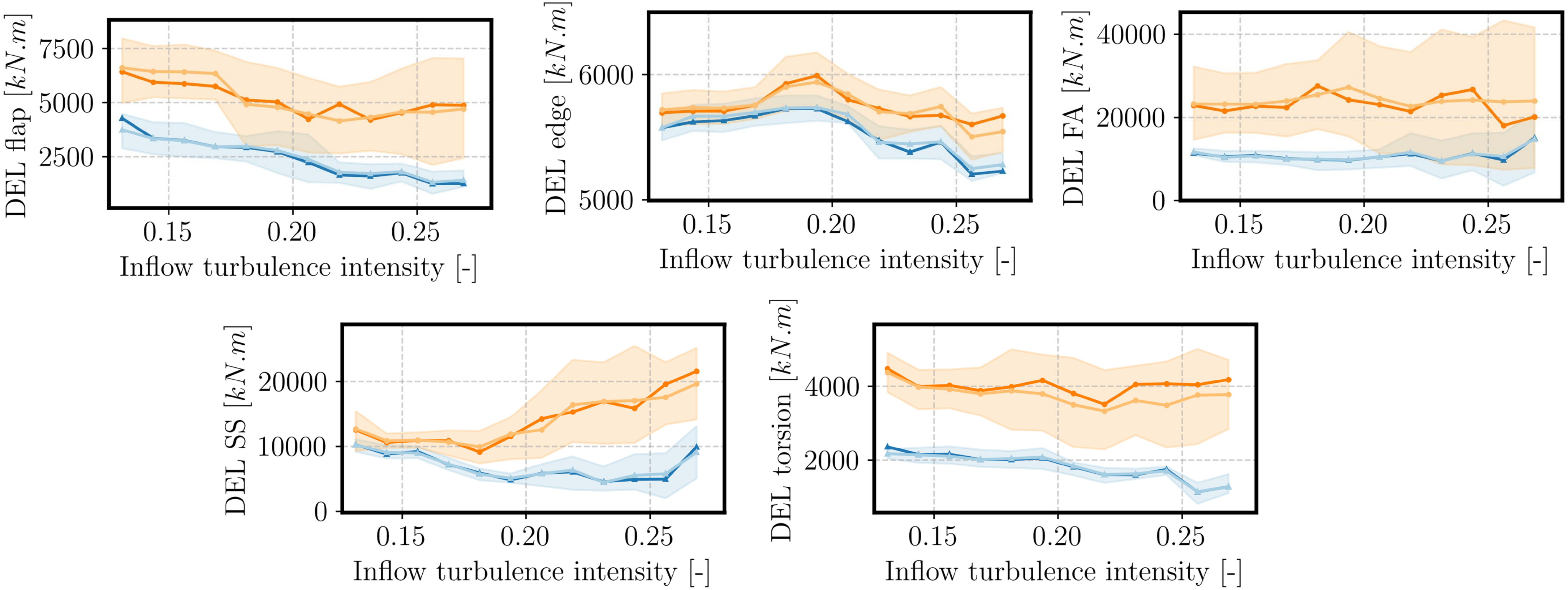
How to estimate uncertainty without completely changing the model?

→ Conformal predictors: use **calibration data** to determine guaranteed prediction intervals, **without strong assumptions** on the model or the underlying data distribution.



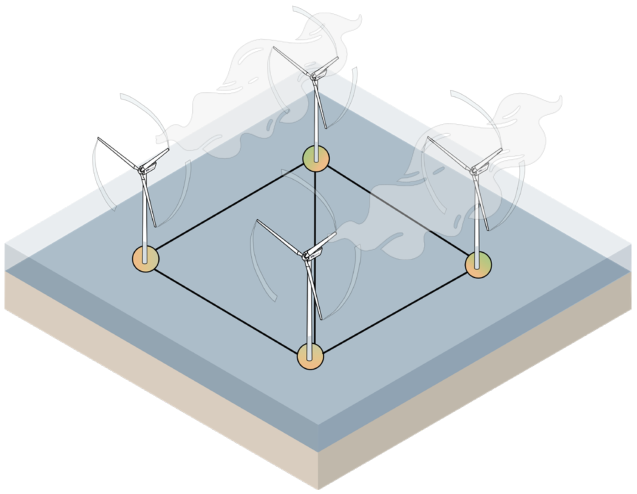
Influence of inflow turbulence on uncertainty





Summary

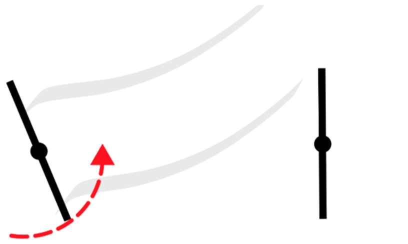
Graph Neural Networks, can serve as **efficient surrogate** models for predicting **wake-induced fatigue**.



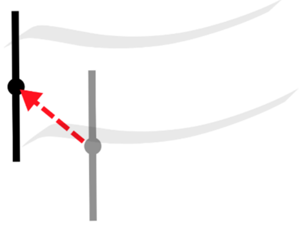
The proposed models are:

- Fast: 10^5 speedup over coupled aeroelastic models
- Flexible: any layout, any inflow
- Transferrable: can be fine-tuned for higher fidelity, different turbines
- Conformalized: per turbine & per variable model uncertainty quantification

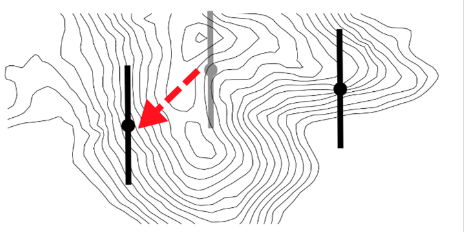
They could be used for difficult optimization scenarios:



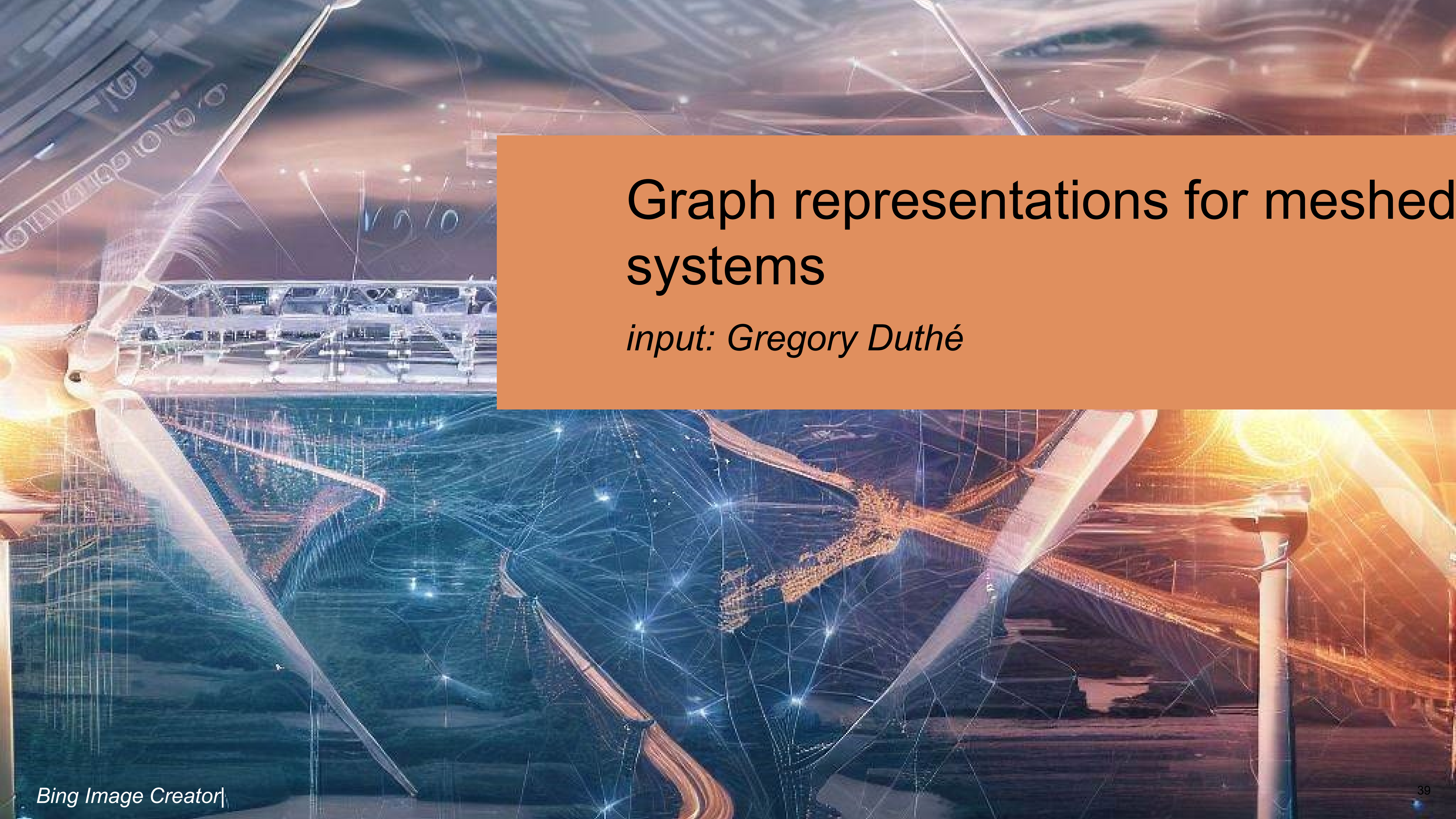
Load-aware wake steering and/or curtailment



Dynamic repositioning of floating offshore turbines



Fatigue-considerate layout optimization for complex terrain

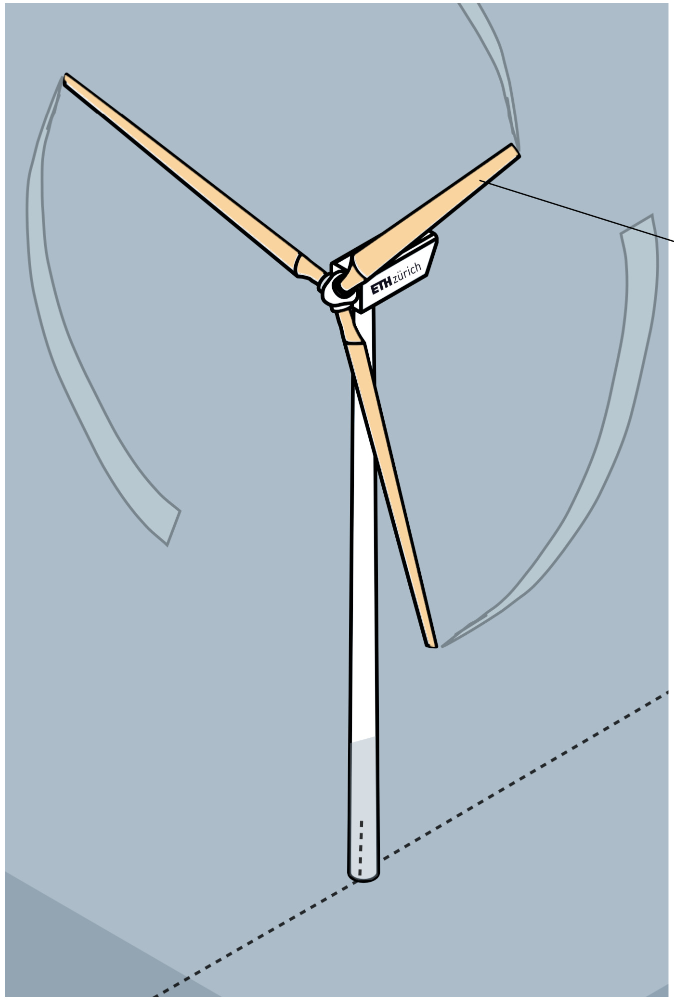


Graph representations for meshed systems

input: Gregory Duthé

Bing Image Creator

Blade monitoring



Difficult to monitor the rotating blades of an operating turbine.

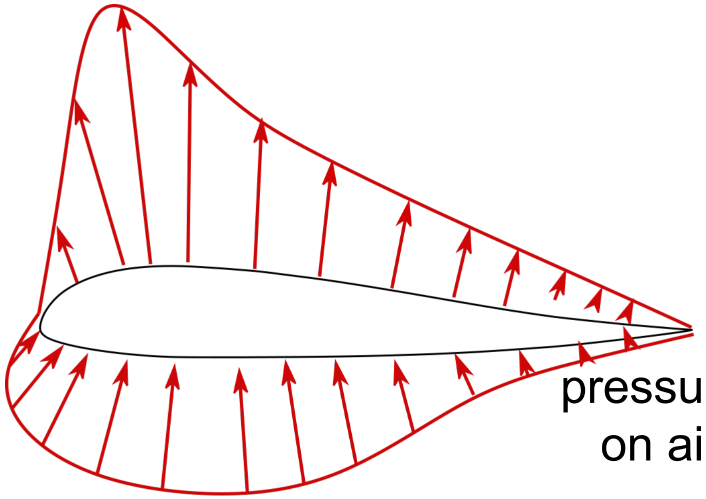
AeroSense system

Given such a system, which can conform to any blade geometry, can we **reconstruct the aerodynamics** from its pressure measurements?

An inverse physics problem

Can we build a ML model to reconstruct the aerodynamics from the surface pressure measurements?

any airfoil shape



pressure ‘measured’
on airfoil surface

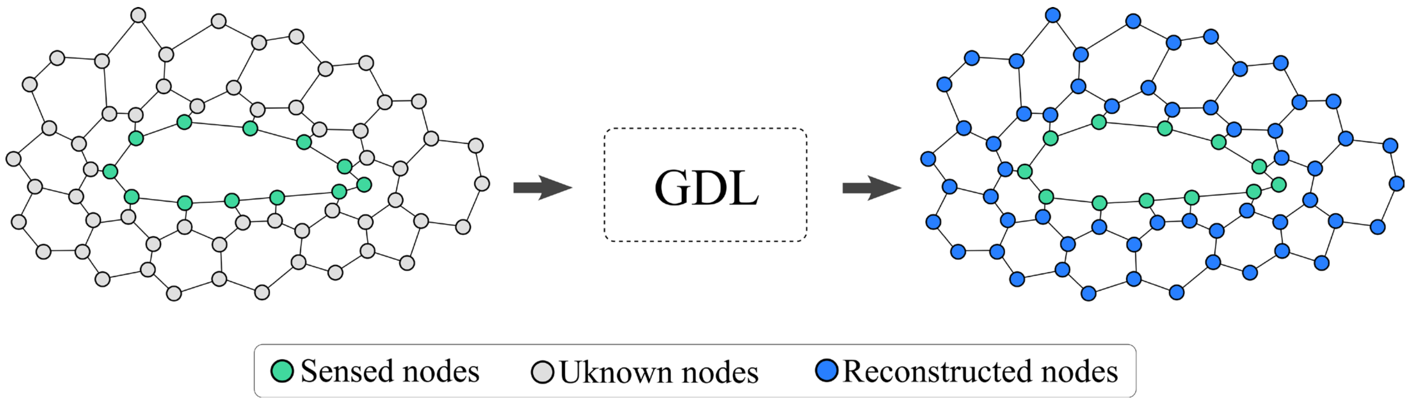
ML

full field velocity and pressure

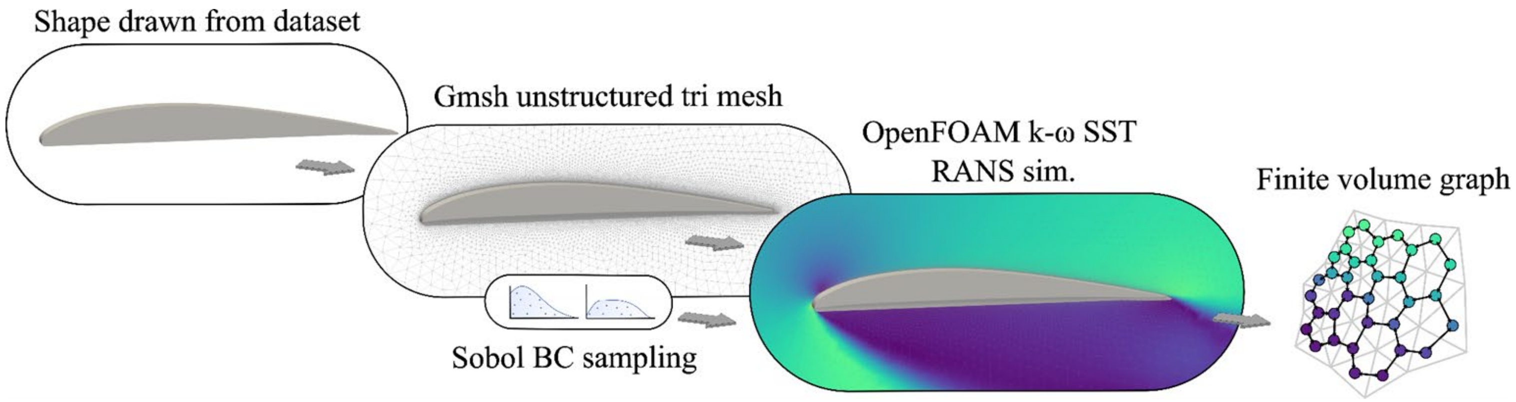
Inverse problems are challenging: **non-uniqueness and ill-posedness**

Flow reconstruction

We cast the problem as a node reconstruction problem on a graph.



Computational Fluid Dynamics (CFD) simulations are used to build a dataset of mesh-derived graphs for training.

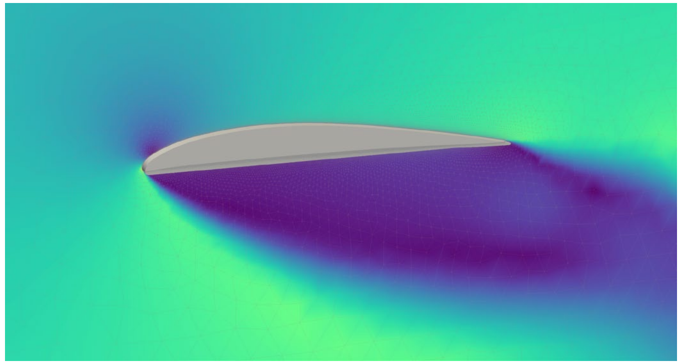


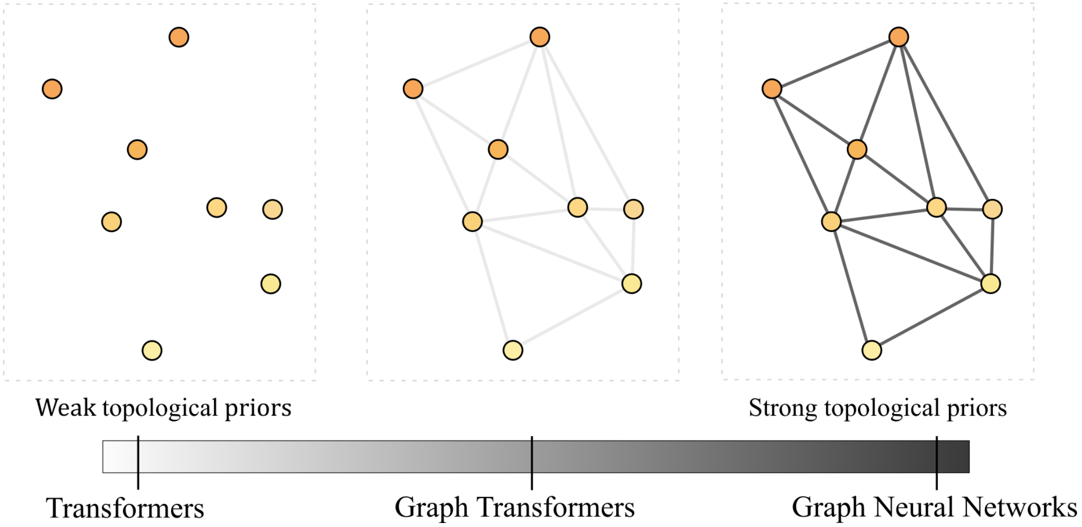
Graph Transformers

Challenge: dense mesh graphs with on average 50’000 nodes.

Long range information transfer is critical to reconstruct flow everywhere, especially for detached flows.

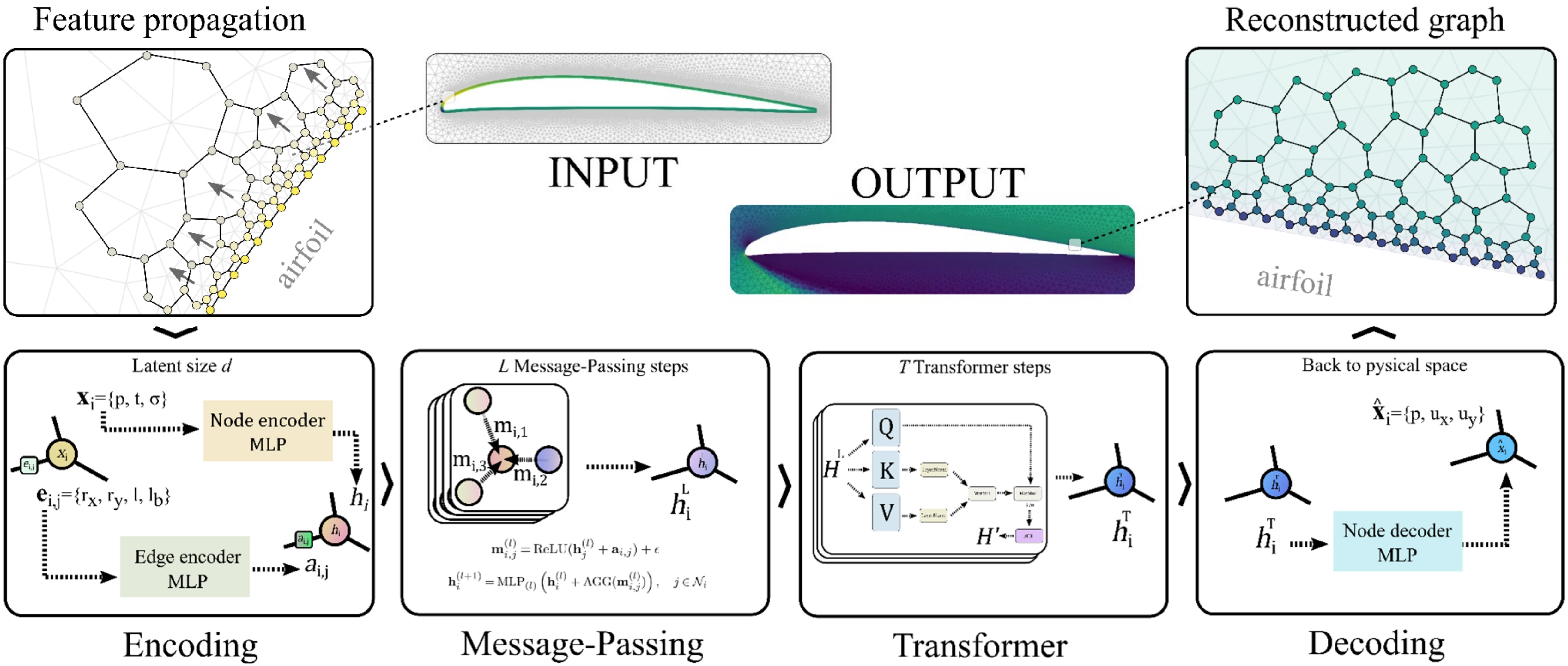
→ message-passing alone is not enough



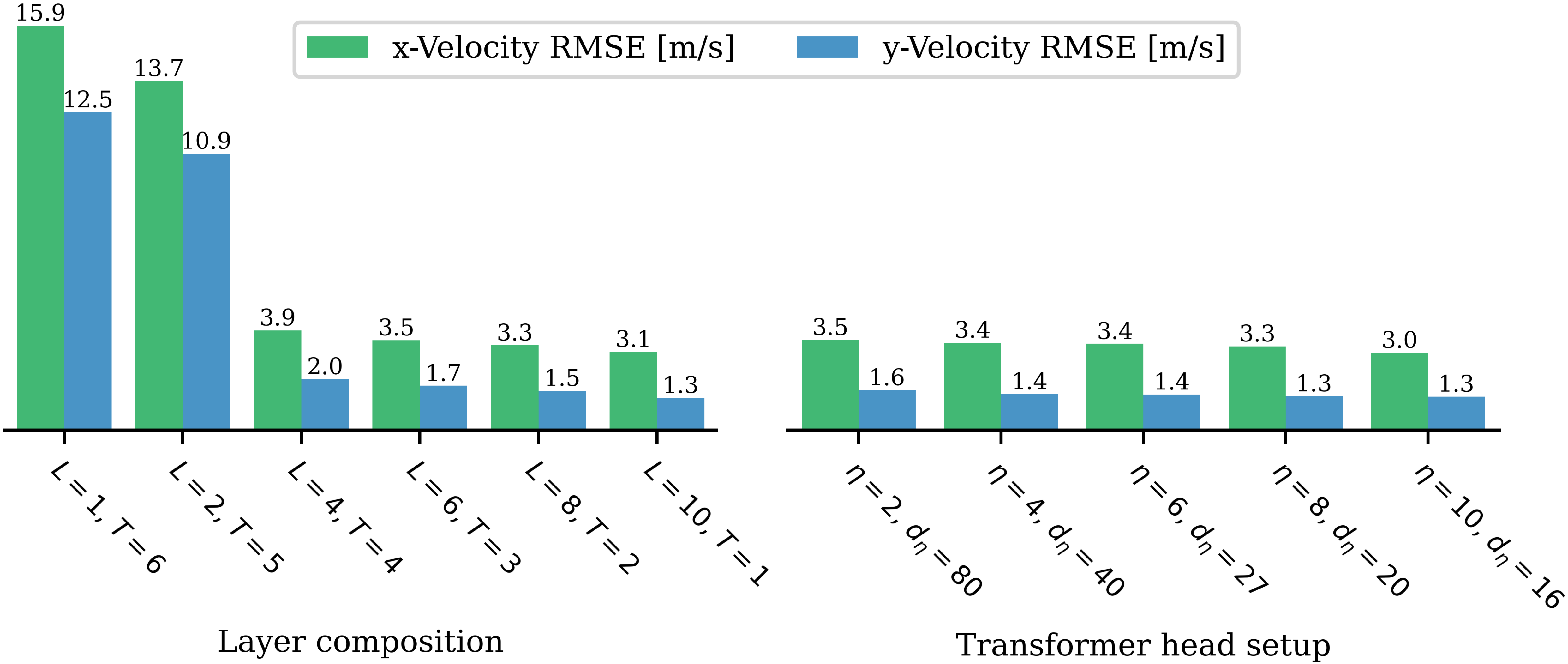


Graph Transformers, offer all-to-all information transfer while still accounting for graph topology.

Flow reconstruction with Graph Transformers

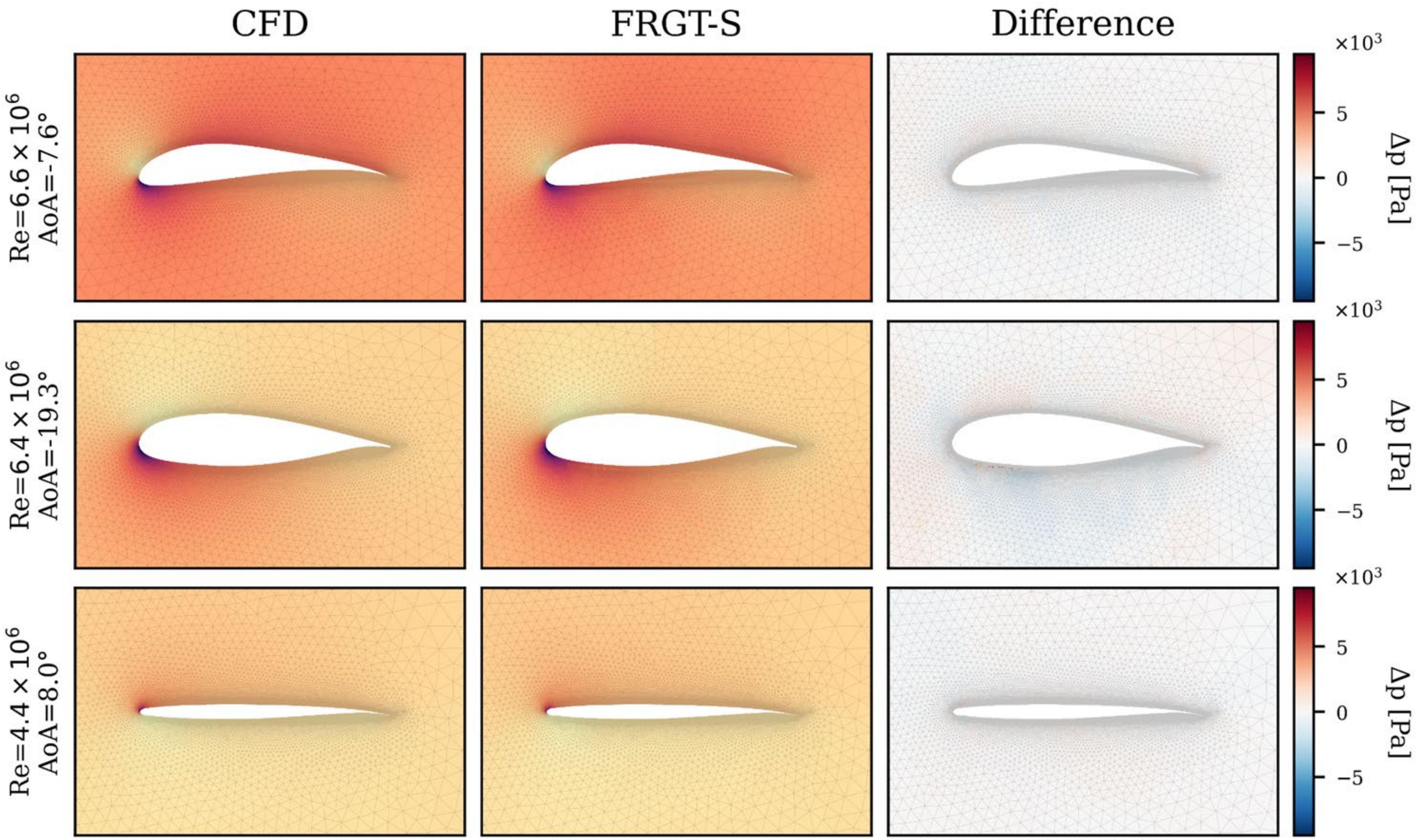


Architecture design trade-offs for the FRGT-S model



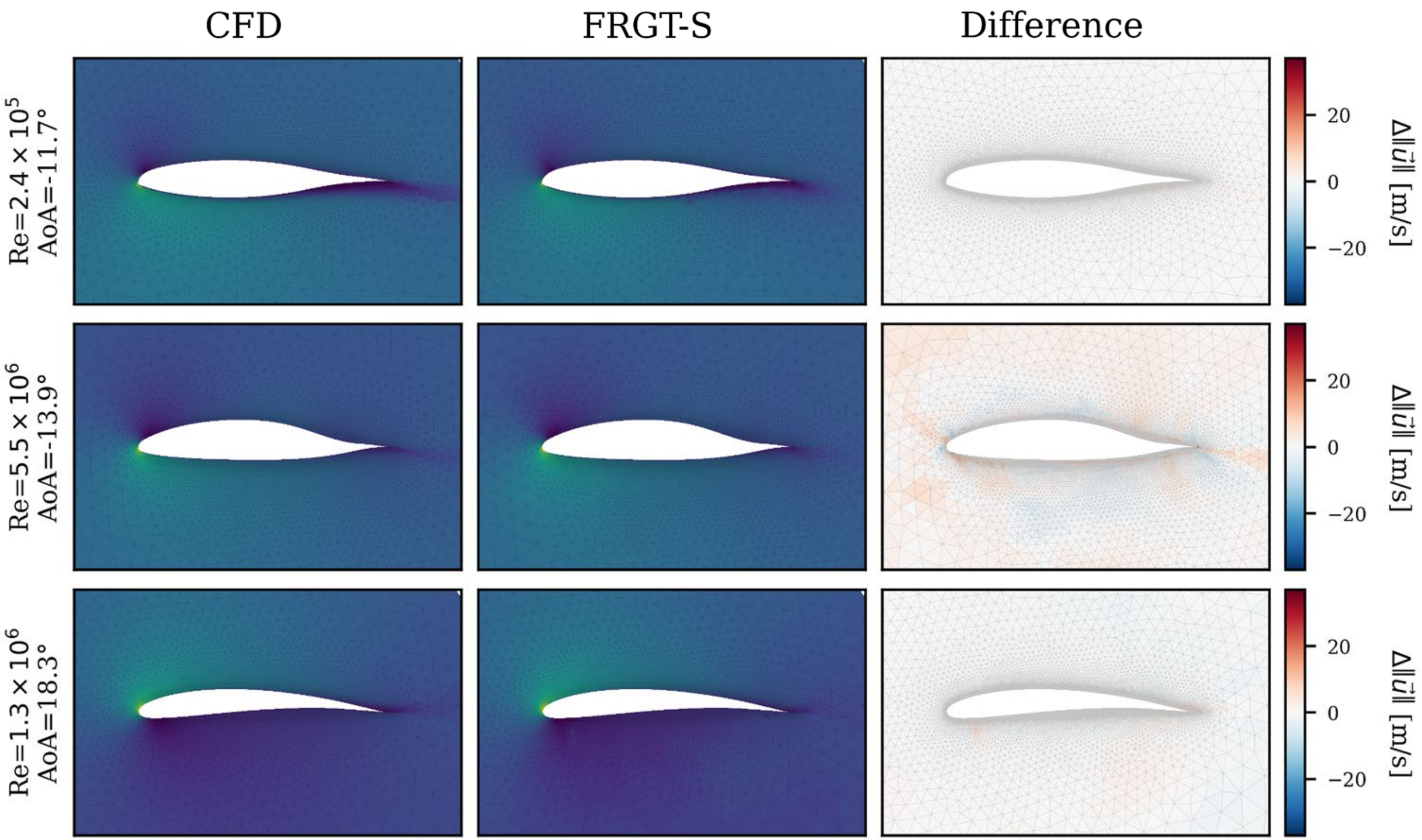
Flow reconstruction with Graph Transformers

- Unseen airfoil shapes, pressure



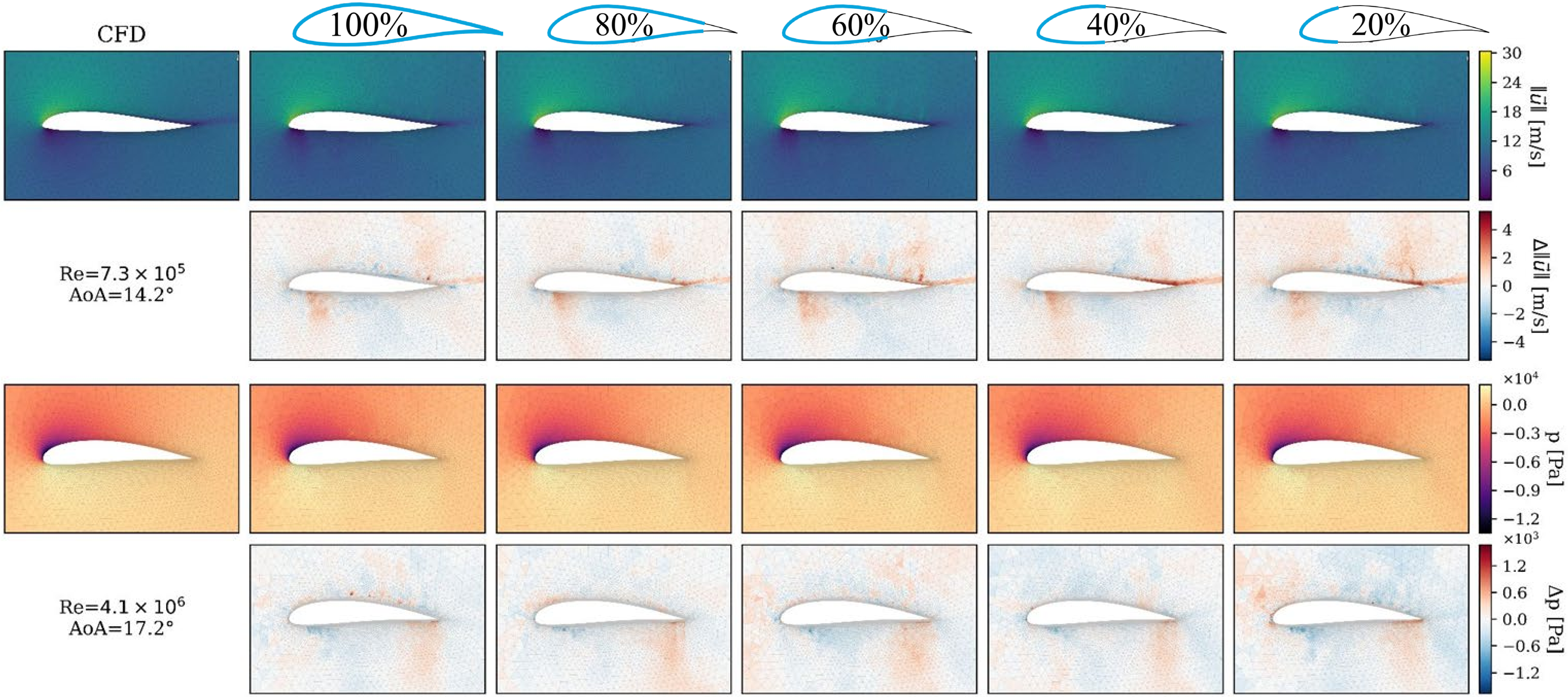
Flow reconstruction with Graph Transformers

- Unseen airfoil shapes, velocity

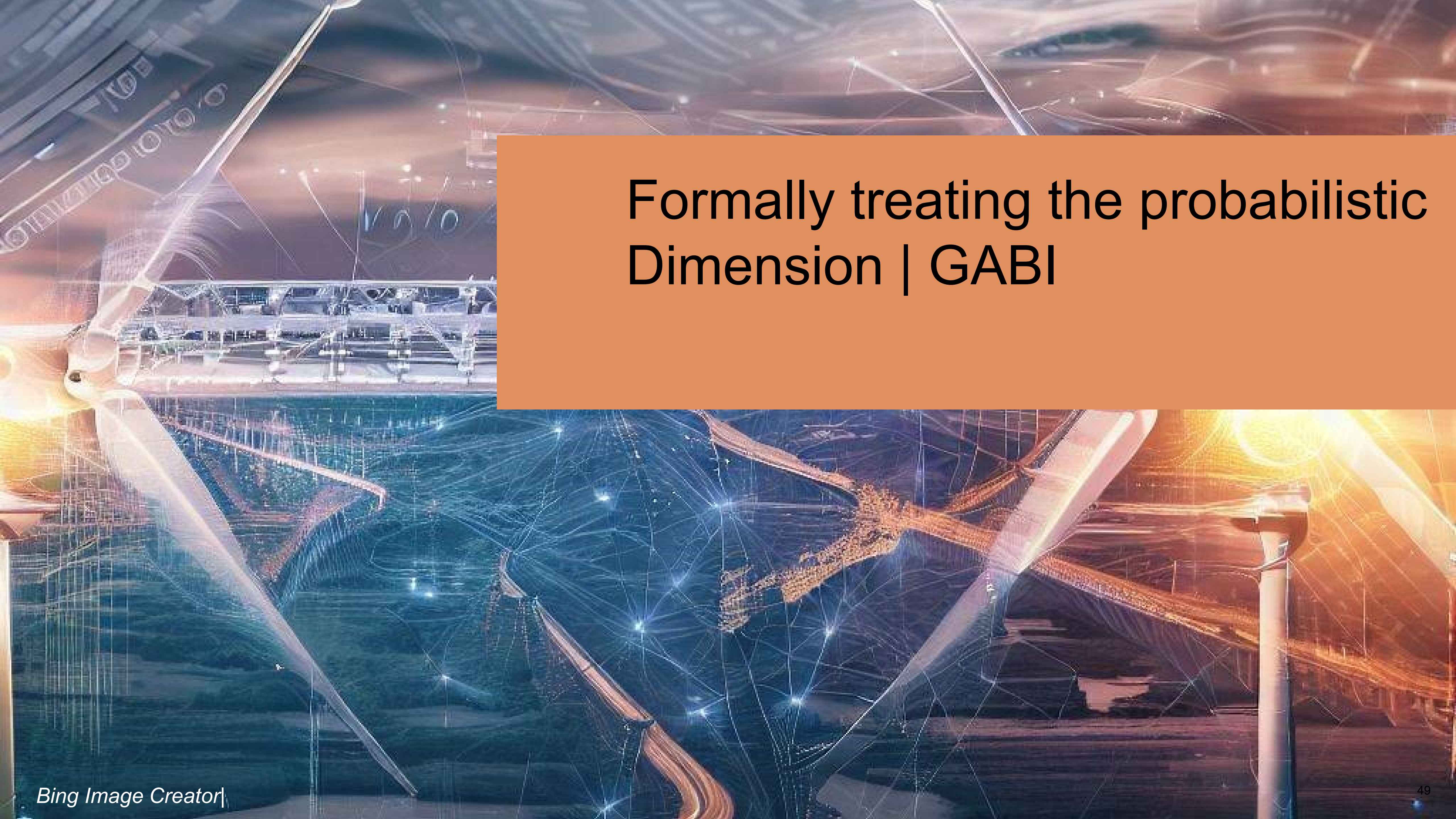


Flow reconstruction with Graph Transformers

- Training with partial coverage



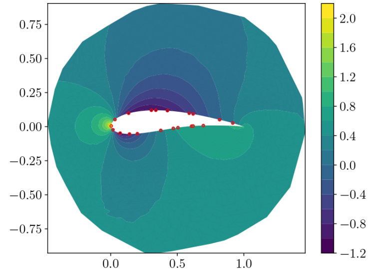
Formally treating the probabilistic Dimension | GABI



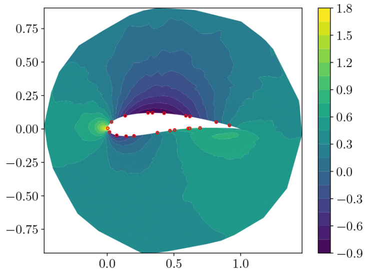
Bing Image Creator|

GABI | Geometric AE priors for Bayesian Inversion
Learn First Observe Later

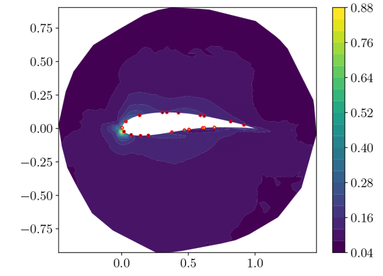
Arnaud Vadeboncoeur, Gregory Duthé, Mark Girolami, Eleni Chatzi



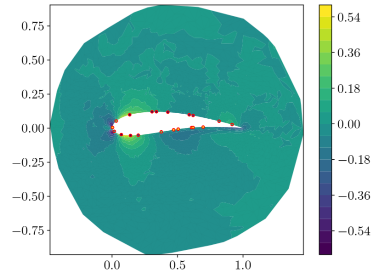
(a) Pressure GT



(b) Pressure Mean



(c) Pressure Stddev.



(d) Pressure Error

Training Phase

- GABI uses graph-based autoencoders to learn a latent representation of physical responses conditioned on geometry, without needing governing equations or boundary conditions.

Inference phase

- Given a new geometry and sparse noisy measurements, GABI uses the trained decoder and approximate Bayesian inference to reconstruct the full-field solution.

Benefits

- Learn geometry-aware priors using autoencoders
- Train once, infer on any compatible geometry (inference decoupled from training)
- Ill-posed inverse problems in variable geometries

GABI | Geometric AE priors for Bayesian Inversion
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Procedure

Train a geometric autoencoder (can use GNN) on many full-field solutions → learn a latent prior

$$z \sim N(0, I), u = D_\psi(z; M)$$

At inference, with new geometry M_0 and observations y_0

define likelihood via the decoder and observation model $\mathrm{p}(y_0|z)$

compute the posterior in latent space $\mathrm{p}(z|y_0)$ via Bayes' rule

Sample from the latent posterior (ABC or MCMC).

Decode posterior latent samples → posterior full-field solutions

$$u^{(k)} = D_\psi\left(z^{(k)}; M_0\right)$$

GABI | Geometric AE priors for Bayesian Inversion
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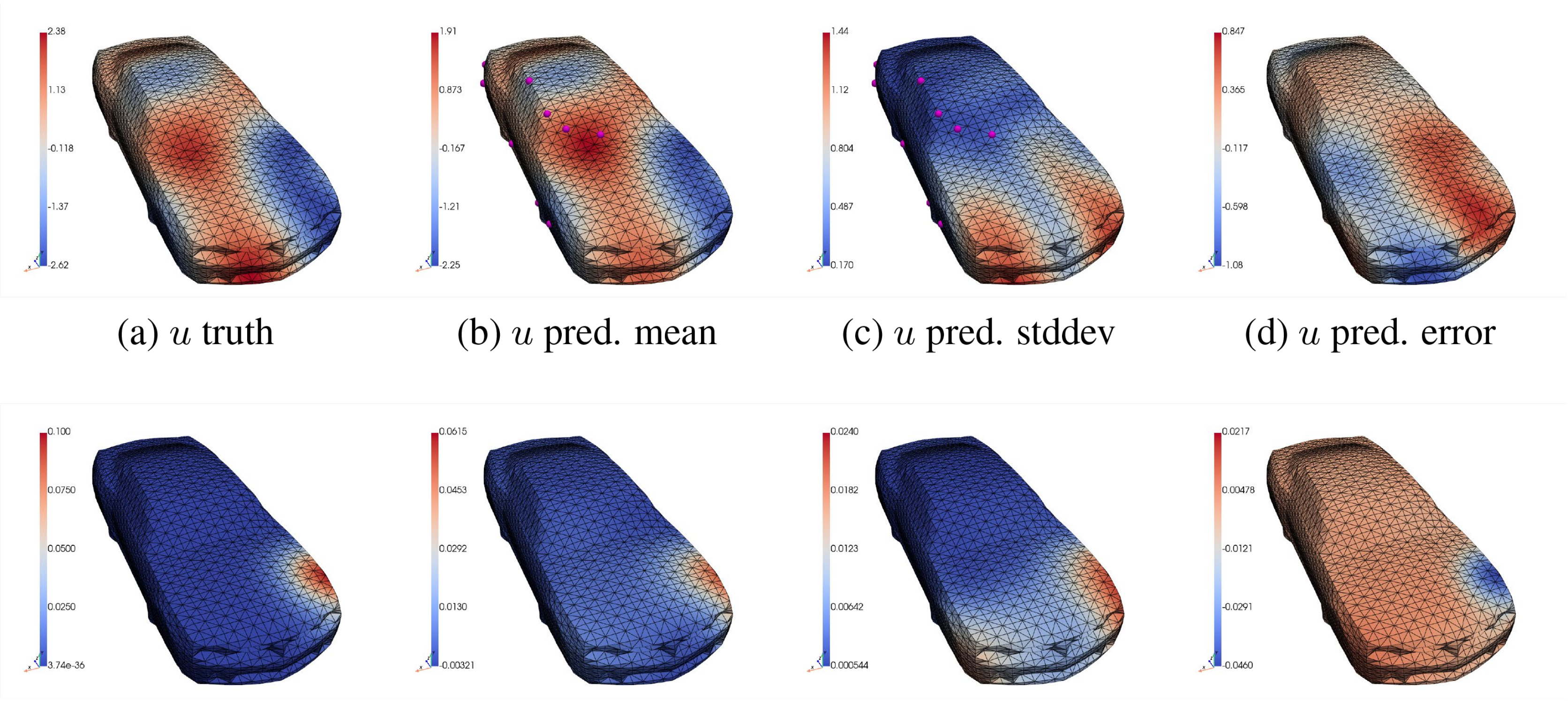
Arnaud Vadeboncoeur, Gregory Duthé, Mark Girolami, Eleni Chatzi

CAR BODY – ACOUSTIC VIBRATION AND SOURCE LOCALIZATION



(a) u truth (b) u pred. mean (c) u pred. stddev (d) u pred. error

(e) f truth (f) f pred. mean (g) f pred. stddev (h) f pred. error

GABI | Geometric AE priors for Bayesian Inversion
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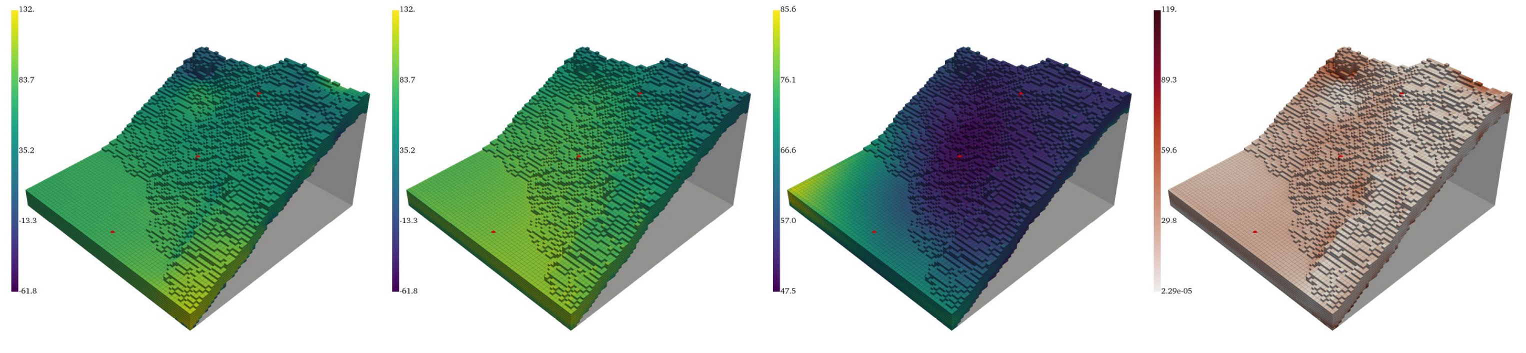
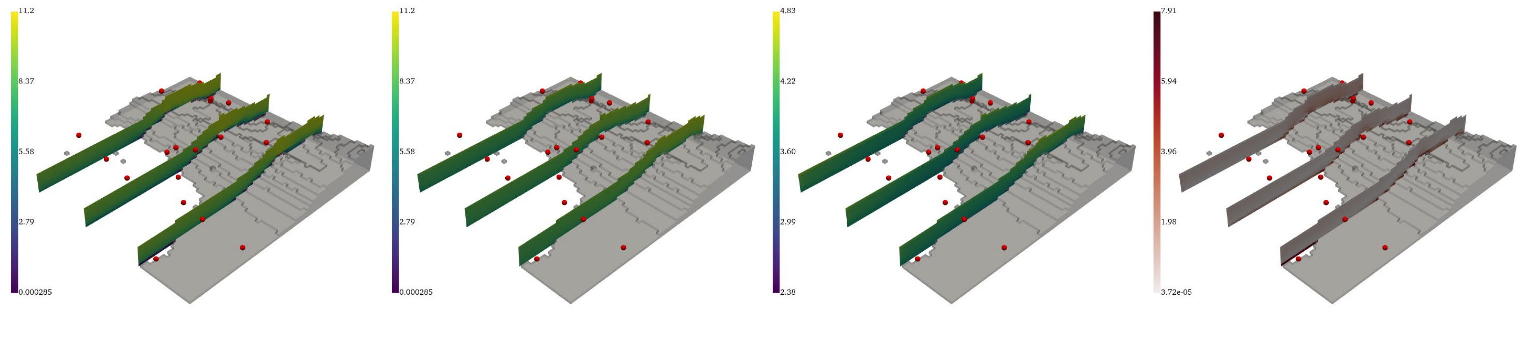
TERRAIN – FLOW FIELD

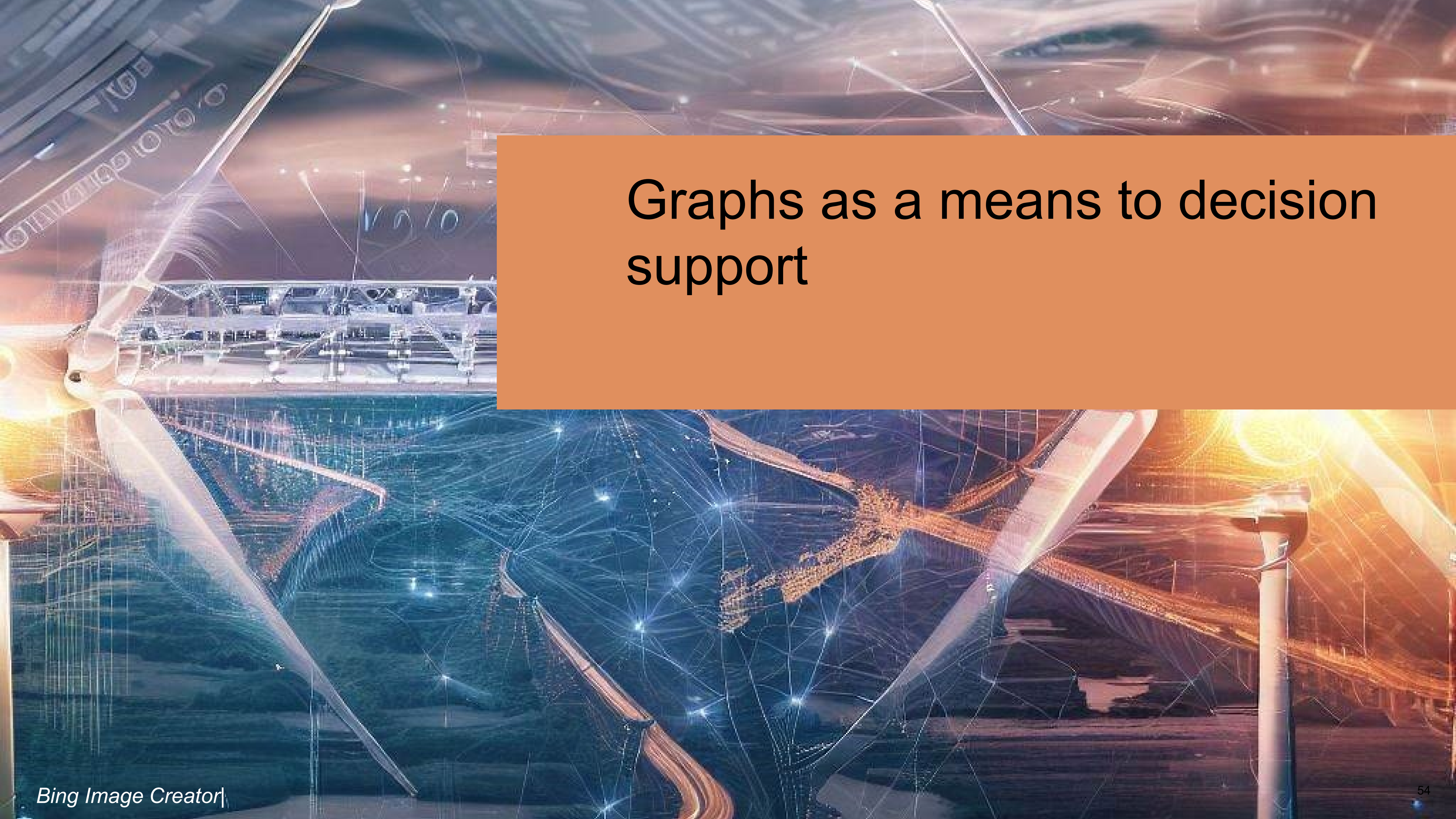


(a) Pressure GT (b) Pressure Mean (c) Pressure Std (d) Pressure Error



(e) $\|v\|$ GT (f) $\|v\|$ Mean (g) $\|v\|$ Std (h) $\|v\|$ Error

Graphs as a means to decision support



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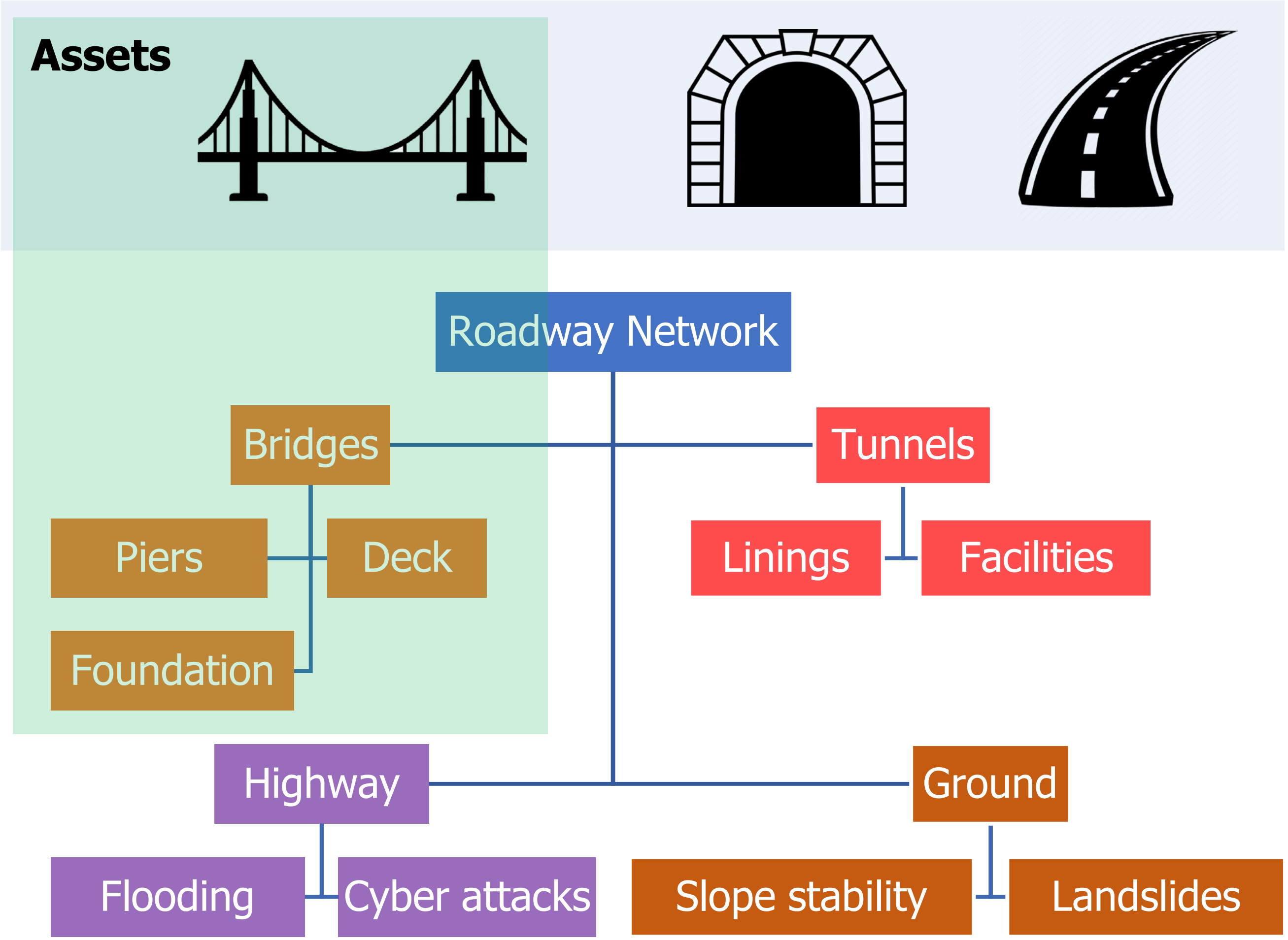
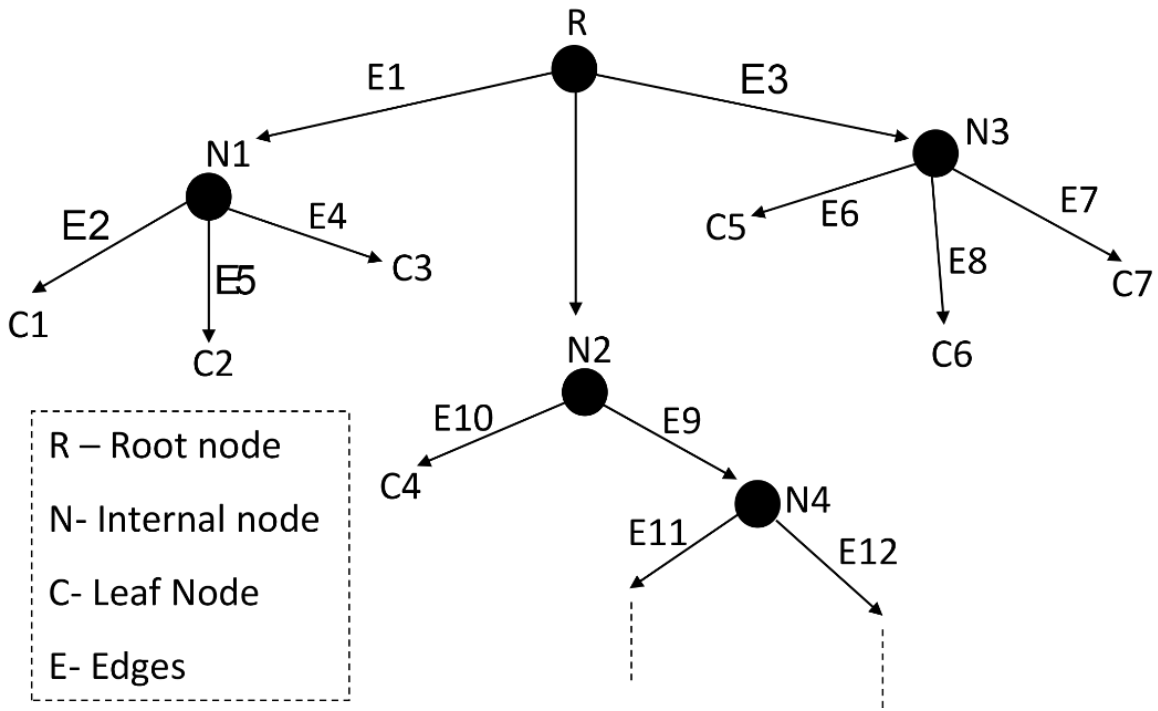
Deciding for systems of systems

To understand a complex hierarchy, it is necessary to break this down in individual components.

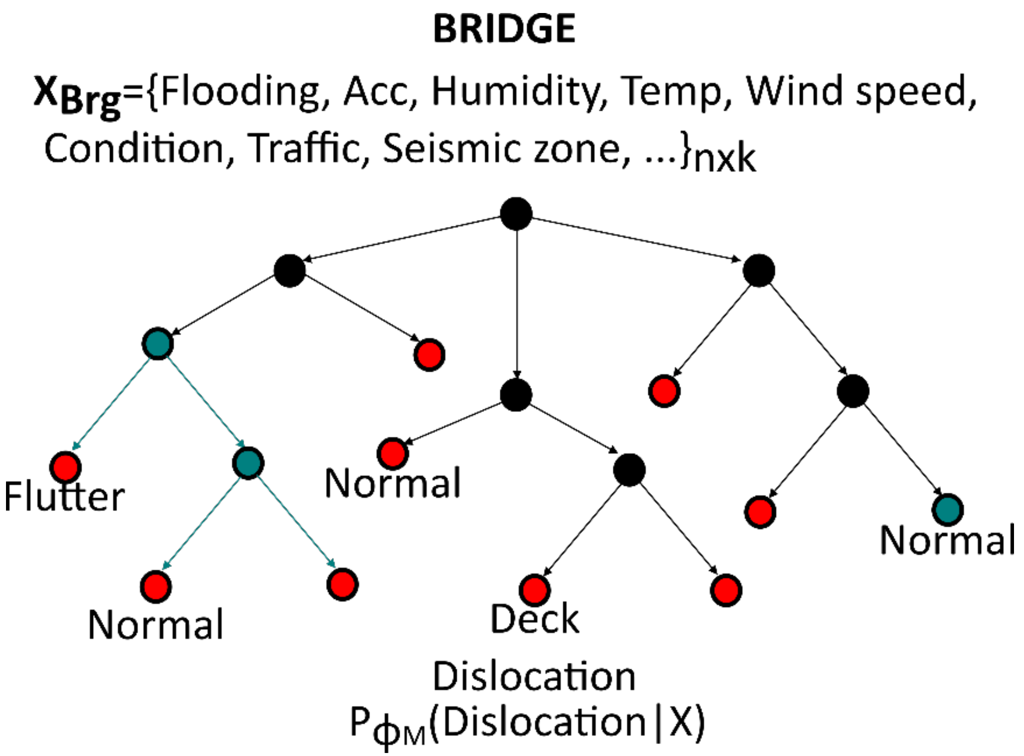
Let us zoom into the level of an object, e.g. bridge:



graphical models for visualization



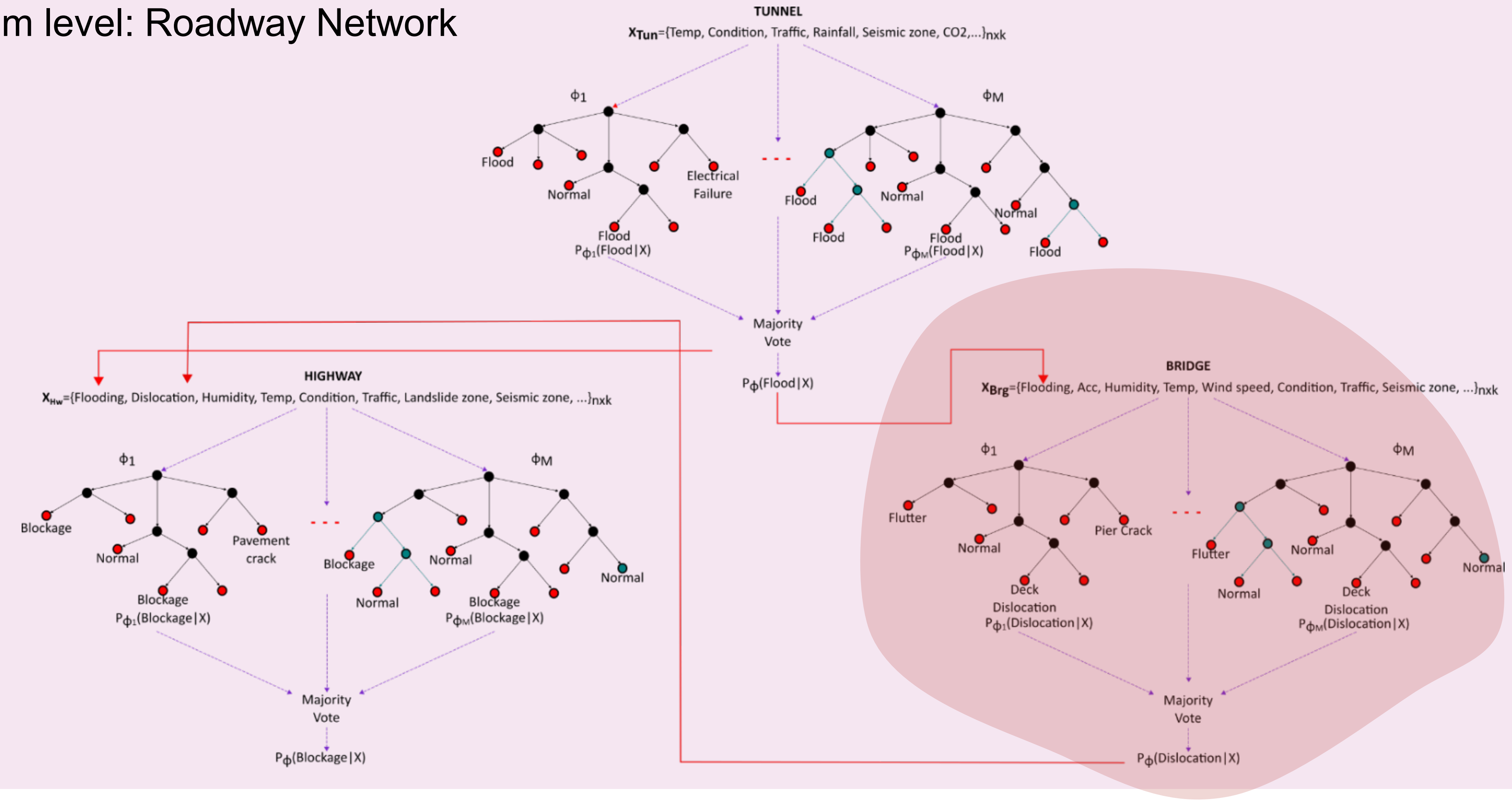
Graphical representation of a decision tree (DT) classifier. DT terminologies are also shown.



Random Forests: an ensemble of decision tree learners for a single system in a system of systems (e.g. bridge)

Random Forests & Decision Trees

System level: Roadway Network



case study: M-30 Madrid Ring Road

Data-driven Diagnosis & Prognosis for Decision Support

Goal: detection of hot-spots under flood events and cyber attacks

Target Predicted Output from the RF:
K-hours ahead traffic prediction

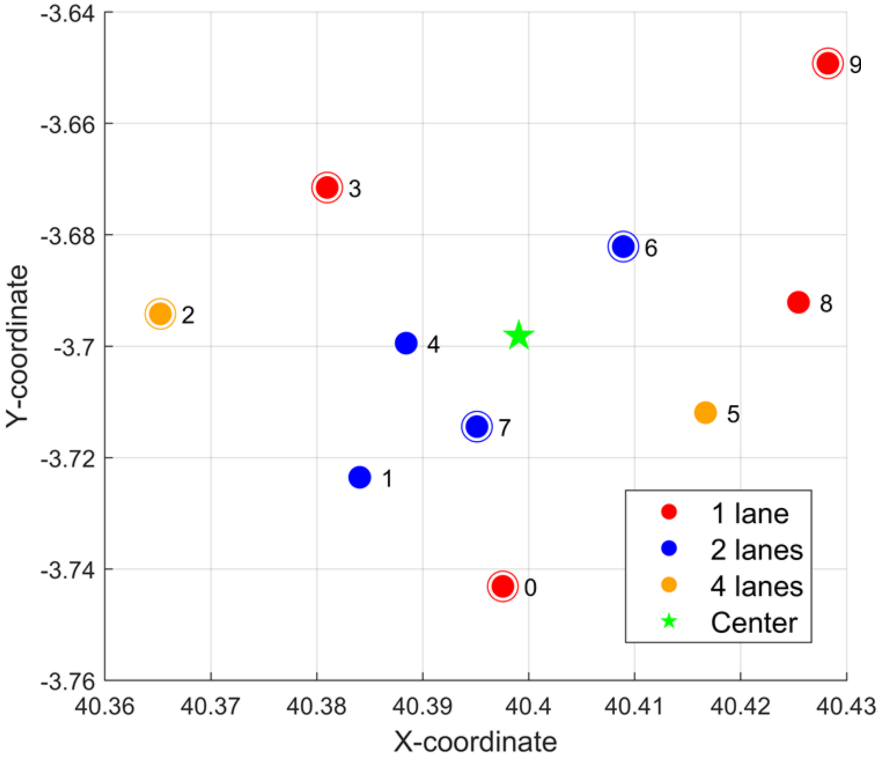
Available Information

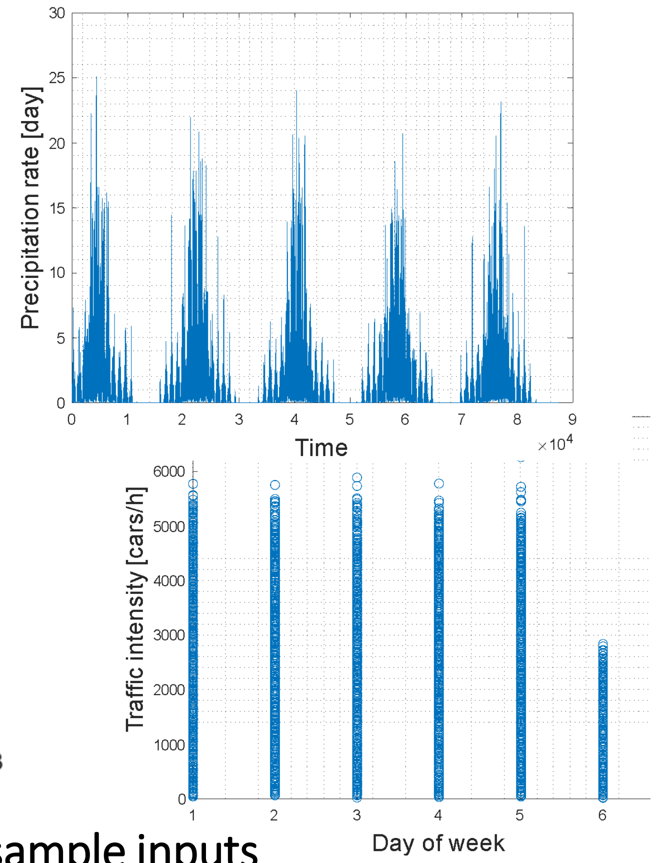
1. Hazard Information: weather and environmental data, information on cyber attacks
2. Model-based traffic simulations (wsp)
3. Traffic Monitoring information (hourly averages)
4. Road Information (lanes, direction, coordinates)
5. Context (holidays, sporting events, accidents, construction)

case study: M-30 Madrid Ring Road

Initiating example: a simplified road network / 1hr-ahead traffic intensity prediction

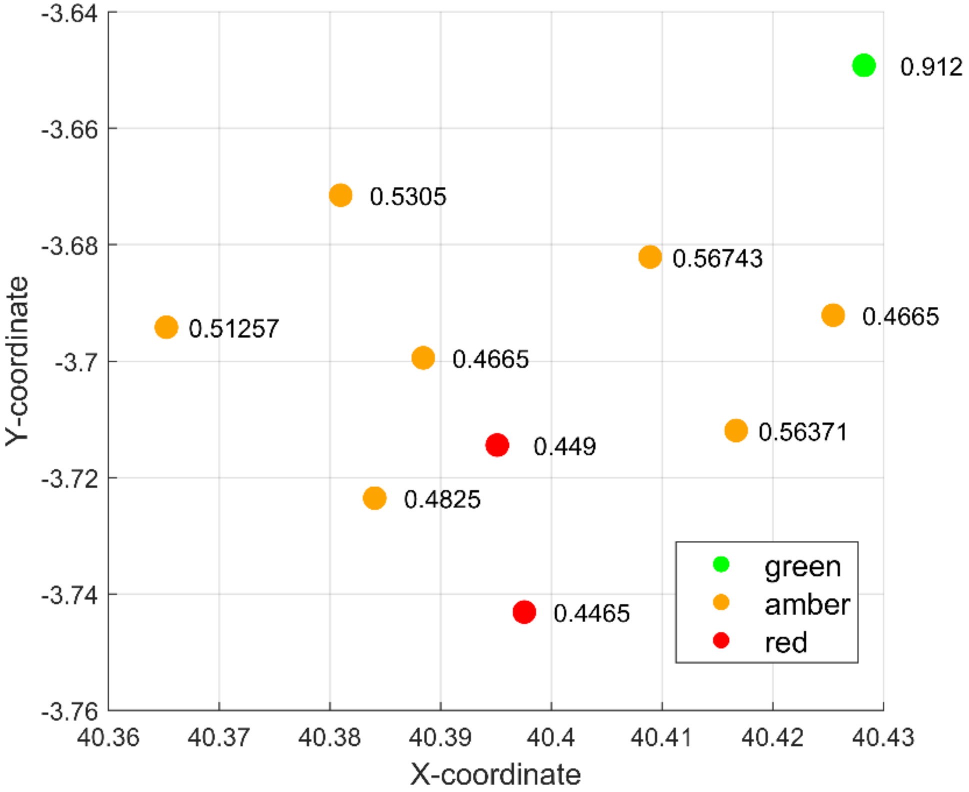
geometry





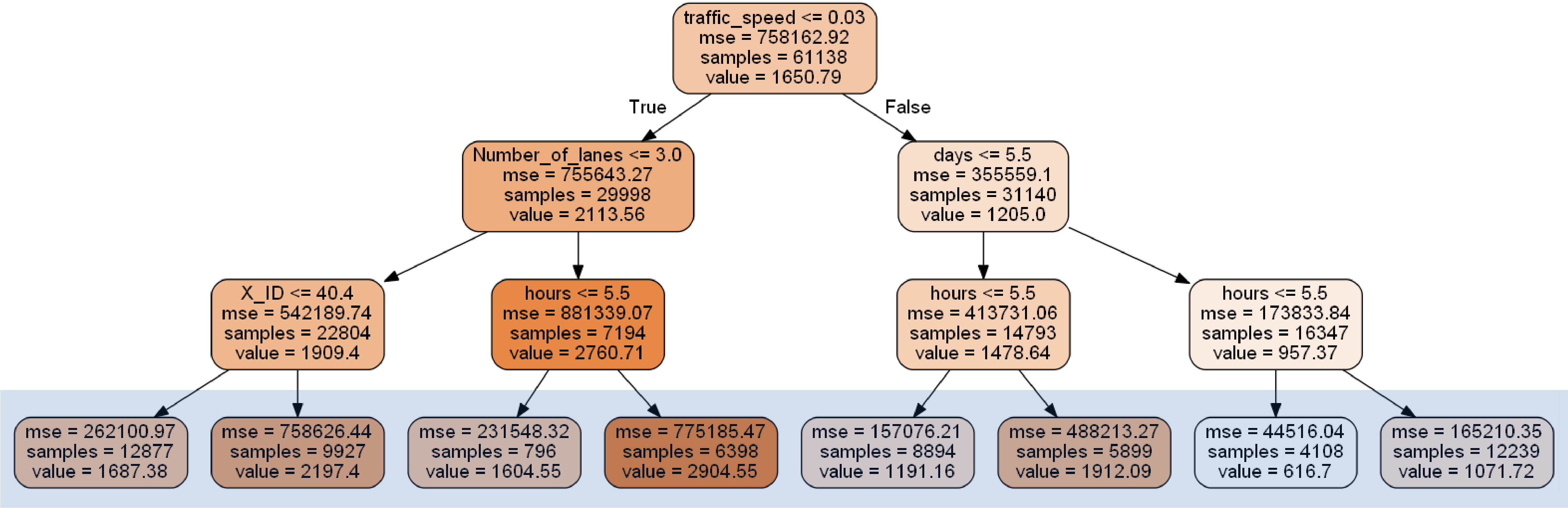
sample inputs

RAG alert system



case study: M-30 Madrid Ring Road

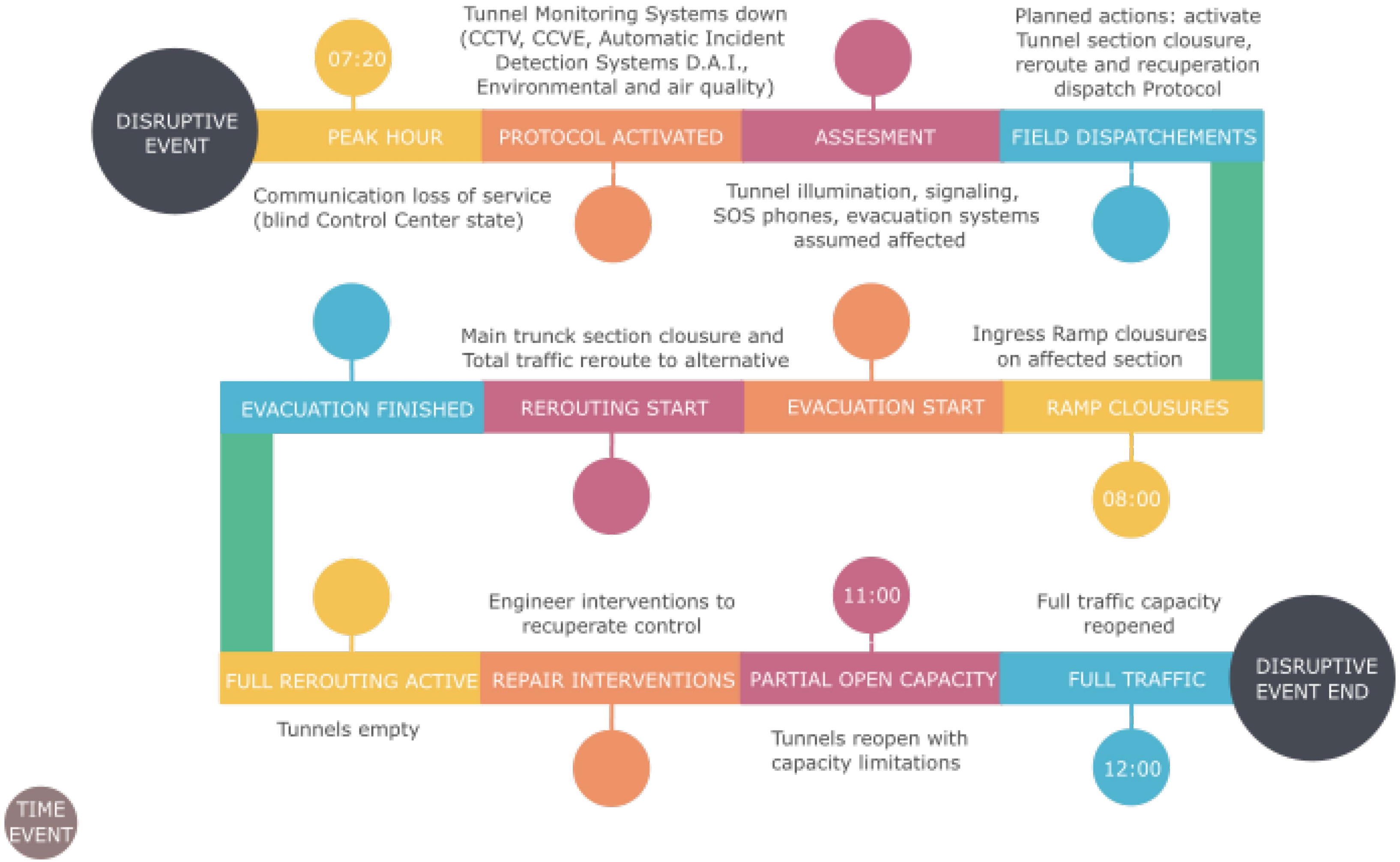
Visualizing a tree within the forest (kept shallow for illustration)

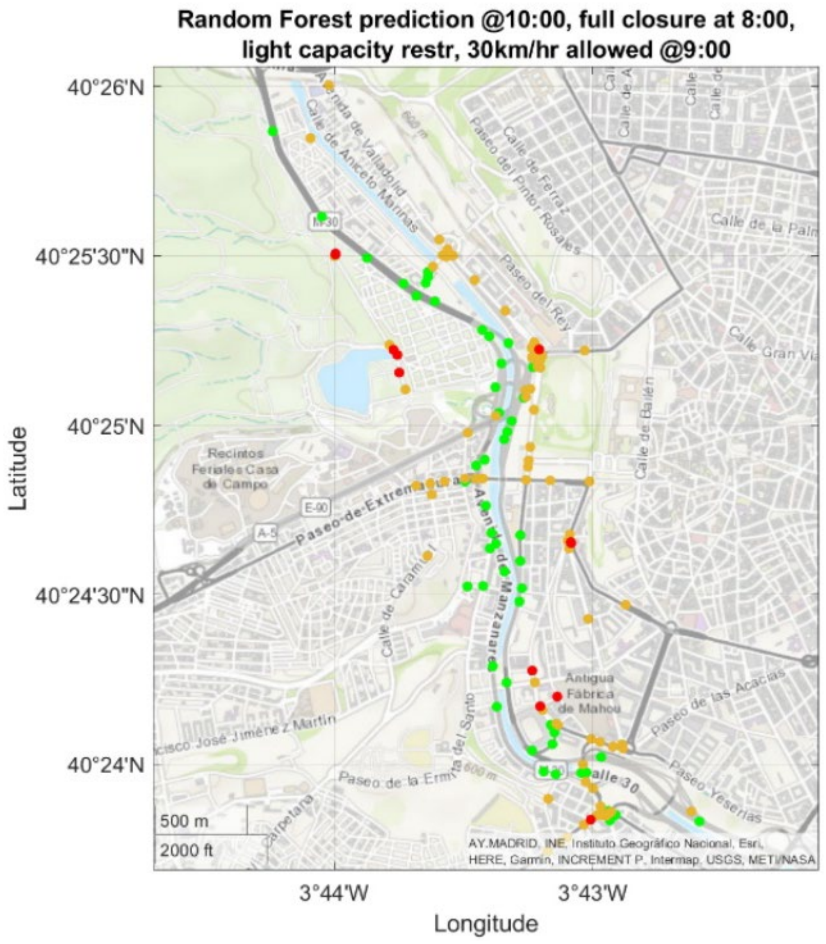


Predicted outputs conditioned on splitting events for the input variables

Cyber Attack scenario

Harnessing the power of graph representations for supporting reactive measures





Abdallah, Chatzi, et al. ESREL, 2018
Abdallah, Chatzi, et al. FORESEE, 2020

What next?

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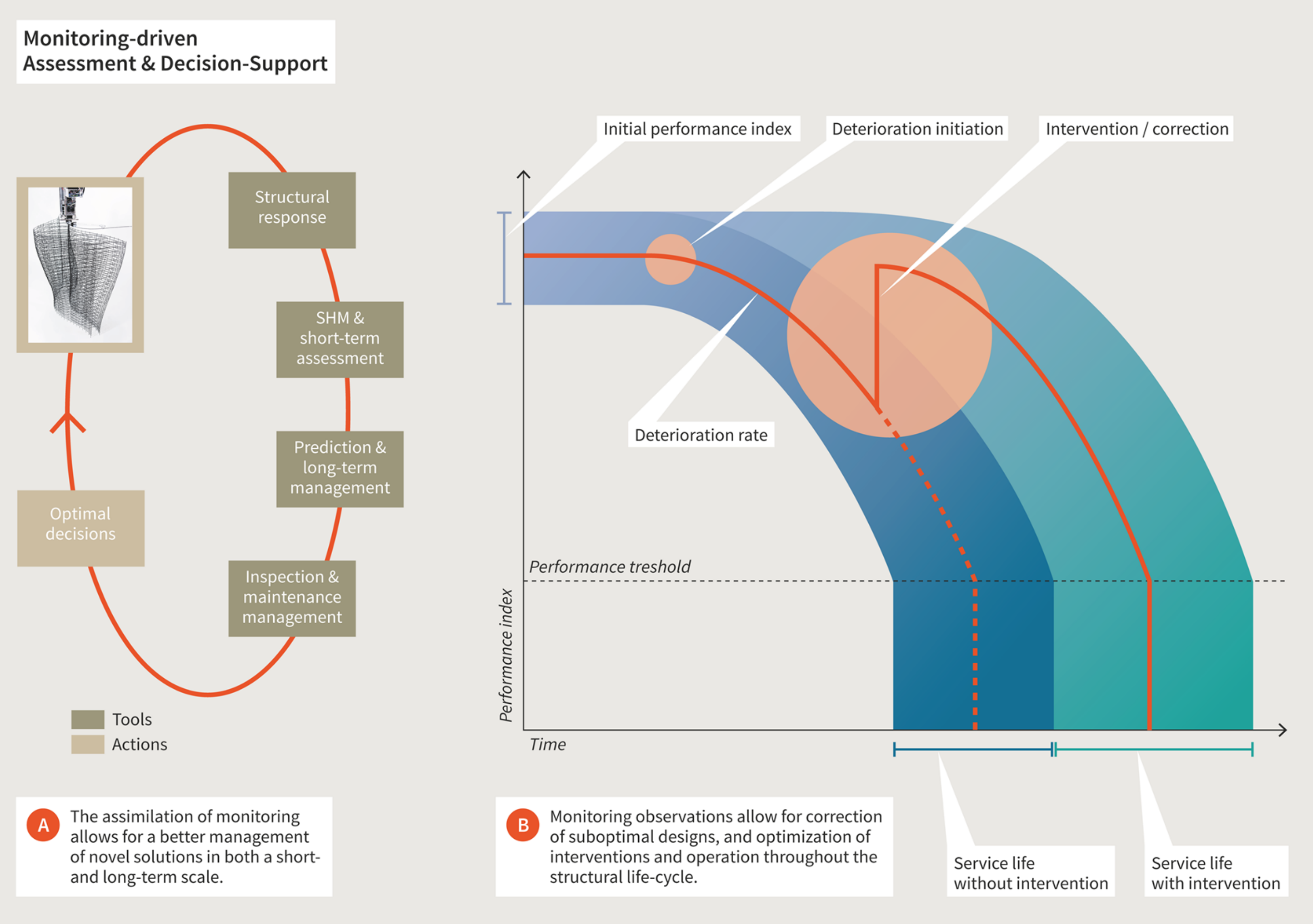
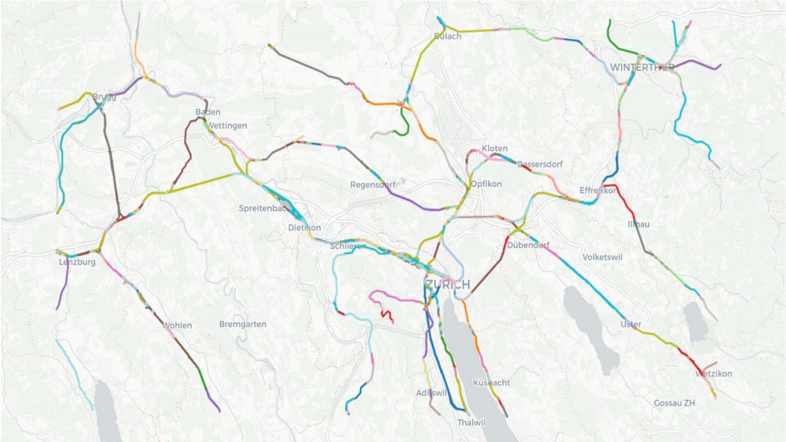
Fostering Impact for Cyber-Physical Infrastructure Systems



Benefits of Monitoring-Informed Assessment of CPS

- optimising design and fabrication,
- Lowering costs for operation and maintenance,
- reducing risks, enabling resilience
- facilitating early adoption of new technologies in building practice.

Data-Driven Digital Twinning for Railway Network Optimal Maintenance Planning with Multi-Agent Reinforcement Learning Solutions



Inference:

- Capture correlation of interlinked sections in:
  - Deterioration
  - Repairing effects
- Model economies of scale

→ Hierarchical Bayesian inference based on **GP-on-graph** technique

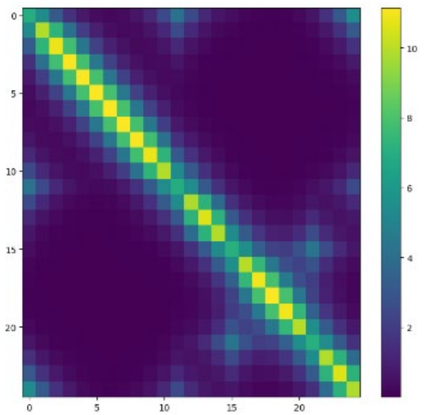
Solution:

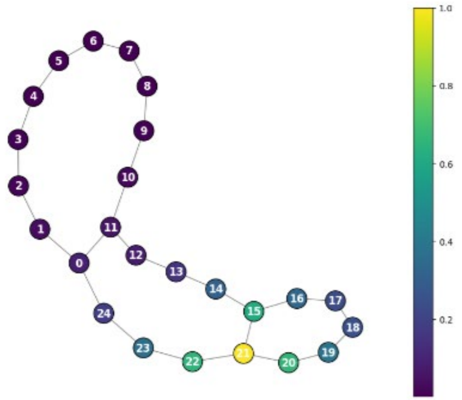
- Cooperation in maintenance/renewal policies of all tracks

→ **Multi-agent** RL

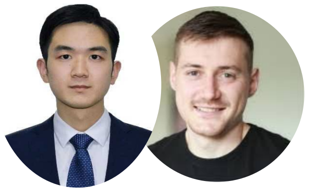
- Inform the (RL) agents about the network topology/graph

→ **Graph**-based deep learning

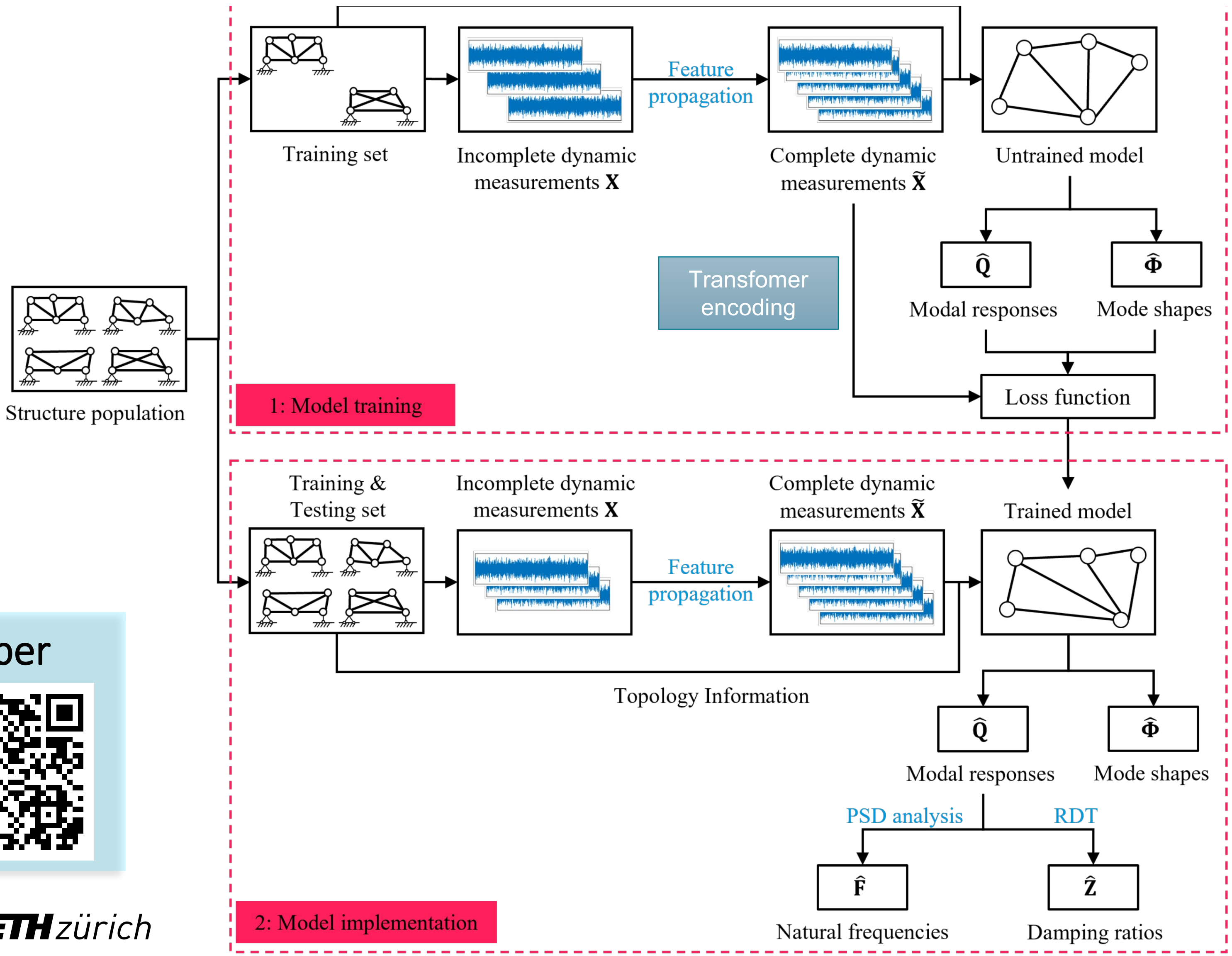


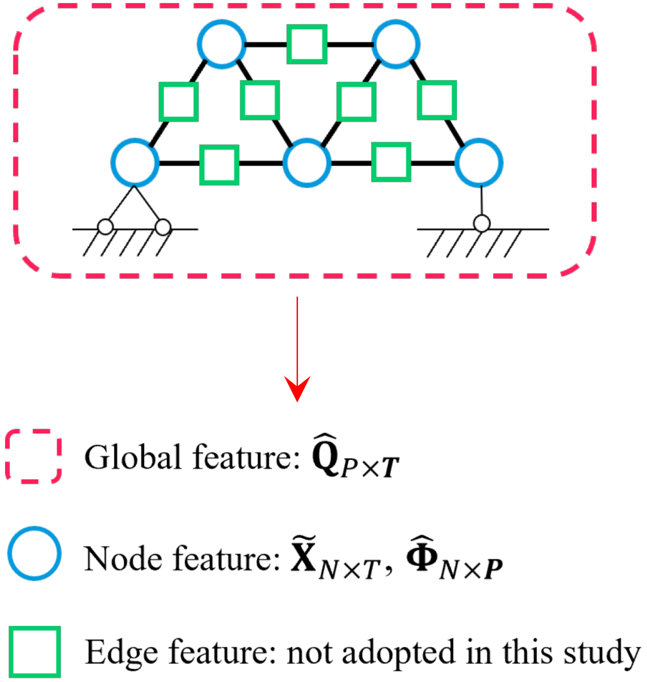


GNNs/Transformers for Population-based SHM



Harnessing the power of graph representations for transfer across populations/fleets





Paper

ETH zürich

Next Step

Differential Equations Discovery

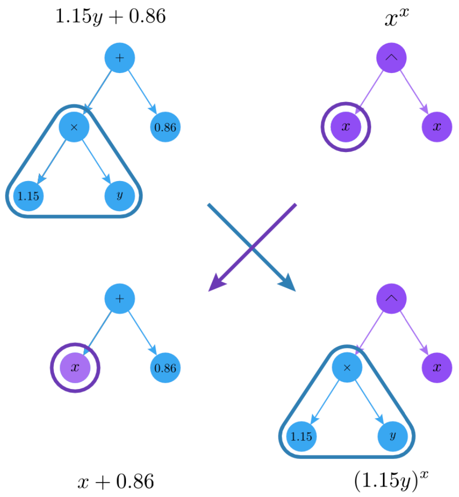
Dictionary-based methods (e.g. SINDy)

$$f(\mathbf{X}) = y(\mathbf{X}) = \Theta(\mathbf{X}) \cdot \Xi$$

$$\mathbf{\Theta}(\mathbf{X}) = \begin{bmatrix} | & | & | & | & & | & | & \\ 1 & \mathbf{X} & \mathbf{X}^2 & \mathbf{X}^3 & \cdots & \sin(\mathbf{X}) & \cos(\mathbf{X}) & \cdots \\ | & | & | & | & & | & | & \end{bmatrix}$$

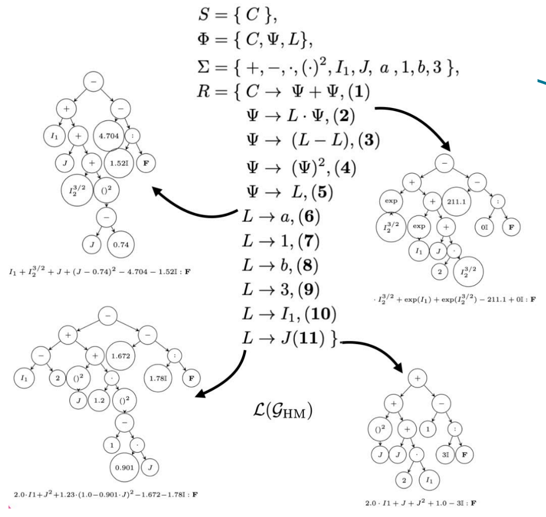
[Brunton et al. 2016]

Genetic Programming (e.g. Eureqa, PySR)



[Cranmer 2023]

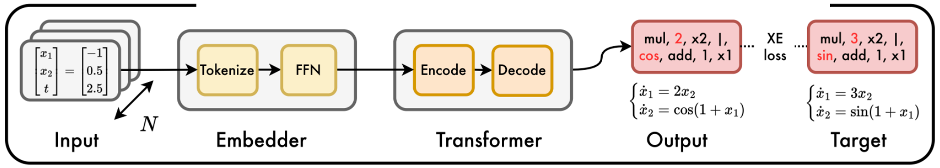
Symbolic Regression Methods



Grammar-based methods (e.g. ProGED)

[Kissas et al. 2024]

Sequence-based methods (e.g. ODEFormer)



[Ascoli et al. 2022]

preprint

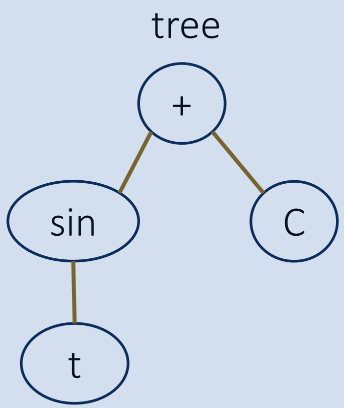
Next Step

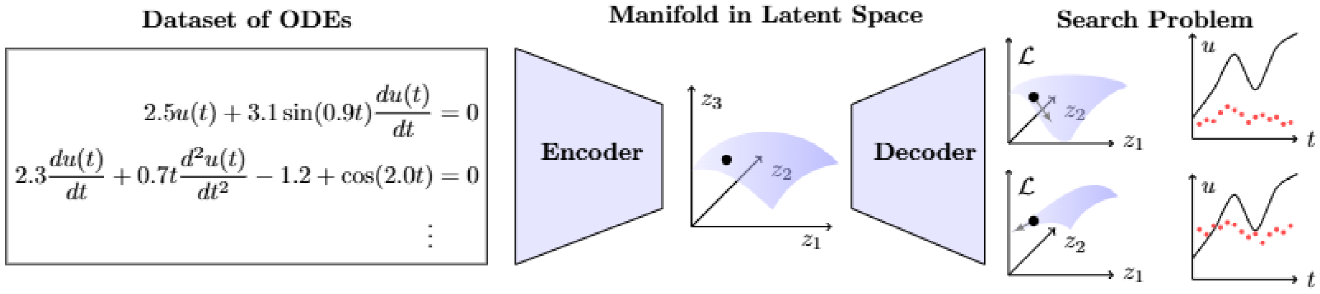
Differential Equations Discovery

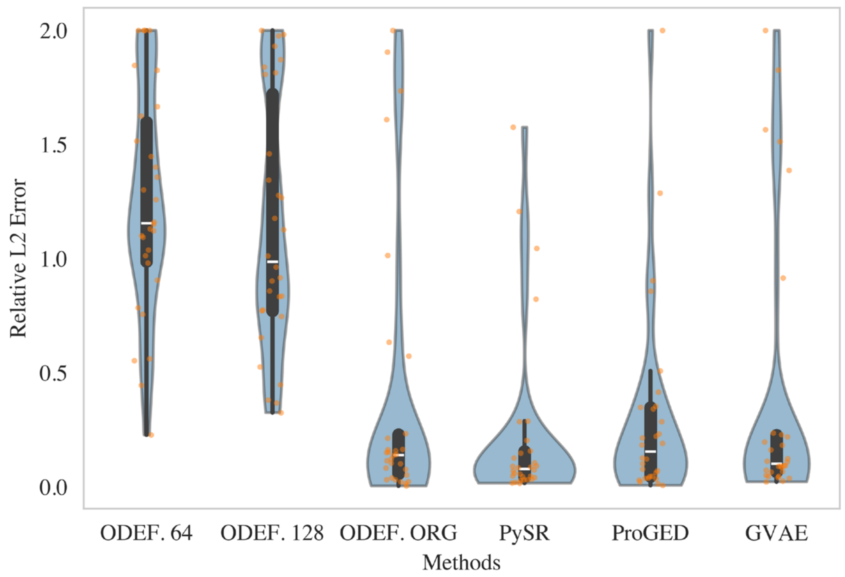
$\sin(t) + C$

Rules sequence:
[1,3,5,7,4]

$\mathcal{S} = \{S\}$
$\mathcal{V} = \{V, F\}$
$\mathcal{T} = \{+, t, \sin(\cdot), \cos(\cdot), C\}$
$\mathcal{P} = \{S \to E + E \ (1),$
$E \to V\ (2) \mid F\ (3) \mid C\ (4),$
$F \to \sin(V)\ (5) \mid \cos(V)\ (6),$
$V \to t\ (7)\}$







Model	ODE
Pendulum	
True	$2\frac{d^2}{dt^2}u(t) + \frac{d}{dt}u(t) + 5u(t) - 2\sin(0.5t) = 0$
ProGED	$\frac{d^2}{dt^2}u(t) + 0.00848\frac{d}{dt}u(t) - 0.000306 = 0$
PySR best	$\frac{d^2}{dt^2}u(t) - \sin(0.500t) + \frac{u(t)}{0.402} + \sin(\sin(\sin(\sin(0.624))))\frac{d}{dt}u(t) = 0$
GVAE	$2.11\frac{d^2}{dt^2}u(t) + 1.06\frac{d}{dt}u(t) + 5.29u(t) - 2\sin(0.5t) = 0$
Duffing oscillator	
True	$5\frac{d^2}{dt^2}u(t) + \frac{d}{dt}u(t) + 7u(t) + 25u^3(t) - \cos(2t) = 0$
ProGED	$\frac{d^2}{dt^2}u(t) - 0.000521t + 0.00382 = 0$
PySR best	$\frac{d^2}{dt^2}u(t) + 30.25u(t) - 28.59\sin(u(t)) = 0$
GVAE	$4.81\frac{d^2}{dt^2}u(t) + 0.958\frac{d}{dt}u(t) + 8.23u(t) + 20.35u^3(t)\cdot\cos(0.0057t^2) - \cos(2t) = 0$

Accounting for engineering considerations:
- Richness of excitation
- Balancing complexity (parsimony) and accuracy

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.

- SNSF MINT Project, 200021L_212718, Modelling and estimation of unsteady aerodynamic flow at high Reynolds number

- SNSF Bridge Discovery project - AeroSense: a novel MEMS-based surface pressure and acoustic IoT measurement system for wind turbines

- TUM-IAS Hans Fischer Fellowship by TÜV SÜD

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Dr. Ch. Mylonas

Karin Yu

Gregory Duthé

Sandia National Laboratories

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Dr. Xudong Jian

Giacomo Arcieri

ETH zürich

We welcome questions/comments/collaboration:

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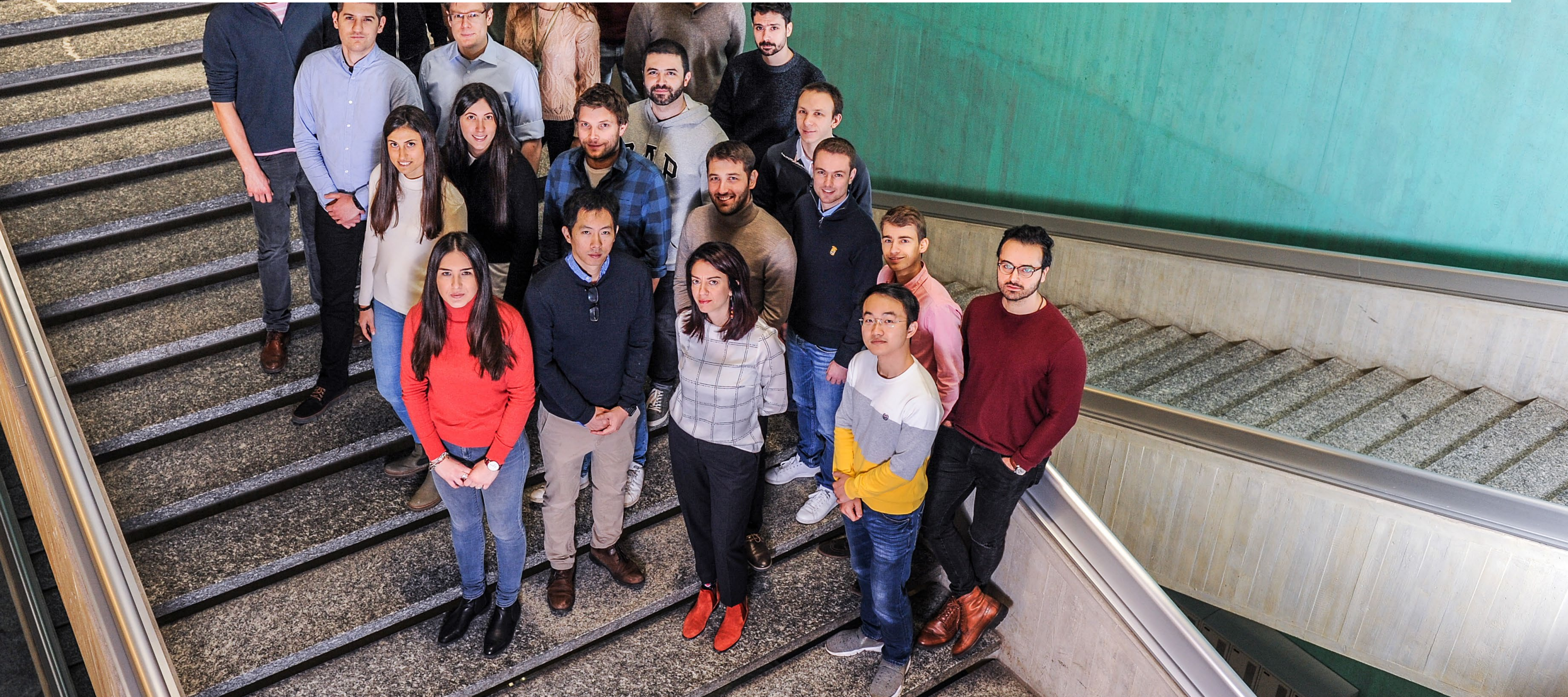

GNN architecture

We use an **Encode-Process-Decode** structure to allow for more expressivity.