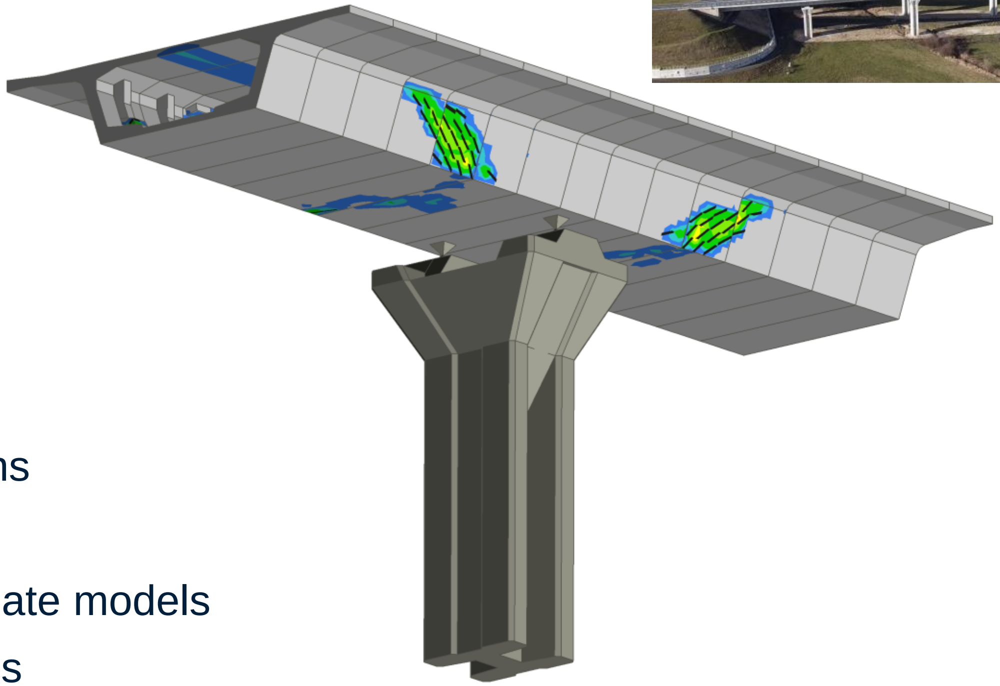
AI Based Surrogate Model for Digital Twins for Structural Health Monitoring



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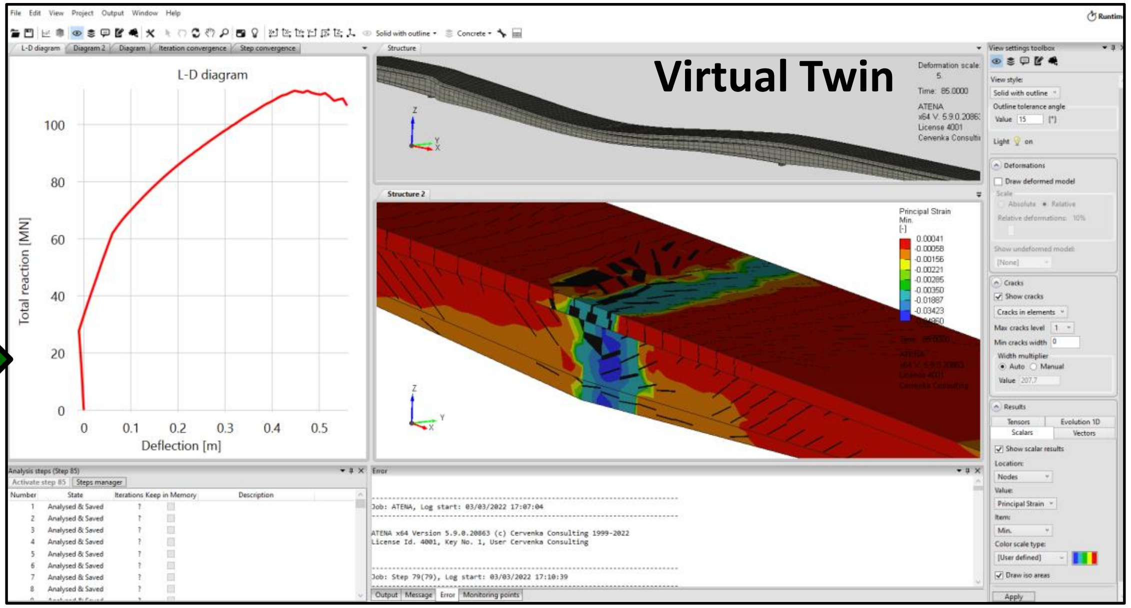
Content:

- Digital Twins
- Application of Machine Learning in Digital Twins for Structural Health Assessment
- Uncertainties and accuracy of AI based surrogate models
- Application to the monitoring of existing bridges

Digital Twins for bridges



Properties of Digital Twin

Short-term performance:

- static/dynamic/cyclic loadings
- non-linear material behaviour (concrete cracking, rebar yielding)
- accidental scenarios
- ....

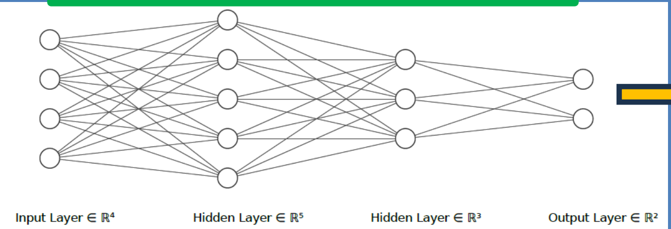
Long-term performance:

- **chloride attack**/carbonation
- reinforcement corrosion
- creep and shrinkage
- ASR/AAR mechanisms
- ....

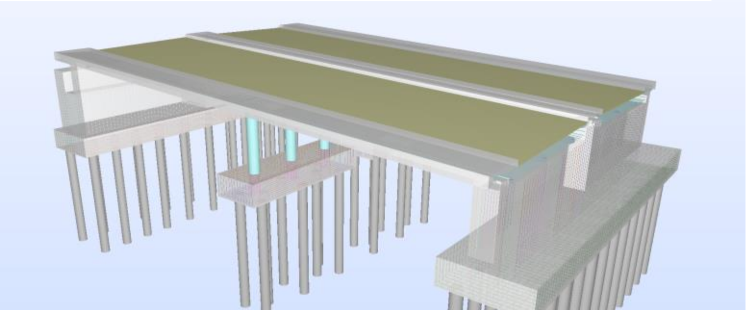
ANN application in Digital Twin for SHM

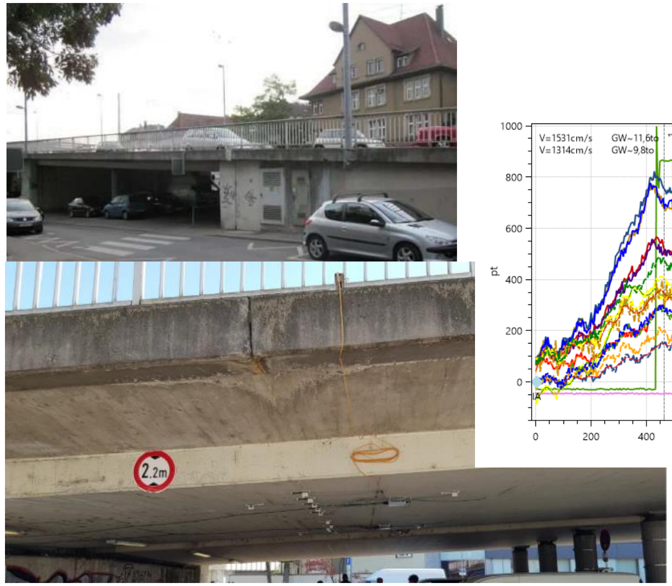
Monitoring data for FE model calibration

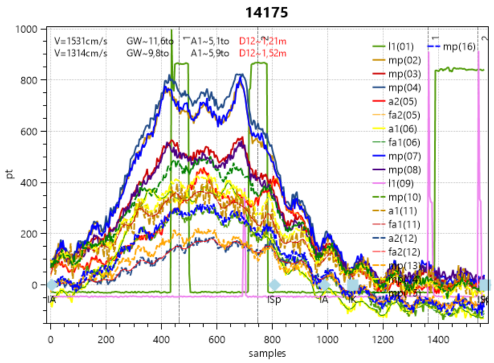
ANN for parameter identification



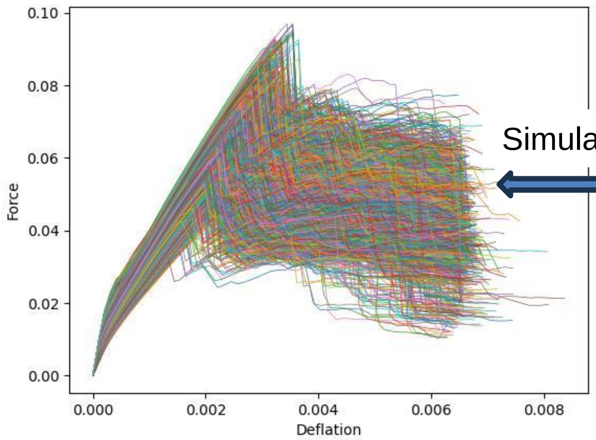
Optimal parameters for FE model, E, fc, ft, GF, ….



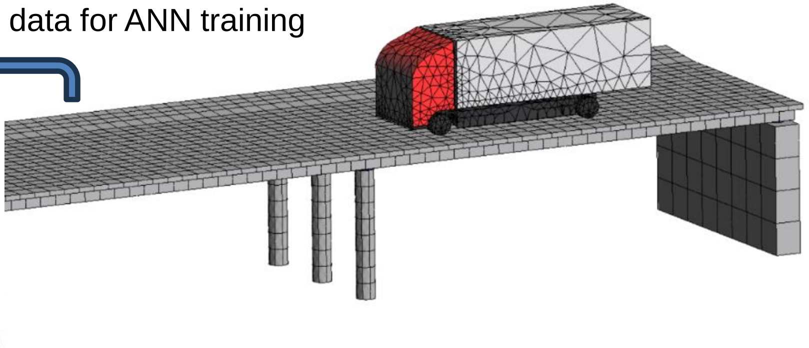




Training parameter identification model

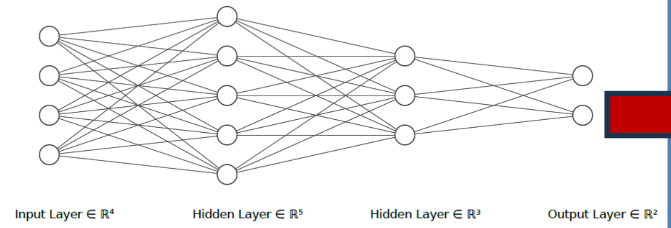


Simulation data for ANN training



Training surrogate model

Monitoring data for bridge SHM (Structural Health Monitoring)

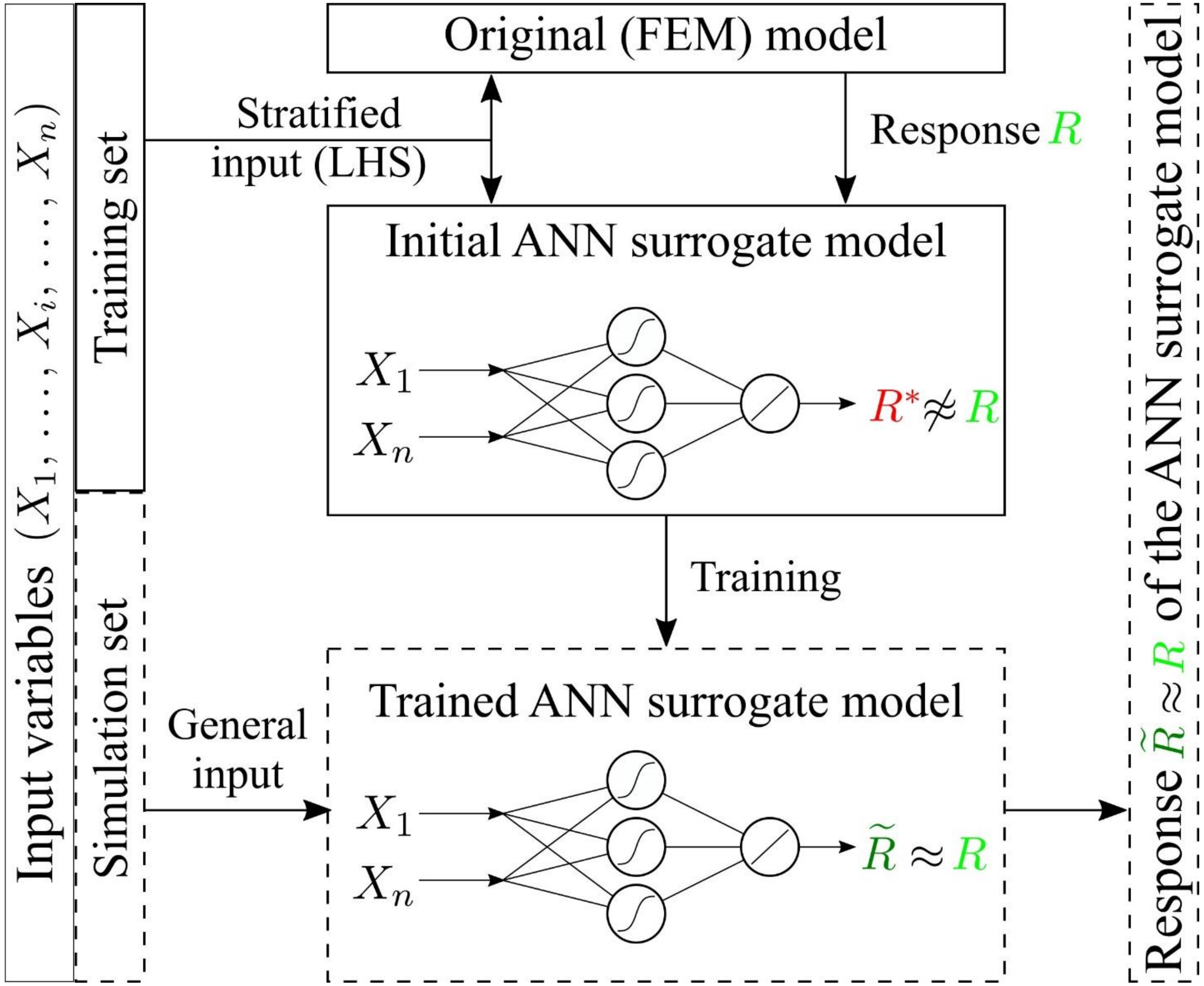


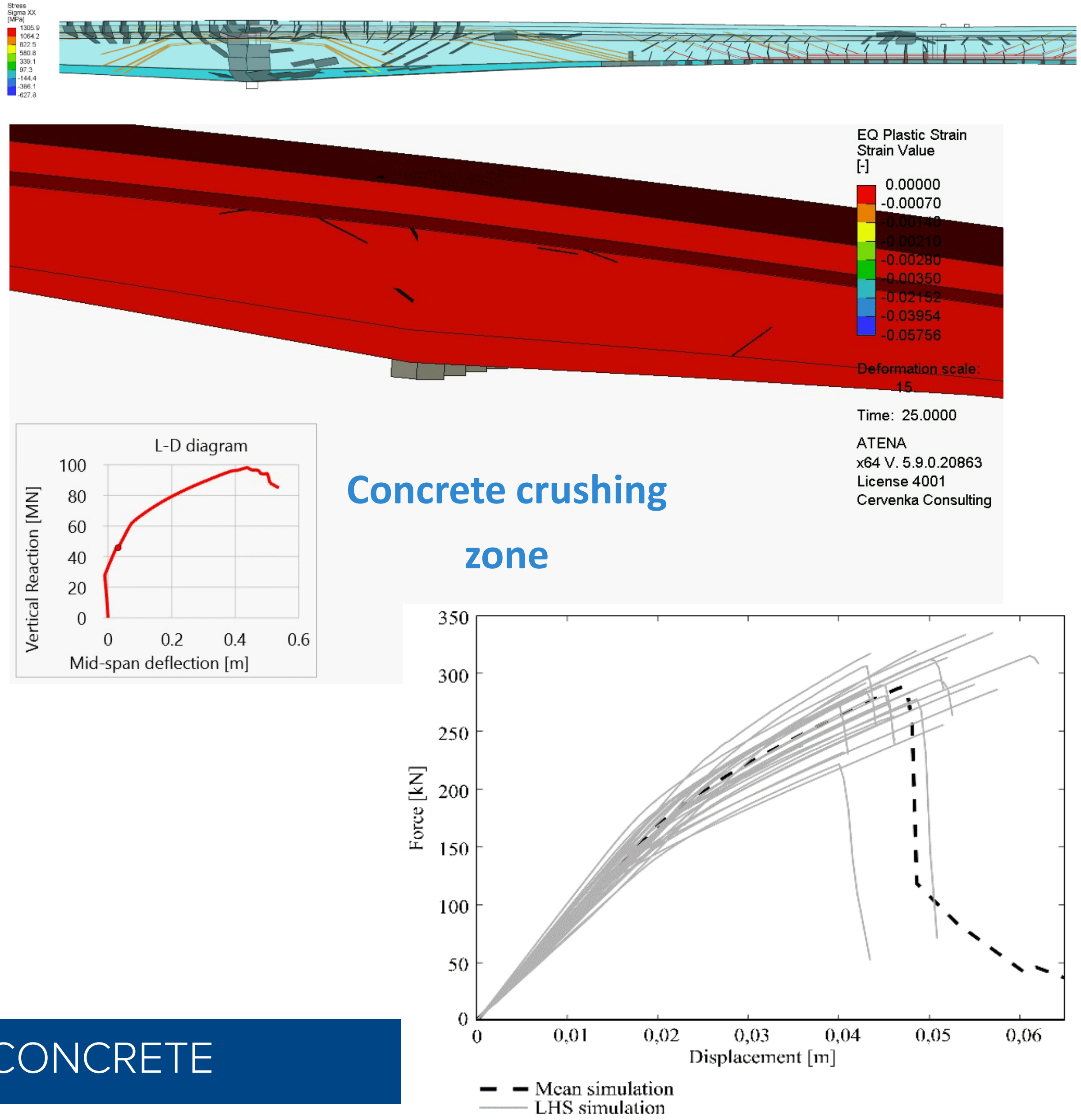
ANN surrogate for engineering interpretation

Engineering quantities for bridge management:

- bridge utilization
- reliability
- max. concrete stress
- max. reinforcement stress

ANN-based surrogate model

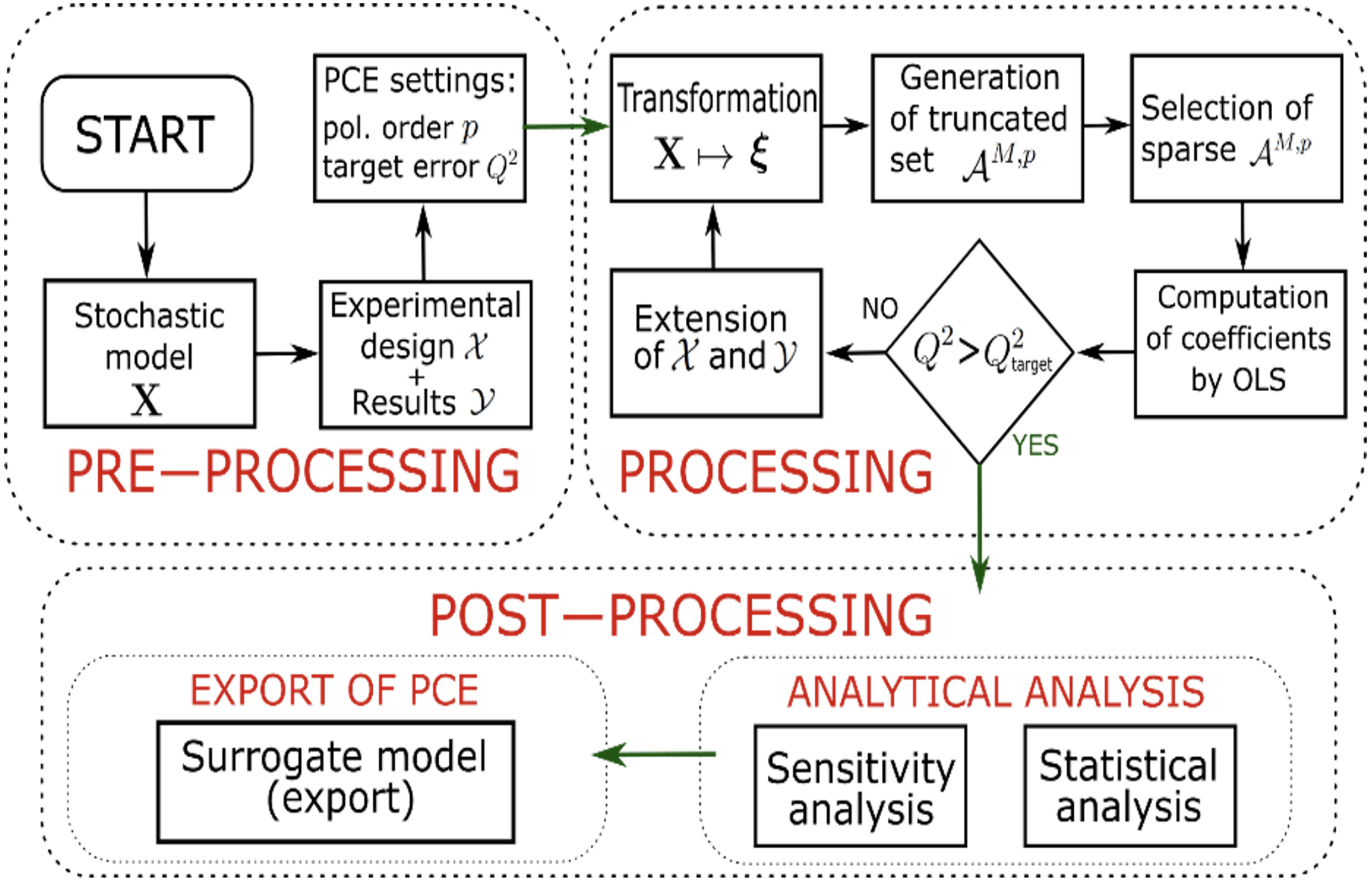




Polynomial Chaos Expansion (PCE)-based surrogate model

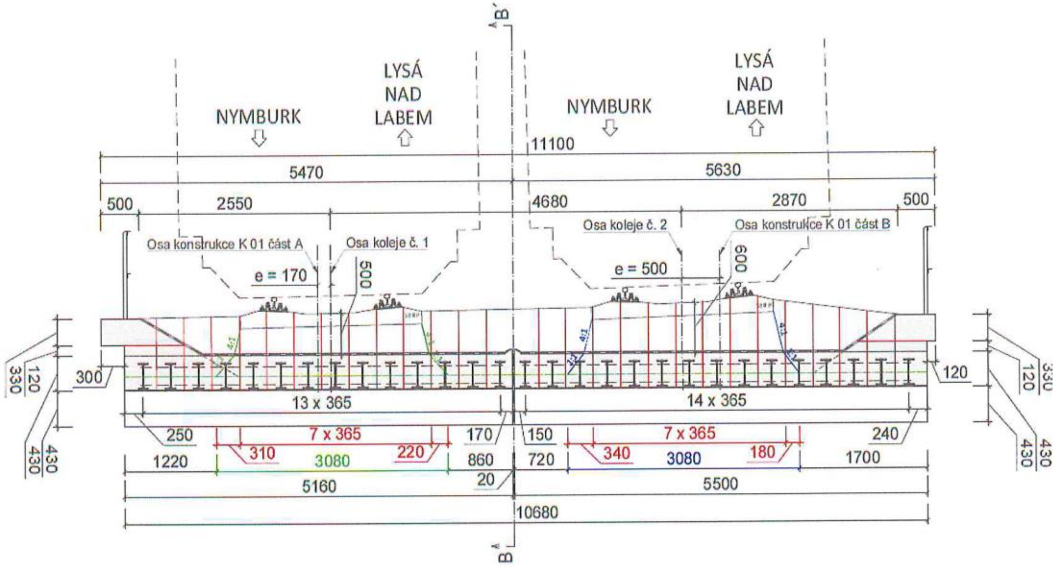
$$Y = \mathcal{M}(\mathbf{X}) = \sum_{\boldsymbol{\alpha} \in \mathbb{N}^M} \beta_{\boldsymbol{\alpha}} \Psi_{\boldsymbol{\alpha}}(\mathbf{X})$$

- β_α deterministic coefficients to be computed (Least Square Regression)
- $\Psi_\alpha(X)$ basis of multivariate polynomials is orthonormal with respect to the joint distribution function (Hermite polynomials)
- M represents size of stochastic model (Curse of Dimensionality)
- Efficient algorithm for Sparse PCE was employed– Least Angle Regression (LAR).



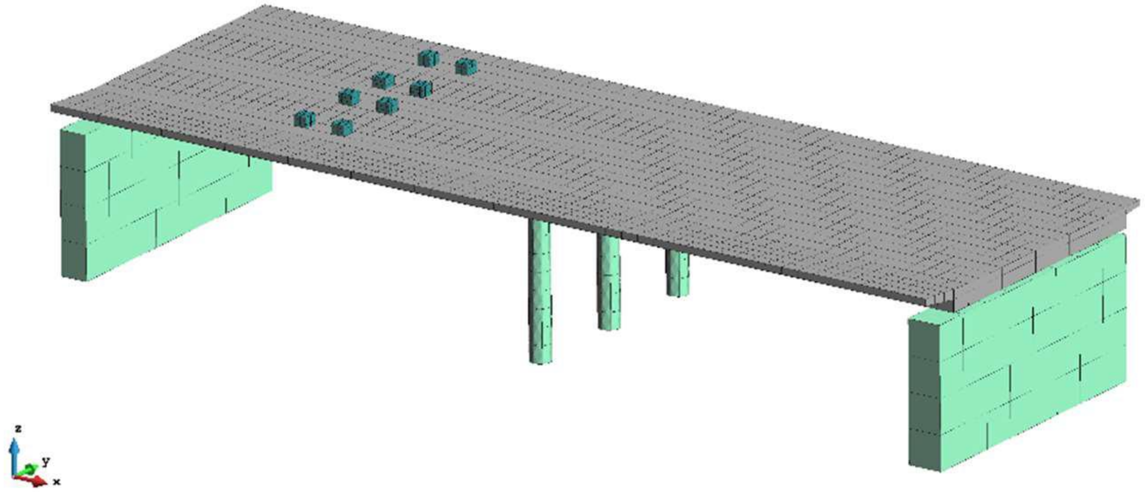
Bridge example 1: small railway bridge, Kostomlaty, Czech Republic

- **spans:** 2 x 5.1 m
- construction finished in 1905, reconstruction 1942
- composite concrete steel structure with imbedded I steel beams
- longitudinal cracks with water seepage and corrosion



Application example 2: **Vogelsang Bridge, Esslingen, Germany**

- 8 sub-structures with 3 different construction types constructed between **1971 – 1973,** total length **595 m**
- measurement and analysis of 2 spans (**13.8 + 13.2 m**)
- **structure type:** continuous non-prestressed RC beam with the height of 0.6 m
- **load:** road traffic and environmental loads



Bridge Monitoring System

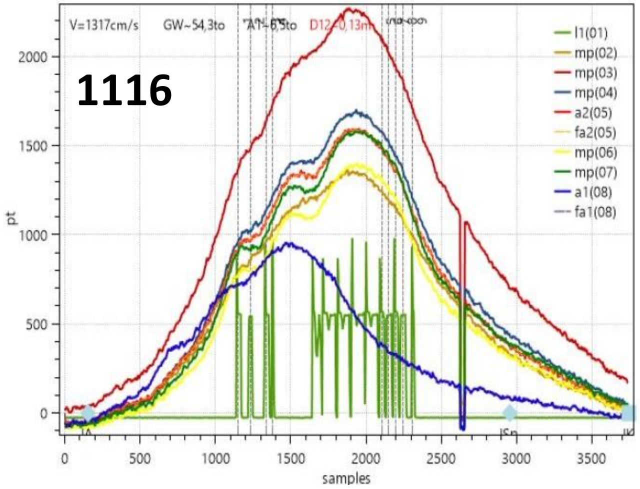
- strain gauges coupled with laser range rangefinder
- suitable for loads above 3.5 tonne
- installation on the underside of the deck

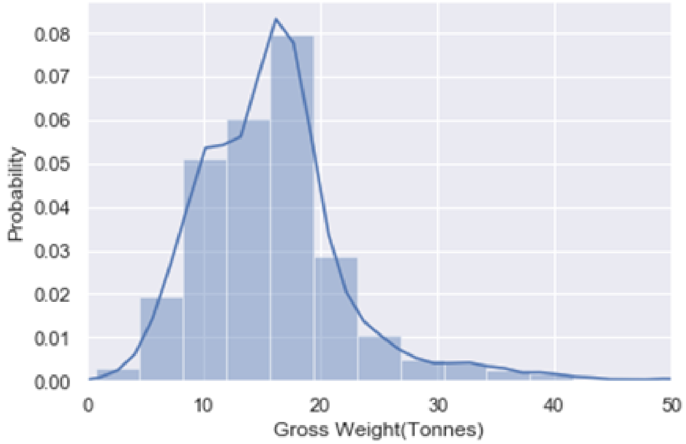
  → no traffic disruption
- strain gauges calibrated before measurements
- **provider:** iBWIM technology by Petschacher Consulting

calibration of the system

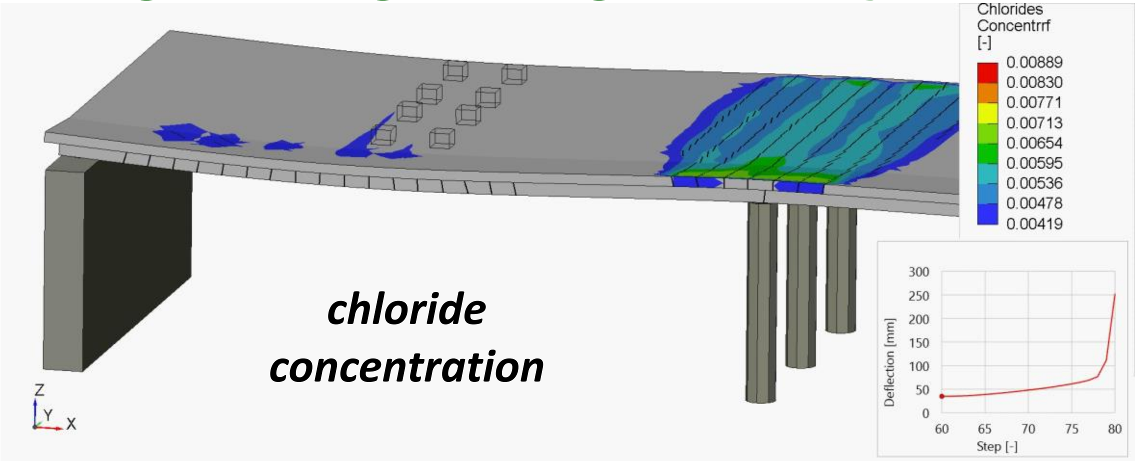
rangefinder

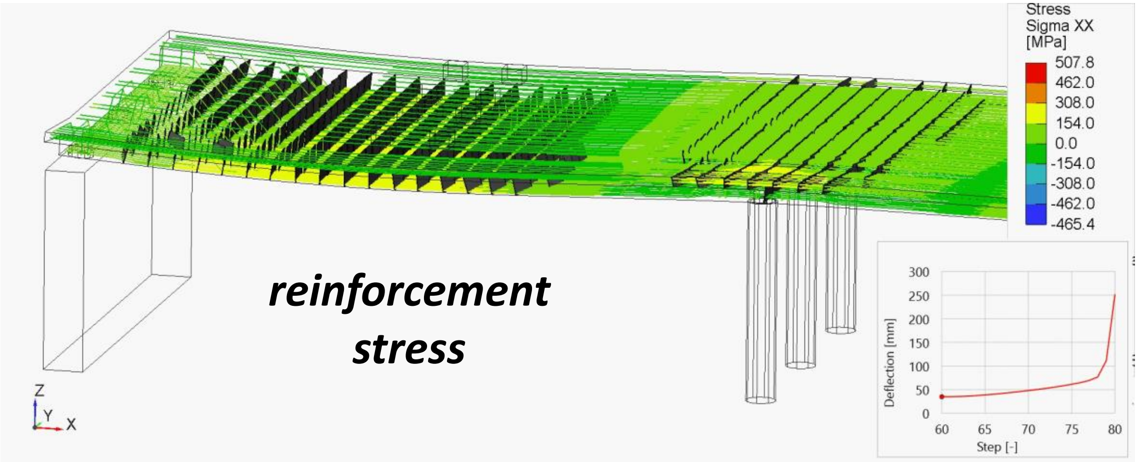
strain gauges

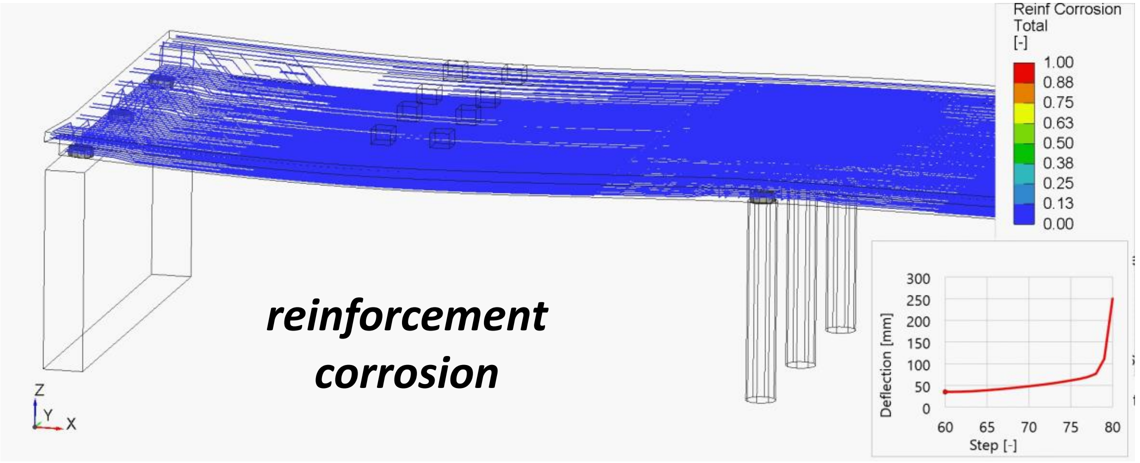


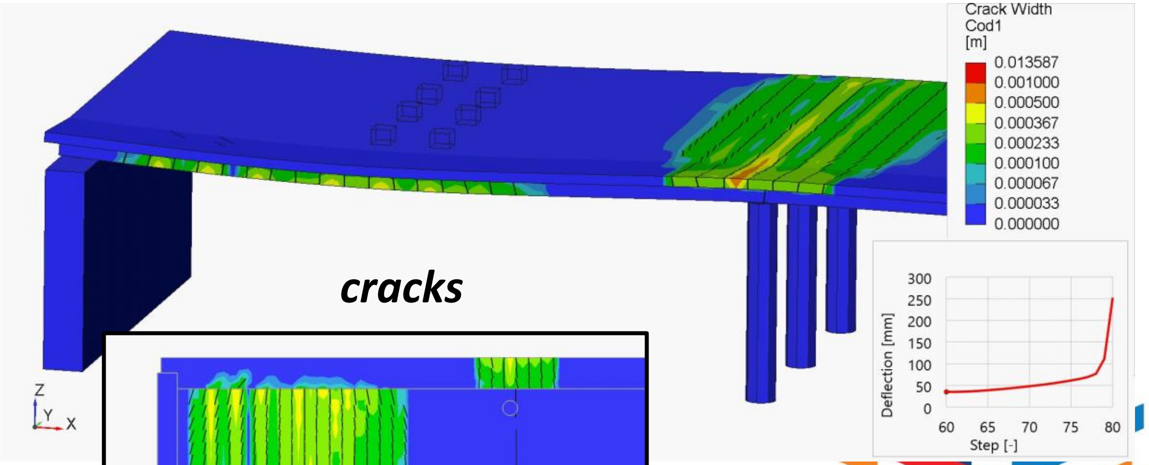


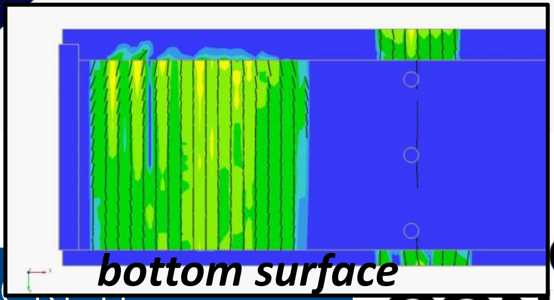
Vogelsang Bridge: 150-years-long Chloride Attack, ATENA modelling











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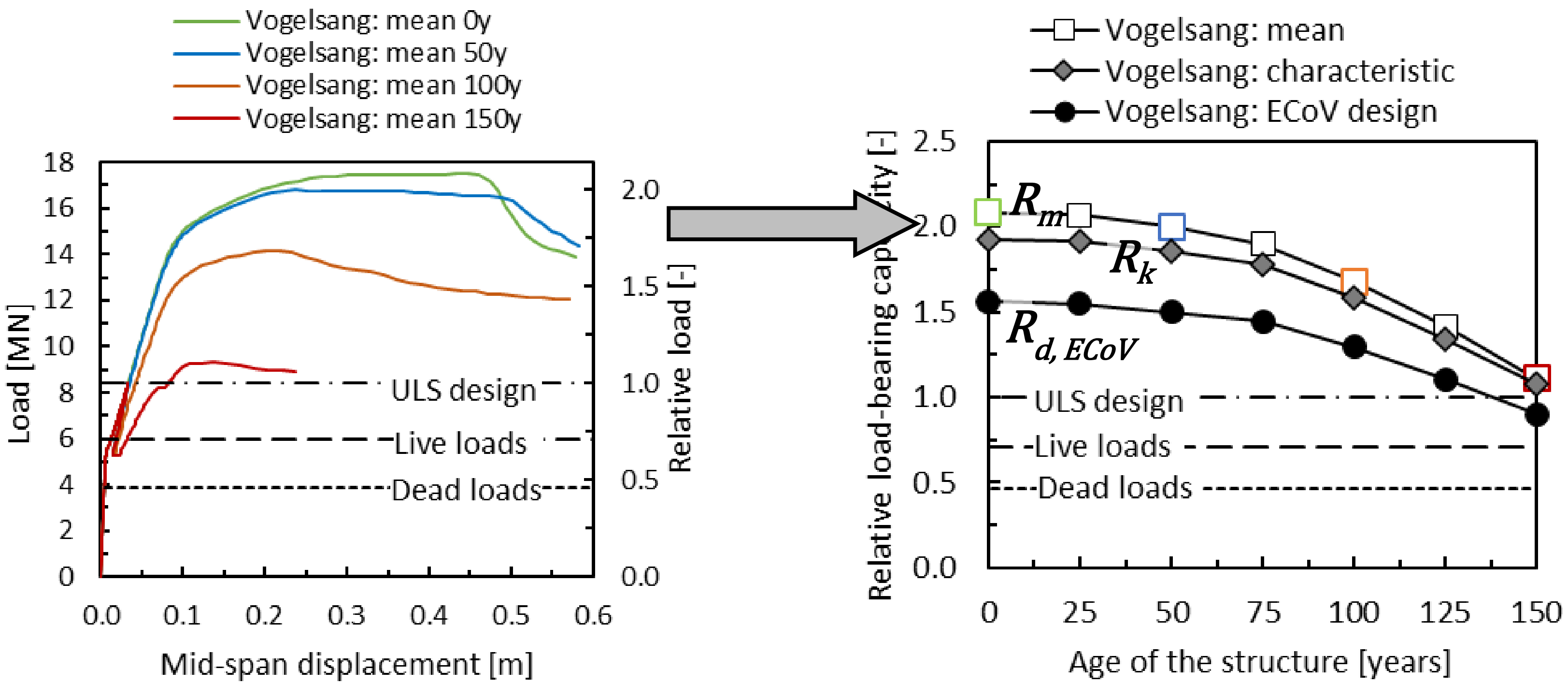
Durability Assessment: Vogelsang Bridge



- structure is sensitive to corrosion due to the bending failure mode mechanism at peak load

ECoV method (*fib* MC 2010):

coefficient of variation:

$$V_R = \frac{1}{1.65} \ln\left(\frac{\boldsymbol{R_m}}{\boldsymbol{R_k}}\right)$$

global resistance factor:

$$\gamma_R = \exp(\alpha_R\, \beta\, V_R) \cong \exp(3.04\, V_R)$$

design structural resistance:

$$R_{d,ECOV} = \frac{R_m}{\gamma_R\, \gamma_{Rd}}$$

design check:

$$\boxed{\boldsymbol{E_d} < \boldsymbol{R_{d,ECoV}}}$$

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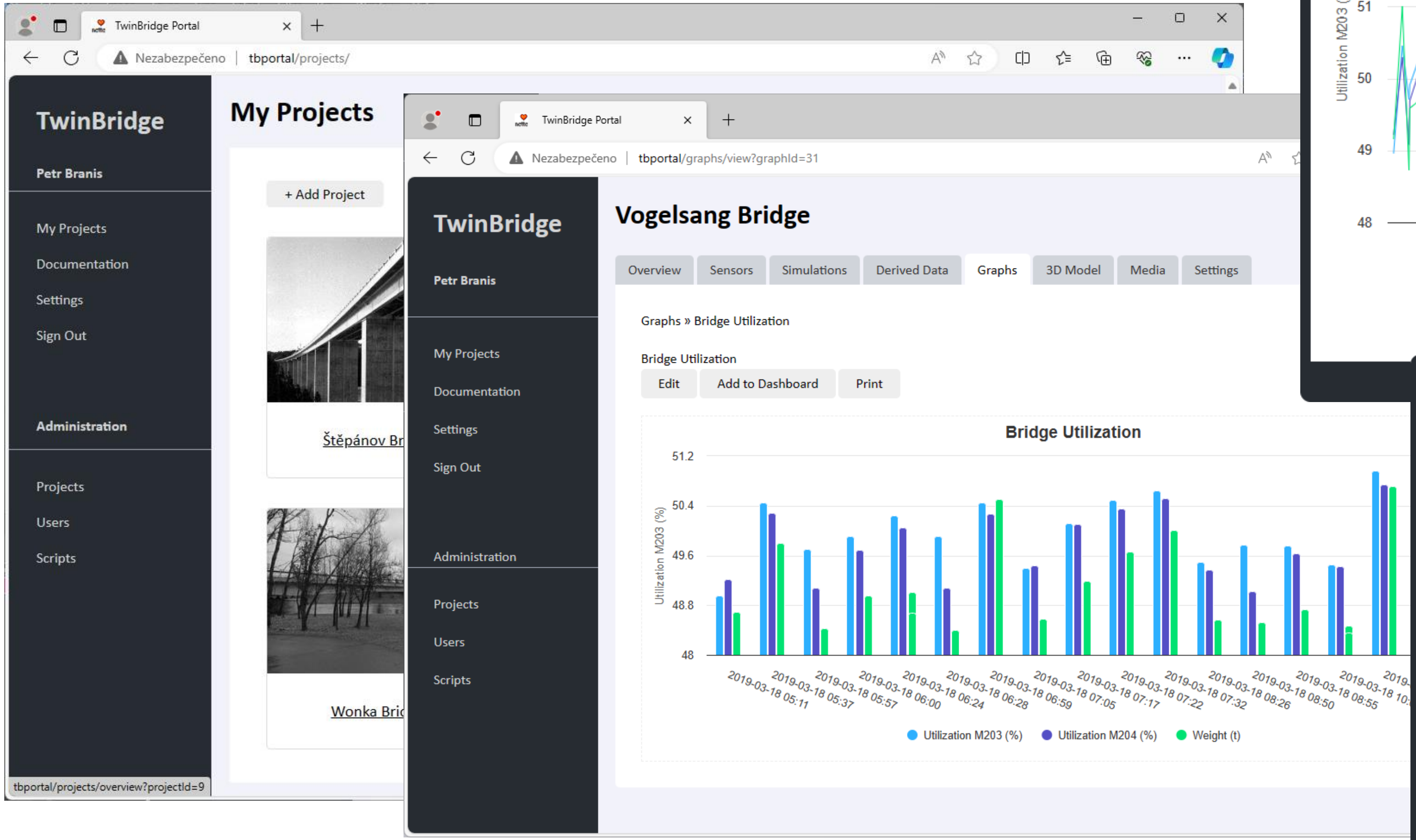
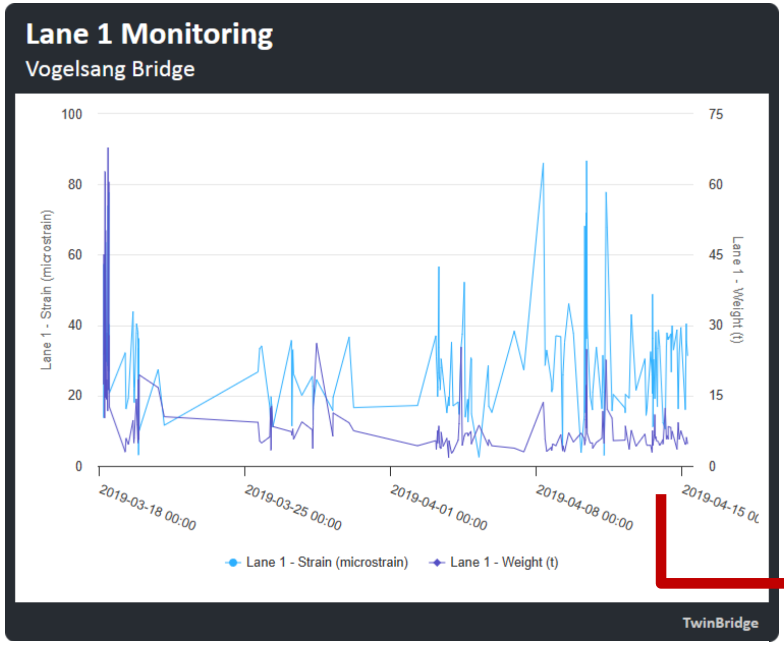
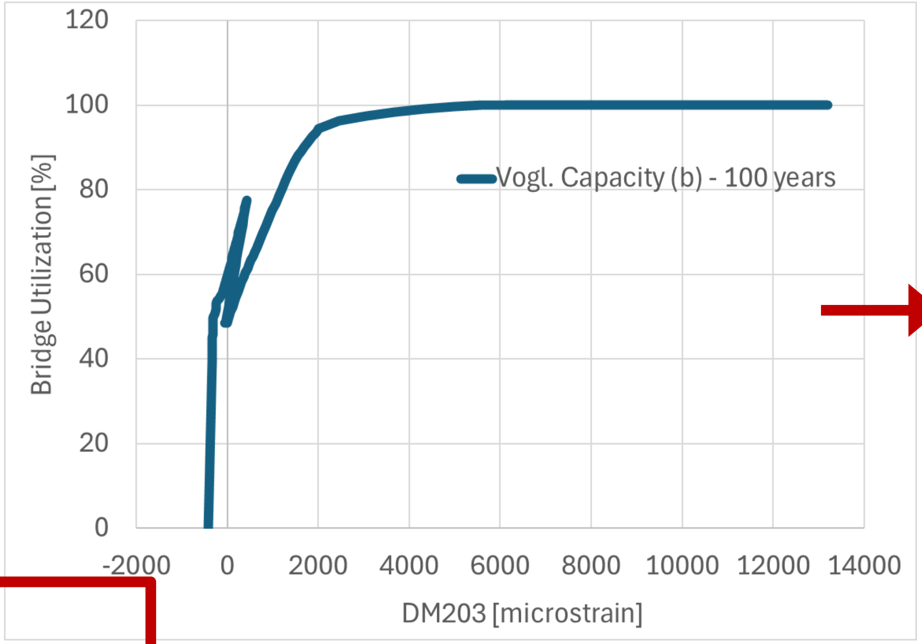
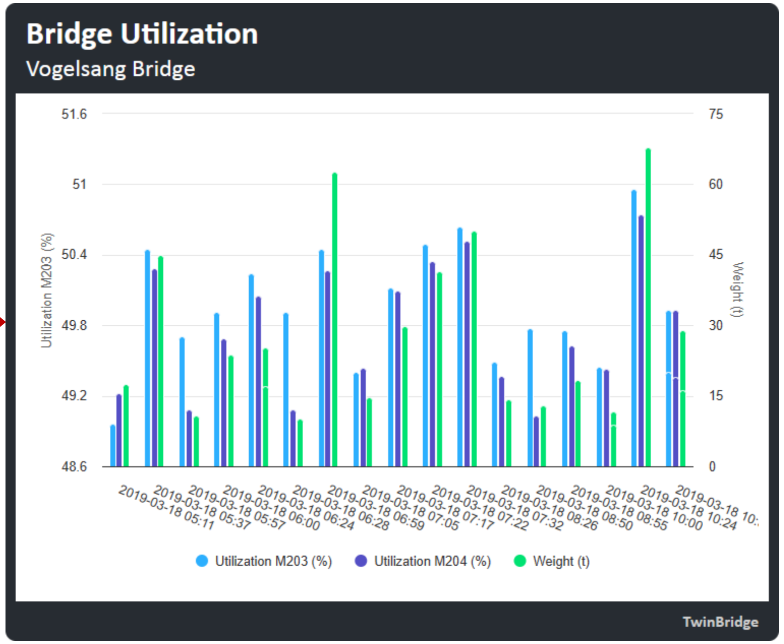
TwinBridge platform – application example

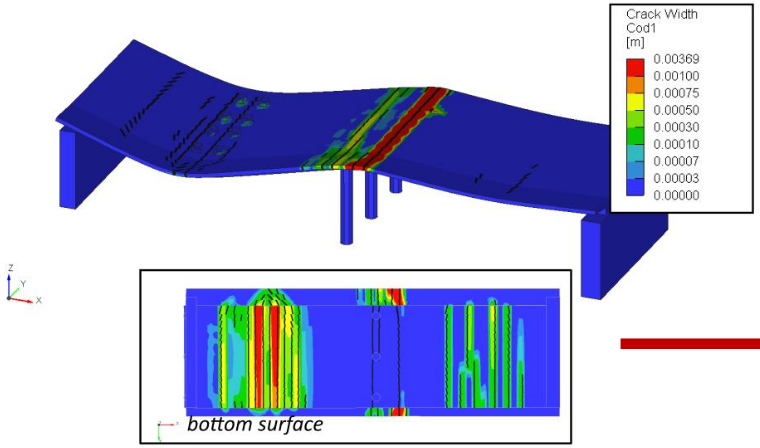


TwinBridge platform – operation example

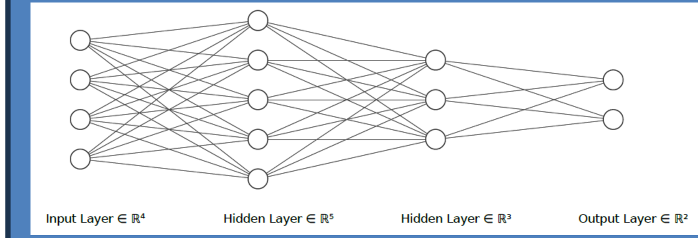






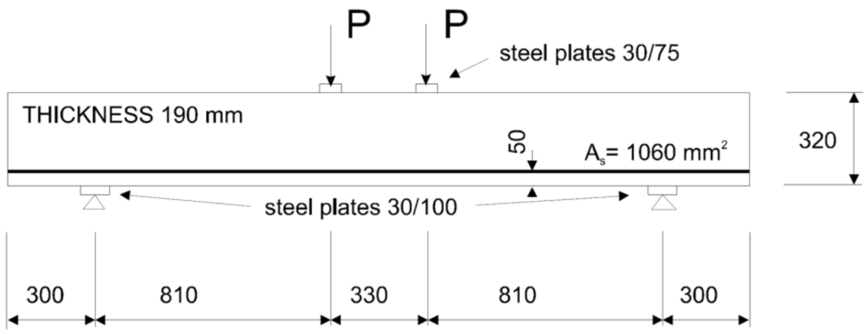


$$\varepsilon_M + \varepsilon_T + \varepsilon_{DL} = \varepsilon$$



ANN surrogate for engineering interpretation

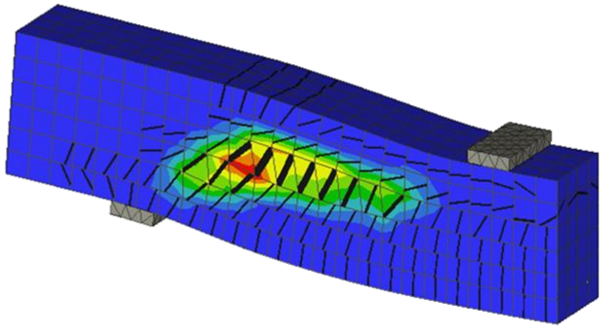
ANN for parameter identification analysis & evaluation

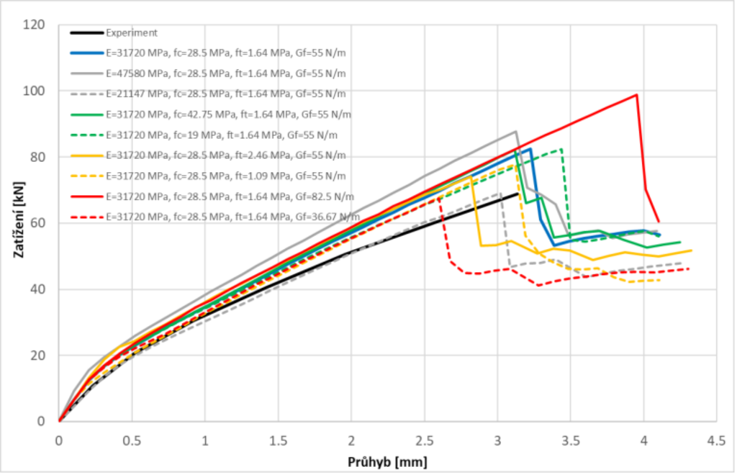


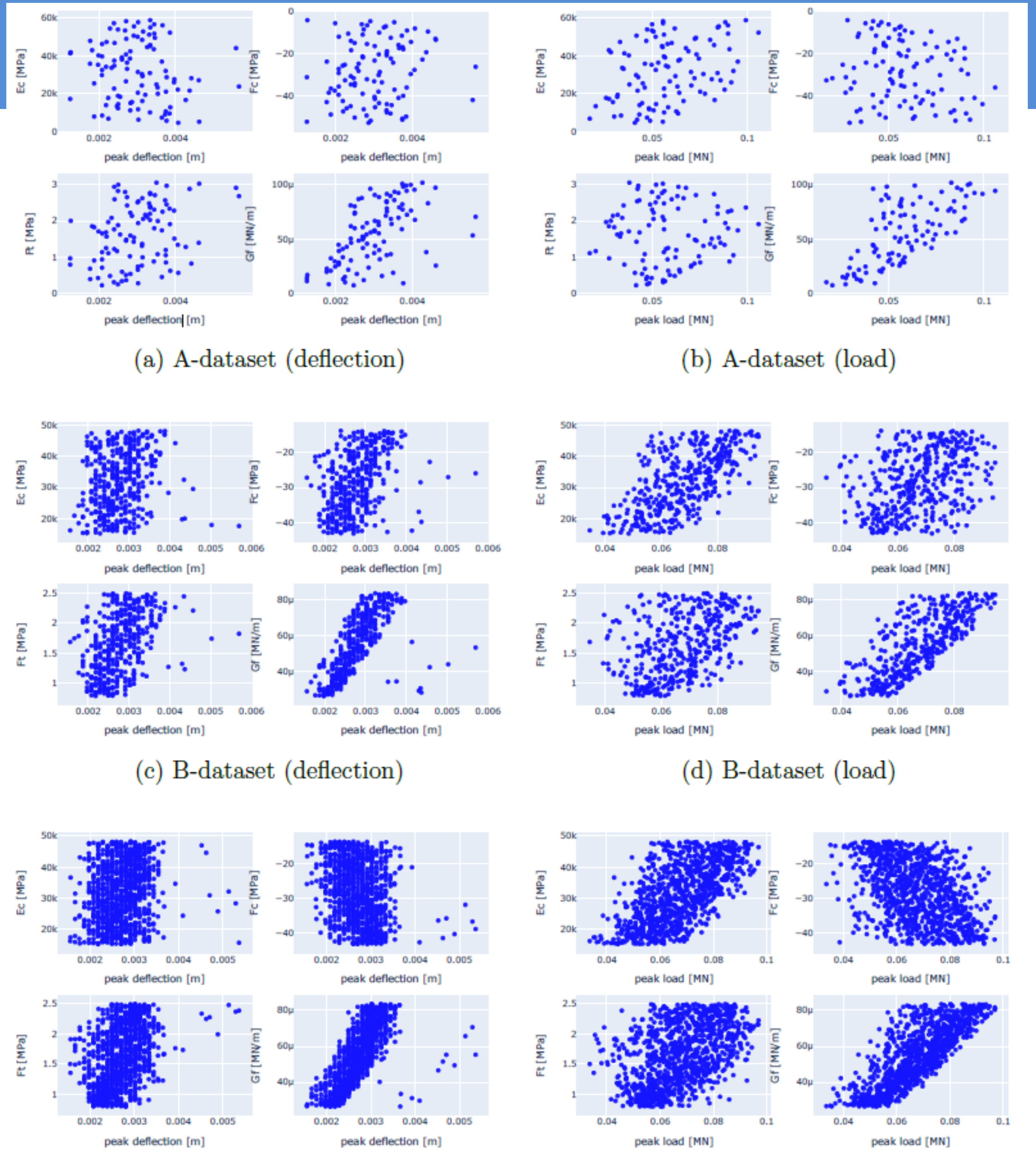
Data set distribution:

80% - training
20% - testing

Leonhard shear beam experiment 1962







(a) A-dataset (deflection) (b) A-dataset (load)

(c) B-dataset (deflection) (d) B-dataset (load)

(e) C-dataset (deflection) (f) C-dataset (load)

ANN for parameter identification analysis & evaluation

	CNN	Dense NN	LSTM NN	L-Maen	L-A-Maen	F-Maen
E_c	0.221	0.169	0.187	**0.136**	0.152	0.177
F_c	0.480	0.424	0.394	0.326	**0.272**	0.541
F_t	0.378	0.348	0.264	0.317	**0.207**	0.271
G_f	0.238	0.251	0.237	0.219	**0.204**	0.334
Mean	0.329	0.298	0.271	0.250	**0.209**	0.331
Model params count	23904	71204	6762	12308	2600	33028
p_e	0.013	0.005	0.055	0.033	**0.184**	0.009

Table 4.4: Full curve: test (A-dataset) (100 samples)

ANN types:

		layers	params
Conventional models:			
CNN:	convolution neural network,	7	23 904
Dense NN:	fully connected (dense) neural network,	5	71 204
LSTM NN:	long short-term memory neural network,	6	6 762

Explainable models:

L-Maen: LSTM Maen

L-A-Maen: LSTM-Attention Maen

F-Maen: Feedforward Maen

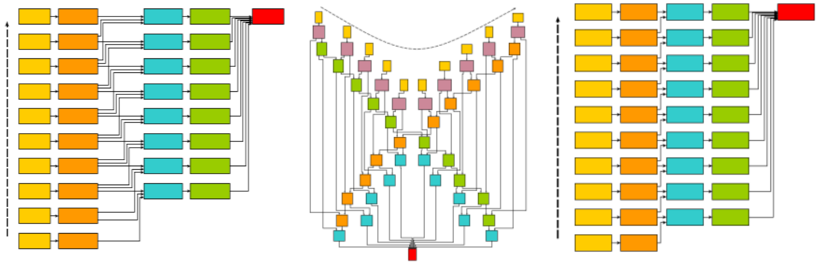


Figure 3.5: LSMT Maen (L-Maen). Figure 3.6: LSMT-Attention Maen (L-A-Maen). Figure 3.4: Feedforward Maen (F-Maen).

	CNN	Dense NN	LSTM NN	L-Maen	L-A-Maen	F-Maen
E_c	0.121	0.068	0.105	0.150	0.087	**0.065**
F_c	0.320	0.310	0.309	0.334	**0.283**	0.347
F_t	0.241	**0.156**	0.245	0.272	0.258	0.224
G_f	0.185	**0.146**	0.174	0.262	0.181	0.202
Mean	0.217	**0.170**	0.208	0.255	0.202	0.210
Model params count	23904	71204	6762	12308	2600	33028
p_e	0.019	0.008	0.071	0.032	**0.190**	0.014

Table 4.8: Full curve: test (B-dataset) (400 samples)

	CNN	Dense NN	LSTM NN	L-Maen	L-A-Maen	F-Maen
E_c	0.119	0.066	0.111	0.103	0.101	**0.063**
F_c	0.331	0.304	0.336	0.317	**0.296**	0.322
F_t	0.231	**0.138**	0.230	0.239	0.208	0.184
G_f	0.179	**0.128**	0.168	0.170	0.173	0.138
Mean	0.215	**0.159**	0.211	0.207	0.194	0.177
Model params	23904	71204	6762	12308	2600	33028
p_e	0.019	0.009	0.070	0.039	**0.198**	0.017

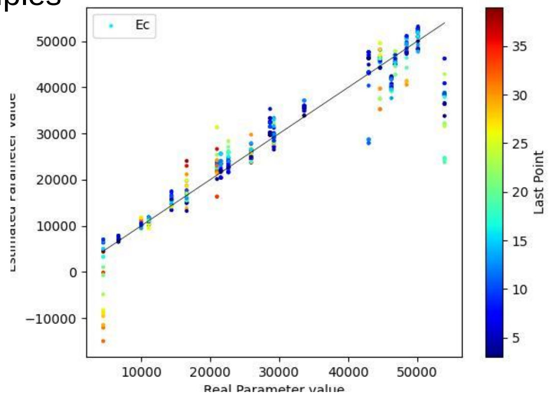
Table 4.12: Full curve: test (C-dataset) (1000 samples)

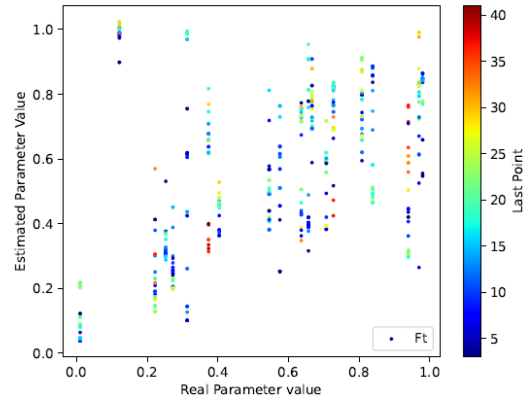
ANN for parameter identification analysis & evaluation

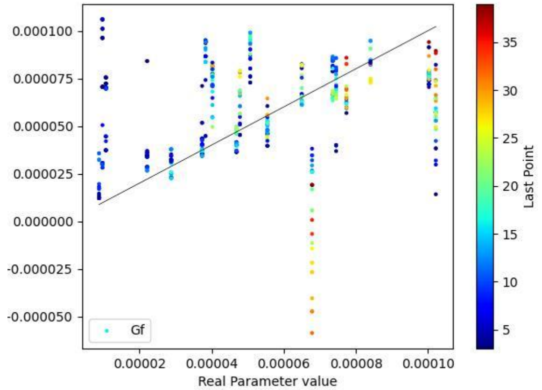
Parameter: E_c f_t G_F f_c

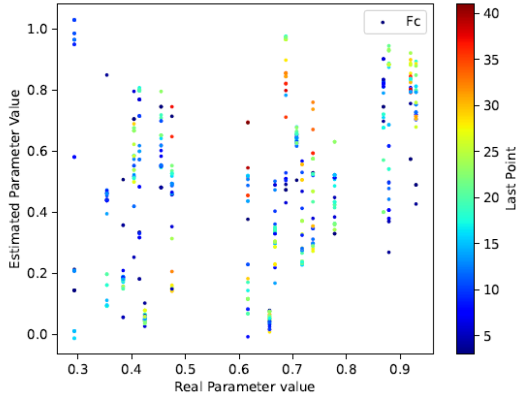
No. of samples

100

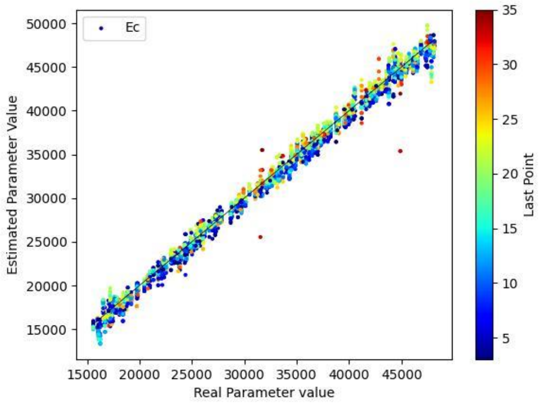


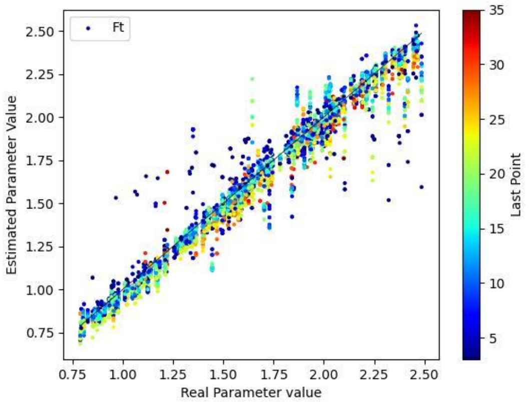


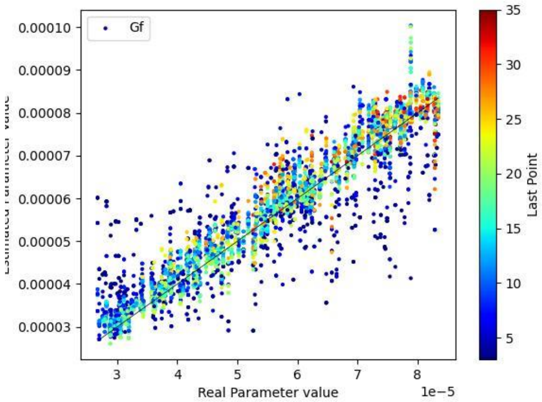


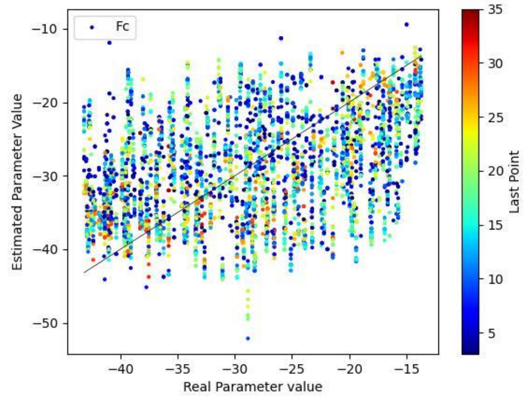


1000









THE WORLD'S GATHERING PLACE FOR ADVANCING CONCRETE

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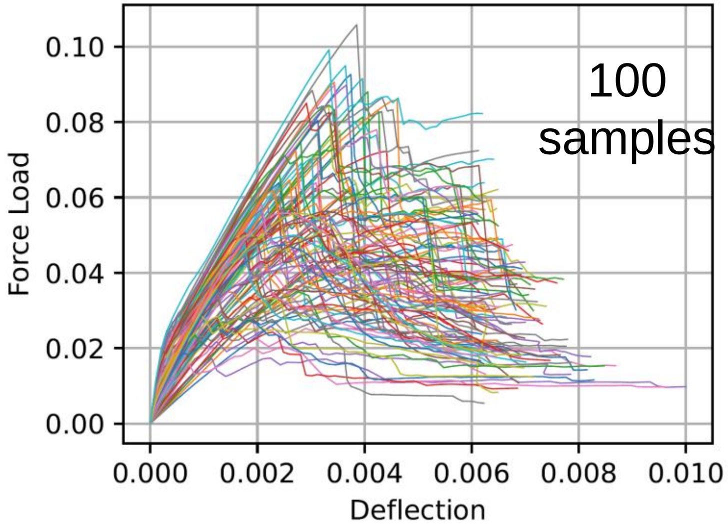
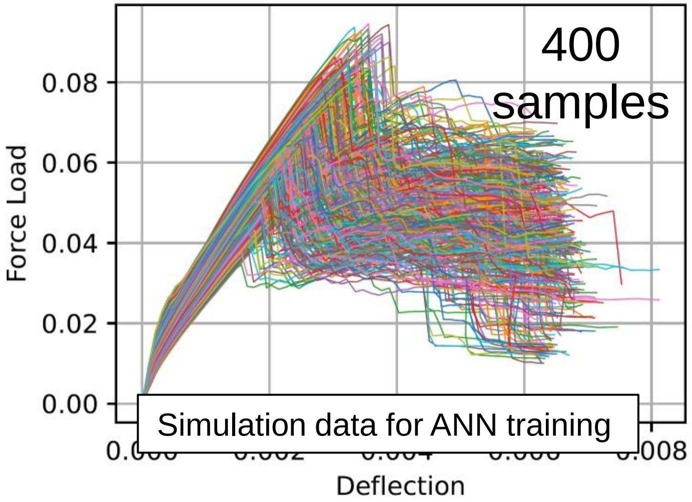
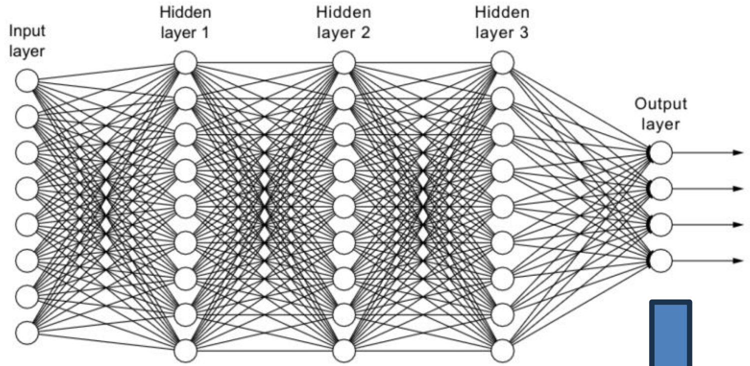
ANN for surrogate engineering model – analysis & evaluation





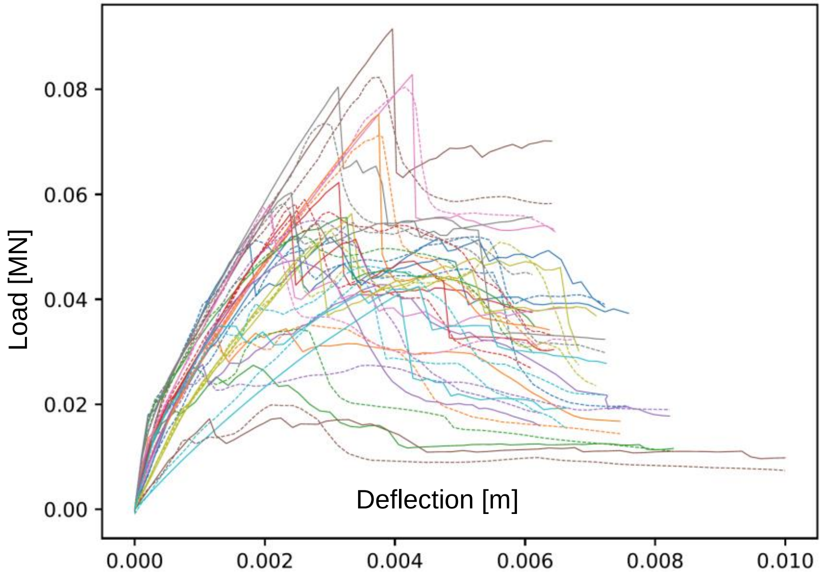
Simulation data for ANN training

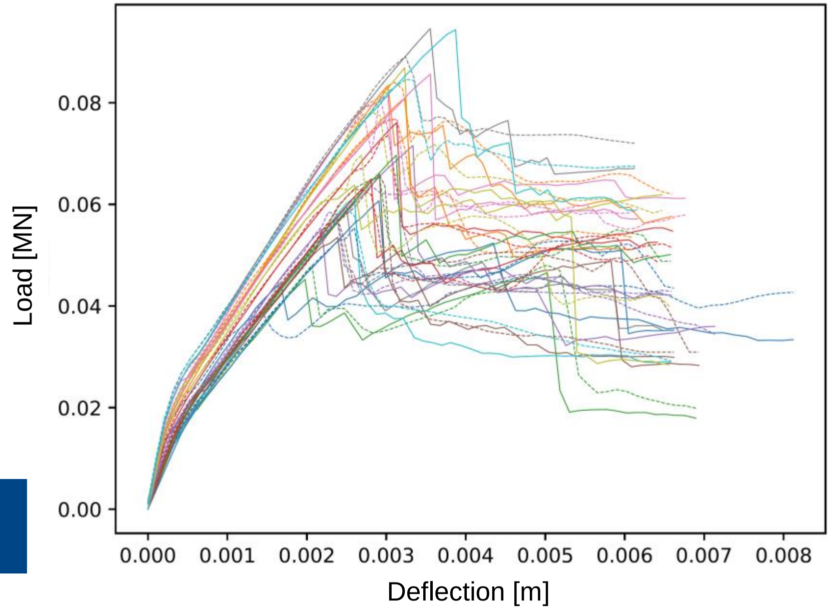


Data set distribution:

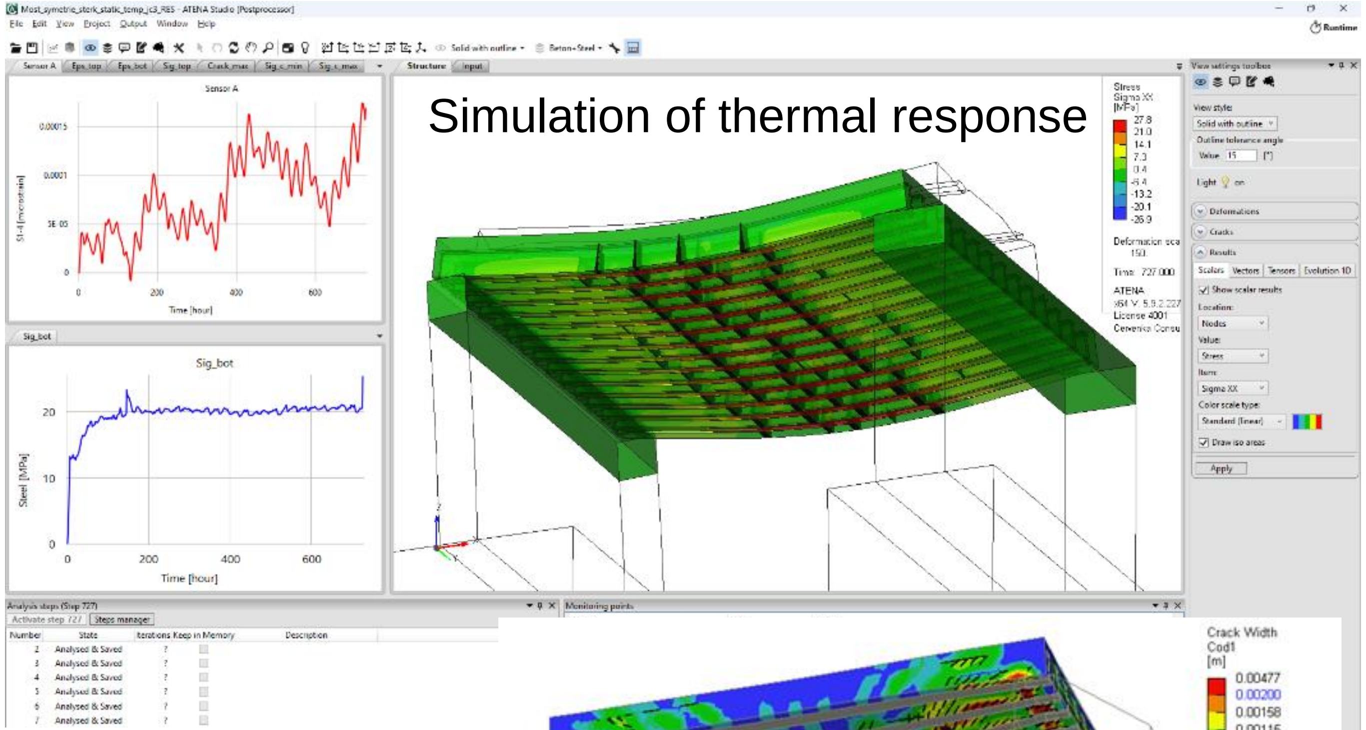
80% - training
20% - testing

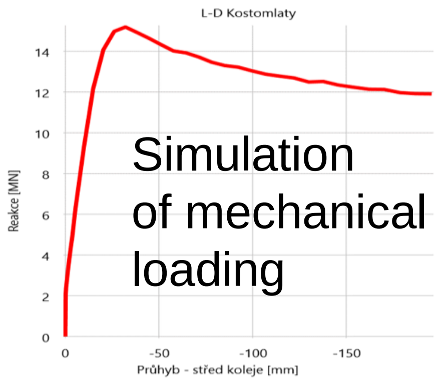
ANN and ML trained to predict the whole response of a beam with shear failure

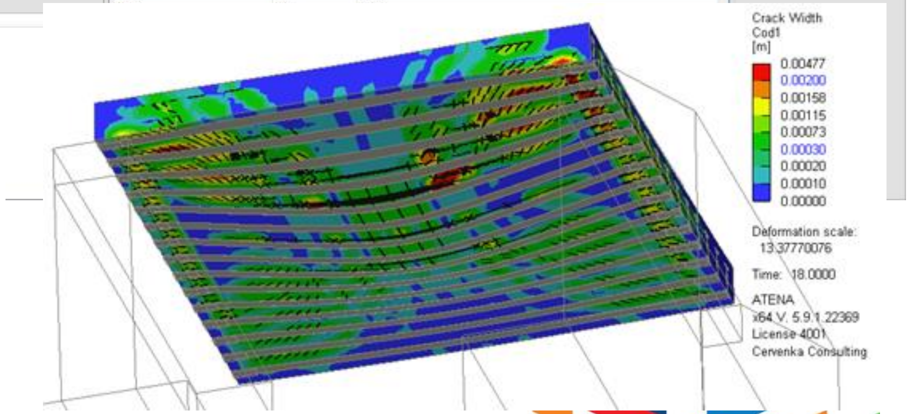




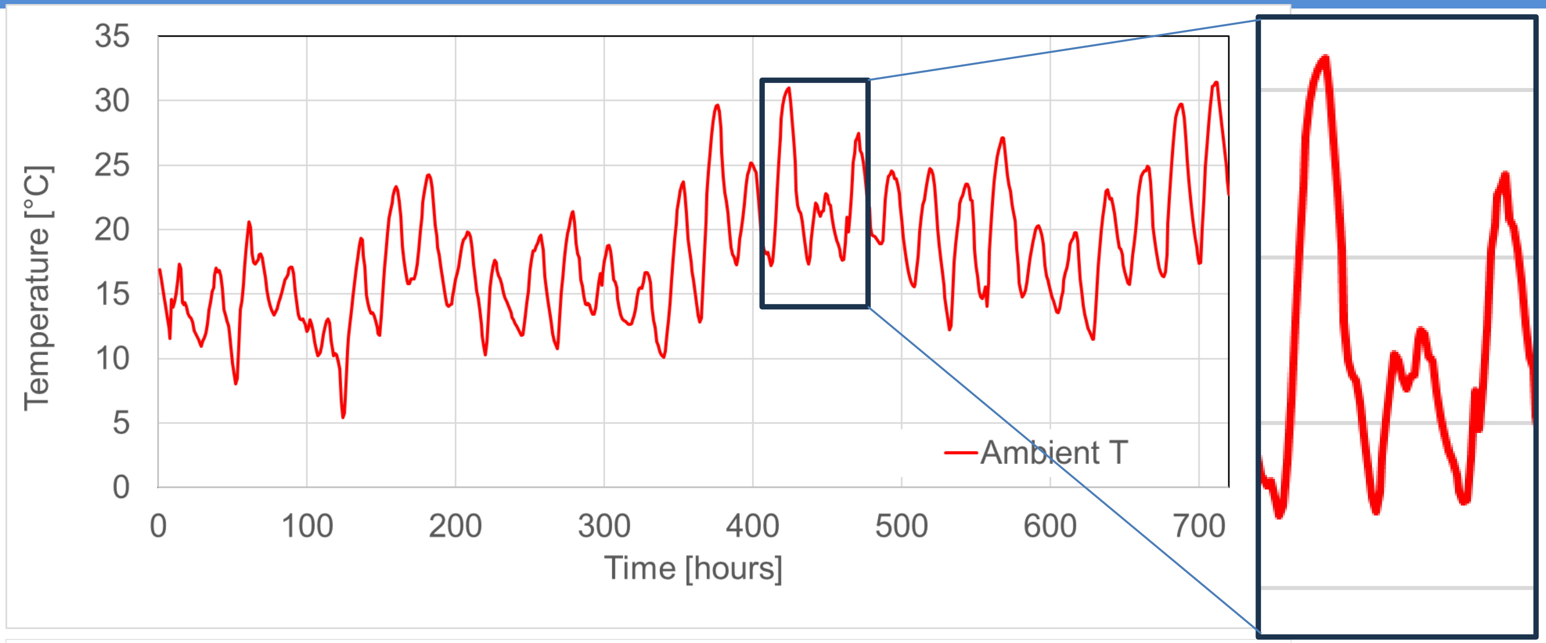
ANN for surrogate engineering model – rapid evaluation of bridge response

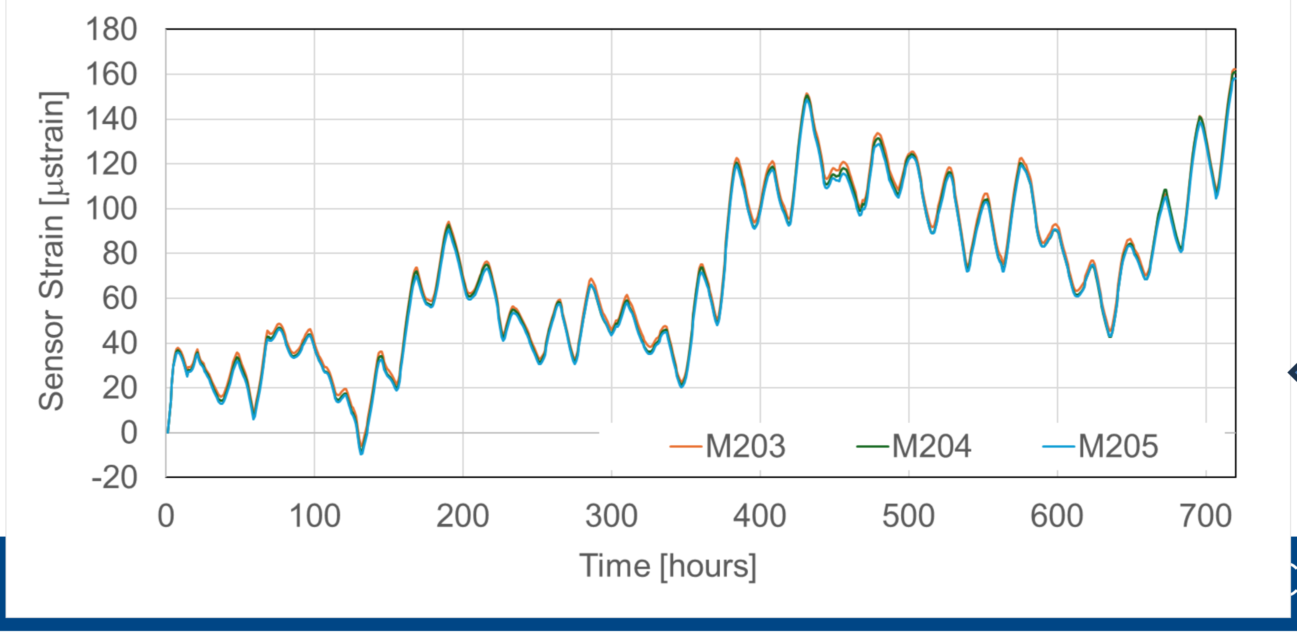






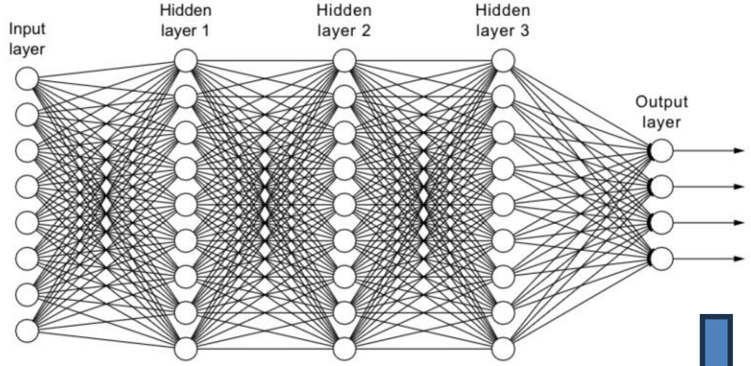
ANN for surrogate engineering model – rapid evaluation of bridge response





Example: Surrogate model to estimate structural response to given temperature history

$$\mathbf{T}_i = \left\{ f_{Ti}(t_{i-24}, t_i), T_{Avg}(t_{i-72}, t_{i-24}) \right\}$$

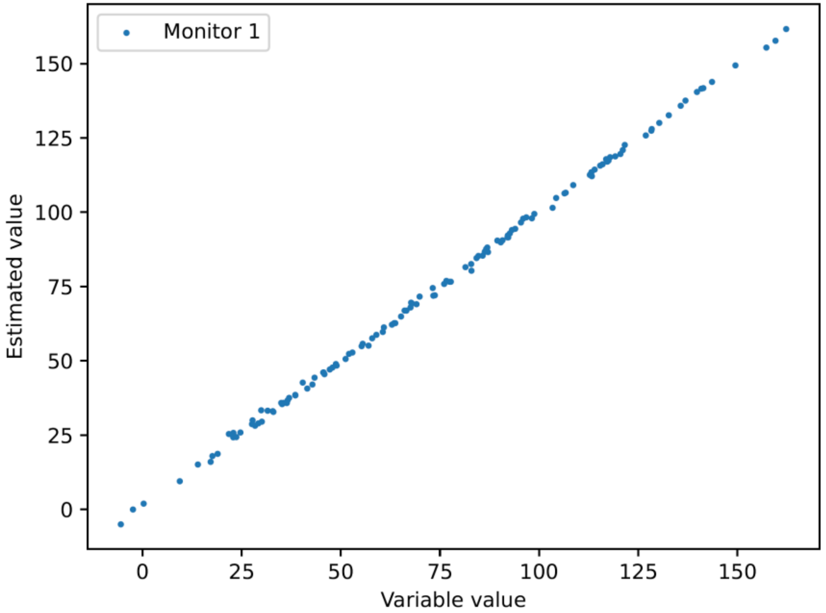


ANN for surrogate engineering model – rapid evaluation of bridge response

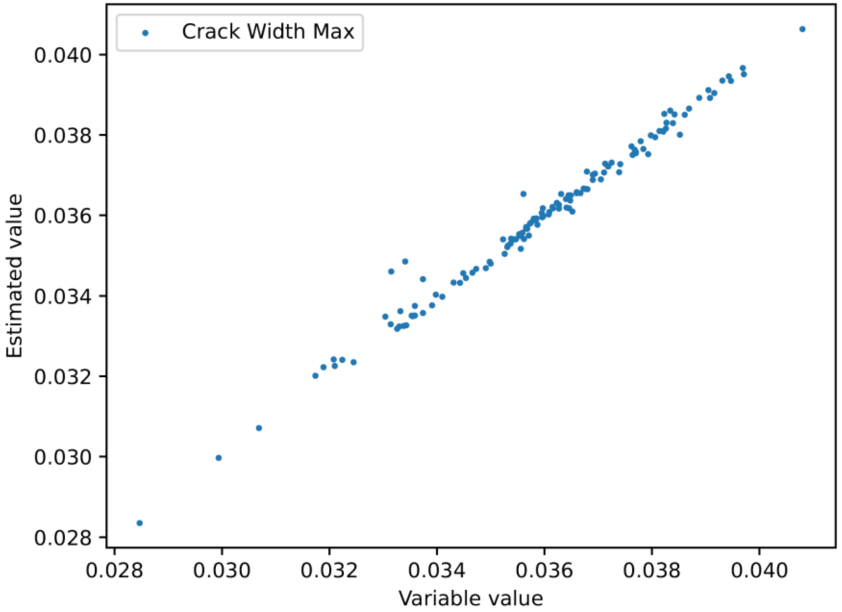
Example: Surrogate model to estimate structural response to given temperature history

Accuracy of predictions

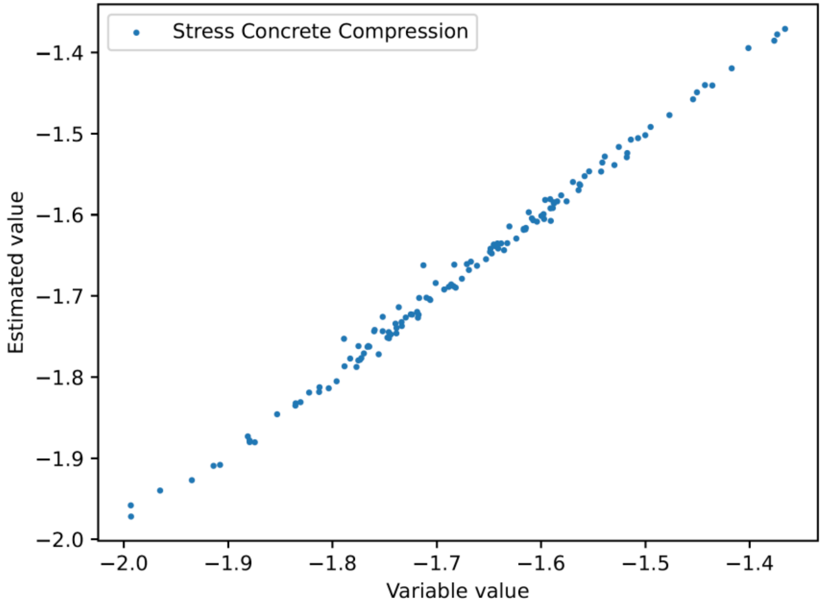
Strain M203 [μstrain]



Maximal Crack Width [mm]

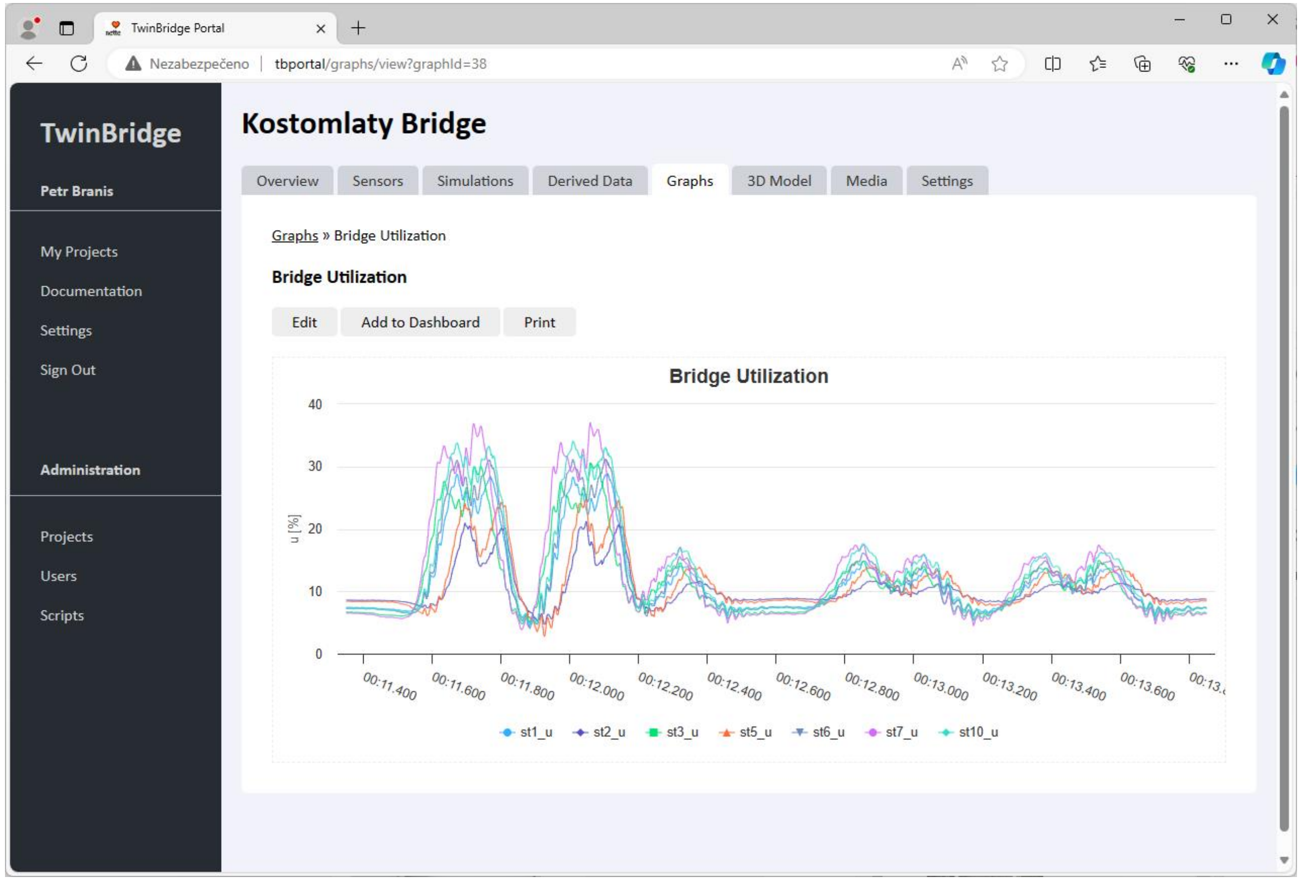


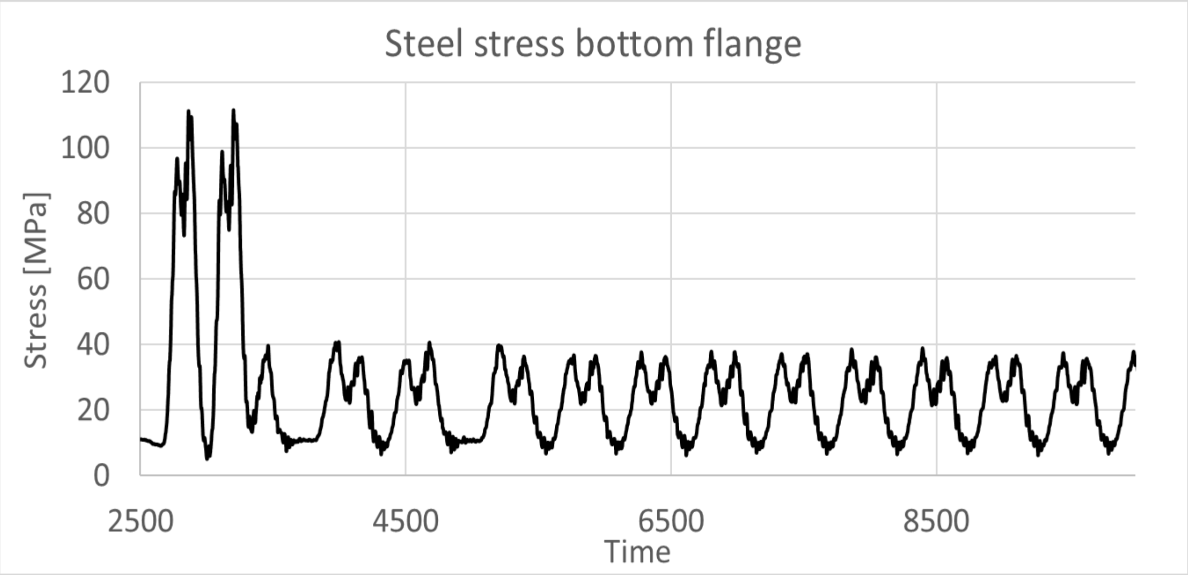
Compressive concrete stress [MPa]

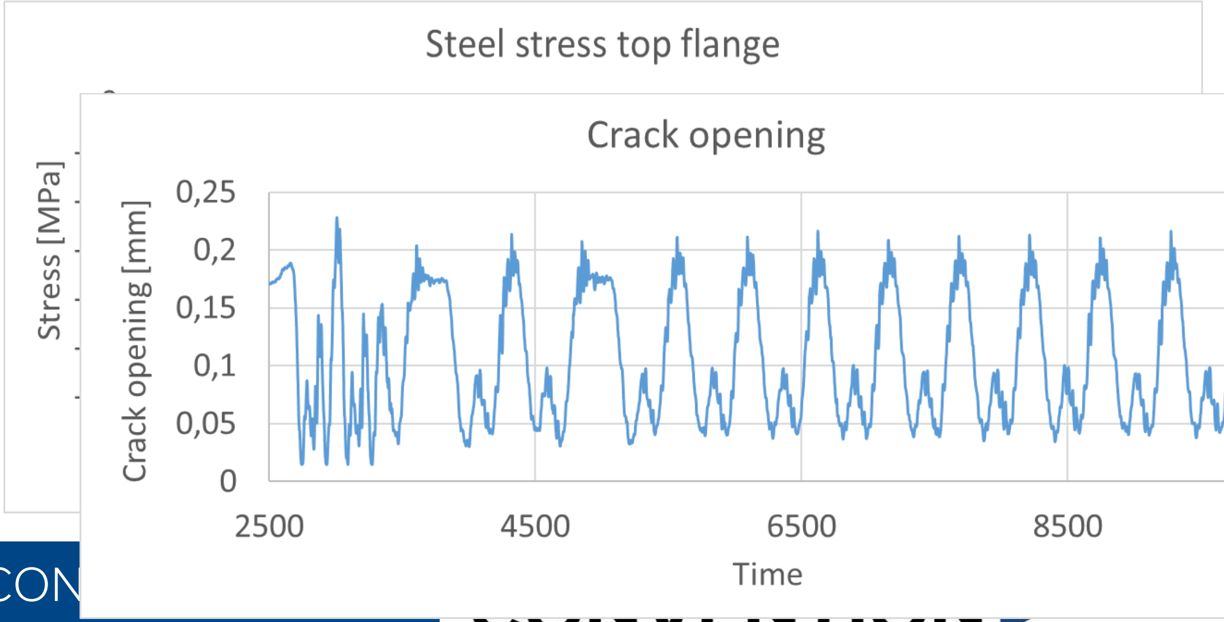


ANN for surrogate engineering model – rapid evaluation of bridge response

Evatuation of bridge utilization, steel stresses crack opening from monitoring data







Conclusions:

- Digital Twin combines monitoring with numerical simulation to provide unique insight into the monitoring data

- Durability model used for long term prediction of structural behavior.

- ANN and ML used for identification of numerical model parameters

- ANN and ML used for real-time mapping of monitoring data to useful engineering quantities for bridge reliability assessment

Thank you for your attention

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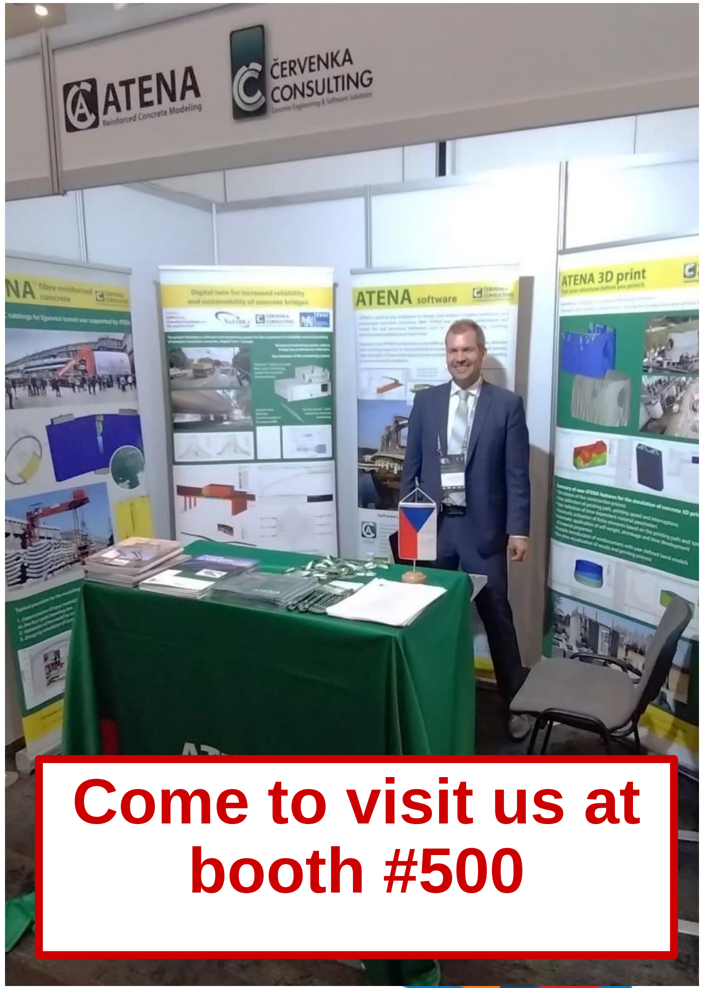

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