Explainable Artificial Intelligence within generative design of footbridges

Institute of Structural Engineering

Guidance: Prof. Dr. W. Kaufmann
Supervisors: Dr. M. A. Kraus, S. Kuhn, S. Buholzer
Student: **Vera Balmer**

Introduction

For conceptual footbridge design, civil engineers nowadays mostly rely on conventional iterative design techniques coupled with computationally time-consuming finite element analyses. Artificial intelligence (AI) has the potential to reinvent this process by allowing for an efficient, innovative and potentially ground-breaking way of design space exploration [1, 2]. For an AI application, the availability of a large data set is indispensable. Such data sets hardly exist for footbridges or rely on tedious data collection and mostly do not include information corresponding to performance parameters such as costs or structural utilisations. Further, XAI methods are seen as “black-box” by many engineers and are hence rarely applied [3]. A workflow as shown in Figure 1 is therefore proposed.

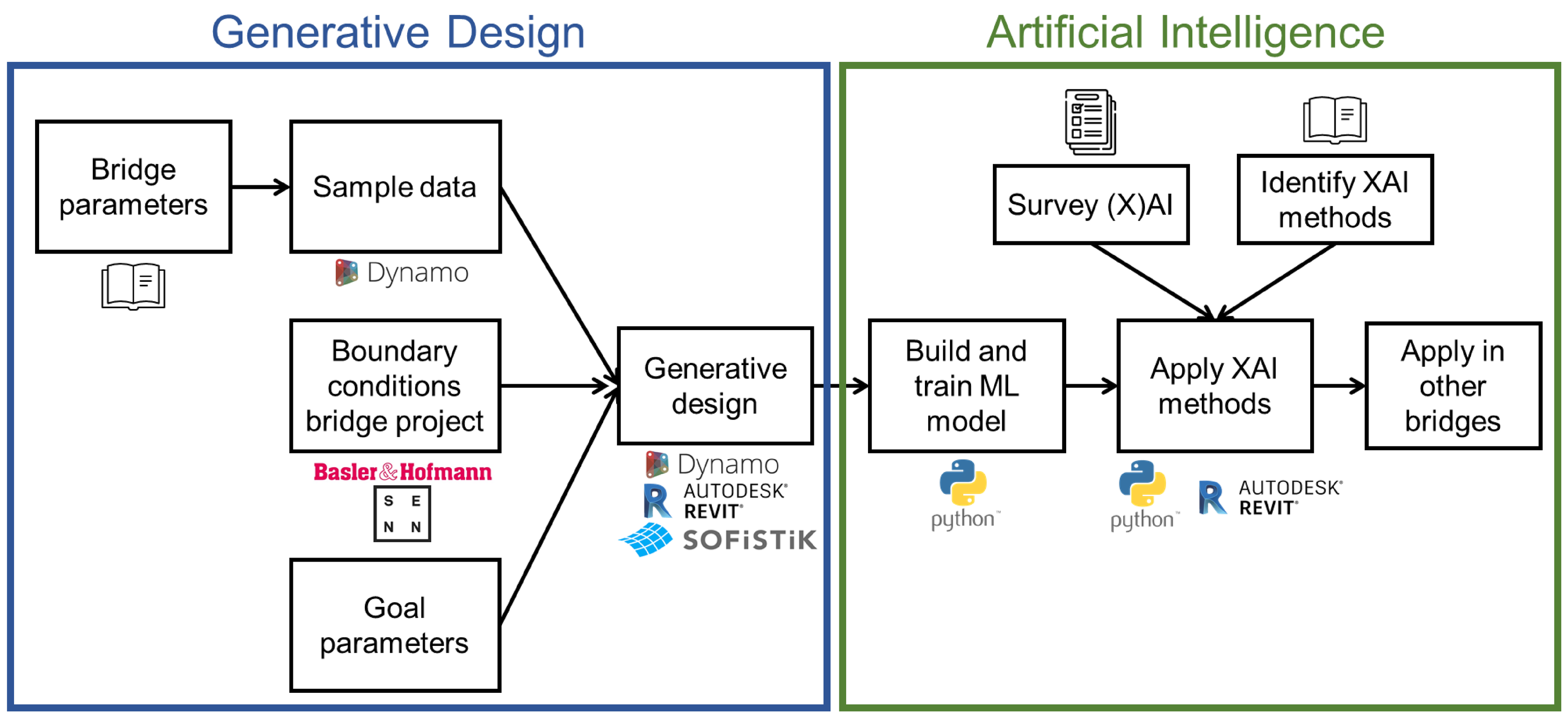

Figure 1: Proposed Workflow of thesis

Generative Design

In generative design, the computer assists in the design process by providing vast quantities of design options, which provide a synthetic data set [4]. Features and Performances are defined for this process as shown in Figure 2a). The generative design is carried out for the design space of the footbridge across the St.Mangen park in St.Gallen, Switzerland (Figure 2 b)).

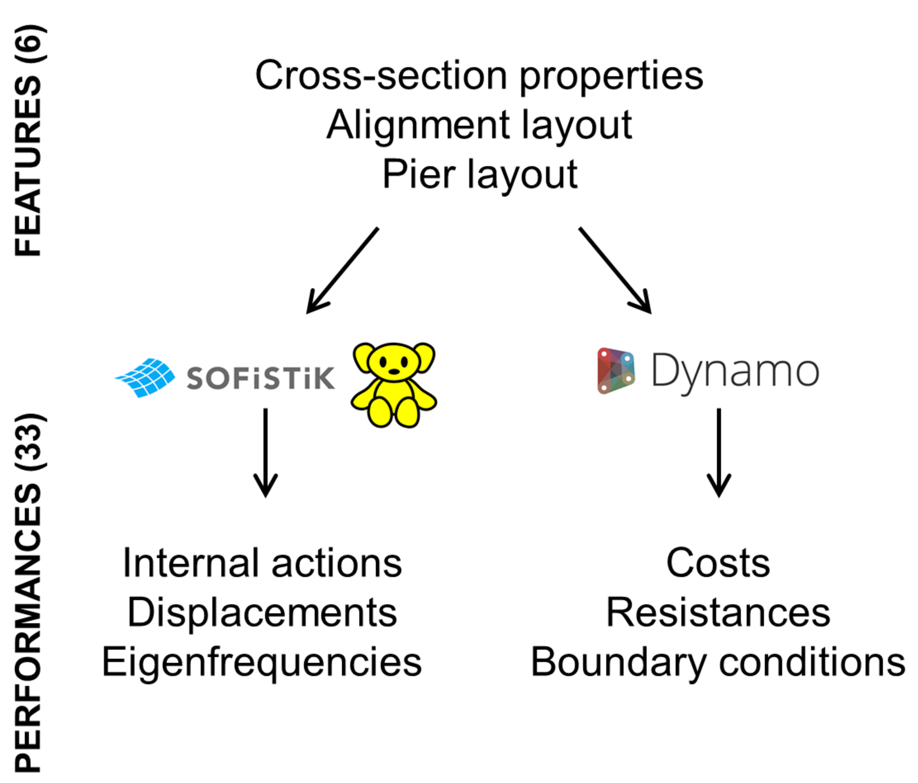

Figure 2a): Definition and type of calculatation of six features and thirty-three performances

Figure 2b): Project site, M 1:400 (Source: Basler & Hofmann)

12'000 footbridges at level of development (LOD) 300 are generated. The features are defined parameter-based and sampled using the Latin hypercube scheme. To carry out the structural analysis in an automated, parametrised manner, a novel connection of Dynamo and Sofistik is created using python and Zero-touch nodes.

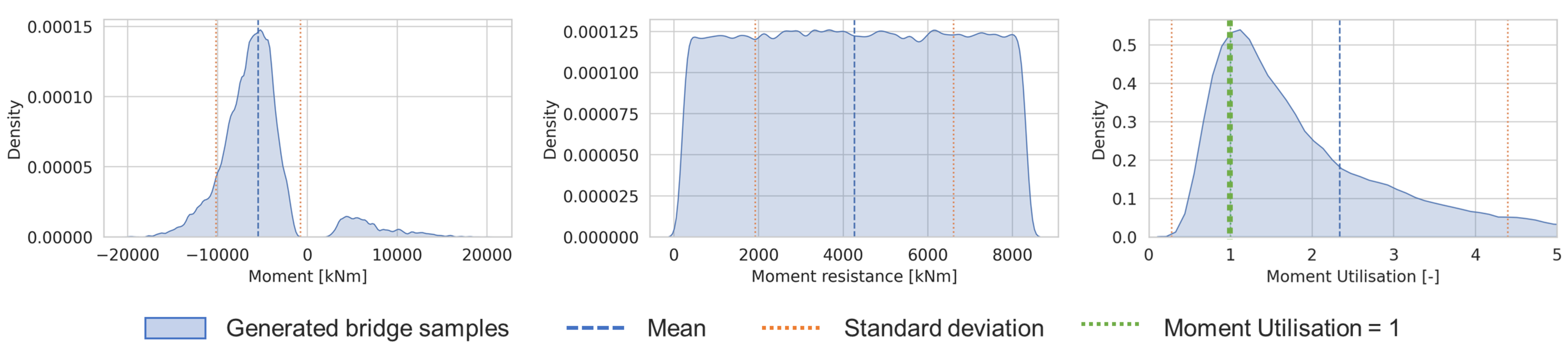

Figure 3: Histograms of three performances () in the sampled data set

The data was successfully generated and analysed subsequently. Figure 3 shows histograms of three performances. They indicate that many samples lie in a structurally inadmissible range. A performance-based sampling technique is thus suggested. The generative design script needed 55 minutes to generate 600 samples.

(Explainable) Artificial Intelligence

Two types of machine learning (ML) replace the traditional design process (as shown in Figure 3): A forward meta-model, which imitates the usual design process but in a faster manner and an inverse meta-model which predicts footbridge features corresponding to user-defined design criteria.

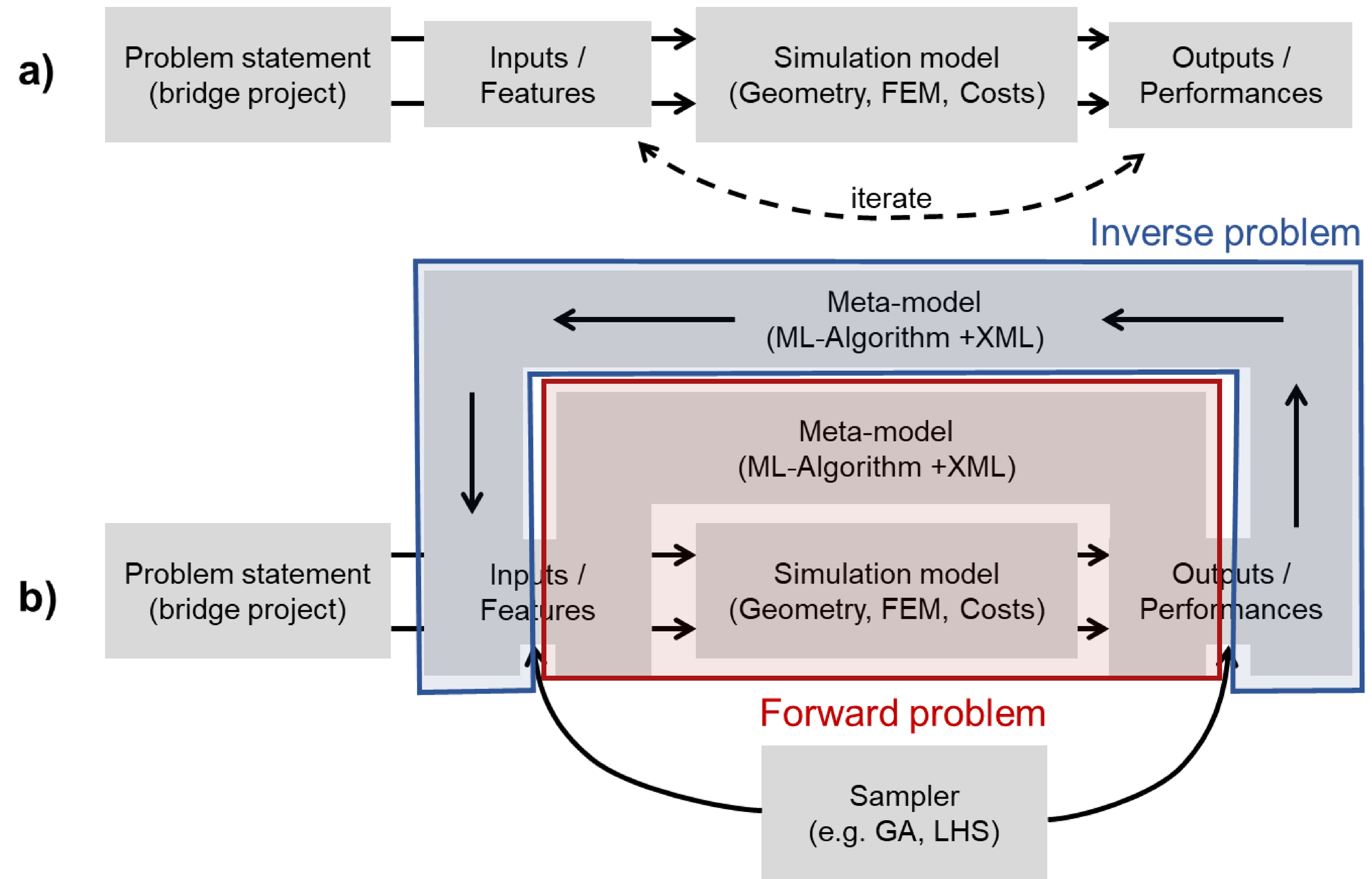

Figure 4: Visualisation of a) conventional workflow and b) workflow with two surrogate models

A survey was conducted in combination with a literature review to choose the type of (X)AI employed and customise it for explanations desired by civil engineers. For the forward model, a decision tree is implemented including intrinsic explainability as well as feature importance plots. For the inverse ML model a conditional variational autoencoder (CVAE) is implemented including the evaluation of the corresponding sensitivities. Figure 5 shows the user interface in Dynamo within Autodesk Revit. The sliders provide design criteria options, while the graphs visualise the resulting bridge designs and corresponding sensitivities.

Figure 5: User interface in Dynamo for inverse model

Conclusion

This thesis successfully establishes a workflow for implementing XAI within conceptual footbridge design problems by applying two different meta-models and a generatively designed data set. It therefore paves the way for future development of XAI applications in conceptual footbridge design and demonstrates the many opportunities and benefits such a tool can provide for digitalisation within the construction sector.

References

[1] Danhaive, R. and Mueller, C. T. (2021). Design subspace learning: Structural design space exploration using performance-conditioned generative modelling. Automation in Construction, 127:103664.

[2] Korus, K., Salamak, M., and Jasi´nski, M. (2021). Optimization of geometric parameters of arch bridges using visual programming fem components and genetic algorithm. Engineering Structures, 241:112465.

[3] Naser, M. (2021). An engineer’s guide to explainable artificial intelligence and interpretable machine learning: Navigating causality, forced goodness, and the false perception of inference. Automation in Construction, 129:103821.

[4] Shen, Q., Vahdatikhaki, F., Voordijk, H., van der Gucht, J., and van der Meer, L. (2022). Metamodel-based generative design of wind turbine foundations. Automation in Construction, 138:104–233.