End-to-End Parametric Workflow for Bridge Design with Automated Cost Analysis and Generative Modeling

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Abstract: This paper presents an end-to-end workflow for conceptual bridge design that integrates parametric modeling, automated cost analysis, and data-driven evaluation. At its core lies a top-down parametric BIM skeleton that governs geometry, earthwork volumes, and adaptive excavation pits. Through automated IFC exchange and integration with cost-analysis software via an application programming interface, component volumes are calculated and linked to a template bill of quantities via matchkeys, ensuring consistent and reproducible cost estimation. The workflow not only enables reliable analysis of bridge variants based on Key Performance Indicators (KPIs), but also produces structured synthetic datasets suitable for training machine learning models. In particular, a Conditional Variational Autoencoder is conceptually introduced to demonstrate how such data can support both forward performance prediction and inverse design conditioned on KPI targets. By improving data fidelity, the approach reduces the demand for extensive training datasets while increasing the robustness of model predictions. This research therefore lays the groundwork for bridging parametric modeling and generative Artificial Intelligence, offering a scalable pathway toward more efficient and data-driven infrastructure planning.

Keywords: Building Information Modeling (BIM), Parametric Modeling, Artificial Intelligence (AI), Conditional Variational Autoencoder (CVAE), Application Programming Interface (API)

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1 Motivation

In 2024, the construction sector in Germany generated approximately €215 billion in gross value added [1]. A substantial share of this investment was directed toward infrastructure development, with bridge construction playing a critical role. Bridges are essential components of transportation networks, facilitating mobility across natural and built barriers and ensuring the continuity of road and rail systems. Many existing structures, particularly those built in the 1960s and 1970s, no longer meet modern structural or economic standards. As a result, reconstruction has become more common than renovation. Of the 42,300 bridges on German federal roads, nearly two-thirds have a span of less than 30 meters [2]. Despite similar design principles, each project still requires individual planning, limiting scalability and consuming resources. Although standardized bridge types exist, their potential for repetition is underutilized. Manual design efforts remain high, even when only a few parameters differ. Tools such as Building Information Modeling (BIM) and parametric modeling have improved design consistency and reusability, but they often operate in isolation, disconnected from evaluation or decision support. Artificial Intelligence (AI) offers new opportunities: By learning from previous models and planning data, it can support recurring decisions, suggest optimized configurations, and provide early, data-driven guidance. Rather than treating each bridge as a standalone task, AI-enabled systems can generalize patterns from past solutions, thereby improving planning speed and quality. Integrating such learning into digital workflows enables automation of routine infrastructure design, especially in repetitive projects. This research advances digital planning with an approach that generates and learns from design variants. By linking parametric modeling with intelligent feedback loops, the system aims to provide a scalable and efficient data-driven approach to the planning of repeatable structures.

2 State of the art

Previous work introduced a parametric bridge modeling approach with a focus on semi-automated cost analysis using matchkeys and embedded design logic within a BIM environment [3]. The model enables dynamic reconfiguration directly within the CAD environment, allowing for rapid adaptation to project-specific requirements. It incorporates cost analysis capabilities through integration with 5D BIM software. The use of matchkeys as a linkage between the 3D model and external analysis tools forms the basis for the semi-automated generation of key performance indicators (KPIs) essential for informed decision-making.

The work by Ji et al. [4] on IFC Bridge proposes a schema extension that integrates parametric geometry into the Industry Foundation Classes (IFC) standard, enabling geometric constraints and relationships essential for automated bridge design. However, IFC implementations still lack the ability to fully export parametric dependencies, which limits automation when transferring data across platforms. To address these limitations, recent research has explored software integration via Application Programming Interfaces (APIs). For example, Herlé and Blankenbach [5] present a hypermedia-driven API linking BIM, GIS, and IoT domains for federated digital twins, demonstrating improved interoperability, data flow, and automation in use cases.

More comprehensively, Pishdad and Onungwa [6] examine 5D BIM workflows, showing how the integration of BIM data with cost estimation systems enables automated and continuous cost analysis. This improves project efficiency by supporting real-time budget tracking, accurate quantity takeoffs, and streamlined payment management. Wortmann and Nannicini [7] provided an overview of black-box optimization approaches in architectural design, highlighting their suitability depending on objective function characteristics, computational effort, and optimization goals. Their work illustrates that classical optimization methods can also make valuable contributions to complex design tasks. Such methods could in principle be combined with the approaches presented here, but are not discussed further, as the focus is placed on the introduction of Conditional Variational Autoencoders (CVAEs).

Danhaive and Mueller [8] introduced a performance-conditioned generative modeling approach using CVAEs for structural design. Their method combines a sampling algorithm to generate diverse high-performing design candidates with a performance-conditioned autoencoder that maps this dataset into a low-dimensional latent space. This space is intuitive for designers to explore, enabling efficient and varied structural design options.

Balmer et al. [9] applied a CVAE framework to 18,000 synthetically generated bridge designs, sampled via Latin Hypercube Sampling and evaluated using structural simulation. Costs were approximated by multiplying material volumes with unit prices from a reference database, enabling scalable, consistent outputs for model training. The CVAE, complemented by sensitivity analysis tools, proved valuable for conceptual design, supporting both performance prediction and inverse design tasks.

Finally, Hoeng et al. [10] developed a pipeline to generate synthetic datasets from parametric BIM models, combining geometry, parameters, and structured metadata. As emphasized in the studies above, such synthetic datasets are essential for training generative models, and this work proposes a structured workflow for their automated creation.

Together, these contributions outline a growing body of research that supports automated, performance-informed infrastructure design by combining parametric modeling, open standards, API integration, synthetic data, and AI-based design space exploration.

3 Methodology

This study proposes a fully automated workflow that integrates parametric modeling, cost analysis, and structured data generation, supporting both classical KPI-based bridge design analysis and the generation of synthetic datasets that can be used for training generative design models.

A bridge model is developed in *Siemens NX* [1] using parameterized geometries and matchkeys, which allow systematic variation and semantic tagging of design elements. The creation of the parametric model in *Siemens NX* is automated through an API, enabling reproducible model generation without manual interaction. The model is connected to a 5D cost analysis environment via API, allowing automated extraction and evaluation of geometry, quantities, and cost-related data. All data transfers are managed through API endpoints to ensure reproducibility and eliminate manual processing. In addition, the integration of a bill of quantities (BoQ) within the cost analysis software enhances the mapping between geometry and unit cost structures. This setup enables the creation of a diverse dataset consisting of geometrically and economically realistic bridge designs for training CVAEs.

At this stage, the concept of the workflow is presented in its entirety, while the implementation currently covers the parametric modeling and the 5D cost analysis.

4 Concept

In conventional bridge planning, engineers manually develop and evaluate design variants based on project-specific requirements. Performing this process manually is very time-consuming, and only a limited number of variants can be explored. To accelerate and simplify this process, the following concept introduces how API interfaces can support analysis workflows and improve outcomes. This

[1] https://plm.sw.siemens.com/en-US/nx/cad-online/

approach also opens multiple additional possibilities, such as the integration of AI. Furthermore, the automated loop provides a solid foundation for generating high-quality synthetic data for training a neural network, with the possibility of performing inverse design tasks through the accessibility of KPIs. In this paper, the integration of cost and Life Cycle Assessment (LCA) is discussed, as both values rely on volume-based KPI analysis. The flow diagram in Figure 1 illustrates how the workflow operates and where an integration of AI is possible.

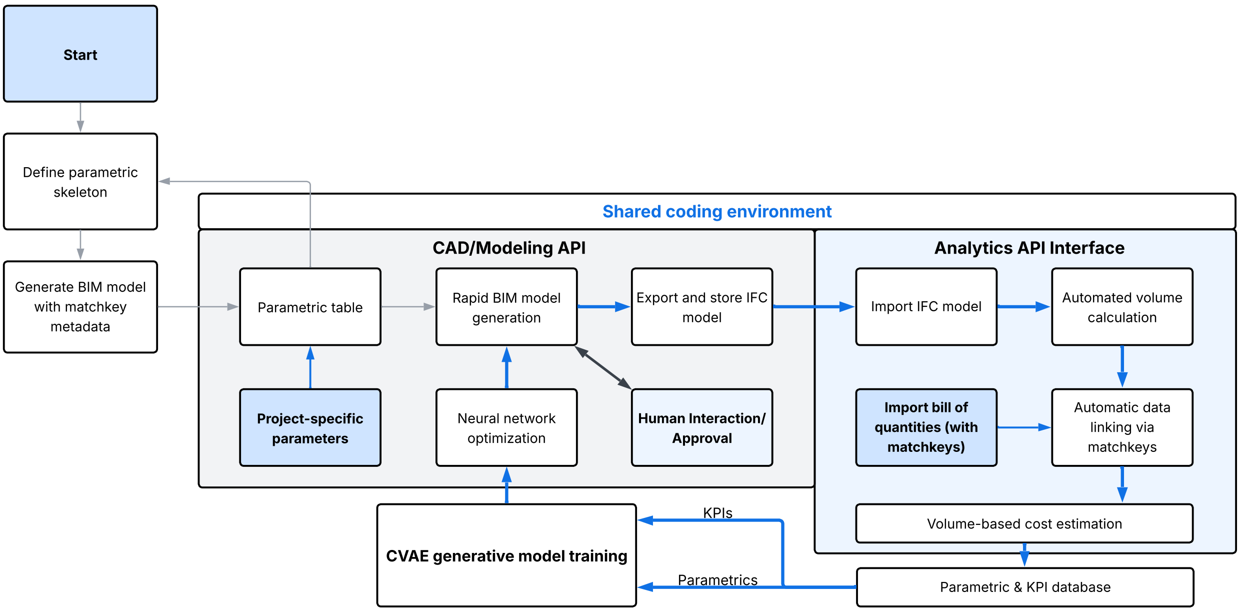

Figure 1: The workflow shows a dataflow loop built on a parametric BIM model with automated cost analysis. It demonstrates how high-quality datasets can be generated and integrated into a central database, providing the foundation for AI model training and optimization.

Starting with the parametric model, the foundation is a parametric skeleton that contains all parameters and the relationships between the individual parts. The model is built using a top-down strategy, as described in previous work, which ensures that the bridge design can be rapidly adapted. The BIM model not only includes information about the structural components themselves but also integrates metadata such as exported IFC classes and matchkey information. These matchkeys can be either uniquely generated by the designer or automatically created identifiers. By means of the parametric table, the BIM model can be fully controlled. Designers are able to integrate project-specific parameters into the CAD software and create an initial BIM model within a short time. This model can then be rapidly adapted through parametric adjustments.

Once the parametric table is defined, all subsequent steps can be centrally managed within a single coding environment. The export of the model from the CAD software and its import into the cost analysis software are executed in a fully automated manner. After importing the model into the cost analysis software, in this case *DesiteMD* [2], the volumes of the individual components are automatically calculated. In a further step, a BoQ is also imported through the interface. This document contains

[2]https://www.thinkproject.com/de/products/desite/

the matchkeys of the bridge elements, establishing the link between the positions in the BoQ and the individual components of the bridge. Although the automated import of the BoQ is not strictly necessary, it accelerates adaptation in case of changes to the document. The enriched document, which now contains cost information, can then be exported to provide the user with an initial cost estimation of the bridge.

The proposed link ensures that even small modifications in the parametric table automatically generate an updated BoQ. The workflow therefore enables highly efficient bridge analysis and opens new potential for streamlined project delivery. The generated parametric data, linked with high-quality KPI values, provides an optimal basis for producing synthetic datasets to train neural networks. In this context, a CVAE represents a particularly promising approach. It not only predicts parameter values in order to achieve specific KPI goals but also allows the definition of target KPI values from which the model can derive the corresponding parameters.

The primary goal is to develop a neural network that supports engineers in generating improved BIM models of bridges. This closes the loop, creating an efficient end-to-end workflow in which parametric modeling, cost analysis, and KPI evaluation are seamlessly integrated, thereby enabling data-driven design and optimization.

4.1 Parametric Bridge Model

In previous work [3], the structural system of the bridge was discussed in detail. Building on this, the present paper extends the scope by including the earthworks, which were previously only mentioned on a conceptual level.

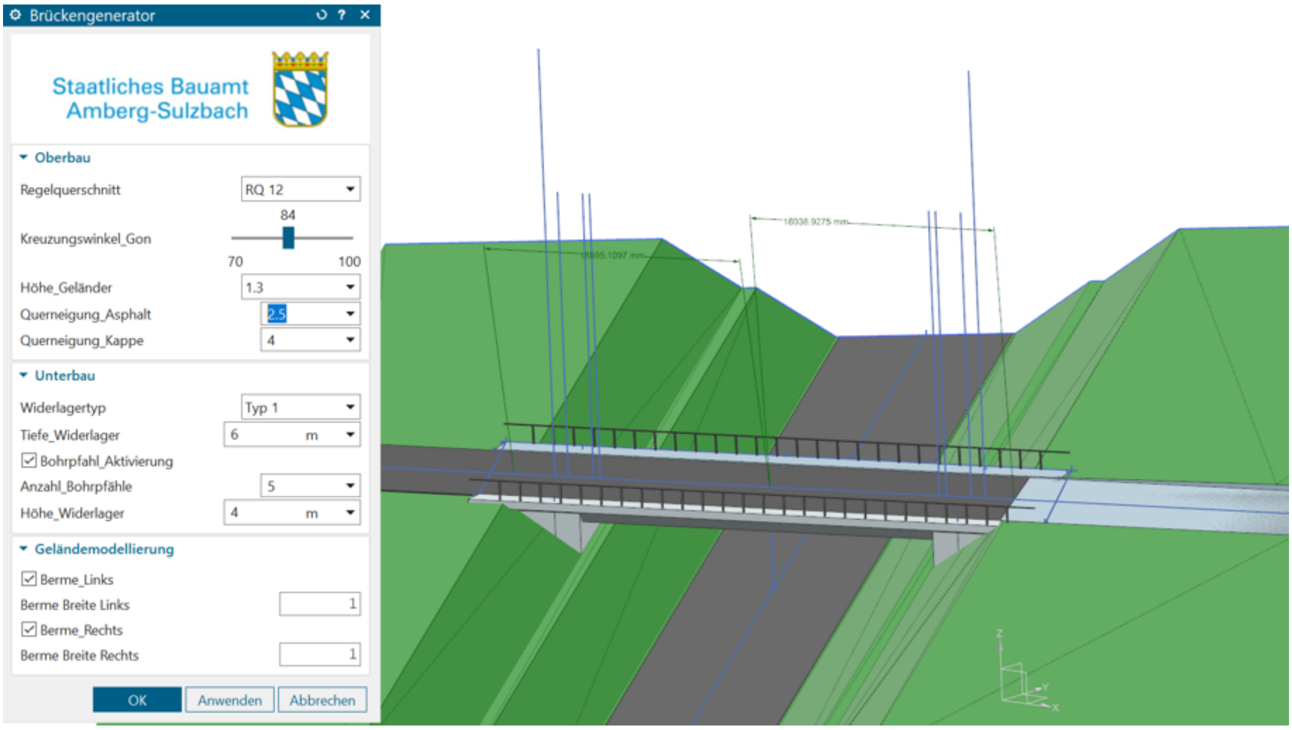

Figure 2: Bridge Generator in *Siemens NX*

As earthworks have a significant impact on the total cost, the parametric model includes an adaptive earthwork volume. The model is based on two routing lines: one for the overpassing structure and one for the underpassing structure. The overpassing line carries a terrain body, which can be modeled in a similar way to other longitudinal extrusions. The underpassing line also contains a body that cuts into the bridge structure using boolean operators. This cutout can be parametrically controlled, allowing all values and the cross-section of the earthworks to be adjusted. Furthermore, adaptive excavation pits are modeled beneath the abutments. These adapt automatically when the abutments are modified and can also affect the overall cost of the bridge. The parametric model, including the earthworks, can be fully modified via a graphical user interface named bridge generator, as illustrated in Figure 2.

4.2 Generating KPI values for a specific analysis

Through an API call, it is possible to export the model from *Siemens NX* and save the IFC file with the chosen settings, such as the IFC schema.

DesiteMD allows volume-based calculations of imported IFC models. For this purpose, a remote control interface enables sending and receiving commands from the software. The IFC bridge model is imported into *DesiteMD*, and the volumes of its components are automatically calculated. Another API call then stores these values in intermediate memory, or alternatively, the volumes can be extracted directly from the software. It is essential that, together with the volumes, the corresponding matchkey values are also requested through the call. In addition to the model import, the BoQ can also be processed. Ideally, this is based on a template BoQ that contains all possible parts, dimensions, and materials. The BoQ also includes matchkey information, enabling the linkage between the IFC model and the individual positions of the BoQ. This link is established by an internally developed script, which is triggered remotely through an API call. An into *DesiteMD* imported and automatically quantified and costed bridge model is illustrated in Figure 3.

This workflow connects the IFC model with cost calculation data and enables automated bridge cost estimation. Afterwards, the BoQ can be exported, providing external access to all results. Beyond supporting automated analysis of bridges with realistic data, the workflow can also be applied to generating synthetic datasets. By integrating an algorithm that generates random input values for the BIM model, synthetic training data can be created in the same way. This approach and its limitations will be discussed further in the discussion section.

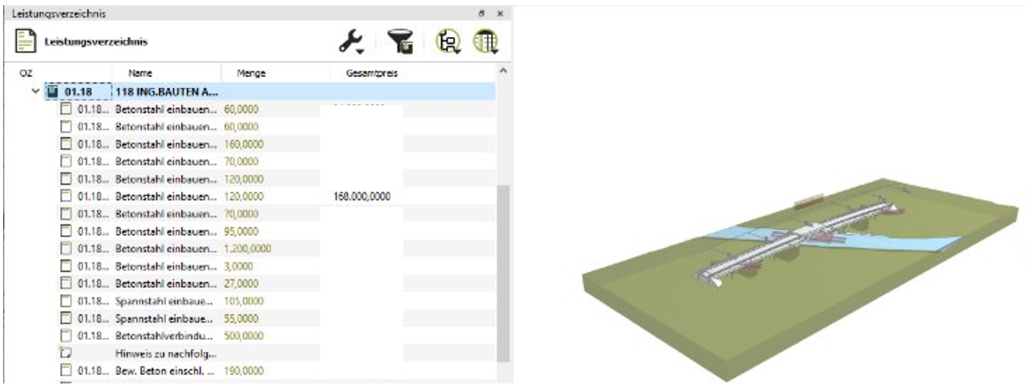

Figure 3: Calculation in *DesiteMD*

4.3 Training Data and CVAE Framework

As outlined in the workflow, the proposed methodology enables the automated evaluation of project data when sufficient real-world information is available, or alternatively, the generation of synthetic datasets. Both serve as a reliable foundation for training machine learning models. In particular, CVAEs require large amounts of training data, as emphasized by [9]. The principle is that the more abundant and higher-quality the training data, the more stable the training and the more reliable the predictions. In this study, the CVAE is introduced at a conceptual level. The training data consist of feature values, derived directly from parametric BIM model parameters and target values, which represent performance indicators such as costs and can be extended to include additional KPIs. Within the CVAE, the encoder maps the complex relationships between features and targets into a reduced latent space, where essential patterns are preserved in a compact mathematical form. The decoder then reconstructs realistic parameter–performance combinations from this latent representation.

This architecture enables forward predictions, where parameters are provided to estimate KPI outcomes, and inverse predictions, where target KPIs such as costs are specified and the model suggests suitable parameter sets. Although the detailed CVAE architecture is not elaborated in this paper, it will be the focus of future work. Here, the emphasis lies on demonstrating that the automatically generated dataset provides a robust basis for establishing such a learning framework and thereby supports the transition from traditional analysis toward data-driven generative bridge design.

5 Discussion and Limitations

The parametric bridge model forms the foundation of the entire approach. Without a consistently structured parametric model, rapid variant generation and reliable adaptations are not feasible, which also deprives the training of a neural network of a solid data basis.

We implemented end-to-end data exchange as an optimization loop. Parametrically generated variants are automatically transferred to a cost analysis application, evaluated, and the results are fed back to guide subsequent variants. This closed loop is enabled by the available interfaces of the tools involved.

A central constraint is the limited availability of reliable API interfaces across different tools. In our case, the coupling was feasible; however, for many other domain models and analyses, comparable integrations are still missing, which currently limits scalability.

From the running loop, we obtain structured, high-quality synthetic datasets. These form the basis for the conceptually employed CVAE. In the forward direction, the CVAE provides rapid KPI estimates for new parameter combinations. In the inverse direction, it generates parameter sets that meet specified target KPIs, supporting goal-directed design decisions.

Looking ahead, we will continue running the loop, curating and extending the dataset, and training the CVAE step by step. With increasing data quality, we expect reduced training effort, more realistic and robust results, and a measurable acceleration of early decision phases in bridge design. At present, throughput is primarily constrained by compute-bound runtimes on workstation hardware, particularly for variant generation, model export, and single-threaded solver runs.

Acknowledgements

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