Assessment and Integration of Sustainability and Circularity Metrics within Generative Bridge Design

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Abstract. Given the construction sector's large environmental impact, analysing and optimising sustainability of a structure becomes increasingly important. The growing number of Life-Cycle Assessment (LCA) tools for buildings is however neither directly applicable nor transferable to bridges. Furthermore, circularity is hardly ever measured, let alone enforced in bridge design. We derived and implemented a software tool that enables automated computational evaluation of the environmental impact and circularity of bridges. The tool is applied within an innovative performance-based design space exploration and multi-objective optimisation framework. A Conditional Variational Autoencoder is trained on synthetically generated bridge alternatives to enable designers to make informed decisions towards more sustainable and circular yet reliable bridge structures. The study proves the framework with integrated LCA and circularity measure valuable for the conceptual design phase and simultaneously identifies challenges for its broader adoption within bridge design.

Keywords. Life Cycle Assessment, Circularity, Generative Bridge Design, Deep Learning

1. Introduction

The construction sector has a strong need to shift towards a more sustainable and circular industry due to its high contribution to global CO_2 emissions and waste production. In addition, the predicted scarcity of sand and gravel resources in the near future poses major challenges to the construction sector. Next to policy and construction specifications, the design and material selection are decisive factors for the environmental impact of the construction sector (Bergmeister et al., 2022). Particularly in early design stages, the application of sustainability and circularity assessments have the potential to substantially reduce environmental impact, raw material consumption and waste production of the construction sector in general.

Life-Cycle Assessment (LCA) is an established method for evaluating the environmental impact of products, offering a life cycle perspective, broad coverage of environmental issues, and a quantitative, science-based approach (Hauschild et al., 2018). While LCA has become popular in many industries, it is not yet an established metric for bridge construction projects, in part due to a lack of computational LCA tools transferable or applicable to bridge structures. While some research has explored the use of LCA in bridge structure case studies (Du, 2015, Hammervold et al., 2013), most studies use hand calculation tools or general LCA software that cannot be used in an automated manner to compare the performance of multiple bridge designs efficiently. To achieve reductions in raw material consumption and waste production, a circular economy has been proposed (Anastasiades et al., 2020). Combining LCA with a circularity assessment is necessary for a satisfactory evaluation of a construction project, as some aspects of the circular economy are not adequately considered within LCA and vice versa. While individual approaches to circularity assessments for buildings and their link to life cycle assessments exist, there are currently no standardised circularity metrics. For bridges only few approaches on development and use of circularity metrics are reported in literature (Coenen et al., 2021, Anastasiades et al., 2020) so far.

Generative design for building structures increasingly incorporates environmental impact metrics as a performance objective. In many cases, state-of-the-art simulation software (incl. LCA tools) has been combined with genetic algorithms to perform generative design of building structures (Caldas, 2008). However, detailed and accurate design evaluation via simulation software becomes computationally expensive when applied to complex and high-dimensional design problems such as bridge structures. In the last few years, studies have focused on using supervised learning algorithms to build efficient and accurate surrogate models for real-time design space exploration and optimization (Jiang et al., 2020). However, they all focus on the "forward design problem", i.e. the prediction of the performance values for a specified design. Only recently generative models (e.g. autoencoders and generative adversarial networks) have been developed and applied to function as an "inverse design" model, allowing for the generation of high-performing design alternatives conditioned on a set of performance constraints (Salamanca et al., 2023, Danhaive et al., 2021). Balmer and Kuhn et al. (2022) developed an AI-augmented bridge design co-pilot, training a variation of a conditional variational autoencoder (CVAE) to function both as forward and inverse design models for a pedestrian bridge.

2. Methods

Based on an investigation of existing sustainability and circularity metrics and their applicability to bridge structures (among others Du, 2015, Hammervold et al., 2013), we conceptualised and implemented a software tool where LCA (Sec. 2.1) is combined with our further development of the bridge circularity index (BCI) (Sec. 2.2) to assess the environmental impact together with the circularity of a bridge. This metric can be directly applied in early design stages, when the level of flexibility in design is still high and various design options have to be explored. The developed tool is integrated into the approach from Balmer and Kuhn et al. (2022) (Sec. 2.3), expanding the approach by environmental impact indicators and the circularity index as performance attributes. This enhancement enables structural engineers to not only make informed decisions towards structurally efficient but also sustainable and circular structures. Finally, the developed framework is applied to a concrete frame bridge in the conceptual design phase (Sec. 2.4) to investigate its potential, quality and efficiency in a realistic setting.

2.1 Life Cycle Assessment (LCA)

Life Cycle Assessment (LCA) is a standardised stepwise approach, including four main phases: Goal and Scope Definition, Life Cycle Inventory Analysis (LCIA), Life Cycle Impact Assessment (LCIA) and Interpretation (ISO14040, 2021). A crucial aspect of the application of LCA to compare multiple design alternatives is the use of accurate and comparable LC data, which contains the characterisation factors (cf. Eq. 1) of individual materials. Our investigation of the widely applied LCI databases KBOB[1], Ökobaudat[2] and Ecoinvent[3] has shown that construction materials used in bridge construction are not sufficiently included within existing LCI databases. Particularly, the databases lack a pertinent distinction of different concrete and steel types, which is highly relevant for LCA of both concrete and steel structures: the

[1] https://www.kbob.admin.ch/kbob/de/home.html
[2] https://www.oekobaudat.de/
[3] https://ecoinvent.org/

environmental impact of concrete strongly depends on its composition, particularly the cement type and amount, whereas for steel it largely depends on the production method (Hauschild et al., 2018). Environmental Product Declarations (EPDs) could help to close this gap as they provide comparable data on the life cycle impact of specific construction materials based on manufacture information that is assessed by independent auditors based on standardised guidelines, following the International Reference Life Cycle Data System (ILCD) method (EN 15804, 2022).

Based on a comparative analysis of the different life cycle stages of a bridge, material manufacturing has been identified as the most important stage, contributing around 80% to the environmental impact (Du et. al., 2018). Furthermore, it has been concluded that the load-bearing elements are responsible for most emissions in bridge structures (Du, 2015). Within this study we therefore define the scope of the LCA calculation as a cradle-to-gate analysis restricted to the load-bearing elements.

To overcome the limitation of existing LCA software and LCI databases we implemented a LCA in Python in a structure-agnostic manner. We provide the ability to save EPDs to a local database, or use more general data from Ecoinvent e.g. for materials where no EPDs are available. Both sources use the ILCD method and are thus comparable. Based on this combined database the environmental impact indicators global warming potential (GWP), acidification potential (AP), ozone depletion potential (ODP), abiotic depletion potential for fossil (ADP_f) and non-fossil resources (ADP_m), and photochemical ozone creation potential (POCP) are calculated:

$$LCA_{\text{indicator}} = \sum_i^n C_i \cdot Q_i \tag{1}$$

C_i:= Characterization factor for material of element i (ISO14040, 2021)

Q_i:= Quantity of element i

The LCA is implemented in an object-oriented manner, providing the resulting environmental impact indicators for the whole structure as well as on the material and element level. The implementation allows for automated analysis of a large number of bridge design alternatives within the design exploration setting.

2.2 Circularity Metric for Bridges

In addition to the environmental impact indicators introduced in Sec. 2.1 our implementation further allows for an automated evaluation of a circularity measure for bridge structures. Due to the absence of a standardised metric, we chose to adopt and implement basic ideas of the bridge circularity index (BCI) according to T. B. J. Coenen et al. (2021) and develop it further:

$$BCI = W_{DI} \cdot DI + W_{RA} \cdot RA + W_A \cdot A + W_{RU_{red}} \cdot RU_{red} \tag{2}$$

The BCI sums up the design input (DI), the resource availability (RA), the adaptability (A) and the reusability (RU), adjusted by individually determined project-specific weights. Detailed analysis of the sub-indicators reveals a big discrepancy of their level of development. They can thus be separated into three categories: (i) measurable, (ii) qualitative, and (iii) not applicable, where the latter are discarded. The definition of the measurable sub-indicators (i) of the BCI metric is mainly adopted from Coenen et al. (2021), whereby additional material constants are defined to describe the recyclability of a material (R_i) and assumptions are made to estimate the fraction of recycled, renewable, and reused materials. These assumptions are based on studies where the recycling content, loop potential and end-of-life of several materials has been investigated (Hillebrandt et al., 2019). The assessment of the transportability is limited to transportation by truck and simplified by considering only the mass of a component as a transport criterion. The sub-indicators (ii) which are not measurable in an objective metric are assessed by expert opinion in the original BCI approach (Coenen et al., 2021). To allow an automated determination of these sub-indicators for this BCI metric, a predefined assessment framework for these sub-indicators is developed based on bridge-specific characteristics, namely the bridge type, connection type and material.

2.3 Forward and Inverse Design Meta Model – Conditional Variational Autoencoder

This study adopts the variant of Conditional Variational Autoencoders (CVAE) suggested by Balmer and Kuhn et al. (2023) as a machine learning meta model for design (cf. Fig. 1). The CVAE variant allows for simultaneous training of a surrogate model (encoder) and a conditional generative model (decoder), making it suitable for solving both, the forward and inverse problem. The trained decoder can generate new samples $\hat{\mathbf{x}}$ based on specified performance metrics $\mathbf{y}$, while the encoder can compute the mapping from $\mathbf{x}$ to an approximate performance metric $\hat{\mathbf{y}}$, enabling examination of the reconstruction error between requested and predicted performance metrics. With neural networks being fully differentiable, the CVAE leverages Automatic Differentiation (AD) for very efficiently computing derivatives of the performance metrics in the output w.r.t. the design variables in the input of the model for a subsequent local sensitivity analysis. This local sensitivity analysis allows for more informed decisions in multi-objective design situations or uncertainty quantification.

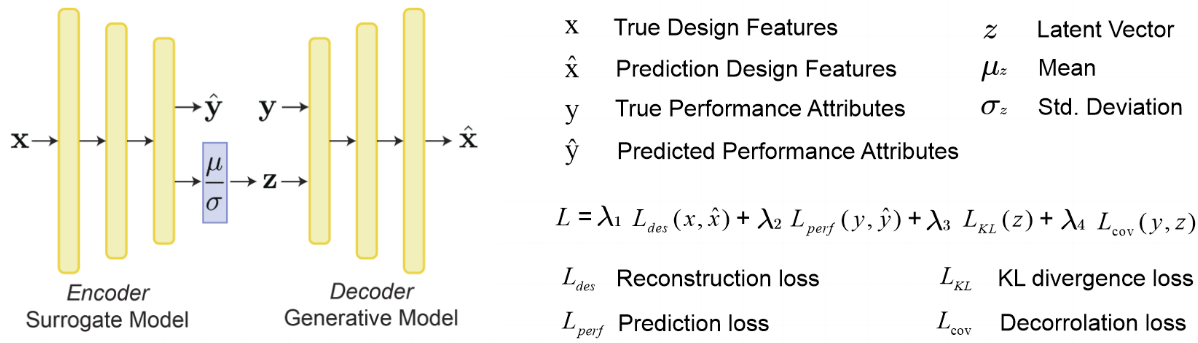

Figure 1: CVAE architecture including its loss function from Balmer and Kuhn et al. (2022).

2.4 Application Example: Concrete Frame Bridges

The proposed framework (Sec. 2.1 - 2.3) is exemplified using a simplified concrete frame bridge (CFB) in the conceptual design phase. CFBs are common structures used in many different settings and construction projects. A schematic plot of the CFB structure with the main design features and their ranges is provided in Fig. 2. For structural modelling, some assumptions and simplifications were made. In addition to self-weight, a uniformly distributed load of 4 kN/m², acting in negative z direction, is applied to the deck slab. The foundations are not modelled but are assumed to provide rigidly clamped line supports along both walls.

For the training of a deep learning algorithm such as the CVAE, a sufficient amount of data is necessary. With state-of-the-art software from the architecture, engineering and construction (AEC) domain, we built a data generation pipeline for parametric structural modelling, linear elastic finite element analysis and cross-sectional analysis including structural utilisation according to SIA 262 (2013) (Fig. 3). The constructed pipeline is able to take a design feature vector as input, and returns the evaluated structural utilisations, environmental impact indicators (Sec. 2.1) and circularity indices (Sec. 2.2). Using latin hypercube sampling (LHS) we sampled 5,300 design feature vectors, which were then iteratively evaluated with the pipeline, forming design space filling synthetic data set of CFB design alternatives.

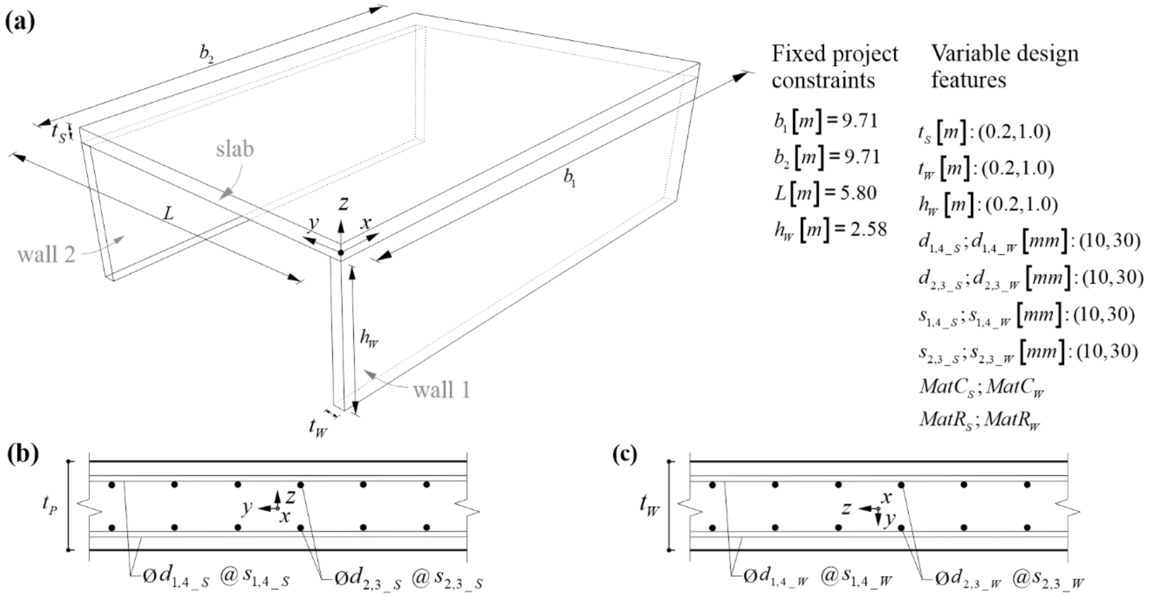

Figure 2: Schematic of the CFB structure with feature definitions and their sampling ranges.

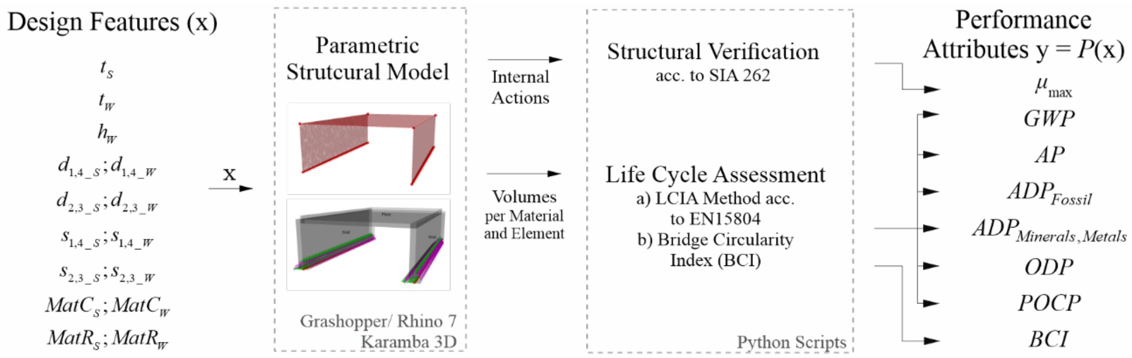

Figure 3: Data generation pipeline for the CFB structures.

One aim of this study is to investigate the environmental impact reduction potential by the choice of concrete and reinforcing steel while ensuring structural admissibility in the early design stage of CFB structures. One potential way to reduce the environmental impact of concrete structures is the use of concrete with clinker-reduced cement, such as CEM II and CEM III type cements instead of CEM I (essentially pure clinker). Such clinker-reduced cements are already widely used e.g. in Switzerland, and no notable difficulties in the durability of concrete structures with such cement types have been reported so far (VDZ Ad-hoc-Arbeitsgruppe, 2008). Nonetheless, some clients are reluctant in using clinker-reduced cements, leading to CEM I being still dominant in many parts of the world. In order to examine the further potential of clinker-reduced cement types to the environmental impact for the example of CFBs, this study compares the average composition of concrete used in Germany 2016[4] to concrete with CEM III/A (estimated with Ecoinvent) for three different strength classes (C30/37, C45/55, C50/60) (Fig. 4a). Additionally, we consider three different reinforcing steel

[4] InformationsZentrum Beton GmbH, 2023 (https://www.beton.org/betonbau/planungshilfen/umweltproduktdeklarationen)

B500B products: European average reinforcing steel (from Ecoinvent database), conventional reinforcing steel produced by ArcelorMittal[5], and Stahl Gerlafingen[6] (Fig. 4b). The latter shows a high reduction of the emissions and resource consumption (except for ODP) due to the production of reinforcing steel from scrap and its production with the electric arc furnace route (EAF) rather than the primary route (BF-BOF). The EAF method is also used by ArcelorMittal for the production of XCarb reinforcing steel[5]. The GWP for the analysed types of concrete and steel is compared in Fig. 4. The concrete and reinforcing steel are varied for the deck slab ($MatC_S$, $MatR_S$) and the walls ($MatC_W$, $MatR_W$) individually.

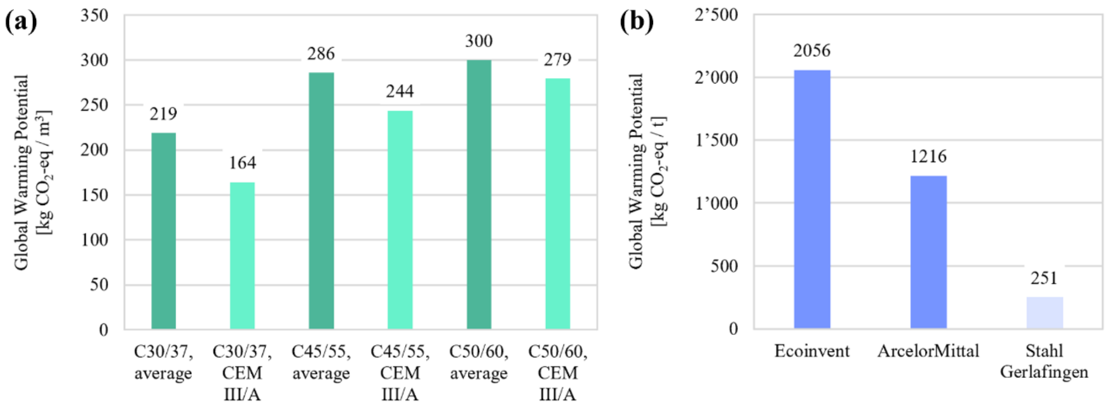

Figure 4: Characterisation factors of GWP of selected (a) concrete compositions, (b) reinforcing steel materials.

3. Results

In the following sections, the synthetically generated data set is described and examined, followed by evaluation of the performance of the trained CVAE model for the forward and inverse predictive quality and capability. Finally, the results of a brief application example of the inverse design model to the CFB optimisation is presented.

3.1 Generated Data Set

The 5,300 CFB design alternatives sampled for the assumed project situation exhibit the targeted space-filling distribution within the defined sampling intervals in the design feature space. Fig. 5 shows the value ranges of the computed environmental impact indicators for all bridges of the generated data set with a utilisation between 0.9 and 1. While all of these bridge structures have very similar max. structural utilisations, they exhibit a large difference in their environmental impacts. One dominant factor responsible for this large range is the use of different reinforcing steel produced with different manufacturing methods.

The bridge circularity index (BCI) results also exhibit the expected behaviour, with all CFBs having almost the same circularity index. This stems from the structure of the BCI assessment, which is mainly dependent on the materialisation and bridge type. As in this study, we compare different CFBs, all circularity sub-indicators are identical for the generated alternatives except the resource availability (RA), which is proportional to the mass of the bridge structures. The

[5] ArcelorMittal (2023): https://constructalia.arcelormittal.com/en/tools/epd
[6] Stahl Gerlafingen (2023): https://www.stahl-gerlafingen.com/Energie-und-Umwelt/Umweltproduktedeklaration-EPD

BCI metric would thus be more informative for studies which compare different bridge types or bridges with different materials.

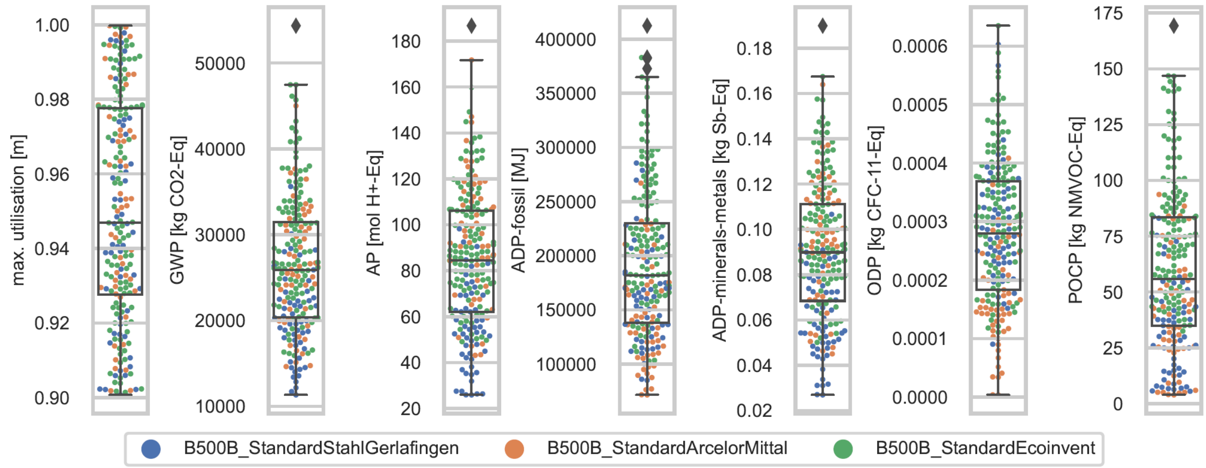

Figure 5: Environmental impact indicator of generated CFBs (filtered for max. utilisation 0.9 - 1.0).

3.2 Model

The generated data set was split into training (70 %), validation (10%) and test (20 %) sets. Before being fed to the CVAE, the continuous and ordinal variables were standardised to zero mean and unit standard deviation while categorical variables were one-hot-encoded. Empirically, 5 multilayer perceptron (MLP) blocks with the widths [512, 256, 128, 64, 32] were chosen and set for both the encoder and decoder network. Each block contained a fully-connected layer with leaky-ReLU activation and batch normalisation followed by a dropout layer with dropout probability of 0.1. The latent space was set to be five-dimensional. The loss term weights were set to $\lambda_1 = 1$, $\lambda_2 = 2$, $\lambda_3 = 0.1$, $\lambda_4 = 0$. For the training, the Adam optimiser was applied with an initial learning rate of 0.001, which was reduced by multiplying it with a factor of 0.1 in case of no loss improvement over six epochs on the validation set. The training of the defined CVAE was stopped after 108 epochs when no further loss improvement could be noticed. The resulting performances of the CVAE for forward and inverse predictions archived after training are summarised in Fig. 7 and plotted for two quantities in Fig. 6.

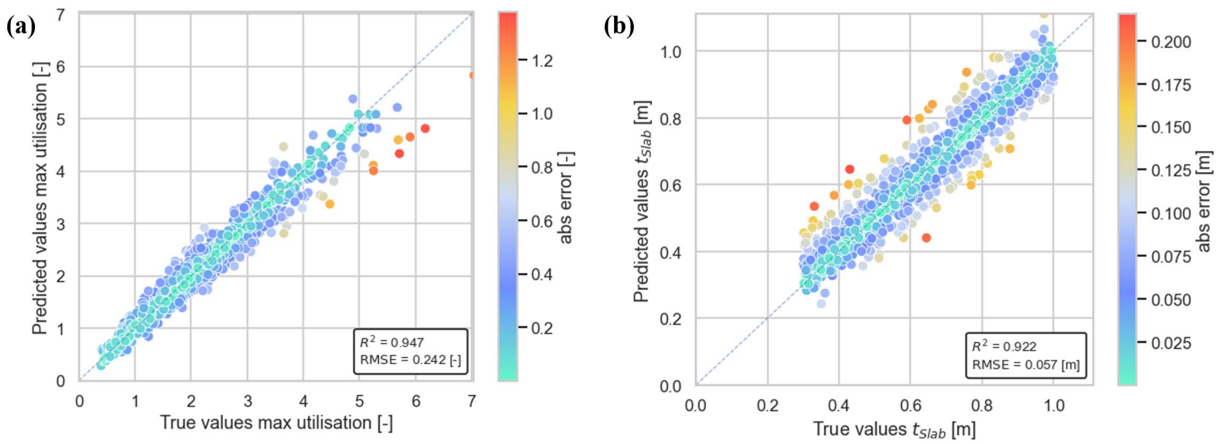

Figure 6: Performance on test set: (a) Forward (surrogate) model predicting max. utilisations, (b): Inverse (generative) model generating suitable deck slab thicknesses.

As a simple demonstration of the capabilities, we used the decoder to generate 7,000 bridge instances conditioned on a utilisation range of 0.9 to 1.1 and then used the encoder to evaluate the performance of the generated design alternatives. To do so, we sampled performance attribute vectors within the selected utilisation range, considering the performance interdependencies by applying kernel density estimation on the data set. Fig. 8a confirms that all generated designs are correctly generated in the requested utilisation range. While all 7,000 design alternatives have similar max. utilisation, they exhibit a large range of GWPs, which are separated for the six considered concrete types (Fig. 8b). While the designs using an average concrete composition (Germany, 2016) exhibit similar mean GWP values for all strength classes, the use of CEM III/A shows a clear reduction of the mean GWP. While the constructed state-of-the-art structural evaluation pipeline (parametric modelling and FEM analysis within Grasshopper using Karamba 3D) took roughly 1.5 h for the evaluation of 1,000 sampled structures on a standard laptop, the CVAE only needed 10 sec. for the generation (decoder) and re-evaluation (encoder) of the 1,000 conditioned samples.

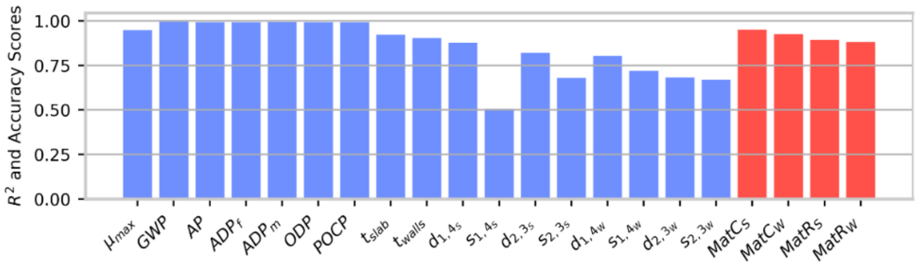

Figure 7: Forward (surrogate) and inverse (generative) model performances on test set (R^2 for continuous (blue) and accuracy for categorical (red) design features and performance attributes.

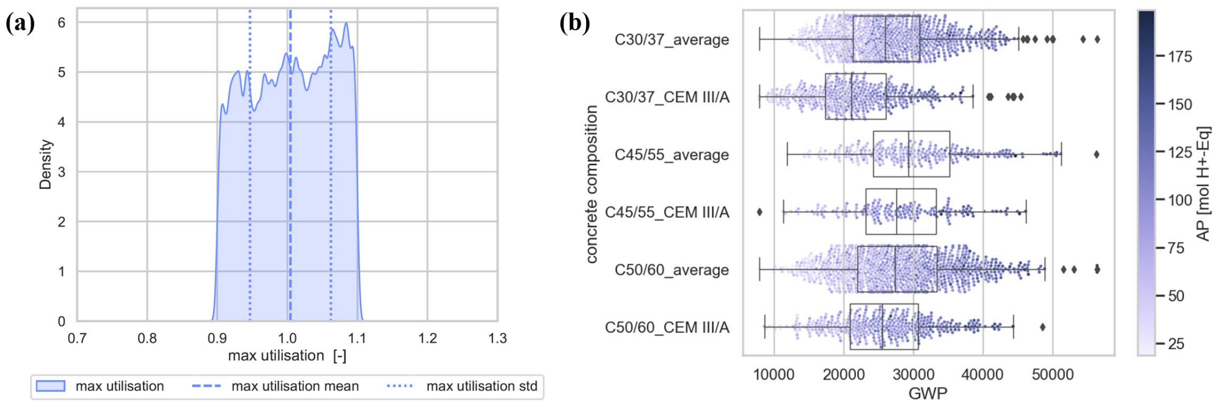

Figure 8: Properties of the 7,000 bridge instances generated with the trained decoder conditioned for a max. utilisation of 0.9-1.1. (a) Density plot of. max. utilisation; (b) GWP values for structures of different concrete types of both deck slab and walls (with Ecoinvent rebar).

4. Discussion

The cradle-to-gate Life Cycle Assessment LCA has been proven as a suitable metric to be implemented into the AI-augmented bridge design framework. Next, to the material manufacturing stage, the LCA implementation could be further expanded to consider other life cycle phases (cradle-to-grave), such as the construction process (e.g. transportation) and the use stage (e.g. replacements). However, especially in an early design stage a lot of uncertainties are present regarding the actual impact of later life cycle phases and with cradle-to-gate already around 80% of the environmental impact of a standard CFB is considered (G. Du et. al., 2018); note that this can vary for other structure types. The large difference in the Life Cycle Inventory (LCI) data of the considered steel options (Fig. 4) logically leads to a non-neglectable difference in the resulting environmental impact of the CFB alternatives (Fig 5). This confirms the fundamental importance of the use of accurate and comparable LCI data from standardised Environmental Product Declarations (EPDs) for specific material products. However, while the use of EPD data has essential advantages and gains in popularity, not all material producers provide them yet. Next to the use of reinforcing steel produced with the more environmentally friendly AEF route (Fig. 5), the use of CEM III/A has shown as an effective approach for all concrete strength classes to reduce the GWP of CFBs (Fig. 8b), while no decrease in the durability (exposition class) necessary for bridge construction projects has to be expected (VDZ Ad-hoc-Arbeitsgruppe, 2008). On the other hand, despite that the LCI data of the average concrete (Germany, 2016) indicates a significantly reduced GWP per unit volume for lower strength concrete (due to reduced cement content, c.f. Fig. 4), this effect is largely diminished by the larger cross-section depth required for structural safety (Fig. 8). This trade-off between an increase in sustainability and reduced strength underlines the necessity to consider a complete set of design performance objectives concurrently in an early design stage, due to their interdependence. This also emphasizes the need and value of computational tools for rapid design search space browsing and evaluation as the tool presented in this paper.

The BCI implementation within this paper has shown several shortcomings concerning its application for bridges in an automated manner due to the absence of standardised, objective metrics for some indicators and sub-indicators. One critical aspect for the further development of a circularity metric for bridges is the consideration of the limited reusability of structural elements from bridge structures due to the high cyclic loading and deterioration due to severe exposure. The latter may be a limiting factor for circularity in bridge design, since circularity concepts established in building structures, such as segmentation, impair the durability of bridges and are thus not a priori applicable or suitable. Nonetheless, the overall analysis of the circular economy applied to bridge structures clearly shows that the idea of disassembling and reusing elements is not considered in bridge design so far and an increase in the circularity of bridges thus implies that pertinent concepts of circularity - accounting for the above-mentioned challenges - are already considered in the design phase of new bridges structures.

With the application example on CFB structures the functionality of the forward and inverse design model was demonstrated. Compared to state-of-the-art simulation methods, it provides computationally more efficient performance prediction while maintaining a high accuracy. The generative model furthermore allows innovatively for efficient and accurate design generation conditioned on specified performance objectives, which is currently not possible at all with software used in AEC practice. While the CVAE provides real time assistance to the structural engineer once trained, the set-up of the data generation pipeline, the data generation and the training process itself require a considerable amount of time. Therefore, design meta models should be as generally applicable as possible. This can be achieved by expanding the design sampling and generation to different possible boundary conditions (e.g. different lengths, spans, loadings, etc.), which is however beyond the scope of this paper.

5. Conclusion

The developed software tool allows for performing cradle-to-gate Life Cycle Assessment (LCA) in an automated, efficient and object-oriented manner for any parametric structure type, using accurate and comparable LCI data from standardised EPDs and further extends LCA by the bridge circularity index. The integration of the tool into a generative deep-learning, performance-based design space exploration and multi-objective optimisation framework proved successful for the application example of concrete frame bridges. It assists the structural engineer in real time, allowing the identification of key aspects to assess and optimise the environmental impact and waste production simultaneously with the conventional bridge design objectives informing the high impact early design decisions.

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