D2.2 EVALUTATION AND RECOMMENDATIONS FOR AN EVIDENCE-BASED DESIGN FOR PRODUCTIVITY, RESOURCE EFFICIENCY, AND SAFETY BASED ON HISTORICAL DIGITAL TWIN DATA

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ABSTRACT

The early design phases of construction projects have a major impact on the success of the projects in terms of cost, construction time, global warming potential and other aspects. However, detailed information on the ongoing design is often lacking in these early project phases. This gap can be filled by using information and data of existing infrastructure. The historic data from past projects is collected, processed, analyzed, and evaluated systematically so that it is made into ready input for design. This is the evidence-based design (EBD) assistant's approach to support design at the early project stages. A database of past footbridge designs provided by the engineering design firm *schlaich bergermann partner* (sbp) is used as the knowledge database to investigate and validate the potential of using historic data for evidence-based design to improve the design of future projects. Data collection was done manually involving digitizing past project data which will be stored in the digital twin for construction. The collected data was cleaned, filtered, and clustered using data analytics methods. Data processing, analyses and evaluation was done using machine learning approaches. The study found that (i) historic data/information is valuable input for design, (ii) historic data/information provides good predictions for performance indicator values (PI-values), and (iii) machine learning models can be used to evaluate and compare accuracies of PI-values. The very limited size of the database and scanty data was a major challenge in the implementation of the approach. However, we recommend that organizations consider growing such knowledge databases to enrich evidence-based design.

KEYWORDS

AECO early design stages, Digital Twin (DT), Knowledge Database, Evidence Based design, Machine Learning.

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DISCLAIMER

ACRONYMS & DEFINITIONS

AECO	Architecture, Engineering, Construction and Operation
ASHVIN	Assistants for Healthy, Safe, and Productive Virtual Construction Design, Operation & Maintenance using a Digitial Twin
BRICS	Bridge Analytics Tool for PI Calculation
DT	Digital Twin
EBD	Evidence Based Design Assistant
FEM	Finite Element Model
GEN	Generative Design Modeler
GWP	Global Warming Potential
KPI	Key Performance Indicator
L	Bridge length
MAE	Mean absolute error
ML	Machine Learning
PI	Performance Indicator
RMSE	Root mean squared error
sbp	schlaich bergermann partner, structural engineering company and ASHVIN project partner
T	Bridge thickness
W	Bridge width

ASHVIN PROJECT

ASHVIN aims at enabling the European construction industry to significantly improve its productivity, while reducing cost and ensuring absolutely safe work conditions, by providing a proposal for a European wide digital twin standard, an open source digital twin platform integrating IoT and image technologies, and a set of tools and demonstrated procedures to apply the platform and the standard proven to guarantee specified productivity, cost, and safety improvements. The envisioned platform will provide a digital representation of the construction product at hand and allow to collect real-time digital data before, during, and after production of the product to continuously monitor changes in the environment and within the production process. Based on the platform, ASHVIN will develop and demonstrate applications that use the digital twin data. These applications will allow it to fully leverage the potential of the IoT based digital twin platform to reach the expected impacts (better scheduling forecast by 20%; better allocation of resources and optimization of equipment usage; reduced number of accidents; reduction of construction projects). The ASHVIN solutions will overcome worker protection and privacy issues that come with the tracking of construction activities, provide means to fuse video data and sensor data, integrate geo-monitoring data, provide multi-physics simulation methods for digital representing the behavior of a product (not only its shape), provide evidence based engineering methods to design for productivity and safety, provide 4D simulation and visualization methods of construction processes, and develop a lean planning process supported by real-time data. All innovations will be demonstrated on real-world construction projects across Europe. The ASHVIN consortium combines strong R&I players from 9 EU member states with strong expertise in construction and engineering management, digital twin technology, IoT, and data security / privacy.

TABLE OF CONTENTS

INDEX OF FIGURES

INDEX OF TABLES

1 INTRODUCTION

1.1 Motivation

The early design phases of building design and construction models have large influence on the overall project success. Generative design can be one approach to increase the productivity in the early design phases along with the quality of constructed design options.

Generative design is already being used successfully as a design concept in many industries. The basic idea is to use a computer to generate a large number of design alternatives for a given design task and then evaluate them on a set of target variables. In civil engineering, and specifically in structural design, this type of design process has now also found its way into several projects. (Diaz, et al., 2021) collected scientific publications on the adoption of generative design principles in structural design projects. Seven application cases for generative design were identified including cantilever optimization for 3D printing, material optimization in slabs, and material optimization for deep reinforced concrete beams. (Rempling, et al., 2019) implemented a set-based parametric design method which was demonstrated by comparing optimized bridge geometries with constructed bridge projects. It was shown that the generated bridge geometries were outperforming the realized bridges both in terms of cost and carbon footprint.

The quality of the underlying parametric model, which represents the basis of all generated variants as a genotype, plays a major role in the success of the generative design process. Apart from the quality of the parametric model, there is another influential parameter, namely the coverage of the design space by the parametric logic together with the parameter envelope.

There are two limits to covering the entire design space using one or more parametric models. On the one hand, the creation of a parametric model suitable for generative design requires an investment of time, and on the other hand, it is very difficult to cover the entire design space in sufficient depth using only one very generic parametric model. Thus, in the sense of an efficient design process, it is necessary to restrict the design space, since only for this limited subspace a parametric model of sufficient quality can be generated with a reasonable expenditure of time.

This limitation of the design space is currently executed by the designing engineer in the earliest design phase. The constraints made then, e.g., regarding a structural typology, have a great influence on the overall success of the design process, because they restrict the design space.

This work deals with the question of how this early design stage, which runs from the receipt of the design task to the creation of the parametric model and thus the delimitation of the design space, can be supported on the basis of project data from existing projects. In other words: How can data from past design projects be used in early design stages to bridge the gap between the design task and a generative design process?

1.2 Historical Digital Twin Data for Construction

This research was conducted within Task 2.2 of the European Union funded Horizon 2020 project ASHVIN, which aims to enable digital twins in the construction industry.

The structural design firm *schlaich bergermann partner* (sbp) as one project partner kindly provided data for their portfolio of footbridge design projects. Therefore, the domain of footbridge design was chosen to demonstrate the applicability of the Evidence Based Design (EBD).

The prior task 2.1 identified the relevant Performance Indicators (PIs) and Key Performance Indicators (KPIs) for footbridge design projects in the domains of productivity, resource efficiency and safety (Krenn, 2021). The assessment of models regarding these PIs is performed using the ASHVIN BRICS Tool, which is also presented later in this document. The PI values together with general project information are stored inside the knowledge database which forms the conceptual basis of the EBD.

The EBD evaluates the knowledge database to provide the user with a broad overview of the design space. This way the bridge designer can make an informed decision on the constraints of the parametric model which is used for further design space exploration.

The creation of this parametric model along with the search for pareto optimal solutions is performed in the succeeding ASHVIN Task 2.3. This Task developed the GEN Tool as a generative design modeller for productivity, resource efficiency and safety.

The additional succeeding ASHVIN Tasks 2.4 and 2.5 deal with the visualization of the EBD and GEN Tool results and the implementation of both tools on the ASHVIN Digital Twin platform.

1.3 Potential Users and Audience

The EBD Approach is aiming towards an audience in the very early stage of footbridge design. The audience includes both engineers and designers as well as decision makers in public and private institutions.

Designers can use the approach after receiving the initial design task and before exploring the design space in more detail using the parametric design and optimization functionality presented in ASHVIN Task 2.3.

But also project developers or public officials can use the EBD prior to the formulation of the design task to quickly get an overview of the realistic KPI ranges for an envisioned project. They can thereby make informed decisions e.g., when comparing different possible footbridge locations.

1.4 Existing solutions for evidence-based design

No market ready solutions are currently available to perform the evidence-based design exploration envisioned in this report. In a broader sense, EBD had large impact in the design of hospitals and other recovery facilities as the influence of parameters like daylight availability were subject of research (Wakamura, et al., 2001), (Southwell, et al., 1995).

For the adaptation within the construction industry, (Rwamamara, et al., 2011) investigated strategies to prevent musculoskeletal injuries on construction sites. Several recommendations were drawn from the study including the involvement of construction planners in the design process and the use of industrialised production procedures.

Within the ASHVIN project the focus lies on the usage of historic Digital Twin (DT) to enable better designs. Several data bases of construction projects are available (e.g., (Administration, 2022)), but these do not include geometric data along with PI (e.g. cost) relevant data that could be used for PI predictions. This is the strength of the knowledge database provided by sbp as this dataset allows for the connection between geometric dimensions and PI values.

1.5 Structure of this report

This work is structured in three main chapters. The overall vision of the ASHVIN design support approach is presented in section 2. Section 3 investigates the data currently available and how it is used within the ASHVIN design process. Section 4 highlights the learnings from the currently available data and presents an approach to enrich the database with data from additional data sources. The final section 4.5 summarizes the main findings.

2 VISION

This chapter presents the vision of the ASHVIN design support approach. It is currently not possible to fully implement this vision mainly due to the lack of Digital Twin data from the design and construction phase (see chapter 3). Therefore, this vision should provide further motivation to implement the ASHVIN Approach to digital twins in the construction industry.

An overview of the ASHVIN design support workflow is shown in Figure 1. Three tools are introduced to support the designer in the early design phase of footbridge design.

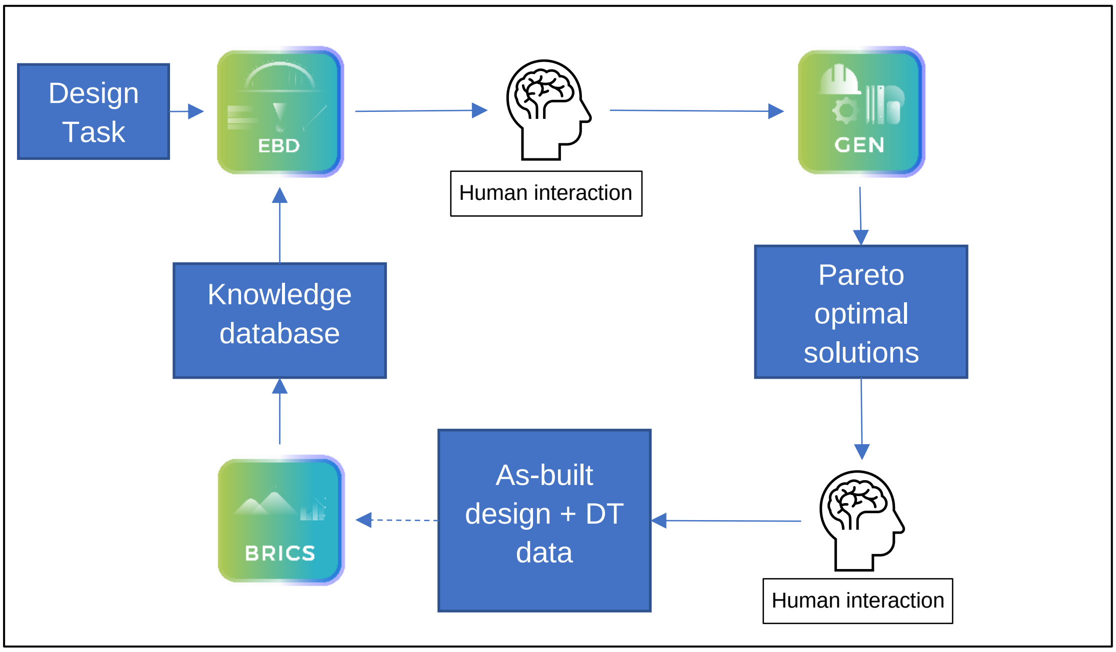


Figure 1: General Concept of the ASHVIN Design Support Tools BRICS, EBD and GEN

The design workflow starts with the creation or receiving of the design task, which includes the project-specific details such as location of the proposed project include requirements for bridge crossing, for example. The constraints from the design task are fed into the Evidence Based Design Assistant (EBD). The EBD is based on a knowledge database of built footbridges, which is used to provide insights for the ongoing design process.

The designer of the new footbridge interacts with the EBD to identify desirable parameter combinations and bridge typologies, thereby enabling the use of a parametric modelling tool to build a more detailed model of the identified subspace of the design space.

The GEN enables to evaluate options according to PIs and, thus, to determine pareto-optimal options, which form the basis for decision-making. These pareto optimal solutions are the to be assessed by decision makers to select one possible bridge design to be investigated further during detailed design.

All newly build projects are then designed and constructed using a digital Twin (DT). This digital twin data can then be assessed using the BRICS (Bridge AnalytICS) tool which computes PIs from the raw DT data. The knowledge database is stored on the ASHVIN platform.

The BRICS tool closes the loop with the knowledge database thereby creating a system which constantly allows for the enrichment of the knowledge database with every newly constructed footbridge.

The task of the EBD is to identify a sufficiently small subspace of the design space for which a parametric model can then be modeled using the GEN tool. The concept of design space and the different roles of the EBD tool and the GEN tool are illustrated in Figure 2.

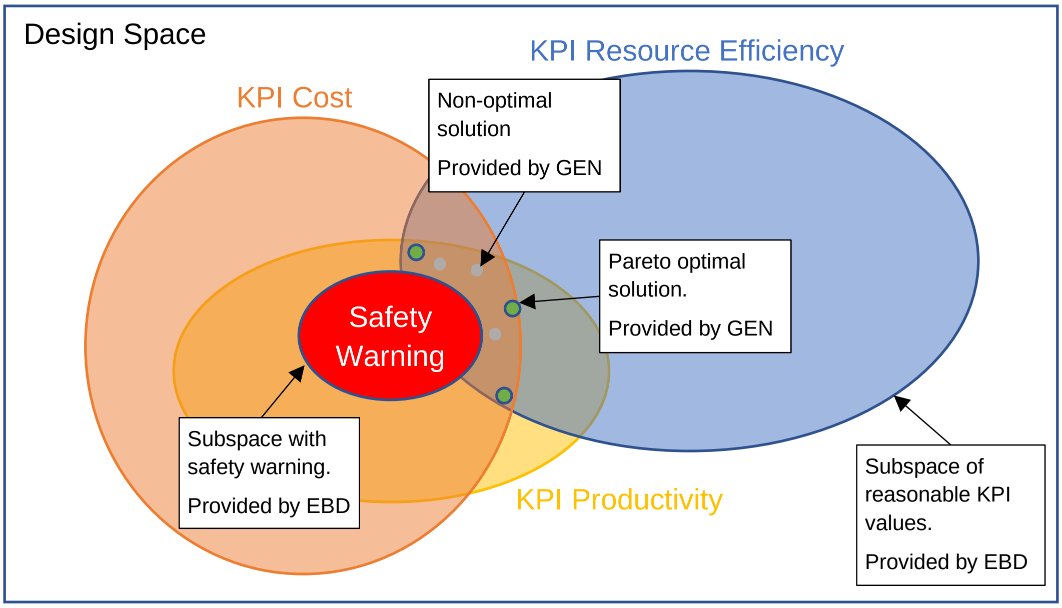


Figure 2: Conceptual Overview of the design space.

At the beginning of the design process, no reliable statement can be made as to which part of the design space contains suitable designs for the current design task. The EBD allows to exclude subspaces of the design space by predicting PI values. The subspaces with PI values within desired limits are shown as colored ovals in the figure. The areas considered reasonable for the different PIs may be in different parts of the design space. The overlap of these subspaces can be identified as the subspace for which further detailed investigation using a parametric model is appropriate.

In addition to the predictions, the EBD tool also outputs warnings that completely exclude areas of the design space. These should then be incorporated into the parametric model as a hard constraint, so that only solutions outside the critical areas can be considered. The subspace with warnings is shown in the figure as a red marking.

The overlapping area of all three PI subspaces excluding the warning area is investigated in more detail with a parametric model. Several alternative solutions are created, from which the pareto-optimal solutions are prompted to the designer to choose the most appropriate design option. The non-optimal solutions are depicted as grey dots in the figure. The pareto optimal solutions are depicted as green dots.

The implementation of a digital twin during the design and construction phase plays the key role in enabling the evidence-based design process discussed in this chapter. The DT of past construction projects are used as guiding examples to get insights into the design space. Therefore, geometric properties of the projects are to be stored along with material information, construction techniques and site information. The critical point is to link this information to the PIs identified in ASHVIN Task 2.1. Thus, it is also necessary to store all available data needed to compute PI values inside the DT database. The following chapter is discussing the steps of the evidence-based design process that are possible with the currently available data.

3 CURRENT STATUS

This chapter presents the current state of the database and what output it can provide for the subsequent ASHVIN Task 2.3.

3.1 sbp footbridge database

The database of historical footbridge projects used in this study was provided by project partner sbp. It is available in the form of nine excel data files. An overview of all nine files is given in Table 1. The individual data files are analyzed and evaluated using diagrams. This section aims to showcase the entirety of all the data provided by sbp and identifies the data tables that are useful for further EBD activities.

All 9 data files are described in detail in the following sections of this chapter. The database contains a total of 238 observations on footbridge projects with each 66 variables. A general problem of the database is the sparseness of the available data (see Figure 3) in addition to many variable values missing to make ample observations. Textbook examples work with much larger datasets containing several thousands of observations (Boehmke, et al., 2019). Therefore, all predictions made on basis of the available data are to be seen as examples on how to process the data when larger datasets are available. The general quality of the predictions will be discussed further in section 3.2.

Table 1: Overview of the sbp footbridge database

File name	description
fb0_location	Location information including continent, country, city and geographic coordinates.
fb1_general_info	General information including architect, contractors, design scope and won awards.
fb2_basic_struct_prop	Basic structural properties including bridge type, material and ground conditions.
fb3_basic_geometry	Basic geometry including length, span, deck area and bridge type specific information.
fb4_timeline	Timeline information including project start/end, scope start/end and construction start/end.
fb5_design_team	Design team information including office location, partner and project manager
fb7_financial_aspects	Financial aspects including total cost, material cost and revenue design
fb9_text	Textual description of the bridge in German and English language
fb10_env_imp	Information on environmental aspects including global warming potential for excavation, structure, construction etc.

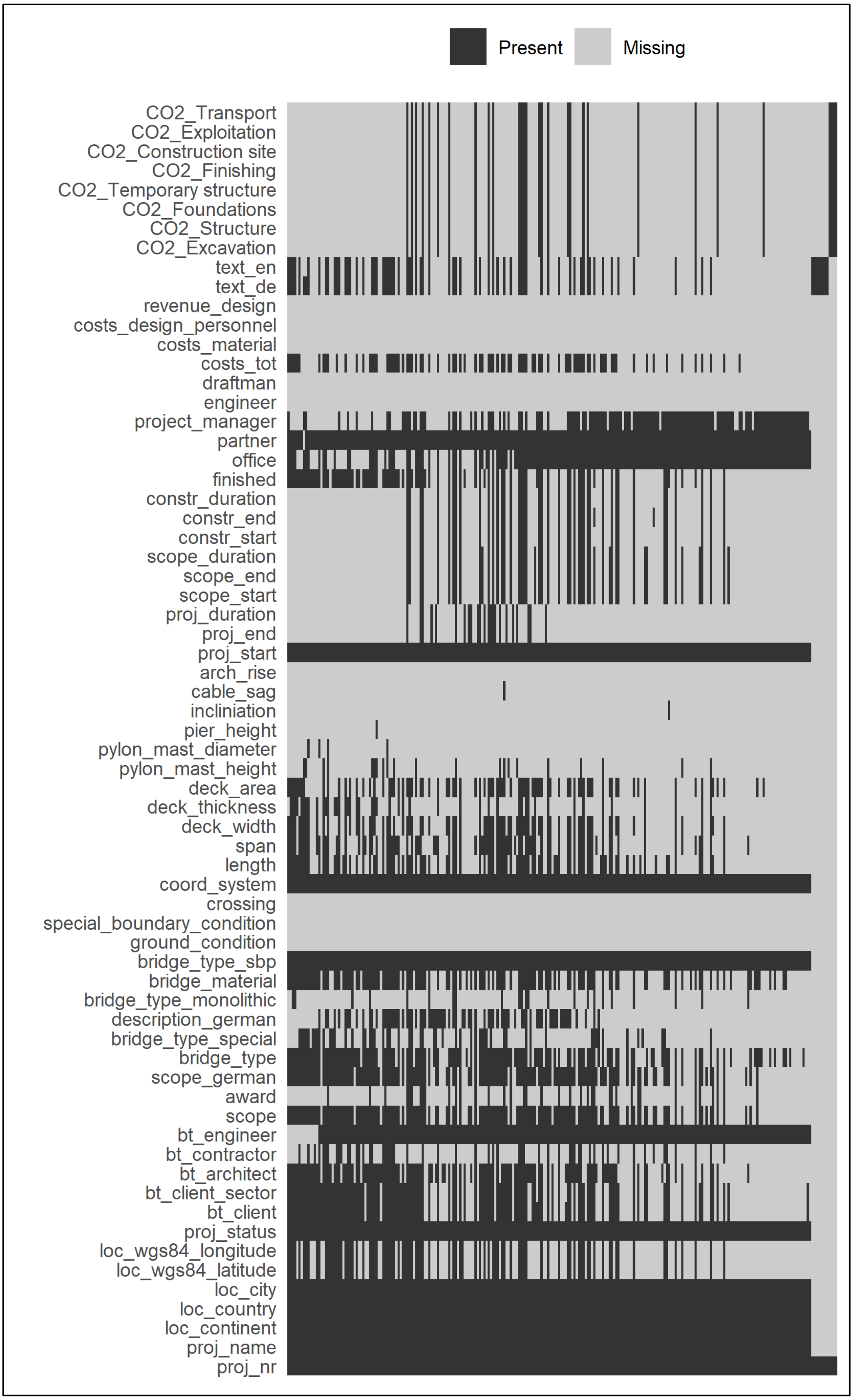


Figure 3: Overview of the sbp footbridge database

3.1.1 Locations

The locations dataset holds location data for the footbridge projects. Every project is identified using its project number (proj_nr). An overview of the different variables in the dataset is given in Table 2. Location data including continent, country and city is present for all footbridge projects, while the geographic coordinates are missing for some observations as can be seen in Figure 3.

Table 2: Overview of the variables in the fb_0_location dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
proj_name	The name of the project.	String
loc_continent	The continent the project is based on.	String
loc_contry	The country the project is based in.	String
loc_city	The city the project is based in.	String
loc_wgs84_latitude	The latitude coordinate of the project location in the WGS84 reference system.	float
loc_wgs84_longitude	The longitude coordinate of the project location in the WGS84 reference system.	float

Figure 4 shows the location of all footbridge projects according to their geographic coordinates. Every red dot represents one footbridge project. Three main geographic areas can be easily distinguished:

1. Europe
2. US
3. South-East Asia

Figure 5 shows the strong focus on the German market in the portfolio of sbp footbridges as many of the footbridge projects in the database where constructed in Germany.

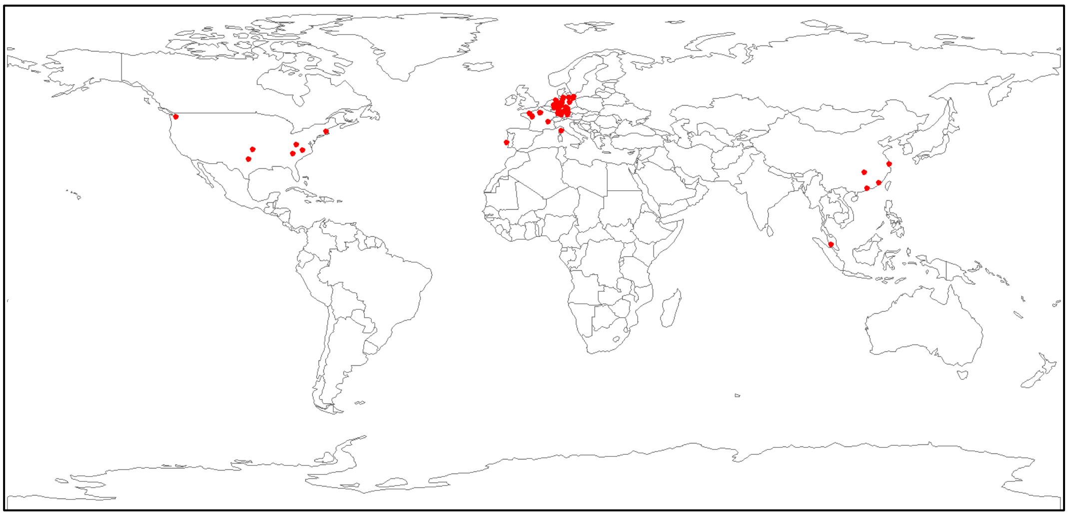


Figure 4: Location of all footbridge projects

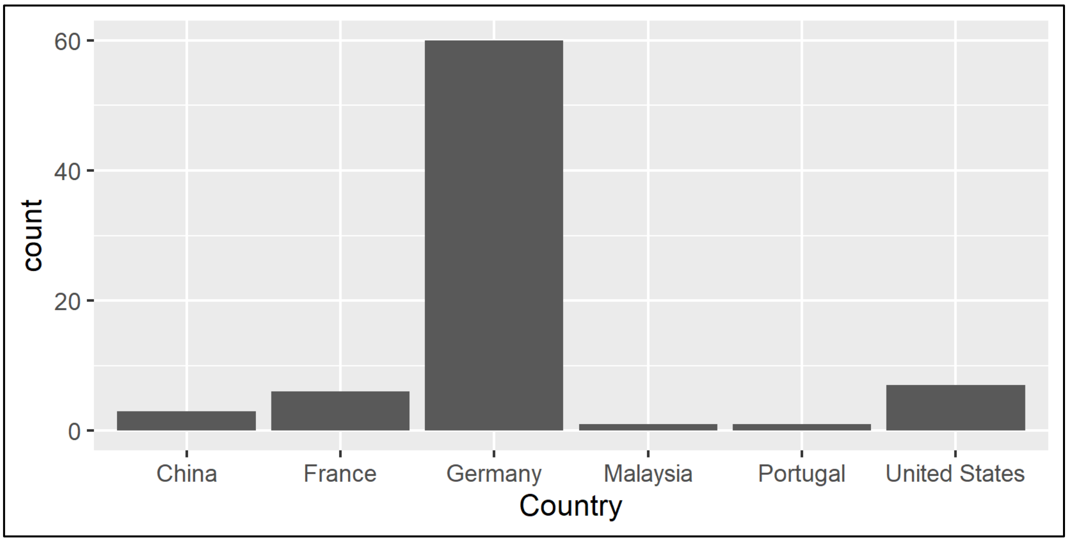


Figure 5: Countries of footbridges in the sbp database

3.1.2 General Information

The variables available in the dataset *fb_1_general_info* are presented in Table 3. This dataset holds information on project stakeholders including the client, architect, contractor, and the engineer. Additionally, the scope of sbp involvement in the project is present.

Table 3: Overview of the variables in the fb_1_general_info dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
proj_status	iu: "in use"; nb: "not built"	String
bt_client	Name of the client	String
bt_client_sector	Sector of the client ("private" or "public")	String
bt_architect	Name of the architecture company of the project	String
bt_contractor	Name of the contractor company of the project	String
bt_engineer	Name of the engineering company of the project	String
scope	Design scope of sbp in the project separated by /	String
awards	Awards won by the projects	String
scope_german	German scope description	String

The project status is especially important as it helps distinguishing between built and not built designs. In the following chapters only built designs are further investigated. From the total of 238 footbridge projects in the database 83 are built and were selected for the further investigation. Only these built examples are useful for the EBD approach as only for these PI values including for example construction time can be recorded.

3.1.3 Basic structural properties

The variables present in the dataset *fb_2_basic_struct_prop* are presented in Table 4.

The three variables ground_condition, special_boundary_condition and crossing, which would be especially interesting for the prediction of PI values are included in the dataset for future data gathering.

Table 4: Overview of the variables in the fb_2_basic_struct_prop dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
bridge_type	One of currently 10 bridge typologies	String
bridge_type_special	Special description of the bridge typology	String
description_german	Description of the bridge in German	String
bridge_type_monolithic	Integral/semi integral or none	String
bridge_material	Bridge materials separated by /	String
bridge_type_sbp	Bridge type description in German	String
Ground_condition	Description of the ground condition of the site	String
Special_boundary_condition	Description of special boundary conditions of the orjects	String
crossing	Object the bridge is crossing	String

The sbp footbridges can be distinguished in 10 different bridge typologies:

- Arch bridges
- Cable-stayed bridges
- Cable-net bridges
- Cantilever bridges
- Frame bridges
- Girder bridges
- Shell bridges
- Stress-ribbon bridges
- Suspension bridges
- Truss bridges

Figure 7 shows the distribution of the different bridge typologies within the dataset. Five typologies have more than five observations in the dataset, namely the arch, cable-stayed, girder, stress-ribbon, and suspension bridges. Girder and suspension bridges both have more than fifteen observations in the dataset.

Figure 6: Present data in the basic structural properties database

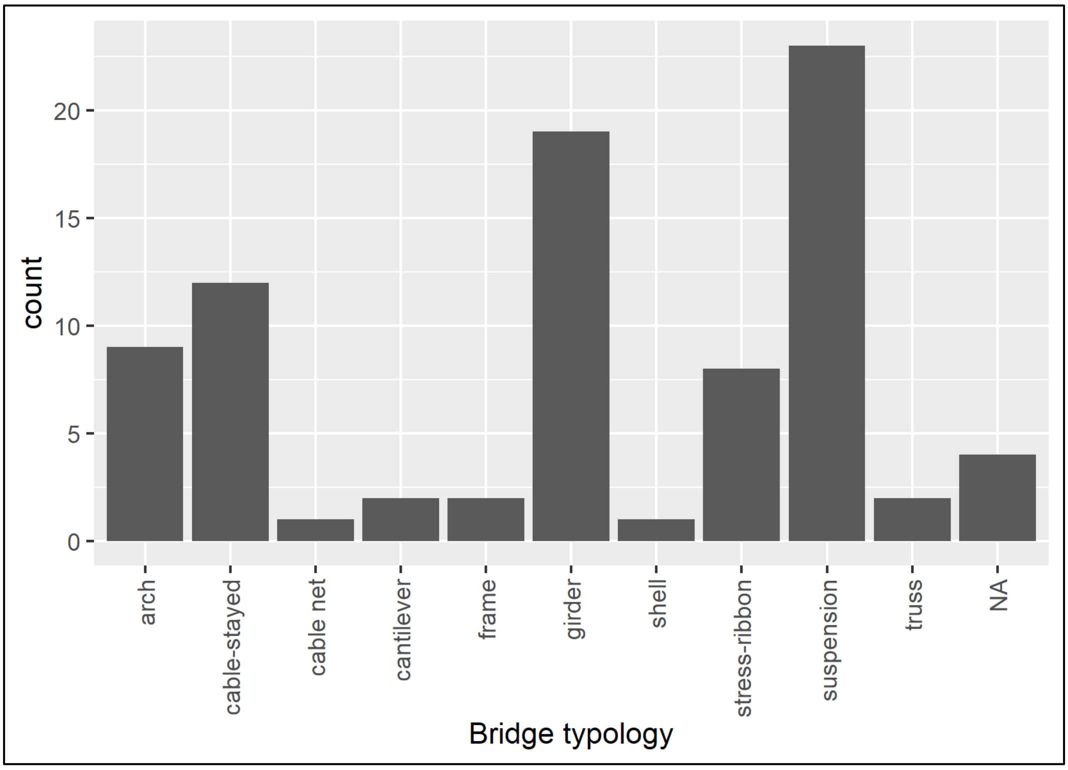


Figure 7: Number of bridges with the different bridge typologies

Figure 8 shows the maximum span of all bridges in the database grouped by the bridge typology. Some general guidelines for the design of footbridges can be derived from this distribution:

- Suspension bridges are built in a wide range of spans from 25 m up to over 200 m.
- Stress ribbon bridges are mostly built in a span range between 25 m and 50 m with some exceptions above 50 m.
- Girder bridges are built in a span range below 40 m with two exceptions above 50 m.
- Cable stayed bridges are built in a span range between 20 m and 80 m.

For the other bridge typologies, the number of observations is not large enough to make an informed statement regarding their typical span lengths.

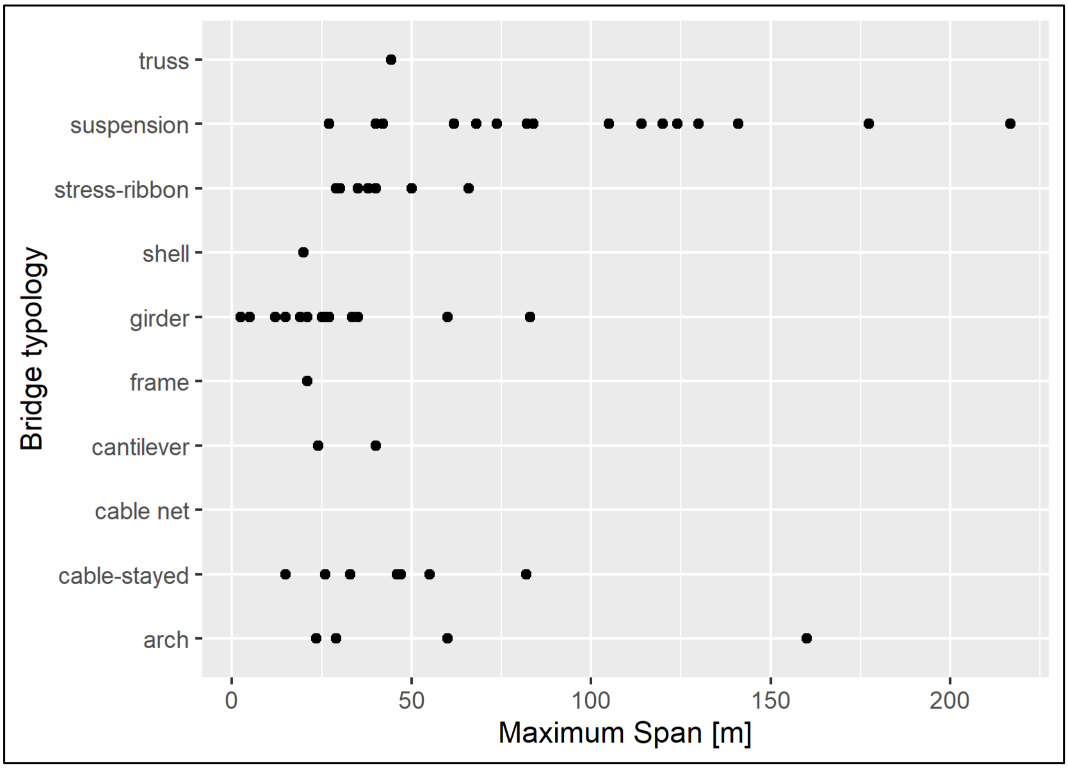


Figure 8: Maximum span of footbridge projects grouped by bridge typology

The bridge material is also present in the basic structural properties database. One bridge can have multiple materials. Figure 9 shows the number of bridges with the different materials. It can be observed that cables, concrete, and steel are the most prominent materials within the sbp footbridge database. Over 70 bridges have components made of steel while about 50 bridges consist of concrete components. Less than half of the 83 total built bridges are constructed using cables.

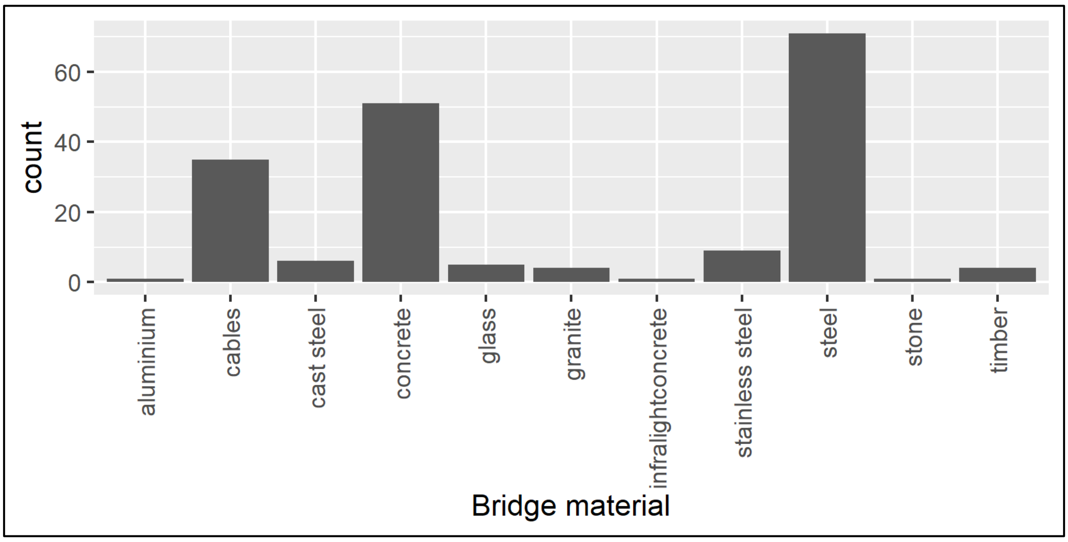


Figure 9: Material used in the database

Figure 10 shows the correlation between the bridge typology and the bridge material. Dark blue indicates no correlation while light blue is read as perfect correlation. As also discussed in the previous figure steel is the most prominent material being present in nearly every bridge typology with perfect correlation. Concrete is also distributed over nearly all bridge typologies. The cables are only present in suspension, stress-ribbon, cantilever, cable net and cable stayed bridges.

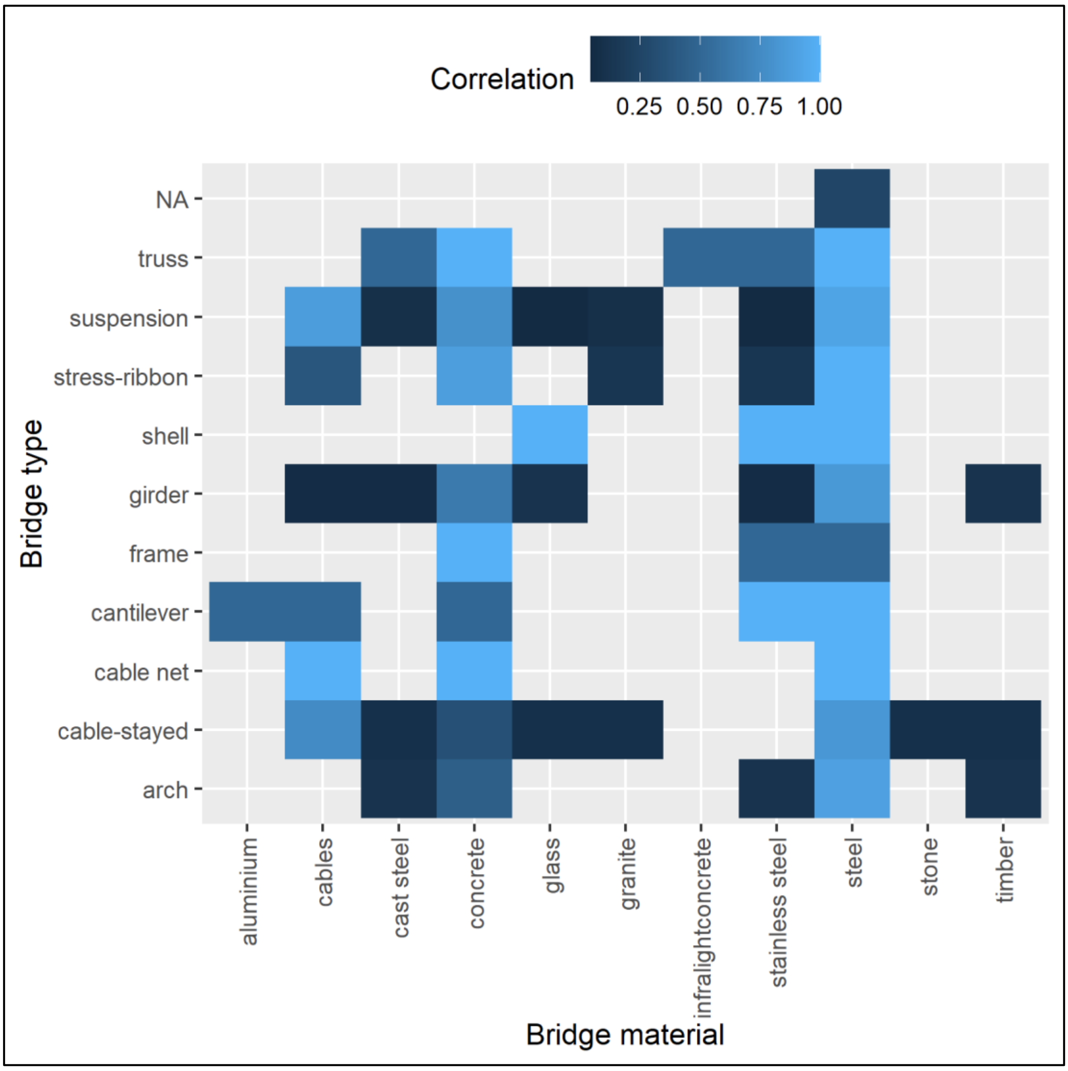


Figure 10: Correlation matrix of bridge typology and bridge material

3.1.4 Basic Geometry

The variables present in the dataset *fb_3_basic_geometry* are presented in Table 5.

Table 5: Overview of the variables in the fb_3_basic_geometry dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
coord system	Coordinate System of the project (“Gauß-Krueger” or “UTM”)	String
length	Bridge length in [m]	float
span	Bridge spans in [m] separated by /	float
deck_width	Bridge deck width in [m]	float
deck_thickness	Bridge deck thickness in [m]	float
deck_area	Bridge deck area in [m²]	float
pylon_mast_height	Height of the pylon in [m]	float
pylon_mast_diameter	Diameter of the pylon in [m]	float
pier_height	Height of the pier in [m]	float
inclinatin	Inclination of the bridge in radians	float
cable_sag	Cable sag of the bridge’s suspension cable in [m]	float
arch_rise	Rise of the bridge’s arch in [m]	float

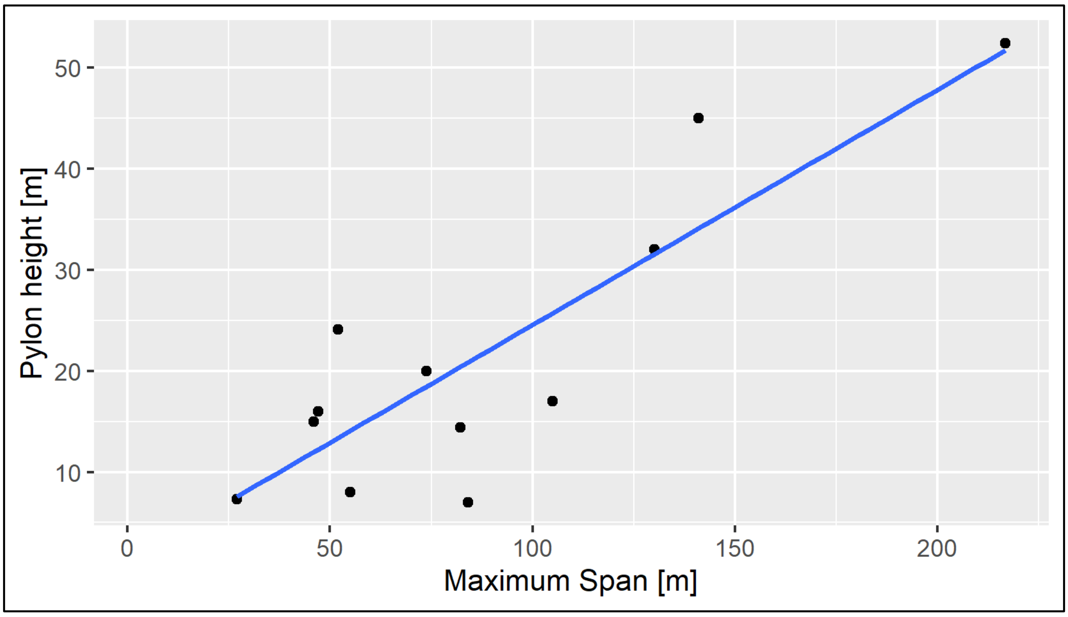


Figure 11: Linear correlation between the maximum span and the pylon height

Very few data is available on the typology specific dimensions like pylon height or arch rise as can be seen in Figure 3. Nevertheless, one interesting correlation can be seen between the bridge maximum span and the pylon height. This is presented in Figure 11. A linear correlation can be observed for the maximum span ranging from 25 m to

200 m and the pylon height between 5 m and 50 m. This correlation can directly feed into the Evidence Based Design Assistant as a dimension recommendation.

In contrast to the pylon height, for the deck thickness no correlation with the maximum bridge span can be observed (see Figure 12). No linear relationship between the two variables is apparent. A k-nearest-neighbours approach might be used to implement the findings of this investigation within the prototypical implementation of the EBD presented in section 3.3.

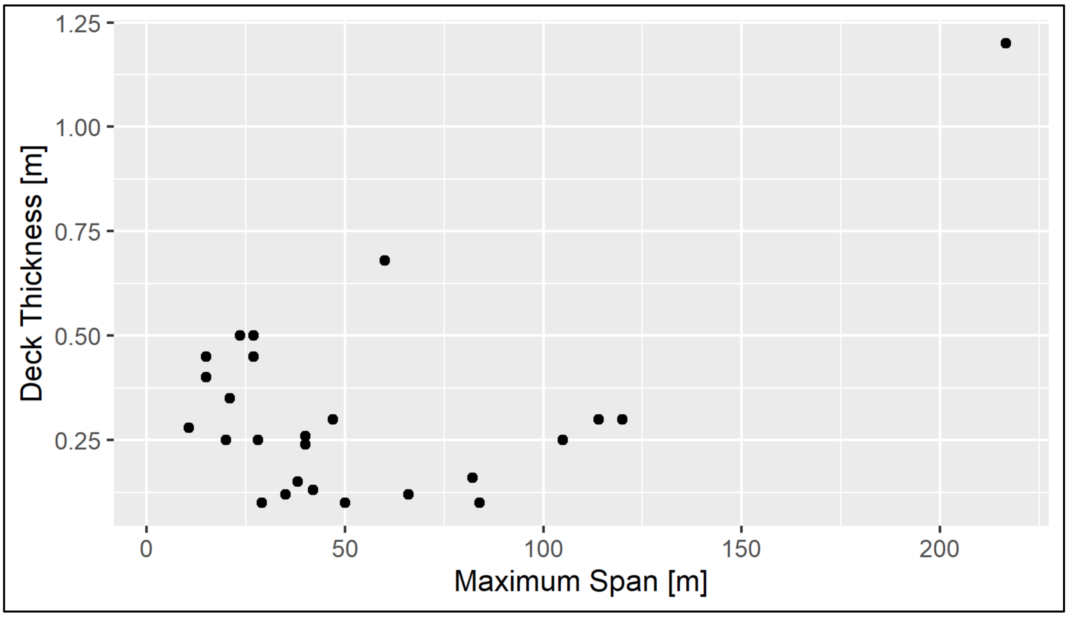


Figure 12: Scatterplot of the deck thickness for different maximum spans

3.1.5 Timeline

The variables present in the dataset *fb_4_timeline* are presented in Table 6. This dataset is especially useful as it contains the construction duration, which can be seen as a PI value for the productivity on the construction site. The construction duration is present in the database for 43 footbridge projects.

Prediction functions for the prediction of the construction time based on geometric properties are investigated in section 3.2.2.

Table 6: Overview of the variables in the fb_4_timeline dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
proj_start	Project start date	date
proj_end	Project end date	date
proj_duration	Project duration in [days]	integer
scope_start	sbp scope start date	date
scope_end	sbp scope end date	date
scope_duration	sbp scope duration in [days]	integer
constr_start	Construction start date	date
constr_end	Construction end date	date
constr_duration	Construction duration in [day]	integer
finished	Project finish date	date

3.1.6 Design Team

The design team dataset holds no relevant data for the further studies.

3.1.7 Financial Aspects

The variables present in the dataset *fb_7_financial_aspects* are presented in Table 7.

This dataset holds financial information for the bridge construction which can be used as a PI for the cost. The total design cost are available for 86 bridges. Analogously to the construction time, prediction functions for the cost are presented in section 0.

Table 7: Overview of the variables in the fb_7_financial_aspects dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
costs_tot	Total design costs of the project in [€]	integer
costs_material	Material costs of the project in [€]	integer
costs_design_personnel	Cost of the design personnel in [€]	integer
revenue_design	Revenue of the design in [€]	integer

3.1.8 Text

The text dataset holds no relevant data for the further studies.

3.1.9 Environmental impact

The variables present in the dataset *fb_10_environmental_impact* are presented in Table 8.

This dataset holds carbon footprint information which can be used as a PI for the sustainability of footbridge design projects. The GWP (Global Warming Potential) data is available for 29 of the footbridge design projects in the database.

Analogously to the construction time and cost prediction functions are investigated in section 0.

Table 8: Overview of the variables in the fb_10_env_impact dataset

Column name	description	data type
proj_nr	Identifier of the project.	integer
CO2_Excavation	Greenhouse gas emissions during the excavations works in [kgCOe]	float
CO2_Structure	Carbon footprint of the structure in [kgCO2e]	float
CO2_Foundations	Carbon footprint of the foundations in [kgCO2e]	float
CO2_Temporary structure	Greenhouse gas emissions of the temporary structures in [kgCO2e]	float
CO2_Finishing	Greenhouse gas emissions of the finishings in [kgCO2e]	float
CO2_Construction site	Greenhouse gas emissions on the construction site in [kgCO2e]	float
CO2_Exploitation	Greenhouse gas emissions of the exploitation in [kgCO2e]	float
CO2_Transport	Greenhouse gas emissions of the transport in [kgCO2e]	float

3.1.10 Summary for geometric and PI values

This section presents a summary of the most relevant data from the sbp database, namely the geometric dimensions and PI values.

Table 9: Overview of the geometric and PI-related data in the sbp footbridge database including minima, maxima and mean values

Name	min	max	mean	unit
length	23	760	119.27	[m]
span	2.5	216.7	51.25	[m]
span_num	1	11	1.53	-
deck_width	1.8	11.5	4.14	[m]
deck_thickness	0.1	1.2	0.34	[m]
deck_area	61.6	10580	580.71	[m²]
pylon_mast_height	7	52.4	20.31	[m]
pylon_mast_diam	0.66	1.2	0.8	[m]
time	81	1310	423.65	[days]
time_per_area	0.11	5.40	1.48	[days/m²]
cost	220000	3.6e+07	2515661	[€]
cost_per_area	1750	22727	5320	[€/m²]
carb	1687	103106	15350	[kgCO2eq]
carb_per_area	9.31	42.83	29.04	[kgCO2eq/m²]

Table 9 includes the minima, maxima and mean values for the geometric dimensions included in the sbp footbridge database. The PI-values for construction time, design cost and carbon footprint are included as total values as well as normalized values per square meter deck area. These normalized values are computed for every project with its specific PI value and deck area. The minimum and maximum values are then identified from these projects specific normalized values.

3.2 PI Predictions from the sbp footbridge database

This section summarizes the PI-predictions for cost, construction time and carbon footprint using linear regression models. These PIs were chosen from the PIs collected in ASHVIN Task 2.1. The design personnel costs are a PI for the KPI cost, the personnel productivity during the construction phase is a PI for the KPI productivity and the Global Warming Potential (GWP) is a PI for the KPI resource efficiency.

Due to the very limited size of the dataset, it is difficult to draw reliable conclusions from the prediction functions. Therefore, the very basic machine learning (ML) class of linear regression models was chosen to demonstrate the evidence-based design approach. These regression models are an output of Task 2.2 and are used as input for the creation of the parametric logic in ASHVIN Task 2.3.

For each of the three PIs five linear regression models with different predictors were created. The basic geometric dimensions bridge length L, bridge width W and bridge thickness T are used as predictors.

In the ML nomenclature, L, W and T are the independent variables, while the PI values for cost, productivity and resource efficiency are the dependent variables.

The different models are compared using three common error measures (Bradley , et al., 2020):

1. Root mean square error (RMSE), objective: minimize.
2. Mean absolute error (MAE), objective: minimize.
3. R^2, objective: maximize.

The linear regression models were created in *R* (The R Foundation, 2022) using the package *caret* (Kuhn, 2022). This package is especially useful to directly perform model testing via cross validation. Additionally, the error measures presented before are computed by the functions form the caret package.

3.2.1 Cost

For the cost PI five different linear regression models were created each using different predictor(s). As can be seen in Table 10 the sample size for the models 4 and 5 using all three predictors is greatly reduced compared to the single predictor models 1 to 3 as the geometric data is only available for a limited number of bridges.

Model 5 uses all three dimensions L, W and T as well as their combinations L*W, L*T, W*T and L*W*T as predictors.

Table 10: Predictor(s) of the linear regression models for cost prediction

Model	predictor(s)	Sample size
1	Bridge length L	54
2	Bridge width W	47
3	Bridge deck thickness T	28
4	Length, width, thickness without interaction	22
5	Length, width, thickness including interaction	22

All models were evaluated using 10-fold cross validations. The resulting accuracy measured using RMSE, MAE and R^2 is shown in Table 11. Model 4 performs best considering RMSE and MAE error measures while model 5 has the best performance regarding R^2.

It has to be emphasized that no general conclusions can be drawn from these investigations due to the very limited size of the dataset. This process is presented as an example to showcase the potential of DT based data in future construction projects.

Table 11: Accuracy of the linear regression models for cost prediction using RMSE, MAE and R^2

Model	RMSE [€]	MAE [€]	R^2 [-]
1	2855840	1864489	0.662
2	4507420	3041447	0.263
3	1261940	1061050	0.483
4	**454148**	**406878**	0.943
5	473036	429627	**0.989**

The coefficients for the derived linear models are shown in Table 12. The general formula for the cost prediction is presented below.

$$cost[€] = c_0 + c_L \cdot L + c_W \cdot W + c_T \cdot T + c_{LW} \cdot L \cdot W$$
$$+c_{LT} \cdot L \cdot T + c_{WT} \cdot W \cdot T + c_{LWT} \cdot L \cdot W \cdot T$$

In this equation the coefficients c_i from Table 12 are input. To illustrate the procedure, the resulting equation for model 4 is shown below.

$$cost_{model4}[€] = -249792€ + 13318\frac{€}{m} \cdot L - 109904\frac{€}{m} \cdot W + 2172682\frac{€}{m} \cdot T$$
$$+0 \cdot L \cdot W + 0 \cdot L \cdot T + 0 \cdot W \cdot T + 0 \cdot L \cdot W \cdot T$$

It is obvious from the coefficients in Table 12 that some predictions made from the available data are not reliable. Examples are the models 1 and 2 with their negative intercepts. These lead to the obviously false prediction that for example short bridges (L < 40m) would correlate with negative design cost. These observations are again indications for the insufficient size of the database.

Table 12: Coefficients for all five models for cost prediction

	Model1	Model2	Model3	Model4	Model5
intercept	-1391717	-4405144	526777	-249792	-1495436
L	35528	0	0	13318	22696
W	0	1700765	0	-109904	393660
T	0	0	2773472	2172682	3751242
L*W	0	0	0	0	-3948
L*T	0	0	0	0	-945
W*T	0	0	0	0	-748154
L*W*T	0	0	0	0	2583

3.2.2 Construction Time

Analogously to the cost also for the construction time five different linear regression models were created and compared. The predictor(s) along with the sample sizes are presented in Table 13. The sample size is even smaller than for the cost predictions

Table 13: Predictor(s) of the linear regression models for construction time prediction

Model	predictor(s)	Sample size
1	Bridge length	29
2	Bridge width	28
3	Bridge deck thickness	13
4	Length, width, thickness without interaction	12
5	Length, width, thickness including interaction	12

In contrast to the design cost prediction model 1 performs best based on the RMSE and MAR error measures as can be seen in Table 14. This model is using the bridge length as a single predictor. For the R^2 error measure models 3 to 5 show the best performance with the perfect R^2 value of 1.0. This performance is to be questioned considering the very small dataset. A high value of R^2 along with the performance in the other two error measures could be an indication for overfitting (Babyak, 2004).

Table 14: Accuracy of the linear regression models for construction time prediction using RMSE, MAE and R^2

Model	RMSE [days]	MAE [days]	R^2 [-]
1	134.06	115.61	0.63
2	230.85	190.58	0.68
3	154.48	152.91	1.00
4	136.53	131.74	1.00
5	479.77	416.19	1.00

The coefficients c_i and the intercept c_0 for all five linear regression models for construction time prediction are shown in Table 15.

Table 15: Coefficients for all five models for construction time prediction

	Model1	Model2	Model3	Model4	Model5
intercept	248.92	178.32	366.30	35.31	84.92
L	1.32	0	0	1.27	-4.40
W	0	55.01	0	47.40	10.65
T	0	0	35.68	3.87	-2.16
L*W	0	0	0	0	1.99
L*T	0	0	0	0	7.99
W*T	0	0	0	0	23.76
L*W*T	0	0	0	0	-2.59

The general formula for the construction time prediction is presented below.

$$time[days] = c_0 + c_L \cdot L + c_W \cdot W + c_T \cdot T + c_{LW} \cdot L \cdot W$$

$$+ c_{LT} \cdot L \cdot T + c_{WT} \cdot W \cdot T + c_{LWT} \cdot L \cdot W \cdot T$$

For model 5 this translates to the following prediction function:

$$time[days] = 84.92\ days - 4.4 \frac{days}{m} \cdot L + 10.65 \frac{days}{m} \cdot W - 2.16 \frac{days}{m} \cdot T$$

$$+1.99 \frac{days}{m^2} \cdot L \cdot W + 7.99 \frac{days}{m^2} \cdot L \cdot T + 23.76 \frac{days}{m^2} \cdot W \cdot T - 2.59 \frac{days}{m^3} \cdot L \cdot W \cdot T$$

3.2.3 Carbon Footprint

Five different carbon footprint prediction models were created as can be seen in Table 16. For these models the sample size was even smaller than for the cost and construction time models. Therefore only 5-fold cross validation could be performed on these models.

Table 16: Predictor(s) of the linear regression models for carbon footprint prediction

Model	predictor(s)	Sample size
1	Bridge length	19
2	Bridge width	17
3	Bridge deck thickness	7
4	Length, width, thickness without interaction	6
5	Length, width, thickness including interaction	6

The accuracy assessment using RMSE, MAE and R^2 in Table 17 shows similar results to the construction time prediction models. Model 1 using the bridge length as the single predictor performs best considering RMSE and MAE while R^2 identifies the models 3 to 5 to be most accurate. Again, the overfitting of the data due to very small sample size has to be taken into consideration especially for these models.

Table 17: Accuracy of the linear regression models for carbon footprint prediction using RMSE, MAE and R^2

Model	RMSE [kgCO2e]	MAE [kgCO2e]	R^2 [-]
1	**10532**	**6326**	0.82
2	17382	12158	0.37
3	12276	11942	**1**
4	13651	13285	**1**
5	48697	48514	**1**

The intercepts c_0 and the coefficients c_i for the five carbon footprint prediction models are presented in Table 18. For model 5 it was not possible to compute all coefficients because the number of coefficients (8) is higher than the sample size (6). This is why only the six first coefficients could be computed for this model.

Table 18: Coefficients for all five models for carbon footprint prediction

	Model1	Model2	Model3	Model4	Model5
intercept	-877.0	-15325.2	-3597.9	-12332.0	4128.9
L	113.85	0	0	48.8	-442.3
W	0	6584.1	0	-130.9	-5333.9
T	0	0	39944.3	44131.2	38107.0
L*W	0	0	0	0	189.9
L*T	0	0	0	0	-219.2
W*T	0	0	0	0	0
L*W*T	0	0	0	0	0

The general equation is shown below:

$$carbon\ footprint\ [kgCO2e] = c_0 + c_L \cdot L + c_W \cdot W + c_T \cdot T + c_{LW} \cdot L \cdot W$$

$$+c_{LT} \cdot L \cdot T + c_{WT} \cdot W \cdot T + c_{LWT} \cdot L \cdot W \cdot T$$

For model 5 this translates to the following specific function:

$$carbon\ footprint\ [kgCO2e] = 4128.9\ kgCO2e - 442.3 \frac{kgCO2e}{m} \cdot L$$

$$-5333.9 \frac{kgCO2e}{m} \cdot W + 38107.0 \frac{kgCO2e}{m} \cdot T + 189.9 \frac{kgCO2e}{m^2} \cdot L \cdot W$$

$$-219.2 \frac{kgCO2e}{m^2} \cdot L \cdot T + 0 \cdot W \cdot T + 0 \cdot L \cdot W \cdot T$$

3.3 Output from the evidence-based design into the parametric design

This section summarizes the connection between the evidence-based design investigations of ASHVIN task 2.2 and the parametric and generative design workflow of ASHVIN task 2.3. The geometric dimensions provided in Table 9 feed into the parametric model of ASHVIN Task 2.3 as parameter ranges. As only one typology is implemented in T2.3 the pylon dimensions are not used in the parametric model. Additionally to the geometric dimensions also the PI predictions explained in section 3.2 are used in the generative design process to score the PI values of the different design options. A summary of the relevant tables feeding into the parametric and generative design workflow of ASHVIN Task 2.3 is given in Table 19.

Table 19: Overview of the data provided to ASHVIN Task 2.3

Table	Description
Table 9	Parameter ranges of geometric values
Table 12	Coefficients for linear regression models for cost prediction
Table 15	Coefficients for linear regression models for construction time prediction
Table 18	Coefficients for linear regression models for carbon footprint prediction

4 MOVING ON

This section contains steps that could be taken to enrich the existing database of footbridge designs along with possibilities to use the presented knowledge database for a prototypical EBD tool.

4.1 Prototypical Implementation of an Evidence Based design Assistant

This section presents a prototypical implementation of an evidence-based design assistant which is based on the knowledge database presented in the previous sections.

4.1.1 General Concept

The evidence-based design assistant is envisioned as a tool helping the footbridge designer in the early design phases to get a broad overview over the design space. With this overview the designer is enabled to take an informed decision on which type of design should be investigated in more detail.

The insights are provided to the user in three distinct categories as presented in Figure 13. These are explained in more detail in the following sections.

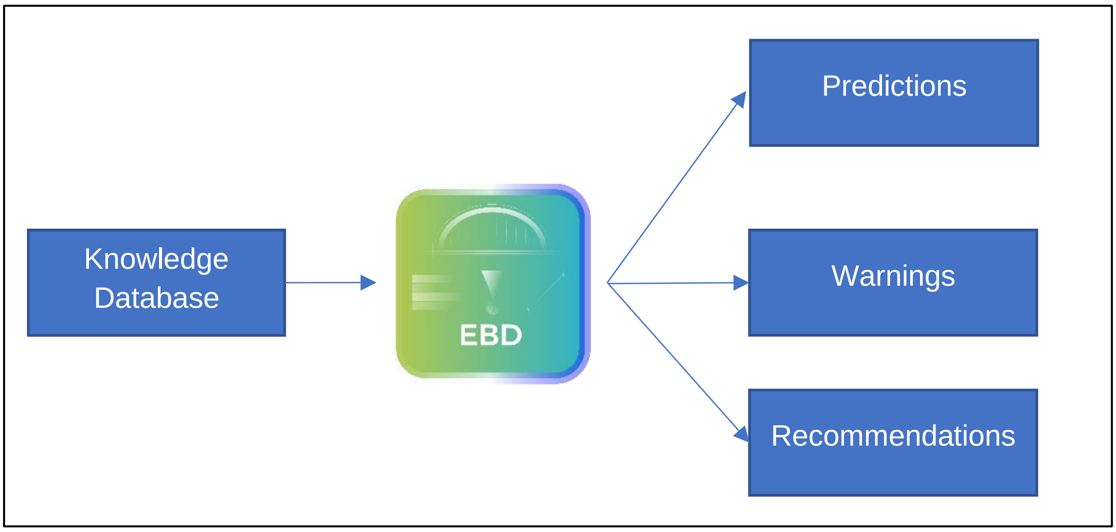


Figure 13: General Concept of the Evidence Based Design Assistant

4.1.1.1 Predictions

Predictions are seen as numerical forecasts of PI-Values based on the input of the user. The input of the user is derived from project requirements like the length of the footbridge and other boundary conditions like loading type and soil conditions. The predictions are made based on data from built footbridge projects.

By providing predictions of PI values the tool enables the designer to take an informed decision on which kind of bridge typology might be further investigated. Predictions can be made in different KPI categories. The productivity KPI could be addressed using the construction time of past footbridge projects. Similarly, also the Cost KPI could be covered with the construction cost. For the Sustainability KPI the Carbon Footprint of the Construction could be used.

In terms of safety a predicted number of accidents might be helpful, although this falls into another category than the other three examples provided before. A construction should ideally always be completed without any construction accidents. Therefore, other measures like warnings were implemented to mitigate the risk for the workers on footbridge construction sites.

4.1.1.2 Warnings

Warnings are mostly connected to the Safety KPI to mitigate risks of construction workers. This is done by identifying critical combinations of input values that could lead to higher risks on the construction site. As some risks are very site specific another idea is to prompt the user with accidents which happened on the construction sites of similar projects to the one currently in design. This helps the design team to keep in mind potential risks and helps mitigating them.

Also, for the other KPIs warnings might be useful to show the risk of not staying in the desired ranges of cost, productivity, or resource efficiency.

4.1.1.3 Recommendations

For different bridge types, rough dimensions can be derived from the data of the existing structures. These are then referred to as recommendations. In addition to rough dimensions, a material recommendation can also be made. Furthermore, relevant standards for the dimensioning or regarding safety aspects on the construction site can be incorporated as a reference.

4.1.2 User Interface

This section presents the user interface of the prototypical implementation of the evidence-based design assistant (EBD). The EBD was implemented as a R shiny dashboard application (RStudio, 2020).

4.1.2.1 Inputs

The user of the tool specifies the basic geometry of the new bridge to be designed in the tool. For the geometry, two initial values are used as a basis:

- Bridge length in [m]
- Bridge width in [m]

In most cases, these two values can be taken from the task description of a new footbridge to be designed. The ranges of definition of the geometric input variables were derived from the minimum and maximum values of the bridges available in the sbp database.

As no safety related data is available in the database an industry expert was contacted to gain insights which constraints might be influencing the construction safety and are at the same time available during the early design phases.

The prefabrication status was identified as one key aspect as for certain types of bridges the possibility to prefabricate major parts greatly reduces the number of connections being manufactured on site. Every single connection poses a potential safety risk and therefore the reduction of the number of connections could be a valid mean for achieving safer construction.

To enable prefabrication warnings within the EBD the possibility to prefabricate larger parts on site or the possibility to deliver large parts is queried from the user.

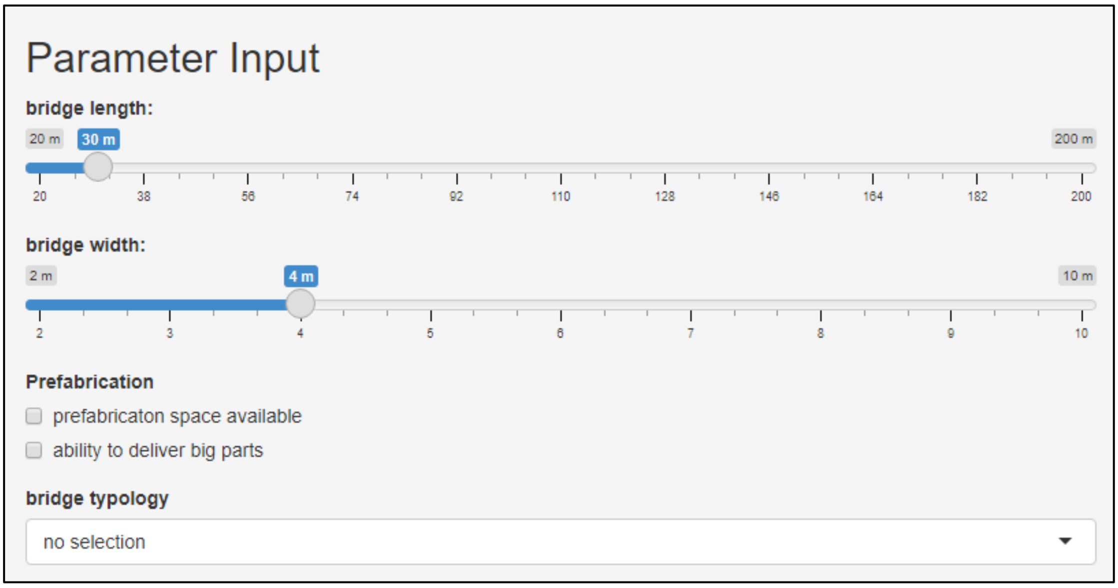


Figure 14: Parameter input of the prototypical Implementation of the Evidence Based Design Assistant

The last input present in the tool is the desired bridge typology. The user can thereby decide if the insights should be provided for a general footbridge or with regards to a specific bridge typology.

The inputs widget of the shiny application is shown in Figure 14.

4.1.2.2 Evidence Landscape

The evidence landscape gives an overview over all footbridge projects in the database that are used for the current predictions and recommendations. It shows a 2-D scatterplot with the two input parameters length and width on the x-axis and y-axis. All footbridge projects within the database are depicted as dots in the plot, in coloured groups based on the bridge type. The current project defined by the inputs is marked with a red dot. For the five selected most similar projects for the nearest neighbours approach the project number is also given within the plot for easy connection with the small data sheets provided in the tool.

Under the evidence landscape a small text tells the user how many footbridge projects were found for the specified typology. A screenshot of the evidence landscape in the shiny application is provided in Figure 15.

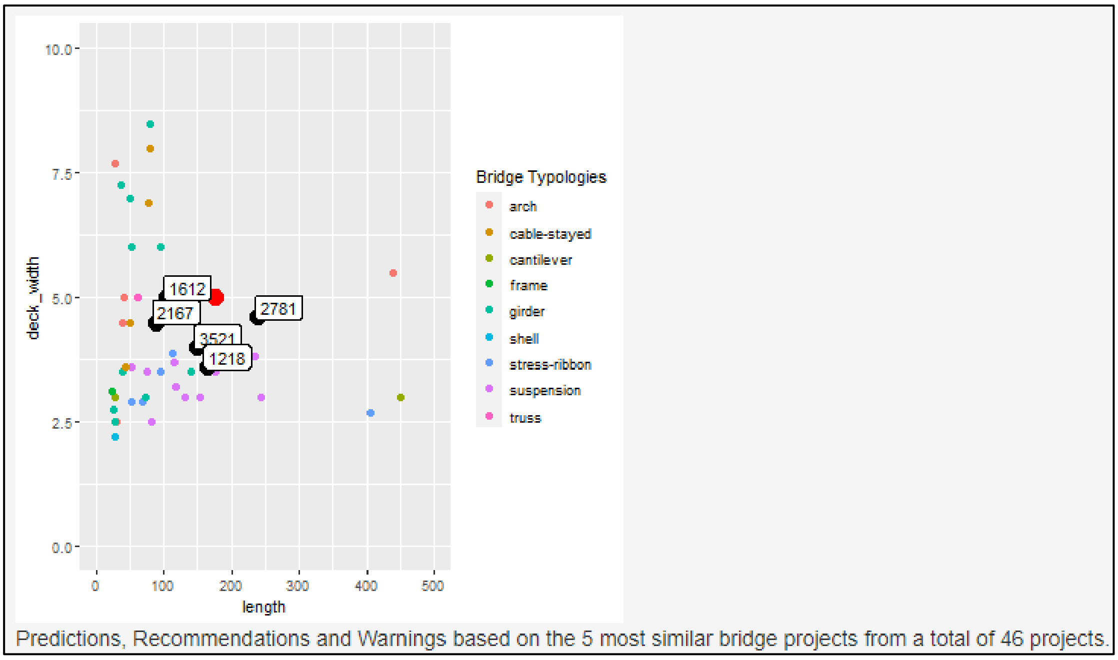
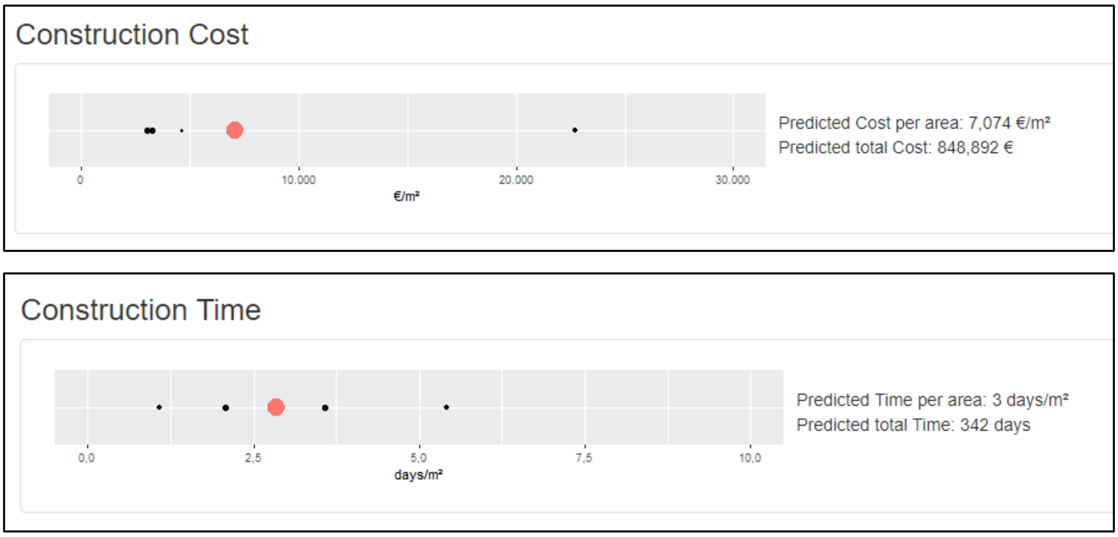


Figure 15: Evidence landscape in the prototypical Implementation of the Evidence Based Design Assistant.

4.1.2.3 Predictions

To enhance the interpretability of the EBDs outputs a k-Nearest neighbours approach was selected for the PI predictions for cost, time and carbon footprint. The predictions are computed using the five most similar footbridge projects. Similarity is evaluated based on the bridge length and width. If a specific bridge typology is selected, only bridges with this typology the five most similar projects with this typology are considered.

A screenshot of the predictions representation is shown in Figure 16. A red dot marks the prediction for the bridge currently under investigation based on the user input. The black dots show the five selected similar footbridge projects with larger dots implying greater similarity. Next to the graphical representation also numerical values are provided both as total values and normalized values per square meter deck area.



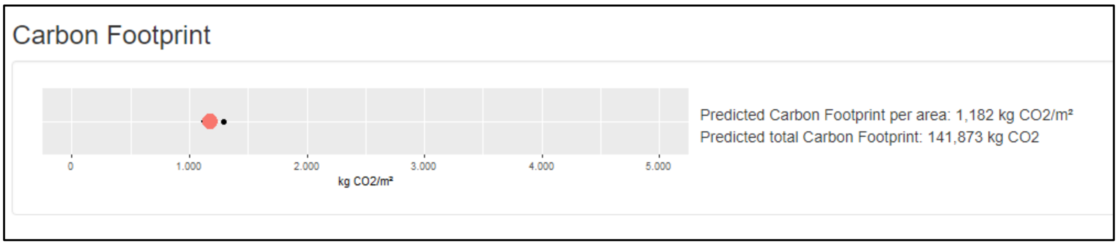


Figure 16: Predictions output in the prototypical Implementation of the Evidence Based Design Assistant

4.1.2.4 Recommendations

Dimension recommendations are given for the different bridge typologies. These are currently based on quasi linear relationships between input and output values. The only observable linear relationship is the pylon height based on the bridge span as shown in section 0. A screenshot of the respective widget is shown in Figure 17.

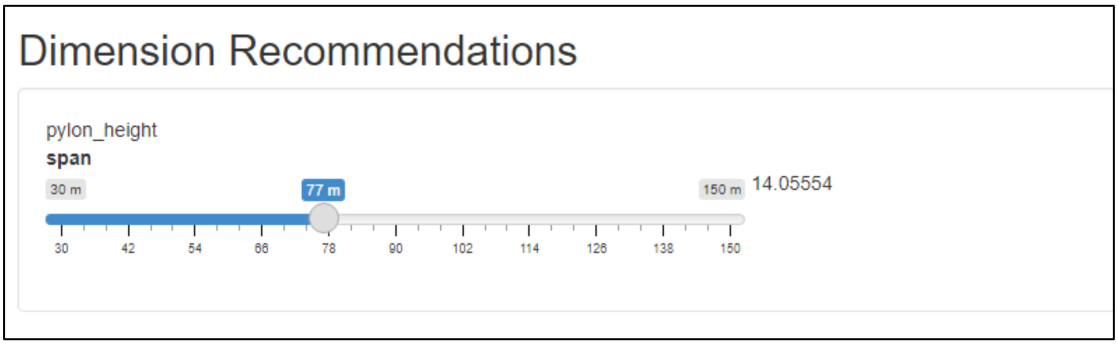


Figure 17: Screenshot of the dimension recommendations widget in the prototypical Implementation of the Evidence Based Design Assistant.

4.1.2.5 Warnings

Two types of warnings are implemented in the EBD-Prototype. The prefabrication warnings are based on the user input and provide insights whether the chosen bridge typology would benefit from prefabrication in the construction safety.

Additionally, the five nearest neighbours identified also for the PI prediction are shown with PI data and possible safety incidents during construction. This way the user of the tool is enabled to take measures preventing similar construction incidents in the upcoming design and construction project. The data on construction incidents needs to be stored within the knowledge database so it can be used for warnings in this widget of the tool.

A screenshot of the warnings widget is shown in Figure 18. The prefabrication warning is currently active (red text) as a bridge type was chosen which would benefit from prefabrication.

Under the pictures of the 5 nearest bridges the number of safety incidents is provided. If there were any safety incidents in the database these could be added here including a small description.

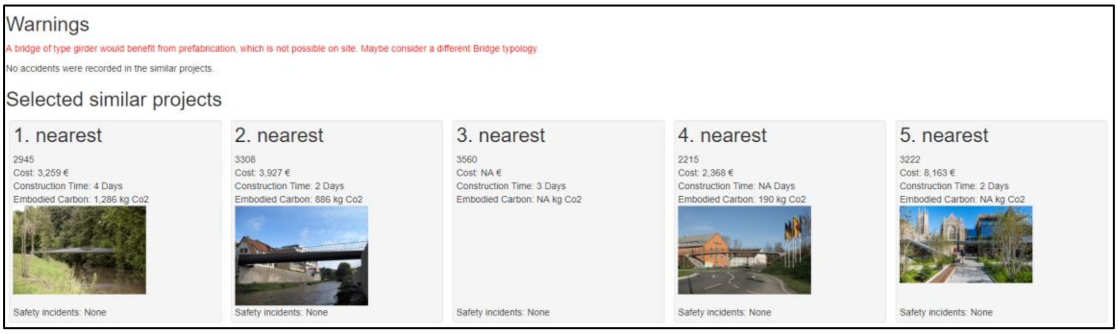


Figure 18: Warnings in the prototypical Implementation of the Evidence Based Design Assistant

4.2 Prototypical implementation of the BRICS Tool for scoring PI values

Two tool prototypes for PI computation are presented in (Merz, 2022), which was written within ASHVIN Task 2.2. These two tools are presented in the following chapters. The tools can be seen as two first components of the BRICS tool for scoring PI values.

Both the Sofistik2CarbonFootprint tool and the ProjectHoursMonitor tool allow for the direct export of the computed PI values into the knowledge database.

4.2.1 Carbon Footprint Calculation from Sofistik Models

Structural analysis can be performed using 3D Finite Element Models (FEM) which can be implemented e.g. using the structural analysis software Sofistik.

This tool provides the functionality to directly compute a carbon footprint of the embodied carbon of the structure from a Sofistik FE model. Figure 19 shows a screenshot of the tool with the input of bridge database and project number on the left side and the textual representation of the computed carbon footprint on the right.

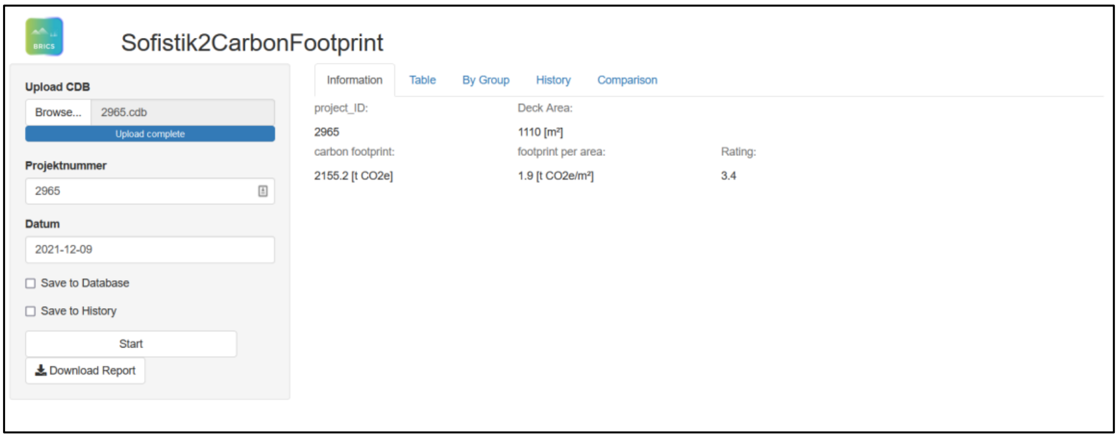


Figure 19: Screenshot of the information tab of the Sofistik2CarbonFootprint Tool

Other graphical representations of the computed carbon footprint are also available in the tool as shown in Figure 20 and Figure 21.

The By Group tab of the tool presents a bar chart of the carbon footprint divided into the different material types and structural elements. The history chart gives insights into the development of the model's carbon footprint when several model iterations are provided.

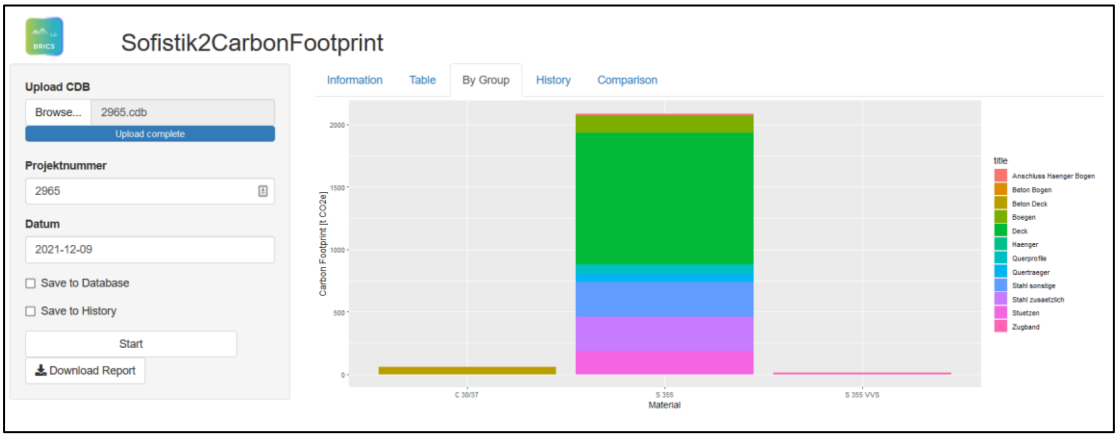


Figure 20: Screenshot of the by group tab of the Sofistik2CarbonFootprint Tool

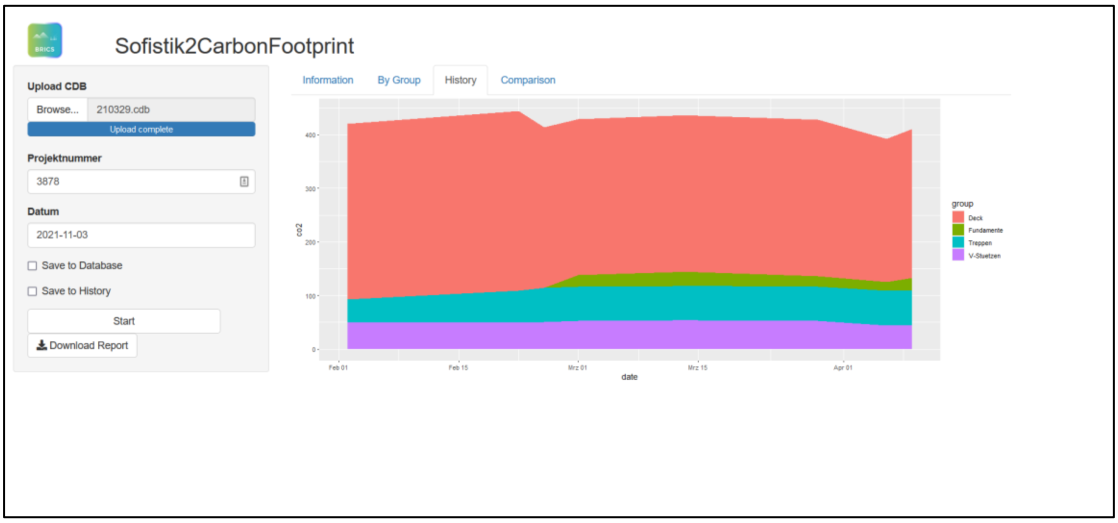


Figure 21: Screenshot of the history tab of the Sofistik2CarbonFootprint Tool

4.2.2 Project design hours calculations from projects hours datasets

The ProjectHoursMonitor uses project hours tables provided by a project hours software to score the current project in comparison with other footbridge design projects from the database.

Figure 22 shows the information tab which is similar to the information tab in the Sofstik2CarbonFootprint tool.

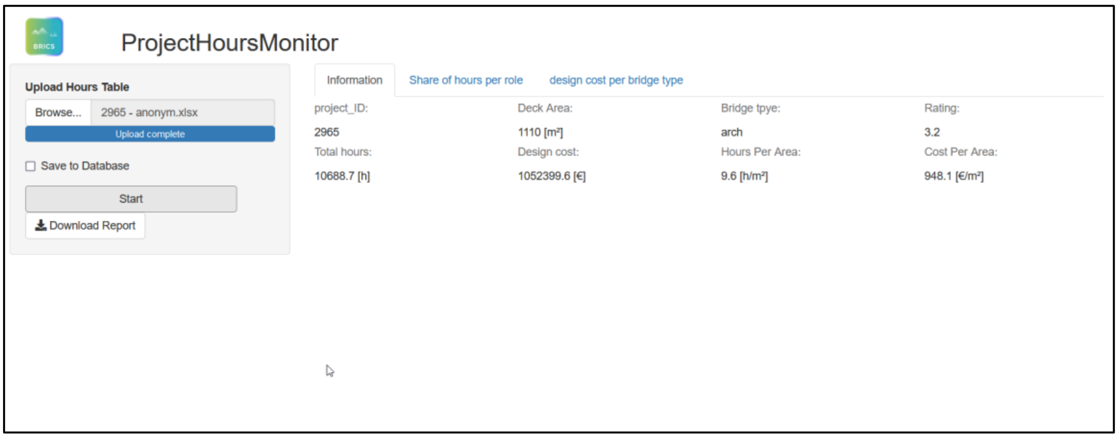


Figure 22: Screenshot of the information tab of the ProjectHoursMonitor Tool

The comparison of the project design hours of different bridge types and the current bridge design marked with a red dot can be seen in Figure 23. This allows for the quick assessment of the status of the current footbridge design project.

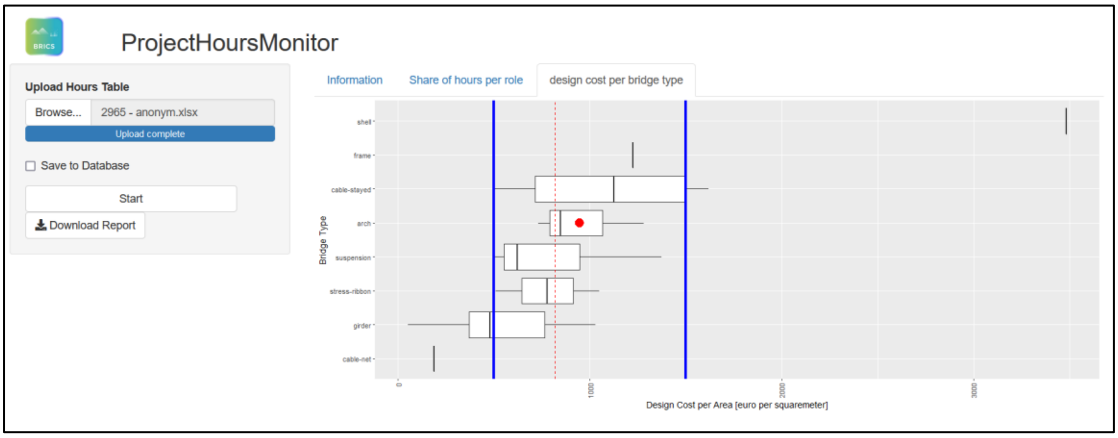


Figure 23: Screenshot of the design cost per bridge type tab of the ProjectHoursMonitor Tool

4.3 Updated database scheme

This section collects learnings from the previous chapter 3 with regards to the available and required data for evidence-based design activities.

4.3.1 Geometric dimensions

For the geometric dimensions an issue in the sbp database is the inconsistency between the length, the width, and the deck area variable. These three variables should be reduced to two variables as the deck area can be computed by multiplying the length with the width.

Additionally, the length variable might be dropped as the length should be computable from the sum of the spans.

Another topic regarding the geometric dimensions would be bridge type specific dimensions. The sbp database currently contains variables like the pylon height which is only applicable for certain bridge types like cable-span bridges or suspension bridges. One solution could be the introduction of generic dimensions in the general database which would be translated to bridge type specific dimensions using a separate data file as shown in Table 20.

Table 20: Example for the connection of bridge typologies and type specific dimensions

bridge type	dimension 1	dimension 2	dimension 3
arch	Arch rise	Number of hangers	Arch cross section area
suspension	Pylon height	Cable sag	Pylon cross section area
cable-stayed	Pylon height	Number of cables	Pylon cross section area

4.3.2 Inclusion of safety incidents and accident descriptions

To provide safety related insights during the design phase it is necessary to the safety incidents during construction inside the knowledge database. Along with the plain number of fatal accidents, non-fatal accidents and near misses also a short description of the accident's cause should be included in the database enabling the designer to learn from previous incidents.

4.3.3 Inclusion of prefabrication related data in the database

To quantify the influence of prefabrication on the PIs of footbridge design the prefabrication status of newly built footbridge design projects should be included in the database. Different approaches for assessing the prefabrication status are available mainly in the building construction sector. An adoption for footbridge design might be useful in this area.

4.4 Data Storage requirements

Database storage requirements accompanied by financial and energy related cost might be a major drawback to the implementation of DT for the early design stages. Therefore storage requirements for the currently available data were investigated along with projections for a greatly increasing database of footbridge projects.

The ASHVIN digital twin platform is currently running two different clusters which are shown in Table 21.

Table 21: Currently used clusters with specification and monthly cost.

Cluster	Specification	Cost
Digital Ocean Cluster x3 nodes	6vCPUs, 12Gb RAM, 240 Gb Disk	24 $/month
AWS EC2 x3 nodes + RDS: t3.xlarge	4 CPUs, 16.0Gb RAM + db.t2.micro - 2vCPUs, 1Gb RAM, Disk on demand (100Gb scalable to 1000Gb)	420$ + 750$ for RDS / month

The footbridge database provided by sbp including around 300 footbridge projects with ca. 70 parameters has a size of 300 kB. For comparison the US National Bridge Inventory database (Administration, 2022) holding over 700,000 us bridges and 123 variables has a size of under 300 MB.

Regarding the power consumption an estimate was made based on (Intel, 2009) a value of between 0.001Kwh and 1Kwh per month was derived for a potential database size of 300 MB. This translates to the emission of between 0,042 gCO2eq and 420 gCO2eg in case of energy production in Germany (Umweltbundesamt, 2022).

It can be concluded that the cost and energy related ramifications of the storage of digital twin data for the design phase of footbridge projects is very small and therefore doesn't pose a major obstacle in the implementation of the approach.

4.5 Sensor-based data within the design workflow

The data presented in this report is based on geometric dimensions or site-specific conditions as well as PI values which are the result of computations or observations during or after the construction. This data is not sensor-based but originates from 3D-models, site investigations or design/construction computations.

As the ASHVIN project has a focus on sensor-based data this section explores the possibilities to interact with this topic in the design phase.

4.5.1 Design insights for sensor placement

One important aspect is the placement of sensor during the construction or maintenance phase of a footbridge. Due to the cost of sensor installation and the large amount of data produced by sensors (especially compared to the database sizes discussed in section 4.4) the strategic placement of a limited number of sensors requires careful attention.

The designers of the footbridge have insight knowledge of its structural behaviour and are thereby predestined to also plan for possible sensor positions in the design stage of the footbridge. These sensor positions should be stored in the DT during the design stage so that their installation in later stages of the lifespan is informed by the designers' decisions.

If the EBD provides safety warnings for the construction of the footbridge the installation of sensors like motion trackers might be prompted to the designer as a recommendation. This way sensor installation could be a mean to enhance construction safety.

4.5.2 Using sensor data in the knowledge database

Another aspect of the sensor data is the inclusion of insights made from this historic DT data into the knowledge database.

One possible use case could be the design load estimation. In the example of footbridges, a strain gauge measuring the strain in the lower part of the cross section could be used to calculate the real loading of the footbridge. Another possibility would be camera images capturing the real occupancy of the footbridge in discrete time intervals. Collecting this data for several footbridges and including it into the knowledge database would enable engineers to compare the loading required by design codes with the evidence-based prediction. If the real loading is significantly smaller than the design load this could lead to a revision of the design code. Smaller design loads then influence the dimensions of newly built footbridges and would lead to less material being necessary, thereby reducing the PIs of material cost and carbon footprint.

5 CONCLUSION

This deliverable includes an explanation of the knowledge-based design system envisioned within the ASHVIN projects. The three distinct approaches of PI computation, evidence-based design and generative design are capsulated into three tool prototypes, of which the evidence-based design assistant and the BRICS tool for PI scoring are presented in this document.

The available data from the sbp footbridge portfolio is analysed and the potential for ML prediction models regarding cost, construction time and carbon footprint is discovered. Different linear regression models were compared and the preferable geometric predictors for different PI values were identified. It has to be noted that the available database is very small and therefore no reliable statements regarding specific values can be made. But it was still possible to showcase the overall workflow and information flow into the following ASHVIN task 2.3.

Steps towards an improved database scheme as well as the BRICS tool for enriching the knowledge database were presented along with the investigation of data storage requirements.

The overall process shows the applicability of the approach even though the available database has major flaws which motivates the introduction of a digital twin as a standardized way of collecting data of future footbridge design and construction projects.

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