D2.3: PARAMETRIC DESIGN TO OPTIMIZE PRODUCTIVITY, RESOURCE EFFICIENCY, AND SAFETY DURING EARLY DESIGN STAGES

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ABSTRACT

Conceptual designs developed at early project stages depend on the quality of data used as design inputs. However, data scarcity at the early project stages is a major challenge. To address this challenge, this study applies historic data from past projects to develop a 3D parametric model. To increase productivity in design, insightful mathematical functions from the historical data are used to computationally generate various design alternatives. The various alternatives generated are presented and a set of pareto-optimal designs is recommended based on the values of their performance indicators. To further support decision-making, the recommended designs will be visualized in 4D to enable designers understand the ramifications of their design choices. We further recommend automating the process to develop designs directly from historic data knowledge bases.

KEYWORDS

Construction Digital Twin (DT), Early design stages, Generative design, Historic data knowledge base, Parametric design, Pareto-optimal designs.

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V1.1	05-02-2023	Final report	Joan Evelyn Ongodia

DISCLAIMER

ACRONYMS & DEFINITIONS

AECO	Architecture, Engineering, Construction and Operation
ASHVIN	Assistants for Healthy, Safe, and Productive Virtual Construction Design, Operation & Maintenance using a Digital Twin
CO_2e	Carbon dioxide equivalent
.csv	Comma-separated values
DT	Digital twin
e.g.	For example
i.e.	That is to say
Kg	Kilograms
L	Length
m	Meters
.txt	Delimited text files
T	Tons
W	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.

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1 INTRODUCTION

1.1 Background

Early project stages require special attention because they determine the conceptual designs for further decision-making. Therefore, the conceptual designs must be based on sound principles and engineering judgement supported by design input data. However, data scarcity in some infrastructure systems at the early project stages (Gray, et al., 2022) is a major challenge which results in inaccurate conceptual designs that make rework inevitable (Eli, 2022; Abdelbary et al., 2020). This challenge can be solved by using historic data from past similar projects as design input for new projects. This is possible with construction digital twins (DTs) which enable data-driven design explorations by allowing historic data from past projects as design input. The data from past projects can be collected and organized into knowledge bases for providing design inputs for future projects.

To demonstrate this novel design approach, this report uses the proposed DT knowledge bases developed under deliverable D2.2 evidence-based design assistant (Merz & Ongodia, 2022) of the ASHVIN H2020 research project. D2.2 provides the evidence and recommendations of using the historic data and create knowledge bases that comprise of various parameters and attributes that can be used to support parametric modelling efforts by means of mathematical functions and/or statistical models for quickly quantifying key performance indicators' values (KPI-values) during design explorations. These parameters and attributes, which eliminate unfavourable situations from past projects, are used for developing more accurate 3D conceptual parametric models. Since these models are developed based on past successfully completed projects, they allow designers to avoid previous design mistakes, thus safety in design is improved. Using these data-supported parametric models, various design alternatives are automatically generated and evaluated using a generative design optimization process. The generative design process uses optimization techniques to support the automation of design space exploration. With each iteration, the generated design alternatives are evaluated, and through various approaches defined by the implemented optimization technique design is evolved towards reaching the objectives defined by the user through the KPIs. The output of the generative approach represents a set of recommended design alternatives that are ranked based on the trade-off made by the model between the defined objectives – often called pareto-front. Therefore, productivity in design is improved since various alternatives of the parametric model are quickly generated, evaluated, and ranked. To further support decision-making, the recommended design alternatives will be visualised in 4D to enable designers understand the ramifications of their design choices. Yet, 4D visualization of the generated alternatives falls under the scope of another deliverable and will not be presented in this report.

In general, the following achievements which are discussed in this report, highlight our contributions to improve safety and productivity in early design stages.

1. Application of gathered historic data (Merz & Ongodia, 2022) as input improves the quality of conceptual parametric models, which improves safety in design.

2. Design productivity is increased by quickly generating, evaluating, and ranking various design alternatives of the parametric model.

1.2 Uniqueness of our Contribution and Potential Users

To the best of our knowledge, no project designs have been built by applying the knowledge of KPIs related to the construction phase of past projects. This study considers a data-driven approach and uses evidence-based parameters and mathematical functions which are encapsulated in knowledge bases of past projects.

The knowledge, illustrations and demonstrations reported herein are relevant for Architecture, Engineering, Construction and Operation (AECO) firms, start-up companies, trainers, researchers, and educators. Other potential users of this knowledge representation include experienced practitioners, early-stage career professionals, and investors.

Design firms will improve safety and productivity in early design phases using parameters and mathematical functions from the knowledge bases to develop accurate parametric models and various design alternatives. The implications of both aspects will be an increase in business profitability.

Our approach may motivate start-up companies to exploit this avenue further to develop innovative tools for supporting construction projects from the early design stage.

Trainers, and educators will use our approach as first-stage concepts for using past project data/information for developing new project designs.

Experienced practitioners can increase productivity in design using the proposed approach as example and develop their own models to quickly generate, evaluate, and rank various design alternatives. They will also understand ramifications of their design choices and project performance from early design phases.

Early-stage career professionals will be supported to develop accurate conceptual designs using the historic data/information from the evidence-based design knowledge base.

The various design alternatives and set of pareto-optimal designs will support investors' decision-making to prioritise their user requirements and user-needs better based on KPI-values.

1.3 Outline of The Document

This section gives a general overview and road map of the entire document.

Chapter 1 briefly introduced and motivated our approach.

Chapter 2 demonstrates our approach to data-driven design for improving construction productivity and safety. It explains how parametric models are developed using knowledge extents from the historic data formalized as mathematical functions to support the generation and evaluation of design alternatives. Moreover, it showcases the ranking of the design alternatives in the form of pareto-optimal solutions to support further decision-making. These three aspects enable improvements in safety, productivity, and decision-making.

Chapter 3 finally concludes the report.

2 DATA-DRIVEN DESIGN

Figure 1 represents the concept of data-driven design which was applied in this study.

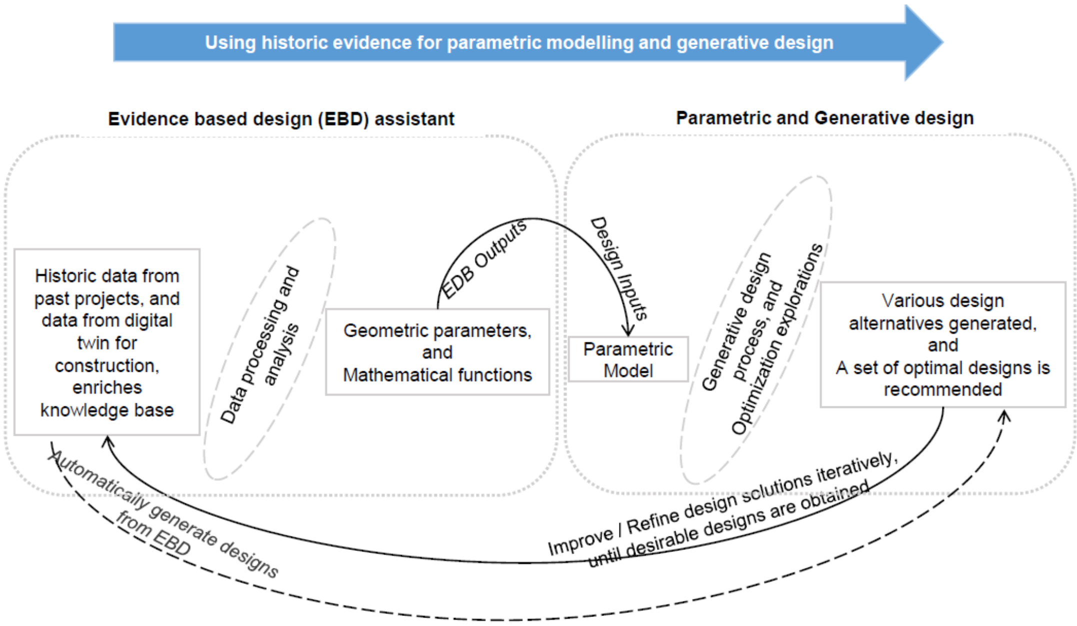


Figure 1: Concept of data-driven design

Data-driven design uses organized historic data from past projects and data collected from built physical infrastructure using construction digital twins (DT). The data is processed and analyzed to create the knowledge bases – this step is covered by deliverable D2.2 (Merz & Ongodia, 2022). Insights from the data determine the design space extents (i.e. minimum and maximum) of various parameters and the mathematical functions which relate to evaluation of project's performance indicators (PIs) during construction. Both the design parameters and mathematical functions which are derived from the historic data are used as design input to improvise for the lack of data/information at the early design stages. This therefore provides the benefit of reducing design assumptions, yet it also comes with limitations. For example, this study only makes three assumptions which are discussed in the next section of this report. The major limitation is that any data-driven approach only covers those situations specific to the past projects – the user must be aware about these and critically identify their applicability to the new situation. Figure 2 summarizes our approach. This approach is further detailed in Figure 3 which illustrates the parametric modelling and generative design workflows. This workflow is custom-tailored for pedestrian bridges (footbridges), but it can be extended to make it applicable for other data-driven design projects. The next subsections cover parts of this approach, as follows: section 2.1 provides details on developing the parametric models based on historical data; section 2.2 provides details on the generation, optimization, and ranking of the design alternatives; section 2.3 provides details on limitations.

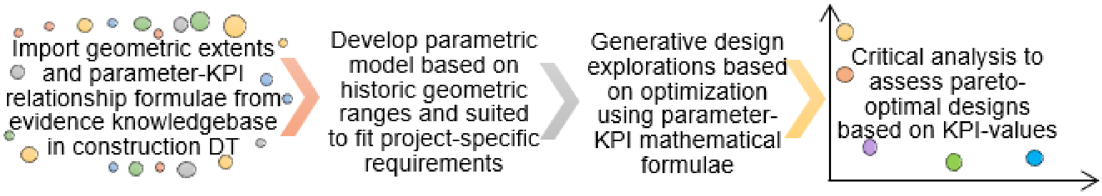


Figure 2: Simplistic summary of our approach: from historic data to new project designs

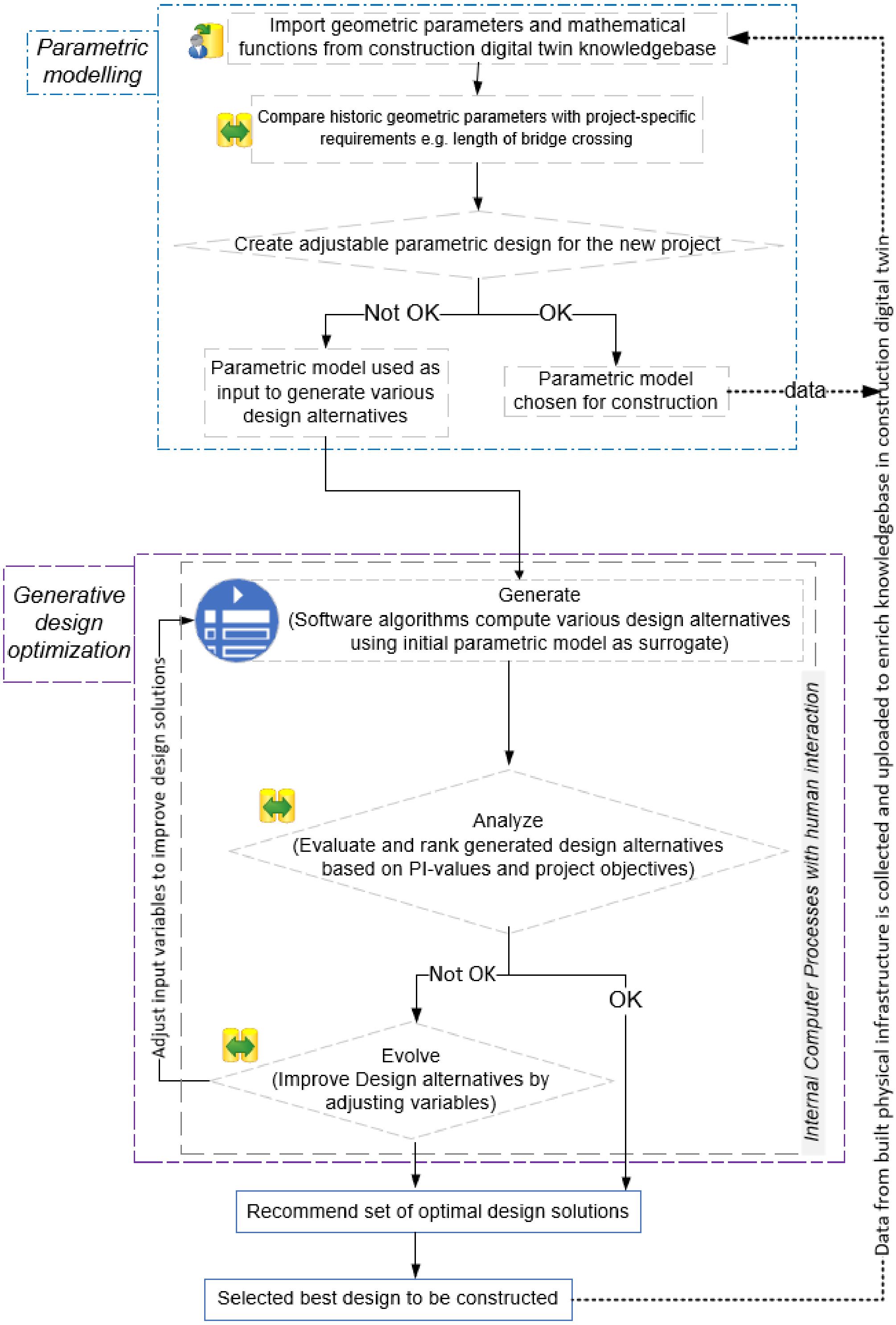


Figure 3: Workflows for parametric modelling and generative design processes

2.1 Developing Parametric Models from Historic Data

Table 1 presents the parameters from the historic data included in D2.2's footbridges knowledge base. The data was used as parameter's ranges/limits and also as changing variables for the design optimization study. The changing variables related to footbridges include the segment length, deck width, deck thickness, carbon per area, time per area, and cost per area. However, since the historic data from D2.2 was based on the total deck area, the following assumptions were made in this study since the main basis of optimization considered was preferred to be based on the most optimal sizes for the deck components. In addition to assuming the total deck area as equivalent to the area of deck segments, other assumptions made were:

- The combined total length of split deck segments equals the total length of 210m which corresponds with the new footbridge length, and
- Volume is computed as the product of the length, width, and thickness. The computed volume is then multiplied by the material unit weight to give the weight of liftable deck segments. Furthermore, since steel was the most predominant material found in the historic knowledge base, the material unit weight of steel is used. This is further supported by the project requirements for a steel girder bridge, in this case study.

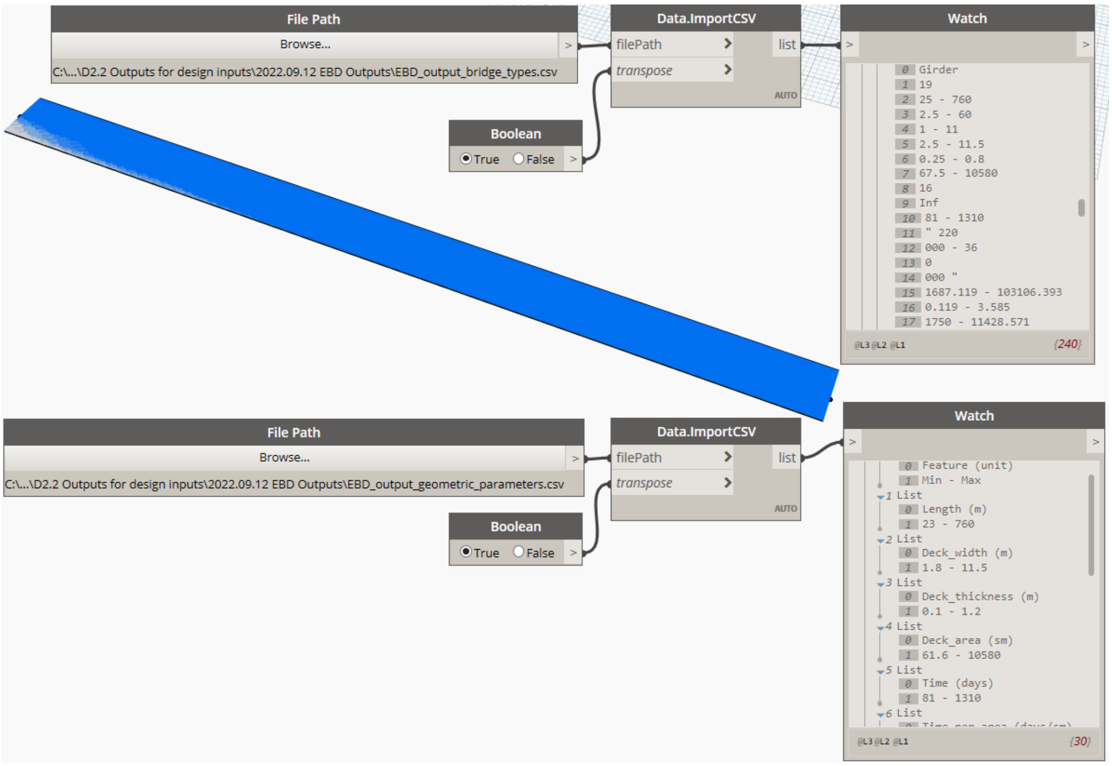


Figure 4: Parametric bridge design based on evidence-based design assistant's output

Figure 4 exemplify the import of the data from knowledge base in DynamoBIM to support the creation of the parametric model. DynamoBIM is an open-source tool supported by Autodesk, and is the tool used in this study to create the parametric model, that also enable the creation of the geometrical embodiments based on the provided input.

Table 1: Parameters extents from the evidence-based design assistant DT knowledge base

Changing variable parameter (unit)	Values (minimum – maximum ranges)	Treatment as design input
Length (m)	23 - 760	Applied ranges of (23 - 50) and (50.05 - 760) as lower and upper limits, respectively for the generative design optimization process. However, in this study this parameter is constrained to 210m, corresponding with the project-specific requirements for bridge crossing.
Span (m)	2.5 - 216.7	*Not considered to simplify the model*
span_num (-)	1 - 11	
deck_width (m)	1.8 - 11.5	Applied ranges of (1.8 - 3) and (3.05 - 11.5) as lower and upper limits, respectively for the generative design optimization process.
deck_thickness (m)	0.1 - 1.2	Applied ranges of (0.1 - 0.5) and (0.55 - 1.2) as lower and upper limits, respectively for the generative design optimization process.
deck_area (m^2)	61.6 - 10580	Not considered. Instead, actual area is computed based on generated geometry
pylon_height (m)	7 - 52.4	*Not considered to simplify the model*
pylon_diameter (m)	0.66 - 1.2	
Construction time (days)	81 - 1310	Applied ranges of (81 - 500) and (500.05 - 1310) as lower and upper limits respectively, for the generative design optimization process.
Construction time per_area (days/m^2)	0.1 - 5.4	Applied ranges of (0.1- 3) and (3.05 – 5.4) as lower and upper limits respectively, for the generative design optimization process.
Construction cost (€)	220000 - 36000000	Not considered
Construction cost per_area (€/m^2)	1750 - 22727.3	Applied ranges of (1750 - 10000) and (10000.05 – 22727.3) as lower and upper limits respectively, for the generative design optimization process.
Construction carbon footprint ($kgCO_2e$)	1687.1 - 103106.4	*Not considered*
Construction carbon footprint	9.3 - 42.8	Applied ranges of (9.3 - 25) and

Changing variable parameter (unit)	Values (minimum – maximum ranges)	Treatment as design input
per_area ($kgCO_2e/m^2$)		(25.05 – 42.8) as lower and upper limits respectively, for the generative design optimization process.

In addition to the changing variables, the design constants and constraints were adopted based on project-specific requirements (see Table 2). Using the imported data, the 3D parametric model of the bridge was built (see Figure 5) in the Dynamo™ tool by locking the actual length to 210m. Other footbridge features included the width (W) and thickness (T) of the footbridge deck that were varied in between the ranges extracted from the knowledge base data. Additionally, the segment length (L) was included in the study to analyze the impact of various segmentation strategies with connection to the construction phase.

Table 2: Constant and constraint parameters from project-specific requirements

Constant and Constraint Parameters	Value	Reference source
Constants (unchanging parameters)		
Loads (kg/m^2)	500	Client specifications of traffic load estimations
Material unit weight (kg/m^3)	7850	Based on the dominant steel material in the DT's knowledge base
Constraints (fixed parameters)		
Total length of bridge crossing (m)	210	Site constraint for bridge crossing requirement

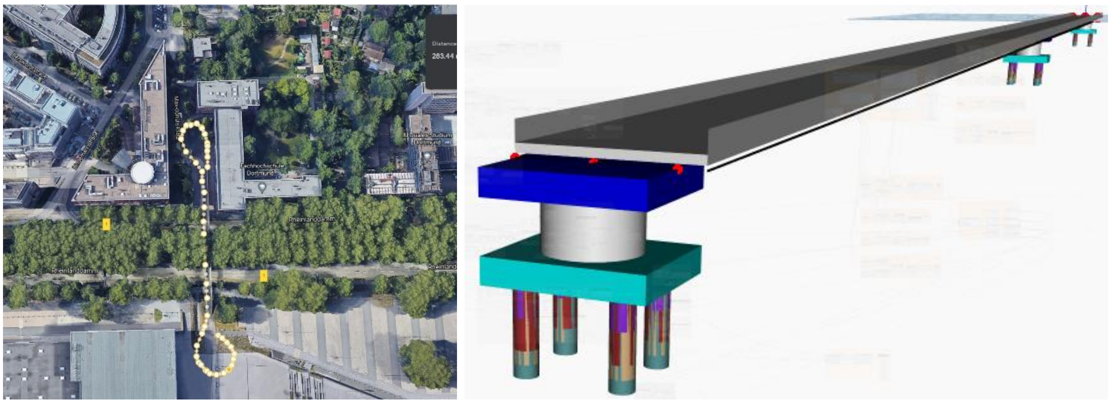


Figure 5: Bridge axis (left) and a footbridge design alternative generated using the parametric model created with Dynamo™ (right)

The following subsection describes briefly the mathematical functions for KPI calculation to support the analysis of the generated design.

2.2 Evaluation of Design Alternatives and Design Optimization

Various design alternatives can be generated using the parametric model developed in the previous section. Yet, these alternatives form the basis for the decision making, and to enable an informed decision-making process, each design alternative need to be evaluated according to a set of KPIs defined by the project team.

Resulted in D2.2, the mathematical functions in Table 3 were coded in the Dynamo environment as custom nodes for computing performance indicator values (PI-values). Each of the models (mathematical fitness functions) specifically address four KPIs of construction resource-efficiency – carbon footprint, construction cost, productivity – construction time, and construction safety – liftable weights.

Equation #1 computes carbon footprint as a function of the deck segment length, deck width, deck thickness, deck segment area, and construction carbon footprint per unit area. It calculates the corresponding carbon footprint for each generated design alternative. Different solution options are explored to give all possible design solutions. The deck area changes according to the different multiples of deck segment lengths and deck widths. The objective for the optimization fitness function is to minimize the carbon footprint. Then, the computed values obtained are the optimization results of the various design alternatives and it is part of considering the resource-efficiency KPI.

Equation #2 computes cost as a function of the deck segment length, deck width, deck thickness, deck segment area, deck segment volume and the construction cost per area. It calculates the corresponding carbon footprint for each generated design alternative. Different design solution options are explored and their corresponding construction cost is calculated. The objective for the optimization fitness function is to minimize the construction cost. The computed cost values obtained are the optimization results of the various design alternatives and it is part of the cost KPI.

Equation #3 computes time as a function of the deck segment length, deck width, deck thickness, deck segment area, deck segment volume, and the construction time per unit area. Different design solutions options are explored based on the variable parameter ranges and their corresponding construction time is calculated. The objective set for this variable for the optimization of fitness function is to minimize the construction time. Then, the computed values obtained are the optimization results based on the automatic exploration of the various design alternatives. Construction time is part of the productivity KPI.

In a similar way, equation #4 helps compute weights of deck segments as a product of the deck segment length, deck width, deck thickness, and the unit weight, and material weight unit. Different design options are explored and the corresponding weight for the segments is calculated. The objective set for this variable for the optimization fitness function is to minimize the weight of the deck segments. Then, the computed values obtained are the optimization results based on the automatic exploration of various design alternatives. We consider weight of the deck segments linked to the safety KPI, in regards that the weights of deck segments for planning adequate equipment lift capacities. Construction safety planning considers adequate equipment lift capacities which correspond with the weights of physical components to be lifted and installed during construction. For example, from the optimization results of this study, the equipment-capacity should consider the maximum weight of 20205.941 tons. Knowledge of this information supports informed decision-making for planning adequate equipment capacities during construction. It may also be possible to explore the possibility of extracting such related information from existing 3D geometrical models.

Table 3: Mathematical functions from D2.2 (2022) knowledge base

#	Mathematical functions embedded as fitness functions in Dynamo™ custom nodes
1	$\text{Carbon footprint [kgCO}_2\text{e]} = 4128.9\ kgCO_2e - 442.3\frac{kgCO_2e}{m}\cdot L - 5333.9\frac{kgCO_2e}{m}\cdot W + 38107.0\frac{kgCO_2e}{m}\cdot T + 189.9\frac{kgCO_2e}{m^2}\cdot L\cdot W - 219.2\frac{kgCO_2e}{m^2}\cdot L\cdot T$
2	$Cost\ [€] = -1495436\ € + 22696\frac{€}{\mathrm{m}}\cdot \mathrm{L} + 393660\frac{€}{\mathrm{m}}\cdot \mathrm{W} + 3751242\frac{€}{\mathrm{m}}\cdot \mathrm{T} - 3948\frac{€}{\mathrm{m}}\cdot \mathrm{L}\cdot \mathrm{W} - 945\frac{€}{\mathrm{m}}\cdot \mathrm{L}\cdot \mathrm{T} - 748154\frac{€}{\mathrm{m}}\cdot \mathrm{W}\cdot \mathrm{T} + 2583\frac{€}{\mathrm{m}}\cdot \mathrm{L}\cdot \mathrm{W}\cdot \mathrm{T}$
3	$\text{Construction time [days]} = 84.92\ days - 4.4\frac{days}{m}\cdot L + 10.65\frac{days}{m}\cdot W - 2.16\frac{days}{m}\cdot T + 1.99\frac{days}{m^2}\cdot L\cdot W + 7.99\frac{days}{m^2}\cdot L\cdot T + 23.76\frac{days}{m^2}\cdot W\cdot T - 2.59\frac{days}{m^3}\cdot L\cdot W\cdot T$
4	$\text{Weight [T]} = \frac{L\cdot W\cdot T\cdot \text{unit weight}\frac{\mathrm{Kg}}{\mathrm{m}^3}}{1000}$

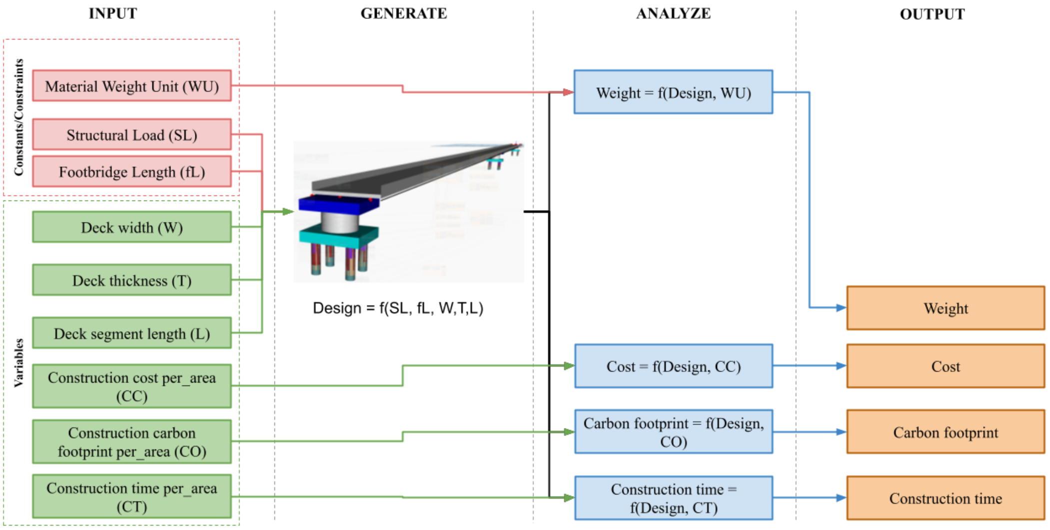
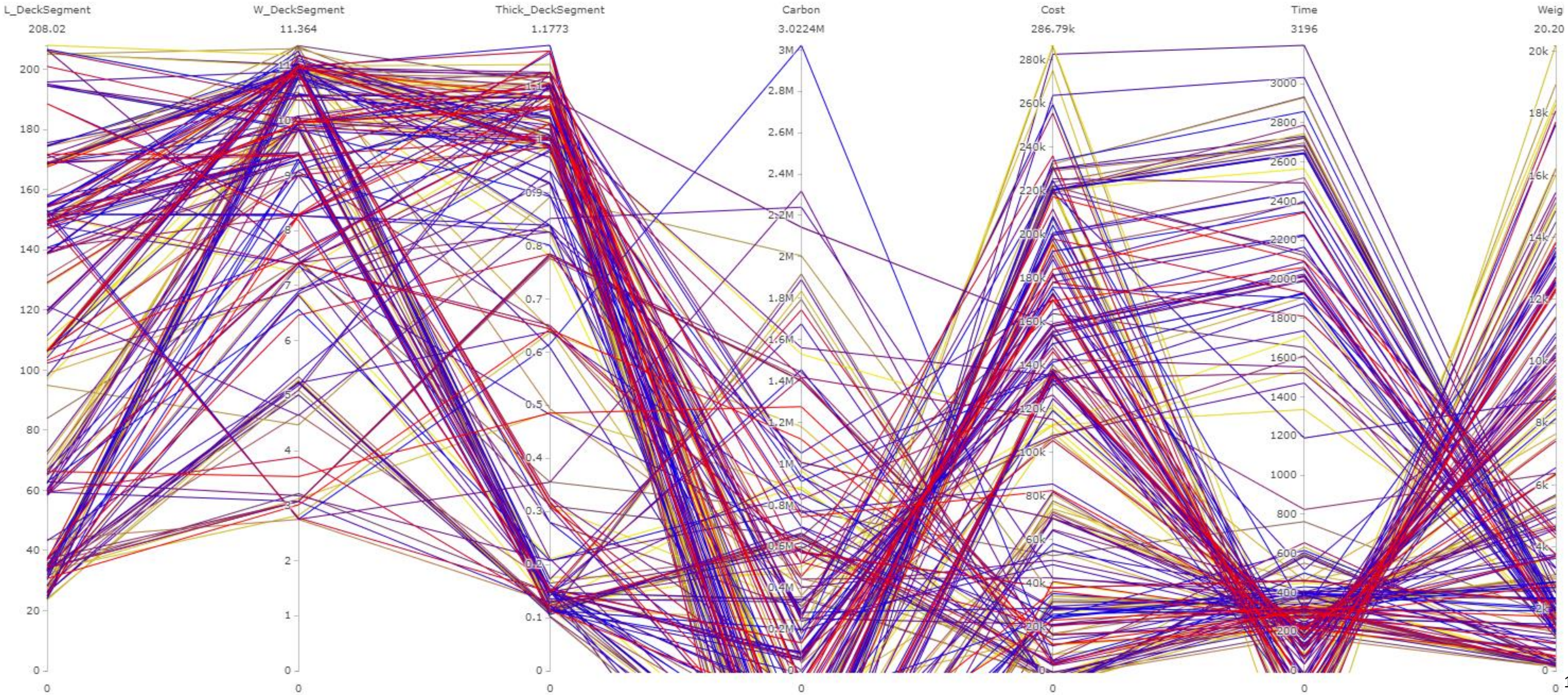


Figure 6: The concept of the parametric model

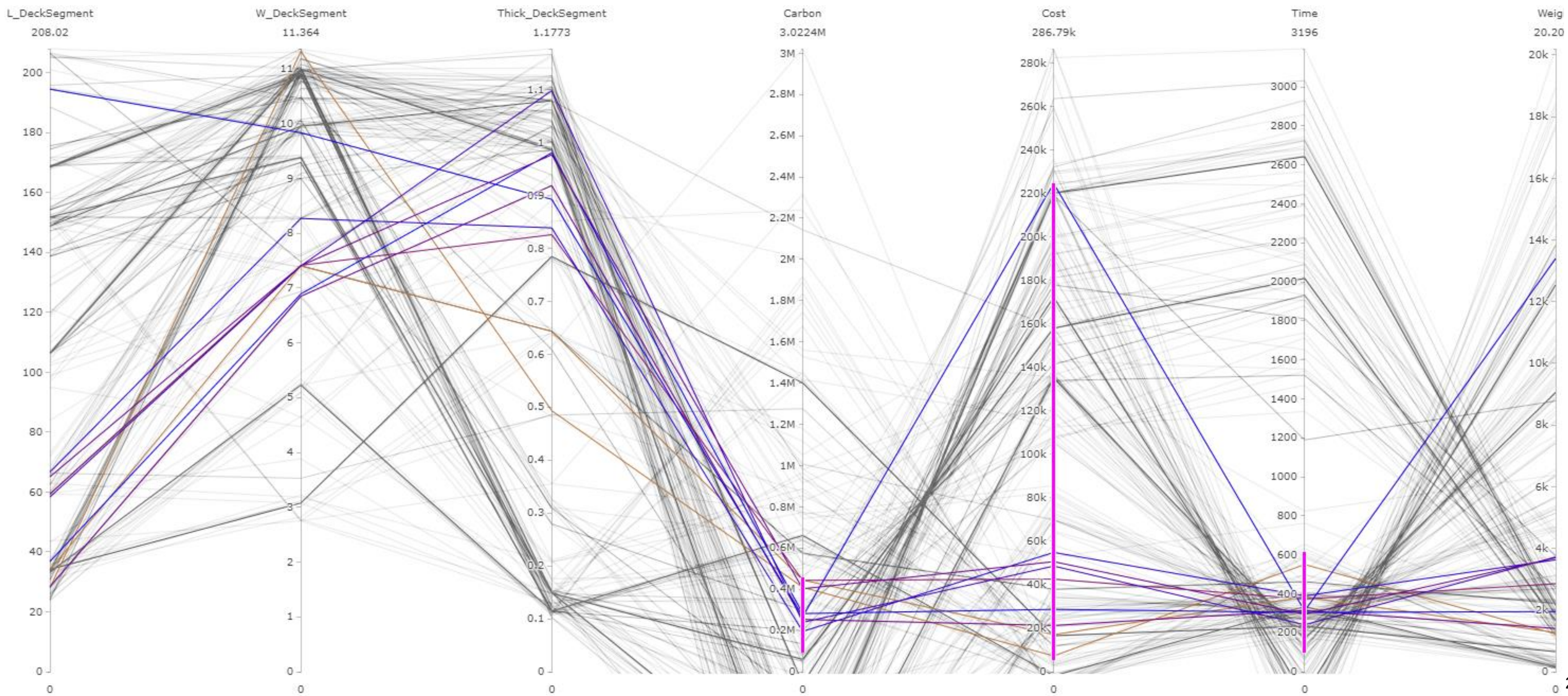
Figure 6 presents the visual workflow of the generation and analysis of design alternatives conceptual model. Based on this, the generated design alternatives (see Figure 7) are visually presented using the parallel plot coordinates. On the left side are presented the input variables and on the right side are shown the outputs. Each line each design variable and output parameter represents a design alternative. Figure 8 uses the pink-coloured brushes to highlight the design options within specific ranges of the PI-values.



[1]

Figure 7: Various design alternatives which are computationally generated

[1]Each line represents one design solution. The erroneous solutions with negative values were truncated.



[2]

Figure 8: Filtering of designs based on desirable ranges of KPI-values

[2] The pink-colored brushes highlight selected designs within the specified range of KPI-values.

The optimization problem is set as a multi objective optimization, with the purpose of minimizing the objectives set for each output parameter and fulfil the constraints. To automatically iterate over various design alternatives (with the scope of generate, analyse, assess each one of them) an optimization algorithm is employed. In our case we chose genetic algorithm.

Figure 9 shows the set of pareto-optimal design solutions which are recommended for construction as they provide a good trade-off between the set of objectives. The pareto-optimal designs are those non-dominated solutions. Table 4 gives the geometries and KPI-values for some of the recommended designs based on the results of KPI-values.

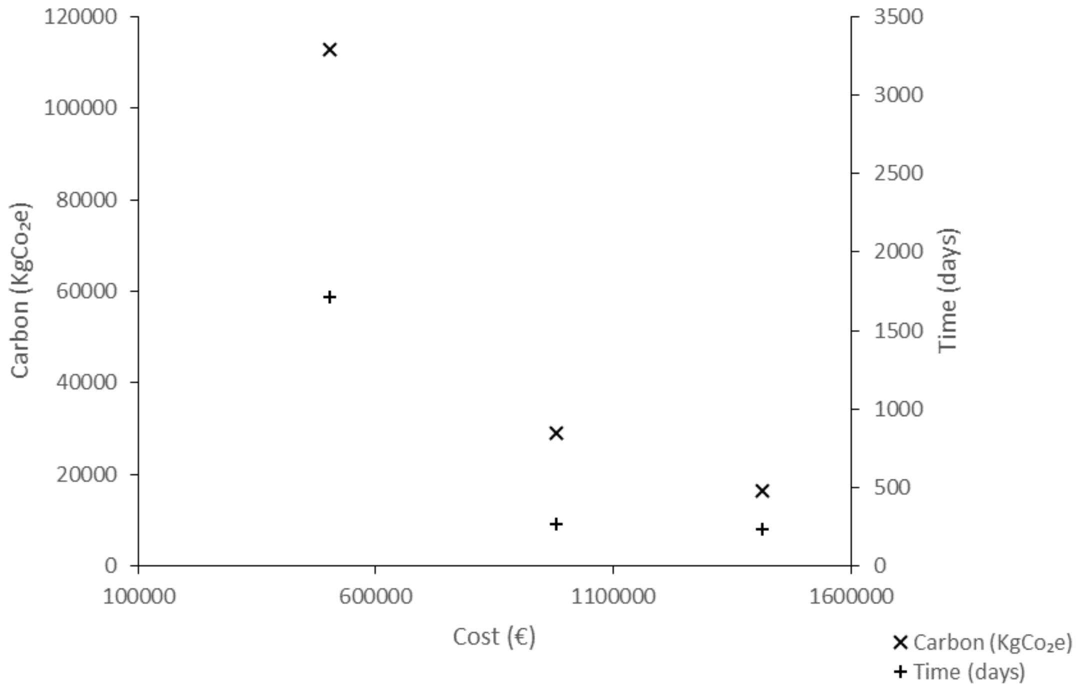


Figure 9: Set of pareto-optimal designs based on carbon, cost and time KPIs

Table 4: Geometries of the recommended pareto-optimal designs

Deck segment length (m)	Deck segment width (m)	Deck segment thickness (m)	Carbon ($KgCO_2e$)	Cost (€)	Time (days)	Weight (T)
36	3	0.776	16283	1414059	236	672
33	5	1.128	29127	981158	269	1490
105	11	0.123	112904	502038	1712	1061

2.3 Delimitations

The designs developed are limited to the historic data available in the knowledge base. This implies that the developed designs are deterministic and limited to the geometric parameters and mathematical functions established from the historic database. This means that when organizations develop good knowledge bases, the overall quality and variety of models will be improved.

The computationally generated designs be sorted to eliminate erroneous solutions as the ones shown in Table 5, for example.

The mathematical functions from the historic knowledge base in D2.2 (Merz & Ongodia, 2022) are experimental, yet it serves as proof of concept for the proposed data-driven approach. Functions which comprise of majority geometric features are better to use than those which consider only a few features. For example, model experimentation was done using $cost_{model4}$ and $cost_{model5}$ because both had high regression coefficients of 0.943 and 0.989, respectively. $Cost_{model5}$ performed better and was therefore adopted in this study. This implies that designers can independently assess the functions and adopt the most suitable option. This enables transparency in design and enables designers to understand the basis of developed design solutions.

Table 5: Examples of erroneous solutions

Deck segment length (m)	Deck segment width (m)	Deck segment thickness (m)	Carbon ($KgCO_2e$)	Cost (€)	Time (days)	Weight (T)
139	9	1.118	148077	181055	-115	11395
24	5	0.115	-6685	599992	277	110
24	9	0.141	-9033	1454721	500	247
201	10	1.126	236041	516870	-478	17727
24	11	0.141	-10331	1795002	589	292

In summary, productivity and safety in early-stage design are improved when the historic data from past projects is used. This is because the new early-stage design will be based on favourable values of the geometric parameters which ensure higher construction performance. This study demonstrates the application of insights from the historic data (geometric extents and mathematical functions) from D2.2's evidence-based design assistant. The geometric extents are used to develop the parametric model. This aspect supports safety in design since the developed model excludes mistakes of previous past projects. When various design alternatives are required, the mathematical functions are used in the optimization study to generate various design alternatives. This aspect improves productivity in design because many designs are generated at once.

3 CONCLUSION AND RECOMMENDATIONS

This chapter concludes the report and summarizes key points to support early-stage design. It uses insights from the historic data (geometric extents and mathematical functions) of past projects to improve safety and productivity in early-stage design. The geometric extents are used to develop the parametric model. Safety in design is improved since the developed parametric model avoids mistakes from past projects. The mathematical functions are used in the generative design optimization study to computationally generate various design alternatives. This aspect therefore improves productivity in design since various designs will be easily created and modified quickly.

To further support decision-making, the recommended designs can be visualized in 4D to enable designers understand the ramifications of their design choices, but this does not fall within the scope of the current report.

We further recommend automating the process to develop designs directly from historic data knowledge bases, including values of carbon footprint data related to both material resources and energy e.g. fuel for construction. DT in construction should track this and feedback into future design projects.

4 REFERENCES

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