Performance-based, AI-ML-assisted Generative EA Design with Bio-inspired Topological Optimisations of a 50m, 3D-printed Steel Bridge

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***Abstract*—AI-ML-assisted Generative Design (GD) using Evolutionary Algorithms (EA) techniques and Topology Optimization (TO) has undergone massive growth over the past few years. As a result, AI and GD have essential applications in many fields, such as Industrial & Product Design, Medicine, Synthetic Biology, Infrastructure, Architecture, Engineering & Construction (AEC). This research paper discusses the performance-based workflows for AI-ML assisted, cloud computation and EA-driven Generative Design with topological optimisation to reduce weight and cost. The discussed research is a lightweight real-world hybrid, awarded 50 m robot 3d-printed bluemint®steel bridge design and off-the-shelf steel tube prefabrication in Germany, completed in June 2023. [3] The generative bridge design with finite element structural analysis (FEA) and cloud-driven deep neural network (GNN) scenarios will demonstrate the largest 3d-printed Wire-and-arc Additive Manufacturing (WAAM) pedestrian/bicycle bridge inspired by biology worldwide.**

***Keywords*—artificial intelligence, evolutionary algorithm, generative design, topological optimizations, additive manufacturing**

I. Introduction

A. *Location and Criteria for the 80 to 50 m Bridge Scenario and Realization Competition*

The assembly location for the bridge is in the Rhine estuary area of the small Emscher river. It is still an area of inaccessible post-industrial land to the general public, with sealed-off brownfield areas. The overall public park design includes the regeneration of the estuary remnants of the industrial era to provide a public, accessible future park location. A competition was held for an 80 to 50 m connection bridge structure, of which the author's team from Miami-Berlin won the commission. Many land surveys, lidar surveys for the WWII bombs, and inventories of existing plants and animals, along with an analysis of the impact on the environment, were undertaken over two years. Due to the diverse soil, hydrologic, and multiple bridge structure loading conditions, a lightweight material-reducing micropile foundation with three micro pylons was designed beyond the sensible existing tree root zone. These considerations had the benefit of making prefabricated bridge modules portable for transportation, assembling them using small machines, with a helicopter flying from the barge on the Rhine, as shown in Fig. 1.

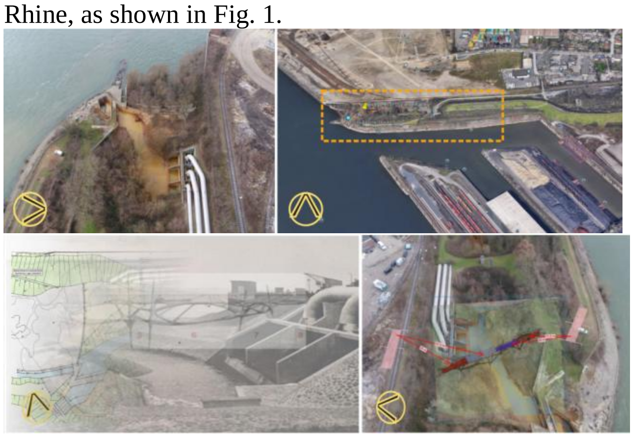

Figure 1. Site view of the park (left), digital twin for the bridge (middle), and assembly location. Source: ©Thomas Spiegelhalter.

II. Methods

A. *AI-ML-assisted Topology Optimization and Generative Design with Graph Neural Networks*

Topology Optimisation (TO) has been around for 20 years but is not a Generative Design. TO usually starts from a single, fully-formed, human-biased, design-cad template concept, with loads and constraints applied according to project requirements [1]. TO only outputs an optimized concept to evaluate from a human-designed model [2]. There is no automated generation of ideas. Finally, it returns an optimized, man-made result of the mesh model that needs to be recreated within a CAD system intended for downstream usage. Generative Design (GD) is a cloud-based, artificial intelligence-enabled modelling-driven design method using GA/EA algorithms to generate high-performance geometries from users' defined engineering requirements [3]. It has excelled in available cloud subscriptions since 2018. The GD for the bridge competition starts with designing preserved areas,

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transition zones, loads, and constraints according to design requirements. AI, rather than humans, defines topological cloud design results created for later evaluation. Furthermore, setting performance parameters and materials components was automated with text-based guidance using a Graph Neural Network (CNN) over data described with Graphs within the non-Euclidean design space [4, 5]. Several Generative Designs (GD) tools are commercially available in design and engineering, including Altair's OptiStruct, Dassault Systemes CATIA V6, SolidWorks, Bentley, Autodesk's Revit-Dynamo Studio, InventorPro, Fusion360, Nastran, Netfabb Shape Generator, Grasshopper-Rhino, and Siemens NX SolidEdge-Frustum. But only Autodesk GDs work fully integrated with the cloud-based storage that supports the AI; other brands still work only locally, as limited versions. The Evolutionary Algorithm (EA) for the most natural-looking growing-like design and the Genetic Algorithm (GA) were tested and compared in iterations of generative bridge designs.

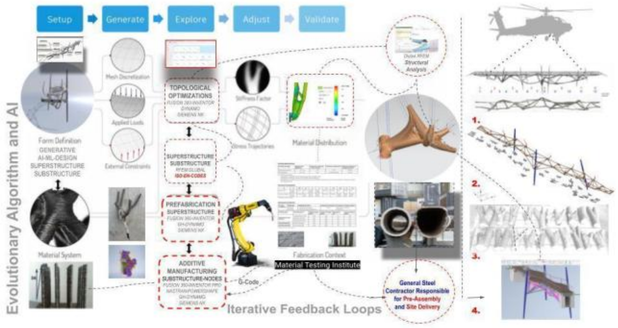

Figure 2. AI-assisted Generative Design Cloud, Iterative Feedback Loops, and Topological Optimization for Additive Manufacturing Flowchart. Source: ©Thomas Spiegelhalter, 2022.

B. *Algorithms and ML for the Generative Design Iterations of the Bridge Competition and Realization*

An Evolutionary Algorithm (EA) is an algorithm that uses natural mechanisms and solves problems by processes that mimic living organisms' behavior. EAs are components of both evolutionary computation and bioinspired computation. Genetic Algorithms (GA) are methods of solving constrained and unconstrained optimization problems based on natural selection, a process driving biological evolution. The GA automatically tweaks the population of single solutions over hundreds of cloud-computing FEA iterations and ideas. In cautious terms, artificially intelligent generative design is the next frontier of design and engineering product development, as it reverses the paradigm for creating and evaluating a projects design performance using artificially intelligent, human-free scripted experiments, rapidly integrated production results, materials results, and cost comparisons, as well as assembly strategies. Furthermore, GA is a common example of a meta-heuristic search algorithm that can examine the parameters model of the black box to discover the best-performing design according to several objectives. (6). The GA is used during the early stage of the design process, autonomously creating hundreds of designs according to performance-based parameters inputs, materials, and production types to lower the weight and production costs. The integrated decision-making also drives the aesthetics through a cloud-modelling of the CAD results that can be edited, highlighting organic growing patterns and lightweight architecture (7). Chapter D describes the methods for prefabricated off-the-shelf components and robot-assisted 3D printing, such as Wire-Arc Additive Manufacturing (WAAM) or laser powder bed printing.

III. Results of Methods 1–8, Iterations and Validations

For this experimental bridge design, Autodesk robot-assisted Structural Analysis, InventorPro, Netfabb, Nastran, CFD Ultimate, ANSYS, and a Fusion360 cloud subscription were used, together with SIEMENS NX and the stand-alone RFEM Dlubal 3D finite element analysis software (Figs. 2–5). Each experimental GD workflow consisted of multiple criteria entry steps depending on the difficulty in setting up a GD workspace for AI-ML-assisted cloud computing. The setup involved running a cloud-based GD search multiple times, with hundreds of outcomes. The first bridge design showed a growth-looking 80-meter-long arching bridge topology. The geometry was based on a starter shape geometry, with a primary structure over a preserved bridge deck geometry. The winning submission in the contest's third bridge design focused on different parametric inputs for load distribution from the 50-meter-long main structure below the preserved bridge geometry and the circulation decks via seven micro-piles over the river estuary.

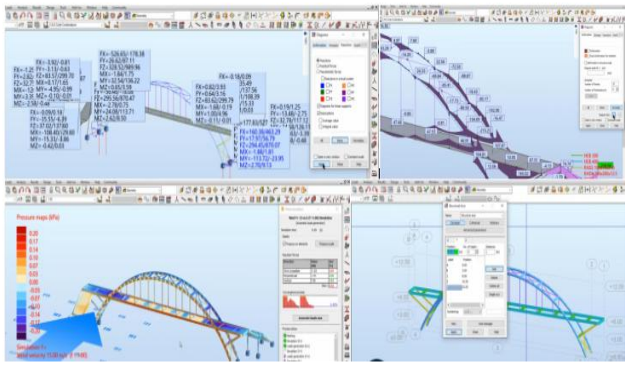

Figure 3. Autodesk Robotic Structural Analysis as a Euclidean standard design solution. Source: ©Thomas Spiegelhalter, 2021.

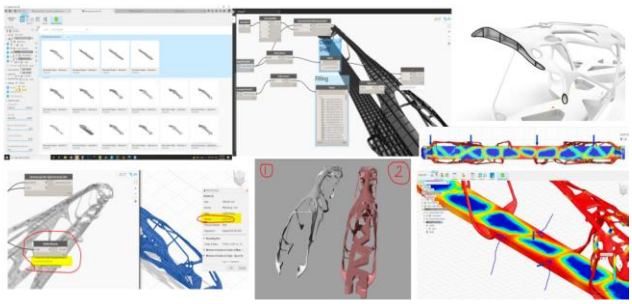

Figure 4. Autodesk InventorPro/Fusion360 Generative Design with organic experimental GA/EA workflows and Dynamo Scripting to topologically optimize the weight and material choices for fabrication. Source: ©Thomas Spiegelhalter, 2021.

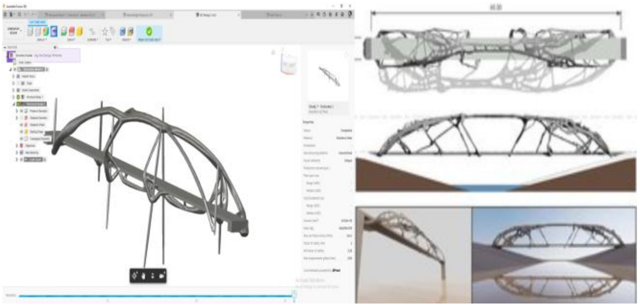

Figure 5. Autodesk Fusion360 Generative Design with organic experimental GA/EA workflows and Dynamo Scripting to topologically optimize the weight and material choices for fabrication. Renderings in Revit-BIM Vers. 2022. Source: ©Thomas Spiegelhalter.

A. Methods 1–2: Design Space, Geometry Optimizations, Load Iterations, and Validations

This time, the preserved geometry with boundaries (the keep in's) stayed in the final modelling space of the starting shape (such as nodes and connection points between tubes and pylons) under the preserved geometry, and the scaled obstacle geometry with the constraints (the keep-outs, clearances). The concrete abutments and micropile foundations were separately computed with other FEA software to calibrate and merge the results into the shared cloud Masterfile. The next step included coding all the relevant structural design conditions and load types based on Eurocode 3 (EN 1993/EC 3). The GD-model settings include the following: Self-weight (0.5 kN/m^2 and 78.5 kN/m^3), vertical and horizontal payloads (5.0 kN/m^2), structural Buckling, nonlinear Stress, and dynamic loads such as modal frequency quasi-static event simulation, dynamic event simulation, wind load, water load, impact loads, and thermal stress loads [8], as shown in Fig. 4–7.

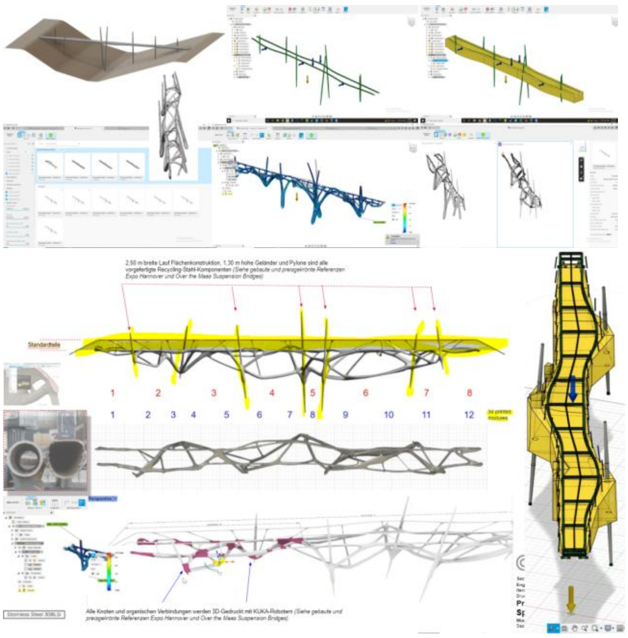

Figure 6. Autodesk InventorPro/Fusion360 Generative Design space, constraints, obstacles, offsets, with genetic and evolutionary Algorithms (GA/EA) and Dynamo Scripting. Source: ©Thomas Spiegelhalter, 2022.

B. Methods 3-8, Iterations and Validations

One of the early intentions was to 3d-print the entire award-winning bridge in stainless steel (SS 308Lsi). Printing the whole structure would take about 11,630 hours for a WAAM 3D printing or about 2,080 hours for printing using more than six Kuka robots. Additionally, it would need 3,488kg of spent wires, X number of gas tanks with protection, and 58.147kWh electricity, all costing around 1,3 Mio. Euros before taxes (including delivery), not including the cost of the project design and planning, permitted simulation tests, and other license fees. Moreover, tying green park schedules with the schedules for several other integrated construction processes in just months made waiting more than one year to have steel bridges printed impossible. The initial desire to only robotically print a world-large steel bridge was rapidly scaled back towards more economically feasible designs. The decision evolved towards striving for a hybrid design with a balanced mixture of prefabricated steel tubes and 3D-printed nodes and posts for handrails to preserve the organic growing aesthetic of the final lightweight bridge design. Within FEA and RFEM structural fitness iterations, pylons were reduced from seven to just three. The initially uncentred growth nodes in hollow tubes were centered, drastically reducing printing costs. The resulting price inquiries and bidding showed a 225% cost reduction. Other challenges include combining data from the additive manufacturers for their various robot G-codes to handle the interference with little cleaning up of files and coding the machine's paths. All computational workflows for the Autodesk simulation mechanical/multiphysics were based on Autodesk simulation Accuracy Verification Examples (AVEs) from NAFEMS USA Benchmark publications [8–10].

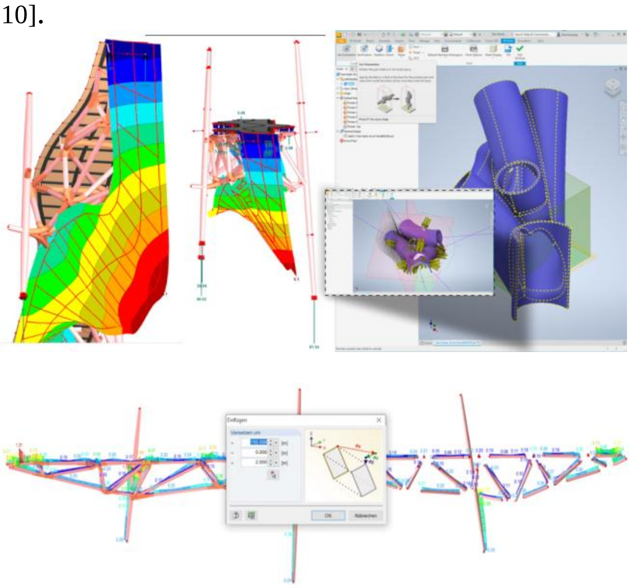

Figure 7. Autodesk InventorPro-Nastran and RFEM Dlubal structural analysis of the non-centred 3d-printed components with fitness tests and optimisations. Source: ©Thomas Spiegelhalter and M. Pfeifer. 2002.

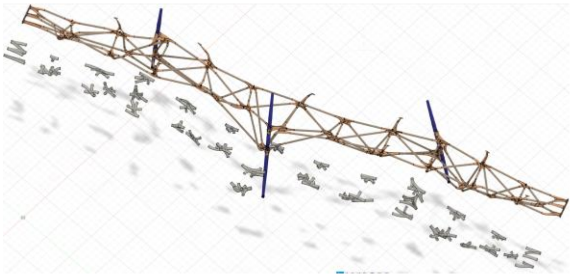

Figure 8. Autodesk InventorPro/Fusion360 Topological Optimizations (TO) of the nodes and entire geometry, with RFEM tests in Dlubal and Dynamo-Grasshopper. Source: ©Thomas Spiegelhalter, 2022.

C. *Artificial Intelligence, Aesthetics Constraints and Workflow Validations*

Once a final geometry was chosen, with all steel tubes centred on the nodes, and analyzed further using topological optimization (to), it was evident that an organic aesthetic was most attractive with the steel tubes not centered on the nodes. Typically, following the stochastic process relies on sampling from a finite number of designs in the GD space. In this context, it is also important to point out that GA-based workflows with metrics and EA cannot capture the human perception of the bridge aesthetics. These aspects, like the beauty, cannot be quantified, so they must be considered manually after a GD is completed and geometry exported for further processing. The original GD and optimized models,

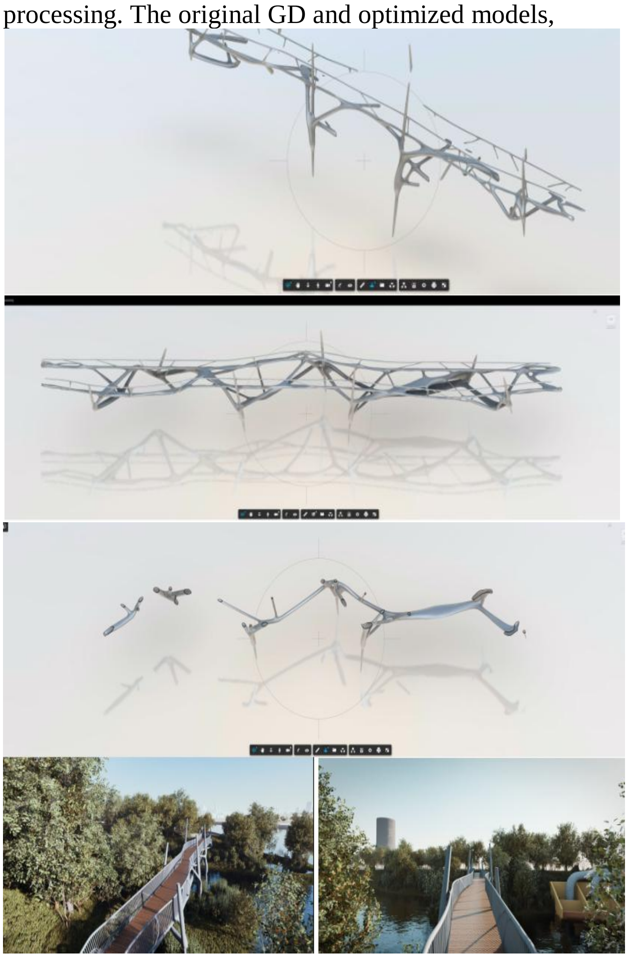

Figure 9. Autodesk InventorPro/Fusion360 perspectives and renderings in Autodesk Revit, Maya and Alias. Source: ©Thomas Spiegelhalter, 2022.

Which have organic growing-like non-centred geometry, are less performant and heavier than models with centring geometry. The end-iteration process included many 1:1 ZOOM workshop sessions on software with the additive manufacturers discussing robotic G-codes and WAAM or laser print capabilities. Then, the German Institute of Steel phase for approvals towards EU-code compliance and permits required further elaboration, as shown in Figs. 8–9.

Figure 10. Autodesk InventorPro/Fusion360 perspectives and renderings in Autodesk Alias and V-Ray. Source: ©Thomas Spiegelhalter, 2022.

IV. Conclusion & Future Work

This research-led realization project demonstrates an innovative AI-assisted computational design approach with deep neural networks that combine bottom-up evolutionary agents-based geometry models for growth processes found in natural systems with top-down genetic algorithms for optimisation. The many iterations with different software applications of these methods to designing a unique steel bridge using optimized 3-D robot WAAM, Laser Printing, and BlueMint() additive manufacturing processes paid off. The finding was clear by performing eight iterations with hundreds of cloud scenarios over four different selected design models for further optimisations: The purely organic growing non-centred geometries were aesthetically more convincing. But in contrast, the multiphysics iterations optimized the configurations in real-world settings to achieve an economical and sustainable mixed additive manufacturing process. As a result, the weight of the hybrid bridge made from a balanced mix of 3D printing and prefabricated steel was reduced dramatically, helping minimize overall production costs. Finally, the developed hybrid computational methods suggest further studies on developing other generative EA workflows with naturalistic deep neural networks using deep GNNs. These could expand evolutionary computing capabilities, excelling higher-performance production solutions and reducing costs.

Conflict of Interest

The author declares no conflict of interest.

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