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Generative Urban Design in the Field of Infrastructure: An Optimizing Solution for Connecting Fier and Vlora County by a 600 m Bridge over Selenica River, Albania

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The way we think about infrastructure is being completely changed by parametric and generative design. Meanwhile the contemporary urban planning process is often viewed as a complicated and fragmented workflow. The main goal is to optimize solutions with tens of thousands of variations while concurrently taking into consideration various limits. This Paper will discuss and demonstrate the use of a generative urban design framework at the local scale. Although relevant to infrastructure, generative design is not limited to architecture. And on the other hand, the construction sector is becoming more specialized and complex. The close cooperation between structural engineers, architects, urban planners and other stakeholders is a major driving force behind modern projects. The building site is cut off from architects and engineers, particularly in the digital age. To ensure a three-dimensional scope of work, digital models are therefore necessary. The difficulty is that the structural model and architectural model do not match up exactly. A generative design is therefore explained in the case of a bridge design. Bridges are effective structures that provide a variety of topologies, materials, and geometries. This paper examines how the geometry and topology of a 600 meters long bridge can bring an optimal solution for connecting two nearby counties, Fieri and Vlora. The performance of the bridge can be examined by altering the geometrical parameters in addition to the topology. By adding more design factors and offering a fresh method for bridge optimization, the study aims in further developing the initial parametric model. Since the process of changing the design is quite quick and the analysis is displayed instantly, using parametric design to study alternative options for bridges could be highly helpful to designers.

Keywords: *generative design, bridge, geometry, typology, optimization, deflection.*

Introduction

The generative urban works in fact count for many urban aspects and corresponding structures. One of them is related to terrain modelling and road planning which several times go hand in hand. However, developing them in 2D poses numerous difficulties and frequently results in time lost through rework. Road and infrastructure engineers may need to start the same project over more than once due to their conflicting perspectives and that of numerous other

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stakeholders. This re-work can be avoided by using a parametric road modelling software solution, which makes road design and terrain modelling considerably simpler and more effective. The road body can be modelled once the terrain's surface and axes have been established. There are several plugins that help towards employing a template-based modelling strategy, which has the benefit of being highly flexible.

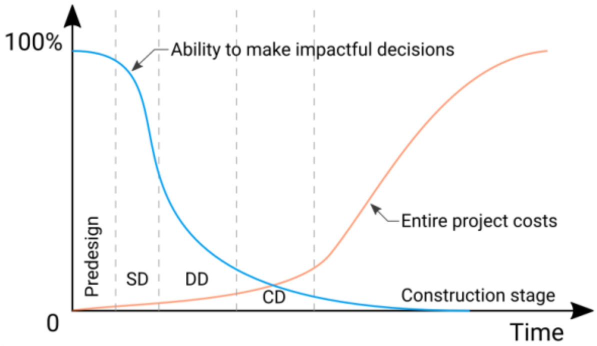
There are four templates that define the fundamental road geometry:

- The road layer structure, standard width, vertical offsets, and lane count are all specified in the cross-section template.
- All of the parameters for the substructure are defined in the sub-base template.
- Every shoulder, ditch, slope, and wall are defined using the roadside templates.
- The calculation parameters for the model are defined by the land requirement template.

The templates are allocated to the axis after they have been constructed. Of course, by setting the inlet and outlet distances, the transitions between adjacent templates are automatically made. A road body's geometry can vary a lot and in this regard the plugins offer numerous detailing functions to improve the structure, preventing the need for hundreds of templates for tiny variations. The templates allow for the overwriting of all previously set parameters to meet specific criteria. The above example of the road preliminary design aspect are very much related also with the bridge design as one important element of the whole terrain modeling.

Nevertheless, it is important to intiate explaining the broad concept of the generative urban design. And in this regard, the three main elements of the generative design process are based on how natural processes create shapes in complicated patterns (Krish 2011). There are several advantages to using these essential elements in product design. The first step is to create design solutions that are effective, resilient and compatible. The use of digital technologies and algorithms to generate a huge number of workable design directions comes in second. The third step is to design beautiful, dynamic forms and patterns.

Figure 1. *Predesign and Schematic Design Stages are when the Majority of Critical Decisions that Affect the Design and Cost of Construction are Made*



Source: BLOG on AEC Innovation. https://www.invokeshift.com/thoughts-on-the-future-of-generative-design-in-aec-from-an-engineering-perspective/.

There are numerous ways to integrate generative design into the design process and by the perspective of a designer, the majority of methods fall into two broad categories: *i) by subtraction* and *ii) by addition*. Parts of a product are examined based on their strength or durability during a subtractive process in order to remove superfluous pieces while preserving performance. Utilizing techniques like shape optimization, trabecular structures, and lattice design, this strategy is accomplished (Autodesk, Inc 2018, Singh and Gu 2012). A subtractive technique has a very short learning curve, although it also originates from too precise designs and offers only minor advancements over existing options. An additive technique produces a wide number of viable solutions that satisfy the design objectives and limitations for a particular challenge.

There are many techniques for additive generative design, including tabernacle structures. Although the generative design far exceeds what human capability could produce on its own, it also makes it difficult to develop algorithms that function as expected, let alone to choose viable and desirable solutions from among the many options generated (Cui and Tang 2012). The role of the designer, who works with computers to create systems that are sophisticated, linked, robust, and novel, is at the centre of this process (McCormack et al. 2004). The authors in fact mention also the iterative design process, a very interesting approach to the design phase too. The relationship between generative design and iterative design process offers an innovative framework where designers may feel at ease utilizing tried-and-true workflows and fusing them with cutting-edge technology, all of which results in more effective and compelling designs.

New strategies and technologies are required to help urban designers plan resilient and sustainable urban landscapes. Numerous computational methods have been suggested, such as automated production of urban design suggestions based on predetermined parameters or various types of spatial analysis to assess the effectiveness of design plans. However, the majority of these ideas have led to isolated tools and disjointed workflows. An appropriate computational representation of the urban design problem is one of the primary obstacles to merging urban analytics and generative approaches in the framework of urban design optimization procedures.

A comprehensive data representation for urban fabrics, including the organization of street networks and parcels, is offered to help overcome this challenge. This form may be effectively employed with evolutionary optimization techniques. It is shown how the data structure developed for the Grasshopper for Rhino3D software can be used as a component of an adaptable, modular, and extensible optimization system that can be applied to a range of urban design issues and can reconcile potentially incompatible design objectives in a semi-automated design process. The proposed case study method intends to help a designer by introducing possibilities into the design phase for deeper investigation. An urban design concept for the communities of Fieri and Vlora is used to illustrate how the system works.

The paper's objectives are to automate bridge modeling in the early design phases, to conduct a full analysis, and to optimize the bridge structure with regard to reinforced concrete material used. According to the study case's findings, designing bridges utilizing optimization and parametric design has some promise. Generative designs can be investigated with minimum effort from the designer with a strong parametric design description. A parametric design approach might be used for its ability to expedite the design process and give the designer access to adaptive design.

In order to analyze the effects of the bridge link for the counties of Fieri and Vlora over the Selenica River, a generative design approach was suggested in this regard. In addition to providing deeper understanding of potential conflicts and trade-offs between design goals, the case illustrates how the Generative Design method can produce effective design strategies. It was possible to demonstrate how, at the heart of generative design, there is always a choice of inputs and constraints that do not absolve the engineer or architect of responsibility but that can be gradually refined by further enhancing the generated strategies and resulting in a more informed design. This can be done by expanding the process to include the generative design for architectural space planning's evaluative component and outlining a new set of metrics for the automatic evaluation of end-user satisfaction inside the defined areas. As a result, when big datasets are available, machine learning can be a useful tool to enhance generative design. In terms of technology, it can attempt to use machine learning at any point during the generative design process.

The Historic Path

Study the past if you want to define the future, advised Confucius. We could get a clear picture of the development of design optimization techniques in architectural and urban design from a summary of historical development (Table 1). From this image, it is anticipated that the benefits (Table 2) and difficulties (Table 3) of the methodologies will be easier to comprehend from a historical standpoint. The development of design optimization methods and strategies to deliver the newest cutting-edge technology to satisfy the continuously changing requirements in architecture and urban design is equally fascinating to observe. This part should respond to the first query.

Prior to being scaled up to urban design, design optimization first appeared in architectural design. Attempts to use optimization techniques to solve design problems may be traced back to 1969 in academia thanks to Simon's ground-breaking paper on the "Science of Design" in his influential book "The Sciences of the Artificial" (Simon 2019). The optimization process was encouraged to be one of the many attempts to demonstrate the scientificity of architecture in addition to its inherently aesthetic aspect during this time, when architecture did not even have a well-established theory (Widdowson 1971). Architects navigate through and add elements one at a time to a rich combinatorial space, which Simon (1975) further characterized as the essence of design creativity. This definition perfectly aligns with mathematical optimization.

Table 1. *The Development of the Methods Used and Respective Instruments into Design Process*

Objects	Developments
1960s-1980s	the objective of a single optimization
1990s	methods instruments based in human logic
2000s	multi-objective simulation-based methods
2010s	methods using artificial intelligence

Source: Miao et al. 2020.

Table 2. *The Advantages of the Optimisation Methods in Different Periods of Time*

Objects	Advantages
1960s-1980s	the scientific framework of architecture in the architectural design
1990s	field design approach and new application methods in regard
2000s	emerged problems which are complex and the corresponding applications in urban design
2010s	technologies used in artificial intelligence and best practices to design phase

Source: Miao et al. 2020.

Table 3. *The Methods of Optimisation and the Challenges in Different Periods of Time*

Objects	Challenges
1960s-1980s	lack of mathematical models
1990s	CAAD community debates on topic
2000s	thriving scenarios
2010s	misalignment of design techniques and data-driven approaches

Source: Miao et al. 2020.

A variety of optimization techniques' uses in architecture and urban planning were explored by Gero (1975). He emphasized how the lack of numerical models in architecture limited the use of this method in design. For decades, efforts to create optimization-based design methodologies in the CAAD field persisted. Through a number of articles in the 1980s, the optimization in the design was first introduced by Gero and Radford (1984), Radford abd Gero (1987), and Balachandran and Gero (1987) to the design field. During this stage, design optimization did succeed in resolving a few related architectural design issues. However, when the design difficulties could not be expressed mathematically, the applied numerical optimization methods frequently failed.

More logic-based AI approaches were created in the 1990s to loosen the restrictions of scientific formulation, but the need for such techniques in design was hotly contested at the time. An intelligent computer-aided design system prototype that placed an emphasis on the collaboration between a computer and a person was proposed by Pohl et al. et al. (1990) and Schmitt and Oechslin (1992) drew attention to the fact that the research frontiers of CAAD were beginning to switching to design support from design automation, urged additional insights into human cognition. A design-oriented approach was put up as a way to assess, criticize, and optimize building energy use and design. Despite numerous attempts during this decade, the CAAD field has faced skepticism and criticisms.

It was indisputable that the created systems' applicability was still very constrained. Internal criticism from the field was also expressed at the same time, which pushed the research agenda forward. The CAAD's seven deadly sins, which Maver (1995) mentioned and which include macro-myopia, d'ej'a vu, xenophilia, unsustainability, failure to validate, failure to evaluate, and failure to criticize, are a well-known example. New approaches, like using genetic programming to explore design spaces, started to emerge as a result to both internal and external criticisms (Broughton et al. 1997). As processing power increased at the start of the twenty-first century, additional derivative-free and stochastic optimization techniques were developed and used to tackle challenging discrete nonlinear issues.

Utilizing generative algorithms to create architectural design shapes is one of the projects Coates et al. (2001) started in Center for Environment and Computing in Architecture. Derix (2009) employed Quantum Annealing to determine desired adjacencies between various land use units and Ant Colony Optimization to create roadway networks for urban design. In addition, fresh perspectives on the application of optimization techniques arose. Using optimization, Bleiberg and Shaviv (2007) improved collaborative design. Multi-objective optimization is also used, research also made strides, leading to the development of outstanding algorithms like SPEA2, NSGA-II, and later HypE (Zitzler et al. 2001, Deb et al. 2002, Bader and Zitzler 2011). Although more and more physical realities, like the Science City Zurich, were made possible with the aid of CAAD, design support tools did not make a substantial impact on design practice (Schmitt 2004).

Within the CAAD discipline, research in design optimization has advanced over the last ten years, moving from architectural design to urban design. Numerous studies in this field centered on exploring the design space. Turrin et al. (2001) created a technique for design exploration a combination of performance-driven geometries parametric modeling and genetic algorithms. Additionally, Stouffs and Rafiq (2015) put forth strategies for fusing generative and evolutionary exploration. When the issue is or can be reformulated as a single objective optimization problem, model-based optimization has been shown to be a faster and more practical alternative to evolutionary algorithms. Hybrid approaches using both metaheuristic and model-based optimization would suitable for multi-objective optimization issues, as has already been demonstrated in other engineering design domains (Sindhya et al. 2012).

A growing variety of quantitative evaluation methods have been brought to urban design with the advent of spatial analysis tools like space syntax, which expand the design requirements that design optimization could meet (Hillier 2007). For land use planning, Cao et al. (2011) employed multi-objective optimization techniques. In contrast to earlier design optimization attempts, their methods reinforce how designers may highlight the value of human intelligence interactions with the generated urban design. This aims to address a major criticism of computational creativity, namely the lack of humanity (Colton et al. 2014). The EMO-based generative methodologies at the heart of their strategy have the potential to improve urban design through benefits like transparency and integrativeness (Monizza et al. 2012, Singh and Gu 2012).

Additionally, this study intends to overcome the representation problem, one of the main obstacles to generative urban design. In their most recent study, the application of EMO to the creation of numerous urban design layouts including urban elements such roadway networks, blocks, lots, and buildings was successful (Koening et al. 2020). Despite progress across academic frontiers, there is still a long way to go in terms of implementation. The absence of quantitative design evaluation metrics and measures continues to be a major problem. Additionally, computer-generated design solutions are frequently straightforward and only appropriate for prototype. Because of the nature of EMO, complex processing is frequently needed even for basic generation, which takes longer than real time. A hybrid strategy is anticipated to be used to resolve these issues.

Methodology

The methodology employed in this work is associated with parametric design, which is defined as a technique for producing geometries based on various parameters and rules in an algorithmic manner. The method will generate a new version of the geometry when the parameter values are altered. With the Rhinoceros add-on visual programming tool grasshopper, parametric design may be utilized. The Rhinoceros viewport is used to preview the geometry once it has been defined in Grasshopper. The structure of the model is one advantage of parametric design. A modification to the parameter will have an impact on the remainder of the design and the model if a collection of parameters defines the curves that serve as its foundation. In this regard, the chosen case study is being further analysed by primary choosing the structure, that of a 600 meters long bridge. After that the technical parameters of the bridge are being selected and the referenced schematic view of the 3D bridge is conceived. The structural sustainability is checked for the modelled bridge by resulting at the end in the proposed version for the connection of the two ground areas divided by the river.

How Does Generative Design Work?

In order to create the normal design process, also known as the traditional design process, calls upon the expertise of the designer. This is frequently a time-consuming process that necessitates designers and engineers to thoroughly comprehend many ideas and processes in order to produce an effective final phase. And then, after spending countless hours on design and analysis, the need to shorten the process frequently leads to less-than-ideal designs. Here is where generative design will play a role in creating the future's most optimal designs. This can be added to the new generation of products that are being developed, which have features of ultra-high performance and are too demanding for the conventional design process.

Designers and engineers may now co-create ideas utilizing parameter driven optimization because to the development of technology like artificial intelligence algorithms and limitless computing, which are far more accessible than at any other time in history. To assist create an optimum solution that satisfies the design goals within the constraints specified in the study setting, generative design tests the structure with each iteration, learns from each step, and applies change at each level. This technique frequently yields designs that the conventional design process would not have been able to produce. The final forms' shapes are distinctive and are referred to as "organic" because they are created to meet a particular requirement.

Figure 2. *As a Subset of Various Disciplines and Skill Sets, Generative Design*

Source: (left scheme) BLOG on AEC Innovation. https://www.invokeshift.com/thoughts-on-the-future-of-generative-design-in-aec-from-an-engineering-perspective/, (right scheme) the authors, 2023.

As was previously said, generative design enables a workflow that is more tightly connected between the designer/engineer and computer (Figure 2). In actuality, they both contribute to the final design.

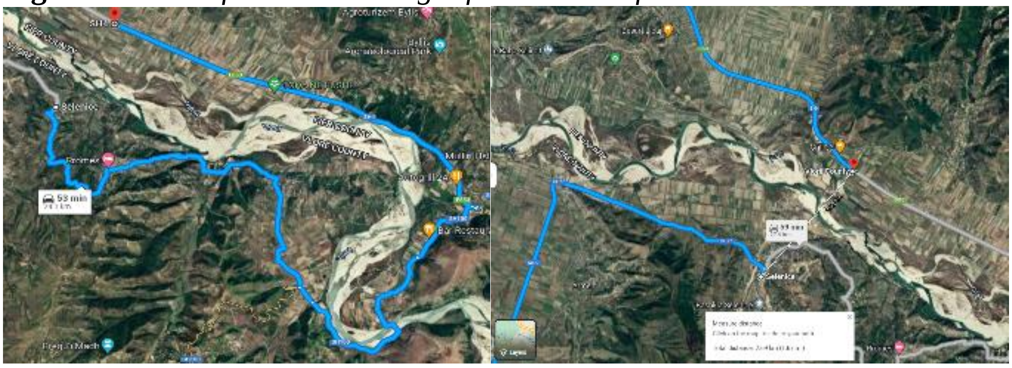
Case Study

Bridges are intricate geometric constructions, and the many structural options typically show substantial geometric differences in their designs. In addition, with the new instruments developed, the construction industry frequently requires reducing the computational cost, shorter model runtime development and analysis, and little to no material waste in light of the environmental emergency. A low level reusing models in projects of a similar size is implied by the modeling complexity.

In order to achieve the aforementioned goals, the present paper suggests a generative technique to improve the bridge design process. This approach increases efficiency by lowering computational costs and modeling efforts. The methodology that follows uses a workflow to develop adaptable geometric models while introducing numerical and parameter correlations between each design parameter. As a result, by changing the parameter settings within the same model, new the elements of a bridge's geometric solutions can be produced via a generative development. Finally, the goal of the current work is to specify a modeling and analytic technique for a bridge project based on structural analysis, parametric development, and optimization. The outcomes can be used to better integrate the structure modeling in order to explore and develop high-probability designs complicated geometries and discover affordable solutions in the future.

Despite the fact that generative design can be applied in a variety of ways, the following is a study case of a connection bridge between the Fieri and Vlora County. Those two counties are being separated by Selenica river where there is no connection between the two existed highways. Taking into account that these areas are less than 3 km far from each-other, in this study there is conducted a generative analysis through the scripts of the grasshopper software and several plugins to give a solution to that. In order to get a wider view of the study case, there have been conducted through google map the measurement of the distance between two areas (Figure 3).

Figure 3. *Photos from the Existing Infrastructure of the Studied Area*



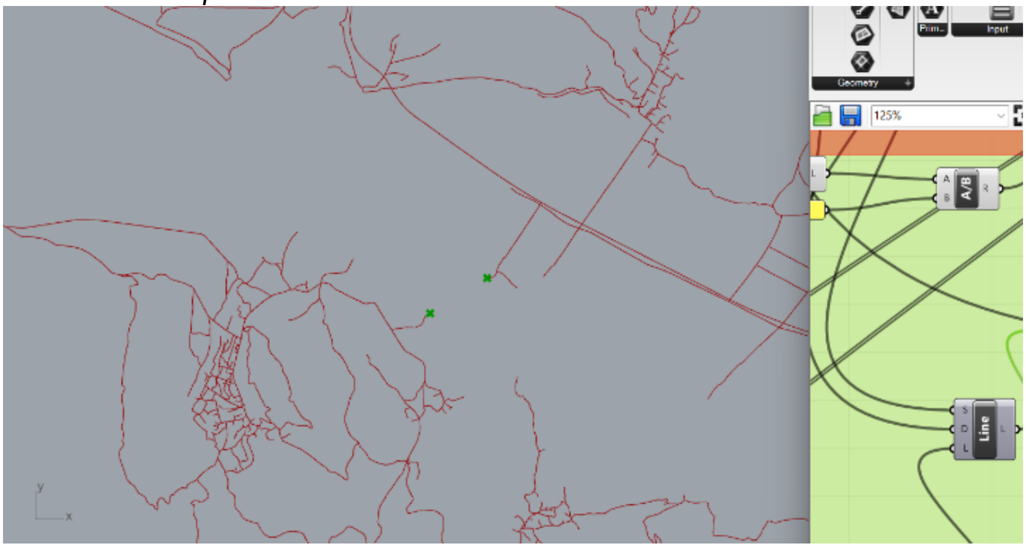
Source: Google Map, 2023.

Using a first script via Urbano plug-in of Grasshopper, it is conceived the converting infrastructure process into vectors. Practically, and programmatically, there is no difference between points and vectors. Both are lists-of-coordinates with a bunch of associated operations. In fact, plenty of programming platforms/ languages do not distinguish between points and vectors, and sometimes not even between vectors and colours.

However theoretically, and mathematically, they are very different entities and it is just easier to think with them if you keep them separate. As mentioned in several authors already, points are locations in space specified using a set of coordinates, whereas vectors are directions magnitudes in space, specified using a set of coordinate differences. Vectors are not geometry, and whenever we draw a vector in some specific place, we can only do so because we know, from the context, where that vector makes sense.

The process is following by finding the closest points between the parts of the infrastructure, which are being separated by Selenica River. In this way, it is very close to mind to make the solution by joining the two close points with a straight line by obtaining in regard a solution: a 600 meters long bridge that connects both sides. The visualized script is given in Figure 4.

Figure 4. *The Converting Infrastructure Process into Vectors and Finding the Closest Points of the Ground Terrain*

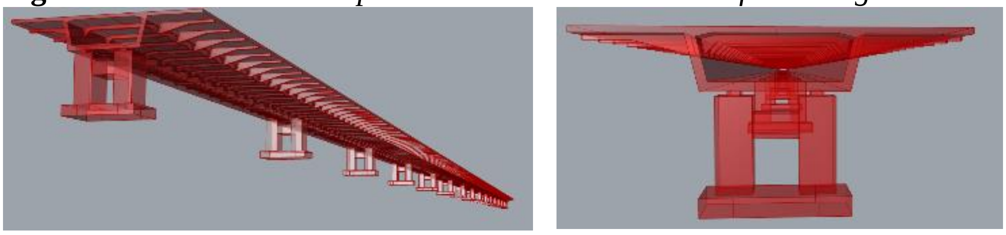


Source: Authors script, 2023.

Simpler Structural Modifications

Sometimes it is necessary to alter the construction of the road, possibly to integrate it with a nearby feature. The model can be adjusted with the robust tools, referred to as "Limits," to accommodate any auxiliary component. A linear element can be readily utilized to align the road model in both the horizontal and vertical directions once it has been captured as an axis. The study case is referred to a 600 metres long bridge with the technical parameters and the modelling bridge proposed for the study case is given in Figure 5.

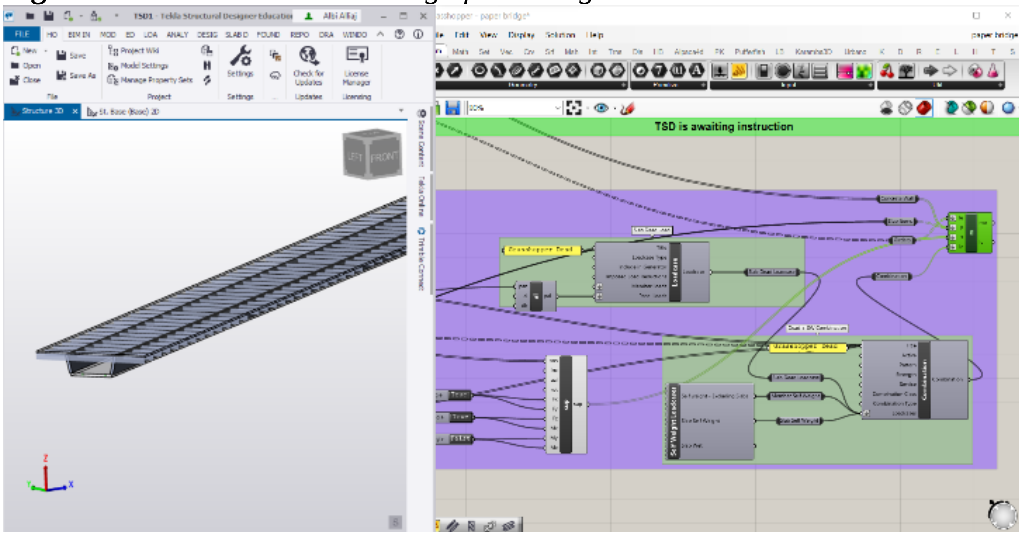
Figure 5. *The Technical Properties and the Cross-section of the Bridge*



Source: Authors design, 2023.

Parametric structural analysis of the deck is done utilizing Tekla Structural Designer Link plug-in inside Grasshopper3d. The first effort, where the girders are modelled with an identical thickness of 20 cm (Figure 6).

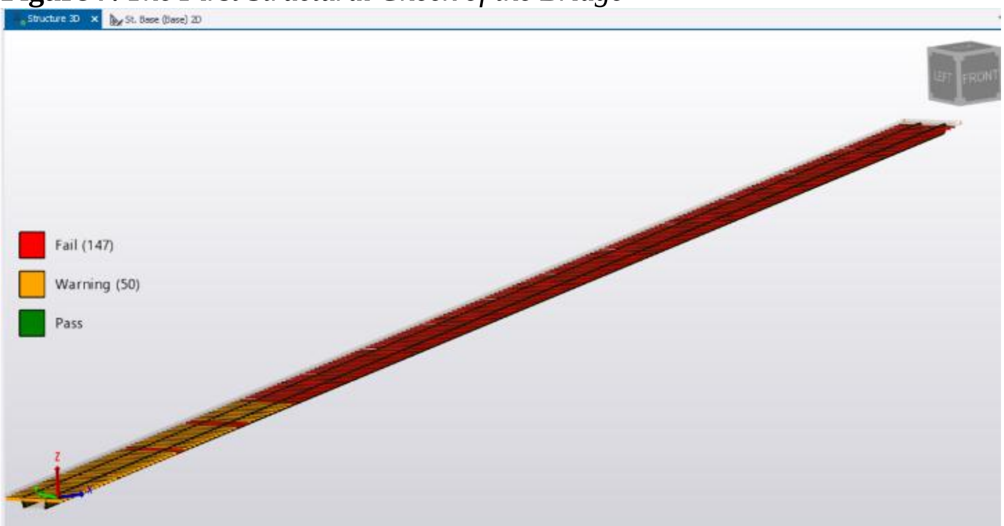
Figure 6. *The Structural Modelling of the Bridge*



Source: Authors script, 2023.

After that, were checked the girders. It resulted that most of the girders failed due to the loads considered (Figure 7).

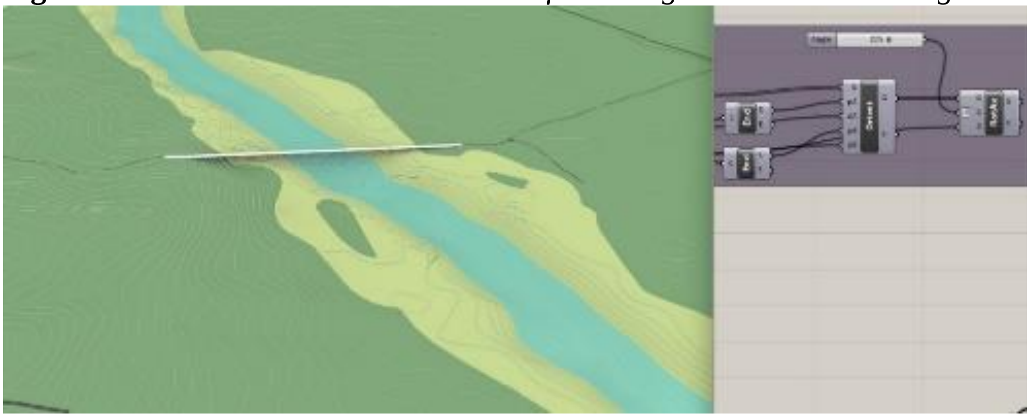
Figure 7. *The First Structural Check of the Bridge*



Source: Authors script.

So, to prevent significant deformations and improve durability, it was simple to switch the model from uniform girders to variable cross-section girders and change the material of concrete class from C30/45 to C40/50. As a final step, it was conducted the verification of the deck structure due to major shear stresses, bending moments and deformations of the deck model of the bridge. As it can be seen from Figure 8, it has been obtained Schematic visualisation of the bridge model placed on the terrain generating by a full script (on the left).

Figure 8. *The Schematic 3D Visualization of the Bridge and the Surrounding*



Source: Authors, 2023.

Although a strong design application has been described in the study, it still needs some components before it can be applied to more bridge situations and be used by practical engineers. It is possible to further develop it, some of which are described below.

- More bridge design options should be included. Evaluating many design options is crucial early in the design process.
- For improved optimization and more accurate optimization outcomes, include surface topology in the definition.
- The members are presently picked from center to center. It follows by a procedure of cutting parts and alter the issues to permit more thorough modeling in, say, Tekla.
- Include a foundations study that takes into account the concrete, reinforcing, and geotechnical piles.
- Using machine learning to choose the best cross-sections for each set of elements.
- Expanding on CO_{2e} as an objective from the perspective of an LCA.
- Test out several optimization algorithms, including the Firefly algorithm, to see if it can get even better results.

Conclusions

In order to increase the effectiveness and efficiency of urban bridge infrastructure, the paper investigates the application of generative design and optimization approaches. It covers the problems with conventional bridge design and optimization techniques and how generative design can offer a better answer. A case study is presented that shows how generative design may be used to optimize a link bridge between two locations in an urban setting, producing a design that is both structurally effective and aesthetically pleasing.

In the framework of sustainable urban design, the use of generative design to optimize bridge infrastructure is also covered in this study. Additionally, an historical path of employing generative design in the context of infrastructure design and urban planning are discussed, along with how generative design might contribute to the development of more effective and sustainable bridge designs.

By adding more design factors and offering a fresh method for bridge optimization, the study was successful in further developing the initial parametric model. Due to the speed with which the design can be changed and the instantaneous display of the analysis, using parametric design to study alternative options for bridges could be highly helpful to designers.

Utilizing generative design is rapidly changing how manufacturers create the newest items. The need for project designs to perform better is one aspect of this. Another is for fresh, cutting-edge designs that provide their consumers exclusivity and customizability while utilizing the most recent manufacturing techniques. And because it is now more reasonably priced than ever before, designers can quickly and efficiently develop thousands of designs in a fraction of the time it would take to do so using a more traditional method.

Even while the definition of a parametric model is pretty solid as it is, it can still be improved. On the other hand, it offers the opportunity to be utilized in a real project in the early stages of design to really appreciate the benefits of the script. The first is whether the script for the following design stage may be utilized as a template (transferring it to Tekla), and the second is the degree of cost estimation accuracy in relation to the final design. Generatively developed products in the future will be networked, measuring information and utilizing it to train the algorithms and increase the technology's effectiveness. Future will be more intriguing than ever as this new generative design and all instruments used take center stage in contemporary design.

Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article and its Supplementary material. Raw data that support the findings of this study are available from the corresponding author, upon reasonable request.

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