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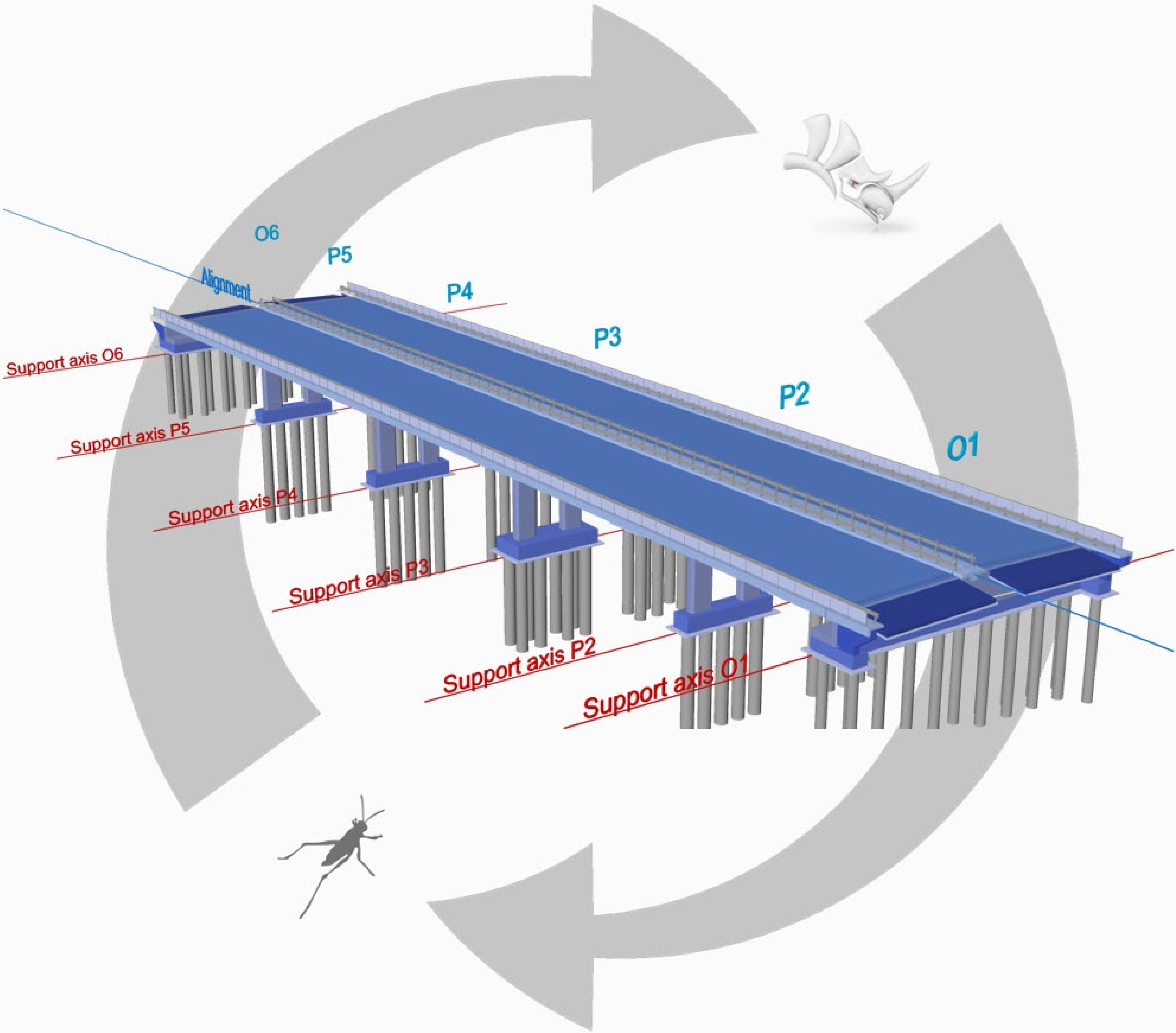

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Dear Readers

*In the first article, you will find information about a bridge that is currently under construction on the Czech highway D3 and the creation of its parametric model. This includes a thorough examination of the generation of 3D reinforcement and the automatic creation of 2D drawings. The article about this award-winning bridge in the Czech-Slovak **Tekla BIM Awards** in the main "Infrastructure Projects" category was prepared by **AFRY**.*

*The second article addresses computational design, optimization, and artificial intelligence embodied in an optimization framework developed by **GEN+** with application to various cases in bridge engineering, such as pile structures, pre-stressed beams, and portal bridges, among other structural components. It also highlights the trend towards the generation of modern and industrialized designs and discusses the future challenges in engineering and innovation that will enable the achievement of objectives and the effective execution of projects.*

*The last article of this edition brings a **case study** in which a steel truss cantilever bridge located in Ontario, Canada, provides a compelling demonstration of data-driven decision-making for structural integrity. Equipped with 35 weldable strain gauges, having a nickel-chromium alloy grid encased in fiberglass-reinforced epoxy phenolic, this bridge underwent meticulous data collection at one-minute intervals for an extensive two-year period.*

*I would like to **thank all the people and companies** that have been cooperating on this issue and helping me put it together; big thanks to the members of the Editorial Board for reviewing the articles and their cooperation, especially **Dr. Vanja Samec** and **Professor Chang-Su Shim**; and also **Sandra Komar** of WSP USA who kindly assisted with proofreading the article by AFRY.*

*We would also like to **thank our partners for their support**.*

*Recently, we have started cooperation with **structurae** which is the largest database of structures. Articles about significant structures are uploaded into the database and we will continue with this cooperation in the future.*

In November 2023, I will travelling in the USA – especially Florida, California, Washington, Delaware, and New York. I will be happy to meet you and your teams and visit your bridge projects.

We are planning one or two special editions of our e-mosty & e-BrIM magazines that will be dedicated to American Bridges; they will be released in 2024. We welcome cooperation with you and will be happy to publish your articles. If you are interested, please contact me.

We are already working on the next issue of e-BrIM which will be released on 20th February 2024. We welcome your articles for the February and May 2024 editions.

The next e-mosty will be released on 20th December 2023.

Magdaléna Sobotková

Chief Editor

INTERNATIONAL ONLINE PEER-REVIEWED MAGAZINE ABOUT BRIDGE INFORMATION MODELLING

e-BrIM

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The magazine **e-BrIM** is an international, interactive, peer-reviewed magazine about bridge information modelling.

It is published at www.e-brim.com and can be read free of charge (open access) with the possibility to subscribe.

It is typically published three times a year:
20 February, 20 May and 20 October.

The magazines stay **available online** on our website as pdf.

The magazine brings **original articles** about **bridge digital technology** from early planning till operation and maintenance**, theoretical and practical innovations,** Case Studies and much more from around the world.

Its electronic form enables the publishing of high-quality photos, videos, drawings, 3D models, links, etc.

We aim to include **all important and technical information, to share theory and practice, knowledge and experience** and at the same time, to show the grace and beauty of the structures.

We are happy to provide media support for important BIM and bridge conferences, educational activities, charitable projects, books, etc.

Our Editorial Board comprises BIM and bridge experts and engineers from academic, research and business environments and the bridge industry.

The readers are mainly bridge leaders, project owners, bridge managers and inspectors, bridge engineers and designers, contractors, BIM experts and managers, university lecturers and students, or people who just love bridges.

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ABOUT BRIDGES

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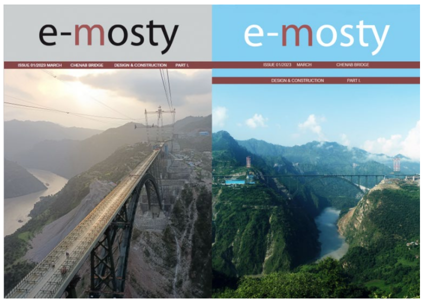

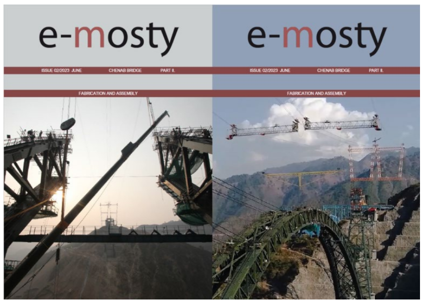

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PARAMETRIC DESIGN AS A PATH TO DRAWINGLESS CONSTRUCTION

Ing. Michal Marvan
Ing. Ondřej Janota
Ing. Pavel Vlasák
AFRY CZ, Czech Republic

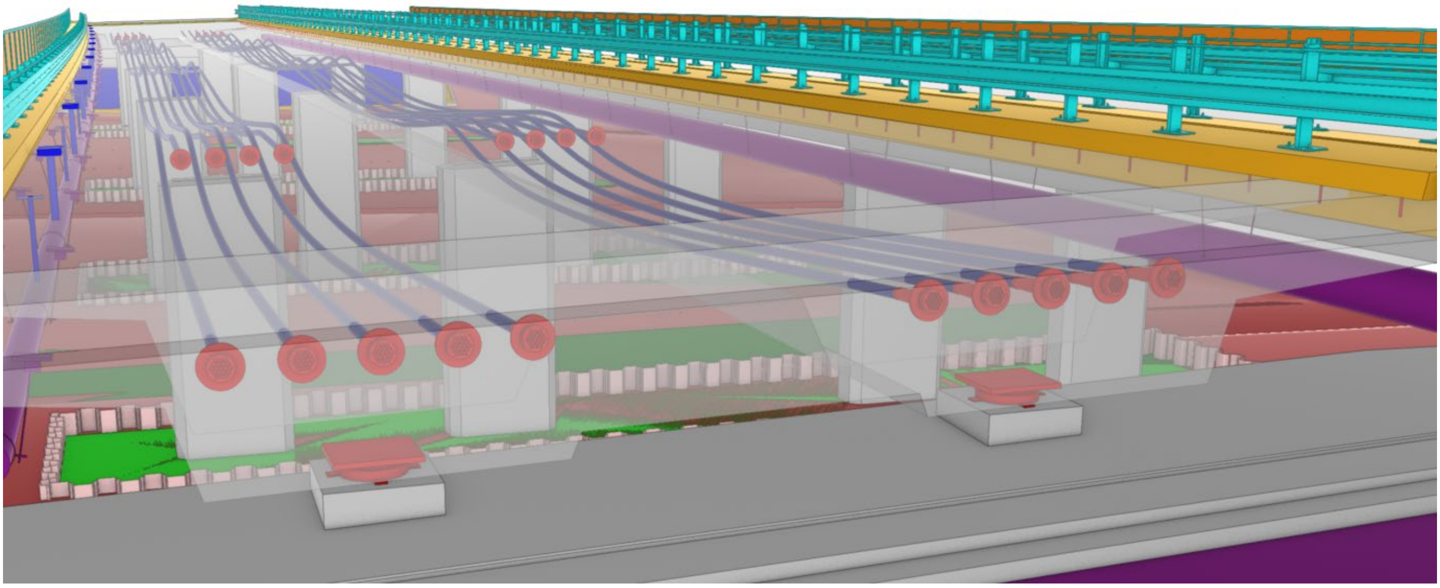


Figure 1: Preview picture of the bridge

INTRODUCTION

A few years ago, we set out to simplify our work while enhancing the efficiency, speed, and quality of our designs. The answer we discovered was parametric design.

In last year's article, we demonstrated how we used parametric design for a smaller bridge project. This design won first place in the Small Scale Projects category at the Czech-Slovak Tekla BIM Awards in 2022.

This year, we took the same approach but applied it to a larger structure. The outcome reaffirms that our method is not only functional but also universally applicable, even when dealing with the design of significant, large structures.

As a result, we secured another victory in the Czech-Slovak Tekla BIM Awards, this time in the main "Infrastructure Projects" category.

In this article, using the example of our award-winning project, the SO204 bridge, currently under construction on the Czech highway D3, we will thoroughly explore the creation of a parametric model. This includes a thorough examination of the generation of 3D reinforcement and the automatic creation of 2D drawings.

However, our ambitions extend beyond this. We are actively working towards eliminating 2D documentation entirely, and we support the promotion of so-called "drawingless construction" in the Czech Republic. In this text, we will also explore this progressive concept.

You also have the opportunity to view an interactive model of a specific bridge, including reinforcement details, directly in the CDE Trimble Connect environment. This model will give you a concrete look at how parametric design can transform the way structures are created and worked on. You can find the model at the end of the article.

THE BRIDGE

The bridge is situated within the stretch of the D3 highway, linking the towns of Třebonín and Kaplice, see Figure 2. This particular segment of the highway serves as a crucial link connecting the highway networks of the Czech Republic and Austria. This connection plays a key role for travellers between these two countries.

The bridge is designed as a continuous five-span beam with spans measuring 20.0 + 28.0 + 28.0 + 28.0 + 20.0 m. The bridge deck of both the left and right bridges consists of a double-beam deck made of prestressed concrete with dimensions of 1.4 m in height and 13.9 m in width.

Serving as a vital highway connection, the bridge features separate structures for each direction of the highway. The combined width of both structures amounts to 29.1 m.

The bridge deck is supported by a pair of piers positioned along each support axis. These piers are connected to the bridge deck through pinned joints and share a common foundation.

The bridge itself is founded on piles with a diameter of 1.2 m. At each end of the bridge, there are abutments that are common to both bridge decks and are connected to the bridge deck with a pair of bearings.

You can examine the bridge in detail by accessing the interactive structure model through CDE Trimble Connect.

PARAMETRIC DESIGN

As the name implies, parameters serve as the foundation of parametric design. These variables influence the properties and forms of structures, impacting dimensions, shapes, and other characteristics.

The structural model is constructed based on these parameters and rules, which define the interconnections and behaviour of individual elements within the model.

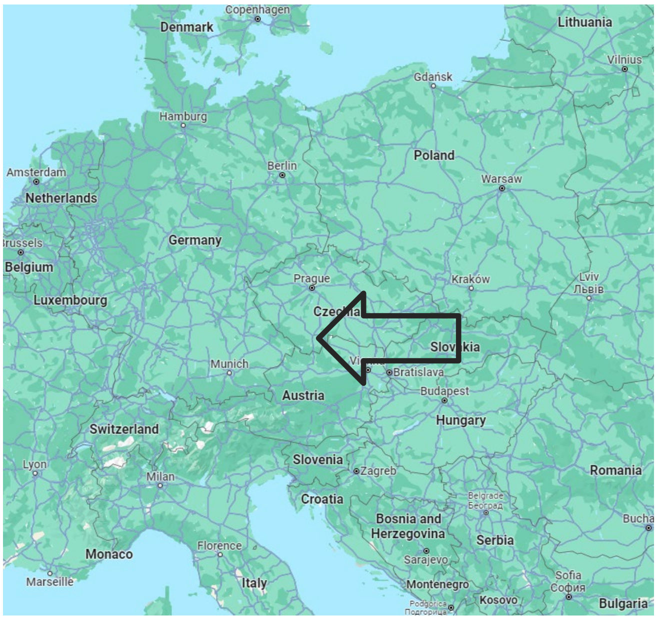


Figure 2: Location of the Bridge (Source: Google Maps)

One of the key advantages of parametric design lies in its capacity to swiftly implement alterations across the structure. This capability proves invaluable to both designers and investors, particularly in cases involving otherwise time-consuming and challenging structural modifications.

To achieve this, at AFRY, we rely on a combination of software tools: Rhinoceros, Grasshopper, and Tekla Structures. What sets these programs apart is their compatibility and interconnectivity, allowing us to make real-time changes and synchronize data across them.

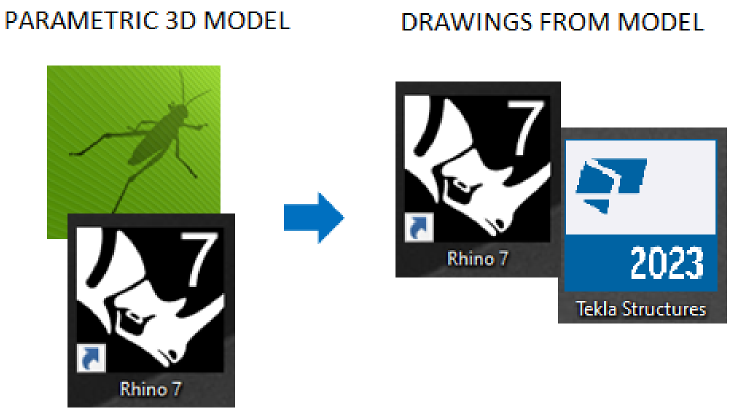


Figure 3: The used workflow

WORKFLOW

The advantages of using 3D models are evident – they offer a visual representation of the object and reveal significantly more detail than traditional 2D drawings. In many cases, a single 3D model can encompass the content of hundreds or even thousands of 2D drawings.

However, there are still certain disadvantages associated with 3D models, particularly during their creation process. Many designers still hold onto traditional practices and find it difficult to embrace the concept of first creating a coordinated 3D model before generating 2D drawings.

In practice, they often follow the opposite sequence, which can result in inefficiencies and errors.

Considering these factors, we have developed a workflow that emphasizes the individual phases leading to our goal, see Figure 3.

The initial step of this workflow involves the creation of fundamental components using Python or C# programming languages, see Figure 4.

This step primarily involves scripting, where all you need is to master basic commands for generating points and curves. These elements constitute the basic geometry of 3D models.

The scripts we create can be subsequently assembled into components, and these components can be interconnected in a manner that results in the desired structure.

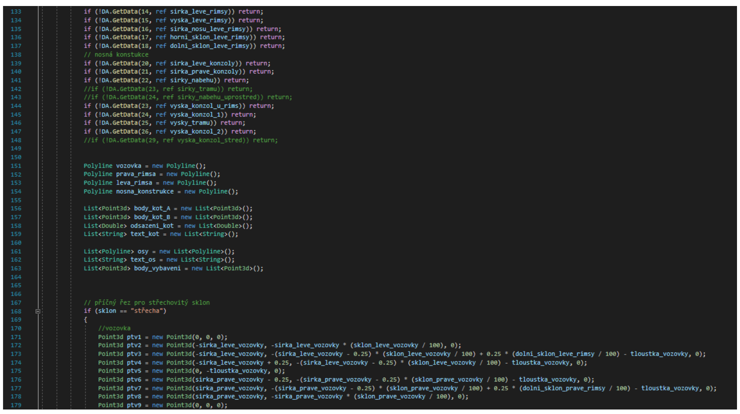


Figure 4: C# code for one of the components

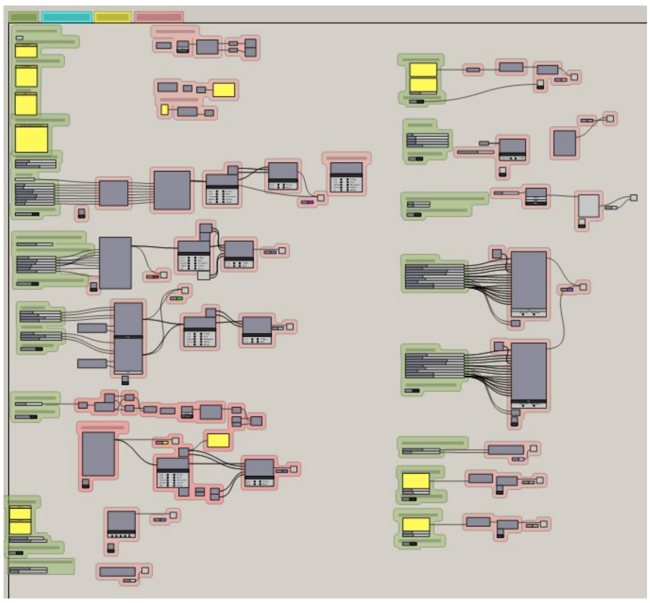


Figure 5: Script in Grasshopper with all concrete parts

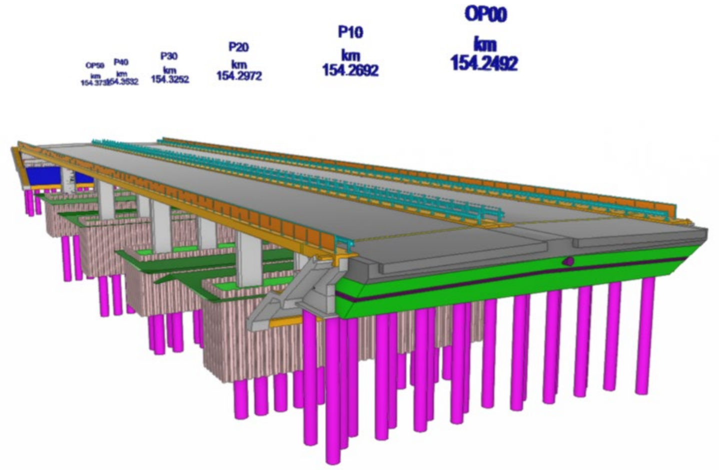
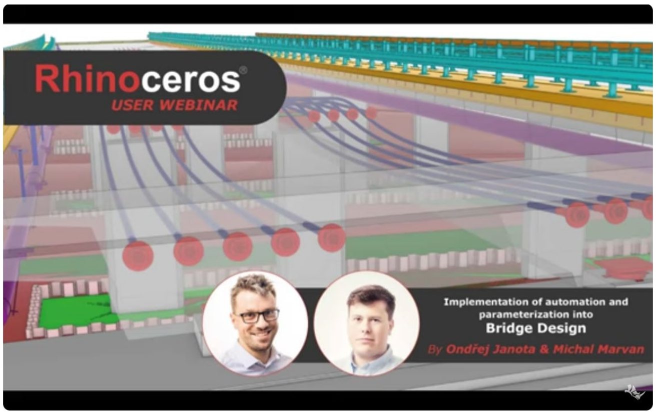


Figure 6: 3D model of the Bridge



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This approach allows us to influence the structure by inputting parametres, thereby gaining control over the resulting model.

Following the configuration and adjustments of the structure, you can generate the model to predetermined levels and further work with it.

The final step of the process is comparing the model with the actual structure.

For a designer, the realization that their model has contributed to solving real-world problems and has eased the construction process can be highly rewarding.

By implementing this approach, we aim to introduce a fresh perspective to the design process and the utilization of 3D models within the construction industry.

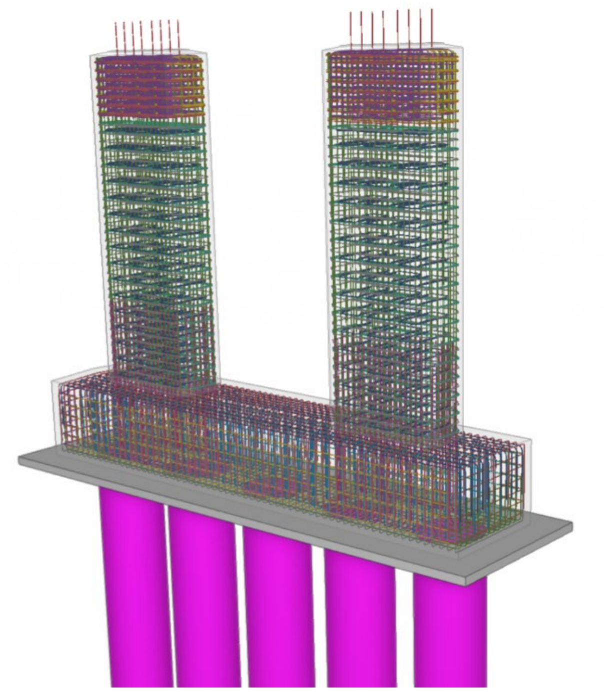


Figure 7: Reinforcement of the foundation and piers in Tekla Structure

Figure 8: Reinforcement of the foundations and piers on the construction site

PARAMETRIC 3D MODEL

Designing a bridge starts with importing an alignment (3D curve) and corridors from the LandXML format (http://www.landxml.org/). Once we have loaded this input data, we move on to the bridge design phase.

We initiate this phase by defining the precise positions on the alignment where the bridge will be situated. This is accomplished by entering the stationing of the axis for each support, Figure 9.

These values act as crucial reference points, establishing the primary location of the bridge structure in relation to the surrounding landscape and the road.

The subsequent step involves creating a cross-section. To achieve this, we utilize one of the components from our comprehensive library within the Grasshopper program. Inputs are then connected to this component, specifying the dimensions, slope, and other attributes of the cross-section.

Once the component is activated, it generates curves in the form of a polyline. One by one we position these individual curves on the designated alignment, securing them in the desired locations using stationing.

Following this, we link these curves through the process of stretching along the curve, ultimately forming the body of the bridge deck, Figure 10.

The foundations of the bridge piers are aligned and positioned according to the designated support axes, see Figure 11. Each foundation is characterized by its length, width, and height.

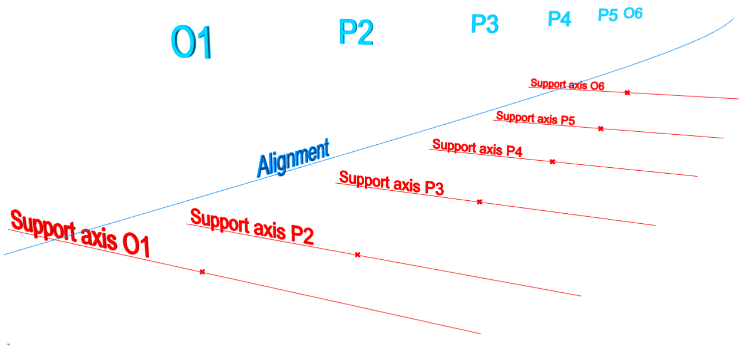


Figure 9: Alignment and support axis

The dimensions of these foundations can either be individually specified for each one separately or set uniformly for all of them.

Following the successful creation of the foundations, we proceed to the construction of the bridge piers. The piers are aligned with the upper edge of the foundation.

Along this edge, we define the precise locations where the piers will be positioned, considering their quantity and distances from the foundation's edges.

The dimensions of the piers are determined by the plan, and the height of each pier is calculated based on its relative position with respect to the bridge deck.

In a manner similar to how we specify the foundations for the piers, we also determine the foundations for the abutments. Each foundation is aligned with the designated support axis.

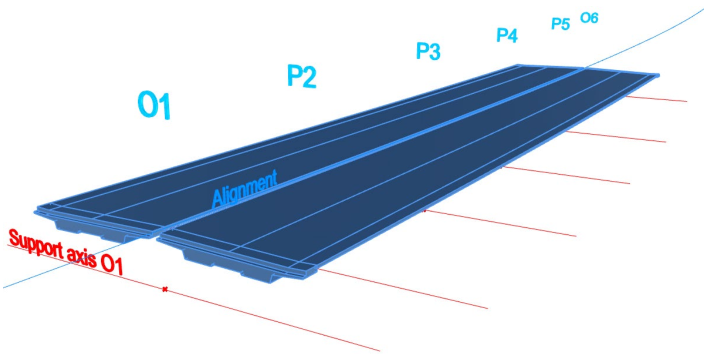


Figure 10: Bridge deck location on alignment

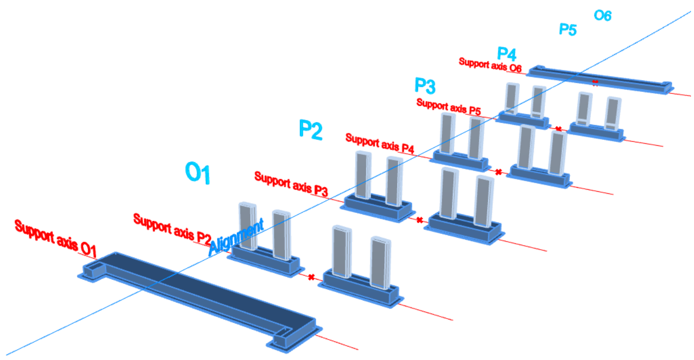


Figure 11: Foundations and piers on the support axes

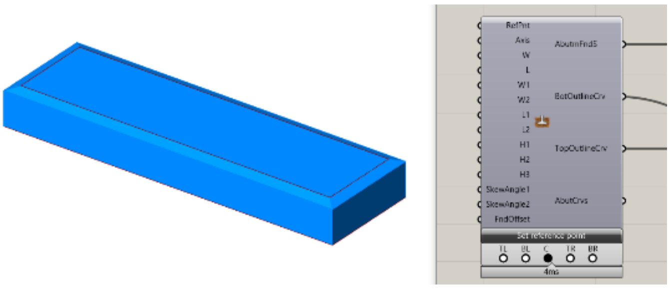


Figure 12: Cubiod abutment foundation without wings

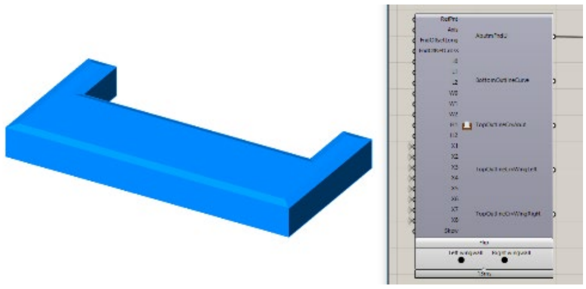


Figure 13: Cubiod abutment foundation "U" shape (with wings)

Initially, we need to decide whether the bridge wing walls will be suspended or connected to the foundation.

If they are suspended, the foundation will take on a cuboid shape, Figure 12. If they are connected, the foundation will assume a "U" shape, and the geometry of the foundation will affect the configuration of the bridge wing walls, Figure 13.

In either case, if there is a need for modifications, the components for the individual foundations can be interchanged.

The remaining components of the abutments are firmly tied to the dimensions of the foundations, from which their plan dimensions are derived. Furthermore, they are closely interrelated with the bridge deck, establishing the height.

The final factor influencing the dimensions of the abutments is the road itself.

The road's geometry dictates the overall height of both the retaining wall and wing walls.

In this manner, all abutment elements are interconnected into a cohesive whole, where each element relies on correctly defined parameters.

The final crucial elements of the bridge structure are the bearings. These components establish a secure connection between the bridge's substructure and the bridge deck, and this connection is firmly defined.

The dimensions of the bearings are determined by the expected applied forces to the bearing. The assumed dimensions for the bearings are then retrieved from the SQL database.

As a result, users have access to approximate dimensions based on the selected bearing type and its anticipated load.

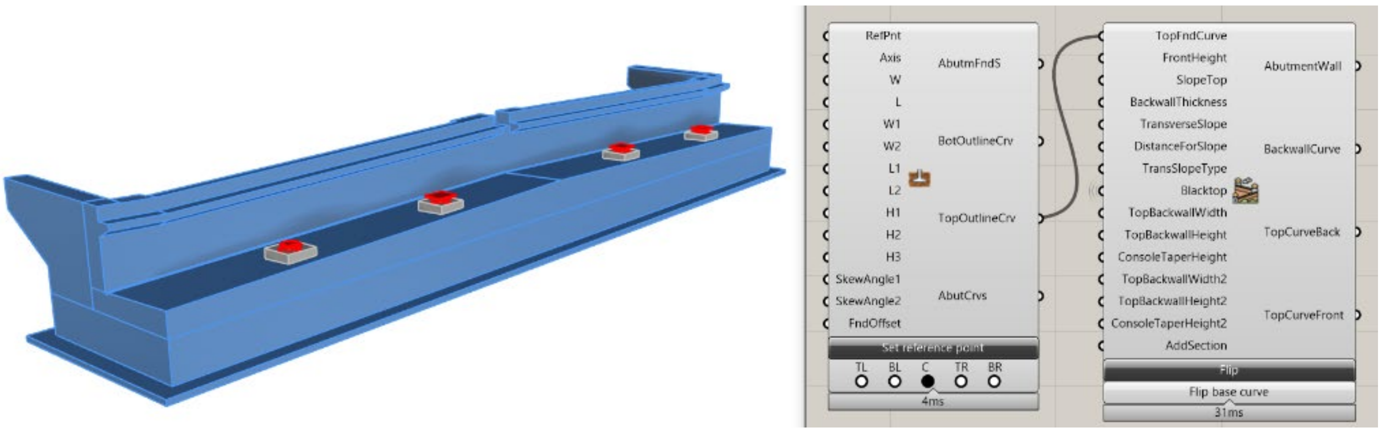


Figure 14: Abutment wall with Grasshopper component

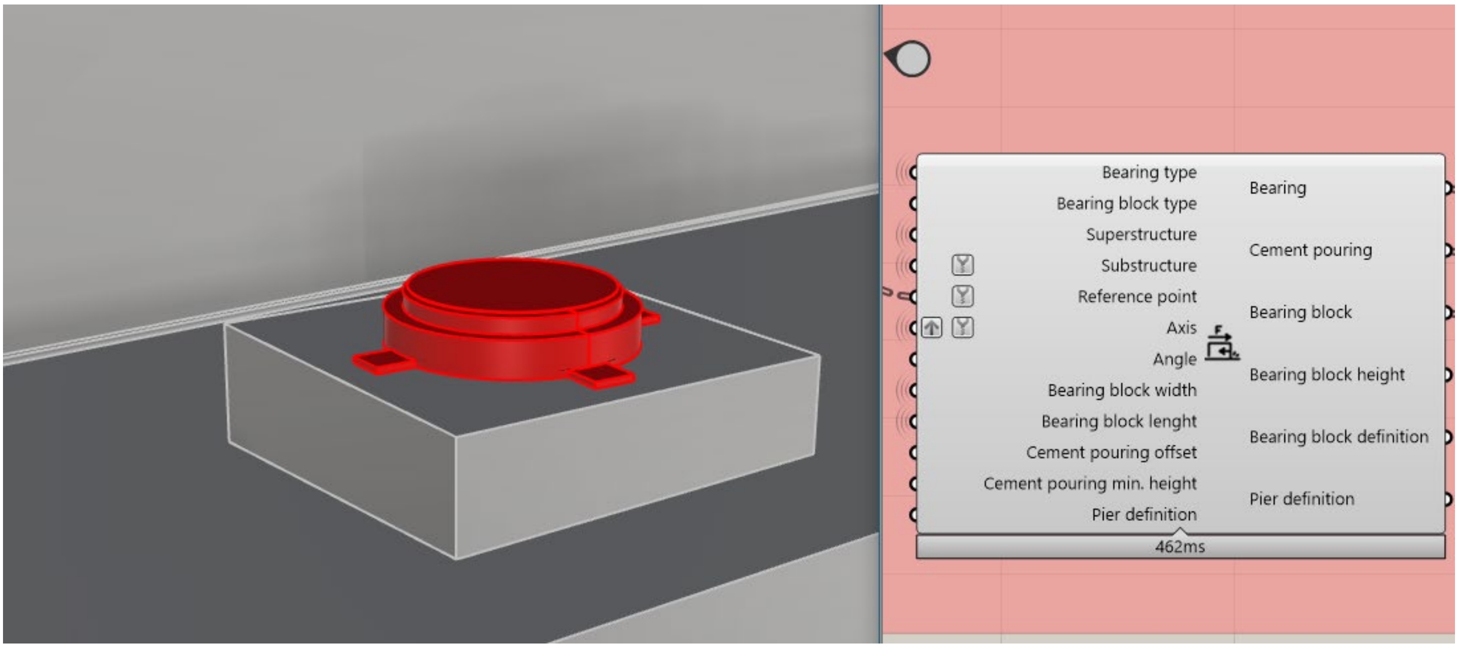


Figure 15: Bearing with a component in Grasshopper

REINFORCEMENT

The reinforcement is designed using Tekla Structures software, made possible by the Grasshopper - Tekla Live Link library, Figure 16. This library seamlessly integrates with Grasshopper, enabling us to establish a smooth connection between the two tools.

This integration facilitates the exchange of data and information between Grasshopper and Tekla Structures programs, allowing us to work with both programs in mutual coordination.

Thanks to the Grasshopper - Tekla Live Link library, we can ensure a coordinated process of reinforcing the model and creating bar groups directly within Tekla Structures.

Considerable time has passed since our initial attempt to integrate these software tools. Over this period, we have steadily improved the reinforcement process within the Grasshopper program.

Today, we have a highly efficient library of elements that allows us to define not only the structure's shapes but also the configurations of the reinforcing bars.

These bar shapes are directly determined by the structure's shape, resulting in automatic adjustments to bar lengths whenever modifications are made to the structure.

Additionally, we have successfully developed a system for dynamically adjusting reinforcement parametres, utilizing a table within the MS Excel program.

This table is linked to the Grasshopper program, where it interfaces with our component responsible for generating attributes for the components of the Grasshopper library - Tekla Live Link.

These innovations have significantly accelerated and improved our ability to work with reinforcement, resulting in enhanced precision and, consequently, an increase in the quality of our results.

THE GENERATION OF DRAWINGS

As 2D drawings continue to play a crucial role in our work, we have implemented a system to generate drawings directly from our model.

We have categorized the drawings into two main groups: the first includes drawings of structural shapes and details, while the other comprises of reinforcement drawings.

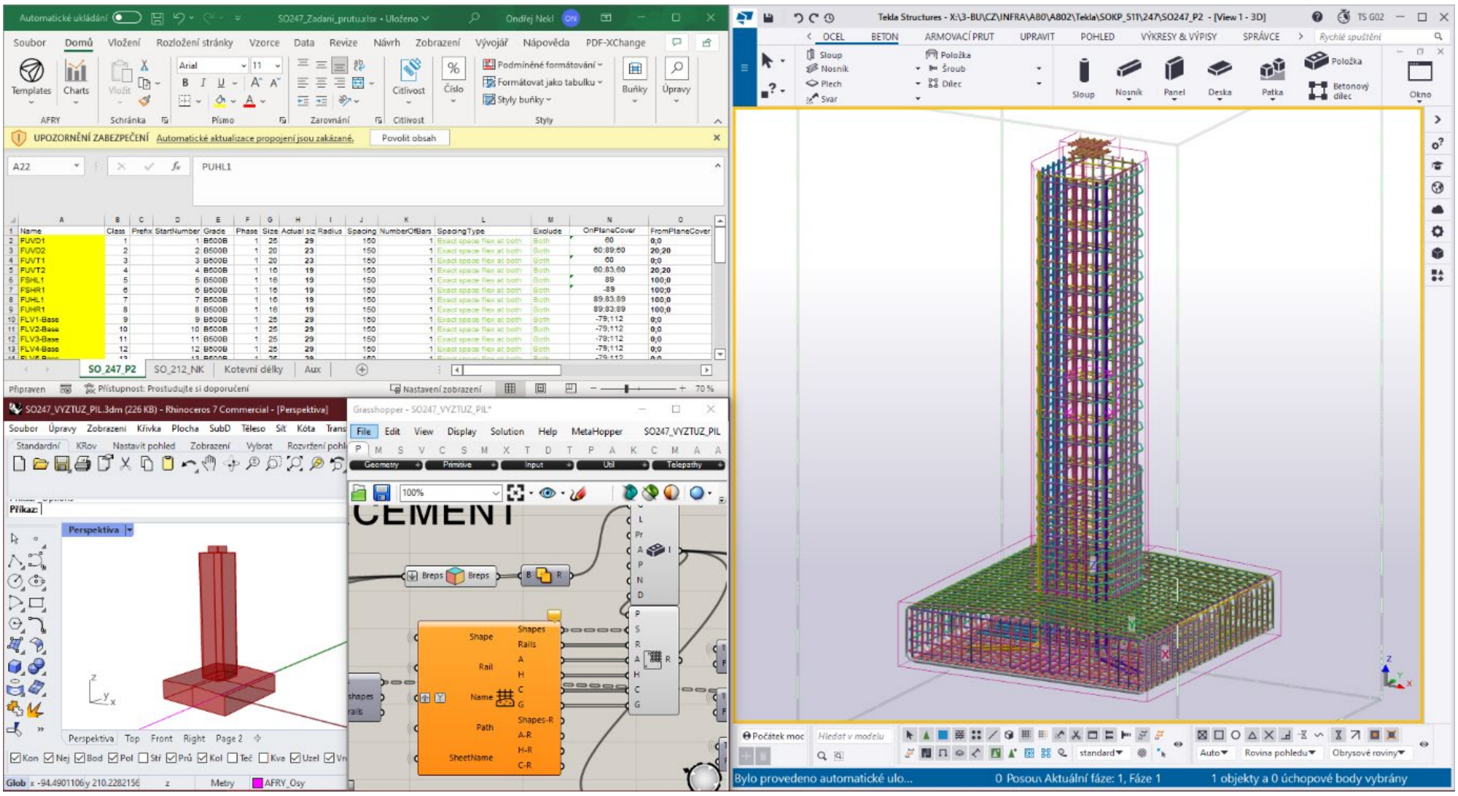


Figure 16: Reinforcement created by Grasshopper - Tekla live link and excel sheet

To create the first group, we utilize a combination of Rhinoceros and Grasshopper programs, while for the second group, we rely on Tekla Structures.

In the initial phase of the process, our primary focus was on automating the generation of drawings.

These drawings are produced based on planes that continually intersect with the structure and its adjacent elements.

To further streamline this process, we employed SW Grasshopper, where planes and individual bridge elements serve as inputs, and outputs are section curves.

These curves are then subject to script-based editing and linked to a predefined reference layer for subsequent processing.

This procedure significantly streamlines our work, particularly when making changes and revisions to drawings while ensuring alignment between the 3D model and 2D documentation.

Manual interventions are only necessary during the final stages of drawing refinement, including tasks such as dimensioning, labelling, hatching, and similar adjustments.

This approach effectively combines automation with the need for precise final refinements in the resulting drawings.

While there is a current need for manual editing of drawings during the final stages, we are actively engaged in seeking ways to eliminate this step altogether.

Our objective is to configure the script to automatically handle dimensioning in drawings. This represents a challenging endeavour that demands a comprehensive solution.

In this context, our primary asset is the existing cross-section generation component.

This component enables us to parametrically define cross-sections while simultaneously automatically adjusting the placement of dimensions on the drawing.

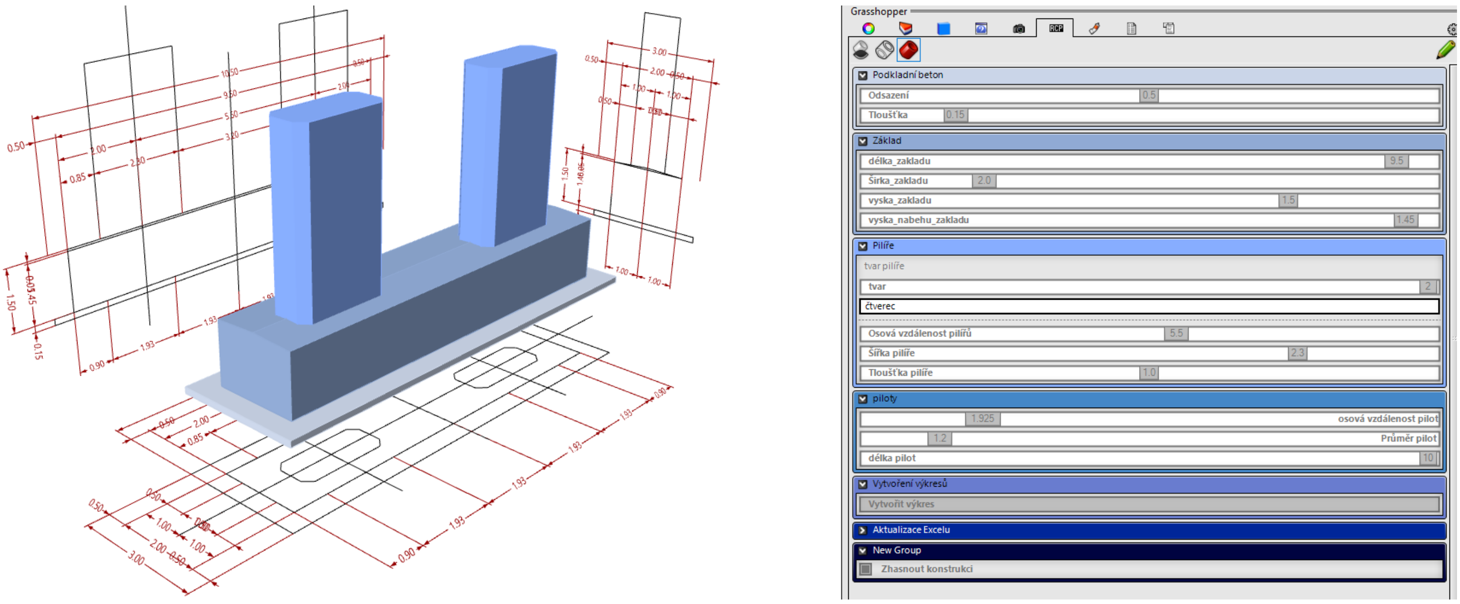


Figure 17: Foundation and piers created in Grasshopper (Remote control panel) with drawings

This integration of dimensioning into the drawing process enhances the efficiency and precision of the resulting 2D documentation.

We are also developing scripts and procedures aimed at automating further aspects of the finished work, with the ultimate goal of reducing the necessity for manual intervention.

This effort is intended to enhance efficiency while maintaining a high level of consistency and precision in our results.

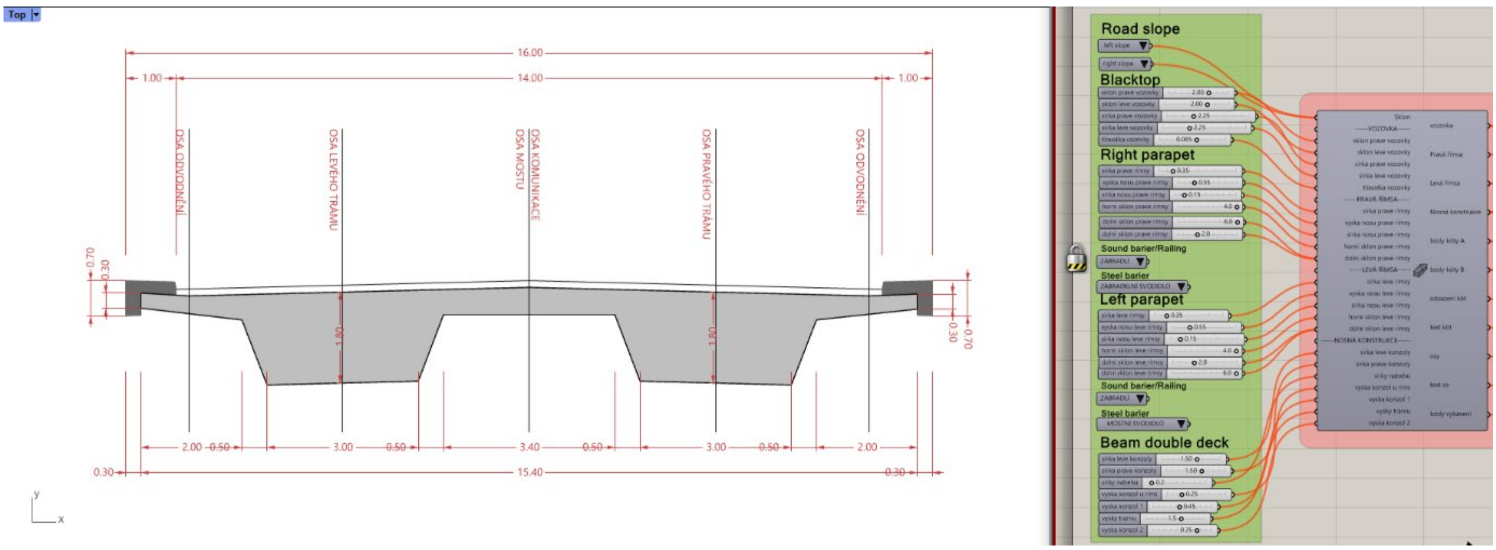


Figure 18: Cross-section created in Grasshopper

DRAWINGLESS CONSTRUCTION - CONSTRUCTION BASED ON 3D MODELS

From our perspective, parametric design represents a fundamental approach, not only for the design of bridge structures but also for a broader range of building projects.

It provides designers with greater control over the object and enables them to address issues that could be easily overlooked when working with 2D drawings.

Parametric design guarantees an interactive response to alterations and accelerates their implementation compared to conventional 2D drawings.

It is, therefore, highly desirable to digitize not only the design process but also the construction itself.

Given that 3D information models are visually illustrative and, unlike traditional 2D drawings, universally comprehensible, the described workflow (Rhinoceros > Grasshopper > Tekla Structures) stands as a pivotal component in constructing a structure without reliance on 2D drawings.

This modern approach transitions the process from paper-based drawings to digital modelling, enabling more efficient work with interactive 3D models.

It is our goal to completely phase out 2D documentation in the future and adopt a drawingless concept for construction.

This approach enables construction to work directly with 3D models instead of relying on 2D drawings.

Moreover, generating 2D drawings places higher demands on designers within the BIM process, which we consider unnecessary.

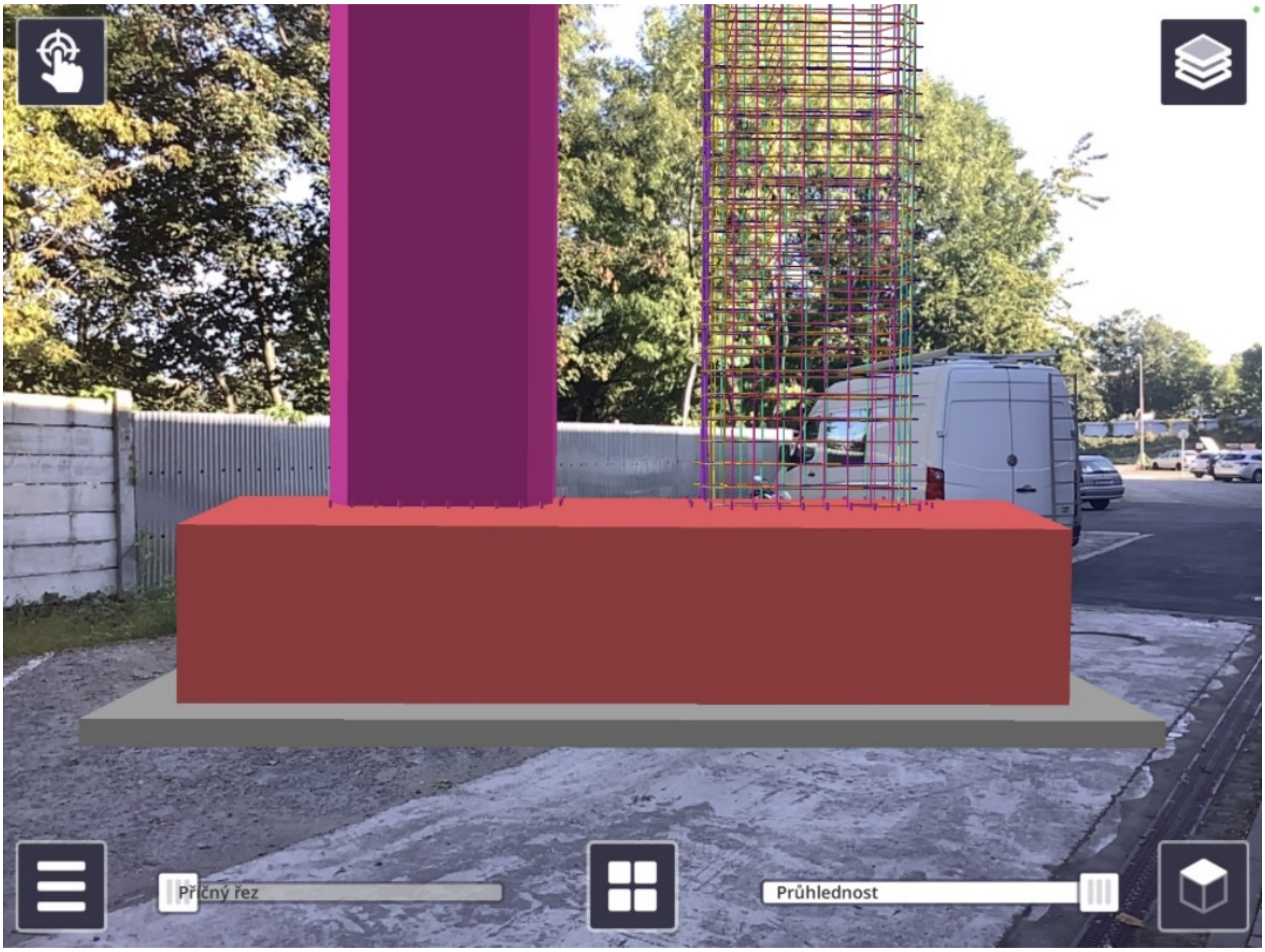


Figure 19: AR demonstration in Trimble Connect application for iOS and Android

We firmly believe that creating simple and clear drawings and diagrams is sufficient, as all other information is already encompassed within the non-graphical data of the 3D model.

In alignment with the principles and trends of BIM, we strongly recommend avoiding the degradation of visually accurate and universally comprehensible 3D information models into cluttered 2D drawings.

As part of our commitment to implement the concept of drawingless construction in the Czech Republic, which relies on 3D models rather than traditional 2D drawings, we aim to collaborate with construction teams to provide advanced sources of information for the construction process.

This includes breaking down BIM models into individual work tasks, ensuring distribution and communication through a Common Data Environment (CDE) using Trimble Connect.

Furthermore, we offer the capability to visualize BIM models according to specific work tasks using Augmented Reality on mobile devices, compatible with both major platforms (Android and iOS), right at the construction site.

This approach offers a modern and enhanced method of project management, significantly increasing efficiency and refining communication among all stakeholders.

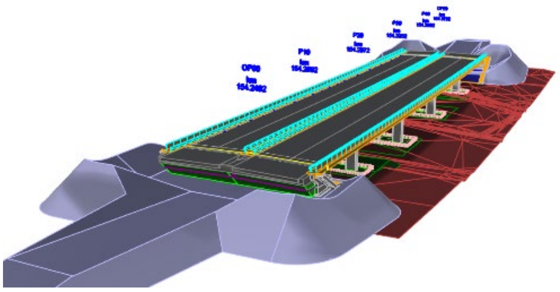
CONCLUSION

In today's digital age, every industry has the opportunity to optimize and streamline its processes and move forward. This principle also applies to the field of bridge design. That is why we strive to remain innovative and avoid clinging to outdated practices.

We view it as inefficient to rely on non-digital methods in an era where technology surrounds us, offering designers the means to save time and concentrate entirely on addressing genuine professional challenges during the design process.

Our commitment is to continually refine and improve our work practices, creating better working conditions for all involved in parametric design.

At AFRY, we are dedicated to providing support and developing tools that simplify project creation, sharing, and collaboration within this dynamic field.



Construsoft 2023 BIM Awards with a video

Click on the image to play the video

QR Code: Model in Trimble Connect

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COMPUTATIONAL DESIGN & STRUCTURAL OPTIMIZATION IN BRIDGES

Alejandro Palpan, Bridge Project Coordinator, TSC Innovation, Perú
Eduardo Vicente, Research & Development, Gen+, Perú
Fabrizio Inga, Research & Development, Gen+, Perú
Anggie Palpan, Research & Development, Gen+, Perú

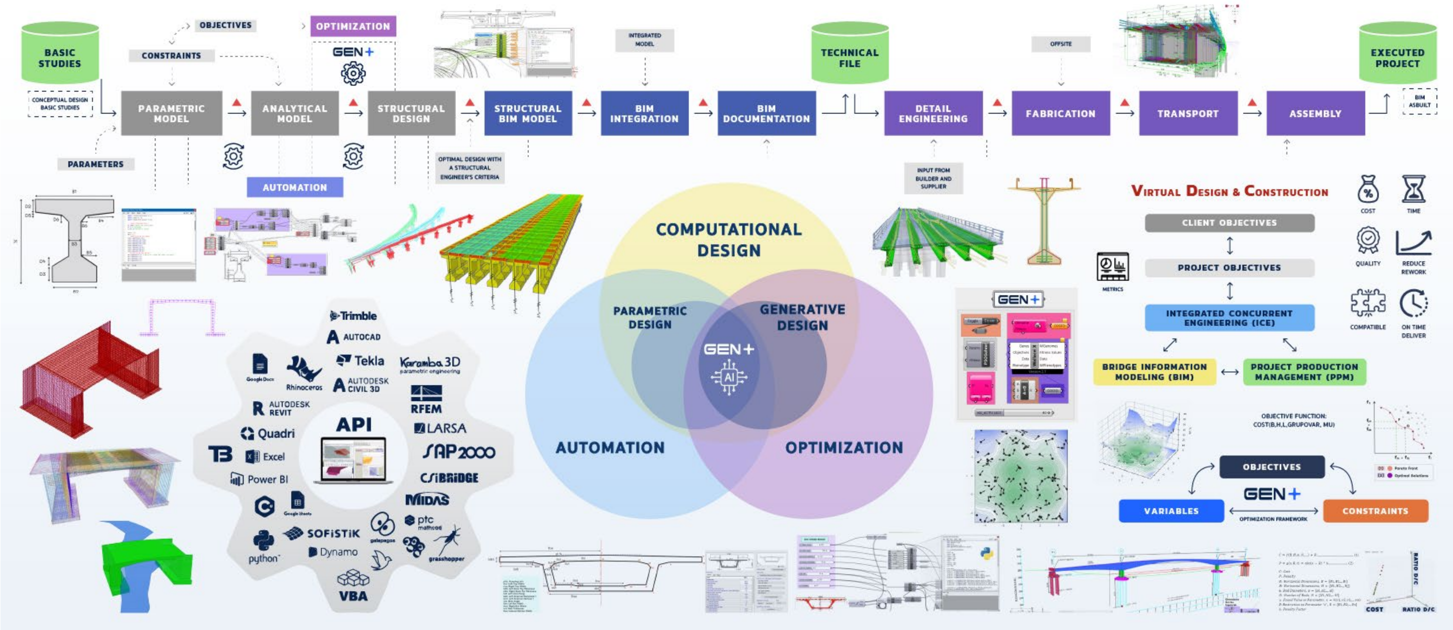

Figure 1: Computational Design & Structural Optimization in Bridges by Gen+

INTRODUCTION

The engineering and construction industry generates one of the largest investments in the world economy driven by investment in resources such as materials, labour, and machinery, among others. This diversity of elements generates an inherent complexity in workflows.

As a result, companies seek to be competitive and obtain "optimal" results by bringing together all the disciplines involved to ensure quality, minimize rework, and avoid additional costs.

While construction optimization can bring benefits, its effectiveness could be maximized by integrating it from the structural design phase.

Real-world application of structural and constructive optimization faces challenges. Complexities in modelling, a lack of precise data, and constraints in time and resources often limit its effective implementation.

This article addresses computational design, optimization and artificial intelligence embodied in an optimization framework developed by GEN+ and with application to various cases in bridge engineering, such as pile structures, pre-stressed beams, and portal bridges, among other structural components.

It also highlights the trend towards the generation of modern and industrialized designs and discusses the future challenges in engineering and innovation that will enable the achievement of objectives and the effective execution of projects.

COMPUTATIONAL DESIGN

Computational design is a method that involves computational tools and techniques to enhance and automate the design process, including simulations, analysis, modelling, and other digital tools that aid in decision-making.

In structural engineering, computational design proves to be the essential means to enable the integration of parametric and generative design, both of which generate the solution space that complies with the corresponding regulatory constraints. This allows us to carry out an optimization process, either through the use of heuristic methods or the utilization of Artificial Intelligence, enabling us to find the optimal solution to various design problems.

Parametric Design

Parametric structural design programming provides the capability to create highly customizable and adaptable models, accommodating various dimensions, materials, components and more.

This is paramount in modern civil engineering, where project variability and parameter adaptation are crucial to meet the specific requirements of each project, enabling a more versatile and efficient approach to structural design.

Generative Design

This design process involves generating multiple solutions, ranging from typical to unconventional solutions, all while adhering to a defined set of rules to achieve a series of established objectives and criteria.

In structural engineering, Generative Design, see Figure 5, is responsible for creating the solution

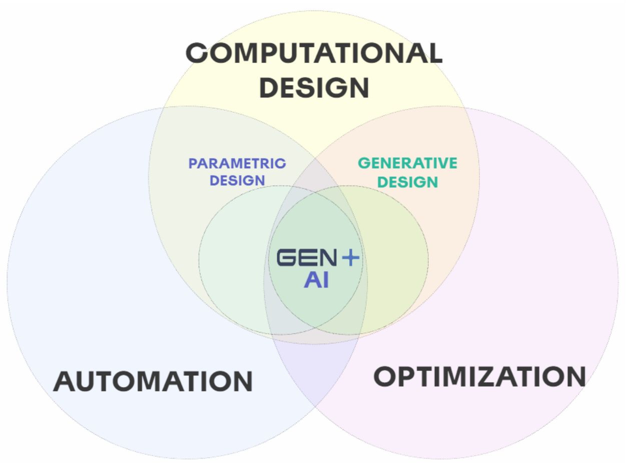

Figure 2: Computational Design, Automation & Optimization by Gen+

space that complies with the constraints of the relevant regulations, from which the optimal solution will be obtained.

Automation

Automation involves utilizing technology to perform tasks automatically and efficiently. In the field of civil engineering, automating processes through software APIs, using programming, enables the minimization of repetitive tasks, time-saving, and resource efficiency.

This efficiency not only reduces human errors, enhancing the quality of design but also allows more time for generating creative ideas, thereby enriching the design process.

Figure 3: Automation & interoperability between various software through API

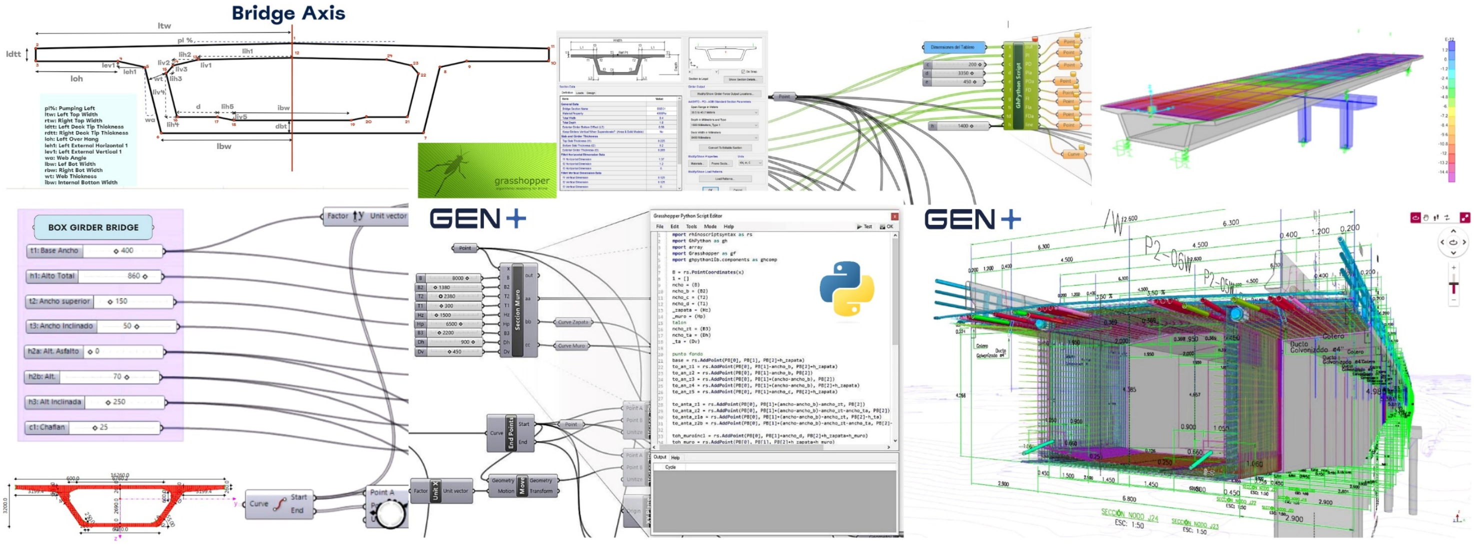

Figure 4: Parametric Design in Bridges

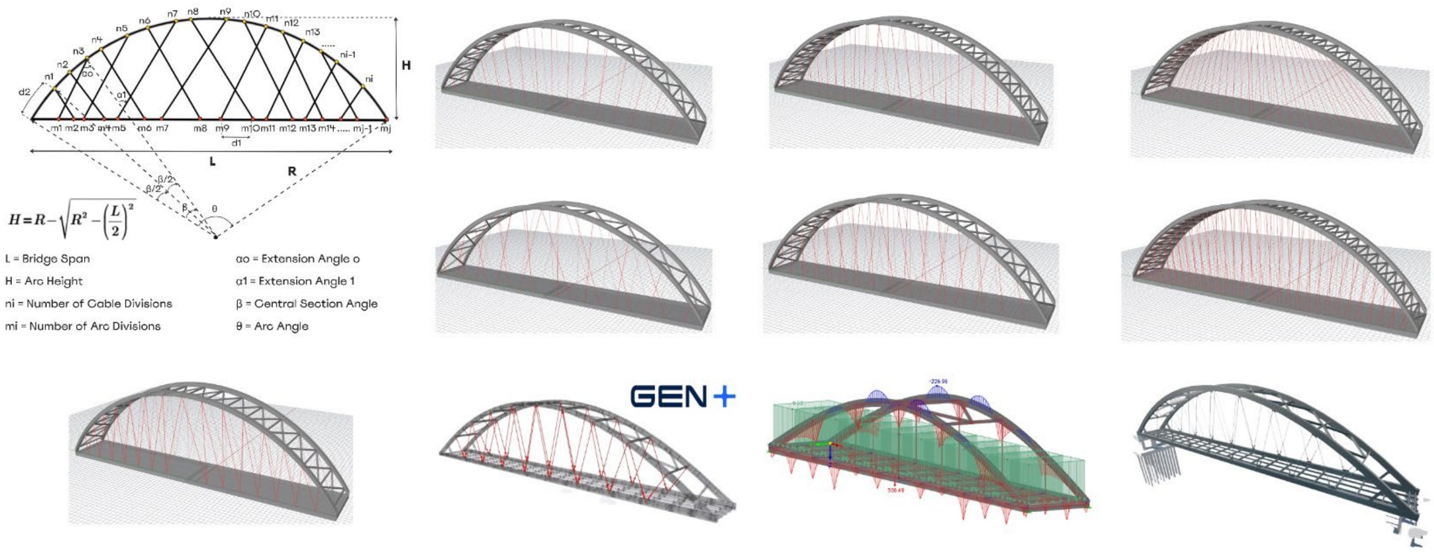

Figure 5: Generative Design in Bridges

<u>Optimization</u>

Optimization is the process of searching for the best option within a solution space constrained by a set of rules and criteria.

It is important to note the various search methods available to locate this optimal configuration. Among them, we have the Exact method that tests all potential combinations through algorithmic programming.

Heuristic methods also exist, designed to imitate natural behaviours like genetic evolution, bee colonies, and musician's harmony, among others.

Additionally, the advancements in Artificial Intelligence offer tools such as Neural Networks in

Machine Learning, which can anticipate the right combination to produce the desired outcomes based on a collection of input and output data.

This way, we will find a variety of combinations that meet the desired results, also known as objective functions. However, among these, the most optimal one must be chosen, especially in a multi-variable approach.

This selection process often employs the Pareto Principle, which asserts that a vector "x" is considered a Pareto optimum if no other vector "x'" can better any of the objective functions without worsening the value of another at the same time.

In structural engineering, optimization focuses on enhancing the performance, efficiency, and safety of a structural element from the design phase onwards. It aims to achieve the optimal configuration of the element based on a set of input data, ensuring compliance with a set of standards or regulations to generate the desired results.

As illustrated in Figure 6, Gen+ has effectively incorporated its vision into an Optimization Framework.

This framework initiates with INPUT, supplying design particulars and input variables. Subsequently, these inputs are then transferred through interoperability to optimization engines such as Galapagos, Octopus, and Wallacei, among others. These engines employ various heuristic methods integrated through the Gen+ engine to provide values.

Through an automated design process and compliance with structural regulatory constraints, the framework generates the required results.

If, during the iterative optimization cycle, any of the predefined constraints are found to be violated, a specific Penalty Value is systematically integrated into the computational model. This Penalty Value has significant implications on the optimization landscape, as it recalibrates and modifies the objective function values.

Thus, by utilizing the optimization framework, we obtain a clear understanding of the encompassing parameters, constraints, and objectives of our optimization process, enabling us to find the optimal structural configuration that yields sought-after results.

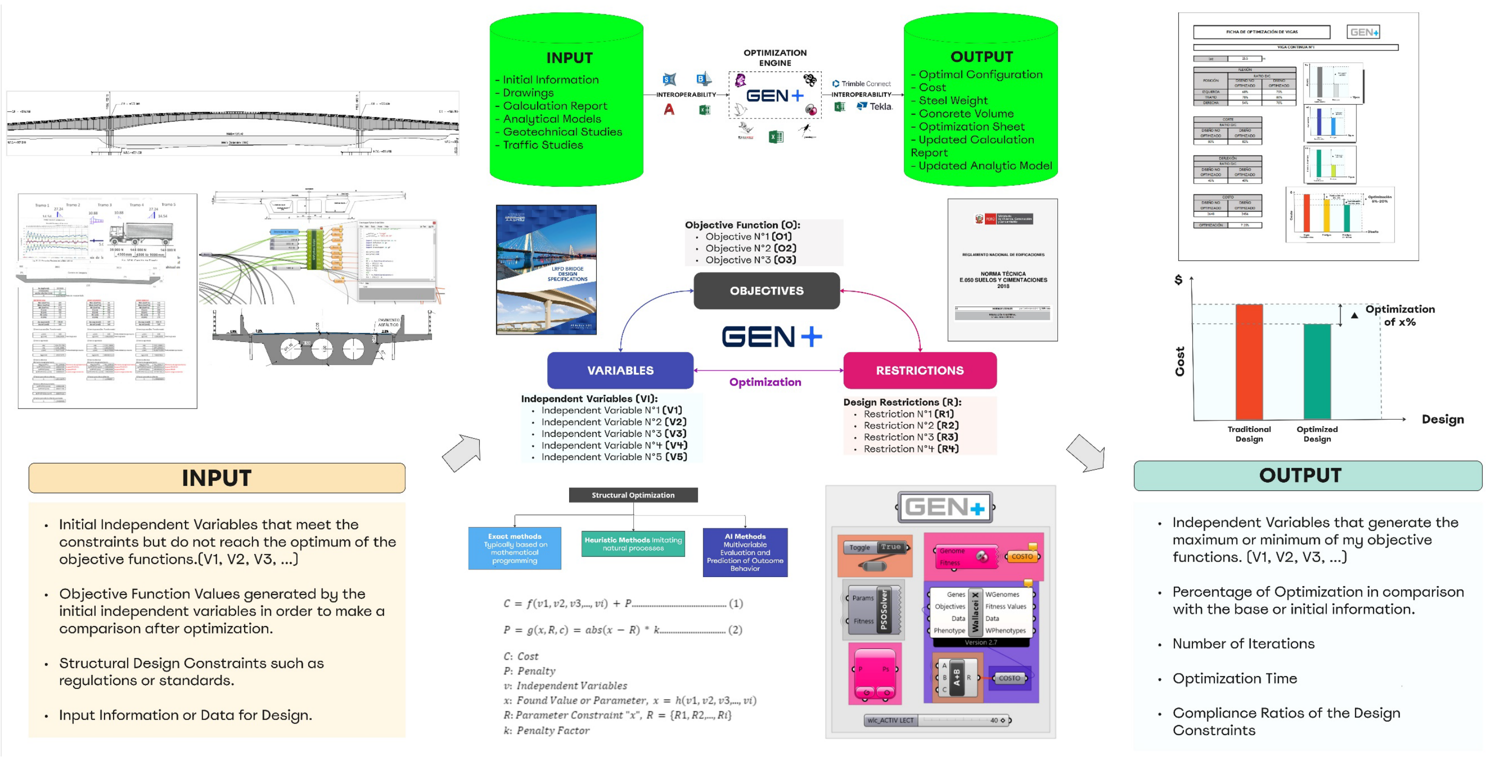

Figure 6: Optimization Framework by Gen+

COMPUTATIONAL DESIGN AND STRUCTURAL OPTIMIZATION IN GEN+

Generative AI and Parametric Modelling for Estimations based on Historical Data

The conception of bridges requires considering multiple design alternatives due to their significant economic, social, and environmental importance. As a result, the effort to choose their typology, estimate quantities, costs, and the viability of each bridge becomes extremely complex and time-consuming.

To address this challenge, it is necessary to properly structure a historical database, which contains information from a wide variety of bridge projects that have been constructed in Peru. Additionally, a significant number of structural elements have been parameterized.

This parametrization facilitates the creation of fully adaptable models, allowing for a rapid and versatile generation of 3D models while considering the pre-design criteria suggested by the AASHTO LRFD regulations.

By structuring the provided data and applying Supervised Machine Learning algorithms, a model has been trained using Python programming with the Scikit Learn library, with the purpose of estimating quantities and costs of the main elements, as well as estimating resource usage and timelines for the development of BIM modeling (Level of Development 400).

It is also necessary to develop a user interface that allows for user-friendly interaction with the model. Through a backend, the data provided by the user is processed by connecting it to the model via an API. In this way, the model receives the data as INPUT, predicts the output data through the same process, and displays it to the user.

It is important to highlight that the degree of accuracy of this development is strongly linked to the size of the database provided for learning, with the limitation being the number of documented bridge projects to which there is access.

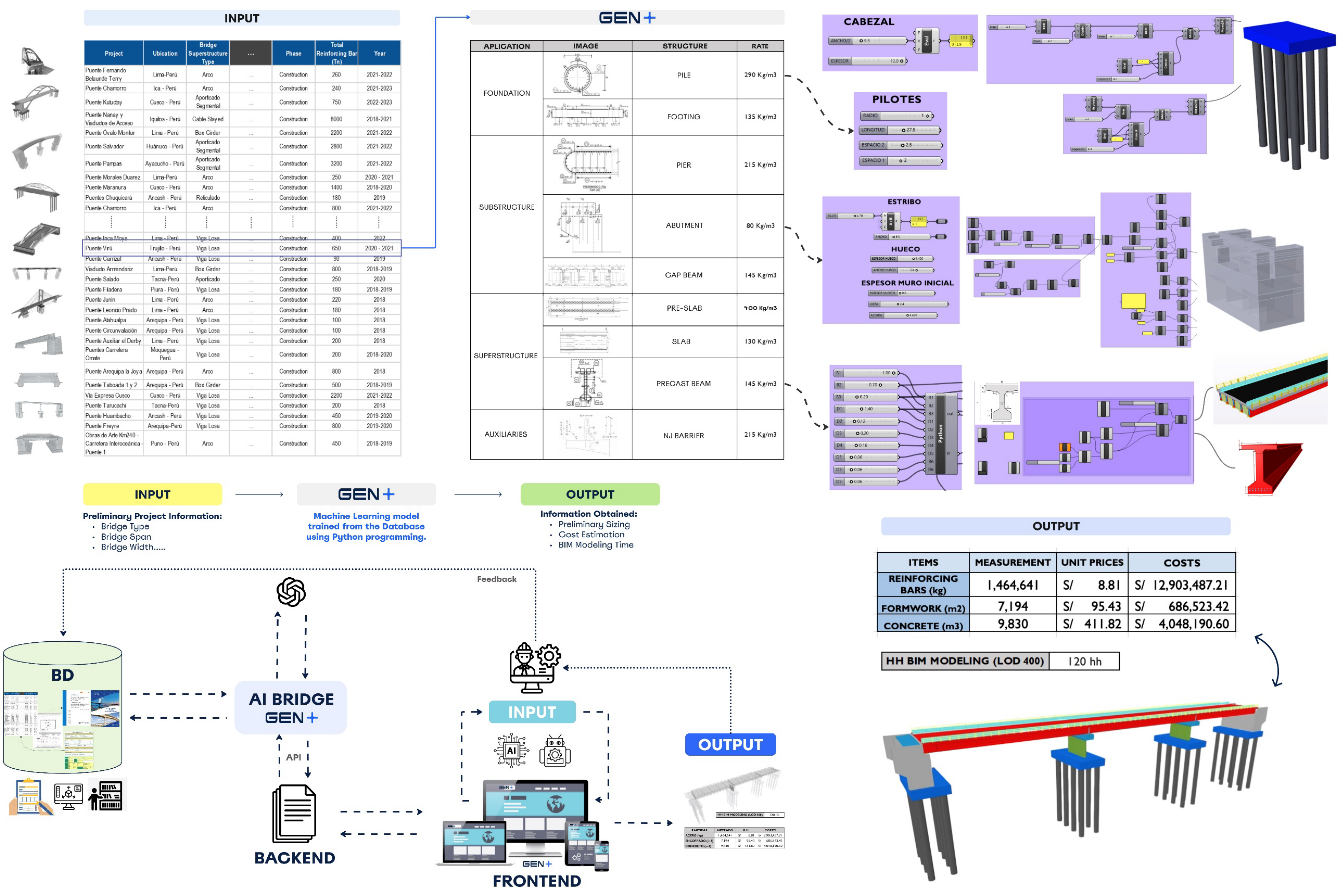

Figure 7: Generative AI and Parametric Bridge modelling based on Historical Data

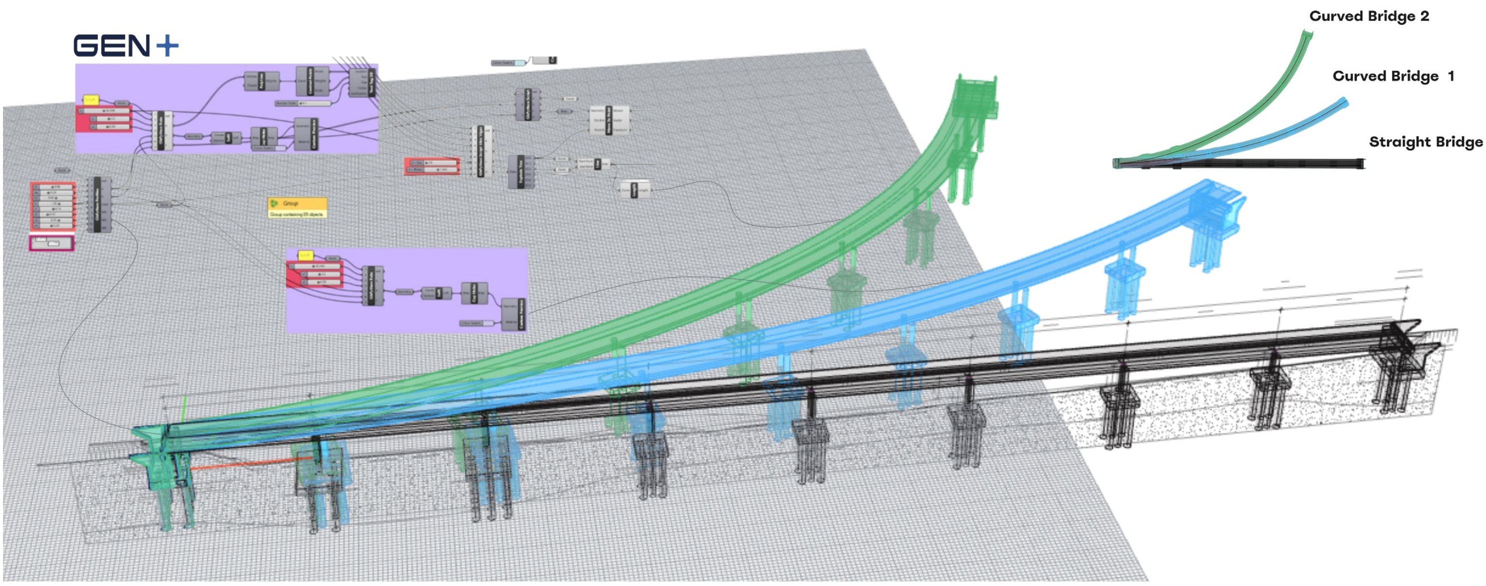

Figure 8: Automation in the parametric generation of bridge alternatives

Parametric Modelling in Segmental Bridges

Segmental bridges involve a complex design process, and it is essential to consider this from early stages, especially during conceptual design. These bridges require numerous iterations and updates between the geometric and analytical models.

Therefore, developing predefined tools that encompass all the parameters of this bridge type is of essential importance.

These tools facilitate a seamless transfer and updating of information between the parametric and analytical models, due to the interoperability between GH and structural analysis software, such as Sofistik, CSI Bridge, and others.

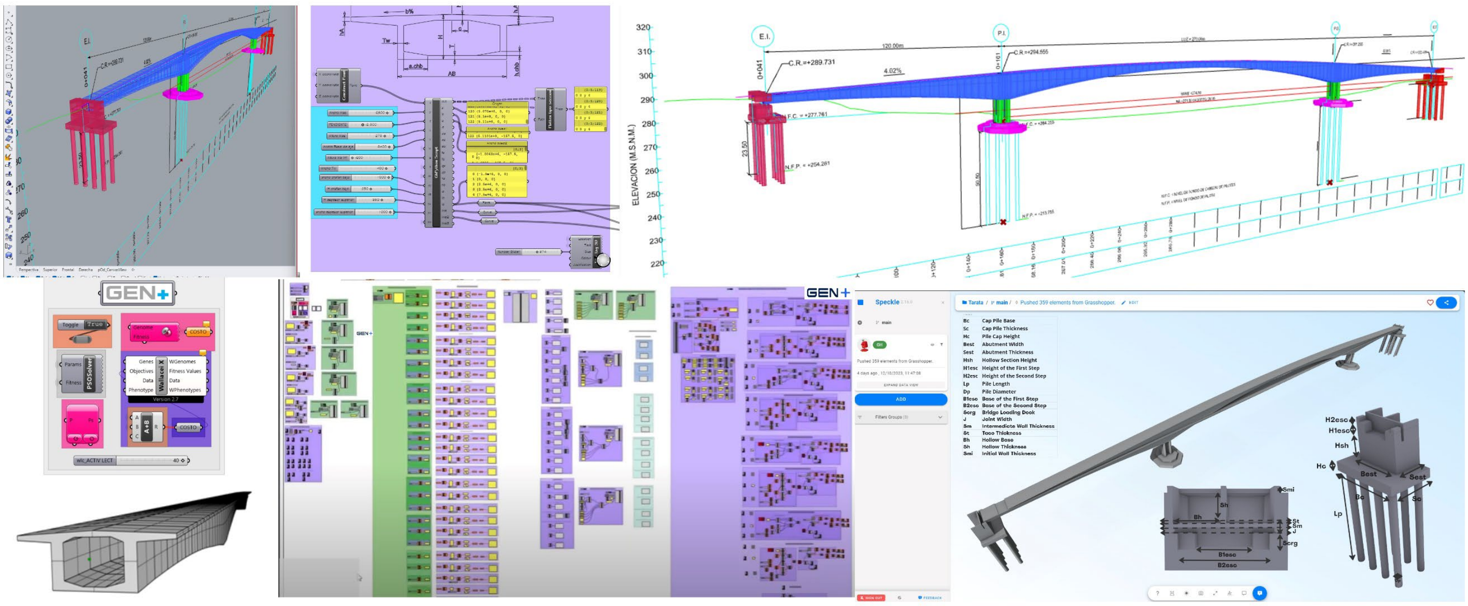

Figure 9: G+SegmentalBridge: Application for Parametric Design for Segmental Bridges

Furthermore, to achieve enhanced adaptability and optimal bridge control, the substructure is parameterized.

This includes elements like piles, pile heads, abutments, post-tensions, inserts, among others. It all begins with a detailed scheme of their geometry, elevation, drainage, and other pertinent aspects. Subsequently, using Grasshopper code, fully parameterized and adaptable elements are generated.

Optimal Pile Design

In the context of projects, pile design is a highly complex task that involves a wide range of geotechnical, structural, and construction factors.

Given the notable costs associated with them, achieving the optimal balance between soil-structure interaction analysis, structural design, and cost-effectiveness in construction is critical.

The variability in the comprehensive design of piles lies in the choice of geometric configuration, encompassing their diameters, location, length, and quantity. These aspects are analyzed in conjunction with the structural design of the sections, which involves selecting diameters for longitudinal steel, determining quantities, and choosing the type of stirrups (closed or spiral).

These critical decisions are made by the design engineer, who faces challenges such as creating the analysis model, updating geotechnical information, commercial pile diameters, operational machinery, redesigns, and more.

The discrete and continuous dynamics of these variables converge to impact structural performance, the supply chain, and the cost of the piling section.

In this regard, through the integration of programming languages like Python, C#, GH, etc., and Application Programming Interfaces (APIs), it enables the development of automated and interoperable processes for parametric modelling, geotechnical-structural analysis software, and reinforcement steel detailing of piles.

For instance, the optimization tool G+Pile, by defining multi-objective functions, adopts heuristic mechanisms for effective exploration within the generative environment of possible solutions.

This aims to find the most suitable global optimal solution for pile geometry and reinforcement steel

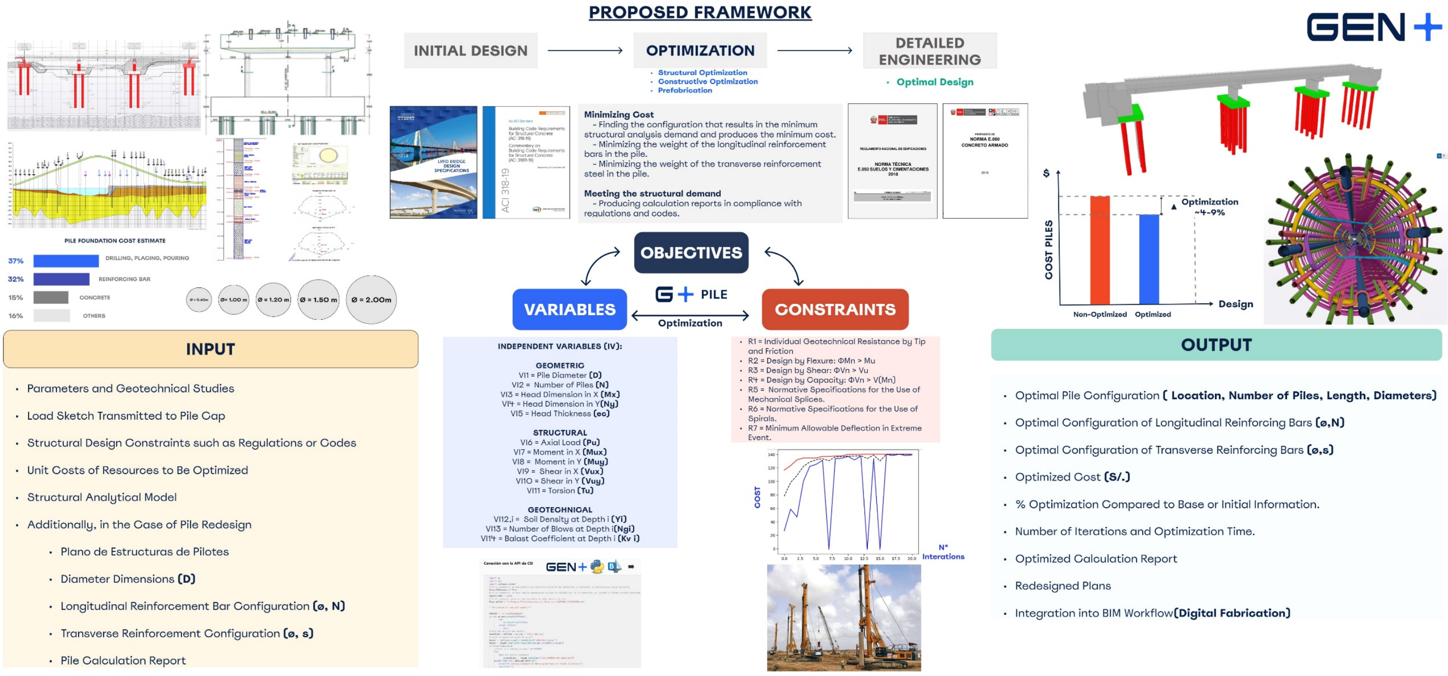

Figure 10: Framework optimal G+Pile

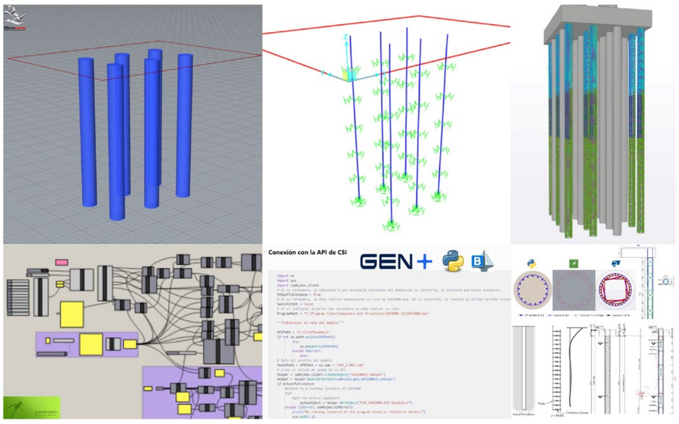

Figure 11: Interoperability between parametrization, geotechnical-structural analysis, and steel reinforcement detailing software

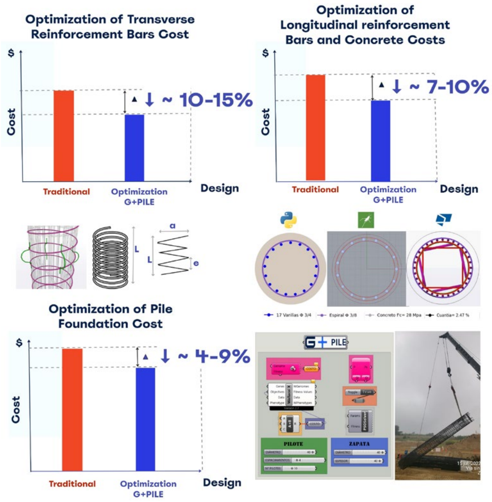

Figure 12: Optimization of Pile Foundation Cost

configurations that comply with codes such as AASHTO LRFD Bridge Design Specifications and ACI 318, among others.

The use of the optimizer can lead to a reduction in piling costs ranging from 4% to 9%. When optimizing both longitudinal reinforcement bars and concrete separately, savings of 7% to 10% in the total cost of these materials can be achieved.

Furthermore, the use of spiral ties improves section ductility, streamlines prefabrication, and reduces transversal reinforcement costs by up to 15%.

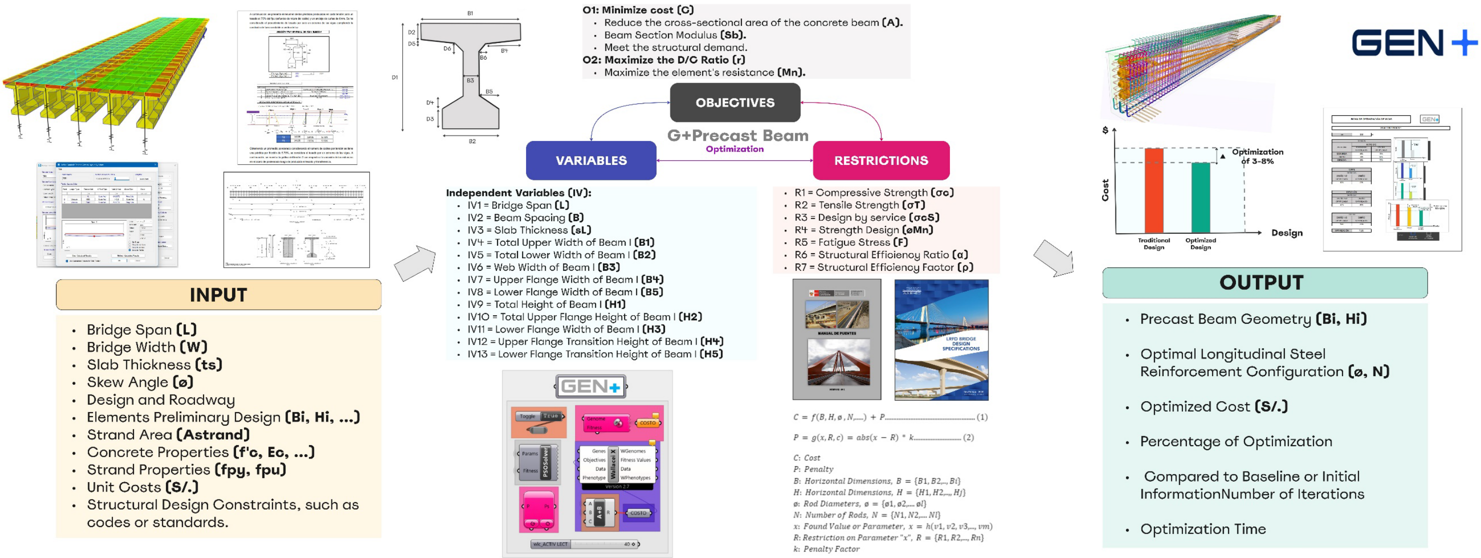

Figure 13: Framework Optimal G+ Precast Beam

Optimal Design of Precast Beams

Precast beams are often a highly convenient solution for builders due to the time savings they offer.

However, this advantage could be even greater if cost optimization of materials is considered from the design stage, which is not typically done, leading to oversizing the element and not achieving a cost-to-strength balance.

Therefore, an optimization design process has been developed. This process can start with the receipt of input information such as bridge geometry, road elements, material properties, and more, obtaining the necessary data for calculating demand loads.

It can also begin with an existing design, in which case it would require the analytical modelling of the bridge, the design engineer's calculation report, and detailed drawings of the prefab beams.

In both cases, the received information is extracted using plugins that work with the API of various software within the Grasshopper environment, such as Swallow, LunchBox, TTToolBox, among others, to bring all the information into a common and controlled environment.

In order to carry out the optimization process, it is necessary to parametrize the beam. This allows the optimization engine G+Precast Beam, which uses the Heuristic method of Genetic Evolution with K-Means clustering, to vary its dimensions.

These dimensions are then transferred to a fully automated design sheet in Excel, and through programming in Visual Basic and Python, each of the regulatory constraints is verified. In case any of these constraints are not met, a penalty function is applied, affecting both cost and strength.

Once the configuration of the beam is determined, it is automatically quantified so that, using predefined unit prices, the direct cost of the beam can be calculated.

This cost, along with the calculated strength, is then returned to Grasshopper (GH) as an output.

The optimization engine in GH receives these outputs and, following the Pareto principle in a multivariable optimization approach, selects the most optimal configuration for the beams.

After this, the optimal configuration is organized and transferred to Excel, where an automatic calculation report is generated.

In the case of redesign, an optimization record is also created, comparing the initial non-optimized quantification with the results obtained by the optimization engine.

Finally, this configuration is also automatically modeled using the Tekla API, which allows us to obtain detailed drawings of the prefab beams.

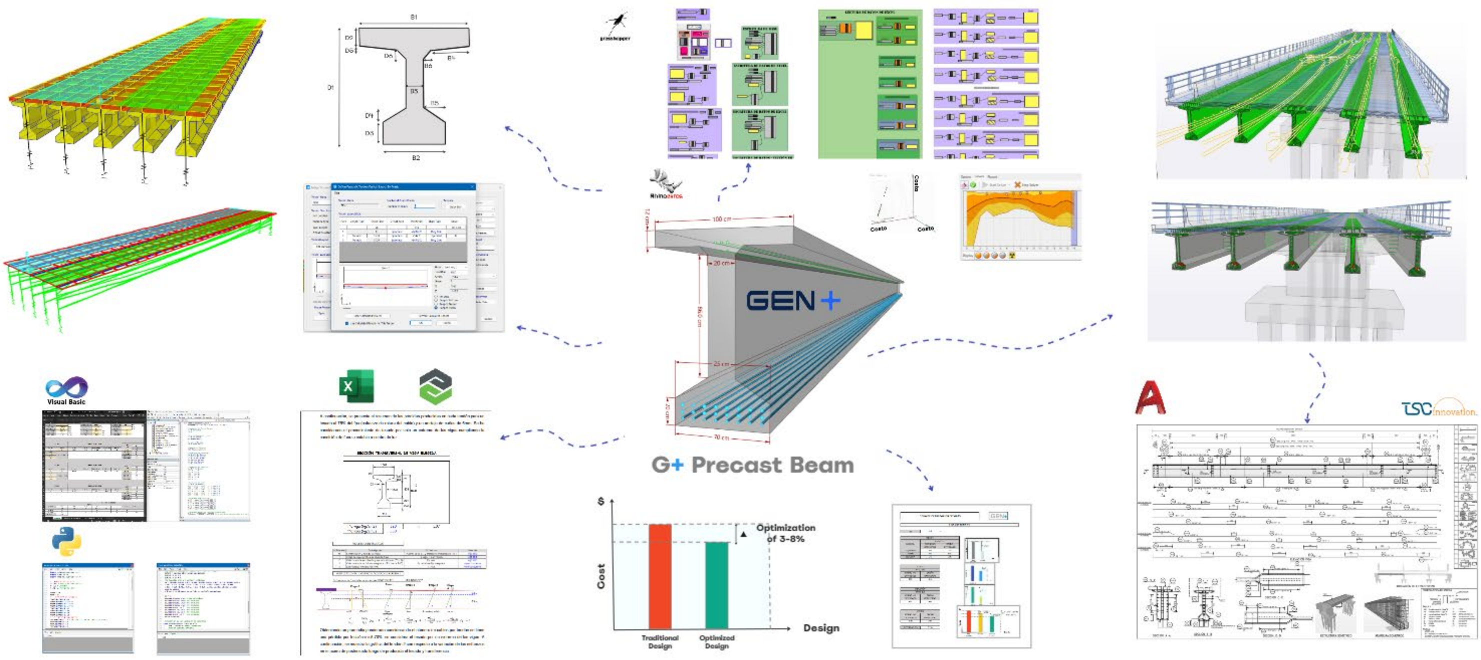

Figure 14: Computational Design and Optimization of G+ Precast Beam

Computational Design of Portal Frame Bridge (PFB)

Vehicular traffic bridge construction for small spans (6 to 25m) has involved the use of concrete structures such as beam or slab bridges.

Selecting the type of bridge has a significant impact on its performance and durability, hence the need to opt for another type of bridge that demonstrates a higher structural behavior, such as portal frame bridges (PFB), whose main advantage is, in contrast to the beam bridge, its hyperstatic condition.

This feature allows it to distribute loads more uniformly, minimizing the concentration of stresses at critical points of the structure, which can help prevent fatigue and premature wear of materials, sparing operation and maintenance costs.

However, its adoption is limited by the few number of specific standards and the uncertainty generated by the lack of experience with this type of bridge compared to beam bridges.

Its design can be complex as it involves multiple variables and requires meticulous consideration of how each component is integrated into the overall structure.

Facing that, modern technology, through computational design, offers solutions where it is possible to parameterize and optimize the design of a PFB using 3D modelling tools and advanced

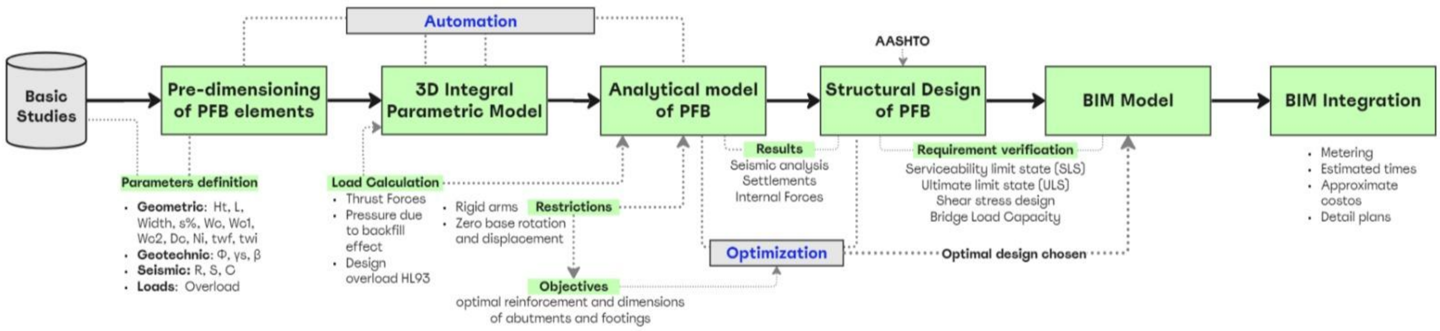

Figure 15: Computational design process of the PFB

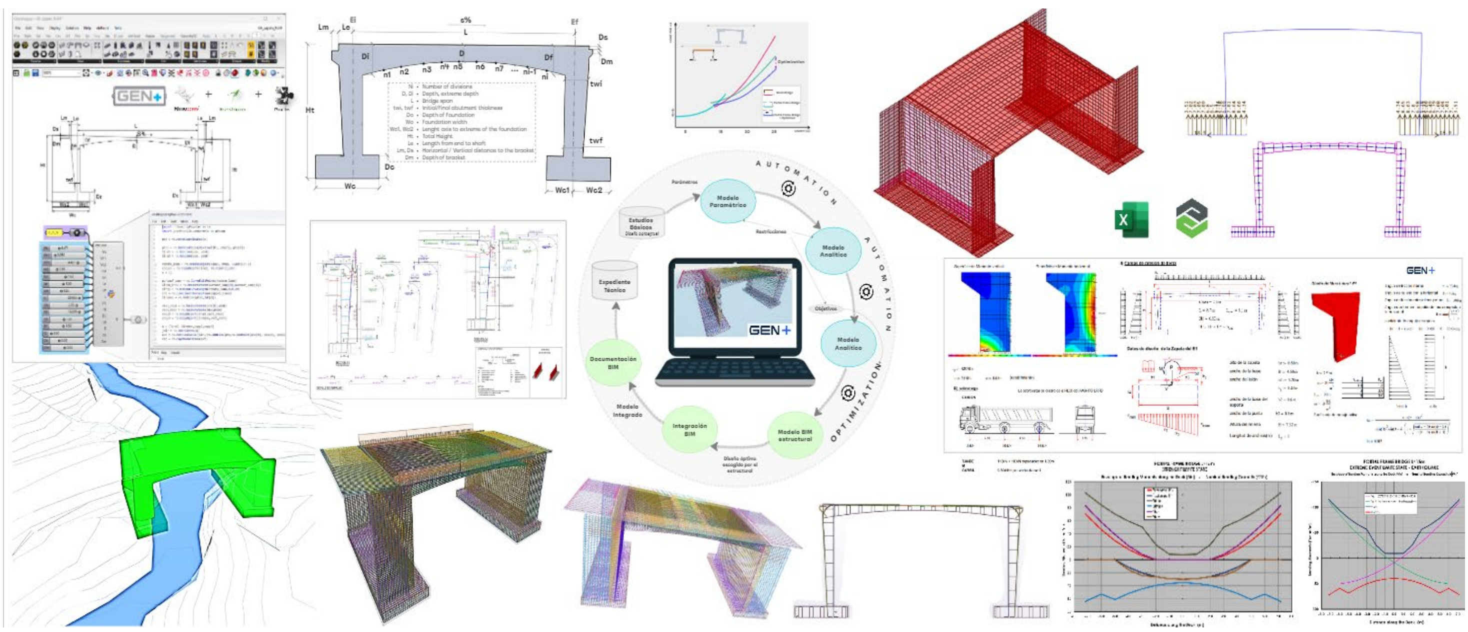

Figure 16: Computational Design for Portal Frame Bridges

structural analysis. It is even possible to start from a beam bridge design and convert to a PFB.

This process starts with the definition of the design parameters, which includes the specific criteria of the geometry (span, available width and height, etc) and the site (geotechnical and seismic conditions).

With this, an integral 3D parametric model of the PFB is created, and connected to the structural calculation software to obtain its analytical model.

Here it is important to consider hypotheses of connections with rigid arms between abutments and deck, and the restriction in displacement and rotation of the bases in order to obtain the structural demands.

The next step is the structural design under AASHTO standards in a spreadsheet, which is integrated with optimization tools that allow exploration of multiple design configurations. By adjusting some parameters and dimensions of the structural elements, the optimal and cost-efficient design is found.

Finally, the PFB model is converted into a BIM model with detailed information that allows for estimating construction times as well as approximate costs. This facilitates the planning and execution of the final bridge construction.

The graph in Figure 16 shows the reduction that occurs when comparing a common girder bridge with a PFB and an optimized one.

CONCLUSIONS

Computational design in bridge engineering integrates both parametric and generative components, enhancing the flexibility of structural design. With automation, it streamlines optimization methods to achieve designs aligned with the proposed objectives.

Despite the advantages of these tools in the search for optimal solutions, the experience and vision of the structural engineer remain essential.

Parametric and generative design in bridge engineering streamlines the development of analytical and constructive models. These approaches enable customizable and adaptive designs, improving process efficiency. Optimization in structural engineering refines design using AI and heuristic methods, ensuring optimal bridge configurations.

The AI's precision during training depends on data, enhancing budget estimations and expediting design decisions with time as a crucial factor.

This revolutionizes how engineers can generate models with accurate volumes during the conceptual design stages, optimizing their workflow and enhancing structural designs.

Pile design's complexity on bridge projects requires a balance of geotechnical, structural and cost factors. The use of integrated software and tools such as G+Pile can optimize designs, which can lead to 4-9% reductions in pile costs while ensuring efficient, safe and cost-effective results.

Structural optimization in precast beams provides an additional contribution to the inherent construction, thereby achieving a material cost optimization estimated by the G+ Precast Beam engine in the range of 3-8% without compromising the structural safety of the element, thus achieving a cost-strength balance.

The adoption of Portal Frame Bridges instead of conventional bridges is a great opportunity to offer innovative and efficient bridges in economic and structural aspects.

This is enhanced by integrated computational design starting from parameterization, structural design to BIM modelling, optimizing element cross-sections and automating processes in optimal time.

Computational design, combined with AI, redefines design processes by leveraging historical data and heuristic analysis, optimizing timelines and costs, and ensuring the safety and functionality of structures. This synergy promotes innovation and opens up a world of possibilities for future research in structural engineering.

EXAMINING STRUCTURAL HEALTH MONITORING AND BRIDGE BEHAVIOUR THROUGH THE LENS OF MACHINE LEARNING

Paraskevas Mylonas, Bridge Engineer, WSP Canada

Ekaterina Ossetchkina, MASc Candidate, University of Toronto

Figure 1: The Alexandra Bridge, Ottawa, Ontario. Source: Architects DCA Inc.

INTRODUCTION

In the realm of civil engineering and infrastructure management, oftentimes, precision and reliability are paramount. In this context, Structural Health Monitoring (SHM) can provide precise, real-time insights into structural conditions and performance by monitoring key parameters over both short and long durations.

SHM entails the continuous observation of a system over time, utilizing periodically recorded system responses that track variations in material and geometric properties.

A robust SHM system can provide owners with a comprehensive understanding of their structure's condition.

Armed with this invaluable data, informed decisions about maintenance activities can be made, potentially extending the structure's service life well beyond its design life and simultaneously mitigating the risk of costly future repairs.

Advanced structural monitoring technologies have made it possible to gather vast datasets from a network of sensors.

However, the challenge lies not in the collection of data but in making sense of it. Time-series data analysis is inherently complex, often compounded by seasonal variations and the harsh environmental conditions these sensors endure, which can compromise the accuracy and reliability of recorded results. For this reason, our team delves into the realm of data-driven decision-making for structural integrity.

Our case study, a steel truss cantilever bridge located in Ontario, Canada, provides a compelling demonstration. Equipped with 35 weldable strain gauges, having a nickel-chromium alloy grid encased in fiberglass-reinforced epoxy phenolic, this bridge underwent meticulous data collection at one-minute intervals for an extensive two-year period.

Python3 is a programming language that has a large collection of open-source scientific and statistical modules available, which allows us to transform the raw data into features for a fitted classification machine learning model. This model's primary mission is the identification of outlier sensor readings, periods when the sensor strain prediction was influenced by environmental conditions and reporting a strain not reflective of the actual loading occurring.

To validate the model's predictive prowess, a rigorous time-series cross-validation (CV) strategy was employed, accounting for the influence of a variety of environmental factors.

Through the application of statistical methodologies and machine learning algorithms to existing bridge sensor data, we aim to ensure the accurate and timely delivery of vital information.

These insights empower engineers with the tools needed to make informed decisions regarding maintenance and repairs, ultimately safeguarding our infrastructure and the safety of those who rely on it.

The importance of implementing precise anomaly detection processes in SHM cannot be overstated. Ontario, having over 15,500 bridges as of 2020 - more than any other Canadian province - faces the task of safeguarding these critical assets.

With an additional ~500 bridge projects currently under construction, the need for robust, automated methods to assess structural health is more pressing than ever.

INFRASTRUCTURE IN CANADA

Canada's extensive network of bridges is essential to the country's transportation infrastructure.

Many of these bridges are located in areas that are subject to extreme weather conditions, such as high winds, heavy snowfall, and seismic activity.

Therefore, it is paramount to ensure their safety and longevity, which is where SHM comes into play.

In SHM, a wide range of sensors are incorporated with the critical components of a structure, and their behaviour is monitored in real-time.

The monitoring of the structure generates data which is dependent on the SHM system and the type of sensors used.

This data is further analyzed and interpreted by engineers, and relevant preventive action is being taken by repair and/or rehabilitation works as necessary.

In addition, SHM applications, especially in bridges, are utilized to monitor the structural behaviour of a structure, detect potential issues to avoid failure events, plan in a timely manner for inspection and maintenance when needed, test the structures when novel materials or design concepts are incorporated, and above all ensure the structure's integrity in the long-term period.

At its core, SHM's primary mission is to detect anomalies early on, thereby mitigating the costs associated with extensive repairs through timely maintenance decisions.

Despite significant academic interest in SHM, it has yet to establish itself as a standard practice within the civil engineering industry.

One notably underexplored facet in the existing literature pertains to the reliability of SHM monitoring sensors.

Questions persist regarding the system's ability to consistently assess structural conditions, its longevity compared to that of the structure itself, and the inherent nature of sensor data and its dependency through time.

It is our belief that the challenge of detecting outliers in SHM data can be framed as a problem of statistical pattern recognition.

For this reason, we explored modelling existing sensor data through a structured process:

1) data acquisition,
2) data cleansing and combining sensor data with environmental data,
3) labelling potential outlier data-points, and
4) feature extraction and statistical model development for feature discrimination.

STRUCTURE DESCRIPTION

The structure of our case study is a steel truss cantilever bridge supported by massive concrete and stone masonry piers located in Ottawa, Ontario. Comprising a total of five spans, with an overall length of 818.0 m, inclusive of approach spans and a trestle, the bridge's largest span is 172.2 m.

There are three separated decks with a total width of 18.9 m in the transverse direction. Originally, the central deck accommodated railway tracks alongside two pedestrian footpaths, while the side cantilever decks facilitated streetcar traffic.

Over the years, this bridge has gone through significant transformations in its functionality. Being in service since 1901, the bridge has gone through many restorations, maintenance and repainting work.

Initially, it was solely used for railways, local electric trolley service and carriage traffic, and later, in 1950, it was redeveloped for vehicles and pedestrian traffic.

At present, the railway has been removed, so the cars are using the downstream and center decks while the pedestrians are using the upstream. Currently, the bridge carries more than 18,000 vehicles per day, including pedestrians and cyclists.

A comprehensive inspection conducted between 2016 and 2017, which included the submerged components, unveiled extensive deterioration and corrosion of the primary structural elements.

These issues necessitated substantial reinforcement and repair work to restore the bridge's load capacity.

The inspection, which involved visual assessments of various sections of the bridge, exposed corrosion at numerous locations on the trusses, main beams, and girders. The corrosion led to a reduction in the cross-sectional area of the steel members, restricting thermal movement and pin rotation. Furthermore, deformations were observed in the bridge's bracing system, potentially linked to its structural performance.

Based on the findings from this thorough examination, an engineering firm proposed a comprehensive rehabilitation plan that outlined the identification of elements requiring repair and replacement.

Additionally, this assessment laid the foundation for the proposition of implementing a Structural Health Monitoring (SHM) system on the bridge.

The SHM initiative commenced on November 9, 2018, and remains in operation to this day. In our study using data from the installed SHM system, we analyzed select results from the original sensors installed at the time of inception of the SHM system.

BRIDGE SENSOR PLACEMENT

The bridge was monitored through the deployment of multiple strain gauges. Strain, which was the primary parameter under scrutiny, serves as a precise indicator of how specific structural elements respond to various conditions.

Any fluctuation in strain within a particular member was directly captured at the precise location where the strain gauges were strategically positioned. Furthermore, this strain data played a pivotal role in the computation of forces and the corresponding stresses generated by each structural component.

To comprehensively assess the bridge's behaviour, a total of 35 strain gauges were strategically embedded within its boundaries.

Each strain gauge was directly connected to a digital sensor interface (DSI) where the analog data from the strain gauge is converted into a digital signal by the DSI.

In this setup, a total of 21 DSIs were integrated into the system. For reference, Figure 3 provides a visual representation of a standard DSI employed within this particular structure.

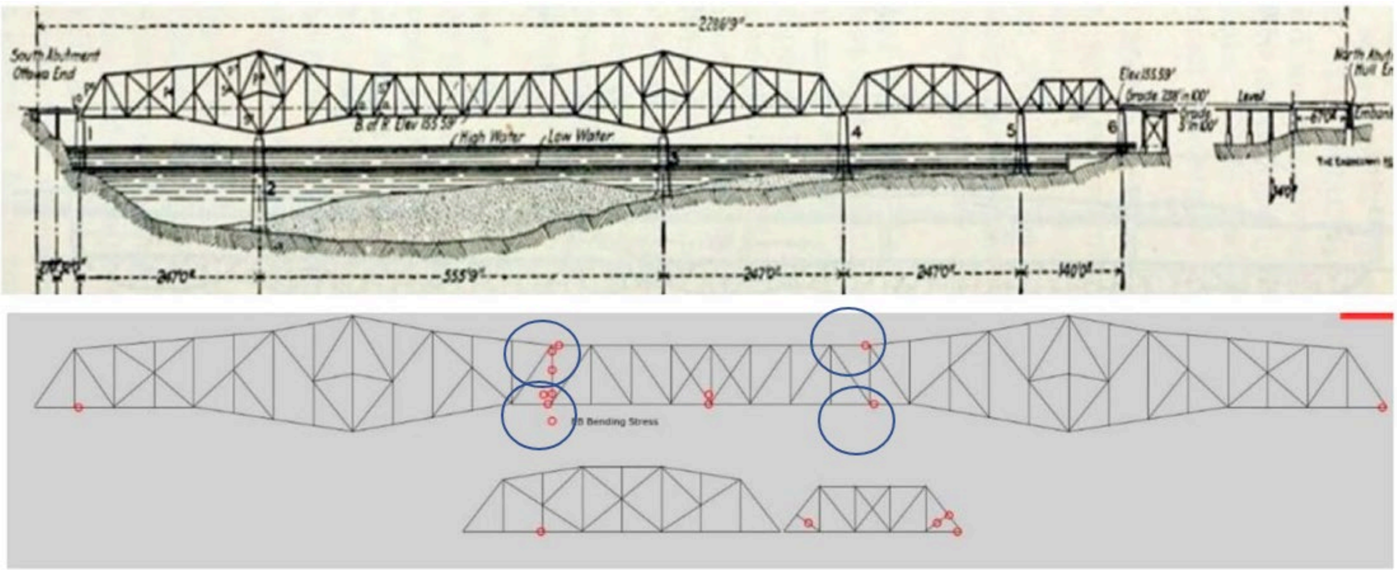

Figure 2: Top: Original structure. Bottom: Strain gauge placement along structure in elements of interest (red dots). Blue circles indicate elements investigated in this study

The converted to digital form signal from the strain gauges was transmitted through cables to data loggers. The majority of DSI units received input from two strain gauges. In instances where a single gauge was located in proximity, it was directly connected to its dedicated DSI box.

Each DSI unit not only captured strain data but also recorded the temperature (°C) of the steel, necessitating their placement as close as possible to the strain gauges for precision and accuracy. The data from all the DSIs were transmitted via wired connections to the data loggers.

Data reading frequency for the loggers was set at 0.25Hz, with data recorded and stored at the top of each minute. Hourly data transmissions occurred via cellular modems from the data loggers. In case of poor reception or network issues, the data loggers possessed the capability to store data for up to twelve 12 hours.

The operational strain range was within ±5000 μm/m, and the normal temperature range encompassed -195°C to +260°C, with a short-term maximum temperature threshold of +290°C.

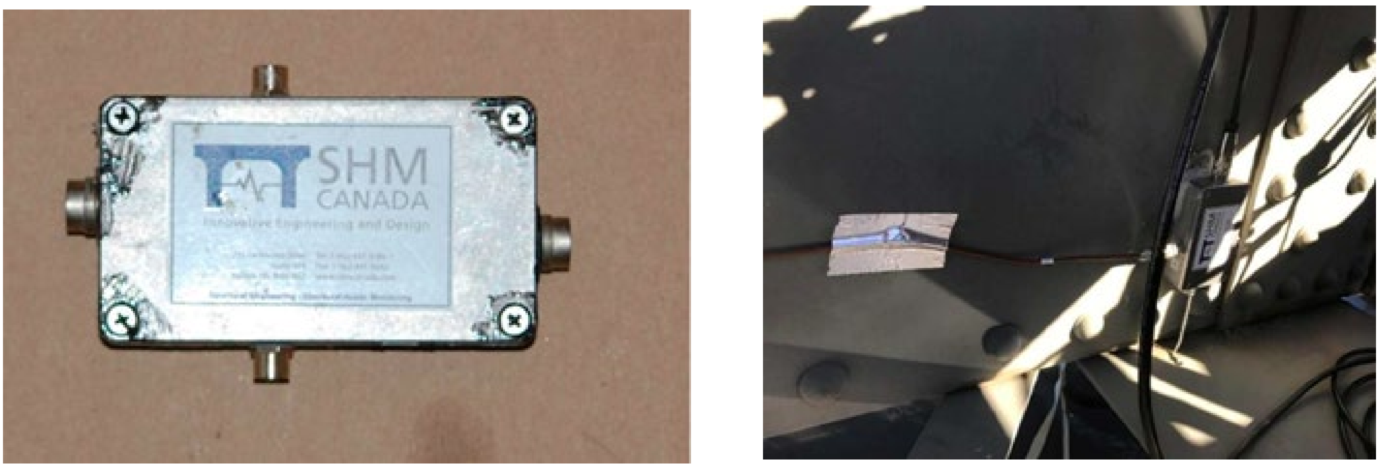

Figure 3: Left: Digital Sensor Interface (DSI). Right: Strain gauge installation

STRAIN GAUGES

For the strain measurements, LWK-Series weldable strain gauges were employed, specifically the LWK-06-W250B-350 model. Figure 3 in the illustration portrays a typical strain gauge utilized in the structural assessment. These gauges are constructed with a nickel-chromium alloy grid encased in fiberglass-reinforced epoxy phenolic material.

Each gauge comes equipped with a three-wire lead system, featuring 250 mm of Teflon-insulated lead wire. This design simplifies temperature compensation for the lead wires and facilitates straightforward connections to the instrumentation cable.

ADDITIONAL DATA SOURCES

Beyond the strain and steel temperature data gathered from the DSI unit, supplementary information was collected from Environment Canada's accessible historical weather datasets. Leveraging Environment Canada's open-source API, data retrieval centered on the Ottawa International Airport weather station (ID 49568, Latitude: 45°19'00 N, Longitude: 75°40'00 W) for the period spanning January 2019 to January 2021.

Given the hourly granularity of this dataset, an alignment was achieved by resampling the DSI data to an hourly format, calculated using the average strain value within each hour time slot, enabling a seamless fusion of these datasets.

The Environment Canada data included additional climate and meteorological data, including ambient temperature, relative humidity, snowfall, precipitation, air pressure, wind speed and direction, and more.

PYTHON

Python has gained prominence within the scientific community owing to its user-friendly low-level syntax and automatic handling of backend functions. These features come at the cost of slightly slower execution times compared to compiled languages like C++.

Benefiting from its open-source nature, Python includes a variety of third-party modules hosted on the Python Package Index (PyPI). This extensive repository empowers users with diverse development possibilities, complementing the standard modules and thriving international community.

In the realm of scientific work, numerous libraries rely on Numpy as their foundation. Numpy enhances Python's capabilities by introducing support for large, multi-dimensional arrays, matrices, and the essential operations associated with these data structures. Statsmodels, another Python library, equips researchers with a toolkit comprising classes and functions tailored for estimating various statistical methods, constructing tests, and exploring data.

Within this research context, Statsmodels played a pivotal role in handling time-series data, utilizing the time series analysis submodule, which incorporates built-in functions to manage data correlations and seasonality (as discussed in the subsequent section). Scikit-learn, on the other hand, offers a suite of straightforward and efficient tools for predictive data analysis, encompassing submodules and functions catering to both supervised and unsupervised machine learning models.

Pandas, with its user-friendly tabular data objects, simplifies the processing of diverse data sources, data labelling, and the creation of relational structures.

Meanwhile, Matplotlib serves as a comprehensive library for crafting data visualizations. These libraries furnish users with fundamental building blocks that streamline the implementation of commonplace algorithms, facilitating the construction of a data analysis pipeline.

EXPLORING DATA AND MODELLING

In our study, the data used was continuously collected from six sensors over a span of two years, commencing in January 2019 until January 2021. Data points were systematically measured and logged at regular time intervals (every minute) throughout this duration.

Working with the dataset had three main challenges, which will be discussed in more detail in the following sections. Firstly, we were working with a time series dataset, in which each data point is dependent on the previous one in time.

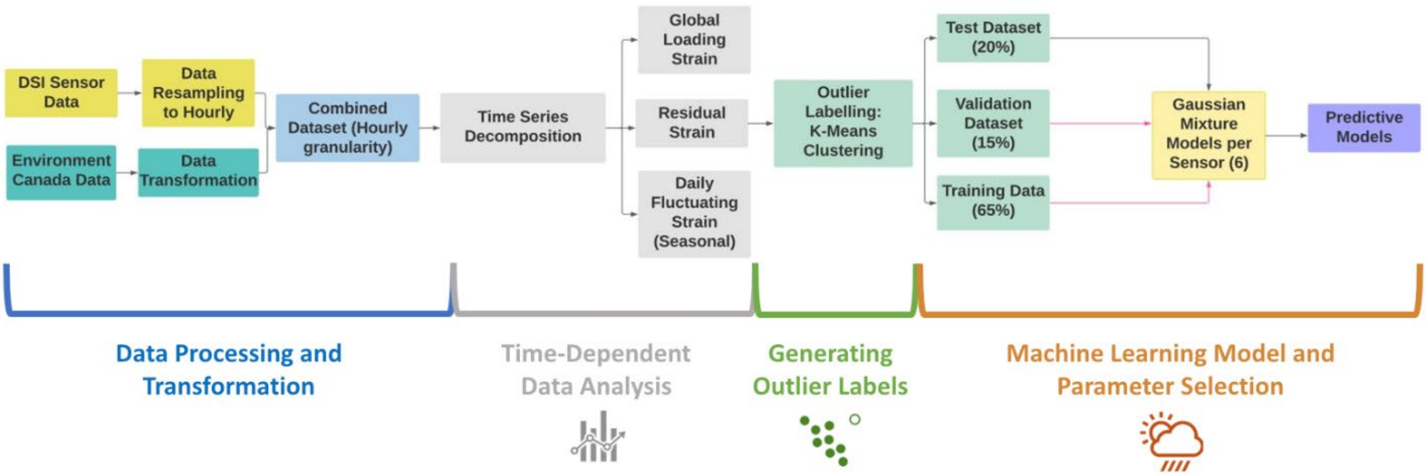

Figure 4: Overview of automated machine learning workflow in Python to combine two data sources (sensor and weather data), perform time series decomposition, outlier labelling and outlier classification with a Gaussian Mixed Model (GMM)

In time-series data, there are period trends that occur (for example, daily fluctuations, and greater fluctuations throughout different seasons), and outlier data points need to be understood in the context of these trends.

Secondly, we needed to develop a consistent methodology to identify and label outliers, as we were working with raw field data that did not have this information.

Finally, we needed a consistent methodology that would work with different sensors, and would also address the unique setup and characteristics which would influence the results. For example, some sensors due to their setup, will be more exposed to direct sunlight and precipitation than others.

In the subsequent sections, we will address initial methodologies and strategies used to tackle these challenges, encompassing time series analysis, machine learning algorithms, and visualization techniques [1].

TIME SERIES DECOMPOSITION - WORKING WITH TIME SENSOR DATA

True strain is an additive property, which is a main component assumed throughout plasticity theories. The total strain which would be recorded by the sensors can be understood as an addition of the strain from loading, temperature, and any other strain, at any point in time.

As the sensor data was provided as a time series, time series (or seasonal) decomposition analysis is a statistical approach employed to break down a time series into its fundamental elements, encompassing the trend, seasonal, and residual components.

Using this technique allows us to look at the patterns occurring in strain over time, rather than understanding it as a point in time, and thus help detect outliers better. The sensor reading at any point in time can be understood as:

$$\textit{Sensor Reading} = \textit{Global Trend} + \textit{Seasonal Trend} + \textit{Residual} \qquad (1)$$

The long-term pattern in the data is represented by the trend component, which is calculated using the first derivative of the measurements.

The trend component captures global changes, like increase or decrease in the strain, can be correlated to the loading occurring on the structure. This is the largest component by magnitude in the time series.

The second component in the decomposition is the seasonal trend. The seasonal component includes all repeating cyclic fluctuations, which is what distinguishes it from the trend component. The seasonal trend picks up smaller patterns, like daily increases and decreases (due to natural temperature increase throughout the day), and also larger scale seasonal patterns, like the transition from summer to winter.

In Figure 5, the seasonal variation was approximately 60 to -40 um daily due to temperature. The final and third component is the residual, strain values that cannot be explained by the global trend or seasonal trends.

The residual component is used for further analysis in this study, and becomes the predictive target of the model, as it accounts for random and unexplained variations in the data—any sensor anomalies that defy explanation by either the overall trend or seasonality [1][2].

In the subplot below for January 2019, the sensor reading averaged close to zero for the residual plots, meaning that most of the strain could be explained by the global or seasonal trend, but there were still a few extreme values that occur in the plots.

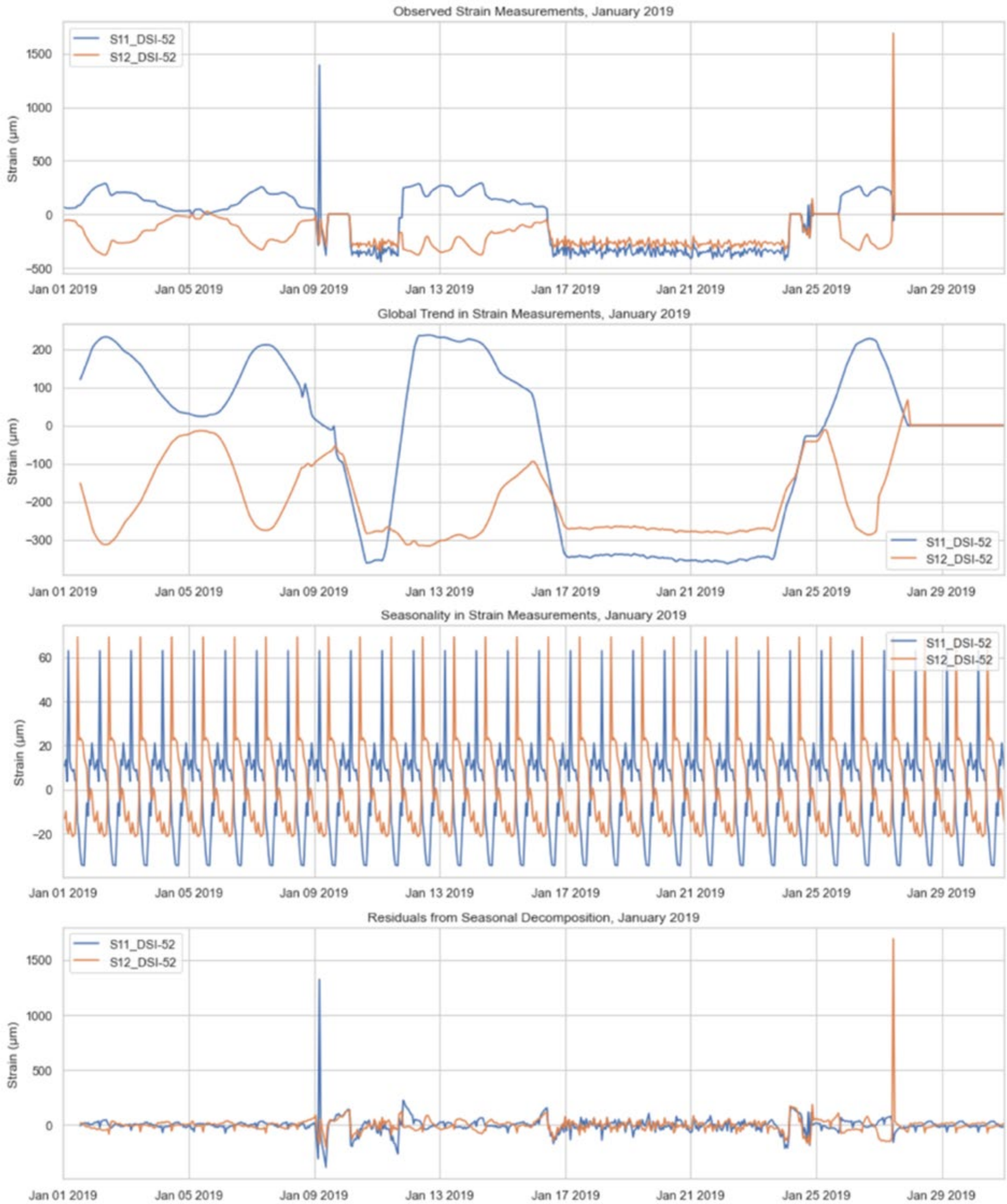

Figure 5: Seasonal decomposition analysis for connected

The first Figure is the observed strain measured by the sensor, and the bottom three plots are part of the time series decomposition in the following order: the global trend (the general pattern of increase or decrease separate from the noise in the data), the seasonal trend (displaying cyclic fluctuations, corresponding to daily repeating patterns in the sensors) and the residual values, which cannot be explained by the global or seasonal trends.

The three plots (global, seasonal, residual), are added to give the total strain (note the y-axis values are not the same).

After analyzing the sensors and removing noise in the data by focusing on the residual trend, visualizing the data points for the two-year duration revealed that the sensors followed a normal distribution, validated by applying a Kolmogorov-Smirnov (K-S) statistic.

A normal distribution, also known as a Gaussian distribution, embodies a continuous probability distribution having a bell-shaped curve, and can be characterized by two fundamental parameters: the mean (μ) and the standard deviation (σ) [1].

A normal distribution facilitates estimating the probability of a specific event occurring, as both of these parameters are known, as well as assigning a statistical significance to an observation.

As many of the residual values are close to zero, these are the majority non-outlier values, and extreme values of strain in the tail of the bell curve represent anomalous observations.

GENERATING OUTLIER AND ANOMALY LABELS

Both anomaly and outlier are terms used to characterize data points that deviate from the norm within a dataset [13].

Given the absence of loading conditions in the SHM system, the residual data extracted from seasonal decomposition includes both anomaly and outlier occurrences.

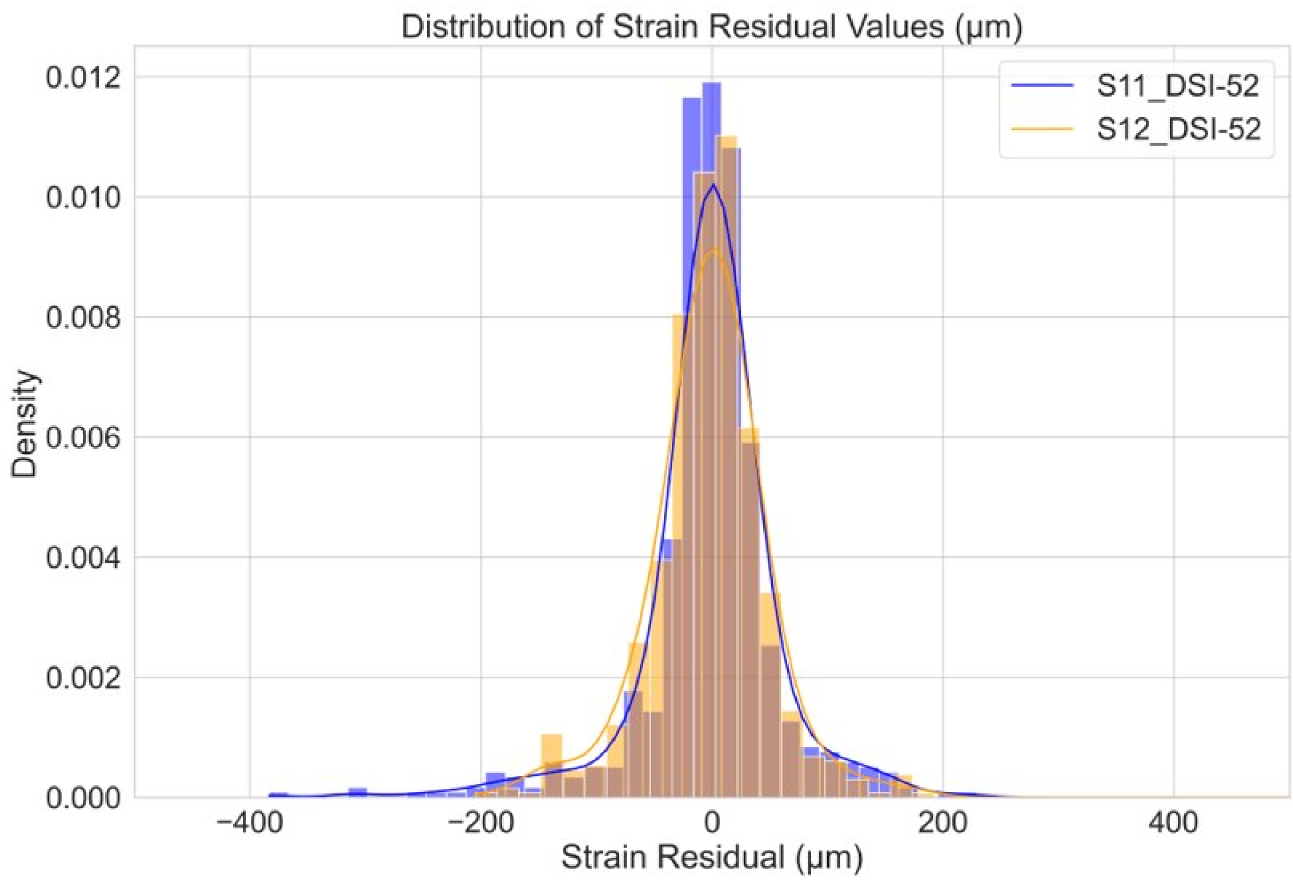

Figure 6: Residual sensor distribution plots for S11_DS1-52 (blue) and S12_DSI-52 (orange) for the 2019-2021 period, displaying a normal distribution

In our analysis, statistical techniques were applied to effectively identify these regions. Values situated within low-probability regions, in the tail end of the normal distribution curve for residuals, will be regarded as outliers and anomaly events.

In conventional classification methods, two or three variables are often utilized simultaneously, whereas machine learning (ML) algorithms possess the capability to employ multiple variables concurrently.

ML algorithms, renowned for their pattern recognition and predictive capabilities, have found increasing utility in the comprehensive analysis of extensive datasets for sensor-based civil engineering applications [3][14].

Machine learning techniques can be categorized into three primary groups based on their learning nature:

1) supervised learning,
2) unsupervised learning, and
3) semi-supervised learning [13].

To construct a model for predicting bridge sensor failures, both unsupervised and supervised methods were employed. Unsupervised learning revolves around the identification of patterns in datasets lacking labelled outcomes, grouping data based on general rules [13].

In the context of SHM, unsupervised learning aids in detecting damage by clustering strain response data.

Conversely, supervised learning, where labelled data is available, proves more suitable for predictive analytics [14].

K-means clustering represents a type of unsupervised ML algorithm that categorizes a set of data points into a specified number (k) of clusters based on their similarity [13]. The algorithm begins by selecting k initial centroids as cluster centers and then assigns each data point to the nearest centroid.

This process iterates until the clusters stabilize, minimizing the distance between the centroids and each point [13]. These clusters were used to generate labels distinguishing outliers (0) from non-outliers (1) within the residual strains. These labels will serve as the target for constructing a predictive supervised learning model.

Figure 7 displays the k-means clustering process of grouping data points into three classes based on their proximity to each other when plotted along the two axes.

When k-means was applied to the dataset in this study, the data points were evaluated along 22 different parameters, including the steel temperature and the different measurements from the Environment Canada data, and points were grouped together to optimize their closeness in the measurement hyper-space.

As a result of the clustering optimization, for each sensor roughly 0.5 to 1% of all recorded values were found to be possible outliers.

It is important to note that for the plotted results in Figure 8, although there are non-outlier (orange) labels dispersed between the outlier labels (blue), the classification was done in a way that optimized outlier labelling across all 22 of the parameter features (where the plots only show values plotted against two axes as an example).

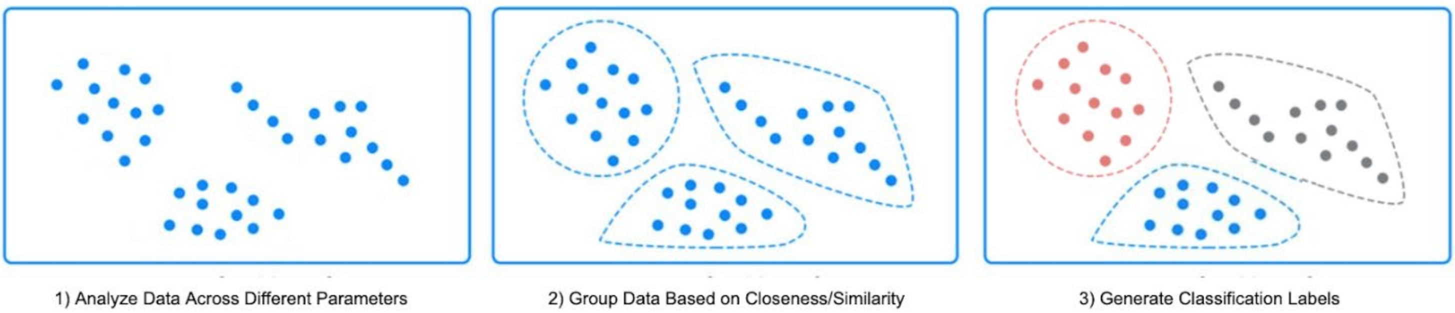

Figure 7: Overview of k-means unsupervised learning process

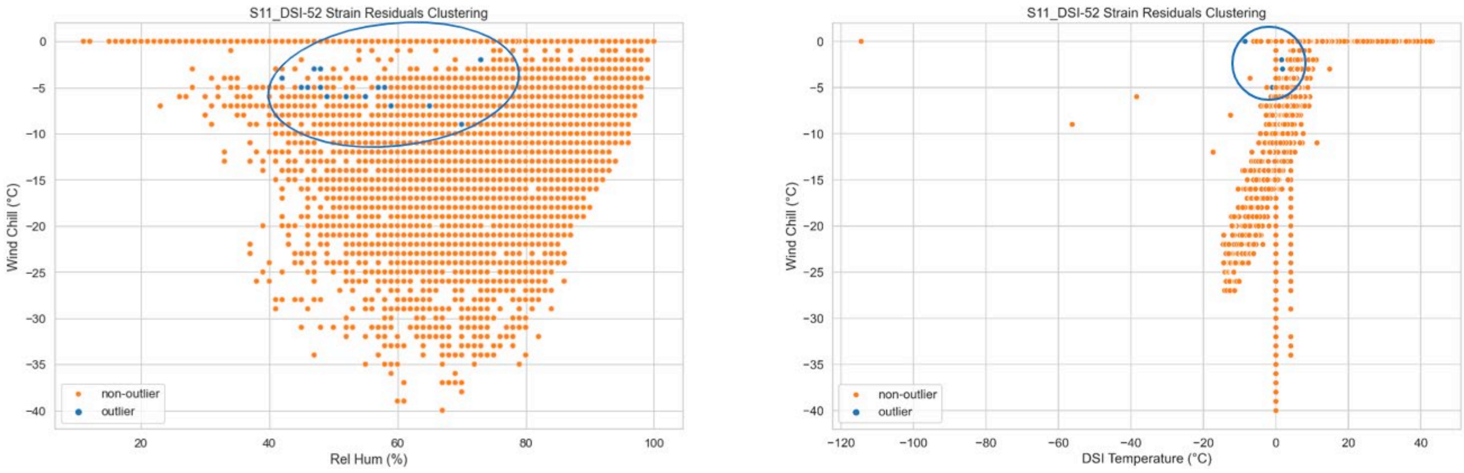

Figure 8: Example of identified outlier strain measurements, displaying results plotted comparing wind chill and relative humidity (left) and DSI steel temperature and wind chill (right)

BUILDING A PREDICTIVE MODEL

An imbalanced dataset is characterized by an uneven distribution of class labels, with one class containing significantly fewer observations compared to the other [13]. In this scenario, the number of observations falling within the outlier/anomaly class was notably lower.

This discrepancy introduces challenges in developing a model capable of achieving high accuracy for the majority class while maintaining acceptable performance in classifying anomalous data [13].

Figure 9 visualizes a few features of the dataset, including the DSI steel temperature, ambient temperature, dew point, and wind speed, with data binned and colour coded based on the outlier and non-outlier label generated from the clustering step earlier.

By doing this visualization, we can see that for some features, such as the steel temperature, ambient temperature and the dew point, the outlier data has a different distribution curve compared to the non-outlier data. In contrast, looking at the wind speed distribution of values, there is not as much variation and difference between outlier and non-outlier curves.

The Gaussian Mixed Model (GMM), a widely employed probabilistic model for anomaly detection, clusters the data to estimate several Gaussian distributions, serving as a means of density estimation [13].

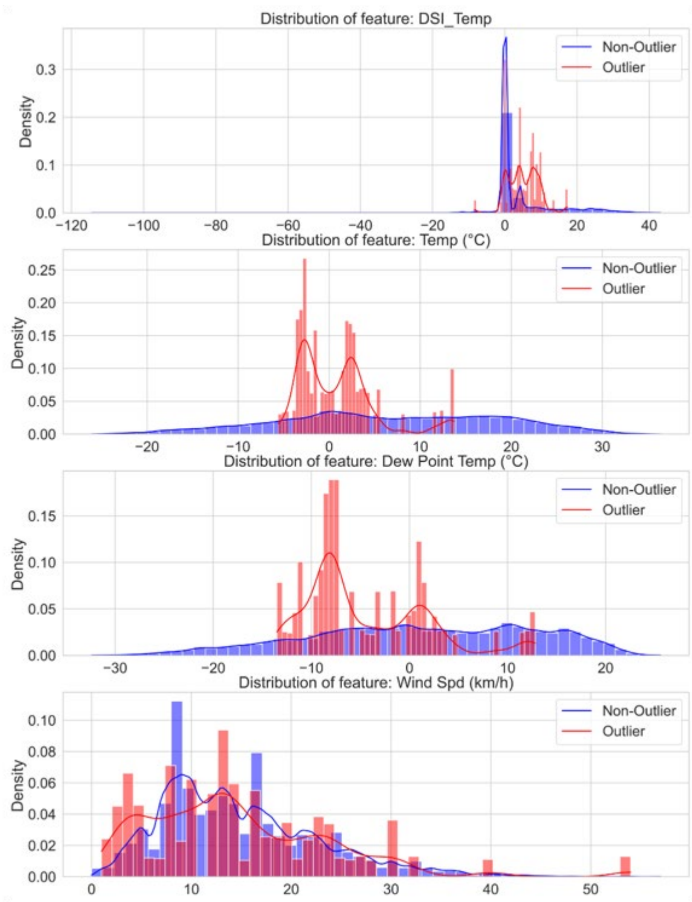

Figure 9: Distribution of feature values (sensor and Environment Canada data) for sensor S11_DSI-52, colour-coded by label (blue = non-outlier, red = outlier/anomalous)

When the curves are more different for a classification for a given feature, this directly correlates to the statistical significance and importance of that feature in deciding the classification of the strain measurement as an outlier or not. The sensor data was divided into three groups: 60% for training, 25% for validation, and 15% for testing. This division was achieved using both random and interval-based methods from the sci-kit learn library [10][13].

Leveraging the GMM, a likelihood function was developed for each data point, allowing for comparisons with the target column to generate model performance metrics. Several GMM models were constructed, utilizing different feature sampling techniques (univariate and multivariate), as well as fittings based on data considering both classes and separate models designed for a single class.

MODEL PERFORMANCE AND RESULTS

It becomes imperative to consider alternative performance metrics to ensure the model's predictions are well across both classes when working with an unbalanced model.

A range of evaluation metrics are available, including Precision, Recall, F1 score, and accuracy [13][14]. These metrics find their origins in a confusion matrix, a common tool for characterizing the performance of classification models.

The confusion matrix encompasses four fundamental parameters: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Precision, more reliable than accuracy for a class imbalanced dataset, was computed through the following equation [13]:

$$Precision = TP / (TP + FP) \quad (2)$$

DISCUSSION AND CONCLUSION

Consistently, the models displayed lower precision scores, a phenomenon linked to a higher prevalence of False Positives. In simpler terms, this means that the models failed to correctly identify some anomaly points as anomalous, which, in turn, increases the denominator in the precision formula [13]. Delving into the feature importance aspect, we gain insight into which variables wield the most significant influence on the model outcomes.

As depicted in Figure 10, it is evident that temperature data directly acquired from the system (T_DSI values) and wind chill consistently exert the most substantial impact on sensor performance and the classification of anomalous behaviour. Relative humidity and ambient temperature also emerge as noteworthy factors.

Wind chill can affect the performance and accuracy of SHM systems, particularly those situated in exposed and challenging environments. Wind chill creates thermal variations on the bridge surface, directly affecting the precision of temperature sensors and strain gauges.

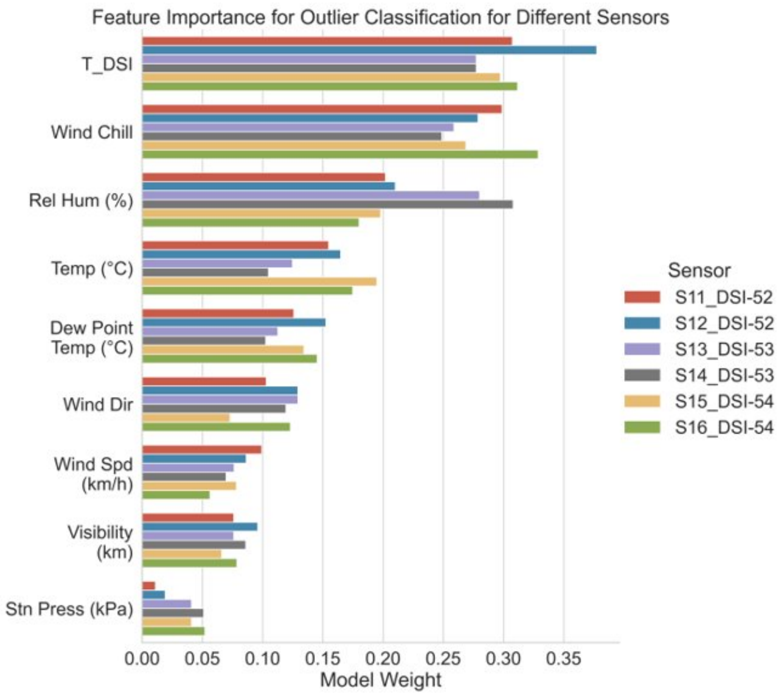

Figure 10: Feature Importance for GMM Models per Sensor

Meanwhile, overall humidity plays a substantial role in the transfer of heat between mediums. Elevated relative humidity levels can diminish the rate of heat transfer from the air to materials like steel, as the moisture in the air functions as a thermal insulator, reducing heat transfer efficiency [3][14].

To enhance our analytical approach, it is worthwhile to explore alternative methods for generating data labels, which can then be compared with the clustering method. One viable avenue involves leveraging statistical control theory processes like the Western Electric Rules. These processes excel in identifying variations by comparing each observation with the mean and standard deviation boundaries of the data. This can prove invaluable in forecasting without imposing substantial computational overhead, offering a valuable alternative to clustering techniques [3][13][14].

Another crucial aspect to consider is the implementation of an in-depth Principal Component Analysis (PCA) for feature engineering. Many of the primary features we've identified can be broken down and comprehended as combinations of each other.

For instance, wind chill can be expressed as a function of ambient temperature and wind effects. Undertaking this reduction not only streamlines the dataset's size but also preserves vital information while eliminating correlations that can boost model performance [13].

In our study, we've introduced a framework designed to facilitate the analysis of sensor data in real-world conditions. This framework incorporates open-source climate data, enabling us to unveil underlying patterns and categorize sensor behaviour.

The insights gleaned from this endeavour can serve as a blueprint for developing new workflows, with the potential for further enhancement through additional information or data processing steps.

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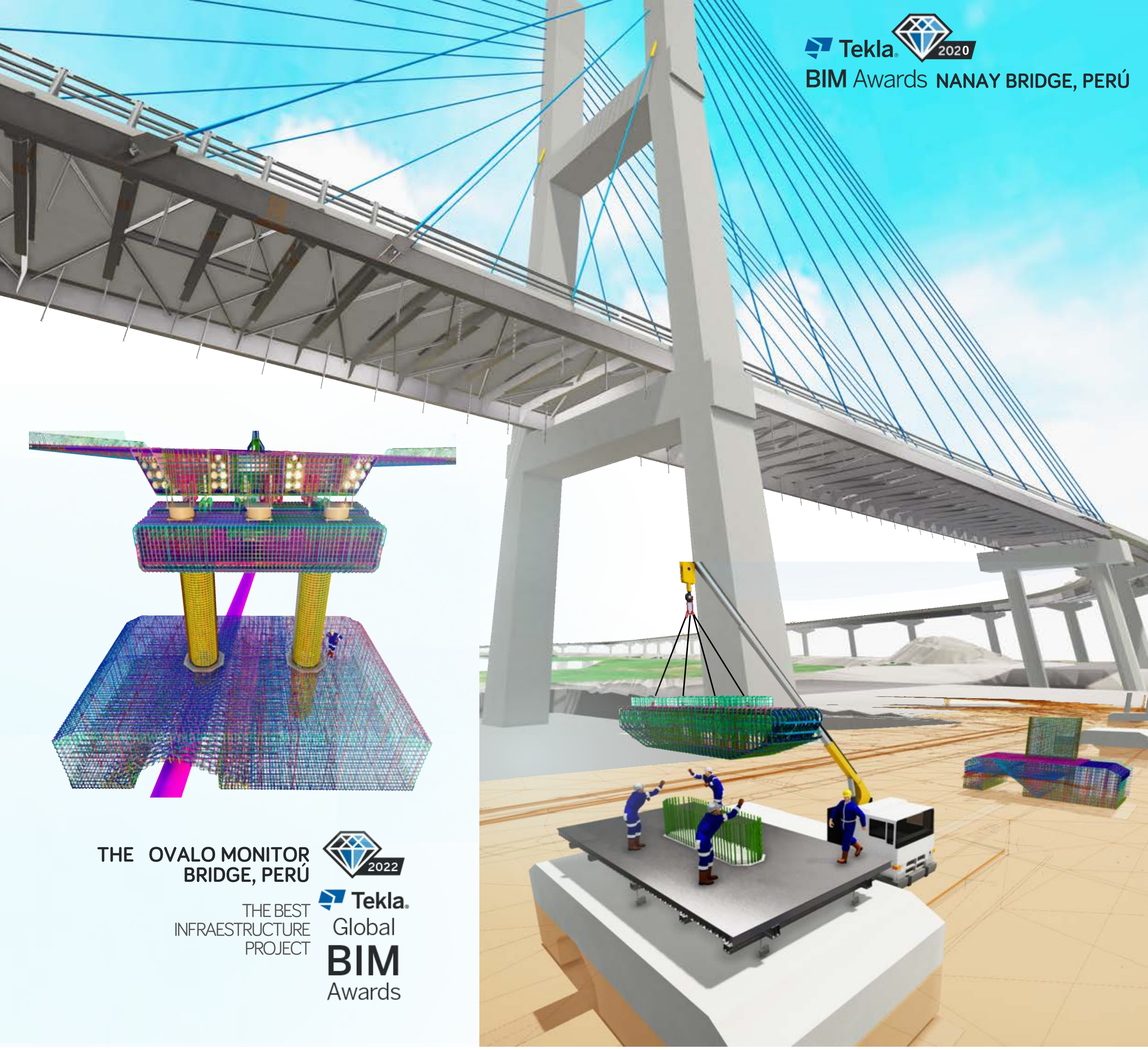

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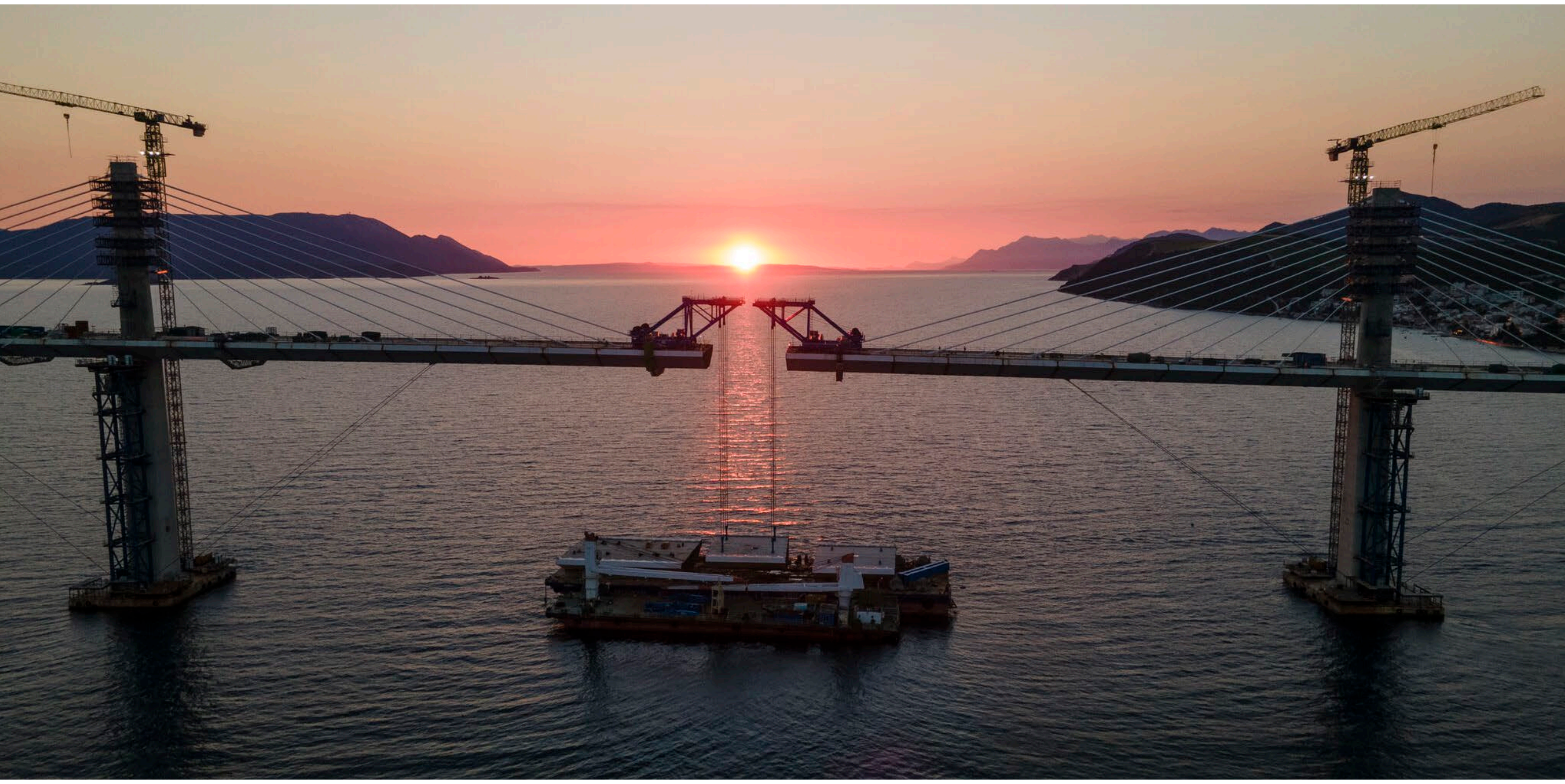

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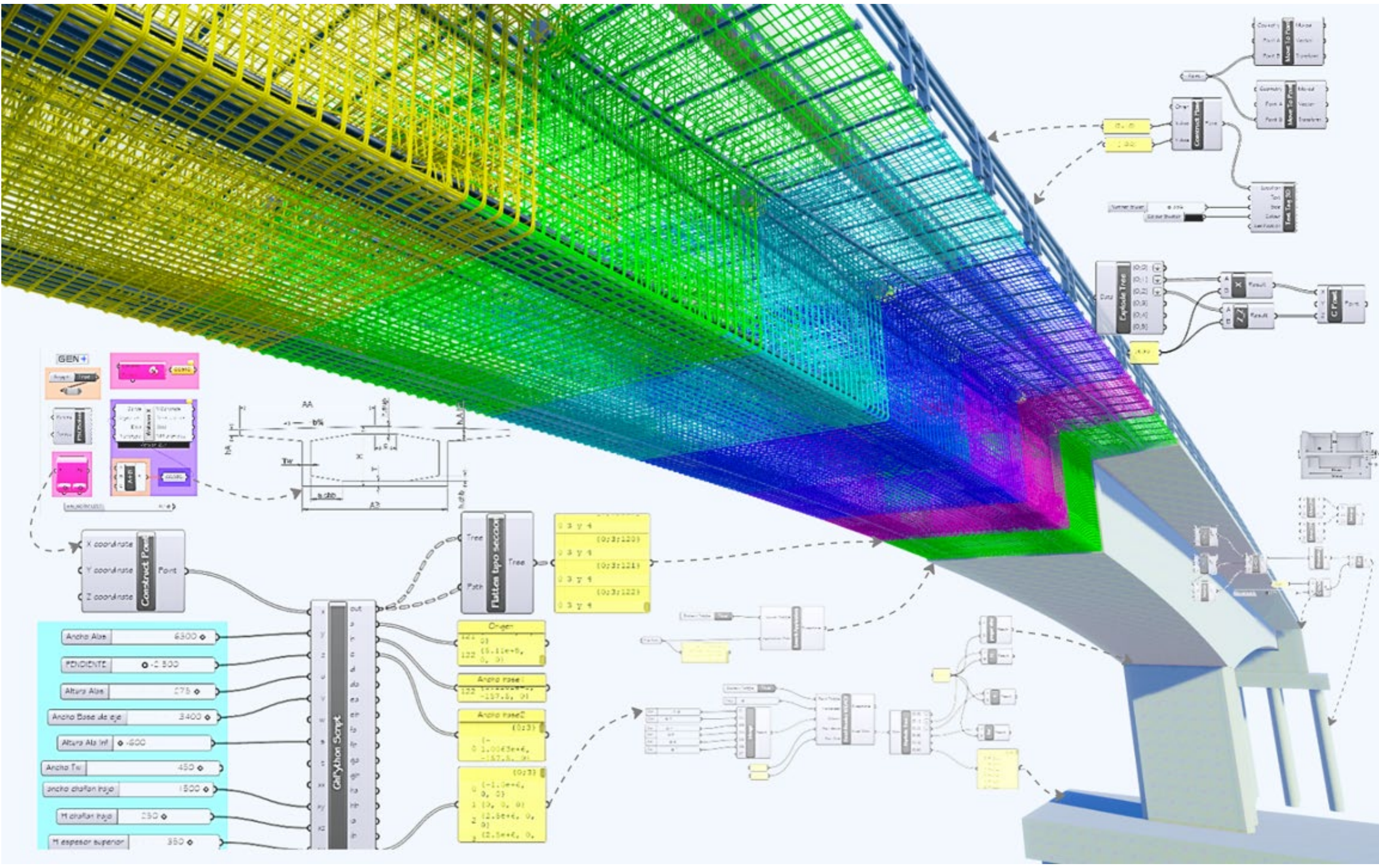

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