

Incorporating Qualitative Metrics into a Computational Model Using Machine Learning

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Abstract: *Within a computational model, quantitative metrics frequently steer the decision-making process, where qualitative metrics, including elements representing the architectural expression, are often neglected. The motivation behind this article is to quantify the elements that establish the harmony between form, material and technique, resulting in a combined tectonic design. This article aims to illustrate how a computational model can include qualitative architectural information and thereby create an honest tectonic design. The most influential theories concerning architectural values have been examined. Based on this, six qualitative values are defined as: symmetry, elements, texture, material placement, scale and variety which describe the architectural value, or aesthetic quality, of a space. Based on the defined qualitative values, a machine learning model has been defined, which is based on a pseudorandom sampling plan and a shallow artificial neural network. A computational model has been developed, implemented with the machine learning model predicting aesthetic quality. An optimisation process is defined, utilising a genetic algorithm to conduct a meta-heuristic optimisation. From this computational model, a case study has been conducted which considers a structural objective, an acoustic objective and an aesthetic constraint. The solution space of the case study has been examined in a generative design process. The results displayed the possibilities of informing a computational model with aesthetic quality while maintaining acoustic and structural integrity. The research conducted in this article presents a novel framework for creating tectonic designs through a computational model.*

Keywords: Tectonic design, Aesthetic Metrics, Computational architecture, Machine Learning, Architectural modelling

1. Introduction

Outstanding building design depends on numerous qualitative metrics, which are difficult to anticipate in the design phase. Some qualitative metrics are the architectural expression, the perception of privacy and the indoor environment. Qualitative metrics are difficult to handle in a quantitative system, and they are complex to incorporate into a computational model [1, 2, 3, 4]. In this context, qualitative is defined as a quantity which is influenced by human judgment. Quantitative is defined as a quantity which is definite and described with numbers. A space within a building must have high architectural value and be functional to achieve the synergy of tectonics. The harmony between form, material and technique must be found so they are inseparable [5]. The harmony is described as a tectonic structure which is driven by the aesthetics in a construction and is elevated above an architectural style. This is illustrated in the following quotation.

“Needless to say, I am not alluding to the mere revelation of constructional technique but rather to its expressive potential. Inasmuch as the tectonic amounts to a poetics of construction, it is art, but in this respect the artistic dimension is neither figurative nor abstract.”

– Frampton (1995) [6]

Furthermore, it is important to incorporate this element in the early design phases, ideally in the conceptual phase, to capture combinations of novelty and creativity. This is done through design diversity in a computational model utilising a generative design process [7]. Computational modelling is a prominent design method to explore designs which are beyond the imagination of a designer and a method to achieve

immediate ranking of each design proposal corresponding to several objectives [8, 9].

The sound of a space is an essential part of the perception thereof. Sound incorporates all dimensions in the space and creates an experience of interiority [10]. The acoustic environment in a room exposes the proportions and function [11]. The acoustic conditions are closely correlated with the general shape of the room, and it is therefore also correlated with the conceptual design phase [12]. To achieve an accurate prediction of the acoustic environment of a space, complicated and time-consuming simulations of a room are required. This is not sensible to do in the early design stage; therefore, machine learning or simple analytical expressions can be utilised to approximate the acoustic environment in the early design phase [12, 13].

Even with extensive simulations of the acoustics, two identical spaces can be perceived as widely different. This is because the acoustics of a space consist of both quantitative and qualitative aspects [14]. This phenomenon corresponds to the architectural experience, which can be divided into two main stages: the aesthetic judgement and the aesthetic emotion [15]. Therefore, it must be possible to subdivide a qualitative value into several tangible metrics. This is achieved by manipulating the relationship between qualitative values using either artificial intelligence or simple analytical approximations [3, 16].

The research in the article is guided by the research question: How can a computational model be further informed with architectural value while maintaining its acoustic and structural integrity, creating a tectonic design? The basis of this research builds on the premise that empirical aesthetics are feasible, to describe the architectural value [17, 18, 19].

This research contributes to emerging design methodologies by enabling qualitative human values to inform early-stage computational models. Such integration ensures more holistic and user-responsive built environments in architectural practice.

The article is organised, where Section 2 aims to describe the architectural value of a space based on existing theory surrounding the experience of architectural spaces and the aesthetic experience. Based on the findings, six qualitative values are proposed to describe the aesthetic quality of a space. Section 3 utilises the defined qualitative values to create an artificial neural network, which is applied in Section 4 to a case study, serving as a proof-of-concept. Section 5 presents a discussion and conclusion on the research conducted in the article.

2. The Experience of Architectural Spaces

The tectonics of a space is the real added to the imaginary, which creates a synergy. The imaginary is also described as the poetics of a space. This is where the aesthetics lie, which is an integral part of the experience of a space, which can be described as the magic of the real. There are several theories describing the architectural experience of a space, but the foundation of this research is built on the definition of magic of the real by Zumthor [20].

2.1. Magic of the Real

The magic of the real is also described by the atmosphere of a space; Zumthor presents a monologue which attempts to answer the question: What is the magic of the real?, which decomposes atmosphere into nine principles [20]. It becomes possible to compare and quantify the individual experience. Three principles are indicated to have the most influence on the aesthetic quality of a space as the body of architecture, material compatibility and levels of intimacy. A pictogram of the principles is presented in Figure 1.

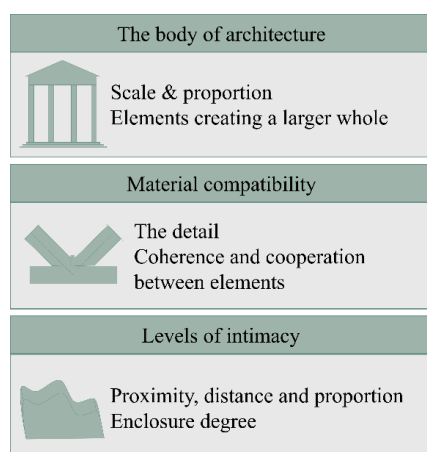


Figure 1: The three selected principles to describe the atmosphere of a space

Material compatibility is the collaboration between two or more materials. Zumthor describes it as a perfect union between materials. Therefore, the small details are crucial, such as the ageing of materials. Furthermore, it describes how there must be a contrast between two materials to achieve an interesting interplay. The materials determine the feeling of

the room and how the feeling changes based on a small change in material. Furthermore, the material has a significant influence on the acoustic quality of a space.

Levels of intimacy is the relationship between proximity, distance and proportion. Intimacy is measured as a feeling of confidentiality, closeness and comprehension. It is related to size differences, where sizes close to the human body are perceived as intimate, whereas larger constructions seem intimidating. A connection between large and smaller components creates harmony in the space. The proportions of a room can be described based on several different aesthetic theories, e.g. the golden ratio or the Vitruvian Man [21, 22].

2.2. Theories of the Aesthetic Experience

The term aesthetic has different definitions depending on the reader. Aesthetics derives from the Greek word *aisthiti*, which means perception through sensation [23]. The motion of empirical aesthetics was pioneered by the German philosopher, physicist and experimental psychologist Gustav Fechner (1801-1887). Empirical aesthetics aimed to parameterise beauty both empirically and psychophysically [17].

Throughout time, empirical aesthetics have branched out and formed several subdomains. One is computational aesthetics, which is a mathematical model for aesthetic appreciation based on the underlying aesthetic form [17]. The origin of computational aesthetics is attributed to George David Birkhoff, who in 1933 published the book titled *Aesthetic measure* [23]. In the book, the aesthetic experience is composed of three phases. The first phase is the preliminary effort, which is the necessary act of perception which corresponds to the complexity, C. The second phase is the feeling of value, which is also the aesthetic measure, M. The third is the actualisation that the object is characterised by symmetry, harmony or order, O. Birkhoff expressed these three phases mathematically in Equation (1).

$$M = \frac{O}{C} \quad (1)$$

An example of aesthetic measure is presented in Figure 2, used on six different polygons arranged in descending aesthetic measure. The class of the objects is assumed to be the same, i.e. same size, colour and material [19].

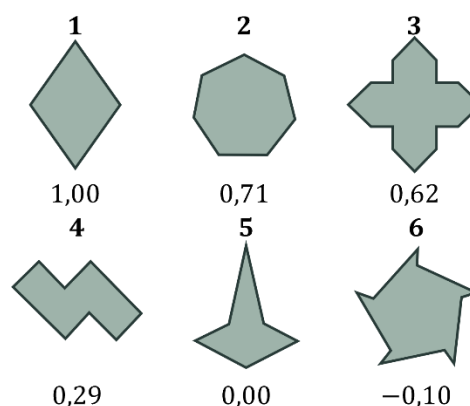


Figure 2: Six polygons with their aesthetic measure according to Equation (1), from [19]

2.3. Qualitative Values of the Aesthetic Experience

This section builds on the theory presented in the previous section and translates it into concrete qualities that can be valued objectively with a subjective meaning. It aims to indicate qualitative values that describe a space's aesthetic quality with straightforward and understandable elements, independent of the function of the space. Further details on the qualitative values of the aesthetic experience are described in the thesis [24].

2.3.1. The Body of Architecture

This principle describes scale and proportion within a space and describes how several elements have the possibility of coming together to create a larger whole. The quality symmetry describes the equilibrium and harmony of a shape. The definition of symmetry is illustrated in Figure 3. The quality investigates the symmetry of a shape in both the vertical and horizontal sections. The horizontal section is evaluated on both the x-axis and y-axis, while the vertical section is evaluated on the z-axis. The quality is converted to a numeric system where a symmetrical section is valued 1, and an unsymmetrical section is valued 0. For the entire space, the sum of all is calculated.

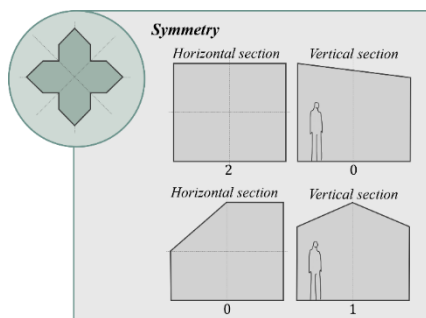


Figure 3: Illustration of the quality, symmetry, in relation to the body of architecture

The second quality within the body of architecture is elements. The value is used to determine the number of elements creating a space. It decomposes the space into the identical elements; it is constructed of. The score of the value is then the number of unique elements to develop a space. The concept is illustrated in Figure 4. The essence of elements is to create repetition and harmony in the space. Repetition is a key Gestalt principle [25], which describes the design principal unity in variety.

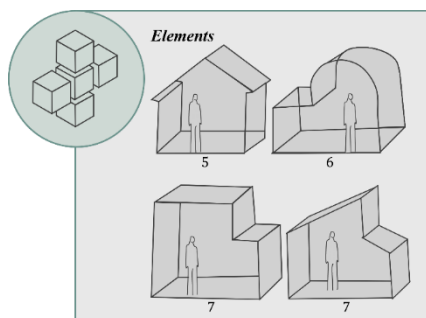


Figure 4: Illustration of the quality, elements, in relation to the body of architecture

One important aspect of the body of architecture is the skeleton of a space and, therefore is noteworthy to reflect on the structural aspect of a space. To create a truly tectonic design, structural transparency must be present. However, it is not included as a quality of the aesthetic experience because it is not a parameter which can be generalised, either it is present or not.

2.3.2. Material Compatibility

This principle describes the coherence and cooperation between different materials. It describes the details between two materials and how they can be conflicting or harmonious.

The quality texture describes the texture of the materials used in the room. This is both the tactile feeling and the visual intrigue. The quality is illustrated graphically in Figure 5, where the texture on a surface change from 0, smooth, to 1, very rough. A surface can consist of several different textures with various textures. Therefore, the ratio between textures from each surface is found to represent the space.

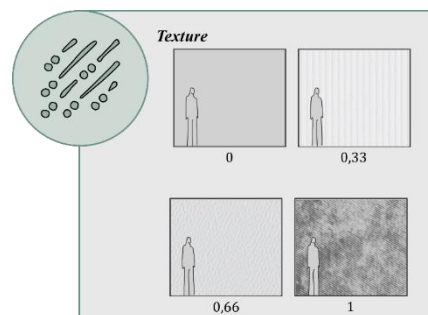


Figure 5: Illustration of the quality, texture, in relation to material compatibility

The quality material placement illustrates how two or more materials interact with each other in one space, illustrated in Figure 6. This quality embraces several variables concerning materials in a space. However, in an attempt to simplify the system, only three variables are analysed. The ratio between the two materials, the complexity representing the number of material elements added to the space and the order which describes the number of unique material elements. The final value is determined with the equation presented in Figure 6. The quality represents the entire space, but it has the ability to be decomposed for each surface.

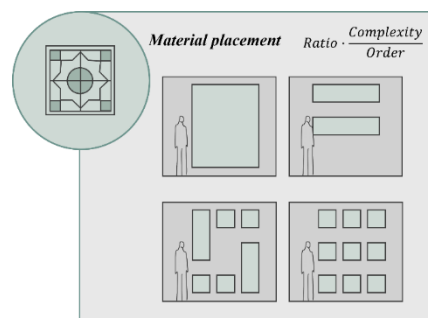


Figure 6: Illustration of the quality, material placement, in relation to material compatibility

2.3.3. Levels of Intimacy

This principle describes how intimate and comfortable a space feels. Most larger spaces tend to have several levels of intimacy, an area which is open and public, and another which is closed and private. The quality scale is heavily inspired by the work of Corbusier with the proportions proposed through Le Modulor. The equation calculating the scale of a space is presented in Figure 7. The scale is set to the human; it must not be too small so it becomes smothering, but also not too spacious that the dimensions of the room fall out of proportion. In this definition, the scale will always represent the ratio between the lowest height of the ceiling and the human body, set to the dimensions of Le Modulor with a height of 216 cm, i.e. $s_1 = 216$ cm.

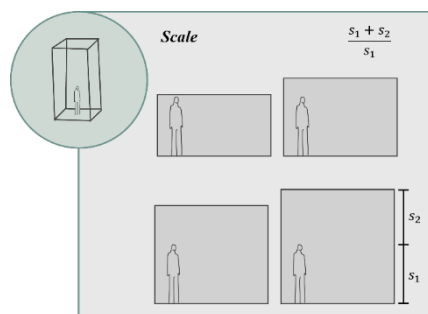


Figure 7: Illustration of the quality, scale, in relation to levels of intimacy

The quality variety is translated to the change of scale throughout a space. It describes how the change of intimacy throughout a space changes the atmosphere. Therefore, variety is defined as the ratio between the highest and lowest points in the ceiling. An illustration of the quality and the equation to calculate it is presented in Figure 8. The ceiling can change height multiple times in the space, but this is not reflected in the quality.

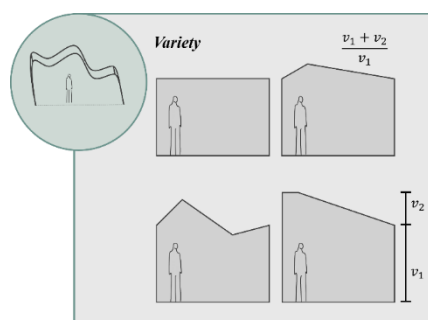


Figure 8: Illustration of the quality, Variety, in relation to levels of intimacy

2.3.4. Scoring system

The six qualitative values, symmetry, elements, texture, material placement, scale and variety, are found by an algorithm which normalises the values when a dataset has been collected. By exploring the space, the aesthetic quality is evaluated by a human. The aesthetic quality is given as a number between 0 and 1, where 0 is undesirable and 1 is desirable.

With this scoring system, there is no indication of a pattern or relationship between each qualitative value. Therefore,

machine learning is implemented through an Artificial Neural Network (ANN), which is utilised to determine the underlying patterns and relationships between the different parameters.

2.4. Discussion of Qualitative Values

One significant quality is the light in a space. It plays a significant role in the atmospheric experience. Not only how light enters the space, but also the places where light is absent. The actual light quality would apply to several other qualities, which would make the framework complex. It should be considered whether the complexity is necessary to achieve true-to life results; to determine this, a sensitivity analysis should be conducted.

Another aspect of the qualities is that they must be formulated generally for an algorithm to decode the qualities independently without the assistance of a human. One such feasibility aspect is the height of a ceiling, which cannot be below the height of a human, because then the human cannot fit within. The qualities defined in the algorithm must be logical, simple and straightforward.

3. Incorporating Qualitative Values into a Computational Model

In this section, the necessary theory for creating a machine learning model is briefly outlined, followed by the development of the aesthetic quality ANN based on the qualitative values defined in Section 2.3.

3.1. Machine Learning

In supervised learning, machine learning approximates the solution surface based on several sampling points and observations [26]. The general representation for developing a machine learning model with supervised learning is presented in Figure 9. The framework consists of six phases, with one iterative loop. Problem identification determines the input and output of the model. This stage is crucial for acquiring suitable preconditions for the machine learning model [26]. Considerations concerning the dimensionality of the problem must be determined in this phase to avoid the curse of dimensionality.

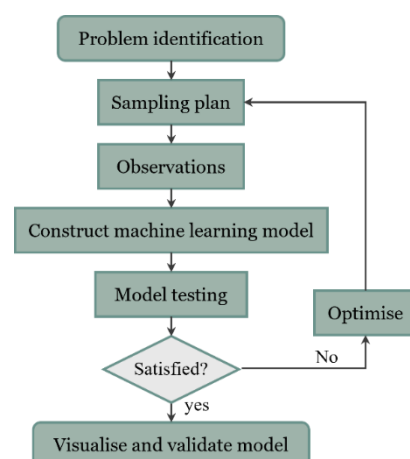


Figure 9: Representation of developing a machine learning model [26], redrawn

The sampling plan and observations are generated from a specific number of points in the design space. This is to obtain data points where information surrounding the variables and the output is obtained. Some sampling plans could be uniform, pseudo-random or Latin hypercube sampling [26].

From the sampling plan and observations, a machine learning model is constructed. The model is developed by using an algorithm such as ANN. The algorithm is chosen based on its ability to be accurate, its robustness and its computational capacity [27]. Afterwards, the model is tested, and its error is determined.

3.2. Development of ANN to Predict Aesthetic Quality

The aim is to develop a generic machine learning model, predicting aesthetic quality, independent of the space's function and underlying computational model. The framework developed contains four phases, illustrated in Figure 10. (1) generating a design proposal based on the variables developed in the computational model, (2) aesthetic judgement of the space, (3) extracting the qualitative values of the geometry and normalising them, and (4) developing a machine learning model to predict the aesthetic quality of other spaces. The machine learning model is developed to predict the aesthetic quality of new design proposals.

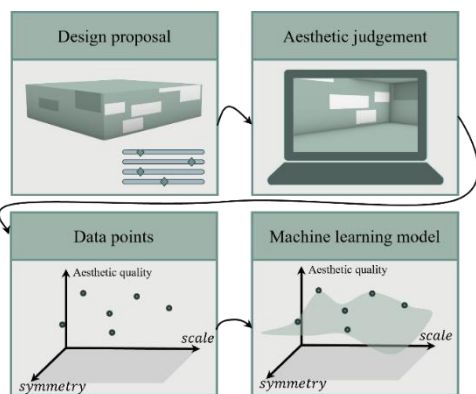


Figure 10: Architecture for development ANN to predict aesthetic quality

3.2.1. Design proposal

The design proposals are developed using a computational model, which can represent rooms with several different functions and visions. The model can therefore assume different volumes and dimensions. The computational model is developed in the software Grasshopper [28], a plugin to Rhino 7.0 [29]. The variables controlling the geometry of the space consist of changing the floor plan geometry, the number of structural gluelam frames in the space, ceiling height, the number and sizes of windows in one wall and the number and sizes of a secondary acoustically absorptive material placed on three of the walls. Some of the designs have been developed manually to ensure that the proposals possess the desired diversity required. The rest of the designs are developed with a genetic algorithm, which found random solutions. This is also a good indication of which results can be expected in the case studies.

3.2.2. Aesthetic Judgement

The aesthetic judgement is accomplished by viewing the space from the inside. This is done in the software Rhino 7.0 [29] where the space is rendered to simulate reality. The timber frames are rendered dark due to a permanent setting in the software, but in reality, they would be a timber colour. The walls are a light grey, the acoustic material is light green, and the windows are almost see-through. An example of the view is presented in Figure 11. Behind the windows is a picture of some buildings to create the illusion of the space interacting with a real environment. The buildings are from Nobel Parken in Aarhus. A person from a stock catalogue from Rhino 7.0 [29] is placed in the model, which is to create a better sense of scale and how the proportions are in relation to a human body. The person is scaled to have a height of 175 cm corresponding to the height of Le Modulor.

3.2.3. Data points

From the design proposals and the aesthetic judgement are data points were developed to form the training and test data for the machine learning model. The input in the qualitative values is automatically developed with the design proposals in the numeric environment, in Grasshopper [28]. Streamlining the qualities, different assumptions have been made:

Symmetry: the algorithm only analyses if the curves developing the space are symmetric, i.e. symmetry along the yz-plane only analyses the two parallel lines in the y-axis. The same with the symmetry along the xz-plane only analyses the two parallel lines in the x-axis. The last symmetric plane is in the xz-plane, which analyses the symmetry between the control points in the ceiling.

Elements: Element similarity is estimated as different surfaces or elements having the same area. This reduces the complexity of the algorithm, which figures out which elements are similar.

Texture: The ceiling, floor, walls and windows have the same texture of 0,05. The absorptive material on the walls has a rough texture of 1,00.

Scale and variety: No assumptions deviating from the original definition have been made.

Material placement: The similarity between elements is also dependent on the area. If they have the same area, they are assumed to be identical.

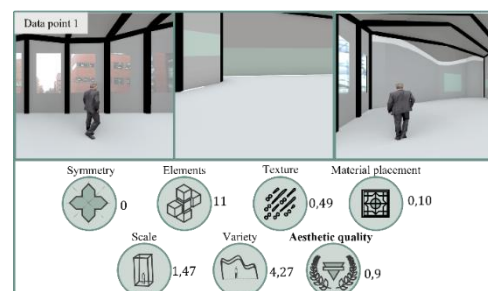


Figure 11: One datapoint of qualitative values and aesthetic quality

The first data point is illustrated in Figure 11. A total of 30 data points are curated to represent the training and test data. The aesthetic quality values range significantly in the different spaces. The scores in the data set are given by the author as an approximation of the first impression of the space.

3.2.4. Construction of Machine Learning Model

The machine learning model is constructed with an ANN. The sample plan with corresponding observations is divided into 5 folds, each with 6 samples, which is used to perform cross-validation on the developed ANN. Each input to the ANN has been normalised before training and testing.

The ANN architecture is illustrated in Figure 12, where a shallow ANN is implemented, due to its computational efficiency.

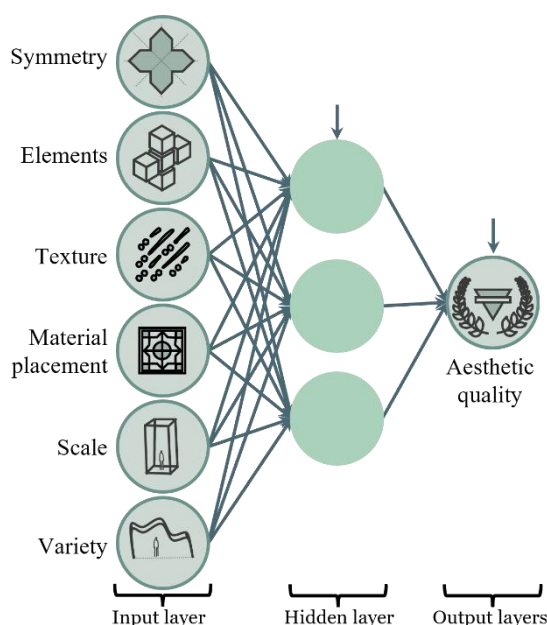


Figure 12: Input and output of the problem, illustrated in a shallow ANN

Initially, it is constructed with 3 neurons in the hidden layer, but this parameter is varied in the sensitivity analysis. The activation function in the hidden layer and the output layer is chosen to be a sigmoid function, and the ANN is trained using a backpropagation algorithm. The ANN is developed by using the Neural Network Trainer and tested by using Neural Network Tester in LunchboxML [30], which is a plugin to Grasshopper [28]. When the ANN has been trained, it is saved to a binary file to save the exact weights and biases trained for the problem. This can be used to test the model and to incorporate the trained model into other computational models. An overview of the settings for developing the ANN is presented in Figure 13.

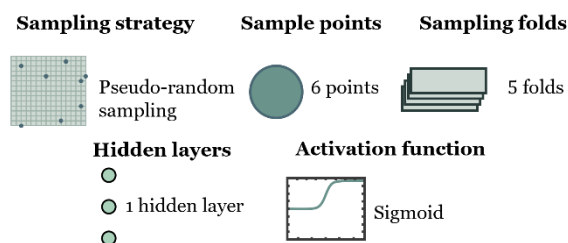


Figure 13: Overview of the settings for developing the ANN

The ANN is tested upon completion of the training. A scatter plot showing the predicted values versus the actual values for training on folds 2, 3, 4 and 5 and testing on fold 1 is illustrated in Figure 14. Ideally, the predicted and actual aesthetic quality should be the same and, therefore, form a straight diagonal line. However, this is not the case in this trained ANN. It is fairly accurate for the data points which have a high aesthetic quality. But the data points with an average aesthetic quality it drastically underestimated.

The model is tested using the RMSE for both the training and test errors. The errors of the ANN training on folds 2, 3, 4 and 5 and testing on fold 1 are presented in Table 1. The results show that the error is slightly higher in the training case than in the test case. This is favorable and it indicates that the ANN is not overfitting.

Table 1: RMSE of the training and test data

	Training error	Test error
	Folds 2, 3, 4 and 5	Fold 1
1 hidden layer, 3 neurons	0,2722	0,1977

3.2.5. Sensitivity Analysis of the ANN

A sensitivity analysis of the ANN accuracy is conducted in this section. The accuracy is solely determined based on the RMSE of the training and test data. The neuron sensitivity is tested in the hidden layer. The motivation behind this change is to test whether the ANN's predictions will increase accuracy when the ANN is defined with more neurons. Furthermore, it is tested to determine when the model begins to underfit or overfit. Three different configurations are examined: 3 neurons, 6 neurons and 9 neurons. In all the configurations, the activation functions and the learning algorithm are kept the same. Each configuration is tested on each fold, as developed in the sampling plan. Thus, 5 ANNs are developed for each neuron combination.

The Root Mean Squared Error (RMSE) of the training and test data for each ANN is presented in Figure 15. The results show clearly that some folds generally perform better than others. This is primarily because it is a small dataset where diversity in the output is not guaranteed for every fold. Concerning the RMSE, it is clear that the ANN overfits at 6 and 9 neurons in the hidden layer. The overfitting is clear when the training error is significantly larger than the testing error. This is true for almost all the folds for 6 and 9 neurons. The only exception is 9 neurons in fold 4, where the training and test errors are approximately the same. The test error is smaller than the training error in folds 1, 4 and 4 with 3 neurons.

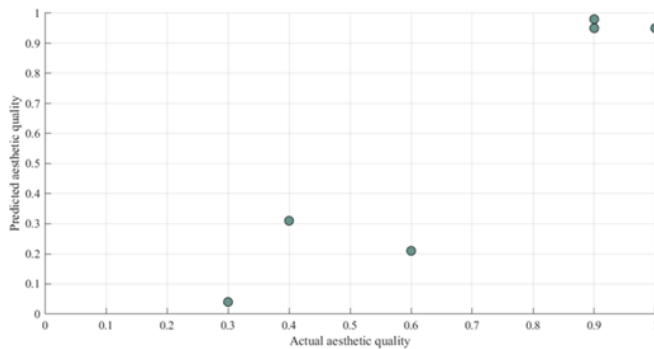


Figure 14: Test data for fold 1, 3 neurons, scatter plot with predicted values versus actual values

This is an indication of an underfitting ANN. The model in fold 1 with 3 neurons is the one where the training and test errors are the closest to each other, while not overfitting. Therefore, the ANN tested on fold 1 with 3 neurons is the best fitting, and this ANN is thus integrated into the computational model used in the Section 4 case study.

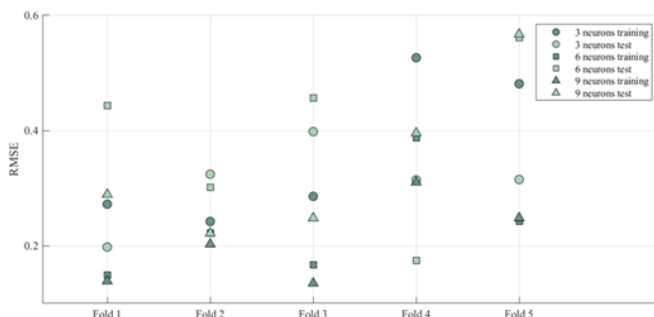


Figure 15: RMSE of the different training and test data for each fold and ANN complexity

3.3. Discussion of the ANN Predicting Aesthetic Quality

One major point of discussion is whether creating a machine learning model to predict something qualitative has any validity in practice. Based on the results from the ANN, illustrate how the ANN has the ability to determine the underlying pattern in aesthetic judgment. Therefore, it is argued that it can be valid to replace human judgment to some degree with a machine learning model. However, it is recognised that the model will not be a 100 % accurate and, therefore, human influence will always be needed to determine which is the best result.

The accuracy of each ANN is very limited, which is due to the limited data acquired. This could be improved by introducing more data and ensuring more geometric diversity in the data points. However, introducing more data would increase the computational power required to train the model. Therefore, it is also important to prune the data and select a suitable sampling plan.

4. Case Study: Structural, Acoustic and Aesthetic Performance

In this section, the framework to incorporate qualitative metrics into a computational model is applied to a case study to serve as a proof-of-concept. A generative approach is used in the case study, and the computational model utilised is

general to determine which solutions the algorithm finds. The designs proposed are conceptual since the framework is developed for the conceptual design phase. One case study is examined, but four further case studies are presented in the original master's thesis [24].

4.1. Generative Design Framework

Generative design has acted as a paradigm shift within the field of architectural and civil engineering [31]. At its core, generative design is a process of design exploration. It is used to determine if there are novel solutions to be discovered within the feasible design space. The framework controlling the generative design process is not fixed and shifts throughout the literature [32, 33, 34]. Figure 16 presents the framework proposed by [33]. The framework is initiated with a solution space which defines the boundaries of the problem, also denoted performance envelopes [32]. The solution space defined the design variables and constraints in the given problem. After the solution space is defined, a set of solutions can be generated. The generator in this phase is the core of the generative design framework [33]. The generator can generate solutions based on the boundaries and definitions in the specific solution space. This is achieved using algorithms, such as a genetic algorithm. The next step is creating models and evaluating solutions.

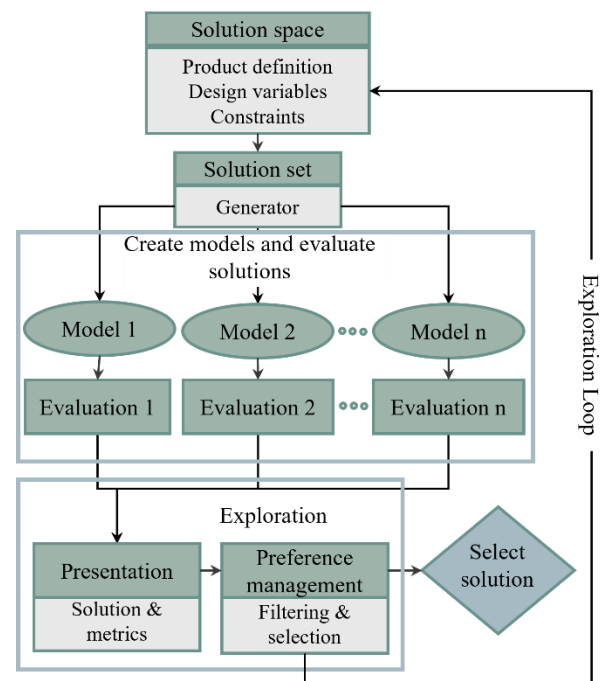


Figure 16: Generative design framework [33], redrawn

The evaluations are conducted concerning several metrics, which are measurable attributes of a solution determined based on the design problem and objectives. Afterwards, the solutions are explored by the user. This is to determine interesting solution regions.

4.2. Preconditions for the Structural System in the Case Study

The primary structural elements are glue-laminated timber frames, GL28h, placed throughout the space. The motivation behind the material choice is based on both the architectural

expression and the environmental sustainability aspects of using timber elements. Figure 17 presents the support and joint conditions in the model. Pinned supports were chosen, and rigid joints connect the beams to the columns. Furthermore, edge beams are modelled to connect each frame. The stability in the space is assumed to be facilitated by shear walls.

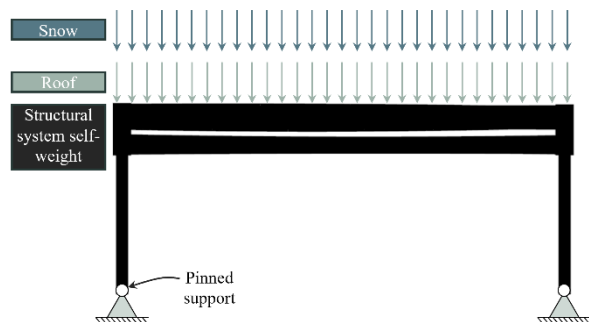


Figure 17: Primary static system of the frames and loads applied to the structure

The structure is assumed to be somewhere in Denmark, and only permanent and variable loads are considered. The permanent load is the weight of the structural system and a surface load of 0,5 kN/m² representing the weight of the roof. The variable load considered is the snow load, which is set to be 0,8 m², and it is a short-term action. Two load cases on the structure are considered: one for ULS and one for SLS. The critical load case for ULS is assumed to be the load combination with dominating snow from [35].

The design strength of glue-laminated timber depends on a modification factor, k_{mod} , which is dependent on the service class of the building and the load duration of the load combination. In this case, service class 1 is assumed, e.g. a dry internal environment [35]. The load duration of the critical load combination is considered a short-term action, less than a week. From [36], these conditions result in a modification factor of $k_{mod} = 0,9$.

4.3. Preconditions for the Acoustic Calculations in the Case Study

Several room acoustic factors could be relevant to analyse in the case study. The case study space is assumed to be an auditorium and, therefore, speech intelligibility is important. The influence on speech intelligibility is the parameters, clarity and definition of the sound reaching the audience. One factor which includes both the clarity and definition of sound is the Speech Transmission Index (STI), which has a high correlation with speech intelligibility. The case study is based on the conceptual design phase, where the model is not detailed and accurate. Therefore, it is not suitable or necessary to conduct complicated acoustic simulations with long evaluation times to achieve an indication of whether the room will have a suitable acoustic environment. To avoid the cumbersome acoustic simulations, the acoustic environment can be approximated using only the reverberation time, T_{60} , in the space. The reverberation time can be estimated with Sabine's formula, which is presented in Equation (2). To use Sabine's formula, several assumptions must be made and be correct in the space, they are the sound field is diffuse, the absorption material is placed homogeneously on all surfaces,

no large openings in the room, no focusing of sound, and the sound disperses in all directions with the same probability. One other limitation of Sabine's formula is that it approximates the reverberation time, T_{60} , in large complex rooms poorly and Sabine's formula tends to underestimate the reverberation time, T_{60} [13].

$$T_{60} = \frac{0,161 \cdot V}{\sum_i S_i \alpha_i} \quad (2)$$

V | Volume of the room [m³]
S | Surface area of material
 α | Sound absorption of the material

The materials in a space have a significant influence on the reflection, scattering and absorption of sound in a room. The absorption coefficient depends on both the surface material and what is underneath, e.g. if there is a layer of gypsum with mineral wool underneath, the sound absorption is higher at the lower frequencies. The materials chosen are based on the principles that the walls, ceiling and floor are reflective with minimal absorption, and the only absorptive material in the room is the wall absorbents added to three of the walls. The absorption coefficients of each material are presented in Table 2.

Table 2: Material absorption coefficients, values extracted from a Niras local material library

Frequency [Hz]	Absorption coefficient							
	63	125	250	500	1k	2k	4k	8k
Gypsum (walls)	0,15	0,15	0,10	0,06	0,04	0,04	0,05	0,05
Glass (windows)	0,15	0,15	0,10	0,06	0,04	0,04	0,05	0,05
Linoleum (floor)	0,02	0,02	0,02	0,03	0,04	0,04	0,05	0,05
Gypsum (ceiling)	0,15	0,15	0,12	0,08	0,06	0,06	0,05	0,05
Gyptone (wall absorbent)	0,40	0,40	0,75	0,85	0,75	0,65	0,65	0,65

4.4. Objectives and Constraints for the Case Study

The case study is performed as an optimisation process using a genetic algorithm. It uses an ideal optimisation, multi-objective, where there is one structural objective and one acoustic objective. The ANN predicting aesthetic quality, developed in Section 2.3, is incorporated as a constraint.

The structural objectives and constraints are presented in equation (3). The constraints $g_2(\mathbf{x})$ – $g_9(\mathbf{x})$ are the utilisation of elements in ULS, all equations are found in [36]. The section forces and displacement are calculated in Karamba3D [37], a plugin to Grasshopper [28]. Using the section forces, the utilisation is calculated in a custom C# script. The constraint $g_{10}(\mathbf{x})$ is the instantaneous deflection in SLS. The optimisation problem is constrained to control the volume. A tolerance of 100 m³ is introduced in $g_{11}(\mathbf{X})$ and $g_{12}(\mathbf{X})$ to give some margin for the algorithm. The space is aimed to be 500 m³, thus resulting in a minimum volume of 400 m³ and a maximum volume of 600 m³.

$$\min f_1(\mathbf{X}) = w$$

$$s. t. g_1(\mathbf{X}) = \left(\frac{\sigma_{c,0,d}}{f_{c,0,d}} \right)^2 + k_m \frac{\sigma_{m,y,d}}{f_{m,y,d}} + \frac{\sigma_{m,z,d}}{f_{m,y,d}} \leq 1$$

$$\begin{aligned}
 s.t \ g_2(\mathbf{X}) &= \left(\frac{\sigma_{c,0,d}}{f_{c,0,d}} \right)^2 + \frac{\sigma_{m,y,d}}{f_{m,y,d}} + k_m \frac{\sigma_{m,z,d}}{f_{m,z,d}} \leq 1 \\
 s.t \ g_3(\mathbf{X}) &= \frac{\sigma_{t,0,d}}{f_{t,0,d}} + k_m \frac{\sigma_{m,y,d}}{f_{m,y,d}} + \frac{\sigma_{m,z,d}}{f_{m,z,d}} \leq 1 \\
 s.t \ g_4(\mathbf{X}) &= \frac{\sigma_{t,0,d}}{f_{t,0,d}} + \frac{\sigma_{m,y,d}}{f_{m,y,d}} + k_m \frac{\sigma_{m,z,d}}{f_{m,z,d}} \leq 1 \\
 s.t \ g_5(\mathbf{X}) &= \frac{\sigma_{c,90,d}}{k_{c,90} f_{c,90,d}} \leq 1 \\
 s.t \ g_6(\mathbf{X}) &= \frac{\tau_d}{f_{v,d}} \leq 1 \\
 s.t \ g_7(\mathbf{X}) &= \frac{\sigma_{c,0,d}}{k_{c,y} f_{c,0,d}} + \frac{\sigma_{m,y,d}}{f_{m,y,d}} + k_m \frac{\sigma_{m,z,d}}{f_{m,z,d}} \leq 1 \\
 s.t \ g_8(\mathbf{X}) &= \frac{\sigma_{c,0,d}}{k_{c,z} f_{c,0,d}} + k_m \frac{\sigma_{m,y,d}}{f_{m,y,d}} + \frac{\sigma_{m,z,d}}{f_{m,z,d}} \leq 1 \\
 s.t \ g_9(\mathbf{X}) &= \frac{\sigma_{m,d}}{k_{crit} f_{m,d}} + \frac{\sigma_{c,d}}{k_{c,z} f_{c,0,d}} \leq 1 \\
 s.t \ g_{10}(\mathbf{X}) &= w_{inst} \leq \frac{l_{max}}{250} \\
 s.t \ g_{11}(\mathbf{X}) &\leq V - 100 \text{ m}^3 \\
 s.t \ g_{12}(\mathbf{X}) &\geq V + 100 \text{ m}^3 \\
 \mathbf{X} &= \text{Design variables}
 \end{aligned} \tag{3}$$

w	Weight of primary structural system
l_{max}	Maximum length of beams
V	Target volume of space
$\sigma_{c,0,d}$	Design compressive stress along the grain
$\sigma_{c,90,d}$	Design compressive stress perpendicular the grain
k_m	Factor considering re-distribution of bending stresses
$\sigma_{m,y,d}$	Design bending stress about the principal y-axis/z-axis
$\sigma_{m,z,d}$	
$\sigma_{t,0,d}$	Design tensile stress along the grain
τ_d	Design shear stress
$k_{c,y}, k_{c,z}$	Instability factor
k_{crit}	Factor used for lateral buckling
w_{inst}	Instantaneous deflection

The acoustic objective is to minimise the reverberation time, T_{60} , in the space to increase speech intelligibility. However, a space with a reverberation time under 0,3 s is qualified as a dead room, which will result in a loss of speech intelligibility over moderate distances. Therefore, a constraint to the reverberation time, T_{60} , is activated at 0,4 s.

$$\begin{aligned}
 \min f_2(\mathbf{X}) &= T_{60} \\
 s.t \ g_{13}(\mathbf{X}) &= T_{60} > 0,4 \text{ s}
 \end{aligned} \tag{4}$$

The aesthetics is incorporated as a constraint to the optimisation process. The constraint is added to both objectives in the algorithm, ensuring that the solutions converge towards an aesthetic solution. The advantage of implementing the aesthetic quality as a constraint is that the solutions with a low predicted aesthetic quality have a low probability of being chosen in the genetic algorithm selection phase. The constraint activates if the aesthetic quality is below a value of 0,8. This value is chosen to allow some tolerance for the algorithm to find a suitable solution. The argumentation is that since the ANN predicting the aesthetic quality is not 100 % accurate, then tectonic solutions could receive a slightly worse aesthetic quality and vice versa.

$$s.t \ g_{14}(\mathbf{X}) = \text{Aesthetic quality} \leq 0,8 \tag{5}$$

If one of the constraints is violated, a penalty function is activated to guide the algorithm back into the feasible solution space. The penalty function is defined in Equation (6) based on all the constraints defined in the optimisation problem. The penalties are scaled to be appropriate to the size of the objective. Furthermore, a slight violation of the constraints receives a small penalty, whereas a significant violation of the constraints receives a proportionally larger penalty. Therefore, the values amplifying the constraint violation are hyperparameters which has been found manually by testing the algorithm. Because the two objectives assume extremely different values, the penalties must be scaled differently to behave properly.

$$\begin{aligned}
 P_1(\mathbf{X}) &= (30 + \max(g_1, g_2, g_3, g_4, g_5, g_6, g_7, g_8, g_9))^3 \\
 &\quad \text{if } \max(g_1, g_2, g_3, g_4, g_5, g_6, g_7, g_8, g_9) \geq 1,0 \\
 P_2(\mathbf{X}) &= (10 + g_{10})^3 \quad \text{if } g_{10} \geq \frac{l_{max}}{250} \\
 P_3(\mathbf{X}) &= (500 - g_{11})^2 \quad \text{if } g_{11} \leq V - 100 \text{ m}^3 \\
 P_4(\mathbf{X}) &= g_{12}^2 \quad \text{if } g_{12} \geq V + 100 \text{ m}^3 \\
 P_5(\mathbf{X}) &= \frac{500 - g_{11}}{10} \quad \text{if } g_{11} \leq V - 100 \text{ m}^3 \\
 P_6(\mathbf{X}) &= \frac{g_{12}^2}{10} \quad \text{if } g_{12} \geq 100 \text{ m}^3 \\
 P_7(\mathbf{X}) &= \frac{3,4}{g_{13} + 1} \quad \text{if } g_{13} \leq 0,4 \text{ s} \\
 P_8(\mathbf{X}) &= ((1 - g_{14}) \cdot 100)^2 \quad \text{if } g_{14} \leq 0,8 \\
 P_9(\mathbf{X}) &= (1 - g_{14}) \cdot 2 \quad \text{if } g_{14} \leq 0,8 \\
 F_1(\mathbf{X}) &= f_1(\mathbf{X}) + P_1(\mathbf{X}) + P_2(\mathbf{X}) + P_3(\mathbf{X}) + P_4(\mathbf{X}) + P_8(\mathbf{X}) \\
 F_2(\mathbf{X}) &= f_2(\mathbf{X}) + P_5(\mathbf{X}) + P_6(\mathbf{X}) + P_7(\mathbf{X}) + P_9(\mathbf{X}) \\
 P &| \text{Penalty for violating a specific constraint}
 \end{aligned} \tag{6}$$

The optimisation is conducted in Grasshopper [28] with the plugin Octopus [38] using the HypE algorithm. In each generation of the optimisation process, 200 solutions are analysed. In the first generation, this is doubled. A preliminary analysis showed that a large number of solutions were needed to introduce a large diversity of solutions. The algorithm runs for a maximum of 10 generations, to save computational power, and it was found that the non-dominated results found after generation 10 were not significantly different from each other. A cross-over factor of 0,8 is used and a mutation probability of 0,2 with a factor of 0,9 for the mutated solutions. Elitism is introduced with a factor of 0,1. A summary of all the optimisation settings, objective and constraints in the optimisation is presented in Figure 18.

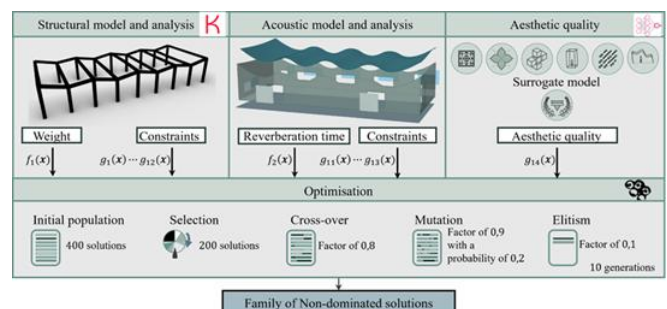


Figure 18: Summary of the multi-objective optimisation problem analysed in the case study

4.5. Results

The results of the case study are presented in the following section. The results include the solution space and a more detailed exploration of certain non-dominated solutions found with the optimisation algorithm.

4.5.1. Solution Space

Five non-dominated solutions were found in the optimisation process, presented in Figure 19.

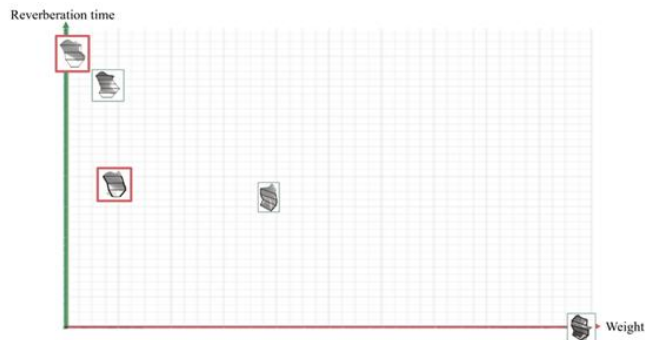


Figure 19: Solution space of non-dominated solutions in the case study, 2 selected nondominated solutions are marked with red outline

The solution space in this case study shows a larger diversity in reverberation times, T_{60} , found among the non-dominated solutions. These solutions are geometrically remarkably different, but they seem to have similar structural systems with four to five frames, which is as expected since fewer frames result in lower weight. Two of the non-dominated solutions, marked with a red outline in Figure 19, have been chosen for further investigation. These are chosen because they appear to have the best trade-off between weight and reverberation time.

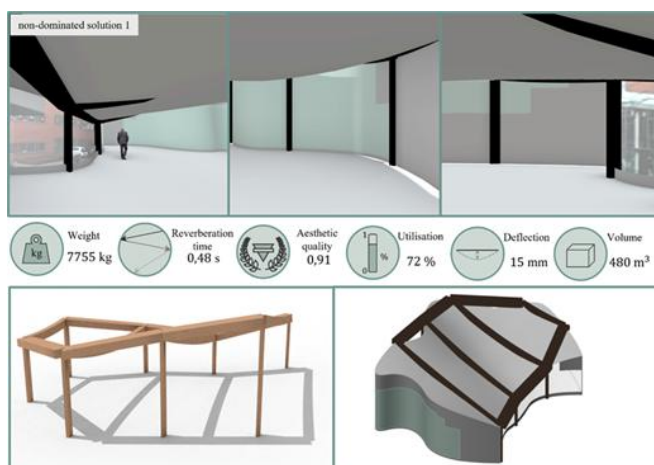


Figure 20: The first chosen non-dominated solution from the case study

4.5.2. Non-dominated Solutions

The first chosen non-dominated solution is presented in Figure 20. The placement of material and windows appears to be slightly arbitrary. However, there are still places where the materials seem to lack the desired harmony. The aesthetic quality of the solution is 0,91, which might be a bit high, but

it does have some alluring aesthetic values, such as its proportions in relation to the human body and movement in the geometry of the space. In terms of the structural aspect is the utilisation is quite a bit larger in this situation, which is primarily because the timber frames span a greater distance. The reverberation time is close to its lower limit, which is preferred.

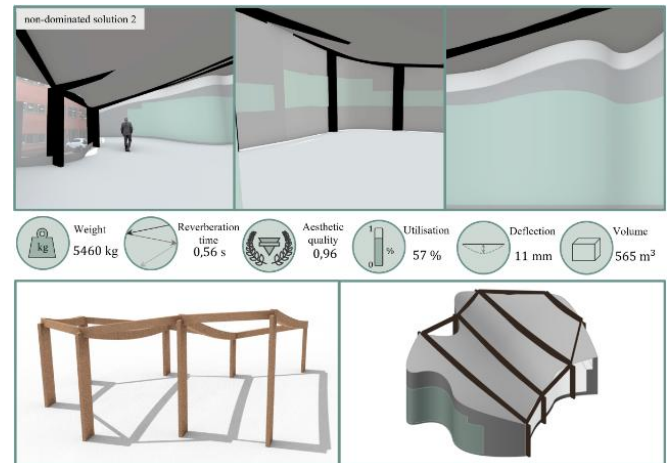


Figure 21: The second chosen non-dominated solution from the case study

The second of the non-dominated solutions chosen is presented in Figure 21. At closer inspection, this solution is remarkably similar to the first chosen solution. It has several of the same aesthetic qualities of proportion and movement in the geometry. However, it seems that this solution has better placement of the materials, which is also rewarded with the higher aesthetic quality prediction of 0,96. In terms of the structural component is the utilisation and deflection are relatively low, which indicates that the cross-sections could be optimised further. The reverberation time is a bit high but still within acceptable limits. The reverberation time is primarily affected by the reduction in absorptive material on the wall opposite the windows. This is generally unwanted since two reflecting surfaces parallel to each other can create standing waves. However, these two walls are not parallel, so standing waves should not be a concern.

Based on this assessment, the best of the two non-dominated solutions is the one presented in Figure 21, because it has better aesthetic and structural results.

5. Discussion and Conclusion

The optimisation of engineering subjects within building design frequently neglects the architectural expression within a space. Therefore, the motivation for this article was to incorporate aesthetic quality into a computational model to improve informed decision-making.

In literature, several descriptions of aesthetics are presented. Recurring terms are qualified as symmetry, harmony, proportion, order and variety. These terms all assist in describing the architectonic expression of a space. From the theory, six qualitative values have been defined to describe the aesthetic quality in a space. I.e. symmetry, elements, texture, material, scale, and variety are all defined as numeric values, which can be translated directly to an algorithm based

on a computational model. Each value describes a different aspect of the aesthetic quality in a space.

A framework to develop an ANN to predict aesthetic quality in building design has been proposed and consists of four phases: (1) generating a design proposal in a computational model, (2) aesthetic judgement, (3) extracting qualitative values of the design proposal, and (4) develop a machine learning model. A machine learning model was developed, constructed with a shallow ANN. The results showed a training error (RMSE) of 0,27 and a test error (RMSE) of 0,19. These were acceptable values, indicating the developed ANN was not overfitting the training data. A sensitivity analysis on the ANN showed that the prediction accuracy was highly sensitive to the number of neurons in the hidden layer, and which folds were the training and which fold was the test data.

When applying the ANN predicting aesthetic quality in a case study, it has been found that the prediction of aesthetic quality was very accurate in the case study, where the proposed design offers a playful base geometry while having a transparent structural design. The research conducted in this article successfully addressed the approach to integrating aesthetic quality into a computational model. Furthermore, the case study indicated that it is possible to inform a computational model with aesthetic quality while maintaining acoustic and structural integrity. The novel framework presented in the article presents a method for creating tectonic designs computationally. Furthermore, a proof of concept was presented where the framework was utilised. This framework holds potential for adoption in professional architectural practice, particularly in early-stage conceptual design processes where aesthetic judgments often lack computational support.

For further development of the framework, more complex computational models could be developed. Furthermore, interviews could be conducted to determine the qualities affecting the architectural value of a space from multiple individuals. Lastly, the aesthetic judgment phase could be incorporated into virtual reality to create a more realistic experience of the room.

Authorship Contributions

Conception and design of study: L. Kærstaa, P. H. Kirkegaard
Acquisition of data: L. Kærstaa Analysis and/or interpretation of data: L. Kærstaa, P. H. Kirkegaard
Drafting the manuscript: L. Kærstaa
Revising the manuscript critically for important intellectual content: P. H. Kirkegaard
Approval of the version of the manuscript to be published: L. Kærstaa, P. H. Kirkegaard.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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