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A critical examination of the use of business intelligence (BI) in the optioneering of generative design models: a case study.

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Abstract − This research outlines the development of a generative design workflow for the architectural space planning of a 1,200 sq.m office located in Dublin, Ireland, and the application of statistical analysis and data visualisation for the optioneering of generated models. First, the paper defines a computational design model with the potential to generate a variety of office layouts, including circulation routes and desk locations. It then identifies three unique performance metrics that evaluate each design option. Finally, the study applies a multi-objective genetic algorithm (MOGA) to explore the high-dimensional design space of all potential options and describes several visualisation techniques that can assist the designer in selecting the most appropriate option. There have been several articles published regarding the use of generative design systems, model evaluation processes and business intelligence (BI). However, a clearly defined methodology for relating all three remains undocumented. The aim of this research is to critically examine the use of business intelligence in the optioneering of generative design models. It is anticipated that this research will go some way to filling the gap in the current published material regarding the impacts that these emerging technologies have on the building design process.

Keywords − Generative Design, Business Intelligence (BI), Building Information Modelling (BIM).

I INTRODUCTION

Generative design (GD) reflects nature's evolutionary method of design [1]. Design team members contribute design goals into a GD system, along with parameters such as spatial constraints, cost, and materials. The system then discovers all possible variations of a solution, instantaneously generating design iterations [1].

Whitelaw [1] discusses the art of generative design and promotes its use within architecture, stating that designers must be able to work on, as well as with, generative design models. Singh & Gu [2] proceed further by identifying the successful implementation of GD systems in architecture and call for the adoption of a framework of an integrated generative design system based on 'reflective practice'. According to Singh & Gu, most existing GD systems are based on a singular GD technique. Their research critically appraises five different techniques from which they deduce the need for compound models of GD systems [2]. Neither article outlines a commercial workflow for the implementation of generative design.

After the generation of all design permutations, the resulting models need to be evaluated to assist with the optioneering process. Caldas [3] proposes one such method of evaluation referred to as GENE_ARCH, an evolution-based generative design system intended to help architects and designers attain sustainable and energy-efficient design solutions. This line of research is continued further by Turrin, von Buelow & Stouffs [4] who confer the resulting benefits of merging parametric modelling and genetic algorithms to accomplish a performance-orientated process in design and offer ParaGen as a supporting tool.

An alternative method for the evaluation of generative design models is put forward by Touloupaki & Theodosiou [5]. While less exhaustive than the research conducted by Turrin, von Buelow & Stouffs [4], Touloupaki & Theodosiou's article [5] is more applicable to the current Irish construction industry as it considers energy performance optimisation as a generative design tool for nearly zero energy buildings (nZEB).

The automated generation of building information models (BIMs) produces vast amounts of associated data. Williams [6] describes the purpose of business intelligence (BI) as to facilitate data-driven decision making with the help of aggregation, analysis, and visualisation of data. This has a direct contribution towards assisting designers in dealing with the appraisal of generative design options [7].

There have been several articles published regarding the use of generative design systems, model evaluation processes and business intelligence. However, a clearly defined methodology for relating all three remains undocumented. The aim of this research is to critically examine the use of business intelligence in the optioneering of generative design models. It is anticipated that this research will go some way to filling the gap in the current published material regarding the impacts that these emerging technologies have on the building design process.

Section 2 of this research paper will critically review the theory of generative design and report on its current usage within the construction industry. It will investigate through a literature study the impacts GD has made when compared to more traditional methods in the building design process and examine the appropriateness of business intelligence for the optioneering of GD models. The paper will also review the application of a workflow for generative design applied to the architectural space planning of a new office and research space in the MaRS Innovation District of Toronto [8].

In Section 3, through experimental research the paper will outline the development of a repeatable artefact with the aim of using statistical analysis to assist designers in the selection of the most appropriate generatively produced model against predefined performance metrics. In Section 4, the proposed solution will be appraised by selected industry professionals through a semi-structured focus group. The gathered data will then be used to evaluate the use of business intelligence in the optioneering of generative design models.

II Literature Review

a) Generative Design

Computational design (CD) is not a single algorithm or process that you can employ [9]. Instead, it can be described as a methodology whereby the designer outlines a set of rules, relationships, and instructions that accurately define the steps required to attain a projected design and its associated geometry or data [9]. Importantly, these steps must be computable.

From a computational design perspective, the designer focuses more on creating the system that would generate a design, rather than the design itself [10]. The task of iterating through design options and their associated data is conducted by a computer. This allows the designer to focus on the more human aspects of the design process, often saving both time and money [10].

Nagy et al. [8] describes generative design as a collaborative design process between both humans and computers, more recently referred to as 'co-design'. Throughout this process, the designer outlines the design criteria and the computer generates a number of design alternatives, evaluates them against measurable goals identified by the designer, evolves the studies with the use of the results from previous generations and designer feedback, and grades the results in comparison to how well they accomplish the designer's initial objectives [11].

Generative design is one particular application of the computational design methodology [12], with the following notable characteristics:

- Rather than defining the exact steps, the designer identifies objectives to attain a design;
- As oppose to just a single design, the computer aids the designer in investigating the design space and generating numerous design options;
- The computer allows the designer to discover a few high-performing results that meet several competing objectives; &
- The designer evaluates various design conditions to discover several design options that best fit the design objectives.

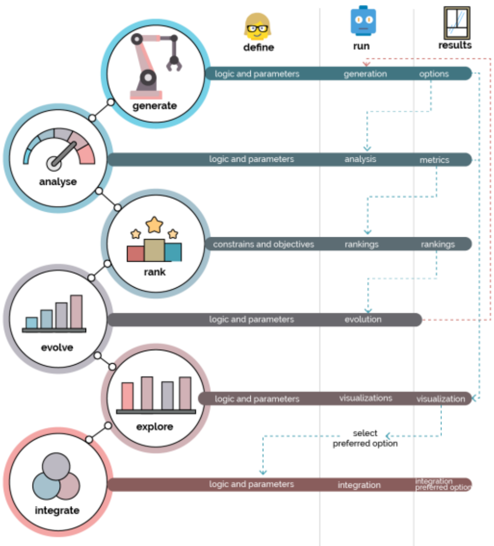

Fig. 1: An overview of the stages and steps of generative design [12]

As mentioned, a generative design method facilitates a more collaborative design process between human and computer. In generative design, Bohnacker et al. [13] describes this process as involving the following stages:

- Generate - design options are generated by the system, using parameters and algorithms employed by the designer;
- Analyse - the design options created in the previous stage are now analysed based on how well they accomplish targets outlined by the designer;
- Rank - the generated designs are ranked and sorted based on the outcomes of the analysis;
- Evolve - the system ranks the generated designs to identify in which direction they should evolve further;
- Explore - the designer investigates the design options, reviewing both the evaluation results and geometry; &
- Integrate - the designer selects a preferred option and incorporates it into the wider project or design model [13].

To benefit from the potential of generative design, the subject parametric model must be expanded in two ways [14]. Firstly, definitive metrics must be included to evaluate each design option. As the computer does not possess any intrinsic sensitivity towards design, the designer is required to express to the computer how to establish which design options rank better than others. Secondly, the model must be linked to a search algorithm that can manipulate the input parameters defined by the designer, retrieve feedback from the results, and logically adjust the parameters to identify high-performing design options whilst also investigating the complete potential of the design space [14].

The multi-objective genetic algorithm (MOGA) is one of the most encouraging and widely used of these algorithms, which utilises principles of evolution to produce sequential generations of designs and evolve them over time to incorporate higher-performing designs [15]. Recently, Autodesk has included an iteration of MOGA in its release of Generative Design for Revit 2021 which forms part of this experimental research.

The use of multi-objective genetic algorithms for the optimisation of intricate mechanical design challenges is well-documented in the field of engineering. Marler & Arora [16] offer a comprehensive overview of several applications. Though, being confined to the objectives of engineering challenges, these uses are constrained to only making use of structural performance as optimisation criteria.

A wide-ranging overview of automated systems for architectural space planning is provided by Liggett [17], including the application of genetic search algorithms. Gerber et al. [18], Chronis et al. [19], Keough & Benjamin [20] and Derix [21] have all used comparable optimisation methods to an array of architectural challenges. However, their criteria for optimisation are equally confined to common and easily simulated physical objectives, for instance environmental and structural performance. Opposingly, this research follows a more adaptable system that can incorporate a range of optimisation criteria as proposed by Nagy et al. [8].

b) Business Intelligence

Forrester Research [22] describes business intelligence (BI) as *"a set of methodologies, processes, architectures, and technologies that transform raw data into meaningful and useful information used to enable more effective strategic, tactical, and operational insights and decision-making"*. In the context of this research, BI relates to the preparation of raw data for the purpose of statistical analysis and data visualisation to assist in the optioneering of generative design models.

In recent years, BI has grown to incorporate more processes and activities to help better performance. These processes include: data mining; reporting; performance metrics; descriptive analysis; querying; statistical analysis; data visualisation; and data preparation [23].

Statistical analysis is an element of data analytics [24]. In the realm of business intelligence, statistical analysis involves gathering and examining every data entry in a set of items from which samples can be taken. In statistics, a sample is a selected representation taken from a total population [24]. Statistical analysis can be subdivided into a few distinct steps, as follows:

- Describe the type of data to be analysed;
- Explore the relationship of the data to the population it was drawn from;
- Create a representative model of the underlying population;
- Prove/disprove the legitimacy of the model; &

- Apply predictive analytics to test scenarios that will help inform future decisions [25].

Noves [26] describes data visualisation as both an art and a science. A primary objective of data visualisation is to communicate data clearly and effectively with the use of statistical graphics, charts, and plots. Successful visualisation makes complex data more accessible, assisting users to analyse and understand data and consume it more easily. Generally, users would have a specific analytical task, such as understanding causality or drawing comparisons, and the design purpose of the graph would support this task [26]. The use of data visualisation is well documented in the work of Gong & Zigo [27], Phillips [23] and Noves [26] whom all promote its use as key to improving the communication of data for construction projects. In line with their work, this research will also use Microsoft PowerBI as the preferred application for business intelligence.

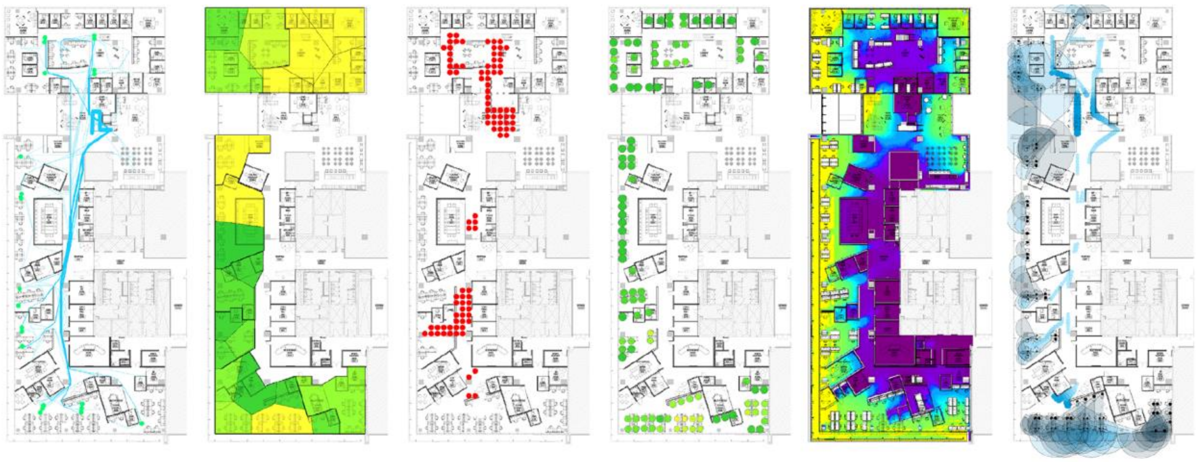

Fig. 2: Project Discover design metrics (from left to right: adjacency preference; work style preference; buzz; productivity; daylight; and views to outside) [8]

c) Project Discover - Autodesk offices in the MaRS Discovery District in Toronto

In comparison to engineering, finding the solution to architectural problems can often become more challenging. They frequently involve qualitative aspects of the experience of space that are more difficult to measure and are less tangible [28]. In 2017, The Living [29] expanded the known constraints of generative design and employed this framework to the design of Autodesk's new office in Toronto.

In their paper, Nagy et al. [8] describe an adaptable workflow for the application of generative design to architectural space planning. They begin with a description of a computational design model that can generate an array of office layouts and locate all required amenities and people using a defined set of input parameters [8]. The Living follow by then outlining six distinctive objectives that evaluate the generated layouts with regards to surveyed worker preferences and architectural performance. Next, they demonstrate the use of a multi-objective genetic algorithm (MOGA) to explore the high-dimensional design space and illustrate a variety of visualisation tools that can assist a designer in the optioneering of generative design models [8].

Prior to The Living's research, the quantification of spatial experience had been documented by several authors. Hillier et al. [30] proposed 'space syntax', a range of analytical tools for exploring spatial configurations. Peponis et al. [31] expand this research further by offering a universal method for identifying plan topologies using linear representation. Turner et al. [32] recommend a view-based ray tracing method for analysing and comprehending spatial configurations. Though the proposed techniques can assist the designer obtain quantitative information about their designs, they are only suggested as methods to facilitate a traditional design process. In contrast, The Living expand these techniques and illustrate how they can be applied as measures of spatial performance to facilitate an automated optimisation workflow [28].

The geometric system proposed by The Living included various levels of constraints such as the extent of the space, the quantity of meeting rooms and amenities and fixed locations for plant rooms and cores [33]. Their objectives, outlined below, relate qualitative facets of human experience with quantitative measures.

- Adjacency preference - calculates the travel distance from each member of staff to their preferred amenities and neighbours;
- Work style preference - calculates the appropriateness of an assigned neighbourhood's distraction and daylight results to the assigned team's surveyed preferences;
- Buzz - calculates the distribution and extent of high-activity zones;
- Productivity - calculates concentration levels at individual desks based on sight lines to noise sources and other employees;
- Daylight - calculates the quantity of natural daylight entering the space; &
- Views to outside - calculates the percentage of desks with an unobstructed view to the nearest window or glass façade [33].

The process offered The Living an opportunity to go beyond the traditional approach to office design and provide a space that was distinct and rich in features. With the use of survey-based data collection and continued monitoring of the workspace, generative design can again be used to recommend new design options and the evaluation systems can be enhanced [29].

The Living conclude by examining the future of such computational workflows in architecture. Their aspiration is that they surpass basic automation to establish an extended role for the human designer and a more collaborative interconnection between human designers and computer design software [8].

III Experimental Research

a) Methodology

The methodology for this research is based upon the design science research (DSR) framework as presented by Kehily & Underwood [34] for the development and evaluation of a BIM technology or practice. DSR is a methodical approach to designing a solution to a known problem that includes the development and examination of artefacts [34].

Hevner et al. [35] write that design science research should add to knowledge by employing knowledge in an innovative or new way, they state that this can be accomplished in various ways. In this research, it is achieved through the application of an existing product to solve a practical problem in a different context to which it was originally designed.

The DSR framework consists of five consecutive stages as illustrated below: the awareness of a problem; the suggestion of a solution; the development of a solution; its evaluation; and a concluding stage with the objective of specifying learning outcomes [34].

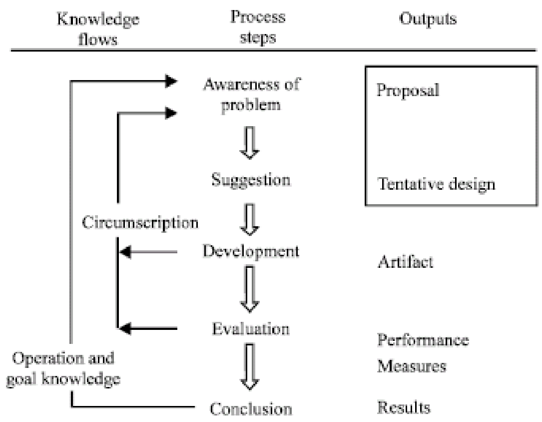

Fig. 3: Stages of the design science research framework [34]

Both Section 1 and Section 2 of this paper convey an awareness of the problems associated with the optioneering of generative design models. The automated generation of models produces large amounts of associated data which can be time consuming for a designer to navigate. For example, on the Project Discover case study previously discussed Nagy et al.'s [8] generative design system produced 10,000 options from the design space which then needed to be analysed and evaluated against the performance criteria.

The researcher's suggested solution for the optioneering of generative design models is organised into four steps:

1. the design of a geometric model which can produce numerous design variations;
2. the design of several performance metrics which can be used to gauge the performance of a particular design option;
3. the study of the model's design space through a multi-objective genetic algorithm; &
4. the examination of the resulting design data through statistical analysis and data visualisation.

In Section 4, the developed solution/artefact will be appraised by selected industry professionals through a semi-structured focus group. The gathered data will then be used to evaluate the use of business intelligence in the optioneering of generative design models before concluding and specifying learning outcomes of the research.

Moreover, this method is proposed as only one element within a wider design process. There are various steps that need to be taken both ‘pre-generative design’ to create a design concept to lead the geometric model and gather required data for the performance metrics. Equally, there are an array of steps that need to be taken ‘post-generative design’ to meet other conditions and develop the preferred design option to the level of detail required for construction.

b) One Molesworth Street

For the purpose of this research the proposed solution will be retrospectively applied to an existing office development located in Dublin, Ireland. The experimental workflow for the production and optioneering of generative design models will be evaluated in comparison to the process used by the architects, C+W O’Brien Architects, for the design of the space.

Situated in the recently constructed One Molesworth Street commercial building, the architect’s scope consisted of the construction management and interior design of the fourth floor of the building for their client Goshawk Aero, a global aircraft leasing company. The 1,200 sq.m office fit-out was designed for 80 employees and included: 13 meeting rooms; a reception entrance; a multi-functional auditorium/town hall; a canteen; a wellness room; changing facilities; and both casual and interactive spaces for staff engagement.

Fig. 4: Photograph of One Molesworth Street [36]

One of the core principles of logo design is to communicate the culture and philosophy of the company to which it is associated. Goshawk Aero has an especially well considered and distinguishable logo. The cylindrical form represents equality, unity, and perpetuation. The logo indicates an aeroplane in elevation and formed the basis of the design concept for the office. With the aeroplane’s propeller centred at reception the workspace and desks were set out radially in plan.

With the intention of fostering a collaborative working environment C+W O’Brien Architects made the Goshawk Aero logo the starting point of their design. This led to further exploration and continually influenced their approach. When interviewed, the architects explained that they:

“wished to create a design that reflected and incorporated the aviation business in which our client operates. We wanted to avoid the typical square box office space and maintain the rotation of the aeroplane propellers as in our initial concept. This concept design was incorporated into our ceiling, flooring, and room design which our client embraced and felt represented their ethos of innovation”.

C+W O’Brien Architects went on to explain that their client’s brief requested an adaptable space that could accommodate 80 staff members but remain flexible enough to expand to 120 in line with the company’s growth forecast. Although not requested by the client, the architects extended the brief with their own parameters for the design of the office space. These included attempts to both maximise views to the outside for employees and reduce travel distances.

The design information for One Molesworth Street was initially produced as hand-drawn sketch for concept stage. This intent was then transposed to .DWG format with the use of Autodesk AutoCAD and a 3D geometrical model was produced with Trimble SketchUp for visualisation purposes. The architects’ tender and construction information were also created with Autodesk AutoCAD which was later interpreted by the contractor to produce a Building Information Model (BIM) with the use of Autodesk Revit.

With adaptable spaces, modern technology, and a design intended to encourage and facilitate a collaborative working style, the project realised the client’s brief. However, the manual reproduction of design information both between incompatible software and different stakeholders is recognised by the design team as having resulted in time inefficiencies during the exchange of information.

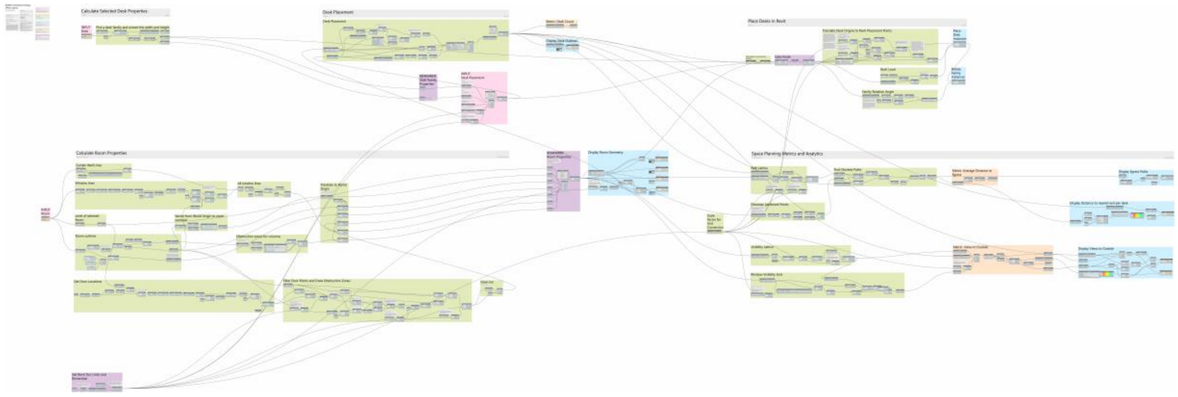

Fig. 5: Dynamo graph illustrating the developed geometric model & design metrics

c) Geometric Model

The first step of the experimental research was to interpret as-built drawings of One Molesworth Street to recreate a geometric model that could define the subject room boundary and position both circulation routes and desks within the space. To generate each of the individual designs, the geometric model applies the algorithm below:

1. Input the geometry and boundary lines of the subject room and obstruction zones;
2. Identify the location of access and egress points;
3. Calculate the extent of façade glazing along the room boundary;
4. Input the geometry of the selected desk/family instance; &
5. Place desks and circulation routes within the space in rows base on a greedy fill algorithm.

At Present, there are no principles for the number of individual parameters a geometric model should include to ensure that a thorough search of the design space is both viable and complex enough to generate a wide array of design options. Generally, the current best practice is to reduce this number as much as possible, while making sure that each crucial aspect of the design is operated by a single and constant variable. The individuality of each parameter is crucial so that the algorithm can directly operate each piece of the design autonomously while searching for the best permutations. The continuity of all parameters is essential as the algorithm must be able to fine-tune the parameter settings by predicting future outcomes based on past experiences. If every setting of a parameter returns entirely different results, it will be more challenging for the algorithm to search through the design space.

Lastly, to facilitate learning within the automated search process, the complete model is required to be entirely deterministic, dependent solely on the input parameters subjected to the algorithm to generate each design. No random parameters or noise should be used in the geometric model.

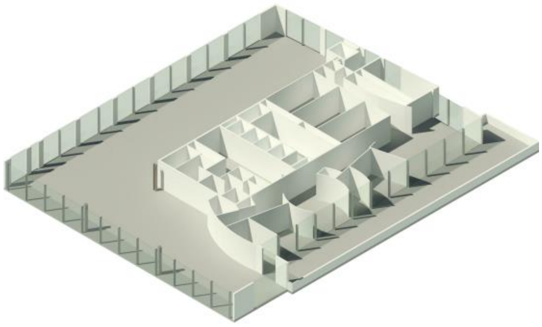

Fig. 6: Revit model illustrating the developed geometric model

d) Design Metrics

To facilitate the search algorithm to automatically calculate the performance of each of the generated designs it is necessary to define a unique set of metrics, or goals, which rate the performance of each option alongside a set of criteria. These goals establish the set of output values that the search algorithm uses to evaluate the performance of each design option, and to structure its search of the design space to uncovering higher-performing options.

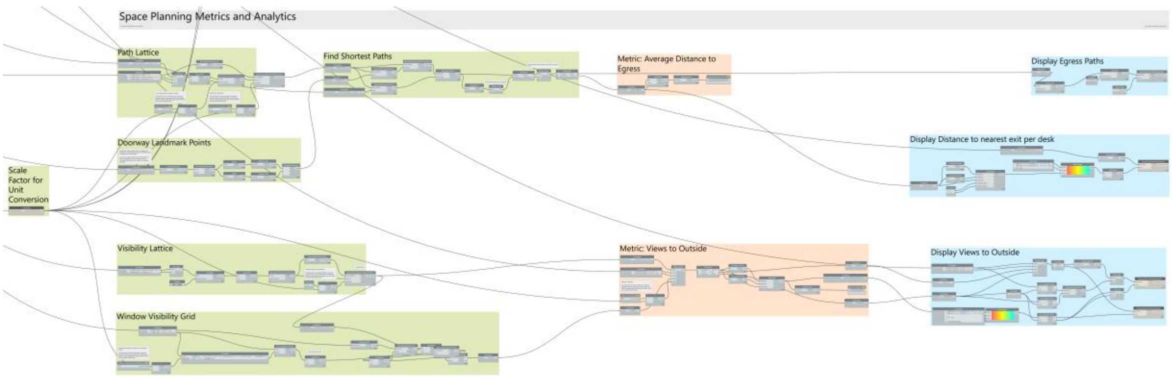

Fig. 7: Portion of the Dynamo graph illustrating the developed design metrics

One evident limitation of the generative design process is that all of a given design system's performance criteria must be subjected to the search algorithm as a numeric value. Therefore, any performance metric we would like the algorithm to incorporate needs to be both computable and quantifiable in an efficient and consistent way for all results within the design space.

However, an architectural design problem regularly contains many complex and competing goals many of which are difficult to quantify, such as: quality of space; novelty; beauty; elegance; and fairness. In response to this potential obstacle, The Living [29] suggest the subdivision of all architectural performance metrics into three classes:

- Metrics that are easily quantifiable and calculated with the use of existing tools, such as daylight analysis;
- Metrics that can be quantified in theory but not computed with the use of existing tools, for which require the development of new computation tools, such as the distribution of high-activity zones; &
- Metrics that cannot be quantified and require to be addressed outside of the generative design system, such as beauty [29].

While this grouping addresses the existing limitations of the generative design process, the conclusion of this research offers some recommendations for future study that suggests machine learning as a method to quantify and appraise goals that are difficult to compute using direct calculation. In this case, the researcher's analysis of the project goals along with discussions with the original design team yielded three distinct design metrics to evaluate each design:

- Occupancy – which measures the number of desks/family instances in the room;
- Views to outside – which measures the average score for the quality of views to outside from each desk; &
- Travel distance – which measures the average distance to access and egress points.

All three metrics were both novel and highly specific to the architects' design goals. For these the researcher developed custom analysis tools with the use of Autodesk Dynamo and Python which were built directly into the generative design system.

While occupancy operates as a simple count, the views to outside metric measures the quality of views from an employee's desk. It calculates and averages the view results throughout all desks by allocating relative values to each desk. Desks without a view receive a value of zero, while the desk with the highest-performing view is set as 1. The intermittent values are located within this range.

The view to outside metric for a single desk is measured as the distance from the desk's seat location point to the nearest point on a curtain wall or window element. A point is only deemed to be within range if it is within a minimum distance of six metres from the seat and is within the delineated view cone, a 110° arc centred on the employee's facing direction.

The travel distance metric calculates the shortest path to each access and egress point from each desk in the room. In the event of the room having multiple access and egress points, it selects the shortest path for each desk. Then, it combines the length of all paths and divides by the quantity of paths. On the office floor of One Molesworth Street there was a total of three access and egress points.

Every new design project has the potential to bring with it a unique set of goals and performance constraints, which will never be entirely realised in any single design software. Therefore, an element of the responsibility of the designer in the generative design process is the ability to make use of computational tools such as parametric modelling and scripting to define their unique design requirements to the computer. Although this can add complexity to the design task, it also has the potential to expand the role of the architect while opening up further possibilities for design through enhanced human-computer collaboration.

The design metrics, together with the geometric model, represent the second half of the total generative design system. It is a closed system that:

1. Uses a distinct set of input parameters;
2. Generates unique design solutions from those parameters;
3. Evaluates the options along a set of defined metrics; &
4. Outputs those metrics as a set of distinct values.

When this system is connected to a search algorithm, in this case the application of MOGA with the use of Generative Design for Revit 2021, it has the potential to automatically explore for good design solutions. However, although the algorithm can generate many more options than feasible through more traditional manual methods, it can only evaluate them upon the defined metrics output by the model. Therefore, it is important that the selected metrics adequately describe the priorities of the design problem and sufficiently capture the relative performance of each design option corresponding to those metrics.

e) Design Evolution

Once the generative design model has been defined, a search algorithm can be used to automatically explore the design space of potential options and uncover unique and high-performing designs. A search algorithm is a division of a typical optimisation algorithm, which is tasked with finding optimal settings of input parameters of a function which maximises the value of one or multiple outputs [15]. Although there are many search algorithms, the one applicable to this paper is the multi-objective genetic algorithm (MOGA) as it is employed by Generative Design for Revit 2021 [33], the platform used for this experimental research.

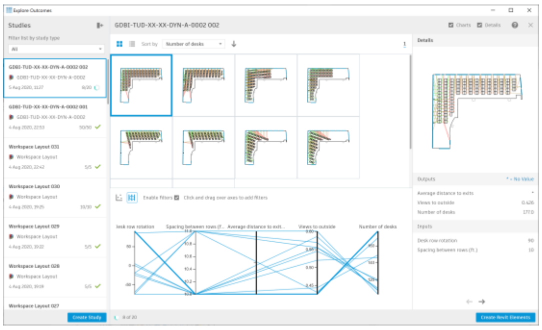

Fig. 8: Image illustrating the user interface of Generative Design for Revit 2021

MOGA produces designs in groups referred to as generations. The initial generation is comprised of a set of preliminary options, either evenly or randomly sampled from the design space. Successive generations are then created by either:

- Elitism – the process of directly taking high-performing options from the preceding generation; or
- Cross-breeding – the process of randomly combining the parameters of two high-performing options to produce a single new design [15].

The input parameters of a new design may also be somewhat altered before it enters the population, this process is referred to as mutation. This process is then replicated for several generations, either until performance fails to develop for a number of generations or the specified number of generations is reached. In this manner, a multi-objective genetic algorithm uses principles found in organic evolution to produce new design options based on the genome, or input parameters, of preceding high-performing designs. Gradually advancing the best designs and 'evolving' higher-performing options over time [15].

There are many benefits to this algorithm in the context of generative design. The MOGA can optimise options along any quantity of output metrics. Moreover, the designer is not required to prioritise the individual metrics in advance as the MOGA identifies relative performance based on the concept of dominance as opposed to the absolute difference in metric values. If a design dominates or performs better in one or more metrics it is deemed better performing than another. Therefore, the algorithm will continue to generate options that are dominant in as many of the metrics as viable, and the designer can later determine how to prioritise. Another benefit of the algorithm is that it works stochastically through experimentation by sampling options from the design space and attempting to learn optimal formations of the input parameters.

Similarly with all optimisation algorithms, the multi-objective genetic algorithm has hyper-parameters that must be set prior to commencing the search process. These hyper-parameters have a considerable effect on how the algorithm operates and therefore are an important part of generating good outcomes. The MOGA hyper-parameters which are set by the user in Generative Design for Revit 2021 prior to running a test include:

- The initial population or sampling method;
- The size of the initial population and successive populations; &
- The termination conditions of the process, such as run for a set amount of generations.

The cross-over rate and the mutation rate are two other hyper-parameters of MOGA, but these are controlled by Generative Design for Revit 2021 and not accessible to the user [33].

In this instance for One Molesworth Street, the researcher used generations of 48 designs each and ran the process for 20 generations creating 960 designs. The initial population of 48 designs was produced by randomly sampling from the design space. The entire process ran over 2 hours on a single Microsoft Surface Pro with a 1.10GHz Intel Core i5 processor and 8 GB RAM.

f) Data Analysis

The generative design model for One Molesworth Street produced a data set containing 960 options, including the input values for each option and its score along the three design metrics. One method at this phase might be to filter the results by the metric scores and intentionally select several high-performing options for further analysis. Though, depending on the intricacy of the design problem such a selection might be difficult for a variety of reasons.

Firstly, the different metrics could be directly competing with one another, meaning that in reality there is no single best option but instead a range of equally high-performing options alongside the trade-off between competing metrics. Second, as already mentioned, the hyper-parameters of the multi-objective genetic algorithm have a substantial effect on the operation of the search, and appropriate tuning of these parameters is reflective of the idiosyncrasies of each generative design model.

Lastly, a key benefit of a learning-based method such as MOGA is that it not only identifies high-performing design options but also conducts the search in a semi-intelligent and structured manner. By examining the search process itself, we can discover more about the true nature of the problem holistically. In an attempt to evaluate this process and obtain a deeper appreciation of the design space, the researcher utilised a variety of data analysis tools to assist the design team in exploring the dataset of options generated by the algorithm. These tools were both inherent to Generative Design for Revit 2021 and custom developed with the use of Microsoft PowerBI.

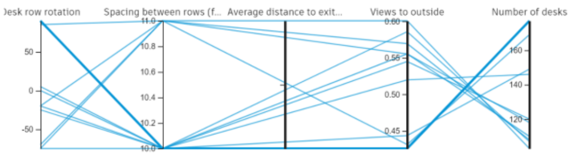

Fig. 9: Graph illustrating inheritance analysis of design options

Inheritance analysis – in conjunction with the input and output values for each option, the system also records a history of how these designs were produced. A plot of this data is illustrated by Fig. 9, with each vector representing a design option, and each column representing a performance metric. Examining such plots allows us to appreciate how the MOGA explored the design space, how dominant design roots were established, and helps identify possible blind spots in the design space overlooked by the algorithm.

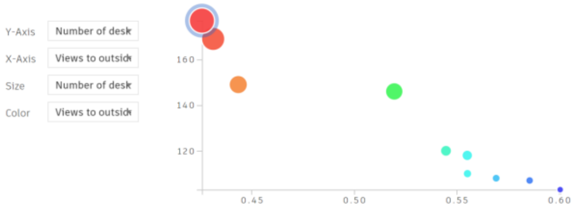

Fig. 10: Plot illustrating metric space analysis of design options

Metric space analysis – after investigating the distribution of options in the input space, we can examine the performance of options along the three design metrics. Often, difficulty can occur when trying to represent three or more metrics on a single plot. For this reason, the researcher chose to produce a pairwise plot of all the output metrics to highlight groupings of metrics that have an interesting relationship or evident trade-off. We can then explore the trade-offs in finer detail by plotting them against one another on a scatter plot, as shown in Fig. 10.

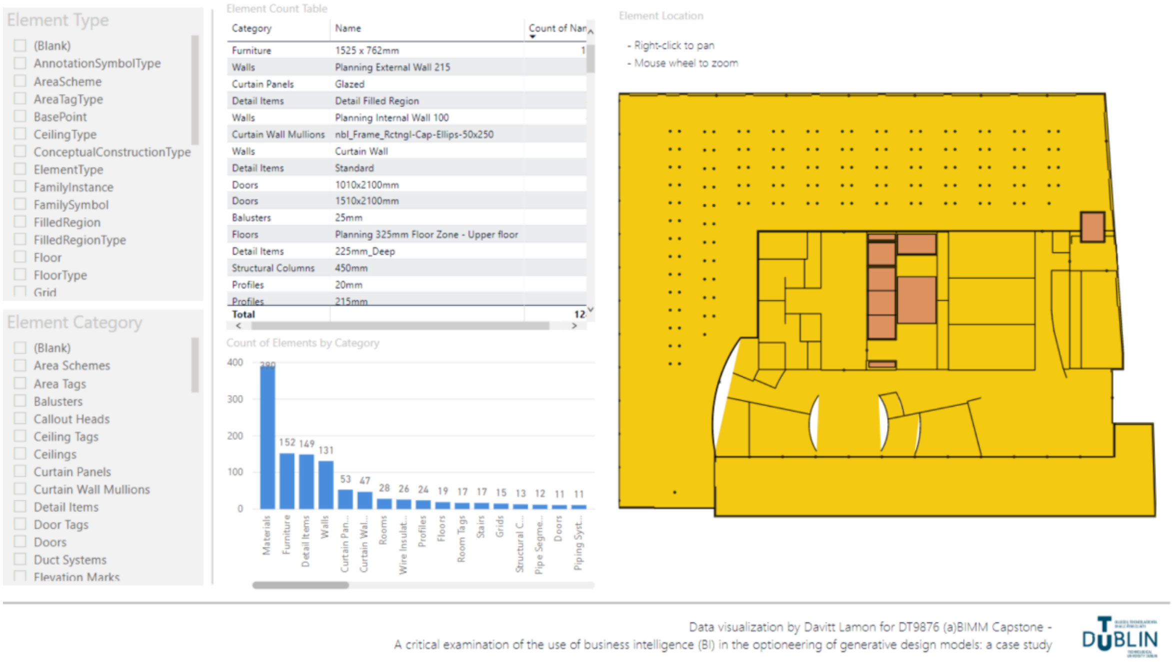

Fig. 11: Image illustrating the interactive Microsoft PowerBI dashboard developed for data visualisation

After examining the performance of the entire dataset of options, we can identify a subset for further manual analysis. As a starting point the algorithm will provide us with the Pareto designs, these are a set of statistically dominant options. To filter the dataset down further and help with optioneering we can search for designs that appear at various points along the trade-offs. This can assist us in understanding the impact of those trade-offs on the resulting design solution. Also, to locate design options where similar performance results were attained by various typologies, we can use the cluster data generated previously.

After a preferred design option is identified, Generative Design for Revit 2021 allows the user to create the associated Revit elements. After this process and the placement of family instances within the One Molesworth Street model, further data was combined and exported to a SQLite database for critical analysis and review by the project's design team with the use of Microsoft Power BI. For illustrative purposes, the design option performing highest with regards to occupancy metric was selected.

IV Evaluation

To evaluate the solution developed as a part of the experimental research, data was collected in the form of a qualitative focus group with the original design team that worked on the One Molesworth Street office fitout for Goshawk Aero. To obtain reliable feedback a total of 8 participants took part in the focus group. The participants comprised of the Project Director; the Project Manager; the Construction Manager; two Architects; two Architectural Technologists; and the Interior Designer, all of whom demonstrate a high-level of engagement throughout.

All participants of the research completed an informed consent form and were made aware that as a participant they had the right to refuse to answer any question and withdraw from the study at any time, without having to give a reason. Personal information collected about contributors was also anonymised, and none of their personal rights were affected as a result of participation in this study.

A focus group was selected as opposed to individual interviews as conversation between participants was intended to facilitate idea generation, potentially getting deeper into the subject matter than the researcher could have achieved one-on-one. Semi-structure questions to keep the focus group on topic were used but time was also allocated to see where the conversation lead. The researcher ensured that sufficient and appropriate questions are asked to draw results and conclusions.

A small number of the individuals who took part in the evaluation understood computational design, but no participant had prior knowledge of generative design. This was anticipated and a brief overview of the subject matter was provided at the start of the session. The focus group was structured as follows:

- Introduction to the project and research;
- An overview of generative design;
- An overview of business intelligence;
- Questions and discussions relating to One Molesworth Street;
- A demonstration of the developed solution for optioneering using Autodesk Dynamo, Generative Design for Revit 2021 and Microsoft PowerBI; &
- Questions and discussions relating to the developed solution.

The research participants were also surveyed post-focus group to capture more metric based and potentially missed questions. These survey questions were directly influenced by the topics discussed and arising from the focus group.

The first aim of the focus group was to gather information from the project team in relation to the office fitout of One Molesworth Street. A particular emphasis was placed on the design process used, software, and both the client's and architect's performance criteria. The second aim was to gauge the positive and negative reaction to the demonstrated workflow, and to explore if the participants potentially saw the benefit of incorporating this workflow into their current design process. In accordance with the primary research aim, the aim of the focus group was to critically examine the use of business intelligence in the optioneering of generative design models in the context of a real-world construction project.

To evaluate the demonstrated solution, each of the participants feedback was reviewed. With regards to the proposed workflow demonstrated at the focus group, when asked how effective the solution was in meeting the client's performance criteria on a scale of 1-10, 10 being most effective. The average response was 9.13.

When compared to the design process used on One Molesworth Street, all participants thought that the demonstrated workflow was more likely to satisfy the client's performance criteria. When compared to their existing design process, all participants also agreed that the proposed solution would result in less human error.

In contrast to the participants existing workflow, all participants thought that the proposed solution would result in a reduction in time spent and estimated a time saving in the region of 61-80%. Within the same time frame (approx. 2 hours), 7 out of 8 participants believed that the use of generative design would allow them to explore more design options than they could have using their current workflows.

Four benefits of the proposed workflow discussed at the focus group were: a reduction in time spent; a reduction in human error; the ability to produce a greater number of design options; and the ability to meet the client's brief more effectively. When the focus group participants were asked to rank these four benefits in descending order of value to them starting with the most valuable the results were:

1. A reduction in time spent;
2. The ability to meet the client's brief more effectively;
3. The ability to produce a greater number of design options; &
4. A reduction in human error.

With regards to the primary aim of the research, when asked if the participants thought that the use of business intelligence (BI), data visualization and dashboards assisted in the optioneering of the most appropriate generative design option they all thought it would. When asked how significantly the use of BI, data visualisation and dashboards assisted in the selection of the most appropriate generative design option on a scale of 1-10, 10 being very significantly, the average response was 9.13.

Based upon the participants first impressions of the proposed workflow, they were asked how likely they would be to adopt the workflow into their own design process. The likelihood to adopt was gauged on a scale of 1-10, 10 being very likely, and the average response was 9. One participant in a managerial and client-facing role was asked to elaborate on their reasons for adoption, and responded:

"If you give a client 2 or 3 options, they are always going to ask about option 4. But if you tell a client that you have studied 900 options and narrowed it down to 3, they can immediately see that it has been explored. Rather than we've given them an option and thought that we'd give them another option just in case they asked for it".

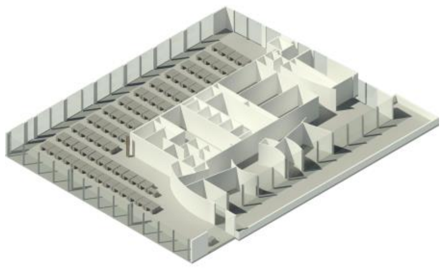

Fig. 12: Generated design option in Revit

Questions regarding the negative aspects of the proposed solution were also put forth to the focus group participants. However, at the time no participant could identify any associated drawbacks. Upon reflection, the researcher highlights one evident limitation of the generative design process which is that all of a given design system's performance criteria must be subjected to the search algorithm as a numeric value. Therefore, any performance metric we would like the algorithm to incorporate needs to be both computable and quantifiable in an efficient and consistent way for all results within the design space.

V Conclusion

This paper outlined the development of a generative design workflow for the architectural space planning of a 1,200 sq.m office floor located in Dublin, Ireland, and the application of business intelligence for the optioneering of generated models.

While the results of this research have been very promising, the workflow has several limitations. Currently, the time associated with developing the generative model can be quite substantial. Also, as each project brings with it a unique set of performance criteria and design metrics, the repeatability of developed solutions is limited.

Another limitation is that the generation of each design option is still comparatively slow, which restricts the amount of investigation we can do. Automatically analysing 960 designs substantially enhances the capacity of a human designer but is somewhat small considering it is sampled from a very high-dimensional design space. Distributing the calculation of designs within a single generation over multiple computers in a network would facilitate the evaluation of many more designs.

Lastly, the developed solution can be enhanced by incorporating other types of modelling, notably machine learning, for measuring elements of the design options that are challenging to compute through direct calculation. This is of particular interest to the researcher as it has the potential to allow the computer to build a knowledge of many design factors such as novelty or comfort that are vital to good design but have been conventionally challenging to relate to a computer.

The benefits of computational design experienced by the researcher while conducting this study align with those highlighted by McNally & Behan [37], such as the ability to evaluate many more design options in comparison to traditional workflows and the capability of developing tools to resolve unique problems. As generative design processes continue to develop into the future, it is anticipated that they will not only facilitate designers in the production of high-performing design options, but also help them appreciate their design challenges more through a cooperative human-machine design experience.

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