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Optimizing MEP design in early AEC projects through generative design

Edgar Pestana [a], Andrew Paice [b,*], Shaun West [b]

[a] Basler & Hofmann, Switzerland
[b] Lucerne University of Applied Sciences and Arts, Switzerland

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ABSTRACT

The digital transformation of the AEC industry through BIM has improved productivity during detailed design and construction planning phases. Early design choices influence a project's success but have yet to benefit from BIM-based approaches. This paper investigates the feasibility and acceptance of employing Generative Design (GD) to optimize early Mechanical, Electrical, and Plumbing (MEP) designs in residential real estate for space efficiency. Interviews indicate the main issue is acceptance due to the belief that a GD approach needs to be more robust. BIM is integrated with GD, utilizing the architectural layout (IFC) as input to generate design variants tailored to minimize technical space while ensuring installation feasibility. Robustness is assessed via Monte Carlo Simulation, revealing an estimated success rate of 99% (81% with 95% confidence). These results quantify the robustness of the approach, paving the way to broader acceptance of GD in the early phases of AEC projects.

1. Introduction

The AEC (Architectural Engineering and Construction) sector is one of the least digitalized industries and has a poor productivity index compared with other economic sectors [1,2]. The AEC industry's digital transformation through BIM (Building Information Modeling) has increased design and construction planning productivity and decreased information losses between project phases [3]. Design companies have implemented BIM from the conceptual design phase, but BIM requires considerably more effort than the conventional planning process when the concept is being defined [3]. The issue is how to apply the BIM methodology in the early phase of the project without significantly more significant effort.

Choosing the right design concept at an early phase of the project greatly impacts its success. A poorly defined concept can significantly increase costs if changes must be made in later phases. Further, even if the idea is ideal for the type of building and its future use, the equipment defined in the concept must fit in the space reserved. A typical example of this issue is the space reservation for technical installations in buildings for the residential real estate market, where space optimization is increasingly a key challenge [4]. Space reservation refers to the space that the architect must consider in the building, which will be occupied by technical installations and cannot be used for living or communal areas. Reserving insufficient technical space in the project's early stage can significantly negatively impact the project's profit. This impact increases the design costs of redefining the architectural layout or technical solution and can affect the building's value. So, it is crucial to analyze different possible concepts in the project's early phase to identify the optimal solution.

The space reservation includes the technical rooms and their horizontal and vertical distribution. A Mechanical, Electrical, and Plumbing (MEP) expert usually gives this estimation and explores and evaluates different solutions for the MEP system with the architect. The final design involves various alternative analyses, calculations, and model representations in BIM. This iterative process changes the building's architectural layout and the MEP system concept, and each iteration requires several weeks of effort. The lack of an automated process that can effectively evaluate spatial issues makes evaluating multiple feasible variants impractical.

In other industry sectors, such as architecture [5] or structural engineering [6], Generative Design (GD) technology is used to create and evaluate a wide range of initial concepts and tasks that could not be carried out in a reasonable time through conventional processes. Industry skepticism is revealed in expert opinions [7] and surveys [8,9], which show that half the interviewees think GD cannot be applied to their projects. The question is whether using a GD method in the initial phase of a building project is feasible and whether it will be robust enough to bring value to the market and improve the traditional method.

To create a GD-based tool that the industry will accept, it must fulfill

* Corresponding author.
E-mail address: andrew.paice@hslu.ch (A. Paice).

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three characteristics: the basis is a class of buildings that can be modeled and for which quantitative evaluations of the solutions may be made, enabling algorithmic comparison. Then, a GD algorithm must find feasible solutions and be robust concerning model variations and calculations. Finally, the algorithm must find the optimal (or near-optimal) solution in a reasonable time.

The motivation for this paper was to present a proof of concept of a BIM-GD method applied to MEP projects for residential buildings in Switzerland. The study was developed by Lucerne University of Applied Sciences and Arts' iHomeLab Research Center and Basler & Hofmann (B&H) in a joint innovation project. Basler Hofmann is a Swiss consultancy, planning, and engineering company. B&H implements BIM early in all projects and is facing an increase in the necessary engineering resources for the above reasons. This increase is more pronounced in MEP Residential Projects, so this study focuses on innovations in this field.

The paper is organized as follows. In Section 2, we present the state of the art regarding Generative Design (GD) algorithms using BIM and introduce methods to prove the robustness of such algorithms. We use Principal Component Analysis (PCA) to visualize solution groups to evaluate the solutions generated. Section 3 describes the paper's approach, based on the V-Model of Systems Engineering [10,11], a general development methodology applicable to complex projects. We then present the results regarding the robustness and implementation of the algorithm. The final sections give a critical discussion and conclusions, including directions for further work.

2. State-of-the-art

This section presents a state-of-the-art review of the Generative Design and BIM technologies relevant to the study's aim. It also introduces the concepts of robustness in the literature related to Genetic Algorithms necessary for validating the results.

2.1. Generative design and BIM

Generative Design (GD) is a rule-driven design process based on an algorithm that uses parametric modeling to automatically explore, iterate, and optimize design possibilities based on predefined high-level constraints and goals. The parametric modeling defines the design space, while the algorithm determines how the parameters are modified to search for the optimal design. In 2010, Krish [12] presented a process to combine CAD systems and Generative Design, which uses the overall scheme of a generative system developed by Bohnack et al. [13]. In [12], the designer is central in continuously modifying the generative scheme to find a viable design solution. Abrishami et al. [14] developed a new BIM-GD framework based on [12]. The framework proposes that project designers define the coding information (design constraints and context) and reflect the client(s)' needs. The engineering team and the client should evaluate the alternative designs created by the generative system.

The methods of GD in this context are based on using a Genetic Algorithm (GA) to perform the parameter search. A GA is an adaptive heuristic approach to optimization first proposed by John Holland in his book "Adaptation in Natural and Artificial Systems" (1975) [15]. The Genetic Algorithm is an adaptive heuristic approach to solving optimization problems. It belongs to the class of Evolutionary Algorithms (EA), see for example [16]. The overall approach is based on a parameterization of the solution space; candidates are evaluated based on a fitness function, and then the best are recombined in the following generation. The population size is preserved in each generation; the new generation is created by recombination of the parameterized potential solutions; in some cases, this is modified with random changes. This process continues until a stopping criterion is reached. This may be having reached a set number of generations, or the fitness function has reached a prescribed level. The best solution according to the fitness function is chosen as the solution to the optimization problem.

GA can solve a Single or Multiple Objective Problem (SOP or MOP). In an SOP, an individual's fitness is evaluated using only one objective to be minimized or maximized. For an MOP, the quality of a solution is defined by its performance against several, possibly conflicting, objectives and represents a range of different trade-offs between these objectives. Selection is made using the concept of dominance. A solution is said to dominate another if its score is at least as high for all objectives and is strictly superior for at least one. A solution is called non-dominated or optimal if it is not dominated by any other. The set of all non-dominated solutions is called the Pareto set or the Pareto Front. The Pareto Front solutions are the ones that will be used to generate the next generation of offspring [17].

Building Information Modeling (BIM) is a widespread methodological approach well-documented in the AEC industry; for example, for an overview, see for example [3]. Generative Design using GA has been integrated into the Autodesk Revit "Generative Design" tool, which runs in Dynamo and uses the GA NGSA-II [31]. Despite this integration, the widespread application of GD in BIM-based projects is still in its infancy and, in particular, has not been applied to the early phases of AEC projects.

2.2. Generative design algorithm robustness and Monte Carlo simulation

One of the key objections to applying GD is that it is not perceived to be robust [8,9]. Robustness may be proved by showing that the GA can solve all possible MEP design problems proposed by an architect for a building's technical spaces. Since the number of potential design problems is infinite, we choose Monte Carlo Simulation (MCS) to estimate the probability that the algorithm will fail. MCS is a well-established approach to estimating probabilities in such complex situations. MCS has been used to evaluate the risk of failure in many different domains and applications, such as in the design of tunnels [17], open-pit mines [18], structural reliability analysis [19–21], or concrete compressive strength prediction [22].

MCS is a numerical method for solving mathematical problems by simulating random variables. Based on the law of large numbers, a failure probability can be estimated based on a random generation of input variables [23]. Each combination of inputs will generate (or simulate) an outcome [24]. To evaluate the probability of failure using the MCS, the outcome is assessed according to rejection or approval criteria. Section 3.4 describes how MCS was applied to evaluate the robustness of a parametric design script developed in this study.

2.3. Evaluation of genetic algorithm performance robustness

The preceding discussion only addresses whether a solution can be found. It is still necessary to ensure the algorithm's robustness. The algorithm should return feasible solutions with a minimum fitness, and this level must be achieved within a specified amount of time. This ensures that the algorithm will work within the application context of MEP planning in the early phase of a residential building project. This corresponds to a Boolean robustness criterium as defined in [25].

According to [16], the variance of an algorithm's performance can be considered across three dimensions, representing three different types of robustness. The GA robustness across problem instances requires the GA to find an acceptable solution when used across all the problem possibilities it intends to solve. When the performance of a GA achieves a good level across the entire range of problems, the GA is widely *applicable*. If the GA performance is lower on some problems, the GA is called *fallible*.

Another popular interpretation of algorithm robustness is related to performance variations caused by different parameter values of the GA and considers the GA robustness across parameter values [17]. In this case, the relevant parameters p of the algorithm are the population size, number of generations, crossover probability, and mutation probability.

When p influences the performance, the GA is called *tunable*; otherwise, it is called *tolerant*. The extra computational effort is needed to apply a larger initial population size in a GA [16]. A typical progress curve of an evolutionary process makes this unnecessary. Usually, a few generations are sufficient to reach the same level, making the extra effort questionable.

Another point is that it is possible to divide the run of a GA into two equally long sections. The progress in fitness increase in the first half of the run is significantly more significant than in the second half. This suggests that the effort spent after a specific time (number of generations) will unlikely improve solution quality. Nevertheless, these two points should be tested and verified.

GA robustness based on the initial seed number may also be used [16], as well as several independent repetitions of a run with the same setup, but different random variable seeds are needed to verify the GA's robustness to the seed value. The GA instance is called stable if the difference between all the best results is insignificant. Otherwise, it is called *unstable*.

To ensure the algorithm is robustly applicable in a real application context, we must check that the performance is appropriate, tolerant, and stable.

2.4. Visualization of results via principal components analysis

Given the many parameters used to describe the solutions, many solutions may perform similarly in the fitness function. Therefore, it is essential to determine whether the algorithm generates solutions over a broad section of the space, as there may be better solutions in other domains. Studies [16,17] suggest analyzing variance (ANOVA) on the different Pareto front solutions to determine if any observed differences are due to random effects. Other studies [26,27] used a Principal Components Analysis (PCA) to visually verify the clusters found in the Pareto solutions.

Principal Components Analysis is an approach to transforming data where each successive axis displays a decreasing variance. PCA produces linear combinations of the original variables to generate the axes, also known as principal components or PCs. In this study, we followed the procedures described in [26,27] to perform the PCA analysis. By creating scatter plots in 3D with just the first few PCs, it is possible to visualize the distribution of the generated solution and estimate the solutions' robustness in the sense that different parts of the parameter space are represented in the solutions.

2.5. Research gap

The research gap identified is first to determine what has prevented the widespread introduction of GD in BIM projects, particularly in the early phases of AEC Projects. Due to the various successful applications of GD in other project phases and the integration of GD technology in BIM tools, acceptance is assumed to be the main problem. Therefore, this paper first concentrates on determining the reasons for a lack of acceptance and then demonstrates how GD can be implemented to address these issues with a prototype.

3. Methodology

The V-Model of Systems Engineering [10] was considered an appropriate approach for developing and testing GD in AEC early-stage projects. It emphasizes a sequential approach, where each development phase is systematically followed by a corresponding testing phase, ensuring a rigorous and structured process. It focuses on validation and verification, ideal for projects requiring clear specifications and thorough testing. The V-Model of Systems Engineering emphasizes clear problem definition, direct stakeholder involvement, and rigorous testing to validate the robustness of solutions. This approach, supporting iterative design processes, ensures that solutions meet stakeholder requirements before presentation, aligning with Systems Engineering's emphasis on technical development and stakeholder engagement. Based on the aim of the research, to test a new approach for developing and testing GD in AEC early-stage projects it was anticipated that the stakeholders would provide precise requirements. In this project, the approach was:

i. Identification of Stakeholder requirements
ii. Problem formulation
iii. Technical Development
iv. Proof of Robustness
v. Presentation to Stakeholders

The tasks performed in each project phase are briefly described in the following sub-sections.

3.1. Identification of stakeholder requirements

The relevant stakeholders are the MEP experts, and we identified five (5) experts with the appropriate experience and roles within the Swiss firm Basler & Hofmann as Interviewees. The interviewees were engineers active in all phases of AEC projects, but in particular, they were personnel involved in the project's early phases. They had the task of making initial estimates of the space required to integrate the MEP systems in residential buildings. The interviewees have over five years of practical experience in such projects and are familiar with BIM and using tools such as Revit in their daily work. Their work profile included identifying the size of technical rooms, shafts, and the horizontal distribution height in the project's early phase, which was a major task for them. From the architectural point of view, their goal was to minimize the technical space to ensure more usable space in the buildings. Ensuring that the predefined space is sufficient and to ensure the installation's feasibility.

The interviews were structured based on the following questions to understand their requirements:

i. What are the central space-related values to be optimized?
ii. Which MEP disciplines require the most space?
iii. What are the architectural layout variables to be considered?

3.2. Problem formulation

According to [28], 84% of the Swiss population lives in buildings with pure residential usage, with 53% living in apartments and 27% in single houses. Accordingly, it was decided to focus only on apartment buildings, a large proportion of buildings in Switzerland. Based on the aim of the study and the stakeholder requirements identified, we can summarize the problem as follows: "How to automatically define the technical space needed for a residential building in Switzerland and prove the robustness of the algorithm and its performance."

Stakeholder requirements were reformulated as optimization criteria, and the overall problem became a multi-objective optimization problem (MOP). We identified the different types of residential buildings in Switzerland. A multi-case analysis was made to determine the possible variants of residential buildings and the variables and constraints required to describe the initial phase of an MEP design. The variables of MEP installations were explored according to the Standard VDI 2050 [29]. This German standard defines technical equipment room space and service shaft requirements. From this standard, it is possible to verify the different possibilities for the positions of a technical room in a building.

Further, it also indicates the architectural variables that influence the building's technical space requirements. We could identify at least one B&H residential MEP project for each variant type, except for buildings in the shape of stars, round, and with an atrium. The projects classified by variant are described in Fig. 1. Finally, the VDI 2050 also indicates

Project Number	Building Type	Building Layout					Technical Room						Number of Shafts			Shaft Arrangement			
		Square/Rectangular	Round	Star-Shape	Atrium	Free-form	A	B	C	D	E	F	Small	Medium	Large	Central	Arbitatry	In a Row	Radial or Perimeter
06652	i	2	0	0	0	1	3	0	0	0	0	0	3	0	0	0	3	0	0
06763	i	1	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0
06860	i	1	0	0	0	0	1	1	0	0	0	0	0	1	0	0	1	0	0
05703	ii	1	0	0	0	4	0	0	0	0	5	0	5	0	0	0	5	1	0
06750	ii	1	0	0	0	2	0	0	0	2	0	0	2	0	0	2	0	0	0
	TOTAL	6	0	0	0	7	4	2	0	2	5	0	10	1	1	2	9	2	0

Fig. 1. BIM residential projects - multi-case analysis.
i – Multifamily House; **ii** - Residential building with secondary use; **A** - Heating, Ventilation, and Plumbing in the same UG Room; **B** - Heating and Plumbing in the same room and Ventilation in different UG Room; **C** - Heating and Ventilation in the same room and Plumbing in different UG Room; **D** - Heating, Ventilation, and Plumbing in different Rooms in UG; **E** - Heating and Plumbing in the same UG Room; Ventilation in the Roof; **F** – Plumbing Room UG; Ventilation and Heating Rooms in the Roof.

the procedure to calculate the technical equipment dimensions according to different building needs, such as required fresh airflow, domestic hot water storage, and heating load. The building needs are obtained using the standard SIA 2024 [30], which indicates typical values for the power and energy requirements in lighting, ventilation, cooling, humidification, heating, and plumbing. These typical values can be used early in the design stage.

3.3. Technical development

After identifying the variables and constraints of an early project MEP system, a prototype was created in the Autodesk Revit "Generative Design" tool, which runs in Dynamo and uses the GA NGSA-II [31]. This evolutionary multi-objective optimization algorithm is applied to various search and optimization problems. NSGA-II uses a fast non-dominated sorting procedure, an elitist-preserving approach, and a parameterless niching operator [32]. Those features reduce its level of complexity and, consequently, the computation time compared to other GAs.

Autodesk Revit was chosen because it is widely used for BIM in the Swiss planning industry. The script was constructed using Dynamo's visual programming language in the calculations involving only one element per Generative Design solution. When the calculations involve a group of elements (Spaces, Apartments, Shafts, Technical Rooms), the equations are written in Python.

3.4. Proof of robustness

The prototype's robustness was tested using a Monte Carlo Simulation, a performance evaluation, and a PCA analysis, as outlined in the state-of-the-art section of this paper.

First, the robustness of the parametric design was tested. The intention was to calculate the value for the probability of failure of the parametric design, meaning how often the algorithm cannot generate a solution for any input given. To evaluate this, different spaces in the models were defined as possible technical rooms, covering all the possible variants previewed in the VDI 2050 for the position of each technical room in a building. Two models were adapted to report on the building layouts with shafts on the building perimeter. Next, a Monte Carlo Simulation was performed using the Random feature of the Revit "Generative Design" add-in.

In the second phase, the robustness of the GA was tested regarding three different types of robustness: problem instances, parameter values, and random seeds (PCA analyses). It was defined as a success if the algorithm performed a 4.5 value in the total ranking of the fitness functions and a computational time lower than 12 h. The algorithm was tuned regarding its initial population size and the number of generations to achieve the desired computation time.

Finally, the models obtained by parametric designs and those planned by the B&H design teams were visually compared.

All test runs concluded calculations successfully in less than 12 h of computation time running on an Intel® Xeon® E-2286 M 2.4GHz, 32GB RAM.

4. Results

This section presents the paper's primary results based on the following structure. First, we frame the problem as a multi-case analysis. The best solution for a residential MEP early project concept involves a trade-off between minimizing the technical space(s) and ensuring that the defined space is enough to ensure the coordination, installation, and maintenance of the different MEP equipment. We then move to the concrete problem formulation. Each factor was normalized to provide a fitness score between 1 (poor) and 5 (excellent). The prototype was developed as described in Section 3.3 and included different system variants according to SIA, with all the features and fitness functions to optimize the objectives described above. Subsequently, we estimate the robustness of the algorithm. The results shown in Table 2 allow us to state with 95% confidence that the number of failures will not differ by more than 19.6% from the actual mean value. This means that the failure probability of the parametric design should be 19.3% at most. So, the algorithm should work in at least 80.7% of the BIM models within the specified domain. Finally, we tune the algorithm parameters to ensure adequate performance by defining the initial population size and the number of generations needed to perform the tests.

4.1. Stakeholder requirements

Based on the stakeholder interviews, it was possible to identify the size of technical rooms, shafts, and the horizontal distribution height as this phase's main space-related goals. From the architectural point of view, it is intended to minimize the technical space to ensure more usable space in the buildings. On the other hand, the engineers must ensure the predefined space is enough to provide the installation's feasibility. Experts identified 215 ventilation, heating, and plumbing as the disciplines that have the most significant impact on space in a residential project. The stakeholders confirmed that the "drawing" time for each solution should be faster than traditional methods and be at least as accurate. Therefore, it was decided to apply only those disciplines in the BIM-GD methodology and to validate the speed and accuracy/robustness of the solutions developed.

4.2. Multi-case analysis

Fig. 1 presents the quantification of the BIM residential projects designed in B&H according to the variables defined in the VDI 2050. As shown below, the most common and repetitively identified shapes in residential projects with an available BIM model were the square/rectangular and free-form shapes. Most of the positions of the technical rooms described in VDI 2050 were found in B&H projects, except variants C and F. VDI 2050 classifies the number of shafts as "small" when it is less than 3 per 1000m^2, "medium" if the value is between 4 and 5 per 1000m^2 and "large" when it is greater than 6 per 1000m^2. In the analyzed projects, it was identified in at least one case for each group, and the "small" type was the most common. Finally, at least one case for all the VDI 2050 variants was identified regarding the shaft arrangement, except buildings with the shaft arrangement in their perimeter.

4.3. Prototype implementation requirements

Following the multi-case analysis results, it was decided to develop a solution based on a residential building with a combination of square/rectangle and free-form architectural design, offering a harmonious blend of structured and organic elements. It incorporates advanced and efficient ventilation, heating, and plumbing systems, ensuring optimal living conditions for the residents and sustainability in energy usage. The positioning of technical rooms within the building follows the guidelines of VDI 2050, with all rooms defined as per standard configurations, except for variants where the heating room is situated on the building's roof. This deviation allows for exploring alternative arrangements while maintaining functionality and convenience for all occupants.

The study identified quantitative fitness measures to apply the GA. These measures were derived from the requirements outlined in interviews with B&H engineers, resulting in the definition of five (5) fitness indicators. Firstly, the "Free height" measure reflects the percentage of the volume occupied by technical installations in spaces under 2.25 m height, with the GA aiming to minimize this indicator. Secondly, the "Coordination of the installation" metric evaluates the total collision volume in the distribution network, indicating how well the different distribution networks are coordinated; this value is to be minimized during the evolution phase. Thirdly, the "Technical room feasibility" measure calculates the adequacy of space available for predicted technical equipment, incorporating maintenance and installation areas, and this function should be maximized. Fourthly, the "Loss of apartment area" gauge represents the percentage of the apartment's floor surface occupied by the vertical distribution, and the GA's objective is to minimize this value. Finally, the "Loss of common floor area to technical installations" metric calculates the percentage of the building's common area floor surface utilized by the technical rooms, with the optimized outcome aiming to be minimized. Each factor was normalized to provide a fitness score between 1 (poor) and 5 (excellent). The prototype was developed as described in Section 3.3 and included different system variants according to SIA, all the features, and the fitness functions to optimize the objectives described above.

Fig. 2 presents the Pareto front results for three different system types obtained by the prototype in a residential building pilot test. This shows that the algorithm successfully identifies distinct solutions with similar fitness but are qualitatively different.

4.4. Robustness test

This section presents the robustness tests done on the developed Generative Design algorithm. The methodology selected followed the theory presented in section 2.2.

4.4.1. Monte Carlo simulation (MCS)

An MCS was performed using the BIM models in Fig. 1. To include all possibilities described in the VDI 2050 in the test, two new BIM models were created, with shafts located in the perimeter of the building. The Revit GD random engine was used to generate the random values for the MCS. This creates a design space of 18 variables, which is used to parameterize the design space used in the GA.

When the Parametric Design was able to create a solution without errors for the input variables, that solution was given a performance value of 1. If the input values return an error, a performance value is zero. The test was conducted with 1000 random samples for each BIM model. The results per model are presented in Table 1.

The upper and lower boundaries for the failure probability of the parametric design were calculated using the MCS theory (Section 2.2). The results shown in Table 2 allow us to state with 95% confidence that the number of failures will not differ by more than 19.6% from the actual mean value. This means that the failure probability of the parametric design should be at most 19.3%. So, the algorithm should work in at least 80.7% of the BIM models in this domain.

GA Tuning: To verify the success of the GA, it was first necessary to tune it by defining the initial population size and the number of generations needed to perform the tests. We present the results of different GA *test runs* to determine the best parameters for the GA within the GD problem.

Initial Population Size: To evaluate the impact of the initial population size on the Generative Design results, all the BIM models (problems – Fig. 1) were tested with population sizes from 8 to 100 individuals. Each test run was performed through 10 generations. For each Pareto front, the average value and the variance of the normalized fitness function were calculated. The solutions with a lower average and variance have the best performance. The results are presented in Figs. 3 and 4.

From the results presented in the figures above, it is possible to verify that the normalized fitness function achieves a better solution (lower value – minimize problem) as the population increases. On the other hand, the variance of the solutions increases its average value with the increase of the population size.

Computational time was also considered a factor in evaluating the GA's performance. Fig. 5 presents the computational time expected for the 180th generation based on the registered times in each test run. As expected, the computational time increases proportionally to the population size.

Considering these results, it was decided to use a population size of 20 to find a good trade-off between the GA fitness function's mean value, variance, and computational time.

Number of Generations: After setting the initial population size to 20, five test runs with five different seed values were performed for each BIM model, using 180 generations each.

Further, the performance of the Pareto results of each generation was measured by the normalized mean of the fitness function. The results are presented in Fig. 6. This shows that 80% of the performance was achieved before the 130th generation in all test runs. This implies that the effort spent after the 130th generation will unlikely improve the solution quality. It was also noticed that only 36% of the test runs needed more than 100 generations to achieve 90% performance and that in only 31% of the test runs, this value was reached before the 50th generation. Also,

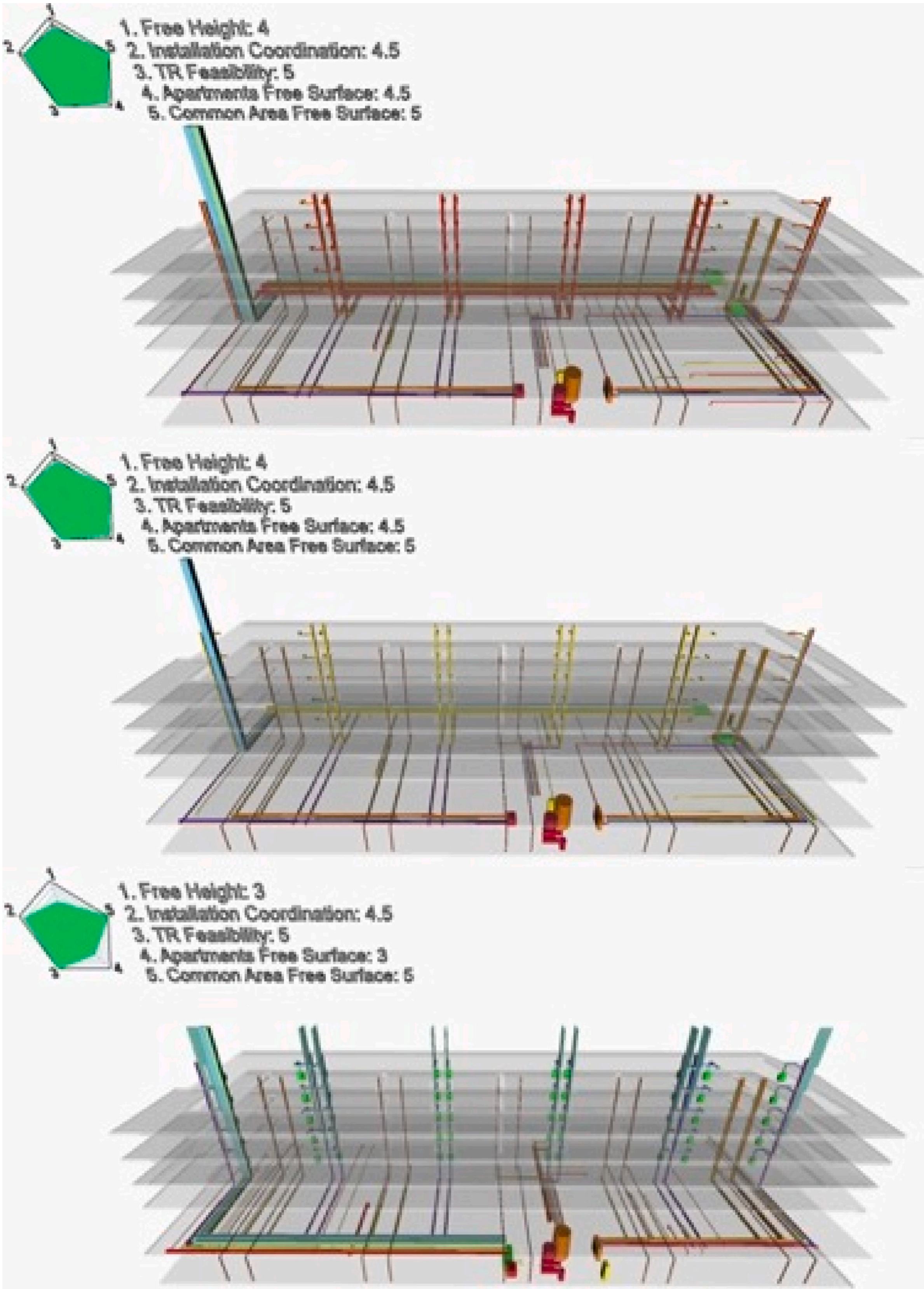

Fig. 2. Pareto front results of a pilot test.

Table 1
Monte Carlo simulation results.

Building	Random Samples	Failures
A	1000	6
B	1000	15
C	1000	12
D	1000	3
E	1000	15
F	1000	6
G	1000	13
H	1000	6
I	1000	4

Table 2
Monte Carlo simulation probability of failure results.

Variable Description	Variable Notation	Value
No. of samples	n	9000
No. of failures	nf	80
Probability of failure	Pf	0.89%
Mean Value of the Samples	$\bar{x}$	0.991
Variance	s2	0.009
Standard Deviation	s	0.094
Cofidence Coefficient for a 95% Confidence Level	Zc	1.96
MCS Percentage Error of the mean	E	19.6
Mean Value of the Samples Lower Bound	$\bar{x}$ L	0.807
Mean Value of the Samples Upper Bound	$\bar{x}$ U	1.175
No. of failures Lower Bound	Nf L	1736
No. of failures Upper Bound	Nf U	0
Probability of failure Lower Bound	Pf L	0%
Probability of failure Upper Bound	Pf U	19.3%

note that the influence of the seed number on the number of generations needed to achieve a high performance was verified.

4.4.2. PCA analysis

As described in Section 2.2 (state-of-the-art), the seed can influence the performance of the GA. So, to verify the algorithm's robustness relative to the seed, a comparison of the fitness indicators was made between the best results generated at the end of 180 generations for each of the five seed values used for each problem. It was verified that all solutions delivered the same fitness value. When different seeds were used, most other indicators showed different values for the same problem. Further, a visual analysis of the resulting building systems confirms different best solutions for each seed value (Fig. 2).

A PCA analysis was performed for each set of five test runs to explore the differences between all the results presented in the Pareto front of the different test runs. Fig. 7 shows different clusters of results for each seed. This difference is more pronounced in models with more feasible possibilities for the technical rooms. However, all solutions have approximately the same fitness.

4.5. Parametric design vs. traditional detailed design

Finally, to validate stakeholder acceptance, the solutions generated by the GA were compared with those developed by B&H design engineers. The MEP discipline visually made the comparison. An example of the comparison is presented in Fig. 8. The same system and technical room(s) selected in the detail design phase were defined as variables to generate the parametric design.

As seen in Fig. 8, the results obtained are similar to the ones presented in the detailed design phase. The outcomes were validated by B&H experts, who agreed that the results have the correct level of detail for this phase of the project applied to space reservation.

This validates two significant stakeholder requirements. Firstly, the algorithm develops acceptable solutions across the entire domain of problems, and secondly, the solutions generated by the algorithm are close to the optimally human-designed solutions. The time spent preparing the BIM model to execute the Generative Design was also compared with the times proposed for the early project phase according to SIA 31. The proposed method saves at least 45% of the time required to generate solutions in this project phase.

5. Discussion

This work aimed to evaluate the possibility of using Generative Design in the initial phase of a residential building project in Switzerland to define the space needed for its technical installations. The results demonstrate that a BIM-GD-based algorithm produces a result in 99.1% of 9000 calculated examples and that we can state that with 95% certainty, the chance of the algorithm failing is less than 19.3%. The implication is that there is a significant potential for applying a BIM-GD method in the early phase of a project. This would increase the decision-making capacity of the project participants more efficiently and improve the industry's productivity levels in this phase of the project. The data confirm that the speed and certainty is better than is the case with the traditional approaches.

The results obtained from the GA robustness tests reveal that the GA can be classified as *widely applicable* across multiple problems and *tolerable* regarding the parameter values. These results can be considered

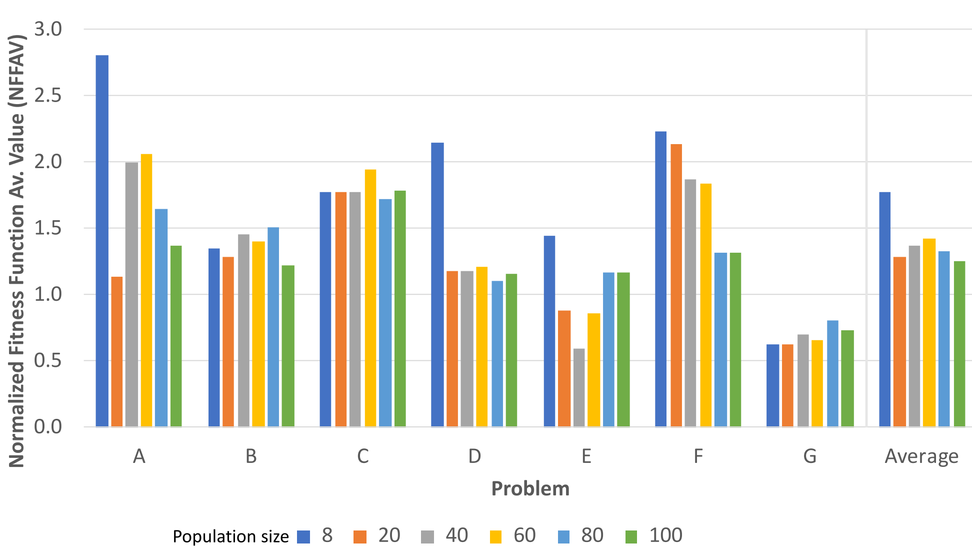

Fig. 3. GA tuning – normalized fitness function av. value (NFFAV): problem vs population size.

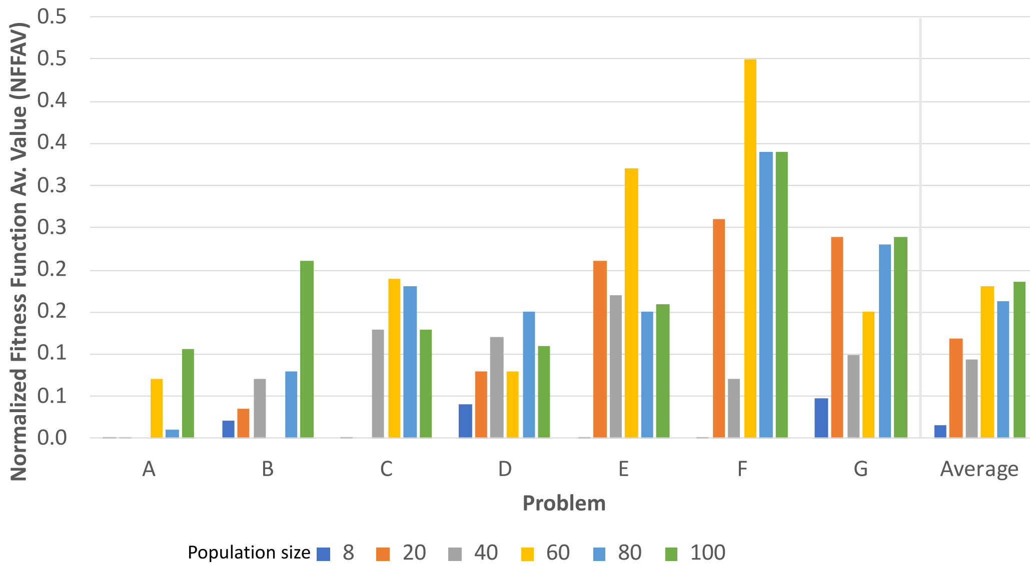

Fig. 4. GA tuning – normalized fitness function variance (NFFV): problem vs population size.

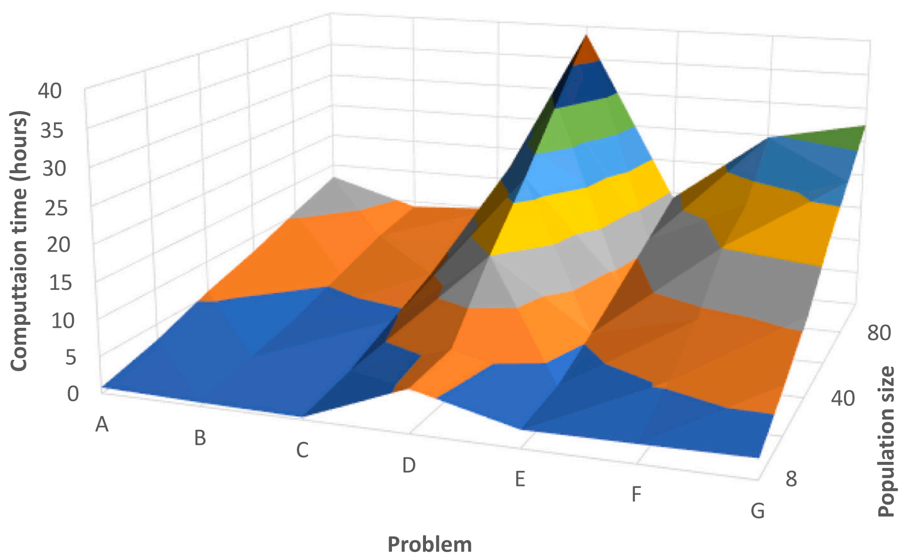

Fig. 5. Monte Carlo simulation time vs population size.

good enough for a 1st GD prototype compared to what the industry expected. Those expectations collected at the project's beginning regarding the robustness levels were much lower. We can confirm this since the method was tested on apartment buildings, which represent the main type of buildings where the Swiss population lives, and we obtained a success rate of at least 81%. This is much higher than expected by stakeholders [8,9] who believe it is not possible to use GD technology in their projects. It will be necessary to introduce the technology into the market so that it can be tested and validated by early adopters, and only then can its performance evolve to more satisfactory levels. The market introduction will be discussed in another paper.

The analysis of the test run results via PCA analysis indicates that different seed values influence the GA's performance, indicating that the solutions found correspond to local optima and not the global optimum. Nevertheless, they are still valid solutions with similar fitness and are obtained more effectively than traditional means. In the real world, if a solution for the same project is given to two different design teams, the probability that they present the same solution is also considered low.

The comparison between the concepts obtained by parametric design and B&H's detailed design projects (Section 4.4) reveals an acceptable level of similarity between the results. If the approach presented in this paper is applied to a real-time project and confirms the results of the pilot tests, it may be considered a future way to work in the early phase of engineering projects. As shown in section 4.3, the calculation time taken in all studies was less than 12 h to complete the 180th generation, increasing acceptance by engineers and project managers alike.

With the performance results shown in the graph in Fig. 6, it can be stated that the improvement in the Pareto front results is slight in most studies from generation 100 onwards. This means that the calculation time can be halved, with most studies achieving Pareto front results in less than 5.5 h. This approach would improve the decision-making capability of the project stakeholders, as an architectural concept can be sent in the morning to the engineering team and discussed in the afternoon, with the best trade-offs calculated by the algorithm and validated by the engineers. In conjunction with the 3d visualization capability obtained with BIM models, results that now take weeks to produce could be analyzed in days, decreasing the production gap of this phase of the AEC project.

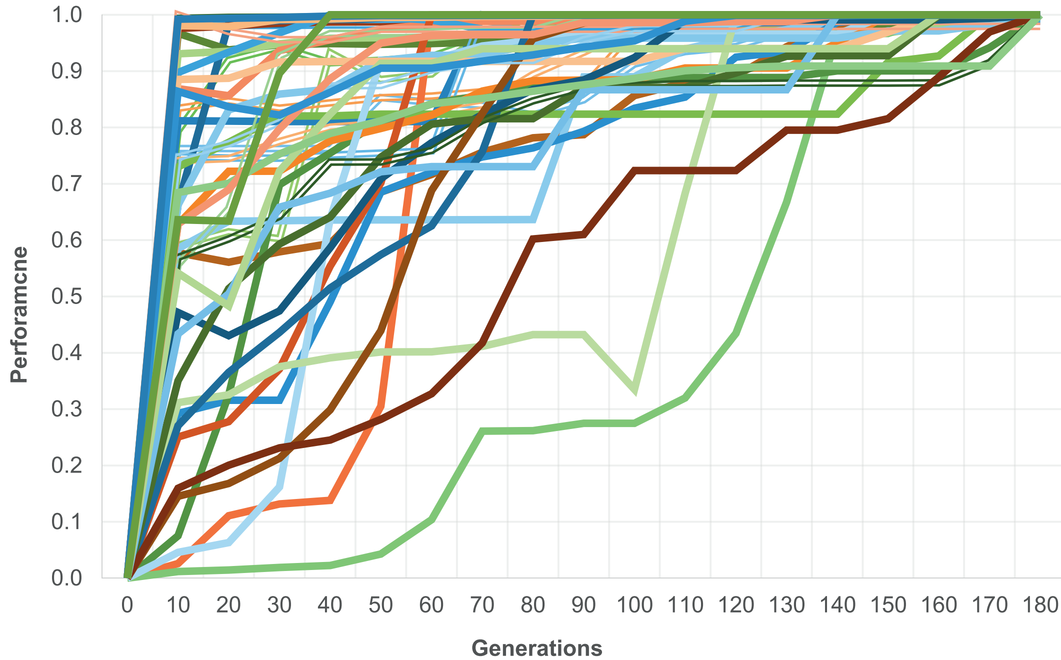

Fig. 6. Monte Carlo simulation probability of failure results. Each line represents the normalized mean fitness for a different seed and building type.

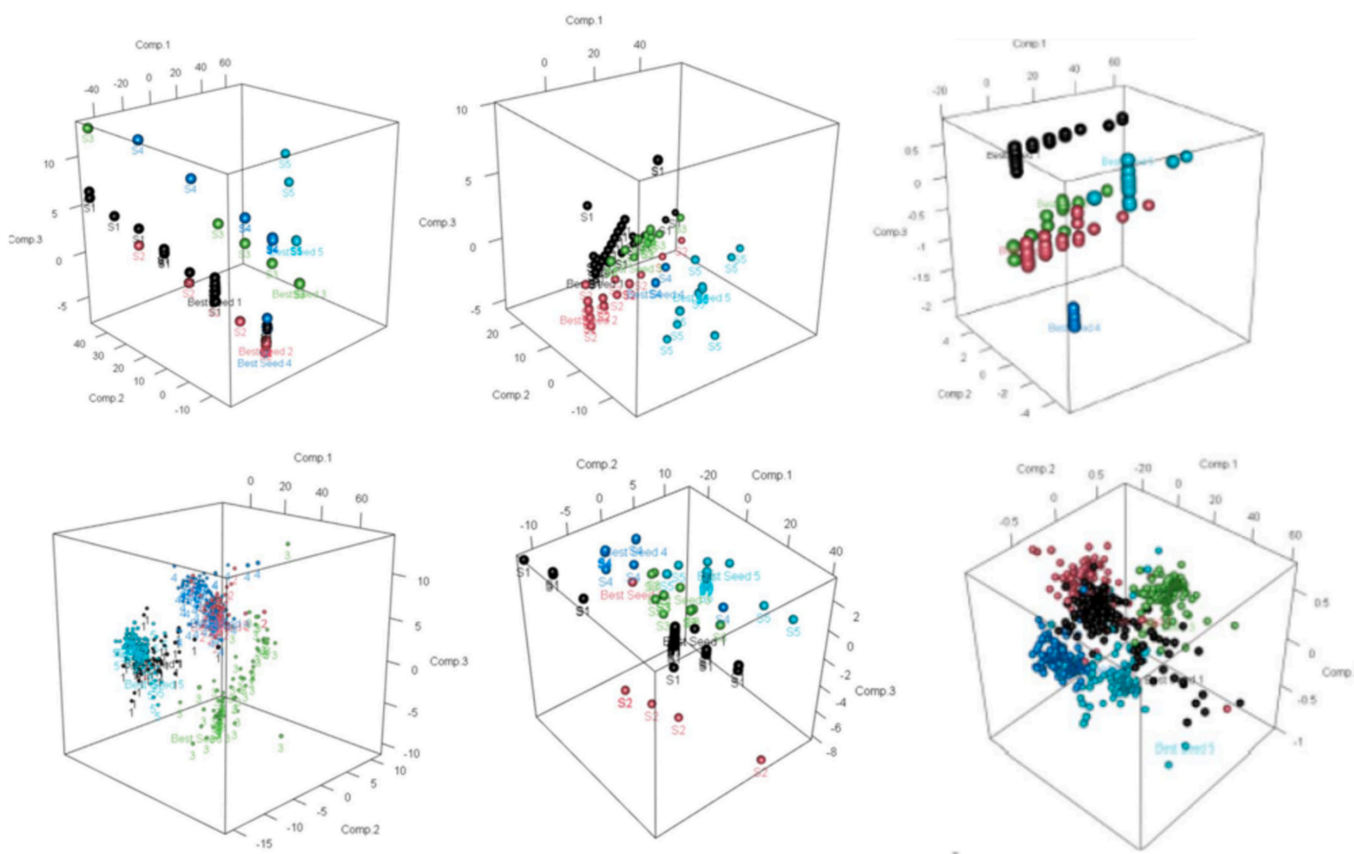

Fig. 7. PCA results for different initial seed values.

5.1. *Theoretical contribution*

This paper addresses the problem of optimizing the design of technical spaces in residential buildings at an early project stage. The key issues include ensuring that these spaces are sufficient for installing and maintaining various mechanical, electrical, and plumbing (MEP) equipment while minimizing the loss of usable area in the apartments and common areas of the building. The problem is reformulated using Building Information Modeling (BIM) and a Generative Design approach as a multi-objective optimization problem and was solved using a

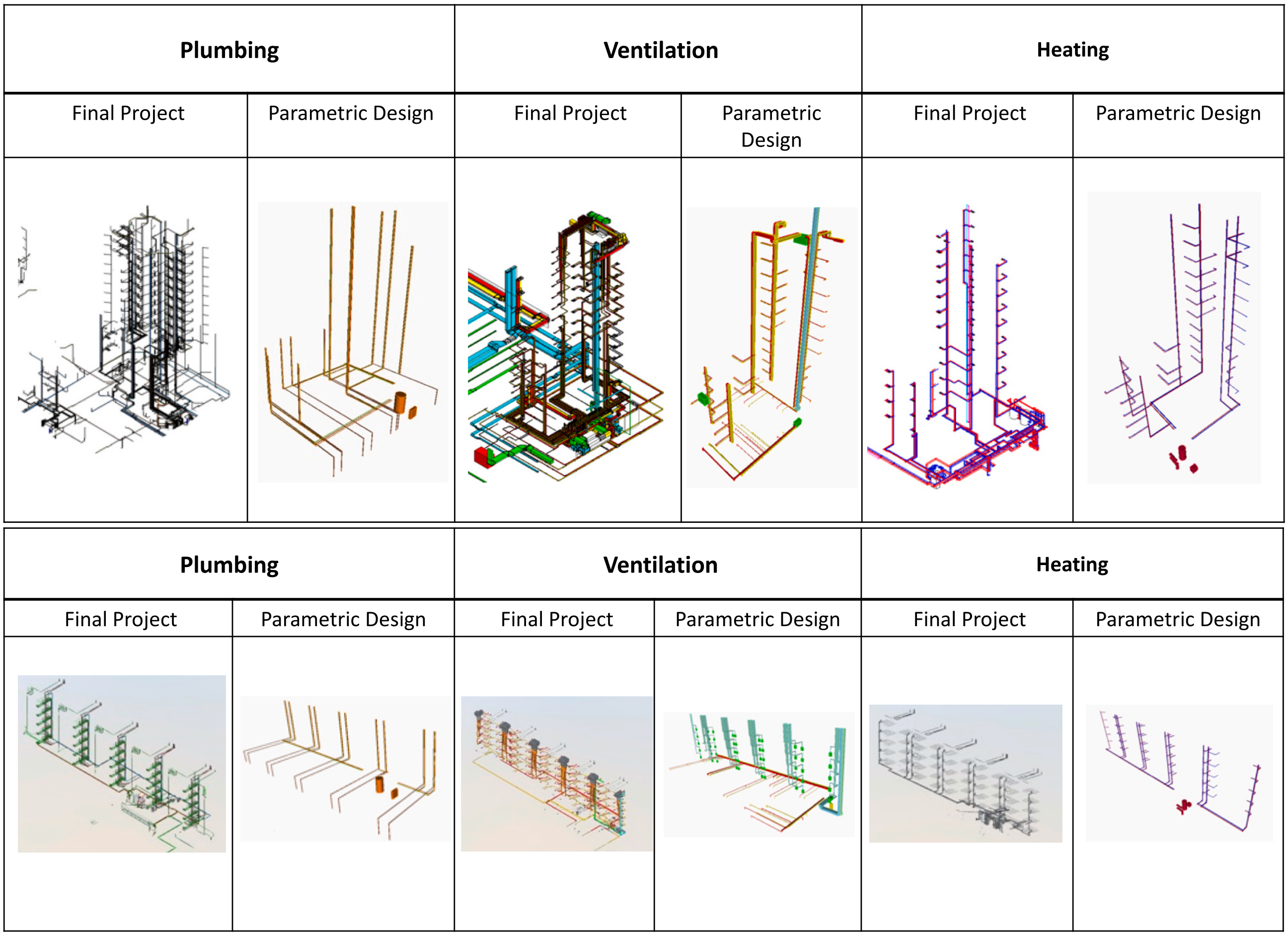

Fig. 8. Visual comparison between B&H's detailed designs and parametric design results.

Genetic Algorithm (GA). The GA was tuned to define the initial population size and the number of generations needed to derive a result. Monte Carlo Simulation (MCS) was used to prove the robustness of the approach for the most significant building arrangement possibilities. The combination of BIM-GD and a robustness proof based on MCS is a novel and significant contribution to the digitization of the AEC industry.

The robustness analysis and problem formulation were based on requirements determined by stakeholder interviews. Therefore, the technical results provide objective arguments for introducing BIM-GD, especially in the early stages of an AEC Project. Thus, in addition to the novel robustness results, the paper establishes a process for proving the suitability of Generative Design for solving real-world problems.

The contributions of this paper are, firstly, the identification of algorithmic robustness as a key acceptance factor in the application of GD methods in AEC early phase projects by interviews with experts; secondly, the develop a prototype implementation based on relevant fitness measures; and thirdly, the application of Monte Carlo Simulation to obtain initial quantitative estimates of the robustness of the prototype. This addresses the research gaps identified: Reasons for the lack of acceptance and robustness results.

5.2. Managerial implications and policy contributions

The solution addresses the industry's main concerns through interviews and validates that the solution addresses these concerns after the implementation of the prototype. The paper presents an approach to reducing the time required for calculation and minimizing the area needed for MEP, improving profitability. The proposed approach can improve the communication and decision-making capability of the project stakeholders, as an architectural concept can be sent in the morning to the engineering team and discussed in the afternoon, with the best trade-offs calculated by the algorithm and validated by the engineers.

This paper contributes by developing an algorithm that will work in at least 81% of the BIM models within the specified domain. This means that the failure probability of the Generative Design should be at most 19%. Further, the algorithm can be run in five hours with acceptable performance. The study results also provide a tool for rapidly evaluating the impact of design changes. Currently, such work is performed manually. Creating these solutions takes significant time and effort, or, more commonly, additional 'safety' space is left to absorb the risk that the MEP equipment might need more space. Reducing the time required for calculation and minimizing the area required for MEP will improve profitability.

The paper also highlights essential policy contributions to promote technological innovation in the AEC industry. Policymakers can play a crucial role by supporting and encouraging the integration of advanced technologies like Generative Design algorithms. Providing incentives, funding research and development, and fostering collaborations between academia and industry can drive the adoption of such innovative tools and methodologies. This paper's results can support policymakers encouraging the introduction of BIM-GD-based problem-solving techniques in the overall AEC industry as it provides proof of the real-world applicability of the approach.

The implication for project management is that it is possible to further improve the efficiency of AEC projects by introducing the use of GD in the project's early phase. Management, policymakers, and tool developers should, therefore, support the further development of such tools and fund additional research into the performance and optimization of the performance of the algorithms.

5.2.1. For practitioners

This document outlines an approach for integrating advanced algorithms with BIM to automate early building design that can support practitioners in becoming more productive and improving their early space allocations. We suggest to focus on critical steps such as data preparation, software integration, and specialized engineering training, and emphasize the importance of ensuring data and system compatibility and provides a structured workflow for seamless integration. This document also highlights best practices for efficient design iterations, stressing the need for streamlined communication and effective decision-making between the algorithm, BIM system, and project team to enhance the overall design process. Practitioners must learn to integrate such models into their normal design processes to support their clients better.

5.2.2. For policymakers

For policymakers, we suggest implementing incentive structures like tax breaks or grants to encourage companies to adopt advanced BIM technologies, emphasizing the importance of government-funded collaborative research projects between universities and industry for developing and testing generative design algorithms. Additionally, the paper advocates for creating specialized training programs and curriculum modules in academic institutions. These initiatives aim to prepare future professionals in the AEC industry for advanced tools, ensuring a skilled workforce and promoting innovation and efficiency.

6. Conclusions

Compared with the traditional approaches, this paper presents an improved approach to reducing the effort introduced by BIM in the concept phase of an AEC project. The problem was analyzed using a systems engineering methodology, identifying the industry's main concerns through interviews and validating that the solution addresses these concerns after implementing the prototype.

A Generative Design approach was developed, implemented in a prototype and tested. The robustness levels obtained in the pilot projects indicate that it is possible to apply Generative Design in the early phase of an MEP project. The results also showed that the solutions found by the Genetic Algorithm represent a local optimum of the design problem. However, all designs in the Pareto front achieved similar fitness values and were considered an acceptable solution for this phase of the project. This reveals the great potential of the GD method to replace the traditional method by enabling the development of similar solutions with much less effort.

Applying the methods developed in the paper paves the way for proving the robustness and real-world applicability of the GD approach in the construction industry. This proves there is still enormous potential for digitizing processes, increasing efficiency, saving costs, and improving quality. This should motivate policymakers to support further research and demonstration projects that explore GD in the construction industry.

7. Future work

The results of the project point to several interesting lines of further research. Firstly, this is just the first prototype. It is expected that significant performance improvements can be achieved when using other optimization approaches with the Genetic Algorithm or developing advanced heuristics based on Machine Learning based on the solutions being generated. Additionally, the discrepancy between the estimated success rate (99.1%) and the success rate calculated with 95% accuracy (80.7%) shows that there is enormous potential to evaluate the robustness of the result correctly. The success rate will be higher than measured, as bugs were found and corrected during the test phase.

As the algorithm is used more often, the number of samples (currently 9000) will increase, automatically leading to a better estimate. Additionally, technical work on the method, for instance, basing the estimate on non-Gaussian distributions, may provide tighter boundaries on the estimate. The algorithm can also be extended or improved by including further disciplines or extending the range of buildings to which it may be applied.

Regarding performance, as the REVIT GD algorithm was used, there were few possibilities to optimize the genetic algorithm or try other optimization approaches. By using a different software framework, significant performance improvements may be possible. To improve performance and increase industry acceptance, the Generative Design Algorithm needs further development based on a close relationship with the early adopters. When GD performance achieves high levels of customer satisfaction and a good level of confidence in the engineering teams, the script can be translated into an open-source environment. This would enable a digital cloud service to allow clients to obtain their project solutions automatically. Migrating to a cloud service could reduce model preparation effort, decrease computational time, and allow customers to test different concepts independently and cost-effectively.

Finally, the results are limited to the residential building use case and could be extended to other use cases, for example, hotels, businesses, or mixed-use buildings.

CRediT authorship contribution statement

Edgar Pestana: Writing – original draft, Validation, Software, Methodology, Formal analysis, Conceptualization. **Andrew Paice:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Shaun West:** Writing – review & editing, Supervision, Methodology, Formal analysis.

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 paper.

Data availability

The data that has been used is confidential.

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