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Research Article

A Comparison of Galapagos and Wallacei Optimization Solvers in High-Rise Building Design

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Abstract

Optimizing designs that meet specific criteria is burdensome for designers and slows down the building production process. Innovative tools can help by performing repetitive and complex calculations quickly to efficiently reach optimization goals. Optimization solvers facilitate this process by generating design variations suitable for single and multiple objectives. This study examines the advantages and capabilities of optimization solvers in high-rise building design. Following a literature review on ML-based tools, the study focused on the Galapagos and Wallacei solvers. A basic parametric high-rise model was created, defining a design problem at two levels of complexity. With each solver, the most suitable design variations for these problems were generated and compared in terms of interface, working mechanisms, effectiveness, and practical contributions. The analyses conducted revealed that Machine Learning (ML) contributes to parametric design processes. The comparison of Galapagos and Wallacei solvers provides a basic understanding of the subject through a simple example. Thus, it has created a different example in this context in terms of the practical applicability of these tools. Furthermore, within the scope of the study, recommendations were made to increase interface usability for different design contexts.

Keywords: *Optimization, High Structures, Optimization Solvers, Galapagos, Wallacei*

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Yüksek Bina Tasarımında Galapagos ve Wallacei Optimizasyon Çözücülerinin Karşılaştırılması

Öz

Belirli kriterleri karşılayan tasarımı optimize etmek, tasarımcılar için bir yük oluşturabilir ve bina üretim sürecini yavaşlatabilir. Tekrarlayan ve karmaşık hesaplamaları gerçekleştirebilen yenilikçi araçlar, hızlı ve çeşitli tasarım seçenekleri sunarak optimizasyon hedeflerine verimli bir şekilde ulaşılmasını sağlar. Optimizasyon çözücüleri, tekli ve çoklu hedeflere uygun tasarım varyasyonları oluşturarak bu süreci kolaylaştırır. Bu çalışma, optimizasyon çözücülerinin yüksek bina tasarımındaki avantajlarını ve yeteneklerini incelemektedir. ML tabanlı araçlara yönelik bir literatür taramasının ardından çalışma kapsamında, Galapagos ve Wallacei optimizasyon çözücülerine odaklanılmıştır. İki farklı karmaşıklık düzeyinde tasarım problemi tanımlayan temel bir parametrik yüksek yapı modeli oluşturulmuştur. Her çözücü ile, bu problemlere yönelik en uygun tasarım varyasyonları üretilmiş ve bu varyasyonlar arayüz, çalışma mekanizmaları, etkinlik ve pratik katkılar açısından karşılaştırılmıştır. Yapılan analizler ile Makine Öğreniminin (ML) parametrik tasarım süreçlerine katkı sağladığı görülmüştür. Galapagos ve Wallacei optimizasyon çözücülerinin karşılaştırılması, konuya basit bir örnek üzerinden temel oluşturmaktadır. Böylece bu araçların pratikte uygulanabilirlikleri açısından bu bağlamda farklı bir örnek oluşturmuştur. Ayrıca çalışma kapsamında farklı tasarım bağlamları için arayüz kullanılabilirliğini artırmaya yönelik önerilerde bulunulmuştur.

Anahtar kelimeler: *Optimizasyon, Yüksek Yapılar, Optimizasyon Çözücüleri, Galapagos, Wallacei*

1. Introduction

In the highly competitive construction industry, Artificial Intelligence (AI) and Machine Learning (ML) tools are now widely used by architects working with software and programming to make work more efficient. Thus, new working methods are constantly being developed to increase productivity. Artificial Intelligence and Machine Learning have great potential not only to accelerate and extend the design process, but also to open it up to designers with less technical expertise. Some elements of AI are now available in design and simulation software products that can significantly speed up the time to market of parts, products, machines and even buildings by using AI to automate some of the laborious parts of design (Schwaar, 2023).

In the initial phases of design creation, generating various model iterations and testing different design solutions can be highly time-consuming. Thus, it is crucial that this early-stage process is both practical and efficient in terms of time and cost. While most companies employ Point-Based Design (PBD) (a method that follows a linear path in the design development, resulting in time-intensive changes and frequent reworking of the design from scratch) this approach can be inefficient, especially given the dynamic nature of early-stage design. To enhance efficiency in early structural design, the utilization of a Parametric Design (PD) approach is recommended. Parametric modeling allows for the easy adjustment of "parameters" or "variables," enabling the creation of multiple variants to identify the optimal solution (Granberg and Wahlstein, 2020). This approach leads to more efficient, responsive, and performance-oriented building designs (Touloupaki and Theodosiou, 2017).

Grasshopper for Rhinoceros 3D serves as a powerful tool in the proposed design workflow, enabling parametric modeling, integration with performance simulations, application of evolutionary algorithms, automation of tasks, and fostering collaboration, all of which contribute to optimizing energy performance in building design (Touloupaki and Theodosiou, 2017). Artificial Intelligence, on the other hand, involves performing design tasks that usually require human intelligence. Generative design, a blend of these two approaches, uses computational processes to explore a large design space and generate an immense number of design alternatives (Schwaar, 2023). For parametric design-based software, many generative design tools have been developed that bring Machine Learning and Artificial Intelligence into the design process. Optimization solvers, which are some of these tools, enable the creation of design variations that give the optimum response according to the suitability targets determined according to certain design objectives. Thus, it is ensured that design variations that meet the design objectives are created more efficiently by reducing time loss. Within the scope of this research model, the study aims to compare two prominent solvers to demonstrate, firstly, how solvers can enhance the design process in terms of interface usability, feature variety, and overall capability, and secondly, how they differ from each other in various aspects.

On the other hand, in a paper on the basics of generic solvers, David Rutten noted that it is important for users to realize that solvers can take a very long time to run, depending on the characteristics of the problem at hand (Rutten, 2014). For this reason, the design problems created in this study are geometrically more simple targets.

One of the examined solvers is Galapagos, which is a popular solver that comes with Grasshopper in Rhino, and the other is Wallacei. The solvers were chosen based on data from a comparison study by Vukorep and Kotov (Vukorep and Kotov, 2021). In their study, Vukorep and Kotov presented the tools that use machine learning in a clear and understandable way and made comparisons between optimization solvers from these tools on two design problems. Their study can guide designers in choosing between optimization solvers and researchers who want to do research on this subject. However, since many solvers were discussed in the study, not much information about their use was given and the results were expressed with the help of tables and graphs. For this reason, in this study, both the interface and the steps in the use of the two solvers selected based on the results obtained by Vukorep and Kotov are included, and the results are written in more detail.

In another study on this topic that about; the preferable green performance of a residential building through parametric optimization in the early design phase, Zhang, Liu and Wang used Galapagos for a secondary optimization to validate the optimization data in their simulation with the Octopus optimization tool. Their study creates a parametric energy optimization process for the early design stage of residential buildings based on Grasshopper. And it shows the importance of the application and popularization of such optimization methods for energy consumption, especially in residential projects (Zhang, Liu and Wang, 2020).

For this study, first it is aimed to obtain data based on the literature review on the properties of these solvers, Galapagos and Wallacei were selected as two optimization solvers using genetic algorithm according to their determinant properties, and as an analysis study, it is aimed to create a simple parametric high-rise structure model with curved façade optimized according to the determined single and multiple fitness goals (As Lu, Lin and Wang (2020) pointed out in their study on facade design optimization for efficient daylighting, curved facades provide larger solution spaces and require fewer independent variables; therefore, they are more effective for defining shapes for optimization. For this reason, a façade shape that creates curved forms is also preferred here.). That will be suitable for both optimization solvers and to compare the optimized design variations generated by the two solvers for this model. Thus, the interfaces, working mechanisms and practical contributions of Galapagos and Wallacei solvers will be revealed (Figure 1).

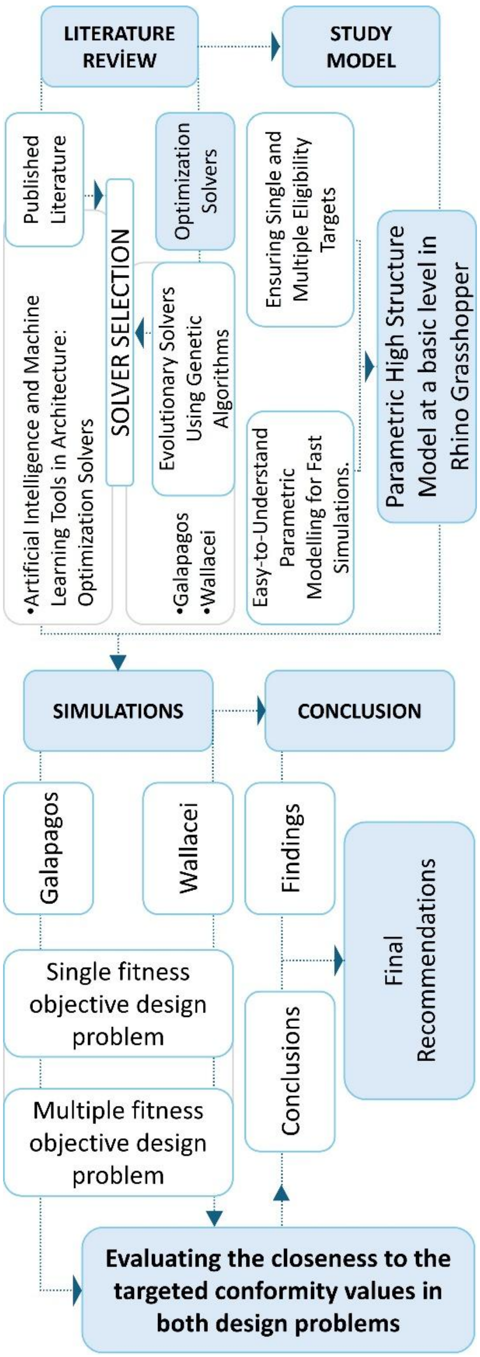


Figure 1. Methodology of the study.

2. Artificial Intelligence and Machine Learning tools in architecture: Optimization Solvers

Artificial Intelligence does not replace an engineer or designer with the designs it generates but frees them from repetitive tasks and multiple error-prone calculations. This allows them to focus on innovation by resolving conflicting design constraints. This category of software not only saves enormous amounts of time in production processes but can also generate more alternatives than designers spend manually creating or evaluating. More importantly, it can also present concepts that you would never have thought possible. In the context of generative design, an AI-driven algorithm can use machine learning techniques to understand design preferences or learn from historical design data. Instead of following specific datasets, these algorithms can generate solutions based on generalized knowledge from data (Schwaar, 2023).

In 1992, one of the first architects to use machine learning in his work was Bojan Baletic, now a professor of architecture at the University of Zagreb. His PhD thesis, titled "Information Codes of Mutant Forms" (Baletic, 1992), used a neural network to identify patterns in floor planning to help architects in their future planning. While there are several uses of Artificial Intelligence (AI) and specifically Machine Learning (ML) algorithms within architectural design processes and research fields (Özerol and Arslan Selçuk, 2023), optimization solvers represent one of the most effective applications of ML. Newly developed optimization plug-ins, in particular, can open up new possibilities for efficient design workflows within widely used software interfaces. Many effective tools are available as plug-ins for parametric extensions of programs like McNeel Rhino 3D and Autodesk Revit.

2.1 Optimization solvers

In 2010, the Galapagos component at Grasshopper led the development of a large class of tools called "Optimization Solvers". These tools have various combined machine learning algorithms that aim to find the best solution for the required objective. It can be said that the class of optimization solvers is one of the most heuristic tools in the entire palette of machine learning methods and they are incredibly powerful. Usually, to run a solver for optimization, it is necessary to define the problem from several aspects. In this context, three concepts are important for achieving meaningful outcomes: the Concept of Optimization, Fitness Landscape and Fine-Tuning, and Single or Multi-Goal Problem Definition. These concepts are explained as follows (Vukorep and Kotov, 2021):

- Concept of Optimization: The desired objectives are called fitness functions and represent the space of potential combinations of the parameters of the model with a value for each state. Maximizing or minimizing the output of the fitness function defines the fitness function for the solver.
- Fitness Landscape and Fine Tuning: To better understand the fitness function, it is necessary to refer to the fitness landscape to visually represent the algorithm's search for some maximum or minimum. Although fitness landscapes of more than three dimensions are difficult for humans to grasp, they are normally hypersurfaces in n-dimensional space, where n is the number of objectives. The properties of this environment are crucial for the overall performance of the optimization solver.

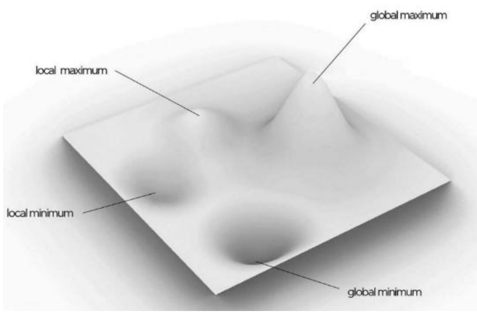


Figure 2. Visualization of a three-dimensional fitness landscape (Vukorep and Kotov, 2021).

-Single or Multi-Goal Problem Definition: A fitness function can be a complex combination of other functions and setting only one final objective would be a "Single-Objective (or Goal) Optimization (SOO)" task because the output contains only a single value. But optimization problems are often more complex and require more than one objective. In this case it is a "Multi-Objective (Goal) Optimization (MOO)" task.

Optimization solvers developed for optimizing design problems in architecture include Galapagos and Octopus, SilverEye, Wallacei, Opossum, Optimus, with Galapagos being the most familiar to many architects and engineers.

Galapagos was one of the two solvers chosen for this study as it is a widely used solver due to its inclusion in Grasshopper, its intuitive working environment and its simplicity. In the study by Vukorep and Kotov (2021) with the mentioned optimization solvers, the Wallacei solver was one of the solvers that gave the best results and can be run for both single and multiple fitness objectives, and its working logic is based on genetic algorithms like Galapagos, making it another of the solvers selected for this study.

For solvers like Galapagos and Wallacei who use genetic algorithms and annealing algorithms, evolutionary algorithms apply the biological principles of mutation, selection and inheritance: "They will populate the landscape with virtual individuals and then continue to breed the highest ones in the hope that their offspring will be closer to the top" (Rutten, 2013).

2.1.1 Galapagos (Built-in Grasshopper)

Galapagos is the first single-objective optimization solver developed by David Rutten. It is based on a representation of genetic evolution and includes an annealing solver. It generates solutions by genetic simulation. Rutten has stated that algorithms using "evolutionary computation" are a tool developed "by programmers for programmers" and when Galapagos had launched, he stated his plans for this tool as "It is my hope that Galapagos will provide a generic platform for the application of Evolutionary Algorithms to be used on a wide variety of problems by non-programmers." (Rutten, 2011). Galapagos has a very intuitive, user-friendly interface (Figure 3) and is a complex and powerful tool. It is built into Grasshopper and is a good solution for both simple and complex problems. For many architects and engineers using Galapagos with its documentation in Grasshopper, this plugin was the first contact with the optimization domain (Vukorep and Kotov, 2021).

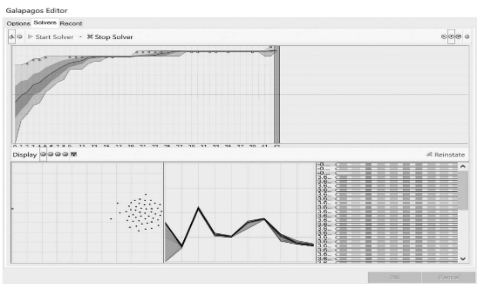


Figure 3. Galapagos interface (Vukorep and Kotov, 2021).

As can be seen in Figure 4, only one fitness goal can be connected to Galapagos' fitness objective input, which poses a problem when using the solver for complex and multiple goals. For those who are looking for a solution to this situation, there are some time-consuming solutions offered by users who are familiar with the solver, which can be found on various internet sources.

2.1.2 Wallacei

Wallacei (Wallacei.com), released in January 2018, is an optimization solver from the family of evolutionary optimization solvers, capable of single and multi-objective optimization.

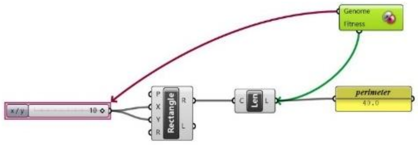


Figure 4. A use case of the Galapagos solver on Grasshopper (URL1).

It has an open user interface for comparing different generations, results, goals, etc. With its advanced interface (Figure 5), it offers great opportunities for analysis of results and has good program performance (Vukorep and Kotov, 2021).

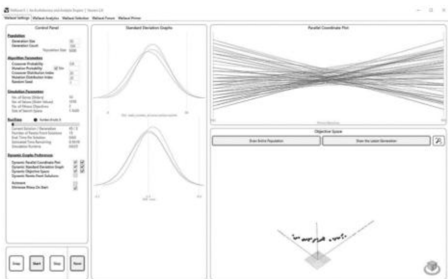


Figure 5. Wallacei interface (Vukorep and Kotov, 2021).

The Wallacei solver has four inputs - Genes, Fitness Objectives, Data (Numerical Data) and Phenotypes - and four outputs - Genomes, Fitness Values, Data and Phenotypes (as well as the variations generated). In addition, more than one (but consistent) fitness goal can be entered into Wallacei's fitness objective input, making Wallacei a more functional tool than Galapagos for more complex and multi-goal designs (Figure 6).

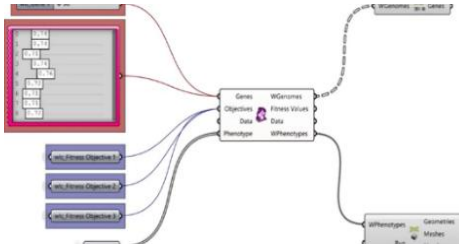


Figure 6. Inputs and outputs of the Wallacei solver (Wallacei Primer).

3. The Study Model

In this study, the objective is to evaluate the capabilities of two design solvers through a two-step testing model. The model involves developing a parametric high-rise design concept using specific fitness goals tailored for the Galapagos (V. 1.0.0007) and Wallacei (V. 2.7) optimization solvers within Grasshopper, a plug-in for Rhino (V. 7). Initially, a design problem with a single fitness objective was formulated, and the performance of the solutions generated by both solvers in relation to this objective was assessed. Subsequently, a design problem incorporating multiple fitness objectives was introduced for the same design. For this multi-objective scenario, a specialized solution was developed for Galapagos, which traditionally handles single-objective optimization, and the results produced by both solvers were compared. This approach facilitated a comparative analysis of the solvers, providing insights into their interface usability, feature variety, and overall capability in delivering optimized designs.

3.1 Generated design model

In Rhino Grasshopper, a high-rise structure of 20 slabs was created with a story height of 3 meters. The slabs have an elliptical geometry with a 2/3 ratio between the short and long sides (10 meters x 15 meters). As the design rises, adjustments were made to the facade to create a parabolic form. A range of values (min. 0.50 and max. 1.50) was created to control the parabolic form with proportions and a range of values (min. 0° and max. 720°) that will rotate the slabs on the central axis as the building rises to affect the facade surface of the building with various factors (Figure 7).

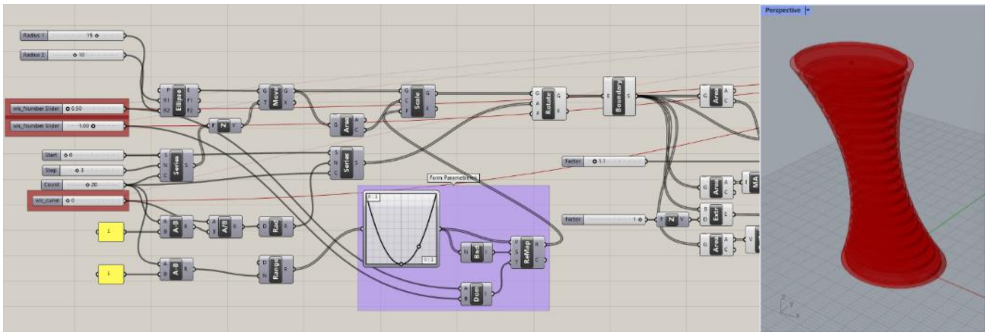


Figure 7. Grasshopper model and perspective view of the design.

3.2 Single fitness objective design problem

The aim is to optimize the coefficient values at the top and end points of the parabolic form and the slab rotation angle by the solver to obtain the desired surface area value.

Within the scope of the first design problem, a total area of 5000 square meters on the facade surface of the building was aimed as the compliance target. Accordingly, two values determining the parabola curve ratios of the building (initially 0.50 and 1.00) and another value determining the degree of rotation of the building slabs (initially 0°) were decided as independent variables. In this case, the total facade surface area of the building also constitutes the dependent variable (Figure 8).

For the stated goal, the Galapagos and Wallacei solvers were run by connecting these values to the corresponding modules. Thus, with Galapagos and Wallacei, it is shown how these solvers can be used to optimize the profile curve of a rotating tower in order to obtain a total surface area of 5000 square meters: by adjusting the ratio and the angle of rotation of the rotating curve along the Z axis, the solvers aim to get as close as possible to the total facade surface area of the structure.

3.2.1 Galapagos

In accordance with the first design problem, the stages of using the Galapagos solver are given below:

1. The number sliders determining the parabola curve of the tower, initially 1.00

and 0.50, and the number slider determining the slab rotation angle, initially 0°, were connected to the "Genome" module of Galapagos (Figure 9).

2. The value containing the total surface area of the facade of the building was linked to the "Fitness" module as a fitness objective (Figure 10).

3. In the Galapagos Editor, the Fitness Objective Value was set to "5000" and the other settings were not changed.

Except for the Fitness Objective Value, the solver was run with the initial settings (Figure 11).

4. The Evolutionary Solver was selected in the Solvers tab and the solver was run by pressing the Start Solver button (Figure 12).

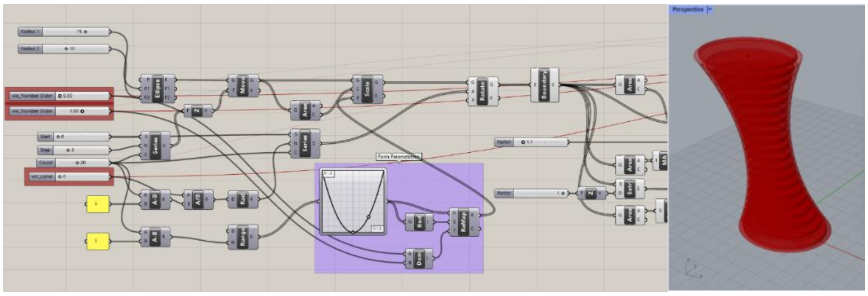


Figure 8. Initial state of the design and parametric values.

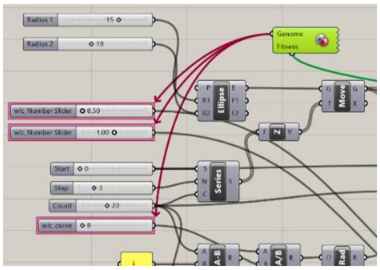


Figure 9. Values connected to the Galapagos solver and its modules 1.

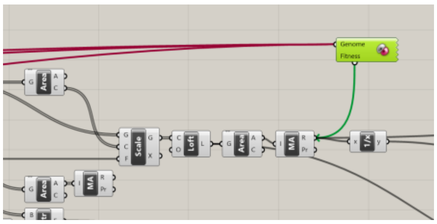


Figure 10. Values connected to the Galapagos solver and its modules 2.

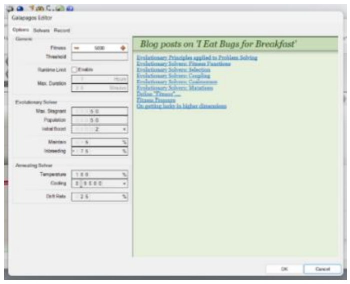


Figure 11. Values set in the Galapagos editor and the solvers tab 1.

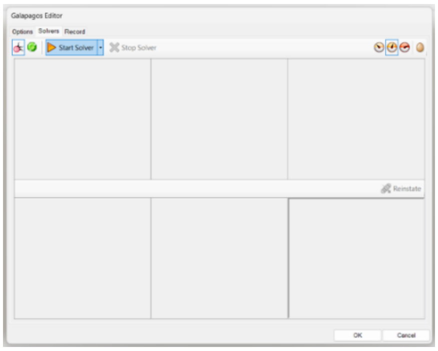


Figure 12. Values set in the Galapagos editor and the solvers tab 2.

5. The solution that closely approximates the goal is given at the top of the bottom right window of the Solvers tab, and this solution appears as the final design in Rhino after running Galapagos (Figure 13).

As a result, Galapagos generated 105 generations and 50 populations in each generation (5250 design variations in total) and developed the solution that best meets the fitness goal. The optimal design variation generated with Galapagos (the optimal solution in the last generation) is shown in Figure 13. Figure 13 also shows the values related to the generated solution, as seen in the panels created to control the values in Grasshopper.

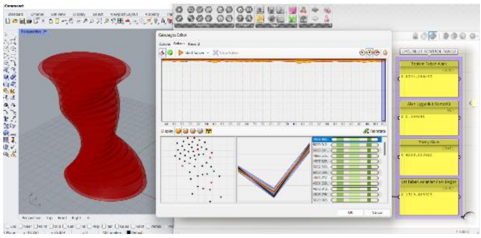


Figure 13. Optimal design variation created with Galapagos.

- Total number of populations created: 5250 (105 x 50)
- Time taken to create the optimal solution: 5 minutes 12 seconds
- The value that determines the center point of the parabolic profile: 0.65
- Value determining the endpoints of the parabolic profile: 1.35
- Degree of rotation of slabs as they rise: 355°
- Total facade surface area: 4999,990919 square meters
- Difference from targeted fitness value (5000): 0.009081

In addition, the data in the Record tab regarding the optimum solution generated by Galapagos according to the fitness objective is given below:
- Generation 105
- Bio-Diversity: 0.122
- Genome[0], Fitness=4999.99, Genes [49% · 15% · 85%]

3.2.2 Wallacei

In accordance with the first design problem, the stages of using the Wallacei solver are given below:
1. The number shifters determining the parabola curve of the tower, initially 1.00 and 0.50, and the number shifter determining the slab rotation angle, initially 0°, were connected to the "Genes" module of Wallacei (Figure 14).
2. The Wallacei solver does not allow the input of a fitness objective value. This solver works in such a way that it minimizes all connected fitness objectives. For this reason, the compliance target of 5000 square meters of total facade surface area was provided by a function. In the function created, the total surface area was set as "x" and the number value of 5000 was set as "y", the absolute value of the difference of these two values was taken and the solution that comes closest to the targeted surface area was aimed to be created by Wallacei by minimizing the fitness objective. Thus, the value that constitutes the difference of the total surface area of the facade of the building compared to the goal is connected to the "Objectives" module as the fitness objective to be minimized (Figure 15).
3. The geometry data of the design was combined as a single value and

connected to the "Phenotype" module but was deactivated while running the simulation (recommended by Wallacei Primer for acceleration and to avoid crashes in the simulation) (Figure 15).

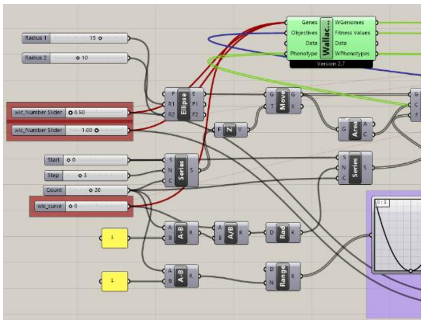


Figure 14. Values connected to the Wallacei solver and its modules 1.

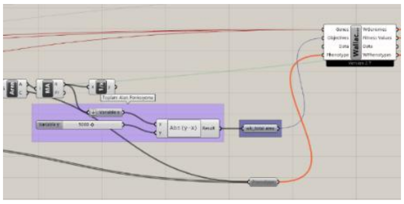


Figure 15. Values connected to the Wallacei solver and its modules 2.

4. In the Wallacei Settings tab of the Wallacei X screen, the simulation was started with Wallacei's own settings without making any changes to the values (Figure 16).

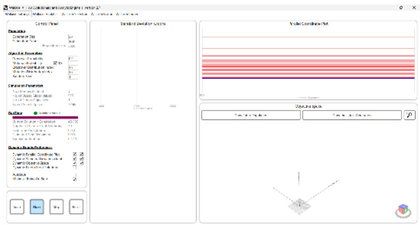


Figure 16. Wallacei settings tab where the simulation was started (after the simulation has ended).

5. After running the simulation, the data related to the solutions developed are displayed in the Wallacei Analytics tab (Figure 17).

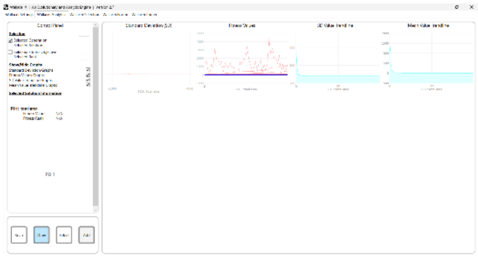


Figure 17. Wallacei analytics tab showing post-simulation data.

6. The last solution as the closest solution to the goal, as well as other solutions (by activating the "Phenotype" value after the end of the simulation), are selected among the solutions of different generations in the Wallacei Selection tab and added to the "Export" list and then exported to Rhino (Figure 18). Thus, the solution closest to the target is brought to the screen.

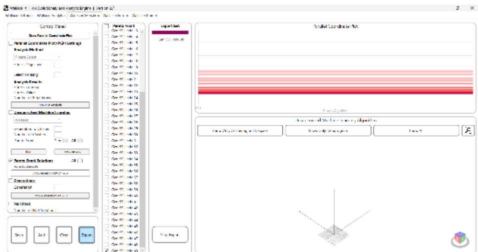


Figure 18. Wallacei selection tab where the most appropriate solution is imported into Rhino.

As a result, Wallacei generated 100 generations and 50 populations in each generation (5000 design variations in total) and developed the solution that best meets the fitness goal. The optimal design variation generated with Wallacei (the optimal solution in the last generation) is shown in Figure 19. Figure 18 also shows the values related to the generated solution, as seen in the panels created to control the values in Grasshopper.

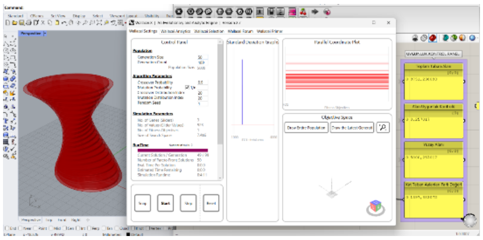


Figure 19. Optimal design variation created with Wallacei.

- Total number of populations created: 5000 (100 x 50)
- Time taken to create the optimal solution: 4 minutes 11 seconds
- The value that determines the center point of the parabolic profile: 0.67
- Value determining the endpoints of the parabolic profile: 1.39
- Degree of rotation of slabs as they rise: 210°
- Total facade surface area: 5000,257017 square meters
- Difference from targeted fitness value (5000): 0.257017

3.3 Multiple fitness objective design problem

The aim here is to create a design where the total floor area is certain, the area difference between floors is minimal and the highest façade area value is obtained.

For the second design problem, the values determining the slab size ratios of the building were separated for each story and the form was reorganized to form a free profile rather than a parabolic one. In this context, the fitness goals were decided to have a total floor area of 5000 square meters in all slabs, to minimize the floor area difference between floors and to maximize the total surface area on the facade. In this direction, a gene pool containing 20 values determining the ratio of the slabs on each floor of the tower (initially all values are 1.00) was created, and this gene pool and another value determining the degree of rotation of the building slabs (initially 0°) were decided as independent variables. In this case, the dependent variables are the total slab floor area, the total facade surface area and the difference of the slab areas with respect to each other (Figure 20).

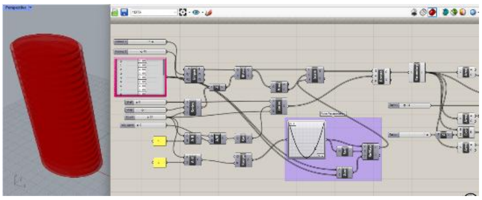


Figure 20. Initial state of the design and parametric values.

In line with the stated goal, the Galapagos and Wallacei solvers were run by connecting these values to the relevant modules. Thus, with Galapagos and Wallacei, it is shown how the solvers can be used to optimize the design of a rotating tower with a total slab area of 5000 square meters in order to obtain a structure with a total slab area of 5000 square meters and the highest facade surface area, such that the difference in area between floors is minimized: by adjusting the proportions of the areas of the slabs rising along the Z-axis, the differences between them and the angles of rotation, the solvers aim to create a reasonable design by reducing the differences between floors while approaching the total slab area and the total facade surface area of the structure as well as possible.

3.3.1 Galapagos

In accordance with the second design problem, the stages of using the Galapagos solver are given below:

1.The gene pool that determines the proportions of the tower's slabs is connected to the "Genome" module of Galapagos, with all values initially set to 1.00 and the number slider that determines the slab rotation angle initially set to 0° (Figure 21).

2. In the Galapagos solver, multiple fitness objectives cannot be connected to the module. Therefore, the desired fitness goals were combined in a function and entered as a single value in the "Fitness" module of Galapagos. In the function created, the total floor area was set as "x" and the 5000 number value was set as "y", the absolute value of the difference of these two values was taken, the difference in floor area between the slabs to be minimized was set as "z", the result was set as "u" by applying the "1/x" operation to the facade surface area value to be maximized and the sum of these three values was taken. Thus, the resulting value was linked to Galapagos as the single fitness objective. As a result, it was aimed at creating the solution that most closely approximates the targeted values by minimizing the fitness objective (Figure 22).

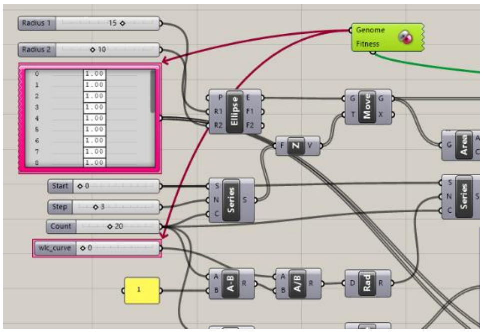


Figure 21. Values connected to the Galapagos solver and its modules 1.

3. In the Galapagos Editor, the Fitness Objective Value was set to "Minimize" and the other settings were not changed. Except for the Fitness Objective Value, the solver was run with the initial settings (Figure 23).

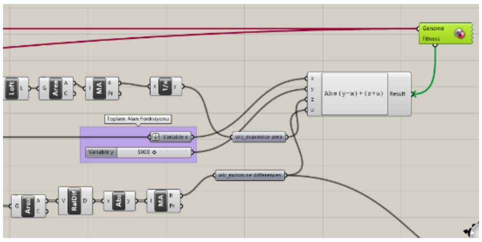


Figure 22. Values connected to the Galapagos solver and its modules 2.

4. The Evolutionary Solver was selected in the Solvers tab and the solver was run by pressing the Start Solver button (Figure 24).

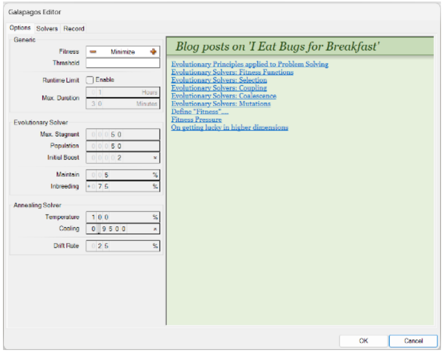


Figure 23. Values set in the Galapagos editor and the solvers tab1.

5. The solution that closely approximates the goal is given at the top of the bottom right window of the Solvers tab, and this solution appears as the final design in Rhino after running Galapagos (Figure 25).

As a result, Galapagos generated 550 generations and 50 populations in each generation (27500 design variations in total) and developed the solution that best meets the fitness goals. The optimal design variation generated with Galapagos (the optimal solution in the last generation) is shown in Figure 25. Figure 25 also shows the values related to the generated solution, as seen in the panels created to control the values in Grasshopper.

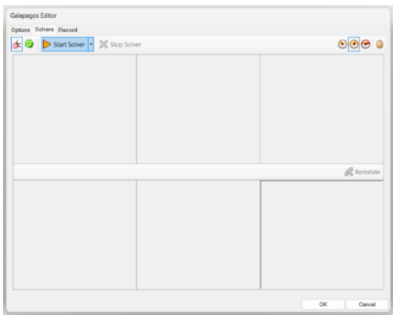


Figure 24. Values set in the Galapagos editor and the solvers tab 2.

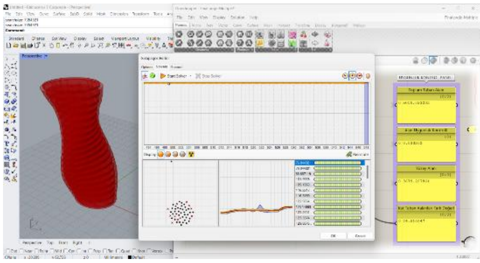


Figure 25. Optimal design variation created with Galapagos.

- Total number of populations created: 27500 (550 x 50)
- Time taken to create the optimal solution: 33 minutes 51 seconds
- The values determining the proportions of the slabs of the building from the floor to the roof slab are: 0.69, 0.69, 0.70, 0.71, 0.72, 0.73, 0.73, 0.73, 0.73, 0.73, 0.73, 0.73, 0.73, 0.73, 0.73, 0.73, 0.72, 0.72, 0.72, 0.76, 0.78, 0.78
- Degree of rotation of slabs as they rise: 204°
- Total floor area: 5000,033202 square meters
- Difference from the targeted total floor area value (5000): 0.033202
- The value of the difference between stories to be minimized: 76,010847
- The value of the facade surface area to be maximized: 3679,287864

The data in the Record tab related to the optimal solution generated by Galapagos according to the fitness objective is given below:

- Generation 550
- Bio-Diversity: 0.021
- Genome[0], Fitness=76.04, Genes [19% · 19% · 20% · 21% · 22% · 23% · 23% · 23% · 23% 23% · 23% · 23% · 23% · 23% · 22% · 22% · 22% · 26% · 28% · 28% · 28%]
- Record: Point Mutation at index 19: 0.28 -> 0.2429

3.3.2 Wallacei

In accordance with the second design problem, the stages of using the Wallacei solver are given below:

1. The gene pool, which determines the proportions of the slabs of the tower, is connected to the "Genes" module of Wallacei with all values initially set to 1.00 and the number slider, which determines the slab rotation angle, is initially set to 0° (Figure 26).
2. The fitness objectives identified in the design problem can also be linked to the Wallacei solver as a single objective with the function created for Galapagos. However, in the Wallacei solver, multiple fitness objectives can be linked to the module separately by pressing the "Shift" key. This solver works in a way to minimize all connected fitness objectives. For this reason, the fitness targets; the result value of a function created by taking the absolute value of the difference of these two values as the total floor area "x" and the 5000 number value "y", the values obtained by applying the "1/x" operation to the value of the inter-story floor area to be minimized as well as the value of the facade surface area to be maximized were separately connected to the "Objectives" module of Wallacei with the "Shift" key. Thus, by minimizing the fitness objectives, it was aimed to create the solution that most closely approximates the targeted values by Wallacei (Figure 27).
3. The geometry data of the design was merged as a single value and connected to the "Phenotype" module but was disabled while running the simulation (recommended by Wallacei Primer for acceleration and to avoid crashes in the simulation) (Figure 27).

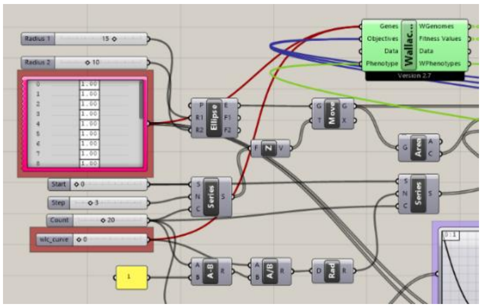


Figure 26. Values connected to the Wallacei solver and the modules they are connected to. 1

4. In the Wallacei X screen, the simulation was started with Wallacei's own settings without making any changes to the values in the Wallacei Settings tab (Figure 28).

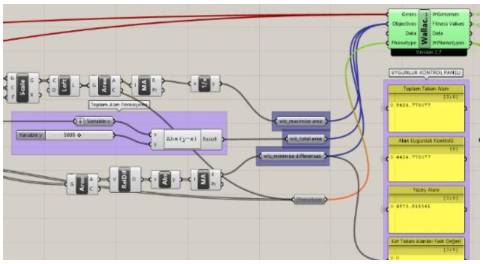


Figure 27. Values connected to the Wallacei solver and the modules they are connected to. 2

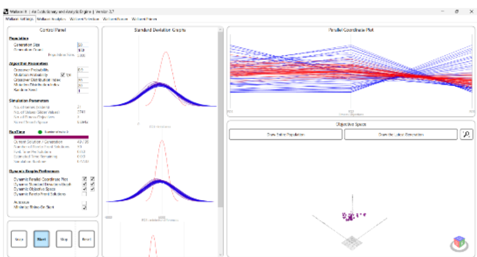


Figure 28. Wallacei settings tab where the simulation was started (after the simulation has ended).

5. After running the simulation, the data related to the solutions developed are displayed in the Wallacei Analytics tab (Figure 29).

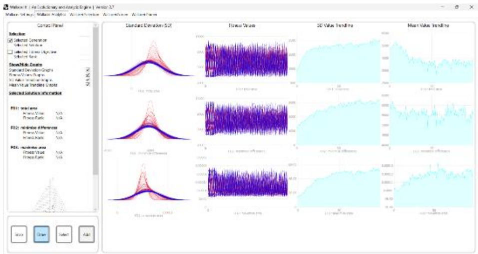


Figure 29. Wallacei analytics tab showing post-simulation data.

6. The last solution and other solutions (by activating the "Phenotype" value after the end of the simulation) are selected from the different generation solutions in the Wallacei Selections tab and added to the "Export" list and then exported to Rhino. Thus, the closest solution to the target was brought to the screen (Figure 30).

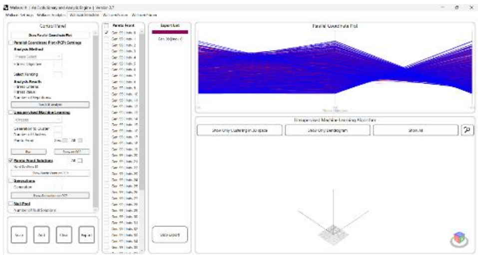


Figure 30. Wallacei selection tab where the most appropriate solution is passed to Rhino.

As a result, Wallacei generated 100 generations and 50 populations in each generation (5000 design variations in total) and developed the solution that best meets the fitness goals. The optimal design variation generated with Wallacei (the optimal solution in the last generation) is shown in Figure 31. Figure 31 also shows the values associated with the generated solution, as seen in the panels created to control the values in Grasshopper.

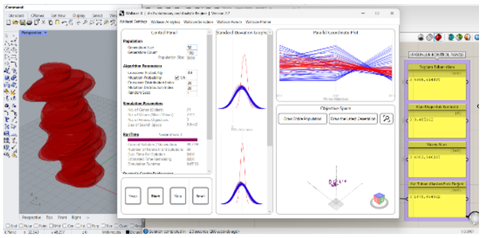


Figure 31. Optimal design variation created with Wallacei.

- Total number of populations created: 5000 (100 x 50)
- Time taken to create the optimal solution: 47 minutes 33 seconds
- Values determining the proportions of the slabs of the building from the floor to the roof slab in order: 0.56, 0.69, 0.54, 0.60, 0.65, 0.68, 0.85, 0.97, 0.94, 0.82, 0.75, 0.71, 0.72, 0.86, 0.55, 0.60, 0.89, 0.88, 0.51, 0.50
- Degree of rotation of slabs as they rise: 719 degrees
- Total floor area: 4999,514837 square meters
- Difference from the targeted total floor area (5000): 0.485163
- The value of the difference between stories to be minimized: 1478,464922
- The value of the facade surface area to be maximized: 4803,946267

4. Findings

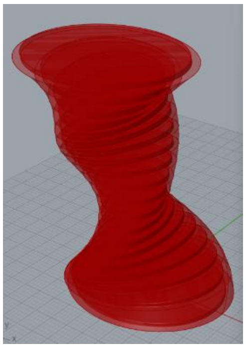
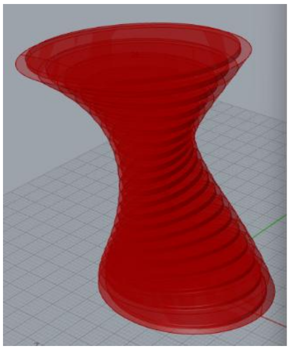
After evaluating the information obtained in the literature review, it can be concluded that the Galapagos solver is an optimization solver that can provide easy and fast solutions for inexperienced users. The highly simplified interface is designed in such a way that users can intuitively grasp how to use the solver. The fact that Wallacei consists of slightly more complex sets compared to Galapagos may lead to a perception that the user may find it difficult to use this solver at first glance. For this reason, it can be assumed that the developers may have included the Wallacei Primer, a file attachment that explains the working principle and usage of the solver, in the component interface.

As a result of the tests performed in the application part of the study, the performances of both solvers in various factors such as speed, computation, fitness to the goal were compared with the tables created in the context of the two design problems.

Table 1. Comparison of Galapagos and Wallacei solvers.

	GALAPAGOS	WALLACEI
Year of Launch	2010	2018
Number of Fitness Objectives	Single	Multiple
Interface	Simple and Clear	More Complex but Understandable
Number of Inputs	2	4
Number of Outputs	-	4

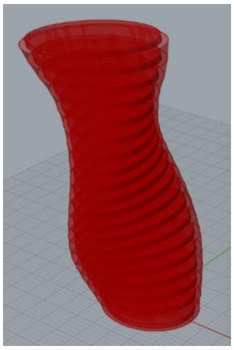
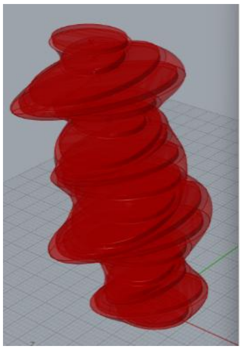
Table 2. Comparison of the solvers' solutions for the first design problem.

First Design Problem	GALAPAGOS	WALLACEI
Number of Population	5250	5000
Duration Time	5:12	4:11
Number of Genes	3	3
Facade Surface Area (Goal: 5000)	4999,990919	5000,257017
Difference with Goal	0,009081	0,257017
Form of The Structure		

In the context of the first design problem, the optimal solutions generated by the Galapagos and Wallacei optimization solvers run according to the single fitness objective with the goal of 5000 square meters of facade surface area are compared with the data in Table 2.

As seen in Table 2, although it takes a little longer for the Galapagos solver to reach the optimum result compared to Wallacei, it is seen that the design obtained responds better to the fitness goal. In addition, while Galapagos directly displays the most appropriate option among all options, in Wallacei, the designer transfers the option that he/she determines as appropriate among the generated design variations to Rhino. However, in Galapagos, only one variation from each generation can be transferred to Rhino. On the other hand, in Wallacei, each design variation can be individually selected by the designer and transferred to Rhino based on the analysis provided by the solver. This situation reveals that one of these solvers may be more functional than the other in different situations, depending on the fitness goals and the context of the design.

Table 3. Comparison of the solvers' solutions for the second design problem.

Second Design Problem	GALAPAGOS	WALLACEI
Number of Population	27500	5000
Duration Time	33:51	47:33
Number of Genes	21	21
Total Floor Area (Goal: 5000)	5000,033202	4999,514837
Difference With Goal	0,033202	0,485163
Story Difference Value (To Be Minimized)	76,010847	1478,464922
Facade Surface Area (To Be Maximize)	3679,287864	4803,946267
Form of The Structure		

In the context of the second design problem, the optimal solutions generated by the Galapagos and Wallacei optimization solvers, which were run according to the three fitness objectives with the objectives of having a total floor area of 5000 square meters, minimizing the floor area difference between floors and maximizing the façade surface area, are compared with the data in Table 3.

As seen in Table 3, the Galapagos solver took less time to reach the optimum result than Wallacei in this case. Compared to the previous design problem, it can be interpreted that the reason for the longer times is the increase in the number of gene values that the solvers need to work on. In the second design problem, it is seen that the design obtained with Galapagos responds better to the fitness goals than Wallacei. An important point to be mentioned here is that the Wallacei solver produced a result more suitable for the goal of maximizing the front surface area value. Although Galapagos created a design that also complied with the desired fitness goals (however, unlike Wallacei, Galapagos created a significant difference compared to the number of populations in Wallacei solutions within the scope of this problem by increasing the number of generations as much as the solver deems appropriate when run, and this is how it reached the design that meets the optimal conditions), Wallacei provided more differentiated designs by using more extreme values and increasing the differences between the fitness objectives. At this point, Galapagos, which passes the most appropriate of all options directly to Rhino, and Wallacei, which gives more control to the designer than Galapagos, where all results can be determined separately with its own analysis features, enable the creation of designs that offer more solutions according to a hierarchy that the designer can determine among the fitness objectives in more complex contexts such as this (compared to the previous design problem). At this point, as in the previous design problem, it is concluded that there are situations where both solvers can benefit more than each other in different contexts and according to different demands.

5. Conclusions and Recommendations

With companies incorporating machine learning into their software with Artificial Intelligence and other tools that produce solutions to more complicated problems, it has become faster, easier and much more optioned to produce design variations. It is obvious that these tools, which differ according to their features, offer highly efficient solutions when used in appropriate contexts. The unique designs provided by today's computing power play a major role in the increased use of such software and tools. Nevertheless, it is important to emphasize that these are just tools and still require people to work on them. Although it is a game-changing technology, it is unlikely to replace skilled designers, architects and engineers. It can be concluded that it is actually the collaboration between humans and machines that makes this technology so powerful.

This study contributes to the literature by testing the aforementioned collaboration in practice within the framework of selected programs within the scope of optimization solvers, making process and result comparisons related to the tools used, and transferring the implementation experiences. Within the framework of the dissemination of similar tools used in this way and, so to speak, "benefiting from the blessings of new technologies in architectural digital applications", this study provides a step-by-step description of the practical application through a simple model. In this way, it differs from previous studies by creating a comprehensible entry-level optimized design method for designers.

A final comparison between Galapagos and Wallacei is that Galapagos is a tool that can be easily used for faster, simpler and clearer solutions, while Wallacei is a tool that provides the user with all the data to analyze, select and compare between all the design variations that can be created and can facilitate work in very specific design contexts. Both solvers, which work with evolutionary solver algorithms, allow designers to use machine learning technology in their parametric models.

At this point, some suggestions can be made to ensure ease of use for both solvers. Galapagos has a very simple, clear and intuitive interface, but offers few options for designer intervention. Although the effects of different ratios of genomes appear in the Registration tab, it is thought that designers could benefit more from the generated solutions if a separate tab could be added to the interface where design variations can be easily selected according to the different ordering of these values among all options. It is also thought that the inability to enter more than one fitness objective value in Galapagos, although the problem was solved with the generated functions in the two design problems studied, may cause this solver not to be used by the designer in much more complex design problems. On the other hand, although Wallacei provides the user with access to more data and options, this data and different design options can be presented to the user in simpler and more understandable ways. For example, some specific design options can be selected from all options by creating analysis criteria according to different suitability objectives, but these design options are only numerically sorted in the Wallacei Selection tab. In this case, the designer has to either memorize the data for these design variations or manually sort them by noting the data in a separate place. It is thought that introducing a function that allows the designs to be re-listed according to their features in the Wallacei Selection tab may be effective in reducing time loss for the user.

As seen in the findings of the study model of the research, although various tools such as Galapagos or Wallacei can be used to improve the designs and optimize them quickly in line with the desired goals, the intervention of the designer is required for the final design, which also shows that the "most optimized solution" is not always the "most accurate solution". In fact, if both of these programs had really created the "most optimized" design for the model in the context of the study, both results should be closer to each other than the results obtained. Of course, at this point, the importance of choosing the solver that matches the expectations for the design to be created is also revealed. Although such tools can easily provide us with the "best/optimized design" as in this example by calculating the data of various factors with machine learning and undertaking repetitive, error-prone and repetitive operations that would take time to be done by humans, there will also be factors that the designer cannot code into the program as a compliance target and there will be situations where he will take the initiative among the options. This situation allows us to clearly say "no" to the question that always comes to mind "Will artificial intelligence replace humans, architects or designers?", for now.

In conclusion, solvers using machine learning and based on algorithms are very effective tools for designers to develop parametric building models, but they should continue to be developed to be more effective, understandable and easy, and designers should continue to collaborate with these technologies so that artificial intelligence can be effective in reducing the overload of architects, engineers and designers in building design with the ease of solving complex calculations and undertaking specific repetitive tasks. Today, as the Internet of Things and Artificial Intelligence become more prevalent in everyday life, it can be said that the designs produced by the tools that utilize them may become the norm in design. Optimized designs enabled by this once inconceivable technology are changing not only the industry but also the way this technology is viewed in building production processes.

Declaration of Ethical Standards

The authors declare that this research was conducted in accordance with ethical standards.

Credit Authorship Contribution Statement

Author 1: Conceptualization, Methodology / Study design, Software, Resources, Research, Experimentation, Writing – original draft Visualization, Writing – original draft.
Author 2: Conceptualization, Methodology / Study design, Resources, Research, Experimentation, Software, Validation, Formal analysis, Methodology, Visualization, Supervision, Project administration, Writing – original draft.
Author 3: Resources, Research, Experimentation, Formal analysis, Validation, Methodology, Visualization, Supervision, Project administration, Writing – original draft.

Declaration of Competing Interest

The authors declare that there is no conflict of interest.

Data Availability

All data generated or analyzed during this study are included in the published article.

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