Technical University of Munich

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Design Optimization in Early Project Stages

A Generative Design Approach to Project Development

Master Thesis

for the Master of Science Program Civil Engineering

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Abstract

Generative design uses the principles of evolution to improve design options iteratively. It adapts the three operators of selection, crossover, and mutation to generate solutions and evaluate them on design goals.

This study focuses on the potential this method holds for early project stages in the AEC industry. The goal is to produce a basic model of a project and optimize it in the aspects relevant to early project development.

To realize this goal, a design concept consisting of variables and constraints has to be developed. A set of relevant design metrics must be identified to evaluate design options and determine the direction of the optimization.

This approach is tested on a specific type of Siemens Real Estate office buildings. Seven variables and eight objectives are identified. A population of 120 solutions is assessed by the genetic algorithm NSGA-II over 50 generations.

The results include 14 different design options with their parameter values as well as their individual scoring in each objective. The solutions can easily be compared to each other based on the provided metrics.

When a well-defined vision of the design and a set of relevant evaluation measures exist, generative design can provide profitable solutions. It can help optimize a project and find the right geometry to fulfill non-geometric goals. However, some aspects that might be trivial to the human designer, but hard to translate into calculatable scores, will be elaborate to implement.

Keywords: Generative design, optimization, NSGA-II, architecture, project development, genetic algorithm, Refinery, multi-objective optimization

Zusammenfassung

Generatives Design ist eine digitale Entwurfsmethodik, die sich die Prinzipien der Evolution zunutze macht. In einem iterativen Prozess werden verschiedene Entwurfsoptionen verglichen und verbessert. Dabei werden die drei evolutionären Operatoren Selektion, Rekombination und Mutation angewendet, um neue Lösungsvorschläge zu generieren und anschließend auszuwerten.

Diese Studie beschäftigt sich mit dem Potential dieser Methodik für die Projektentwicklung in der Bauindustrie. Das Ziel ist es, ein Bauklötzchenmodell eines Projekts zu erzeugen und dieses im Hinblick auf die relevanten Aspekte der frühen Projektphasen zu optimieren.

Dafür wird ein abstraktes Design-Konzept benötigt, das die Entwurfsidee mit Hilfe von Randbedingungen und variablen Eigenschaften beschreibt. Außerdem müssen die Merkmale festgelegt werden, in denen die Entwurfsoptionen bewertet werden, da diese die Richtung der Optimierung bestimmen.

Dieser Ansatz wird an einem bestimmten Gebäudetypus von Siemens Real Estate Bürogebäuden getestet. Dabei werden sieben Entwurfsvariablen und acht Bewertungskategorien festgelegt. Mit dem genetischen Algorithmus NSGA-II wird eine Population mit 120 Individuen über 50 Generation optimiert.

Das Ergebnis besteht aus 14 verschiedene Entwurfsoptionen mit den jeweiligen Eigenschaften und Merkmalen. Die Ergebnisse lassen sich durch die vorhandene Bewertung gut miteinander vergleichen.

Es zeigt sich, dass durch generatives Design nützliche Entwürfe entstehen können, wenn die Entwurfsvision präzise definiert ist und die Beurteilungsparameter behutsam gewählt werden. Generatives Design kann dabei helfen, ein Projekt zu optimieren und die richtige Geometrie im Bezug auf nicht-geometrische Ziele zu finden. Manche Aspekte, die ein menschlicher Designer automatisch einhält, sind jedoch schwer in messbare Merkmale zu überführen und daher aufwendig in der Implementierung.

Schlüsselwörter: Generative Gestaltung, Optimierung, NSGA-II, Architektur, Projektentwicklung, genetischer Algorithmus, Refinery, Pareto-Optimierung

Table of Content

List of Abbreviations and Symbols

AI	Artificial intelligence
ANN	Artificial neural networks
BIM	Building information modeling
ConEx	Siemens Real Estate Construction Excellence
CSV	Comma-separated values
EA	Evolutionary algorithm
GA	Genetic algorithm
GUI	Graphical user interface
MOO	Multi-objective optimization
NSGA-II	Nondominated sorting genetic algorithm
SRE	Siemens Real Estate
wp	workplace

1 Introduction

1.1 Introduction

With the continuous research and public debate on artificial intelligence, it appears compelling to introduce the computer into the design process as well. Its creativity is untouched by convention or tradition, so when we give it the freedom to experiment, unexpected structures might emerge.

As humans, when we are faced with the task to arrange a floorplan, we are immediately drawn to rectangular shapes. An algorithm, however, has no idea how rooms usually look like and only respects the constraints we set. So, if the only constraint given is a list of rooms with desired sizes, it will start experimenting by assembling different shapes. We can influence the direction of these experiments by setting a goal for the algorithm, such as minimizing material.

On the right, the layout of an elementary school can be seen. Joel Simon used this rather traditional floorplan and converted it to a room program with size information for every room as well as adjacency requirements, such as the cafeteria must be placed next to the kitchen (Simon, 2017). These requirements were handed to a genetic algorithm (GA) for optimization. The goal of the study was set to minimize traffic flow between classrooms.

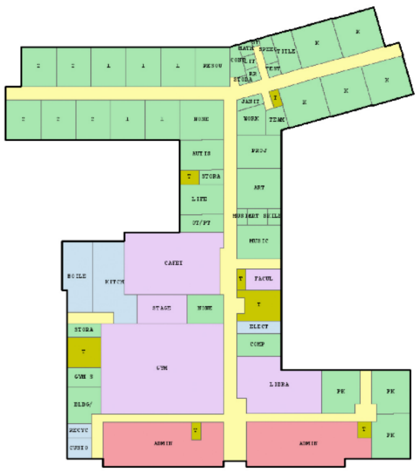


Figure 1 Original floorplan of a school in Maine, USA (Simon, 2017)

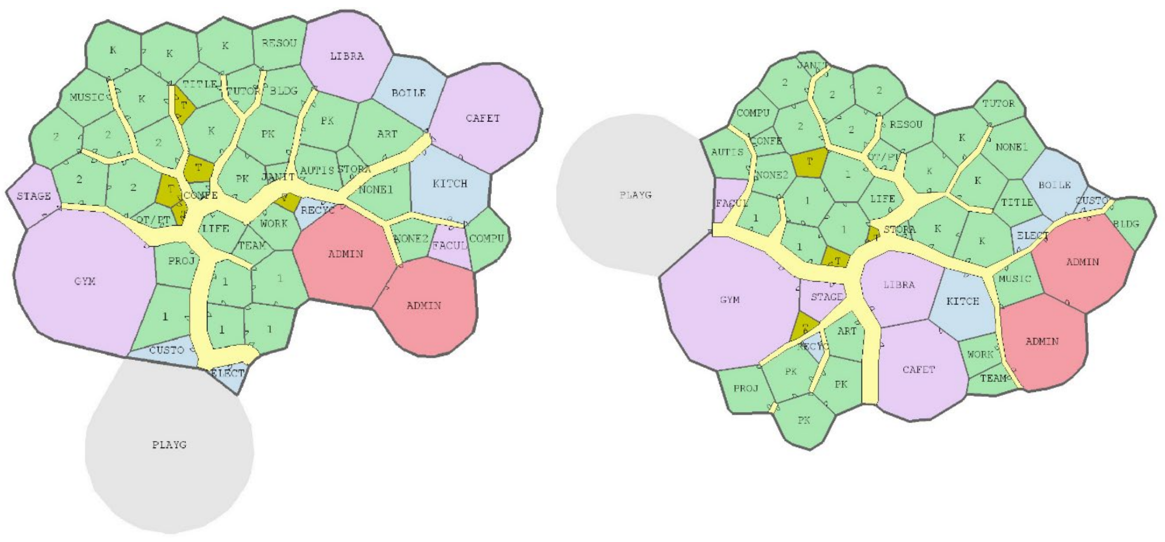


Figure 2 Results after optimization for minimal traffic between classes (left) and additional optimization for minimal fire escape paths (right); from: Simon (2017)

The results have an almost biological appeal, defying all rules of traditional architecture. The rooms become cell-shaped entities connected by vein-like corridors. When also optimized for daylight in the classrooms, the structure forms interior courtyards (Simon, 2017).

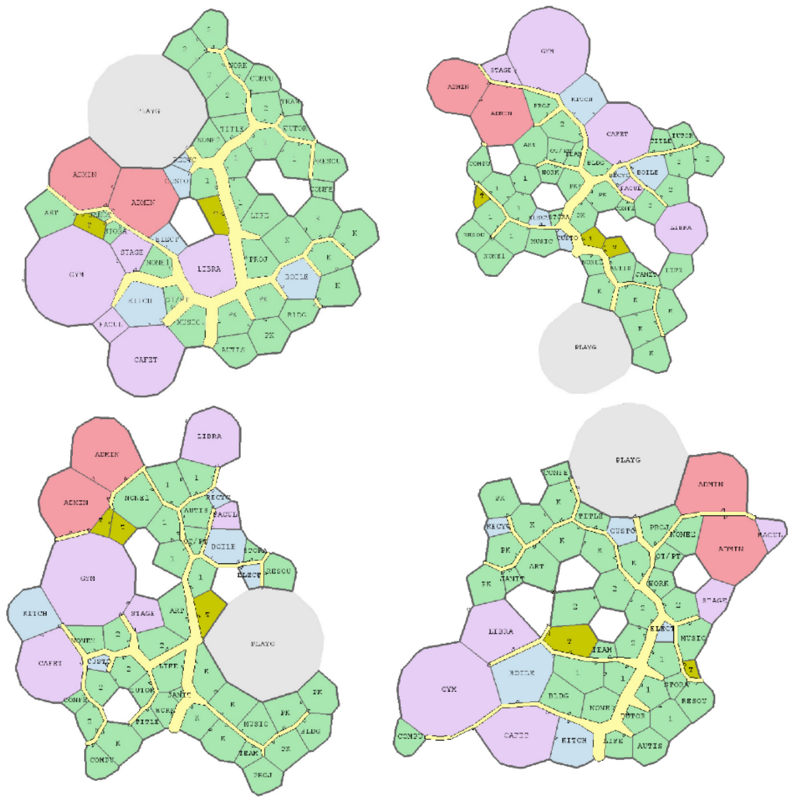


Figure 3 Results after windows were implemented as additional fitness function. Classrooms received higher priority for daylight than storage rooms; from: Simon (2017)

Needless to say, these constructs would be expensive in production as well as impractical in use. However, the experiment can be an inspiration to what effect artificial intelligence can have on the design process. At least, it can be a reminder of the boundaries we set our creativity as we proceed in age and academic education.

It also highlights the importance of setting clear constraints when working with generative design. The computer has no inherent understanding of the problem it is faced with. It can only apply the rules we teach it. Therefore, developing an abstract concept of the design is the first step in a generative design study. The concept consists of a set of geometric and arithmetic rules, that limit the space of possibilities just enough so the results can be useful in the eye of the human designer but leaving enough room for the algorithm to find unexpectedly positive solutions.

In this study, a respective design concept is developed and optimized in a generative design workflow. The design problem at hand consists of finding the right position, size, layout, and desk configuration for a Siemens office building on a pre-defined site. As it involves meta-elements such as position of the building on-site as well as micro-entities like a single desk, it is hard for a human designer to regard all aspects simultaneously. Experimentation shall determine whether generative design can provide a fruitful solving mechanism to this problem.

1.2 Motivation

The motivation of this research is to help with early-stage decisions in the project development process. If parts of the design finding procedure can be automated, reliable data is available sooner, and information significant to project development can be drawn from a model rather than from estimates.

Four stages are identified to set up a generative design study for a specific design problem:

1) Outlining of constraints and geometric rules, as well as open variables
2) Identification of criteria significant to early project stages and concurring design goals
3) Implementation of a model that allows to explore different design options as well as to assess them
4) Integration of said model into an optimization workflow

It is the goal of this study to use the generative design approach to optimize a specific type of Siemens office buildings in a pre-defined environment. For this purpose, a workflow consisting of three repetitive steps (generate – evaluate – evolve) must be customized to the project.

Furthermore, the right settings for the evolution (population size, number of generations, etc.) have to be detected to allow the algorithm to find optimal solutions. Finally, the results found can be assessed by the Siemens project developers.

1.3 Structure

In chapter 2, the basics of generative design are introduced. The concept of multi-objective optimization (MOO) is explained, and different genetic algorithms (GA) are compared. The nondominated sorting genetic algorithm (NSGA-II) is illustrated in more detail, as it will be used in the study.

Chapter 3 introduces the example studied in this paper, which is an architectural standard called Siemens Real Estate Construction Excellence. Furthermore, the three elements that make up a generative design study are defined: a parametric model that covers the entire solution space, a well-defined set of design goals and an optimization engine that drives the evolution – in this case, a software product called Refinery.

In chapter 4, two different approaches are followed to verify the functionality of both the NSGA-II algorithm and Refinery.

Chapter 5 focusses on the computational implementation of the study. The programming is executed in the form of a Dynamo graph. In this chapter, the elements and algorithms of the graph are explained as well as the settings of the generative design study in Refinery.

In chapter 6, experiments are run based on a real-life Siemens project in Hannover. The specifications of this project are discussed, as well as the limitations of the research. Finally, the results of the study are presented and assessed in an interview with Siemens Real Estate project managers.

Chapter 7 elaborates the findings of the research as well as the problems that occurred. It touches on further development of the tool as well as its integration into BIM processes.

2 Generative Design

2.1 Background

Design problems are multidimensional by nature (Nagy, 2017a). They consist of a complex network of non-linear functions, of which the solution is supposed to satisfy a multitude of goals like function, appearance, economic value, socio-political perception, etc. Since the time frame of a design process is usually limited, a human designer cannot possibly explore the entire design space but can only test and improve a minor amount of designs before deciding on a final solution.

With the advancement of artificial intelligence (AI) arises the idea of a symbiosis between the human designer and the power of a computer. While the computer has the computational capacities to produce copious quantities of design solution, the human designer possesses the intuition and experience to decide what makes a good design.

To attain this form of cooperation, we can learn from nature's evolutionary approach to design. Evolution is fueled by procreation – which is the intermixing of different sets of genes – combined with mutation – which brings in new random genes occasionally. The resulting offspring are then tested in the troubles of life leaving those to procreate (the most) which perform best. This eventually leads to a well-adapted set of genes.

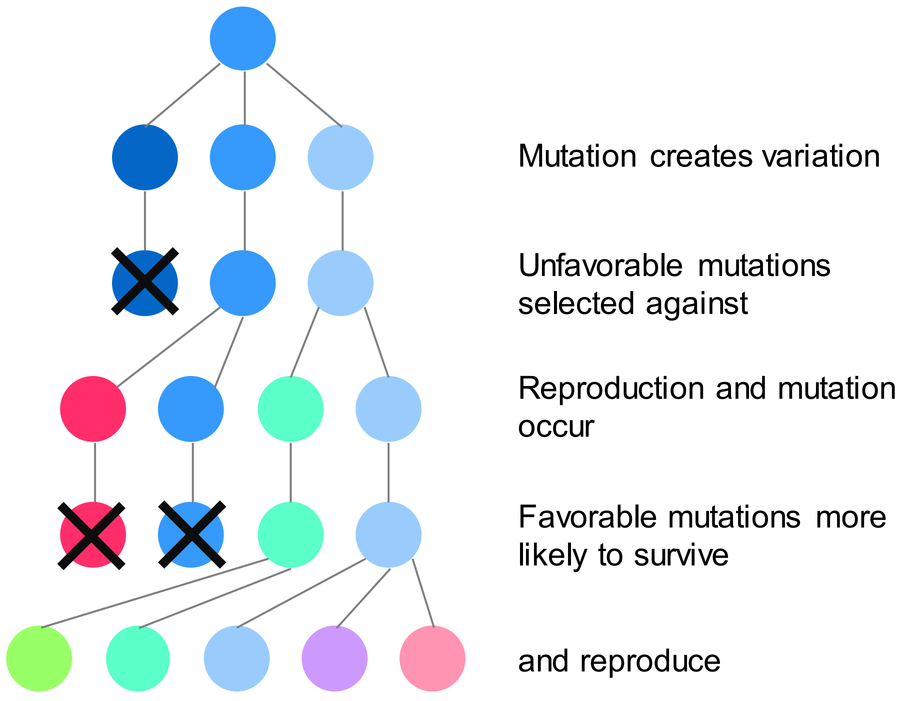

Mutation creates variation
Unfavorable mutations selected against
Reproduction and mutation occur
Favorable mutations more likely to survive
and reproduce

Figure 4 The evolutionary process in nature; inspired by Nagy (2017a)

Generative design mimics this process. It is able to “learn from designs it has analyzed, and apply that knowledge to generate new, better performing designs” (Nagy, 2017b). Its ability to learn makes this technology part of the larger framework of artificial intelligence. However, it does not make use of artificial neural networks (ANN), but falls into the category of metaheuristics – or “search algorithms” (Nagy, 2017b). The search algorithm that is used in most generative design studies is called genetic algorithm (GA), which is part of evolutionary algorithms (EA). It is based on three consecutive principles (Nagy, 2017a):

Generate

A population of different (design) solutions is created.

Evaluate

The fitness of the individual solutions is calculated.

Evolve

The best performing solutions are crossed over to generate a new population.

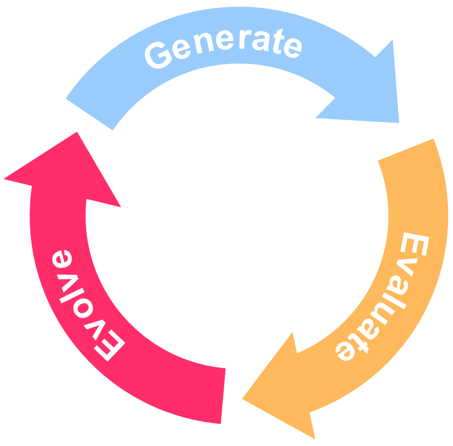


Figure 5 Iterative optimization process

This process is repeated for a declared number of generations or until a stop criterion is satisfied. For the algorithm to optimize the fitness of a population from generation to generation and eventually find the desired solution, it must be able to explore the entire solution space. The solution space is made up of the variety of every possible combination of “genes”. The genes, in this case, are the design variables – or more specifically, the parameters of a parametric model. A specific combination of values for these parameters produces a specific outcome which can then be evaluated.

If we think of a parametric model of a curtain wall façade, the defining parameters might be the amount of vertical and horizontal beams. With the surface of the façade being constant, the size of the glass panels results directly from those two parameters. An increasing number of beams leads to smaller glass panels and vice versa. The solution space of this example covers a variety of designs – from a façade with just a single panel (H = 0, V = 0), via very elongated panels (H < V), to a highly fragmented appearance (H = V = 100).

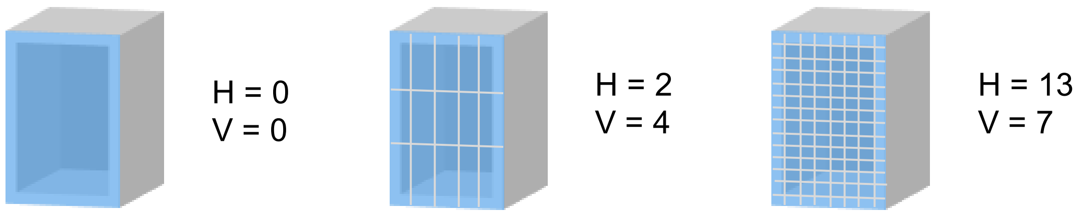


Figure 6 Three different façade configurations

To accelerate the installation of the façade, the number of glass panels shall be decreased. However, since bigger panels are harder to produce, the price/m² rises significantly with the size. Every possible façade can, therefore, be evaluated based on its number of panels and the total cost for all panels. They make up the fitness of a solution.

Minimizing panel quantity and minimizing cost are the design goals in this example. They determine the direction in which the optimization is heading. The solutions with the highest fitness value form the base for the next generation of designs.

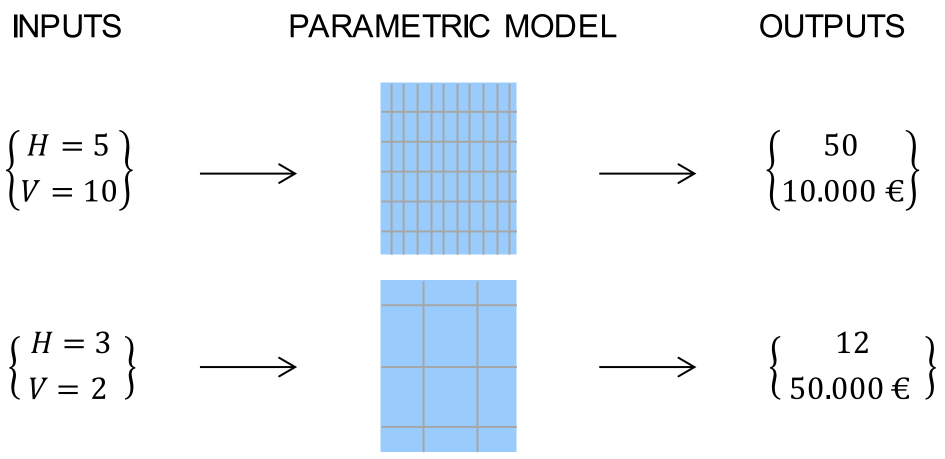


Figure 7 The function of the parametric model

Hence, the parametric model is a curial part of a generative design study. The model must be capable of taking in different values of its design variables and output the corresponding evaluation results. It is the task of the human designer to define the design parameters – and hereby the solution space – as well as the design goals – and hereby, the measures by which a solution is evaluated. The genetic algorithm can then explore the solution space by changing the parameters' values and registering the outcome. The parametric model itself remains a black box to the algorithm. By defining design goals (minimize or maximize an outcome), the algorithm can learn which values increase the performance and optimize the model to a desirable outcome.

2.2 Multi-Objective Optimization

The complexity of the design process usually arises from the multitude of criteria that are to be satisfied but contradict each other in nature. For example, maximizing the comfort of an apartment leads to an increased floor area, but at the same time, minimizing rent leads to a decreasing floor area.

Finding optimal decisions in the presence of two or more conflicting goals is called multi-objective optimization (MOO). “For a nontrivial multi-objective optimization problem, no single solution exists that simultaneously optimizes each objective” (Multi-objective optimization, 2019). A trade-off situation occurs, in which no objective function can be increased in value without reducing at least one of the other objective values. Hence, there cannot be one single solution to satisfy all objectives, but instead, several Pareto optimal solutions exist. A solution is called Pareto optimal or nondominated when none of its objective values can be improved without decreasing some of its other values. Therefore, no solution exists that performs better in all of the objectives.

From a mathematical perspective, a MOO-problem can be described as:

$$\min\left(f_1(x), f_2(x), \ldots, f_k(x)\right);$$

$$s, t, x \in X;$$

(Miettinen, 1999)

The functions f_1 to f_k represent objective functions, with k being the number of objectives. A vector of input data X describes every possible design in the system. X is usually limited by some constraint functions. Maximizing a particular objective function can be achieved by minimizing its negative. “An element $x^* \in \mathrm{X}$ is called a feasible solution or a feasible decision. A vector $z^* := f(x^*) \in R^k$ for a feasible solution x^* is called an objective vector or an outcome “ (Multi-objective optimization, 2019).

The goal of a MOO is to find a set of nondominated solutions. A solution $x^1 \in \mathrm{X}$ dominates another solution, if

1. $f_i(x^1) \leq f_i(x^2)\ for\ all\ indices\ i \in \{1, 2, \dots, k\}$ and
2. $f_j(x^1) < f_j(x^2)\ for\ at\ least\ on\ index\ j \in \{1, 2, \dots,\ k\}$. (Miettinen, 1999)

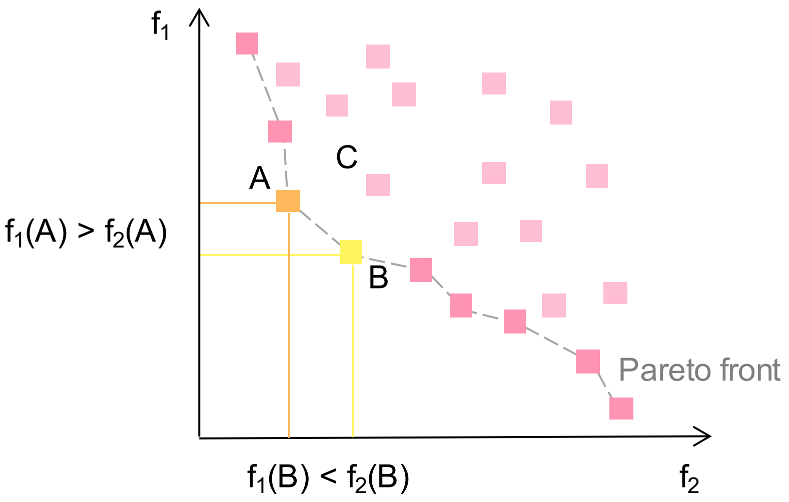


Figure 8 "Point C is not on the Pareto frontier because it is dominated by both point A and point B. Points A and B are not strictly dominated by any other, and hence lie on the frontier" (Dréo, 2006); inspired by Dréo (2006)

All solutions not dominated by any other solution form the Pareto frontier. It is the goal of generative design to deliver a diverse set of solutions converging near the Pareto frontier. This enables a human decision-maker to pick a favorable design solution knowing that it cannot be optimized further.

2.3 Genetic Algorithms

Genetic algorithms (GA) are used for solving multi-objective optimization (MOO) problems. The first-ever GA was proposed by John Holland in his book "Adaptation in Natural and Artificial Systems" (1975).

> *"It is possible to give genetic processes an algorithmic formulation that makes them available as control procedures in a wide variety of situations. By using an appropriate production (rule-based) language, it is even possible to construct sophisticated models of cognition wherein the genetic algorithm, applied to the productions, provides the system with the means of learning from experience."*
>
> *John Holland (Holland, 1984).*

Holland translated the principles of evolution into a computational algorithm. His model proved to “search the space of chromosomes in a way much more subtle than a ‘random search with preservation of the best ‘” (Holland, 1984).

In general, the workflow of a GA can be described as follows:

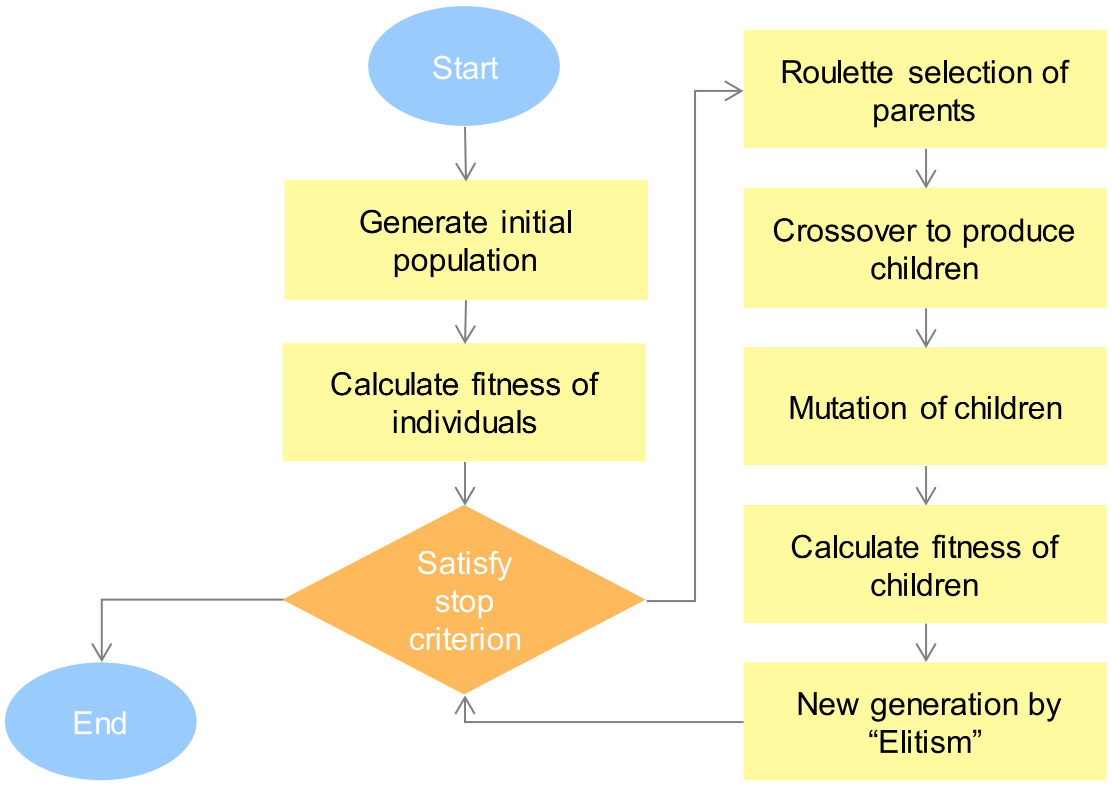

Start
Generate initial population
Calculate fitness of individuals
Satisfy stop criterion
End
Roulette selection of parents
Crossover to produce children
Mutation of children
Calculate fitness of children
New generation by “Elitism”

Figure 9 Basic model of a genetic algorithm (GA); inspired by Nagy, 2017b

An initial population of individuals is created randomly. They form the parent population of the first generation. Then the fitness of each individual is calculated. If the fitness value of one of the solutions satisfies a stop criterion, the algorithm ends. If not, the evolutionary principles of selection, breeding, and mutation are applied. Two individuals of the first generation are selected to mate, meaning their chromosomes get crossed over to form a new individual – the children population of the first generation. Then mutation is randomly applied to the children to bring in random fresh, possibly fitter DNA.

Afterward, the fitness of the individuals in the children population is calculated. Together with the parent population, all individuals of the first generation get sorted by their achieved fitness level. The process of ranking the children population together with the parent population is called elitism. It ensures the preservation of previously found good solutions. The highest-ranking individuals form the next generation in the optimization process.

Since the early model developed by Holland, different variations of the genetic algorithms (GA) or evolutionary algorithms (EA) have been proposed. They vary mostly in the way they rank and select solutions for the new parent population.

Early GAs with low computational complexity but no elitism are (Samuelson Hong, 2012):

- VEGA (Vector evaluated GA) (Schaffer, 1985)
- MOGA (Multi-objective GA) (Fonseca & Fleming, 1993)
- NPGA (Niched Pareto GA) (Horn, Nafpliotis & Goldberg, 1994)

They either fail to provide a diverse set of solution or converge to the Pareto frontier very slowly. Elitism, however, has shown to speed up the performance of a GA while preserving good solutions once they are found (Deb, Pratap, Agarwal, & Meyarivan, 2002). In the following three commonly known elitist GAs are discussed (Samuelson Hong, 2012).

PAES – Pareto Archived Evolution Strategy (Knowles & Corne, 1999)

The PAES is the simplest of the three. It keeps a population size of 1 and uses local search to optimize the solution. Previously found solutions are stored in a reference archive against which candidate solutions are compared by Pareto dominance (Knowles & Corne, 1999).

While it ensures the preservation of previously found solutions, the lack of population size slows down the system, and the overall performance is based on the size of the searched neighborhood (Samuelson Hong, 2012).

SPEA – Strength Pareto Evolutionary Algorithm (Zitzler & Thiele, 1999)

SPEA uses an external archive as well as a population size that is usually bigger than the size of the archive (Brownlee, 2015). It ranks solutions based on a combination of domination and estimation of density of the Pareto front. However, these calculations are computationally expensive (Samuelson Hong, 2012).

NSGA – Nondominated Sorting GA (Srinivas & Deb, 1994)

NSGA uses fast nondominated sorting to compute the domination rank of a solution and crowding-distance computation to achieve a diverse set of solutions. Initially, the algorithm lacked elitism and had a computational complexity of $O(MN^3)$ for M objectives and N population size, making the algorithm cubically more expensive with increasing population size. However, a new version of the algorithm was introduced in 2000 called NSGA-II. It has a computational complexity of O(MN^2) and is elitist as the parents and the offspring are combined before ranking. NSGA-II gained much appreciation and is widely used in optimization problems (Samuelson Hong, 2012) (Garcia & Trinh, 2019) (Machairas, Tsangarassoulis, & Kleo, 2014).

Different MOO problems require different solution strategies. In the design problem at hand, it is very important to provide a diverse set of solutions, so that a human decision-maker can choose a design favorite based on his or her subjective preferences. NSGA-II has proven to outperform PAES and SPEA in its ability to find a diverse set of solutions (Deb, Pratap, Agarwal, & Meyarivan, 2002). This is also the case when compared to the improved version SPEA2 (Zitzler, Laumanns, & Thiele, 2001). SPEA2 shows less clustering, but NSGA-II provides a broader spread of solutions, i.e., “found solutions closer to the outlying edges of the Pareto-optimal front” (Kunkle, 2005). Therefore, it is chosen for the study at hand and explained in more detail in the following chapter.

2.4 NSGA-II

Any algorithm striving to solve a MOO problem can be rated by its capability to accomplish the following goals (Chiandussi, Codegone, Ferrero, & Varesio, 2012):

- its preservation of previously found nondominated points
- its progress toward the Pareto front (convergence rate)
- the diversity of points on the Pareto front it provides
- its ability to provide the human decision-maker with an appropriately sized number of solution points for selection

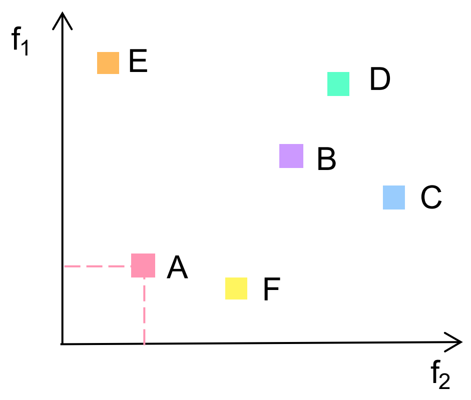
NSGA-II uses three characteristic properties to enhance its optimization – a fast non-dominated sorting approach, a fast crowded distance estimation procedure, and a simple crowded-comparison operator (Yusoff, Ngadiman, & Zain, 2011). The algorithm sorts a population into hierarchic sub-populations based on their rank of Pareto dominance. Within a group, the similarity of solutions is measured to maintain diversity. Deb et al. (2002) state that in several different test problems “NSGA-II was able to maintain a better spread of solutions and converge better in the obtained nondominated front comparted to […] PAES and SPEA” (Deb et al., 2002).

A closer look into the elements that make up NSGA-II is given in the following chapter concluded by an overview of the entire workflow.

2.4.1 Fast Nondominated Sorting

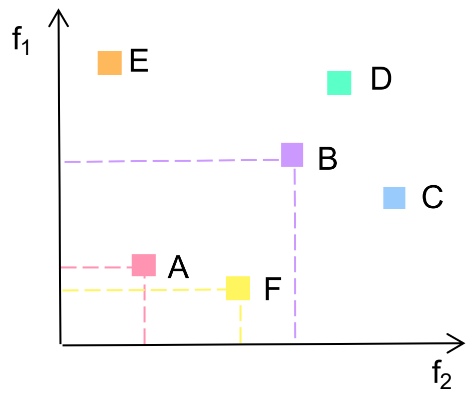
A crucial question concerning MOO problems is: In the face of multiple objectives, how do you compare one solution to another? How can the overall fitness of a solution be calculated so that the solutions of a population can be ranked amongst each other?

The NSGA-II uses a fast procedure of sorting solutions into groups. Every solution p receives a domination count n_p “the number of solutions which dominate the solution p” and S_p “a set of solutions that the solution p dominates” (Deb et al., 2002). This involves $O(MN^2)$ comparisons (Deb et al., 2002).



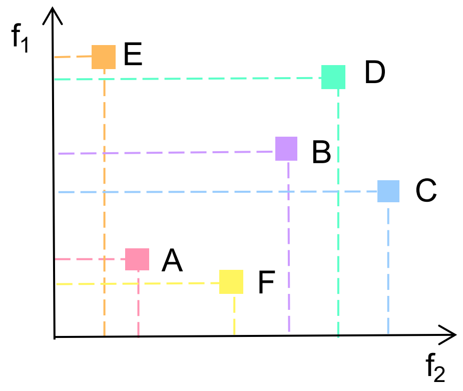
	n_p	S_p
A	0	
B		
C		
D		
E		
F		

Figure 10 When we look at A, it is not dominated by any other solution. Therefore, its domination count is 0.



	n_p	S_p
A	0	{B}
B	2	
C		
D		
E		
F		{B}

Figure 11 When we look at B, it is dominated by A and F. Therefore, its domination count is 2 and B is added to the dominated set S_p of A and F.



	n_p	S_p
A	0	{B, C, D}
B	2	{D}
C	2	null
D	3	null
E	0	null
F	0	{B, C, D}

Figure 12 After all comparisons are finished, each solution is equipped with a domination count and a set of dominated solutions.

```
fast-non-dominated-sort($P$)
for each $p \in P$
   $S_p = \emptyset$
   $n_p = 0$
   for each $q \in P$
      if $(p \prec q)$ then                If $p$ dominates $q$
         $S_p = S_p \cup \{q\}$             Add $q$ to the set of solutions dominated by $p$
      else if $(q \prec p)$ then
         $n_p = n_p + 1$                    Increment the domination counter of $p$
   if $n_p = 0$ then                        $p$ belongs to the first front
      $p_{\text{rank}} = 1$
      $\mathcal{F}_1 = \mathcal{F}_1 \cup \{p\}$
$i = 1$                                     Initialize the front counter
while $\mathcal{F}_i \neq \emptyset$
   $Q = \emptyset$                          Used to store the members of the next front
   for each $p \in \mathcal{F}_i$
      for each $q \in S_p$
         $n_q = n_q - 1$
         if $n_q = 0$ then                  $q$ belongs to the next front
            $q_{\text{rank}} = i + 1$
            $Q = Q \cup \{q\}$
   $i = i + 1$
   $\mathcal{F}_i = Q$
```

Figure 13 Pseudocode of the fast nondominated-sorting algorithm; from: Deb et al. (2002)

All solutions that have a domination count $n_p = 0$ lie on the first nondominated front. Now for each solution with $n_p = 0$, the members of its set S_p are visited, and their domination count is reduced by one (Deb et al., 2002).

	n_p	S_p
A	0	{B, C, D}
B	2	{D}
C	2	null
D	3	null
E	0	null
F	0	{B, C, D}

$\longrightarrow$

	n_p	S_p
A	-	-
B	0	{D}
C	0	null
D	1	null
E	-	-
F	-	-

Figure 14 In the first step, all solutions with a domination count of 0 are grouped into the first front. The members of their dominated sets S_p receive a reduction of 1 in their domination count

Afterward, all solutions with $n_p = 0$ are grouped as the second nondominated front. Now the members in the sets of these solutions are visited. This process is continued until all solutions are grouped into fronts (Deb et al., 2002).

	n_p	S_p
A	-	-
B	0	{D}
C	0	null
D	1	null
E	-	-
F	-	-

$\longrightarrow$

	n_p	S_p
A	-	-
B	-	-
C	-	-
D	0	null
E	-	-
F	-	-

Figure 15 In the second step, this process repeated with the solutions that now have a domination count of 0.

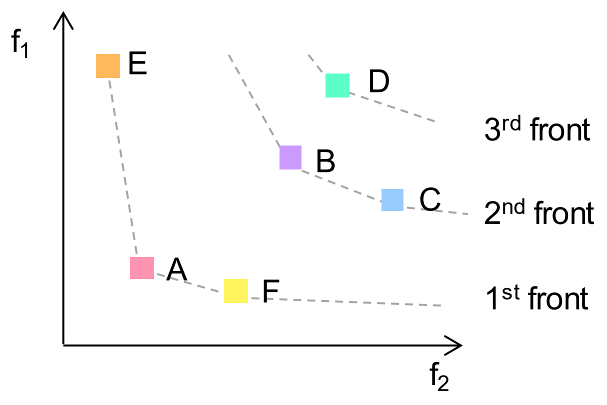


Figure 16 This process is repeated until all solutions are sorted into fronts.

2.4.2 Crowding Distance Computation and Operator

As earlier mentioned, it is desired that, along with convergence to the Pareto optimal front, the algorithm also maintains a level of variety in its solutions. This helps to avoid convergence to local minima and offers a diverse set of options to the human decision-maker. This means – when at the same fitness level – a solution from a less crowded region is preferred to a solution in a crammed region. To estimate the density of a solution's neighborhood, the NSGA-II established the crowding distance computation.

For a solution p, the average distance of two points on either side of this point along each of the objectives is calculated (Deb et al., 2002).

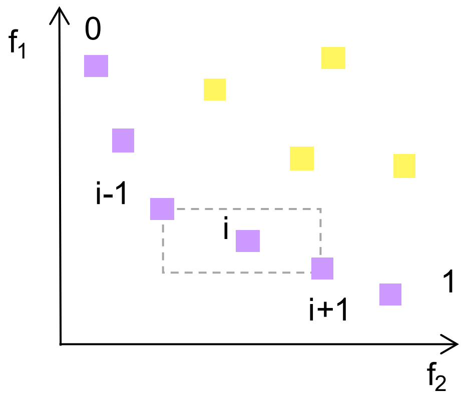


Figure 17 Crowding distance calculation (Points marked in purple are solutions of the same non-dominated front); inspired by Deb et al. (2002)

In the case of two objectives f_1, f_2 the crowding distance of the ith solution is the average side length of the rectangle formed by the two closed points within its rank (marked in purple) (Deb et al., 2002).

After the crowding-distance computation, every solution is equipped with two attributes: a nondomination rank i_{rank} based on its nondominated front and a crowding distance $i_{distance}$. When the crowded-comparison operator $<_n$ is presented with two solutions, it returns the solution with the lower rank, or if the rank is equal, it prefers the solution from a less crowded region (Deb et al., 2002).

$$\begin{aligned}
&i <_n j \ if \ (i_{rank} < j_{rank}) \\
&or \ ((i_{rank} = j_{rank}) \\
&and \ (i_{distance} > j_{distance}))
\end{aligned}$$

Figure 18 The crowded-comparison operator $<_n$

2.4.3 Main loop

For every generation t (t ≠ 0)[1] there exists a set of parent solutions P_t and offspring solutions Q_t. Each set is of size N. They form the combined population $R_t = P_t \cup Q_t$.

In a first step, the population R_t is sorted into fronts according to nondominated sorting. Since the combined population is sorted, previously found well-performing solutions are included, and Elitism is guaranteed.

Now, the parent population P_{t+1} of the next generation is to be created from the best members of the previous generation. If the size of F_1 is smaller than N, all members of F_1 are transferred P_{t+1}. Subsequent sets are chosen in the same fashion until P_{t+1} contains N members. If the last chosen set has more members than the remaining positions in P_{t+1}, crowding distance sorting is applied to the set in order to find the best solution to complete the population (Deb et al., 2002).

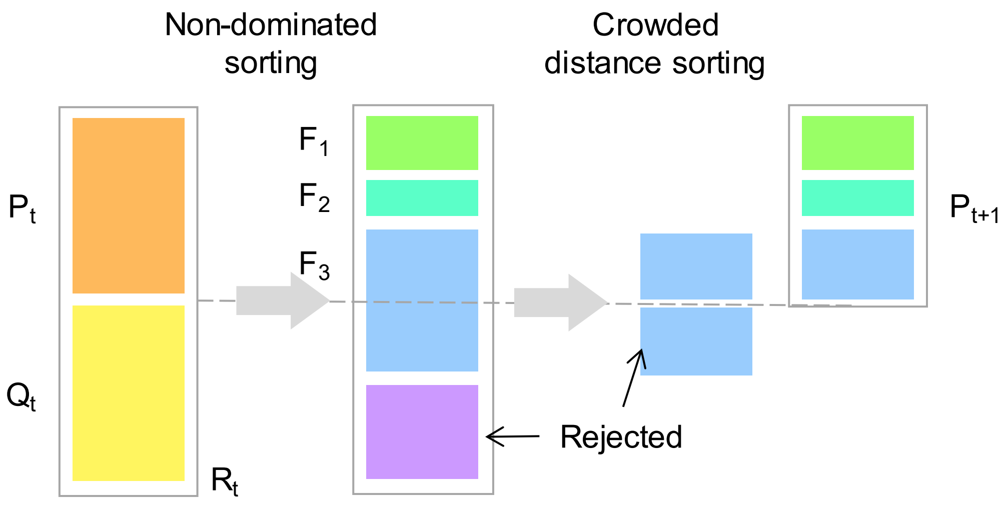


Figure 19 The NSGA-II procedure; inspired by Deb et al. (2002)

The advantage of this practice is that sorting within a rank is not necessary unless it is split up, which makes the algorithm faster. The new parent population P_{t+1} is now used to create its offspring population Q_{t+1} through selection, crossover, and mutation.

[1] Since the first generation has no parent population, the first population P_0 is generated randomly.

2.4.4 Tournament selection

In the selection process members of a parent population are chosen to be inserted into a mating pool. The solutions in the mating pool are used to generate offspring. Better solutions are to procreate more than lower-performing solutions in hopes of creating offspring with higher fitness. The selection pressure describes the "degree to which the better individuals are favored" (Sivanandam & Deepa, 2008). The selection pressure pushes the GA to improve the population fitness. Therefore, a higher selection pressure accelerates the convergence rate to the Pareto front. However, when the selection pressure is too high, the GA might prematurely converge to a local minimum.

To select solutions for mating, tournaments are held among the members of a parent population. How these tournaments are executed, determines the selection pressure. The procedure used in NSGA-II is called binary tournament selection. Two individuals are randomly chosen and compete against each other. The winner gets determined through the crowding distance operator, which means the solution with the lower domination rank i_{rank} wins unless the competitors have the same rank in which case the solution with lower crowding distance $i_{distance}$ wins (Deb et al., 2002).

A copy of the winner enters the mating pool. The original solution is still available for tournament, which means better solutions have a higher chance of entering the mating pool several times. Consequently, it will produce more offspring (Sivanandam & Deepa, 2008). The tournaments get repeated until the mating pool is filled. For instance, a binary tournament for a population of 6 solutions {A, B, C, D, E, F} (in order of fitness) could look like this:

Tournament 1:	{A, E}	→	A
Tournament 2:	{C, B}	→	B
Tournament 3:	{F, E}	→	E
Tournament 4:	{D, A}	→	A
Tournament 5:	{E, B}	→	B
Tournament 6:	{C, F}	→	A

Changing the number of tournament participants or hosting two-stage tournaments increased the selection pressure. If e.g., 4 participants enter the tournament it is much more likely that the best solution is part of the tournament and therefore it will occur more often in the mating pool.

{A, E, C, B}	→	A
{F, E, D, A}	→	A
{E, B, C, F}	→	B
{B, D, E, A}	→	A
{C, B, F, E}	→	B
{F, E, D, C}	→	C

		Stage 1		Stage 2
{A, E}	→	A	→	A
{C, B}	→	B		
{F, E}	→	E	→	A
{D, A}	→	A		
{E, B}	→	B	→	A
{C, F}	→	A		

2.4.5 Crossover and Mutation

Crossover is the process of recombining the chromosomes of two parents for reproduction. The chromosomes in a generative design study are the design variables of the parametric model. The values of these variables are stored in bit arrays. To crossover two parents are randomly chosen from the mating pool. Since better solutions have entered the mating pool multiple times, they have a higher probability of being chosen. Next, the chromosomes of the parents form an offspring.

There are multiple ways to determine which chromosome from which parent enters the genome of the child, the simplest being the single-point crossover. A random point is chosen on both parents' chromosomes. The sections behind that point get switched to form two child solutions. Each of them carries some genetic information from each of its parents.

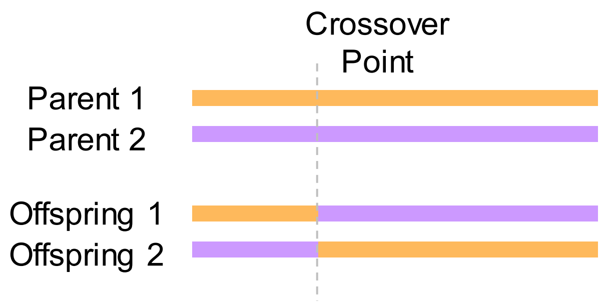


Figure 20 Single-point crossover

This form of crossover can be performed with more than one point, in which case it is called two-point or multi-point crossover (Sivanandam & Deepa, 2008).

A completely different approach is presented by the uniform crossover. A random binary mask is generated with the same length as the number of chromosomes. Now the offspring is created by copying parent chromosomes according to the crossover mask. For the first child, if there is a 1 in the crossover mask, the chromosome is taken from the first parent, and if there is a 0 in the mask, the second parent's chromosome is copied. For the second child, the rules are switched. (Sivanandam & Deepa, 2008).

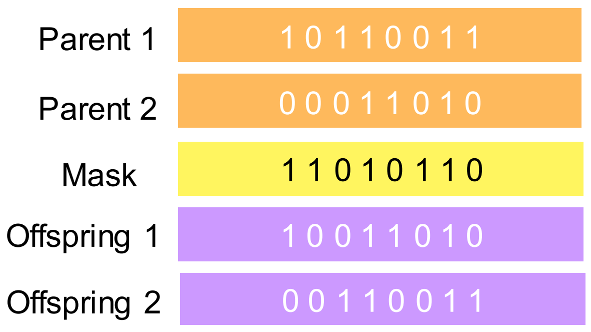


Figure 21 Uniform crossover; inspired by Sivanandam & Deepa (2008)

Other crossover strategies include three-parent crossover, shuffle crossover, precedence preservative crossover (PPX), partially matched crossover (PMX), etc. (Sivanandam & Deepa, 2008).

Crossover is made in the hope that good parts of the parents' chromosomes are combined and together makeup even better chromosomes and increase the fitness of an offspring solution. However, it does not add any new genetic information to the population. Therefore, after crossover, mutation is applied to the newly formed solutions. It ensures the exploration of the entire solution space and hence contributes to the avoidance of local minima.

The frequency in which mutation occurs is determined by the mutation probability (P_m). If the mutation probability is set to a low value, the population is subjected to very little mutation, and the GA might run the risk of converging to a local minimum. If the probability is set to a very high value, then GA is equal to a random search (Sivanandam & Deepa, 2008).

Three common forms of mutation are:

Flipping

A chromosome is chosen for flipping according to P_m, which means the bit is changed from 0 to 1 and 1 to 0. The higher P_m, the more bits are flipped. This is true for all three mutation methods.

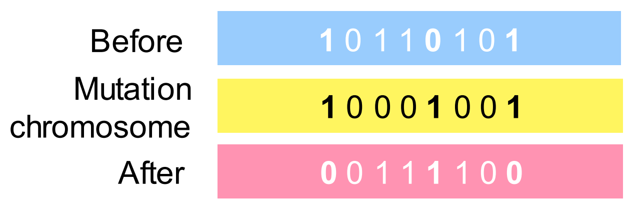


Figure 22 Flipping; inspired by Sivanandam & Deepa (2008)

Interchanging

Two random positions on the string are chosen, and their bits are exchanged.

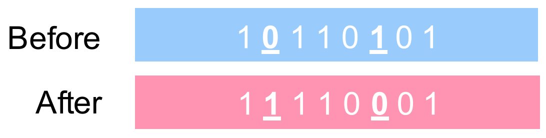


Figure 23 Interchanging; inspired by Sivanandam & Deepa (2008)

Reserving

Two neighboring bits are chosen and switched.

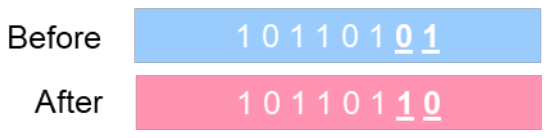
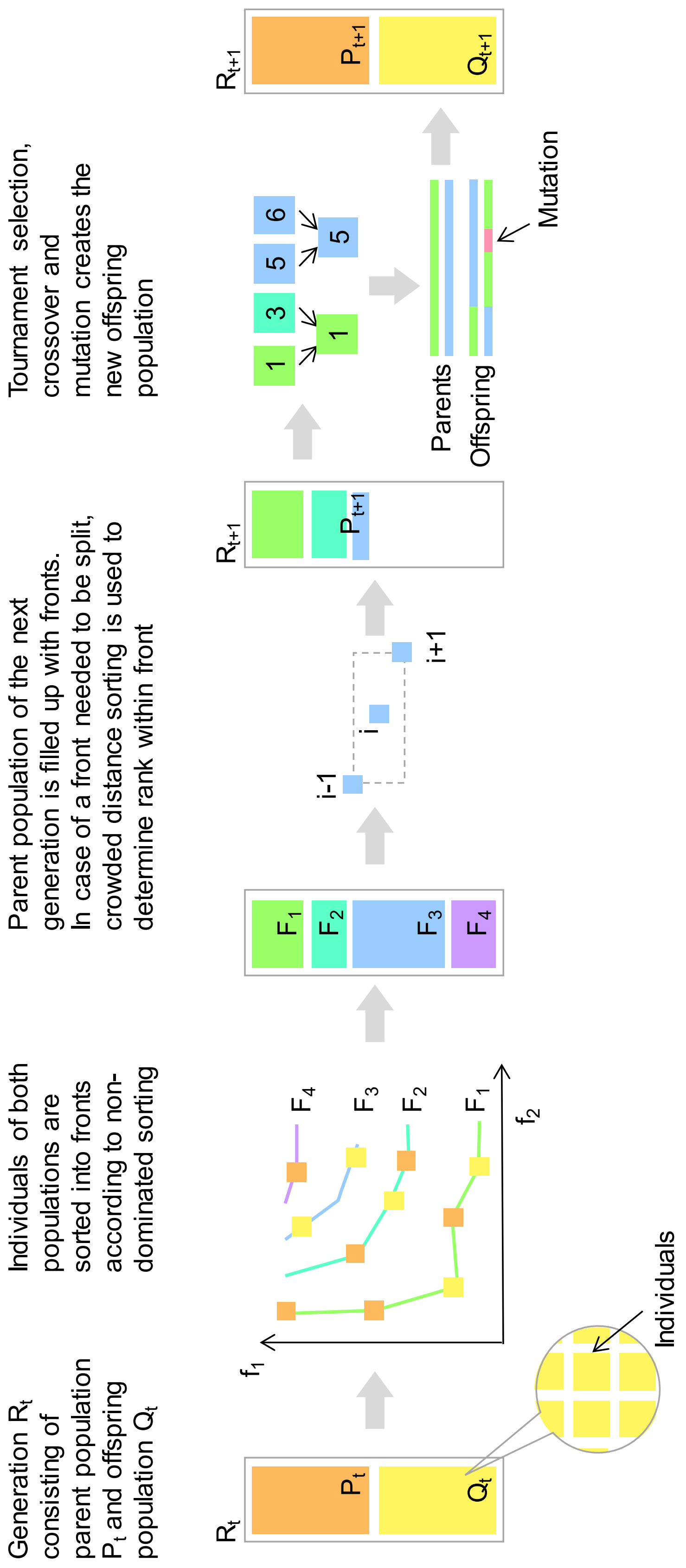


Figure 24 Reserving; inspired by Sivanandam & Deepa (2008)

2.4.6 Summary


Generation R_t consisting of parent population P_t and offspring population Q_t
R_t
P_t
Q_t
Individuals
Individuals of both populations are sorted into fronts according to non-dominated sorting
f_1
f_2
F_1
F_2
F_3
F_4
Parent population of the next generation is filled up with fronts. In case of a front needed to be split, crowded distance sorting is used to determine rank within front
F_1
F_2
F_3
F_4
i-1
i
i+1
R_{t+1}
P_{t+1}
Tournament selection, crossover and mutation creates the new offspring population
1
3
5
6
1
5
Parents
Offspring
Mutation
R_{t+1}
P_{t+1}
Q_{t+1}

3 Methodology

3.1 Project Development

Project development marks the first phase of a potential construction project. During this phase, it is evaluated if and how a project could be beneficial or profitable. At the end of this stage, the developer should be able to make an educated decision about the realization of the project (Zimmermann, 2017).

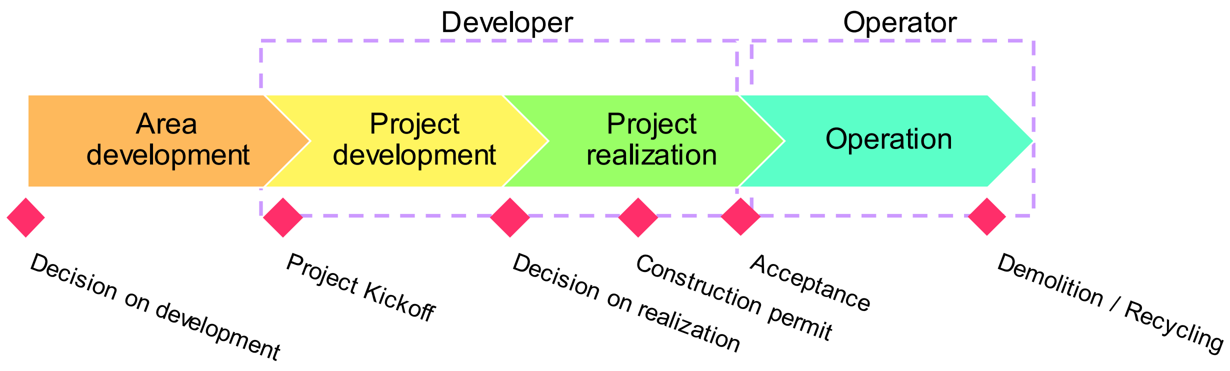


Figure 25 Phases of real estate development; inspired by Zimmermann (2017)

To make this decision, a series of studies, investigations, and calculations are carried out. One element is cost-benefit-analysis in which the anticipated costs of constructions are challenged against the potential revenue from rent or sale (Zimmermann, 2017).

However, since a reliable design of the project does not exist yet, the developer has to rely on assumptions and benchmarks to make the calculations. The less that is known about the geometry and the equipment of the project, the vaguer are the predictions.

The goal of this paper is to find out if generative design can be of help to these early stages of a project. Can some of the planning decisions already be made in project development, so that the relevant numbers can be based on design rather than benchmarks?

Siemens Real Estate (SRE) serves as an example in this study. They develop and operate Siemens' offices and factories all over the world.

> *Siemens Real Estate (SRE) is responsible for all of Siemens' real estate activities – managing the company's real estate portfolio, optimizing the utilization of space, and overseeing the operation of its real estate holdings including all real-estate-related services, as well as having responsibility for leasing and disposing of real estate assets and implementing all construction projects Siemens-wide.*
>
> *Siemens Real Estate Website (Siemens, 2019)*

The focus of the research is to develop a generative design tool that delivers and optimizes the design of an SRE office building for a specific project. The generated model should deliver the relevant information for project development and should be optimized to the requirements of both Siemens and specific project conditions.

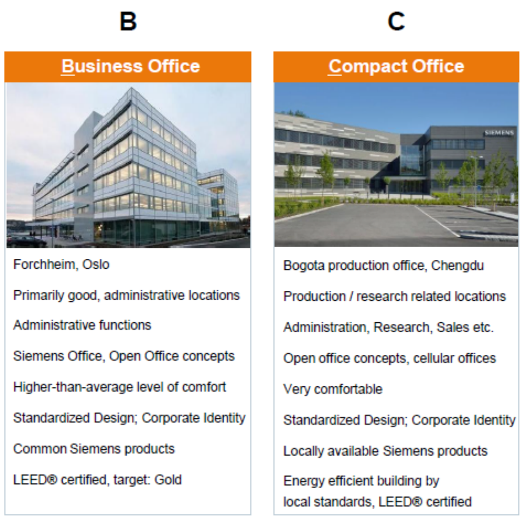
3.2 Siemens Real Estate Construction Excellence

The Siemens Real Estate Construction Excellence (ConEx) is a technical and architectural standard developed by SRE.

"Construction Excellence […] is a strategic approach to provide market-ready office buildings, which are suitable for Siemens and/or other users. Those buildings incorporate Construction Excellence Standards and Siemens' branding features." (Construction Excellence Office EMEA „Design Principles", 2015).

It describes the elements that compose a Siemens office building from a single workplace to complex ventilation systems. Its modular approach is adaptive to different climate zones, market levels, site conditions, and market-typical office typology.

Depending on the function of the office, two different quality levels can be chosen - market-level B for administrative functions and market-level C for administration, research, and sales. The market-typical office typology decides the choice between a narrow and a wide layout. Each layout can then be used in different configurations like block shape, H-shape, E-shape, or courtyard type.



B	C
Business Office	Compact Office
Forchheim, Oslo	Bogota production office, Chengdu
Primarily good, administrative locations	Production / research related locations
Administrative functions	Administration, Research, Sales etc.
Siemens Office, Open Office concepts	Open office concepts, cellular offices
Higher-than-average level of comfort	Very comfortable
Standardized Design; Corporate Identity	Standardized Design; Corporate Identity
Common Siemens products	Locally available Siemens products
LEED® certified, target: Gold	Energy efficient building by local standards, LEED® certified

Figure 26 Quality levels in ConEx

Standardized buildings are specifically convenient for parametric modeling – and consequently generative design – since there is a predefined set of design variables and design restrictions. In case of ConEx, there is a fixed building width of 15.60 m in the narrow and 24.00 m in the wide building type.[2] In a broader sense, the building consists of three basic elements: core units, office units, and seam units.

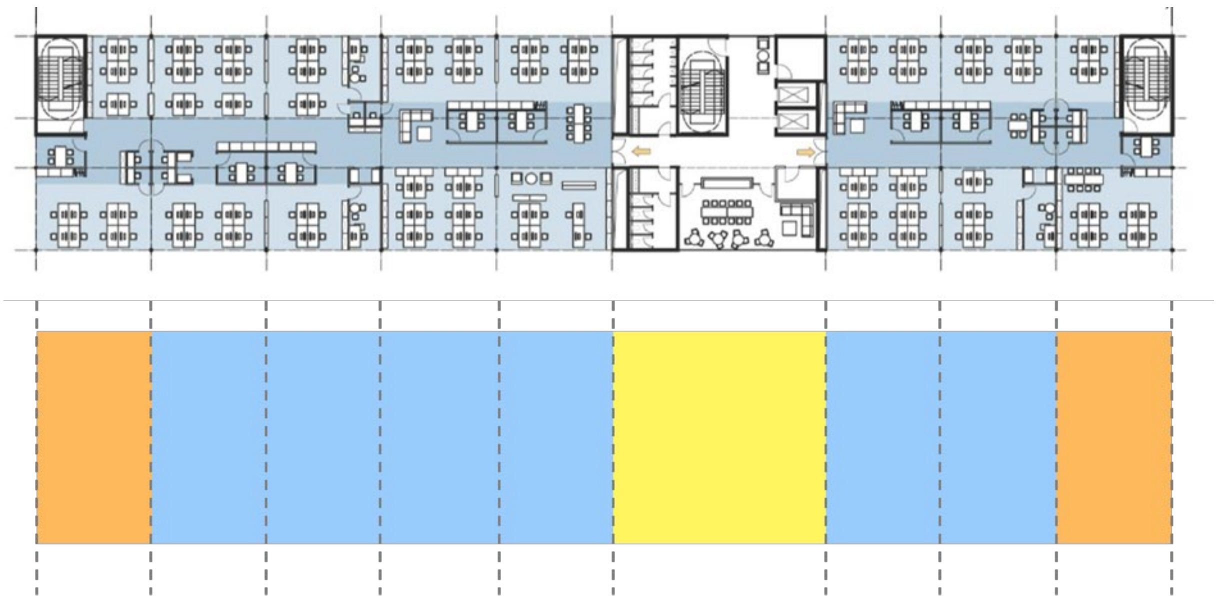


Figure 27 Core unit (yellow), office units (blue) and seam units (orange) in a standard ConEx layout

Core units contain the elements necessary for vertical circulation like stairs and elevators as well as sanitary and maintenance facilities. The office units accommodate the workplaces. Apart from standard workplaces, there is also a choice of hot desks, think tanks, phone boxes, and lounges provided to the employees. The seam units are of

[2] In case of structural grid width of 8.40 m. Structural grid width may vary according to local standards.

the same dimensions as the office units but contain fewer workplaces as they include a second pair of stairways.

For reasons of fire safety and building services, a sequence of four consecutive office units must be followed by either a core or a seam unit.

Analogous to ConEx, only the implementation of the block-shaped office is described in detail in this generative design study. The implementation of other configurations is discussed in Chapter 7 Discussion and Outlook.

3.3 Parametric Model

> *"Parametric models used in design are composed of a variety of modules that combine computation with geometric operations, none of which are easily differentiable."*
>
> *Danil Nagy (The problem of learning, 2017)*

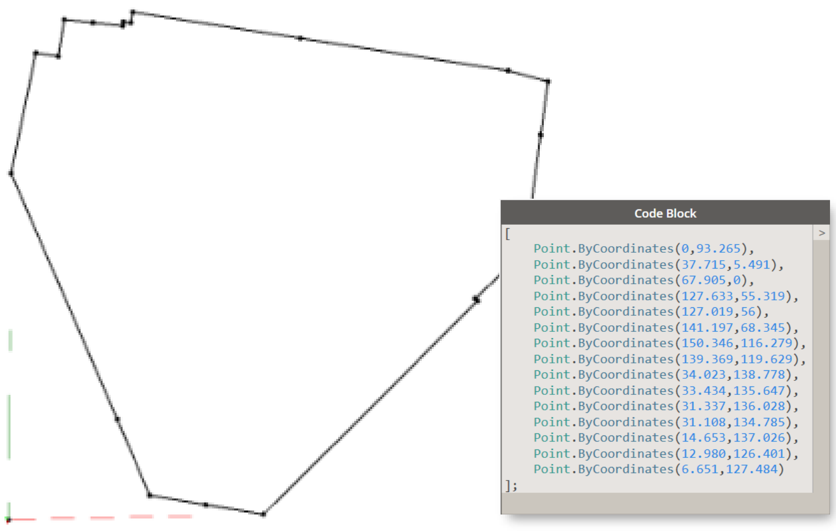
As illustrated in 2.1, the parametric model lies at the heart of a generative design study. Its parameters represent the design variables which ultimately serve as inputs for the GA. The goal of the optimization ultimately is to find a set of parameter values that produce the best possible design performance.

The parameters with their individual value range dictate the size of the explorable design space. They are chosen and defined by the human designer shifting his task from developing a single object to describing an abstract multidimensional concept (Nagy, 2017c). The parameters should be picked with care since too many inputs might lead to a design space too big to explore, while too few inputs could exclude a potential optimum.

In the case of Siemens, two different kinds of inputs must be differentiated: parameters with fixed values and parameters with variable values. The fixed parameters contain all the project-specific information. These are:

- Number of employees scheduled to be accommodated in the new office building (Integer)
- Outline of the property on which the building is developed (Polyline)
- Site entry points, e.g., from parking lot or public streets (Points by coordinates)
- Ground floor height (Double)

- Regular floor height, usually 3.6 m (Double)
- Grid width, usually 1.2 or 1.35 m (Double)



```
[
    Point.ByCoordinates(0,93.265),
    Point.ByCoordinates(37.715,5.491),
    Point.ByCoordinates(67.905,0),
    Point.ByCoordinates(127.633,55.319),
    Point.ByCoordinates(127.019,56),
    Point.ByCoordinates(141.197,68.345),
    Point.ByCoordinates(150.346,116.279),
    Point.ByCoordinates(139.369,119.629),
    Point.ByCoordinates(34.023,138.778),
    Point.ByCoordinates(33.434,135.647),
    Point.ByCoordinates(31.337,136.028),
    Point.ByCoordinates(31.108,134.785),
    Point.ByCoordinates(14.653,137.026),
    Point.ByCoordinates(12.980,126.401),
    Point.ByCoordinates(6.651,127.484)
];
```

Figure 28 The site polyline defined by corner points in form of coordinates

The parameters that describe design variables serve as input parameters to the GA. Their value can be changed by the algorithm to generate different designs and explore the solution space.

The parametric model is implemented in Dynamo, which is a visual programming tool for design. For that reason, it is best to describe the variables in the order of their appearance in the script.

Looking at the blank site, the first thing to be determined is the position and the orientation of the building. This is described by a total of four parameters:

- Start Point X-Coordinate (double, range: 0 to 1, step: 0.01)
- Start Point Y-Coordinate (double, range: 0 to 1, step: 0.01)

The start point is described in relation to a bounding box surrounding the site. At (0/0) the start point would be located at the lower left corner of the bounding box (min point), and at (1/1) it lies on the upper right corner of the bounding box (max point).

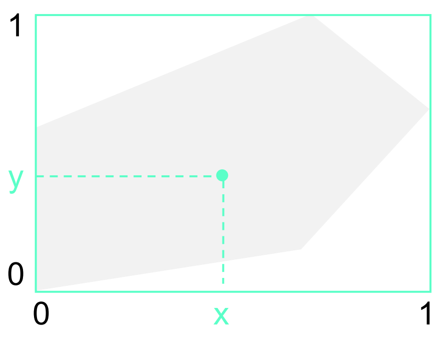


Figure 29 Determination of the start point according to a virtual bounding box

- Orientation U-value (double, range: -1 to 1, step: 0.1)
- Orientation V-value (double, range: -1 to 1, step: 0.1)

The two orientation values span a vector used as the x-vector of the coordinate system in which the building is created.

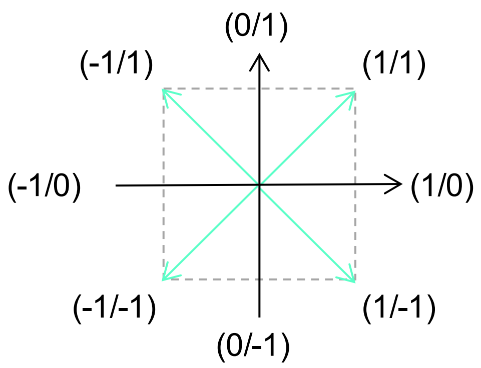


Figure 30 Different directions of the orientation vector based on u and v values

With this information, the boundaries of the construction space can be determined by calculating the largest inscribed rectangle. Since the width of the building is fixed, the rectangle is bound to be of the same width. The purpose of the rectangle is to provide a simple checking method to test if the building is fully within the boundaries of the site.

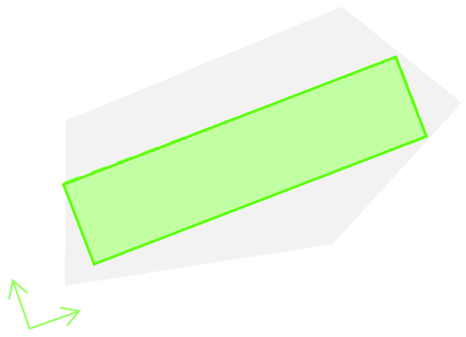


Figure 31 Step one: The largest inscribed rectangle is created

As a next step, the length of the building must be determined. First, a core unit is placed onto the start point.

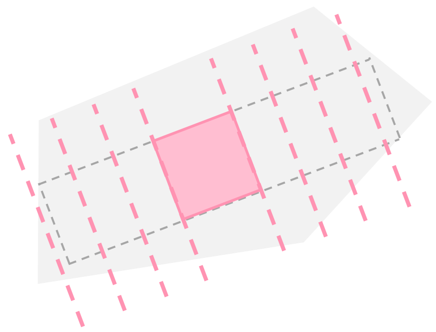


Figure 32 Step two: The core is placed so that its centre lies on the start point

The length is mainly dependent on how many office units (and potential core units) are attached to this core. Consequently, two more parameters are needed:

- Number of units left (integer, range: 2 to ~10, step: 1)
- Number of units right (integer, range: 2 to ~ 10, step: 1)

The upper range limit should be set in accordance with the size of the property. If it is impossible to fit a building with 20 office units into the site, then the range should be narrowed to avoid having an unnecessarily big design space.

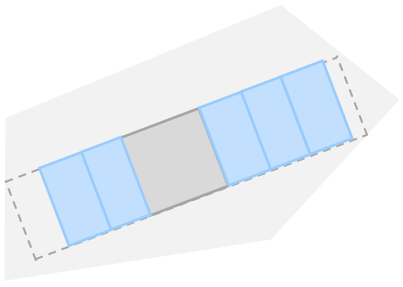


Figure 33 Step three: The units are placed on either side of the core

The office units are then attached onto the core, adding another core unit if there are more than 4 consecutive office units. Afterward, the last office units on each side are turned into seam units. At this point, the footprint of the building is established.

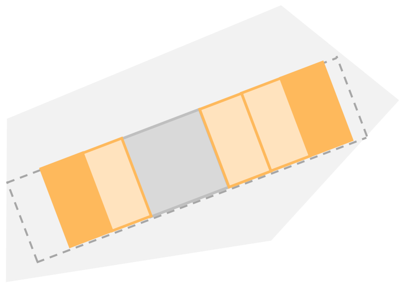


Figure 34 Step four: The last unit on each side is turned into a seam unit

The height of the building depends on the number of floors needed to accommodate all workplaces. Studying the ConEx showed that there is a total of six possibilities to position desk in the office units of the upper floor – ranging from a very dense combination of 20 desks in one unit to an airier arrangement of 11 desks.

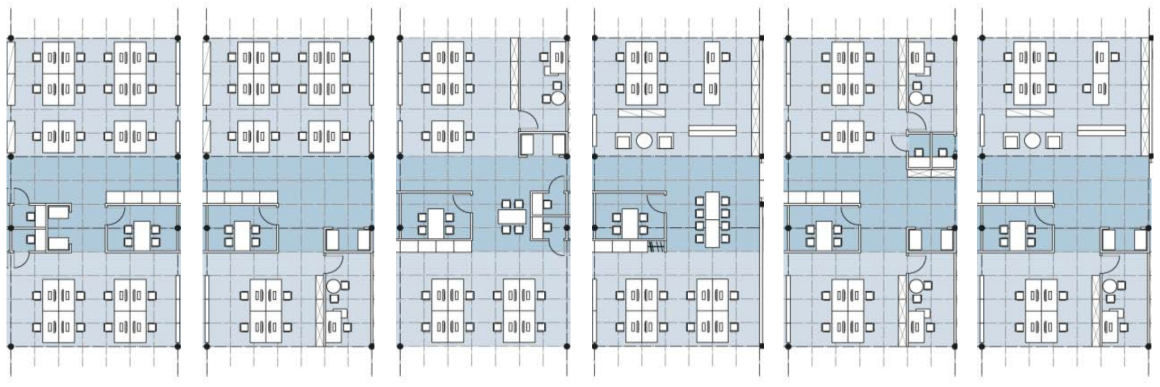


Figure 35 The 6 different workplace configurations, from left: 20, 17, 15, 14, 12, 11 desks per unit

The desk placement is controlled by a parameter called

- Workplace density ρ_{wp} (double, range: 0 to 5, step: 0.1)

An algorithm translates this number into a value between 11 and 20 and now distributes desks in the units in a way that the average number of desks comes as closest as possible to this value.

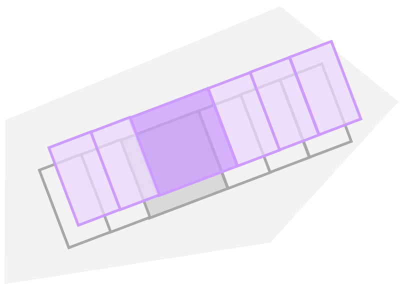


Figure 36 Step five: Each unit is assigned with a number of workplaces

In the ground floor, there are only three workplace configurations since the layout is a bit different (see Figure 33). To achieve a similar workplace density, the number of desks is translated from the units above. So, whenever there are 11 or 12 workplaces in the first floor unit, the corresponding units on the ground floor are equipped with 10 workplaces. 14 or 15 workplaces in the first floor lead to 13 workplaces in the ground unit, and 17 or 20 first floor workplaces lead to 16 ground floor workplaces.

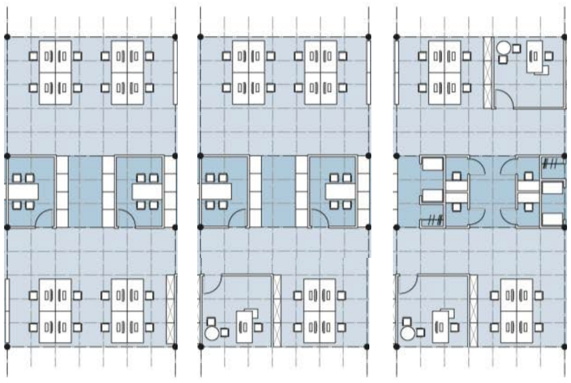


Figure 37 Different workplace configurations on the ground floor, from left: 16, 13, 10 desks per unit

At this point, the ground floor, as well as the first floor, are established. If the sum of all workplaces on the ground and first floor is below the total number of required workplaces, another floor with the same desk configuration is added. This is repeated until the required amount of workplaces is reached or exceeded. This concludes the generation process of the building.

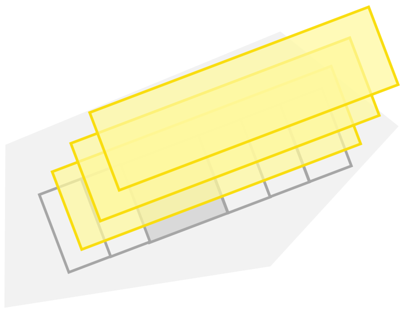


Figure 38 Step six: Floors are replicated until total number of workplaces is reached

In summary, there is a total of 7 design variables. Whenever the value of one of them changes a completely new building arises. For example, when more office units are added, there are more workplaces on one floor. Consequently, less floors might be needed, and the building shrinks. The workplace density has a similar effect. More workplaces per office unit might make a complete floor obsolete, while a more lavish workplace density requires more floors place all workplaces.

The orientation and the position of the building, on the other hand, are in relation to the site of the building. There are some combinations of start point, orientation, and number of slices that will lead to invalid designs since the resulting building would be (partially) outside of the property. In these cases, the design will be marked with a bad value in the evaluation phase to teach the algorithm where to position the building.

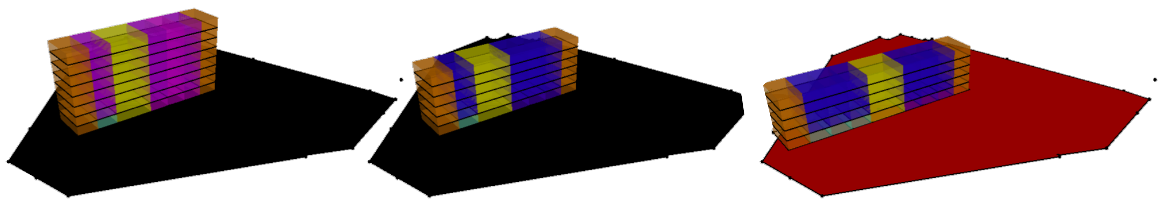


Figure 39 Three versions of a model with different parameter values; left: workplace density set to a very low value, hence more floors have to be installed to accommodate all employees; centre: workplace density set to a very low value, some upper floors become obsolete since workplaces are more densely arranged; right: increased number of units on the right, number of floors sinks even more, but model becomes invalid because it exceed the borders of the site

3.4 Design Goals

The design goals describe what makes a good design. These measures can be subjective to the human decision-maker like aesthetics or comfort, or rational like profit or the hours of daylight inside of the building. Once the design goals are decided, they must be paired with indicators that are quantitatively measurable. This allows for the designs to be compared amongst each other on an objective level.

Together with the project development team of Siemens, 8 design goals were identified.

1) Comfort

Indicator: rentable area/workplace

Calculation: according to ConEx, 8% of floor space is consumed by construction. Of the remaining area, technical-functional space and vertical traffic space cannot be rented. Since it is known exactly how much space is consumed by these functions, the remaining rentable area can be precisely calculated for the different units.

Therefore, rentable area/workplace $A_{r,w}$ is calculated as:

$$Ar,w = \frac{(48.576 * nc + 120.5568 * no + 98.9568 * ns) * f}{wtotal};$$

n_c = number of core units = 1, unless $n_{unit,left}$ or $n_{unit,right} < 4$;

n_o = number of office units = ($n_{unit,left}$ -1) + ($n_{unit,right}$ -1);

n_s = number of seam units = 2;

f = number of floors;

w_{total} = total number of workplaces on all floors (not to be confused with $w_{required}$);

Table 1 Rentable area in each kind of unit

	Core unit	Office unit	Seam unit
total floor area	243.36	131.04	131.04
net floor area	223.8912	120.5568	120.5568
rentable area	48.576	120.5568	98.9568

Objective: Maximize – the more rentable area per workplace, the more comfortable for the working employee

2) Functionality

Indicator: meeting area/workplace

Calculation: the meeting rooms are located on the ground floor of the building and preferable in one bulk on one side of the main core. So, it is assumed that the meeting rooms are all positioned in the right units on the ground floor. To calculate the meeting area, the horizontal traffic space must be subtracted from the rentable area. The meeting area/workplace $A_{m,w}$ is calculated as:

$$A_{m.w} = \frac{(a_{m,regular} * (n_{unit,right} - 1) + a_{m,seam})}{w_{total}} ;$$

$a_{m,regular}$ = Meeting area in regular unit = 95.357 m² ;

$a_{m,seam}$ = Meeting area in seam unit = 77.357 m² ;

w_{total} = total number of workplaces on all floors

Objective: Maximize – the more meeting area / workplace, the more likely there is a meeting room available when needed

3) Soil sealing

Indicator: footprint

Calculation:

$$A_{foot} = l * w ;$$

l = length of all units combined;

w = 15,6 m/ 24,00 m;

Objective: Minimize – the smaller the footprint, the less invasive in terms of soil sealing

4) Cost

Indicator: façade area (because it has the highest price/m² in construction and contributes to the operating costs in terms of heat loss)

Calculation:

$$A_{facade} = 2 * l * h + 2 * w * h\,;$$

l = length of all units combined;

w = 15,6 m;

h = $h_{\text{ground floor}}$ + (f - 1) * $h_{\text{upper floor}}$;

Objective: Minimize – the less façade area, the lower the construction as well as operating cost

5) Energy consumption

Indicator: form factor (surface to volume ratio)

Calculation:

$$F_{form} = \frac{2 * l * h + 2 * w * h + l * w}{l * w * h}\,;$$

l = length of all units combined;

w = 15,6 m;

h = $h_{\text{ground floor}}$ + (f - 1) * $h_{\text{upper floor}}$;

Objective: Minimize – the smaller the form factor, the less energy is consumed by the building

6) Daylight exploitation

Indicator: orientation in relation to east-west axis

Calculation: the orientation value a ranging from 0 to 1 is used to describe the “east-west-ness” of the building. At 0 the building is directed from north to south, at 1 the building is directed from east to west.

The orientation value a is calculated as:

$$a = \frac{x}{90};$$

$x = |90 - \alpha|;$

$\alpha = cos^{-1}\left(\frac{u * v}{|u| * |v|}\right);$

$u = \begin{pmatrix}1\\0\end{pmatrix};$

$v = vector\ determined\ by\ orientation\ of\ building = \begin{pmatrix}orientation\ u\\orientation\ v\end{pmatrix};$

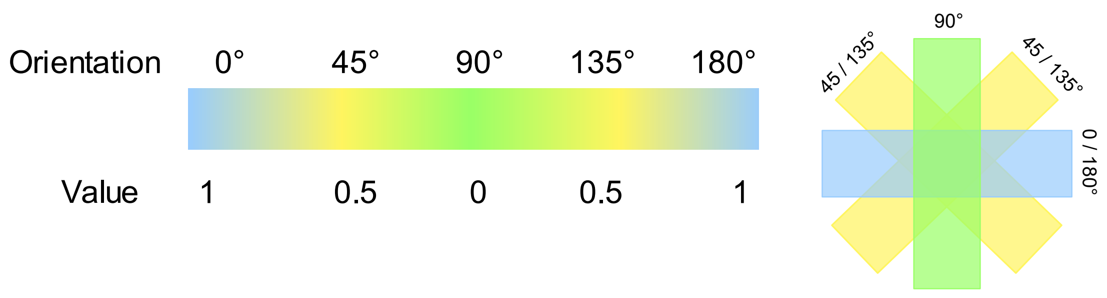


Figure 40 Explanation of orientation value

Objective: maximize for W-E-orientation, minimize for N-S-orientation (the objective varies depending on the latitudinal position)

7) Circulation

Indicator: length of all paths from site entry points to building entrance

Calculation: The shortest path from a site entry point to the building entrance cannot easily be calculated but is found through a series of iterations on a 2D grid with diagonal connections (Walmsley, 2019).

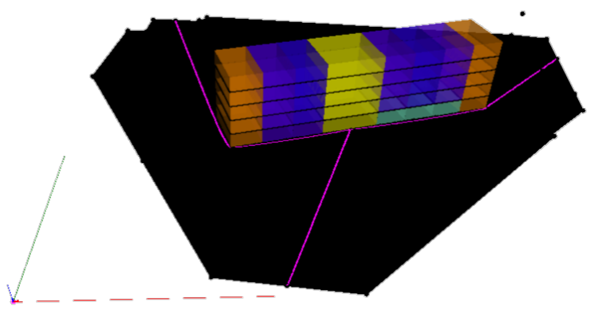


Figure 41 Computation of pathways (in pink)

Objective: Minimize – the shorter the pathways, the more efficient the circulation on the property

8) Workplace accuracy

Indicator: excess workplaces

Calculation:

$$w_{excess} = w_{total} - w_{required}$$

Objective: Minimize – the fewer excess workplaces, the more accurate to the demand

3.5 Evolution

To carry out the optimization study, the Dynamo graph was paired with a generative design tool called Refinery. The design variables of the parametric model serve as inputs in its optimization algorithm. Refinery docks onto these parameters and changes their values. It registers the corresponding outcomes and can thereby learn what input values generate a good design. To optimize the designs, Refinery makes use of NSGA-II. The number of generations and the population size is defined by the user.

Besides optimization, Refinery offers three other methods to generate designs. However, they do not offer any intelligence and are purely deterministic methods.

Randomize

Generates a user-defined number of random parameter configurations

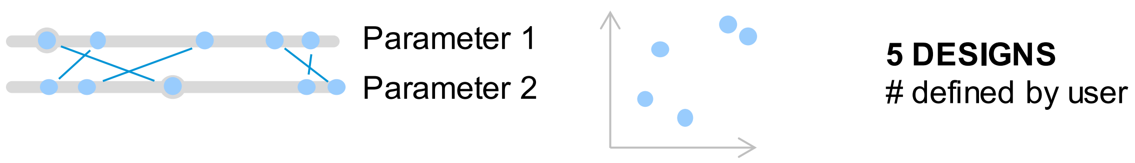


Figure 42 The Randomize method

Cross Product

Creates designs to all possible parameter combinations to a user-defined sampling density

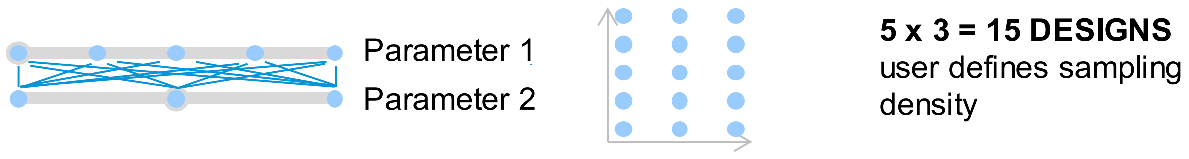


Figure 43 The Cross Product method

Like This

Applies slight variations to a parameter configuration

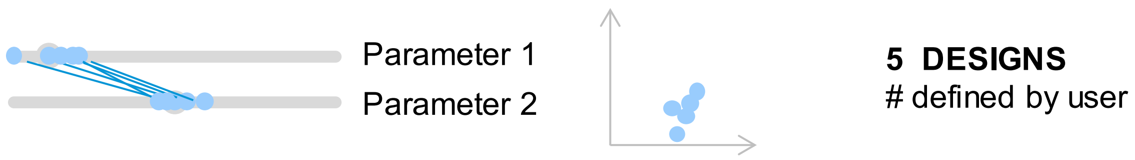


Figure 44 The Like This method

4 Verification

4.1 Arithmetic Verification

In order to prove that the Genetic Algorithm (GA) is capable of finding the best solution, it is tested on a smaller example. A model that resembles a simple trade-off situation is set up. In this case, it is possible to calculate the optimum of the example, because the design is composed of a single differentiable function. The result found through calculation can then be compared to results found through optimization by the GA.

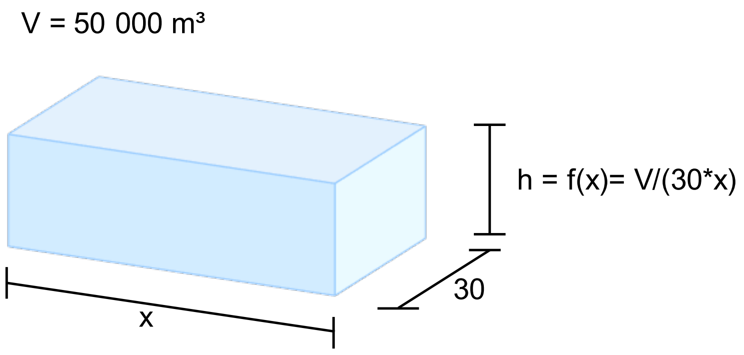


Figure 45 Example cuboid

The example model consists of a simple cuboid with a constant width of 30 m and a constant volume of 50 000 m³. The length and the height of the volume are variable with the length defined as x. Therefore, h is defined as a function of x.

$$V = 50\,000 = x * h * 30;$$

$$h = f(x) = \frac{50\,000}{30\,x}\ ;$$

The form factor proves itself as an ideal design goal in this situation, as it shrinks with increasing length up to a certain minimum after which it continues to grow again. The form factor is calculated as the ratio between the exposed surface and the volume of the cuboid. It can be calculated as:

$$Form\ factor = g(x) = \frac{2xh + 2 * 30h + 30x}{V};$$

$$g(x) = \frac{2xh + 60h + 30x}{50\ 000};$$

$$= \frac{2x\left(\frac{50\ 000}{30x}\right) + 60\left(\frac{50\ 000}{30x}\right) + 30x}{50\ 000};$$

$$= \frac{3x + \frac{1000x + 30\ 000}{3x}}{5000};$$

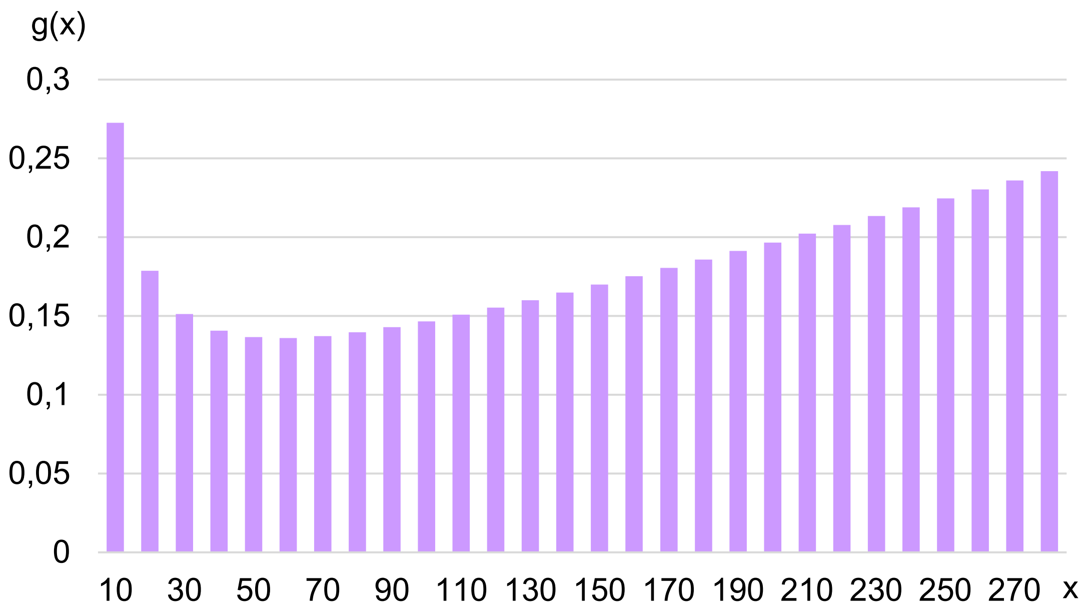


Figure 46 The form factor of the cuboid according to growing values of x

The function g(x) can be differentiated as:

$$g'(x) = \frac{1}{5\ 000} * \left(3 - \frac{10\ 000}{5\ 000\ x^2}\right);$$

$$= \frac{3\ x^2 - 10\ 000}{5\ 000\ x^2};$$

To calculate the minimum of g(x), the derivative is set to zero:

$$0 = \frac{3\ x^2 - 10\ 000}{5\ 000\ x^2};$$

$$0 * 5000 * x^2 = 3x^2 - 10\ 000;$$

$$0 = 3x^2 - 10\ 000;$$

$$x^2 = \frac{10\,000}{3}\,;$$

$$x = \pm\sqrt{\frac{10\,000}{3}}\,;$$

$$x_1 = 57.735 = min\,;$$

$$(\,x_2 = -\,57.735\,)\,;$$

$$g(57{,}735) = 0.136\,;$$

The minimum of g(x) can be found at x = 57.735 with a form factor of 0.136.

To find the minimum through optimization by a GA, a parametric model is created. The length of the cuboid is the only variable. The height is calculated accordingly, and the width is set to 30 m. A simple graph generates the parametric model and draws the form factor from it.

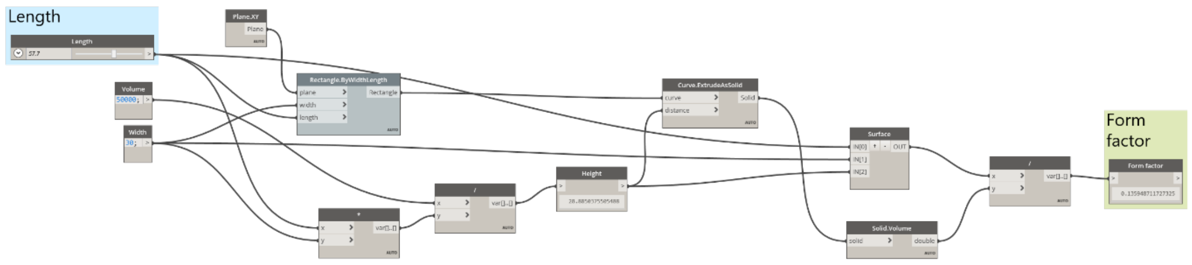
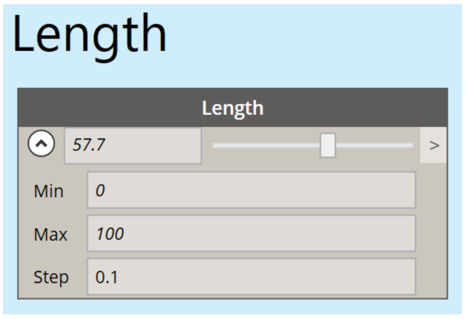


Figure 47 Dynamo graph

The length is set to be the input parameter of the GA, and the form factor serves as an output. The length is limited to a range from 0 to 100 with a step size of 0.1.


Length

Length

57.7

Min 0

Max 100

Step 0.1

Figure 48 Dynamo node

An optimization study with a population size of 20 showed the following results when instructed to minimize the form factor.

Form factor	Length
0.136462	65.2
0.136771	49.5
0.137687	72.2
0.13815	44.9
0.13831	44.5
0.138633	76.2
0.138685	76.4
0.138836	43.3
0.139355	78.9
0.14075	83.6
0.141099	84.7
0.142924	90.1
0.144531	94.5
0.160398	25.5
0.167743	22.9
0.22396	13.4
0.285073	9.4
0.713688	3.1
0.782632	2.8
1.5	0.2

Form factor	Length
0.135949	57.7
0.135949	57.9
0.135949	57.5
0.135956	56.9
0.135965	56.5
0.135968	56.4
0.135977	56.1
0.135985	55.9
0.135985	55.9
0.135985	55.9
0.135985	55.9
0.136009	60.2
0.136009	60.2
0.136014	60.3
0.136024	55.1
0.136047	60.9
0.136095	54.1
0.136109	61.8
0.136109	61.8
0.136109	61.8

Form factor	Length
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
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0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7
0.135949	57.7

Figure 49 Results after 1 generation (left), 6 generations (centre) and 10 generations (right)

It can be seen that the algorithm quickly narrows is results down to the minimum. In generation 6, the desired length of 57.7 m appears for the first time. By generation 10, all members of the population are Pareto optimal.

At first, the algorithm generates a diverse set of solutions and then learns which of these perform best.

4.2 Brute Force Verification

A different approach to verify the results found by the GA would be to generate all possible solutions in the design space. In the last example, there was only one perfect solution. However, in design, there is usually a set of Pareto optimal solutions. If the entire design space is generated, it can be determined if the GA finds all of these solutions. Therefore, a more complex model is needed with functions that are not easily differentiable.

The cuboid in the second example is fixed in its dimensions with x = 57.7 m. Instead, by introducing site boundaries, the placement of the cuboid is evaluated. Three variables are installed:

- Position x
- Position y
- Orientation α

The position is described in relation to a bounding box surrounding the site. At (0/0) the start point would be located at the lower left corner of the bounding box (min point), and at (1/1) it lies on the upper right corner of the bounding box (max point).

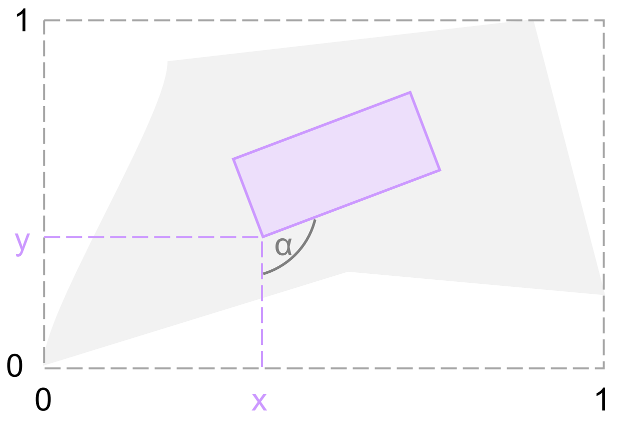


Figure 50 Position and orientation of the cuboid

The orientation is given as an angle between 0 and 90 by which the cuboid is rotated.

To keep the design space at a viable size, the range of the parameters is set to:

- Position x E {0..1}, step size 0.1 → 10 variations
- Position y E {0..1}, step size 0.1 → 10 variations
- Orientation α E {0..90}, step size 30 → 4 variations

Thus, the design space consists of 10*10*4 = 400 possible combinations. It can be imagined as a 3-dimensional space with 4 layers of cuboids at every possible position within the bounding box of the side. In each layer, the cuboids are rotated to a different degree.

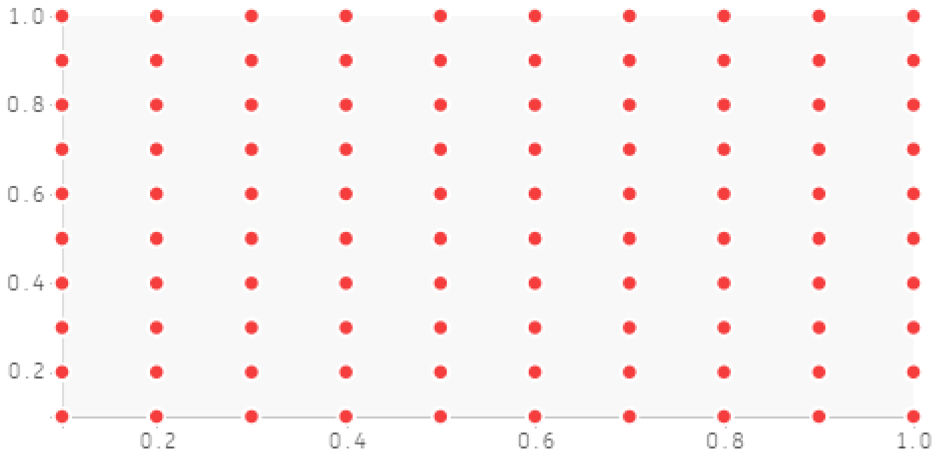


Figure 51 All possible solutions sorted by their position on x and y axis; each dot contains 4 solutions with different rotations

The solutions are evaluated according to a containment value and an orientation value. The containment value describes whether the cuboid lies fully within the borders or not. It returns either 0 for correct placement or 10 000 in case of an insufficient placement. Because of the irregular shape of the site, it is not easy to describe the behavior of the model in a function that could then be differentiated.

The orientation value rates the daylight exposure of the design. Assuming an N-S-orientation is favored, the orientation value should be minimized.

Therefore, all solutions that lie within the site and are rotated to an N-S-orientation are Pareto optimal. They have a minimal containment value and a minimal orientation value.

Refinery’s cross over option allows for the entire design space to be generated.

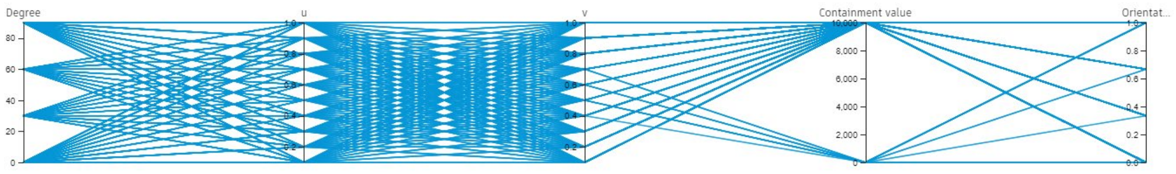


Figure 52 Overview of the generated solutions, each line represents one solution

The results of the cross over study show that of the 400 generated designs, 20 lie fully within the site. Of these 20, 5 have minimal orientation value.

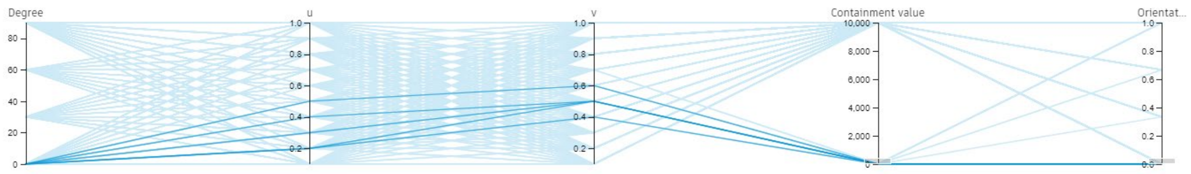


Figure 53 Solutions filtered by containment value and orientation value

These solutions have the following coordinates:

Solution set = {(0.4/0.2), (0.5/0.2), (0.5/0.3), (0.5/0.4), (0.6/0.5)}

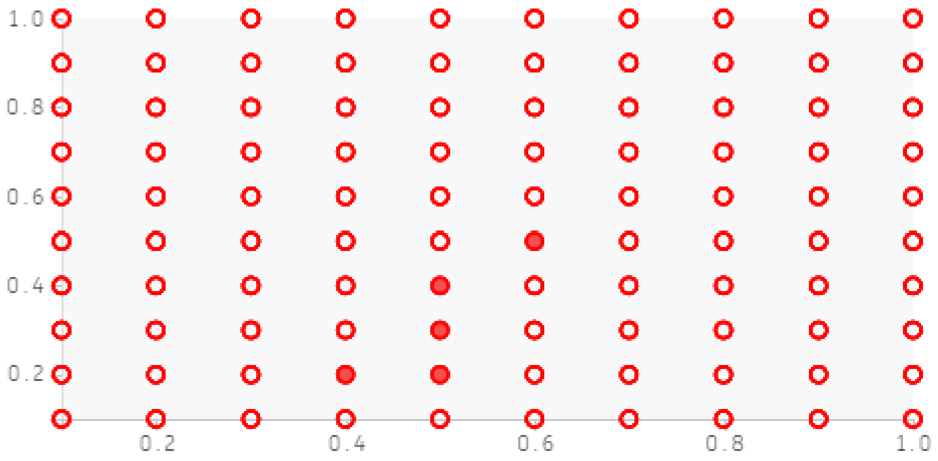


Figure 54 Coordinates of the selected solutions

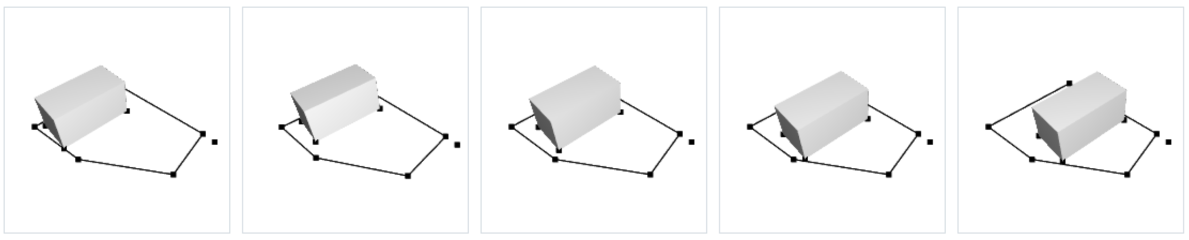


Figure 55 Visualisation of the 5 solutions found through the brute force approach

An optimization study will reveal if the GA finds the same set of solutions. The study is executed with a population size of 60.

After 6 generations it returns a set of 5 solutions. They match exactly the Pareto optimal designs found in the brute force approach. Thus, the GA did not only find all the desired solutions, but it also only needed to generate 360 designs to do so. This is a reduction of 10% compared to the brute force approach.

It should also be noticed that the actual number of different designs created is much smaller than 360 since well-performing solutions are passed on through the generations. Hence the GA found the solution by exploring only a fraction of the design space. With a larger design space, the effect can be expected to rise significantly.

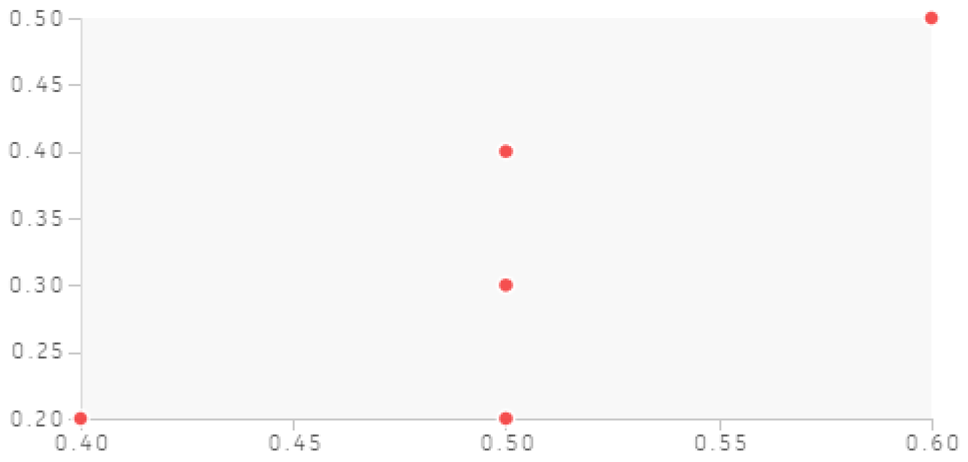


Figure 56 Solutions found in the optimization study

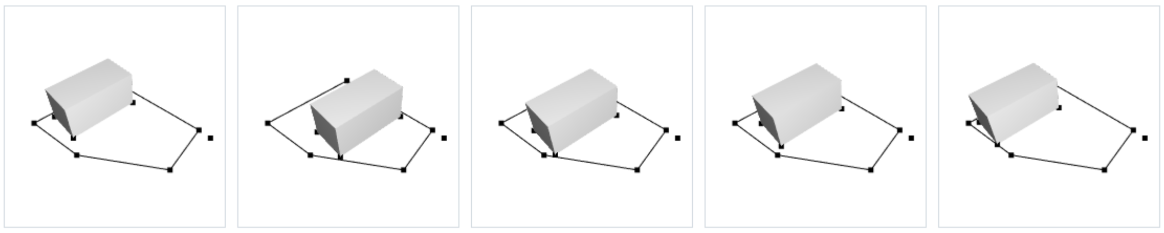


Figure 57 Visualisation of the 5 solutions found in the optimization study

5 Implementation

To execute the generative design study, two different software products are used: Dynamo, a visual programming software, and Refinery, an optimization tool for the AEC industry in its beta phase.

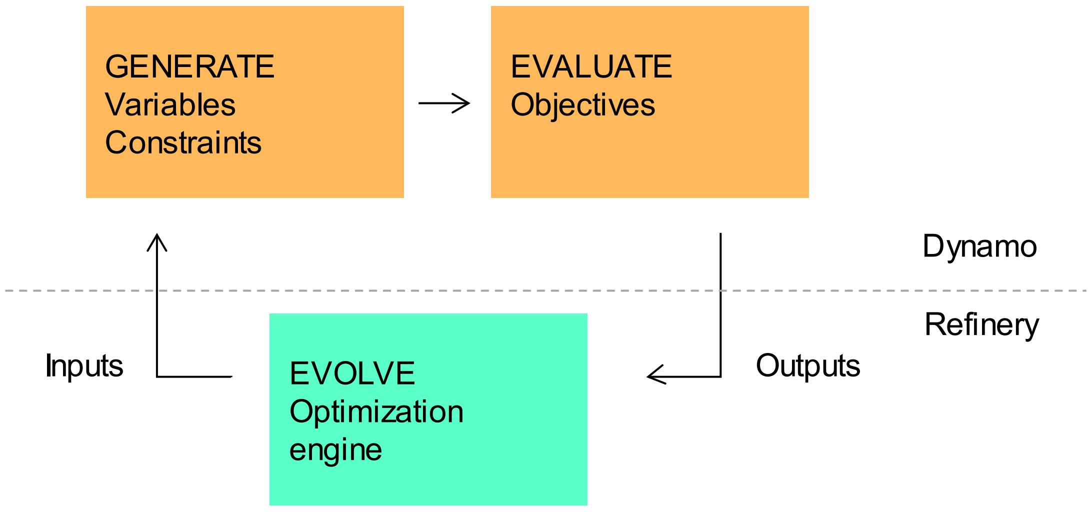


Figure 58 Workflow of the generative design study

In Dynamo, a graph is developed that generates a ConEx office building when paired with input values. It also evaluates the generated building and returns its fitness according to the design objectives.

Refinery is a plug-in for Dynamo and uses NSGA-II for its optimization. It runs locally and is controlled by its own GUI. It docks onto the graph, generates new sets of input values, and registers the corresponding outputs. It learns what values result in high performing solutions and optimizes the designs in that direction through crossover and mutation.

Summarizing previous chapters, the constraints, variables, and objectives of the study manifest as follows:

CONSTRAINTS

Number of required workplaces
Site polyline
Site entry points
Ground floor height
Regular floor height
Grid width

VARIABLES

Start point (X and Y)
Orientation (U and V)
Number of units left
Number of units right
Workplace density

OBJECTIVES

Rentable area / workplace
Meeting area / workplace
Footprint
Façade area
Form factor
Orientation
Length of outside paths
Excess workplaces

Figure 59 Constraints, variables and objectives of the generative design study

5.1 Dynamo

In visual programming, textual commands are replaced with graphical elements. These can be combined and manipulated to execute a desired task. In Dynamo, the graphical elements are called nodes. “Each node performs an operation - sometimes that may be as simple as storing a number, or it may be a more complex action such as creating or querying geometry” (The Dynamo Primer, 2018).

Dynamo comes with a choice of pre-installed node libraries. To add further functionality, it offers three options:

- Install more libraries – Nodes developed by other users can be downloaded and installed through the package manager
- Create custom nodes – In case of a repetitive task, several nodes can be combined to form a custom node
- Run external script – There are multiple ways to run a textual script in Dynamo, the easiest being through a Python node. It allows writing a set of commands directly in Dynamo as well as process information within the graph

Dynamo’s node syntax is very convenient for creating visual objects, but it does not allow recursion and looping. Therefore, combining it with a textual scripting language like Python facilitates more complex operations.

In the case of the ConEx design problem, a graph must be implemented that produces a parametric model which is able to explore the entire solution space as well as measure a solution’s performance. The following two chapters will explain how the graph is designed to fulfill this task. The graph consists of a total of 380 nodes and 536 connections. Therefore, the description will only focus on the most important aspects and algorithms of the graph.

5.1.1 Generate

The workflow to generate a design solution consists of three algorithms and two tests. A color scheme structures the nodes according to their function. Red marks constraints, green indicates variables. Nodes that execute a certain command are sorted into grey groups, and tests are highlighted in orange.

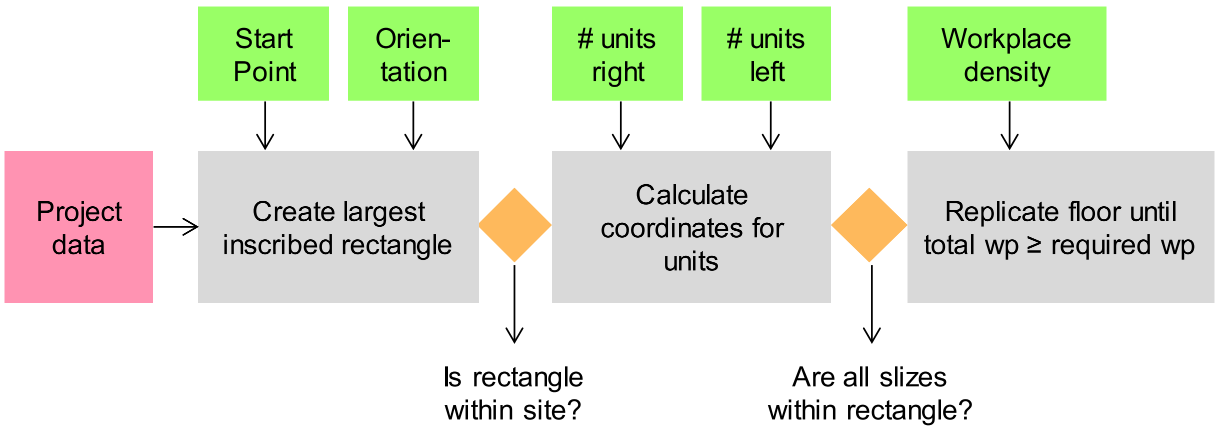

Start Point
Orien-tation
# units right
# units left
Workplace density
Project data
Create largest inscribed rectangle
Calculate coordinates for units
Replicate floor until total wp ≥ required wp
Is rectangle within site?
Are all slizes within rectangle?

Figure 60 Implementation of the parametric model

Largest Inscribed Rectangle

From the start point and the orientation vector, the largest inscribed rectangle can be created. It marks the area in which the building can spread. It will help to determine whether the building is placed fully within the borders of the property.

First, the start position is determined. It is defined in relation to a bounding box surrounding the site by two variables x, y. Their values vary between 0 and 1.

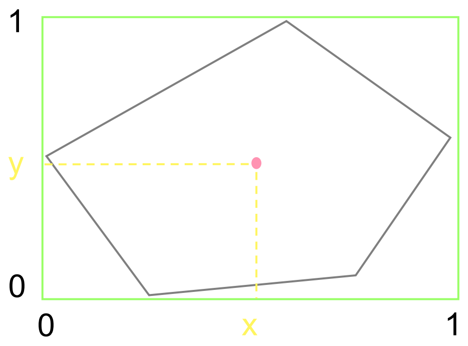


Figure 61 The start point is positioned in relation to the bounding box

The two orientation variables u and v span a vector that serves as the x-vector of the coordinate system, that the building is built in. To create a rectangle of the right width, two points are found that are half the building's width away from the start point in positive and negative y-direction.

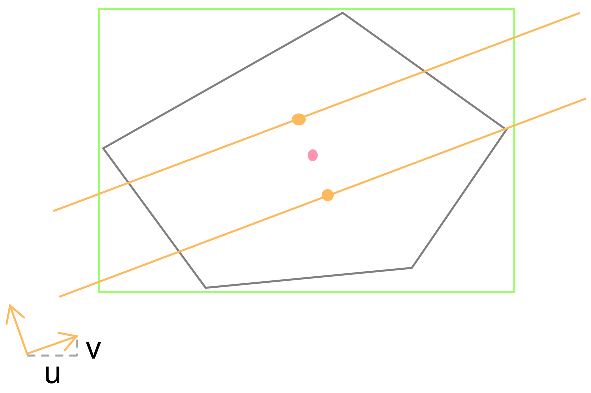


Figure 62 The width of the rectangle is created

From these points, vectors are shot in both positive and negative x-direction until they intersect with the property outline. From the four intersection points, the two that lie closest to the start position are chosen and mirrored onto the opposite vector line so that a rectangle is formed.

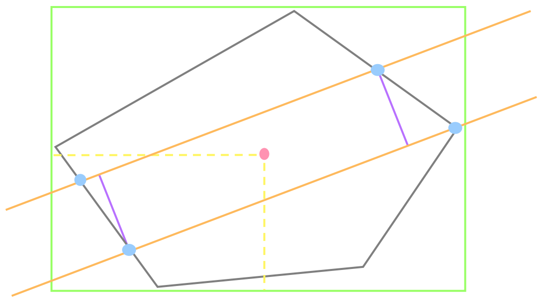


Figure 63 The rectangle is closed

After the largest inscribed rectangle is found, a test is carried out to check whether the rectangle lies fully inside the boundaries of the sit. Through irregular site shapes, there is a chance that the rectangle includes an area that does not belong to the site. Or if the start point itself lies outside the site, the algorithm will not be able to form a rectangle at all. In both cases, the test will be marked as failed.

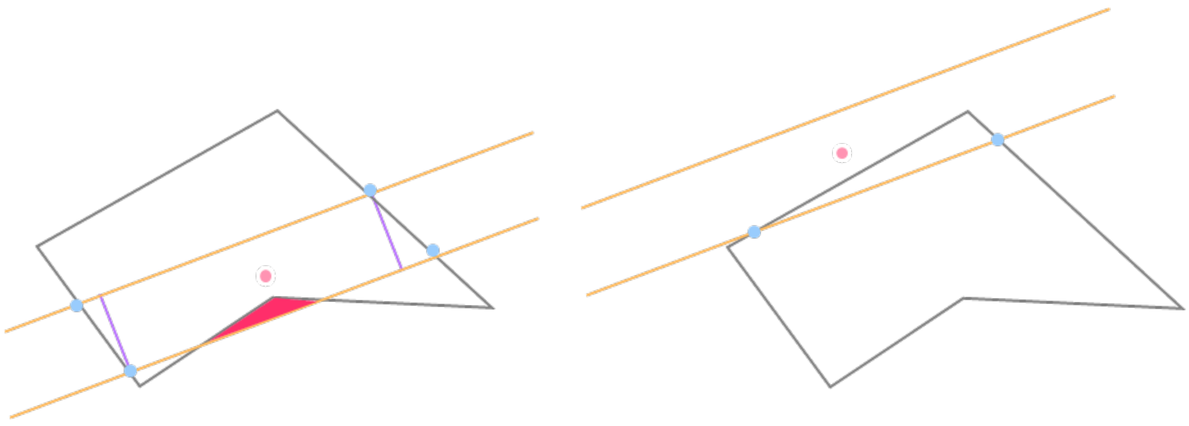
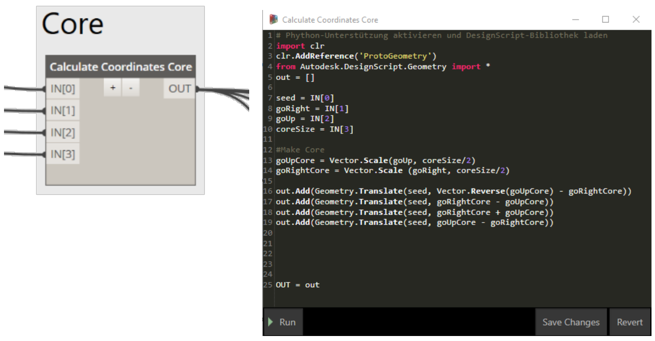


Figure 64 Failed construction of the rectangle

Position of Core, Office and Seam Units

All units are created by calculating its corner coordinates, connecting them to form a rectangle and then extruding the rectangle by the floor's height.

At first, the core unit of the ground floor is placed. Its coordinates are calculated in a Python node. A Python node can take multiple inputs, runs a set of commands, and returns an output. When double-clicked, an editor window shows up in which a script can be written. The algorithm to calculate the core coordinates is straight forward. It scales the x- and y-vectors of the buildings coordinate system (goRight, goUp) to half the size of the core and copies the start point (seed) four times according to a combination of the resulting vectors.



```python
# Phython-Unterstützung aktivieren und DesignScript-Bibliothek laden
import clr
clr.AddReference('ProtoGeometry')
from Autodesk.DesignScript.Geometry import *
out = []

seed = IN[0]
goRight = IN[1]
goUp = IN[2]
coreSize = IN[3]

#Make Core
goUpCore = Vector.Scale(goUp, coreSize/2)
goRightCore = Vector.Scale (goRight, coreSize/2)

out.Add(Geometry.Translate(seed, Vector.Reverse(goUpCore) - goRightCore))
out.Add(Geometry.Translate(seed, goRightCore - goUpCore))
out.Add(Geometry.Translate(seed, goRightCore + goUpCore))
out.Add(Geometry.Translate(seed, goUpCore - goRightCore))





OUT = out
```

Figure 65 Example of a custom Python node to calculate the corners of the core

The algorithm to place the office and seam units is similar but slightly more complicated. It must reflect on the number of units for each side. To create the units on the right side, the two right corners of the core are copied by a vector in x-direction scaled to the width of an office unit. The original and the new points form the corner points of the new office unit. The two new points are then copied by the same vector to generate the next unit and so forth. This is repeated until all units are created. However, when the number of units is larger than 4, after the fourth unit, another core unit must be added. This process works analogously for the left side of the building.

After all units are placed, the second test is executed to check if the building exceeds borders of the largest inscribed rectangle.

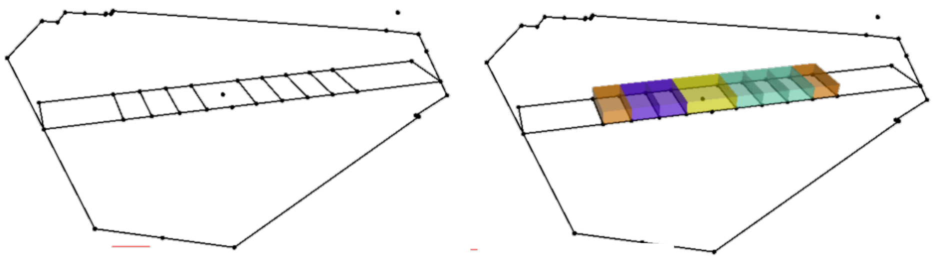


Figure 66 Left: The corner points of the units are calculated, right: The rectangles are extruded to form the units of the ground floor

Workplace Distribution

All floors above ground level receive the same desk layout. The workplace density determines how concentrated the desks are placed. It is given as a decimal number between 0 and 5 because there are six different workplace variations:

$$options \; = \; [11, 12, 14, 15, 17, 20];$$

The density number i relates to the ith item in the array. A workplace density of 0 will result in 11 workplaces in all office units. A density of 2 leads to 14 workplaces per unit. For every decimal, the workplaces are distributed by an algorithm to average to the given workplace density. For instance, if the workplace density is 3.2, the average of workplaces per unit calculates as:

$$average = \text{options}[3] + 0.2 * (\text{options}[4] - \text{options}[3]) = 15 + 0.2 * 2 = 15.4\,;$$

The office units then get assigned with workplaces while the current average is constantly calculated and compared to the goal average. If the average is below the goal, the lower workplace option is chosen for the next unit. If it is higher than the goal, the upper option is chosen.

For the example above, it is assumed that the number of units is 8 on the left side and 4 on the right side. The last unit on each side is turned into a seam unit with a fixed number of 13 workplaces. Thus, there are 10 office units per floor. A workplace density of 3.2 would result in the following desk configuration:

Unit	Workplaces	Average
1	17	17
2	15	16
3	15	15.667
4	15	15.5
5	15	15.4
6	15	15.333
7	17	15.571
8	15	15.5
9	15	15.444
10	15	15.4

Figure 67 Example of the workplace distribution algorithm for a density of 3.2

Since the layout of the ground floor is different from the upper floors, there are only three workplace configurations:

$$options = [10, 13, 16];$$

To achieve a similar workplace density, the number of desks is translated from the units above. So, whenever there are 11 or 12 workplaces in the first floor unit, the corresponding units on the ground floor are equipped with 10 workplaces. 14 or 15 workplaces in the first floor lead to 13 workplaces in the ground unit, and 17 or 20 first floor workplaces lead to 16 ground floor workplaces. It should be kept in mind that on the ground floor only the units on the left side are equipped with workplaces since the units on the right are turned into meeting rooms.

In the above example, this would lead to the following workplace distribution in the 7 office units of the ground floor: [16, 13, 13, 13, 13, 13, 16]. The seam units on the ground floor hold 8 workplaces.

Consequently, there are 180 workplaces on the first floor and 105 workplaces on the ground floor. This results in a current total of 285 workplaces.

The first floor is replicated until the total number of required workplaces is reached. Assuming the building is developed to contain 600 workplaces, this adds two more floors to the building resulting in a total of 645 workplaces.

All units are colored according to their function. Cores appear yellow, and seam units are depicted in orange. The color of office units varies according to the number of workplaces they accommodate from pink to blue. Office units with meeting rooms appear in turquoise.

This concludes the generation process for the different design solutions.

5.1.2 Evaluate

Once a design is generated, its fitness can be evaluated according to the indicators of the 8 design goals.

Footprint, Façade area, Form factor

At first, a Boolean union is performed on all the cuboids that make up the building. Dynamo is well-equipped with nodes for graphical operations. So, drawing the volume from the resulting cuboid can easily be done with a single node. The cuboid can also be exploded into its surfaces that can then be analyzed for their area. This way, the calculation of these three objectives is executed.

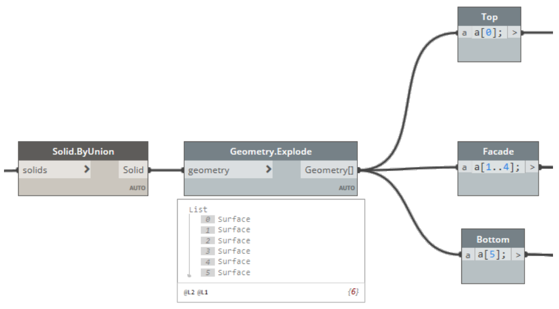


Figure 68 The solid formed by all units is exploded into its surfaces

In the example above the results are:

Footprint = 2059.2 m²

Façade area = 5018.4 m²

Form factor = 0.202

Rentable Area/wp, Meeting Area/wp, Excess workplaces

First, the total rentable area and meeting area must be calculated. This is done by multiplying the number of office, core and seam units with their according rentable and meeting area (see 3.4 Design Goals) and dividing the result by the total number of workplaces.

In the case of the example office, this results in 6002.53 m² of rentable area and 363.43 m² of meeting area. With 645 workplaces in total, the rentable area/wp is 9.31 m², and meeting area/wp is 0.57 m². The rentable area is critically low in this case, as should preferably range between 10 – 12 m² per workplace. It is a result of high workplace density. When the workplace density is changed to 0.6, for instance, the rentable area/wp rises to 11.83 m². However, since another floor has to be added to accommodate all workplaces, the façade area rises to 6081.12 m².

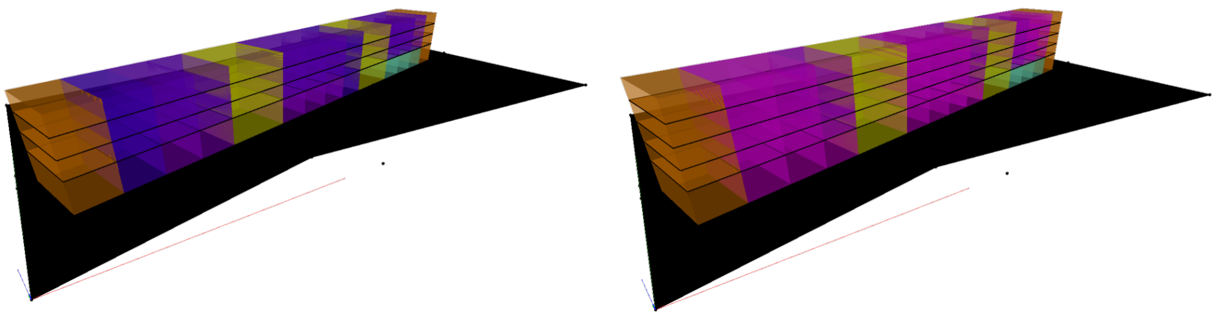


Figure 69 When the workplace density is changed to a lower value more floors are needed

Circulation

To implement pathfinding, custom nodes from a package called Space Analysis were used. They work with a SpaceLattice object, which is a 2D grid with diagonal connections. The building is set to be a barrier on the grid, which means paths have to go around it. An object called PathField allows for multiple routes to one endpoint to be calculated at the cost of a single calculation. The site entry points act as the start points to these routes.

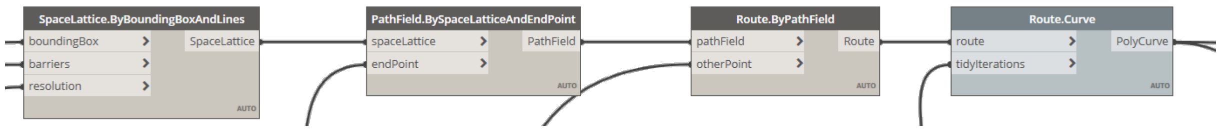


Figure 71 Custom nodes from the Space Analysis package

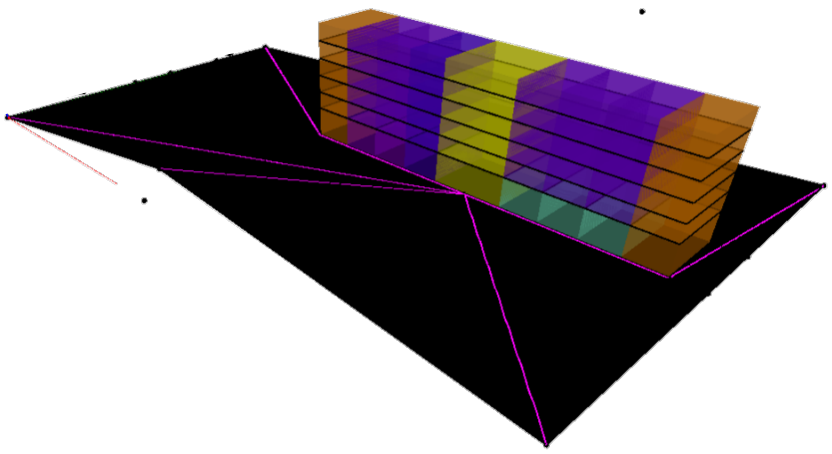


Figure 70 Path finding in Dynamo

Visualization

After the evaluation is concluded, the results are visualized in a radar chart. The chart is created by placing concentric octagons and spanning vectors from the center to the outer corners. The vector is then scaled according to the results in each objective and used to place a point at its end. These points are connected to form a polygon. The closer to the center a point is the worse is the fitness according to the corresponding objective. When variables are altered, the chart offers an intuitive overview of the performance of the resulting solution.

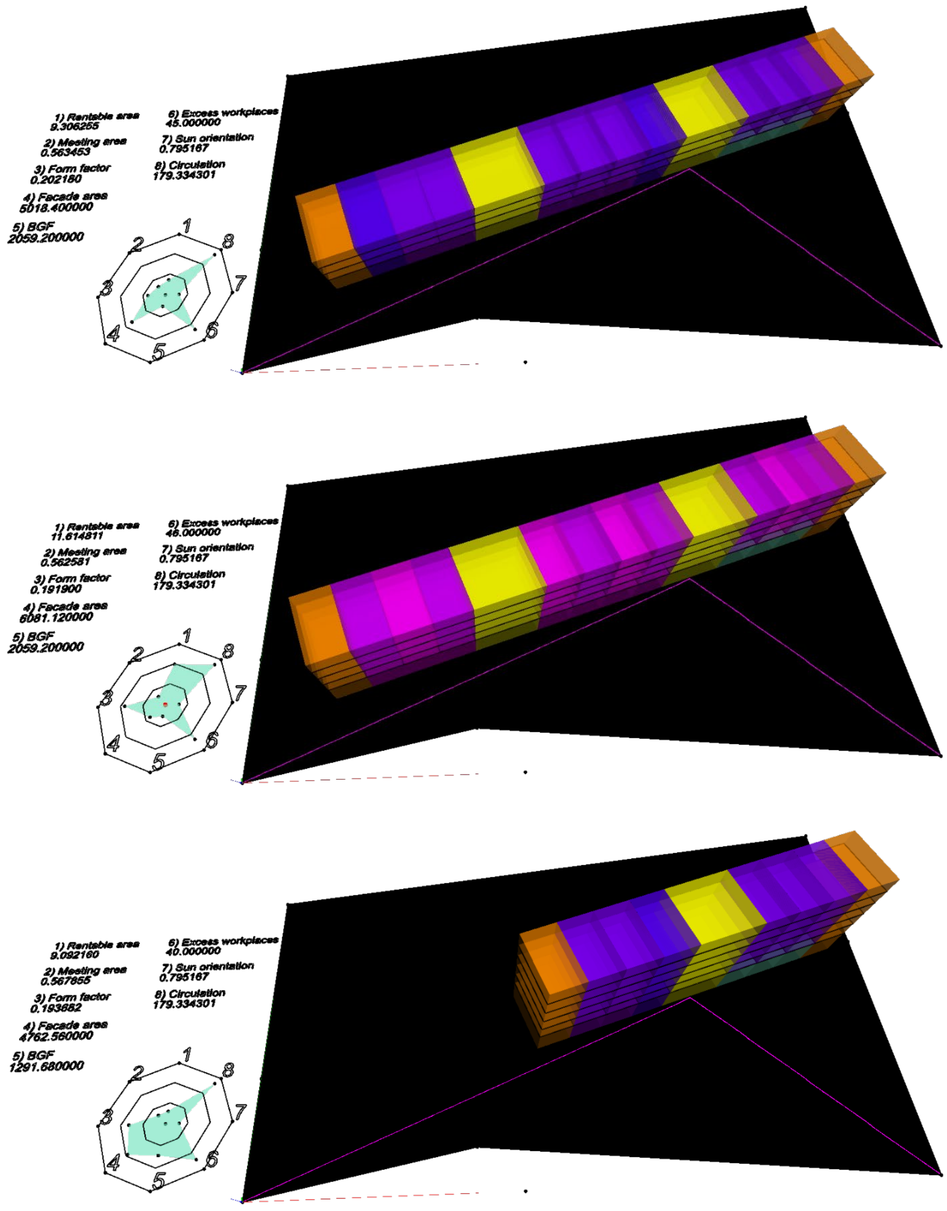


Figure 72 Different versions of the model with a radar chart of their evaluation

5.2 Refinery

5.2.1 Punishment Methods

Some combinations of position, orientation, and building length will lead to invalid design solutions. In these cases, one or both tests in the generation phase of the design will fail. In some way, this has to be reflected in the evaluation phase. The invalid designs need to be recognized by the GA and discarded in the evolution.

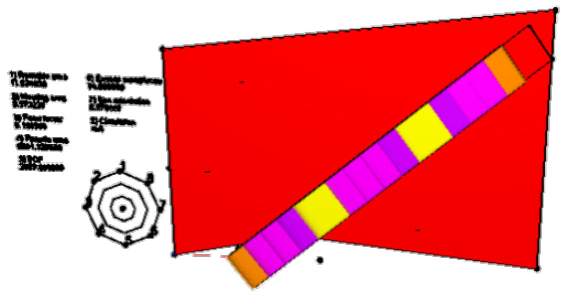


Figure 73 An invalid solution

There are different methods of how to mark these solutions so that they are not favored. The model from chapter 4.1 can be used to examine which method works best.

In chapter 4.1, the model is equipped with one input value (length) and optimized to one output (minimal form factor).

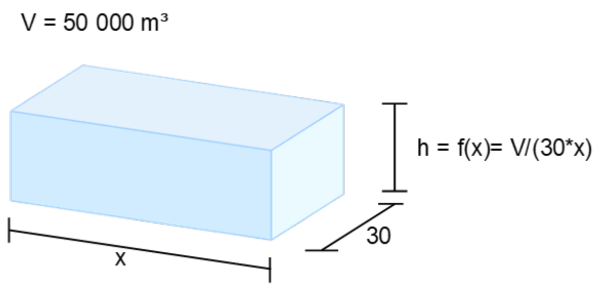


Figure 74 The example cuboid

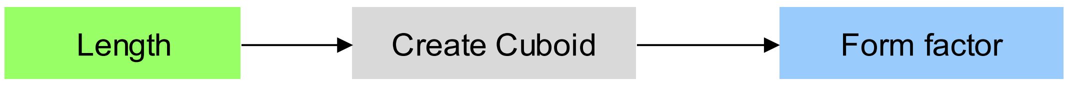


Figure 75 Workflow of generating and evaluating the cuboid

The GA proved to be capable of quickly finding the optimal length. Introducing a site polyline to the model, it can also be evaluated based on its position. The algorithm is faced with two problems: it has to optimize the cuboid's length as well as fit the cuboid into the site.

To identify invalid solutions, their fitness has to be diminished significantly so that they do not further procreate. Three different methods of how to punish invalid solutions are identified. They all use four inputs to describe the cuboid: the length, which determines its shape, its position on x- and y-axis and a rotation degree α.

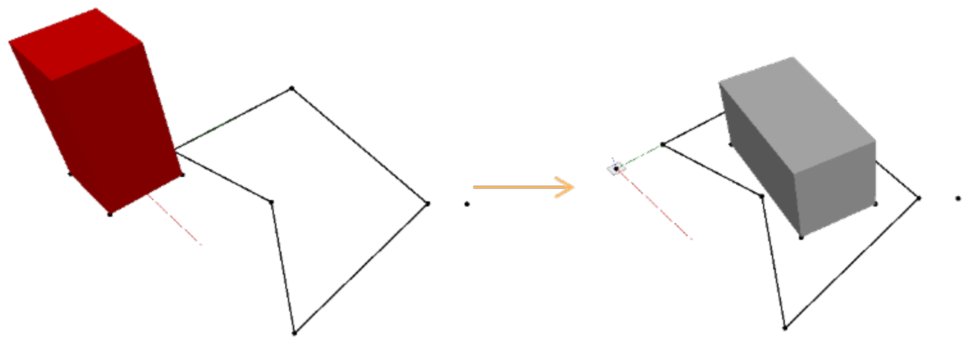


Figure 76 The algorithm is now faced with the challenge to optimize length as well as position of the cuboid

1) Fixed penalty

First, the cuboid is generated. Afterward, a test determines whether the cuboid is fully enclosed in the site. If the test is passed, the output is set to the true value of the form factor taken from the cuboids shape. If the test is failed, then the form factor is set to a very high penalty value, e.g., 10 000. Since the GA is set to minimize the form factor, it will rule out the solutions that lie outside the site.

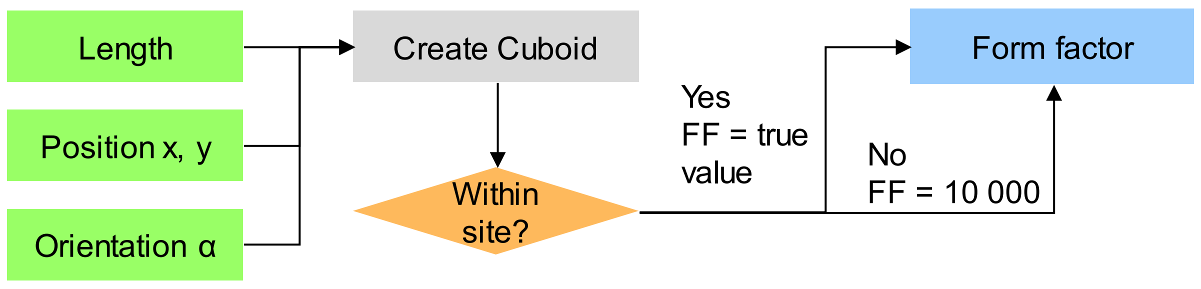


Figure 77 The fixed penalty method

2) Added objective

In this method, instead of penalizing the form factor output, a second objective is introduced to the system. It can have either of two values: 0 if the cuboid is within the site and 100 if the cuboid is outside the site. The GA is then set to minimize containment. Thus, it will favor solutions with a lower form factor and a lower containment value over solutions with higher values in either or both outputs.

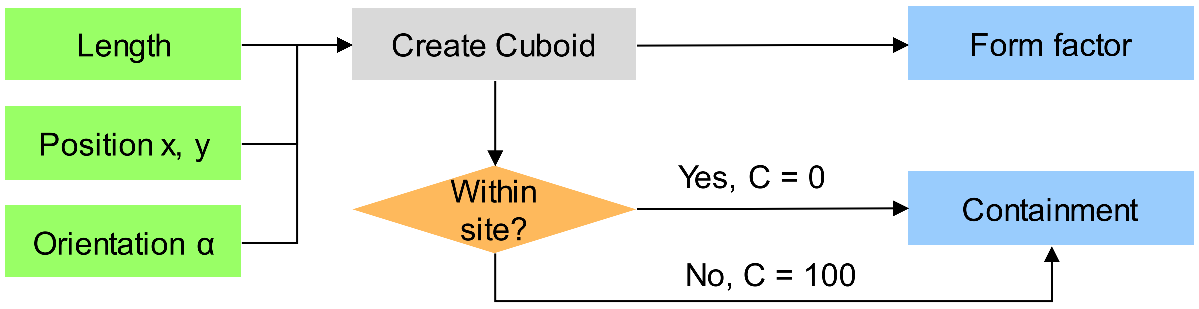


Figure 78 The added objective method

3) Penalty factor

This method is similar to the first method. However, instead of replacing the true value of the form factor with a penalty value, the form factor is multiplied with a penalty factor for all solutions that fail the containment test. This way the dimensions of the cuboid are still regarded, even when the building lies outside the site. Of the failed solutions, those with a lower form factor are preferred. The hopes of this is that the algorithm learns to find the right length of the cuboid simultaneously with learning about the borders of the site. However, this might put lighter pressure on the solutions to move into the site, since solutions can also improve by optimizing their length without optimizing their position. With a fixed penalty, solutions must always move into the site to improve their fitness.

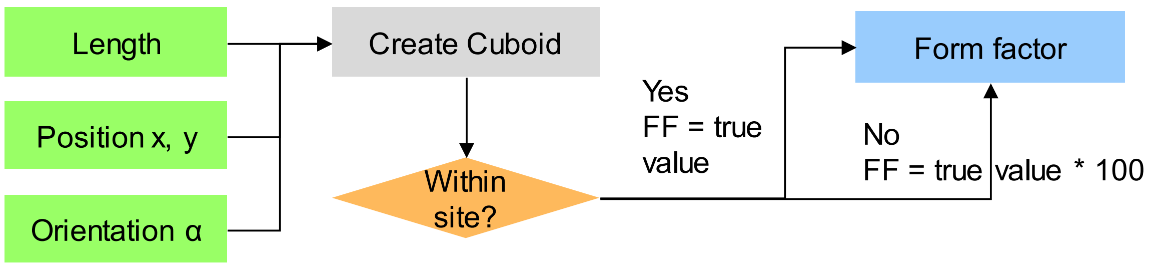


Figure 79 The penalty factor method

For each of the method, a graph is implemented, and a generative design study is carried out in Refinery. They are compared by the number of generations it takes until all members of a population of a) 20 and b) 100 are within the site and have the optimal length of 57.7 m (minimal form factor, see Chapter 4 Verification).

For the basic script with no regards to the site the GA takes

a) 9 generations
b) 8 generations

to optimize the design to minimal form factor.

The results for the three different punishment methods are:

1) Fixed penalty

a) 71 generations
b) 16 generations

2) Second objective

a) 15 generations
b) 12 generations

3) Penalty factor

a) 26 generations
b) 17 generations

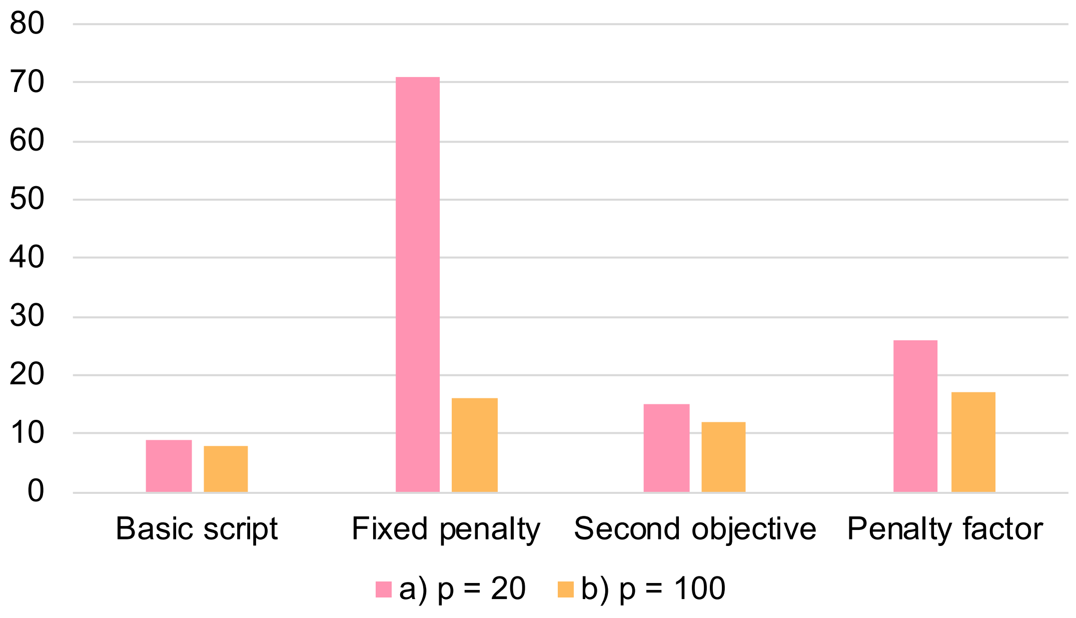


Figure 80 Number of generations each method needed to optimize its solutions

The best performance is achieved by the second method. Even with a small population size, it was able to optimize the entire population within a low number of generations by introducing a second objective. However, translating the effect to the ConEx study might be difficult, since there are eight design goals. Introducing a containment objective might not add the same kind of pressure on the optimization. The fixed penalty-method performed bad for the small population size because the algorithm cannot detect any changes in the output values unless there is a design within the site. Therefore, when none of the solutions lie within the site in the first generations, it cannot learn anything about which length produces a good form factor. It depends on the randomization of the first generation and the mutation afterward how fast the designs find its way into the site. With a larger population size the chances of a valid solution within the first generations rise, and then the algorithm performs decently because the selection pressure is quite high as the output of the valid solutions is so significantly lower compared to invalid solutions.

The penalty factor method performs better than the fixed penalty method for a smaller population size because of its ability to simultaneously learn about sizes and site limits. However, its performance does not increase significantly when introduced to a bigger population size. This might be due to the selection pressure not being high enough. Depending on the value of the penalty factor itself, it can happen that an invalid solution with a low form factor is favored over a solution within the site but with a high form factor.

A clear decision as to which method suits the ConEx optimization problem best is hard to draw from these results. Further experiments on the actual problem are needed to answer the questions:

- Does introducing a single objective concerning containment add enough significance to the position to cancel out invalid solutions?
- Does introducing a fixed penalty add too much pressure to the system, making it impossible for the GA to learn?
- Does a penalty factor put enough pressure on the GA to favor solutions within the site?

The goal is to rule out the invalid solutions as soon as they occur so that the optimization can focus mainly on improving good solutions.

Therefore, the three punishment methods are tested on the ConEx optimization graph in a short run of 5 generations to see which method is able to remove invalid solutions as quickly as possible. The three optimizations start with the same set of solutions for the first population. It consists of 200 solutions, of which only 6 are valid (3%). After 5 generations, it is counted how well the solutions propagated. The results are as follows:

1) Fixed penalty: 127/200 (63.5%)
2) Added objective: 14/200 (7%)
3) Penalty factor: 163/200 (81.5%)

The results of the second method increased to 28/200 (14%) when the containment output was duplicated four times, so it would have a bigger weight on the evolution compared to the other 8 objectives. However, it can be seen that the factoring method performed best at removing invalid solutions. When comparing the quality of the valid solutions, the overall fitness of the penalty factor method population was slightly higher than the population of the fixed penalty method. Therefore, the penalty factor method was chosen for the ConEx optimization. Fine-tuning the factors can improve the effects of the method even further. A penalty factor of 100 for objectives that are supposed to be minimized and -100 for objectives to be maximized proved to enhance performance.

5.2.2 Population Size, Number of Generations and other NSGA-II settings

When Refinery is installed in Dynamo, it adds the functionality to define nodes in the graph as inputs and outputs of the optimization.

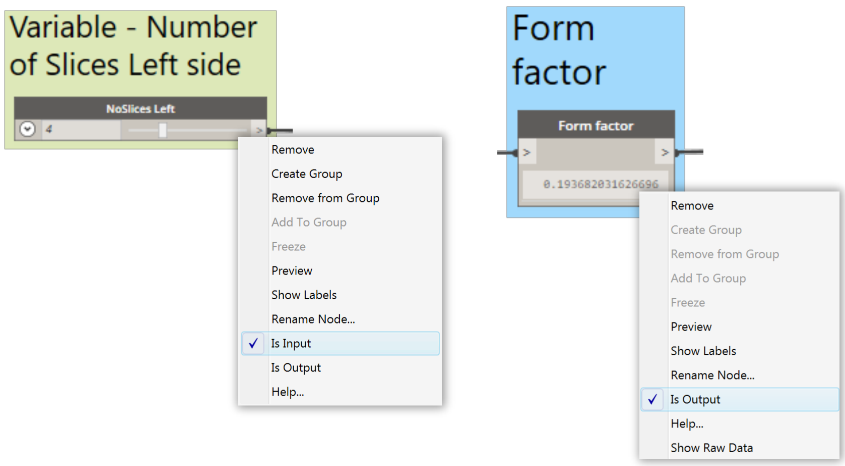


Figure 81 Inputs and outputs in the Dynamo user interface

This way, Refinery gains the control to change the input nodes' values and read the value of the output nodes. The inner workings of the script remain of no interest to Refinery.

To start a new optimization study, Refinery has to be launched. A window opens in which a new study can be created. Before initializing the study, several decisions must be made.

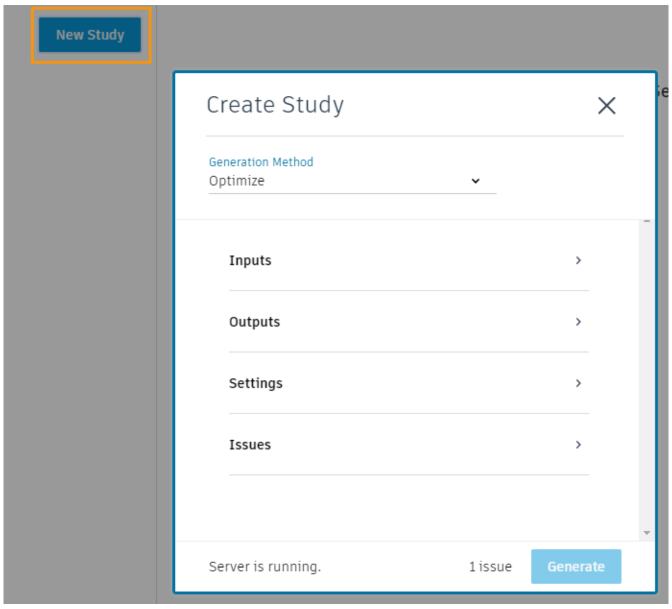


Figure 82 Creating a new study in Refinery

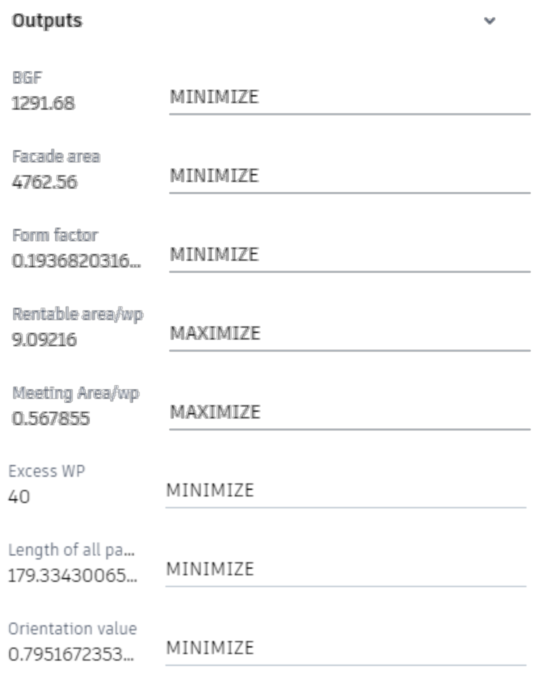
First of all, the outputs should be set to their equivalent objective (maximize / minimize). In the case of ConEx, the following outputs should be minimized:

- Footprint
- Façade area
- Form factor
- Excess workplaces
- Length of all exterior paths

On the other hand, the algorithm should strive to maximize:

- Rentable area / workplace
- Meeting area / workplace

The orientation value should be minimized when an N-S-orientation is desired and maximized for a W-E-orientation.



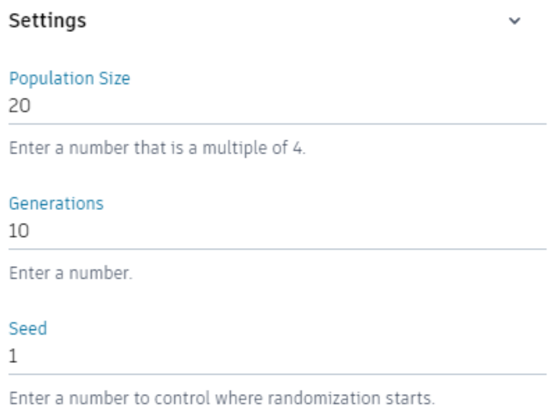
Outputs

BGF 1291.68	MINIMIZE
Facade area 4762.56	MINIMIZE
Form factor 0.1936820316...	MINIMIZE
Rentable area/wp 9.09216	MAXIMIZE
Meeting Area/wp 0.567855	MAXIMIZE
Excess WP 40	MINIMIZE
Length of all pa... 179.33430065...	MINIMIZE
Orientation value 0.7951672353...	MINIMIZE

Figure 83 Objectives in the Refinery user interface

As a next step, the population size has to be set as well as the number of generations the study is supposed to run. The population size must be a multiple of four because Refinery uses binary tournament selection.

The seed is a number that triggers the randomization of the first generation. Different seed values produce different values for the inputs of the first generation. Executing another study with the same seed value will produce the same set of values in the initialization.


Settings

Population Size
20
Enter a number that is a multiple of 4.

Generations
10
Enter a number.

Seed
1
Enter a number to control where randomization starts.

Figure 84 Settings in the Refinery user interface

Other settings of NSGA-II cannot be directly manipulated by the user. This includes:

$$Crossover\ probability\ =\ 0.8\ ;$$

$$Mutation\ probability\ =\ 0.4\ ;$$

$$For\ each\ input{:}\ Mutation\ independent\ probability\ =\ 1 - 0.5^{\frac{1}{numInputs}}\ ;$$

However, the developers of Refinery plan to make these settings available to be modified by the user in Advance Settings in the future.

5.2.3 Presentation of Results

After the study is concluded, the results are presented in two different forms: in Refinery itself and exported into CSV files. Inside the Refinery GUI, the so-called “Hall of Fame” of results is presented. It features those solutions that belong to the first non-dominated front. They appear with a small 3D preview of the design and can be sorted and filtered. A graph offers the possibility to map them based on the different inputs and outputs.

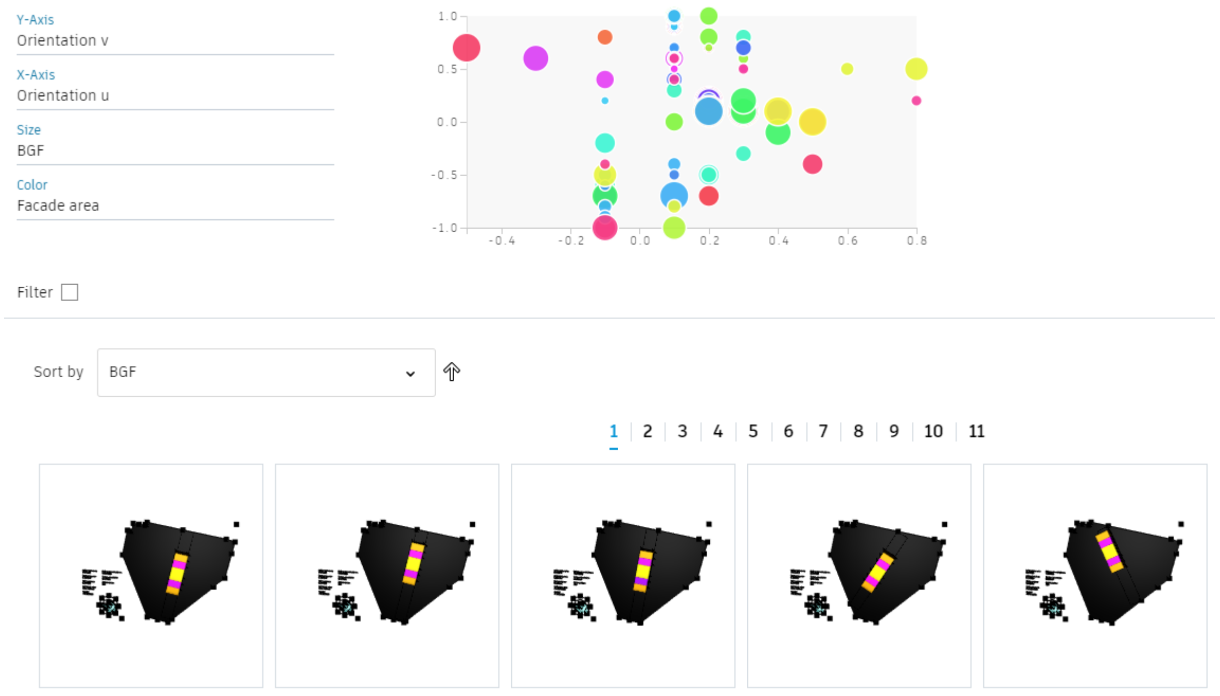

Y-Axis
Orientation v
X-Axis
Orientation u
Size
BGF
Color
Facade area
Filter ☐
Sort by BGF

Figure 85 Presentation of results in Refinery

To examine the solutions in more detail and further process the information, four CVS files are offered, which can be imported into Excel:

- Solution set: the solutions of the last generation
- Solution set history: the solutions of each generation
- Hall of Fame: the best solutions in the last generation
- Hall of Fame history: the best solutions of previous generations

The files include the values of all inputs and all outputs of each solution. They can be used to filter and process the solutions further.

It contains a list of all solutions in each generation with their input and output values.

6 Experiments

6.1 Set-Up

To create a realistic setting, the graph is tested on a property that has been recently developed by Siemens Real Estate. It is located in Hannover, Germany, and will accommodate approximately 600 employees. The planning phase of the project is already completed, and the building is currently under construction.

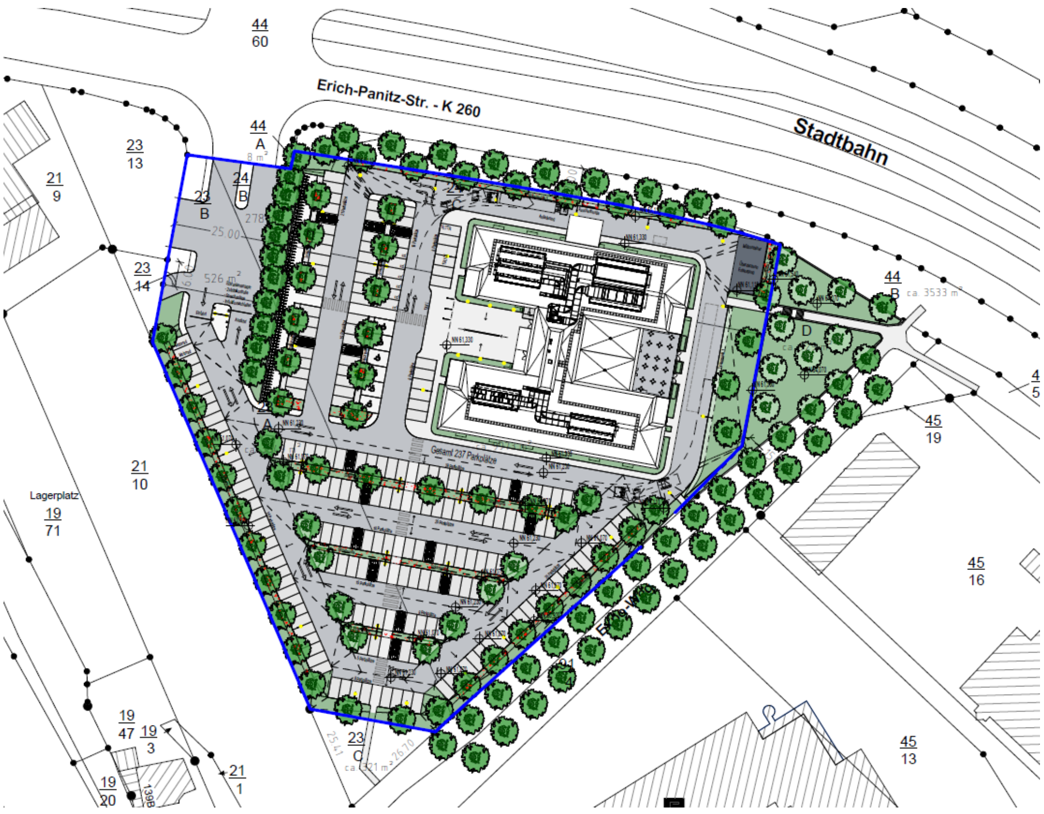


Figure 86 Siemens Real Estate project in Hannover

The site can be described by 15 corner points with 3 site entries. Besides the building, the SRE project also contains parking area. Consequently, when choosing a solution from the generative design study, it should also be reflected whether there is enough space available to include the same amount of parking lots.

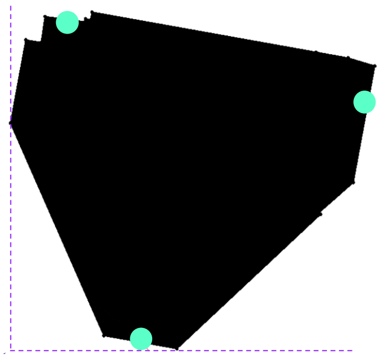


Figure 87 Representation of the site in Dynamo (turquoise: site entry points)

With an assumed workplace ratio of approximately 0.8 per employee, the total number of required workplaces is 500. The ground floor height, as well as the regular floor height, was chosen to be 4m. Since the project is located in Middle Europe, the narrow layout option was chosen, and an N-S-orientation is preferred.

6.2 Limitations and Assumptions

Population size and number of generations have a big effect on the performance of the GA and the results it finds. However, research has not yet found rules for how to best set these two parameters, since two different optimization problems can vary significantly in their behavior.

Vrajitoru (2000) and Gotshall & Rylander (2002) conclude that larger population sizes will improve the accuracy of the GA. The greater the initial population, the higher are the chances that one of the solutions lies on the Pareto front (Vrajitoru, 2000) (Gotshall & Rylander, 2002). However, a greater population size also causes the number of generations needed to converge to the Pareto front to increase. In greater populations, more mutation will occur, and more generations are needed to eliminate those mutations that do not cause the fitness to increase (Gotshall & Rylander, 2002).

The optimal population size is at the balance between the accuracy of the algorithm and the number of generations needed to converge. This problem itself can be defined as another optimization problem, which could then be solved by another GA. This process is called meta-optimization and requires large resources of computation power and time, as it simultaneously runs multiple optimizations (Nagy, Evolving design, 2017d). In practice, this process is more often done by experimentation. Starting with smaller sizes, the population size is increased to a point at which it performs best. Afterward, the number of generations can be increased to see at which point the solutions do not improve further.

In this scenario, eight population sizes ranging between 60 and 200 are tested to see in which case the GA provided the best results after a short run of 10 generations. To compare the different runs, the overall fitness of the populations has to be estimated. This is done by looking at the Hall of Fame solutions of each run.

First, the fitness of each solution is estimated by normalizing its results in the different objectives and then adding them. Then the average fitness of these solutions is calculated. For instance, there are two solutions with the following results:

Table 2 Two example solutions

	BGF	Facade	Form factor	Rent. area	Meet. area	Circu-lation	Orien-tation	Excess wp
1	1 535	4 560	0.1985	9.95	0.52	256	0.24	12
2	767	5 702	0.1915	10.55	0.39	292	0.50	8

They are normalized with the overall highest and lowest values from all runs. For the maximizing objectives (rentable area/wp, meeting area/wp), the results must be inversed (1 – normalized value).

Table 3 After normalization

	BGF	***Façade***	***Form factor***	***Rent. area***	***Meet. Area***	***Circu-lation***	***Orien-tation***	***Excess wp***
1	0.59	0.52	0.37	0.61	0.65	0.73	0.24	0.12
2	0.05	0.90	0.23	0.48	0.77	0.13	0.50	0.08

The sum of the normalized values serves as a fitness estimate, with low values indicating a high fitness. In the case of the two example solutions, the fitness estimate is 3.31 for solution 1 and 3.14 for solution 2. Assuming that the population only contains these two solutions on the Pareto front, the average fitness of that run would result in 3.225. This way, the runs of varying population sizes can be compared.

After analyzed in the described fashion, the results for the different test runs of 10 generations appear as such:

P = 60	3.12772
P = 80	3.127512
P = 100	2.96939
P = 120	2.96784
P = 140	2.994057
P = 160	3.02282
P = 180	3.090961
P = 200	3.135763

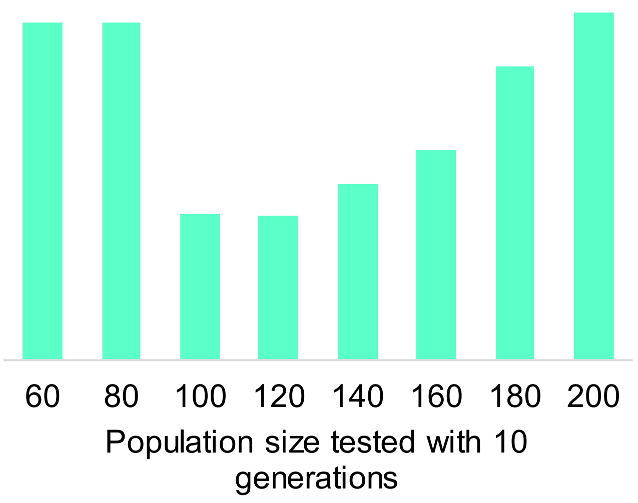


Figure 88 Average fitness estimate after 10 generations of different population sizes

The results show that at about a population size of 120 solutions, the performance peaks. Now, this population size can be chosen for further optimization with increasing numbers of generations.

In further experimentation, the optimal number of generations is determined. For this, studies with rising numbers of generations are executed until the found solutions improve no further or very little. Looking at the Hall of Fame solutions found after each number of generations and estimating their average fitness, it can be seen that the improvement starts to flatten after 40 generations. Therefore, after 50 generations, the optimization was ended.

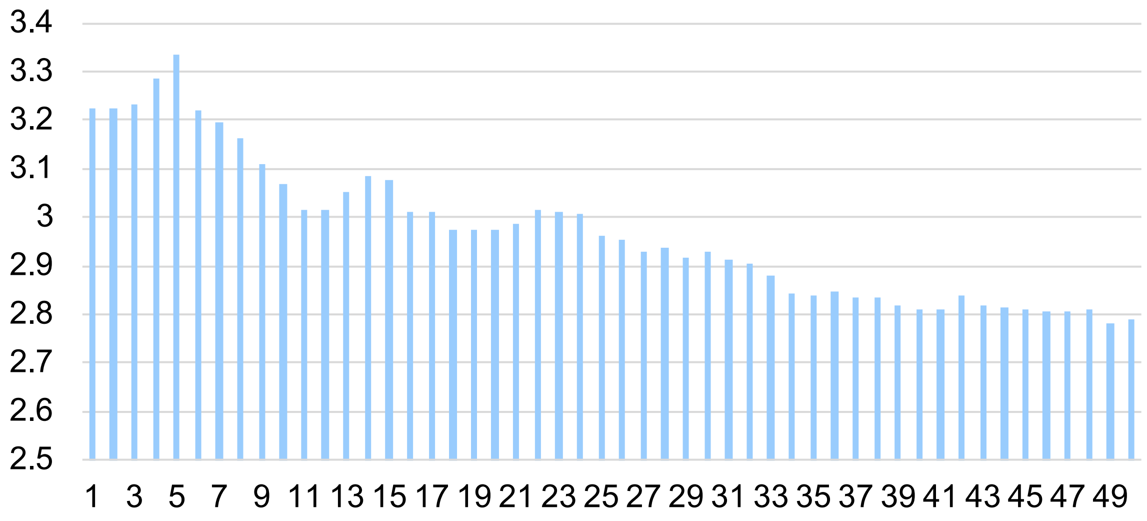


Figure 89 Average fitness estimate after increasing numbers of generations

As Refinery runs locally, its performance can be influenced by the power of the machine it is used on. In that case, time might also play a role in setting the population size and number of generations. If the optimization time needs to be reduced, it is recommended to reduce the number of generations rather than diminishing the population size. Research has shown that larger populations tend to improve the effectiveness more than a high number of generations (Vrajitoru, 2000).

6.3 Results

After 50 generations and with a population size of 120 solutions, the algorithm presents 14 design options that lie on the Pareto front [3] (for details, see Appendix A).

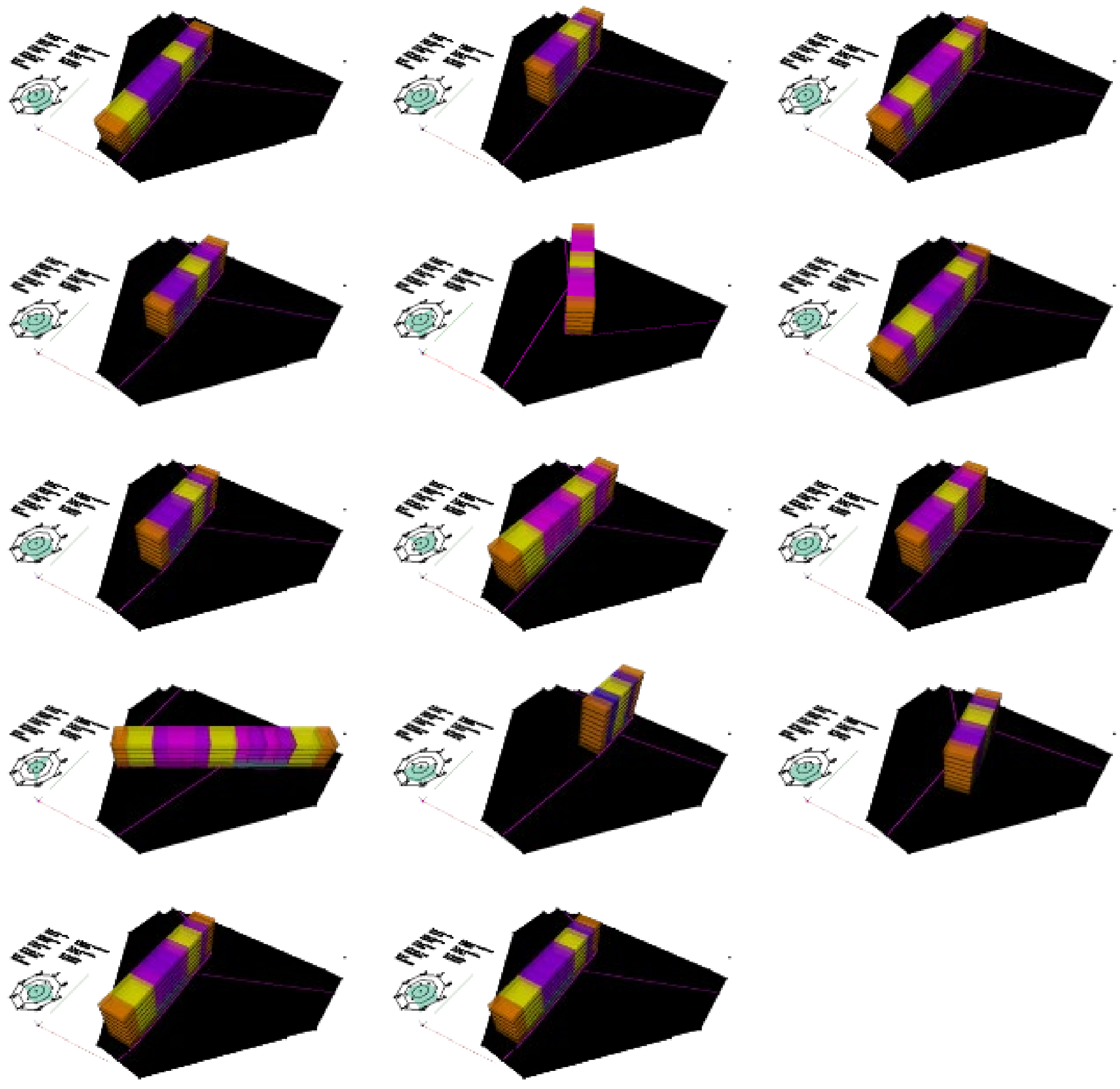


Figure 90 Results found in the optimization; for details see Appendix A

Contrary to the chosen design in Hannover, the GA favors a position on the left side of the property. It seems to be ideal as it allows for an N-S-orientation as well as short paths to the entrance of the building.

[3] After the removal of duplicates

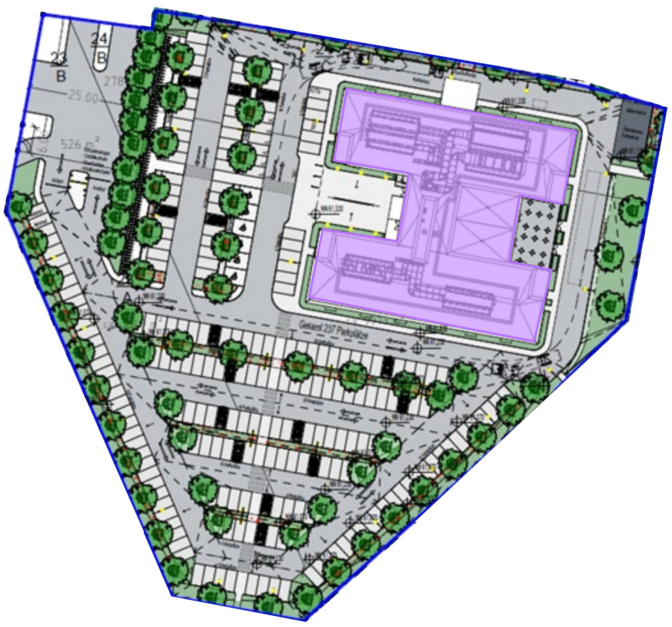


Figure 92 Design chosen by SRE for comparison

Deviance from that strategy can be seen in case of a longer building, that only fits the site diagonally, or when there is a trade-off situation between minimal pathways and optimal solar orientation. In that case, a position at the center of the site is chosen.

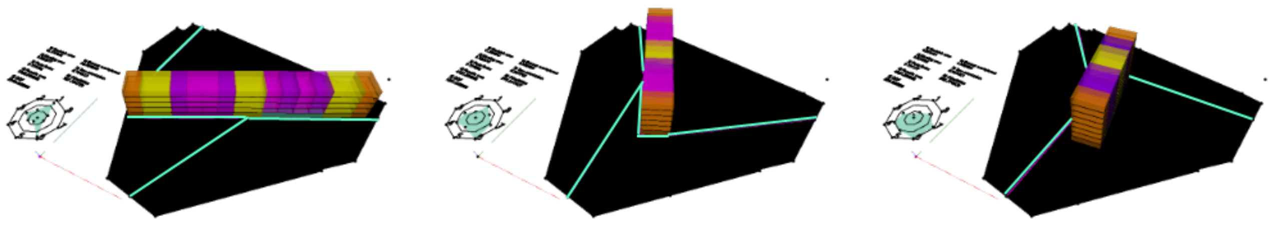


Figure 91 Solutions (selected) with paths highlighted

Furthermore, it can be seen that – if not equal – the number of units on the right is usually higher than on the left. This is to provide sufficient meeting area for the employees.

Solution #	Orientation u	Orientation v	Start Point x	Start Point y	No. Units Left	No. Units Right	Workplace Density
1	-0.1	-1	0.36	0.61	2	6	0.9
2	-0.1	-1	0.4	0.64	2	4	1.7
3	0.1	1	0.34	0.54	5	3	2
4	-0.1	-1	0.38	0.59	2	6	1.4
5	-0.3	0.7	0.38	0.65	4	4	0.2
6	-0.1	-1	0.38	0.61	3	4	1.9
7	-0.1	-1	0.36	0.53	3	4	0.9
8	-0.1	-0.5	0.39	0.59	3	5	0.4
9	-0.1	-1	0.38	0.56	2	4	2
10	0.6	0.3	0.53	0.56	5	5	0.5
11	0.1	0.6	0.48	0.75	2	2	4.1
12	0.1	-1	0.46	0.56	2	3	2.3
13	-0.1	-1	0.36	0.56	2	5	1.7
14	-0.1	-1	0.36	0.58	2	5	2.2

Figure 94 Input values of the solutions

It can also be seen that higher workplace densities are avoided. With one exception, the solutions do not exceed a workplace density of 2.3, which is equivalent to 14.3 workplaces per unit. The effects of a denser workplace configuration are less ground area covered or fewer levels needed to fit all workplaces, which leads to higher scores in footprint or façade area. However, these benefits do not seem to increase in the same volume as the benefits of a looser layout, which leads to more rentable area per workplace.

Solution #	Footprint	Facade area	Form factor	Rentable area/wp	Meeting area/wp	Excess wp	Orientation value	Circulation
1	1535.04	5472	0.190197	12.1479889	1.10167157	3	0.13920897	243.6091
2	1029.6	4569.6	0.19422244	10.1816719	0.72540359	1	0.06345103	244.7991
3	1535.04	4560	0.19853033	10.184064	0.5361408	0	0.06345103	246.2073
4	1535.04	5472	0.190197	11.5074169	1.04357966	31	0.06345103	244.4528
5	1291.68	4723.2	0.19402638	11.5685535	0.72251928	3	0.25776212	278.8179
6	1160.64	4320	0.19675352	10.1709413	0.72540359	1	0.06345103	248.9874
7	1160.64	5040	0.19080113	11.0500283	0.67551524	38	0.06345103	246.0619
8	1535.04	6384	0.18424462	12.0419676	0.77497297	92	0.12566592	250.7488
9	1029.6	4569.6	0.19422244	9.94350409	0.70843509	13	0.06345103	242.4554
10	2040.48	5856	0.19349565	12.5778462	0.88227692	20	0.70483276	307.7948
11	767.52	4665.6	0.19663331	8.31141818	0.32710909	28	0.10513691	258.1264
12	898.56	4684.8	0.19417735	9.65333333	0.53188571	4	0.06345103	258.7746
13	1404	5913.6	0.18614164	10.9684942	0.80067016	73	0.06345103	242.566
14	1404	5068.8	0.19209402	10.6464379	0.90668775	6	0.06345103	242.8643

Figure 93 Output values of the solutions

There is one exception to this observation, which is Solution #11. It follows a high-rise approach. In this extreme case, the aspect of very low ground area and a low façade area might outbalance the effect of a high workplace density.

For Siemens Real Estate it is good practice when developing a new building not to exceed 5 floors. This is to meet low-rise standards and avoid additional conditions and regulations that apply to high-rise buildings. These regulations exist mainly for fire safety reasons. In Germany, for instance, in case of a high-rise building, 2 fire escapes need to be available at any point in the building and within walking distance of max. 35 m. Therefore, it was agreed within SRE that high-rise buildings are uneconomic and should be avoided.

Interestingly, in the optimization, most results have more than 5 floors. The number of floors rages between 5 and 9, with an average of 6.57 floors. Some of the best scores for form factor are achieved by designs with 6 to 7 floors. From an energetic perspective, a lower form factor leads to lower heat loss in cold temperatures and less heat intake in hot weather.

So, to fit all workplaces, from an operation's perspective, it can be better to add more levels instead of widening the layout by attaching more units and worsening the scores in form factor and footprint.

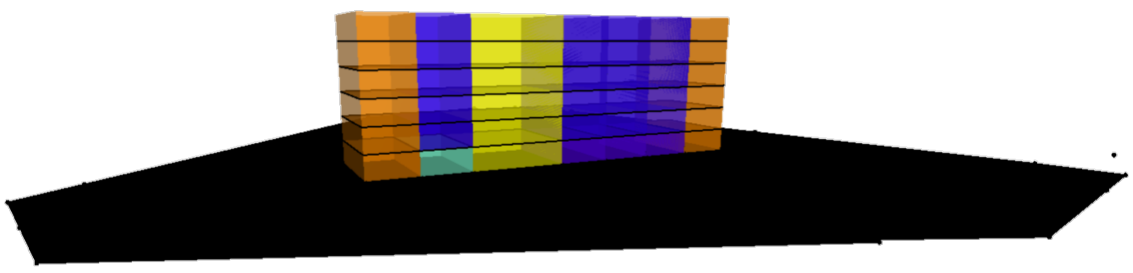


Figure 95 A solution with 6 floors and 3 fire escapes

With a parametric model, it is also very easy to check if the high-rise standards for escape routes are met. Designs with escape routes longer than 35 m can be ruled out. This way, high-rise designs can be found that are economically sensible in construction as well as operation.

The 5-floor-limit might serve as an example of a rule that makes sense in traditional design but becomes obsolete in the face of optimization. It is a rule of thumb that was put in place to avoid high-rise regulations. However, sometimes, high-rise regulations might be met without creating higher costs. So, limiting the building height to a maximum of 5 floors might unnecessarily narrow the solution space with some optima lying outside the searchable space.

6.4 Interview with Siemens

Six SRE project managers are interviewed on the findings of the experiment as well as the generative design process in general. The results were presented to them as in Appendix A. All answers can be found in Appendix B.

In general, the generative design is perceived well. It is viewed as a good approach to achieve an objective and data-driven basis for decision making. The interviewees like that advantages and disadvantages of different design/layout options are presented and think it will prevent manipulation of the decision process by personal, internal, or political interests. In comparison to a human, the computer is able to look at a much higher number of designs. However, one interviewee stresses that it cannot be the single source of truth. “The human touch, emotional evaluation, and inclusion of non-tangible soft facts” still need to play a role in the evaluation. But the advantage of generative design would be that potential options would not be ruled out by “the human nature of pre-selection and early limitation of ideas.” One interviewee states that he “would expect this to lead to better-designed buildings as we get better at defining and quantifying soft facts to define ‘a good indoor / outdoor environment.’”

Most interviewees agree that generative design would be beneficial for SRE. Their standardized buildings and office modules form “a perfect basis” for generative design, once the other configurations are implemented and rules are refined. It is seen as an additional base for discussion and decision making and “can lead to being more efficient, effective, and faster.”

One interviewee, however, has a more pessimistic view on the implementation of generative design in SRE. New processes would need to be implemented, and the education, tools are resources are not available. Also, the parameters would need to be re-adjusted for each project, which is seen as a hurdle.

Another point of criticism is that the set of evaluation parameters is incomprehensive and seems arbitrary. There is a wish to include objectives like site topology, local code requirements, and surrounding landscape and buildings.

The size of the solution set, however, is perceived as pleasant. They enjoy the possibility of choice and agree the last decision should always be made by humans. The generative design process provides a solid base upon which soft criteria can lead to a preferred option. One suggests “it would be better to review – say max. 10 – solutions, pick three and then run an optimization process – possibly with altered parameters or an altered weigh of the parameters. This way, people and computer could complement each other in this iterative process”.

The Hannover experiment shows “what possibilities algorithms can offer in the early project phase.” However, it is hard to compare the solutions to the actual design in Hannover. One interviewee explains: “The chosen design was an H formed building. A direct comparison would be quite difficult also because not all ConEx specification were followed. I cannot say why but I assume there were good reasons for the decision”.

7 Discussion and Outlook

Having a clear concept of the constraints, variables, and design measures is crucial to the success of a generative design study. In case of standardized buildings like the Siemens Real Estate Construction Excellence, this concept already exists and only needs to be broken down into parameters which is particularly adjuvant to a generative design study.

When this kind of concept does not exist, it lies in the hands of the architect to be able to abstract his vision into a set of variables and constraints, as well as carefully select a set of objectives.

It is crucial to the outcome of the study to know exactly what objectives the design should be optimized to. There is a virtually limitless amount of measures that a design can be evaluated by – functional, energetic, sustainable, financial. Some might even not be possible to asses, such as beauty or emotional stimulus. But knowing which ones are most important to the stakeholders is key. In case of Siemens Real Estate, there has been a well-defined process in place for how designs coming from different architects are compared which this study could build on. But other institutions might have to evaluate and analyze their workflows before being able to use generative design for their purposes.

Furthermore, some aspects of the design evaluation might seem trivial to the human designer but are hard to translate into calculatable scores. For example, it is easy for a human to solve geometric operations like placing a rectangle inside another shape if both shapes are visually available. However, since a computer lacks this form of perception, it proved difficult to implement this capacity into the system. A lot of focus was spent on teaching the algorithm how to produce designs that lie within the site as illustrated in Chapter 5.2. Other aspects like beauty are even harder to implement as they are highly subjective and hard to translate into abstract rules.

Personally, the effect of the computer taking over part of one's work was perceived as liberating by the researcher. Setting up the parametric model allowed for creativity, combined with the certainty that the best versions of the parametric model would then be found by the algorithm shifted focus on the former. In a real-life scenario, with less time spent on refining design parameters in the end, the human designer has more time to focus on the creative process in the beginning. It allows for a deeper reflection on the idea leading to the design concept. The process of developing the concept itself seemed similar to the traditional design process despite the outcome being more formal. Afterward, the tool took over the task of fine-tuning the concept into a reasonable and optimized design solution.

Hence, the term generative design might be misleading to some extent. The computer does not generate the design. It finds the best design options out of a large pool of combinations through optimization. The pool however – meaning the form and extent of the design options - is generated by the human designer.

The responsibility of picking a final design option also remains with the user. However, the process becomes very transparent and can be entirely data-based. The relevant information is provided, and solutions can easily be compared – especially when the data from the CSV-file is processed in Excel and depicted in radar charts. It allows the user to choose what objectives are most important to him or her and then focus on these while sorting through the provided options.

Once a solution in the Refinery GUI is selected, the model in Dynamo is immediately changed to match the chosen design option. To integrate this into the BIM process, a data exchange with Revit would be conceivable. In a closed-loop, the polyline of the site can be imported into Dynamo from Revit. After the optimization the final design is chosen and automatically generated in Revit by using pre-modeled families of each kind of unit.

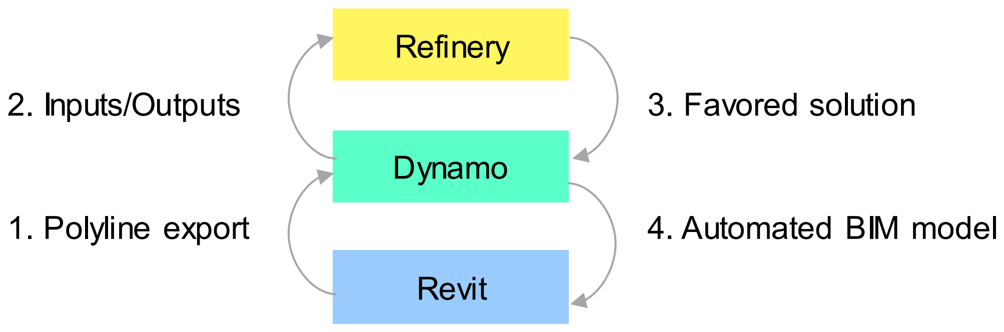


Figure 96 Integration of Revit

To further develop the parametric model for the purposes of Siemens Real Estate, more building configurations like H-shape, L-shape, etc. could be implemented along with an option for the wide layout.

Furthermore, the inclusion of more objectives might make the findings more comprehensive. The topology of the site, as well as the area surrounding the site, also plays a significant role in design finding. Corresponding objectives can easily be added to the evaluation. However, this would require the existence of an adequate environmental model.

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Appendix A

Overview of results

Solution #	Footprint	Facade area	Form factor	Rentable area/wp	Meeting area/wp	Excess wp	Orientation value	Circulation	Orientation u	Orientation v	Start Point x	Start Point y	No. Units Left	No. Units Right	Workplace Density
1	1535.04	5472	0.190196998	12.14798887	1.101671571	3	0.139208975	243.6091	-0.1	-1	0.36	0.61	2	6	0.9
2	1029.6	4569.6	0.194222444	10.18167186	0.725403593	1	0.063451035	244.7991	-0.1	-1	0.4	0.64	2	4	1.7
3	1535.04	4560	0.198530331	10.184064	0.5361408	0	0.063451035	246.2073	0.1	1	0.34	0.54	5	3	2
4	1535.04	5472	0.190196998	11.50741695	1.043579661	31	0.063451035	244.4528	-0.1	-1	0.38	0.59	2	6	1.4
5	1291.68	4723.2	0.194026384	11.56855348	0.722519284	3	0.257762118	278.8179	-0.3	0.7	0.38	0.65	4	4	0.2
6	1160.64	4320	0.196753515	10.17094132	0.725403593	1	0.063451035	248.9874	-0.1	-1	0.38	0.61	3	4	1.9
7	1160.64	5040	0.190801134	11.05002825	0.675515242	38	0.063451035	246.0619	-0.1	-1	0.36	0.53	3	4	0.9
8	1535.04	6384	0.184244617	12.04196757	0.774972973	92	0.125665916	250.7488	-0.1	-0.5	0.39	0.59	3	5	0.4
9	1029.6	4569.6	0.194222444	9.943504094	0.708435088	13	0.063451035	242.4554	-0.1	-1	0.38	0.56	2	4	2
10	2040.48	5856	0.193495648	12.57784615	0.882276923	20	0.704832765	307.7948	0.6	0.3	0.53	0.56	5	5	0.5
11	767.52	4665.6	0.196633312	8.311418182	0.327109091	28	0.105136913	258.1264	0.1	0.6	0.48	0.75	2	2	4.1
12	898.56	4684.8	0.19417735	9.653333333	0.531885714	4	0.063451035	258.7746	0.1	-1	0.46	0.56	2	3	2.3
13	1404	5913.6	0.186141636	10.96849424	0.800670157	73	0.063451035	242.566	-0.1	-1	0.36	0.56	2	5	1.7
14	1404	5068.8	0.192094017	10.64643794	0.906687747	6	0.063451035	242.8643	-0.1	-1	0.36	0.58	2	5	2.2

For more detailed information on each solution please click on the respective #

1	*Very good result*
2	*Good result*
3	*Ok result*
4	*Poor result*
5	*Very poor result*

Solution #1

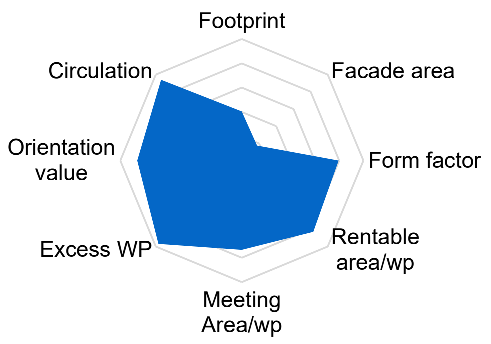
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.36
Start Point y	0.61
No. Units Left	2
No. Units Right	6
Workplace Density	0.9

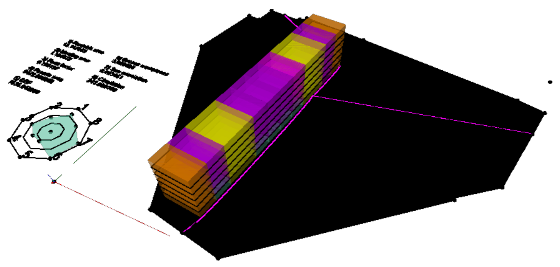
Model output

Item	Result
Footprint	1535.04
Facade area	5472
Form factor	0.190197
Rentable area/wp	12.1479889
Meeting Area/wp	1.10167157
Excess WP	3
Orientation value	0.13920897
Circulation	243.6091

Results radar chart



Graphical overview of result



Solution #2

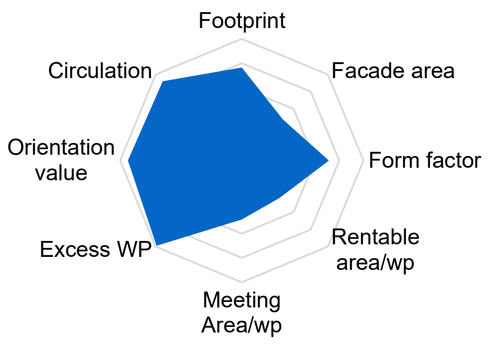
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.4
Start Point y	0.64
No. Units Left	2
No. Units Right	4
Workplace Density	1.7

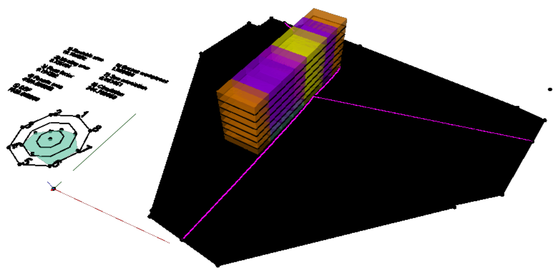
Model output

Item	Result
Footprint	1029.6
Facade area	4569.6
Form factor	0.19422244
Rentable area/wp	10.1816719
Meeting Area/wp	0.72540359
Excess WP	1
Orientation value	0.06345103
Circulation	244.7991

Results radar chart



Graphical overview of result



Solution #3

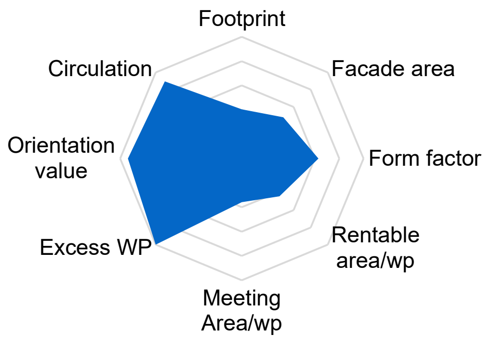
Input variables

Variable	Input
Orientation u	0.1
Orientation v	1
Start Point x	0.34
Start Point y	0.54
No. Units Left	5
No. Units Right	3
Workplace Density	2

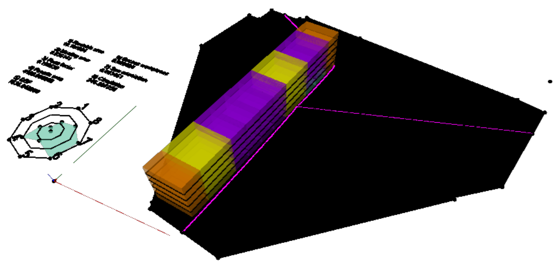
Model output

Item	Result
Footprint	1535.04
Facade area	4560
Form factor	0.19853033
Rentable area/wp	10.184064
Meeting Area/wp	0.5361408
Excess WP	0
Orientation value	0.06345103
Circulation	246.2073

Results radar chart



Graphical overview of result



Solution #4

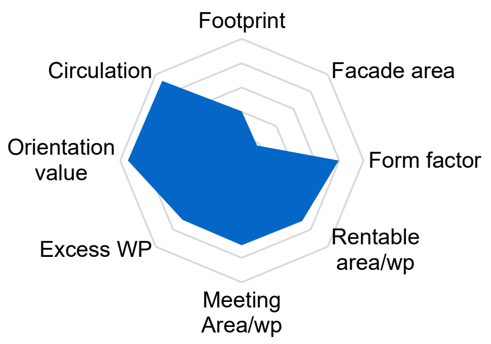
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.38
Start Point y	0.59
No. Units Left	2
No. Units Right	6
Workplace Density	1.4

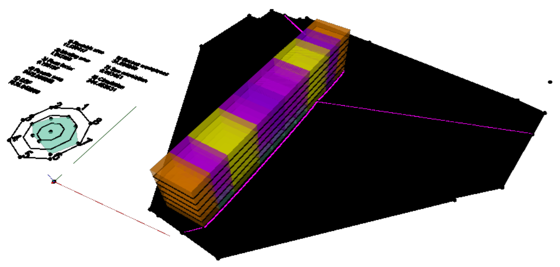
Model output

Item	Result
Footprint	1535.04
Facade area	5472
Form factor	0.190197
Rentable area/wp	11.5074169
Meeting Area/wp	1.04357966
Excess WP	31
Orientation value	0.06345103
Circulation	244.4528

Results radar chart



Graphical overview of result



Solution #5

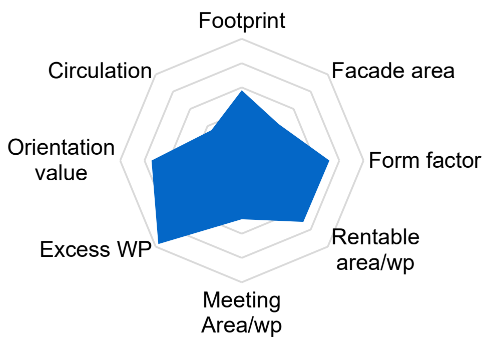
Input variables

Variable	Input
Orientation u	-0.3
Orientation v	0.7
Start Point x	0.38
Start Point y	0.65
No. Units Left	4
No. Units Right	4
Workplace Density	0.2

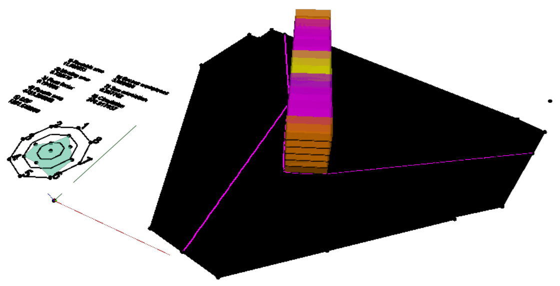
Model output

Item	Result
Footprint	1291.68
Facade area	4723.2
Form factor	0.19402638
Rentable area/wp	11.5685535
Meeting Area/wp	0.72251928
Excess WP	3
Orientation value	0.25776212
Circulation	278.8179

Results radar chart



Graphical overview of result



Solution #6

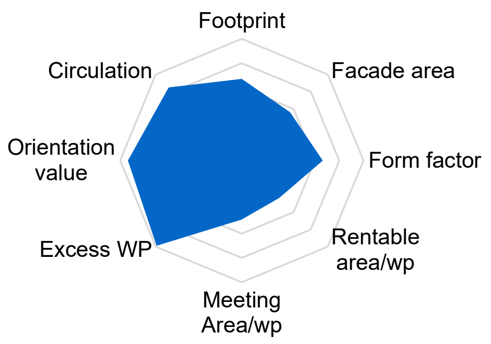
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.38
Start Point y	0.61
No. Units Left	3
No. Units Right	4
Workplace Density	1.9

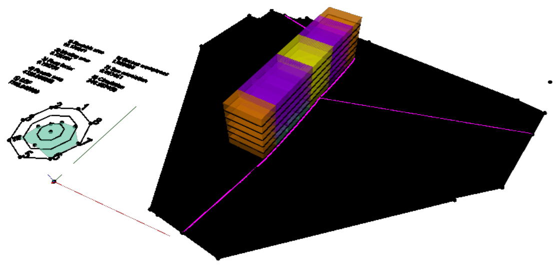
Model output

Item	Result
Footprint	1160.64
Facade area	4320
Form factor	0.19675352
Rentable area/wp	10.1709413
Meeting Area/wp	0.72540359
Excess WP	1
Orientation value	0.06345103
Circulation	248.9874

Results radar chart



Graphical overview of result



Solution #7

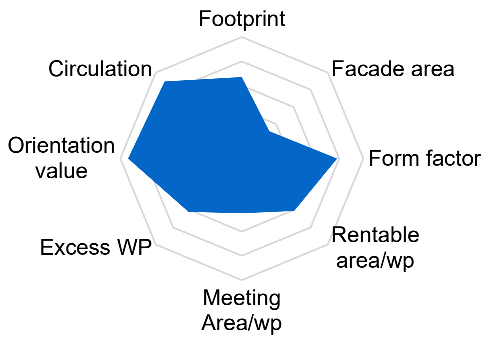
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.36
Start Point y	0.53
No. Units Left	3
No. Units Right	4
Workplace Density	0.9

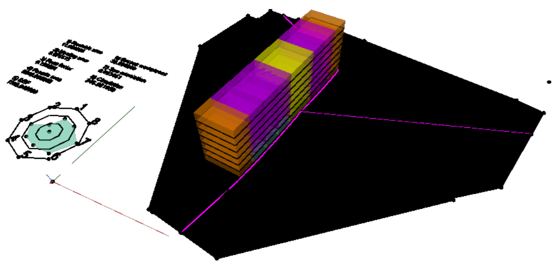
Model output

Item	Result
Footprint	1160.64
Facade area	5040
Form factor	0.19080113
Rentable area/wp	11.0500283
Meeting Area/wp	0.67551524
Excess WP	38
Orientation value	0.06345103
Circulation	246.0619

Results radar chart



Graphical overview of result



Solution #8

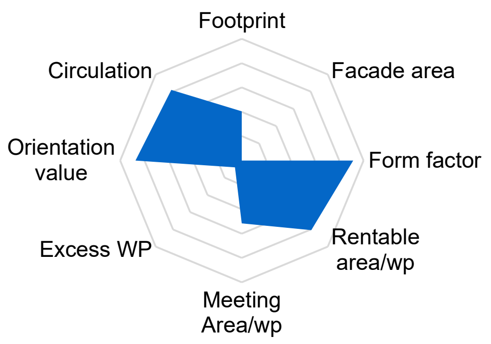
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-0.5
Start Point x	0.39
Start Point y	0.59
No. Units Left	3
No. Units Right	5
Workplace Density	0.4

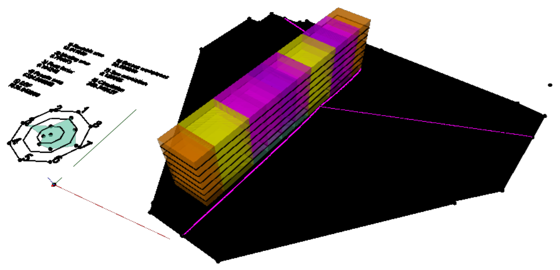
Model output

Item	Result
Footprint	1535.04
Facade area	6384
Form factor	0.18424462
Rentable area/wp	12.0419676
Meeting Area/wp	0.77497297
Excess WP	92
Orientation value	0.12566592
Circulation	250.7488

Results radar chart



Graphical overview of result



Solution #9

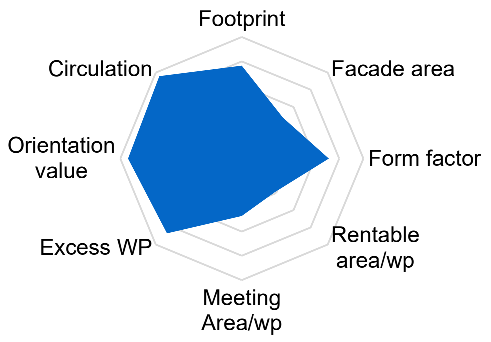
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.38
Start Point y	0.56
No. Units Left	2
No. Units Right	4
Workplace Density	2

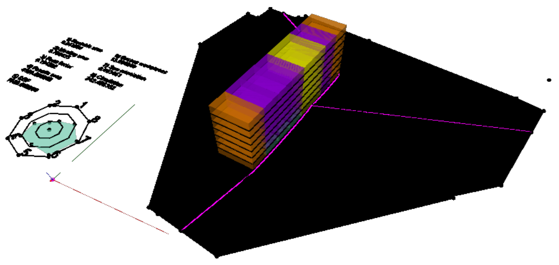
Model output

Item	Result
Footprint	1029.6
Facade area	4569.6
Form factor	0.19422244
Rentable area/wp	9.94350409
Meeting Area/wp	0.70843509
Excess WP	13
Orientation value	0.06345103
Circulation	242.4554

Results radar chart



Graphical overview of result



Solution #10

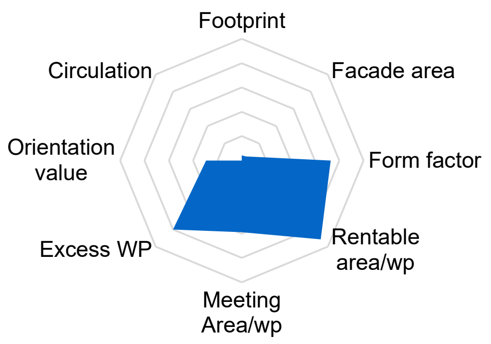
Input variables

Variable	Input
Orientation u	0.6
Orientation v	0.3
Start Point x	0.53
Start Point y	0.56
No. Units Left	5
No. Units Right	5
Workplace Density	0.5

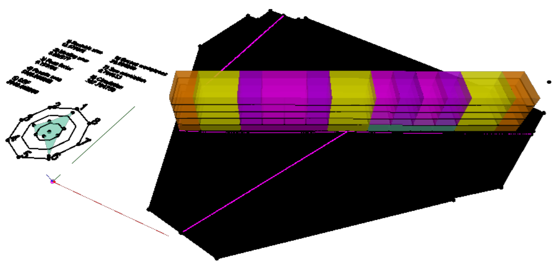
Model output

Item	Result
Footprint	2040.48
Facade area	5856
Form factor	0.19349565
Rentable area/wp	12.5778462
Meeting Area/wp	0.88227692
Excess WP	20
Orientation value	0.70483276
Circulation	307.7948

Results radar chart



Graphical overview of result



Solution #11

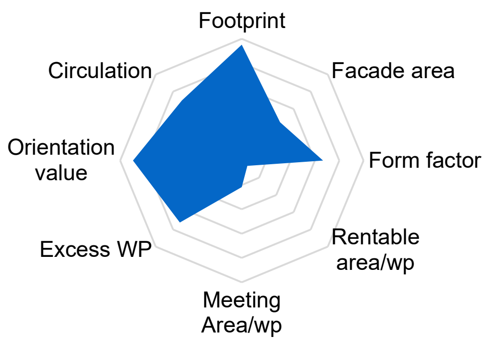
Input variables

Variable	Input
Orientation u	0.1
Orientation v	0.6
Start Point x	0.48
Start Point y	0.75
No. Units Left	2
No. Units Right	2
Workplace Density	4.1

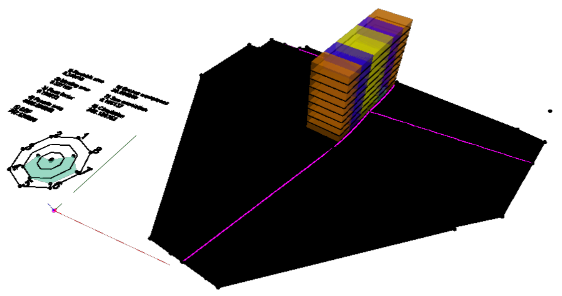
Model output

Item	Result
Footprint	767.52
Facade area	4665.6
Form factor	0.19663331
Rentable area/wp	8.31141818
Meeting Area/wp	0.32710909
Excess WP	28
Orientation value	0.10513691
Circulation	258.1264

Results radar chart



Graphical overview of result



Solution #12

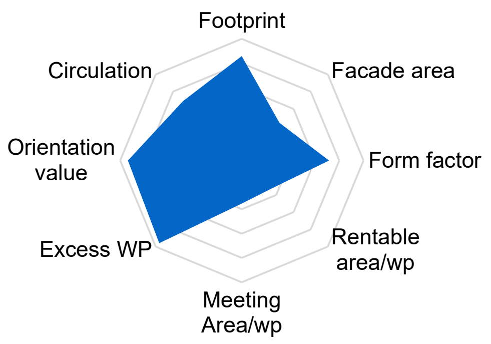
Input variables

Variable	Input
Orientation u	0.1
Orientation v	-1
Start Point x	0.46
Start Point y	0.56
No. Units Left	2
No. Units Right	3
Workplace Density	2.3

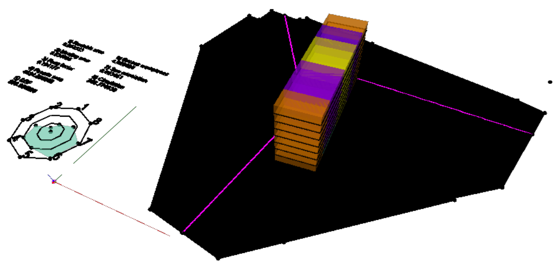
Model output

Item	Result
Footprint	898.56
Facade area	4684.8
Form factor	0.19417735
Rentable area/wp	9.65333333
Meeting Area/wp	0.53188571
Excess WP	4
Orientation value	0.06345103
Circulation	258.7746

Results radar chart



Graphical overview of result



Solution #13

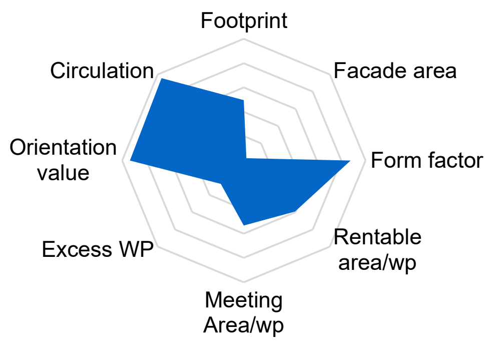
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.36
Start Point y	0.56
No. Units Left	2
No. Units Right	5
Workplace Density	1.7

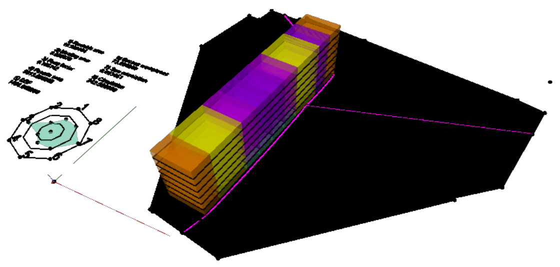
Model output

Item	Result
Footprint	1404
Facade area	5913.6
Form factor	0.18614164
Rentable area/wp	10.9684942
Meeting Area/wp	0.80067016
Excess WP	73
Orientation value	0.06345103
Circulation	242.566

Results radar chart



Graphical overview of result



Solution #14

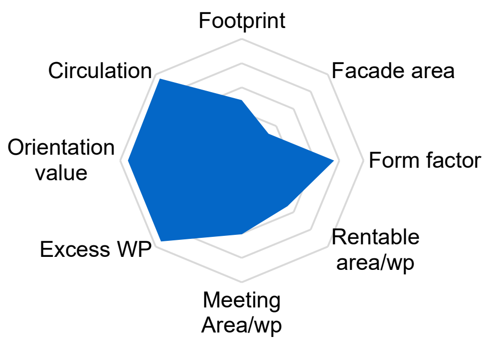
Input variables

Variable	Input
Orientation u	-0.1
Orientation v	-1
Start Point x	0.36
Start Point y	0.58
No. Units Left	2
No. Units Right	5
Workplace Density	2.2

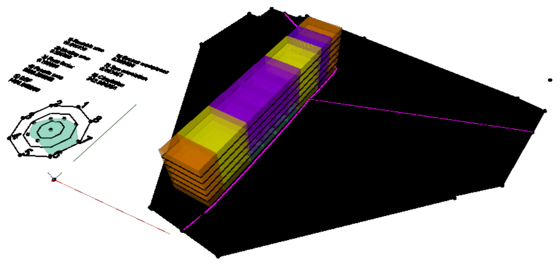
Model output

Item	Result
Footprint	1404
Facade area	5068.8
Form factor	0.19209402
Rentable area/wp	10.6464379
Meeting Area/wp	0.90668775
Excess WP	6
Orientation value	0.06345103
Circulation	242.8643

Results radar chart



Graphical overview of result



Appendix B

What are your thoughts on the generative design approach overall?

Interviewee A

It's a very good approach to show up an objective and data driven basis for decision making. Presented pros and cons of different building design/layout possibilities - i.e. decision processes are often kind of "manipulated" by personal, internal, political, strategic or other stakeholder interests, with sometimes significant consequences in planning and execution phase or even in the end for the customer during/after handover. This approach supports transparent and objective prioritizing of design criteria and data bases decision making.

Needless to say all the positive commercial aspects like cost calculation, rating of design/concept changes, etc..

Interviewee B

Ein guter Ansatz für die Optimierung von Gebäuden in der frühen Phase. In Kombination mit dem Wissen über die örtlichen und baurechtlichen Gegebenheiten ist das in Zukunft eine gute Unterstützung zur Bestimmung des optimalen Designs. Mir fehlen jedoch die Parameter, die sich aus den Gegebenheiten des Grundstücks ergeben (z.B.: Zufahrt, Höhenverlauf).

Interviewee C

In my opinion generative design generally offers an enormous potential in the field of architecture – especially in the early project phases. Wherever design plays a role, generative design and artificial intelligence can help due to the very high number of design variants. For example, in other industries generic design is almost standard. For example, in the automotive or food industries. I think the example of the Hannover building already shows SRE, what possibilities algorithms can offer in the early project phase. An automatic configuration tool for office buildings, based on ConEx, could be a first step for SRE. But it can't be the single source of truth.

Interviewee D

The future for (building) design is via parametric design, as I see it. The opportunity to connect design parameters and letting them interact via modelling will bring new insights into the prioritizing of technical parameters and quantifiable soft facts. Will it fix all? No. The "human touch", emotional evaluation and inclusion of non-tangible soft facts will still need to be added as part of an evaluation of the machine generated out option. The upside, as I see it, is that the human nature of pre-selection or early limitation of ideas is not limiting theoretical options up front. I would expect this to lead to better designed buildings as we get better at defining and quantifying soft facts to define "a good indoor / outdoor environment".

Interviewee E

In general, it is an interesting approach to finding optimal design alternatives. It is, however, very limited with the typical constraints that we are facing in the conceptual phase. Most decision in the end are arbitrary and based on aesthetics and the surrounding landscape or how the landscape will be altered to make a comfortable environment.

Interviewee F

A suitable approach for very early design phases and for evaluations regarding the possibilities of suing a site. Local code requirements 8for example: if a building has to stand on a certain line, not "somehow" on the site, should be possible to enter, to ensure that the options generated are actually – at least somewhat – realistic.

It would also be helpful if the parameters can be changes – this is what happens in an iterative design process: not only the solutions develop, but also the parameters they are measured against, because we never know everything from the beginning.

Do you think that it can be beneficial to Siemens Real Estate in the near future?

Interviewee A

Yes! Standardized building configurations and office modules are a perfect basis for this approach.

Interviewee B

Ja. Für die Entwicklung zukünftiger Design ist das eine gute Unterstützung und bietet einen zusätzlichen Diskussions- und Entscheidungsansatz.

Interviewee C

Yes, it may be beneficial for SRE to use an iterative generic design process in the near future. Generative design can help SRE to find the most efficient form in the early project phase. If SRE has such an automatic configuration tool, SRE could consider a wide range of solutions for customers. This can lead to being more efficient, effective and faster. With generic design and artificial intelligence, architects and designers can be supported in the planning process with a high level of design solutions.

Interviewee D

Yes ;-)

Interviewee E

Unfortunately, I do not see any benefits for now. It also depends on what you mean by “near future”? One year? Ten years? Even if it is ten years, the responsibilities would have to be specified to implement new processes (education, tools etc). It does not seem to me that the resources for this are available and I do not see an immediate financial benefit as the task is more an architect (established in the thesis also) task then it is the task of the building owner i.e. we would be helping the architect (see 2 paragraphs down for the reasoning why I do not see the immediate benefit with Siemens). The thesis also states “There is a virtually limitless amount of measures that a design can be evaluated by” which kind of confirms the impossible implementation of this method in real projects. Two of the more pressing “parameters” would be for example surrounding landscape and buildings because they already influence the existing eight parameters but were not considered.

Also, based on the eight parameters you were considering (if not weighted) and taking into account all forms in ConEx, the solutions would converge to TYPE B_OPTION 9 (from ConEx), unless the site geometry is elongated (mostly not the case) due to the simple reason that it positively influences (compared to other available forms) the highest number of parameters considered (BGF, Façade area, form factor, rentable and meeting area as well as circulation).This is due to a simple geometry fact which in its extreme turns out to be a circle (sphere). The effect can be observed in the thesis on page 8 Figures 2 and 3.

It must be clear that the algorithm does not find the most efficient design alternative it finds a design alternative based on arbitrary parameters that can vary from project to project and would have to be specified first. Also, the parameters would have to be adjusted to incorporate all influences. To use the method, it would have to be resolved who decides this and does it really represent a benefit for Siemens? Maybe a topic for another thesis?

There are many other factors influencing the implementation in real projects. The ones I specified here should give a good basis though.

Interviewee F

Generally yes, but the range of solutions needs to be expanded to other configurations as well and the configuration rules need to be refined. Currently too many uneconomic options are generated and too many options favour an east-west orientation, which would not be given preference over a north-south orientation in reality.

How happy are you with the size of the solution set? Would you have preferred to be presented with one optimal solution or do you enjoy the possibility of choice?

Interviewee A

Following my statements in 1) and 2) I would like to have the possibility of choice. Especially for decision making process, this different view may also help to find a compromise when different/contrary needs, requirements or boundary conditions have to be considered.

Interviewee B

Die Vielzahl an Lösungen ist gut. Es wird eine Entscheidungsgrundlage gegeben auf Basis derer unter Berücksichtigung weiterer weicher Faktoren und einer angepassten Entscheidungsmatrix die optimale Lösung gefunden werden kann.

Bei Reduzierung auf nur ein oder zwei Lösungen würde die ganzheitliche Betrachtung und Diskussion nicht mehr stattfinden würde.

Interviewee C

For me it is extremely exciting to see what is possible with the use of algorithms. I think it is helpful to have more than just one optimal computer-generated solution. I think with the variety of possible solutions, there will always be solutions that can be preferred and solutions that cannot. I think the last decision should always be made by humans. However, in order to make an optimal decision, it is helpful and necessary for designers and architects to know as many solutions as possible. Of course, a lot of soft variables still need to be considered, which are self-evident to the human eye, but not for a program. So far it exists no “one size fits all”-solution – at least not yet.

Interviewee D

The set of 14 is fine. I do not believe in “one optimal solution”. Adding the human touch or adding additional design parameters would, as I see, it be the next step to select a preferred option.

Interviewee E

As stated in the previous answers, there are many other factors that determine the decision on the placement of the building that were not considered. Whether one alternative is better than the other would require an interpretation based on the parameter values for every solution. This interpretation might vary from project to project but just looking at 8 arbitrary numbers does not aid in the decision. The interpretation would also have to weigh the factors because they might have a different influence on the design. The problem of the eight factors is that they all favour one type of form.

Interviewee F

There are too many solutions, and they are too much alike. It would be better to review – say max. 10 – solutions, pick three and then run an optimization process – possibly with altered parameters or an altered weigh of the parameters. This way, people and computer could complement each other in this iterative process.

The range of choice is preferable, as it is not possible to enter all parameters and the decision for a certain design will be based on many more factors. For example, the usability of the site is not very good, if the building stands diagonally on the site, but accommodating enough parking on the site might be critical. I think, it could provide a good first guess, but needs more work

How do the solutions compare to the design chosen for Hannover? (If possible, please include numbers)

Interviewee A

I’m not involved in detail in Hannover project.

Interviewee B

Der Vergleich der Lösungen aus dem Modell mit dem geplanten Objekt in Hannover ist eigentlich nicht möglich, da dem Lösungsansatz aus dem Modell zusätzliche Parameter fehlen, die für die Entwicklung des Konzepts in Hannover relevant waren (Erschließung, Höhenprofil, Schaffung zusätzl. Baurechts, Hochhausgrenze).

Für einen direkten Vergleich würde ich die Varianten 6 und 7 heranziehen. Bei beiden Varianten erscheint es Möglich die o.g. Faktoren ebenfalls entsprechend umzusetzen.

Interviewee C

Interviewee D

No idea.

Interviewee E

The chosen design was an H formed building. A direct comparison would be quite difficult also because not all ConEx specification were followed. I cannot say why but I assume there were good reasons for the decision.

BGF was1350 m2, Façade area 5343 m2, 13m2/wp primary usable area (not to be confused with rentable area / wp which would result in 17m2/wp), think tank area 228 m2, phone box area 21 m2, meet & talk area 181 m2, 11 individual offices.

Interviewee F

Hannover is an H shaped building and it is very hard to compare the options.

The H shape is of course very efficient with regard to circulation, as there is only one central core in the building. The block-shaped buildings seem to take up much more of the site and leave less are for parking etc. Due to the sometimes arbitrary looking placement, the site gets cut into some inefficient shapes, where is would be hard to accommodate parking etc.

I think, several options should not have “survived”: option 1, 3, 4, 8, 10 and 13 have either two or even three cores which are placed at the end of the building with another staircase next to them. This does not make sense. But I guess, it shows the limitations, if you don’t tell the machine that this is not an option, it may think, it is a good one!

I would have liked to see more options which are placed parallel to the main street like the actual design.

If you had to pick one or two of the solutions, which ones would be your favorite? Why?

Interviewee A

I’m not involved in detail in Hannover project.

Interviewee B

Mein Favoriten sind 5 und 6. Beide erscheinen sehr kompakt und wirtschaftlich.

Interviewee C

Interviewee D

Looking only at the existing parameters I would tend to focus less on build space and façade area and lean more towards functional parameters such as circulation and meeting area/WP as I believe these parameters leads to a “better building”. I believe it would depend on the parameters not included in the parametric set of goals.

Interviewee E

If I had to pick, I would probably go for #12 or #9. The elongated alternatives block a lot of the panoramic view of the site and I prefer symmetry in regard to neighbouring sites in this scenario since I do not have information on neighbouring buildings and the landscape developments around the building. It seems safer to have a more centrally positioned building.

Interviewee F

Probably one of the solutions which has a single core.