

Topo-Metric Variations for Design Optimization

Introducing a Generative Model for simultaneously varying metric and topological properties of facade geometry

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Abstract. *The conception of a Generative Model (GM) is an important step when applying optimization methods in architectural design. The variant spectrum generable with a GM determines if an optimal solution for the different demands placed on a design can be found. Using the example of optimizing façades (more specifically window-layouts), it is shown that GM that exclusively vary either metric or topological properties of the geometry are not sufficient, because they only cover a highly restricted solution-space. To keep the solution space as large as possible, it is argued, that it is necessary to vary both topological and metric properties. The combination of both properties is called topo-metric properties. A GM for the generation of facade variants is presented, that is able to systematically vary these topo-metric properties. The effectiveness of the developed GM compared to conventional GMs is demonstrated using a simple test scenario.*

Keywords. *Design optimization; modeling; evolutionary algorithms, topo-metric properties.*

BACKGROUND

Optimization methods are an essential tool for performance-based design in architecture. So far, a lot of examples exist for generating an architectural solution (such as building envelopes or facades) from certain performance criteria by using such methods (see e.g. Caldas, 2008; Dillenburger et al., 2009; Gerber et al., 2012; Geyer, 2006; Kämpf and Robinson, 2010; Wright and Mourshed, 2009). These examples clearly demonstrate the potential of optimization methods for solving architectural design problems. However, it needs to be noted that the results from optimization processes largely depend on the

mathematical model used to describe the problem (Papalambros and Wilde, 2000; Radford and Gero, 1988). In this model, an algorithm is defined, which is able to generate possible solutions to a given problem. This algorithm is also referred to as the Generative Model (GM). The conception of this GM is a crucial step, because an object can only be optimized inside the scope of the spectrum of variants that the GM can generate. This spectrum (also called solution space) is defined (in the case of building geometry optimization) by rules for varying the geometric attributes. When defining the rules one must

distinguish between metric and topological properties. Metric properties define the size and position of elements, such as the position, width and height of a window. Topological properties define the relations of the elements to one another (e.g. window X is located in wall Y). A consideration of previously developed GMs shows that these are based either on the variation of metric or on the variation of topological properties.

Metric versus Topological GMs

In the case of GMs, where only the metric properties are varied, the topological properties are set in advance of the optimization process (as used e.g. in Caldas, 2008; Gerber et al., 2012; Kämpf and Robinson, 2010). This means that although the dimensions of a window can be varied, the number of windows in a wall cannot be controlled. Assuming that important decisions in the design of buildings are defined by the topological properties, such models are only suitable for solving partial problems. Grid-based approaches try to solve this problem by using a grid in which it is possible to assign each of the grid cells a certain state (Dillenburger et al., 2009; Geyer, 2006; Shea et al., 2006; Wright and Mourshed, 2009). Here one can vary the topological properties (for example the number of windows in a wall is not pre-defined), but the metric properties remain fixed (e.g. the size of the single windows).

The conception of a Generative Model (GM) is an important step when applying optimization methods in architectural design. The variant spectrum generable with a GM determines if an optimal solution for the different demands placed on a design can be found. To put it bluntly, if a solution is not generable with a GM, the optimization behaves like the “man who, having lost his keys one night, searches under the lamp post, not necessarily because that was where he lost his keys but because that is where the light is” (Radford and Gero, 1985). Thus, to find innovative solutions for various problems, it is necessary to keep the solution space as large as possible. And for this it is necessary to vary both the topological and metric properties of the geometric model.

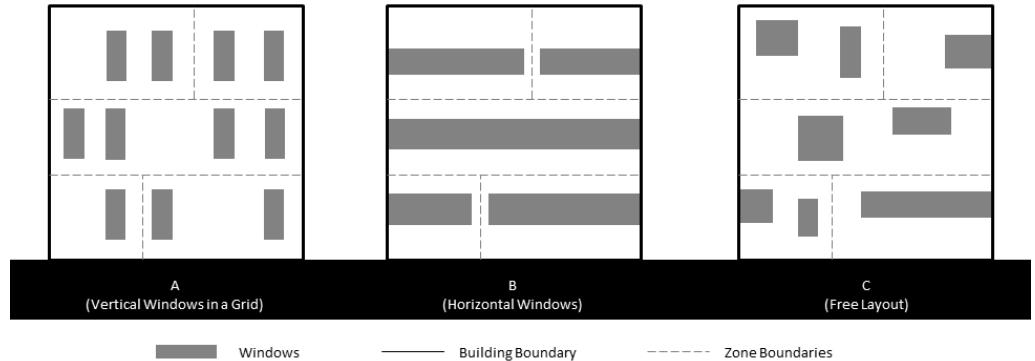
The combination of both properties we call topometric properties. Using the example of optimizing the window layout on a building envelope, we present a GM for the generation of facade variants that is able to systematically vary these properties.

A general model for façade generation

The allocation and dimension of windows on a building façade has an important influence on the function, aesthetics and energy performance of buildings. They allow natural daylight into the interior (and thus reduce electricity consumption), afford a view outside and warm up the interior through direct sunlight. To optimize a façade according to these criteria, a GM for generating façade variants is needed. Here one has to consider that different types of facades are conceivable, such as vertical windows in a grid, long horizontal windows or freely arranged layouts (Figure 1). As seen before, the results of optimization strongly depend on the GM used to perform the optimization. Since the aim of performance-based design is to derive form from a set of desired performance criteria, the prior definition of one facade type would contradict this idea. Furthermore, the definition of a GM that is only able to create one of these types will allow one to find an optimum for one style. This optimum represents just a local optimum compared with all the possible variants of all other types. In order to overcome such local optima, the GM needs to be as general as possible. Since the different types of façades, shown in Figure 1, differ in their metrical as well as in their topological properties, both properties need to be variable by the GM.

In the following a GM is introduced, which makes it possible to vary topological properties (the number of windows in a wall) and metrical properties (dimensions and position) of a façade simultaneously. This enables the design optimization of a facade, where neither the number of windows is predetermined nor are they constrained to a grid with a fixed cell size. Accordingly, we expect that the optimization results would depend less on a predetermined facade type.

Figure 1
Examples of different façade variants for one building.



A TOPO-METRIC GM FOR FAÇADE GENERATION

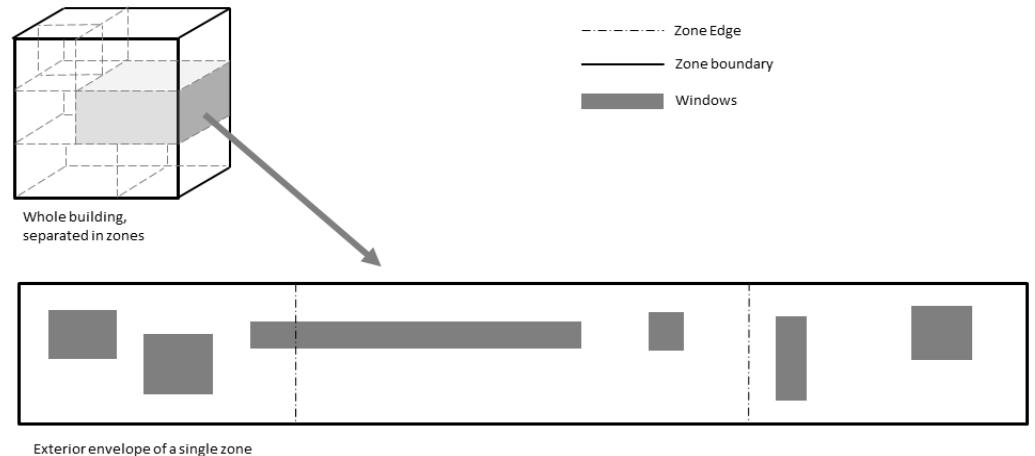
The algorithm was developed for an existing building model (which was developed as part of the research project FOGEB). The different boundary conditions that this must fulfill are explained below.

Building Model

For representing the building as a whole, we use a simple model in which the building is a set of single building zones (Figure 2 top left). Each of these zones can later be used for zone-based energy calculations (Clarke, 2001). The whole facade consists

of the exterior envelopes of all zones (Figure 2). Each of these exterior envelopes serves as a boundary for placing windows. Thereby different constraints are applied: The shape of each window is a rectangle. Windows can only be placed within the envelope boundary. A window shall not intersect with another window. Windows can overlap the edges of a zone. This is important since it opens up the possibility of creating corner windows. Lastly, the size of a window must not fall below or exceed the minimal or maximal widths and heights defined by the user. In Figure 2 an exemplary facade variant is shown which fulfills the aforementioned constraints.

Figure 2
Building model, generative constraints and an exemplary façade variant for a single zone of a simple 3-storey building.



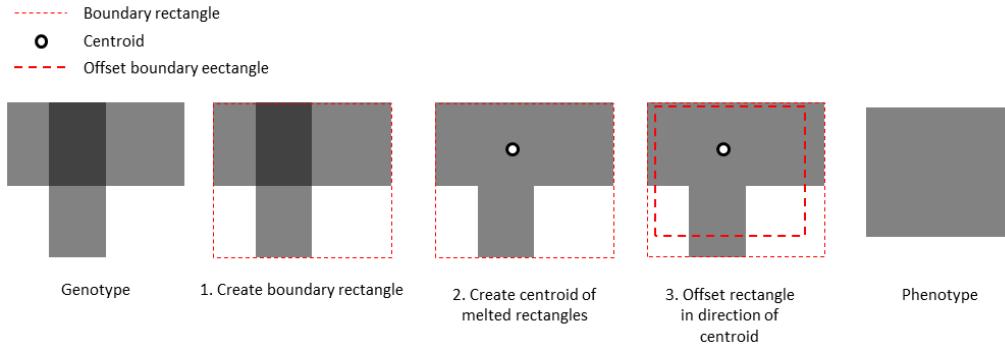


Figure 3
Algorithm for cleaning overlapping rectangles.

A Generative Model allowing topo-metric variations

The functionality of a GM depends on the optimization model it is used for. As an optimization model we use an evolutionary strategy (ES). ESs which are inspired by the process of biological evolution create solutions in an iterative process of generation, evaluation, selection and variation of individuals (Rechenberg, 1994). They are well suited to our purposes due to their flexibility. To arrive at a solution with certain properties, no a-priori patterns for guiding the search process are necessary. This is particularly important because we want to investigate the influence certain parameters have on a solution. For this it is important to exclude confounding factors, such as a conscious change of solutions.

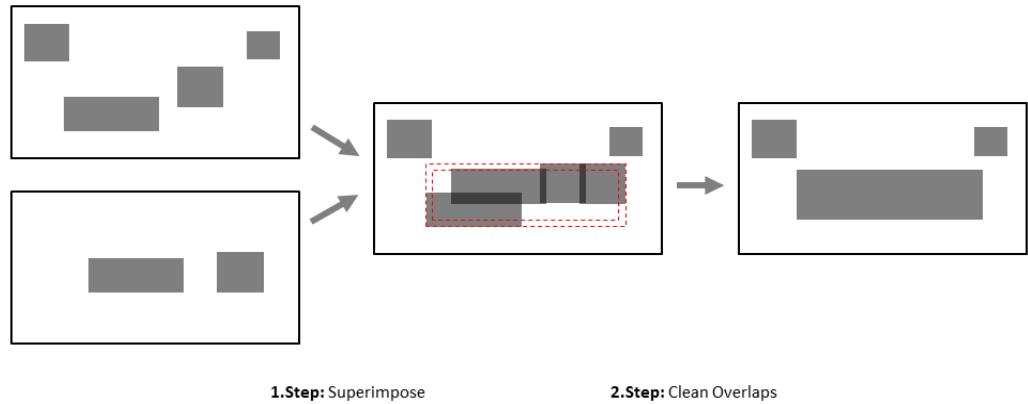
When using an ES, the GM must be able to carry out both mutation and crossover operations to create new variants (individuals). A critical issue for these operations is the mutation step size (Rechenberg, 1994). This indicates how much the performance of an individual changes with the variation of an individual. In our case, performance is primarily influenced by the size of the whole window surface and by the insertion of a window on a previously windowless wall. In order to effectively search for optima, both large and small mutation steps must be taken. If only small mutation steps are made there is the danger that one remains trapped in local optima. If only large mutation steps are undertaken it is not possible to continuously iterate towards an

optimum. Metric attributes can be changed in both large and in small steps. Topological changes (such as adding a window) usually have a very large impact on the performance of a solution. To systematically search for metrically and topologically different solutions, the topological properties must be changed as continuously as possible. In the following we present an algorithm in which we attempt to achieve this. To ease the understanding of the GM we show the basic principles for a single zone.

A facade variant consists of n rectangles ($n = 0 \dots \max N$) randomly placed inside the envelope boundary. The maximal number of rectangles ($\max N$) is the number of maximally placeable windows of minimal size ($\min \text{Width}$, $\min \text{Height}$). The n rectangles represent the genotype of an individual. The rectangles stored in the genotype are allowed to overlap. The phenotype represents the final solution which is taken for further evaluation. The phenotype of an individual is made up by cleaning the overlaps occurring in the genotype. If two or more rectangles overlap, a bounding rectangle is created. This boundary rectangle is scaled down in order to have the same surface area as the overlapping rectangles. Thereby the edges of this rectangle are moved in the direction of the centroid of the melted overlapping rectangles (Figure 3).

This simple step, on the one hand, satisfies the boundary condition that the window may not overlap, and on the other, the algorithm helps in the implementation of mutation and crossover operations,

Figure 4
Crossover of two individuals.



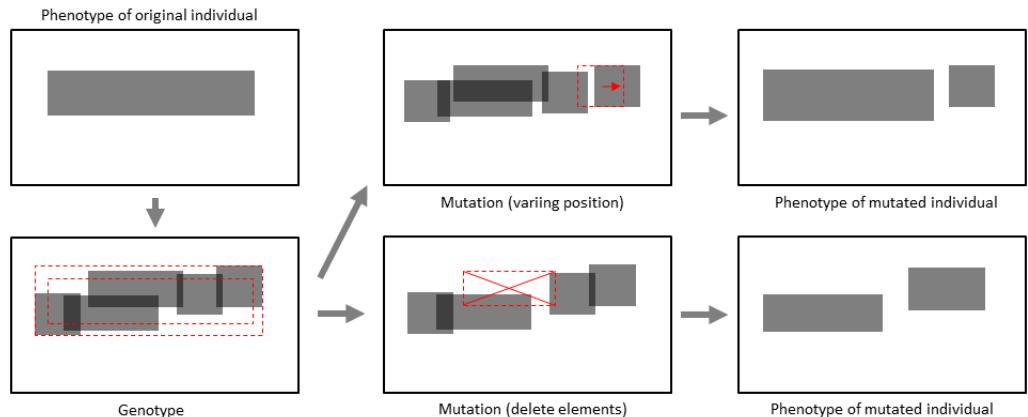
as discussed below.

After randomly generating individuals in the first generation, in each new generation individuals are generated by mutation or mating (crossover) existing ones. The crossover mechanism is not trivial since the amount of elements (number of windows) in each variant can be different and thus each genotype has a different length. However, by making use of the previously described cleaning algorithm, the crossover of two topologically different individuals is quite simple: First, the phenotypes of two individuals are superimposed. This results in the genotype of a new individual. By applying the cleaning algo-

rithm the phenotype of the new individual is generated. This phenotype represents a good compromise between the two parent individuals and can be topologically different from them (Figure 4).

The crossover-mechanism on its own is problematic, since after some iterations the surface covered by windows tends to constantly increase. To overcome this problem the mutation mechanism randomly deletes elements. In addition to deletion, elements are changed in their dimensions and position. Both operations (deletion and changing) are performed on the genotype. In Figure 5 an example for both mutation operations is shown. The exam-

Figure 5
Two different mutations of one individual.



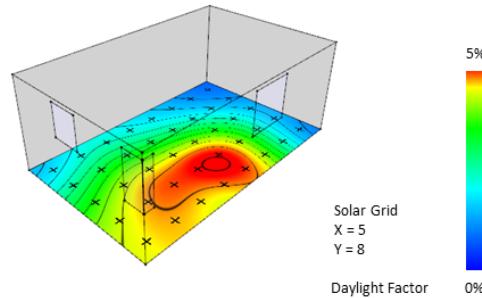
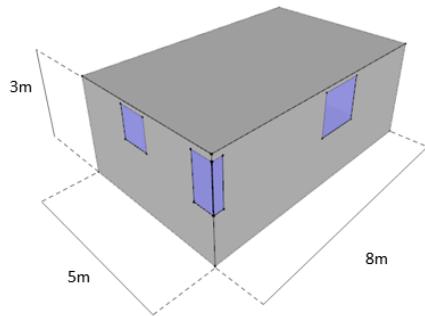


Figure 6
Test scenario (left: Dimensions of the zone; right: Solar analysis of the interior).

ple demonstrates how the algorithm can gradually change a long horizontal window into two smaller windows.

Using the aforementioned coding of the phenotype, each individual carries several topologically different solutions in itself. These can be evoked by simply moving, scaling, adding or deleting rectangles in the genotype. In the process, the size of the windows (in the phenotype) mostly varies only slightly, which is important to keep the mutation step size small. In the following, the functionality of this GM is demonstrated in test scenario and its performance is compared to two ordinary GMs.

VALIDATION - COMPARISON OF DIFFERENT GM

To demonstrate the functionality and performance of the described GM we have implemented three different GMs and compared them with one another in a test scenario. The implementation was undertaken in a self-developed optimization framework, based on FREAC (Koenig et al., 2010). The first GM is the GM presented in the previous section for varying topo-metric properties (Topometric-GM). The second GM is an algorithm that can vary the metric characteristics (position, length and height) of the windows (Metric-GM). It is assumed that one window is located on each wall. The third GM is a grid-based GM. Here, a uniform grid is superimposed on the wall surfaces. Each grid cell can be switched active or inactive. If a cell is active, a window with fixed dimensions (1m x 1m) is inserted at this position.

The test scenario is to optimize the window layout of one building zone with a width of 5m and a length of 8m and a height of 3m (Figure 6 left). The allocation of the windows takes place on the two outer walls (west and south exposure). As an optimization strategy, we use a (2+8)-ES. This means that in every generation the two best individuals are retained and from these, 8 children are generated by mutation and crossover.

The goal of the optimization is to sufficiently illuminate the interior of the zone. For daylight analysis, a self-developed GPU-based algorithm is used, allowing real-time solar analysis [1]. For this an analysis grid (with 5 x 8 points of analysis) is created in the interior of the zone (Figure 6 right) and the Daylight Factor (DF) is calculated for each of the grid points. Three objective criteria are formulated: first, the average DF of all grid points shall be 5%. Second, the DF should not be below the minimum value of 2%, in order to avoid dark places in the room. Thirdly, the standard deviation shall be minimal in order to illuminate the room as evenly as possible. The various performance measures are summarized in a fitness function as follows:

$$f(x) = abs(5 - avgDF) + stdDevDF + \begin{cases} abs(2 - minDF) & \text{if } minDF < 2 \\ 0 & \text{else} \end{cases}$$

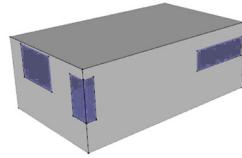
$$f(x) \rightarrow \min$$

Based on these optimization and evaluation models, 20 optimization runs have been conducted for each GM. In Figure 7, the 6 best results for each GM are shown.

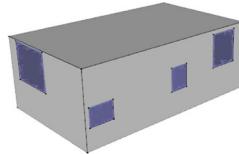
Comparing the best results derived from the

Figure 7
Results after optimization
using the 3 different GM (100
Generations).

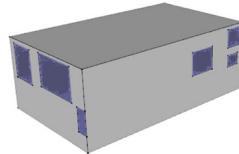
Topometric-GM



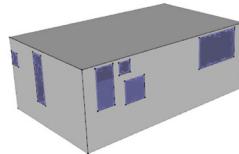
$f(x) = 1,18$



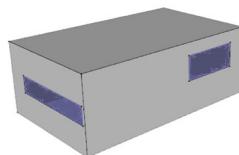
$f(x) = 1,20$



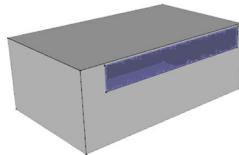
$f(x) = 1,21$



$f(x) = 1,28$

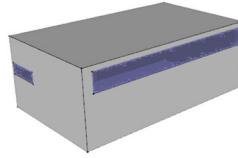


$f(x) = 1,49$

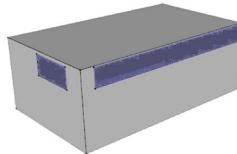


$f(x) = 1,59$

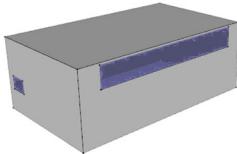
Metric-GM



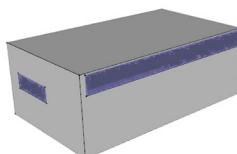
$f(x) = 1,08$



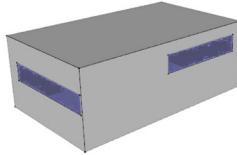
$f(x) = 1,34$



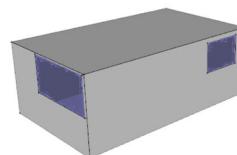
$f(x) = 1,37$



$f(x) = 1,38$

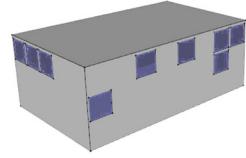


$f(x) = 1,39$

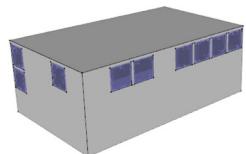


$f(x) = 1,47$

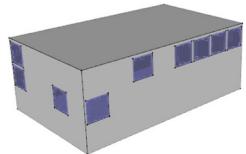
Gridbased-GM



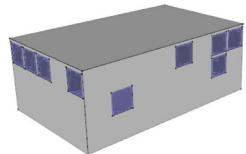
$f(x) = 1,21$



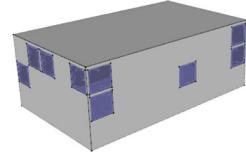
$f(x) = 1,22$



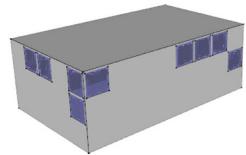
$f(x) = 1,23$



$f(x) = 1,27$



$f(x) = 1,29$



$f(x) = 1,33$

three different GMs after optimization, it can be concluded that despite the diversity of variants, the quality of daylight as formulated in the goals is not significantly different. This is interesting because it means that the aesthetic composition (style) of the facade is generally not determined by the daylight performance.

Comparing the performance of all the results from the three GMs with one another, it should be noted that after 20 optimization runs, the average performance is slightly different. The average performance of results derived from the Topo-metric-GM is 1.629, while from the Metric-GM it is 1.485 and from the Grid-based-GM it is 1.432. The standard deviation is low for the latter two GMs (0.163 and 0.177) but relatively high in the Topo-metric-GM (0.548). The worse average performance and the high standard deviation is due to the fact that the Topo-metric-GM often gets stuck in local optima. This in turn is due to the large search space generated by this GM. The search space of the other two GMs is comparatively limited, which makes it easier to find good solutions.

In terms of the variety of solutions, it can be seen that the resulting variants in the three GMs differ greatly. Using the Metric-GM, two different types emerged (Figure 7 middle column). On the one hand there are variants with a long and narrow window on the long wall and a small window on the short wall. On the other hand, variants emerged with big compact windows in the corners of the two walls.

Using the Grid-based-GM no such types can be identified, but another problem, the so-called signature problem (Schnier, 2008), becomes apparent. The signature problem means that the geometric representation of the elements used always produces a certain formal arrangement. Thus, despite the strong topological differences in the results that have arisen from the Grid-based-GM, the variants exhibit a high degree of similarity.

Looking at the results that were produced by the Topo-metric-GM, no consistent pattern can be discovered. Thus, variants with one long narrow window, two to three larger compact windows, win-

downs on just one wall, as well as facades with many different sized windows can be found. The Topo-metric-GM combines the advantages of the other two GMs making it possible to create a different number of windows on the one hand and flexible window sizes on the other. This larger variety means greater flexibility when tackling different problems. If, for example, additional performance criteria are added, with the Topo-metric-GM it will still be possible to find an optimal solution due to the large variety, while using the Metric-GM, for example, only two facade types fulfill the performance criteria perfectly.

CONCLUSION AND OUTLOOK

GMs that make it possible to systematically vary topo-metric properties are an important means of actually deriving a form based on certain performance requirements. Based on the algorithm described, facade variants can be generated which vary in their topological as well as in their metrical properties. It has been proven in a case study that, compared with a pure metric GM and a pure topological GM, the topo-metric GM generates a wider range of different optimal solutions with approximately equal performance.

In the current implementation of the topo-metric GM, the optimization partly remains stuck in local optima. To avoid this we are currently developing some additional operations which make the transition between topologically different solutions more continuous. In the process, we will test the directed creation of facades with similar metrics (area of windows) but different number of windows. Furthermore the current implementation of the optimization algorithm is quite simple and allows no systematic multi-criteria-optimization. For the future we are planning to use the open-source optimization framework Aforge.Net [2], which offers a wide range of multi-criteria-optimization routines.

ACKNOWLEDGEMENTS

This study was carried out as part of the research project FOGEB (Green Efficient Buildings), funded by

the Thuringian Ministry for Economics, Labour and Technology and the European Social Funds (ESF).

We'd like to thank Christian Tonn, who programmed the algorithm for Real-Time Solar Analysis and helped with the implementation of the optimization framework.

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[1] <https://vimeo.com/67046926> (Retrieved 01.06.2013)

[2] <http://www.aforgenet.com/> (Retrieved 29.05.2013)

