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A Methodology for daylight optimisation of high-rise buildings in the dense urban district using overhang length and glazing type variables with surrogate modelling

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A Methodology for daylight optimisation of high-rise buildings in the dense urban district using overhang length and glazing type variables with surrogate modelling

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Abstract. Urbanization and population growth lead to the construction of higher buildings in the 21st century. This causes an increment on energy consumption as the amount of constructed floor areas is rising steadily. Integrating daylight performance in building design supports reducing the energy consumption and satisfying occupants' comfort. This study presents a methodology to optimise the daylight performance of a high-rise building located in a dense urban district. The purpose is to deal with optimisation problems by dividing the high-rise building into five zones from the ground level to the sky level, to achieve better daylight performance. Therefore, the study covers five optimization problems. Overhang length and glazing type are considered to optimise spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE). A total of 500 samples in each zone are collected to develop surrogate models. A self-adaptive differential evolution algorithm is used to obtain near-optimal results for each zone. The developed surrogate models can estimate the metrics with minimum 98.25% R^2 which is calculated from neural network prediction and Diva simulations. In the case study, the proposed methodology improves daylight performance of the high-rise building, decreasing ASE by approx. 27.6% and increasing the sDA values by around 88.2% in the dense urban district.

1. Introduction

High-rise buildings have been designed to gain additional floor area in the limited urban plot since the early examples [1]. In the 21st century, population growth and a trend towards urbanization lead to increasingly constructing higher buildings. Owing to a raise in constructed spaces, this suggests an increment on the energy consumption to meet the requirements for thermal and visual comfort [2]. In this respect, daylight becomes an important performance aspect for high-rises, because designing spaces with good daylight performance helps reducing the energy consumption and satisfying occupants' comfort requirements. However, this is a complex task owing to design decisions given in the conceptual phase. First, many design parameters such as shape of the building, design of the shading devices, and material properties, suggest an enormous number of design alternatives affecting the building performance. Thus, finding a desirable set of parameters during the decision is very challenging in the early phases. Secondly, daylight requirements can vary relevantly depending on the indoor functions, which are often mixed in high-rises. Thirdly, in several climates the need of daylight conflicts with the need of reducing indoor solar loads. Finally, a possible design solution cannot be applied at all heights of the high-rise. In fact, due to the surrounding buildings in the dense districts, optimal design parameters for good daylight performance can be different starting from the ground level to the sky level.

Very limited studies can be found for daylight optimisation of high-rises. One study [3] focuses on proposing modifications to extend the daylight deeper into the space using extra interior height, alternative glazing and an external light shelf for a commercial high-rise building. In another study [4], authors presented a holistic passive design approach to evaluate a typical high-rise residential building focusing on daylight, natural ventilation and thermal comfort. Recently, researchers [5] considered a simulation-based multi-objective optimisation to minimize energy loads, reduce CO_2 emissions, and improve occupants' health and comfort for high-rise and low-rise buildings. All these studies present promising results and conclusions. However, none of these studies considered different design parameter sets for different parts of the high-rises that can further improve the daylight performance. This study presents a methodology to optimise daylight performance of a whole high-rise building located in a dense urban district considering a variety of parameter sets at different zones of the building.

2. Methodology

Daylight availability in the upper zones of the high-rise building, which are close to the sky, is different than daylight availability in the lower zones near the ground level, since the surrounding buildings cause obstruction on the facade in dense urban environments. Such a situation may result in specific requirements on daylight performances at each floor/zone levels in the building. For instance, an optimised parameter set near the sky level may not perform desirable performance solutions for the ground level, and the other way around. Thus, the idea of the proposed methodology is based on a holistic approach, which aims to consider each corresponding zone of high-rise buildings as an optimisation problem. In this respect, desirable parameter sets for each zone/level can be tested and evaluated. There are four steps which are proposed in methodology (Figure 1). These are:

- Form finding: A parametric model of a high-rise building is generated defining design parameters. 5 equally divided zones are defined (zone 1-5) for the performance assessment.
- Performance evaluation: Corresponding floors are selected for daylight simulation in all zones.
- Surrogate modelling: Uniformly generated samples are collected for each part to define fitness function and constraint using surrogate modelling based on artificial neural networks (ANN).
- Optimisation: The most desirable parameter sets in each zone are discovered using computational optimisation algorithm.

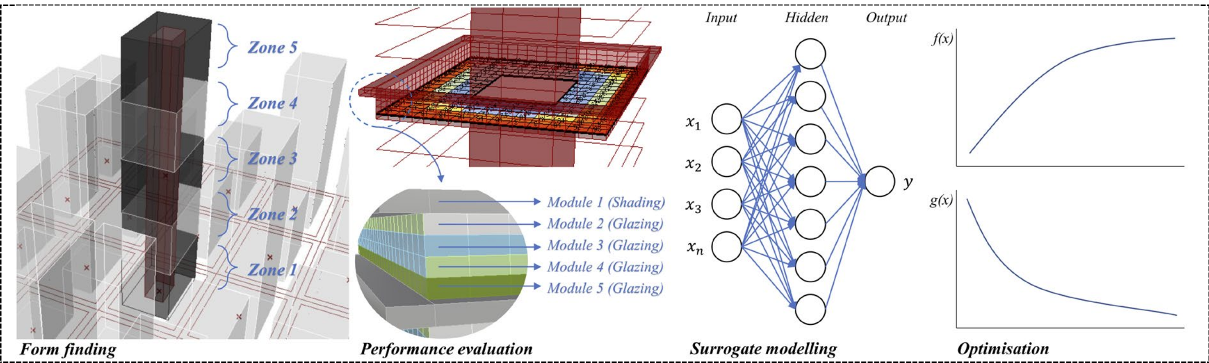

Figure 1. Schematic explanation of proposed methodology.

2.1. *Form finding*

A hypothetical urban district with 25 plots is generated in Grasshopper 3d (GH) [6]. Each plot has 1800 m^2 with randomly generated heights from 50 m to 150 m. The central plot is defined as the case area having 40 floors, 200 m height, 72000 m^2 area, and 36 to 50 m façade length. The generated building is divided into five zones named as Zone-1 (Z1), Zone-2 (Z2), Zone-3 (Z3), Zone-4 (Z4), and Zone-5 (Z5). The floors in the middle part of each zone are selected for the simulation. The façade is divided into 5 vertical modules. The first four modules are defined as glazing. The last module is defined as overhang. It is possible to assign four types of glazing material to each four modules of each orientation, whereas the length of each overhang can vary from 0 m to 2 m. Parameters with boundaries are given in Table 1. The alternative amount of 20 variables is 47.223665e+20.

Table 1. Design parameters

Parameters	Explanation	Type	Boundary
$x_1,\ldots,x_4$	Glazing type for North (N) orientation	Discrete	[1, 4]
$x_5,\ldots,x_8$	Glazing type for South (S) orientation		[1, 4]
$x_9,\ldots,x_{12}$	Glazing type for East (E) orientation		[1, 4]
$x_{13},\ldots,x_{16}$	Glazing type for West (W) orientation		[1, 4]
$x_{17},\ldots,x_{20}$	Overhang length for N-S-E-W orientations	Continues	[0.0, 2.0]

2.2. *Performance evaluation*

Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE) are considered to assess the daylight performance in each zone. According to the Illumination Engineering Society (IES) [7], sDA is a metric for sufficient daylight illuminance, whereas ASE is a metric for the potential visual discomfort owing to the direct sunlight. More specifically, sDA calculates the percentage of an analysis area, which meets with the minimum illuminance level, for a specified operating hour per year. ASE calculates the percentage of an analysis area, which exceeds a specified direct sunlight illuminance level more than a specified number of hours per year. Diva plugin [8] in GH is used to simulate these metrics. An analysis plane, which is 0.8m above the finished floor with 184 sensors, is generated. $sDA_{300,50\%}$, which achieves the illumination threshold of 300 lux for 50% of the analysis period, is considered. $ASE_{1000,250h}$, which exposes the illumination threshold of 1000 lux for 250 hours of the analysis period, is used. For both metrics 10 hours (8am-6pm) is specified. Glazing types (Table 2) are assigned to all orientations in sequence. Radiance parameters of the daylight simulation are given in Table 3. One simulation is recorded as 103.9 seconds with the given radiance parameters.

Table 2. Material characterization of glazing types

Material	Explanation	Vis. Trans.	U value	G value
Glazing 1 (G1)	Tinted Float 8mm Blue – 12 mm Air – Temperable Low-E 8mm Blue	0.22	1.6	28%
Glazing 2 (G2)	Temperable Low-E 8mm Neutral – 12 mm Air – Clear Float 8 mm – 12 mm Air – Temperable Low-E 8 mm Green	0.45	0.9	40%
Glazing 3 (G3)	Tinted Float 8 mm Green	0.68	5.6	51%
Glazing 4 (G4)	Ultra-clear Float 8 mm – 12 mm Cavity Air – Ultra Clear Float 8 mm	0.82	2.8	81%

Table 3. Radiance parameters

-aa	-ab	-ad	-ar	-as
0.15	2	512	256	128

2.3. *Surrogate modelling*

500 samples are collected for each zone to develop the surrogate models. A uniform distribution function, coded in C#, is used to generate random values. Every recorded data contains 20 design parameters and simulation results for sDA and ASE. In total, 2500 samples are collected for 5 different zones in 72.1 hours. Implementing simulation results of these 500 design samples, ANN models are developed using a Backpropagation neural network algorithm with bipolar sigmoid activation function using Dodo plugin [9]. After several experiments, 20 input, 1 hidden, and 1 output layers are considered. To sum up, five ANN models for sDA and five models for ASE are developed. sDA and ASE values of collected samples are given in Table 4. These predicted values (outputs) obtained from ANN are compared to outputs from Diva simulations with similar design parameters, calculating the R^2 values of each model (Table 5). This procedure shows us the applicability of the ANN model.

Table 4. sDA (%) and ASE (%) distributions for each zone

	Z1-sDA	**Z1-ASE**	**Z2-sDA**	**Z2-ASE**	**Z3-sDA**	**Z3-ASE**	**Z4-sDA**	**Z4-ASE**	**Z5-sDA**	**Z5-ASE**
Min	80.6	25.7	85.8	31.5	87.2	33.3	84.2	33.8	88.5	32.1
Max	100.0	49.6	100.0	58.4	100.0	58.4	100.0	66.5	100.0	66.5
Avg	95.9	42.6	98.2	47.0	98.8	47.2	99.0	49.2	99.1	49.6

Table 5. Parameters and R-squares of ANN models

	Neurons per layer	**Number of layers**	**Learning rate**	**Sigmoid alpha**	**Max iter**	**R^2-Z1**	**R^2-Z2**	**R^2-Z3**	**R^2-Z4**	**R^2-Z5**
sDA	20	1	0.1	2.0	10000	98.25%	99.43%	99.26%	99.43%	99.85%
ASE				0.5		99.95%	99.74%	99.82%	99.94%	98.95%

2.4. *Optimisation*

Subsequently, the optimisation problem is formulated as follows:

$$\max(sDA_{300,50\%}) \tag{1}$$

subject to

$$ASE_{1000,250h} \leq 20\% \tag{2}$$

The single-objective self-adaptive differential evolution (jDE) algorithm [10], coded in C#, is used for optimisation. The implementation is based on DE/rand/1/bin scheme, which uses 3 individuals to generate the mutant population, and employs one-to-one comparison for the next generation. Rather than constant mutation (MR) and crossover (CR) rates, in jDE, these values are updated for each individual in D dimensions during the optimisation. In addition, to cope with the constraint, the superior-of-feasibility (SF) procedure [11] is implemented. SF considers three cases, which are: Pick the solution with better fitness value, pick the feasible solution, or pick the solution with smaller violation.

3. Results

Average values of initial and 500th generation with a population size of 30 are conducted for each zone. To prove the proposed methodology, simulation results for regular building cases using only one glazing material without overhang were conducted (Table 6). The convergence of the optimisation process is presented in Figure 2. Until the 250th generation, ASE values decreased, whereas, during the last 100 generations, sDA values did not present a significant alteration. From the point of comparison between initial and optimised populations, the average of optimised results reached a minimum value of 27.6% smaller ASE than initial results. However, this caused a maximum value of 10.3% decrement on sDA. When we compare the optimised and regular (G1 to G4) results, the proposed methodology found significantly smaller ASE values than each case. In general, most of the optimised values presented a maximum value of 11.8% decrement on sDA. Finally, optimised parameters were applied to corresponding zones to finalize the design of the high-rise (Figure 3). Since the optimised ASE range was very narrow for all zones, results having the highest sDA values were picked. Colours of materials were defined as blue for G1, light green for G2, dark green for G3, white for G4, and grey for overhangs. In the optimised high-rise building, the total usage amount of glazing material was 47.5% for G1, 17.5% for G2, G3, and G4. Average overhang distances were reported as 1.4m in Z1, 1.5m in Z2, 2.0m in Z3, 1.2m in Z4, and 1.1m in Z5. It was observed that, overhang distances and material selections were differentiated in all zones and orientations to find the best near-optimal solution.

Table 6. Results for initial, optimised, and regular building cases

	Init. sDA			**Init. ASE**			**Opt. sDA**			**Opt. ASE**			**G1 (0.22)**		**G2 (0.45)**		**G3 (0.68)**		**G4 (0.82)**	
	min	max	avg	min	max	avg	min	max	avg	min	max	avg	sDA	ASE	sDA	ASE	sDA	ASE	sDA	ASE
Z1	84.5	100	95.1	26.1	47.7	36.8	87.6	89.2	**88.2**	23.6	23.6	**23.6**	63.0	37.9	95.3	49.0	100	49.0	100	49.6
Z2	93.4	100	98.4	36.1	49.2	44.2	88.0	88.6	**88.3**	29.2	29.2	**29.2**	64.8	46.7	98.8	49.0	100	50.2	100	58.4
Z3	95.6	100	99.2	35.6	48.4	43.0	88.6	94.3	**90.0**	32.2	31.2	**31.2**	65.4	46.7	100	49.0	100	51.4	100	58.4
Z4	94.2	100	98.9	37.3	54.3	44.1	96.6	97.4	**97.0**	31.1	31.1	**31.1**	66.0	49.0	99.4	49.6	100	58.4	100	67.7
Z5	89.9	100	98.4	35.9	52.5	44.3	88.1	100	**97.6**	29.1	29.5	**29.3**	66.6	49.0	99.4	49.6	100	58.4	100	67.7

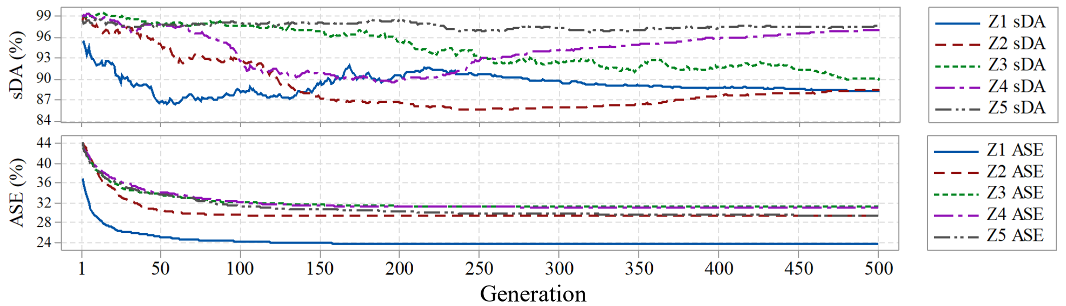

Figure 2. Average sDA and ASE values during the optimisation.

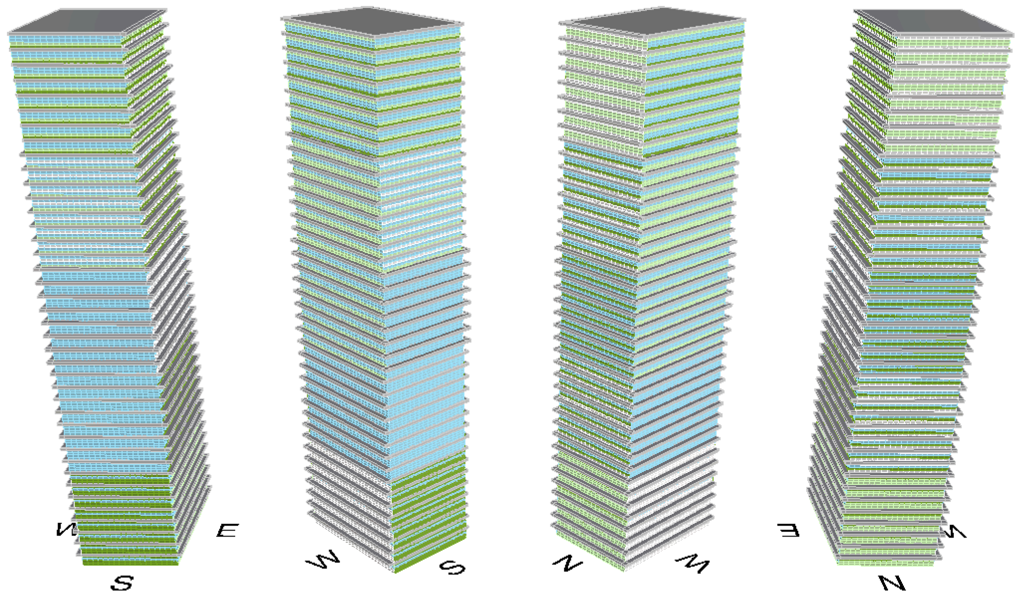

Figure 3. Schematic distribution of optimised parameters.

4. Discussions and Conclusion

This paper presents a methodology to optimise sDA and ASE for high-rise buildings in dense urban districts. Surrogate models successfully approximated metrics with a minimum value of 98.25% R^2, when predicted ANN outputs are compared to simulation outputs. In case of simulation-based optimisation, the required time for metaheuristics would correspond to one simulation time for 15000 function evaluations. Using ANN with 500 samples for each zone, we saved approximately 90 days to conduct the presented results. The number of samples can exceed thousands with more design parameters. In this case, an additional optimisation process would be necessary to find the best architecture and parameters for ANN. Here, results of initial population and regular building cases were compared with the optimised solution. The proposed methodology clearly showed that daylight performance of the high-rise building was improved in all zones. The minimum enhancement for ASE was 27.6% in Z3, whereas the maximum advancement was 35.9% in Z1. sDA was reported in the acceptable margins between 88.2% and 97.6%, indicating spaces successfully benefiting from daylight. Although optimised solutions were not checked against thermal performance, higher ASE values (23-31%) than required draw our attention to a potential of overheating in these cases. So, this study can be an initial step to suggest further research for testing decrements on thermal energy consumption of such high-rise buildings in temperate-humid climates. Thus, zones at varying levels of high-rise buildings require combinations of parameter sets to perform the best solution in this sense. Specifically, infeasible ASE values remind us of the necessity of a shading approach once again.

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