Light & Engineering
Vol. 28, No. 6, pp. 41–50, 2020

https://doi.org/10.33383/2020-047
Svetotekhnika # 6, 2020, pp. 60–67

FACADE OPTIMIZATION FOR AN EDUCATION BUILDING USING MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

Arda Agirbas[1] and Ebru Alakavuk[2]

Department of Architecture, Yasar University, Izmir, Turkey
E-mails: [1]arda.agirbas@yasar.edu.tr, [2]ebru.alakavuk@yasar.edu.tr

ABSTRACT

Architectural design of a facade, both at the aesthetic point of view and from the point of view of internal daylighting performance of the building, can be considered as a complex task. In this study, we implement a multi-objective evolutionary algorithm to formally exploration the process of reconstruction of the education building's facade. The purpose of this research is to create a facade configuration by considering the size and location of elements and their materials when creating a suitable internal daylight distribution. The total construction cost of the building's exterior and the daylight performance of the building's interior are considered as objectives. The problem formulation includes two conflicting objectives, which are to increase daylighting aspect on each floor and reduce the total construction cost of the facade. To detect the approximation of Pareto fronts, including non-dominated solutions, we used a fast and elitist multi-objective genetic algorithm (NSGA-II). Computational and architectural results show that NSGA-II is efficient enough to demonstrate eligible facade design alternatives.

Keywords: facade design, multi-objective optimization, education building design, computational design

1. INTRODUCTION

The architectural design procedure is often described as a complex process because it requires the ability to respond to different needs of people at the same time. In addition, the design process involves making decisions on many parameters simultaneously in order to maximize objective performance while satisfying design constraints [1]. Decisions in this process affect final solutions.

In the discipline of architecture, educational buildings are one of the most multi-layered organizations types due to the diversity of spatial requirements in relation to the type of education. The existence of various persons, materials, providers, and high skilled qualifications to provide the service creates management issues [2]. The architectural design of an education building should be able to respond to different types of spatial requirements in relation to educational purposes. Educational building design relates to the design of the physical environment that includes interior layout and design (e.g., adjacencies and furnishing of different purposed spaces), internal environmental qualities (e.g., lighting) [3], and the building's exterior features (e.g. building's envelope, facade systems).

When designing educational buildings, building envelope systems can be considered as important architectural elements that have a positive contribution to daylight design [4] and should be carefully evaluated at the early stages of design. The existence of daylighting in enclosed spaces can improve the effectiveness of education and the quality of learning, while reducing stress [5]. In [6], the authors tried to prove the relationship between daylighting and human behaviour in a relative environment. Daylight autonomy [7] was used as a calculated metric in modelling to build a relationship between the probabilistic potential of daylight and the comfort of lighting in relation to society. The influence of changes in window sizes, orientation, and glazing material on achieving satisfactory lighting values is studied. Experiments have shown that sufficient lighting can be achieved by a small amount of glazing in certain orientations. In [8], the authors demonstrated the influence of daylighting on users in addition to reducing the energy consumption of artificial lighting. In [9], authors presented an optimization study for a glazing system, considering the maximum useful daylight while reducing energy consumption. Based on the literature, one may argue that the optimization methodology is associated with parametric computer-based simulations to determine the glazing system design.

This paper aims to use parametric workflows and optimization methods to improve the design of the external glazing of the educational building. It focuses on optimizing the geometry of the external facade geometry of a building in Yasar University by configuring the placements and sizes of the elements for controlling solar penetration and improving daylight performance while reducing the overall cost of the structure. To investigate this problem, we employ the non-dominated sorting genetic algorithm II (NSGA-II).

In this study, the south-west and south-east facing facades of the education building at Yasar University campus are re-designed in order to increase the usage of daylighting inside the building. The building is in the district of Bornova, Izmir, Turkey, having 38° 27′ *N* latitude, 27° 12′ *E* longitude, and 17 m altitude. The dimensions and materials of existing facade elements are defined as decision variables in order to create daylight analysis.

Table 1. Initial Widths of the Glazing

Notations	Width, m
G_1	4.00
G_2	12.00
G_3	4.00
G_4	6.00
G_5	2.00
G_6	1.00
G_7	4.00

In the rest of the paper, section 2 explains the parametric model, including decision variables and their impact on the geometric form-finding. Section 3 describes the problem formulation with constraints and objective functions. Section 4 highlights the key features of the algorithm that was used throughout the study. Section 5 presents computational and architectural results. Finally, in section 6, conclusions of the study are presented.

2. PARAMETRIC MODEL

The parametric model is generated in *Grasshopper* parametric modelling environment, which is a

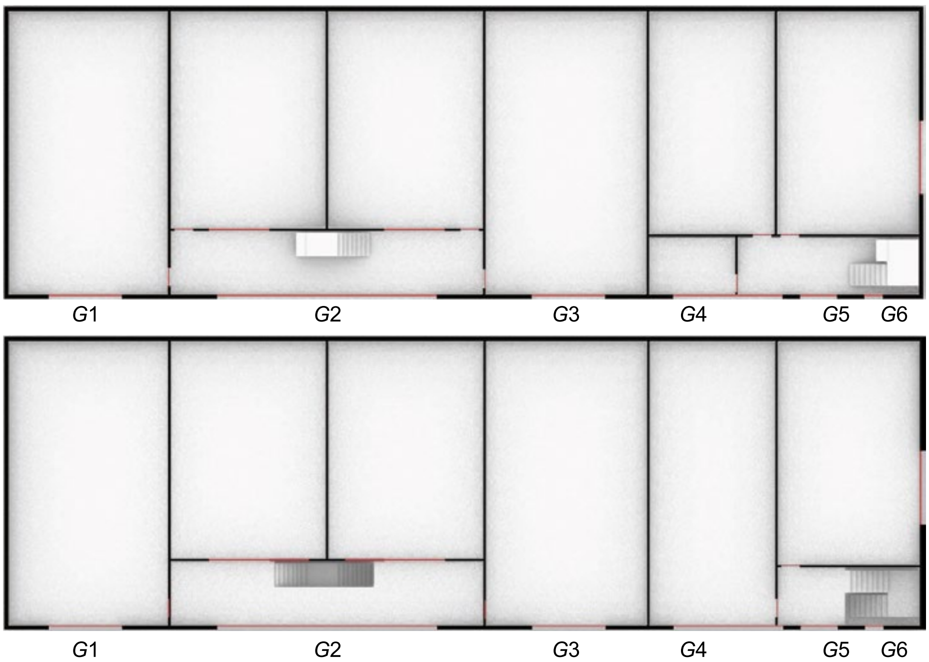

Fig. 1. Notations of the existing glazing

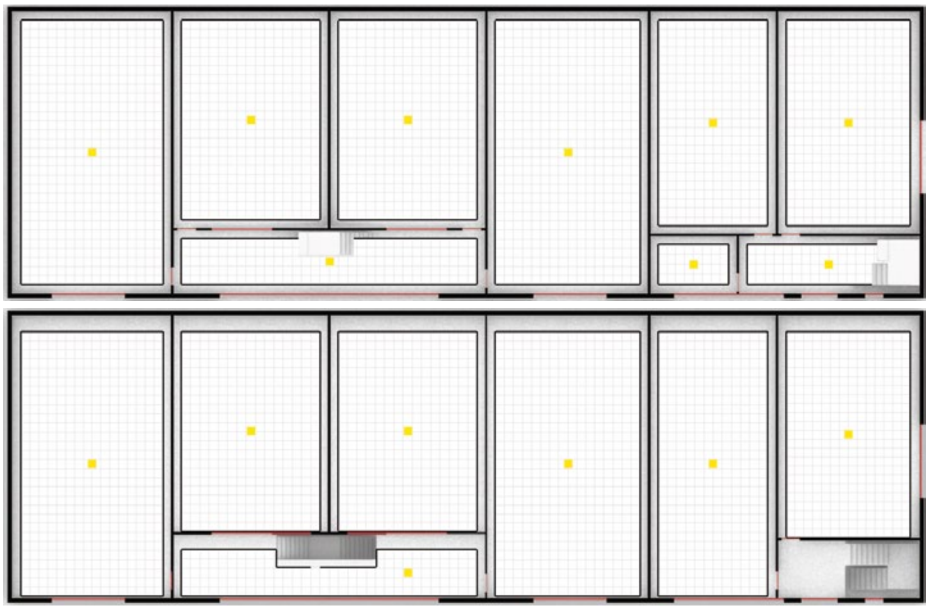

Fig. 2. The measuring grids glazing with their surroundings

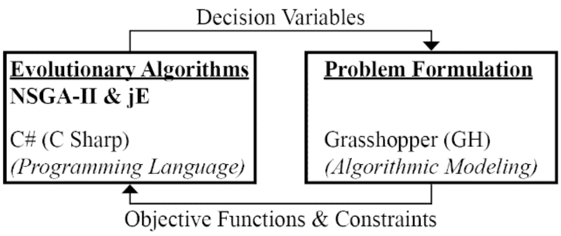

Fig. 3. The workflow diagrams

plug-in developed for *Rhinoceros 3D* software. In this study, we focus on a building within the boundaries of Yasar University campus that has measures of 50 m (width) and 16 m (depth).

As shown in Fig. 1, the building skin includes seven curtain-wall type glazing elements. The total height of the building is 5.80 m. The height of the glazing elements is fixed at 5.80 m, and widths are defined as decision variables.

The model considers the centrelines of each glazing as relative reference lines in the 1-D scaling process, since the height of the building is fixed. A complete list of the initial dimensions of each glazing is presented in Table 1.

Table 2. Decision Variables

Notation	Type	Range, m
G_1	Real	[4.00, 10.00]
G_2	Real	[10.00, 16.40]
G_3	Real	[3.00, 10.00]
G_4	Real	[4.00, 7.40]
G_5	Real	[1.00, 3.00]
G_6	Real	[0.60, 1.70]
G_7	Real	[4.00, 13.00]

3. PROBLEM FORMULATION

3.1. Objective Functions

We consider two objective functions: minimizing of the facade system's construction cost $\left(C_{facade}\right)$ and increasing the penetration of the daylight into the foyer area. Measurement grids are created for each room in relation to their floors to measure and evaluate the daylight performance of each floor separately. Measurement grids are shown in Fig. 2. Daylight autonomy (*DA*) metric [10] is used to optimize the interior daylight distribution. The notations related to decision variables are shown in Table 2. We formulate the problem as a multi-objective optimization problem (MOP) as follows:

$$Min\left(\frac{1}{P_{DA}}, C_{facade}\right), \text{ where}$$

$$P_{DA} = \sum\nolimits_{i=1}^{n} \begin{Bmatrix} 0, E_i < E_{min} \\ 1, E_i \geq E_{min} \end{Bmatrix}. \quad (1)$$

$$C_{facade} = C_{glazing} + C_{wall}, \quad (2)$$

where C_{facade} is the total construction cost of building facade, P_{DA} is the performance of daylight autonomy, $C_{glazing}$ is the total cost of glazing, C_{wall} is the total cost of exterior walls, E_{min} is the

Step 1: set $t = 0$ and construct a random parent population P_t with N size;

Step 2: generate offspring population Q_t with N size, perform SBX and PM;

Step 3: if termination criterion is satisfied, stop and return P_t;

Step 4: in order to combine parent and offspring populations, set $R_t = P_t \cup Q_t$;

Step 5: to find the non-dominated fronts $f_1, f_2, .., f_k$, apply the fast non-dominated sorting algorithm to R_t;

Step 6: for $i = 1, .., k$, do following steps:

Step 6.1: for solutions in f_i, calculate crowding distance;

Step 6.2: create P_{t+1} as follows:

- $if\ |P_{t+1}| + |f_i| \leq N$, then set $P_{t+1} = P_{t+1} \cup f_t$;
- $if\ |P_{t+1}| + |f_i| > N$, then add the least crowded $N - |P_{t+1}|$ solutions from f_i to P_{t+1};

Step 7: use crowded tournament selection to choose parents from P_{t+1}. Then, employ SBX and PM to P_{t+1} in order to get offspring population Q_{t+1} with N size;

Step 8: set $t = t + 1$ and go to $step$ 3.

Fig. 4. Steps of NSGA-II

specified threshold for daylight performance evaluation, E_i is the illuminance at a sample point in a specific hour provided that average spatial daylight autonomy is

$$sDA > 50\%. \qquad (3)$$

3.2. Daylight Objective

DA is considered as a metric for calculating daylight performance, mentioned in [10], which resulted in many discussions in the early 1900s. Later on, it was integrated into the building standards and considered as a standard for buildings since then [11]. *DA* is formulated as the percentage of annual daytime hours that a specific point is above a specified illuminance level. For this study, the specific illuminance threshold (E_{min}) is defined as 300 lx in relation to Leadership in Energy and Environmental Design (LEED) criteria.

DA is calculated using values that are obtained by using the simulation software named *Radiance*. To create a workflow between *Radiance* and *Rhinoceros* CAD program, *DIVA*, which is a plugin for *Grasshopper,* is used to calculate *DA* values. *DA* evaluates the hourly illuminance values for each measurement point in relation to the specified illuminance level, considering the working hours. For each hour, the values of 1 and 0 are assigned, considering their relationship to the specified threshold value. Hours above the threshold considered as 1, else are considered as 0, and the ratio is defined considering the summation of these hours and all working hours during the year. For this study, the working hours are defined as from 08:00 a.m. to 17:00 p.m. The *DA* calculation is expressed as follow:

$$DA(Point_a) = \sum\nolimits_{i=1}^{n} \begin{Bmatrix} 0, E_i < E_{min} \\ 1, E_i \geq E_{min} \end{Bmatrix}. \qquad (4)$$

For daylight calculations, we adopt *DA* values. Since the calculation of DA includes direct sunlight calculations, thus leads to more accurate results considering obsolete metrics, such as daylight factor [11]. The building has two south-facing elements, this situation creates a suitable environment for using *DA* to calculate daylight performance of a focused building, since it includes the direct sunlight calculations as well as the location of the building. For our study, we define the measurement grid as 0.5 m from each wall and 0.8 m above the floor plates. Our objective is determined to obtain the LEED criterion that achieves a minimum of 50 % of the space above 300 lx during working hours throughout the year [11].

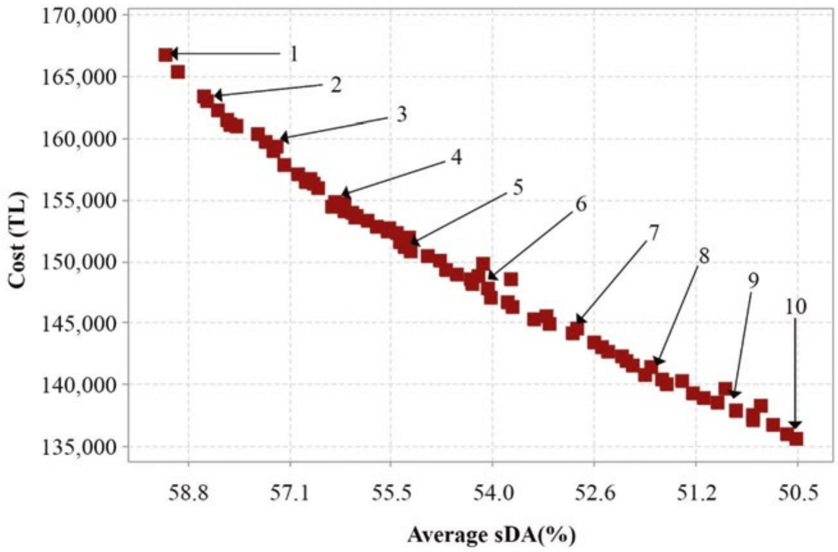

Fig. 5. Pareto front chart of non-dominated solutions at the 50th generation

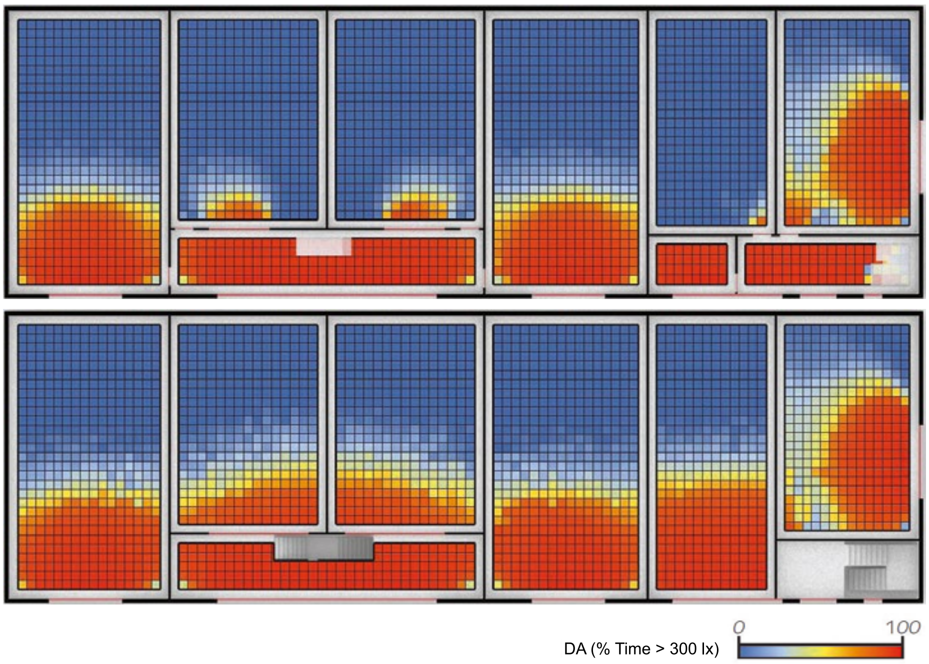

Fig. 6. *DA* measurement results of the initial state of the building

3.3. Cost Objective

As shown in the eq. (5), C_{facade} can be found by adding the total construction cost of walls (C_{wall}) and the total cost of glazing elements ($C_{glazing}$).

$$C_{facade} = C_{wall} + C_{glazing}. \quad (5)$$

$$C_{wall} = C_{uw} \cdot A_{wall}. \quad (6)$$

$$C_{glazing} = C_{ug} \cdot A_{glazing}. \quad (7)$$

where A_{wall} is the total area of exterior walls, $A_{glazing}$ is the total area of glazing, C_{uw} is the unit price of glazing per sq. m, C_{ug} is the unit price of wall per sq.m.

These costs depend on the area of the relative element in relation to the unit cost per square meter.

3.4. Constraint

As shown in eq. (3), there is a constraint related to the calculated *DA* values. In order to satisfy the LEED criterion [11], the minimum value of spatial daylight autonomy (*sDA*) should be larger than 50 %.

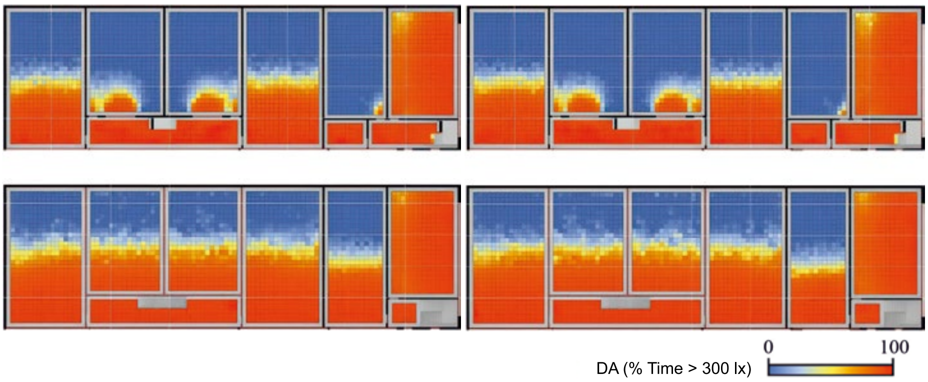

Fig. 7. *DA* measurement results for case 1 and case 2

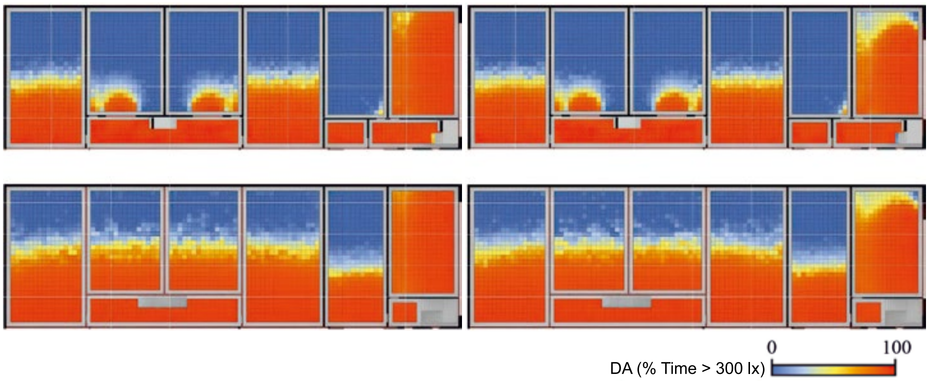

Fig. 8. *DA* measurement results for case 3 and case 4

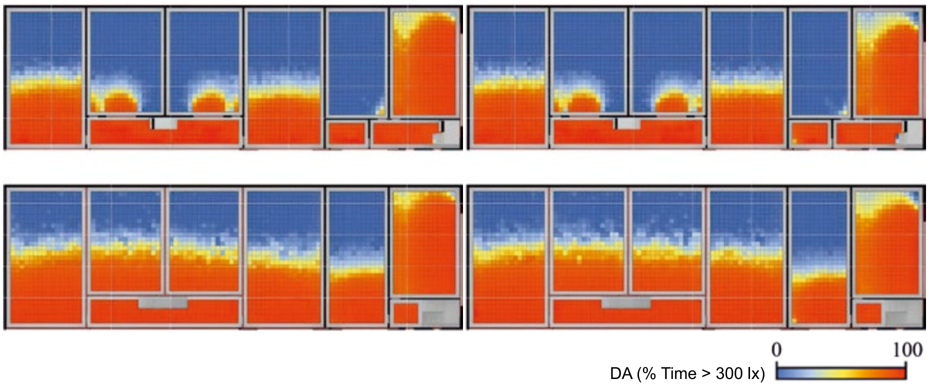

Fig. 9. *DA* measurement results for case 5 and case 6

4. EVOLUTIONARY ALGORITHM

In the current literature, there are various studies, which include the multi-objective optimization problems (MOPs). In terms of optimization algorithms, evolutionary algorithms (EAs) can be considered as an effective optimization algorithm type due to its unique way to deal with problems. In this respect, multi-objective evolutionary algorithms (MOEAs) are defined as the implementations of EAs within MOPs. In this research area, NSGA-II [12] and SPEA2 [13] are well-known and effective algorithms. Implementing genetic operators of EAs to MOEAs, several MOEAs are developed for multi-objective architectural problems (MOAPs) [14–20], also in [21]. The process diagram of the workflow shows how to integrate the NSGA-II algorithm into our parametric model in Fig. 3.

In terms of MOEAs, NSGA II, which is developed by [12], can be considered as one of the most powerful algorithms. The outline of NSGA-II is shown in Fig. 4. NSGA-II is known as being capable of dealing with very difficult MOPs. Key features of this algorithm are expressed as follows:

1. To discover non-dominated solutions, it employs $O\left(MN^2\right)$ sorting algorithm;

2. In terms of the cuboid volume neighbouring between elements that attend for the same rank value, it calculates the "crowding distance";

3. Using a crowding distance, superior of feasibility, as well as ranking for diversity preserving through binary tournament selection;

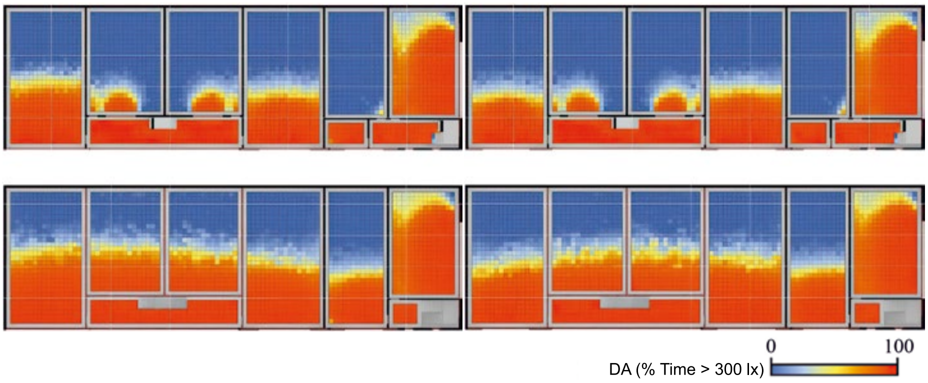

Fig. 10. *DA* measurement results for case 7 and case 8

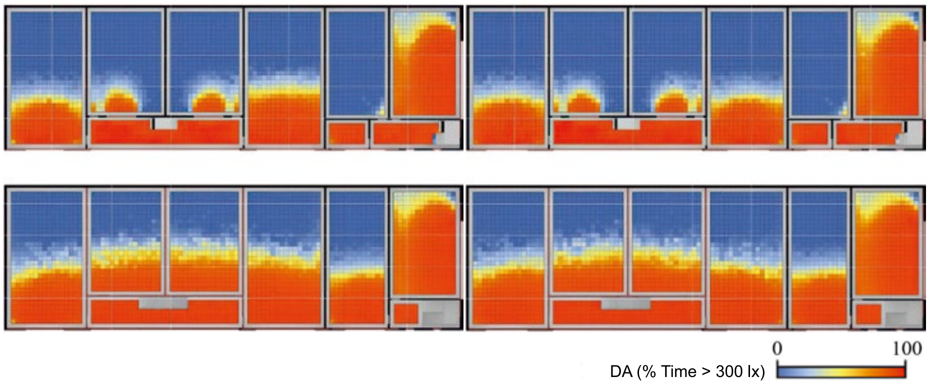

Fig. 11. *DA* measurement results for case 9 and case 10

4. Elitism strategy specifically, using the combination of elite parents and offspring members;

5. Utilization of the genetic operator namely, "simulated binary crossover (SBX)" [12];

6. Utilization of polynomial mutation operator (PM) [12].

5. COMPUTATIONAL AND ARCHITECTURAL RESULTS

For calculations, a computer with a data processing speed of 4.4 GHz and 32 GB of DDR4 RAM is used. The population sizes are defined as 100 people. Since the development of a single individual during the optimization process takes approximately 150 s, the algorithm is stopped at the 50th generation that defines our termination criteria. For 5000 function evaluations of the algorithm, the computer is run for approximately 209 hours. The Pareto front chart of non-dominated solutions at the 50th generation for 100 population size is given in Fig. 5.

After the optimization process concluded, we observed that NSGA-II discovered cost values within a range (135617.54–166798.34) TL. In terms of daylight performance, the algorithm suggested results within a range (50.02–59.20) %. The average values for total construction cost and daylight performance are 149499.92 TL and 54.50 %, respectively. Ten results are selected uniformly from the Pareto front and compared with each other, as well as the initial state of the building. In terms of daylight performance and cost objectives, a statement can be made that the decision variables, which are the widths of the exterior glazing elements have a significant effect on total construction cost and interior daylight distribution.

In terms of daylight performance of the building's initial state, the *sDA* values 28 % and 31 % are achieved for the ground floor and the first floor, respectively. The *DA* distribution in relation to the respective floors is shown in Fig. 6 and the values of relative decision variables and objectives for the initial state of the building are presented in Table 3. According to these results, it can be argued that opaque interior walls prevent sunlight to penetrate spaces that do not have a glazing surface. Therefore, both floors are below the daylight constraint $sDA > 50$ %. The *DA* distribution in relation to the respective floors for each case is shown in Figs. 7–11. The values of relative decision variables and objectives for each case are presented in Table 4 and Table 5.

For the optimization problem, the unit cost of glazing per sq·m (C_{ug}) is defined as 400 TL, and

Table 3. The Decision Variables and Objectives for Initial State of the Building

Notations	Value		Notations	Value
G_1	4.00 m		G_6	1.00 m
G_2	12.00 m		G_7	4.00 m
G_3	4.00 m		sDA	29.5 %
G_4	6.00 m		C_{facade}	–
G_5	2.00 m		R_w	35.7 %

Table 4. The Decision Variables and Objectives for Each Case from 1 to 5

	Case 1	Case 2	Case 3	Case 4	Case 5
C_{facade}	166798.34	163086.34	161044.74	154919.94	150465.54
sDA	59.2 %	58.5 %	58.01 %	56.43 %	55.01 %
R_w	77.8 %	73.1 %	70.6 %	63.5 %	58.8 %
G_1	10.00 m	10.00 m	9.80 m	10.00 m	10.00 m
G_2	16.40 m	16.40 m	16.40 m	16.40 m	16.40 m
G_3	9.60 m	9.80 m	9.80 m	9.80 m	6.00 m
G_4	7.40 m	5.20 m	4.40 m	5.00 m	5.00 m
G_5	1.00 m	1.40 m	1.00 m	1.00 m	1.00 m
G_6	1.00 m	0.60 m	0.60 m	0.60 m	0.60 m
G_7	12.60 m	12.60 m	12.80 m	8.80 m	10.20 m

the unit cost of wall per sq. m (C_{uw}) is defined as 80 TL. Added construction costs, transportation, workmanship, etc. are not taken into account. To enhance the daylight performance results, translucent partition walls (P_T) are employed on the first floor. For the exterior glazing clear glass material is used, which has transmittance value (E_{mat}) of 88 %. For the translucent interior partition walls, double-pane glass material, which has E_{mat} of 65 % is employed.

In terms of daylight performance and cost objectives, a statement can be made that some of the decision variables have a significant effect on total construction cost and interior daylight distribution in comparison to others. For the width of the glazing 2 (G_2) the algorithm selected the largest value of the range in each example. It can be argued that it is a required condition to satisfy the daylight constraint, otherwise the results would be below the required minimum value. Furthermore, for the width of the glazing 7 (G_7), the algorithm did not suggest any values below 8.60 m. Although the minimum value in its range is 4.00 m, the algorithm employed higher values in this range due to glazing 7's location and relation to the sunlight has a substantial effect on interior daylight distribution.

On the other hand, for the width of the glazing 6 (G_6), the algorithm employed the minimum value of its range. It can be argued that the effect of G_6 to the interior daylight distribution is relatively small than the other variables. Considering their range, the algorithm selected the maximum possible values for decisions variables of G_1, G_2, G_4. In comparison, the decision variables of G_5 and G_6 are defined in relation to the minimum values of their ranges. According to these results, we can consider that G_5 and G_6 have almost no effect on interior daylight distribution whereas, it greatly affects the total construction cost. The other decision variables mediated between their range to find suitable design solutions.

6. CONCLUSION

In this study, the NSGA-II algorithm is implemented for a building facade design problem in an education building, which described as a real-parameter constrained MOP. We formulated the de-

Table 5. The Decision Variables and Objectives for Each Case from 6 to 10

	Case 6	Case 7	Case 8	Case 9	Case 10
C_{facade}	147867.14	144897.54	140814.34	137844.74	135617.54
sDA	54.1 %	53.2 %	51.9 %	50.7 %	50.0 %
R_w	56.1 %	53.2 %	49.3 %	46.7 %	44.7 %
G_1	10.00 m	10.00 m	5.20 m	4.20 m	4.60 m
G_2	16.40 m	16.40 m	16.40 m	16.40 m	16.40 m
G_3	7.20 m	5.60 m	6.40 m	6.40 m	4.60 m
G_4	4.00 m	4.20 m	5.00 m	4.40 m	4.60 m
G_5	1.20 m	1.00 m	1.00 m	1.00 m	1.00 m
G_6	0.60 m	0.60 m	0.60 m	0.60 m	0.60 m
G_7	8.40 m	8.40 m	8.60 m	8.60 m	8.60 m

sign task to reach the minimum value of the total construction cost, while contributing to the daylighting aspects of interior space, using the daylight autonomy as the performance metric. Throughout the study, seven decision variables related to glazing widths and one constraint are taken into consideration to develop the best possible set of solutions for two objectives. As the results show, considering the termination criteria, the algorithm is efficient enough to demonstrate eligible facade design alternatives.

The implementation of numerous important design aspects that the facade design process contains is achieved. However, additional incorporation of various aspects related to performance may bring benefits. As an example, an investigation of using different construction materials for glazing parts of the facade can be a direction for further study. Last but not least, dynamic metrics for daylight performance, such as the daylight autonomy (*DA*), presents more accurate results, but the simulation takes longer time. There is no doubt that static metrics, mainly daylight factor (*DF*), require less computation time compared to *DA*. At this point, dealing with such a long simulation time for these metrics should be discussed, **c**onsidering the local climate and the buildings' direct exposure to sunlight.

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Arda Agirbas,
M. Sc., Artiyans Architecture. His research interests include digital design methods and multi-objective evolutionary optimization in the field of architecture. With a special focus on digitally-driven architectural form-finding and optimization studies, he especially explores the effects of digital concepts and methods in the context of architectural design

Ebru Alakavuk,
Ph.D., Yasar University. She studies on sustainable buildings, advanced facade systems and advanced construction systems