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EVOLUTIONARY OPTIMIZATION OF BUILDING ENVELOPE DESIGN WITH PHOTOVOLTAICS-INTEGRATED SHADING DEVICES

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Abstract: During performance-based architectural design, façade elements that have an influence on performance need to be integrally considered. This study addresses the need to support building envelope design, and specifically the design of photovoltaics-installed shading devices. Photovoltaics-installed shading devices simultaneously influence various performance criteria such as building energy consumption, daylighting and electricity production. Therefore, their design needs the support of optimization tools that help evaluate different design alternatives based on these performance criteria. This paper presents an evolutionary optimization approach that is extended from a model developed previously by the author, which optimizes multiple performance objectives towards the search for optimal envelope configurations. The tool is tested on a number of building forms with different photovoltaics-integrated shading devices, and a comparative evaluation is presented. The results show that genetic optimisation can provide meaningful insight to the problem towards well-informed decisions being taken.

Keywords: Building-integrated photovoltaics; shading device; energy use; daylighting performance, evolutionary optimization.

1 INTRODUCTION

Building shading devices and building-integrated photovoltaics (PV) are building elements that help improve building performance. Shading elements help control solar gains and reduce cooling loads and the associated energy use resulting from solar radiation. They also increase heating loads due to reduced solar gains during heating season. Shading devices can also mitigate the negative consequences of direct sunlight such as visual discomfort and glare. Moreover, shading elements have an impact on indoor environmental quality and occupant comport. Correct daylighting improves indoor conditions when used as the primary lighting source and reduces the need for artificial lighting, resulting in reduced energy consumption. Another benefit of shading is that they allow for larger opening areas and help increase visual access to the outside environment.

PV modules can be used on buildings by replacing other building components or become a part of the envelope when suitable insolation and temperature conditions are satisfied (Lai and Hokoi 2015). For instance, shading devices can be used to install BIPV, so that they can simultaneously control solar gains and generate electricity from solar energy. PV module orientation is an important decision, as the monthly solar irradiation values of different orientations are different (Figure 1). Moreover, shading devices can also reduce daylight availability and block useful solar radiation in winter (Mandalaki, Zervas

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et al. 2012). Therefore, PV-installed shading design is a multi-objective decision problem that needs the satisfaction of conflicting objectives. Previous research has addressed the design of PV-installed shading devices to study the effects of different shading-type PV cladding designs on the total energy saving (Sun and Yang 2010), for ventilated double façade remodeling of the BIPV (Yoo and Manz 2011) or for different climates and fixed shading device types (Mandalaki, Zervas et al. 2012). However, these existing approaches have limitations regarding the evaluation of several selected alternatives with no guarantee of reaching optimality. Evolutionary methods, when integrated with performance simulation tools, have proven to be effective in supporting design decisions.

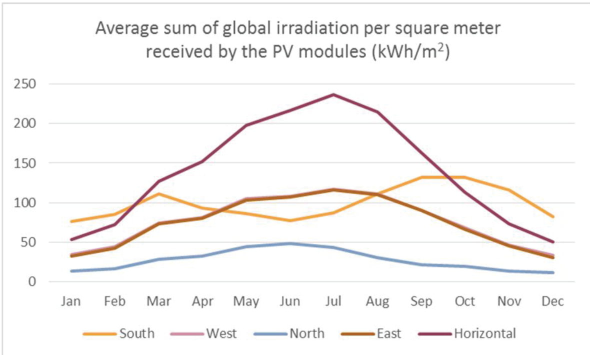

Figure 1: Monthly global irradiation received by typical PV panels (kWh/m2) for Ankara, Turkey. Results obtained from PVGIS (Šúri, Huld et al. 2005).

2 EVOLUTIONARY METHODS FOR DESIGN OPTIMIZATION

Simulation-based optimization methods can effectively support building design towards well-informed decision making. Multi-objective optimization that can provide visual and analytical feedback for early stage decision-making (Lin and Gerber 2014). Exploring large solution spaces during performative design and solving design problems with difficult fitness landscapes is possible by the systematic evaluation of performance using evolutionary computation (Turrin, von Buelow et al. 2011). Especially for the design of buildings with high energy performance, optimization methods can successfully automate design search (Attia, Hamdy et al. 2013).

Evolutionary multi-objective methods have shown great potential for early-design decision-making in reaching optimal solutions that satisfy multiple objectives. NSGA-II (Non-dominated Sorting Genetic Algorithm-II) is a dominance-based elitist optimization algorithm that can balance exploitation and exploration (Deb, Pratap et al. 2002). During selection, a higher bias is applied towards non-dominated solutions for exploitation. In general, a solution S_1 is said to dominate solution S_2 if it is no worse than S_2 in all objectives, and if S_1 is better than S_2 in at least one objective. For exploration, NSGA-II aims to preserve solution diversity by assigning individuals a crowding distance that indicates the density of their neighbourhood in the objective space. Crossover and mutation are applied on individuals with different probabilities, the old and new individuals are merged and the new list is sorted. The best individuals in this extended list are transferred to the new generation. This process is repeated until the non-dominated solutions of the final generation, namely the Pareto-front, are generated.

3 THE OPTIMIZATION MODEL

An optimization tool that implements multi-objective genetic algorithm (NSGA-II algorithm) that was previously developed by the author (Dino and Üçoluk 2016) is adapted for this study. For this study, shading devices and PV panels are integrated to the existing energy models and the optimization algorithm. The tool varies the parameters of the shading devices together with the window-wall ratios. The tool is seamlessly integrated with EnergyPlus through the OpenStudio SDK to quantify the two objective functions.

3.1 Calculation of performance objectives

The tool aims to minimize the building's net energy consumption (NEC) and maximize daylight autonomy (DA). NEC is calculated by aggregating heating, cooling and lighting energy use, and subtracting from this value the photovoltaics generated energy (Equation 1). It must be noted that NEC does not represent the total energy consumption, but only those that are influenced by the façade. Daylighting performance is calculated using daylight autonomy (DA), which aggregates the number of hours that thermal zones are illuminated without the need of artificial lighting (Equation 2). For this, the target illumination level for each thermal zone (ET_z) needs to be specified, and the actual daylight illumination level (EM_z) needs to be calculated by simulation. An asymmetrical Gaussian membership function is formulated that assesses zones' hourly DA on a scale of 0 to 1, while favouring the positive areas in the vicinity of its peak point. The reason that lighting performance is made part of both objective functions is because they can be in conflict with each other when there is too much daylighting. While $Q_{electricity}$ minimizes lighting electricity use by maximizing the daylight, DA seeks for the closest match between the required lighting and actual daylighting values.

$$NEC = Q_{EU} - Q_{PV} \tag{1}$$

$$Q_{EU} = Q_{heating} + Q_{cooling} + Q_{electricity}$$

$$DA = \sum_{z=1}^{t} \sum_{h=0}^{k} DA_z^h \ a_z$$

$$DA_z = e^{\frac{-(EM_z - ET_z)^2}{2\sigma^2}}$$

$$\sigma = \begin{cases} k, & EM_z < ET_z \\ l, & EM_z \geq ET_z \end{cases} \tag{2}$$

3.2 Modelling and parameterization of the photovoltaic panels, shading devices and windows

PV panels are used on shading devices and at the rooftop (Figure 2 and 3). On the south, continuous overhang shading devices are placed on each floor. The distance from the floor level (h_f) and from the building (d_b), the depth of shading surfaces (d_s) and the distance of tilt (d_t) define the shadings. On the west, vertical louvres are defined by the distance from the building (d_b), the depth of shading surfaces (d_s), distance of tilt (d_t) and panels spacing (h_f). These parameters are varied by the genetic algorithm. The conversion efficiency solar cells on shading devices is 17% and their fraction of the surface area with active solar cells is 90%. For the rooftop PV panels, the model is simplified such that a cumulative value for the fraction of active solar cells is taken as 65%, which considers both the placement gaps between the panels (placed with a 32^0 angle) and solar exposure reduction due to self-shading. The rooftop panels' conversion efficiency is 17%. All PV panels, placed both on the shading devices and at the rooftop, are connected to a generator with an electric power output value of 9000W. The electricity generated by the generators (Q_{PV}) are used as part of the objective value in Equation 1. A high-performance window material is used on the south, east and west facades with a U-value, solar heat gain coefficient (SHGC) and visible transmittance (VT) of 3W/m^{2}K, 0.35 and 0.45. On the north façade, the same performance parameters are 3W/m^{2}K, 0.86 and 0.90 respectively. The windows are placed on all four façade directions, 10m apart from each other. The window dimensions are varied by the algorithm while maintaining an aspect ratio of 1:2 horizontally.

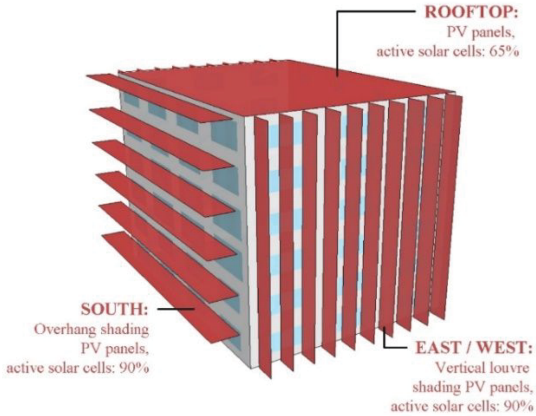

Figure 2: The placement of PV panels

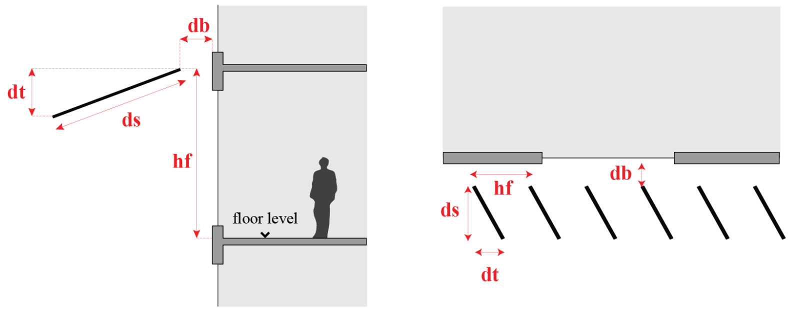

Figure 3: The parameterization of the shading devices on the south façade, side view (left) and on the east and west façade, plan view (right)

The chromosomes maintain the shading device dimensions (h_f, d_b, d_s and d_t) and the thermal zones' wwr values (Table 1) using value encoding scheme. The NSGA-II algorithm is used for selection, cross-over and mutation. During crossover, a selective bias is placed upon either parent, such that the genes of the preferred parent are transferred to the offspring with a higher probability of 70%. Individuals are selected with binary tournament selection. After crossover, individuals are mutated with a probability of %10 by replacing the current value with a new random value.

Table 1: Decision variables of GA

GA variables	Allowed value ranges
h_f	(4.0, 5.5)
d_b	(0.1, 1.0)
d_s	(2.0, 6.0)
d_b	(0, 2.5)
wwr (for each zone, four directions)	(0, 1)

4 CASE STUDY

To test the proposed optimization tool, a comparative study that applies the optimization algorithm on different building forms is carried out. The test building has a 7200 m^2 building program with thermal zones with different performance requirements (Table 2). Five rectangular prisms with different aspect ratios (width: depth: height) of are instantiated (Figure 4). Aspect ratio has an influence on GA fitness values due to (1) different façade areas on the south façade made available for PV panels, (2) different rooftop floor areas made available for PV panels, (3) different spatial depths that have an influence on daylighting, (4) form compactness (building volume / surface area) that has an influence on thermal gains/losses. The PV panels are placed on south-facing shading devices and the rooftop in Building A,B,C and D, and the east / west facing shadings and the rooftop in Building E. EnergyPlus 8.2 is used to calculate the energy use, PV energy production and daylight illumination. The Gaussean fitness function is applied to calculate DA with values for k and l taken as 30 and 150. The genetic operations use the probability values presented in Section 3.3. The population size is 70, and the number of generations is 50. The resulting Pareto-fronts are shown in Figure 5.

Table 2: Performance metrics of the building thermal zones

Thermal zone	People (p/m^2) (for 120 W/p)	Lights + Electric equip. (W/m^2)	Illum. setpoint (E_{Zi}) (lux)
1. Study	0.056511	20.76	500
2-Books	0.005	10.58	150
3-Offices	0.056511	20.76	400
4-Cafeteria	0.29	16.4	250
5-Meeting	0.056511	20.76	150
6-Leisure	0.29	16.4	250

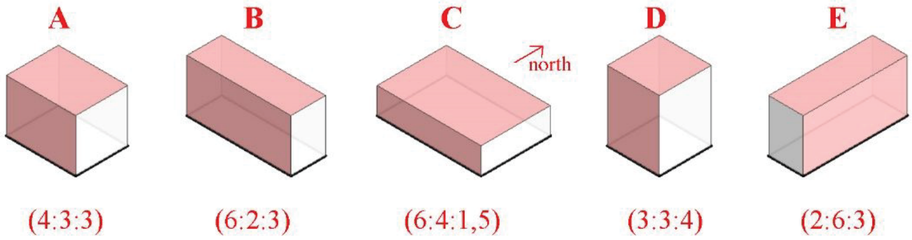

Figure 4: Five form alternatives with different aspect ratios (width:depth:height). Red surfaces indicate the PV-installed surfaces

4.1 Discussion on results

To analyse the results, we use several metrics to characterize different forms, such as form compactness (V/A), footprint (wd) and south façade area (wh), building energy performance (*NEC,* Q_{EU}, Q_{PV}), daylighting performance (*DA*), *wwr* and shading device parameters (Table 3). The results show that Q_{PV} is most determinant in the eventual energy performance, which is also proportional to the building surfaces made available for PV installation. The maximization of the rooftop (Form C) has a bigger impact than of the south façade (Form B), as monthly average solar irradiation on horizontal planes is much higher than of vertical planes (Figure 1). Therefore, although active solar cells constitute only %65 of the rooftop, Form C generates more energy than Form B. Similarly, Form C consumes less energy (Q_{EU}) than Form B due to its larger footprint and compact form. On the other hand, Form C performs relatively poorly in DA due to its large footprint, spatial depth and its failure to illuminate all it's the spaces with daylight. A trade-off between two objectives becomes apparent in buildings with large footprints. In such cases, alternative solutions that introduce daylight into spaces, such as atriums or light wells, can be formulated.

Daylight autonomy is highest in A, B and D, which are compact forms with less spatial depth (V/A = 0.55 for A and D) or have an east-west orientation (wh = 18 for B). Spatial depth and south-west orientation has a negative effect on daylighting performance. PV gain is the second highest in E due to its freedom to arrange the frequency of PV panels (dt). Although east and west oriented PVs benefit less from solar irradiation, their high density can considerably increase PV electricity production. However, another objective –that was not considered by the algorithm- is the initial and lifecycle costs of PV panels. E increases the number of panel on east and west facades to increase PV gain, but at the same time increases the initial cost, which might reduce the advantages made apparent by the algorithm. Moreover, the orientation of E has a negative effect on daylighting, as daylight in the east/west direction is difficult to control even with shading devices.

The wwr values show that high aspect ratio of the building footprint (Building B) has a negative influence on window opening sizes. On the contrary, building forms with large footprint area (Building C) have to increase the wwr to be able to introduce sufficient daylight to the depths of the form. In addition to energy use and daylighting, wwr also has an effect on visual openness and can positively contribute to indoor environmental quality. Therefore, high wwr values might be desirable for all or some façade orientations. Although not considered as an objective function in this tool, the wwr can be integrated as part of the evaluation procedure, such that it is maximized in the desired directions while also satisfying other performance objectives.

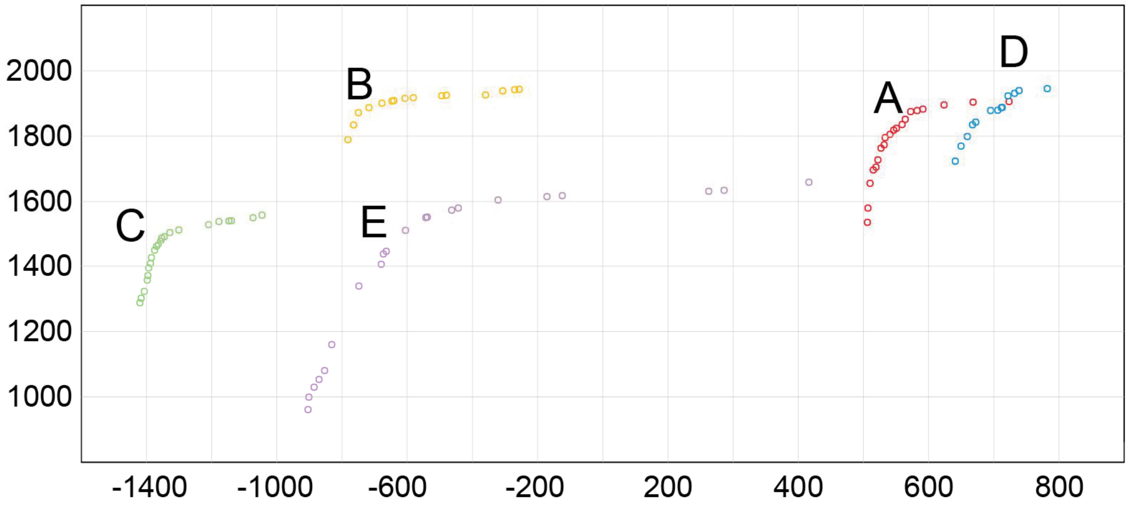

Figure 5: Pareto solutions

Table 3: The average values of the Pareto solutions of buildings A, B, C, D and E

	unit	A	B	C	D	E
Compactness (V/A)		0.55	0.50	0.46	0.55	0.50
South facade (wh)		12.00	18.00	9.00	12.00	6.00
Footprint (wd)		12.00	12.00	24.00	9.00	12.00
Energy use	(kWh)	918.70	-597.39	1330.72	1201.55	-470.205
Energy Con.	(kWh)	4629.43	3949.63	3890.76	4390.31	4801.92
PV gain	(kWh)	3710.73	4547.02	5221.48	3188.76	5150.25
Daylight Auto.	(lux)	1789.03	1905.63	1439.93	1864.51	1342.953
wwr gross		29.67	23.71	33.66	25.31	39.58
wwr North		23.01	10.77	25.38	12.17	40.26
wwr East		24.01	21.21	29.96	23.37	27.02
wwr South		42.41	37.57	41.28	23.90	32.36
wwr West		27.26	23.43	38.36	41.79	54.33
hf	(m)	5.43	5.46	5.38	5.30	2.10
hl	(m)	1.65	1.42	1.36	1.39	4.00
db	(m)	0.42	0.47	0.28	0.22	1.50
ds	(m)	5.93	5.92	5.98	5.91	4.00
total PV area		24.00	30.00	33.00	21.00	48.00

If the results are to be implemented, generalizations regarding the energy model first need to be concretized. The tested buildings have a very simple geometry and theoretical material properties, which need to be substituted with the detailed form and material specifications. Similarly, the PVs need to be modelled after actual product specifications rather than simple performance characteristics and approximated sizes. The HVAC system is simplified into an ideal air load system with full efficiency, which needs to be replaced with actual HVAC components.

5 Conclusions

An optimization tool for building envelope design with PV-integrated shading devices and an approach to evaluate optimization results are presented. The comparative analyses show that different building forms respond in various ways to the tested envelope elements. Moreover, it becomes evident that other objectives that were not formally considered as part of the initial objective function can play an important role in optimization, such as initial costs of PVs or wwr. Therefore, there is a need to enrich the objective space in the future to make a thorough evaluation of buildings.

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