DESN3002 Final Report

Daylight-Informed Exploration of Window Configurations in Modular Temporary Shelters Using Machine Learning

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Abstract

Partnered with IKEA and the UNHCR, Better Shelter designed a relief housing unit (RHU) that could be quickly deployed, assembled, and adapted to any emergency context for the displaced. Despite its interchangeable window panels, this feature has not been thoroughly leveraged and has consequently invited criticism regarding poor indoor daylight performance due to uniform assembly in refugee camps. Moreover, conducting iterative daylight analysis to investigate this problem is also extremely time intensive. Thus, this project uses machine learning to facilitate design exploration, develop insights regarding window configurations and orientation as design variables, and predict both instantaneous daylight analysis and good window configurations through a surrogate and generative model, respectively. Using Rhino's Grasshopper plugin, data will be collected using daylight autonomy as the primary metric and visualized with Python. Results demonstrated that the standard assembly of two windows in the middle of each long wall does not take advantage of consecutive and corner panels. Although a minimal number of north and south windows can be tolerated, the east and west sun gives more consistent daylight, especially if it aligns with the length of the unit. The models themselves performed above average and successfully gave daylight analysis results 30 times faster than Ladybug and Honeybee components. Once other factors are introduced and more data collected, this system can allow for more accessible iterative daylight analysis when exploring modular designs of temporary shelters for both analysis and energy efficiency, especially for on-site assemblers to meet local needs, ensure quality control in practical settings, and improve the adaptability of emergency responses.

Introduction

i. Background

As of 2023, 110 million people have been forcibly displaced, the highest recorded number since the beginning of the century (IRC, 2023). The ratio of displaced to global population doubled from 1 in 124 to 1 in 73 in less than a 10-year period, leading to a surge in temporary housing needs (UNHCR, 2023). Refugee settlements that do not have access to local building materials often require humanitarian aid from third parties to fund temporary shelters. Although there have been several attempts to mass produce collapsible and customizable designs, only three types fell under affordable costs for wide deployment: tents, ex-containers upcycled from shipping cargo waste, and relief housing units (RHU) (Laylin, 2014).

(Figure 1 – Relief housing unit (RHU))

Partnered with IKEA and UNHCR, Better Shelter designed the RHU and deployed around 190,000 units in 80 different countries since its inception in 2015 (Cerini, 2023). It consists of 71 steel rods and necessary joints as a structural wireframe anchored to the ground in which 31 thin plastic panels and a lockable door are attached to form four walls and a roof (Brownell, 2020) *(see Figure 1)*. With a lifespan of three years and an option to upgrade into a permanent home to last seven more, the RHU serves as a long-term and durable alternative to tents (Snow, 2013). Despite offering the same privacy and security as an ex-container, its flat-pack approach allows for quick deployment of higher quantities, which are then easily assembled with little labor and virtually no tools or machines (Szondy, 2013). Both tents and ex-containers lack modularity in their expansion and reusability in different locations (Peters, 2021). This unique appeal, formally recognized by Design Museum in their given 'Beazley Design of the Year' award in 2016, is why it was selected as this project's case study (Wainwright, 2017).

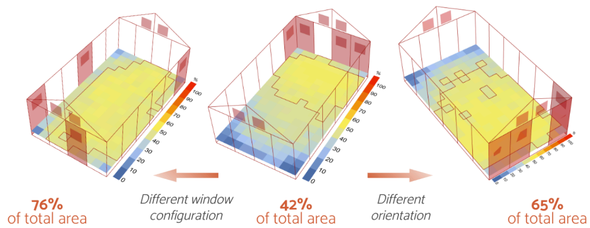
ii. Problem

However, critics claimed that the unit neglected many basic design needs, most notably its daylight performance (Johnson, 2015) *(see Figure 2)*. Only having four small windows to cover 188.4 feet^2 of indoor area, there have been complaints about how dark it is in a practical setting without artificial lights, leading to the abandonment of some units and the transformation of others into storage spaces (Dunn, 2015). Although the polyolefin panels are semi-opaque and two more windows were introduced into the design's second iteration, these mostly addressed material and ventilation concerns without much effect on daylight improvement (Fairs, 2017).

(Figure 2 – Inside of the RHU)

Because refugee camps usually prioritize building as many shelters as quick as possible in a certain space while still adhering to safety distances and efficient aid transportation routes, these units are often assembled the exact same but in wildly varying orientations (Jahre et al. 2018). Despite the RHU's interchangeable window panels, most units have two windows in the middle of both long walls directly opposite from one other (Scott-Smith, 2017) *(see Figure 3)*. Since window configuration and orientation can have a significant effect on daylight performance *(see Figure 4)*, this uniform assembly fails to take full advantage of the design's intended modular feature to meet daylight needs.

(Figure 3 – Syrian refugee settlement)



(Figure 4 – Preview effect of design variables)

Moreover, conducting daylight analysis itself can take a very long time. Thorough design exploration and optimization is iterative in nature, so running through thousands of window configurations does not only freeze up the software and prevent overall usage, but also takes days to compute. Adding in a second variable like orientation only compounds this problem even further, making daylight analysis wildly inconvenient and time intensive.

iii. Objective and Scope

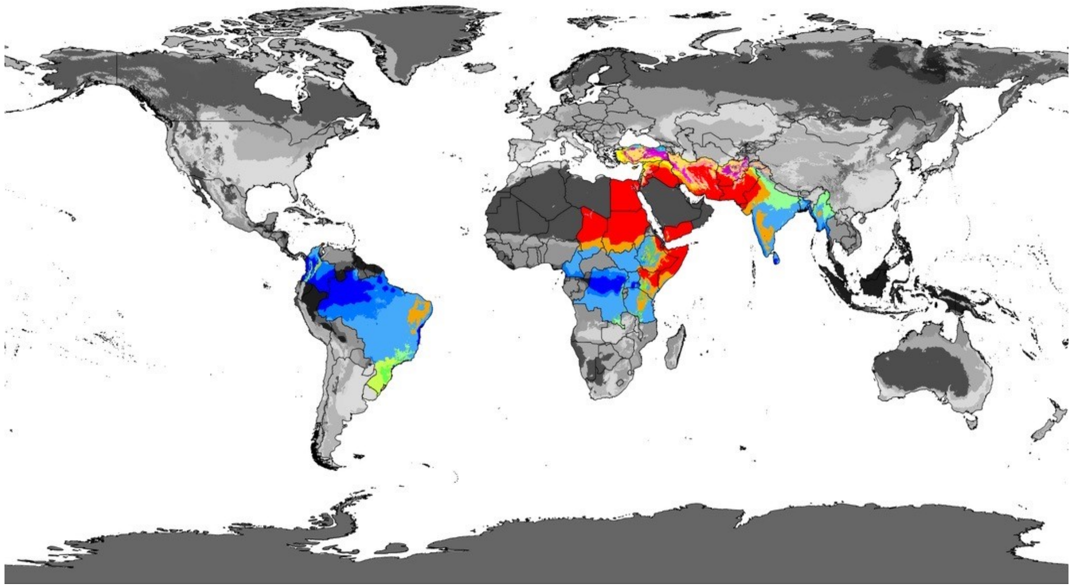
Hence, this project uses machine learning to explore the RHU’s modular design, develop general insights, and improve analysis tools. Looking closely at window configurations and orientation as the design variable scope, the first part of this investigation intends to make sense of collected data through Python visualizations, identifying the reasons behind which combinations lead to maximized and even indoor exposure as daylight objectives and whether or not they adhere to the conventional window configuration of two windows in the middle of each long wall. The second part revolves around enhancing tool efficiency by constructing surrogate and generative models, which simulate instantaneous daylight analysis results and predict good window configurations, respectively. These findings can help ensure quality control, improve refugees' standard of living, progress toward more energy efficient design, and inform more adaptive assembly.

Literature Review

Daylight analysis includes several different metrics such as useful daylight illuminance (UDI), annual sunlight exposure (ASE), and daylight factor (DF) (Chopson, 2024). However, the metric best tailored for this case study is spatial daylight autonomy (DA) for a more general indoor preview focused on maximizing daylight instead of mitigating for other concerns like excessive solar gain or glare. DA is represented by the percentage of time when a threshold of illumination, measured by lux, is reached (Dyvik, 2023). There are several factors that can affect real and perceived DA.

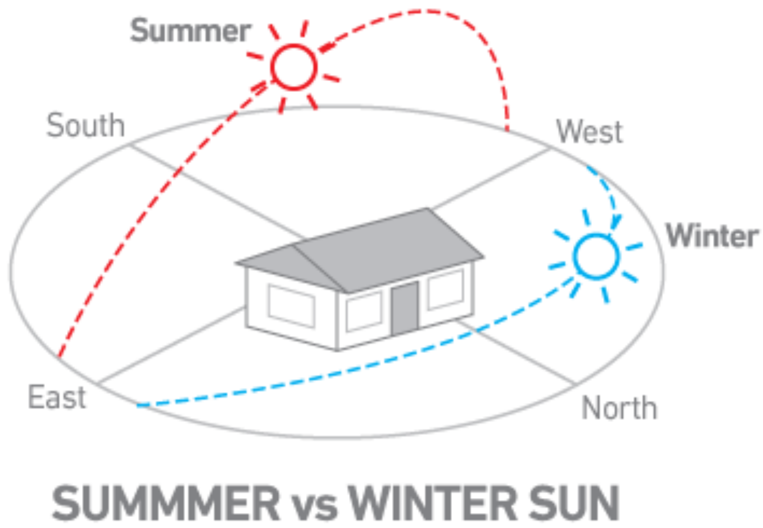
Different settings and activities require different lux levels. For example, single space homes need at least 150 lux for basic day-to-day living, classrooms need at least 300 lux for extensive reading and writing, and clinics need at least 500 lux for general treatment (Kumar, 2023). Thus, this largely affects perceived DA in terms of sufficient illumination for the tasks at hand.

Location can have a huge effect on daylight as well. In *Figure 5*, the countries with the most populated refugee camps are mostly arid (A) and tropical (B) zones according to the Köppen climate zone classification system, which are found within 0-30° from the equator (Köppen, 1936). This range alone can have as much as a 60% difference in daylight performance, demonstrating the impact of latitude on daylight hours (Munox et al., 2014). Different climate zones also have different vulnerabilities to natural disasters like floods and types of extreme weather like droughts (Terne, 2022).



(Figure 5 – Countries with most populated refugee camps and their Köppen climate zones)

The height and shape of windows can affect both the amount and type of daylight, high horizontal windows providing more indirect and even light and low vertical windows providing more direct and uneven light (Farivar & Shabnam, 2023). It is also quite intuitive that the larger the window, the more daylight observed. The placement of these windows in relation to each other varies largely on the type of windows and space you are working with (Zomorodian et al., 2016). However, what differentiates primary windows from accessory windows can have a lot to do with orientation. Although the sun always rises in the east and sets in the west, its path changes from directly overhead in the summer to a much lower angle in the winter (Kaminska, 2020) *(see Figure 6)*. This is the reason why countries in the northern hemisphere would benefit from southern exposure and the southern hemisphere from northern exposure.



(Figure 6 – Effect of seasons on sun path and unit orientation)

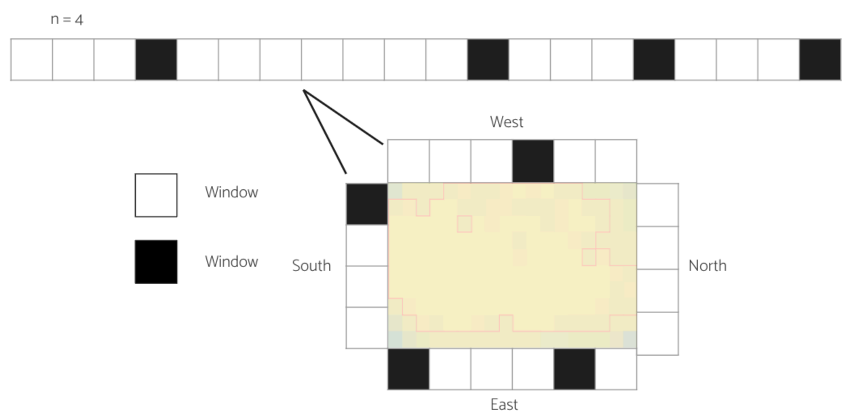
While it is clear that all these factors can influence daylight, how they interact with each other in the context of modular temporary housing has not yet been explored yet, specifically for the selected design variables of window configurations and orientation. The difference between temporary shelters and other conventional houses is working with slightly stricter restraints regarding a standard kit's number of windows, window type, and possible window placements, which technically fall under larger contextual restraints like costs, mass production, and easy deployment.

There have been a few recent studies that have used similar machine learning to speed up simulation processes. Apart from the studies that focused solely on their enhancing the accuracy of their artificial neural networks on various architectural case studies (Lorenz & Jabi, 2017; Ngarambe et al., 2020; Deshpande et al., 2022), there were two related investigations that selected a handful of design variables for a single geometry. One study measured exterior UDI with varying building layouts (Luan et al., 2022), so it did not use the same indoor metric of DA or the design variable of window configurations and orientation. As for the other study, a more holistic approach was taken and several daylight metrics and design variables like unit orientation, space dimension, and window type were recorded (Hanieh et al., 2021). However, due to the number of factors involved, each variable only had two different iterations, lacking thorough exploration of one or two variables in particular. The windows also remained on one wall, disinviting in-depth discussion about the interaction of window configurations and orientation. Thus, there is a research gap when it comes to analyzing daylight of different types of shelters in their broader contexts and exploring selected design variables to different degrees.

Methodology and Implementation

i. Setup for Data Collection

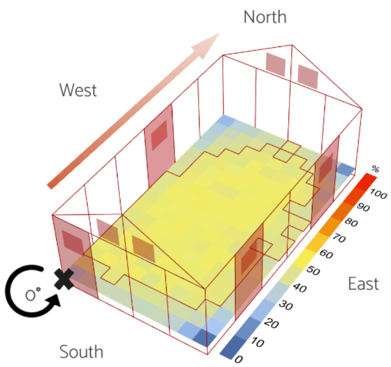
Using the Grasshopper plugin in Rhino, the RHU's geometry is first modeled to scale before conducting Ladybug and Honeybee daylight analysis. Performance is measured by annual DA with daylight hours scheduled for 9am-5pm every day throughout the year. Location is set to Syria due to the high number of RHU deployments there and the threshold is 150 lux to meet minimum standards for a single space home and day-to-day living. The unit geometry will stick to using the standard kit of one singular unit not expanded. These three components are the primary controls used when running the analysis.

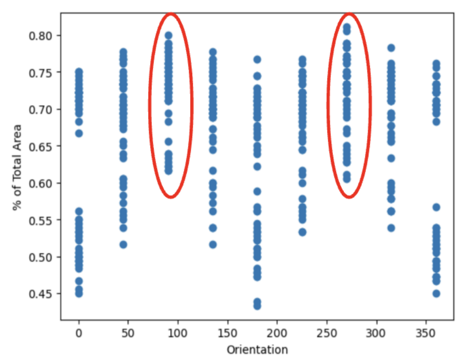


(Figure 7 – Window configurations in the form of panel binaries)

The first design variable of window configurations is measured by a single array of 20 binary values that represents the wall positions of the four interchangeable window panels *(see Figure 7)*. This assumes that the door is closed for the sake of security and privacy reasons. The ventilation outlets are not considered as interchangeable windows and are thus kept in the same position to retain its safety purpose.

The second design variable of orientation is measured by the degree of counterclockwise rotation from the unit's anchor point *(see Figure 8)*. For the sake of eliminating repetitive performances *(see Figure 9)*, iterations only include 15° intervals from 0°-180°. Thus, the unit's short walls face north and south while its long walls face east and west in the default view in all included figures.





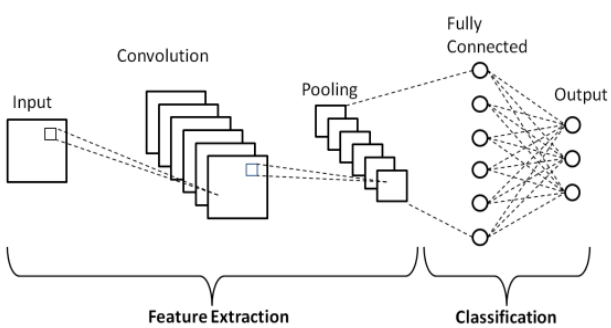
(Figure 8 – Model orientation and DA values) *(Figure 9 – DA performance 0-360°)*

Daylight is measured by the DA values of all 180 sensors of the RHU's total floor area. Outlined sensors select DA values that are above 40% and represented by a percentage of total area to evaluate daylight maximization. The average sensor value simply gets the average DA value of all 180 sensors to account for any dark corners and evaluate even distribution.

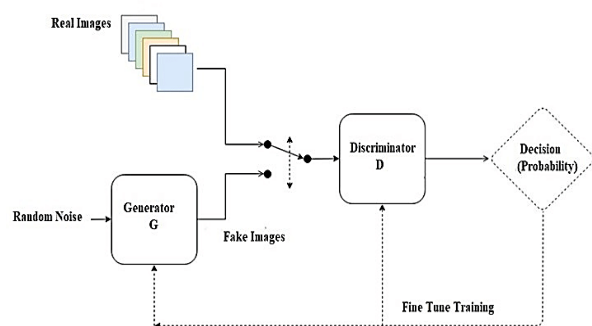
These values of all five components – panel binaries, orientation, individual sensors, percentage of total area, and average sensor – are recorded for all 3000 random window configurations, 250 of which were randomly selected to iterate through the different orientations. As a result, all visualized data are derived from these two comprehensive .csv files. However, the machine learning models were not fed any orientation data due to time constraints.

ii. Machine Learning Models

Despite using the same inputs, the surrogate model is trained with most of the 3000 data points and tested on a small subset while the generative model is only fed the 500 best performing window configurations. This is because the surrogate model is meant to predict daylight analysis results instantaneously and the generative model good window configurations. Convolutional neural networks, a type of deep learning algorithm for analyzing visual data, are used as the primary framework of both models to extract input patterns and capture spatial relationships (Phung & Rhee, 2019) *(see Figure 10)*. This foundation is needed to both perform regression tasks that output continuous values and turn random noise into new convincing data samples (Goyal, 2020) *(see Figure 11)*.



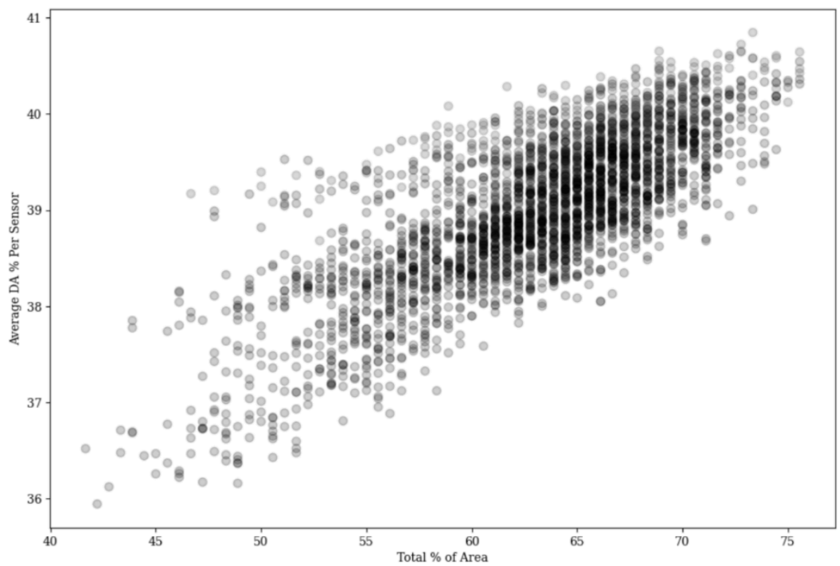
(Figure 10 – Framework of CNN)



(Figure 11 – Framework of GAN)

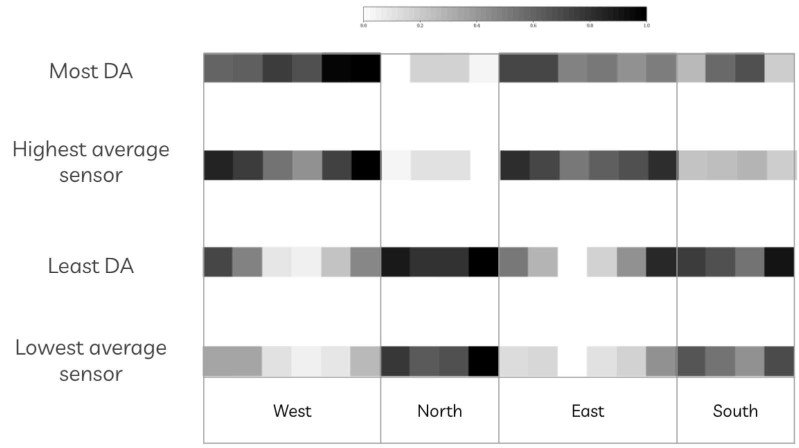
Findings and Discussion

i. Data Insights



(Figure 12 – Scatterplot of all 3000 window configurations controlling for orientation (0°))

(See Figure 12) The percentage of total area that reached 150 lux at least 40% of the year had as much as a 34% difference between varying window configurations, ranging from 42% to 76%. However, there was very minimal effect on even distribution, the average sensor ranging only from 36% to 41% with a 5% difference. However, a few window configurations with poor DA performance had surprisingly equal evenness, demonstrating a higher variability in evenness as compared to those with higher DA performance. Although this can be attributed to the neglected dark edges right beneath these windows that may drag down the average, the effect does not seem to be too significant to change one's preference between the two window configurations.

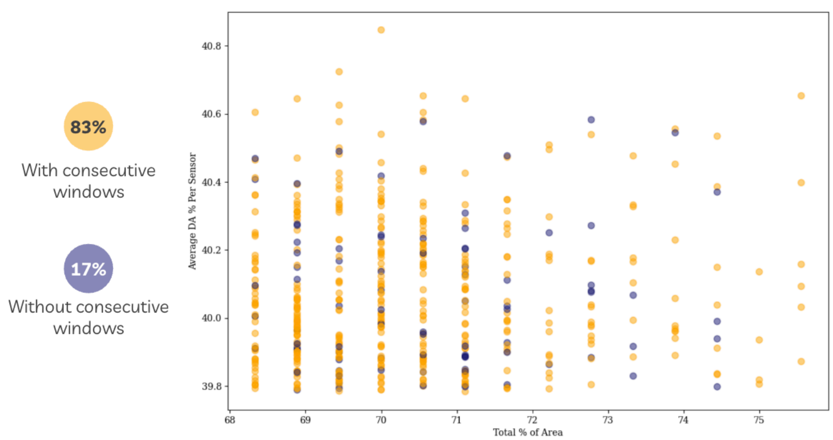


(Figure 13 – Frequency of panels in best and worst window configurations (normalized))

(See Figure 13) For the 500 window configurations with the most annual DA and the 500 with the highest average sensors, it is very evident that north-facing windows are the least important for both maximization and even distribution objectives. Vice versa can be observed with the window configurations with the least annual DA and lowest average sensors as well. This checks out with the location effect on daylight since Syria is above the equator and would consequently benefit from southern exposure for winter seasons.

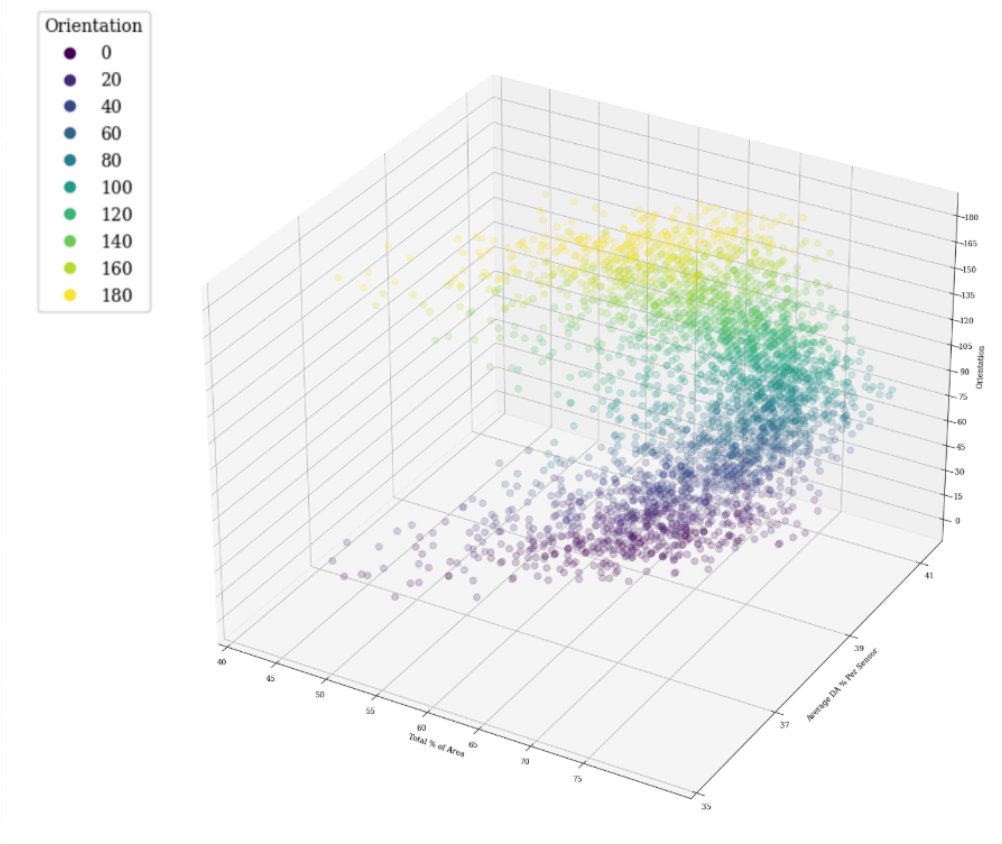
However, for both the best and worst performing window configurations, a majority of the corner panels on the walls with the most occurrent windows seem to be more frequent than their respective middle panels. This leads to the idea that the performance of corner windows is quite variable as well but should not be too quickly dismissed as a placement option.

(Figure 14 – 25 best performing window configurations (left) and 25 worst performing (right))



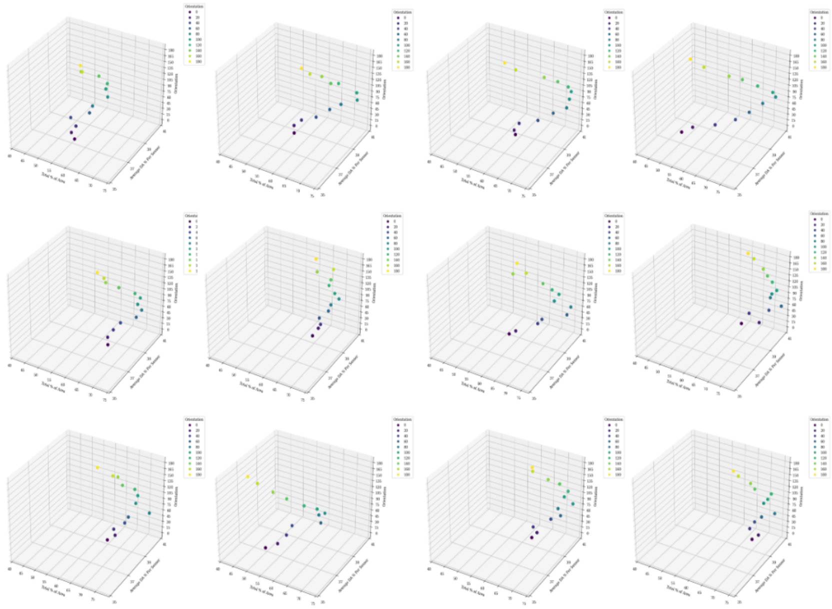
(Figure 15 – 500 best performing window configurations and if they have consecutive windows)

It is obvious that spacing plays a crucial role in daylight maximization since the worst 25 window configurations are clearly more clumped together than the best 25 *(see Figure 14)*. However, 83% of the top 500 had at least two consecutive windows *(see Figure 15)*, meaning that this notion of even spacing between windows does not necessarily lead to more indoor area coverage.

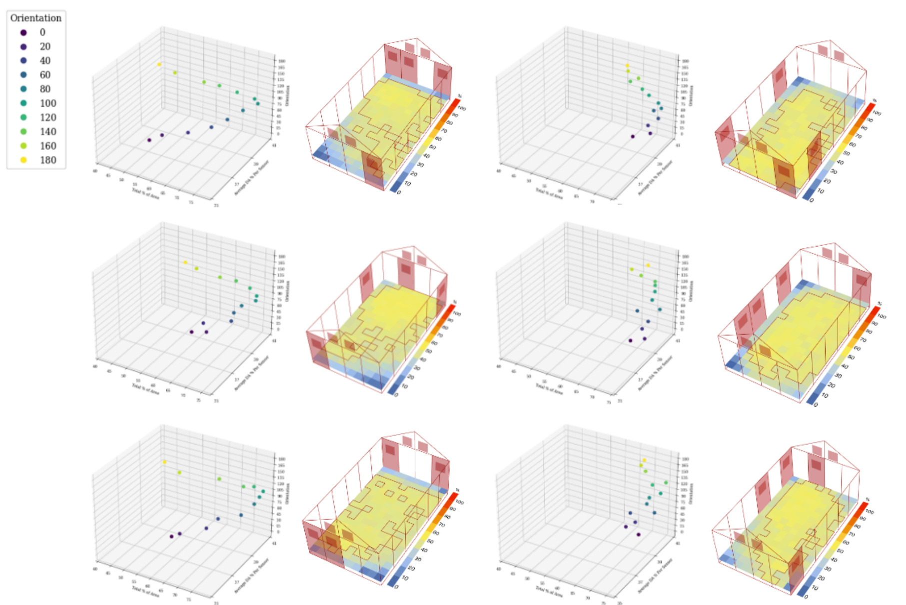


(Figure 16 – 3D scatterplot between daylight objectives and orientation)

(See Figure 16) As for the orientation effect, daylight performance clearly increased around the 90° rotation interval. This possibly could be explained by the rectangular shape of the unit. Considering the clearly significant impact of seasonal sun paths, it makes sense for the unit to receive more consistent daylight when its length aligns with the east and west sun. This allows for further area reach as compared to if the width aligned with the east and west sun and subjected the length to the volatility of the north and south sun.



(Figure 17 – Variable daylight performances of differently oriented window configurations)



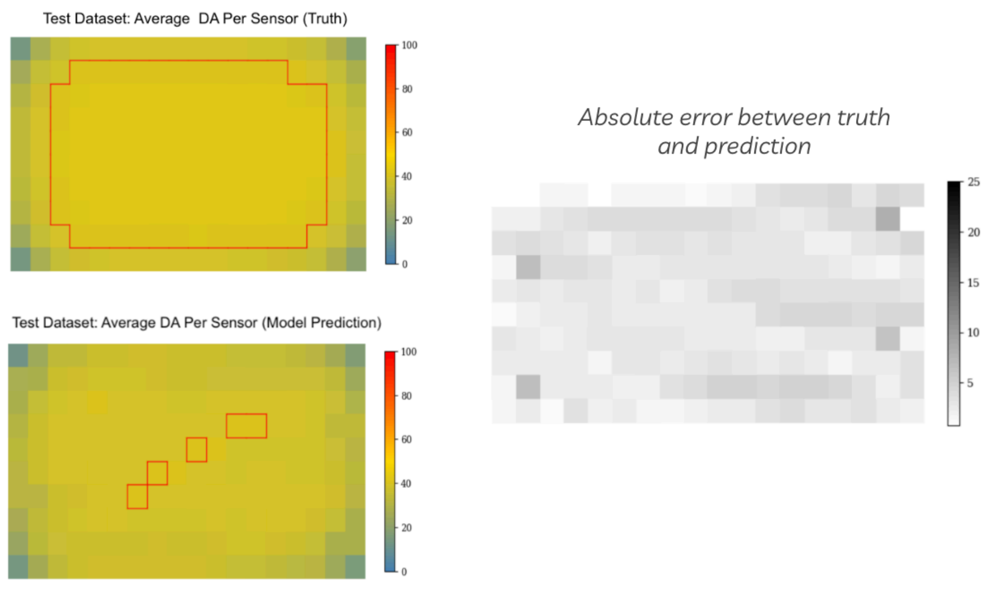
(Figure 18 – Window configurations with variable and consistent performance)

When isolating each window configuration in this three-dimensional plot, it is evident that orientation affects some to a much higher degree than others *(see Figure 17)*. This possibly could be attributed to the number of north and south windows *(see Figure 18)*. The more variable window configurations have at least two windows in those directions while the consistent ones only have one. Interestingly enough, this means that the complete omission of north and south windows is not necessarily a one-size-fits-all solution. Instead, they can be tolerated as accessory windows as long as they are kept to a minimum.

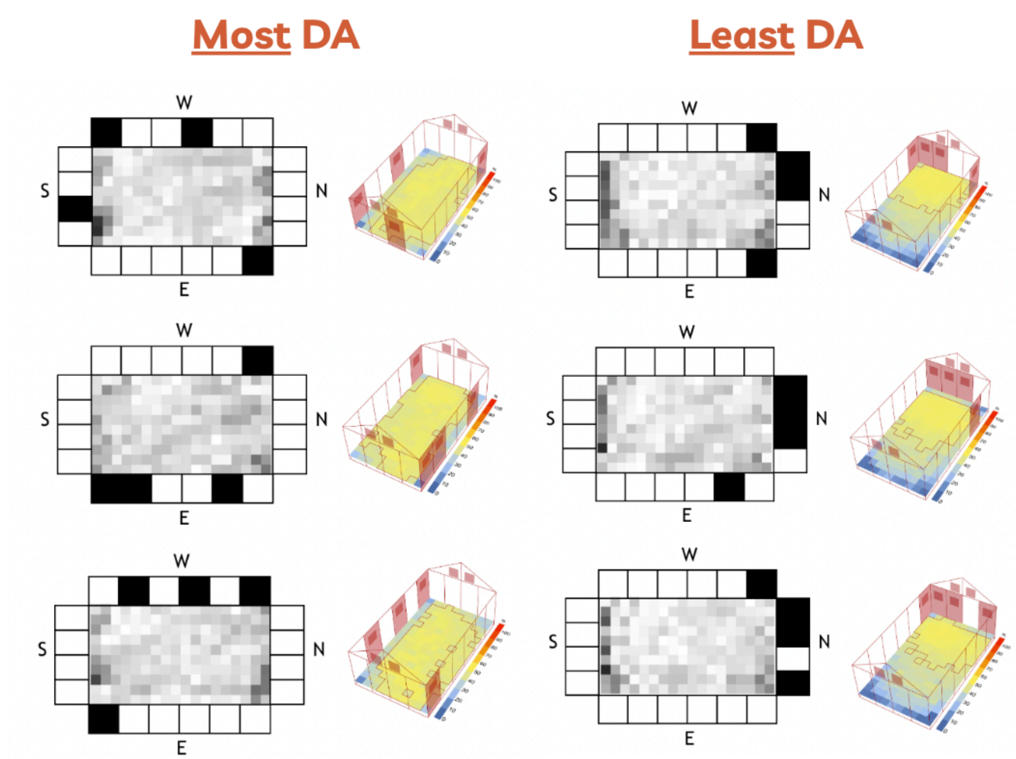
Therefore, it is reasonable to conclude that window configurations that make use of consecutive panels and corners can be used effectively, rejecting the preconception of a strict need for evenly spaced middle panel windows. There was also minimal effect on even distribution. As for which walls would work best, it is important to consider the winter sun and the number of north and south windows since this determines how much orientation will affect performance variability and can possibly lead to significantly less seasonal daylight. It is also more effective to align the length of the unit with the east and west sun since its consistent daylight would have further indoor area coverage.

ii. Model Evaluation

The surrogate model was able to produce results that looked very similar to the truth and had very minimal average absolute error per sensor between the two *(see Figure 19)*. However, small errors can interfere significantly with threshold selection despite being identical to the eye. However, underestimating DA values is preferable since that errs on the side of caution regarding objective achievement.

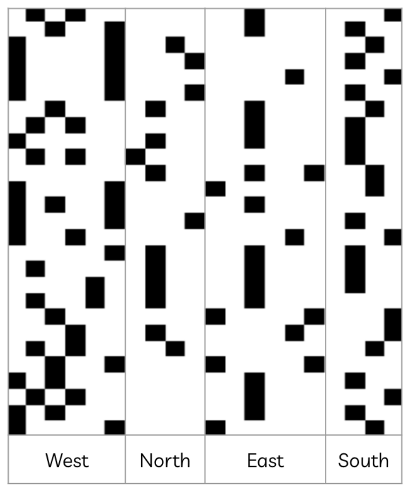


(Figure 19 – Truth and model prediction (left) and average error per sensor (right))



(Figure 20 – Error between truth and prediction for 3 best and worst window configurations)

(See Figure 20) Higher error was also found with darker window configurations. This could correlate with how they tend to have more variable distribution, which makes it harder to learn and predict accurately. Most errors were found in the dark corners and edges as well, but this poor prediction of darker areas might be explained by the model's lack of exposure to data variation. The exclusion of different numbers of windows probably prevented the model from learning that less windows would have less daylight and so on.



(Figure 21 – Generative model's first set of good window configurations)

(See Figure 21) The first set of panel binaries produced by the generative model did not perform the best at first. Despite the data showing the effectiveness of consecutive windows and less north and south windows, the given image disregarded both aspects. 29% performed in the 75th percentile (>67%), 43% above average (>62%), and 28% underperformed in general. These results improved with some more refinement, but some window configurations somehow outperformed the truth dataset's maximum value by almost 10%. Again, there is always room to fine-tune the model even further and fix any underfitting.

After plugging these models back into Grasshopper, the predicted daylight results of good window configurations were able to be simulated with just a click of the button. Instead of taking one minute to compute, it only took around two seconds to generate, making the process around 30 times faster than the original analysis tool. This allows for much more efficient design exploration and iterative daylight analysis in a much more simplified and user-friendly manner.

iii. Limitations

Due to personal shortcomings in all technical aspects required, this study can undoubtedly benefit from more expertise. Finding the methodology best tailored to a specific case study and making sense of all important data is a lot easier with more interdisciplinary collaboration, whether that be from daylight analysts, programmers, or even humanitarian workers. Being able to work with various skilled specialists also means expanding one's access to different information resources and technology. Relatively weak computers can barely handle basic analysis tools, leading to more generic data and frequent crashes. Time constraints played a major role as well. Because this project had a huge learning curve, a lot of trial and error was involved when toying around with new software plugins, collecting the right data, figuring out how to creatively visualize that data in Python, and making sure the machine learning models worked well.

Conclusion

In conclusion, using of east and west windows in addition to consecutive and corner panels can help increase indoor daylight significantly, which is why window configuration and orientation need to be seriously considered when assembling RHUs in refugee camps. The idea of instantaneous daylight analysis for iterative exploration can expand beyond temporary shelter, expedite investigative processes, and even push forward concepts of modularity in design. This, of course, would require extensive data collection that will only exponentiate the more variables are introduced into the system. However, making daylight analysis tools more efficient and user-friendly can eventually translate into accessible evaluation tools for on-site RHU assemblers, empowering those who are more involved with local dialogue to make better-informed decisions about technical practicalities. This way, the system can be used to predict window configurations with the best daylight performances no matter the orientation, location, setting, geometry, window type, and much more to truly adapt to any emergency.

Leveraging the unit's modular feature of interchangeable window panels to meet daylight needs can help ensure the health, safety, and productivity of all inhabitants and show receptiveness to the needs of the marginalized. This could also decrease their dependence on artificial light, conserve energy, and save costs on solar panel maintenance and production. Quality control would curb unit disuse and waste and prepare better emergency responses to any given circumstance, an element important to future-proof design for handling contemporary global issues like climate change and increasingly tense geopolitics. Once the project's overall reliability as a good temporary shelter alternative that meets basic needs is increased, its reach can be broadened and, in turn, more high-quality homes can be built for millions of people.

References

Better Shelter. (2022). *Annual review 2022.* Global Compact Communication on Progress. https://bettershelter.org/wp-content/uploads/2023/07/2022_Annual-review-FINAL-for-design-Better_Shelter-078-01-1.pdf

Brownell, E. (2020, April 1). *Better Shelter.* https://ebrownell.com/wp-content/uploads/2020/04/1.-brownell-better-shelter-proofs-2019.pdf

Cerini, M. (2023, August 31). *Home in a box: Rethinking disaster relief, IKEA style.* CNN. https://edition.cnn.com/style/better-shelter-home-disaster-ikea-dfi/index.html

Chopson, P. (2024, May 11) *Daylight Analysis - sDA + ASE.* Covetool. https://help.covetool.com/en/articles/3468219-daylight-analysis-sda-ase

Deshpande, R., Nisztuk, M., Cheng, C., Subramanian, R., Chavan, T., Weijenberg, C., & Patel, S.V. (2022). *Synthetic Machine Learning for Real-time Architectural Daylighting Prediction.* CAADRIA proceedings. https://www.researchgate.net/publication/361107709_SYNTHETIC_MACHINE_LEARNING_FOR_REAL-TIME_ARCHITECTURAL_DAYLIGHTING_PREDICTION

Dunn, E. C. (2015, October). *Ikea's Flat-Pack Shelters for Refugees Are Better Than Tents—but Still Worse Than Houses.* Slate Magazine. https://slate.com/technology/2015/10/ikea-gives-10000-flat-pack-shelters-for-refugees.html

Dyvik, E. H. (2023, December 11). *Major refugee-hosting countries worldwide 2023.* Statista. https://www.statista.com/statistics/263423/major-refugee-hosting-countries-worldwide/

Fairs, M. (2017, April 27). *IKEA refugee shelter to be redesigned following safety fears and design flaws.* Dezeen. https://www.dezeen.com/2017/04/27/ikea-unhcr-refugee-better-shelter-redesign-safety-fears-flaws/

Farivar, S., & Shabnam Teimourtash. (2023). *Impact of Window Design on Dynamic Daylight Performance in an Office Building in Iran.* Journal of Daylighting, 10(1), 31–44. https://doi.org/10.15627/jd.2023.3

Goyal, B. (2020, August 15). *Introduction to GANs - Analytics Vidhya - Medium.* Medium; Analytics Vidhya. https://medium.com/analytics-vidhya/introduction-to-gans-38a7a990a538

Hanieh Nourkojouri, Nastaran Seyed Shafavi, Tahsildoost, M., & Zahra Sadat Zomorodian. (2021). *Development of a Machine-Learning Framework for Overall Daylight and Visual*

Comfort Assessment in Early Design Stages. Journal of Daylighting, 8(2), 270–283. https://doi.org/10.15627/jd.2021.21

IRC. (2023, June 13). *110 million people displaced around the world: get the facts.* IRC. https://www.rescue.org/article/110-million-people-displaced-around-world-get-facts#:~:text=With%20over%20110%20million%20people,the%20country%20that%20resettle%20refugees

Jahre, M., et al. (2018, March 9). *Approaches to the design of refugee camps: An empirical study in Kenya, Ethiopia, Greece, and Turkey.* Journal of Humanitarian Logistics and Supply Chain Management, 8(3), 323–345. https://doi.org/10.1108//JHLSCM

Johnson, N. (2015). Construction & Architecture News. Architecture & Design. https://www.architectureanddesign.com.au/news/ikea-produces-10-000-flat-pack-shelters-for-un-ref

Kaminska, A. (2020). *Impact of Building Orientation on Daylight Availability and Energy Savings Potential in an Academic Classroom.* Energies, 13(18), 4916–4916. https://doi.org/10.3390/en13184916

Köppen, W. (1936). *Das geographische System der Klimate [The geographic system of climates].* Vol. 1. Berlin: Borntraeger. https://koeppen-geiger.vu-wien.ac.at/pdf/Koppen_1936.pdf

Kumar, M. (2023, April 7). *Illuminance Levels Indoors: Your Standard Lux Level Chart.* Prana Air. https://www.pranaair.com/blog/illuminance-levels-indoors-the-standard-lux-levels/

Laylin, T. (2014, March 15). *10 refugee shelters we hate to love.* Green Prophet. https://www.greenprophet.com/2014/03/pros-and-cons-10-refugee-shelters/

Lorenz, C.-L., & Wassim Jabi. (2017, December 20). *Predicting Daylight Autonomy Metrics Using Machine Learning.* ResearchGate; unknown. https://www.researchgate.net/publication/322049892_Predicting_Daylight_Autonomy_Metrics_Using_Machine_Learning

Luan Le-Thanh, Nguyen-Thi-Viet, H., Lee, J., & H. Nguyen-Xuan. (2022). M*achine learning-based real-time daylight analysis in buildings.* Journal of Building Engineering, 52, 104374–104374. https://doi.org/10.1016/j.jobe.2022.104374

Munoz, C., Esquivias, P. M., David Moreno Rangel, & Navarro, J. (2014, June). *Climate-based daylighting analysis for the effects of location, orientation and obstruction.* ResearchGate; SAGE. https://www.researchgate.net/publication/273592036_Climate-based_daylighting_analysis_for_the_effects_of_location_orientation_and_obstruction

Ngarambe, J., Irakoze, A., Geun Young Yun, & Kim, G. (2020). *Comparative Performance of Machine Learning Algorithms in the Prediction of Indoor Daylight Illuminances.* Sustainability, 12(11), 4471–4471. https://doi.org/10.3390/su12114471

Peters, A. (2021, February 10). *These quick-build disaster shelters can later become permanent houses.* Fast Company. https://www.fastcompany.com/90602483/these-quick-build-disaster-shelters-can-later-become-permanent-houses

Phung, & Rhee. (2019, October 23). *A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image...* ResearchGate; MDPI. https://www.researchgate.net/publication/336805909_A_High-Accuracy_Model_Average_Ensemble_of_Convolutional_Neural_Networks_for_Classification_of_Cloud_Image_Patches_on_Small_Datasets

Scott-Smith, T. (2017, December 14). *A Slightly Better Shelter?* Limn. https://limn.it/articles/a-slightly-better-shelter/

Snow, S. (2013, June 26). *A New Ingeniously Designed Shelter For Refugees--Made By Ikea.* Fast Company. https://www.fastcompany.com/2682416/a-new-ingeniously-designed-shelter-for-refugees-made-by-ikea

Szondy, D. (2013, July 1). *Ikea's turns its flat-pack philosophy to improving refugee shelters.* New Atlas. https://newatlas.com/ikea-refugee-shelter/28105/

Terne, M. (2022, November 28). *Where we work.* Better Shelter. https://bettershelter.org/where-we-work/

UNHCR (2023). *Refugee Data Finder.* https://www.unhcr.org/refugee-statistics/

Wainwright, O. (2017, January 27). *Why Ikea's flatpack refugee shelter won design of the year.* The Guardian. https://www.theguardian.com/artanddesign/2017/jan/27/why-ikea-flatpack-refugee-shelter-won-design-of-the-year

Zomorodian, Z., Korsavi, S., & Tahsildoost, M. (2016). *The effect of window configuration on daylight performance in classrooms : A field and simulation study.*International Journal of Architectural Engineering and Urban Planning, 26(1), 15–24. https://core.ac.uk/download/pdf/228155082.pdf