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Artificial Neural Network to Predict Curvature Light Shelf Design Related Daylighting Optimization on Office Spaces

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Abstract

Energy Optimization in building design field now has been revolutionized due to AI and machine learning applications. Leveraging daylight to reduce artificial lighting consumption holds promise for significant energy savings, yet the nonlinear nature of daylight patterns poses challenges in prediction and optimization. This study proposes a novel approach to automated light shelf design using machine learning algorithms, specifically artificial neural networks (ANNs) such as recurrent neural networks (RNN) by long short term memory (LSTM), to accelerate daylighting simulation and optimization processes. The methodology employed two distinct approaches: Firstly, we employed the theoretical-analytical approach to explore methods for utilizing machine learning in natural lighting and light shelf parameters. Second, the practical and applied method involved creating a predictive model for designing the light shelf using appropriate AI and ML techniques. This model is based on an office geometry model at the El Arish weather file in Egypt, four-dimensional training room models with three internal zones-oriented south. Rhinoceros and Grasshopper, two parametric simulation tools, are used to normalize and optimize light shelf parameters like geometry cross-section, curvature surface, width, height position, depth, tilt angle, and reflectance materials. Then, the Galapagos plug-in and Colibri2 are used for dataset creation and optimization. The results demonstrate that automated light shelf operation has a significant impact on internal daylighting quality. RNNs enable rapid prediction of optimization models, reducing time consumption in the early design phase. ML facilitates decision-making by generating evaluative criteria from user-selected design options. RNNs were classified as good and bad and used LSTM to enhance prediction accuracy for efficient illuminance values metric in zones 1 and 2. Challenges include increasing the simulation procedure's efficiency. The results of model accuracy reached 99%. Hence, future research should prioritize resolving the previously identified concerns. In conclusion, this study underscores the importance of ML-driven approaches in early design phases to optimize building energy consumption and pave the way for sustainable architectural practices.

1. Introduction

It is now widely understood around the world how important it is to improve buildings' performance and sustainability. Because of this, smart design choices are needed to reduce lighting system electricity [1]. An environmentally conscious methodology for amplifying energy efficiency [2] involves the integration of daylighting strategies, as underscored by the International Energy Agency [3]. This encompasses the efficient management of natural daylight within architectural structures, as expounded upon by Reinhart and Mardaljevic [4,5] and further elaborated by Ayoub in 2020 [5].

The issue of building energy consumption has emerged as a prominent global concern, prompting numerous countries to propose and adopt criteria and objectives aimed at enhancing building energy efficiency [6]. In recent years, Egypt has experienced a notable urban expansion in residential sectors, a development associated with a concomitant deterioration in indoor environmental conditions, as reported by Ayoub [7]. To ensure adequate illuminance with minimal energy consumption, it is imperative to adhere rigorously to optimal design principles and technical specifications concerning artificial lighting [8].

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Nomenclature

AI	*Artificial Intelligence*
ML	*Machine Learning*
MLAs	*Machine Learning Algorithms*
ANNs	*Artificial Neural Networks*
RNN	*Recurrent Neural Network*
LSTM	*Long Short Term Memory*
DA	*Daylight Autonomy*
BIM	*Building Information Modeling*
BPA	*Building Performance Analysis*
IOT	*Internet of Things*
HPC	*High-Performance Computing*

In sustainable architectural design, there is a growing use of climate-based daylight autonomy (DA) metrics for quantifying the ingress of natural light into a structure and the consequent energy conservation achieved [9]. Furthermore, it is noteworthy that lighting energy serves as a primary heat source, exerting a substantial influence on the demand for cooling power. Natural daylight provides notable health advantages to occupants within a building and concurrently diminishes the energy demand associated with artificial lighting [10]. Furthermore, well-planned daylighting systems effectively decrease energy usage and harmonize the heating and cooling demands of structures while also promoting human well-being and facilitating various activities [11]. Daylight augmentation heightens human visual responsiveness, amplifies motivation, and results in elevated user performance and productivity among workers [11].

Buildings are expected to demonstrate sustained performance over their entire life cycle, and the reduction of energy consumption is just one of the various factors that are increasingly prioritized and anticipated. Design professionals and researchers are progressively engaging with energy efficiency considerations because of enhanced accessibility to insights derived from building performance assessments. Nevertheless, conventional methods of data analysis encounter difficulties in managing potentially vast quantities of data generated during the design phase [12]. Daylight serves as the principal illuminant in office buildings, primarily during daylight hours, to create a comfortable and productive workspace. Adequate daylighting, complemented by artificial lighting systems, fulfills the criteria for both visual and psychological comfort conditions [11].

Recently, there has been a notable focus on optimizing both energy efficiency and visual comfort in indoor environments. This emphasis has resulted in regulations aimed at effectively harnessing natural light in combination with artificial lighting systems. The integration of lighting controls and blind control holds promise for reducing energy costs [13]. Computerized building design has evolved to enhance the efficiency of the design process. Researchers have explored the use of machine learning methodologies to forecast the performance of building designs. Presently, within existing building design software, the fusion of optimization techniques with computerized design tools remains relatively limited. Only a select few tools have incorporated certain optimization methods, such as genetic algorithms [14].

While machine learning-based models have garnered significant interest in expediting daylight simulation processes, it is worth noting that their overall capacity for generalization remains constrained [10]. Chatzikonstantinou et al. suggested that the utilization of advanced computational simulation methods can offer valuable insights during the design phase of performance-centric architectural projects. Nonetheless, the substantial computational demands associated with these tools often impede the design process, particularly during the early conceptual stage when critical decisions need to be made. Consequently, decision-makers frequently resort to evidence instead of the more comprehensive and precise data afforded by contemporary computational approaches [15]. To advance the development of automated daylight control systems, research efforts have been directed toward the creation of intelligent prediction algorithms. These algorithms are essential because of the non-linear attributes of daylight. Nevada et al. investigated predictive algorithms for this purpose [13]. Lighting control systems can substantially enhance their performance through precise predictions of energy consumption and natural light levels. Simplified or data-driven methodologies are typically preferred in scenarios demanding rapid responses, particularly in the context of advanced real-time control and optimization applications [16,17]. In contemporary architectural practice, the adoption of green building information modeling (BIM) has become indispensable for architects and design teams. This integrated approach enables comprehensive design and analysis [18].

The performance of daylight-linked control systems exhibits a significant dependency on the placement of sensors. Specifically, the illuminance measurements recorded by the photo sensors responsible for luminaire operation do not consistently correlate directly with the illuminance levels at the work plane. This disparity in measurements leads to inaccurate data inputs for daylight-linked control systems, thereby diminishing their efficacy [8]. We can use the neural network algorithm's machine learning capabilities to make sure that the light levels at the work plane are consistent with those measured on a different surface. The inclusion of luminance-based criteria in architectural design practice is computationally intensive and time-consuming because of the requirement of generating luminance maps for each time step throughout the entire year, which is a necessity for annual simulations [19].

A lot of attention has been paid to using machine learning-driven models to speed up the daylight simulation process, but their limited ability to generalize has kept them from being widely used [10]. Artificial neural networks (ANNs) were employed to forecast indoor environmental parameters instead of relying on computationally demanding simulations [9]. Using machine learning (ML) can help architects and decision-makers figure out how well a building will work at first by taking into account things like blocked views and the design of facades, so they don't have to do as much analysis [7,20], when doing ML-based modeling [21]. There is a chance that machine learning algorithms could be used to make an accurate indoor daylight simulation tool that can be used to evaluate daylight performance early on in the design process and to set up energy-efficient daylight control systems [21]. To precisely and effectively control the level of light and uniformity of light in indoor spaces that are affected by changes in daylight is a difficult task, mostly because lighting control systems are not linear and change over time [22,23].

The use of building performance analysis (BPA) aids individuals in comprehending the efficacy of their design concepts. This comprehension, in turn, streamlines the design decision-making process and establishes a foundation for the ongoing refinement and enhancement of design proposals [18]. In the realm of architectural design, initial determinations regarding the architectural structure and the configuration of windows have a pronounced impact on the yearly illumination performance of office spaces. Daylight has the capacity to diminish the reliance on electric lighting within indoor building environments. This process is made possible through the deployment of sensors that transmit illuminance information to a lighting control system [24].

A prerequisite for generating precise and expeditious predictions from freshly input data is the extraction of pertinent information from the daylighting field. Among the multitude of technologies, both historical and contemporary, that serve this purpose, one notable solution is the use of shading devices as a light shelf tool. These devices are indispensable in hot and humid climates because they shield indoor buildings from solar radiation infiltration, which mitigates the energy demand associated with cooling. Optimal light shelf angles vary seasonally to enhance energy efficiency and indoor illumination uniformity.

2. Research significance

The benefits of daylight are diverse, encompassing aesthetic, physiological, and economic advantages. Optimizing the admission and distribution of natural light in buildings enhances their capacity for energy efficiency and creates a conducive indoor environment that promotes health and comfort.

Employing sustainable lighting technologies, such as side daylighting systems and active daylighting systems, will address several issues associated with current passive daylighting systems, including reliance on artificial illumination and energy consumption.

Automated Light Shelf is an effective system in dark zones with integrated advanced tools and sensors and in a test room as an office space. Conduct a simulation to collect and analyze the performance of daylighting, and use data science techniques to evaluate the results to get the best possible daylighting performance. Genetic algorithm based on illuminance values of daylight metrics and data science of machine learning.

Data-Mining is a framework for an automated light shelf in a space with an ML concept and occupant's needs lighting system, which detects data from occupants and the environment and adjusts its output in real-time to meet predefined goals such as energy efficiency and user-dependent variables.

3. Objectives of the study

Practitioners and researchers require extended daylighting simulations to predict the efficacy of their design techniques and decisions. The method of machine learning can be used to predict these various types of lighting and gather valuable information from the predicted results, and it can also help to reduce the time for testing and redesign in the development of new lighting systems such as light shelves.

The main goals of the research are to provide designers with automation tools that can relieve them of menial tasks, provide data-driven insights to guide the design process, and aid in the evaluation of complex, high-dimensional designs in office spaces.

One of the challenges is the difficulty in precisely evaluating and reducing the time required for the simulation process. This would entail employing techniques such as machine learning and doing analysis on additional time periods in order to enhance the validity of the results.

This research focuses on the diverse office spaces within office buildings, which are known for their high electrical energy consumption. The deep layout of the internal environment, which necessitates daylighting throughout the rear internal areas, primarily accounts for this heightened energy demand. Given that office buildings are typically in use during daylight hours, implementing daylight strategies presents an opportunity for energy conservation. These strategies could include the integration of automated light shelf tools paired with artificial light sensors. The study proposes using machine learning techniques to develop a predictive model for designing the light shelf tool about daylight availability. By utilizing artificial neural networks, this approach aims to expedite the design process and optimize energy savings in the early stages of building planning.

4. Research problem

The study was in El Arish, Egypt, to evaluate an office space with a curved automated light shelf system in a hot, dry climatic zone according to the Köppen-Geiger classification. The South's light is useful, but it is undesirable for the interior space due to excessive heat and sun exposure in the near window zone. Furthermore, proper light distribution minimizes the use of artificial lighting in two internal zones of space, especially the middle and rear zones, which all lead to energy savings in the building. An analysis of the measured illuminance allows for a precise evaluation of the benefits of employing an automated light shelf in three distinct interior areas. A thorough study was done to look at the differences in the levels of brightness between models with curved mirror aluminum and prismatic panel sliding light shelves on an externally positioned and flat mirror internally light shelf model.

5. The study limitations and assumption

The research posits that by utilizing the offered smart lighting technology through an AI/ML-automated light shelf system, it is possible to optimize the distribution of daylighting indoor space

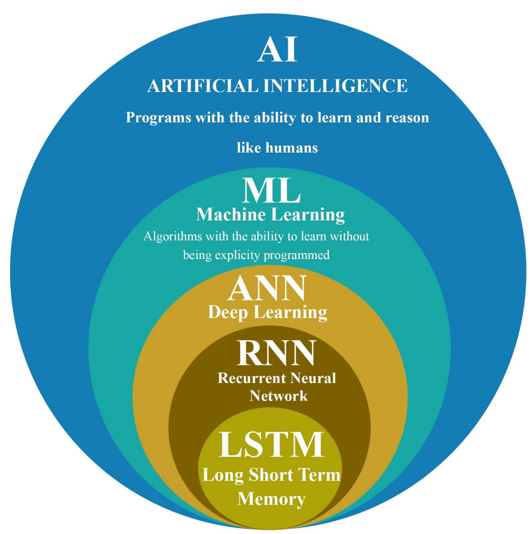


Fig. 1. Long short-term Memory is a type of recurrent neural network.

within the built environment while achieving maximum energy reduction through the use of a genetic algorithm. The study presents a machine learning (ML) approach, specifically neural networks (NN), which has the potential to accelerate daylighting simulations. Arthur Samuel, one of the early pioneers of AI, described machine learning as the "field of study that gives computers the ability to learn without being explicitly programmed" [25]. ML is the study of statistical models and algorithms that use a dataset's variables to recognize relevant spatiotemporal patterns and information [5]. MLAs are used in buildings to predict luminous conditions and daytime lighting performance. Artificial neural network (ANN) is a type of machine learning model that is inspired by the structure and function of the human brain. It is composed of interconnected nodes, called neurons, that work together to process and analyze data [26]. Artificial Neural Network (ANN) models, functioning akin to "black box" models, demand minimal detailed information about the system and are "able to learn the relationship between a big set of data variables in input and the controlled and uncontrolled variables by studying previously recorded data, similar to the way a non-linear regression might perform". Artificial Neural Network (ANN) is described as a methodology akin to regression in statistics, utilized for deriving mathematical models from input and output data. Recurrent Neural Network (RNN) is a type of neural network architecture that is designed to handle sequential data, such as text, or time series data. The key feature of an RNN is that it maintains an internal state or "memory" that allows it to make decisions based on not only the current input but also the previous inputs and the network's own previous outputs [27]. This makes RNNs well-suited for tasks where the current output depends on the previous inputs, such as language modeling. In a traditional feed-forward neural network, each input is processed independently. In contrast, an RNN processes the input sequence one element at a time, and the hidden state of the network is updated at each step, allowing the network to "remember" information from previous inputs. This allows RNNs to capture dependencies in sequential data that would be difficult to model with a traditional neural network [28].

The neurons in each layer are connected to the neurons in the next layer, and each connection has an associated weight. These weights determine the strength of the connection between neurons by using long short term memory (LSTM) [29]. Long short term memory is a type of recurrent neural network architecture designed to overcome the vanishing gradient problem and efficiently capture long range dependencies in sequential data by introducing specialized memory with gating mechanisms to control the flow of information [30], as shown in Fig. 1. Lars Junghans describes in detail the direction toward "automated building optimization algorithms". The most advanced method in the area of automation in design synthesis can be found in the research led by Stanford professor Vladlen Koltun, whose work has been focused on visual computing and design synthesis using machine learning.

This system accomplishes this by conducting a limited number of simulations and using the results to forecast the effectiveness of daylighting for thousands of different design configurations. Exploiting computational systems that apply machine learning tools dynamically through automated light shelves on shadings has the potential to enhance natural daylighting.

The study utilized parametric software Rhinoceros such as Grasshopper (Climate Studio) for modeling and simulation of daylight analysis, the Galapagos plug-in for controlling performance automation, and the integrated Colibri2 plug-in for creating datasets. The work was then framed using AI concepts and data science by the MATLAB program [31]. Grasshopper is a software plugin that operates within Rhinoceros 3D and functions as a parametric modeling extension. It utilizes algorithmic processes to generate geometric shapes, as shown in Fig. 2.

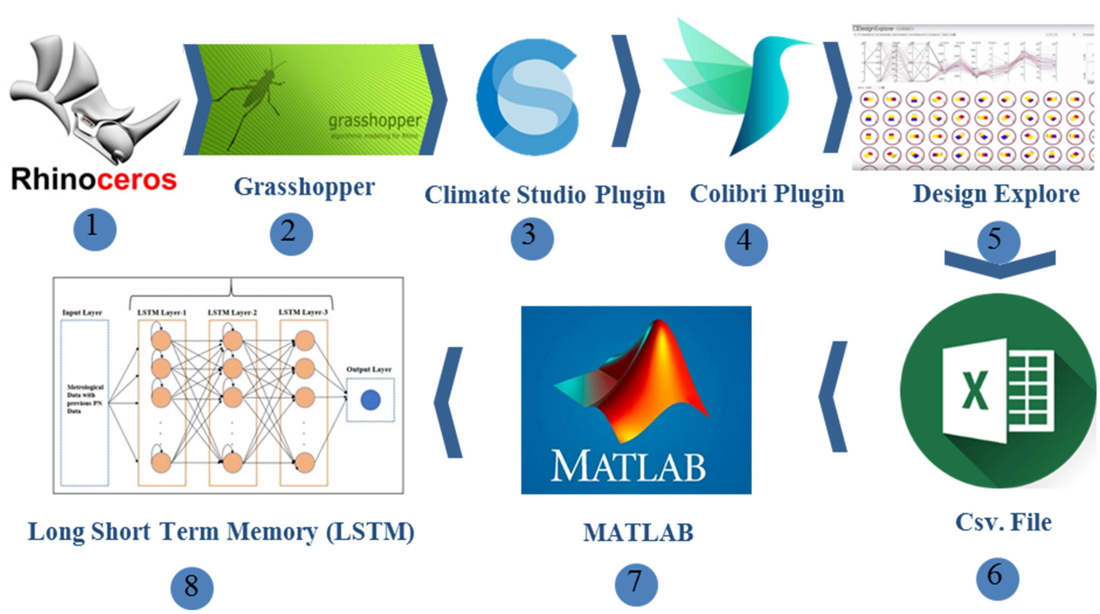


Fig. 2. The workflow for the predictive daylight modeling.

6. Methodology

The practical and applied methodology involved creating a predictive model for designing the light shelf using appropriate artificial intelligence and machine learning techniques, specifically employing a neural network type, to expedite the simulation process and facilitate decision-making that enhances design efficiency. By utilizing the design explore tool, architects can systematically explore various combinations of light shelf parameters, efficiently evaluating their impact on daylighting performance.

This approach allows for the identification of optimal light shelf designs that effectively distribute daylight within the building, enhancing occupant's visual comfort and reducing the need for artificial lighting. This method can efficiently explore a wide range of design possibilities with a small number of samples. It has been proven to be significantly more effective than random sampling in numerous situations. When using ML to enhance daylighting inside a building specifically by optimizing light shelf parameters in the next research workflow as shown in Fig. 3.

In this study, the focus is on improving the internal natural lighting environment through parametric decision support in four distinct office spaces. According to the Köppen-Geiger classification, the weather file for Arish, Egypt, is used. The study methodology involves simulating office structures using curved light shelves in a hot climate and analyzing their effects on internal light distribution. The study measures two distinct days—one in summer and the other in winter—at noon to illustrate the variation in dynamic light shelving. The subsequent phase involves machine learning to select optimal light shelf positions based on internal distribution, with sensors deployed in each area of artificial lighting. Decisions regarding the light shelf are made based on distance, rotation angle, and height from the window sill. The average illumination for each area serves as the output measurement.

The South's light is useful, but it is undesirable for the interior space due to excessive heat and sun exposure in the near window zone. Furthermore, proper light distribution minimizes the use of artificial lighting in two internal zones of space, especially the middle and rear zones, which all lead to energy savings in the building.

The examination of measured absolute illuminance values offers a quantitative evaluation of the benefits of utilizing an automated light shelf across three distinct internal zones. A thorough study was done to see how the illuminance levels reached between zones in models with mirror aluminum and prismatic panel light shelves and a model with an external light shelf and an internal mirror light shelf. The objective is to create a machine learning (ML) algorithm, particularly neural networks (NN), with the potential to accelerate daylighting simulation procedures by conducting a limited subset of simulations to

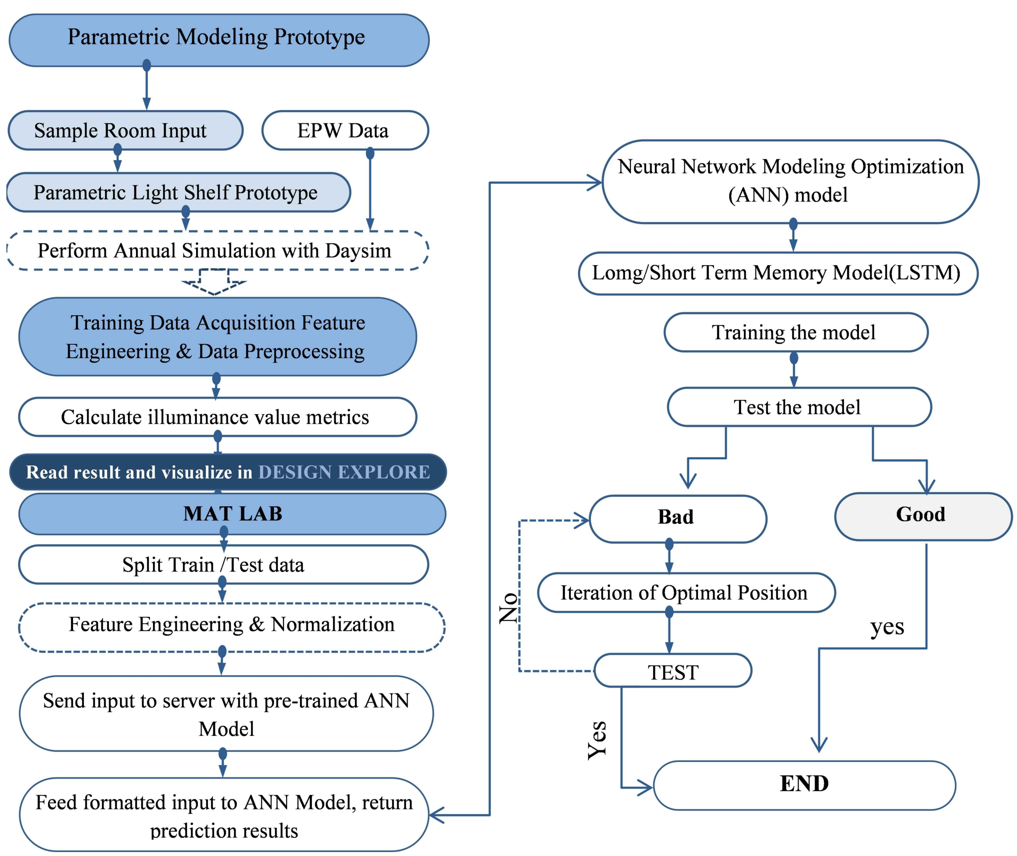


Fig. 3. The workflow for the predictive daylight modeling.

forecast the daylighting performance of numerous design configurations.

The potential contribution of exploiting computational systems applied to machine learning tools on dynamic by automated light shelves on shadings in terms of enhancing natural daylighting. To address the aforementioned challenges, this study endeavors to pioneer an inventive design concept aimed at exploring adaptive, automated light shelf geometries and devising novel approaches to enhancing architectural aesthetics and human health through the design of building envelopes. Moreover, the incorporation of high-performance computing (HPC) has the potential to expedite the entire process, enabling near-instantaneous predictions of intricate daylighting simulations instead of prolonged durations spanning hours or even days.

Professionals and scholars require prolonged daylighting simulations to forecast the efficacy of their design tactics and choices. New machine-learning techniques that let humans and machines work together to analyze complex datasets may combine machines' abilities to find complex statistical patterns in large datasets with humans' abilities to use a wide range of background knowledge to come up with plausible explanations and new hypotheses.

The method of machine learning can be used to predict these various types of lighting and gather valuable information from the predicted results. Simulation of predicted lighting systems can also help to set design requirements and evaluate the work of lighting designers by comparing the predicted results with the actual results. In an office room, each point within a room is given a sensor number as a categorical attribute on the middle line. However, the spatial correlation between points is not preserved during this procedure. The workflow includes steps such as creating a prototype model with parameters, gathering training data, doing feature engineering, preprocessing the data, and designing the topology of a neural network. The subsequent sections contain detailed explanations for each stage to aid in the implementation of the suggested workflow as shown in Fig. 3.

6.1. Parametric modeling

The office model's properties, such as the dimensions of the space (width, depth, and height), the reflective surfaces, the orientation of the office (south-facing window direction), and the size and position of the windows, can be modified parametrically about the light shelf parameters. Windows have a direct impact on energy consumption in two ways. Firstly, during warm seasons, sunlight entering through windows increases the need for cooling, resulting in higher energy usage. Secondly, during cold seasons, windows contribute significantly to heat loss due to the high thermal transmittance of the glass. Therefore, an essential aspect in the

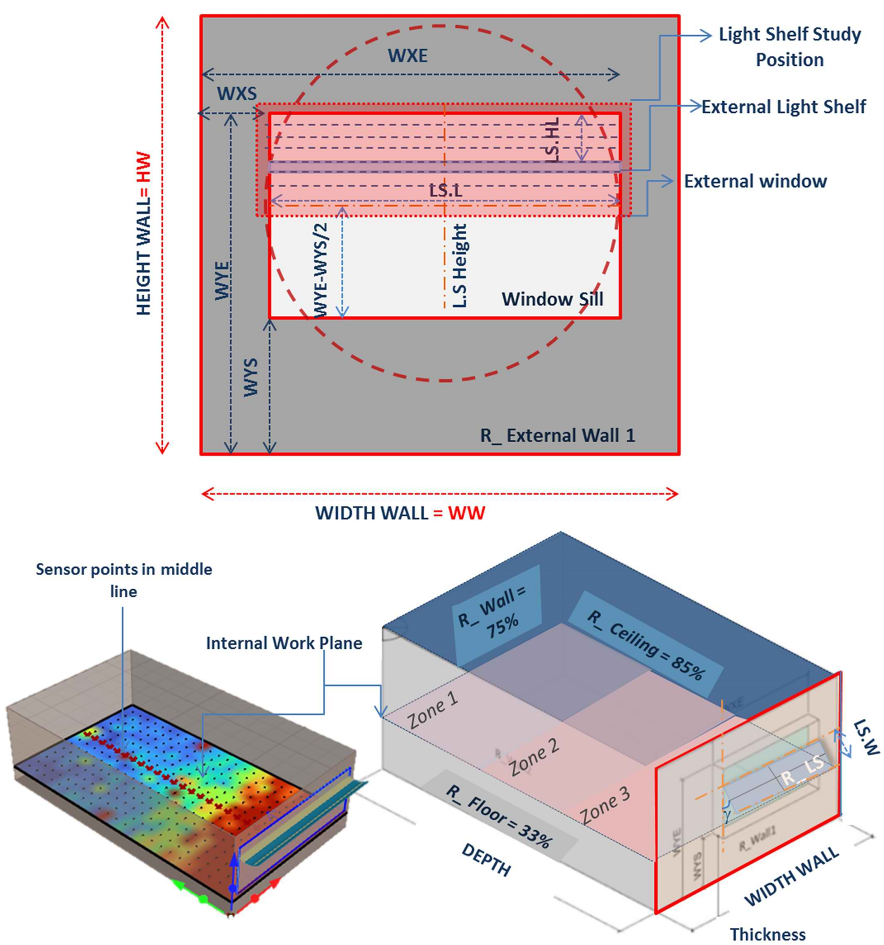


Fig. 4. Parametric prototypes of models of variable design.

Table 1. Room specification and parameters.

Room specification			
El Arish, North Sinai- Egypt		Location	
Office		occupation	
Single clear glass 6mm		Glazing	
88%		Visual transmittance VT	
6.121		U-Value (W/m2 K)	
Input	**Range**	**Steps**	**Explanation**
Room Parameters			
Width	3.0 m ~ 15.0 m	1.0	Width of Room (m)
Depth	4.0 m ~ 15.0 m	1.0	Depth of Room (m)
Height	3.0 m ~ 3.5 m	0.5	Height of Room (m)
Thickness	0.25 m	1.0	Thickness of External Wall
WXS	0.50 m ~15.0 m	0.5	Window Start Position
WXE	1.0 m ~ 15.0 m	0.5	Window End Position
WYS	0.90 m ~ 4.0 m	0.50	Window Sill Height
WYE	1.50 m ~ 3.5 m	0.50	Window Top Height
Orientation	S	1	South
Light Shelf Parameters			
LXS = WXS	0.50 m ~15.0 m	0.20	Light shelf Start Position / Length
LXE =WXE	1.0 m ~ 15.0 m	0.20	Light shelf End Position / Length
LW	0.20 m ~ 1.20 m	0.20	Light shelf Width
LA°	-30 +30	5°	Light Shelf Angle
R_LS	73%, 95%	2%	Reflectance of Light shelf surface

development of energy-efficient buildings is the design of a window system that incorporates shading devices, such as a light shelf.

A light shelf is a contrivance meticulously designed to harness daylight, particularly sunlight, to channel it towards the rear section of a given space [32]. A light shelf can be located outside or inside a structure, or perhaps both [33]. The configuration, design, and placement of a light shelf dictate how it diffuses incoming daylight. A light shelf's key characteristic is that it has glazing directly above its surface. The glazing on a light shelf is intended solely to allow natural sunlight to enter the space. Installing glazing beneath a light shelf can provide both a view and natural daylight. A well-designed light shelf enhances a space's physical and visual comfort by redirecting incoming daylight and improving light diffusion.

6.2. Light shelf materials

6.2.1. Prismatic panel

The prismatic panel is composed of a cluster of small prisms arranged in a serrated form, similar to a Fresnel lens. However, unlike a Fresnel lens, the prismatic panel can redirect light towards a specific target. It exhibits several geometrical forms, including a pyramid shape, a more slender shape, or even a configuration resembling a plated film [34]. The prismatic panels consist of transparent acrylic prisms arranged in a series. One side of the panels has curvature, while the other side has prismatic faces. These faces may be partially coated with an aluminum coating that has a high level of specular reflectance. The prismatic panels enable the redirection of natural light into the room's interior and can also function as shade devices at the same time. The systems can be utilized as either stationary or portable systems, situated in the vertical orientation of the building's exterior or on the rooftop, positioned between the glass panels (in a fixed arrangement), either on the outside, it is more suitable to employ it at the upper half area of the windows. Prism sheets are chosen and used by the features of the product: because their condensing adhesions are different; the prism tip's angle; properties of scratch resistance based on tip form; the method of surface treatment; Refraction and regression characteristics [35].

6.2.2. Aluminum/Mirror panel

It is an upper part of the shelf design with a 60-cm width and curvature surface and a silver polish material with 95% reflectance. The surface reflectance was derived from prior studies, which commonly employed a consistent set of values: 75% for wall reflectance, 85% for ceiling reflectance, 33% for floor reflectance, and 0.5 for window transmittance. The equivalent range was established by expanding the base value in both directions for a more versatile application. Tables 1 and 2 display the domains and steps for the office space variables.

Certain combinations of the parameters are deemed incorrect, for example:

- WXE must always have a greater magnitude than WXS. The same principle applies to WYE and WYS.
- Ensure that the ratio of windows to walls is not less than 15%.
- The limitations WXE-WXS > 1.0 and WYE-WYS > 1.0 were added.
- The light shelf length is consistent between WXS and WXE.

Table 2. Fixed and variables parameters for model training.

		Variables in training dataset	Number of alternatives	Variables in the validation dataset	Number of alternatives
Fixed parameters	Location	North Sinai, Egypt	-	North Sinai, Egypt	-
	Occupation	Office occupancy time: **(8:00 AM- 5:00 PM)**	-	Office occupancy time: **(8:00 AM- 5:00 PM)**	-
	Window Glass Type	Single pane glass	1	Single pane glass	1
	Space Height	3.5 m	1	3.5 m	1
	Window Orientation	south	1	south	1
	Space Dimensions (X,Y)	(6mx7m), (8mx10m), 7mx12m), (7mx15m)	4	-	-
	Reflectance Interior Surfaces (ceiling, walls, floor)	85%, 75%, 33%	1	Reflectance Interior Surfaces (ceiling, walls, floor)	1
	Internal light shelf	Internal (mirror)	1	Internal (mirror)	1
Variable parameters	Window sill	Min.90 m - vary	vary	Window sill	Automated
	Window lintel	Max. 2.9 m - vary	vary	Window lintel	Automated
	Window width	Connected and equal variation	vary	Window width	Automated
	Light shelf width		vary	Light shelf width	Automated
	External Light shelf Height/position	1/2 Of Upper Window Height	vary	Light shelf Height/position	Automated
	internal Light shelf Height/position	Connected external Light shelf	30 cm depth	Connected external shelf	Automated
	Light shelf angle	Automated	vary	Light shelf angle	Automated
	Light shelf length	Min. 60 m –Max.1.20m	3	Light shelf length	Automated
	Light shelf material	Prismatic panel Aluminum sheet	2	Light shelf materials	Automated
	Total number of iterations /each room/each season = **676 (5408)**				

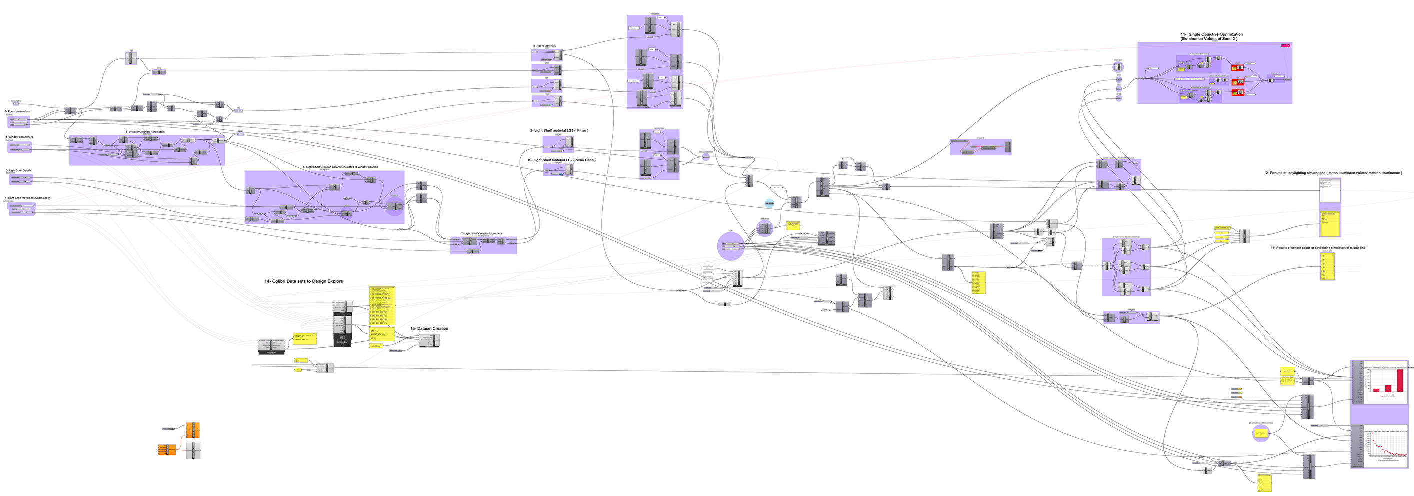


Fig. 5. Parametric script of room model with automation concept by Grasshopper canvas plugin.

Table 3. Time of calculations.

Summer	1 June to 31 August	Target day	Target time
		21-06-2023	**(12 pm at noon)** South window
Winter	1 December to 28 February	21-12-2023	

- As a result, around half of the potential pairings were eliminated for further processing.

An hourly measurement of multidimensional spaces for samples, which will be made for two days a year, is as follows: Table 3.

7. Results

Not only is the amount of light controlled, but its direction and distribution are also crucial factors in daylighting design. To create a more even distribution of light across the office space, an efficient side-lighting system will lower the amount of light coming in via the windows in zone (3) and raise it in the sections farther away from the windows in zones (2) and (1).

A prediction model based on recurrent neural networks (RNN) is created using a synthetic database that contains the design factors and illuminance values of daylight. This database is used to train and test the predictive model. The parametric model established in the preceding section is employed to produce CSV. File by Colibri2 plug-in iterator generates files for various regions in the daylight simulation. To train the light shelf model, it is necessary to carefully determine the types, ranges, and steps for each variable. We also need representative room samples to provide the training data, for example, a room (15 m x 7 m) extracts to design the Explore website.

The attempt to integrate data from rooms of different sizes, meanwhile, encountered the issue of contradictory data. The analysis grid of the working plane, positioned at a height of 0.76 m, identified the specific number of target output zones for each room. The sensor sites were positioned centrally within each room. The study aimed to optimize the illuminance output of daylighting performance (300 lux to 500 lux), as shown in equation 1. Each sample must have a predetermined number of sensor points, resulting in a distribution of sensor points along the central axis of the room when the room's dimensions are altered. The challenge was resolved by manipulating the spatial characteristics of the sensor points through feature engineering, namely by reorienting and normalizing their zones in each room as shown in Figs. 4-6.

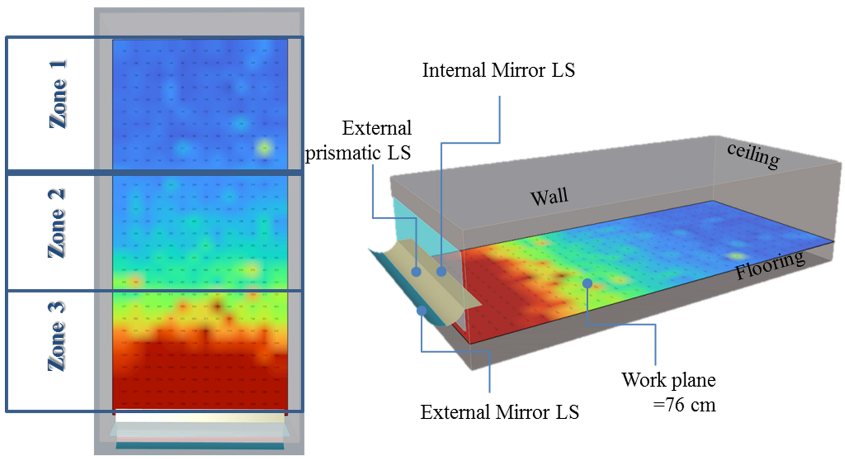


Fig. 6. Parametric prototype model of the light shelf study scenario involves normalizing each zone and installing an interior light shelf to eliminate glare next to the window.

Fig. 7. Structure of the proposed ANN.

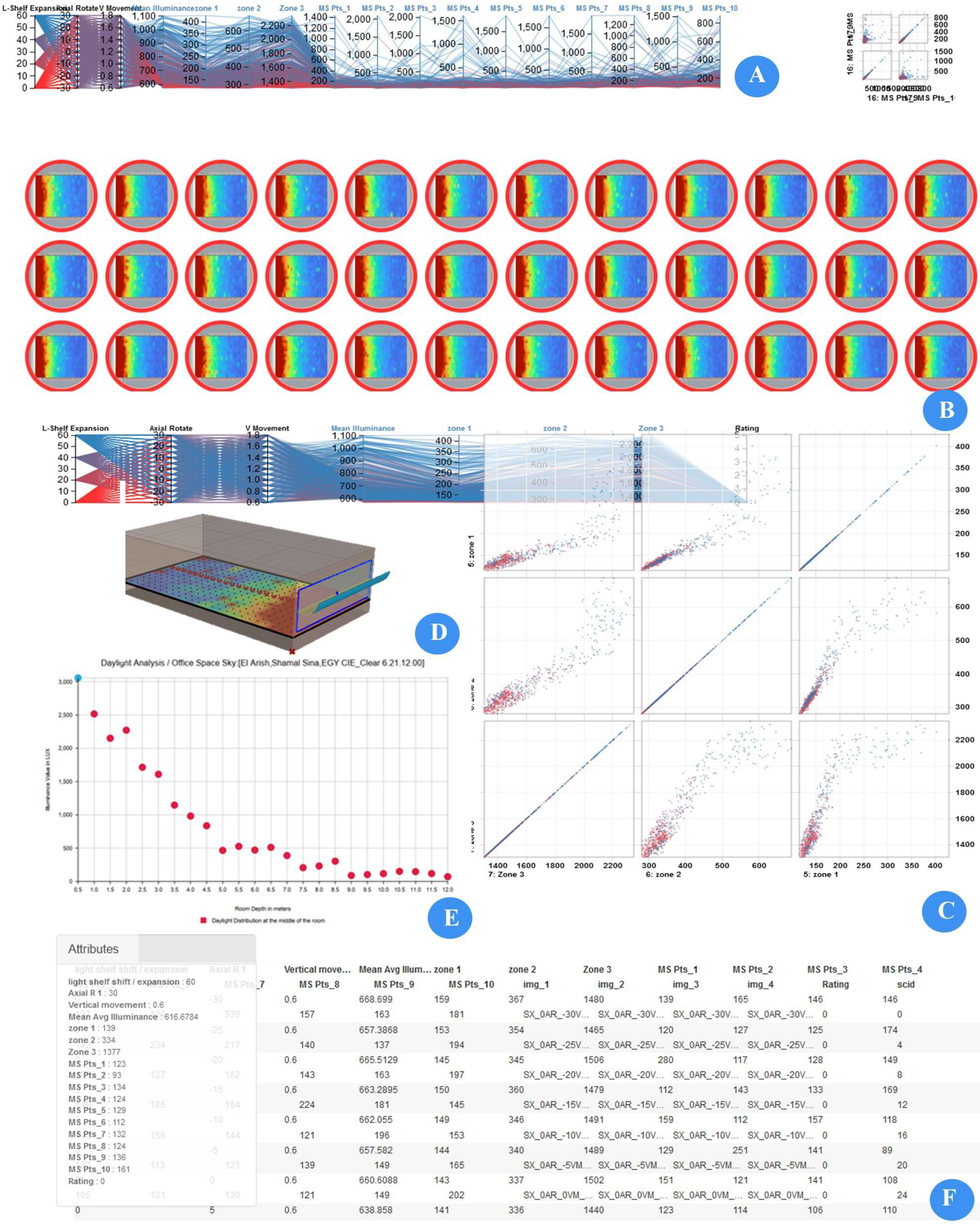
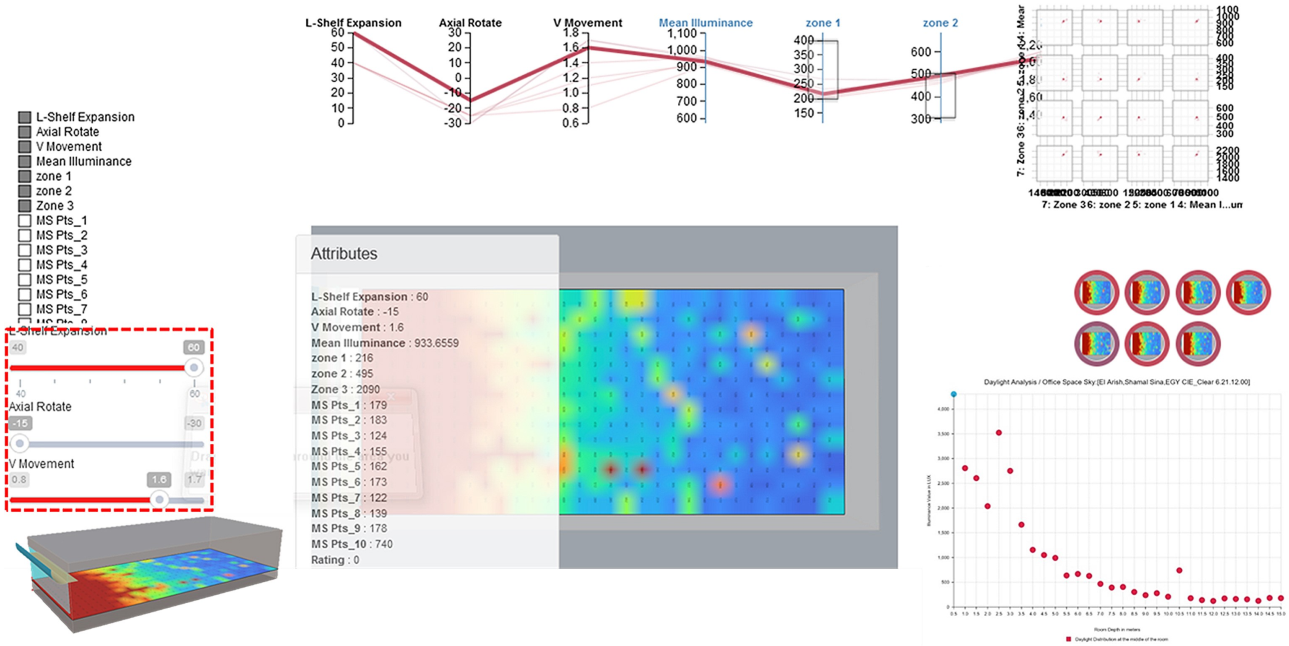
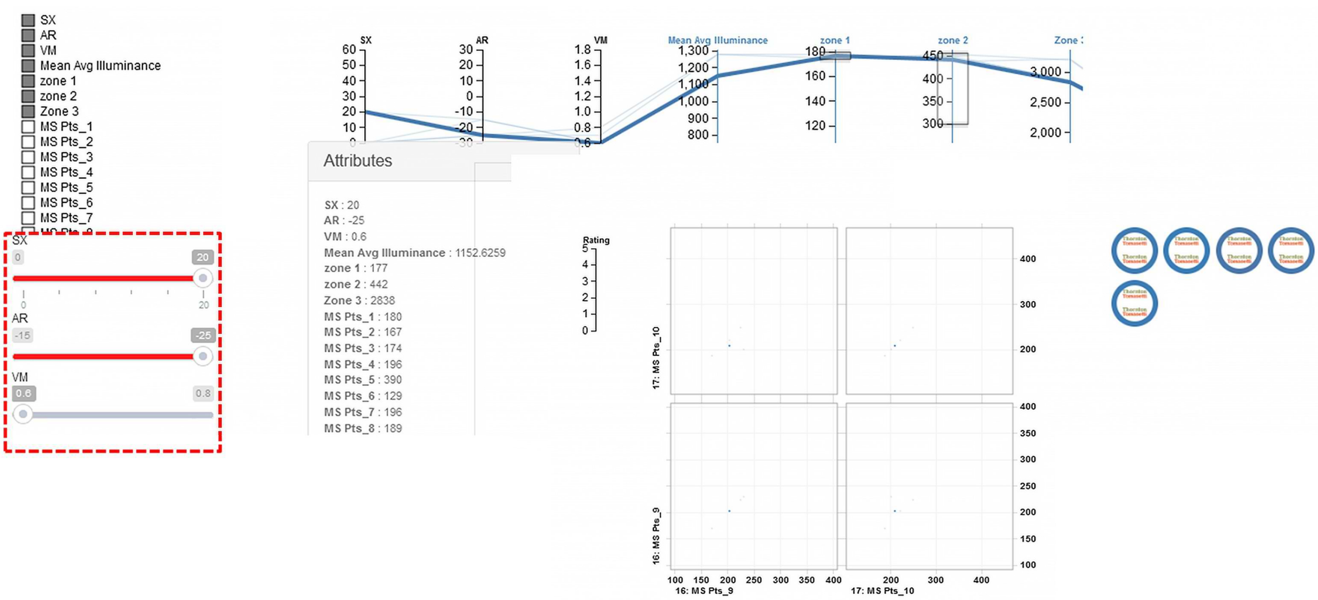


Fig. 8. Designs explore visualization of the data set; A- Matrix Bar Analysis, B- Plans of Simulated Cases, C- Chart of Simulated Cases, D- Isometric, E- Sensor Points in Middle Line, F- Sheet Spread of Cases (Source: https://tt-acm.github.io/DesignExplorer/?ID=aHR0cHM6Ly9kcml2ZS5nb29nbGUuY29tL2RyaXZlL2ZvbGRlcnMvMU9rZ0JDekNaNWJwb1FrRkJ2NnRJaUk0MFVkd3dNcS1YP3VzcD1zaGFyaW5n).



L-Shelf Expansion	Axial Rotate	V Movement	Mean Illuminance	zone 1	zone 2	Zone 3	MS Pts_1	MS Pts_2	MS Pts_3	MS Pts_4	MS Pts_5	MS Pts_6	MS Pts_7	MS Pts_8	MS Pts_9	MS Pts_10	Rating
40	-25	0.8	913.0756	205	477	2057	93	117	120	121	173	123	163	167	146	245	1
40	-25	1.2	919.3199	219	483	2056	176	120	184	127	177	124	228	181	300	219	1
60	-15	1.6	933.6559	216	495	2090	179	183	124	155	162	173	122	139	178	740	1
40	-25	1.1	937.7527	201	460	2153	319	152	125	101	148	153	149	917	161	148	1
60	-30	1.7	948.8566	267	473	2107	155	132	141	129	481	175	131	161	1192	402	1
40	-25	1.4	957.7918	209	488	2177	142	327	167	137	200	222	177	152	203	212	1
40	-30	1.7	961.4099	233	465	2187	167	201	152	168	138	157	154	1266	183	240	1

Fig. 9. Designs explore visualization ample room 7m x 15 m in the summer season.



light shelf expasion	Axial Rotation	Vertical Movement	Mean Avg Illuminance	zone 1	zone 2	Zone 3	MS Pts_1	MS Pts_2	MS Pts_3	MS Pts_4	MS Pts_5	MS Pts_6	MS Pts_7	MS Pts_8	MS Pts_9	MS Pts_10	img	Rating
20	-25	0.6	1152.6259	177	442	2838	180	167	174	196	390	129	196	189	203	209	SX_20AR_-25VM	1
20	-15	0.6	1165.8036	175	450	2872	154	157	153	123	174	219	162	183	224	249	SX_20AR_-15VM	1
0	-15	0.6	1162.6129	176	448	2864	172	150	171	176	152	160	235	216	170	187	SX_0AR_-15VM_	1
0	-25	0.7	1279.1743	175	454	3209	150	136	138	200	153	150	187	213	230	201	SX_0AR_-25VM_	1
0	-15	0.7	1155.8743	174	452	2842	107	169	145	212	174	186	179	199	251	166	SX_0AR_-15VM_	1
0	-25	0.8	1280.8613	178	438	3226	143	126	129	246	177	164	164	206	203	221	SX_0AR_-25VM_	1

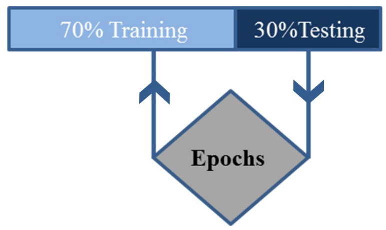
Fig. 10. Designs explore visualization of room 7m x 15 m in winter season.

7.1. Neural network architecture and parametric optimization

The benefits of this feature engineering are threefold: It explicitly defines the spatial relationship between the different points and decouples the spatial feature from the room dimension and orientation; the recurrent neural network (RNN) can learn and anticipate the exact illuminance value for each zone using continuous spatial input. This means that it is now feasible to retrieve the illuminance value for every zone without being limited to a predetermined simulation grid; this greatly augments the sample size, hence enhancing the potential for improved model performance.

$$Ave.\,illuminance\ value\ in\ zone\ \underline{1\&2} = \frac{\sum i(wf_i \times t_i)}{\sum t_i} \in [0,1], wf_i \begin{cases} 1\ if\ 300\ lux \leq Ave.\,illuminance\ value\ \leq 500\ lux \\ 0\ if\ 300\ lux > Ave.\,illuminance\ value\ > 500\ lux \end{cases} \quad (1)$$

where (t_i) is the occupied hour of the year and ($w.f_i$) is a weighting factor that depends on the average illuminance values at zones 1 and 2 due to the illuminance level (300-500 lux), as shown in Figs. 6 and 7, and Figs. 8-10 show the results of a room measuring 7m x 15m in both the summer and winter seasons for example.




```
x = 300
PQDs_event = 2×1 categorical
bad
good
Starting parallel pool (parpool) using the 'local' profile ...
Connected to the parallel pool (number of workers: 2).
layers =
  10x1 Layer array with layers:

     1   ''         Sequence Input          Sequence input with 1 dimensions
     2   ''         BiLSTM                  BiLSTM with 100 hidden units
     3   'tanh1'    Tanh                    Hyperbolic tangent
     4   ''         BiLSTM                  BiLSTM with 100 hidden units
     5   'tanh2'    Tanh                    Hyperbolic tangent
     6   ''         BiLSTM                  BiLSTM with 100 hidden units
     7   'tanh3'    Tanh                    Hyperbolic tangent
     8   ''         Fully Connected         2 fully connected layer
     9   ''         Softmax                 softmax
    10   ''         Classification Output   crossentropyex
```

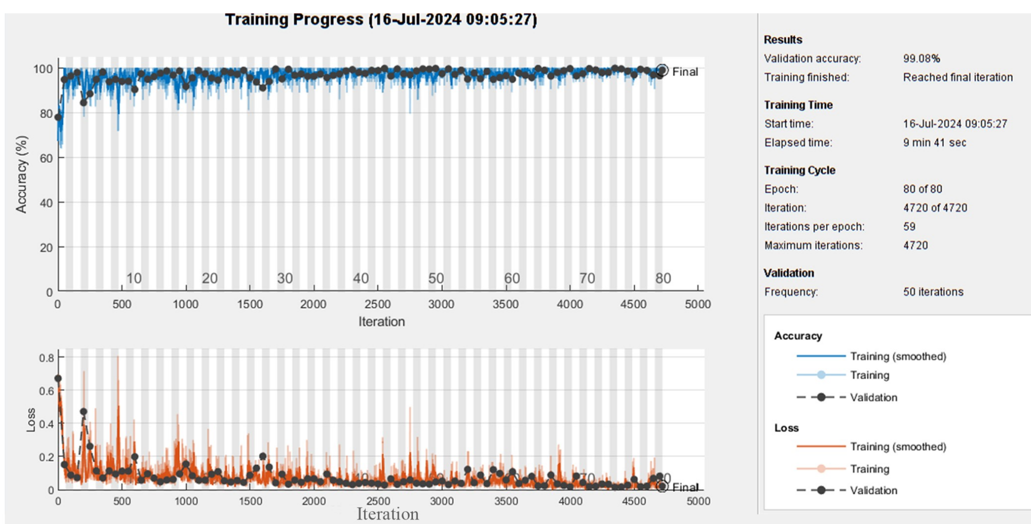


Fig. 11. RNN model with 70 % training data and 30% test model in MATLAB program and generate algorithm two classifications good and bad, 100 hidden layers, then predict a model to the right position of the automated light shelf.

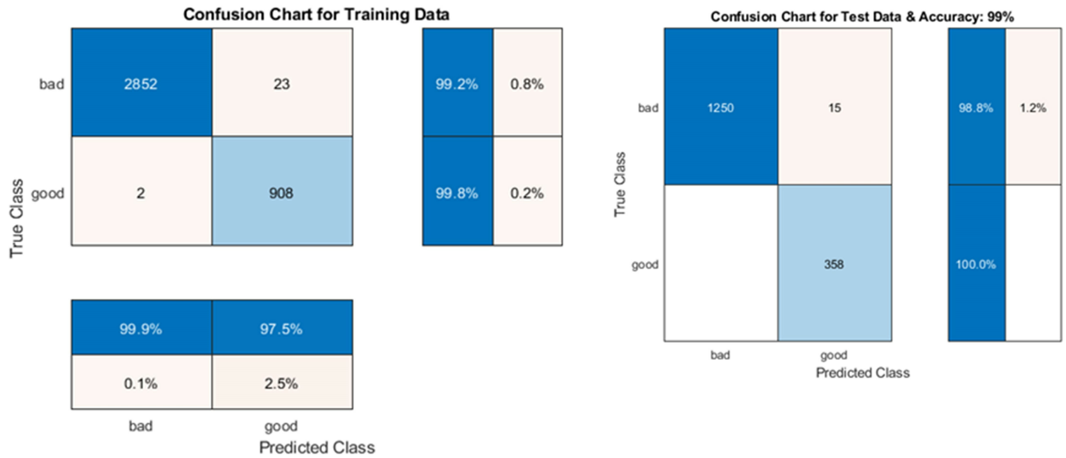


Fig. 12. Accuracy of RNN model by confusion matrix left: training data, and right: test data, which shows 99%.

The study neglected illumination in zone 3 because the light shelf enhances the middle and rear areas in space. The result shows the different internal illuminance values in the office, and then the need to automate light shelf with a learning algorithm to optimal design position and uniform indoor distribution range from 300 lux to 500 lux. The RNN model is a subset of the ANN model by using short-term memory, which consists of 100 hidden layers as shown in Fig. 11. A confusion matrix is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one. It is used in classification models, as shown in Fig. 12.

The model demonstrates very high accuracy at 99%. It has:

- Excellent performance in correctly identifying 'good' instances with no false negatives.
- Very few false positives (15 out of 1265 instances).

Components of the Training Confusion Matrix:
True Positives (TP): The number of instances correctly classified as positive (good). Here, it is 908.
True Negatives (TN): The number of instances correctly classified as negative (bad). Here, it is 2852.
False Positives (FP): The number of instances incorrectly classified as positive (good) when they are (bad). Here it is 23.
False Negatives (FN): The number of instances incorrectly classified as negative (bad) when they are positive (good). Here it is 2.
Cells in Test the Confusion Matrix:
Top-left (1250): True Negative (TN); The model correctly predicted 'bad' for 1250 instances that were actually 'bad'.
Top-right (15): False Positive (FP); The model incorrectly predicted 'good' for 15 instances that were actually 'bad'.
Bottom-left (0): False Negative (FN); The model incorrectly predicted 'bad' for 0 instances that were actually 'good'.
Bottom-right (358): True Positive (TP); The model correctly predicted 'good' for 358 instances that were actually 'good'.

When evaluating the model's performance in classifying good and bad lighting conditions, test inputs of 300 lux and 800 lux were utilized. The model classified 300 lux as 'good,' resulting in the light shelf being adjusted to the optimal position. Conversely, 800 lux was classified as 'bad, prompting a recommendation for the light shelf to adjust accordingly. These outcomes indicate that the model demonstrates a high degree of effectiveness in accurately distinguishing between 'good' and 'bad' instances within the test data.

8. Discussion

The dynamic nature of daylight, influenced by seasonal changes, necessitates consideration of illumination duration, making it challenging to prescribe specific daylight levels in buildings due to this variability. The study's goal is to come up with a way to use artificial neural networks and genetic solvers to look into large solution domains in office spaces, using the evaluation criteria used by designers of light shelf systems as a guide. At the early stage of the design concept, the external parts of the light shelf were combined into two parts: the lower is mirror material, and the upper is prismatic material. Then we replaced the positions of the parts so that the lower is prismatic and the upper is mirror material. This procedure enhanced the illuminance values in Zones 1 and 2 in the rear and middle areas, which is the optimal light shelf design.

The design concept of an external light shelf found a large amount of glare near the window area in zone 3 in the first scenario. We then developed the design to integrate an internal light shelf with a depth of 30 cm and automated the external part in the upper half window height. This addition enhanced illuminance values in indoor spaces in three zones. The RNN model is a subset of the ANN model by using long short-term memory, in which the confusion matrix is a specific table layout that allows visualization of the performance of an algorithm. The model demonstrates very high accuracy at 99%.

9. Conclusion

Over time, the development of indoor lighting control systems has undergone a significant transformation, marked by the pioneering utilization of sensors, the Internet of Things (IOT), and machine learning algorithms. Daylight simulation in architecture provides precise indoor lighting measurements but is inefficient and requires computational resources. Window design is a complex optimization task, that affects building energy performance, daylighting, and quality of view, especially in office spaces.

Decision-making tools are needed for effective balancing factors. The study explores a method using advanced computer simulations to create prediction models using machine learning algorithms, gaining academic interest as a surrogate for simulations.

The study uses Artificial Neural Networks (ANN) to predict daylighting performance in sustainable buildings. The RNN model predicts mean illuminance levels in zones 1 and 2 and the probability of daylight glare within the room. The model is used to make fast decisions about integrated daylight strategies at the early stage of the design process. The training data framework was populated with over 676 simulations of each room configuration to effectively harness the power of machine learning. The use of high-performance computing (HPC) enabled the efficient execution of simulations for training data, allowing for the prediction of necessary light amounts for room operation. This optimization can minimize building operating costs. The simulations for illuminance and values took around one minute, compared to two hours on a desktop computer. The office model features a south-oriented light shelf in the upper half of the window, with two materials (mirror and prismatic) and sliding curvature surfaces with a 60 cm width mimicking the biomimicry approach. Biological inspiration is valuable in engineering design [36]. The module uses the armadillo as a light shelf design concept. The internal part has a polished mirror upper surface and a white bottom surface with a 30 cm width. An automated light shelf is a dynamic mobility system with internal and external components. It minimizes glare during summer and has a 30 cm depth. The external part consists of two curved surfaces, with a mirror at the bottom and a prismatic part at the top. Modifications improve illuminance levels. The approved configurations' average illuminance values ranged from approximately 300 to 500 lux. In zone (3), however, the range of less than 2000 lux is considered insignificant, particularly in the vicinity of the window area. The dynamic light shelf system enhances the indoor environmental awareness of occupants throughout the summer, spring, and autumn seasons, and winter.

The workplace's southern window area receives more sunlight than farther areas. A dynamic shading system enhances daylight quality. Machine learning models can improve daylight simulations, allowing informed choices during design. ML approaches can optimize window design, lighting control systems, and overall building energy efficiency.

10. Recommendations

Focus on common areas like commercial and residential structures for early estimations of Machine Learning Algorithms (MLAs) during conceptual design. Increase MLA usage for studying difficult climatic zones and weather conditions, considering the specific location and meteorological dataset. Research on the use of Multi-Layer Analysis to predict daylighting in various systems is limited, but their performance could significantly improve energy-efficient façade designs, especially in heavily blocked environments, and could be beneficial for angular screens, optical light redirection, side lighting, and sun-tracking systems. The current daylighting conditions method is accurate but requires further research. Deep learning techniques like RNN can minimize retraining time and effort, reusing the first-constructed model for future tasks. Architects are encouraged to incorporate machine learning principles into their curricula, as it can significantly improve construction processes like performance simulations, data quantification, form-finding assistance, and energy efficiency optimization. Feature Selection and Sensitivity Analysis are crucial for identifying daylighting inputs and analyzing weather data effects. However, MLA influence has not been examined in other weather files.

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Contributions

O. S. zekry; conceptualization, methodology, and writing of original manuscript. A. A.Fekry; overall research supervision. R. D. Hamed; advisor of research work-flow.

Declaration of competing interest

The authors declare no conflict of interest.

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