Faculty of Architecture and the Built Environment
MSc Building Technology

Machine learning-based assessment tool for predicting daylight and visual comfort

Master Thesis

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Abstract

Early design choices in building shape and fenestration significantly influence the yearly daylight performance of office buildings. Annual daylight performance must be analyzed at the conceptual design stage to support building form and fenestration design decisions. However, the simulation modeling and daylight calculations necessary for the annual daylight forecast are extraordinarily time-consuming, which negatively influences its early design viability. Machine learning-based methods that experimentally learn from simulation-derived data have been implemented to decrease the time of daylight simulations. We concentrate on the visual comfort of working environments. This particular sort of area demands more visual comfort than others. Four machine-learning methods are compared concerning their applicability in spatial daylight autonomy, annual sunlight exposure, and spatially disturbing glare. This research proposes a machine learning-based modeling strategy for predicting yearly daylight performance early in the design stage. The developed prediction model results for the sDA(Spatial Daylight Autonomy), ASE (Annual Sunlight exposure), and sDG(Spatial Disturbing Glare) settings. After comparing the models for each output the best chosen model attained R2 scores of 0.85, 0.65, and 0.26 and MAE scores of 3.33, 22.5, and 22.16, respectively.

Nomenclature

ASE Annual Sunlight Exposure

DA Daylight Autonomy

DGP Daylight Glare Probability

MAD Mean Absolute Deviation

MAE Mean Absolute Error

MSE Mean Square Error

$R2$ Coefficient of Determination

$RMSE$ Root Mean Square Erro

sDA Spatial Daylight Autonomy

sDG Spatial Disturbing Glare

SVM Support Vector Machine

UDI Useful Daylight Illuminance

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Chapter 1

Introduction

1.1 Context and Topic

Multidisciplinary optimization has demonstrated their use in assisting with design decision-making. In the design informatics discipline within the studio, it is possible to explore AI for soft criteria in multi-objective and multidisciplinary architectural design optimization. In recent years, the use of machine learning approaches as a substitute for constructing simulation software has increased. The purpose of this project is to evaluate machine learning techniques for the prediction of daylight and visual comfort parameters.

The envelope of a building substantially impacts energy consumption, to the degree that building facades account for more than 40% of heat loss in winter and overheating in summer. (Yan, Li, Wang, & Lyu, 2019)Large glass windows and curtain wall systems, commonly employed in office buildings, can be severely influenced by direct solar radiation depending on the direction of the facade.(Yan et al., 2019). This makes them primarily reliant on solar radiation, which might result in significant cooling demands during periods of extreme heat. On the other hand, As a result of high radiation and glare, lighting energy has accounted for over 19% of total power consumption (Light's, 2006) , and more than 20% of the energy utilized in office buildings (Ayoub, 2020). To escape such glare, building occupants typically close all blinds and rely on artificial lighting, mechanical air ventilation, or air conditioning, which significantly increase energy consumption (Reffat & Ahmad, 2020). Therefore, solar shading devices are required for maximizing and controlling sun radiation entering offices. Moreover, in office buildings where users cannot easily modify their position, optimal solar shading can improve Indoor Environmental Quality and provide a productive work environment.

On the other hand, due to the potential impact on occupants' productivity and well-being, office buildings are increasingly addressing issues of visual comfort and sufficient daylight. The quality and intensity of daylight vary depending on building form, fenestration, material optical properties, geographical latitude, and local climate. High-performance design relies heavily on the space's visual comfort and daylight qualities, and designers can make more informed decisions by predicting occupant preferences using established metrics and thresholds.Also, accurate daylight predictions can support design decisions and help architects understand the relationship between design variables and building daylight performance. In recent years, most of a building's design decisions have been made during the preliminary design phase. Since the early design stage offers the most significant possibility of achieving high-performance structures, designers must be able to collect relevant building performance data (Echenagucia, Capozzoli, Cascone, & Sassone, 2015). Shading systems play a crucial role in the management of solar radiation. Thus, selecting suitable shadings should occur early in the design phase because it substantially impacts the building's energy balance.

Despite shading systems' massive impact on building performance, they are primarily addressed during the detailed design phase or not extensively modeled and analyzed during the early design phase. This questions early space and window specifications. Shades should be chosen based on space and window characteristics. To do so, the user must compare design options. Due to simulation time and complexity, experts and businesses cannot provide these facilities. This study offers a tool that uses AI to allow non-expert users to choose from various possibilities and observe the repercussions of their decisions in the shortest time possible during the early design stages.

1.2 State of the Art

Daylight can favor a person's psychological and physiological health by activating the human circadian cycle, which can reduce depression, increase sleep quality, reduce lethargy, and prevent disease.(Edwards & Torcellini, 2002). On the other hand, Lighting prediction is crucial for building energy efficiency. (Amasyali & El-Gohary, 2018). Incorporating daylighting solutions that involve the controlled use of natural daylight within buildings is one of the sustainable ways to improve energy efficiency while enhancing aesthetic and thermal comfort (Nasrollahi & Shokri, 2016). Such factors become crucial for architecture and building design. However, despite ongoing efforts to integrate these strategies into the design process, the tools and professional procedures now utilized to predict daylighting effectiveness in buildings are impracticable (Nault, Moonen, Rey, & Andersen, 2017).

(Ayoub, 2020) has referred to 5 different Methods for predicting daylighting in the literature, including diagrams (Millet, Adams, & Bedrick, 1980), scale models (Littlefair & Aizlewood, 1996), mathematical formulas (Tzempelikos & Athienitis, 2007)(Copping, 1987), protractors (Dufton, 1946), and rules of thumb (Reinhart & LoVerso, 2010) Newly developed methods referred to as white-box or engineering have expanded traditional practices to simulation-derived approaches (Ward, 1994) involving Daylight Coefficient (DC) and Climate-Based Daylight Modelling (CBDM) (Reinhart & Walkenhorst, 2001), (Mardaljevic, 2000). While the scale and complexity of daylight simulation methodologies range from simple internal spaces to complex facade fenestrations, they all share a standard set of steps (Reinhart, Mardaljevic, & Rogers, 2006). They use physically-based simulation tools to quantify spatiotemporal luminous conditions at given sensor grid points in a constructed environment, On the other, machine learning-based algorithms may predict annual daylight performance, Based on correlated variables. This is a potential method for enhancing the early efficiency of building design. Numerous authors have combined machine learning and simulation to predict annual daylight metrics. Furthermore, the building daylighting simulation modeling process is time-consuming and laborious, creating a divide between daylight performance evaluation and early design decision-making, thereby limiting the potential benefits from performance evaluation (Reinhart & Walkenhorst, 2001). However, machine learning-based algorithms may forecast yearly daylight performance based on correlated data, which is a potential strategy for enhancing the early design efficiency of buildings. Light simulation software can overcome some physical model limitations. Modern simulation software is more flexible and accurate than real-world measurements. As models and computing power have improved in recent decades, this has become a suitable choice. This approach's high computational cost may hinder conceptual design, where rapid feedback is crucial. In the early stages of architectural design, a method that combines accuracy, speed, and application simplicity is desirable. Machine Learning offers new opportunities to extract information from data and better understand eventual correlations. Such potential is not yet exploited in several domains important for the built environments, such as visual comfort.

1.3 Research Question

1.3.1 Problem Statement

There is a rising interest in computational daylight simulations as the most accessible technique to gather accurate and exhaustive data on the lighting conditions of buildings. The primary reason for using daylight simulation technologies is to accelerate and test the design process early on. The design of the external shadings has a significant influence on indoor daylight distribution. Designers need to conduct considerable simulation work to calculate the daylight metrics and explore better alternative designs. However, implementing daylighting and visual comfort simulation in the early design process, where many vital decisions are made, is difficult, as many designers usually ignore it due to the lack of time and the complex process of simulations. In addition to speeding up daylight computations, computational tools are the only reliable simulation approach. The recognition and application of simulation-based daylighting techniques might be a powerful component of a comprehensive building plan. The procedure is complicated and time-consuming, which is one of the most significant disadvantages of using this approach.

Using machine learning algorithms to predict daylight availability and glare to reduce the time and costs of daylight computation in the early design stages is not a new topic in the field. However, there is a gap in using AI methods to predict visual comfort in the decision-making stage for solar shading design. Studies have considered different daylight metrics to predict daylight using machine learning methods. However, three daylight metrics (sDA, ASE, and sDG) as performance metrics have not been fully explored.

Main Research Question

- How can machine learning algorithms be used as an assessment tool in visual comfort prediction in early design stages based on different solar shading designs?

Sub-Questions

- How can a facade system be assessed in terms of visual comfort?
- What are the requirements and parameters that characterize the Shading design in terms of visual comfort?
- What design approach could be best to avoid glare while simultaneously optimizing the amount of daylight in the building?

- Which machine learning algorithm is most suitable for capturing relations and similarities of different shading design?
- Which machine learning algorithm will result in higher accuracy in the prediction of visual comfort?
- What are the differences in processing time and results from values acquired by simulations and machine learning algorithms?

1.4 Method or Approach

In this thesis, a shoebox model was initially built, and then two typical solar shading models with their respective variables were applied to the area. For each solar shading, metrics related to daylight and glare were simulated. The obtained data set consisted of office space with different shading designs, which created a database containing 1000 options. The accompanying simulation outcomes were used as training data for a supervised learning method. Different determined metrics presented to optimal machine learning models, including Random forest, L2 Regression, SVM, k Nearest Neighbor(kNN), and Logistic Regression. The purpose is to compare differences in processing time and results from values acquired by simulations and machine learning algorithms. The machine learning training procedure should be performed independently for each shading model and output. Since optimizing hyperparameters using the Gridsearch technique is very time-consuming, the above methods were only studied on the dataset with louver shading. The following methodology scheme (Figure 1.1) shows an overview of the structure in which this research has been conducted.

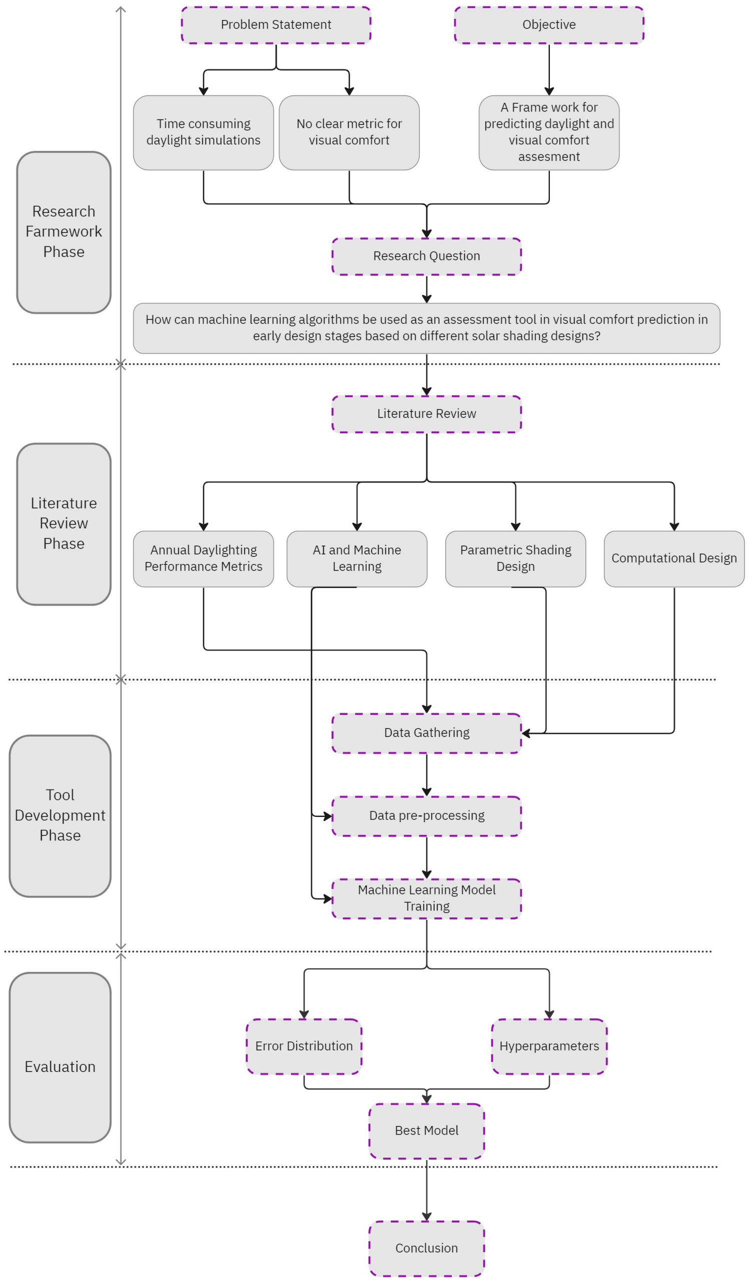

Figure 1.1: The methodology scheme

Chapter 2

Background

2.1 LEED and BREEAM Daylight Criteria

In regards to green building certification, such as Leadership in Energy and Environmental Design (LEED) or Building Research Establishment Environmental Assessment Method (BREEAM), daylight simulation is now a requirement (Giarma, Tsikaloudaki, & Aravantinos, 2017). LEED and BREEAM are critical criterion for future occupants to assess a building's sustainability level. The BREEAM certification standard is a British certification standard an the main focus is primarily on three aspects: environmental (66%), social (29%) and economic (5%) aspects. However, The LEED certification, is an American certification standard for green building certifications, which considers energy consumption, occupant comfort, and other factors. It focuses on the environment (52%), the social (43%) and the economy (5%) aspects. BREEAM and LEED are both credited for quality views, interior lighting, and sufficient daylighting, 1.1% and 2.7% respectively. However, when both certifications are compared, LEED is more advanced in terms of daylight metrics, which are Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE).(Giarma et al., 2017)

2.2 Annual Daylighting Performance Metrics and Visual Comfort

There are multiple Daylight Performance Metrics, used by researches that measure the various attributes of natural light, including glare, (Atzeri, Cappelletti, Tzempelikos, & Gasparella, 2016), daylight availability, (Carlucci, Causone, De Rosa, & Pagliano, 2015), and visual discomfort, in addition to the non-visual consequences of daylight, (Konis, 2017). Static and dynamic DPMs are classified depending on the analysis period (point-in-time vs. yearly) and sky model (standard vs. climate-based), (Nabil & Mardaljevic, 2005). Dynamic metrics, including Useful Daylight Illuminance (UDI), Daylight Autonomy (DA), Annual Sunlight Exposure (ASE), and Spatial Daylight Autonomy (sDA), forecast absolute quantities, for instance, illuminance over an entire year. In addition to location and building orientation, space geometry and material optical characteristics influence these measurements.(Nabil & Mardaljevic, 2005).Recently, Illuminating Engineering Society (IES) presented definitions for sDA(Spatial Daylight Autonomy) and ASE (Annual Sunlight Exposure) metrics (IES, 2013). The purpose of these new climate-based metrics is to enhance the predictive performance of old metrics, such as the Useful Daylight Illuminance. In this thesis the focus is on sDA, DGP and ASE performance metrics.

2.2.1 Spatial Daylight Autonomy (sDA)

The first evidence-based yearly daylighting performance statistic is Lighting Measurement 83 (LM-83), which introduces Spatial Daylight Autonomy and Annual Sunlight Exposure (ASE). The annual performance metrics were developed for more precise measurement to provide designers with a guide for achieving sufficient daylight illumination by the IES Daylight Metrics Committee(LM, 2013). Using hourly illuminance grids on the horizontal work plane, Spatial Daylight Autonomy (sDA) assesses whether a place receives adequate daylight yearly during regular operation hours (8 a.m. to 6 p.m.). According to the Approved Method IES- LM-83-121 (LM, 2013), sDA is a dynamic metric for a precise daylight measurement. It describes the annual sufficiency of interior ambient daylight levels. Floor areas or grid points that reaches a certain amount of illumination (e.g. 300 lux) for at least half of the analysis hours are considered to have met the daylighting criteria in the building model. sDA values might be between 0% and 100% of the concerned floor area. An sDA rating of 75% indicates a location where daylighting is "preferred" by the inhabitants; in this situation, occupants would find the daylight levels adequate and able to function properly without using artificial lights. When the sDA value is between 55 and 74 percent, daylighting is "accepted" by the occupants. Overall, designers should try to attain sDA values of at least 55% in places where some daylight is required and in spaces like open-plan offices, which are regularly occupied by at least 75%.

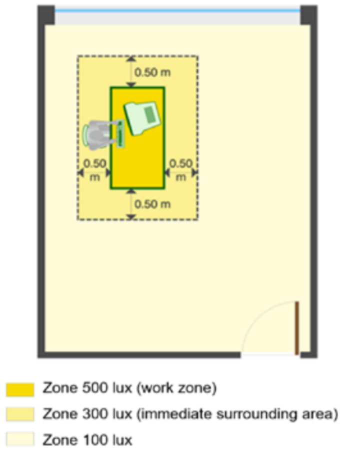

Figure 2.1: The minimum illuminance in an office room. From: (Council, 2014)

$$sDA_{300/50\%} = \frac{\Sigma_i S(i)}{\Sigma_i p_i} \in [0,1], S(i) = \begin{cases} 1, & \text{if } s_i \geq \tau t_y, \\ 0, & \text{if } s_i < \tau t_y. \end{cases} \tag{2.1}$$

This dynamic daylight meter (sDA) is based on hourly measurements with either manual or electrically operated window blinds, depending on how much direct sunlight enters the area through windows to ensure visual comfort. The blinds open and shut following the 2% regulation (LM, 2013). When more than 2% of the analysis grid points get 1000 lux or higher (direct sunshine), blinds for each window group will shut together until fewer than 2% receive direct sunlight. Windows must be classified before the position of the blinds is set on an hourly basis.

Calculating the sDA requires simulation software that takes into account the occupant's behavior and interaction with blinds. LEED establishes a minimum requirement of 300 lux for 50% of annual daylight hours over a portion of the occupied area. Where sDA300/50% achieves a value of 75%, 3 points are awarded, 55% for 2 points, and 40% for 1 point. As an illustration of spatial daylight autonomy,(Figure 2.2) depicts that 65% of the surface area of a working plan at a height of 0.76m receives a minimum illuminance value of 300 lux for at least 50% of the total annual operational hours from 8:00 to 18:00.(LM, 2013). It may be portrayed as follows:

sDA 50% $\geq 300lux(8:00 - 18:00)$

The sDA300lux/50% = 65%; therefore, this value exceeds the acceptable threshold for sufficient daylight per LEED v4.1.

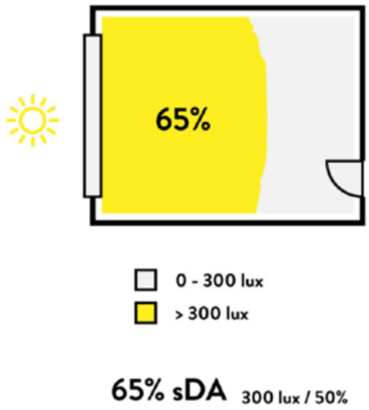

Figure 2.2: An example that represents the Spatial Daylight Autonomy (sDA). From:(Council, 2014)

2.2.2 Annual Sunlight Exposure (ASE)

According to IES- LM-83-12, Annual Sunlight Exposure (ASE) is a dynamic daylight metric representing visual discomfort, glare, direct sunlight and overheating inside a building. It is to assess the potential danger posed by excessive sunlight. It details the percentage of each analysis grid that has investigated an area that receives more direct sunlight than allowed for a predetermined amount of operational hours each year without any additional input from the sky.(LM, 2013) As an illustration of the Annual Sunlight Exposure, ("Figure 2.3") demonstrates that 8% of the surface area of a working plan at a height of 0.76m receives daylight above the maximum recommended illuminance value, which is 1000 lux, for more than 250 hours of the total annual operational hours from 8:00 to 18:00. It can be represented as the following: ASE 8% $\geq 1000lux(8:00-18:00)(Nassimos\ etal.,$2021)

ASE1000ux/250h equals 8% This value is below the acceptable visual comfort threshold value for LEED v4.1, which is less than 10%.

$$ASE_{1000/250h} = \frac{\Sigma_i A(i)}{\Sigma_i p_i} \in [0,1], A(i) = \begin{cases} 1, & \text{if } a_i \geq_y, \\ 0, & \text{if } a_i <_y . \end{cases} \tag{2.2}$$

2.2.3 Discomfort Glare Probability (DGP)

According to (Carlucci et al., 2015), The Discomfort Glare Probability (DGP) is a suggested short-term, local, one-tailed measure. in(Wienold & Christoffersen, 2005). This is its formulation:

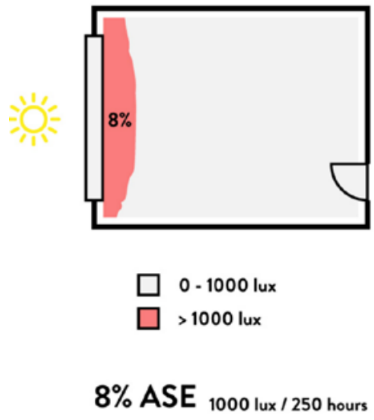

Figure 2.3: an example that represents the Annual Sunlight Exposure (ASE). From:(Council, 2014)

Formula will be added

$$DGP = 5.87 \times 10^{-5}.E_v + 9.18 \times 10^{-2}.\log\left(1 + \sum_{j=1}^{n} \frac{L_s.j^2.\omega_s.j}{E_v^1.87.P_j^2}\right) + 0.16 \quad (2.3)$$

Where Ev is the vertical eye illuminance generated by the light source (in lx), LS is the source's luminance (in cd/m2), and s is the observed solid angle of the source. P is the position index, which describes the variation in uncomfortable glare related to the angular displacement (azimuth and elevation) of the source from the observer's line of sight. The equation is applicable for DGP values between 0.2 and 0.8 and Ev levels over 380 lx.

The previously investigated glare indices only consider the contrast ratio between the average brightness of the background and the luminance of the glare source (Suk, Schiler, & Kensek, 2013). However, the DGP incorporates an evaluation of the observer's perception of illuminance, denoted by the word Ev. Therefore, DGP has a more vital link with the user's sense of glare (Wienold & Christoffersen, 2005). According to (Suk et al., 2013), this would be the optimal metric for analyzing fundamental glare problems. In addition to the easy analytic computations required by the other glare indices, the technique typically requires significantly more user effort and computing time. There are several simplified versions of the formula, but in this thesis, the simplified version of DGP by A study by (Wienold et al., 2007) has proposed a simplified version of DGP where the logarithmic term depending on the local quantities (luminance and solid angle of the source seen from the observation point) is neglected. They cannot be used for absolute glare factor conditions that include a direct view of glare sources in the observer's field of view.

2.2.4 Spatial Disturbing Glare(sDG)

In this thesis the annual climate-based glare calculation is needed. As it is defined by the climateStudio,(*SolemmaLLC*, 2020), The percentage of regularly occupied floor area views that experience Disturbing or Intolerable Glare (DGP >38%) for at least 5% of occupied hours can be defined as Spatial Disturbing Glare(sDG). The calculation is based on the hourly DGP values for eight different view directions from each vantage point within the building. The default view height is 1.2 metres above the ground (eye height for a seated observer). The frequency of disturbing glare is represented in the Rhino viewport by eight directional pie slices, with the colour representing the frequency from 0% to 5%, as can be seen in the 2.4.

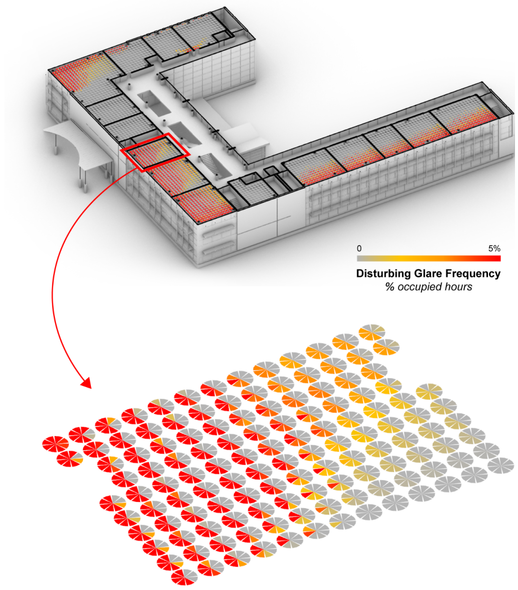

Figure 2.4: he frequency of disturbing glare. From:(*SolemmaLLC*, 2020)

2.3 Artificial Intelligence and Machine learning

Machine learning is a branch of computer science that examines statistical models and algorithms that use a dataset's variables to discover pertinent spatiotemporal patterns and information. Machine learning provides computer systems with new capabilities, as they can make rapid predictions from newly input data without being explicitly programmed to do so (Mitchell, 1997). Machine learning searches sample training data to develop and formulate a mathematically-fit model, which maps the complicated relationships between independent inputs and target outputs. Here, evaluation metrics assess the performance of the model (Li & Lou, 2018).(Ayoub, 2020) has categorised the machine learning process consists of the following steps: Before developing the model, (i) Data Collection involves acquiring pertinent historical, experimental, observational, or simulation-derived data. The data quality directly affects the accuracy of the predictive model. (ii) Data Preparation necessitates data standardization, scaling, and randomization, as the ranges of data variables might vary greatly, altering how MLAs operate. Randomization of data is also employed to prevent the order of input from influencing learning. (iii) Data Exploration and Visualization employing statistical and visualization techniques are essential to evaluate if there are meaningful associations between input variables and to uncover any data imbalances so that the produced model is not skewed toward predicting a specific range of variables. (iv) During Data Pre-Processing, the data are divided into three sections. The first, the largest, is used for training the model; the second is for testing or evaluating the model's performance during training; the third is for validating or fine-tuning MLAs(Machine Learning Algorithms) hyperparameters to offer more performance improvements. Finally, (v) predictions are made, at which point the value of machine learning is recognized. MLAs vary in technique, types of variables to manage, and nature of problems to solve. Nonetheless, they can be divided into three categories based on the learning technique: supervised, unsupervised, and reinforced(Bishop & Nasrabadi, 2006)("Figure 2.5"), each of which has its benefits and disadvantages. Supervised learning examines potentially generalized dataset to construct a model that relates input variables to output variables based on a training dataset containing many input-output pairings. The model can then forecast variables of interest based on newly input data. The supervised learning methods for classification and regression include MLR(Multiple Linear Regression), ANN(Artificial Neural Network), SVM(Support Vector Machine), Nave Bayes (NB), DT(Decision Tree), and

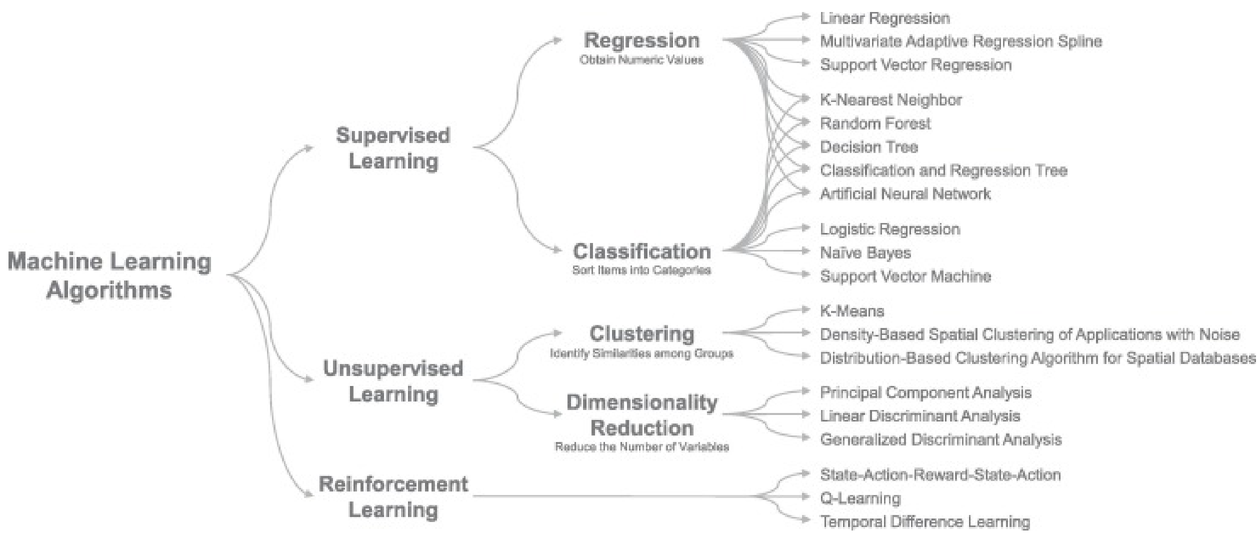

Figure 2.5: Different Categories of MLAs According to Learning Technique. From:(Ayoub, 2020)

Random Forest (RF). Unsupervised learning identifies unknown patterns in a dataset to recognize target variables without output data. The model sorts unsorted data according to similarities, differences, and patterns. Unsupervised learning algorithms for clustering, feature selection, and dimensionality reduction include Hierarchical Clustering, K-means, and Principal Component Analysis (PCA). In a dynamic context, reinforcement learning pursues a specific objective without knowing if the model converges on the objective. It requires activity as input and creates a maximum expected reward as output, with the process being driven by feedback from the environment.

2.4 Related Work

A review of existing research has been done in two sections for this study: 1.Parametric shading design. 2.Utilization of artificial intelligence to evaluate the performance of shadings.

2.4.1 Parametric Shading Design and Optimization

The shade design technique used in this study is parametric design. Tools for parametric design facilitate the modification of variables and let the user view design variants in near real-time, record and compare them. Due to the time implications of rewriting all model variants, optimization becomes a viable alternative for generating all iterative simulations in a single, more precise procedure(López Ponce de Leon, 2016).

According to (Jalilzadehazhari, Johansson, Johansson, & Mahapatra, 2019), 34% of the 105 reviewed papers assessed the visual comfort performance of different window and blind designs. By applying overhangs to an office building with variables such as installation height, depth, tilt angle, distance from the wall, and kind of glass,(Manzan, 2014) determined the primary energy and UDI100-2000lux (Useful Daylight Illuminance) for two cities in Italy with contrasting climates. Trieste's energy consumption decreased by up to 19%, and Rome's by up to 30%, due to using a unique strategy to minimize primary energy. By optimizing factors such as number, breadth, and tilt for the exterior louvers of a Sydney office building, (González & Fiorito, 2015) examined factors such as DA and UDI and yearly energy usage. The findings demonstrated a 35% reduction in yearly energy usage relative to the baseline scenario. The optimal design comprised 14 louvers with a negative ten-degree slope and a depth of twenty centimeters.

(Manzan, 2014) generated optimum overhang models for two exposures of an office building in Italy, with the following results: for the southern exposure, a 20% reduction in energy consumption and a 90% UDI, and for the southwestern exposure, a 23% decrease in energy consumption. In addition, the usage of exterior shadings significantly decreased the time the interior blinds had to operate by enhancing the quality of available natural light.

(Lee, Han, & Lee, 2016) employed optimization and simulation techniques to determine the ideal shading design among models, including horizontal and vertical louvers, two models of vertical panels with geometric patterns, and random horizontal and vertical louvers. This study's variable factors include the angle of tilt of the louvers, the number of louvers, the depth of the louvers, the number of window divisions, and the Window to wall ratio. The output parameter represented the proportion of space area with DF between 2% and 5%. The simulation approach determined that vertical louvers achieved the most outstanding value (94%) among the six shade forms, while vertical panels received the lowest value (65%). The optimization procedure yielded results ranging from 44 to 86%. The horizontal louvers had the most value (86%), whereas the vertical panel had the most negligible value (44%).

(Uribe, Veraand, & Bustamante, 2017) designed Venetian blinds with slat angles of 0° and 45°, essential woven shade, and perforated screen panels in three cities, considering factors such as glazing type, Window to wall ratio, shading angle, etc. In Chile, Antofagasta, Santiago, and Punta Arenas, Window to wall ratio values of more than 90% were attained due to an increase in daylight, which decreases lighting energy consumption. In Antofagasta, single clear glass was selected; however, double clear glazing was preferred in two other cities. Because they give visual comfort, 45-degree louvers and conventional woven shade were the optimal shading alternatives.

(Ishac & Nadim, 2021) established a fundamental model, sought an efficient solution, and verified the optimal solution [19]. The optimization approach to evaluate the light shelves and vertical fins yielded the following ideal alternatives: 1) In the south, a 120-centimeter exterior light shelf with a 5-degree upward slope and an 80 cm inside light shelf. 2) In the east, a 120-centimeter exterior light shelf, an 80-centimeter interior light shelf, 20-centimeter vertical fins, a -5-degree angle, and a 40-centimeter gap between each fin. One or two shading models with restricted variable parameters have been examined in the research, and the space-related factors have been considered fixed. Therefore the findings cannot be generalized. As previously indicated, owing to the significance of shading characteristics and their influence on other space parameters, choices about these parameters should be made concurrently and early in the design process. Moreover, the view and cost analyses have been retained to analyze the performance of shadings.

2.4.2 Machine Learning Algorithms and Hyperparameters

Because of their lack of complicated inputs, speed, low cost, and accurate predictions, the building design community can use machine learning algorithms.(Ayoub, 2020) assessed recent studies that used these algorithms to predict the daylighting of spaces, the characteristics of the investigated buildings, the algorithms used, the type of issues solved, the input parameters, outputs, and error metrics.

Machine Learning Algorithms' criteria may be implemented through problem categories, chosen MLAs and their hyperparameters, input parameters, and output parameters. Previous research has identified three problem-type categories: regression, classification, and clustering. The most commonly used algorithms in previous studies, according to(Ayoub, 2020), were neural network algorithm (ANN), multiple linear regression (MLR), and support vector machine (SVM). The most commonly used output parameters are luminance values, DA, and sDA, while the most commonly used error metrics are, RMSE, PE, R2, and MSE.

Hyperparameters are parameters whose values regulate the learning process and determine the model parameter values that a learning algorithm eventually learns. According to the review paper from (Ayoub, 2020), Until 2012, only four MLAs (ANN, SVM, AR, and DT) were used to address regression issues, with the addition of NB to identify illumination types (Ahmed, Korres, Ploennigs, Elhadi, & Menzel, 2011). Later, MLR, RF, LSMR, DBSCAN, k-NN, and GPs were used to deal with regression, classification, and clustering problems.

As ANN is the most commonly used MLA, its hyperparameters are also the most commonly used: Hidden Neurons, Hidden Layers, Epochs, Activation Function, and Learning Rate are all examples of hidden neurons.

To produce accurate predictions using MLA, relevant data must be used to build mathematically-fit models, which only apply to the data range from which they were created. Once a model is built, it can quickly make predictions. During the early design phases, basic building designs are repeatedly updated to find optimal choices; data distribution is also modified. This may alter outputs, making it challenging to generalize daylighting performance for new designs. Machine learning models must be recreated and retrained with new data. Transfer Learning across old and new data domains reduces time-consuming tasks(Pan & Yang, 2009). Using MLAs as a holistic approach to the single model output might be difficult since every performance outcome requires a distinct procedure. Architects rarely use machine learning (Khean, Fabbri, & Haeusler, 2018), but with more targeted implementations, this would change.

2.4.3 Input and Output Parameters

Regarding the input parameters, as (Ayoub, 2020) reviewed, the evaluated studies demonstrate that the selected parameters fall into two primary categories: external and internal. Climate Conditions; Temporal Settings; External Obstructions; Building Physical Features, Openings, and Shading Devices; Occupancy and Sensor Data, which can be seen in the ("Figure 2.6") Some of the most commonly used input parameters are Orientation, window width, window height, room width, room length, room height, global horizontal radiation, time of day, diffuse horizontal radiation, windows location, sensor point identification, shading device, shading parameters, wall material, floor material, ceiling material, and glazing properties.

According to the Literature most researches focused on predicting DA, sDA300/50%, Daylight Glare Probability (DGP), Daylight Factor (DF), ASE1000/250h, UDI, Continuous Daylight Autonomy (CDA) and CIE Glare Index (CGI). The authorized technique of daylight metrics IES LM-83-12 (2012), released by the IES in 2012, enhanced these temporal measures with sDA300/50% and ASE1000/250h to account for spatial considerations. The values sDA300/50% and ASE1000/250h indicate the proportion of an area that gets an appropriate quantity of daylight and an excessive amount of sunshine, respectively. sDA300/50% is the proportion of a space that meets the minimum goal illu-

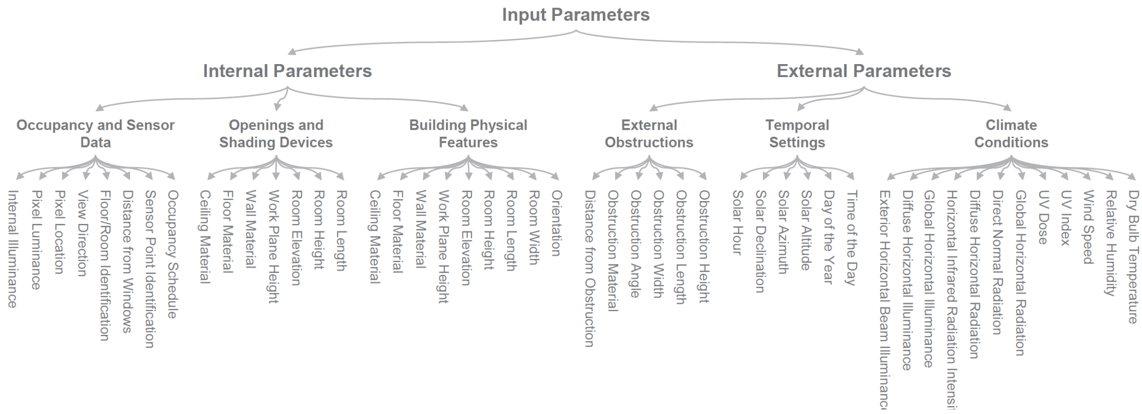

Figure 2.6: Different sets of input parameters to predict daylighting. From:(Ayoub, 2020)

minance of 300 lx for 50% of the yearly occupied hours:

glare formula by introducing DGP, which combines vertical eye illuminance with glare source brightness measured at the same location. DGP, like other glare indices, needs the source's brightness, size, and relative location.

2.4.4 Data Sources and Sizes

Data Sources, Sizes, and Temporal Granularities may be used to classify the Data used for training and testing machine learning models. Two data sources have been identified in prior research (Simulation-Derived and Field Measurements). This thesis focused on simulation-derived datasets. Using simulation tools like DIVA-for-Rhino, Radiance, DAYSIM, Ecotect, Honeybee, and ClimateStudio, the Simulation-derived data is used to create machine learning models that take into account both existing spaces and conceptual designs. The forms of simulated data used for machine learning include training and test. As (Ayoub, 2020) has indicated, Simulation-Derived Training Data vary in size from 195 to 5400, and simulation-Derived Testing Data ranges from 21 to 729. The average ratio between training and testing data is roughly 3:1.

2.4.5 Evaluation metrics

After developing a machine learning model, evaluation metrics are used to analyze its training and testing performance. Before forecasts can be made for real-world applications, it is necessary to evaluate models to determine their correctness. RMSE and MSE were utilized in most of the studied research that addressed regression problems as(Ayoub, 2020) studied.Both measures emphasize outliers and extreme error values by squaring the difference between the anticipated and actual values before averaging. Since the square term in RMSE, MSE, and MAE, and the absolute term in MAE, cancel out negative errors, they do not show whether the model overestimates or underestimates the predictions.(Le-Thanh, Nguyen-Thi-Viet, Lee, & Nguyen-Xuan, 2022)

In contrast, other measures, such as PE and MBE, reveal positive and negative errors. How outliers and excessive mistakes are handled determines the best error measure. Each metric exposes distinct errors. MBE and MAE are easier to read, but they do not contribute as much to model correctness. MSE's square component makes common errors quadratically larger than RMSE, punishing the model for generating slightly off predictions. Thus, MSE and MAE propose a significant penalty for a little mistake or a moderate cost for a more significant error(Twomey & Smith, 1995). Since MSE values increase, it becomes difficult to grasp how well a model works; thus, RMSE is utilized in such situations, as it turns squared error values into their initial unit, making them more straightforward to read and compare with the original data. RMSE combines error magnitudes into a single number. Hence outliers must be eliminated from the dataset before using it. *******formulas to be added

$$PE = \frac{(\hat{y}_i - y_i)}{y_i} 100\% \tag{2.4}$$

$$MBE = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i) \tag{2.5}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i| \tag{2.6}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 \tag{2.7}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2} \tag{2.8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_i)^2} \tag{2.9}$$

2.4.6 Machine-Learning Framework for daylight assessments

In most studies, as (Daneshi, Fard, Zomorodian, & Tahsildoost, 2022) stated, variable parameters were primarily related to space, such as window dimensions, window orientation, space dimensions, obstruction dimensions, glazing parameters, etc. In a few articles, including studies by: (Logar, Kristl, & Škrjanc, 2014), (Ahmad, Hippolyte, Mourshed, & Rezgui, 2017), (Navada, Adiga, & Kini, 2016), (Uribe et al., 2017) and (Verso, Mihaylov, Pellegrino, & Pellerey, 2017),one or two typical shading models and a few variable parameters were assumed for each.

In research by (Nourkojouri, Zomorodian, Tahsildoost, & Shaghaghian, 2021), a machine learning system was created to predict daylight and visual comfort parameters at the early phases of design. A dataset including 2,880 options was developed, with the room, window, and shade parameters. Useful daylight illuminance, spatial daylight autonomy, mean daylight autonomy, yearly sunlight exposure, spatial-visual discomfort, and view quality were the outcomes. A neural network approach was used, and the average accuracy of the predictions was projected to be 97%. In this study, a louver model was tested with restricted parameters.

In a different research, Lin et al. [26] employed machine learning algorithms to design facades and estimate daylight performance. For this purpose, a parametric model of a vertical panel with properties such as Sky Exposure, Sky View, Visible Rate, Sunlight Hours, etc., was created. A database of 225 distinct facade conditions and 860 test surface points was developed. The daylight model was then trained with an artificial neural network and could estimate the DA and ASE hours per grid with excellent precision using the test dataset (R2 values 0.91 and 0.88, respectively).

The averaged daylight autonomy (DA), daylight factor (DF), and daylight glare probability (DGP) were predicted using ANNs by (Radziszewski & Waczyńska, 2018), using a dataset of 2763 randomly selected office spaces that were drawn from a distribution of seven normally distributed design parameters. With speed increases of 31, 3, and 17 times, respectively, over the Daysim simulation, this method produced percentage errors for DA, DF, and DGP of 2.82 percent, 0.15 percent, and 1.06 percent. In order to predict DA for 28 identically sized rooms with various window sizes and locations, (Lorenz, Packianather, Spaeth, & Bleil De Souza, 2018) trained ANNs. Daysim was used to generate a total of 2057 training samples, with the sensor point coordinate, point id, window dimensions, and location serving as inputs and the output being the DA at each sensor point. The findings revealed that for four different test cases, the mean absolute error (MAE) and

RMES varied from 2.71, 3.44 percent to 3.99 percent and 6.96 percent, respectively. In two latter studies The numerous DA and DF metrics employed in these works do not contain an upper limit of daylight illuminance to indicate excessive daylight. In addition, averaged daylight metric was utilized to describe a total room, which oversimplified the interior daylight dispersion feature.

In a recent study conducted by (Ekici, Kazanasmaz, Turrin, Taşgetiren, & Sariyildiz, 2021), MUZO methodology has been created which is focused on the optimization problems and algorithms, results, and validation of the method. As a case study, Berk has studied two shading designs, diagrid, and quad-grid. He has considered DA and ASE as performance metrics. The R2(How well the regression predictions match the actual data points) of comparable research focusing on ML applications in daylight has been undertaken to compare the accuracy findings offered for various design issues. As he compared, there are promising results for DA, sDA, illumination level, and useful daylight illuminance in the relevant literature. However, visual comfort measurements such as daylight glare probability (DGP) have only low accuracy for ML applications. Due to the difficulties in forecasting comfort measurements, this investigation obtained a similar result for the ASE metric.

Chapter 3

Machine Learning Based Design tool

In this section, we would focus on data preparation and machine learning algorithm selection. In the construction industry, data sources that influence the energy performance of the built environment as well as the health and well-being of residents are increasing. It is critical in machine learning to understand what a dataset is, how to obtain it, and what characteristics a valid dataset possesses. A dataset in machine learning is essentially a collection of data points that can be handled by a computer for the purposes of analysis and prediction. Because machines do not perceive data in the same way that humans do, the collected data must be standardized and machine-readable. After gathering the data, it must be preprocessed by cleaning and finishing it, as well as annotated with machine-readable tags containing useful information. The diagram of the main process can be seen in the figure 3.1

3.1 Dataset Generation

The parametric model used the CimateStudio simulation programme v1.8.8244 for Rhino to simulate sDA, ASE, and DGP metrics using a weather data file for Tehran at 32.4279° N, 53.6880° E. A shoe box model was simulated as can be seen in the 3.2. Regarding the input settings of Climate Studio, the height of the analysis surface is equivalent to the height of the user's desk in the office environment (0.76 meters), and the grid size is 0.6 meters.According to (LM, 2013), the setup simulated sDA300/50% and ASE1000,250h. According to the software's advice, the ab parameter was set to its default value of 6, and 4094 samples were evaluated for each sensor. According to office

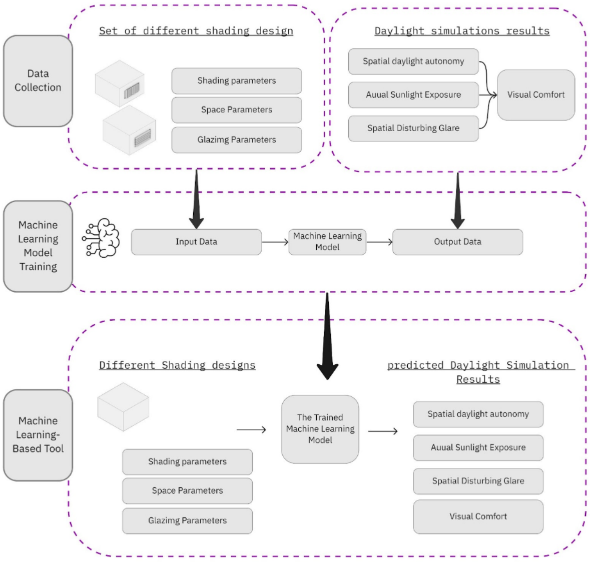

Figure 3.1: Diagram Of The Main Process

hours, the occupancy time of users was assumed to be between 8am to 6pm. Four different glazing type has been consider for the simulation with different visual transmittance values that can be seen yin the figure 3.3

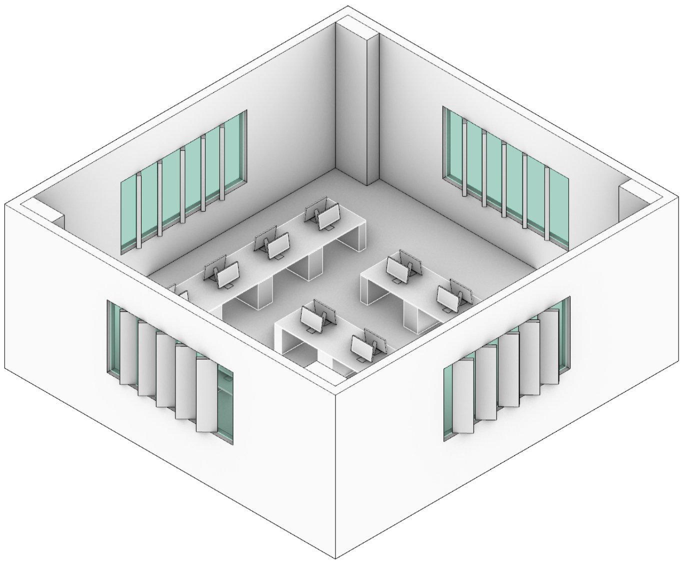

Figure 3.2: The Shoe box model used for daylight simulations

	Name	Layers	Tvis	Rvis.front	Rvis.back	UVal [W/(m²·K)]	SHGC
Glazing Type 1	Solarban 67 (2) on Pacifica - Clear	Double	25,1%	7,8%	14,7%	1,66	0,19
Glazing Type 2	Solarban 60 (2) - Solarban 60 (4) - Clear	Triple	55,3%	12,3%	14,2%	0,89	0,31
Glazing Type 3	Solexia	Single	76,8%	7,5%	7,6%	5,82	0,62
Glazing Type 4	Solarban 60 (2) on Starphire	Single	81,3%	5,6%	4,7%	3,22	0,46

Figure 3.3: Different glazing types used as input

Several fixed and variable factors have been established for the target space, a Tehran office space. This area's height ranges between 4 and 5. The length (Y) and width (X) of the space remain constant which is 10 meter x 10 meter. IES LM-83 (LM, 2013) determines the average material reflectance values of interior surfaces. Constant window characteristics include the window sill, the window's height, and the number of windows. Except for space-related aspects, two typical shading models have been examined for the opening: louvers and vertical panels, each of which has distinct characteristics that have been applied independently to the area. Both variable and fixed parameters have been provided for each item that can be seen in the 3.5.Using the Colibri GH plugin, simulations were done parametrically following parametric modeling and variable parameter.There are a total of 1000 for two different shading designs.The simulations and dataset creation required ten days. A system with an Intel Corei7 processor with a 12 GB Ram system ran concurrently for 16 hours daily. After simulations, the input parameters and output data were sorted, classified, and readied for computer programming. Figure 3.4 shows a summary of variables and their respective ranges. The overall number of options is 1,000, with 500 for each shading type.

Explanation	Notation	Orientation	Boundry	Unit
Number of vertical sahdes	x1, x5, x9, x13	North-south-east-west	[0-8]	Meter
Length of vertical devices	x2, x6, x10, x14	North-south-east-west	[4-5]	Meter
Rotation of vertical devices	x3, x7, x11, x15	North-south-east-west	[-60-60]	Degree
Width of vertical devices	x4, x8, x12, x16	North-south-east-west	[0,05 - 0,35]	Meter
Height	H	North-south-east-west	[4-5]	Meter
GLZ	GLZN, GLZS, GLZE, GLZW	North-south-east-west	1,2,3,4	_

Figure 3.4: Notions and boundaries of parameters used as input

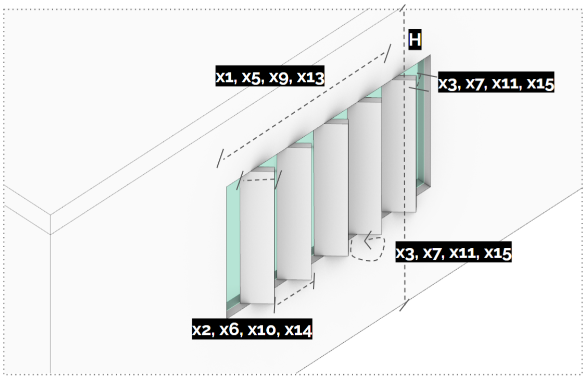

Figure 3.5: Shading parameters used as input

3.2 Statistical Data Analysis and Data Preprocessing

3.2.1 Statistical Data Analysis

Statistical data analysis is a process involving the execution of a variety of statistical processes. The primary objective of statistical data analysis is to identify patterns. Statistical approaches aid in correlating, organizing, and interpreting data, and statistical analysis reveals the underlying patterns in a data set; correlation, for instance, demonstrates a link between two variables(Sheuly et al., 2021). As a part of this framework, it is essential to understand data structures and to know if any pre-processing for the data set is needed, such as scaling. For this purpose, some statistical analysis has been done for the produced dataset such as: univariate analysis, which can be seen in Fig 3.6,3.7, and 3.8, showing the range and distribution of sDA, ASE, sDG values. According to Fig 3.6, sDA values follow the normal distribution within the range of [40, 100]. Fig 3.7 and 3.8 shows ASE and sDG somehow follows the pattern of skewed normal distribution with some outliers within the range of [10, 46] and [10, 38] accordingly.

Besides, three parallel coordinates plots on all variables in the dataset colored by ASE, sDG and sDA can be seen in Fig 3.9, 3.10 and 3.11 accordingly. These plots show how different combinations of values for other variables result in specific values for each target variable (ASE, sDG and sDA).

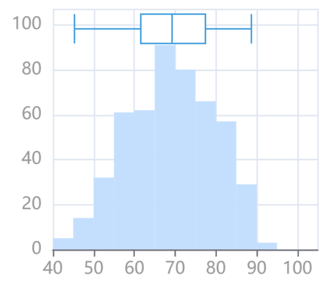

Figure 3.6: Univariate analysis on sDA

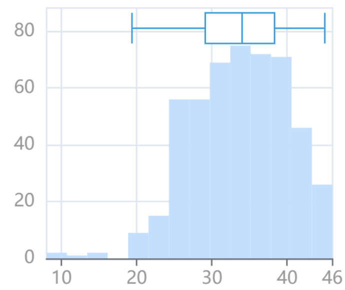

Figure 3.7: Univariate analysis on ASE

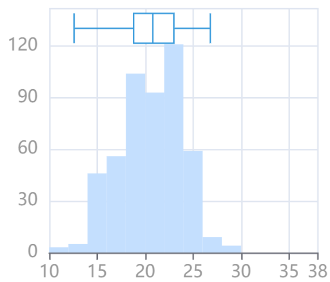

Figure 3.8: Univariate analysis on sDG

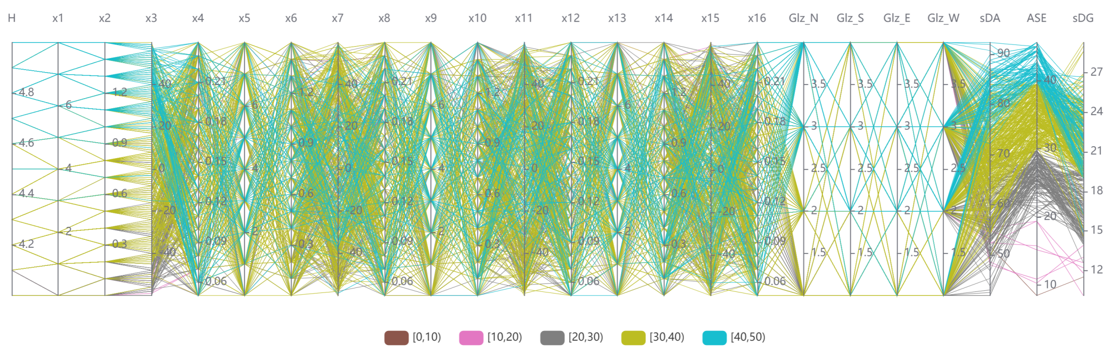

Figure 3.9: Parallel coordinates plot on 24 variables, colored by ASE

3.2.2 Data Scaling

The construction of Machine learning algorithms starts with data reading and scaling, typically involving parameters with multiple units and metrics. Scaling the dataset bring all inputs and outputs inside the same bounds after the reading process. In this research, the min-max scaling approach is used

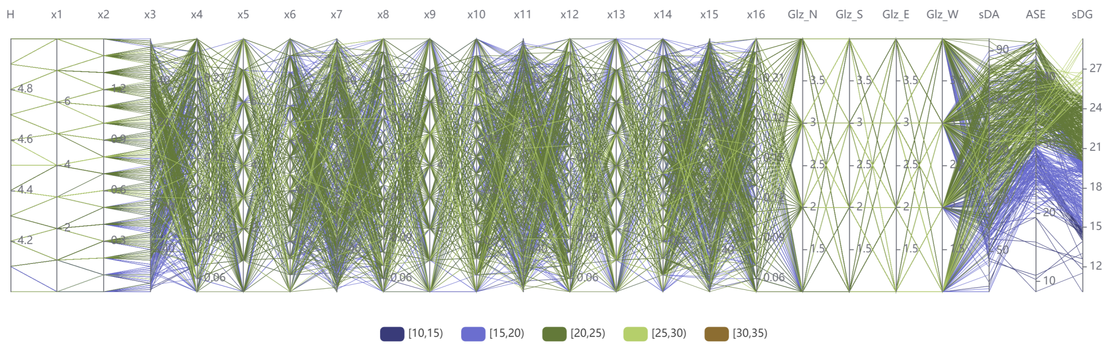

Figure 3.10: Parallel coordinates plot on 24 variables, colored by sDG

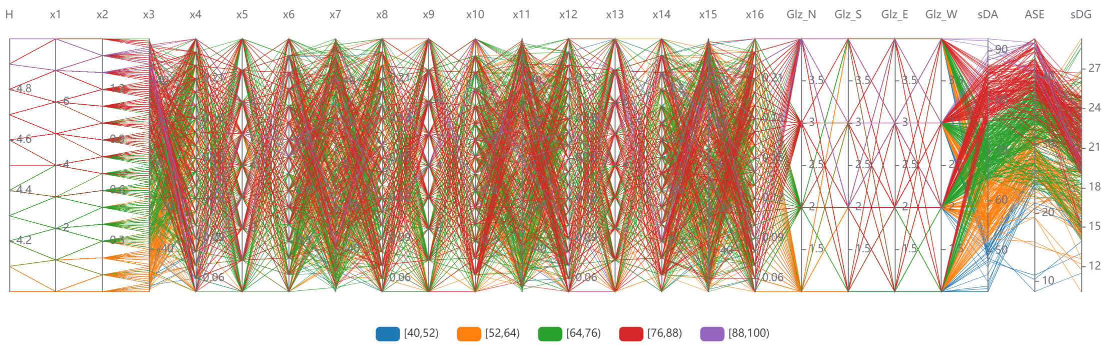

Figure 3.11: Parallel coordinates plot on 24 variables, colored by sDA

to properly normalize the training data to train the estimation model. This method helps the model to learn faster and more precisely. For min-max scaling, data are normalized as follows:

$$x'_i = \frac{x_i - min}{max - min} \tag{3.1}$$

x_i is the original value of x and x'_i is the new value of x after applying the min-max scaling.

3.2.3 Feature Generation: Visual Comfort

A new feature is generated based on ASE, sDA and sDG, called as Visual Comfort. The threshold is defined as follows:

$$
\text{Visual Comfort} = \begin{cases} "Preferred", & \text{if } sDA > 55 \ \& \ ASE < 20 \ \& \ sDG < 12.5, \\ "Neutral", & \text{if } sDA \leq 55 \ \& \ ASE < 30 \ \& \ sDG < 15, \\ "Acceptable", & \text{if } sDA \leq 55 \ \& \ ASE < 35 \ \& \ sDG < 20, \\ "Unacceptable", & \text{Otherwise} \end{cases} \tag{3.2}
$$

Four different visual comfort levels is defined as preferred, neutral, acceptable and unacceptable. The histogram of visual comfort variable can be seen in Fig 3.12. These levels will be used in Chapter 4.5.

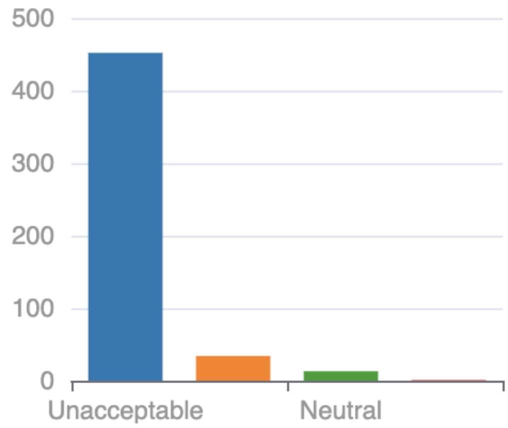

Figure 3.12: Visual comfort categories generated by ASE, sDG and sDA

3.3 Machine Learning Algorithm Selection and Model Training

According to the problem structure, a supervised learning strategy was used throughout the study. The following research is based on different MLAs such as Random forest, L2 Regression, SVM, k-Nearest Neighbor(kNN), and Logistic Regression responding to the gathered data structure and problem. An overview of the machine learning frame work is shown in the figure **??**

3.4 Hyperparameter Optimization

Several strategies, such as random search, grid search, manual search, Bayesian optimization, etc., may be used to choose model parameters. GridSearchCV,

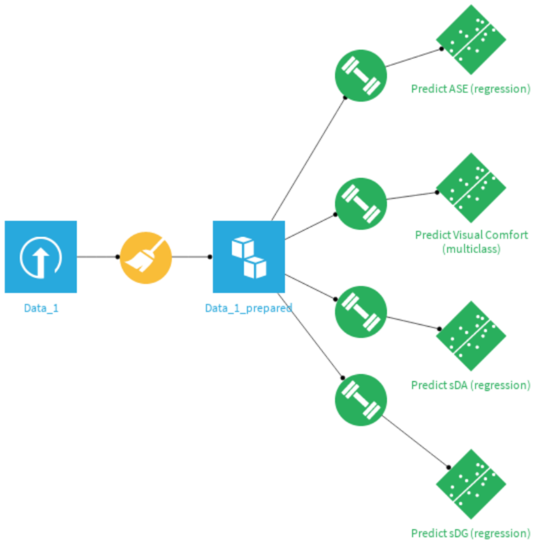

Figure 3.13: Diagram Of The Machine Learning Framework

which employs the Grid Search approach to determine the ideal hyperparameters to improve model performance, has been used in this thesis. Each machine learning model has different hyperparameter optimization method. A random forest consists of many decision trees. This means a Random Forest comprises several trees arranged in a "random" manner. Each tree is constructed from a unique subset of rows, and at each node, a special subset of characteristics is chosen for splitting. Each tree makes its prediction. The average of these forecasts is then used to give a single outcome.

Decision trees effectively discover nonlinear connections between input characteristics and the goal variable. A Decision Tree may be seen as a collection of if-then circumstances. It starts with a single node at the very top. This node then divides into two decision nodes, a left, and a right. Then, these nodes are separated into their respective left and right nodes. **??**

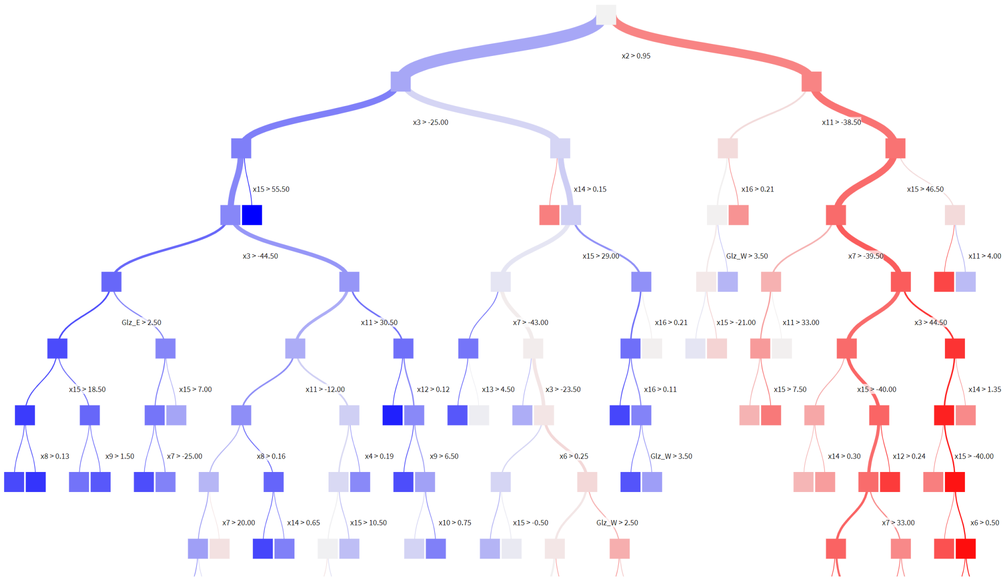

Figure 3.14: Decision tree in the Random forest model, A Random Forest Regressor prediction is the average of the forecasts generated by the forest's trees.

Chapter 4

Evaluation

In this chapter the final results of different machine learning models, their hyperparameters and the error distributions will be discussed.

4.1 Objective

In this chapter we aim to find the optimal machine learning model for predicting sDA, ASE, sDG and the visual comfort.

i. **Step 1: Dataset preparation**

4.2 sDA prediction

For predicting sDA value, 3 Machine learning algorithm has been chosen, Random forest, L2 Regression, and k-Nearest Neighbors. The optimal model is selected based on the grid search results at this stage. The criteria are the highest R2 with the lowest MAE and MSE. The results of these evaluation metrics can be found in the Table 4.1.

Name	MSE	RMSE	MAE	R2
Random forest	17.93	4.23	3.33	0.85
Ridge (L2) Regression	17.19	4.15	3.33	0.86
K Nearest Neighbors	23.36	4.83	3.91	0.81

Figure 4.1: The comparison of different evaluation metrics for sDA Prediction

According to this table, we can see that the L2 Regression model has outperformed the other two models, with R2=0.86. Based on literature(Ayoub, 2020), the value of R2 above 0.65, qualifies as a “good” result.

In the L2 Regression model, the hyperparameter we tried to optimize based on grid search optimization is the alpha. The best alpha value using grid search equals 0.1, which can be seen in the graph. 4.2, resulting the R2=0.86.

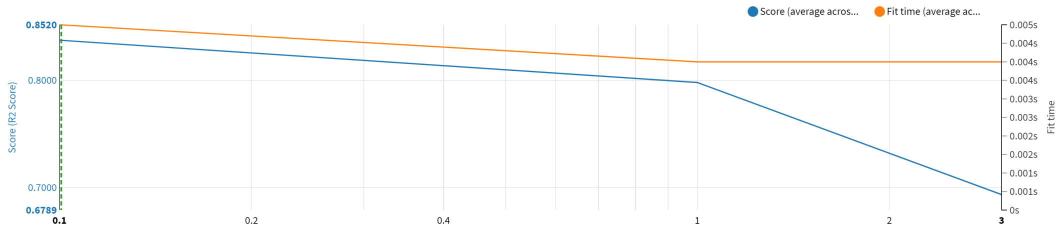

Figure 4.2: Hyperparameter optimization for L2 regression in sDA prediction

According to L2 Regression, the top 7 most essential variables in sDA prediction coefficients can be seen in 4.3. The positive coefficient, which can be seen in the green color, has a positive effect on the target variable, which means the greater the value of these variables is, the greater the sDA is.The following sensitive parameters are the Width of vertical devices, Length of vertical devices, the height of the room, and the glazing types which have the most effect on predicting the target variable, sDA.

Variable	Coefficient
H	7.1659
x8	5.3196
x4	-4.0638
x2	2.9230
Glz_N	2.2764
Glz_E	2.0453
Glz_S	1.7553

Figure 4.3: Regression Coefficient for L2 regression model in sDA prediction

The difference between predicted and actual values can be seen for different outputs and the associated error. It can be seen in the 4.4. Ideally, the error values should be centered around zero. As shown in 4.5, around 70% of the test data set has the error in the range of[-4,4]. It means that the model can predict sDA values 70% of the time with the estimation of $\pm 4\ correct values$.

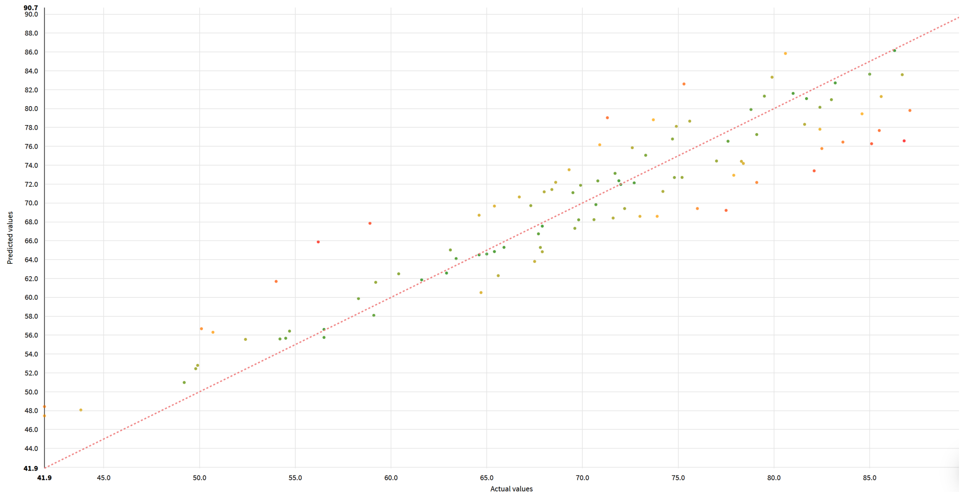

Figure 4.4: Scatter plot for sDA prediction, the differences between predicted and actual value can be seen in this plot

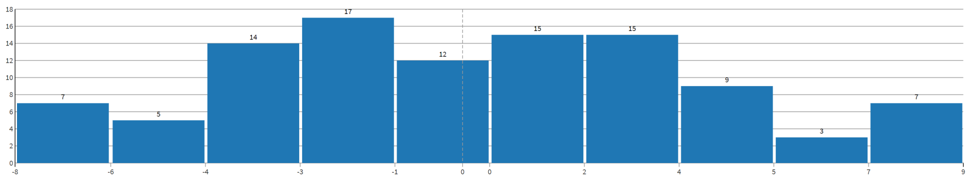

Figure 4.5: Error distribution for sDA prediction

4.3 ASE prediction

Same as sDA,for predicting ASE value, 3 Machine learning algorithm Random forest, L2 regression, and k-Nearest Neighbors have been selected. The best model is chosen based on the grid search results. The criteria is the highest R2 with the lowest MAE and MSE. The outcomes of these assessment measures may be seen in the Table 4.6. According to this table, we can see that the Random forest model has outperformed the other two models, with R2=0.67.

Name	MSE	RMSE	MAE	R2
Random forest	11,7	3,42	2,5	0,67
Ridge (L2) Regression	14,16	3,76	2,94	0,61
K Nearest Neighbors	15,86	3,98	3,14	0,56

Figure 4.6: The comparison of different evaluation metrics for ASE Prediction

In the Random forest model, the hyperparameter we tried to optimize based on grid search optimization is maximum depth. The best max-depth value using grid search equals to 15, which can be seen in the graph. 4.7, resulting the R2=0.67.

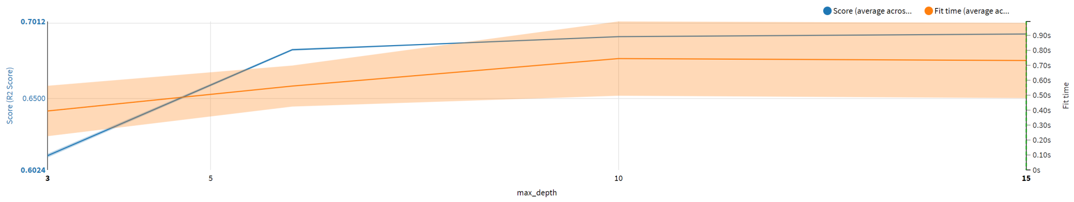

Figure 4.7: Hyperparameter optimization for Random forest in ASE prediction

According to Random forest, the top 5 most important variables in ASE prediction coefficients can be seen in 4.8. These variables have the most significant effect on the target variable. The following sensitive parameters are the Rotation of vertical devices on the North, South, west, and east sides and the length of vertical shading devices.

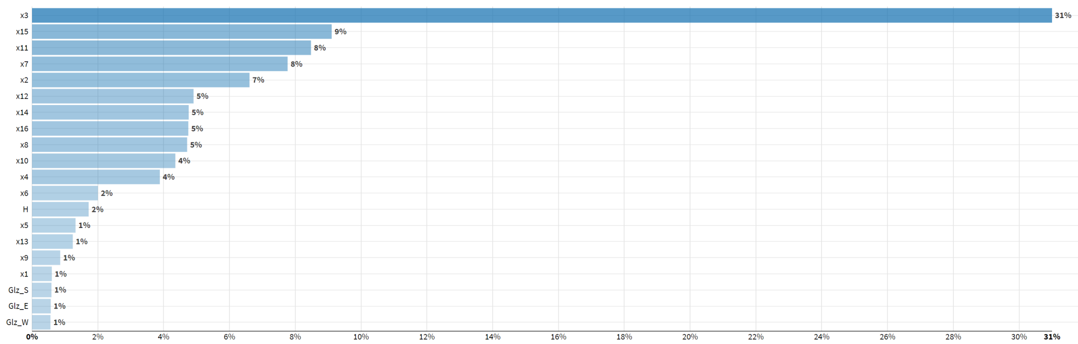

Figure 4.8: Variable importance in ASE prediction

The difference between predicted and actual values can be seen for different outputs and the associated error. It can be seen in the 4.9. Ideally, the error values should be centered around zero. As shown in 4.10, around 63% of the test data set has the error in the range of[-4,4]. It means that the model can predict ASE values 63% of the time with the estimation of $\pm 4\ correct values$.

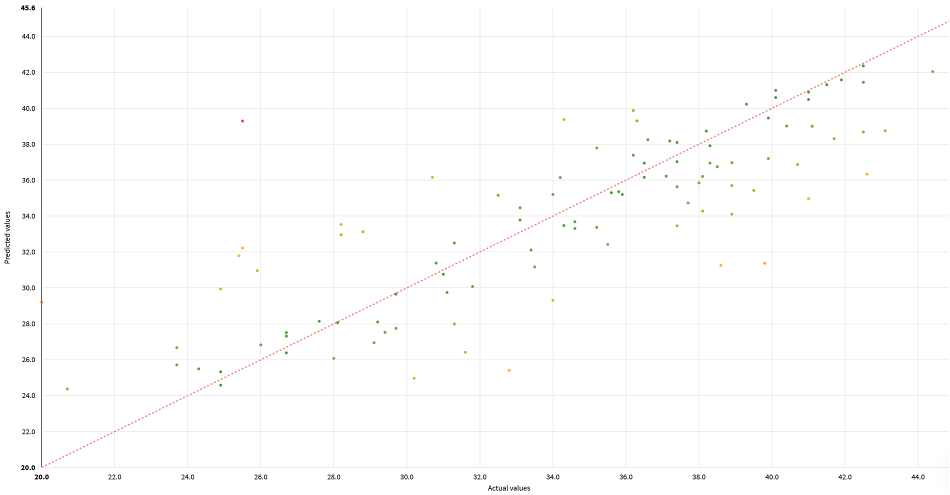

Figure 4.9: Scatter plot for ASE prediction, the differences between predicted and actual value can be seen

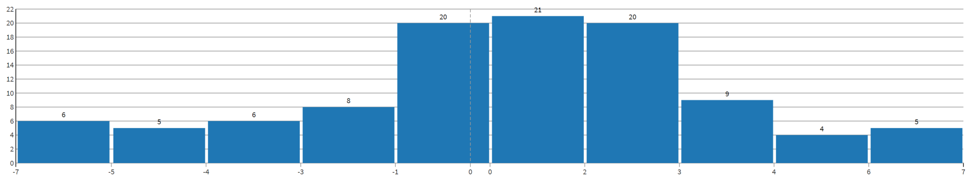

Figure 4.10: Error distribution for ASE prediction

4.4 sDG prediction

For predicting sDG, 3 Machine learning algorithms, Random forest, L2 regression, and k-Nearest Neighbors have been selected. Same as the two previous outputs, the best model is chosen based on the grid search results. The criteria are the highest R2 with the lowest MAE and MSE. The outcomes of these assessment measures may be seen in the Table 4.6. According to this table, we can see that the Random forest model has outperformed the other two models, with R2=0.25.

The hyperparameter optimization for sDG is the same as ASE. the hyperparameter we tried to optimize based on grid search optimization is maximum depth. The best max-depth value using grid search equals 6, which can be seen in the graph. 4.12, resulting the R2=0.25. The R2 value for sDG is low, although Regression models with low R2 values can be good models for several reasons; in this research, more study is needed to understand the correlations between the variables and sDG, As sDG has not been thoroughly

Name	MSE	RMSE	MAE	R2
Random forest	7,62	2,76	2,16	0,25
Ridge (L2) Regression	8,47	2,91	2,39	0,16
K Nearest Neighbors	8,45	2,91	2,32	0,16

Figure 4.11: The comparison of different evaluation metrics for sDG Prediction

studied in the literature. But some reasons for low R squared value can be: (i) The data might be contaminated by outliers, inconsistent measurements, or ambiguities in what is being measured,; (ii), We may require a large sample to achieve in the presence of low correlations. The scatter plot of actual and predicted values for sDG can be seen in 4.13.

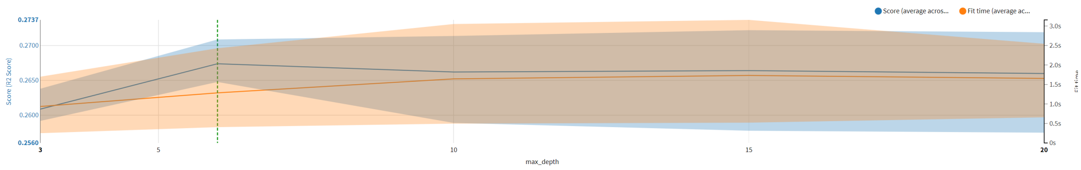

Figure 4.12: Hyperparameter optimization for Random forest in sDG prediction

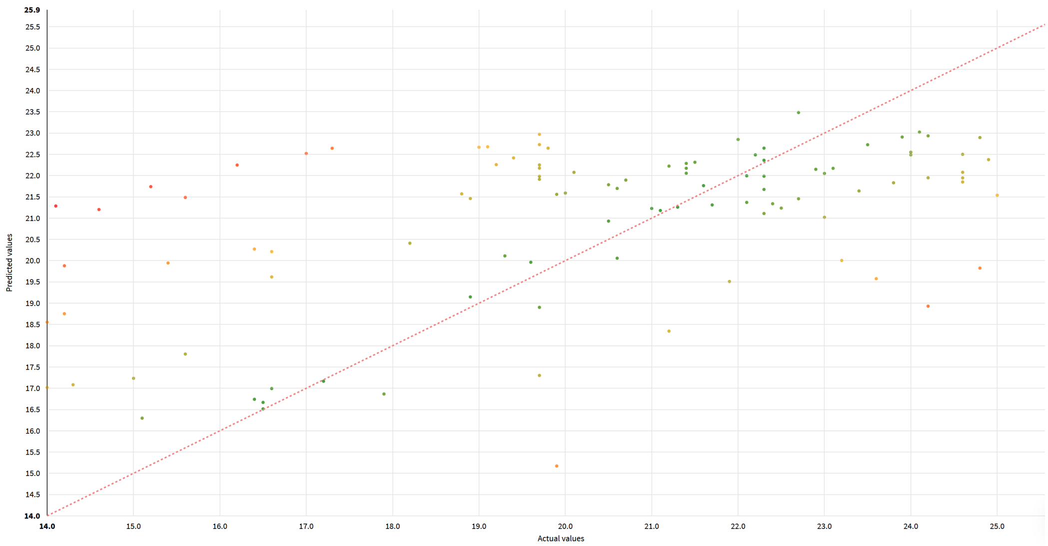

Figure 4.13: The scatter plot of actual and predicted values for sDG

4.5 Visual Comfort prediction

As mentioned in the previous chapter, Considering sDA, ASE and sDG, we have defined a new feature that classifies visual comfort into four categories: Preferred, neutral, acceptable, and unacceptable. In this model, the output prediction would be one of those above. Random forest, L2 Regression, k Nearest Neighbors, and SVM have been tested. Random forest with the ROC AUC value of 0.873 has outperformed the others. The confusion matrix of the visual comfort can be seen in **??**

	Predicted				
Actual	Unacceptable	Acceptable	Neutral	Preferred	
Unacceptable	99 %	1 %	0 %	0 %	100 %
Acceptable	43 %	57 %	0 %	0 %	100 %
Neutral	67 %	33 %	0 %	0 %	100 %
Preferred	-	-	-	-	100 %

Figure 4.14: Confusion matrix for predicted and actual values

According to Random forest, the top 5 most important variables in visual comfort prediction can be seen in 4.15. These variables have the most significant effect on the target variable. The following sensitive parameters are the Rotation of vertical devices on the North, the width of the shading device on the North, length of vertical devices on the north and east sides.

This density graph 4.16 demonstrates the model's success in classifying (and identifying) the data (e.g., 1 and 0 for binary classification). It displays the distribution of the test dataset's actual classes following the model's projected likelihood that a given class would be encountered. In contrast to rows that do not truly belong to the observed class, the two density functions display the probability density of rows in the test dataset. A perfect model entirely separates the density functions: the colored areas should not overlap the density function of not Acceptable should be entirely on the left the density function of Acceptable should be entirely on the right The dotted vertical lines mark the medians.

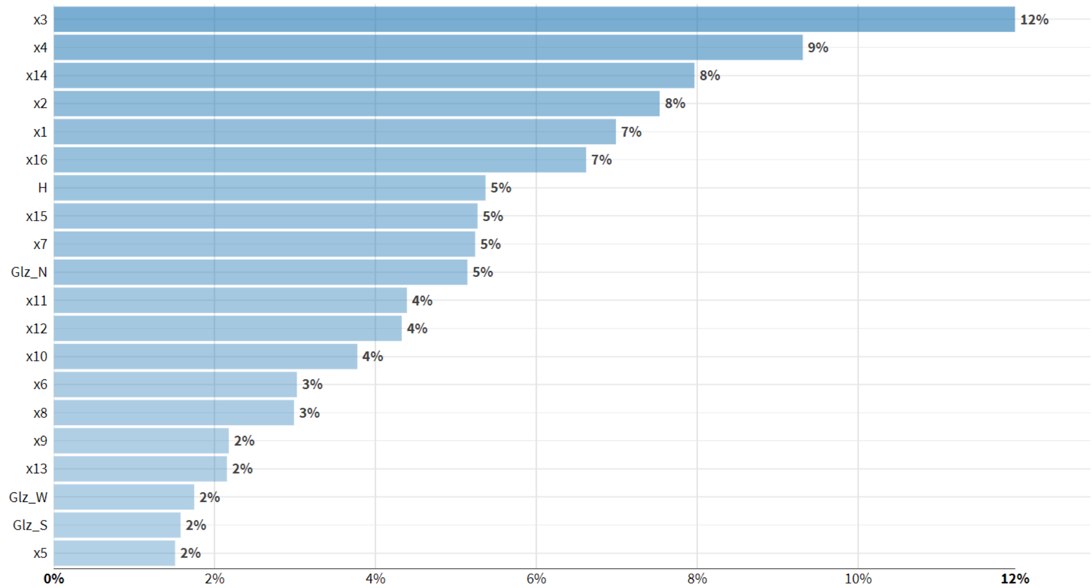

Figure 4.15: Variable importance in visual comfort prediction

4.6 Discussion

This study demonstrates that artificial intelligence can perform assessment and decision-making among many design possibilities, which was previously challenging and expensive. Due to varying constraints of space, window, and neighborhood, designing shading may be a complex undertaking. The suggested framework would enable the user to make choices of these in the early phases of design with acceptable precision and speed. One thousand distinct alternatives were introduced to machine learning algorithms to accomplish this, and the resulting learning model could predict outputs with high accuracy. Due to the various parameters, those having the most significant effect on the outcomes were highlighted. This analysis considered a single office space in Tehran with various variable factors based on review studies; nonetheless, this study did not address many parameters. For instance, the space may be investigated in multiple climates and sizes. Additionally, various models of exterior or interior shadings, such as blinds, may be explored. In addition, the materials used in this study were the recommended standard materials, although the material reflectance value has the potential to be a proper parameter. As for the neighborhood, just one structure was modeled in front of the entrance; this size may be increased. - In this investigation, ASE, sDA, and sDG were employed to assess visual outcomes. Other visual

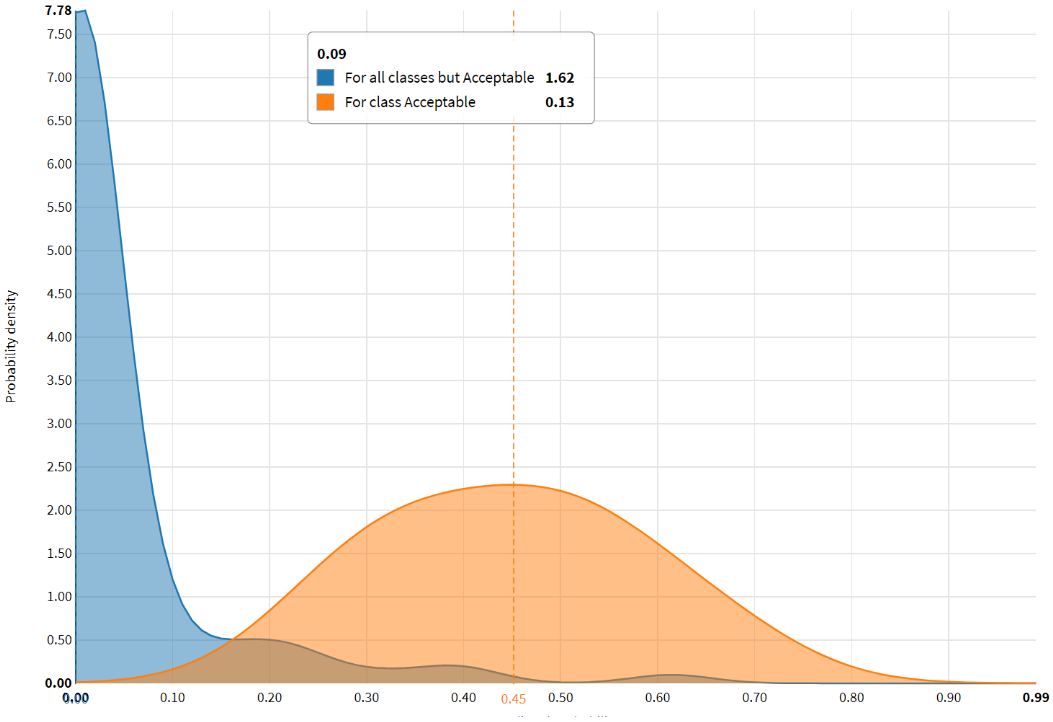

Figure 4.16: the density function of "not Acceptable" and the density function of "Acceptable"

comfort measures, such as DGP, may also be estimated, particularly for more precise glare measurement. The DGP measure may be evaluated for hours of the year with the highest amount of illumination in each direction. Additionally, it would be good to share inside photographs. In addition, Shading design substantially influences energy usage, particularly cooling and lighting energy; therefore, measuring energy-related metrics may assist users in making more informed selections. Other performance comparison indicators, such as the percentage of improvement for sDA or ASE relative to the state without shading, may also facilitate decision-making. - In this work, simulation and optimization techniques were used to generate and develop datasets. There are several methods for validating a machine learning model, and this study used the train and test split technique. In addition, a new database may be constructed outside the assumed range for each parameter, and the estimation accuracy of the learning model can be evaluated. The anticipated parameter range may be expanded if acceptable precision is attained.

4.6.1 Design scenario application

It is crucial to underline that the goal of using machine-learning models in the design process should be to enhance early-stage decision-making(Wilkinson, Hanna, Hesselgren, & Mueller, 2013). In order to demonstrate the potential contribution of approximation techniques to building design, an application aiming at aiding the early design decision-making process will be shown. Consider the next design difficulty: To design an office space module for a new building with static shading, the glazing type, rotation angle, and size of shading devices must be specified. Given these presumptions, we strive to find the ideal lighting and comfort conditions for as much of the office interior as feasible in terms of shading parameters. In other words, we aim to choose a window treatment that will allow sufficient sunshine while reducing glare. This assignment might benefit from a quick evaluation of the sDA, ASE, and sDG values at different office locations and layouts. Despite the fact that estimating precision should not be the primary priority during the conceptual design phase, it is acceptable to sacrifice precision in return for substantial time savings. Thus, the designer is able to adjust other design elements, such as the office's dimensions, glass type, and viewing position, and obtain instantaneous feedback on the new design's circumstances.In an alternative investigation into the impact of different shading design on the annual daylight, designer can decide about the design results. At this stage, attaining the aforementioned outcomes requires the usage of specialist tools, which the designer may not have access to or expertise with. This is due to the fact that the described framework approach has not yet been included into a design environment. A product based on the suggested approach could be incorporated into parametric design environments or as a web-based platform which could replace the conventional simulations.

As an example, The designer can benefit from the pre-processing results in the design. Figure 4.17 shows a What-if scenario in a designed dash board from the prediction results. Here, the designer can see what are the most influential features for ASE. In this case it is x15, the rotation of vertical devices. On the left slider in this figure , one can change any input variable and see what is the result on the ASE prediction.

In the figure 4.18 it can be seen what is the corresponding input to get the min value for ASE, which we aim for.Figure 4.19 shows the possibility of Freezing all variables with the reference value and search for the Minimum ASE Prediction Based on only one Values. The same dashboards for other metrics has been designed and can be found in the appendix.

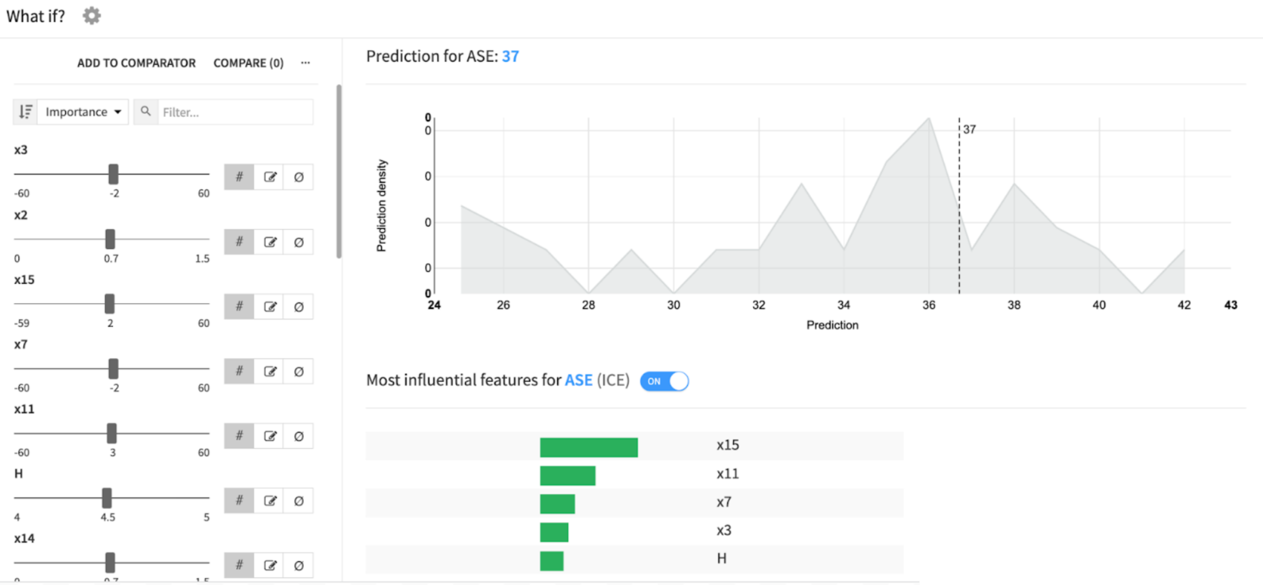

Figure 4.17: What-if Scenarios for ASE Prediction

Figure 4.18: The corresponding input to get the min value for ASE

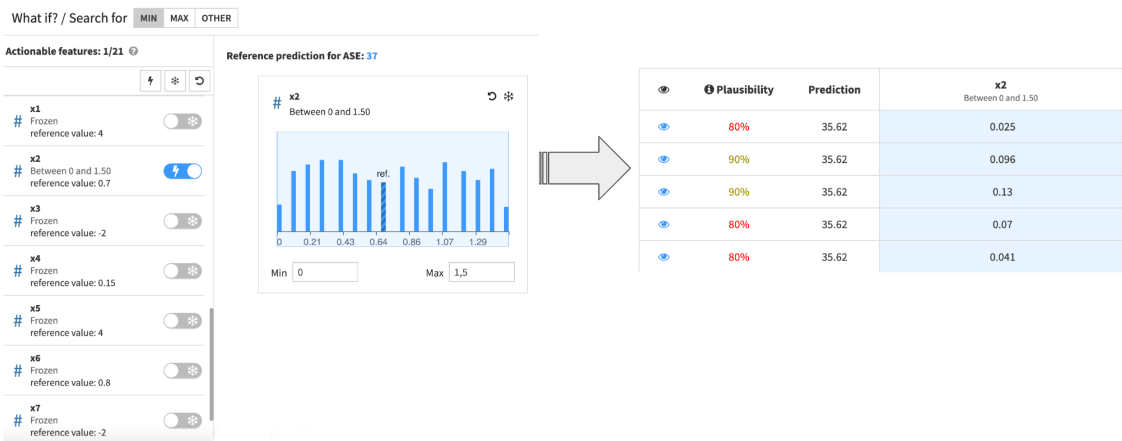

Figure 4.19: Minimum ASE Prediction Based on x2 Values

Chapter 5

Conclusion

This thesis develops a framework based on machine learning models that can be used to predict daylight and visual comfort, considering static solar shadings and evaluating their performance. As shading, space, and openings are integrated, design parameters are related to these elements, while evaluation metrics focus on daylight and glare. Simulated and estimated outputs for two different shading models applied to a single shoebox space. Machine learning results indicated that sDA (Spatial Daylight Autonomy) and ASE (Annual Sunlight Exposure) could be predicted with high accuracy and speed by the optimal estimation model, which was the L2 Regression and random forest model, respectively. The R2 value for the sDG (Spatial Disturbing Glare) was lower than the two other metrics. This procedure could form a tool capable of overcoming the current costly and time-consuming methods and can be used for designing and evaluating the majority of solar shading options for various spaces at the early stages of design.

5.1 Limitations and future development

To provide more precise and trustworthy information, it seems considerable to indicate the limitations present in the study, together with recommendations for future researches.

- The main limitation relates to the nature of the dataset creation process. Designing for daylighting performance is a complicated task mainly based on simulation-derived analyses. It is suggested that future studies develop indoor illuminance predictive models based on accurate field data from multiple buildings with different design configurations.

- The current study considered daylight performance in a shoe-box model with limited space, which is not necessarily a general representation of many built working spaces. Future studies should attempt to establish a prototype model that can be used for daylight studies on the scale of the whole building. Automating the transfer of Machine learning results to existing interfaces for visualization and feedback can facilitate design exploration and user interaction with the results.

- The dataset lacks sufficient interior and exterior parameters. This lack of capabilities prevents the framework from supporting diverse design scenarios. Future research should train ML-based models with a more comprehensive dataset.

- The annual enhanced simplified DGP simulations were conducted utilising the new subprogram developed by ($SolemmaLLC$, 2020).The sDG and its correlation to other features have not been studied thoroughly in the literature. More understanding regarding this would enhance the better prediction results.

Chapter 6

Reflection

This is a reflection on the graduation thesis with the topic: Machine learning-based assessment tool for predicting daylight and visual comfort. Multi-disciplinary optimization has demonstrated its use in assisting with design decision-making. In the design informatics discipline within the studio, it was possible to explore AI in multi-objective and multidisciplinary architectural design optimization.

Research Method and Approach

he result of the project is a machine learning model to predict visual comfort and annual daylight metrics in the early design stages. This is achieved using a research methodology consisting of five phases: The research framework phase, literature review phase, data gathering phase, data processing phase, training the machine learning model phase, and result phase. All the stages play a role in achieving the result. A background study is the first step in the research framework. The problem statement identifies the main issue that needs to be addressed, followed by the research objective to help solve the problem. A research question is formulated with various sub-questions based on this framework to define the research in steps. Literature Review provides all necessary information about the topic required to proceed further in the research. The categories into which these topics were divided are

- The state of the art of machine learning models for personal comfort
- Understanding the fundamentals of light and visual comfort
- Understanding the principles of data gathering for daylight metrics.

In the first stage of this research, the aim was to predict the visual preference of occupants based on different parameters, which included occupants subjective criteria, Occupants' feedback about their visual/privacy comfort (through questionnaires) corresponding to their location. After gathering data from the questionnaire, it turns out that the daylight and shading design criteria were the most important for the occupants. The location played a role mainly in the case that the location had any direct sunlight or view outside. As the research goal was visual comfort prediction using machine learning methods, and the dataset plays the most critical role in the machine learning models, collecting thousands of data using only questionnaires was not possible for this thesis. As a result, based on the conclusions from 50 responses gathered in two weeks in the Tu Delft library, the main question was changed to objective criteria instead of subjective criteria to predict visual comfort.

A shoebox model was first constructed, and then two conventional solar shading models, each with their own set of variables, were applied to the area. Three main daylight metrics were chosen, such as sDA(spatial daylight autonomy), ASE(Annual sunlight exposure), and sDG(spatial disturbing glare) was simulated by ClimateStudio, which is an advanced daylighting simulation tool. The data set, which included multiple shading designs for office spaces and a database with 1000 possibilities, was used as training data for a supervised learning method. The data have been pre-proceed, and the machine learning algorithm based on the data type has been chosen for daylight features. The machine learning model was trained with simulation data to predict occupants' visual comfort with annual daylight metrics. In the end, the model's accuracy was tested to predict the visual preference of a group of occupants.

Project Relevancy

Daylighting is a major theoretical inquiry since Le Corbusier emphasized the topic's relevance as one of three critical requirements throughout the design of projects. The most sophisticated study on thermal comfort and microclimate demonstrates its effect on occupants' comfort conditions following sustainable architectural design principles. The most recent results in the physiology study a favorable long-term influence of daylight on individual well-being as it regulates the circadian rhythm. The significance of implementing optimal daylighting practices in buildings has increased interest in computational daylight simulations, which have become the most accessible method for evaluating interior lighting conditions. However, during the master's thesis, I discovered that this procedure is time-consuming and costly. The study's primary objective is to investigate AI potentials to lower the time required for computational calculations and 3D model preparation. This thesis addresses the possibility of substituting a simulation engine with an algorithm for machine learning. As the literature review is built upon studies from other disciplines, such as computer science, its interpretation through Building Technology relates to contemporary discussions of AI and architecture. This means the project uses knowledge formulated from external disciplines to an alternative design strategy. Therefore the project is relevant in academic and general discussions.

Difficulty in the process and final phase

A lot of background knowledge in computer science was required for this topic, so the research and learning phase was quite long. Another challenge was the data gathering. Machine learning models require a massive amount of data to be most optimized. Gathering that amount of data with an average laptop is challenging, so a smaller dataset was gathered to train the models. In the final part of the graduation period, the spatial disturbing glare(sDG) needs to be investigated more to understand its correlation with other inputs used in the thesis.

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Appendix

A visualization of histogram on visual comfort can be seen here.

Unacceptable	90%	452
Acceptable	7%	34
Neutral	3%	13
Preferred	0%	1

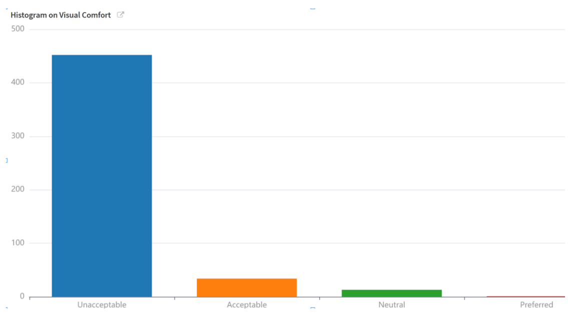

Figure 1: A visualization of histogram on visual comfort

What-if scenario dashboards for sDA and sDG can be seen bellow.
Samples of generated data from grasshopper and climatestudio.

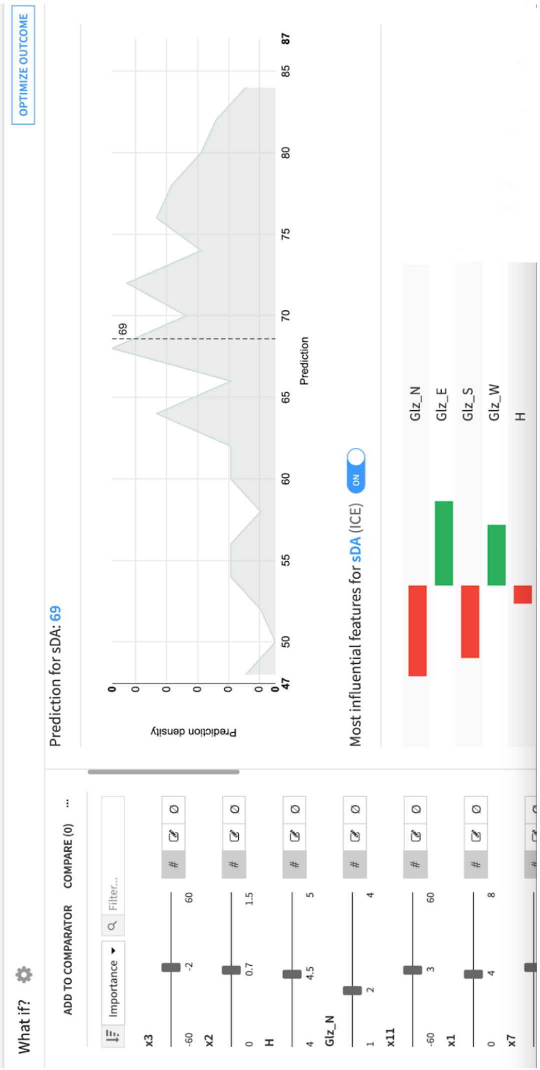

Figure 2: What-if scenario for sDA

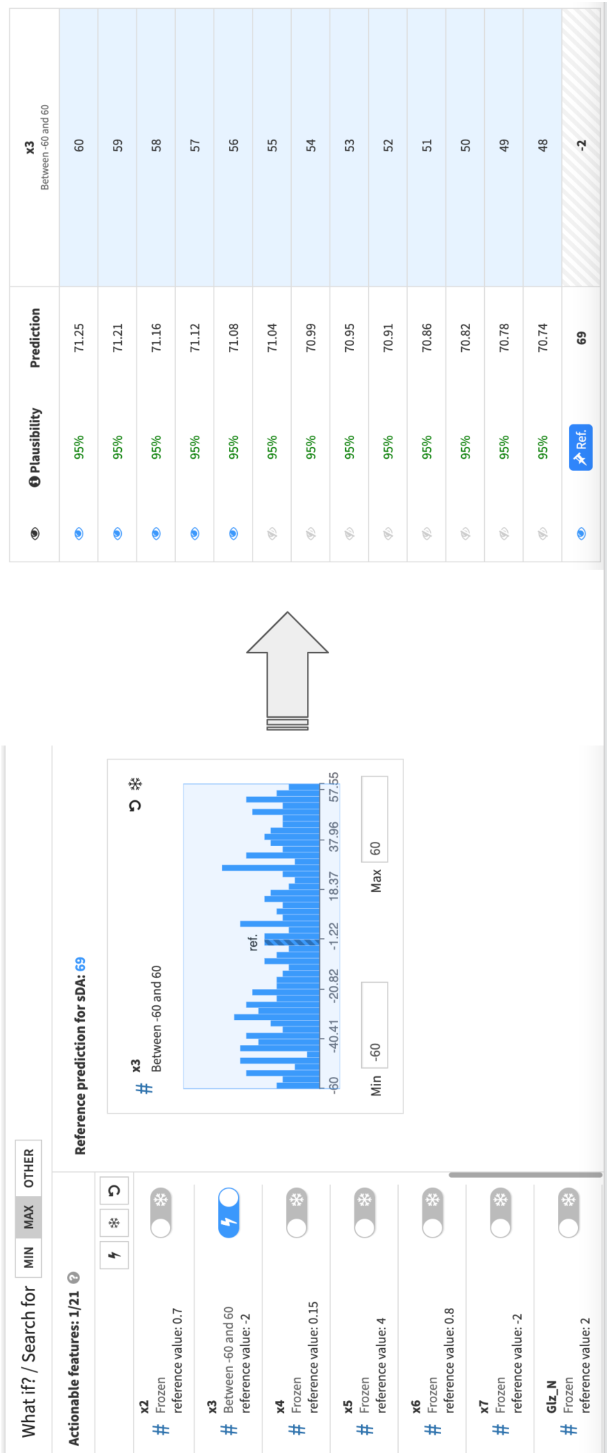

Figure 3: What-if scenario for sDA

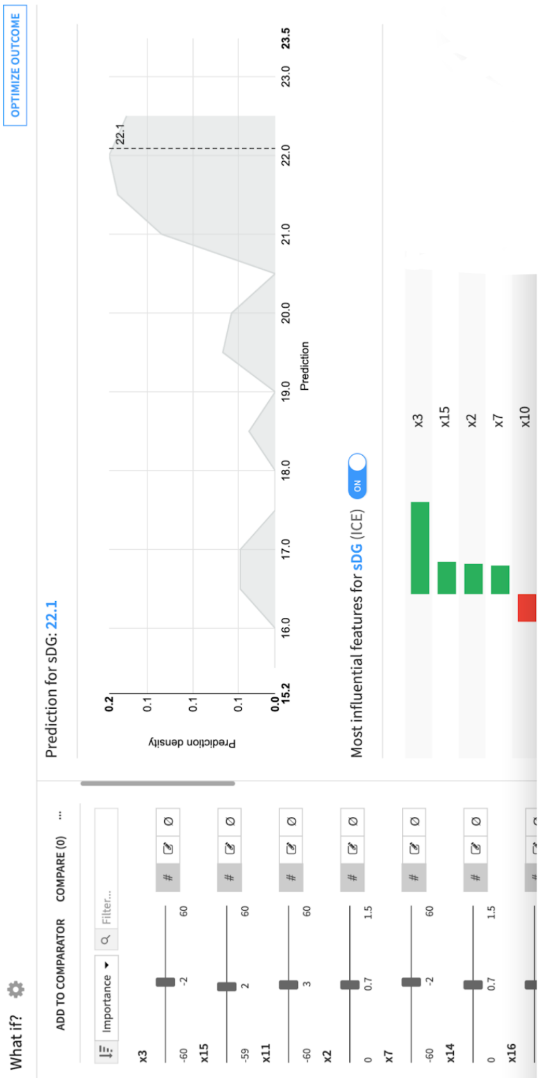

Figure 4: What-if Scenarios for Maximum sDA Prediction Based on x3 Values

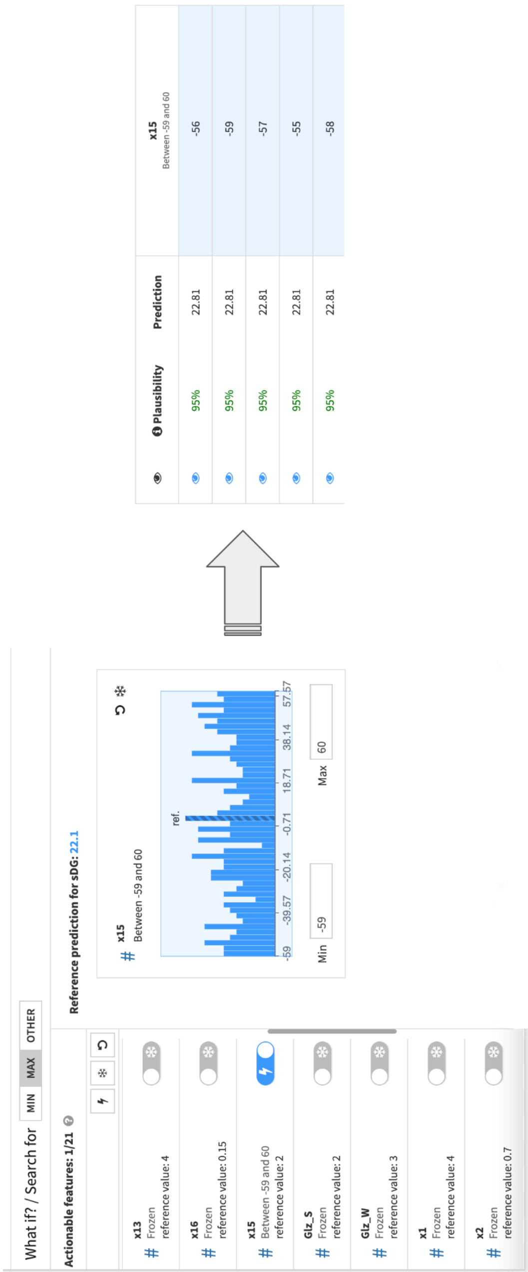

Figure 5: What-if Scenarios for Maximum sDG Prediction Based on x15 Values

H	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
4,6	5	0,9	12	0,24	4	0,3	7	0,15	2	0,9	-37	0,07	5	1,4	21	0,19	3	3	2	3	78	35,9	20,3
4,8	7	1,2	39	0,21	3	0,6	-21	0,19	3	0,5	-13	0,2	5	1,3	9	0,06	3	2	2	3	79,5	41,5	23,1
4,5	4	0,8	2	0,09	2	1,1	-26	0,10	6	0,4	32	0,21	5	1	10	0,17	3	2	3	3	74,2	38,9	21,4
4,8	7	1,2	38	0,09	1	1,2	-40	0,21	6	0,1	37	0,22	7	0,8	47	0,18	3	2	3	4	81,7	35,2	21,3
4,3	2	0,4	-27	0,16	8	1	59	0,06	6	1,1	23	0,23	0	0,5	-57	0,07	2	4	3	1	62,7	35	23,8
4,7	6	1,1	25	0,09	2	0,2	-34	0,21	1	0,7	-44	0,18	3	0,4	-10	0,2	3	2	1	2	69,5	35,9	24
4,8	7	1,2	40	0,23	2	1	-34	0,14	5	1,3	17	0,18	4	1,3	4	0,07	3	2	3	3	81,5	41	26,7
4,3	3	0,5	-19	0,07	1	1,4	-38	0,13	7	1,2	50	0,09	4	1,4	1	0,2	2	2	4	3	69	37,4	21,1
4,9	7	1,4	51	0,06	3	1,4	-12	0,22	7	0,4	51	0,13	1	1,4	-39	0,22	4	2	4	2	83,2	42,5	19,7
4,3	2	0,5	-24	0,08	5	1,4	13	0,17	7	0,8	52	0,07	4	1,3	-2	0,17	2	3	4	2	68,1	30,4	19,7
4,8	6	1,1	31	0,06	7	1,2	45	0,18	7	0	40	0,11	5	0,3	22	0,09	3	4	3	3	85,2	41,9	25,9
4,7	5	1	22	0,24	5	0,9	15	0,06	5	1,5	16	0,12	7	0,4	38	0,15	3	3	3	3	86,7	40,9	21,2
4	0	0	-57	0,20	6	0,6	37	0,19	3	0,8	-10	0,06	8	1,4	58	0,16	1	3	2	4	48,6	10,3	13,9
4,8	6	1,1	30	0,13	5	0,6	20	0,11	3	1,5	-11	0,24	6	1	28	0,23	3	3	2	3	79,6	42,5	21,4
4,1	1	0,2	-43	0,11	8	1,4	58	0,10	8	0,6	54	0,2	0	0,3	-59	0,19	1	4	4	1	54	34	23,6
4,6	4	0,8	7	0,16	8	1,4	60	0,21	7	0,8	52	0,05	2	0,7	-24	0,07	3	4	4	2	75	33,1	23,8
4,3	2	0,4	-29	0,20	3	1,5	-12	0,10	8	0,6	58	0,19	7	0,1	50	0,11	2	2	4	4	69,6	32,7	19,6
5	8	1,5	57	0,08	2	0,8	-35	0,21	4	1,2	6	0,12	0	0,2	-53	0,07	4	2	3	1	78,8	39,5	24,8
5	8	1,5	58	0,07	3	0,4	-22	0,06	2	0,6	-25	0,22	3	0,3	-18	0,06	4	2	2	2	82,4	45	22,4
4,7	5	1	22	0,05	5	1,3	16	0,14	7	0,4	45	0,21	5	0,7	14	0,15	3	3	4	3	87,1	41,5	23,8
4,4	4	0,7	-6	0,12	5	0	22	0,07	0	1	-58	0,19	1	0,9	-44	0,18	2	3	1	1	58,7	31,3	23
4,7	5	1	19	0,18	3	0,9	-11	0,20	5	1,2	12	0,18	7	1,3	45	0,21	3	2	3	4	80,1	41,1	19,7
5	8	1,5	57	0,24	3	0,5	-20	0,23	3	0,2	-21	0,15	4	0,2	6	0,21	4	2	2	3	85	45	23,1
4,5	4	0,7	-2	0,21	2	0,9	-26	0,15	5	1,2	10	0,13	7	0,3	42	0,13	2	2	3	4	72,8	37,7	21,4
4,4	4	0,7	-7	0,07	2	0,1	-27	0,10	1	0,7	-51	0,13	3	0,1	-14	0,07	2	2	1	2	59,5	31,3	19,2
4,2	2	0,3	-35	0,09	3	0,7	-13	0,10	4	0,3	-4	0,1	5	0,7	12	0,15	2	2	2	3	63,4	31,1	25,3
4,8	6	1,1	31	0,11	3	0,7	-14	0,20	4	1,1	-3	0,13	5	1,2	9	0,22	3	2	2	3	78,4	42,5	20,5
4	0	0	-60	0,18	0	1,1	-53	0,09	6	0,5	25	0,11	7	0,3	42	0,12	1	1	3	4	55,9	28	18,3
4,9	7	1,4	49	0,20	8	1	58	0,15	5	1,2	22	0,2	7	0,4	47	0,21	4	4	3	4	82,5	35,2	24,1
4,4	3	0,6	-16	0,21	5	1,1	13	0,12	6	1,1	28	0,22	4	0,2	-6	0,06	2	3	3	2	71,2	34,9	19,4
4,1	1	0,2	-43	0,12	4	0,9	-1	0,09	5	0,4	12	0,05	3	0,5	-12	0,05	1	2	3	2	56,6	35,5	24,4

H	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
4,4	3	0,6	-9	0,22	1	0,8	-45	0,15	4	0,2	5	0,08	7	1	38	0,18	2	1	3	3	64,6	25,9	16,4
4,7	6	1,1	28	0,18	3	0,5	-15	0,09	3	0,3	-21	0,18	7	0,2	46	0,16	3	2	2	4	78,1	40	23
4,3	2	0,4	-29	0,18	1	0,1	-41	0,19	1	1,2	-52	0,14	4	1,1	0	0,07	2	1	1	3	55,6	26,9	19,2
4,3	2	0,4	-26	0,14	4	1,1	2	0,16	6	1,1	30	0,21	4	0,1	-6	0,16	2	3	3	2	69,9	34,6	21,9
4,7	6	1	23	0,05	3	0,2	-22	0,07	1	0,6	-43	0,07	7	0,2	38	0,1	3	2	1	3	71,9	30,7	25
4,7	6	1,1	28	0,24	4	0,5	2	0,14	3	0,1	-19	0,24	4	0,9	6	0,06	3	3	2	3	85,9	43,7	22,2
4,4	3	0,5	-17	0,10	4	1,2	0	0,16	6	0,5	37	0,05	1	1,1	-39	0,12	2	2	3	2	63,2	25,4	15,3
4,2	2	0,3	-37	0,20	7	0,4	46	0,10	2	0,3	-24	0,18	6	0,6	30	0,09	2	4	2	3	67,9	35,5	22,6
4,7	6	1	24	0,24	1	0,4	-49	0,16	2	0,1	-25	0,07	3	1,4	-22	0,18	3	1	2	2	68,5	36,5	21,1
4,1	1	0,1	-50	0,16	4	1,4	1	0,21	8	1,3	53	0,2	4	0,4	-7	0,17	1	3	4	2	60,6	29,8	16,3
5	8	1,5	58	0,12	3	1,1	-19	0,09	6	0,7	27	0,16	3	0,1	-16	0,2	4	2	3	2	84,4	44,4	24,8
4,4	4	0,7	-7	0,24	6	0,2	27	0,21	1	0,9	-45	0,14	7	0,4	42	0,06	2	3	1	4	66,3	27,1	15,1
4,2	2	0,3	-34	0,12	6	1,1	31	0,18	6	0,2	31	0,21	3	1,5	-15	0,24	2	3	3	2	62,9	21,2	14,6
4,6	5	0,9	13	0,14	7	0,8	41	0,07	4	0,1	5	0,16	1	1	-48	0,18	3	4	3	1	77,6	38,3	23,6
4,6	5	1	18	0,11	1	0,6	-48	0,18	3	0,9	-10	0,2	4	1	7	0,09	3	1	2	3	70	36,8	19,8
4,2	1	0,3	-40	0,21	1	1,3	-48	0,16	7	1,3	44	0,21	4	0,1	-2	0,19	2	1	4	2	59,4	28,9	14,6
4,8	6	1,1	31	0,20	4	0,5	-7	0,07	3	1	-17	0,19	4	1,2	3	0,14	3	2	2	3	80,4	42,5	21,9
4,4	4	0,7	-6	0,20	8	1,2	60	0,16	6	1,3	33	0,08	4	1,1	-4	0,05	2	4	3	2	64,6	28,2	17
4,3	2	0,4	-29	0,12	3	1,4	-8	0,14	7	0,8	52	0,18	7	0,2	48	0,14	2	2	4	4	70,7	34	23,6
4,2	1	0,3	-39	0,05	6	1,2	33	0,05	7	0,4	39	0,2	7	1,4	51	0,17	2	3	3	4	59,8	22,9	19,4
4,6	5	0,9	12	0,06	4	0,4	-6	0,24	2	0,6	-29	0,08	6	0,8	31	0,06	3	2	2	3	68,6	28,8	14,1
4,6	5	0,9	15	0,22	0	1,4	-53	0,19	8	1,1	53	0,13	4	1	-2	0,21	3	1	4	2	66,2	25,3	18,8
4,9	7	1,3	44	0,07	6	0,4	25	0,20	2	0,5	-31	0,2	4	0,7	-4	0,22	4	3	2	2	84,2	41	22
4	0	0	-58	0,21	0	0,4	-60	0,20	2	0,1	-28	0,14	6	0	31	0,11	1	1	2	3	51,1	26,1	14,6
5	8	1,5	59	0,16	2	1,5	-33	0,08	8	1	59	0,1	3	1,3	-8	0,21	4	2	4	2	79,9	44,4	19,7
4,9	8	1,4	54	0,21	8	0	58	0,20	0	0,2	-59	0,12	1	0,6	-46	0,08	4	4	1	1	66,5	34	29
4,2	2	0,4	-31	0,19	5	1,5	18	0,13	8	0,9	58	0,23	3	0	-14	0,15	2	3	4	2	64,7	22,4	17
4,4	3	0,6	-10	0,16	3	1,5	-9	0,10	8	0,3	57	0,11	3	0,9	-17	0,21	2	2	4	2	70,5	38,3	26
4,8	6	1,2	34	0,23	1	0,4	-47	0,05	2	0,7	-29	0,09	3	0	-21	0,05	3	1	2	2	68,1	35,4	19,4
4,6	5	0,9	13	0,21	8	0,1	55	0,09	1	0,7	-49	0,1	3	0,5	-8	0,24	3	4	1	2	73,8	31	26,8
5	8	1,5	57	0,22	0	0,3	-59	0,07	2	1,4	-37	0,23	6	1,2	27	0,21	4	1	2	3	74,9	43,1	19,3
4,6	5	1	17	0,22	2	0,5	-31	0,06	3	0,8	-20	0,19	1	0,7	-45	0,22	3	2	2	1	67,9	36,2	23,5

H	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
4	0	0	-60	0,24	3	0,2	-21	0,08	1	0,5	-44	0,07	1	0	-40	0,14	1	2	1	1	41,9	23,7	16,5
4,2	2	0,3	-34	0,14	6	1,1	29	0,13	6	0,7	31	0,17	6	0,3	27	0,07	2	3	3	3	67,7	35,4	19,3
4,8	6	1,2	33	0,18	4	0,2	-2	0,17	1	0,9	-47	0,23	2	0,3	-34	0,07	3	2	1	2	69,9	38,1	19,8
4,6	5	0,9	9	0,08	2	0,5	-29	0,10	3	1,1	-17	0,07	6	1,1	30	0,12	3	2	2	3	70,8	26,3	18,3
4,9	7	1,3	44	0,10	1	1,3	-49	0,07	7	1,2	46	0,17	7	1,1	51	0,07	4	1	4	4	75,3	37,1	19,6
4,7	6	1,1	29	0,18	3	0	-20	0,21	0	0,6	-59	0,21	4	1,1	-7	0,07	3	2	1	2	67,3	35,6	24,1
4	0	0	-60	0,13	4	0,8	-6	0,08	4	0,4	0	0,21	3	0,9	-13	0,13	1	2	3	2	55,3	26,7	14,8
4,4	3	0,6	-10	0,20	7	0,2	44	0,15	1	0,2	-42	0,1	7	1,2	49	0,07	2	4	1	4	64,2	24,4	19,8
4,8	6	1,2	36	0,06	2	0,9	-34	0,12	5	1,4	9	0,18	3	0,9	-8	0,08	3	2	3	2	80,4	41,1	24,9
4,3	2	0,4	-24	0,20	4	0,1	1	0,14	1	0,4	-48	0,19	1	1	-42	0,1	2	3	1	1	57,3	29,1	15,3
4,3	2	0,4	-28	0,12	8	0,6	59	0,18	3	0,8	-15	0,11	8	0,6	55	0,14	2	4	2	4	67,8	25,6	15
4	0	0,1	-55	0,15	6	0,8	28	0,14	4	0,3	1	0,2	2	0	-33	0,21	1	3	3	2	58,7	28	16,1
4,2	2	0,3	-33	0,15	4	1,4	-6	0,11	8	0,7	54	0,11	3	0,8	-18	0,24	2	2	4	2	59,2	22,8	14,4
4,9	7	1,3	44	0,17	1	1,1	-51	0,19	6	0,2	29	0,23	1	0,5	-39	0,12	4	1	3	2	79,9	38,2	19,6
4,5	4	0,8	3	0,07	1	0,3	-40	0,17	2	1,1	-32	0,21	3	1,1	-9	0,13	3	1	2	2	63,1	28,2	18,8
5	8	1,4	56	0,12	0	0,9	-57	0,11	5	1,3	8	0,24	1	0,4	-44	0,07	4	1	3	1	70,7	37,1	22,9
4,4	3	0,6	-13	0,14	2	1	-31	0,24	5	1,2	20	0,23	2	1,3	-37	0,22	2	2	3	2	67,5	37,7	25,9
4,4	3	0,5	-17	0,18	5	1,1	22	0,09	6	1,4	30	0,22	4	1,1	-1	0,2	2	3	3	2	69,7	31,2	21,2
4,6	5	0,9	15	0,24	1	1,3	-39	0,21	7	0,1	44	0,09	1	0,5	-39	0,21	3	2	4	2	81,4	38,3	20,1
4,5	4	0,8	6	0,05	1	0,9	-39	0,07	5	0,9	10	0,09	7	0,2	40	0,23	3	2	3	4	79,4	36,8	22,7
4,9	7	1,4	52	0,09	4	0,2	0	0,12	1	1,4	-44	0,22	7	0,4	43	0,21	4	3	1	4	81	37,7	21,9
4,6	4	0,8	6	0,05	7	1,3	48	0,07	7	0,7	47	0,16	1	0,1	-52	0,07	3	4	4	1	72,6	33,1	19,4
4,3	2	0,4	-29	0,19	4	0,1	-6	0,23	1	1,5	-50	0,19	3	1	-21	0,07	2	2	1	2	56,8	28,2	19,2
4,3	3	0,5	-21	0,22	8	0,8	59	0,19	4	1,1	3	0,21	1	1,2	-39	0,16	2	4	3	2	69,8	34,9	22,9
4,2	1	0,3	-38	0,16	4	0,2	-2	0,19	1	1,1	-44	0,22	2	0	-23	0,07	2	2	1	2	56	25,5	19,7
4,7	5	1	18	0,15	4	1,5	-1	0,18	8	0,1	57	0,15	7	1,4	42	0,17	3	2	4	4	83,5	38,7	23,9
4,9	7	1,4	52	0,21	3	1,4	-12	0,16	8	0,4	55	0,21	2	0,1	-36	0,1	4	2	4	2	85,3	44,4	24,9
4,5	4	0,7	-1	0,10	8	1	56	0,19	5	0,7	18	0,21	1	1,1	-46	0,22	2	4	3	1	68,2	37,1	21,6
5	8	1,5	57	0,23	7	1,5	50	0,09	8	1,3	59	0,11	8	0,9	56	0,15	4	4	4	4	75,4	36,5	19,7
4,2	2	0,4	-32	0,21	7	0,8	52	0,08	4	0,2	5	0,13	7	0,9	50	0,06	2	4	3	4	68,6	26,9	16,8
4,3	2	0,4	-30	0,08	8	0,9	57	0,06	5	0,6	12	0,16	8	0,5	55	0,1	2	4	3	4	70,5	32,3	19,6
4,9	8	1,4	54	0,18	7	0,8	39	0,21	4	0,1	2	0,06	2	0,2	-35	0,23	4	3	3	2	84,3	44,4	23,9

H	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
4,5	4	0,7	-2	0,16	8	0,4	57	0,24	2	0,6	-30	0,2	5	0,7	18	0,05	2	4	2	3	73,8	38,9	21
4,5	4	0,8	6	0,17	3	0,1	-20	0,12	1	0,1	-50	0,2	1	1,1	-46	0,23	3	2	1	1	58,7	31,3	19,8
4,2	2	0,3	-32	0,17	2	1	-36	0,18	5	0,1	18	0,11	1	0,2	-52	0,24	2	2	3	1	58,7	30,1	20,1
4,9	7	1,4	49	0,24	2	0,1	-23	0,08	1	0,1	-51	0,09	3	1,4	-17	0,12	4	2	1	2	73	38,9	23,5
4,5	4	0,8	1	0,21	3	1,1	-16	0,14	6	0,6	27	0,17	0	0,2	-53	0,22	3	2	3	1	67,6	38,3	22,1
4,8	6	1,2	35	0,22	7	0,9	48	0,13	5	0,9	16	0,07	7	1	42	0,11	3	4	3	4	83,9	39	21,2
4,4	3	0,6	-10	0,16	1	0,3	-52	0,10	2	0	-33	0,1	6	1,4	32	0,15	2	1	2	3	60,2	23,2	16
5	8	1,5	59	0,15	4	0,1	-7	0,16	0	0	-55	0,16	6	0,4	24	0,22	4	2	1	3	78,7	41,3	19,7
4,1	0	0,1	-53	0,18	6	0,4	37	0,10	2	0,8	-28	0,1	6	0,2	33	0,13	1	3	2	3	54,9	15,2	12,6
4,4	3	0,6	-12	0,17	3	0,1	-19	0,15	1	0	-48	0,06	3	1	-20	0,19	2	2	1	2	59,1	31	19,9
4,7	6	1,1	28	0,23	1	0,2	-46	0,07	1	0,6	-40	0,17	4	0,7	6	0,2	3	1	1	3	67,1	34,4	22,9
4,8	7	1,2	40	0,13	1	0,3	-43	0,19	2	0,9	-33	0,14	4	1,5	7	0,17	3	1	2	3	73,9	39,3	19,9
4,4	3	0,7	-8	0,09	7	0,2	39	0,13	1	0,3	-41	0,05	8	1,2	59	0,18	2	3	1	4	60,4	21,6	17,3
5	8	1,5	57	0,20	7	0,5	47	0,12	3	0,8	-19	0,17	4	0,3	-3	0,17	4	4	2	2	81,1	42,5	19,9
4,3	2	0,4	-28	0,16	3	0,2	-15	0,05	1	0	-40	0,14	0	1	-53	0,23	2	2	1	1	53,1	27,6	15,9
4	0	0	-58	0,07	6	1,3	36	0,15	7	0,9	47	0,18	7	1,3	50	0,12	1	3	4	4	48	10,9	13
4,2	1	0,3	-39	0,11	4	0,6	-3	0,15	3	0	-9	0,19	1	0,4	-51	0,21	2	2	2	1	54,5	32,9	23,3
4	0	0	-57	0,11	4	0,2	-2	0,15	1	1,2	-45	0,05	1	0,8	-47	0,08	1	2	1	1	41,9	23,7	16,6
4,4	3	0,6	-15	0,12	6	1	23	0,15	5	1,1	17	0,09	7	0	41	0,16	2	3	3	4	77,5	42,3	26,3
4,1	1	0,1	-49	0,11	6	0,2	30	0,24	1	1,1	-43	0,05	7	0,1	42	0,15	1	3	1	4	54,8	28	17,9
4,5	4	0,7	-3	0,07	5	1	13	0,24	5	0,6	16	0,08	3	1,3	-9	0,17	2	3	3	2	76,2	38,3	20,5
4,3	2	0,4	-27	0,23	6	1,2	27	0,11	6	0,9	34	0,22	7	1,5	38	0,1	2	3	3	3	63,4	20	16,6
4,9	7	1,4	51	0,15	4	0,1	-2	0,11	0	1,3	-54	0,1	2	0,1	-26	0,22	4	2	1	2	72,8	37,7	24,8
4,2	1	0,2	-41	0,10	1	0,3	-51	0,13	2	0,7	-37	0,18	4	0,1	6	0,19	1	1	2	3	56,6	29,1	16,1
4,6	5	1	17	0,12	4	1,5	-3	0,20	8	0,8	58	0,19	7	1,5	51	0,21	3	2	4	4	70	29,6	16,2
4,9	7	1,4	50	0,16	1	0,3	-48	0,18	2	1	-34	0,09	6	1	32	0,18	4	1	2	3	72,6	39,5	21,4
4,2	1	0,2	-42	0,13	3	0	-10	0,08	0	1	-56	0,18	1	1,4	-44	0,21	1	2	1	1	43	28	14,9
4,8	6	1,1	31	0,22	6	0,7	29	0,23	4	1,1	-2	0,08	2	1,4	-23	0,19	3	3	2	2	76,4	41,2	19,3
4,5	4	0,8	5	0,15	2	0,5	-25	0,22	2	0,8	-23	0,24	2	0,5	-25	0,17	3	2	2	2	70,3	34,3	19,9
4	0	0,1	-55	0,12	6	0,3	24	0,15	2	0,9	-37	0,16	5	0,3	20	0,06	1	3	2	3	57,8	26,7	18,9
4,9	7	1,4	52	0,20	1	0,5	-44	0,23	3	0,9	-18	0,24	5	1,2	21	0,24	4	1	2	3	75,3	38,9	19,6
4,9	7	1,4	48	0,13	6	0,6	24	0,07	3	1	-15	0,07	4	0,7	4	0,1	4	3	2	3	84,8	45,6	25,3

H	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
4,1	1	0,2	-48	0,23	1	1,4	-41	0,10	8	0,3	54	0,15	0	0,6	-56	0,24	1	1	4	1	47,8	29,2	19,9
4,1	1	0,2	-45	0,17	7	1	49	0,18	5	1,4	18	0,24	2	1	-32	0,12	1	4	3	2	56,2	29,7	16,4
4,6	4	0,8	7	0,22	4	0	-7	0,07	0	1,4	-56	0,14	6	1	23	0,07	3	2	1	3	70,2	34,3	26,4
4,1	1	0,1	-49	0,22	3	1,2	-19	0,20	6	1,3	37	0,12	5	1,2	12	0,06	1	2	3	3	54,7	24,9	16,4
4,1	1	0,2	-45	0,18	2	1	-33	0,18	5	0,8	21	0,23	5	0,9	19	0,09	1	2	3	3	57,2	32,6	23,9
4,6	5	0,9	12	0,06	0	0,4	-58	0,06	2	1	-27	0,18	6	1,3	35	0,24	3	1	2	3	65,7	23,8	17,3
4,9	7	1,3	47	0,23	4	1,2	-1	0,10	6	1	36	0,15	6	1,5	24	0,1	4	2	3	3	78,6	39,5	23,3
4,2	2	0,3	-33	0,24	5	1,1	12	0,11	6	0,6	28	0,13	1	0,3	-44	0,11	2	3	3	1	62,1	31,1	24,6
4,1	1	0,1	-50	0,05	5	1,4	16	0,20	7	0,1	52	0,1	3	1,2	-11	0,18	1	3	4	2	64,7	31,6	19,9
4,6	4	0,8	6	0,22	5	0,6	8	0,19	3	1	-11	0,23	4	0,2	-6	0,17	3	3	2	2	75,8	34,3	28,6
4,6	5	0,9	9	0,17	6	1,1	34	0,07	6	0,3	27	0,12	8	0,8	57	0,13	3	3	3	4	74,7	24,1	18,6
4,8	6	1,2	33	0,15	1	0	-43	0,09	0	0,4	-58	0,11	2	0,4	-37	0,11	3	1	1	2	65,4	32,3	28,6
4,3	2	0,4	-28	0,11	7	0,3	38	0,15	2	1	-36	0,21	5	1,4	11	0,05	2	3	2	3	68,1	33,8	23,5
4,9	7	1,4	51	0,06	1	1,5	-47	0,24	8	0,2	57	0,2	7	0,6	51	0,09	4	1	4	4	86,3	38,3	21,1
4,2	2	0,3	-36	0,14	6	0,9	33	0,24	5	1,1	13	0,14	2	0,2	-24	0,16	2	3	3	2	67,4	33,6	20,7
4,2	1	0,2	-42	0,12	4	0,3	7	0,07	2	0,9	-35	0,09	5	0,4	13	0,16	1	3	2	3	61,6	35,1	29,3
4,7	6	1,1	26	0,18	8	1,2	55	0,20	6	0,1	35	0,23	2	1,3	-32	0,22	3	4	3	2	78,1	40,3	23,9
4,3	2	0,4	-25	0,15	3	0,6	-11	0,24	3	0,6	-12	0,1	8	0,8	58	0,12	2	2	2	4	63,1	27,1	14,5
4,8	7	1,3	41	0,07	0	0,9	-57	0,09	5	1	15	0,14	6	0,8	26	0,23	4	1	3	3	79,9	39,3	23,5
4,5	4	0,8	2	0,24	7	0,4	40	0,14	2	0,9	-28	0,07	2	1,4	-33	0,2	3	4	2	2	76	34	21,5
4,7	5	1	20	0,21	6	1,2	33	0,14	7	0,3	38	0,11	6	0,3	25	0,07	3	3	3	3	82,4	34,3	24,6
4,1	1	0,2	-44	0,15	7	0,9	47	0,23	5	0,1	12	0,18	0	0,4	-59	0,18	1	4	3	1	55,6	35,5	22,3
4,7	6	1,1	28	0,16	6	1,1	37	0,17	6	0,8	26	0,05	6	0,7	32	0,18	3	3	3	3	80,4	37,5	19
4,1	1	0,2	-43	0,24	7	0,1	45	0,07	0	0,7	-53	0,21	6	0,9	32	0,07	1	4	1	3	50,1	26	14,2
4,7	5	1	21	0,06	8	0,1	57	0,24	1	1,4	-48	0,24	1	0,1	-42	0,19	3	4	1	1	70,8	32,5	25,8
4,8	6	1,1	30	0,16	4	0,4	0	0,14	2	0,8	-32	0,15	8	0,2	54	0,19	3	2	2	4	81,6	43,6	23,4
4,3	2	0,5	-23	0,08	3	1,3	-9	0,24	7	1,5	47	0,06	5	0,8	8	0,17	2	2	4	3	66,7	34,7	22,3
4,5	4	0,8	6	0,06	4	1,1	-6	0,12	6	0,1	31	0,05	1	1,1	-46	0,09	3	2	3	1	67,4	33,7	26,1
4,6	5	0,9	14	0,10	5	0,3	21	0,20	2	0,6	-36	0,24	3	1,1	-14	0,08	3	3	2	2	75,5	35,9	22,3
4,7	6	1,1	27	0,08	6	1,3	27	0,18	7	0,7	43	0,2	3	0,7	-18	0,22	3	3	4	2	82,7	40,9	19,9
4,6	4	0,8	7	0,17	8	1	57	0,12	5	0,2	21	0,09	4	0,9	-6	0,13	3	4	3	2	77	37,4	22,7
4,5	4	0,7	-2	0,09	4	0,5	-4	0,05	3	0,3	-18	0,18	2	1,2	-24	0,2	2	2	2	2	66,2	36,4	22,5

H	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
5	8	1,5	59	0,14	1	0,2	-50	0,14	1	1,3	-47	0,11	5	0,1	22	0,21	4	1	1	3	73,7	38,3	22,5
4,4	3	0,6	-15	0,23	5	0,1	22	0,18	0	1,2	-54	0,24	0	0,5	-56	0,17	2	3	1	1	59,4	30,7	25,4
4,5	4	0,8	0	0,18	6	0,9	23	0,21	5	0,2	13	0,17	7	1,4	43	0,15	3	3	3	4	75	32,2	24,9
4,1	1	0,2	-43	0,19	7	0,6	41	0,05	3	1,3	-16	0,14	1	0,9	-49	0,23	1	4	2	1	49,6	30,7	20,7
4,6	4	0,8	7	0,14	7	0,9	43	0,15	5	0,1	12	0,09	0	0,3	-55	0,23	3	4	3	1	77,5	38,6	26,3
4,9	8	1,4	53	0,15	2	1	-23	0,16	5	0,5	22	0,22	1	0,7	-45	0,23	4	2	3	1	75,3	39,5	24,8
4,2	2	0,3	-37	0,13	1	1,3	-49	0,16	7	0	45	0,23	5	1	18	0,24	2	1	4	3	66,5	30,9	24,8
4,9	7	1,3	48	0,06	3	0,9	-19	0,12	5	0,8	11	0,21	6	0,6	30	0,05	4	2	3	3	86,5	45,6	20,5
4,3	3	0,5	-20	0,08	8	0,9	57	0,13	5	1,2	8	0,16	1	1,1	-45	0,05	2	4	3	1	61,9	35,5	26,7
4,5	4	0,7	-1	0,21	4	0,9	6	0,24	5	1	15	0,06	3	0,9	-15	0,2	2	3	3	2	73,8	37,7	21,1
4,5	4	0,7	-3	0,18	8	0,4	56	0,23	2	0,7	-29	0,07	6	0,8	34	0,21	2	4	2	3	70,2	35,5	23,9
4,3	2	0,4	-27	0,24	0	1,3	-54	0,21	7	1,3	43	0,15	7	0,6	42	0,1	2	1	4	4	65,5	27,4	18,8
4,4	3	0,6	-15	0,12	5	1,1	21	0,12	6	0,7	27	0,16	1	0,7	-45	0,23	2	3	3	1	65,3	37,1	23,8
4,3	3	0,5	-22	0,20	2	0,3	-32	0,12	2	0,6	-36	0,08	8	0,4	53	0,13	2	2	2	4	67,9	31,1	24,2
4,2	1	0,3	-39	0,09	2	0,3	-27	0,11	1	0,2	-38	0,06	7	0,5	49	0,2	2	2	2	4	63,8	33,6	20,8
4,9	7	1,3	43	0,09	5	0,9	21	0,14	5	0,7	10	0,17	4	1,3	-1	0,05	4	3	3	2	88,7	41	20,3
4,4	3	0,6	-12	0,19	4	0,7	7	0,15	4	0,3	-3	0,22	7	1,1	43	0,23	2	3	2	4	69,6	34,1	23,4
4,5	4	0,8	4	0,06	2	0,7	-24	0,20	4	0,4	-1	0,06	1	1,3	-51	0,09	3	2	2	1	63,1	34,3	26,9
4,4	3	0,6	-14	0,10	5	1,3	12	0,18	7	0,9	42	0,09	8	0,9	54	0,14	2	3	4	4	72,3	31,2	21,1
4,8	6	1,2	33	0,14	0	0,7	-57	0,12	4	0	-7	0,15	3	0,1	-20	0,08	3	1	2	2	71,7	38,5	21,2
4,3	3	0,5	-19	0,14	5	1,1	10	0,10	6	1,2	29	0,08	7	1,4	45	0,21	2	3	3	4	67,1	28,5	18,3
4,8	6	1,2	32	0,07	4	1,1	5	0,10	6	1	24	0,18	1	0,9	-41	0,17	3	3	3	1	77,3	38,1	21,7
4,8	6	1,1	31	0,14	0	0	-58	0,15	0	1	-59	0,06	5	0,3	8	0,11	3	1	1	3	71,5	35	20,7
4,6	5	0,9	12	0,15	7	1,4	46	0,20	7	1,5	48	0,09	7	1,3	50	0,11	3	4	4	4	70	25,1	18,5
4,6	5	0,9	16	0,08	2	0,7	-33	0,12	4	0,6	-6	0,07	7	1,2	50	0,22	3	2	2	4	75,2	38,6	24,8
4,8	7	1,3	40	0,20	4	0,5	2	0,07	3	1,1	-16	0,09	8	0,3	58	0,24	4	3	2	4	86,3	41	22
4,5	4	0,7	-2	0,18	1	0,3	-52	0,10	2	0,5	-34	0,17	7	0,3	51	0,07	2	1	2	4	68,7	35,2	24,1
4,5	4	0,7	-5	0,22	5	1	22	0,23	5	1,4	21	0,11	1	1,1	-50	0,11	2	3	3	1	67,8	37,4	21,4
4,8	7	1,3	41	0,10	2	1,4	-27	0,17	7	0,1	48	0,16	4	0,5	4	0,09	4	2	4	3	86,6	38,9	23,1
4,9	7	1,3	45	0,22	1	0,7	-43	0,09	4	0,3	-6	0,06	3	0,2	-10	0,1	4	1	2	2	74,7	37,2	20,6
4,9	7	1,3	43	0,17	5	0,6	13	0,21	3	0,1	-12	0,17	6	0,2	37	0,14	4	3	2	3	86	38,9	24,8
4,3	3	0,5	-22	0,05	3	0,5	-14	0,16	2	1	-23	0,18	5	0,3	21	0,22	2	2	2	3	63,6	35,3	19,5

Figure 6: data generated from grasshopper and climatestudio

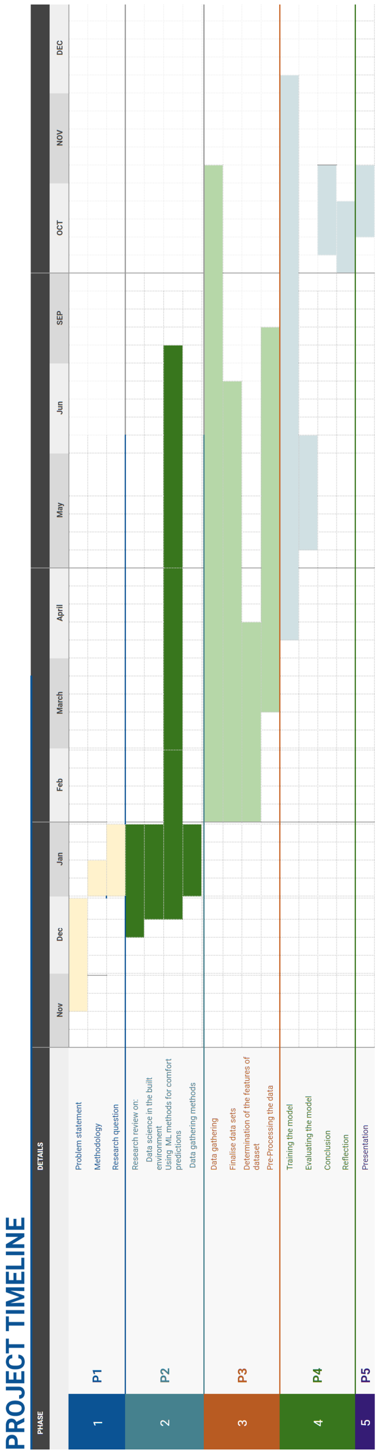

Figure 7: Project timeline