Delft University of Technology

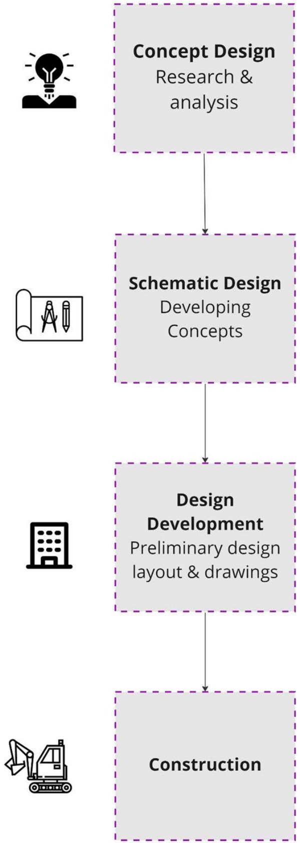
Development of a machine learning-based assessment tool for predicting daylight and visual comfort

BUILDING TECHNOLOGY MASTER TRACK
Faculty of Architecture and the Built Environment

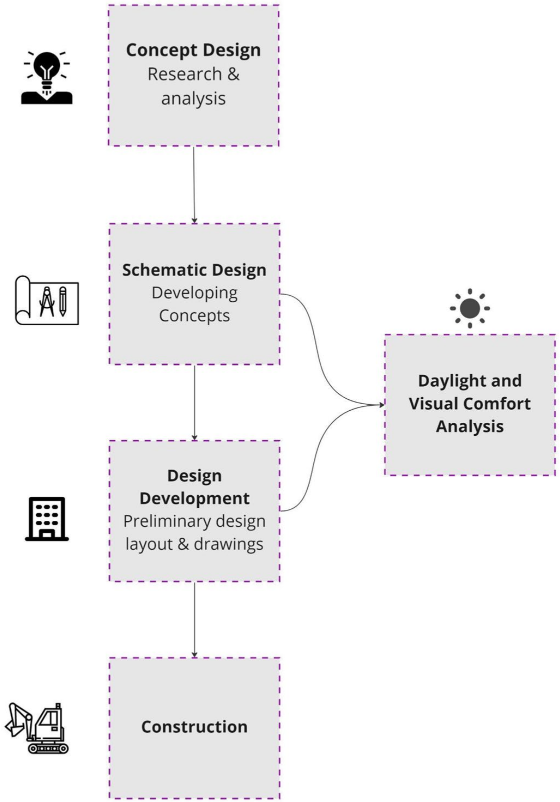
First Mentor: Dr. Michela Turrin, Design Informatics
Second Mentor: Dr. Charalampos Andriotis, Structural Design & Mechanics
Student: Maryam Abouie Mehrizi

Introduction

Design Process

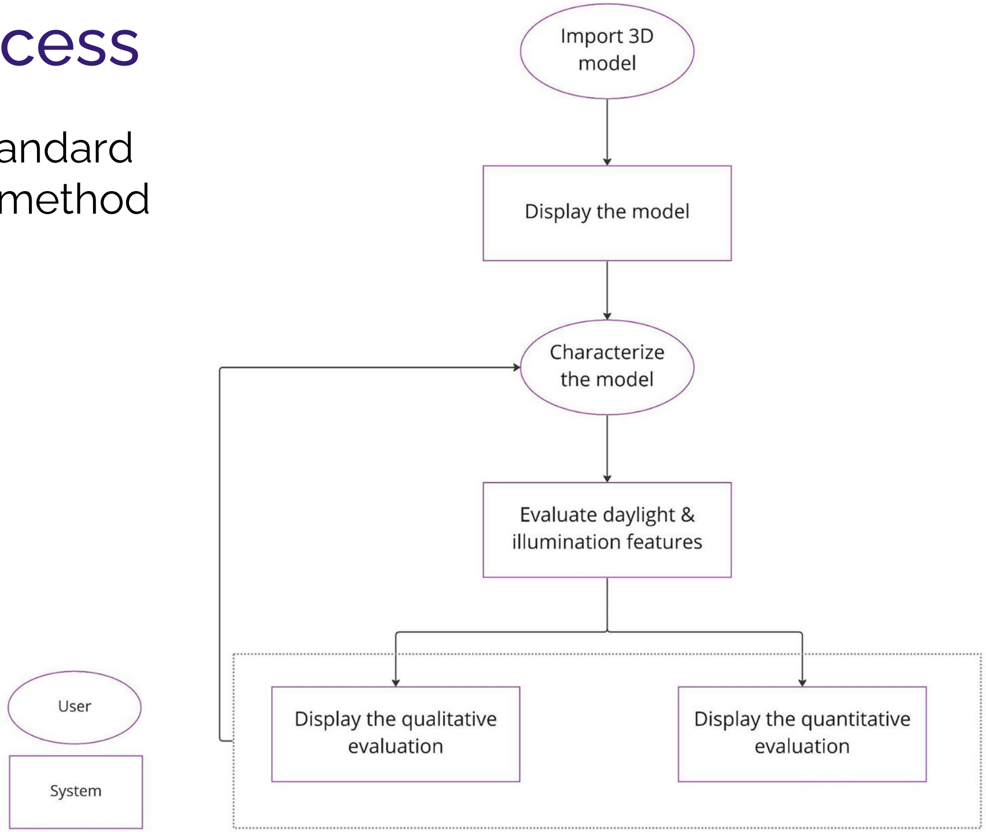


Design Process



Design Process

The process of standard support decision method



Artificial Intelligence (AI)

Artificial intelligence leverages computers and machines to mimic the problem-solving and decision-making capabilities of the human mind

Artificial Intelligence (AI)

“ Productivity can be increased by 40% through artificial intelligence. This would allow people to spend their time more effectively” “Valuer”

AI in Daylight and visual comfort

Early Stage Shading Design

Accelerating the Conceptual Design Process, Time & Cost efficiency?

Research Question

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?

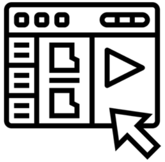
Sub-Research Questions

- 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?

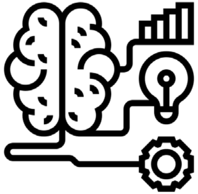
Objectives

The workflow of the thesis can be used to explore application of AI as an assessment tool for predicting illuminance-based visual comfort in the conceptual design phase

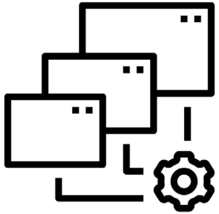
To design shading parametrically



To generate a dataset from climate-based simulation software

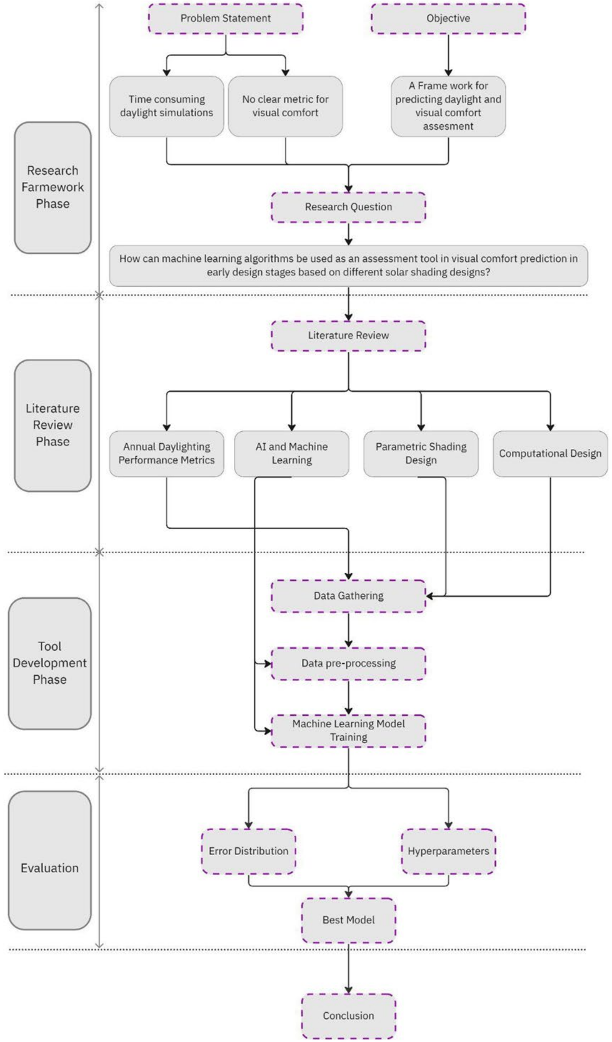


To Train a machine learning model to predict desired output



To create a workflow for application of the Machine learning as an assessment tool during conceptual design for visual comfort prediction

Research Framework



Visual Comfort

Visual Comfort

- Glare
- Daylight distribution
- View to outside
- Internal and external lighting levels

Glare, “condition of vision in which there is discomfort or a reduction in the ability to see details or objects, caused by an unsuitable distribution or range of luminance, or by extreme contrasts” [CIE 2019]

Source: https://www.ny-engineers.com/blog/avoiding-glare-in-lighting-design

Visual Comfort

- Glare
- Daylighting
- View to outside
- Internal and external lighting levels

→ Objective Criteria

Glare, “condition of vision in which there is discomfort or a reduction in the ability to see details or objects, caused by an unsuitable distribution or range of luminance, or by extreme contrasts” [CIE 2019]

Source: https://www.ny-engineers.com/blog/avoiding-glare-in-lighting-design

Leadership in Energy and Environmental Design (LEED)

Offers simulation-based options for achieving its Daylight Credit by Simulating daylight availability throughout the entire year

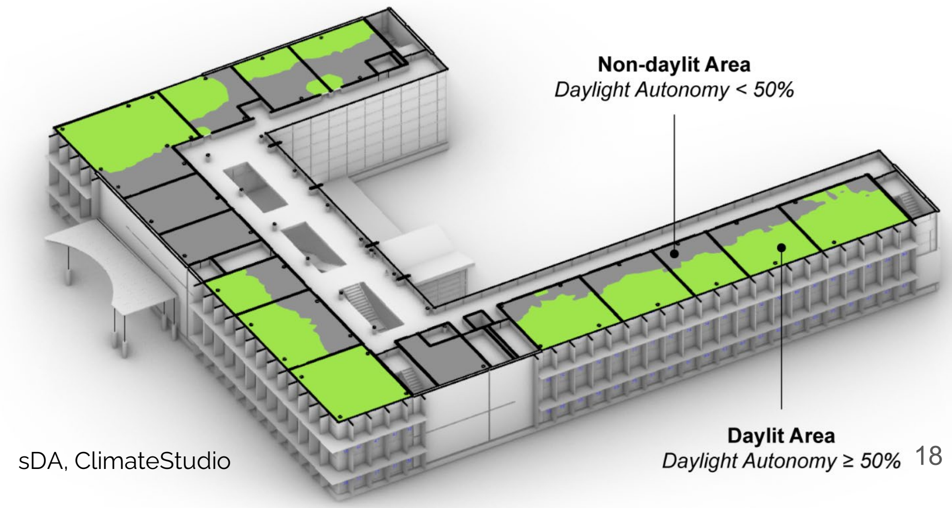
Annual Daylight Metrics Based On LEED Daylight Credit

Spatial Daylight Autonomy(sDA) :

whether a space receives sufficient daylight on a work plane during standard operating hours on an annual basis.
Target >> 300 lux for 50% of the occupied period.

	Version 4.1
sDA ≥ 40%	1 point
sDA ≥ 55%	2 points
sDA ≥ 75%	3 points

LEED Pointing system
(Solemma)



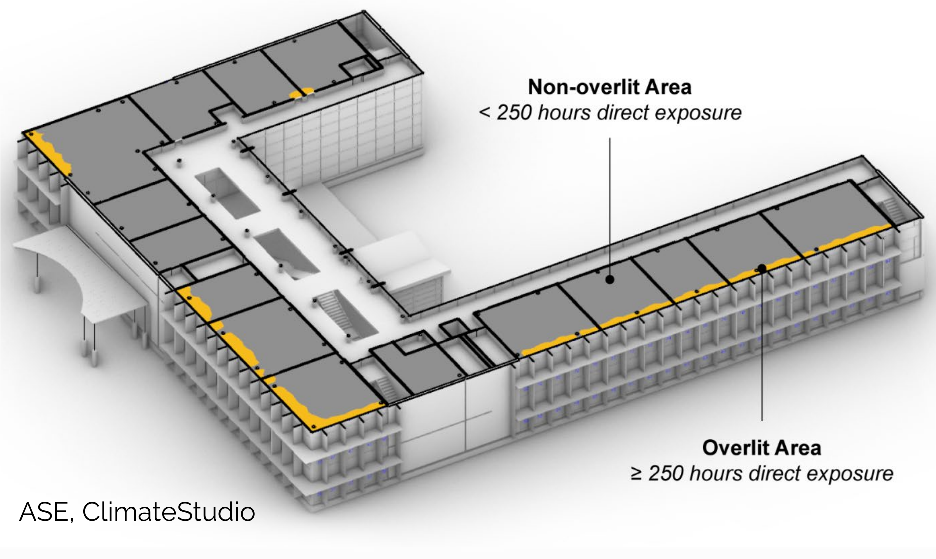
sDA, ClimateStudio

Annual Daylight Metrics Based On LEED Daylight Credit

Annual Sunlight Exposure (ASE):

The percentage of the regularly occupied floor area that is “overlit.”

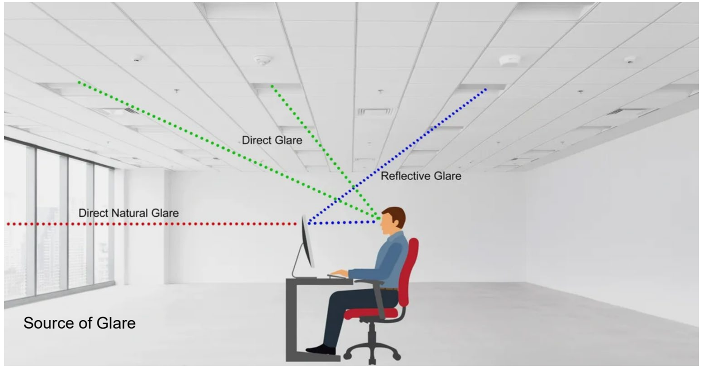
Overlit >> locations are those receiving direct sunlight (>1000 lux directly from the solar disc) for more than 250 occupied hours



ASE, ClimateStudio

Annual Glare

Daylight Glare Probability(DGP): predicts the likelihood that an observer at a given view position and orientation will experience discomfort glare



Discomfort glare: "results in an instinctive desire to look away from a bright light source or difficulty in seeing a task. It generally does not impair visibility but causes an uncomfortable sensation. It increases when the light source is facing the observer."

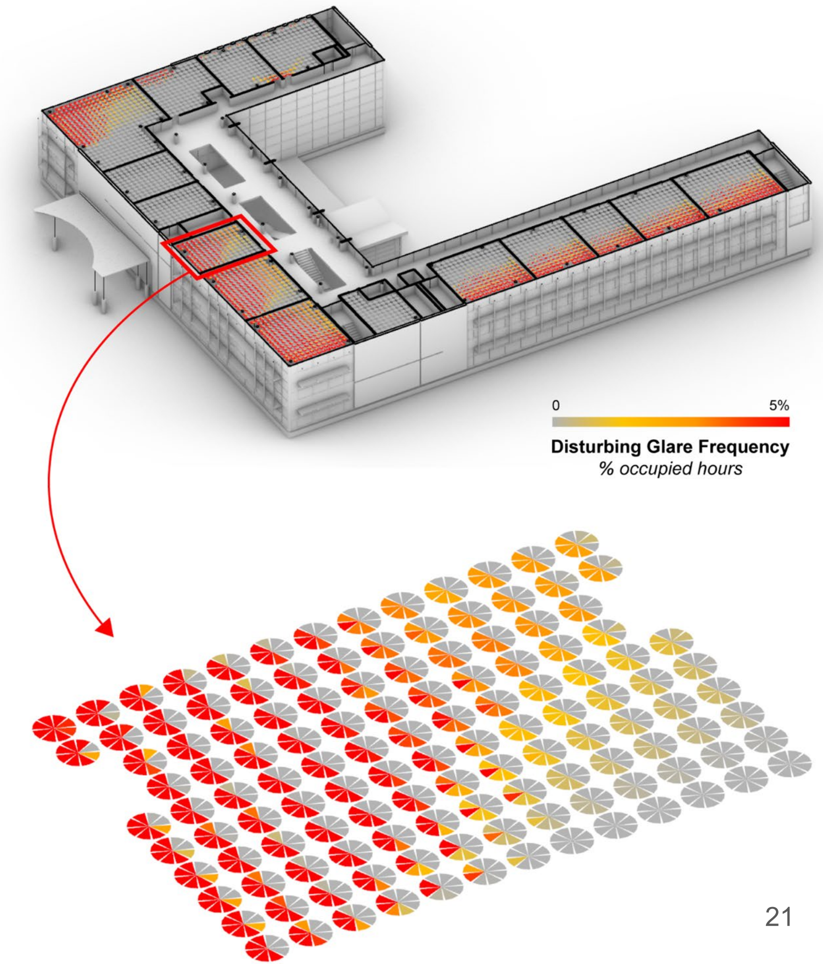
Source:https://supervisor.store/blog/f/what-is-glare

Annual Glare

Spatial Disturbing Glare (sDG):

The percentage of views across the regularly occupied floor area that experience Disturbing or Intolerable Glare (DGP > 38%) for at least 5% of occupied hours.

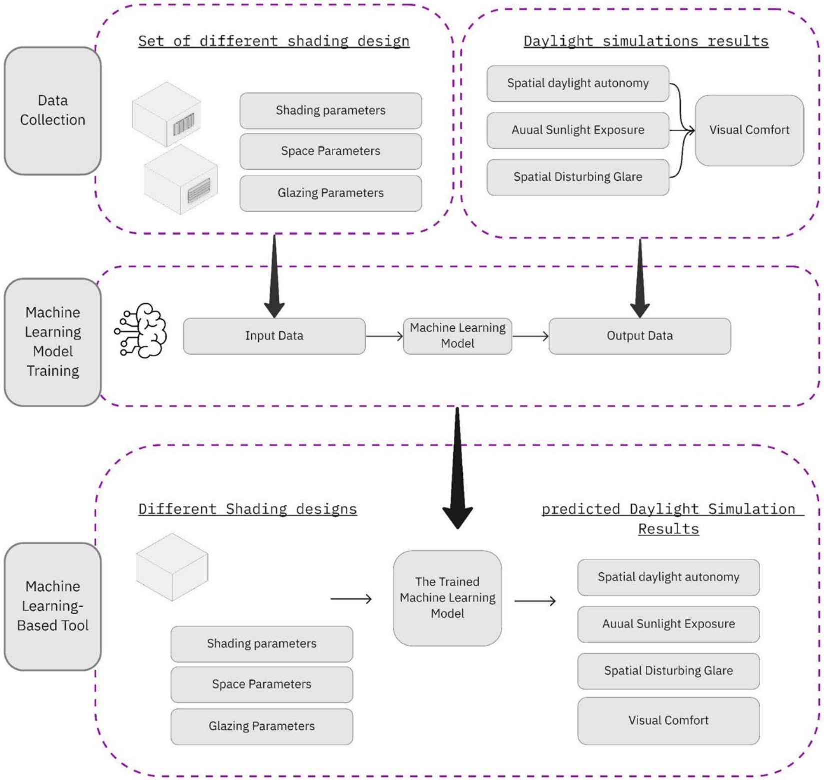
Imperceptible glare	Perceptible glare	Disturbing glare	Intolerable glare
DGP ≤ 34%	34% < DGP ≤ 38%	38% < DGP ≤ 45%	45% < DGP



ASE, ClimateStudio

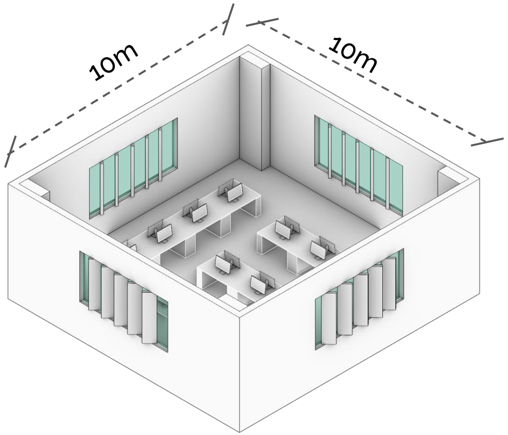
Methodology

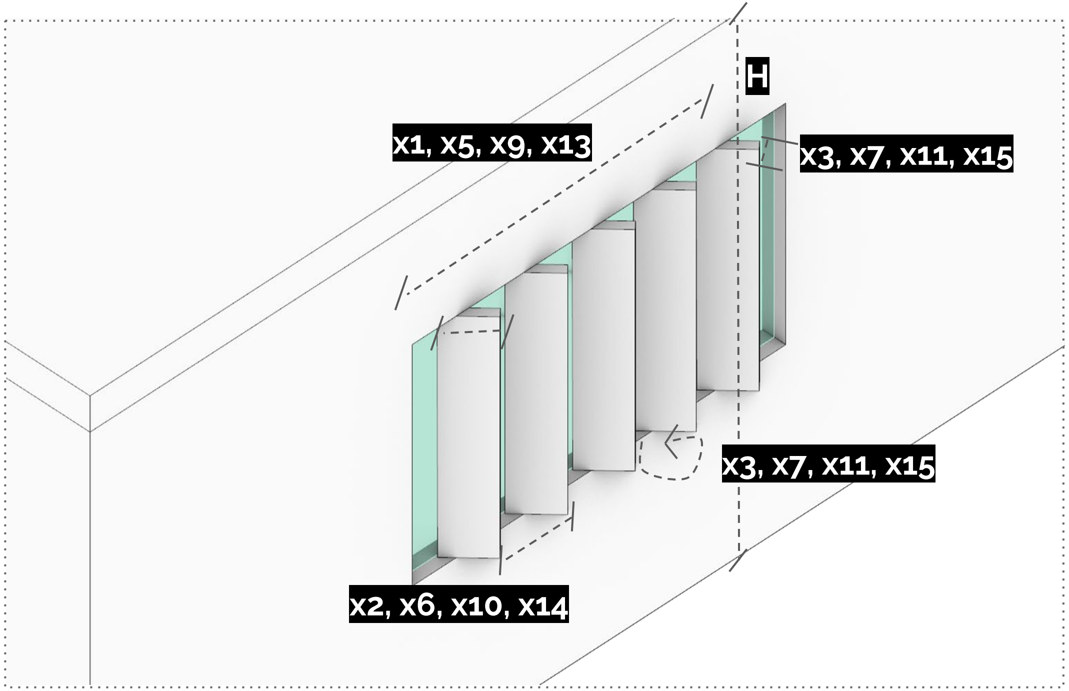
Diagram Of The Main Process



Data Generation

Parameters



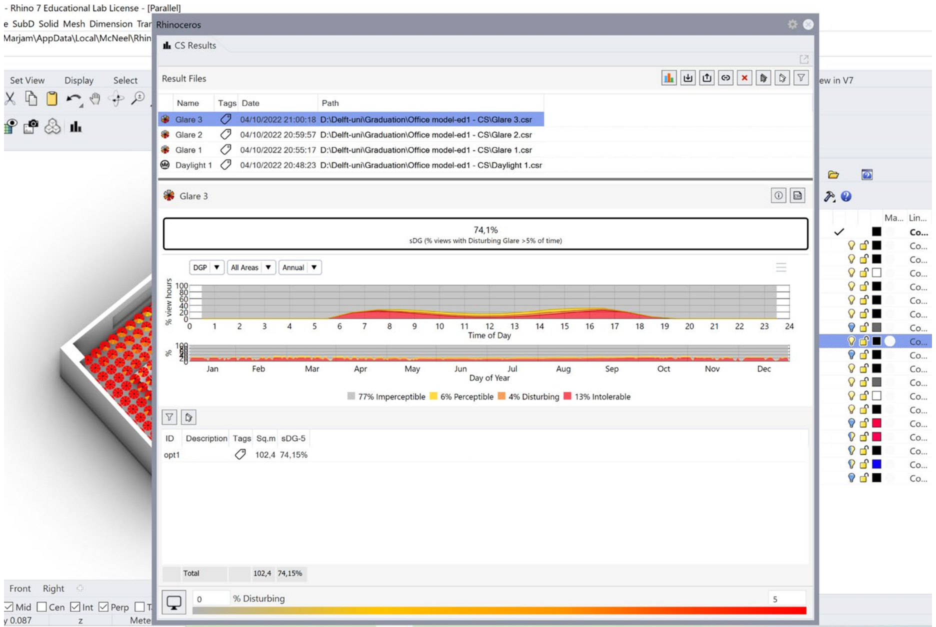


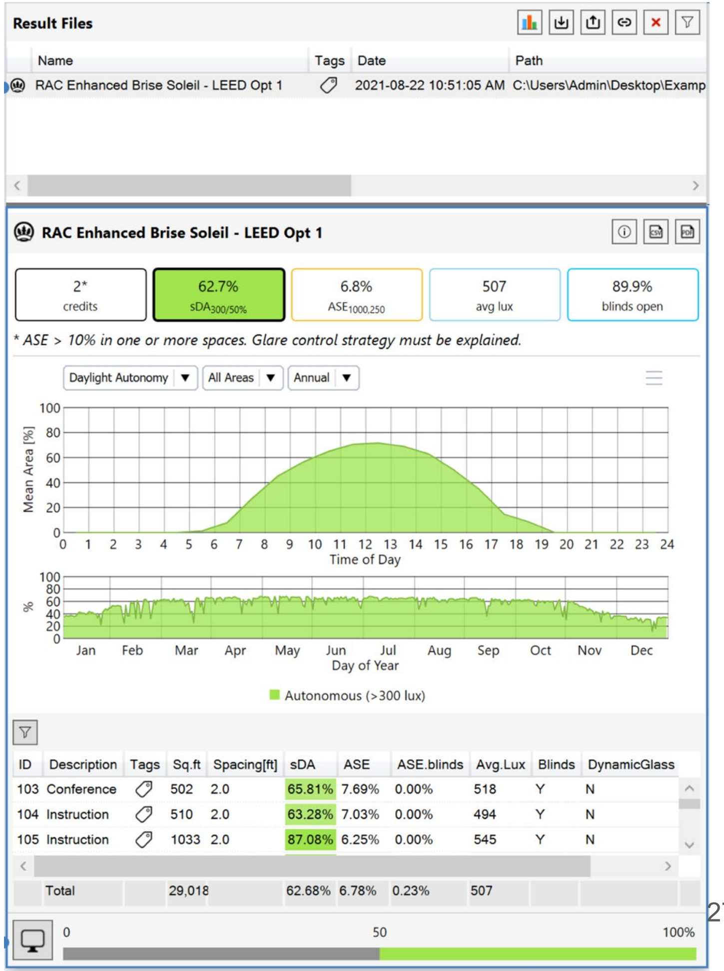
Explanation	Notation	Orientation	Boundry	Unit
Number of vertical sahdes	x1, x5, x9, x13	North-south-east-west	[0-10]	_
Length of vertical devices	x2, x6, x10, x14	North-south-east-west	[0-1,5]	Meter
Rotation of vertical devices	x3, x7, x11, x15	North-south-east-west	[-60-60]	Degree
Width of vertical 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	_

Different Glazing Types

		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

Daylight and Glare Data





Parameters

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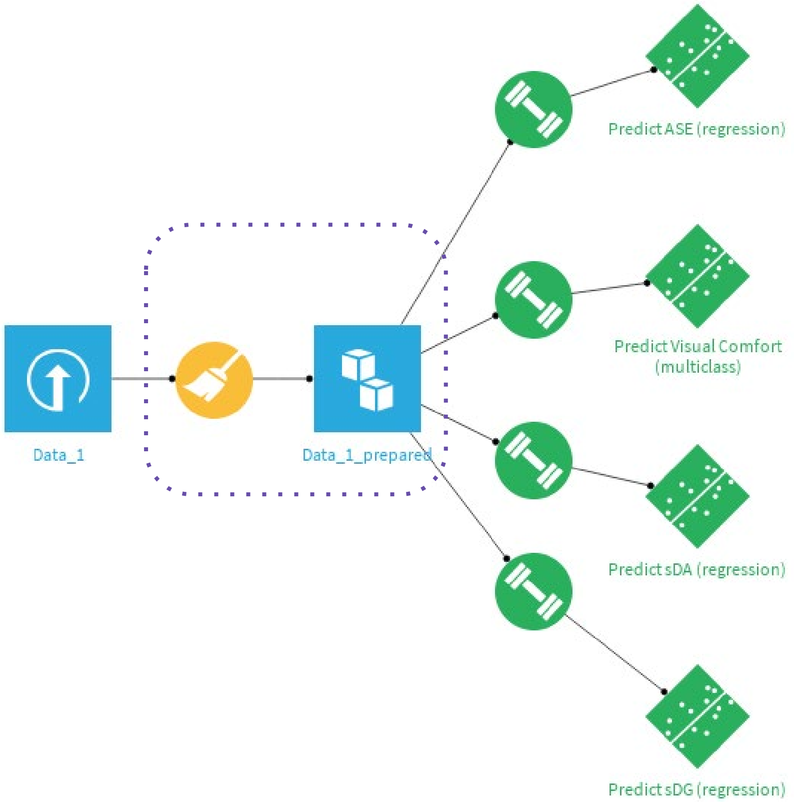
GLZ	GLZN, GLZS, GLZE, GLZW	North-south-east-west	1,2,3,4	_

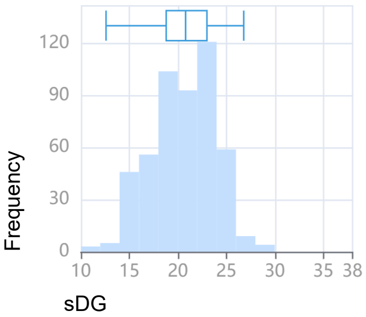
x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	x14	x15	x16	GlzN	GlzS	GlzE	GlzW	sDA	ASE	sDG
5	0,9	12	0,24	4	0,3	7	0,15	2	0,9	-37	0,07	5	1,4	21	0,19	3	3	2	3	78	35,9	20,3
7	1,2	39	0,21	3	0,6	-21	0,19	3	0,5	-13	0,2	5	1,3	9	0,06	3	2	2	3	79,5	41,5	23,1
4	0,8	2	0,09	2	1,1	-26	0,10	6	0,4	32	0,21	5	1	10	0,17	3	2	3	3	74,2	38,9	21,4
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
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
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
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
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
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
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
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
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
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
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
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	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
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
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
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
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	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
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
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	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	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
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
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
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
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
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
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

Statistical Data Analysis and Data Preprocessing

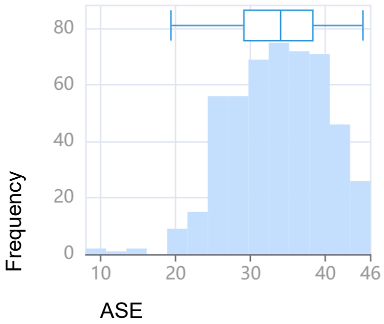
Diagram Of The Machine Learning Framework



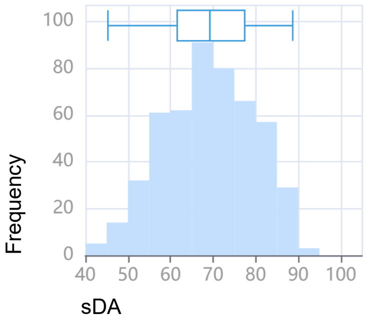
Statistical Data Analysis



Univariate analysis on **sDG**



Univariate analysis on **ASE**



Univariate analysis on **sDA**

Data Scaling

Why? Variables that are measured at different scales do not contribute equally to the model fitting & model learned function and might end up creating a bias.

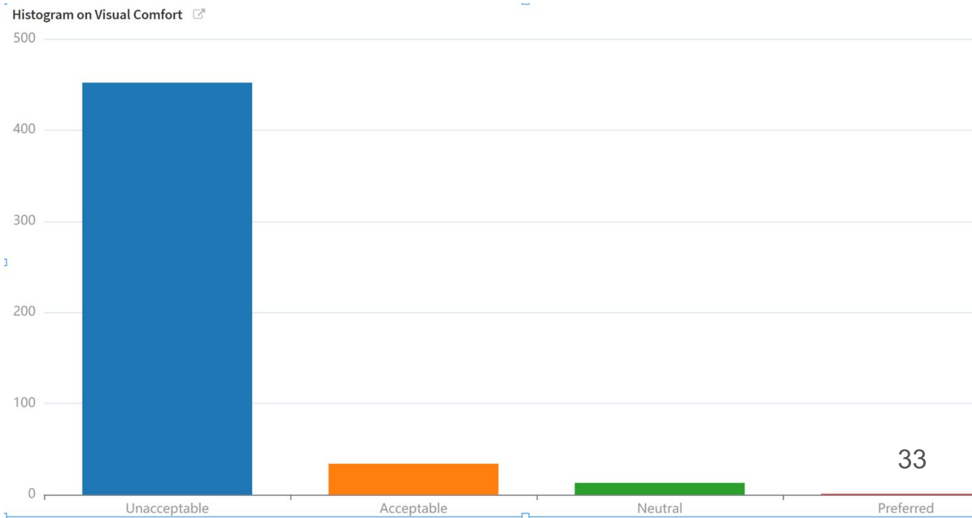
$$x_{scaled} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

The values of the features are within the range **[0,1]** or **[-1,1]** following the Min-Max scaling.

Feature Generation-Visual Comfort

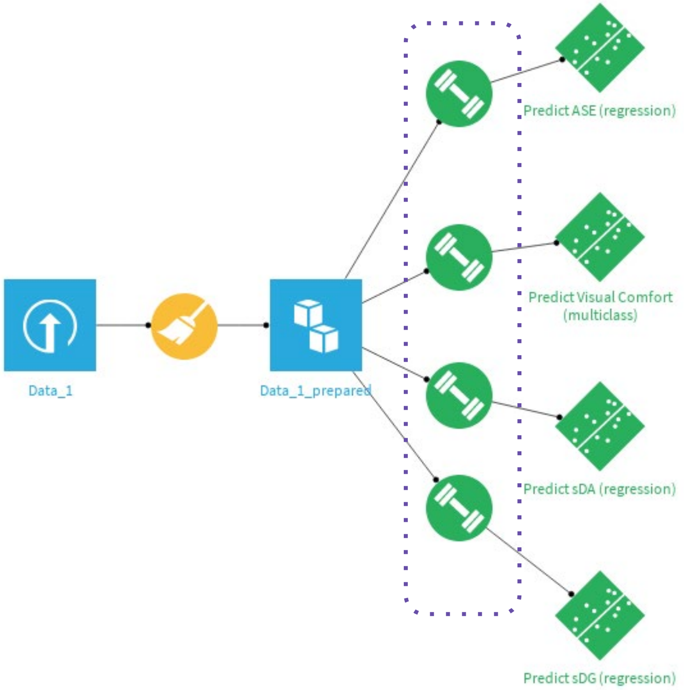
$$\text{Visual Comfort} = \begin{cases} \text{"}Preferred\text{"}, & \text{if } sDA > 55 \ \& \ ASE < 20 \ \& \ sDG < 12.5, \\ \text{"}Neutral\text{"}, & \text{if } sDA \leq 55 \ \& \ ASE < 30 \ \& \ sDG < 15, \\ \text{"}Acceptable\text{"}, & \text{if } sDA \leq 55 \ \& \ ASE < 35 \ \& \ sDG < 20, \\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

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



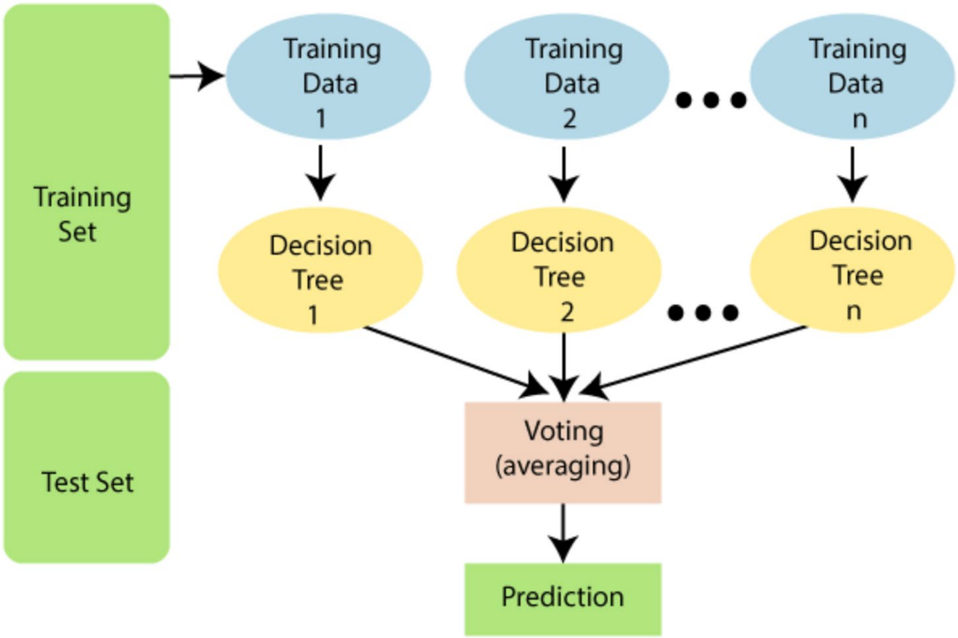
Machine Learning Models

Diagram Of The Machine Learning Framework



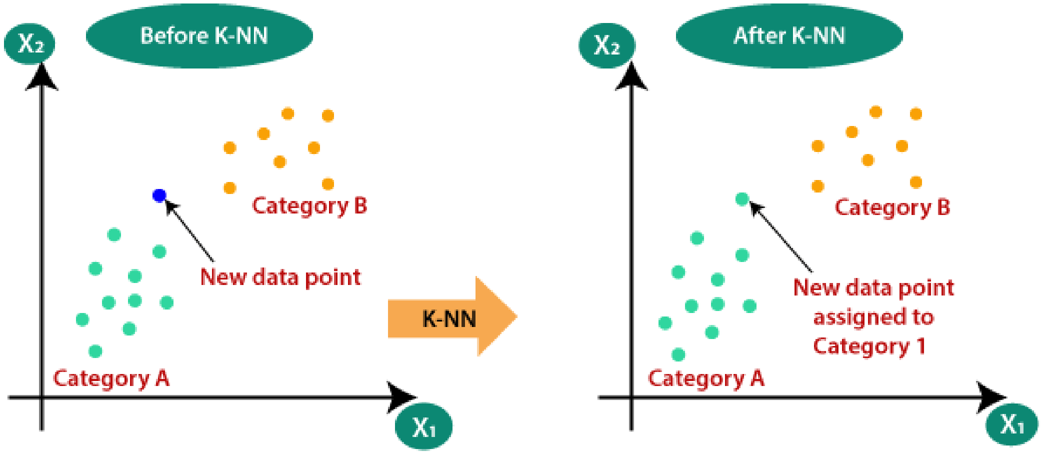
Random Forest

- It takes less training time as compared to other algorithms.
- It predicts output with high accuracy
- It can also maintain accuracy when a large proportion of data is missing.



K Nearest Neighbor

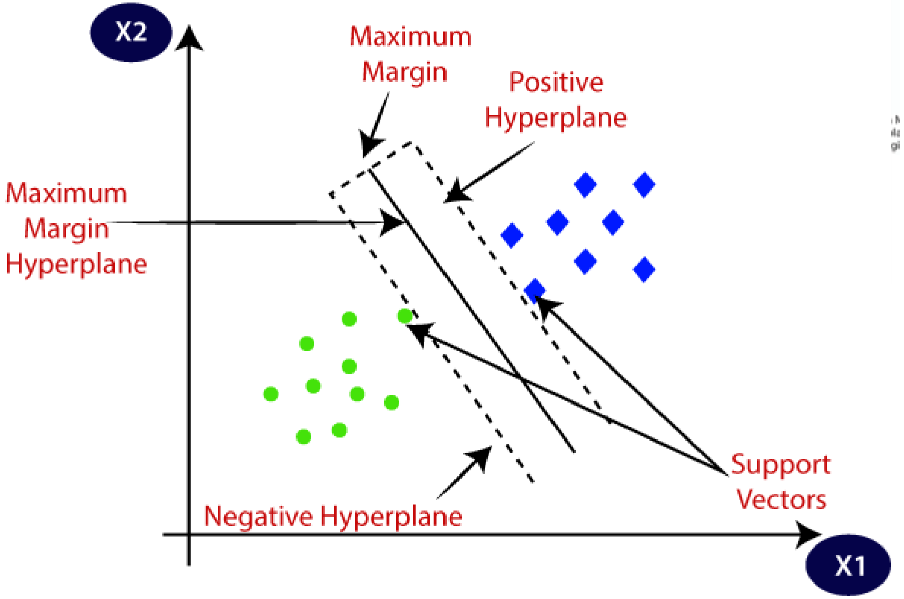
- The Algorithm is simple and accurate
- Few hyperparameters



KNN Algorithm. From:https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning

SVM

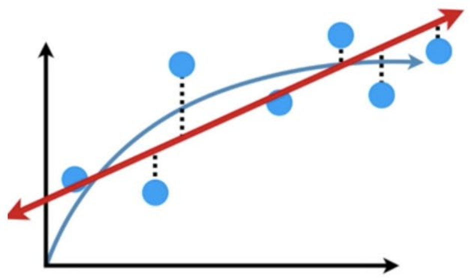
- Performs well with small data set
- It works well with a clear margin of separation

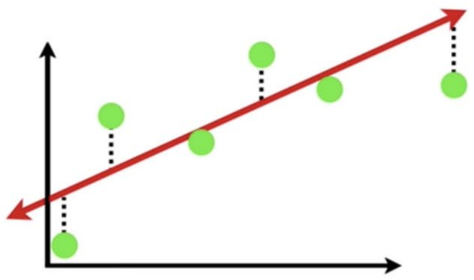


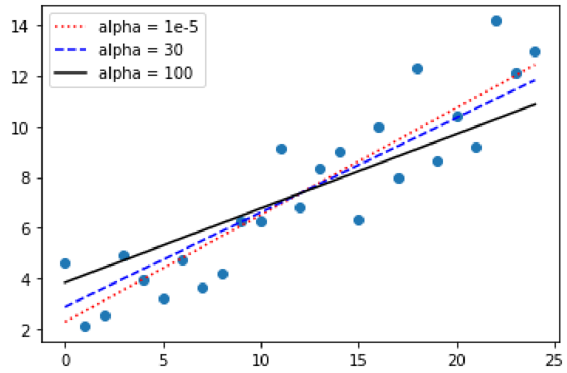
SVM Algorithm. From:https://www.javatpoint.com/svm-algorithm-for-machine-learning

Ridge (L2) Regression

- Better predictions in comparison to linear regression.
- Is useful in solving problems where we have less Data



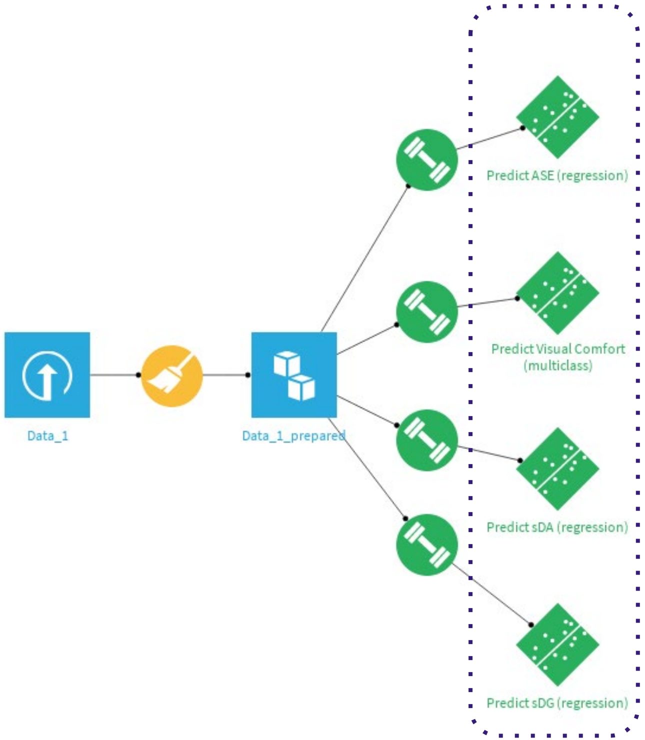




https://machinelearningjourney.com/index.php/2020/02/13/ridge-regression/

Machine Learning Implementation

Diagram Of The Machine Learning Framework



sDA(Spatial Daylight Autonomy) Prediction-Regression

sDA Prediction-Regression

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

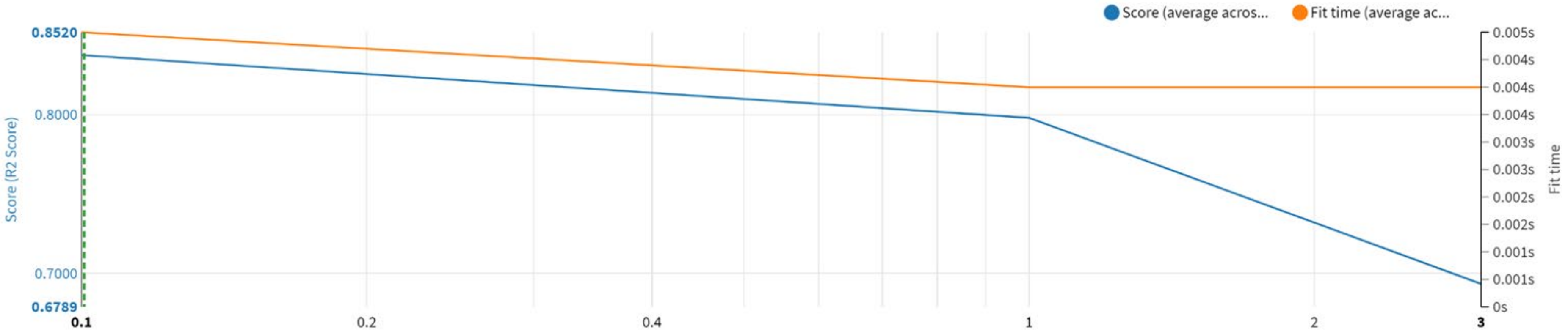
$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|$$

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

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

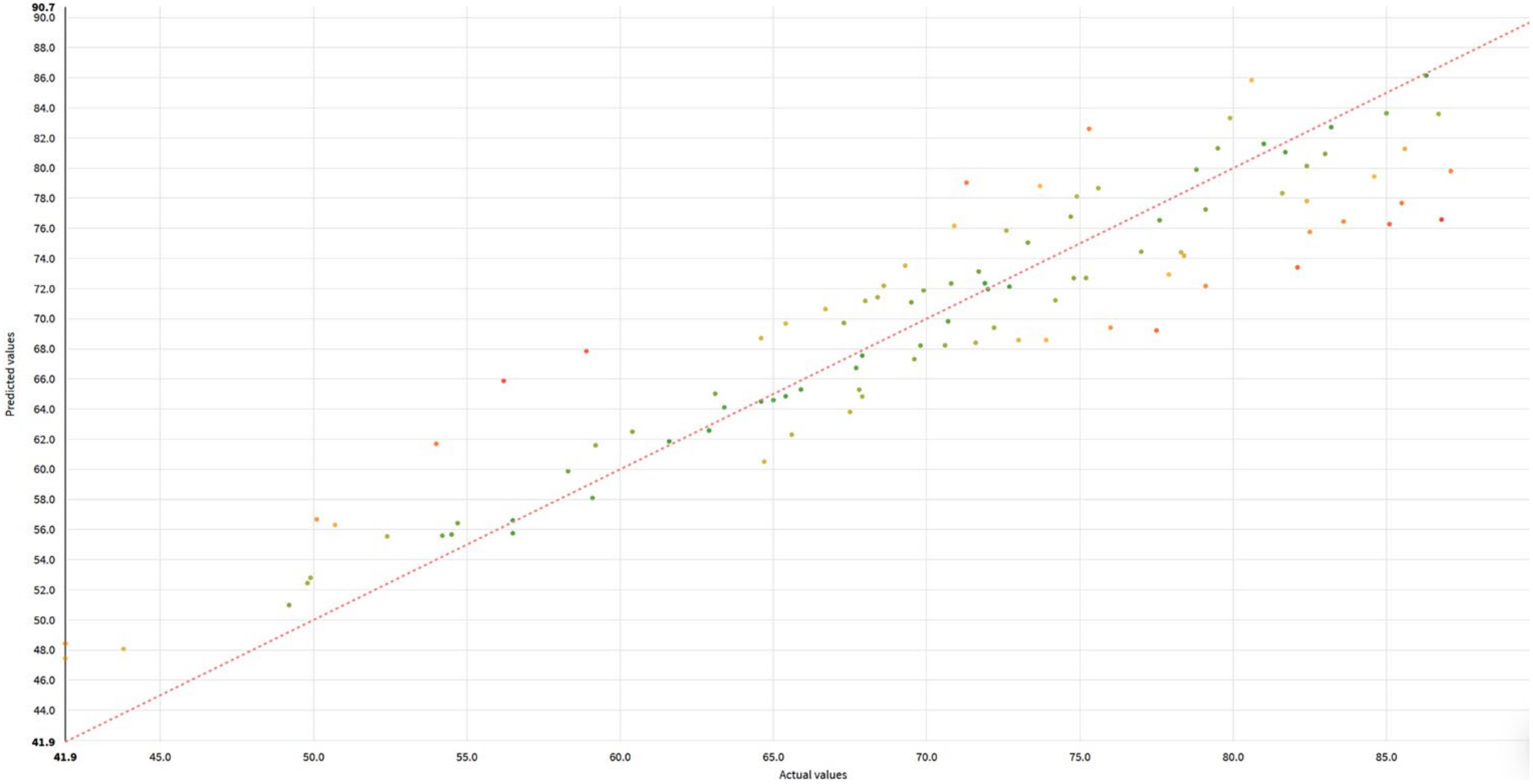
$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y}_i)^2}$$

Evaluation metrics

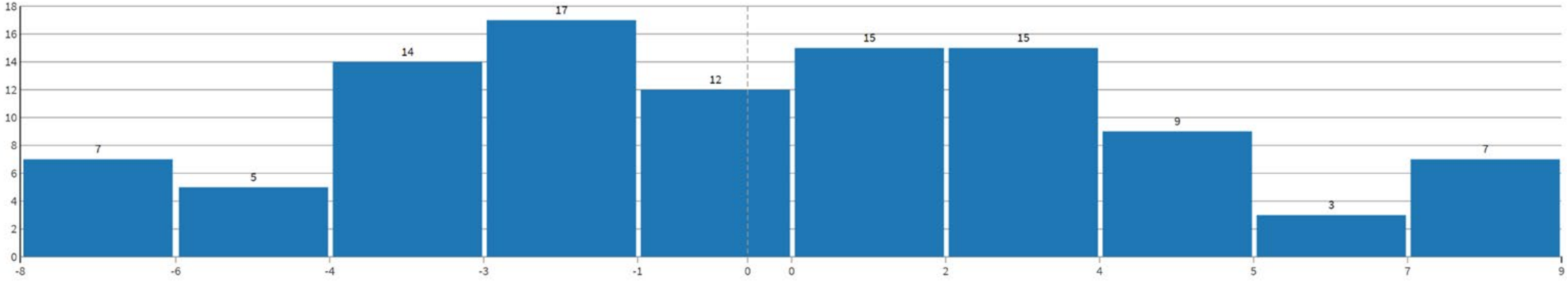


Hyperparameter Optimization l2 Regression Based on alpha values

sDA/Scatter Plot



sDA/Error Distribution



sDA/Coefficient

X11: Rotation of Vertical Device on the South Side

X2 Length of Vertical Device on the North Side

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

H: Height of the Room

X8: Width of the Vertical Device on the South Side

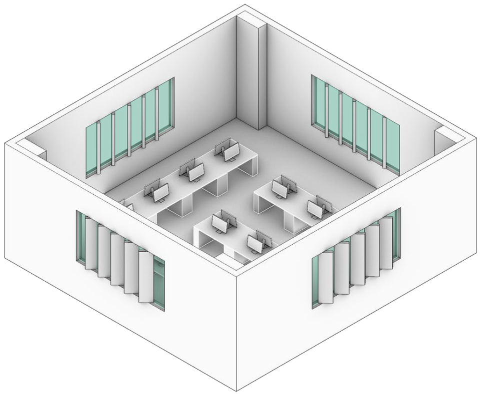
X4: Width of the Vertical Device on the North Side

X2: Length of the Vertical Device on the North Side

GLN: Glazing type on the North Side

GLE: Glazing type on the East Side

GLS: Glazing type on the South Side

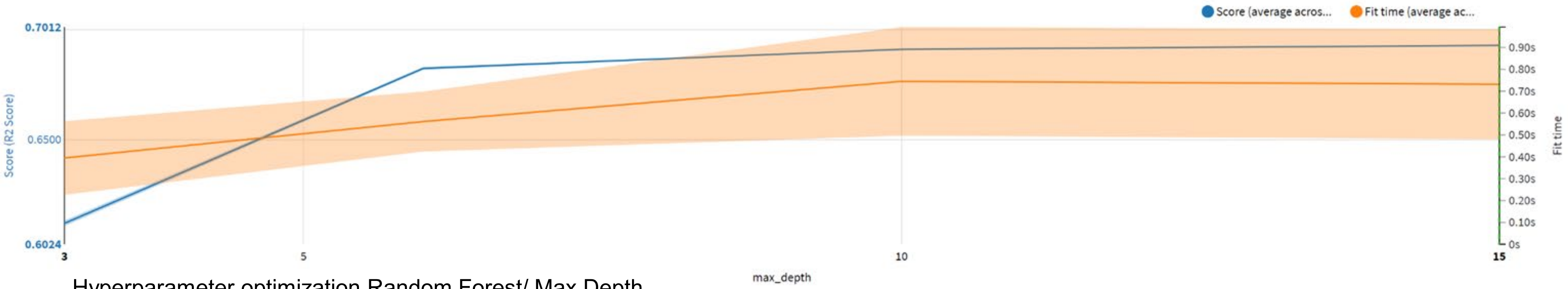


Explanation	Notation	Orientation	Boundry	Unit
Number of vertical sahdes	x1, x5, x9, x13	North-south-east-west	[0-10]	Meter
Length of vertical devices	x2, x6, x10, x14	North-south-east-west	[0-1,5]	Meter
Rotation of vertical devices	x3, x7, x11, x15	North-south-east-west	[-60-60]	Degree
Width of vertical 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	_

ASE(Annual Sunlight Exposure) Prediction-Regression

ASE Prediction-Regression

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



Hyperparameter optimization Random Forest/ Max Depth

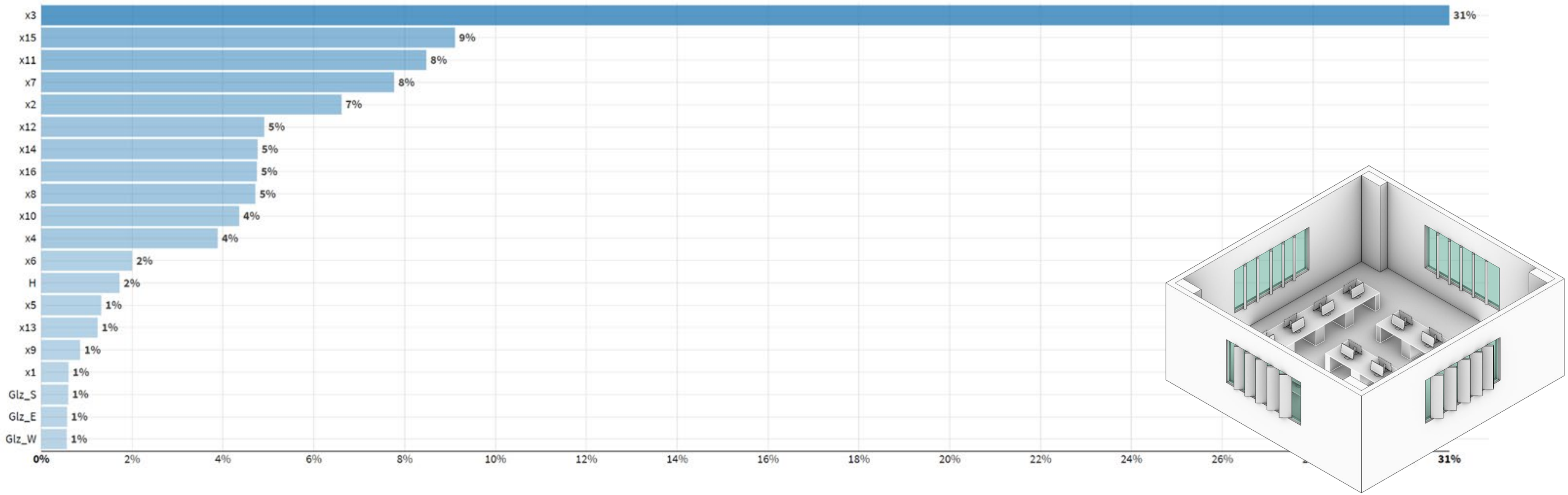
X3: Rotation of Vertical Devices on the North Side

X15: Rotation of Vertical devices on the West Side

X11: Rotation of Vertical Device on the South Side

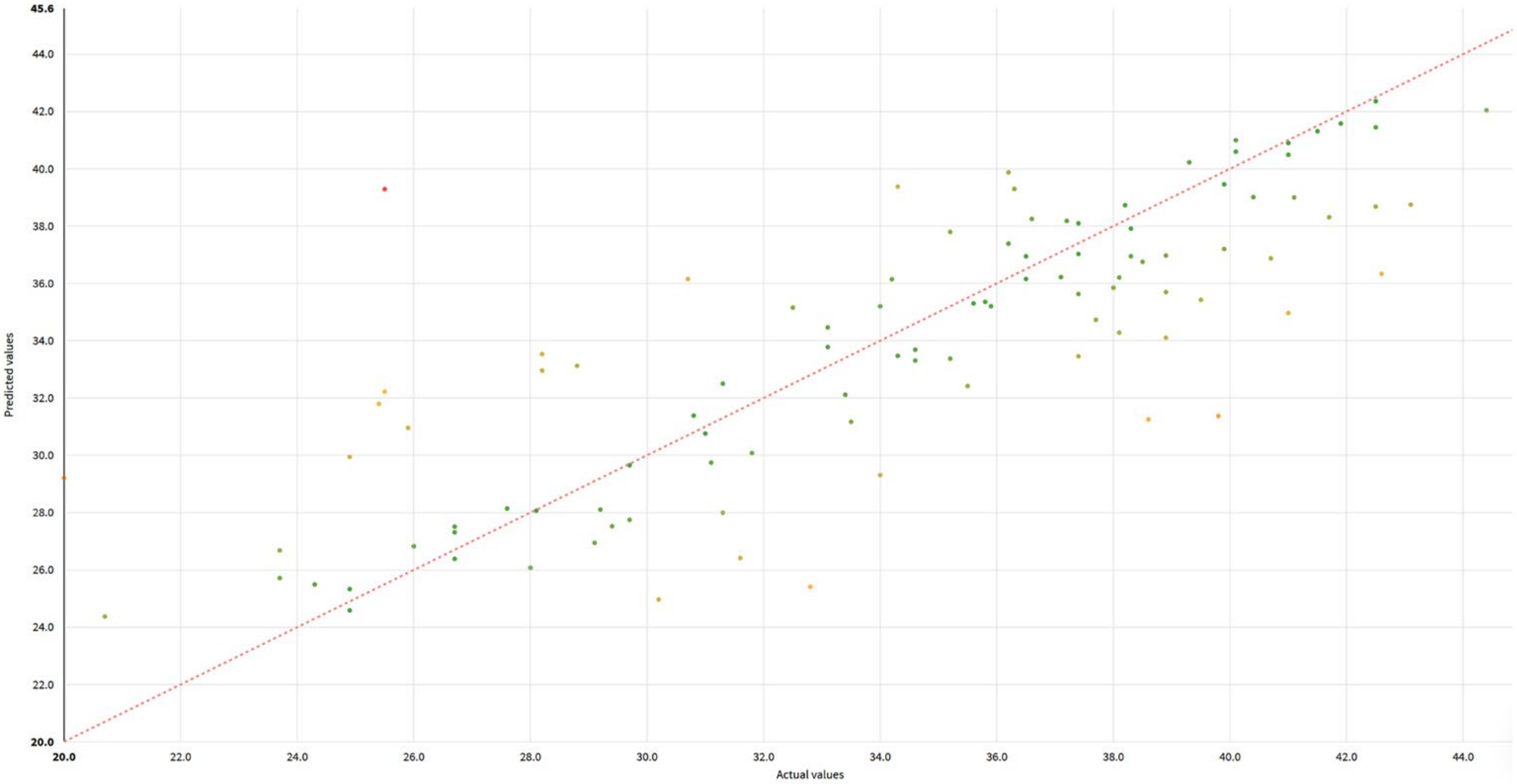
X2 Length of Vertical Device on the North Side

ASE/Variable importance

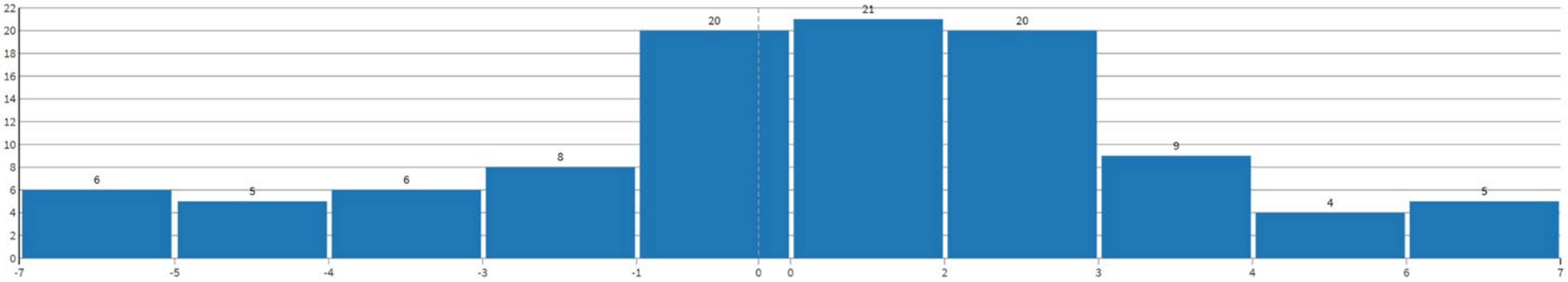


Explanation	Notation	Orientation	Boundry	Unit
Number of vertical sahdes	x1, x5, x9, x13	North-south-east-west	[0-10]	Meter
Length of vertical devices	x2, x6, x10, x14	North-south-east-west	[0-1,5]	Meter
Rotation of vertical devices	x3, x7, x11, x15	North-south-east-west	[-60-60]	Degree
Width of vertical 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	_

ASE/Scatter Plot



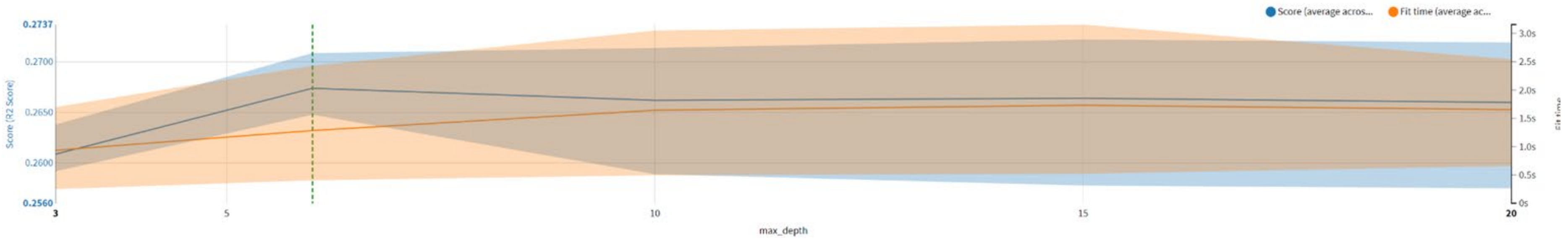
ASE/Error Distribution



sDG(Spatial Disturbing Glare) Prediction-Regression

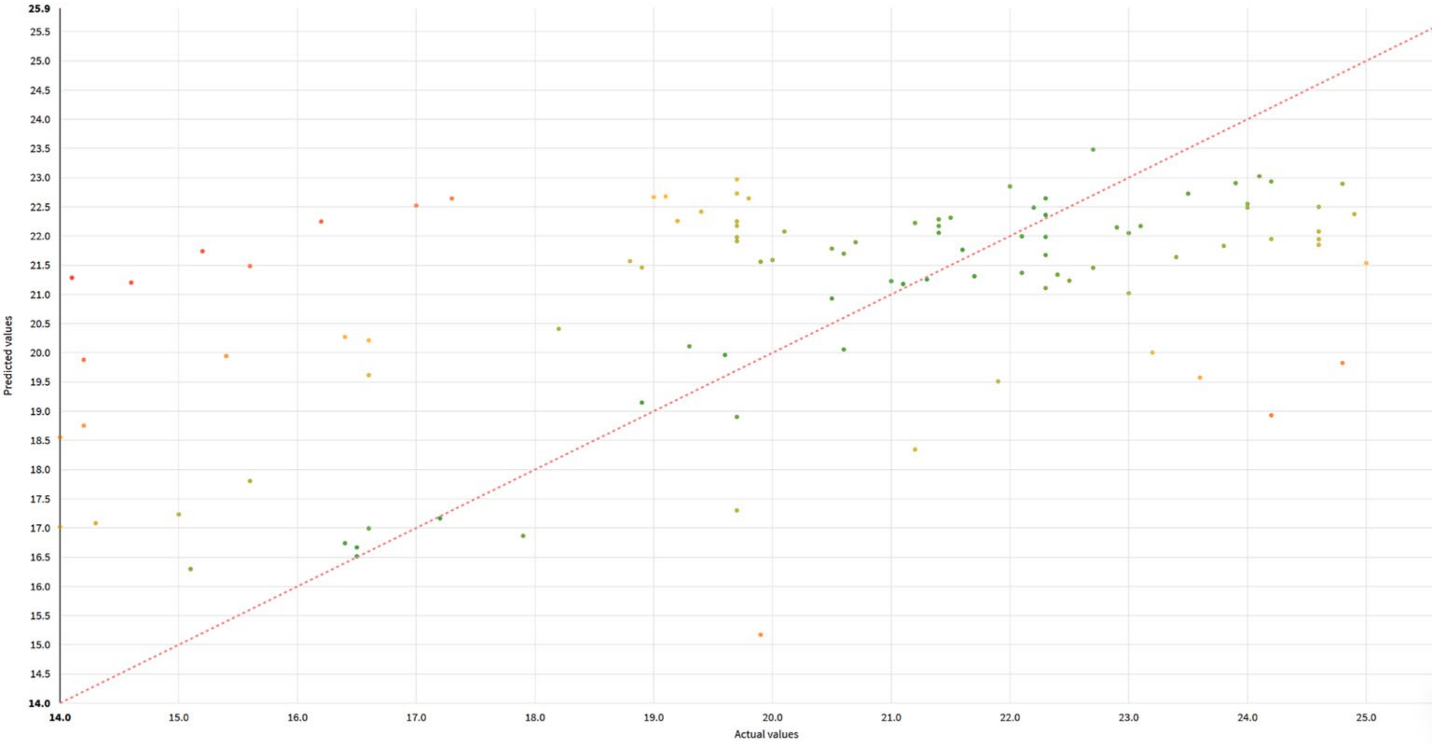
sDG Prediction-Regression

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

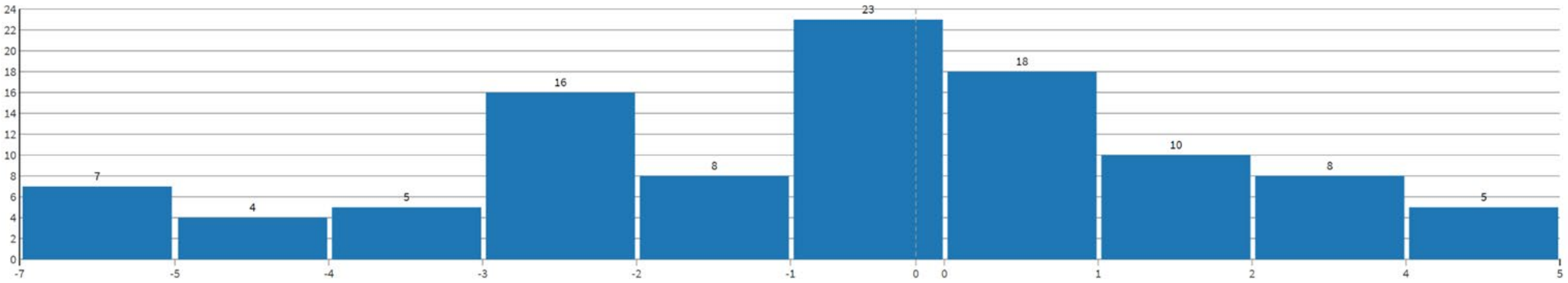


Hyperparameter optimization Random Forest/ Max Depth

sDG/Scatter Plot



sDG/Error Distribution



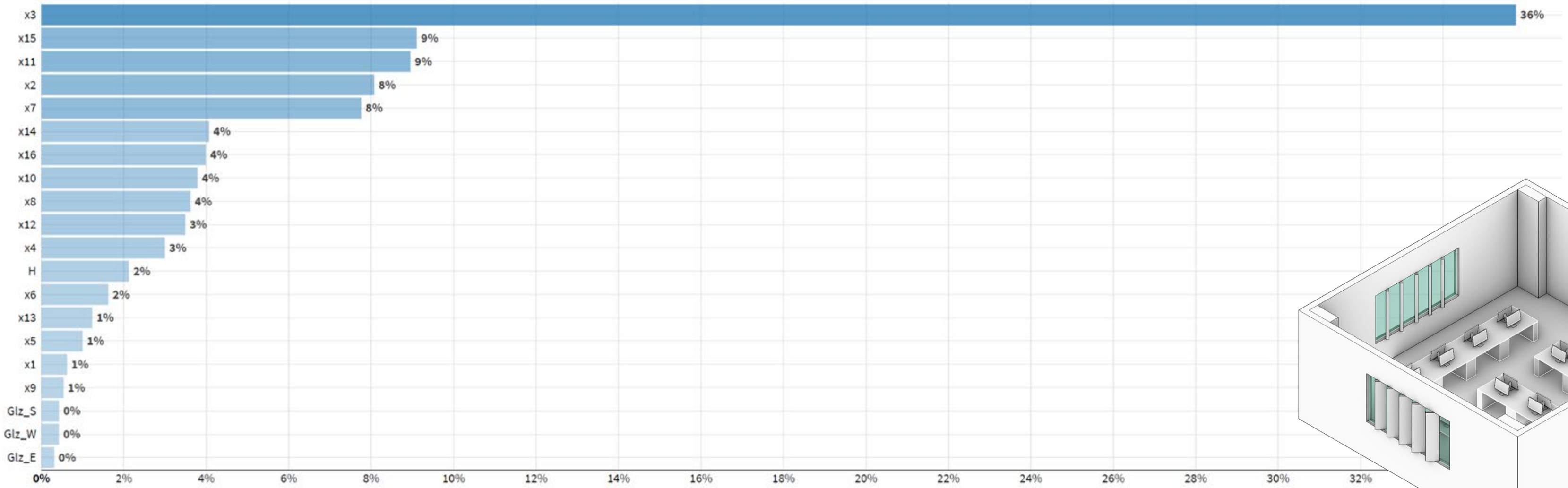
sDG/Variable importance

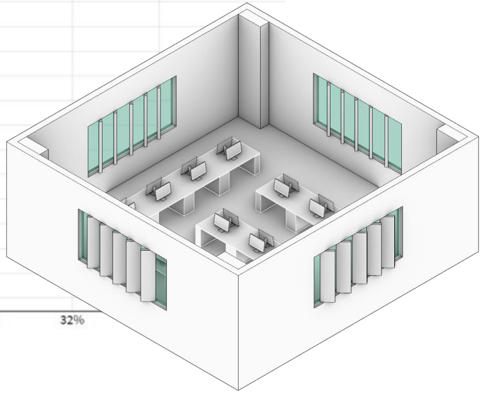
X3: Rotation of Vertical Devices on the North Side

X15: Rotation of Vertical devices on the West Side

X11: Rotation of Vertical Device on the South Side

X2 Length of Vertical Device on the North Side





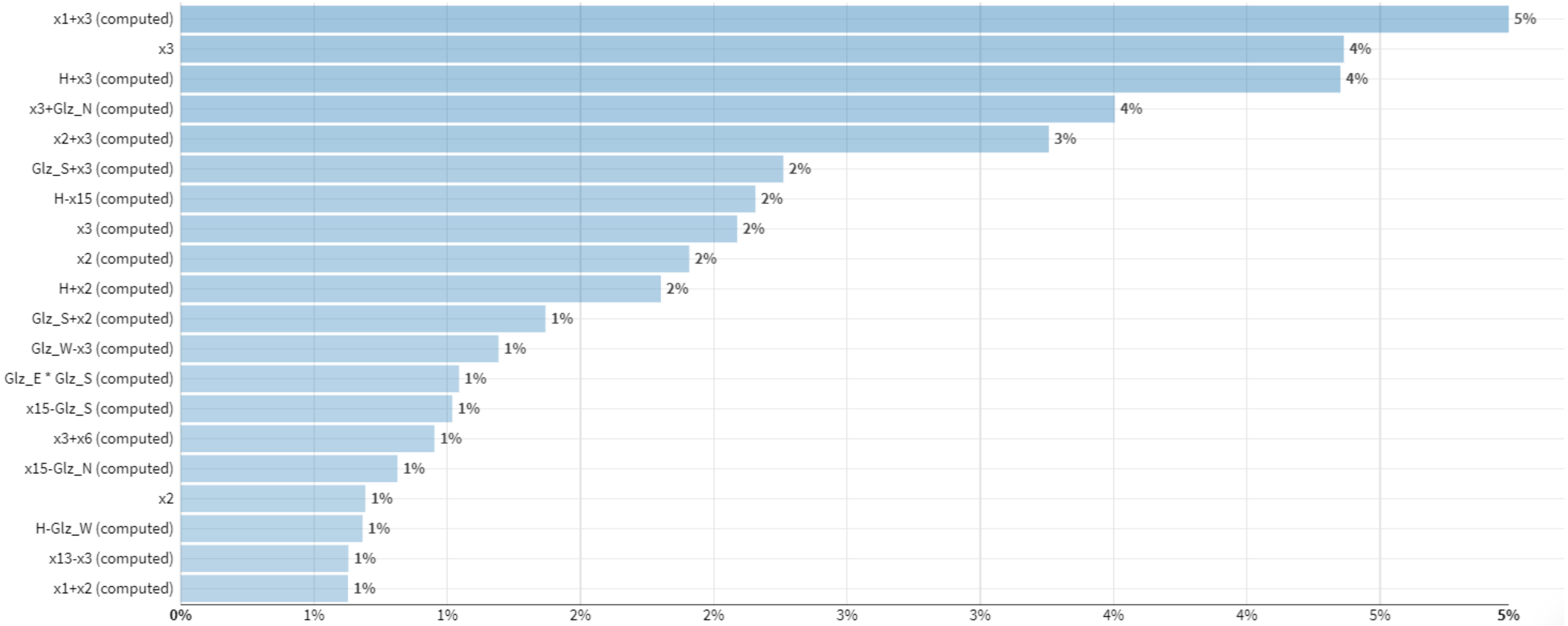
Explanation	Notation	Orientation	Boundry	Unit
Number of vertical sahdes	x1, x5, x9, x13	North-south-east-west	[0-10]	Meter
Length of vertical devices	x2, x6, x10, x14	North-south-east-west	[0-1,5]	Meter
Rotation of vertical devices	x3, x7, x11, x15	North-south-east-west	[-60-60]	Degree
Width of vertical 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	_

Improvements sDG Prediction-Regression

- A data set with 380 new rows were added
- Considering linear and non-linear combinations of input features (eg., x1+x2, x1*x4 …)

R2=0.25 → R2=0.47

Variable importance sDG considering the linear and non-linear combination of features

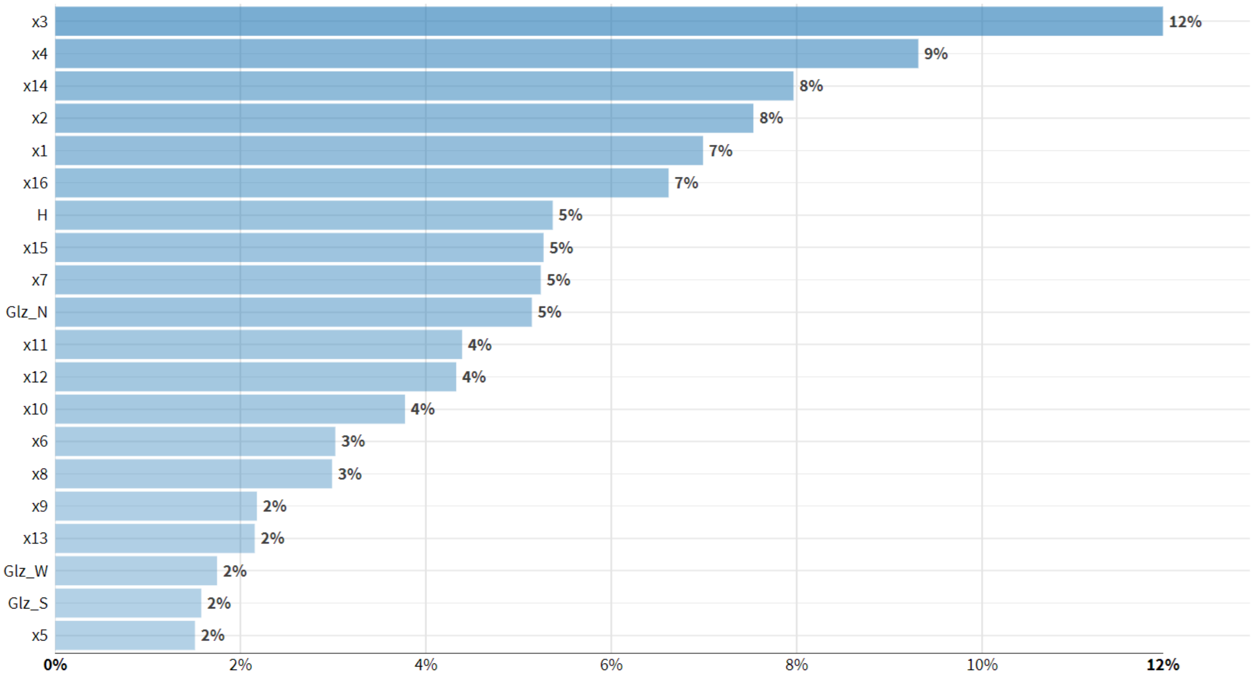


Visual Comfort Prediction-Regression

Visual Comfort / Variable importance

Name	Accuracy	ROC AUC
Random forest	0,93	0,87
SVM	0,91	0,85
K Nearest Neighbors	0,92	0,7

Visual Comfort / Variable importance

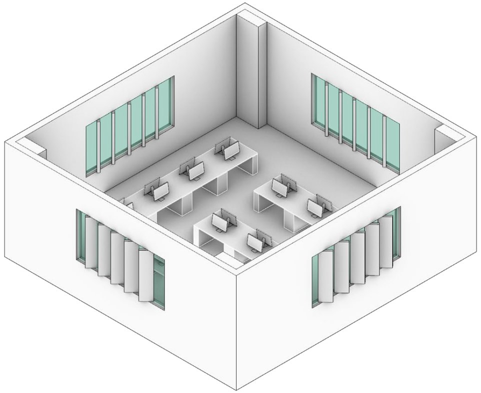


X3: Rotation of Vertical Devices on the North Side

X4: Width of Vertical devices on the North Side

X14: Length of Vertical Device on the East side

X14: Length of Vertical Device on the East side



Explanation	Notation	Orientation	Boundry	Unit
Number of vertical sahdes	x1, x5, x9, x13	North-south-east-west	[0-10]	Meter
Length of vertical devices	x2, x6, x10, x14	North-south-east-west	[0-1,5]	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	_

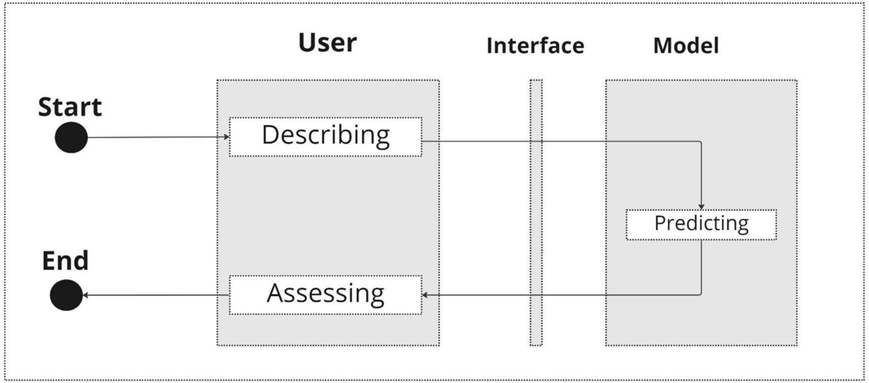
Visual Comfort Prediction-Classification/Confusion Matrix

- The data set is imbalanced

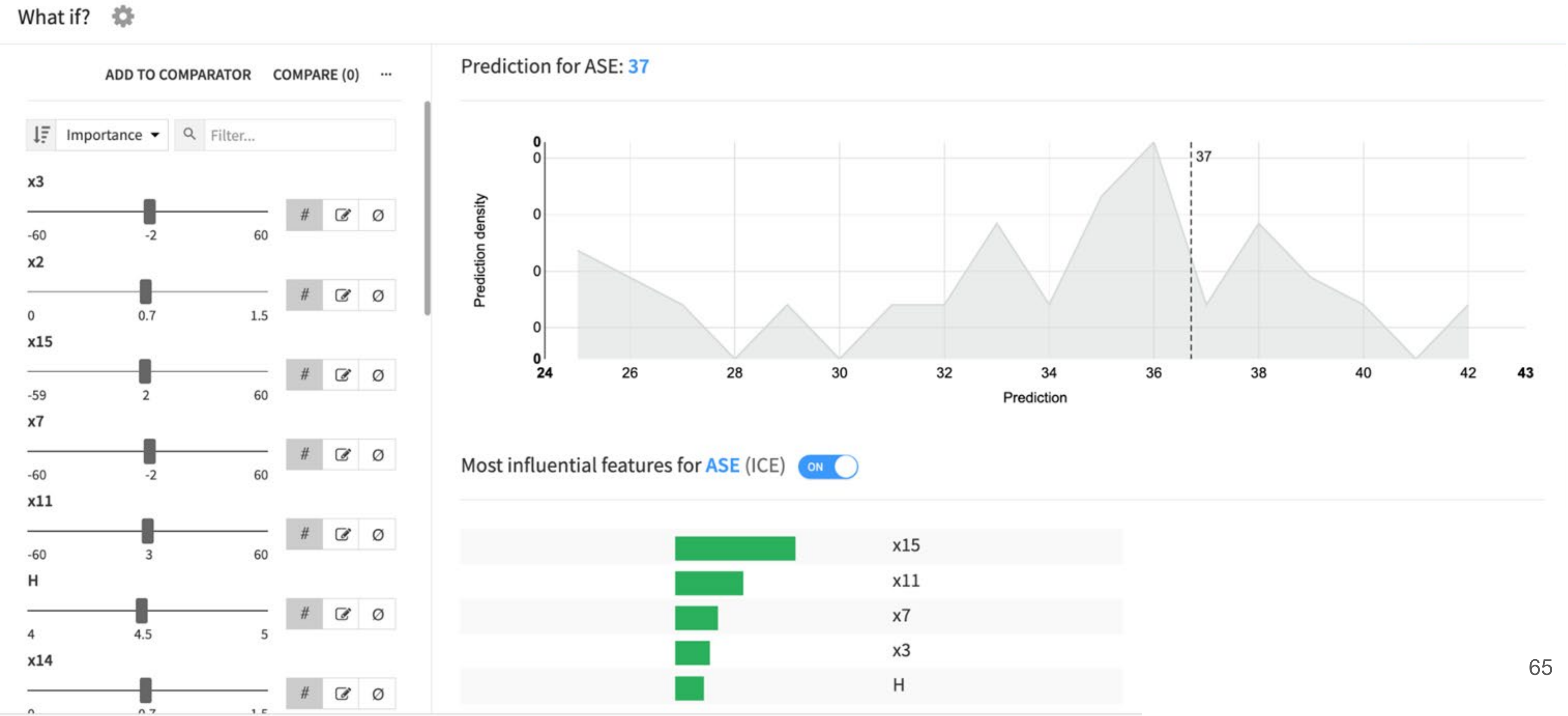
	Predicted				
Actual	Unacceptable	Acceptable	Neutral	Preferred	
Unacceptable	99 %	1 %	0 %	0 %	100 %
Acceptable	43 %	57 %	0 %	0 %	100 %
Neutral	67 %	33 %	0 %	0 %	100 %
Preferred	-	-	-	-	100 %

Post Processing

Design Process



What-if Scenarios for ASE Prediction

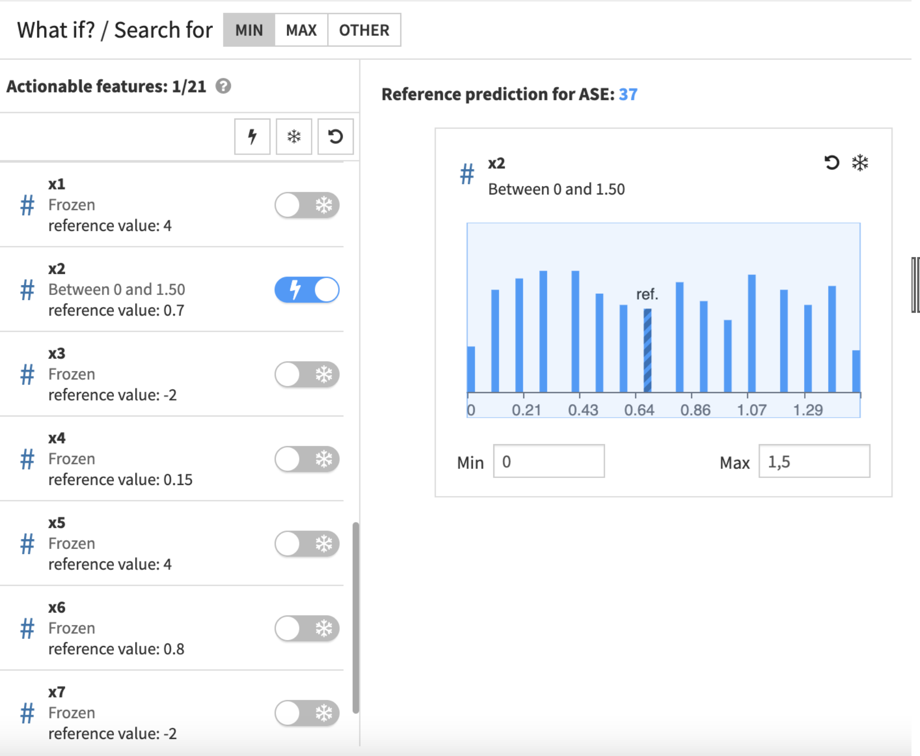


What-if Scenarios for ASE Prediction

	Plausibility	Prediction	x8 (Between 0.050 and 0.24)	Glz_E (Between 1 and 4)	x9 (Between 0 and 8)	H (Between 4 and 5)	x10 (Between 0 and 1.50)	x12 (Between 0.050 and 0.24)	x11 (Between -60 and 60)	x14 (Between 0 and 1.50)	x13 (Between 0 and 8)	x16 (Between 0.050 and 0.24)	x15 (Between -59 and 60)	Glz_S (Between 1 and 4)	Glz_W (Between 1 and 4)	x1 (Between 0 and 8)	x2 (Between 0 and 1.50)	x3 (Between -60 and 60)	x4 (Between 0.050 and 0.24)	x5 (Between 0 and 8)	x6 (Between 0 and 1.50)	x7 (Between -60 and 60)	Glz_N (Between 1 and 4)
	55%	19.77	0.15	2	3	4.197	0.921	0.1328	48	0.824	2	0.1894	51	3	2	4	0.549	-56	0.1701	6	1.179	55	3
	35%	20.70	0.2074	2	2	4.077	0.484	0.1195	-30	0.721	5	0.068	52	3	3	2	0.481	-51	0.1231	7	0.339	39	4
	45%	20.71	0.1219	2	2	4.566	0.267	0.1094	-13	0.917	7	0.1862	54	3	3	6	0.63	-52	0.1353	7	0.301	39	1
	30%	20.95	0.182	2	7	4.222	0.51	0.1103	32	0.197	3	0.1757	5	3	2	0	0.081	-56	0.084	1	0.602	55	2
	30%	21.59	0.2307	4	2	4.452	1.245	0.1822	-27	0.917	5	0.151	54	2	3	6	0.635	-51	0.1085	1	0.752	48	2

Which value of input feature result in the min value of ASE

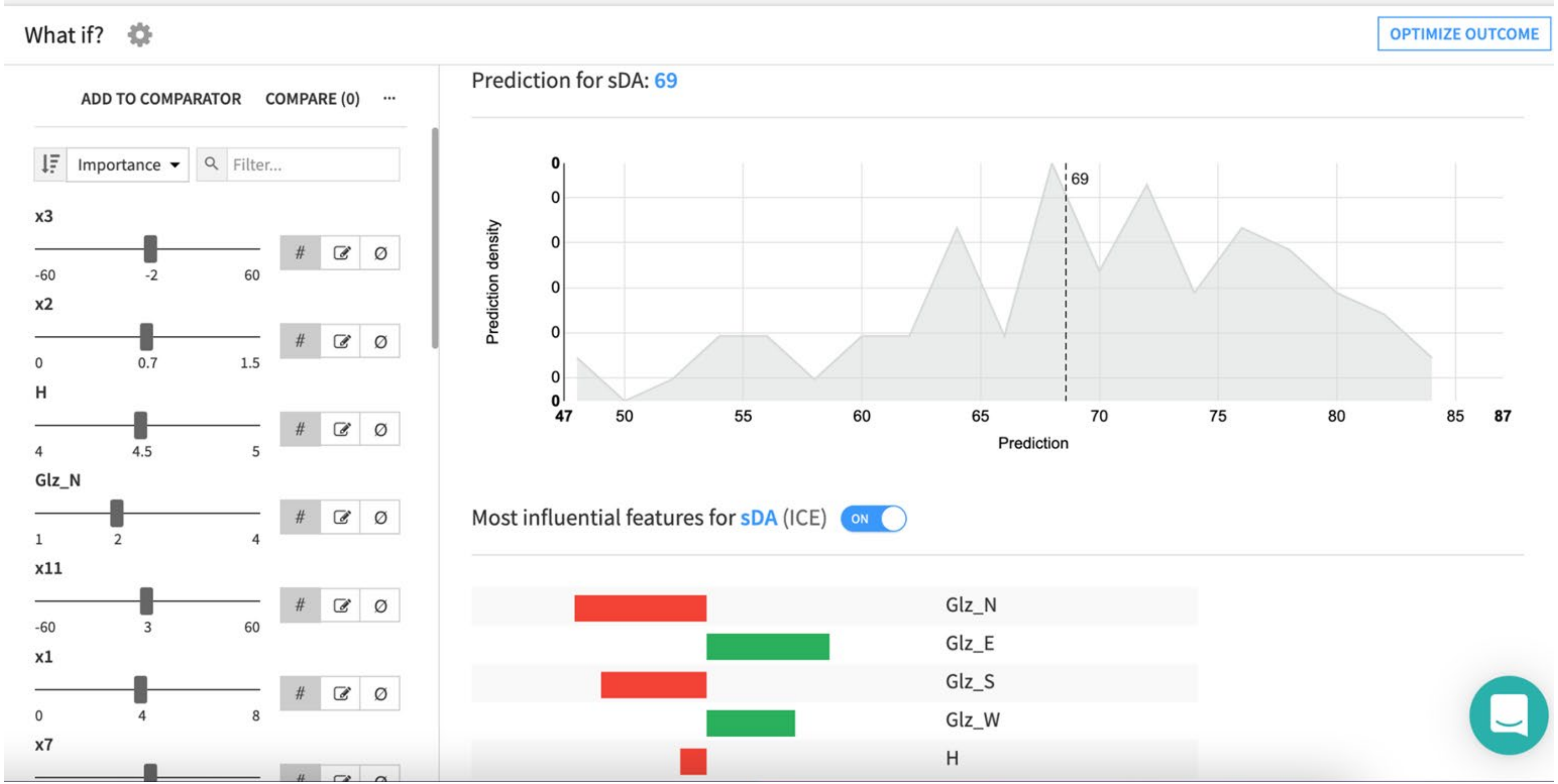
What-if Scenarios for Minimum ASE Prediction Based on x2 Values



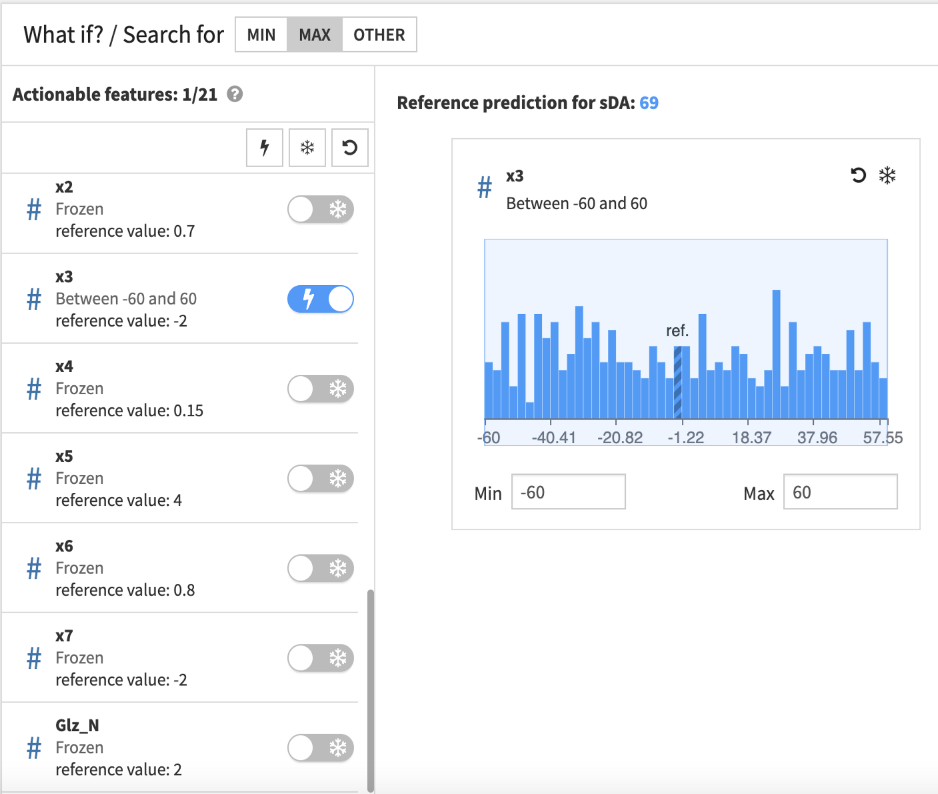
	Plausibility	Prediction	x2 Between 0 and 1.50
	80%	35.62	0.025
	90%	35.62	0.096
	90%	35.62	0.13
	80%	35.62	0.07
	80%	35.62	0.041

The x2 values that result in min ASE value

What-if Scenarios for sDA Prediction

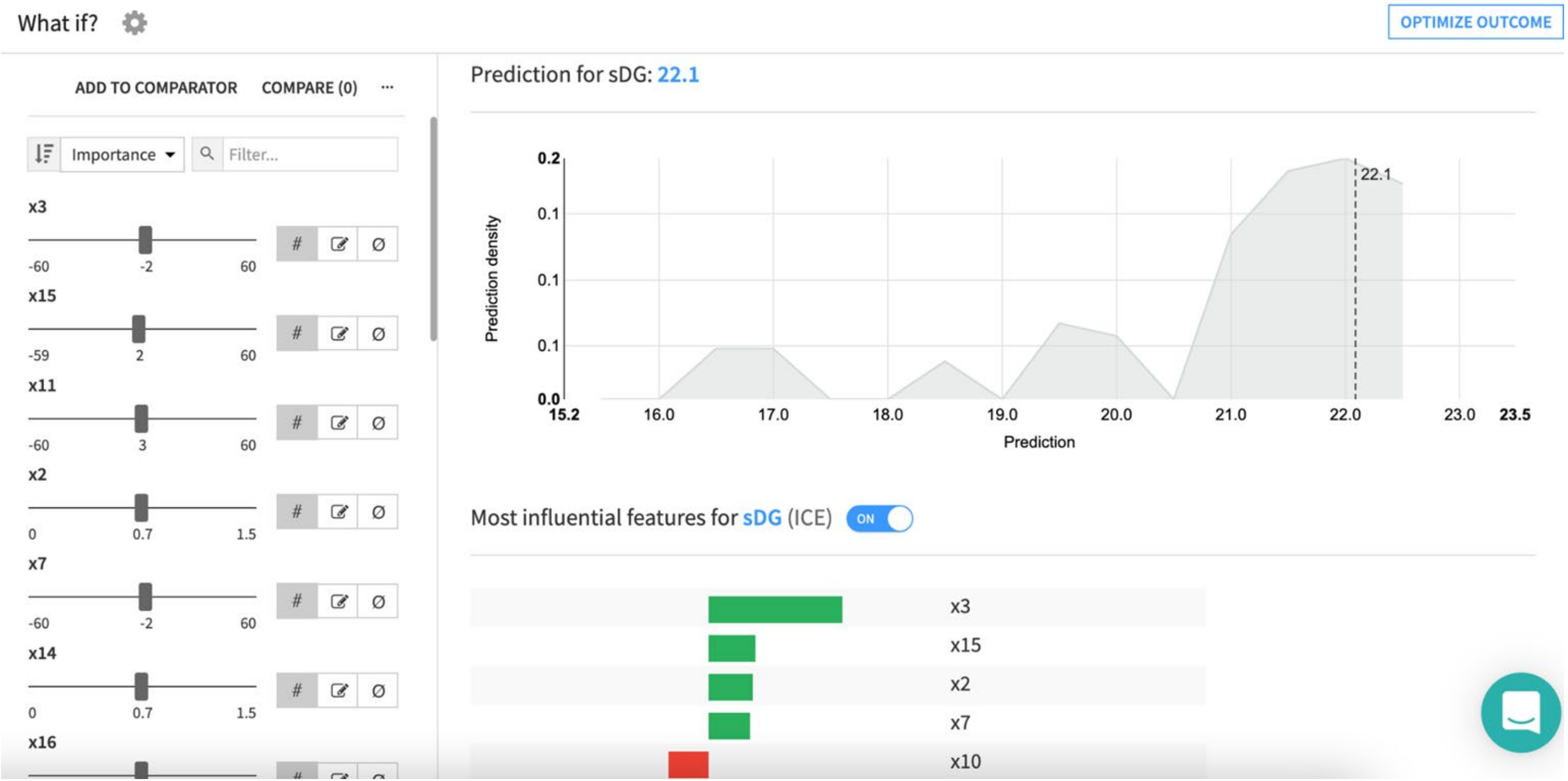


What-if Scenarios for Maximum sDA Prediction Based on x3 Values

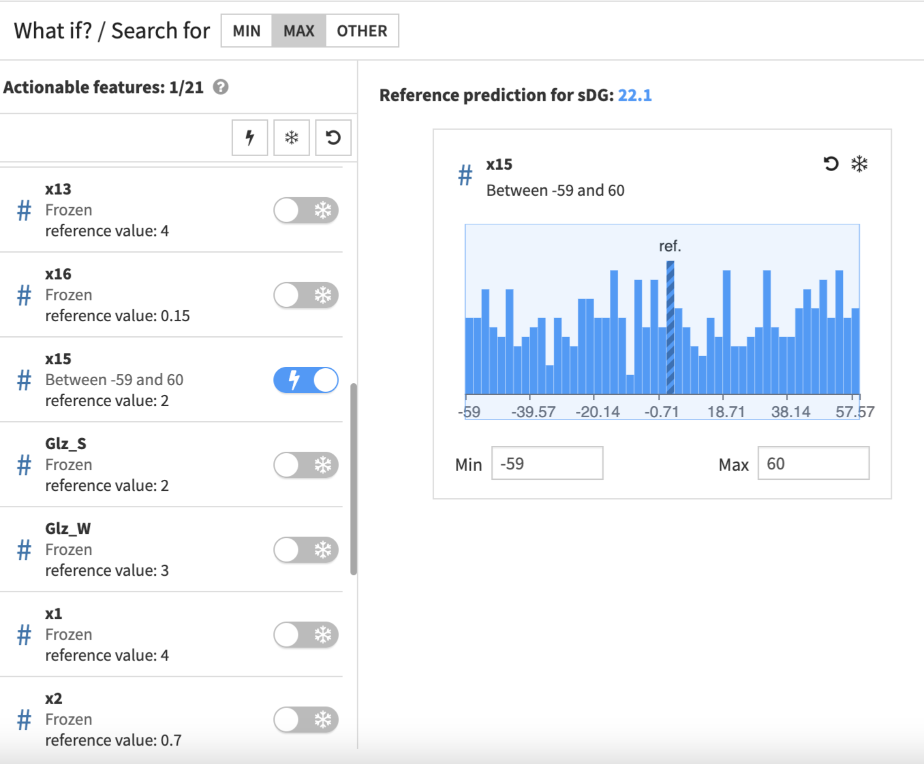


	Plausibility	Prediction	x3 Between -60 and 60
	95%	71.25	60
	95%	71.21	59
	95%	71.16	58
	95%	71.12	57
	95%	71.08	56
	95%	71.04	55
	95%	70.99	54
	95%	70.95	53
	95%	70.91	52
	95%	70.86	51
	95%	70.82	50
	95%	70.78	49
	95%	70.74	48
	Ref.	69	-2

What-if Scenarios for sDG Prediction

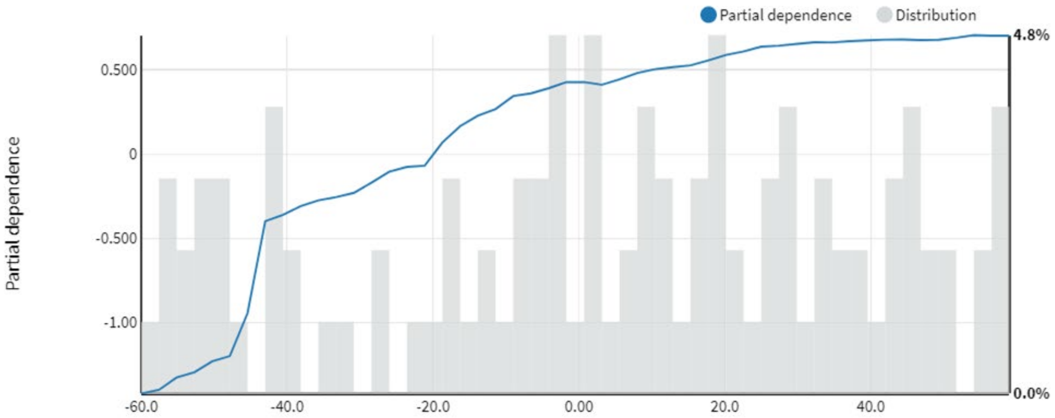


What-if Scenarios for Maximum sDG Prediction Based on x15 Values



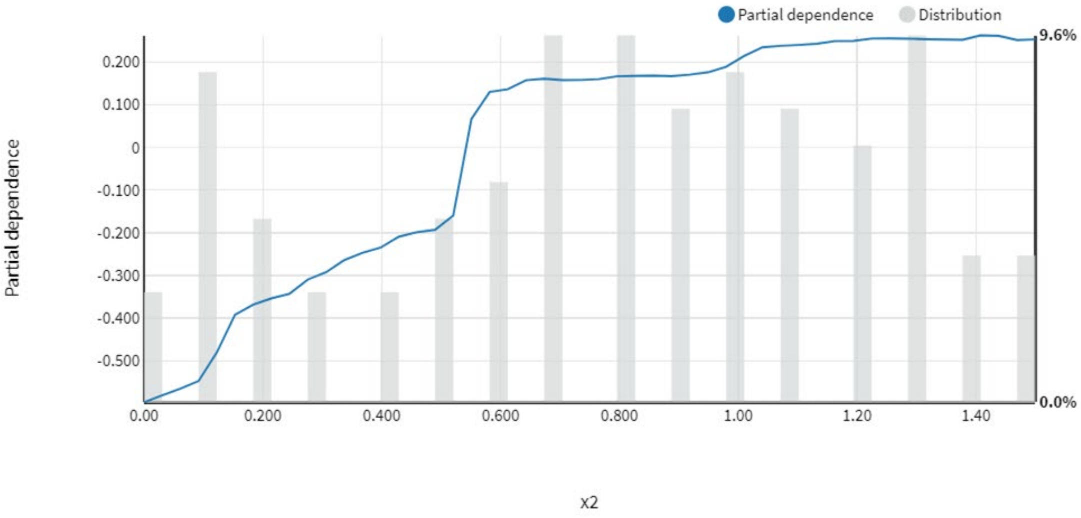
	Plausibility	Prediction	x15 Between -59 and 60
	95%	22.81	-56
	95%	22.81	-59
	95%	22.81	-57
	95%	22.81	-55
	95%	22.81	-58

Partial Dependency of X3 for sDG prediction



x3

Partial Dependency of X2 for sDG prediction



Conclusion

Conclusion

- 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. For the Annual Glare more investigation is needed.
- Although the predicted result of the Machine Learning Models might not be accurate, but in the conceptual phase of design, the speed and low cost simulation can be prioritised over the accuracy.
- The Visual comfort results as a classification label in the interfaces like climate studio or grasshopper can be used by designers.

Limitation and Future Development

- 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
- 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.
- What Error distribution is acceptable in the field of Daylight study?

Thank you!