Predicting Daylight Autonomy Metrics Using Machine Learning

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Abstract: This study analyses the efficacy of using machine learning though artificial neural networks (ANN) to predict daylight autonomy metrics in typical office spaces. Based on a literature review of the use of ANN for non-linear problems, the chosen approach was deemed promising for its use in predicting daylight performance with the assumption that previous training data can be provided. The ANN approach, while empirical, has advantages when compared to conducting full simulations in the areas of speed and computing resources. In this study, several network architectures were analysed against several test cases. The accuracy of the obtained results mirror those in other studies when applied to daylight autonomy metrics. In addition, accuracy improved with the addition of a larger set of training data as well as the enhancement of the network architecture itself.

Keywords: Daylight, Daylight Autonomy, Machine Learning, Neural Networks

Introduction

In the field of sustainable building design, daylighting is an emerging design factor improving the performance of a building (Bodart and De Herde, 2002; Pollock *et al.*, 2009). Good daylight design has been shown to have a positive impact on human health and performance (Heschong, Wright and Okura, 2002) and the potential to create visually pleasing indoor environments (Galasiu and Veitch, 2006) To date, however, predicting daylight performance required computationally expensive simulations that may not be feasible in a highly iterative design process (Hu *et al.*, 2014). This paper introduces an alternative approach to predicting daylighting performance using machine learning and artificial neural networks (ANN) that have been previously shown to be suitable for complex non-linear problems (Suykens *et al.*, 2012).

The assessment of daylight using climate-based metrics is increasingly gaining recognition as a design tool improving occupant comfort and reducing energy consumption. This paper focuses on daylight autonomy (DA300lux) as a suitable metric for daylight performance due to its increasing adoption (Reinhart and Fitz, 2006). The definition of Daylight Autonomy (DA) was first given by the Association Suisse des Electriciens in 1989 (Reinhart *et al.*, 2013) and further developed as a measure for the percentage of occupied hours in which a minimum illuminance threshold at a sensor point can be maintained by daylight alone (Reinhart and Walkenhorst, 2001). The target used depends on the determined use of the space – typically 300 lux or 500 lux for office work.

Briefly, artificial neural networks (ANN) are computer models made of units called neurons, arranged in an input layer (that accepts input parameters), an output layer (which provides the actual prediction) and a varying number of hidden layers in the middle (Figure 1). Using varying strengths, the connections between neurons transmit an activation signal from one neuron to another (Jain *et al.*, 1996). Backpropagation is a typical method to train neural networks. The backpropagation algorithm uses gradient descent to adjust the connection weights and to find the minimum value of the error function (Rojas, 1996).

The next section of the paper briefly reports on previous research in the areas of predicting building thermal and daylighting performance using backpropagation neural networks. Following that, the methodology used in this study is described, including the design setup of the model and the various network architectures and settings. Consecutively, the obtained results are reported. The last section of this paper reflects on the overall approach and findings and outlines recommendations for future work.

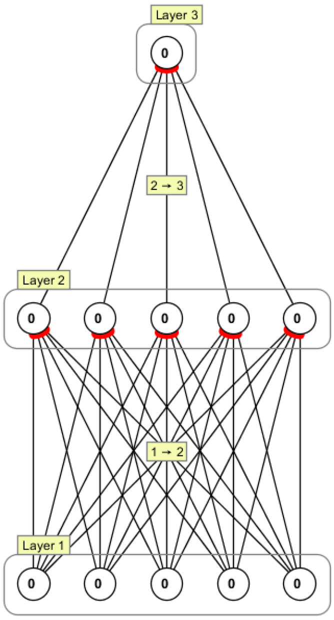

Figure 1. Neural network architecture (Simbrain, 2017) with five neurons in the input and hidden layer (Layer 1, Layer 2) and one neuron in the output layer (Layer 3)

Predicting building performance using neural networks

Several researchers have studied the application of neural networks for predicting building energy performance including heating and cooling loads and the overall energy consumption of buildings with successful results (Wong *et al.*, 2010; Zhao and Magoulès, 2012). Studies show that the accuracy of these predictions does not fall behind that of other thermal simulation tools (Neto and Fiorelli, 2008), making neural networks a possible alternative approach to time-consuming and computationally expensive simulations. This can be feasible only if the required data is within a set design scope and previous measurements are available for training the neural network. The successful application of neural networks in thermal building performance and their ability to address non-linear problems suggest that they may be applicable for daylight analysis. Thus, this paper sets out to experiment with using back-propagation neural networks to predict daylight performance and the Daylight Autonomy metric.

Compared to the implementation of neural networks for thermal predictions, research is rather sparse on the implementation of neural networks for daylighting and illuminance predictions. However, the few results that are available are promising: In a study by (Lopez and Gueymard, 2007), a neural network was used to predict the luminous efficacy under cloudless conditions, suggesting a possibility to predict the illuminances on surfaces based on measurements of solar irradiance. In another study, Janjai and Plaon were able to predict sky luminance for a year, giving more accurate results than the CIE model for clear and overcast skies, but not for cloudy skies (Janjai and Plaon, 2011). Comparisons have also been made between different models for predicting sky irradiance and illuminance and neural networks showed superior performance (Pattanasethanon *et al.*, 2008).

Neural network-based modeling has also been successfully applied to predicting the horizontal illuminance in an office building (Kazanasmaz *et al.*, 2009). The results had a low average error of 3% when compared to measured illuminances. In a classification problem, a similar study was able to determine the category of climate-based metric UDI (classification problem) for various ranges of lux levels (<100 lux, 100 – 2000 lux, >2000 lux) with a high accuracy of 96% when combining a neural network with principal component analysis (Zhou and Liu 2015). These studies suggest neural networks can be used as a computational tool with potentially very accurate prediction capabilities given appropriate model selection and well-defined parameters.

Achieving accurate results was a key point in the above studies. Nonetheless, it should be noted that some of the studies also faced challenges and occasional failures. This seems to be the case especially when the input parameters are complex and have a wider range of values (e.g. Janjai and Plaon, 2011; Conraud-bianchi, 2008) and is consistent with findings in the application of neural networks for thermal comfort predictions (Magnier and Haghighat, 2010) and those aiming to include occupant behavioural patterns (Neto and Fiorelli, 2008). Therefore, it becomes evident that there is a necessity to accurately retrace input parameters that impact any variations in the results, and empirically search for a neural network architecture that is capable of reconstructing more complex and dynamic relationships.

There is not yet sufficient research that explores the range of application possibilities for ANNs to measure daylight performance within buildings. The lack of studies undertaken in this field also points to a need for validation and a more thorough investigation of the advantages and limitations of this approach. Regarding daylighting predictions, the need for training data to include various climate and sky conditions as well as sun positions has made generating the training data for neural networks a tedious task, albeit one that can be used to generate instantaneous results thereafter.

This study uses a backpropagation neural network to measure Daylight Autonomy over the course of a year, thereby bypassing the need to use sky conditions and sun positions as input parameters as well as conducting intensive simulations or recording measurements associated with collecting the data.

Methodology

Design setup

A generic typology for the ground floor of an office building was developed to investigate the performance of neural networks for the prediction of daylight autonomy (Figure 2). As part of the process of generating the target data required for training the neural network, the daylight autonomy calculations were done using Diva for Rhino. Diva is a radiance-based and validated tool (McNeil and Lee, 2012) that uses the daylight coefficient approach to determine the daylight contributions for all sensor points within a building (Bourgeois *et al.*, 2008). The daylight autonomy was determined for a horizontal illuminance of 300 lux for 300 sensor points that were generated at a work plane height of 85 cm. The internal reflectance values within the building were set to 20%, 50% and 70% for floor, walls and ceiling, respectively. The daylight autonomy results for all sensor points were then extracted for further application in the neural network.

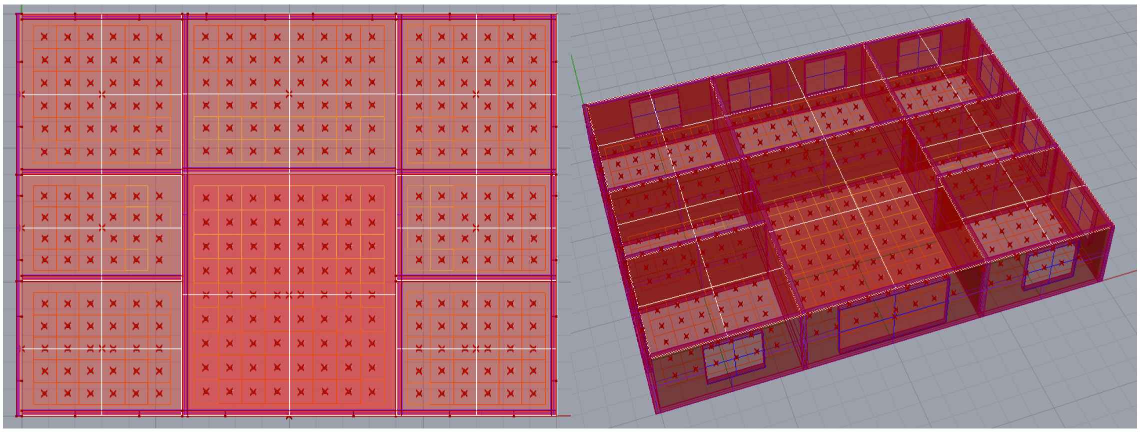

Figure 2. Layout A: Illustration of basic building model geometry and the location of sensor points

The design variables affecting the daylight autonomy results were identified as follows:

- The X-Y coordinates of the sensor locations to identify the different points
- A unique room ID was assigned to specify the rooms in which the sensor points were located as seen in (Kazanasmaz *et al.*, 2009)
- The average distance of the sensor points to the center of the windows to describe proximity of the sensor points to the light source.
- The overall dimensions, window dimensions, number of windows and their respective orientation. Window orientation was represented using four input parameters, one each describing the north, south, east and west orientations as a binary value.

The input parameters were treated as continuous variables and normalized between the range 0 and 1 with 0 indicating the minimum value of the variable and 1 its maximum.

Automated data generation using Grasshopper

The building design was parametrically built in Grasshopper for Rhino (Figure 3). The above identified input parameters were extracted within Grasshopper and assigned to each of the sensor points in the building. The data was then exported as an excel sheet to convert it into the training data for the neural network.

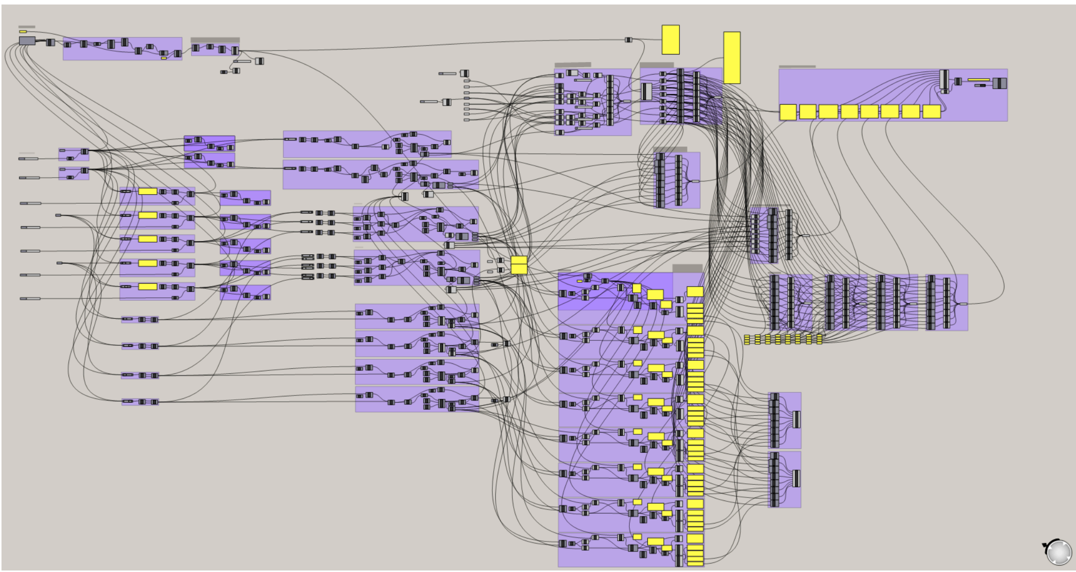

Figure 3. Layout A: Illustration of basic building model geometry and the location of sensor points

Neural network training and testing

A feed-forward neural network was chosen as a baseline for training and this application. The neural network was trained using the backpropagation method (Hecht-Nielsen, 1989) using the software tool Simbrain (Simbrain, 2017). A sigmoidal activation function was chosen in the hidden as well as output layers and all weights were randomized before training. The training and testing of the neural network was carried out in four parts as outlined below.

1) Neural network training with one and two hidden layers: In an experiment, several neural network architectures were trained by changing the number of hidden layers and the number of neurons they contain. Although a rule of thumb suggests that the number of neurons from input to output layer should follow a pyramidal rule - for example 7 neurons in the first layer, 5 neurons in the second layer and 1 neuron in the third layer (Joe, 2009), other studies have more successfully implemented a higher number of neurons in the hidden layer than the number of neurons in the input layer (Chow *et al.*, 2002; Conraud-bianchi, 2008; Zhou and Haghighat, 2009).

For the above outlined building, 300 sets of data were generated for each sensor point. 10% of the data was withheld for validation of the neural network. The network was then trained with a momentum of 0.7 and a learning rate of 0.25. No maximum number of epochs was selected, although training was halted when either the mean square error (MSE) did not go down any further or when the results deteriorated with further training. In this way, the MSE was calculated for several neural networks with a varying number of neurons in architectures with both one and two hidden layers. The set up of the network architecture and the corresponding results are listed in Table 2.

2) Neural network training and validation using different input parameters: Having established the MSE results for different neural network architectures, the prediction power for the DA300lux metrics was tested using four different sets of input parameters (Table 1). The first set maintained all parameters as described above while the second set removed the coordinates as identifiers of the sensor points. In the third set, the coordinates were added back as input parameters, but the distances of sensor points to windows were removed. The fourth set omitted the room ID as an input parameter. This input parameter was considered a duplicate, as the attributes of the rooms were already described through the remaining input parameters.

Table 1. Input data used for neural network training

Input Parameter Set A	Input Parameter Set B	Input Parameter Set C	Input Parameter Set D
Room dimension	Room dimension	Room dimension	Room dimension
Window dimension	Window dimension	Window dimension	Window dimension
North orientation	North orientation	North orientation	North orientation
South orientation	South orientation	South orientation	South orientation
East orientation	East orientation	East orientation	East orientation
West orientation	West orientation	West orientation	West orientation
No. of windows	No. of windows	No. of windows	No. of windows
Average distance to windows	-	Average distance to windows	Average distance to windows

-	Coordinates of sensor points	Coordinates of sensor points	Coordinates of sensor points
Room ID	Room ID	Room ID	-

3) Daylight Autonomy predictions for an alternative layout: The validation of the neural network in the above outlined part was done for sensor points set within the design scope from which the training data was taken. To stress test neural network predictions, an alternative layout (Layout B) was developed, for which the DA values were then calculated. Alongside the location of sensor points, the room dimensions as well as the location of windows were changed. The alternative layout is illustrated in Figure 4. The test used input parameter set C as it had previously yielded the best results. Additionally, an ANN constituting of 15 neurons in the hidden layer was used for training as preliminary results gave a low MSE of 0.006 for said architecture when trained with 300 data points. Although it was expected that there would be a larger error margin based on the numerous design changes affecting daylight performance, this case was chosen as an initial assessment to gauge the performance of neural network predictions in a changing design scope.

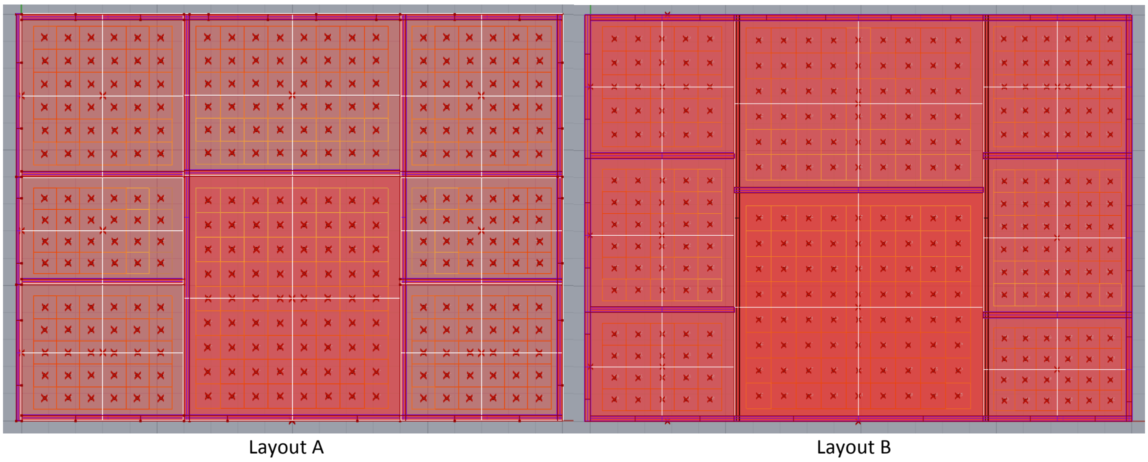

Figure 4. Basic building layout used for training (Layout A - left) and an alternative layout developed for validation (Layout B - right)

4) Daylight Autonomy predictions for a single room with varying depth: In a fourth test, the above experiment was simplified. Under the assumption that neural networks function as a model mimicking the behaviour of a building, with an innate potential to adjust to a changing design scope based on the training data provided to the neural network, DA predictions were made for a singular south facing room, where the design was varied only by changing room depth and sensor point location (Figure 5). Predictions were made with an increasing number of training data sets and results were compared using neural networks with one and two hidden layers.

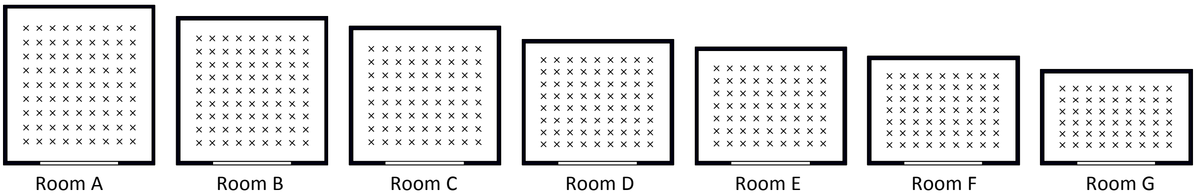

Figure 5. Rooms used for progressive network training

Results

Neural network training results for networks with one and two hidden layers

Several neural network architectures were tested to determine the impact of the number of neurons and number of hidden layers on the ability of the neural network to fit the input data to the provided target data (prediction results). The achieved MSE results for each of the tested ANN architectures are shown in Table 2.

The ANNs with one hidden layer yielded a lower MSE than ones with two hidden layers. The three-layered ANNs also seemed to reach convergence at an MSE of 0.0011 when implementing both a higher and lower number of neurons in the hidden layer than number of neurons in the input layer, confirming the above outlined assumption that the ANN architecture does not need to be formed of a pyramidal structure.

Table 2. MSE results for varying neural network architectures

No. of hidden layers	No. of neurons within hidden layers	MSE
1	5	0.0017
1	9	0.0011
1	12	0.0011
1	15	0.0011
2	5-5	0.0022
2	7-5	0.0019
2	9-5	0.0028

Neural network training and validation using different input parameters

Following the initial testing of neural network architectures, the architecture with twelve neurons in one hidden layer was selected to predict the DA results using the four different sets of input parameters outlined in Table 1 above. The MSE for the data sets is shown in Table 3. The results reveal that both coordinates of sensor points and average distance of sensor points to the windows lower the MSE. The neural network results could further be improved by removing room ID as an input parameter, achieving an overall improvement of the MSE from 0.0013 to 0.0007. This impact of the MSE results becomes clearer in the error analysis of the input sets (Figure 6). A lower MSE led to better DA predictions and an average prediction error ranging between 3.5% to 2.3% for the different input parameters, thereby providing results comparable to those from validation studies done for daylight analysis using Daysim and Radiance (Reinhart and Walkenhorst, 2001).

Table 3. MSE results for varying input parameter sets

	MSE
Set A	0.0011
Set B	0.0013
Set C	0.0007
Set D	0.0008

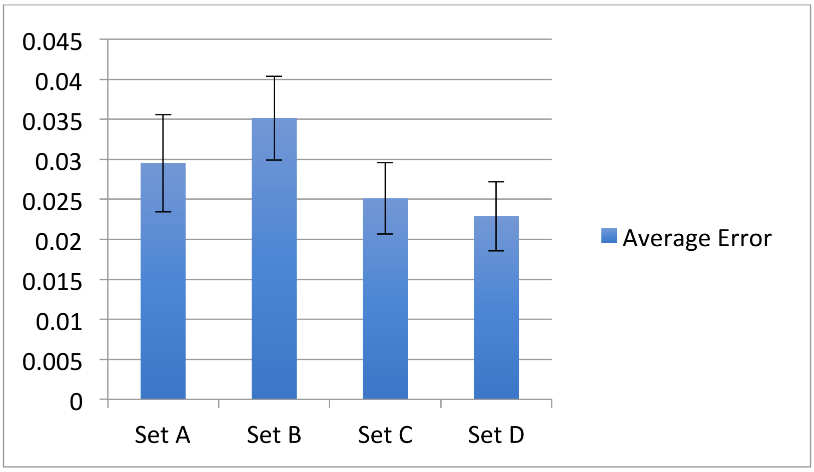

Figure 6. Prediction errors obtained for the varying input parameter sets

Additionally, the errors obtained for each of the sensor points are presented in Figure 7. The error rates of the predictions are of a volatile nature and show no apparent consistency between implemented input parameter set and error, meaning errors can be lower for a specific sensor point using one input set, but higher for another sensor point. Further analysis of the data shows that the errors using input parameter sets C and D are less erratic, suggesting a more robust neural network.

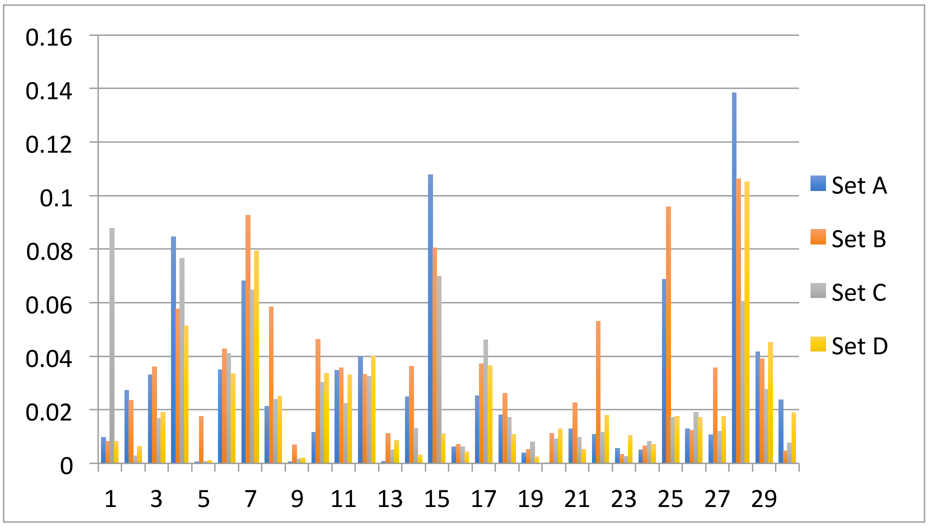

Figure 7. Prediction errors obtained for each sensor point

Daylight Autonomy predictions for an alternative layout

The overall error for the DA predictions for building layout (B) with new room dimensions, window positions and sensor point locations increased from 2.3% to 7.66%. The error for each of the sensor points is shown in Figure 8. A noticeably lower error was achieved for rooms with smaller changes in dimensions and the corner rooms with windows facing two orientations. A further analysis of the results revealed that the error gradually increased towards the rear for each room with one orientation.

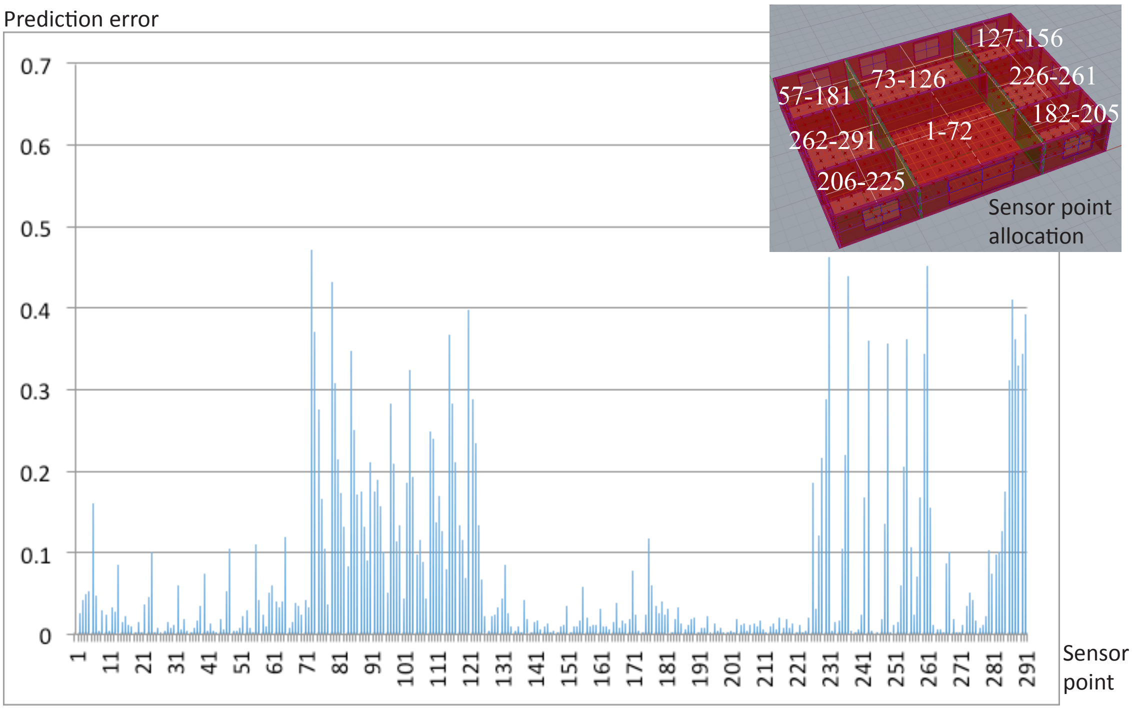

Figure 8. Prediction errors obtained for each sensor point on an alternative layout

Daylight Autonomy predictions for a single room with varying depth

Neural network training and testing results for DA predictions for rooms C, G and D are given in Tables 4, 5 and 6, respectively. As shown in these tables, as the number of training data increased (by adding more rooms) the error margins decreased. Additionally, neural network architectures with one as opposed to two hidden layers generally better fit the training data, as indicated by lower mean square errors (MSE). Nonetheless, when considering average error rates, neural network architectures with two hidden layers on average showed much better results than networks with one hidden layer. Analyses did however reveal one peculiar result: neural network training for DA predictions for room G (Table 5) led to an unexpectedly strong increase in average error when including room D into the analysis. This increase in error rate from 4.46% to 28.96% for one hidden layer and an increase from 1.96% to 2.07% for two hidden layers might hint towards over-fitting.

Table 4. Neural network training and testing results for DA_{300lux} predictions of Room C

Training Data	MSE		Average Error	
	One hidden Layer	Two hidden Layers	One hidden Layer	Two hidden Layers
Room A	0.0006	0.0011	41.54%	41.54%
Room A+E	0.0007	0.0014	25.18%	6.93%
Room A+E+G	0.0005*	0.0013	15.64%	6.93%
Room A+B+E+G	0.0009	0.0013	4.68%	3.10%
Room A+B+E+F+G	0.0007	0.0012	3.21%	3.32%
Room A+B+D+E+F+G	0.0008	0.0012	3.25%	3.30%

*A neural network architecture of 4-25-1 neurons was chosen for this training data set as it had provided a lower MSE in preliminary testing. All other results were compiled using a network architecture of 4-20-1 and 4-

20-4-1 neurons in the layers.

Table 5. Neural network training and testing results for DA_{300lux} predictions of Room G

Training Data	MSE		Average Error	
	One hidden Layer	Two hidden Layers	One hidden Layer	Two hidden Layers
Room A	0.0006	0.0011	78.76%	79.17%
Room A+E	0.0007	0.0014	21.11%	3.11%
Room A+C+E	0.0008	0.0012	14.52%	2.92%
Room A+B+C+E	0.0008	0.0012	13.16%	2.78%
Room A+B+C+E+F	0.0007	0.0012	4.46%	1.96%
Room A+B+C+D+E+F	0.0007	0.0012	28.96%	2.07%

Table 6. Neural network training and testing results for DA_{300lux} predictions of Room G

Training Data	MSE		Average Error	
	One hidden Layer	Two hidden Layers	One hidden Layer	Two hidden Layers
Room A+B+E+F+G	0.0006	0.0012	1.81%	2.53%

Conclusion

One of the limitations of using ANNs is their empirical nature. Researchers often develop an intuition about the suitability of various network architectures and settings that best fit a given problem. Yet, once these issues are overcome, ANNs provides an excellent alternative to solving complex and non-linear problems. Promising initial results in this study point to the efficacy of using artificial neural networks for predicting daylighting performance in simple office spaces. As predicted, an increase in training data generally yielded better accuracy in the predicted results. Additionally, the use of two hidden layers improved the results in most cases. Overall, the error margins were within an acceptable range using less time and computational resources than computer simulations. The suitability of this approach, however, is dependent on a cost-benefit analysis regarding the ratio between the needed input training data and the required number of predictions since generating the training data continues to depend on conducting full computer simulations or real-world measurements. An intriguing possibility, that is yet to be explored, is the use of predicted data as training input for subsequent predictions. This heavily depends on the robustness of the process and the accuracy of the predictions. Data drift and thus accuracy deterioration could prove a limiting factor. Additional planned future work includes experimentation with more complex design scenarios, fine tuning the validation process and increasing the robustness of the overall research methodology.

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