Machine Learning-Based Framework to Predict Single and Multiple Daylighting Simulation Outputs Using Neural Networks

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Abstract

Building energy consumption accounts for 30% of global energy consumption (EIA, 2017). To support the development of energy-efficient built environments and cities, architects, urban planners, and engineers have begun to utilize building performance simulation (BPS). Supporting decision-making and steering the design toward high performance is crucial in the early design phase when decisions have the biggest impact on the final building's energy consumption and costs (Attia et al., 2012; Hygh et al., 2012; Kanters & Horvat, 2012). However, BPS tasks are usually time-consuming. Therefore, there is a need for a framework that would speed up the BPS process. This paper aims to develop a machine learning (ML) algorithm, specifically neural networks (NN), that can potentially speed up the process of daylighting simulations by executing only a small subset of the simulations to predict the performance of daylighting of thousands of design configurations. Furthermore, the paper will investigate the use of NN to predict single and multiple outputs of point-in-time and annual based daylighting simulations respectively.

Key Innovations

- Machine learning algorithm to predict single as well as various daylighting simulation outputs.
- Using high-performance computing (HPC) to speed up the production of the dataset needed to train the NN model.
- Using the K-fold strategy to improve prediction resulting from executing NN using a small training dataset.

Practical Implications

The framework introduced in this paper could serve as a model to speed up the prediction of daylighting performance in buildings using NN. Furthermore, the integration of HPC could speed up the entire process to obtain almost instant predictions of complex daylighting simulations instead of working for hours and even days, thus empowering architects and engineers to access the daylighting performance of various building configurations in the early design stages.

Introduction

A significant amount of energy can be saved by using daylight to light buildings to reduce artificial lighting consumption and, therefore, reduce heating and cooling loads (EIA, 2017; Lee, 2006). Daylighting not only saves energy but also improves students' performance on tests (Group, 1999) and increases worker productivity, which, in turn, increases the economic value of happy workers (C F Reinhart, 2013).

Although daylighting in buildings has been proven to be an asset, carrying out medium- to large-scale daylighting simulations to determine the daylighting performance of various building configurations can take days or even weeks to complete. However, practitioners in the construction industry usually adhere to strict project deadlines that prevent them from performing lengthy simulation tasks (Nguyen et al., 2014). Therefore, there is high demand for frameworks that could speed up the simulation process.

One emerging framework that can be utilized to speed up such a process is machine learning. Several researchers have examined the application of ML to predict the performance of the built environment in terms of energy consumption, daylighting harvesting, and thermal comfort. Researchers have proven that ML algorithms, specifically artificial neural networks (ANNs), accurately predict the energy consumption and other performance aspects of buildings (Wong et al., 2010; Zhao & Magoulès, 2012; Zhou & Liu, 2015). For example, Wong et al. examined the use of a NN model to predict the energy and daylighting performance of an office building. The researchers used a parametric building model that had nine variables as the input parameters: four variables related to the external weather conditions (daily average dry-bulb temperature, daily average wet-bulb temperature, daily global solar radiation, and daily average clearness index), four variables related to the building envelope designs (solar aperture, daylight aperture, overhang, and side-fins projections), and a day type variable (i.e., weekdays, Saturdays, and Sundays). The NN model was used to estimate daily electricity use for cooling, heating, and electric lighting. The accuracy metric for the NN-modeled cooling, heating, electric lighting, and total building electricity use was 0.994, 0.940, 0.993, and 0.996, respectively, indicating the excellent strength of the model's predictive ability. (Zhou & Liu, 2015). Other studies proved the success of using NN models to accurately predict the thermal performance of buildings for the ultimate energy-efficient and comfortable building design. For example, Neto and Fiorelli used a NN model to predict the thermal performance of the administration building of the University of Sao Paulo. Neural networks showed agreement between energy consumption forecasts and actual values, with an average error of about 10% (Neto & Fiorelli, 2008).

https://doi.org/10.26868/25222708.2021.30261

Although recent studies have investigated the use of different ML algorithms to predict a single output of daylighting simulations, researchers have not fully investigated the use of ML, specifically NN, to predict various daylighting simulation outputs. In this paper, NN is used to examine the accuracy of the prediction made by the NN model when used with a point-in-time single-output daylighting simulations and multiple-output annual daylighting simulations.

Method

As mentioned in the previous section, this paper discusses two applications of the proposed NN to predict the performance of daylighting in a room. The first application of the NN algorithm is examined using single-output point-in-time simulations, and the second one is examined using multiple-output annual daylighting simulations.

For both applications, the author used a 4x5m small office room located in New York City, which has one window oriented in different ways (see Table 1). The geometric model of the room contains ten different parametric variables (Table 1). Some parameters, such as the ceiling height and the lightshelf depth, are geometrically related; other parameters, such as the ceiling reflectance values and transmittance values, define the optical properties of the room's material. Each parameter contains a set of different values, with total of 25 different values that lead to 5,120 unique room configurations.

Radiance and Daysim (Larson, 1998; Christoph F Reinhart & Breton, 2009) were used for this research study the -ab (ambient bounce value was set to 5).

Table 1Variables embedded in the geometrical model

Variable	Configuration	Num
Room Hight	3m, 4m	2
Glazing Ratio	50%, 60%	2
Lightshelf Depth	0.5m, 1m	2
Lightshelf Location	Top of the window, shifted	2
Walls Reflectance	50%, 60%, 70%,80%, 90%	5
Lightshelf reflectance	80%, 90%	2
Ceiling Reflectance	80%, 90%	2
Floor reflectance	50%, 70%	2
Glazing transmittance	30%, 50%	2
Window orientation	North, South, East, West	4
Total number of room configurations		5,120

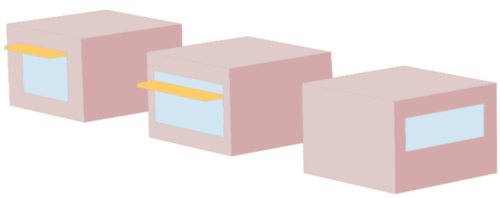

Figure 1 Three examples of the different configurations of the office room.

First Case Study; Single-output NN

For this case study, the author carried out point-in-time daylighting simulations to examine the use of the NN model to predict one output, which in this case is the value of the average illuminance in lux. The average illuminance value is calculated using illuminance values of 144 sensor points in the office room. The point-in-time simulations are executed for the winter solstice at 12:00.

Second Case Study; Multiple-output NN (an output that contains 144 values for each grid point)

For this case study, annual daylighting simulations were used to calculated daylight autonomy (DA) values over a grid of 144 sensor points (multiple outputs, 144).

High Performance Computing (HPC)

To calculate the time required for producing a test dataset, an initial DA simulation took two minutes to complete, in contrast to the illuminance level simulation which took 0.25 minutes to complete. This is mainly because the calculation procedure of DA determines the hourly illuminance level in all 144 analysis grid points in the test room for the entire year (Christoph F. Reinhart et al., 2006). The preliminary simulations were performed on a fairly fast Intel i7- 2.2 GHz laptop.

It was evident that running 5,120 configurations could be a complex and time-consuming task; therefore, the NN algorithm is crucial for speeding up such a process since the NN model uses only a subset of the simulations to predict the outcome. The author used two small subsets of 506 (illuminance, and DA) simulations of random room configurations to predict the performance of all 5,120 configurations. Although NN allowed the use of a small subset, executing 506 illuminance and DA simulations would still be a time-consuming process, taking about two hours and 16 hours, respectively. Therefore, a HPC environment was used to execute simulations. HPC facilitates the execution of various commands and processes in parallel on individual computing nodes that are part of a computing cluster. Various researchers confirmed that HPC provides an economical solution for executing large-scale computing processes. (Pérez-Lombard et al., 2008; Thain et al., 2005; Zhai et al., 2011).

Both subsets were executed on the HPC environment using a method similar to the one introduced in 2019 by Labib and Baltazar (Labib & Baltazar, 2019). A 120 HPC computing nodes were utilized in parallel. The illuminance simulations of the subset were completed in roughly one minute (1.1 minutes), and the DA simulations took about 8.5 minutes.

The NN Model

The NN framework was applied to the datasets that resulted from the daylighting simulations of both case studies. The following steps were applied to prepare the data and establish the NN model:

1. Data Normalization: Both data samples contained only 506 simulations, split between 404 training samples and 102 test samples. Each feature (e.g., the glazing ratio) in the dataset had

https://doi.org/10.26868/25222708.2021.30261

a different scale. For instance, some values were proportions, which take values between 0 and 1; others take values between 50 and 80, others between 3 and 4, and so on. Therefore, a data normalization technique was used to unify the scale of all the features in the dataset. This process was completed by subtracting the mean of the feature and dividing by the standard deviation so that the feature was centred around zero.

2. Developing the NN Model: Because the dataset was small, the NN model might have suffered from overfitting, which leads to performing poorly on new data. To mitigate this problem, a small NN model was constructed with two intermediate layers, each with 64 units, and one layer that contained only one output unit. The model was complied with the loss function mean squared error (MSE) (Equation 1), which is the square of the difference between the predictions and the targets. At the same time, the mean absolute error (MAE) was calculated to monitor the absolute value of the difference between the predictions and the targets.

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(y_i - \tilde{y}_i)^2 \qquad (1)$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_i - \tilde{y}_i| \qquad (2)$$

where n = The number of data points, y = The actual value of the output, $\tilde{y}$ = The Predicted value, and, i = the index of the data point.

3. Validating the ANN Approach with K-fold Cross- validation: To evaluate the ANN model while adjusting parameters, such as the number of layers, the number of units in each layer, and the number of epochs, some of the training data could be used for validation. However, the validation set would end up being very small considering that we had a small dataset. Therefore, the validation scores might change every time we changed the model's parameter due to our choice of data points used for validation and training. This leads to high variance in the validation scores, making the evaluation process of the model unreliable. To mitigate this problem, the PI used K-fold cross-validation, which consists of splitting the available data into K-partitions and training the model on all partitions except one used for validation. The process was then repeated by cycling through all the partitions. The validation score for the model used then was the average of the K validation scores obtained from all the cycles (see *Figure 2* and Figure 3). This method reduces variance in performance metrics (MSE, MAE). For the purpose of this work, K = 4 was used to apply the K-fold cross-validation method.

It is worth mentioning that upon executing the K-fold method explained in the previous section, better results could be obtained by creating a new NN model to be trained using the epoch that produces the lowest MSE value. Other parameters in the new model could also investigated, such as the number of layers in the NN model and the number of neurons in each layer. This process is usually completed manually to choose the best parameter of the NN model that results in the lowest MSE value in order to improve the accuracy of the predictions.

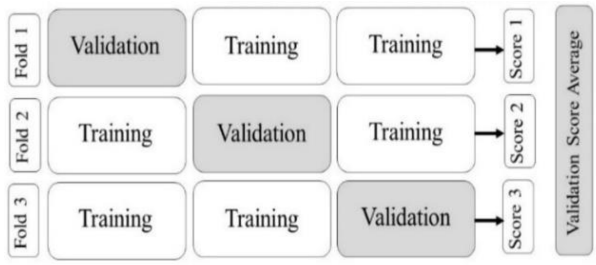

Figure 2 The K-fold cross-validation method, where the average of the three resulted scores are considered to evaluate the NN model

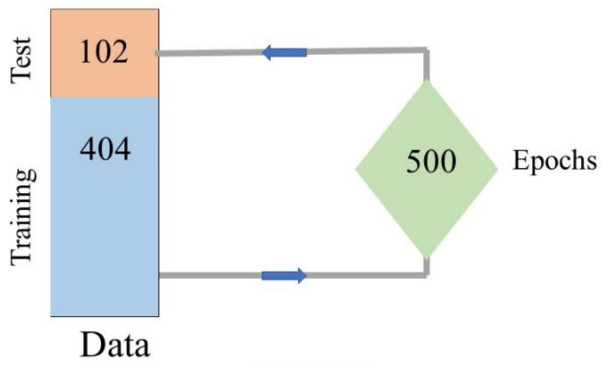

Figure 3 Illustration of the workflow of training the NN model over different epochs

Results

Single Output Case Study

The calculated MSE and MAE over 400 epochs resulting from applying the proposed NN model to the point-on-time illuminance simulations data are shown in Figure 4. It is evident that running the NN model with 130 epochs produced the best results before the model started to overfit. The MSE and MAE values were equal to 0.015 and 0.094, respectively. This means that the predicted average illuminance values are 94 points (Lux) off the actual value (considering that the MAE was multiplied by 1,000 because the initial average illuminance values were divided by 1,000). This is considered a highly accurate model where the actual average illuminance levels in the

https://doi.org/10.26868/25222708.2021.30261

data set ranged from 6,000 to 15,000 lux. The results of this research study confirmed that NN algorithm can be a great alternative to existing traditional BPS tools. The NN reduced the time required to examine more than 5,000 room configurations from about a couple of hours to a few minutes with an error margin of 0.94%.

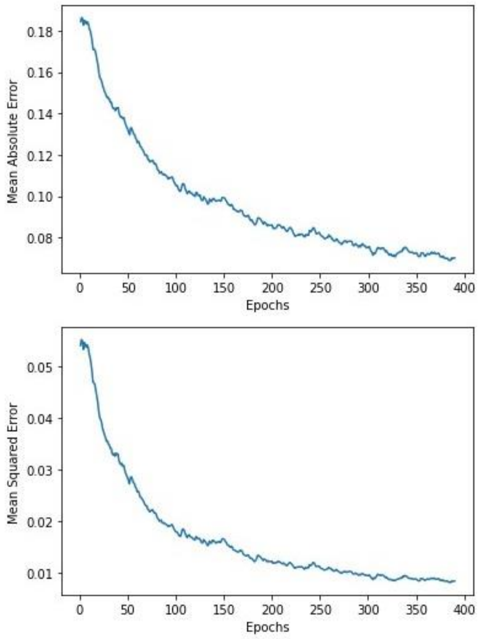

Figure 4 MAE (top) and MSE (bottom) values over different numbers of epochs when running the NN model for a single output (illuminance average)

Single-output Case Study Validation

The NN model was applied to nine different room configurations to examine the accuracy of the resulted predictions. Table 2 shows the predicted average illuminance values compared to the simulated values that were produced by implementing the NN model. The difference between the simulated values and the predicted values ranges from 20 to 79 lux.

Table 2 The simulated average illuminance values of different room configurations(i.e., window size, orientation, lightshelf specifications) compared to the values predicted by the proposed NN model. The simulations are carried out using Dec 21 at 12:00 sky file.

Configuration	Simulated	Predicted
1	2646	2731
2	2707	2726
3	2583	2490
4	2457	2392
5	2892	2840
6	3105	3059
7	2873	2901
8	2570	2595
9	3067	3089

Multi-output Case Study

The MAE and MSE resulting from applying the proposed NN model over 500 epochs are illustrated in Figure 5. It was determined that the best results before the model overfit is obtained when the NN model is applied with 175 epochs, where the MSE and MAE values were equal to 7.6 and 14.8, respectively.

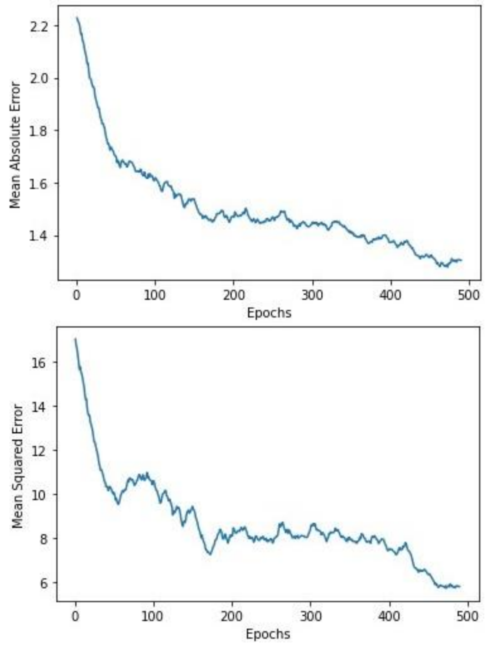

Figure 5 MAE (top) and MSE (bottom) values over different numbers of epochs when running the NN model for the multi-output (144 DA values) case study

Multi-output Case Study Validation

Similar to the validation method used to examine the accuracy of the single-output model, the author applied the NN model to compare the predicted DA values to their respective simulated values using three different room configurations (See Table 1 and Figure 6).

Table 3 Configurations used to validate the results of the proposed NN model

Variable	Config1	Config2	Config3
Room Hight	3m	4m	3m
Glazing Ratio	50%	50%	60%
Lightshelf Depth	1m	1m	0.5m
Lightshelf Location	Shifted	Top	Shifted
Walls Reflectance	90%	90%	90%
Lightshelf reflectance	90%	80%	90%
Ceiling Reflectance	90%	90%	80%
Floor reflectance	50%	50%	50%
Glazing Trans.	50%	60%	60%
Window orientation	East	North	South

https://doi.org/10.26868/25222708.2021.30261

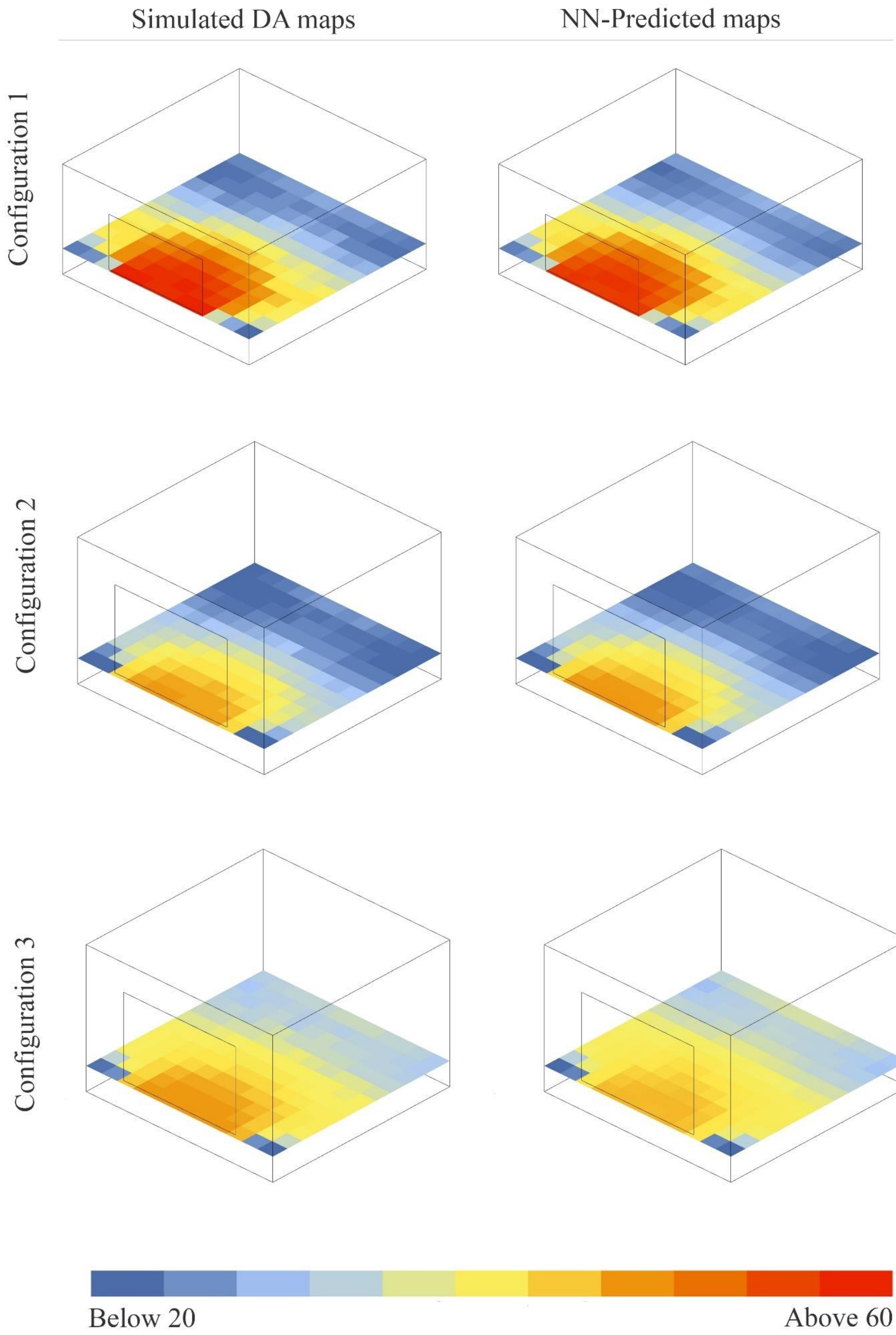

Figure 6 Daylight Autonomy maps of three room configurations. Right, the NN-predicted DA maps, Left, the simulated DA maps

https://doi.org/10.26868/25222708.2021.30261

Discussion

Current simulation processes are frequently run from popular parametric modeling environments. Often, sending data from these parametric modeling environments to HPC and executing ML requires combined knowledge of programming and Linux operating systems, two skills that many designers do not possess. Therefore, there is an urgent need to develop a set of graphically interfaced tools that integrate with parametric modeling environments allowing the non-programming user to send and receive simulation data to and from the proposed cloud environment without any programming, Linux OS, and machine learning knowledge.

Conclusion

This paper examined the use of NN, a machine learning application, to predict the daylighting performance of 5,120 different room configurations. The proposed NN model was used to predict one output, the average illuminance value inside the room, and multiple outputs, or 144 DA values. To be able to use a machine learning framework, training data was populated by executing 506 simulations of random room configurations. Running daylighting simulations is time-consuming, and it was evident that running 506 simulations was not practical. Therefore, this author automated the execution of all 506 simulations on an HPC cluster that contains 120 computing nodes that facilitated the execution of simulations in parallel. The utilization of the HPC environment facilitated executing the simulations needed to obtain the training data in a time-efficient manner. The illuminance simulations were completed in roughly one minute (1.1 minutes) and the DA simulations took about 8.5 minutes. The execution of these simulations on a desktop computer would have normally taken two hours and 16 hours, respectively.

When applying the proposed NN model to the point-on-time average illuminance value,the calculated loss function, MSE was equal to 0.015 and MAE was equal to 0.094. The NN model showed highly accurate results, where the average illuminance values of the validated configurations were within 95 points of the actual value. Considering that the average illuminance values of the validated configurations ranged from around 2000 to 3000 lux, a 95-point range of error is negligible.

Similarly, the NN model was examined to predict multiple outputs: 144 DA values of the analysis grid points. The MSE and MAE values were equal to 7.6 and 14.8, respectively. The predicted DA values were plotted against the actual values that are resulted from simulations (see Figure 6). The

In conclusion, the proposed NN model showed fairly accurate results in predicting single and multiple outputs, although it was observed that the NN model showed higher accuracy in predicting single outputs. In addition to accuracy, coupling the HPC with NN increased time efficiency.

Acknowledgement

This work used the Extreme Science and Engineering Discovery Environment (XSEDE), which is supported by National Science Foundation grant number ACI-1548562.

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