Title:
Use of Neural Network Supervised Learning to Enhance the Light Environment Adaptation Ability and Validity of Green BIM

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Green BIM, neural network supervised learning, CNS illuminance standards

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Motivation and goal:
Green building information modeling (Green BIM) integrated design and analysis procedures have become an important tool for architects and design teams wishing to select and improve design proposals. Nevertheless, when using building performance analysis (BPA) software to predict building performance in actual environments, there are inevitably discrepancies between simulation data obtained from the software and measurements in the actual environment (Fig. 1), which has caused the software's simulation performance validity to be questioned. This project therefore seeks to use supervised learning by a neural network to reduce this gap, and enhance the optimization ability of Green BIM.

Fig. 1: Discrepancies consistently exist between performance simulation data and actual measurement data.

Literature review:
This study addressed the subjects of Green BIM, construction technology, BIM usage, facility management mechanisms, and neural network supervised learning.

Green BIM involves building information modeling (BIM) and building performance analysis (BPA), and these two methods have been used extensively in sustainable building design. BIM involves the two subjects of building information modeling and building information management. The use of BIM encompasses the entire building life cycle, including building design, construction drawing production, construction, operation management, and even waste recycling. In his 1999 "Building Product Models,"[4], Prof. Chuck Eastman defined building product model concepts, technologies, and standards, which set the stage for BIM. Eastman's 2008 "BIM Handbook"[5] defined BIM and related technologies, and provided BIM applications and illustrative cases for various types of participants (project owners, project managers, designers, engineers, and contractors, etc.). While BPA and BIM consist of two different technologies, they have become increasingly integrated. BPA [2], which is also known as building performance simulation (BPS), involves the use of computer software to predict building performance and output visualized images, data, statistical analysis charts, and forms resulting from simulation. BPA can help users to understand the performance of their design proposals, which will facilitate design decision-making and provide a basis for the continuing optimization of design proposals. BPA is an effective, scientific, internationally-acknowledged tool [1]. In recent years, BPA has gradually come to be seen as part of integrated design procedures, and is generally integrated with a BIM platform.

BPS is based on hypothetical models of real situations, and provides approximate values. As a consequence, discrepancies inevitably exist between the results of performance simulation and the real data, which has caused the validity of the software to be extensively questioned. Nevertheless, the use of BIM models to monitor actual building operating performance during the operating management stage can provide environmental and building performance data that can be used to improve actual building management and enhance building performance. If this data could be used for comparative purposes, and specifically to revise the predictive values obtained during the design stage, it should be possible to improve the predictive accuracy of Green BIM [6]. In the following sections, this project employs supervised learning by a neural network to reduce BIM's predictive discrepancy.

Theory and method:

To summarize the foregoing literature, Green BIM emphasizes the use of BIM has a basic design tool from the earliest stage of the design process. Responding to local climatic conditions, BPA can be used in the decision-making cycle consisting of design and analysis steps to achieve the continuing optimization of design and generate an optimized proposal consistent with environmental performance requirements [3]. Nevertheless, when an optimized proposal derived using Green BIM is realized under real-world conditions, the simulation values obtained by the software invariably have discrepancies with the actual measured environmental performance. Taking light environment adaptation as an example, when working surface illuminance value with window opening ratio of X% derived by a simulation tool is Y' lux, and the actual measured illuminance value in a real environment with a similar window opening ratio is Y lux, a discrepancy will exist between Y' and Y. (Fig. 2)

This study employed supervised learning with a back propagation network (BPN) in an effort to reduce the data discrepancy. In a basic neural network such as the one shown in Fig. 3, data undergoes four processing stages from input to output, including (1) input, (2) aggregator function (sometimes an activation function must be added to make the aggregator function more sensitive), (3) transfer function, and (4) output. In addition, the system estimates the cost of the output value and desired value, calculates the error, and adjusts the weight (ωn) in accordance with the error. The process that begins from the time the neural network starts revision until the error is less than a certain preset threshold value is termed learning, training, or adaptation. In principle, a good hypothesis must be generalized well, which will allow the system to make correct predictions concerning unknown examples [7].

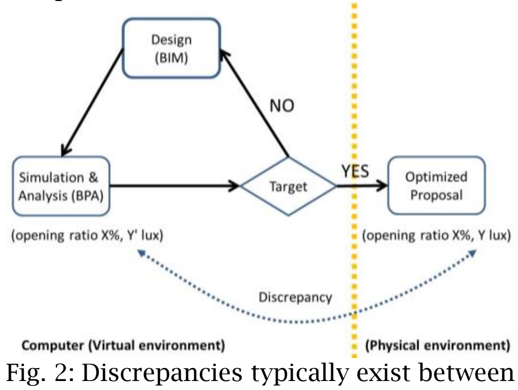

Fig. 2: Discrepancies typically exist between simulation values and actual measured performance data.

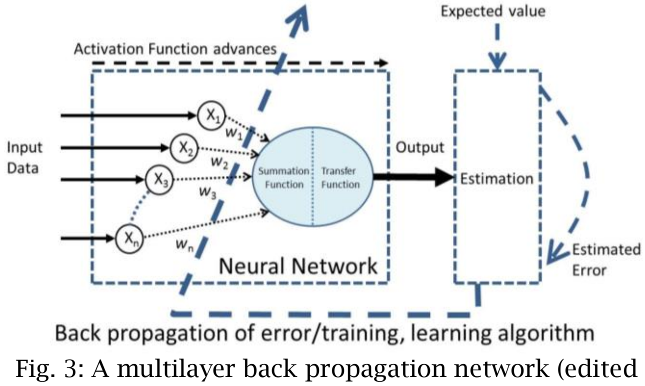

Fig. 3: A multilayer back propagation network (edited by Principe, 2000 [7]).

Experimental verification:

In accordance with the foregoing neural network learning characteristics and steps, this study verified the feasibility of this method in a six-step, two-stage experimental process. (Fig. 4, 5)

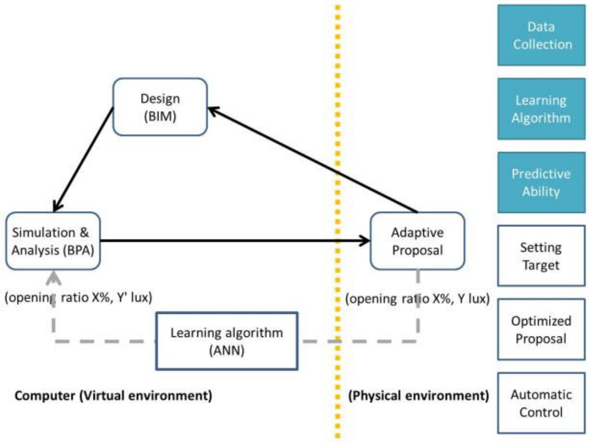

Fig. 4: Stage 1

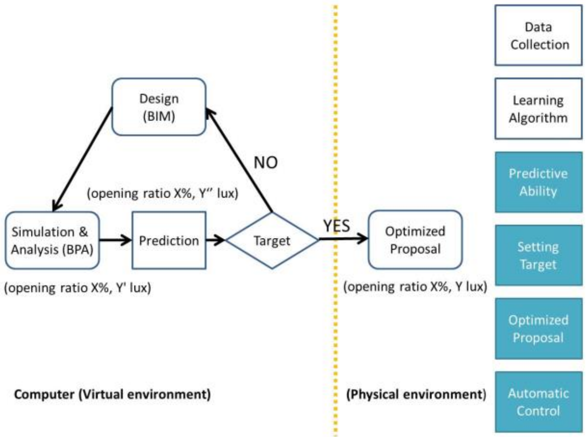

Fig. 5: Stage 2

Stage 1: data collection, learning algorithm, acquiring predictive ability (Fig. 4)
The steps are as follows

1. BIM modeling:

Revit was used in modeling, and Dynamo plug-in software was used to control the Revit model in adjusting the façade window opening ratio X%

2. BPA performance simulation:

The BIM model was imported in order to perform analysis of the performance of the light environment. The Revit model was output in gbXML format to Ecotect for simulation of working surface illuminance, and the simulated illuminance value (Y' lux) was obtained from an exported text file. The latitude and longitude in this trial consisted of 24.1638, 120.6471, and the date of the simulation analysis was December 25. The four red dots in Fig. 6 (sp1-sp4) represent the simulated illuminance value (Y' lux) at different points in time. The recorded illuminance values for the start of each hour and 30 min. past each hour were used as the training set input values (left, Fig. 7), while the recorded data for 15 min. and 45 min. past each hour were used as the testing set input values (right, Fig. 7).

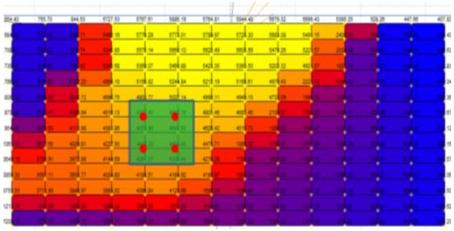

Fig. 6: illuminance simulation.

time	sp1	sp2	sp3	sp4
7:00	561	573	566	583
7:30	1332	1346	1408	1440
8:00	2767	2789	2936	2960
8:30	3955	3991	4256	4330
9:00	4987	4976	5347	5389
9:30	5442	2436	6003	6038
10:00	2371	2389	2887	2908
10:30	2220	2249	2691	2738
11:00	2009	2047	2425	2532
11:30	1836	1890	2251	2307
12:00	1654	1740	1988	2100
12:30	1463	5102	1772	1819
13:00	1316	1399	1600	1690
13:30	1150	1205	1396	1457
14:00	1016	1058	1238	1289
14:30	889	9344	1059	1152
15:00	737	778	899	955
15:30	585	611	709	750
16:00	422	438	517	546
16:30	259	277	280	301
17:00	110	115	135	143

time	sp1	sp2	sp3	sp4
7:15	720	726	759	777
7:45	2110	2114	2208	2251
8:15	3369	3393	3613	3658
8:45	4500	4534	4831	4875
9:15	5341	5368	5761	5815
9:45	2365	2473	2865	2980

Fig. 7: Exported text file; acquired simulated illuminance values (Y').

3. Production of an actual structure and illuminance measurement:

The actual structure was produced and used in accordance with the BIM model. The latitude and longitude at actual structure was the same as that of the simulated location, and the date was also December 25. The four red spots (rp1-rp4) in Fig. 8 represent the actual measured illuminance at different points in time. The recorded illuminance values for the start of each hour and 30 min. past each hour were used as the training set input values, while the recorded data for 15 min. and 45 min. past each hour were used as the testing set desired value (blue background, Fig. 9)

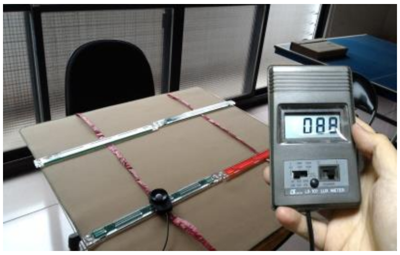

Fig. 8: Illuminance measurement.

	rp1	rp2	rp3	rp4
7:00	59	65	90	84
7:15	152	160	222	210
7:30	337	352	471	454
7:45	547	556	799	734
8:00	940	1006	1302	1232
8:15	1790	1912	2110	2150
8:30	2440	2090	2920	3180
8:45	1598	1681	2570	2140

Fig. 9: Actual illuminance value (Y).

4. Collection of sample data, implementation of supervised learning training, acquisition of predictive ability:

Collected BPA light environment simulated BPA data was used as the input values, and the measured illuminance values from the actual structure served as the desired values. After implementing supervised learning training, the neural back propagation network acquired predictive ability, and was able to predict the approximate Y" (predictive values) from the Y' lux (simulation values).

(1) This study employed NeuroSolution software, and opted to use a multilayer back propagation network (BPN) as the learning algorithm. The training set and testing set were both selected from the sample data.

(2) Definition of the input values and desired values in the rows and columns of the training.

(3) Definition of the cross validation data set percentage: 20% in this example.

(4) Definition of the transfer function

(5) Training set learning

(6) After acquiring predictive ability, the sample data in the testing set was used to perform validation. The left side of Fig. 15 shows the predictive value of Y", and the right side shows the actual measured value of Y.

(7) It was confirmed that the network system had learned from the sample data and possessed predictive ability. In the table below, the values with a blue background comprise the testing set, and the absolute value of the predictive value (apn) minus the measured value (rpn) was consistently less than the simulation value (spn) minus the measured value (rpn). (Fig. 10) For instance, at time 0715, 220 < 568, at time 0815, 263 < 1579, and so on. This verified that all predictive values Y" were far closer to the measured value Y than the simulation value Y'.

	rp1	rp2	rp3	rp4	Δ(sp1-rp1)	Δ(sp2-rp2)	Δ(sp3-rp3)	Δ(sp4-rp4)	sp1	sp2	sp3	sp4	Δ(ap1-rp1)	Δ(ap2-rp2)	Δ(ap3-rp3)	Δ(ap4-rp4)	ap1	ap2	ap3	ap4
7:00	59	65	90	84					561	573	566	583								
7:15	152	160	222	210	568	566	537	567	720	726	759	777	220	188	162	48	372	348	384	258
7:30	337	352	471	454					1332	1346	1408	1440								
7:45	547	556	799	734	1563	1558	1409	1517	2110	2114	2208	2251	27	25	0	60	520	581	799	794
8:00	940	1006	1302	1232					2767	2789	2936	2960								
8:15	1790	1912	2110	2150	1579	1481	1503	1508	3369	3393	3613	3658	263	44	577	735	2053	1868	2687	2885
8:30	2440	2090	2920	3180					3955	3991	4256	4330								
8:45	1598	1681	2570	2140	2902	2853	2261	2735	4500	4534	4831	4875	599	286	328	1030	2197	1967	2898	3170

Fig. 10: Comparison of training set and testing set data.

Stage 2: Setting of targets in accordance with prediction, finding an optimized adaptation plan, and performing script-oriented automated control (Fig 5.).

The following steps were employed:

5. Finding an optimized adaptation plan:

After the system acquired predictive ability, it was able to use the predictive value Y" as its target setting conditions and find an optimized adaptation plan. As for setting targets, taking the light environment as an example, illuminance levels can be set according to a space's planned uses and activities referring to CNS illuminance standards. For instance, the function of the location of the actual measurements was designated as a "studio," which had the uses of reading and writing. As a result, the appropriate illuminance scope for working surfaces within the space was set as 500-1000 lux. The window opening ratio X% and predictive value Y'' in the adaptation plan had to satisfy this target setting scope.

6. Implementation of script-oriented automatic control:

In accordance with the parameters of the optimized proposal, Dynamo relied on linkage with the Firefly and Arduino plugins to perform script-oriented automatic control driving the adaptive façade elements of the actual structure. This system operated in cyclic fashion, and enhanced environmental quality by responding to environmental changes employing adaptive mechanisms.

Conclusions and recommendations:

BPS simulation values are approximations of the real values. The greater the validity of Green BIM, the better it can discover problem early in the design stage, enabling the proposal of precise decision-making strategies and dramatic reductions in construction and operating costs. This study focused on the empirical verification of the use of supervised learning involving a neural network to reduce the discrepancy between predictive and actual values, and determine the feasibility of this approach to enhancing the validity of Green BIM. This study further applied supervised learning to sample data representing a certain period of time, and designated inputs and expected outputs. In theory, the longer the time learning from sample data, the better the predictive values should be; further research accompanied by long-term observations will be needed to verify this point.

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