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Use of neural network supervised learning to enhance the light environment adaptation ability and validity of Green BIM

Shang-yuan Chen

Feng Chia University, Taiwan

ABSTRACT
This study proposes that a “predictive value” obtained through neural network learning be used instead of the “simulation value” in judging whether design goals have been met, and thereby enhance the optimization ability of Green BIM in the design decision-making process as a whole. There are inevitably discrepancies between Green BIM ‘s simulated performance data and the performance data obtained from the actual completed environment, neural network learning can be used in conjunction with training to obtain a predictive ability, and the resulting predictive values are more representative of actual performance than simulation values. In order to construct a simulated adaptive building façade based on light environment performance, this project plans to conduct the following six steps in a two-stage process:

Stage 1: data collection, learning algorithm, achieving predictive ability: (1) BIM modeling, (2) BPA performance simulation, (3) production of an actual structure and illuminance measurement, (4) and collection of sample data in order to perform training in supervised neural network learning.

Stage 2: After obtaining a predictive ability, finding an optimized proposal and implementing automated control: (5) Setting targets in order to find an optimized adaptation plan, and (6) implementation of script-oriented automatic control.

KEYWORDS
Green BIM; neural network supervised learning; CNS illuminance standards

1. 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.

2. 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. Eddy Krygiel's and Bradley Nies' book “Green BIM: Successful Sustainable Design with Building Information Modeling” first proposed the Green BIM concept in 2008, and explained the integrated application of BIM and BPA to promote the development of sustainable design [15]. “McGraw-Hill Construction, 2010” points out that Green BIM can greatly enhance the results of sustainable design through the application of BIM tools [18].

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. The term BIM” originated from the Autodesk Company's use in 2002 of the building information modeling concept to explain the function and design of its AEC (architecture, engineering, and construction) products [1]. Nevertheless, in his 1999 “Building Product Models,” [10], Prof. Chuck Eastman defined building product model concepts, technologies, and standards, which set the stage for BIM. Eastman's 2008 “BIM Handbook” defined BIM and related technologies, and provided BIM applications and illustrative cases for various types of participants (project owners,

CONTACT Shang-yuan Chen shangyuanc@gmail.com

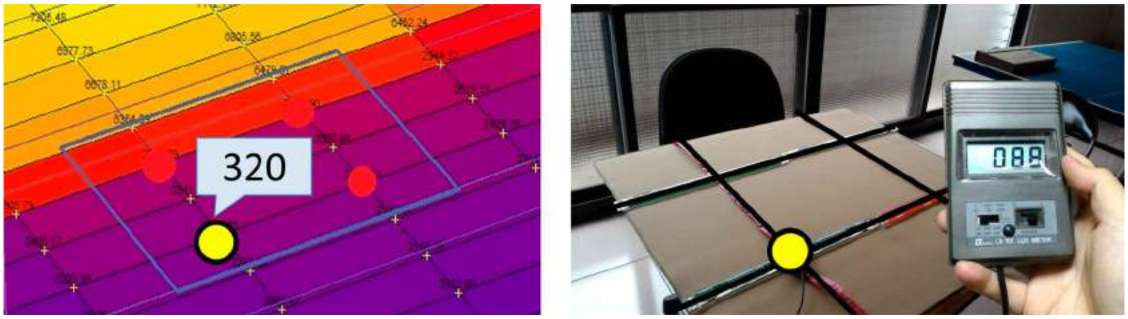

Figure 1. Discrepancies consistently exist between performance simulation data and actual measurement data.

project managers, designers, engineers, and contractors, etc.) [11].

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 [21]. Early modeling tools and performance simulation tools were independent, and performance simulation tools usually consisted of two parts, where the first part was a simulation engine, which included formulas and procedures, and the second part consisted of a user interface, which facilitated the input of parameters and data and display of results, and handled various user needs (Fig. 2) [17]. Basic building simulation work began in the 1960s and '70s, and focused on building cooling performance, specifically thermal load calculations and energy consumption analysis [16, 8]. By the 1980s, researchers performed analytical verification and

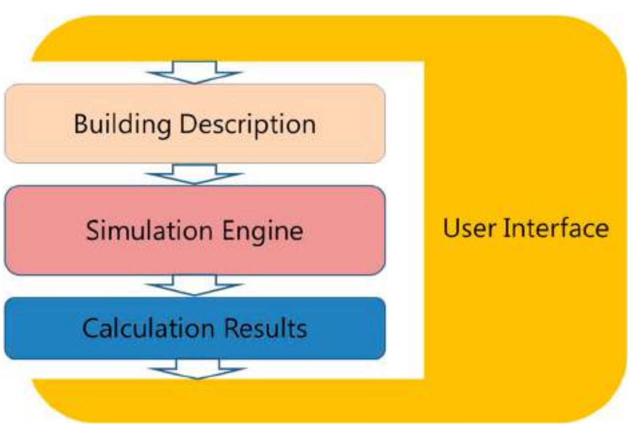

Figure 2. General framework of performance simulation tools.

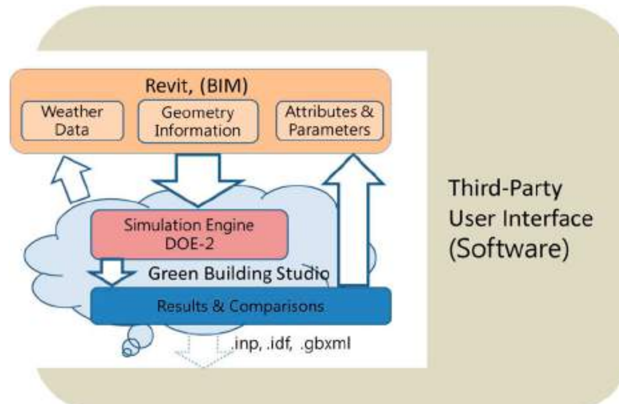

Figure 3. Integration of BIM and BPA technologies.

experimental testing in order to improve simulation tools [4]. The focus of performance analysis efforts shifted from energy consumption to many other building performance characteristics during the early 1990s [3], and integrated modeling was used to assess heat and mass transfer, air flow, and visual and acoustic performance.

In recent years, BPA has gradually come to be seen as part of integrated design procedures, and is generally integrated with a BIM platform. For instance, Autodesk's BIM software (Revit) includes a built-in BPA function (such as energy and lighting analysis) menu. After performing modeling with BIM software, designers can also transmit geometric and non-geometric data to simulation engines in the cloud (such as Green Building Studio), and the visualized results of analysis will be transmitted back to the BIM software [12]. Although the results of analysis by simulation engines required the use of third-party user interface software (such as Design Builder) for display in the past, this role is gradually being assumed by BIM software platforms (such as Revit) (Fig. 3).

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 [5]. In the following sections, this project employs supervised learning by a neural network to reduce BIM's predictive discrepancy.

3. 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 [7]. 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. 4)

Neural network learning roughly includes the three categories of supervised learning, unsupervised learning, and reinforcement learning. This study employed supervised learning with a back propagation network (BPN) in an effort to reduce the data discrepancy; the principles and theory of this process are as follows:

Supervised learning is an inferential process in which the corresponding functions are derived from the inputs and outputs for given examples. For instance, the network will generate a function h approximating f from a group of examples of f. An example consists of a set (x, f(x)), where x is the input, f (x) is the output of the function applied to x. Function h is termed the "hypothesis," and the set of all possible hypotheses is termed the "version space." All hypotheses in the version space must be consistent with examples. Supervised learning takes prior knowledge as the basis for a current best hypothesis search in the version space, and this consists of a search for hypothesis h best approximating the target function f. The process of searching for function f or its optimal hypothesis in a version space is known as learning or training [14].

In a basic neural network such as the one shown in Fig. 5, 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. Supervised learning refers consists of constantly revision of the network's transmission weights to achieve consistency with the expected value. In the training process, weights are adjusted in order to reduce the discrepancy between the network's output values and the target output values, until the difference is less than a certain threshold value, at

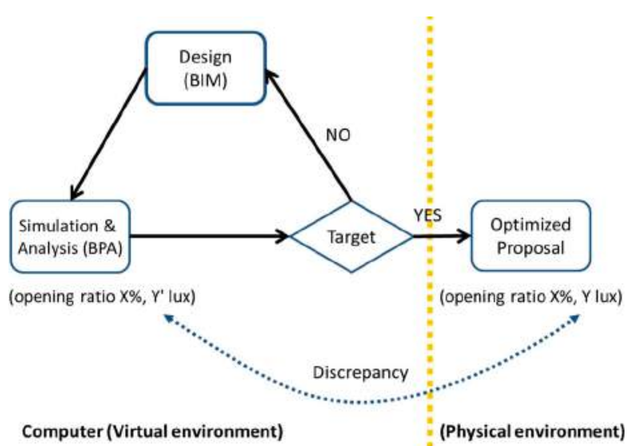

Figure 4. Discrepancies typically exist between simulation values and actual measured performance data in Green BIM.

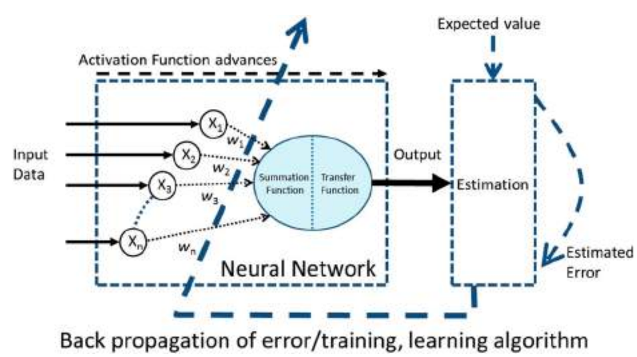

Figure 5. A multilayer back propagation network (edited by Principe, 2000 [20]).

which point the process stops [6]. In principle, a good hypothesis must be generalized well, which will allow the system to make correct predictions concerning unknown examples [20].

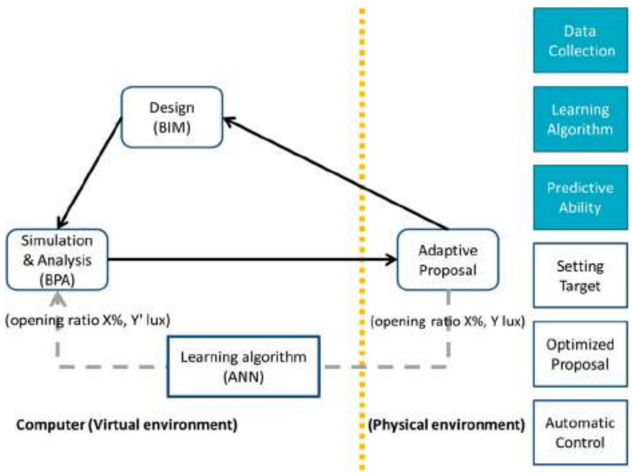

Figure 6. Stage 1.

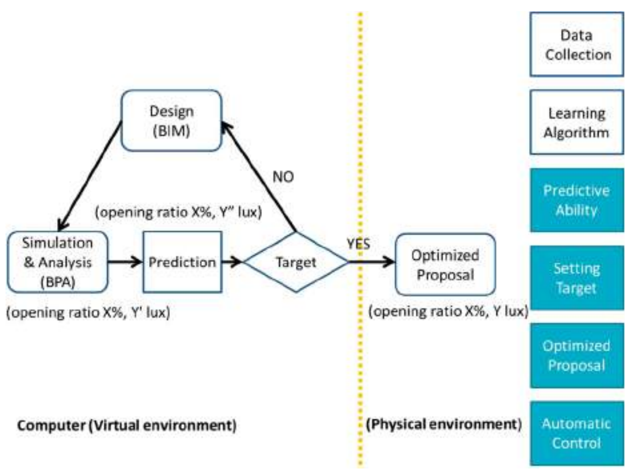

Figure 7. Stage 2.

4. 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. 6, 7)

A. Stage 1: data collection, learning algorithm, acquiring predictive ability (Fig. 6)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% (Fig. 8).

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. 9 (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. 10), while the recorded data for 15 min. and 45 min. past each hour were used as the testing set input values (right, Fig. 10).

3. Production of an actual structure and illuminance measurement:

The actual structure was produced and used in accordance with the BIM model. Dynamo was linked with the plugins Firefly and

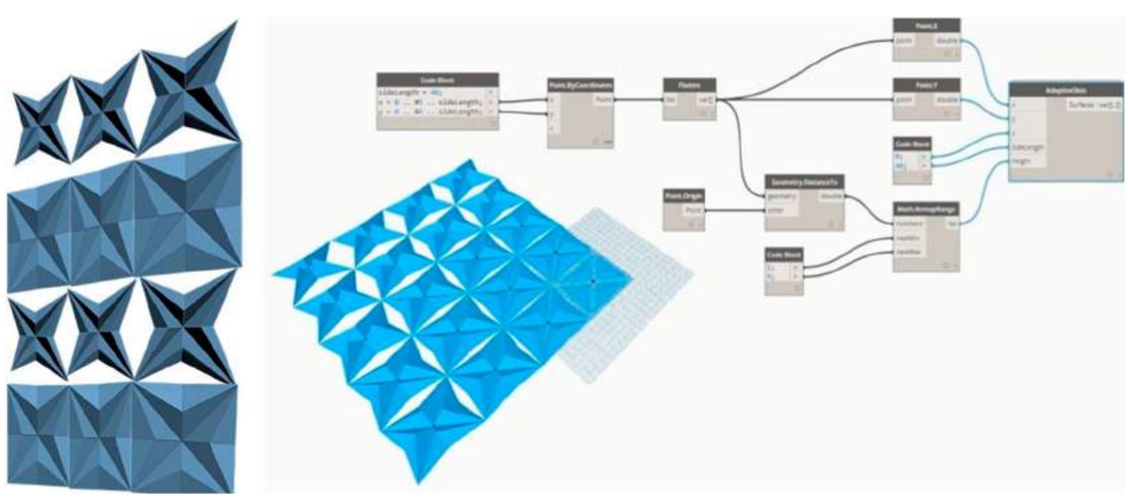

Figure 8. Revit modeling using Dynamo plug-in software to adjust the façade window opening ratio X%, drawn by Yen-Hsuan HO.

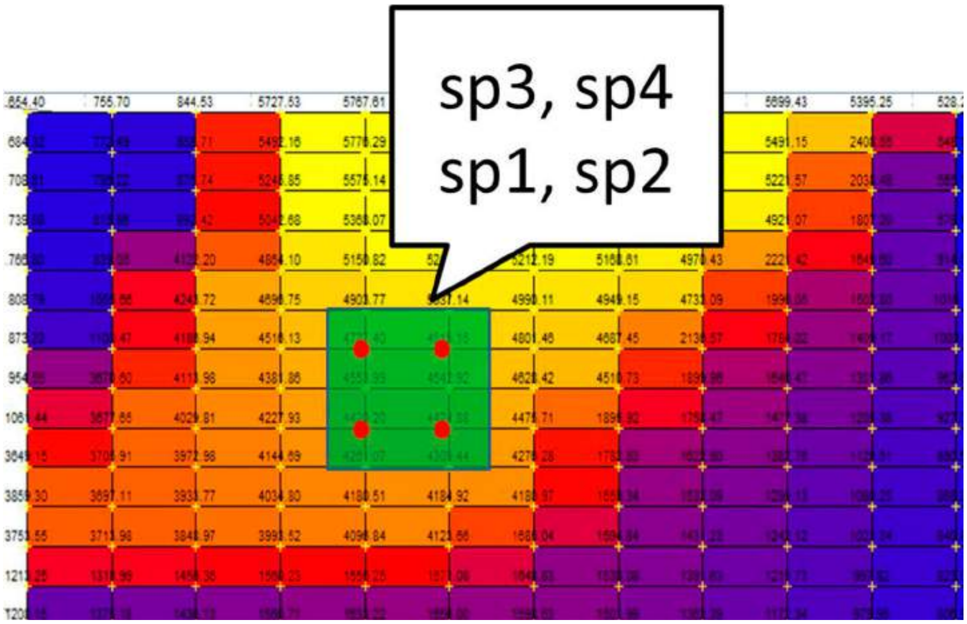

Figure 9. Illuminance simulation.

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	5436	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

Figure 10. Exported text file; acquired simulated illuminance values (Y').

Arduino, and the window opening ratio (X%) was entered into Arduino to drive and control the adaptive building façade in the actual structure, and a light meter was used to measure the actual illuminance of the working surface. 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. 11 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. 12).

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). The following steps were employed when using neural network software to perform learning from the sample data:

(1) This study employed NeuroSolution software [19], 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. (Fig. 13)
(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. (Fig. 14)
(4) Definition of the transfer function.
(5) Training set learning. (Fig. 15)

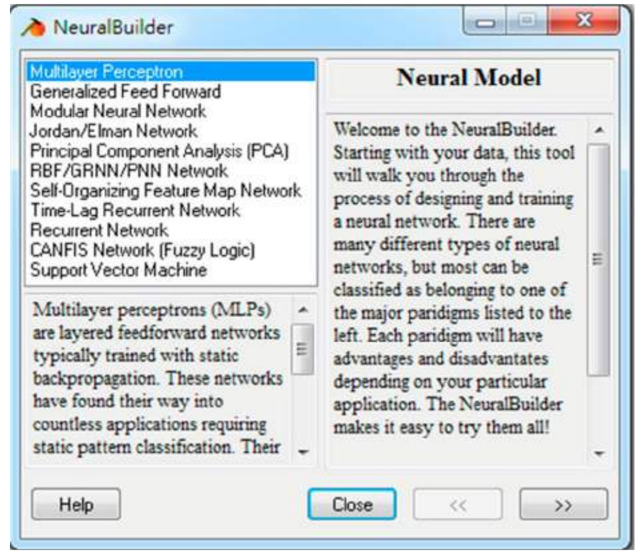

Figure 13. Selection of a multilayer back propagation network (BPN).

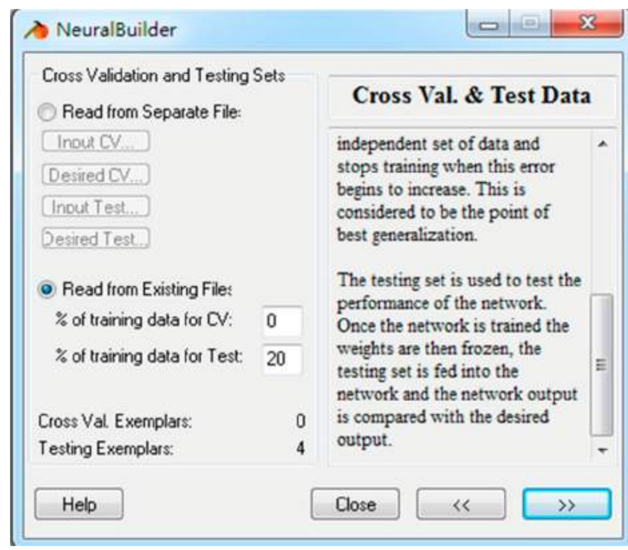

Figure 14. Setting of the cross validation data set percentage.

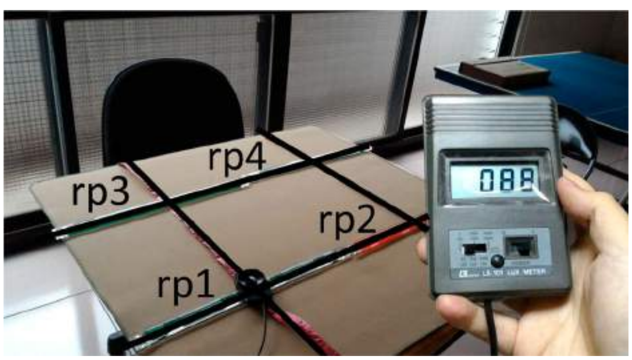

Figure 11. Illuminance measurement.

A	B	C	D	E
Time	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
9:00	2460	2100	3510	4070
9:15	1693	1766	2820	3100

Figure 12. Actual illuminance value (Y).

(6) After acquiring predictive ability, the sample data in the testing set was used to perform validation. The left side of Fig. 16 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). 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' (Fig. 17).

B. Stage 2: Setting of targets in accordance with prediction, finding an optimized adaptation plan, and performing automated control (Fig. 7)The following steps were employed:

5. Finding an optimized adaptation plan:

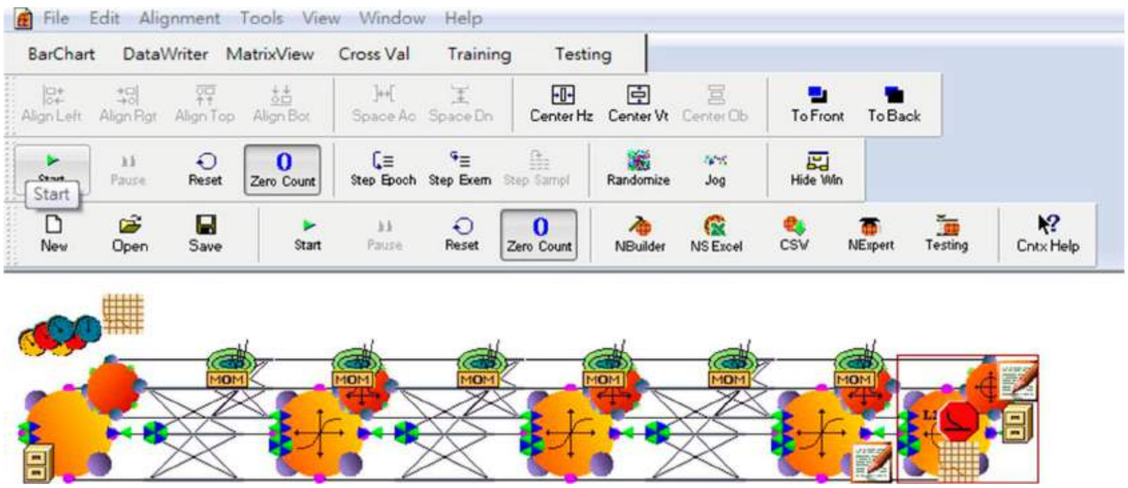

Figure 15. Training set learning.

Output

(ap1) Out rp1	(ap2) Out rp2	(ap3) Out rp3	(ap4) Out rp4
250.580555182206	197.793184629429	300.150123616620	257.761476091570
436.451100470386	389.165159720916	504.848582245509	544.347160196270
2101.052983781251	1843.418324024299	2845.297092029667	3023.717166985813
2249.308422975354	1988.017497585538	2951.097626656223	3488.846402194374
2233.734250461689	1985.398514998208	2932.304344312126	3454.765586261523
1285.501922930220	1293.348806034518	1772.668851113841	1704.597893374817

Time	rp1	rp2	rp3	rp4
07:15:00 AM	152	160	222	210
07:45:00 AM	547	556	799	734
08:15:00 AM	1790	1912	2110	2150
08:45:00 AM	1598	1681	2570	2140
09:15:00 AM	1693	1766	2820	3100
09:45:00 AM	1491	1513	2020	1985

Figure 16. Comparison of predictive value Y″ and actual value Y.

Time	rp1	rp2	rp3	rp4	(sp1-rp1)	(sp2-rp2)	(sp3-rp3)	(sp4-rp4)	sp1	sp2	sp3	sp4	(ap1-rp1)	(ap2-rp2)	(ap3-rp3)	(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
9:00	2460	2100	3510	4070					4987	4976	5347	5389								
9:15	1693	1766	2820	3100	3648	3602	2941	2715	5341	5368	5761	5815	490	190	938	47	2183	1956	1882	3147

Figure 17. Comparison of training set and testing set data.

Table 1. CNS indoor illuminance standards [9].

Illuminance	Living room	Studio	Children's room
2000 ~ 1000	⊙ Handicrafts		
1000 ~ 750	⊙ Sewing		
750 ~ 500	⊙ Reading ⊙ Makeup ⊙ Telephone use	⊙ Writing ⊙ Reading	⊙ Homework ⊙ Reading

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. In other words, in the future, it will only be necessary to input a simulation value set as the testing set in the trained neural network, and the network will be able to obtain the corresponding predictive values. 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 (Tab. 1). For instance,

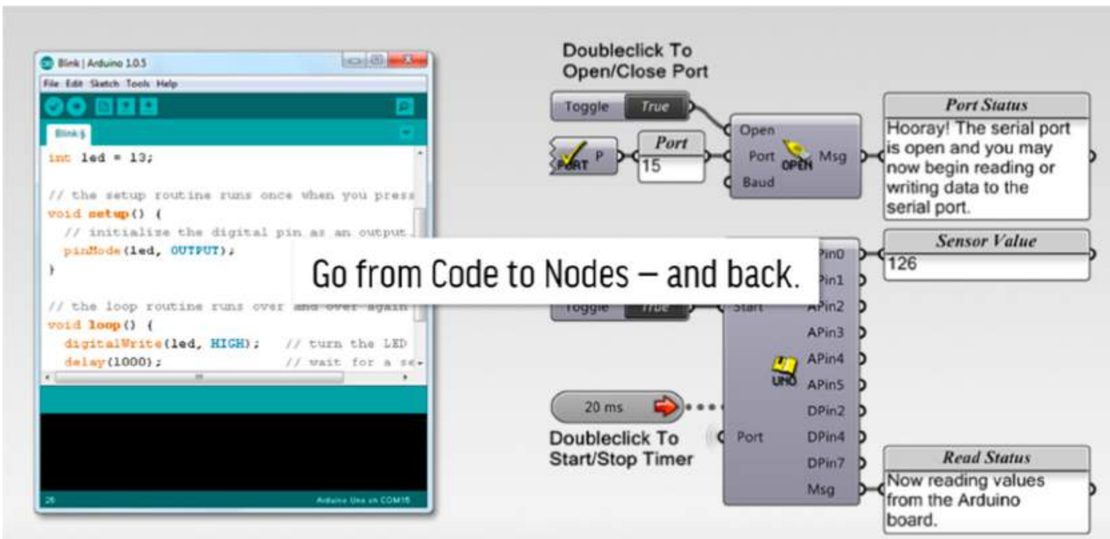

Figure 18. Firefly plugin driving Arduino IED (source: Firefly, 2016 [13]).

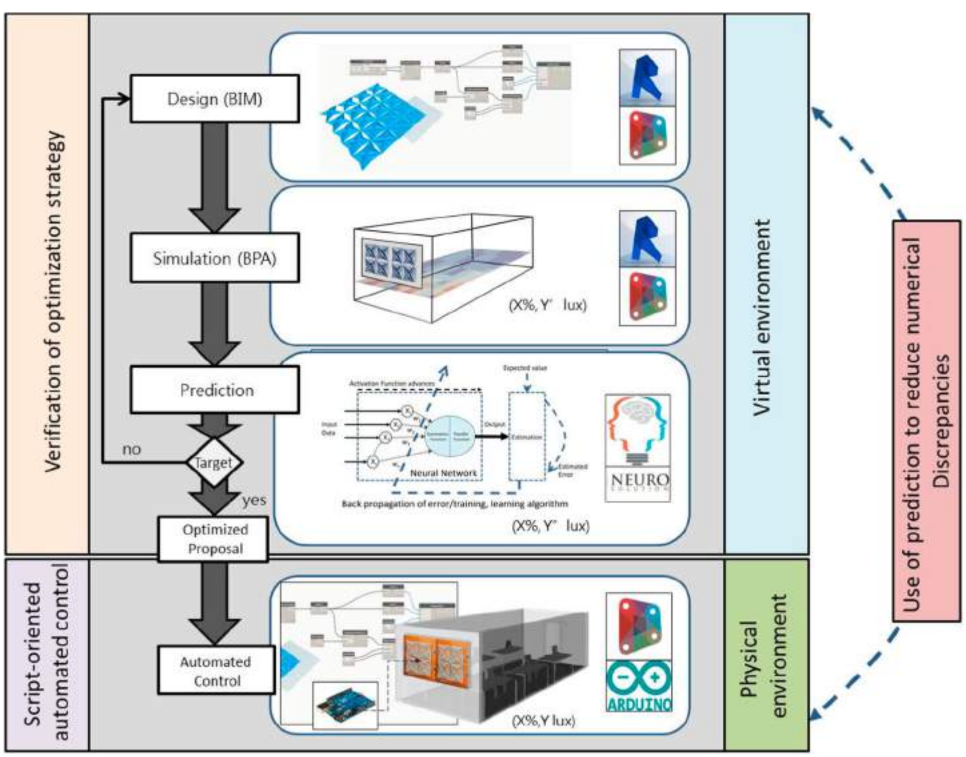

Figure 19. System design.

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. The figure below shows Dynamo employing the Firefly plugin to send and receive data, and the embedded control microprocessor (Arduino IED) implementing the physical model and sending script implementation to the operating end [13] (Fig. 18).

5. 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.

In accordance with the foregoing theory and method, a six-step, two-stage process was employed to verify the optimization strategy in a virtual environment, construct an adaptive mechanism based on the light environment in a physical environment, and perform script-oriented automated control. The completed system was compiled as shown in Fig. 19. This system enables design and analysis work during the initial stage of Green BIM to be used in conjunction with environmental data during the operating management stage, which can boost the validity of government through the use of environmental data records and feedback.

In addition, BPA is gradually being considered part of integrated design procedures, and is increasingly integrated with BIM platforms. A BIM platform (Revit) can already use a lighting analysis plugin to perform analysis of natural lighting and visualization of illuminance. However, this plugin lacks a numerical output function. The Ecotect software used in this study was withdrawn from use in March 2015, and illuminance analysis could be performed only by exporting data from the Revit model in gbXML format to Ecotect, which cannot be considered a fully-integrated part of the BIM platform. In the future, if lighting analysis plugins can add a numerical output function, this will facilitate the convenient generation of predictive value and enable script-oriented automatic control. In this way, the integrated light environment adaptive capability of Green BIM will become increasingly accurate and effective.

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ORCID

Shang-yuan Chen http://orcid.org/0000-0003-0249-5900

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