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

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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 facade 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.

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,
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 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 as 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](image4.png)

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

![Figure 5](image5.png)

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].

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

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Figure 6. Stage 1.

Figure 7. Stage 2.

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

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,

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<th>D</th>
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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:

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**Figure 15.** Training set learning.

**Figure 16.** Comparison of predictive value $Y''$ and actual value $Y$.

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