A COLLABORATIVE DIGITAL DESIGN WORKSHOP

An ANN-based paradigm approach

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Abstract. This paper relies on observation and analysis an internationally digital design exchange activity, “The FCU & Bartlett School of Architecture, university college London (UCL) digital architecture workshop” to propose an educational model based on the artificial neural network (ANN). We expect that the results of this work can lead to the establishment of a scoring mechanism that can "adapt" to the difficulty of assigned problems and assess students' progress. An international technological exchange workshop based on the theme of digital design is helpful to attain an accelerated heightening in the quality and experience of education. This is going to be an educational trend and increasingly prevalent in the future. A successful educational curriculum in digital design relies on a concerted effort amongst curriculum framework, learning activities, and course content. While, an internationally exchange digital design workshop is different from traditional "semester-based" units of curriculums. The short-term educational models are required high degrees interaction and collaboration. On the other hand, artificial neural network system that is context aware in ill-defined and complex environments is highly adaptive. It can extract, interpret and use the context information and adapt its functions to obtain an optimal correspondence between “context change” and “desired goal” efficiently. Therefore, an ANN-based pedagogical mechanism is able to encourage students to select relatively difficult design problems and promote more design originality, interaction and collaboration.
1. Background and Objective

Since the introduction of the computer-aided design and the application of internet technologies, CAAD pedagogical paradigms have shifted to the design-oriented teaching, which have to not only satisfy the inheritance of computer technology but also streamline the design thinking (CHEN, 2004). The educational environment of architectural design has been changed and evolved. Electronic design workshops (MCCULLOUGH, 1900); virtual design studios (BRADFORD, 1994); and collaborative design workshops, (CHIU, 2001) have subsequently emerged, and set a foundation for digital design learning. However, excessive emphasis on the application of digital utility technology is not entirely beneficial to the creativity in design, therefore, in the ACADIA '98 international conference, the “digital design studio” was its theme, (SEEBOHM, 1998). The domain is expanding, and pedagogy shifts from technology-driven, toward methodology-driven.

The nature of pedagogy is to strive for a well-functioning "adaptive" system. While there should be positive, flexible interaction between the content of instruction and the quality and quantity of learning within such a system, design instruction is full of inherent indeterminacy and complexity. Thereby, whether do achievements of a design workshop, a special case derived from digital design studio, truly reflects students’ progress especially under such a short-term teaching and learning? It becomes absolutely indispensable to know how to operate, evaluate, understand, construct and analyze a design workshop.

Based on literature review, this paper proposes certain hypothesis, and relies on experimental education, actual research, and participant observation. Expected results include: (1) reflective analysis on computer-assisted design educational models, (2) establishment of theoretical framework, (3) operation of digital design and records of its physical fabrication process (4) assessments of differences between theory and reality, (5) conclusions and suggestions.

2. Theory and Method

Can Students’ level be proved upgraded within extreme short-term learning? Artificial intelligence experts in the field of design have proposed a long series of "cognitive models" attempting to explain designers' design behavior. Additionally, “Cognition Models” can serve as reference to teaching framework, platform for pedagogical research or tool for developing computer-aided-design. A design cycle may be regarded as”
process of delivering information to solve the problems”, (NEWELL, 1957), it requires to be decomposed into distinctive steps and well-defined plan that the “Decision tree” will not stretch out without limits. Therefore, the process to modify a problem shall be involved in “Decision-making circle” (ASIMOW, 1962). However, the aforesaid models that base on “Rule-based Algorithm” have congenital limitation and are applied to well-defined problems solely, whereas most of the design addresses Ill-Defined problems (ROWE, 1987). Creative design is usually expelled by normal rules. Artificial neural network, which is good at addressing ill-defined and non-structured problems, has scientific algorithm and evaluation index. It thus provides better solutions to develop “Design Cognition” and therefore, promote “Design learning”.

Figure 1. Poster, (copy from FCU.)
The research is to observe an internationally collaborative digital design workshop—The Archi, FCU & Bartlett, UCL, digital architecture workshop (SHU, 2005), (Figure 1). We propose a neural network model operating in a virtual environment and conforming to circumstances in accordance with the workshop’s instructional framework, features, and requirements. We then validate and revise the ANN-based instructional model via on-site observation and participation in the instructional process. The ANN-based framework shall represent design process and evaluation index in virtual environment through simulation of Neural-Solution software and can obtain from learning the predictability that is based on induction and inference, (Figure 2).

![Figure 2. Nature system and formal models, (PRINCIPE, 2000)](image)

3. Process and Result

3.1 FCU & BARTLETT, AND UCL DIGITAL ARCHITECTURE WORKSHOP

International design workshops give students or academics an opportunity to share ideas and achieve progress in design learning. The Archi, FCU & Bartlett, UCL, digital architecture workshop invited Marcos Cruz and Mariano Colletti, the lecturers of Bartlett School of Architecture, University College London, to give an eight-day teaching demonstration of digital design in Taiwan. In spite of the short length of this activity it elicited exceptionally high expectations. The workshop required students to produce works and fast converge toward a certain level learning result. It also
emphasized students’ collaboration. During the eight-day curriculum (0302–0309/ 2005), they attempted to "individually express their own works", and then, to "compile them into an architecture", which was not only a technical “content-aware smart entity” (MARI, 2000) but also a feasibility of visual and dynamic “zoomorphic form” (HUGH, 2004). The curriculum was divided into 3 phases. During Phase I, The 26 qualified and selected students and they were to individually develop the feasibilities by two groups: inhabit wall and sp-line animal. During Phase II, after critique (Figure 3), the students’ creations were classified by attributes into 6 elements (including architecture structure and facility installation) such as external wall, internal wall, canopy, furniture, sensor and cable as well as animation. And, following was to “integrate” those elements. During Phase III, the integrated design did not stay in virtual space but proceeds cutting of substantive materials (timber, metal and so on) by Computer Numerical Control (CNC) machines. And accompanying with draft-models and animations, recording design process, the cut or bended parts were assembled for review and exhibition in order to display instructional results, (CHEN, 2005), (Figure 4).

Figure 3. critique
3.2 CONSTRUCT NEURAL NETWORK MAP SITUATION MODEL

An artificial neural network uses computer to simulate organism’s nerve network. Network algorithm is executed by parallel and distributive units—neurons and their connections (synapses). It is good at synchronizing process of multiple data and its output values may be approximate to desired output values through adjusting synaptic weights of neurons. Therefore, there is no need to make any prior assumptions about the relationship between the input data and output value when sufficient cases are provided. This “adaptive” algorithm is especially appropriate to judge non-structured decision-making. It is able to learn, recall, induce and deduce from the input environmental information, (CHANG, 2004). Basically, design of neural network depends on following principles. Firstly, the network architecture is decided by the complexity of events to be processed. The contents of which includes deciding quantity and layers’ number of neurons, back-propagation or feedback mode. Secondly, supervised or un-supervised learning is judged by whether desired output values exist in learning process. Finally, selecting suitable learning algorithm according to characteristics of problems to be processed (GIRIOSI, 1995). We have built up a neural network to simulate...
teaching process according to characteristics of digital design workshop. The network was constructed according to the following steps:

3.2.1 Decide network model:

![Diagram of neural network](image)

*Figure 6. Chaining of operations in the back propagation algorithm (PRINCIPE, 2000)*

In order to obtain a certain quantity of teaching achievements within a short period, parallel process of designs shall be adopted at initial stage. In consideration to limited budget for entity construction and endeavor for students’ collaboration, the better strategy is to classify different elements from numerous teaching results and, select them thereof to integrate a design creation, process construction drawings and construction accordingly. Input end shall be multi-dimensional vector, output end unitary-dimensional vector. Network framework (architecture) is presented by “multi-layer perceptron, (MLP.), plus back-propagation, (BP), network” (Figure 6).

3.2.2 Determination of learning attributes:

We adopted "supervised" learning for fast convergence. Supervised learning means that the network weights are adjusted in accordance with the "teacher's" desired value. Adjustment on weights shall be performed until difference (error) between output and desired values less than certain “threshold value”.

3.2.3 Select algorithm:

Selecting “Least-Mean Square algorithm, LMS” is the most common use according to characteristics of reinforcement (back-propagation) network architecture and attributes of “supervised” learning. It looks for “Mean-Square-Error, MSE” ,(3), by adjusting weight value $\Delta w_j$ , (4), according to “steepest decent”. MSE is also named as “Cost Function”, which is index of error between “output value $y_k$ ”, (1), and “desired value $d_k$ ” of neuron,
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(3), Whereas rate of “adjusting weights”, (5), is named as “learning rate \( \eta \)”. The \( \eta \) value affects rate and stability of learning. Important functions, (4), and equation of “Least-Mean Square algorithm, LMS” are per followings, (HAYKIN, 1999).

- In the network, input value of number \( j \) neuron in the \( n \)th layer is
  
  Non-linear function of neuron in the \( (n-1) \)th layer, “output value” of the \( (n-1) \)th layer
  
  \[ Y_j^n = f(\text{net}_j^n) \]  
  
- “summation function” of the \( (n-1) \)th layer
  
  \[ \text{net}_j^n = \sum w_{ji} y_j^{n-1} - b_j \]  
  
- “mean-square error function”:
  
  \[ E = \left( \frac{1}{2} \right) \sum_k (d_k - y_k) \]  
  
- “weight adjusting value”
  
  \[ \Delta w_{ji} = \eta \frac{\partial E}{\partial w_{ji}} \]  
  
- “adjusted weight value”
  
  \[ w_{ji}(p) = w_{ji}(p - 1) + \Delta w_{ji} \]  

3.3 ENCODING DATA AND NEURAL NETWORK TESTING

<table>
<thead>
<tr>
<th>Inhabit Wall</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
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</table>

We had to encode the data in order to perform simulation and verification using the neural network software, “Neuro-Solutions”. During phase I of design workshop, students were grouped into two: inhabit wall and sp-line
animal. Teachers select 9 works from each group. They were encoded: Prefix “1” represented inhabit wall group (i.e. 11, 12, 13 etc.), and prefix “2” represented sp-line animal group (i.e. 21, 22, 23 etc.), (Table 1).

3.3.1 To select train and test data set:
During Phase II, students carefully selected every time 4 from above 18 works to play such architecture elements as external wall, internal wall, canopy and furniture that affect the “style” and, assembled those elements to a whole creation. Assembled works are displayed in sequential order and noted down individual code of those four elements for open review and critique. The aforesaid 4 codes shall become “input end” of train date and scores gained by assembled creations become “desired value”. As shown in the table that the winner work 3 is composed of 25, 14, 22, 19, scored 90 (Table 2). Additionally, it was required to group data in two: one was “train set” (Table 3), the other was “Test set” (Table 4).

<table>
<thead>
<tr>
<th>No.3</th>
<th>25</th>
<th>14</th>
<th>22</th>
<th>19</th>
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### TABLE 2. Work No.3 is composed of (25, 14, 22, 19), scored= 90

<table>
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<tr>
<th>Work</th>
<th>Ex-wall</th>
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<th>Canopy</th>
<th>Furniture</th>
<th>Score</th>
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<tr>
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<td>17</td>
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<td>19</td>
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<tr>
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<td>23</td>
<td>28</td>
<td>12</td>
<td>80</td>
</tr>
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3.3.2 Training

We manipulated “Neuro-Solutions” software as train simulation, firstly we selected multi-layer back-propagation networks, And then to proceed the followings in sequence: to input train data, to select LMS algorithm, to select activation function, to adjust learning rate and set “threshold” of MSE between output scores and target output scores (Figure 7), (Table 5), It stopped at 325 epochs when “Mean-Square-Error, (MSE)”= 0.001 and learning curve approached to stability.

<table>
<thead>
<tr>
<th>Works</th>
<th>Ex-wall</th>
<th>In-wall</th>
<th>Canopy</th>
<th>Furniture</th>
<th>Score</th>
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</table>

**Figure 7.** Training process flowchart for Neuro-Solutions software
3.3.3 Result
Output values of “train set” will be very close to desired scores if the network training is completed. It represents that the system has capabilities of induce and deduce. Therefore, the new output value should be close to desired scores while using “test set” to confirm training results. In fact, although their currents map each other approximately yet there sometimes existed large differences between values. We can deduce that means value inferred by network is higher than what students actually obtain if output value is higher than desired score, and therefore, there existed space for students to progress. Vice versa, students’ level have exceeded over the value inferred by network (Works’ No. 12; 13; 17), (Table 6).

TABLE 6. Test Results: Output scores Vs. Desired scores
In accordance with these observations, student achievements under this instructional framework are influenced by two main types of factors, one of which being the students’ talent and effort, the other being the difficulty of integrating the selected architectural elements. The former is implicit and difficult to measure, while the latter is explicit. Design results can be obtained and expressed as the output value of a neural network. This output value can serve as a standard of the difficulty of integrating architectural elements. In addition, the difference between the output score of the neural network's "machine calculations" and the desired score obtained by "human cognition" provides a yardstick for determining whether a student is making progress. Therefore, it is worth noting that these findings indicate that design learning is not a totally goal-oriented process. Design learning can be considered a process of dynamically adjusting weights to achieve corresponding “desired value.”

4. Conclusions and Suggestions

The success of the Archi, FCU & Bartlett digital architecture workshop was to highlight skillful control of design procedure that presented context relation through input data mapping output results. ANN-based architecture allowed close and intensive collaboration among teachers and students to fast converge toward high quality design results. The educational model in design learning was different from traditional ones that restricted input conditions with rigid specifications; design results were required to meet the rules set under constrains. Therefore, it became time consuming to induce process; and the design focuses were usually too dispersed to be converged by inexperienced designers. The demonstration in this digital design workshop was though very short but design results are highly recognized. Exhibitions were held March 12 –18, 2005 at “Ren-Yan” exhibition Hall, Fen Chia University; (Figure 8), from September 9, 2005, at Hamburg Culture Policy Research Institute, Germany, and then, at The Bartlett department of Architecture, University of London, UK afterwards. Not only that, this research represented design process through manipulating neural network algorithm. The differences between network “output value” and “desired score” proved that the teaching program promoted students’ progress substantially.

In addition, several neural network algorithms have been developed to meet different problems. However, are those theories suitable to support the other cases of design education? Or are they able to be adopted to construct computer design-aided system? For example, it may be more appropriate to adopt “dynamic” “Time-Delay Neural Network” if the evaluation of a design
work is influenced by the evaluation of the previous work. Or it is possible to construct computer design-aided system by adopting genetic algorithm and adopt its crossover and mutation functions to sort out poor architecture elements at an early stage to ensure design quality and generate design creativity. We believe that, in the field of design, neural networks should not be used exclusively in design education, but also in the development of computer-aided design systems.

Figure 8. Installation and exhibition at “Ren-Yan” exhibition Hall, Fen Chia University

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