USE OF ARTIFICIAL NEURAL NETWORKS TO PRODUCE OPTIMUM PRELIMINARY DESIGNS

by

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Abstract

In practical designs of multi-disciplinary in nature, extensive involvement of many experts is required to produce optimum designs. One example is the design of large buildings. However, in building designs, architects handle the conceptual and preliminary designs, where most of the important decisions are taken without participation of other professionals. This is because, the architect has to generate a form for the building first and to get the consent of the client before other experts participate. Therefore, the architect has to deal with uncertainty and complexity in design without much knowledge about the outcome of his decisions. In such instances, computer tools which can predict the outcome of design decisions would be extremely useful in producing good designs. This paper explains the use of artificial neural networks to develop such computer tools for thermal design of buildings.

1.0 Introduction

Design of an object primarily consists of four stages, namely, conceptual design, preliminary design, detailed design and design documentation. In most instances, the design process is handled by an expert designer where advice is sought from other specialists as required. However, in some areas, the designs are of multi-disciplinary in nature; they need extensive involvement of many experts to produce optimum designs. One example is the design of large buildings, where all the experts should participate in the decision making process even at conceptual and preliminary design process.

However, in building designs, architects handle the conceptual and preliminary designs where major decisions on aesthetics, facade types, visual, thermal and acoustic comfort are made. These decisions affect the capital costs and specially the running costs of the buildings since some of these decisions can affect the energy demand of the buildings drastically. Thus, the advice of Heating, Ventilation and Air Conditioning (HVAC) engineers should be sought at the conceptual and preliminary design stages to produce optimum designs with respect to thermal comfort and energy usage. However, HVAC engineers also will have problems in using sophisticated computer packages to simulate the thermal performance of a building since they work from detail to whole building whereas architects tend to work from whole to detail (Holm, 1993). Thus, these computer simulations may lack sufficient data at these initial stages. By the time sufficient data is available, the architect and the client may be attracted to the design so much, they may not be willing to optimise the design further using the advice given by HVAC engineers.

In order to overcome this difficulty, it is possible to develop Artificial Neural Networks (ANN). An artificial neural network is an information processing system consisting of a number of interconnecting processing units referred to as neurons. Each of these connections has numerical weights associated with them. These weights determine the nature and strength of the influence between the interconnected neurons. The neural network can be trained and tested using a suitable set of data. When it is sufficiently trained, it can be used to make the predictions for new cases.

Once an ANN is produced to predict the thermal performance of buildings, they will be able to provide approximate energy demand depending on the orientation, shape, facade type, shading devices, opening sizes, surface area to floor area ratios, floor area per each storey etc. When such tools are available, the ar-
chitect will be able to predict the implications of his decisions with respect to operating cost of the building at conceptual and preliminary design stages. Thus, they will be able to take appropriate action to control the energy demand while meeting other criteria like functionality, aesthetics, and hence leading to optimised designs. This approach is possible since the time taken by the ANN is generally independent of the complex nature of the problem. HVAC engineers also will be able to check the results that they obtain with detailed computer simulations with the results of ANNs so that comparisons can be made. The data from detailed simulations can also be used to continuously upgrade the ANN.

2.0 Nature of Design

Design is a process of generating a specific fully defined object from an initial incomplete and general set of objectives and specifications. Design is often considered as an iterative feedback process. In design, the objects created are repeatedly checked with the objectives. Adjustments are made as a result of design calculations from which information about what can be achieved at an acceptable cost is obtained. In generating an object that satisfies a set of objectives, the designer is grappling with both uncertainty and complexity. Thus, the reasons for uncertainty and complexity and the means of managing them in design are discussed.

2.1 Managing uncertainty in design

In design, the designer has to deal with uncertainty that arises due to (Boyle, 1989):

1. uncertainty about the design objectives, and
2. uncertainty arising from the effects of design decisions

Uncertainty about the design objectives: In many practical design problems, the client and hence the designer do not have a fixed set of design objectives. Initial clients brief serve only as rough guidelines to the designer. The objectives tend to be refined during the design process, as the designer develops an understanding of the design objectives which can be achieved at an acceptable cost. For example, the client’s brief may be quite vague with respect to the facade shape and materials to be used. It is also possible that the client is not certain about the goal with respect to cost. It could be either minimum capital cost or minimum life cycle cost. The life cycle cost includes the initial capital cost and operating costs. There is a possibility that this decision is taken after considering the costs of alternative solutions. Thus, computer tools that assist in generating alternative solutions could be useful.

Uncertainty arising from the effects of design decisions: In multi-disciplinary design, the precise effects of certain decisions on the behaviour or performance of the object are difficult to predict accurately without performing detailed calculations and simulations. Thus, the designer must perform trial designs and analyse the results. This information can be used to modify the design. For example, if a building is designed with life cycle costs in mind, the designer would have to compare the thermal performances of few alternative facades before selecting the best or coming up with a completely new arrangement. In such instances, the uncertainty about the effects of design decisions can be tackled effectively by the designer when he is able to use computer tools which allow the generation of solutions rapidly.

2.2 Managing complexity in design

Designers handling practical design problems have to deal with the complexity associated with such problems. The complexity is due to (Boyle, 1989):

1. amount of expertise required for problem solving,
2. the design techniques involved, and
3. the object that is designed.

The amount of expertise required for problem solving: In practical designs, the designer should have a wide range of expertise to produce efficient designs. One way of tackling this problem is to break the complex problem into small manageable sub problems and organise them into a suitable hierarchy. Once this is done, it may be possible to develop computer tools to guide the designer in these sub problems specially at the conceptual and preliminary design stages. In design of buildings, it would be necessary to provide the architect with approximate computer tools, which can handle such problems. These can cover the areas that need special expertise. However, the solutions provided by such tools need not be as accurate as those used for detailed designs. The management of complexity arising from the wide range of expertise required may result in more desirable designs.

The design techniques involved: Some design techniques need complex analysis which makes it difficult to use those at the conceptual and preliminary design stages. The decisions taken at the conceptual and preliminary stages will need flexibility to change as required by the designer. Thus, the complex analyses that are time consuming may not be feasible at the initial stages of the design process. For example, there are computer simulations tools which can be used to make detailed calculations on the thermal performance of buildings such as MEDIA-LC and DOE-2
(Kennington & Monaghan, 1993). These tools need accurate input and a lot of time for giving the final answers on reasonably fast computers.

The object that is designed: The object that is designed may have characteristics that are particularly difficult to handle; this may be due to complicated interactions between variables. In the design of large buildings, a conflict resolution would be required between the service engineers and structural engineers since their design objectives may be in conflict. For example, service engineers are concerned about efficient installation of various duct work to optimise the performance of HVAC system whereas structural engineers may be interested in controlling the number of locations that the ductwork penetrate through the structural members. In such instances, a lot of interaction would be required among the professionals involved at the conceptual and preliminary design stages to arrive at a compromise.

This discussion shows that computer tools, which can assist the designer in specific tasks to reduce uncertainty and complexity, could be useful at conceptual and preliminary design stages.

3.0 Optimum Solutions for Designs

Optimum solutions for designs are often found by considering single criterion such as costs or benefits. However, such single criterion approach to design may produce bias designs (Cohan, 1985). The solution for this may be the use of multi-criteria optimisation since design itself is multi-criteria in nature. For example, in design of buildings, minimum capital cost or minimum life cycle cost need not be the criteria since there may be many other factors such as aesthetics or constructability that may be more important.

In multi-criteria problems, the optimum solutions are replaced by a concept called noninferiority which means other solutions will not yield a better solution in one criterion without causing a degradation in at least one other criterion (Cohan, 1985). For example, in a building with its front facing east, a large glass facade may be necessary although it is not desirable with respect to the thermal performance of the building located in a tropical environment. In such instances, a tool that predicts the effects of windows of various sizes may be extremely useful for the architect to reach a compromising solution, which not only has a desirable thermal performance, but satisfies functionality, aesthetics and constructability.

4.0 The Building Design Process

The diversity of tasks within the building design process has required the delegation of certain responsibilities among the members of the design team. It is common for architects to take the responsibility for the overall coordination of the design team in addition to specialist tasks of looking after aesthetics, spatial and functional aspects. The structural engineers are engaged to design and formulate a suitable structural configuration. The mechanical and electrical service engineers have the task of designing and installing suitable plant and machinery. Contractor and client also may have varying involvement in the design (Mathews & Rafiq, 1995).

At the conceptual design stage, major decisions that determine much of the final cost of the building are taken. This is done without much participation of experts in the relevant fields. These can also determine the life cycle cost of buildings as well. It is at this early stage in the design process that one preferred concept is usually selected and agreed by the client. This then becomes the focus of all subsequent design activity. Once the client starts to appreciate the design, it would be extremely difficult to make major alterations such as major modifications to facades or locations of openings subsequently to improve the performance of the building.

At this stage, the architects generally tend to work independently since a form has to be first generated for others to contribute with their expertise. Therefore, computer tools that can provide quick approximate answers to the questions such as thermal performance can be useful in providing efficient designs. The importance of such tools can be highlighted by considering the energy savings that are possible with energy efficient designs. According to Mathews & Richards (1993), carefully planned energy efficient buildings and improvements to existing buildings in United States of America can result in a saving of US $ 100 billion a year by 2010.

5.0 Development of Artificial Neural Networks for Thermal Design

An artificial neural network is a system of interrelated but very simple data processors. These are not programmed in the usual serial way of relating data to decisions. Instead, using cases of inputs and outputs, the network is assigned the computational task of building an appropriate decision model.

In order to train the network, it is necessary to present a sufficient number and range of input-output sets to the network. These progressively tune the weight ap-
plied to the inter-connecting nodes to give the solution algorithm. Convergence error indicators are used to follow the progress in this. Once trained, the network can be used for applications (Begum et al., 1995).

Neural networks have been successfully used in many disciplines in engineering such as prediction of pile capacities (Chow et al., 1995), in many civil engineering applications (Goh, 1994), multi-objective and multi-recourse decision support systems (Wei & Singh, 1995), control systems (Macnab & D'Elenterio, 1995) etc.

5.1 Generation of data for artificial neural network

The objective of the neural network is to predict the air-conditioning energy required for a given building to overcome the external thermal gains where the building may be equipped with a number of passive elements. The preparation of training data for neural networks is a matter of considerable importance. If too little data is presented to the net, the training will give unsatisfactory results in that the internal features and relationships in the problem will not be adequately represented. Thus, the network will not be able to give reasonable approximations to the unseen test data. Therefore, it is important to select a training set which can give sufficient coverage to all possible problems (Jenkins, 1995). Since, buildings differ from one another, it is necessary to identify a suitable set of variables to represent most of the buildings. The variables that can be used for a building are as follows:

1. The presence of windows on north and south faces: For buildings constructed in Sri Lanka, north and south faces are most appropriate for locating windows since those can be shaded by suitable shading devices. Even without shading, the amount of direct solar radiation penetrating into the building is not very high and it is also limited to a duration of five months a year for each face. For large buildings, the shading devices as shown in Figure 1 can be used to effectively cut down the penetration of direct solar radiation specially at high altitude angles.

2. The presence of windows on east and west faces: It is very difficult to cut down the direct solar gains through windows facing east and west by using shading devices. Windows facing west are the worst since most of the direct solar radiation is allowed into the building when the temperature of the surrounding environment is also reasonably high.

3. The window to wall ratio (WWR): This indicates the window area on a given facade with respect to the exposed total wall area. This can affect the amount of direct and diffuse solar radiation gains by the building.

4. The glass type used: The glass type used for windows can have some effect on the thermal performance of the building since heat reflecting glass allows much less direct and diffuse solar radiation than clear glass.

5. The size of the building: The solar heat gained by a building is a function of the total area of the facades and roof. This can be represented by surface area to floor area ratio (SA/FA). This factor was used by Sahu & Prakash (1979) in their studies on solar heat gains of multi-storey buildings. This factor is a better indication than the net floor area per floor since SA/FA can represent the actual area available for external heat gains.

6. The indoor temperature: The temperature that will be maintained inside the building has a considerable effect on the external thermal gains.

In order to generate the data required, few buildings were simulated using simulation tool CASAMO. For each building, the usable floor area is selected to be between 75% to 80% of the total floor area. The total floor to roof height was maintained at 3.6 m for all the buildings. Since the top floor can gain more heat due to the presence of the roof, two simulations were performed for a given building. Those are for an intermediate floor and the top floor. The walls of the building were considered as consisting of 200 mm thick concrete or masonry with 20 mm thick plaster or similar finishes on either side. The roof of buildings were considered as consisting of 150 mm thick concrete slab with 10 mm of bituminous water proofing membrane.

Since the location of sun changes due to the tilt of axis of the earth, the annual energy demand per m2 was determined by performing six simulations representing the months of February, April, June, August, October and December.

The percentage of fenestration area on each wall is important with respect to daylighting as well as the thermal comfort. For example, a higher value would be desirable for the former, but not for the latter. Therefore, three sizes were considered for windows. The height of Type A window was 3.0 m, Type B was 1.8 m and Type C was 1.2 m as shown in Figure 2. The length of the window was considered as that of the corresponding wall. The mullion factor, which is the
percentage of glass with respect to gross window, was taken as 0.8.

In all the buildings, it is assumed that windows will be provided on the northern and southern faces. These windows can be effectively shaded if necessary. The effects of providing windows on east or west or east and west were also considered. The extent of windows on each facade was defined in terms of the Window to Wall Ratio (WWR). The possible values for WWR were zero (no windows), 0.83 (for window type A), 0.5 (for window type B) and 0.33 (for window type C). The possibility of using clear glass and heat reflecting glass was also considered. Double glazing was not considered for the simulations.

Since the indoor set temperature has a considerable influence on the external heat gains and the air conditioning loads, internal temperatures of 22°C, 24°C, 26°C, 28°C and 29°C were considered. It was shown by Jayasinghe & Attalage (1999) that Sri Lankans can be thermally comfortable even at 29°C when the relative humidity is maintained at about 60% and with sufficient ventilation. The comfort zones for different internal air velocities are given in the Psychrometric chart given in Figure 3.

Once the annual energy demands were known for an intermediate floor and the top floor, the effects of SA/FA ratio were determined by considering buildings from two to twenty storeys. For example, for the building identified as X, which is given in Figure 4, SA/FA ratio was 1.47 for a two storey building whereas it is 0.867 for a twenty storey building.

The above strategies were adopted to get sufficient variation for each variable so that the neural network would be able to capture the effects that each variable has on the final output.

5.2 Development of artificial neural network

For the development of the artificial neural network (ANN), a network with 3 layers was found to be the optimum. The number of input nodes was 8. The number of nodes selected for the middle layer was 3. The output of the neural network was the annual air conditioning load.

During the training session, the neural network assesses what data is relevant by assigning low connection weights to irrelevant input data. Another ability of the neural net is to train with sufficient accuracy with inconsistent data. During training, the network constructs non-linear mapping between the input and output data. The main advantage of neural network model is that once training (weight adjustment) is complete, it provides rapid results. The user only needs to input glass type, WWR for windows facing north and south, WWR for windows facing east, WWR for windows facing west, the availability of shading devices for windows facing north and south, the temperature expected to be maintained inside the building, SA/FA ratio and the net floor area per floor. The net floor area per floor and SA/FA ratio are able to accurately define the size of the building.

A sample of the data used for X building for generating the data for the neural network is given in Tables 1 and 2. These data have been combined for buildings with different number of floors to obtain a range of SA/FA values. The notations used are also given.

R = top floor of the building with roof
P = building with clear glass windows
T = building with heat reflecting glass windows
X = square building with glass facade facing north and south

<table>
<thead>
<tr>
<th>Internal temperature °C</th>
<th>PXA</th>
<th>PXAS</th>
<th>PXB</th>
<th>PXBS</th>
<th>PXASE</th>
<th>PXASW</th>
<th>PXASEW</th>
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<td>22</td>
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<td>10.92</td>
<td>17.79</td>
<td>12.21</td>
<td>18.01</td>
<td>19.20</td>
<td>21.78</td>
</tr>
<tr>
<td>29</td>
<td>12.02</td>
<td>5.78</td>
<td>11.11</td>
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<td>10.42</td>
<td>12.42</td>
<td>14.05</td>
</tr>
</tbody>
</table>
Table 2

Annual air conditioning load values for the top floor of a square building with clear glass - notations as given above. The unit is kWh/m²/year

<table>
<thead>
<tr>
<th>Internal temperature °C</th>
<th>RPXA</th>
<th>RPXAS</th>
<th>RPXB</th>
<th>RPXBS</th>
<th>RPXASE</th>
<th>RPXASW</th>
<th>RPXASEW</th>
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<tr>
<td>22</td>
<td>76.49</td>
<td>69.57</td>
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<td>77.92</td>
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<td>57.10</td>
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<td>28</td>
<td>16.62</td>
<td>11.03</td>
<td>14.62</td>
<td>10.79</td>
<td>16.26</td>
<td>18.04</td>
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<td>29</td>
<td>8.52</td>
<td>5.25</td>
<td>6.85</td>
<td>5.34</td>
<td>7.74</td>
<td>10.71</td>
<td>11.94</td>
</tr>
</tbody>
</table>

Table 3

A set of data generated for X building for the neural network with internal temperature 220°C, clear glass - notations as given above. The unit is kWh/m²/year

<table>
<thead>
<tr>
<th>Number of floors</th>
<th>PXA</th>
<th>PXAS</th>
<th>PXB</th>
<th>PXBS</th>
<th>PXASE</th>
<th>PXASW</th>
<th>PXASEW</th>
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<tbody>
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<td>57.74</td>
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<td>68.94</td>
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</tr>
<tr>
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<td>58.32</td>
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<td>56.83</td>
<td>68.57</td>
<td>68.61</td>
<td>74.45</td>
</tr>
</tbody>
</table>

A = glass facade of height 3.0 m
B = glass facade of height 1.8 m
C = glass facade of height 1.2 m
S = glass facade provided with shading devices
E = glass facade facing east
W = glass facade facing west

Thus, PXASEW means square building X with clear glass window type A provided with shading on north and south facades. This building is also provided with windows of similar type on east and west facades as well. These windows are not shaded since shading devices are not effective.

5.3 Validation of ANN

Once sufficient number of data is obtained, part of that data can be used for training of the network. The remaining data can be used for testing of the network.

Generally, the training data can be about 60% - 70% of the total data. These should be carefully selected to give a sufficient coverage for all practically possible combinations of variables.

For the same set of training data, a number of different neural networks can be developed by changing the number of middle layers, the number of nodes in the middle layers and target errors. Once trained, the network can be used to predict the values for the test data. The optimum net out of these alternative networks can be determined by comparing the test file used for testing the neural network with the output file predicted by the trained network (declared output).

For the comparison purposes, the correlation coefficient of the test file and declared output can be determined for each trained net. The net giving the highest correlation coefficient (close to 1) can be selected as
the best trained network. In this particular case, the optimum neural network gave a correlation coefficient of 0.998.

5.4 Use of ANN

It is extremely easy to use the trained neural network. For this purpose, a data file has to be created with the inputs, which represent the building under consideration, with output as zero. When this data file is run by the neural network, which takes only a fraction of a second, the annual energy demand will be given as the output. Thus, architects will be able to compare a number of alternative designs with minimum time and this will help them to reduce the uncertainty and complexity involved in design at conceptual design stage. This will also help them to reach compromising solutions.

For example, it would be possible for them to go for less optimised facades when the building is intended to be maintained at elevated temperatures. On the other hand, they might consider optimising the building as much as possible when it is necessary to maintain the building at lower temperatures which may be determined by the equipment used in the building.

6.0 Conclusion

It is desirable to have close to optimum design solutions found for practical design problems. It is shown that practical designs are of multi-criteria in nature and hence the solutions found may not satisfy single optimisation criterion. In such instances, it is necessary to reach a compromise between a number of different criteria.

In practical designs, reaching such solutions manually is not an easy task due to uncertainties and complexities involved. In such instances, the development of computer tools that can provide rapid answers with minimum input data will be quite valuable, even though such answers would be of approximate nature. This is exactly the capability of artificial neural networks.

It is shown with an example that for a complex process of building design, architects will be able to find the effects of their design decisions on the thermal performance of the building using an ANN. Such tools will reduce the uncertainty associated with conceptual design stages and also help them to reach compromising solutions that satisfy a number of design criteria as well.

7.0 References


CASAMO - Version 2.0, Ademe-AIT RUE Project, Asian Institute of Technology.


