Developments in Hyper Real-Time Simulation of Transient Heat-Flow in Buildings

I. Flood, R.R.A. Issa, and C. Abi-Shdid, University of Florida,Gainesville, FL 32611, USA, flood@ufl.edu

Summary

This paper reports on the latest results in the development of a new approach for simulating the thermal behavior of buildings that overcomes the limitations of conventional heat-transfer simulation methods such as FDM and FEM. The proposed technique uses a coarse-grain approach to model development whereby each element represents a complete building component such as a wall, internal space, or floor. The thermal behavior of each coarse-grain element is captured using empirical modeling techniques such as artificial neural networks (ANNs). The main advantages of the approach compared to conventional simulation methods are: (a) simplified model construction for the end-user; (b) simplified model reconfiguration; (c) significantly faster simulation runs (orders of magnitude faster for two and three-dimensional models); and (d) potentially more accurate results.

The paper demonstrates the viability of the approach through a number of experiments with a model of a composite wall. The approach is shown to be able to sustain highly accurate long-term simulation runs, if the coarse-grain modeling elements are implemented as ANNs. In contrast, an implementation of the coarse-grain elements using a linear model is shown to function inaccurately and erratically. The paper concludes with an identification of on-going work and future areas for development of the technique.

1 Introduction

This paper describes and evaluates a new approach to modeling the thermal performance of buildings, for evaluating alternative building designs (such as insulation thickness, glazing areas, etc) operating under different occupant usage profiles. The approach is aimed at overcoming the limitations of current modeling methods (the finite difference method (FDM), and the finite element method (FEM)), namely, long model development and validation lead times, inconvenient model reconfiguration (for evaluating alternative building designs), long simulation runs, and inaccurate results. The proposed approach constructs transient heat flow simulation models of buildings, from artificial neural network modules (ANNs), as proposed by Flood (1999). The paper first describes the principles underlying the approach, and then proves the viability of the concept and the validity of its results in a series of trial experiments.

2 Coarse-Grain Simulation Modeling Approach

2.1 Coarse-Grain Elements

The basis of the proposed approach is the construction of a model from a menu of coarse-grain modeling elements. The coarseness of the elements is such that they each represent a complete component in a building, such as an exterior wall, interior wall, floor, enclosed space, or the heating, ventilating and cooling system. Most elements will represent composite components comprising a variety of material types across all three dimensions. Figure 1 shows an example assembly of coarse-grain elements (in plan and cross section) for a simple structure. These elements can be divided into two broad categories: (i) the boundary elements, typically

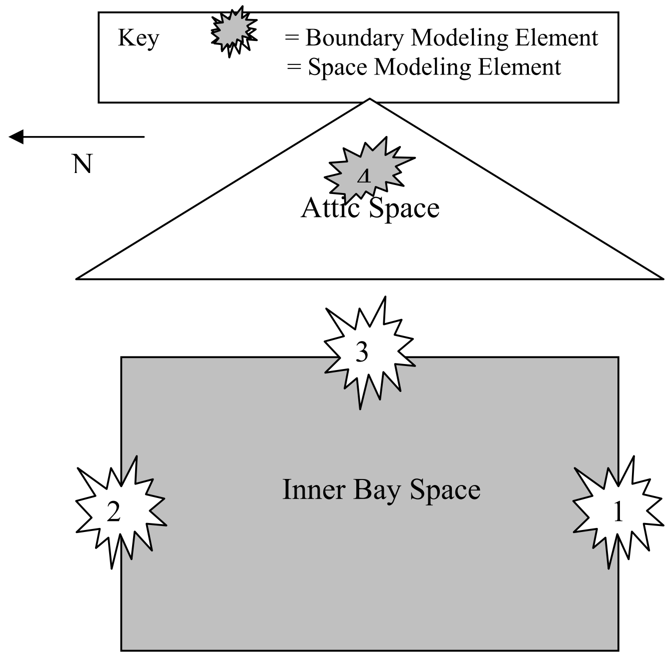

Figure 1: Assembly of Elements for Modeled Structure

representing boundary components between spaces (walls or parts of walls, floors, and roof components); and (ii) the space elements, typically representing bounded spaces. A third type of element could be considered, representing sub-systems such as air infiltration, heating and ventilating – alternatively, these functions can be integrated into the boundary and/or spatial elements of a model.

Figure 2 shows, in more detail, the types of connections that may exist between the elements and their environment. Part (a) of the figure shows typical connections for the boundary modeling elements. Element 1, representing an external wall, samples the external temperature, internal room temperature, a number of attributes of the building component it represents (such as, insulation thickness, thermal conductivity of the insulation, percentage glazing, orientation, and a shading factor), and includes recursive-feedback (measuring, for example, its mean rate of energy emission/absorption per unit area). Part (b) of the figure shows how a space element would connect all the elements defining a bounded space. In particular, the space element receives input from each of the boundary elements (measuring their rate of energy emission/absorption), registers attributes of the space (such as its volume, heating and cooling usage profiles, and ventilation profiles), and samples and updates the mean temperature of the space.

Figure 3 shows an example building with composite components and the typical temperature sampling points of its corresponding coarse-grain modeling element. From this it can be seen that the coarse-grain modeling element only samples temperatures in the internal and external spaces. In contrast, a FEM model must sample temperatures at multiple points across the walls in addition to sampling from the internal and external spaces. Consequently, the FEM approach requires the model to be rebuilt if there is any change in the design of the wall, such as the thickness of the insulation. The coarse-grain approach would not require any rebuilding of the model to account for such changes – changes in design variables such as the thickness of insulation or the percentage of glazing in the wall are represented as inputs to the modeling element and can be changed by simply adjusting the values at those inputs. However, the

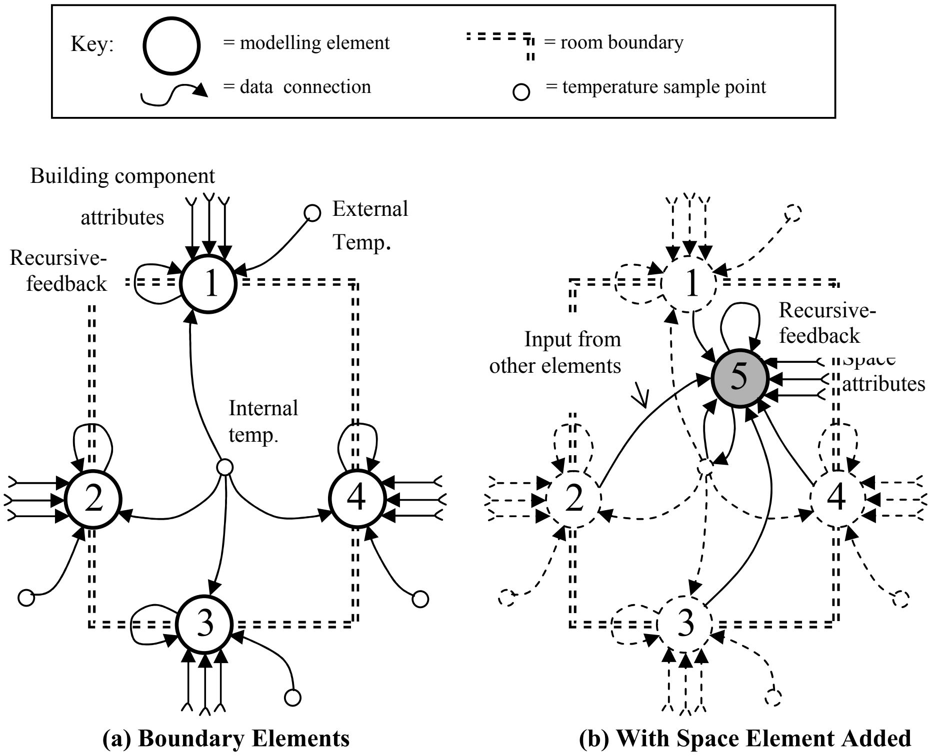

Figure 2: Data Input and Output Connections

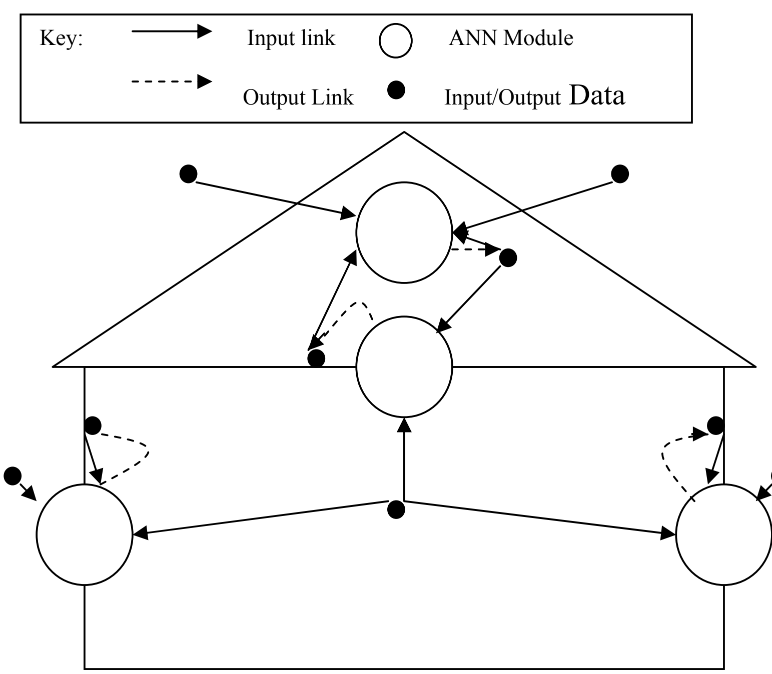

Figure 3: Spatial Sampling Points of Temperature for a Coarse-Grain Model

internal thermal state (temperature distribution) of the wall will influence the rate of energy emission/absorption at the internal surface of the wall, and so it may seem that not including this information would mean the coarse-grain modeling element has insufficient information to make its predictions. The solution to this problem is to provide the coarse-grain modeling element with historic temperature readings sampled from a series of points in time, for both the external and internal spaces. In effect, the modeling approach is substituting spatial sampling across the wall for temporal sampling of its environment.

2.2 Empirical Model Development

Simulating the thermodynamic behavior of a system requires some form of modeling of its driving thermodynamic equations. For fine-grain modeling techniques, such as FEM, the equations are established from basic thermodynamic theory and are discretized in both the spatial and temporal domains to allow a step-wise simulation of the system's behavior. However, for coarse-grain models (whereby each element represents an intricate composite of materials with varying thermodynamic properties and where the spatially-distributed state of the system is substituted with a thermal-loading history) the driving equations cannot be derived from basic thermodynamic theory, and so an empirical modeling approach is required. This involves making discrete observations of the system (at fixed locations and instants in time) and then developing some form of mapping function that provides a best fit to these observations. In this case, the chosen empirical technique will have to deal with modeling situations that involve: non-linearities in the behavior of the system; the development of the mapping function from very large numbers of observations - a large number of observations may be required to ensure all complexities in the mapping function are represented; error or ambiguities in observed data; and large numbers of input variables.

The RGIN method (Flood, 1999) (a form of artificial neural network (ANN) that constructs mapping functions from Radial-Gaussian functions in a stepwise manner) has been found to work well for engineering problems that exhibit all of the above characteristics (see, for example, Gagarin et al (1994)), and so was adopted for this study. For comparison, multi-variate linear regression was also considered. Other empirical methods, including alternative forms of ANN, will be considered in a later study.

2.3 Potential Benefits of the Coarse-Grain Modeling Approach

The potential advantages of the proposed coarse-grain approach compared to fine-grain methods, such as FDM and FEM, are as follows:

a) Model development is greatly simplified since the coarse-grain approach requires far fewer elements to construct a model. This advantage increases with the complexity of the composite structure and the size of the system being modeled, and is particularly significant for two and three-dimensional models. Developing FEM models can be further complicated if the model-builder has to determine an appropriate size for the elements (and shape in the case of two and three dimensional models) to achieve the desired level of accuracy in results. The coarse-grain approach requires no such experimentation.

b) Experimenting with variations in the design of a building is also greatly simplified by the coarse-grain approach. Not only are alternative building designs easy to model using the coarse-grain approach, in many cases no new model is required. For example, building design variables such as *wall insulation thickness*, *window size, or eaves overhang,* are represented as input variables to the corresponding coarse-grain element and thus can be changed by simply adjusting the values at these inputs. In comparison, FEM models require the configuration of the elements to be altered to implement changes in such building design variables.

c) The amount of time required to run a simulation will be significantly less for the coarse-grain approach since it comprises far fewer elements. Of course, it could be argued that if the coarse-grain element is implemented as an ANN then the amount of processing required to advance the element through one time step could be significantly greater than that for an FEM element (typically, an ANN will be functionally more complicated than an FEM element). Nevertheless, each ANN-based coarse-grain element will substitute for many thousands or millions of FEM fine-grain elements and is thus still expected to operate several orders of magnitude faster.

d) A final potential advantage of the coarse-grain approach is greater accuracy in the simulation results. The accuracy of FEM models is dependent, in part, on the fineness of the modeling elements – the smaller the size of the elements then potentially the greater the accuracy. However, there are two practical limits on how far the element size can be reduced and, thus, the degree of accuracy that can be achieved. Firstly, the number of elements required in a FEM model will increase geometrically with respect to a decrease in element size, and so very soon the model will become too large to process in an acceptable period of time. Secondly, for heterogeneous materials, it is unlikely that there will be any significant gain in accuracy by reducing the element size once it approaches that of the grains comprising the material. The coarse-grain modeling approach, on the other hand, is not subject to these limitations since it achieves accuracy in representation through empirical emulation (specifically, through training in the case of ANNs) rather than through analytical decomposition.

2.4 Related Work

The proposed approach is radically different to existing methods of simulating the behavior of dynamic systems and so there is limited related work from which to draw direction and make comparisons. However, ANNs have been shown capable of simulating the dynamics of chaotic functions (Ensley & Nelson 1992), discrete stochastic construction processes (Flood and Worley 1995), and the anisotropic rate dependent behavior of clays (Penumada et al. 1994). These works demonstrate the ability of ANNs to model dynamic functions to the degree of accuracy necessary to sustain an accurate representation of behavior over many time steps.

Work by Flood (1999) demonstrated the feasibility of using ANNs to simulate continuous non-linear heat transfer processes for use in situations where the governing equations are poorly understood. The work proposed here takes this to the next stage, evaluating the ability of the technique to model composites.

3 Development of a Trial Coarse-Grain Element

3.1 Input/Output Structure of the Trial Element

The main objective of this study was to prove the viability of the proposed coarse-grain approach, in terms of providing a sustained and accurate simulation of the thermal performance of a composite structure that exhibits non-linear behavior. A coarse-grain model representing a 2-D external wall section, ceiling, room, and attic were developed (see Figure 3 for attic space).

The sets of inputs and outputs chosen for this example element are shown in Figure 4. A maximum of 8 historic external air temperatures were included as part of the input, ranging from (t - 1hr) to (t - 8hrs) (this number is varied in a later study as part of a sensitivity analysis assessing the dependence of modeling error on the number of temperature histories used as inputs). The insolation (solar loading), and surface temperature of the inside of the wall, make up the two remaining inputs to the element. A fixed internal air temperature was considered for this trial, although in future studies a set of histories of internal temperatures will be required to allow for greater modeling accuracy for situations where the internal air temperature varies sharply in time. The output from the coarse-grain element is the change in the wall's internal surface temperature over a small increment in time (for this study, 30 second time intervals were considered). This value is fed back to the appropriate input of the element, where it is added to the previous value, as indicated in Figure 4. Alternatively, the coarse-grain element could have been developed to predict the actual temperature of the wall's inside surface at the next point in time, which would then be fed back to the inputs to become the new internal surface temperature at the current point in time.

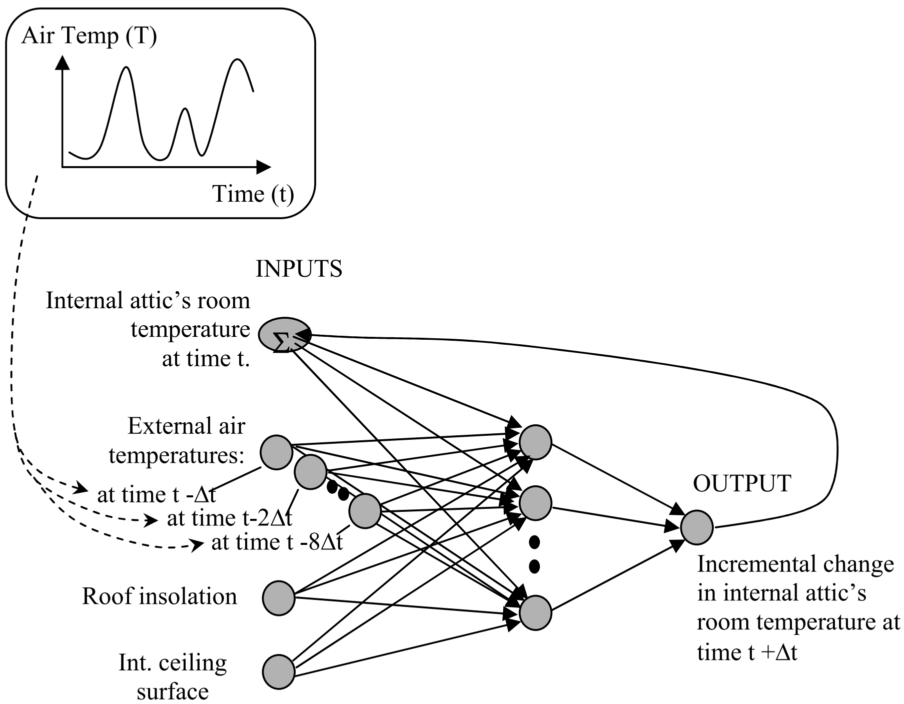

Figure 4: Trial ANN Module Modeling the Attic Space Shown in Figure 3.

3.2 Training and Testing the ANN Implementation of the Trial Element

Development of an ANN requires a representative set of examples (training patterns) of how the system behaves under different circumstances. In this case (referring to Figure 4), each training pattern will specify what output value the ANN should generate (the change in the wall's inside surface temperature over the next minute) in response to a given set of input values (the current inside surface temperature of the walls, and the insolation history).

Training and testing patterns were generated from 15 FDM simulation runs, each using a different combination of insulation thickness and internal air temperature. Three alternative insulation thicknesses were considered (12 cm, 16 cm, and 20 cm) along with 5 alternative internal air temperatures (ranging from 15 °C to 19 °C). Each FDM simulation was run for a one-year period, using the outdoor air temperature profile measured at Alexandria, Kentucky, for year 2001 (NOAA, 2001). At random points in time, the state of the system was measured to generate a training pattern for the ANN. A total of 8,250 training patterns were produced in this way (the memory limit of the ANN software). The range in the values of the outputs for the training patterns was –0.00569165 °C/min to +0.022335968 °C/min. Similarly, a set of 5,250 testing patterns were generated for evaluating the performance of the ANN.

Figure 5 shows progress in the performance of the ANN during the training process. Performance is measured as the mean absolute error for all patterns in the training set. A distinctive feature of the RGIN system (Flood, 1999) is that it develops the ANN one hidden neuron at a time, with each hidden neuron being trained on the part of the problem the previous hidden neurons failed to learn (the residual error). As more hidden neurons are trained and added to the ANN, the residual error for the set of training patterns is reduced. Thus, the curves in Figure 5 show performance relative to the number of hidden neurons developed for the network. Typically, training should proceed until there is no significant improvement in the performance of the ANN as measured for the test patterns, which was found to be around 350 hidden neurons.

Figure 6 plots the ANN prediction versus the FDM targets for each pattern in the testing set. If the ANN had developed a perfect model able to generalize to examples of the problem not used in training, then all points in Figure 6 would fall on the line indicated. It can be seen from these plots that the ANN provides consistently good performance across the range of possible output values, and there are no distinct outlying points (representing large localized errors in the ANN model). Moreover, the correlation coefficient of 0.971207 for the testing patterns indicates the ANN is an excellent predictor of the FDM target. The ultimate test of the ANN however, will be its ability to sustain accurate performance in a lengthy simulation – this will be considered in the next section.

Although the thermal behavior of a wall component is non-linear (due to the convection at its surfaces), it was decided to compare the performance of the ANN with a linear model. If the linear model can perform sufficiently well then it would be the better choice since it is much simpler in form than the ANN. The linear model was developed for the same patterns used to train the ANN, using multi-variate linear regression analysis by the "least squares" method. The correlation between the linear model and the FDM target, for the testing patterns, was

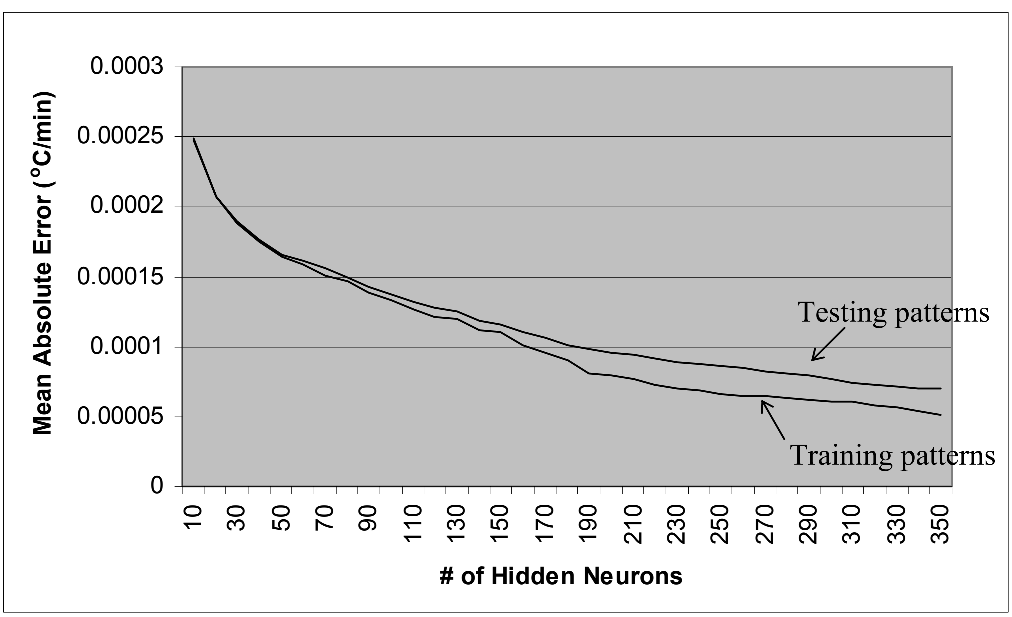

Figure 5: Learning Curves for the ANN Trial Element

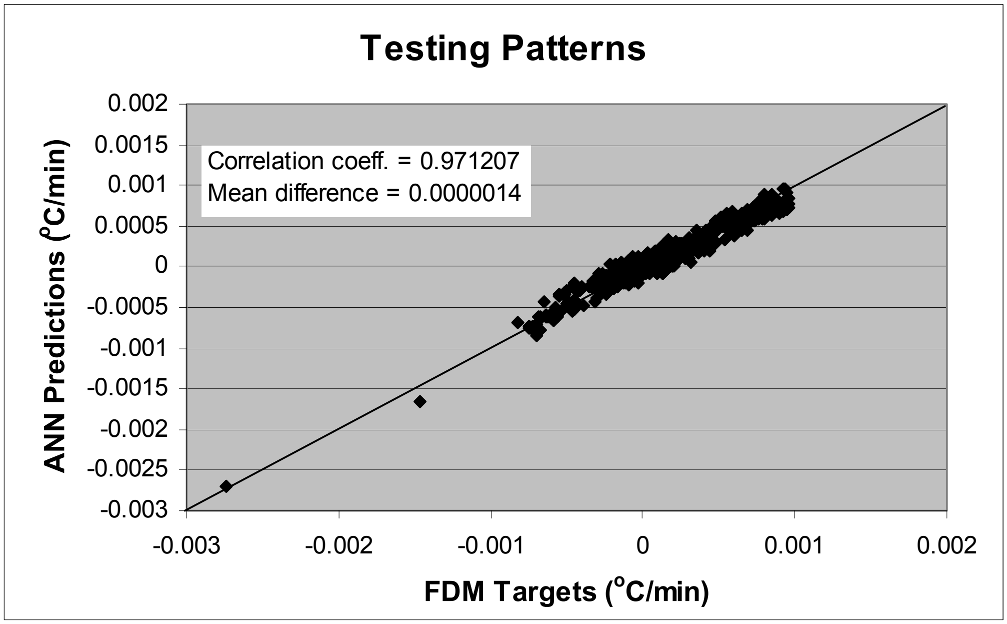

Figure 6: Correlation between ANN Predictions and FDM Targets for Testing Patterns

found to be 0.9938181. This was actually slightly better than the value obtained for the ANN (0.971207), although this does not necessarily mean that the linear model will out perform the ANN during a lengthy simulation, as is found to be the case in the following section.

Although the thermal behavior of a wall component is non-linear (due to the convection at its surfaces), it was decided to compare the performance of the ANN with a linear model. If the linear model can perform sufficiently well then it would be the better choice since it is much simpler in form than the ANN. The linear model was developed for the same patterns used to train the ANN, using multi-variate linear regression analysis by the "least squares" method. The correlation between the linear model and the FDM target, for the testing patterns, was found to be 0.9938181. This was actually slightly better than the value obtained for the ANN (0.971207), although this does not necessarily mean that the linear model will out perform the ANN during a lengthy simulation, as is found to be the case in the following section.

4 SIMULATION RESULTS AND ANALYSIS

The ANN and linear models were tested in a one-year simulation, using a 15 °C internal air temperature and 16 cm insulation thickness. The 15°C internal air temperature value was selected since it falls at the edge of the problem domain defined by the training patterns, a location where ANNs often do not perform so well. The external air temperature profile for the simulation was that measured at Alexandria, Kentucky, for year 2001 (NOAA, 2001).

The results for these simulations are shown in Figures 7 and 8. The first of these figures shows the wall internal surface temperature profiles, for days 1 and 2 in the simulation, produced by both the ANN and linear models – for comparison, the target profile (as produced by the FDM analysis) is also shown. Figure 8 shows the same information for days 364 and 365. For the first two days of the simulation, the profile produced by the ANN is so close to the target that the two are indistinguishable. The linear model, while follows the general trend of the target, very quickly develops significant errors. For days 364 and 365 of the simulation, it can be seen that the ANN output is still fairly accurate and is following the trend of the target very closely. The linear model's temperature profile includes some very large errors and has a trend that bears no resemblance to the target profile. Moreover, better results could probably have been obtained for the ANN if its calibration factor (0.0000014, taken from its average error on testing patterns) had been applied following each iteration during the simulation (rather than after the simulation had been completed) so that the errors would not compound. This approach to calibration will be considered in a later study.

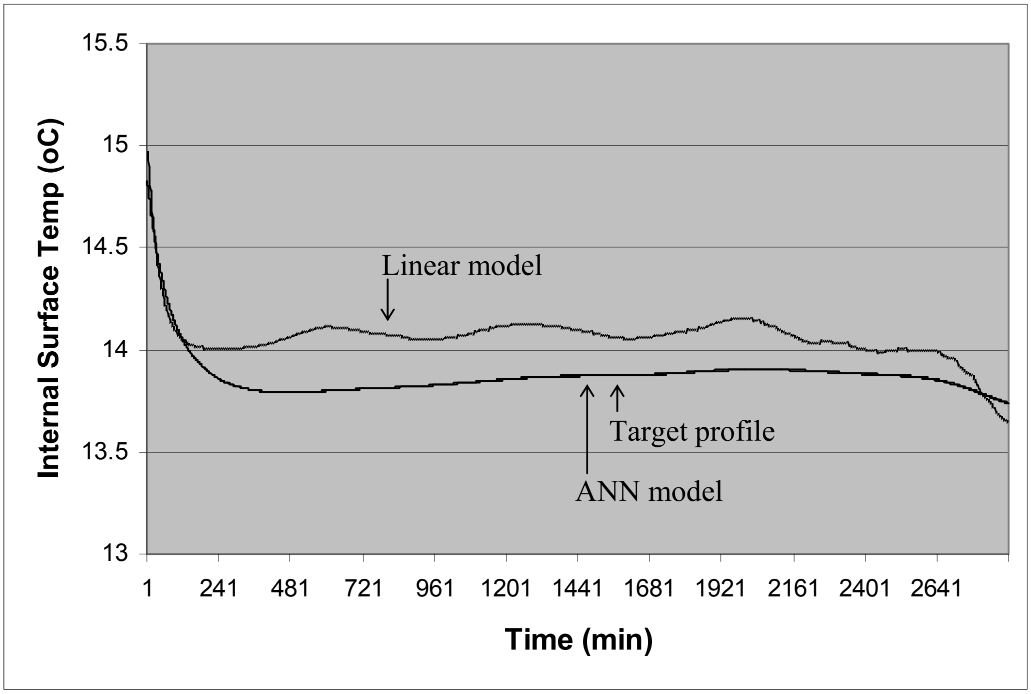

Figure 7: Results for Days 1 and 2 of a Simulation Run

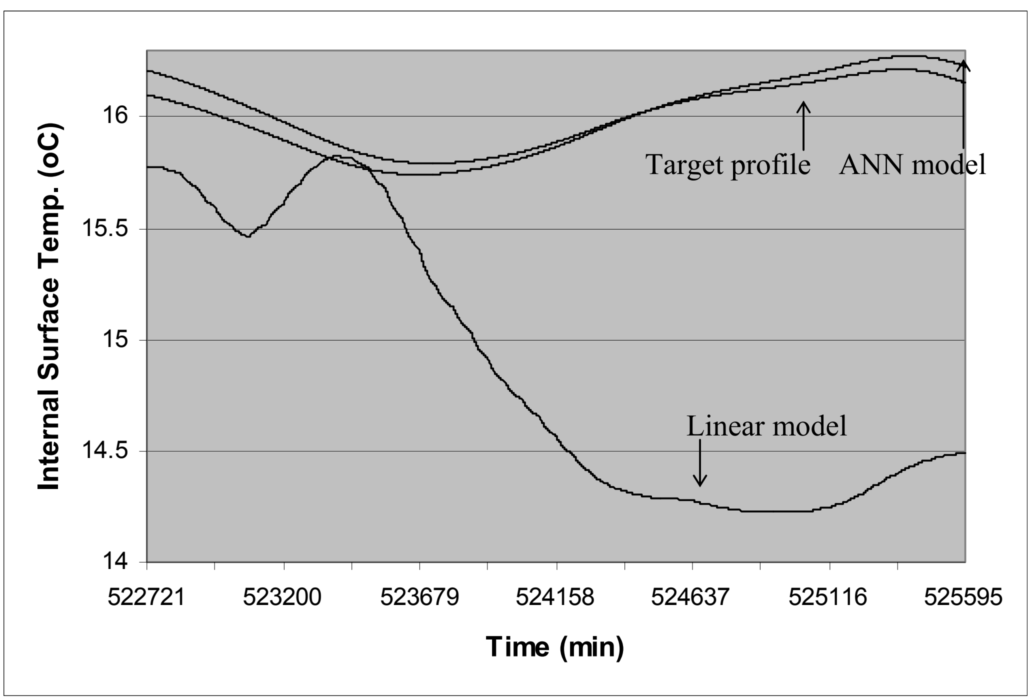

Figure 8: Results for Days 364 and 365 of a Simulation Run

The simulation of the thermal behavior of a building will ultimately require the models to operate in three spatial dimensions. For the wall component considered in this study (see Figure 3), with 16 cm of insulation, a height of 3 m, a length of 5 m, and a sampling spacing of 1 cm, the FDM modeling approach would require in the order of 3,750,000 modeling elements. In computational terms, each FDM modeling element is roughly comparable to a hidden neuron in an ANN-based coarse-grain modeling element. Given this, a 350 hidden neuron ANN (such as that developed for this study) would operate over 10,000 times faster than the FDM model – a simulation run for the FDM model that took say 24 hrs to execute could be completed by the ANN-based coarse-grain model in less than 10 seconds.

5 Conclusions and Recommendations

The paper has proposed and demonstrated the viability of a novel approach to simulating the time-wise thermal behavior of buildings, using models built from coarse-grain elements. A series of experiments showed the approach capable of sustaining a long and accurate simulation of the thermal behavior of a composite wall. The new approach has several important advantages over conventional simulation methods (such as FDM or FEM): (a) models comprise very few elements and so can be assembled very easily; (b) testing the impact of a design variable (such as insulation thickness) can be undertaken by changing the value of a corresponding input to the model, without having to reconfigure the whole model; and (c) simulations will run many orders of magnitude faster than conventional simulation methods. Moreover, the approach has the potential to provide results that are more accurate than conventional simulation techniques, if training of the ANNs is performed using observations of the performance of real systems.

The next stage in the work is to test the performance of the proposed approach using two-dimensional and three-dimensional assemblies of modeling elements, representing systems with enclosed spaces. A second major extension to the work will be the training of the ANN modeling elements using data collected from a real building, and determining whether that allows greater accuracy in results to be obtained relative to the conventional FDM and FEM simulation techniques. Other developments will include: (a) increasing the number of input parameters to a modeling element to allow for other attributes (such as percentage glazing, orientation, and solar loading profiles); (b) implementing the modeling elements as a hybrid of an ANN and linear model; and (c) comparing the performance of the system for alternative types of output from the modeling elements (such as, predicting changes in the rate of energy transfer per time step, versus predicting the actual rate of energy transfer at the next point in time).

6 References

Flood, I.,(1999). Modeling Dynamic Engineering Processes Using Radial-Gaussian Neural Networks, Journal of Intelligent and Fuzzy Systems, 7, pp 373-385.

Gagarin, N., Flood, I., and Albrecht, P. (1994). Computing Truck Attributes with Artificial Neural Networks, Journal of Comp. in Civil Engineering, ASCE, 8 (2), pp 179-200.

Ensley, D., and Nelson, D.E. (1992). Extrapolation of Mackey-Glass Data Using Cascade Correlation, Simulation, 58, 5, pp 333-339.

Flood, I., and Worley K. (1995). An Artificial Neural Network Approach to Discrete-Event Simulation. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 9, Cambridge University Press, pp 37-49.

Penumada, D., Jin-Nan, L., Chameau, J-L., and Sandarajah, A. (1994). Anisotropic Rate Dependent Behavior of Clays Using Neural Networks. In proceedings of the XIII ICSMFE, New Delhi, 4, pp 1445-1448.

NOAA (2001), National Data Buoy Center, 2001 Temperature Records, www.ndbc.noaa.gov.

7 Acknowledgements

The authors would like to express their deep gratitude to CertainTeed Corporation, the sponsors of the work presented in this paper.