SIMULATION AND REASONING: INTELLIGENT BUILDING THERMAL PROBLEM DETECTION

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ABSTRACT

This paper discusses a model for integrating a rigorous thermal simulation with computational reasoning. This model is used to build an intelligent computer-aided system that assists designers throughout the design process. The model uses rigorous hierarchical thermal simulation modules linked to several databases. In addition, Artificial Intelligence Techniques are used to build a multilevel reasoning structure for both the initial and the final design. Neural networks are utilized for the initial design stage problem detection where problems are incomplete. The neural networks are integrated with a multi-knowledge reasoning structure that utilizes the blackboard framework. This structure is used for problem detection in the intermediate to final design stages and for advice throughout the design process.

INTRODUCTION

Uncertainties in building thermal design are often encountered due to the dependency of the design upon a large number of variables in various levels. Artificial Intelligence Techniques provide a framework for solving complex problems. Computer assistance using Artificial Intelligence Techniques can provide solutions to uncertainty problems in thermal design decisions.

Several research projects were conducted that took advantage of knowledge based systems emerging from the artificial intelligence field (Fenves et al. 1992; Shaviv and Kalay 1992; Jog 1992; Papamichael and Selkowitz 1990; Brown 1990; Mayer et al. 1991; Carroll and Hitchcock 1991; Phol et al. 1990; Case et al. 1990; Amor and Groves 1990). These systems utilize rules of thumb in their knowledge and strategies. The use of rules of thumb prevents their use in thermal design optimization for case specific situations where accurate problem identification is essential for criticism and advice.

One approach developed to solve this problem using Artificial Intelligence Techniques is a multi-knowledge structure using uncertainty reasoning (Malkawi, 1994). This approach is used in a rigorous design oriented method for an intelligent computer-aided design system that evaluates, critiques and optimizes energy use and design in buildings. The focus of this method is on the relationship between detailed thermal analysis using the Transfer Function Method and advice and criticism for case sensitive energy design optimization. The method is based on a hierarchical representation of building elements in the simulation mode to establish a well-defined output taking into consideration possible element interactions and conflicts. The output is designed to provide changeable factual knowledge of the proposed design and is used to build associations with the inference process and related knowledge sources. The inference process is used to optimize the building energy design by providing problem detection and advice. These are conducted using Artificial Intelligence uncertain reasoning, heuristics and search methods. Their framework utilizes the Blackboard model to facilitate dynamic multi-knowledge interaction and conflict avoidance within problem solving.

This approach was built to accommodate problem detection in the intermediate to final design stages. To provide problem detection early in the design, the framework of the system is currently being refined and expanded to include neural networks as part of its overall reasoning structure. The project investigates the potential use of neural networks in building thermal design. It examines their use in aiding the system in locating thermal problems for the initial design where information about the building is incomplete. This is established by training neural networks using well known building thermal output based on heating and cooling loads. The neural networks are being integrated in the reasoning structure of the system. This allows it to perform its problem detection based on the changeable factual knowledge of the design simulation and provide links to the system's advice inference process.

This paper describes the intelligent system framework. The interacting structures of the simulation and reasoning mechanism are illustrated. Conclusions and findings are presented.

SYSTEM MODEL

The system consists of four major components that are organized in an integrated framework. These components are: 1. the graphical user interface 2. the simulation program 3. the databases 4. the intelligent agents, figure (1).

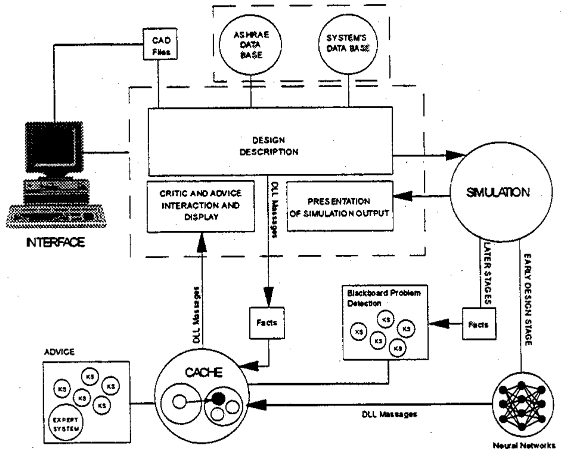
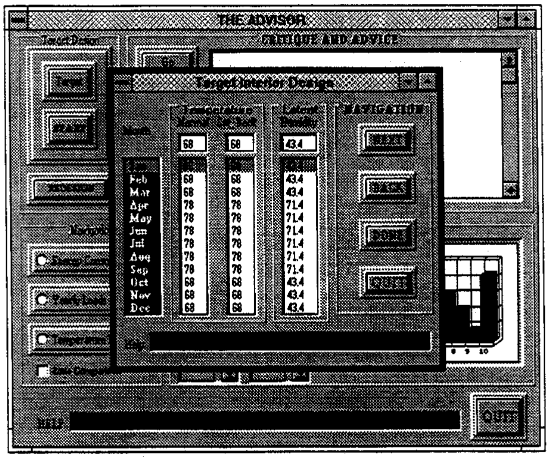


Figure 1. The system model.

THE INTERFACE

The interface in this system is built to provide a flexible tool to propose the design problem and to navigate and interact with the system's output and intelligent agents. This was accomplished by providing a Graphical User Interface that performs all the necessary criteria in one environment, figure (2). The interface allows the user to define the thermal design problem, start a detailed simulation, navigate the outcome, interact with the intelligent agents and based on this, allow alterations to the design. The interface is designed to allow integration with other CAD software. It accepts files that have been generated in CAD software. The interface reads these files and incorporates them into its own interface. In addition, the interface has the ability to save files that can be used to update CAD attributes.



Month	Temperature		[illegible]
	68	68	43.4
[illegible]	[illegible]	[illegible]	[illegible]
Feb	68	68	43.4
Mar	68	68	43.4
Apr	78	78	71.4
May	78	78	71.4
Jun	78	78	71.4
Jul	78	78	71.4
Aug	78	78	71.4
Sep	78	78	71.4
Oct	68	68	43.4
Nov	68	68	43.4
Dec	68	68	43.4

Figure 2. Sample interface form.

THE SIMULATION MODEL

The simulation in this system uses Transfer Function Method (TFM) algorithms for analysis. All the TFM procedures have been fully implemented. The simulation provides the designer with a precise thermal evaluation of the proposed design for every hour of the day and every day of the year in any specified location. The simulation program is used to calculate the cooling and heating loads the building generates and to provide a passive and active interior temperature analysis. This is based on the heat extraction and floating temperature procedures. These procedures were programmed in a separate module to accept the TFM output cooling loads as the input for their calculations.

In building the simulation model, all the mathematical procedures have been programmed in hierarchical modules. These modules are used to provide a distinction between different levels in the calculation procedures and to facilitate the dependencies between building elements. After the calculation takes place, all these loads are stored in multidimensional arrays that describe their values, origin and their dependency.

The simulation of building thermal behavior relies on the cooling load output generated from the individual building elements rather than the heat gain produced. In heating gain, only the individual element's amount of heat gain or loss contributing to the building are considered. On the other hand, through the use of weighting factors, the cooling load takes into consideration the building elements, space configuration and the delayed portion of cooling load interactions. This enables the reasoning process to use accurate analysis as its factual knowledge to determine the design fault considering time and interaction dependencies.

THE DATABASES

The system makes use of two databases: the system database and the ASHRAE database. The system database contains files that include weather data. In addition, these files include atmospheric and ASHRAE standards (ASHRAE, 1989). These files are accessed automatically according to the city and state name.

The ASHRAE database contains weighting factors (WF) data that are based on the results of the dynamic response to heat gain for more that 200,000 zones (Falconer et al., 1993). In addition it contains Conduction Transfer Function (CTF) coefficients for a wide variety of walls, roofs, partitions, floors and ceilings. Both the WF and CTF that closely match the current design parameters can be accessed and read by the system if required.

THE INTELLIGENT AGENT STRUCTURE

The intelligent structure in the system consists of the problem detection and the advice agents. Both agents in the system use the blackboard model supported by a multi-knowledge statistical reasoning framework. The statistical reasoning supports modeling the uncertainty that is present within the reasoning. The control in the intelligent agent is based on a combination of backward and forward reasoning and backtracking. Currently the problem detection agent is being revised to include an additional model that uses the neural network as its reasoning structure to support problem detection in incomplete designs. Both models are being connected to the multi-knowledge intelligent advisory structure, figure (3).

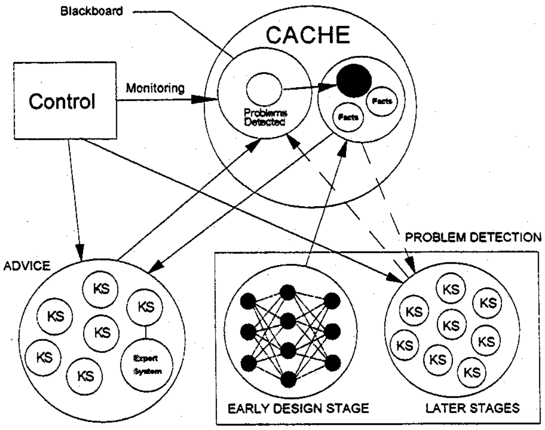


Figure 3. The intelligent agents structure.

PROBLEM DETECTION

After the simulation is complete, the building's physical and spatial characteristics are forwarded to the static fact portion of the working memory (cache). The simulation program produces a module output of factual knowledge regarding the building's thermal behavior. If the design is in its early state, this knowledge will be filtered and provided to the neural networks as input for problem detection. Otherwise, this knowledge is forwarded and stored as static facts in the system's intelligent agent working memory to be used by the blackboard structure for exact problem detection, figure (4).

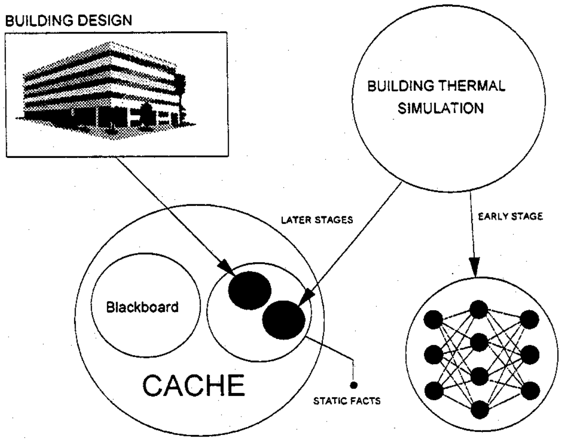


Figure 4. Problem detection agent's interaction with the building design and its simulation.

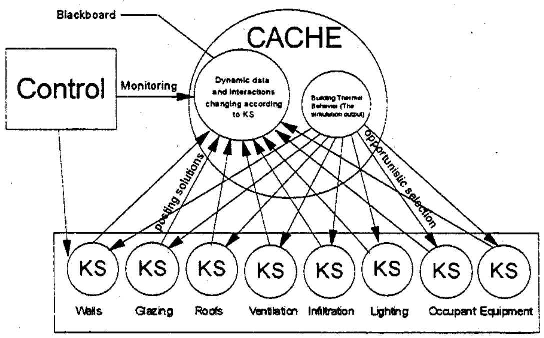
PROBLEM DETECTION USING NEURAL NETWORKS

Neural Networks are being developed to assist in finding solutions for problems that are incomplete. This facilitates the process of detecting problems early in the design where the designer does not have sufficient information about the building. At this stage, default values will be used and simulation will be carried out. The outcome of this simulation will be filtered and provided to the neural network to predict potential problems in the design. The neural network uses its trained ability to correctly classify new patterns from building simulation output and make predictions of potential thermal problems.

Several criteria are taken into consideration in training the neural networks for the prediction of the thermal problems in buildings. One such criteria is deciding on variables to be used for learning by the neural networks (Rich and Knight, 1991). Variables used for the input to train the neural networks to detect thermal problems have to have enough data to cover the entire problem domain. As a result, sufficient information has to be gathered and reasoned about before it is given to the neural networks. Building elements that affect the thermal behavior of the building are used as variables for problem training input. This includes walls, roofs, glazing, lighting, ventilation, infiltration, equipment and occupants. Another criteria is to decide on the range of data necessary for providing acceptable problem representation. In detecting thermal problems, data about heating and cooling loads are not provided for every possible set of variables. Only a minimum and maximum value as well as a good spread of values in between are presented for the variables. If a variable has no influence on the outcome the neural network will learn to ignore it (Wasserman, 1989).

PROBLEM DETECTION USING THE BLACKBOARD STRUCTURE

The problem detection using the blackboard model uses eight knowledge sources, a blackboard resident in the dynamic portion of the cache, static facts and a controller to perform its reasoning. The eight knowledge sources used are the building elements and systems that affect the thermal behavior of the building. These are: the walls, the glazing, the roofs, the ventilation, the infiltration, the occupancy, the lighting and the equipment, figure (5).



One knowledge source posts the fact, the others might modify it.

Figure 5. Problem detection using blackboard structure.

The controller of the intelligent agent monitors the blackboard and the knowledge sources. When a problem is given to the problem detection agent, the controller declares that a solution is being sought by placing the request on the blackboard. The knowledge sources recognize what is on the blackboard and investigate the factual knowledge present about the building's thermal behavior. The first knowledge source that can contribute to solving the problem posts its finding on the blackboard. At this stage, knowledge sources again will observe the problem being solved on the backboard and investigate the thermal factual knowledge simultaneously. The first knowledge source that can contribute to finding the solution will post its answer. This answer can modify, erase or replace some of the solution segments on the blackboard. This reveals the dynamic nature of the problem detection reasoning that takes into consideration solving conflicts between different knowledge sources by basically eliminating these conflicts.

INTEGRATING PROBLEM DETECTION AND THE INTELLIGENT AGENT ADVISORY STRUCTURE

When problems are detected, they will be forwarded from the blackboard or the neural networks to the factual knowledge portion of the working memory where they reside with the building description and its thermal behavior to be used as part of the advice reasoning framework. The advice framework structure and reasoning architecture is similar in principle to the blackboard problem detection. When the designer requests advice for the problems being detected by the system, the intelligent agent controller declares that a solution is being sought by placing the request on the blackboard. The advice knowledge sources recognize the blackboard information and investigate the problem detection outcome and the factual knowledge about the building's spatial and physical configuration. The first knowledge source that can contribute to finding comprehensive advice, posts its guidance on the blackboard. At this stage, knowledge sources will observe the problem being solved on the blackboard and investigate both the problems detected and the building's factual knowledge configuration simultaneously. The first knowledge source that can contribute to the advice will post its guidance. This guidance can modify, erase or replace any of the solution segments for the advice on the blackboard.

HIERARCHICAL LEVELS OF PROBLEM DETECTION AND ADVICE

Different levels of problem detection and advice are used in the system. The problem detection structure was designed to capture different hierarchical building representations and dependencies. It investigates three criteria problems that facilitate different modes of generalities within the design process. These investigation criteria include: the worst problems in the design, the worst problems in each zone of the design and the worst problems in the worst zone of the design.

The system is designed to accommodate higher levels of advice by building a framework structure that enables expert knowledge systems to be integrated within the overall advice framework mentioned above. This was done by partitioning the levels of knowledge. The lower level contains the knowledge sources and the higher levels contain expert systems. The expert systems are triggered when the knowledge sources associated with them in the lower level are activated.

Expert systems will act as any of the other knowledge sources by accessing the factual knowledge and monitoring the blackboard. If the expert system can contribute to the advice by changing or adding to it, it will then post its findings on the blackboard. This strategy allows the expert system to be part of the overall advice solution and refinement. In addition, it facilitates different levels of advice and avoids conflicts by making use of the blackboard and taking into consideration the problem detection outcome, the other knowledge sources and expert system's own constraints and variables.

For example, when advice is being sought on the blackboard and within the process the system discovers that glazing is a major problem for heating, cooling or heating and cooling in any of the zones, the glazing knowledge source might attempt to contribute giving portions of advice for this problem. The glazing knowledge source will then attempt to use the expert system knowledge by activating it. The expert system at this stage will act as any of the other knowledge sources by accessing the factual knowledge and monitoring the blackboard. If the expert system can contribute to the advice by changing or adding to it, then it will post its findings on the blackboard. This strategy allows the expert system to be part of the overall advice solution and refinement. In addition, it facilitates allowing different levels of advice and avoids conflicts by making use of the blackboard and taking into consideration the critic outcome, the other knowledge sources and expert system's own constraints and variables.

The critic and advice reasoning are based on many dependent variables which make uncertainty likely when predicting problems and giving advice for these problems. These variables include the building structural, spatial and physical elements, its systems, their locations, the problems they might generate and their interactions. For example, a building's primary problem might be heating and cooling. A zone in this building might produce only a heating problem due to the combination of all elements in the zone and its location. The worst problem in the zone might be glazing that produces a cooling load problem. In this case, the system is uncertain if glazing is the worst problem in relation to that particular zone or to the building in general.

To accommodate uncertainty reasoning in the critic and advice and to control the best matching criteria in the expert systems, certainty factors (cf) were used. The certainty factors in this system range from -100 to 100 where 100 represents complete certainty, 20 represents minimum belief, 0 represents no evidence, negative numbers represent belief that the fact is false and -100 represents complete certainty that the fact is false. These certainty factors were associated with the rule's conclusions and facts to indicate the degree of belief. When a conclusion is being sought, two independent rules might be found to provide the same conclusion. In addition, the conclusion of one rule might be the premise of one rule or several rules. This suggests that the weight of certainty factors for one rule might affect the conclusion of another if they both collaborate to find a solution.

The system uses the inference engine to combine the certainty factors of these rules and manipulate their use. These combinations and manipulation is based on several mathematical formulas (Cimflex, 1991). This combination took into consideration several assumptions including the assumption that the final certainty is independent of the order in which evidence is found and the accumulation of positive evidence approaches but can not pass 100. In addition, certainties below 100 cannot combine to produce 100. According to these combinations the certainty of a conclusion of a rule is reduced if the truth of the premise is uncertain. The certainty of conjunction, disjunction and negation are all taken into consideration.

For example, if the worst problem in a zone was found to be a wall that produces cooling load with a cf of 50 and another conclusion was made about this wall from another source which also found it to be the worst problem in cooling with a cf of 30, then the conclusion will be that this wall's worst problem in that zone is cooling with a cf of 60. Based on this single evidence, if the problem in the zone was a cooling problem, then the belief that the first problem in the zone is a wall will be greater. If the zone produces a heating problem, the belief that the walls are the first problem in the zone is considerably lowered. On the other hand, if the zone produces both heating and cooling problems then the belief might be neutral. This reasoning is carried out in hierarchical order to reach the building level by using different variables in every level and associate dependencies between these levels.

CONCLUSIONS

Thermal design contains many variables and constraints that must be taken into consideration. These variables and constraints increase as the design evolves and make it more difficult to detect potential problems in the design.

The system developed suggests a framework that allows different models and techniques to be used to provide a wide range of case dependent problem detection and advice. It suggests the potential use of neural networks in providing problem detection early in the design where parameters are incomplete. In addition, it demonstrates the success of multi-knowledge structures and the blackboard models in providing a framework for building case specific problem detection and advice throughout the design process.

The system establishes that different problem detection strategies and different levels of advice are fundamental for thermal design aid within the design process. The use of the blackboard framework within the system presents a method for allowing the knowledge sources to interact and avoid conflict while solving problems. This blackboard provides a conceptual framework that provides flexibility for integrating and developing complex environments that aid in thermal design optimization for all stages of design. The system, without the neural networks, is available and has been used successfully for the last year.

REFERENCES

Amor, R.W. and L.J. Groves, "Integrating Design Tools For Building Design," ASHRAE Transactions 1990; Vol.96, Pt.2:501-507.

ASHRAE, "ASHRAE/IES Standard 90.1: Energy Efficient Design of New Buildings Except New Low-Rise Residential Buildings," Atlanta: ASHRAE, 1989.

Brown, G.Z., "Desirable Interface Characteristics of Knowledge-Based Energy Software Used By Architects," ASHRAE Transactions 1990; Vol.91, Pt.2:550-555.

Carroll, W.L. and R.J. Hitchcock, "Using Advanced Computer Technology to Design an Energy Savings Analysis Tool," ASHRAE Transactions 1991; Vol.97, Pt.2:685-692.

Case, M.P., McConkey I., McGraw, K. and S.C-Y. Lu, "Multiple Cooperating Knowledge Sources for the Design of Building Energy Systems," ASHRAE Transactions 1990; Vol.96, Pt.2:490-499.

Cimflex Teknowledge. "M.4 User's Guide," Palo Alto: Cimflex Teknowledge Corporation, 1991.

Falconer, D.R., Sowell, E.F., Spitler, J.D. and B.B. Todorovich, "Electronic Tables for the ASHRAE Load Calculation Manual," ASHRAE Transactions 1993; Vol.99, Pt.1.

Fenves, S.J., Flemming, U., Hendrickson, C. and M.L. Maher, "Performance Evaluation in an Integrated Software Environment for Building Design and Construction Planning," In: Kalay Y.E., ed.

Evaluating and Predicting Design Performance. New York: John Wiley & Sons, 1992:159-169.

Jog, B., "Evaluation of Designs for Energy Performance Using A Knowledge-Based System," In: Kalay Y.E., ed. Evaluating and Predicting Design Performance. New York: John Wiley & Sons, 1992:293-303.

Malkawi, A., "An Approach to Rigorous Intelligent Computer-Aided Systems: Architectural Thermal Design", Proceedings of the 7th International Conference on Systems Research, Informatics and Cybernetics, August 15-21, 1994, Baden -Baden, Germany.

Mayer, R., Degelman, L.O., Su, C.J. and A. Keen, "A Knowledge-Aided Design System for Energy-Efficient Buildings," ASHRAE Transactions 1991; Vol.97, Pt.2:479-493.

Papamichael, K.M. and S.E. Selkowitz, "Modeling the Building Design Process and Expertise," ASHRAE Transactions 1990; Vol.96, Pt.2:481-507.

Phol, J., Myers, L. and A. Chapman, "ICADS: An Intelligent Computer-Aided Design Environment," ASHRAE Transactions 1990; Vol.96, Pt.2:473-480.

Rich, E. and K. Knight, "Artificial Intelligence," 2nd ed. New York: McGraw-Hill, Inc., 1991.

Shaviv, E. and Y.E. Kalay, "Combined Procedural and Heuristic Method to Energy-Conscious Building Design and Evaluation," In: Kalay Y.E., ed. Evaluating and Predicting Design Performance. New York: John Wiley & Sons, 1992.

Wasserman, P., "Neural Computing, Theory and Practice," New York: Van Nostrand Reinhold, 1989.