2002

Application of artificial neural networks to sensitivity analysis and modeling of small office buildings

Quan Tang
University of Northern Iowa

APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO SENSITIVITY ANALYSIS AND MODELING OF SMALL OFFICE BUILDINGS

An Abstract of a Thesis

Submitted

in Partial Fulfillment

of the Requirements for the Degree

Master of Arts

Quan Tang

University of Northern Iowa

May 2002

ABSTRACT

Sensitivity analysis and Multiple Linear Regression (MLR) are the most extensively used techniques in studying the input-output relationship in building thermal systems. However, both MLR and most methods for sensitivity analysis do not account for nonlinear components embedded in building energy systems. Thus, their results might be distorted.

In this study, the Artificial Neural Networks (ANN) technique was applied to sensitivity analysis and modeling of an imaginary small office in order to (a) examine how the annual energy consumption responded to 40 building design parameters and evaluate relative contributions of these parameters to the variation of the building energy performance, and (b) develop models to represent the relationship between the annual energy usage with input parameters and then use these models to predict energy consumption. The data used for sensitivity analysis and modeling were generated by DOE-2.1E simulation program.

Both Differential Sensitivity Analysis (DSA), the most conventional sensitivity analysis method, and ANN techniques were employed to analyze the sensitivity of building annual energy consumption to 40 design parameters. The relative importance of these parameters to the energy usage was ranked by the sensitivity coefficients coming from both DSA and ANN methods.

The relationship between building energy consumption and input parameters was then modeled by both MLR and ANN techniques using the most

important 5, 10, or 15 parameters yielded in the above sensitivity analysis experiments. A comparison of the results demonstrated that:

1. ANN models were better than MLR models in predicting energy consumption because the error between DOE-2.1E simulation and ANN model prediction was smaller than that from MLR models.

2. ANN sensitivity analysis was better than DSA because models developed with ANN-derived important parameters more precisely predicted building energy consumption, implying ANN sensitivity analysis more efficiently evaluated the relative importance of input parameters.

The results of this project illustrated that ANN technique can be adopted to perform sensitivity analysis and develop models to quantify the input-output relationship in building energy systems. The results showed that the ANN method had better performance than both DSA and MLR, which have been extensively used in building thermal system studies.

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This Study by: Quan Tang

Entitled: Application of Artificial Neural Networks to Sensitivity Analysis and Modeling of Small Office Buildings

has been approved as meeting the thesis requirement for the

Degree of Master of Arts in Industrial Technology

11/30/01

Date

Dr. Recayi Pecen, Chair, Thesis Committee

11/30/01

Date

Dr. Md Salim, Thesis Committee Member

11/30/01

Date

Dr. William M. Stigliani, Thesis Committee Member

3/20/02

Date

Dr. John W. Somervill, Dean, Graduate College

ACKNOWLEDGEMENTS

I would like to thank the Chair of my thesis committee, Dr. Recayi Pecen, for his guidance, encouragement, and valuable suggestions throughout this study. In addition, I would like to thank Dr. Md Salim and Dr. William M. Stigliani for their contributions and supports during my graduate program and completion of this thesis.

I would also like to thank the Graduate College of University of Northern Iowa, for providing a funding for getting the DOE2.1E simulation program, which is used in this study.

My deepest appreciation to my parents for their love and support during my pursuing this degree. Thanks for all the encouragement and expectation they grant me all the time. My sister is always there willing to help.

A special thank you goes to my husband, Dr. Yuxi Fu. Without both academic and emotional support from him, I would never have been able to complete this program.

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CHAPTER I

INTRODUCTION

Background

Sensitivity analysis and Multiple Linear Regression (MLR) have been extensively used in studying building thermal systems (Katipamula, Reddy, & Claridge, 1998; Lam & Hui, 1996; Lomas & Eppel, 1992).

The aim of sensitivity analysis is to observe how the building energy performance responds to the changes of design parameters and further evaluate the relative importance of these parameters. Sensitivity analysis is a general concept and there is no formal or well-defined procedure for performing sensitivity analysis (Lam & Hui, 1996). Different researchers use different approaches to examine the sensitivity of the output of a system to the changes of input parameters. Lomas and Eppel (1992) reviewed and compared three techniques, Differential Sensitivity Analysis (DSA), Monte Carlo Analysis (MCA), and Stochastic Sensitivity Analysis (SSA) for thermal systems and building energy simulation. DSA is the most extensively used one in previous studies (Cammarata, Fichera, & Marletta, 1993; Corson, 1992; Lam & Hui, 1996; Lomas & Eppel, 1992), in which the first-order differential sensitivity coefficient is employed to assess the sensitivity of the output with respect to input parameters, which is also termed as influence coefficient (Spitler, Fisher, & Zietlow, 1989). This method has been proved to be efficient to reveal relative contribution of input parameters to the output (Lam & Hui, 1996).

However, sensitivity coefficient defined by the DSA method only reflects the linear component of the sensitivity of the output to the input parameters studied. The nonlinear part is omitted and not addressed. Actually, none of methods for sensitivity analysis so far can simultaneously (a) correctly account for nonlinearity embedded in the input-output relationship of the system, and (b) generate the sensitivity of the output to individual input parameter changes. MCA takes nonlinearity into account but individual sensitivities can not be obtained through it, while DSA and SSA generate individual sensitivities but they assume the system is linear and the effects of input parameters are superposable (Lomas & Eppel, 1992).

Multiple Linear Regression (MLR) is another commonly used method in building energy performance analysis in which linear mathematical models are developed to represent the relationship between building energy consumption and design parameters. The reason of the popularity of MLR method is that it is very simple to develop models through it, and the models derived are very easy to be utilized into practice compared to those building energy simulation programs such as DOE-2 (Bronson, Hinchey, Haberl, & O'Neal, 1992; Copeland, 1983; Diamond & Hunn, 1981) or simplified systems modeling (Katipamula & Claridge, 1993). MLR models have been used to analyze the energy consumption in residential buildings (Fels, 1986), commercial buildings (Abushakra, Zmeureanu, & Fazio, 1995; Boonyatikarn, 1982; Haberl & Claridge, 1987; MacDonald, 1988; Mazzucchi, 1986; Sullivan & Nozaki, 1984), and even a military base (Leslie, Aveta, & Sliwinski, 1986).

On the other hand, MLR has its own limitations. One major limitation was the regression technique used by most investigators cited above was linear regression, either single or multiple parameters. As described by Bouchlaghem and Letherman (1990), the thermal design of buildings is a multi-variable optimization problem with non-linear object function and linear constrains on the variables, implying the nonlinear input-output connection in building energy systems. The relationship between energy performance and design variables in buildings is so complicated that simple mathematical equations, like linear functions, might not be adequate for its representation. Therefore, the input-output relationship might be distorted in MLR models since the nonlinearity in the system is completely omitted by this method.

In summary, due to the linear assumption, both DSA and MLR can only partly or approximately describe nonlinear systems because only the properties of linear components within the system are correctly revealed. Obviously, nonlinear methods probably model building energy system more precisely and help design buildings saving more energy which is worthy both economically and environmentally. In this study, the artificial neural networks (ANN) technique, which is good at nonlinear analysis, was applied to sensitivity analysis and building energy consumption modeling.

A huge amount of studies in the past 20 years have demonstrated that the artificial neural networks, especially multi-layer-forward neural networks with supervised learning algorithms, could be successfully applied to a variety of problems to extract the input-output relationship of nonlinear systems (Hertz, Krogh, & Palmer, 1991). It has also been used in the HVAC thermal dynamic system identification (Teeter & Chow, 1998).

Essentially, an artificial neural networks is an information processing paradigm that is inspired by the way biological nervous systems process information. The key element of this paradigm is the novel structure, which is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve problems. ANN extracts input-output relationship by learning samples, involving adjustments of the strengths of connections (weights) between neurons. After the learning (also called training), the input-output relationship will be stored as the weights of connections between neurons.

Since ANN is particularly good at extracting nonlinear input-output relationship, it could be able to tackle the problems existing in sensitivity analysis through DSA and modeling through MLR. Through analyzing the structure of weights after learning plenty of design parameters and energy consumption data pairs, relative contribution of input parameters to the output can be quantitatively evaluated. For sensitivity analysis, ANN method not only generates the sensitivity of the output to individual input parameter changes but also fully accounts for nonlinearity embedded in the input-output relationship of the system. For building energy consumption modeling, through feeding new input values into the networks after learning, the energy consumption could be predicted. Because ANN reveals both linear and nonlinear components of the relationship between input parameters and building energy consumption, the prediction of ANN models are expected to be more precise than that of MLR models.

Statement of Problem

The intent of this study is to apply Artificial Neural Networks approach to sensitivity analysis and prediction of the energy usage of an imaginary small office building located in Waterloo, Iowa, in order to (a) examine how the annual building energy consumption responds to 40 building design parameters and evaluate relative contributions of these parameters to building energy performance, and (b) create ANN models to represent the relationship between annual building energy usage and input parameters, then use them to predict building energy consumption under conditions which are not included in the database by which the model is developed. The objectives of the present study are:

1. Using building simulation program DOE-2.1E to develop an imaginary small office building located in Iowa. Forty design factors from building load, HVAC systems, and HVAC refrigeration plant are selected as input parameters.

The building yearly energy consumption from the report of DOE-2.1E simulation is used as output of the system.

2. Using DSA method to calculate three different forms of sensitivity coefficients for all 40 input parameters in order to study the corresponding effects on the simulation output after introducing perturbations to the studied parameters. By this way, the relative importance of input parameters are evaluated.

3. Besides performed by DSA method, sensitivity analysis of building energy performance is also conducted by using ANN approach. After training a two-layer feed-forward artificial neural networks with a number of input-output data pairs created by DOE-2.1E simulations, the sensitivity coefficients of all 40 parameters can be determined by the final values of weights connecting input, output, and hidden units. Hopefully the response properties of building energy to input parameters can be revealed more precisely compared to DSA in Step 2, because ANN approach is likely to be more powerful in extracting information from nonlinear systems than DSA based sensitivity coefficients which assume the system response is linear.

4. Model the building using both MLR and ANN methods. Input parameters used here are 5, 10, or 15 parameters with most importance revealed by both DSA in Step 2 and ANN sensitivity study in Step 3. Then evaluate the goodness of linear and ANN models by comparing their powers in predicting building energy consumption under conditions that are not used in

modeling. At the same time, by comparing the prediction powers of models with different sets of input parameters coming form different sensitivity analysis methods, it could be identified which sensitivity analysis method is more efficient in assessing relative importance of parameters.

Research Hypotheses

The questions that the present study pursue to fulfill are:

1. Does the neural networks reveal the sensitivity of building energy performance to design parameters more efficiently than traditional differential sensitivity analysis does? Can it reveal the relative contributions of input parameters more precisely?

2. Compared with linear regression models, does ANN models have more prediction power?

Thus, the equivalent hypotheses to answer these research questions are:

1. The neural networks is better than DSA methods to perform sensitivity analysis because it can more correctly evaluate the relative importance of parameters fed into the system.

2. The neural networks model is stable enough to get acceptable solution. Compared to linear regression model, it can predict building energy consumption more precisely.

Assumptions

1. The database used for both linear regression and neural networks training is generated by DOE-2.1E simulation. This study assumes DOE-2.1E

can accurately simulate the thermal response of the modeled building. Some studies have shown that the prediction of DOE-2 simulation matched the measured data pretty well (Lee, 1999; Sorrell, Luckenbach, & Phelps, 1985).

2. This study assumes that the most current personal computers powered by Pentium III processors are fast enough to perform the training of neural networks modeling building energy system. Although the artificial neural networks have remarkable ability to derive meaning from complicated system, the complexity of its computation is still a main issue of this technique.

Limitations

The limitations of this study is presented below:

1. Using DOE-2 to simulate building energy system is not easy because there are a huge amount, usually several hundreds, of input parameters which need to be understood and carefully collected by users. The accuracy and reliability of the database used in this study largely depend on the skill of the author.

2. Due to the very rapid increase in training time requirements as the number of parameters increases, only a portion of design parameters (40) are investigated in this study. The selection of these parameters mostly depends on the author's understanding of the modeled building, which is not necessarily to be consistent with others.

CHAPTER II

REVIEW OF LITERATURE

Heating, Ventilation and Air Conditioning (HVAC) systems consume as much as 50% (Kammers, 1994) or 30-70% (Swanson, 1993) of total building energy budget, while buildings approximately use 36% of the primary energy in the United States today (Blum, 1994). Shoureshi (1993) suggested that a mere 1% improvement in energy efficiency of HVAC systems could save millions of dollars annually at the national level. Field surveys also indicated considerable energy waste when HAVC systems are poorly operated and maintained (Swanson, 1993). Therefore, it makes sense to consider new technologies to increase HVAC system performance and efficiency thus save energy.

Many methods of achieving energy savings have been proposed accompanying with the development of HVAC industry, especially after the impact of oil crisis and energy crunch in the 1970s. Most of these building energy conservation technologies are based on the studies of how the energy performance of buildings is affected by design and operation factors of building construction and HVAC systems. Developing building energy saving technologies is mostly equivalent to analyzing input-output relationship of building energy system, where the input includes design and operation factors, the output is the energy consumption. Only after characterizing input-output relationship of the building energy system, the building can be designed more energy-efficiently by selecting proper design and operation factors. Hence, the essential problem in developing building energy conservation technologies is to analyze the input-output relationship of the building energy system.

There are a variety of empirical and theoretical methods by which the input-output relationship of building energy system can be qualitatively or quantitatively addressed. In this chapter, computer building energy simulation, sensitivity analysis, and multiple regression techniques are reviewed in succession. All these methods have been extensively applied in the study of building thermal characteristics. Finally, the Artificial Neural Networks (ANN), one of the artificial intelligence techniques, is introduced.

Building Energy Simulation

Nowadays, with the aid of rapidly developing computer technologies and well established building energy analysis methods, building design and operation factors can be systematically examined with building energy simulation programs (Hui & Cheung, 1998). Typically, after taking input information including local weather, building design, air conditioning system, and operation strategy, the approach of "LSPE" (load-system-plant-economics) is used by the dynamic simulation programs to simulate the energy flow in the building modeled (Hui & Cheung, 1998). In the "load" stage, the cooling, heating, and fresh air loads are calculated based on thermal properties of the building and design criteria in order to determine the flow rate and the capacity of the air conditioning system (McQuiston & Spitler, 1992). After calculating the load of rooms, simulation programs further estimate the energy consumption of the air-side and water-side systems in the "system" stage. Finally, the annual energy consumption of the air conditioning plant is determined in the "plant" stage. The energy consumption of the plant is considered as the final energy usage of the building since it provides all energy necessary for air conditioning of the rooms and the operation of equipment. The energy fed into the plant can be electricity, gas, oil, hot water, cold water, and others. Sometimes, the energy budget is calculated according to the local energy prices by carrying out "economics" analysis after plant simulation.

The main difference of building energy simulation from other modeling approaches like sensitivity analysis or regression analysis is building energy simulation uses physical thermal models to simulate details of building thermal system while the others develop simple expressions describing the relationship between design parameters and energy consumption which do not account for the details of thermal flow in the building.

There are many different types of computer software available for building energy simulation. BLAST (Building Loads Analysis and System Thermodynamics) and DOE are milestones in the history of computer building energy simulation. They were developed and released in late 1970s and early 1980s by the U.S. Army Construction Engineering Research Laboratory (USACERL) and the Lawrence Berkeley National Laboratory (http://www.lbl.gov), respectively. They were developed for design engineers or architects for sizing appropriate HVAC equipment, developing retrofit studies, and optimizing energy performance. However, they were usually used for research purpose in the past because they are so sophisticated and complicated (Hui & Cheung, 1998). In recent years, they are beginning to be adopted by average building designers along with the rapid development of computer technology. In April 2001, a new-generation building energy simulation program, EnergyPlus 1.0 was released through the Lawrence Berkeley National Laboratory. EnergyPlus 1.0 inherits most popular features and capabilities of BLAST and DOE-2. It can be considered as a hybrid of BLAST and DOE-2.

Beside DOE and BLAST, there are some simulation programs developed by commercial companies such as HAP developed by Carrier Corporation and TRACE developed by Trane Company. Commercial simulation software are usually easier to use and more accepted by engineers. However, the calculation usually is simplified because of the commercial background of developers (Hui & Cheung, 1998).

In this study, building energy simulation program DOE-2.1E is used to generate database for sensitivity analysis, model development and testing.. Then the underlying question is how well the DOE program predicts actual energy usage in a building. As part of the DOE-2 Verification Project conducted by the Los Alamos Scientific Laboratory, Diamond and Hunn (1981) compared DOE-2 simulations with measured utility data for a set of seven existing commercial buildings of various types in a variety of climate zones. Their results revealed that there was a standard deviation of less than 8% and a maximum difference of

12% between predicted and measured data for annual total energy budget. In the validation study to determine the accuracy of three hourly simulation programs, DOE-2.1B, EMPS 2.1, and TRAP84, Sorrell at al. (1985) concluded the accuracy in predicting absolute energy consumption was 5% to 20% for a one to three day period, while generally showing better agreement for a longer time period. In Lee's validation study (1999), DOE-2.1E showed very good accuracy in predicting cooling and heating energy, with mean errors of 1.9% and -6.3%, respectively. All these validation studies suggest that DOE has fairly satisfactory accuracy in the prediction of building energy consumption.

Sensitivity Analysis of Building Energy Performance

When performing building energy simulations, energy consumption changes from certain input variables are more significant than those from others, implying these selected inputs should be given particular attention during modeling (Corson, 1992) since they are more important from both technical and economic points of view. Hence, they should be designed with utmost care if optimization of the system performance is to be achieved. A great deal of engineering work is devoted to testing the sensitivity of systems to input variables (Deif, 1986). These studies are collectively called sensitivity analysis and involve a range of different analytical methods.

Sensitivity theory has been used for assessing the thermal response of buildings and their energy and load characteristics (Athienitis, 1989; Buchberg, 1969, 1971; Cammarata et al., 1993; Lam & Hui, 1996; Lomas & Eppel, 1992).

The aim of sensitivity analysis is to evaluate the variation of the thermal load due to a fluctuation in a given design parameter around its normal value (Cammarata et al., 1993). Particularly, Lam and Hui (1996) examined the sensitivity of energy performance of office buildings in Hong Kong. They analyzed how the annual energy consumption and peak design loads of the model building responded to the modification of 60 design parameters, including coefficients of materials properties, design of building envelop, and selected HVAC systems, from which 12 important parameters were yielded. Obviously, if the relationships and relative importance of parameters used in design are well understood, optimal building energy performance could be reached through proper selection of certain design variables and conditions.

However, sensitivity analysis is a general concept and there is no formal or well-defined procedures for performing sensitivity analysis (Lam & Hui, 1996). In brief, sensitivity analysis could be considered as quantitatively comparing the changes in output with the changes in input. Thus, it is an "input-output analysis" of the simulation system (Corson, 1992). Sensitivity analysis can be conducted on input parameters one by one or on several simultaneously. If input parameters are analyzed separately, it has to be assumed that the interactions between the inputs can be omitted, i.e., the effects of the inputs are superposable.

Different researchers use different approaches to examine the sensitivity of the output of a system to the changes of input parameters. The most common sensitivity analysis is sample-based in which the model is executed repeatedly for combinations of values sampled from the specific distribution of the input parameters. In general, following step are involved:

1. Specify the output function and select the input factors of interest.
2. Assign a distribution to the selected factors.
3. Randomly generate input combinations within the distribution.
4. Evaluate the model and compute the distribution of the output.
5. Select a method for assessing the influence or relative importance of each factor on the output function.

In engineering economics, sensitivity analysis measures the economic impact from alternative values of uncertain variables that affect the economics of the project and the results can be presented in text, tables, or graphs (Marshall, 1996). For thermal systems and building energy simulation, Lomas and Eppel (1992) reviewed and compared three techniques, Differential Sensitivity Analysis (DSA), Monte Carlo Analysis (MCA), and Stochastic Sensitivity Analysis (SSA). DSA involves varying just one input for each simulation while the remaining inputs stay fixed at their mostly likely "base case" values. The changes in the output (y) are therefore a direct measure of the effect of the change made in the single input parameter (i). The value of $\Delta y/\Delta i$ can be considered as the first-order differential sensitivity of the output y with respect to the input i. MCA method is a kind of multivariate sensitivity analysis in which all input parameters are simultaneously perturbed thus the total uncertainty in the output can be evaluated. The advantage of MCA technique is it fully accounts for the interaction between the input parameters. However, the sensitivity for individual parameter can not be derived. SSA is a relatively new technique in which all parameters are varied simultaneously as the simulation progresses, typically at every time-step. This is very different from DSA and MCA in which the uncertain parameters are varied before the simulation then held constant for the duration of the simulation. SSA, like DSA, also generates the sensitivity of the output to the individual parameter uncertainties. The main attraction of SSA is that information about the time-delay response of the outputs, due to the variations in the inputs, could be obtained. However, SSA is rarely used because the implementation is very difficult which needs access to the simulation program to input stochastic information of input parameters.

Although there are plenty of different methods for sensitivity analysis, DSA is the most extensively used one in building energy studies. In previous studies, most researchers (Cammarata et al., 1993; Corson, 1992; Lam & Hui, 1996; Lomas & Eppel, 1992) employed the first-order differential sensitivity coefficients to measure the sensitivity of the output with respect to input parameters, which also has been termed as influence coefficient (Spitler et al., 1989). If there are more than two perturbations used for the input parameter examined, the slope of the regression straight line, rather than $\Delta y/\Delta i$, could be used to determine the sensitivity of building energy performance with respect to a specific design or input parameter. DSA method has been proved to be efficient to reveal relative contribution of input parameters to the output (Lam & Hui, 1996).

However, influence coefficient defined by the DSA method only reflects the linear component of the sensitivity of output to the input parameters studied. It is the "first order sensitivity." Obviously, this approach assumes that the relationship between the output and input parameters is linear. Thus, it is a linear estimate of sensitivity of building energy usage, and the nonlinear part of the sensitivity of the output is not reflected efficiently. In the present study, sensitivity coefficients derived from DSA are used to be compared with the sensitivity coefficient yielded from artificial neural networks method.

Modeling Buildings Using Multiple Regression

Another popular approach in building energy investigation is multiple linear regression (MLR), in which energy equations are derived from observed or computer-generated data to express the relationship between energy consumption of buildings and design parameters. Energy equations could be utilized in predicting energy usage and determining retrofit savings. Regression analysis models are simple to develop and easy to use compared to those building energy simulation programs such as DOE-2 (Bronson et al., 1992; Copeland, 1983; Diamond & Hunn, 1981) and simplified systems modeling (Katipamula & Claridge, 1993). The input database for regression analysis can be created by measured data from real buildings (Katipamula et al., 1998), or by a series of simulations using computer simulation programs like DOE-2 (Lam, Hui, & Chan, 1997; Sullivan & Nozaki, 1984).

Regression models have been used to analyze the energy consumption in residential buildings (Fels, 1986), commercial buildings (Abushakra et al., 1995, Boonyatikarn, 1982; Haberl & Claridge, 1987; MacDonald, 1988; Mazzucchi, 1986; Sullivan & Nozaki, 1984), and even a military base (Leslie et al., 1986). The most remarkable advantage of regression analysis is its simplicity, both in model developing and application. For model developing, there are a lot of computer software can be used for conducting regression analysis, such as statistics package of SPSS produced by the SPSS Incorporated and statistics toolbox of Matlab produced by the MathWorks. Moreover, the procedure of energy consumption prediction using equations derived by regression analysis is very easy and fast because regression models only contain a small number of parameters, not like other hourly computer simulation programs such as BLAST, DOE-2, and TRACE which are too complicated, time-consuming and costly (Lam et al., 1997), usually containing hundreds of even more input parameters.

Although regression approach has been extensively used for building energy consumption analysis, it has its own limitations. One major limitation of previous studies is the regression technique used by most investigators cited above was linear regression, either single or multiple parameters. However, for building systems, the relationship between energy performance and design variables is so complicated that simple mathematical relationships, like linear functions, are not adequate for its representation. Bouchlaghem and Letherman (1990) described the thermal design of buildings as a multi-variable optimization problem with non-linear object function with linear constrains on the variables. Some researchers have tried to utilize nonlinear models to analyze building energy performance. For example, Lam and his colleagues (1997) developed energy equations through both linear and nonlinear multivariable regression to predict building energy consumption. However, the form of their nonlinear equations were so specific that it remains unknown if they can be generalized to energy consumption studies for different buildings under different conditions.

In summary, due to the nonlinear nature of the building energy system, sensitivity analysis and modeling through linear methods can only partly or approximately describe the system because only the properties of linear components in the system are correctly revealed. Obviously, nonlinear methods could model building energy system more precisely and help design buildings saving more energy which is worthy both economically and environmentally. Nevertheless, it is not easy to develop nonlinear models for a complex system since there is no general form of nonlinear equation and no general solution to nonlinear systems. Usually, the methods researchers model nonlinear systems are to transform nonlinear equations to linear or treat them as linear equations by simplifying them.

<u>Artificial Neural Networks and Nonlinear Systems</u>

In recent years, along with the rapid development in computer technology and remarkable progress in neurobiology, the Artificial Neural Networks (ANN), a kind of artificial intelligence technique which could be applied to an increased number of real-world problems of high complexity, attracts a lot of researches after a long period of frustration and disrepute from the late 1960s to the late 1970s. A huge amount of studies in past 20 years have shown that the artificial neural networks, especially multi-layer-forward neural networks with supervised learning algorithms, have been successfully applied to a variety of problems to extract the input-output relationship of nonlinear systems (Hertz et al., 1991). It has also been used in the HVAC thermal dynamic system identification (Teeter & Chow, 1998).

Basically, an artificial neural network is an information processing paradigm that is inspired by the way biological nervous systems, such as the human brain, process information. The key element of this paradigm is the novel structure, which is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve specific problems. Figure 1 shows the architecture of a two-layer (input-hidden layer and hidden-output layer) feed-forward artificial neural networks. Each neuron, denoted by N in Figure 1, computes a weighted sum of its inputs, then outputs this sum after a transformation which usually is a pure linear or sigmoid (S-shaped) function (Hertz et al., 1991). ANN extracts input-output relationship by learning samples, which involves adjustments of the strengths (weights) of connections between neurons. One sample is one pair of input-output data. The most striking advantage of ANN is in solving problems that are too complicated for conventional technologies-problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be found. After the learning (also called training), the input-output relationship will be stored as the weights of connections between neurons. Through analyzing the structure of weights after learning, relative contribution of input variables to the output can be quantitatively evaluated. Through feeding new input data which is not used for training into the networks after learning, the output could be correctly predicted.

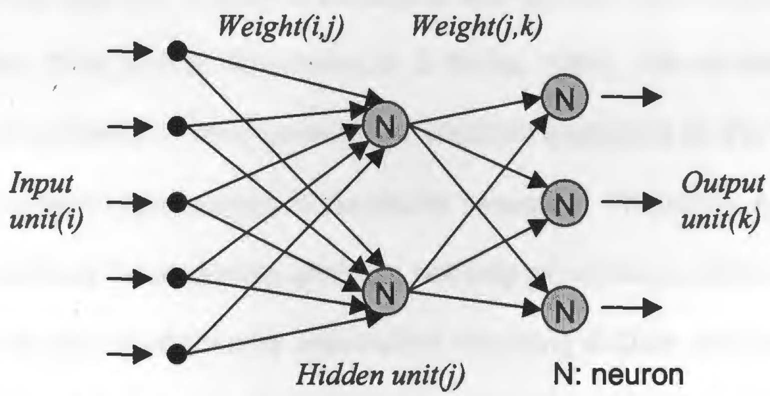

Figure 1. An example of two-layer feed-forward ANN.

Since the building energy system is likely to be nonlinear system and it is hard to accurately study it through linear techniques, artificial neural networks might be a good means to extract the relationship between building energy performance and design parameters.

In this study, the ANN technique is used both in sensitivity analysis and building energy system modeling. The main problem of sensitivity analysis techniques used in previous studies is none of them could (a) correctly account for nonlinearity embedded in the input-output relationship, and (b) generate the sensitivity of the output to individual input parameter changes. DSA and SSA generate individual sensitivities but they assume the system is linear and superposable. MCA takes nonlinearity into account but individual sensitivities can not be obtained through it. There is no question that ANN can efficiently extract input-output relationships from nonlinear systems because it has been mathematically proved that ANN shown in Figure 1 with one hidden layer activated by sigmoid function is enough to approximate any continuous function (Cybenko, 1989; Hornik, Stinchcombe, & White, 1989). On the other hand, the relative importance of input parameters could be evaluated by the strength of weights connecting elements in the neural networks. Therefore, ANN might be a good technique for sensitivity analysis, not only generating individual sensitivities but also getting rid of linearity assumption occurring in DSA and SSA approaches. Moreover, building energy models developed by the ANN technique are expected to be better than linear regression models because ANN can extract nonlinear components in the relationship between design parameters and building energy consumption which are omitted by linear regression models.

CHAPTER III

METHODOLOGY

Overview of the Experimental Design

The Artificial Neural Networks (ANN) was applied to perform sensitivity analysis and develop energy consumption models of buildings in the present study. An imaginary small office building located in Waterloo, northeast Iowa was used as the model building. Compared to real buildings, imaginary buildings have several advantages in quantitative analysis of building energy systems:

1. Real buildings, such as residential houses, restaurants, and office buildings, are designed for specific purposes while an imaginary building can be configured with design parameters common to most buildings in a specific geographical area. Such a building could be considered as a typical building and research results from it could be generalized to more applications than those from specifically designed real buildings.

2. The design parameters of an imaginary building can be arbitrarily varied with computer modeling programs so that a systematic parametric study can be conducted. However, the features of a real building can not be changed conveniently to study its thermal properties once it is built.

3. A complicated and expensive measurement system has to be employed to monitor the weather, parameters to be studied, and energy consumption, if a real building is used. Apparently, modeling imaginary buildings on computers is more economical and efficient.

Building energy consumption is determined by the weather, building load, HVAC system, and refrigeration plant. In this study, the weather condition was considered to be fixed, using the typical year weather file in TMY2 format for Waterloo in Iowa (National Renewable Energy Laboratory, 1995). Load, system, and plant were parameterized into 40 input variables. Each parameter had a base case reference value, a minimum, and a maximum value, selected from common engineering and design practice. The building annual energy consumption was investigated as the output of the system, which could be considered as the final energy end-use of the building.

After formulating the base case reference building and selecting parameters to be studied, a series of computer experiments as follows were conducted:

1. Simulated the base case building with computer simulation program DOE-2.1E (Lawrence Berkeley Laboratory, 1993).

2. Introduced perturbations to the selected parameters near their base case values, then studied the corresponding effects of the perturbations on simulation outputs. Each time only one parameter was varied while all the others fixed.

3. Calculated three different forms of sensitivity coefficients for each parameter using Differential Sensitivity Analysis (DSA) technique (Lomas & Eppel, 1992).

4. Generated 1024 input-output data pairs using DOE-2.1E with all 40 input parameters randomly distributed from their minimum to maximum values. After training a two-layer feed-forward ANN with these data pairs, the sensitivity coefficients of input parameters were yielded by the weights of ANN.

5. Compared sensitivity coefficients derived from DSA and ANN methods in order to determine important parameters. Important parameters have larger sensitivity coefficients and contribute more to the variation of the building energy consumption than those less important parameters.

6. Used both Multiple Linear Regression (MLR) and ANN techniques to develop models representing the relationship between design parameters and building energy usage. Five, 10, or 15 important parameters ranked by sensitivity coefficients were used in modeling.

7. Compared prediction accuracy of regression model and ANN model. The accuracy of prediction was measured by Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of model predicted energy usage with respect to DOE-2.1E simulation results.

8. By comparing models developed with different sets of important parameters coming from different sensitivity coefficients, the efficiencies of both DSA and ANN sensitivity analysis methods were evaluated.

Model Building

The model building used in this study was an imaginary office building located in Waterloo, Iowa. The geographical location of Waterloo is in 42.55

degrees north latitude and 92.4 degrees west longitude, and an elevation of 869.42 feet above sea level. The model building is a small single-story building with a total of 2429.75 ft^2 of floor area and 14 feet of building height.

The main door of the building faces true south in base case although the azimuth of the building is a variable in parametric study. The building consists of five office rooms, a meeting room, a copier room, two restrooms, a lobby for reception, and two corridors, which are divided into 12 cubic spaces for modeling convenience in DOE-2.1E. Figure 2 shows the building layout and Table 1 summarizes the information of all rooms. Dotted lines in Figure 2 splits the continuous space including the lobby and corridors into three cubic spaces because cubic spaces are easier to be described than irregular spaces in DOE-2.1E Building Description Language (BDL; Lawrence Berkeley Laboratory, 1993). Room codes in Table 1 are identifiers of spaces used in DOE-2.1E simulation input files. The building is designed to be single-zone. All rooms use ceiling plenums to return air from individual space to the central Air Handling Unit (AHU) of the system. All conditioned spaces share a common plenum space between ceiling and roof.

The building has a flat roof which is composed of 2 inch heavy weight concrete, 4 inch horizontal air space, 2 inch heavy weight concrete again, 4 inch insulation, and 1 inch washed river rock, from inside to outside. Between roof and ceiling is the plenum with 5.5 inch of height. Ceiling is 8.5 inch high with average U-value (heat transmission coefficient) 0.317. The floor is 4 inch concrete covered by carpet with average U-value 0.609.

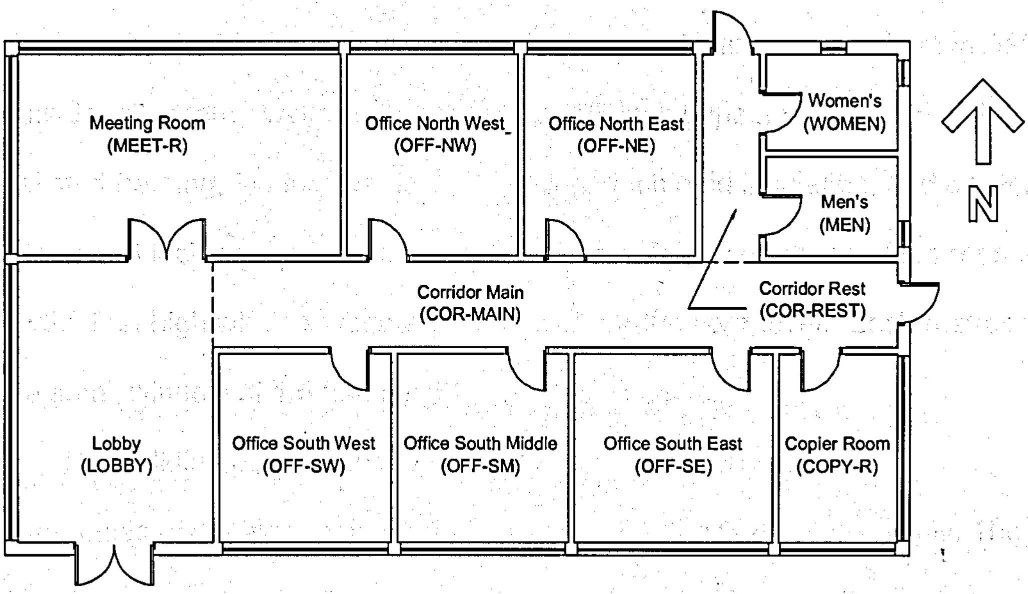

Figure 2. Layout of the model building.

Table 1
Room Information of the Model Building

Room code	Description	Width (ft)	Depth (ft)	Ceiling height (ft)	Plenum height (ft)
LOBBY	Lobby	15.25	21.25	8.5	5.5
OFF-SW	Office south west	13.5	14.25	8.5	5.5
OFF-SM	Office south middle	13.5	14.25	8.5	5.5
OFF-SE	Office south east	15.5	14.25	8.5	5.5
COPY-R	Copier room	9.25	14.25	8.5	5.5
COR-MAIN	Corridor main	53.75	6.5	8.5	5.5
MEET-R	Meeting room	25.25	15.25	8.5	5.5
OFF-NW	Office north west	13.5	15.25	8.5	5.5
OFF-NE	Office north east	13.5	15.25	8.5	5.5
COR-REST	Corridor next to restrooms	4.5	15.75	8.5	5.5
MEN	Men's restroom	10.25	7.5	8.5	5.5
WOMEN	Women's restroom	10.25	7.25	8.5	5.5

The exterior walls are horizontally divided into two parts by the ceiling, lower part and higher part. Conditioned spaces of the building are surrounded by lower exterior walls and the plenum space is surrounded by the higher exterior walls. The construction materials layers of exterior walls are similar. From inside to outside, all exterior walls are composed of 5/8 inch gypsum board, 3.5 inch metal stud framing, 3/4 inch vertical air space, 1 inch rigid insulation, and a layer of 4 inch or 6 inch heavy concrete. The exterior walls except those of restrooms have 5.5 feet high windows located 3.5 feet above the floor level. Each restroom has a small window of 1.5 feet height and 2 feet width.

The building does not have any external shading device. Solar absorptances of the exterior walls and roof are 0.65 and 0.29, respectively. The inside film resistance of walls and roof, which is combined convective and radiative air film-resistance for the inside wall surface, is 0.68. Table 2 describes thickness and thermal properties of materials used for the construction layers.

The materials data in this study was mainly coming from Lee's doctoral dissertation (Lee, 1999). In his study, the Energy Resource Station located on the campus of the Des Moines Area Community College, Iowa, was used as test building. The Energy Resource Station is owned and operated by the Iowa Energy Center, and specifically built for building energy research. Therefore, the building envelop should be representative of Iowa state. In present study, the construction layers of the model building were very similar to those of the Energy Resource Station used in Lee's dissertation.

Table 2
Thermal Properties of Construction Layers

Layer code	Mat. code	Description	T	K	D	Cp	R
LAY-R1		Inside surface					
	CC02	2 in heavy weight concrete	2	0.7576	140	0.2	0.22
	AL23	4 inch horizontal air space	4				0.87
	CC02	2 in heavy weight concrete	2	0.7576	140	0.2	0.22
	Q-VB1*	Vapor barrier					0.06
	IN47	4 in insulation	4	0.0133	1.5	0.38	25.06
	AR02	Single-ply membrane			70	0.35	0.44
	RG02	Washed river rock	1	0.834	55	0.4	0.1
		Outside surface					
LAY-WB1		Inside surface					
	GP02	5/8 in gypsum board	0.625	0.0926	50	0.2	0.56
	Q-VB1*	Vapor barrier					0.06
	Q-IN1*	Metal stud framing w/ R13 batt	3.5	0.025	0.6	0.2	12.96
	AL11	3/4 in vertical air space	0.75				0.9
	IN43	1 in rigid insulation	1	0.0133	1.5	0.38	6.26
	CC03	4 in pre-cast concrete	4	0.7576	140	0.2	0.44
		Outside surface					
LAY-WT1		Inside surface					
	GP02	5/8 in gypsum board	0.625	0.0926	50	0.2	0.56
	Q-IN1*	Metal stud framing w/ R13 batt	3.5	0.025	0.6	0.2	12.96
	AL11	3/4 in vertical air space	0.75				0.9
	IN43	1 in rigid insulation	1	0.0133	1.5	0.38	6.26
	CC04	6 in pre-cast concrete	6	0.7576	140	0.2	0.66
		Outside surface					
LAY-P1		Inside surface					
	GP02	0.625 in gypsum board	0.625	0.0926	50	0.2	0.56
	IN13	Metal stud framing with fiberglass	3.5	0.0225	3	0.33	12.96
	GP02	0.625 in gypsum board	0.625	0.0926	50	0.2	0.56
		Outside surface					

Note. T: thickness, inch; K: conductivity, Btu/hr-ft-°F; D: density, lb/ft^2; Cp: specific heat, Btu/lb-°F; R: resistance, hr-ft^2-°F/Btu;
LAY-R1: layer for roof; LAY-WB1: layer for lower exterior walls below ceiling;
LAY-WT1: layer for higher exterior walls above ceiling;
LAY-P1: layer for interior walls separating rooms.
Material codes without asterisks are standard materials defined in DOE-2.1E material library. The author defined those materials with asterisks.

Since the model building is imaginary, the design parameters could be very flexible. Two HVAC systems, constant-volume reheat fan system (RHFS) and variable-volume system with optional reheat (VAVS), were extensively modeled on model building. Fourteen system factors were parameterized and studied. The HVAC plant was relatively simple in this study, which included one hermetic centrifugal compression chiller and one electric hot-water boiler.

Development of DOE-2.1E Input Files

Before performing model building simulation with DOE-2.1E, it is essential to determine what input parameters are to be studied. In this study, total 40 parameters which represented a variety of different factors in model building design were prepared for analysis. All these parameters are listed in Table 3 and categorized into three main groups as building load, HVAC systems, and HVAC refrigeration plant.

Selecting and defining the input parameters is often a complicated task that requires good engineering judgement and knowledge of the simulation system. Breakdown of the parameters was worked out according to the building description language (BDL) of the DOE-2.1E program so that maximum effectiveness and compatibility could be achieved.

After determining the design variables to be studied, a base case value and a range of different values, termed as perturbations, were assigned to each of the input parameters. The base case value is most likely value in practice and in this study it was used as a reference in sensitivity analysis to calculate sensitivity coefficients. The perturbation range was used to limit the variation of input parameters when generating database for regression and ANN modeling.

Table 3
Studied Input Parameters

Parameter index	Parameter code	Description	Base case	Unit	Minimum	Maximum
Load						
1	L-BLA	Building azimuth	0	Degree	0	45
2	L-WSC	Window shading coefficient	0.6		0	1
3	L-WGC	Window glass conductance	1.0	Btu/Hr-Ft^2-F	0.1	1.6
4	L-WNP	Window number of panes	2		1	3
5	L-SAT	Space air temperature	70	F	64	76
6	L-IFR	Infiltration rate	0.6	AC/Hr	0	1.2
7	L-EPL	Equipment load	2.0	W/Ft^2	1	3
8	L-LTL	Lighting load	1.5	W/Ft^2	0.5	2.5
9	L-LTT	Lighting type	SUS-FLUOR			
10	L-OPD	Occupant density	0.02	Person/Ft^2	0.0025	0.04
System						
11	S-SYT	System type	VAVS			
12	S-CSP	Cooling set point	72	F	66	76
13	S-HSP	Heating set point	68	F	64	74
14	S-TST	Thermostat type	PROPORTIONAL			
15	S-TTR	Throttling range	2	F	0.25	4
16	S-OAF	Outdoor air flow rate	19	CFM/Person	1	31
17	S-OAC	Outdoor air control	TEMP			
18	S-FDT	Fan air delta T	6	F	0	8
19	S-FPC	Fan power consumption	0.002	KW/CFM	0.00025	0.004
20	S-FCT	Fan control	INLET			
21	S-FMP	Fan motor placement	IN-AIRFLOW			
22	S-FPM	Fan placement	DRAW-THROUGH			
23	S-RDT	Reheat delta T	55	F	45	65
24	S-MCR	Minimum CFM ratio	0.2		0.1	0.5
Plant						
25	P-CST	Chilled water supply T	42	F	38	48
26	P-CTR	Chilled water throttling range	3.5	F	1.5	4.5
27	P-CMT	Chilled water minimum entering air T	65	F	55	70
28	P-CCP	Chilled water condenser power ratio	0.06		0.02	0.1
29	P-CGB	Chilled water hot gas bypass PLR	0.5		0.2	0.7
30	P-CDT	Chilled water design delta T	9	F	7	13
31	P-CPH	Chilled water pump head	60	Ft	20	100
32	P-CIE	Chilled water pump impeller efficiency	0.8		0.6	0.9
33	P-CPL	Chilled water fraction of pump loss	0.01		0.005	0.02
34	P-CME	Chilled water pump motor efficiency	0.85		0.8	0.95
35	P-HBL	Hot water boiler loss	0.04		0.005	0.08
36	P-HDT	Hot water design delta T	30	F	10	50
37	P-HPH	Hot water pump head	60	Ft	20	100
38	P-HIE	Hot water pump impeller efficiency	0.8		0.6	0.9
39	P-HPL	Hot water fraction of pump loss	0.01		0.005	0.02
40	P-HME	Hot water pump motor efficiency	0.85		0.8	0.95

The base case value of a parameter roughly sits in the middle in the whole range of this parameter. The selecting of the range of perturbations of a parameter is a subjective task, mostly from engineering and design practice. The parameter ranges in this study were roughly estimated on the basis of values in the literature (Lam & Hui, 1996), DOE-2.1E user's manuals (Lawrence Berkeley Laboratory, 1993), and design practice of the author. The base case value, minimum and maximum values of all input parameters are listed in Table 3.

After all parameters to be studied were determined, input files for simulation were generated then submitted to DOE-2.1E program. One set of parameter values was used in one simulation and the annual model building energy consumption was extracted from output files of the simulation program. Those parameters which were not studied in this study were fixed in default values set by DOE-2.1E program. DOE-2.1E input files were written in Building Description Language (BDL). The input file for base case model building is presented in Appendix A.

Differential Sensitivity Coefficients

Differential Sensitivity Analysis (DSA) technique was used in this study to yield sensitivity coefficients in order to measure how much the model building energy consumption responded to the changes of different input parameters. Sensitivity coefficients were also used to rank the relative importance of input parameters. DSA technique involves varying just one input for each simulation whilst the remaining inputs stay fixed at their most likely "base case" values

(Lomas & Eppel, 1992). In this study, the procedure of sensitivity analysis of a specific parameter was conducted as follows:

1. Take a parameter to be analyzed.

2. Select several values as input data set within the range of the parameter. The base case value was included.

3. Generate DOE-2.1E input files. Each input file contained one value selected above. All the other parameters were fixed to be base case values.

4. Run simulation for all input files.

5. Analyze simulation output files to get building energy consumption under all values determined in Step 2. One energy consumption paired with one input parameter value.

6. Do a linear regression between input data set and corresponding energy consumption values using least squares method (Khazanie, 1986) in order to get the slope of the regression straight line.

7. Calculate sensitivity coefficients in forms in Table 4.

Table 4
Definitions of Differential Sensitivity Coefficients

Sensitivity Coefficients	Description	Definition
SC1	Slope of linear regression line	dy / dx
SC2	Normalized sensitivity coefficient	$(dy / dx) / (mean(y) / mean(x))$
SC3	Normalized sensitivity coefficient	$(dy / dx) / (base(y) / base(x))$

Three forms of sensitivity coefficients, denoted as SC1, SC2, and SC3, were used to evaluate the sensitivity of the annual energy performance of the building to input parameters. Table 4 lists all of them, where x is the input parameter studied, y is corresponding energy consumption from DOE-2.1E simulation, dy / dx is the slope of linear regression line, $base(y)$ is the energy consumption when the input parameter is set to be base case value. These forms of sensitivity coefficients have been wholly or partly applied in previous studies (Cammarata et al., 1993; Corson, 1992; Lam & Hui, 1996; Lomas & Eppel, 1992).

<u>Artificial Neural Networks (ANN) Method</u>

The Artificial Neural Networks (ANN) have been successfully applied to a variety of problems to extract input-output relationship of nonlinear systems. In this study, two-layer feed-forward neural networks were trained to extract the relationship between design parameters and building annual energy consumption. The architecture of the ANN used is shown in Figure 3. The networks takes parameters as input and outputs the building annual energy consumption of the model building.

The neural networks is composed of two layers: layer from input to hidden units and layer from hidden units to output. W_{jk} is the weight from input unit k to hidden neuron j; W_{ij} is the weight from hidden neuron j to output neuron i. Structures surrounded by dotted line boxes are neurons. Each neuron takes a weighted sum from other neurons or input vector, then outputs it after a transformation by an activation function. In Figure 3, hidden units takes a weighted sum from input parameters then makes the output after a hyperbolic tangent transformation $tanh(x) = (e^x - e^{-x}) / (e^x + e^{-x})$, while output unit O takes input from hidden units then outputs the annual energy consumption after a pure linear transformation $f(x) = x$.

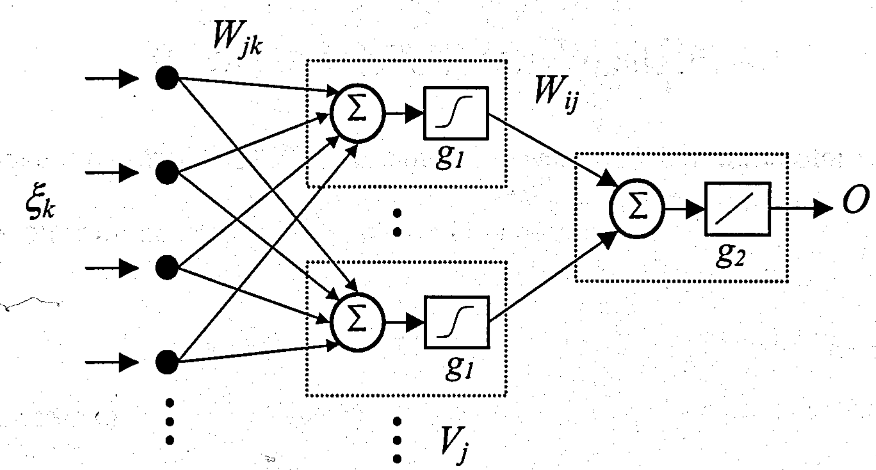

Figure 3. Architecture of the two-layer neural networks.

Given an input vector ξ_k, hidden unit j receives a net input

$$h_j = \sum_k W_{jk} \xi_k \tag{3.1}$$

and produces output

$$V_j = g_1(h_j) = g_1(\sum_k W_{jk} \xi_k) . \tag{3.2}$$

Output unit O thus receives

$$h_i = \sum_j W_{ij} V_j = \sum_j W_{ij} g_1(\sum_k W_{jk} \xi_k) \tag{3.3}$$

and produces the final output

$$O_i = g_2(h_i) = g_2(\sum_j W_{ij} V_j) = g_2(\sum_j W_{ij} g_1(\sum_k W_{jk} \xi_k)). \tag{3.4}$$

Because the output vector of the neural networks used in this study has only one element, annual energy usage, $i \equiv 1$, thus

$$O = g_2(h_1) = g_2(\sum_j W_{1j} V_j) = g_2(\sum_j W_{1j} g_1(\sum_k W_{jk} \xi_k)) \tag{3.5}$$

Suppose the output of DOE-2.1E simulation with the input parameter values ξ_k is ζ, the error measure or cost function of the neural networks

$$E[W] = \frac{1}{2}[\zeta - O]^2 \tag{3.6}$$

now becomes

$$E[W] = \frac{1}{2}\left[\zeta - g_2(\sum_j W_{1j} g_1(\sum_k W_{jk} \xi_k))\right]^2. \tag{3.7}$$

The ability of neural networks of extracting input-output relationship comes from its competence to learn from a training set of input-output pairs $\{\xi^u, \zeta^u\}$ in order to derive the input-output relationship. The procedure of learning is also called training. For a set of input-output pairs, the cost function becomes

$$E[W] = \frac{1}{2}\sum_u\left[\zeta^u - g_2(\sum_j W_{1j} g_1(\sum_k W_{jk} \xi_k^u))\right]^2. \tag{3.8}$$

The goal of training is to compare the outputs of the network with known target output ζ^u then minimize cost function $E[W]$ by adjusting weights connecting units in the network through specific algorithms. Because the target outputs ζ^{u} are used in the training, this learning procedure is supervised learning.

The most challenging part of the neural networks technique is to develop a fast algorithm of weight adjustment. The back-propagation algorithm is central to much work on learning in neural networks (Hertz et al., 1991). The algorithm gives a prescription for changing the weights in any feed-forward networks to learn a training set of input-output pairs. The basis of the back-propagation algorithm is simply gradient decent weight updating rule

$$\Delta W = -\eta \frac{\partial E}{\partial W} \tag{3.9}$$

in which the weights are moved in the direction of the negative gradient of the error or cost function, η is the learning rate. Obviously, equation (3.8) is a continuous differentiable function of every weight, so gradient decent weight updating rule can be applied in learning to force the error decrease.

The training normally needs multiple weight updating until the error of the networks is less than a target error level. Each time of updating, also called one "epoch", involves all weights. Completed back-propagation algorithm is described in plenty of literatures (Bishop, 1995; Hagan, Demuth, & Beale, 1996; Hassoun, 1995; Hertz et al., 1991). The brief back-propagation procedure is:

1. Prepare input-output pairs. Input includes parameters to be studied. Output is the correct output of the system. Initialize the weights to small random numbers, such as in the range of [-1,1].

2. Compute the error using equation (3.8).

3. If the error is less than the target error, stop training.

4. Compute the gradient of the error with respect to every weight.

5. Update weights according to the updating rule.

6. Go back to Step 3 for next epoch.

The basis of the back-propagation algorithm is simple and easy to be complemented. However, it is too slow for practical problems. In present study, another algorithm named Resilient Back-Propagation (RPROP) was used. The main difference of RPROP from basis back-propagation is a different updating rule is applied. The RPROP algorithm is much faster than basis back-propagation algorithm. A complete description of RPROP algorithm is given in the work of Riedmiller and Braun (1993).

A method for improving model generalization, early stopping, was used in this study. The available data for each training was divided into three subsets which were not overlapped. The first set, training set, was used for computing the gradient and updating the network weights. The second subset was the validation set. The third set, testing set, was used to test the prediction accuracy of the networks after training was done. The error on the validation set was monitored during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the networks begins to overfit the data, the error on validation set will typically begin to rise. When the validation error increases for a specific number of epochs, the training is stopped. In this study, the training stopped when either one of following conditions was satisfied:

1. The error on the training set was less than or equal to the target error.
2. The validation error did not decrease in the most recent 50 epochs.

In this study, the number of input units equaled the number of design parameters to be studied. The number of output was always 1, which was the annual energy consumption of the building. The sizes of training set, validation set, and testing set were 1024, 256, and 256 input-output pairs, respectively. All input parameters were randomly generated within their ranges specified in Table 3 then normalized, so that they fell in the range of [0,1]. The output data were generated by DOE-2.1E simulations.

The next question is: how many hidden units should be used in the networks? In general, the number of hidden units depends on the complexity of the problem and there is no common method to know it. If there are too many hidden units, the networks maybe too complicated to converge after a lot of epochs; if there are too few hidden units, the networks might be not complex enough to represent the input-output relationship. A batch of networks with different number of hidden units were trained in order to determine how many hidden units were suitable for model building energy system. Figure 4 shows Mean Square Errors on testing data set defined as

$$E[W]/n = \frac{1}{2}\sum_{n=1}^{256}\left[E^{n}_{DOE2.1E} - E^{n}_{networks}\right]^2 / 256 \tag{3.10}$$

after training the neural networks with a series of different number of hidden units. Input parameters of the networks were all 40 design parameters listed in Table 3. One thousand five hundred and thirty six input-output pairs were used of which 1024 were used as training set, 256, validation set, and 256, testing set. For each number of hidden units, 20 trainings were conducted and the mean results were shown in the figure where error bars are standard error of the mean. A clear trend is shown that larger number of hidden units generally results in

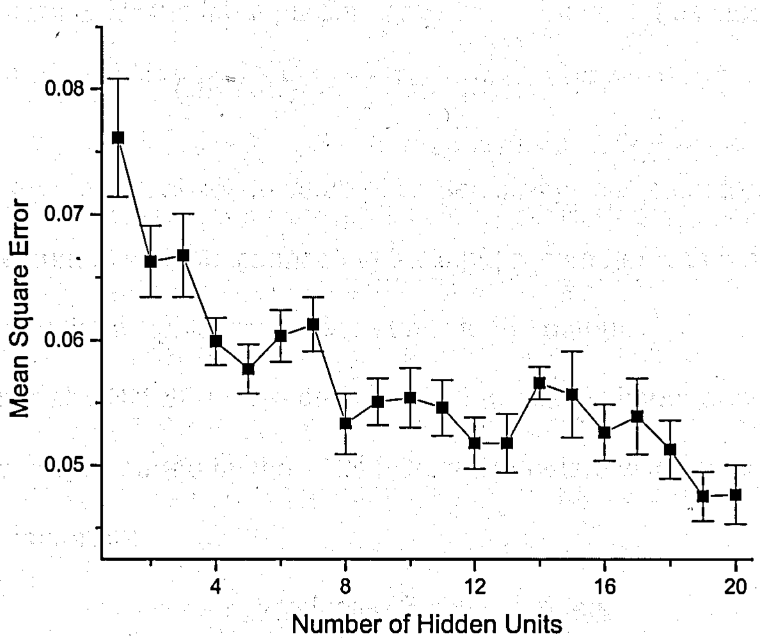

Figure 4. Results of training with different number of hidden units.

smaller error on testing. However, larger number of hidden units remarkably slows down the training. In present study, 4 hidden units was used in all neural networks trainings which was a compromise between computation complexity and network performance.

The networks training program was provided by Dr. Yuxi Fu at University of California at Berkeley, written in C programming language.

Sensitivity Coefficient Revealed by ANN

After training, the input-output relationship is represented by the values of weights and the architecture of the networks. Through analyzing the weights connecting input parameters and the output, the sensitivity of the output to input parameters can be quantified. A form of sensitivity coefficient revealed by the neural networks for the input parameter ξ_k was defined in this study as

$$(ANNSC)_k = \sum_j abs(W_{jk} W_{1j}), \tag{3.11}$$

where $abs(x)$ returns absolute value of x. Sensitivity coefficient from ANN (*ANN SC*) is the sum of weights connecting the input parameter with hidden units multiplied by the weights from hidden units to the output.

After all ANN SCs were determined, the relative importance of input parameters were sorted by the ANN SCs. Parameters with larger ANN SCs are relatively important.

Developing Building Models

Multiple Linear Regression (MLR) analysis and ANN were used to develop building models. The input parameters used in modeling were 5, 10, or 15 most important parameters ranked by both sensitivity coefficients SC1, SC2, SC3 from DSA, and ANN SC from ANN. Therefore, there are 6 main combinations of models, MLR5, MLR10, MLR15, ANN5, ANN10, and ANN15, or 24 detailed combinations of models, MLR5-SC1, MLR5-SC2, ..., MLR5-ANN SC, ..., ANN15-SC1, ANN15-SC2, ..., and ANN15-ANN SC.

Same database was used in both MLR and ANN modeling. The database was generated by DOE-2.1E simulations. Data set of modeling (training for ANN) contained 1024 input-output pairs; Data set of validation (only used for ANN) contained 256 input-output pairs; Data set of testing also contained 256 input-output pairs. In all data set, 40 design parameters were randomly selected within their ranges.

The prediction power is measured by Mean Absolute Error (MAE)

$$MAE = \left(\sum_{i=1}^{256} \left| E_{model} - E_{doe-2.1E} \right| \right) \div 256, \tag{3.12}$$

and Root Mean Square Error (RMSE)

$$RMSE = \left[\left(\sum_{i=1}^{256} (E_{model} - E_{doe-2.1E})^2 \right) \div 256 \right]^{\frac{1}{2}}, \tag{3.13}$$

on testing data set, where E_{model} is building annual energy consumption predicted by models, $E_{doe-2.1E}$ is the energy annual consumption calculated by DOE-2.1E simulation.

Modeling with Multiple Linear Regression

Multiple Linear Regression (MLR) analysis is the most extensively used method in modeling linear systems or approximately modeling nonlinear systems. MLR takes observed input-output data pairs to derive linear equations expressing input-output relationship of the system. The linear equations derived by MLR have simple formats. For example, for MLR15 model, the energy equation has the form of:

$$E = \left[\sum_{i=1}^{15} a_i x_i \right] + b, \tag{3.14}$$

where E is the predicted annual energy consumption, x_i is input parameter, a_i and b are coefficients which need to be figured out by the regression. The Matlab statistics toolbox (http://mathworks.com) was used to perform linear regression.

Modeling with ANN

Using the same data set, ANN models are also developed. Twenty trainings were conducted for each model. The MAE and RMSE on testing data set was the avarage of 20 trainings.

CHAPTER IV

RESULTS AND DISCUSSIONS

Base Case Model

The base case model is very important in sensitivity analysis because all subsequent calculations and analysis are based on the comparison with it. Using DOE-2.1E program, a base case model was developed with 40 parameters shown in Table 3 under base case values. After simulation with the input file presented in Appendix A, the energy performance data of the base case model building was extracted from DOE-2.1E report files. The building consumes 200.8 Megawatt Hour (MWh) electricity annually. Load peak is 49.6 Kilowatt (KW), occurring at 8:00 am, February 2nd. Figure 5 and Figure 6 show components of annual and monthly energy consumption of the base model. Obviously the

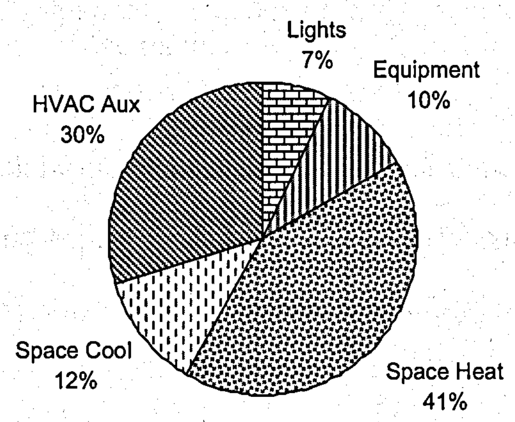

Figure 5. Components in annual energy consumption of the base case model.

heating is the largest part of the whole energy usage because northeastern Iowa has long and cold winter which makes the heating demand very high. The HVAC system and plant approximately consume 30% total energy while lights and equipment consume 17% totally. Space cooling demand is relatively low due to the short or moderate summer in Iowa. Figure 6 shows the distributions of these

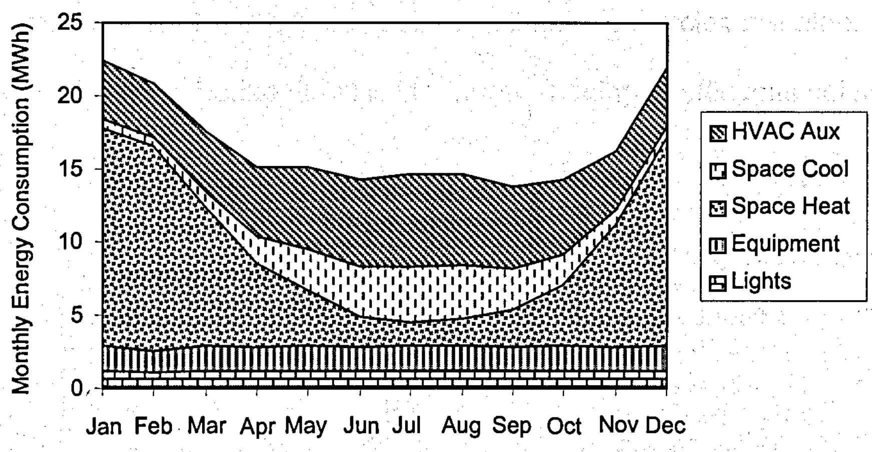

Figure 6. Components in monthly energy consumption of the base case model.

components month by month in the whole year. The heating mostly occurs in winter while cooling appears mostly in summer. The lighting and equipment energy usage are pretty constant across the whole year, from January to December.

Differential Sensitivity Analysis

Three forms of sensitivity coefficients SC1, SC2, and SC3 defined in Table 4 were calculated to evaluate the sensitivity of the annual energy performance of the building to 40 parameters in Table 3. Appendix B lists results of sensitivity analysis on all these parameters with DSA method. Figure 7 is the sensitivity analysis of the window shading coefficient, showing how the annual energy consumption responds to the changes of window shading coefficient. Simulations with 6 perturbations on window shading coefficient were conducted with DOE-2.1E program while all other parameters kept fixed. In Figure 7, square marker denotes the base case condition, open circles are other perturbation values, horizontal axis is window shading coefficients selected within

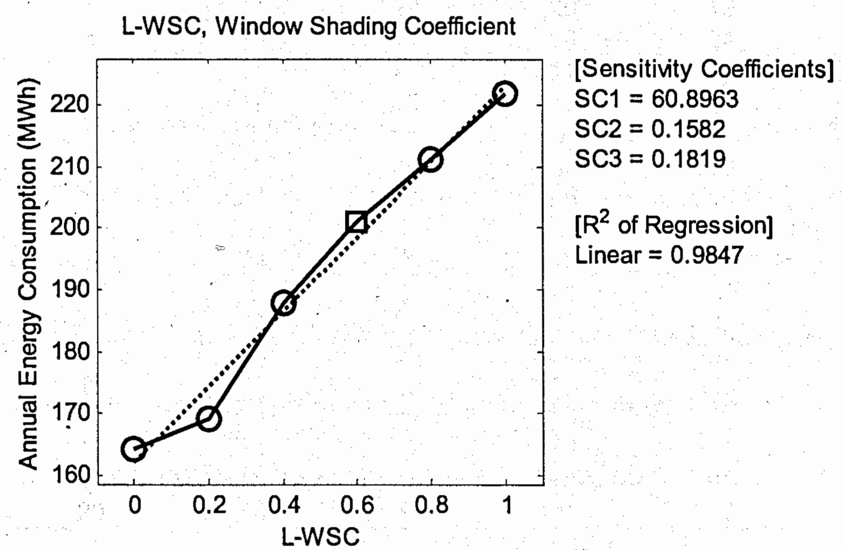

Figure 7. Sensitivity analysis of window shading coefficient.

normal ranged defined in Table 3, vertical axis is annual energy consumption in MWh extracted from DOE-2.1E reports, dotted line is linear regression straight line, on the right sensitivity coefficients and the coefficient of determination (R^2) of the linear regression are listed. The coefficient of determination (R^2) represents the goodness of curve fitting. By comparing the sensitivity coefficients of different input parameters, the relative importance or contributions of these input parameters can be assessed. Table 5 shows the most important 20 parameters ranked by sensitivity coefficients. Numbers in the table are parameter indexes by which the parameters can be looked up from Table 3.

Table 5
Relative Importance of Input Parameters

Ranking	SC1	SC2	SC3	ANN SC
1	19	12	12	19
2	10	13	13	11
3	33	5	5	20
4	28	20	20	12
5	39	11	10	24
6	35	24	11	2
7	24	10	19	10
8	2	2	2	3
9	11	16	24	13
10	29	19	16	16
11	3	7	7	6
12	20	3	3	5
13	6	8	8	7
14	32	28	28	8
15	7	25	18	32
16	8	29	25	35
17	34	14	29	1
18	14	32	32	38
19	12	18	6	40
20	13	6	31	25

Figure 8 shows sensitivity coefficients of all parameters normalized by the maximum absolute value for each type. The parameters having larger sensitivity coefficients should be carefully considered in building and HVAC design and operation since they contribute more to building energy consumption. On the other side, parameters with smaller sensitivity coefficients are not that important so they can be chosen freely in their normal range because they do not play crucial roles in energy conservation.

Among all sensitivity coefficients shown in Figure 8, results in forms SC2 and SC3 are similar because all of them were calculated by the slope of linear regression line normalized by either base case value or mean value. Form SC1 shows large fluctuation in the value of sensitivity coefficient because the amplitude of a parameter greatly depends on its unit.

Each sensitivity coefficient analysis method has its own advantages and disadvantages. For example, the SC1 may have problems when it is used in comparing relative importance of different parameters because the value of it depends on the unit of the input, and different units for same parameter may yield very different values of sensitivity coefficient. So it is not expected to be a good statistics to evaluate parameter importance.

Now the problems are: which one is better? Which one is more efficient in applications? The most intuitive approach to compare the goodness or application efficiency of different sensitivity coefficients is to develop models with the most important parameters selected by different sensitivity coefficients, then compare the prediction power of these models. The ones yielding better models are considered as better sensitivity coefficients. In this study, three differential sensitivity coefficients, together with the one revealed by the artificial neural networks, were assessed using this approach.

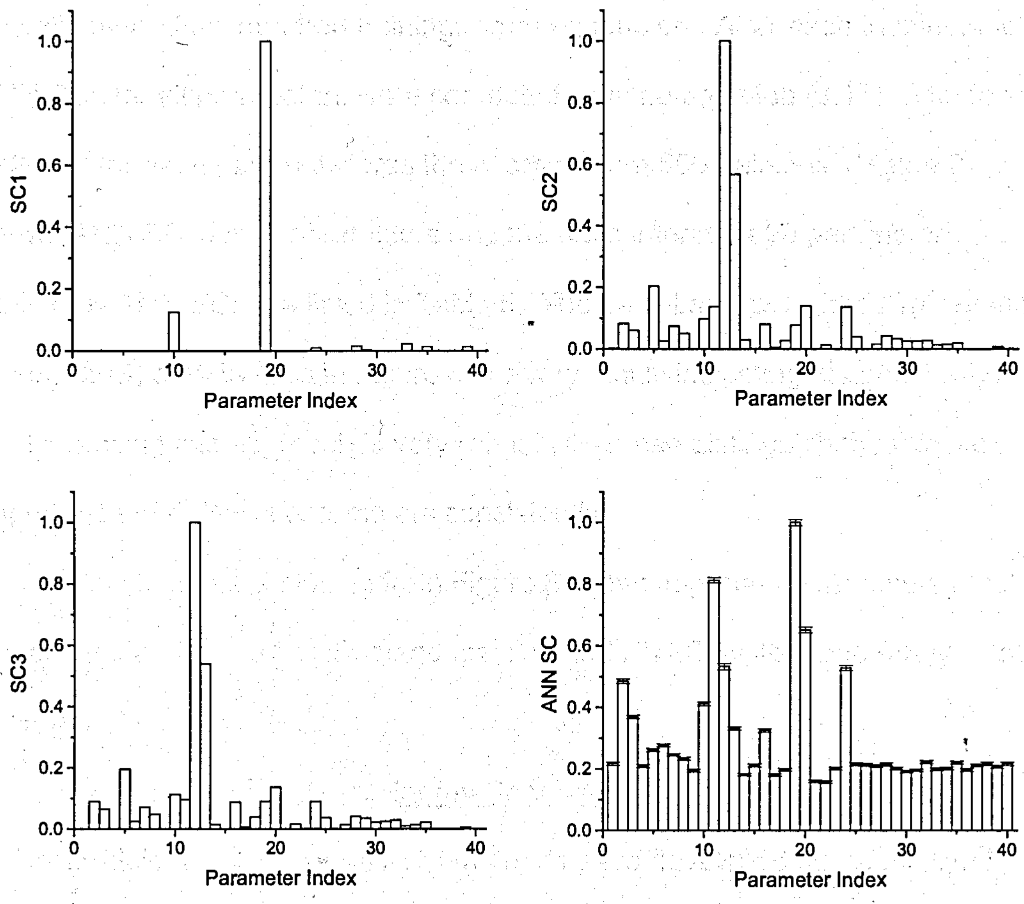

Figure 8. Four forms of sensitivity coefficients of 40 parameters.

Sensitivity Coefficient Revealed by Artificial Neural Networks

In this study, the Artificial Neural Networks (ANN) technique was utilized in sensitivity analysis. To the author's knowledge, this was the first time that the ANN was used for sensitivity analysis in building energy study. A two layer feed-forward ANN showing in Figure 3 was used. In order to calculate ANN SCs of design parameters, the networks with all 40 parameters randomly initialized were trained. The data used for training included 1024 pairs for training and 256 pairs for validation. Five hundred trainings were conducted. After each training, the ANN SCs for all parameters were computed with the equation (3.11). The final ANN SC for each parameter was the average from 500 trainings. Figure 8 shows ANN SCs for all parameters and the most important 20 parameters ranked by ANN SCs are listed in Table 5. The error bars (Standard Error of the Mean, SEM) of ANN SCs in Figure 8 are very small, indicating the sensitivity analysis using this approach is very robust which can distinguish the relative importance of different parameters consistently.

An obvious conclusion from Figure 8 is that important parameters mostly are distributed in parameter categories load and HVAC system and rarely located in HVAC plant.

Models for Energy Consumption Prediction

Models using MLR and ANN methods were developed successfully. 5, 10, or 15 most important parameters ranked by both differential sensitivity coefficients SC1, SC2, SC3, and ANN SC yielded by neural networks were used in modeling as input parameters. So there are 6 major classes of models (MLR5, MLR10, MLR15, ANN5, ANN10, and ANN15) and 24 subclass models (MLR5-SC1, MLR5-SC2, ..., MLR5-ANN SC, ..., ANN15-SC1, ANN15-SC2, ..., and ANN15-ANN SC).

After each model was created with 1024 pairs of input-output data from DOE-2.1E simulation, 256 pairs testing data were used to measure the prediction accuracy. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) defined in equations 3.12 and 3.13 were used as prediction accuracy indicators. Both of MAE and RMSE were used in order to make sure if data trends and conclusions change under different error measures. The results showed that no matter which one was used, the conclusions of this project would not change. Since the RMSE is the most extensively used statistics to evaluate model prediction accuracy (Lam et al., 1997; Lee, 1999; Ruch, Chen, Haberl, & Claridge, 1993; Sorrell et al., 1995), in the following sections all results are discussed in RMSE.

Multiple Linear Regression Models

Figure 9 shows prediction results of MLR15 models based on 15 important parameters coming from three DSA and one ANN sensitivity coefficients. Each dot represents the energy consumption from DOE-2.1E simulation (horizontal axis) and the prediction of the model (vertical axis) for one combination of all 40 parameters. Totally 256 simulations and predictions are drawn in the figure. This result suggests that MLR model with 15 input parameters can predict building energy consumption correctly with RMSEs (normalized by mean DOE-21.E simulation results) of all dots from 14.71% to 20.62%. Another conclusion from this figure is that the model with parameters ranked by ANN sensitivity analysis is the best in predicting energy usage, implying the ANN method is better than DSA method in sensitivity analysis.

MLR10 and MLR5 models have similar prediction trend as that of MLR15 models. The models coming from ANN SC also has the best prediction performance. The difference of MLR10 and MLR5 models from MLR15 is on the accuracy of their prediction. The RMSEs of MLR10 and MLR5 models are17.25% and 25.39%, respectively, for ANN SC-derived input parameters,

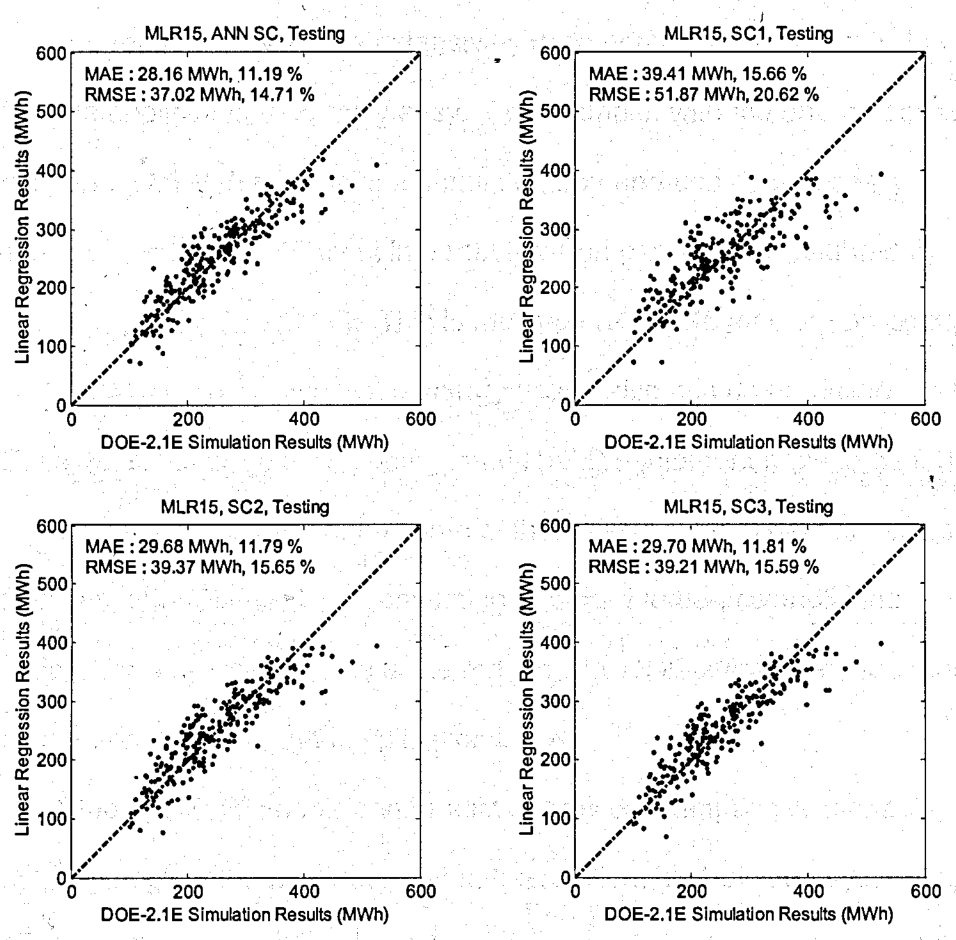

Figure 9. Energy consumption prediction of MLR15 models.

while it is 14.71% in MLR15-ANN SC model. This is very natural because a model with more parameters is more accurate than a model with less parameters. The disadvantage of increasing the number of parameters in modeling is the complexity of the model also increases, which usually makes the model developing harder and more time-consuming. Figure 10 shows prediction results of MLR5 models, in which the model with parameters coming from ANN SC shows best prediction performance.

The reason why MLR is extensively used comes from its simplicity which makes the application extremely easy. For example, with the energy equation developed by MLR15 models, the annual energy end-use can be easily calculated by summing 15 most important design parameters weighted by coefficients in equation (3.14). This is much more simple than the procedure of DOE-2.1E simulation in which the energy usage also can be predicted. In DOE-2.1E, all details of the building design and HVAC equipment have to be fed into the simulation program although some of them can be set to default values. This task is very complicated, time-consuming and hard to be accomplished, especially for a new user. This is the reason why DOE-2 programs are mostly used in research rather than applications.

Although MLR models can predict energy consumption reasonably, they completely neglect the nonlinear part in the relationship between system input and output. Therefore, linear models for a nonlinear system such as building energy system may lose information embedded in the database and describe the system insufficiently.

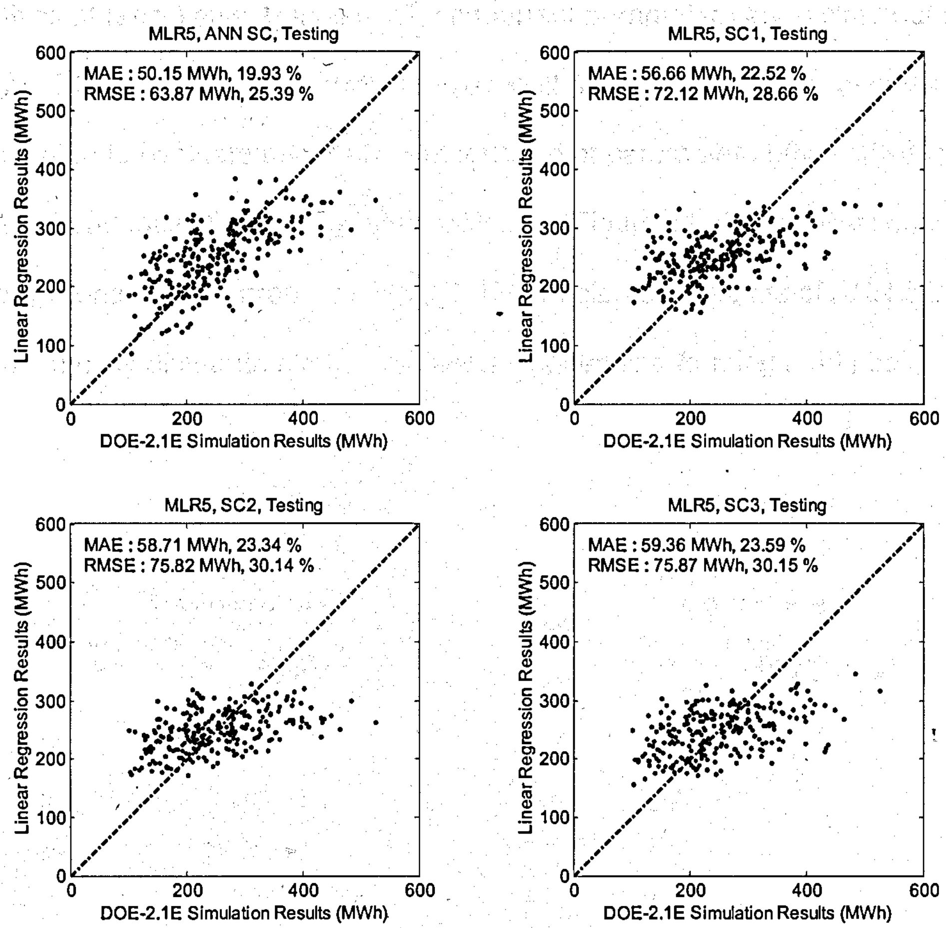

Figure 10. Energy consumption prediction of MLR5 models.

Artificial Neural Networks Models

Using the same data set as used in developing MLR models, ANN models were also developed. All ANN5, ANN10 and ANN15 prediction results showed that models with parameters yielded by ANN sensitivity analysis had best prediction performance compared to models based on differential sensitivity coefficients. Models based on SC2 and SC3 showed similar prediction performance. The reason is the definitions of SC2 and SC3 are largely equivalent (see Table 4) thus similar important parameters are picked out by them. SC1-based models always have worst prediction accuracy because SC1 is not able to evaluate the relative importance of parameters efficiently due to the unit-dependency of the sensitivity coefficient. Figure 11 shows the annual energy consumption predicted by ANN15 models. Data points of ANN SC-based model mostly distribute along the diagonal dotted line forming a thin belt,

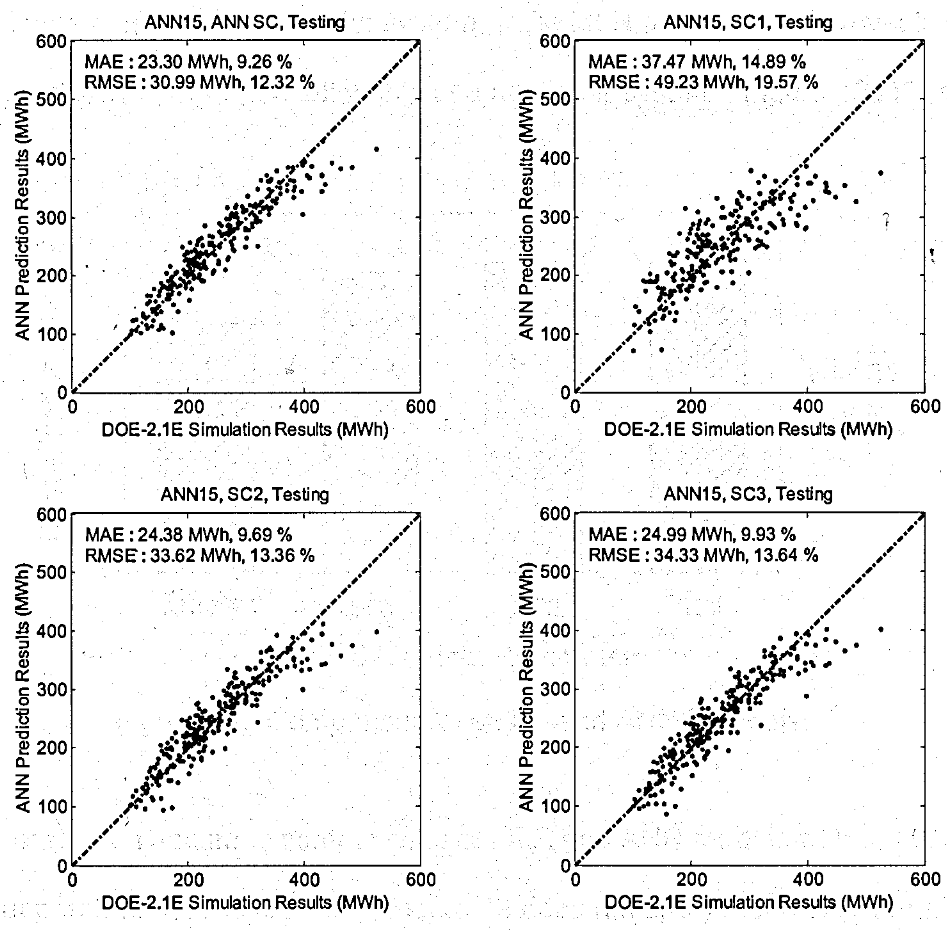

Figure 11. Energy consumption prediction of ANN15 models.

implying the DOE-2.1E results and model prediction match very well in this model. The data points of SC1-, SC2-, and SC3-based model obviously distribute more broadly around the diagonal line indicating worse prediction.

Beside the superiority of ANN sensitivity analysis over conventional differential sensitivity analysis, it is also shown that the ANN models have stronger prediction power than MLR models. This could be explained by the nonlinearity of neural networks. ANN models can extract both linear and nonlinear components from the system, while MLR approach only reveals linear part of the input-output relationship of a nonlinear system. Figure 12, 13, and 14

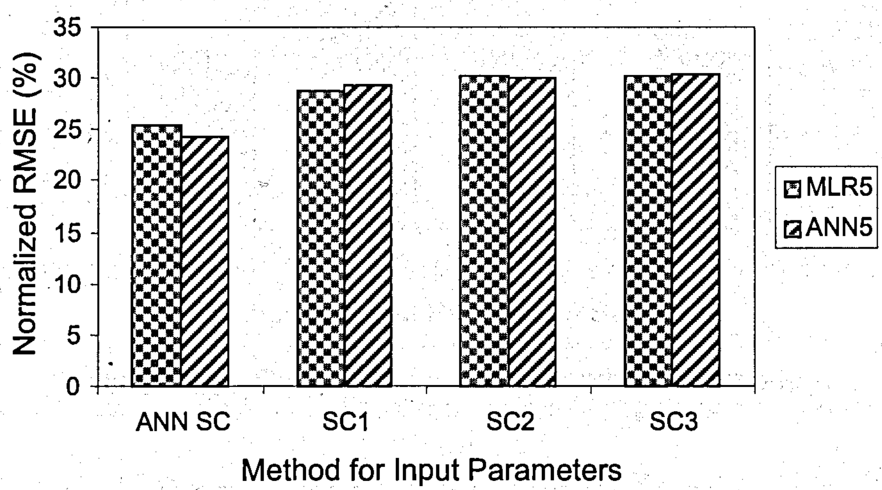

Figure 12. Comparison of MLR5 and ANN5 models.

are prediction accuracy comparisons of MLR and ANN models with 5, 10, and 15 input parameters, respectively. Figure 12 does not show much difference between MLR and ANN models in which MLR models have similar prediction performance to that of ANN models. One possible explanation is that the ability of extracting nonlinear relationship of ANN is not very useful for this case because only five parameters are used and there is not much inter-parameter nonlinear interaction. The most obvious finding from this figure is that the models based on parameters from ANN sensitivity analysis (ANN SC) have smaller RMSEs (or better prediction accuracy) than other models based on SC1, SC2, and SC3. The prediction performance of SC1-, SC2-, and SC3-based models

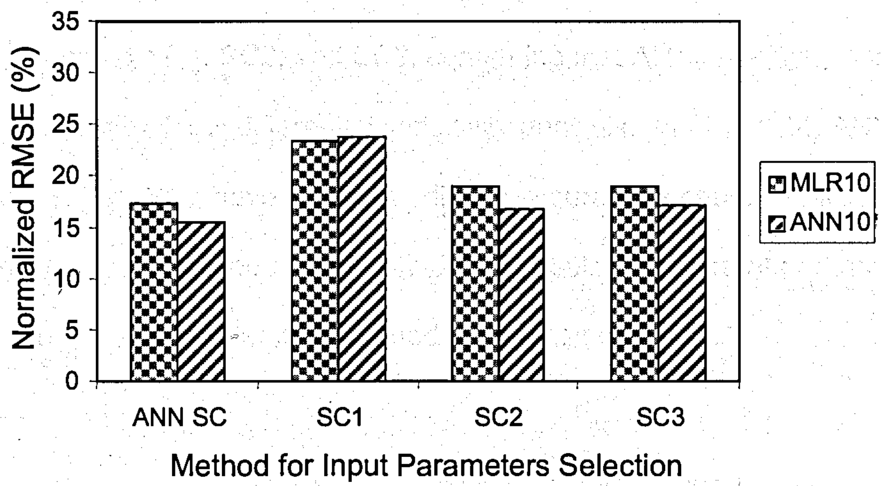

Figure 13. Comparison of MLR10 and ANN10 models.

are roughly same in Figure 12, implying these three sensitivity coefficients have similar efficiency if only a few important parameters are to be identified. The RMSEs in Figure 13 are smaller than those in Figure 12 and those in Figure 14 are further smaller than those in Figure 13. When the number of parameters increase, the model prediction accuracy also increases because models with more parameters take more information of input-output relationship into account.

From Figure 13, ANN models start to show their ability to extract nonlinear relationship. Except ANN10-SC1, all other comparisons in Figure 13 show that ANN models are better than MLR models in predicting building energy consumption. In Figure 14, all ANN models have smaller RMSEs than corresponding MLR models. It is likely to be true that with more input parameters, ANN models can more efficiently extract input-output relationship which can not be reflected by linear regression models. Like those in Figure 12, models with ANN SC-derived parameters in Figure 13 also predict better than models based on SC1, SC2, and SC3, confirming that ANN sensitivity analysis is better than conventional differential sensitivity analysis. In Figure 14, ANN SC, SC2, and SC3 models have similar prediction accuracy because different sensitivity analysis methods tend to yield similar sets of important parameters when the number of parameters needed is increasing.

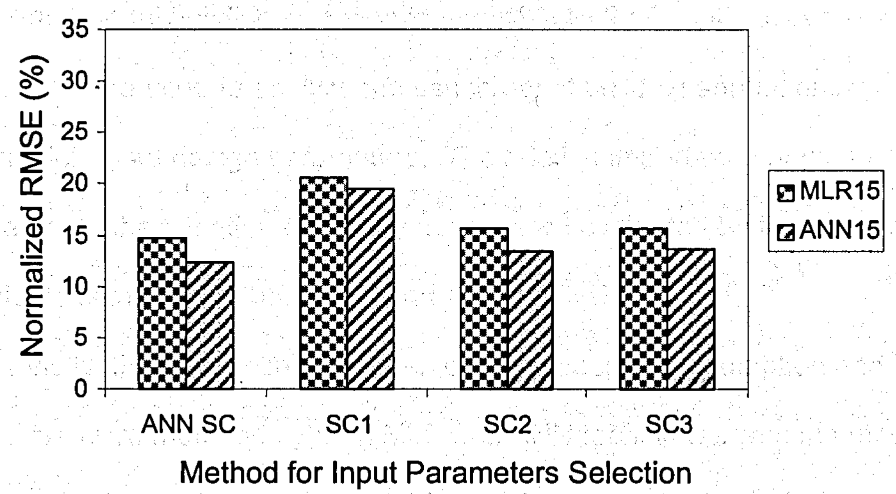

Figure 14. Comparison of MLR15 and ANN15 models.

CHAPTER V

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Summary and Conclusions

The Artificial Neural Networks (ANN) technique was applied to sensitivity analysis and modeling of an imaginary small office located in Iowa, and then compared with conventional Differential Sensitivity Analysis (DSA) and Multiple Linear Regression (MLR) methods that have been extensively used in studying the input-output relationship in building thermal systems.

The model building was described in DOE-2.1E Building Description Language (BDL; Lawrence Berkeley Laboratory, 1993). Forty design factors from building load, HVAC systems, and HVAC refrigeration plant were selected as input parameters to be studied. The building annual energy consumption from the report of DOE-2.1E simulation was used as the output of the system.

After model building was developed by DOE-2.1E, both DSA and ANN techniques were used to analyze the sensitivity of building annual energy consumption to 40 design parameters. The relative importance of these parameters to the variation of energy usage were evaluated by the sensitivity coefficients coming from both DSA and ANN analysis.

Finally, the relationship between building energy consumption and input parameters were modeled by both MLR and ANN techniques with the most important 5, 10, or 15 parameters yielded in above sensitivity analysis experiments in order to predict energy performance of the modeled building.

The main results and conclusions of this study are:

1. ANN models are better than MLR models in predicting energy consumption because the error between DOE-2.1E simulation and ANN model prediction was smaller than that from MLR models. This is largely due to the capacity of the neural networks in extracting input-output information from nonlinear systems.

2. ANN sensitivity analysis is better than DSA because models developed with ANN-derived important parameters more precisely predicted the building energy consumption, implying ANN sensitivity analysis more efficiently evaluated the relative importance of input parameters. The results concluded that ANN sensitivity analysis could simultaneously account for nonlinearity of the system and generate the sensitivity of the systm output to individual input parameter changes, showing the superiority of ANN sensitivity analysis over conventional sensitivity analysis methods like DSA in which the system is assumed to be linear, and MCA in which individual sensitivities can not be obtained (Lomas & Eppel, 1992).

3. Both DSA and ANN sensitivity analysis showed that important parameters tended to be distributed in HVAC system then building load, and rarely located in HVAC plant. This finding roughly agrees with the sensitivity analysis on a typical office building located in Hong Kong (Lam & Hui, 1996), indicating similar sensitivity characteristics of building energy performance can be found in different geographical locations.

The results of this project suggest that ANN technique can be adopted to perform sensitivity analysis and develop models to quantify the input-output relationship in building energy systems. The results showed that the ANN method had better performance than both DSA and MLR which have been extensively used in building thermal system studies.

Recommendations

Thermal characteristics of the building envelop, except some properties of window glasses, were not parameterized and investigated in this study due to the lack of construction knowledge by the author. Although some studies have shown that the building energy performance was less sensitive to measures affecting the building envelop (Corson, 1992; Lam & Hui, 1996), it remains unknown if their findings could be generalized to other geographical locations under different climate conditions. In the future research, factors regarding building envelop thermal properties could be studied.

The definition of ANN sensitivity coefficient in equation (3.11) is very intuitive but not necessarily the best one. The accuracy of it could be affected by the activation function of the hidden units since the weights before and after hidden units are linked by this function. It might be reasonable to try some other forms of ANN sensitivity coefficients which take the activation function of hidden units into account in the future and compare their efficiency with that of the current one.

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APPENDIX A

DOE-2.1E INPUT FILE FOR BASE CASE MODEL

```
$*****************************************************************************
$ FILE    : INPUT FILE FOR MODEL BUILDING ENERGY SIMULATION UNDER DOE-2.1E  *
$ CREATOR : AUTOMATIC INPUT FILE GENERATOR WRITTEN BY QUAN TANG             *
$ VERSION : 3.0                                                             *
$*****************************************************************************

$ TIME: 31-Oct-2001 17:10:36
$ TYPE: BASE CASE

$ PARAMETER VALUES USED IN CURRENT INPUT FILE
$  L-BLA = 0 DEGREE              Building Azimuth
$  L-WSC = 0.6                   Window Shading Coefficient
$  L-WGC = 1.0 BTU/HR-SQFT-F     Window Glass Conductance
$  L-WNP = 2                     Window Number of Panes
$  L-SAT = 70 F                  Space Air Temperature
$  L-IFR = 0.6 AC/HR             Infiltration Rate
$  L-EPL = 2.0 W/SQFT            Equipment Load
$  L-LTL = 1.5 W/SQFT            Lighting Load
$  L-LTT = SUS-FLUOR             Lighting Type
$  L-OPD = 0.02 PERSON/SQFT      Occupant Density
$  S-SYT = VAVS                  System Type
$  S-CSP = 72 F                  Cooling Set Point
$  S-HSP = 68 F                  Heating Set Point
$  S-TST = PROPORTIONAL          Thermostat Type
$  S-TTR = 2 F                   Throttling Range
$  S-OAF = 19 CFM/PERSON         Outdoor Air Flow Rate
$  S-OAC = TEMP                  Outdoor Air Control
$  S-FDT = 6 F                   Fan Air Delta T
$  S-FPC = 0.002 KW/CFM          Fan Power Consumption
$  S-FCT = INLET                 Fan Control
$  S-FMP = IN-AIRFLOW            Fan Motor Placement
$  S-FPM = DRAW-THROUGH          Fan Placement
$  S-RDT = 55 F                  Reheat Delta T
$  S-MCR = 0.2                   Minimum CFM Ratio
$  P-CST = 42 F                  Chilled Water Supply T
$  P-CTR = 3.5 F                 Chilled Water Throttling Range
$  P-CMT = 65 F                  Chilled Water Minimum Entering Air T
$  P-CCP = 0.06                  Chilled Water Condenser Power Ratio
$  P-CGB = 0.5                   Chilled Water Hot Gas Bypass PLR
$  P-CDT = 9 F                   Chilled Water Design Delta T
$  P-CPH = 60 FT                 Chilled Water Pump Head
$  P-CIE = 0.8                   Chilled Water Pump Impeller Efficiency
$  P-CPL = 0.01                  Chilled Water Fraction of Pump Loss
$  P-CME = 0.85                  Chilled Water Pump Motor Efficiency
$  P-HBL = 0.04                  Hot Water Boiler Loss
$  P-HDT = 30 F                  Hot Water Design Delta T
$  P-HPH = 60 FT                 Hot Water Pump Head
$  P-HIE = 0.8                   Hot Water Pump Impeller Efficiency
$  P-HPL = 0.01                  Hot Water Fraction of Pump Loss
$  P-HME = 0.85                  Hot Water Pump Motor Efficiency
$  Note: P-L-APP = 1/L-OPD in load parameter list below

$**** LOAD: STARTING ********************************************************
```

```
INPUT LOADS
      INPUT-UNITS=ENGLISH  OUTPUT-UNITS=ENGLISH ..

$**** PARAMETERS FOR LOAD: START *********************************************
PARAMETER P-L-BLA=0 ..
PARAMETER P-L-WSC=0.6 ..
PARAMETER P-L-WGC=1.0 ..
PARAMETER P-L-WNP=2 ..
PARAMETER P-L-SAT=70 ..
PARAMETER P-L-IFR=0.6 ..
PARAMETER P-L-EPL=2.0 ..
PARAMETER P-L-LTL=1.5 ..
PARAMETER P-L-LTT=SUS-FLUOR ..
PARAMETER P-L-APP=50 ..
$**** PARAMETERS FOR LOAD: END ***********************************************

TITLE LINE-1 *MODEL BUILDING INPUT FILE* ..
TITLE LINE-3 *AUTHOR: QUAN TANG, 8/2001* ..

ABORT ERRORS ..
DIAGNOSTIC WARNINGS
           CAUTIONS ..

RUN-PERIOD JAN 1 2000 THRU DEC 31 2000 ..
BUILDING-LOCATION LATITUDE=42.55       LONGITUDE=92.4
                  ALTITUDE=869.4226   TIME-ZONE=6
                  AZIMUTH=P-L-BLA     HOLIDAY=NO
                  DAYLIGHT-SAVINGS=NO ..

$BUILDING-SHADE

LOADS-REPORT      $VERIFICATION=(ALL-VERIFICATION)
                  VERIFICATION=(LV-A,LV-B,LV-D,LV-E,LV-F,LV-H,LV-I)
                  $SUMMARY=(ALL-SUMMARY)
                  SUMMARY=(LS-A,LS-C,LS-D,LS-F)
                  REPORT-FREQUENCY=HOURLY
                  HOURLY-DATA-SAVE=FORMATTED ..

$ LV-A: GENERAL PROJECT AND BUILDING INPUT
$ LV-B: SUMMARY OF SPACES
$ LV-D: DETAILS OF EXTERIOR SURFACES
$ LV-E: DETAILS OF UNDERGROUND SURFACES
$ LV-F: DETAILS OF INTERIOR SURFACES
$ LV-H: DETAILS OF WINDOWS
$ LV-I: DETAILS OF CONSTRUCTIONS

$ LS-A: SPACE PEAK LOADS SUMMARY
$ LS-C: BUILDING PEAK LOAD COMPONENTS
$ LS-D: BUILDING MONTHLY LOADS SUMMARY
$ LS-F: BUILDING MONTHLY LOAD COMPONENTS IN MBTU

$**** MATERIAL DEFINITIONS **************************************************
Q-VB1 = MATERIAL    RESISTANCE=0.06 ..
Q-IN1 = MATERIAL    THICKNESS=0.2917
                    CONDUCTIVITY=0.025
                    DENSITY=0.6
                    SPECIFIC-HEAT=0.2 ..

$**** LAYER DEFINITIONS *****************************************************
LAY-R1   =LAYERS MAT=(RG02,AR02,IN47,Q-VB1,CC02,AL23,CC02) I-F-R =.61 ..
```

```
LAY-WB1   =LAYERS MAT=(CC03,IN43,AL11,Q-IN1,Q-VB1,GP02)      I-F-R =.68 ..
LAY-WT1   =LAYERS MAT=(CC04,IN43,AL11,Q-IN1,GP02)            I-F-R =.68 ..
LAY-P1    =LAYERS MAT=(GP02,IN13,GP02)                       I-F-R =.68 ..

$**** CONSTRUCTION TYPES OF ROOF, WALL, CEILING, PARTITION, GROUND GLOOR ****
ROOFS        =CONSTRUCTION LAYERS=LAY-R1    ABSORPTANCE=0.29 ..
WALL-BOTTOM  =CONSTRUCTION LAYERS=LAY-WB1   ABSORPTANCE=0.65 ..
WALL-TOP     =CONSTRUCTION LAYERS=LAY-WT1   ABSORPTANCE=0.65 ..
WALL-INT     =CONSTRUCTION LAYERS=LAY-P1 ..
CEIL         =CONSTRUCTION U-VALUE=0.317 ..
FLOORG       =CONSTRUCTION U-VALUE=0.609 ..

$**** GLASS TYPES OF WINDOW & GLASS DOOR ************************************
WINDOWS     =GLASS-TYPE SHADING-COEF=P-L-WSC GLASS-CONDUCTANCE=P-L-WGC
                        PANES=P-L-WNP ..
GDOOR       =GLASS-TYPE SHADING-COEF=P-L-WSC GLASS-CONDUCTANCE=P-L-WGC
                        PANES=P-L-WNP ..

$**** INTERNAL LOAD SCHEDULE ************************************************
PPLSCH =SCHEDULE THRU DEC 31 (ALL) (1,7)(0) (8,18)(1) (19,24)(0) ..
LGTSCH =SCHEDULE THRU DEC 31 (ALL) (1,7)(0) (8,18)(1) (19,24)(0) ..
EQPSCH =SCHEDULE THRU DEC 31 (ALL) (1,7)(0) (8,18)(1) (19,24)(0) ..

$**** SET DEFAULT VALUES ****************************************************

$**** SPACE CONDITIONS OF ALL ROOMS & PLENUMS *******************************
ROOM-COND     =SPACE-CONDITIONS
               ZONE-TYPE               =CONDITIONED
               TEMPERATURE             =(P-L-SAT)
               INF-METHOD              =AIR-CHANGE
               AIR-CHANGES/HR          =P-L-IFR
               PEOPLE-SCHEDULE         =PPLSCH
               AREA/PERSON             =P-L-APP
               PEOPLE-HG-LAT           =205
               PEOPLE-HG-SENS          =245
               LIGHTING-SCHEDULE       =LGTSCH
               LIGHTING-TYPE           =P-L-LTT
               LIGHT-TO-SPACE          =0.8
               LIGHTING-W/SQFT         =P-L-LTL
               EQUIP-SCHEDULE          =EQPSCH
               EQUIPMENT-W/SQFT        =P-L-EPL
               FLOOR-WEIGHT            =20 ..

PLENUM-COND   =SPACE-CONDITIONS
               ZONE-TYPE               =PLENUM ..

$**** SPACE DESCRIPTION OF ALL PLENUMS **************************************

$ PLENUM 1: P-ALL
P-ALL =SPACE
       X=0.5 Y=0.5 Z=8.5 AZIMUTH=0
       SPACE-CONDITIONS=PLENUM-COND AREA=2553
       VOLUME=14041.5  FLOOR-WEIGHT=5 ..

WE-P-ALL    =EXTERIOR-WALL
             X=69 Y=0 Z=0 AZIMUTH=90 HEIGHT=5.5 WIDTH=37
             CONSTRUCTION=WALL-TOP ..

WS-P-ALL    =EXTERIOR-WALL
             X=0 Y=0 Z=0 AZIMUTH=180 HEIGHT=5.5 WIDTH=69
```

```
          CONSTRUCTION=WALL-TOP ..

WW-P-ALL    =EXTERIOR-WALL
             X=0 Y=37 Z=0 AZIMUTH=270 HEIGHT=5.5 WIDTH=37
             CONSTRUCTION=WALL-TOP ..

WN-P-ALL    =EXTERIOR-WALL
             X=69 Y=37 Z=0 AZIMUTH=0 HEIGHT=5.5 WIDTH=69
             CONSTRUCTION=WALL-TOP ..

ROOF-P-ALL =ROOF
             X=0 Y=0 Z=5.5 AZIMUTH=180 TILT=0
             HEIGHT=37 WIDTH=69 GND-REFLECTANCE=0
             CONSTRUCTION=ROOFS ..

$**** SPACE DESCRIPTION OF ALL ROOMS ***************************************

$ SPACE 1: LOBBY, LOBBY
LOBBY =SPACE
       X=0.5 Y=0.5 Z=0 AZIMUTH=0
       SPACE-CONDITIONS=ROOM-COND AREA=324.0625
       VOLUME=2754.51325 ..

    WS-LOBBY =EXTERIOR-WALL
              X=0 Y=0 Z=0 AZIMUTH=180 HEIGHT=8.5 WIDTH=15.25
              CONSTRUCTION=WALL-BOTTOM ..

    DRS-LOBBY =WINDOW
               X=4.625 Y=0 HEIGHT=7 WIDTH=6
               GLASS-TYPE=WINDOWS ..

    WW-LOBBY =EXTERIOR-WALL
              X=0 Y=21.25 Z=0 AZIMUTH=270
              HEIGHT=8.5 WIDTH=21.25
              CONSTRUCTION=WALL-BOTTOM ..

    WINW-LOBBY =WINDOW
                X=0.125 Y=3.5 HEIGHT=5 WIDTH=21
                GLASS-TYPE=WINDOWS ..

    C-LOBBY   =INTERIOR-WALL
              HEIGHT=21.25 WIDTH=15.25
              NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-LOBBY   =UNDERGROUND-FLOOR AREA=73
              CONSTRUCTION=FLOORG ..

$ SPACE 2: OFF-SW, OFFICE SOUTH-WEST
OFF-SW =SPACE
        X=16.25 Y=0.5 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=192.375
        VOLUME=1635.1875 ..

    WS-OFF-SW =EXTERIOR-WALL
               X=0 Y=0 Z=0 AZIMUTH=180 HEIGHT=8.5 WIDTH=13.5
               CONSTRUCTION=WALL-BOTTOM ..

    WINS-OFF-SW =WINDOW
                 X=0.25 Y=3.5 HEIGHT=5 WIDTH=13
                 GLASS-TYPE=WINDOWS ..
```

```
    WW-OFF-SW =INTERIOR-WALL
               HEIGHT=8.5 WIDTH=14.25
               NEXT-TO=LOBBY CONSTRUCTION=WALL-INT ..

    C-OFF-SW  =INTERIOR-WALL
               HEIGHT=14.25 WIDTH=13.5
               NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-OFF-SW  =UNDERGROUND-FLOOR AREA=55.5
               CONSTRUCTION=FLOORG ..

$ SPACE 3: OFF-SM, OFFICE SOUTH-MIDDLE
OFF-SM =SPACE
        X=30.25 Y=0.5 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=192.375
        VOLUME=1635.1875 ..

    WS-OFF-SM =EXTERIOR-WALL
               X=0 Y=0 Z=0 AZIMUTH=180 HEIGHT=8.5 WIDTH=13.5
               CONSTRUCTION=WALL-BOTTOM ..

    WINS-OFF-SM =WINDOW
                 X=0.25 Y=3.5 HEIGHT=5 WIDTH=13
                 GLASS-TYPE=WINDOWS ..

    WW-OFF-SM =INTERIOR-WALL
               HEIGHT=8.5 WIDTH=14.25
               NEXT-TO=OFF-SW CONSTRUCTION=WALL-INT ..

    C-OFF-SM  =INTERIOR-WALL
               HEIGHT=14.25 WIDTH=13.5
               NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-OFF-SM  =UNDERGROUND-FLOOR AREA=55.5
               CONSTRUCTION=FLOORG ..

$ SPACE 4: OFF-SE, OFFICE SOUTH EAST
OFF-SE =SPACE
        X=44.25 Y=0.5 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=220.875
        VOLUME=1877.4375 ..

    WS-OFF-SE =EXTERIOR-WALL
               X=0 Y=0 Z=0 AZIMUTH=180 HEIGHT=8.5 WIDTH=15.5
               CONSTRUCTION=WALL-BOTTOM ..

    WINS-OFF-SE =WINDOW
                 X=0.25 Y=3.5 HEIGHT=5 WIDTH=15
                 GLASS-TYPE=WINDOWS ..

    WW-OFF-SE =INTERIOR-WALL
               HEIGHT=8.5 WIDTH=14.25
               NEXT-TO=OFF-SM CONSTRUCTION=WALL-INT ..

    C-OFF-SE  =INTERIOR-WALL
               HEIGHT=14.25 WIDTH=15.5
               NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-OFF-SE  =UNDERGROUND-FLOOR AREA=59.5
```

```
              CONSTRUCTION=FLOORG ..

$ SPACE 5: COPY-R, COPIER ROOM
COPY-R =SPACE
        X=60.25 Y=0.5 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=131.8125
        VOLUME=1120.40625 ..

    WE-COPY-R =EXTERIOR-WALL
              X=9.25 Y=0 Z=0 AZIMUTH=90 HEIGHT=8.5 WIDTH=14.25
              CONSTRUCTION=WALL-BOTTOM ..

    WINE-COPY-R =WINDOW
                X=0.125 Y=3.5 HEIGHT=5 WIDTH=14
                GLASS-TYPE=WINDOWS ..

    WS-COPY-R =EXTERIOR-WALL
              X=0 Y=0 Z=0 AZIMUTH=180 HEIGHT=8.5 WIDTH=9.25
              CONSTRUCTION=WALL-BOTTOM ..

    WINS-COPY-R =WINDOW
                X=0.125 Y=3.5 HEIGHT=5 WIDTH=9
                GLASS-TYPE=WINDOWS ..

    WW-COPY-R =INTERIOR-WALL
              HEIGHT=8.5 WIDTH=14.25
              NEXT-TO=OFF-SE CONSTRUCTION=WALL-INT ..

    C-COPY-R  =INTERIOR-WALL
              HEIGHT=14.25 WIDTH=9.25
              NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-COPY-R  =UNDERGROUND-FLOOR AREA=47
              CONSTRUCTION=FLOORG ..

$ SPACE 6: COR-MAIN, CORRIDOR MAIN
COR-MAIN =SPACE
          X=15.75 Y=15.25 Z=0 AZIMUTH=0
          SPACE-CONDITIONS=ROOM-COND AREA=349.375
          VOLUME=2969.6875 ..

    WE-COR-MAIN =EXTERIOR-WALL
                X=53.75 Y=0 Z=0 AZIMUTH=90 HEIGHT=8.5 WIDTH=6.5
                CONSTRUCTION=WALL-BOTTOM ..

    DRE-COR-MAIN =WINDOW
                 X=1.75 Y=0 HEIGHT=7 WIDTH=3
                 GLASS-TYPE=WINDOWS ..

    WS2-COR-MAIN =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=13.5
                 NEXT-TO=OFF-SW CONSTRUCTION=WALL-INT ..

    WS3-COR-MAIN =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=13.5
                 NEXT-TO=OFF-SM CONSTRUCTION=WALL-INT ..

    WS4-COR-MAIN =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=15.5
                 NEXT-TO=OFF-SE CONSTRUCTION=WALL-INT ..
```

```
    WS5-COR-MAIN =INTERIOR-WALL
                   HEIGHT=8.5 WIDTH=9.25
                   NEXT-TO=COPY-R CONSTRUCTION=WALL-INT ..

    C-COR-MAIN  =INTERIOR-WALL
                  HEIGHT=6.5 WIDTH=53.75
                  NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-COR-MAIN  =UNDERGROUND-FLOOR AREA=120.5
                  CONSTRUCTION=FLOORG ..

$ SPACE 7: MEET-R, MEETING ROOM
MEET-R =SPACE
        X=0.5 Y=22.25 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=385.0625
        VOLUME=3273.03125 ..

    WW-MEET-R =EXTERIOR-WALL
                X=0 Y=15.25 Z=0 AZIMUTH=270
                HEIGHT=8.5 WIDTH=15.25
                CONSTRUCTION=WALL-BOTTOM ..

    WINW-MEET-R =WINDOW
                  X=0.125 Y=3.5 HEIGHT=5 WIDTH=15
                  GLASS-TYPE=WINDOWS ..

    WN-MEET-R =EXTERIOR-WALL
                X=25.25 Y=15.25 Z=0 AZIMUTH=0
                HEIGHT=8.5 WIDTH=25.25
                CONSTRUCTION=WALL-BOTTOM ..

    WINN-MEET-R =WINDOW
                  X=0.125 Y=3.5 HEIGHT=5 WIDTH=25
                  GLASS-TYPE=WINDOWS ..

    WS1-MEET-R =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=15.25
                 NEXT-TO=LOBBY CONSTRUCTION=WALL-INT ..

    WS6-MEET-R =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=10
                 NEXT-TO=COR-MAIN CONSTRUCTION=WALL-INT ..

    C-MEET-R  =INTERIOR-WALL
                HEIGHT=25.25 WIDTH=15.25
                NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-MEET-R  =UNDERGROUND-FLOOR AREA=81
                CONSTRUCTION=FLOORG ..

$ SPACE 8: OFF-NW, OFFICE NORTH-WEST
OFF-NW =SPACE
        X=26.25 Y=22.25 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=205.875
        VOLUME=1749.9375 ..

    WN-OFF-NW =EXTERIOR-WALL
                X=13.5 Y=15.25 Z=0 AZIMUTH=0
                HEIGHT=8.5 WIDTH=13.5
```

```
                 CONSTRUCTION=WALL-BOTTOM ..

      WINN-OFF-NW =WINDOW
                   X=0.25 Y=3.5 HEIGHT=5 WIDTH=13
                   GLASS-TYPE=WINDOWS ..

      WS-OFF-NW =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=13.5
                 NEXT-TO=COR-MAIN CONSTRUCTION=WALL-INT ..

      WW-OFF-NW =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=15.25
                 NEXT-TO=MEET-R CONSTRUCTION=WALL-INT ..

      C-OFF-NW  =INTERIOR-WALL
                 HEIGHT=15.25 WIDTH=13.5
                 NEXT-TO P-ALL CONSTRUCTION=CEIL ..

      F-OFF-NW  =UNDERGROUND-FLOOR AREA=57.5
                 CONSTRUCTION=FLOORG ..

$ SPACE 9: OFF-NE, OFFICE NORTH-EAST
OFF-NE =SPACE
        X=40.25 Y=22.25 Z=0 AZIMUTH=0
        SPACE-CONDITIONS=ROOM-COND AREA=205.875
        VOLUME=1749.9375 ..

      WN-OFF-NE =EXTERIOR-WALL
                 X=13.5 Y=15.25 Z=0 AZIMUTH=0
                 HEIGHT=8.5 WIDTH=13.5
                 CONSTRUCTION=WALL-BOTTOM ..

      WINN-OFF-NE =WINDOW
                   X=0.25 Y=3.5 HEIGHT=5 WIDTH=13
                   GLASS-TYPE=WINDOWS ..

      WS-OFF-NE =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=13.5
                 NEXT-TO=COR-MAIN CONSTRUCTION=WALL-INT ..

      WW-OFF-NE =INTERIOR-WALL
                 HEIGHT=8.5 WIDTH=15.25
                 NEXT-TO=OFF-NW CONSTRUCTION=WALL-INT ..

      C-OFF-NE  =INTERIOR-WALL
                 HEIGHT=15.25 WIDTH=13.5
                 NEXT-TO P-ALL CONSTRUCTION=CEIL ..

      F-OFF-NE  =UNDERGROUND-FLOOR AREA=57.5
                 CONSTRUCTION=FLOORG ..

$ SPACE 10: COR-REST, CORRIDOR NEXT TO RESTROOMS
COR-REST =SPACE
          X=54.25 Y=21.75 Z=0 AZIMUTH=0
          SPACE-CONDITIONS=ROOM-COND AREA=70.875
          VOLUME=602.4375 ..

      WN-COR-REST =EXTERIOR-WALL
                   X=4.5 Y=15.75 Z=0 AZIMUTH=0
                   HEIGHT=8.5 WIDTH=4.5
```

```
                CONSTRUCTION=WALL-BOTTOM ..

    DRN-COR-REST =WINDOW
                 X=0.75 Y=0 HEIGHT=7 WIDTH=3
                 GLASS-TYPE=WINDOWS ..

    WW-COR-REST =INTERIOR-WALL
                HEIGHT=8.5 WIDTH=15.25
                NEXT-TO=OFF-NE CONSTRUCTION=WALL-INT ..

    C-COR-REST  =INTERIOR-WALL
                HEIGHT=15.75 WIDTH=4.5
                NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-COR-REST  =UNDERGROUND-FLOOR AREA=40.5
                CONSTRUCTION=FLOORG ..

$ SPACE 11: MEN, MEN'S RESTROOM
MEN =SPACE
     X=59.25 Y=22.25 Z=0 AZIMUTH=0
     SPACE-CONDITIONS=ROOM-COND AREA=76.875
     VOLUME=653.4375 ..

    WE-MEN =EXTERIOR-WALL
           X=10.25 Y=0 Z=0 AZIMUTH=90
           HEIGHT=8.5 WIDTH=7.5
           CONSTRUCTION=WALL-BOTTOM ..

    WINE-MEN =WINDOW
             HEIGHT=1.5 WIDTH=2
             GLASS-TYPE=WINDOWS ..

    WS-MEN =INTERIOR-WALL
           HEIGHT=8.5 WIDTH=10.25
           NEXT-TO=COR-MAIN CONSTRUCTION=WALL-INT ..

    WW-MEN =INTERIOR-WALL
           HEIGHT=8.5 WIDTH=7.5
           NEXT-TO=COR-REST CONSTRUCTION=WALL-INT ..

    C-MEN  =INTERIOR-WALL
           HEIGHT=7.5 WIDTH=10.25
           NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-MEN  =UNDERGROUND-FLOOR AREA=35.5
           CONSTRUCTION=FLOORG ..

$ SPACE 12: WOMEN, WOMEN'S RESTROOM
WOMEN =SPACE
       X=59.25 Y=30.25 Z=0 AZIMUTH=0
       SPACE-CONDITIONS=ROOM-COND AREA=74.3125
       VOLUME=631.65625 ..

    WE-WOMEN =EXTERIOR-WALL
             X=10.25 Y=0 Z=0 AZIMUTH=90
             HEIGHT=8.5 WIDTH=7.25
             CONSTRUCTION=WALL-BOTTOM ..

    WINE-WOMEN =WINDOW
               HEIGHT=1.5 WIDTH=2
```

```
                 GLASS-TYPE=WINDOWS ..

    WN-WOMEN =EXTERIOR-WALL
               X=10.25 Y=7.25 Z=0 AZIMUTH=0
               HEIGHT=8.5 WIDTH=10.25
               CONSTRUCTION=WALL-BOTTOM ..

    WINN-WOMEN =WINDOW
                 HEIGHT=1.5 WIDTH=2
                 GLASS-TYPE=WINDOWS ..

    WS-WOMEN =INTERIOR-WALL
               HEIGHT=8.5 WIDTH=10.25
               NEXT-TO=MEN CONSTRUCTION=WALL-INT ..

    WW-WOMEN =INTERIOR-WALL
               HEIGHT=8.5 WIDTH=7.25
               NEXT-TO=COR-REST CONSTRUCTION=WALL-INT ..

    C-WOMEN  =INTERIOR-WALL
               HEIGHT=7.25 WIDTH=10.25
               NEXT-TO P-ALL CONSTRUCTION=CEIL ..

    F-WOMEN  =UNDERGROUND-FLOOR AREA=35
               CONSTRUCTION=FLOORG ..


END ..
COMPUTE LOADS ..

$**** SYSTEM: STARTING **********************************************************

INPUT SYSTEMS ..

$**** PARAMETERS FOR SYSTEM: START ******************************************
PARAMETER P-S-SYT=VAVS ..
PARAMETER P-S-CSP=72 ..
PARAMETER P-S-HSP=68 ..
PARAMETER P-S-TST=PROPORTIONAL ..
PARAMETER P-S-TTR=2 ..
PARAMETER P-S-OAF=19 ..
PARAMETER P-S-OAC=TEMP ..
PARAMETER P-S-FDT=6 ..
PARAMETER P-S-FPC=0.002 ..
PARAMETER P-S-FCT=INLET ..
PARAMETER P-S-FMP=IN-AIRFLOW ..
PARAMETER P-S-FPM=DRAW-THROUGH ..
PARAMETER P-S-RDT=55 ..
PARAMETER P-S-MCR=0.2 ..
$**** PARAMETERS FOR SYSTEM: END ********************************************

SYSTEMS-REPORT   VERIFICATION=(SV-A,SV-B)
                 SUMMARY =(SS-A,SS-D,SS-H,SS-J)
                 REPORT-FREQUENCY=HOURLY
                 HOURLY-DATA-SAVE=FORMATTED ..

$ SV-A: SYSTEM DESIGN PARAMETERS
$ SV-B: ZONE FAN DATA

$ SS-A: SYSTEM MONTHLY LOADS SUMMARY
```

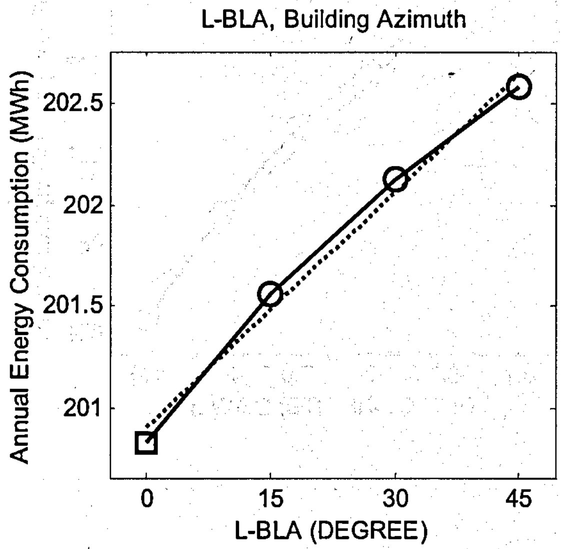
```
$ SS-D: PLANT MONTHLY LOADS SUMMARY
$ SS-H: SYSTEM MONTHLY LOADS SUMMARY
$ SS-J: SYSTEM PEAK HEATING AND COOLING DAYS

$**** ZONE CONTROL SCHEDULES *************************************************
HEATTEMPSCH  =SCHEDULE THRU DEC 31 (ALL) (1,24) (P-S-HSP) ..
COOLTEMPSCH  =SCHEDULE THRU DEC 31 (ALL) (1,24) (P-S-CSP) ..

$**** ZONE-R CONTROL *********************************************************
Z-CONTROL-R  =ZONE-CONTROL
              DESIGN-HEAT-T=P-S-HSP
              HEAT-TEMP-SCH=HEATTEMPSCH
              DESIGN-COOL-T=P-S-CSP
              COOL-TEMP-SCH=COOLTEMPSCH
              THERMOSTAT-TYPE=P-S-TST
              THROTTLING-RANGE=P-S-TTR ..

$**** ZONE-R AIR *************************************************************
Z-AIR-R      =ZONE-AIR
              OA-CFM/PER =P-S-OAF ..

$**** OPERATION OF ZONE-P PLENUM *********************************************
P-ALL        =ZONE
              ZONE-TYPE=PLENUM ..

$**** OPERATION OF ZONE-R ****************************************************
LOBBY        =ZONE
              ZONE-TYPE=CONDITIONED
              ZONE-AIR=Z-AIR-R
              ZONE-CONTROL=Z-CONTROL-R ..

OFF-SW       =ZONE LIKE LOBBY ..
OFF-SM       =ZONE LIKE LOBBY ..
OFF-SE       =ZONE LIKE LOBBY ..
COPY-R       =ZONE LIKE LOBBY ..
MEET-R       =ZONE LIKE LOBBY ..
OFF-NW       =ZONE LIKE LOBBY ..
OFF-NE       =ZONE LIKE LOBBY ..
MEN          =ZONE LIKE LOBBY ..
WOMEN        =ZONE LIKE LOBBY ..
COR-MAIN     =ZONE LIKE LOBBY ..
COR-REST     =ZONE LIKE LOBBY ..

$**** SYSTEM CONTROL SCHEDULE ************************************************
HEATINGSCH   =SCHEDULE THRU DEC 31 (ALL) (1,24) (1) ..
COOLINGSCH   =SCHEDULE THRU DEC 31 (ALL) (1,24) (1) ..
SYSFANSCH    =SCHEDULE THRU DEC 31 (ALL) (1,24) (1) ..

$ **** SYSTEM CONTROL ********************************************************
S-CONTROL = SYSTEM-CONTROL
            MAX-SUPPLY-T=95
            MIN-SUPPLY-T=55
            HEATING-SCHEDULE=HEATINGSCH
            COOLING-SCHEDULE=COOLINGSCH
            COOL-CONTROL=CONSTANT
            COOL-SET-T=55 ..

$**** SYSTEM AIR *************************************************************
S-AIR   = SYSTEM-AIR
          OA-CONTROL=P-S-OAC ..
```

```
$**** SYSTEM FANS ***********************************************************
S-FAN    =SYSTEM-FANS
          FAN-SCHEDULE=SYSFANSCH
          FAN-CONTROL=P-S-FCT
          SUPPLY-DELTA-T=P-S-FDT
          SUPPLY-KW=P-S-FPC
          MOTOR-PLACEMENT=P-S-FMP
          FAN-PLACEMENT=P-S-FPM ..

$**** SYSTEM TERMINAL *******************************************************
S-TERMINAL =SYSTEM-TERMINAL
             REHEAT-DELTA-T=P-S-RDT
             MIN-CFM-RATIO=P-S-MCR ..

$**** SYSTEM OPERATION ******************************************************
AHU1    =SYSTEM
         SYSTEM-TYPE=P-S-SYT
         SYSTEM-CONTROL=S-CONTROL
         SYSTEM-AIR=S-AIR
         SYSTEM-FANS=S-FAN
         SYSTEM-TERMINAL=S-TERMINAL
         HEAT-SOURCE=HOT-WATER
         SIZING-OPTION=COINCIDENT
         RETURN-AIR-PATH=PLENUM-ZONES
         PLENUM-NAMES=(P-ALL)
         ZONE-NAMES=(LOBBY,OFF-SW,OFF-SM,OFF-SE,COPY-R,MEET-R,
                     OFF-NW,OFF-NE,MEN,WOMEN,COR-MAIN,COR-REST,P-ALL) ..

PLANT1 =PLANT-ASSIGNMENT  SYSTEM-NAMES=(AHU1) ..

END ..
COMPUTE SYSTEMS ..

$**** PLANT: STARTING *******************************************************

INPUT PLANT  ..

$**** PARAMETERS FOR PLANT: START *******************************************
PARAMETER P-P-CST=42 ..
PARAMETER P-P-CTR=3.5 ..
PARAMETER P-P-CMT=65 ..
PARAMETER P-P-CCP=0.06 ..
PARAMETER P-P-CGB=0.5 ..
PARAMETER P-P-CDT=9 ..
PARAMETER P-P-CPH=60 ..
PARAMETER P-P-CIE=0.8 ..
PARAMETER P-P-CPL=0.01 ..
PARAMETER P-P-CME=0.85 ..
PARAMETER P-P-HBL=0.04 ..
PARAMETER P-P-HDT=30 ..
PARAMETER P-P-HPH=60 ..
PARAMETER P-P-HIE=0.8 ..
PARAMETER P-P-HPL=0.01 ..
PARAMETER P-P-HME=0.85 ..
$**** PARAMETERS FOR PLANT: END *********************************************

PLANT1 = PLANT-ASSIGNMENT  ..

PLANT-REPORT  VERIFICATION=(PV-A)
```

```
                 SUMMARY=(PS-A,PS-B,PS-C,PS-D,PS-E,PS-F,PS-H,BEPS,BEPU)  ..
$ PV-A: EQUIPMENT SIZES

$ PS-A: PLANT UTILIZATION SUMMARY
$ PS-B: MONTHLY PEAK AND TOTAL ENERGY USE
$ PS-C: EQUIPMENT PART LOAD OPERATION
$ PS-D: PLANT LOADS SATISFIED
$ PS-E: MONTHLY ENERGY END USE SUMMARY
$ PS-F: ENERGY RESOURCE PEAK BREAKDOWN BY END USE
$ PS-H: EQULPMENT USE STATISTICS
$ BEPS: BUILDING ENERGY PERFORMANCE SUMMARY
$ BEPU: BUILDING ENERGY PERFORMANCE SUMMARY (UTILITY UNITS)

P-CHILLER  PLANT-EQUIPMENT  TYPE=HERM-CENT-CHLR  SIZE=-999 ..
P-BOILER   PLANT-EQUIPMENT  TYPE=ELEC-HW-BOILER  SIZE=-999 ..

PLANT-PARAMETERS  CHILL-WTR-T=P-P-CST
                  CHILL-WTR-THROTTLE=P-P-CTR
                  MIN-COND-AIR-T=P-P-CMT
                  HERM-CENT-COND-PWR=P-P-CCP
                  HERM-CENT-COND-TYPE=AIR
                  HERM-CENT-UNL-RAT=P-P-CGB
                  CCIRC-DESIGN-T-DROP=P-P-CDT
                  CCIRC-HEAD=P-P-CPH
                  CCIRC-IMPELLER-EFF=P-P-CIE
                  CCIRC-LOSS=P-P-CPL
                  CCIRC-MOTOR-EFF=P-P-CME
                  E-HW-BOILER-LOSS=P-P-HBL
                  HCIRC-DESIGN-T-DROP=P-P-HDT
                  HCIRC-HEAD=P-P-HPH
                  HCIRC-IMPELLER-EFF=P-P-HIE
                  HCIRC-LOSS=P-P-HPL
                  HCIRC-MOTOR-EFF=P-P-HME ..

DIAGNOSTIC COMMENTS
           WARNINGS ..

END  ..
COMPUTE PLANT ..

STOP ..
```

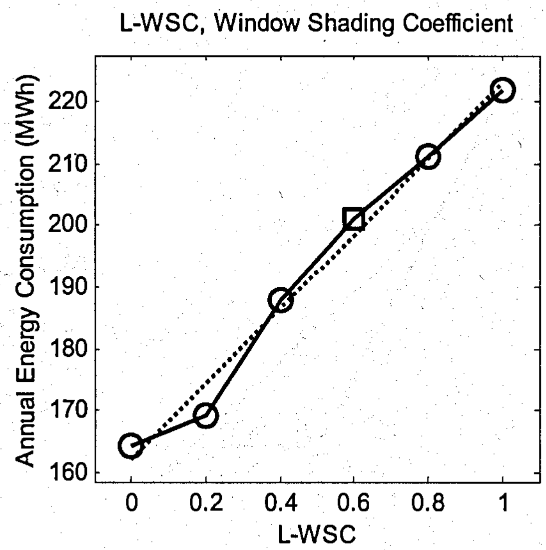
APPENDIX B

DIFFERENTIAL SENSITIVITY ANALYSIS ON 40 INPUT PARAMETERS



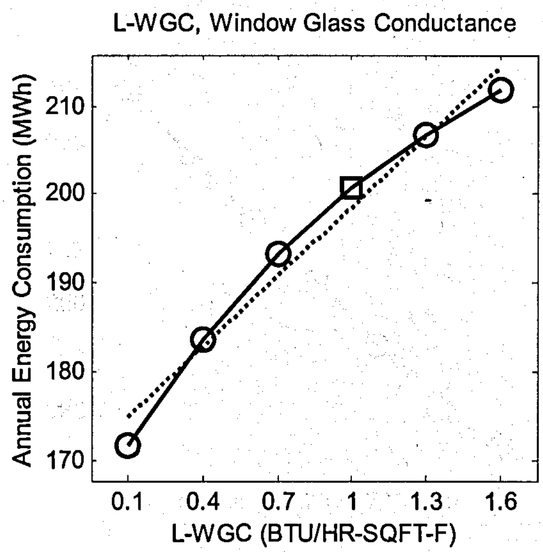
[Sensitivity Coefficients]
SC1 = 0.0389
SC2 = 0.0043
SC3 = 0.0029

[R^2 of Regression]
Linear = 0.9894



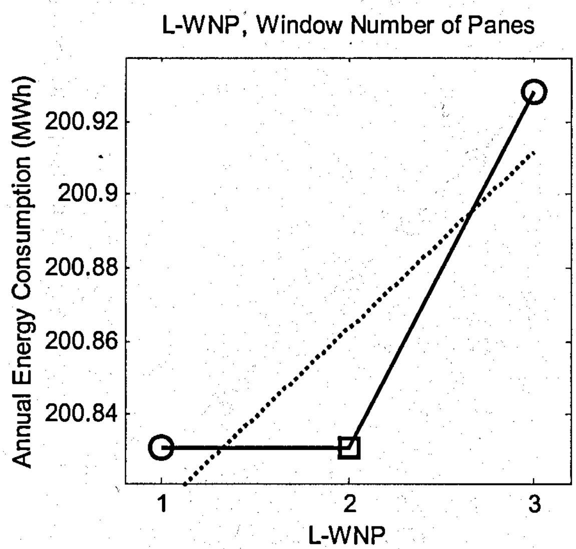
[Sensitivity Coefficients]
SC1 = 60.8963
SC2 = 0.1582
SC3 = 0.1819

[R^2 of Regression]
Linear = 0.9847



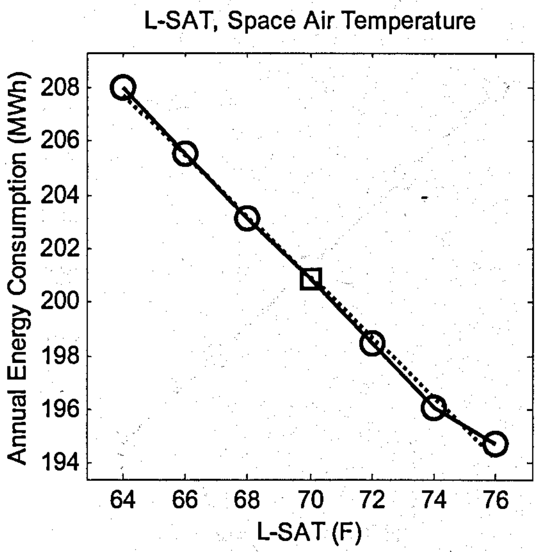
[Sensitivity Coefficients]
SC1 = 26.4477
SC2 = 0.1155
SC3 = 0.1317

[R^2 of Regression]
Linear = 0.9740



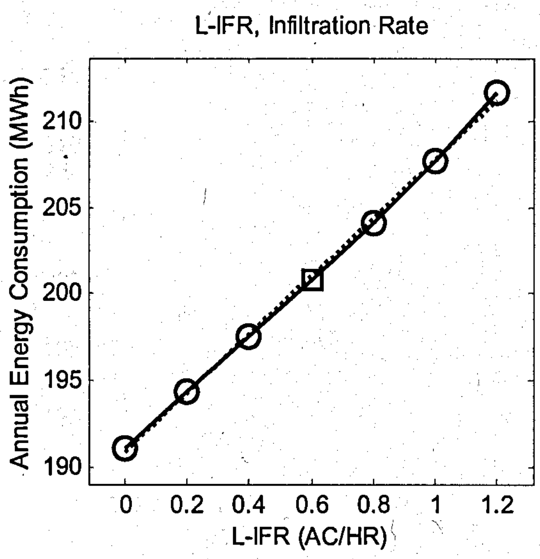
[Sensitivity Coefficients]
SC1 = 0.0485
SC2 = 0.0005
SC3 = 0.0005

[R^2 of Regression]
Linear = 0.7500



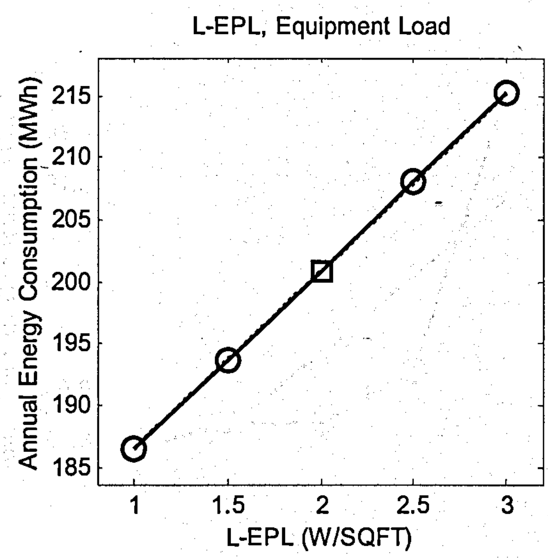
[Sensitivity Coefficients]
SC1 = -1.1281
SC2 = -0.3929
SC3 = -0.3932

[R^2 of Regression]
Linear = 0.9959



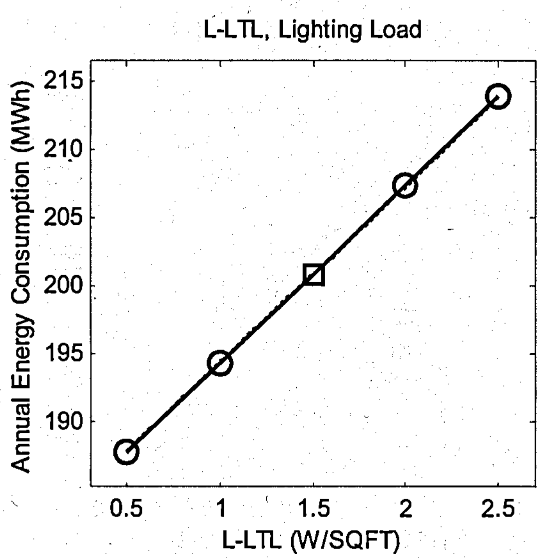
[Sensitivity Coefficients]
SC1 = 16.8623
SC2 = 0.0503
SC3 = 0.0504

[R^2 of Regression]
Linear = 0.9988



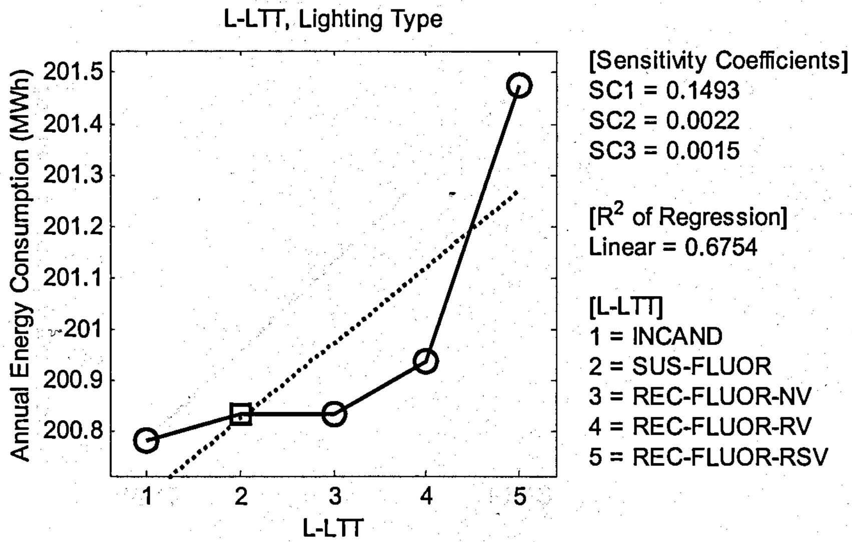
[Sensitivity Coefficients]
SC1 = 14.3494
SC2 = 0.1429
SC3 = 0.1429

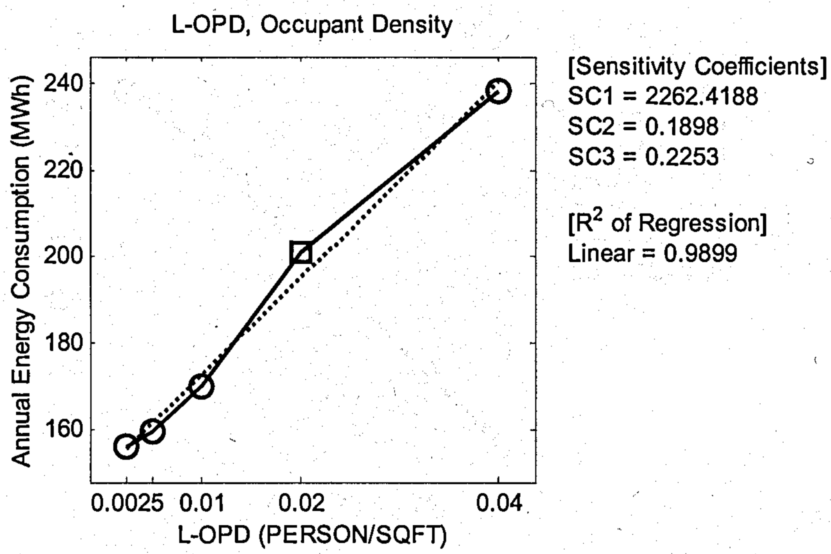
[R^2 of Regression]
Linear = 1.0000



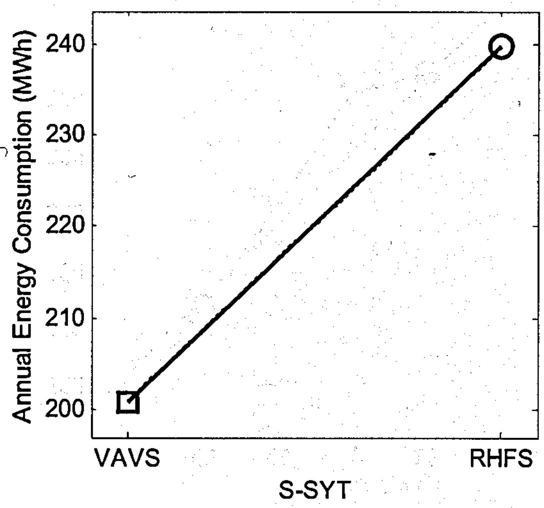
[Sensitivity Coefficients]
SC1 = 13.0556
SC2 = 0.0975
SC3 = 0.0975

[R^2 of Regression]
Linear = 1.0000


L-LTT, Lighting Type
Annual Energy Consumption (MWh)
201.5
201.4
201.3
201.2
201.1
201
200.9
200.8
1
2
3
4
5
L-LTT
[Sensitivity Coefficients]
SC1 = 0.1493
SC2 = 0.0022
SC3 = 0.0015
[R2 of Regression]
Linear = 0.6754
[L-LTT]
1 = INCAND
2 = SUS-FLUOR
3 = REC-FLUOR-NV
4 = REC-FLUOR-RV
5 = REC-FLUOR-RSV


L-OPD, Occupant Density
Annual Energy Consumption (MWh)
240
220
200
180
160
0.0025
0.01
0.02
0.04
L-OPD (PERSON/SQFT)
[Sensitivity Coefficients]
SC1 = 2262.4188
SC2 = 0.1898
SC3 = 0.2253
[R2 of Regression]
Linear = 0.9899

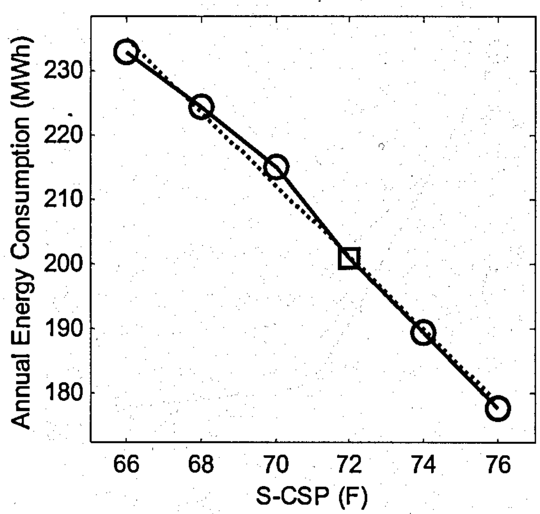
S-SYT, System Type



[Sensitivity Coefficients]
SC1 = 38.9480
SC2 = 0.2652
SC3 = 0.1939

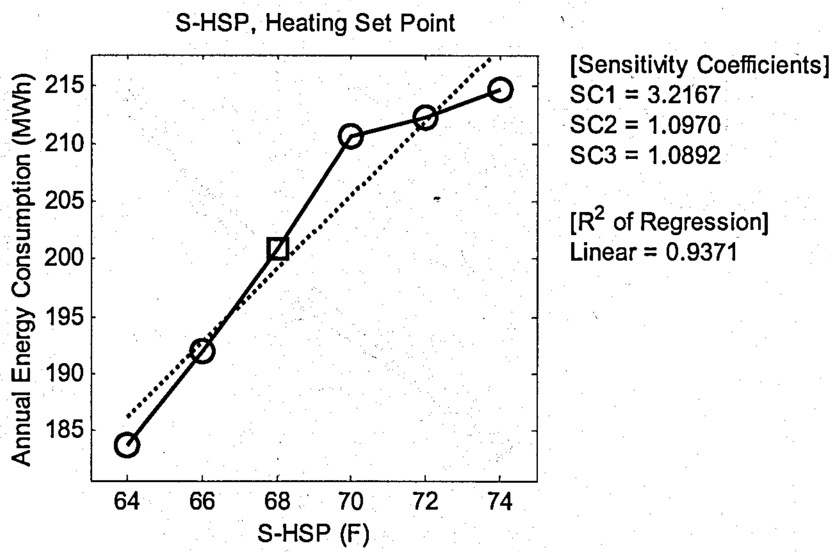
[R^2 of Regression]
Linear = 1.0000

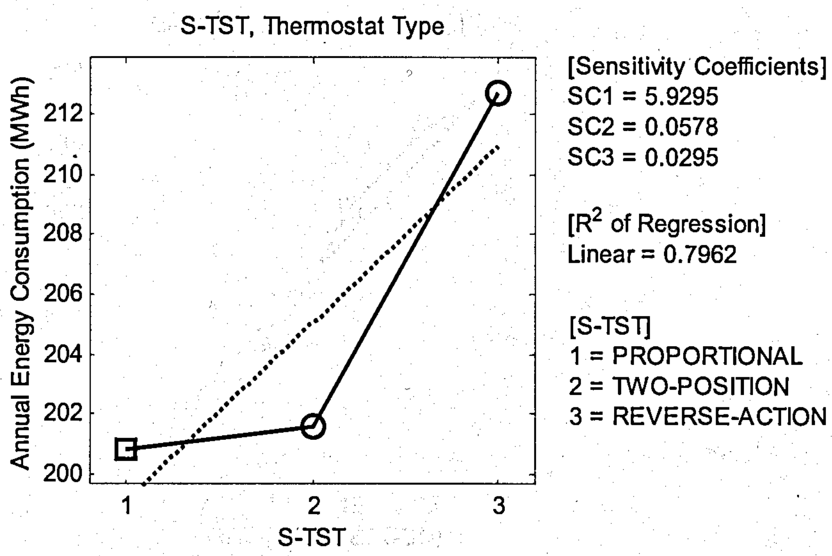
S-CSP, Cooling Set Point

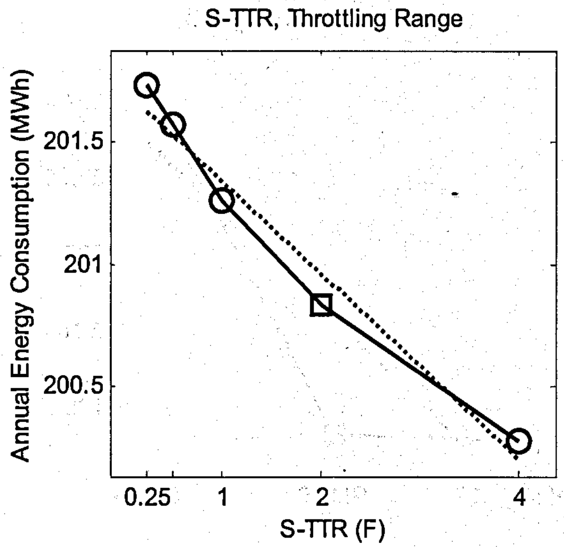


[Sensitivity Coefficients]
SC1 = -5.6395
SC2 = -1.9370
SC3 = -2.0218

[R^2 of Regression]
Linear = 0.9943

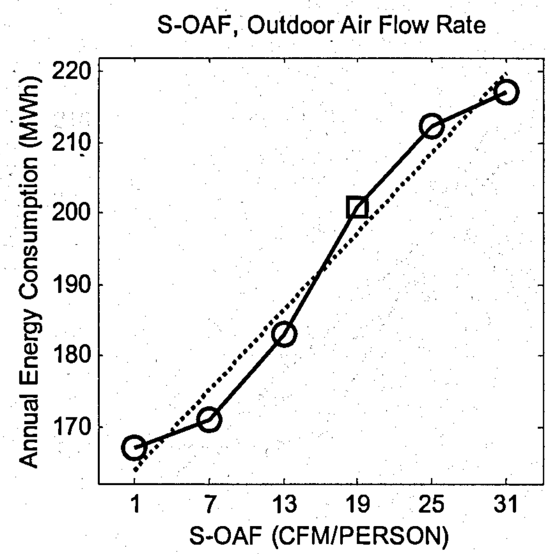

S-HSP, Heating Set Point
Annual Energy Consumption (MWh)
185
190
195
200
205
210
215
64
66
68
70
72
74
S-HSP (F)
[Sensitivity Coefficients]
SC1 = 3.2167
SC2 = 1.0970
SC3 = 1.0892
[R2 of Regression]
Linear = 0.9371


S-TST, Thermostat Type
Annual Energy Consumption (MWh)
200
202
204
206
208
210
212
1
2
3
S-TST
[Sensitivity Coefficients]
SC1 = 5.9295
SC2 = 0.0578
SC3 = 0.0295
[R2 of Regression]
Linear = 0.7962
[S-TST]
1 = PROPORTIONAL
2 = TWO-POSITION
3 = REVERSE-ACTION



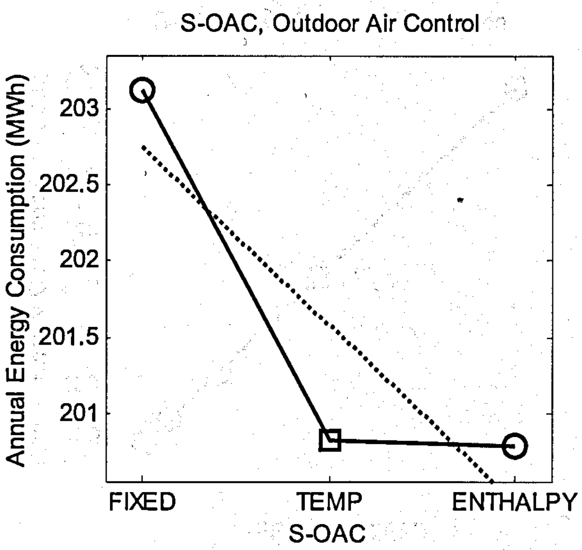
[Sensitivity Coefficients]
SC1 = -0.3790
SC2 = -0.0029
SC3 = -0.0038

[R^2 of Regression]
Linear = 0.9695



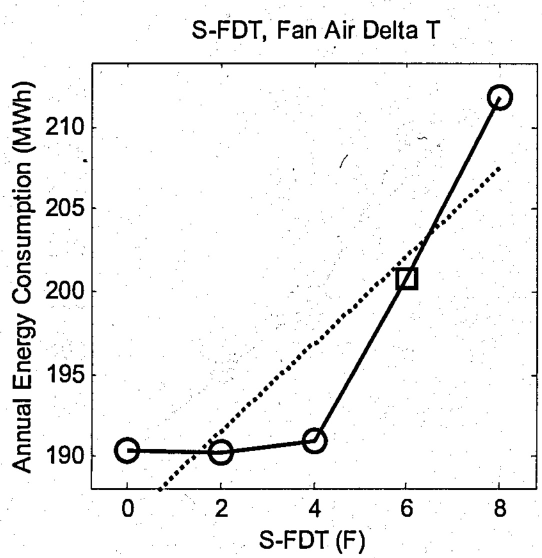
[Sensitivity Coefficients]
SC1 = 1.8681
SC2 = 0.1558
SC3 = 0.1767

[R^2 of Regression]
Linear = 0.9691



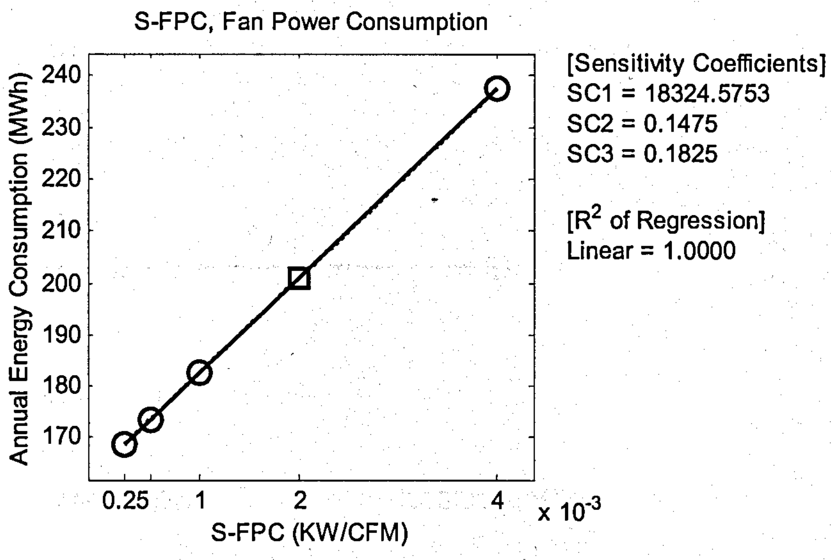
[Sensitivity Coefficients]
SC1 = -1.1625
SC2 = -0.0115
SC3 = -0.0116

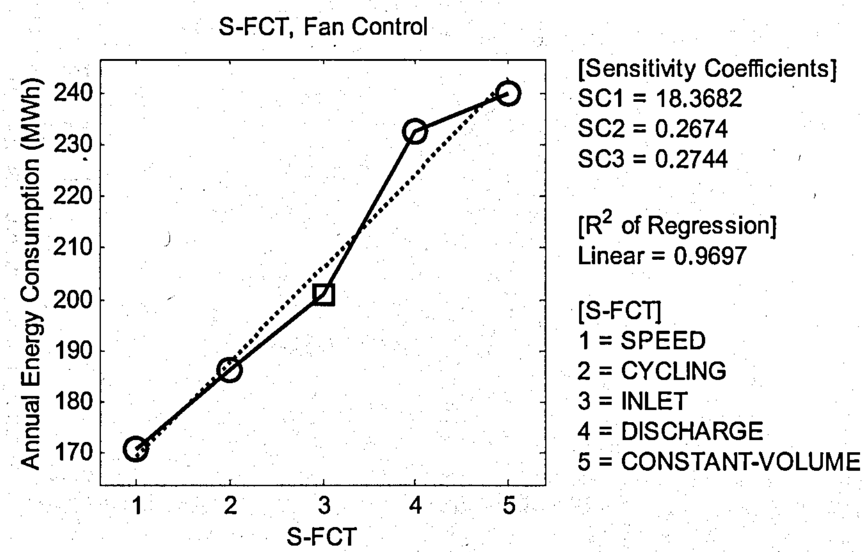
[R^2 of Regression]
Linear = 0.7629

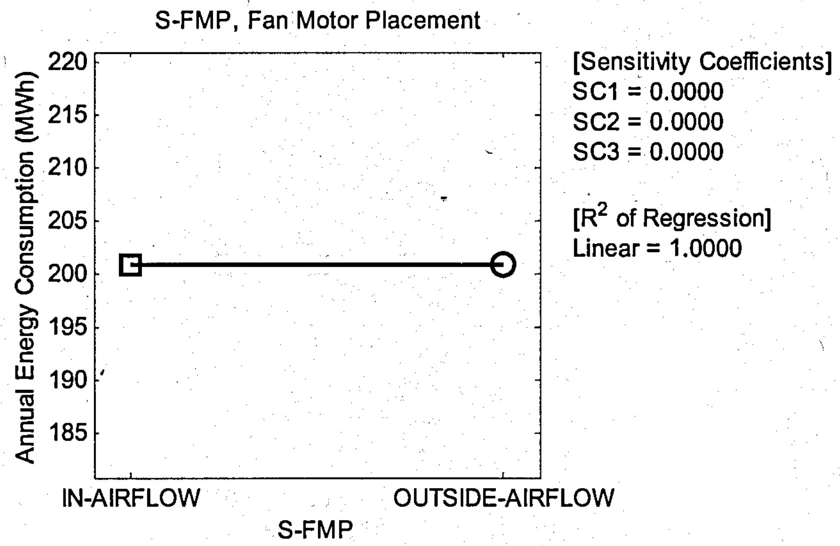


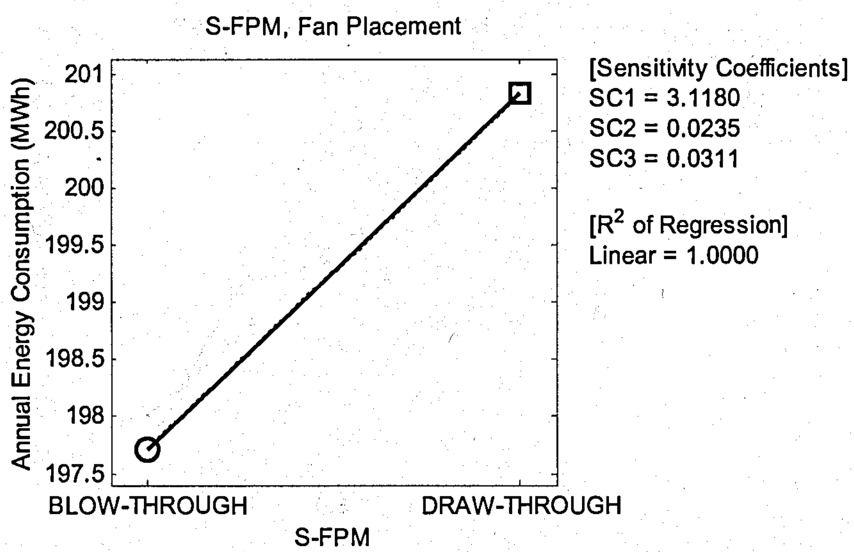
[Sensitivity Coefficients]
SC1 = 2.6660
SC2 = 0.0542
SC3 = 0.0796

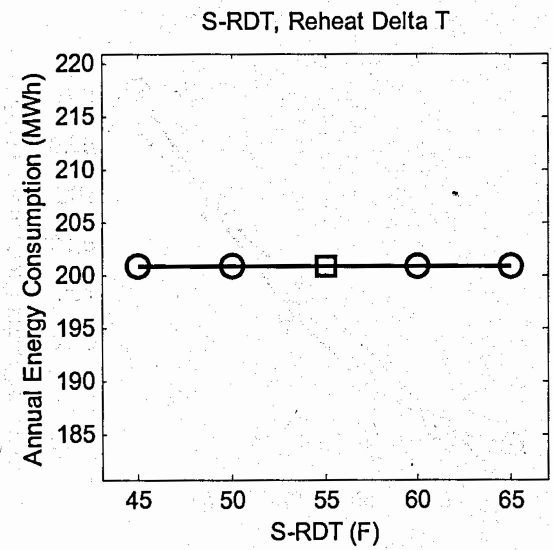
[R^2 of Regression]
Linear = 0.7953


S-FPC, Fan Power Consumption
Annual Energy Consumption (MWh)
240
230
220
210
200
190
180
170
0.25
1
2
4
x 10-3
S-FPC (KW/CFM)
[Sensitivity Coefficients]
SC1 = 18324.5753
SC2 = 0.1475
SC3 = 0.1825
[R2 of Regression]
Linear = 1.0000


S-FCT, Fan Control
Annual Energy Consumption (MWh)
240
230
220
210
200
190
180
170
1
2
3
4
5
S-FCT
[Sensitivity Coefficients]
SC1 = 18.3682
SC2 = 0.2674
SC3 = 0.2744
[R2 of Regression]
Linear = 0.9697
[S-FCT]
1 = SPEED
2 = CYCLING
3 = INLET
4 = DISCHARGE
5 = CONSTANT-VOLUME

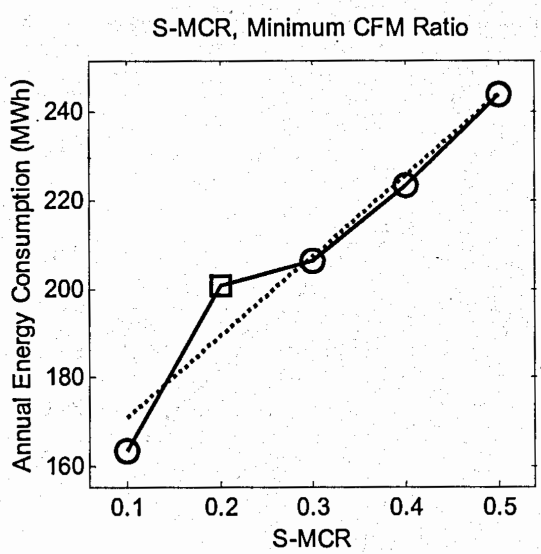

S-FMP, Fan Motor Placement
Annual Energy Consumption (MWh)
220
215
210
205
200
195
190
185
IN-AIRFLOW
OUTSIDE-AIRFLOW
S-FMP
[Sensitivity Coefficients]
SC1 = 0.0000
SC2 = 0.0000
SC3 = 0.0000
[R2 of Regression]
Linear = 1.0000


S-FPM, Fan Placement
Annual Energy Consumption (MWh)
201
200.5
200
199.5
199
198.5
198
197.5
BLOW-THROUGH
DRAW-THROUGH
S-FPM
[Sensitivity Coefficients]
SC1 = 3.1180
SC2 = 0.0235
SC3 = 0.0311
[R2 of Regression]
Linear = 1.0000



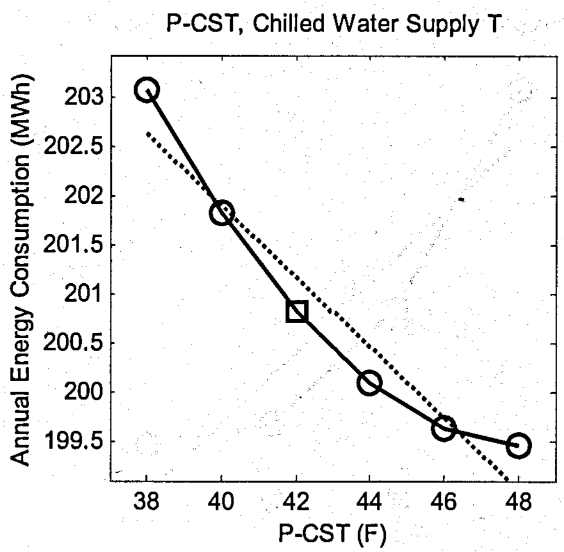
[Sensitivity Coefficients]
SC1 = 0.0000
SC2 = 0.0000
SC3 = 0.0000

[R^2 of Regression]
Linear = 1.0000



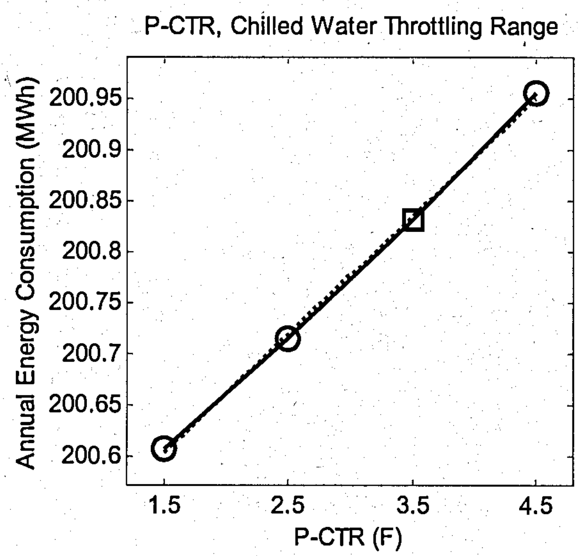
[Sensitivity Coefficients]
SC1 = 182.1820
SC2 = 0.2634
SC3 = 0.1814

[R^2 of Regression]
Linear = 0.9441



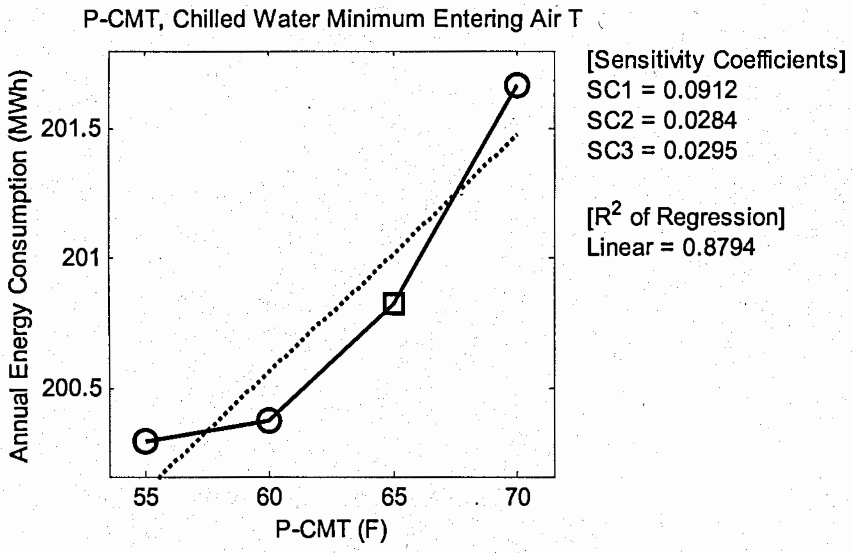
[Sensitivity Coefficients]
SC1 = -0.3617
SC2 = -0.0774
SC3 = -0.0756

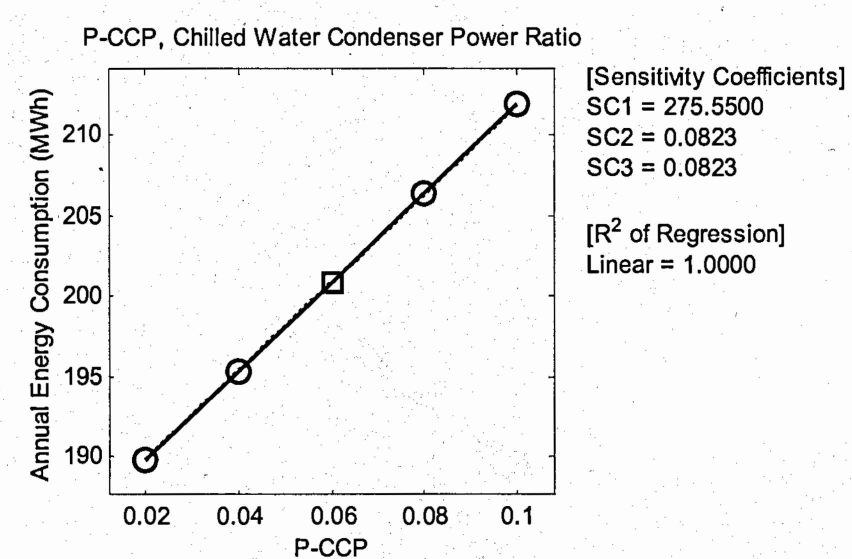
[R^2 of Regression]
Linear = 0.9305

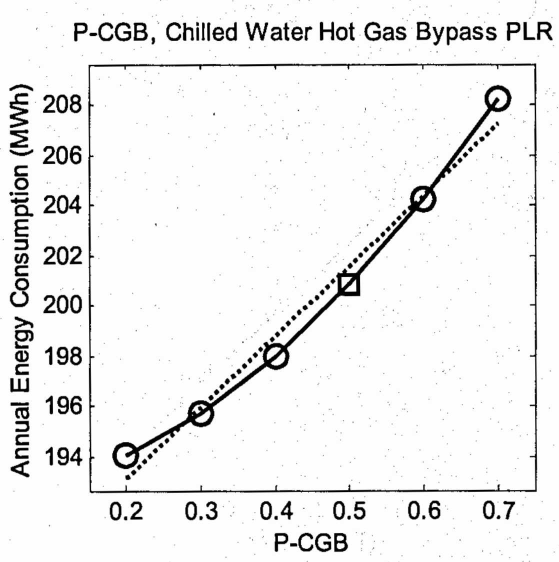


[Sensitivity Coefficients]
SC1 = 0.1157
SC2 = 0.0017
SC3 = 0.0020

[R^2 of Regression]
Linear = 0.9989

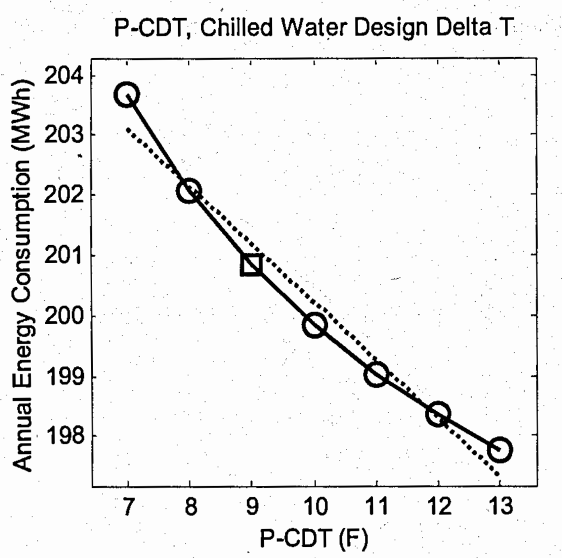

P-CMT, Chilled Water Minimum Entering Air T
Annual Energy Consumption (MWh)
201.5
201
200.5
55
60
65
70
P-CMT (F)
[Sensitivity Coefficients]
SC1 = 0.0912
SC2 = 0.0284
SC3 = 0.0295
[R2 of Regression]
Linear = 0.8794


P-CCP, Chilled Water Condenser Power Ratio
Annual Energy Consumption (MWh)
210
205
200
195
190
0.02
0.04
0.06
0.08
0.1
P-CCP
[Sensitivity Coefficients]
SC1 = 275.5500
SC2 = 0.0823
SC3 = 0.0823
[R2 of Regression]
Linear = 1.0000



[Sensitivity Coefficients]
SC1 = 28.2314
SC2 = 0.0635
SC3 = 0.0703

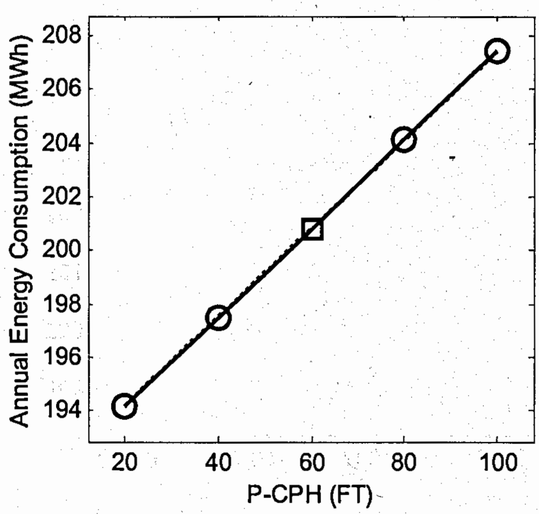
[R^2 of Regression]
Linear = 0.9784



[Sensitivity Coefficients]
SC1 = -0.9620
SC2 = -0.0480
SC3 = -0.0431

[R^2 of Regression]
Linear = 0.9688

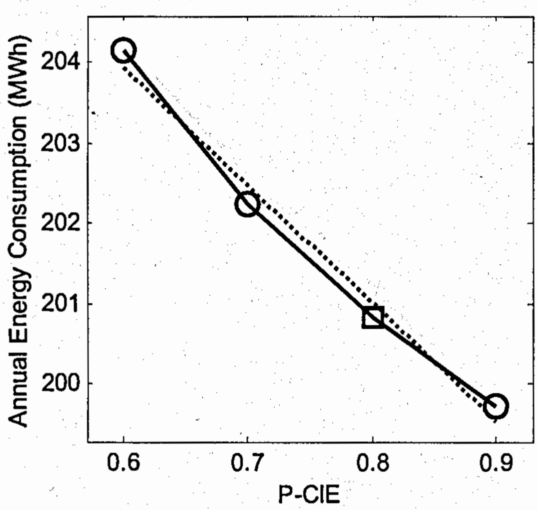
P-CPH, Chilled Water Pump Head



[Sensitivity Coefficients]
SC1 = 0.1655
SC2 = 0.0494
SC3 = 0.0494

[R^2 of Regression]
Linear = 1.0000

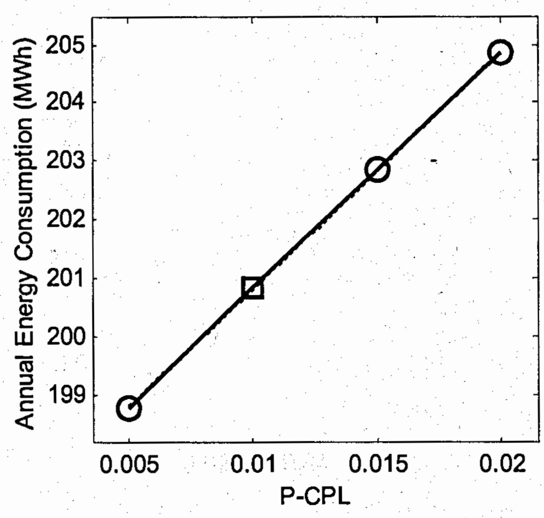
P-CIE, Chilled Water Pump Impeller Efficiency



[Sensitivity Coefficients]
SC1 = -14.6450
SC2 = -0.0544
SC3 = -0.0583

[R^2 of Regression]
Linear = 0.9857

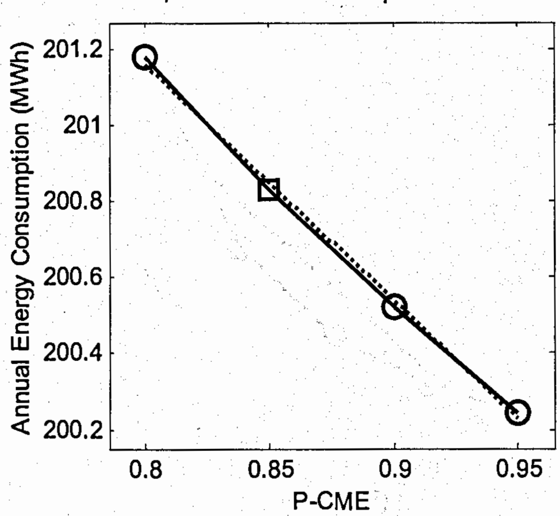
P-CPL, Chilled Water Fraction of Pump Loss



[Sensitivity Coefficients]
SC1 = 404.3600
SC2 = 0.0250
SC3 = 0.0201

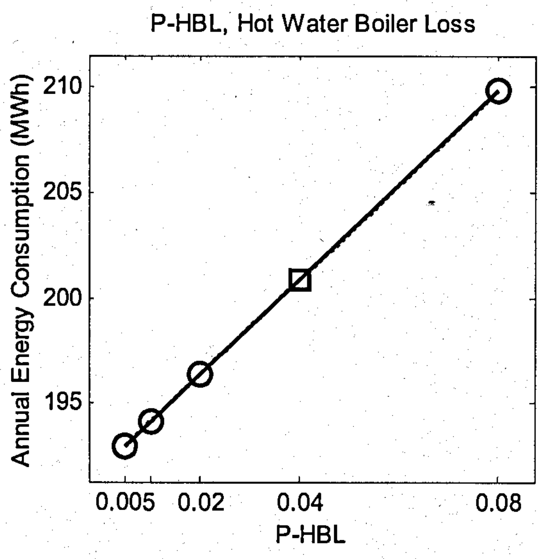
[R^2 of Regression]
Linear = 1.0000

P-CME, Chilled Water Pump Motor Efficiency



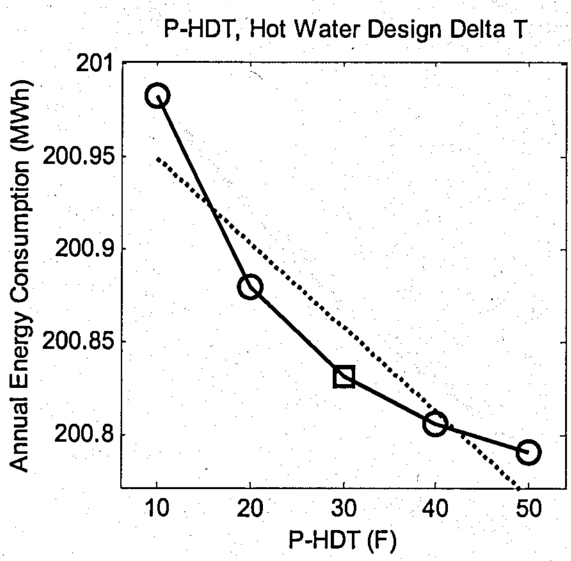
[Sensitivity Coefficients]
SC1 = -6.2220
SC2 = -0.0271
SC3 = -0.0263

[R^2 of Regression]
Linear = 0.9975



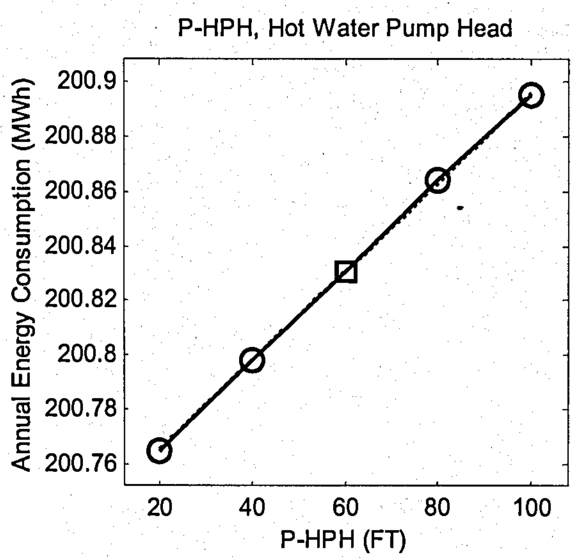
[Sensitivity Coefficients]
SC1 = 223.9868
SC2 = 0.0349
SC3 = 0.0446

[R^2 of Regression]
Linear = 1.0000



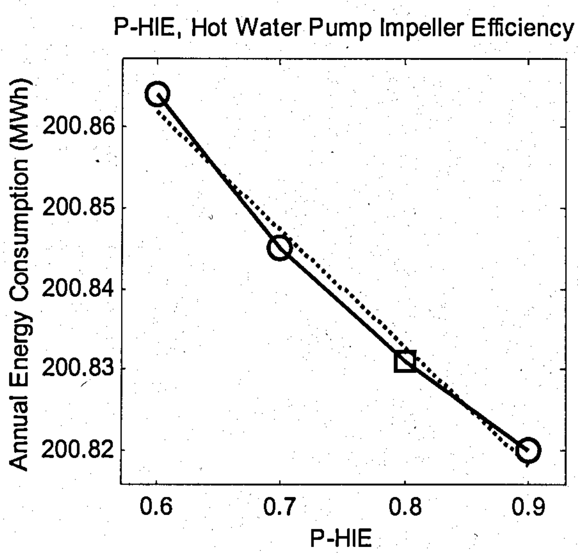
[Sensitivity Coefficients]
SC1 = -0.0045
SC2 = -0.0007
SC3 = -0.0007

[R^2 of Regression]
Linear = 0.8721



[Sensitivity Coefficients]
SC1 = 0.0016
SC2 = 0.0005
SC3 = 0.0005

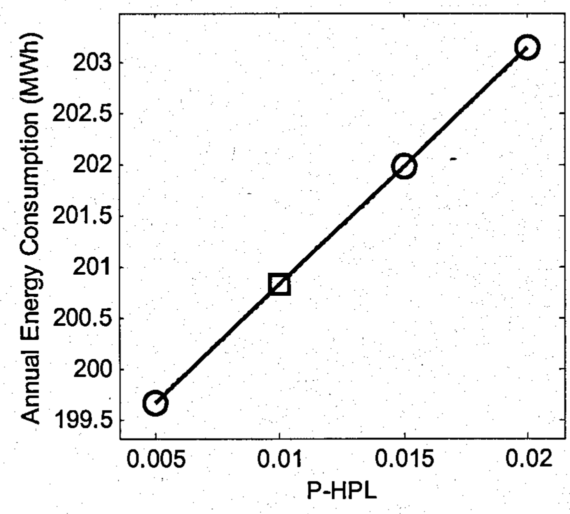
[R^2 of Regression]
Linear = 0.9998



[Sensitivity Coefficients]
SC1 = -0.1460
SC2 = -0.0005
SC3 = -0.0006

[R^2 of Regression]
Linear = 0.9850

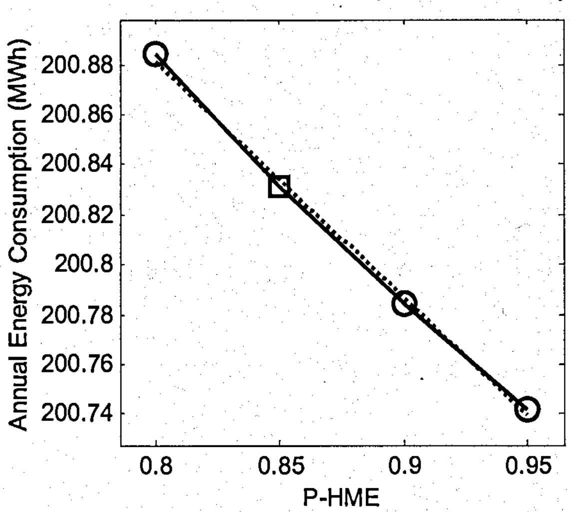
P-HPL, Hot Water Fraction of Pump Loss



[Sensitivity Coefficients]
SC1 = 231.4000
SC2 = 0.0144
SC3 = 0.0115

[R^2 of Regression]
Linear = 1.0000

P-HME, Hot Water Pump Motor Efficiency



[Sensitivity Coefficients]
SC1 = -0.9460
SC2 = -0.0041
SC3 = -0.0040

[R^2 of Regression]
Linear = 0.9973