"ANN" - ARTIFICIAL NEURAL NETWOKS AND FUZZY LOGIC MODELS FOR COOLING LOAD PREDICTION

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ABSTRACT

In this thesis Artificial Neural Networks (ANN) and fuzzy logic models of the building energy use predictions were created. Data collected from a Hawaian 42 storey commercial building chiller plant power consumption and independent hourly climate data were obtained from the National Climate Data Center of the USA. These data were used in both ANN and the fuzzy model setting up and testing. The tropical climate data consisted of dry bulb temperature, wet bulb temperature, dew point temperature, relative humidity percentage, wind speed and wind direction.Both input variables and the output variable of the central chiller plant power consumption were fuzzified, and fuzzy membership functions were employed. The Mamdani fuzzy rules (32 rule) in If –Then format with the centre of gravity (COG; centroid) defuzzification were employed. The average percentage error levels in the fuzzy model and the ANN model were end up with 11.6% (R^2=0.88) and 10.3% (R^2=0.87), respectively. The fuzzy model is successfully presented for predicting chiller plant energy use in tropical climates with small seasonal and daily variations that makes this fuzzy model.

ÖZET

Bu tezde binalarda enerji kullanımını tahmin etmek amacıyla yapay sinir ağları ve bulanık mantık modelleri oluşturulmuştur. Veriler Amerika Birleşik Devletleri (ABD), Hawaii'de bulunan 42 katlı bir ticari binanın soğutma sisteminden soğutucu yükü toplanarak ve bağımsız saatlik iklim verileri ABD'nin ulusal klima data merkezinden sağlanmıştır. Bu data her iki yapay sinir ağları (YSA) ve bulanık mantık modelleri için eğitme ve test etme amaçlı kullanılmıştır. Tropikal klima datası kuru termometre sıcaklığı, yaş termometre sıcaklığı, çiğ noktası sıcaklığı, bağıl nem yüzdesi, rüzgar hızı ve rüzgar yönünden meydana gelir. Hem girdi değişkenleri hem de çıktı değişkeni olan merkezi chiller yük tüketimi yapay sinir ağları kullanılarak bulanıklaştırıldı ve bulanık üyelik fonksiyonları uygulandı. Eğer-o zaman yapısındaki Mamdani bulanık kurallarına (32 kural) ağırlık merkezi durulaştırması uygulandı. Bulanık modelin ortalama yüzde hata seviyesi % 11.6 (R^2=0.88) ile yapay sinir ağları modelinin ortalama yüzde hata seviyesi % 10.3 (R^2=0.87) olarak gerçekleşti. Chiller'ın küçük mevsimsel ve günlük değişiklikler gösterdiği tropik iklimlerde enerji kullanımının Bulanık model ile tahminlenmesi bu çalışmada başarıyla gösterilmiştir.

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CHAPTER 1

INTRODUCTION

Artificial intelligence (AI) methods, including neural networks, fuzzy logic and genetic algorithms, have been finding applications in building engineering since the past decade. A review study by (Krarti 2003) describes artificial intelligence methods and provides example uses in the building engineering. The most common applications of AI are building energy usage prediction and forecasting, HVAC controls, and system modeling. The building energy use prediction and forecasting are mostly based on artificial neural networks (Yalcintas and Akkurt 2005). Fuzzy logic based methods and genetic algorithms are more often used in HVAC controls and fault diagnosis (Guillemin 2002). While earlier system modeling studies used artificial neural networks, recent studies use fuzzy logic or neural fuzzy networks (Kesgin and Heperken 2005).

A building energy usage is generally expressed as a function of weather, occupancy and time variables. In the past, various neural network architectures have been applied in whole building energy predictions including backpropagation, recurrent neural networks, autoassociative neural networks, and general regression neural network with relatively successful results having coefficient of variations in the range of 2% to 40% (Haberl and Thamilseran 1996). These variations in the accuracy of the predictions depend mostly on the ANN architecture used, the regularity of the building operation, and the accuracy of data measurement devices.

An ANN model based on backpropogation algorithm was developed by (Yalcintas and Akkurt 2005). The model predicted a Honolulu high rise building's chiller plant power consumption. The model correlation coefficient was 0.88, which is a very good indication of the predictive power of the ANN. Another significance of this study was to do with the tropical climate content of the building data used in the model. The current study deals with modeling the same chiller plant power consumption based on fuzzy logic. To the authors knowledge, up to date there is no modeling study for the building energy prediction based on fuzzy logic method. Thus, this study presents the applicability and potential use of the fuzzy logic method for building energy prediction.

One particular use of building energy prediction is estimation of energy savings due to an equipment retrofit in an existing building. The main challenge in predicting the energy savings due to equipment retrofit lies in identifying the comparative data after an equipment replacement/retrofit. The variations in weather, building internal loads such as occupancy, lighting and miscellaneous loads, and HVAC equipment operation schedules make the building energy use dependent upon the variability of these parameters. This situation disqualifies the building energy measurements in the pre-retrofit period from being accurately compared to the actual energy use measurement in the post-retrofit period in determining the energy savings. This disqualification, along with the limitations in linear regression methods that are most commonly used in processing the measured data, causes large variations between the estimated energy savings and the actual energy savings of an equipment retrofit. Thus, there is a significant need for a better method which can effectively predict the energy savings of a retrofit. In this regard, Artificial Neural Networks (ANN) or fuzzy logic method can be an effective method to fulfill this need with much better accuracy. The fuzzy logic method developed in this study, and the ANN method presented by (Yalcintas and Akkurt 2005) illustrate the potential capacity of these methods in accurate energy savings estimates.

The building that was studied in this thesis is located in Honolulu, Hawaii which is situated in tropical climate where variations between the day and night and summer and winter are minimal. The building is a 42 storey high-rise building which is air conditioned by a central chilled water plant consisting of three chillers with a total 1250-ton capacity. The chiller plant data collected from the building were augmented with meteorological data to create ANN and Fuzzy logic models.

The thesis is composed of six chapters the second of which explains the parameters studied in model construction like the HVAC (heating ventilation and air conditioning) parameters.

The third chapter presents computational details of the ANN and fuzzy logic methods. Fourth chapter discusses the previous ANN and fuzzy logic modeling studies related to HVAC systems. In chapter five the ANN and Fuzzy logic model construction work performed in this thesis is presented. The final sixth chapter lists the conclusions.

CHAPTER 2

DEFINING MODEL PARAMETERS

2.1. Ventilation Systems

There are significant spatial and seasonal variations in the volume of air delivered by most Heating, Ventilation, and Air Conditioning (HVAC) Systems. HVAC operators must understand the variations to know how to provide occupants with adequate fresh air in all spaces throughout the year. The ventilation features most important to an intelligent air control are the way in which supply air volume is controlled, and the way in which outdoor air delivery is controlled.

In most HVAC systems a portion of ventilation air supplied to occupied spaces is fresh air and a portion is recirculated air. The Variable Air Volume (VAV) system is a mechanical system that circulates a mixture of fresh and conditioned air throughout the occupied spaces of a building to maintain comfort. Variations in the thermal requirements of a space are satisfied by varying the volume of air that is delivered to the space at a constant temperature (WEB_4 2005). The total volume of air is important for two reasons:

- Air movement contributes to thermal comfort. The lack of air movement can create a sensation of hot/stuffy air.
- In many VAV systems, outdoor air is a constant fraction of the total supply air. Thus, the total volume of outdoor air depends on both the outdoor air fraction, and the supply air volume.

There are two major types of HVAC systems based upon the use of airflow to control temperature the Constant Volume (CV) system, and the Variable Air Volume (VAV) system.

2.1.1. Constant Volume (CV) Systems

In a Constant Volume (CV) ventilation system, variations in the thermal requirements of a space are satisfied by varying the temperature of a constant volume of air delivered to the space. A constant fraction of outdoor air will mean that a constant volume of outdoor air will be delivered to occupied spaces. This volume can be set to satisfy applicable ventilation standards. CV systems are less energy efficient than VAV systems, but controls for outdoor air delivery are simpler to manage (WEB_4 2005).

2.1.2. Variable Air Volume (VAV) Systems

In a Variable Air Volume (VAV) ventilation system, variations in the thermal requirements of a space are satisfied by varying the volume of air that is delivered to the space at a constant temperature. VAV systems reduce HVAC energy cost by 10-20% over CV systems but complicate the delivery of outdoor air. If the fraction of outdoor air is constant, the total volume of outdoor air will be reduced as the supply air volume is reduced. An inadequate outdoor air fraction, combined with an inadequate VAV box minimum setting, may result in inadequate outdoor airflow to occupant spaces. This would occur during part-load conditions. VAV systems also complicate pressure relationships in the building and make testing, adjusting, and balancing more difficult.

Most of the year, the volume of outside air may be reduced to about a third of the outdoor air volume at design load. This could result in indoor air quality problems. Separate controls to ensure adequate outside air year round do not increase energy costs. Some new VAV systems incorporate these controls (WEB_4 2005).

2.1.3. Economizer

Economizers are controls of the outdoor air designed to save energy by using cool outside air as a means of cooling the indoor space. When the enthalpy of the outside air is less than the enthalpy of the recirculating air, conditioning the outside air is more energy efficient than conditioning recirculating air.

2.2. HVAC Components

Many HVAC components are particularly important to maintaining good an intelligent air control. Tips for optimum functionality of HVAC components are described next.

2.2.1. Coils and Drain Pans

- Malfunctioning coils, including dirty coils, can waste energy and cause thermal discomfort. Leaky valves that allow hot or chilled water through the coil when there is no demand waste energy and create thermal discomfort.
- Cooling coils dehumidify the air and cause condensate water to drip into a drain pan and exit via a deep seal trap.
- Standing water will accumulate if the drain pan is not properly designed and maintained, creating a microbial habitat. Proper sloping and frequent cleaning of the drain pans is essential to good indoor air quality.

2.2.2. Humidification and Dehumidification Equipment

- Potable water rather than boiler water should be used as a source of steam to avoid contaminating the indoor air with boiler treatment chemicals.
- Wet surfaces should be properly drained and periodically treated as necessary to prevent microbial growth.
- Duct linings should not be allowed to become moist from water spray.

2.2.3. Outdoor Air Dampers

Screens and grilles can become obstructed. Remove obstructions, check connections, and otherwise ensure that dampers are operating to bring in sufficient outdoor air to meet design-level requirements under all operating conditions.

2.2.3.1. Air Filters

- Use filters to remove particles from the air stream.
- Filters should be replaced on a regular basis, on the basis of pressure drop across the filter, or on a scheduled basis.
- Fans should be shut off when changing the filter to prevent contamination of the air.
- Filters should fit tightly in the filter housing.
- Low efficiency filters (ASHRAE Dust Spot rating of 10%-20%), if loaded to excess, will become deformed and even “blow out”, leading to clogged coils, dirty ducts, reduced indoor air quality and greater energy use.
- Higher efficiency filters are often recommended as a cost-effective means of improving an intelligent air control performance while minimizing energy consumption. Filtration efficiency should be matched to equipment capabilities and expected airflows.

2.2.3.2. Ducts

A small amount of dust on duct surfaces is normal. Parts of the duct susceptible to contamination include areas with restricted airflow, duct lining, or areas of moisture or condensation, (WEB_3 2005). Problems with biological pollutants can be prevented by:

- Minimizing dust and dirt build-up
- Promptly repairing leaks and water damage
- Keeping system components dry that should be dry
- Cleaning components such as coils and drip pans
- Good filter maintenance
- Good housekeeping in occupied spaces.

Duct leakage can cause or exacerbate air quality problems and waste energy. Sealed duct systems with a leakage rate of less than 3% will usually have a superior life cycle cost and reduce problems associated with leaky ductwork. Common problems include:

- Leaks around loose fitting joints.
- Leaks around light Troffer-type diffusers at the diffuser light fixture interface when installed in the return plenum.
- Leaks in return ducts, in unconditioned spaces or underground can draw contaminants from these spaces into the supply air system.

2.2.4. Exhaust Systems

In general, slightly more outdoor air should be brought into the building than the exhaust air and relief air of the HVAC system. This will ensure that the building remains under slight positive pressure, (WEB_3 2005).

- Exhaust should be located as close to the source as possible.
- Fan should draw sufficient air to keep the room in which the exhaust is located under negative pressure relative to the surrounding spaces, including wall cavities and plenums.
- Air should flow into, but not out of, the exhaust area, which may require panels in doors or walls to provide an unobstructed pathway for replacement air.
- The integrity of walls and ceilings of rooms to be exhausted must be well maintained to prevent contaminated air from escaping into the return air plenum.
- Provisions must be made for replacing all air exhausted out of the building with make-up outside air.

2.2.5. VAV Boxes

In a VAV system, a VAV box in the occupied space regulates the amount of supply air delivered to the space, based on the thermal needs of the space. Malfunctioning VAV boxes can result in thermal discomfort and fail to prevent buildup of indoor air contaminants. It is important to insure that VAV box minimum settings (e.g., 30% of peak flow) combined with the outdoor air fraction provide enough supply air so that sufficient outdoor air enters the space at partial loads.

2.2.6. Cooling Towers

Water is a convenient incubator for microbial growth, with potentially fatal consequences, such as Legionnaires Disease, for building occupants. Periodically monitoring water quality and chemical treatment to prevent microbial growth is essential. Physical cleaning to prevent sediment accumulation and installation of drift eliminators may also be necessary.

2.2.7. Boilers

Fossil fuel combustion boilers provide the potential for contamination with carbon monoxide or other combustion by-products.

- Maintain gaskets and breaching to prevent carbon monoxide from escaping.
- Maintain the room in which the boiler is located under sufficient positive pressure relative to the outside to prevent back drafting of flue gases. Back drafting occurs when flue gases fail to be drawn up the flue and spill out into the room. Provide combustion air directly from the outside to prevent back drafting. A smoke tube can be used to check for back drafting.
- Provide high enough exhaust stacks to prevent re-entrainment into the building, and maintain fuel lines to prevent leaks.

2.3. Control of Temperature and Relative Humidity

The thermal requirements of the space are designed to provide thermal comfort to occupants during all hours of occupancy. Requirements for temperature, relative humidity, and air movement during all seasons should be established and monitored to ensure that thermal comfort requirements are met, (Kreider et al. 2002).

2.3.1. ASHRAE Thermal Comfort Requirements

ASHRAE Standard 55-1992 (ASHRAE STANDART 1992), Thermal Environmental Conditions for Human Occupancy, identifies many factors that influence thermal comfort and the perception of thermal conditions. Among them are temperature, radiation, humidity, air movement, vertical and horizontal temperature differences, temperature drift, personal activity and clothing.

As a practical matter, maintaining a building within the following ranges of temperature and relative humidity will satisfy thermal comfort requirements of this standard in most cases. The ASHRAE comfort chart in Table 2.1 indicates the acceptable ranges of operative temperature and humidity during light sedentary activity, assuming typical summer or winter clothing, respectively.

Table 2.1. Optimal operative temperature and humidity ranges

Measurement Type	Winter	Summer
Dry Bulb at 30% RH	20.3°C – 24.4°C	23.3°C – 26.7°C
Dry Bulb at 50% RH	20.3°C – 23.6°C	22.8°C – 26.1°C
Wet bulb maximum	17.8°C	20°C
Relative humidity *	30% - 60%	30% - 60%
* Upper bound of 50% RH will also control dust mites.		

2.3.1.1. Humidity and Microbial Growth

In addition to thermal comfort, the control of relative humidity is important to limit the growth of microorganisms such as mold and dust mites. To control microorganisms, it is best to keep relative humidity below 60% (to control mold) and 50% (to control dust mites) at all times, including unoccupied hours. High relative humidity can foster proliferation of mold and dust mites.

2.4. Dry bulb Temperature

The dry bulb temperature is the temperature of air measured by a thermometer freely exposed to the air but shielded from radiation and moisture. In construction, it is an important consideration when designing a building for a certain climate. Nall (Nall 2004), (as cited in "References") called it one of "the most important climate variables for human comfort and building energy efficiency".

2.5. Wet Bulb Temperature

The wet bulb temperature also uses a standard thermometer; however, a wet piece of cloth covers the bulb of the thermometer. As air passes over the wet cloth, the water in the cloth evaporates, drawing heat out of the thermometer.

If the air is very humid (moist), only a small amount of moisture will evaporate from the cloth. This means the wet bulb temperature will only be a little lower than the dry bulb temperature.

Conversely, if the humidity of the air is low (dry), the moisture will evaporate from the cloth quickly. This means that the wet bulb temperature will be much lower than the dry bulb temperature.

If it is raining or there is heavy fog, the air is saturated, and the dry bulb temperature will be equal to the wet bulb temperature, (WEB_2 2005).

2.6. Dew Point Temperature

The dew point or dew point of a given parcel of air is the temperature to which the parcel must be cooled, at constant barometric pressure, for the water vapor component to condense into water, called dew. When the dew point temperature falls below freezing it is called the frost point, instead creating frost or hoar frost by deposition.

With higher temperatures the equilibrium partial pressure of water vapor increases thus more water evaporates. The behavior of water vapor does not depend on the presence of air. The formation of dew would occur at the dew point even if the only gas present was water vapor.

The dew point determines relative humidity. When the relative humidity is high, the dew point is closer to the current air temperature. If the relative humidity is 100%, the dew point will be equal to the current temperature. As relative humidity falls, the dew point becomes lower, given the same air temperature.

Humans tend to react with discomfort to high dewpoints. Those accustomed to continental climates often begin to feel discomfort when the dew point reaches between 15° and 20° C (59° and 68° F). Most inhabitants of these areas will consider dewpoints above 21° (70° F) to be oppressive. Some consider a dewpoint above 10° C (50° F) to be uncomfortable, (WEB_1 2005)

2.7. Relative Humidity

Relative humidity is the ratio of the current vapor pressure of water in any gas (especially air) to the equilibrium vapor pressure, at which the gas is called saturated at the current temperature, expressed as a percentage. Equivalently, it is the ratio of the current mass of water per volume of gas and the mass per volume of a saturated gas. The saturation vapor pressure is the vapor pressure of water when air is saturated with water (having the maximum amount of water vapor that air can hold for a given temperature and pressure), (WEB_1 2005).

2.8. Wind Speed

Wind speed is the speed of movement of air relative to a fixed point on the earth. It usually means the movement of air in an outside environment, but the speed of movement of air inside a building or structure may also be referred to as “wind speed”.

Wind speed is important in many areas, including weather forecasting, aircraft and maritime operations, building and civil engineering. High wind speeds can cause unpleasant side effects, and strong winds often have special names, including gales, hurricanes, and typhoons. Wind speed can affect sporting achievements either beneficially or adversely. Most outdoor sports have limits of wind speed outside of which records are considered invalid, (WEB_1 2005).

2.9. Wind Direction

The direction from which the wind is blowing. For example, an easterly wind is blowing from the east, not toward the east. It is reported with reference to true north, or 360 degrees on the compass, and expressed to the nearest 10 degrees, or to one of the 16 points of the compass (N, NE, WNW, etc.), (WEB_1 2005).

2.10. Total Building Chiller Power Consumption

A Chiller is an air conditioning unit used primarily in commercial and industrial facilities to provide high capacity HVAC control. A Chiller differs from common air conditioners in both capacity and design. A typical Chiller is rated between 15 to 1000 tons (180,000 to 12,000,000 BTU*) or more in cooling capacity. It also incorporates features such as screw-driven compressors and water-cooled condensors. The power consumption refers to the electrical energy over time that must be supplied to a chiller to maintain its operation. (* 1000 BTU/h is approximately 293 W).

If the building is electrically cooled but not electrically heated, as is the case with our prototypical building, the maximum power corresponds to the hottest drybulb temperatures. This temperature dependence, with power use increasing with outdoor temperature, cooling system power is highly dependent on outdoor temperature. But it also depends on building loads, such as solar loads, lighting and appliance use, and people. In general, the load is met by a single chiller at low outdoor temperatures, and by both chillers at high outdoor temperatures. Wind speed is another weather-dependent variable that has a bearing on loads (Kreider 2002).

CHAPTER 3

NEURAL NETWORKS AND FUZZY LOGIC

Artificial intelligence is separated into two significant concepts; ANNs and fuzzy logic. Both ANNs and fuzzy logic is proved to be useful in modeling and simulation of a system, with one or more variables.

3.1 Artificial Neural Networks (ANN)

ANN is one of the powerful data modeling tools motivated from the operation of human nervous system. Therefore, ANN became the most important tool to solve complex problems by using networks. Networks are used to model a wide range of phenomena in physics, computer science, biochemistry, etiology, mathematics, sociology, economics, telecommunications, and many other areas.

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron is a computational model inspired in the natural neurons. Natural neurons receive signals through *synapses* located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal though the *axon*. Figure 3.1 shows basic architecture of the network that consist of dendrites, axon and synapse.This signal might be sent to another synapse, that might activate other neurons.

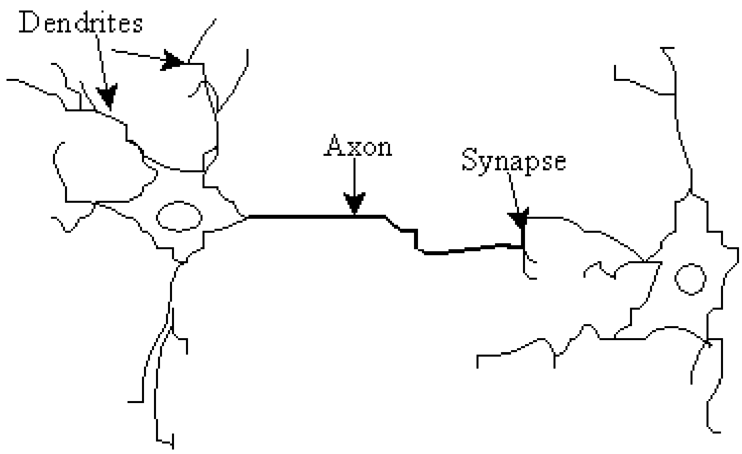

Figure 3.1. Natural neurons.

The complexity of real neurons is highly abstracted when modeling artificial neurons. These basically consist of *inputs* (like synapses), which are multiplied by *weights* (strength of the respective signals), and then computed by a mathematical function which determines the *activation* of the neuron. Another function (which may be the identity) computes the *output* of the artificial neuron (sometimes in dependence of a certain *threshold*). ANNs combine artificial neurons as shown in Figure 3.2 in order to process information.

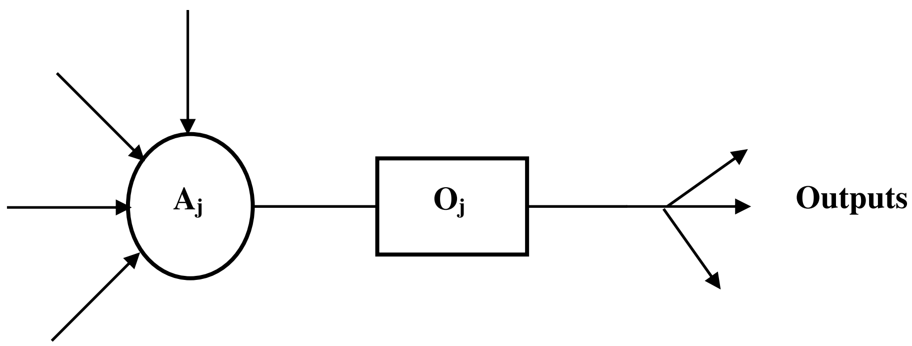

Figure 3.2. An artificial neuron, $A_{j:}$ activation function, $O_{j:}$ output function.

The higher the weight of an artificial neuron is, the stronger the input that is multiplied by it will be. Weights can also be negative, so we can say that the signal is *inhibited* by the negative weight. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron we can obtain the output we want for specific inputs. But when we have an ANN of hundreds or thousands of neurons, it would be quite complicated to find by hand all the necessary weights. But we can find algorithms, which can adjust the weights of the ANN in order to obtain the desired output from the network. This process of adjusting the weights is called *learning* or *training*. The simple form of network architecture is given below Figure 3.3 :

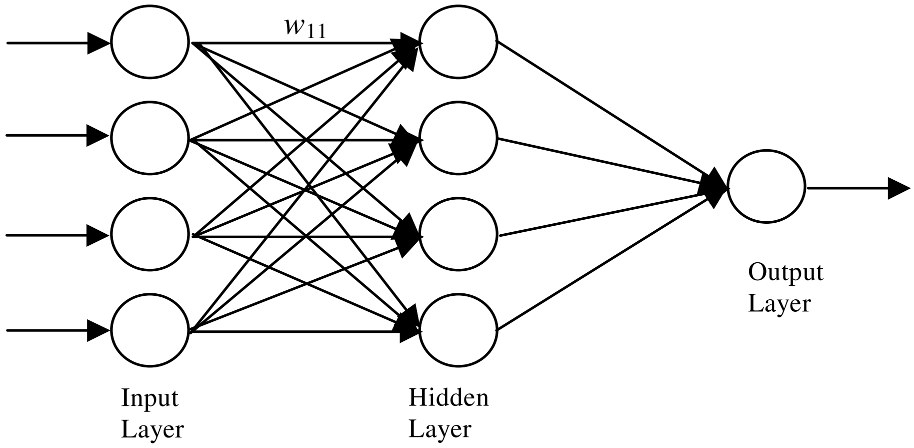

Figure 3.3. A simple form of neural network architecture with four input parameters,four hidden layer neurons and one output parameter. (4x4x1 layer)

The number of types of ANNs and their uses is very high. Since the first neural model by (McCulloch and Pitts 1943) there have been developed hundreds of different models considered as ANN. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. Also there are many hybrid models where each neuron has more properties than the ones we are reviewing here. Because of matters of space, we will present only an ANN, which learns using the backpropagation algorithm (Rumelhart and McClelland 1986) for learning the appropriate weights, since it is one of the most common models used in ANNs, and many others are based on it.

Since the function of ANN is to process information, they are used mainly in fields related with it. There are a wide variety of ANN that are used to model real neural networks, and study behaviour and control in animals and machines, but also there are

ANN that are used for engineering purposes, such as pattern recognition, forecasting, and data compression.

3.1.2 The Backpropagation Algorithm

The backpropagation algorithm (Rumelhart and McClelland 1986) is used in layered feed-forward ANN. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an *output layer*. There may be one or more intermediate *hidden layers*. The backpropagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the backpropagation algorithm is to reduce this error, until the ANN *learns* the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal.

The activation function of the artificial neurons in ANNs implementing the backpropagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their respective weights w_{ji}):

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \tag{3.1}$$

We can see that the activation depends only on the inputs and the weights.

If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoidal function:

$$O_j(\bar{x}, \bar{w}) = \frac{1}{1 + e^{A_j(\bar{x}, \bar{w})}} \tag{3.2}$$

The sigmoidal function is very close to one for large positive numbers, 0.5 at zero, and very close to zero for large negative numbers. This allows a smooth transition between the low and high output of the neuron (close to zero or close to one). We can see that the output depends only in the activation, which in turn depends on the values of the inputs and their respective weights.

Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual and the desired output, the error depends on the weights, and we need to adjust the weights in order to minimize the error. We can define the error function for the output of each neuron:

$$E_j(\bar{x}, \overline{w}, d) = (O_j(\bar{x}, \overline{w}) - d_j)^2 \quad (3.3)$$

We take the square of the difference between the output and the desired target because it will be always positive, and because it will be greater if the difference is big, and lesser if the difference is small. The error of the network will simply be the sum of the errors of all the neurons in the output layer:

$$E(\bar{x}, \overline{w}, \bar{d}) = \sum_j (O_j(\bar{x}, \overline{w}) - d_j)^2 \quad (3.4)$$

The backpropagation algorithm now calculates how the error depends on the output, inputs, and weights. After we find this, we can adjust the weights using the method of gradient descendent:

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \quad (3.5)$$

This formula can be interpreted in the following way: the adjustment of each weight (Δw_{ji}) will be the negative of a constant eta (η) multiplied by the dependance of the previous weight on the error of the network, which is the derivative of E in respect to w_i. The size of the adjustment will depend on η, and on the contribution of the weight to the error of the function. This is, if the weight contributes a lot to the error, the adjustment will be greater than if it contributes in a smaller amount. Equation 3.5 is used until we find appropriate weights (the error is minimal).

3.2. Fuzzy Logic

(Zadeh 1975) proposed his theory of approximate reasoning by means of which a powerful technique for reasoning of imprecise and uncertain information was provided. The general structure of the fuzzy logic modeling is presented in Figure 3.4 According to Figure 3.4, the model basically consists of four components: fuzzification, fuzzy rule base, fuzzy output engine, and defuzzification. Fuzzification converts each piece of input data to degrees of membership by lookup in one or more several membership functions. The key idea in fuzzy logic is allowance of partial belongings of any object to different subsets of a universal set instead of complete membership to a single set. The membership function (MF) helps the partial belongings numerically which have values between 0 and 1. Fuzzy membership functions may take many forms; in fact in practical applications, simple linear functions, like triangular, trapezoidal ones, are preferable.

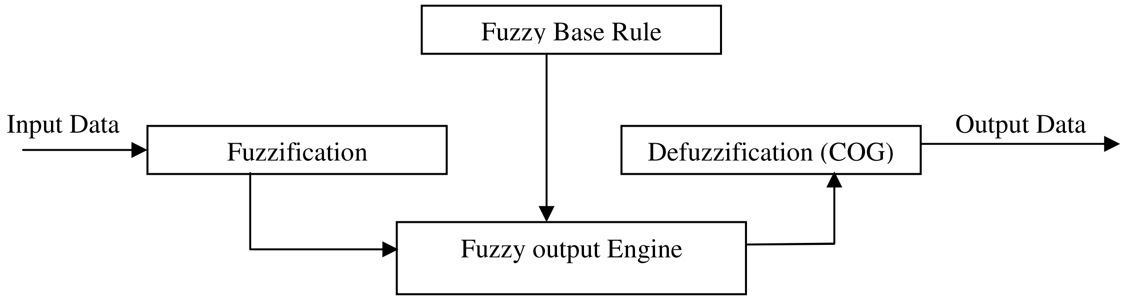

Figure 3.4 The basic structure of the fuzzy logic modeling.

The central fuzzy rule base is the concept of the fuzzy If-Then rule, which is a mathematical interpretation of the linguistic If-Then rule. The basic linguistic If-Then rule is a linguistic row, which is written, in simple form below:

If "α" is A and "β" is B, then "λ" is C

A, B and C are the corresponding linguistic values, the inputs are α, β and λ. The fuzzy rule base defines the names of variables α, β and λ with the universes in which the fuzzy values A, B and C live. In the fuzzy approach, there are no mathematical equations and model parameters, and all the uncertainties, nonlinear relationships, and model complications are included in the descriptive fuzzy inference procedure in the form of If-Then format. There are basically two types of fuzzy rules: (Jantzen 1999).

Fuzzy inference engine takes into account all the fuzzy rules in the fuzzy rule base and learns how to transform a set of inputs to corresponding outputs. There are basically two kinds of inference operators: minimization (min) and product (prod).

(Jantzen 1999) pointed out that both methods works properly in general. In this study we used the prod method due to its performance.

Membership functions are used to retranslate the fuzzy output into a crisp value. This technique is known as defuzzification and can be performed using several methods. There are many defuzzification methods such as centre of gravity (COG) or centroid, bisector area (BOA), mean of maxima (MOM), leftmost maximum (LM), rightmost maximum (RM), etc. (Jantzen 1999). In this study, we employed the most widely used centroid technique, and for the discrete case, it is expressed as:

$$K_x^* \equiv \frac{\sum_i \mu(K_{xi}) K_{xi}}{\sum_i \mu(K_{xi})} \tag{3.6}$$

Where K_x^* is the defuzzified output value, K_{xi} is the output value in the *i*th subset, and $\mu(Kxi)$ is the membership value of the output value in the *i*th subset.
If there is continuity, the summations in Equation 3.6 are changed by integrals. Further information can be obtained from Munakata (Munakata 1998).

3.2.1. Fuzzy Logic Example: One

In order to better present the fuzzy logic modeling technique an example from the literature will be helpful, (Goodrich 2001). Let's consider the problem of trying to decide whether or not to turn on the heater in an apartment. Suppose that having a thermometer that gives three readings, A = {"T < 30"; "30 ≤ T ≤ 60"; "T > 60"} where using quotation marks to indicate that these statements can be interpreted as predicates. Prefer to think of these three predicates as A = {IsCold, IsCool, NotCold}. In addition to these three input predicates, two actions available B ={HeatOn, HeatOff}. Suppose further that having a rule base that says:

Reading(a) $\Rightarrow$ *Action (b)*
T < 30 $\Rightarrow$ *HeatOn*
30 ≤ T ≤ 60 $\Rightarrow$ *HeatOn*
T > 60 $\Rightarrow$ *HeatOff*

In this case, the implies in the statement "T < 30" $\Rightarrow$ HeatOn does not mean "if T < 30 it follows logically that the heat is on" but rather "if T < 30 it follows logically from what my goals are that the heat should be turned on." In this latter case, implication is nothing more than a relation between readings and actions:

$$\begin{array}{l} \\ T < 30 \\ 30 \leq T \leq 60 \\ T > 60 \end{array} \begin{array}{c} \begin{array}{cc} \textit{HeatOn} & \textit{HeatOff} \end{array} \\ \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \end{array}$$

3.2.2. Fuzzy Logic Example: Two

As a second example, let's return to the temperature/heater example. Suppose that you bring a date to your (underheated) apartment and she or he has a thermometer that reads temperature in one degree increments. You don't want to change your reading/action rulebase (it was programmed in Fortran in 1978), so you instead write a new program that translates the temperature on your date's thermometer into one of the three classes known to your Fortran program. In other words, you create a new relation Q_{CA}, where $C = \{0,1,\ldots,120\}$ is the range of the thermometer. The relation is defined in terms of the membership function $\mu_{QCA}(c,a)$ as

Table3.1. The relation is defined in terms of the membership function $\mu_{QCA}(c,a)$

	a		
c = T	"T < 30"	"30 ≤ T ≤ 60"	"T > 60"
c < 30	1	0	0
30 ≤ c≤ 60	0	1	0
c> 60	0	0	1

Let P_{CB} denote the new relation between the temperature reading from your date's thermometer and the decision to turn on your heater. How do I combine Q_{CA} with R_{AB} to find P_{CB}? We do this by the composition operator,

$$P_{CB}(c, b) = Q_{CA}(c, a) \circ R_{AB}(a, b) \tag{3.7}$$

which is defined as a relation on C x B such that $(c,b) \in P_{CB}$ if and only if there exists at least one $a \in A$ such that (a,b) E R_{AB} and $(c,a) \in Q_{CA}$. In other words, you will turn the HeatOn whenever your date reports a temperature for which the relation between this temperature and either one of the categories "T < 30" and "30 ≤ T ≤ 60"; is true.

The trick is to come up with a formula on the membership functions of μ_{RAB} and μ_{QCA} that correctly produces μ_{PCB}. The formula is given by

$$\mu_{P_{CB}}(c,b) = \mu_{Q\circ R}(c,b) = \max_{a\in A} \mu_{Q_{CA}} * \mu_{R_{AB}}(a,b) \tag{3.8}$$

Basically, this formula says that the truth of the predicate P_{CB}, which was created by combining the predicates Q_{CA} and R_{AB}, is obtained by seeing if both predicates Q and R are simultaneously true for any object $a \in A$. If I can find at least one object for which both predicates are true then the composition of these two predicates is also true. Otherwise, the composition is false.
Let's check to see that this works for the case when? Is implemented as a minimum,

$$\mu_{Q\circ R}(c,b) = \max_{a\in A} \min\{\mu_{Q_{CA}}(c,a), \mu_{R_{AB}}(a,b)\} \tag{3.9}$$

Suppose that your date's thermometer reads 32. Then c = 32. We want to find out if HeatOn is true. So, calculating

$$\mu_{Q\circ R}(32, HeatOn) = \max_{a\in\{"T<30","30\le T\le 60","T>60"\}} \min\{\mu_{Q_{CA}}(32,a), \mu_{R_{AB}}(a, HeatOn)\}$$
$$\mu_{Q\circ R}(32, HeatOn) = \max\left\{\begin{array}{l} \min\{\mu_{Q_{CA}}(32,"T<30"), \mu_{R_{AB}}("T<30", HeatOn)\}, \\ \min\{\mu_{Q_{CA}}(32,"30\le T\le 60"), \mu_{R_{AB}}("30\le T\le 60", HeatOn)\}, \\ \min\{\mu_{Q_{CA}}(32,"T>60"), \mu_{R_{AB}}("T>60", HeatOn)\} \end{array}\right\}$$
$$\mu_{Q\circ R}(32, HeatOn) = \max\left\{\begin{array}{l} \min\{0,1\}, \\ \min\{1,1\}, \\ \min\{0,0\} \end{array}\right\}$$
$$\mu_{Q\circ R}(32, HeatOn) = \max\{0,1,0\}$$
$$\mu_{Q\circ R}(32, HeatOn) = 1.$$

So, at least for this temperature reading you should turn the HeatOn.

3.2.3. Fuzzy Logic Example: Three

Now, suppose that your date's thermometer reads 82. Then c = 82. We want to find out if HeatOn is true. So, calculating

$$\mu_{Q\circ P}(82, HeatOn) = \max_{a\in\{"T<30","30\leq T\leq 60","T>60"\}} \min\{\mu_{Q_{CA}}(82, a), \mu_{R_{AB}}(a, HeatOn)\}$$

$$\mu_{Q\circ R}(82, HeatOn) = \max\begin{Bmatrix} \min\{\mu_{Q_{CA}}(82,"T<30"), \mu_{R_{AB}}("T<30", HeatOn)\}, \\ \min\{\mu_{Q_{CA}}(82,"30\leq T\leq 60"), \mu_{R_{AB}}("30\leq T\leq 60", HeatOn)\}, \\ \min\{\mu_{Q_{CA}}(82,"T>60"), \mu_{R_{AB}}("T>60", HeatOn)\} \end{Bmatrix}$$

$$\mu_{Q\circ R}(82, HeatOn) = \max\begin{Bmatrix} \min\{0,1\}, \\ \min\{0,1\}, \\ \min\{1,0\} \end{Bmatrix}$$

$$\mu_{Q\circ R}(82, HeatOn) = \max\{0,0,0\}$$

$$\mu_{Q\circ R}(82, HeatOn) = 0.$$

So, at least for this temperature reading you should not turn the HeatOn.

CHAPTER 4

RELATED PAST STUDIES USING ANN AND FUZZY MODELS

The ANN has been investigated for its applicability in building energy predictions over the past ten years (Ansett and Kreider 1993, Curtiss et al.1993, Cohen and Krarti 1995, Kreider et al. 1995, Haberl and Thamilseran 1996, Breekweg et al. 2000). Various neural network architectures have been applied in energy predictions. They include backpropagation, recurrent neural networks, autoassociative neural networks and general regression neural network demonstrating relatively successful results having coefficient of variations in the range of 2–40% (Ansett and Kreider 1993, Curtiss et al.1993, Cohen and Krarti 1995, Kreider et al.1995, Haberl and Thamilseran 1996, Breekweg et al. 2000). These variations in the accuracy of the predictions depend mostly on the ANN architecture used, the regularity of the building operation and the accuracy of data measurement devices. More specifically, in a study by (Ansett and Kreider 1993), building utility measurement data from a university campus centre, including electricity, natural gas, water and steam use, were modelled. The study considered weather, building occupancy and activity as the independent variables. Backpropagation architecture was used in this effort. The main focus was on testing different training methods, layering and data input order. The study presented encouraging potential for the application of neural networks in building energy modeling. The study also stated the need for future investigation in selecting more accurate and effective learning algorithms.

(Curtiss et al. 1993) used ANN to optimize energy consumption on an HVAC system. In this approach, the weather and building occupancy were considered as independent variables, and the HVAC system setpoints such as mixed air temperature, chilled water temperature, duct static pressure and chilled water flow rate were considered as dependent variables. Varying the dependent variables that would yield the minimum electricity consumption identified optimum setpoints. The building data were generated an HVAC Laboratory.

The results of this study showed the need to apply the model to larger sized buildings with actual building measurement data, in order to validate the ANN method's efficiency. (Cohen and Krarti 1995) used energy consumption data generated from the DOE-2.1E Building Energy Analysis Program as input to the ANN model developed. The model was based on multi-layered feedforward networks. This study mentioned the potential use of ANN methods in building energy savings estimates and recommended that future ANN modeling studies be done based on 'real' building measurement data.
(Kreider et al. 1995) investigated the prediction of future building energy consumption and system identification without the knowledge of immediate past energy consumption. Recurrent neural networks were used in the modeling. According to the authors, the recurrent networks offer an accurate method for predicting hourly energy use well into the future for thermal end uses when only weather data are known. During network training, actual measured data from a few past hours were used as input to the model. However, during the prediction period, the network's own outputs were cycled back into the inputs. The building energy data for this model were also generated from the DOE-2.1E Building Energy Analysis Program. Although the error rate was relatively higher in this method when compared to, for example, the backpropagation method, it was still presented as an applicable method in predicting the future building energy use for retrofit energy savings estimation purposes. This study also stated the need for future study based on 'real' building measurement data.

As part of an energy predictor competition titled 'Great Energy Predictor Shootout', (Chonan et al. 1996) applied Bayesian neural network for estimating building energy use. In this method, the known relationship between the input variables and output was used in combination with the neural network training. (Jang et al. 1996) used an auto-associative neural network in predicting missing building input–output data based on feedforward network identity mapping. This method is effectively used when the building data have been available for some periods of time and missing for other periods of time. The noise filter capabilities of auto-associative neural networks proved to be effective in preprocessing the model data. In another study, (Curtiss 1996) described the use of neural networks in continuous control of feedback loops in an HVAC system and overall building energy use prediction. In this method, the input and output training data set were updated with new input data and a neural network output prediction from one previous time segment. The training data set was renewed with the latest building information and kept current for the near future predictions. Additionally, in this study, Curtiss used the neural network control algorithm along with the traditional PI control algorithm to develop the optimum control parameters and enhance control capabilities of both methods. (Breekweg et al. 2000) evaluated a number of ANN techniques in the development of a generalized method for building energy-related fault detection. Real-time data from four different buildings and simulation data from one building were modelled based on normalized radial basis function (RBF), specifically the general regression neural network (GRNN) as the normalized RBF was used. The coefficient of variation was higher, in the range of 20–40% for most buildings, except two buildings, which were in the range of 4–8%. The large deviations in the results were attributed to the quality of data measurement, building operation consistency and minimization of the noise elements in the data set. This study also reported the necessity to test the developed ANN model with energy data from different buildings in order to ensure the generalizing capacity of the model.

Artificial neural networks have successfully passed the research stages and found real time applications in many technologies including aerospace, defense, automotive, manufacturing process controls, etc.

Accomplishing a model of the total power consumption of chiller plant is a complex process. The fuzzy logic model objective is to capture output variable of the central chiller plant power consumption by means of input variables. In a study by (Kesgin et.al. 2005) a fuzzy logic model was developed to predict the drying time and the power demand depending on condensation pressure and temperature and evaporation pressure. The fuzzy multi-objective linear programming approach was used by (Chedid and Mezher 1999) to solve the energy allocation problem. Both ANN and fuzzy logic model were used to model an appropriate lighting controller integrated in a self-adaptive building control system by (Guillemin et al. 2001). Fuzzy logic is used like a mathematical model to fulfill representation of human decision and assesment process. In addition to this, the fuzzy logic approach supplies potential rules making connection between input variables and the output variables. Also, the detailed exposition of the application that combined the linguistic approach to the optimization under the input variables to the output is presented. Therefore, the load forecasting can be crucial to strategy management of the multipurpose building sector energy demand.

Additionally, a literature search was conducted for building energy use prediction models developed for tropical climates. However, to the authors' knowledge, no specific study was found on the topic.

CHAPTER 5

MODEL CONSTRUCTION

5.1. Building Properties

A 42 storey commercial building with approximately 41,800 m^2 space in downtown Honolulu, Hawaii was selected for a case study for ANN building energy prediction. The basement housed the chiller room, a mechanical pump room, building maintenance offices, and a parking garage. The plaza level first floor and second floor contained the entry lobby restaurants and retail offices, and additional parking garages. Parking garage spaces took up 5–12 floors. The 14th floor and the upper levels of the building are separated into two towers: an office tower and a residential condominium tower. The 14th floor also contains a recreational deck with a residential lounge and a pool. The cooling towers, exhaust fans and some other mechanical elevator equipment are located on the roof of the residential tower. The building is air conditioned by a central chilled water plant consisting of three chillers with a total 1250-ton capacity. Air conditioning in the office tower is provided for 13–15 h during the day, and air conditioning for the residential tower is provided 24 h a day, which is controlled by thermostats in each residential unit. Floor air handlers circulate the conditioned air through variable air volume (VAV) terminal units. This multiple utility building requires the building equipment to operate '24/7' and has a building automation system (BAS). The chiller electricity consumption, chilled water flow rate, chilled water supply and return temperatures and air handling unit electricity use is monitored continuously. For this study, which was done over a period of three weeks, the hourly chilled water flow rate, chilled water supply and return temperatures, building occupancy rate, and hourly local climate data were used in predicting the total chiller power by the ANN method and the fuzzy logic model. Figure 5.1 shows the chiller plant power consumption trend for this time period.

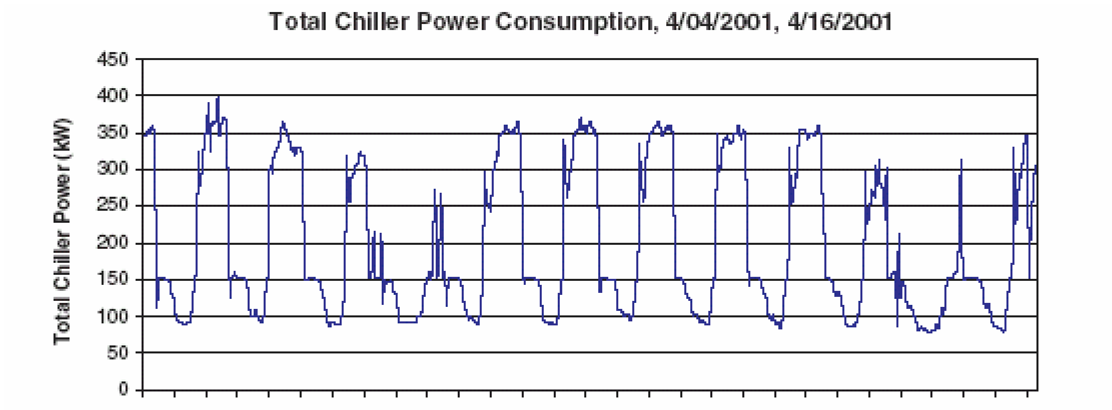

Figure 5.1 Chiller plant power consumption trend for the time period studied (April 2001), Source: (Yalcintas and Akkurt 2005).

The building that was studied has two unique characteristics. Firstly, it is located in the tropical climate of Honolulu, Hawaii where variations between the day and night, and summer and winter are minimal. In summer, the maximum dry bulb temperature average for Honolulu is 31.1^{o}C and the minimum dry bulb temperature average is 24.48 ^{o}C. The average wet bulb temperature is 22.88 ^{o}C. In winter, the maximum dry bulb temperature average is 27.28 ^{o}C and the minimum dry bulb temperature average is 19.58 ^{o}C. The average wet bulb temperature is 18.98 ^{o}C. Average wind velocity in both summer and winter is relatively consistent at 16 kph. In this climate, air conditioning is required during the day, through the whole year and during the night, most of the time.

Secondly, the building houses a variety of functions including office, residential, restaurants and recreation. All of these have different air conditioning requirements and schedules, while energy use throughout the day and night is continuous. The small variations in the seasonal weather conditions and continuous building use presents consistent data for the ANN analysis and this in turn gives a better prediction capacity for the developed ANN energy model.

In this study, the power consumption of the central chiller plant, including the chillers, cooling tower and pumps, was first modeled based on the ANN method. The data used in the model covered the time period from 4 April 2001 to 16 April 2001.

Independent input variables mainly consisted of climate data, and the model output was the chiller plant power consumption.

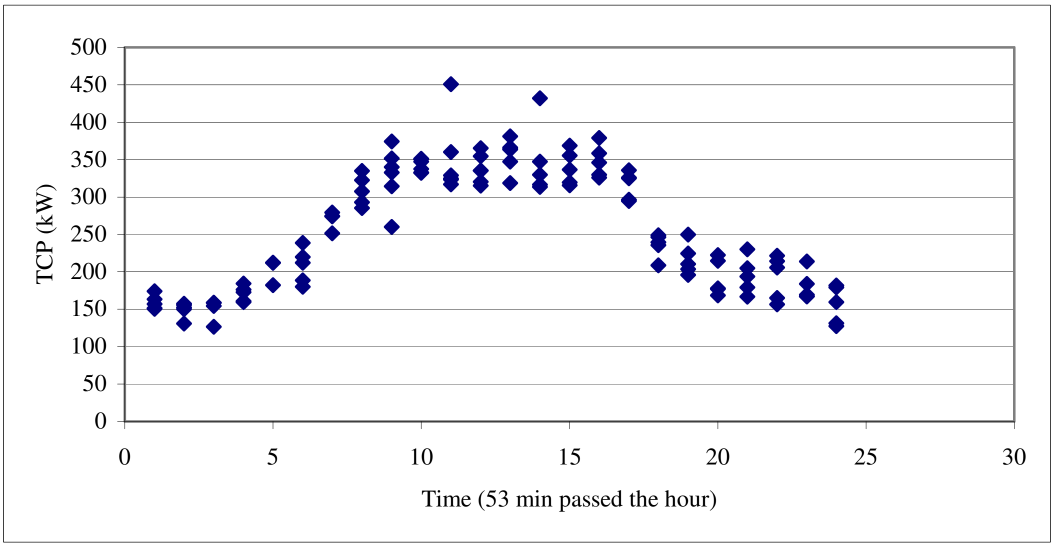

Figure 5.2 Chiller plant power consumption versus Time.

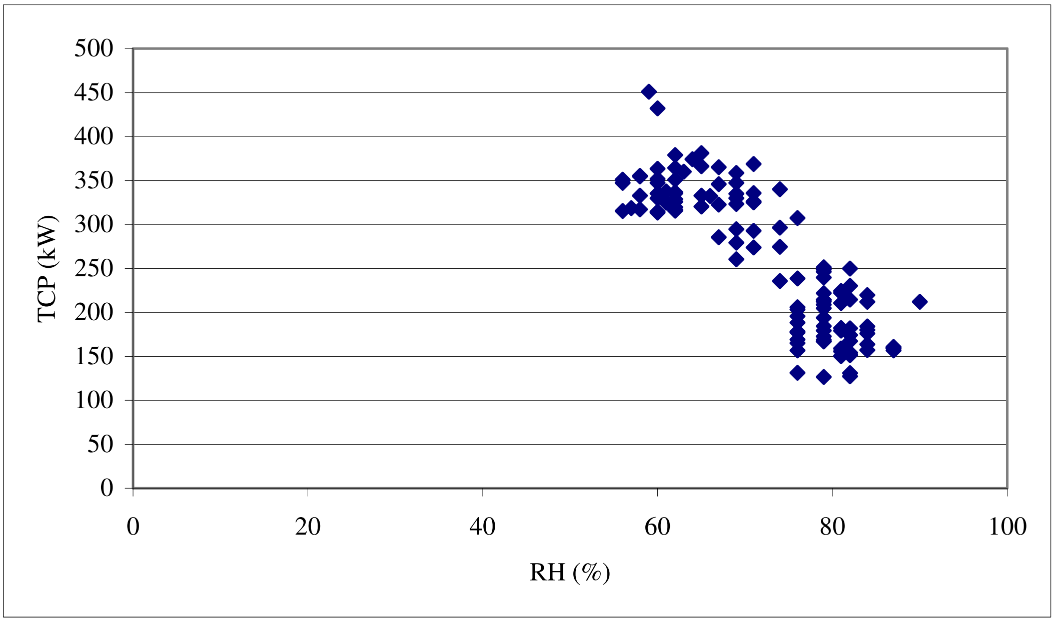

Figure 5.3. Chiller plant power consumption versus relative humiditiy.

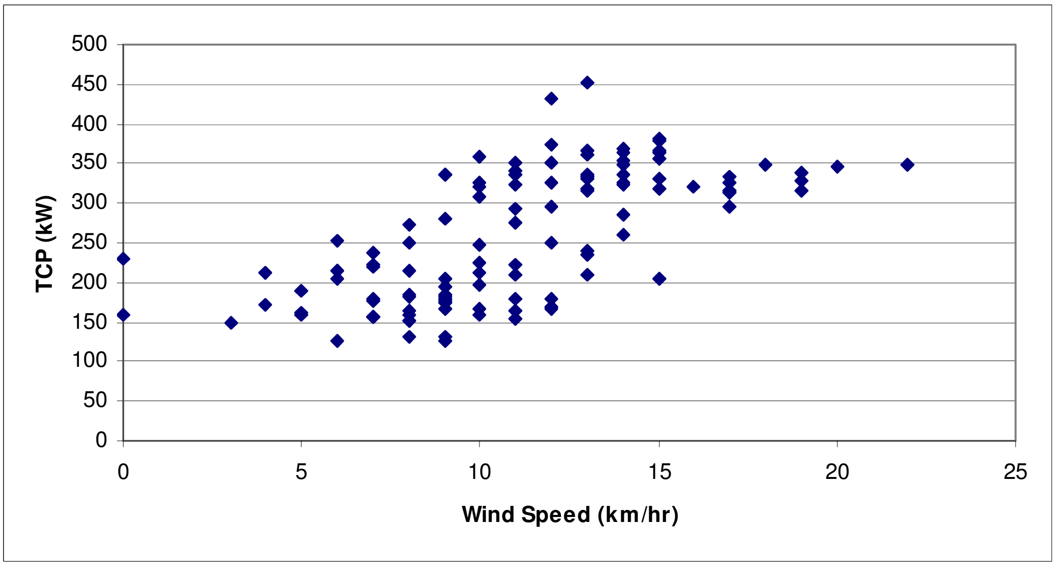

Figure 5.4. Chiller plant power consumption versus wind speed.

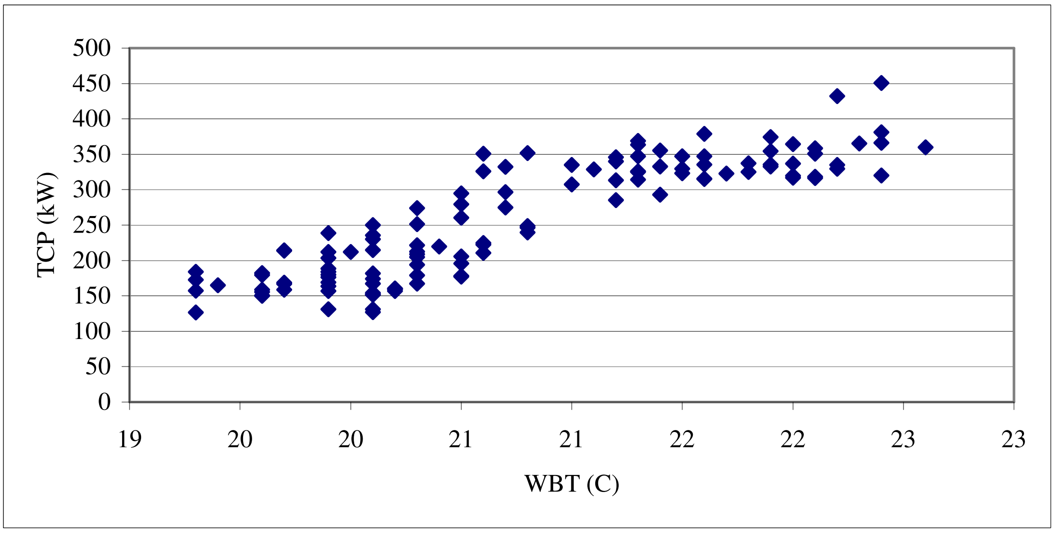

Figure 5.5. Chiller plant power consumption versus wbt.

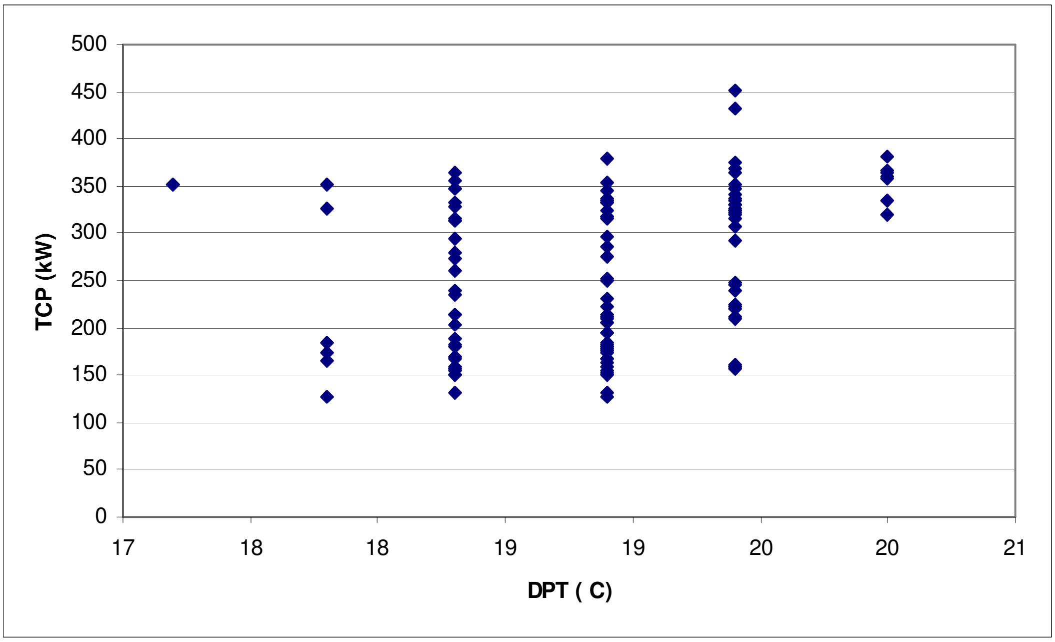

Figure 5.6. Chiller plant power consumption versus dpt.

Due to the fact that, correlations of wet bulb temperature, dew point temperature, relative humidity percentage and wind speed, with total chiller power consumption are not all linear, the choice for modeling such relation ship would give better prediction capability if ANN or Fuzzy Logic are used.(see Figures 5.2, 5.3, 5.4, 5.5, 5.6 and 5.7)

Hourly climate data were obtained from the National Climate Data Center for April 2001. The climate data variables considered were specifically: dry bulb temperature, wet bulb temperature, dew point temperature, relative humidity percentage, wind speed and wind direction. Table 1 lists the input and output variables used in model construction. Unlike the weather data, the data for hourly power consumption of the chiller plant were not available for every hour of the 24 h a day. Therefore, a matching of the weather and chiller power data produced a total of 121 data sets to be used for the model creation. This was less than the total number of possible combinations of 312 for 13 days.

5.2. Data Collection

The data used in this study were previously used in another study on the ANN model for chiller plant power consumption (Yalcintas 2005). The data were collected from two different sources: A 42 storey commercial building in Honolulu, Hawaii, USA and the National Weather Service that provided the meteorological data used in fuzzy model construction. More details about the building's air conditioning system are provided in (Yalcintas et.al. 2005).

In the previous ANN model created by Yalcintas et.al. 2005, there were 7 input variables and one output variable of total chiller plant power consumption Table 5.1. In this study, however, only five input parameters were employed because the fuzzy logic models require rule sets that expand significantly when the number of parameters increases.

Table 5.1. The parameters used in ANN and Fuzzy model construction.

Parameter	Short notation for parameters	Parameters used in ANN model of reference 2	Parameters used in ANN model in this study	Parameters used in Fuzzy model in this study
Time (hour)	t	x_1	x_1	x_1
Dry bulb temperature	dbt	x_2		
Wet bulb temperature	wbt	x_3	x_2	x_2
Dew point temperature	dpt	x_4	x_3	x_3
Relative humidity	rh	x_5	x_4	x_4
Wind speed	ws	x_6	x_5	x_5
Wind direction	wd	x_7		
Total building power consumption	power	y_1	y_1	y_1

The increase in the number of rule sets follows a 2^n function where n=the number of input parameters. When, for example, two input parameters are used only four rule sets must be written. For 7 input parameters the total number would be 2^7=128, which was too large for fuzzy rule sets. Therefore only 5 input parameters were selected in this study. The dry bulb temperature and wind direction were eliminated from the new model because they were thought to be the least effective parameters. Time is considered as a function of building occupancy.

The whole list of parameters is given in Table 5.1 for all the three models that are:

- the first 7 input parameter ANN model in (Yalcintas 2005),
- the 5 input parameter ANN model created in this study and
- the 5 input parameter fuzzy model created in this study.

There were a total of 121 sets of data each containing 7 input parameters and one output parameter. The data were randomly split into two by Yalcintas (2005); the first one had 80 data sets while the second contained 41 data sets. The latter 41 sets were used for comparison of the errors of the three models. For ANN model the first 80 sets were used for model creation and the latter 41 sets for model testing. For fuzzy logic model the same 41 sets were used for model validation (Table 5.2).

Table 5.2. Part of the data that was used for model validation consisted of 41 sets. This part of data was used for ANN and fuzzy logic model testing.

						Measured
	t	wbt	dpt	rh	ws	Power
Data set	hr*	(^{o}C)	(^{o}C)	%	(mph)	kW
81	10	21.5	19.4	69	14	347.3
82	21	20.3	18.9	79	9	193.9
83	16	21.5	19.4	69	13	329.7
84	20	20.5	18.9	76	12	178.1
85	12	22.3	20.0	67	15	365.2
86	11	22.6	20.0	63	13	360.1
87	6	19.9	18.3	76	5	188.5
88	7	20.3	18.3	71	8	274.0
89	3	20.1	18.9	82	11	154.2
90	22	20.3	18.9	79	11	221.7
91	24	19.6	18.3	81	11	179.3
92	13	21.3	18.3	60	18	347.3
93	4	19.3	17.8	79	8	184.2
94	19	19.9	18.3	76	15	203.4
95	6	20.3	18.9	79	10	212.3
96	21	20.3	18.9	79	6	204.7
97	17	21.3	19.4	71	14	326.1
98	5	19.9	18.9	84	4	212.2
99	20	20.5	18.9	76	9	177.1
100	21	19.7	18.3	79	10	167.0
101	2	19.6	18.3	81	3	150.1
102	3	19.6	18.3	81	10	158.9
103	10	21.9	18.9	58	13	332.6
104	21	20.3	18.9	79	9	179.2
105	18	20.8	19.4	79	12	248.8
106	13	22.4	20.0	65	15	381.2
107	10	22.1	19.4	62	12	350.8
108	13	22.1	18.9	57	13	318.5
109	12	21.6	18.3	56	17	315.3
110	14	21.6	18.3	56	22	347.3
111	4	20.2	19.4	87	8	159.7
112	17	20.7	18.9	74	17	296.4
113	18	20.1	18.3	74	13	235.7
114	22	20.5	18.9	76	9	205.7
115	10	21.8	18.9	61	19	337.3
116	24	20.2	19.4	87	0	159.5
117	2	19.6	18.3	81	7	155.7
118	16	21.2	18.9	67	20	345.9
119	9	20.8	17.8	60	11	351.8
120	8	21.7	19.4	67	11	322.7
121	23	20.3	18.9	79	12	167.2

*hr : 53 minutes past hour

5.3. Model Construction

The schematic diagram of conceptual modeling of the central chiller plant power consumption using Fuzzy Logic is presented in Figure 3.4 The original data used in a previous article for ANN modeling were applied in this thesis for fuzzy model set up. A new ANN model which had five input parameters [time (53 min after hour), wet bulb temperature (^oC), dew point temperature (^oC), relative humidity percentage (%), and wind speed (mph)] and one output parameter of the central chiller plant power consumption (kW) was created in this study. These parameters were believed to represent the more important factors based on visual and graphical inspection done on our previous model.

The newly constructed ANN model had three layers: input, hidden and output. The input and hidden layers had five neurons, while the output layer had one. No bias term was used in training. The number of iterations was 20000 for training of the model. Table 2 shows that the reduction in the total number of input parameters from 7 to 5 resulted in a slight increase in the percentage average absolute errors (PAAE) for both the 5 parameter ANN model and the fuzzy model, as already expected (Eqn. 5.1). For the fuzzy model decreasing the number of inputs gives a slight increase in PAAE that's resulted from fuzzy logic model restrictions which mentioned in data collection part.

$$PAAE = \left| \frac{observedpower - predictedpower}{observedpower} \right| * 100 \tag{5.1}$$

The constructed membership functions are shown in Figure 5.7 There were a total of 32 fuzzy rule sets, which are listed in Table 5.3.

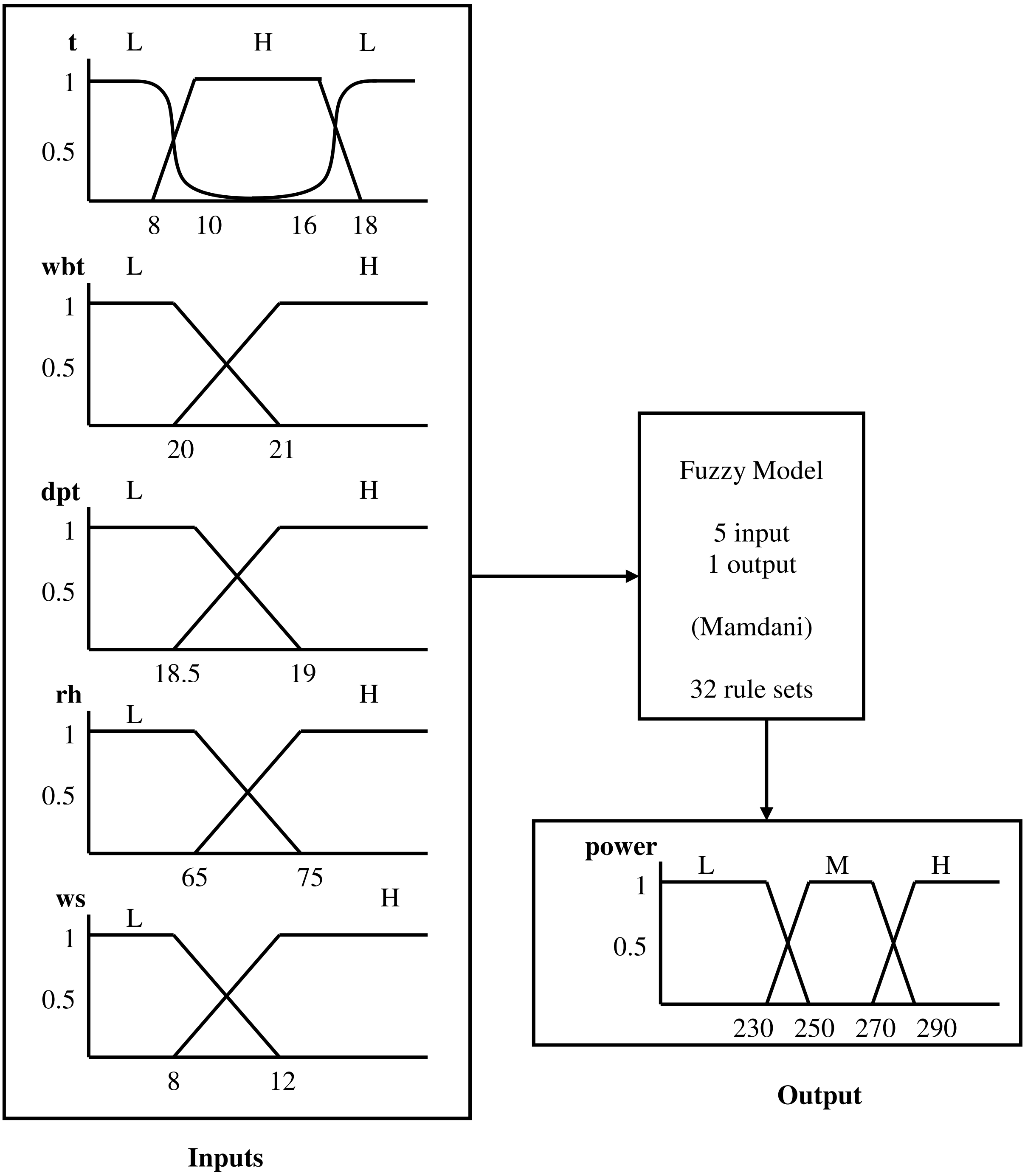

Figure 5.7. Membership functions for input and output parameters used for the fuzzy modeling.

Table 5.3. The whole 32 fuzzy rule sets used in this study.

	#	t	wbt	dpt	rh	ws	Power
IF	1	L	L	L	L	L	M
	2	L	L	L	L	H	L
	3	L	L	L	H	L	L
	4	L	L	L	H	H	L
	5	L	L	H	L	L	L
	6	L	L	H	L	H	M
	7	L	L	H	H	L	L
	8	L	L	H	H	H	L
	9	L	H	L	L	L	L
	10	L	H	L	L	H	H
	11	L	H	L	H	L	L
	12	L	H	L	H	H	L
	13	L	H	H	L	L	L
	14	L	H	H	L	H	L
	15	L	H	H	H	L	L
	16	L	H	H	H	H	L
IF	17	H	L	L	L	L	L
	18	H	L	L	L	H	H
	19	H	L	L	H	L	H
	20	H	L	L	H	H	H
	21	H	L	H	L	L	H
	22	H	L	H	L	H	M
	23	H	L	H	H	L	H
	24	H	L	H	H	H	H
	25	H	H	L	L	L	H
	26	H	H	L	L	H	H
	27	H	H	L	H	L	H
	28	H	H	L	H	H	H
	29	H	H	H	L	L	H
	30	H	H	H	L	H	H
	31	H	H	H	H	L	H
	32	H	H	H	H	H	H

L, low; M, medium; H, high

5.4. Model Application

The fuzzy-logic toolbox of the MatLAB® was used to construct the fuzzy model. The prod and centre of gravity (COG) methods were employed as the inference operator and defuzzification methods, respectively. The prediction results of the measured data by the developed fuzzy model are shown in Table 5.4 According to Table5.4 the fuzzy model predicted the measured data successfully, and its performance was as good as the other ANN models. The results indicated a PAAE of 11.6% (R^2=0.885) for the fuzzy model. This quantity was about 10.0% (R^2=0.883) for the ANN model created in (Yalcintas and Akkurt 2005) and 10.3% (R^2=0.875) for the 5 parameter ANN model created in this study. Both ANN models were similar as far as their errors are concerned. The fuzzy model gave slightly higher error. Comparison of the observed total chiller plant power and predicted values by the fuzzy model is presented in Figure 5.8 The results of the seven parameter ANN model is shown in Figures 5.9 and 5.10, The results of the five parameter ANN model is shown in Figures 5.11 and 5.12.

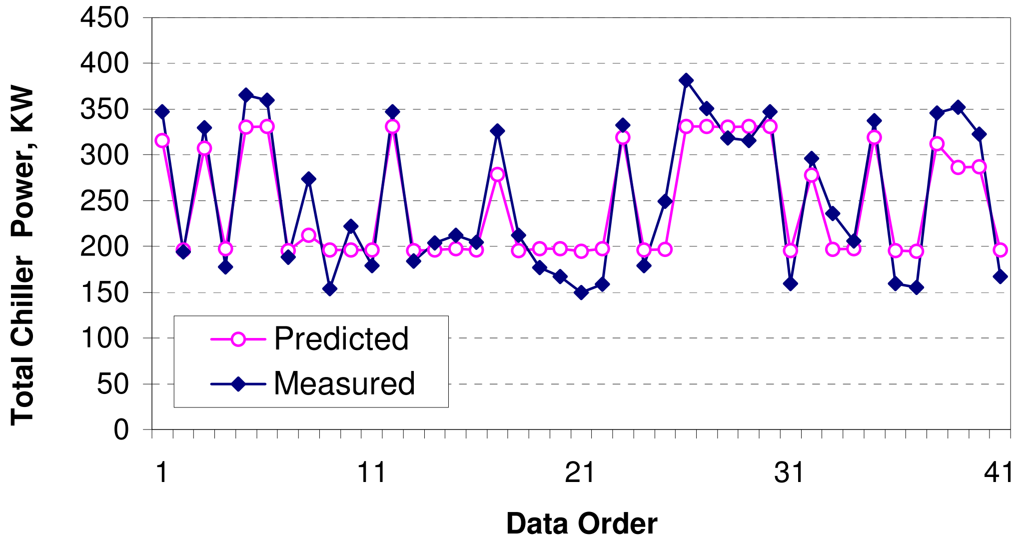

Figure 5.8. Comparison of the observed total chiller plant power and predicted values by the fuzzy model.

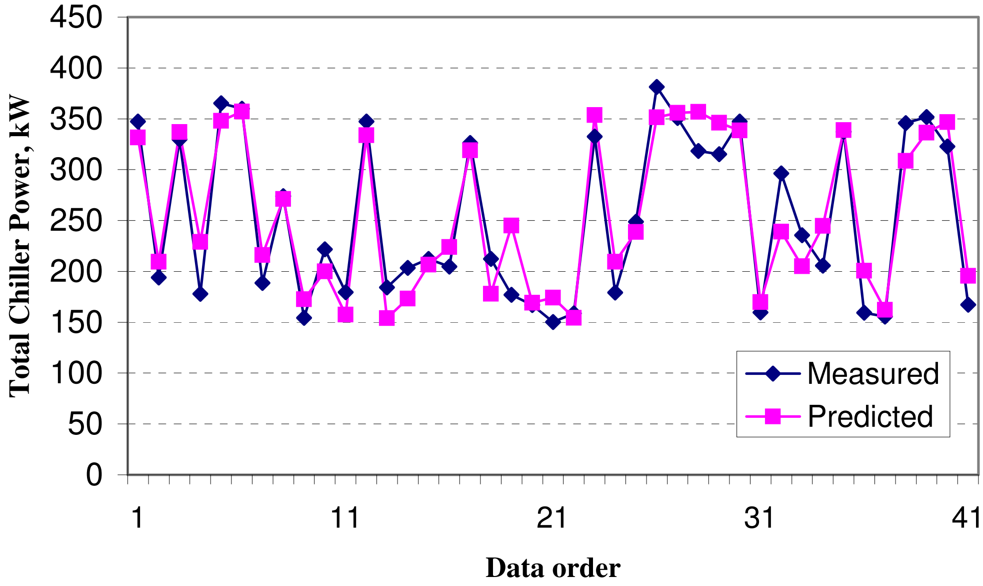

Figure 5.9. Comparison of the observed total chiller plant power and predicted values by the seven parameter ANN model.

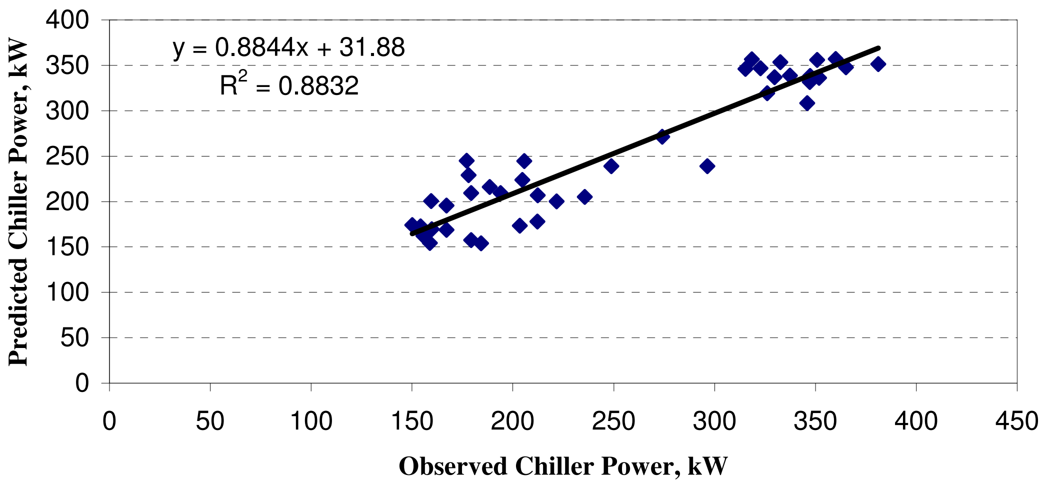

Figure 5.10. Comparison of the observed total chiller plant power & predicted values by the seven parameter ANN model. Calculation of R^2=0.88 is shown.

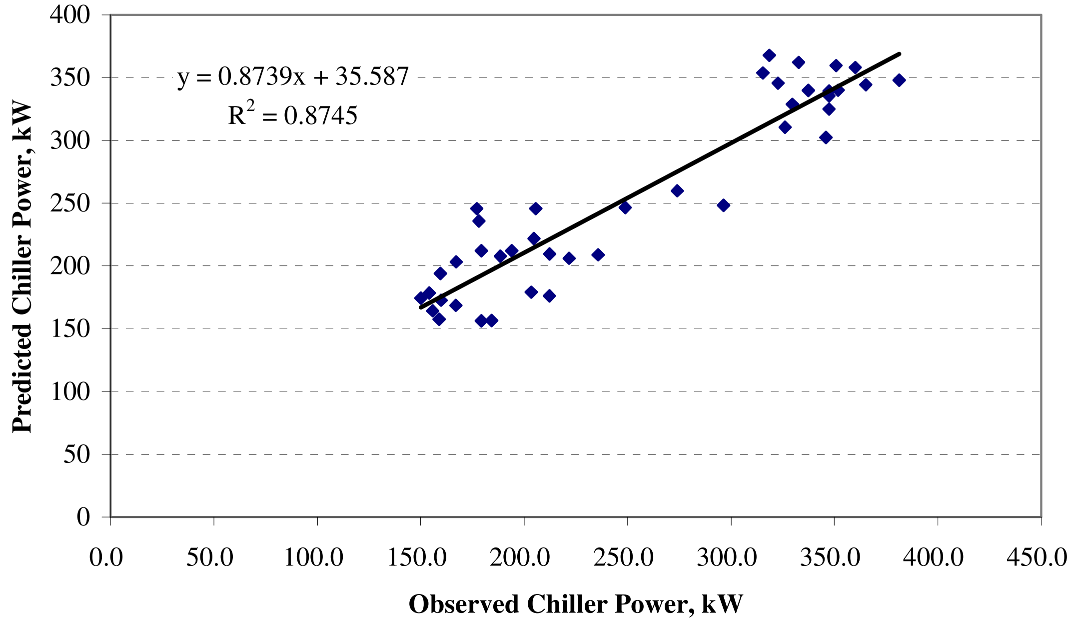

Figure 5.11. Comparison of the observed total chiller plant power & predicted values by the five parameter ANN model. Calculation of R^2=0.87 is shown.

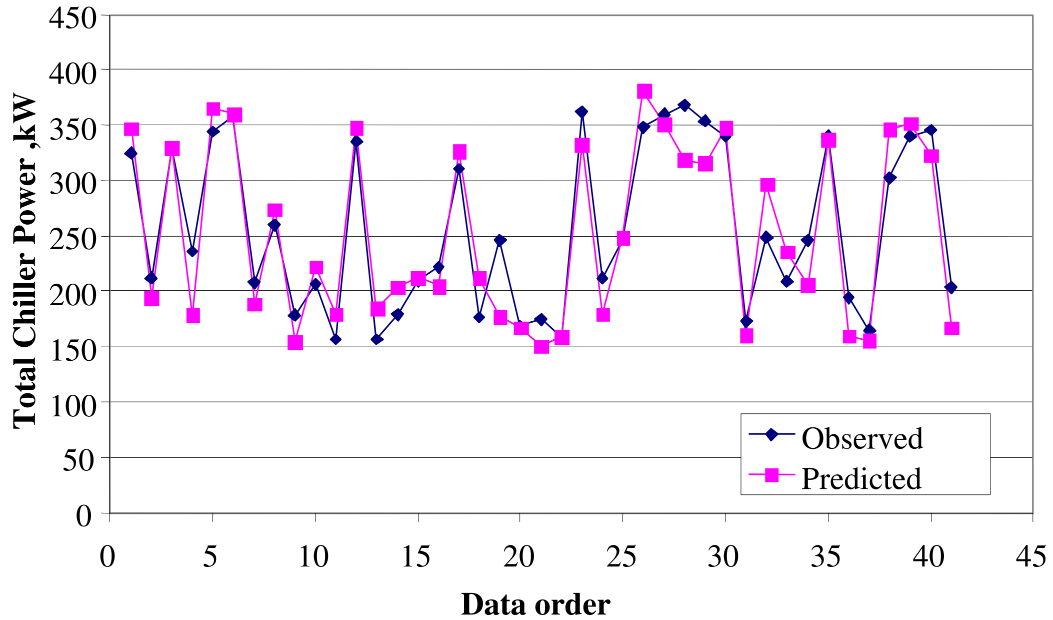

Figure 5.12. Comparison of the observed total chiller plant power and predicted values by the five parameter ANN model.

Table 5.4 Fuzzy logic and ANN model constructions-testing results.

		Model predictions			PAE		
		Yalcintas ANN	ANN model	Fuzzy model	Yalcintas ANN	ANN model	Fuzzy model
	Measured	model	in this study	in this study	model	in this study	in this study
	Power	Power	Power	Power	Power	Power	Power
Data set	kW	kW	kW	kW	kW	kW	kW
81	347.3	331.5	325.0	315.5	4.5	6.4	9.1
82	193.9	209.3	212.1	196.1	7.9	9.4	1.1
83	329.7	337.0	328.8	307.1	2.2	0.3	6.8
84	178.1	229.1	235.7	197.0	28.6	32.4	10.6
85	365.2	348.0	344.2	330.0	4.7	5.7	9.6
86	360.1	357.0	358.0	331.0	0.9	0.6	8.1
87	188.5	215.9	207.7	195.5	14.6	10.2	3.7
88	274.0	271.2	259.9	211.8	1.0	5.1	22.7
89	154.2	172.5	178.5	195.8	11.9	15.7	27.0
90	221.7	200.1	206.1	196.1	9.7	7.0	11.6
91	179.3	157.4	156.3	195.8	12.2	12.8	9.2
92	347.3	333.8	335.4	331.0	3.9	3.4	4.7
93	184.2	154.0	156.4	194.9	16.4	15.1	5.8
94	203.4	173.3	179.2	195.8	14.8	11.9	3.8
95	212.3	206.7	209.5	197.0	2.6	1.3	7.2
96	204.7	224.0	221.7	196.1	9.4	8.3	4.2
97	326.1	319.1	310.4	278.3	2.1	4.8	14.7
98	212.2	177.9	176.1	195.6	16.2	17.0	7.8
99	177.1	245.1	245.7	197.0	38.4	38.8	11.3
100	167.0	169.0	168.6	197.0	1.2	1.0	18.0
101	150.1	174.2	174.3	194.8	16.0	16.1	29.7
102	158.9	154.3	157.7	197.0	2.9	0.7	24.0
103	332.6	353.6	362.1	319.3	6.3	8.9	4.0
104	179.2	209.3	212.1	196.1	16.8	18.3	9.4
105	248.8	238.8	246.4	196.6	4.0	1.0	21.0
106	381.2	351.5	347.9	331.0	7.8	8.7	13.2
107	350.8	356.0	359.6	331.0	1.5	2.5	5.6
108	318.5	356.8	367.8	330.1	12.0	15.5	3.6
109	315.3	346.0	353.7	331.0	9.7	12.2	5.0
110	347.3	338.4	339.3	330.8	2.6	2.3	4.8
111	159.7	169.6	172.6	195.6	6.2	8.1	22.4
112	296.4	239.1	248.2	277.8	19.3	16.3	6.3
113	235.7	205.1	208.8	196.6	13.0	11.4	16.6
114	205.7	244.6	245.7	197.0	18.9	19.4	4.2
115	337.3	338.8	339.8	319.3	0.4	0.7	5.3
116	159.5	200.4	194.0	195.6	25.7	21.7	22.6
117	155.7	162.2	164.3	194.8	4.2	5.6	25.1
118	345.9	308.5	302.3	312.4	10.8	12.6	9.7
119	351.8	336.3	340.0	286.2	4.4	3.3	18.6
120	322.7	346.6	345.6	287.2	7.4	7.1	11.0
121	167.2	195.7	203.2	196.1	17.1	21.6	17.3
				PAAE	10.0	10.3	11.6

In addition, the ANN models in the work cited here have used building energy data from building simulation, laboratory experiments and actual building measurement data. While for the sake of simplicity the simulation data in the initial ANN modeling stages are useful, it is essential to use actual building data during the later development stages to account for the possible imperfections in the measured data. Also, the actual building data are the best indicator of the building features, operation and equipment efficiency. However, as mentioned earlier, the noise in the measurement data also has to be dealt with when employing actual measurements in the ANN modeling. Therefore, repeated building data measurements from different buildings should be used in developing the ANN model.

An advantage of the fuzzy logic is that all the rules are written verbally, much like the human thought process. ANN models, however, are black box models, not immediately visible to the user. The ANN model provides only a set of weight matrices that does not provide explicit results. Chiller plant operators can easily adapt to the verbal rule creation process.

CHAPTER 6

CONCLUSIONS

A fuzzy logic model was successfully created to predict the chiller plant power consumption obtained from the commercial building. Input parameters used in model creation process included time, wet bulb temperature, dew point temperature, percentage relative humidity, and wind speed.

The model was created from independent hourly climate data that were obtained from the National Climate Data Center, in Hawaii, USA. A five-parameter ANN model was used to compare the fuzzy model output and the ANN model output.

Successful predictions of the observed outputs by the fuzzy logic model indicated that fuzzy logic could be a useful modeling tool for engineers and the operators of the chiller system.

The successful predictions of the total chiller plant power consumption data by the fuzzy model indicated that the employed prod activator and centroid deffuzzification methods were appropriate.

Future study may involve other modeling techniques like gene expression programming. Chiller plant data can be collected for longer periods in the post retrofit period to better understand effects of retrofits in the HVAC system.

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