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Adaptive Hierarchical Fuzzy controller for HVAC Systems in Low Energy Buildings

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DEDICATION

I dedicate this thesis to my father and my mother in recognition of their endless help and support; I also dedicate this work to my lovely brother, sister, aunt and grandmother for inspiring me.

ACKNOWLEDGEMENT

At the beginning, I thank ALLAH for giving me the strength and health to let this work see the light. I thank my supervisor Dr. Eng. Basil Hamed for his time, consideration, suggestions, ideas and advice during this thesis.

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Abstract

Proper control for low energy buildings is more difficult than conventional buildings due to their complexity and sensitivity to operating conditions. Therefore, Suitable controller is essential for better performance. In this thesis, Adaptive Hierarchical Fuzzy control is used to control Heating, Ventilating and Air Conditioning (HVAC) System which is time varying nonlinear system. The proposed Controller is capable of maintaining comfort conditions under time varying thermal loads. Adaptive Hierarchical Fuzzy is consist of two levels; first fuzzy level is to control two varying feedback parameters (Air temperature and Air quality) and to make the controller adapt with these changes and make it easy to consider any energy from renewable energy sources; the second fuzzy level is to control the Error and Change of Error that comes from first level.

A hierarchical structure is used to reduce the number of rules, easily to extract fuzzy rules, to trim redundant information and reduce the computing time required for the simulation processes, so it is suitable for nonlinear temperature control with large low energy buildings with features such as large capacity and longtime delay. The controller is developed using a computer simulation of a virtual building contains most parameters of a real building. Fuzzy rules are learned from experts and system performance observations.

Matlab program is used to simulate HVAC system and to see the results of the new controller.

ملخص البحث

الحاجة الى استخدام تحكم مميز للمباني الموفرة للطاقة مطلوب في هذا الوقت الذي يتم فيه استهلاك كميات كبيرة من الطاقة الغير متجدده و العمل على استعمال اكبر قدر ممكن من الطاقة المتجددة, مثل هذه المتحكمات تكون اصعب في المباني الموفرة للطاقة عن المباني الاعتيادية و حساسيتها لحالات التشغيل و هي اساسية لجودة افضل. في هذا البحث نعرض التحكم المتكيف الهرمي الضبابي ليتحكم في اجهزة التدفئة المركزية المخصصة للمساحات الواسعة المغلقة كالاسواق الكبيرة و القاعات الدراسية في الجامعات مثلا و تتميز حرارة الهواء في هذه المساحات الواسعة بأنها تتغير مع الزمن بمعنى ان نسبة التدفئة و المكان ممتلئ ليست نفس النسبة و المكان ليس به احد او دخول هواء بارد من نوافذ او ابواب كبيرة. التحكم المتكيف الهرمي الضبابي مكون من مستويين, المستوى الضبابي الاول ليتحكم بالمتغيرات التي تحدث في المكان من تغير في درجة الحرارة او تغير في جودة الهواء و جعل المتحكم يتكيف مع هذه المتغيرات و يرسلها الى المستوى الضبابي الثاني الذي هو مكون من مقدار الخطء, اي الفرق بين درجة الحرارة المطلوبة و درجة الحرارة داخل المبنى.

لقد استعملنا التحكم الضبابي الهرمي لكي نقلل من عدد القواعد التى تستعمل لتعطي النتيجة الملائمة و النظام الهرمي يعمل على تسهيل عملية استخراج القواعد و تقليل الوقت المطلوب في الحسابات لاخراج النتيجة, لهذا هي مناسبة للانظمة الغير خطية و المتغيرة مع الزمن مثل انظمة التدفئة المركزية للمباني الكبيرة الموفرة للطاقة.

استعملنا برنامج الماتلاب لنطبق هذا المتحكم على نظام مبنى افتراضي مع الحرص على ان تكون كل الحالات المتوقع حدوثها موجودة في هذا النظام, قواعد هذا النظام تم تعلمها من خبراء في مجال التدفئة المركزية.

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Chapter 1 Introduction

1.1 Introduction

The consumption of energy by heating, ventilating, and air conditioning (HVAC) equipment in industrial and commercial buildings constitutes 40% of the world energy consumption. In spite of the advancements made in microprocessor technology and its impact on the development of new control methodologies for HVAC systems aiming at improving their energy efficiency, the process of operating HVAC equipment in commercial and industrial buildings is still an inefficient and high-energy consumption process. Classical HVAC control techniques such as the ON/OFF controllers (thermostats) and the proportional-integral-derivative (PID) controllers are still very popular because of their low cost. However, in the long run, these controllers are expensive because they operate at a very low-energy efficiency.

One important factor affecting the efficiency of air conditioning systems is the fact that most HVAC systems are set to operate at design thermal loads while actual thermal loads affecting the system are time-varying. Therefore, control schemes that take into consideration time varying loads should be able to operate more efficiently and better keep comfort conditions than conventional control schemes. This thesis presents Adaptive Hierarchical Fuzzy controller the HVAC system capable of maintaining comfort conditions within a thermal space with time varying thermal loads acting upon the system with high air quality. To achieve this objective, we carry out the design of an HVAC control system that counteracts the effect of thermal loads on the space comfort conditions. The controller achieves this objective by adapting the varying parameters of thermal loads acting upon the system and using the hierarchical fuzzy with two levels to take the appropriate control actions to maintain space comfort conditions.

First fuzzy level is adaptive level for varying parameters; it control the deference temperature just after enter the room and the real temperature in the room and this varying in temperature due to slow spread nature of heating the air in an open large spaces and it is due to changes happened in this space as large windows opened or any external disturbances; the second varying parameter is the quality of air inside this space cause if place is crowded in this space CO_2 concentration will change and the need of new air is essential, so a new cold air must enter the space. These varying parameters are nonlinear and can't be expected when it will be changed so such an adaptive controller is needed, also an intelligent controller as Fuzzy control method is very useful and flexible with unknown systems.

1.2 Statement of Problem

The problem is the difficulty of controlling low energy buildings than conventional buildings due to their complexity and sensitivity to operating conditions and the difficulty of getting a model or equation for the system. Suitable controller is essential for better performance and less energy consumption.

1.3 Motivation

The main stimulus of choosing this thesis is the need of lowering energy consumption and the concern of replacing the conventional temporal energy sources by renewable energy sources. Therefore, a large amount of researches have been done in renewable energy sources but if we think; till now renewable energy sources still can’t cover the amount of energy needed. So let us study the other side of the problem which is energy consumption, if we lower the energy consumption we can help to reach the level of using a pure energy sources. Fuzzy theory is a great science which belongs to intelligent control theories; Fuzzy theory opened a large space to make researches, because it is near a human thinking method, and the idea to design a fuzzy controller is very interested for systems which don’t need a precise calculations.

Heating, Ventilation and Air Conditioning in commercial and industrial environment is the greatest compared to other equipment. So the work in the field of Adaptive Hierarchical Fuzzy Control of HVAC Systems will increase the knowledge of intelligent systems and develop the control systems which used in Renewable Energy field.

1.4 Objectives

The main objectives on this thesis are to have a proper controller for an HVAC system to maintain:

- Indoor comfort temperature conditions.
- Good air quality.
- Less energy consumption.

1.5 Literature Review

Fuzzy logic has been around since 1965, when L.A. Zadeh laid the foundation of the linguistic model [1]. Fuzzy sets theory provides a systematic frame work for dealing with different types of uncertainty with a single conceptual framework. The work of Mamdani and Asilian in 1975 showed the first practical application of fuzzy control that implemented Zadeh's fuzzy sets theory [2]. An optimized fuzzy controller is presented for the control of the environmental parameters at the building zone level by D. Kolokotsa in 2002[3]. The occupants' preferences are monitored via a smart card unit. Genetic algorithm optimization techniques are applied to shift properly the membership functions of the fuzzy controller. In this study the controller can't obtain a large number of parameters like heat and water heat and cooling and ventilation and so on of other parameters.

Adaptive Fuzzy Output Feedback controller for HVAC systems is used by Jaeho Baek and Euntai Kim; they apply an adaptive fuzzy output feedback control based on observer for an uncertain HVAC system with the unknown state variables. The state observer is first designed to estimate state variables via which fuzzy control schemes are formulated. The adaptive fuzzy output feedback controller tracks the desired temperature and humidity ratio. Simulations have proved that the adaptive fuzzy output feedback controller is better than classical controllers but it didn't take in consideration the important of CO2 concentration and this model is for one building system with special parameters.

A three-level hierarchical fuzzy rule-based supervisory control scheme is described that is capable of optimizing the operation of a renewable energy building system, Zhen Yu 2007[4]. For the first level rules, a fuzzy decision tree is used to choose the appropriate set of rules according to weather and occupancy information; the second level fuzzy rules generate an optimal energy profile; and the third level fuzzy rules determine the mode of operation of the equipment and select the control variables so as to achieve the optimal energy profile.

Clas A. Jacobson 2011, presented Energy efficient buildings Achieving >50% over current standards (ASHRAE 90.1) is possible; proof points occur for all sizes and climates; buildings designed using climate responsive design principles [5].

1.6 Methodology

Combination of fuzzy control and adaptive scheme is used. First we use the principle or the structure of adaptive control to build the controller. Then blocks that make the construction of adaptive control is fuzzy control. The controller is consist of two fuzzy control levels with three inputs from temperature sensors and one output to heating system. Discrete Virtual model is used to study controller reactions.

1.7 Contribution

The novel approach, which is proposed in this thesis, is: Design Adaptive Hierarchical Fuzzy for unknown HVAC equation model. In this thesis Adaptive Hierarchical Fuzzy Controller has been constructed which is used to control Heat, Ventilation and Air condition Systems for large buildings and large closed spaces. This controller has been tested using Matlab/Simulink program under different temperatures and load variation conditions.

Two approaches are used in this thesis, which are compensation heat losses and stability air heat output. The results show a logical response from the controller under different situations.

1.8 Outline of the Thesis

This thesis is organized as follows. In Chapter 2, the Fuzzy Control and Hierarchical Fuzzy are presented. Chapter 3 presents Time varying systems and Adaptive Control. Low energy Buildings is presented in Chapter 4. The design of Adaptive Hierarchical Fuzzy Controller and Simulation results are presented to show the performance of the proposed control system which is presented in Chapter 5. Chapter 6 presents conclusions and final comments.

Chapter 2 Fuzzy logic control

2.1 Introduction

Fuzzy logic is a form of many-valued logic or probabilistic logic; it deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets where variables may take on true or false values fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false. The understanding of most physical processes is based largely on imprecise human reasoning; this imprecision when compared to the precise quantities required by computers is nonetheless form of information that can be quite useful to humans. The ability to embed such reasoning in hitherto intractable and complex problems is the criterion by which the efficacy of fuzzy logic is judged.

Undoubtedly, this ability cannot solve problems that require precision problems such as shooting precision laser beams over tens of kilometers in space; milling machine components to accuracies of parts per billion; or focusing a microscopic electron beam on a specimen the size of a nanometer. The impact of fuzzy logic in these areas might be years away, if ever. But not many human problems require such precision; today, Fuzzy Logic concept used widely in many implementations like automobile engine & automatic gear control systems, air conditioners, video enhancement in TV sets, washing machines, mobile robots, sorting and handling data, Information Systems, Pattern Recognition (Image Processing, Machine Vision), decision support, traffic control systems and many, many others.

Requiring precision in engineering models and products translates to requiring high cost and long lead times in production and development. For other than simple systems, expense is proportional to precision: more precision entails higher cost. When considering the use of fuzzy logic for a given problem; an engineer or scientist should ponder the need for exploiting the tolerance for imprecision. Not only does high precision dictate high costs but it also entails low tractability in a problem [6].

Since the idea of the fuzzy set was proposed in 1965, many developments have occurred in this area Fuzzy logic is used in system control and analysis design, because it shortens the time for engineering development and sometimes, in the case of highly complex systems, is the only way to solve the problem. Fuzzy logic is the way the human brain works, and we can mimic this in machines so they will perform somewhat like humans not to be confused with Artificial Intelligence, where the goal is for machines to perform exactly like humans.

2.2 A Historical Perspective:

Of course, the leading theory in fuzzy set theory from the late nineteenth century until the late twentieth century had been the probability theory. However, the gradual evolution of the expression of uncertainty using probability theory was challenged, first in 1937 by Max Black, with his studies in vagueness, then with the introduction of fuzzy sets by Lotfi Zadeh (1965). Zadeh's paper had a profound influence on the thinking about uncertainty because it challenged not only probability theory as the sole representation for uncertainty but also the very foundations upon which probability theory was based: classical binary (two-valued) logic (Klir and Yuan, 1995).

Probability theory dominated the mathematics of uncertainty for over five centuries. Probability concepts date back to the 1500s, to the time of Cardano when gamblers recognized the rules of probability in games of chance.

The concepts were still very much in the limelight in 1685, when the Bishop of Wells wrote a paper that discussed a problem in determining the truth of statements made by two witnesses who were both known to be unreliable to the extent that they tell the truth only with probabilities P_1 and P_2, respectively. The Bishop's answer to this was based on his assumption that the two witnesses were independent sources of information (Lindley, 1987).

The twentieth century saw the first developments of alternatives to probability theory and to classical Aristotelian logic as paradigms to address more kinds of uncertainty than just the random kind. Jan Lukasiewicz developed a multivalued, discrete logic (circa 1930). In the 1960s, Arthur Dempster developed a theory of evidence, which, for the first time, included an assessment of ignorance, or the absence of information. In 1965, Lotfi Zadeh introduced his seminal idea in a continuous-valued logic that he called fuzzy set theory [6].

2.3 Fuzzy logic and fuzzy sets:

Making decisions about processes that contain nonrandom uncertainty, such as the uncertainty in natural language, has been shown to be less than perfect. The idea proposed by Lotfi Zadeh suggested that set membership is the key to decision making when faced with uncertainty.

The notion of a fuzzy set provides a convenient point of departure for the construction of a conceptual framework which parallels in many respects the framework used in the case of ordinary sets, but is more general than the latter and, potentially, may prove to have a much wider scope of applicability, particularly in the fields of pattern classification and information processing. Essentially, such a framework provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined criteria of class membership rather than the presence of random variables [6].

In crisp sets, an element in the universe has a well-defined membership or non-membership to a given set. Membership to a crisp set A can be defined through a membership function defined for every element x of the universe as:

$$\mu A(x) = \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases} \tag{2.1}$$

$$\mu A(x) \in \{0, 1\}$$

But in Fuzzy Set can have an infinite number of membership functions

$$\mu A \in [0, 1]$$

Point a in Figure 2.1a is clearly a member of crisp set A; point b is unambiguously not a member of set A. Figure 2.1b shows the vague, ambiguous boundary of a fuzzy set $\underset{\sim}{A}$ on the same universe X: the shaded boundary represents the boundary region of $\underset{\sim}{A}$. In the central (unshaded) region of the fuzzy set, point a is clearly a full member of the set. Outside the boundary region of the fuzzy set, point b is clearly not a member of the fuzzy set. However, the membership of point c, which is on the boundary region, is ambiguous. If complete membership in a set (such as point a in Figure 2.1b) is represented by the number 1, and no-membership in a set (such as point b in

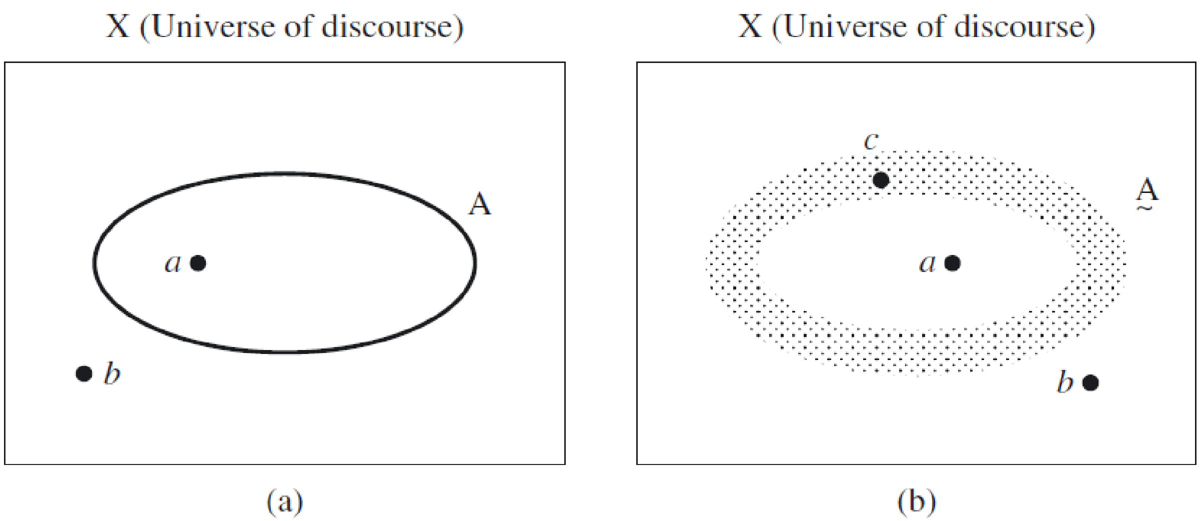


Figure 2.1: Diagrams for (a) crisp set boundary and (b) fuzzy set boundary.

Figure 2.1b) is represented by 0, then point c in Figure 2.1b must have some intermediate value of membership (partial membership in fuzzy set $\underset{\sim}{A}$) on the interval [0,1]. Presumably, the membership of point c in $\underset{\sim}{A}$ approaches a value of 1 as it moves closer to the central (unshaded) region in Figure 2.1b of $\underset{\sim}{A}$ and the membership of point c in $\underset{\sim}{A}$ approaches a value of 0 as it moves closer to leaving the boundary region of $\underset{\sim}{A}$.

In fuzzy logic, linguistic variables take on linguistic values which are words with associated degrees of membership in the set. Thus, instead of a variable temperature assuming a numerical value of 70 C^o, it is treated as a linguistic variable that may assume, for example, linguistic values of “hot” with a degree of membership of 0.92, "very cool" with a degree of 0.06, or "very hot" with a degree of 0.7. Each linguistic term is associated with a fuzzy set, each of which has a defined membership function. Formally, a fuzzy set is defined as a set of pairs where each element in the universe F has a degree of membership associated with it:

$$E = \{(x, \mu E(x)) \mid x \in F, \mu E(x) \in [0, 1]\} \tag{2.2}$$

The value $\mu E(x)$ is the degree of membership of object x to the fuzzy set E where $\mu E(x) = 0$ means that x does not belong at all to the set, while $\mu E(x) = 1$ means that the element is totally within the set [7].

2.4 Fuzzy Set Operations:

The most important operators in classical set theory with ordinary (crisp) sets are complement, intersection, union. These operations are defined in fuzzy logic via membership functions. Moreover, fuzzy set theory offers the vast range of operations on fuzzy sets that don't exist in the classical theory [8].

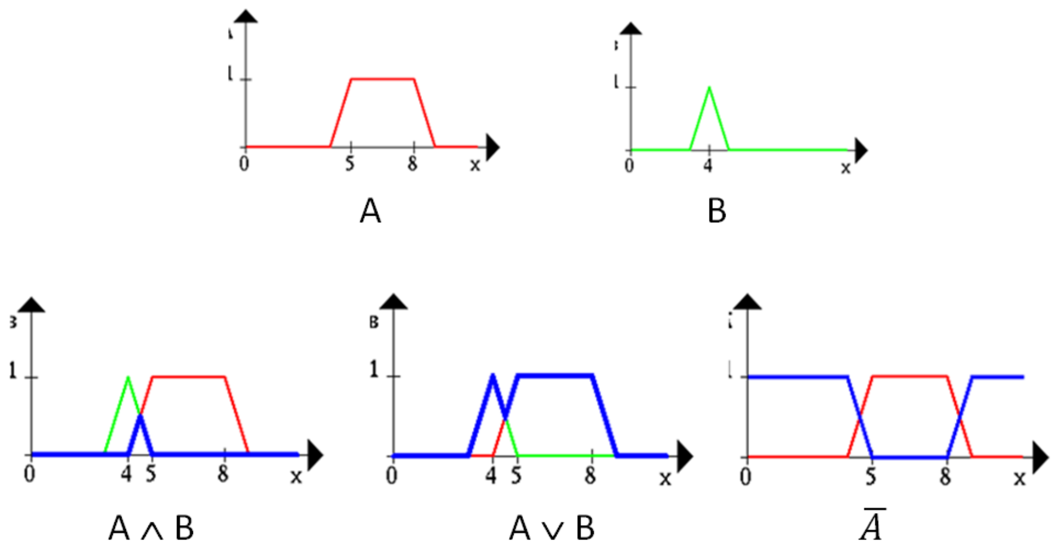


Figure 2.2: Intersection, Union and Complement of fuzzy sets

2.4.1 Complement

Complementation in fuzzy set theory corresponds to the complementation in classical set theory. For example, the element belongs to the fuzzy subset B with a level 0.6. It means that it does not belong to B with a level 0.4. Mathematically the membership values in a complement subset $\bar{B}$ are:

$$\mu\bar{B}\,(x) = not\,(\mu\, B(x)) = 1 - B(x). \tag{2.3}$$

2.4.2 Intersection or triangular norms

For the intersection of fuzzy sets, Zadeh [8] suggested the min operator and the algebraic product. Following Zadeh's idea a lot of researchers proposed various operators for this operation [9]. Let A and B be two fuzzy sets in U universe of discourse, with membership functions µA and µB respectively. The most important intersection operators are:

- min operator

$$\mu A(x) \text{ and } \mu B(x) = \min \{\, \mu A(x), \mu B(x)\} \tag{2.4}$$

2.4.3 Union triangular

For the union of two fuzzy sets, the most used in the literature are:

- Max operator
  $\mu A(x)$ *or* $\mu B(x) = \max\ \{\mu A(x), \mu B(x)\}$ (2.5)

2.5 Membership function:

Membership Functions characterize the fuzziness of fuzzy sets. There is an infinite # of ways to characterize fuzzy → infinite ways to define fuzzy membership functions. Membership function essentially embodies all fuzziness for a particular fuzzy set; its description is essential to fuzzy property or operation. The shape of membership function depends on the application and can be monotonic, triangular, trapezoidal or bellshaped as shown in Figure 2.3 [16].

The membership function could be defined as a graphical representation of the quantity of participation of the inputs. It links a value with each of the inputs parameters that are treated, defines functional overlap amongst inputs, and finally defines an output parameter. The rules usually take the input membership parameters as features to establish their weight over the „fuzzy output sets‟ of the final output response. Once the functions are deduct, scaled, and combined, they have to be defuzzified into a crisp output which leads the application. There are some different memberships functions linked to each input and output parameter.

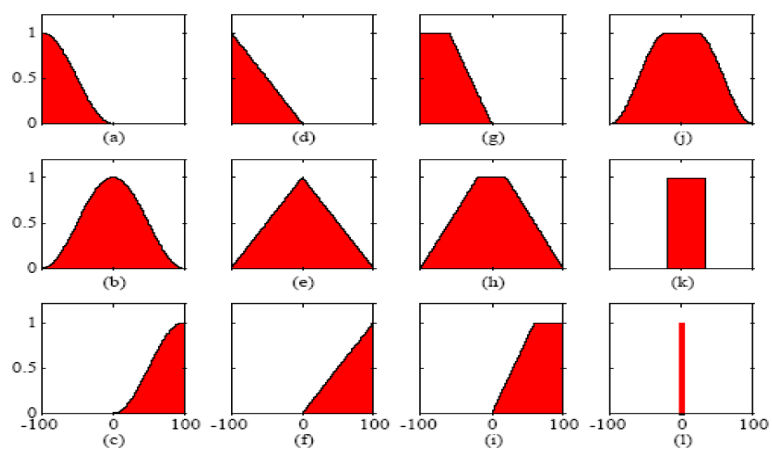


Figure 2.3: Different shapes of membership function: (a) S-function. (b) π-function. (c) Z-function. (d-f) triangular versions. (g-i) Trapezoidal function. (J) Flat π-function. (k) Rectangle. (L) Singleton.

2.6 Fuzzy logic:

FL is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster.

Fuzzy logic makes it possible to imitate the behavior of human logic, which tends to work with “fuzzy” concepts of truth. Fuzzy Logic shows a usual rule-based IF condition AND condition THEN action. It approaches to a solving control problem rather than intending to model a system based on math.

2.6.1 Fuzzy Logic Process:

It is one thing to compute, to reason, and to model with fuzzy information; it is another to apply the fuzzy results to the world around us. Despite the fact that the bulk of the information we assimilate every day is fuzzy, most of the actions or decisions implemented by humans or machines are crisp or binary. The decisions we make that require an action are binary, the hardware we use is binary, and certainly the computers we use are based on binary digital instructions. In giving instructions to an aircraft autopilot, it is not possible to turn the plane “slightly to the west”; an autopilot device does not understand the natural language of a human. We have to turn the plane by 15◦, for example, a crisp number.

When fuzzy sets are used to solve the problem without analyzing the system; but the expression of the concepts and the knowledge of it in human communication are needed. Human usually do not use mathematical expression but use the linguistic expression. Another example, if you see heavy box and you want to move it, you will say, "I want strong motor to move this box" we see that, we use strong expression to describe the force that we need to move the box. In fuzzy sets we do the same thing we use linguistic variables to describe the fuzzy sets. Linguistic variable is “a variable whose values are words or sentences in a natural or artificial language”. Each linguistic variable may be assigned one or more linguistic values, which are in turn connected to a numeric value through the mechanism of membership functions.

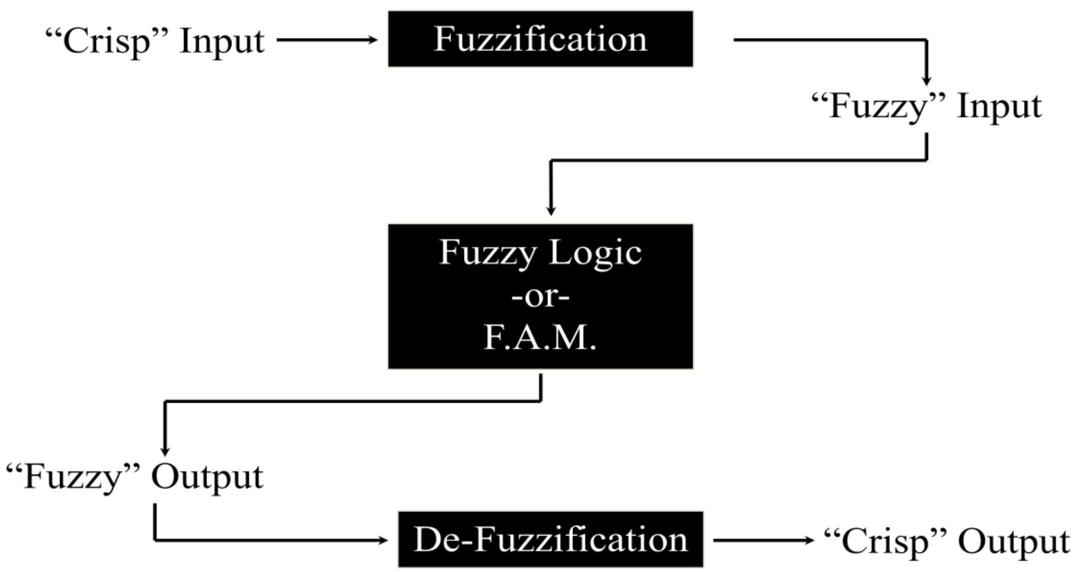


Figure 2.4: Fuzzy Logic Process

The basic parts of every fuzzy controller are displayed in the following Figure 2.5 .The fuzzy logic controller (FLC) is composed of a fuzzification interface, knowledge base, inference engine, and defuzzification interface.

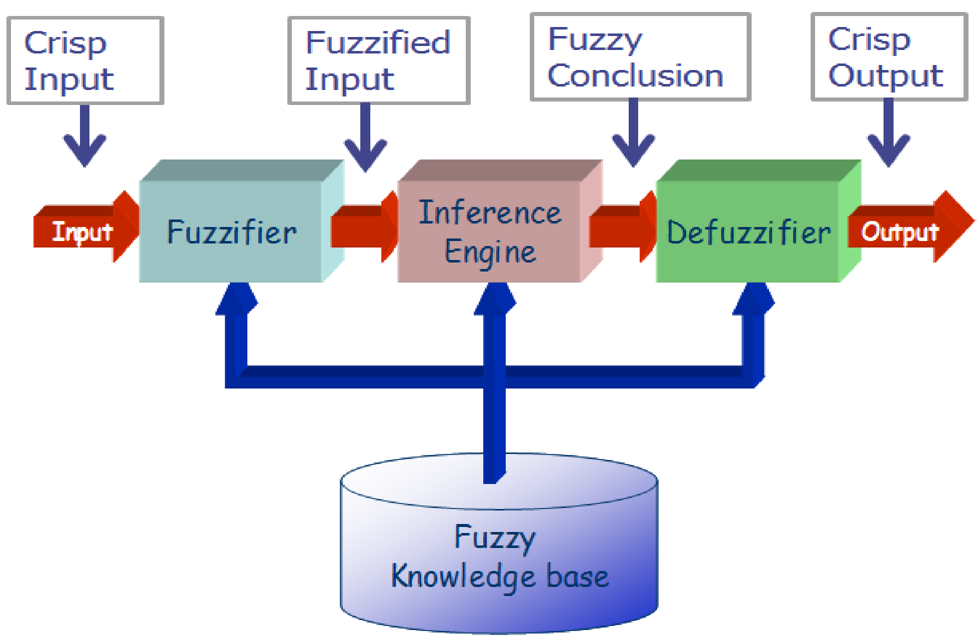


Figure 2.5: Fuzzy Logic Process

2.6.2 Fuzzification of the input variables:

Fuzzification is the process of making a crisp quantity fuzzy. We do this by simply recognizing that many of the quantities that we consider to be crisp and deterministic are actually not deterministic at all; they carry considerable uncertainty. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, then the variable is probably fuzzy and can be represented by a membership function.

Simply, Fuzzification Converts the crisp input to a linguistic variable using the membership functions stored in the fuzzy knowledge base. An example of Fuzzification is shown in Figure 2.6. The figure shows a crisp voltage reading to a fuzzy set, say "low voltage." In the figure, we see that the crisp reading intersects the fuzzy set "low voltage" at a membership of 0.3, that is, the fuzzy set and the reading can be said to agree at a membership value of 0.3.

So, Fuzzification converts the crisp input (1 V) to a linguistic variable (Low voltage) using the membership functions (0.3) stored in the fuzzy knowledge base.

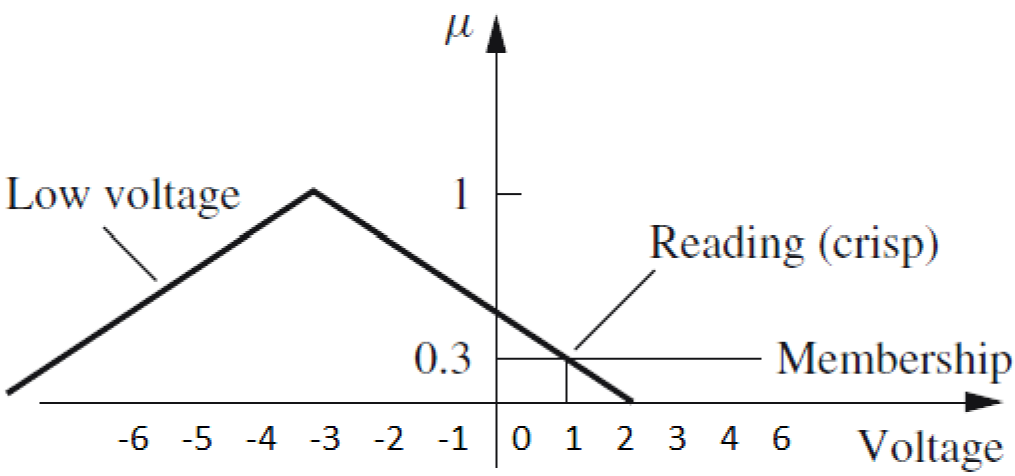


Figure 2.6: Fuzzification

2.6.3 Knowledge Base:

The knowledge base of Fuzzy Logic Controller (FLC) is comprised of two parts:

- A data base.
- A fuzzy control rule base.

In the data base part, there are four principal design parameters for an FLC: discretization, normalization of universe of discourse, fuzzy partition of input and output spaces and membership function of primary fuzzy set [10].

A fuzzy system is characterized by a set of linguistic statements usually represented in the form of "if-then" rules.

2.6.4 Source of fuzzy control rules:

There are two principal approaches to the derivation of fuzzy control rules. The first is a heuristic method in which rules are formed by analyzing the behavior of a controlled process. The derivation relies on the qualitative knowledge of process behavior.

The second approach is basically a deterministic method which can systematically determine the linguistic structure of rules.

We can use four modes of derivation of fuzzy control rules. These four modes are not mutually exclusive, and it is necessary to combine them to obtain an effective system:

- Expert experience and control engineering knowledge: The fuzzy control rule is based on information obtained by a controlled system. Experience rules are the most important part of fuzzy control.
- Operators' control actions: observation of human controller's actions in terms of input-output operating data.
- The fuzzy model of a process: linguistic description of the dynamic characteristics of a process.
- System self-learning: The system has an off-line learning method and builds a rule base with the help of other algorithms. Self-organizing controller is an example of a controller that finds the rules itself. Neural networks are another possibility.

These four modes are not mutually exclusive, and it is necessary to combine them to obtain an effective system. Fuzzy control rules have two types of presentations. The first is a state evaluation type, and the second is an object evaluation type.

a) State evaluation:

State variables are in the antecedent part of rules and control variables are in the consequent part [11].

In the case of MISO (multiple input single output), they are characterized as a collection of rules of the form.

R1: if x is A1,…, and y is B1 then z is C1

R2: if x is A2,…, and y is B2 then z is C2 (2.6)

…

Rn: if x is An,…, and y is Bn then z is Cn

Where x,…, y and z are linguistic variables representing the process state variable and the control variable. Ai,…, Bi and Ci are linguistic values of the variables x,…, y and z in the universe of discourse U.

b) Object evaluation:

It is also called predictive fuzzy control. They predict present and future control actions, and evaluate control objectives. A typical rule is described as:

R1: if (z is C1 → (x is A1 and y is B1)) then z is C1.

R2: if (z is C2 → (x is A2 and y is B2)) then z is C2. (2.7)

…

Rn: if (z is Cn → (x is An and y is Bn)) then z is Cn.

A control action is determined by an objective evaluation that satisfies the desired states and objectives. Note x and y are performance indices for the evaluation and z is control command.

2.6.5 Fuzzy Inference Engine:

Fuzzy inference is the computation of fuzzy rules which represent the relationship between observations and actions. Since the precondition (IF-part) can consist of multiple conditions linked together with AND or OR conjunctions. Conditions may be negated with a NOT. In general, the inference is a process to obtain new information by using existing knowledge. The fuzzy inference engine performs the actual decision-making process [12].The engine have two key inference methods:

1. Generalized modus tollens (GMT): is object-oriented inverse fuzzy theory. For example:

   Fact: y is $\bar{b}$

   Rule: If x is a then y is b (2.8)

   Result: x is $\bar{a}$

2. Generalized modus pones (GMP): is forwarding linking inference modus. For example:
   Fact: x is a
   Rule: If x is a, then y is b (2.9)
   Result: y is b

The modus ponens is used in the forward inference and the modus tollens is in the backward one. In GMP, when data is input, the output can be inferred according to rules; therefore, GMP is applicable for a fuzzy control inference mechanism.

There are a lot of inference methods which deals with fuzzy inference like: Mamdani method, Larsen method, Tsukamoto method, and the Sugeno style inference Takagi-Sugeno_Kang (TSK) method. The most important and widely used in fuzzy controllers are the Mamdani and Takagi-Sugeno methods. Mamdani method is the most commonly used fuzzy inference technique.In 1974, Professor Ebrahim Mamdani of London University built one of the first fuzzy systems to control a steam engine and boiler combination. He applied a set of fuzzy rules supplied by experienced human operators. The Mamdani-style fuzzy inference process is performed in four steps [8]:

- Fuzzification of the input variables.
- Knowledge Base
- Fuzzy Inference Engine.
- Defuzzification.

2.6.6 Mamdani method:

Step1: Fuzzification

The first step in the application of fuzzy reasoning is a Fuzzification of inputs in the controller, which is to take the crisp inputs, x1 and y1, and determine the degree to which these inputs belong to each of the appropriate fuzzy sets. It means that to every crisp value of input we attribute a set of degrees of membership (mj, j=1,n) to fuzzy sets defined in the universe of discourse for that input[13].

Step2: Rule evaluation

The second step is to take the Fuzzified inputs, $\mu(x=A1) = 0.5$, $\mu(x=A2) = 0.2$, $\mu(y=B1) = 0.1$ and $\mu(y=B2) = 0.7$, and apply them to the antecedents of the fuzzy rules. If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation. This number (the truth value) is then applied to the consequent membership function.

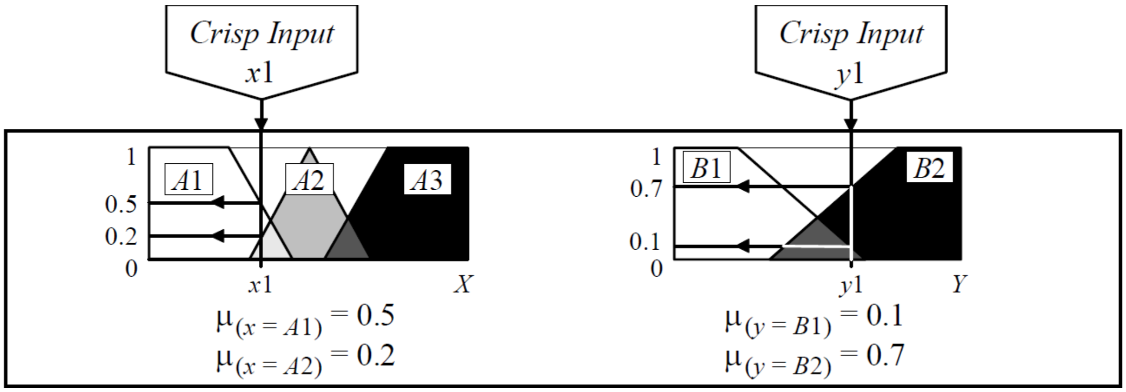


Figure 2.7: Fuzzification stage

To evaluate the disjunction of the rule antecedents, we use the OR fuzzy operation. As shown Operations with fuzzy sets the most used approach for the union is to get the maximum:

$$\mu A \cup B(x) = max\ [\mu A(x),\ \mu B(x)] \tag{2.10}$$

Similarly, in order to evaluate the conjunction of the rule antecedents, we apply the AND fuzzy operation intersection which used minimum approach:

$$\mu A \cap B(x) = min\ [\mu A(x),\ \mu B(x)] \tag{2.11}$$

Step3: Aggregation of the rule outputs

Aggregation is the process of unification of the outputs of all rules. We take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. The input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable.

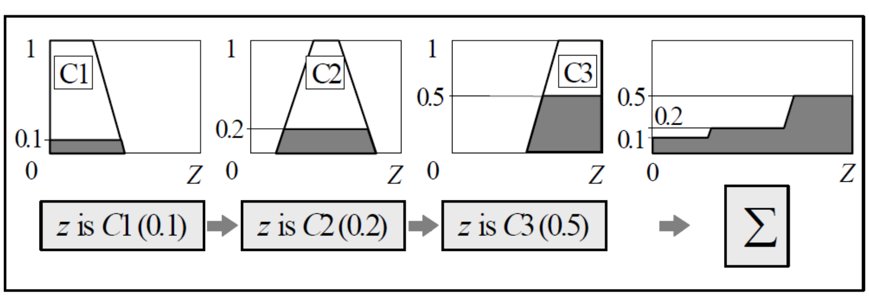


Figure 2.8: Aggregation stage in Mamdani method

Step4: Defuzzification

Defuzzify the aggregate output fuzzy set into a single number.

2.6.7 Defuzzification:

The reverse of fuzzification, defuzzification converts the resulted fuzzy sets defined by the inference engine to the output of the model to a standard crisp signal. This process gives output control signals to the controlled system. There is no systematic procedure for choosing a good defuzzification strategy, but the selection of defuzzification procedure depends on the properties of the application. There are several methods available for defuzzification of fuzzy control inference as Max-membership principle, weighted average method and the method we used in this thesis is Centroid of area (COA):

- Centroid of area (COA)

It is the best known defuzzification operator method. It is a basic general defuzzication method that determines the value of the abscissa of the center of gravity of the area below the membership function.

$$z^* = \frac{\int \mu_{\underset{\sim}{B}}(z) z dz}{\int \mu_{\underset{\sim}{B}}(z) dz} \tag{2.12}$$

As an example:

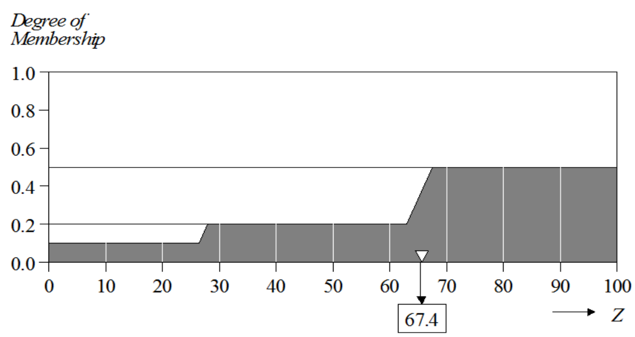


Figure 2.9: Center of gravity (COG) defuzzfication method

Calculated as:

$$\frac{(0+10+20)\times 0.1+(30+40+50+60)\times 0.2+(70+80+90+100)\times 0.5}{0.1+0.1+0.1+0.2+0.2+0.2+0.2+0.5+0.5+0.5+0.5} = 67.4$$

2.7 Hierarchical Fuzzy control:

So far, we have seen various concepts associated with fuzzy logic and control. In order to design a fuzzy system with a good amount of accuracy, an increase in the number of input variables to the fuzzy system results in an exponential increase in the number of rules required. If there are n input variables and m fuzzy sets are defined for each of these, then the number of rules in the fuzzy system is m^n, this can be shown with the help of a small example. Suppose there are 5 input variables and for each variable 3 fuzzy sets are defined, then the total number of rules is $3^5 = 243$.

Now, suppose the number of fuzzy sets is increased to 5 (to increase the accuracy of the system), then the new number of the rules would be $5^5 = 3120$. This is a significant increase in the number of rules. The idea behind the construction of a two-level hierarchical scheme is to make a layered structure of control where each layer takes into account a certain number of variables and gives a single variable as the output. Hence the complexity of the system reduces, and along with it, the number of rules to be framed [14].

There are two types of hierarchical fuzzy logic; one is parallel type and series type, in the parallel type more than one fuzzy controller in one stage and the output of two fuzzy controllers enter the higher stage into one fuzzy controller and so on, but the series type; fuzzy controller in the higher stage with two inputs one of them from a fuzzy controller and the other from any input not from a fuzzy controller, hierarchical fuzzy rule-based control of renewable energy building systems is an example of a hierarchical fuzzy logic series type[4]:

A hierarchical fuzzy rule based control strategy is proposed for the optimum control of the heating system. Fuzzy rule based controllers are widely used on systems with high uncertainties and can be interpreted linguistically. The rules are of the following forms and are as shown in figure 2.10:

Rule Level 1: IF A1 is LOW & B1 is HIGH Then C2 is 3.4

Rule Level 2: IF C2 is LOW & D2 is HIGH Then E3 is 5.6

Rule Level 3: IF E3 is LOW & F3 is HIGH Then G4 is 1

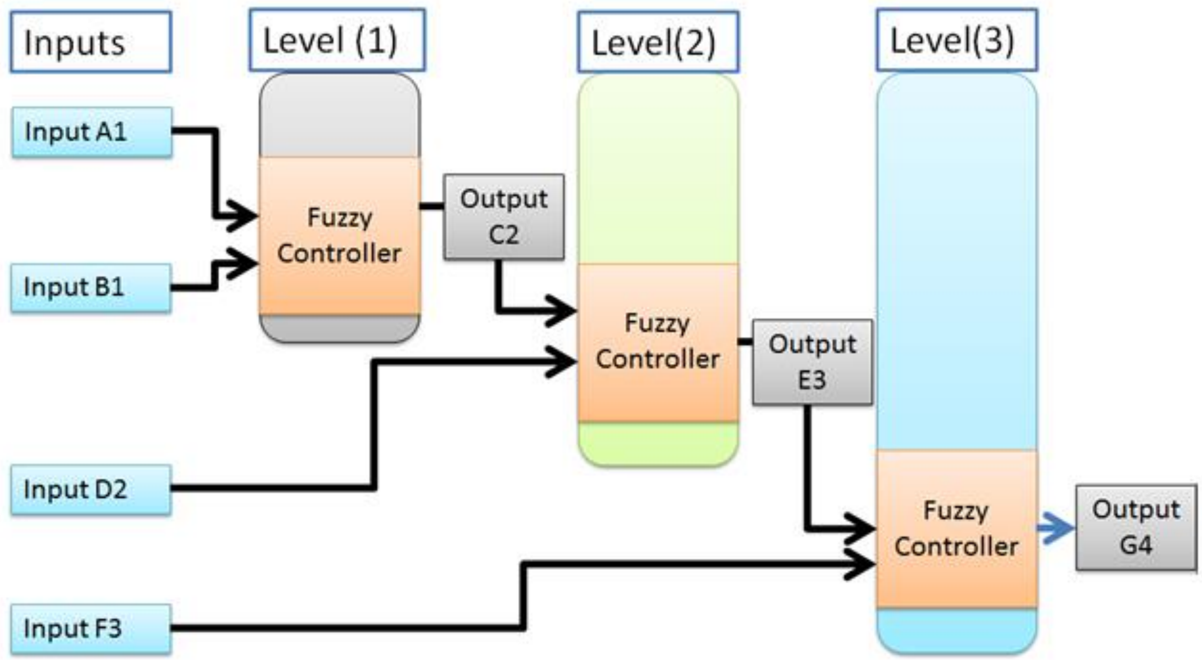


Figure 2.10: A three level Hierarchical Fuzzy control

Fuzzy rules are generated from optimization results calculated for values of the inputs at the centers of the fuzzy sets. Even if it is assumed that each of the fuzzy input variables is described by 5 fuzzy sets, the total number of rules would be very large (625). It would therefore take many years to generate the rules and they would be very difficult to understand. A hierarchical approach is adopted to reduce the number of fuzzy rules to 25 rules each level only which mean (75) rules for whole system with reduction of (550) rules with conventional method. The control strategy is split into 3 levels. At the first level, the date, time, schedule and prediction of the future outdoor temperatures are used to decide which of the rules at the second level and third level will be used. At the second level, predictions of the future solar radiation, outdoor temperature and internal load are used to find the optimal tank and building temperatures. At the third level, the room and tank temperature set points are used, together with a measurement of the current solar radiation and an estimate of the excess energy that is currently available, to determine the control command for each device in the heating system.

Chapter 3 Time Variant Systems and Adaptive Control

3.1 Introduction:

A general problem in the control field is to derive a model of the system to be controlled. The classical approaches consists in building a mathematical model on the basis of the laws governing the system (e.g. mechanical, physical, economical) and then exploit it for designing a model-based control law that fulfills the desired specifications. However, such approach is not always possible for two main reasons: the incomplete knowledge of the system laws and its nonlinearity which, respectively, do not enable to derive an accurate and tractable model.

On the other hand, considering that the most of the existing systems are nonlinear, the model to be derived should be a trade-off between accuracy and tractability. Indeed, the accuracy of the model, employed to design the control system plays a crucial role since the performance achievable by the controlled system strongly depends on the size of the modeling error.

In the presence of a poor accurate model, not only performance degradation may occur, but the closed loop stability may also be missed. The literature of nonlinear control usually assumes that the system to be controlled and its model are well known, although this is not always true as pointed out above. In particular, the nonlinear models usually employed are neural networks or parametric models whose parameters are identified from input/output data of the process. Due to the nature of these models does not exist; a systematic procedure to obtain a suitable description of the uncertainty associated with them which in turn hampers a systematic dealing of the robust stability. Thus, in order to investigate the control of nonlinear and unknown systems guaranteeing the stability of the closed loop system in the presence of model uncertainty.

A common practice in the engineering community, when modeling physical systems is at hand, is to work with approximating models, the quality of which is satisfactory for the intended application. Although the world we are living in is nonlinear and time-varying in some sense, engineers prefer to work with linear, time invariant models. The latter significantly simplify the interpretations and the computational cost. A trade-off is sought between the accuracy of the model and the convenience of using it. However, recent progress (over the last decades) in the field of digital signal processing, and in the availability of huge computer memories and computing power give the possibility to the engineer of using more complex models and algorithms, even for real-time applications. The safe boundaries of linear time invariant systems are prudently crossed and new expansions are explored.

3.2 Dynamic systems:

A dynamical system is a concept in mathematics where a fixed rule describes the time dependence of a point in a geometrical space. Examples include the mathematical models that describe the swinging of a clock pendulum, the flow of water in a pipe, and the number of fish each spring time in a lake.

At any given time a dynamical system has a state given by a set of real numbers (a vector) that can be represented by a point in an appropriate state space (a geometrical manifold). Small changes in the state of the system create small changes in the numbers. The evolution rule of the dynamical system is a fixed rule that describes what future states follow from the current state. The rule is deterministic; in other words, for a given time interval only one future state follows from the current state [18].

The concept of a dynamical system has its origins in Newtonian mechanics. There, as in other natural sciences and engineering disciplines, the evolution rule of dynamical systems is given implicitly by a relation that gives the state of the system only a short time into the future. (The relation is either a differential equation, difference equation or other time scale.) To determine the state for all future times requires iterating the relation many times each advance time a small step. The iteration procedure is referred to as solving the system or integrating the system. Once the system can be solved, given an initial point it is possible to determine all its future positions, a collection of points known as a trajectory or orbit.

Before the advent of fast computing machines, solving a dynamical system required sophisticated mathematical techniques and could be accomplished only for a small class of dynamical systems. Numerical methods implemented on electronic computing machines have simplified the task of determining the orbits of a dynamical system. For simple dynamical systems, knowing the trajectory is often sufficient, but most dynamical systems are too complicated to be understood in terms of individual trajectories. The difficulties arise because:

1- The systems studied may only be known approximately; the parameters of the system may not be known precisely or terms may be missing from the equations. The approximations used bring into question the validity or relevance of numerical solutions. To address these questions several notions of stability have been introduced in the study of dynamical systems, such as Lyapunov stability or structural stability. The stability of the dynamical system implies that there is a class of models or initial conditions for which the trajectories would be equivalent. The operation for comparing orbits - to establish their equivalence - changes with the different notions of stability.

2- The type of trajectory may be more important than one particular trajectory. Some trajectories may be periodic, whereas others may wander through many different states of the system. Applications often require enumerating these classes or maintaining the system within one class. Classifying all possible trajectories has led to the qualitative study of dynamical systems, that is, properties that do not change under coordinate changes. Linear dynamical systems and systems that have two numbers describing a state are examples of dynamical systems where the possible classes of orbits are understood.

3- The behavior of trajectories as a function of a parameter may be what is needed for an application. As a parameter is varied, the dynamical systems may have bifurcation points where the qualitative behavior of the dynamical system changes. For example, it may go from having only periodic motions to apparently erratic behavior, as in the transition to turbulence of a fluid.

4- The trajectories of the system may appear erratic, as if random. In these cases it may be necessary to compute averages using one very long trajectory or many different trajectories. The averages are well defined for ergodic systems and a more detailed understanding has been worked out for hyperbolic systems. Understanding the probabilistic aspects of dynamical systems has helped establish the foundations of statistical mechanics and of chaos.

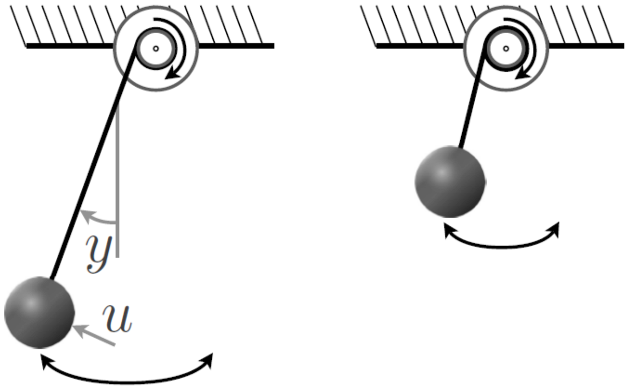


Figure 3.1: Example of a parameter varying system

A tower crane while raising/lowering a load, or conceptually comparable, a mass swinging at the extremity of a rod with a varying length as illustrated in Figure 3.1. The figure shows a swinging pendulum with a shortened rod, in a gravitational field. The resonance frequency is inversely proportional to the square root of the length of the rod. u(t) is the driving force while y(t) - the response of the system - is the resulting angle w.r.t. a vertical line.

For a small swinging amplitude (w.r.t. the length of the rod), this pendulum behaves linearly. As the length of the rod changes, the resonance frequency changes too. The length of the rod is then the dynamical parameter.

3.3 Time-varying systems:

Time-varying systems are often interpreted as being a special case of parameter varying systems. Informally, a dynamic system is called 'parameter varying' when its dynamics depend on one or more measurable and controllable external parameters, called scheduling parameters [17].

A time-varying system can be thought of as a system, the dynamic properties of which are changing with time. Contrary to parameter varying systems, the cause of the time dependence is not necessarily directly measurable. The time variation can simply be due to an evolution of some properties of the system. Example of such systems, The impedance of a metal which is subjected to an electrochemical reaction such as aluminum is being subjected to pitting corrosion[19]. As the metal is being corroded, small holes are formed which grow with time, and passivate. This process alters the impedance.

3.4 Black box, data driven modeling:

As is clear from the previous section, dynamic systems and time-varying systems emerge in all fields of engineering. Each of those application examples is governed by its own physical laws which, however, all are formalized by differential equations.

Black box modeling deals with systems in abstraction of the underlying governing physics. That is, the variables in the mathematical expressions defining the model can be any physical quantity, or a functional combination of more of them. The structure of the mathematical expressions doesn't even have to reflect the physics. This yields unified modeling approaches, independent of the particular application at hand. In this thesis, the sole goal of the model is to be a 'good' description of the data (i.e. measurements of the physical quantities) provided, hence the designation data driven modeling.

3.5 Non-linear System:

A nonlinear system is one that does not satisfy the superposition principle, or one whose output is not directly proportional to its input; a linear system fulfills these conditions. In other words, a nonlinear system is any problem where the variables to be solved cannot be written as a linear combination of independent components.

A nonhomogeneous system which is linear apart from the presence of a function of the independent variables is nonlinear according to a strict definition, but such systems are usually studied alongside linear systems, because they can be transformed to a linear system of multiple variables.

Nonlinear problems are of interest to engineers, physicists and mathematicians because most physical systems are inherently nonlinear in nature. Nonlinear equations are difficult to solve and give rise to interesting phenomena such as chaos [20]. Some aspects of the weather are seen to be chaotic, where simple changes in one part of the system produce complex effects throughout.

3.6 Nonlinear Model:

In mathematics, a linear function f(x) is one which satisfies both of the following properties:

- Additivity $f(x+y) = f(x) + f(y)$ (3.1)
- Homogeneity $f(\alpha x) = \alpha f(x)$

Additivity implies homogeneity for any rational α, and for continuous functions for any real α. For a complex α homogeneity does not follow from additivity; for example, an antilinear map is additive but not homogeneous. The conditions of additivity and homogeneity are often combined in the superposition principle

$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y)$$

An equation written as

$$f(x) = C$$

is called linear if $f(x)$ is a linear map as defined above and nonlinear otherwise. The equation is called homogeneous if $\mathrm{C} = 0$.

The definition $f(x) = C$ is very general in that x can be any sensible mathematical object (number, vector, function, etc.) and the function $f(x)$ can literally be any mapping, including integration or differentiation with associated constraints such as boundary values. If $f(x)$ contains differentiation of x, the result will be a differential equation.

Nonlinear algebraic equations, which are also called polynomial equations, are defined by equating polynomials to zero. For example,

$$x^2 + x - 1 = 0 \tag{3.2}$$

For a single polynomial equation, root-finding algorithms can be used to find solutions to the equation (i.e., sets of values for the variables that satisfy the equation). However, systems of algebraic equations are more complicated; their study is one motivation for the field of algebraic geometry, a difficult branch of modern mathematics. It is even difficult to decide if a given algebraic system has complex solutions. Nevertheless, in the case of the systems with a finite number of complex solutions, these systems of polynomial equations are now well understood and efficient methods exist for solving them.

3.7 Adaptive control:

3.7.1 Overview:

Adaptive Control is the control method used by a controller which must adapt to a controlled system with parameters which vary, or are initially uncertain. For example, as an aircraft flies, its mass will slowly decrease as a result of fuel consumption; a control law is needed that adapts itself to such changing conditions. Adaptive control is different from robust control in that it does not need a priori information about the bounds on these uncertain or time-varying parameters; robust control guarantees that if the changes are within given bounds the control law need not be changed, while adaptive control is concerned with control law changing themselves [22].

Adaptive Control covers a set of techniques which provide a systematic approach for automatic adjustment of controllers in real time, in order to achieve or to maintain a desired level of control system performance when the parameters of the plant dynamic model are unknown and/or change in time. Consider first the case when the parameters of the dynamic model of the plant to be controlled are unknown but constant at least in a certain region of operation. In such cases, although the structure of the controller will not depend in general upon the particular values of the plant model parameters, the correct tuning of the controller parameters cannot be done without knowledge of their values. Adaptive control techniques can provide an automatic tuning procedure in closed loop for the controller parameters. In such cases, the effect of the adaptation vanishes as time increases. Changes in the operation conditions may require a restart of the adaptation procedure. Now consider the case when the parameters of the dynamic model of the plant change unpredictably in time. These situations occur either because the environmental conditions change (ex: the dynamical characteristics of a robot arm or of a mechanical transmission depend upon the load; in a DC-DC converter the dynamic characteristics depend upon the load) or because we have considered simplified linear models for nonlinear systems a change in operation condition will lead to a different linearized model. These situations may also occur simply because the parameters of the system are slowly time-varying (in a wiring machine the inertia of the spool is time-varying). In order to achieve and to maintain an acceptable level of control system performance when large and unknown changes in model parameters occur, an adaptive control approach has to be considered. In such cases, the adaptation will operate most of the time and the term non-vanishing adaptation fully characterizes this type of operation also called continuous adaptation. Further insight into the operation of an adaptive control system can be gained if one considers the design and tuning procedure of the "good" controller illustrated in Figure 3.2. In order to design and tune a good controller, one needs to [23]:

1- Specify the desired control loop performances.
2- Know the dynamic model of the plant to be controlled.
3- Possess a suitable controller design method making it possible to achieve the desired performance for the corresponding plant model.

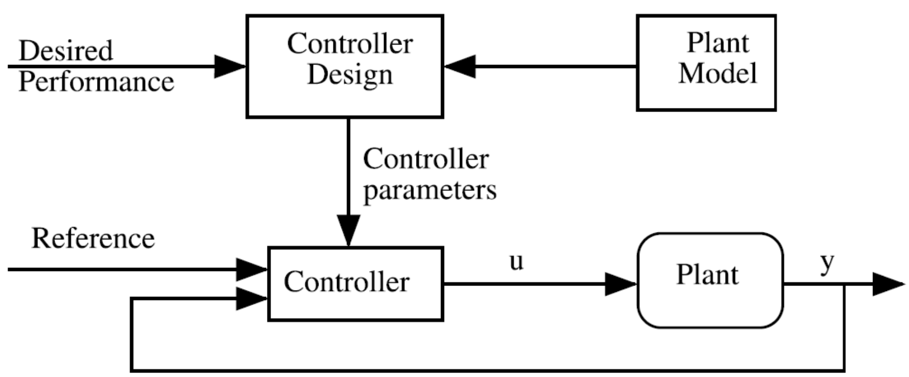


Figure 3.2: Principles of controller design

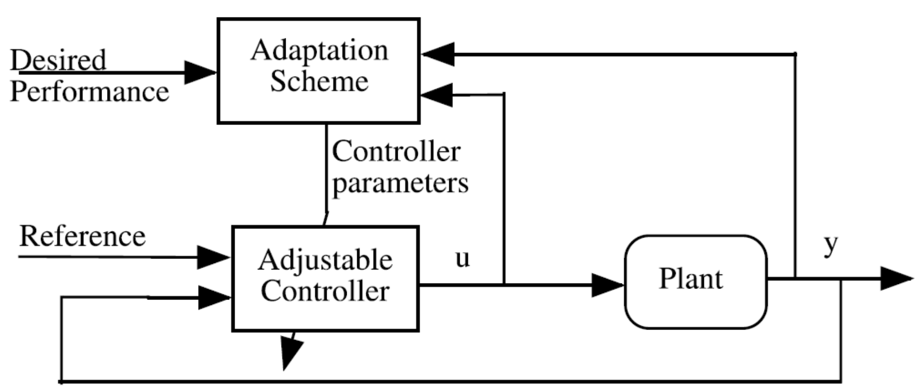


Figure 3.3: An adaptive control system

The dynamic model of the plant can be identified from input/output plant measurements obtained under an experimental protocol in open or in closed loop. One can say that the design and tuning of the controller is done from data collected on the system. An adaptive control system can be viewed as an implementation of the above design and tuning procedure in real time. The tuning of the controller will be done in real time from data collected in real time on the system. The corresponding adaptive control scheme is shown in Figure 3.3.

The way in which information is processed in real time in order to tune the controller for achieving the desired performances will characterize the various adaptation techniques. From Figure 3.3, one clearly sees that an adaptive control system is nonlinear since the parameters of the controller will depend upon measurements of system variables through the adaptation loop.

3.7.2 Adaptive Control versus Conventional Feedback Control:

The unknown and immeasurable variations of the process parameters degrade the performances of the control systems. Similarly to the disturbances acting upon the controlled variables, one can consider that the variations of the process parameters are caused by disturbances acting upon the parameters (called parameter disturbances). These parameter disturbances will affect the performance of the control systems. Therefore the disturbances acting upon a control system can be classified as follows:

a) Disturbances acting upon the controlled variables
b) Parameter disturbances acting upon the performance of the control system.

Feedback is basically used in conventional control systems to reject the effect of disturbances upon the controlled variables and to bring them back to their desired values according to a certain performance index. To achieve this, one first measures the controlled variables, then the measurements are compared with the desired values and the difference is fed into the controller which will generate the appropriate control. A similar conceptual approach can be considered for the problem of achieving and maintaining the desired performance of a control system in the presence of parameter disturbances. We will have to define first a performance index (IP) for the control system which is a measure of the performance of the system (ex: the damping factor for a closed-loop system characterized by a second-order transfer function is an IP which allows quantifying a desired performance expressed in terms of “damping”). Then we will have to measure this IP. The measured IP will be compared to the desired IP and their difference (if the measured IP is not acceptable) will be fed into an adaptation mechanism. The output of the adaptation mechanism will act upon the parameters of the controller and/or upon the control signal in order to modify the system performance accordingly. A block diagram illustrating a basic configuration of an adaptive control system is given in Figure 3.4. Associated with Figure3.4, one can consider the following definition for an adaptive control system.

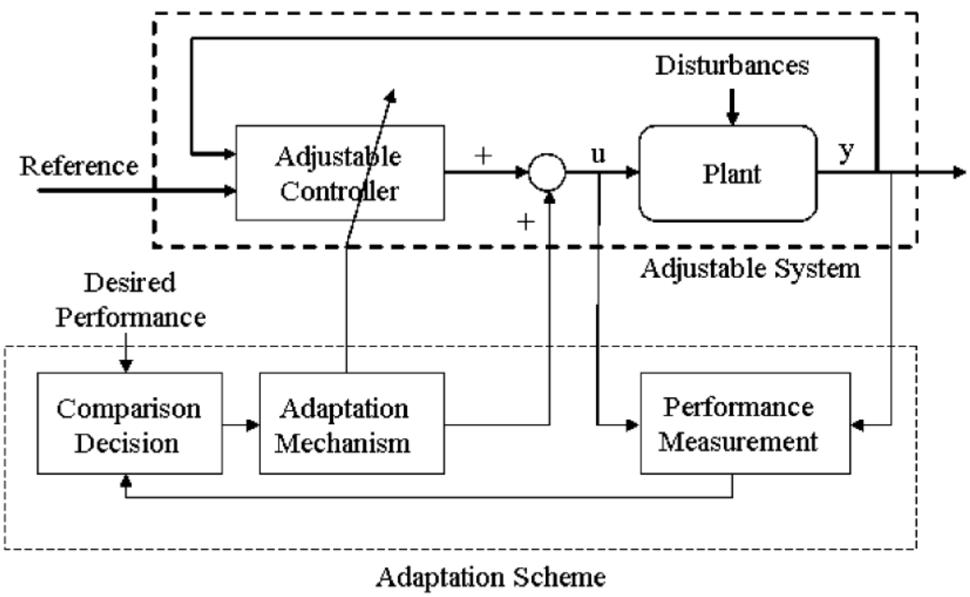


Figure 3.4: Basic configuration for an adaptive control system

3.7.3 Adaptive control system definition:

An adaptive control system measures a certain performance index (IP) of the control system using the inputs, the states, the outputs and the known disturbances. From the comparison of the measured performance index and a set of given ones, the adaptation mechanism modifies the parameters of the adjustable controller and/or generates an auxiliary control in order to maintain the performance index of the control system close to the set of given ones (i.e., within the set of acceptable ones). Note that the control system under consideration is an adjustable dynamic system in the sense that its performance can be adjusted by modifying the parameters of the controller or the control signal. The above definition can be extended straightforwardly for "adaptive systems" in general [24]. A conventional feedback control system will monitor the controlled variables under the effect of disturbances acting on them, but its performance will vary (it is not monitored) under the effect of parameter disturbances (the design is done assuming known and constant process parameters). An adaptive control system, which contains in addition to a feedback control with adjustable parameters supplementary loop acting upon the adjustable parameters of the controller, will monitor the performance of the system in the presence of parameter disturbances.

Consider as an example the case of a conventional feedback control loop designed to have a given damping. When a disturbance acts upon the controlled variable, the return of the controlled variable towards its nominal value will be characterized by the desired damping if the plant parameters have their known nominal values. If the plant parameters change upon the effect of the parameter disturbances, the damping of the system response will vary. When an adaptation loop is added, the damping of the system response will be maintained when changes in parameters occur. While the design of a conventional feedback control system is oriented firstly toward the elimination of the effect of disturbances upon the controlled variables, the design of adaptive control systems is oriented firstly toward the elimination of the effect of parameter disturbances upon the performance of the control system. An adaptive control system can be interpreted as a feedback system where the controlled variable is the performance index (IP). One can view an adaptive control system as a hierarchical system:

- Level 1: conventional feedback control;
- Level 2: adaptation loop.

In practice often an additional “monitoring” level is present (Level 3) which decides whether or not the conditions are fulfilled for a correct operation of the adaptation loop.

3.7.4 Adaptive Feedforward Compensation of Disturbances:

In a number of applications including active vibration control, active noise control it is possible to get a measurement highly correlated with the disturbance an image of the disturbance. Therefore one can use an adaptive feedforward filter for compensation of the disturbance eventually on top of a feedback system. This is particularly interesting for the case of wide band disturbances where the performance achievable by feedback only may be limited (limitations introduced by the Bode “integral” of the output sensitivity function). The feedforward filter should be adapted with respect to the characteristics of the disturbance.

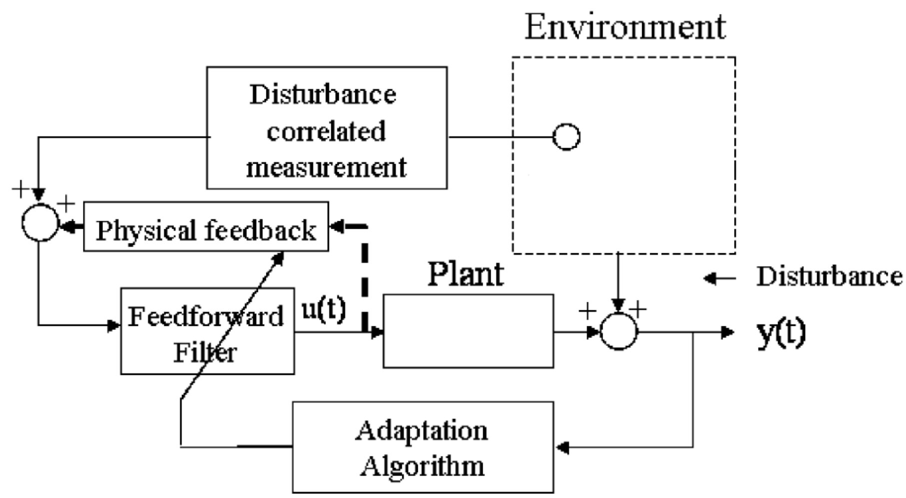


Figure 3.5: Adaptive feedforward disturbance compensation

It is important to mention that despite its “open-loop character”, there is an inherent positive feedback in the physical system, between the actuator and the measurement of the image of the disturbance. Therefore the adaptive feedforward filter operates in closed loop with positive feedback. The adaptive feedforward filter should stabilize this loop while simultaneously compensating the effect of the disturbance. The corresponding block diagram is shown in Figure 3.5.

3.7.5 Adaptive control indirect method:

In this case, the estimated parameters refer to the plant, and the controller is designed based on those parameters. For example, an energy consumption coefficient is estimated; a linearized version of the plant is produced, which is then used in a pole placement method to calculate the gains of the final controller [25]. The main problem is to make sure that the controller behaves well in cases when the estimation of the plant is not good, like for example, during transients. In principle, the indirect method is applicable to all types of plants. A block diagram for indirect method is shown in Figure 3.6.

3.7.1 Adaptive control direct method:

Now the plant model is parameterized based on the controller parameters, which are then estimated directly without intermediate steps. Example is the self-tuning PID loop. The same problems as in the indirect case can be encountered here. This method can be safely applied only to minimum phase systems. A block diagram for direct method is shown in Figure 3.7.

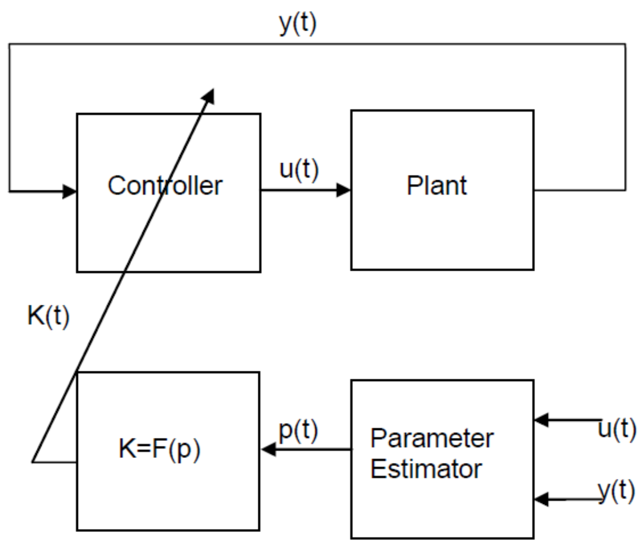


Figure 3.6: Indirect Method

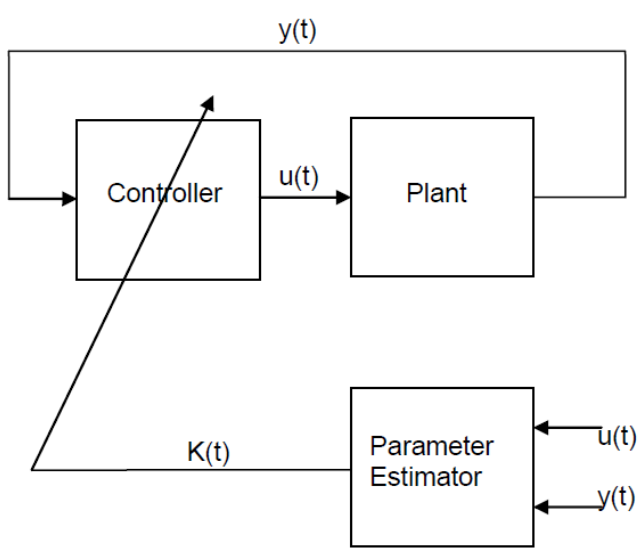


Figure 3.7: Direct Method

CHAPTER 4 Low Energy Buildings

4.1 INTRODUCTION:

The greatest energy consumption in buildings occurs during their operation rather than during their construction there are many types of construction buildings, some of these buildings are called low energy buildings. Low energy buildings are any type of buildings that from design, technologies and building products uses less energy, from any source than a traditional or average contemporary building.

In the practice of sustainable design, sustainable architecture, low-energy building, energy-efficient landscaping low-energy houses often use active solar and passive solar building design techniques and components to reduce their energy expenditure. The implementation of different control methodologies for controlling parameters of heating, ventilating and air-conditioning (HVAC) systems as a part of building automation systems and other energy consumption factors and energy sources were investigated [26].

Proper control of low energy buildings, which is more difficult than in conventional buildings due to their complexity and sensitivity to operating conditions, is essential for better performance. Low-energy buildings typically use high levels of insulation, energy efficient windows, low levels of air infiltration and heat recovery ventilation to lower heating and cooling energy. These homes may use hot water heat recycling technologies to recover heat from showers and dishwashers. Lighting and miscellaneous energy use is alleviated with fluorescent lighting and efficient appliances. Weatherization provides more information on increasing building energy efficiency. Passive Houses are required to achieve a whole building air change rate of no more than 0.6 ac/hr (Air circulation per hour) under forced pressurization and depressurization testing at 50Pa (Pascal) minimum. On site blower door testing by certified testers is used to prove compliance [27].

A significant feature of ultra-low-energy buildings is the increasing importance of heat loss through linear thermal bridging within the construction. Failure to eliminate thermal pathways from warm to cold surfaces creates the conditions for interstitial condensation forming deep within the construction and lead to potentially serious issues of mold growth and rot. With near zero filtration losses through the fabric of the dwelling, air movement cannot be relied upon to dry out the construction and a comprehensive condensation risk analysis of every abutment detail is recommended.

Heating is the most power consumption in a building, a study of energy consumption in USA is shown in Figure 4.1. Normally, thermal comfort depends on a great number of parameters such as air velocity, mean radiant temperature, people's activity, etc.

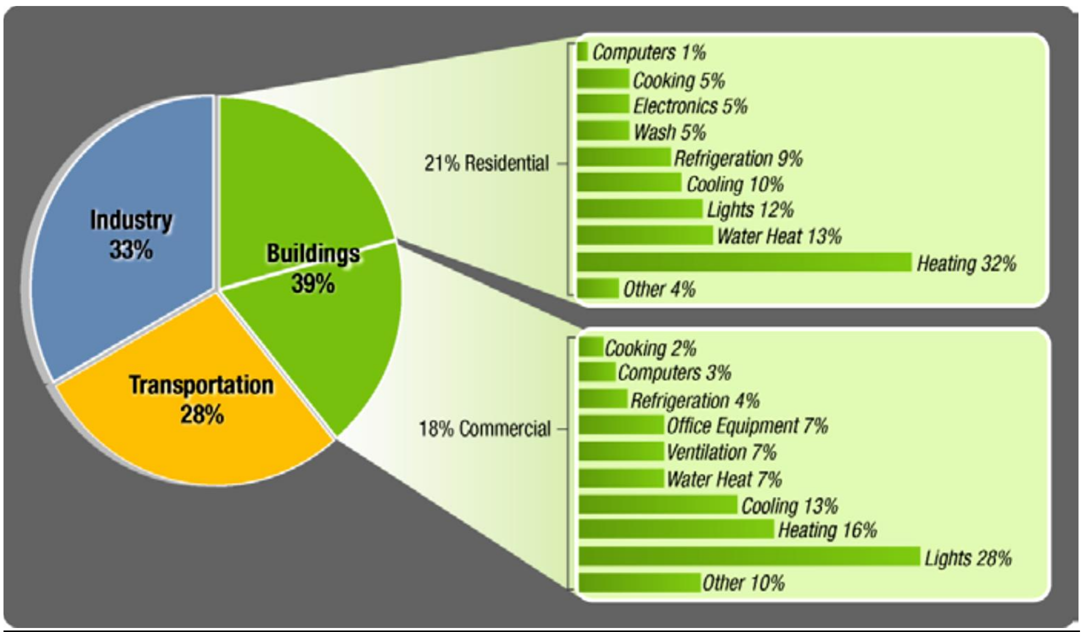


Figure 4.1: Energy Breakdown by Sector, Ryan and Nicholls 2004

Other energy consumption is lighting energy; and to minimize the total primary energy consumption, there are many passive and active day lighting techniques. The structure of the buildings is one of these techniques integrated with light sensors Figure 4.2 shows some architecture designs. For low light level days, non-day lighted spaces, and nighttime; the use of creative-sustainable lighting design using low-energy sources such as 'standard voltage' compact fluorescent lamps and solid-state lighting with Light-emitting diode-LED lamps, organic light-emitting diodes, and PLED - polymer light-emitting diodes; and 'low voltage' electrical filament-Incandescent light bulbs, and compact Metal halide, Xenon and Halogen lamps, can be used [28].

Figure 4.2: Efficient Lighting, Tulane Lavin Bernie, New Orleans LA

Solar powered exterior circulation, security, and landscape lighting - with photovoltaic cells on each fixture or connecting to a central Solar panel system, are available for gardens and outdoor needs. Low voltage systems can be used for more controlled or independent illumination, while still using less electricity than conventional fixtures and lamps. Timers, motion detection and natural light operation sensors reduce energy consumption, and light pollution even further for a Low-energy house setting. Low-energy buildings are those that use, on average over the course of a year, no imported energy -zero-energy buildings- or even those that generate a surplus -energy-plus houses- both of which have been and are being successfully built. This can be achieved by a mixture of energy conservation technologies and the use of renewable energy sources. However, the mix between these and consequently the energy-use profile and environmental impact of the building can vary significantly.

At one end of the spectrum are buildings with an ultra-low space heating requirement that therefore require low levels of imported energy, even in winter, approaching the concept of an autonomous building. At the opposite end of the spectrum are buildings where few attempts are made to reduce the space heating requirement and which therefore use high levels of imported energy in winter. While this can be balanced by high levels of renewable energy generation Figure 4.3 throughout the year, it imposes greater demands on the traditional national energy infrastructure during the peak winter season. (Super insulation, Plus Energy)Low-energy building design is not just the result of applying one or more isolated technologies. Rather, it is an integrated whole-building process that requires advocacy and action on the part of the design team throughout the entire project development process. The whole-building approach is easily worth the time and effort, as it can save 30% or more in energy costs over a conventional building designed in accordance with Federal Standard [29].

Moreover, low-energy design does not necessarily have to result in increased construction costs. Indeed, one of the key approaches to low energy design is to invest in the building's form and enclosure (e.g., windows, walls) so that the heating, cooling, and lighting loads are reduced, and in turn, smaller, less costly heating, ventilating, and air conditioning systems are needed.

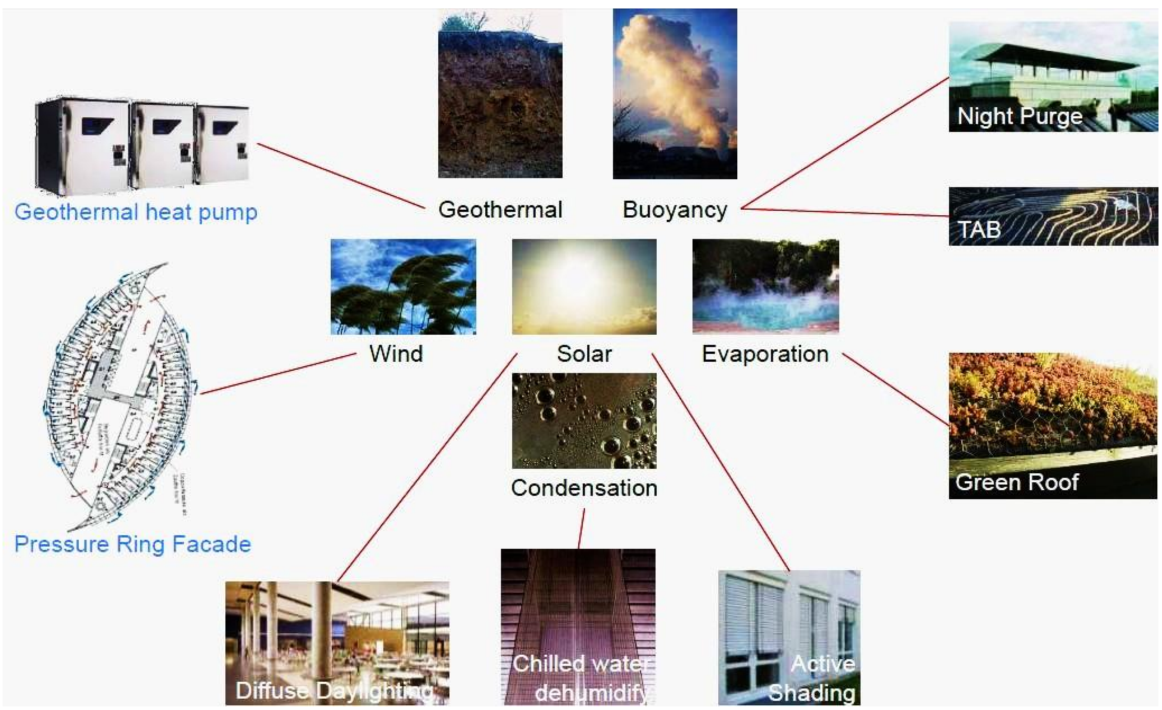


Figure 4.3: Energy resources

4.2 Passive House:

The term „Passive House" is used for an internationally established building standard with very low energy consumption, which has been proven in practice. The Passive House standard is comfortable, sustainable and economically attractive. Independently of the climate and functionality, the Passive House Concept is defined as follows, Feist 2007 [27]:

A Passive House is a building in which thermal comfort can be guaranteed by post-heating or post-cooling the fresh-air mass flow required for a good indoor air quality. This is the case where the heating load can be limited to 10 W per m² living area. In Central Europe, this means a space heat demand of 15 kWh/(m²a) at the most this corresponds to a saving of 75% in comparison with the current standard and a saving of at least 90% in relation to existing buildings. A further reduction in the heating energy demand involves high investment costs which cannot be re-financed by the energy savings. However, it is already so low that it would be possible to meet the remaining heating requirement using a light bulb the heating energy demand is about the same as the heat emitted by persons and devices which are internal heat sources.

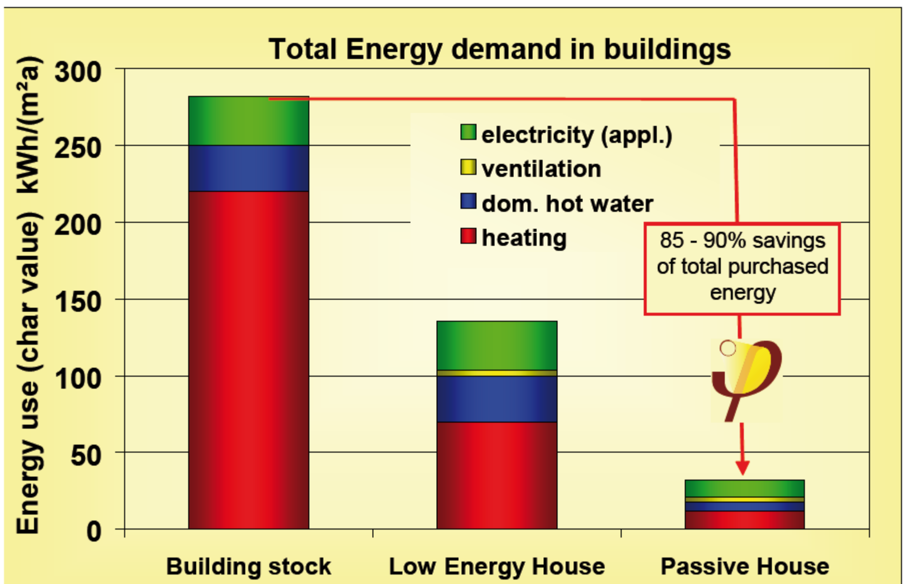


Figure 4.4: Total Energy demand in buildings

In the Passive House, a requirement for the total primary energy demand including all electrical applications is made. The limit for the Passive House standard is 120 kWh/(m²a) (kWh/m2a means kilowatt hours per sq. meter per annum) of the total primary energy. The criteria for the Passive House standard for houses in Central Europe are [33]:

- Space heat demand ≤ 15 kWh/(m²a)
- Heating load ≤ 10 W/m²
- Excessive temperature frequency ≤ 10% (> 25°C)

This is achieved by substantially improving the construction details for each relevant component. In particular, the strategies for achieving the Passive House standard in cool and cold climates are:

- Very good insulation of the building envelope and careful execution in detail
- High level of airtightness of the building (50Pa (Pascal),value ≤ 0.6ac/h)
- Windows with very low heat losses (including frames and thermal bridges) and at the same time, high heat gains(„Passive House windows“)
- Ventilation system with highly-efficient heat recovery
- Efficient building services
- Efficient electrical devices and lighting

Passive Houses in other climate zones principally ensure a comfortable ambient climate by providing good indoor air quality through conditioning of the necessary air quantities. The use of efficient building services and electrical devices remains a principle requirement for this. The limit values for the heating or cooling demand can be lower or higher outside of Central Europe, an example of passive house structure is shown in Figure 4.5.

Above all in colder climates, improved thermal protection is essential in order to achieve the Passive House standard. This applies more especially to the windows and ventilation. In warm and hot climates, summer cooling and dehumidification is additionally required. In these situations, minimization of the solar loads is of central importance.

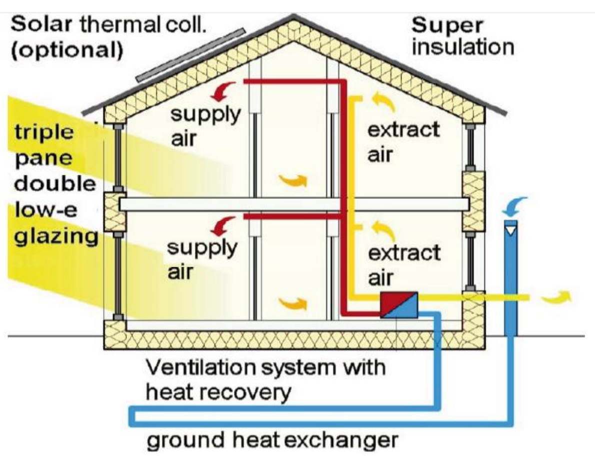


Figure 4.5: example of passive house

The minimization of internal loads, good insulation and an airtight building envelope is also advisable for most warm climates. From the very first, Passive Houses have been scientifically monitored and meteorologically evaluated: the prototype in Darmstadt Kranichstein Figure 4.6, the buildings and estates in the context of the Research Group for Cost-efficient Passive Houses and within the framework of the European CEPHEUS Project and many others.

Figure 4.6: View of the North side of the passive house at Darmstadt Kranichstein

4.3 BUILDING AUTOMATION SYSTEM (BAS):

In recent years, the quality and complexity of mechanical and electrical systems in buildings have been increased. Integrated systems like building automation system are suitable alternatives to monitor, control and manage the modern structures with complex control functions.

A BAS is an integration of subsystems like heating, ventilating and air-conditioning system (HVAC), lighting control, automatic fire alarm system and security system. Carlson (1991) reported a BAS is a more effective and efficient control tool to be used for building [30]. Automatic control of indoor parameters is provided by Building automation systems (BAS) (Kastner et al., 2005).According to Kastner, the core and root of BAS is the automation of heating, ventilation and air-conditioning systems in large functional buildings. The primary goals of using BAS are saving energy and decreasing the cost. A BAS is an integration of several subsystems like heating, ventilating and air-conditioning (HVAC) control, illumination control, fire security system, security and access control, power monitoring and transportation control [31]. The tasks of these subsystems are helping to understand and realize the situation of building performance, measuring building energy consumption, optimizing system running strategy and improving system management. Although, at first glance the building automation and the building control appear the same, by this definition building control is deduced as a part of building automation. After the early 1970s, while the oil price shocked everyone, the need for power-saving arose and highlighted the automation related to energy managing. Control of active systems like HVAC was applied significantly for BAS to save energy and cost.

4.4 HVAC (heating, ventilation, and air conditioning):

HVAC (heating, ventilation, and air conditioning) is the technology of indoor and automotive environmental comfort. HVAC system design is a sub discipline of mechanical engineering, based on the principles of thermodynamics, fluid mechanics, and heat transfer. HVAC is important in the design of medium to large industrial and office buildings such as skyscrapers and in marine environments such as aquariums, where safe and healthy building conditions are regulated with respect to temperature and humidity, using fresh air from outdoors.

The invention of the components of HVAC systems went hand-in-hand with the industrial revolution, and new methods of modernization, higher efficiency, and system control are constantly introduced by companies and inventors worldwide. The three central functions of heating, ventilating, and air-conditioning are interrelated, especially with the need to provide thermal comfort and acceptable indoor air quality within reasonable installation, operation, and maintenance costs. HVAC systems can provide ventilation, reduce air infiltration, and maintain pressure relationships between spaces Figure 4.7 shows an example of HVAC. The means of air delivery and removal from spaces is known as room air distribution [32].

4.5 An overview of conventional control systems in buildings:

Surveys have shown that conventional control systems in buildings have been carried out, using the following methods or some combinations of them: Classical controllers, Digital controllers and Fuzzy controllers. Regarding the increase in the nonlinearity and uncertainty in recent building structures, mathematical description of the system has become more difficult or impossible by Classical control which is involved with mathematical models of the system that govern the relationships among system inputs and outputs. Processing of inputs and feedbacks from the previous state is used by control algorithm to optimize the control of the system in the next time step.

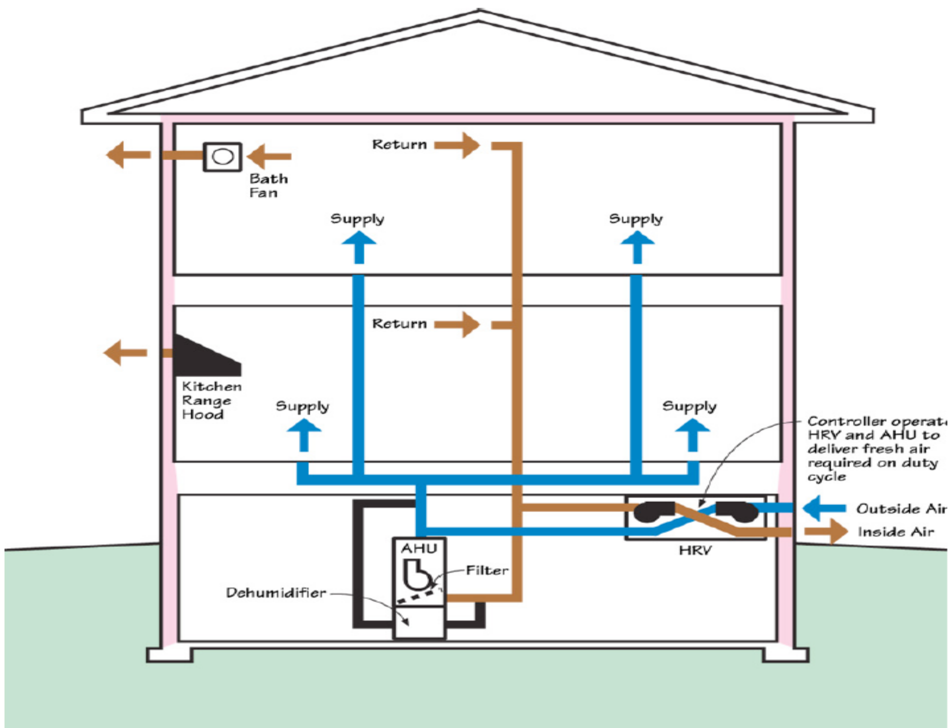


Figure 4.7: A small, single-zone residential heat, cooling, filtration and ventilation system that shares the ductwork between systems but separates the critical functions.

Due to measurement inaccuracies or incomplete observation of the process state, the control of complex processes is tremendously cumbersome. In other words, classical control and mathematical models are vulnerable to inaccurate and noisy inputs or feedbacks, making them disadvantageous. Digital computer is used for real-time control of system; in contrast with classical control systems, digital control utilizes the digital or discrete technology instead of analog components. The major reason why analog technology was simply replaced by digital technology was cost. The numbers of control loops increase the cost of analog system, linearly. Despite the large initial cost of digital system, the cost of additional loop is small.

Therefore digital control is suitable for large installation. Informational and technological development era increases the system's complexity, involving system's mathematical model and in addition integration of some systems is so difficult and sometimes impossible. On the other hand, the control strategies like classical control which are used as mathematical model to define the relationship between inputs and outputs of system are very difficult to apply when dealing with mathematical model of non-linear or uncertain information systems. In comparison with other conventional methods fuzzy controllers offer better response and have been successfully applied in case of complex nonlinear and time varying conditions; the design of fuzzy controllers is similar to human reasoning. The advantage of this controller is linguistic model instead of mathematical models.

4.6 Example of a HVAC Model:

A single-zone HVAC system is shown in Figure 4.8 [34]. It consists of the following components: a heat exchanger (air conditioner), a circulating air fan, the thermal space, the chiller providing chilled water to the heat exchanger, connecting ductwork, dampers, and mixing air components. In our discussion, we assume the system is operating on the cooling mode (air conditioning). The basic operation of the system in the cooling mode is as follows.

- First, 25% of fresh air is allowed into the system and it gets mixed with 75% of the recirculated air (position 5) at the flow mixer.
- Second, air mixed at the flow mixer (position 1) enters the heat exchanger where it gets conditioned.
- Third, the air coming out of the heat exchanger is already conditioned to enter the thermal space, and it is called supply air (position 2).
- Fourth, the supply air enters the thermal space to offset the sensible (actual heat) and latent (humidity) heat thermal loads acting upon the system.
- Finally, the air in the thermal space is drawn through a fan (position 4), 75% of this air gets recirculated and the rest is exhausted from the system.

The controller maintains the thermal space temperature and humidity at the set points of 21^{o} C, and 55% RH (relative humidity), respectively.

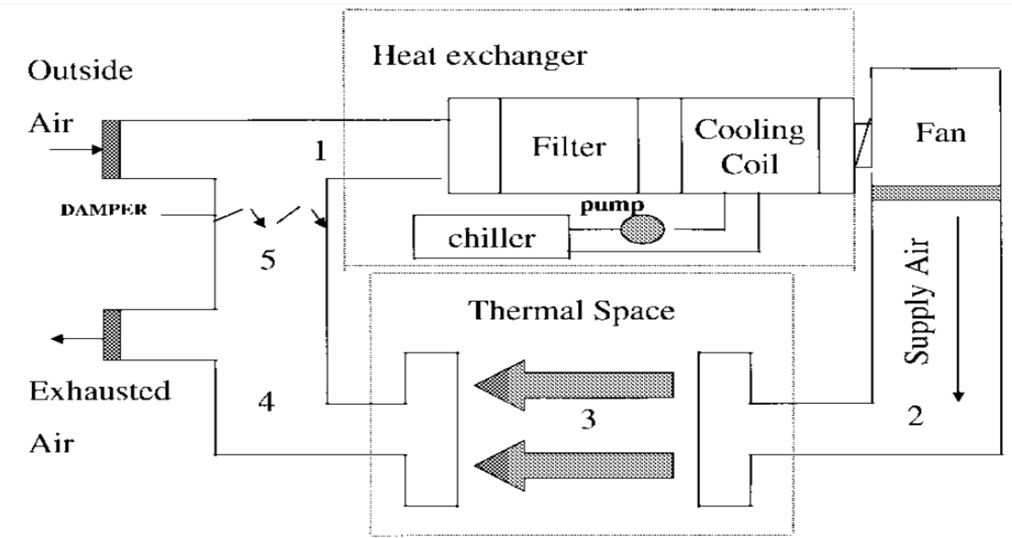


Figure 4.8: Model of the HVAC system.

The control inputs for the system are the pumping rate of cold water from the chiller to the heat exchanger and the circulating air flow rate using the variable speed fan. This set of control actions characterize the HVAC system as:

- A variable-air-volume system (VAV) that results in the lowest energy consumption
- A variable chilled water flow rate system that allows a reduction of pump energy at light loads.

There has been extensive research in the realm of control systems for HVAC systems since the oil crisis of the 1970's. The research works that have been done recently are all based on a linearized mathematical model of the HVAC plant and the controllers are designed using linear quadratic regulator theory. The research work presented here exploits the inherently nonlinear nature of the HVAC process to design a feedback controller that will have a better performance over a wider range of loading conditions. Our objective is to design an HVAC control system aiming at maintaining comfort conditions within a thermal space, with low energy consumption. The importance of the problem at hand lies on the impact that energy efficient HVAC systems can have on industrial and commercial energy consumption.

Chapter 5 Adaptive Hierarchical Fuzzy controller Design

5.1 Introduction:

Because complete information about a dynamical system and its environment are never available such as heating system in large building, the system and excitation cannot be modeled exactly. The air-handling plant of large building must be designed to cope with wide range of operating conditions because weather and occupants' activities change significantly and periodically from day to night and from season to season; The air-conditioning process is highly nonlinear and the interaction between temperature control and air quality control loops is significant so to control such system we need adaptive controller. Classical control design methods based on a single nominal model of the system may fail to create a control system that provides satisfactory performance; intelligent controller structure must be used with time variant nonlinear system and varying parameters. So we present a novel control method that is adaptive hierarchical fuzzy control for HVAC system; this new method will work without knowing the model of the system or its parameters, in this thesis we will depend on random feedback from a virtual system and the controller will adapt to these random feedback to give the desired results that is needed in the building, the control system is flexible to changes that controller want.

One important task of a central heating system is to accurately maintain the desired room temperature to maintain a good comfort level and lower energy consumption. Therefore the heating power has to be adequately adapted. Manual heating control is complex and imprecise, so modern control systems adjust the heating power automatically especially in large open zone buildings. Heating is the most power consumption in a building. So we will work to get best control for heating system and to reach stability so we can lower energy consumption.

In this chapter we will explain the overall system and the new controller method then the results will be shown; we implement the virtual system with Matlab as a simulation program.

Over all system is shown in Figure 5.1, the system is consisting of several blocks: the System block, bypass system, Air quality controller, heat exchanger, controller and Air Handling Unit (AHU).

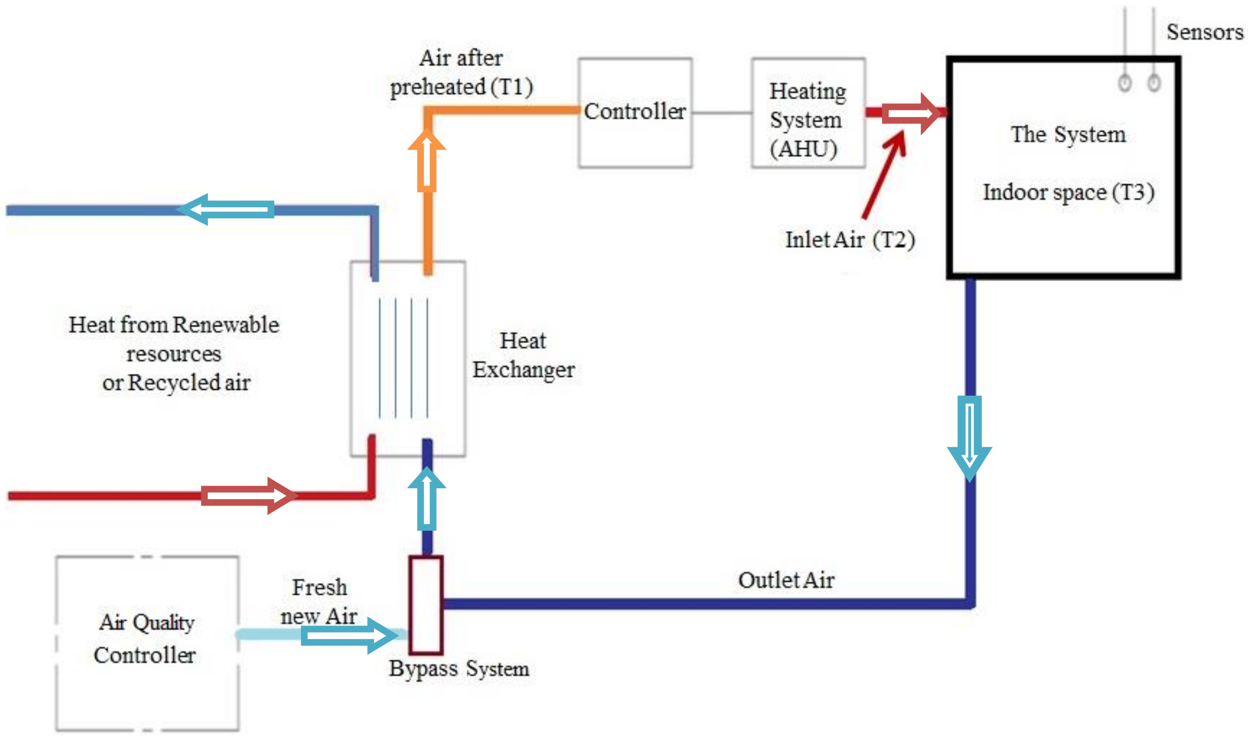


Figure 5.1: HVAC system

5.2 The Indoor Air Temperature system:

The system we study is large buildings and large halls as: malls, hypermarkets, large study halls, indoor stadiums, factories, airports and so on. Figure 5.2 shows example of a mall building. The building that we study is a virtual building model that presents one of the above systems where it contains most of the parameters and specification of a large building and contains the actions that can be happened during system running. Figure 5.1 shows the building indoor space block and it is consisting of three main things: Inlet Air, Outlet Air and Sensors; two sensors are used in this project Temperature sensor and Air quality sensor.

Inlet Air: Inlet Air is the air enters the room or the space which required to be heated and inlet air may be recycled air or fresh air or mix between them, inlet air comes after AHU.

Outlet Air: Outlet air is the air which has been vacuumed from the room and returned to be recycled or to get rid of it.

Figure 5.2: Large Mall

5.2.1 Temperature Sensor:

Temperature sensors are devices used to measure the temperature of a medium. There are 2 kinds of temperature sensors: contact sensors and noncontact sensors. However, there are 3 main types thermometers, resistance temperature detectors, and thermocouples [35]. All three of these sensors measure a physical property (i.e. volume of a liquid, current through a wire), which changes as a function of temperature. In addition to the 3 main types of temperature sensors, there are numerous other temperature sensors available for use.

Contact Sensors: Contact temperature sensors measure the temperature of the object to which the sensor is in contact by assuming or knowing that the two (sensor and the object) are in thermal equilibrium, in other words, there is no heat flow between them.

Noncontact Sensors: Most commercial and scientific noncontact temperature sensors measure the thermal radiant power of the Infrared or Optical radiation received from a known or calculated area on its surface or volume within it, in this project we use a Noncontact Sensors; an example of noncontact temperature sensors is a Resistance Temperature Detectors(RTD).

Resistance Temperature Detectors (RTD): Resistance temperature detector also known as resistance thermometer. The RTD provides an electrical means of temperature measurement, thus making it more convenient for use with a computerized system. An RTD utilizes the relationship between electrical resistance and temperature, which may either be linear or nonlinear. RTDs are traditionally used for their high accuracy and precision.

5.2.2 Indoor air quality sensor:

Indoor air quality (IAQ) is a term which refers to the air quality within and around buildings and structures, especially as it relates to the health and comfort of building occupants. IAQ can be affected by gases (including carbon monoxide, radon, and volatile organic compounds), particulates, microbial contaminants (mold, bacteria) or any mass or energy stressor that can induce adverse health conditions. Source control, filtration and the use of ventilation to dilute contaminants are the primary methods for improving indoor air quality in most buildings.

Determination of IAQ involves the collection of air samples, monitoring human exposure to pollutants, collection of samples on building surfaces and computer modeling of air flow inside buildings; an example of indoor air quality sensor is Grove - Air Quality Sensor Figure 5.3.

This sensor is designed for comprehensive monitor over indoor air condition. It's responsive to a wide scope of harmful gases, as carbon monoxide, alcohol, thinner, formaldehyde and so on. Due to the measuring mechanism, this sensor cannot output specific data to describe target gases' concentrations quantitatively. But it's still competent enough to be used in applications that require only qualitative results, like auto refresher sprayers and auto air cycling systems [36].

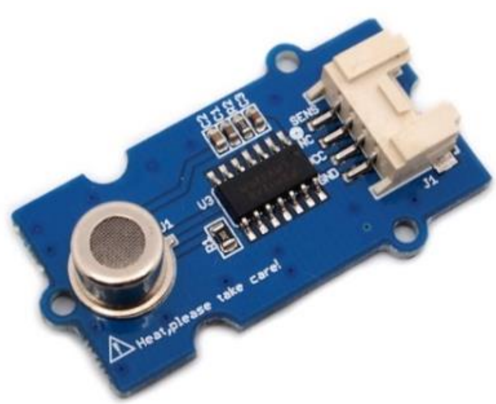


Figure 5.3: Grove - Air Quality Sensor

5.3 Air quality Controller:

We seek to maintain indoor comfort in the zone level based on default user requirements. The main parameters that influence the occupants comfort are: (i) thermal comfort, (ii) visual comfort and (iii) indoor air quality. As we mentioned before we want air quality sensor to maintain good air quality so we want to control air quality. This can be done by controling the outlet air and inlet air, if the sensor detect that the air quality is not good as an example (the place is too crowded and CO_2 concentration trends up) then the controller must let a new fresh air to enter indoor space to return CO_2 concentration to its normal ratio Figure 5.1 shows the Air quality controller with a Bypass system to make a good control.

5.3.1 Bypass System:

Automatic by-pass system can be used in HVAC systems to circulate the air and enter a fresh new air, by-pass system must maintain the same ratio of air enters and out the indoor space.

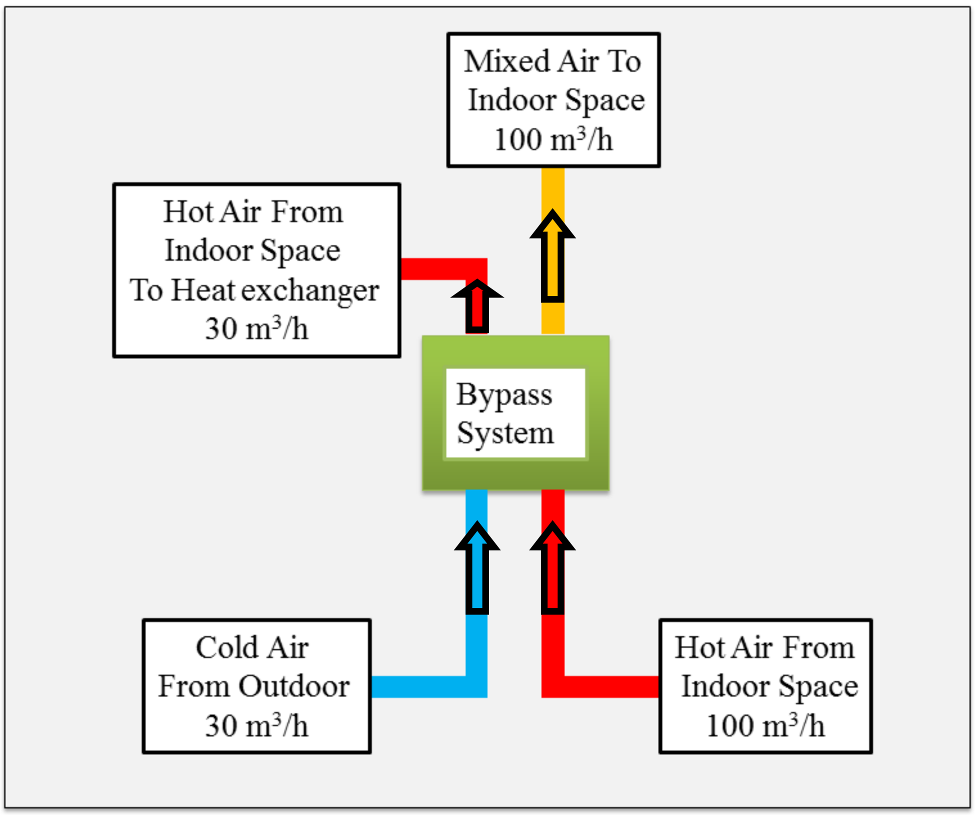


Figure 5.4: Example of bypass system

Bypass system is to ensure a stable pressure inside the building Figure 5.4 shows example how bypass system work. If the air flow of 100 m^3/h enters the indoor space; the same amount of air stream has to leave the indoor space. Fuzzy controller can control automatic bypass system to get smooth transition ratio between fresh and recycled air. In addition, the rest of bad quality hot recycled air will enter heat exchanger.

5.3.2 Renewable energy heat sources:

5.3.2.1 Integrated Renewable energy

We can gain energy consumption from the construction type of the building some of these buildings are low energy buildings. Low energy buildings are any type of buildings that from design, technologies and building products uses less energy, from any source than a traditional or average contemporary building in Figure 5.5 an example of an integrated renewable energy with a low energy building.

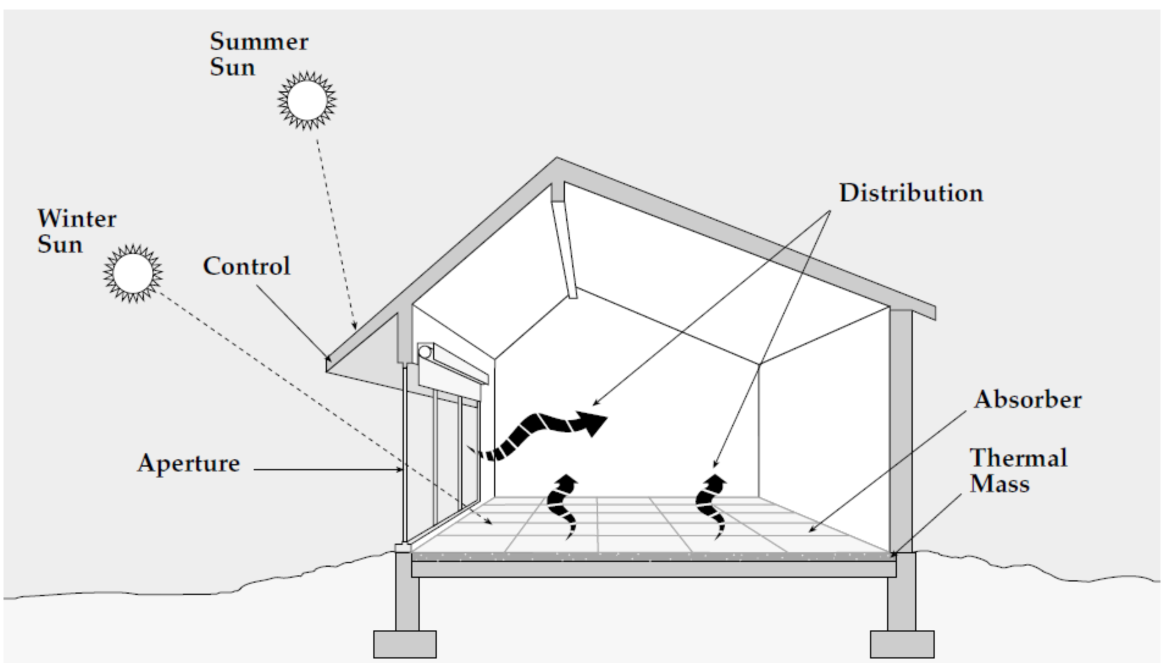


Figure 5.5: Passive Solar Design

Here are the five elements that constitute a complete passive solar design, using a direct gain design as an example. Each performs a separate function, but all five must work together for the system to be successful [37].

Aperture Collector: the large glass window area through which sunlight enters the building. Typically, the apertures should not be shaded by other buildings or trees from 9 a.m. to 3 p.m. each day during the heating season.

Absorber: the hard, darkened surface of the storage element. This surface which could be that of a masonry wall, floor, or that of a water container sits in the direct path of sunlight. Sunlight hits the surface and is absorbed as heat.

Thermal mass: the materials that retain or store the heat produced by sunlight. The difference between the absorber and thermal mass, although they often form the same wall or floor, is that the absorber is an exposed surface whereas storage is the material below or behind that surface.

Distribution: the method by which solar heat circulates from the collection and storage points to different areas of the house. A strictly passive design will use the three natural heat transfer modes conduction, convection, and radiation exclusively.

Control: roof overhangs can be used to shade the aperture area during summer months. Other elements that control under and/or overheating include: electronic sensing devices, such as a differential thermostat that signals a fan to turn on; operable vents and dampers that allow or restrict heat flow; low-emissivity blinds; and awnings.

5.3.2.2 Separated renewable energy sources:

The heating system passes through two levels air preheat and air heating, preheating is from heat exchanger with renewable energies as heat from ventilating photovoltaic panels and recycled bad quality air.

5.3.3 Heat exchanger:

A heat exchanger is a piece of equipment built for efficient heat transfer from one medium to another. The media may be separated by a solid wall, so that they never mix, or they may be in direct contact [15]. They are widely used in space heating, refrigeration, air conditioning, power plants, chemical plants, petrochemical plants, petroleum refineries, natural gas processing, and sewage treatment. The classic example of a heat exchanger is found in an internal combustion engine in which a circulating fluid known as engine coolant flows through radiator coils and air flows past the coils, which cools the coolant and heats the incoming air, Figure 5.6 shows the operation.

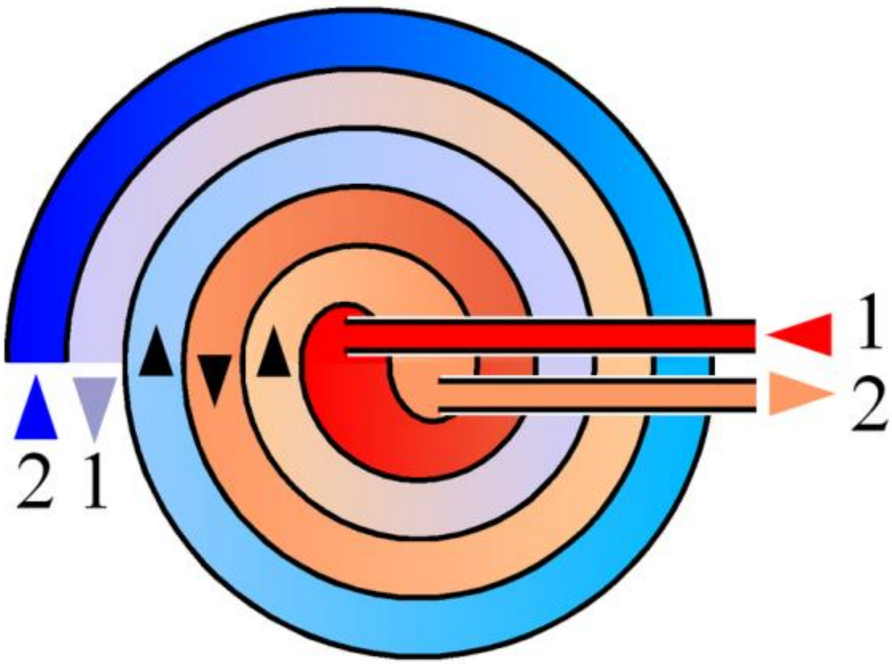


Figure 5.6: a spiral heat exchanger

5.4 Air Handling Unit (AHU):

An air handler, or air handling unit often abbreviated to AHU, is a device used to condition and circulate air as part of a heating, ventilating, and air-conditioning (HVAC) system. An air handler is usually a large metal box containing a blower, heating or cooling elements filter racks or chambers, sound attenuators, and dampers.

Air handlers usually connect to a ductwork ventilation system that distributes the conditioned air through the building and returns it to the AHU. Sometimes AHUs discharge supply and admit return air directly to and from the space served without ductwork.

Small air handlers, for local use, are called terminal units, and may only include an air filter, coil, and blower; these simple terminal units are called blower coils or fan coil units. A larger air handler that conditions 100% outside air is known as a makeup air unit (MAU).

An air handler designed for outdoor use, typically on roofs, is known as a packaged unit (PU) or rooftop unit (RTU).Air handlers may need to provide heating, cooling, or both to change the supply air temperature, and humidity level depending on the location and the application.

Such conditioning is provided by heat exchanger coils within the air handling unit air stream; such coils may be direct or indirect in relation to the medium providing the heating or cooling effect.

Direct heat exchangers include those for gas-fired fuel-burning heaters or a refrigeration evaporator, placed directly in the air stream. Electric resistance heaters and heat pumps can be used as well. Evaporative cooling is possible in dry climates.

5.5 Adaptive hierarchical fuzzy controller:

In order to design a fuzzy system with a good amount of accuracy, an increase in the number of input variables to the fuzzy system results in an exponential increase in the number of rules required. So we use hierarchical fuzzy logic control. In addition, our system is time variant nonlinear system so we must use adaptive controller then adaptive hierarchical fuzzy controller is used in this project.

Adaptive Control is the control method used by a controller which must adapt to a controlled system with parameters which vary, or are initially uncertain. The general structure of an adaptive control system is shown in Figure 3.3.

In large buildings as malls and hypermarkets and large centers it is extremely hard to get mathematical model to the system then we must adapt the varying parameters and the essential varying parameters is:

- Occupants Crowded and the amount of heat needed
- Air quality degradation and need of fresh air
- Doors and windows opening make disturbance of the system

So it is hard to expect these varying parameters offline or online, and by applying the adaptive principle with fuzzy control our controlled system structure will be as shown in Figure 5.7.

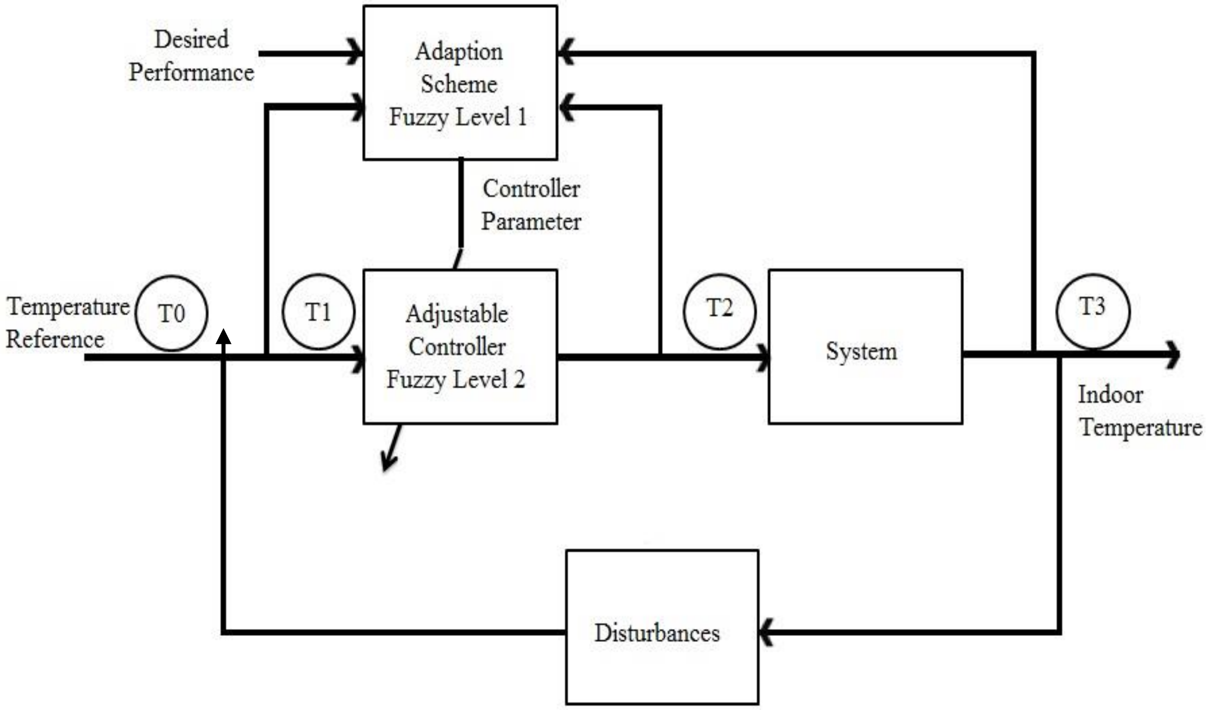


Figure 5.7: Controller Scheme

System is consisting of:

1- System: Air temperature inside the room or hall.
2- Fuzzy Level1: Control the error of varying parameters to adjust main controller.
3- Fuzzy Level2: Is the main temperature controller.
4- Disturbances: As opining windows or doors and Co2 concentration.
5- Temperature T0: The reference Air Temperature.
6- Temperature T1: Air Temperature after disturbances.
7- Temperature T2: Air Temperature after being heated from heating system (AHU).
8- Temperature T3: Air Temperature inside the room.
9- Desired performance: Is rules of fuzzy controllers from system experts.

5.6 Adaptive hierarchical Fuzzy Logic Controller Simulation on Matlab/Simulink:

Figure 5.8 illustrates the Simulink block diagram for the system and we will explain every block and how it is working.

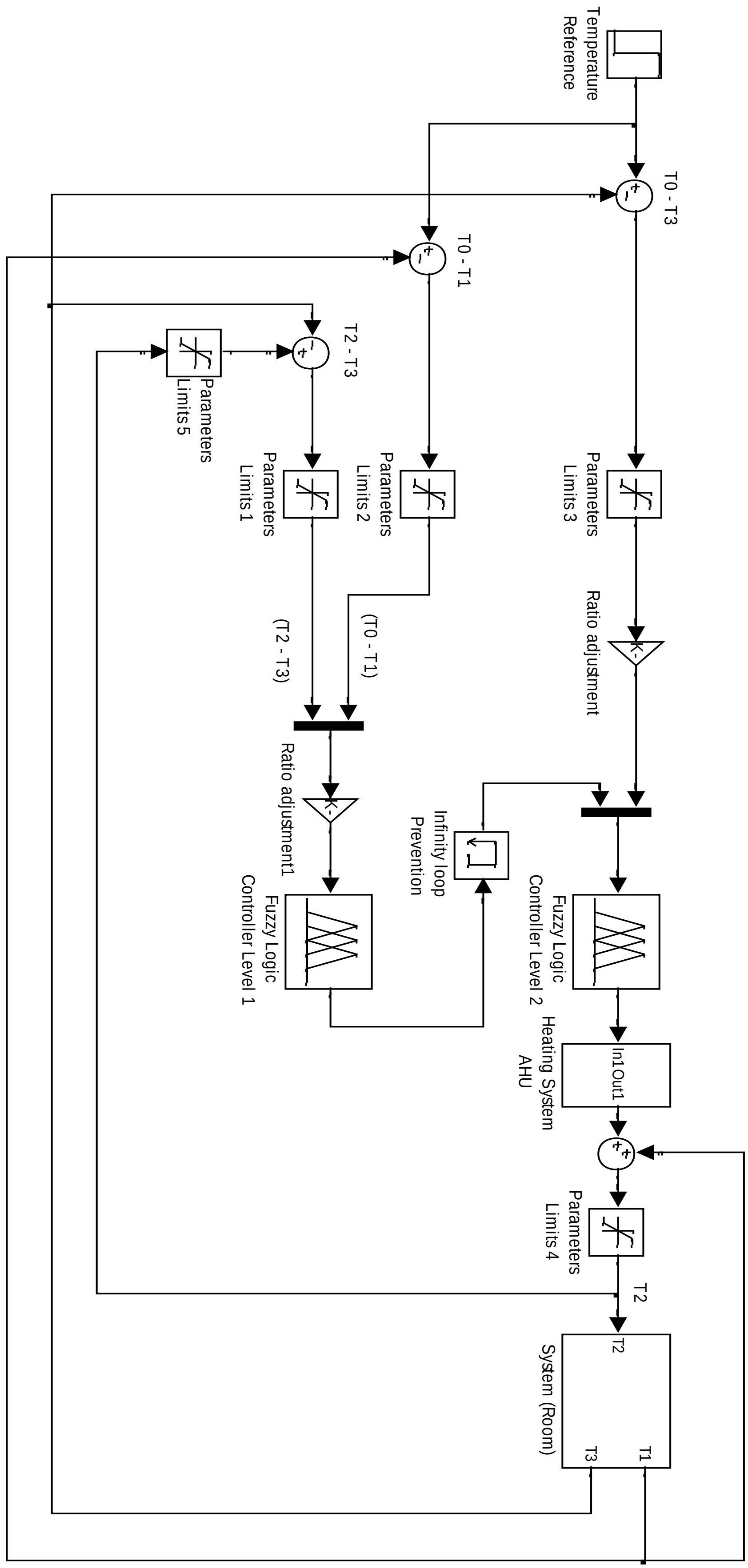


Figure 5.8: HVAC Controller Simulink block diagram

5.6.1 Fuzzy logic controller:

In this project we use hierarchical Fuzzy controllers with Mamdani method and we will explain the steps of fuzzy control:

Step 1: Fuzzification

The first step in the application of fuzzy reasoning is a Fuzzification of inputs in the controller, which is to take the crisp inputs for example (T0 – T1) and (T2 – T3), (T0 – T1) is the difference between the reference Air temperature and Air temperature after Bypass system (Feedback value) and (T2 – T3) is the difference between Air temperature just before enters the room (after heating system) and Air temperature inside the room.

Let us suppose that reference air temperature is T0 = 30^o C, Air temperature after disturbances T1= 10 c^o, Air temperature after heating system T2 = 37.5^o C and Air temperature inside the room T3= 25, then the Fuzzification will be as shown in Figure 5.9:

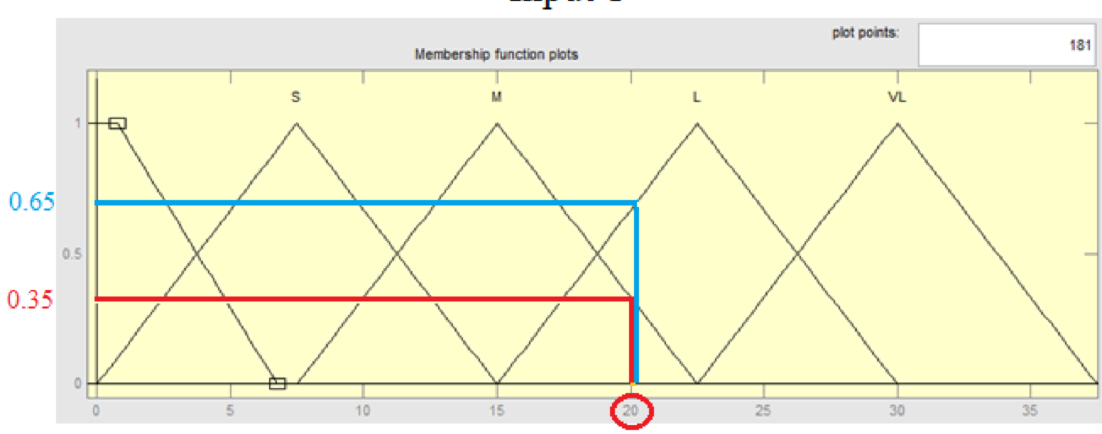
(T0 – T1) = 30 – 10 = 20 Input (1)

(T2 – T3) = 37.5 – 25 = 12.5 Input (2)

Now we will determine the degree to which these inputs belong to each of the appropriate fuzzy sets; every crisp value of input attribute a set of degree of membership to fuzzy sets defined in the universe of discourse for that input in Figure 5.9 shows fuzzification process.

Input 1 and 2 have five Memberships which are Zero(Z), Small(S), Medium (M), Large (L) and Very Large(VL)

Input 1



Input1 = 20

Figure 5.9: Fuzzification stage

Figure 5.9 shows if input (1) =20 crisp number then Fuzzification will convert it to 0.35 of fuzzy set medium (M) and 0.65 of fuzzy set large (L), and after evaluate input (2) =20 it will give 0.4 of fuzzy set small (S) and 0.6 of fuzzy set medium (M).

The second input T2-T3 is shown in Figure 5.10 and the crisp number 12.5 after fuzzification will be 0.4 medium and 0.6 small.

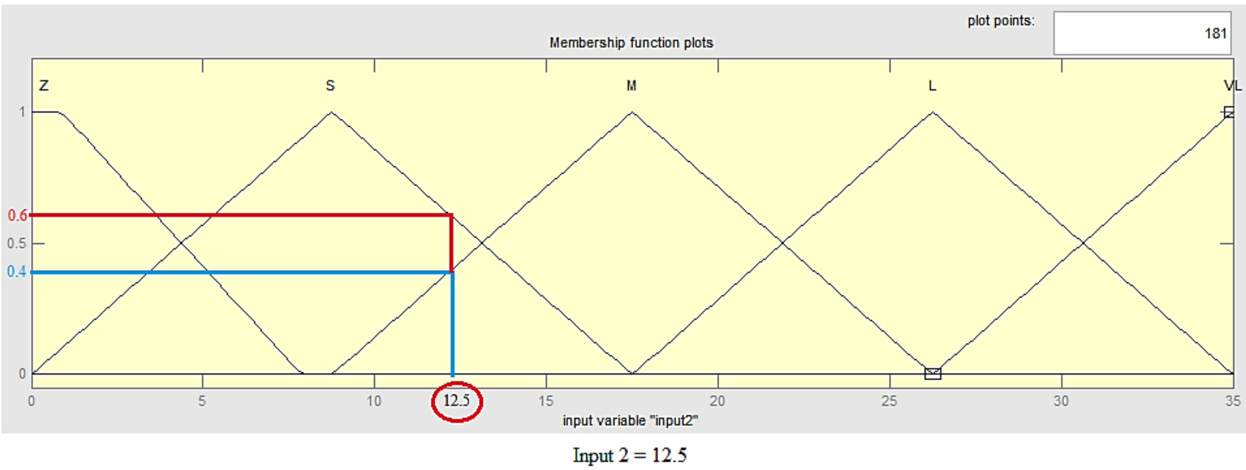


Figure 5.10: Fuzzification stage

Step 2: Rule evaluation

The second step is to take the Fuzzified inputs and apply them to the antecedents of the fuzzy rules. We get fuzzy rules from experts of the system to construct the Fuzzy Associative Memory (FAM) table; FAM table is a Fuzzy Truth Table that shows all possible outputs for all possible inputs. We use the same FAM table (Table 5.1) for the two fuzzy controllers.

Table 5.1: Fuzzy Associative Memory

Input 1/ Input 2	Zero	Small	Medium	Large	Very Large
Zero	Z	S	M	L	VL
Small	S	M	L	VL	VL
Medium	M	L	VL	VL	VL
Large	L	VL	VL	VL	VL
Very Large	VL	VL	VL	VL	VL

Rules can be presented from matlab as rule surface Figure 5.11.

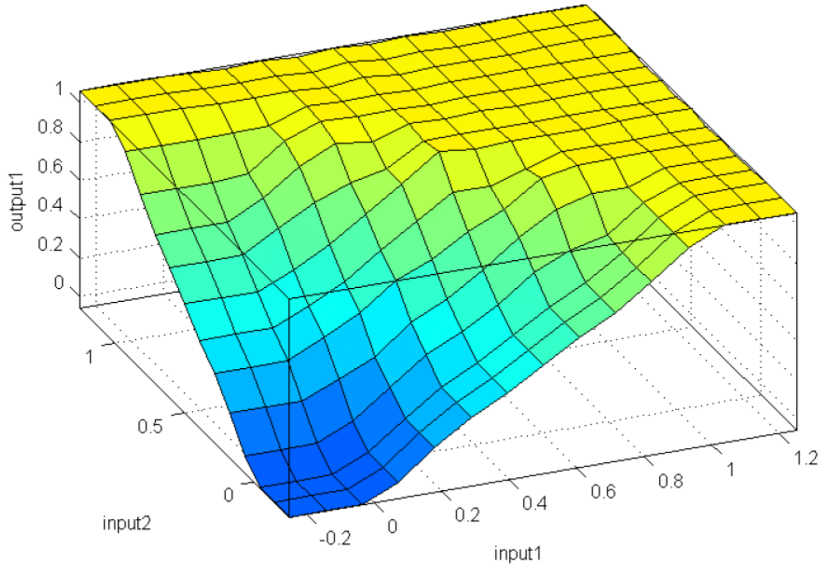


Figure 5.11: rule surface

Similarly, in order to evaluate the conjunction of the rule antecedents, we apply the AND fuzzy operation intersection which used minimum approach as in equation 2.11, we will evaluate the rules that apply to results of previous example:

1- IF *Input 1* is **medium** and *Input 2* is **Small** Then *Output 1* is **Large**
   IF 0.35 and 0.4 Then [0.35 Large]
2- IF *Input 1* is **medium** and *Input 2* is **medium** Then *Output 1* is **Very Large**
   IF 0.35 and 0.6 Then [0.35 Very Large]
3- IF *Input 1* is **Large** and *Input 2* is **Small** Then *Output 1* is **Very Large**
   IF 0.65 and 0.4 Then [0.4 Very Large]
4- IF *Input 1* is **Large** and *Input 2* is **medium** Then *Output 1* is **Very Large**
   IF 0.65 and 0.6 Then [0.6 Very Large]

Step 3: Aggregation of the rule outputs

Aggregation is the process of unification of the outputs of all rules. We take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. The input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable.

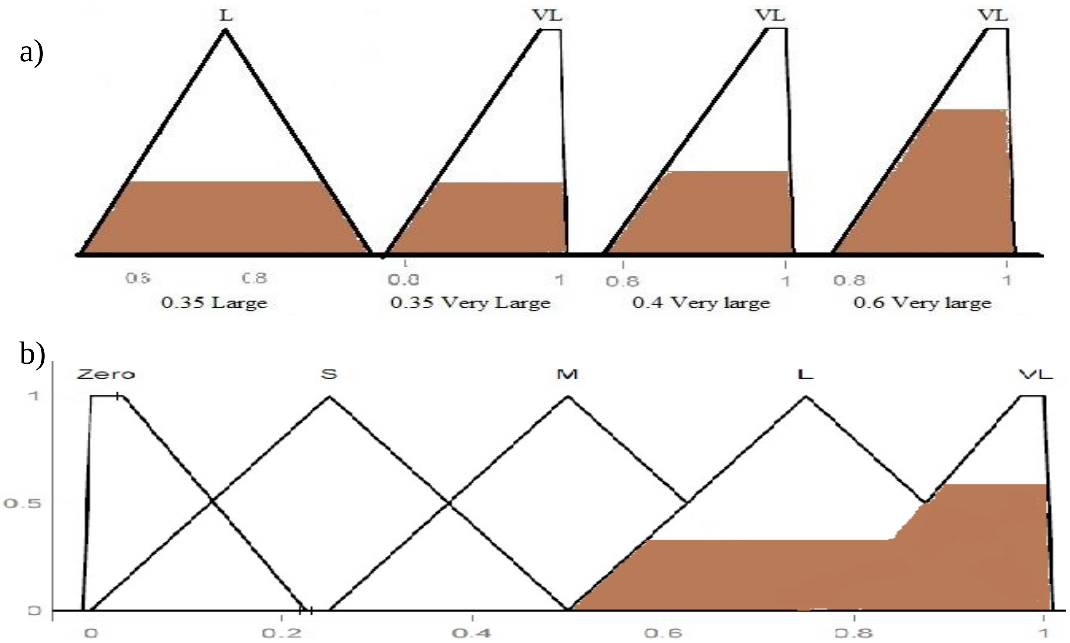


Figure 5.12: Aggregation of the rule outputs, a) Rules results b) Maximum of Rules results

Step 4: Defuzzification

The reverse of fuzzification, defuzzification converts the resulted fuzzy sets defined by the inference engine to the output of the model to a standard crisp signal.

Centroid of area (COA) is used it is the best known defuzzification operator method. It is a basic general defuzzification method that determines the value of the abscissa of the center of gravity of the area below the membership function; completion for example in the project Figure 5.13 shows the defuzzification method to a crisp number.

$$z^* = \frac{\int \mu_{\tilde{B}}(z) z dz}{\int \mu_{\tilde{B}}(z) dz}$$

Calculated as:

$$\frac{(0.6+0.7+0.8)\times 0.35+(0.9+1)\times 0.6}{0.35+0.35+0.35+0.6+0.6} = 0.833$$

This process gives output to second level of fuzzy controller as a crisp input to begin execute all the steps mentioned above and these steps repeated continuously .

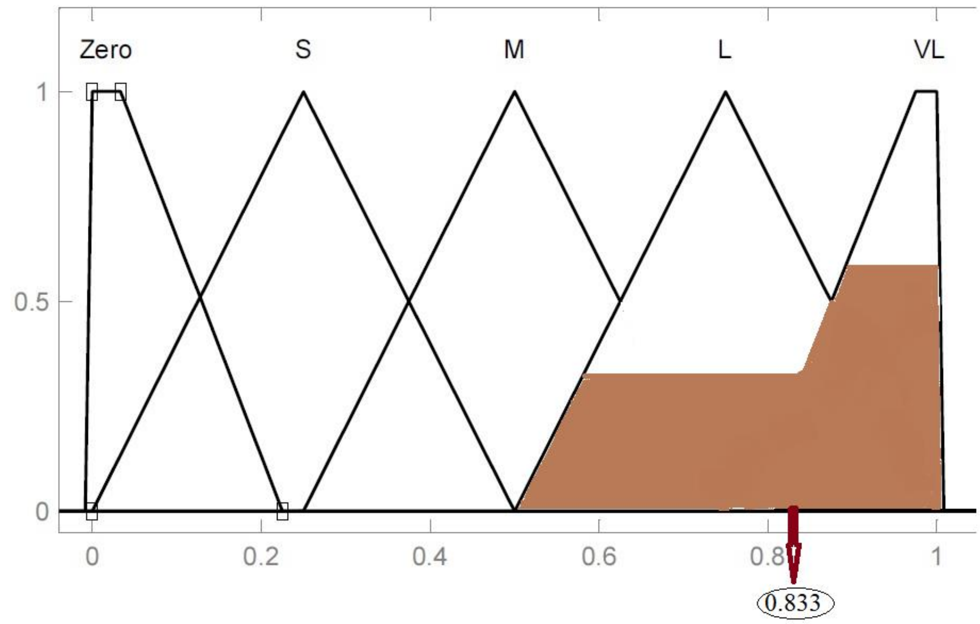


Figure 5.13: defuzzification method

The membership of the output will be symmetric as input 1 and 2 as shown in figure 5.14. Same membership functions for inputs and output of level 2.

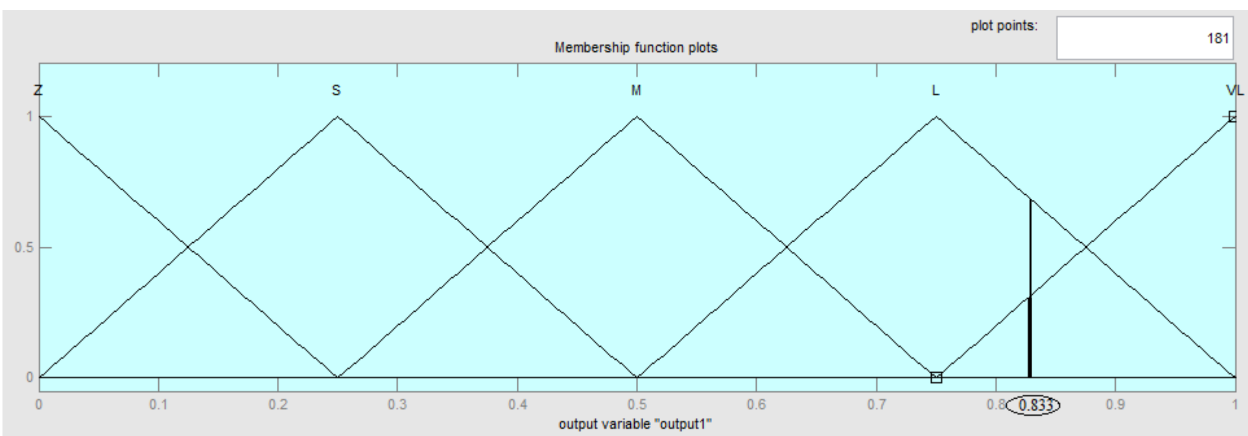


Figure 5.14: Output membership function

5.6.2 Indoor system block:

System block is consisted of several blocks the general structure inputs outputs are shown in Figure 5.15; one input is (T2) air temperature that enters the system and two outputs are air temperature after disturbances (T1) and room air temperature (T3) and these outputs from the system is the time varying parameters.

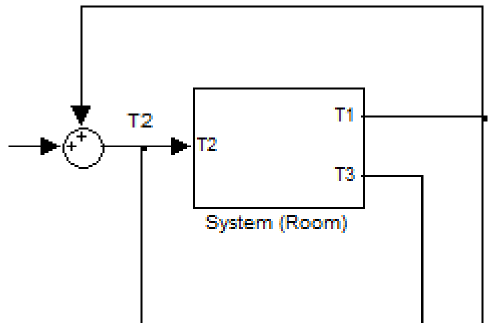


Figure 5.15: Indoor space block

Since T1 and T2 are varying parameters so we can suppose random values for these parameters but real logic values; we build it after experience of system nature we deal with. Figure 5.15 shows the structure of system block.

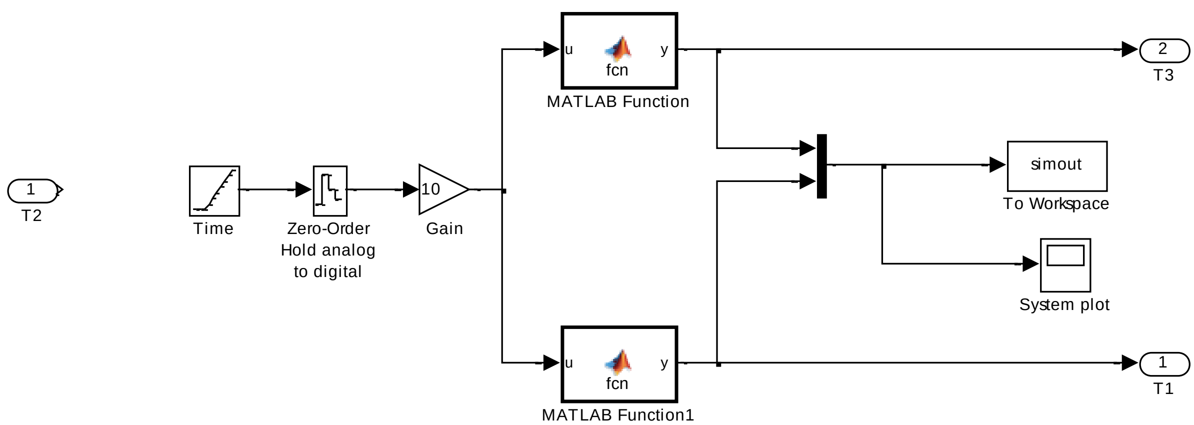


Figure 5.16: Indoor space system structure

In system block we use a matlab function that depends on c language to write the function that contains the action which can be happened during system running.

Matlab function depend on time; time block is used to get a time varying system then we use Zero-order hold to discretizes time from continuous to discrete and we do this step cause matlab can’t calculate large fuzzy operations continuously with complicated clos loop. Result of this system block is shown in Figure 5.16.

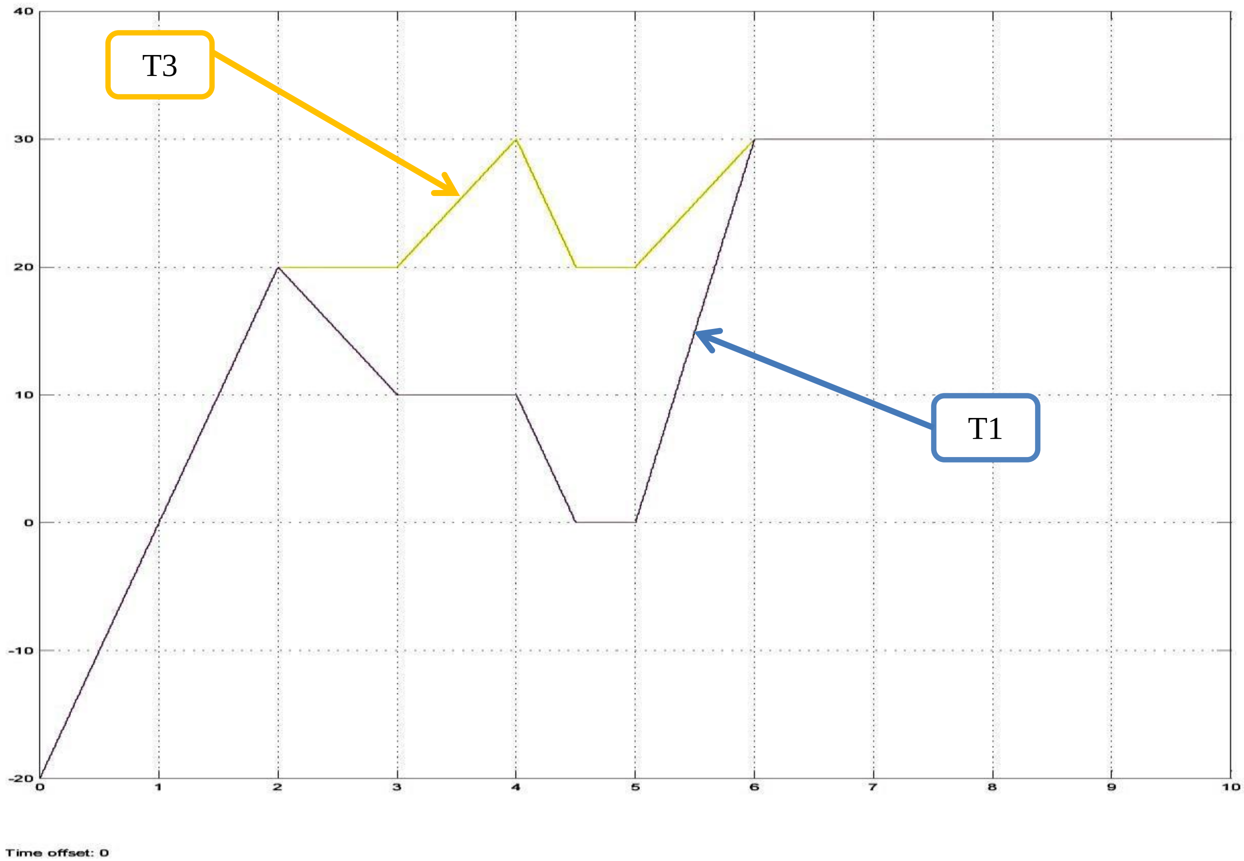


Figure 5.17: Air temperature T1 and T3

We can descript the system as follow; suppose that the initial air temperature value will be -20 C^o for both T1 and T3 and same temperature until it reach 20 C^o and this because in beginning of the day we predict that no new air is needed then a variation in temperature between T1 and T3 is happened due to disturbances we previously talked about.

Controllers' performance in the range between -20^o C and 30^o C or until system stability will be supervised and studied to know if the controller gives the desired performance or not.

5.6.3 Controller working methods:

As we say before the system is time varying and we need an intelligent controller as fuzzy control approach. The control method is depending on two control level; In level 2 Fuzzy inputs are the error and the result of fuzzy control level 1(Change of Error). Error is deference between reference air temperature (T0) and the air temperature inside the room (T3) - as any traditional close loop control - and fuzzy control level 1(Change of Error) correct control operation of fuzzy level 2 because of these reasons:

1- If a new fresh air enters the system there is no feedback for this change and based on that no change in the error T0 – T3.
2- The nature of heat spread is slow so we can't know what is air temperature just after heating system and if we don't take it in consideration it never mind that heating system works as On / Off method (Open loop control for heating system)

So these problems make fuzzy control level 1 is very important to correct this control loop. Fuzzy control Level 1 adaptive to the varying parameters if it comes from disturbances or unexpected system performance; there are two ways in adaptive control level in this project:

Compensation Method:

This method depends on compensating the loss of air temperature by the same amount of loss. In other words, if the reference air temperature (T0) was 30 C^o and room temperature (T3) was 20 C^o then controller output must be 40 C^o. As we see there is 10 C^o losses the controller compensate it with 10 C^o plus the reference point and this method is to reach the stability desired point as fast as we can, but we use some limits to upper heat air temperature of controller output (T2). The amount of compensation is programed with fuzzy control rules or by fuzzy output membership. Inputs of Fuzzy controller level 1 will be:

A. (T0–T1) that observe the variations come from entering a fresh new air from Air Quality Performance.
B. (T2 – T3) that observe the deference between air temperature enters the room (after heating system) and air temperature inside the room. Compensation Method control structure is shown in Figure 5.8.

Stability Method:

In this method we seek to get a stable output (T2) allover the time regardless of parameter variation. The main deference between Compensation method and Stability method is the second input of Fuzzy controller level 1; we replace input (T2 – T3) by (E – (T2 – T3)). Stability Method structure is shown in Figure 5.18.

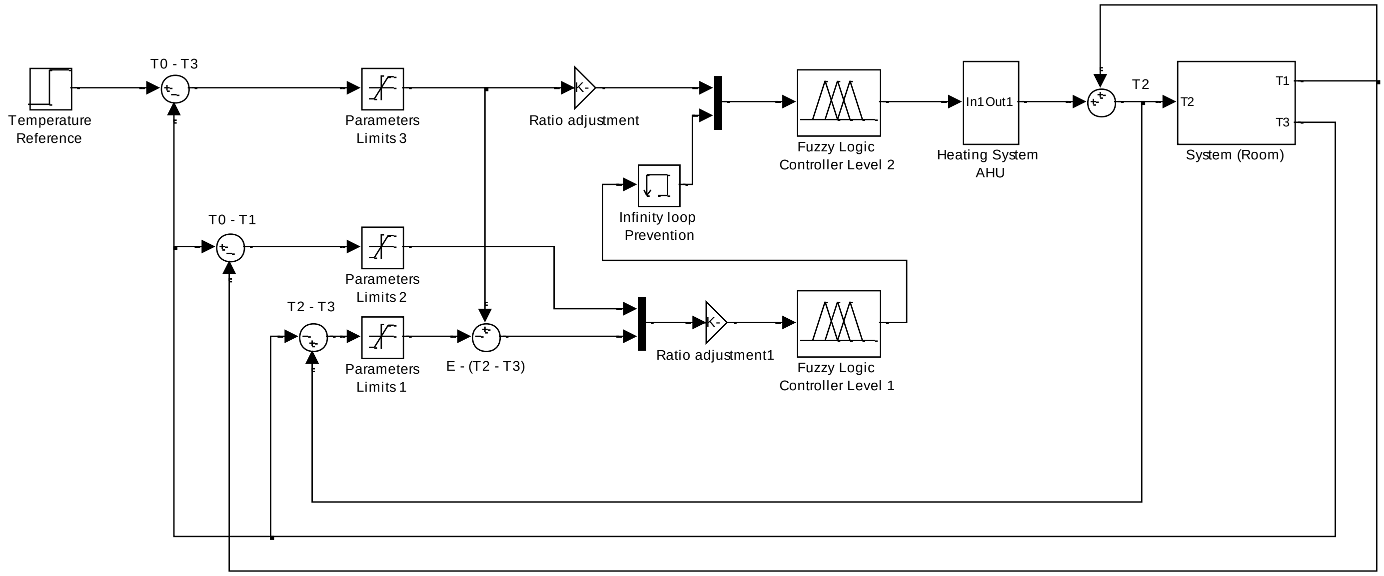


Figure 5.18: System block structure (Stability method)

5.6.4 Heating System:

Heating system (AHU) is a device which changes the air temperature from low degrees to higher degrees; and controller such as our controller how gives the orders for this system to which degree the air must be heated.

There are many sizes and capacities of heating systems and we discuss these systems in the above sections. In this project it is assumed that Heating System is ideal with gain of 30 degrees immediately and this assumption is from experts. Heating system block is shown in Figure 5.19.

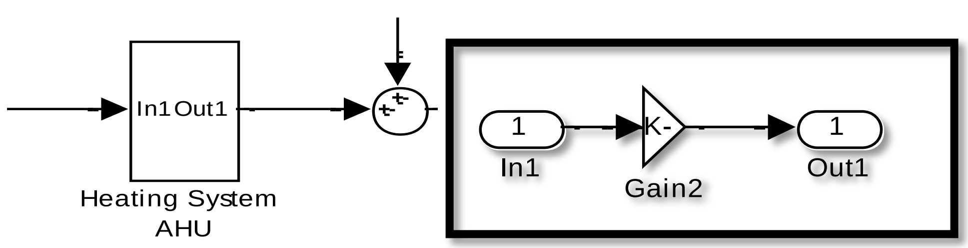


Figure 5.19: Heating System block

5.6.5 Results:

1- Results of compensation method with a desired reference temperature of 30 C° is shown in Figure 5.20.

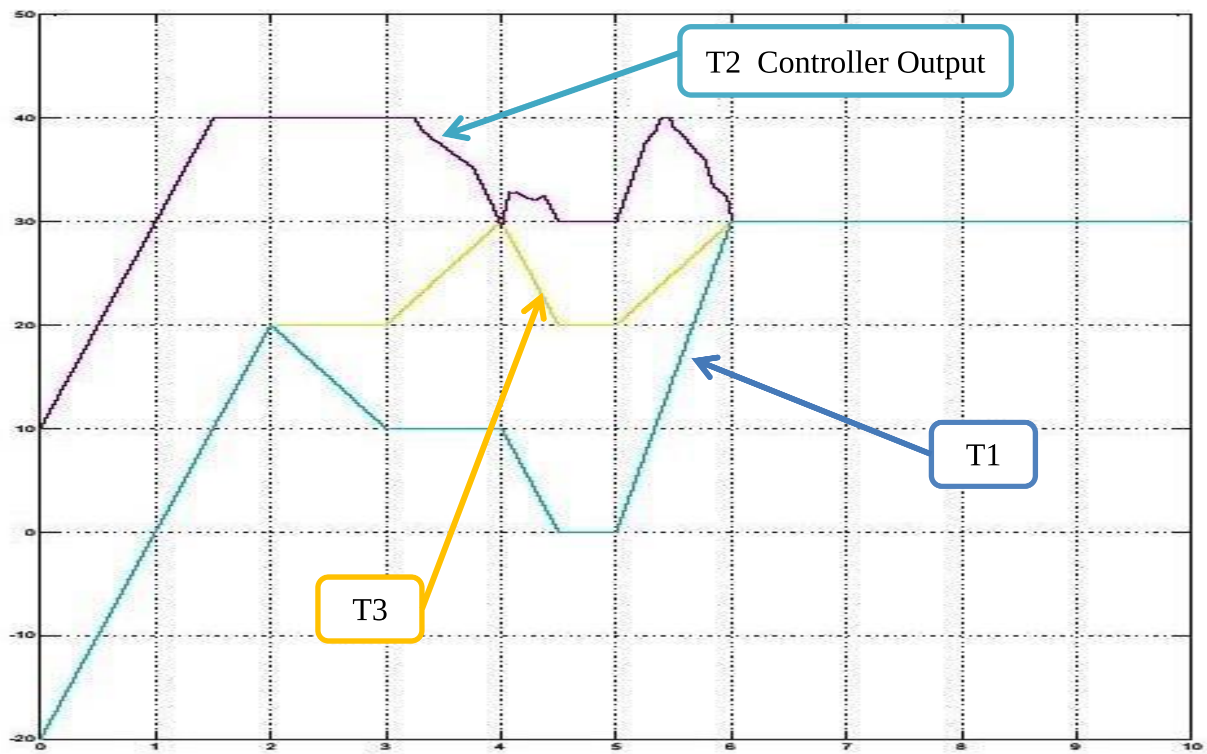


Figure 5.20: Compensation Method result: Pink Line is T2, Yellow Line is T3 and Blue Line is T1

The Figure shows at time:

- T=0 (system initial value): If T1 and T3 is -20 controller will work to maximum and maximum is 30 degrees upper the air temperature enters heating system.
- T=2: If T1 and T3 are 20 and the desired is 30 then compensation control will give 40 or higher but upper limit specification is 40 and this is upon building management requirements.
- T=4: If T3 reached the required value or reference value and T1 is 10 degrees then the controller will compensate lose in temperature only for fresh new air to 30 degrees not higher because the Error = 0.
- T=6: If system reach desired temperature the controller will stop heating air T0=T3=T2

2- Results of Stability method with a desired reference temperature of 30 C^o is shown in Figure 5.21.

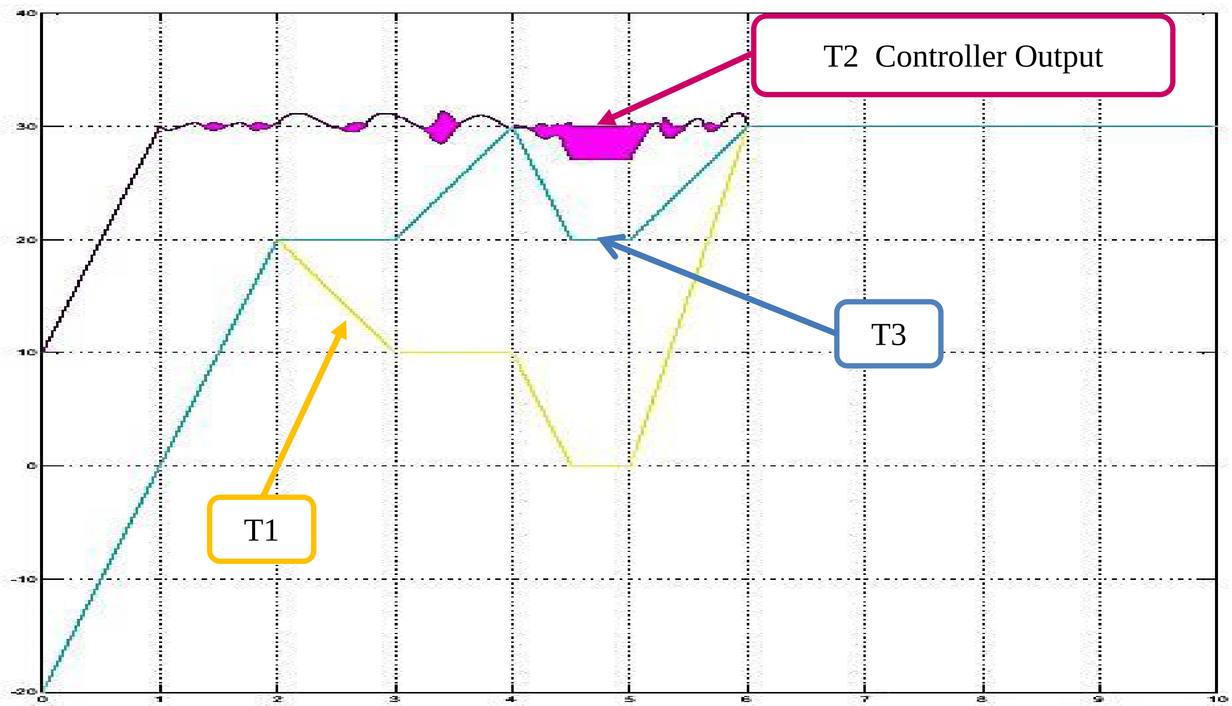


Figure 5.21: Stability Method result: Pink Line is T2, Yellow Line is T1 and Blue Line is T3

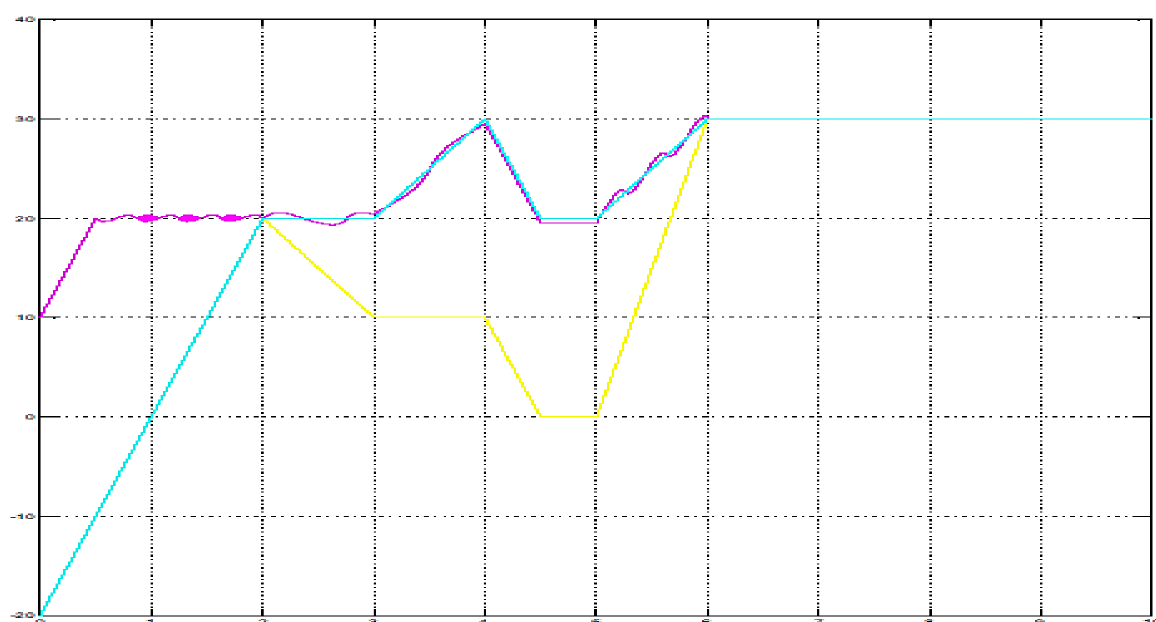


Figure 5.22: Reference temperature = 20^o C

In Figure 5.21 the controller work to make T2 stable and equal the reference temperature T0 regardless of variation and disturbances affect the system.

If the reference temperature is 20^{o} C the result will be as shown in figure 5.22. If reference temperature is 40^{o} C the result will be as shown in figure 5.23.

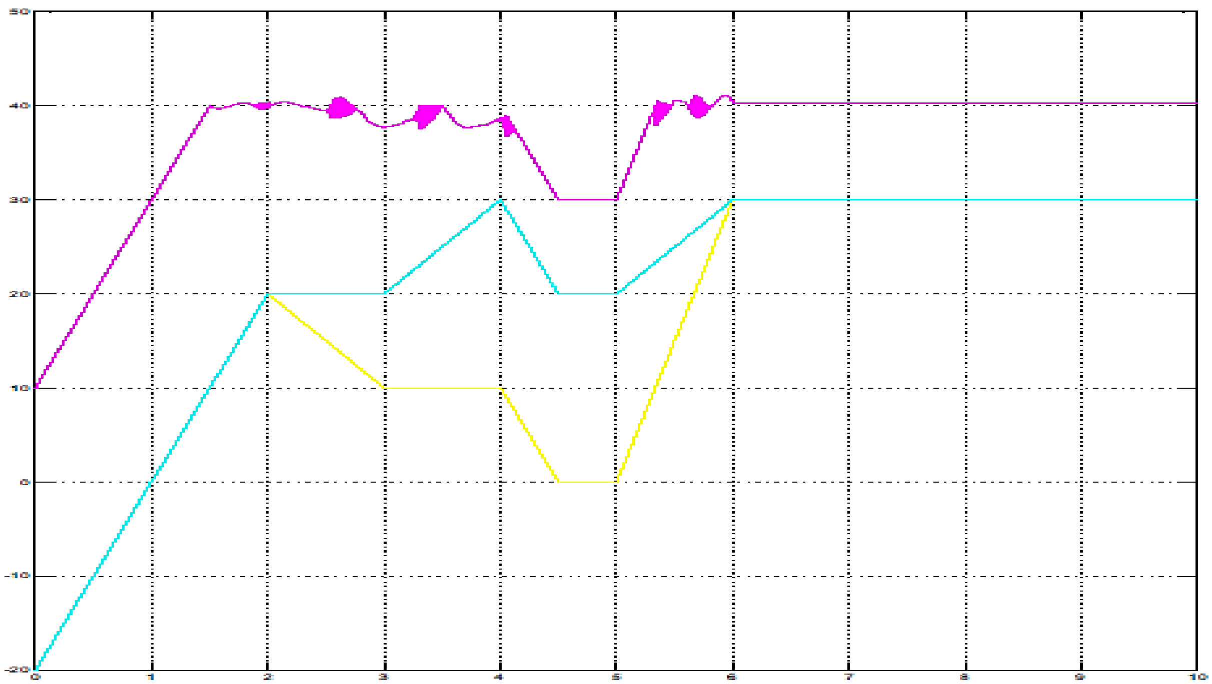


Figure 5.23: Reference temperature = 40^{o} C

5.6.6 Matlab functions and problems:

1- We use saturation block to give boundaries for the values enters controllers or the output of these controllers, as an example let us consider the Error value is (T0 – T3) and if we suppose the initial value of the system T0 = 30 and T3 = -20 thus T0 – T3 = 30 + 20 = 50, if T0 = 30 and T3 is over heated and equal 40 then T0 – T3 = 30 – 40 = -10, but the variation deference boundaries is between 0 and 30 lower than 0 will be 0 and the controller will stop heating air and higher than 30 will be 30 and the controller will work at maximum.

2- Gain block is used to correct the ratio of the boundaries of the system. If the system works between 0 and 30 degrees the controller work in unity form from 0 to 1, then the correction factor will be 30, if the system work from 0 to 40 then the correction factor will be 40.

3- Memory block is used cause the control loop is hierarchical fuzzy close loop which mean that fuzzy controller level 1 gives fuzzy controller level 2 then the output will return to fuzzy controller level 1 Figure 5.24 shows the problem, so we use the memory block to prevent an infinity loop for matlab processes by a not effective delay between two controllers.

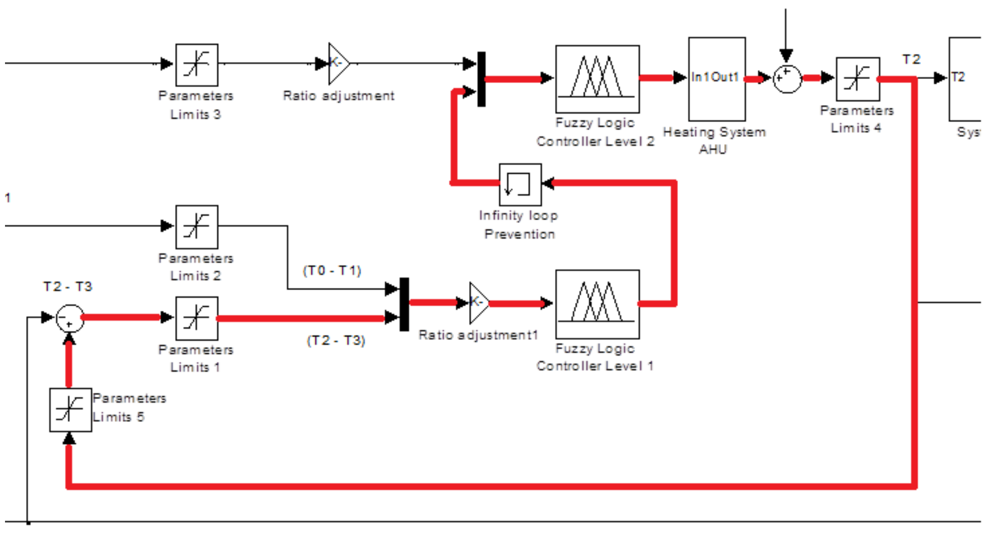


Figure 5.24 Infinity loop problem

4- Some Matlab problems faces us during constructing the system block, when function block is used matlab couldn't be able to processes the function cause the writing language is C++ and matlab requested a C++ compiler.

Chapter 6 Conclusion and Future work

Adaptive hierarchical fuzzy control approach is introduced in this thesis to control a HVAC system for Low energy buildings. This novel approach reduces the fuzzy rule numbers but still maintains the linguistic meaning of fuzzy variables and adapt to changes and disturbances that may be happened to the system in any time. Two methods have been used to control the system. Compensation method seeks to reach the stability point as fast as possible, the second method is stability method; it seeks to give a stable output regardless of parameters changing. These two methods give good results; compared to previous few researches about such time varying nonlinear HVAC systems they are special due to their flexibility and adaptively to any system model. Hierarchical fuzzy method helps to reduce the number of rules used in this controller and make it easy to understand rules evaluation and make it possible to increase the number of inputs without fearful of rules increase. Hierarchical fuzzy make it easy to partition the controller and this thing gives a better understand of controller running.

Adaptive Hierarchical Fuzzy Controller also preserve Air Quality beside Air temperature to give overall good comfort level for occupants. The controller pre-heat the new air that enter the system and heated it to keep indoor air temperature not changed and this thing help the system to stay stable.

Future work can consider this controller in a real place with a large space to study rules optimization and membership shapes. Other future work can be a full integrated control of renewable energy sources in Low energy Buildings. Controllers take in consideration any amount of energy that can be shared.

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Appendices

Appendix A Indoor Virtual System Function Block Code

1- Temperature (T3):

```
function y = fcn(u)
a=((u.*2)-20).*(u>=0).*(u<20);
b=20.*(u>=20).*(30>u);
c=(u-10).*(40>u).*(u>=30);
d=(-u+55).*2.*(45>=u).*(u>=40);
e=20.*(50>=u).*(u>45);
f=(u-30).*(60>u).*(u>50);
g=30.*(u>=60);
y=(a+b+c+d+e+f+g);
```

2- Temperature (T1):

```
function y = fcn(u)
a=((u.*2)-20).*(u>=0).*(u<20);
b=(-u+40).*(u>=20).*(30>u);
c=10.*(40>u).*(u>=30);
d=(-u+45).*2.*(45>=u).*(u>=40);
f=(3.*u-150).*(60>u).*(u>=50);
g=30.*(u>=60);
y=(a+b+c+d+f+g);
```

Appendix B FUZZY RULES

FUZZY RULES FOR THE TWO FUZZY CONTROLLERS:

1- IF *Input 1* is **Zero** and *Input 2* is **Zero** Then *Output 1* is **Zero**
2- IF *Input 1* is **Zero** and *Input 2* is **Small** Then *Output 1* is **Small**
3- IF *Input 1* is **Zero** and *Input 2* is **medium** Then *Output 1* is **medium**
4- IF *Input 1* is **Zero** and *Input 2* is **Large** Then *Output 1* is **Large**
5- IF *Input 1* is **Zero** and *Input 2* is **Very Large** Then *Output 1* is **Very Large**
6- IF *Input 1* is **Small** and *Input 2* is **Zero** Then *Output 1* is **Small**
7- IF *Input 1* is **Small** and *Input 2* is **Small** Then *Output 1* is **medium**
8- IF *Input 1* is **Small** and *Input 2* is **medium** Then *Output 1* is **Large**
9- IF *Input 1* is **Small** and *Input 2* is **Large** Then *Output 1* is **Very Large**
10- IF *Input 1* is **Small** and *Input 2* is **Very Large** Then *Output 1* is **Very Large**
11- IF *Input 1* is **medium** and *Input 2* is **Zero** Then *Output 1* is **medium**
12- IF *Input 1* is **medium** and *Input 2* is **Small** Then *Output 1* is **Large**
13- IF *Input 1* is **medium** and *Input 2* is **medium** Then *Output 1* is **Very Large**
14- IF *Input 1* is **medium** and *Input 2* is **Large** Then *Output 1* is **Very Large**
15- IF *Input 1* is **medium** and *Input 2* is **Very Large** Then *Output 1* is **Very Large**
16- IF *Input 1* is **Large** and *Input 2* is **Zero** Then *Output 1* is **Large**
17- IF *Input 1* is **Large** and *Input 2* is **Small** Then *Output 1* is **Very Large**
18- IF *Input 1* is **Large** and *Input 2* is **medium** Then *Output 1* is **Very Large**
19- IF *Input 1* is **Large** and *Input 2* is **Large** Then *Output 1* is **Very Large**
20- IF *Input 1* is **Large** and *Input 2* is **Very Large** Then *Output 1* is **Very Large**
21- IF *Input 1* is **Very Large** and *Input 2* is **Zero** Then *Output 1* is **Very Large**
22- IF *Input 1* is **Very Large** and *Input 2* is **Small** Then *Output 1* is **Very Large**
23- IF *Input 1* is **Very Large** and *Input 2* is **medium** Then *Output 1* is **Very Large**
24- IF *Input 1* is **Very Large** and *Input 2* is **Large** Then *Output 1* is **Very Large**
25- IF *Input 1* is **Very Large** and *Input 2* is **Very Large** Then *Output 1* is **Very Large**