Thesis for the Degree of Master Degree

Fuzzy Logic Controller Design with Unevenly-distributed Membership Function for High Performance Chamber Cooling System

By

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비등구간 멤버십함수를 이용한 고성능 냉각챔버 시스템의 퍼지제어기 설계

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ABSTRUCT

Recently, the performance of chamber cooling system (CCS) focused on high precision of temperature control and strong robust. It is used for offering an accurate and stable environment to support the biotechnology and medical sciences research. In addition, the global warming problem arouse scientist pay more attention on the energy saving of equipment. The variable speed refrigeration cycle is highly focused on an industrial field of chamber cooling system because of its energy saving ability. In the variable speed refrigeration system, the inside temperature is modulated by regulating the motor speed of compressor. And superheat is changed by manipulating the opening angle of electronic expansion valve.

For driving the refrigeration cycle to output accurate temperature, there are lots of control manners. Otherwise, the original mathematic model base controllers are difficult to design because the inherent nonlinear characteristics of refrigeration cycle in operation ranges. Thus, the fuzzy logic controller which is not depending on the mathematic model is better for controlling the refrigeration cycle. And the linguistic logic express is easier for engineer to design and modify the controller by empirical. However, the big steady-state error is usually exist in the common fuzzy logic control, it because the characteristic of the fuzzy control. And the noise is happened from inverter which set in the variable speed refrigeration cycle used for regulating the motor rotation speed. The harmonic noises disturbing the fuzzy inference result in the controller output unstable.

Fuzzy logic controller adopting unevenly-distributed membership function (UMF) is presented with the purpose of enhancing performance of the temperature control precision, robustness and work efficiency for the

CCS. The control precision realized by reducing the chamber temperature steady-state errors, robustness is realized by the noise rejecting.

The histogram equalization was applied to modify the error membership function for reducing the steady-state error of chamber temperature and the domain encompasses method was applied to modify the error change membership function for rejecting the noise disturbance to improv the robustness. In the characteristic experiment of CCS, the system achieved highest working efficiency when the superheat around 8℃. The working efficiency is improved by reducing the steady-state error of superheat through the manipulated opening angle of electronic expansion valve by fuzzy logic controller with unevenly-distributed membership function.

The comparison results in simulation and real experimental is listed for proving the control effective of fuzzy logic controller with unevenly-distributed membership function is better than the evenly-distributed membership function. In each simulation and real experiment, all of the conditions are trying to keep in same except the membership function of fuzzy logic controllers. The smaller steady-state error of chamber temperature and superheat by unevenly-distributed membership function in the simulation proved the control precision is enhanced successfully. Under the noise disturbance, the stable frequency output by unevenly-distributed membership functions proved the noise disturbance is rejected successfully.

The experimental results show that the steady-state error was reduced around 40% and the noise disturbance was rejected successfully even though noise range was more than 60% of the control precision range. The control precision was improved by reducing the steady-state error and the robustness was enhanced by rejecting noise disturbance through the fuzzy logic controller with unevenly-distributed membership function. Moreover, the stable output frequency can contribute to improvement of superheat control performance, thereby keeping the steady-state error of superheat within ±2℃, the system can achieve high efficiency for saving energy cost and the service time of EEV is extend by applying UMF to chamber temperature control process of CCS.

This thesis is studied on enhancing performance of the fuzzy logic controller by membership function's modification. It can be quoted by the engineer to improve the control performance not only base on the experience but also base on the real response of the control plant.

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Nomenclature

A	fuzzy set	
x	the elements of A fuzzy set	
$\boldsymbol{\mu}(x)$	the membership value of element x	
T	truth value	
U	the universe of the set	
Z^*	error in complex domain	
$\overline{Z}$	controid of each symmetric membership function	
$\boldsymbol{e}$	error fuzzy set	
ee	error change rate fuzzy set	
T	chamber temperature	[℃]
SH	superheat	[℃]
Δf	manipulated variable of frequency	[Hz]
ΔVO	manipulated variable of EEV opening angle	[%]
$e_{r\min}$	the minimum membership function range of the $\boldsymbol{e}$	
$e_{\max}$	the muximum membership function range of the $\boldsymbol{e}$	
n	the membership functions on fuzzy set	
t_s	sampling time	[sec]
U^{crisp}	crisp output of fuzzy inference	
μ_i	output of fuzzy inference	
C_1	controller of chamber temperature control	
C_2	controller of superheat control	

G_1 transfer function of chamber temperature control

G_2 transfer function of superheat control

Chapter 1

Introduction

1.1 Background of this study

The chamber cooling system (CCS) is one kind of refrigeration devices consists of three parts： chamber, refrigeration cycle, and controller. It is widely used in lots of areas such as electrostatics, electronics, petrochemical, packaging, pharmaceutical, plastics and biomedical. Inside temperature of the chamber can be adjusted and kept with accurate temperature by the refrigeration cycle with controller. High precision of temperature control and robust performance are necessary for the system to meet the requirements of these areas.

Recently, the variable speed refrigeration manner as a capacity control is highly focused on an industrial field of CCS because of its energy saving ability. Therefore, the CCS is designed based on the variable speed refrigeration cycle in this thesis. This refrigeration cycle is adopted not only to solve the global warming and energy efficiency problems, but also to offer high precision control of chamber temperature. The variable speed refrigeration system (VSRS) is composed of four main components: variable speed compressor, condenser, evaporator, and electronic expansion valve (EEV). The controller for CCS design is mainly focused on two control variables, the superheat and chamber temperature. The superheat is manipulated by adjusting the opening angle of EEV to maintain the superheat at a constant level. And the chamber temperature is manipulated by changing the rotating speed of compressor continuously to match the refrigeration capacity to the thermal load. In this thesis, the refrigeration capacity control is used to manipulate the chamber temperature and superheat control is used to realize the high efficiency. Furthermore, the liquid back problem can be solved by the superheat control too.

In VSRS, the thermostatic expansion valve (TEV) is limited to a very narrow range of mass flow conditions and the superheat is no longer optimum for a wide range of operating conditions. Hence the electronic expansion valve (EEV) which adjust opening angle by step motor has been used to cope with superheat under severe load variations instead of TEV [1~2].

In CCS, the sensitive thermocouple sensor is adopted to obtain the temperature information as input variables of controller. TC module of programmable logic controller (PLC) is applied to transform the input temperature information to digital signals. Then the central processing unit (CPU) not only calculates the input digital signals with control logic but also output the calculations in digital. After that, the output digital signals are transformed to analog signals by D/A module of PLC. Finally, the analog signals are sent to the inverter and EEV driver to dive the compressor rotation motor and EEV step motor.

Generally, the controller usually can be divided into three types. First is model base controller, the controller which depends on accurate mathematical model, such as proportional-integral-derivative (PID) controller. Second is artificial intelligent (AI) controller, the controller usually depends on the experience of human, such as fuzzy logic controller (FLC). Third is sequence controller, the controller depends on the settings, such as on/off controller.

For the model based controller, PID and modern control are widely used because of those simple structure and high precision control performance. However, the PID controller has disadvantages with low robust performance and hard to build the accurate mathematic model. In CCS, the plant is composed complex components and there are lots of factors disturb the control performance. Thus, the mathematical model is not the most suitable for controller design for CCS. For sequence control, it is easy to control the plant and the controller price is cheap. However, the control precision is low and it cost lots of energy.

The fuzzy logic controller is one kind of the AI controller. In the fuzzy logic controller, the experience of the engineer can be expressed by using the linguistic of human, it is easier to realize the man-machine conversation and edit the rules for fuzzy logic controller. The engineers can easily design and adjust the controller rule-base depended on experience. Thus, the fuzzy logic controller is selected to control the chamber temperature and superheat at the same time to achieve our goals of high performance for CCS. Nowadays, because the advantages of FLC, it is famous adopted by engineers in lots of places.

1.2 Review of the previous study

Li Hua et al[11] presented that the components in the refrigeration cycle are connected with various pipes and valves each other. Hence, the whole system has inherent nonlinear characteristics in operational ranges. As a result, it is very difficult to identify the dynamic characteristics of practical refrigeration systems exactly. In reality, a sophisticated mathematical model also has a defect for designing control system because complex nonlinear characteristics take deal with high-order differential terms in the modeling process. Thus, a simple empirical model is preferred for engineers in the industrial fields[12~13]. Fuzzy logic controller (FLC) which does not depend on the accurate mathematical model is more suitable for controlling the CCS[14~16]. FLC is a kind of empirical controller, which is designed by the real characteristics of the system and designers' experiences. The rule base of the FLC is edited by the human linguistics, so it is easier for engineers to understand and to design. In addition, the characteristics of the FLC can play an important role to obtain a good performance on the nonlinear control system[17~19]. For regulating the motor rotation speed of the compressor in the VSRS, the V/f constant type inverter is employed. The inverter generates a certain degree of interference noise to disturb control system. The harmonic noises disturbing the fuzzy inference result in the controller output unstable. On the other hand, the steady state error occurs due to the FLC operation[20]. If more membership functions were added in the membership function, the increased density of the logical case will improve the control precision. However, more rules that correspond to the membership functions are needed, so that computing load will be increased.

1.3 Objective of this study

The objectives of this thesis are to realize the high precision temperature control and strong robustness of the CCS as shown in Fig. 1.1. The initial fuzzy sets are designed as evenly-distributed membership function (EMF), because it is easy to design after the control variable domain was defined based on the design information and some simple empirical knowledge. However, the control precision is low because of the big steady state error of chamber temperature and robustness is weak because of the noise disturbance in EMF. Thus, this thesis presents unevenly-distributed membership function (UMF) approach to enhance the inside chamber temperature control precision and robustness of the FLC. Furthermore, the UMF used in the superheat control process is realized to reduce the steady-state error of superheat that the system can work with maximum COP for high working efficiency.

The UMF is modified from the initial EMF of the FLC, and the EMF is designed based on the method which was presented by Li Hua et al[21]. The rule base is connected with the experiences of engineers during control operation. There are many rules in rule base, and each rule is edited by the engineers' experiences obtained from characteristic experiments of system.

It is difficult to modify the rules one by one for enhancing the FLC performance after they are determined by the designer.

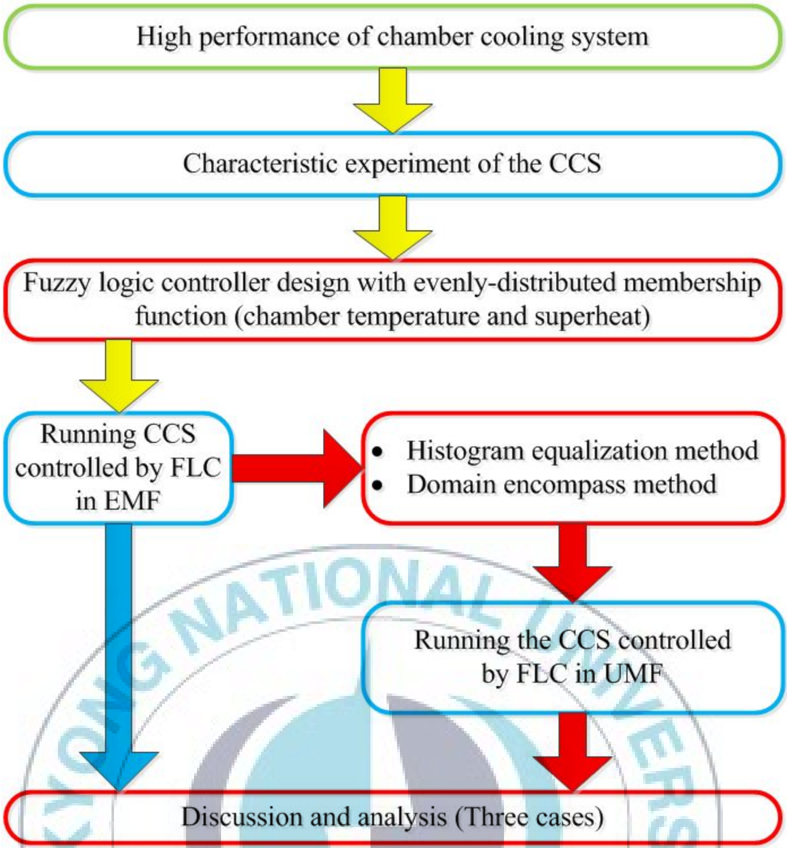


Fig. 1.1 The objective of this thesis

Therefore, this thesis proposes the histogram equalization method and domain encompasses method to modify the membership function (MF) of the error (*e*) and the error change rate (*ee*) [22]. The input MFs of *e* and *ee* are modified into unevenly distributed to reduce the steady state errors and reject the noise disturbances respectively[23]. Furthermore, the output MF is modified to establish correct and rapid output response that correspond the modified *e* MF. The chamber temperature control and superheat control operated at same time in the simulation and experiment. In this thesis, there adopted three cases for the results the comparison to check the control effective of UMF fuzzy controller are below:

CASE 1: EMF in chamber temperature and superheat control process.

CASE 2: UMF in chamber temperature process and EMF in superheat control process.

CASE 3: UMF in chamber temperature and superheat control process.

The results showed the steady-state error of chamber temperature in UMF is reduced 40% compare with the EMF, and the control precision is kept within ±0.5℃. And the frequency output with UMF fuzzy controller is more stable than that of EMF result when the CCS got noise disturbance at 60% of the control precision range. For the superheat, the final control precision is ±1.5℃, and the UMF applied to the superheat control process make the EEV step output more stable.

1.4 The outline of this research

This thesis studied the methods for modifying the membership function of fuzzy sets into unevenly-distributed to enhance the control performance of fuzzy logic controller. The controller is applied to the CCS with VSRS as the refrigeration cycle. Finally the good control effective of UMF fuzzy logic controller was proved by the comparison results of simulations and real experiments.

This thesis consisted of five chapters. The chapter 1 as the introduction part introduces the background, reviews the previous research and objective of this thesis. Totally, this chapter introduced brief outlines of the whole thesis.

Chapter 2 presents the basic theory of the fuzzy logic control for more understanding of fuzzy logic control. Firstly, this chapter explains the definition and composition of fuzzy logic control. Secondly, fuzzy operation part explained the reason of steady-state error happened in fuzzy logic controller and noise disturbed the fuzzy logic inference.

Chapter 3 is divided into two parts. The first part mainly introduced the composition and operation of CCS in detail. It is explained the relationship between manipulated variables and controlled variables in VSRS. The second part is focused on explaining the fuzzy logic controller design with CCS. At first, the initial EMF is designed based on the design target and characteristics of the CCS. Then, the membership functions are modified to

UMF using histogram equalization method and domain encompasses method by response of the CCS.

Chapter 4 list the simulation results and real experiment results in three case comparison. Through the results, we can easily know the control performance of each control case with different membership function in same condition.

Chapter 5 is the conclusion of the study.

Chapter 2

Theory of the fuzzy logic control

In CCS, all the components in the refrigeration cycle are linked with pipes, demonstrating inherently nonlinear behaviors. Hence, it is unfeasible to exactly identify dynamic characteristics of practical refrigeration system. The precise mathematical model based on mass and energy conservative law has involved complexity and high-order term, it is not directly applicable to real control system design. Therefore, in order to guarantee high precision temperature control, robustness and energy saving capability for the VSRS, the fuzzy logic control which design do not depend on the exactly mathematics model is better for the CCS. The advantages in the easy design, certain robustness and easy for adjusting the controller. In this chapter, the theory of the fuzzy logic control will be introduced.

The development of control system theory has since gone through an evolutionary process. Starting from some basic, simplistic, frequency-domain analysis for single-input single-output (SISO) linear control systems, and generalized to a mathematically nonlinear systems, and generalized to a mathematically sophisticated modern theory of multi-input multi-output (MIMO) linear or nonlinear system described by differential and/or difference equations.

It is believed that the advances of space technology in the 1950s completely changed the spirit and origination of the classical control systems theory: the challenges posed by the high accuracy and extreme complexity of the space systems, such as space vehicles and structures, stimulated and promoted the existing control theory very strongly, developing it to such a high mathematical level that can use many new concepts like state-space and optimal controls. The theory is still rapidly growing today; it employs many-advanced mathematics such as differential geometry, operation theory, and functional analysis, and connects too many theoretical and applied sciences like artificial intelligence, computer science, and various types of engineering. This modern control system theory, referred to as conventional or classical control systems theory, has been extensively developed. The theory is now relatively complete for linear control systems, and has taken the lead in modern technology and industrial applications where control and automation are fundamental. The theory has its solid foundation built on contemporary mathematical sciences and electrical engineering, as was just mentioned. As a result, it can provide rigorous analysis and often prefect solutions when a system is defined in precise mathematical terms. In addition to these advances, adaptive and robust as well as nonlinear systems control theories have also seen very rapid development in the last two decades, which have significantly extended the potential power and applicable range of the linear control systems theory in practice.

Conventional mathematics and control theory exclude vagueness and contradictory conditions. Consequently, conventional control systems theory does not attempt to study any formulation, analysis, and control of what has been called fuzzy systems, which may be vague, incomplete, linguistically described, or even inconsistent. Fuzzy set theory and fuzzy logic will be explained in this chapter, play a central role in the investigation of controlling such systems. The main contribution of fuzzy control theory, a new alternative and branch of control systems theory that uses fuzzy logic, is its ability to handle many practical problems that cannot be adequately managed by conventional control techniques. At the same time, the results of fuzzy control theory are consistent with the existing classical ones when the system under control reduces from fuzzy to no fuzzy. In other words, many well-known classical results can be extended in some natural way to the fuzzy setting. In the last three chapters, we have seen many such examples: the interval arithmetic is consistent with the classical arithmetic when an interval becomes a point; the fuzzy logic is consistent with the classical logic when the multi-valued inference becomes two-valued; and the fuzzy Lyapunov stability and fuzzy controllability (and observability) become the classical ones when the fuzzy control systems become nonfuzzy.

Basically, the aim of fuzzy control systems theory is to extend the existing successful conventional control systems techniques and methods as much as possible, and to develop many new and special-purposed ones, for a much larger class of complex, complicated, and ill-modeled systems – fuzzy systems. This theory is developed for solving real-world problems. The fuzzy modeling techniques, fuzzy logic inference and decision-making, and fuzzy control methods to be studied in the following chapters, should all work for real-world problems – if they are developed correctly and appropriately. The real-world problems exist in the first place. Fuzzy logic, fuzzy set theory, fuzzy modeling, fuzzy control methods, etc. are all man-made and subjectively introduced to the scene. If this fuzzy interpretation is correct and if the fuzzy theory works, then one should be able to solve the real-world problems after the fuzzy operations have been completed in the fuzzy environment and then the entire process is finally returned to the original real-world setting. This is what is called the "fuzzification-fuzzy operation-defuzzification" routine in the fuzzy control systems theory. We will study this routine in detail for various control systems design and applications in this chapter [24].

2.1 The fuzzy logic controller

Fuzzy controller can be handled as a system that transmits information like a conventional controller with inputs containing information about the plant to be controlled and an output that is the manipulated variable. From outside, there is no vague information visible, both, the input and output values are crisp values. The input values of a fuzzy controller consist of measured values from the plant that are either plant output values or plant states, or control errors derived from the set-point values and the controlled variables.

Most commercial fuzzy products are rule-based systems that receive current information in the feedback loop from the device as it operates and control the operation of a mechanical or other device[25]. A fuzzy logic system has four blocks as shown in Fig. 2.1. Crisp input information from the device is converted into fuzzy values for each input fuzzy set with the fuzzification block. The universe of discourse of the input variables determines the required scaling for correct per-unit operation. The scaling is very important because the fuzzy system can be retrofitted with other devices or ranges of operation by just changing the scaling of the input and output. The decision-making-logic determines how the fuzzy logic operations are performed (Sup-Min inference), and together with the knowledge base determine the outputs of each fuzzy IF-THEN rules. Those are combined and converted to crispy values with the defuzzification block. The output crisp value can be calculated by the center of gravity or the weighted average.

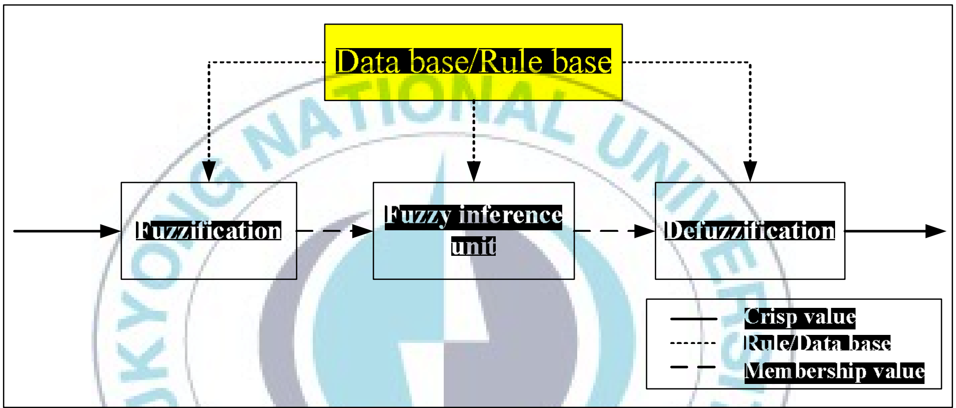


Fig. 2.1 The compose of fuzzy logic controller

Base on this figure, the after contents will explain the each control process in detail.

2.1.1 Membership function and fuzzification

A. Features of the membership function

Since all information contained in a fuzzy set is described by its membership function, it is useful to develop a lexicon of terms to describe various special features of this function. For purpose of simplicity, the functions shown in the following figures will all be continuous, but the terms apply equally for both discrete and continuous fuzzy sets. Fig. 2.2

assists in this description.

The core of a membership function for some fuzzy set **A** is defined as that region of the universe that is characterized by complete and full membership in the set **A**. That is, the core comprises those elements x of the universe such that $\mu_{\mathbf{A}}(x)=1$.

The support of a membership function for some fuzzy set **A** is defined as that region of the universe that is characterized by nonzero membership in the set **A**. That is, the support comprise those elements x of the universe such that $\mu_{\mathbf{A}}(x)>0$.

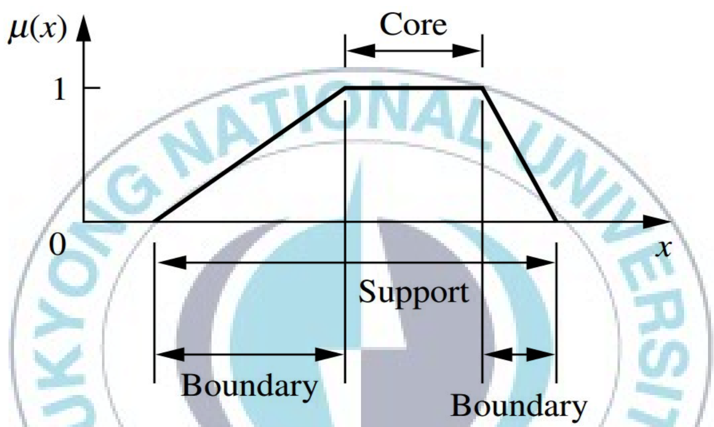


Fig. 2.2 Core, support, and boundaries of a fuzzy set

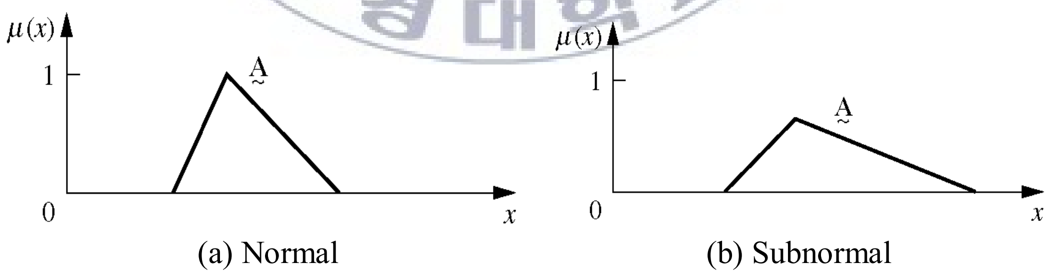


Fig. 2.3 Fuzzy sets in normal and subnormal

The boundaries of a membership function for a membership function for some fuzzy set **A** are defined as that region of the universe containing elements that have a nonzero membership but not complete membership. That is, the boundaries comprise those elements x of the universe such that $0<\mu_{\mathbf{A}}(x)<1$. These elements of the universe are those with some degree of fuzziness, or only partial membership in the fuzzy set **A**. Fig. 2.2 illustrates the regions in the universe comprising the core, support, and boundaries of a typical fuzzy set.

A normal fuzzy set is one whose membership function has at least one element *x* in the universe whose membership value is unity. For fuzzy sets where one and only one element has a membership equal to one, this element is typically referred to as the prototype of the set, or the prototypical element. Fig. 2.3 illustrate typical normal and sub normal fuzzy sets.

A convex fuzzy set is described by a membership function whose membership values are strictly monotonically increasing, or whose membership values are strictly monotonically increasing then strictly monotonically decreasing with increasing values for elements in the universe. Said another way, if, for any elements x, y, and z in a fuzzy set **A**, the relation $x < y < z$ implies that

$$\boldsymbol{\mu}_{\mathbf{A}}(y) \geq \mathbf{min}[\boldsymbol{\mu}_{\mathbf{A}}(x), \boldsymbol{\mu}_{\mathbf{A}}(z)] \tag{2.1}$$

then **A** is said to be a convex fuzzy set [26]. Fig. 2.4 shows a typical convex fuzzy set and a typical nonconvex fuzzy set. It is important to remark here that this definition of convexity is different from some definitions of the same term in mathematics. In some areas of mathematics, convexity of shape has to do with whether a straight line through any part of the shape goes outside the boundaries of that shape. This definition of convexity is not used here; Eq. 2.1 succinctly summarizes our definition of convexity.

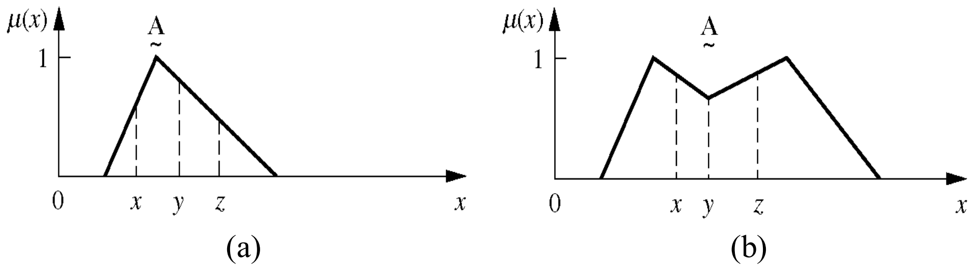


Fig. 2.4 Convex, normal fuzzy set (a) and nonconvex, normal fuzzy set (b)

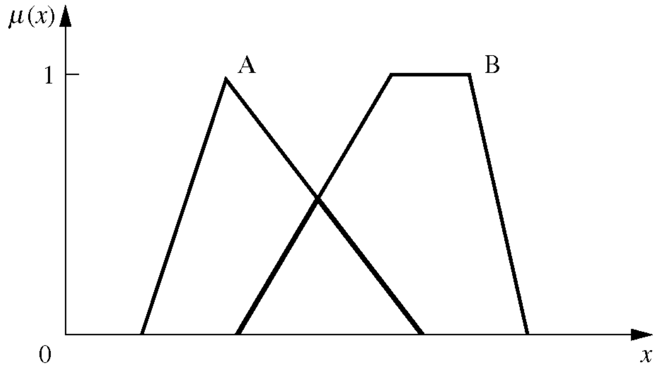


Fig. 2.5 The intersection of two convex fuzzy sets produces a convex fuzzy set

A special property of two convex fuzzy sets, say **A** and **B**, is that the intersection of these two convex fuzzy sets is also a convex fuzzy set, as shown in Fig. 2.5. That is, for **A** and **B**, which are both convex, $\mathbf{A} \cap \mathbf{B}$ is also convex.

The crossover points of a membership function are defined as the elements in the universe for which a particular fuzzy set **A** has values equal to 0.5, i.e., for which $\mu_{\mathbf{A}}(x)=0.5$.

The height of a fuzzy set **A** is the maximum value of the membership function, i.e., hgt(**A**)=max{ $\mu_{\mathbf{A}}(x)$ }. If the hgt(**A**)<1, the fuzzy set is said to be subnormal. The hgt(**A**) may be viewed as the degree of validity or credibility of information expressed by **A**[27].

If **A** is a convex single-point normal fuzzy set defined on the real line, then **A** is often termed a fuzzy number.

B. Various forms

The most common forms of membership functions are normal and convex. However, many operations on fuzzy sets, hence operations on membership functions, result in fuzzy sets that are subnormal and nonconvex.

Membership functions can be symmetrical or asymmetrical. They are typically defined on *one*-dimensional universes, but they certainly can be described on multidimensional (or *n*-dimensional) universes. For example, the membership functions shown in this chapter are *one*-dimensional curves.

In two dimensions, these curves become surfaces and for three or more dimensions these surfaces become hypersurfaces. These hypersurfaces, or curves, are simple mappings from combinations of the parameters in the *n*-dimensional space to a membership value on the interval [0, 1]. Again, this membership value expresses the degree of membership that the specific combination of parameters in the n-dimensional space has in a particular fuzzy set defined on the *n*-dimensional universe of discourse. The hypersurfaces for an *n*-dimensional universe are analogous to joint probability density functions; but, of course, the mapping for the membership function is to membership in a particular set and not to relative frequencies, as it is for probability density functions.

Fuzzy sets of the types depicted in Fig. 2.3 are by far the most common ones encountered in practice; they are described by ordinary membership functions. However, several other types of fuzzy membership functions have been proposed[27] as generalized membership functions. The primary reason for considering other types of membership functions is that the values used in developing ordinary membership functions are often overly precise. They require that each element of the universe x on which the fuzzy set **A** is defined be assigned a specific membership value, $\mu_{\mathbf{A}}(x)$. Suppose the level of information is not adequate to specify membership functions with this precision. For example, we may only know the upper and lower bounds of membership grades for each element of the universe for a fuzzy set. Suppose the level of information is not adequate to specify membership functions with this precision. Such a fuzzy set would be described by interval-valued membership functions, as the one shown in Fig. 2.6. In this figure, for a particular element, $x=z$, the membership in a fuzzy set **A**, i.e., $\mu_{\mathbf{A}}(z)$, would be expressed by allowing their intervals to become fuzzy. Each membership interval then becomes an ordinary fuzzy set. This type of membership function is referred to in the literature as type-2 fuzzy set. Other generalizations of the fuzzy membership functions are available as well[27].

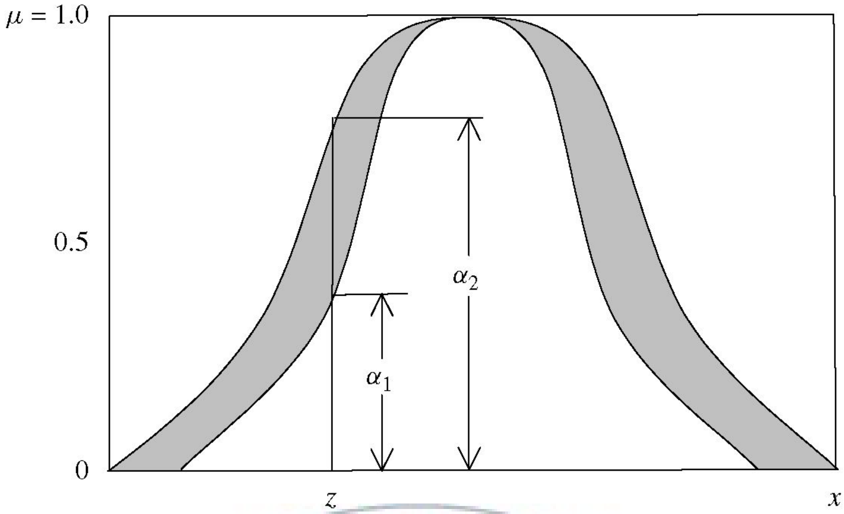


Fig. 2.6 An interval-valued membership function

C. Fuzzification

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.

In the real world, hardware such as a digital voltmeter generates crisp data, but these data are subject to experimental error. The information shown in Fig. 2.7 shows one possible range of errors for a typical voltage reading and the associated membership function that might represent such imprecision.

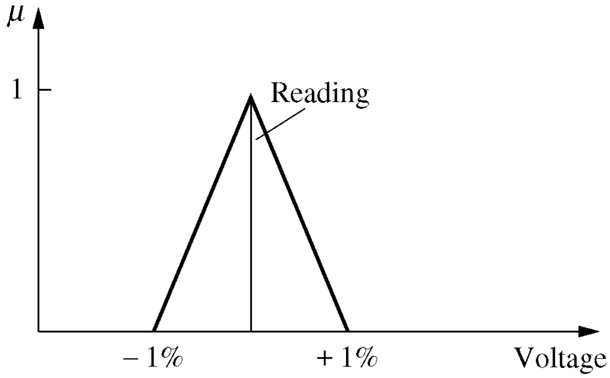
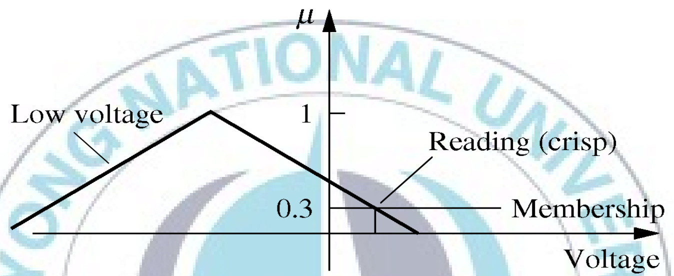
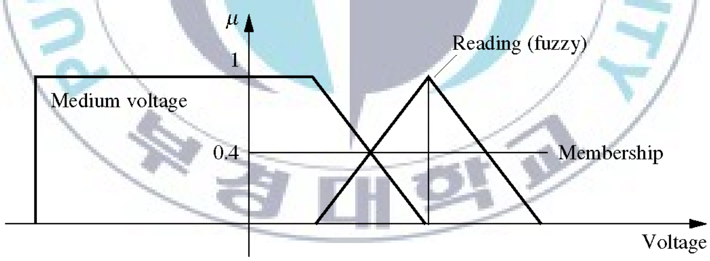


Fig. 2.7 Membership function representing imprecision in "crisp voltage reading."



(a) Fuzzy set and crisp reading



(b) Fuzzy set and fuzzy reading

Fig. 2.8 Comparisons of fuzzy sets and crisp or fuzzy readings

The representation of imprecise data as fuzzy sets is a useful but not mandatory step when those data are used in fuzzy systems. This idea is shown in Fig. 2.8, where we consider the data as a crisp reading, Fig. 2.8(a), or as a fuzzy reading, as shown in Fig. 2.8(b). In Fig. 2.8(a) we might want to compare 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, i.e., the fuzzy set and the reading can be said to agree at a membership value of 0.3. In Fig. 2.8(b) the intersection of the fuzzy set "medium voltage" and a fuzzified voltage reading occurs at a membership of 0.4. We can see in Fig. 2.8(b) that the set intersection of the two fuzzy sets is a small triangle, whose largest membership occurs at the membership value of 0.4.

2.1.2 The fuzzy logic and rule-base

A. Fuzzy logic

The restriction of classical propositional calculus to a two-valued logic has created many interesting paradoxes over the ages. For example, the Barber of Seville is a classic paradox (also termed Russell's barber). We conclude that the only way for this paradox (or any classic paradox for that matter) to work is if the statement is both true and false simultaneously. This can be shown, using set notation[28]. Let **S** be the proposition that the barber shaves himself and $\overline{\mathbf{S}}$ (not **S**) that he does not. Then since $\mathbf{S} \rightarrow \overline{\mathbf{S}}$ (**S** implies not **S**), and $\overline{\mathbf{S}} \rightarrow \mathbf{S}$, the two propositions are logically equivalent: $\mathbf{S} \leftrightarrow \overline{\mathbf{S}}$. Equivalent propositions have the same truth value; hence,

$$T(\mathbf{S}) = T(\overline{\mathbf{S}}) = 1 - T(\mathbf{S})$$

which yields the expression

$$T(\mathbf{S}) = \frac{1}{2}$$

As seen, paradoxes reduce to half-truths (or half-falsities) mathematically. In classical binary (bivalued) logic, however, such conditions are not allowed, i.e., only $T(\mathbf{S})$=1 or 0 is valid; this is a manifestation of the constraints placed on classical logic by the excluded middle axioms.

A fuzzy logic proposition, **P**, is a statement involving some concept without clearly defined boundaries. Linguistic statements that tend to express subjective ideas and that can be interpreted slightly by various individuals typically involve fuzzy propositions. Most natural language is fuzzy, in that it involves vaguer and imprecise terms. Statements describing a person's height or weight or assessments of people's preferences about colors or menus can be used as examples of fuzzy propositions. The truth value assigned to **P** can be any value on the interval [0, 1]. The assignment of the truth value to a proposition is actually a mapping from the interval [0, 1] to the universe ***U*** of truth values, *T*, as indicated in Eq. 2.2.

$$T : u \in \boldsymbol{U} \rightarrow (\boldsymbol{0}, \boldsymbol{1}) \tag{2.2}$$

As in classical binary logic, we assign a logical proposition to a set in the universe of discourse. Fuzzy propositions are assigned to fuzzy sets. Suppose proposition **P** is assigned to fuzzy set **A**; then the truth value of a proposition, denoted *T*(**P**), is given by

$$T(\mathbf{P}) = \boldsymbol{\mu}_{\mathbf{A}}(x) \quad \textbf{where } \boldsymbol{0} \leq \boldsymbol{\mu}_{\mathbf{A}} \leq \boldsymbol{1} \tag{2.3}$$

Eq. 2.3 indicates that the degree of truth for the proposition $\mathbf{P} : x \in \mathbf{A}$ is equal to the membership grade of x in the fuzzy set **A**.

The logical connectives of negation, disjunction, conjunction, and implication are also defined for a fuzzy logic. These connectives are given in Eq. 2.4~2.7 for two simple propositions: proposition **P** defined on fuzzy set **A** and proposition **Q** defined on fuzzy set **B**.

Negation:

$$T(\overline{\mathbf{P}}) = \boldsymbol{1} - T(\mathbf{P}) \tag{2.4}$$

Disjunction

$$\mathbf{P} \vee \mathbf{Q} : x \textbf{ is A or B} \quad T(\mathbf{P} \vee \mathbf{Q}) = \max(T(\mathbf{P}), T(\mathbf{Q})) \tag{2.5}$$

Conjunction

$$\mathbf{P} \vee \mathbf{Q} : x \textbf{ is A and B} \quad T(\mathbf{P} \vee \mathbf{Q}) = \min(T(\mathbf{P}), T(\mathbf{Q})) \tag{2.6}$$

Implication [29]

$$\mathbf{P} \rightarrow \mathbf{Q}: \ x \textbf{ is A, then } x \textbf{ is B}$$

$$T(\mathbf{P} \rightarrow \mathbf{Q}) = T(\overline{\mathbf{P}} \vee \mathbf{Q}) = \max(T(\overline{\mathbf{P}}), T(\mathbf{Q})) \tag{2.7}$$

As before in binary logic, the implication connective can be modeled in rule-based form; **P→Q** is, IF x is **A**, THEN y is **B** and it is equivalent to the following fuzzy relations, $\mathbf{R} = (\mathbf{A} \times \mathbf{B}) \cup (\overline{\mathbf{A}} \times \mathbf{Y})$, just as it is in classical logic. The membership function of **R** is expressed by the following formula:

$$\boldsymbol{\mu}_R(x, y) = \max[\boldsymbol{\mu}_A(x) \wedge \boldsymbol{\mu}_B(y)), (\mathbf{1} - \boldsymbol{\mu}_A(x))] \tag{2.8}$$

B. Linguistic Descriptions

The linguistic description provided by the expert can generally be broken into several parts. There will be “linguistic variables” that describe each of the time-varying fuzzy controller inputs and outputs. For example, in the chamber temperature control with CCS,

“error (e)” describes $e(t)$

“error changing rate (ee)” describes $\frac{d}{dt}e(t)$

“manipulating frequency (ΔHz)” describes $u(t)$

Note that we use quotes to emphasize that certain words or phrases are linguistic descriptions, and that we have added the time index to, for example, $e(t)$, to emphasize that generally e varies with time. There are many possible choices for the linguistic descriptions for variables. Some designers like to choose them so that they are quite descriptive for documentation purposes. However this can sometimes lead sidle, yet accurate enough so that they adequately represent the variables. Regardless, the choice of the linguistic variable has no impact on the way that the fuzzy controller operates; it is simply a notation that helps to facilitate the constructions of the fuzzy controller via fuzzy logic.

Just as $e(t)$ takes on a value of, for example, 0.1 at t=2 (e(2)=0.1), linguistic variables assume “linguistic values.” That is, the values that linguistic variables take on over time change dynamically. Suppose for the temperature controlling example that “error,” “error changing rate” and “manipulating frequency” take on the following values:

NB describes “Negative Big”
NM describes “Negative Medium”
NS describes “Negative Small”
ZE describes “Zero”
PS describes “Positive Small”
PM describes “Positive Medium”
PB describes “Positive Big”

Note the that we are using “Negative Big” as an abbreviation for “Negative Big error of chamber temperature” and so on for the other variables. Such abbreviations help keep the linguistic descriptions short yet precise. For an even shorter description, we could use integers:

“-3” to represent “NB”
“-2” to represent “NM”
“-1” to represent “NS”
“0” to represent “ZE”
“1” to represent “PS”
“2” to represent “PM”
“3” to represent “PB”

This is a particularly appealing choice for the linguistic values since the descriptions are short and nicely represent that the variable we are concerned with has a numeric quality. We are not, for example, associating “-1” with any particular number of radians of error; the use of the numbers for linguistic descriptions simply quantifies the sign of the error (in the usual way) and indicates the size in relation to the other linguistic values. We shall find the use of this type of linguistic value quite convenient and hence will give it the special name, “linguistic-numeric value”.

The linguistic variables and values provide a language for the expert to express her or his ideas about the control decision-making process in the contest of the framework established by our choice of fuzzy controller inputs and outputs.

C. Rule-base

The rules in the fuzzy logic controller, are always saved in the knowledge base. Rules are made by the linguistic quantification words and logical of fuzzy. Most times, the rules are designed base on the experience of designer with the real operation of the system. In the CCS the rules is came from the knowledge of designer on the refrigeration system operation and multiple experiments of the CCS. The Table 2.1 list the rules what support the fuzzy logic controller to operate with the CCS.

Table 2.1 The rule-base of the fuzzy logic controller

		ee						
e		NB	NM	NS	Z	PS	PM	PB
	NB	NB	NB	NB	NB	Z	Z	Z
	NM	NB	NB	NM	NM	Z	Z	Z
	NS	NB	NM	NS	NS	Z	Z	Z
	Z	NM	NS	Z	Z	Z	Z	Z
	PS	NS	Z	Z	Z	PS	PM	PB
	PM	Z	Z	Z	PS	PM	PB	PB
	PB	Z	Z	Z	PB	PB	PB	PB

(a) rule-base support for compressor speed control

		ee						
e		NB	NM	NS	Z	PS	PM	PB
	NB	NB	NB	NM	NM	NS	Z	Z
	NM	NB	NM	NS	NS	Z	Z	Z
	NS	NM	NS	NS	Z	Z	Z	Z
	Z	NM	NS	Z	Z	Z	Z	Z
	PS	NS	Z	Z	Z	PS	PM	PB
	PM	Z	Z	Z	PS	PS	PM	PB
	PB	Z	Z	Z	PS	PM	PB	PB

(b) the rule-base support for EEV opening angle control

For simple, these rules is listed in the table form, it also can translate to human linguistic forms, for example the rules in (a) case:

"IF the input *e* is NB AND input *ee is* NB THEN the output is NB "
"IF the input *e* is PB AND input *ee is* ZE THEN the output is PS "
…

The reader should convince him or herself that the other rules are also valid and take special note of the pattern of rule consequents that appears in the body of the table: Notice the diagonal of zeros and viewing the body of the table as a matrix we see that it has certain symmetry to it. This symmetry that emerges when the rules are tabulated is no accident and is actually a representation of abstract knowledge about how to control the compressor speed; this relationship can be found from checking the characteristic experiment of the CCS. The detail constant of how to design the fuzzy logic controller of CCS will explain in chapter 3.

2.1.3 The inference and defuzzification

A. Inferences

The modus ponens deduction is used as a tool for making inferences in rule-based systems. A typical if-then rule is used to determine whether an antecedent (cause or action) infers a consequent (effect or reaction). Suppose we have a rule of the form IF **A**, THEN **B**, where A is a set defined on universe **X** and **B** is a set defined on universe **Y**. This rule can be translated in to a relation between sets **A** and **B**, $\mathbf{R} = (\mathbf{A} \times \mathbf{B}) \cup (\bar{\mathbf{A}} \times \mathbf{Y})$. Now suppose a new antecedent, say $\mathbf{A}'$, is known. There can use the modus ponens deduction to infer a new consequent, say $\mathbf{B}'$, the resulting from the new antecedent. That is, the "IF $\mathbf{A}'$, THEN $\mathbf{B}'$" can be deduce in the rule form. Since "**A** implies **B**" is defined on the Cartesian space $\mathbf{X} \times \mathbf{Y}$, B' can be found through the following set-theoretic formulation,

$$\mathbf{B}' = \mathbf{A}' \circ \mathbf{R} = \mathbf{A}' \circ ((\mathbf{A} \times \mathbf{B}) \cup (\overline{\mathbf{A}} \times \mathbf{Y}))$$

Where the symbol $\circ$ denotes the composition operation. Modus ponens deduction can also be used for the compound rule IF A, THEN B, ELSE C, where this compound rule is equivalent to the relation defined as $\mathbf{R} = (\mathbf{A} \times \mathbf{B}) \cup (\overline{\mathbf{A}} \times \mathbf{C})$. For this compound rule, if we define another antecedent $\mathbf{A}'$, the following possibilities exist, depend on (1) whether $\mathbf{A}'$ is fully contained in the original antecedent $\mathbf{A}$, (2) whether $\mathbf{A}'$ is contained only in the complement of $\mathbf{A}$, or (3) whether $\mathbf{A}'$ and $\mathbf{A}$ overlap to some extent as described next:

IF $\mathbf{A}' \subset \mathbf{A}$, THEN y=B
IF $\mathbf{A}' \subset \overline{\mathbf{A}}$, THEN y=C
IF $\mathbf{A}' \cap \mathbf{A} \neq \varnothing$, $\mathbf{A}' \cap \overline{\mathbf{A}} \neq \varnothing$, THEN y=$\mathbf{B} \cup \mathbf{C}$

The rule IF $\mathbf{A}$, THEN $\mathbf{B}$ (proposition **P** is defined on set **A** in universe **X,** and proposition **Q is** defined on set **B** in universe **Y**), i.e., $(P \to Q) = R = (A \times B) \cup (\overline{A} \times Y)$, is then defined in function-theoretic terms as:

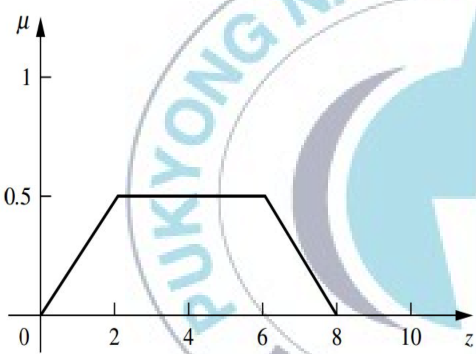
$$X_R(x, y) = \max[(X_A(x) \wedge X_B(y)), ((1 - X_A(x)) \wedge 1)]$$

where $X(\ )$ is the characteristic function for the controlled system.

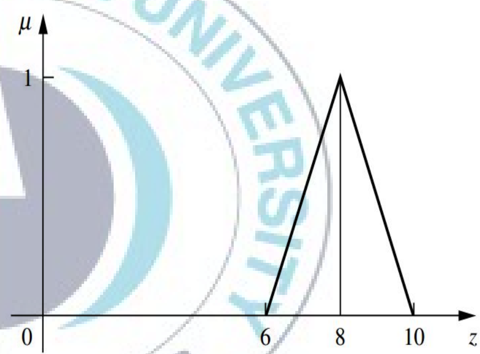
B. Defuzzification

As mentioned in the introduction, there may be situations where the output of a fuzzy process needs to be a single scalar quantity as opposed to a fuzzy set. Defuzzification is the conversion of a fuzzy quantity to a precise quantity, just as fuzzification is the conversion of a precise quantity to a fuzzy quantity. The output of a fuzzy process can be the logical union of two or more fuzzy membership functions defined on the universe of discourse of the output variable. For example, suppose a fuzzy output is comprised of two parts: the first part, $\mathbf{C}_1$, a trapezoidal shape, shown in Fig. 2.9(a), and the second part, C_2, a triangular membership shape, shown in Fig. 2.9(b). The union of these two membership functions, i.e., $\mathbf{C} = \mathbf{C_1} \cup \mathbf{C}_2$, involves the max operator, which graphically is the outer envelope of the two shapes shown in Fig. 2.9(a) and (b); the resulting shape is shown in Fig. 2.9(c). Of course, a general fuzzy output process can involve many output parts (more than two), and the menership function representing each part of the output can have shapes other than trangles and trapezoids. Further, as Fig. 2.9(a) shows, the membership functions may not always be normal. In general, we can have

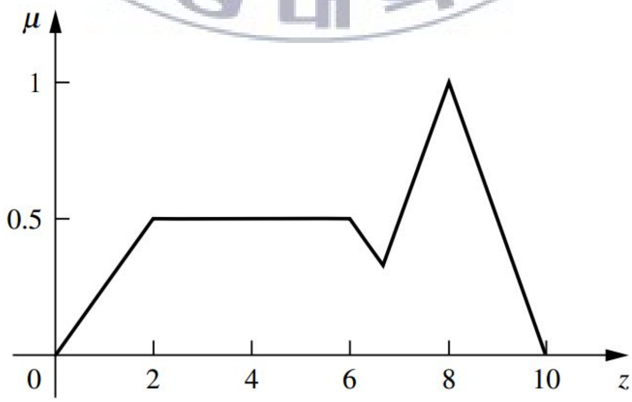
$$\mathbf{C}_k = \bigcup_{i=1}^{k} \mathbf{C}_i = \mathbf{C}$$



(a) First part of fuzzy output



(b) Secnd part of fuzzy output



(c) Union of both parts

Fig. 2.9 Typical fuzzy process output

C. Centroid method

The centroid method (also called center of area) is the most prevalent and physically appealing of all the defuzzification methods[30~31]; it is given by the algebraic expression

$$z^* = \frac{\int \mu_C(z) \cdot z}{\int \mu_C(z)} \tag{2.8}$$

Where ∫ denotes an algebraic integration. This method is shown in Fig. 2.10.

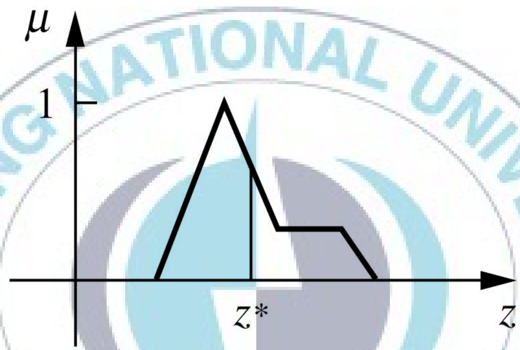


Fig. 2.10. The centroid defuzzification method

D. Weighted average method

The weighted average method is also called by centroid of weight method sometimes. It is the most frequently used in fuzzy applications since it is one of the more computationally efficient methods. Unfortunately it is usually restricted to symmetrical output membership functions. It is given by the algebraic expression

$$z^* = \frac{\sum \mu_C(\bar{z}) \cdot \bar{z}}{\sum \mu_C(\bar{z})} \tag{2.9}$$

Where Σ denotes the algebraic sum and where $\bar{z}$ is the controid of each symmetric membership function. This method is shown in Fig. 2.11. The weighted average method is formed by weighting each membership function in the output by its respective maximum membership value. As an example, the two functions shown in Fig. 2.11 would result in the following general form for the defuzzified value:

$$z^* = \frac{a(0.5) + b(0.9)}{0.5 + 0.9}$$

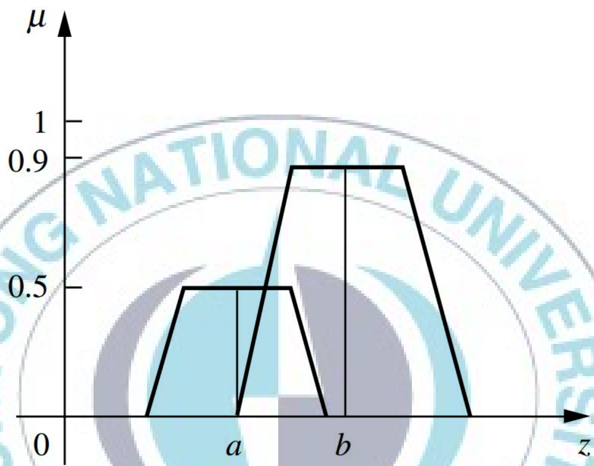


Fig. 2.11. The weighted average defuzzification method

2.2 Operation of the fuzzy logic controller in CCS

2.2.1 Compose of control plant with chamber cooling system

The fuzzy logic controller is instead the conventional model base controller in CCS. In the system, the controller which operate the fuzzy logical is PLC. The temperature information is collected by the thermo couples and transform to digital signal by TC module of PLC. The information is computed by the fuzzy logical in CPU of PLC, and the manipulated variables output from the D/A module of the PLC to each driver of the controlled devices.

The look-up table method is used to program the fuzzy logic by personal computer (PC) with PLC program. After the programming, the fuzzy logical program will upload from PC to PLC.

The analog signal comes from the D/A module to the invertor and step valve control interface. The inverter is used to output frequency to change the rotation speed of motor in compressor, and the step valve control interface is used to output the steps to change the opening angle of electronic expansion valve. That the control plane contained the programming part, control logical operating part and manipulated part. The thermo couple is the feedback loop exist in CCS. Fig. 2.12 shows compose of the control system.

2.2.2 The processing of the signal transform

In CCS, there are two control targets, one is chamber temperature and another is the superheat of the refrigeration cycle. Both variables are controlled respectively by different fuzzy controllers at same time. However the processing of signal transforms of each control variables are same.

The temperature information as the input variables are measured by the thermocouple sensor from the refrigeration cycle directly. The temperature information is translated to digital signals by TC module of the PLC. Then the central processing unit (CPU) not only calculates the input digital signals with control logic but also output the calculations in digital. After that, the output digital signals are transformed to analog signals by D/A module of PLC.

The output analog signal for compressor speed control is transformed to frequency output by inverter; the output analog signal for EEV opening control is transformed to pulse output by EEV driver. The compressor rotation speed is changed by frequency output and EEV opening angle is changed by the pulse output.

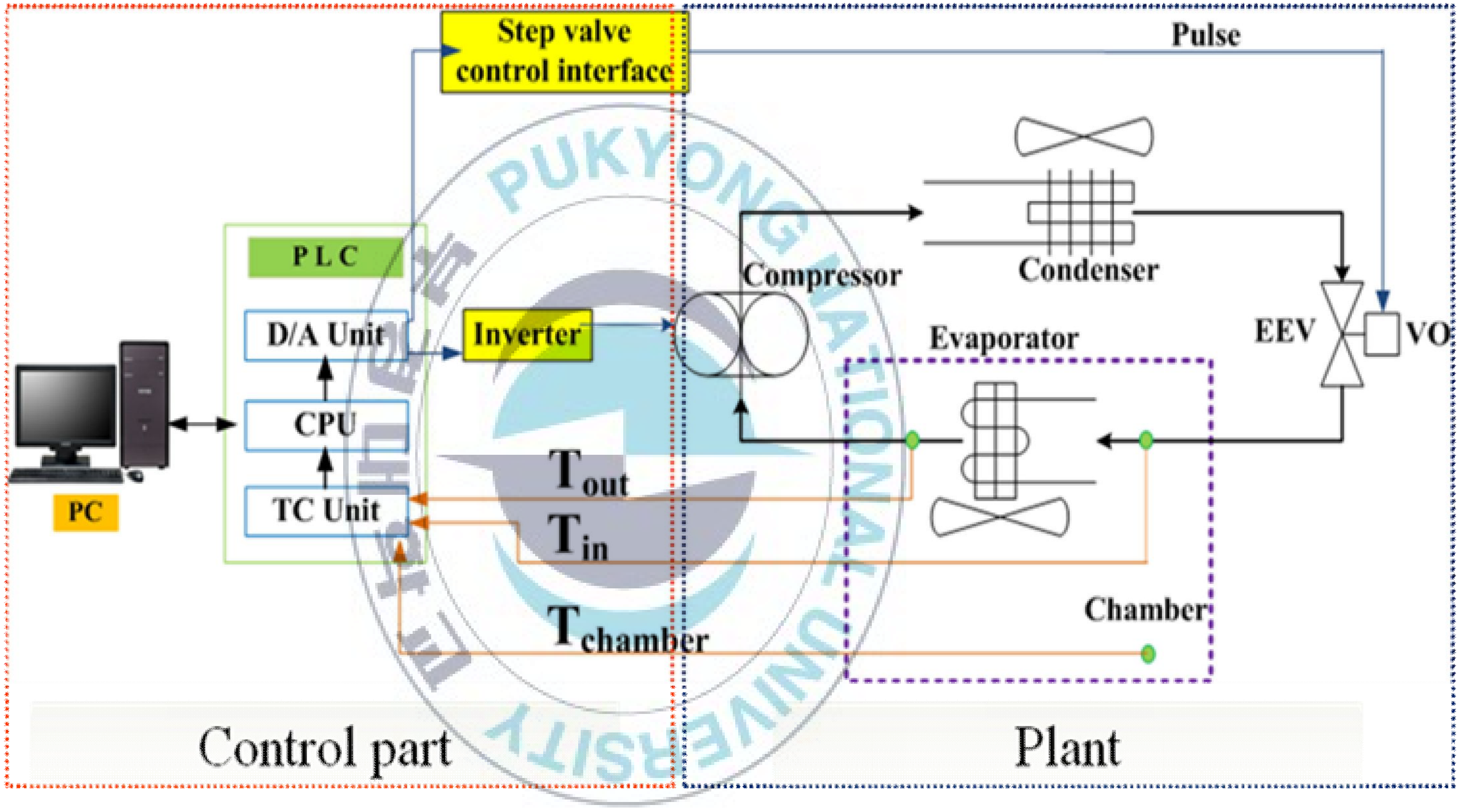


Fig. 2.12 The compose of the control system

The motor speed of compressor changes the chamber inside temperature and opening angle of EEV changes the superheat. The Fig. 2.13 is the flow chat of the signal transform.

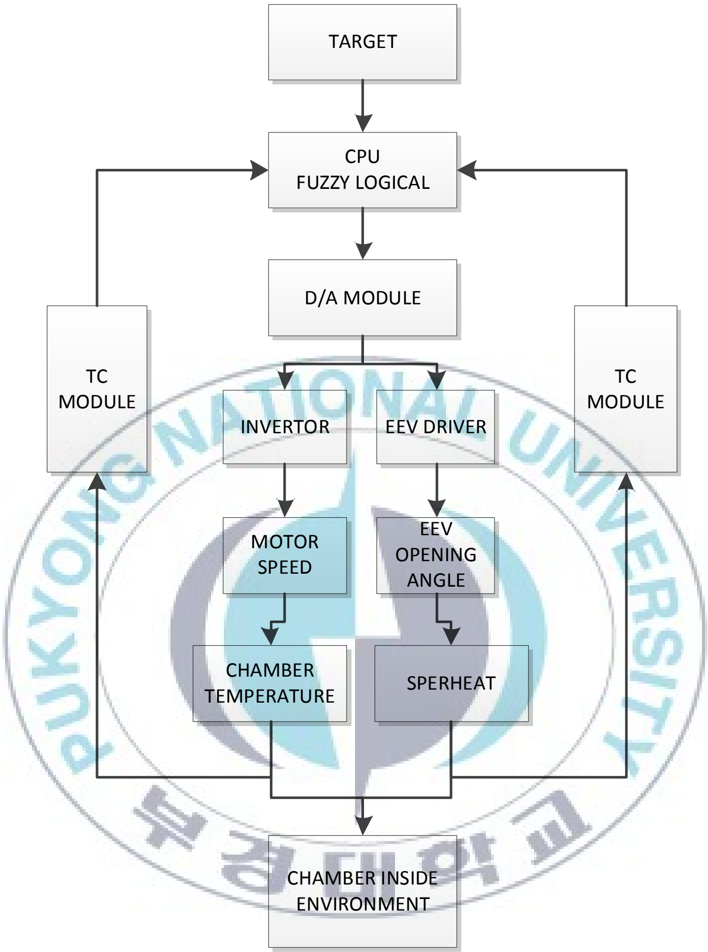


Fig. 2.13 The flow chat of the signal transform in CCS

2.2.3 Operation of fuzzy logical in CPU

The fuzzy controller is the handle controller that follow with the rule-base that designed by the engineer, the system is manipulated by the output crisp variables of fuzzy logic controller. Error and error change rate are input fuzzy sets for FLC. In the steady-state, the error of input variable will turn to zero and same for the error change rate. The control performance can be checked from the phase-plane of the fuzzy logic controller, as shown in Fig. 2.14.

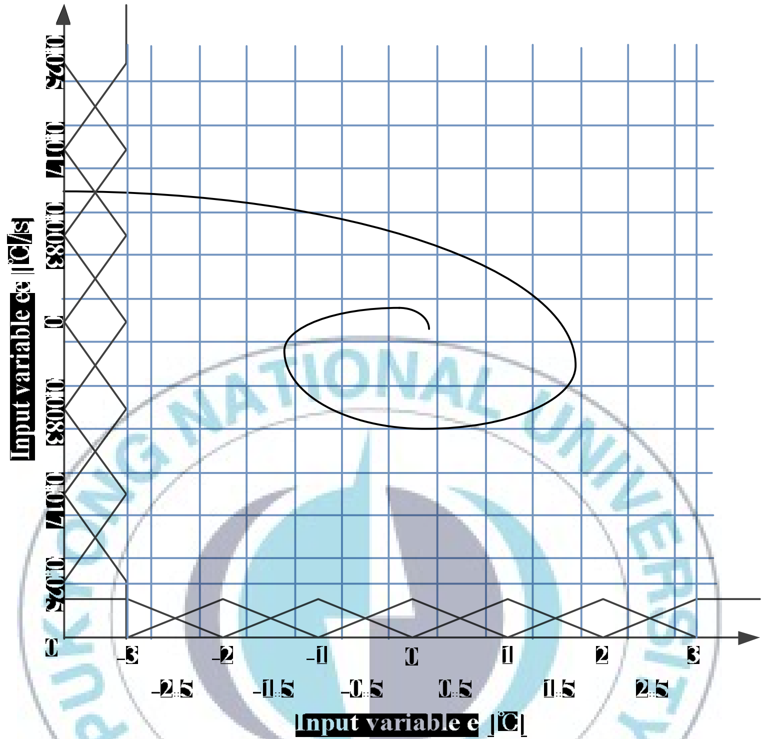


Fig. 2.14 The phase-plane of fuzzy logic controller with EMF

In Fig. 2.14, the *x* axis signed the fuzzy set of error; the *y* axis signed the fuzzy set of error change rate. The look-up table method is applied to edit the fuzzy logical program for PLC operation. Thus, the crisp output variables from fuzzy logic are made in case by case. In Fig. 2.14, one cell correspond one crisp output variable. The fuzzy logic controller outputs crisp manipulated variable to system when controlled variable goes into the correspond cell. After the system goes into the steady-state, the system response can be printed as a spiral curve. Whether the signal is based on *x*-axis or *y*-axis as the reference, the final values of error and error change rate should go into the zero cell.

In fact, CCS always gets noise disturbance. Especially, the disturbance is very serious for membership function of error change rate. Because, the domain of membership functions on *ee* fuzzy set is not big enough to contain the error change rate of noise inside. Thus the system always make mistake output because the noise disturbance. Furthermore, the center cell range of the errors is from +0.5 ºC to -0.5 ºC, the temperature control precision is hard to keep inside of this range because the temperature changes have delay characteristic.

For solving these problems, the unevenly-distributed membership function is adopted in this thesis. The operation of unevenly-distributed membership function is shown in Fig. 2.15.

After modifying the error membership function into unevenly-distributed, the domain of center cell is narrowed around zero. The steady-state error is reduced within ±0.5ºC by the narrowed membership function.

The domain encompasses method is used to modify the error change rate membership function as shown in the Fig. 2.15 (*y* axis). The noise disturbed the error change rate membership function a lot. After widening the center membership function, even the noise exist in the system, the error change rate values will not over than the center membership function in the steady-state. However, the fuzzy logic controller also can identification the temperature is changed to higher or lower, based on the noise signal. Because the error range is smaller than before, the sensibility is not reduced.

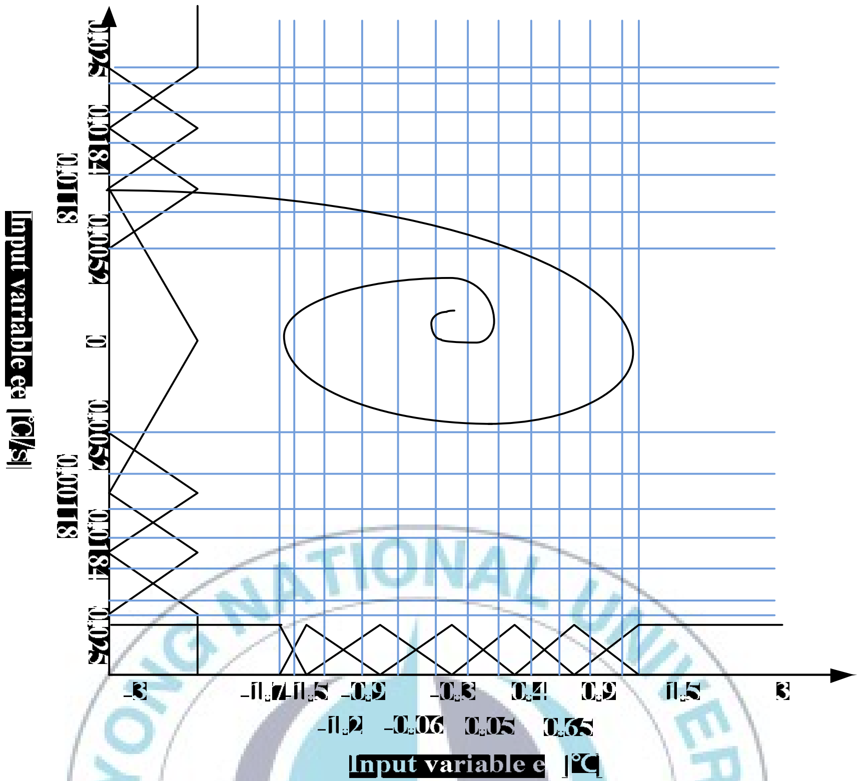


Fig. 2.15 The phase-plane of fuzzy logic controller with UMF

Chapter 3

Chamber cooling system and controller design

CCS is widely used in lots of areas, especially in the scientific research and medicine storage usages, the chamber temperature need high precision control even it is in the complex environment. Because of the glob warming problem, the energy saving is very necessary for a contentiously working system like CCS.

CCS is based on the unit refrigeration system. For the high efficiency system of saving energy, the refrigeration system used VSRS. As known the refrigeration system mostly is nonlinear system. Thus it is very hard to definition the accurate mathematic model for model base controller.

Normally, the fuzzy logic controller has weakness at low control precision with big steady-state error. And with the control operation the noise always disturbed the control system. That made the system output wrong regulated value from the controller. Combine these two problems for rising the control precision and robustness performance of the CCS, this thesis used histogram equalization method to modify the EMF to UMF.

Mainly, this chapter is divided into two parts. First part introduced the composition of chamber cooling system. Then most important refrigeration cycle is explained next with the composition instruction. The experimental apparatus and ambient condition of system will introduced after explaining the refrigeration cycle. In Second part, the evenly-distributed membership function of fuzzy controller will explained first, then the method of modify the membership function into unevenly-distributed will explained in detail.

3.1 Chamber cooling system

The chamber cooling system (or environmental chamber) is an enclosure used to test the effects of specified environmental conditions on biological items, industrial products, materials, and electronic devices and components.

Such a chamber can be used:

- as a stand-alone test for environmental effects on test specimens;
- as preparation of test specimens for further physical tests or chemical tests;
- as environmental conditions for conducting testing of specimens;

The chamber cooling system in this study designed for the biological technology and medical storage. The optimize temperature for blood saving is at 4ºC, thus the target of the design is aim at 4ºC. The low temperature determines the refrigeration cycle is the main operate device of the chamber cooling system.

3.1.1 Composition of chamber cooling system

Fig. 3.1 shows the real system composition. Base on the function of the parts, the chamber cooling system can divide into two parts, one is controller and another is control plant.

For the controller, Fuzzy logic control program is written by the personal computer and uploaded into the PLC. Inlet and outlet refrigerant temperature of the evaporator and chamber temperature are detected by T type thermocouple. The temperature information is collected by a TC module of PLC. Fuzzy inference is calculated in the CPU of PLC. The D/A module of PLC converts digital signal into analog signal and the PLC outputs the analog signal to the drive device.

The control plant is built on the basic refrigeration cycle, so it consists of a variable-speed compressor, an EEV, a condenser and an evaporator installed inside chamber. The inverter and step valve control drive are used to control compressor speed and EEV opening angle. The chamber temperature and superheat are controlled by regulating the rotational speed of compressor and opening angle of EEV.

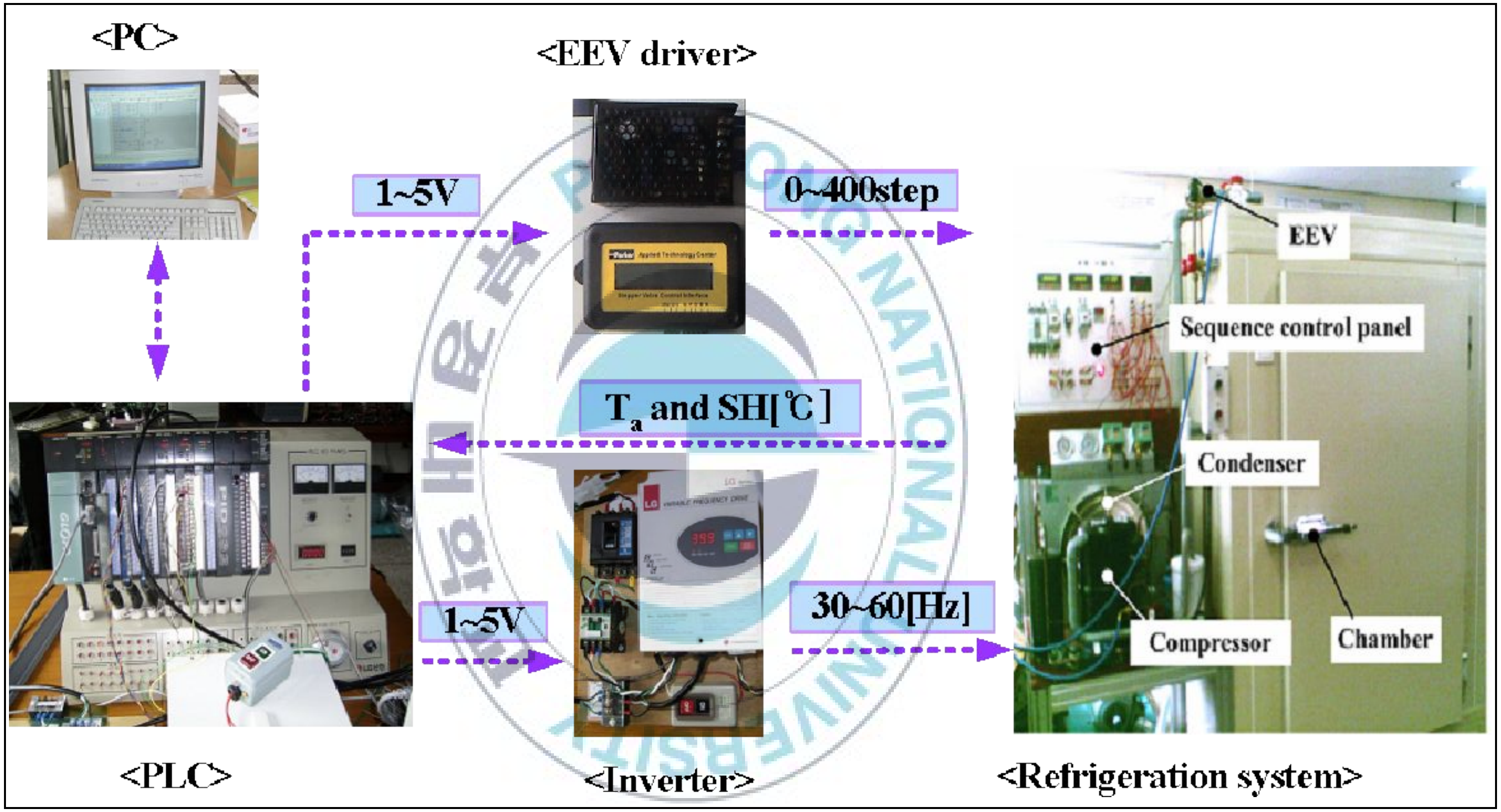


Fig. 3.1 The devices of the chamber cooling system

3.1.2 Variable speed refrigeration cycle

A variable speed drive (VSD) is a device that regulates the speed and rotational force, or output torque of mechanical equipment. Effect of applying VSDs are in both productivity improvements and energy savings in pumps, fans, compressors and other equipment[32]. FLC is designed to control VSRS with VSD in this paper. The VSRS is based on basic refrigeration cycle with VSDS which are inverter and step valve control drive. The inverter regulates rotational speed of induction motor inside compressor and the step valve control drive adjusts opening angle of EEV[21]. The target control variable in CCS is chamber temperature. The superheat which is defined temperature difference between inlet and outlet of an evaporator is also controlled to keep high coefficient of performance (COP) and prevent damage of the compressor due to the phenomenon of liquid back when the mass-flow rate of refrigerant is changed rapidly. The chamber temperature and superheat are controlled by regulating rotational speed of compressor and opening angle of EEV.

For controlling the chamber temperature and the superheat, two FLCs are employed separately. There are double inputs and single output in each FLC. Thus, three MFs are needed to transform the values between the crisp value and membership value. Fig. 3.1.2 shows a conceptual diagram of FLCs for CCS. Input variables of each FLC are error e and error change rate ee. Where the subscripts T and SH describe chamber temperature and superheat, control variables. The membership values of μ_e and μ_{ee} are transformed from the crisp values of e and ee. The output variables of each FLC are frequency Δf and opening angle ΔVO for controlling inverter and EEV driver respectively. The symbol Δ describes the increment value of each output variable. In inference process, input membership values are inferred to get output membership values (μ_{oT} and μ_{oSH}) with the rules that edited in rule base by a designer. At last, the crisp manipulated variables (Δf and ΔVO) are calculated by the centroid of gravity (COG) method using output membership values and output MFs.

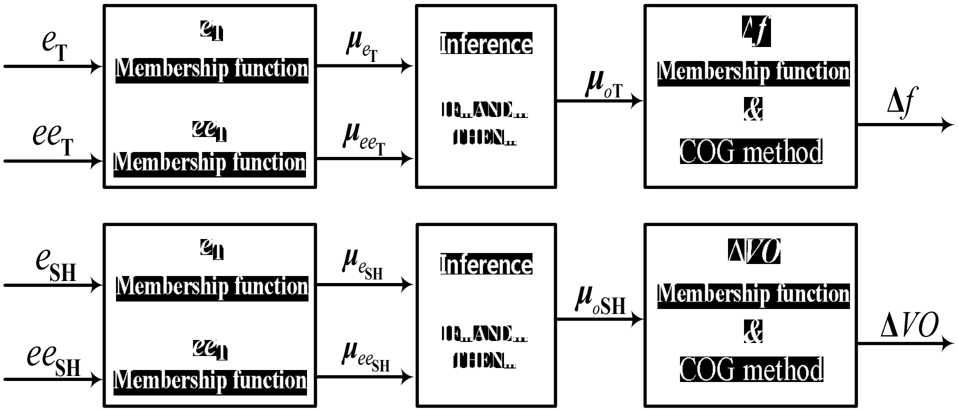


Fig. 3.2 Fuzzy control process in CCS

3.1.3 Experimental apparatus and ambient temperature

Base on the introduction of 3.1.1, the experiment detail specifications of test unit is list in table 3.1 in detail.

For the chamber temperature control, the set value was decided as 4℃± 0.5℃ considering the optimum temperature for blood saving used in the medicine storage chamber. For high efficiency control performance, the superheat target was set at 8℃ to keep the maximum COP. The ambient temperature was kept with 23℃. The manipulated frequency range of compressor was decided from 30Hz to 60Hz considering the minimum heat load and resonance. The 1.5 kW electrical heater was used to add heat load inside chamber. The range of detected noise incorporated in the temperature information of feedback signal link was ±0.3℃.

In experiments, two FLCs were used to control the chamber temperature and superheat. Two types of MFs, EMF and UMF, were employed for controlling the chamber temperature. On the other hand, only one type MF, EMF, was employed for controlling the superheat.

Table. 3.1 The specifications of test unit

Equipment		Parameter
Compressor	Type	Vertical, reciprocating
	Power	220 V, 60 Hz, 1.5 kW
Condenser	Type	Fin-tube type
	Capacity	4 kW
Evaporator	Type	Fin-tube type
	Capacity	0.79 kW
Electronic expansion valve	Model	JHEV 14 A
	Port size	Φ14 mm
	Operating range	0-506 pulse
	Rated voltage	DC 12 V
Refrigerant	Type	R22
Chamber	Size	1200*700*1650 [mm]
Inverter	Type	PWM
	Capacity	1.5 kW
Step valve control drive	Input voltage	DC 12 V
	Output voltage	DC 1-5 V or 4-20 mA
	Output	0-400 step

3.2 Fuzzy controller design

There are two control variables in the CCS. First is the chamber temperature and second is superheat. The chamber temperature is the main target for this study, and for keeping the maxim COP the superheat also be controlled at the same time with chamber temperature control. Thus, two fuzzy logic controllers are needed to correspond each control variable. The Fig. 3.2 shows two control processes.

The fuzzy logic controller is designed by the real system response and operating experience. The membership function in evenly-distributed is designed base on the characteristic experiment and control goals. However, the control effective is not as good as the expectant. Then evenly-distributed membership function is modified by the Histogram equalization method and the domain encompasses method.

3.2.1 EMF fuzzy controller design

A. Evenly membership functions of input and output variable

The input e MF for obtaining output frequency is designed to establish the target temperature precision of the CCS. Seven fuzzy sets are employed for MF to consider the control precision and the appropriate computing load. Fig. 3.3 shows the structure of the fuzzy sets with triangle types which is distributed in evenly. Fig. 3.3(a) shows the EMFs of FLC in chamber temperature control and Fig. 3.3(b) shows the EMFs of FLC in superheat control. Chamber temperature control precision in steady state is mainly depended on e MF. It can be described as Eq. 3.1:

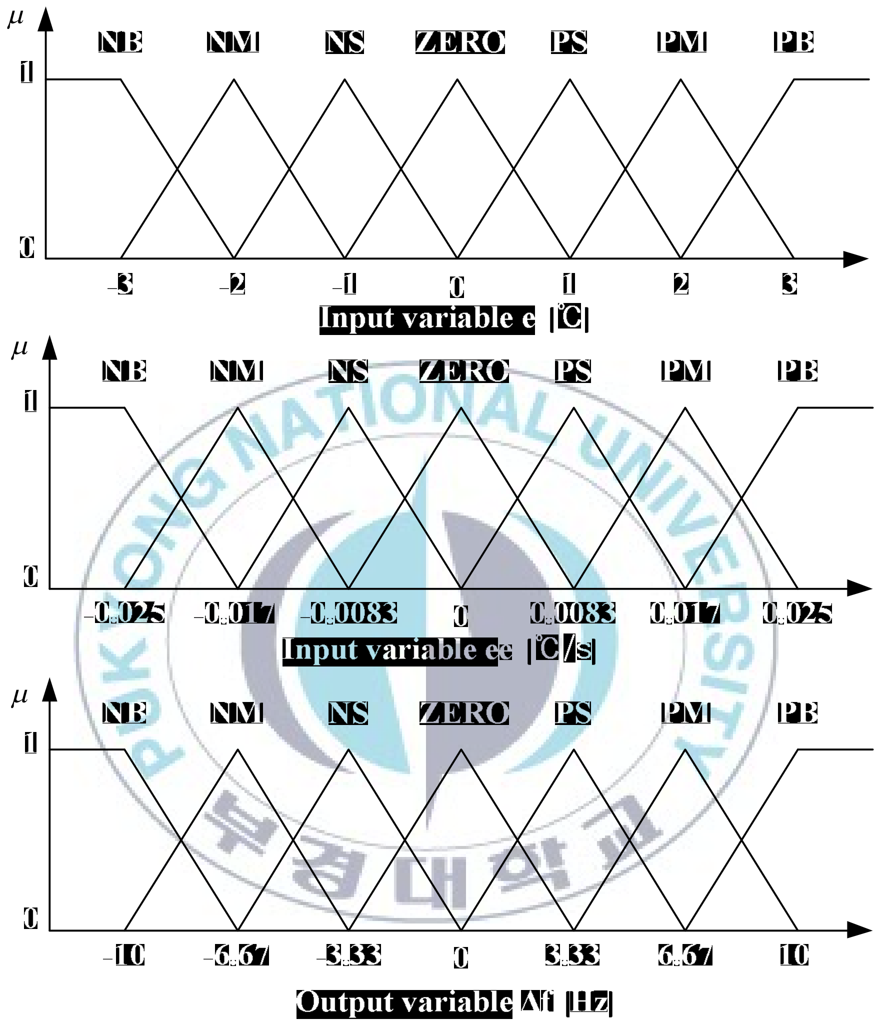
$$e_{r\min} = \frac{\pm e_{\max}}{n-1} \tag{3.1}$$

Where, $e_{r\min}$ means the minimum error range of the control variable, chamber temperature; $e_{\max}$ is the maximum error value; n is the numbers of the fuzzy sets. As one of our goals in MF design is to control the steady state error of chamber temperature within ±0.5℃, the $e_{\max}$ is determined as 3℃. Thus the e MF range is defined as ±3℃. The range of each fuzzy set distributed in evenly can be easily calculated as shown in Fig. 3.3 (a).

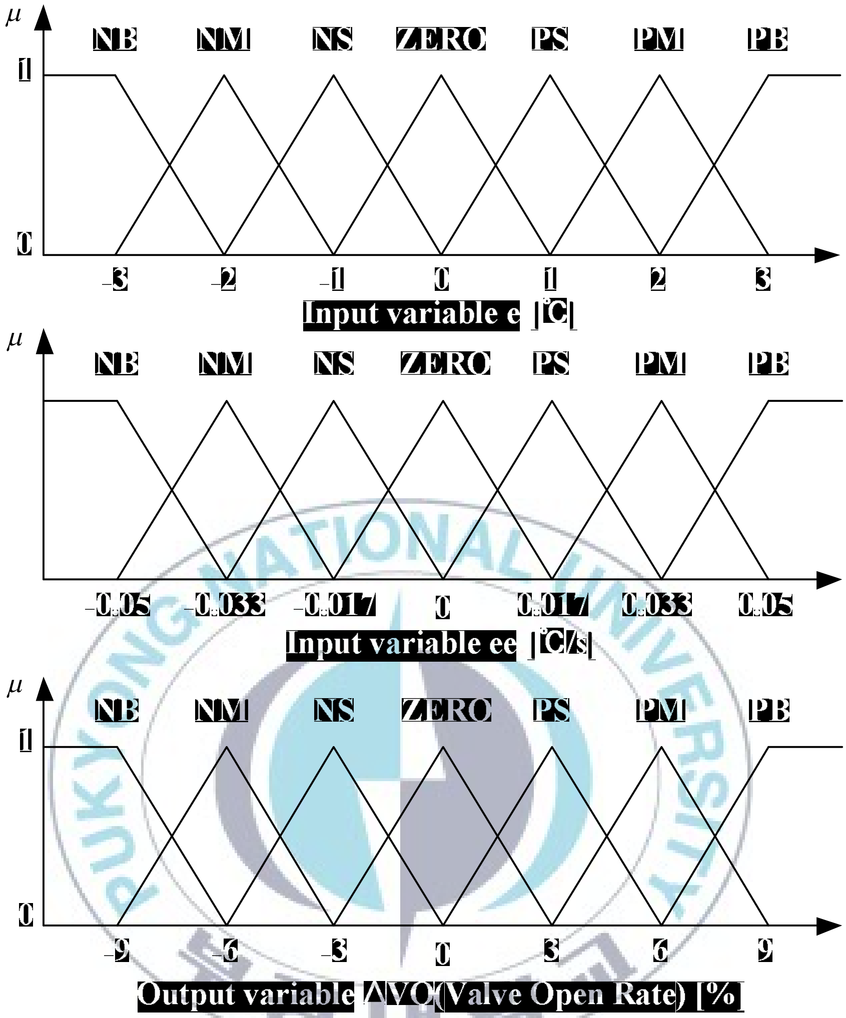
The error change rate ee indicates variation of chamber temperature during sampling time as shown in Eq. 3.2:

$$ee = \frac{\Delta e}{t_s} \tag{3.2}$$

Where Δe is the error variation in temperature; t_s is sampling time. Practically, the value of Δe is determined considering the characteristic of transient state of chamber temperature through static experiments. The ee MF range was determined as ±0.025℃/s because maximum error variation in chamber temperature was obtained as ±0.75℃ during 30 seconds by static experiment. As the seven fuzzy sets are designed in EMF in initial step, each fuzzy set range can be decided as shown in Fig. 3.2(a).



(a) EMF for chamber temperature FLC



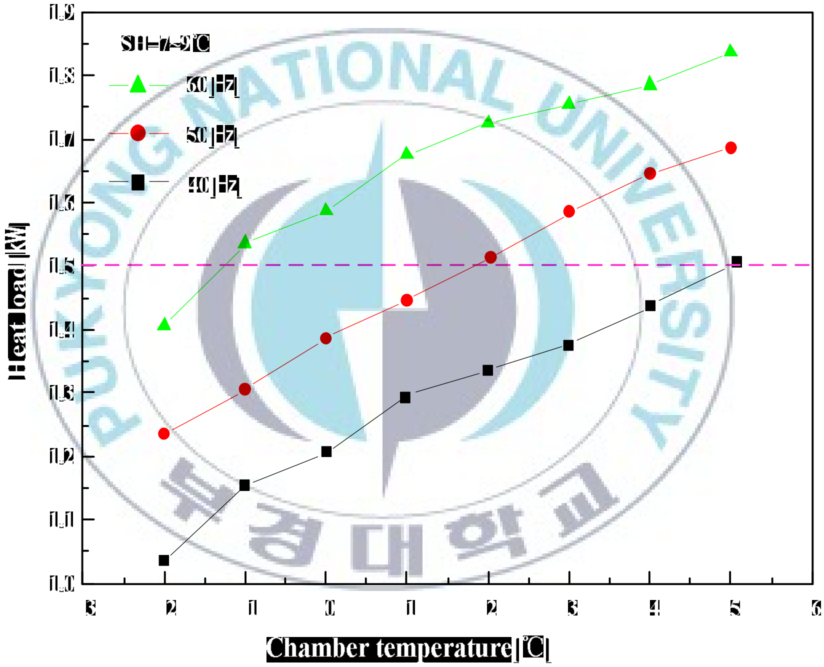
(b) EMF for superheat FLC

Fig. 3.3 Evenly membership functions for fuzzy logic controllers

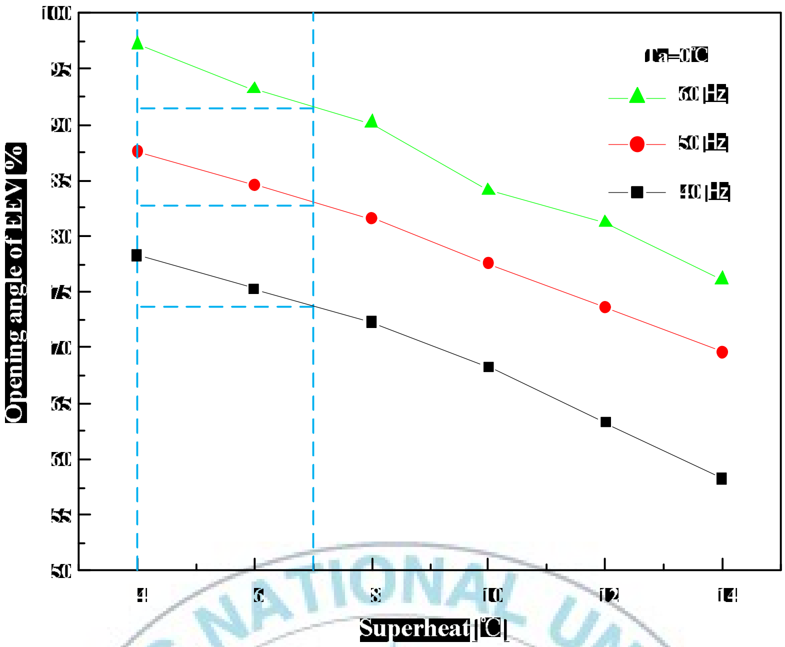
On the other hand, the output frequency range is set up as ±10Hz because the amount of 10Hz can change the chamber temperature error with 3℃. And this relationship between chamber temperature and compressor frequency is shown in Fig. 3.4 (a).

The other goal in FLC design is to control the superheat with 8℃, because the maximum COP was obtained in the superheat range over 4~8℃ from static experiment[33]. For designing the MFs of the superheat FLC, the same design method applied to MFs of chamber temperature FLC is used. The desired superheat control precision is supposed ±0.5℃, so the e MF range is decided by ±3℃ with Eq. 3.1. The ee MF range is determined as ±0.05℃/s from equation 3.2.

Fig. 3.4(b) shows the relationship between EEV opening angle and superheat, the opening angle range is set up as ±9% because the amount of 9% angle variation can regulate the superheat error with 3℃. Fig 3.4(b) shows the designed MFs of EEV opening angle control by considering the relationship.



(a) Relationship between chamber temperature and compressor frequency



(b) Relationship between superheat and EEV opening angle

Fig. 3.4 Static experimental results in CCS

B. Rule-base and defuzzification

Table 3.2 and Table 3.3 show the rule bases of FLCs in CCS. They are designed base on the objective factor and experiences of the controller designer. In these rule bases, "IF…AND…THEN…" logic is used to realize fuzzy inference process.

Table 3.2 Rule base for chamber temperature fuzzy logic controller

		ee						
		NB	NM	NS	Z	PS	PM	PB
e	NB	NB	NB	NB	NB	Z	Z	Z
	NM	NB	NB	NM	NM	Z	Z	Z
	NS	NB	NM	NS	NS	Z	Z	Z
	Z	NM	NS	Z	Z	Z	Z	Z
	PS	NS	Z	Z	Z	PS	PM	PB
	PM	Z	Z	Z	PS	PM	PB	PB
	PB	Z	Z	Z	PB	PB	PB	PB

Table 3.3 Rule base for superheat fuzzy logic controller

		ee						
		NB	NM	NS	Z	PS	PM	PB
e	NB	NB	NB	NM	NM	NS	Z	Z
	NM	NB	NM	NS	NS	Z	Z	Z
	NS	NM	NS	NS	Z	Z	Z	Z
	Z	NM	NS	Z	Z	Z	Z	Z
	PS	NS	Z	Z	Z	PS	PM	PB
	PM	Z	Z	Z	PS	PS	PM	PB
	PB	Z	Z	Z	PS	PM	PB	PB

The COG method is applied to the defuzzification process. It used to transform the membership values to the crisp manipulated values. The formula of COG is shown in Eq. 3.3:

$$U_o^{crisp} = \frac{\Sigma\mu(i)b_i}{\Sigma\mu(i)} \tag{3.3}$$

Where $\mu(i)$ is output membership value; b_i indicates the centre of area of MFs, U_o^{crisp} means output crisp value of fuzzy inference.

3.2.2 UMF fuzzy controller design for chamber temperature control

In CCS such as the medicine storage chamber, the most important target is to control the chamber temperature precisely. The object of superheat control is to obtain high efficiency to save the energy cost. So the slight error of the superheat in steady state is not a big problem to maintain high COP. Moreover, the effect of interference from superheat to chamber temperature is also slight. Therefore, the EMF was adapted to the FLC in superheat control without modification into UMF.

In the case of the EMF designed in 2.2 for CCS, the big steady state error of chamber temperature is inevitable because of wide range of fuzzy set in *e* MF. Also the output frequency for controlling the chamber temperature is sensitively fluctuated with the noise disturbance due to the narrow range of the center part of fuzzy set in *ee* MF. Therefore, the UMF is suggested in this paper for improving the control performance by reducing the steady state error and enhancing the robustness by rejecting the noise disturbance.

Firstly, the modification of *e* MF is considered. Practically, it is hard to achieve the control precision of the steady state error in chamber temperature within ±0.5℃ what we mentioned as a design goal even though Eq. 3.1 are used. Because the EMF was adopted in *e* MF although the real system has inherent nonlinear characteristics. The domain of *e* fuzzy sets around the ZERO as shown in Fig. 3.3(a) is not sufficient to react precisely for reducing the steady state error. The small input errors in the steady state cannot be clearly distinguished each other and they trigger for same fuzzy control output [23].

The histogram equalization method was used to modify the EMF into UMF about *e* MF for reducing the steady state error of chamber temperature. This method is based on the steady state response of chamber temperature obtained from experiments by EMF with sinusoidal wave inputs. Mostly, the experimental response is used into histogram equalization method, however if the accurate model of the system is known, it is better to use the simulations for saving the design time.

Fig. 3.5 represents the UMF design process by histogram equalization. The error data in steady state are collected and disposed according to the order of size as shown in Fig. 3.3(a). In this figure, the *x*-axis means the steady state error value corresponding to each fuzzy set domain of EMF and the *y*-axis describes the running sums of occurrence number of each steady state error. Each of the steady state error data is connected point by point with the vertical dotted line. The seven horizontal lines which parallel with the *x*-axis indicate the fuzzy sets obtained by dividing the total error data number evenly. And the seven vertical lines can be defined from the intersection points between each of the seven horizontal lines and a line connected with each of the steady state error data. Hence, the each vertical line in Fig. 3.5(a) specifies the domain of each fuzzy set in Fig. 3.5(b).

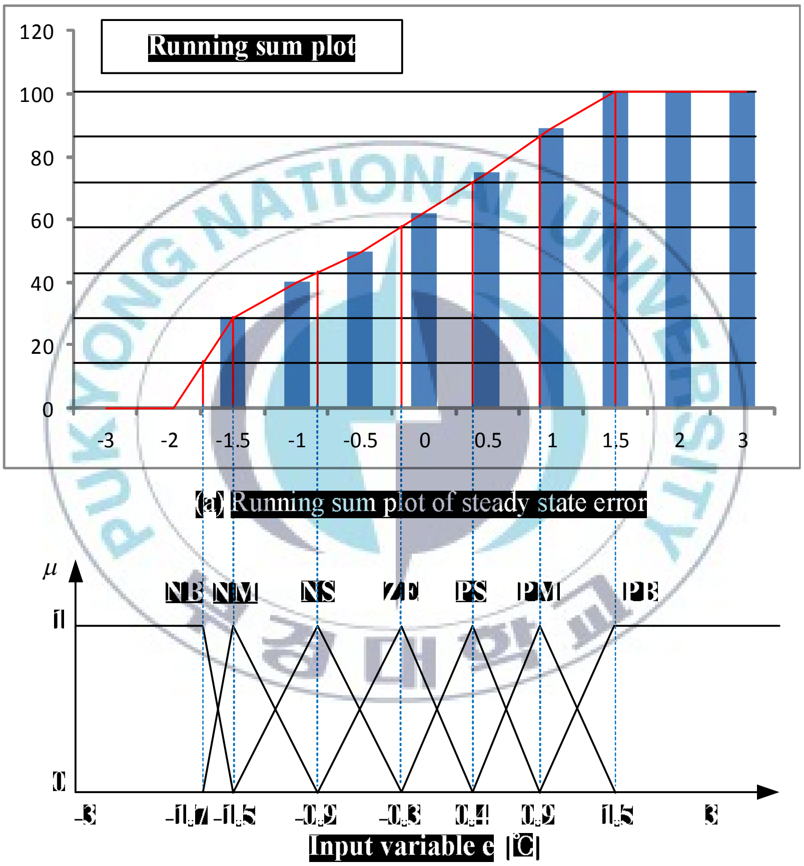
A histogram represents the number of data distributed at different values that are widely used in data processing to enhance data distribution including histogram stretch, shrink, shift, and equalization [34]. In Fig. 3.5(a), the steady state error is staying between -2℃ to 1.5℃, there are no errors happened outside of this range in steady state. It means, for reducing the steady state errors, the fuzzy sets should be narrowed to the domain within -2℃~1.5℃. Specially, from the -2℃ to -1.5℃, the error numbers are suddenly changed from 0 to 29, thus more dense of fuzzy sets should be designed at this range to face the rapid changes of error numbers. However, as there are no errors happened outside of -2℃ and 1.5℃ in steady state, therefore many fuzzy sets are not required for reducing the steady state error.

In theory, the MFs can be repeatedly modified by the histogram equalization method many times until the steady state error is reduced to 0. Here, the histogram equalization is used only once to modify the *e* MF of chamber temperature control considering noise disturbance rejection. Because, if the range of fuzzy sets is smaller than ±0.3℃ which is noise range, the noise disturbance will affect the inference of *e* MF of chamber temperature control. The FLC of chamber temperature will fall into instability and the steady state error will be bigger than the one before modification.

Secondly, the modification of MF was considered. Actually, it is not easy to keep output frequency stable even in real steady state due to the noise disturbance that unintentionally penetrate to feedback signal of chamber temperature because of adoption of VSD for VSRS.

As mentioned in 3.2.1, the initial *ee* MF is designed as EMF as shown in Fig. 3.3(b). The range of ZERO fuzzy set is fixed by the calculation of Eq. 3.2. In the real system, variation of noise during sampling time induced by an inverter may be bigger than the error change rates of chamber temperature in steady state. As a consequence the inference of the initial EMF of ee is affected by the noise while the system is staying in steady state. Eventually, this affection results in the instable output frequency in steady state of chamber temperature control. For rejecting the noise disturbance, the ZERO range of *ee* in EMF is widened regarding the real noise range of an inverter.

Fig. 3.6 represents an example of detected noises from chamber temperature feedback information of the tested CCS. Maximum noise disturbance is occurred when the frequency of the inverter operates around 30Hz and its range is ±0.3℃. Meanwhile the superheat range is ±0.1℃.



(a) Running sum plot of steady state error

(b) The e fuzzy set for chamber temperature control

Fig. 3.5 UMF design by histogram equalization for chamber temperature control

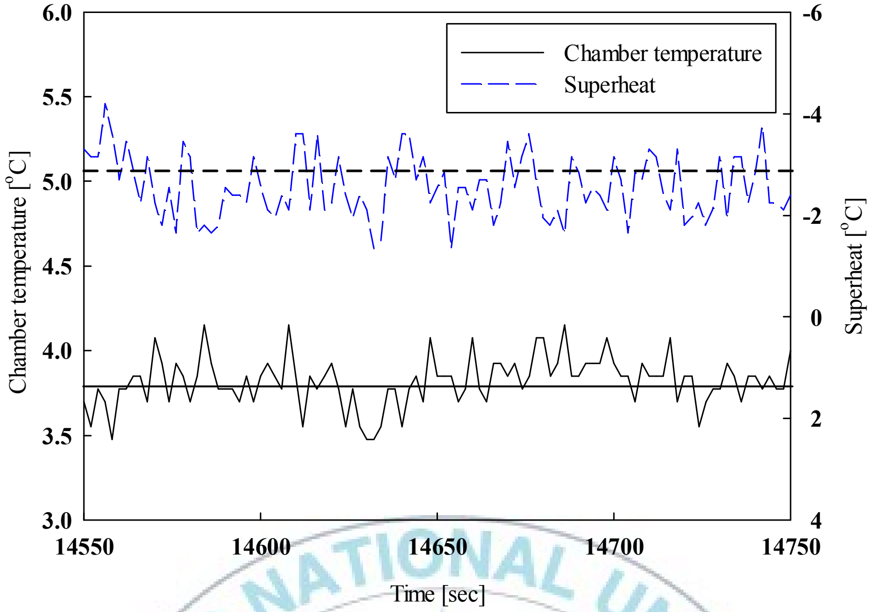


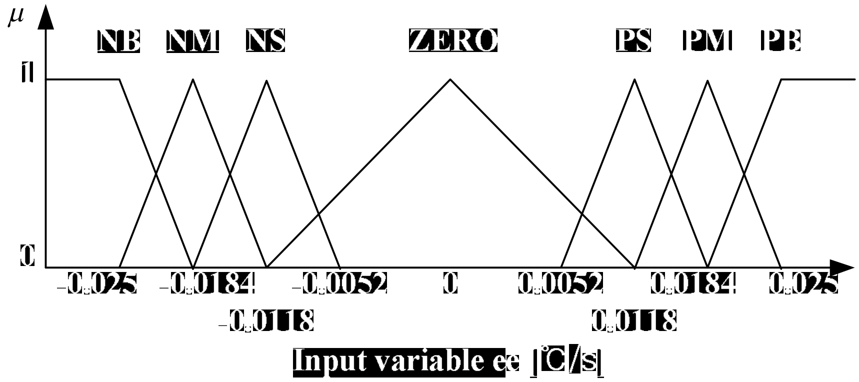
Fig. 3.6 Noise detection result

If the noise error change rate ee_{rn} as defined in Eq. 3.4 is bigger than the ZERO fuzzy set range, the noise disturbance can affect to ee MF inference. Thus the range of ZERO fuzzy set in ee MF should be widened to exceed ee_{rn} for ignoring the influence of noise disturbance.

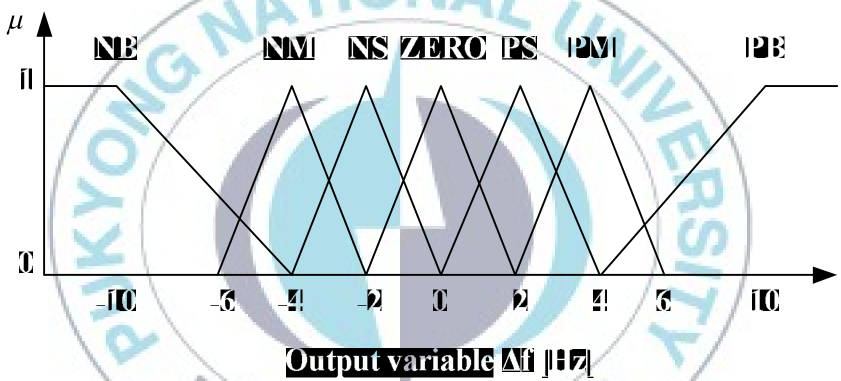
$$ee_{rn} = \frac{\pm e_n}{t_s} \tag{3.4}$$

Where e_n is maximum noise value, 0.3℃. The t_s indicates sampling time, 30 seconds in this case. Then the ee_{rn} is calculated as ±0.01℃/s. The range of ZERO fuzzy set is considered as ±0.012℃/s in this paper in order to exceed ee_{rn}. In addition, other fuzzy sets except ZERO fuzzy set are still distributed in evenly.

There is corresponding relationship between output frequency and the chamber temperature as shown in Fig. 3.4(a). To keep this corresponding relationship, the fuzzy sets of output frequency MF is also narrowed to the center part after the design of e UMF. Fig. 3.7(a) illustrates the UMF for ee and Fig. 3.7(b) represents the UMF for output frequency.



(a) The *ee* fuzzy set for chamber temperature



(b) The output fuzzy set for chamber temperature

Fig. 3.7 The UMF of *ee* and output fuzzy sets for chamber temperature control

3.2.3 UMF fuzzy controller design for superheat control

Nowadays, energy cost as an important problem is paid more attention by engineers. As known, the maximum COP means the refrigeration system works with high efficiency. And the maximum COP is obtained by the fix superheat. Thus, the control precision and robust performance of superheat are necessary to impose in good control performance.

The histogram equalization method is adopted to modify the *e* fuzzy set and the domain encompasses method is adopted to modify the *ee* fuzzy set. Fig. 3.8 shows the the *e* fuzzy set was modified by the histogram equalization method.

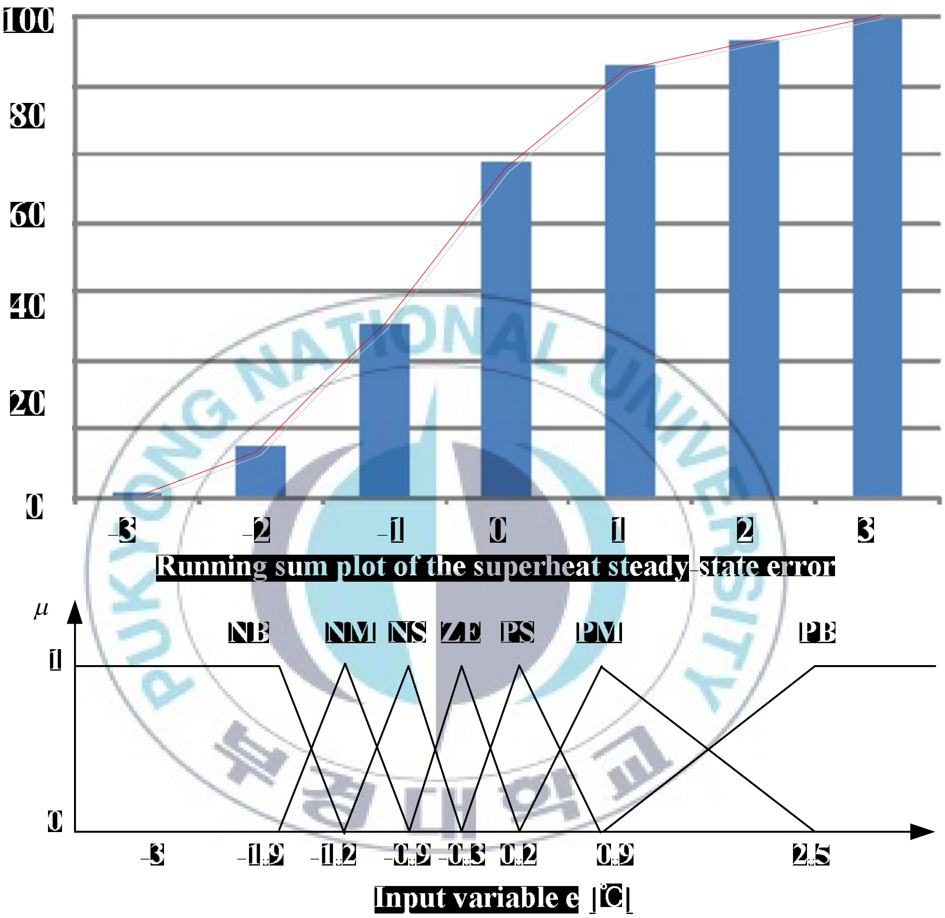
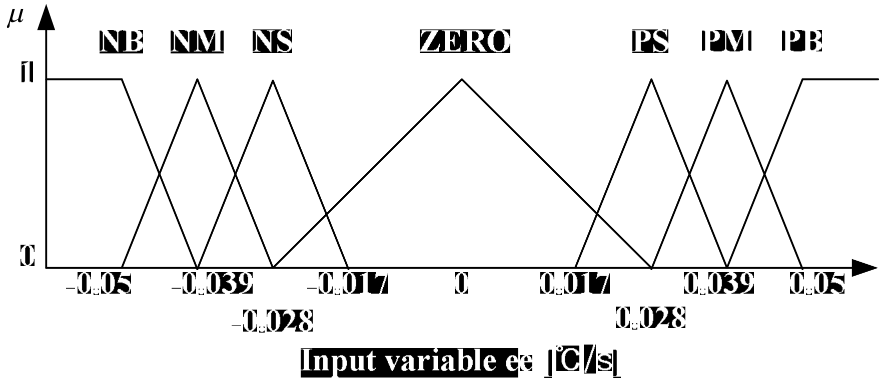


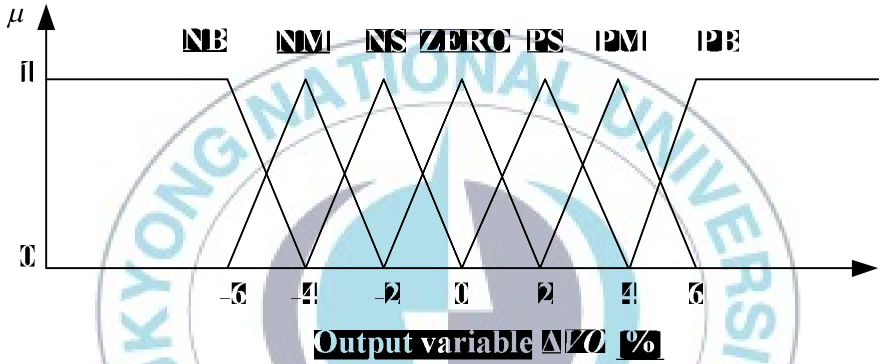
Fig. 3.8 UMF design by histogram equalization for superheat control

Base on the noise detection results of Fig. 3.6. The *ee* fuzzy set is modified by the domain encompasses method into unevenly distributed. The fuzzy set is show in Fig 3.9(a).

The output fuzzy set is narrowed to the center part for corresponds the changes of *e* fuzzy set. The fuzzy set is shown in Fig 3.9(b)



(a) The *ee* fuzzy set for superheat control



(b) The output fuzzy set for superheat

Fig. 3.9 The UMF of *ee* and output fuzzy sets for superheat control

Chapter 4

Experiment result and analysis

The simulation and real experiment did for proving the control effective can be enhanced by the fuzzy logic controller with unevenly-distributed membership function. The external environmental condition in the experiment is always kept in same. Thus, the experimental data with the different cases can be compared together. And, the enhancement control effective can be checked out from the comparison.

This chapter lists and analysis the simulation and experimental results. The high performance of the chamber cooling system is proved with the real experimental results. In the results, there are three cases:

CASE 1: chamber temperature control done with the fuzzy logic controller in EMF; superheat control is also done with the fuzzy logic controller in EMF.

CASE 2: chamber temperature control done with the fuzzy logic controller in UMF; and superheat control is done with the fuzzy logic controller in EMF.

CASE 3: chamber temperature control done with the fuzzy logic controller in UMF; and superheat control is done with the fuzzy logic controller in UMF.

4.1 Simulation results and analysis

The fuzzy logic controller design usually base on the real experimental results and experiences of engineers. It is not based on the accurate mathematics a lot. However, the simulation is needed for checking the controller performance before the real experiments. And the accurate mathematics modeling is necessary for the simulations, such as transfer functions. Except the fuzzy controllers, the simulations in this thesis are realized base on the mathematics modeling designed by Li Hua et. al[21].

The block diagrams of variable speed refrigeration system with interfering loops shows in Fig. 4.1. The C_1 and C_2 used fuzzy logic controller that is designed base on the fuzzy tools of MATLAB®.

In Fig. 4.1, The G_{1_Ta}, G_{1_SH} and G_{2_SH} are transfer functions of the CCS. The G_{1_Ta} and G_{2_SH} are transfer functions for the compressor plant and EEV plant. G_{1_SH} is the transfer function of interfering loops. The Fig. 4.1 shows two inferring loops, they are G_{1_SH} and G_{2_Ta}. The disturbance of frequency change to superheat is big, but the disturbance of EEV opening angle to chamber temperature is small enough to ignore [25]. Then the G_{2_Ta} will not add to the simulation diagrams. The Three transfer functions are showed in Eq. 4.1 to Eq. 4.3.

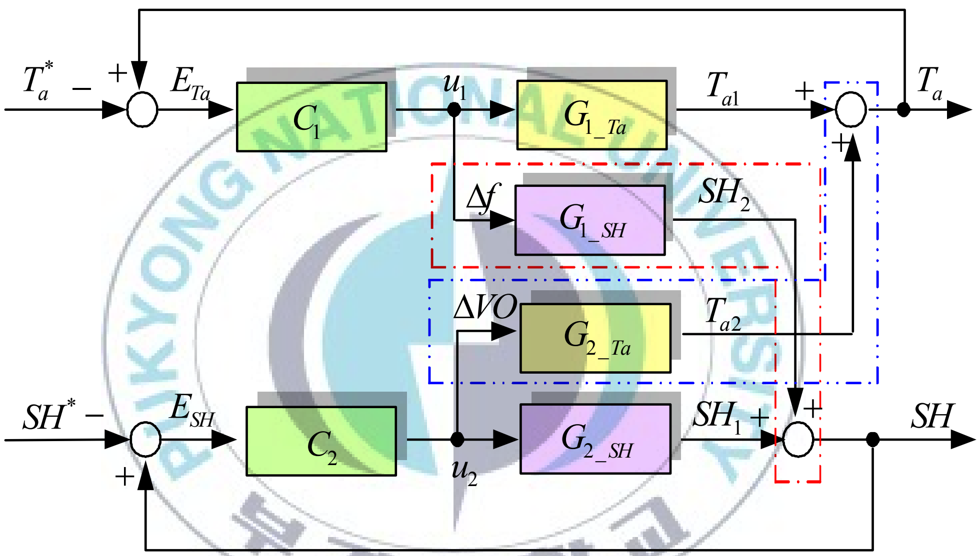


Fig. 4.1 Block diagram of VSRS control system with the interfere loops

$$G_{1\_Ta} = \frac{\Delta T_a}{\Delta f} = \frac{-0.42}{680s+1} \tag{4.1}$$

$$G_{1\_SH} = \frac{\Delta SH}{\Delta f} = \frac{\Delta T_{eo}}{\Delta f} - \frac{\Delta T_{ei}}{\Delta f} = \frac{-0.47}{780s+1} - \frac{-0.15}{30s+1} e^{-25s} \tag{4.2}$$

$$G_{2\_SH} = \frac{\Delta SH}{\Delta VO} = \frac{-0.38}{57s+1} e^{-16s} \tag{4.3}$$

The Eq. (4.2) can be further simplified using Padé Approximation to

$$G_{1\_SH} \approx \frac{-131.1s^2 + 7.612s - 0.0256}{23400s^3 + 2682s^2 + 65.8s + 0.08} \tag{4.4}$$

And the transfer function G_{2_SH} can be expressed using Padé Approximation as

$$G_{2\_SH} \approx \frac{0.38s - 0.0475}{57s^2 + 8.125s + 0.125} \tag{4.5}$$

The Eq. 4.1, Eq. 4.4 and Eq. 4.5 are adopted to the Simulink diagram done the simulations. The diagram is shown in Fig. 4.2.

As shown in Fig. 4.2, the upside part is the chamber temperature control process, the manipulated variable is compressor speed and control variable is chamber inside temperature. In down side, it is the superheat control process, the manipulated variable is opening angle of EEV and control variable is superheat. The middle part is the interfering loop from the variable frequency to superheat.

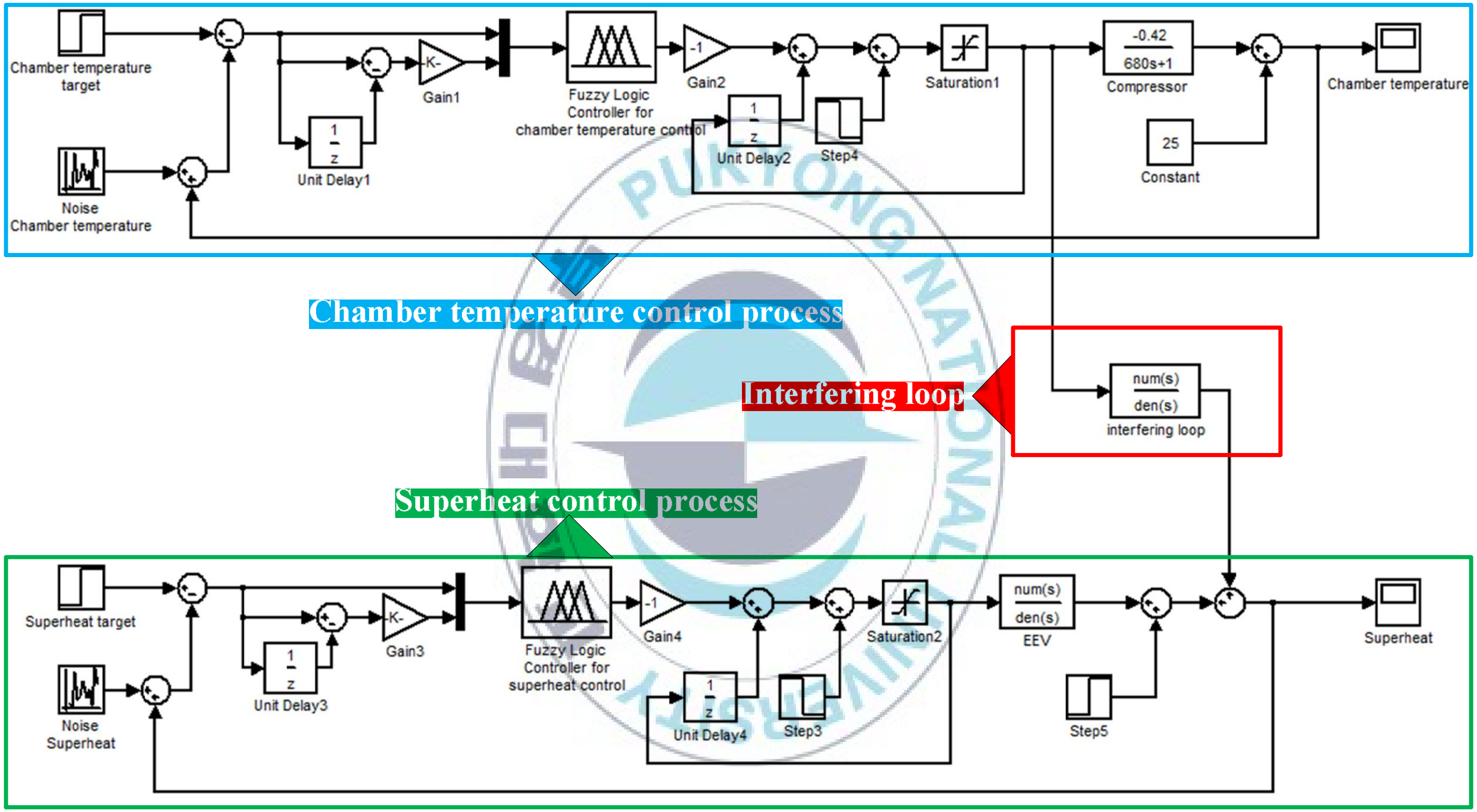


Fig. 4.2 Simulation diagram for CCS

4.1.1 Comparison of chamber temperature response

The chamber temperature is the main target in this study. The 4℃ as the optimize temperature of blood saving set as the control target and the ±0.5℃ as the target of the control precision set in the simulations.

Frequency manipulated variable range of CCS was set at 30Hz～60Hz. Chamber temperature was changing from 25℃ to 4℃. In this simulation program, we added random noise signal because the real system always got the noise disturbance. The noise range adding to chamber temperature set at ±0.3℃. The data of simulation is shown in Fig. 4.3.

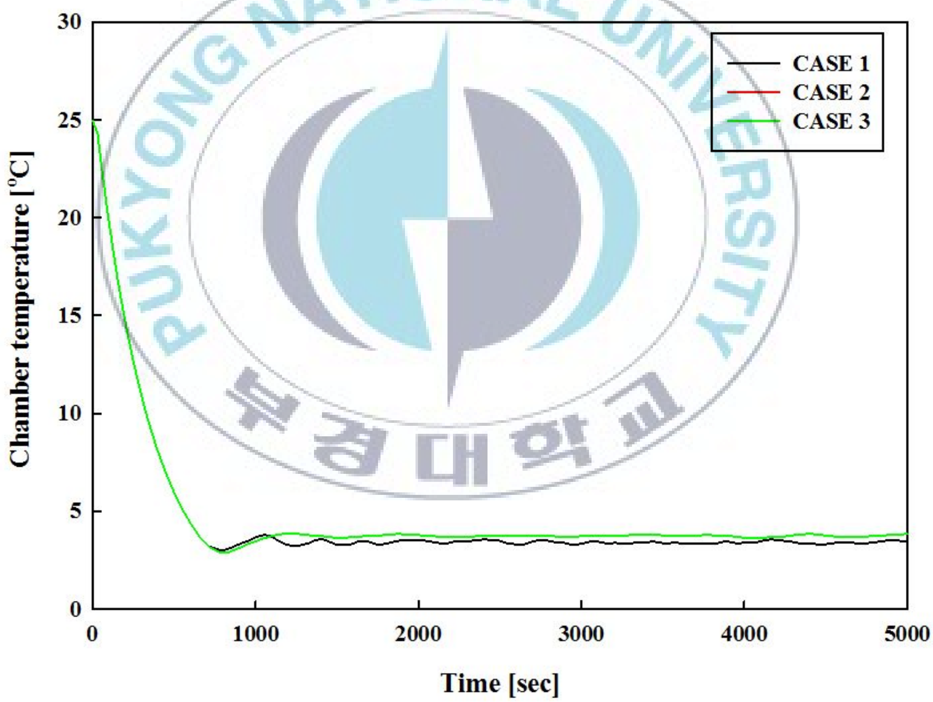


Fig. 4.3 The simulation result of chamber temperature response

The chamber temperature of the CASE 2 and CASE 3 were achieved the design goal of 4±0.5℃. Through compare the results of three cases, the fuzzy logic controller with UMF could make the chamber temperature steady-state errors reduced successfully.

4.1.2 Comparison of frequency reference

In CCS, the chamber temperature was changed by regulated the speed of compressors. If the system disturbed by the noise, the fuzzy logic controller always output mistake manipulated variable of frequency to change the compressor speed, it made the steady-state error of chamber temperature. However, the error change rate fuzzy set in chamber control process was changed to UMF to solve the noise disturbance problem. Hence, the frequency response of CASE 2 and CASE 3 should be more stable than CASE 1. The simulation results in Fig. 4.4 proved this deduction. The CASE 3 was adopted same UMF in fuzzy logic controller, thus the result of the simulation is same. The simulation results of CASE 3 and CASE 2 were covered with each other.

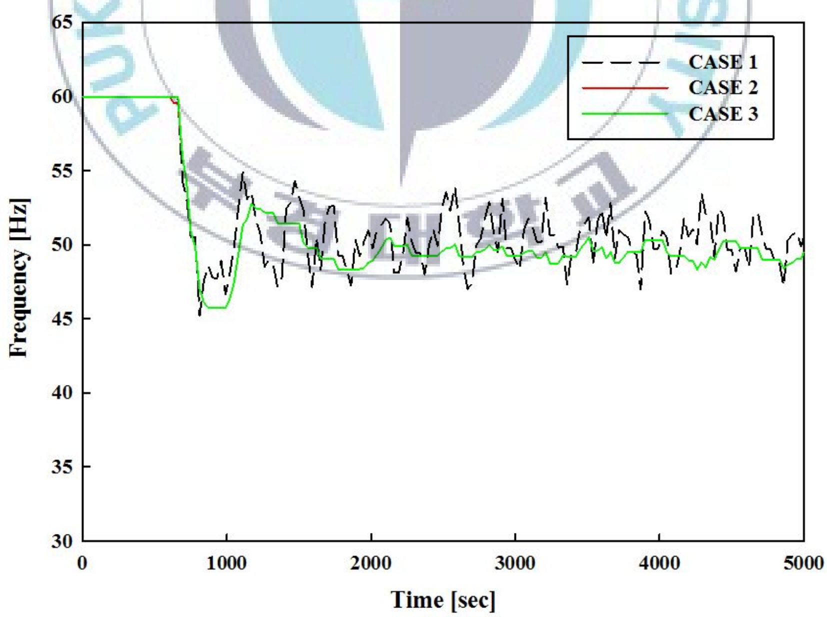


Fig. 4.4 The simulation results of frequency reference

The output frequency of the CASE 2 and CASE 3 were more stable compared with the CASE 1. It means, the UMF that applied in fuzzy logic controller in CASE 2 and CASE 3 rejected the noise disturbance successfully.

4.1.3 Comparison of superheat response

The refrigeration cycle can achieve the maximum COP when the superheat is around 6℃. However, for the superheat, it is hard to keep the temperature in a high control precession. Because the EEV is too sensitive and there have a lot elements to disturb the superheat control. Actually, the COP of the CCS didn't have big difference when the superheat control precision is keep around ±2℃. Hence, the superheat control precision target was set as ±1.5℃.

In the CCS, there is a strong interfering loop between the frequency changes and superheat control. If the frequency always changed in big step, the superheat is hard to keep in the stable. And this coupling relationship has already analysis by Li Hua et.al [21]. So, from the results of Fig. 4.4 we can infer the steady-state error of CASE 2 will be smaller than CASE 1. The simulation results of the superheat are shown in Fig. 4.5. Furthermore, the UMF applied to superheat control in CASE 3 is used to reduce the steady-state error, so the steady-state error of CASE 3 will be smaller than CASE 1 and CASE 2.

In the Fig. 4.5, the superheat of CASE 1 oscillation range is more than 6℃. However, the superheat steady-state error of CASE 2 oscillation range is around ±2.5℃. In CASE 3, the steady-state error of superheat is around ±1℃, it was achieve the control target.

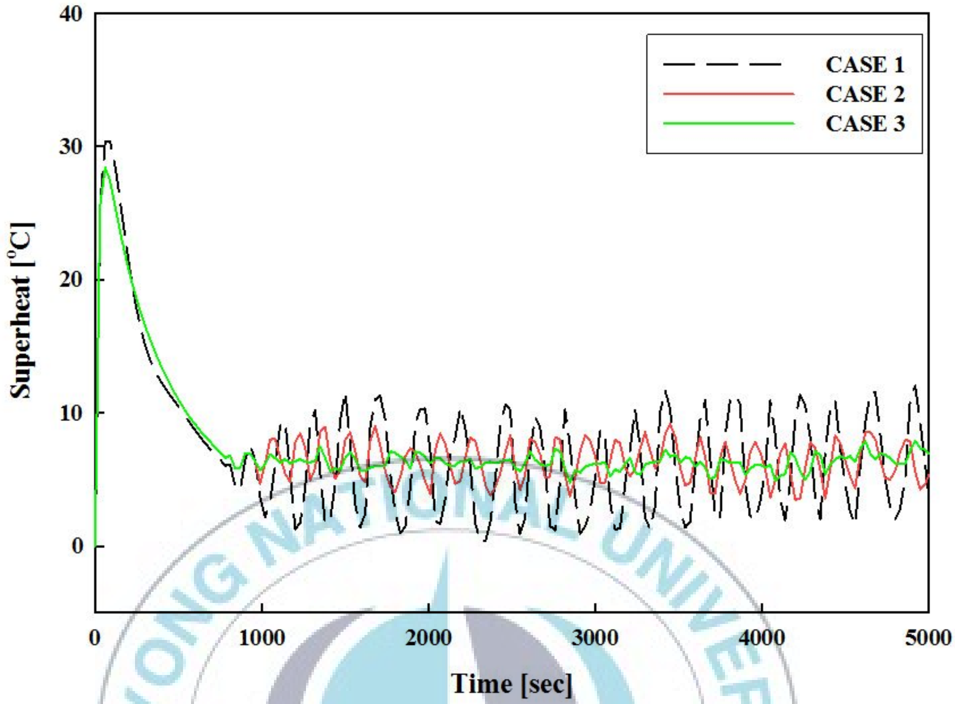


Fig. 4.5 The simulation results of superheat response

4.1.4 Comparison of steps reference

The manipulated step range is from 50~500 steps. The EEV is very sensitive; therefore, small steady-state error range of superheat means the step output manipulated range is also small. The simulation results are shown in Fig. 4.6.

In Fig. 4.6, the inferred manner is proved by the smaller manipulated range of CASE 2. And in CASE 3, the manipulated times of EEV is smaller than CASE 1 and CASE 2.

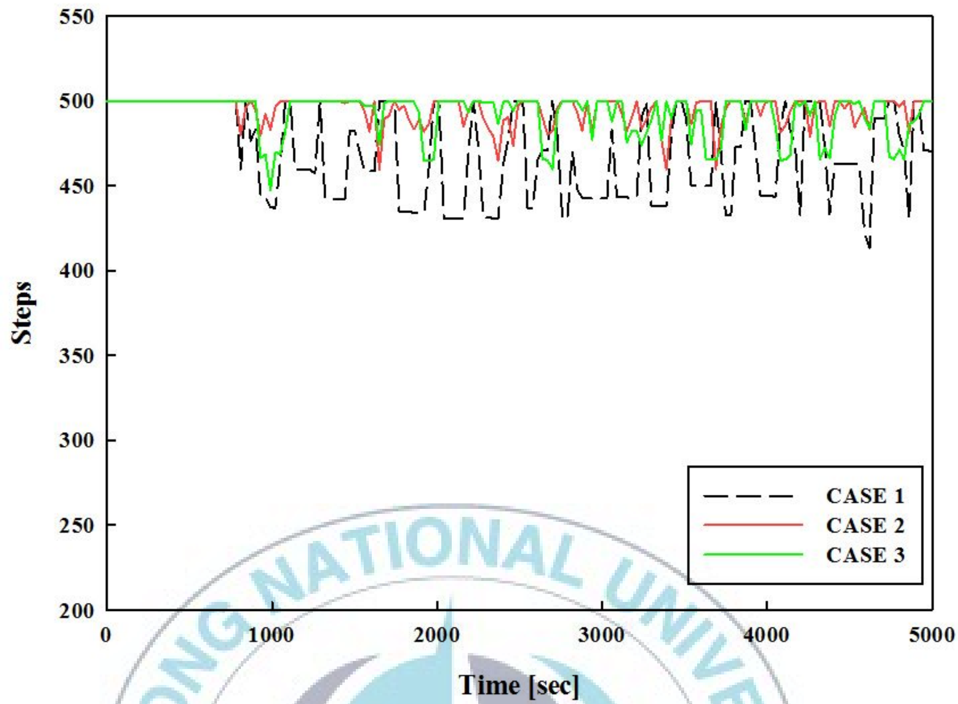


Fig. 4.6 The simulation results of the steps output reference

4.2 Experimental results and analysis

For the chamber temperature control, the set value was decided as 4℃ ±0.5℃ considering the optimum temperature for blood saving used in the medicine storage chamber. For high efficiency control performance, the superheat target was set at 6℃ to keep the maximum COP. The ambient temperature was kept with 25℃. The manipulated frequency range of compressor was decided from 30Hz to 60Hz considering the minimum heat load and resonance. The 1.5 kW electrical heater was used to add heat load inside chamber. The range of detected noise incorporated in the temperature information of feedback signal link was ±0.3℃.

In experiments, two FLCs were used to control the chamber temperature and superheat. Two types of MFs, EMF and UMF, were employed for controlling the chamber temperature. On the other hand, only one type MF, EMF, was employed for controlling the superheat.

The starting experimental results are shown in Fig. 4.7 to Fig. 4.10. Fig. 4.7 shows the chamber temperature responses of CCS and its frequency reference of compressor is shown in Fig. 4.8. Meanwhile, Fig. 4.9 shows the superheat response of CCS and its step reference of EEV was shown in Fig. 4.10. In Fig. 4.9 and Fig. 4.10, The black color is the results of CASE 1, red color is the results of CASE 2 and green color is the results of CASE 3.

4.2.1 Comparison of chamber temperature response

Fig. 4.7 shown the chamber temperature response of the CCS with three cases. The CASE 2 and CASE 3 were adopted UMF in fuzzy logic controller to reduce the steady-state errors of chamber temperature. And the control effective could be easily checked out by this Fig. 4.7. Through statistics of the experimental data, the steady-state error of CASE 2 and CASE 3 were reduced more than 40% compare with CASE 1.

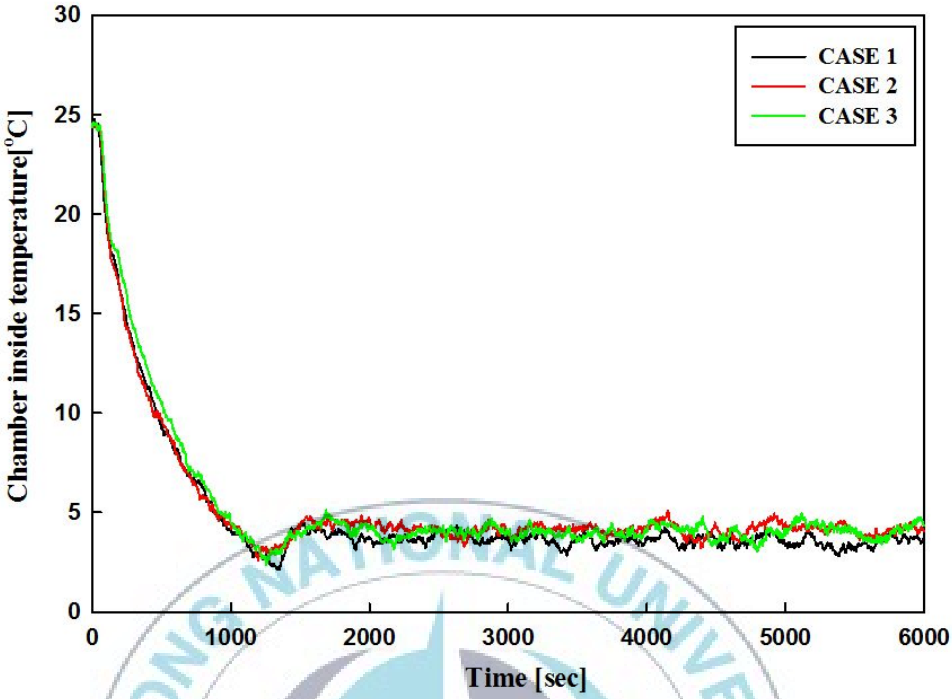


Fig. 4.7 The experimental results of chamber temperature response

As a result, the control goal in chamber temperature were satisfied as 4℃ ±0.5℃ by CASE 2 and CASE 3.

4.2.2 Comparison of frequency reference

The noise disturbance was rejected by fuzzy logic controller that was used UMF in *ee* fuzzy set of chamber temperature control process. The control effective was mainly reflected in the stable frequency response of the compressor. In Fig. 4.8, the frequency response of CASE 2 and CASE 3 were more stable than the CASE 1. And the frequency change times was fewer for CASE 2 and CASE 3. The noise is successfully rejected by last two cases.

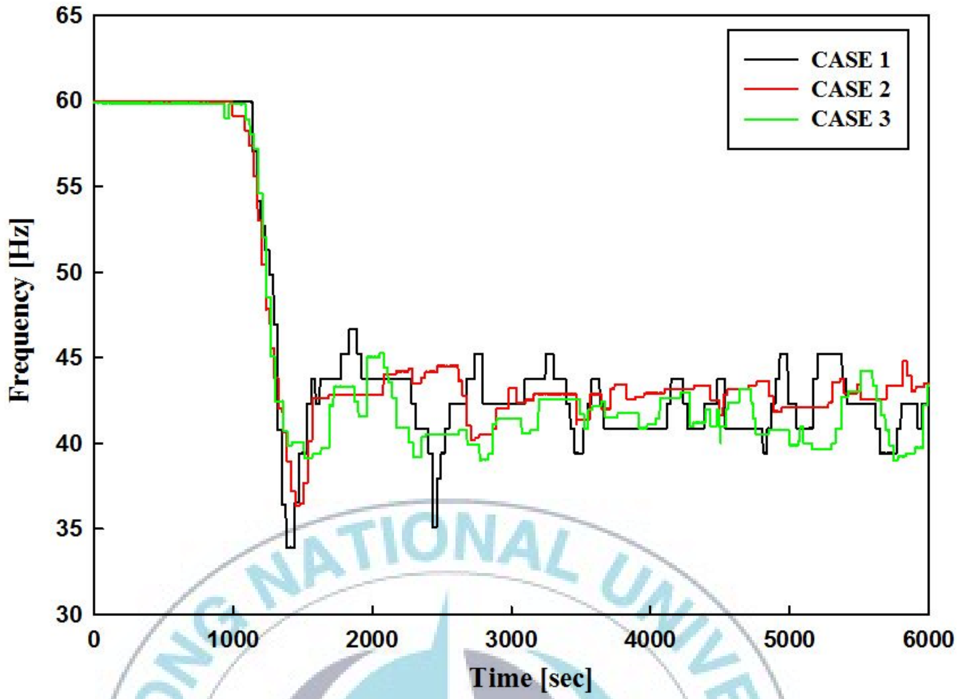


Fig. 4.8 The experimental results of frequency reference

4.2.3 Comparison of superheat response

The steady-state error of superheat was visibly shown in Fig. 4.9. It was noted that steady state error of superheat in CASE 3 reached to ±1.5℃. In CASE 2, the smaller steady-state errors of superheat proved there were inferring loop between the chamber temperature control and superheat [21]. Thus, the stable frequency could make the superheat more stable. However, the most effective modification was adopted the UMF to the superheat too. Therefore, the CASE 3 got smaller steady-state errors of superheat control than CASE 2. Finally, the result of CASE 3 is satisfied the ±1.5℃ control target in completely.

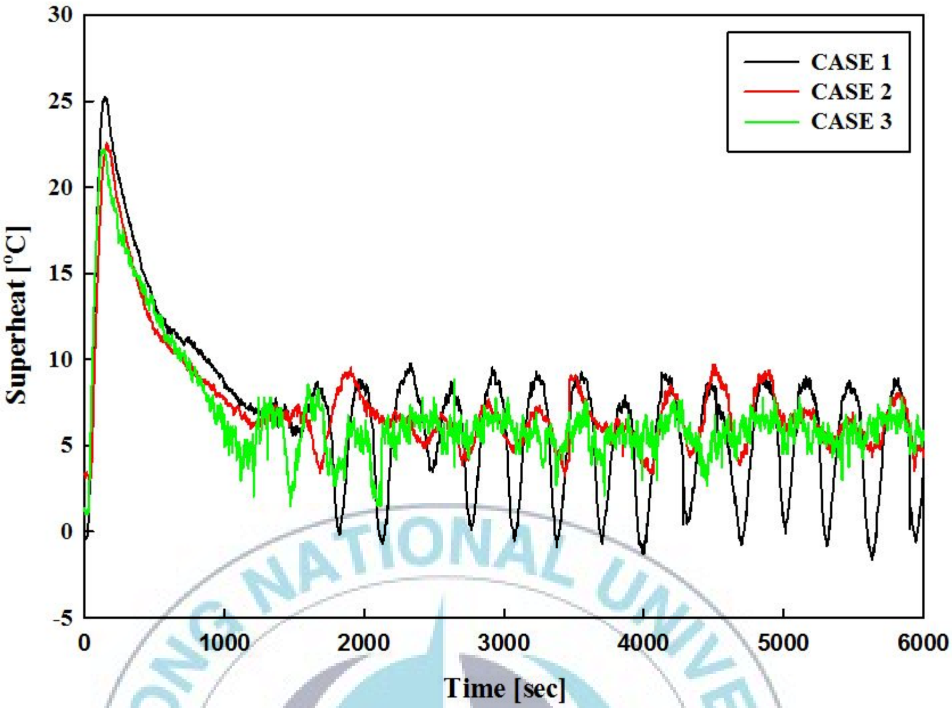


Fig. 4.9 The experimental results of superheat response

4.2.4 Comparison of steps reference

In Fig. 4.10, the step reference of CASE 3 is more stable than the other two cases. The noise disturbance and interference by manipulated frequency were rejected by UMF in successfully.

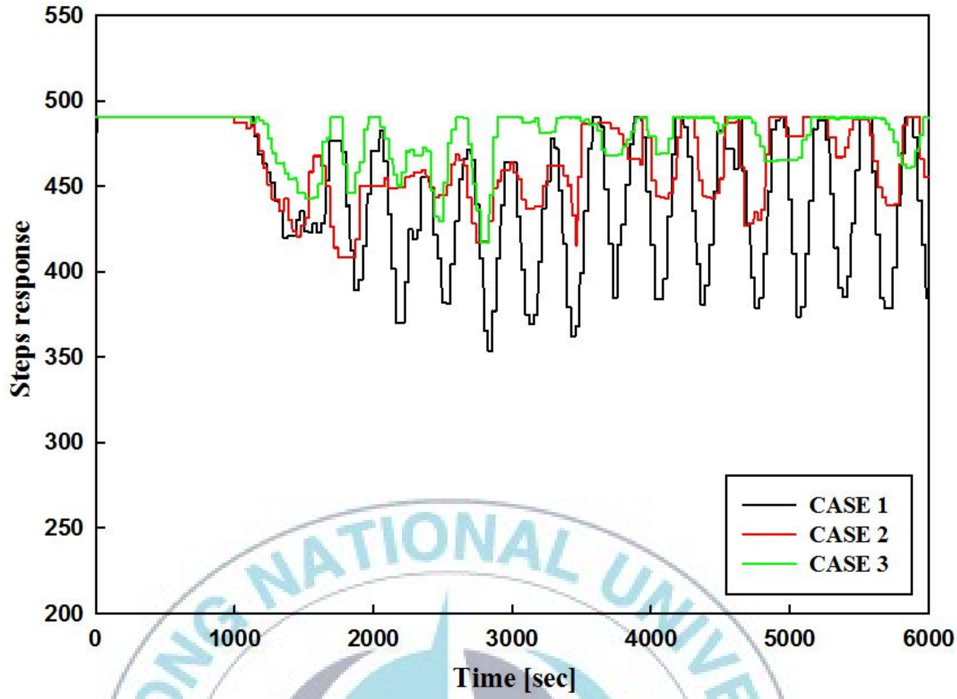


Fig. 4.10 The experimental results of the steps reference

In conclusion, the control by UMF can reduce the steady state error of chamber temperature, and also it contributes to high precision control of superheat owing to stable frequency reference by UMF. Furthermore, the service life of EEV is extended by avoiding the frequent operation owing to stable step reference with UMF and energy efficiency is also improved by running the superheat at the optimum operating point for maximum COP.

Chapter 5

Conclusions

In this thesis, the UMF of a fuzzy logic control was adopted to enhance the control performance of CCS by improving the chamber temperature control precision and ensuring robustness. The chamber temperature control precision and robustness were enhanced by reducing the steady-state error and rejecting noise disturbance respectively.

Some simulations were performed to check the control effectiveness before the real experiments. The simulation results proved the UMF could make the CCS high precision control and strong robust system. Real experiments were conducted to prove the validity of the proposed system. Through the simulation and experimental results, the key conclusions are lift as follows:

1. The result of CCS with EMF fuzzy logic controller had big steady-state error in chamber temperature and superheat control. And the robust performance was weak on the noise rejecting. In the supeaheat control, the control precision and robust performance was not satisfactory.
2. The chamber temperature control precision performance was improved by modifying membership function of the *e* fuzzy set into UMF by using the histogram equalization method.
3. Moreover, the robustness performance was improved by modifying membership function of *ee* fuzzy set into UMF by the domain encompass method.
4. The modification on changing EMF into UMF for superheat fuzzy set made the control of superheat more precise and more robustness.
5. With the noise disturbance. The steady-state errors of chamber temperature was achieved the control goals of 4±0.5℃. And the steady-state errors of superheat were also kept within ±1.5℃. Consequently, the UMF was giving better result EMF.Furthermore,

the COP of CCS which applied with UMF was higher, temperature control precision and robustness were also better than those of CCS with EMF.

6. The method of histogram equalization and domain encompass were easy to modify the EMF into UMF.

Reference

[1] Y.T. Lee, Y.C. Kim, M.S. Kim, 1996, Performance of an inverter refrigeration system with a change of expansion devices. Journal of SAREK, Vol. 11, No. 6, pp. 928-936.

[2] J.D. Kim, H.K. Oh, J.I. Yoon, 1995, A study on dynamic characteristics of a refrigeration system by controlling the evaporator superheat, Journal of KSME, Vol. 19, No. 8, pp. 2012-2021.

[3] S.O. Choi, J.H. Kim, H.S. Yang, J.S. Kim, 1994, Study on control of refrigeration flow rate and characteristics of superheat in evaporator using electronic expansion valve, Journal of SAREK, Vol. 6, No. 4, pp. 380-387.

[4] J.M. Choi, Y.C. Kim, 2002, Superheat control of an inverter-driven heat pump using PI control algorithm, International Journal of Air-conditioning and Refrigeration, Vol. 10, No. 2, pp. 106-115.

[5] W. Chen, Z.J. Chen, R.Q. Zhu, Y.Z. Wu, 2002, Experimental investigation of a minimum stable superheat control system of an evaporator, International Journal of Refrigeration, Vol. 25, pp. 1137-1142.

[6] Donal P. Finn, 2000, Control and optimization issues associated with algorithm-controlled refrigeration throttling devices, ASHRAE, Vol. 106, No. 1, pp. 1-10.

[7] H.S. Yang, H.S. Kim, J.H. Kim, S.B. Kim, J.S. Kim, 1993, Control of refrigeration compressor capacity using inverter, Journal of SAREK, Vol. 5, No. 2, pp. 94-101.

[8] Y.C. Park, M.K. Kim, 1997, A study of frequency control of an inverter heat pump for indoor air temperature adjustment, Journal of KSME, Vo. 21, No. 10, pp. 1262-1272.

[9] D.S. Jung, M.S. Kim, M.S. Kim, W.Y. Lee, 2000, Capacity modulation of a multi-type heat pump system using PI control, Journal of SAREK, Vol. 12, No. 5, pp. 466-475.

[10] D.S. Jung, M. Kim, M.S. Kim, 1999, PID control of multi-type heat

pump system, Autumn proceeding of SAREK, pp. 541-545.
[11] Li Hua, Seok-Kwon Jeong, Jung-In Yoon, 2006, Decoupling control design for refrigeration system of a ship, Journal of the Korean Society of Marin Engineering, Vol. 30, No. 7, pp. 808-815.
[12] L. Hua, S. K. Jeong, 2007, Design and analysis of fuzzy control in a variable speed refrigeration system, International Journal of Air-Conditioning and Refrigeration, Vol. 15, No. 2, pp. 61–69.
[13] H. Li, J.Y. Fei, 2011, Fuzzy control for a variable speed refrigeration system, International Conference on Measuring Technology and Mechatronics Automation, Shang Hai, pp. 272–275.
[14] Y. Hao, 1994, Practical design of nonlinear fuzzy controllers with stability analysis for regulating processes with unknown mathematical models, Automatica, Vol. 30, No. 7, pp. 1185-7795.
[15] M. Becker, D. Oestreich, H. Hasse, and L. Litz, 1994, Fuzzy control for temperature and humidity in refrigeration systems, Proceedings of IEEE International Conference on Control and Applications, pp. 1607–1612.
[16] S. Han and S. Hong, 1998, Refrigerator temperature control using fuzzy logic and neural network, International Symposium on Industrial Electronics, pp. 186–191.
[17] Y. Hao, WILLIAM SILER and JAMES J. BUCKLEY, 1990, Fuzzy control theory-a nonlinear case, Autimatica, Vol. 26, No. 3, pp. 513-520.
[18] J. P. Cao and S. J. Y. Jung, 2012, Robust fuzzy control with unevenly distributed membership function for chamber cooling system, Conference of Society of Air-conditioning and Refrigerating Engineers of Korea (SAREK), Korea, pp. 229-231.
[19] F. H. F. Leung, H. K. Lam, and P. K. S. Tam, 1998, Design of fuzzy controllers for uncertain nonlinear systems using stability and robustness analyses, Systems & Control Letters, Vol. 35, No. 4, pp. 237-543.
[20] B. S. Butkiewicz, 1998, Steady-state error of a system with fuzzy controller, IEEE Transactions on Systems. Man. and Cybernetics. Part B, Vol. 28, No. 6, pp. 855-860.

[21] L. Hua and S. K. Jeong, 2007, Design and analysis of fuzzy control in a variable speed refrigeration system, International Journal of Air-Conditioning and Refrigeration, Vol. 15, No. 2, pp. 61–69.
[22] J. Lu and Y. Hu, 2006, A histogram modification approach for analysis of membership function relocation in fuzzy logic control, Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 10, No. 6, pp. 913-920.
[23] H. Zhuang and X. Wu, 2001, Membership function modification of fuzzy logic controllers with histogram equalization, IEEE transactions on systems. man. and cybernetics. Part B, Vol. 31, No.1, pp. 125–132.
[24] G. Chen, T. T. Pham, Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems, CRC Press, 1999.
[25] S.D. Dhamakale, S.B. Patil, 2011, Fuzzy Logic Approach with Microcontroller for Climate Controlling in Green House, International Journal on Emerging Technologies, Vol. 2, No. 1, pp. 17-19.
[26] T. Ross, 1995, Fuzzy logic with engineering applications, McGraw-Hill, New York.
[27] G. Klir, B. Yuan, 1995, Fuzzy sets and fuzzy logic: theory and applications, Prentice Hall, Upper Saddle River.
[28] B. Kosko, 1992, Neural networks and fuzzy systems, Prentice Hall, Englewood Cliffs.
[29] L. Zadeh, 1973, Outline of a new approach to the analysis of complex systems and decision processes, IEEE Trans. Syst., Man, Cybern., vol. SMC-3, No. 1, pp. 28–44.
[30] M. Sugeno, 1985, Industrial applications of fuzzy control, North-Holland, New York.
[31] C. Lee, 1990, Fuzzy logic in control systems: fuzzy logic controller, Parts I and II, IEEE Trans. Syst., Man, Cybern., Vol. 20, No. 2, pp. 404–435.
[32] R. Saidur, S. Mekhilef, M. B. Ali, A. Safari, and H. A. Mohammed, 2012, Applications of variable speed drive (VSD) in electrical motors energy savings, Renewable and Sustainable Energy Reviews, Vol. 16, No. 1, pp. 543–550.

[33] H. Li, S. K. Jeong, and S. S. You, 2009, Feedforward control of capacity and superheat for a variable speed refrigeration system, Applied Thermal Engineering, Vol. 29, No. 5-6, pp. 1067–1074.
[34] M. J. Carlotto, 1987, Histogram analysis using a s cale-space approach, IEEE Transactions on Pattern Analysis and Machine Intelligenge, Vol. PAMI-9, No. 01, pp. 121–129.

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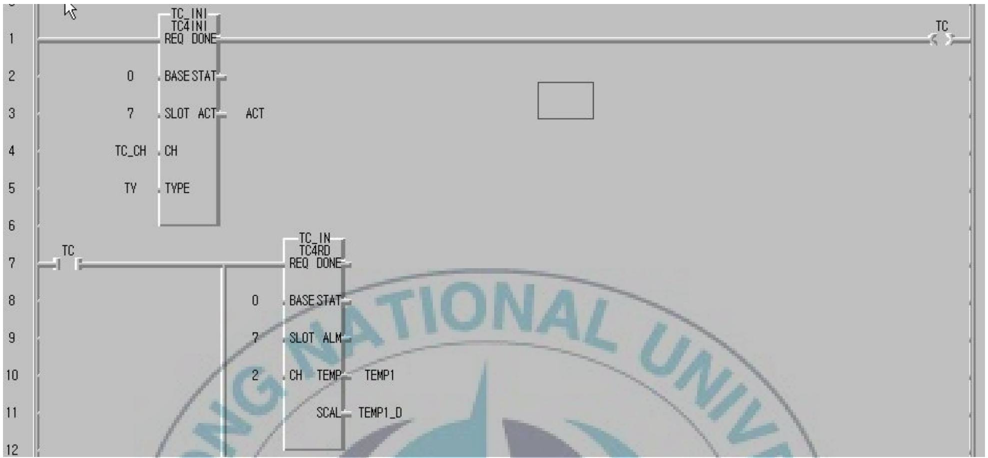
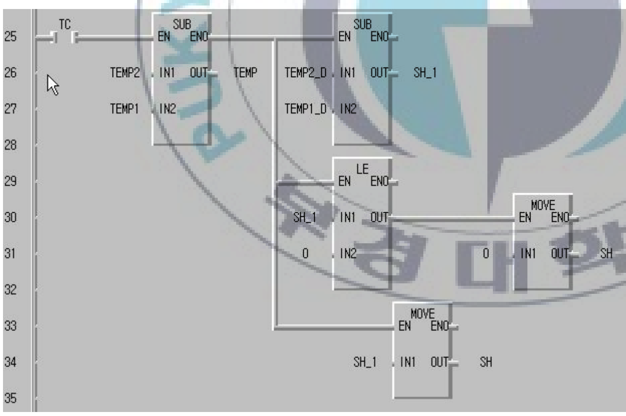
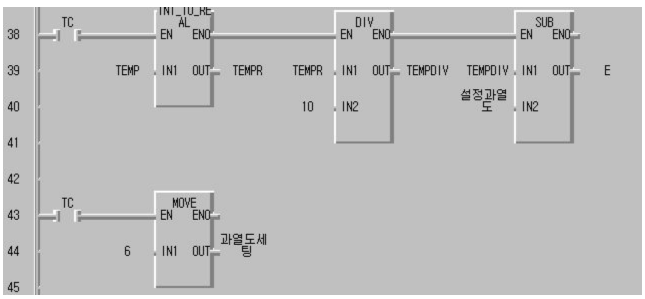
Cao Jianpeng

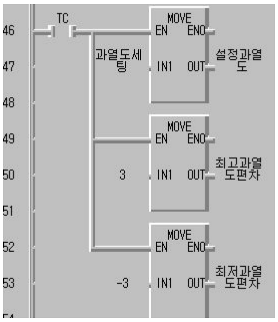
Appendix

Appendix A: PLC program of fuzzy control





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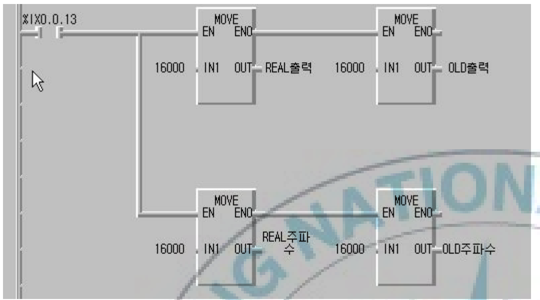
MOVE
3
최고과열도편차
MOVE
-3
최저과열도편차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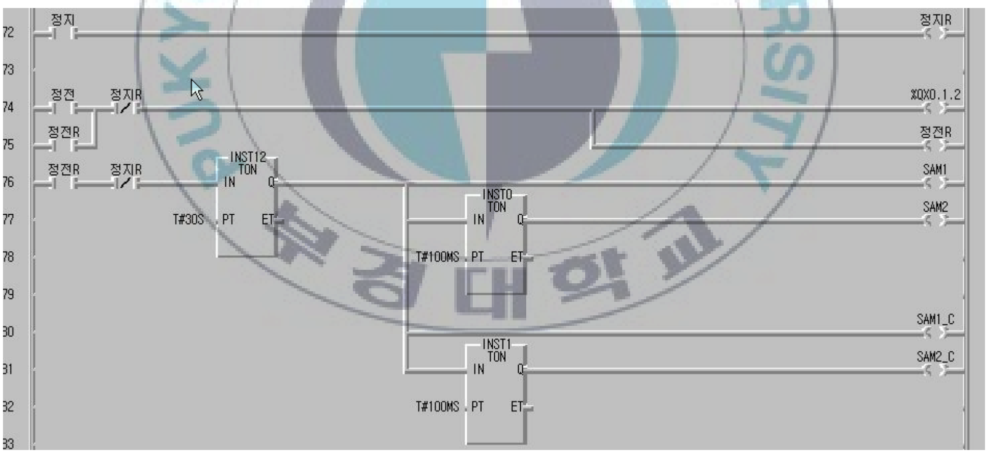
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PT ET
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INST0
SAM2
T#100MS
SAM1_C
INST1
SAM2_C


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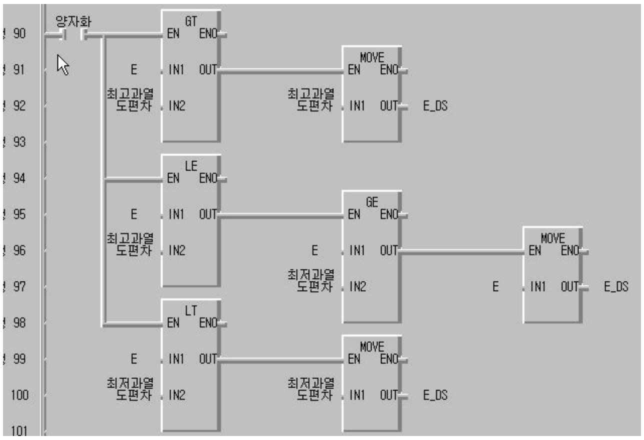
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LE
EN ENO
E IN1 OUT
최고과열 도편차 IN2
GE
EN ENO
E IN1 OUT
최저과열 도편차 IN2
MOVE
EN ENO
E IN1 OUT E_DS
LT
EN ENO
E IN1 OUT
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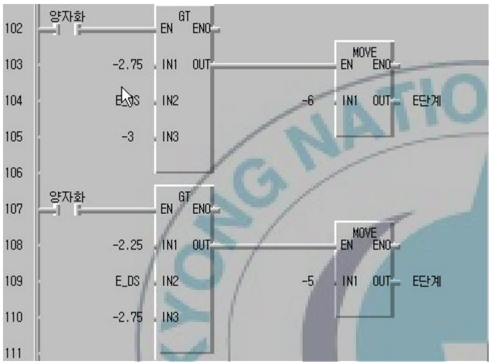
MOVE
EN ENO
최저과열 도편차 IN1 OUT E_DS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-3 IN3
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-6 IN1 OUT E단계
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E_DS IN2
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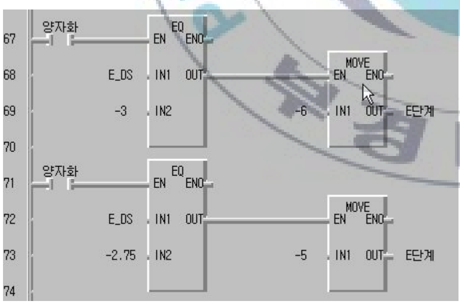
MOVE
EN ENO
-5 IN1 OUT E단계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EN ENO
-6 IN1 OUT E단계
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EQ
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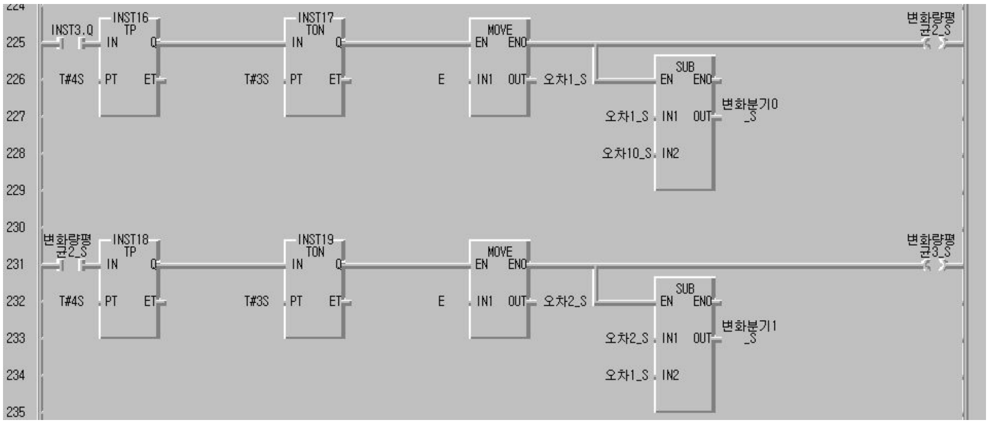
-2.75 IN2
MOVE
EN ENO
-5 IN1 OUT E단계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오차10_S IN2
변화량평균2_S
변화량평균2_S
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변화량평균3_S


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변화분기3_S IN4
변화분기4_S IN5
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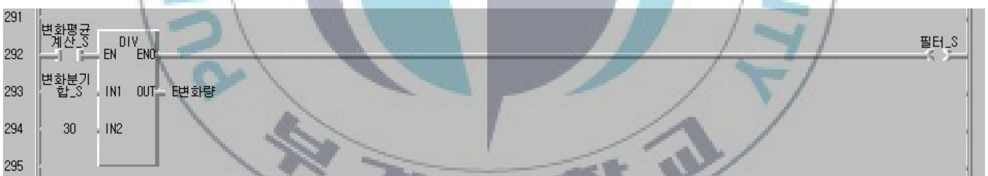
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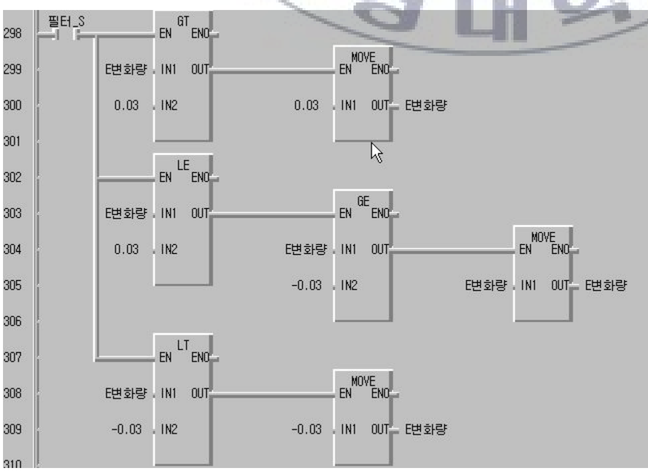
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0.03 IN2
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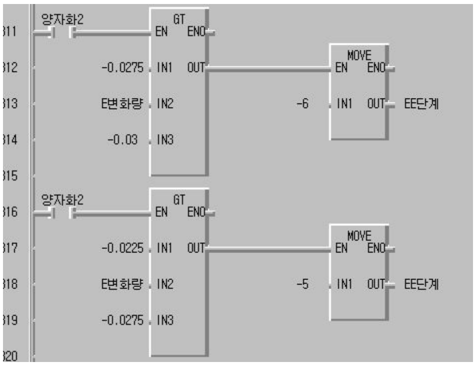
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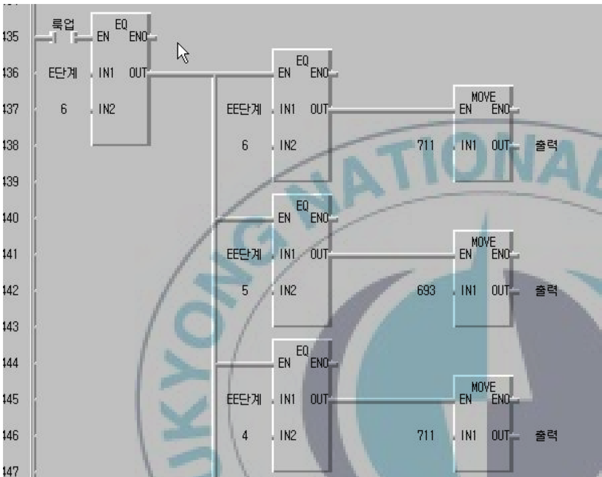
EE단계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4
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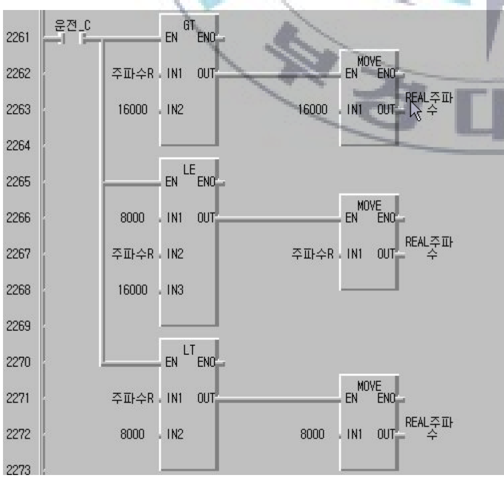
출력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8000
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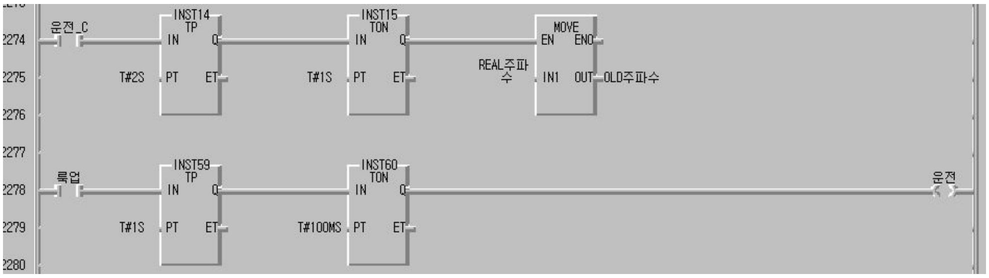
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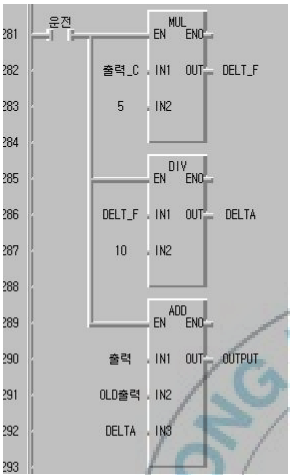
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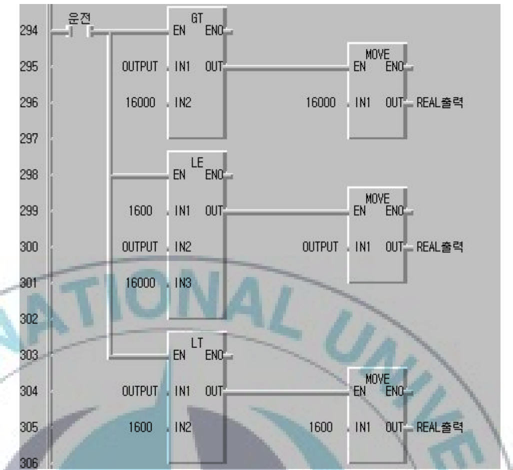
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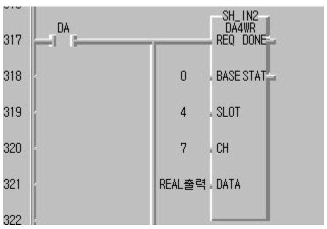
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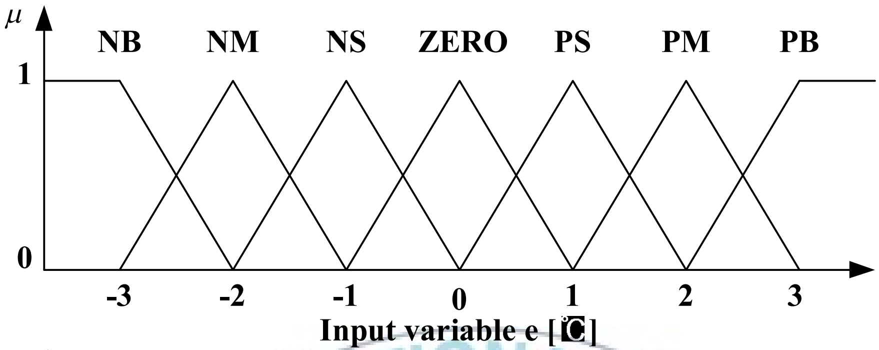
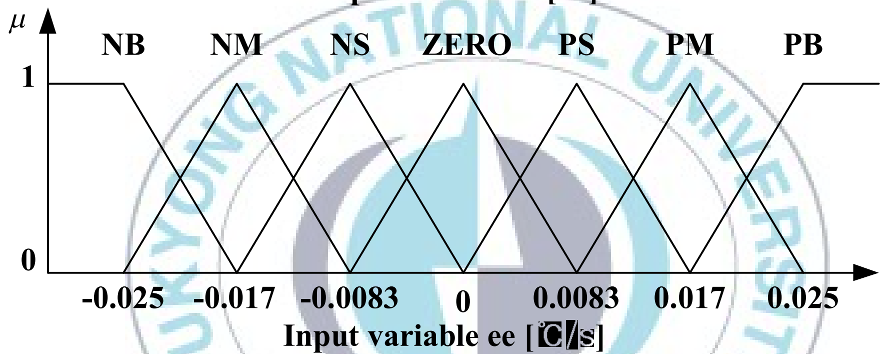
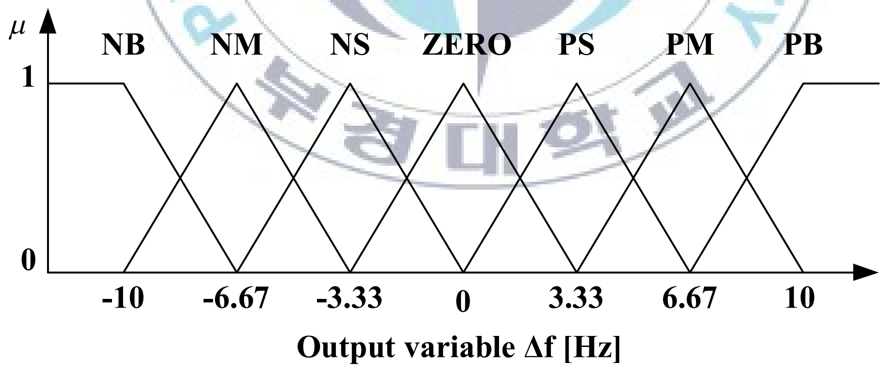
Appendix B: The fuzzy set for three cases in experiment

CASE 1:

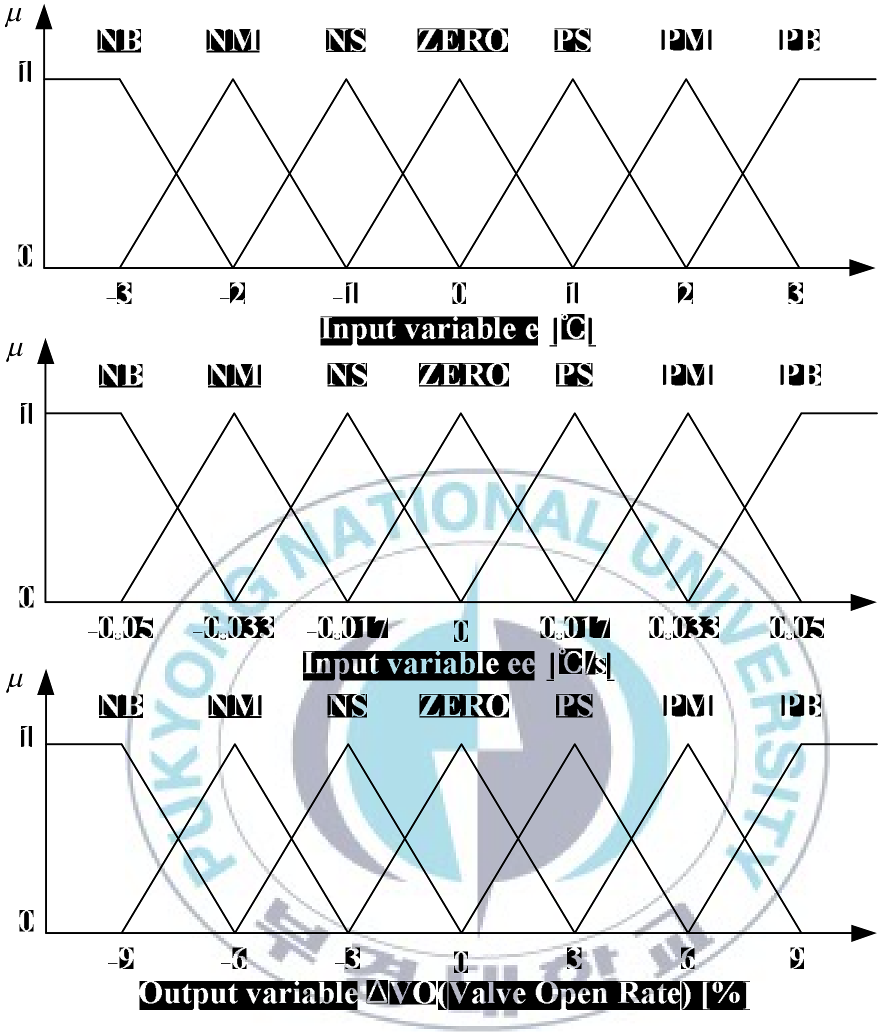
The fuzzy set for chamber temperature control





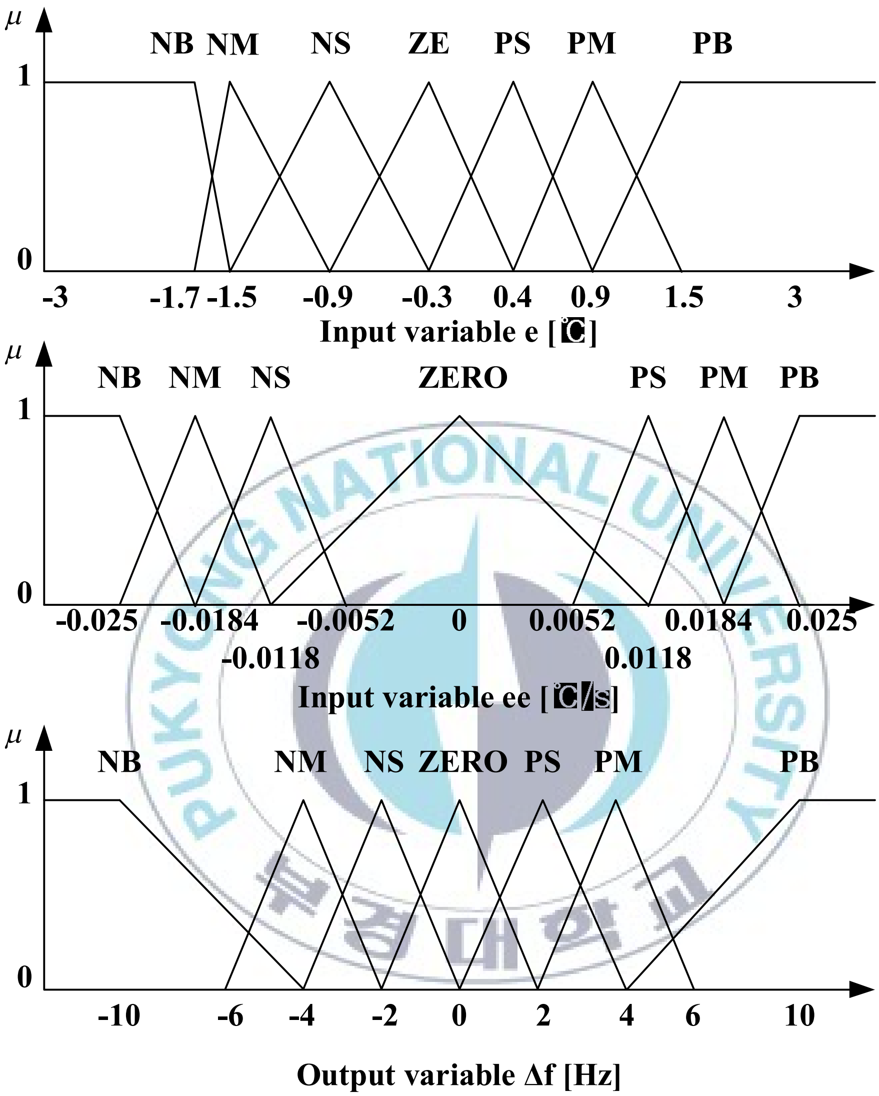


The fuzzy set for superheat control

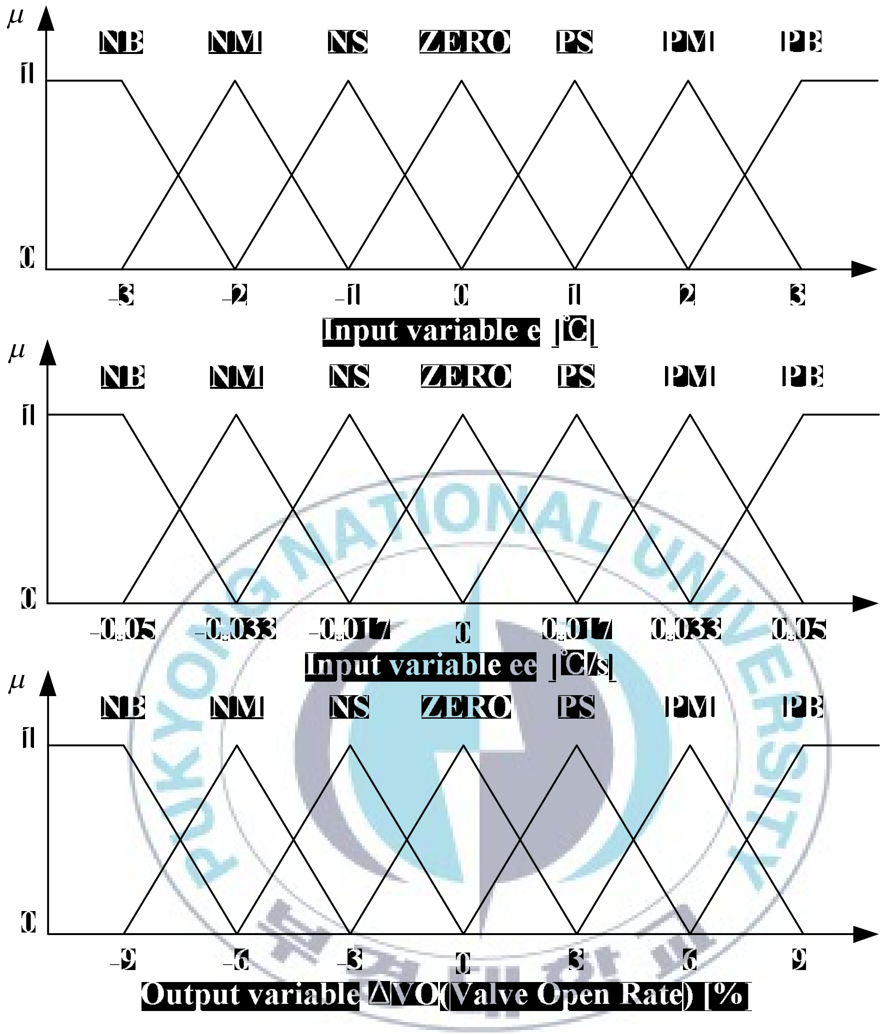


CASE 2:

The fuzzy set for chamber temperature control

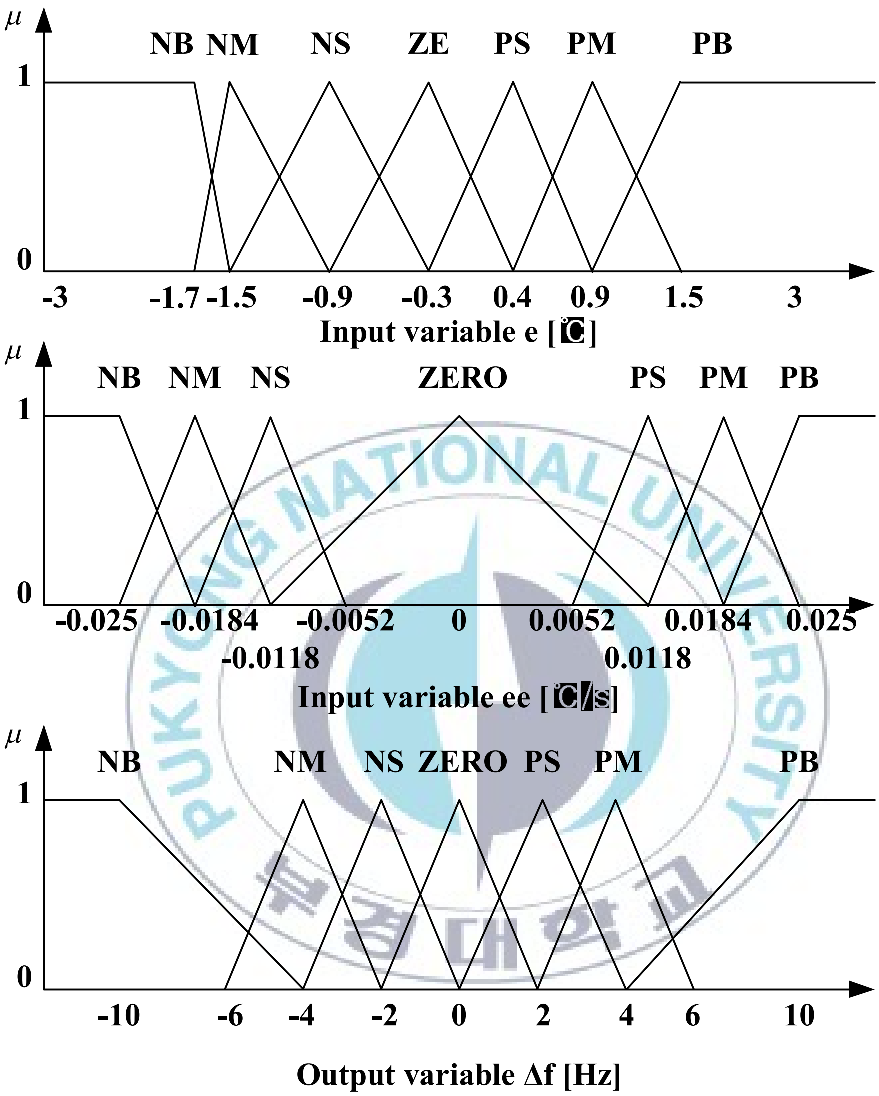


The fuzzy set for superheat control



CASE 3:

The fuzzy set for chamber temperature control



The fuzzy set for superheat control