

IMPROVING THE DESIGN OF FUZZY SYSTEMS USING TYPE-2 FUZZY RULES

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LUCKNOW

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CERTIFICATE

It is certified that the work contained in the thesis entitled “**Improving the design of fuzzy systems using type-2 fuzzy rules**”, by **Bharti Mall**(Roll No. 1180449002), for the award of **Master of Technology** from Babu Banarasi Das University has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.



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ABSTRACT

Fuzzy logic is a computing approach which deals with uncertain and imprecise information. It is different from Boolean algebra and based on degree of truth rather than true or false. The word fuzzy mean uncertain or vague but type -1 fuzzy sets has no uncertainty associated with it. Type -2 fuzzy sets are generalization of type-1 fuzzy sets to handle more uncertainty. In this paper a new student performance indicator system is proposed and implemented using Juzzyonline which is a java based library to design, construct and visualize a type -1, interval type-2 and general type -2 fuzzy systems. Also student performance indicator system is designed with guaje an open access software and interpretability and accuracy parameters are also studied.

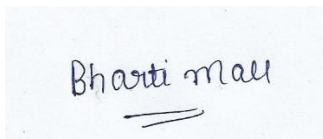
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It is indeed a matter of great pleasure and privilege to able to present this project on **“Improving the design of fuzzy systems using type-2 fuzzy logic”**

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A rectangular box containing a handwritten signature in blue ink that reads "Bharti Mall" with a double underline beneath the name.

Signature of student

Bharti Mall

Date : 20/7/2020

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CHAPTER 1

INTRODUCTION

Fuzzy logic is different from Boolean logic on which the modern computer is based. It is a computing approach that deals with degree of truth rather than true or false. Fuzzy logic is a superset of Boolean logic. Fuzzy logic was first introduced by Dr. Lotfi Zadeh in 1965. Fuzzy logic is a way of reasoning that really works and Boolean algebra or Boolean logic is a simply special case of it. Fuzzy logic includes 0 and 1 and values between 0 and 1 also. eg. Comparison of tallness between two objects gives result not only tall or short but 0.28 of tallness.

Fuzzy logic seems closer to our human brain. Fuzzy logic developed by Lotfi Zadeh is a multivalued logic. It is different from Boolean logic in terms that Boolean logic takes a value either true or false while in fuzzy logic the value of a variable can be any real number between 0 and 1. Real world problems which include uncertainty can be easily solved by fuzzy logic. It is a generalization of Boolean algebra in which the value of a variable is between completely true and completely false. Fuzzy logic deals with unclear or uncertain things when we can't determine the state true or false then fuzzy logic provides flexibility to deal with that situation. So any uncertainty or inaccuracy is dealt with fuzzy logic. In Boolean algebra there is no concept of partial truth or false but we can use intermediate values present between truth and false that is partially true or false. The term fuzzy refers to matters which aren't clear or are vague. In the actual world in many instances we come upon a situation while we can't decide whether the state is true or false, then fuzzy logic provides a completely valuable flexibility for reasoning. In this way, we can bear in mind the inaccuracies and uncertainties of any situation. The term fuzzy implies matters which are not very clear or vague. In real life, we may encounter a state of affairs in which we cannot determine whether or not the announcement is real or false. At that time, fuzzy logic gives very precious flexibility for reasoning. We can also remember the uncertainties of any scenario. Fuzzy logic algorithm enables to clear up a problem after considering all available data. Then it takes the quality feasible decision for the given input. The FL approach imitates the way of selection making in a human which keeps in mind all the possibilities between virtual values T and F. Fuzzy logic is supposed to version logical reasoning with vague or vague statements like "Petr is young (rich, tall, hungry, etc.)". It refers to an own family of many-valued logics (see entry on many-valued logic) and for this reason stipulates that the truth value (which, in this situation amounts to a point of reality) of a logically compound proposition, like "Charles is tall and Chris is rich", is decided via the truth value of its components. In different words, like in classical logic, one imposes truth-functionality. A fuzzy set assigns a degree of membership, typically a real quantity from the interval $[0, 1]$, to elements of a universe. Fuzzy logic arises via assigning ranges of truth to propositions. The standard set of reality values (levels) is $[0,1]$, where 0 represents "definitely false", 1 represents "absolutely true", and the opposite numbers refer to partial fact, i.e., intermediate ranges of fact. Fuzzy Logic is a technique to variable processing that permits for a couple of values to be processed via the identical variable. Fuzzy logic tries to solve troubles with an open, obscure spectrum of information that makes it feasible to gain an array of correct conclusions. Fuzzy logic is designed to solve problems by thinking about all available information and making the nice possible

selection given the input. Fuzzy logic stems from the mathematical look at of fuzzy principles which also includes fuzzy units of information. Mathematicians might also use a lot of terms when regarding fuzzy standards and fuzzy analysis. Broadly and comprehensively these terms are categorized as fuzzy semantics. In practice, these constructs all allow for multiple values of the "true" condition. Instead of true being numerically equal to 1 and false being equal to 0 (or vice versa), the True condition might be any variety of values much less than one and more than zero. This creates opportunity for algorithms to make decisions primarily based on stages of price facts instead of one discreet statistics point. Fuzzy logic research reasoning systems wherein the notions of fact and falsehood are taken into consideration in a graded fashion, in assessment with classical arithmetic where best absolutely true statements are considered. The two different points of view exist in the study of fuzzy logic : in a narrow and in a broad sense. Fuzzy logic in broad sense serves specifically as apparatus for fuzzy control, analysis of vagueness in natural language and several other utility domains. It is one among the strategies of soft-computing, i.e. computational techniques tolerant to sub optimality and impreciseness (vagueness) and giving quick, easy and sufficiently good solutions. Fuzzy logic in narrower sense is symbolic logic with a comparative belief of truth evolved fully in the spirit of classical logic (syntax, semantics, axiomatization, fact-preserving deduction, completeness, etc.; both propositional and predicate good judgment). It is a branch of many-valued logic primarily based on the paradigm of inference under vagueness. In classical mathematics one offers with collections of objects called (crisp) sets. Some universe U is fixed then each element is assumed to be included in it. Think of a set A as a function from U which takes value 1 on objects which are the member to A and 0 on which is not the member while fuzzy sets generalize this definition elements belongs to given set by certain degree. Instead of considering characteristic functions with value in $\{0, 1\}$ we consider now functions valued in $[0, 1]$. Fuzzy logic has a vulnerable connection to probability theory. Probabilistic methods that cope with imprecise expertise are formulated in the Bayesian framework but fuzzy logic does not want to be justified the use of a probabilistic approach. The common direction is to generalize the findings of multivalued logic in such a way as to preserve part of the algebraic structure. Fuzzy logic is based on the concept of fuzzy units that is a generalization of the classical set theory. Saying that the idea of fuzzy sets is a generalization of the classical set idea way that the latter is a special case of fuzzy sets concept. To make a metaphor in set principle speaking, the classical set principle is a subset of the theory of fuzzy units. A fuzzy idea is a concept of which the boundaries of application can vary significantly according to context or conditions, in place of being constant as soon as and for all. This method the concept is indistinct in a few way, lacking a constant, unique meaning, without however being uncertain or meaningless altogether. Fuzzy logic are used in Natural language processing and numerous extensive programs in Artificial Intelligence. Fuzzy logic are drastically utilized in current control structures such as expert structures. Fuzzy Logic is used with Neural Networks as it mimics how someone might make decisions, best much faster. For the development of sophisticated control systems fuzzy logic is one of the most successful technology .Applications that resembles human decision making is addressed by fuzzy logic and it generate precise solutions from certain or approximate information. It fills the gap in engineering design methods by using mathematical and logic based approaches in system

design. There should be accurate method to model the real world problems while fuzzy logic accommodate all the uncertainty between human logic and language. Fuzzy logic allows the computers to determine the differences between data with the shades of gray as similar to the: for instance, what type of controller to apply and how to decide the controller structure and parameters largely rely on the choice and preference of the designer, mainly when a couple process of human reasoning. Fuzzy systems and fuzzy control theories as an emerging era targeting industrial applications have introduced a promising new measurement to the prevailing area of conventional control systems engineering. It is now a common belief that once a complicated physical system does now not provide a fixed of differential or difference equations as a specific or reasonably correct mathematical model, in particular while the system description requires positive human experience in linguistic terms, fuzzy structures and fuzzy control theories have some salient capabilities and distinguishing merits over many different approaches. Fuzzy control strategies and algorithms, including many specialized software and hardware to be had available on the market today, can be labeled as one sort of intelligent control. This is because fuzzy systems modeling, analysis, and control include a certain amount of human understanding into its components (fuzzy sets, fuzzy logic, and fuzzy rule base). Using human information in device modeling and controller layout is not handiest advantageous but often necessary. Classical controller design has already incorporated human skills and information of choices are possible. The relatively new fuzzy control technology provides one extra desire for this consideration; it has the purpose to be an alternative, rather than a simple replacement, of the existing manipulate strategies inclusive of classical control and other intelligent control methods (e.g., neural networks, expert systems, etc.). Together, they supply systems and control engineers with a more complete toolbox to cope with the complex, dynamic, and unsure real world. Fuzzy manage technology is one of the many equipment in this toolbox that is advanced not best for elegant mathematical theories but, extra importantly, for plenty practical problems with various technical challenges. Compared with traditional approaches, fuzzy control utilizes more records from domain professionals and relies much less on mathematical modeling about a physical system. On the other hand, fuzzy control theory may be rigorous and fuzzy controllers can have particular and analytic structures with guaranteed closed loop system stability and some performance specifications, if such traits are intended. In this direction, the ultimate goal of the present day fuzzy systems and fuzzy control studies is appealing: the fuzzy control device era is moving closer to a stable foundation as part of the present day control theory. A fuzzy set can be described mathematically by using assigning to each possible character within the universe of discourse a value representing its grade of membership inside the fuzzy set. This grade corresponds to the degree to which that character is comparable or well suited with the idea represented by using the fuzzy set. Thus individuals may also belong within the fuzzy set to an extra or lesser degree as indicated by way of a larger or smaller membership grade. It is inherently robust since it does no longer require precise, noise-free inputs and may be programmed to fail properly if a feedback sensor quits or is destroyed. The output manage is a smooth manage function no matter a wide range of input variations. Since the FL controller procedures user-defined rules governing the target control system, it may be modified and without problems to enhance or drastically alter machine performance.

New sensors can easily be included into the system clearly by means of generating suitable governing rules. FL isn't always restrained to three feedback inputs and one or two manage outputs, neither is it important to degree or compute rate-of-change parameters in order for it to be implemented. Any sensor data that provides some indication of a device's moves and reactions is sufficient. This allows the sensors to be inexpensive and obscure thus maintaining the overall system cost and complexity low. Because of the rule-based totally operation, any reasonable number of inputs may be processed (1-8 or more) and several outputs (1-4 or extra) generated, although defining the rulebase quickly becomes complicated if too many inputs and outputs are selected for a single implementation since rules defining their interrelations should additionally be defined. It could be better to break the control device into smaller chunks and use several smaller FL controllers disbursed on the device, every with more restricted responsibilities. FL can control nonlinear systems that could be hard or not possible to model mathematically. This opens doorways for control systems that would usually be deemed unfeasible for automation. Fuzzy logic, which is the logic on which fuzzy control is based, is much nearer in spirit to human thinking and natural language than the conventional logical systems. Basically, it presents an effective way of shooting the approximate, inexact nature of the real world. Viewed in this perspective, the essential part of the fuzzy logic controller (FLC) is a set of linguistic control rules related with the aid of the dual standards of fuzzy implication and the compositional rule of inference. In essence, then, the FLC gives an algorithm that could convert the linguistic control approach based on expert expertise into an automatic control approach. Experience suggests that the FLC yields results superior to those received through conventional control algorithms. In particular, the technique of the FLC appears very useful when the methods are too complicated for evaluation via conventional quantitative techniques or in particular the available assets of statistics are interpreted qualitatively, inexactly, or uncertainly. Thus fuzzy common sense manage may be viewed as a step in the direction of a rapprochement between conventional specific mathematical control and human-like decision making. However, at present there is no systematic procedure for the design of an FLC present. Research includes fuzzification and defuzzification strategies, the derivation of the database and fuzzy control rules, the definition of a fuzzy implication. Fuzzy logic is concerned with the formal principles of approximate reasoning, with precise reasoning viewed as a restricting case. In more precise terms, what is central approximately fuzzy logic is that, unlike classical logical systems, it objectives at modeling the obscure modes of reasoning that play an essential role in the exquisite human capability to make rational selections in an environment of uncertainty and imprecision. This ability depends, in turn, on our capacity to infer an approximate solution to a question primarily based on a shop of knowledge this is inexact, incomplete, or not totally reliable.

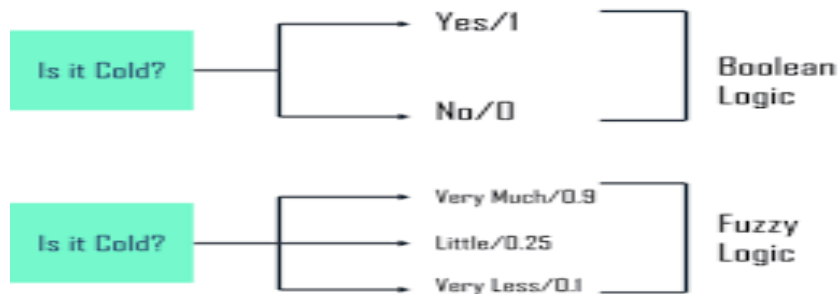


Figure 1.1 Fuzzy vs boolean

1.1 HISTORY OF FUZZY LOGIC

Fuzzy logic concept is being studied from 1920 but the term fuzzy logic was introduced by Zadeh a professor of UC Berkeley in California in 1965. He observed that conventional computer is not suitable to deal with unclear or uncertain information. Fuzzy logic is used with data which is neither true nor false. It is similar to human reasoning. In 1965 Zadeh published his famous book on "fuzzy sets". Zadeh extend possibility theory into a formal system of mathematical logic. Buddha who lived in India around 500BC and founded the religion Buddhism was first person to develop the fuzzy logic. His philosophy was based on thought that world is made up of contradictions and there exist opposite of each and every thing. The thing can be A and opposite of it that is not- A. After 200 years later Greek scholar Aristotle thought that world is made of opposite's male and female, active vs passive, hot vs cold and hot vs wet etc. Aristotle's binary logic was accepted and proved scientifically correct by logic. In 1965 Lotfi Zadeh proposed an infinite valued logic. He proposed each element can have a membership function which describes membership value of the set. Zadeh logic was called fuzzy set theory and some misunderstand it by imprecise or vague. In 1965 Zadeh published "fuzzy sets" which was foundation of fuzzy sets and fuzzy logic. Zadeh observed that conventional computers can't process the subjective or vague data so he created fuzzy logic. In fuzzy logic computers can process the subjective data similar to human reasoning. Although, the concept of fuzzy logic have been studied since the 1920's. The time period fuzzy good judgment became first used with 1965 through Lotfi Zadeh a professor of UC Berkeley in California. He found that conventional computer logic changed into no longer capable of manipulating information representing subjective or uncertain human ideas. Fuzzy common sense has been carried out to diverse fields, from manipulate idea to AI. It turned into designed to allow the computer to determine the differences among facts that is neither genuine nor false. Something similar to the procedure of human reasoning. Like Little dark, some brightness, etc. From many years the problems of uncertainty, imprecision and vagueness have been discussed. These problems have been much debate in philosophical topics in major areas, in particular, about the behavior of vagueness and the ability of traditional Boolean logic to cope with standards and perceptios which are obscure or vague. It is discovered that it is closely related to-Fuzzy Sets Theory, and successfully used in Fuzzy Systems. You would possibly think that fuzzy common sense is quite current and what has worked for a brief time, however its origins date back as a minimum to the Greek philosophers. It even seems potential to hint their origins

in China and India. Because plainly they were the first to take into account that everyone things need no longer be of a certain type or quit, however there are a stopover between. That is, be the pioneers in considering that there may be varying degrees of truth and falsehood. In case of colors, we can say that their lies between white and black there is a whole infinite scale: the shades of gray. Some current theorems display that during precept fuzzy good judgment may be used to version any non-stop system, be it based totally in AI, or physics, or biology, or economics, etc. Investigators in many fields may find that than any standard mathematical ones fuzzy, commonsense models are more useful, and more accurate. We examine here the history and improvement of this problem. As we know, logic is the look at of the structure and ideas of correct reasoning, and greater specifically, attempts to establish the concepts that guarantee the validity of deductive arguments. The central approach of validity is for fuzzy , because while we deal with the validity of a controversy are pronouncing that it's far impossible that its end is fake if its premises are genuine. Propositions are descriptions of the world, that is, are affirmations or denials of events in various possible worlds, of which the “real world” is just one among them. There is an extended philosophical tradition of distinguishing between truth necessary (a priori or “logical”) and facts “contingent” (a posteriori or “factual”).Both have absolutely led the two standards of logical truth, without being adverse to every other, are quite different: the conception of truth as coherence, and the conception of truth as correspondence. According to the point of view of consistency, a proposition is authentic or false depending on their courting with respect to a given set of propositions, because they have been consistently applied the rules of that system. Under the terms of correspondence, a proposition is authentic or fake, if it consents with reality, that is, the reality referred to. The well-acknowledged American Professor Bart Kosko highlighted the differences between Eastern and Western philosophies concerning the concept of truth, summing up in competition towards Aristotle Buddha. In fact, Kosko said that Western philosophy, Aristotle's successor, has accepted uncritically the bivalent as the system that is useful, however overly simplifying complex reality. Simply we can say that : what has won in simplicity is lost in accuracy. By contrast, Eastern philosophies: Buddha, Lao Tse, Confucius, etc. Always have standard the strict harmony of opposites, of what they call (as we know) the yin and yang. On the other hand, if it is actual that Aristotle was the extraordinary introducer of bivalence absolute, we should no longer ignore that he was no longer spent entirely ignored factors could be fuzzy propositions, as whilst he commented that: “In any case, what is said according to these (qualities) helps arguably the most and least”, or whilst we talk approximately that we are able to come to know-how, but without the certainty of it. If Aristotle did no longer study this concept, it may have been lacking the necessary mathematical expertise for development. It was now not until the arrival of a Calculus an increasing number of systematic and operational, combinatorial and possibility theory, or the brand new theory, now known as 'Crisp', or Classic, Sets, initiated by Cantor, as well as modern information and matrix calculations. As mentioned earlier, Aristotle did now not have the mathematical apparatus for developing a fuzzy common sense. The gestation of this construct starts offevolved with Newton and Leibniz, who developed calculus inside the seventeenth century. Despite the approach with accuracy in maths has made them perfectly applicable sentence Einstein: “the extent that maths refer toreal world , now not proper. And to the extent

they are proper, now not refer to reality”. But does now not say Einstein is undoubtedly the deductive equipment developed via mathematics facilitates the expertise of reality. The rationalization given through Aristotle movement is replaced by way of the most innovative in Newton, however thanks to a sharp appoggiatura in calculus, without which it would not have been possible. However, the infinitesimal calculus in depth was only used for the study of physics in the following centuries, experiencing spectacular increase with Euler, Laplace, Lagrange, Fourier, and so on. Today permeates all sciences, both social and human and natural. This Calculus Mathematics introduced the query of degree: to what degree is modified via converting seamlessly B, where A is a based variable B? Classical Aristotelian logic has been shown, therefore, and for an extended time, pretty powerful in technology so-called “hard”, such as math or physics. But it is insufficient when the predicates include imprecision, uncertainty or vagueness, on the other hand, is how the brain actually works and human reasoning, and in general, is how structures behave round us. Fuzzy common sense has also helped that the software can interpret judgments of this kind. When Aristotle and his predecessors devised their theories of logic and arithmetic, they got here up with the so-called Law of the Excluded Middle, which states that each proposition should both be authentic or fake.; grass clearly cannot be both green and not green. But no longer had everybody agreed, and Plato indicated there was a third region, beyond genuine and false, in which these opposites "tumbled about." In the 19th century, George Boole created a system of algebra and set concept that might deal mathematically with such two-valued logic, mapping real and fake to at least one and 0, respectively. Then in the early 20th century, Jan Lukasiewicz proposed a three-valued logic (genuine, possible, false), which by no means gained huge acceptance. In the Aristotelian international view, good judgment treated values. In the 19th century, George Boole created a system of algebra and set concept that might deal mathematically with such two-valued good judgment, mapping real and fake to at least one and 0, respectively. Then in the early 20th century, Jan Lukasiewicz proposed a three-valued good judgment (genuine, possible, false), which by no means gained huge acceptance. In 1965, Lotfi A. Zadeh of the University of California at Berkeley published "Fuzzy Sets," which laid out the arithmetic of fuzzy set idea and, via extension, fuzzy logic. Zadeh had determined that conventional computer logic couldn't manipulate information that represented subjective or vague ideas, so he created fuzzy logic to permit computers to decide the differences among records with shades of gray, much like the system of human reasoning. Although, the generation turned into introduced inside the U.S., U.S. And perhaps because of its unconventional name European scientist and researchers largely ignored it for years. They refused to take it seriously something childlike sounded things. Some mathematicians argued that fuzzy logic become merely chance in disguise. But fuzzy logic changed into effortlessly general in Japan, China and different Asian countries. The greatest variety of fuzzy researchers today are located in China, with over 10,000 scientists. Japan, although considered at the leading fringe of fuzzy studies, has fewer human beings engaged in fuzzy research. A decade ago, the Chinese University of Hong Kong surveyed customer products the use of fuzzy logic, producing a 100-plus-page report list washing machines, camcorders, microwave ovens and dozens of different kinds of electrical and electronic products. Fuzzy refers to a lack of clarity. There are many times when you can't make a simple 'Yes or No' decision. In those cases, you'll need to

make a dynamic desire. Fuzzy logic allows you in that regard. It gives you a flexible preference and enables you to cause with more facts and variables. There are many applications of fuzzy logic in AI because you can't use Boolean or similar common sense everywhere. It resembles human reasoning and considers all the opportunities that exist between Yes and No of desire. Usual logic handiest considers two possibilities: Yes and No. But people don't make decisions like that. They have many possibilities between Yes and No such as, Possibly Yes, and Possibly No. Fuzzy logic takes into consideration all of the ones possibilities. Fuzzy logic might appear a little complicated, however it's a flexible machine learning approach that you could put in force very easily. It allows you to mimic human thought. It's also ideal for solving troubles in which uncertainty is high. It allows you to assemble nonlinear capabilities that possess arbitrary complexity. But you should ensure that you construct it after having sufficient knowledge of the same because it's easy to make errors in this case. The first most important distinction between the fuzzy and probability is the situation be counted they deal with. Fuzzy logic works with facts, whereas probability works with events which can or might not occur. Fuzzy logic conveys partial reality, while probability conveys partial knowledge. Also, fuzzy common sense takes fact as its mathematical basis, whereas probability builds a version of ignorance.

1.2 WHY FUZZY LOGIC?

Fuzzy logic enables to work in uncertain situations. It is used to solve ambiguous problems or problems with incomplete information. In fuzzy everything is matter of degree. In fuzzy exact reasoning is viewed as subset of approximate reasoning. It is highly suitable method for approximate reasoning. Boolean logic results are confined to 0 and 1 while fuzzy results are somewhere between 0 and 1. Fuzzy logic deals with ideas we normally face in day to day life. Fuzzy logic is increasingly similar to human reasoning since it depends on degree of truth and linguistic variables. Fuzzy logic deals with the degree of truth while conventional logic is concerned with truth of the statement. Fuzzy logic is simple and easy to understand. Fuzzy deals with imprecise data. As we know fuzzy systems can't replace the conventional systems but can simplify their implementation. Basics of fuzzy are human reasoning and it is based on natural language. Fuzzy logic is conceptually easy to understand. It is flexible and can tolerate imprecise data. Fuzzy logic is based on natural language and can model nonlinear functions of arbitrary complexity. Fuzzy logic is one of the successful concepts in today's technologies as it is simple to address such applications. It resembles human decision making and generates precise solutions from an imprecise or certain information. Fuzzy logic can model real world problems with ambiguities. Any logical system can be fuzzified. This device can work with any kind of inputs whether it's imprecise, distorted or noisy input information. The creation of Fuzzy Logic systems is simple and understandable. Fuzzy logic comes with mathematical standards of set theory and the reasoning of that is pretty simple. It provides a very common solution to complicated issues in all fields of life as it resembles human reasoning and selection making. The algorithms can be defined with little data, so little memory is required. Fuzzy is used in the aerospace area for altitude control of spacecraft and satellite. It has used inside the automotive device for speed control, traffic manipulate. It is used for selection making guide systems and private evaluation inside the large organization business. It has application in chemical industry

for controlling the pH, drying, chemical distillation process. Fuzzy logic are used in Natural language processing and diverse intensive programs in Artificial Intelligence. Fuzzy good judgment are drastically used in present day control systems such as expert systems. Fuzzy Logic is used with Neural Networks as it mimics how a person could make decisions, handiest a lot faster. It is performed by Aggregation of statistics and converting into extra meaningful information through forming partial truths as Fuzzy sets. The structure of Fuzzy Logic Systems is simple and understandable. Fuzzy logic is broadly used for industrial and sensible purposes. It helps you to manipulate machines and purchaser products. It might not offer correct reasoning, however the simplest perfect reasoning. It lets you deal with the uncertainty in engineering mostly strong as no particular inputs required. It may be programmed to within the scenario when feedback sensor stops working. It can easily be modified to enhance or alter system performance. Less expensive sensors can be used which helps you to hold the overall machine cost and complexity low. It offers a most effective answer to complex issues. Generally, on this system, we can take imprecise, distorted, noisy input information. Also, these logics are smooth to construct and understand. Basically, it's solution to complicated problems such as medicine. Also, we will relate math in idea within fuzzy logic. Also, those principles are very simple. Due to the power of fuzzy logic, we are able to add and delete rules in FLS system. Generally, it's a technique of reasoning. Although, resembles human reasoning. Also, it has an approach to selection making in humans. As they involve all intermediate possibilities between virtual values YES and NO. In contrast to other computers, it includes a range of opportunities between YES and NO, in a human decision. Basically, it could be implemented in structures with diverse sizes and capabilities. That ought to be variety from mall micro-controllers to large. Also, it can be implemented in hardware, software, or a mixture of each in artificial intelligence. We can use it to purchaser products and control machines. Although, now not give accurate reasoning, but suited reasoning. Also, this logic facilitates to cope with the uncertainty in engineering. Fuzzy logic implements human reviews and preferences through membership capabilities and fuzzy rules. Fuzzy membership functions can have exceptional shapes depending on the designer's desire and/or experience. The fuzzy rules, which describe relationships at an excessive level (in a linguistic sense), are usually written as antecedent consequent pairs of IF-THEN statements. Basically there are 4 methods to the developing fuzzy rules (1) extract from expert experience and control engineering knowledge, (2) observe the behavior of human operators, (3) use a fuzzy model of a process, and (4) research relationships through enjoy or simulation with a gaining knowledge of process. These approaches do now not must be jointly exclusive. Due to using linguistic variables and fuzzy rules, the device may be made understandable to a non-expert operator. In this way, fuzzy logic can be used as a general technique to comprise knowledge, heuristics or theory into controllers and decision-makers.

1.3 TYPES OF FUZZY LOGIC

There are mainly two types of fuzzy logic

1. Type -1
2. Type -2

1.3.1 TYPE-1 FUZZY LOGIC: Type-1 fuzzy sets are used to model uncertainty. In type-1 fuzzy systems antecedent and consequent membership function are type-1 fuzzy sets. Membership functions are type-1 fuzzy sets in type-1 fuzzy logic and they are unable to handle directly rule uncertainties. So criticism was made about type-1 from beginning of fuzzy theory as fuzzy is all about uncertainty. In type-1 fuzzy the inference engine combines rules and gives a mapping from input type-1 fuzzy sets [1]. User behavior under specific conditions is modeled and utilize crisp and precise type-1 sets. Type-1 membership function is totally precise so uncertainty disappears when type-1 fuzzy sets are chosen. User believes that using precise membership function uncertainty can be handled but by using type-1 fuzzy sets uncertainty disappears. Membership function of type-1 fuzzy sets are two-dimensional and membership grade of each element of type -1 fuzzy sets are crisp between 0 and 1. Type-1 fuzzy sets membership function are totally crisp so it can't model rule uncertainties directly. In Type 1 fuzzy set, Expert should decide the degree of achieving the traits of the object. For example, when you have a 3 different red balls. The first is red by means of 75%, second is red 85%, and third is red 95%. That the original fuzzy logic (FL), type-1 FL, can't handle (that is, version and minimize the results of) uncertainties sounds paradoxical because the phrase fuzzy has the connotation of uncertainty. In a type-1 FLS, the inference engine combines rules and gives a mapping from input type-1 fuzzy sets to output type-1 fuzzy sets [1]. Type-1 FL handles uncertainties by the usage of particular membership functions (MFs) that the person believes capture the uncertainties. When the type-1 MFs were chosen, all uncertainty disappears due to the fact type-1 MFs are definitely particular. Type-2 FL, on the alternative hand, handles uncertainties about the meanings of words by using modeling the uncertainties using type-2 MFs. In a type -1 FLS, the inference engine combines rules and offers a mapping from input type-1 fuzzy units to output type-1 fuzzy sets. Multiple antecedents in rules are connected through the \wedge -norm (corresponding to intersection of sets). The membership grades within the input sets are mixed with those inside the output units with the use of the sup-star composition. Multiple rules can be mixed using the \vee -conorm operation (corresponding to union of units) or at some point of defuzzification by means of weighted summation. In the type-2 case, the inference technique could be very similar. The inference engine combines rules and offers a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. In a type-1 FLS, the defuzzifier produces a crisp output from the fuzzy set this is the output of the inference engine, i.e., a type-0 (crisp) output is acquired from a type-1 set. In the type-2 case, the output of the inference engine is a type-2 set; so we use extended versions of type -1 defuzzification methods. This prolonged defuzzification gives a type-1 fuzzy set. Since this operation takes us from the type-2 output units of the FLS to a type-1 set, we call this operation type reduction and the type-reduced set so received a type-reduced set.

1.3.2 TYPE-2 FUZZY LOGIC: It is extension of type-1 fuzzy logic. In type-2 fuzzy logic antecedents and consequents are type-2 fuzzy sets. It is generalization of type-1 fuzzy to handle more uncertainty. Defuzzification block of type-1 fuzzy logic is replaced by output processing block that defuzzification followed by type reduction. Type-2 fuzzy sets allow for linguistic grades of membership, thus assisting in knowledge representation and they also offer

improvement on inferencing with type-1 sets [2]. Type-2 fuzzy has one extra degree of freedom which is FOU (Footprint of uncertainty) to handle the rule uncertainties. Type-2 fuzzy sets are extension of basic sets i.e. type-1 fuzzy sets. Membership function of type-2 fuzzy sets are three dimensional which is fuzzy set between 0, 1. Third dimension of type-2 fuzzy sets provide extra degree of freedom to handle rule uncertainties. Type-2 fuzzy sets are used when we can't determine the exact membership function of fuzzy sets. Type-2 fuzzy directly model uncertainties as membership function of these sets are fuzzy sets. If uncertainty is not present then type-2 fuzzy sets reduces to type-1 fuzzy sets as probability reduces to determinism when uncertainty vanishes. In Type 2 Fuzzy set, Expert cannot decide exactly the degree of attaining the traits. For example, when you have a three exclusive red balls. The first is red by using 75%-80%, second is red 85%-90%, and third is red by 95%-100%. Type-2 fuzzy set itself is fuzzy, with a brand new dimension called the footprint of uncertainty, which characterizes type-2 fuzzy logic. Type-2 fuzzy logic systems—in which the antecedent or consequent membership functions are type-2 fuzzy units. The idea of a type-2 fuzzy set was delivered with the aid of Zadeh as an extension of the idea of an everyday fuzzy set (henceforth called a type-1 fuzzy set). Such units are fuzzy sets whose membership grades themselves are type-1 fuzzy sets; they're very beneficial in instances in which it is tough to determine a precise membership function for a fuzzy set. Hence, they are beneficial for incorporating uncertainties. Quite often, the information used to construct rules in a fuzzy logic system (FLS) is unsure. This uncertainty leads to rules having uncertain antecedents and/or consequents, which in turn interprets into uncertain antecedent and/or consequent membership functions. Type-2 fuzzy sets allow us to handle linguistic uncertainties, as typified by way of the adage “words can mean different things to different people. Type-2 fuzzy sets permit for linguistic grades of membership, consequently supporting in understanding representation and additionally they offer improvement on inferencing with type-1 sets. To date, type-2 sets and FLS's have been used in decision making solving fuzzy relation equations, survey processing, time-collection forecasting, function approximation, manipulate of mobile robots, and preprocessing of data. We believe that other promising regions in which type-2 FLS's can be positive over type-1 FLS's include mobile communications, communication networks, sample recognition, and strong manipulate, because often the information to be processed in these regions is unsure. We introduce a type-2 fuzzy logic system (FLS) that can take care of rule uncertainties. FLS involves the operations of fuzzification, inference, and output processing in the implementation of this type-2. We recognition on “output processing,” which is composed of type reduction and defuzzification. Type reduction strategies are extended variations of type-1 defuzzification strategies. Type reduction captures more records approximately rule uncertainties than does the defuzzified value (a crisp number), however, it's computationally intensive, besides for interval kind-2 fuzzy sets for which we offer a simple type-reduction computation procedure. We also observe a type-2 FLS to time-varying channel equalization and reveal that it provides higher performance than a kind-1 FLS and nearest neighbor classifier. In a type-2 fuzzy logic system (FLS) type reduction is an “extended” version of the defuzzification operation in a type-1 FLS. Fuzzy Logic Systems are comprised of rules. Quite often, the expertise that is used to construct these rules is uncertain. Such uncertainty leads to rules whose antecedents or consequents are

unsure, which translates into unsure antecedent or consequent membership functions. A Non-Singleton system deals with the uncertainty in the input, whereas a type-2 system deals with the uncertainty in our knowledge about the system[2]. Type-1 fuzzy systems whose membership functions are type-1 fuzzy sets, are not able to directly take care of such uncertainties. Type-2 fuzzy systems, wherein the antecedent or consequent membership capabilities are type-2 fuzzy sets. Such units are fuzzy sets whose membership grades themselves are type-1 fuzzy sets; they are very beneficial in circumstances in which it is hard to determine a precise membership characteristic for a fuzzy set. A type-2 fuzzy set is characterized through a fuzzy membership characteristic, i.e., the membership grade for each detail of this set is a fuzzy set in $[0, 1]$, in contrast to a type-1 set in which the membership grade is a crisp number in $[0, 1]$. Such sets may be used in situations in which there's uncertainty approximately the club grades themselves, e.g., an uncertainty in the shape of the membership feature or in a number of its parameters. Consider the transition from regular units to fuzzy units. When we cannot determine the membership of an element in a hard and fast as 0 or 1, we use fuzzy units of type-1. Similarly, while the situation is so fuzzy that we have hassle figuring out the membership grade while a crisp wide variety in $[0, 1]$, we use fuzzy units of type-2. This does not suggest that we want to have extremely fuzzy situations to apply type-2 fuzzy sets. There are many real-world troubles wherein we cannot determine the exact shape of the membership functions, e.g., in time series prediction because of noise in the data. Another way of viewing this is to recall type-1 fuzzy sets as a primary order approximation to the uncertainty within the real-world. Then type-2 fuzzy units can be considered as a second order approximation. Of course, it is feasible to don't forget fuzzy units of higher types but the complexity of the fuzzy gadget will increase very rapidly. All these output are combined by type reducer sets in some way (In the same way a type-1 defuzzifier combines the type-1 rule output sets) and then performs a centroid calculation on this type-2 set, which leads to a type-1 set that we call the "type-reduced" set [3].

CHAPTER 2

FUZZY INFERENCE SYSTEM

Fuzzy inference system is main building block of fuzzy logic systems whose primary work is decision making. It always produce a fuzzy output so we need defuzzification block to convert fuzzy to crisp. The fuzzy inference system is a famous computing framework based on the ideas of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It has observed successful applications in a wide variety of fields, including automated control, facts classification, selection analysis, expert structures time collection prediction, robotics, and sample recognition. Because of its multidisciplinary nature, the fuzzy inference system is thought by several different names, consisting of fuzzy-rule-based system, fuzzy expert system, fuzzy model, fuzzy associative memory, fuzzy logic controller, and simply (and ambiguously) fuzzy system. Fuzzy inference method has first been proposed in the context of the mission associated with water heater and boiler automatic control. The main idea of the author was to connect through the usage of production regulations fuzzy values of the input variables and fuzzy values of the output variable on whose basis the manage impact on a technical tool turned into developed. The necessity to introduce the sort of fuzzy control become due to the aim to escape from strict correlations between the inputs and outputs of the manage system which are function of classical systems of automatic manage as well as to make sure the flexibility concerning the modifications of the values of the input variable and the output variable. Systems of fuzzy inference have found wide application inside the duties where necessary records resources are either missing or insufficient, and the only source of facts is expert's opinion. Note that the fundamental fuzzy inference system can take both fuzzy inputs and crisp inputs (that are viewed as fuzzy singletons), but the outputs it produces are almost usually fuzzy sets. Sometimes it is necessary to have a crisp output, particularly in a state of affairs in which a fuzzy inference system is used as a controller. Therefore, we need a technique of defuzzification to extract a crisp value that best represents a fuzzy set. A nonlinear mapping from its inputs space to output space is implemented by fuzzy inference system. Fuzzy inference systems are widely used in various areas of human activity. Their most giant use lies within the field of fuzzy control of technical devices of different type. Another direction of the use of fuzzy inference systems is modelling and assessment of different kind of dangers beneath inadequate or missing goal preliminary data. Fuzzy inference is concluded by using the technique of defuzzification of the resulting fuzzy sets. A large range of strategies for imposing the defuzzification process are to be had nowadays. This mapping is carried out by a number of fuzzy if-then rules, every of which describes the local behavior of the mapping. In particular, the antecedent of a rule defines a fuzzy region within the input space, at the same time as the consequent specifies the output within the fuzzy region. Fuzzy Inference System is the key unit of a fuzzy logic machine having choice making as its number one work. It makes use of the "IF...THEN" rules together with connectors "OR" or "AND" for drawing crucial decision rules. The output from FIS is always a fuzzy set irrespective of its input which may be fuzzy or crisp. When it is used as a controller it is necessary to have fuzzy output. A defuzzification unit could be there with FIS to convert fuzzy variables into crisp variables. A fuzzification unit supports the software of several

fuzzification methods, and converts the crisp input into fuzzy input. An expertise base - series of rule base and database is fashioned upon the conversion of crisp input into fuzzy input. The defuzzification unit fuzzy input is eventually transformed into crisp output. Fuzzy Inference Systems take inputs and technique them based on the prespecified rules to provide the outputs. Both the inputs and outputs are actual valued, whereas the inner processing is primarily based on fuzzy rules and fuzzy arithmetic. Let us look at the processing of fuzzy inference system with an example. To make things simple, let us consider a system with only two inputs and one output. Consider the inputs as distance from obstacle in front and automobile at proper lane. Consider the output as steering. The first aspect to be carried out is to divide all inputs and outputs into membership functions. To make things very simple, allow the input distance from obstacle in the front have 3 membership features which are near, a ways and very a long way. The first membership capabilities are Gaussian, whereas the 0.33 is sigmoidal. Further, allow the enter automobile at right lane have simplest two membership capabilities, which might be close to and a ways. Both the membership functions are taken as Gaussian. Let the output steerage have 5 membership capabilities steep left, left, no guidance, right and steep proper. It should be stressed that the real-life systems may have a large quantity of membership capabilities relying upon the complexity. Rule 1: If distance from obstacle in front is near and vehicle at right lane is far, then steering is steep right Rule 2: If distance from obstacle in front is far and vehicle at right lane is far, then steering is right. Precise quantitative analysis is suitable when a high degree of precision is required. However, the challenge of deciding something approximately a pollution event by way of processing a fixed of measurements is via its very nature an uncertain one. The measurements are corrupted via noise, and, extra importantly, the interplay among variables is hard to interpret inside a quantitatively perfect model. The same beginning of the phenomena below study robotically gives rise to uncertainties or ambiguities about its evolution and the importance that play exceptional conditions (e.g. meteorological parameters, automobile traffic, etc.) on the estimation. Although the idealization of causes effects relationships is beneficial aiming to the analytical components of the problems, which also permits to bench mark the algorithms, it is some distance from being a sensible hypothesis. On the alternative hand, the capacity to summarize statistics and to about describe a process performs a critical role in the characterization of complicated phenomena. FISs appear to be very good tool as they preserve the nonlinear conventional approximation property, and they may be able to handle experimental information as well as a priori know-how at the unknown solution, which is expressed by inferential linguistic guidelines in the shape IF±THEN whose antecedents and consequents make use of fuzzy sets rather than crisp numbers. It consist of following components:

1. Fuzzification unit
2. Defuzzification unit
3. Rule base
4. Knowledge base
5. Database

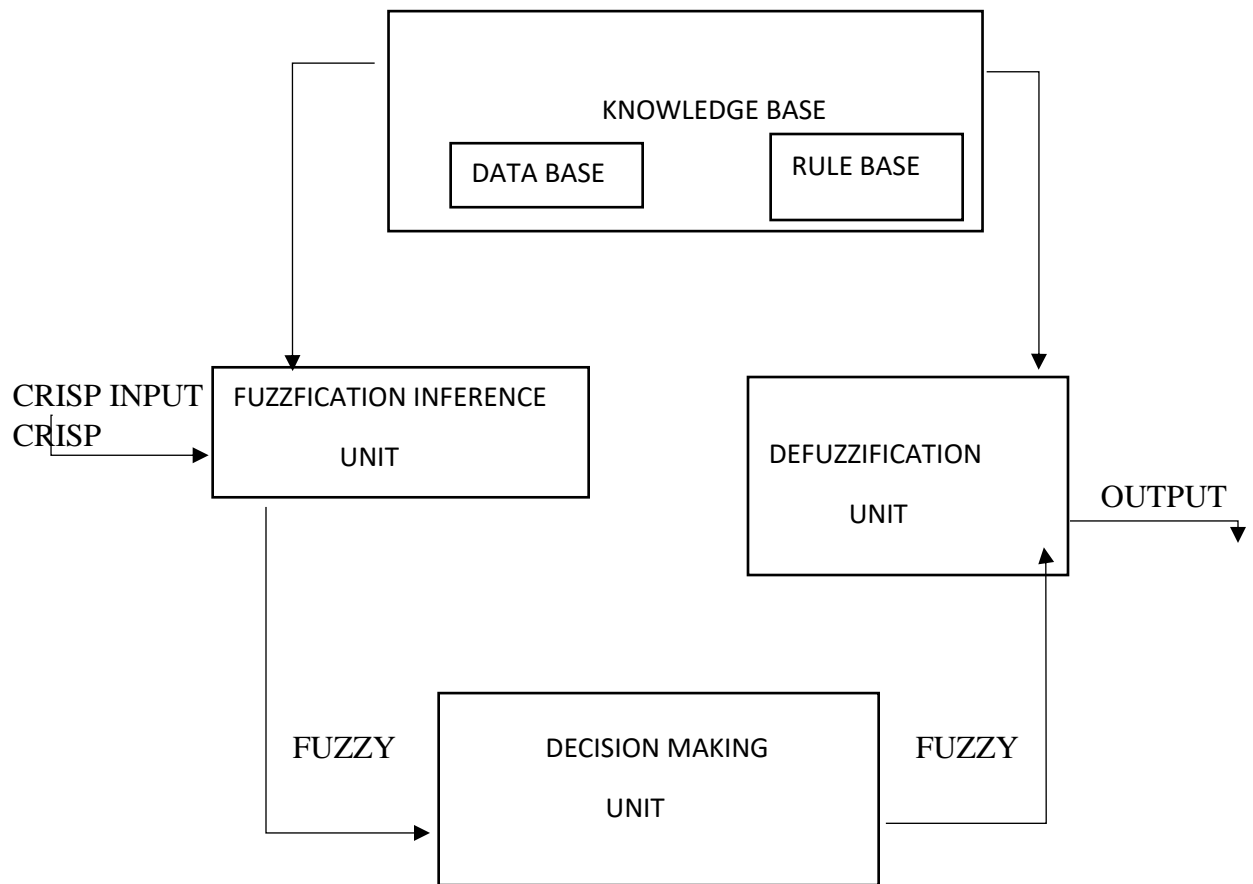


Figure 2.1 Functional blocks of fis

RULE BASE: Rule base contains fuzzy if –then rules and rules are made of antecedent and consequent parts. Premise is made of if part while conclusion is consequent. Rules are made of two main blocks: Antecedent block (It is present between if and then) while consequent is followed by then part.

IF (antecedent) THEN (consequent)

Antecedent and consequent either have single argument or multiple argument. Fuzzy units and fuzzy sets operations are the subjects and verbs of fuzzy logic. If-Then rule statements are used to formulate the conditional statements that contain fuzzy logic. Fuzzy if –then rule are of form

If x is A1 Then y is B2

Wherein A1 and B2 are linguistic variables defined with the aid of fuzzy units on the ranges (i.e. Universe of discourse) X and Y respectively. The If-part of the rule ‘x is A1’ is referred to as the antecedent or premise and the Then-a part of the rule ‘y is B2’ is called the consequent. In other words, the conditional statement may be expressed in a mathematical form

If A1 Then B2 or $A1 \rightarrow B2$

Speed and strain of a steam engine may be expressed with the subsequent linguistic conditional statement

If Speed is Slow Then Pressure have to be high

Rule Forms for any linguistic variables in general, three forms of rule exist .

- Assignment statement

E.g. x is not large AND not very small

- Conditional statement

E.g. IF X is very big THEN Y is medium

- Unconditional statement

E.g. set pressure high

Premise, is made from a number of antecedents that are negated or mixed by one-of-a-kind operators inclusive of AND or OR computed with t -norms or t -conforms. In a fuzzy rule system, some variables are linguistic variables and the dedication of the MF for each fuzzy subset is critical. MFs may be selected consistent with human intuition, or by learning from education data. Fuzzy logic can be used as the idea for inference systems. A fuzzy inference is made from several rules with the same output variables. Given a set of fuzzy rules, the inference end result is a combination of the fuzzy values of the conditions and the corresponding actions. Fuzzy rule-based systems are one of the most important areas of utility of fuzzy units and fuzzy logic. Constituting an extension of classical rule-based totally systems, these had been successfully implemented to a wide range of troubles in different domain names for which uncertainty and vagueness emerge in a couple of ways. In a vast sense, fuzzy rule-based structures are rule-based systems, where fuzzy units and fuzzy logic are used as tools for representing different types of expertise about the problem at hand, in addition to for modeling the interactions and relationships present between its variables. The use of fuzzy statements as one of the main parts of the rules lets in capturing and coping with the ability uncertainty of the represented information. On the opposite hand, thanks to the use of fuzzy logic inference methods have come to be more robust and flexible. A fuzzy system is characterized via a set of linguistic statements based on professional knowledge. The expert knowledge is commonly in the form of "if-then" guidelines, which are easily implemented by means of fuzzy conditional statements in fuzzy logic. The series of fuzzy control regulations that are expressed as fuzzy conditional statements forms the rule base or the rule set of an FLC., we shall observe the following topics related to fuzzy control policies: choice of technique state (input) variables and control (output) variables, source and derivation, justification, forms of fuzzy control regulations, and homes of consistency, interactivity, and completeness.

- A. Choice of Process State Variables and Control Variables of Fuzzy Control Rules: Fuzzy control rules are extra without difficulty formulated in linguistic in place of numerical terms. The proper choice of system state variables and control variables is vital to the characterization of the operation of a fuzzy system. Furthermore, the choice of the linguistic variables has a massive effect on the performance of an FLC. As was said earlier, experience and engineering understanding play an essential role in the course of this selection stage. In particular, the choice of linguistic variables and their membership feature have a robust effect on the linguistic shape of an FLC. Typically, the linguistic variables in an FLC are the state, state error derivative, state mistakes integral, etc.
- B. Source and Derivation of Fuzzy Rules: For derivation of fuzzy control rules there are four rules. These 4 modes are not together exclusive, and it seems probable that a combination of them might be important to construct an effective technique for the derivation of fuzzy control rules. Fuzzy control rules have the shape of fuzzy conditional statements that relate the state variables inside the antecedent and method manage variables within the consequents. In this connection, it have to be cited that in our everyday life maximum of the records on which our selections are based is linguistic in place of numerical in nature. Seen in this perspective, fuzzy control policies provide a natural framework for the characterization of human behavior and choices analysis. Many professionals have located that fuzzy manage guidelines provide a convenient manner to specific their domain knowledge. The formulation of fuzzy control rules can be achieved through two heuristic approaches. The most common one includes an introspective verbalization of human expertise. A typical instance of such verbalization is the operating guide for a cement kiln. Another approach consists of an interrogation of experienced experts or operators using a carefully organized questionnaire. In this manner, we can shape a prototype of fuzzy manipulate rules for a particular utility domain. For optimized performance, the use of reduce and trial procedures is typically a necessity. In many industrial man-system control structures, the input-output relations aren't recognised with sufficient precision to make it viable to classical control idea for modeling and simulation. And yet skilled human operators can control such systems quite effectively without having any quantitative fashions in mind. In effect, a human operator employs-consciously or subconsciously-a fixed of fuzzy if-then regulations to control the process. As turned into pointed out by means of Sugeno, to automate such processes, it's far expedient to specific the operator's control rules as fuzzy if-then rules employing linguistic variables. In the linguistic method, the linguistic description of the dynamic characteristics of a controlled process can be viewed as a fuzzy model of the process. Based at the fuzzy version, we can generate a set of fuzzy control guidelines for attaining optimal performance of a dynamic system. The set of fuzzy control policies forms the guideline base of an FLC. Although this technique is somewhat greater complicated, it yields higher overall performance and reliability, and provides a greater tractable structure for dealing theoretically with the FLC. However, this technique to the design of an FLC has not as but been completely developed.

- C. There are principal processes to the derivation of fuzzy control rules. The first is a heuristic approach in which a set of fuzzy control guidelines is shaped by analyzing the behavior of a controlled process. The control policies are derived in such a way that the deviation from a favored state can be corrected and the control objective can be achieved. The derivation is purely heuristic in nature and is predicated at the qualitative know-how of process conduct.

DATABASE: Database defines membership functions of fuzzy sets. Membership function is used to represent the situation graphically. In fuzzy logic systems, the fuzzy understanding base represents the statistics of the policies and linguistic variables based on the fuzzy set idea so that the knowledge base systems will permit approximate reasoning. It stores the knowledge and understanding about all the input-output fuzzy relationships. It additionally has the membership characteristic which defines the input variables to the fuzzy rule base and the output variables to the plant under control. The decision making unit is the kernel of an FLC; it has the functionality of simulating human decision making based totally on fuzzy ideas and of inferring fuzzy control actions using fuzzy implication and the policies of inference in fuzzy logic.

FUZZIFICATION INFERENCE UNIT: Crisp sets are converted to fuzzy sets by this fuzzification inference unit. On the basis of information stored in the knowledge base fuzzifier converts the crisp input to fuzzy sets. Gaussian, triangular, trapezoidal MFs are most commonly used for fuzzification process. MFs are defined by various parameters. It is the method of converting a crisp amount into a fuzzy quantity. This can be executed by way of identifying the various recognised crisp and deterministic quantities as absolutely nondeterministic and quite uncertain in nature. This uncertainty may additionally have emerged due to vagueness and imprecision which then lead the variables to be represented by a membership characteristic as they membership be fuzzy in nature. Fuzzification is the system of converting a crisp input value to a fuzzy value this is performed by using the information inside the knowledge base. Although various kinds of curves may be seen in literature, Gaussian, triangular, and trapezoidal MFs are the most commonly used in the fuzzification. These styles of MFs can easily be implemented by using embedded controllers. Fuzzification is the first step inside the fuzzy inferencing process. This involves a name transformation where crisp inputs are translated into fuzzy inputs. Crisp inputs are actual inputs measured with the aid of sensors and surpassed into the control system for processing, which includes temperature, pressure, rpm's, etc... Fuzzification is done based totally on the form of the inference engine or the strategy of inference like disjunction rule-primarily based or composition based totally. Fuzzification is the method of converting a clear input to fuzzy input. Fuzzification is the technique of creating a crisp amount fuzzy. We do this through simply recognizing that many of the portions that we keep in mind to be crisp and deterministic are absolutely now not deterministic at all: They carry giant uncertainty. If the form of uncertainty happens to arise because of imprecision, ambiguity, or vagueness, then the variable might be fuzzy and may be represented through a membership function. Fuzzification is the primary step to apply a fuzzy inference system. Most variables exist in the actual real world are crisp or classical variables. One needs to convert the ones crisp variables (both enter

and output) to fuzzy variables, and then apply fuzzy inference to method the ones data to attain the preferred output. Finally, in most cases, the ones fuzzy outputs want to be transformed returned to crisp variables to complete the desired control objectives. Generally, fuzzification involves processes: derive the membership functions for enter and output variables and constitute them with linguistic variables. This method is equal to changing or mapping classical set to fuzzy set to varying degrees. Fuzzification is the first step to use a fuzzy inference system. Most variables present in the actual world are crisp or classical variables. One needs to convert those crisp variables (both input and output) to fuzzy variables, and then practice fuzzy inference to gain the preferred output. Finally, in most cases, those fuzzy outputs want to be converted back to crisp variables to finish the favored control objectives. Generally, fuzzification involves processes: derive the membership functions for input and output variables and constitute them with linguistic variables. This system is equal to changing or mapping classical set to fuzzy set to varying degrees. First segment of fuzzy logic intending is to deliver input parameters for given fuzzy device based on which the output result might be calculated. These parameters are fuzzified with use of pre-described input membership features, which can have extraordinary shapes. The most common are: triangular shape, but bell, trapezoidal, sinusoidal and exponential may be additionally used. Simpler functions are not complex and not require complex computing and will not overload the implementation process. The degree of membership function is decided with the aid of putting a chosen input variable at the horizontal axis, whilst vertical axis indicates quantification of grade of membership of the input variable. The simplest situation a membership function must meet is that it must range between zero and one. The value zero approach that input variable is not a member of the fuzzy set, while the cost one means that input variable is completely a member of the fuzzy set. With every input parameter there is a completely unique membership characteristic is associated. The membership features associate a weighting element with values of every input and the powerful rules. For each active rule these weighting factors determine the degree of influence or degree of membership (DOM). For each active rule we computing the logical product of the membership weights, and a set of fuzzy output response magnitudes are produced. These output responses are defuzzified. Fuzzy logic is a complex mathematical approach that allows solving hard simulated problems with many inputs and output variables. The fuzzification interface includes the following functions:

- a) Measures the values of enter variables,
- b) Plays a scale mapping that transfers the variety of values of input variables into corresponding universes of discourse, plays the feature of fuzzification that converts input records into appropriate linguistic values which can be viewed as labels of fuzzy sets.

Fuzzification is related to the vagueness and imprecision in a natural language. It is a subjective valuation which transforms a measurement right into a valuation of a subjective value, and hence it can be described as a mapping from a located enter area to fuzzy units in certain input universes of discourse. Fuzzification plays a vital role in dealing with uncertain information which might be goal or subjective in nature. In fuzzy manipulate applications, the located statistics are typically crisp. Since the records manipulation in an FLC is based totally on fuzzy

set theory, fuzzification is necessary during an in advance stage. Experience with the design of an FLC suggests the subsequent principal ways of managing fuzzification.

1. A fuzzification operator “conceptually” converts a crisp value into a fuzzy singleton inside a certain universe of discourse. Basically, a fuzzy singleton is a precise value and therefore no fuzziness is introduced by way of fuzzification on this case. This method has been broadly used in fuzzy control packages since it's far natural and clean to implement.
2. Observed statistics are disturbed by means of random noise. In this case, a fuzzification operator must convert the probabilistic information into fuzzy numbers, i.e., fuzzy (possibilistic) information. In this way, computational efficiency is enhanced for the reason that fuzzy numbers are much easier to control than random variables. In an isosceles triangle was selected to be the fuzzification feature. The vertex of this triangle corresponds to the mean value of a statistics set, while the base is twice the standard deviation of the records set. In this way, we form a triangular fuzzy number which is convenient to manipulate. In this connection, it has to be stated a bijective transformation which transforms a possibility degree into a possibility measure with the aid of using the idea of the degree of necessity. Basically, the need of an event, E, is the added chance of elementary events in E over the possibility assigned to the maximum frequent elementary occasion outside of E. Based on the method the histogram of the measured records can be used to estimate the membership characteristic for the transformation of opportunity into possibility.
3. In big scale systems and different applications, some observations regarding the behavior of such system are precise, even as others are measurable only in a statistical sense, and some, noted as “hybrids,” require both probabilistic and possibilistic modes of characterization. The method of fuzzification in this example is to apply the concept of “hybrid numbers” which involve each uncertainty (fuzzy numbers) and randomness (random numbers). The use of hybrid number arithmetic in the design of an FLC indicates a promising direction this is in need of in addition exploration.

DEFUZZIFICATION INFERENCE UNIT: It converts fuzzy sets to crisp sets. This is the final step where single crisp output is produced from fuzzy sets. It is reverse of fuzzification process. There are several methods of defuzzification. Most commonly used defuzzification method is center of area also known as center of gravity in which center of gravity of fuzzy sets are calculated. It is the inversion of fuzzification, there the mapping is done to transform the crisp into fuzzy results but right here the mapping is done to convert the fuzzy results into crisp results. This method is able to generating a nonfuzzy control action which illustrates the possibility distribution of an inferred fuzzy manipulate action. Defuzzification is the inverse system of fuzzification where the mapping is done to convert the fuzzy results into crisp results. Defuzzification is the system of manufacturing a quantifiable result in Crisp logic, given fuzzy sets and corresponding membership degrees. It is normally needed in fuzzy manipulate systems. Defuzzification is the process of convert the set of controller output values into a single pointwise value and plays output renormalization that maps the pointwise cost of the controller

output into its physical domain. The conclusion or manage output derived from the mixture of input, output membership capabilities and fuzzy rules is still a vague or fuzzy element, and this method is called fuzzy inference. To make that conclusion or fuzzy output to be had to real applications, a defuzzification procedure is needed. The defuzzification procedure is supposed to transform the fuzzy output back to the crisp or classical output to the control objective. Remember, the fuzzy end or output remains a linguistic variable, and this linguistic variable desires to be converted to the crisp variable through the defuzzification system. Following functions are performed by defuzzification inference unit :

- a) A scale mapping, which converts the variety of values of output variables into corresponding universes of discourse,
- b) defuzzification, which yields a nonfuzzy manipulate motion from an inferred fuzzy control motion.

2.1 TYPES OF FUZZY INFERENCE SYSTEM

Two types of fuzzy inference systems exist:

1. Mamdani fuzzy inference system
2. Takagi-Sugeno fuzzy inference system

2.1.1 MAMDANI FUZZY INFERENCE SYSTEM: In the rule base consequent part of mamdani fuzzy inference system is fuzzy sets. So output of mamdani is fuzzy sets so we need defuzzification to convert it crisp sets. If A is X1 and B is X2 then C is X3 (X1, X2, X3 are fuzzy sets). It is most commonly used technique. Professor mamdani creates a new type of fuzzy systems to control a steam engine and boiler combination. Fuzzification, rule evaluation, aggregation of rules and defuzzification is steps performed in mamdani type controller. Mamdani rules are easy to understand they are suited to expert systems where rules are created by human expert knowledge eg. Medical diagnosis. Output of each rule is fuzzy in mamdani controllers. Mamdani systems have more interpretable rule bases. Mamdani systems are not computationally efficient. It is having computational burden. Mamdani can be MIMO (multiple input multiple output) and MISO (multiple input single output) systems. Five steps are present in mamdani fuzzy inference system

Step 1: Fuzzify input variables

Step 2: Apply fuzzy operator

Step 3: Apply implication method

Step 4: Apply aggregation method

Step 5: Defuzzification

1 Fuzzify Input Variables: The first step is to transform the crisp numerical values of input variables into the equivalent membership values of the appropriate fuzzy sets through membership functions. No matter what the input variables describe, through the fuzzification

technique the output is usually degree of membership inside the associated fuzzy linguistic sets in the interval between zero and 1.

2. Apply fuzzy operator: When the fuzzy inference machine contains more than one input variable, the antecedent of If-Then rule might continually be defined by a couple of fuzzy linguistic set, due to the fact in most cases every input variable has one corresponding fuzzy set based totally on which to figure out degree of membership.

3. Apply implication method: The consequent a part of If-Then rule is another fuzzy linguistic set defined through an appropriate membership function. Unlike the result from antecedent part of If-Then rule that a single numerical value is generated, the inference method in Then-part is to reshape the fuzzy set of consequent part consistent with the result related to the antecedent, or say the single quantity. This process is called implication method. The AND operation is implemented which truncates the fuzzy set of consequent element. The extent of deformation of the output fuzzy set in each rule must rely on the specific single range coming from the matching antecedent of the rule.

4. Apply aggregation method: After every of the If-Then rules generating a changed fuzzy set as output, the aggregation method is implemented to mix these fuzzy units that constitute the outputs of rules into a single fuzzy set that allows you to make a decision. The final combined fuzzy set is the output of the aggregation process, and every output variable of the fuzzy inference device will have a single matching mixed fuzzy set for reference. Function max, sum, and probabilistic OR are all relevant for aggregation operation, however function max is chosen for all discussion because it's far more sincere and well accepted.

5. Defuzzification: The last step of fuzzy inference technique is defuzzification, via which the combined fuzzy set from aggregation system will output a single scalar quantity. As the name implies, defuzzification is the alternative operation of fuzzification. Since in the first method the crisp values of input variables are fuzzified into degree of membership with respect to fuzzy sets, the ultimate manner extracts a precise quantity out of the variety of fuzzy set to the output variable. Among the numerous defuzzification strategies which have been proposed in the literature, the Centroid Method (also known as middle of vicinity or middle of gravity) that's the most generic and physically appealing of all of the defuzzification techniques.

2.1.2 SUGENO FUZZY INFERENCE SYSTEM: In sugeno rule base consequent part is linear function of input variables. It gives an output that is weighted (linear) or constant expression. If A is X_1 and B is X_2 then C is $aX_1 + bX_2 = c$ (liner expression) (a,b,c are constants). Sugeno fuzzy inference is very much similar to mamdani only the consequent or resultant of rules is linear function in input variables. Sugeno suggested to use fuzzy singleton as membership function of the rules. A fuzzy singleton is a fuzzy set whose membership function is unity at a single particular point and zero everywhere else. Fuzzy singleton is $\mu_A(x) = 1$ at a single particular point. In sugeno fuzzy inference system fuzzification of output is done and then fuzzy operators are also applied. Sugeno systems are computationally efficient and not having defuzzification process. Crisp output is obtained using weighted average of rules consequent parts. They are not very interpretable so used in mathematical analysis. Takagi, Sugeno and Kang developed a

systematic approach for creating fuzzy rules from a given dataset. Sugeno Fuzzy Inference version popularly referred to as TSK model was introduced by Takagi, Sugeno and Kang. Fuzzy Inference Systems (FIS) are based totally on three components particularly rule base, database and reasoning mechanism. The rule base consists of the antecedents and consequents of the subsequent form: If A is antecedent then B is consequent. The database defines the membership feature which represents the degree to which an item belongs to a set. Reasoning uses the antecedent information, the rules and the membership degrees to find the output. It is similar to the Mamdani technique in many aspects. The first two components of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator, are exactly the same. The major distinction between Mamdani and Sugeno is that the Sugeno output membership features are both linear and constant. . A typical rule in a Sugeno fuzzy model has the form:

If Input 1 = x and Input 2 = y, then Output is $z=ax+by+c$

Higher-order Sugeno fuzzy models are possible, however they introduce vast complexity with little obvious merit. Because of the linear dependence of each rule on the enter variables, the Sugeno technique is right for acting as an interpolating manager of a couple of linear controllers which can be to be applied, respectively, to extraordinary operating situations of a dynamic nonlinear system. A Sugeno fuzzy inference machine is extraordinarily well suited to the task of smoothly interpolating the linear gains that would be applied throughout the input space. It is natural and efficient benefit scheduler. Similarly, a Sugeno system is proper for modeling nonlinear systems by means of interpolating between multiple linear fashions.

2.3 MAMDANI VS SUGENO FUZZY INFERENCE SYSTEM

The most primary difference between mamdani type and sugeno type systems is the mode the crisp outcome is generated from fuzzy inputs [3]. Consequent part in mamdani is fuzzy set while of sugeno is linear sum of inputs. The basic difference is regarding the membership function in sugeno it is linear sum of inputs while in mamdani it is fuzzy sets. Their aggregation and defuzzification process is also different. In Sugeno mathematical rules are more in comparison to mamdani fuzzy inference system. Mamdani controller has less adjustable parameters as sugeno controllers. Sugeno controllers are computationally efficient and well suited in mathematical analysis. Mamdani and Sugeno systems describes antecedents parts by fuzzy linguistic variables while consequent part of mamdani system is described by linguistic variable while sugeno systems is drescribed by linear combination of input variables.

2.4 TERMINOLOGIES

2.4.1 LINGUISTIC VARIABLE: A variable whose value is words or sentences in artificial or natural language called linguistic variable. Truth is a linguistic variable can value true, very true, absolute true, not very true, untrue etc. Linguistic variable is quintuple which is characterized by (L, T (L), U, G, M) where L is name of variable, T (L) is term set which is collection of linguistic values, U is universe of discourse, G is syntactic rule, M is semantic rule. Fuzzy logic is concerned with imprecise terms these terms are called fuzzy or linguistic variables. It is important concept in fuzzy set theory. Values of linguistic variables is linguistic values. Eg. Temperature is hot then linguistic variable temperature takes linguistic value hot. Linguistic variables values represents the variables universe of discourse. If age is a linguistic variable then term set T (L) is sum of linguistic values.

T (age) = young + old + not young + very young.....

Linguistic variables constitute crisp facts in a form and precision suitable for the problem. For example, to reply the question "What is it like outside?" one might observe "It is heat outside." Experience has shown that if it is "warm" and the time is mid-day, a jacket is unnecessary, but if it's far heat and early evening, it might be smart to take a jacket along (the day will change from warm to cool). The linguistic variables like "warm", so commonplace in everyday speech, convey records approximately our environment or an object under observation. We will display how linguistic variables may be described and used in a selection of not unusual packages, which include home surroundings control, product pricing, and procedure control. The use of linguistic variables in many packages reduces the general computation complexity of the application. Linguistic variables have been shown to be particularly beneficial in complicated non-linear programs. Linguistic variables are central to fuzzy logic manipulations, but are often omitted in the debates on the merits of fuzzy logic.

Linguistic hedge: Linguistic hedges modifies the meaning of shapes of fuzzy sets. It can modify shapes of membership functions by suppressing it. Hedges includes adverbs and modify the shape of fuzzy sets. Adverbs are such, very, somewhat, quite, more, slightly. Linguistic variable with fuzzy qualifiers is called linguistic hedges. Advantage of using linguistic hedges is

1. It use simple shaped membership function.
2. Less number of rules of inference.
3. Rules are independent of experts.

Representation of hedges in fuzzy logic:

Hedge	Mathematical Expression
A little	$[\mu_A(x)]^{1.3}$
Slightly	$[\mu_A(x)]^{1.7}$
Very	$[\mu_A(x)]^2$
Extremely	$[\mu_A(x)]^3$
Very very	$[\mu_A(x)]^4$

Table 2.1 Representation of linguistic hedges

2.4.2 MEMBERSHIP FUNCTION: Membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1[4]. A membership function for a fuzzy set A on universe of discourse X is defined as:

$$\mu_A: X [0, 1] \quad (2.1)$$

Where X is mapped between 0 and 1. This value is called membership value or degree of membership. Membership value defines the value of membership of each element in X. Membership function is graphically representing a fuzzy set. X axis represents universe of discourse while Y axis represents membership degree in interval [0, 1]. In fuzzy concepts using complex functions to define a membership doesn't give precision so simple functions are used to build membership functions. Fuzzy logic systems are widely used for control, device identification, pattern recognition problems, and plenty of greater applications from industry to academia. The membership functions (MFs) play an essential role within the overall performance of fuzzy representation. The MFs are the building blocks of fuzzy set theory, that is, fuzziness in a fuzzy set is determined through its MF. Accordingly, the shapes of MFs are vital for a particular trouble on the effect on a fuzzy inference system. They may additionally have one-of-a-kind shapes which includes triangular, trapezoidal, Gaussian, and so forth. The handiest condition a MF should simply satisfy is that it must range between zero and 1. The MFs may be of any form and shape as long as because it maps the given facts with suitable degree of memberships. As a long way as choice of MFs is concerned, it is up to us to decide. This is in which fuzzy system offers individual degree of freedom. With experience, one will come to recognize which shape of MF is good for the application below consideration. There are infinite number of ways to graphically depict the MFs that describe this fuzziness as there are infinite number of ways to characterize fuzziness. The preference of which of the strategies to use depends entirely on the problem size and trouble type. Instead of selecting the shape of MF, setting the interval and wide variety of MFs also are very important. For instance, to version a temperature control gadget by way of fuzzy logic, it is certainly vital to know what number of MFs are needed (e.g., low, med, and excessive MF) and additionally selecting the durations of MFs. These two elements also have an amazing effect on the outcome of a fuzzy logic system. In addition, looking on the distribution of the records is a good idea. Although, trial and error technique is often used for MF shape, because there is no exact approach for selecting the MFs. The form of MFs depends on how one believes in a given linguistic variable. It is more a question of intuition than criteria. The only situation a MF ought to definitely fulfill is that it have to vary between zero and 1. The characteristic itself can be an arbitrary curve whose shape we will outline as a feature that suits us from the factor of view of simplicity, convenience,

speed, and efficiency. Therefore, the kind of MF does not play an important role in shaping how the model performs. Membership functions signify fuzziness (i.e., all the statistics in fuzzy set), whether the elements in fuzzy units are discrete or continuous. Membership functions may be defined as a technique to resolve practical problems via experience in preference to knowledge. Membership functions are represented through graphical forms. Rules for defining fuzziness are fuzzy too. Membership functions characterize the fuzziness in a fuzzy set, whether the elements inside the set are discrete or continuous, in a graphical shape for eventual use within the mathematical formalisms of fuzzy set theory. But the shapes used to describe the fuzziness have only a few regulations indeed. Nevertheless, as with any formal mathematical structure, some fashionable terms associated with the shape of membership functions have developed over the years, and these terms are defined here. Just as there are an endless quantity of methods to signify fuzziness, there are an endless variety of approaches to graphically depict the membership features which describe fuzziness. Since the membership function essentially embodies all fuzziness for a selected fuzzy set, its description is the essence of a fuzzy property or operation. Because of the importance of the membership function's "shape" a fantastic deal of attention currently has been targeted on development of these capabilities. This describes best a completely small range of possibilities for these membership features. Since all information contained in a fuzzy set is defined with the aid of its membership function, it's far beneficial to expand a lexicon of terms to describe numerous special capabilities of this function. For functions of simplicity, the functions shown in the following figures will all be continuous, however the terms apply equally for both continuous and discrete fuzzy sets. There are in many ways to assign membership values or features to fuzzy variables as there are to assign probability density features to random variables. This assignment process can be intuitive or it may be based on some algorithmic or logical operations. The list underneath provides some of the methods described inside the literature to assign membership value or capabilities to fuzzy variables

- Intuition
- Inference
- Rank-Ordering
- Angular Fuzzy Sets
- Neural Networks
- Genetic Algorithms

This approach desires little or no introduction. It is truly derived from the potential of humans to broaden membership functions through their own innate intelligence and understanding. Intuition entails contextual and semantic knowledge about an issue; it can also contain linguistic fact values approximately this information. An automatic generation of membership functions also can be accommodated by using the crucial function of inductive reasoning, which derives a general consensus from the particular (derives the regular from the specific). The induction is completed by the entropy minimization principle, which clusters most optimally the parameters corresponding to the output classes. This method is based on an ideal scheme that describes the input and output relationships for a well-established statistics base, i.e., the approach generates membership capabilities based totally completely on the information provided. The technique

can be pretty useful for complicated systems in which the facts is plentiful and static. In situations where the statistics is dynamic, the approach might not be beneficial, considering that the membership features will constantly trade with time. To subdivide our information set into membership functions we need some method to establish fuzzy thresholds between lessons of records. We can determine a threshold line with an entropy minimization screening method, then begin the segmentation method first into two classes. By partitioning the primary two classes one greater time, we are able to have 3 specific classes. Therefore, a repeated partitioning with threshold value calculations will permit us to partition the statistics set into a number of classes, or fuzzy sets, relying on the shape used to describe membership in each set. The membership characteristic is a graphical illustration of the magnitude of participation of every input. It associates a weighting with every of the inputs which might be processed, define practical overlap between inputs, and in the long run determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output units of the very last output conclusion. Once the capabilities are inferred, scaled, and combined, they may be defuzzified into a crisp output which drives the system. There are exceptional membership capabilities associated with each input and output response. The most frequently used function and the most practical is the triangular membership function, inspite of it other shapes are also used. One is the trapezoid which contains more information than the triangle. A fuzzy set can also be represented by a quadratic equation (involving squares, n^2 , or numbers to the second power) to produce a continuous curve. Three additional shapes which are named for their appearance are: the S-function, the pi-function, and the Zfunction.

TYPES OF MEMBERSHIP FUNCTION: Most commonly used membership function are triangular, gaussian, and trapezoidal

1. Triangular function: defined by lower and upper limits a and b and a value m where $a < m < b$

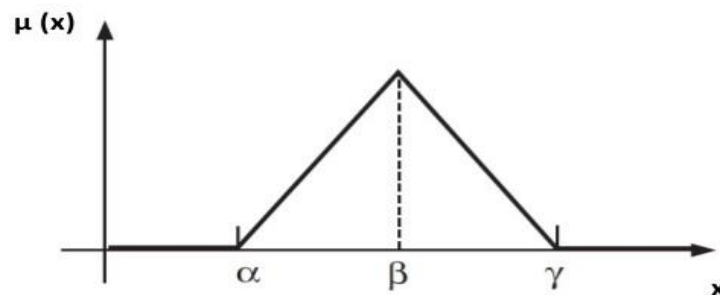


Figure 2.2 Triangular membership function

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{m-a}, & a < x \leq m \\ \frac{b-x}{b-m}, & m < x < b \\ 0, & x \geq b \end{cases}$$

(2.2)

Trapezoidal function: defined by lower limit, upper limit, lower support limit and upper support limit a, d, b and c where $a < b < c < d$

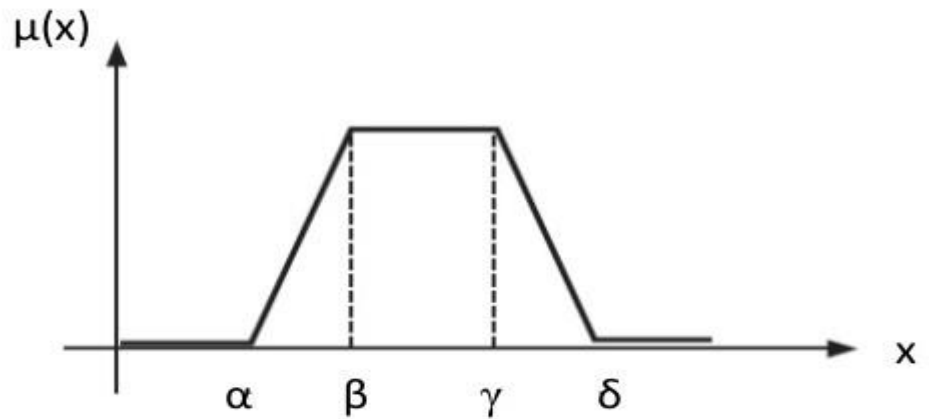


Figure 2.3 Trapezoidal membership function

$$\mu_A(x) = \begin{cases} 0, & (x < a) \text{ or } (x > d) \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c \leq x \leq d \end{cases}$$

(2.5)

Gaussian function: defined by standard deviation $K>0$ and central value m . Smaller value of K results in narrower bell.

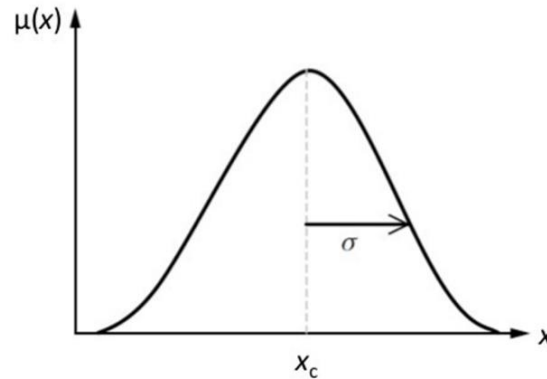


Figure 2.4 Gussian membership function

$$\mu_A(x) = e^{-\frac{(x-m)^2}{2k^2}}$$

(2.6)

Features of membership function:

Core: All the elements of universe of discourse X for a fuzzy set A for which there is complete or full membership degree of element is defined as core of membership function. It can be defined as

$$\mu_A(x) = 1 \quad (2.7)$$

Support: All the elements of universe of discourse X for a fuzzy set A for which there is nonzero membership value or degree is defined as support of membership function. It is defined as

$$\mu_A(x) = 0 \quad (2.8)$$

Boundary: All the elements of universe of discourse X for a fuzzy set A for which not complete membership value is defined as boundary of membership function. It is defined as

$$\mu_A(x) \in (0, 1) \quad (2.9)$$

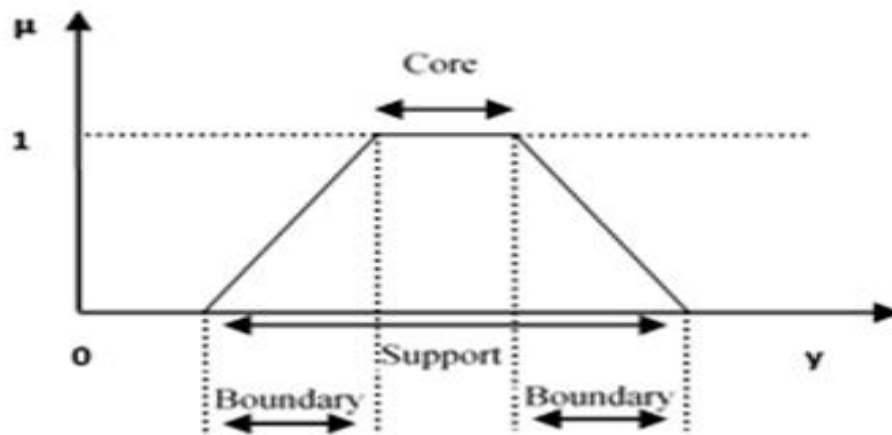


Figure 2.5 Features of membership function

Universe of discourse: For a fuzzy set A we have $A = \{(x, \mu_A(x)) \mid x \in X\}$ X is referred to as universe of discourse and $\mu_A(x)$ is called membership function of fuzzy set A . Membership function is a function such that it associates each $x \in X$ to a value between $[0,1]$.

CHAPTER 3

FUZZY SETS AND CRISP SETS

Fuzzy set theory and crisp theory are based on two different theories. Fuzzy set is multivalued logic while crisp is a bivalued logic. Initially expert system applications were based on Boolean logic where crisp sets either true or false were used. Human questioning doesn't always follow crisp sets which is yes or no. That gives rise to fuzzy set theory which was based on human thinking.

Crisp set definition: Crisp set is collection of different objects having some common properties such as countability and finiteness. A crisp set A over a universe of discourse U is defined as group of elements where each element either belong to the set or doesn't belong to the set A. There are two possible ways in crisp sets an element belong to the set or don't belong to the set A. Crisp set A containing the group of elements over universe of discourse U having some property P is defined as:

$$A(x: x \in U \text{ and } x \text{ has same property } P) \quad (3.1)$$

It exhibit properties commutativity, distributivity, associativity, identity, transitivity, involution and idempotancy etc. operations on crisp sets are union, intersection, compliment and difference. Crisp logic is a traditional logic which does not interpret the imprecise data. It is based on probability theory and classical logic

Fuzzy sets: In fuzzy sets elements having varying degree of membership. Fuzzy means unclear or vague. Limits of fuzzy set is vague and impression. Fuzzy is infinite valued logic. A fuzzy set is denoted by tilde sign over a text. Each and every element has changing degree of membership function. It was proposed by Lotfi Zadeh in 1965 and after that lots of theoretical development has been done in this field. It provide a mathematical method to deal with uncertainties related to human reasoning and can also handle the uncertainties.

Difference:

1. Fuzzy set is defined by intermediate boundaries. These boundaries are uncertain in fuzzy logic. Crisp set is defined by crisp boundaries and these boundaries are certain or precise in crisp sets.
2. Fuzzy sets elements have gradual membership degree while crisp sets can have total or not membership degree.
3. Development of efficient expert system is motive of fuzzy and crisp sets. There are several applications of crisp and fuzzy sets.
4. Fuzzy set theory is infinite-valued while crisp set theory is bi-valued.
5. Fuzzy is used in fuzzy controllers and crisp is used in digital design applications.

6. Elements in fuzzy are allowed to have a partial membership while in crisp element is either member of set or not member of sets.

7. Fuzzy is based on imprecise or vague properties. Crisp sets are defined by precise and certain properties.

3.1 CRISP SET PROPERTIES

Set theory is one of important concept in mathematics. A crisp set is well defined collection of objects with 0 and 1 membership degree of elements. A crisp logic is based on Boolean algebra having true or false two answers. Some properties of crisp logic are

Commutativity: $(A \cup B) = (B \cup A)$

$$(A \cap B) = (B \cap A)$$

Associativity: $(A \cup B) \cup C = A \cup (B \cup C)$

$$(A \cap B) \cap C = A \cap (B \cap C)$$

Distributivity: $A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$$

Idempotent:

$$A \cup A = A$$

$$A \cap A = A$$

Identity:

$$A \cup \Phi = A \Rightarrow A \cup E = E$$

$$A \cap \Phi = \Phi \Rightarrow A \cap E = A$$

Here Φ is empty set and E is universal set or universe of discourse.

Law of absorption: If A is subset of B

$$A \cup (A \cap B) = A$$

$$A \cap (A \cup B) = A$$

Transitivity:

$$\text{If } A \subseteq B, B \subseteq C, \text{ then } A \subseteq C$$

Involution law: $(A^c)^c = A$

Law of excluded middle: $(A \cup A^c) = E$

Law of contradiction: $(A \cap A^c) = \Phi$

De Morgans law: $(A \cup B)^c = A^c \cap B^c$

$$(A \cap B)^c = A^c \cup B^c$$

3.2 OPERATIONS ON CRISP SETS

Union: If A and B are two sets then their union is denoted by $A \cup B$ and defined the sum of all the elements of set A and set B.

Intersection: If A and B are two crisp sets then their intersection is denoted by $A \cap B$ and defined by all the common elements in A and B.

Difference: Difference of two sets A-B is all those elements present in A but not in B

3.3 FUZZY SET OPERATIONS

A fuzzy set operation is generalization of operations performed on crisp sets. Fuzzy set operations are performed at fuzzy sets. The most widely used fuzzy operations union, intersection and complement are called standard fuzzy operations. \tilde{A} And \tilde{B} are two fuzzy sets and $\mu_A(x)$ and $\mu_B(x)$ are their respective membership functions and X is the universe of discourse and x an element of universe then operations performed on fuzzy sets are as follows:

1. Union
2. Intersection
3. Complement

Union: $\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x))$

Intersection: $\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x))$

Complement: $\mu_{\tilde{A}}(x) = 1 - \mu_A(x)$

Other important fuzzy operations:

1. Bounded sum of two fuzzy sets
2. Bounded difference of two fuzzy sets
3. Concentration of two fuzzy sets

Bounded sum of two fuzzy sets: If A and B are two fuzzy subsets of universe of discourse X then bounded sum is denoted by $A \oplus B$ is

$$\mu_{A \oplus B}(x) = \min(1, \mu_A(x) + \mu_B(x))$$

Bounded difference of two fuzzy sets: If A and B are two fuzzy subsets of universe of discourse X then bounded difference is denoted by $A \ominus B$

$$\mu_{A \in B}(x) = \max(0, (\mu_A(x) - \mu_B(x)))$$

Concentration of two fuzzy sets: It is denoted by A^2 and defined by

$$\mu_{A^2}(x) = \mu_A(x)^2/x$$

Dilation of two fuzzy sets: It is denoted by $A^{1/2}$ and defined by

$$\mu_{A^{1/2}}(x)/x = (\mu_A(x))^{1/2}/x$$

3.4 FUZZY SET PROPERTIES

Basic properties of fuzzy sets: The basic properties of fuzzy sets are commutativity, associativity, distributivity, idempotent, identity, transitivity. Law of excluded middle and law of contradiction doesn't hold as fuzzy sets can overlap.

Commutativity: $A \cup B = B \cup A$

$$A \cap B = B \cap A$$

Associativity: $(A \cup B) \cup C = A \cup (B \cup C)$

$$(A \cap B) \cap C = A \cap (B \cap C)$$

Distributivity: $A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$

$$A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$$

Idempotent: $A \cup A = A$

$$A \cap A = A$$

Identity: $A \cup \Phi = A \Rightarrow A \cup X = X$

$$A \cap \Phi = \Phi \Rightarrow A \cap X = A$$

Transitivity: $A \subseteq B, B \subseteq C$ then $A \subseteq C$

Involution: $(A^c)^c = A$

Other important properties of fuzzy sets:

Properties	
1.	Equality of two fuzzy sets
2.	Subset of fuzzy sets
3.	Cardinality of a fuzzy set
4.	An empty fuzzy set
5.	α cuts of a fuzzy sets

Table 3.1 Properties of fuzzy sets

Equality of two fuzzy sets: Two fuzzy sets A and B are said to be equal if and only if

$$\mu_A(x) = \mu_B(x)$$

Subset of a fuzzy set: Fuzzy set A is called included in fuzzy set B or subset of fuzzy set B if and only if

$$\mu_A(x) \leq \mu_B(x) \quad \forall x \in X$$

Cardinality of a fuzzy set: Cardinality of fuzzy set A so called sigma count is the sum of value of membership functions of A

$$\text{Card } A = \mu_A(x_1) + \mu_A(x_2) + \dots + \mu_A(x_n)$$

An empty fuzzy sets: A fuzzy set A is empty if and only if

$$\mu_A(x) = 0 \quad \forall x \in X$$

α - Cuts of fuzzy sets: α -cuts of fuzzy set $A \subset X$ is ordinary set $A_\alpha \subset X$ such that

$$A_\alpha = \{x \in X; \mu_A(x) \geq \alpha\} \quad 0 \leq \alpha \leq 1$$

3.5 FUZZIFICATION PROCESS IN FUZZY LOGIC

Fuzzification is a process to convert the crisp values to linguistic variables. Process of transforming crisp set to fuzzy sets is known as fuzzification. By using the information stored in knowledge base we convert crisp input value to fuzzy value. Gaussian, triangular, and trapezoidal MFs are most commonly used in fuzzification process. Fuzzy controllers can easily implement these types of membership functions. By choosing suitable membership function fuzzification begins. It is the first step in fuzzy inference system. Crisp inputs are temperature, pressure etc. is exact inputs measured by the sensors and passed to control systems to perform processing. Fuzzification translates precise quantity to fuzzy quantity.

METHODS OF FUZZIFICATION: There are two important methods of fuzzification:

1. Support fuzzification method
2. Grade fuzzification method

Support fuzzification method: In support fuzzification fuzzified set is represented by following equation

$$\tilde{A} = \mu_1 Q(x_1) + \dots + \mu_n Q(x_n) \tag{3.2}$$

$Q(x_i)$ is a fuzzy set which is called kernel of fuzzification. μ_i is kept constant while varying the x_i to fuzzy set $Q(x_i)$.

Grade fuzzification method: This method is similar to support fuzzification method the difference is x_i is kept constant while varying the μ_i to fuzzy sets.

3.6 DEFUZZIFICATION OF FUZZY SETS

Defuzzification is the process to convert fuzzy sets or fuzzy members to crisp sets or crisp members. In many applications it is necessary to defuzzify the fuzzy results to obtain the crisp results. Process of defuzzification is also called rounding off. Given the fuzzy sets and corresponding membership degrees defuzzification process produces quantifiable results. Process to map fuzzy sets to crisp sets is defuzzification. IT is needed in control systems. It is the process of obtaining the single number from the aggregated fuzzy sets. It selects or choose the correct value from the given fuzzy sets. In fuzzy systems internal data is represented by fuzzy sets but the output should be a crisp value. Based on fuzzy sets based crisp value is selected. Defuzzification is also called rounding off because where fuzzy sets having different values of membership is reduced to single scalar quantity. From an application point of view the following features are important defuzzification end result continuity, computational efficiency, design suitability, and compatibility with fuzzy system. Under defuzzification result continuity is considered the following function: small modifications in membership values of the output fuzzy set should no longer deliver huge changes inside the consequences of defuzzification. This feature is crucial inside the case of fuzzy controllers, which require input-output continuity: small changes of input parameters should supply small modifications of output values. Computational performance depends totally on a kind and some of operations required for acquiring the result of defuzzification. Design suitability expresses the effect of a defuzzification method on a software program or hardware implementation and tuning of fuzzy system. Compatibility to the other operations used in a fuzzy system, like inference and composition, may additionally be important.

Methods of defuzzification

1. Max membership principle
2. Centroid method
3. Weighted average method
4. Mean-max membership
5. Center of sums
6. Center of largest area

Max membership function: This method is confined to the peak output and this method is also known as height method or max height method. This method is given by

$$\mu(z^*) \geq \mu(z) \text{ for all } z \in Z \quad (3.3)$$

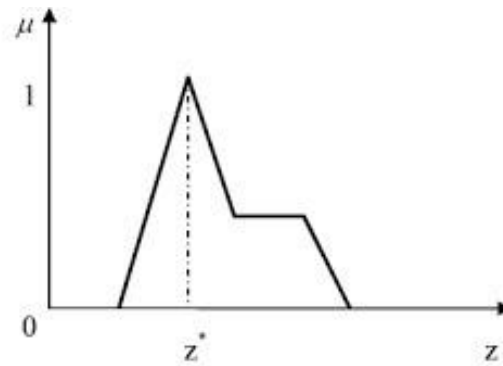


Figure 3.1 Max membership function

Centroid method: This method is also known as center of mass, center of area, center of gravity .It is one of the easiest and most commonly used method. The defuzzified value is represented as

$$z^* = \frac{\int \mu(z).zdz}{\int \mu(z)dz} \quad (3.4)$$

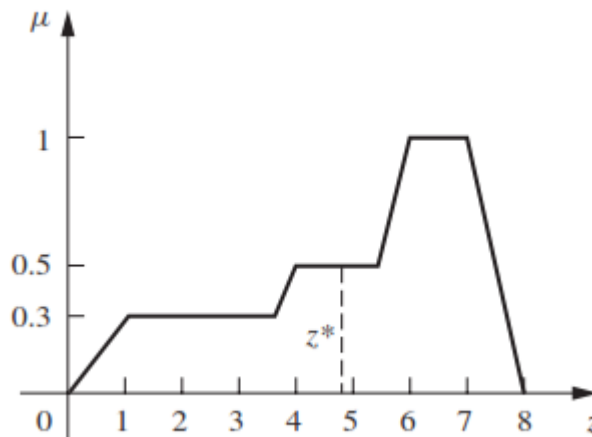


Figure 3.2 Centriod method

Weighted average method: this method is used to calculate symmetrical output membership function. Maximum membership value is used for weighing of membership function. Defuzzified Output is given as

$$z^* = \frac{\sum \mu(z').z'}{\sum \mu(z')} \quad (3.5)$$

; where z' is the maximum value of the membership function.

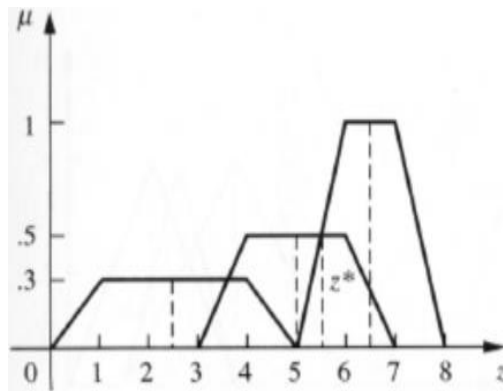


Figure 3.3 Weighted average method

Mean-max membership: IT is also called as middle of maxima. This is closely related to max-membership method. The difference between max membership method and mean-max membership method is that the locations of maximum membership can be not unique. Output here is given by

$$z^* = \sum z' / n \quad (3.6)$$

where z' is the maximum value of the membership function.

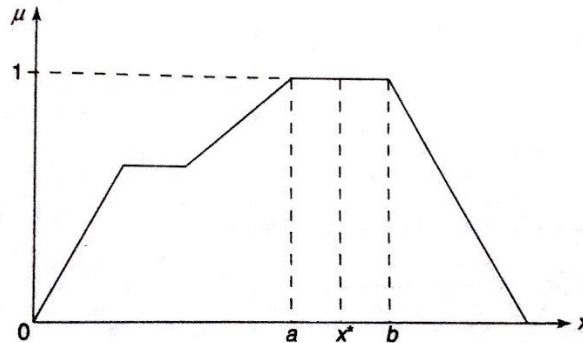


Figure 3.4 Mean –max membership

Center of sums: Instead of union of fuzzy subsets algebraic sum of individual fuzzy sets are calculated in this method. These calculations are very fast, but the drawback is that the intersecting sections are added twice. The defuzzified value z^* is given by

$$z^* = \int z^* \sum \mu(z) \cdot z dz / \int \sum \mu(z) dz \quad (3.7)$$

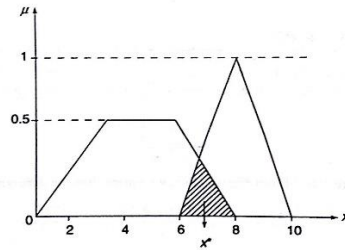


Figure 3.5 Center of sums

Center of largest area: When the output of at least two convex fuzzy subsets are not overlapping then this method is used. In this case the output is biased towards a side of one membership function. The center of gravity of the convex fuzzy subregion having the largest area is used to obtain the defuzzified value z^* when output fuzzy sets has atleast two convex regions. The value is given by

$$z^* = \frac{\int \mu_c(z).zdz}{\int \sum \mu_c(z)dz} \quad (3.8)$$

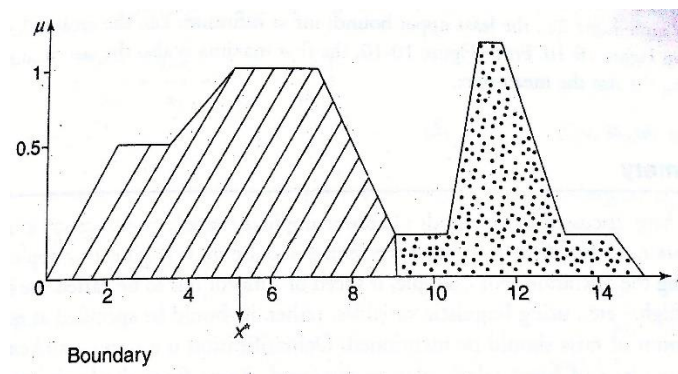


Figure 3.6 Center of largest area

Difference between fuzzification and defuzzification

1. Fuzzification precise or definite data is converted to imprecise or fuzzy data while in defuzzification indefinite or imprecise data is converted to the precise or crisp data.
2. Fuzzification is getting fuzzy results from crisp results whereas defuzzification is inverse of it.
3. Fuzzification is quite simple whereas defuzzification is difficult as comparison to fuzzification.
4. Fuzzification uses if then rules to obtain the fuzzy sets. Defuzzification uses center of gravity methods to obtain the centroid of the sets.
5. Methods of fuzzification are support and grade fuzzification and methods of defuzzification are center of gravity, center of largest area, center of sums, max membership function etc.

6. Fuzzification example are voltmeter and defuzzification example are stepper motor.

3.7 ADVANTAGE OF FUZZY LOGIC

- Fuzzy logic describes systems in terms of aggregate of numeric and linguistic (symbolic). This has benefits over pure mathematical (numerical) approaches or pure symbolic approaches because very often system information is available in these combination.
- The logic measures the certainty or uncertainty of membership of element of the set. Analogously the person makes decision throughout the intellectual and physical activities. The solution of certain case is determined at the principle of policies that had been defined by using fuzzy logics for comparable instances.
- Fuzzy algorithms are regularly robust, in the sense that they're no longer very sensitive to converting environments and inaccurate or forgotten guidelines.
- The reasoning procedure is regularly simple, in comparison to computationally precise systems, so computing energy is stored. This is a totally exciting feature, mainly in actual time systems.
- Fuzzy methods usually have a shorter development time than traditional methods.
- A Fuzzy Logic System is flexible and permit modification inside the rules.
- Even imprecise, distorted and error input information is likewise accepted by using the system.
- The systems may be easily constructed.
- Since those systems involve human reasoning and choice making, they are beneficial in providing answers to complicated answers in different forms of applications
- The shape of Fuzzy Logic Systems is straightforward and understandable
- Fuzzy logic is widely used for commercial and sensible purposes
- It lets you manipulate machines and consumer products
- It may not offer accurate reasoning, however the handiest ideal reasoning
- It lets you deal with the uncertainty in engineering
- Mostly flexible as no precise inputs required
- It can be programmed to in the situation when feedback sensor stops working
- It can without problems be modified to improve or alter device performance
- Less expensive sensors may be used which lets you hold the overall gadget cost and complexity low.
- It provides a handiest solution to complex issues
- It is a robust system where no unique inputs are required
- These structures are capable of accommodate several varieties of inputs which include vague, distorted or vague data
- In case the feedback sensor stops working, you may reprogram it in line with the situation
- The Fuzzy Logic algorithms can be coded using much less data, in order that they do no longer occupy a huge memory space

- As it resembles human reasoning, these structures are able to solve complicated troubles where ambiguous inputs are to be had and take decisions accordingly
- These systems are flexible and the rules may be modified
- The structures have a simple shape and may be built easily
- You can save gadget fees as cheaper sensors may be accommodated by using these structures.
- Cheaper – Developing a FLC is comparatively inexpensive than growing model based totally or other controller in terms of performance.
- Robust – FLCs are extra robust than PID controllers due to their capability to deal big variety of operating conditions.
- Emulate human deductive thinking – Basically FLC is designed to emulate human deductive thinking, the technique human beings use to deduce conclusion from what they know.
- Reliability – FLC is extra dependable than traditional control system.
- Efficiency – Fuzzy good judgment provides more efficiency while applied on top of things system.

3.8 DISADVANTAGE OF FUZZY LOGIC

- Fuzzy good judgment isn't constantly accurate, so the results are perceived based totally on assumption, so it is able to not be broadly accepted.
- Fuzzy systems don't have the functionality of system gaining knowledge of as-well-as neural network kind sample recognition.
- Validation and Verification of a fuzzy knowledge-based system needs substantial trying out with hardware.
- Setting exact, fuzzy policies and, membership features is a tough task.
- Some fuzzy time logic is confused with possibility concept and the terms.
- The regulations of mixing membership functions mentioned above are referred to as the minmax rule for conjunctive (AND) and disjunctive (OR) reasoning. These rules have a chief drawback: They aren't robust at all. If we attempt to mimic the manner human beings reason, the minmax rule is definitely not the way.
- Many researchers have proposed different rules of combining conjunctive or disjunctive clauses: for example, in preference to taking the minimal or the maximum of the membership functions, they take the mathematics or the geometric mean. These rules are arbitrary, and there are masses of them. It is feasible, if we have enough schooling data, i.e. situations and class assignments by way of the experts, to educate our device in order that it chooses the first-rate rule that fits the manner of reasoning of the expert that did the classification.
- Another drawback of the rules discussed earlier is that they give the same significance to all factors that are to be combined. For example, it's miles viable that the function of soil depth or rock permeability isn't always of the equal importance to soil erosion as the

position of slope. This issue can be resolved if we do no longer insist on all membership features taking values between zero and 1.

- It is tedious to develop fuzzy rules and membership features and fuzzy outputs can be interpreted in some of approaches making analysis hard. In addition, it require for lot of facts and expertise to develop a fuzzy system. It does now not give generalizable effects and the program needs to be run for each individual patient. Therefore, its scientific applicability and utilization is hard without the supply of preprogrammed software's for special pathologies and the basic training of clinicians to use these programs.
- The accuracy of those systems is compromised as the device mainly works on inaccurate facts and inputs.
- There is no single systematic approach to solve a trouble with the usage of Fuzzy Logic. As a result, many solutions rise up for a particular problem, leading to confusion.
- Due to inaccuracy in results, they're not widely accepted.
- A major disadvantage of Fuzzy Logic manage systems is that they're completely dependent on human knowledge and expertise.
- You need to frequently replace the rules of a Fuzzy Logic control systems.
- These systems cannot recognize machine learning or neural networks.
- The structures require plenty of checking out for validation and verification.
- FLC needs lots of data to be applied.
- FLC is not beneficial for programs a great deal smaller or large than historical facts.
- This is one drawback as the accuracy of the machine relies upon on the know-how and knowledge of human beings.
- The rules have to be up to date with time.

3.9 Applications of fuzzy logic

- Aerospace: In aerospace, fuzzy logicis used inside the following areas

Altitude manage of spacecraft

Satellite altitude manipulate

Flow and aggregate law in aircraft deicing vehicles

- Automotive: In automotive, fuzzy logic is used within the following areas

Trainable fuzzy structures for idle speed manipulate

Shift scheduling technique for automated transmission

Intelligent toll road structures

Traffic manipulate

Improving performance of automated transmissions

- Business: In the following areas in business, fuzzy logic is used –
Decision-making help structures
Personnel evaluation in a huge company
- Defense: In defense, fuzzy common sense is used within the following areas –

Underwater target popularity

Automatic target reputation of thermal infrared images

Naval selection aid aids

Control of a hypervelocity interceptor

Fuzzy set modeling of NATO selection making

- Electronics: In electronics, fuzzy good judgment is used inside the following areas

Control of automatic publicity in video cameras

Humidity in a clean room

Air conditioning structures

Washing machine timing

Microwave ovens

Vacuum cleaners

- Finance: In the finance field, fuzzy logic is used within the following areas
Banknote transfer manipulate
Fund management
Stock marketplace predictions

- Industrial Sector: In industrial, fuzzy common sense is used in following areas

Cement kiln controls heat exchanger manipulate

Activated sludge wastewater treatment method manipulate

Water purification plant manage

Quantitative pattern analysis for industrial first-rate assurance

Control of constraint satisfaction issues in structural design

Control of water purification plants

- Manufacturing: In the producing industry, fuzzy logic is used in following areas

Optimization of cheese production

Optimization of milk production

- Marine: In the marine field, fuzzy good judgment is used in the following area

Autopilot for ships

Optimal route selection

Control of self-sufficient underwater vehicles

Ship steering

- Medical :In the scientific field, fuzzy logic is used within the following areas
Medical diagnostic assist system
Control of arterial pressure throughout anesthesia
Multivariable manage of anesthesia
Modeling of neuropathological findings in Alzheimer's patients
Radiology diagnoses
Fuzzy inference prognosis of diabetes and prostate cancer
- Securities: In securities, fuzzy good judgment is used in following areas
Decision structures for securities trading
Various security appliances
- Transportation: In transportation, fuzzy good judgment is used inside the following areas

Automatic underground train operation

Train schedule manipulate

Railway acceleration

Braking and stopping

- Pattern Recognition and Classification: In Pattern Recognition and Classification, fuzzy logic is used inside the following areas –
Fuzzy logic primarily based speech recognition
Fuzzy common sense based
Handwriting popularity
Fuzzy good judgment primarily based facial feature analysis
Command evaluation
Fuzzy photo search

CHAPTER 4

LITERATURE REVIEW

Jimmy Singla (2015): In this paper for diagnosis of diabetes two fuzzy inference systems Mamdani type and Sugeno type is used. Comparative study of both fuzzy inference systems were done. For the simulation of both the models MATLAB toolbox is used. Sugeno type fuzzy inference system give more accurate outputs as comparison to Mamdani type fuzzy inference system. Both inference systems uses same designing process but defuzzification of crisp output is different for them. Sugeno type fuzzy inference systems can be used with various optimization techniques. In mamdani type fuzzy inference systems acceptably diagnosed patient cases is 95.33% and wrongly diagnosed patient 4.67% while in sugeno fuzzy inference system acceptably diagnosed patient cases is 97.33% and wrongly diagnosed patient is 2.67%.

Nilesh N. Karnik, Jerry M. Mendel (1998): Using type-2 fuzzy sets type-2 fuzzy systems were designed. Type-2 fuzzy systems involves type reduction followed. Set theoretic operations on type-2 fuzzy sets were studied in detail. Along with it properties of membership, defuzzification, type-2 relations and compositions are also studied. Type-2 fuzzy sets handle uncertainties that are different from type-1 fuzzy sets. Non singleton fuzzy sets are those which can handle rule uncertainties in inputs whereas type-2 fuzzy systems can deal with knowledge uncertainty.

Praveen Kumar Shukla, Surya Prakash Tripathi (2014): fuzzy sets model the uncertainty of systems. High dimensional data sets have explode the search space of generated rules and results in loss of interpretability. A new entropy based method for cluster center generation is used. A new fuzzy classifier “Teacher-performance fuzzy classification system” is developed using evolutionary multiobjective optimization method to deal with interpretability accuracy tradeoff. To implement evolutionary multiobjective optimization MATLAB is used and to design the classifier “Guaje” software is used.

Anagha V. Vaidya, Pravin S. Metkewar, Sachin A Naik (2018): Membership function is graphical representation of mapping of input space to membership values (0, 1). Input space is referred as universe of discourse. In spite of fuzzy design a new fitness finding method is proposed. Fuzzy based algorithm is used to generate an automatic membership function in fuzzy logic module of algorithm. Stock investment management system datasets were taken for case study. Three parameters: - Units of investment, Interest rates and Risk factors associated with the investment were considered. It calculates degree of truth rather than true or false like Boolean algebra.

Nilesh N. Karnik, Jerry M. Mendel and Qilian Liang (1999): Type-2 fuzzy logic systems were applied to time-varying channel equalization for which channel uncertainty can be captured by only type-2 fuzzy systems and not by type-1 fuzzy systems. Type-2 fuzzy sets are important for engineering applications where lots of uncertainty is present. Interval type-2 fuzzy sets uses singleton fuzzifiers. Mamdani type fuzzy inference system is used to develop type-2 system. Design and applications of interval type-2 were also explored.

Praveen Kumar Shukla, Surya Prakash Tripathi(2011): In the design of complex high dimensional fuzzy systems obtaining high degree of Interpretability and Accuracy is difficult. Several approaches such as context adaptation, hierarchical fuzzy modelling, multiobjective optimization are present. This is the survey of all the approaches to deal with I-A tradeoff.

Jerry M. Mendel, Robert I. Bob John (2002): New representation theorems for type-2 fuzzy sets were presented and these theorems used to derive formulas for type-2 fuzzy sets union, intersection and complement without using the extension principle. The goal was to make type-2 fuzzy sets easier to understand and to work with it. We can define centroid of type-2 fuzzy sets in easier way by using the new representation theorem. Without using the extension principle same results are produced. Type-2 fuzzy sets can handle uncertainties in rule based systems but they are difficult to use and understand than type-1 fuzzy sets. There are four sources of uncertainties in type-1 fuzzy logic systems: (1) meaning of words (2) Consequents may have histogram of values. (3)Measurements may be noisy. (4) Data used may be noisy.

Qilian Liang and Jerry M. Mendel (2000): Theory and design of interval type-2 fuzzy systems is proposed. A new general inference formula is used to compute the input and antecedent operations for interval type-2 FLSs. This approach is efficient and simplified. For designing an interval type-2 FLS a new method is proposed to tune its parameters. Type-2 fuzzy logic systems for time-series forecasting is designed and demonstrate improved performance over type-1 fuzzy systems.

Praveen Kumar Shukla, Surya Prakash Tripathi (2016): Fuzzy logic has great capability to deal with uncertain and imprecise information. Genetic algorithms are used to improve the design of fuzzy systems. Interpretability and accuracy are used during design of fuzzy systems which is concerned with improvement of performance and usability. Both are reciprocal to each other. Engineering Student-Fuzzy Classification System (ES-FCS) is proposed and this system is implemented with both type-1 and type-2 fuzzy logic. Application of linguistic hedges is done for accuracy improvement. Interpretability accuracy tradeoff is experimentally studied in evolutionary multi-objective framework by using type-1 and type-2 fuzzy logic.

Nilesh N. Karnik, Jerry M. Mendel (1998): Defuzzification followed by type reduction in type-2 fuzzy logic is extension of defuzzification of type-1 fuzzy logic. Structure of type-2 fuzzy logic is reviewed. Type reduction process is described in detail. Center of sets type reducer is illustrated and explained with example. They clearly discussed type reduction operations. Singleton fuzzification is used i.e. in input space only one point has non zero membership and this membership equal to 1. Type reduction captures more information about the uncertainties rather than the defuzzification and it seems to be fundamental concept to design fuzzy systems that include linguistic uncertainties.

Christian Wagner, Hani Hagrass (2008): Interval type-2 fuzzy logic systems which is high order fuzzy logic system have shown to deal with large amount of uncertainties of real world applications. This capability is further extended by general type-2 fuzzy logic systems. But due to computational requirement and complexity generally prevented a foray to general type-2 fuzzy logic research. An alternative approach that is z-slices will lead to a smooth transition

from interval to general type-2 fuzzy systems. Z-slices will lead to a significant reduction in both the complexity and the computational requirements for general type-2 fuzzy logic systems. Hence, general type-2 fuzzy logic systems are applied to many real world problems.

Prabhash Chandra, Devendra Agarwal and Praveen Kumar Shukla (2018): Fuzzy logic provides a mathematical framework to deal with uncertainties. Linguistic computation is integrated with decision making. Several fuzzy knowledge base systems (FKBS) are developed by using subjective knowledge in the form of fuzzy if-then rules. In this paper Mobiclass FKBS is proposed and it is implemented by “Guaje” free open access software. Interpretability and accuracy parameters are also studied. They are contradictory to each other and one can be increased at the cost of other. Performance is analyzed by interpretability and accuracy parameters. For generation of rules Wang Mendel method is used.

L. Magdalena (2018): Hierarchical fuzzy systems reduces the complexity of fuzzy systems. Complexity is an important criteria to measure interpretability. Synthetic variables generated at intermediate levels of the hierarchy in complexity reduction. These synthetic variables are affected by absence of semantics minimizing the interpretability of fuzzy systems. In hierarchical fuzzy systems complexity semantics will be considered so complexity should be part of equation. Intermediate variable should be interpretable in terms of problems under consideration. Role of intermediate variables is explored, different aspects of interpretability concerning hierarchical fuzzy systems is discussed.

Hisao Ishibuchi, Yusuke Nojima (2009): accuracy and interpretability maximization is two important goals of fuzzy systems. To find a fuzzy system with good I-A tradeoff is various approaches has been proposed. Interpretability maximization is not easy. In this paper difficulties in interpretability maximization of fuzzy rule base systems using simple examples is discussed. How to measure the interpretability is concerned in this paper.

Praveen Kumar Shukla, Surya Prakash Tripathi (2012): Rule learning, rule selection, membership function tuning, fuzzy partition are major concern to deal with interpretability accuracy tradeoff. Various issues related to this tradeoff is discussed in EMO framework. Optimization task including optimization of Membership Functions (MF), optimizing the rule selection, adaptation, tuning and learning of other fuzzy system parameters is considered in design and development of FKBS.

Maowen Nie, Woei Wan Tan (2008): For interval type-2 (IT2) fuzzy logic systems (FLSs) an alternative type reduction with either continuous or discrete secondary membership function is introduced. The proposed type reduction algorithm is developed by using vertical slice representation. Computational complexity is also lower in vertical slice representation. So computationally efficient alternative of K-M type reduction algorithm is proposed.

CHAPTER 5

PROBLEM DEFINITION

5.1. INTERPRETABILITY ACCURACY TRADEOFF

Fuzzy systems deal with uncertain and imprecise information. Two issues are encountered in the design of fuzzy systems: interpretability and accuracy maximization. Interpretability can be increased at the cost of accuracy and vice versa, which is known as the I-A tradeoff. There are two types of fuzzy modeling systems. Linguistic fuzzy modeling (Mamdani fuzzy systems) mainly focuses on interpretability, whereas precise fuzzy modeling (Takagi-Sugeno) is concentrating on accuracy [5]. Two conflicting goals, interpretability and accuracy maximization, are encountered in the design of fuzzy systems. Numerous approaches are found to deal with the tradeoff. Accuracy maximization is easy, while due to the subjective nature, interpretability maximization is difficult. To deal with the I-A tradeoff, Multi-Objective Evolutionary Algorithms (MOEA) are commonly used. In complex fuzzy systems, finding a good tradeoff of interpretability and accuracy is important. Interpretability is not easy to quantify, while accuracy is the quantification of closeness between modeled and real systems. In general, the strategies of fuzzy modeling are oriented to acquiring rule primarily based systems with excessive accuracy; however, they are hardly ever interpretable according to fuzzy logic principles. Both standards are in conflict, and it is vital to acquire an awesome alternate tradeoff among the two elements. On the aggregation of simple indices of complexity and similarity, the interpretability index is based. Interpretability is acknowledged as the primary gain of fuzzy systems and must receive a primary role in fuzzy modeling. Classical systems are regarded as black containers due to the fact that mathematical formulas set the mapping among inputs and outputs. At the contrary, fuzzy structures (if they may be built regarding some constraints) may be visible as grey bins in the sense that each detail of the entire machine may be checked and understood via an individual. Interpretability is critical for those packages with high human interaction, as an example, decision support systems in fields like medicine, economics, etc. Considering the fact that interpretability is not assured by means of definition, a big attempt has been carried out to find out the primary constraints to be superimposed throughout the fuzzy modeling process. Knowledge of interpretability is a subjective project which strongly relies upon background (experience, preferences, and knowledge) of the person who makes the assessment. Even though there were a few attempts to outline interpretability indices, there's nevertheless not a universal index widely accepted. It refers to the potential of the fuzzy model to precisely describe the behavior of the system in an understandable way. This is often a subjective property that depends on several factors, mainly the model structure, the number of input variables, the amount of fuzzy rules, and the amount of linguistic terms, and therefore the shape of the fuzzy sets. With the term interpretability, we englobe different criteria appeared within the literature such as compactness, completeness, consistency, or transparency. As the complexity of a device increases, our capacity to make unique and but tremendous statements about its conduct diminishes until a threshold is reached beyond which precision and importance (or relevance). Therefore, to obtain high degrees of interpretability and accuracy is a contradictory process. Accuracy and

interpretability are conflicting goals. It is usually assumed that the extra complicated the FRBS, the smaller its interpretability that mean implicitly complexity is thought to be associated with loss of interpretability. The objective of FM isn't always simplest to maximize the interpretability however also to look for high accuracy. To sum up, two essential tendencies are observed regarding the improvement of the accuracy–interpretability tradeoff in the context of fuzzy structures. On the one hand, device designers first awareness at the interpretability of the version, and then they are attempting to improve its accuracy. On the opposite hand, designers first build a FRBS focusing on the version accuracy and then try to enhance its interpretability. First approach is called linguistic fuzzy modeling (LFM) with improved accuracy, and the second one is known as precise fuzzy modeling (PFM) with improved interpretability. Defining interpretability is hard because it offers with the the relation occurring between heterogeneous entities: a fuzzy system and a human user performing as an interpreter of the gadget's information base and running engine. To pave the manner for defining such a relation, some essential properties want to be included into a fuzzy machine, so that its formal description turns into compatible with the user's know-how representation. The definition of interpretability, therefore, requires the identity of several features; amongst them, the adoption of a fuzzy inference engine based totally on fuzzy rules is simple to approach the linguistic-based components of concepts which is regular of human abstract thought. A distinguishing characteristic of a fuzzy rule-based machine is the double level of information representation: (i) the semantic degree made via the fuzzy units described in phrases of their membership features, in addition to the aggregation features used for inference, and (ii) the syntactic stage of representation, in which understanding is represented in a formal structure wherein linguistic variables are involved and reciprocally connected by some formal operators (e.g. "AND", "THEN", etc.). A mapping is defined to provide the interpretative transition that is quite not unusual inside the mathematical context: semantics is assigned to a formal shape via mapping symbols (linguistic phrases and operators) to objects (fuzzy sets and aggregation functions). In principle, the mapping of linguistic terms to fuzzy units can be arbitrary. Nevertheless, the mere use of symbols in the high level of expertise illustration implies the establishment of some of semiotic relations which can be fundamental for the preservation of interpretability of a fuzzy system. Thus we often want to maximize the accuracy of fuzzy rule-based systems without degrading their interpretability [4]. In particular, linguistic terms— as usually picked from natural language—need to be fully meaningful for the expected reader since they denote concepts, i.e. Mental representations that allow the reader to attract appropriate inferences approximately the entities she encounters. As a consequence, standards and fuzzy sets are implicitly connected by the commonplace linguistic terms they are associated to; the key essence of interpretability is consequently the property of cointension between fuzzy sets and principles, consisting inside the capability of relating to similar instructions of objects: such a possibility is confident by the use of not unusual linguistic phrases. Interpretability is a quality of fuzzy structures that isn't always on the spot to quantify. Nevertheless, a quantitative definition is required each for assessing the interpretability of a fuzzy device and for designing new fuzzy systems. A not unusual method for a quantitative definition of interpretability is based at the adoption of some of constraints and standards that, taken as a whole, offer for a (at least partial)

definition of interpretability. The relation between interpretability and accuracy is contradictory which means one can be improved at the cost of the other [5].

5.1.1 INTERPRETABILITY: Interpretability is system behavior is human understandable or not by seeing it. Interpretability is of two types

1. Complexity based interpretability
2. Semantic based interpretability

Main focus in CBI is reducing the complexity of obtained model while SBI is concerned with semantics of membership function. Interpretability depends on various parameters such as transparency of fuzzy partitions, complexity of fuzzy models, complexity of fuzzy rule base, complexity of fuzzy reasoning. SBI is related to preserve the semantics associated with Membership Functions (MFs) [6].

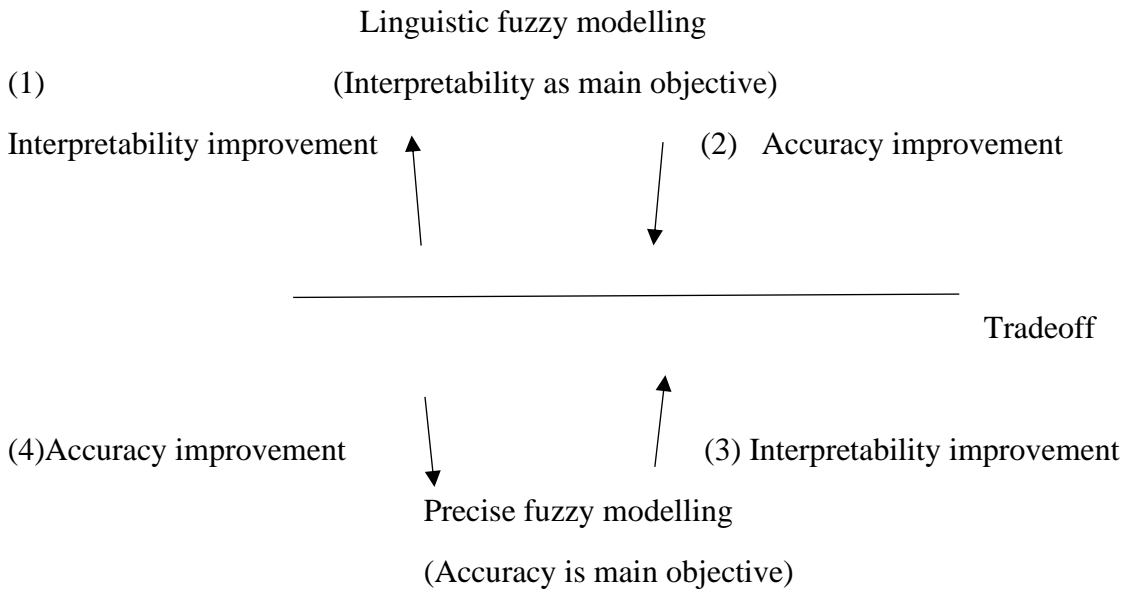


Figure 5.1 Interpretability accuracy tradeoff

Interpretability indices: Interpretability suggests how easily an FLS may be understood through human beings. In current years, the hobby of researchers in acquiring extra interpretable fuzzy fashions has improved. However, the choice of the precise interpretability measure remains an open discussion because of its subjective nature and the huge quantity of factors worried. Substantial studies on interpretability measures proposed interpretability indices for FLSs. Nauck index and Fuzzy index are the most common interpretability indices.

Nauck index: Nauck index is a numerical index brought with the aid of Nauck to be able to measure fuzzy rule-based classification system. It is the product of three terms:

$$\text{Nauck index} = \text{comp} \times \text{cov} \times \text{part} \quad (5.1)$$

Comp: It represents the complexity of FLSs .It is measured as number membership functions (MFs) of output variables divided by the number of input variables in FLSs rules. IT is computed as

Cov: Coverage degree of fuzzy partition is cov.

Part: part stands for the partition index which is computed as the inverse of the number of MFs minus one for each input variable.

Fuzzy model is more interpretable when Nauck index is closer to 1 while less interpretable when Nauck index is closer to 0.

Fuzzy Index: Fuzzy index that is inspired by way of Nauck's index is proposed in interpretability assessment. Six variables are taken as input of a fuzzy device namely;total number of rules, total number of input variables, number of rules using one input variable, number of rules using two input variables, number of rules using three or more input variables, average number of linguistic terms defined for each input variable. Fuzzy index closer to 1 implies highly interpretable while fuzzy index closer to 0 implies less interpretable.

5.1.2ACCURACY: It is closeness between real and modeled system. It is related to the complexity of the system. More complex systems are more accurate but less interpretable. Extremely good accuracy means extremely high computational complexity. Capability of fuzzy model to faithfully represent the modeled system is called accuracy of the system. Closeness between real and modeled system is similarity between the responses of real and modeled systems. Accuracy is also called approximation .If model is closer to the real system higher is the accuracy of the fuzzy system. It refers back to the functionality of the fuzzy model version to faithfully represent the modeled system. The closer the model to the device, the higher its accuracy. As closeness we apprehend the similarity between the responses of the real gadget and the fuzzy model. That is why the term approximation is also used to express the accuracy being a fuzzy model a fuzzy function approximation model. Accuracy concerns the ability of a model to make correct predictions. Apart from the improvement in accuracy, it is also important to simultaneously improve the system interpretability because highly accurate systems with higher interpretability are the prime requirements of the modern control systems [7].

5.2 Curse of dimensionality: High dimensionality of data sets and interpretability accuracy trade-off are two major issues in developing the fuzzy systems [8].Although the fuzzy logic system can be applied to model or to control a complex nonlinear system a well-known problem in fuzzy logic system is with the increase in number of variables rules increases exponentially. As the number of variables increases rules of fuzzy systems increase exponentially. Today curse of dimensionality is the key problem of fuzzy logic. Fuzzy logic is based on if-then rules and when more inputs are added to this system results in exponential growth in rules. One method to deal with this problem is use of disjunctive forms of fuzzy rules. So we can say rule explosion is the fundamental issue of fuzzy systems because as the number of input variable increases rules increases exponentially. Rule bases with higher number of rules and input variables tends

to loss in all good features such as transparency, ability to generalize, accuracy etc. also hierarchical fuzzy systems are used to deal with curse of dimensionality problem. So hierarchical organization of fuzzy rule bases reduces complexity of fuzzy systems. Number of rules in hierarchical fuzzy systems is linearly proportional to the number of input variables. Large fuzzy system is hierarchically decomposed in several simple fuzzy systems. In hierarchical fuzzy systems output of one rule base serves input to another rule base. In rule explosion with the increase in number of antecedents the if-then rule bases increases exponentially. Use of type-2 fuzzy sets make the system computationally expensive and reduction in interpretability [9]. Fuzzy rule based classifiers are the automatic classification structures wherein the information is represented by way of fuzzy if-then rules. These are the vital tools for system learning framework. Designing fuzzy structures for the excessive dimensional information sets is important research issue because these information sets ends in exponential boom in terms of rule seek space. Several strategies are proposed and applied to develop accurate and interpretable fuzzy systems handling high dimensional records sets. Excessive dimensional regression hassle has been evolved using multiobjective evolutionary algorithms. This framework carries out studying of the database in phrases of variables, granularities and displacements in fuzzy partitions. High dimensional and massive statistics units are handled in the evolutionary multiobjective framework. A rule explosion is an essential limitation of fuzzy systems due to the fact the variety of rules will increase exponentially because the wide variety of input variables increases. Suppose that we have n inputs and m fuzzy sets defined for each of them then the wide variety of the rules of the usual fuzzy systems is m^n . A rule base with many input variables and the huge range of guidelines has a tendency to lose all top features - transparency, ability to generalize, accuracy etc. Hierarchical organization of fuzzy rule bases is the manner how reduce the complexity of the fuzzy system and enhance the insight into the system behavior. Also design, transparency, tuning etc. come to be simpler for the systems consisting of smaller fuzzy systems. Several approaches cause the design of the hierarchical fuzzy systems. Usually the massive fuzzy systems is decomposed into numerous fuzzy systems whose structure is simple. The small fuzzy systems are interconnected according the given topology. This approach still want to develop a massive complex fuzzy systems. The performance and generalization of this model can be poor for this reason the splitting process ought to fail. Usually some sort of the rule base evaluation is used to break up the massive rule base. The “curse of dimensionality” is one of the key problems facing fuzzy structures idea today. Fuzzy systems are based on a set of IF–THEN guidelines and the structure of those fuzzy guidelines causes an exponential growth within the number of rules when greater inputs are added, resulting in unwieldy rulebases. Many strategies were proposed to alleviate the curse of dimensionality. When designing a FRBS to model an excessive dimensional problem, a trouble with a huge range of variables or requiring large term sets, designers must deal with what is usually referred to as the curse of dimensionality, i.e., the exponential growth within the quantity of rules related to the variety of input variables. This situation has a poor effect on interpretability. Among solutions taken into consideration to palliate the effects of this curse of dimensionality are using compact rule structures, sparse rule bases, or hierarchical fuzzy system (HFS). The first query to recall is that the feasible shape of a hierarchical fuzzy system

isn't always unique. Different hierarchies, i.e. exclusive structures, are possible. The most important differences amongst them relate to the components of the overall fuzzy device being stricken by the hierarchical decomposition. At least three alternatives can be considered: decompose at the level of fuzzy partitions, at the extent of variables, or at the extent of rules. The first option to be taken into consideration for the hierarchy is that dividing at the level of rules. The definition of a hierarchy of policies primarily based on rules of each one, lets in a prioritization within the use of the guidelines. The policies may be grouped in levels in keeping with its specificity. This concept creates a hierarchical structure by way of specificity, in which the more precise rules get hold of a higher precedence, while precedence is lower for more generic rules. The effect of this technique is that a regularly occurring rule is applied simplest while no specific rule is applicable. This shape has clear effects from the factor of view of output explanation, where interpreting the output involves the use of the idea of specificity of the rule. Properly the use of this concept is extremely important for interpretability, due to the fact that in many cases the particular rules can be inconsistent with the common policies, overruling them. A second alternative is establishing a hierarchy of partitions for each variable. Partitions at unique stages will provide an exclusive granularity. In this case the hierarchical structure is composed of a fixed of layers where each one contains linguistic partitions (for the identical set of variables) with exceptional granularity degrees. At the identical time, each layer contains linguistic rules wherein linguistic variables consider the partitions contained in the corresponding layer. The idea is somehow related to that of generic/specific rules, however now the specificity of the rule is based at the specificity of the partition. The third approach to HFSs, being the most common one is the hierarchy of variables. The result can be a hierarchy splitting a large system into a cascade of several smaller systems. Those smaller systems might be acquired by way of decomposing the (high dimensional) input spaces into several input spaces with a reduced number of variables. Each input variable will only be considered at a certain level of the hierarchy. The different ranges are then aggregated with the aid of considering the output of every stage as one of the inputs to the subsequent stage. With the hierarchical decomposition goal achieved is reduction of the number of rules of the FRBS, i.e. the palliation of the curse of dimensionality problem. Designing fuzzy systems for the high dimensional data sets [10] is critical research issue because these data sets leads to exponential growth in terms of rule search space.

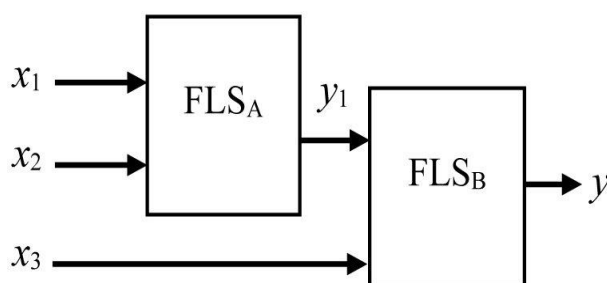


Figure 5.2 Heirarchical fuzzy system

5. 3. **Computational requirements complexity of general type-2 fuzzy systems:** Higher order fuzzy systems such as interval type-2 fuzzy systems are widely used for higher level of uncertainties present in majority of real world applications. Computational complexity of general type-2 fuzzy systems prevent its applications to many real world problems. Z slices based general type-2 fuzzy systems results in reduction of both computational requirements and complexity of the systems. Type-1 fuzzy systems are simple and most widely used but recent years have shown a significant increase in research toward more complex forms of fuzzy logic that is interval type-2 and general type-2. FUZZY logic is credited with being an adequate methodology for designing strong systems which might be capable of deliver a quality performance inside the face of uncertainty and imprecision. Hence, the Fuzzy Logic System (FLS) has become mounted as an adequate method for a range of applications. While type-1 fuzzy logic has been the most popular form of fuzzy logic, current years have proven a significant increase in research in the direction of extra complex sorts of fuzzy logic, in particular, interval type-2 fuzzy logic and, even extra recently, General type-2 fuzzy logic. This transition from type-1 to greater complex styles of fuzzy logic has been in large part motivated by the conclusion that type-1 fuzzy sets simplest provide confined scope for modeling uncertainty and, as such, can't manage the high ranges of uncertainty, which are commonly present in real-world applications. Type-2 fuzzy logic allows for better modeling of uncertainty as type-2 fuzzy units embody a Footprint of Uncertainty (FOU) which, related to third dimension gives more stages of freedom in comparison to type-1 fuzzy sets to type-2 fuzzy sets. General type-2 FLSs have only currently been investigated in more detail as the excessive complexity associated with their layout and their computational requirements made them seem unsuitable for real-world use. Given the experience with interval type-2 FLSs, it is predicted that the popular type-2 fuzzy units employed within the well-known type-2 FLS will have the ability to model uncertainty more accurately than interval type-2 fuzzy sets which, in turn, will bring about the capability for a superior control performance in comparison to type-1 and interval Type-2 FLSs. Higher order fuzzy logic systems (FLSs), together with interval type-2 FLSs, had been shown to be very well desirable to deal with the high ranges of uncertainties present in the majority of real-world applications. General type-2 fuzzy systems can further extend this capability to deal with higher levels of uncertainty by providing additional degrees of freedom through the third dimension of the type-2 fuzzy sets [11]. This General type-2 FLSs are anticipated to further make bigger this capability. However, the big computational complexities associated with general type-2 FLSs have, until recently, avoided their utility to real-world control problems. Several efforts were made as a way to restriction the complexity of trendy type-2 fuzzy logic; in particular, new sorts of representations had been devised which will enable the use of general type-2 FLSs in real-global applications. Geometric representation of general type-2, representation based on alpha planes and z Slices-based representation is proposed by many authors. So several efforts have been made in order to limit the complexity of general type-2 fuzzy logic. The initial idea for introducing hierarchical fuzzy systems in fuzzy modeling was related to the reduction of structural complexity they provided [12].

CHAPTER 6
METHODOLOGY

1. Student performance indicator system: A student performance indicator system is proposed with following parameters to evaluate the performance of students in examination.

Input parameters

1. Marks
2. Attendance
3. Human values
4. Co-cular activities

1. Marks: This is the mark obtained by the student in the subjective examination of that particular subject. Marks of one subject is taken to evaluate the performance of the students.

2. Attendance: Attendance is criteria to judge hardworking of the student. So it is calculated at the end of session in theory and lab sessions of particular subject.

3. Human values: when one human interact with other than virtues possessed by them is also important to evaluate the performance of students. Principles, conviction, and internal beliefs adopted by human's plays important role in today's world.

4. Co-cular activities : activities performed by the students outside the normal curriculum of colleges or schools and which take place outside the classroom without pen and pencil plays important role in today's education system.

Output parameter:

Level: level of the student will be good, avg, bad based on performance of the students. For a good student level is 3, for an avg student level is 2 and for a bad student level is 1.

Good [3]

Avg [2]

Bad [1]

Input parameters values

Sr.no.	Input parameters	range
1.	Marks	[0,100]
2.	Attendance	[0,100]
3.	Human values	[0,50]
4.	Co-cular activities	[0,50]

Table 6.1 Input parameters

Output parameter values

Sr. no.	Output parameter	range
1.	Level	[1,3]

Table 6.2 Output parameters

6.1 Interpretability and accuracy by Guaje tool: GUAJE stands for Generating Understandable and Accurate fuzzy models in a Java Environment. It is licensed under GPL-v3. It is freely available tool. Its aim is to design an interpretable and accurate fuzzy model in java environment. It supports the design of interpretable and accurate fuzzy systems by means of combining several preexisting open source tools. Guaje pays special attention on interpretability of the systems. It is user friendly portable tool licensed under GPL-v3. It is upgraded version of free software called KBCT (Knowledge base configuration tool). It makes knowledge extraction and representation of fuzzy systems easier .Guaje provides supervised and fully automatic learning capabilities and user can define expert variables and rules. Both type of knowledge expert and induced knowledge are integrated ensuring interpretability, consistency and simplicity of systems. Interpretability is systems behavior is human understandable or not while accuracy is the closeness between modelled and real systems. Guaje is user friendly dynamic tool to measure the interpretability and accuracy of systems. Understand the behavior of Fuzzy Rule- based Systems (FRBSs) at inference stage is a complex task that allows the designer to produce less complicated and effective systems. The fuzzy inference-grams –knownas fingrams– establish a novel and mighty device for know-how the shape and behavior of fuzzy systems. Fingrams constitute FRBSs as social networks made from nodes representing fuzzy policies and edges representing the degree of interaction among pairs of rules at inference level (no edge method no massive interaction). We can examine fingrams acquiring helpful data such as detecting potential conflicts among rules unused rules and redundant ones.

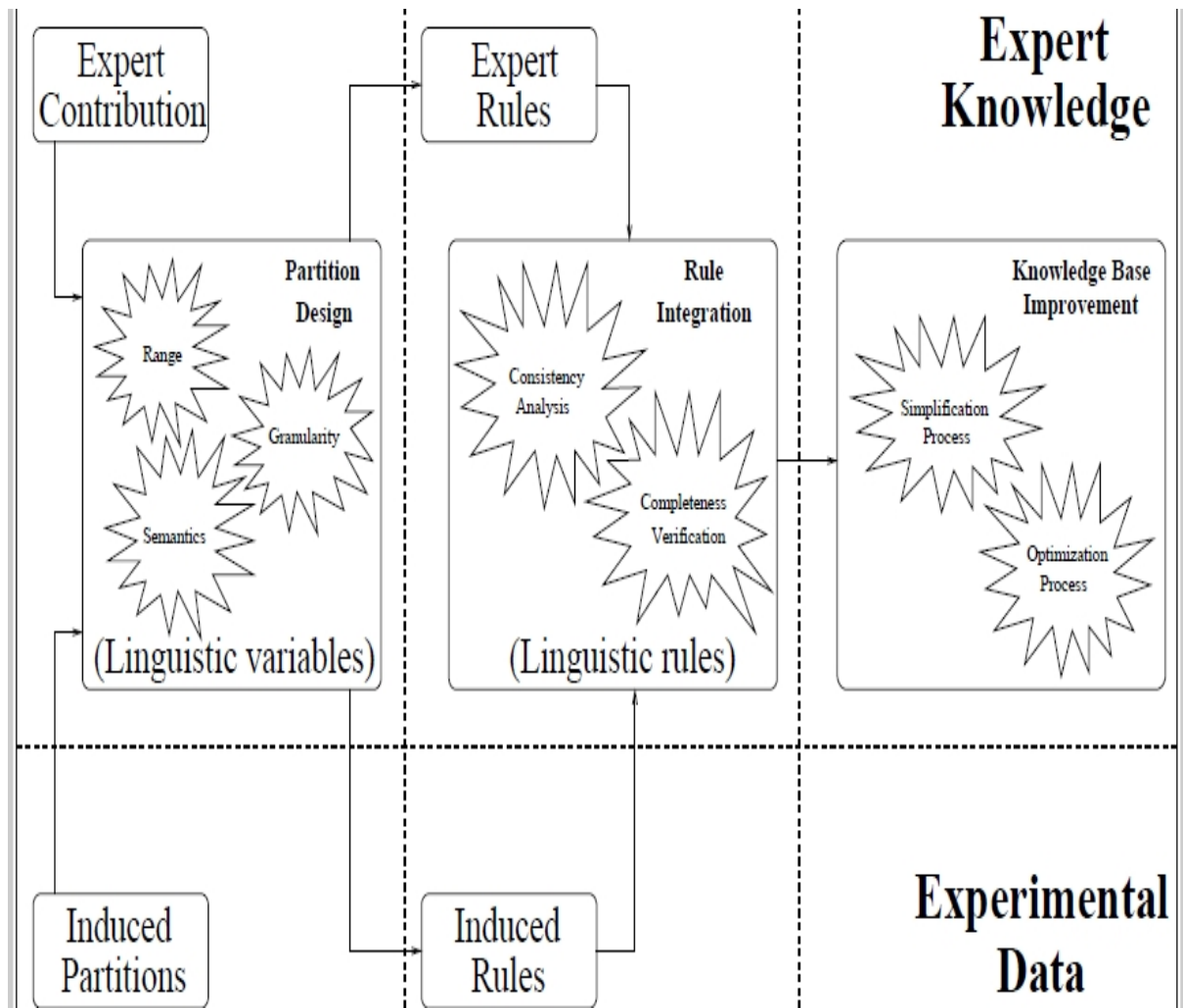


Figure 6.1 Guaje interface

Guaje is the combination of several system modelling tools such as Fispro, ORE, Graphviz, Weka etc. for designing of interpretable fuzzy systems.

Fispro: Fispro is used for simulating a physical or biological systems. It is open source tool used in guaje for creating fuzzy inference systems (FIS) that is used for reasoning purposes. For generating fuzzy partitions and rules from experimental data many algorithms are used in fispro most of them are implemented in C programs. Algorithms such as K-means, hierarchical fuzzy partition (HFP), Wang and Mendel (WM), fast prototyping algorithm (FPA), fuzzy decision tree (FDT) is provided by fispro which is used in guaje fuzzy tool.

Graphviz: Graph visualization software graphviz is used to represent structural information as diagrams of abstract graphs and diagrams. It is open source graph visualization software. It consist of web and interactive graphical interfaces, and auxiliary tools, libraries, and language bindings. Diagrams in several useful formats such as images, SVG for web pages, postscript

are made by graphviz layout programs. For concrete diagrams many useful features such as font, colors, and link styles is also present in graphviz. IT is collection of free software for viewing and manipulating abstract graphs. Module of GUAJE responsible for a novel interpretability analysis at fuzzy inference level (fingrams analysis) uses graphviz. Under the Eclipse Public License the graphviz is licensed.

ORE (ontology rule editor): IT is open source java based platform independent application for testing, managing, defining inference rules represented by specific ontology. For visulising domain ontologies guaje calls to libraries provided by ORE.IT makes knowledge extraction process easier.

JMetal: JMetal comprises a set of Metaheuristic algorithms implemented in Java. It is a free software. By combining guaje with JMetal we are looking for embedding HILK into a multi-objective evolutionary framework.

Weka: It is open source tool providing lots of algorithms for data miming. It includes implementation of many classical algorithms such as J48.

MATLAB fuzzy toolbox: most widely used commercial tool for fuzzy systems. It advantage is that it is fully integrated with all functionalities pro-vided by Matlab environment which is most commonly used in engineering applications.

Xfuzzy: A free software for generating FIS environment. It integrates set of tools that ease the user to cover all stages required in designing process. It is in java and its tools are written in XFL3.

The principle curiosity of the GUAJE approach is that it is the first one consolidating a few software tools (not only libraries) with the point of building interpretable fuzzy models. Notice that, interpretability is the main requirement and it is thought about along the entire modelling process. All kind of systems must achieve minimum accuracy so accuracy is also not forgotten. If minimum accuracy is not achieved then system becomes useless. KBCT (version 3.0) is upgraded with new functionalities and implementing the HILK (Highly Interpretable Linguistic Knowledge) fuzzy modeling methodology in guaje. Guaje is an open source software for knowledge representation and extraction. Induced knowledge (knowledge form experimental data) and expert knowledge is combined by guaje. Data will be preprocessed and translated into a manner that will be handled by guaje. When dealing with complex problems feature selection is needed. Definition of linguistic variable is done .Both partitions that is partition from experimental data and expert partitions are compared. For each input variable best partition based on expert knowledge and data distribution are chosen. Then two sets of linguistic rules expert and induced rules define the behavior of the system by combining the previously generated linguistic variables. Linguistic rules are if premise then conclusion rules. Premises and conclusions are expressed as linguistic propositions. After checking integrality, consistency parameters both set of rules are integrated as unique one. Resultant kb (knowledge base) is improved regarding interpretability and accuracy. Finally validation of final fuzzy system is done and native code is generated.

STEPS

Data preprocessing: Data will be converted into the format that is used in guaje. In this step data visualization and data analysis is done.

Feature selection: most significant input variables are identified. For complex system significant input variables is defined.

Partition design: characterization of each input variable as linguistic variable is done based on justifiable number of linguistic terms. Attached membership function is defined by expert. It can also be derived from data using machine learning techniques. We can define linguistic variable for problem. For each input variable linguistic terms can range from 2-9. Linguistic variable must be meaningful. We can select from several predefined vocabulary tuples (low-high, small-large and so on) .linguistic terms characterization can be done by two approaches. Either expert can define by choosing prototype of them or guaje can derive partitions using several induction method. Guaje imposes the use of strong fuzzy partition in order to maximize the interpretability of system.

Rule base definition: this module defines the fuzzy rules. Behavior of the system can be defined by fuzzy if-then rules. Guaje can derive the rules from the data or expert can define the rules. User can create rules by two different methods. Using expert knowledge rules are defined or machine learning techniques can derive rules from data. Guaje uses Wang and Mendel, fast prototyping, fuzzy decision tree algorithms for rule induction. In addition, the user can choose among typical methods for rule conjunction (minimum, product, or Łukasiewicz) and disjunction (maximum or sum).

Knowledge base visualization: this module shows graphically interaction between rules at inference level .Regarding the pairs of rules simultaneously fired by each problem instance guaje first generates co-firing matrix. Pathfinder scales the graph. Kamada-Kawai algorithm is used to find the placement of nodes. After that graph is enhanced with information related to rules such as coverage, goodness etc. Resultant fingrams are generated to user. User can analyze it and can interact with it. User can make zoom in, zoom out, making changes in nodes and so on.

Knowledge base improvement: this module finds good interpretability accuracy tradeoff. Guaje has two ways to enhance I-A tradeoff of fuzzy rule base systems. Rule base simplification results reduction in complexity and improvement in readability of the system. Second way is tuning of fuzzy partitions to increase the accuracy.

Rule base simplification: the goal is to generate most compact FRBS. We look for redundant elements then they can be removed by altering the accuracy of the systems. Then it tries to merge elements that are used together.

Partition optimization: the goal is improve accuracy without changing interpretability of systems. Optimization only affects the fuzzy partitions.

Membership function using guaje

1. Membership function for marks

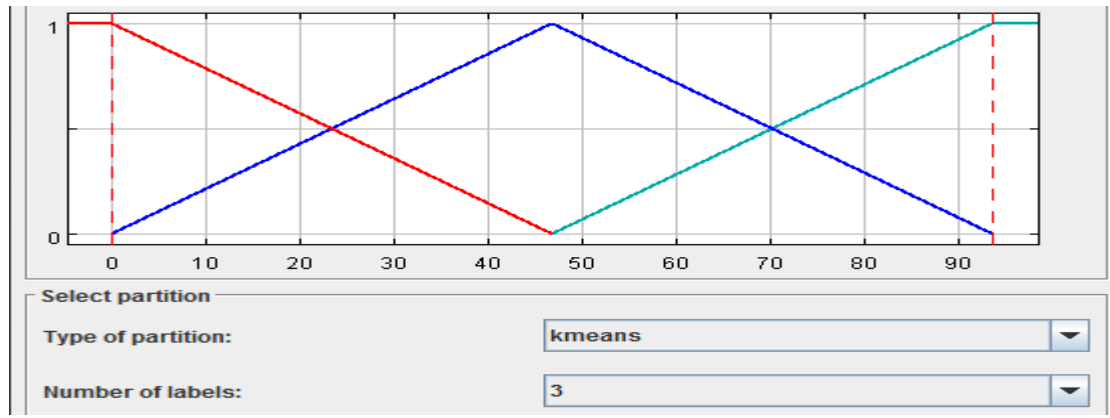


Figure 6.2 Membership function of marks

2. Membership function for attendance

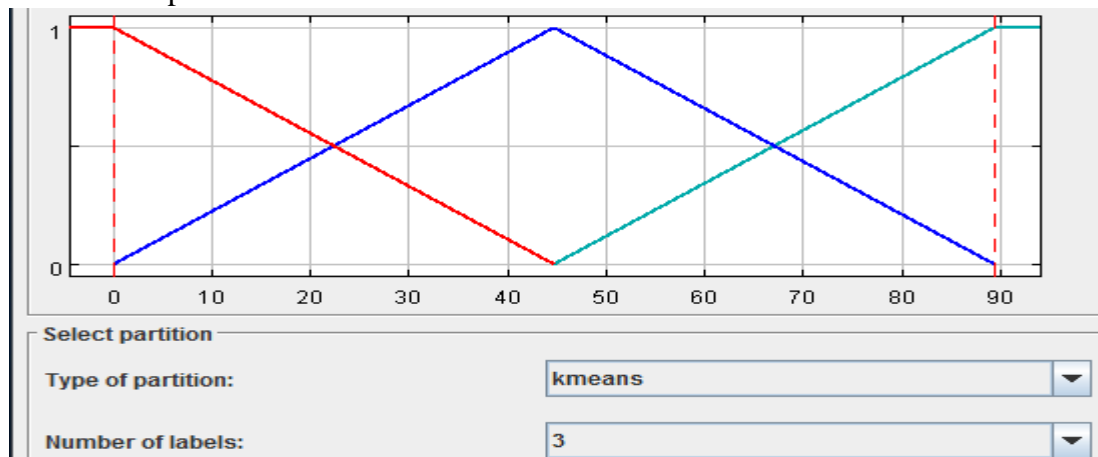


Figure 6.3 Membership function of attendance

3. Membership function for human values

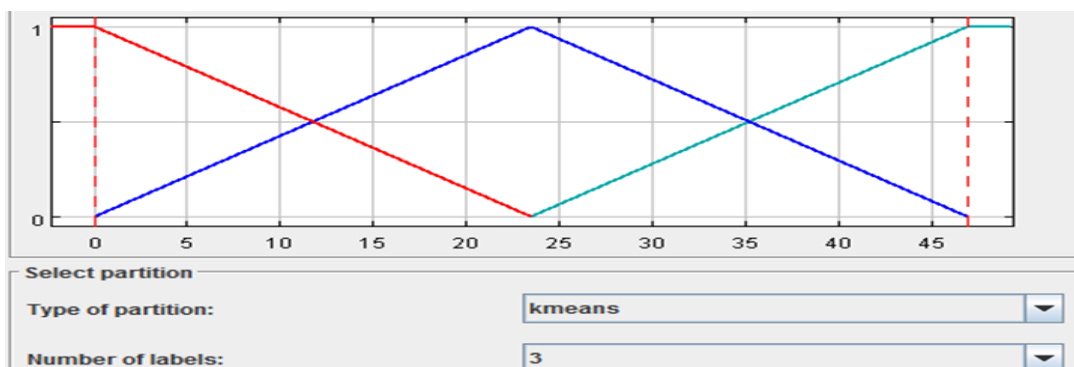


Figure 6.4 Membership function of human values

4. Membership function for co- cular activities

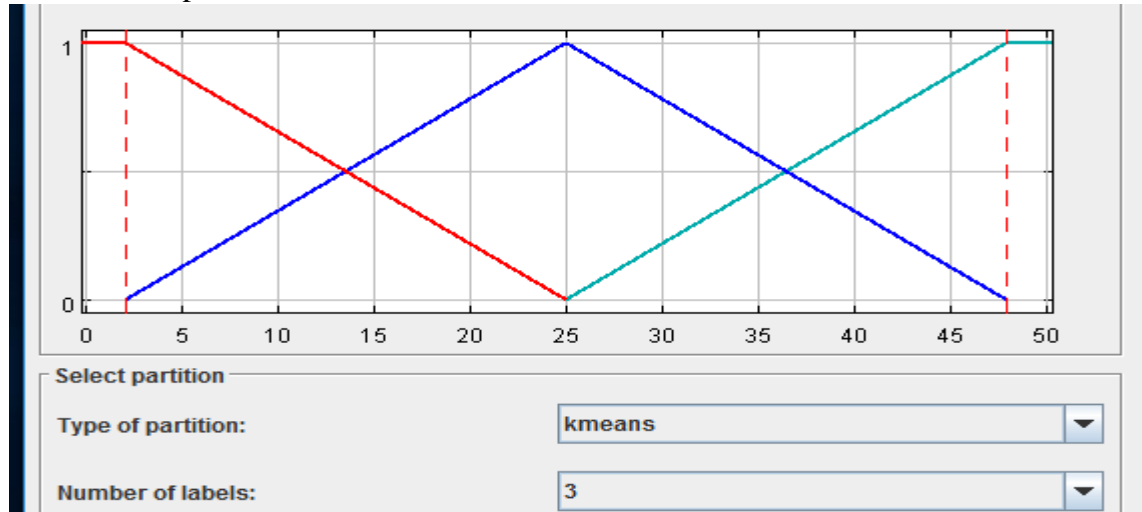


Figure 6.5 Membership function of co-cular activities

6.2 Performance of the student using juzzyonline: Juzzyonline is an internet platform aimed at allowing each novices and superior practitioners to design, assemble, execute, analyse and visualize fuzzy logic systems. Including different t-Norms and both singleton and non-singleton fuzzification a wider variety of FLSs are supported, including type-1, interval type-2 and general type-2 FLSs, with a variety of options. An online fuzzy logic toolkit for design, sharing, implementation and execution of type-1, interval type -2 and general type-2 fuzzy logic systems. Main aim to develop this toolkit is to develop a free to use fuzzy logic toolkit which is freely available platform independent and easily accessible. This toolkit doesn't require any knowledge of programming. Accessibility of fuzzy logic systems were enhanced by this toolkit in research and industrial applications. Implementation of new methods is difficult where there is lack of software. For a person without a programming background, the access to new methodologies and/or tools is often challenging. So there is need of tools those provide straightforward access to new methodologies. Although there are many toolkits are available for fuzzy systems but they require user to have prior knowledge to the fuzzy logic systems and good understanding of programming also. To address these points, we have developed a free, openly accessible, cloud-based online toolkit, which can be used to design, execute and share both T1 and T2 FLSs. Juzzy online provides online access through web based GUI to many features of java based fuzzy toolkits that were developed previously. This toolkit doesn't require any programming knowledge. It facilities the development and design of type-1, interval type-2 and general type-2 FLSs as well as straightforward sharing and execution of the resulting systems. Juzzyonline is web browser based so it is easily accessible to anyone through web browsers. Juzzyonline is also platform independent. We don't need any additional code or any

software to use this application. These features makes this toolkit more accessible than previously developed toolkit. We expect that this toolkit will provide direct and easy access to basic and most advanced fuzzy systems to both students and professionals.

6.2.1Background: T1 FLSS are implemented using MATLAB. Type-1 FLSs are implemented using toolkit provided by MATLAB allowing users to design the systems by command-line inference. Toolkit for T2 FLSs are also developed however there use is limited. Researchers from within the fuzzy logic community released free-to-use source code but using and modifying of source codes requires in depth knowledge of MATLAB programming language. It also requires insight into fuzzy logic algorithms making its use challenging. Another MATLAB based toolkit was developed which provides GUI for development of interval T2 FLSs. This facilitates access to T2 fuzzy logic algorithms. Still imposes a considerable hurdle for their wider adoption as the software is subject to license fees. Next toolkit which was developed by wagner was based on R programming language. R is a freely accessible, platform-independent language which is popular within research communities from Psychology to Computer Science. R programming language also uses command line interface similar to the MATLAB. The toolkit don't provide a GUI but contains some functions with which plot visualizations to fuzzy sets. Other toolkits whose focus is T1 fuzzy logic systems include the open-source native applications KBCT and GUAJE (an upgraded version of KBCT). Fispro is also available. Fispro is open source toolkit for creating fuzzy inference systems. It also provide visualizations using GUI.Xfuzzy is also available tool which is based on specification language XFL. To aid in the development of FLSs the toolkit also provides a graphical user interface .

Recently juzzyonline toolkit was developed for T1, interval T2, and z slices based general T2. Juzzyonline was developed by java programming language which is freely available platform independent which enables the application to run on variety of hardware platforms and operating systems. It supports the use of multiple processors for the parallel processing of general T2 Systems. It is the first toolkit to implement the z slices bases general type-2 fuzzy systems. No GUI is provided for this toolkit. It contains functions for plotting fuzzy systems. Juzzyonline not require an in-depth knowledge of FLSs and it enables straightforward sharing of FLSs. Juzzyonline also not require prior knowledge of any programming language.

6.2.2Features: The juzzy toolkit provides all of the functions required to construct MISO (multi output single output) Mamdani type fuzzy logic inference systems of type-1, interval type-2 or general type-2. MIMO (multi input multi output) systems can also be implemented as a series of MISO systems. Juzzyonline is freely available and complete with the source code. For all types of FLS the toolkit provides the number of membership functions such as trapezoidal, Gaussian, triangular. Juzzyonline provide height and centroid type of defuzziication methods. KM algorithm is used for type reduction of type-2 fuzzy sets and systems. For processing of z Slices based general type-2 FLSs multiple processors are used by juzzyonline.

Type-1 fuzzy sets: fig shows triangular MF of juzzyonline. A triangle is defined by left, right and center coordinates.

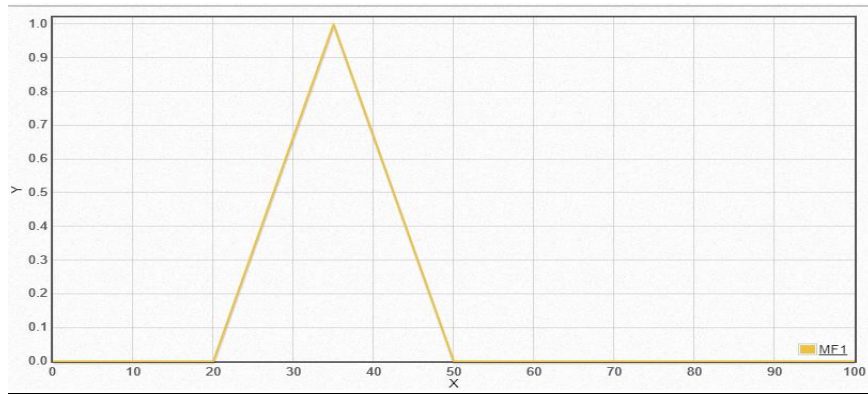


Figure 6.6 An example of T1 FS with triangular MF

T1 fuzzy logic with trapezoidal MF is defined by two left and two right coordinates and shown in fig.

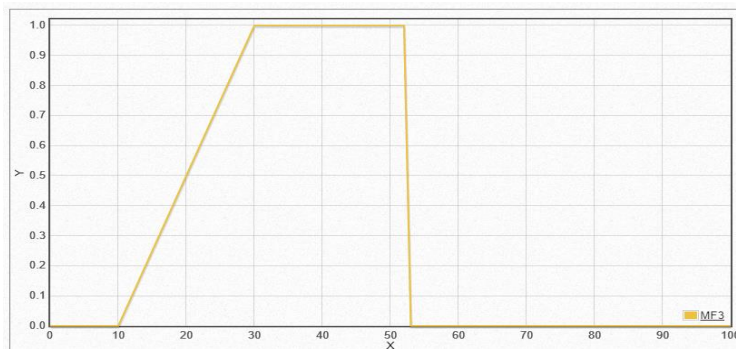


Figure 6.7 An example of trapezoidal membership function

For gaussian membership function mean and standard deviation is taken.

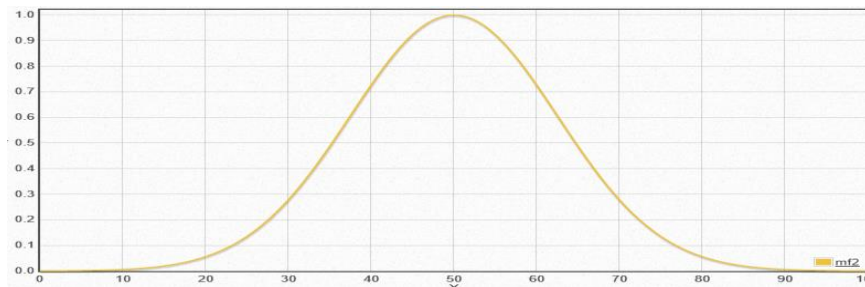


Figure 6.8 An example of a T1 FS with a Gaussian MF

Gau-Angle MF, for which the left, right and centre coordinates are chosen is shown in fig.

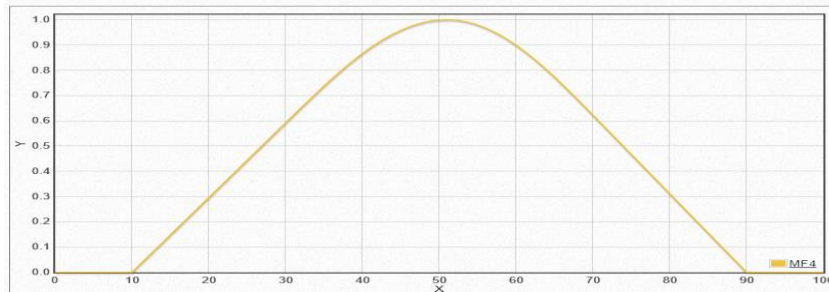


Figure 6.9 Example of a T1 FS with a Gau-Angle MF

Interval Type-2 Fuzzy Sets: Interval T2 FSs use the same MF types as type-1 fuzzy systems, and the coordinates of the lower and upper MFs are chosen independently.

General type-2 fuzzy systems: General type-2 fuzzy systems are created using z-slices. Z-slices of general type-2 fuzzy systems are created using a series of z-slices where each z-slice is an interval T2 FS with a secondary membership value z_i for the i th z-slice. This is not like regular interval type T2 FSs for which the secondary membership function value is always 1. Z-slices are distributed evenly throughout the footprint of uncertainty, and any number of z-slices can be taken.

6.2.3 Inputs to juzzyonline: As in the proposed student performance indicator system, performance was calculated by considering four parameters: marks, attendance, human values, and co-curricular activities.

Marks: Marks of the student are the marks obtained in particular subjective examination. Marks are shown by trapezoidal and triangular membership functions in juzzyonline.

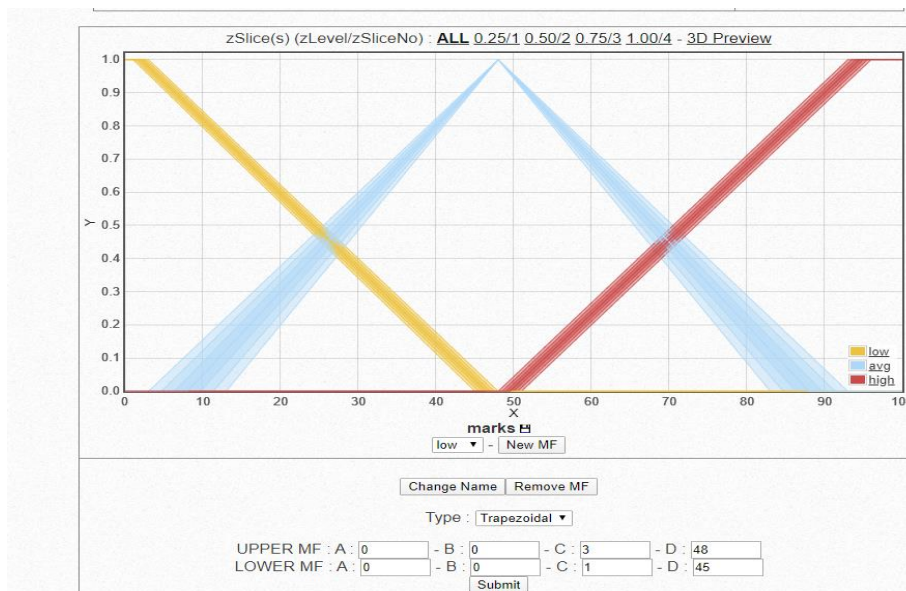


Figure 6.10 Input marks

Attendance: attendance is a criteria to reflect the hardworking of the students. Attendance is calculated at the end of the semester. It is calculated for both theory and practical subjects. It is represented by triangular and trapezoidal MFs in juzzyonline.

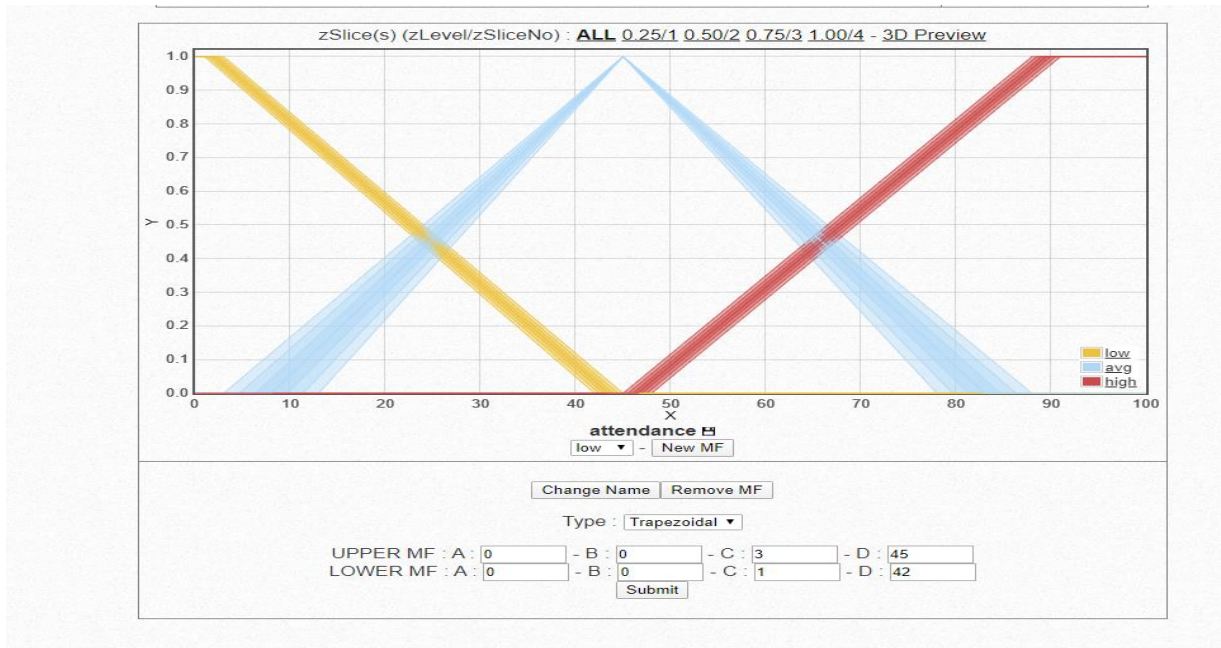


Figure 6.11 Input attendance

Human values: while interacting with others the virtues possessed by them is also an important criteria to evaluate the performance of the students.

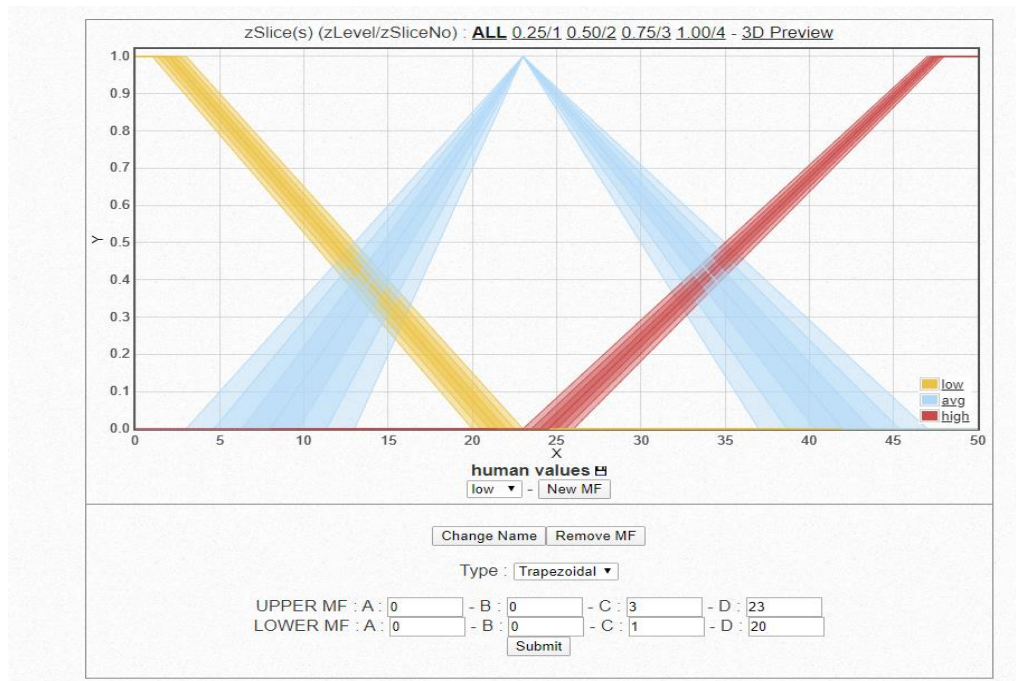


Figure 6.12 Input human values

Co-cular activities: students do some extra activities outside the normal curriculum of colleges without pen or papers termed as co-cular activities. In juzzyonline trapezoidal and triangular functions are used to represent them.

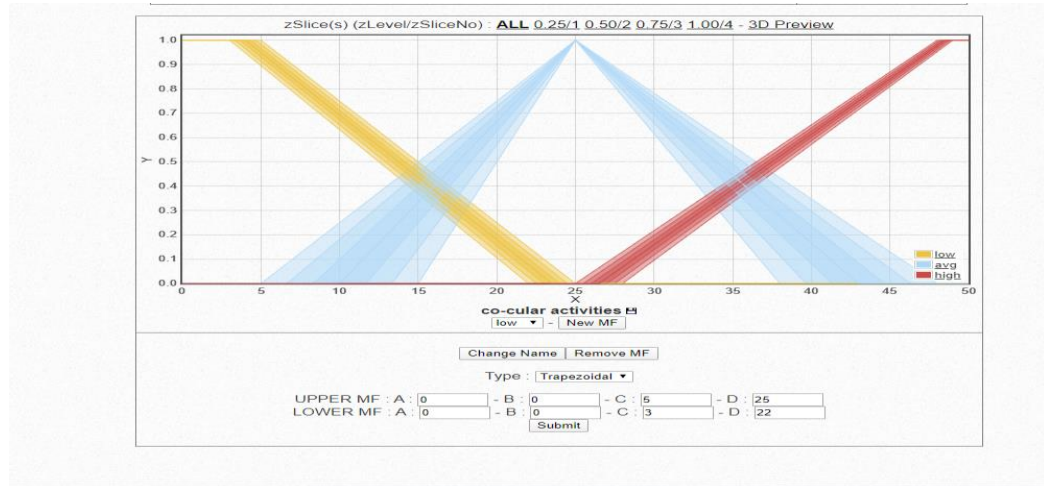


Figure 6.13 Input co-cular activities

6.2.4 Output to juzzyonline: output is represented by triangular MFs in juzzyonline. Output level takes value between 1-3. For a good student output is 3 while for a bad student output is 1. Avg student output is represented as 2.

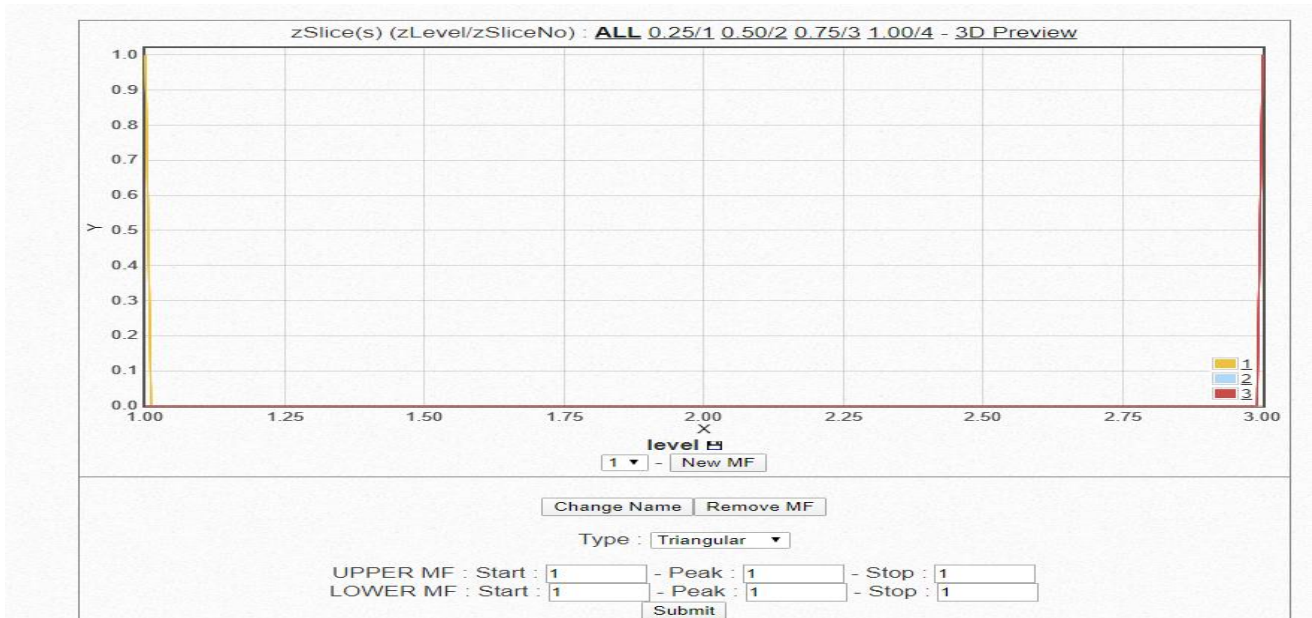


Figure 6.14 Output to juzzyonline

CHAPTER 7

Results and discussions

7.1 Guaje results

7.1.1 Accuracy and interpretability by different algorithms

ALGORITHM	RULES	ACCURACY	INTERPRETABILITY
Fuzzy decision tree	13	0.803	0.042
Wang and Mendel	42	0.858	0.009
Fast prototyping	54	0.811	0.007

Table 7.1 Accuracy and interpretability by different algorithms

Fuzzy decision tree: Inputs are sorted according to their importance for minimizing the entropy. Then the tree is sorted in quite general incomplete rules. The main parameters to be defined are

Tree file

Tree depth

Minimum significant level.

Leaf minimum cardinality

Tolerance threshold

Minimum entropy

Wang and Mendel: for each data sample one rule is generated in the training set but new rules will complete with existing rules. Complete rules will be generated which is quite specific. This algorithm gives highly interpretable and accurate system.

Fast prototyping: more general rules than the Wang Mendel is produced but at the same time more specific than the fuzzy decision tree.

7.1.2 Changing type of partition and number of lables

There are three types of fuzzy partition

1. K means
2. Regular
3. Hfp

K means: It uses well known clustering method of same name. For a given variable there is no priori relationship between the partition centers for partitions of different sizes.

Regular: standardized uniform strong fuzzy partition. Regular partition with 3 labels gives more accurate and interpretable fuzzy system.

K means	2	0.543	0.018
K means	3	0.827	0.009
K means	4	0.449	0.006
K means	5	0.220	0.004
K means	6	0.134	0.004
K means	7	0.063	0.003
K means	8	0.039	0.003
K means	9	0.039	0.002
Regular	2	0.465	0.018
Regular	3	0.858	0.009
Regular	4	0.614	0.006
Regular	5	0.236	0.004
Regular	6	0.102	0.004
Regular	7	0.055	0.003
Regular	8	0.039	0.003
Regular	9	0.031	0.002
hfp	2	0.441	0.018
hfp	3	0.787	0.009
hfp	4	0.394	0.006
hfp	5	0.094	0.004
hfp	6	0.055	0.004
hfp	7	0.024	0.003
hfp	8	0.024	0.003
hfp	9	0.016	0.002

Table 7.2 Lables using different type of partition

Hfp: for each variable two fuzzy sets are merged. The computational time can be very high and depends on initial number of fuzzy sets. There are two ways to build an initial partition.

7.2 Juzzyonline results: when different input values are given then overall defuzzified value is shown in the table

MARKS	ATTENDANCE	HUMAN VALUES	CO-CULAR ACTIVITIES	OVERALL DEFUZZIFIED VALUE
95	95	45	45	3.00
50	50	35	35	2.16
45	45	35	35	1.92
35	35	20	20	1.71
30	30	15	15	1.53
90	95	40	45	2.99

Table 7.3 Juzzyonline results

When marks was 50, attendance was 50, human values was 35 and cocular activities was 35 then overall defuzzified value is 2.16.

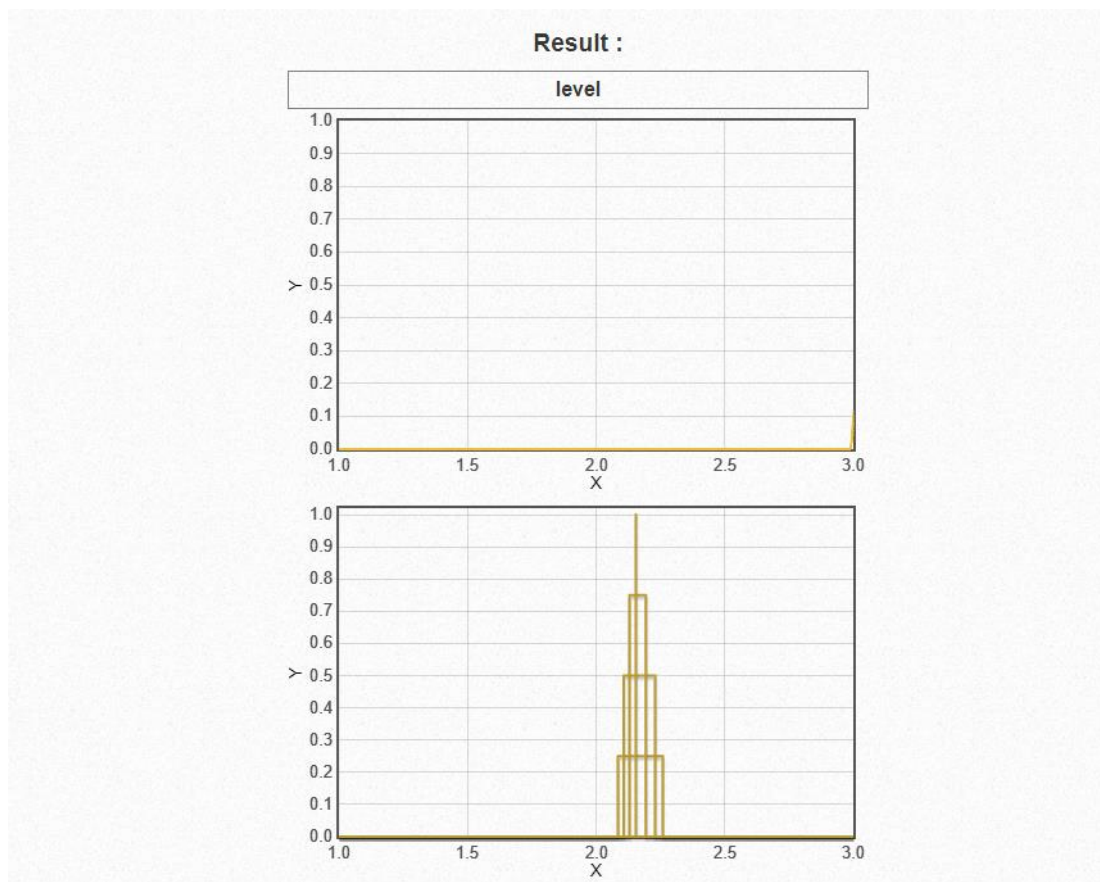


Figure 7.1 Results in graphical forms

Defuzzification method :

		level	
zSlice No	zLevel		Output
1	0.25	Centroid	2.0851063829787235 2.2586206896551726
		Defuzzified Value	2.1718635363169483
2	0.50	Centroid	2.1068633353401562 2.229390681003584
		Defuzzified Value	2.1681270081718704
3	0.75	Centroid	2.128913443830571 2.1934846989141166
		Defuzzified Value	2.1611990713723435
4	1.00	Centroid	2.154791154791155 2.154791154791155
		Defuzzified Value	2.154791154791155
All		Overall Centroid	2.130473800431537 2.1917020767569313
		Overall Defuzzified Value	2.161087938594234

Figure 7.2 Results in tabular forms

7.2.1 Centroid type defuzzification: The most commonly used defuzzification technique is the center of area (COA), also commonly referred to as the centroid approach. This method determines the center of area of fuzzy sets and gives a corresponding crisp value.

CHAPTER 8

CONCLUSION

Fuzzy systems has capability to deal with uncertain and imprecise environment. Interpretability is system behavior is human understandable or not while accuracy is the difference between modeled system and real system. This paper introduces a new fuzzy knowledge base system using juzzyonline and guaje for the performance of the students. The performance is analyzed by guaje with two parameters interpretability and accuracy. Wang and Mendel algorithm for rule creation gives more interpretable and accurate fuzzy systems. Centroid type defuzzification method is used by juzzyonline to generate a crisp value from a fuzzy value. This paper introduces zlices based general type-2 fuzzy system using juzzyonline. Accuracy of the student performance indicator system was 80% using juzzyonline. Accuracy of the system with guaje software were 85.8% and interpretability was .009.

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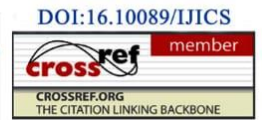
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