

DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

**FUZZY DESIGN OF WASTEWATER TREATMENT
PLANTS**

by
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September, 2006
İZMİR

FUZZY DESING OF WASTEWATER TREATMENT PLANTS

**A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Master of Science in
Environmentsl Engineering, Environmental Technology Program**

**by
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**September, 2006
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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled “**FUZZY DESIGN OF WASTEWATER TREATMENT PLANTS**” completed by **ALPER KAYA** under supervision of **Prof. Dr. ORHAN USLU** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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FUZZY DESIGN OF WASTEWATER TREATMENT PLANTS

ABSTRACT

In the recent years the designing and operating wastewater treatment plants have come to be more important. Especially lots of multi-way methods and studies are being done for control and automation.

Fuzzy logic is one of the most popular methods for controlling and it has large application areas from space shifts to digital cameras.

In this thesis fuzzy logic is applied on controlling a wastewater treatment plant which is designed for nitrification and COD removal by traditional methods. Most of the parameters such as dissolved oxygen, alkalinity, waste sludge flowrate, MLSS concentration in aerobic tank and NO_x regulation in anoxic tank are controlled with automation by on-line measurable sensors with combination of MATLAB program installed on operators PC.

With fuzzy logic control method the operating problems caused by existence of strong non-linearity, time variant parameters and complex multivariable couplings are overcome easily.

The success of this method also relies on the capability and experience of the operator who designs and sets the fuzzy logic rules.

Keywords: Fuzzy logic, automation, wastewater, activated sludge, biological process

ATIKSU ARITMA TESİSLERİNİN BULANIK MANTIK İLE TASARIMI

ÖZ

Son yıllarda atıksu arıtma tesislerinin tasarımı ve işletilmesi daha önemli bir hal almıştır. Özellikle çok yönlü metotlar ve çalışmalar kontrol ve otomasyon için yapılmaktadır.

Bulanık mantık kontrol için en önemli metotlardan biridir ve uzay mekiklerinden digital kameralara kadar çok geniş bir uygulama alanı vardır.

Bu tezde bulanık mantık, nitrifikasyon ve KOI giderimi için geleneksel metotlarla tasarlanan bir atıksu arıtma tesisi kontrolü için uygulanmıştır. Çözünmüş oksijen, alkalinite, fazla çamur atma hızı, aerobik tanktaki aktif çamur konsantrasyonu ve NO_x gibi birçok kontrol edilebilir parametreler on-line ölçülebilir sensörler yardımı ile ve operatörün bilgisayarına yüklü MATLAB programı ile kontrol altına alınmıştır.

Bulanık mantık kontrolü ile güçlü düzlemsel olmayan, zaman değişkenli parametreler ve karışık çok değişkenli birleşmelerin yol açtığı işletme problemlerin üstesinden gelinmiştir.

Bu metodun başarısı, bulanık mantık kurallarını koyan ve tasarlayan işletmecinin yeteneğine ve deneyimine de bağlıdır.

Anahtar Kelimeler: Bulanık Mantık, otomasyon, atıksu, aktif çamur, biyolojik proses

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CHAPTER ONE

A SURVEY TO FUZZY LOGIC

1.1 Introduction

Fuzzy Logic was initiated in 1965 by Lotfi A. Zadeh, professor for computer science at the University of California in Berkeley.

Basically, Fuzzy Logic (FL) is a multivalued logic that allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more humanlike way of thinking in the programming of computers.

Fuzzy systems are an alternative to traditional notions of set membership and logic that has its origins in ancient Greek philosophy. The precision of mathematics owes its success in large part to the efforts of Aristotle and the philosophers who preceded him. In their efforts to devise a concise theory of logic, and later mathematics, the so-called "Laws of Thought" were posited. One of these, the "Law of the Excluded Middle," states that every proposition must either be True or False. Even when Parmenides proposed the first version of this law (around 400 B.C.) there were strong and immediate objections: for example, Heraclites proposed that things could be simultaneously True and not True. It was Plato who laid the foundation for what would become fuzzy logic, indicating that there was a third region (beyond True and False) where these opposites "tumbled about." Other, more modern philosophers echoed his sentiments, notably Hegel, Marx, and Engels. But it was Lukasiewicz who first proposed a systematic alternative to the bi-valued logic of Aristotle. Even in the present time some Greeks are still outstanding examples for fussiness and fuzziness, (note the connection to logic got lost somewhere during the last 2 millenniums).

Fuzzy Logic has emerged as a profitable tool for the controlling and steering of systems and complex industrial processes, as well as for household and entertainment electronics, as well as for other expert systems and applications.

1.2 Introduction to Fuzzy Sets

Fuzzy set theory generalizes classical set theory in that the membership degree of an object to a set is not restricted to the integers 0 and 1, but may take on any value in $[0,1]$. By elaborating on the notion of fuzzy sets and fuzzy relations we can define fuzzy logic systems (FLS). FLSs are rule-based systems in which an input is first fuzzified (i.e., converted from a crisp number to a fuzzy set) and subsequently processed by an inference engine that retrieves knowledge in the form of fuzzy rules contained in a rule-base. The fuzzy sets computed by the fuzzy inference as the output of each rule are then composed and defuzzified (i.e., converted from a fuzzy set to a crisp number). A fuzzy logic system is a nonlinear mapping from the input to the output space.

Simply put, fuzzy sets are a clever way to deal with vagueness as we often do in our daily life. For example, suppose you were advising a driving student on when to apply the brakes, would your advice be like: “Begin braking 74 feet from the crosswalk,” or would it be more like: “Apply the brakes when approaching the crosswalk”? Obviously the latter, since the former instruction is too precise to easily implement. Everyday language is the cornerstone example of vagueness and is representative of how we assimilate and act upon vague situations and instructions. It may be said that we all assimilate and use (act on) fuzzy data, vague rules, and imprecise information, just as we are able to make decisions about situations which seem to be governed by an element of chance. Accordingly, computational models of real systems should also be able to recognize, represent, manipulate, interpret, and use (act on) both fuzzy and statistical uncertainties.

Fuzzy interpretations of data structures are a very natural and intuitively plausible way to formulate and solve various problems. Conventional (i.e., crisp) sets contain objects that satisfy precise properties required for membership. The set H of numbers from 6 to 8 is crisp; we write $H = \{r \in \mathbb{R} \mid 6 \leq r \leq 8\}$, where $\mathbb{R}$ is the set of real numbers. Equivalently, H is described by its membership (or characteristic, or indicator) function (MF), $\mu_H: \mathbb{R} \rightarrow \{0, 1\}$, defined as

$$\mu_H(r) = \begin{cases} 1 & 6 \leq r \leq 8 \\ 0 & \text{otherwise} \end{cases}$$

Every real number (r) either is in H or is not. Since μ_H maps all real numbers $r \in \mathbb{R}$ onto the two points $(0, 1)$, crisp sets correspond to a two-valued logic: is or is not, on or off, black or white, 1 or 0. In logic, values of μ_H are called truth-values with reference to the question, “Is r in H ?” The answer is yes if and only if $\mu_H(r) = 1$; otherwise, no. In conventional set theory, sets of real objects, such as the numbers in H , are equivalent to, and isomorphically described by, a unique membership function such as μ_H . However, there is no set-theory equivalent of “real objects” corresponding to fuzzy sets. Fuzzy sets are always (and only) functions, from a “universe of objects,” say X , into $[0,1]$. As defined, every function $\mu: X \rightarrow [0,1]$ is a fuzzy set. While this is true in a formal mathematical sense, many functions that qualify on this ground cannot be suitably interpreted as realizations of a conceptual fuzzy set. In other words, functions that map X into the unit interval may be fuzzy sets, but become fuzzy sets when, and only when, they match some intuitively plausible semantic description of imprecise properties of the objects in X .

Defining the real numbers between 6 and 8 is a problem that is inherently crisp (i.e., mechanistic system) and would not require the use of fuzzy sets. A situation closer to what we would find in everyday life (i.e., humanistic system) consists of deciding whether a person is tall or not. The property “tall” is fuzzy per se. Indeed, reasoning

according to Aristotelian logic, we would need to define a height threshold that divides tall people from non-tall ones. If someone is taller than the threshold (even by 1/10 of an inch) then he or she is tall, otherwise, not tall. This is obviously far from the way we decide whether someone is tall or not. Our perception of the person is better described as a sort of soft switching rather than a threshold mechanism. This is also why we often add a modifier to the word “tall” (i.e., not, not very, somewhat, very, etc.) in order to express “degrees of tall” rather than absolute true or false answers. The difference in a fuzzy and a crisp definition of tall is illustrated in Fig. 1.1 where for different heights the corresponding degree of membership to some subjective crisp and fuzzy sets tall are indicated with μ_c and μ_f , respectively. In defining the crisp “tall person” set we fixed a threshold somewhere between 5’5” and 6’, say 5’10”. Therefore, someone who is 5’9” would not be tall, while someone who is 5’11” would. Conversely, in the fuzzy set “tall person” a degree of tall is defined, thus providing a continuum rather than an abrupt transition from true to false.

Tall ?

$\mu_c = 0$	$\mu_c = 0$	$\mu_c = 0$	$\mu_c = 1$	$\mu_c = 1$	$\mu_c = 1$
$\mu_f = 0$	$\mu_f = 0.2$	$\mu_f = 0.5$	$\mu_f = 0.9$	$\mu_f = 0.98$	$\mu_f = 1$

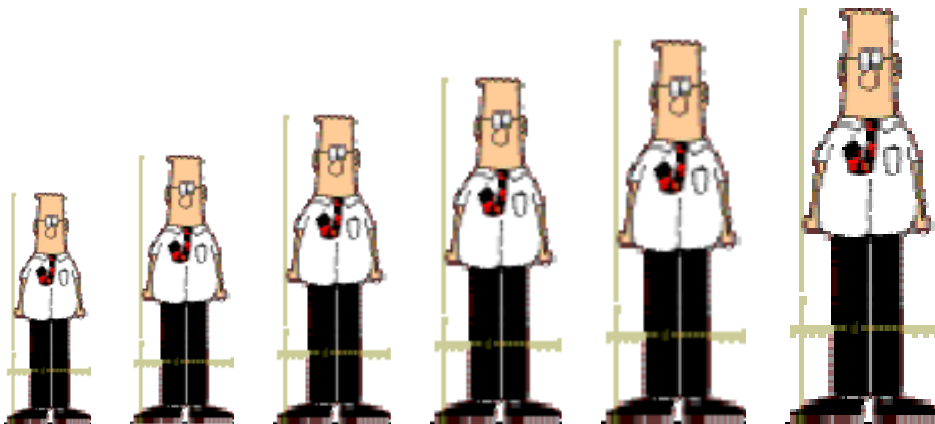


Figure 1.1. Crisp and fuzzy sets for the attribute ‘tall person’

Consider next the set F of real numbers that are *close to 7*. Since the property “close to 7” is fuzzy (as the property “tall person” is), there is *not a unique* membership function for F . Rather, the modeler must decide, based on the potential application and properties desired for F , what μ_F should be. Properties that might seem plausible for μ_F include:

- (i) Normality, i.e., $\mu_F(7) = 1$;
- (ii) Monotonicity, i.e., the closer r is to 7, the closer $\mu_F(r)$ is to 1, and conversely;
- (iii) Symmetry, i.e., numbers equally far left and right of 7 should have equal memberships.

Given these intuitive constraints, a lot of different functions could be a representation for F . One can easily construct a MF for F so that every number has some positive membership in F , but we would not expect numbers “far from 7,” 10^9 for example, to have much! One of the biggest differences between crisp and fuzzy sets is that the former generally have unique MFs, whereas every fuzzy set has an infinite number of MFs that may represent it. This is at once both a weakness and strength; uniqueness is sacrificed, but this gives a concomitant gain in terms of flexibility, enabling fuzzy models to be “adjusted” for maximum utility in a given situation.

One of the first questions asked about this scheme, and the one that is still asked most often, concerns the relationship of fuzziness to probability. Are fuzzy sets just a clever disguise for statistical models? Well, in a word, NO. Perhaps an example will help.

Example 1. Potable liquid: fuzziness and probability.

Let the set of all liquids be the universe of objects, and let fuzzy subset $L = \{\text{all potable (i.e., “suitable for drinking”) liquids}\}$. Suppose you had been in the desert for a week without drink and you came upon two bottles, A and B. You are told that the (fuzzy) membership of the liquid in A to L is 0.9 and also that the probability that the

liquid in B belongs to L is 0.9. In other words, A contains a liquid that is potable with degree of membership 0.9, while B contains a liquid that is potable with probability 0.9. Confronted with this pair of bottles and given that you must drink from the one that you choose, which would you choose to drink from first? Why? Moreover, after an observation is made regarding the content of both bottles what are the (possible) values for membership and probability? The bottle you should drink from is A, because this 0.9 value means that the liquid contained in A is fairly close to being a potable liquid¹, thus it is very likely to not be harmful. On the other hand, B will contain a liquid that is very probably potable but it could be very harmful for us 1 out of 10 times on average, so we could be drinking sulfuric acid from B ! Moreover, after an observation is made and the content of the bottles is revealed, the membership for A stays the same while the probability for B changes and becomes either 0 or 1 depending on the fact that the liquid inside is potable or not.

Another common misunderstanding about fuzzy models over the years has been that they were offered as replacements for crisp (or probabilistic) models. To expand on this, first note that every crisp set is fuzzy, but not conversely. Most schemes that use the idea of fuzziness use it in this sense of embedding; that is, we work at preserving the conventional structure, and letting it dominate the output whenever it can, or whenever it must.

1.3 Fuzzy Set Theory

This section introduces some elements of fuzzy set theory in a more formal way than the previous one. The properties and features of classical set theory are used to introduce their corresponding fuzzy counterparts. Most of the operators and essential definitions are also collected in a glossary in the front of the dissertation.

Let X be a space of objects and x be a generic element of X . A classical set A , $A \subseteq X$, is defined as a collection of elements or objects $x \in X$, such that each element (x) can either belong or not to the set A . By defining a characteristic (or membership) function for each element x in X , we can represent a classical set A by a set of ordered pairs $(x,0)$ or $(x,1)$, which indicates $x \notin A$ or $x \in A$, respectively. Unlike a conventional set, a fuzzy set expresses the degree to which an element belongs to a set. Hence the membership function of a fuzzy set is allowed to have values between 0 and 1 that denote the degree of membership of an element in the given set.

Definition 1.1. Fuzzy sets and membership functions. If X is a collection of objects denoted generically by x , then a fuzzy set A in X is defined as a set of ordered pairs $A = \{(x, \mu_A(x)) \mid x \in X\}$, where, $\mu_A(x)$ is called the membership function (MF) for the fuzzy set A . The MF maps each element of X to a membership degree between 0 and 1 (included).

Obviously, the definition of a fuzzy set is a simple extension of the definition of a classical (crisp) set in which the characteristic function is permitted to have any value between 0 and 1. If the value of the membership function is restricted to either 0 or 1, then A is reduced to a classical set. For clarity, we shall also refer to classical sets as ordinary sets, crisp sets, non-fuzzy sets, or just sets. Usually, X is referred to as the universe of discourse, or simply the universe, and it may consist of discrete (ordered or

non-ordered) objects or it can be a continuous space. This can be clarified by the following examples.

Example 2. Fuzzy sets with a discrete non-ordered universe. Let $X = \{\text{Baltimore, San Francisco, Boston, Los Angeles}\}$ be the set of cities one may choose to live in. The fuzzy set $A = \text{“desirable city to live in”}$ may be described as follows: $A = \{(\text{Baltimore}, 0.95), (\text{San Francisco}, 0.9), (\text{Boston}, 0.8), (\text{Los Angeles}, 0.2)\}$. Apparently, the universe of discourse X is discrete and it contains non-ordered objects – in this case, four big cities in the United States. As one can see, the foregoing membership grades listed above are quite subjective; anyone can come up with four different but legitimate values to reflect his or her preference.

Example 3. Fuzzy sets with a discrete ordered universe. Let $X = \{0, 1, 2, 3, 4, 5, 6\}$ be the set of numbers of children a family may choose to have. Then the fuzzy set $B = \text{“desirable number of children in a family”}$ may be described as follows: $B = \{(0, 0.1), (1, 0.3), (2, 1.0), (3, 0.8), (4, 0.7), (5, 0.3), (6, 0.1)\}$. Here we have a discrete ordered universe X . Again, the membership grades of this fuzzy set are obviously subjective measures.

From the previous examples, it is obvious that the construction of a fuzzy set depends on two things: the identification of a suitable universe of discourse and the specification of an appropriate membership function. The specification of membership functions is subjective, which means that the membership functions specified for the same concept by different persons may vary considerably. This subjectivity comes from individual differences in perceiving or expressing abstract concepts and has little to do with randomness. Therefore, the subjectivity and non-randomness of fuzzy sets is the primary difference between the study of fuzzy sets and probability theory, which deals with objective treatment of random phenomena.

In practice, when the universe of discourse X is a continuous space, we usually partition it into several fuzzy sets whose MFs cover X in a more or less uniform manner.

These fuzzy sets, which usually carry names that conform to adjectives appearing in our daily linguistic usage, such as “large,” “medium,” or “small,” are called linguistic values or linguistic labels. Thus, the universe of discourse X is often called the linguistic variable. An example on this follows.

Example 4. Linguistic variables and linguistic values. Suppose that $X = \text{“age.”}$ Then we can define fuzzy sets “young,” “middle aged” and “old” that are characterized by MFs. Just as a variable can assume various values, a linguistic variable “age” can assume different linguistic values, such as “young,” “middle aged” and “old” in this case. If “age” assumes

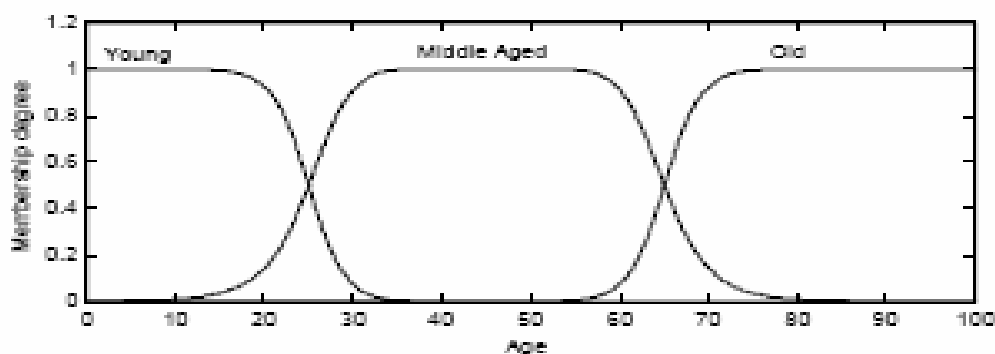


Figure 1.2 An example of MFs for these linguistic values

the value of “young,” then we have the expression “age is young,” and so forth for the other values. An example of MFs for these linguistic values is displayed in Fig. 1.2, where the universe of discourse X is totally covered by the MFs and the transition from one MF to another is smooth and gradual.

1.4 Fuzzy Logic

1.4.1 *Why use fuzzy logic?*

FL offers several unique features that make it a particularly good choice for many control problems.

1) It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations.

2) Since the FL controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.

3) FL is not limited to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate-of-change parameters in order for it to be implemented. Any sensor data that provides some indication of a system's actions and reactions is sufficient. This allows the sensors to be inexpensive and imprecise thus keeping the overall system cost and complexity low.

4) Because of the rule-based operation, any reasonable number of inputs can be processed (1-8 or more) and numerous outputs (1-4 or more) generated, although defining the rulebase quickly becomes complex if too many inputs and outputs are chosen for a single implementation since rules defining their interrelations must also be defined. It would be better to break the control system into smaller chunks and use several smaller FL controllers distributed on the system, each with more limited responsibilities.

5) FL can control nonlinear systems that would be difficult or impossible to model mathematically. This opens doors for control systems that would normally be deemed unfeasible for automation.

1.4.2 When not to use fuzzy logic?

Fuzzy logic is not a cure-all. When should you not use fuzzy logic? The safest statement is the first one made in this introduction: fuzzy logic is a convenient way to map an input space to an output space. If you find it's not convenient, try something else. If a simpler solution already exists, use it. Fuzzy logic is the codification of common sense—use common sense when you implement it and you will probably make the right decision. Many controllers, for example, do a fine job without using fuzzy logic. However, if you take the time to become familiar with fuzzy logic, you'll see it can be a very powerful tool for dealing quickly and efficiently with imprecision and nonlinearity.

1.4.3 How is FL used?

- 1) Define the control objectives and criteria: What am I trying to control? What do I have to do to control the system? What kind of response do I need? What are the possible (probable) system failure modes?
- 2) Determine the input and output relationships and choose a minimum number of variables for input to the FL engine (typically error and rate-of-change-of-error).
- 3) Using the rule-based structure of FL, break the control problem down into a series of IF X AND Y THEN Z rules that define the desired system output response for given system input conditions. The number and complexity of rules depends on the number of input parameters that are to be processed and the number fuzzy variables associated with each parameter. If possible, use at least one variable and its time derivative. Although it is possible to use a single, instantaneous error parameter without knowing its rate of change, this cripples the system's ability to minimize overshoot for a step inputs.

- 4) Create FL membership functions that define the meaning (values) of Input/Output terms used in the rules.
- 5) Create the necessary pre- and post-processing FL routines if implementing in S/W, otherwise program the rules into the FL H/W engine.
- 6) Test the system, evaluate the results, tune the rules and membership functions, and retest until satisfactory results are obtained.

CHAPTER TWO

FUZZY LOGIC SYSTEMS

2. Fuzzy Logic Systems

2.1 Linguistic Variables

In 1973, Professor Lotfi Zadeh proposed the concept of linguistic or "fuzzy" variables. Think of them as linguistic objects or words, rather than numbers. The sensor input is a noun, e.g. "temperature", "displacement", "velocity", "flow", "pressure", etc. Since error is just the difference, it can be thought of the same way. The fuzzy variables themselves are adjectives that modify the variable (e.g. "large positive" error, "small positive" error, "zero" error, "small negative" error, and "large negative" error). As a minimum, one could simply have "positive", "zero", and "negative" variables for each of the parameters. Additional ranges such as "very large" and "very small" could also be added to extend the responsiveness to exceptional or very nonlinear conditions, but aren't necessary in a basic system.

2.2 The Rule Matrix

The fuzzy parameters of error (command-feedback) and error-dot (rate-of-change-of-error) were modified by the adjectives "negative", "zero", and "positive". To picture this, imagine the simplest practical implementation, a 3-by-3 matrix. The columns represent "negative error", "zero error", and "positive error" inputs from left to right. The rows represent "negative", "zero", and "positive" "error-dot" input from top to bottom. This planar construct is called a rule matrix. It has two input conditions, "error" and "error-dot", and one output response conclusion (at the intersection of each row and column). In this case there are nine possible logical products (AND) output response conclusions.

Although not absolutely necessary, rule matrices usually have an odd number of rows and columns to accommodate a "zero" center row and column region.

This may not be needed as long as the functions on either side of the center overlap somewhat and continuous dithering of the output is acceptable since the "zero" regions correspond to "no change" output responses the lack of this region will cause the system to continually hunt for "zero". It is also possible to have a different number of rows than columns. This occurs when numerous degrees of inputs are needed. The maximum number of possible rules is simply the product of the number of rows and columns, but definition of all of these rules may not be necessary since some input conditions may never occur in practical operation. The primary objective of this construct is to map out the universe of possible inputs while keeping the system sufficiently under control.

2.3 Starting the Process

The first step in implementing FL is to decide exactly what is to be controlled and how. For example, suppose we want to design a simple proportional temperature controller with an electric heating element and a variable-speed cooling fan. A positive signal output calls for 0-100 percent heat while a negative signal output calls for 0-100 percent cooling. Control is achieved through proper balance and control of these two active devices.

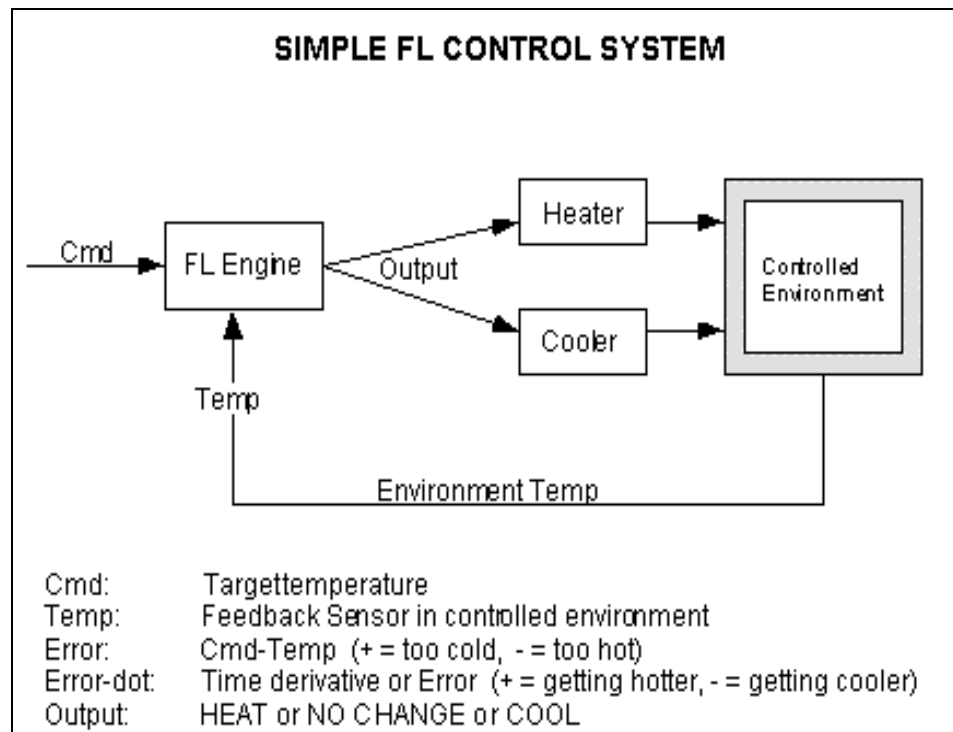


Figure 2.1 A simple block diagram of the control system.

It is necessary to establish a meaningful system for representing the linguistic variables in the matrix. For this example, the following will be used:

"N" = "negative" error or error-dot input level

"Z" = "zero" error or error-dot input level

"P" = "positive" error or error-dot input level

"H" = "Heat" output response

"-" = "No Change" to current output

"C" = "Cool" output response

Define the minimum number of possible input product combinations and corresponding output response conclusions using these terms. For a three-by-three matrix with heating and cooling output responses, all nine rules will need to be defined.

The conclusions to the rules with the linguistic variables associated with the output response for each rule are transferred to the matrix

2.3.1 What is being Controlled and How?

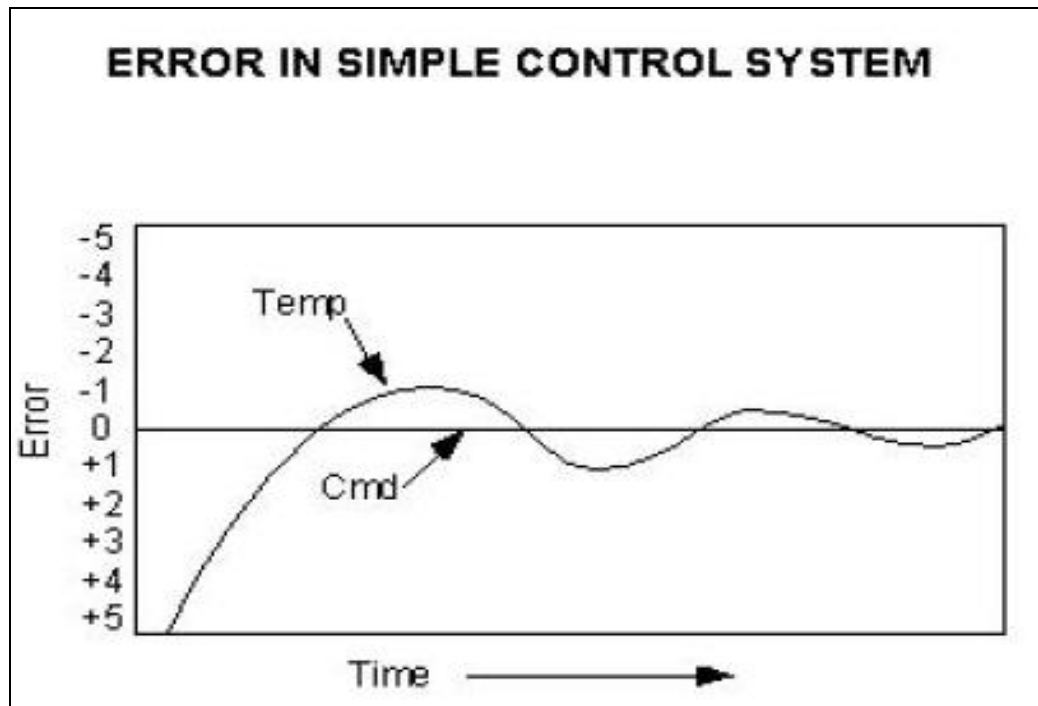


Figure 2.2 Typical control system responses

Figure 2.2 shows what command and error look like in a typical control system relative to the command setpoint as the system hunts for stability. Definitions are also shown for this example.

Definitions:

INPUT#1: ("Error", positive (P), zero (Z), negative (N))

INPUT#2: ("Error-dot", positive (P), zero (Z), negative (N))

CONCLUSION: ("Output", Heat (H), No Change (-), Cool (C))

INPUT#1 System Status

Error = Command-Feedback

P=Too cold, Z=Just right, N=Too hot

INPUT#2 System Status

Error-dot = $d(\text{Error})/dt$

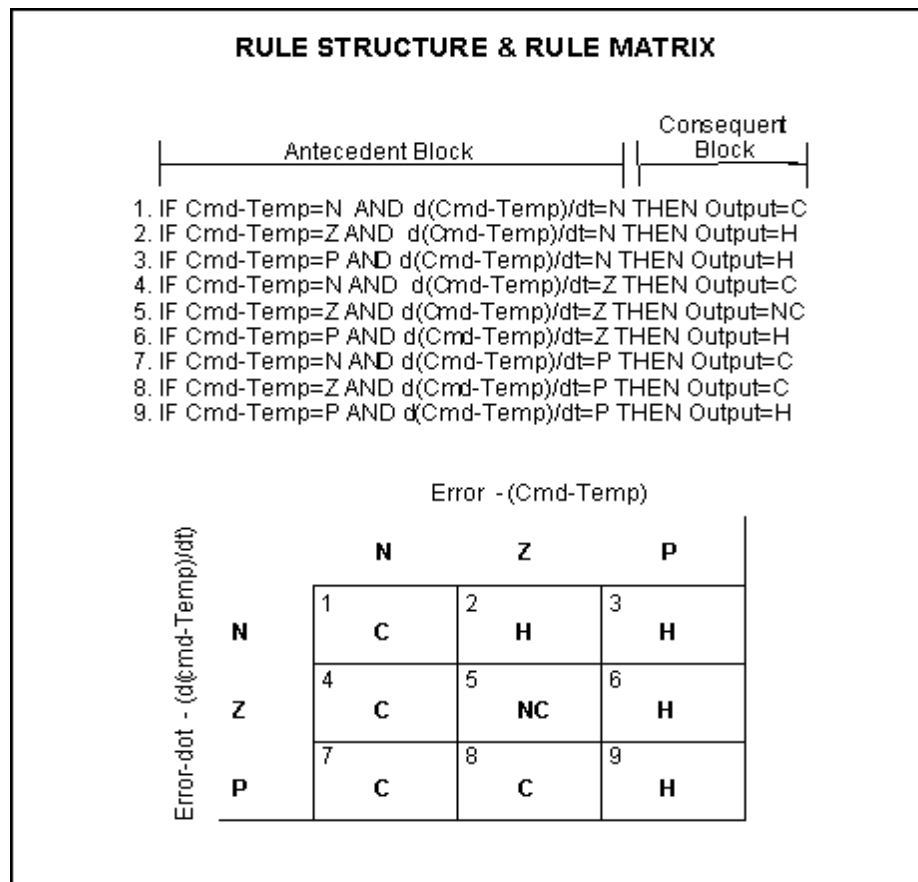
P=Getting hotter Z=Not changing N=Getting colder

OUTPUT Conclusion & System Response

Output H = Call for heating - = Don't change anything C = Call for cooling

2.3.2 System Operating Rules

Linguistic rules describing the control system consist of two parts; an antecedent block (between the IF and THEN) and a consequent block (following THEN). Depending on the system, it may not be necessary to evaluate every possible input combination (for 5-by-5 & up matrices) since some may rarely or never occur. By making this type of evaluation, usually done by an experienced operator, fewer rules can be evaluated, thus simplifying the processing logic and perhaps even improving the FL system performance.



Figures 2.3 & 2.4 - The rule structure.

After transferring the conclusions from the nine rules to the matrix there is a noticeable symmetry to the matrix. This suggests (but doesn't guarantee) a reasonably well-behaved (linear) system. This implementation may prove to be too simplistic for some control problems; however it does illustrate the process. Additional degrees of error and error-dot may be included if the desired system response calls for this. This will increase the rulebase size and complexity but may also increase the quality of the control. Figure 4 shows the rule matrix derived from the previous rules.

2.4 Membership Functions

In the last article, the rule matrix was introduced and used. The next logical question is how to apply the rules. This leads into the next concept, the membership function.

The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. Once the functions are inferred, scaled, and combined, they are defuzzified into a crisp output which drives the system. There are different membership functions associated with each input and output response. Some features to note are:

SHAPE - triangular is common, but bell, trapezoidal, haversine and, exponential have been used. More complex functions are possible but require greater computing overhead to implement.. HEIGHT or magnitude (usually normalized to 1) WIDTH (of the base of function), SHOULDERING (locks height at maximum if an outer function. Shouldered functions evaluate as 1.0 past their center) CENTER points (center of the member function shape) OVERLAP (N&Z, Z&P, typically about 50% of width but can be less).

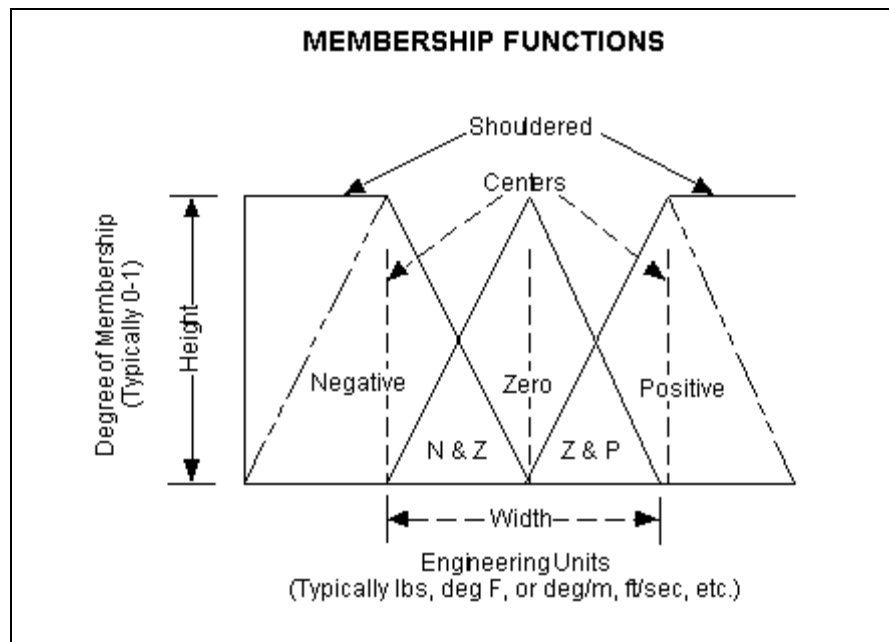


Figure 2.5 The features of a membership function

Figure 2.5 illustrates the features of the triangular membership function which is used in this example because of its mathematical simplicity. Other shapes can be used but the triangular shape lends itself to this illustration.

The degree of membership (DOM) is determined by plugging the selected input parameter (error or error-dot) into the horizontal axis and projecting vertically to the upper boundary of the membership function(s).

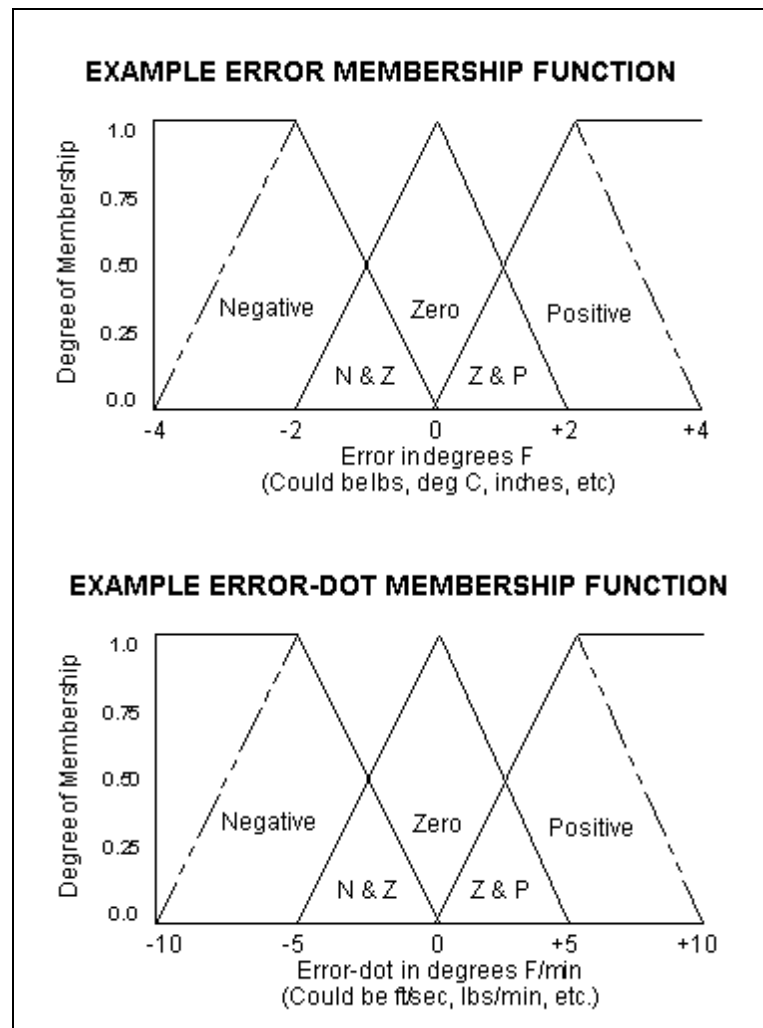
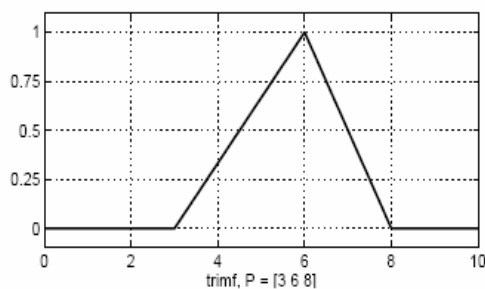


Figure 2.6 A sample case

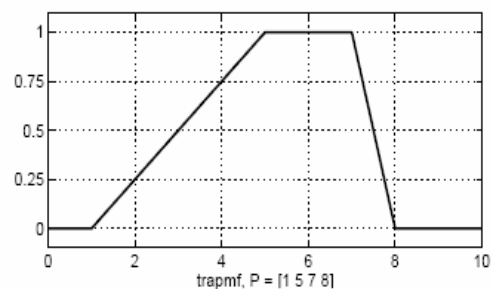
In Figure 2.6, consider an "error" of -1.0 and an "error-dot" of +2.5. These particular input conditions indicate that the feedback has exceeded the command and is still increasing.

2.4.1 Example of membership functions

The simplest membership functions are formed using straight lines. Of these, the simplest is the *triangular* membership function, and it has the function name `trimf`. It's nothing more than a collection of three points forming a triangle. The *trapezoidal* membership function, `trapmf`, has a flat top and really is just a truncated triangle curve. These straight line membership functions have the advantage of simplicity.

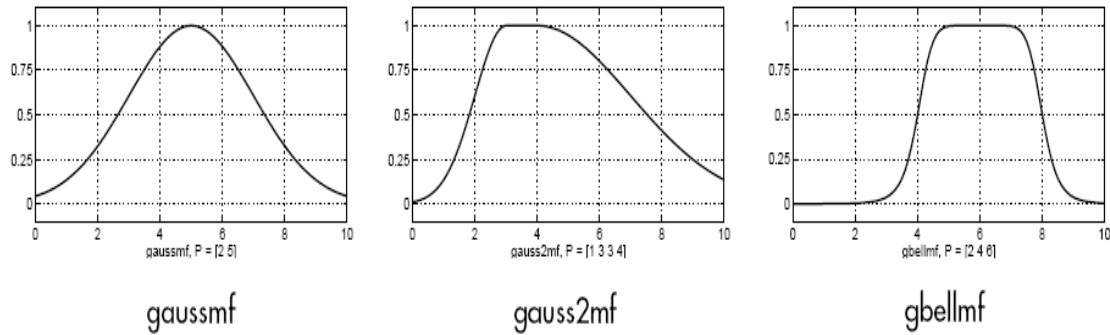


trimf

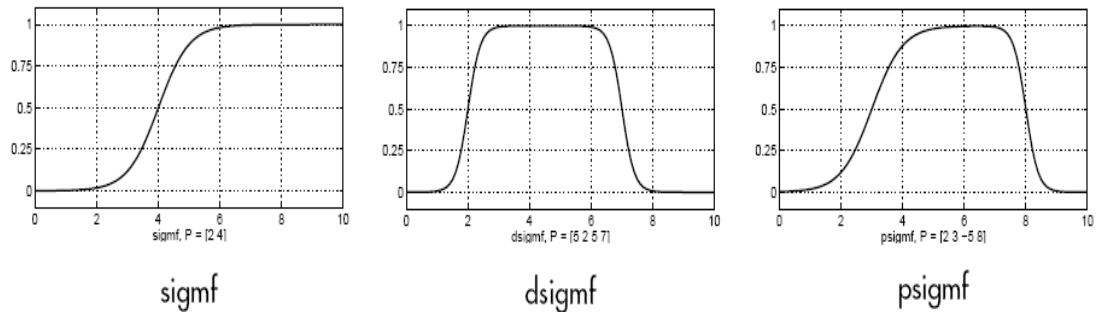


trapmf

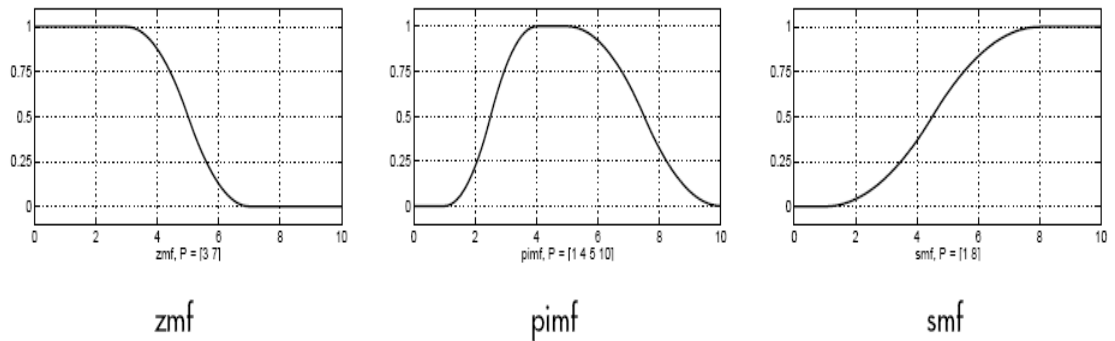
Two membership functions are built on the Gaussian distribution curve: a simple Gaussian curve and a two-sided composite of two different Gaussian curves. The two functions are `gaussmf` and `gauss2mf`. The generalized bell membership function is specified by three parameters and has the function name `gbellmf`. The bell membership function has one more parameter than the Gaussian membership function, so it can approach a non-fuzzy set if the free parameter is tuned. Because of their smoothness and concise notation, Gaussian and bell membership functions are popular methods for specifying fuzzy sets. Both of these curves have the advantage of being smooth and nonzero at all points.



Although the Gaussian membership functions and bell membership functions achieve smoothness, they are unable to specify asymmetric membership functions, which are important in certain applications. Next we define the *sigmoidal* membership function, which is either open left or right. Asymmetric and closed (i.e. not open to the left or right) membership functions can be synthesized using two sigmoidal functions, so in addition to the basic `sigmf`, we also have the difference between two sigmoidal functions, `dsigmf`, and the product of two sigmoidal functions `psigmf`.



Polynomial based curves account for several of the membership functions in the toolbox. Three related membership functions are the *Z*, *S*, and *Pi* curves, all named because of their shape. The function `zmf` is the asymmetrical polynomial curve open to the left, `smf` is the mirror-image function that opens to the right, and `pimf` is zero on both extremes with a rise in the middle.



There's a very wide selection to choose from when you're selecting your favorite membership function. If this list seems bewildering, just remember that you could probably get along very well with just one or two types of membership functions, for example the triangle and trapezoid functions. The selection is wide for those who want to explore the possibilities, but exotic membership functions are by no means required for perfectly good fuzzy inference systems. Finally, remember that more details are available on all these functions in the reference section, which makes up the second half of this manual.

2.4.2 Error & Error-dot Membership Function

The degree of membership for an "error" of -1.0 projects up to the middle of the overlapping part of the "negative" and "zero" function so the result is "negative" membership = 0.5 and "zero" membership = 0.5. Only rules associated with "negative" & "zero" error will actually apply to the output response. This selects only the left and middle columns of the rule matrix.

For an "error-dot" of +2.5, a "zero" and "positive" membership of 0.5 is indicated. This selects the middle and bottom rows of the rule matrix. By overlaying the two regions of the rule matrix, it can be seen that only the rules in the 2-by-2 square in the lower left corner (rules 4, 5, 7, 8) of the rules matrix will generate non-zero output conclusions. The others have a zero weighting due to the logical AND in the rules.

2.5 Putting It All Together

As inputs are received by the system, the rulebase is evaluated. The antecedent (IF X AND Y) blocks test the inputs and produce conclusions. The consequent (THEN Z) blocks of some rules are satisfied while others are not. The conclusions are combined to form logical sums. These conclusions feed into the inference process where each response output member function's firing strength (0 to 1) is determined.

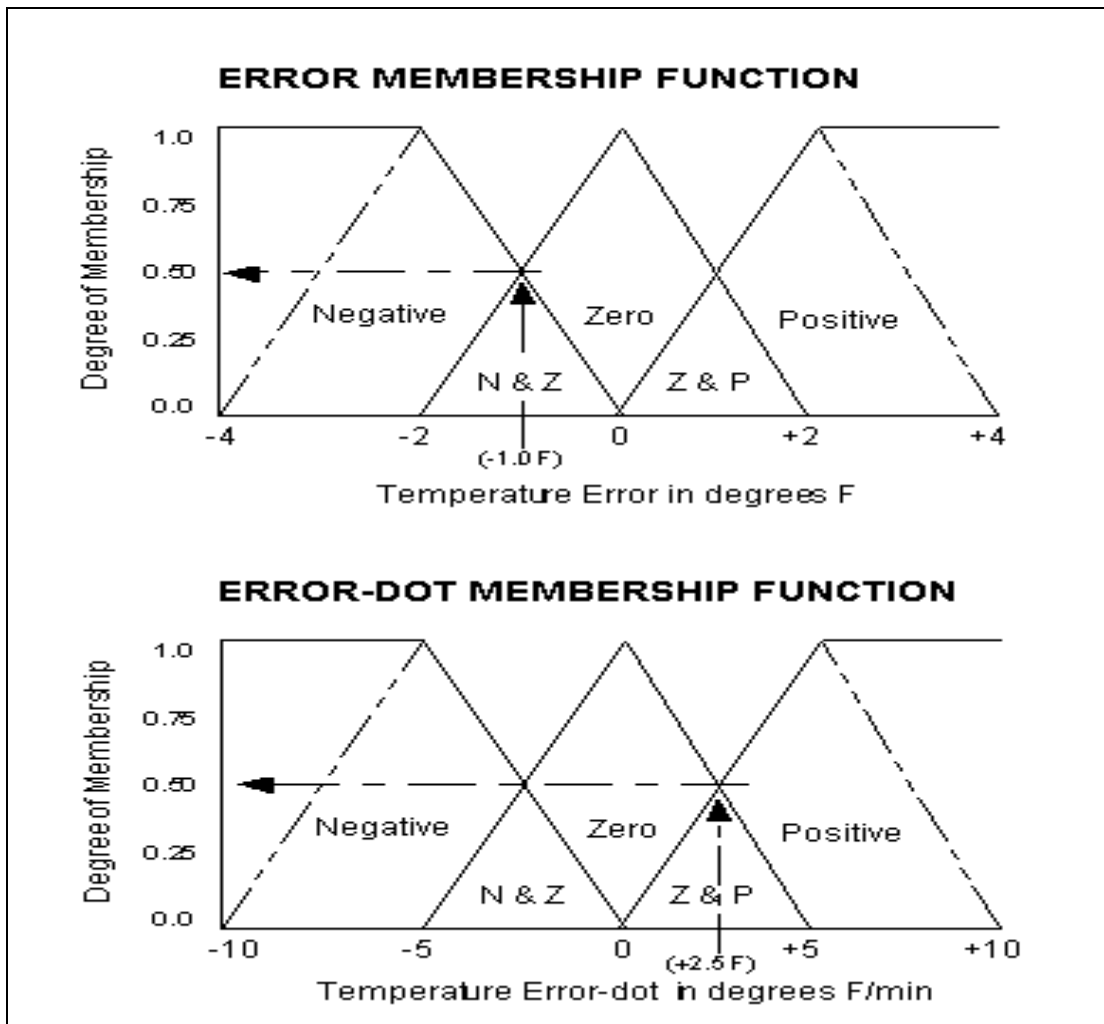


Figure 2.7 - Degree of membership for the error and error-dot functions in the current example

Data summary from previous illustrations:

INPUT DEGREE OF MEMBERSHIP

"error" = -1.0: "negative" = 0.5 and "zero" = 0.5

"error-dot" = +2.5: "zero" = 0.5 and "positive" = 0.5

ANTECEDENT & CONSEQUENT BLOCKS (e = error, er = error-dot or error-rate)

Now referring back to the rules, plug in the membership function weights from above. "Error" selects rules 1, 2, 4, 5, 7, 8 while "error-dot" selects rules 4 through 9. "Error" and "error-dot" for all rules are combined to a logical product (LP or AND, that is the minimum of either term). Of the nine rules selected, only four (rules 4, 5, 7, 8) fire or have non-zero results. This leaves fuzzy output response magnitudes for only "Cooling" and "No_Change" which must be inferred, combined, and defuzzified to return the actual crisp output. In the rule list below, the following definitions apply: (e)=error, (er)=error-dot.

1. If (e < 0) AND (er < 0) then Cool 0.5 & 0.0 = 0.0
2. If (e = 0) AND (er < 0) then Heat 0.5 & 0.0 = 0.0
3. If (e > 0) AND (er < 0) then Heat 0.0 & 0.0 = 0.0
4. If (e < 0) AND (er = 0) then Cool 0.5 & 0.5 = 0.5
5. If (e = 0) AND (er = 0) then No_Chng 0.5 & 0.5 = 0.5
6. If (e > 0) AND (er = 0) then Heat 0.0 & 0.5 = 0.0
7. If (e < 0) AND (er > 0) then Cool 0.5 & 0.5 = 0.5
8. If (e = 0) AND (er > 0) then Cool 0.5 & 0.5 = 0.5
9. If (e > 0) AND (er > 0) then Heat 0.0 & 0.5 = 0.0

2.5.1 Inferencing

The last step completed in the example in the last article was to determine the firing strength of each rule. It turned out that rules 4, 5, 7, and 8 each fired at 50% or 0.5 while rules 1, 2, 3, 6, and 9 did not fire at all (0% or 0.0). The logical products for each rule must be combined or inferred (max-min'd, max-dot'd, averaged, root-sum-squared, etc.) before being passed on to the defuzzification process for crisp output generation. Several inference methods exist.

The MAX-MIN method tests the magnitudes of each rule and selects the highest one. The horizontal coordinate of the "fuzzy centroid" of the area under that function is taken as the output. This method does not combine the effects of all applicable rules but does produce a continuous output function and is easy to implement.

The MAX-DOT or MAX-PRODUCT method scales each member function to fit under its respective peak value and takes the horizontal coordinate of the "fuzzy" centroid of the composite area under the function(s) as the output. Essentially, the member function(s) are shrunk so that their peak equals the magnitude of their respective function ("negative", "zero", and "positive"). This method combines the influence of all active rules and produces a smooth, continuous output.

The AVERAGING method is another approach that works but fails to give increased weighting to more rule votes per output member function. For example, if three "negative" rules fire, but only one "zero" rule does, averaging will not reflect this difference since both averages will equal 0.5. Each function is clipped at the average and the "fuzzy" centroid of the composite area is computed.

The ROOT-SUM-SQUARE (RSS) method combines the effects of all applicable rules, scales the functions at their respective magnitudes, and computes the "fuzzy" centroid of the composite area.

This method is more complicated mathematically than other methods, but was selected for this example since it seemed to give the best weighted influence to all firing rules.

2.5.2 Defuzzification - Getting Back to Crisp Numbers

The RSS method was chosen to include all contributing rules since there are so few member functions associated with the inputs and outputs. For the ongoing example, an error of -1.0 and an error-dot of +2.5 selects regions of the "negative" and "zero" output membership functions. The respective output membership function strengths (range: 0-1) from the possible rules (R1-R9) are:

$$\text{"negative"} = (R1^2 + R4^2 + R7^2 + R8^2) \text{ (Cooling)} = (0.00^2 + 0.50^2 + 0.50^2 + 0.50^2)^{.5} = 0.866$$

$$\text{"zero"} = (R5^2)^{.5} = (0.50^2)^{.5} \text{ (No Change)} = 0.500$$

$$\text{"positive"} = (R2^2 + R3^2 + R6^2 + R9^2) \text{ (Heating)} = (0.00^2 + 0.00^2 + 0.00^2 + 0.00^2)^{.5} = 0.000$$

The defuzzification of the data into a crisp output is accomplished by combining the results of the inference process and then computing the "fuzzy centroid" of the area. The weighted strengths of each output member function are multiplied by their respective output membership function center points and summed. Finally, this area is divided by the sum of the weighted member function strengths and the result is taken as the crisp output. One feature to note is that since the zero center is at zero, any zero strength will automatically compute to zero. If the center of the zero function happened to be offset from zero (which is likely in a real system where heating and cooling effects are not perfectly equal), then this factor would have an influence.

$$\frac{(\text{neg_center} * \text{neg_strength} + \text{zero_center} * \text{zero_strength} + \text{pos_center} * \text{pos_strength})}{(\text{neg_strength} + \text{zero_strength} + \text{pos_strength})}$$

= OUTPUT

$$\frac{(-100 * 0.866 + 0 * 0.500 + 100 * 0.000)}{(0.866 + 0.500 + 0.000)} = 63.4\%$$

$$\frac{(-100 * 0.866 + 0 * 0.500 + 100 * 0.000)}{(0.866 + 0.500 + 0.000)} = 63.4\%$$

$$(0.866 + 0.500 + 0.000)$$

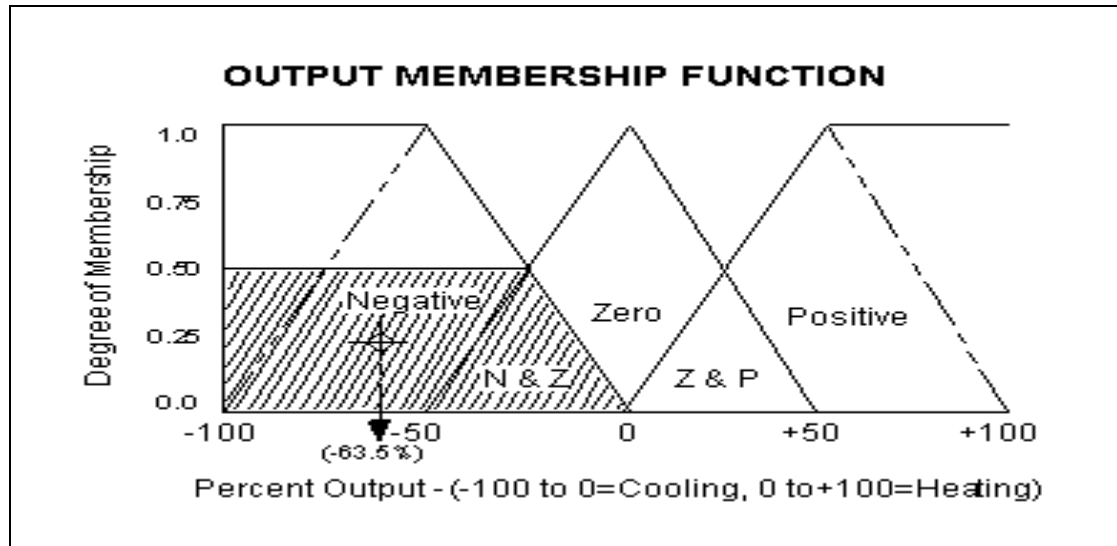


Figure 2.8 The horizontal coordinate of the centroid is taken as the crisp output

The horizontal coordinate of the centroid of the area marked in Figure 8 is taken as the normalized, crisp output. This value of -63.4% (63.4% Cooling) seems logical since the particular input conditions (Error=-1, Error-dot=+2.5) indicate that the feedback has exceeded the command and is still increasing therefore cooling is the expected and required system response.

2.5.3 Tuning and System Enhancement

Tuning the system can be done by changing the rule antecedents or conclusions, changing the centers of the input and/or output membership functions, or adding additional degrees to the input and/or output functions such as "low", "medium", and "high" levels of "error", "error-dot", and output response.

These new levels would generate additional rules and membership functions which would overlap with adjacent functions forming longer "mountain ranges" of functions and responses. The techniques for doing this systematically are a subject unto itself.

2.6 Takagi-Sugeno Fuzzy Logic Systems

The fuzzy logic systems described in the above sections are commonly referred to as pure fuzzy logic systems or Mamdani fuzzy logic systems. An alternative to these FLSs is offered by Takagi-Sugeno (TS) fuzzy logic system. In a TS-FLS the consequent of each rule is not a fuzzy set but it is a local model of the system (function) to be controlled (approximated). Thus the l -th rule of a TS-FLS has the form:

$R(l)$: IF e_1 is $A_{1k(1,l)}$ and e_2 is $A_{2k(2,l)}$ and ... e_n is $A_{nk(n,l)}$, THEN $y = g_l(e_1, e_2, \dots, e_n)$

Here i is a logical function that connects the sentences forming the condition, y is the output, and g is a function of the inputs. A simple example is

If error is Zero and change in error is Zero then output $y = c$

where f is a crisp constant. This is a *zero order* model, and it is identical to singleton output rules. A slightly more complex rule is

If error is Zero and change in error is Zero then output

$$y = a * \text{error} + b (\text{change in error}) + c$$

where a, b and c are all constants. This is a *first order* model. Inference with several rules proceeds as usual, with a firing strength associated with each rule, but each output is linearly dependent on the inputs. The output from each rule is a moving singleton, and the defuzzified output is the weighted average of the contributions from each rule. The controller interpolates between linear controllers; each controller is dominated by a rule, but there is a weighting depending on the overlap of the input membership functions.

CHAPTER THREE

FUZZY LOGIC CONTROL OF W.W.T.P

3.1 Automatic process control

The purpose of wastewater automatic control system is to maintain one or several parameters such as SRT, DO, or clarifier sludge depth at a fixed value. If there were no changes in external conditions, such as flowrate variation, process control would be a simple task. However, external conditions are changing constantly, and, as a result some dynamic control over treatment process is needed. The dynamic behavior of activated sludge processes is governed by numerous and intricate biological and physical-chemical mechanisms which are not yet completely understood. Different mechanistic models of these processes have been reported in the literature of wastewater treatment techniques. These models are always very complex and often require a lot of a priori experimental information and knowledge that are difficult to gather on a real wastewater treatment plant (WWTP). That is why the control of such processes using classical control tools is difficult and sometimes impossible.

The fuzzy set theory enables the development of knowledge-based control strategies for complex, non-linear, time-variant processes. It provides a way to avoid cumbersome mechanistic modeling and allows taking human expertise into consideration.

Several studies have been reported in the literature to describe different attempts of applying fuzzy control either to theoretical dynamic process simulations or to limited parts of an activated sludge process (aeration, settler...). Rather few works have been dedicated to the fuzzy control of the whole process including biological reactors and settler. In thesis, the development and the validation of a hierarchical fuzzy rule based controller of a nitrifying-denitrifying activated sludge process WWTP which was design by traditional methods and equipped with on-line sensors placed in the different parts pf the system will be optimized and automatized where the main control goals are to meet the discharge limits (organic matter, ammonium,

nitrate and suspended solids concentrations) of the effluent and to minimize energy consumption.

3.2 Wastewater treatment plant description

The w.w.t.p (see also appendices for design) configuration is given in figure 1. It corresponds to a two-stage (nitrification–denitrification) activated sludge process based on a classical modified Ludzack-Ettinger (MLE) scheme. The first biological step (anoxic reactor of 950 m³), allows anoxic heterotrophic microorganisms to reduce nitrate and oxidize the organic matter. The second biological step (aeration basin of 7025 m³) allows aerobic heterotroph and autotroph microorganisms to oxidize the organic matter and ammonia, respectively. The third step is a settling tank (clarifier, volume 2400 m³). It achieves the effluent clarification and the sludge thickening. Two recycling loops return thickened sludge and nitrate to the anoxic reactor. Monitoring points are indicated by black dots along the process flow.

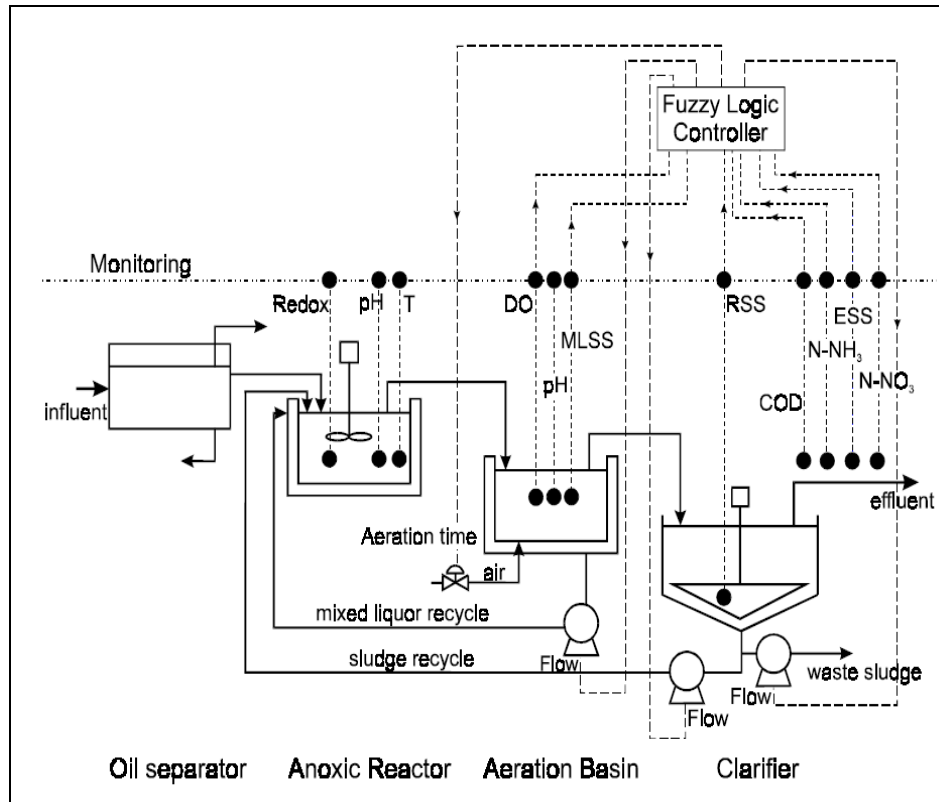


Figure 3.1 Wastewater treatment plant figure

3.3 Processing control and monitoring

The process monitoring relies on data provided by on-line and off-line sensors as summarized in table 1 (see nomenclature for the notations). On-line sensors mainly consist in turbidimetry probes for the estimation of suspended solids (SS) and a dissolved oxygen (DO) probe. Their data sampling rate is fixed to approximately 120 data/hour. The off-line sensors consist in elementary chemical analysis (COD, N-NH₃, N-NO₃). Their sampling rate is approximately 1 data/day.

The control variables are the aeration time in the aeration basin and three flowrates: the mixed liquor recycling, the sludge recycling and the waste sludge drain. They represent the four possible actions of the controller to optimize the process performance.

Table 3.1 Monitored data

	Anoxic Reactor	Aeration Basin	Clarifier
On-line sensors	T, pH, redox	MLSS, pH, DO	ESS, RSS
Off-line sensors			COD, N-NH ₃ -N-NO ₃
Calculated data		OUR	

3.3.1 Controller architecture

Two main tasks have to be fulfilled by the controller: the direct control of the process variables, based on predetermined setpoints and to decide on the evolution of these setpoints, on a global process diagnostic. To this aim, a hierarchical architecture has been adopted to build the fuzzy controller (figure 2). Two distinct layers exist: the Supervision Block (upper level) and the Control Block (lower level).

This structure involves different fuzzy logic rule bases. Each of these components is defined by a set of IF-THEN rules describing the system behavior and input/output associated membership functions which characterize linguistic labels. The practical run of fuzzy logic uses three steps:

- Fuzzification: translates crisp values of observed variables into grade of membership associated to linguistic terms (fuzzy states),
- Inference: evaluates output fuzzy states (linguistic terms) from input fuzzy ones and IF-THEN rules,
- Defuzzification: calculates crisp numerical values of outputs from output fuzzy states.

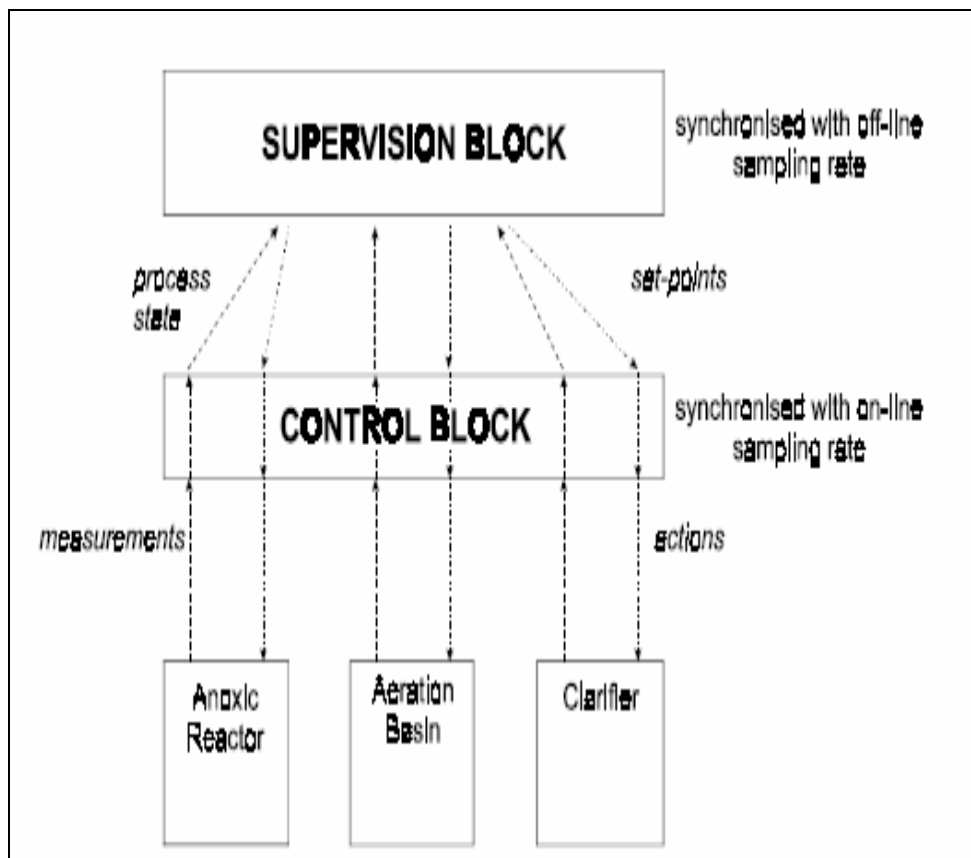


Figure 3.2: Controller structure

3.3.2 Supervision Block

The Supervision Block is synchronized with the data acquisition rate of the offline sensors (mostly chemical analysis, approximately 1 data/day). It establishes the control strategy of the whole controller by fixing setpoints for the control block. This is done by means of fuzzy rules using off-line and calculated data:

- the setpoint for the MLSS concentration control is fixed on the basis of the specific oxygen uptake rate OUR in the aeration tank,
- the setpoint for the DO in the aeration basin is fixed on the basis of the N-NH₃ residual effluent concentration.

Table 2 presents a set of 8 fuzzy rules used in the supervision block to determine the MLSS and DO setpoints. Linguistic terms used to label the input variables (OUR and N-NH₃) and the setpoints (MLSSsp, DOsp) are Small (S), Medium (M), Large (L) and Very Large (VL).

Table 3.2: Example of fuzzy rules used in the supervision block

	IF	IS	THEN	IS
Setpoint for MLSS	OUR	S	MLSSsp	S
	OUR	M	MLSSsp	M
	OUR	L	MLSSsp	L
	OUR	VL	MLSSsp	VL
Setpoint for DO	N-NH ₃	S	DOsp	S
	N-NH ₃	M	DOsp	M
	N-NH ₃	L	DOsp	L
	N-NH ₃	VL	DOsp	VL

3.3.3 Control Block

The Control Block is synchronized with the data acquisition rate (approximately 120 data/hour) of the on-line sensors (*MLSS*, *ESS*, *RSS*, *DO*...). Off-line data are measured every day or, if necessary, estimated at the required frequency using a linear prediction algorithm. The control of the operating parameters is achieved by means of four individual fuzzy control loops acting respectively on:

- the blowers power, inferred from the DO level in the aeration basin,
- the NO_x regulation, inferred from the N-NO_3 effluent concentration,
- Alkalinity regulation, inferred from CaCO_3 concentration in aeration tank,
- Return sludge flowrate, inferred from MLSS concentration in the aeration basin,
- the excess sludge flowrate Q_w , inferred from the RSS and ESS concentrations at the bottom and the top of the clarifier respectively.

3.3.4 Software/Hardware

Three distributed network personal computers (PC) are used to monitor and control the plant operation: a supervisory computer responsible for data acquisition, data storage, equipment control, and hosting a web server; a second computer that controls the sequential injection analysis (SIA) system; a third local PC is used to command peristaltic pumps. The LabVIEW (National Instruments, USA) graphical development environment was used for the distributed software tasks of signal acquisition and processing, measurement analysis, data presentation, network and Data Socket communication, and Internet publication. Data are acquired periodically and recorded to Excel format files. The supervisory computer is equipped with a PCI 6024-E board (National Instruments, USA). Two PCL-718 boards (Advantech, Taiwan) are installed in the pumps control PC. The Fuzzy Logic toolbox for MATLAB (The Mathworks, Inc., USA) was used to embed the fuzzy logic system in LabVIEW.

3.4 Dissolved Oxygen Control

The dissolved oxygen (DO) is an influential ecological parameter. Its control is of extremely importance in the field of pollution removal biologic processes used by wastewater treatment plants. Its knowledge provides invaluable information related to the good behavior of these processes. The DO concentration strongly varies according to various system parameters like temperature, salinity or pressure. It can be considered as:

A pollution indicator: reduced organic or mineral matters are biologically or chemically oxidized in water, involving the oxygen consumption and a dissolved oxygen concentration reduction. Oxygen impoverished water can for this reason be considered as polluted.

A biological activity indicator: the dissolved oxygen rate in water can be interpreted as the result of photosynthetic or respiratory activity for various aquatic organisms or even like as the potentiality of aerobic and anaerobic organisms' development.

The dissolved oxygen setpoint in the aeration tank is selected as 2 mg/l therefore the first input for fuzzy rules is error ($D.O_{sp} - D.O_{feedback}$) and the second input is the rate of change of error ($dError / dt$) and the output is the power regulation of the air blowers in the w.w.t.p system. As shown in table there are 5 linguistic variables for both DO_{er} and percentage increments on power such as Large negative, Negative, Zero/Nominal, Positive and Large positive and 3 linguistic variables for the rate of change of error such as Negative, Zero and Positive.

Table 3.3 Fuzzy rules for dissolved oxygen control in the aeration basin.

If D.O_{er} is (mg/l)	And	If dD.O/dt is (mg.lt/min)	Then	Increments on Power (kW)
LNegative		Negative		LNegative
LNegative		Zero		LNegative
LNegative		Positive		LNegative
Negative		Negative		Negative
Negative		Zero		Negative
Negative		Positive		Negative
Zero		Negative		Positive
Zero		Zero		Nominal
Zero		Positive		Negative
Positive		Negative		Positive
Positive		Zero		Positive
Positive		Positive		Positive
Lpositive		Negative		Lpositive
Lpositive		Zero		Lpositive
Lpositive		Positive		Lpositive

As it is shown in the table above there are 15 fuzzy rules created for the control of the dissolved oxygen concentration about 2 mg/l in the aeration tank. The fuzzy sets of input variables D.O_{error} (mg/l), change of rate of error dDO/dt (mg.lt/min) and the output variable percentage increments on power of air blowers in the system are created and shown in figures given below.

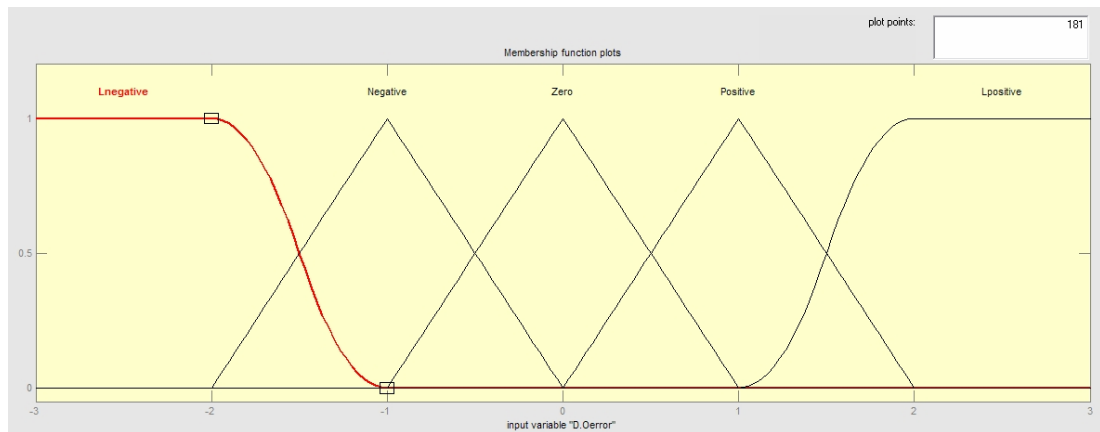


Figure 3.3 Fuzzy sets for dissolved oxygen errors (mg/l).

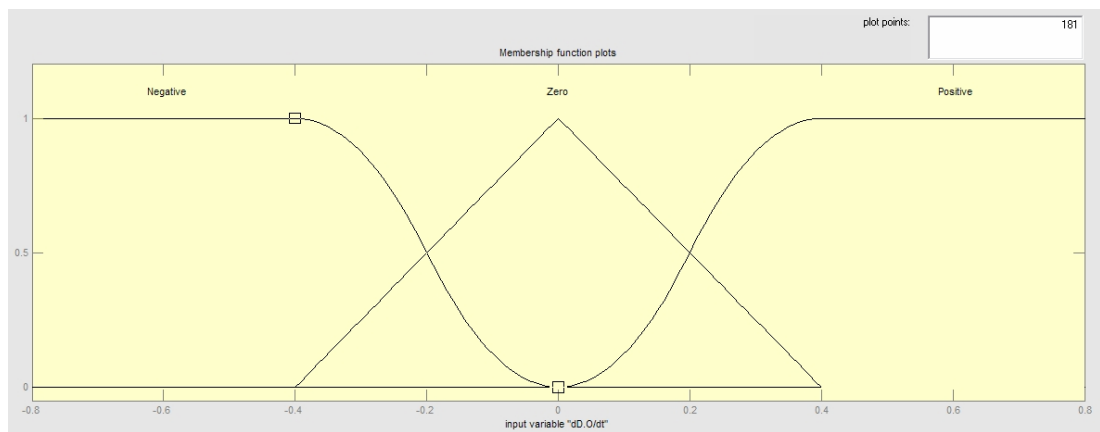


Figure 3.4 Fuzzy sets for rate of changes of errors (mg.l/min)

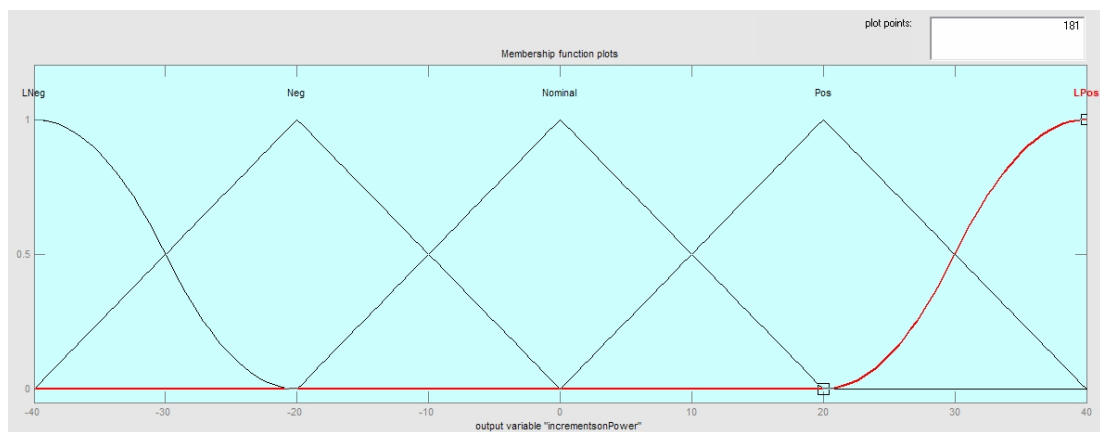


Figure 3.5 Fuzzy sets for percentage increment on power of air blowers

3.5 Mixed Liquor Suspended Solids Control

The performance of biological processes used for wastewater treatment depends on the dynamics of substrate utilization and microbial growth. Effective design and operation of such systems requires an understanding of the biological reactions occurring and an understanding of the basic principles governing the growth of microorganisms. Further, the need to understand all of the environmental conditions that affect the substrate utilization and microbial growth rate cannot be overemphasized, and it is a must to control the mixed liquor suspended solids concentration at the required level in the system.

In this thesis the M.L.S.S setpoint concentration in the aeration tank of the wastewater treatment plant is considered as 2.8 g /lt (see appendices). The sensors in the aeration tank measure the concentrations of M.L.S.S and transmit the data to operators PC and a response is given to the actuator of return sludge pumps according to rules created for different situations of M.L.S.S concentrations in aeration tank such as L negative, Negative, Zero, Positive and Lpositive. The output variables also change such as Vlow, Low, Nominal, High and Vhigh.

In the table given below there are 5 fuzzy rules created for the regulation of M.L.S.S to maintain about 2.8 mg/lt.

Table 3.4 Fuzzy rules for MLSS concentration in aeration tank.

If MLSS_{er} is (mg/lt)	Then	Percentage increment on power (kW)
Lnegative		Vlow
Negative		Low
Zero		Nominal
Positive		High
Lpositive		Vhigh

As it is shown in the table above there are 5 fuzzy rules created for the control of the mixed liquor suspended solids concentration about 2.8 mg/l in the aeration tank. The fuzzy sets of input variable $MLSS_{er}$ (mg/l) and the output variable percentage increments on power of return sludge pumps in the system are created and shown in figures given below.

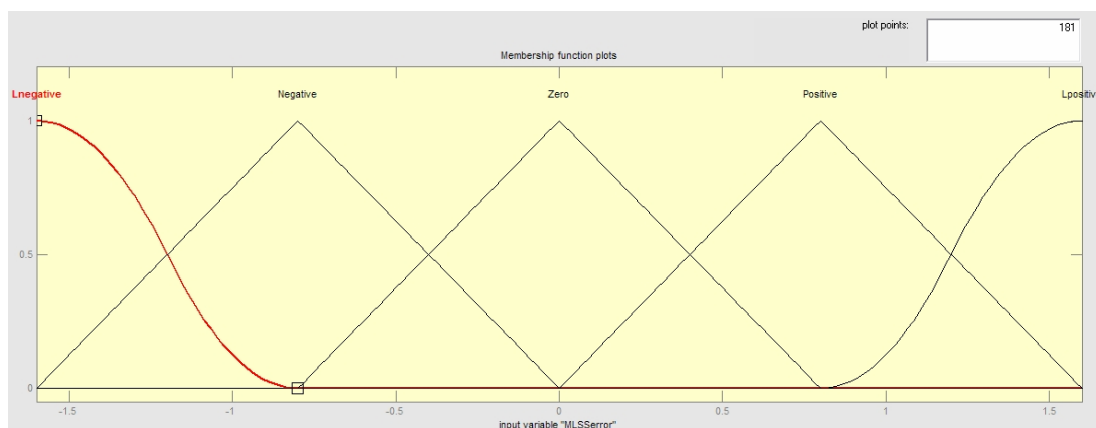


Figure 3.6 Fuzzy sets for MLSS errors in the aeration basin (g/l) (input)

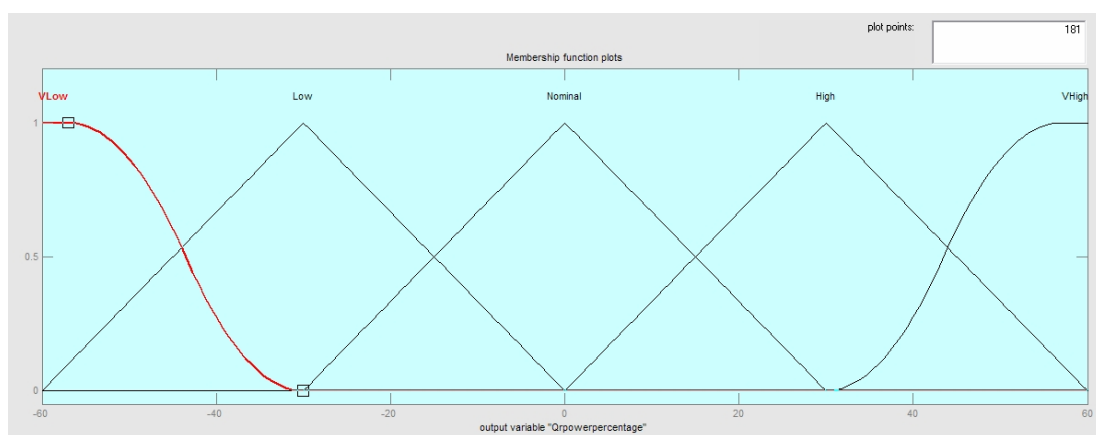


Figure 3.7 Fuzzy sets for percentage increments on power of return sludge pump (kW) (output)

3.6 Alkalinity control

Alkalinity in wastewater results from the presence of the hydroxides $[\text{OH}^-]$, carbonates $[\text{CO}_3^{2-}]$, and bicarbonates $[\text{HCO}_3^-]$ of elements such as calcium, magnesium, sodium, potassium, and ammonia. Of these, calcium and magnesium bicarbonates are most common. Borates, silicates, phosphates, and similar compounds can also contribute to the alkalinity. The alkalinity in the wastewater helps to resist changes in pH caused by the addition of acids

Alkalinity is a major chemical requirement needed for nitrification. The amount of alkalinity required for nitrification, taking into account cell growth, is about 7.07 g CaCO_3 / g $\text{NH}_4\text{-N}$. In addition to the alkalinity required for nitrification, additional alkalinity must be available to maintain the pH in the range from 6.8 to 7.4.

In this thesis the amount of residual alkalinity setpoint is selected as 80 mg CaCO_3/L to maintain pH near a neutral point. The input for fuzzy rules is error ($\text{CaCO}_{3\text{error}} - \text{CaCO}_{3\text{feedback}}$) and the output is the percentage increments on power of the CaCO_3 dosage pump in the w.w.t.p system.

As shown in table there are 3 linguistic variables for both $\text{CaCO}_{3\text{error}}$ such as Negative, Nominal, Positive and percentage increments on power such as Large negative, Negative, Zero/Nominal, Positive and Large positive and 3 linguistic variables for the rate of change of error such as Negative, Zero and Positive

Table 3.5 Fuzzy rules for CaCO_3 control in the aeration tank

If $\text{CaCO}_{3\text{error}}$ is (mg/l)	Then	Percentage increment on power (kW)
Negative		Low
Nominal		No_Change
Positive		High

As it is shown in the table above there are 3 fuzzy rules created for the control of the alkalinity about 80 mg CaCO_3/lt in the aeration tank. The fuzzy sets of input variables $\text{CaCO}_3_{\text{error}}$ (mg/lt) and the output variable percentage increments on power of CaCO_3 dozer in the system are created and shown in figures given below.

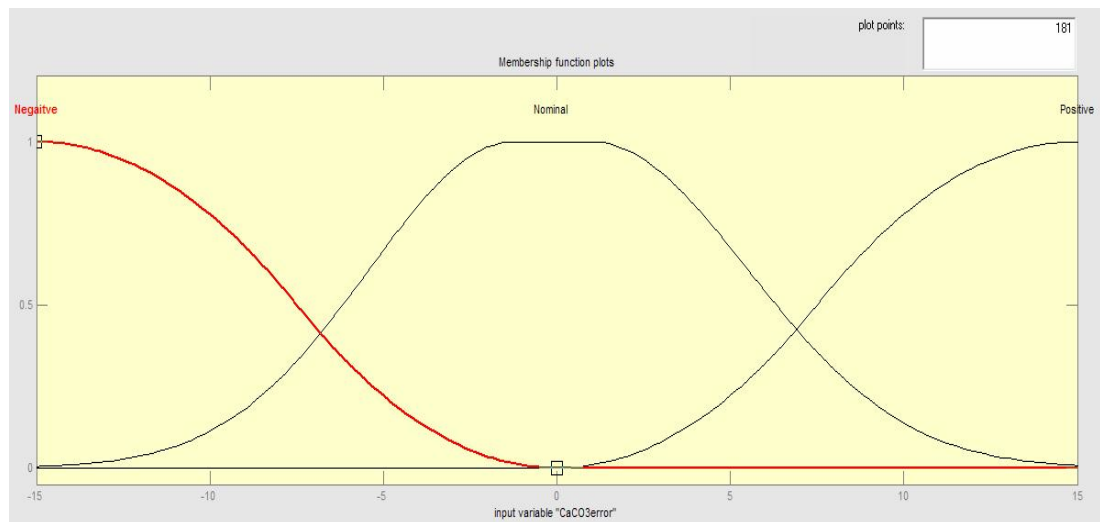


Figure 3.8 Fuzzy sets for CaCO_3 error in aeration tank (input)

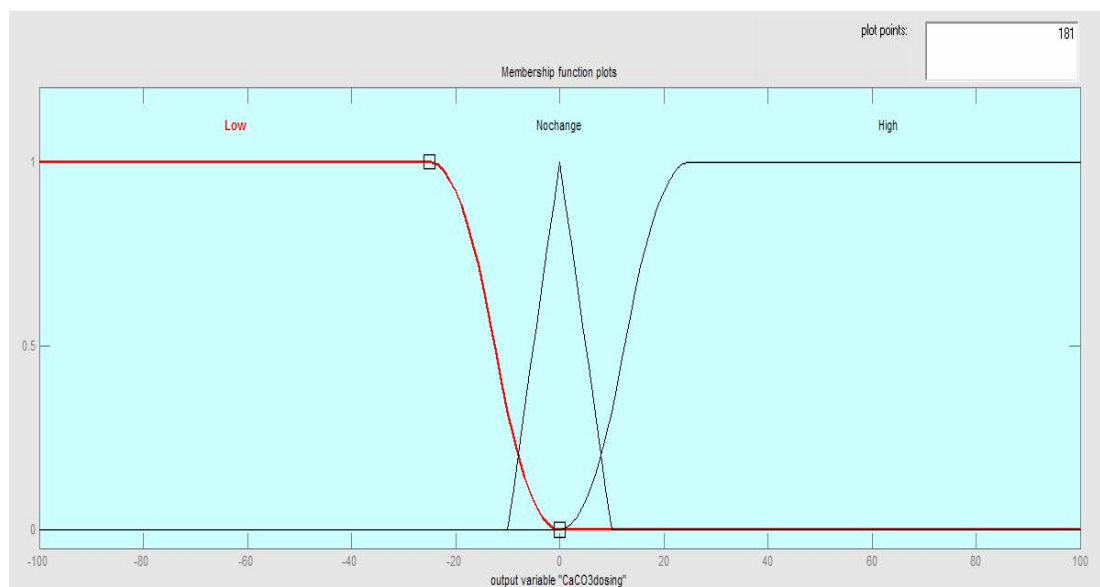


Figure 3.9 Fuzzy sets for percentage increments on power of CaCO_3 dosage pump (output)

3.7 Residual Nitrate concentration control

Nitrate nitrogen is the most oxidized form of nitrogen found in wastewaters. Where secondary effluent is to be reclaimed for groundwater recharge, the nitrate concentration is important. The U.S. EPA primary drinking water standards (U.S. EPA, 1977) limit nitrogen to 45 mg/l as NO_3^- , because of its serious and occasionally fatal effects on infants. Nitrates may vary in concentration from 0 to 20 mg/L as N in wastewater effluents. Assuming complete nitrification has taken place, the typical range found in treated effluents is from 15 to 20 mg/L as N.

When the wastewater treatment plant was designed (see also appendices) the effluent nitrate concentration from clarifier was considered to be 8 mg/l. The effluent concentration goal for $\text{NO}_3\text{-N}_{\text{eff}}$ is achieved by changing the IR pumps which returns MLSS from aeration tank to anoxic tank.

The input for fuzzy rules is error ($\text{NO}_3\text{-N}_{\text{sp}} - \text{NO}_3\text{-N}_{\text{feedback}}$) and the output is the power regulation of the IR pumps in the w.w.t.p system. As shown in table there are 5 linguistic variables for $\text{NO}_3\text{-N}_{\text{er}}$ such as Large negative, Negative, Zero/Nominal, Positive and Large positive and for percentage increments on power of IR pumps such as Vlow, Low, Nominal, High, Vhigh.

Table 3.6 Fuzzy rules for residual nitrate concentration

If $\text{NO}_3\text{-N}_{\text{er}}$ is (mg/l)	then	Percentage increment on power (kW)
Lnegative		Vhigh
Negative		High
Zero		Nominal
Positive		Low
Lpositive		Vlow

According to the fuzzy rules given above in the table, the fuzzy set for input and output variables are shown in the figures given below.

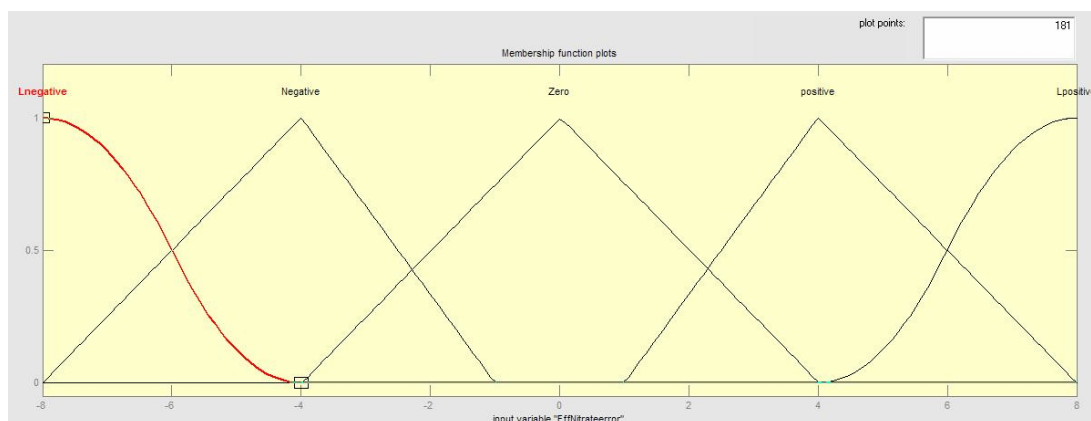


Figure 3.10 Fuzzy sets for Nitrate errors ($\text{NO}_3\text{-N}_{\text{error}}$ mg/l) at the clarifier effluent (input)

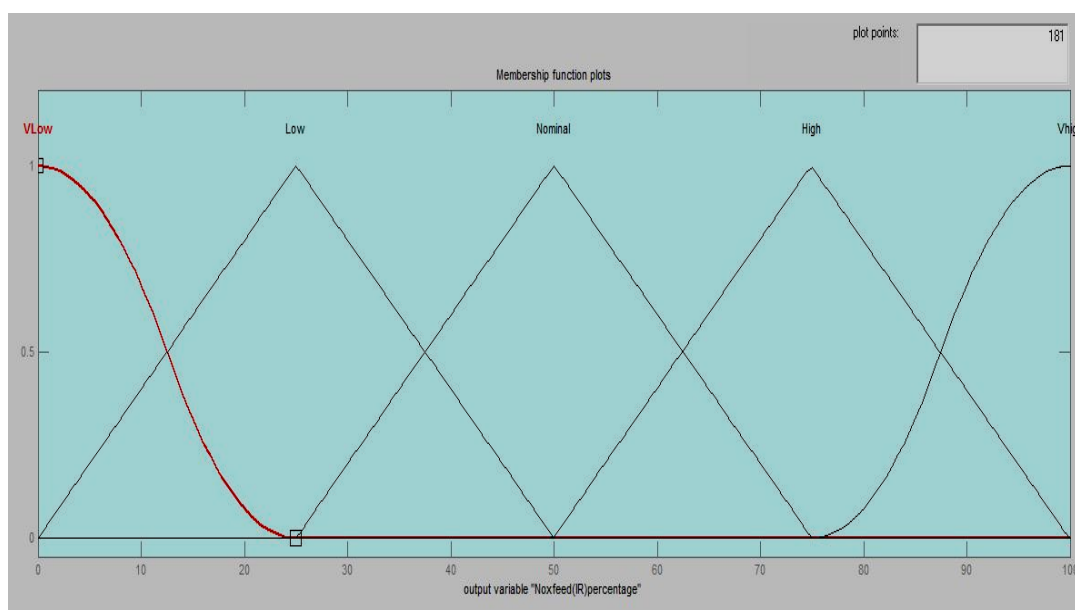


Figure 3.11 Fuzzy sets for percentage increments on power of IR pump (output)

3.8 Sludge control

To maintain a given solids retention time (SRT), the excess activated sludge produced each day must be wasted. The most common practice is to waste sludge from the return sludge line because return activated sludge is more concentrated and requires smaller waste sludge pumps. The waste sludge can be discharged to the primary sedimentation tanks for co-thickening tanks, or to other sludge-thickening facilities. An alternative method of wasting sometimes used is withdrawing mixed liquor directly from aeration tank effluent pipe where the concentration of solids is uniform.

The importance of sludge control and handling is to keep SRT value constant which is one of the most vital parameter for biological processes in wastewater treatment.

In this thesis, according to design considerations (see appendices) the return sludge concentration from clarifier to anoxic tank is assumed as 7.5 g / lt.

Usually in w.w.t.p designs the effluent suspended solids are assumed to be very low and they are not taken into account as a designated parameter about the amount of sludge to be wasted but here we will take this parameter into account. The setpoint for effluent suspended solids is accepted as 15 mg / lt. The inputs are concentrations of return sludge from bottom of the clarifier and the effluent suspended solids from the top of the clarifier and the output is the percentage increments on power of purge pumps.

Fuzzy rules are shown in the table given below.

Table 3.7 Fuzzy rules for sludge control

If RSS_{er} is (g/l)	And	If effluent SS_{error} is (mg/l)	Then	Increments on Power (kW)
Neg		Lnegative		Lpositive
Zero		Lnegative		Positive
Positive		Lnegative		Negative
Neg		Negative		Lpositive
Zero		Negative		Positive
Positive		Negative		Negative
Neg		Zero		Positive
Zero		Zero		No_Change
Positive		Zero		Negative

As it is seen in the table there are 9 rules for sludge control. However the linguistic variables for RSS_{er} are in a range from negative to positive the linguistic variables for effluent suspended solids error are in a range from Lnegative to Zero because there is no need for positive values to take into account. For example; if the effluent S.S concentration is 7 mg /lt then the SS_{error} is $10 - 7 = 3$ mg/lt thus the variable is considered to be positive. As it is understood, there are no needs to respond the system in the positive values of SS_{error} because its positive values show that the system works correctly. The input and output fuzzy sets are given below.

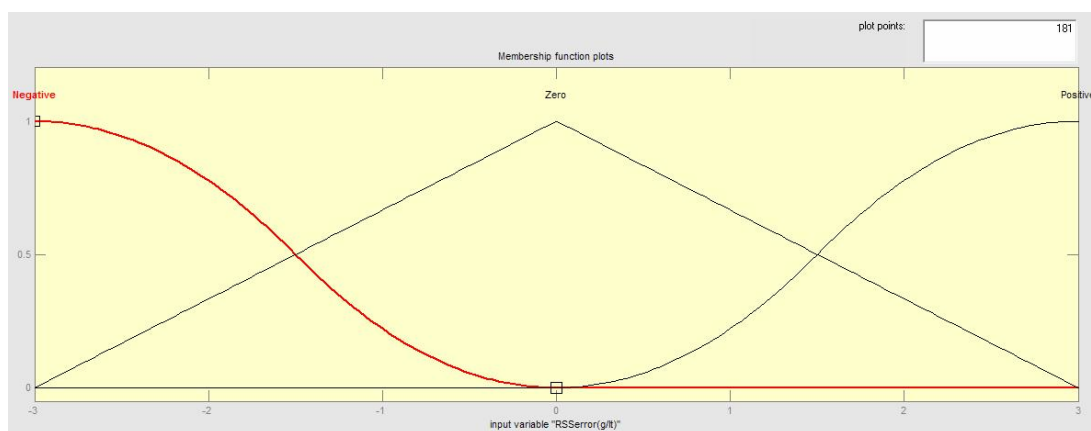


Figure 3.12 Fuzzy sets for return suspended solids concentration error (g/l) input

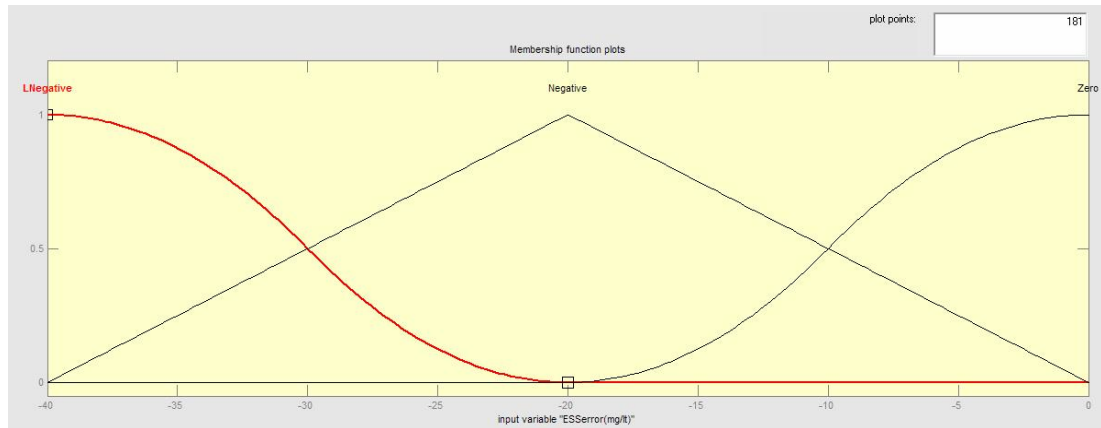


Figure 3.13 Fuzzy sets for effluent suspended solids error (mg/l) input

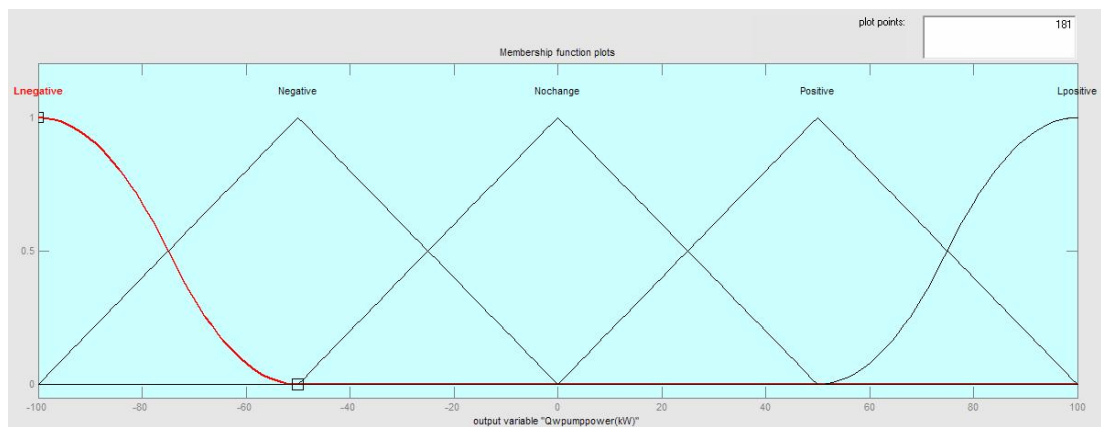


Figure 3.14 Fuzzy set for percentage increments of purge pump (kW) output

CHAPTER FOUR

RESULTS AND DISCUSSIONS

Different types of parameters are controlled by fuzzy logic and fuzzy rules are and fuzzy rules and fuzzy sets are created to achieve to maintain the setpoint at its level. Now let us see the control surfaces and view of rules for any input values and output value which is a respond to given input value.

The data acquisition and control program runs under the LabVIEW® environment. The fuzzy controller architecture was designed with DataEngine®, also running under the LabVIEW® environment.

The figure of control surface of dissolved oxygen concentration in the airtation tank is given below.

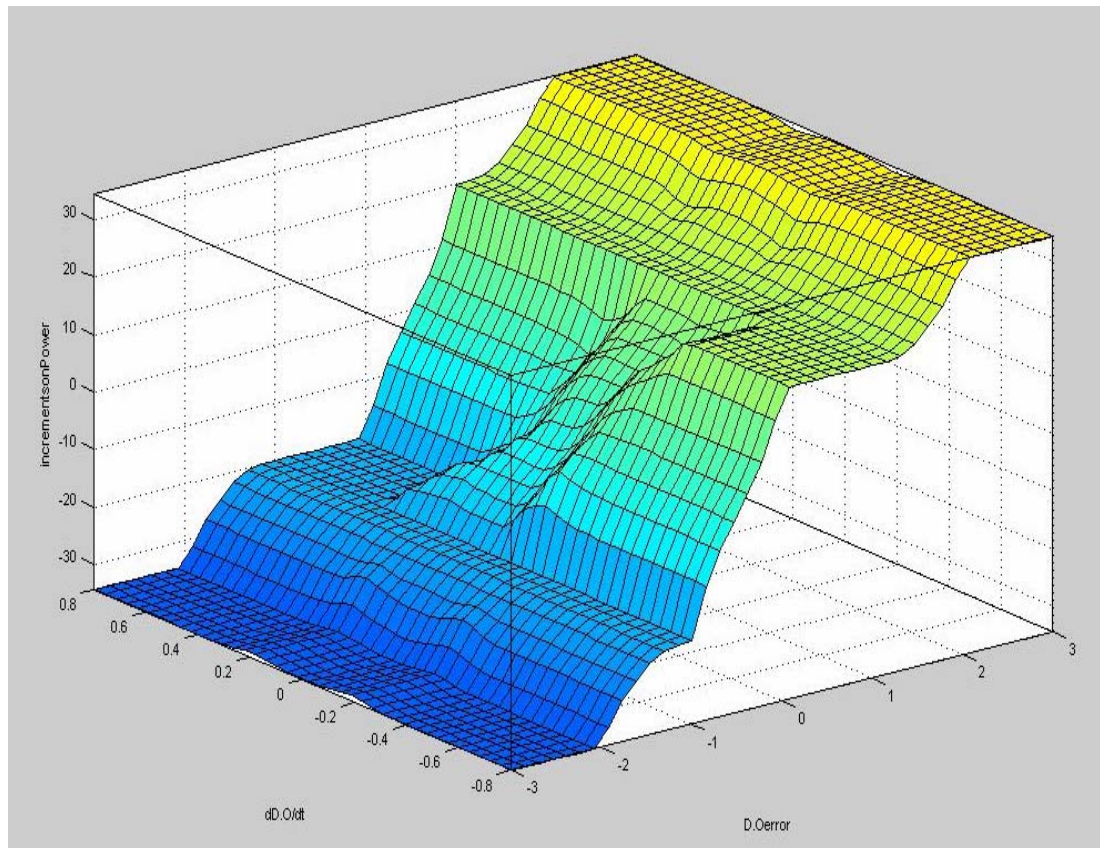


Figure 4.1 Control surface of dissolved oxygen concentration control in the airtation tank

Here is an example of a response output comes out from the created fuzzy rules and fuzzy sets for a situation which is the $D.O_{er}$ is 1.36 and dDO/dt is -0.22 mg.lt/min. According to the created rules and fuzzy sets the output defuzzified value is 34.4 % increase on power of air blowers.

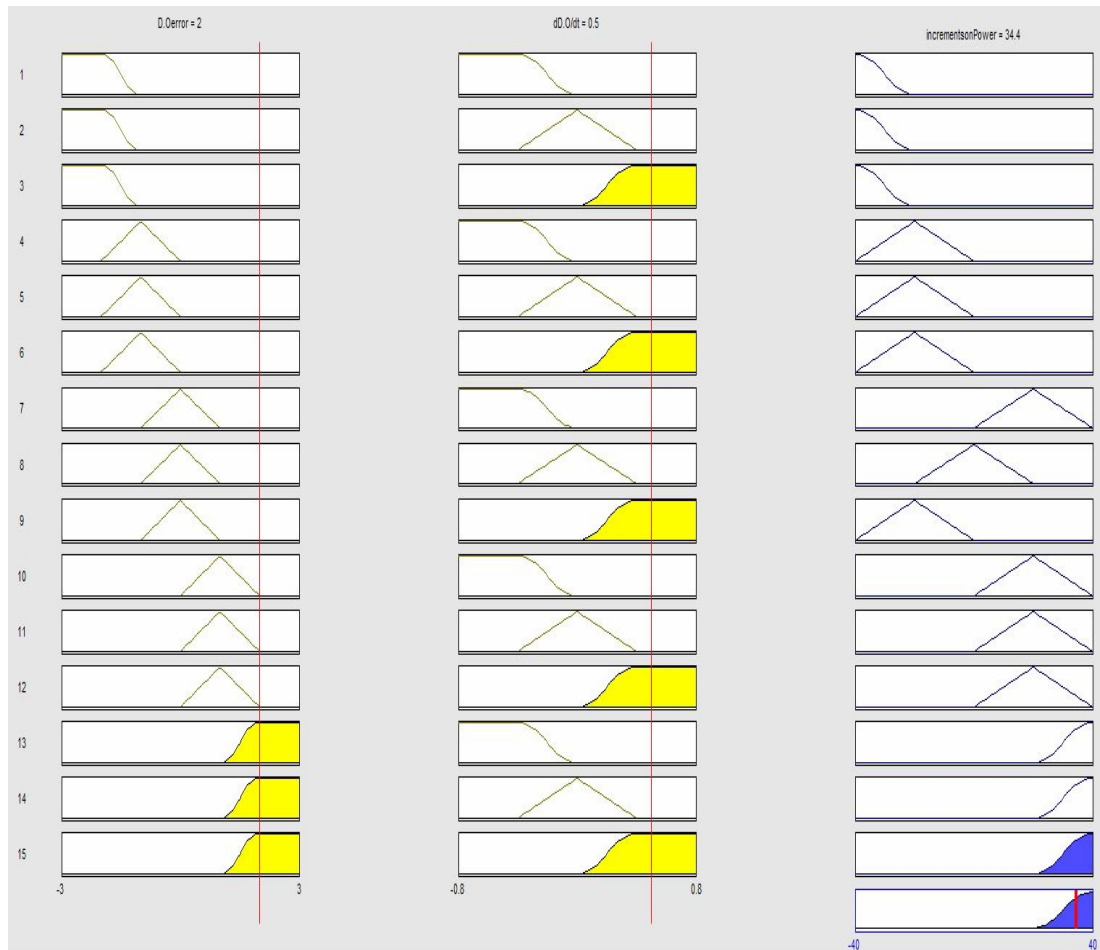


Figure 4.2 Rule viewer of D.O concentration control in aeration tank.

If we take a look at the residual nitrate concentration control the surface will be like:

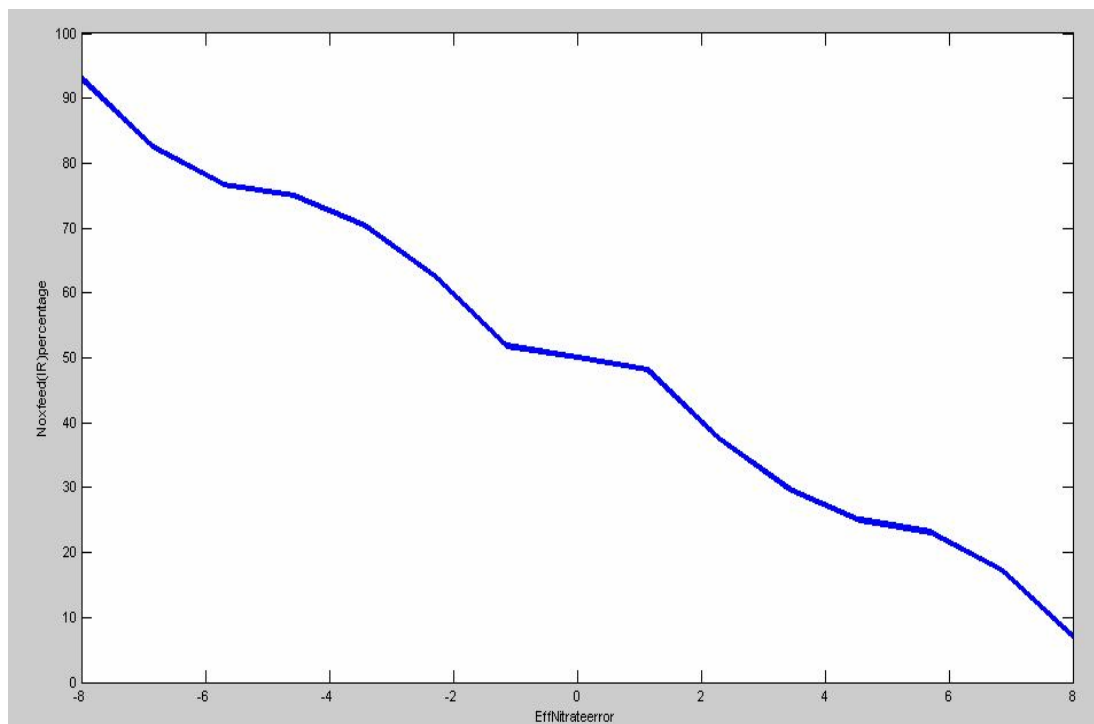


Figure 4.3 Control surface of residual nitrate concentration control

At the figure we can see that there is a non linear proportion decrease of NO_x feed with effluent nitrate error. Here is an example about this relation between $\text{NO}_3\text{-N}$ error with the value of 3 and IR pumps power increases 32.6 %

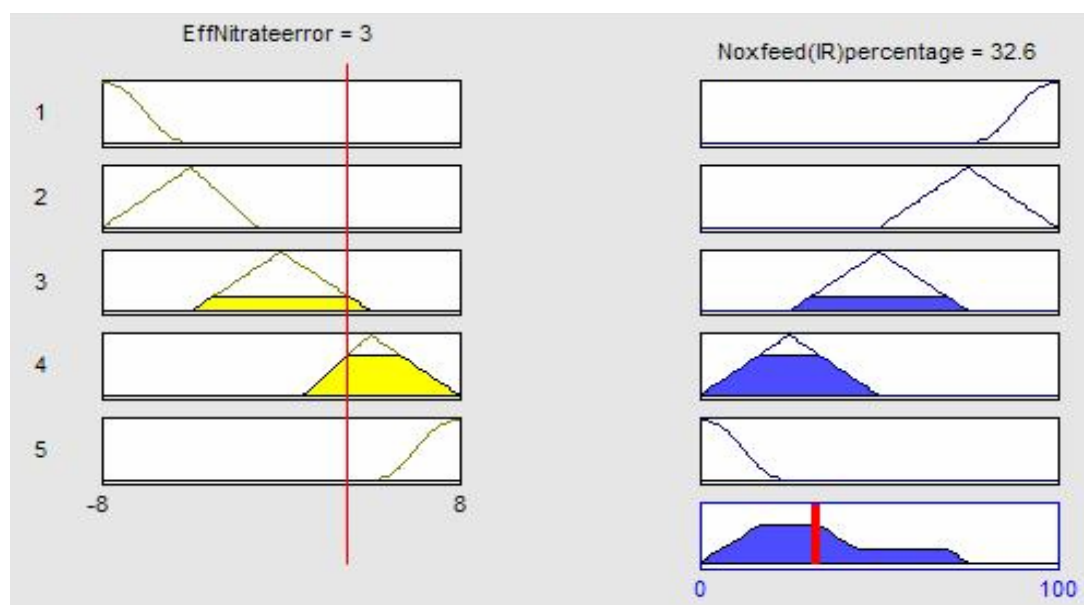


Figure 4.4 Rule viewer of residual nitrate concentration

If we take a look at the MLSS concentration control the surface will be like:

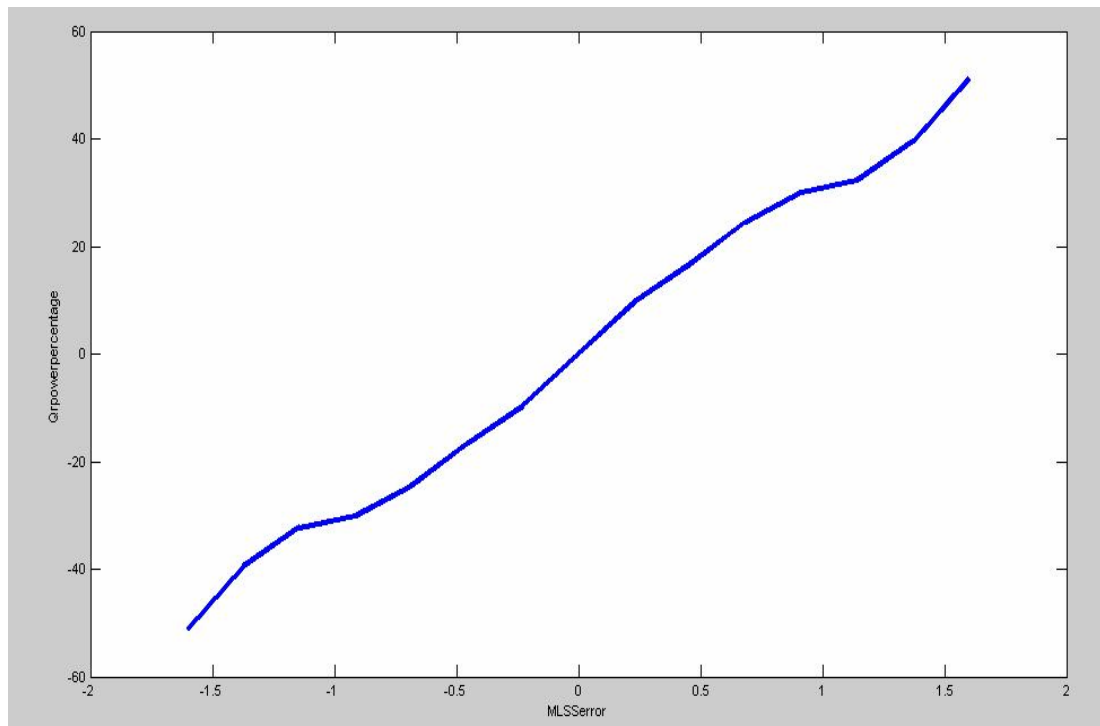


Figure 4.5 Control surface of mixed liquor suspended solids control

At the figure we can see that there is a non linear proportion increase of Q_r with MLSS error. Here is an example about this relation between MLSS error with the value of -1.4 and sludge recycle pumps power increases -40.5% .

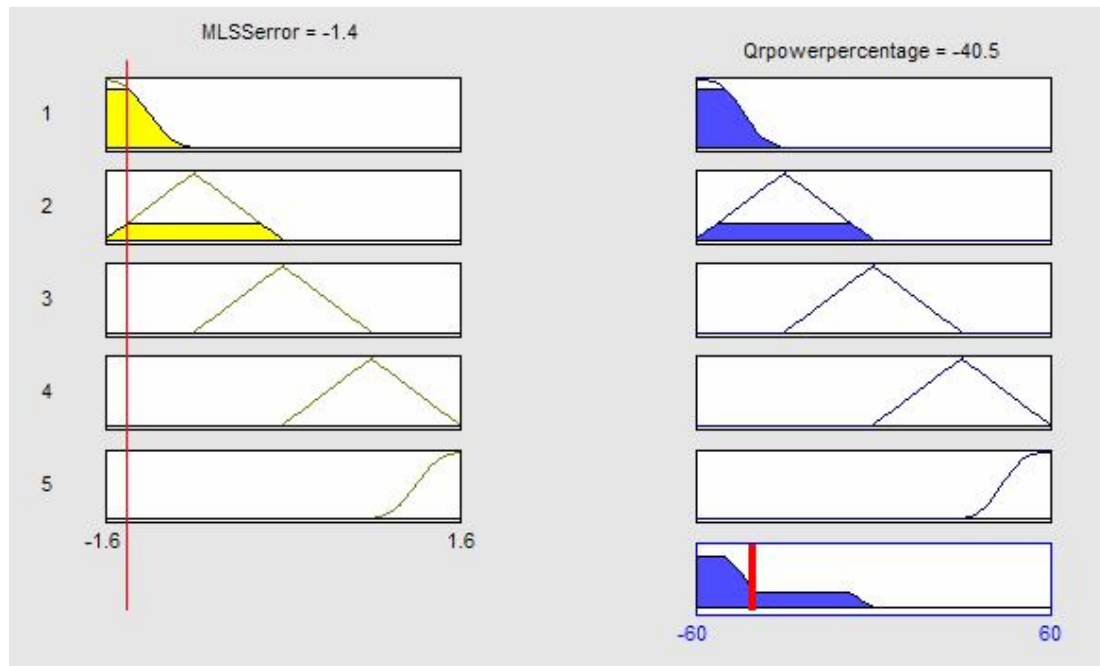


Figure 4.6 Rule viewer of MLSS concentration control.

If we look at the alkalinity control in the aeration tank:

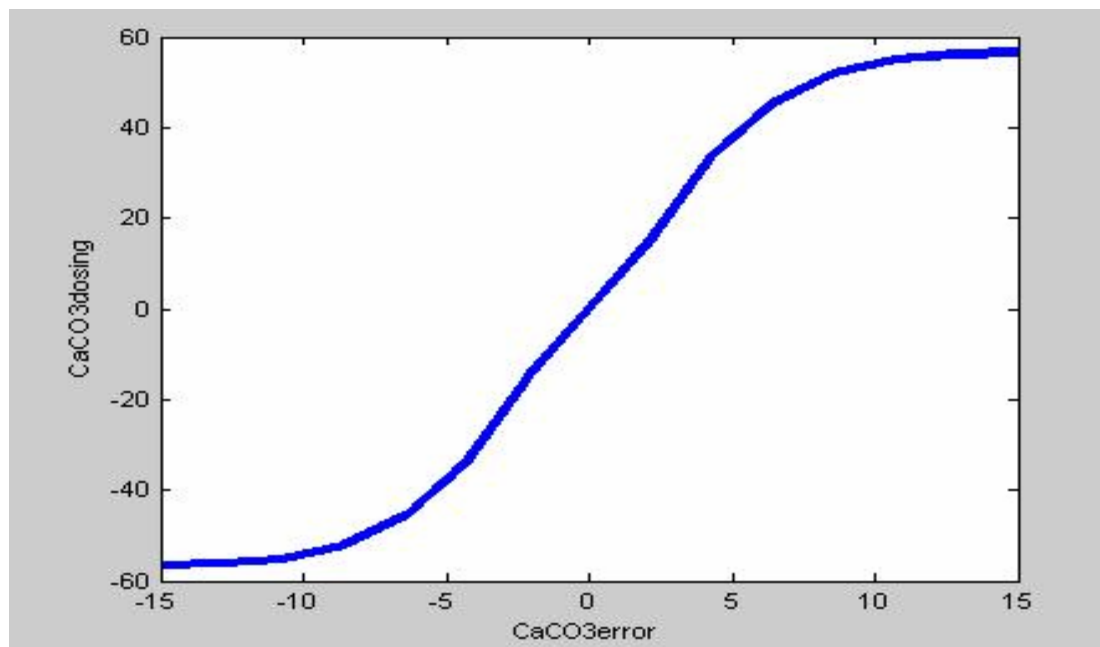


Figure 4.7 Control surface of alkalinity control in aeration tank.

At the figure we can see that there is a non linear proportion increase of CaCO_3 dosage pump power with CaCO_3 error. Here is an example about this relation between CaCO_3 error with the value of 4.48 and CaCO_3 dosing pumps power increases 35.2 %.

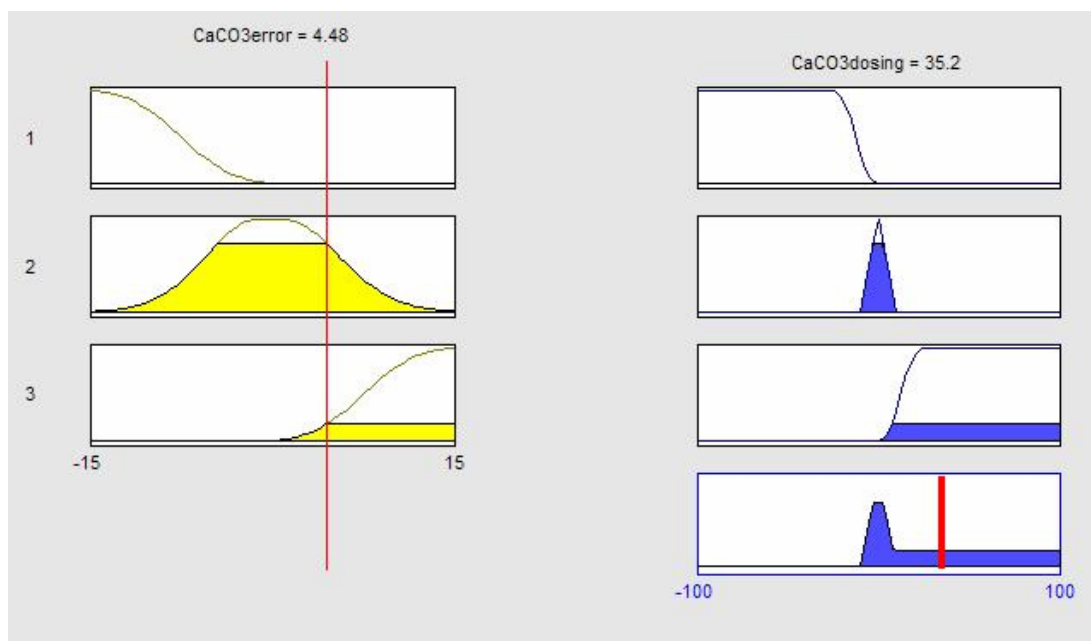


Figure 4.8 Rule viewer of alkalinity control.

If we take a look for the results of the sludge control we can see that Q_{waste} increases return suspended solids error and decreases with effluent suspended solids error.

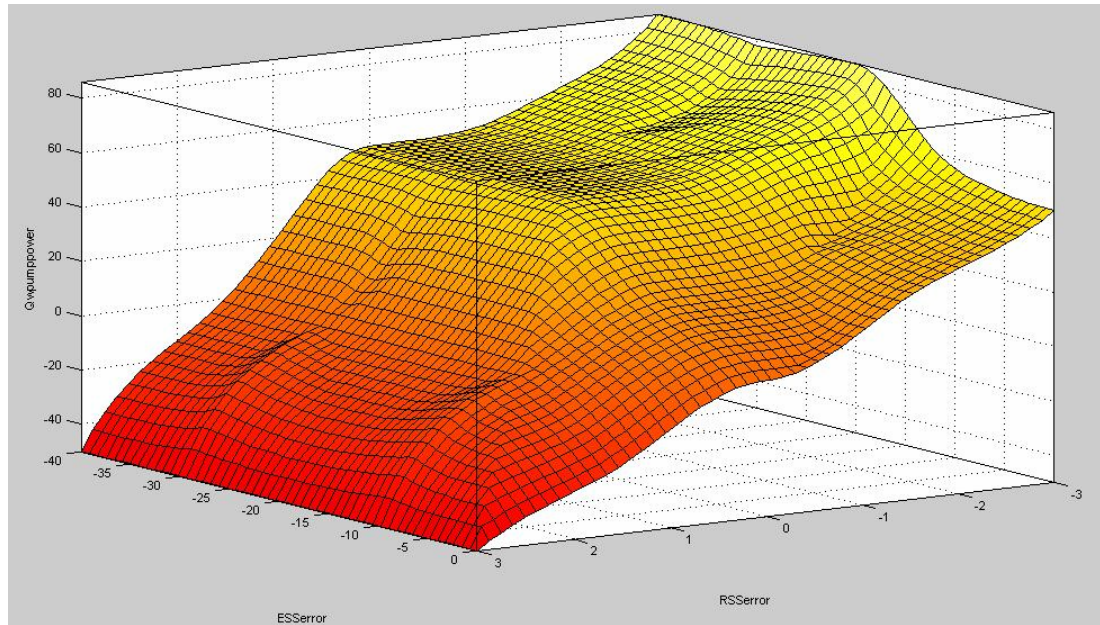


Figure 4.9 Control surface of sludge control.

As it is seen in the figure, purge sludge flowrate smoothly increases or decreases with the errors of ESS or RSS concentrations. Sludge control is one of the most important issues in wastewater treatment plant operation. The waste sludge controlling also controls the sludge age.

Here is an example of a response output comes out from the created fuzzy rules and fuzzy sets for a situation which is the RSS_{er} is -1 mg/l and ESS_{er} is -6 mg/l. According to the created rules and fuzzy sets the output defuzzified value is - 19 % decrease on power of sludge pumps.

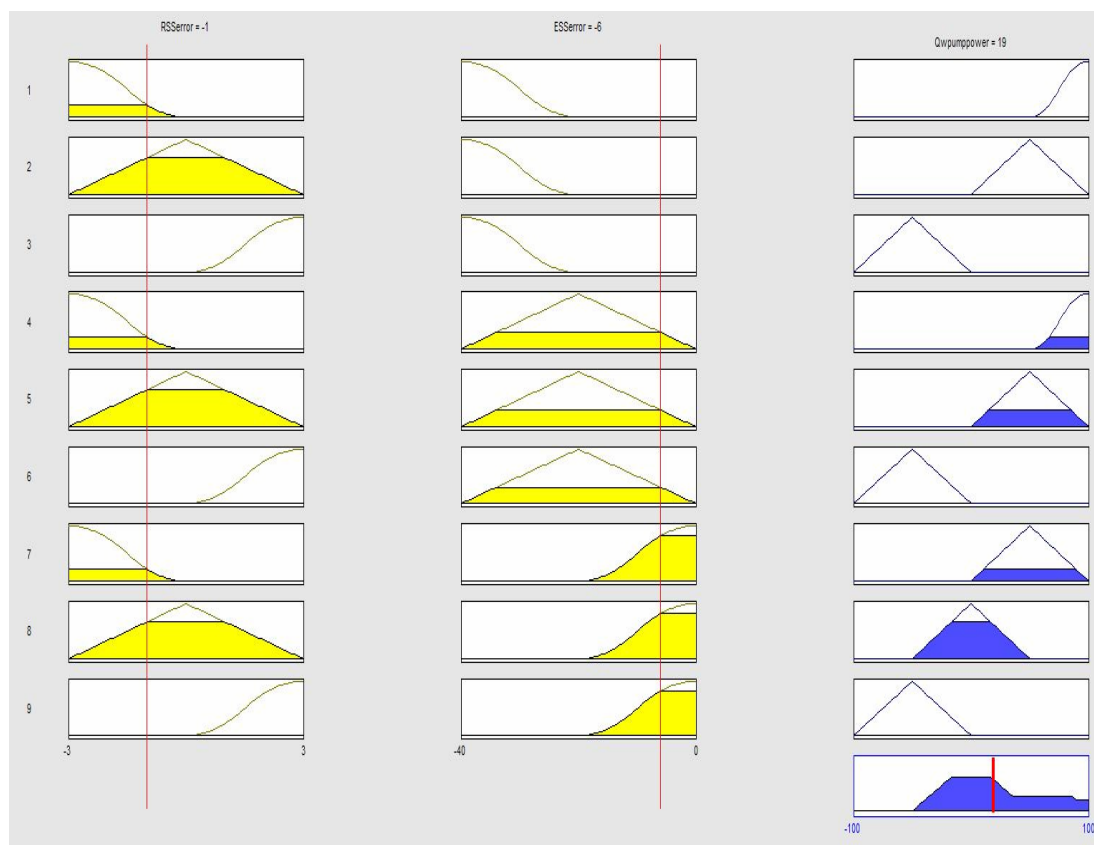


Figure 4.10 Rule viewer of sludge control.

CHAPTER FIVE

CONCLUSIONS

A supervisory expert system based on fuzzy logic rules was developed for diagnosis and control of a theoretically designed wastewater treatment plant comprising anoxic/aerobic modules for combined biological N and C removal. The design and implementation of a computational environment in LabVIEW for data acquisition, plant operation and distributed equipment control is described. The Fuzzy Logic toolbox for MATLAB was also used for the development of the fuzzy logic rule based system. The fuzzy rules were generated from quantitative and qualitative information, to identify the status of the plant operation and to decide the best commands to be sent to the final control elements to recover the stable operation in case of variable parameters of the processes.

These controlled parameters are dissolved oxygen concentration maintained at a value of 2 mg/l, mixed liquor suspended solids concentration at a value of 2.8 g/l, alkalinity control as CaCO_3 at a value of 80 g/m³, waste sludge flowrate control to maintain the SRT value at 12.5 days and effluent $\text{NO}_3\text{-N}$ concentration to maintain at a value of 8 g/l.

Although there are different types of controlling are different methods to such as on/off , proportional integrative derivative (PID) control the wastewater treatment plants the easiest and the most effective method is accepted as fuzzy logic control.

In the design of control strategy the selected instruments are very important. Suitable and capable engines should be selected to reach at the variable power alternatives and also sensors should be sensitive and at enough numbers to calculate the controllable parameters.

What is the most important parameter is the human experience who is the designer of all the rules and fuzzy sets for the variable parameters.

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APPENDICES

Complete mix Activated Sludge Process Design for BOD removal with Nitrification

Design a CMAS process to treat 15000 m³/d of primary effluent to accomplish BOD removal and nitrification with an effluent NH₄-N concentration of 0,5 g/m³ NO₃-N concentration of 8.0 g/m³ and BOD_e and TSS ≤ 15 g/m³. The aeration basin mixed-liquor temperature is 12⁰C

The following wastewater characteristics and design conditions apply :

Wastewater Characteristics :

<u>Constituent</u>	<u>Concentration, g/m³</u>
BOD	180
sBOD	90
COD	340
sCOD	170
rbCOD	95
TSS	85
VSS	70
TKN	40
NH ₄ -N	20
TP	5
Alkalinity	180 as CaCO ₃
bCOD/BOD ratio	1.5

Design conditions and assumptions :

1. Fine bubble ceramic diffusers with an aeration clean water O₂ transfer efficiency = 40%
2. Liquid depth for aeration basin = 5.0 m
3. The point of air release for the ceramic diffusers is 0.35m above the tank bottom
4. D.O in aeration basin = 2 g/m³
5. Site elevation is 500 m (pressure = 95.6 kPa)
6. Aeration α factor = 0.65 for nitrification β for both conditions and diffuser fouling factor F = 0.90
7. Design MLSS X_{TSS} concentration = 2800 g/m³ values of 2000 to 3000 g/m³ can be considered
8. TKN peak/average factor of safety FS = 1.5
9. Mixing energy for anoxic reactor is 10 kW / 10³ m³
10. Nitrate concentration in RAS = 6 g/m³

Develop the wastewater characteristics needed for design .

1. **Find bCOD** $b\text{COD} = 1.5 (\text{BOD}) = 1.5 (180) = \mathbf{270 \text{ g/m}^3}$
2. **Find nbCOD** $nb\text{COD} = \text{COD} - b\text{COD} = (340 - 270) \text{ g/m}^3 = \mathbf{70 \text{ g/m}^3}$
3. Find effluent sCOD_e (assumed to be nonbiodegradable)
 $s\text{COD}_e = s\text{COD} - 1.5 (s\text{BOD}) = 170 - 1.5 (90 \text{ g/m}^3) = \mathbf{35 \text{ g/m}^3}$
4. Find nbVSS $nb\text{VSS} = (1 - b_p \text{COD} / p\text{COD}) \text{VSS}$
 $(b_p\text{COD}) / (p\text{COD}) = ((b\text{COD} / \text{BOD}) (\text{BOD} - s\text{BOD})) / (\text{COD} - s\text{COD})$
 $(b_p\text{COD} / p\text{COD}) = 1.5 (\text{BOD} - s\text{BOD}) / (\text{COD} - s\text{COD})$
 $= 1.5 [(180 - 90) \text{ g/m}^3] / [(340 - 170) \text{ g/m}^3] = 0,79$
 $nb\text{VSS} = (1 - 0,79) 70 \text{ g VSS/ m}^3 = \mathbf{14,7 \text{ g /m}^3}$

5. **Find iTSS** $iTSS = TSS - VSS = (85 - 70) \text{ g/m}^3 = \mathbf{15 \text{ g/m}^3}$

Determine the specific growth yield rate η_n for the nitrifying organisms. The nitrification rate will control the design because the nitrifying organisms grow more slowly than the heterotrophic organisms that remove organic carbon.

$$\eta_n = [(\eta_{n,m} N) / (K_n + N)] [(DO / K_0 + DO)] - k_{dn}$$

Find $\eta_{n,m}$ at $T = 12^\circ\text{C}$

$$\eta_{n,m,12^\circ\text{C}} = (0.75 \text{ g/g.d}) (1.07)^{12-20} = \mathbf{0.44 \text{ g/g.d}}$$

Find K_n at $T = 12^\circ\text{C}$

$$K_{n,12^\circ\text{C}} = (0.74 \text{ g/m}^3) (1.053)^{12-20} = \mathbf{0.49 \text{ g/m}^3}$$

Find k_{dn} at $T = 12^\circ\text{C}$

$$k_{dn,12^\circ\text{C}} = (0.08 \text{ g/g.d}) (1.04)^{12-20} = \mathbf{0.06 \text{ g/g.d}}$$

$$N = \mathbf{0.50 \text{ g/m}^3}, DO = \mathbf{2.0 \text{ g/m}^3}, K_0 = \mathbf{0.50 \text{ g/m}^3}$$

$$\eta_n = [(\eta_{n,m} N) / (K_n + N)] [(DO / K_0 + DO)] - k_{dn} = \mathbf{0.12 \text{ g/g.d}}$$

$$\text{Theoretical SRT} = (1 / \eta_n) = (1 / 0.12 \text{ g/g.d}) = \mathbf{8.33 \text{ d}}$$

Determine the design SRT :

$$FS = \text{TKN peak} / \text{TKN average} = 1.5$$

$$\begin{aligned} \text{Design SRT} &= (FS) (\text{theoretical SRT}) \\ &= 1.5 (8.33 \text{ d}) = \mathbf{12.5 \text{ d}} \end{aligned}$$

Determine biomass production

$$\begin{aligned} P_{X,bio} &= [QY(S_0 - S) / 1 + (k_d) \text{SRT}] + [(f_d)(k_d) QY(S_0 - S) \text{SRT} / 1 + (k_d) \\ &\text{SRT}] + \\ &\quad [QY_n(\text{NO}_x) / 1 + (k_d) \text{SRT}] \end{aligned}$$

$$Q = 15000 \text{ m}^3 / \text{d}$$

$$Y = 0.4 \text{ gVSS} / \text{g bCOD}$$

$$S_0 = 270 \text{ g bCOD} / \text{m}^3$$

$$\text{SRT} = 12.5 \text{ d}$$

$$k_d = 0.088 \text{ g/g.d}$$

$$\eta_m = 3.5 \text{ g/g.d}$$

Determine S : $S = K_s [1 + (k_d) \text{SRT}] / \text{SRT} (\eta_m - k_d) - 1$

$$S = 1.0 \text{ g bCOD} / \text{m}^3$$

$$Y_n = 0.12 \text{ g VSS} / \text{g NO}_x \text{ (table 8-11)}$$

$$k_{dn,12}^{\circ\text{C}} = 0.06 \text{ g/g.d}$$

Assume $\text{NO}_x \approx 0.80\%$ (TKN) therefore $\text{NO}_x = 0.80 (40 \text{ g} / \text{m}^3) = 32 \text{ g} / \text{m}^3$

$$\mathbf{P_{x,bio} = 768.57 \text{ kg/d} + 157.4 \text{ kg/d} + 32.91 \text{ kg/d}}$$

$$\mathbf{= 958.88 \text{ kg VSS} / \text{d}}$$

Determine the amount of nitrogen oxidized to nitrate. The amount of nitrogen oxidized to nitrate can be found by performing a nitrogen balance.

$$\mathbf{NO_x = TKN - N_e - 0.12 P_{x,bio} / Q}$$

$$= 40 \text{ g/m}^3 - 0.5 \text{ g/m}^3 - (0.12 \text{ g N} / \text{g VSS}) (958.88 \text{ kg VSS} / \text{d}) (10^3 \text{ g/kg}) / (15000 \text{ m}^3 / \text{d})$$

$$= (35 - 0.5 - 6.2) \text{ g} / \text{m}^3 = \mathbf{31.82 \text{ g/m}^3}$$

Determine the concentration and mass of VSS and TSS in the aeration basin.

$$\text{Mass} = P_x (\text{SRT})$$

Calculate the con. of VSS and TSS in the aeration basin

$$\mathbf{P_{x,VSS} = P_{x,bio} + Q (nbVSS)}$$

$$= (958.88 + 220.5) \text{ kg} / \text{d} = \mathbf{1179.38 \text{ kg/d}}$$

$$\mathbf{P_{x,TSS} = [(P_{x,bio} / 0.85) + Q (nbVSS) + Q (TSS_0 - VSS_0)]}$$

$$[(958.88 \text{ kg/d}) / 0.85] + (220.5 \text{ kg/d}) + 15000 \text{ m}^3 / \text{d} (85 - 70) \text{ g/m}^3]$$

$$= \mathbf{1573.6 \text{ kg/d}}$$

Calculate the mass of VSS and TSS in the aeration basin

Mass of MLVSS ;

$$(X_{VSS}) (V) = (P_{x,VSS}) \text{SRT}$$

$$= (1179.38 \text{ kg/d}) (12.5 \text{ d}) = \mathbf{14742.25 \text{ kg}}$$

Mass of MLSS ;

$$(X_{TSS})(V) = (P_{X,TSS}) SRT$$

$$= (1573.6 \text{ kg/d})(12.5 \text{ d}) = \mathbf{19670 \text{ kg}}$$

Select a design MLSS mass conc. and determine the aeration tank volume and detention time using the TSS mass computed before.

$$(V)(X_{TSS}) = 19670 \text{ kg} \quad \text{at MLSS} = \mathbf{2800 \text{ g/m}^3};$$

$$V = [(19670 \text{ kg})(10^3 \text{ g/kg}) / (2800 \text{ g/m}^3)] = \mathbf{7025 \text{ m}^3}$$

$$\tau = V / Q = (7025 \text{ m}^3)(24 \text{ h/d}) / (15000 \text{ m}^3/\text{d}) = \mathbf{11.24 \text{ hr.}}$$

Determine MLVSS

$$\text{Fraction VSS} = (14742.25 \text{ kg VSS} / 19670 \text{ kg TSS}) = 0.75$$

$$\mathbf{MLVSS} = 0.75 (2800 \text{ g/m}^3) = \mathbf{2100 \text{ g/m}^3}$$

Determine F/M and BOD volumetric loading

$$\mathbf{F/M} = (Q S_0 / XV) = \text{g BOD} / \text{g MLVSS.d}$$

$$= [(15000 \text{ m}^3/\text{d})(180 \text{ g/m}^3) / (2100 \text{ g/m}^3)(7025 \text{ m}^3)]$$

$$= \mathbf{0.18 \text{ g/g.d}}$$

Determine volumetric BOD loading

$$\mathbf{L_{org}} = Q S_0 / V = \text{kg BOD} / \text{m}^3.\text{d}$$

$$= [(15000 \text{ m}^3/\text{d})(180 \text{ g/m}^3) / (10^3 \text{ g/kg})(7025 \text{ m}^3)] = \mathbf{0.38 \text{ kg/m}^3.\text{d}}$$

Determine the observed yield based on TSS and VSS

$$\text{Observed yield} = \text{g TSS} / \text{g bCOD} = \text{kg TSS} / \text{kg bCOD}$$

$$P_{X,TSS} = 1573.6 \text{ kg/d}$$

$$\text{bCOD removed} = Q(S_0 - S) = (15000 \text{ m}^3/\text{d})[(270 - 1) \text{ g/m}^3](1 \text{ kg} / 10^3 \text{ g})$$

$$= 4035 \text{ kg/d}$$

Observed yield based on TSS

$$Y_{\text{obs,TSS}} = (1573.6 \text{ kg/d}) / (4035 \text{ kg/d}) = 0.39 \text{ g TSS} / \text{g bCOD}$$

$$= (0.39 \text{ g TSS} / \text{g bCOD})(1.5 \text{ g bCOD} / \text{g BOD}) = \mathbf{0.58 \text{ g TSS} / \text{g BOD}}$$

Observed yield based on VSS

$$Y_{\text{obs,VSS}} : \text{VSS} / \text{TSS} = 0.75$$

$$= [(0.39 \text{ g TSS} / \text{g bCOD}) / (0.75 \text{ g VSS} / \text{g TSS})]$$

$$= 0.292 \text{ g VSS} / \text{g bCOD}$$

$$= [(0.292 \text{ g VSS} / \text{g bCOD}) (1.5 \text{ g bCOD} / \text{g BOD})]$$

$$= \mathbf{0.44 \text{ g VSS} / \text{g BOD}}$$

Calculate the O₂ demand (Concerning nitrification step only)

$$R_o = Q (S_o - S) - 1.42 P_{x,\text{bio}} + 4.33 Q (\text{NO}_x)$$

$$= (15000 \text{ m}^3 / \text{d}) [(270 - 1) \text{ g} / \text{m}^3] (1 \text{ kg} / 10^3 \text{ g}) - 1.42 (958.88 \text{ kg} / \text{d}) +$$

$$(4.33 \text{ g O}_2 / \text{gN}) (15000 \text{ m}^3 / \text{d}) (31.82 \text{ g} / \text{m}^3) (1 \text{ kg} / 10^3 \text{ g})$$

$$R_o = 4035 \text{ kg} / \text{d} - 1361.6 \text{ kg} / \text{d} + 2066.71 \text{ kg} / \text{d}$$

$$= \mathbf{4740.1 \text{ kg} / \text{d} = 197.5 \text{ kg} / \text{h}}$$

Fine bubble aeration design :

Determine the SOTR: ($\alpha = 0.65$ $\beta = 0.95$ and $F = 0.9$)

$$\text{SOTR} = \text{AOTR} [C_{s, 20} / \alpha F (\beta C_{s,T,H} - C)] (1.024^{20-T})$$

$$C_{s,T,H} = 11.93 \text{ g} / \text{m}^3$$

$$\text{SOTR} = ((197.5 \text{ kg} / \text{h}) (9.08 \text{ g} / \text{m}^3) (1.024)^{20-12}) / (0.65) (0.9) [(0.95) (11.93 \text{ g} / \text{m}^3) - 2 \text{ g} / \text{m}^3] = \mathbf{397.1 \text{ kg} / \text{h}}$$

Determine the air flowrate (Concerning nitrification step only)

$$\text{Air flowrate, m}^3 / \text{min} = (397.1 \text{ kg} / \text{h}) / [(0.35) (60 \text{ min} / \text{h}) (0.27 \text{ kg O}_2 / \text{m}^3 \text{ air})]$$

$$= \mathbf{70.5 \text{ m}^3 / \text{min}}$$

Check alkalinity: prepare an alkalinity balance

Alkalinity to maintain pH ~ 7 = influent Alk – Alk used + Alk to be added

Influent alkalinity: 180 g/m³ as CaCO₃

Amount of nitrogen converted to nitrate: NO_x = 31.82 g/m³

Alkalinity used for nitrification = (7.14 g CaCO₃ / g NH₄-N) 31.82 g/m³

$$= 227.2 \text{ g} / \text{m}^3 \text{ used as CaCO}_3$$

Residual alkalinity concentration needed to maintain pH in the range of 6.8- 7.0 = 70 to 80 g/m³ as CaCO₃ ; select **75 g/m³**

$$75 \text{ g/m}^3 = \text{Inf. Alk} - \text{Alk. Used} + \text{Alk. To be needed}$$

$$75 \text{ g/m}^3 = 180 - 227.2 + \text{Alk. To be needed}$$

$$\text{Alkalinity needed} = 122.2 \text{ g/m}^3 \text{ as CaCO}_3$$

$$= (15000 \text{ m}^3 / \text{d}) (122.2 \text{ g/m}^3) (1 \text{ kg} / 10^3 \text{ g})$$

$$= \mathbf{1833 \text{ kg / d as CaCO}_3}$$

Determine the alkalinity needed as sodium bicarbonate Na(HCO₃)

$$\text{Equivalent weight of CaCO}_3 = 50 \text{ g / equivalent}$$

$$\text{Equivalent weight of Na (HCO}_3) = 84 \text{ g / equivalent}$$

$$\text{Na (HCO}_3) \text{ needed} = [(1833 \text{ kg / d CaCO}_3) (84 \text{ g NaHCO}_3 / \text{eq}) / (50 \text{ g CaCO}_3 / \text{eq})]$$

$$= \mathbf{3079 \text{ kg / d NaHCO}_3}$$

Estimate effluent BOD

$$\text{BOD}_e = \text{sBOD}_e + (\text{g BOD} / 1.42 \text{ g VSS}) (0.85 \text{ g VSS} / \text{g TSS}) (\text{TSS, g / m}^3)$$

$$\text{Assume sBOD}_e = 3 \text{ g/m}^3$$

$$\text{TSS} = 10 \text{ g / m}^3$$

$$\text{BOD}_e = 3 + (0.7) (0.85) (10 \text{ g/m}^3) = \mathbf{8.95 \text{ g/m}^3}$$

Secondary Clarifier Design :

First calculate Q_w

$$Q_w = VX / \text{SRT} \cdot X_r$$

$$X_r \text{ is selected } 7500 \text{ g / m}^3$$

$$Q_w = [(7025 \text{ m}^3 \cdot 2800 \text{ g / m}^3) / (12.5 \text{ d} \cdot 7500 \text{ g / m}^3)]$$

$$Q_w = \mathbf{210 \text{ m}^3 / \text{d}}$$

Define return sludge recycle ratio :

$$Q_w \cdot X_r = [X (Q + Q_r)] - (Q_r \cdot X_r)$$

$$(210 \text{ m}^3/\text{d}) (7.5 \text{ kg / m}^3) = 2.8 \text{ g/m}^3 (15000 \text{ m}^3/\text{d} + Q_r) - (Q_r \cdot 7.5 \text{ kg / m}^3)$$

$$Q_r = \mathbf{8601 \text{ m}^3 / \text{d}}$$

$$\text{RAS recycle ratio} = (Q_r / Q) = (8601 / 15000) = 0.57$$

Determine the size of clarifier ;

Accept range of solids loading of 4 to 6 kg/m² h . **Accept 5 kg/ m².h**

$$\text{Solids loading} = (Q + Q_r) (MLSS) / A$$

Where A is area of the clarifier ;

$$5 \text{ kg/ m}^2.\text{h} = [(23601 \text{ m}^3/\text{d}) (2800 \text{ g/ m}^3)] / A$$

$$A = 550.7 \text{ m}^2 \approx 600 \text{ m}^2 \text{ (600 m}^2 \text{ is selected for the design)}$$

Use 3 Clarifiers (1 for each aeration tank)

$$\text{Area / clarifier} = 600 / 3 = 200 \text{ m}^2$$

Clarifier Diameter = 16 m. (for each clarifier)

$$\text{Hydraulic Application Rate} = (15000 \text{ m}^3 / \text{d}) / 600 \text{ m}^2$$

Hydraulic Application Rate = 25m³/m²d the range is 16 to 28

Acceptable

Anoxic Tank Design :

Determine the active biomass concentration in anoxic tank for denitrification

$$X_b = [Q (SRT) / V] [Y (S_0 - S) / 1 + (k_d) SRT] \text{ where } S_0 - S \approx S_0$$

$$\begin{aligned} X_b &= [(15000 \text{ m}^3/\text{d}) (12.5 \text{ d}) (0.4 \text{ g VSS / g COD}) (270 \text{ g bCOD/ m}^3)] / \\ &\quad [1 + (0.088 \text{ g/g.d}) (12.5 \text{ d})] (7025 \text{ m}^3) \\ &= 1373 \text{ g/m}^3 \end{aligned}$$

Determine the IR ratio

$$\text{Aerobic tank NO}_3\text{-N concentration} = N_e = 8 \text{ g/m}^3$$

$$IR = (NO_x / N_e) - 1 - R = (31.82 \text{ g/m}^3) / (8 \text{ g / m}^3) - 1 - 0.57 = 2.4$$

Determine the amount of NO₃-N fed to anoxic tank

$$\text{Flowrate to anoxic tank} = IR Q + RQ$$

$$= 2.4 (15000 \text{ m}^3/\text{d}) + 0.57 (15000 \text{ m}^3 / \text{d})$$

$$= 44662 \text{ m}^3 / \text{d}$$

$$\text{NO}_x \text{ feed} = (44662 \text{ m}^3/\text{d}) (6 \text{ g/m}^3) = 267972 \text{ g/d} \approx 268 \text{ kg/d}$$

Determine the anoxic volume :

As a first approximation use a detention time = 1.5 h

$$\tau = (1.5 \text{ h}) / (24 \text{ h/d}) = 0.0625 \text{ d}$$

$$V_{\text{nox}} = \tau \times Q = 0.0625 \text{ d} (15000 \text{ m}^3 / \text{d}) = 937.5 \text{ m}^3 \approx \mathbf{950 \text{ m}^3}$$

Determine F/M_b :

$$F/M_b = (QS_o) / (V_{\text{nox}} X_b) = [(15000 \text{ m}^3/\text{d}) (180 \text{ gBOD} / \text{m}^3)] / (937.5 \text{ m}^3) (1373 \text{ g} / \text{m}^3)$$

$$\mathbf{F/M_b = 2.1 \text{ g} / \text{g.d}}$$

Determine SDNR value using curve given in Metcalf Eddy Fourth Edition on paper 755.

$$\mathbf{\text{Fraction of rbCOD} = \text{rbCOD} / \text{bCOD} = (95 \text{ g/m}^3) / (270 \text{ g/m}^3) = \mathbf{35 \%}}$$

$$\text{SDNR}_{20} = 0.33 \text{ g/g.d}$$

$$\mathbf{\text{SDNR}_{12} = 0.33 (1.026)^{12-20} = \mathbf{0.27 \text{ g/g.d}}}$$

Determine the amount of nitrate that can be reduced :

$$\mathbf{NO_r = (0.27 \text{ g/g.d}) (950 \text{ m}^3) (1373 \text{ g/m}^3) = \mathbf{352175 \text{ g/d}}}$$

Capacity ratio = $(352175 / 267972) = 1.3$ therefore , $\tau = 1.5 \text{ h}$ is acceptable.

Compare the computed value to conventional observed SDNR values, based on MLSS ;

$$\text{SDNR (MLSS)} = (0.27) (X_b / X_T) = (0.27) (1373 / 2800) = 0.13 \text{ g/g.d}$$

The computed value is in the range of reported SDNR values (0.04 to 0.42 g/g.d)

Reconsider the amount of net oxygen required for nitrification step by taking into account the oxygen supplied from nitrate reduction in denitrification step ;

$$\mathbf{\text{Oxygen Credit} = (2.86 \text{ g O}_2 / \text{g NO}_3\text{-N}) [(31.82 - 8) \text{ g} / \text{m}^3] (15000 \text{ m}^3/\text{d}) (1 \text{ kg} / 10^3 \text{ g})}$$

$$= 1022 \text{ kg} / \text{d} = \mathbf{42.6 \text{ kg} / \text{h}}$$

$$\mathbf{\text{Net O}_2 \text{ required} = R_0 = (197.5 - 42.6) \text{ kg} / \text{h} = \mathbf{155 \text{ kg} / \text{h}}}$$

Note that oxygen required in nitrification step is reduced to 21.6 percent.

Check alkalinity.

Prepare a mass balance.

Alkalinity to be added to maintain pH ~ 7 = Influent Alk – Alk used + Alk produced

Influent alkalinity = 180 g/m^3 as CaCO_3

Alkalinity used = $7.14 (31.82 \text{ g NO}_3\text{-N g / m}^3) = 227.2 \text{ g/m}^3$

Alkalinity produced = $3.57 [(31.82 - 8) \text{ g / m}^3] = 85 \text{ g/ m}^3$

Alkalinity needed to maintain neutral pH = 80 g / m^3 as CaCO_3

Solve the above expression for Alk to be added

$$\begin{aligned} \text{Alk to be added} &= (80 - 180 + 227.2 - 85) \text{ g/ m}^3 \\ &= 42.2 \text{ g/m}^3 \text{ as } \text{CaCO}_3 \end{aligned}$$

$$\begin{aligned} \text{Mass of Alk needed} &= (42.2 \text{ g/m}^3) (15000 \text{ m}^3/\text{d}) (1 \text{ kg} / 10^3 \text{ g}) \\ &= \mathbf{633 \text{ kg / d as } \text{CaCO}_3} \text{ and also } \mathbf{1064 \text{ kg / d as } \text{NaHCO}_3} \end{aligned}$$

$$\text{Alk savings} = 3079 - 1064 = \mathbf{2015 \text{ kg NaHCO}_3}$$

Determine anoxic zone mixing energy.

Mixing energy = $15 \text{ kW} / 10^3 \text{ m}^3$ (given)

Volume = 950 m^3

$$\text{Power} = (950 \text{ m}^3) (10 \text{ kW} / 10^3 \text{ m}^3) = \mathbf{9.5 \text{ kW total}}$$

DESIGN SUMMARY

<u>Design Parameter</u>	<u>Unit</u>	<u>Preanoxic System</u>
Average wastewater	m^3 / d	15000
Average BOD load	kg / d	2700
Average TKN load	kg / d	600
Aerobic SRT	d	12.5
Aeration Tank Volume	m^3	7025
Anoxic Tank Volume	m^3	950
τ in Aeration Tank	h	11.24
τ in Anoxic Tank	h	1.5
MLSS	g / m^3	2800
MLVSS	g / m^3	2100
F/M	g/g.d	0.18
BOD loading	$\text{kg BOD} / \text{m}^3.\text{d}$	0.38
Sludge Production	kg/d	1574
Observed Yield	$\text{kg TSS} / \text{kg bCOD}$	0.58
	$\text{kg VSS} / \text{kg BOD}$	0.44
Oxygen Required	kg / h	155
Air flowrate at average w.w flow	m^3 / min	55.4
RAS ratio	unitless	0.57
Clarifier hydraulic application rate	$\text{m}^3 / \text{m}^2.\text{d}$	25
Clarifier diameter	m	16
Alkalinity addition as $\text{Na}(\text{HCO}_3)$	kg/d	1064
Mixing power for Anoxic Tank	kW	9.5
Effluent BOD	g/m^3	8.95
Effluent $\text{NO}_3\text{-N}$	g/m^3	8.0
TSS_e	g/m^3	10
Effluent $\text{NH}_4\text{-N}$	g / m^3	≤ 0.5
Q_w	m^3 / d	210
IR		2.4

Sludge Concentration Meter (MLSS Meter)



- Underwater suspended solid concentration
- With an range of 0-20000 mg/l (0-20.00 g/l)
- 90% response within 20 seconds
- Conversion of concentration by coefficient input
- Temperature: 0-40°C, pressure: 0-0.2 MPa (0-2 kgf/cm²)
- Indicator adjustment gauge: AC 100-115 V, 50/60 Hz or AC 200-240 V, 50/60 Hz, 20 VA
- Calibration: Cleaner operated while submerged or detector submerged in fresh water followed by manual zero calibration or automatic zero calibration in submerged state (calibration cannot be performed with air cleaning) (Calibration may not be able to be performed if air bubbles are present in the cleaning water.)

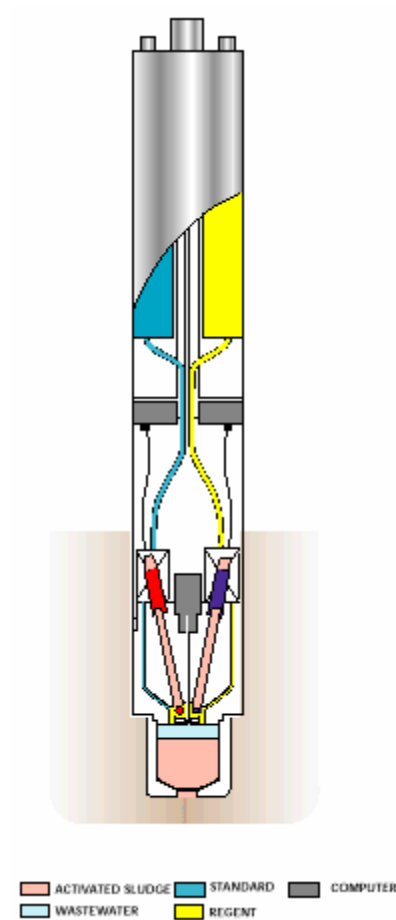
Dissolved Oxygen Converters:



- Free measuring range of 0 to 50 mg/l. Minimum span of 1 mg/l that can be arbitrarily set.
- Either mg/l, ppm, or % saturation can be selected as the unit for display.
- Response time with 0- 90% : 10 s
- Performance: DO (at t process = 25 degrees C)
 - Linearity : equal to or less than $0.03 \text{ mg/l} \pm 0.02 \text{ mA}$
 - Repeatability : equal to or less than $0.03 \text{ mg/l} \pm 0.02 \text{ mA}$
 - Accuracy : equal to or less than $0.05 \text{ mg/l} \pm 0.02 \text{ mA}$
- Transmissions Signals: Two isolated outputs of 0/4-20 mA DC with common negative. Maximum load 600 Ω . The range of mA1 output can be switched by remote control. (Remote wash cycle start is unavailable when this function is selected.)

Auxiliary output can be chosen from temperature, DO, PI control, burn up (22 mA) or burn down (0 or 3.5 mA) to signal failure

Ammonia and Nitrate Meter:



- Measurement directly in aeration basins
- Automatic self-calibration using standard addition method
- Measuring range:
 - 0.1 - 50 mg/liter $\text{NH}_4\text{-N}$ (Ammonium)
 - 0.1 - 50 mg/liter $\text{NO}_3\text{-N}$ (Nitrate)
- Analysis delay time:
 - 5 minutes (NH_4)
 - 3 minutes (NO_3)
- Programmable concentration alarm

Alkalinity Meters:



- Alkalinity of clean or raw water (CaCO_3 equivalent: Equivalence point pH 4.8)
- Continuous measurement, fixed period (previous value held). Interval: 10 min. + hold time (arbitrary setting in range 0.0 to 24 hrs)
- Two outputs (Alkalinity, pH)
Note: pH output is valid during measurement.
4 to 20 mA DC (max. load resistance: 600 Ω)
Burnout upscale/downscale selectable in range 2.0 to 22.0 mA
- Temperature: 0 to 40 $^{\circ}\text{C}$
- Flowrate: 1 to 3 l/min or less (approx. 50 g sample water per analysis)
- Pressure: 20 to 500 kPa