Estimation of Fat in Fresh Milk through Adaptive Neuro-Fuzzy Inference System

CHAPTER – 03

Theoretical Background
1. Introduction:

The detection of quality of milk is a key issue since last few decades. Mainly the fat contains in milk decides the quality of milk that of other contains like protein, lactose, minerals, vitamins etc. The fat contain estimation in milk depends on temperature at which it is measured and the methodology used. Hence the temperature of milk sample needs to be controlled precisely. This can be achieved by using conventional or some modern temperature controlling techniques. Currently industries are using the conventional temperature controllers such as Proportional Integral (PI) or Proportional Integral and Derivative (PID) type and also some of the industries have implemented advanced techniques like Fuzzy Logic Control (FLC) and Adaptive Neuro-Fuzzy Inference System (ANFIS).

As depicted in the literature fuzzy logic controller finds various applications that are related to temperature type controllers or other control actions. Here the fuzzy logic system is considered to control temperature of milk sample at a given set point. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is advanced and modified technique that tunes FLC membership function parameters in accordance with input-output data of the system to be implemented.

The various fat detection method techniques are present and Ultrasound Technique is one of them. Ultrasound generates the pressure waves that propagate through given medium. It can be used as a diagnostic tool in different fields. The characteristics of ultrasound may change with respect to medium in which it is propagating. The prime aim of developing ultrasound was to detect submarines during world war – I and was successfully implemented in world war – II. French physician firstly introduced piezoelectric material as transmitter and receiver of high frequency as a mechanical disturbance further known as Ultrasound wave. Ultrasound frequencies are used now a day for wide range of applications. As mentioned in literature ultrasound is successfully implemented to estimate the fat content in fresh milk.
2. Ultrasonic Propagation:

Ultrasound waves are the pressure waves that propagate through a medium. Depending on the particular application the wave pattern or its frequency gets changed. In the medical field the ultrasonic propagation is used for diagnostic tool considering patient as a medium. The ultrasound waves are widely used in medical sector in treatment of cancer and physical therapy since 1930.

The fluid medium consists of small molecules that are in continuous random motion (figure 3.1 (a)). Ultrasound waves are the mechanical pressure waves propagates in fluid medium. According to the force applied to medium the molecules present in fluid medium either compress (figure 3.1 (b)) or rarefaction (figure 3.1 (c)) takes place. Molecules from the surrounding medium move in these two regions that changes the density of molecules. Ultrasonic transducers generates pressure wave to insert into the medium (figure 3.1 (d)). The wave at frequency range from 20 Hz to 20,000 Hz is audible to human. Frequency wave below minimum value i.e. 20 Hz is not audible by human and is termed as infrasonic wave. The wave above 20,000 Hz is also not audible to human and termed as ultrasonic. Normal frequency range used in ultrasound is between 1 MHz to 20 MHz.

The attenuation term is referred when absorption, scattering and reflection takes place in an ultrasound beam penetrating in the medium. If the transmitted ultrasound signal is received with loss in energy on other end, this ultrasound is said to be absorbed. The lost energy is converted in some other form – increase in random motion of molecules in medium. The increased random motion of the molecule can be measured by observing change in temperature of medium. If part of transmitted beam or all is deflected in the medium, it is termed to be reflected. Finally if the beam changes its direction of propagation then it is said as scattered.

Behavior of the ultrasound beam depends on particle size acting as an obstacle in the medium through which wave is propagating at a certain wavelength. The ultrasound wave changes its direction of propagation if particle size acting as obstacle is larger as that of wavelength of ultrasound. From rest of
beam, partly is reflected and remaining ultrasound beam is transmitted at low intensity through medium. The scattering effect is observed when the obstacle size is smaller or about same to wavelength.

Figure 3.1: Ultrasound propagation.
(a): Molecules in the medium uniformly distributed.
(b): Movement of ultrasound wave to produce compression.
(c): Movement of ultrasound wave to produce rarefaction.
(d): Longitudinal wave generated in medium.
Ultrasounds are widely used in sensing systems due to its non-invasive measurements, rapid response time, low power consumption etc., however, substances under investigation must be acoustically conductive and also signal may corrupt due to bubbles and attenuates at high frequency. The amplitude of an ultrasound beam decreases exponentially as a function of distance that it travels through a medium.

\[ A(z) = A_0 e^{-\alpha z} \]  

(3.1)

where \( A \) is the attenuated amplitude of the ultrasonic beam, \( A_0 \) is the initial amplitude of the beam at distance 0, \( z \) is the distance (thickness of the sample) and \( \alpha \) is the amplitude attenuation coefficient.

or by alternating solution

\[ p(t, x) = p_0 e^{-\alpha x + j \omega (t - \frac{x}{c})} \]  

(3.2)

where \( p_0 \) is the wave amplitude in \( x = 0 \), for \( t = 0 \), \( \alpha \) the spatial attenuation and \( c \) the velocity of the ultrasound wave which propagates with the wavelength

\[ \lambda = \frac{c}{f} \]  

(3.3)

The speed of propagation \( c \) and the spatial attenuation \( \alpha \) are specific of the material which the wave propagates in. In detail, for simple liquids:

\[ c_{\text{liquids}} = \sqrt{\frac{K}{\rho}} \]  

(3.4)

With \( \rho \) the density of the liquid and \( K \) its bulk modulus (inverse of the compressibility \( \beta \)). The spatial attenuation on the contrary depends on several contributions: the absorption, the viscous, thermal and scattering losses and the losses due to the relaxation processes; the latter, in turn, depend on other material-specific parameters [20].

When an ultrasound wave passes through medium it transfers energy to that medium. The rate at which this energy is transferred is known as power and if it is focused known as intensity. Intensity is normally described with a reference. It may be mentioned with respect to transmitted wave intensity and received wave intensity. This wave intensity is measured in decibel unit and defined as:
\[ dB = 10 \log \frac{I}{I_0} \]

Where \( I_0 \) is the reference intensity.

Also the power can be compared is similar manner as:

\[ dB = 10 \log \frac{\text{Power}}{\text{Power}_0} = 10 \log \frac{E}{E_0} \quad (3.5) \]

- If the received is at higher intensity as that of reference or transmitted then resultant ratio is positive in decibel
- If the received is at lower intensity as that of reference or transmitted then resultant ratio is negative in decibel
- If wave intensity is increased by some factor, similar increase is added in dB to the intensity.

The velocity of ultrasound wave depends on mediums physical properties. Velocity of ultrasound wave is found to be relatively low in the mediums of air and other gases. It is relatively high for solids. The velocity changes in different liquid mediums.

One more important parameter of ultrasound wave is its acoustic impedance (\( Z \)) that is given as:

\[ Z \approx \rho c \quad (3.6) \]

This parameter indicates the behavior of ultrasound wave at interface of two different materials. As that of electromagnetic wave, some part of the ultrasound wave gets reflected back in the original medium from boundary between two mediums and the wave that is able to penetrate in new medium continues to propagate further. In this regards the reflected coefficient (\( R \)) and transmission coefficient (\( T \)) are represented as:

\[ R = \frac{Z_2 - Z_1}{Z_1 + Z_2} \quad (3.7) \]

\[ T = 1 + R \quad (3.8) \]

where \( Z_1 \) is the acoustic impedance of first material and \( Z_2 \) is acoustic impedance of new material.
If the ultrasound wave is going to propagate through different mediums the matching network needs to be found, so that maximum power can be transmitted at the other end.

Apart from all the merits discussed so far, the ultrasonic propagation finds few de-merits. The medium in which ultrasound wave is propagating needs to be acoustically conductive. There may be necessity of complex post processing of responding signal. In some of the applications, mediums acoustic properties must be known. Also the ultrasound wave face problems related to gas bubbles and attenuation at high frequencies.
3. **Fuzzy Inference System:**

To solve the control problems either mathematical or engineering techniques are employed. Depending upon the need of feedback the control problem can be categorized as open – loop and closed – loop control system. The classical control theory approach is based on mathematical modeling. An alternative problem solving approach in control system: Fuzzy Logic Control (FLC), neural network and combination of fuzzy and neural – intelligent control system.

The impreciseness that occurs in natural language can be modeled mathematically by fuzzy sets. When the available information is uncertain, imprecise, vague and incomplete, fuzzy set theory can provide mathematical model to approximate reasoning process.

Human is capable to do many controlled actions such as riding bicycle or kicking a ball. To do this human do not require any differential equations that human brain to control the desired action. Also a skilled human can carry out some complex tasks. The reason behind such kind of behavior of human control system is its learning process through experience, audio, visual and feeling sensing, etc which is governed by “if – then” rules.

The block diagram 3.2 shows basic constructing blocks of FLC. It consists intermediate block such as knowledge base and decision making, and fuzzification interface at input side and de-fuzzification interface at the output side.

1. Fuzzification interface is a process that maps the given input to an fuzzy domain by measuring values of input variables. The provided input values are converted into respective universe of discourse.

2. The operators experience and goals are expressed in knowledge base block. This block consist linguistic control rule base and data base that provides necessary definitions used to define linguistic
control rules. Set of linguistic control rules are created by domain experts to have control goals and control policy.

3. The kernel acts as decision making logic which simulates human decision making.

4. The de-fuzzification convert fuzzy crisp value into concern universe of discourse as that, at the input side value was converted to fuzzy domain.

Based on the operators knowledge, fuzzy conditional statements can be represented in the linguistic form:

\[
\text{if (a set of conditions are satisfied)}
\]

\[
\text{then (a set of consequences can be inferred)}
\]

The fuzzy if – then rules are associated with fuzzy linguistic term that is antecedent at input application domain and consequent is a control action, hence

![Figure 3.2: Basic block diagram of Fuzzy logic Controller (FLC)](image)
are so called fuzzy conditional statements. The fuzzification operator has capacity to convert crisp data into fuzzy sets as:

\[ x = \text{fuzzifier} \left( x_0 \right) \]  

(2.9)

where \( x_0 \) is crisp input value from controlled process or plant, \( x \) is fuzzy set and \textit{fuzzifier} is fuzzification operator.

The rules are interconnected or combined by using sentence connectives \textit{and} and \textit{also}. The respective fuzzy rule represents a fuzzy relation, but overall performance of the fuzzy system is combination of few or all such fuzzy relations that are connected together with the help of sentence connectives.

\[ R = \text{also} \left( R_1, R_2, R_3, \ldots, R_n \right) \]  

(2.10)

where \textit{also} represents sentence connective.

The control action to be taken on the control process or plant needs the nonfuzzy (crisp) value. Defuzzification operator does the needful that converts fuzzy set to crisp value that gives control action and represented as:

\[ z_0 = \text{defuzzifier} \left( z \right) \]  

(2.11)

where \( z_0 \) is nonfuzzy control output and \textit{defuzzifier} is defuzzification operator.

The \textit{membership function} can be represented in two ways based on universe of discourse.

1. \textit{Numerical definition} that represents fuzzy set in vector form and its dimension depends on number of discrete values.

2. \textit{The functional definition} represents fuzzy set in functional form such as triangle shape function, bell shaped function, trapezoid shaped function, etc [47].

The fuzzy logic system is introduced in various applications such as washing machine, consumer goods and products, and process control in the
industry. It is a logical system that deals with multi-valued logic. Fuzzy logic is related to fuzzy set theory that defines boundaries of membership. Here the linguistic variables are words instead of a number. It can be viewed as computation of words instead of numbers. As words are closer to human interpretations rather than using numbers that are more precise.

The input space can be mapped with output space in a convenient way by fuzzy logic. Here are few of examples of mapping:

- Fuzzy logic can tell you about amount of tip to be given depending on service information at a restaurant.
- A faucet valve can be adjusted by fuzzy logic system for heating water at specific temperature.
- The camera lens may be tuned with respect to subject located far away using fuzzy logic.
- The gears of your car can be shifted depending on the information made available from motor speed.

The main reasons behind usage of fuzzy logic system are based on general observations made:

- Conceptually fuzzy logic is easy to understand.
- It is flexible to use fuzzy logic.
- Imprecise data can be efficiently handled.
- Non-linear functions can be modeled in fuzzy system.
- Depending on experience of the expert fuzzy system can be built.
- Natural language is used in fuzzy logic.

The decision of making use of fuzzy logic is a common sense. Fuzzy logic is a convenient way to map input with output. When other convenient methods are available, it would be right to implement the problems using them.

The list of if – then rule is employed to map input space to output space in fuzzy logic system. These rules operate in parallel manor, whatever may be the order of rules arranged. The individual rule is important as adjectives define them with the help of variables. Consider if it said that “water is hot”, it is required to describe the range of word hot. The term hot may refer different temperature level
for different person. The figure 3.3 provides process for fuzzy inference. The example of tipping is shown in that describes amount of tip should be given depending on quality of service provided. The tip is defined in terms of cheap, average and generous whereas the service is poor, good and excellent. Hence if–then rules can be arranged accordingly which understand input values known as input vector and depending on set of rules, generates output values in the output vector.

![Diagram of Fuzzy Inference Process](image)

*Figure 3.3: Fuzzy Inference Process [75]*

The fuzzy logic system deals with fuzzy set that tries to well define boundaries of set in fuzzy set. It may consist fractional part of membership with given elements. Fuzzy set is a classical set that clearly separates elements which are included and excluded. Without any doubt it can be said that Tuesday, Wednesday and Sunday are the days of week and liberty, butter and dorsal fins are excluded.
As the above fact is known, this type of set is known as classical set and was formulated by Aristotle. Another form of the law is:

“of any subject, one thing must be either asserted or denied”

The demands bifurcation of two categories say it belongs to set – A or not – A. If another example is considered as weekend days. One can clearly agree with Saturday and Sunday as the weekend days but it will be ambiguous to say Friday as weekend day as shown in figure 3.4
Hence the Friday try to “straddle on the fence” and which is not tolerated by classical set or the normal set. Whereas when human experience is considered it is somewhat different and “straddling the fence” is section of life. Also it may depend on individual and his related cultural background. As per individual perception, one can consider the start of weekend from Friday night and / or Saturday morning and ends with Sunday night and / or Monday morning. This kind of considerations does not provide any sort of firm boundaries, that makes hard to take decisions yes – no. Here fuzzy reasoning can be helpful when people try to define such kind of concept like weekend. More or less the fuzzy logic can be given in statement:

“In fuzzy logic, the truth of any statement becomes a matter of degree”

The fuzzy reasoning has advantage to reply a statement with not-quite-yes-or-no.

Fuzzy reasoning can be implemented using Boolean logic of yes – no. If it is considered logic 1 for yes or true condition and logic 0 for no or false condition, also fuzzy logic indicates values between say 0.3 and 0.7.

Question: Tuesday is a weekend day ?
Answer: 0
Question: Saturday is a weekend day ?
Answer: 1
Question: Friday is a weekend day ?
Answer: 0.6
Question: Sunday is a weekend day ?
Answer: 0.9

It can be clear from above questions and respective answers that human thinking is possible to implement in a system with the help of fuzzy logic system, which is very difficult to have it in logical system implementation. The figure 3.5
and figure 3.6 represents weekend-ness for two membership and multiple membership respectively.

Figure 3.5: Representation of weekend days with two valued membership [75]

Figure 3.6: Representation of weekend days with multiple membership [75]
Figure 3.7: Representation of weekend days with two value membership for continuous time scale [75]

Figure 3.8: Representation of weekend days with multiple membership for continuous time scale [75]
Now, if the question is raised that “Does X is member of set – A?”. Probable answers may be yes, no or any of one intermediate value from thousand of numbers in between. So, X can be said to be partial member of A. On the basis of continuous time scale weekend – ness plot is plotted as shown in figure 3.7 and figure 3.8.

The continuous representation of weekend – ness will help in justifying day in weekend. It can be seen from figure 3.7 that indicates sharp boundary condition at midnight of Friday 12 O’clock shifting from 0 towards 1. This kind of hard boundaries may not work in real life. Whereas plot in figure 3.8 have smooth boundary curve. It can be seen that plot starts uplifting values from Thursday itself. Here the input value is mapped with input space, known as membership function.

Membership Function:

The mapping of each input space value sometimes also known as universe of discourse, with a curve of membership value between 0 and 1 is a membership function.

Consider a example of tall people. The average height of people is in range of 3 feet to 9 feet and if it is said that people having height greater than 6 feet would be considered as tall. On accounting basis classical set will indicate sharp boundary that bifurcates people having height 6 feet or above 6 feet as tall and with a hair difference less than 6 feet would be called as short. Which is absurd when dealed with real world (figure 3.9).

Thus hard boundaries would not work in real life. As that was discussed in previous section for the plot of weekend days, a smooth curve can work for real world consideration as shown in figure 3.10.

This smooth curve known as membership function defines boundary of not – tall and tall with membership value limited between 0 and 1 and normally
designated as $\mu$. Both people in figure 3.10 tall by some degree, but one is less tall when compared with other.

Figure 3.9: Indication of tall people [75]
Figure 3.10: Membership function for indication of tall people [75]

Thus membership function can thought as arbitrary curve having convenient shape. Different shapes are defined in fuzzy toolbox of MATLAB environment as shown in figure 3.11.
Figure 3.11 (a): Triangular Membership Function

Figure 3.11 (b): Trapezoidal Membership Function
Figure 3.11 (c): Simple Gaussian Membership Function

Figure 3.11 (d): Two sided Gaussian Membership Function

Figure 3.11 (e): Generalized bell Membership Function
Figure 3.11 (f): Sigmoidal Membership Function

Figure 3.11 (g): Difference Sigmoidal Membership Function

Figure 3.11 (h): Product Sigmoidal Membership Function
Figure 3.11 (i): Z – polynomial based curve Membership Function

Figure 3.11 (j): Pi – polynomial based curve Membership Function

Figure 3.11 (k): S – polynomial based curve Membership Function

Figure 3.11: Different shapes of membership Function [75]
As discussed earlier fuzzy logic tries to map input and output space and this mapping is carried out by Fuzzy Inference System using various stages. It makes use of previously discussed “Membership function”, “if – then rules”, and “logical operations” (explained now). The fuzzy reasoning is realized using logical operator. In real sense standard Boolean logic generates result as either logic 1 or logic 0 as depicted in figure 3.12.

![Logical AND operation](image)

**Figure 3.12 (a):** Logical AND operation.
Figure 3.12 (b): Logical OR operation.

Figure 3.12 (c): Logical NOT operation.

Figure 3.12: Truth table for Logical AND, OR and NOT operation [75].
Figure 3.13 (a): Modified Logical AND operation.

Figure 3.13 (b): Modified Logical OR operation.

Figure 3.13 (c): Modified Logical NOT operation.

Figure 3.13: Modified Truth table for Logical AND, OR and NOT operation [75].

The real numbers may be in between 0 and 1 and fuzzy logic deals with statement that matter for degree. It’s the matter of having real numbers coming
between 0 and 1 to map in truth table for logical operations. The solution can be sorted as have \textit{min} operation with respect to logical AND operation, considering both inputs would be in range [0, 1]. Similarly logical OR operation can be related to \textit{max} function and logical NOT $A$ can be represented as $1 - A$. Hence the previous truth table can be modified as shown in figure 3.13.

Now intermediate values can be considered which are in between 0 and 1. The intermediate value representation is depicted in figure 3.14, that consist two – valued representation in upper part and multi – valued representation is shown in next half part.

![Figure 3.14: Representation of intermediate values for logical operation [75]](image)

The fuzzy inference system can be implemented in two ways: Mamdani – type and Sugeno – type in MATLAB fuzzy toolbox. The types differ in generation of output. The Mumdani – type inference make use of single spike to produce output membership function instead of having distributed fuzzy set. Whereas Sugeno – type uses weighted average that gives linear or constant output membership function. The figure 3.15 show a general fuzzy inference process for the example of tipper.
Figure 3.15: Representation of Fuzzy Inference System for tipper problem [75]

It is a two input system and single output where information is flowing from left side to right side. The rules operates in parallel which is one of the important feature of fuzzy logic.

**Fuzzy Input** is arranged to a degree using fuzzy set and assigned to input membership function. This is a numerical crisp value inputted to fuzzy toolbox in MATLAB and is restricted to universe of discourse. Here input is considered in range of [0 10]. Both of the inputs (Service and Food) are assigned same input range values [0 10]. The input is fuzzified and lookup table is prepared. In current example three rules are built, which linked with linguistic terms for service: poor, good and for food: rancid, delicious etc.

**Fuzzy operator** is applied to fuzzified input, when input part assigned to rule satisfy the antecedent condition. Fuzzy operator applies to multiple inputs to get resultant output value. Thus a single output value is generated apart from number of input(s) as shown in figure 3.16.
Implication method is applied before which weight of rules are determined. The given number by antecedent is assigned a weight. The weight may be in between [0 1]. Respective rule will have different weight value. Once weighting procedure is completed implication method is applied depicted in figure 3.17.

Figure 3.16: Fuzzification operation and applying operator [75]

Figure 3.17: Applying implication method [75]
Aggregation of output is carried out of all the outputs generated by respective fuzzy rules. The outputs available after if – then rule is combined together to form single fuzzy set. Three inbuilt methods are available aggregate the outputs from different rules are max, probor and sum as shown in figure 3.18.

![Figure 3.18: Aggregation of outputs available from rules](image)

Figure 3.18: Aggregation of outputs available from rules [75]
Defuzzification of the value obtained from aggregation is done in this final stage. The range of output single value is the conversion of extreme aggregated values. In all built-in five methods are available: “smallest of max, largest of max, centroid, middle of max and bisector”.

Finally fuzzy inference system can be collectively represented as shown in figure 3.20. It represents overall procedure that is carried out to implement fuzzy system.
Figure 3.20: Fuzzy Inference System a collective look [75]
4. Adaptive Neuro-Fuzzy Inference System:

The replicate of biological neural network of human brain is done in the Artificial Neural network (ANN). In ANN the performance properties of biological neural network is distributed in parallel to process information (figure 3.21).

The neural network consist connection between nodes or neurons in same or different layers. The nodes are interconnected with the help of links that process the incoming signal to the next node. The interconnected link processes this signal based on strength or weights assigned to them. The assignment of these strength or weights is carried out by learning process or by training the network.

The motivation to introduce neural network is obtained from the working principle of human brain. Human brain is the best example of parallel computing, non-linear and complex system. Thus in few of the cases human brain can compute complex data at the faster rate as compared with existing digital computers [74].

The digital computer system normally performs four operation cycles repeatedly:

1. Fetching of instruction from memory
2. Fetching of data that is required for above instruction
3. Execution of above fetched instruction
4. Storing of result obtained in step 3
5. Repeat the above steps from 1 to 4 and so on …

The above steps can be implemented in the form of algorithm. The algorithm may be well defined to achieve desired answer. The suitable example is to implement a equation in the form of algorithm. The lengthy algorithm can be broken into different statements that computer executes.
The computer system persists following properties:

- The computer system should be known about the proper sequence of execution of algorithm and detailed steps of program to be executed.
- Well defined data type or data in the precise form that will not create any sort of confusion while handling data.
- Multifunctioning of any memory location may lead to destruction of whole computer system or the computer system may crash.
- The communication between machine hardware and semantic object needs to be clearly addressed.

Many of the sophisticated tasks that human brain can do, is found to be difficult to implement in the form of algorithm. For example human brain can recall the visual scene that was observed or seen previously, with the help of simple cue. Even very sophisticated data base packages available today cannot perform such a task. These types of tasks may be performed more easily by machines/systems which emulate the human brain [74].

Figure 3.21: The Biological Neuron [74]
Neural Networks Properties:

The ANN replicates characteristics of human brain in two ways:

1. It acquires the knowledge by learning.
2. To store knowledge synaptic weights are used between the connections of neurons.

The learning process is used to identify synaptic weights of network. This process of finding or modifying synaptic weights is known as learning algorithm. The synaptic weights are so adjusted to achieve desired objective.

The knowledge representation in neural network is the major strength. In the designed system, stored information represents knowledge about model. This knowledge can be represented when information is made explicit and is further physically encoded. A better intelligent system can be formed by proper representation of knowledge. The knowledge in real world may be facts that are known or the observations that are made.

The first kind of information can be easily represented in any conventional computer system. It is mainly the second kind of information which contributes to the intelligence either natural or artificial. Humans or even animals have the ability to observe the world and learn (gain knowledge) from these observations. An ANN is designed to perform a similar task. The expected neural network should learn real world model and perform satisfactorily to achieve desired goals of implemented application system.

The parallel distributed structure and the learning ability of neural network makes it innovative to replicate real world. Hence neural network is found to be capable of solving complex problems [74].

The basic block diagram of ANN where neuron acts as fundamental processing element is shown in figure 3.22. Here $x$ indicates general input that varies from 1 to $n$. These inputs are real world environment element that are feed to neurons.
The weights are added to each and every input $x_i$ as required and they reached to main body via connection strength factor $w_i$. The resultant is the product of $x_i$ and $w_i$. Output of the neuron is generated by summation of all incoming signals with an additional bias term $b$. The bias term is added or exceeded from the overall output $O$. Also the output $O$ may consist the input from some other neuron or neurons. The mathematical expression of output of a neuron is:

$$O_i = f_i \left(u_i\right) \text{ where}$$

$$u_i = \sum_{j=1}^{n} W_{ij} x_{ij} - b_i$$  \hspace{1cm} (3.12)$$

The two most popular activation functions are hard limiter and the sigmoid. All the activation functions depicted in figure 3.23 are all bounded they have an upper and/or lower limit such as $\pm 1$, $\pm \frac{1}{2}$. In actual networks the user chooses the value of the bounds. The three activation functions shown in figure 3.23 can be expressed mathematically as follows (with bounds of 0 and 1).
hard limiter or threshold function

\[
f(u) = \begin{cases} 
1 & \text{if } u \geq 0 \\
0 & \text{if } u < 0
\end{cases}
\]  
(3.13)

sigmoid function

\[
f(x) = \frac{1}{1 + e^{-ax}}
\]  
(3.14)

Where \( a \) is the slope parameter of the sigmoid function. By varying the parameter \( a \), sigmoid function of different slopes can be obtained.

Ramp or Piece wise linear function (with bounds of \( \pm \frac{1}{2} \))

\[
f(u) = \begin{cases} 
1 & u \geq \frac{1}{2} \\
u & -\frac{1}{2} < u < \frac{1}{2} \\
0 & u \leq -\frac{1}{2}
\end{cases}
\]  
(3.15)

The processing performed by a single neuron is simple, but the strength of a neural network depends on how the individual neurons are connected and how information is distributed among them.
Neural Network Functioning:

The basic rules describing the functioning of a neural network are as follows.

1. Information processing occurs at neurons as described in the previous section.

2. The signals are made to pass through connections between nodes.
3. The connection strength is represented by its respective weight applied on the connection link.

4. The output is determined by applying non-linear transformation known as activation function.

The connection between the nodes is represented by patterns, which represent architecture of neural network. The neural network also indicates connection weights known as learning.

**Network Architectures:**

In neural network the neurons arranged to link with different layers that trains network using learning algorithm. The neural network can be classified as: single (Hopfield net), bi-layer (Adaptive Resonance net) and multi - layer (back propagation net). Also it can be classified based on information flow direction and processing as: feed-forward network and feed-back network. The feed-forward network may consist various hidden layers arranged in the layered structure, that feeds input signal at input side and the output is taken at output layer. The different hidden layers are present in between that are having one or more neurons. Hence the information gets propagated from input side to output side.

The neurons in same layer are not connected with each other in this case, rather they are connected to next layers neurons. The generated output in a layer
depends only on previous layers neuron output, which is feed to current layer neuron and its respective weights.

The second classification corresponds to feed-back network. As the name indicates information flows bi-directionally between input and output side. This is achieved by feeding the output of next layer neuron to the input of previous layer neuron. In few of the cases lateral connections are also preferred [74].

**Learning in Artificial Neural Network:**

The important property of ANN is its ability to learn. The learning process of network is from its environment. The learning process can be defined as the adaptation of neural network parameters in the environment where it is to be embedded. According to changes occurring in learning parameters the types of learning may be identified.

In accordance to input stimulus the network adjusts its parameter so to produce an actual output response. Once the desired output is achieved the learning process is completed and network is said to have gained knowledge. Different people may adopt different methods learning methods, the various learning methods are proposed in artificial neural network and its classification is shown in Figure 3.25.

The learning process in ANN is broadly classified as learning algorithm and learning paradigms. The learning algorithm is further classified in four categories. The Boltzmann learning algorithm is based on information theoretic and thermodynamic consideration. This algorithm is named in the honor of L. Boltzmann.

The author Donel Hebb proposed a conceptual learning in 1949. According to Donel Hebb if a cell A is enough close to cell B and they have effect of firing of cell A on other cell B, will generate change in the assigned weight. The relative change that occurs in between cell A and cell B will modify the synaptic strength of link between cell A and cell B.

The generated output of neurons, when compared with other neuron is considered under competitive learning. The output of one neuron when a stimulus
is applied at the input side is compared with the other output signal to achieve nearest output signal to the target.

In the supervised learning, when the stimulus is applied at the input side it generates corresponding output signal. The generated output response is compared with the desired or expected output response and relative error signal is generated. With the help of this error signal synaptic weights of the network are calculated and then adjusted accordingly to minimize the error signal. The Delta rule and Gradient Descend rule are commonly used supervised learning.

<table>
<thead>
<tr>
<th>Learning algorithm (rules)</th>
<th>Learning paradigms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error Correction Learning</td>
<td>Supervised Learning</td>
</tr>
<tr>
<td>Boltzmann Learning</td>
<td>Reinforced Learning</td>
</tr>
<tr>
<td>Hebbian Learning</td>
<td>Unsupervised Learning</td>
</tr>
<tr>
<td>Competitive Learning</td>
<td></td>
</tr>
</tbody>
</table>

![Figure 3.25: Classification of Learning Process](image)

The Reinforced learning makes use of one or more neurons at output layer. Here it does not checks whether the output is achieved or not as it is done in supervised learning. The input stimulus is applied and its corresponding output response is taken. This is validated with desired output which is not known to the network. Hence if the target output is not achieved again the network parameters are adjusted to change the output and process is repeated to achieve target. In this
case generated error signal is in the form of binary during training process indicating either target achieved or not.

When the target output is not known to the network and it is trained with the help of various excitations at the input that generates different patterns at the output. The output patterns are arranged in different categories. Hence by applying a particular input and the provided output by network is categorized to indicate class.

**Feed Forward Networks:**

In engineering applications supervised learning is normally used which is associated with feed forward neural network (FNN). With the help of various pattern recognitions, the concerned FNN architecture can be chosen. The pattern mapping is important in engineering applications when FNN is in use. The mapping of input-output patterns can be achieved with the help of back-propagation algorithm in a multi-layer FNN. The error back-propagation algorithm is found to be implemented successfully in multilayer FNN for solving difficult problems using supervised learning. It can be also termed as error correcting learning rule. The multi-layer FNN can be categorized in three different ways:

1. A differential non-linear activation function in network is assign to every neuron and its activation function is given by sigmoid function:

   \[ y_j = \frac{1}{1+\exp(-u_j)} \]  \( \text{(3.16)} \)

   where \( u_j \) is the net internal activity level of neuron \( j \) and \( y_j \) is the output of the neuron

2. The different layers are arranged by using neurons where the first layer acts as input layer of the source node. At this stage computation is not performed, the layer passes the input values to next layer. The output layer is the last layer in the network that produces output in response to applied input pattern. The single layer FNN corresponds to one input layer and a output layer, while multi-layer
FNN will consist more than one intermediate layers between input and output known as hidden layers and neurons as hidden neurons.

3. In this case the neurons of one layer are connected to next layer all neurons. These neurons are not interconnected with each other in same layer. The figure 3.26 depicts a FNN with three input neurons and two output neurons. Also figure 3.26 shows four hidden neurons. The architecture of this network is denoted as 3:4:2 indicating the number of neurons in different layers. The nodes in the input layer are represented differently from other neurons as these nodes do not perform any computation.

Normally two signals propagate in the network. The first one is the signal that enters from input side, propagates in the network and is emerged in output side of network and is emerged in output side of network is known as function signal. The second signal is generated at the output end and propagates in reverse direction towards input side known as error signal.

![Figure 3.26: A Typical Two Layer Feedforward Neural Network](image)

**Adaptive Neuro-Fuzzy Inference System:**

The fuzzy system is normally employed to the control problem when the crisp rules are found to be difficult to define or implement. Thus fuzzy system gives the flexibility to define or describe fuzzy rules that matches the real world control problem. Also fuzzy rules are capable of interpreting individual output generated by respective rule.
The fuzzy system needs the expert that defines fuzzy rules. The defined fuzzy rules may not produce expected output, as the fuzzy system parameters needs to be tuned. The fuzzy system parameters are the membership function parameters. The tuning of these parameters usually takes long time when number of rules defined is more.

It is possible to overcome the above problems faced by fuzzy system. The reverse situation is observed in the field of neural network. Here, it is found to be difficult to implement priori knowledge about the system, but the implementer is capable to train the neural network. The behavior of the neural system cannot be predicted for a particular situation.

The researchers have taken affords to compensate de-merits of a system with the merits of other system. Researchers have proposed a hybrid system that combines the features of fuzzy systems and neural networks, which gives rise to ANFIS (Adaptive-Network-Based Inference system or Adaptive Neuro-Fuzzy Inference System).

With the help of given input-output data-set the ANFIS generates fuzzy inference system. The respective membership function parameters can be tuned by back-propagation algorithm or both back-propagation and least square method. Hence the tuning of membership function takes place to achieve the matching between input-output data-set.

Thus by providing the learning parameters (input-output data-set) fuzzy modeling can be tuned with the help of neural network. The given input-output data is tracked by computing the parameters of membership function.

The ANFIS interprets input-output mapping by associating the inputs with input membership function and its parameters, then the outputs with output membership function and its parameters. The parameters of respective membership function get changed during the learning process. These membership parameters are adjusted by a gradient vector that provides the measures to model fuzzy inference system for the given set of input-output data-set. The obtained gradient vector can be used to optimize membership function parameters that will reduce the error. ANFIS may use only back-propagation or the combination of
back-propagation and least square method to train the membership function parameters.

The adaptive network consists of nodes and directional links through which the nodes are interconnected. Almost each and every node is adaptive, that depends on parameter(s) affecting nodes and the parameters of membership function that forms various rules to minimize the error measure.

The piecewise differentiability is the only constraint on node function in the adaptive network. The description of learning rule and the architecture of adaptive network is discussed so far. The ANFIS structure leads a limitation that the network configuration must be feed-forward.

Now consider two inputs $x$, $y$ and one output $z$, fuzzy inference system with Takagi and Sujeno type two fuzzy if-then rules as:

Rule 1: If $x$ is $A_1$ and $y$ is $B_1$, then $f_1 = p_1x + q_1y + r_1$,

Rule 2: If $x$ is $A_2$ and $y$ is $B_2$, then $f_2 = p_2x + q_2y + r_2$,

The illustration of above fuzzy reasoning is shown in figure 3.27 and its respective ANFIS architecture is depicted in figure 2.28.

\[
O_i^1 = \mu_{A_i}(x) \quad (3.17)
\]

where,
A – represents linguistic label of concerned node function

\( x \) – is input to node O

Consider a bell-shaped membership function represented with maximum 1 and minimum 0 as:

\[
\mu_{A_i}(x) = \frac{1}{1 + \left( \frac{x-c_i}{a_i} \right)^{2\gamma_i}} \quad (3.18)
\]

\[
\mu_{A_i}(x) = \exp \left\{ - \left[ \left( \frac{x-c_i}{a_i} \right)^{2\gamma_i} \right] \right\} \quad (3.19)
\]

here \( \{a_i, b_i, c_i\} \) represents parameter set. The shape of the bell-shaped function changes with respect to change in above parameters, which gives rise to different forms of membership function on linguistic label \( A_i \). Also the trapezoidal or triangular membership functions are commonly used to represent node function.

Layer 2: The circular node in this layer which is represented by H, indicates the multiplication of input signal and gives out the product. The respective node gives firing strength:

\[
\omega_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2. \quad (3.20)
\]
Layer 3: The circular node that is labeled as N represents ratio of \(i^{th}\) node rule’s firing strength to the sum of all rules firing strength.

\[
\bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}; \quad i = 1, 2.
\]  
(3.21)

Layer 4: This layer represents the square of node with node function:

\[
O_i^4 = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i)
\]  
(3.22)

The output of layer-3 is \(\omega_i\) and \(p_i, q_i, r_i\) is the parameter set.

Layer 5: The layer calculates overall output of system. The circular node labeled as E, takes sum of all incoming signals.

\[
O_i^5 = OverallOutput = \sum \bar{\omega}_i f_i = \frac{\sum \omega_i f_i}{\sum \omega_i}
\]  
(3.23)

The above equation indicates overall output of fuzzy inference system formed by summing the inputs at circular node labeled as E. The different ANFIS outputs can be achieved with the help of various de-fuzzification methods [9].
5. **Carbon as a Electrode:**

The carbon is the first element of Group IV-A, that appears to be in most striking fashion than the other groups. Carbon atom has an important feature of bond to other carbon atoms that forms chains and rings of enormous variety. The covalent bonding of two or more atoms of the same element to one another is referred to as catenation. There are two allotropic forms of carbon: graphite and diamond. Both of the allotropes have solid covalent network structure. Graphite has a layered structure with black substance. The every layer of carbon atom is bonded to three other carbon atoms that gives hexagonal pattern of carbon. This forms a plane and one layer of carbon atoms in graphite is attached to other by van der Waals forces. Due to delocalized bonding within layers graphite is a good conductor. The graphite has hexagonal crystal structure with density around 2.27 g/cm$^3$. One of the important property of graphite is its melting point which is 3800$^o$K and the resistance measured is $1.37 \times 10^{\text{E}-5}$ ohm-inch [68]. The resistivity of graphite changes with respect to change in graphite grain size.

![Structure of Graphite](image.png)
It can be observed in figure 3.29 that the carbon atoms are covalently bonded in hexagonal pattern. These hexagonal patterns form sheets of carbon called graphite. When each carbon atom is covalently bonded to other four, that forms tetrahedral directions to have three dimensional network solid of diamond shown in figure 3.30. One sp³ hybrid orbit on one carbon atom overlaps on other sp³ hybrid orbit on carbon atom forming C – C bonding. The unit cell of diamond can be represented with the help of zinc blende (figure 3.31). Here the zinc blende, Zn²⁺ ions are replaced by carbon atoms the dark spheres and Zn²⁻ ions by carbon atom, the light spheres to obtain unit cell of diamond.

Another allotrope of carbon: Graphite consisting covalently bonded hexagonal arrays of carbon atoms forming large, flat sheets of carbon. These sheets are stacked one on top of other. Each sheet is described by resonance formula.

To explain the graphite properties, layered structure that is observed under electron micrographs is shown in figure 3.32. It depicts that graphite sheets separates easily as they slide on each other. A “lead” in pencil is a best example that when rub to make pencil mark by graphite layer.
Electrical conductivity is an important property of graphite, since the electrons in bonds are localized. As delocalization leads to free electrons within each carbon atom layer, the graphite is found to be a good conductor [68].

As the graphite has good conductivity property and layer structure is available that makes is suitable for various applications. Already the graphite based rods are in use of electric motor brushes and electrical appliances.

Figure 3.31: Unit cell of Diamond [68]
Figure 3.32: Electron micrograph of graphite [68]
6. Conclusion:

Since last two decades it has been studied the benefits of using non-conventional type of controllers to solve control problems. The basic conceptual study of Fuzzy Logic Control (FLC) and Adaptive Neuro-Fuzzy Inference system (ANFIS) is presented. Both FLC and ANFIS can be successfully implemented in temperature control type applications. Also the basic properties of ultrasound wave and carbon are explored. The features of ultrasound wave and carbon will be combined with FLC or ANFIS to estimate the fat content of milk in the forthcoming study.