CHAPTER 3
SIMULATION AND DEVELOPMENT OF A SENSOR SYSTEM

In this chapter simulated sensor system is described for two applications of environmental monitoring and household items recognition.

3.1 Smell Sensor system:-

Figure 3.1 shows a typical sensor system having three major components. In this thesis work, two e-nose sensor systems have been proposed and simulated for two different applications. Each system consists of a different TGS sensor array with two different classification techniques for each application.

![Figure 3.1 Block diagram of the Sensor System](image)

In the first application, Ten (10) different toxic chemicals have been used for smell detection that present in our environment and responsible for making it polluted. So this application is related to environment monitoring. Second
application is related to smell detection of fourteen (14) household items in which a particular household item can be detected by its smell.

The e-nose developed consists of three key components: sampling chamber, sensor array chamber and pattern classifier. Figure 3.2 shows developed electronic nose having all three key components with additional interface circuitry to see response of sensors on LabVIEW screen.

![Figure 3.2 Developed Electronic Nose](image)

Now each key components used in electronic nose system will be discussed in detail.

**3.1.1 Sampling Chamber**

A sampling chamber having a glass bottle equipped with a rubber stopper which has two holes and each one is attached to a plastic tube. Another bottle is used to pass fresh air for cleaning purpose of sensor array chamber. Dry air enters in the bottle from one side and via water goes to 3 way valve. Sampled odor from sampling chamber also goes to the valve, which is connected to measurement
chamber or sensor array chamber. Figure 3.3 shows arrangement of sampling chamber, valve, pump and sensor array chamber.

![Diagram of sampling and sensor array chambers](image)

Figure 3.3 Arrangement of sampling and sensor array chambers

To increase the flow, a miniature air diaphragm pump is used to suck odors from the sampling chamber to the sensor chamber.

### 3.1.2 Sensor Array Chamber

The sensor array chamber is made of Perspex glass which is non-reactive to chemical or food vapors. It has 20 cm × 8 cm × 6 cm dimensions and is airtight. Twelve thick film metal oxide sensors (Figaro USA, Inc.) were mounted on a PCB and kept inside glass chamber as shown in Figure 3.4. Eight different types of sensors are arranged in symmetrical form. Four sensors are used two times in the array of twelve sensors.
Types of sensors used for environment monitoring application or for sensing 10 chemicals are shown in Figures 3.5. They all are of Figaro TGS2000 series sensors.

Types of sensors used for household items application or for sensing 14 smells are shown in Figures 3.6. They all are of Figaro TGS800 series sensors.
TGS 2000 series sensors and TGS800 series sensors with their corresponding sensitivity to a particular gas are listed in Table 3.1.

**Table 3.1 Sensitivity of different TGS sensors** [101-104]

<table>
<thead>
<tr>
<th>Sensor name</th>
<th>Highest Sensitivity to a gas</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TGS800 Series Sensors</strong></td>
<td></td>
</tr>
<tr>
<td>TGS830</td>
<td>Chlorofluorocarbons</td>
</tr>
<tr>
<td>TGS 822</td>
<td>Ethanol(organic solvents)</td>
</tr>
<tr>
<td>TGS 821</td>
<td>Hydrogen</td>
</tr>
<tr>
<td>TGS 842</td>
<td>Methane</td>
</tr>
<tr>
<td>TGS 825</td>
<td>Hydrogen sulfide</td>
</tr>
<tr>
<td>TGS 813</td>
<td>LP gas and Methane</td>
</tr>
<tr>
<td>TGS 880</td>
<td>Cooking vapors</td>
</tr>
<tr>
<td>TGS 826</td>
<td>Ammonia (Toxic gases)</td>
</tr>
<tr>
<td><strong>TGS2000 Series Sensors</strong></td>
<td></td>
</tr>
<tr>
<td>TGS 2630</td>
<td>Refrigerant gases</td>
</tr>
<tr>
<td>TGS 2602</td>
<td>General air contaminants</td>
</tr>
<tr>
<td>TGS 2610</td>
<td>CLP gas/ LP gas</td>
</tr>
<tr>
<td>----------</td>
<td>----------------</td>
</tr>
<tr>
<td>TGS 2620</td>
<td>VOC(volatile organic compounds/vapours)</td>
</tr>
<tr>
<td>TGS 2201</td>
<td>Automobile Ventilation gases</td>
</tr>
<tr>
<td>TGS 2612</td>
<td>Gas alarms for home/gas boilers/boats/vehicles</td>
</tr>
<tr>
<td>TGS 2444</td>
<td>Refrigerant gases/Ventilating gases in Poultry &amp; Agriculture</td>
</tr>
<tr>
<td>TGS 2442</td>
<td>CO(Carbon Monoxide)</td>
</tr>
</tbody>
</table>

There are no specific rule in selecting the types of sensor and number of sensors in an array. However, sensors must be of different sensitivity to ensure the E-nose selectivity and more number of sensors increased selectivity of the sensor system.

### 3.1.3 Pattern Classifier

The measured signals or data obtained from sensor array chamber is applied to the pattern classifier which consists of mathematical analysis tool that compare the new data with old saved data in its database and distinguish the smell. For each smell data pattern is different, some of the data is used to train the pattern classifier and some to test the pattern classifier. Once it is trained and tested, any new odor can be applied to it for detection and distinguishing. For classification purpose RBFN and ANFIS have been used and results are compared. There are so many classification techniques as discussed in 2.7. Some are untrained techniques like PCA or other MDA (Multi variable data analysis) techniques which are useful when no known sample is available or when hidden relationship between sample and variable suspected. Some are trained techniques like neural networks; fuzzy systems etc. provide exact information of sample or smell but for that, first training is required then testing data is applied. Neural networks are based on different function approximation techniques but RBFN became more popular because it is the best function approximation technique also with the advantages of easy design,
stable and good generalization ability, good tolerance to input noise, and online learning ability, RBF networks are strongly recommended as an efficient and reliable way of designing dynamic systems [105]. So RFFN has been chosen for this work. ANFIS combines the advantages of both neural network and fuzzy logic which offers good results. Learning duration of ANFIS is very short than neural network case. It implies that ANFIS reaches to the target faster than neural network. When a more sophisticated system with a huge data is imagined, the use of ANFIS instead of neural network would be more useful to overcome faster the complexity of the problem. In training of the data, ANFIS gives results with the minimum total error compared to other methods. This shows that the best learning method is ANFIS among the others. So it has been chosen as another classification technique for this work to fulfill comparison purpose.

Now for the two applications chosen toxic chemicals and household items will be explained. Then each part of the sensor system will be explained one by one. First toxic chemicals will be explained that have been taken for environmental monitoring.

3.2 Toxic Chemicals

3.2.1 Carbon monoxide (CO):- Carbon monoxide slightly less dense than air is a colorless, odorless, and tasteless gas. When in higher concentrations it is toxic to humans and animals. It is also produced in normal animal metabolism in low quantities, and has some normal biological functions. It is spatially variable and short lived, and has a role in the formation of ground-level ozone in the atmosphere.

3.2.2 Sulfur dioxide (also sulphur dioxide SO₂):- In Earth's atmosphere, it exists in trace amounts of 1 part per billion by volume (ppbv), primarily as a pollutant commonly released by various industrial processes. Since coal and petroleum often
contain sulfur compounds, their combustion generates sulfur dioxide unless the sulfur compounds are removed before burning the fuel. It is released naturally by volcanic activity and is a potent global warming gas. In the presence of a catalyst such as NO$_2$, the oxidation of SO$_2$, forms H$_2$SO$_4$, and acid rain take place.

3.2.3 Nitrogen oxides (NO$_x$):- One of the most prominent air pollutants, this reddish-brown toxic gas has a characteristic sharp, biting odor. Nitrogen dioxide, one of several nitrogen oxides is a chemical compound with the formula NO$_2$. Nitrogen oxides are expelled from high temperature combustion, and are also produced during thunderstorms by electric discharge.

3.2.4 Ammonia (NH$_3$):- It is a gas with pungent odor. Ammonia is emitted from agricultural processes. Ammonia contributes significantly to the nutritional needs of terrestrial organisms by serving as a precursor to foodstuffs and fertilizers. Either directly or indirectly ammonia is also a building block for the synthesis of many pharmaceuticals. It is both caustic and hazardous.

3.2.5 Copper: - Copper interferes with salmon’s sense of smell, which reduces their ability to avoid predators, find their way back to their birthplace to spawn, and find mates. Copper is a special concern. While people may not be harmed by small amounts of copper, even low levels of the chemical are a significant threat to salmon and other fish in Puget Sound.

3.2.6 Lead: - Lead is a natural element in the environment but most lead-related health and environmental problems are the result of human activities. Lead is a known persistent bio-accumulative toxic chemical. Lead is present in Puget Sound from past uses such as when lead was added to gasoline, household products like ammunition, and uses in glass manufacturing. Lead can affect blood pressure,
reproduction, brain development, behavior and growth in children and adults. Lead affects animal species also for example waterfowl are at risk if they ingest it while feeding.

3.2.7 Polychlorinated biphenyls (PCBs):- They are widely used as dielectric and coolant fluids, in transformers, capacitors, and electric motors. They were also used as plasticizers in paints and cements, stabilizing additives in flexible PVC coatings of electrical wiring and electronic components, reactive flame retardants, lubricating oils, cutting oils, hydraulic fluids, pesticide extenders and sealants for caulking in schools and commercial buildings, casting agents, vacuum pump fluids, adhesives, de-dusting agents, waterproofing compounds, fixatives in microscopy, surgical implants, wood floor finishes paints, and in carbonless copy ("NCR") paper.

3.2.8 DDT (Dichloro Diphenyl Trichloroethane) known for its insecticidal properties. It is a colorless, tasteless, crystalline, and almost odorless organochloride. It has been formulated in almost every conceivable form, including solutions in xylene or petroleum distillates, granules, aerosols, emulsifiable concentrates, smoke candles, water-wettable powders and charges for lotions and vaporizers. It was banned years ago but is still present in the environment.

3.2.9 Nonylphenol: - It is a compound often found in industrial air emissions and when detergents break down. Nonylphenol is a subset of the alkylphenols. It is disruptor of balance of hormones in affected organisms.

3.2.10 Polybrominated Diphenyl Ethers (PBDEs) They are organobromine compounds and are used as flame retardant. PBDEs have been used in a wide
range of products, including electronics, motor vehicles, polyurethane foams, furnishing, building materials, airplanes, plastics and textiles.

3.3 The 14 Household Items

3.3.1 Distilled Water: - This water has nothing but hydrogen and oxygen molecules, with a pH level of 7 and no minerals, additional gases or contaminants. Natural water has some microscopic contaminants, some dissolved minerals like calcium and iron. By distillation process means boiling until it changes to steam, these elements can be removed. And steam is cooled down and condenses into liquid form and becomes purified water called distilled water.

3.3.2 Lighter fluid: - It is a highly flammable, colorless, easily liquefied gas. It is used in cigarette lighters. It may refer to Butane.

3.3.3 Soda Water: - It is a carbonated water. It is a beverage that typically contains a sweetener and a flavoring agent. The sweetener may be sugar, fruit juice, high-fructose corn syrup, sugar substitutes or some combination of these. Soft drinks may also contain preservatives, colorings, caffeine, and other ingredients.

3.3.4 Perfume Jasmine: - It is used to give the objects, animals, food, human body and living spaces a pleasant scent. It is a mixture of fragrant essential oils or aroma compounds, fixatives and solvents. It is found from ancient texts and archaeological digs that it is existed in earliest civilizations. Present day perfumery began in the late 19th century with the commercial synthesis of aroma compounds such as vanillin or coumarin that provide the different composition of perfumes with smells which is almost impossible to get from natural aromatics alone.
3.3.5 Orange Juice: - Orange juice is acidic because of its citric acid content with a typical pH of around 3.5. It is a natural preservative/conservative and is also used to add an acidic or sour taste to foods and drinks. Citrus juices contain flavonoids (especially in the pulp), that may have health benefits. Orange juice is also a source of the antioxidant hesperidin. Flavonoids are classified as bioflavonoids, isoflavonoids and neoflavonoids. Citric acid is a weak organic acid and is a commodity chemical, and by fermentation process it is produced more than a million tons are produced every year. It is as an acidifier, a flavoring, and a chelating agent.

3.3.6 Coffee: - Coffee is a brewed beverage prepared from the roasted seeds of several species of an evergreen shrub of the genus Coffee. Coffee is slightly acidic (pH 5.0–5.1) and can have a stimulating effect on humans because of its caffeine content. It is one of the most popular drinks in the world.

3.3.7 Rose water: - It is a by-product of the production of rose oil for use in perfume and is the hydrosol portion of the distillate of rose petals. It is used to flavor food, for religious purposes and as a component in some cosmetic and medical preparations. It is a normal component of perfume.

3.3.8 Glass cleaner: - It is generally Isopropyl Alcohol 2-Hexoxyethanol or Ammonium Hydroxide. It is used for cleaning the glasses, windows, mirrors etc.

3.3.9 Honey: - The physical properties of honey changes with water content, pasturage (the type of flora used to produce it), temperature, and the proportion of the specific sugars it contains. Honey gets its sweetness from glucose and the mono saccharides fructose and has almost same sweetness as granulated sugar. Fresh honey is a supersaturated liquid that is it contains more sugar than the water
Honey is a super-cooled liquid at ambient temperatures, in which the glucose will precipitate into solid granules. It is a semisolid solution of precipitated glucose in a solution of fructose and other ingredients.

3.3.10 Vinegar: - It contains acetic acid (CH$_3$COOH) and water. The acetic acid is produced by the fermentation of ethanol by the bacteria of acetic acid. Historically, it was used as the most easily available mild acid and it had a great variety of industrial, medical, and domestic uses, some of which (such as a general household cleanser) are still promoted today. Now mainly it is used as a cooking ingredient.

3.3.11 Shoe Polish: - It is made of a waxy colloidal emulsion, which has a number of partially immiscible solids and liquids mixed together. The ingredients are lanolin, turpentine, naphtha(65-70%), gum arabic, ethylene glycol, wax (often Carnauba wax), and sometimes a colorant, such as carbon black or an azo dye. It is negligibly soluble in water and high amount of volatile substances ensures dryness and hardness after application, while retaining its shine.

3.3.12 Correction Fluid: - It is a white and opaque fluid applied to paper to correct errors in written text. Once it is dried, we can write over again. It contained toluene, which is toxic so it was banned. Later, it contained a skin irritant widely banned 1,1,1-trichloroethane, that deplete the Ozone Layer, and then it contained the slightly safer trichloroethylene. Currently correction fluid includes bromopropylene.

3.3.13 Fresh Milk: - It contains Water, Cholesterol, Calcium, Protein, Monounsaturated fatty acids, polyunsaturated fatty acids, Fat Saturated fatty acids, Carbohydrate (i.e the sugar form of Lactose). It is a white liquid produced by the mammary glands and is the first source of food and nutrition for young mammals.
before they become able to digest other foods. Early-lactation milk contains 
colostrum, which has mother's antibodies. It prevents the baby from risk of many 
diseases.

3.3.14 Contact Cement: - It is used to join two thing or broken parts. It contains 
solvent Naphtha, Toluene, Acetone, Various Resins, Synthetic Rubber, and 
Hexane. It is highly flammable liquid and vapor that may cause flash fire. It can 
cause eye, skin, nose and throat irritation. It can cause nerve damage to arms and 
legs and effects may be permanent.

3.4 TGS Sensors

3.4.1 Operation Principle
The sensing material in TGS gas sensors is metal oxide, most typically SnO₂. 
When a metal oxide crystal such as SnO₂ is heated at a certain high temperature in 
air, oxygen is absorbed on the crystal surface with a negative charge as shown in 
Figure 3.7.

![Figure 3.7 Model of inter-grain potential barrier (in the absence of gases)]
Then donor electrons in the crystal surface are transferred to the absorbed oxygen, resulting in leaving positive charges in a space charge layer. Thus, surface potential is formed to serve as a potential barrier against the electrons flow. Inside the sensor, electric current flows through the conjunction parts (grain boundary) of SnO2 micro crystals. At grain boundaries, adsorbed oxygen forms a potential barrier which prevents carriers from moving freely [106].

![Model of inter-grain potential barrier (in the presence of gases)](image)

The electrical resistance of the sensor is attributed to this potential barrier. In the presence of a deoxidizing gas, the surface density of the negatively charged oxygen decreases, so the barrier height in the grain boundary is reduced as shown in Figure 3.8. The reduced barrier height decreases sensor resistance. The relationship between sensor resistance and the concentration of deoxidizing gas can be expressed by the following equation over a range of gas concentration:

\[ R_S = A[C]^{-\alpha} \]

where: \( R_S \) = electrical resistance of the sensor
A = constant
[C] = gas concentration
α = slope of $R_S$ curve

3.4.2 Sensor Characteristics

3.4.2.1 Dependency on partial pressure of oxygen

Figure 3.9 illustrates the relationship between oxygen pressure in the atmosphere ($P_{O_2}$) and the resistance of a typical TGS sensor in clean air. Note that reduced oxygen pressure will decrease the sensor’s resistance.

![Figure 3.9 Typical dependency on $P_{O_2}$](image)

3.4.2.2 Sensitivity to gas

The relationship of sensor resistance to gas concentration is linear on a logarithmic scale within a practical range of gas concentration (from several ppm to several thousand ppm). Figure 3.10 shows a typical example of the relationship between sensor resistance and gas concentration.
Figure 3.10 Typical sensitivity characteristics

The sensor will show sensitivity to a variety of deoxidizing gases, with relative sensitivity to certain gases optimized by the formulation of sensing materials and operating temperature. Since actual sensor resistance values vary from sensor to sensor, typical sensitivity characteristics are expressed as a ratio of sensor resistance in various concentrations of gases ($R_S$) over resistance in a certain concentration of a target gas ($R_O$) [106].

3.4.2.3 Sensor response

Figure 3.11 demonstrates typical behavior when the sensor is exposed to and then removed from a deoxidizing gas. Sensor resistance will drop very quickly when exposed to gas, and when removed from gas its resistance will recover to its original value after a short time. The speed of response and reversibility will vary according to the model of sensor and the gas involved.
3.4.2.4 Initial action

As shown in Figure 3.12, all sensors exhibit a transient behavior referred to as “Initial Action” when stored un-energized and later energized in air. The $R_s$ drops sharply for the first few seconds after energizing, regardless of the presence of gases, and then reaches a stable level according to the ambient atmosphere.
The length of initial action depends on the atmospheric conditions during storage and length of storage and varies by sensor model. This behavior should be considered when designing a circuit since it may cause activation of an alarm during the first few moments of powering.

3.4.2.5 Dependency on temperature and humidity

The detection principle of TGS sensors is based on chemical adsorption and desorption of gases on the sensor’s surface. As a result, ambient temperature will affect sensitivity characteristics by changing the rate of chemical reaction. In addition, humidity causes a decrease in $R_S$ as water vapor adsorbs on the sensor’s surface. Figure 3.13 shows a typical example of these dependencies. A compensation circuit for temperature dependency should be considered when using TGS sensors [106].

![Figure 3.13 Typical temperature and humidity dependency](image)

Figure 3.13 Typical temperature and humidity dependency
3.4.2.6 Long term stability

Figure 3.14 shows typical data of long term stability for TGS series sensors. Generally, TGS sensors show stable characteristics over time, making them suitable for maintenance-free operation.

Figure 3.14 Typical long term stability

3.4.2.7 Heater voltage dependency

TGS sensors are designed to show optimum sensitivity characteristics under a certain constant heater voltage. Figure 3.15 shows a typical example of how gas sensitivity varies depending on heater voltage. Since the sensor has a heater voltage dependency, a constant regulated heater voltage must be supplied to the sensor according to specifications.
3.4.3 Basic measuring circuit

Figure 3.16 shows the basic measuring circuit for use with TGS. Circuit voltage ($V_C$) is applied across the sensor element which has a resistance between the sensor’s two electrodes and the load resistor ($R_L$) connected in series. The sensor signal ($V_{RL}$) is measured indirectly as a change in voltage across the $R_L$. The $R_S$ is obtained from the formula $R_S = (V_C - V_{RL})R_L/V_{RL}$.
3.4.4 Circuit & operating conditions

The ratings shown in Table 3.2 should be maintained at all times to insure stable sensor performance [106].

Table 3.2 Ratings for stable sensor Operation

<table>
<thead>
<tr>
<th>Item</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circuit Voltage ($V_c$)</td>
<td>max. 24V AC/DC</td>
</tr>
<tr>
<td>Heater Voltage ($V_{H}$)</td>
<td>5V±0.2V AC/DC</td>
</tr>
<tr>
<td>Heater Resistance (Room Temperature)</td>
<td>30±3Ω</td>
</tr>
<tr>
<td>Load Resistance ($R_L$)</td>
<td>Variable(min=[$V_c^2$/60]kΩ)</td>
</tr>
<tr>
<td>Sensor Power Dissipation ($P_s$)</td>
<td>$\leq$15mW</td>
</tr>
<tr>
<td>Operating &amp; Storage Temperature</td>
<td>-40°C ~ +70°C</td>
</tr>
<tr>
<td>Optimal Detection Concentration</td>
<td>500 ~ 10000 ppm</td>
</tr>
<tr>
<td>Sensor Resistance</td>
<td>5kΩ ~15kΩ</td>
</tr>
<tr>
<td>Sensor resistance ratio ($R_s/R_o$)</td>
<td>0.60 ± 0.05</td>
</tr>
<tr>
<td></td>
<td>$R_s/R_o=R_s$(3000 ppm methane)/$R_s$(1000 ppm methane)</td>
</tr>
<tr>
<td>Heater resistance ($R_{H}$)</td>
<td>approx. 167 mA</td>
</tr>
<tr>
<td>Heater Power Consumption ($P_{H}$)</td>
<td>approx. 835mW</td>
</tr>
</tbody>
</table>

3.5 Smell Finger Print

When we apply a smell in an array of sensor each sensor gives a specific signal according to its sensitivity with respect to that smell and combination of all these signals generated by sensor array is called smell fingerprint. So for each smell we get a specific pattern from the signals generated by resistance change occurred in each sensor as shown in Figure 3.17.
3.5.1 The shape of a signal

The shape of a signal depends on the type of sensor, the type of stimulus, the physical arrangement of the apparatus, and the way by which the stimulus is introduced to the sensor [107]. Basic shape of signal is shown in figure 3.18.

The signals obtained from e-Noses normally have one of two basic shapes-
a. When the stimulus is introduced long enough for the sensor to reach a steady state (typically a couple of minutes), a steady-state signal is obtained.
b. When the stimulus is introduced only for a short duration (typically 20–30 s), a transient signal is obtained.

3.5.2 Features of the Signal

Let $\Psi_i(t)$ be the measured signal of the $i^{th}$ sensor. The most popular feature is the difference between the signal’s peak and its baseline, $\Psi_i^{\text{max}}$. Features of signals are shown in Figure 3.19.

![Figure 3.19 Popular features of signals](image)

Other options are to take the area beneath the curve, $A_i$, the area beneath the curve left of the peak, $A_i^{\text{max}}$, and the time it takes for the signal to reach its peak, $T_i^{\text{max}}$. These features have been successfully used for many applications [107].

Definitions of the four most popular features in transient signals are:
(a) The difference between the peak and the baseline, $\Psi_i^{\text{max}}$.
(b) The area under the curve, $A_i$. 
(c) The area under the curve left of the peak, $A_i^{\text{max}}$.
(d) The time from the beginning of the signal to the peak $T_i^{\text{max}}$.

### 3.5.3 Feature Extraction using Lorentzian Model

The analytic model, which we henceforth call the Lorentzian model, is derived from a very simple physical description of the measurement process. It uses four parameters, all with a precise physical meaning, that are obtained from a fast and robust curve-fitting process. This model shows excellent robustness with respect to changing these parameters. It is tested against two different sensor modules differing by the type of sensors i.e. quartz microbalance (QMB) sensors and metal-oxide (MOX) sensors [107].

Variation in resistance of sensor for Lorentzian model

$$R_i(t) = \begin{cases} 
0, & t < t_i, \\
\beta_i \tau_i \tan^{-1} \left( \frac{t - t_i}{\tau_i} \right), & t_i \leq t \leq t_i + T, \\
\beta_i \tau_i \left[ \tan^{-1} \left( \frac{t - t_i}{\tau_i} \right) - \tan^{-1} \left( \frac{t - t_i - T}{\tau_i} \right) \right], & t > t_i + T.
\end{cases}$$

Where

$T_i$ is just the time when the signal starts to rise.

$T$ is just $T_i^{\text{max}}$

$\tau_i$ characterizes the decay time of the signal, which they have found not to fluctuate too for different stimuli. Examining the entire dataset they found typical value of $\tau_i$ for each sensor that is used for initialization.
βi is related to the amplitude of the signal.

\[ \psi_i^{\text{max}} = \beta_i \tau_i \tan^{-1} \left( \frac{T}{\tau_i} \right) \]

3.6 Pattern Recognition Techniques/Classification Techniques:

3.6.1 Artificial Neural Network (ANNs)

McCulloch and Pitts [108] were the first persons who introduced a model of an elementary computing neuron in 1943. The McCulloch-Pitts model of a neuron is simple yet has substantial computing potential. It also has a precise mathematical definition. However, this model is so simplistic that it only generates a binary output and also the weight and threshold values are fixed. The neural computing algorithm has diverse features for various applications [109]. Thus, we need to obtain the neural model with more flexible computational features. In 1949 Hebb [110] proposed learning rules. The Hebbian theory is often summarized as "Cells that fire together, wire together". ANNs have seen a rapid growth (after back propagation) and it has been applied widely in many fields. ANN could extend its applications such as pattern classification, function approximation, identification purposes for linear or nonlinear, multivariable systems. A simple NN has been composed of neurons, links which connect the neurons and weights that assigned to neurons and the bias which assigned to neurons.

The nature of NN is made of mathematical equations which mimic the brain. Since, NN is made up several neuron and different layers; therefore, it would be possible to perform the massive parallel computation. The position and the different neuron connection lead to have several NN and classified in the different groups. The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modeled. Traditional linear models are
simply inadequate when it comes to modeling data that contains non-linear characteristics.

The most common neural network model is the multi-layer perceptron (MLP). This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

![Figure 3.20 Working of a Neural Network](image)

The MLP and many other neural networks learn using an algorithm called back propagation. With back propagation, the input data is repeatedly presented to the neural network. With each presentation the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back-propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model gets closer and closer to producing the desired output. This process is known as "training" and shown in Figure 3.20.
3.6.1.1 Radial basis function networks (RBFN)

They are two-layer feed-forward networks. Figure 3.21 shows layers of Radial basis function networks. The hidden nodes implement a set of radial basis functions (e.g. Gaussian functions). The output nodes implement linear summation functions as in a Multi-layer perception.

The network training is divided into two stages: first the weights from the input to hidden layer are determined, and then the weights from the hidden to output layer. Figure 3.22 shows two different structures of Radial basis function networks.

Figure 3.21 Layers of Radial basis function networks

Figure 3.22 Two different structures of Radial Basis Function networks
The training/learning is very fast. The networks are very good at interpolation.

A range of theoretical and empirical studies have indicated that many properties of the interpolating function are relatively insensitive to the precise form of the basis functions \( f(r) \). Some of the most commonly used basis functions are:

- **i.** Gaussian Functions
- **ii.** Multi-Quadric Functions
- **iii.** Generalized Multi-Quadric Functions
- **iv.** Inverse Multi-Quadric Functions
- **v.** Generalized Inverse Multi-Quadric Functions
- **vi.** Thin Plate Spline Function
- **vii.** Cubic Function
- **viii.** Linear Function

### 3.6.2 Fuzzy Logic

The concept of Fuzzy Logic (FL) was introduced by Zadeh (1965) [111] and presented not as a control methodology, but as a way of processing data by allowing partial set membership rather than crisp set membership or non-membership. After Zadeh, several researchers developed the application and the function definitions for the different controller systems that it could be mention to Mamdani (1975) [112] and Takagi (1985) [113], that each of them has their special function. Unlike classical logic which is based on crisp sets of “true and false,” fuzzy logic views problems as a degree of “truth,” or “fuzzy sets of true and false” (Nikravesh, M., 2004)[114].

FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information (Young, V.R., 1996) [115]. Also, some of the definitions are necessary to know which are described in the following:
**Membership Function:** It is a function by using of that it would be possible to present the input. The aim of using this function is by using the weights which is with the inputs, the functional overlap between the inputs would be defined and lead to output determination.

**Rules:** is some instruction which by using them it would be possible for input that by using the membership values and their definitions, give the final output.

**FL operators:** One of the most popular FL systems is consist of some rules or "if-then" rules. Sometimes there are some fuzzy prepositions which describe dependence of one or more variable of output to one or more input variables.

There are two types of fuzzy inference systems that can be implemented in the fuzzy logic applications: Mamdani-type and Sugeno-type.

These two types of inference systems vary somewhat in the way outputs are determined (Jang, J.S.R., C.T. Sun, 1997[116]; Mamdani, E.H. and S. Assilian, 1975) [117].

The parameters that should be given attention and play an important role in FL ability are membership functions, distributions of MFs, the fuzzy rules composition. Trial and error is one of the methods which by using it the parameter selection would be done. Furthermore, user's experience is one of the parameters that could have an effect on FL modeling. Therefore, all of these problem and lack of knowledge and time lead us to combine both neural networks and fuzzy logic to minimize the error and reach the optimized and better decision about the FL parameters.

### 3.6.3 Adaptive neuro fuzzy inference system (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a kind of neural network that is based on Takagi–Sugeno fuzzy inference system. Since it integrates
both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. The ANFIS is the abbreviated of *adaptive neuro-fuzzy inference system*. Actually, this method is like a fuzzy inference system with this different that here by using a back propagation tries to minimize the error. The performance of this method is like both ANN and FL.

In both ANN and FL case, the input pass through the input layer (by input membership function) and the output could be seen in output layer (by output membership functions). Since, in this type of advanced fuzzy logic, neural network has been used, therefore, by using a learning algorithm the parameters have been changed until reach the optimal solution. Actually, in this type the FL tries by using the neural network advantages to adjust its parameters. As we know, the different between real and network output in ANN is one of the common method to evaluate its performance. Therefore, ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation (Jang, J.S.R., C.T. Sun, 1997) [116].

The advantages of FL for grade estimation is clear because it prepare a powerful tool that is flexible and in lack of data with its ability which is if-then rules would able to solve the problems. As discussed, one of the biggest problems in FL application is the shape and location of membership function for each fuzzy variable which solve by trial and error method only. In contrast, numerical computation and learning are the advantages of neural network, however, it is not easy to obtain the optimal structure (number of hidden layer and number of neuron in each hidden layer, momentum rate and size) of constructed neural network and
also this kind of artificial intelligent is more based on numerical computation rather than symbolic computation. Both FL and NN have their advantages, therefore, it is good idea to combine their ability and make a strong tool that improve their weakness and lead to least error. Jang (1992, 1993) [117, 118]combined both FL and NN to produce a powerful processing tool named NFSs which is a powerful tool that have both NN and FL advantages and the most common one is ANFIS.

**Figure 3.23 Structure of a typical ANFIS network**

ANFIS is considered as a class of adaptive networks that perform as a framework for adaptive fuzzy inference [119] systems. Figure 3.23 shows typical ANFIS structure. Generally, it is a multilayer feed forward adaptive network where each node realizes a particular node function of its corresponding inputs and the nodes in ANFIS include adaptive and fixed ones, and ANFIS is characterized with the parameter set that is the union of the parameter sets associated with all adaptive nodes. The use of a neuro-fuzzy system for crop yield [120] estimate has some
interesting characteristics. Using fuzzy sets instead of the actual values as inputs, shifting to the semantics of the data, rather than its measure, is obtained [119]. ANFIS is a system that accepts numerical inputs and produces a single output value. ANFIS is susceptible to the “curse of dimensionality”. The training time increases exponentially with respect to the number of fuzzy sets per input variable used.

3.6.3.1 ANFIS Structure

Adaptive Neuro-Fuzzy Inference System (ANFIS) Fuzzy logic was introduced by [119, 121] to represent and manipulate data and information in which there are various forms of uncertainty. Fuzzy rule-based systems use linguistic variables to reason using a series of logical rules that contain IF-THEN rules which connect antecedent(s) and consequent(s), respectively. Fuzzy rules can have multiple antecedents connected with AND or OR operators, where all parts are calculated simultaneously and resolved into a single number. Consequents can also be comprised of multiple parts, which are then aggregated into a single output of a fuzzy set [122]. Fuzzy inference [123] is a process of mapping from a given input to an output using the fuzzy set methods. The fuzzification component transforms each crisp input variable into a membership grade based on the membership functions defined. The inference engine then conducts the fuzzy reasoning process by applying the appropriate fuzzy operators in order to obtain the fuzzy set to be accumulated in the output variable. The defuzzifier transforms the fuzzy output into a crisp output by applying a specific defuzzification method.

The ANFIS proposed by [124] and [125], implements a Sugeno fuzzy inference method. The ANFIS architecture contains a six-layer feedforward neural network [126]. Layer 1 is the input layer that passes external crisp signals to Layer 2, known as the fuzzification layer, to determine the membership grades for each input implemented by the given fuzzy membership function. Standard ANFIS
architecture consists of five layers of nodes. Out of the five layers, the first and the fourth layers consist of adaptive nodes while the second, third and fifth layers consist of fixed nodes. The adaptive nodes associated with their respective parameters, get duly updated with each subsequent iteration while the fixed nodes are devoid of any parameter [122] [127-128].

ANFIS use a strategy of hybrid training algorithm to tune all parameters. It takes a given input/output data set and constructs a fuzzy inference system whose membership function parameters are tuned, or adjusted, using either a back propagation algorithm in combination with a least squares type of method.

3.6.3.2 Training of Adaptive Neuro-Fuzzy Inference System

Training of neuro-fuzzy has several steps. At the first step of training, the initial fuzzy sets should be determined. Actually the fuzzy sets define the number of sets for each input variable and their shapes. The note that should be attention is that large number of sets may produce better fitness in training process but a poor validation Therefore, to avoid from these problems, after several experiments, we selected 5 sets for each input variable. During training, all of the training dataset would be present to network and it tries by learning the spatial relationship between the data to minimize the error. Sometime lower error could not guaranty the better performance of network and it may because of network overtraining.

There is need to monitor how well the network is learning. It is important to mention that when the input pass through the network, the aim of the ANN is to by parameters adjusting lead the network to the smallest error "as much as possible". Therefore, by error monitoring of training dataset, it would be possible to supervise on network training. The objective function which has been used here is MES (Mean Square Error).
3.6.3.3 Training Method

Training of ANFIS can use alternative algorithms to decrease the error of the training. A combination of least squares algorithm and the gradient descent algorithm is used for an effective search of the optimum values. The main advantage of this hybrid approach is that its convergence is much faster, because it decreases the search space dimensions of the method of neural network back propagation method. Fuzzy approaches have been used in many areas of the medical field like finding relapse probability [121] and the prediction of patients’ survival rate [129], [130].

3.7 Some recent developments in Electronic nose systems

Che Soh A. et al [131] demonstrated that the neural network-based electronic nose technique promises a successful technique in the ability to classify distinctive odor pattern for aromatic herbs species. The system consist multi-sensor gas array and output from individual sensors were collectively assembled and integrated to produce a distinct digital response pattern. By using five samples of herbs, the E-nose system has been tested with five different types of sensors. From the results, E-nose system with five sensors has the highest capability in classifying herbs sample. Accuracy in classifying the correct herbs increased with the number of sensors used.

Tomasz Dymerski et al [132] presented practical utilization of an electronic nose prototype, based on the FIGARO semiconductor sensors, in fast classification of Polish honey types—acacia flower, linden flower, rape, buckwheat and honeydew ones.

Kasbe M.S. et al [133] developed an electronic nose consists of a semiconductor gas sensor array and an artificial neural network (ANN) which is
used to detect the freshness of non-destructive fruits. A gas sensor array (SnO2 type) detects aroma which is emitted from the fruits in the different ripening stages of the fruits. The typical gas emitted from the fruits, e.g. alcohol, methane, carbon dioxide, ammonia and carbon monoxide, have been detected by the sensor array. An artificial neural network is designed in LabVIEW software. A comparison is also made between the various ripening stages (under ripe, ripe and over ripe) of banana and guava. They claimed that as a novel system of low cost and require minimum space. DAQ card is used to interface an array of MQ-gas sensors and (computer) LabVIEW software.

Westenbrinka, E. et al [134] have developed a new electronic nose instrument at the University of Warwick to measure the gas/volatile content of urine headspace, based on an array of 13 commercial electro-chemical and optical sensors. An experimental setup was arranged for a cohort of 92 urine samples from patients of colorectal cancer (CRC), irritable bowel syndrome (IBS) and controls to be run through the machine.

Manuela Baietto et al [135] have explored current and potential utilization of electronic-nose devices with specialized sensor arrays and instruments that are very effective in discriminating complex mixtures of fruit volatiles, as new effective tools for more efficient fruit aroma analyses to replace conventional expensive methods used in fruit aroma assessments.

Tharun Konduru et al [136] designed a gas sensor array, consisting of seven Metal Oxide Semiconductor (MOS) sensors that are sensitive to a wide range of organic volatile compounds, to detect rotten onions during storage. These MOS sensors were enclosed in a specially designed Teflon chamber equipped with a gas delivery system to pump volatiles from the onion samples into the chamber. The
electronic circuit mainly comprised a microcontroller, non-volatile memory chip, and trickle-charge real time clock chip, serial communication chip, and parallel LCD panel. User preferences are communicated with the on-board microcontroller through a graphical user interface developed using LabVIEW.

Sharmaa, Prolay et al [137] presented a method of real-time monitoring to detect the optimum fermentation time of black tea using an electronic nose consisting of eight quartz crystal microbalance (QCM) sensors. The sensor was coated with glucose derivative coating materials viz. maltose (MAL), maltodextrin (MDEX), β-cyclodextrin (β-CD), d-glucose (d-GLU) and polyethylene glycols (PEG) with different molecular weights, 200, 1500, 4000, and 6000. Optimum fermentation times were determined for twelve black tea samples, and the results shown good agreement with the estimations of the ultra-violet-visible (UV) spectrophotometer based reference method.

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