Electronic Tongue and Their Analytical Application Using Artificial Neural Network Approach: A Review

Maria Jamal\(^1\), M R Khan\(^2\), S A IMAM\(^3\)

Abstract: A brief and historical overview of research and development in the field of artificial neural network based electronic tongue system is presented. The electronic tongue using artificial neural network approach for taste classification, based on the organizational principals of biological sensory systems, developed rapidly during the last few years. Current achievements of scientific groups working in this field are outlined and critically reviewed. The performance of electronic tongue in quantitative analyses and in classification of multi-component media is considered. The exciting possibility of establishing a correlation between the output from an electronic tongue and human sensory assessment of food flavour, thereby enabling quantification of taste and flavour is described. Analysis of multivariate data is also essential part of any electronic tongue. Pattern recognition techniques are described, with artificial neural network. Application areas of electronic tongue in model analysis and in foodstuffs, beverage and water monitoring applications are also discussed.

Index Terms - Artificial neural network, Electronic tongue. Multi-component analysis, pattern recognition, taste quantification

I. INTRODUCTION

Taste is a survival mechanism, alerting us to potential harmful or potential nutritious substances. Approximately 10,000 chemoreceptors or taste buds reside on the tongue. These chemoreceptors or taste buds fall into five basic categories: sour, bitter, salt, sweet, and umami, with grouped receptors dissipated over the surface of the tongue for each stimulus. Taste depends on physiological and psychological factors[1]. Physiological factors such as temperature and texture clearly affect the perception of taste. Psychological factors can influence taste perception. Several industries – chemical, pharmaceutical, agricultural and food – have interest in developing an efficient, low cost instrument to fast analyze and classify complex chemical solutions. Brazilians researchers developed an “electronic tongue” - e-tongue hereafter - having a very high sensitivity and the Brazilian Agricultural Research Corporation (EMBRAPA) applied an international patent on it. The e-tongue system comprises an array of capacitive sensors having different responses when immersed in different chemical solutions. The measured values of electric capacitance for each unit represent the variation on physical-chemical characteristics of sampled solutions. The e-tongue name refers to the human tongue, which contain receptor molecules that trigger nerve signals when they encounter taste-imparting molecules thus detecting different tastes (sweet, salty, sour and bitter) [14]. There is a vast range of applications for the e-tongue, for instance: continuous control on product quality; detection of pollutants in water (environmental applications); detection of analytes in low concentration solutions difficult to be distinguished by human being or even impossible [5]. It is worth to mention that the e-tongue sensors have no specific discrimination of particular substance and it is based on the subjectivity of the analysis miming the human tongue. The e-tongue system (ETS) uses several sensors fabricated from nanostructured thin films of different polymers that are deposited on the top of an interdigitated micro electrode. The e-tongue instrument is based on the values of the electric capacitance of the sensor units measured by the impedance technique [9, 15]. Measurements over the frequency range from 10 Hz to 10 kHz allow detecting traces of tastants and inorganic contaminants in liquids. Also, several statistical methods have been applied to identify the sampled liquids. The Principal component analysis (PCA) is a multivariate method that consists in reducing the number of variables and is mostly used due to its simplicity and efficiency. PCA can be used to reduce the dimensionality of a data set retaining the characteristics that most contribute to its variance, i.e., keeping only the lower-order principal components and ignoring the higher-order ones. Such low-order components often contain the “most important” aspects of the data, since the higher-order components represent the same event (high correlation) [11]. The PCA analysis is suitable for identification of different groups based on characteristics that are linearly separable. More sophisticated tools such as multi-layer Artificial Neural Networks [12] should be used to analyze samples with a great complexity. For instance, it was shown that is...
possible to identify wines considering vintage, producer and type of grape. Studies applying such techniques on samples obtained with ETS to pattern recognition have been conducted using specific tools. Previous studies applying PCA to data obtained from the ETS has been conducted using MatLab, and Artificial Neural Networks (ANN) by means of Weka (Waikato Environment for Knowledge Analysis) and SNNS (Stuttgart Neural Network Simulator)[2]. Such tools require input files adequately following a pre-defined format. Therefore, the use of external tools introduces an additional step on data analysis: data should have a specific format. Such task could be incorporated on pre-processing stage but different investigations would require different types of files impairing the process of analysis. This work aims to create a computational solution to collect data – using the ETS – and analyze the data sets, thus: an example of the symbiosis of Computer Science with another domain of knowledge [4], where Computer Science is the main base of this technological advance. Previous studies allowed us to choose the techniques for data analysis and to define the application requirements. This paper is organized as follows: Section 2 presents Human taste System and Artificial Taste System; Section 3 presents the e-tongue system; Section 4 presents a brief description of the Pattern Recognition and Artificial Neural Networks; Section 5 describes the software data analyses modules, Section 6 presents conclusions and suggestions for further work.

II. HUMAN TASTE SYSTEM AND THE ARTIFICIAL TASTE SYSTEM

The basic stimulus for taste arises from the contact of substances with our receptors, i.e., taste buds, located throughout our tongue. The chemical interaction at the receptors leads to chemical change which generates a neural impulse [24]. The impulses are transmitted along the nerve fiber into the brain that leads to taste perception [25]. The perception of taste is acquired through a learning process. The design of the artificial taste sensory system is based on biological principles of human taste sensory system. The taste sensor acts as a receptor and the neural network plays a similar role to human brain; to recognize the taste.

III. ELECTRONIC TONGUE

The name “electronic tongue” refers to an array of sensors that are immersed in liquids, in order to identify their different physical-chemical characteristics, for example, “tastes”. The e-tongue can be used in many sectors and it has widespread application in food and beverage industries and any other trades to monitor the quality of products. In beverage industries, for instance, tests for the taste evaluation is carried out by human tasters, thus they can be assisted by the e-tongue allowing continuous and precise measurements. The advantage of the e-tongue is that there is no decrease on sensitivity during a long period of exposition which does not occur with human being. A possible application in the pharmaceutical industry would be the search for new compositions that neutralizes the bitter taste in medicines. As pointed out, one can notice the importance of a system like the ETS since it was developed a portable and compact which allows to perform measurements at place. The e-tongue allows to prevent the exposition of human beings to toxic substances or to awkward tastes [12].

The e-tongue system uses an array of sensors made of ultrathin films of polymers such as Langmuir-Blodgett (LB) films of 16-mer polyaniline, polypyrrole (PPy), stearic acid (SA) and composite films of several polymers [14]. Such films were deposited on top of a glass substrate that holds interdigitated microelectrodes. Sensors prepared from different materials produce different electric responses and the their variation is desired since allows a “fingerprint” of the samples [14].

The first multi-sensor system for liquid analysis was based on a poor selectivity approach introduced by Toko et al in 1990 and termed it as taste sensor system[26]. Later the instrument was named as “Electronic tongue”. The multi-sensor array system [27,28] or electronic tongue shows the clear correlation of the instrument output with human perception for various substances. We can state Electronic tongue as “the system for automatic analysis of liquid including an array of non-specific chemical sensors with partial specificity for different component in liquid samples and an appropriate pattern recognition capable of recognizing the qualitative and quantitative composition of sample and complex solutions”. These system shows the following advantages: (a) requires small sample volume, (b) decreased measurement time, (c) objectivity compared to sensory panel, (d) small size of sensors, (e) easily operated by unskilled personnel and (f) amenability to fully automatic long-term routine application.

A. Electronic Tongue System

The e-tongue system is composed by hardware and software components. The hardware is used for the capacitance measurements of sensorial units of and the software controls the data acquisition, perform the calculations and analyze the electrical signals.

The main hardware components are: signal generator; signal amplifier; multiplexer; data acquisition board and a lap-top computer. The ETS was developed by Cabral [29] and the hardware was conceived to deal with up to eight arrays of sensors, each one comprising up to eight sensor units, thus up to 64 sensor units can be handled simultaneously. The software component deal with electrical signals and provides the capacitance values which are stored into files using a pre-defined format. The following parameters can be de fined by the user: file name – , defining the file name to save data from each array; substance under analysis; sensor units, to define the sensor units to be considered on measurements; measurements, the frequency to be used on measurements – the values can be 10,100 Hz, 1 and 10 kHz; also, the software indicates the units from which the data acquisition is performed (or not) when an experiment is started for each array used in the experiment activate. The software displays the general parameters for the measurement, as follows: Heads, to activate or deactivate all arrays simultaneously; sets, to define the number of measures to be performed on each array; multiple, to define how many series of measurements will be done; interval, allows specifying the time interval (minutes and seconds) between a series of measurements defined by multiple
parameter; and delay, specify the period to delay an acquisition. In addition, an option in the Menu – Start All – allows to start the measurements of all arrays without setting up the parameters – in this case, the previous parameters used in the last measurement are employed.

By combining the response of the sensor units it is possible to obtain enough data to determine which sort of substance is under analysis. For instance, it is possible to differentiate substances with similar taste, like distinct mineral water, coffee and wine. It is important to notice that the good distinction of tastants is made at low level of concentrations, below the human threshold [30, 31, 14]. For the discrimination of the liquids, analyses are conducted using the techniques described in the section 4.

B. Fabrication of Taste Sensor
Screen-printing technology is one of the taste fabrication technique whereby the screens allow ink or paste to be applied into a substrate with a squeegee in a particular size, shape and sequence of the print. The open pattern in the screen defines the pattern that will be printed on the substrate. Each of the screen-printed electrodes was printed in arrays of eight tracks of working electrodes and a track printed with Ag/AgCl, as the reference electrode. The electrodes were manufactured by Screen Technology Corporation, Malaysia. The final step of the fabrication is the deposition of lipid membranes with a dispenser into the working electrodes of the array.

C. Important Benefits Of Electronic Tongue[3]
- Evaluate and quantify bitterness scores of new chemical entities (NCE).
- Optimizes and increases the formulation development process.
- Within the formulation, it measures the efficiency of complexation/coating.
- Various combinations of sweeteners, enhancers, exhausters, aromas and masking agents can be tested in less time.
- Benchmark analysis: compares the palatability of new formulations with competitor’s products.
- Serving a quality control function for flavored products and excipients.
- Developing suitable matching bitter placebo for double blind clinical testing.
- During the scale-up process from small production batches to full-scale manufacturing, it defines consistency of organoleptic quality.

D. Objectives
1. Identification between bitter, sweet and sour substances by using electronic tongue; study the possible memory effect of these substances on its sensors.
2. Separating the different substances eliciting the same taste (sour, bitter, sweet).
3. Evaluation of the ability of the electronic tongue to identify drug preparations containing active substance and placebo substance.
4. Check ability of electronic tongue to quantify the content of selected bitter and sweet substances.
5. Assessment of different taste masking approaches i.e. addition of different quantities of sweeteners and flavors to active substance to reduce its bitter intensity.
6. Quantification of the effect of taste masking of

E. Application Of Electronic Tongue[6]
1. Foodstuffs Industry
   - Food quality control during processing and storage (water, wine coffee, milk, juices…)
   - Optimization of bioreactors.
   - Control of ageing process of cheese, whiskey.
   - Automatic control of taste.
2. Medicine
   - Non-invasive diagnostics (patient’s breath, analysis of urine, sweat, skin, odor).
   - Clinical monitoring in vivo.
   - Identification of unpleasant taste of pharmaceuticals.
3. Safety
   - Searching for chemical/biological weapon.
   - Searching for drugs, explosives.
   - Friend-or-foe identification.
4. Environmental pollution monitoring
   - Monitoring of agricultural and industrial pollution of air and water.
   - Identification of toxic substances.
   - Leak detection.
5. Chemical Industr
   - Products purity.
   - In the future – detection of functional groups, chiral distinction.
6. Quality control of air in buildings, closed accommodation (i.e. space station, control of ventilation systems).

7. Legal protection of inventions – digital “fingerprints” of taste and odors.

F. Other Analytical Applications

Taste quantification and foodstuff recognition are the main area of application of the taste sensor.

Taste sensor sensitivity was studied in aqueous solution of five basic taste substances: salty (NaCl, KCl, and KBr), sour (HCl, citric and acetic acids), bitter (quinine), sweet (sucrose), and umami (monosodium glutamate)[7,8]. Different patterns for chemical substances with different taste and similar patterns for substances with similar tastes were obtained by taste sensor.

Sensor sensitivity to sour and salty substances, e.g. HCl, organic acid, NaCl, KCl, KBr was approximately 50-60 mV/pX, to glutamate (umami substance) was approximately 13 mV/pX, to quinine hydrochloride (bitter substance) was approximately 50 mV/decade, to natural bitter alkaloid caffeine was only approximately 5 mV/pX, to natural sweet substances (sucrose) was very low, whereas to an artificial sweetener (aspartane) was about 40 mV/pX. For this reason an enzymatic glucose-selective sensor was used with the taste sensor when determination of the sugar concentration was crucial[10].

Bitterness of 18 different antibiotics and antiviral drug formulation for pediatric use were evaluated as suspension in water and in an acidic sport drink[13]. Bitterness intensities of suspension in an acidic sport drink and in water were compared using the taste sensors. Suspension in an acidic sport drink would enhance or reduce the bitter intensity of the pediatric drug formulation compared with suspension in water; taste sensors were able to predict it.

Bitter taste suppression was studied by using sweet substances to mask the bitterness of the drug. Degree of bitterness for quinine solution and modeling was calibrated by taste sensor by using principal component regression. The bitterness of the mixed solution was predicted by use of the model. The mixed solution contained 1mmole L⁻¹ of quinine solution and 1mmol L⁻¹ to 1mole L⁻¹ of sucrose solution [19] and phospholipid cocktail[20]. As concentration of the sucrose increase to 1 mole L⁻¹ degree of bitterness estimated dropped significantly. The same experiment was repeated for artificial sweet substances-phospholipids, which is used in pharmacology to mask the bitter taste of drug.

Different kinds of commercial mineral water were classified by using the taste sensor[16]. Mineral water was classified on the basis of the hardness of water. The tastes of 20 bottled nutritive drinks, all commercially available on the Japanese market were evaluated both in human sensory test and by using electronic tongue. The electronic tongue was able to differentiate between low price group products, middle price group products, high price group products and played important role in evaluating the palatability of bottled nutritive drinks[23].

Different varieties of tomato were recognized using taste sensor by measuring the crushed tomatoes[17]. The taste sensor were first calibrated in canned tomato juice to which four basic taste substances, NaCl, citric acid, monosodium glutamate, and glucose were added, for quantification of tomato taste. Taste sensors also found a wide use in diary industry. Taste sensors were found capable in discriminating between fresh and spoiled milk and to follow the deterioration of the milk quality when it was stored at room temperature. Two packaged commercial milk; the ultra high temperature (UHT) and the pasteurized milk were tested[18].

Ten brands of coffee of different origin (one of which was used as standard) were measured at 60°C by using taste sensors[19]. Oleic acid contained in sensor was correlated with coffee acidity as perceived by tasters with a correlation coefficient of 0.98. The correlation between coffee bitterness and the response of the sensor contained dioctyl phosphate (DOP) and Triocylmethyl ammonium chloride (TOMA) was found to be 0.94. An electronic tongue made up of micro-sensor array of three enzyme sensors had been developed for determination of glucose, urea, and triglyceride (triolein)[20]. Tasting extracts of American oak (Quercus alba) was difficult due to the variety of bitter and astringent chemical compounds that they contain. These extracts were analyzed by an array of global selectivity chemical electronic tongue sensors, which offered a simple and rapid method of analysis of oak wood extract with excellent repeatability[22]. The components of medical liquids- dialysis solutions for an artificial kidney that contained Ca²⁺, HCO₃⁻, H₂PO₄⁻, Na⁺, K⁺, Cl⁻, Mg²⁺, pH were determined by quantitative performance of the electronic tongue [22]. Measurement procedures were developed such that the system detects with precision of 2%-4% acceptance for clinical analysis.

IV. PATTERN RECOGNITION

The electronic tongue system performance is dependent on the quality of functioning of its pattern recognition block. Various techniques and methods can be used separately or together to perform the recognition of the samples. After measurement procedure the signals are transformed by a preprocessing block. The results obtained are inputs for Principal Component Analysis, Cluster Analysis or Artificial Neural Network.
A. Artificial Neural Networks

Artificial Neural Networks (ANN) are distributed parallel systems composed by nodes (neurons), which are simple processing units performing mathematical functions – they are essentially simple mathematical models defining a function \( f : X \rightarrow Y \). The nodes are arranged in layers and linked through connections (synapses), usually unidirectional. Weights are associated to the connections and such values are used to weigh the input of each neuron, as a parameter to the mathematical model to be used [32].

An artificial neural network does not have to be adaptive by itself since in order to produce a desired result it requires algorithms that are designed to alter the weight of the network connections. In this sense, the ANN must be trained before its effective use. Therefore, a learning procedure is conducted: a group of examples is submitted to the network in order to prepare it for analyzing phase. The network “extracts” the characteristics necessary to represent the information present in the data set as training. The knowledge remaining in the ANN, represented by weights associated to the connections among nodes, keeps the characteristics used to represent the solutions for the future problems to be analyzed [32,33].

The ANN is able to generalize an input data set – used for training – to produce results whenever another input data submitted to it, which is the great advantage of this technique. It is possible to notice that an ANN can deal with the identification of groups not linearly separable. However, the disadvantage is the need of training and consequently, a data set for its accomplishment should be known.

A.I. ANN Architecture

The definition of the ANN architecture is an important parameter – it restricts the type of problem that can be treated since the structure chosen and the learning algorithm used for training the network are dependent [32]. The following parameters define ANN architecture:

. Number of layers: on networks with only one layer, the input layer projects itself on the output layer. The input layer is not considered, since no computation is accomplished by those neurons – only the input values are attributed. The ANN with multiple layers has more than one neuron connecting the input to the output. The neurons that compose the hidden layers mediate the external input and the output (results obtained [33]);

. Number of nodes in each layer: The amount of nodes contained in each layer;

. Type of the connection among nodes: The network can be classified as non-fully connected and fully connected network. In the connected network, each node is connected to all nodes to the following layer. If one connection is missing, the network is named non-fully connected [32];

. Topology: the topology is defined as how the neurons are connected. The nodes can have feedforward connections – the connections between nodes do not form cycles, always is connecting a neuron output to the input of any other neuron in same or in previous layer – or feedback connections – the output of a neuron in ith layer is used as input on nodes belonging to jth layer, where \( j \leq i \) [32].

A.II Learning Process

An ANN requires the training before its use. During such process, the ANN extracts information about patterns presented to it; the learning consists in adjusting iteratively the weights associated to the connections. The values of weights represent the knowledge acquired by the ANN, allowing the network recognizing the patterns [32]. The learning algorithm consists of well-defined procedures to adjust the weights. There are several learning algorithms, each one using a different heuristic to adjust the connection weights [33]. The main approaches developed are: supervised and unsupervised learning, and their particular cases – reinforcement and learning by competition. Most of the training algorithms work well in the training using a particular fixed dataset with the correct parameters. However, selecting and tuning a training algorithm on unseen data requires a significant amount of experimentation. Previous studies were conducted to investigate how suitable an algorithm is. Among the learning algorithms, it was chosen the back-propagation algorithm which is used on multiple layer networks. This algorithm proposes a way to define the nodes error on intermediate layers allowing weights adjustment. These adjustments are accomplished using the gradient method [32]. For learning, it is necessary to minimize the error function, defined by the sum of the quadratic error and represented as Equation 1:

\[
E = \frac{1}{2} \sum_{i=1}^{k} (d_i - y_i)^2 \tag{1}
\]

where \( E \) is the total error, \( k \) the number of output units, \( d_i \) the output expected and \( y_i \) is the ith output obtained. This equation defines the total error accomplished by the ANN. The delta rule requires that the activation functions be semi-linear. The activation value is obtained by the Equation 2.

\[
y_p^j = f_j(\text{net}_p^j) \tag{2}
\]

Where

\[
\text{net}_p^j = \sum_{i=1}^{n} x_i^p w_{ji} \tag{3}
\]

The constant \( n \) represents the number of input connections on node \( j \), and \( w_{ji} \) represents the weight of connections between the input \( x_i^p \) and the node \( j \). The training happens in two phases: forward (used to define the network output for an input data) and backward (use the expected output and the output obtained to update the weights of their connections). In addition, it is possible to use the momentum term to accelerate the training process and to avoid local minima. The use of the momentum term reduces the instability and increases the learning rate [33].
A.III. Activation Function

Another important factor to define an ANN is the activation function, which is responsible for converting the linear combination of input values and weights, correctly calculating the neuron output. The mathematical functions mostly used are: Threshold, Linear, Ramp, Signum and Logistics. The Signum function is semilinear and a limited function used in Artificial Neural Network [33]. It is represented by equation 4:

$$y = \frac{1}{1 + \frac{-z}{T}}$$

(4)

where T represents how soften the curve should be.

V. DATA ANALYSIS MODULES TO ELECTRONIC TONGUE

The interface of the ANN module was divided in three parts: Modeling Area, Analysis Area and Utility Bar. In the first one, the architecture of the ANN is defined: one creates the neurons, organizes them in layers, and defines the synaptic connections between them. The neuron is represented by a rectangle subdivided vertically in two parts: the right side represents the output and the left side the input. Considering that a neuron might have multiple inputs, the left side is subdivided horizontally to represent them. Straight line segments between neurons represent the synaptic connections. The Modeling Area is also used to carry out the ANN tests. In the Analysis Area is possible to follow the ANN error during the training process and the results obtained. In Utility Bar are given the options to construct, to train and to test an ANN – parameters as maximum error, learning rate, number of iterations and to enter the momentum. The ANN module is composed by three classes representing the neuron, the neural network and the modeling area, named Neuronio, RedeNeural and RNAreaModelagem, respectively. The arquivoClass, the same used in PCA module, is used to read the input values from files. Neurónio class is created from TImage class and it is used to show the neurons in the Modeling Area. Besides the attributes from TImage class, the Neurónio class has attributes to represent an artificial neuron, as: number of inputs, weight of each one, activation function value, error value and a flag to identify the neuron type (input, output or hidden layer neuron). The RedeNeural class has network attributes and it is referred when a new network is created or when a network is restored from files. As in the PCA module, each training file is responsible to show an output (samples for an expected result), and each file has the number of sensors sampled representing the amount of input values for the ANN. Such parameters are used to create Neurónio objects, both to input and output neurons. After defining the ANN architecture the training phase can be initiated. To conduct the validation test, the input values are read from files following the format established in the data acquisition system. After chosen the neuron output, the ANN test is conducted using the same standard input, the net function calculation and activation function used in training phase.

VI. CONCLUSION AND FURTHER WORK

Electronic tongues are an emerging and promising field in modern chemical sensor science. The electronic tongue proved to be a valuable tool for assessment and prediction of the taste. Electronic tongue systems seem to be very useful for process monitoring and as a quality-control tool in the food industry, in clinical analysis, and in research laboratories. The pattern recognition technique used here is Artificial Neural Network (ANN) module which is a user-friendly graphical interface to facilitate the definition of the artificial neural network. The use of the ANN module on data analysis allows one to speed the ANN tasks: no restriction on the number of hidden layers and numbers of nodes in each layer; it does not require artificial neural network completely connected; and the artificial neural network can be stored for posterior use with their weights saved. In addition, the input files for the training process and for analyzing, are read from the ETS files – data acquisition module – using the same file format. Despite of the software is coupled to the ETS instrument it is possible to use the PCA and ANN modules for analyzing data obtained with several experimental setups. In this case it is necessary to use files formatted according to the standards defined for the ETS. In addition, the analysis of the data is easier since no external software is needed. As further work new improvements are suggested to the software – for instance, 3D graphical presentation for PCA, creation of “bias” bound to input files on ANN, the implementation of learning algorithms derived from back-propagation as RProp and Quick-

REFERENCES


MARIA JAMAL

Maria Jamal received her B.Sc Engg(Electrical) and M.Tech(Control and Instrumentation) in 1998 from Delhi College Of Engineering, Delhi.
Since 1999, she has been the part of Indira Gandhi Institute Of Technology(GGSIPU), Kashmere Gate,where she is Assistant Professor in the Department of Electronics And Communication Engineering.
Her current research interests are in the field of Artificial Intelligence, Financial Market, Bio-medical Engg, Control And Instrumentation and Circuit Analyses.
E-mail: jammalaria@yahoo.com

M R KHAN

MR Khan has received his B.Sc Engg(Electrical Engg) in 1967 and M.Sc Engg(Electrical Engg ) in 1970 from Aligarh Muslim University. He did his PhD from IIT-Delhi in 1975.Supervised about six PhD’s.
Since 1995, he has been part of Jamia Millia Islamia University, where he is Professor in the Department of Electronics and Communication Engineering. He has more than 60 publications in journals and conf. of repute.

His current research interests are in the field of artificial Neural Networks, Smell and taste sensors.
E-mail: mrkhan_45@yahoo.com

S A IMAM


c

Syed A Imam has received the M. Sc. Engg degree from AMU, Aligarh and PhD. degree in Electronics & Comm. Engg from Jamia Millia Islamia Central University, New Delhi, in 1998, and 2008, respectively.

Since 1990, he has been part of Jamia Millia Islamia University, where he is Assistant Professor in the Department of Electronics and Communication Engineering. He has more than 50 publications in journals and conf. of repute.

His current research interests are in the field of sensing technologies, electronic and biosensors, signal processing and digital circuits.
E-mail: imam_jmi@yahoo.co.in