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Simulation and Optimization of Artificial Neural Network Based Air Quality Estimator

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Abstract: ***E-sensor which are generally based on concept of E-nose are specially made to distinguish odours .In the present research work. E-sensor is developed using artificial intelligence technique to identify the concentration of carbon monoxide in a polluted environment. Data record access using Metal oxide sensor. The available data is broken into the number of segments .The length of data segment and the neurons in hidden layer is varied in number to find the optimized model of artificial neural network model using Mat Lab Coding. The artificial neural network model is optimized by verification in terms of mean squared error and regression. The regression is verified for training ,testing, validation and all. The mean squared error and regression are the artificial neural network model performance parameter.***

Keywords: e-nose, Air quality

I. INTRODUCTION

A.The electronic nose overview

The "electronic nose" originates by an idea of the instrument and that a part of system use for smelling can also be referred as olfaction. In the latter, upon being sniffed through nasal during the rectification of a product, volatile compounds reach the olfactory epithelium. Electrical stimuli is produced which are transmitted to the brain due to the Togetherness of odorants with the suitable sensor receptors. [1,2,]. A pattern recognition process starts along with the use of all the data to classify and detect the odor . A single neuron reacts to several other olfactory odorants so that every single odorant is sensed by various smelling neurons . In the similar way, electronic noses are based on identification of the response of sensors. Therefore items with different smell show differences of its pattern. The sample step is in electronic nose system is done by a syringe, and filling it into the detector, or by taking along with a gas stream. Volatile compounds provoke the series of signals which are further processed by pattern identification program. A different type of a system called as portable is launching in the market which has an ability to understand new patterns and connect them with new smell via training as humans do. This type of instruments are very sensitive at ppb level with a fraction of millisecond. Other instruments hardly go below the ppb levels with a change in time in seconds .

Metal oxide sensors (MOS) faces non-selectivity and it was considered a major drawback of electronic nose technology intended as analytical tool [3-7].Brief description of commercially available sensors given in next section.

B. Metal Oxide Sensor

Metal-oxide semiconducting film coated by a ceramic substrate (e.g. Alumina) form a mos sensor. The sensitivity depends on semiconductor type. [8-9]

A. Conducting polymer (CP) sensor

CP sensors are fabricated from conducting material, fragrant or heteromatic collected onto a substrate and among electrodes plated with gold-[10]. Although especially fragile to polar unstable compounds, their selectivity and sensitivity may be enhancing via the usage of various functional groups, polymer structure and doping ions [5]. Polymer system may include Biomaterials including enzymes, antibodies, and cells [4, 6]

B. Thickness Shear Mode Sensor

Gold electrodes, covered with a membrane are the primarily constituent of thick mode sensor with piezoelectric quartz crystal.l Composition of coating decides Selectivity and sensitivity of coating membrane which also depend on the running frequency. [11]. Proper calibration techniques allows to correlate data acquired with one of a kind sensors .

II. REVIEWS

Although evaluation of body liquids(urine ,blood, sputum,) to find disease in human body and tracking the disease is daily scientific work, human breath observations methodologies that make the most the safe nature of these technique are nonetheless under-evolved. Exhaled breath turned into identified as a comparatively safe tool to cure sicknesses. Breath measuring devices first seemed in 1784 when carbon monoxide was found in exhaled breath of guinea pigs by st Lavoisier .From that time, colorimetric analysis and chromatography is used to investigate organic compounds which are volatile in nature, in breath of human in portions various from mill molar to Pico molar mixture. The latter fuel sensitivity restrict became done with the use of Linus Pauling's chromatography-primarily analysis of breath device in 1971 [12-14]. The human breath contain about four hundred organic compounds which are volatile in nature among which only thirty detected for identification of disease and are indicators of a couple of type of diseases [15,16]: Nitrogen Oxide and carbon monoxide present in the exhaled breath of human are the prime indicators of a disease present in the human body and are become major area of research for electronic nose system . [17]

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The advantage of growing research on electronic nose in modern generation is extremely good. This paper creates a specialty of the synthesis of a nose sensor which could test concentrations of CO gas in the environment.

In the current work, a set of rules has been formed based totally on a Nano sensor and its miles described in the element. Because of the selectivity of the sensor, detection algorithms applied on standard sensor array data. To estimate the proportion of an analyate, the resistance of the sensor is transformed to a signal in form of voltage..

III. METHODOLOGY

- Acquisition and analysis of the olfactory signal: An e-nose is Gas Acquisition System that used an array of multiple sensors. The sensors react to gases with a version of resistance [18,19] in Figure 2, it's far viable to look a typical reaction of a sensor S1 (Tin Oxide) and Carbon monoxide level. After the sensor response recording the second factor issue is the pre-processing and dimensionality reduction segment. Each measure includes three principal phases: before every measure the tool inhales the analyzed gas CO, producing response of the sensors as a resistance; finally the instrument returns to the reference line, prepared for a new measure. After pre-processing, feature extraction executed using the most suitable statistics from the signal. Here few descriptors are defined from the sensors responses that are able to represent information characteristics inside the maximum efficient way. Considering that we used four sensors, each measure might be defined by 2 functions. Among all features it's been necessary to find the ones capable of maximizing the informative components and, therefore, to make contributions to improve the accuracy of the classifier. It is discovered that the most discriminative functions between the 2 training 'high' and 'low' Carbon Monoxide concentration had been the subsequent descriptors (R (t) is the curve representing the resistance version all through the size and R_{min} is the resistance at the beginning of the measure indicated as R_{base} and other is R_{max} taken as divergence.

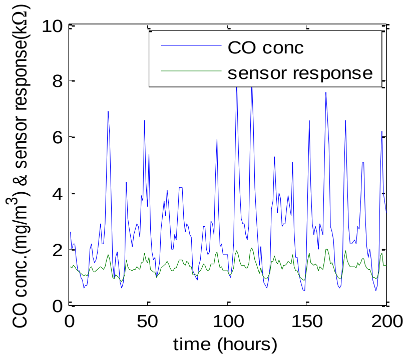

Figure1. CO concentration and sensor response plot.

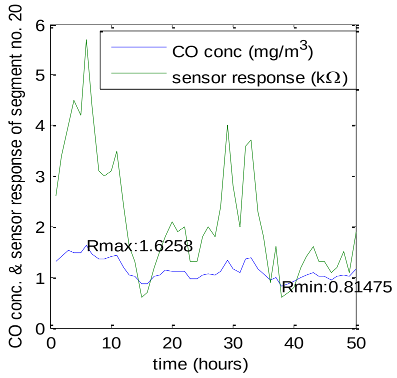

Figure 2 – Sensor response at segment 1 with R_{min} and R_{max} features

A. Artificial Neural Network (ANN):

ANN is a modeling tools used to find complex relationships among inputs and outputs. In particular, we selected to use a feed-forward neural network with one hidden layer, wherein inputs are the bottom and divergence value of sensor resistance for a precise segment and the output is an unmarried neuron assuming the level 1 if the presence of the CO is detected and zero in any other case. Finally, we set a distinctive number of neurons within the hidden layer from 2 to 16.Since ANN's outcomes depend on the values of the initialization, we trained the network 5 times and we pick the quality configuration. Additionally, a few variances are discovered inside the complexity of the specified data evaluation and statistics algorithms at special segment lengths; as a result, we additionally trade the phase interval of five hours.

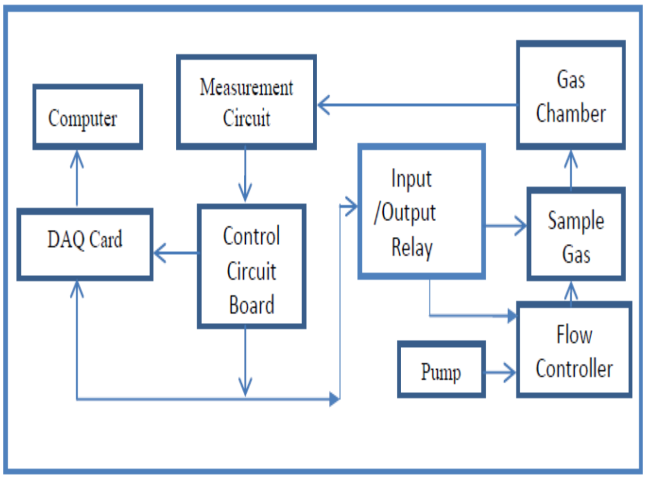

Figure 3 the schematic diagram of the E-nose system

B. Data

The information document is taken from the University of California (UCI) machine learning repository Air exceptional records set documents. This fact is from a singular multi-sensor device developed with the aid of Pirelli Labs for pollutants monitoring. [18] The tool constructed up with a metallic case which is 32 cm×26 cm×11 cm .A global system for mobile communication ,Microcontroller based data acquisition system along with signal conditioning circuit is attached with the tool finally capable to run simple sensor fusion algorithms.

The proposed multi-sensor device has a hosting of metal oxide chemo resistive sensors whose short characteristics are shown in Table 1of data sheet. Linear correlation coefficients computed amongst analyzed species the use of on field recorded facts Carbon monoxide, Nitrogen oxide ,Nitrogen dioxide,Benzene and non methanic hydrocarbons .Table 2 of data sheet documents the linear correlation coefficients computed for analyzed species . The hidden neuron switch feature changed into the MATLAB tansig feature. Networks had been educated the usage of the resilient again-propagation set of rules [20] and early stopping as a degree to save you over-training problems .

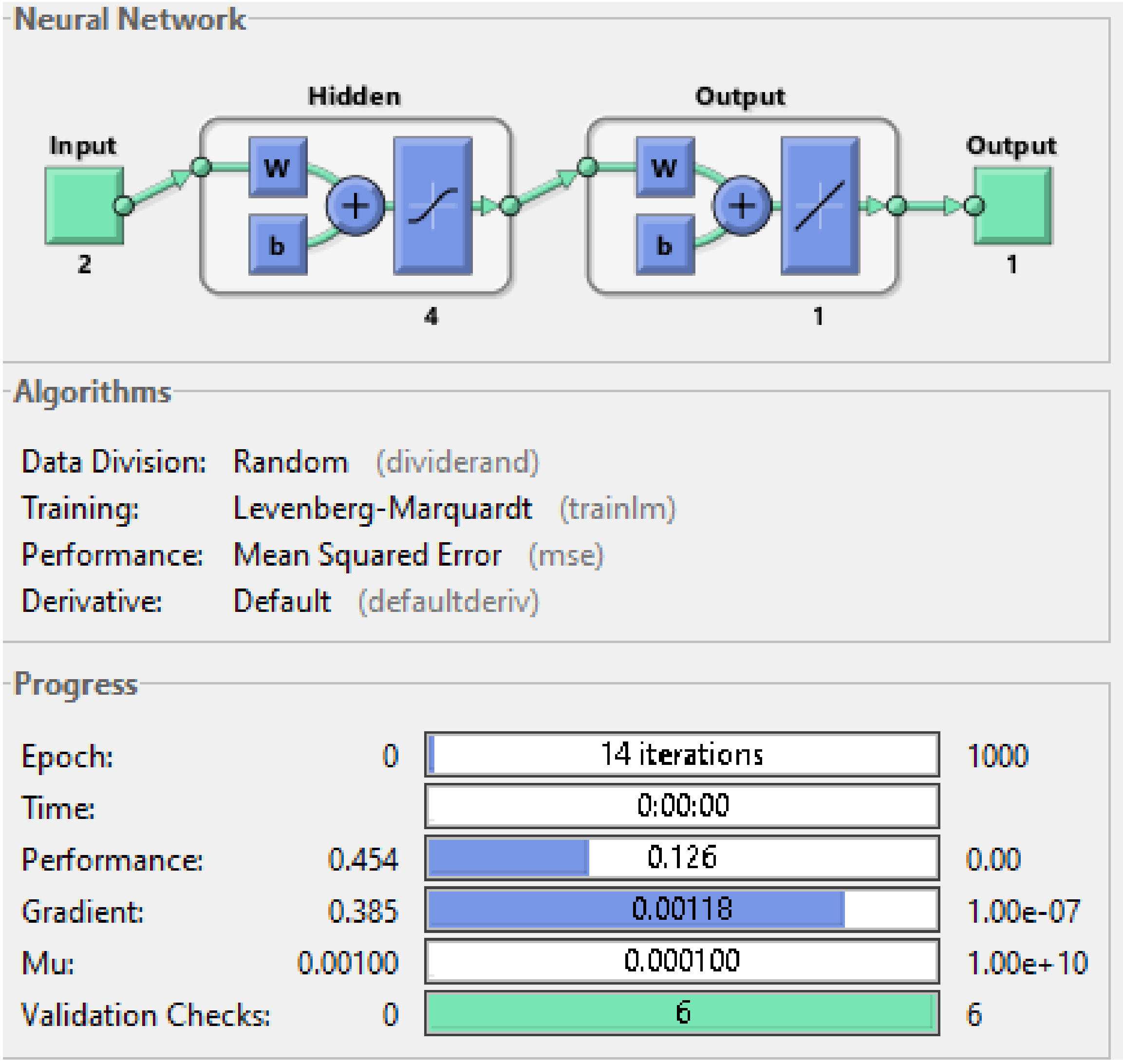

Figure 4 Neural Network Setup

Table 1: Mean squared Error at Different Node and Segment Length

Mean squared Error								
No. of Nodes N➔	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**
Segment Length L :								
10	0.1379	0.1608	0.1312	0.131	0.1345	0.1404	0.1332	0.1491
15	0.1348	0.1505	0.1689	0.1585	0.1113	0.1432	0.1331	0.1288
20	0.1182	0.1734	0.123	0.1257	0.1328	0.1428	0.1608	0.1429
25	0.1461	0.1422	0.1331	0.1196	0.1438	0.1509	0.1306	0.1178
30	0.1638	0.1581	0.1325	0.1017	0.1391	0.1363	0.1643	0.1293
35	0.1345	0.1711	0.1672	0.1581	0.1713	0.1193	0.1063	0.1878

40	0.2064	0.063	0.2172	0.1274	0.1479	0.1333	0.0631	0.1816
45	0.1252	0.18	0.1143	0.0999	0.1644	0.1425	0.1498	0.1507
Minimum Value	0.1182	0.063	0.1143	0.0999	0.1113	0.1193	0.0631	0.1178

Table 2:Regression Values for Training, Testing, Validation and All at Different Node and Segment Length

	Table 2A: Regression Train Values								Table 2B: Regression Test Values							
N	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**
L:																
10	0.7	0.71	0.7	0.7	0.69	0.7	0.69	0.68	0.67	0.696	0.67	0.68	0.7	0.72	0.76	0.75
15	0.68	0.71	0.7	0.72	0.7	0.69	0.7	0.72	0.75	0.698	0.77	0.6	0.54	0.78	0.61	0.54
20	0.68	0.65	0.67	0.71	0.67	0.67	0.69	0.73	0.75	0.809	0.66	0.65	0.66	0.7	0.7	0.44
25	0.71	0.71	0.74	0.72	0.76	0.7	0.72	0.73	0.8	0.739	0.62	0.65	0.67	0.84	0.79	0.7
30	0.7	0.67	0.72	0.58	0.64	0.7	0.69	0.71	0.65	0.773	0.55	0.83	0.82	0.71	0.66	0.62
35	0.68	0.69	0.65	0.62	0.68	0.61	0.64	0.69	0.67	0.462	0.73	0.69	0.7	0.68	0.57	0.61
40	0.66	0.67	0.72	0.73	0.71	0.72	0.64	0.68	0.78	0.55	0.75	0.54	0.75	0.75	0.7	0.64
45	0.69	0.66	0.72	0.7	0.73	0.68	0.72	0.68	0.55	0.775	0.37	0.51	0.52	0.54	0.61	0.75
Maximum value	0.71	0.71	0.74	0.73	0.76	0.72	0.72	0.73	0.8	0.809	0.77	0.83	0.82	0.84	0.79	0.75
	Table 2C: Regression Validation Values								Table 2D:Regression all Values							
N	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**2**	**4**	**6**	**8**	**10**	**12**	14	**16**
L:																
10	0.67	0.59	0.67	0.68	0.67	0.66	0.67	0.64	0.69	0.69	0.69	0.69	0.69	0.69	0.7	0.69
15	0.67	0.64	0.56	0.61	0.74	0.65	0.66	0.7	0.68	0.694	0.69	0.69	0.69	0.69	0.68	0.69
20	0.67	0.52	0.72	0.67	0.69	0.67	0.6	0.66	0.68	0.657	0.67	0.69	0.68	0.67	0.67	0.67
25	0.63	0.66	0.68	0.72	0.66	0.67	0.7	0.73	0.72	0.707	0.71	0.71	0.73	0.72	0.72	0.72
30	0.57	0.61	0.69	0.79	0.67	0.68	0.59	0.64	0.68	0.672	0.68	0.65	0.67	0.7	0.67	0.69
35	0.65	0.56	0.58	0.61	0.57	0.72	0.77	0.58	0.68	0.64	0.65	0.63	0.66	0.64	0.65	0.66
40	0.43	0.86	0.57	0.72	0.65	0.68	0.86	0.63	0.65	0.683	0.69	0.7	0.71	0.71	0.69	0.66
45	0.73	0.58	0.72	0.77	0.58	0.7	0.62	0.66	0.68	0.657	0.67	0.68	0.67	0.64	0.69	0.69
Maximum value	0.73	0.86	0.72	0.79	0.74	0.72	0.86	0.73	0.72	0.707	0.71	0.71	0.73	0.72	0.72	0.72
N : Number of Nodes					L: Segment Length						Maximum value : Maximum Value of Regression					

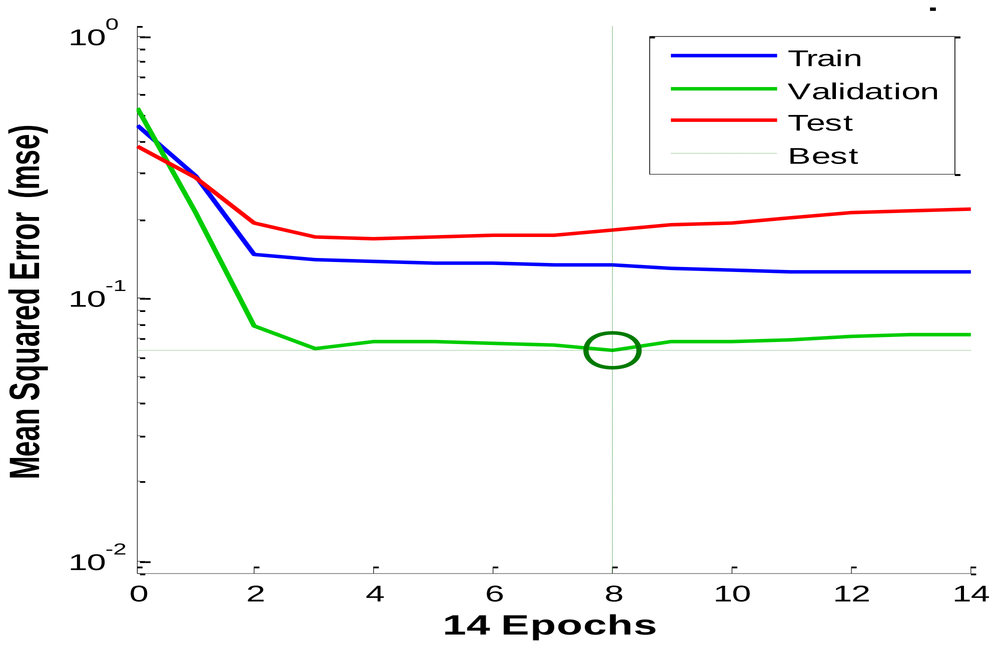

Figure 5 MSE Error Graph Best validation performance is 0.063096 at Epoch 8 (No. of iterations=14)

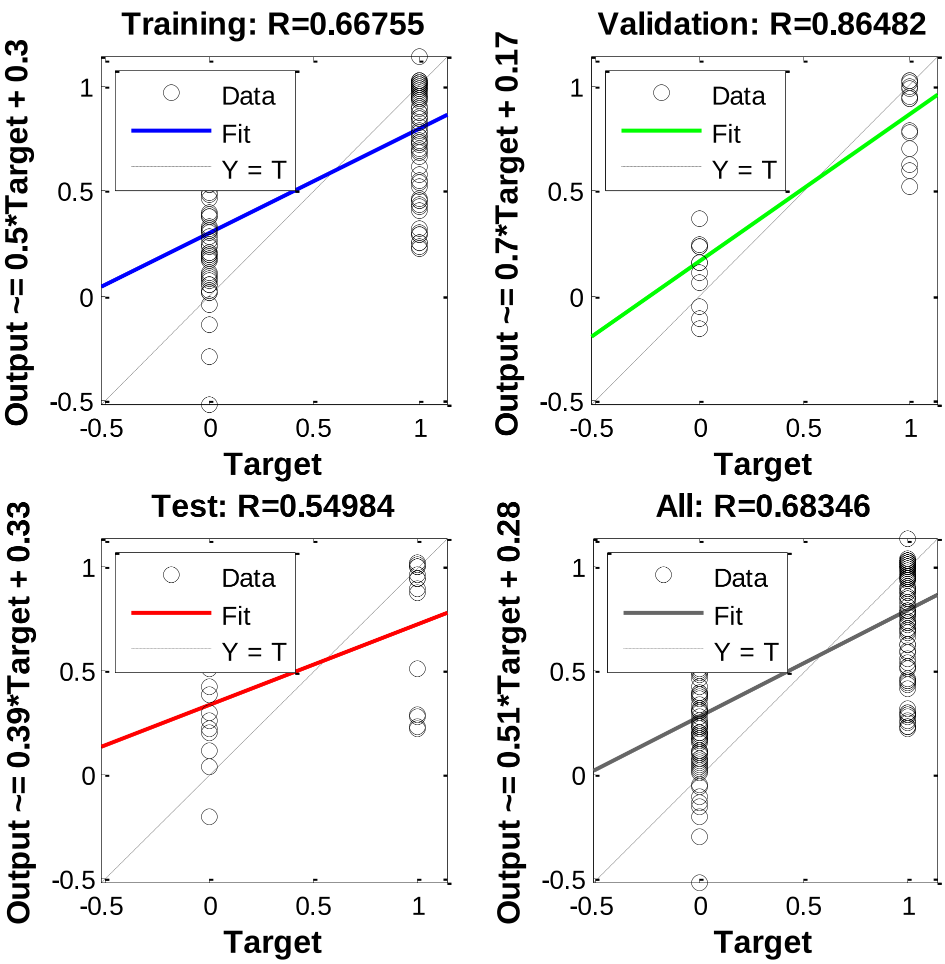

Figure 6 Regression plot for training, testing, and validation data

IV. CONCLUSION

This paper describes new carbon mono oxide detection model-based approach with enhanced artificial neural network based Artificial Intelligence techniques. The aim of this work is to accurately classify the carbon mono oxide level in terms of high and low concentration. This objective is achieved using an optimal artificial neural network model at specific data segment length and no. of nodes of the hidden layer.

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The Number of neurons and data segment length is varied to optimize the artificial neural network Model. The system performance is optimized in terms of Minimum Value of Mean Squared Error and Maximum Value of Regression analysis. Results show that the artificial neural network prediction accuracy is highly dependent on the data segment length and network parameters. The accuracy of prediction is improved by systematic selection of data and network parameter with minimum no of features. Work further may be enhanced by applying Genetic Algorithm Based Optimize Search on artificial neural network Platform. It is expected that the development model is helpful in application related to the environmental hazards that include carbon mono oxide related air pollution. Hence this work can support the target of air quality required in the open area and also in the buildings such as hospitals, hotels, and industries where Carbon Monoxide is very common due to the inadequate combustion process.

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