FUZZY INFERENCE SYSTEMS FOR GAS CONCENTRATION ESTIMATION

Ekrem ÇALIŞKAN , Fevzullah TEMURTAŞ, Nejat YUMUŞAK

Özet - **Bu çalışmada, Mamdani ve Sugeno bulanık sonuç çıkarım sistemleri (BSÇS) kararlı hal sensor cevapları kullanılarak Toluen gazının konsantrasyon tahmini için kullanılmış ve sunulmuştur. Bir yapay sinir ağı (YSA) yapısıda ayrıca mukayese için kullanılmıştır.Gaz sensörü olarak Kuartz Kristal Mikrobalans tip sensor kullanılmıştır. BSÇS ve YSA ile yapılan konsantrasyon tahminlerinde kabul edilebilir performanslar elde edilmiştir. Sonuçlar gaz konsantrasyon tahmini için Sugeno BSÇS'nin Mamdani BSÇS'den daha iyi performans sağladığını göstermektedir. Sugeno BSÇS'nin tahmin sonuçları YSA'nın tahmin sonuçlarına oldukça yakındır.**

Anahtar Kelimeler - **Fuzzy Inference Sistem, Yapay Sinir Ağları, Konsantrasyon Tahmini, Gas Sensörleri.**

Abstract - **In this study, Mamdani's and Sugeno's fuzzy inference systems (FIS) is presented for the concentration estimation of the Toluene gas by using the steady state sensor response. An artificial Neural Network (ANN) structure is also used for comparison. The Quartz Crystal Microbalance (QCM) type sensors were used as gas sensors. Acceptable performances were obtained for the concentration estimation with FISs and ANN. The results show that Sugeno's FIS performs better than Mamdani's FIS for gas concentration estimation. The estimation results of Sugeno's FIS are very closer to estimation results of ANN.**

Keywords - **fuzzy inference systems, artificial neural networks, concentration estimation, gas sensors.**

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I. INTRODUCTION

The volatile organic vapours in ambient air are known to be reactive photo-chemically, and can have harmful effects upon long-term exposure at moderate levels. These type organic compounds are widely used as a solvent in a large number of the chemical industry and in the printing plants [1].

One of the applied concentration estimation methods is using of artificial neural networks (ANN's)[2-6]. The most important parts of the neurons are activation functions. However, in the hardware implementation concept of neural networks, it is not so easy to realize sigmoid activation functions. So, adaptation of ANN's to the handle systems including microcontrollers for detection of gas concentration is not easy. Because of the simplicity of the fuzzy structure, fuzzy logic can be easily adapted to the handle systems[3].

In this study, Mamdani's [7] and Sugeno's [8] fuzzy inference systems are employed as a concentration estimation method with a QCM gas sensor, which shows good performance regardless of the ambient temperature-humidity variations as well as the concentration changes and the performance for the Toluene gases and the suitability of this method are discussed based on the experimental results. An artificial Neural Network structure is also used for comparison.

Usually, the steady state responses of the sensors are used for concentration estimations of the gases [2-6]. In this method, the steady state responses of the sensors were used. Steady state response means no signals varying in time. So, it's easy to apply fuzzy inference mechanism.

II. SENSORS AND MEASUREMENT SYSTEM

The Quartz Crystal Microbalances (QCM) is useful acoustic sensor devices. The principle of the QCM sensors is based on changes Δf in the fundamental oscillation frequency to upon ad/absorption of molecules from the gas phase. To a first approximation the frequency change Δf results from increase in the oscillating mass Δm [9].

$$\Delta f = -\frac{C_f f_0^2}{A}\Delta m \quad . \tag{1}$$

where, A is the area of the sensitive layers, C_f the mass sensitivity constant (2.26 10-10 $m^2 s\ g^{-1}$) of the quartz crystal, f_o fundamental resonance of the quartz crystals, Δm mass changes.

The piezoelectric crystals used were AT-Cut, 10 *MHz* quartz crystal (ICM International Crystal Manufacturers Co., Oklahoma, USA) with gold plated electrodes (diameter ϕ = 3 *mm*) on both sides mounted in a HC6/U holder. The both faces of two piezoelectric crystals were coated with the phthalocyanine [10]. The instrumentation utilized consist of a Standard Laboratory Oscillator Circuit (ICM Co Oklahoma, USA), power supply and frequency counter (Keithley programmable counter, model 776). The frequency changes of vibrating crystals were monitored directly by frequency counter.

A Calibrated Mass Flow Controller (MFC) (MKS Instruments Inc. USA) was used to control the flow rates of carrier gas and sample gas streams. Sensors were tested by isothermal gas exposure experiments at a constant operating temperature. The gas streams were generated from the cooled bubblers (saturation vapour pressures were calculated using Antoine Equation [11]) with synthetic air as carrier gas and passed through stainless steel tubing in a water bath to adjust the gas temperature. The gas streams were diluted with pure synthetic air to adjust the desired analyte concentration with computer driven MFCs. Typical experiments consisted of repeated exposure to analyte gas and subsequent purging with pure air to reset the baseline. The sensor data were recorded every 3-4 *s* at a constant of 200 *ml/min*.

In this study, the frequency shifts (*Hz*) versus concentrations (*ppm*) characteristics were measured by using QCM sensor for the Toluene gas as shown in Figure 1. At the beginning of each measurement gas sensor is cleaned by pure synthetic air. Each measurement is composed of six periods. Each period consists of 10 minutes cleaning phase and 10 minutes measuring phase. During the periods of the measurements, at the first period 500 *ppm*, and at the following periods 1000, 3000, 5000, 8000, and 10000, *ppm* gases are given.

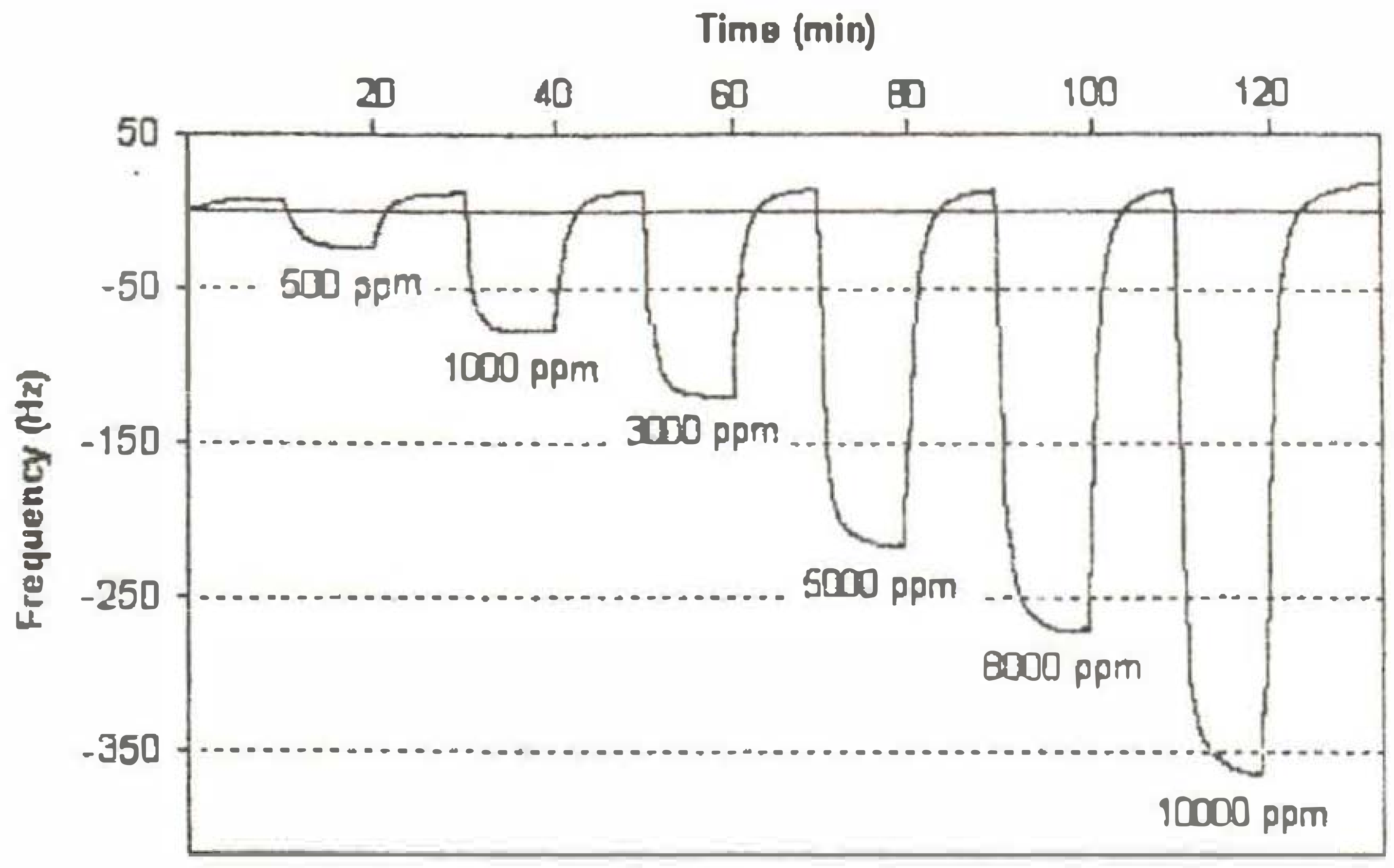


Fig. 1. Sensor response of QCM for Toluene gas

III. FUZZY LOGIC BASED CONCENTRATION ESTIMATION

Fuzzy logic is widely used in the field of intelligent control, classification, pattern matching, image processing, etc. In such applications, it describes the imprecise, vague, qualitative, linguistic, nonlinear relationship between input and output states of a system with a set of rules generally. Such rules are called fuzzy, and can be expressed as follows in general form [12].

IF x_1 is A_1^i AND ··· AND x_n is A_n^i THEN y is B^j (2)
where x is input, y is output, A_k^i, $k = 1, ..., n$ and B^j are linguistic variables which represent vague terms such as small, medium or large defined on the input and output variables, respectively.

At the first study, a fuzzy logic based algorithm which includes Mamdani's fuzzy inference method was used for determination of the concentrations of the Toluene gas within steady state sensor response. In this system, one input, frequency change of the sensor Δf and one output, concentration of the introduced gas *PPM* are used. From the relations of the input and output, that is, the frequency change of the sensor is large, when the concentration of the introduced gas is high and small when the concentration is low, we can extract n fuzzy rules and corresponding defuzzification equation as follows:

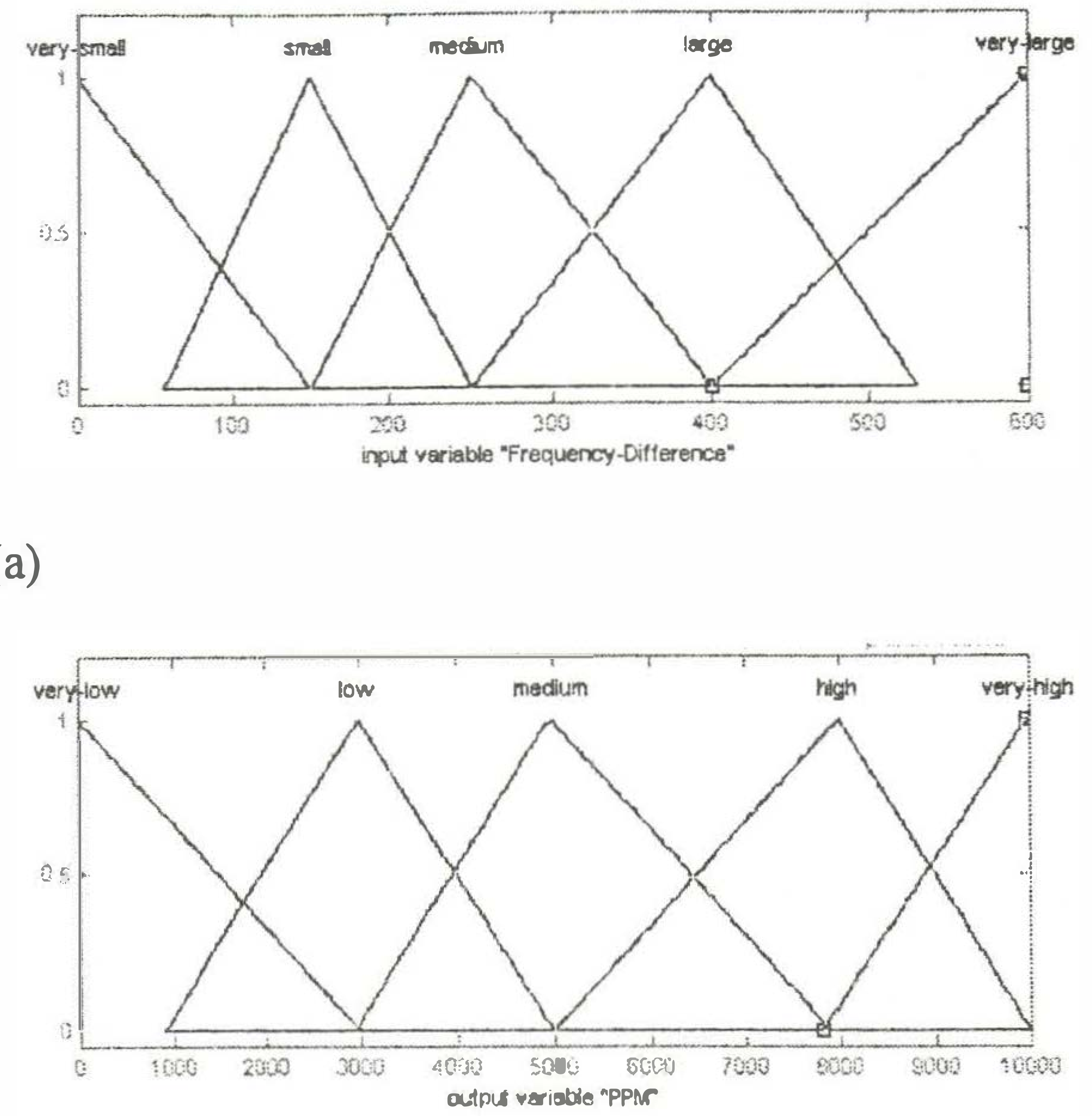
Rule i: IF Δf is A_i THEN PPM is B_i $(i = 1,2,...,n)$ (3)

$$\mu_{\Delta fi} = A_i(\Delta f),\ \ \mu_{PPMi} = B_i(PPM) \tag{4}$$

$$PPM = \frac{\sum_{i=1}^{n} \mu_{PPMi} * PPMi}{\sum_{i=1}^{n} \mu_{PPMi}} \tag{5}$$

At the first step, n is 3 and i = 1,2,3 means small, medium, large for premise and low, medium, high for consequence, respectively. At the second step, n is 5 and

i = 1,2,3,4,5 means very small, small, medium, large, very large for premise and very low, low, medium, high, very high for consequence, respectively. Figure 2 shows the sample Δf and PPM membership functions.



(a)

(b)

Fig. 2. Δf (a) and PPM (b) membership functions for n=5.

Figure 3 illustrates an example of Mamdani's fuzzy inference, aggregation and defuzzification for the concentration estimation.

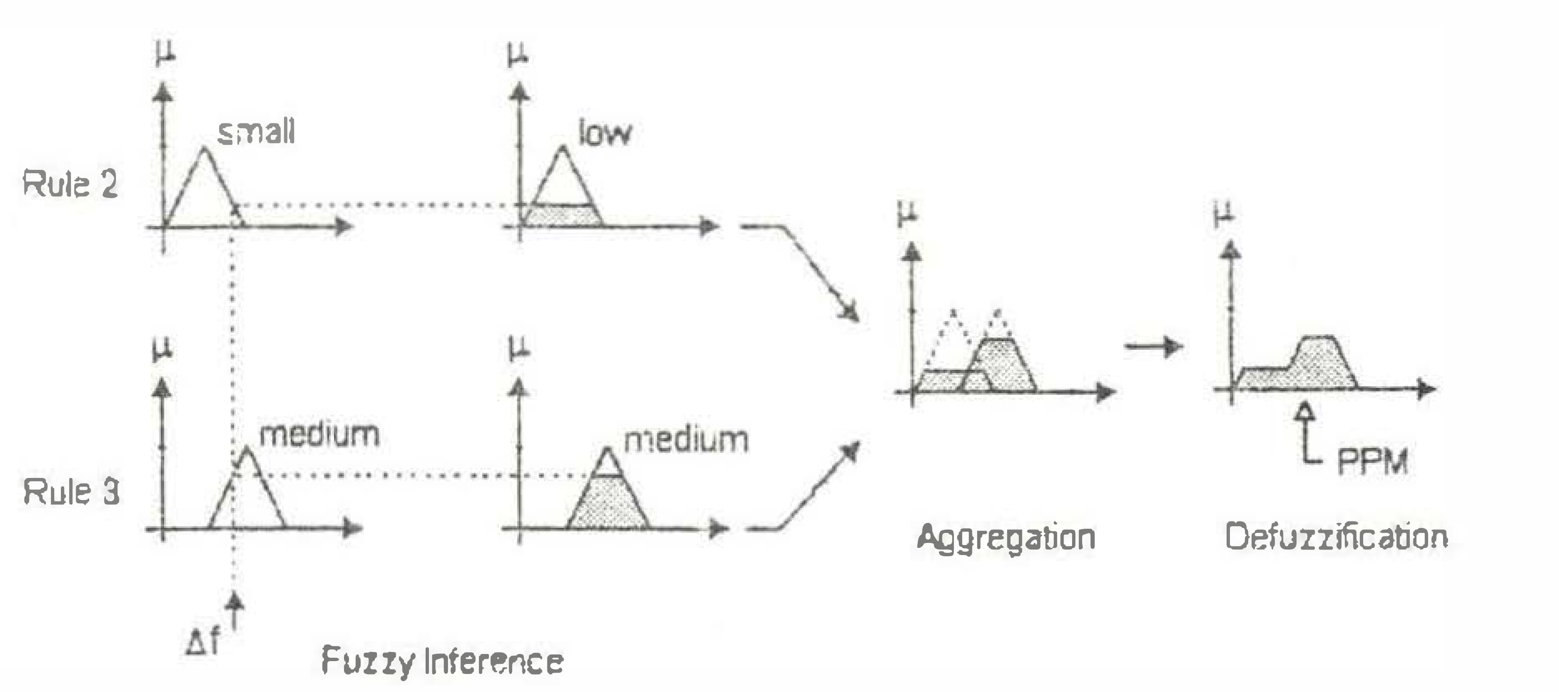


Fig. 3. An example of Mamdani's fuzzy inference, aggregation and defuzzification.

At the second study, a Sugeno's fuzzy inference method was used for determination of the concentrations of the Toluene gas within steady state sensor response. In this system, one input, frequency change of the sensor Δf and one output, concentration of the introduced gas PPM are used. In Sugeno's fuzzy inference systems, the input membership functions of Mamdani's fuzzy inference systems were used as input membership functions (Figure 2.a). For Sugeno's fuzzy inference systems, we can also extract n fuzzy rules and corresponding defuzzification equation as follows:

Rule i: IF Δf is A_i THEN $PPMi = f(\Delta f) = c_i * \Delta f$ $(i = 1,2,\ldots,n)$ (6)

$$PPM = \frac{\sum_{i=1}^{n} wi * PPMi}{\sum_{i=1}^{n} wi} \quad (7$$

$$wi = \mu_{\Delta fi} = A_i(\Delta f) \quad (8$$

At the first step, n is 3, i = 1,2,3, c_i =19.9, 20, 19.3, and A means small, medium, large respectively. At the secon step, n is 5 , i = 1,2,3,4,5, c_i =19.8, 20.2, 20.4, 19.5, 19. and Ai means very small, small, medium, large, ve large respectively.

Figure 4 illustrates an example of the Sugeno's fuz inference, aggregation and defuzzification for th concentration estimation.

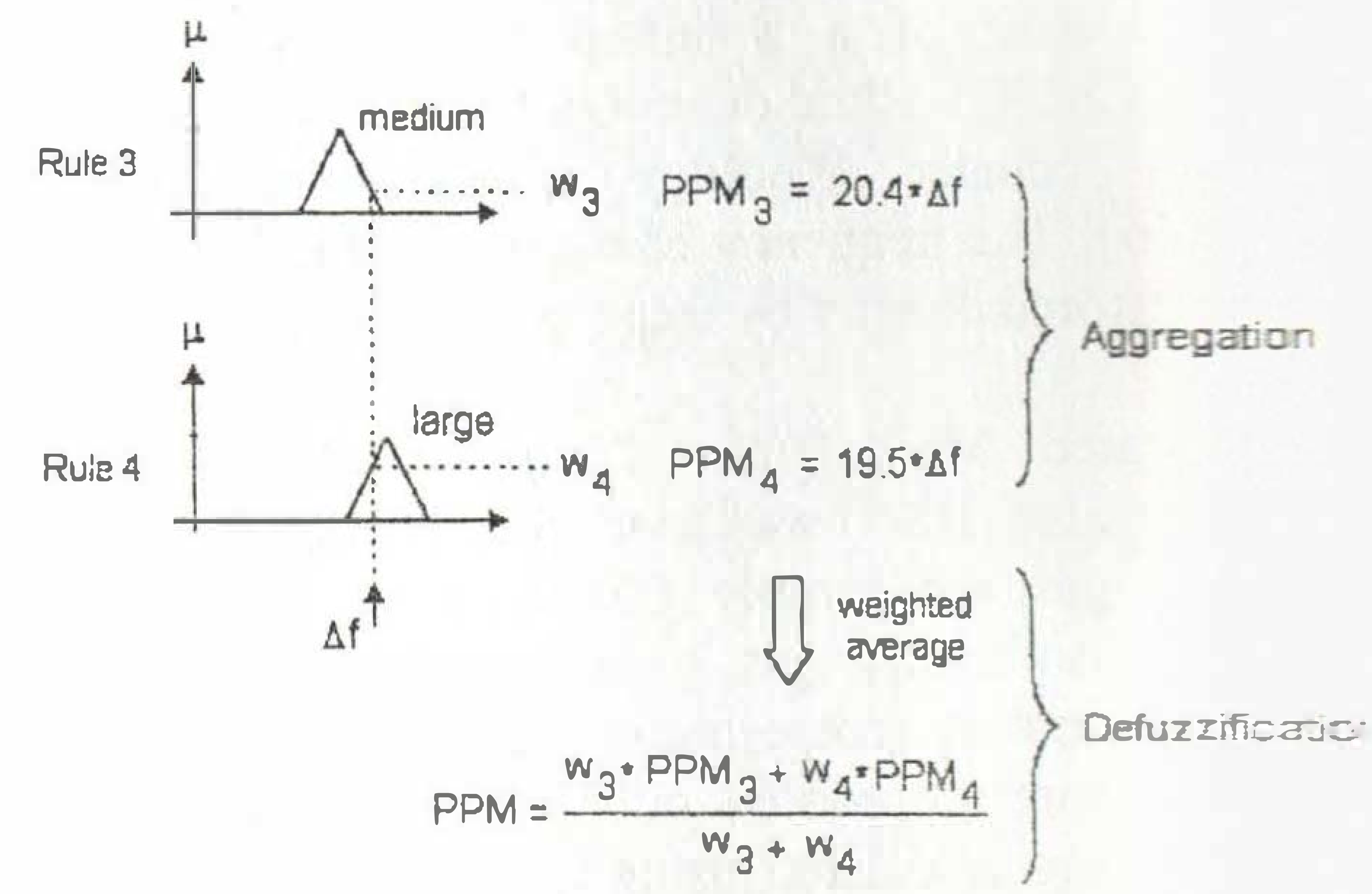


Fig.4. An example of Sugeno's fuzzy inference, aggregation a defuzzification.

IV. NEURAL NETWORK BASED CONCENTRATION ESTIMATION

A multi-layer feed-forward ANN used for determinati of the concentrations of the Toluene gas. The netwo structure is shown in Figure 5. The input, u, is the sens frequency shift value and the output, y, is the estimat concentration. The network has a single hidden layer wi 10 hidden layer nodes [3,4] and a single output node.

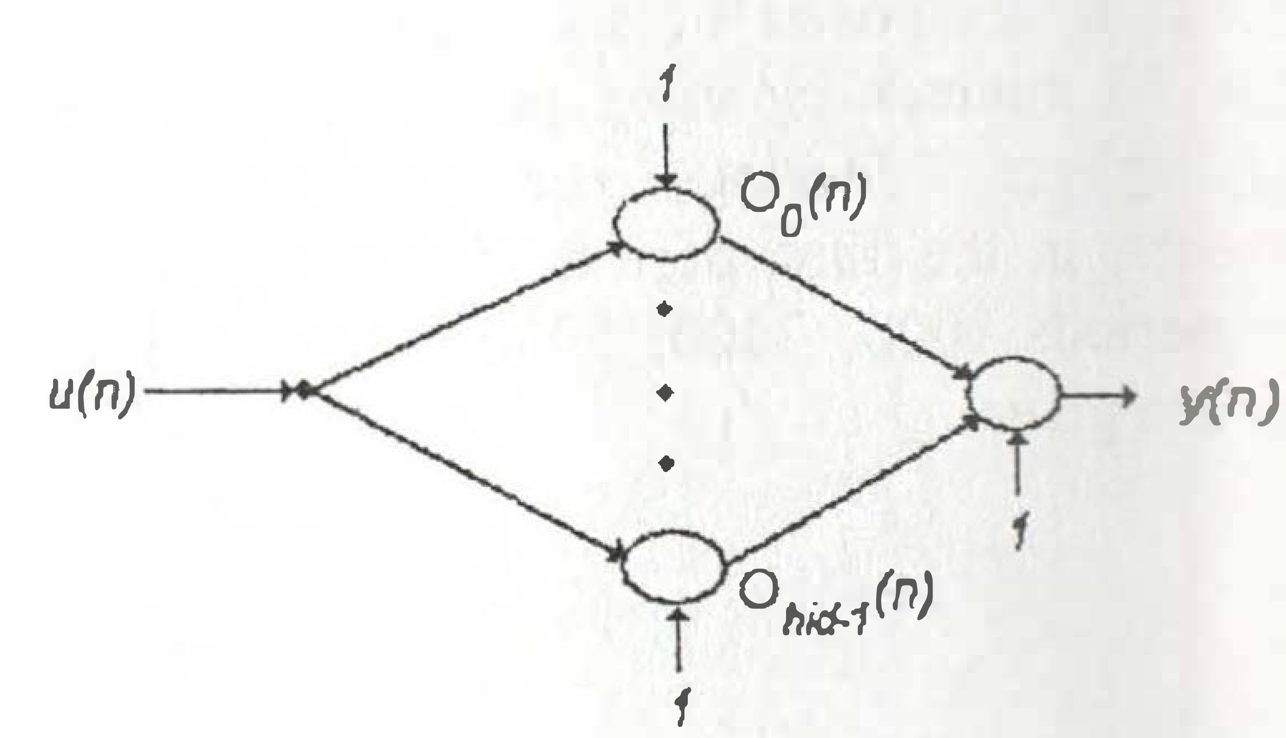


Fig. 5. Artificial neural network model

Equations which used in the neural network model are shown in (9), (10), and (11). As seen from equations, the activation functions for the hidden layer nodes and the output node are tangent-sigmoid transfer function.

$$net_j(n) = b_j + w_j u(n) \tag{9}$$

$$O_j(n) = f\left(net_j(n)\right) = 1 - \frac{2}{1+e^{2\cdot net_j(n)}} \tag{10}$$

$$y(n) = 1 - \frac{2}{1+e^{\left(b+\sum_{j=0}^{hid-1} w_j O_j(n)\right)}} \tag{11}$$

The back propagation (BP) method is widely used as a teaching method for an ANN. The main advantage of the BP method is that the teaching performance is highly improved by the introduction of a hidden layer [13]. In this paper, five different type high performance BP training algorithms which use different optimization techniques were used. These are, BP with momentum and adaptive learning rate (GDX) [13], Resilient BP (RP) [13], Fletcher-Reeves conjugate gradient algorithm (CGF) [13,14], Broyden, Fletcher, Goldfarb, and Shanno quasi-Newton algorithm (BFG) [13,15], and Levenberg-Marquardt algorithm (LM) [13,16].

V. PERFORMANCE EVALUATION

For the performance evaluation, we have used the mean relative absolute error [2,3]:

$$E(RAE) = \frac{1}{n_{test}} \sum_{testset}\left(\frac{\left|\left(C_{prdicted} - C_{true}\right)\right|}{C_{true}}\right) \quad \forall C_{true} \neq 0 \tag{12}$$

where, $C_{predicted}$ is estimated concentration, C_{true} is real concentration and n_{test} is number of test set.

VI. RESULTS AND DISCUSSIONS

The ability of the Mamdani's and Sugeno's fuzzy inference systems to estimation of Toluene gas concentrations with related to the number of memberships functions are given in table 1. As seen in the table, accuracy of the estimation can be improved by increasing the number of membership functions. This result supports the expectations of B.Yea at all [12] and our previous results [3]. When the number of membership functions is 5, estimations result in acceptable errors [3,12] for both fuzzy inference systems. When the number of membership functions is 3, Sugeno's fuzzy inference results in acceptable errors. Based on the results shown in the table, it is seen that the errors of Sugeno's fuzzy inference systems are less than those of Mamdanis's fuzzy inference systems for Toluene gas concentrations estimations.

Table 1. Fuzzy inference systems concentration estimation results for Toluene

Fuzzy Inference System	Number of membership functions (n)	E(RAE) (%)
Mamdani's	3	17.2
	5	3.6
Sugeno's	3	2.9
	5	1.3

For easy understanding of the effect of the numbers of membership functions, error (%) versus membership functions graph for Toluene is given in Figure 5. From these figure and table, it's shown that the increasing membership functions results improving accuracy at the concentration estimations.

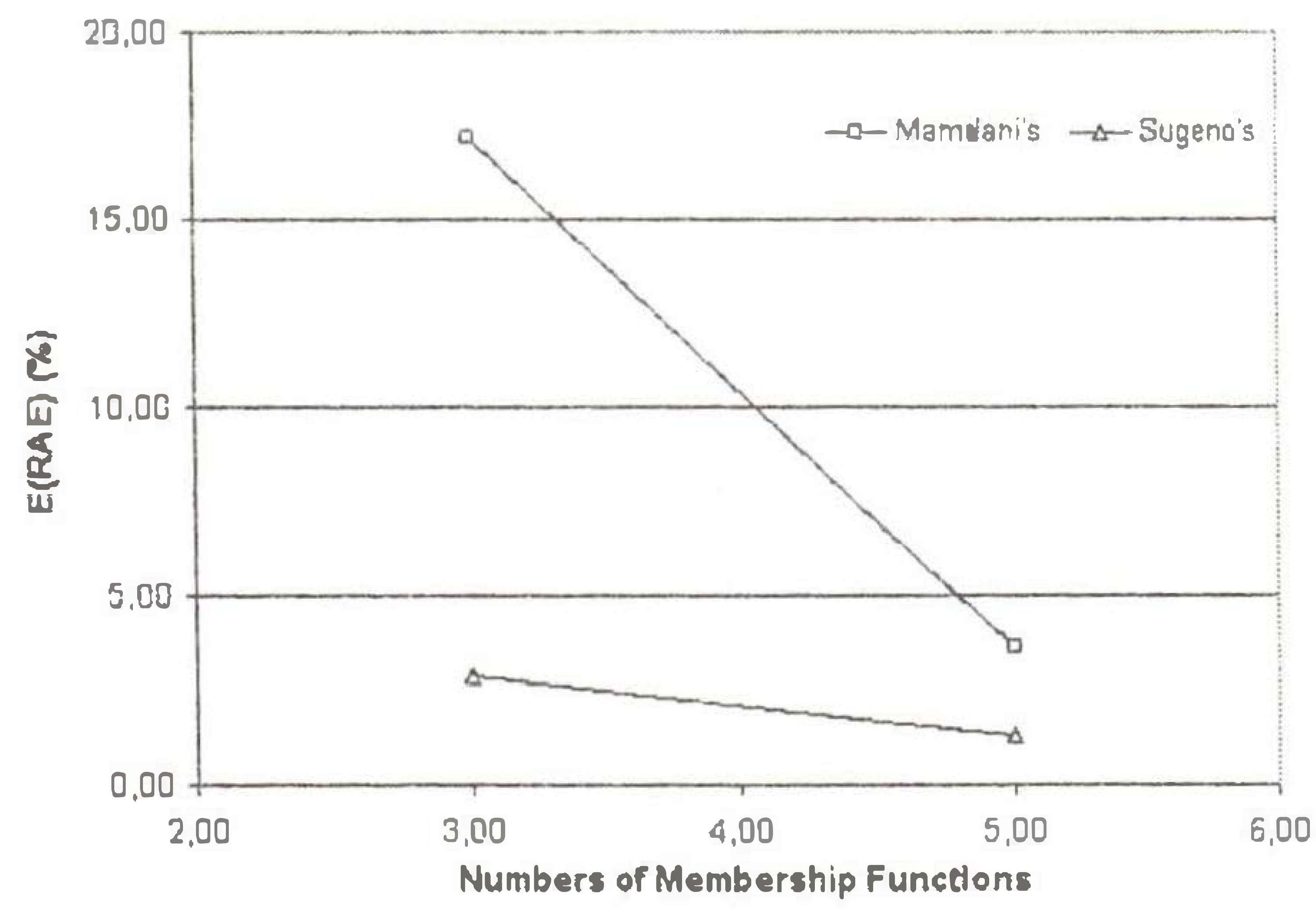


Fig. 5. Error (%) versus numbers of membership function graph for Toluene

The ability of the ANN structure to estimation of Toluene gas concentrations is given in table 2. As seen in the table, estimations result in acceptable errors [3,12] for all training methods. From the same table, it can be seen easily that Levenberg-Marquardt training algorithm gives the best results for concentration estimation of Toluene.

Table 2. ANN concentration estimation results for Toluene

ANN Training Method	E(RAE) (%)
GDX	2.3
RP	0.2
CGF	0.7
BFG	0.2
LM	0.0

From table 1 and 2 it can be seen easily that, the estimation results of Sugeno's fuzzy inference system are very closer to estimation results of ANN.

In this study we saw that fuzzy logic structures are simple applicable and acceptable errors can be achieved. Results of ANN structures are also very well. Because of difficulties in realizing sigmoid activation functions, adaptation of ANN's to the handle systems including microcontrollers for detection of gas concentration is not easy. However, because of the simplicity of the fuzzy structure, fuzzy inference systems can be easily adapted to the handle systems for detection of gas concentration.

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