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"Automatic Detection of CO Content in Smoke Condensate Using Adaptive Neuro-Fuzzy Inference Systems",



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Abstract A new approach based on adaptive neuro-fuzzy inference system (ANFIS) was presented for the detection of CO content in smoke condensate. The domain contained records of well known cigarettes produced by different Tobacco factories. Given a training set of such records, the ANFIS classifiers learned how to differentiate a new case in the domain. The fifth ANFIS classifiers were used to detect CO in smoke condensate when 4 basic features defining cigarette clases indications were used as inputs. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. Some conclusions concerning the impacts of features on the detection of tar content in smoke condensate were obtained through analysis of the ANFIS. The results confirmed that the proposed ANFIS model has some potential in detection of tar content in new class of cigarrete. The ANFIS model achieved accuracy rates which were higher than that of the stand-alone neural network model.

TOPIC UNITS

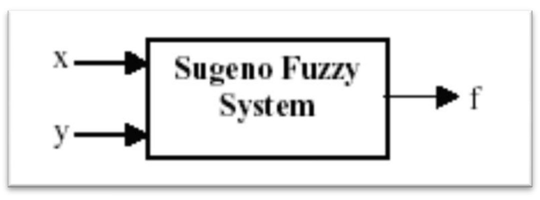
- Introductinon
- Sugeno fuzzy model
- ANFIS architecture
- Problem description
- Experimental
- Conclusion

Sugeno fuzzy model

A typical fuzzy rule in a two-input-single-output Sugeno fuzzy mode has the format:

$$\text{If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } z = f_1(x,y)$$

Where A_1 and B_1 are fuzzy sets in the antecedent;
$z=f_1(x,y)$ is a polynomial in the input variables x and y.



We assume that this system has only two inputs *x* and *y* and one output *f*. The fuzzy sets of the input variables are shown in Figure. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy *if-then* rules is as follows:

Rule 1: If x is A_1 and y is B_1, then
$f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_2 and y is B_2, then
$f_2 = p_2x + q_2y + r_2$

The overall output of this Sugeno Fuzzy System is given by (using center-average defuzzification):

$$f = \frac{\mu_{A_1}(x)\mu_{B_1}(y)(p_1x+q_1y+r_1)+\mu_{A_2}(x)\mu_{B_2}(y)(p_2x+q_2y+r_2)}{\mu_{A_1}(x)\mu_{B_1}(y)+\mu_{A_2}(x)\mu_{B_2}(y)}$$

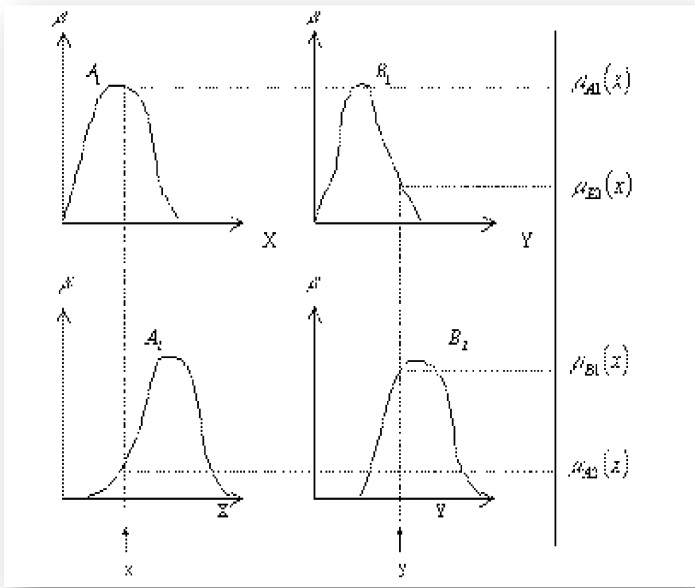
where $\mu_{A_1}(x), \mu_{A_2}(x), \mu_{B_1}(y), \mu_{B_2}(y)$ are fuzzy membership functions.

The overall output can be rewritten as:

$$f = \frac{\varpi_1 f_1 + \varpi_2 f_2}{\varpi_1 + \varpi_2} = \varpi_1 f_1 + \varpi_2 f_2,$$

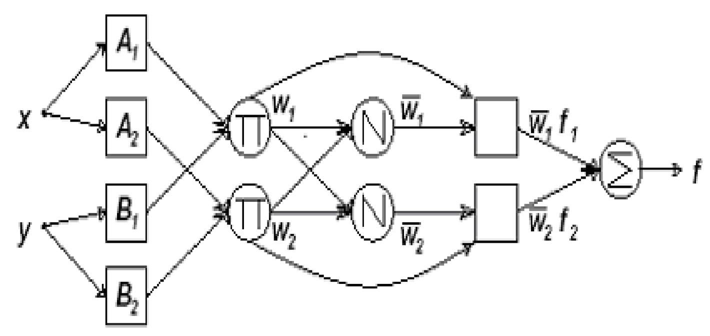
where
$$\varpi_1 = \mu_{A_1}(x)\mu_{B_1}(y)$$
$$\varpi_2 = \mu_{A_2}(x)\mu_{B_2}(y)$$

$$\varpi_1 = \frac{\varpi_1}{\varpi_1 + \varpi_2}$$
$$\varpi_2 = \frac{\varpi_2}{\varpi_1 + \varpi_2}$$



ANFIS architecture

From Sugeno Fuzzy Model, Adaptive Neural-Fuzzy Inference System (ANFIS) was proposed by Roger Jang in 1992 [2,3]: .The architecture of a two-input two-rule ANFIS is shown in Figure.



The ANFIS has five layers, in which node functions of the same layer have the same function type as described below [2,3]:
Layer 1: Every node *i* in this layer is an adaptive node with node function:

$$O_{j,i} = \mu_{A_i}(x) = \frac{1}{1+\left(\frac{x-c_i}{a_i}\right)^{2b_i}}$$

or

$$O_{j,i} = \mu_{B_i}(y) = \frac{1}{1+\left(\frac{y-c_i}{a_i}\right)^{2b_i}}$$

where $\{a_i, b_i, c_i\}$, are premise parameters updated through Back Propagation Learning Algorithm.

Layer 2: Every node i in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$$O_{2,i} = \varpi_i = \mu_{A_i}(x) \times \mu_{B_i}(x)$$

Layer 3: Every node i in this layer is a fixed node labeled N. The *ith* node calculates the ratio of the *ith* rule's firing strength to the sum of all rules' strengths:

$$O_{3,i} = \varpi_i = \frac{\varpi_i}{\varpi_1 + \varpi_2}$$

Layer 4: Every node i in this layer is adaptive node with node function:

$$O_{4,i} = \varpi_i f_i = \varpi_i (p_i(x) + q_i(y) + r_i)$$

where $\{p_i, q_i, r_i\}$, are consequent parameters [2,3], updated through Recursive Least-Squares Estimation.

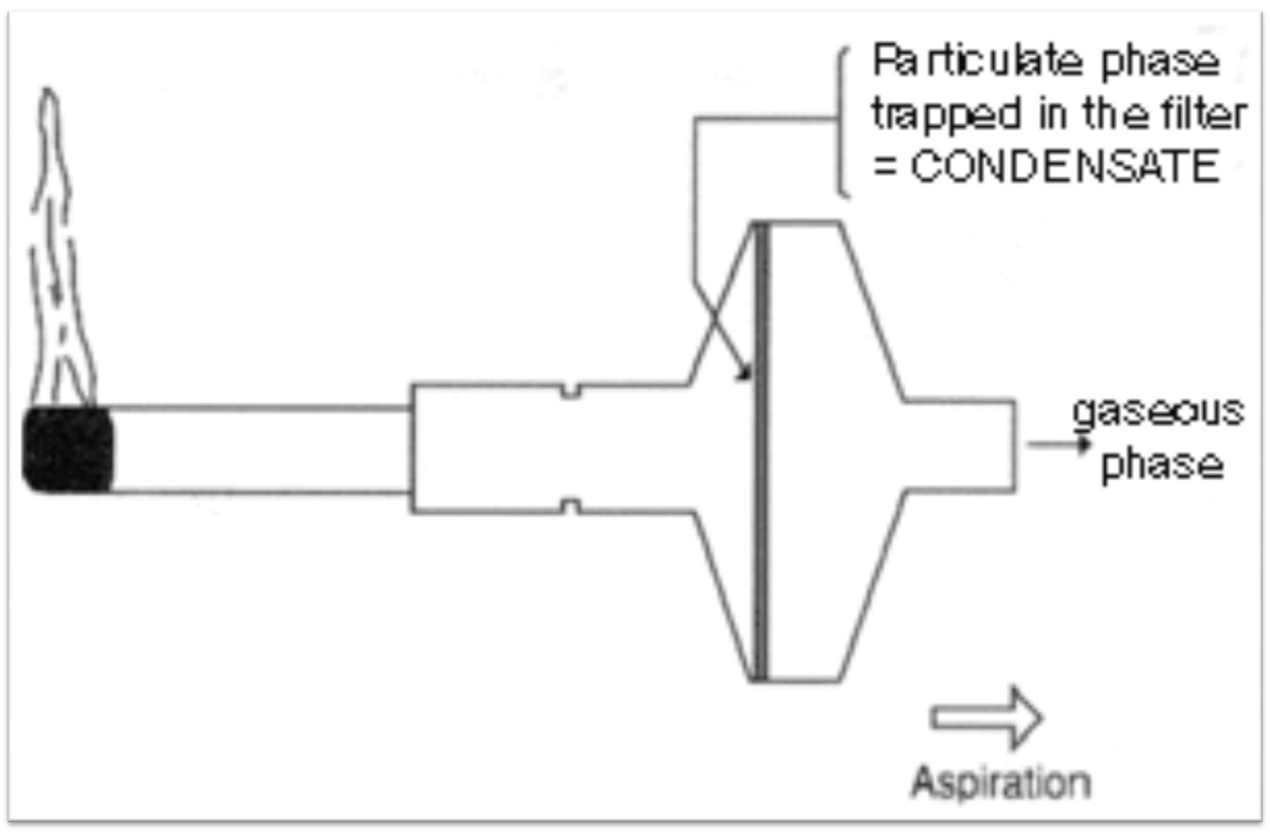
Layer 5: The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all the incoming signals:

$$O_5 = \sum_i \varpi_i f_i = \frac{\sum_i \varpi_i f_i}{\sum_i \varpi_i} = \frac{\varpi_1 f_1 + \varpi_2 f_2}{\varpi_1 + \varpi_2}$$

Functionally speaking, the ANFIS architecture is completely equivalent to a Sugeno fuzzy inference system.

Problem description

Tar or tobacco smoke condensate refers to the sticky particles comprised of thousands of chemicals created by burning tobacco. It is a particulate component of tobacco smoke without nicotine and water. The tar yield, measured in mg tar/cigarette, is the amount of tar trapped in a filter during standardised smoking. Cigarette smoke contains an amazing array of gaseous and particulate compounds. This includes (in approximate order by mass): carbon dioxide, water, carbon monoxide, particulate matter (mostly tar), nicotine, nitrogen oxides, hydrogen cyanide, ammonia, formaldehyde, phenol and dozens of other well known toxic compounds. Some of these components are present in extremely high concentrations. We used approximately a typical smoking pattern that consists of one 35 cm3 "puff" of 2 seconds duration once per minute.



Mainstream (MS) smoke is the smoke which is directly inhaled by the smoker, whereas sidestream (SS) or secondhand smoke is the smoke which is released to the environment from the burning cigarette. Measurements on both SS and MS smoke have been made for many of the toxic constituents in cigarettes . The ratio of the mass released in SS vs MS smoke is ~ (1-10) for a typical smoking pattern. This means that total emissions are greatest in the SS smoke, although this depends on the compound and the type of cigarette. Many cigarette brands have 3 ventilation slits in or near the filter, which will dilute the concentration of tar, CO and other compounds in the MS smoke. Our goal was to predict concentration of CO minimizing the complexities as much as possible. We ignore differentiation between MS and SS smoke and instead of it we want to focus on a total smoke sample obtained by continuously "smoking" the cigarette. We used differente classes of cigarettes with filter.

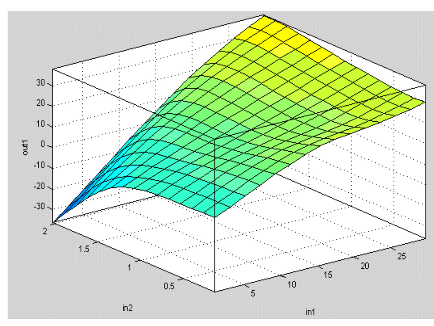
Experimental

Prediction of contrentation CO in filtered cigarette is a typical nonlinear regression problem, in which several attributes of the cigarette's profile information are used to predict another continuous attribute, that is, the CO contentration. The training data was used from Tobbaco laboratories in Sarajevo. It contains the data collected from cigarettes of various manufactures.

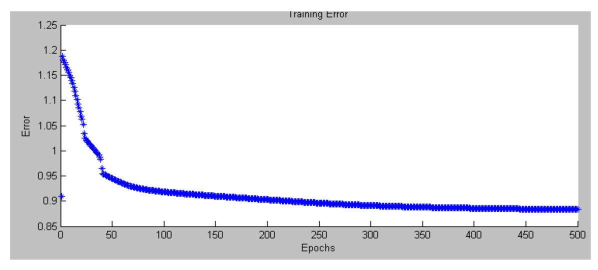
The four input attributes are: length of cigarette/mm, weight of cigarrete/g, tar/mg, nicotine/mg; the output variable to be predicted is the CO concentration. (The Cigarette's manufacturers and models in the first column of Table. are not used for prediction. The data set is obtained from the original data file 'cigarette.dat' (a part of Table is shown below):

Brand	Tar (mg)	Nicotine (mg)	Weight (g)	CO(mg)
Camel Lights	8	0,67	0,928	10,2
Carlton	4,1	0,4	0,9462	5,4
Chesterfield	15	1,04	0,8885	15
Golden Lights	8,8	0,76	1,0267	9
Kent	12,4	0,95	0,9225	12,3
Kool	16,6	1,12	0,9372	16,3
L & M	14,9	1,02	0,8858	15,4
Lark Lights	13,7	1,01	0,9643	13
Marlboro	15,1	0,9	0,9316	14,4
Merit	7,8	0,57	0,9705	10
D.d. soft	12	0,9	0,981	10,1
A.s.light	4	0,4	1,02	9,7
Code	8	0,7	0,99	10

In a real-world domain, just like the one used in the present study, all of the features used in the descriptions of instances may have different levels of relevancy. In the present study, the changes of the final (after training) generalized bell shaped membership functions, with respect to the initial generalized bell shaped membership functions of the input parameters, were examined. The input-output surface of the best two-input ANFIS model for CO prediction is shown in Figure.



Then we partition the data set into a training set and a checking set and try to find the input attributes that have better prediction power for ANFIS modeling. 'Weight' and 'Tar' are selected as the best two-input variables. The feature 'Length of filter' has bigger impact on CO in cigarette than type of filter. The training and checking errors are getting distinguished, indicating the out set of overfitting. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm [4]. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [2,3]. We trained the fifth ANFIS classifier to combine the predictions of the four ANFIS classifiers. The outputs of the four ANFIS classifiers were used as the inputs of the fifth ANFIS classifier. We used a generalized bell shaped membership function. Average testing error is shown in Figure.



It is a surface in which the predicted CO increases with the increase in 'Weight' and decrease in 'Filter Lenght'. The training RMSE (root mean squared error) is 0.883; the checking RMSE is 0.95. For comparison, a simple linear regression [5], using all input candidates, results in a training RMSE of 4.452, and a checking RMSE of 4.598.

Conclusion

This paper presented a new application of the ANFIS model for the detection of CO in different types of cigarettes. The use of fuzzy logic enabled us to use this uncertainty in the classifiers designs and consequently to increase the credibility of the systems outputs. The four ANFIS classifiers were used to detect CO in different types of cigarretes. The predictions of the ANFIS classifiers were combined with the fifth ANFIS classifier. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. The total classification accuracy of the ANFIS model was 96.5%. We have, therefore, concluded that the proposed ANFIS model can be used in detecting CO in cigarrettes by taking into consideration the misclassification rates.

Literature

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