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Adaptive Neuro Fuzzy Inference System Mathematical Model for Detecting Gasoline Type Using Inter Digital Capacitance Sensor

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ABSTRACT - In the context of global warming, governments worldwide are striving to control emissions from combustion engines by promoting higher RON gasoline types. However, the higher cost of these fuels has led to a decrease in their usage. Detecting the type of gasoline in a vehicle is a complex and inefficient process. Therefore, this research presents a mathematical model for identifying gasoline type and its components using an Inter Digital Capacitor (IDC) sensor, a small and cost-effective sensor. The model aims to establish a relationship between gasoline type and the components, as well as identify gasoline components in the electrical characteristics. The model has achieved high accuracy, with a small error of 4.03 × 10^-5, demonstrating its effectiveness in building these relations. The conclusion of this study is that mathematical modeling with ANFIS can be used to explain the relationship between the components that make up gasoline and the capacitance value of the IDC sensor used to measure it.

Keywords: sensor, inter digital capacitor (IDC), gasoline, research octane number, ANFIS.

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INTRODUCTION

Over the last decade, a substantial body of research has been dedicated to identifying and implementing effective methods for mitigating the consequences of global warming. One of the simplest and most popular ways to reduce global warming is to use green energy. Today, the world is moving toward green energy in order to support sustainable development goals. In Indonesia, the concept of green energy in the transport sector is reflected in the shift toward less-polluting fuels, specifically those with higher research octane numbers (RON) of RON 92 and RON 95, which offer improved combustion efficiency and reduced emissions (Suhaldin et al., 2022), to achieve Euro 3 emissions standards. However, this type of fuel is expensive, and thereby almost everyone is still using a cheaper one, such as RON 90.

Traditionally, to determine which fuel is in the car tank, there is a need to take a fuel sample for the purpose of laboratory analysis. This process was time-consuming and very costly. Therefore, to enforce the policy, the government needs a cheaper device that acts as a sensor to easily detect fuel type in the car tank and provide faster readings than traditional ones.

Several investigations are carried out using the inter digital capacitor (IDC) sensor to detect liquid content (Ludeña-Choez et al., 2025). IDC sensor is a capacitive sensor that converts physical parameters into electrical quantities (capacitance) (Rahayu et al., 2019). The interaction of the dielectric material with the electric field transmitted by the coplanar IDC electrode sensor can change the capacitance value (Zhou et al., 2024). Gonçalves et al. (2007) propose IDC to verify the quality of automotive ethanol fuel. According to Gonçalves' results, each fuel type can be distinguished by its compositional profile, provided that an appropriate mathematical model is available.

This research introduces the adaptive neuro fuzzy inference system (ANFIS) mathematical model, which was developed based on the capacitive value obtained from the IDC sensor. This method enables the easy identification of fuel type based on the electrical characteristics in the car tank. The potential impact of these results on future developments in fuel detection is promising, inspiring optimism for further advancements in this field.

METHODOLOGY

Adaptive neuro fuzzy inference system (ANFIS)

Bellman & Zadeh (1970) created a fuzzy system 1970 for decision-making in an uncertain environment. However, today, fuzzy systems are mainly used for control, such as controlling robot movement (Dewi et al., 2024). However, fuzzy systems can be used for a wide range of applications, from optimization (Suwoyo et al., 2024) to decision-making (Romahadi et al., 2024). ANFIS is basically an upgrade to a fuzzy system, which combines a fuzzy system with a neural network, allowing it to adjust the nodes based on calculations. Similar to other neural network methods in machine learning, they are capable of addressing practical challenges, including the prediction and analysis of gas flow (Adrianto et al. 2025), Seismic Reservoir Characterization (Widarsono et al., 2022), and total organic carbon prediction (Wardhana et al., 2021). ANFIS architecture based on Jang's (1993) work can be seen in Figure 1.

The square-shaped nodes represent adaptive nodes, while the circular shapes represent fixed nodes. In stage one, each output is represented by 0^{1}_{i}, which increases the degree of membership .

$$0^{1}_{i} = \mu Ai(x) \text{ and } 0^{1}_{i} = \mu Bi(x), i = 1,2 \tag{1}$$

In this stage, every membership function can be used, but in Jang's method, generalized bell membership functions were used to provide two outputs: which is maximum equal to 1, and minimum equal to 0 (Jang 1993). Therefore, the following was obtained:

$$\mu Ai(x) = \frac{1}{1 + \left[\left(\frac{x - Ci}{ai}\right)^{2}\right] bi} \tag{2}$$

The second stage is constructed by multiplying the two input signals (Equations 1 and 2). Every node represents the firing strength of fuzzy inference.

$$O^{2}_{i} = \mu Ai(x).\mu Bi(x), i = 1,2 \qquad (3)$$

For the next stage, normalization was applied to each fuzzy inference firing strength.

$$O^{3}_{i} = Wi = \frac{Wi}{W1 + W2}, i = 1,2 \qquad (4)$$

The next stage involves calculating the output based on the rule's consequent parameters.

$$O^{4}_{i} = \mathrm{Wi}\,.\,\mathrm{Fi} = \mathrm{Wi}\,(\mathrm{Pix} + \mathrm{Qix} + \mathrm{Rix}), \quad i = 1,2 \qquad (5)$$

The last stage computes the overall output as the summation of all input signals.

$$O^{5}_{i} = \text{total Output} = \sum_{k=0}^{n} \mathrm{Wi\ Fi} = \frac{\sum_{k=0}^{n} \mathrm{Wi\ Fi}}{\sum_{k=0}^{n} \mathrm{Wi}} \qquad (6)$$

Since ANFIS learns using gradient descent and the chain rule, the error rate needs to be known for each node's output during training. Assuming the i-th position node outputs as O_i while the training data set has P number of entries, the error function can be measured as:

$$Ep = \sum_{m=1}^{\#L} (\mathrm{Tmp} - O^{L}_{mp})^2 \qquad (7)$$

Tmp is the m component from the P output target vector, and is the m component from the actual output vector that the P input vector has produced. Hence, the error rate can be calculated as:

$$\frac{\partial Ep}{\partial O^{k}_{i\,p}} = \sum_{m=1}^{\#k+1} \frac{\partial Ep}{\partial O^{k+1}_{m\,p}} \frac{\partial O^{k+1}_{m\,p}}{\partial O^{k}_{i\,p}} \qquad (8)$$

where 1 ≤ k ≤ L-1 is the error rate of an internal node, it is expressed as a linear combination of the error rates of the nodes in the next stages. For all 1 ≤ k ≤ L and 1 ≤ i, $\frac{\partial Ep}{\partial O^{k}_{i\,p}}$ ca be found using Equations 7 and 8. According to the results, α is a parameter of the adaptive network.

$$\frac{\partial E}{\partial \alpha} = \sum_{O*\epsilon S} \frac{\partial Ep}{\partial O*} \frac{O*}{\partial \alpha} \qquad (9)$$

S denotes the set of nodes whose outputs depend on α. Derivative for overall error measurement E with respect to α is:

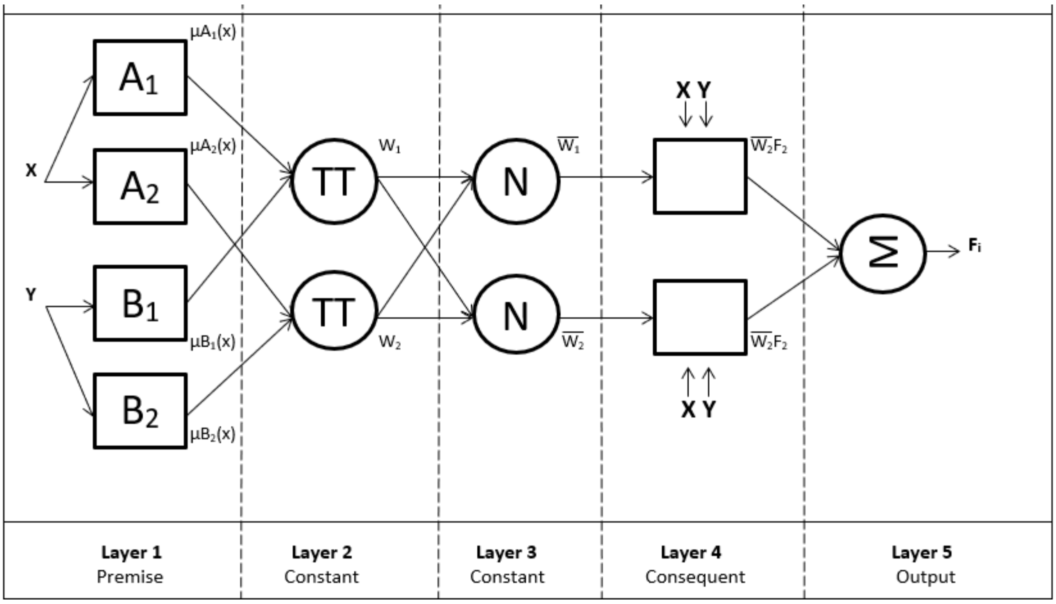


Figure 1. ANFIS Architecture (Jang et al., 1997). This figure represents a two-input, two-rule ANFIS architecture where fuzzy inference is enhanced through neural network learning to adapt membership and consequent parameters.

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{p} \frac{\partial Ep}{\partial \alpha} \tag{10}$$

Therefore, the updated formula for the generic parameter α is as follows:

$$\Delta\alpha = \eta \frac{\partial E}{\partial \alpha} \tag{11}$$

where η is a learning rate that can be written as,

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} (\frac{E}{\alpha})^2}} \tag{12}$$

In this equation, k is the step size, the length of each gradient transition in the parametric space.

Inter digital capacitor (IDC) sensor

IDC model is a form of development of the basic concept of parallel plate capacitors (Habboush et al., 2024). In parallel-plate capacitors, the capacitance depends on the magnitude of the electric field in the capacitor's plates and the permittivity of the material. The parallel-plate capacitor model has a capacitance (C) proportional to the permittivity of free space (ε_0) and the relative permittivity of the material (ε_r). The considerable capacitance value is influenced by the dimensions of the electrode surface area (A) and the distance between the plates (D), which are formed in a mathematical equation (Rahayu et al., 2019):

$$C = \varepsilon_0 \varepsilon_r \frac{A}{D} \tag{13}$$

The morphology of the IDC-S system can be viewed as a form of coplanar capacitor with continuous repetition. The periodicity of the electrode spacing creates an electric field above the electrode plane (Ren et al., 2024). Figure 2 shows the interdigital structure of a capacitor with two electrodes, namely the signal source (electrode-A) and the receiver (electrode-B). Therefore, because A is a continuous repetition, Equation 13 can be simplified to become :

$$C = \varepsilon_0 \varepsilon_r \frac{(L.W.N)}{G.(N-1)} \tag{14}$$

Gasoline versus RON number

According to Myers et al. (1975), gasoline octane numbers are a linear combination of the isoparaffin index, the aromatic content (volume %), the lead content (g/gal), and the sulfur content (weight %). Therefore, the chemical composition can be defined, as shown in Equation 15.

$$\text{RON} = P + I + Ar + Le + Su \tag{15}$$

where :

RON= is Gasoline RON number.

P =is Parafin content which have a methyl to methylene ratio between 5.0 and 0.4.

I = is Isoparaffin Index.

Ar = is Aromatic Content.

Le = is Lead Content.

Su = is Sulfur Content.

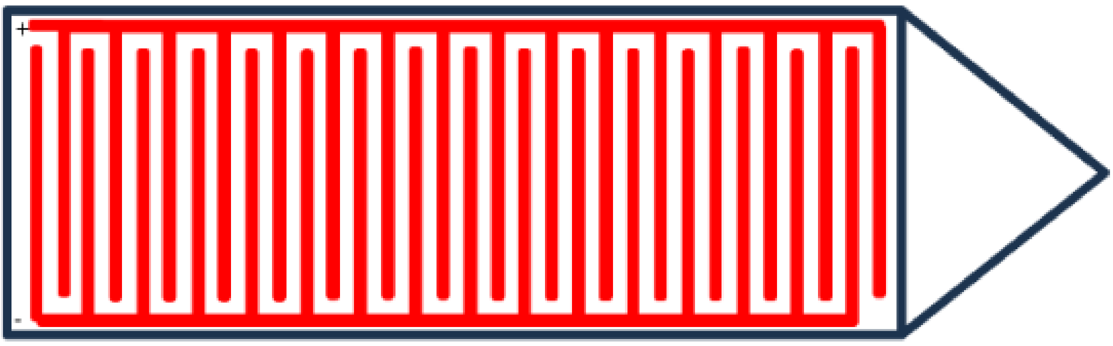


Figure 2. IDC Sensor design. The figure shows a planar interdigital capacitor (IDC) sensor, consisting of interleaved metal fingers that produce a fringing electric field.

Lead poses well-documented hazards to human health, leading to its removal from gasoline formulations and its discontinued use as a RON-enhancing additive (Kerr & Newell 2003). Therefore, Equation 15 has become obsolete. Viteri then built a table for Gasoline composition classified by hydrocarbon groups using PIONA analysis, which has been distributed in Saudi Arabia (Naggar et al., 2017) and China (Tang et al., 2015). However, several unknowns and others are not specified, including Naphthenes and Total C14, which have only two values in Viteri, hence, they are removed from Table 1.

The table 1 shows that differences in gasoline composition directly influence the RON value, where high-octane fuel (RON 95) contains more high-octane aromatic and olefin compounds while low-octane gasoline (RON 92) relies more on paraffins and octane-boosting additives like MTBE.

RESULT AND DISCUSSION

Fuel measurement using IDC sensor

Gasoline types that are used in ASEAN were RON 90, RON 92, RON 94, and RON 95 (E. & W., 1987). However, RON 92 and RON 95 can be measured because RON 90 will be phased out according to the emission regulation (Kementrian LHK 2017), and RON 94 is not available in Indonesia. The measurement is carried out based on the respective RON value as seen in Figure 2 and Table 2.

Table 2. RON number versus gasoline measurement

RON number	Capacitance value (pF)
92	23.45
95	23.04

Table 1. RON number versus gasoline composition (Tang et al., 2015).

RON number	Paraffins	Isoparaffins	Olefins	Aromatics	Metil tersier butil eter	Aniline
92	50.2	50.2	9	31.9	4.3	0.28
95	37.4	37.4	12.4	41.4	1.8	0.24

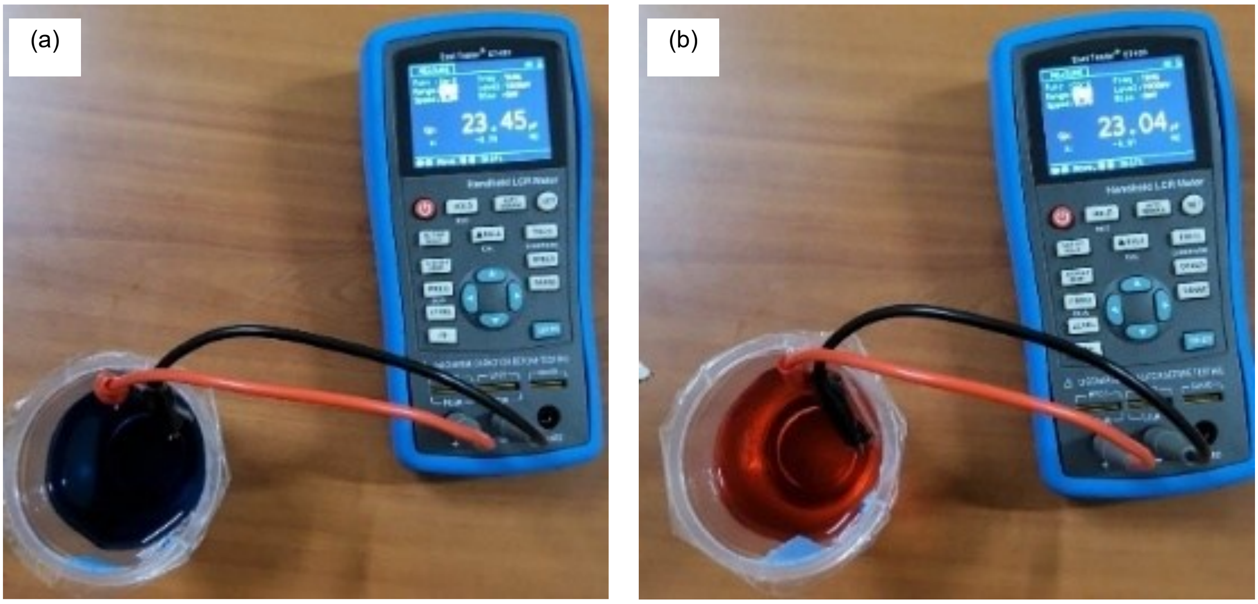
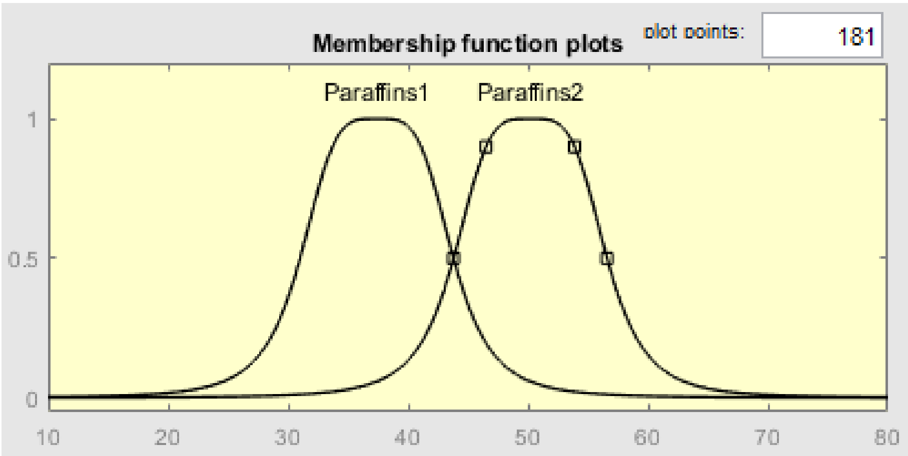


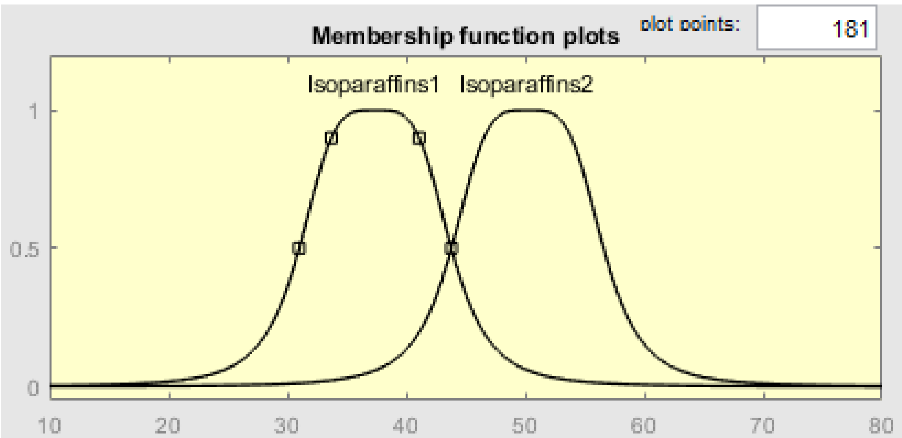
Figure 3. Gasoline measurement using IDC. (a). RON 92 measurement and (b). RON 95 measurement . This measurement demonstrates a non-destructive, electrical property based method for determining the octane rating of gasoline using IDC capacitive sensor as the dielectric detector and RLC/LCR meter for accurate capacitance measurement.

ANFIS mathematical model for gasoline composition versus capacitance

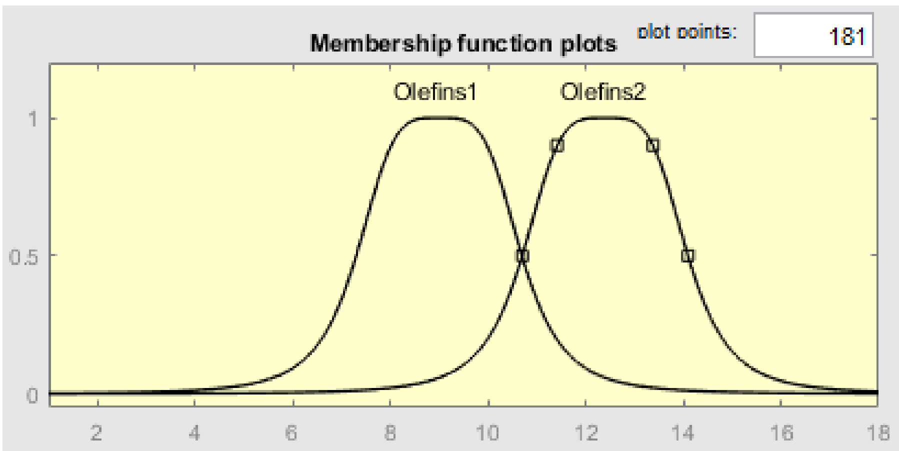
In this section we model the ANFIS using matlab 2025b software. According to Tables 1 and 2, all gasoline compositions are organized according to RON values as input variables. LCR measurement is employed as the output variable. This method enables the construction of an ANFIS mathematical model that illustrates the relationship between gasoline chemical composition and the corresponding electrical variable, in this case, capacitance. Fuzzification is using the generalized bell function; hence, the input model can be seen in Figure 4:



(a)



(b)



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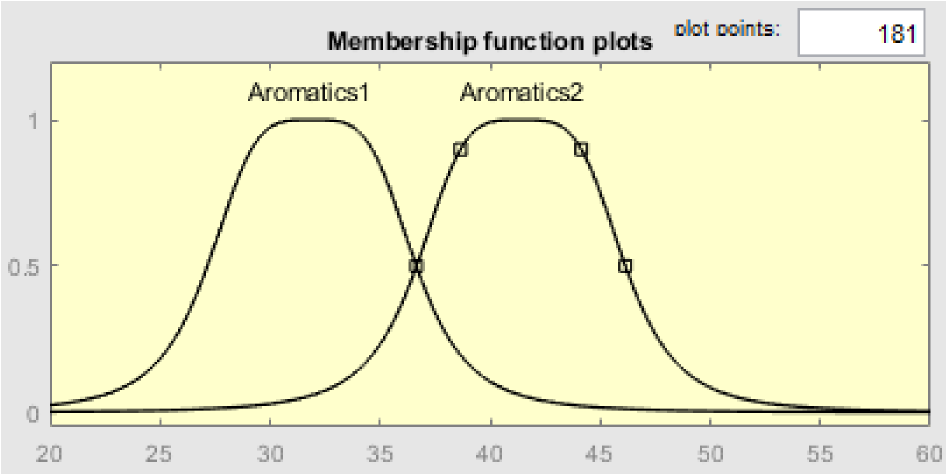

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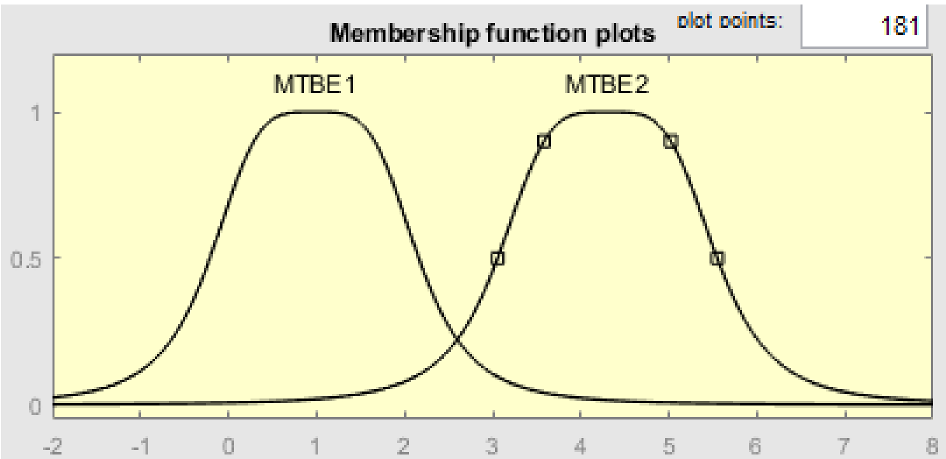
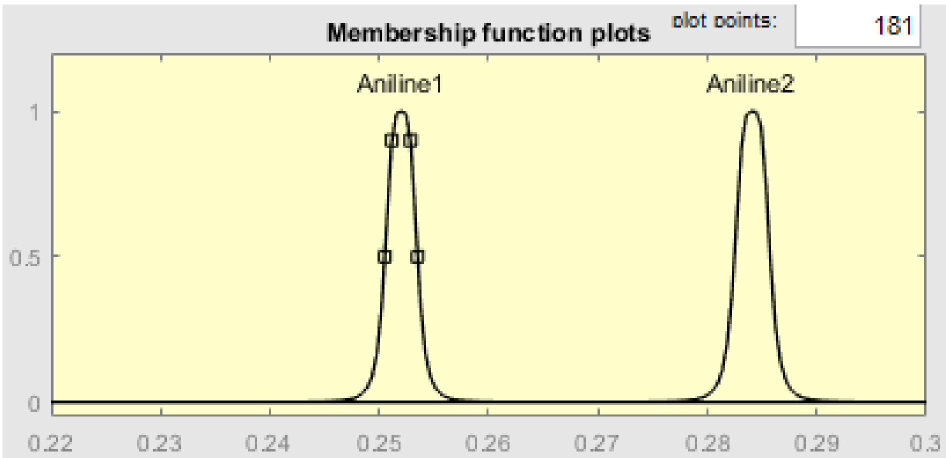


(e)



(f)

Figure 4. fuzification model for each gasoline component. (a). Paraffins, (b). Isoparaffins, (c). Olefins, (d). Aromatics, (e). Methyl tertiary butyl ether, and (f). Aniline. Figure 4 shows fuzzification of gasoline component concentrations using generalized bell shaped membership functions with two overlap fuzzy sets that plotted on the same axis.

Table 3. Fuzification model for each gasoline component.

Linguistic Variable	Fuzzification input		
	a	b	c
Paraffins 1	6.399	2.001	37.4
Paraffins 2	6.399	2.001	50.2
Isoparaffins 1	6.399	2.001	37.4
Isoparaffins 2	6.399	2.001	50.2
Olefins 1	1.698	2.001	8.999
Olefins 2	1.698	2.001	12.4
Aromatics 1	4.749	2.001	31.9
Aromatics 2	4.749	2.001	41.4
MTBE 1	1.247	2.001	1.798
MTBE 2	1.247	2.001	43.02
Aniline 1	0.001671	2	0.236
Aniline 2	0.001629	2	0.2841

Table 4. Fuzzy constant output

Index No.	Fuzzy Constant Output F_A^P	Index No.	Fuzzy Constant Output F_A^P	Index No.	Fuzzy Constant Output F_A^P	Index No.	Fuzzy Constant Output F_A^P
1	0.1031	17	0.006059	33	0.006059	49	0.000507
2	0.00613	18	0.1043	34	0.1043	50	1.778
3	0.005993	19	0.000504	35	0.000504	51	0.00263
4	0.1055	20	1.798	36	1.798	52	30.63
5	1.757	21	0.1031	37	0.1031	53	0.006061
6	0.000469	22	0.006128	38	0.006128	54	0.1043
7	0.102	23	0.005995	39	0.005995	55	0.000505
8	0.006198	24	0.1055	40	0.1055	56	1.797
9	1.766	25	0.1037	41	0.1037	57	0.006094
10	0.0004676	26	0.006094	42	0.006094	58	0.1037
11	0.1025	27	0.006028	43	0.006028	59	0.000506
12	0.006164	28	0.1049	44	0.1049	60	1.787
13	30.1	29	1.767	45	1.767	61	0.1037
14	0.0019	30	0.000468	46	0.000468	62	0.006092
15	1.747	31	0.1026	47	0.1026	63	0.00603
16	0.0004703	32	0.006161	48	0.006161	64	0.1049

According to Zadeh (1975), fuzzy foundation was developed from "Linguistic Variables and Their Applications to Approximate Reasoning" based on input from the uncertainty environment. Building on these foundations, fuzzy rule was developed to model the qualitative aspects of human expertise, reasoning based on experience, and to address or adapt to the problem effectively (Bellman & Zadeh 1970). Therefore, using Equation (3), the rule can be written and shown in Equation 16.

$$W_1^i = P_1^i(\mathrm{x}).I_1^i(\mathrm{x}).Ar_1^i(\mathrm{x}).LE_1^i(\mathrm{x}).Su_1^i(\mathrm{x}) \quad (16)$$

where :

W_1^i = Rule weight for Fuzzy firing strenght.

P_1^i = Parafin from first sets until i-sets.

I = Isoparaffin from first sets until i-sets.

Ar = Aromatic from first sets until i-sets.

Le = Lead from first sets until i-sets.

Su = Sulfur from first sets until i-sets.

x = Value of each component.

Furthermore, fuzzy constant output for the ANFIS mathematical model can be seen in Table 4.

The mathematical model for this can be seen in Equation 17 .

$$B_i = \frac{\sum_{k=0}^{n} \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^{2b_i}\right]} \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^{2b_i}\right]} F_A^P}{\sum_{k=0}^{n} \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^{2b_i}\right]} \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^{2b_i}\right]}} \quad (17)$$

Using the mathematical model in Equations 17 and 1000 loops for data training, the model then achieves an error of 4.03×10^{-5} .

The results in Table 2 and Figure 3 demonstrate that the IDC capacitive sensor is capable of distinguishing gasoline types based on their respective Research Octane Number (RON) values. The capacitance values obtained for RON 92 and RON 95 gasoline were 23.45 pF and 23.04 pF, respectively. Although the difference appears relatively small, the measurable variation indicates that the dielectric characteristics of gasoline change according to chemical composition and octane rating. This confirms that the IDC method provides a non-destructive and real-time measurement approach, offering an alternative to conventional chemical analysis techniques that typically require laboratory equipment and destructive sample preparation.

The development of the ANFIS mathematical model further reinforces the relationship between gasoline composition and sensor output. The fuzzification process applied to six gasoline components paraffins, isoparaffins, olefins, aromatics, MTBE, and aniline enables representation of nonlinear interactions using generalized bell shaped membership functions, as shown in Figure 4 and Table 3. These membership functions reflect the actual compositional variability of commercial gasoline blends and provide a realistic mapping structure for the fuzzy inference engine.

The ANFIS model optimization process, utilizing 1000 training loops, results in a very low error value of 4.03×10^{-5}, demonstrating strong agreement between predicted and measured capacitance values. This indicates that the model successfully captures the underlying nonlinear correlation between gasoline composition and the electrical property detected by the IDC sensor. Additionally, the fuzzy constant output matrix presented in Table 4 supports multi rule structural configuration, allowing the model to adapt to variations in mixture components.

CONCLUSION

In conclusion, the proposed model has effectively established the relationships among gasoline types, their components, and electrical characteristics. By utilizing the IDC sensor and ANFIS, a highly accurate gasoline identification was achieved with an error as low as 4.03×10^{-5}. These results underscore the broad applicability and potential of the methodology. Future work will involve extending this method to include diesel fuels, thereby further enhancing the scope and impact of the research. Overall, these findings confirm that combining IDC capacitive sensing with ANFIS modeling is a feasible and reliable method for identifying gasoline octane rating based on real-time electrical measurements. The approach shows potential for practical implementation in fuel quality monitoring systems. Although this method can be use for real world field measurement, however the scope of this study was limited to commercially available RON 92 and RON 95 fuels due to the phase-out of RON 90 and the unavailability of RON 94 in Indonesia. Therefore, future work may expand testing to wider sample variations and investigate environmental factors such as temperature and contamination effects.

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GLOSSARY OF TERMS

Symbol	Definition	Unit
RON	Research Octane Number	-
ANFIS	Adaptive Neuro Fuzzy Inference System, a hybrid machine learning system between a Neural network and fuzzy	-
$\mu Ai(x)$	Fuzzy Sets	-
O_i^1	Fuzzy, degree of membership	-
O_i^2	Fuzzy, Multiplying input	-
O_i^3	Fuzzy, Normalization input	-
O_i^4	Fuzzy, Rule Consequent	-
O_i^5	Fuzzy, summation of all inputs	-
Ep	Error function based on P number	-
ıp	m component from the P output vector	-
O_{mp}^L	m component from actual output	-
Ep	Error rate calculation	-
	Parameter of the adaptive network	-
$\frac{\partial E}{\partial \alpha}$	Derivative for the overall error Measurement E with respect to α	-
η	Learning rate	-
	Capacitor Value	Farad
ε_0	Permittivity of free space	F/m
ε_r	Relative permittivity of the material	F/m
	Distance between the plates	Meter
	Electrode Surface Area	Meter
	Electrode Length	Meter
	Electrode Width	Meter
	Number of periodic Electrodes	
	Gap width between the electrodes	Meter
	Paraffins, which have a methyl to methylene ratio between 5.0 and 0.4	-
	Isoparaffin Index	-
	Aromatic Content	volume %
	Lead Content	g/gal
	Sulfur Content	weight %
R	An instrument used to measure the inductance, capacitance, and resistance of components	Henry, Farad, Ohm
F_A^P	Fuzzy Constant Output	-
	Input variables for ANFIS	-
a_i	Describe the broadness of the membership function input.	-
b_i	Describe the form of the curve on either side of the middle input.	-
c_i	Describe the center of the membership function input.	-
	Total summation of ANFIS Inference Output such as capacitance value	-

REFERENCES

Adrianto, A., Syihab, Z., Marhaendrajana, T., & Sutopo, S. (2025). Backpropagation neural networks for solving gas flow equations in porous media. International Journal of Artificial Intelligence (IJ-AI), 14(5), 3744–3756. https://doi.org/10.11591/ijai.v14.i5.pp3744-3756.

A.S. Nasution. (1987). Cooperative Determination of Octane Requirement For Car Populations In Asean Countries. Scientific Contributions Oil and Gas, 10(3). https://doi.org/10.29017/SCOG.10.3.1149.

Bellman, R. E., & Zadeh, L. A. (1970). Decision-Making In A Fuzzy Environment, NASA Contractor Report 1594.

Dewi, T., Bambang, M. R., Kusumanto, R., Risma, P., Oktarina, Y., & Sakuraba, Takahiro Fudholi, Ahmad Rusdianasari, R. (2024). Fuzzy logic-based control for robot-guided strawberry harvesting: visual servoing and image segmentation approach. Sinergi, 28(3). https://doi.org/10.22441/sinergi.2024.3.021.

Gonçalves, L., Mendonça, D., Torikai, D., & Ibrahim, R. C. (2007). Interdigitated Capacitive Sensor To Verify The Quality Of Ethanol Automotive Fuel. In 19th International Congress of Mechanical Engineering.

Habboush, S., Rojas, S., Rodríguez, N., & Rivadeneyra, A. (2024). The Role of Interdigitated Electrodes in Printed and Flexible Electronics. Sensors, 23(9), 2717. https://doi.org/https://doi.org/10.3390/s24092717.

Jang, J.-S. R., Sun, C.-T., & Mizutani, E. (1997). Neuro-Fuzzy and Soft Computing A Computational Approach to Learning and Machine Intelligence. Prentice Hall.

Jang, J. S. R. (1993). ANFIS: Adaptive-Network-Based Fuzzy Inference System. IEEE Transactions on Systems, Man and Cybernetics, 23(3), 665–685. https://doi.org/10.1109/21.256541.

Kerr, S., & Newell, R. G. (2003). Policy-induced technology adoption: Evidence from the U.S. lead phasedown. The Journal Of Industrial Economics, 51(3), 317–343. https://doi.org/10.4324/9781351161084-11.

LHK, P. (2017). Peraturan Menteri Lingkungan Hidup Dan Kehutanan Republik Indonesia. Nomor P.20/MENLHK/SETJEN/Kum.1/3/2017 Tentang baku Mutu Emisi Gas Buang Kendaraan Bermotor Tipe Baru Kategori M, Kategori N, Dan Kategori O. Indonesia: Kementrian Lingkungan Hidup Dan Kehutanan, Republik Indonesia.

Ludeña-Choez, J., Choquehuanca-Zevallos, J. J., Carranza-Oropeza, M. V., Salas-Arias, E. C., & Pérez-Montaño, H. S. (2025). Comparative study of the capacitance sensitivity of interdigital capacitive sensors based on graphene for the measurement of Cd+2 concentration. Computers and Electronics in Agriculture, 230(December 2024). https://doi.org/10.1016/j.compag.2024.109810.

Myers, M. E., Stollsteimer, J., & Wims, A. M. (1975). Determination of Gasoline Octane Numbers from Chemical Composition. Analytical Chemistry, 47(13). https://doi.org/10.1021/ac60363a015.

Naggar, A. Y. E., Elkhateeb, A., Altalhi, T. A., El Nady, M. M., Alhadhrami, A., Ebiad, M. A., Elhardallou, S. B. (2017). Hydrocarbon compositions and physicochemical characteristics for the determination of gasoline quality: An implication from gas chromatographic fingerprints. Energy Sources, Part A: Recovery, Utilization and Environmental Effects, 39(15), 1694–1699. https://doi.org/10.1080/15567036.2017.1370515

Rahayu, E. R., Aminudin, A., & Iryanti, M. (2019). Design and characterization of capacitive sensor for soil water content measurement. Journal of Physics: Conference Series, 1280(2). https://doi.org/10.1088/1742-6596/1280/2/022060.

Ren, Y., Luo, B., Feng, X., Feng, Z., Song, Y., & Yan, F. (2024). Capacitive and Non-Contact Liquid Level Detection Sensor Based on Interdigitated Electrodes with Flexible Substrate. Electronics (Switzerland), 13(11). https://doi.org/10.3390/electronics13112228.

Romahadi, D., Feriyanto, D., Anggara, F., Wijaya, F. P., & Dong, W. (2024). Intelligent system design for identification of unbalance and misalignment using Fuzzy Logic methods. Sinergi, 28(2), 241–250.

Suhaldin, Syafiudin, & Haruna. (2022). The Effect of Fuel Octane Value on Emission Levels in Manual (Four-Stroke) Motorcycles. Journal of Vocational and Automotive Engineering, 1(1), 2022–2030.

Suwoyo, H., Hajar, M. H. I., Indriyanti, P., & Febriandirza, A. (2024). The use of Fuzzy Logic Controller and Artificial Bee Colony for optimizing adaptive SVSF in robot localization algorithm. Sinergi, 28(2), 231–240. https://doi.org/10.22441/sinergi.2024.2.003

Tang, G., Sun, J., Wu, F., Sun, Y., Zhu, X., Geng, Y., & Wang, Y. (2015). Organic composition of gasoline and its potential effects on air pollution in North China. Science China Chemistry, 58, 1416–1425. https://doi.org/10.1007/s11426-015-5464-0.

Wardhana, S. G., Pakpahan, H. J., Simarmata, K., Pranowo, W., & Purba, H. (2021). Algoritma Komputasi Machine Learning untuk Aplikasi Prediksi Nilai Total Organic Carbon (TOC). Lembaran Publikasi Minyak Dan Gas Bumi, 55 (2), 75–87. https://doi.org/10.29017/lpmgb.55.2.606.

Widarsono, B., Saptono, F., Wong, P. M., & Munadi, S. (2022). Application of Artificial Neural Network for Assisting Seismic-Based Reservoir Characterization. Scientific Contributions Oil and Gas, 25(1), 2–11. https://doi.org/10.29017/SCOG.25.1.879.

Zadeh, L. A. (1975). The Concept of a Linguistic Variable and its Application to Approximate Reasoning. Information Sciences, 8(3), 199–249.

Zhou, Z., Wang, R., Yang, Z., Shen, X. F., Xiong, Y., & Feng, Y. (2024). The semi-analytical model of electric field and capacitance in a multilayer-structured interdigital electrode capacitor. Applied Mathematical Modelling, 136, 115632. https://doi.org/10.1016/j.apm.2024.08.004.