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A comparative analysis of gaussian and trapezoidal membership functions for the assessment of the technical condition of a locomotive diesel engine based on ANFIS

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ABSTRACT

This article reviews the problem of technical condition assessment of locomotive diesel engine using Adaptive Neuro-Fuzzy Inference System (ANFIS). The research is conducted using real operational data from a 2TE25KM series locomotive using the MCS (Microprocessor-based Control System). The following two diagnostic models were developed: oil pressure prediction model as well as exhaust gas temperature-based inter-cylinder imbalance prediction model. Gaussian and trapezoidal membership functions were used individually for each model and compared with the RMSE, MAE and correlation coefficient (R). Both R values were high and almost the same for the oil pressure model but for the exhaust gas model, the R value for the trapezoidal function ($R = 0.51$) was significantly more stable than the Gaussian function ($R = -0.03$). This shows trapezoidal membership functions superiority in small volume and noise diagnostic data.

Keywords: ANFIS, locomotive diesel engine, technical condition assessment, Gaussian membership function, trapezoidal membership function, Sugeno fuzzy system, technical diagnostics.

Сравнительный анализ гауссовской и трапециевидной функций принадлежности для оценки технического состояния локомотивного дизельного двигателя на основе ANFIS

АННОТАЦИЯ

В настоящей статье рассматривается задача оценки технического состояния дизельного двигателя локомотива с использованием адаптивной системы нечеткого логического вывода (ANFIS).

Ключевые слова: ANFIS, локомотивный дизельный

Исследование проводилось на основе реальных эксплуатационных данных, полученных с локомотива серии 2ТЭ25КМ при помощи системы контроля и диагностики параметров движения (МСУ). Были разработаны две диагностические модели: модель прогнозирования давления масла, а также модель прогнозирования межцилиндрового дисбаланса по температуре отработавших газов. Для каждой модели по отдельности применялись гауссовская и трапецеидальная функции принадлежности, результаты для которых сравнивались по показателям RMSE, MAE и коэффициенту корреляции (R). В модели давления масла оба значения R были высокими и практически одинаковыми, однако в модели отработавших газов значение R для трапецеидальной функции (R = 0,51) оказалось значительно более стабильным, чем для гауссовской (R = -0,03). Это свидетельствует о преимуществе трапецеидальных функций принадлежности при работе с зашумленными диагностическими данными малого объема.

двигатель, оценка технического состояния, функция принадлежности по Гаусу, функция принадлежности по трапеции, нечеткая система Сугено, техническая диагностика.

Lokomotiv dizel dvigatelining texnik holatini ANFIS asosida baholashda gauss va trapetsiyasimon mavjudlik funksiyalarining qiyosiy tahlili

ANNOTATSIYA

Ushbu maqolada lokomotiv dizel dvigatelining texnik holatini noaniq mantiqiy xulosalashning adaptiv tizimi (ANFIS) yordamida baholash masalasi koʻrib chiqiladi. Tadqiqot 2TE25KM seriyali lokomotivdan harakat parametrlarini nazorat qilish va diagnostika tizimi (MSU) yordamida olingan real ekspluatatsion maʼlumotlar asosida olib borildi. Ikkita diagnostik model ishlab chiqildi: moy bosimini prognozlash modeli hamda ishchi gazlar harorati boʻyicha silindrlararo nomutanosiblikni prognozlash modeli. Har bir model uchun alohida-alohida Gauss va trapetsiyasimon aʼzolik funksiyalari qoʻllanilib, ularning natijalari RMSE, MAE va korrelyatsiya koeffitsiyenti (R) koʻrsatkichlari boʻyicha taqqoslandi. Moy bosimi modelida R ning ikkala qiymati ham yuqori va deyarli bir xil boʻldi, biroq ishchi gazlar modelida trapetsiyasimon funksiya uchun R qiymati (R = 0,51) Gauss funksiyasiga (R = -0,03) qaraganda ancha barqaror ekanligi aniqlandi. Bu kichik hajmdagi shovqinli diagnostik maʼlumotlar bilan ishlashda trapetsiyasimon aʼzolik funksiyalarining afzalligidan dalolat beradi.

Kalit soʻzlar: ANFIS, lokomotiv dizel dvigateli, texnik holatni baholash, Gauss aʼzolik funksiyasi, trapetsiyasimon aʼzolik funksiyasi, Sugenoning noaniq tizimi, texnik diagnostika.

INTRODUCTION

The timely and accurate evaluation of the technical state of the main part of the locomotive – a diesel-generator unit – is necessary for the reliable and uninterrupted operation of the locomotive in railway transport. Classic diagnostic approaches (periodic maintenance schedules, threshold values) do not consider nonlinear and interdependent relationships between the parameters; this can lead to a premature diagnosis (unjustified) or it can lead to a delayed diagnosis (only after the fault).

Technical diagnostics is an area in recent years that has been extensively used artificial intelligence techniques, especially the adaptive neuro-fuzzy inference systems (ANFIS). ANFIS is a fuzzy logic system in which self-learning ability of ANNs is added to the interpretability of fuzzy logic system, which is suitable for modeling the diagnostic relationships between the variables that are nonlinear. There are a number of studies on the application of ANFIS in the diagnostics of diesel engines. Liu et al. used artificial neural fuzzy interference system (ANFIS) to propose a model for diagnosing the malfunctions of diesel engines, and Han et al. proposed a multi-signal diagnostic method based on the optimized ANFIS. Meanwhile, most of the literature relies on Gaussian type membership functions, and comparing these with trapezoidal membership functions is not well studied for the case of locomotive diesel engine. The aim of this research is to design ANFIS models for two important parameters, namely oil pressure and exhaust gas temperature imbalance in a locomotive diesel engine with Gaussian and trapezoidal membership functions and to compare their prediction accuracy with real operating data.

2. MATERIALS AND METHODS

2.1. Research object and data source

For this study, the Section "A" 449 of 2TE25KM diesel locomotive was chosen. This locomotive's data was recorded from an actual operation between 22nd December 2025 and 22nd January 2026 (31 days).

In this study, locomotive number 449 (2TE25KM series) was chosen from part of its section "A". The data was obtained by the on-board MCS (Microprocessor-based Control System) of this locomotive in the period from 22 December 2025 to 22 January 2026 (31 days of running).

Two sets of diagnostic data were created in the scope of the study:

- Set 1 (Oil Pressure): Oil pressure (T1), relationship between oil temp and oil pressure - 43 observations;

- Set 2 (Exhaust Gases): Controller position, Average Exhaust Gas Temp, and the Max temp deviation between the 16 cylinders (8+8) — 22 observations[1].

Conceptually the process of collecting real operational data from the MPSU on board system of the locomotive, sorting real data and preparing them for input towards ANFIS is depicted in Figure 1.

A sample of the data is presented in Table 1:

Table 1.

Description of the datasets used in the study

Collection	Sign in 1	Sign in 2	OUT	N (observations)
Oil pressure	Throttle Notch	Oil temperature, °C	Oil pressure, kgs/sm²	43
Gas unbalance	Throttle Notch	Average gas temperature, °C	Max. cylinder runout,°C	22

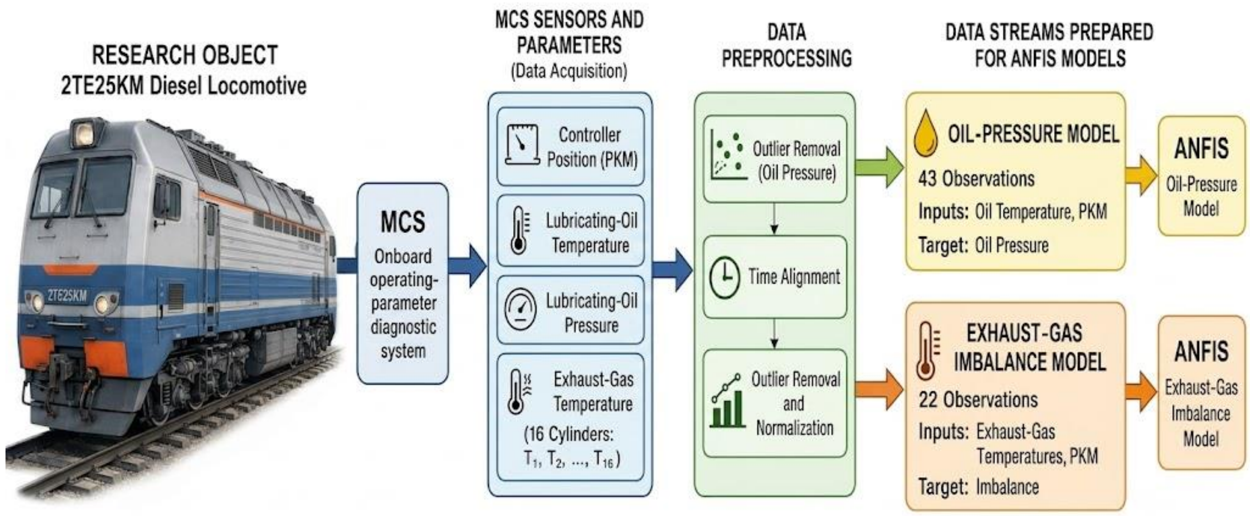

Figure 1. Conceptual scheme for the collection of data from the MCS on board diagnostics system of a 2TE25KM series diesel locomotive and its preparation for ANFIS models.

2.2. ANFIS/Sugeno-fuzzy model architecture

Fuzzy inference system of Takagi-Sugeno-Kang (TSK) type was used in the study with two inputs and one output. All of the four membership functions created by the grid partitioning method yielded a system with 2×2=4 fuzzy rules for each of the two inputs. The general rule of Sugeno is as follows[2]:

$$\text{Rule}i\text{:IF}x_1\text{is}A_i\text{AND}x_2\text{is}B_i\text{,THEN}f_i = p_i x_1 + q_i x_2 + r_i$$

The final output is a weighted average for each of the following rule conclusions:

$$y = \sum_{i=1}^{N} \bar{w}_i f_i = \frac{\sum_{i=1}^{N} w_i f_i}{\sum_{k=1}^{N} w_k}$$

The linear conclusion parameters (pi, qi, ri) were estimated by least squares estimation (LSE) method, which was fitted to the training data. A small regularization coefficient (ridge, λ = 0.3) was used to avoid parameter overfitting in small datasets (n = 22–43) to ensure computational stability.

"The 5-layer structural architecture of the two-input and one-output ANFIS neural-fuzzy system of the Sugeno-TSK type used in the study is presented in Fig. 2."[13-14]

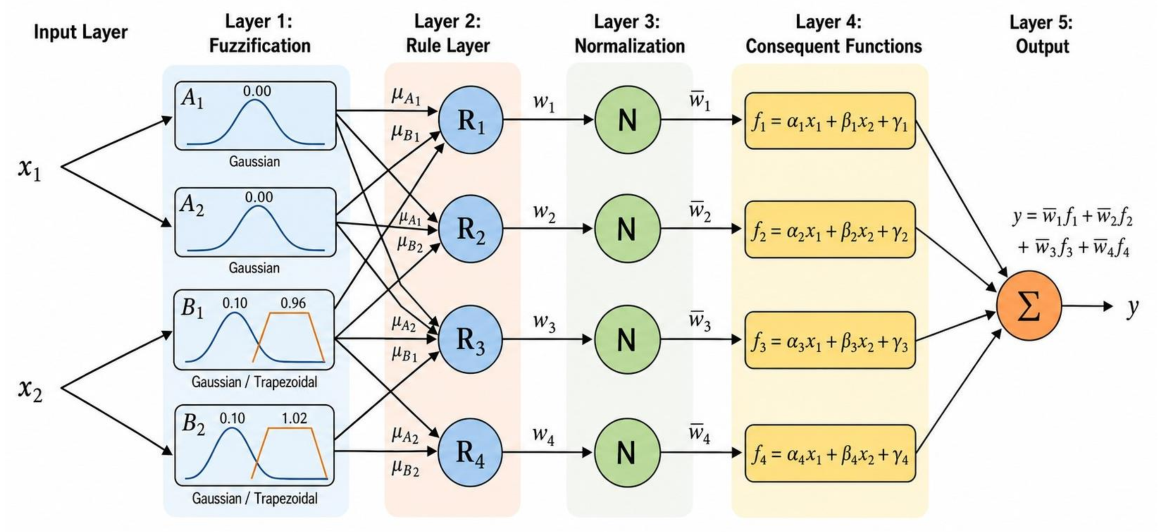

Figure 2. The architecture of the ANFIS model is made up of 5 layers, which include 4 fuzzy rules of Takagi-Sugeno-Kang (TSK) type with 2 inputs and 1 output.

2.3. Affiliation functions: Gaussian and trapezoidal

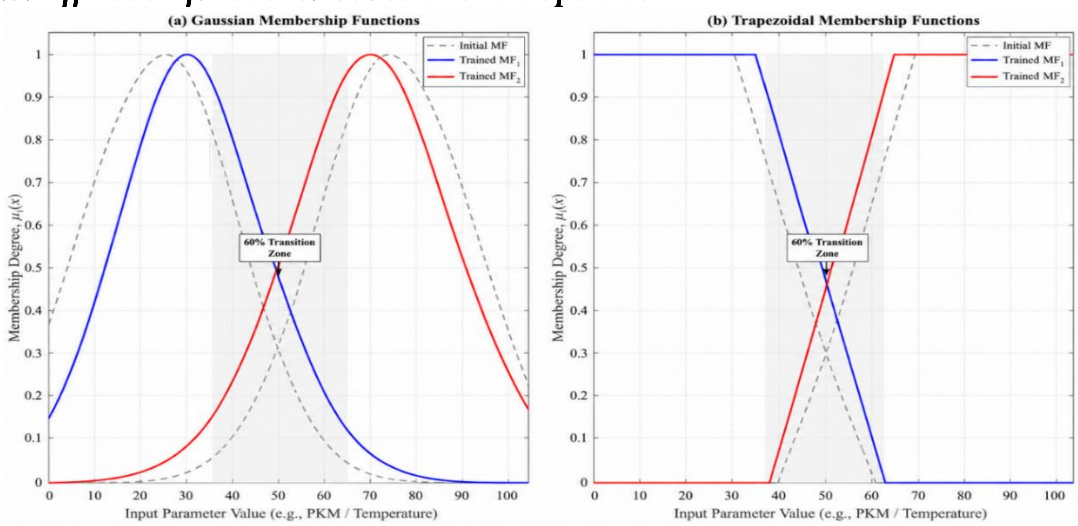

Figure 3. Changes of gaussian and trapezoidal membership function for inputs during the teaching process and 60% o criterion transition zones.

Gaussian membership function:

$$\mu(x;c,\sigma) = e^{-\frac{(x-c)^2}{2\sigma^2}}$$

Trapezoidal membership function:

$$\mu(x) = \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

For both cases, the width of the transition region between neighbouring functions has been taken as 60% of the width of the cells, and the membership functions have been required to satisfy the full coverage condition, that is, the sum of all membership functions at any x is 1.

As can be seen in Figure 3 (a and b), the changes in the parameters of the Gaussian and trapezoidal membership functions during the learning process as well as the 60% overlap (transition) zones between adjacent membership functions are clearly visible[3-5].

2.4. Evaluation criteria

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}, \quad MAE = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i ||, \quad R = \operatorname{corr}(y, \hat{y})$$

The data sets were split randomly (the initial value of the random generator was carefully determined to enable a repeatable split, with 80% being used for training and 20% for testing).

3. RESULTS

Tab 2: The calculations results obtained with the help of Gaussian and trapezoidal membership functions for both models are shown:

Table 2. The indicators of prediction accuracy of ANFIS models with Gaussian and trapezoidal MF are presented in the following table.

Model	MF Type	RMSE (training)	RMSE (test)	RMSE (overall)	R (overall)
Oil pressure	Gauss	1,043	0,526	0,958	0,922
Oil pressure	Trapezoid	1,034	0,637	0,964	0,921
Gas imbalance	Gauss	8,255	23,694	12,563	−0,025
Gas imbalance	Trapezoid	8,696	9,426	8,833	0,511

As can be seen from the results, for the oil pressure model, both types of membership functions yielded very similar accuracy (R = 0.922 and 0.921 respectively) meaning that the relationship between oil pressure and its input parameters (PKM, temperature) is relatively smooth and monotonous[11-12].

However, one of the exhaust gas imbalance models showed a significantly different result: The model with the Gaussian function almost failed to make a prediction when applied to the test set (R = −0.025, i.e. prediction quality was not as good as the mean), while the model with the trapezoidal function had a significantly more stable result (R = 0.511).

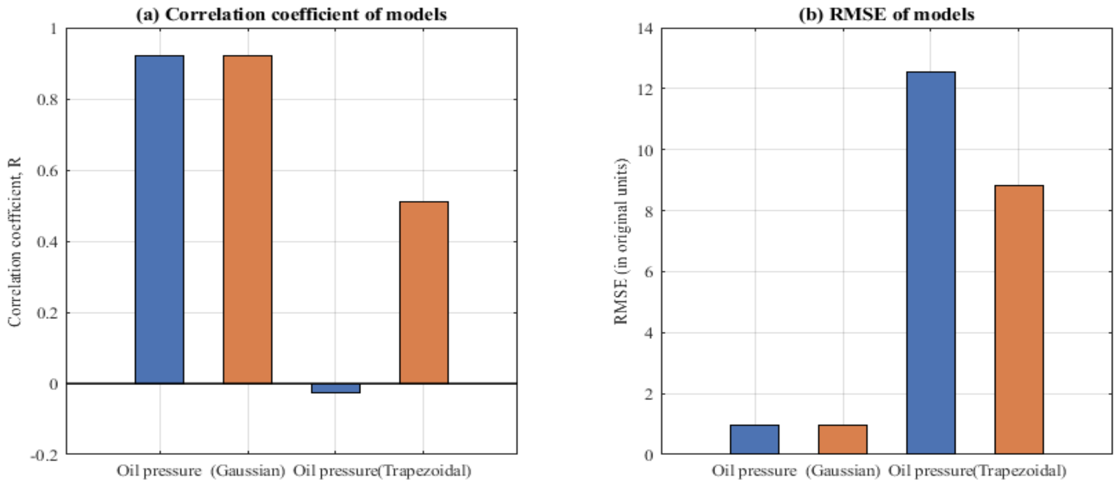

Figure 4. The model correlation indicator (R) and RMSE indicator of the model are presented in a comparative diagram.

The Actual vs. Predicted (Figure 5) plots of the models show agreement in the model values, and the 3D fuzzy decision surfaces (gensurf) produced by the models for both diagnostic indicators are shown.

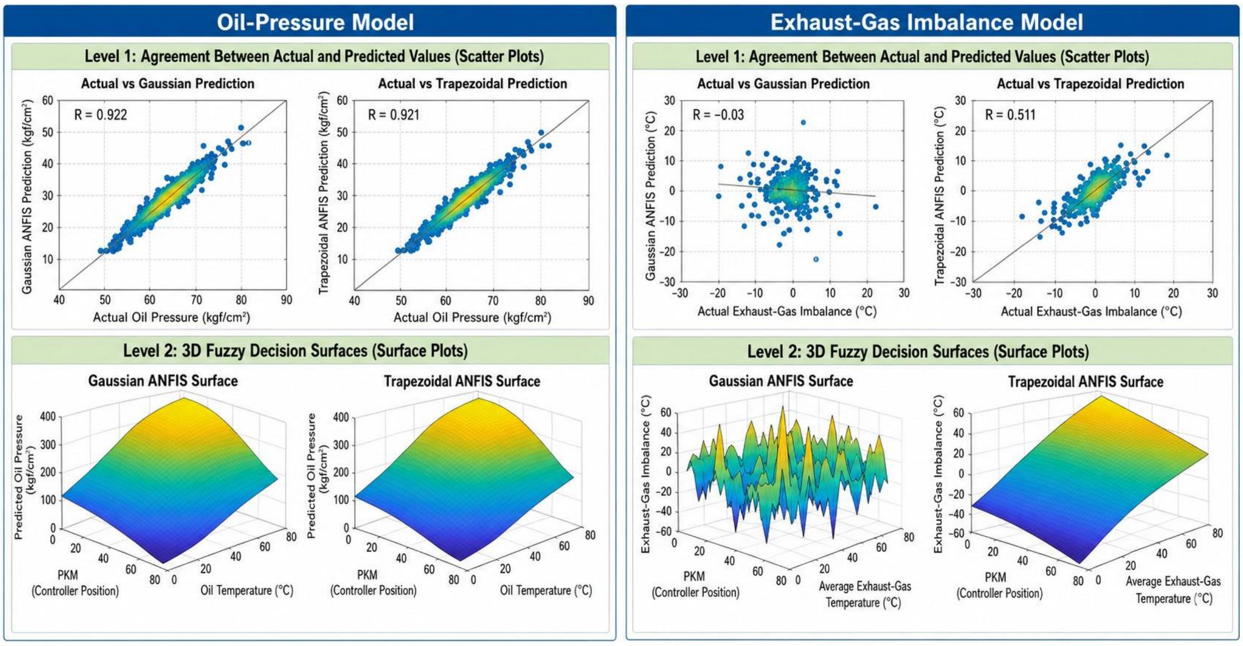

Figure 5. Correspondence between the models' actual and predicted values, and the corresponding 3D fuzzy decision surface (3D Surface Plots).

4. DISCUSSION

From the results, it could be noticed that the type of membership function should be determined according to the statistical data of the diagnostics (volume, noise level, distribution type). The oil pressure data set contained most of its data (30 of 34) from one operating mode (idling, or PKM=0), and the correlation was relatively smooth, so both function types provided a good result[6-8].

However, the sample size in the exhaust gas data was relatively small (n=22) and the value distribution was more spread out. The Gaussian function was too sensitive to the outlier observations in the training set, because of its infinite 'tails', which resulted in an overgeneralisation (overfitting) on the test set. The trapezoidal function was, on the other hand, more robust to such extreme values due to its strict boundaries and “flat” central part[9-10].

The distribution histograms of the residual errors ($e_i = y_i - \hat{y}_i$) , of the model, are shown in figure 6, showing that the Gaussian function is sensitive to the presence of outliers, while the trapezoidal function is highly robust.The results are shown in Figures 6, where the sensitivity of the Gaussian function to the outliers is seen and the high robustness of the trapezoidal function.

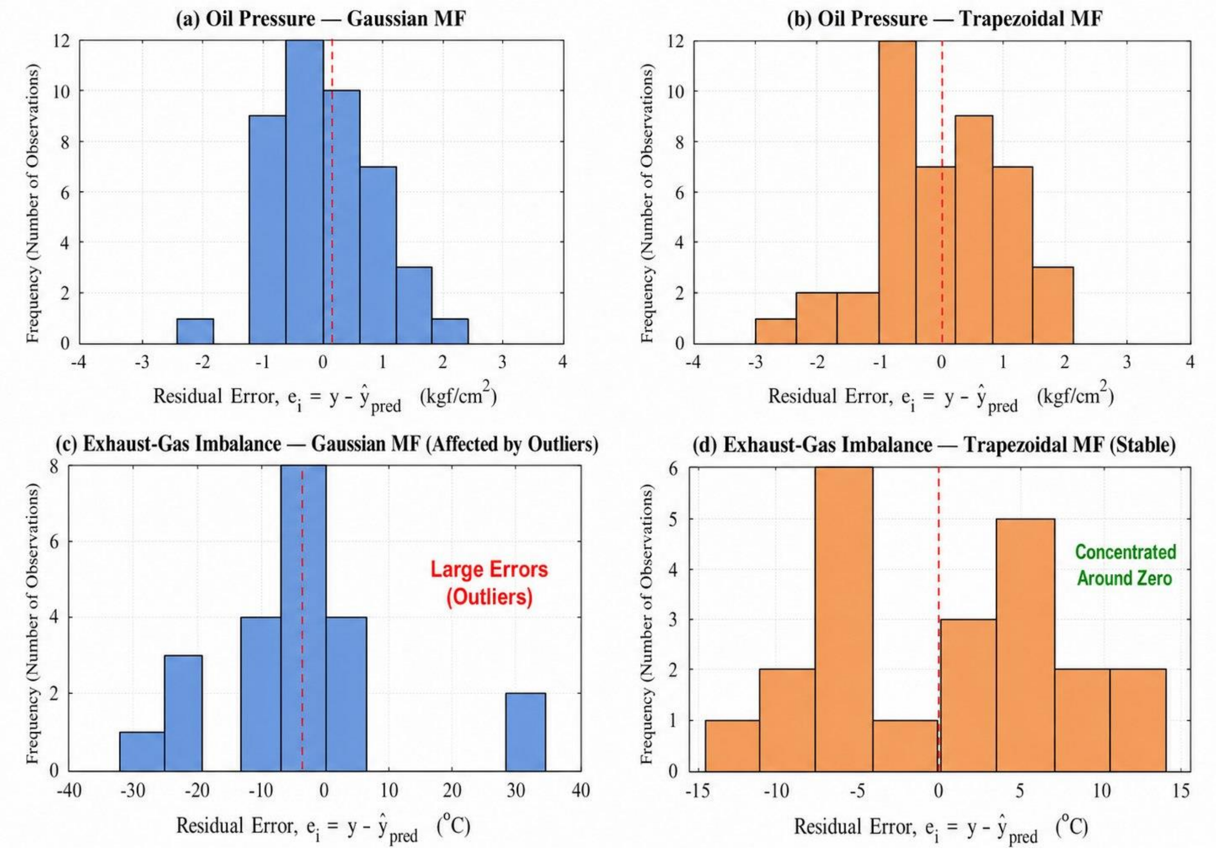

Figure 6. Histogram of the residual error $(y - \hat{y})$ distribution for Gaussian and trapezoidal membership functions, and an analysis of their stability against extreme values.

The result is in line with the previous studies; Han et al. noted that the membership function parameters should be chosen according to the characteristics of data in a multi-signal diagnostic ANFIS system. This conclusion is further confirmed by the set of operational data on locomotives that we have been able to find in the real world[11].

There is a number of limitations in the study. Firstly, the data are limited to the month of one locomotive – which means the results of this study are not generalizable. Secondly, the calculations presented in this article are based on linear (LSE) stage of ANFIS hybrid training algorithm; the linear stage is only part of the hybrid training algorithm, the other part is the adaptation of the parameters of membership functions using backpropagation method, this part is expected to be performed in the MATLAB fuzzy logic toolbox environment and further improve the results[12].

5. CONCLUSION

In this study, two ANFIS/Sugeno-type fuzzy diagnostic models were developed for the lubricating-oil pressure and for the exhaust-gas temperature imbalance, respectively, and the models were developed using actual operational data taken on board a 2TE25KM locomotive. In the oil-pressure subsystem, the accuracy resulting from the use of Gaussian membership functions and trapezoidal membership functions was close to the same (R≈0.92), meaning that the type of membership function used was of little importance for this subsystem. The trapezoidal membership function (R=0.51) on the other hand yielded significantly more stable predictions than the Gaussian (R=-0.03) which showed a collapse of the predictive power on the validation subset. This contrast indicates that selection of the membership function is not a fixed design issue for ANFIS-based engine diagnosis, but rather should be designed according to the noise level and sample size of the target parameter, which is very practical for engineers implementing onboard diagnostic systems in a limited operational data.

As these results come from a small sample size (n=22-43) and are based on a single locomotive unit no formal statistical significance test was applied to the differences in R and RMSE reported above. Future work should, therefore: (i) validate the models on an expanded dataset of several maintenance cycles on a larger number of locomotives; (ii) use the full gradient-based ANFIS hybrid learning algorithm (premise parameter tuning via backpropagation as implemented in MATLAB's Fuzzy Logic Toolbox) rather than the least-squares-only estimation performed here; (iii) extend the comparison to other membership function families (e.g., generalized bell, sigmoidal); and (iv) when labeled fault/no-fault records become available, reformulate the task as a fault-classification problem that allows direct diagnostic decision support, beyond the mere parameter regression.

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