UDK: 621.314.25

AN ADAPTIVE MULTI-LEVEL FUZZY LOGIC FRAMEWORK WITH DYNAMIC WEIGHT ADJUSTMENT FOR POWER TRANSFORMER FAULT DIAGNOSIS AND HEALTH INDEX ASSESSMENT

Abdullabekova Dilafruz Rustamovna
Head of the Department of "Energy Supply Systems", Tashkent University of Information Technologies named after Muhammad al-Khwarizmi, Associate Professor (DSc)
E-mail: abdullabekova_94@mail.ru
Shukurulloyev Sarvar Anvarovich
Assistant of the Department of ETT, Tashkent University of Information Technologies named after Muhammad al-Khwarizmi
E-mail: s.shukrullayev@tuit.uz

Annotatsiya. Kuch transformatorlari holatini baholash to‘liq bo‘lmagan va qat’iy chegaralarga tayangan turli ma’lumotlarga asoslanadi. Taklif etilgan adaptiv noravshan tizimda Mamdani quyi tizimlari gazlar, yog‘ eskirishi va issiqlik-elektr zo‘riqishini baholaydi, holat indeksi ularni ma’lumotlar ishonchliligi va ish rejimiga bog‘liq vaznlar bilan birlashtiradi. Aniqlik 68,4 % dan 86,9 % gacha oshdi, yolg‘on signallar ikki baravar kamaydi; tizim prognozli texnik xizmat uchun mo‘ljallangan.

Kalit so‘zlar: kuch transformatori, noravshan mantiq, adaptiv vaznlar, texnik holat indeksi, nosozliklarni tashxislash, erigan gazlar tahlili, ma’lumotlar ishonchliligi, texnik holatni baholash.

Аннотация. Оценка состояния силовых трансформаторов опирается на разнородные неполные данные и жёсткие пороги. В предложенной адаптивной нечёткой системе подсистемы Мамдани оценивают газы в масле, деградацию масла и термоэлектрическую нагрузку, а индекс состояния объединяет их с весами по достоверности данных и режиму. Точность выросла с 68,4 до 86,9 %, ложные срабатывания сократились вдвое; система предназначена для прогнозного обслуживания.

Ключевые слова: силовой трансформатор, нечёткая логика, адаптивные веса, индекс технического состояния, диагностика дефектов, анализ растворённых газов, достоверность данных, оценка технического состояния.

Abstract. Transformer condition assessment relies on heterogeneous, often incomplete data judged against rigid limits. In the proposed adaptive multi-level fuzzy framework, Mamdani subsystems rate dissolved-gas fault severity, oil degradation and thermal-electrical stress, and a health index fuses them with weights driven by data reliability and operating stress. In an ablation study accuracy rose from 68.4 % to 86.9 % and false alarms halved against a threshold baseline; the framework is intended for predictive maintenance of substations.

Keywords: power transformer, fuzzy logic, adaptive weights, health index, fault diagnosis, dissolved gas analysis, data reliability, condition assessment.

INTRODUCTION.

Power transformers are among the most expensive and least replaceable assets of an electrical network, and their failures cause long outages and high repair costs. Most failures are preceded by gradual processes such as insulation ageing, oil deterioration, thermal overstress and partial discharge activity, which can be detected by periodic tests and online monitoring [1, 2]. Timely recognition of these processes is therefore the basis of condition-based and predictive maintenance.

Conventional diagnostics compare each measured quantity with limits given in standards such as IEC 60599 for dissolved gases and IEC 60422 for insulating oil [3, 4]. Such limits are simple and widely accepted, but they treat each parameter separately, ignore the nonlinear character of degradation and react poorly to measurement uncertainty and missing data. Utilities therefore combine heterogeneous results – dissolved gas analysis (DGA), physico-chemical oil tests, temperatures and electrical measurements – into a single health index (HI) [5, 6].

The problem addressed in this paper is that the information available for a given transformer changes over time: sensors drift, laboratory results carry different uncertainty, some tests are missing, and the importance of thermal and electrical evidence grows with loading and age. A health index with fixed weights, or a fuzzy system with static membership functions, cannot follow these changes, so the same data quality problem leads to different errors at different times. The topic is relevant for the transition of transmission utilities to digital substations, where data from many sources arrive continuously and with uneven quality.

The aim of this work is to develop an adaptive multi-level fuzzy logic framework that combines DGA, oil, thermal and electrical evidence into a health index and a fault class, with weights adjusted to the reliability of the data and to the operating stress of the unit. The scientific novelty consists in: a weighting rule in which the contribution of each fuzzy subsystem is proportional to the aggregated reliability of its input data; a modulation of these weights by an operating stress and ageing indicator; a constrained tuning of membership parameters that preserves the order of linguistic terms and thus interpretability; and a single structure that yields both a continuous health index and a discrete fault class.

HEALTH INDEX METHODS.

The health index condenses DGA, oil and electrical test results into one score used to rank units for maintenance and replacement [5]. Tamma et al. combined the HI value with its rate of decrease to refine the assessment of high-voltage

ISSN 3030-3907

transformers [7], and reviews have systematised HI formulations from the perspective of survivability and condition assessment [6] and of asset-management methodologies for oil-immersed transformers [8]. Two recent reviews document the growing use of machine learning for transformer health and lifetime assessment, one of them covering more than 200 publications [9, 10]. Measurement and interpretation techniques for dissolved gases were reviewed by Bakar et al. [11].

FUZZY LOGIC IN TRANSFORMER DIAGNOSTICS.

Fuzzy set theory [12] and Mamdani inference [13] provide a transparent way to express expert limits as linguistic rules. Abu-Elanien et al. calculated a fuzzy health index for oil-immersed transformers rated below 69 kV [14]; Abu-Siada and Hmood identified transformer criticality from dissolved gases with a fuzzy approach [15]; Bakar and Abu-Siada applied fuzzy logic to remnant-life prediction and asset-management decisions [16]. In these systems the membership functions and weights are defined by experts. The work closest to the present study is that of Nguyen et al., who combined five DGA interpretation methods (Duval triangle, IEC, Rogers and Doernenburg ratios, key gas) as fuzzy modules and optimised their weights by gradient descent on labelled samples, reporting 99.4 % accuracy on 160 test samples [17].

DATA-DRIVEN AND UNCERTAINTY-AWARE APPROACHES.

Neural and other machine-learning models have been trained to reproduce HI values [18, 19], reduced feature sets have been examined to lower the testing effort [20], and uncertainty in input data has been treated explicitly [21, 22]. Putra et al. showed that class imbalance strongly affects HI classifiers and raised classification accuracy from 85.84 % to 97.56 % by synthetic minority oversampling [23].

In most of the reviewed schemes the contribution of each evidence source is set by experts or learned once from a given dataset. The reliability of each data source at the moment of assessment and the operating stress of the unit rarely enter the aggregation explicitly. In [17] the weights are learned once from labelled DGA data and the output is a fault class. In the present framework the weights change at each assessment with the reliability of the data and the operating stress of the unit, the evidence covers gas, oil, thermal and electrical data, and the output includes a health index in addition to the fault class.

RESEARCH METHODOLOGY.

Structure of the framework

The diagnostic system is organised as a multi-level fuzzy inference structure (Fig. 1). The input layer contains the raw diagnostic attributes; the first level consists of fuzzy subsystems that compute partial condition indices; the second

ISSN 3030-3907

level combines these indices with adaptive weights into a transformer health index (THI) and a fault class.

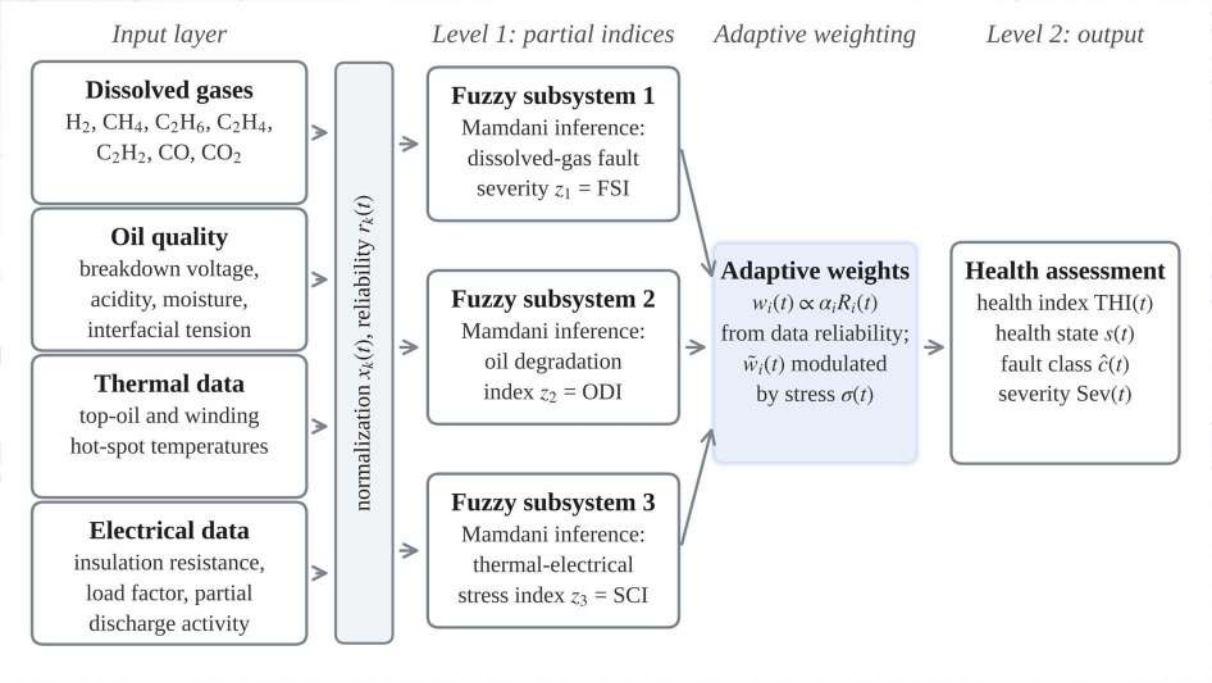


Fig. 1. Structure of the adaptive multi-level fuzzy diagnostic framework (developed by the author)

Four groups of attributes are used: dissolved gases (H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2); oil quality (breakdown voltage, acidity, moisture content, interfacial tension); thermal parameters (top-oil and winding hot-spot temperatures); and electrical indicators (insulation resistance, load factor, partial discharge activity).

Normalization and data reliability

A transformer is observed at times $t \in T$. Each raw attribute is mapped to the interval [0, 1] by bounded normalization (1):

$$x_k(t) = \mathrm{clip}\left(\frac{\tilde{x}_k(t)-\tilde{x}_k^{\min}}{\tilde{x}_k^{\max}-\tilde{x}_k^{\min}}, 0, 1\right), \qquad (1)$$

where the bounds are engineering limits taken from standards, fleet statistics or expert judgement. Each attribute receives a reliability score $r_k(t) \in [0, 1]$ defined by (2):

$$r_k(t) = r_k^{\mathrm{sens}}(t) \cdot r_k^{\mathrm{qual}}(t) \cdot r_k^{\mathrm{miss}}(t), \quad (2)$$

Where the three factors describe sensor condition and calibration age, measurement quality (noise, laboratory uncertainty) and availability of the value, the last factor being zero for a missing value. For subsystem i with attribute set K_i, the aggregated reliability is given by (3):

$$R_i(t) = \frac{\sum_{k\in K_i} v_{ik} r_k(t)}{\sum_{k\in K_i} v_{ik}}, \quad v_{ik} > 0, \qquad (3)$$

ISSN 3030-3907

where v_{ik} are expert importance coefficients of the attributes within the subsystem.

MEMBERSHIP FUNCTIONS.

For each input, linguistic terms are described by parametric triangular (4) and trapezoidal (5) membership functions:

$$\mu_{\text{tri}}(x;a,b,c)=\begin{cases}0, & x\le a,\\ \frac{x-a}{b-a}, & a<x\le b,\\ \frac{c-x}{c-b}, & b<x<c,\\ 0, & x\ge c;\end{cases} \quad (4)$$

$$\mu_{\text{trap}}(x;a,b,c,d)=\begin{cases}0, & x\le a,\\ \frac{x-a}{b-a}, & a<x\le b,\\ 1, & b<x\le c,\\ \frac{d-x}{d-c}, & c<x<d,\\ 0, & x\ge d.\end{cases} \quad (5)$$

The parameters are first set from standard limits and expert knowledge and may later be tuned by (15).

First-level fuzzy subsystems

Three Mamdani subsystems are used. The DGA subsystem evaluates the membership of the fault in the thermal, electrical and mixed classes using rules derived from IEC 60599 and expert knowledge [3] and returns a fault severity index z_1 = FSI. The oil subsystem processes oil quality indicators against the categories of IEC 60422 [4] and returns an oil degradation index z_2 = ODI. The thermal-electrical subsystem combines temperatures, insulation resistance, load factor and partial discharge indicators into a stress condition index z_3 = SCI. All partial indices are severities: larger values mean worse condition.

A rule ℓ of subsystem i has the form: IF x_{k1} is L_1 AND … AND x_{kp} is L_p THEN y_i is $B_{i\ell}$, where L are linguistic terms of the inputs and $B_{i\ell}$ is an output fuzzy set. The firing strength of the rule is computed with the minimum t-norm (6), the rule outputs are aggregated by (7), and a crisp partial index is obtained by the centroid method (8):

$$\lambda_{i\ell}(t)=\min_{u=1,\dots,p}\mu_{k_u j_u}\left(x_{k_u}(t)\right), \quad (6)$$

$$\mu^*_{y_i}(y)=\max_{\ell=1,\dots,M_i}\min\left(\lambda_{i\ell}(t),\mu_{B_{i\ell}}(y)\right), \quad (7)$$

$$z_i(t)=\frac{\int_0^1 y\mu^*_{y_i}(y)dy}{\int_0^1 \mu^*_{y_i}(y)dy}. \quad (8)$$

Adaptive weighting

ISSN 3030-3907

With base importance factors $\alpha_i > 0$, the adaptive weight of subsystem i is proportional to the reliability of its data (9):

$$w_i(t) = \frac{\alpha_i R_i(t)}{\sum_{j=1}^{S} \alpha_j R_j(t)}, \qquad (9)$$

so that the weights sum to one and more reliable subsystems have more influence. To reflect ageing and operating severity, the weights are modulated by a stress indicator $\sigma(t) \in [0, 1]$, for example a load factor or a hot-spot temperature percentile (10):

$$\widetilde{w}_i(t) = \frac{w_i(t)\exp(\beta_i \sigma(t))}{\sum_{j=1}^{S} w_j(t)\exp(\beta_j \sigma(t))}, \qquad (10)$$

where β_i sets the sensitivity of subsystem i to stress. Under normal operation $\sigma(t) \approx 0$ and the modulated weights coincide with (9).

Second-level aggregation and health states

Two aggregation options are provided. In option A, the weighted partial indices are inputs of a second-level Mamdani system with input terms {Low, Medium, High} and output terms {Excellent, Good, Moderate, Poor, Critical}; its rules encode expert logic, for example "IF DGA severity is High AND oil degradation is High THEN THI is Critical". Option B is a transparent analytical baseline (11), useful for ablation and interpretation:

$$\mathrm{THI}(t) = 1 - \sum_{i=1}^{S} \widetilde{w}_i(t) z_i(t). \qquad (11)$$

Discrete health states are obtained with thresholds $\tau_1 > \tau_2 > \tau_3 > \tau_4$ (12):

$$s(t) = \begin{cases} \text{Excellent}, & \mathrm{THI}(t) \geq \tau_1, \\ \text{Good}, & \tau_2 \leq \mathrm{THI}(t) < \tau_1, \\ \text{Moderate}, & \tau_3 \leq \mathrm{THI}(t) < \tau_2, \\ \text{Poor}, & \tau_4 \leq \mathrm{THI}(t) < \tau_3, \\ \text{Critical}, & \mathrm{THI}(t) < \tau_4. \end{cases} \qquad (12)$$

Fault type and severity

The DGA subsystem returns membership degrees $\pi_c(t)$ of the fault classes C = {thermal, electrical, mixed}. The fault class is selected by the maximum membership (13), and the severity is the weighted sum (14) with class-severity coefficients ρ_c:

$$\hat{c}(t) = \arg\max_{c \in C} \pi_c(t), \qquad (13)$$

$$\mathrm{Sev}(t) = \sum_{c \in C} \rho_c \pi_c(t). \qquad (14)$$

Constrained tuning of membership parameters

When labelled historical events $\{(x(t_n), y_n)\}$, $n = 1, \ldots, N$, are available, the membership parameters θ are tuned by the regularised problem (15):

$$\min_{\theta} L(\theta) = \sum_{n=1}^{N} \delta(\hat{y}_n(\theta), y_n) + \lambda \|\theta - \theta_0\|_2^2, \qquad (15)$$

ISSN 3030-3907

where $\delta(\cdot)$ is a classification loss, θ_0 are the expert initial values and λ limits the deviation from them. The constraints $a < b < c < d$ for every membership function keep the order of linguistic terms and therefore the interpretability of the rule base.

Evaluation protocol

The contribution of each module was quantified by an ablation study in which components were removed or simplified step by step. The full method is denoted AMF-DW (adaptive multi-level fuzzy with dynamic weights). The variants were evaluated with the same data split, preprocessing and evaluation pipeline: V0 – threshold baseline with fixed limits from standards and maintenance rules; V1 – a single DGA fuzzy subsystem without oil, thermal and electrical data; V2 – multi-attribute fuzzy HI with fixed expert weights and no reliability modelling; V3 – hierarchical fuzzy structure with constant weights; V4 – dynamic weights driven only by operating stress $\sigma(t)$; V5 – dynamic weights driven by data reliability $R_i(t)$ without membership tuning; V6 – full AMF-DW with reliability-aware dynamic weights and constrained membership tuning. The metrics were accuracy (Acc), macro-averaged F1 score, false alarm rate (FAR) and mean lead time (LT) before confirmed events.

RESULTS AND DISCUSSION.

The proposed model was tested using historical operational data from high-voltage power transformers (110–220 kV). The dataset includes long-term DGA records, oil test results and thermal monitoring data for [10] transformers of [tashkent] over [period:10.05.2026-1.10.2026], in total [M] diagnostic records. Fault labels were taken from [internal inspections / repair reports / expert decisions] and comprise [K] confirmed events (thermal, electrical, mixed). The data were split [by transformer / by time] into training and test parts in the ratio, and the split was repeated [R] times; membership tuning (15) used only the training part of each split. Lead time was measured as the interval between the first alarm of the model and the confirmed event. Table 1 summarises the ablation results.

Table 1

Ablation study results (mean ± std over repeated splits; compiled by the author)

№	Model	Key components	Acc, %	Macro-F1	FAR, %	LT, days
1	V0	Threshold baseline	68.4 ± 2.1	0.62 ± 0.03	14.8 ± 1.4	2.3 ± 0.5
2	V1	DGA-only fuzzy	74.2 ± 1.9	0.70 ± 0.02	12.1 ± 1.2	3.4 ± 0.6
3	V2	Static multi-attribute fuzzy HI	77.6 ± 1.7	0.73 ± 0.02	10.9 ± 1.0	4.1 ± 0.7

ISSN 3030-3907

№	Model	Key components	Acc, %	Macro-F1	FAR, %	LT, days
4	V3	Multi-level fuzzy, static weights	80.1 ± 1.6	0.76 ± 0.02	9.6 ± 0.9	4.9 ± 0.8
5	V4	Dynamic weights (stress only)	82.0 ± 1.5	0.78 ± 0.02	9.2 ± 0.8	5.3 ± 0.7
6	V5	Reliability-aware dynamic weights	84.7 ± 1.4	0.81 ± 0.02	8.1 ± 0.7	5.9 ± 0.6
7	V6	Full AMF-DW (proposed)	86.9 ± 1.3	0.83 ± 0.02	7.4 ± 0.6	6.2 ± 0.6

The results show four effects. First, moving from V1 to V2 and V3 raises the macro-F1 score by 0.03 and 0.06, respectively, so multi-attribute integration and hierarchical decomposition improve fault discrimination. Second, the transition from static weights (V3) to stress-driven dynamic weights (V4) increases accuracy by 1.9 percentage points and lowers FAR by 0.4 points. Third, reliability-aware weighting (V5) gives the largest gain among the weighting mechanisms, 2.7 points of accuracy and 1.1 points of FAR relative to V4. Fourth, constrained membership tuning (V6) adds a further 2.2 points of accuracy and lowers FAR by 0.7 points. The largest single step, 5.8 points of accuracy, is the replacement of fixed thresholds by fuzzy DGA inference (V0 to V1).

Relative to the threshold baseline V0, the accuracy gain of AMF-DW is (16):

$$\Delta\mathrm{Acc} = \frac{86.9-68.4}{68.4} \times 100\ \% \approx 27.0\ \%, \quad (16)$$

and the false alarm rate is halved, from 14.8 % to 7.4 %, while the mean lead time increases from 2.3 to 6.2 days.

Among the adaptive mechanisms, reliability-aware weighting contributes most, which agrees with the attention that [21, 22] give to data uncertainty in health index estimation. Accuracies reported in other studies, for example [23], were obtained on different datasets and labels and are therefore not directly comparable with Table 1. Because every partial index and weight is explicit, the operator can see which data source drove a given assessment and how much its reliability reduced its influence.

CONCLUSIONS AND RECOMMENDATIONS.

An adaptive multi-level fuzzy logic framework with dynamic weight adjustment for power transformer fault diagnosis and health index assessment has been developed. The framework integrates DGA, oil quality, thermal and electrical parameters in a hierarchical fuzzy structure, weights the subsystems according to data reliability and operating stress, and returns both a continuous health index and a fault class. In the ablation study the full model reached an accuracy of 86.9 % against 68.4 % for the threshold baseline and halved the false alarm rate.

ISSN 3030-3907

The following is recommended: to include the reliability of each data source in transformer condition assessment rather than discarding or silently imputing questionable data; to calibrate membership parameters on the utility's own records using the constrained tuning (15), so that interpretability is preserved; and to confirm the gains on independent fleets with unit-wise and time-wise data splits before operational deployment. The framework can be integrated into SCADA and digital substation environments to support predictive maintenance and asset management. Future work will address automatic tuning of membership functions by machine learning and real-time online monitoring with IoT sensor networks.

REFERENCES

1. Zhang X., Gockenbach E. Asset-management of transformers based on condition monitoring and standard diagnosis // IEEE Electrical Insulation Magazine. – 2008. – Vol. 24, No. 4. – P. 26–40. DOI: 10.1109/MEI.2008.4581371.
2. Islam M.M., Lee G., Hettiwatte S.N. A review of condition monitoring techniques and diagnostic tests for lifetime estimation of power transformers // Electrical Engineering. – 2018. – Vol. 100, No. 2. – P. 581–605. DOI: 10.1007/s00202-017-0532-4.
3. IEC 60599:2015. Mineral oil-filled electrical equipment in service – Guidance on the interpretation of dissolved and free gases analysis. – Geneva: International Electrotechnical Commission, 2015.
4. IEC 60422:2013. Mineral insulating oils in electrical equipment – Supervision and maintenance guidance. – Geneva: International Electrotechnical Commission, 2013.
5. Jahromi A., Piercy R., Cress S., Service J., Fan W. An approach to power transformer asset management using health index // IEEE Electrical Insulation Magazine. – 2009. – Vol. 25, No. 2. – P. 20–34. DOI: 10.1109/MEI.2009.4802595.
6. Li S., Li X., Cui Y., Li H. Review of transformer health index from the perspective of survivability and condition assessment // Electronics. – 2023. – Vol. 12, No. 11. – Art. 2407. DOI: 10.3390/electronics12112407.
7. Tamma W.R., Prasojo R.A., Suwarno. High voltage power transformer condition assessment considering the health index value and its decreasing rate // High Voltage. – 2021. – Vol. 6, No. 2. – P. 314–327. DOI: 10.1049/hve2.12074.
8. Jin L., Kim D., Abu-Siada A. State-of-the-art review on asset management methodologies for oil-immersed power transformers // Electric Power Systems Research. – 2023. – Vol. 218. – Art. 109194. DOI: 10.1016/j.epsr.2023.109194.
9. Zemouri R. Power transformer prognostics and health management using machine learning: a review and future directions // Machines. – 2025. – Vol. 13, No. 2. – Art. 125. DOI: 10.3390/machines13020125.

ISSN 3030-3907

10. Zahra S.T., Imdad S.K., Khan S., Khalid S., Baig N.A. Power transformer health index and life span assessment: a comprehensive review of conventional and machine learning based approaches // Engineering Applications of Artificial Intelligence. – 2025. – Vol. 139. – Art. 109474. DOI: 10.1016/j.engappai.2024.109474.
11. Bakar N., Abu-Siada A., Islam S. A review of dissolved gas analysis measurement and interpretation techniques // IEEE Electrical Insulation Magazine. – 2014. – Vol. 30, No. 3. – P. 39–49. DOI: 10.1109/MEI.2014.6804740.
12. Zadeh L.A. Fuzzy sets // Information and Control. – 1965. – Vol. 8, No. 3. – P. 338–353. DOI: 10.1016/S0019-9958(65)90241-X.
13. Mamdani E.H., Assilian S. An experiment in linguistic synthesis with a fuzzy logic controller // International Journal of Man-Machine Studies. – 1975. – Vol. 7, No. 1. – P. 1–13. DOI: 10.1016/S0020-7373(75)80002-2.
14. Abu-Elanien A.E.B., Salama M.M.A., Ibrahim M. Calculation of a health index for oil-immersed transformers rated under 69 kV using fuzzy logic // IEEE Transactions on Power Delivery. – 2012. – Vol. 27, No. 4. – P. 2029–2036. DOI: 10.1109/TPWRD.2012.2205165.
15. Abu-Siada A., Hmood S. A new fuzzy logic approach to identify power transformer criticality using dissolved gas-in-oil analysis // International Journal of Electrical Power & Energy Systems. – 2015. – Vol. 67. – P. 401–408. DOI: 10.1016/j.ijepes.2014.12.017.
16. Bakar N.A., Abu-Siada A. Fuzzy logic approach for transformer remnant life prediction and asset management decision // IEEE Transactions on Dielectrics and Electrical Insulation. – 2016. – Vol. 23. – P. 3199–3208. DOI: 10.1109/TDEI.2016.7736886.
17. Nguyen K.-A., Le H.H., Phung B.T. An adaptive multi-fuzzy logic model for diagnosing transformer faults using dynamic weight optimization // e-Prime – Advances in Electrical Engineering, Electronics and Energy. – 2025. – Vol. 13. – Art. 101048. DOI: 10.1016/j.prime.2025.101048.

ISSN 3030-3907