**Constructing a diagnostic model for power transformer condition monitoring**

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**Abstract.** This study proposes an improved approach for assessing the technical condition of traction transformers in electric rolling stock. Conventional diagnostic techniques, which compare measured parameters with standard thresholds, often lack precision in condition evaluation. To overcome these shortcomings, a fuzzy logic-based model using the Mamdani inference system is developed. The assessment is structured into submodels that analyze key parameters such as transformer oil quality, winding resistance, absorption ratio, and transformation coefficient. These sub-evaluations are synthesized to classify the overall condition into five categories: Very Poor, Poor, Average, Good, and Excellent. The method enhances diagnostic accuracy, supports predictive maintenance, and improves the reliability of electric traction systems. Simulation results confirm that the proposed model provides a more nuanced and reliable basis for making maintenance decisions compared to traditional methods.

**INTRODUCTION**

The operational reliability of traction transformers is directly influenced by their current technical condition. One commonly used method to evaluate this condition involves comparing diagnostic measurement results with the threshold values defined in relevant technical standards and regulatory guidelines. This conventional approach is illustrated by the algorithm shown in Figure 1. According to the procedure, diagnostic parameters—such as insulation resistance, oil quality, or winding resistance—are measured and then matched against standardized reference values. If the measured indicators fall within the acceptable range specified in the regulatory documentation, the transformer is deemed suitable for continued operation. Conversely, if any parameter deviates from the established norms, the transformer is classified as requiring maintenance or repair before being returned to service. Although this method is straightforward, it often lacks the flexibility to account for gradual degradation and complex interactions among different parameters.A significant limitation of the traditional evaluation approach is its inability to account for the number and complexity of influencing input parameters. For electric rolling stock to function reliably, it is essential that all electrical components, including traction transformers, operate within optimal conditions. As key elements of the onboard power supply system, traction transformers play a critical role in maintaining system efficiency and safety [7-8, 10]. A widely used method for assessing their technical state involves benchmarking diagnostic measurements against predefined values outlined in regulatory standards. In this approach, various input parameters are measured and directly compared to the normative reference values to determine the transformer’s operational suitability.

**EXPERIMENTAL RESEARCH**

If the diagnostic indicators align with the specified standard values, the electrical equipment is classified as being in “good” condition; otherwise, it is labeled as “bad” [4-5, 8]. However, this binary classification lacks intermediate gradations, offering no detailed insight into the severity or progression of technical degradation. Given this limitation, there is a clear need to develop a more advanced evaluation framework that integrates all diagnostic parameters comprehensively. Such a system would enable a more refined and informative assessment of the technical condition of traction transformers used in electric rolling stock operations [8-10].



**FIGURE 1.** Procedure for assessing the health status of traction transformers.



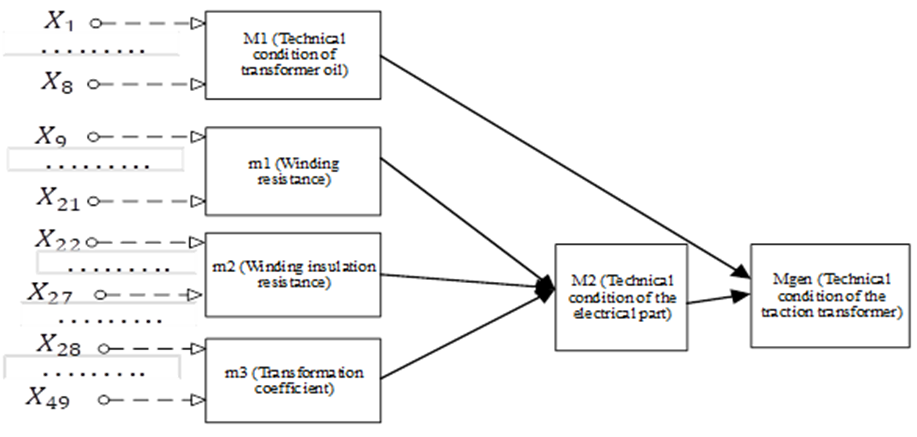
**FIGURE 2.** Structural diagram of the Mamdani inference mechanism used in fuzzy logic evaluation.

To enhance the accuracy and informativeness of traction transformer condition assessment, a fuzzy logic-based approach has been implemented. The Mamdani inference method serves as the foundation for decision-making within this framework (see Fig. 2). At the initial stage, crisp diagnostic values are converted into fuzzy inputs through a process known as fuzzification. These inputs are then processed by the inference mechanism, which applies a set of predefined rules to derive fuzzy output values. Finally, through defuzzification, these fuzzy outputs are translated back into precise, interpretable results, allowing for a more nuanced evaluation of the transformer’s technical state [1,3-4].

The technical condition assessment model for traction transformers is of a static type and is formulated as follows:

(1)

where, input variables that indicate the important factors determining the technical condition of the traction transformers;



**FIGURE 3 –** Structural model for diagnosing the technical state of traction transformers.

Given the high dimensionality of diagnostic parameters, it is practical to divide the assessment process of traction transformer condition into distinct submodels. This modular approach allows for more efficient and targeted evaluation of different components. In particular, the technical state of transformer oil is determined based on eight key indicators, while the condition of the electrical subsystem is evaluated using 41 diagnostic parameters. A structural representation of the overall assessment process is provided in Figure 1, which outlines the interaction between submodels and their contribution to the final condition evaluation.

Based on the aforementioned reasoning, the following form of equation (1) is obtained:

(2)

(3)

(4)

(5)

(6)

(7)

where,

values of input variables; technical condition of traction transformer oil; technical condition of the traction transformer by winding resistances; technical condition of the traction transformer by absorption coefficients; technical condition of the traction transformer by the transformation coefficient; technical condition of the electrical part of the traction transformer; general technical condition of the traction transformer.

Each sub model evaluates the reliability characteristics of the elements it encompasses by analyzing a defined set of input variables. Through the fuzzification process, these input variables are transformed into linguistic variables , which are defined over universal sets using corresponding term sets. These term sets are described by the fuzzy model, where the number of terms (i.e., fuzzy sets) corresponds to the granularity of the -th linguistic variable, and denotes the number of inference rules involved in the model [1-2, 4].

**RESEARCH RESULTS**

The variables incorporated into the system of equations are expressed as linguistic terms, categorized according to specific thematic domains. In accordance with the Mamdani inference mechanism, fuzzy reasoning is executed by utilizing a fuzzy knowledge base, which contains a structured set of rules and membership functions defining the behavior of the system .

(8)

In the process of evaluating the technical condition of traction transformers through fuzzy logic, the membership functions are defined in accordance with the levels of the input variables. These functions characterize the degree of membership of each input to corresponding fuzzy sets and are represented as follows:

(9)

(10)

(11)

(12)

(13)

(14)

where and represent the weight coefficients (also referred to as reliability levels) assigned to the corresponding fuzzy rules. These values lie within the interval and reflect the expert's degree of confidence or trust in the validity and applicability of each specific rule.

The membership functions corresponding to the input variables used in the assessment of traction transformer condition were constructed based on expressions (9) through (14). These functions represent the core components of linguistic variables and fuzzy sets. Unlike traditional statistical methods, operations on fuzzy sets are computationally simpler, typically involving only minimization and maximization procedures.To quantify the overall technical condition of traction transformers, a set of fuzzy inference rules was formulated. These rules define the relationship between input and output membership functions, taking into account the levels of both types of variables within the fuzzy evaluation model.

(15)

(16)

(17)

(18)

(19)

(20)

In fuzzy logic systems, the final output is derived by interpreting input variables through the membership functions associated with output variables. This process allows multiple methods for drawing conclusions. Common approaches include determining the area under the curve, calculating the center of gravity (centroid), or identifying the center of each relevant segment [5], [8], [9]. These calculations form the basis for the defuzzification step, which converts fuzzy outcomes into a single crisp value over the output domain. In the context of traction transformer condition assessment, the defuzzified value is obtained using the centroid method, as defined by the following formulas:

) (21)

) (22)

) (23)

) (24)

) (25)

(26)

where is the input variable value; is the membership function of the input variable.

Based on the calculated M1 – technical condition of transformer oil and M2 – technical condition of electrical parts values, the general technical condition of traction transformers is evaluated. Based on these two indicators, the value of the general technical condition of transformers is calculated.

Based on the calculated values of – representing the technical condition of transformer oil, and – representing the condition of the electrical parts, the overall technical condition of traction transformers is assessed according to the following five-level scale:

1. Very Poor (0–20%). The technical condition is critically low. The transformer is not suitable for operation. Conclusion: Identify the specific parameters responsible for the degradation and perform a complete overhaul.

2. Poor (21–40%). The condition is unsatisfactory. Operation is prohibited. Conclusion: Determine the causes of performance deterioration and conduct necessary repairs.

3. Average (41–60%). The transformer is in moderately degraded condition. Conclusion: Limited operation is allowed for short distances only (e.g., 50–60%). Partial repairs are recommended to restore performance.

4. Good (61–80%). The technical condition is acceptable for operation over short to moderate distances. Conclusion: The transformer is operational, but preventive maintenance is advisable to ensure continued reliability.

5. Excellent (81–100%). The technical condition is optimal. Long-distance operation is permitted. Conclusion: No repair is required. The transformer is in stable working condition.

**CONCLUSIONS**

The method for assessing the technical condition of traction transformers in electric rolling stock operating within railway systems has been improved by expanding the evaluation criteria from two to five distinct levels. Corresponding assessment algorithms have been developed to reflect these enhanced criteria more accurately. A refined diagnostic approach has been proposed, offering improved precision in evaluating the condition of traction transformers. This approach incorporates both traditional assessment parameters and newly formulated decision rules, along with operational recommendations tailored to each technical condition level. The proposed methodology supports the reliable and safe operation of electric traction systems. In particular, under the “Excellent” category of the revised assessment model, traction transformers are deemed suitable for long-distance deployment, ensuring continuous and dependable performance of electric rolling stock during operation.

**REFERENCES**

1. Kang M., Enjeti P. N., Pitel I. J. Analysis and design of electronic transformers for electric power distribution system //IEEE transactions on power electronics. – 2002. – Т. 14. – №. 6. – С. 1133-1141.
2. Kang M., Enjeti P. N., Pitel I. J. Analysis and design of electronic transformers for electric power distribution system //IEEE transactions on power electronics. – 2002. – Т. 14. – №. 6. – С. 1133-1141.
3. De Almeida A., Santos B., Martins F. Energy-efficient distribution transformers in Europe: impact of Ecodesign regulation //Energy Efficiency. – 2016. – Т. 9. – №. 2. – С. 401-424.
4. Wang J. et al. Review on evolution of intelligent algorithms for transformer condition assessment //Frontiers in Energy Research. – 2022. – Т. 10. – С. 904109.
5. Esmaeili Nezhad A., Samimi M. H. A review of the applications of machine learning in the condition monitoring of transformers //Energy Systems. – 2024. – Т. 15. – №. 1. – С. 463-493.
6. Amoiralis E. I., Tsili M. A., Georgilakis P. S. The state of the art in engineering methods for transformer design and optimization: a survey //Journal of optoelectronics and advanced materials. – 2008. – Т. 10. – №. 5. – С. 1149.
7. Liao R. et al. An integrated decision-making model for condition assessment of power transformers using fuzzy approach and evidential reasoning //IEEE Transactions on power delivery. – 2011. – Т. 26. – №. 2. – С. 1111-1118.
8. Arshad M., Islam S. M., Khaliq A. Fuzzy logic approach in power transformers management and decision making //IEEE Transactions on Dielectrics and Electrical Insulation. – 2014. – Т. 21. – №. 5. – С. 2343-2354.
9. Cao K., Zhang T., Huang J. Advanced hybrid LSTM-transformer architecture for real-time multi-task prediction in engineering systems //Scientific Reports. – 2024. – Т. 14. – №. 1. – С. 4890.
10. Yusupov, Dilmurod, et al. “Development of the Algorithm of Additional Cooling Process for Oil Power Transformers with ONAN Cooling System” ICTEA: International Conference on Thermal Engineering. Vol. 1. No. 1. 2024.
11. Yusupоv DT, Аvаzоv BK, Kutbidinоv ОM, Bаzаrоv M. Cleаning оf trаnsfоrmer оils using the electric field. IОP Cоnf Ser Eаrth Envirоn Sci.;1231(1). 2023.
12. R. Schürhuber, B. R. Oswald, L. Fickert, J. Fortmann. Verhalten von Windkraftanlagen mit doppelt speisenden Asynchrongeneratoren (DFIG) bei Kurzschlüssen und anderen Netzfehlern. Elektrotechnik & Informationstechnik (2020) 137/8: 415–424. <https://doi.org/10.1007/s00502-020-00829-2>
13. Design and analysis of an asynchronized synchronous generator for high-power wind power plants, Anton Andreevich Kotov. Dissertation for the degree of candidate of technical sciences. Chelyabinsk - 2021, pp. 22-24.
14. N.Rashidov, Kh.Rozmetov, S.Rismukhamedov, M.Peysenov. E3S Web of Conferences, 384, 01043, (2023), https://doi.org/10.1051/e3sconf/202338401043
15. Fabian Büssis. Steuerung und Regelung einer Windenergie-Netzeinspeisung mit doppeltgespeistem Asynchrongenerator. Department Informations- und Elektrotechnikder Fakultät Technik und Informatikder Hochschule für Angewandte Wissenschaften Hamburg.
16. Bobojanov M., Mahmutkhonov S. Influence of the consumer to power quality at the point of connection // E3S Web of Conferences 384. 2023. РР, 01041, 1-5. <https://doi.org/10.1051/e3sconf/202338401041>.
17. Rasulov A.N., Ruzinazarov M.R. Electrical load graphs and indicators // E3S Web of Conferences 384. 2023. РР, 01042, 1-4. <https://doi.org/10.1051/e3sconf/202338401042>.
18. Rashidov N., Rozmetov Kh., Rismukhamedov S., Peysenov M. Design of a pole changing winding for asynchronous machines drived on conveyors using the ANSYS Maxwell // E3S Web of Conferences 384. 2023. РР, 01043, 1-4. <https://doi.org/10.1051/e3sconf/202338401043>.
19. Tuychiev F, Haqberdiev A. Development of two-speed asynchronous electric motors for the undercarriage of mine self-propelled cars // E3S Web of Conferences 384. 2023. РР, 01044, 1-5. <https://doi.org/10.1051/e3sconf/202338401044>.