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Design and Development of a Fuzzy Inference System for Transformer Fault Diagnosis

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Abstract:

This paper presents the development of a fuzzy logic-based diagnostic model for evaluating fault severity in power transformers. The model utilizes three critical operational parameters—oil temperature, winding temperature, and gas content—as input variables to assess the internal health of the transformer. A Mamdani-type Fuzzy Inference System (FIS) is designed and implemented using MATLAB to process these inputs and generate a fault severity index ranging from 0 to 10, where 0 indicates no fault and 10 signifies a severe fault. The fuzzy logic approach enables the system to handle uncertainty and imprecise sensor data effectively, providing a more flexible and accurate diagnostic tool compared to traditional threshold-based methods. Simulation results demonstrate the model's capability to evaluate fault conditions reliably, making it a valuable addition to transformer condition monitoring systems for early fault detection and preventive maintenance.

Keywords: Fuzzy Logic, Transformer Fault Diagnosis, Condition Monitoring

Introduction

This research focuses on the design and implementation of an intelligent diagnostic model based on fuzzy logic for assessing the severity of faults in power transformers. Transformers are critical components in electrical power systems, and their reliable operation is essential for maintaining power quality and system stability. Faults in transformers, if not detected and addressed in a timely manner, can lead to catastrophic failures, resulting in costly repairs and power outages. Hence, accurate and early fault detection mechanisms are crucial. This study addresses this need by introducing a fuzzy logic-based model that evaluates the fault severity level using three key operational parameters. The proposed model considers oil temperature, winding temperature, and gas content within the transformer as the primary diagnostic indicators. These parameters are selected because they are among the most significant indicators of internal transformer faults. Oil temperature reflects the thermal condition of the insulating oil, which plays a crucial role in heat dissipation. Winding temperature indicates the thermal stress on the windings, which is often associated with overloading or insulation failure. Gas content, especially dissolved gases like hydrogen, methane, and ethylene, is a well-established indicator of electrical or thermal faults within the transformer. By monitoring these three parameters collectively, a comprehensive understanding of the transformer's internal condition can be achieved. The system utilizes a fuzzy inference system (FIS), designed and simulated using MATLAB, to interpret these input parameters and provide a single output: the fault severity level. This output is expressed as a scalar value on a scale from 0 to 10, where 0 indicates a normal operating condition with no fault detected, and 10 signifies a severe fault that requires immediate intervention. The fuzzy logic approach is particularly well-suited for this application because it allows the system to handle the inherent uncertainty and imprecision in sensor data and transformer operating conditions. Unlike conventional threshold-based methods, fuzzy logic enables more nuanced decision-making by considering the degrees to which various conditions are met. The FIS developed in this research employs the Mamdani-type reasoning method, which is widely used in engineering applications for its intuitive rule-based structure and interpretability. Membership functions are defined for each input parameter to represent different qualitative levels, such as low, medium, and high. A set of fuzzy rules is then established based on expert knowledge and transformer diagnostic standards. These rules are used to infer the fault severity by evaluating the fuzzy relationships between the inputs. Finally, defuzzification is performed to convert the fuzzy output into a crisp numerical value. The MATLAB simulation of the proposed system demonstrates its effectiveness in accurately diagnosing fault severity levels under various operating scenarios. This model can be integrated into transformer monitoring systems to provide real-time diagnostics and improve preventive maintenance strategies. By reducing the risk of unexpected failures, the fuzzy logic-based diagnostic model contributes significantly to enhancing the reliability and efficiency of power system operations.

Model Architecture

Model architecture of the fuzzy inference system is shown below

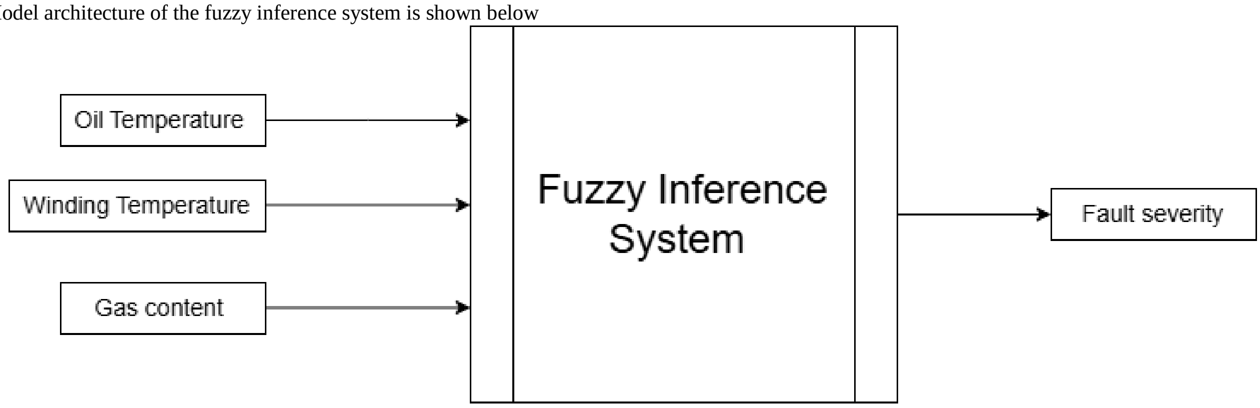

Figure 1 Fuzzy inference system for fault diagnosis

Input Variables

The proposed system considers the following input parameters:

- **Oil Temperature (°C):** Reflects the thermal condition of the transformer's cooling medium. The range is set between 40°C and 120°C.
  - *Low*: [40 40 60 70]
  - *Medium*: [60 80 100]
  - *High*: [90 100 120 120]
- **Winding Temperature (°C):** Indicates the internal heating of transformer windings, ranging from 50°C to 150°C.
  - *Low*: [50 50 70 85]
  - *Medium*: [80 100 120]
  - *High*: [110 130 150 150]
- **Gas Content (ppm):** Represents the dissolved gas content, which is a crucial indicator for internal faults. The range is from 0 to 1000 ppm.
  - *Low*: [0 0 200 400]
  - *Medium*: [300 500 700]
  - *High*: [600 800 1000 1000]

The membership function of input variable is shown below

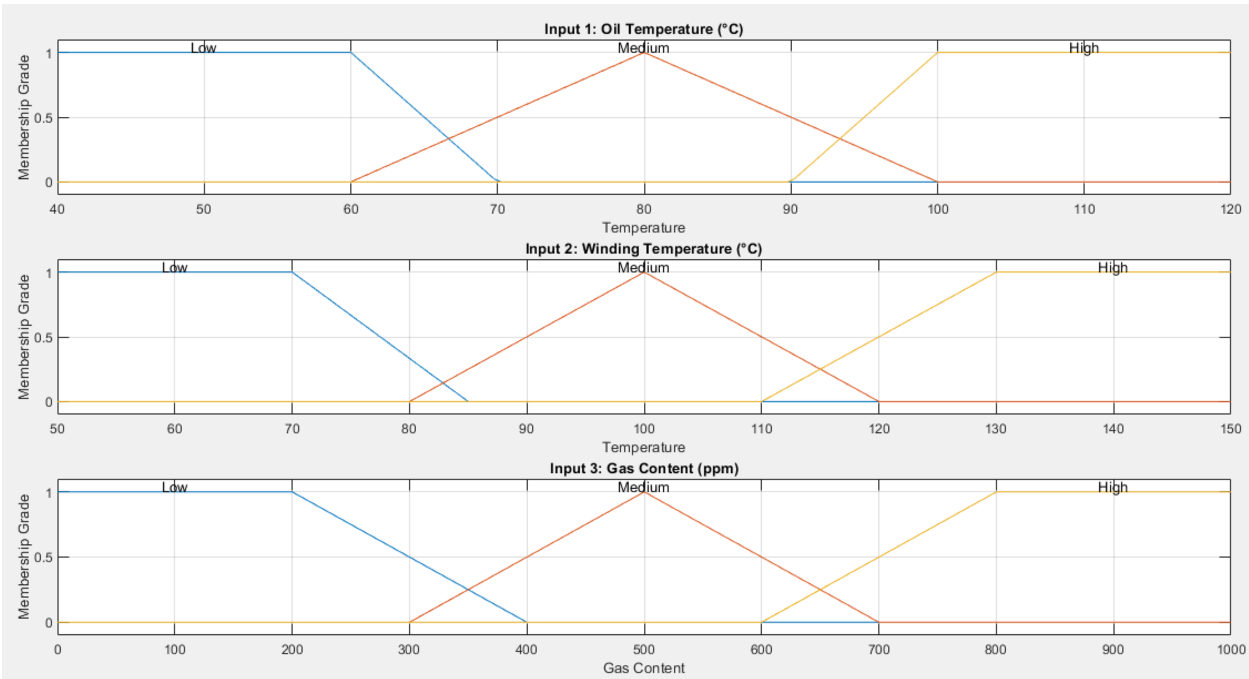

Figure 2 Membership function of input variables

Output Variable

- **Fault Severity:** A scalar output indicating the degree of fault within the transformer on a scale from 0 to 10.
  - *Low*: [0 2 4]
  - *Medium*: [3 5 7]
  - *High*: [6 8 10]

Membership function of output variable is shown below

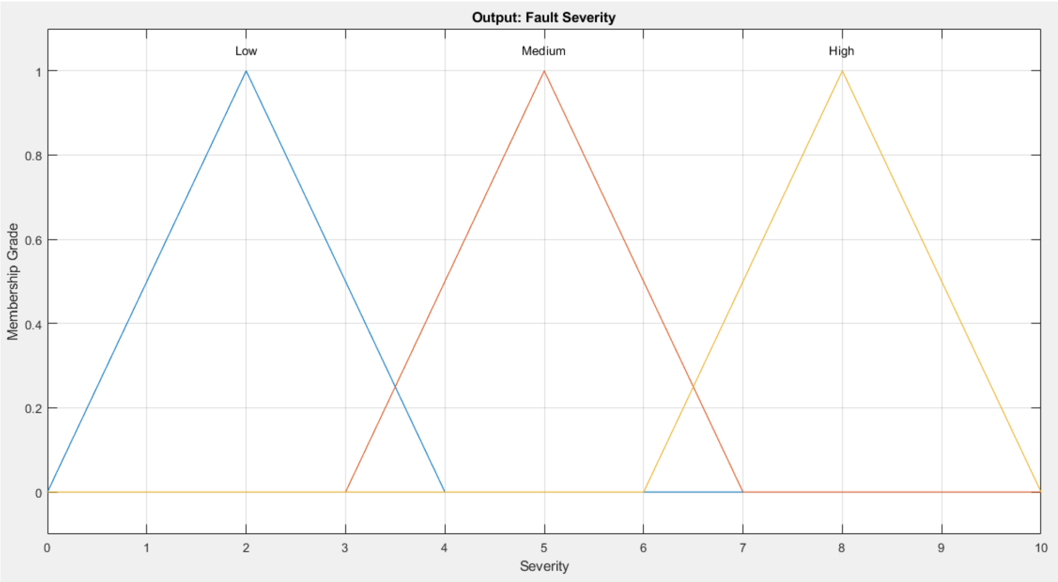

Figure 3 Membership function of output variable

Fuzzy Inference Rule Base

A total of **9 fuzzy rules** have been defined to map combinations of the input variables to the corresponding output severity levels. The rules follow expert domain knowledge and observed transformer behavior:

Table 1 Fuzzy inference rule base

Oil Temp	Winding Temp	Gas Content	Fault Severity
Low	Low	Low	Low
Medium	Medium	Medium	Medium
High	High	High	High
High	Medium	Medium	High
Medium	High	Medium	High
Medium	Medium	High	High
Low	High	High	Medium
High	Low	High	Medium
High	High	Low	Medium

Experimental Results and analysis

Case study 1: TestInput:

- Oil Temp = 100.0°C
- Winding Temp = 95.0°C
- Gas Content = 600.0 ppm

Fuzzy Logic Predicted Fault Severity: 8.00 (0:Low, 10:High)

Conventional Diagnosis Severity: 5.00 (0:Low, 10:High)

Case study 2: Test Input:

- Oil Temp = 120.0°C
- Winding Temp = 95.0°C
- Gas Content = 600.0 ppm

Fuzzy Logic Predicted Fault Severity: 8.00 (0:Low, 10:High)

Conventional Diagnosis Severity: 9.00 (0:Low, 10:High)

Testing with the input dataset of Fuzzy based approach and conventional approach

This MATLAB code implements and compares two diagnostic approaches—**Fuzzy Logic-based** and **Conventional Rule-based**—for transformer fault severity classification. A fuzzy inference system (FIS) previously saved as 'TransformerFaultFIS' is loaded, and a synthetic dataset containing input features (oil temperature, winding temperature, and gas content) along with expert-labeled fault severity is used for evaluation. The fuzzy logic model processes each input using fuzzy rules and membership functions to produce a continuous output, which is then discretized into three fault severity classes (low, medium, high). In parallel, a conventional rule-based method classifies severity based on hard thresholds applied to the same inputs. The final predictions from both methods are compared against the expert labels. The effectiveness of both approaches is quantified by calculating classification accuracy for each method. Results show the percentage of correctly identified fault severity cases out of the total dataset. A bar chart visualizes the accuracy comparison, highlighting the potential improvement offered by fuzzy logic in handling uncertainty and nonlinear behavior in diagnostic systems. This comparison effectively demonstrates the advantage of fuzzy logic in scenarios where strict thresholds might fail to capture subtle variations in the input data.

Fuzzy Logic Accuracy: 90.00%

Conventional Logic Accuracy: 50.00%

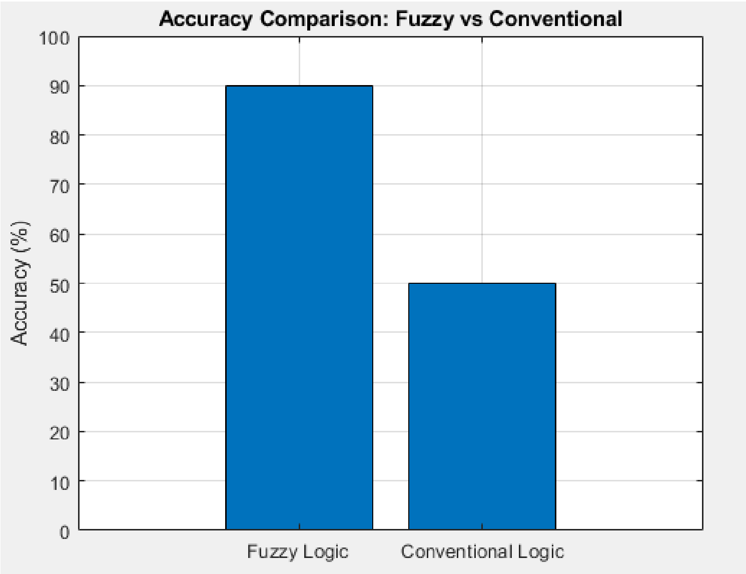

Figure 4 Efficiency improvement over conventional system

Conclusion

The proposed fuzzy logic-based transformer fault diagnosis system effectively models uncertainty and nonlinearity present in transformer fault detection. By using temperature and gas parameters, the system provides an interpretable, robust output that assists in condition monitoring and predictive maintenance of power transformers. The model can be extended further by incorporating more input features or hybridizing it with neural networks for adaptive intelligence.

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