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Fuzzy Algorithms for Diagnosis of Furnace Transformer Insulation Condition

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Abstract: Implementation of the smart transformer concept is critical for the deployment of IIoT-based smart grids. Top manufacturers of power electrics develop and adopt online monitoring systems. Such systems become part of high-voltage grid and unit transformers. However, furnace transformers are a broad category that this change does not affect yet. At the same time, adoption of diagnostic systems for furnace transformers is relevant because they are a heavy-duty application with no redundancy. Creating any such system requires a well-founded mathematical analysis of the facility's condition, carefully selected diagnostic parameters, and setpoints thereof, which serve as the condition categories. The goal hereof was to create an expert system to detect insulation breach and its expansion as well as to evaluate the risk it poses to the system; the core mechanism is mathematical processing of trends in *partial discharge* (*PD*). We ran tests on a 26-MVA transformer installed on a ladle furnace at a steelworks facility. The transformer is equipped with a versatile condition monitoring system that continually measures apparent charge and *PD* intensity. The objective is to identify the condition of the transformer and label it with one of the generally recognized categories: Normal, Poor, Critical. The contribution of this paper consists of the first ever validation of a single generalized metric that describes the condition of transformer insulation based on the online monitoring of the *PD* parameters. Fuzzy logic algorithms are used in mathematical processing. The proposal is to generalize the set of diagnostic variables to a single deterministic parameter: insulation state indicator. The paper provides an example of calculating it from the apparent charge and *PD* power readings. To measure the indicativeness of individual parameters for predicting further development of a defect, the authors developed a method for testing the diagnostic sensitivity of these parameters to changes in the condition. The method was tested using trends in readings sampled whilst the status was degrading from Normal to Critical. The paper also shows a practical example of defect localization. The recommendation is to broadly use the method in expert systems for high-voltage equipment monitoring.

Keywords: furnace transformer; technical condition; monitoring; fuzzy logic; diagnostic criteria; diagnostic sensitivity

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1. Introduction

The smart transformer is a key concept in digital industry and energy development. CIGRE's guidelines can be generalized to define the smart transformer as an energy-saving unit equipped with digital control systems and online condition monitoring systems [1]. This concept is pursued by the top manufacturers of power electrical equipment. Known developments affect grid transformers in electric power systems as well as unit transformers used at power plants. However, another class of transformers—furnace transformers—so far remains unaffected by these developments. The reason is that such transformers are used by steelworks facilities that feature a complete technological cycle; these units are uncommon.

However, a scientific validation and practical implementation of a smart furnace transformer is a relevant undertaking for the industry. The critical challenge consists in developing the theory, methods, and systems for predictive condition monitoring in real time. Condition analysis should be based on a set of features combined into a generalized parameter. This paper covers some aspects of the problem. However, we first need to cover the diagnostic features and methods for condition monitoring, which are applicable to any class of transformers.

1.1. Development of Online Monitoring Systems

Paper [2] notes that *high-voltage equipment is a special category of complex equipment subject to continuous diagnosis. In that category, it is power transformers that require most attention and regular checkups*. The reason is that they are critical for uninterrupted electricity delivery to consumers [3]. Paper [4] states that *power transformers are significant and valuable units, and that this is why condition monitoring is crucial in their case. Should a critical transformer fail in a transmission grid, energy security might be jeopardized.*

Unscheduled shutdown of a furnace transformer disrupts the process cycle of the steelworks facility. Such disruption will result in undersupply and multimillion losses. Worse than that, furnace transformers have no redundancy, unlike their grid or unit counterparts. The service life of a power transformer depends on the condition of its insulation, which is degraded by loads of various physical natures. These include *thermal, electrical, mechanical, and environmental loads* [5].

The adoption of smart grid technologies [6,7] and the advancement of IIoT-based smart grids [8–11] have brought attention to the condition monitoring of power transformers. Paper [12] considers using AI for condition analysis. Its authors claim that *novel methods are capable of accurate fault detection even where data is uncertain.* Papers [13–16] presents an overview of transformer condition testing methods for use in smart distribution grids. It analyzes the latest methods in terms of their strengths and weaknesses [8,17–21].

Constant enhanced monitoring is necessary for the transformers of high-power electric arc furnaces and ladle furnaces. This is heavy-duty machinery operating under asymmetric, drastically variable loads. The windings of a furnace transformer are exposed to electrodynamic shock loads resulting from current surges that in turn are a result of the electric arc melting technology [22,23]. Besides this, on-load tap changing, which occurs several times a year in case of a grid transformer, might be performed up to 1000 times a day on a furnace transformer [24]. However, condition monitoring of furnace transformers remains under-investigated.

Designing an online monitoring system for complex equipment consists in completing two related objectives: They are:

- hardware and software development;
- validation of mathematical analysis methods and selection of diagnostic parameters and condition categories.

Below are considered some aspects of the second objective for online monitoring systems implemented on the transformers of two ladle furnaces at a steelworks facility [25,26].

1.2. Validation of Condition Analysis Methods Fuzzy Logic

Paper [27] states that *in recent years, several developments haven taken off that rely on AI models: neural networks, support vector machines, hybrid methods*, etc. *They are intended to diagnose power transformer malfunctions by analyzing the gases. These methods, although performing quite well, face limitations with respect to the accuracy of identifying the exact moment of multiple small-scale malfunction; besides, they are difficult to implement*. Partial discharge monitoring is a commonly recognized method for early fault diagnosis. This is why it is proposed to diagnose emergent failures by *PD* monitoring enabled by fuzzy logic (*FL*).

FL methods are common in condition assessment of high-voltage equipment [28–32]. The reason for this is that the condition of most physical objects cannot be described in binary terms: serviceable vs. faulty. There are multiple intermediate states that would be logical to determine by means of *FL*. Paper [33] emphasizes that *the relation between faults and their causes is complex in case of power equipment. This is why FL is the method of choice for internal transformer diagnostics*. A similar conclusion is drawn in [34]: *fuzzy logic is a smart and accurate tool for the automated detection of transformer faults*.

FL applications for diagnosing faults in power transformers are covered in [35–40]. However, most developments concern dissolved gas analysis (*DGA*); *FL* diagnosis based on other monitoring methods remains understudied.

1.3. Selection of Diagnostic Parameters—Partial Discharge Monitoring

PD monitoring is a promising, rapidly developing method for high-voltage equipment condition monitoring [41–43]. *PD* intensity is an important diagnostic feature of oil and solid insulation condition. IEC 60270 defines *partial discharge as a localized electrical discharge that only partially bridges the insulation between conductors* [44]. In practice, *PDs are both symptoms and causes of insulation aging, and they can cause equipment failure in the long term* [45]. *PD* monitoring helps prevent early aging of insulation. Meanwhile, *it is crucial to know the characteristics of the discharge itself for the purposes of monitoring. The next step is to apply fuzzy logic to evaluate equipment condition*. This approach, stated in [46], is the foundation of the research presented herein.

The core *PD* readings are:

1. *Apparent discharge*, Q_{02} [nC], which is quantitatively proportional to the maximum pulse amplitude [44,47].
2. *PD power*, usually reduced to *PDI—Partial Discharge Intensity*. This parameter is defined as the total energy of discharges divided by the time of their summation, which is why it has the same dimensionality as power [maw]. The parameter describes the power and intensity of *PD* and is determined by the dependency [48,49].

$$PDI = \frac{1}{T}\sum_{i=1}^{m} Q_i U_d, \tag{1}$$

where m is the number of pulses recorded over the observation time T; U_d is the effective voltage.

A drastic increase in Q_{02} and *PDI* is an unambiguous sign of insulation destruction. If these values change significantly over 3–4 observations, or at least double over a year, then the insulation has an expanding defect [50].

1.4. Generalized Transformer Condition Indicators

Cluster analysis is a promising mathematical tool for assessing equipment condition from *PD* readings [51–53]. PD intensity can be analyzed, and PD clusters can be localized *PD* in the transformer tank. However, quantifying insulation wear is difficult. The reason for this is that there is not a single condition indicator based on *PD readings*.

Papers [54,55] validate a risk indicator for power transformers, which is based on electrical measurements (an *EM* indicator). A similar condition parameter was adopted for *DGA* results. Paper [56] presents an algorithm for quantifying the *EM* indicator. They also quantify the generalized oil analysis-based indicator. Thus, they validated condition indicators for three diagnostic methods: *DGA*, electrical measurements, and oil analysis. Apparently, this approach should also be applicable to PD localization as a condition indicator.

Thus, the key objective hereof is to find such a generalized transformer condition indicator based on continually monitored *PD* readings and *FL* algorithms. Another objective is to evaluate the sensitivity of *PD* parameters for predictive condition monitoring.

Similar problems are addressed in [57–60]. In [61], they adopt the *insulation state indicator* (*ISI*) to quantify the degradation (aging) of insulation in electric machines. The indicator is the standard deviation between reference and later measurements. They compare the amplitude spectra of voltage as recorded for a machine in normal condition against later measurements. This paper presents a similar approach to deriving insulation condition from PD readings.

2. Problem Statement

2.1. Monitoring System Description

Below are the results of studies performed on ETTsNKV-40000/110-UHL-4 transformers manufactured by Elektrazavod JSC (St. Petersburg, Russia). They are installed on ladle furnace transformers at a full-cycle steelworks facility. Table 1 shows the nominal parameters [49].

Table 1. Parameters of the transformer ETTsNKV-40000/110.

Type	Rated Capacity, kVA	Rated Coil Voltage, V	Diagram and Group of Coil Connection	Number of OLTC Positions	Cooling System	Mass, Tons	Length × Width × Height, mm
ETTsNKV-40000/ 110-UHL-4	26,000–20,282	110,000 HV 421–289.5 LV	ϒ/Δ-11	9	Suspended"OFWF"	80	4840 × 3540 × 6200

The online monitoring systems were based on the diagnostic equipment manufactured by Dimrus, Perm, Russia, complemented with a MINITRANS continuous gas and oil humidity monitor *(Kelman)* [62]. The key diagnostic device is *TDMS* (*Transformer Diagnostics Monitor Special*). It consists of five primary sensor modules, a microprocessor module, and a PSU, all installed in a cabinet, see Figure 1. For details on the modules, see [26].

Figure 1. TDMS structure.

Figure 2 shows a simplified functional diagram of the system. Electrolocation is used to measure the *PD* readings. The method consists in using DB sensors installed on the PIN terminals of high-voltage bushings; the sensors record the flowing current pulses [63]. Apparent charges are derived from the signal amplitudes, whereas the number of discharges is derived from pulse rates. For details on the system, see [49,64]

The system registers pulses that last ≤640 ns; however, there should be no pulses with an amplitude of >30% of the original pulse amplitude for at least 2560 ns. Failure to meet this requirement classifies the pulse as noise and prevents it from being logged. A *PD* pulse is considered to periodically repeat if its repetition rate is 0.2 pulses per grid voltage period. The measured apparent charge Q_{02} is quantitatively proportional to the maximum amplitude of the repeated discharge of pulse U_{02}. It is determined by the linear dependency $Q_{02} = U_{02}/k_0$, where $k_0 = 32.56$ is a coefficient set in the system configuration. Thus, the values Q_{02} and U_{02} are related and are essentially the identical *PD* readings.

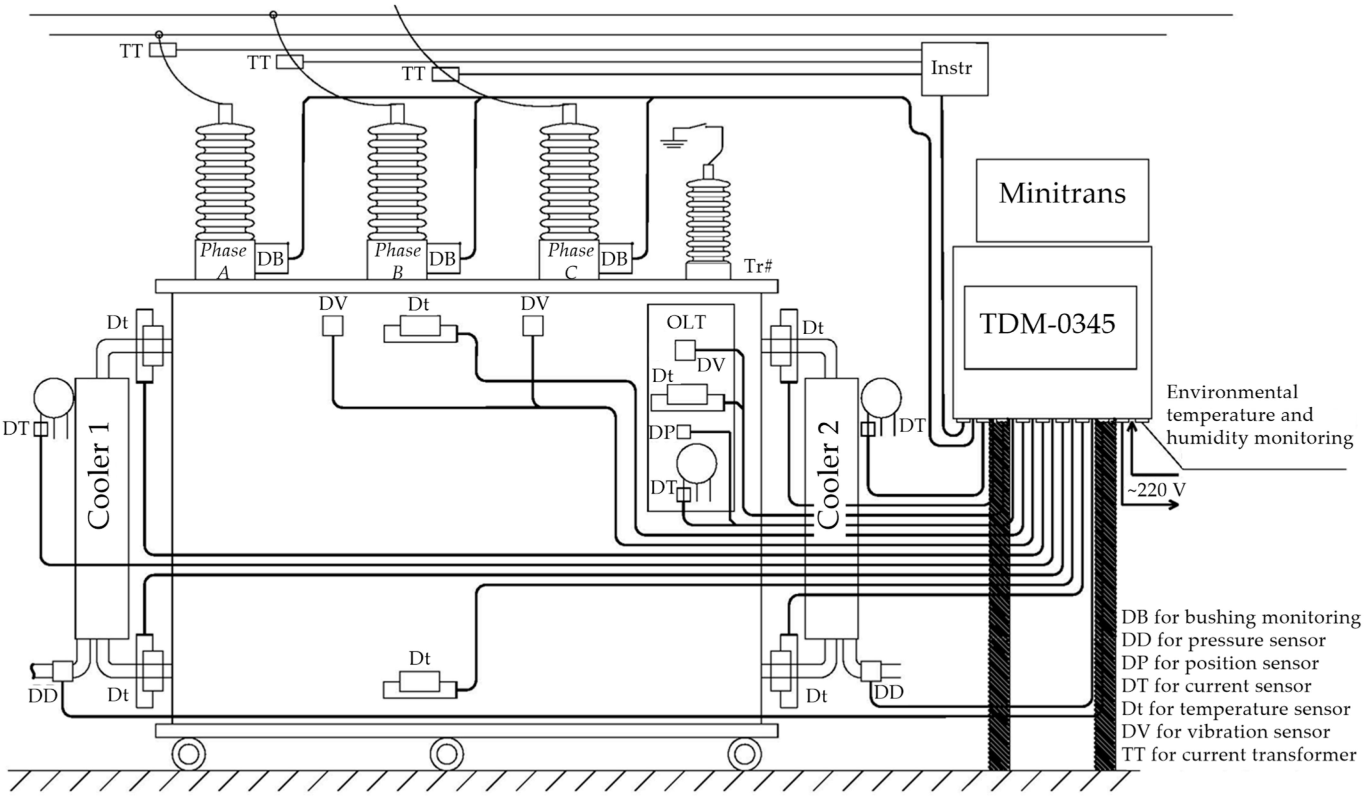


Figure 2. Part of the functional diagram of the furnace transformer condition monitoring system.

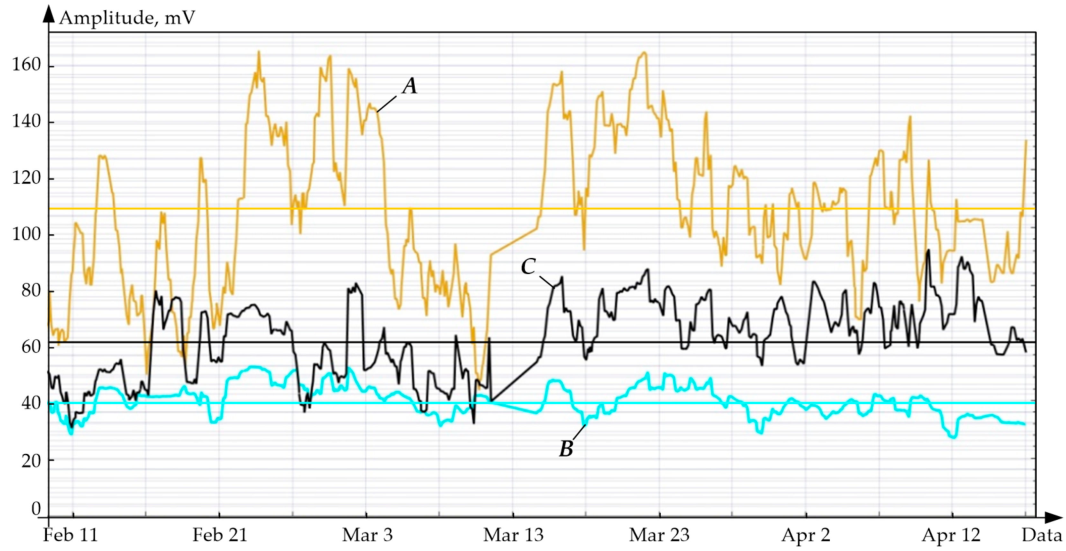
The second *PD* reading is its power. This parameter is reduced to the integral *PDI*, which is found by the dependency (1). Both parameters can be used to indirectly assess insulation condition on the basis of the *PD* readings (Table 2) [65].

Table 2. Classification of insulation conditions based on PD parameters.

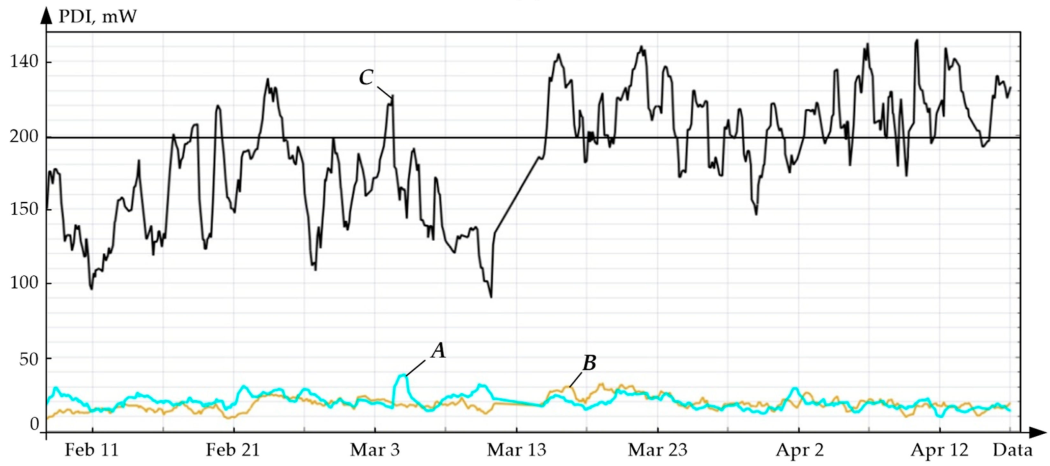
Insulation Condition	Maximum Amplitude of Apparent Discharge, pC	Recurrence Rate, Pulses/s	PD Power, MW
Dry, clear–concentration of impurities < 50 particles/mL	<30	25–30	<0.2
Relatively clear–after repair with insulation flushing	250–380	120–150	0.5–0.9
Contaminated with hard impurities	300–400	120–150	50–90
Wet, heavily polluted with impurities	220–400	1000–1800	470–800

2.2. Experimental PD Analysis

In course of the research, we used the newly adopted system to analyze the *PD* readings in transformer phases from 1 January to 31 December 2015. Figure 3 shows the trends in these readings as logged from 11 February to 22 April 2015 [66]. Figure 3a shows trends in U_{02} as recorded when monitoring constant discharges; Figure 3b shows trends in *PDI*.



(**a**)



(**b**)

Figure 3. Trends in the repeated discharge amplitude (**a**) and PDI (**b**) in Phases *A*, *B*, *C* of high-voltage bushings.

Table 3 shows normalized limits for each condition category, which can be derived from *PD* readings [67]. For furnace transformers, the boundary values indicative of the poor insulation condition (U_{1D} and P_{1D}) can be found by the inequalities [49]:

$$U_{02} > U_{1D} = 80 \text{ mV } (Q_{02} > Q_{1D} = 2.5 \text{ nC}); PDI > P_{1D} = 60 \text{ mW};$$

For critical condition: (Q_{2D} and P_{2D})

$$U_{02} > U_{2D} = 160 \text{ mV } (Q_{02} > Q_{2D} = 5 \text{ nC}); PDI > \mathrm{P}_{2D} = 80 \text{ mW}.$$

The limit values determining the object's state based on the results of the discharge activity control were not determined specifically for furnace transformers, and they are not provided in the regulatory documents. Therefore, the values such as U_{1D}, U_{02}, U_{2D} (etc.) were selected the same way as the grid transformer parameters. They are set out in the Methodology Guidelines MU 0634-2006 [67].

Table 3. Determination of transformer condition based in discharge monitoring results.

Classification According to [67]	Classification of Condition	Defect Evolution in Compliance with RD EO-0069-97 RU	Values of Maximum Amplitudes of Partial Discharges, C		
			In Windings and between Coils	*Main Insulation, Barriers, According to RD cl.4.9.4*	*Inputs According to RD cl.4.9.4*
Failed condition	PRE-EMERGENCY	Limit condition	Over 5 nC	Over 100 nC	Over 10 nC
	IMPAIRED	Fatal defect	Up to 2.5 nC	5–25 nC	0.5–2.5 nC
	NORM with significant deviations	Major defect	Up to 500 pC	1–5 nC	Up to 500 pC
Operative condition	NORM with deviations	Minor defect	Up to 100 pC	Up to 1000 pC	Up to 100 pC
	NORM	No evident defects	-	Up to 100 pC	-

Comparison against the dependencies (Figure 3) revealed an expanding destructive process. However, it is not always possible to unambiguously classify the condition of a transformer into one of these categories. Thus, Phase *A* insulation has the worst condition, as shown in Figure 3a. Its mean charge of 3.2 nC (the solid line) corresponds to poor condition per Table 3. Phase *B* and Phase *C* bushings are in a better condition. Their discharge intensity ranges between 0.5−2.5 nC, although the condition is also poor per Table 3.

However, should we analyze the dependencies in Figure 3b, we find Phase *C* to be in the worst condition. The mean total *PD* power (solid line) equals ~200 mW, whereas the thresholds are 60 mW and 80 mW. In other phases, however, the insulation is stable and *normal*. Thus, these readings are confusing with regards to the transformer condition. The reason for this is that Q_{02} describes the *PD* amplitude; however, there can be defects, whose expansion increases the number and total power of pulses without affecting the amplitude. This is why *PDI* is believed to be more defect-sensitive. Authors of several papers, in particular [48], agree.

This analysis proves the relevance of creating an expert system for assessing transformer condition on the basis of its *PD* readings. To that end, we hereby introduce a generalized indicator: *insulation state indicator* based on *partial discharge* (ISI_{PD}). This parameter is a linguistic variable for *FL* studies.

To test the informativeness of readings, we need to evaluate the diagnostic sensitivity (*DSe*) of U_{02} (or Q_{02}) and *PDI* to the actual transformer condition. Papers [68–70] discuss application of a similar metric to analyze the condition of power system equipment; papers [71,72] present a similarly designed comparison of transformer models. However, these developments have not found a practical application yet. It would be relevant to devise a *DSe* calculation method based on *PD* readings, and to verify the method experimentally.

3. Materials and Methods

In pursuit of the objectives hereof, the authors were guided by research presented in [73]. The paper proposes a method that applies fuzzy logic to calculate the probability of condition features manifesting (or not manifesting); it returns a formalized result. For condition features, they used gas concentration in the oil as well as thermal imaging-detected overheated spots. Four condition categories were specified, each with a specific range of the selected indicators within the specified limits.

The weakness of the method lies in its assumption that the condition categories are independent. Thus, transformer condition should be described by a set of independent features. However, many features are not [74]. This can be seen, in particular, in the presented analysis of *PD* readings, see Figure 3.

For condition testing, we use the parameters U_{02} and *PDI*. A stable reading of any of these characterizes the expansion of insulation defects when compared against the set thresholds. From the standpoint of ordinary crisp sets, insulation condition can be shown as in Figure 4.

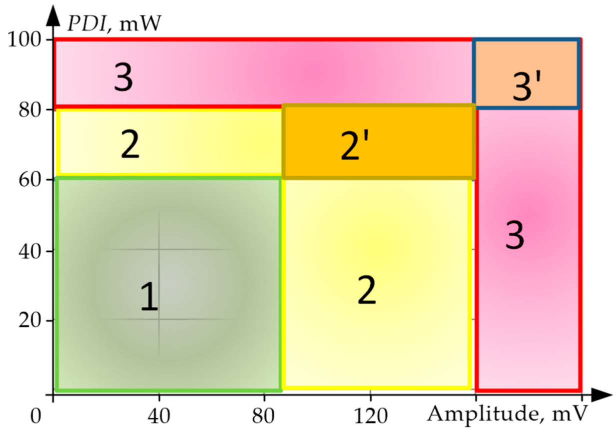


Figure 4. Transformer insulation condition assessment based on *PD* readings and using crisp sets: 1 for normal condition; 2 for poor condition; 3 for critical condition; 2′ for near-critical condition; 3′ for emergency condition.

In this case, condition can be diagnosed by applying the characteristic function $\mu_A(U_{02}, PDI)$ of membership in one of the three condition sets:

- normal condition (1) if $0 \leq U_{02} < U_{1D}$ or $0 \leq PDI < P_{1D}$;
- poor condition (2) if $U_{1D} \leq U_{02} < U_{2D}$ or $P_{1D} \leq PDI < P_{2D}$;
- critical condition (3) if $U_{2D} \leq U_{02}$ or $P_{2D} \leq PDI$.

As can be seen in the figure, there are two more subsets:

- near-critical condition (2′) if $U_{1D} \leq U_{02} < U_{2D}$ or $P_{1D} \leq PDI < P_{2D}$;
- emergency condition (3′) if $U_{2D} \leq U_{02}$ or $P_{2D} \leq PDI$.

In fact, the transition between insulation conditions at a threshold is purely conventional and indefinite. This is why *FL* is the best condition assessment method. A literature overview reveals many approaches that use fuzzy linguistic variables in decision making. Software that applies fuzzy set theory to address the problems of industrial equipment operation is quite common [75,76]. In this research, we used *Fuzzy Logic Toolbox for MatLab*.

The degree of a member's membership in a fuzzy set is determined by the membership function whose specific value is characterized by the membership coefficient. The variables used in fuzzy statements of the subconditions of fuzzy inference rules serve as the input linguistic variables. In turn, the variables used in subconclusion statements are the output linguistic variables. For each of the selected variables, specify corresponding term sets and membership functions.

The input linguistic variables are the maximum *PD* amplitude and power *PDI*, whereas the output linguistic variable is ISI_{PD}. Table 4 shows the linguistic variables and their corresponding term sets.

Table 4. Linguistic variables.

Linguistic Variable Type	Name	of the Term Set
Input	PD amplitude (U_{02})	Low Medium High
	PD power (*PDI*)	Low Medium High
Output	Insulation condition ISI_{PD})	Normal Poor Critical

Insulation condition was determined by a matrix of rules as a function of *PD* readings, see Table 5. The table was used to formulate 9 fuzzy inference rules for condition assessment.

Table 5. Insulation Condition Assessment Rule Matrix.

Maximum *PD* Amplitude (U_{02})	***PD* Power (*PDI*)**		
	Low	**Medium**	**High**
Low	*Normal*	*Poor*	*Critical*
Medium	*Poor*	*Poor*	*Critical*
High	*Critical*	*Critical*	*Critical*

Rule 1: ***if*** *U_{02} is Low **AND** PDI is Low, the condition is Normal.*
Rule 2: ***if*** *U_{02} is Medium **AND** PDI is Low, the condition is Poor*
etc.

The Gaussian membership function was used for the input variables. This is explained by the natural use of the standard data distribution law relative to the maximum of the membership function for the terms such as 'low', 'medium', and 'high'. Besides this, the Gaussian function is smooth and takes non-zero values throughout the applicable domain. The output variable of insulation state relies heavily on the discrete valuation. In this case, it is feasible to use a triangular membership function for the output linguistic variables.

Each condition has a weight F_i, (i = 1, 2, ... 9) ranging in [0, 1]. For initial rulemaking, the weights are assumed to equal 1. Further optimization of the fuzzy inference rule base and its adjustment for the real-world data led to adjustments in the weights.

For fuzzy models, the input signals are the U_{02} and *PDI* readings that uniquely determine the inputs. That means that for the given inputs, the outputs should be uniquely determined as well. These sets interact through a fuzzy system that has an input fuzzifier and an output defuzzifier [77].

For the inputs, the assumption is that the maximum *PD* amplitude ranges from 0 to $1.25 \cdot U_{2D}$ = 200 mV, and the *PD* power ranges from 0 to $1.25 \cdot P_{2D}$ =100 mW. For the output variable *Insulation Condition*, the range is 0 to 10 points. The input variables have three functions named *Low*, *Medium*, and *High*. Assume that the first two variables are Gaussian,

$$gaussmf(x,\ \sigma,\ c) = \exp\left[-\left(\frac{x-c}{\sigma}\right)^2\right], \tag{2}$$

whereas the last variable is a two-sided Gaussian membership function

$$gauss2mf(x,\ \sigma_1,\ c_1, \sigma_2,\ c_2), \tag{3}$$

where c is the mathematical expectation; σ is the standard deviation; and σ_1, c_1, σ_2, c_2 are the Gaussian function parameters that determine the membership function curve shape to the left and to the right of the modal value.

For the output variables, set three triangular membership functions named *Normal, Poor, and Critical.* Poor condition is set at 5 points, and critical condition corresponds to 7.5 points. Description of a triangular membership function is known

$$trimf(x,\ a,\ b,\ c) = \begin{cases} 0, x \le a \\ \frac{x-a}{b-a}, a \le x \le b \\ \frac{c-x}{c-b}, b \le x \le c \\ 0, x \ge c \end{cases}. \tag{4}$$

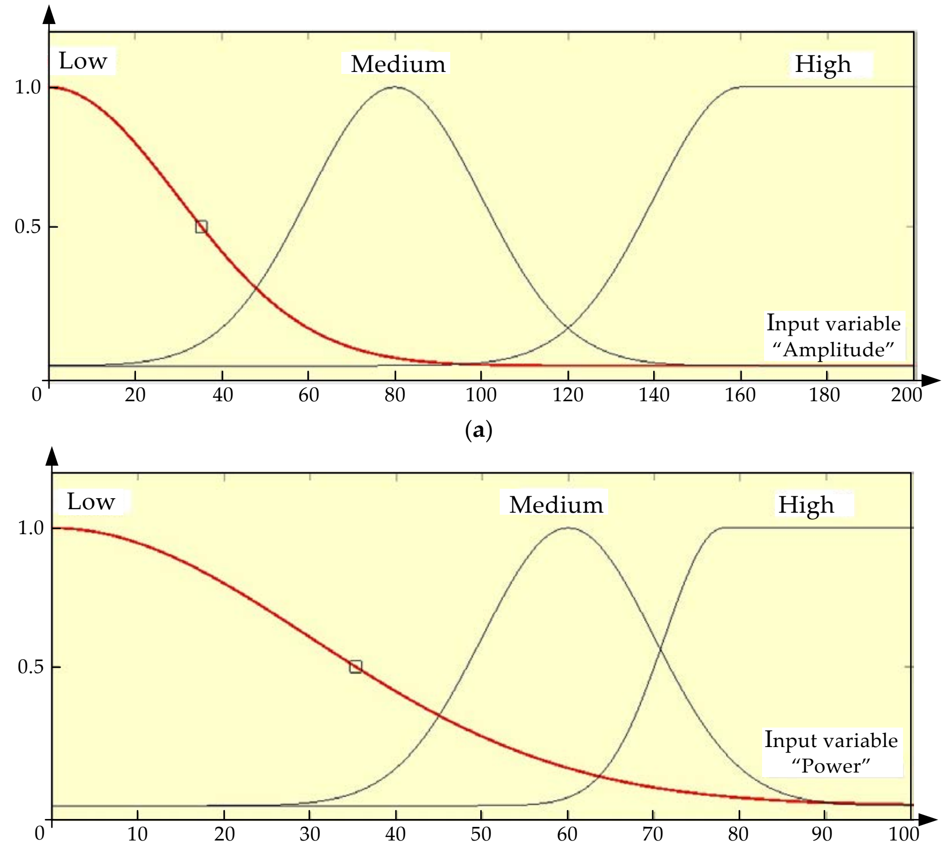
where a, b, c are numerical parameters whereby $a \le b \le c$.

Table 6 shows the membership function specifications; Figure 5 shows the functions themselves for the input and output variables.

Table 6. Specifications of membership functions for input and output variables.

Name	of the Term Set	Membership Function Type	Values of the Membership Function Parameters
Maximum PD amplitude	*Low*	Gaussian	$[x; 30; 0]$
	Medium	Gaussian	$[x; 30; U_{1D}]$
	High	Two-sided Gaussian	$[x; 30; U_{2D}; 3, 4;$ $1, 25 \cdot U_{2D}]$
PD power	*Low*	Gaussian	$[x; 20; 0]$
	Medium	Gaussian	$[x; 10; P_{1D}]$
	High	Two-sided Gaussian	$[x; 6, 8; P_{2D}; 3, 4;$ $1, 25 \cdot P_{2D}]$
Insulation condition	*Normal*	Triangular	[−4; 0; 4]
	Poor	Triangular	[1; 5; 9]
	Critical	Triangular	[6; 10; 14]

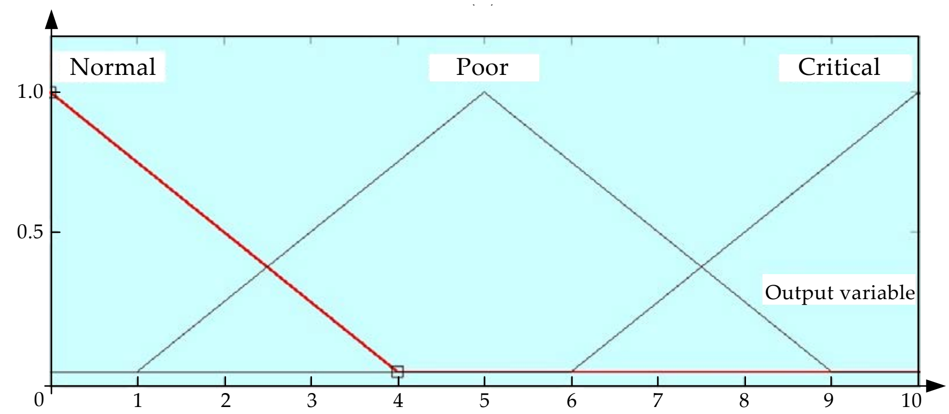
Figure 6 shows a surface diagram based on this data and the selected membership functions; the diagram shows how the linguistic inputs affect the linguistic output ISI_{PD}. This surface was produced by applying fuzzy inference rules to assess operational hazard with the given defuzzifier (Mamdani algorithm). For the selected membership functions, the output variable had a high of 8.7 points and a low of 1.3 points. As specified in the model, poor condition corresponded to ~5 points, and critical condition corresponded to ~7.5 points. *Matlab evalfis* can be used to obtain fuzzy inference function values to further plot the output parameter as a function of one of the input variables.



(**a**)

(**b**)

Figure 5. *Cont.*



(**c**)

Figure 5. Membership functions for the input variables: *Maximum PD Amplitude* (**a**); *PD Power* (**b**); and for the output variable *Insulation Condition* (**c**).

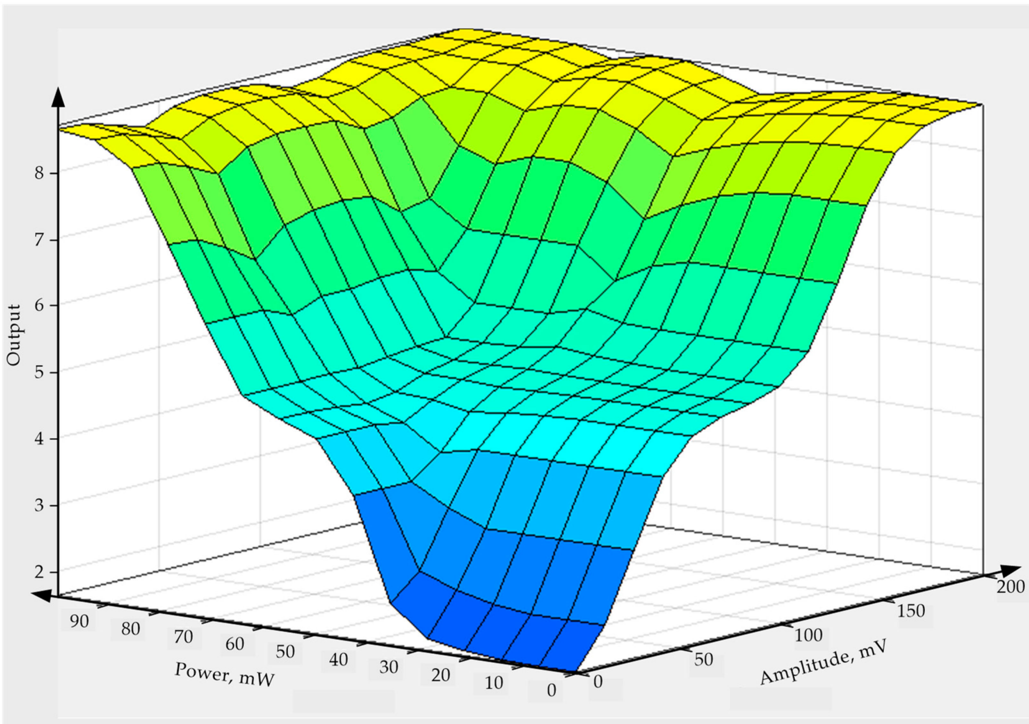


Figure 6. This surface shows how *PD* power and amplitude affect the output linguistic variable (in points).

4. Implementation

4.1. Example of Generalized Indicator-Based Transformer Condition Assessment

Figure 7 shows the online readings of *PD* amplitude U_{02} and *PDI* for the tested transformer as points. Input data were smoothed by moving the average over 50 points and are shown as solid lines [49]. These data was collected from 9 September to 22 December 2016; the sample was ~650 points for each phase. Such late data retrieval was due to the fact that it was in this period that the transformer's condition went from normal to poor. Timely diagnosis prevented its escalation to critical. No similar situations have arisen since. This is why these trends in PD readings, although not being freshly collected data, do contain important (and, to an extent, unique) diagnostic information. To further support this statement, we hereby report that we have not been able to find similar data in the literature.

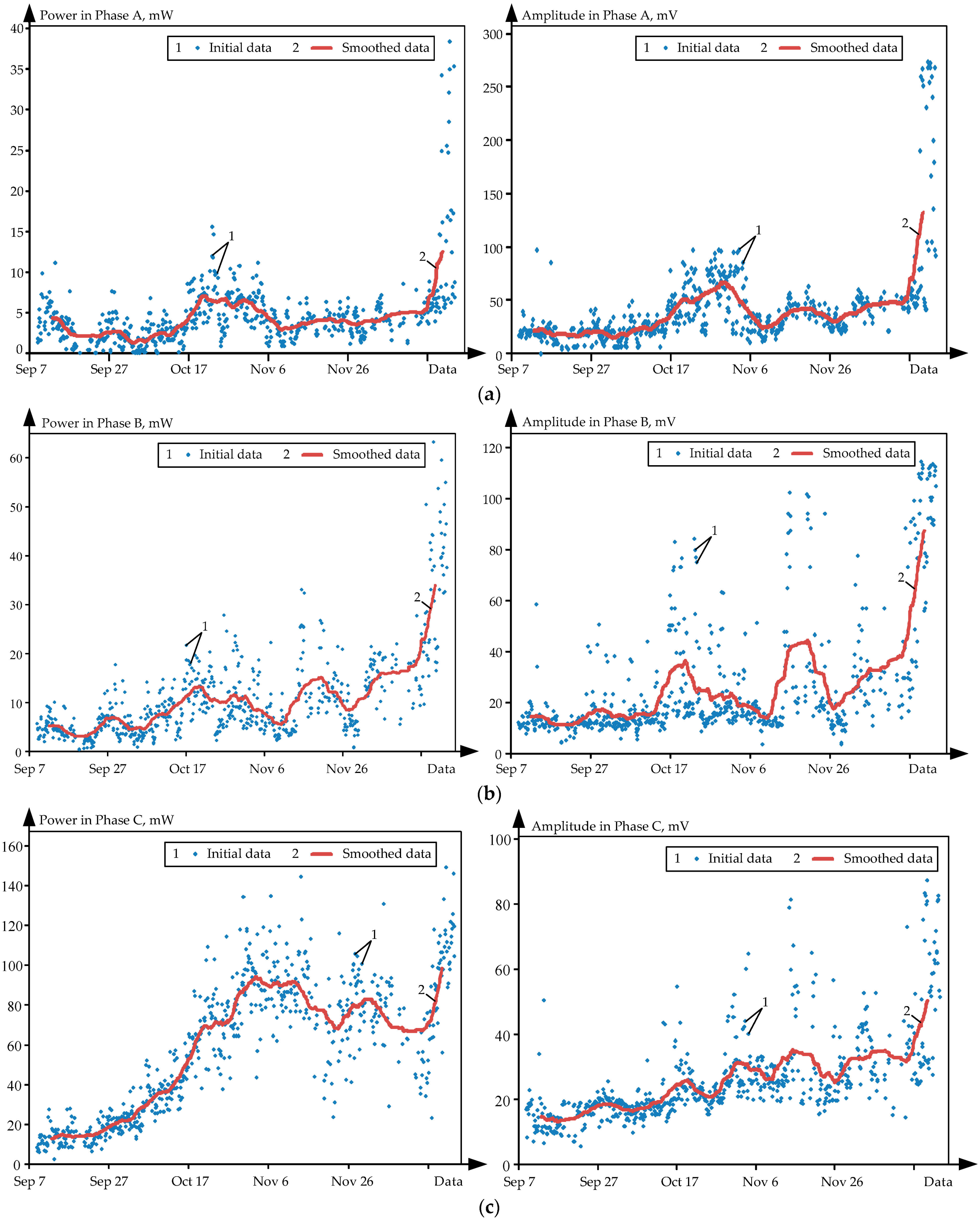


Figure 7. Input and smoothed trends of power and amplitude of partial discharges from 9 September to 22 December 2016: (**a**)—Phase A; (**b**)—Phase B; (**c**)—Phase C.

In the data sample, a drastic increase in *PD* intensity can be observed in all phases from late September to early October. *PDI* rose the most in Phase *C*, see Figure 7c. Thus, on ~18 October it exceeded 60 mW (the poor condition threshold); on 28 October, it went past 80 mW (the critical condition threshold). In late October, *PD* power and amplitude began decreasing in Phases *A* and *B*, see Figure 7a,b; however, they kept increasing monotonically in Phase *C*. This continued until Nov 3 (*PDI* ≈ 98 mW); then, the process stabilized in Phase *C*, but the power settled at a higher level. After a relatively flat segment in the *PDI* trend, *PD* intensity began to rise drastically, starting on ~15 December. In all phases, *PD* power and amplitude rose 1.5–2-fold. In Phases *A* and *B*, there was an increase in amplitude (U_{02} > 80 mV), whereas in Phase *C*, power rose to poor and then to critical levels (*PDI* > 80 mW).

Figure 8 shows a change in ISI_{PD} in phases over the same timeframe. To that end, *PD* power and amplitude readings were processed in *Fuzzy Logic Toolbox for MatLab*. Smoothed data shown in Figure 7 as solid lines were used as input variables.

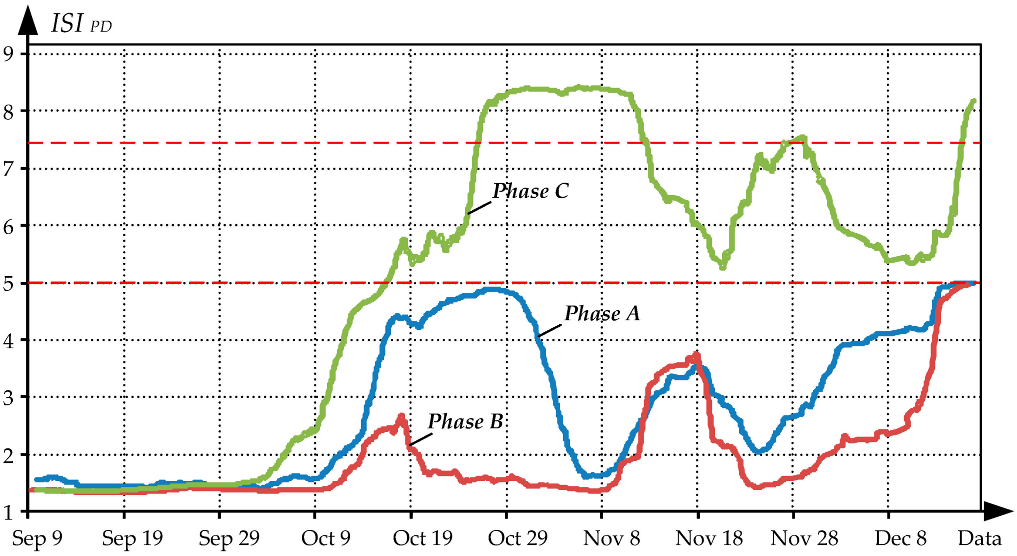


Figure 8. Change in the generalized diagnostic parameter ISI_{PD} from 9 September to 22 December 2016.

Broken lines show poor and critical condition levels (5 points and 7.5 points), as validated above. As can be seen in Figures 7 and 8, Phase *C* is the most 'problematic' one. It is in this phase where, starting from ~18 October, we can observe a *poor condition* that becomes *critical* in 10 days. ISI_{PD} then drops to ~5 points, beginning to rise again on 13–15 December; it simultaneously increases in Phases *A* and *B*. By 20 December, Phase *B* readings reached a *poor condition*, whereas Phases *A* and *C* reached a *critical condition*.

4.2. PD Readings Sensitivity Testing

Pursuant to the objectives, we further proceeded to test the reliability of U_{02} and *PDI* readings as insulation condition indicators. Tests relied on the aforesaid indicator *DSe*. Calculations were based on experimental data. The developed methodology included the following steps.

1. For quantification, it is proposed to use a generalized indicator descriptive of the hazard of *PD* for insulation. In this case, such an indicator has to be a normalized characteristic of the informative parameters $\overline{Y}_i$ with respect to the difference between the poor/critical condition threshold (Y_{jD}) and normal (background) readings. Y_{i0}

$$\overline{X}_i = \frac{\left|\overline{Y}_i - Y_{i0}\right|}{\left|Y_{jD} - Y_{i0}\right|}. \tag{5}$$

Normalized values ($\overline{X}_i$) ensure that the requirements of dimensionlessness and 0–1 rating scale uniformity are met at $Y_{i0} \leq \overline{Y}_i \leq Y_{iD}$.

2. Since *PD* activity is measured by reading the voltage U_{02} and the power *PDI*, they correspond to two normalized indicators: X_U and X_P. For the parameter of their co-effect, we suggest the geometric mean hereinafter referred to as *PD Activity Level*.

$$L_{PD} = \sqrt{X_U \cdot X_P}. \tag{6}$$

Given the expressions (5) and (6)

$$L_{PD} = \sqrt{\frac{|P_i - P_0|}{|P_{jD} - P_0|} \cdot \frac{|U_i - U_0|}{|U_{jD} - U_0|}}, \tag{7}$$

where P_0 and U_0 are the initial *PDI* and U_{02}, P_{jD}, U_{jD} are the thresholds for poor condition (j = 1) and critical condition (j = 2).

3. Calculate the mean of each signal over the specified timeframe

$$\overline{Y}_i = \frac{1}{N}\sum_{k=1}^{N}(X_k). \tag{8}$$

or the Euclidean norm

$$\overline{Y}_i = \sqrt{\sum_{k=1}^{N}(X_k)^2}, \tag{9}$$

where N is the number of points for the specified timeframe. These parameters need to be introduced because P_i and U_i are random values that can deviate substantially from the means. In order to prevent random scatter, assume values averaged over a small interval, which are calculated by the dependencies (8) or (9).

4. To find out which of the parameters (*PDI* or U_{02}) is more sensitive to insulation condition, we hereby suggest considering how the difference in their normalized values changes over time:

$$\Delta X = \frac{|P_i - P_0|}{|P_{jD} - P_0|} - \frac{|U_i - U_0|}{|U_{jD} - U_0|}. \tag{10}$$

When critical condition is observed, calculate the magnitude and sign of ΔX from the readings. If a high-*PD* phase is confirmed to have a defect as detected, e.g., by transformer disassembly, a positive ΔX signifies a higher influence of *PDI*, whereas the minus sign signifies a more pronounced influence of the amplitude U_{02}.

5. Results and Discussion

The method was tested on the online readings shown in Figure 7 as initial data. As shown above, the condition of the object changed from normal to critical in this range. Initial *PDI* and U_{02} values (shown as P_0 and U_0) were sampled by averaging a 7-day data span from 9 September to 15 September 2016. As in the previous case, data were smoothed by moving the average.

Figure 9a shows trends in L_{PD} for three phases as calculated by the proposed method. Calculations were based on the averaged values $\overline{P}_i$ and $\overline{U}_{02i}$, as calculated by the Formula (9) for timeframes of 1 to 3 h. Figure 9b shows trends in the difference ΔX of normalized power and amplitude as calculated by the dependency (10). Apparently, Phase C had the greatest activity, which was rising significantly starting from mid-October.

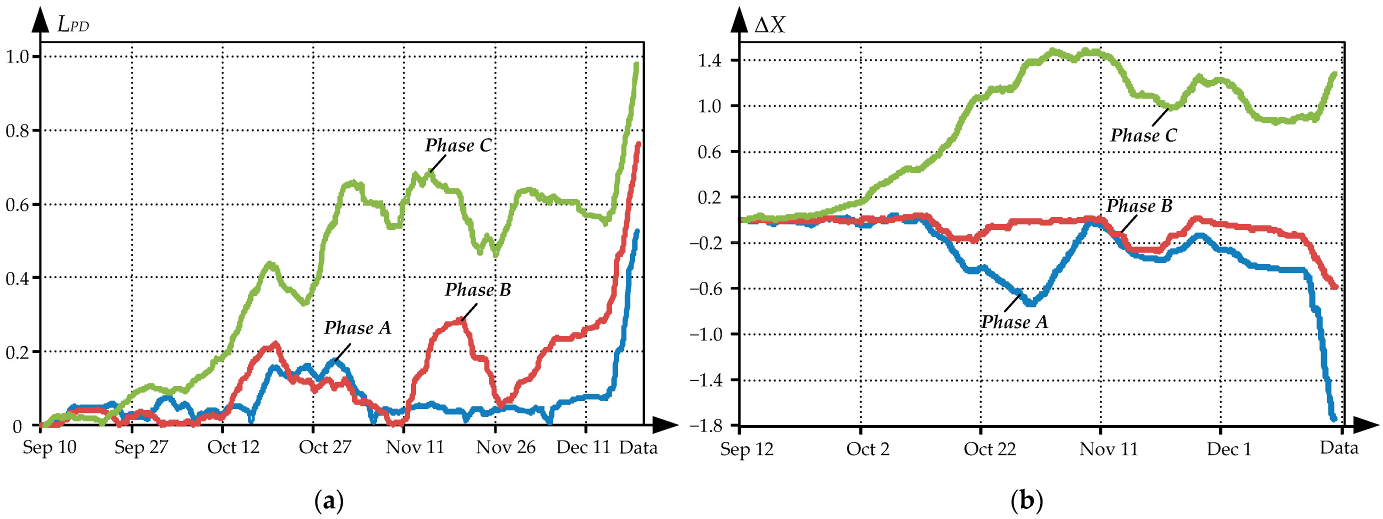


Figure 9. Trends in L_{PD} (**a**) and ΔX (**b**) from 9 September to 22 December 2016 (defect expansion timeframe).

Trend analysis leads to the following conclusions:

1. Over the time when the transformer was in a normal condition (from the initial readings to ~10 October), *PD activity level* (Figure 9a) did not change significantly for any phase. Therefore, neither reading (*PDI* or U_{02}) could be considered conclusive.
2. A further positive increase in ΔX signified a substantial increase in the effect of *PDI* on discharge activity. Therefore, from ~10 October until mid-December, i.e., when the condition was *poor*, *PDI* would be the more informative parameter.
3. Once the transformer's condition became critical (after ~18 October), the discharge activity index L_{PD} (Figure 9a) went up in all phases. That being said, an increased *PD* intensity was reported by the sensors installed at the *PIN* terminals of three high-voltage bushings.
4. After ~18 October, in light of the looming emergency, it became again difficult to choose the preferable diagnostic parameter: Figure 9b shows a positive change in ΔX in Phase *C* and a negative change in Phases *A* and *B*.
5. In *poor condition*, the greatest increase in discharge activity was observed in Phase *C*, whereas the activity in Phases *A* and *B* was not significant, see Figure 9a. It would be therefore logical to assume that the critical condition was caused by an expanding defect in Phase *C*, see proof below.

Given the situation, the ladle furnace was shut down on 23 December 2016. Partial disassembly revealed a defect, see Figure 10. It was caused by an inappropriate bend in the wire connecting the high-voltage bushing to the primary winding. As a result, Phase *C* output of the high-voltage winding was dangerously close to the acute angle of the plate welded to the booster transformer beam. Given that charge concentrates on pointed surfaces, *PDs* intensified.

Figure 10. Identified 'source' increased discharge activity (Highlighted in a red circle).

After the issue was fixed, we analyzed *PD* readings dated 1 January to 12 March 2017. 500 points were sampled for each phase, smoothed by moving the average over 50 points. Minimum values of the entire timeframe were picked for background values, which coincided with the values averaged over the period from 9–15 September 2016. These data were used to plot the trends shown in Figure 9.

Figure 11a shows trends in *PD Activity Level* similar to the curves in Figure 9a. They show L_{PD} values to be relatively low in all phases, decreasing further after 15 February and never rising above 0.2 again. Figure 11b shows trends in normalized power and amplitude difference; apparently, compared to Figure 9b, the $\Delta X(t)$ dependencies change in a narrower range in all phases. This leads to the conclusion that the *PD*-raising fault had been fixed.

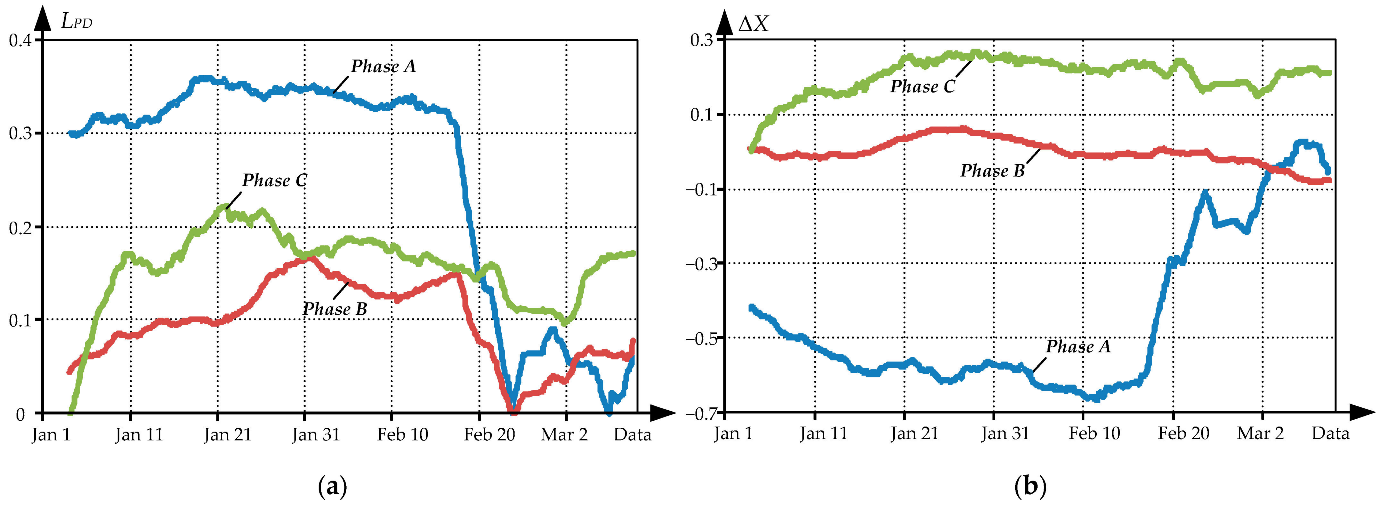


Figure 11. Trends similar to those in Figure 9 but sampled from 1 January to 12 March 2017 (after the fix).

6. Conclusions and Future Work

Thus, this paper proposes a method for convolution of two particular *PD* readings into a generalized indicator; the method uses fuzzy logic. For the first time, a generalized determinate *insulation state indicator* based on *partial discharge* was rationalized. It allows for the monitoring of the insulation state based on the results of online monitoring of the apparent charge and the *PD* power.

The authors developed a procedure to assess the diagnostic sensitivity of the *PD* parameters to the changes in the technical state. The diagnostic sensitivity of parameters such as U_{02} and *PDI* to the actual state of the transformer was used as the criterion. The key features of the procedure include the following:

- Calculating the standardized indicator to satisfy the requirements for the grade scale zero-dimensionality and uniformity.
- Determining the geometric average *PD* activity level;
- Calculating the average value for each of the signals within the set interval (or Euclidean norm);
- Determining the sensitivity of the *PDI* and U_{02} to the insulation state in terms of the size and sign of the standardized indicator.

Based on the analysis of the parameter trends identified during the changing of the state from normal to pre-emergency, the authors proved the consistency of using the suggested procedure to determine the technical state. The authors provided a practical example of defect localization that confirmed the efficiency of technical state assessment for the high-voltage equipment using the ISI_{PD} parameter.

The effects of *PD* amplitude and power are combined into a single deterministic parameter: *an insulation condition indicator based on PD readings*. This is a normalized value that indicates insulation condition.

Logic rules were compiled with the weights F_i being equal to 1. These values are subject to adjustment when optimizing the fuzzy inference rule base. Additional experimental data allow the adjustment of the weights to rank the rules by whether *PDs* can render the transformer unusable.

The generalized indicator value has been proven theoretically and experimentally to be relevant for predicting poor or critical condition of a transformer. Continuous *PD* monitoring of a transformer in poor condition and the further examination by the repair crew prove the statement above.

A comparison of trends in normalized power (*PDI*) and *PD*(U_{02}) difference showed *PDI* to be more sensitive for the assessment (and prediction) of insulation wear in normal condition.

It seems promising to further advance this method in order to adopt integrated diagnostics. Thus, *PD* monitoring would be advisable in combination with *DGA*. This will enable more informative diagnosis and more reliable condition assessment.

Another area of focus consists in developing methods for localization and identification of transformer faults. A literature overview shows that methods based on locating *PD* hotspots and comparing their location to the equipment layout (windings, OTLCs, etc.) in the transformer tank [78–80] are more promising.

Since furnace transformers are among the most complex pieces of power equipment, fuzzy diagnostics tested on them could find much broader use. They are recommendable in particular for online monitoring of high-voltage switchgear equipment: overvoltage protections, high-voltage circuit breakers, bushing insulators, etc. Such systems have been developed and implemented on the closed 110-kV switchgear in the electric steelmaking shop of the steelworks. The developed method will have a specific application in these systems.

Overall, the research conducted promotes the further development of the predictive control theory for the state of high-voltage equipment. It also supports the practical implementation of the smart furnace transformer concept. The development and introduction of smart online state monitoring systems is a relevant IIoT-based upgrade area for the metal industry.

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