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Comparative Analysis of GPR and RBF Models for Predicting the Breakdown Voltage of Insulating Oils

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Abstract: ***Accurately forecasting the breakdown voltage of insulating oils is a prerequisite for the reliable design and operation of high-voltage equipment. The present work focuses on developing data-driven artificial intelligence (AI) models to predict the breakdown voltage of transformer oil as a function of temperature and electrode spacing. Two different machine learning algorithms are applied and compared: Gaussian Process Regression (GPR) and Radial Basis Function (RBF) neural network. The experimental data for electrode distances of 5 mm and 20 mm are used to train, test, and validate the models using a 60/20/20 data-splitting scheme. The predictive capacity of the models is evaluated using the three metrics: mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R). Experimental results confirm that the model predictions are in excellent agreement with the measurements at short electrode distances for both models. Nevertheless, at longer distances, the differences between the two performances become quite substantial. The GPR method is more reliable and generalises better, particularly at 20 mm, where it yields lower validation errors than the RBF approach. In addition, as a probabilistic method, GPR enables the estimation of predictive uncertainty, which is essential for applications oriented toward safety and dependability. Overall, the present work has demonstrated GPR's capability to determine the breakdown voltage of insulating oils and its potential for high-voltage insulation diagnostics and design.***

Keywords: ***Breakdown Voltage, Gaussian Process Regression (GPR), Radial Basis Function (RBF) Neural Network, Transformer oil.***

Nomenclature:
RBF: Radial Basis Function
GPR: Gaussian Process Regression
RMSE: Root Mean Square Error
MAE: Mean Absolute Error
AI: Artificial Intelligence

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I. INTRODUCTION

Transformer oil is undoubtedly one of the most critical components in high-voltage equipment. It serves as both an electrical insulating medium and a cooling fluid. As a dielectric medium, the reliability and performance of power transformers largely depend on the dielectric characteristics of the oil, particularly its breakdown voltage under various operating conditions. When the dielectric strength of the oil decreases, the hardware may fail, resulting in inevitable service interruptions and irreparable damage. Hence, electrical breakdown studies of transformer oil remain a focus of research in high-voltage engineering [1].

Various physical and environmental factors affect the breakdown voltage of transformer oil, including electrode shape, electrode spacing, moisture, compounds formed by ageing, and operating temperature. One of the most critical factors is temperature, which affects the oil's physicochemical properties, including viscosity, density, and the mobility of charge carriers. Numerous experimental publications report that temperature has a pronounced effect on the breakdown characteristics of insulating oils. Still, the patterns of change vary with experimental conditions and oil properties [2].

The temperature effect on the breakdown voltage of insulating oils is still a puzzling problem and an open issue of discussion; in fact, the temperature changes can either improve the dielectric strength or weaken it, depending on the physicochemical characteristics of the oil, the distance between the electrodes, and the conditions under which the experiment is carried out. Moreover, temperature changes typically do not act in isolation but interact with other parameters. For example, temperature interacts with the dissolved moisture content in the oil and with the gases present in the oil, making the breakdown highly nonlinear and complex to represent by simple analytical relationships. Traditional empirical methods, while still valuable for limited purposes, do not necessarily reflect the actual behaviour of transformer oil under temperature changes and varying operating conditions [3].

In view of this complication, AI-based algorithms have significant potential for modelling electrical breakdown in insulating oils. Among the various data-driven methods, those that can handle nonlinear dependencies and interactions among multiple factors are by far the most appropriate. Notably, GPR offers several advantages when working with experimental data from small samples, while also modelling highly nonlinear relationships and providing uncertainty estimates for predictions. For this, the current study put its main emphasis on the breakdown voltage prediction of transformer oil, which is dependent on the temperature together with the inter-electrode distance, electrode distance, by means of the optimized GPR model and then compared its performance with a Radial Basis Function (RBF) neural network to check their respective accuracy and robustness.

II. PHYSICAL MECHANISMS AND CHARACTERISTIC EQUATIONS OF ELECTRICAL BREAKDOWN

A. Physical Mechanisms of Electrical Breakdown in Insulating Oil

Electrical breakdown in insulating oils is a complex process that primarily results from interactions among electrical, thermal, and hydrodynamic mechanisms. In contrast to gaseous dielectrics, where breakdown is controlled mainly by fully understood ionization processes, breakdown in insulating liquids is very much determined by the existence of local flaws, such as gaseous microbubbles, solid impurities, or microscopic defects within the medium [1], [5].

When an electric field is applied to weak regions, it promotes charge accumulation and the initiation of partial discharge. The expansion of these discharges may result in the formation of transient conductive channels, also known as liquid filaments or streamers, which develop until they connect the electrodes when the electric field exceeds a critical value. The unpredictable nature of the onset and evolution of these channels explains the high scatter in experimental breakdown-voltage measurements, even when the conditions are theoretically identical [6], [7], [8].

B. Characteristic Equations and Statistical Approach to Electrical Breakdown

In a first simplified approach, the average electric field between two electrodes separated by a distance d can be expressed as:

$$E = \frac{U_c}{d} \quad \dots \quad (1)$$

where:
E is the average electric field (V/m),
U_c is the breakdown voltage (V),
d is the inter-electrode distance (m).

Electrical breakdown is assumed to occur when the local electric field reaches a critical value. E_{cr}, characteristic of the insulating medium under consideration. Under this assumption, the breakdown voltage can be approximated by:

$$U_c = E_c . d \qquad (2)$$

However, this relationship holds only under idealised conditions, particularly for quasi-uniform electric fields and homogeneous media. In practice, electrical breakdown in insulating oils exhibits intrinsically stochastic behaviour, necessitating a statistical approach to describe the dispersion of experimental results. This relation nevertheless allows comparison of breakdown conditions in different insulating media and electrode configurations.

For liquid insulating media and specific electrode arrangements, an empirical relationship is also commonly used to estimate the dielectric strength R from measured breakdown voltages [5]:

$$R = T \cdot \left(\frac{1{,}12}{D}\right) \quad \dots \quad (3)$$

where:
R is the dielectric strength (kV/cm),
T is the measured breakdown voltage (kV),
D is the inter-electrode distance (cm).

Electrical breakdown in insulating liquids is a random phenomenon and is mainly attributed to impurities, microbubbles, and local electric-field fluctuations. To explain the variety of results in breakdown, breakdown behaviour is usually analysed statistically, and the Weibull distribution [6], [7], [9] is the most commonly used model in dielectric strength tests. With this approach, a breakdown probability can be defined depending on the voltage applied and the variability in experimental results can be more reasonably explained:

$$P(U) = 1 - exp\left[-\left(\frac{U}{U_0}\right)^m\right] \quad \dots \quad (4)$$

where:
$P(U)$ is the breakdown probability,
U_0 is the characteristic voltage parameter,
m is the dispersion (shape) parameter.

These equations provide a valuable basis for analysing experimental outcomes, comparing various insulating materials, and predicting the behaviour of systems under high electric stress. They provide the theoretical foundation for research concerning dielectric strength and the effectiveness of electrical insulation.

C. Thermophysical Influence of Temperature and Inter-Electrode Distance

Temperature influences the thermophysical properties of insulating oil, particularly viscosity, electrical conductivity, and the solubility of dissolved gases. An Arrhenius-type law can describe the variation of viscosity with temperature:

$$\eta(T) = \eta_0 . \exp\left(\frac{E_\alpha}{RT}\right) \quad \dots \quad (5)$$

where $\eta(T)$ Is the dynamic viscosity at the temperature? T, η_0 is a constant, E_α is the activation energy, and R is the universal gas constant.

Nonetheless, the effect of temperature on the breakdown voltage of insulating oils should not be explained only by changes in viscosity. Depending on the experimental setup and the dominant physical regime, heating can exert two opposing effects on the breakdown process. These effects include the change of gaseous bubbles' dynamics, the variation of moisture content in the oil, and the change of the electric field distribution in the oil [3].

Therefore, the net effect of temperature on breakdown voltage results from the interplay between deteriorating and stabilising mechanisms, accounting for the different trends observed in the literature across various insulating oils and experimental setups. Such non-universal behaviour clearly explains why it is so challenging to write down a single analytical formula that describes the impact of temperature on electrical breakdown.

Furthermore, the inter-electrode distance constitutes a key parameter in the

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breakdown process. Its increase is generally associated with a rise in breakdown voltage, due to improved homogenization of the electric field and a reduction of local electrical stresses. Nevertheless, this influence remains strongly coupled with thermal conditions and the intrinsic properties of the insulating medium.

In general, the breakdown voltage can be expressed as a nonlinear function depending simultaneously on temperature and inter-electrode distance:

$$Uc = f(T, d) \quad \dots \quad (6)$$

The absence of a closed-form analytical expression that accurately describes this relationship across a wide range of operating conditions justifies the use of data-driven approaches, such as artificial intelligence methods, for reliable prediction of breakdown voltage in insulating oils.

III. EXPERIMENTAL METHODOLOGY

A. Transformer Oil Used

The transformer oil used in this study is BORAK 22, a mineral oil formulated explicitly for high-voltage applications. This oil is widely employed for insulation and cooling purposes in power transformers. Good dielectric properties, high thermal stability, and strong resistance to oxidation and moisture characterize it.

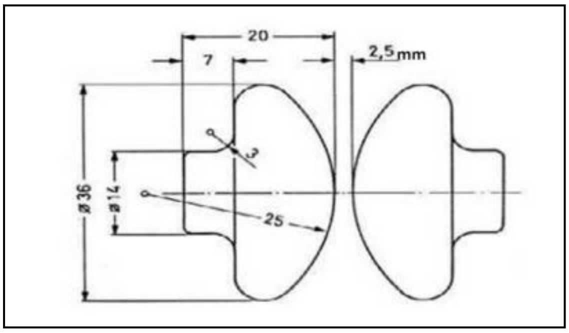
The main electrical and physicochemical properties of the oil are summarized in the following table [6],[7]:

Table I: Oil Properties

Electrical/ Physicochemical property	Unit	Requirement for new oil	Standard	Measured value
Breakdown voltage after rest	KV	> 70	CCEI 156	38.8 - 72
Dielectric dissipation factor	-	$< 5.00 \times 10^{-3}$	CEI 247	0.87×10^{-3}
Kinematic viscosity at 40°C	mm^2/s	< 11	ISO 3104	6.940
Flash point	°C	> 130	ISO 2719	1.37
Density	-	$< 8.95 \times 10^{-1}$	ISO 12185	8.57 E-01
Acidity index	Mg KOH/g	$< 3.00 \times 10^{-2}$	CEI 296	$(2.00–5.8) \times 10^{-2}$
Water content	ppm	< 30	CEI 814	< 0.5
Color index	ppm	< 02	ASTM D 1500	-

B. Experimental Methodology

[Fig.1:Test Transformer]



[Fig.2: Hemispherical Electrodes]

In this study, the inter-electrode distance was held constant within each test series to isolate the geometric influence on the electrical breakdown phenomenon. In parallel, the temperature of the insulating oil was deliberately varied to evaluate its thermal effect on dielectric strength. The oil samples were heated using a laboratory thermal oven at controlled temperatures ranging from 35 °C to 70 °C, a range representative of operating conditions encountered in power transformers.

For each inter-electrode distance considered, breakdown voltage measurements were performed at several temperatures, enabling analysis of the combined effects of thermal and geometric parameters on the oil's dielectric behaviour. This cross-experimental approach ensures consistent evaluation of the sensitivity of breakdown voltage to temperature variations under fixed geometric configurations.

For every test condition (distance and temperature), six successive measurements were recorded under precisely the same conditions without any break following the ASTM D877 standard guidelines. The tests were conducted using standard hemispherical electrodes and the same high-voltage generator to minimise equipment-related scattering sources and ensure electric-field uniformity.

This strict experimental protocol thus allows the effect of temperature on the dielectric strength of transformer oil to be reliably analysed, while ensuring measurement reproducibility and the statistical robustness of the results.

[Fig.3: The Oven]

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C. Results

Table II shows the evolution of the oil breakdown voltage as a function of temperature.

Table II: Oil Breakdown Voltage as a Function of Temperature and Inter-Electrode Distance

Temp(°C)	D(mm)	Measured Uc (kV)			Average Uc (kV)
		Test 1	*Test 2*	*Test3*	
35	5	4	4,1	4	4,03
35	20	9	9,1	9,5	9,2
37	5	4,3	4,4	4,5	4,4
37	20	9,5	9,1	9,3	9,1
39	5	4,4	4,6	4,7	4,57
39	20	10	10,2	11	10,4
41	5	4,5	4,8	4,8	4,7
41	20	11	11,2	11,1	11,1
44	5	4,9	4,9	4,9	4,9
44	20	11	11,3	11,4	11,23
50	5	6	6,4	6	6,13
50	20	20	20,4	20,3	20,23
52	5	6,7	6	6,8	6,5
52	20	22	22,5	23	22,5
54	5	7,1	8	8,5	7,87
54	20	23,9	24,5	23,9	24,1
57	5	9	10	10,5	9,83
57	20	26	27	26	26,33
60	5	11	12	12	11,67
60	20	29	28,5	28	28,5
62	5	14,2	14	14,2	14,13
62	20	33	32	33	32,67
65	5	17	14,5	14,5	15,33
65	20	34	35	37	35,33
67	5	15,4	15,2	16	15,53
67	20	36	40	40	38,67
70	5	17,5	17,5	18	17,67
70	20	41	42	41	41,33

D. Inter-Electrode Distance(mm); Uc: Breakdown Voltage(kV)

The data in Table II illustrate a marked increase in the breakdown voltage of transformer oil with increasing temperature. The effect is quite dramatic between 35 C and about 60 C. Most of this behaviour can be attributed to the decrease in oil viscosity with increasing temperature. Lower viscosity increases the freedom of charge carriers and, at the same time, diminishes the local buildup of space charge, thereby delaying ionisation and electric discharge.

Naidu and Kamaraju [4] have explained that a rise in the temperature of insulating oils can temporarily increase dielectric strength by reducing internal mechanical stresses and improving the electric field distribution. The result is an increase in the breakdown voltage, consistent with the experimental findings up to 60 °C.

However, beyond this temperature interval, the breakdown voltage appears to level off, as indicated by the results. As mentioned in [4], such a situation is caused by the onset of various thermal mechanisms, especially the production of gaseous microbubbles due to local vaporisation or the release of dissolved gases in the oil. These microbubbles act as regions of low dielectric strength, thereby intensifying the local electric field and limiting any further increase in breakdown voltage.

The observed evolution, therefore, is the result of a compromise between two opposing effects: at first, the dielectric strength improvement that is physically related to viscosity decrease and, at high temperatures, the appearance of adverse thermal effects that limit the oil's insulating properties. The model's data are essentially the experimental data from the insulating oil. The breakdown voltage for each test set was determined as the average of several successive tests, in accordance with the experimental protocol adopted. The parameters taken into consideration are the distance between the electrodes (mm), the oil temperature (C), the fixed electrode geometry, and the type of applied voltage (AC)

Experimental data were arranged as input matrices, with rows corresponding to individual data points. Data preprocessing was performed before use in the predictive models to ensure numerical consistency. Continuous variables (inter, electrode distance, and temperature) were normalised, while discrete parameters were properly encoded for integration into the artificial intelligence models.

First, the database was split into three subsets: 60% for model training, 20% for testing, and 20% for validation. Such an approach ensures that the model's generalisation capability is reliable while limiting overfitting.

E. Discussion

The experimental findings reveal a significant effect of temperature and electrode spacing on the breakdown voltage of insulating oil. In all configurations examined, a general increase in breakdown voltage is observed as temperature increases, particularly in the moderate temperature range. This behaviour can be linked to a decrease in oil viscosity, which facilitates charge release and distribution, and to a reduction in local defects that may trigger electrical breakdown. Simultaneously, a rise in the distance between electrodes results in a considerable increase in breakdown voltage, indicating a direct relationship between the observed dielectric strength and the electric field's geometry.

However, a close examination of the data reveals several breakdown voltages that differ substantially, particularly at high temperatures and large electrode separations. The observed variation in the data indicates the complexity of the breakdown in insulating liquids, which is influenced by various physical phenomena. Some of these are local ionisation, microbubble generation, thermal effects, and a non-uniform electric field. These phenomena are tightly connected, and their behaviour is highly nonlinear with respect to thermal and geometric parameters; therefore, it is not possible to develop a universal analytical model that fully explains the observed behaviour.

Moreover, classical statistical methods, such as Weibull analysis, can characterise data dispersion and dielectric reliability. Still, they are not very effective at breaking down voltage prediction when it depends on multiple, interrelated parameters. The experimental data suggest that the relationship between temperature, the distance between the electrodes, and breakdown voltage cannot be adequately represented by simple deterministic

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models. This complexity necessitates the use of advanced modelling techniques that can learn from experimental data and capture the nonlinearities of the phenomenon. In this respect, artificial intelligence methods appear to be highly effective tools for precise prediction of breakdown voltage, thereby enabling more robust and flexible predictive modelling approaches.

IV. PREDICTIVE MODELING USING ARTIFICIAL INTELLIGENCE

A. Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) is a non-parametric probabilistic approach widely used for modelling unknown functions. This method is based on the assumption that experimental observations are realizations of a Gaussian stochastic process, fully characterized by a mean function $m(x)$and a covariance function $k(x, x')$ [1]. The GPR model can be expressed as:

$$f(x) \sim GP\big(m(x), k(x, x')\big) \quad \dots \quad (7)$$

For a new input x_*, the GPR prediction conditioned on the training dataset $D = \{(\boldsymbol{x_i}, \boldsymbol{y_i})\}_{i=1}^{n}$ follows a normal distribution.

Here, n denotes the total number of observations in the training set. The predictive distribution is given by [1]:

$$f(x_*)|X, y, x_* \sim N\big(\mu(x_*), \sigma^2(x_*)\big) \quad \dots \quad (8)$$

where the predictive mean and variance are defined as:

$$\mu(x_*) = k(x_*, X)[K(X, X) + \sigma_n^2\, I]^{-1}$$

$$\sigma^2(x_*) = k(x_*, x_*) - k(x_*, X)[K(X, X) + \sigma_2^n\, I]^{-1} k(X, x_*)$$

In these expressions, I denotes the identity matrix of size $n * n$, and $K = k(X, X) + \sigma_2^n I$ represents the covariance matrix of the training data corrected for measurement noise.

Where:

- $k(X, X)$is the covariance matrix of the training data, σ_n^2 is the noise variance,
- $k(x_*, X)$ represents the covariance vector between the test input $x_*$and the training points.

In this study, the adopted kernel consists of a combination of two components:

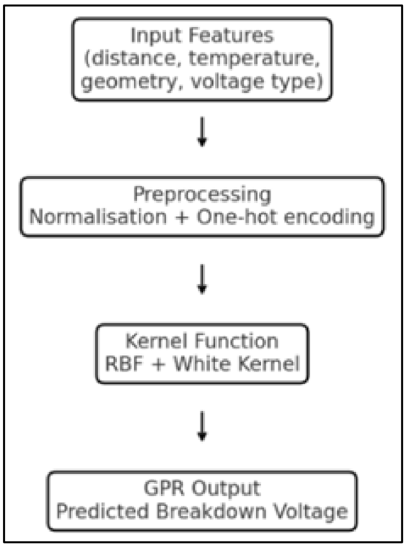
- an RBF (Radial Basis Function) kernel, used to model the smooth variability of the phenomenon;
- a noise term (White Kernel), accounting for uncertainties associated with experimental measurements.

The general expression of the employed kernel is given by:

$$k(x_i, x_j) = \sigma_f{}^2 \exp\left(\frac{\| x_i - x_j \|^2}{2\ell^2}\right) + \sigma_n^2 \delta(x_i, x_j) \quad \dots \quad (9)$$

where $\sigma_f{}^2$is the output variance, ℓ is the correlation length (model hyperparameter),σ_n^2 denotes the noise variance, and $\delta(x_i, x_j)$ is the Kronecker delta function.

This formulation provides the GPR model with a direct probabilistic interpretation of the results, enabling not only the estimation of breakdown voltage but also the quantification of the uncertainty associated with each prediction. This property is particularly advantageous for predicting the breakdown voltage of insulating oils, where experimental datasets are limited and inherently dispersed.



[Fig.4: Architecture du Modèle GPR [8]]

B. Radial Basis Function (RBF) Neural Network

Radial Basis Function (RBF) neural networks enable effective modelling of complex, nonlinear relationships between input and output variables [10]. These networks consist of three layers: an input layer, a hidden layer, and an output layer, as illustrated in Fig. 5. The input layer receives the input data, with the number of neurons corresponding to the number of input variables, such as temperature, humidity, and inter-electrode distance. The hidden layer employs Gaussian kernel functions to process these data, with the activation of each hidden neuron calculated as follows:

$$Zj(xi) = exp\left(-\frac{1}{2\sigma_j^2}\left\|x_i - c_j\right\|^2\right) \quad \dots \quad (10)$$

In the output layer, a single neuron represents the predicted breakdown voltage, which is determined by the following equation:

$$y_k(x_i) = \omega_{k0} + \sum_{j=1}^{M} \omega_{kj}\, Z_j(x_i) \quad \dots \quad (11)$$

Here, ω_{kj} denotes the synaptic weight connecting the $j^{éme}$ neuron of the hidden layer to the $k^{éme}$ neuron of the output layer, and ω_{k0} represents the output bias. Adjusting these synaptic weights is crucial for optimising the performance of the RBF network.

The performance of the network strongly depends on the appropriate selection of the number of neurons in the hidden layer. Ideally, the data should be partitioned into subspaces (clusters) represented by centres; however, complex distributions of the training data may require additional adjustments to improve the model's ability to fit the data accurately.

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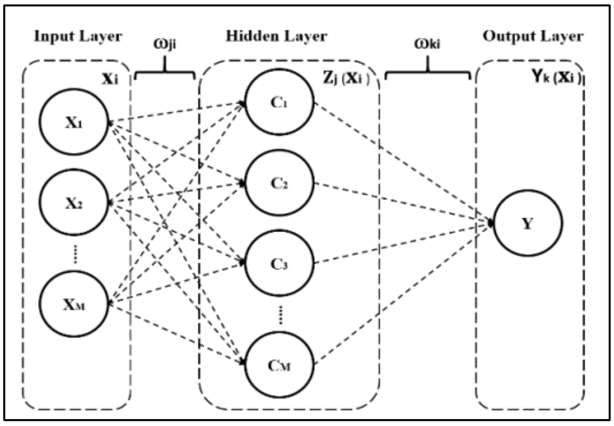
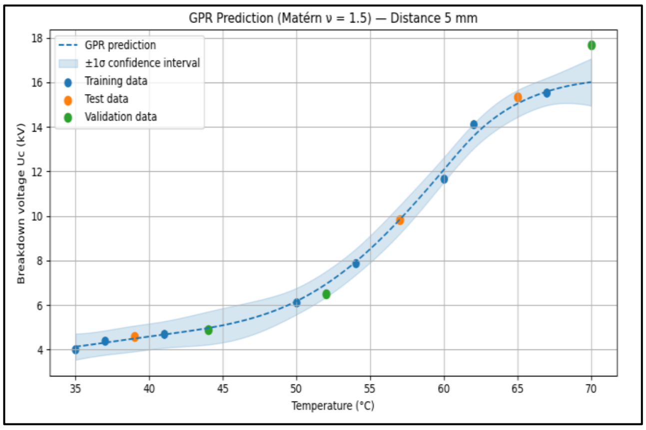


[Fig.5: Plot of the Structure of an RBF Neural Network]

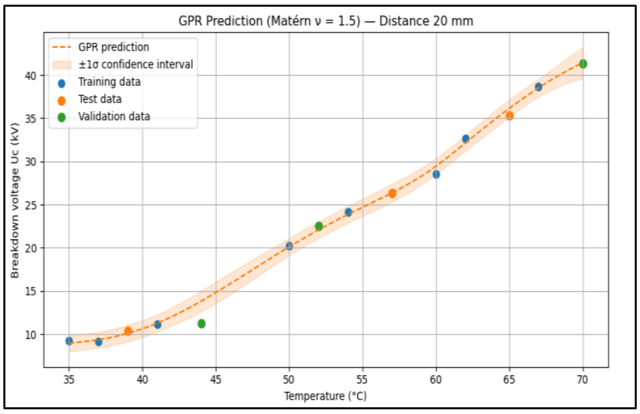
V. RESULTS AND DISCUSSION

A. Results



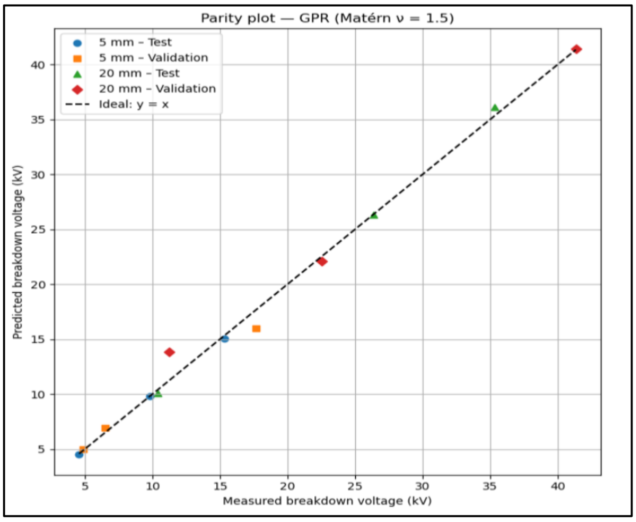
[Fig. 6. GPR-Based Prediction of Breakdown Voltage with Confidence Band (±1σ) for a 5 mm Inter-Electrode Configuration]

Figure 7 presents the estimation of the breakdown voltage as a function of inter-electrode distance obtained using the Gaussian Process Regression (GPR) model for a 20 mm configuration. The dashed curve corresponds to the mean prediction of the model, while the shaded area represents the confidence band associated with predictive uncertainty (±1σ). The markers indicate the experimental data used for training, testing, and validation.



[Fig.7: GPR-based Prediction of Breakdown Voltage with Confidence Band (±1σ) for a 20 mm Inter-Electrode Configuration]

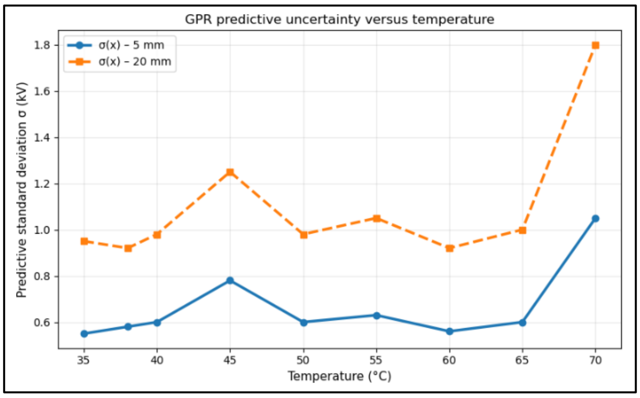
The parity diagram in Fig. 8 compares the measured and predicted values obtained using the GPR model for inter-electrode distances of 5 mm and 20 mm, distinguishing between the test and validation datasets.



[Fig.8: Parity Plot Comparing Measured and Predicted Breakdown Voltages Obtained using the GPR Model for Inter-Electrode Distances of 5 mm and 20 mm]

The results obtained using the Gaussian Process Regression (GPR) model, illustrated by predictions for inter-electrode distances of 5 mm and 20 mm, as well as by the associated parity diagram, highlight the model's excellent ability to reproduce the nonlinear dependence of breakdown voltage on temperature. The close agreement between the experimental data points and the predicted curve, as well as their proximity to the ideal line in the parity diagram, confirms the model's accuracy and robustness and demonstrates consistency across the training, test, and validation datasets.

As shown in Fig. 9, the predictive uncertainty of the GPR model remains low and relatively stable for an inter-electrode distance of 5 mm. In contrast, a noticeable increase in σ is observed for the 20 mm configuration, particularly at higher temperatures.



[Fig.9: Predictive Uncertainty (σ) Versus Temperature for 5 mm and 20 mm Inter-Electrode Distances]

The analysis of predictive uncertainty highlights a distinct behaviour of the GPR model depending on the inter-electrode distance considered. For the 5 mm configuration, the predictive standard deviation

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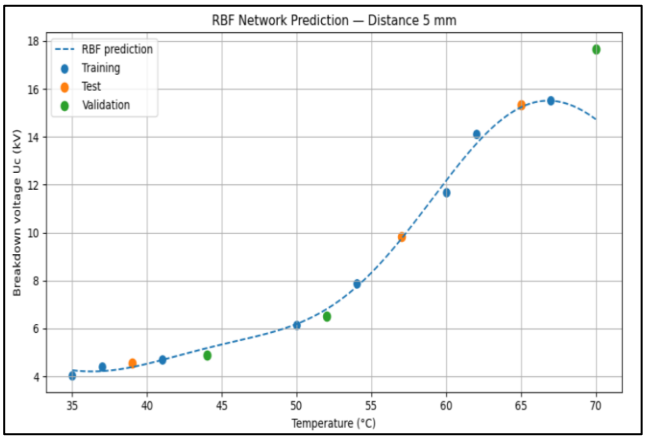
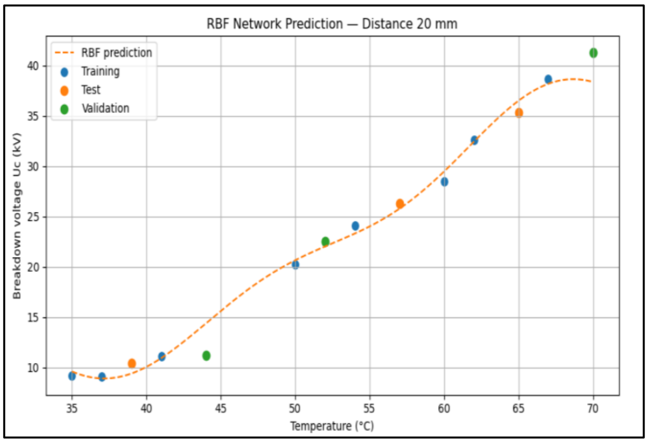
σ remains globally low and relatively stable over the entire investigated temperature range, reflecting a high level of confidence in the model's estimations. In contrast, at 20 mm, higher σ values are observed, particularly at elevated temperatures, indicating greater variability in the breakdown phenomenon and greater sensitivity to thermal conditions. This increase in uncertainty is mainly attributed to the physical complexity of the breakdown process at larger inter-electrode distances, as well as to the reduced density of experimental data in certain regions. These results confirm that the GPR model can provide not only accurate predictions but also a reliable quantitative estimate of the associated uncertainty, representing a significant advantage over classical deterministic approaches.

Fig. 10 shows the breakdown-voltage prediction as a function of temperature obtained using the RBF neural network for an inter-electrode distance of 5 mm, along with the distributions of the training, test, and validation datasets.



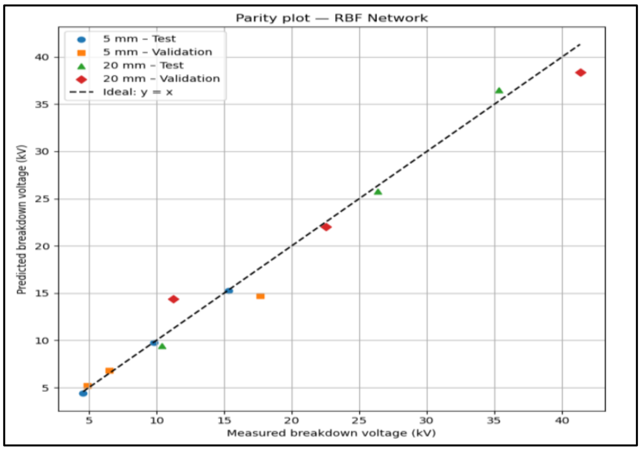
[Fig.10: RBF Neural Network Prediction of Breakdown Voltage as a Function of Temperature for an Inter-Electrode Distance of 5 mm]

Figure 11 presents the prediction results of the RBF model for an inter-electrode distance of 20 mm, including the training, test, and validation datasets.



[Fig.11: RBF Neural Network Prediction of Breakdown Voltage as a Function of Temperature for an Inter-Electrode Distance of 20 mm]

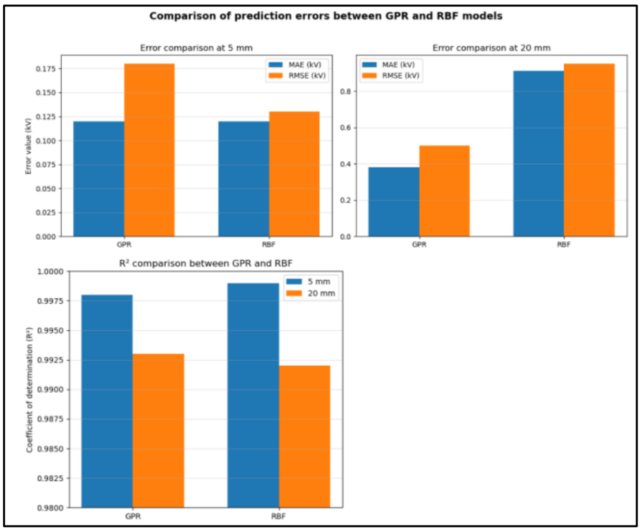
Figure 12 presents the parity diagram of the RBF network, illustrating the relationship between experimental and predicted values for inter-electrode distances of 5 mm and 20 mm.



[Fig.12: Parity Plot of Measured Versus Predicted Breakdown Voltages using the Radial Basis Function (RBF) Neural Network at Inter-Electrode Distances of 5 mm and 20 mm]

The predictions from the Radial Basis Function (RBF) neural network for inter-electrode distances of 5 mm and 20 mm, along with the corresponding parity diagram, indicate that the model captures the general trend in the variation of breakdown voltage with temperature. However, a slightly more pronounced dispersion of the data points around the predicted curve and the ideal line is observed, particularly under certain experimental conditions, indicating lower accuracy than that of the GPR model.

Fig. 13 quantitatively compares the performance of the GPR and RBF models using the MAE, RMSE, and R^2 indicators for inter-electrode distances of 5 mm and 20 mm.



[Fig.13: Comparison of GPR and RBF Performance Metrics (*MAE, RMSE, R²*)]

The quantitative comparison of the performance of the GPR and RBF models, based on the MAE, RMSE, and the coefficient of determination R^2, clearly highlights the superiority of the GPR model for both inter-electrode distances investigated. The GPR exhibits lower prediction errors and higher R^2 values, confirming its superior generalisation capability and suitability for accurate estimation of the breakdown voltage of insulating oil.

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Table III: Comparison of Measured and Predicted Values using GPR and RBF Models

Temp(°C)	D (mm)	Measured Uc (kV)	Predicted Uc –GPR (kV)	Predicted Uc – RBF (kV)
39	5	4.57	4.50	4.39
57	5	9.83	9.83	9.74
65	5	15.33	15.04	15.23
44	20	11.23	13.81	14.39
70	20	41.33	41.42	38.38

Source: Inter-Electrode Distance(mm); Uc: Breakdown Voltage(kV)

B. Discussion

The numerical results clearly confirm the overall superiority of the Gaussian Process Regression (GPR) model compared to the Radial Basis Function (RBF) neural network, particularly as the complexity of the phenomenon increases. At an inter-electrode distance of 5 mm, both models exhibit comparable performance during testing, with low prediction errors. However, during validation, the GPR model demonstrates better generalisation, with a mean absolute error below 1 kV. In contrast, the RBF model shows a more pronounced increase in error, indicating greater sensitivity to data variability.

This trend becomes significantly more pronounced at an inter-electrode distance of 20 mm, where the performance gap between the two approaches is substantial. The GPR model maintains a moderate validation error (MAE ≈ 1.04 kV). In comparison, the RBF model achieves a much higher validation error (MAE > 2 kV), indicating significant performance degradation outside the training domain. Similarly, the RMSE values follow the same pattern, with a markedly more substantial increase for the RBF model than for the GPR model at larger inter-electrode distances.

Although high coefficients of determination are obtained for both models, the decrease observed in the RBF model during validation further confirms its lower robustness to increased complexity in the breakdown mechanism. These results indicate that, although the RBF model provides satisfactory estimates under relatively simple conditions, the GPR model stands out for its superior stability and generalisation performance. This robustness is further enhanced by the probabilistic nature of the GPR approach, which enables the quantification of predictive uncertainty—an essential advantage for the analysis and modelling of critical phenomena such as electrical breakdown in insulating oils.

VI. CONCLUSION

This study enabled an experimental and numerical analysis of the influence of temperature and inter-electrode distance on the breakdown voltage of transformer oil. The experimental results revealed a progressive increase in breakdown voltage with temperature, followed by stabilization at higher temperatures. This behaviour is primarily attributed to reduced oil viscosity, increased charge-carrier mobility, and the formation of gaseous microbubbles. In addition, increasing the inter-electrode distance increases the breakdown voltage due to a more homogeneous electric field distribution and a reduction in local electric stresses, consistent with observations reported in the literature. Given the complexity and highly nonlinear nature of the electrical breakdown phenomenon, classical analytical and empirical models exhibit significant limitations, particularly when applied under varying operating conditions. To overcome these limitations, artificial intelligence–based approaches were implemented in this work to predict breakdown voltage.

A Gaussian Process Regression (GPR) model was developed and applied to the experimental data. The results demonstrate excellent predictive accuracy, with low mean absolute errors and a high coefficient of determination, confirming the GPR model's ability to reproduce experimental trends accurately. One of the main advantages of the GPR model is its probabilistic nature, which enables not only the estimation of the predicted breakdown voltage but also the quantification of its associated uncertainty. The uncertainty band analysis revealed physically consistent behaviour, with increased uncertainty at the extremes of the temperature range and at larger inter-electrode distances, reflecting the greater complexity of breakdown mechanisms under these conditions. In addition, a Radial Basis Function (RBF) neural network was employed as a deterministic comparison model. The results indicate that the RBF model achieves good predictive accuracy, particularly for small inter-electrode distances, where the breakdown behaviour remains relatively regular.

However, as the inter-electrode distance increases and the phenomenon becomes more dispersive, the performance of the RBF model degrades compared to that of the GPR model, as demonstrated by the analyses based on MAE, RMSE, and parity diagrams. This comparison highlights that, although the RBF model is an attractive alternative due to its simplicity and computational efficiency, it remains limited by its deterministic nature and the absence of intrinsic uncertainty quantification. The comparative analysis between the GPR and RBF models therefore shows that the GPR approach offers superior robustness and generalization capability, particularly under more complex breakdown conditions. Moreover, access to predictive uncertainty information confers a significant advantage on the GPR model in applications related to the reliability and safety of high-voltage insulation systems.

In conclusion, this work demonstrates that combining a physical understanding of the breakdown phenomenon with artificial intelligence–based methods constitutes a powerful tool for estimating breakdown voltage in insulating oils. The results obtained confirm that the GPR model is a reliable, high-performance alternative to classical analytical models. In contrast, the RBF model can be used as a comparative or fast-predictive tool in less complex configurations. Future work will focus on extending the methodology to

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other electrode–insulator configurations, integrating additional variables such as moisture content and contamination, and developing hybrid models that combine physical knowledge with machine learning to improve prediction accuracy and reliability further.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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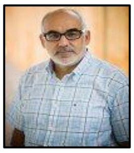

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