
POWER TRANSFORMER INCIPIENT FAULT PREDICTION USING DISSOLVED GAS ANALYSIS AND ARTIFICIAL BEE COLONY OPTIMIZED RANDOM FOREST MODEL

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ABSTRACT

Power transformers are critical assets in electric power systems, and their reliable operation is essential for preventing catastrophic failures and power outages. Continuous condition monitoring is therefore necessary for the early detection of incipient faults. Dissolved Gas Analysis is widely adopted as a diagnostic technique but its effectiveness can be constrained by variability in diagnostic results. Conventional methods have limited capability to provide reliable fault diagnosis and often produce ambiguous or “no decision” outcomes when gas ratios fall outside standard ranges or overlap across multiple fault zones. Similarly, standalone artificial intelligence and machine learning algorithms may have limited generalization capability and perform poorly under new or varying data conditions due to non-optimal hyperparameters. Their performance is also highly dependent on the quality and quantity of training data, making them susceptible to noise, missing values, class imbalance, overfitting, and underfitting. To address these limitations, this study proposes a data-driven transformer fault diagnosis framework based on Artificial Bee Colony (ABC) hyperparameter optimization. The proposed framework employs ABC to optimize the hyperparameters of Random Forest classifiers while Support Vector Machine and Deep Neural Network are included as a benchmark models. The DGA dataset consists of 589 samples with five gas features and was partitioned into training (70%), validation (15%), and testing (15%) subsets. The classification results show that the baseline classifiers achieved accuracies of 78.4% for SVM, 80.4% for RF, and 83.3% for DNN. Following ABC-based hyperparameter optimization, the optimized Random Forest classifier achieved a significantly improved accuracy of 91.2%. The superior classification performance and robustness of the proposed ABC-optimized Random Forest demonstrate its potential for practical application in reliable and accurate real-world power transformer fault diagnosis.

Keywords: Random Forest; Artificial Bee Colony; Power Transformer; Dissolved Gas Analysis

1. INTRODUCTION

Power transformers are among the most critical and expensive assets in modern electrical power systems, linking generation, transmission, and distribution networks. Their reliable operation underpins continuous electricity supply, power quality, and grid stability. Given their strategic importance and high replacement cost, unexpected failures carry severe technical, economic, and environmental consequences, including service interruptions, equipment damage, and reduced system reliability (Mishra et al., 2026). Transformer failures are rarely sudden; they are typically preceded by gradual deterioration processes such as insulation aging, thermal degradation, moisture contamination, partial discharge, arcing, and winding deformation. These early-stage abnormalities, known as incipient faults, produce detectable changes in operating parameters well before catastrophic failure occurs, making their timely identification central to effective condition monitoring and asset management (Saleh et al., 2026; Wang, X.J. (2024).

Conventional transformer health assessment has relied on periodic inspections, offline diagnostic tests, and expert interpretation of data such as Dissolved Gas Analysis (DGA), oil quality, and electrical test results (Dhiman & Kumar, 2023). While informative, these methods are labour-

intensive, time-consuming, and reactive, and they struggle to capture the complex nonlinear relationships among operational variables required for accurate fault prediction (Veerappan, 2025). As transformer fleets age under increasingly demanding loading and environmental conditions, the need for intelligent, automated predictive maintenance has grown correspondingly urgent. Machine learning offers a powerful means of extracting meaningful patterns from large volumes of monitoring data (Azmi *et al.*, 2025). Among available algorithms, Random Forest (RF) has attracted particular attention for its high classification accuracy, robustness against overfitting, and effectiveness on nonlinear, high-dimensional datasets (Jing, 2025). However, RF performance depends heavily on proper hyperparameter selection, such as the number of trees and tree depth; poorly chosen values can reduce accuracy and limit generalization (Muneeb, 2024). Metaheuristic optimization techniques have increasingly been used to address this limitation. The Artificial Bee Colony (ABC) algorithm, a swarm-intelligence method inspired by honeybee foraging behaviour, is particularly noted for its strong global search capability, simplicity, and flexibility (Erkan *et al.*, 2023).

The performance of a Random Forest (RF) model is significantly influenced by several key hyperparameters, particularly the number of trees (NumTrees), number of predictors sampled at each split (NumPredictorsToSample), minimum leaf size (MinLeafSize), and maximum number of splits (MaxNumSplits). The number of trees is commonly varied within a range of 50–500, with MATLAB using 100 trees as a typical default (Zhu & Zhang, (2022). The number of predictors sampled at each split controls feature randomness and tree diversity, while the minimum leaf size, commonly varied between 1 and 20, influences tree complexity and overfitting. Similarly, the maximum number of splits controls the depth and complexity of individual trees (Alenezi *et al.*, 2026). Optimal tuning of these hyperparameters is essential for achieving the best possible RF performance (Mumtahina *et al.*, 2024). Conventional approaches such as random search, grid search, and Bayesian optimization can be used; however, they may suffer from limitations related to computational cost, search efficiency, or dependence on predefined search strategies (Dimgha & Andreas, 2024). Therefore, employing a metaheuristic optimization algorithm, such as Artificial Bee Colony (ABC), provides an intelligent search mechanism for exploring the hyperparameter space and identifying near-global optimal parameter combinations (Al Hourani *et al.*, 2025). Despite the growing application of Random Forest (RF) models for power transformer fault diagnosis and the increasing use of metaheuristic algorithms for hyperparameter optimization, relatively few studies have systematically integrated metaheuristic-based hyperparameter tuning with RF for incipient fault prediction in power transformers (Alenezi *et al.*, 2026; (Wong *et al.*, 2022). Existing studies often employ default or manually selected RF parameters, which may limit the model's ability to achieve optimal classification performance (Hoang & Vu, 2022; Yadav *et al.*, 2023). This creates a research gap in the development of an intelligently optimized RF model in which key hyperparameters, such as the number of trees, number of predictors sampled at each split, minimum leaf size, and maximum number of splits, are systematically optimized. Addressing this gap can enhance the predictive capability, robustness, and reliability of RF-based transformer fault diagnosis. This study addresses that gap by proposing an intelligent framework for power transformer incipient fault prediction using a Random Forest model optimized through the Artificial Bee Colony algorithm. The specific objectives are to develop an ABC-optimized Random Forest model for incipient fault classification using historical transformer condition-monitoring data and evaluate the model's predictive performance against a non-optimized baseline.

2. METHODOLOGY

This study developed an Artificial Bee Colony-optimized Random Forest (ABC-RF) model for predicting incipient faults in power transformers. A dataset containing 589 transformer fault samples collected from electrical utilities and the literature was used. Five dissolved gases H_2 , CH_4 , C_2H_6 , C_2H_4 , and C_2H_2 served as input features, while the output comprised six fault classes: PD, D1, D2, T1, T2, and T3 (Taha *et al.* 2021)). The dataset was cleaned to remove missing and inconsistent observations and subsequently divided into 70% training, 15% validation, and 15% testing data. The training set was used to develop the Random Forest classifier, while the validation set was used during hyperparameter optimization. The independent testing set was reserved for final model evaluation. Random Forest was selected because of its ability to model nonlinear relationships and provide robust multiclass classification. The hyperparameters, including the number of trees, maximum tree depth, minimum

samples for splitting, minimum samples per leaf, and number of features considered at each split, were optimized using the Artificial Bee Colony algorithm. In the ABC optimization process, each bee represented a candidate set of RF hyperparameters. Candidate solutions were iteratively improved through the employed-bee, onlooker-bee, and scout-bee phases. Validation accuracy was used as the fitness function, and the hyperparameter combination producing the best validation accuracy was selected. The optimized RF model was subsequently retrained and evaluated using the independent test dataset. Model performance was assessed using accuracy, precision, recall, F1-score, and confusion matrix analysis. To assess the robustness of the observed improvement, the RF and ABC-RF models were evaluated over multiple independent runs using different random train-test partitions, and the mean accuracy and standard deviation were recorded. The performance of the optimized ABC-RF model was compared with conventional Random Forest. Figure 1 shows the flowchart of the ABC-optimized random forest model.

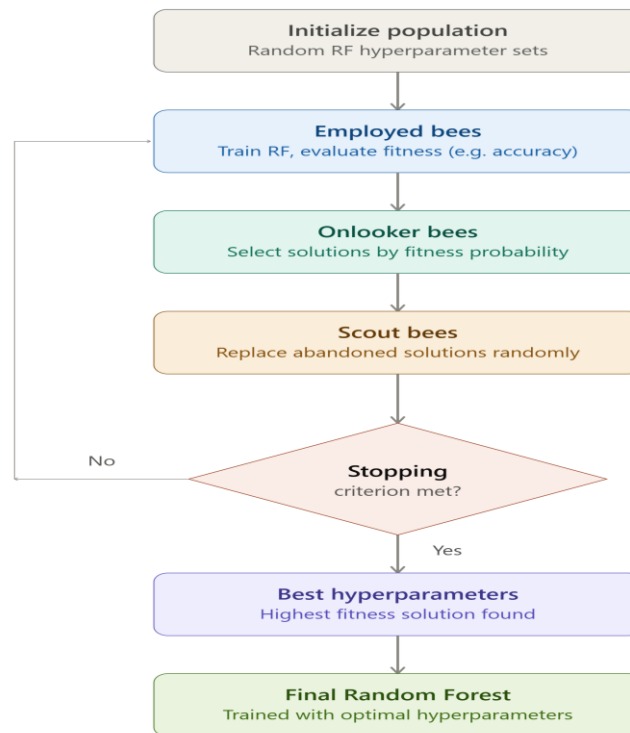


Figure 1: Flowchart of the ABC-Optimized Random Forest Model

2.1 ABC-Random Forest Model

The following steps show how artificial bee colony is used to find the optimal Random Forest hyperparameters automatically:

1. **Initialize:** Define the hyperparameter ranges, such as number of trees, maximum tree depth, and minimum leaf size.
2. **Generate solutions:** ABC randomly generates different combinations of these hyperparameters.
3. **Evaluate:** Train a Random Forest for each combination and calculate its fitness, such as validation Accuracy or F1-Score.
4. **Search:** Employed, onlooker, and scout bees explore and improve the hyperparameter combinations.
5. **Select best solution:** The combination with the best fitness is retained.
6. **Terminate:** The process continues until the maximum iterations or convergence criterion is reached.
7. **Final model:** The Random Forest is trained using the optimal hyperparameters and evaluated on the test data.

3. RESULTS AND DISCUSSION

Table 1 shows the results for the performance of models. The results indicate a clear improvement in classification performance across the evaluated models. SVM achieved the lowest overall performance, with an accuracy of 78.4% and an F1-score of 73.0%. RF performed slightly better, achieving 80.4% accuracy and an F1-score of 80.1%, indicating improved balance between precision and recall. DNN further improved the results, recording 83.3% accuracy, 81.5% precision, 84.1% recall, and 83.2% F1-score. The proposed ABC-RF model achieved the best performance across all evaluation metrics, with 91.2% accuracy, 92.4% precision, 90.5% recall, and 91.5% F1-score. Compared with the conventional RF model, ABC-RF improved accuracy by 10.8 percentage points and F1-score by 11.4 percentage points. To assess the robustness of the observed improvement, the RF and ABC-RF models were evaluated over multiple independent runs using different random train–test partitions, and the mean accuracy and standard deviation were recorded. The consistently higher mean accuracy of ABC-RF, together with its lower variability across runs, indicates that the 10.8 percentage-point improvement is not attributable to random variation from a single train–test split. This substantial improvement demonstrates that ABC-based hyperparameter optimization effectively enhances the Random Forest model, resulting in more accurate, consistent, and reliable classification performance.

Table 1: Performance of Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	78.4	77.2	76	73
RF	80.4	79.2	79.9	80.1
DNN	83.3	81.5	84.1	83.2
ABC-RF	91.2	92.4	90.5	91.5

Table 2 shows the Random Forest hyperparameters before and after ABC optimization. ABC increased the number of trees from 100 to 148, while the minimum leaf size remained at 1. The maximum number of splits increased to 65 compared with the default value of 50. The number of predictors sampled at each split was optimized to 4. Overall, ABC identified a parameter combination expected to provide better model performance than the default Random Forest settings.

The confusion matrix in Figure 2 shows that the proposed model achieved strong classification performance across the six classes (D1, D2, PD, T1, T2, and T3). Most observations are correctly classified, as indicated by the relatively high values along the main diagonal. In particular, D1, D2, PD, T1, T2, and T3 recorded 18, 23, 27, 25, 26, and 21 correct predictions, respectively.

Table 2: Hyper Parameter Values Range and Optimized Values

Hyperparameter	Name	Default	Search Range	Optimized
Number of trees	Num_Trees	100	50-200	148
Minimum leaf size	MinLeafSize	1	1-5	1
Number of Splits	MaxNumSplits	50	10–500	65
Number of predictors	NumPredictorsToSample	1 -p	Sqrt (p)	4

		Confusion Matrix					
True Class	D1	18	6	5		1	
	D2	3	23	3			
	PD	1	1	27			
	T1			2	25	3	
	T2		2	2		26	
	T3			6	1	2	21
		D1	D2	PD	T1	T2	T3
		Predicted Class					

Figure 2: ABC-Random Forest Confusion Matrix

Some misclassification occurred between closely related classes. D1 is misclassified 6 times as D2, 5 times PD and 1 as T2; while T3 has 6 misclassified as PD, once as T1 and twice as T2. The misclassification of D1 and T3 can be attributed to the overlapping dissolved-gas characteristics of these fault conditions with other fault classes. D1 was misclassified mainly as D2 and PD, while T3 was occasionally classified as PD, T1, and T2. This overlap may arise because similar gas generation patterns can occur under different fault conditions, particularly when fault severity and operating conditions vary. Consequently, some samples may exhibit features that are not sufficiently distinctive for the classifier to clearly separate the fault classes. Overall, the high concentration of predictions along the diagonal demonstrates that the model can effectively distinguish the different fault classes, with only limited confusion between classes

4. CONCLUSION

In conclusion, the results demonstrate that the proposed ABC-RF model provides superior classification performance compared with SVM, conventional RF, and DNN models. The model achieved an accuracy of 91.2%, precision of 92.4%, recall of 90.5%, and an F1-score of 91.5%, confirming its effectiveness in distinguishing between the different transformer fault classes. Except for PD and T3 samples misclassified, the relatively high precision indicates that the model generates few false-positive classifications, while the strong recall demonstrates its ability to correctly identify most fault conditions. The findings demonstrate that integrating Artificial Bee Colony (ABC) optimization with Random Forest enhances diagnostic performance by identifying more suitable model hyperparameters. Overall, the proposed ABC-RF model offers a robust and reliable approach for power transformer fault diagnosis with considerable potential for supporting early fault identification in practical power systems.

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