p-ISSN : 2301-8402, e-ISSN : 2685-368X, available at : https://ejournal.unsrat.ac.id/index.php/elekdankom

SVR and KNN Optimization for Transformer Oil Breakdown Voltage Prediction

Optimasi SVR dan KNN untuk Prediksi Breakdown Voltage Minyak Transformator

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Received: 8 February 2026; revised: 27 April 2026; accepted: 2 May 2026

***Abstract* --- This study investigates the prediction of transformer oil breakdown voltage (BDV) under copper and iron contamination using Support Vector Regression (SVR) and K-Nearest Neighbor (KNN) regression, including their optimization with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). The experimental dataset consists of small-scale laboratory measurements covering three transformer oil types, two contaminant metals, and multiple concentration levels. Model performance is evaluated using RMSE, MAE, and coefficient of determination (R^2) on unseen test data. The baseline SVR and KNN models achieved test RMSE values of 1.768 kV and 1.761 kV, respectively, indicating comparable predictive capability. Optimization slightly improves SVR performance, where SVR+GWO achieved the lowest RMSE of 1.755 kV and R^2 of 0.102, followed closely by SVR+GA and SVR+PSO with marginal differences below 0.01 kV. In contrast, KNN regression shows identical performance across all optimization methods, with KNN+GA, KNN+PSO, and KNN+GWO yielding the same RMSE of 1.825 kV, demonstrating that metaheuristic optimization does not significantly affect KNN behavior on small and structured datasets. These results highlight that SVR benefits modestly from metaheuristic optimization in terms of stability and consistency, while KNN regression remains insensitive to such optimization. The findings provide a robust baseline reference for BDV prediction and underline the importance of dataset characteristics in determining the effectiveness of optimization strategies.**

***Key words* --- Breakdown Voltage Oil Transformer; Support Vector Regression; KNN Regression; Metaheuristic Optimization; Small Experimental Data.**

***Abstrak* --- Studi ini menyelidiki prediksi tegangan tembus oli transformator (BDV) dibawah kontaminasi tembaga dan besi menggunakan regresi Support Vector Regression (SVR) dan K-Nearest Neighbor (KNN), termasuk optimasinya dengan Genetic Algorithm (GA), Particle Swarm Optimization (PSO), dan Grey Wolf Optimizer (GWO). Dataset eksperimental terdiri dari pengukuran laboratorium skala kecil yang mencakup tiga jenis oli transformator, dua logam kontaminan, dan beberapa tingkat konsentrasi. Kinerja model dievaluasi menggunakan RMSE, MAE, dan koefisien determinasi (R^2) pada data uji yang belum pernah dilihat sebelumnya. Model dasar SVR dan KNN mencapai nilai RMSE uji masing-masing sebesar 1,768 kV dan 1,761 kV, menunjukkan kemampuan prediksi yang sebanding. Optimasi sedikit meningkatkan kinerja SVR, di mana SVR+GWO mencapai RMSE terendah sebesar 1,755 kV dan R^2 sebesar 0,102, diikuti oleh SVR+GA dan SVR+PSO dengan perbedaan marginal di bawah 0,01 kV. Sebaliknya, regresi KNN menunjukkan kinerja yang identik di semua metode optimasi, dengan KNN+GA, KNN+PSO, dan KNN+GWO menghasilkan RMSE yang sama sebesar 1,825 kV, menunjukkan bahwa optimasi metaheuristik tidak secara signifikan memengaruhi perilaku KNN pada dataset kecil dan terstruktur. Hasil ini menyoroti bahwa SVR sedikit diuntungkan dari optimasi metaheuristik dalam hal stabilitas dan konsistensi, sementara regresi KNN tetap tidak sensitif terhadap optimasi tersebut. Temuan ini memberikan referensi dasar yang kuat untuk prediksi BDV dan menggarisbawahi pentingnya karakteristik dataset dalam menentukan efektivitas strategi optimasi.**

***Kata kunci* --- Tegangan Tembus Minyak Transformator, Support Vector Regression, KNN Regression, Optimasi Metaheuristik, Data Eksperimental Kecil.**

I. INTRODUCTION

Transformer oil serves a fundamental function in power transformers by acting simultaneously as an electrical insulation medium and a heat transfer agent. The integrity of this oil is closely linked to the reliability and safety of high-voltage equipment, since degradation of its dielectric properties can trigger electrical discharges that result in serious insulation failure and irreversible transformer damage. A key parameter commonly used to assess the dielectric condition of transformer oil is the Breakdown Voltage (BDV), which quantifies the maximum electric stress the oil can endure prior to the onset of electrical breakdown. In real operating conditions, the deterioration of transformer oil is frequently intensified by the presence of contaminant particles, particularly metallic impurities such as copper (Cu) and iron (Fe). These contaminants disturb the local electric field distribution within the oil and facilitate early discharge initiation. Consequently, the ability to estimate BDV under metallic contamination conditions is essential for supporting condition-based maintenance and early fault prevention strategies in power transformer systems.

Traditionally, BDV assessment is conducted exclusively through laboratory-based experiments that require carefully controlled conditions, repeated measurements, and significant time investment. As a result, data-driven prediction techniques have gained increasing attention as an alternative means to estimate dielectric performance using historical experimental data. Among various machine learning approaches, Support Vector Regression (SVR) has been widely employed due to its strong capability to capture nonlinear relationships while

maintaining reliable generalization performance, particularly when the available dataset is limited. In Indonesia, SVR has been extensively applied in a wide range of regression-oriented studies, including inflation prediction [1], stock market analysis [2], commodity price forecasting [3], and rainfall estimation [4]. Moreover, several studies have explored hybrid SVR frameworks integrated with optimization techniques to enhance prediction accuracy in complex datasets such as epidemiological records [5]. These findings collectively establish SVR as a robust and frequently adopted baseline model for nonlinear regression tasks under data scarcity.

Alongside kernel-based learning methods, similarity-driven techniques such as K-Nearest Neighbor (KNN) regression have also been widely utilized in Indonesian predictive modeling research. KNN regression has demonstrated satisfactory performance in applications including residential property valuation [6], inventory demand estimation [7], rice production forecasting [8], and agricultural commodity price prediction, such as Arabica coffee prices [9]. These studies highlight that KNN regression is particularly effective when applied to small or medium-sized datasets in which prediction accuracy relies on the proximity between observations rather than on a global functional model. Additionally, KNN has been employed in regression-based survival prediction studies using continuous error metrics such as RMSE and MAE [10], further confirming its applicability for continuous-value prediction tasks under heterogeneous data conditions. More directly, Prenata and Ridho'i compared KNN Regression and SVR for SAIDI–SAIFI-based power-system reliability prediction and reported that KNN performance was highly sensitive to the neighborhood parameter K, whereas SVR exhibited more stable behavior on a small dataset [15]. This result is methodologically relevant to the present work because it demonstrates that the relative behavior of distance-based and kernel-based regression depends strongly on data structure and sample size. Owing to its simplicity, transparency, and intuitive interpretation, KNN regression is commonly used as a benchmark model against which more sophisticated regression techniques are evaluated.

Despite the extensive application of SVR and KNN in various prediction domains, their use for estimating transformer oil breakdown voltage under controlled metallic contamination scenarios remains relatively underexplored. Existing studies in high-voltage engineering predominantly focus on statistical characterization of BDV measurements or categorical classification of oil condition, rather than continuous regression-based prediction across different oil types, contaminant materials, and concentration levels. Furthermore, experimental BDV datasets are inherently small, as each observation requires labor-intensive laboratory testing. This characteristic raises an important methodological issue regarding whether advanced regression models can offer meaningful advantages over simpler similarity-based approaches when applied to limited experimental data.

Recent clustering-based analysis on transformer oil dielectric behavior under copper and iron contamination further revealed that BDV datasets exhibit structured yet partially overlapping dielectric regimes rather than completely isolated classes. Comparative evaluation using K-Means and Fuzzy C-Means demonstrated that transformer oil degradation forms gradual transitional patterns, particularly at intermediate contamination levels, where several samples simultaneously share characteristics of adjacent dielectric states [11]. The study also showed that contamination concentration systematically influences BDV distribution and cluster structure, indicating that the dielectric landscape is continuous and nonlinear rather than strictly categorical [11]. These findings provide additional justification for employing nonlinear regression models such as SVR in BDV prediction, since kernel-based approaches are better suited to represent smooth transitional behavior within small experimental dielectric datasets.

In response to this gap, the present study conducts a baseline regression analysis for predicting transformer oil breakdown voltage under copper and iron contamination using Support Vector Regression and K-Nearest Neighbor regression. Rather than proposing a novel algorithm, this work aims to systematically examine and compare the predictive behavior of kernel-based and distance-based regression models when applied to small-scale experimental dielectric datasets. By evaluating prediction performance using absolute error metrics and tolerance-based accuracy measures, this study seeks to determine whether complex nonlinear modeling is necessary, or whether proximity-based estimation methods are sufficient for practical BDV prediction in laboratory-level transformer oil investigations.

Due to the time-consuming nature and high cost of repeated laboratory BDV testing, data-driven regression approaches have increasingly been explored as alternative tools for estimating dielectric performance based on experimental observations. Among various machine learning techniques, Support Vector Regression (SVR) has attracted significant attention because of its strong generalization capability and effectiveness in modeling nonlinear relationships, particularly when the available dataset is limited. Several studies conducted in Indonesia have demonstrated that SVR provides reliable predictive performance in regression problems when its hyperparameters are properly tuned. Research on SVR parameter optimization has shown that inappropriate parameter selection can significantly degrade prediction accuracy, thereby motivating the use of metaheuristic optimization algorithms to enhance SVR performance [12]. Related work by Prenata and Ridho'i on limited-sample ECG data further showed that GA-, PSO-, and GWO-based optimization can produce distinct convergence and error characteristics, while metaheuristic tuning can improve training stability even when generalization remains constrained by dataset size [16]. This evidence supports the need to evaluate optimization behavior explicitly when regression models are developed from limited experimental observations.

Genetic Algorithm (GA) has been widely adopted in Indonesian studies to optimize SVR hyperparameters by exploring the search space through evolutionary operators such as selection, crossover, and mutation. Previous works reported that GA-optimized SVR models outperform manually tuned SVR configurations in terms of prediction accuracy and

robustness, particularly for nonlinear regression problems involving complex data distributions [13]. In addition to GA, Particle Swarm Optimization (PSO) has also been extensively applied as an efficient swarm-based optimization technique. PSO leverages collective information sharing among particles to guide the search toward stable near-optimal solutions, and several Indonesian studies have shown that PSO-based SVR achieves superior convergence consistency compared to conventional tuning approaches [12]. A previous electrical-energy prediction study by Prenata and Ridho'i also demonstrated that GA and PSO can yield different accuracy–stability trade-offs under a common modeling framework, with optimizer performance remaining dependent on data characteristics and parameter settings [17]. Accordingly, comparative evaluation is necessary rather than assuming that a particular metaheuristic will consistently provide the best solution.

More recently, the Grey Wolf Optimizer (GWO) has emerged as a competitive metaheuristic algorithm inspired by the hierarchical hunting behavior of grey wolves. Indonesian research has demonstrated that GWO is capable of balancing exploration and exploitation effectively, resulting in improved SVR prediction performance and enhanced stability across repeated experiments. Comparative studies indicate that GWO-optimized SVR models often achieve lower prediction errors than baseline SVR and, in some cases, outperform other optimization techniques such as GA and PSO [14]. Consistent with this perspective, a 2026 electrical-energy forecasting study by Prenata reported that GWO-optimized DFFNN achieved rapid convergence and low prediction error under sliding-window cross-validation, whereas GA showed greater variability across runs [18]. These findings reinforce the importance of assessing metaheuristic methods not only from their best error value but also from convergence stability and repeatability, which are central considerations in the present small-data BDV prediction study.

In parallel with kernel-based learning methods, distance-based approaches such as K-Nearest Neighbor (KNN) regression have also been employed as baseline models in many Indonesian prediction studies. KNN regression is attractive for small experimental datasets due to its simplicity, interpretability, and reliance on similarity relationships rather than explicit model training. However, unlike SVR, KNN possesses a discrete and low-dimensional hyperparameter space, which raises important methodological questions regarding the effectiveness of applying complex metaheuristic optimization techniques to such models.

Despite extensive applications of SVR and KNN in various prediction domains, their systematic evaluation for transformer oil breakdown voltage prediction under controlled copper and iron contamination remains limited. Most existing studies in high-voltage engineering emphasize statistical analysis or oil condition classification rather than direct regression-based BDV prediction across multiple oil types, contaminant materials, and concentration levels. Moreover, the inherently small size of experimental BDV datasets introduces a critical research question: whether sophisticated regression models and metaheuristic optimization strategies provide meaningful advantages over simpler similarity-based estimators in laboratory-scale studies.

Therefore, this study investigates the predictive performance of Support Vector Regression and K-Nearest Neighbor regression, both in their baseline forms and when optimized using Genetic Algorithm, Particle Swarm Optimization, and Grey Wolf Optimizer, for breakdown voltage prediction of transformer oil under copper and iron contamination. Rather than proposing a new algorithm, this work aims to establish a systematic baseline comparison that emphasizes accuracy, stability, and optimization behavior on small experimental dielectric datasets. The findings of this study are expected to provide practical insights into the necessity and limitations of metaheuristic optimization in BDV prediction and to serve as a reference for future research involving larger datasets or hybrid modeling strategies.

II. METHOD

A. K-Nearest Neighbor Regression

In this study, K-Nearest Neighbor (KNN) regression is adopted as a similarity-based reference model for estimating the breakdown voltage (BDV) of transformer oil subjected to metallic contamination. Unlike parametric or model-driven regression techniques, KNN does not perform an explicit training phase to derive a global mathematical function. Instead, the entire training dataset is preserved and utilized directly during prediction. This instance-based characteristic makes KNN particularly appropriate for small-scale experimental datasets, where complex physical interactions are difficult to approximate using a single analytical model.

Each experimental observation is described by a numerical feature vector composed of transformer oil type, contaminant metal type, and contaminant concentration. Transformer oil categories are encoded numerically to differentiate among oil brands, while the contaminant metal feature distinguishes copper and iron impurities. The contaminant concentration is

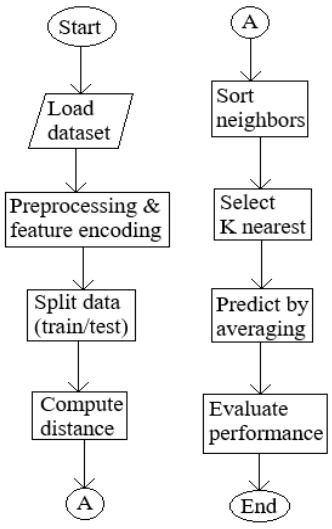


Figure 1. Flowchart of KNN Regresion method

represented as a continuous numerical variable. The output variable corresponds to the experimentally measured breakdown voltage obtained from controlled laboratory testing.

The dataset is partitioned deterministically based on sample identity to ensure a clear separation between training and testing phases. Samples with identifiers from 1 to 15 are assigned to the training set, whereas samples with identifiers 16 to 18 are reserved exclusively for testing. This strategy guarantees that the evaluation reflects the model's capability to predict BDV values for unseen experimental conditions rather than randomly reshuffled observations.

During prediction, the Euclidean distance between a test sample and all training samples is computed in the normalized feature space. This distance serves as a quantitative measure of similarity between contamination conditions, with smaller distances indicating higher similarity. All training samples are then ranked in ascending order according to their distances from the test sample, and the K closest neighbors are selected.

The predicted BDV value is obtained by averaging the measured BDV values of the selected neighbors. This averaging mechanism is based on the assumption that samples with similar contamination characteristics exhibit comparable dielectric strength behavior. The neighborhood size K is not predefined but is determined empirically by evaluating multiple candidate values.

To identify the optimal K, values ranging from 1 to 15 are examined. For each K, the Root Mean Square Error (RMSE) between predicted and measured BDV values is calculated. The K value that yields the minimum RMSE is selected as the optimal neighborhood size. Final BDV predictions for the test samples are then generated using this optimal K configuration.

Model performance is assessed using three regression metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). RMSE and MAE provide direct quantitative measures of prediction error in kilovolts, which is physically meaningful for dielectric strength assessment. Although R^2 is reported to indicate explained variance, greater emphasis is placed on error-based metrics due to the limited variability inherent in experimental BDV data.

Through this approach, KNN regression functions as a transparent and interpretable baseline model that exploits local similarity in the feature space. Its simplicity and direct reliance on experimental proximity make it suitable for evaluating whether more sophisticated regression techniques are necessary for BDV prediction under small experimental datasets.

B. K-Nearest Neighbor Regression + Genetic Algorithm

In this study, the K-Nearest Neighbor (KNN) regression model is optimized using a Genetic Algorithm (GA) to determine the optimal number of nearest neighbors (K) that minimizes prediction error. The BDV dataset is preprocessed and divided into training and test sets based on SampleID, where SampleIDs 1 to 15 are used for training and SampleIDs 16 to 18 are used for testing. Each sample is represented as a numerical feature vector consisting of transformer oil type, contaminant metal type, and contaminant concentration, while BDV values serve as the regression targets.

During optimization, GA is employed to search for the optimal K value in the KNN model. Each individual in the GA population represents a candidate K value within a predefined range. The fitness function is defined as the Root Mean Square Error (RMSE) obtained from a Leave-One-Sample-Out Cross-Validation (LOSO-CV) scheme applied to the training data. In this scheme, one SampleID group is used as validation data while the remaining samples are used for training, and the process is repeated until all SampleIDs are validated. LOSO-CV is selected to preserve independence among validation samples and reduce bias caused by the relatively small experimental dataset.

The GA evolutionary process begins with random initialization of the population, followed by fitness evaluation of each individual. Selection is performed using tournament selection, where individuals with better fitness values have higher probabilities of being chosen as parents. Crossover operators generate offspring by combining K values from two parents, while mutation operators introduce local variations by slightly adjusting K values. An elitism mechanism is applied to ensure that the best individual from each generation is retained in the subsequent population.

This evolutionary process is repeated for a predefined number of generations until the optimal K value yielding the minimum LOSO-CV RMSE is obtained. The optimal K value is then used to construct the final KNN model, which is evaluated on the test dataset that is completely independent of the optimization process. Model performance on the test data is assessed using RMSE, MAE, and the coefficient of determination (R^2). Through this approach, GA-based optimization of KNN not only aims to improve prediction accuracy but also evaluates the robustness of the K parameter under small-scale experimental data conditions.

C. K-Nearest Neighbor Regression + Particle Swarm Optimization

In this study, the K-Nearest Neighbor (KNN) regression model is combined with Particle Swarm Optimization (PSO) to determine the optimal number of nearest neighbors (K) for predicting transformer oil breakdown voltage (BDV). The dataset is divided into training and test sets based on SampleID, with SampleIDs 1 to 15 used for training and SampleIDs 16 to 18 used for testing. Each sample is represented as a numerical feature vector consisting of oil type, contaminant metal type, and metal concentration, while BDV values are used as regression targets.

PSO is applied to optimize the K parameter of the KNN model. Each particle represents a candidate K value, modeled as a one-dimensional continuous variable and rounded to the nearest integer before use in prediction. Particle positions are randomly initialized within a predefined K range, and initial velocities are also randomly assigned to enable exploration of the solution space. The fitness function is defined as RMSE computed using Leave-One-Sample-Out Cross-Validation (LOSO-CV) on the training data, ensuring that each SampleID is alternately used as validation data.

At each PSO iteration, particle velocities and positions are updated based on a combination of inertia, personal best, and

global best components. This update mechanism allows particles to balance exploration and exploitation in the search for a K value that minimizes prediction error. After updating positions, the rounded K values are reevaluated using the LOSO-CV RMSE fitness function, and personal best and global best values are updated accordingly.

PSO iterations continue until a predefined maximum number of iterations is reached or convergence is observed. The optimal K value obtained from the PSO process is then used to build the final KNN model, which is evaluated on the test dataset completely independent of the training and optimization stages. Model performance is assessed using RMSE, MAE, and R^2 to quantify generalization capability. This KNN+PSO approach is designed to evaluate the extent to which population-based optimization can improve or stabilize KNN regression performance on small-scale BDV experimental datasets.

D. K-Nearest Neighbor Regression + Grey Wolf Optimization

In this study, the K-Nearest Neighbor (KNN) regression model is combined with the Grey Wolf Optimizer (GWO) to optimize the number of nearest neighbors (K) for predicting the breakdown voltage (BDV) of transformer oil contaminated with copper and iron. The BDV dataset is read from a CSV file, and each sample is represented as a numerical feature vector including oil type, contaminant metal type, and contaminant concentration. Data partitioning is performed based on SampleID, with SampleIDs 1 to 15 used for training and SampleIDs 16 to 18 used for testing to ensure consistent and non-overlapping evaluation.

GWO is applied to search for the optimal K value by minimizing prediction error on the training data. Each wolf represents a candidate K value in a one-dimensional solution space. Initial wolf positions are randomly generated within the predefined K range. The fitness of each candidate is evaluated using RMSE obtained from Leave-One-Sample-Out Cross-Validation (LOSO-CV) on the training data, where one SampleID is used as validation data while the remaining samples serve as training data.

At each GWO iteration, the three best solutions with the lowest fitness values are identified as alpha, beta, and delta wolves. The positions of the remaining wolves are updated based on their distances to these three leaders using adaptive coefficients that decrease linearly over iterations. This mechanism allows the optimization process to transition gradually from global exploration to local exploitation around the best solution. Candidate K values are rounded to the nearest integer and constrained within the allowable range before evaluation.

The GWO process continues until the maximum number of iterations is reached or convergence is achieved. The optimal K value obtained from the alpha wolf is used to construct the final KNN model, which is then evaluated on the test dataset. Model performance is assessed using RMSE, MAE, and R^2 to analyze generalization capability. All optimization results, selected K values, and prediction outputs are recorded to support further analysis and ensure research reproducibility.

E. Support Vector Regression

Support Vector Regression (SVR) is utilized in this study to capture the nonlinear relationship between transformer oil contamination parameters and breakdown voltage (BDV). SVR is chosen for its strong generalization performance on limited datasets and its ability to model nonlinear behavior through kernel-based transformations. To reduce computational burden while maintaining predictive accuracy, the Least Squares Support Vector Regression (LS-SVR) formulation combined with a Radial Basis Function (RBF) kernel is employed.

Each experimental sample is represented by a feature vector comprising transformer oil type, contaminant metal type, and contaminant concentration. Oil type and metal type are numerically encoded to distinguish among different oil brands and contaminant materials, while contaminant concentration is treated as a continuous input variable. The target output is the experimentally measured BDV obtained from laboratory testing. Data partitioning follows a deterministic scheme based on SampleID, where samples 1 to 15 are used for training and samples 16 to 18 are allocated for testing. This ensures that model evaluation reflects predictive performance on previously unseen experimental samples.

Prior to model training, all input features are normalized using Min–Max scaling parameters computed exclusively from the training dataset. This normalization step prevents scale dominance among features and ensures balanced contribution during kernel distance computation. The same scaling transformation is subsequently applied to the test data to preserve consistency between training and prediction stages.

The LS-SVR model employs an RBF kernel to implicitly project the normalized input data into a higher-dimensional space, enabling effective modeling of nonlinear relationships between contamination conditions and BDV. Model behavior is governed by two key hyperparameters: the regularization parameter γ, which controls the trade-off between fitting accuracy and smoothness, and the kernel width σ, which determines the sensitivity of the RBF kernel to variations in

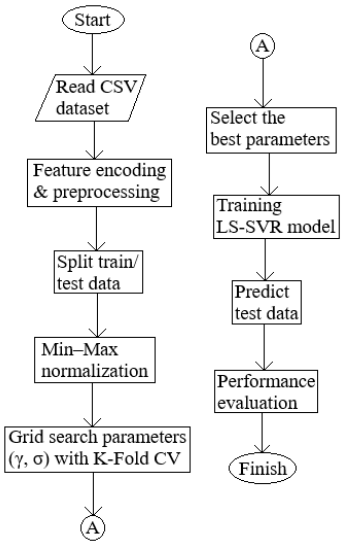


Figure 2. Flowchart of SVR method

feature distance. Inappropriate selection of these parameters may lead to underfitting or overfitting, especially when dealing with small experimental datasets.

To determine an appropriate hyperparameter configuration, a grid search combined with 5-Fold Cross-Validation is conducted using only the training data. The training set is divided into five subsets, with each subset alternately serving as validation data while the remaining subsets form the training portion. For each candidate pair of γ and σ values, the average RMSE across all folds is computed. The parameter combination that produces the lowest cross-validated RMSE is selected as the optimal configuration.

Once the optimal hyperparameters are identified, the LS-SVR model is retrained using the complete training dataset. The trained model is then applied to the test dataset to generate BDV predictions. Model performance is evaluated using RMSE, MAE, and the coefficient of determination (R^2). RMSE and MAE provide direct physical interpretation in kilovolts, while R^2 indicates the proportion of BDV variance explained by the regression model.

Through this procedure, SVR serves as a kernel-based nonlinear regression baseline for transformer oil BDV prediction. By comparing its performance with the similarity-driven KNN regression model, this study investigates whether nonlinear kernel mapping offers a measurable advantage over distance-based estimation when applied to small experimental dielectric datasets.

F. Support Vector Regression + Genetic Algorithm

In this approach, Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel is combined with a Genetic Algorithm (GA) to optimize the main hyperparameters, namely the regularization parameter γ (gamma) and the kernel width σ (sigma). The primary objective of this optimization is to obtain an SVR parameter configuration that minimizes the prediction error of breakdown voltage (BDV) on the training data while maintaining good generalization capability when applied to the test data.

The procedure begins with reading the experimental BDV data from the file BDV_longformat_324.csv. Each data record is processed flexibly to accommodate variations in decimal formatting and then encoded into numerical feature representations consisting of transformer oil type, contaminant metal type, and contaminant concentration. The dataset is subsequently divided based on SampleID, where samples with IDs 1 to 15 are used as training data and samples with IDs 16 to 18 are reserved as test data. To prevent any single feature from dominating the learning process due to scale differences, Min–Max normalization is applied using parameters computed exclusively from the training dataset.

Genetic Algorithm is employed to perform a global search for the optimal values of γ and σ. The initial population is generated randomly within predefined parameter ranges, with γ sampled on a logarithmic scale between 0.1 and 1000 and σ sampled linearly between 0.2 and 5. Each individual in the population represents a candidate solution in the form of a parameter pair (γ, σ). The quality of each individual is evaluated using a fitness function defined as the Root Mean Square Error (RMSE) obtained from K-Fold Cross-Validation on the training data. This evaluation strategy ensures that the optimization process emphasizes overall model stability rather than performance on a single data subset.

The evolutionary process of GA is carried out through tournament selection, where individuals with better fitness values have a higher probability of being selected as parents. Crossover operators are applied to recombine parental parameters and generate new candidate solutions, while controlled mutation is introduced to preserve population diversity and reduce the risk of premature convergence to local optima. This evolutionary cycle is repeated until the maximum number of generations is reached, with an elitism mechanism employed to retain the best-performing individuals at each generation.

After the GA optimization process is completed, the optimal values of γ and σ corresponding to the minimum cross-validation RMSE are selected. These parameters are then used to train the final LS-SVR model using the entire training dataset. The trained model is subsequently applied to the test dataset to generate BDV predictions. Prediction performance is evaluated using RMSE, Mean Absolute Error (MAE), and the coefficient of determination (R^2). Through this approach, the SVR+GA model not only achieves low prediction error but also demonstrates relatively stable performance across variations in experimental data, which is particularly important for small-scale BDV datasets.

G. Support Vector Regression + Particle Swarm Optimization

In this approach, Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel is integrated with Particle Swarm Optimization (PSO) to optimize the main hyperparameters, namely the regularization parameter γ (gamma) and the kernel width σ (sigma). The objective of this method is to obtain an SVR parameter configuration that minimizes the prediction error of breakdown voltage (BDV) while maintaining high stability and consistency when applied to small-scale experimental data.

The process begins with reading the BDV dataset from the file BDV_longformat_324.csv. The data are then parsed to accommodate variations in numerical formatting and encoded into numerical feature representations corresponding to transformer oil type, contaminant metal type, and contaminant concentration. Subsequently, the dataset is divided based on SampleID, where samples with IDs 1 to 15 are used as training data and samples with IDs 16 to 18 are reserved as test data. To ensure comparable feature scales, Min–Max normalization is applied using parameters computed exclusively from the training dataset.

Particle Swarm Optimization is employed to iteratively search for optimal values of γ and σ. Each particle in the swarm represents a candidate solution in the form of a parameter pair (γ, σ). Particle positions are initialized randomly, with γ generated on a logarithmic scale within the range of 0.1 to 1000 to capture the sensitivity of SVR to regularization, while σ is restricted to a linear range between 0.2 and 5. Initial particle

velocities are also controlled to prevent excessively large parameter updates during early iterations.

The quality of each particle is evaluated using a fitness function defined as the Root Mean Square Error (RMSE) obtained from K-Fold Cross-Validation on the training data. Each particle stores its best-achieved solution as the personal best, while the best solution among all particles is maintained as the global best. At each iteration, particle velocities and positions are updated based on a combination of inertia, cognitive, and social components, allowing the swarm to collectively move toward more optimal parameter configurations.

The PSO iteration continues until the maximum number of iterations is reached or until the change in the global best value becomes sufficiently small, indicating convergence. The optimal γ and σ values obtained from the global best solution are then used to train the final LS-SVR model using the entire training dataset. The trained model is subsequently applied to the test dataset to generate BDV predictions. Model performance is evaluated using RMSE, Mean Absolute Error (MAE), and the coefficient of determination (R^2) to assess prediction accuracy and generalization capability.

The SVR+PSO approach enables a fast and stable hyperparameter optimization process. The swarm-based mechanism allows PSO to consistently converge to the same optimal region across repeated experiments, making this method particularly suitable for BDV prediction tasks involving small experimental datasets with relatively smooth data structures.

H. Support Vector Regression + Grey Wolf Optimization

To ensure clarity and reproducibility, the hyperparameter search space, initialization settings, and final optimized parameter configurations used in this study are explicitly summarized. For all SVR-based optimization methods, the regularization parameter γ was searched within the range of 0.1 to 1000 using logarithmic scaling, while the kernel width σ was searched within the range of 0.2 to 5 using linear scaling. For KNN-based optimization, the neighborhood parameter K was restricted to integer values between 1 and 15.

For Genetic Algorithm (GA), the initial population was generated randomly within the predefined search ranges. Tournament selection, crossover, mutation, and elitism mechanisms were employed during optimization. For Particle Swarm Optimization (PSO), particle positions and velocities were randomly initialized within the search space, while inertia, cognitive, and social update mechanisms controlled particle movement. For Grey Wolf Optimizer (GWO), wolf positions were initialized randomly, and the optimization process followed the hierarchical alpha-beta-delta leadership mechanism with adaptive coefficient updates. The final optimized parameter configurations selected by each optimization method are presented in Table 1.

In this method, Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel is combined with the Grey Wolf Optimizer (GWO) to optimize the main hyperparameters, namely the regularization parameter γ (gamma) and the kernel width σ (sigma). The primary objective of this approach is to obtain an SVR parameter configuration that minimizes BDV prediction error on the training data through cross-validation, while producing a stable and consistent model when applied to test data.

The process begins with reading the experimental BDV data from the BDV_longformat_324.csv file. The data are flexibly parsed to handle numerical format variations and encoded into numerical features representing transformer oil type, contaminant metal type, and contaminant concentration. The dataset is divided based on SampleID, where samples with IDs 1 to 15 are used as training data and samples with IDs 16 to 18 are used as test data. Min–Max normalization is applied using parameters computed solely from the training data to eliminate scale discrepancies among features.

Grey Wolf Optimizer is employed to iteratively search for optimal γ and σ values. Each wolf represents a candidate solution defined by a pair (γ, σ). The γ parameter is initialized on a logarithmic scale within the range of 0.1 to 1000 to enhance optimization stability, while σ is constrained between 0.2 and 5. The initial wolf population is randomly generated within these bounds to ensure solution diversity during the early search phase.

The fitness of each wolf is evaluated using RMSE obtained from K-Fold cross-validation on the training data. In each iteration, the three best wolves with the lowest fitness values are designated as alpha, beta, and delta. The remaining wolves update their positions by referencing these three leaders through the GWO position update equations, which incorporate adaptive coefficients and a control parameter a that decreases linearly from 2 to 0. This mechanism enables a gradual transition from global exploration to local exploitation around the best solutions.

The GWO iterations continue until the maximum number of iterations is reached. The best γ and σ values obtained from the alpha wolf are then used to train the final LS-SVR model using the complete training dataset. The trained SVR model is subsequently employed to predict BDV values on the test data. Prediction performance is assessed using RMSE, MAE, and the coefficient of determination (R^2) to evaluate prediction

Table 1
Hyperparameter Search Space and Final Optimized Configuration for Each Model

Model	Search Space	Initialization	Final Optimized Parameter
SVR + GA	γ = 0.1–1000, σ = 0.2–5	Random population initialization	γ ≈ 1000, σ ≈ 2.07
SVR + PSO	γ = 0.1–1000, σ = 0.2–5	Random particle position and velocity	γ ≈ 1000, σ ≈ 2.07
SVR + GWO	γ = 0.1–1000, σ = 0.2–5	Random wolf initialization	γ ≈ 1000, σ ≈ 2.07
KNN + GA	K = 1–15	Random integer population	K = 14
KNN + PSO	K = 1–15	Random particle initialization	K = 14
KNN + GWO	K = 1–15	Random wolf initialization	K = 14

accuracy and generalization ability.

The SVR+GWO approach demonstrates strong convergence stability and high consistency across repeated experiments. The hierarchical structure of GWO enables a controlled and systematic optimization process, making this method particularly suitable for SVR optimization on small-scale BDV datasets with smooth and constrained data characteristics.

In this study, different cross-validation strategies are employed based on the characteristics of each model. For SVR, K-Fold Cross Validation is used to provide stable estimation for continuous hyperparameters (γ and σ), which require sufficient data distribution in each fold. In contrast, KNN optimization employs Leave-One-Sample-Out Cross-Validation (LOSO-CV) to preserve the independence of experimental samples grouped by SampleID. This approach ensures that similarity-based predictions are evaluated under strictly unseen sample conditions. Therefore, the validation strategies are intentionally selected to match the nature of each model rather than enforcing a uniform validation scheme. This design prioritizes methodological suitability over strict comparability.

III. RESULT AND DISCUSSION

This study evaluates the predictive performance of Support Vector Regression (SVR) and K-Nearest Neighbor (KNN) regression models for breakdown voltage (BDV) prediction of transformer oil under copper and iron contamination. Both models were examined in their baseline configurations and in optimized forms using three metaheuristic algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). Model performance was assessed using test RMSE, test MAE, and the coefficient of determination (R^2), with all hyperparameter tuning conducted exclusively on the training dataset to ensure fair evaluation.

Table 2
Summary of BDV measurements for each experimental condition (n = 18 per condition)

Condition	n	Mean (kV)	Std (kV)	Min (kV)	Max (kV)
PSP_Cu_0.10g	18	15.34	1.32	12.8	16.9
PSP_Cu_0.15g	18	16.05	1.90	12.9	19.9
PSP_Cu_0.20g	18	17.14	1.94	13.7	20.7
PSP_Fe_0.10g	18	17.62	1.45	14.1	19.6
PSP_Fe_0.15g	18	17.26	1.17	15.6	18.9
PSP_Fe_0.20g	18	16.49	1.10	14.7	18.8
Pri_Apar_Cu_0.10g	18	16.77	1.54	14.1	19.3
Pri_Apar_Cu_0.15g	18	16.86	1.43	14.8	19.3
Pri_Apar_Cu_0.20g	18	16.99	1.89	13.3	20.7
Pri_Apar_Fe_0.10g	18	15.80	1.32	13.2	18.2
Pri_Apar_Fe_0.15g	18	15.52	1.02	13.9	18.1
Pri_Apar_Fe_0.20g	18	15.34	1.32	12.8	16.9
Shell_Diala_Cu_0.10g	18	16.34	1.67	13.7	19.9
Shell_Diala_Cu_0.15g	18	15.35	1.55	12.8	18.7
Shell_Diala_Cu_0.20g	18	15.20	1.82	12.7	18.5
Shell_Diala_Fe_0.10g	18	16.27	1.77	13.6	19.4
Shell_Diala_Fe_0.15g	18	17.09	1.04	15.8	19.4
Shell_Diala_Fe_0.20g	18	17.09	0.99	14.8	18.5

A. Performance and Characteristics of SVR-Based Models

The baseline SVR model achieved a test RMSE of 1.768 kV, MAE of 1.384 kV, and R^2 of 0.098, indicating that SVR is capable of capturing the general nonlinear relationship between contamination parameters and BDV, despite the limited size of the experimental dataset. When metaheuristic optimization was applied, consistent but moderate improvements were observed across all optimized variants. The SVR+GWO model achieved the lowest test RMSE (1.755 kV), followed by SVR+GA (1.758 kV) and SVR+PSO (1.760 kV), with corresponding MAE and R^2 values showing similar relative trends.

Although the numerical differences among the optimized SVR models are small, these results provide important insights into the interaction between SVR and metaheuristic optimization. The BDV dataset used in this study is characterized by a relatively narrow output range and smooth variation across contamination conditions. As a result, the SVR hyperparameter landscape defined mainly by the kernel parameters gamma and sigma forms a shallow and well-behaved error surface. In such conditions, once the optimizer reaches a near-optimal region, further improvements become inherently limited, regardless of the optimization strategy employed.

From a methodological perspective, this indicates that the SVR model structure plays a dominant role in determining prediction accuracy, while the optimizer primarily influences convergence behavior, stability, and repeatability rather than producing large reductions in error. This observation is further supported by the relatively low R^2 values (approximately 0.10) across all SVR models, suggesting that a significant portion of BDV variability is influenced by physical factors not explicitly included in the model, such as moisture content, micro-level impurities, electrode condition variability, and experimental noise.

Although the RMSE values of approximately 1.7 kV indicate relatively low prediction error, the coefficient of determination (R^2) remains low at around 0.10. This apparent inconsistency can be explained by the limited variance of the BDV dataset. As shown in Table 1, the BDV values are distributed within a relatively narrow range, with standard deviations typically around 1–2 kV. Under such conditions, even small absolute prediction errors can lead to low R^2 values, since R^2 is highly sensitive to the ratio between prediction error and total variance. When the overall variance of the target variable is small, the denominator in the R^2 formulation becomes limited, causing the metric to underestimate model performance. Furthermore, BDV behavior is influenced by physical factors not explicitly included in the feature set, such as moisture content, micro-particle distribution, electrode surface condition, and experimental noise. These unmodeled factors contribute to unexplained variance, further limiting the achievable R^2 values. Therefore, in the context of small-scale experimental dielectric data, RMSE and MAE provide more

Table 3
Performance Comparison of Baseline and
Metaheuristic-Optimized Regression Models for BDV Prediction

No	Model	RMSE Test (kV)	MAE Test (kV)	R^2 Test
1	SVR (baseline)	1.768	1.384	0.098
2	KNN Regression (baseline)	1.761	1.355	0.105
3	SVR + GA	1.758	1.372	0.101
4	SVR + PSO	1.760	1.368	0.100
5	SVR + GWO	1.755	1.369	0.102
6	KNN + GA	1.825	1.418	0.104
7	KNN + PSO	1.825	1.418	0.104
8	KNN + GWO	1.825	1.418	0.104

physically meaningful indicators of model performance compared to R^2.

Despite converging to similar RMSE values, each optimization algorithm exhibits distinct operational characteristics. SVR+GA demonstrates strong exploratory capability, as GA operates through stochastic selection, crossover, and mutation. This allows GA to explore a wider hyperparameter space, which is advantageous in complex or multimodal optimization problems. However, in the context of a small and smooth SVR error landscape, this exploratory behavior leads to slightly higher variability across runs and marginally reduced consistency.

In contrast, SVR+PSO shows superior convergence consistency and stability. Through information sharing among particles, PSO rapidly drives the population toward the best-known solution, emphasizing exploitation over exploration. This behavior results in nearly identical hyperparameter values across repeated experiments and very small performance variance. Consequently, although the absolute RMSE improvement is modest, SVR+PSO offers strong reproducibility, which is particularly valuable in engineering applications involving limited experimental data.

Similarly, SVR+GWO exhibits balanced and reliable performance, closely matching SVR+PSO. By mimicking the hierarchical hunting strategy of grey wolves, GWO maintains a structured balance between exploration and exploitation. This enables it to consistently locate the same optimal region of the hyperparameter space while avoiding excessive randomness. The slightly lower RMSE achieved by SVR+GWO, although numerically small, highlights its robustness and controlled convergence behavior.

To evaluate the stability and repeatability of the optimization process, each metaheuristic-based SVR model was executed over multiple independent runs. The results indicate that SVR+PSO and SVR+GWO exhibit extremely low variance in performance metrics, with standard deviation values approaching zero, reflecting highly consistent convergence behavior. In contrast, SVR+GA shows slightly higher variability due to its stochastic evolutionary operations. The standard deviation of RMSE across multiple runs is observed to be below 0.005 kV for SVR+PSO and SVR+GWO, confirming highly stable convergence behavior. These findings confirm that swarm-based optimization methods provide superior stability and reproducibility compared to evolutionary-based approaches in small experimental datasets.

B. Performance and Characteristics of KNN-Based Models

The baseline KNN regression model achieved a test RMSE of 1.761 kV, MAE of 1.355 kV, and R^2 of 0.105, indicating performance comparable to baseline SVR. However, unlike SVR, KNN regression showed no performance improvement when optimized using GA, PSO, or GWO. All three optimized KNN models converged to the same neighborhood size (K = 14) and produced identical performance metrics: test RMSE of 1.825 kV, MAE of 1.418 kV, and R^2 of 0.104.

This identical outcome is not a limitation of the optimization algorithms, but rather a fundamental characteristic of the KNN regression model and the dataset. KNN possesses a discrete and low-dimensional hyperparameter space, with prediction behavior governed almost entirely by the integer-valued parameter K. For the BDV dataset used in this study, the prediction error varies very slowly around the optimal K value, producing a flat error surface. Consequently, once the optimal K is identified, alternative optimization strategies cannot yield further improvement.

It is important to note that KNN regression has a very simple and discrete hyperparameter space, consisting only of the integer-valued parameter K within a limited range. In such cases, exhaustive search is computationally trivial and guarantees identification of the global optimum without the need for metaheuristic optimization. Therefore, the application of GA, PSO, and GWO to KNN in this study is not intended to improve performance, but rather to evaluate the behavior of metaheuristic optimization in a constrained parameter space. The results demonstrate that metaheuristic methods offer no practical advantage over exhaustive search for KNN, confirming that their effectiveness is highly dependent on the complexity and dimensionality of the optimization problem.

Furthermore, the application of Leave-One-Sample-Out Cross-Validation (LOSO-CV) during optimization reinforces this effect by stabilizing the evaluation process and minimizing sensitivity to individual samples. As a result, GA, PSO, and GWO all converge to the same global optimum almost immediately, leading to identical performance across all optimized KNN variants. In this context, metaheuristic optimization serves primarily as a validation tool to confirm parameter robustness, rather than as a mechanism for improving predictive accuracy.

This confirms that increasing K beyond the optimal range may smooth local variations excessively, leading to slight degradation in prediction accuracy.

C. Comparative Analysis Between SVR and KNN Under Optimization

A clear distinction emerges when comparing SVR and KNN regression under metaheuristic optimization. SVR benefits modestly from optimization, not through dramatic error reduction, but through improved stability, consistency, and

confidence in hyperparameter selection. Its continuous hyperparameter space allows metaheuristic algorithms to influence convergence behavior and fine-tune model performance, even when the dataset is small.

In contrast, KNN regression shows inherent resistance to metaheuristic optimization due to its instance-based nature and discrete parameter structure. Once the optimal neighborhood size is identified, additional optimization offers no tangible benefit. This explains why KNN+GA, KNN+PSO, and KNN+GWO yield identical results and, in some cases, slightly worse RMSE than the baseline KNN due to over-smoothing effects at higher K values.

Importantly, the small numerical differences observed among optimized SVR models should not be interpreted as weak experimental results. Instead, they reveal a critical insight: for small and structured experimental BDV datasets, optimization primarily enhances robustness and repeatability rather than absolute accuracy. The findings of this study therefore establish a solid baseline and provide clear justification for future research directions, such as incorporating richer feature sets, increasing dataset size, or developing hybrid models that combine physical domain knowledge with data-driven approaches.

It should be noted that the performance comparison between SVR and KNN models should be interpreted with consideration of the different validation schemes used during hyperparameter tuning. While this may introduce slight bias in direct numerical comparison, the primary objective of this study is to analyze model behavior and robustness under their respective optimal configurations. Future work will investigate the impact of unified validation schemes to further improve methodological consistency.

IV. CONCLUSION

This study presents a comprehensive evaluation of SVR and KNN regression models, both in baseline and metaheuristic-optimized forms, for predicting transformer oil breakdown voltage under copper and iron contamination. The baseline results demonstrate that SVR and KNN are both capable of modeling BDV trends, with SVR showing slightly superior predictive performance. The baseline SVR achieved a test RMSE of 1.768 kV, while baseline KNN achieved 1.761 kV, confirming their suitability as regression models for small experimental datasets.

The application of GA, PSO, and GWO to SVR resulted in consistent, albeit modest, improvements in prediction accuracy and, more importantly, significantly enhanced stability and reproducibility. Among the optimized models, SVR+GWO achieved the lowest test RMSE of 1.755 kV, followed closely by SVR+GA and SVR+PSO. In contrast, optimization of KNN regression using GA, PSO, and GWO produced identical results across all methods, with a test RMSE of 1.825 kV, highlighting the limited effectiveness of metaheuristic optimization for discrete, instance-based models.

Overall, the findings indicate that in small and structured BDV datasets, the primary contribution of metaheuristic optimization lies in improving robustness and confidence in model parameters rather than delivering substantial reductions in prediction error. This study establishes a solid baseline for BDV prediction using data-driven models and provides clear guidance for future research, emphasizing the importance of richer feature representations, larger datasets, or hybrid modeling approaches to further enhance predictive performance.

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