INSULATED PIERCING CONNECTOR (IPC) TORQUE PREDICTION USING RANDOM FOREST(RF) MODEL AND ANOMALY DETECTION USING ISOLATION FOREST FOR LOW VOLTAGE OVERHEAD DISTRIBUTION NETWORKS

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Abstract

Efficient electrical connections are critical for maintaining the reliability of aerial bundled cable (ABC) systems, where Insulation Piercing Connectors (IPC) play a vital role. This study focuses on predicting torque values in IPC installations using machine learning techniques to enhance mechanical performance and reduce failure risks. Three mechanical tests were conducted, including Shearhead, Continuity, and Body tests, using IPC samples provided by TeknoBumi. The data were analyzed using Random Forest, Decision Tree, and Artificial Neural Network models.Data preprocessing included normalization, and model performance was evaluated using R-squared, Mean Squared Error, Root Mean Squared Error, and Mean Percentage Error. Among the models, Random Forest showed the highest accuracy across all tests. In addition, anomaly detection methods including Isolation Forest, One-Class Support Vector Machine, and Local Outlier Factor were applied to identify abnormal torque values that could indicate potential installation issues or defects. Isolation Forest proved to be the most consistent and reliable method for detecting outliers. The findings of this study demonstrate that integrating AI-based predictive modeling and anomaly detection can support early identification of mechanical inconsistencies, improve IPC installation quality, and enhance the overall reliability of low-voltage overhead distribution systems.

Keywords: *Insulation Piercing Connector, Torque Prediction, Machine Learning Models, Anomaly Detection, Low Voltage Distribution Network.*

INTRODUCTION

Insulated Piercing Connectors (IPC) are crucial components in power distribution, particularly in aerial bundled cable (ABC) systems. These connectors allow for efficient electrical connections without the need for stripping insulation, reducing installation time and minimizing conductor damage. Proper torque application during installation is vital for ensuring a reliable connection and maintaining the mechanical integrity of the system. Incorrect torque can cause loose connections, leading to increased contact resistance and overheating, while excessive torque can damage both the connector and the cable, leading to system failure. (Croccolo et al., 2023). Previous studies, such as those conducted by Sun et al. (2020) and Kasi and Thiyagarajan (2019), emphasize the importance of accurate torque application in maintaining stable electrical contact and mechanical strength in IPC systems.

International standards play an important role in maintaining the reliability of IPC. Specifically, NF C 33-020 (2013), a widely used French standard for 0.6/1 kV IPC, and BS EN 50483-4 (2009), the European standard for low-voltage aerial bundled cable accessories, specify detailed mechanical and dielectric tests including shear-head removal, continuity verification, and aging under heat cycles. These standards require that connectors meet strict performance criteria after testing to ensure long-term reliability in field applications. Differences in mechanical outcomes, such as connectors showing excessive torque or failing prematurely, highlight the need for outlier analysis to maintain consistent product quality.

AI predictive modeling, especially through machine learning (ML), is key for forecasting torque in IPC installations, as demonstrated by Abdulrazzaq et al. (2024). Machine learning is increasingly recognized for its real-time and cost-effective prediction capabilities. For instance, Aslam et al. (2022) demonstrated the effectiveness of hybrid machine learning and data mining algorithms in system management. ML algorithms like Artificial Neural Networks (ANN), Decision Trees, and Random Forests analyze historical data on IPC performance and environmental factors to predict optimal torque. Studies, such as those by Parekh et al. (2021), demonstrated the use of deep learning for predicting performance indicators, including torque. Similarly, Siddani and Balachandar (2024) applied ML for predicting torque in multiphase flows, showing its adaptability across industries.

Recent advancements in machine learning for complex system forecasting have been made by Arun Kumar Thimalapur, Doddabasappaar et al. (2024), emphasizing its growing effectiveness in predictive analytics. Self-prediction is a form of self-supervised learning that enables systems to predict their future states based on historical data, as discussed by Singh et al. (2024) and Yu et al. (2023). Catt et al. (2023) introduced a self-predictive model for decision-making without relying on predefined plans. Additionally, Abdulrazzaq et al. (2024) explored using self-supervised learning to predict machine faults from unlabeled data, which could improve prediction accuracy for systems with limited labelled datasets, as was also done by Pinheiro et al. (2021).

Outlier detection, also known as anomaly detection, is a critical field in data analysis that identifies unusual observations or events deviating from normal patterns (Md Nazmul Kabir Sikder & Feras A. Batarseh, 2021). This comparative analysis of unsupervised anomaly detection algorithms focuses on Isolation Forest, One-Class SVM, and Local Outlier Factor (LOF) across various domains. These methods have shown effectiveness in identifying rare patterns in complex datasets (Sadeq Darrab et al., 2023).

Isolation Forest is an efficient tree-based anomaly detection method that exploits the susceptibility of anomalies to isolation. This approach is computationally efficient and well-suited for high-dimensional data (Liu et al., 2012). One-Class Support Vector Machines (OCSVM) are effective for anomaly detection, particularly when only normal data is available for training (Mennatallah Amer et al., 2013). However, they are sensitive to outliers and parameter choices, which can affect performance in high-dimensional spaces (Zheng et al., 2021). Local Outlier Factor (LOF) is a density-based outlier detection algorithm that assigns a degree of "outlierness" to each data point based on its local density deviation compared to its neighbors (Breunig et al., 2000).

In industrial applications, such as screw tightening processes, Isolation Forest and Autoencoder demonstrated high-quality anomaly discrimination, comparable to supervised methods (Ribeiro et al., 2021). For seismic data analysis in Indonesia, One-Class SVM emerged as the most effective, followed closely by Isolation Forest, while LOF showed less precision (Airlangga, 2024). The performance of these algorithms varies depending on the dataset type, with SVM excelling in point anomaly detection and Isolation Forest in identifying collective anomalies (Lu, 2025). These advancements of anomalies detection method highlight the potential for enhancing torque prediction in IPC systems, ultimately improving system integrity and reducing operational failures.

METHODOLOGY

The methodology in this study involves two main parts. First, three machine learning models, namely Random Forest, Decision Tree, and Artificial Neural Network, were used to predict torque values from IPC mechanical tests including Shearhead, Body, and Continuity. The data was normalized and the models were evaluated using performance metrics such as R^2, Mean Squared Error, and Root Mean Squared Error. Second, three anomaly detection techniques, which are Isolation Forest, One-Class Support Vector Machine, and Local Outlier Factor, were used to identify outliers in the dataset. This process helps ensure the accuracy and reliability of the mechanical test data.

Self-Prediction Of 3 Mechanical Tests Of Ipc Using 3 Machine Learning Models

Three machine learning algorithms were selected: Random Forest (RF), Decision Tree (DT), and Artificial Neural Network (ANN). These models were chosen to capture both linear and non-linear relationships in the data, with the assumption that torque values in mechanical testing can vary based on several complex interactions between features.

The data preprocessing involved normalizing the test features to ensure that each input variable contributed equally to the models. StandardScaler was used to scale the features so that each had a mean of zero and a standard deviation of one. The models were trained on the available historical data by using 80:20 ratio and their performance was evaluated using standard metrics: R^2 (Coefficient of Determination), MSE (Mean Squared Error), and RMSE (Root Mean Squared Error). After training, the models were used to self-predict the torque values and correlation of each test were known. By means of these performance metrics, the best outperforming algorithm was to be suited to this IPC's torque prediction and correlation of each test has also been acknowledged.

Additionally, Mean Percentage Error (MPE) was used to quantify the average percentage difference between the actual and predicted torque values, offering a clearer view of prediction accuracy. Visualization techniques, such as scatter plots and line graphs, were employed to compare actual versus predicted values and to observe the distribution of errors across the three mechanical tests.

Anomaly Detection Techniques

Three machine learning algorithms were employed for anomaly detection: Isolation Forest, One-Class SVM, and Local Outlier Factor (LOF). These methods were selected to effectively identify outliers in the dataset, which is crucial for ensuring the integrity of mechanical test results. The data preprocessing involved scaling the features using StandardScaler to standardize the input variables, ensuring that each feature contributed equally to the anomaly detection models.

The Isolation Forest algorithm was utilized to isolate anomalies by constructing a random forest of decision trees. The model was trained on the scaled dataset, with a contamination parameter set to 0.05, indicating the expected proportion of outliers. After training, the model predicted anomalies, and the anomaly scores were calculated to assess the severity of each detected outlier. The performance of the Isolation Forest was evaluated based on the number of detected anomalies and their corresponding scores.

The One-Class SVM method was also applied to identify anomalies by learning the boundary of normal data points in a high-dimensional space. The model was trained using the scaled features, with a nu parameter set to 0.05, representing the expected fraction of outliers. Following the training phase, the model predicted anomalies and provided anomaly scores, which were used to evaluate the model's effectiveness in distinguishing between normal and anomalies observations.

Lastly, the Local Outlier Factor (LOF) algorithm was implemented to detect anomalies based on the local density of data points. The model was trained on the scaled dataset, with a specified number of neighbours set to 20 and a contamination parameter of 0.05. After fitting the model, it predicted anomalies and calculated anomaly scores based on the local density comparison. The performance of the LOF method was assessed by analyzing the number of detected anomalies and their respective scores.

From the comparative analysis, Isolation Forest demonstrated the most consistent and reliable performance across all tests, with clear visual separation of anomaly scores and stable detection rates. Therefore, it was identified as the most suitable technique for ensuring data integrity in IPC torque mechanical testing.

RESULTS AND DISCUSSION

The results and discussion section summarizes the performance of machine learning models used for torque prediction and anomaly detection in IPC mechanical tests. It explains how each model was evaluated, compares their accuracy, and identifies the most suitable models for each task. The section also includes visual analysis and performance metrics to support the findings and highlight the reliability of the approaches used.

Self-Prediction Of 3 Mechanical Tests Of Ipc Using 3 Machine Learning Models

Self-prediction in this study refers to use all this machine learning models to self-predict of its own and to see the correlation between all these Mechanical datasets. By means of comparing each algorithm performance using standard metric, the suitable algorithm for this self-prediction IPCs were found and the correlation of each data set has also been noted.

Table 1: Self-Prediction and Correlation for each Mechanical Testing Dataset

Machine Learning Model	Shearhead Test			Continuity Test			Body Test		
	R2	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE
Random Forest (RF)	0.9841	0.0269	0.1639	0.9881	0.0027	0.0521	0.9990	0.0078	0.0078
Decision Tree (DT)	0.9854	0.0247	0.1571	0.9902	0.0022	0.0473	0.9997	0.0024	0.0487
Artificial Neural Network (ANN)	0.9623	0.0636	0.2522	0.7272	0.0624	0.2498	0.9122	0.6542	0.8088

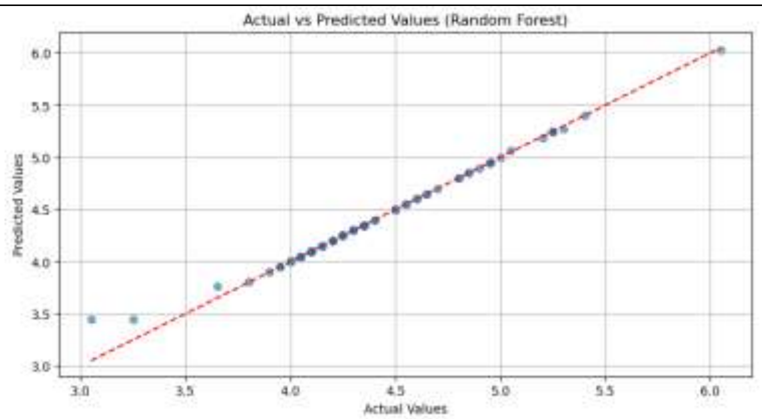
Table 1 shows the Random Forest (RF) model outperformed other machine learning models in predicting torque values across all three mechanical tests:

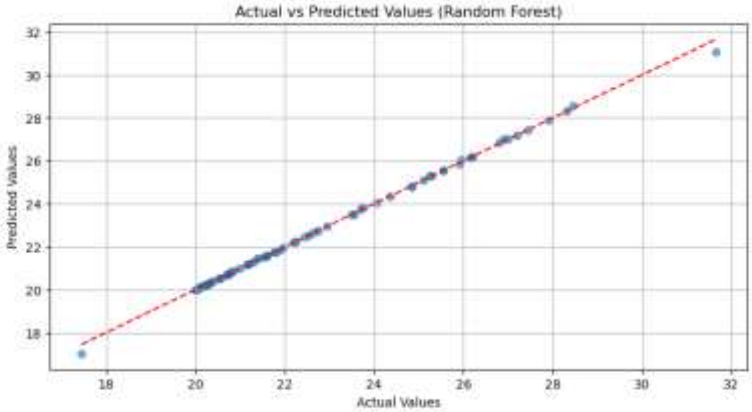
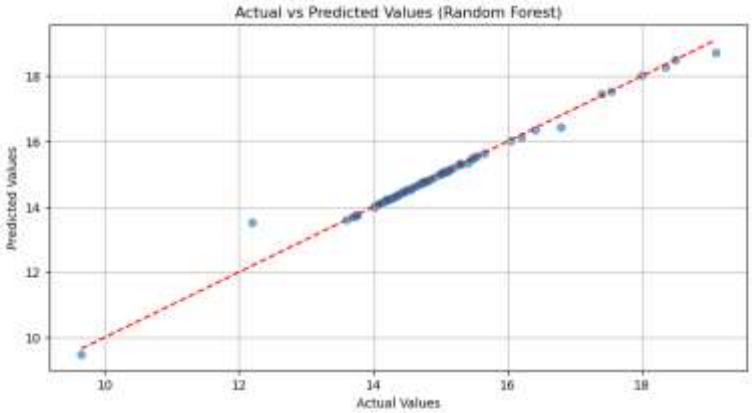
Shearhead, Continuity, and Body. The model consistently achieved high R^2 scores and low error values (MSE and RMSE), demonstrating both accuracy and reliability. This ensemble approach effectively reduces variance and minimizes the risk of overfitting by averaging the outputs of multiple decision trees, making the model more robust to data variations and better suited for generalization. In comparison, the Artificial Neural Network (ANN) also showed strong performance in the Shearhead and Body Tests, but its lower accuracy in the Continuity Test reflects less consistent results.

On the other hand, the Decision Tree (DT) model also showed high R^2 values. However, as a single-tree model, it lacks the averaging mechanism and is more prone to overfitting, where the model fits the training data too closely and performs poorly on new data. This fundamental risk makes the Decision Tree less reliable, even when the training metrics appear strong. In contrast, Random Forest maintained high predictive accuracy while offering more stable and reliable predictions across all mechanical tests.

Table 2 provides a concise summary of how accurately the machine learning model predicted torque values for each of the three mechanical tests: Continuity Test, Body Test, and Shearhead Test. The Mean Percentage Error (MPE) is used as the metric to evaluate the average difference between the actual measured torque values and the values predicted by the model, expressed as a percentage of the actual value.

Table 2: Mean Percentage Error and Prediction Accuracy for Each Mechanical Test

Mechanical Test	Mean Percentage Error (%)	Actual vs Predicted Values
Continuity Test	0.32	

Body Test	0.12	
Shearhead Test	0.25	

The Body Test recorded the lowest error at 0.12%, indicating that the model predicted torque values with extremely high precision in this category. This result highlights the strength of the selected features and the model's robustness in capturing the underlying patterns of this test.

The Continuity Test followed closely with a mean error of 0.32%, while the Shearhead Test showed an error of 0.25%. These values demonstrate the model's ability to generalize well across different testing scenarios with minimal deviation. Overall, the consistently low error percentages across all tests reinforce the reliability of the machine learning approach, particularly the Random Forest model, in performing accurate self-prediction of mechanical torque values in IPC applications.

Anomaly Detection

To check the accuracy and quality of the IPC mechanical test data, three machine learning methods were used to detect abnormal values. These methods are Isolation Forest, One-Class Support Vector Machine (SVM), and Local Outlier Factor (LOF). Each method works in a different way to find data points that do not follow the normal pattern. By testing these three methods on the Continuity, Body, and Shearhead tests, the most effective way to detect torque-related errors was identified.

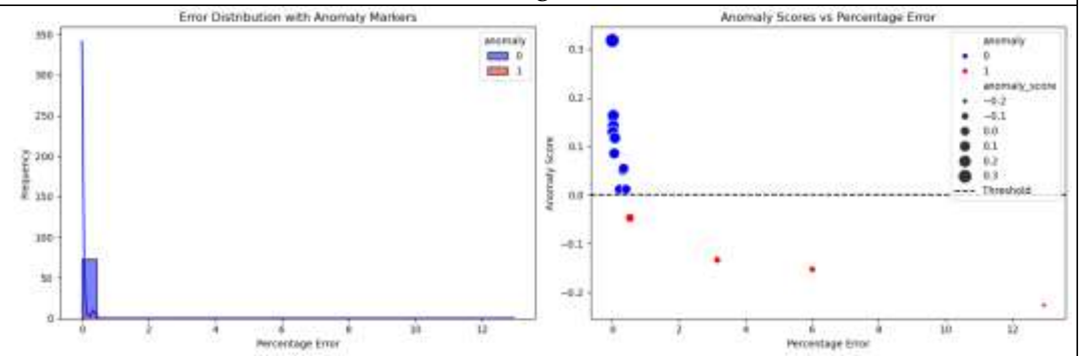
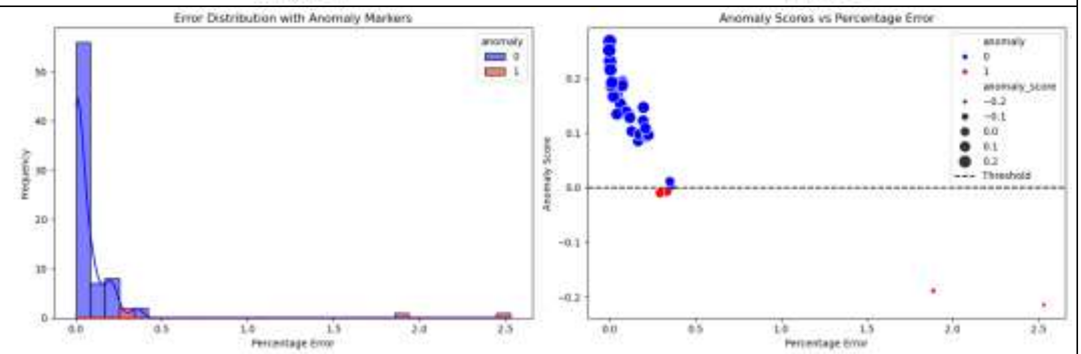
a) Isolation Forest

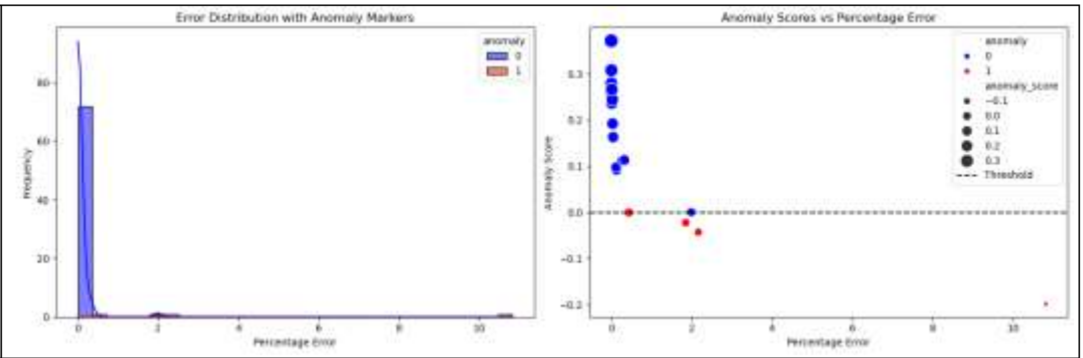
Table 3 shows that the model identified four potential anomalies for each of these tests, indicating that there were consistent outliers across different mechanical aspects. This similar number of anomalies suggests that the data distributions in each test had a comparable level of anomalies that the model could effectively detect. The contamination parameter, set at 0.05, helped the model determine the expected amount of anomalies, ensuring a good balance between being sensitive to outliers and avoiding overfitting.

Table 3: Number of Potential Anomalies for Isolation Forest

Mechanical Test	Potential Anomalies
Continuity Test	4
Body Test	4
Shearhead Test	4

Table 4: Error Distribution with Anomaly Markers and Anomaly Scores vs Percentage Errors for Isolation Forest

Mechanical Test	Error Distribution with Anomalies Marker and Anomalies Scores vs Percentage Errors
Continuity Test	
Body Test	

Shearhead Test	

The results in Table 4 show that the error distributions with anomaly markers clearly indicated that the detected anomalies were outside the normal error trend. The plots comparing anomaly scores and percentage errors further confirmed that the model was good at spotting significant differences. In the Continuity Test, the identified anomalies were linked to data points that had a sharp increase in prediction errors, which might suggest problems with torque measurement or sensor calibration. Similarly, the Body and Shearhead Tests showed clear groups of anomalies, possibly due to mechanical test issues or wear on components.

The Isolation Forest algorithm is strong because it works well with complex data without needing to rely on distance measures. By randomly dividing the data, it can effectively find anomalies with fewer assumptions about the data patterns. This makes it especially useful for industrial datasets like IPC torque measurements, where normal behaviour is common and outliers are rare but important. With its consistent detection rate and clear separation of scores, the Isolation Forest proved to be effective and offers a practical way to detect anomalies in torque-related IPC mechanical testing.

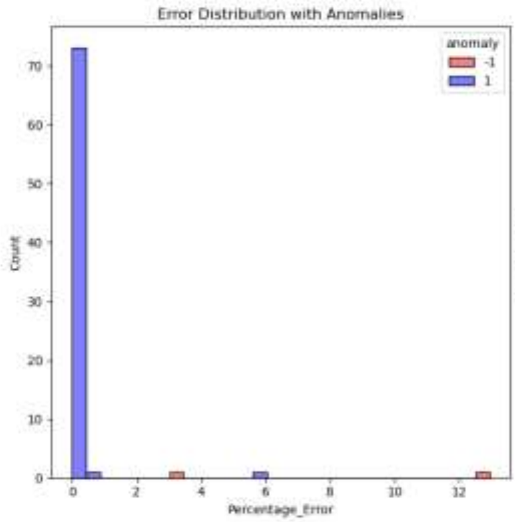
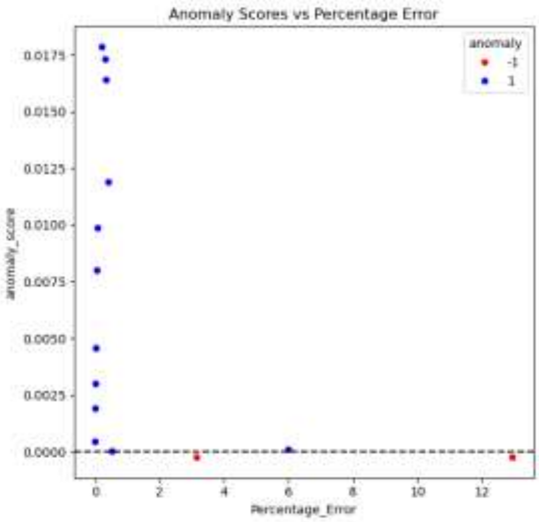
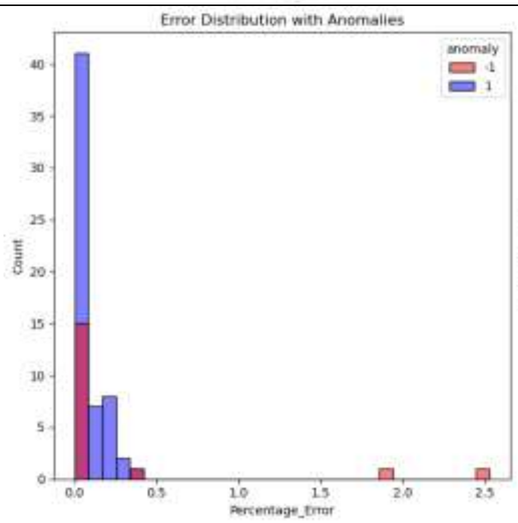
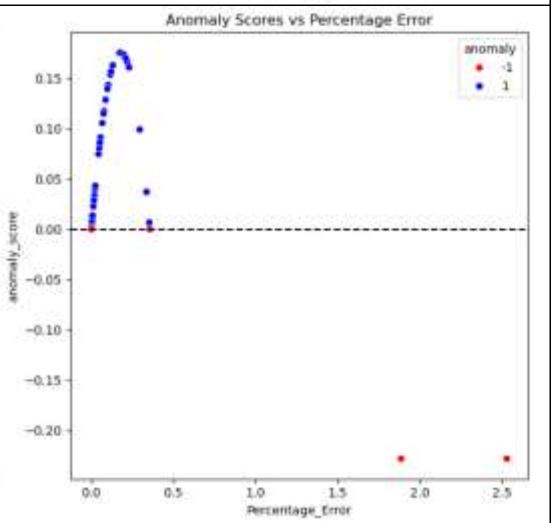
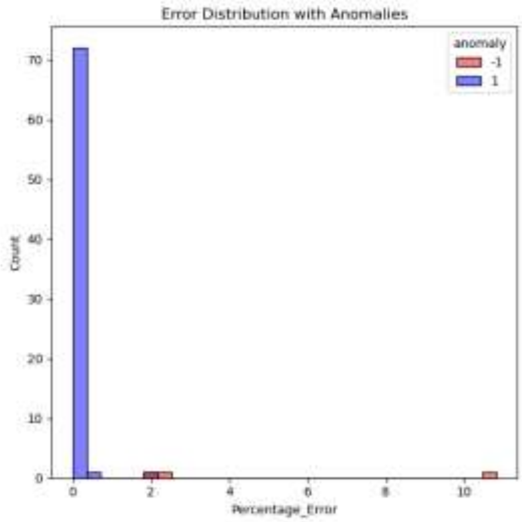
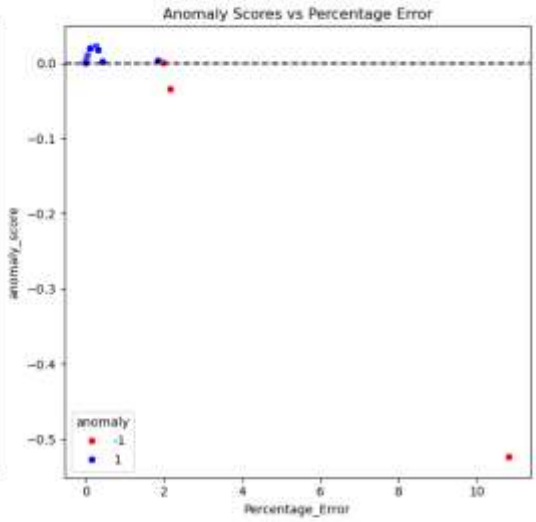
b) One-Class Support Vector Machine

According to Table 5, this method produced a wider range of anomaly counts across the mechanical tests, finding 2 anomalies in the Continuity Test, 18 in the Body Test, and 3 in the Shearhead Test. The large number of anomalies detected in the Body Test suggests that the One-Class SVM may have been more sensitive to small changes in data patterns, which can be affected by complex internal features or noise.

Table 5: Number of Potential Anomalies for One-class SVM

Mechanical Test	Potential Anomalies
Continuity Test	2
Body Test	18
Shearhead Test	3

Table 6: Error Distribution with Anomaly Markers and Anomaly Scores vs Percentage Errors for One-class SVM

<table>
<tr><th>Mechanical Test</th><th colspan="2">Error Distribution with Anomalies Marker and Anomalies Scores vs Percentage Errors</th></tr>
<tr><td>Continuity Test</td><td>
</td><td>
</td></tr>
<tr><td>Body Test</td><td>
</td><td>
</td></tr>
<tr><td>Shearhead Test</td><td>
</td><td>
</td></tr>
</table>

Error distribution plots with anomaly markers showed that the One-Class SVM identified points with relatively higher prediction errors, especially in the Body Test. However, some of these detected outliers may not significantly differ from the overall error trend, suggesting that the model might be overfitting or misclassifying borderline data points as anomalies, particularly in high-dimensional or noisy datasets. The plots comparing percentage error and anomaly scores also showed a wider spread, especially for the Body Test, which corresponds with the high number of anomalies detected.

Even though One-Class SVM is mathematically sophisticated in creating a non-linear boundary around normal data, its effectiveness can be limited by the sensitivity of the nu parameter and the challenges of high-dimensional data. In this case, the model's performance was inconsistent, particularly in overestimating anomalies in the Body Test. Therefore, while One-Class SVM can be useful when the normal data structure is clear and consistent, its effectiveness in torque prediction for IPC mechanical testing may be restricted without further adjustments or reducing the number of dimensions.

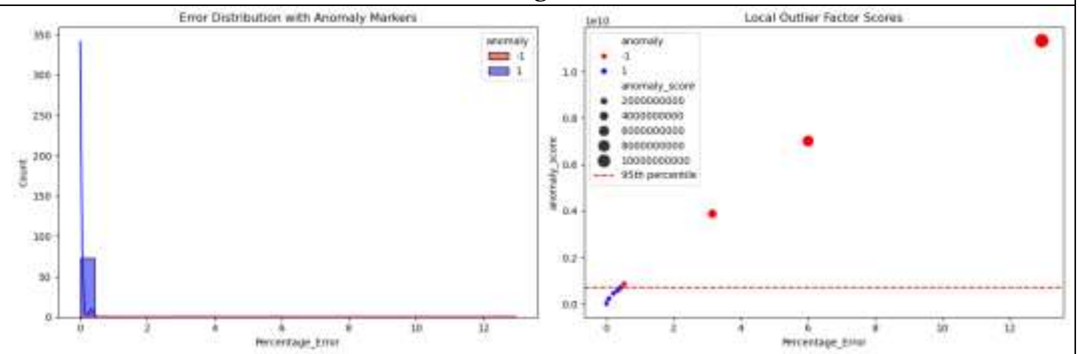
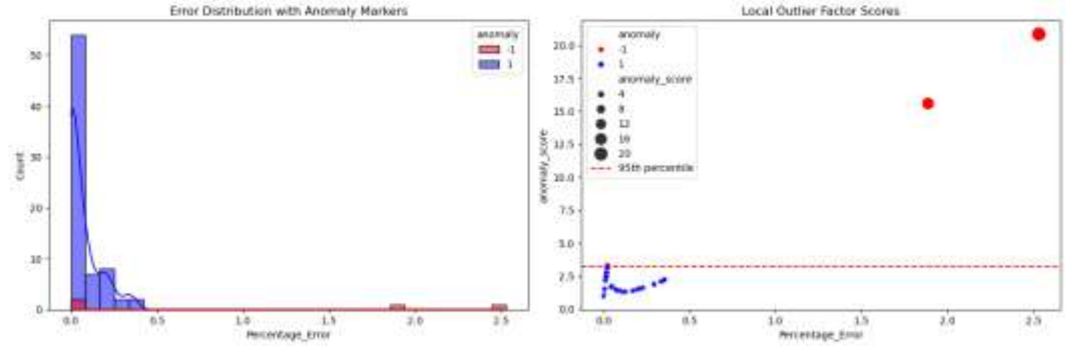
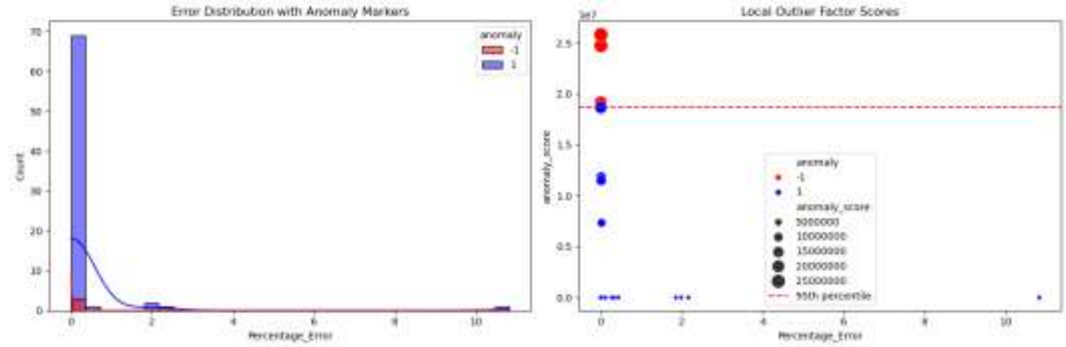
Local Outlier Factor

Table 7 shows that LOF identified 4 anomalies in both the Continuity and Body Tests, and 3 anomalies in the Shearhead Test. These results align with those from the Isolation Forest method, particularly in the Continuity and Body datasets, indicating that certain data points consistently show unusual behavior, regardless of the detection technique used.

Table 7: Number of Potential Anomalies for LOF

Mechanical Test	Potential Anomalies
Continuity Test	4
Body Test	4
Shearhead Test	3

Table 8: Error Distribution with Anomaly Markers and Anomaly Scores vs Percentage Errors for One-class SVM

Mechanical Test	Error Distribution with Anomalies Marker and Anomalies Scores vs Percentage Errors
Continuity Test	
Body Test	
Shearhead Test	

The error distribution plots showed that LOF was effective in identifying outliers in less populated areas of the data distribution. The graphs comparing anomaly scores and percentage errors provided clearer separation between normal and abnormal points than the One-Class SVM did. For example, in the Shearhead Test, LOF identified points with much lower local densities as anomalies, which matched well with higher prediction errors in those cases. This demonstrates the model's strength in detecting contextual outliers that differ from their local surroundings.

LOF's unsupervised approach and focus on density estimation make it especially suitable for datasets with varying distributions and localized irregularities, like mechanical testing data. However, its performance depends on the choice of neighbors (n_neighbors), which was set to 20 in this study. Overall, LOF provided a balanced and consistent detection of anomalies across all tests and showed strong agreement with the findings from the Isolation Forest. This reinforces its value as a supplementary or confirmatory tool in assessing the quality of IPC mechanical testing data.

Comparison Of Anomaly Detection Techniques

A comparative analysis of three anomaly detection techniques, namely Isolation Forest, One-Class Support Vector Machine (SVM), and Local Outlier Factor (LOF), was conducted to find the best method for identifying outliers in IPC mechanical test data. The evaluation focused on consistency in the number of detected anomalies, how well the results matched the actual error distribution, and the clarity of separation in anomaly scores across the Continuity, Body, and Shearhead Tests.

Among the three methods, Isolation Forest showed the most balanced performance, consistently detecting four anomalies in each test. This consistency indicates that it effectively modeled the overall structure of the data without overfitting. The anomaly score plots displayed a clear gap between normal and anomalous instances, confirming its ability to identify significant deviations confidently. Its use of random partitioning through decision trees makes it efficient and well-suited for high-dimensional engineering data like IPC torque readings. In contrast, One-Class SVM was less stable, particularly in the Body Test, where it flagged 18 anomalies, indicating excessive sensitivity that could lead to false positives. LOF provided results similar to Isolation Forest, effectively capturing local anomalies by examining density variations, but its performance relies on the choice of neighborhood size.

Overall, Isolation Forest is considered the most suitable technique for this study. It consistently detected anomalies, provided clear separation in scoring, and showed robustness against data variability. Its efficiency and ensemble nature make it a reliable tool for improving fault detection and data integrity in predictive maintenance for IPC torque mechanical datasets.

CONCLUSION

This study demonstrates the effectiveness of machine learning models, particularly Random Forest, in accurately predicting torque values for Insulation Piercing Connectors based on mechanical test data from Shearhead, Continuity, and Body tests. The Random Forest model consistently achieved the highest performance across all evaluation metrics, indicating its strong suitability for torque prediction tasks in IPC applications. In addition, the use of anomaly detection techniques such as Isolation Forest, One-Class Support Vector Machine, and Local Outlier Factor provided critical insights into the integrity of the mechanical test data. Among these, Isolation Forest proved to be the most consistent and reliable in detecting potential anomalies, supporting early identification of outliers that may indicate installation errors or material defects. The findings confirm that the integration of predictive modeling and anomaly detection can enhance the accuracy, reliability, and overall quality assurance of IPC installations, ultimately contributing to the robustness of low-voltage overhead distribution networks.

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