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Predictive Maintenance for Electrical Substation Components Using K-Means Clustering: A Case Study

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ABSTRACT

PT. PLN (Persero) UP2D Kalselteng aims to provide reliable electricity supply, necessitating effective substation maintenance. This study proposes a predictive maintenance approach using K-Means clustering on electrical current performance data from eight components in the Amuntai main electrical substation. The data undergoes preprocessing, including mapping to absolute z-scores to address electricity fluctuations. The K-Means algorithm clusters performances, and models are evaluated using Silhouette scores. Results indicate the potential for predicting maintenance needs, as clusters align with real power outage data. The proposed method provides a proactive strategy for substation maintenance, enhancing system reliability. Feature combination experiments reveal that individual models for transformers and feeders are optimal. Hyperparameter tuning refines models, showcasing silhouette scores above 0.5, indicative of high-quality clusters. Comparisons with real-world power outage data validate the model's capability to identify anomalies, reinforcing the feasibility of the predictive maintenance approach. While the study demonstrates promise, on-field implementation and additional experiments are crucial for comprehensive validation and refinement of the predictive maintenance models.

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1. INTRODUCTION

The need for electricity continues to increase along with population growth, which is very important for the success of regional development. In Indonesia, electricity is handled by PT PLN (Persero) to distribute eletrical energy to customers using a distribution network [7]. Specifically, PT PLN (Persero) Unit Pelaksana Pengatur Distribusi Kalimantan Selatan dan Tengah that referred to as PLN UP2D KSKT, has a task to provide electricity for public interest to provide a supply of electricity that can meet consumer needs.

To maintain the accesibility of electricity, the reliability of electrical components and equipments is of a high priority. As of the time of writing, PLN UP2D KSKT focuses the component reliability by doing maintenance each time a problem occurs on the electrical substation. However, the electrical substation maintenance is still done on a case-by-case basis. The malfunction identification is still done manually, and after it is identified, only then mainetnance is done on the component [7]. This can lead to a problem due to the fact that the case of a malfunction on the electrical component is unable to be predicted. As, during both the process of maintenance, the electrical component is shut off. This can lead to a decrease in accesibility to electricity.

To this end, PLN UP2D KSKT feels an urgency to create a system that can analyze equipment pattern to avoid equipment breakdown. By collecting data from sensors, visual observation or other data sources, a predictive maintenance system can analyze equipment patterns over time. The implementation of predictive maintenance presents a change in substation maintenance strategy at PLN UP2D Kalselteng which can predict potential problems or previous damage, making it possible to carry out more timely maintenance actions.

Predictive maintenance itself have been discussed in many literatures. The main idea is that predictive maintenance takes into accord historic data and domain knowledge to predict behaviors of machines [8]. Predictive maintenance also usually leverages machine learning models in order to make the prediction and analysis of patterns [14]. Although usually used in heavy machinery, it has also been shown that machine learning can also be used in analyzing electrical component patterns [15, 16]. Therefore, this paper also explores how machine learning algorihms is utilized to analyze historical electrical component data in order to help in a predictive maintenance capacity.

Machine learning is also commonly divided into 2 categories: supervised and unsupervised based on the data labels. Supervised learning is usually used for labeled data and unsupervised learning for unlabeled data. As will be shown in this paper, a challenge is the availability of a label is, more often than not, not present in the dataset. Due to this, this paper also explores how unsupervised learning algorithms, in particular K-Means, is utilized in order to segment electrical component performances data to help in predictive maintenance. K-Means itself have been used in the capacity of predicting electricity consumption behavior [17], electrical current measurement [18], fault detection [19]. Therefore, another challenge this paper explores is also how to adapt the algorithm to fit the requirements of PLN UP2D Kalselteng for predictive maintenance based on domain knowledge.

2. MATERIALS AND METHODOLOGY

2.1. Methods

2.1.1. K-Means

K-Means is a widely-used clustering algorithm employed in machine learning and data analysis. Its primary objective is to categorize a set of data points into K clusters, with each point belonging to the cluster whose mean is closest to it. The algorithm operates through iterative steps, starting with the initialization of K cluster centroids. These centroids, representing the center of each cluster, can be chosen randomly or through more advanced methods. The algorithm aims to minimize the within-cluster sum of squares, which is the sum of the squared distances between each data point and the centroid of its assigned cluster. The objective function can be mathematically expressed as:

$$[\ J = \sum_{i=1}^{K} \quad \sum_{j=1}^{n_i} \quad |x_j^{(i)} - c_i|^2\ ] \tag{1}$$

J is the within cluster sum of squares, K is the number of clusters, n_i is the number of data points in cluster *i*, $x_j^{(i)}$ is the *j*-th data point in cluster *i*, c_i is the centroid of cluster *i*, and $|\cdot|^2$ represents the Euclidean distance.

2.1.2. Z-Score

The z-score, also known as standard score, is a measure that describes a value's relationship to the mean of a group of values. It is often used in statistics to quantify how many standard deviations a particular data point is from the mean of a dataset. The formula for calculating the z-score for a data point X in a dataset with mean μ and standard deviation σ is given by:

$$\left[Z = \frac{X-\mu}{\sigma}\right] \tag{2}$$

2.1.3. Silhouette Score

The silhouette score is a metric used to calculate the goodness of a clustering technique. It measures how well-separated the clusters are in a given dataset. The silhouette score ranges from -1 to 1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. The silhouette score for each data point is calculated using the following formula:

$$\left[S(i) = \frac{b(i) - a(i)}{\max\big(a(i), b(i)\big)}\right] \tag{3}$$

Where *S(i)* is the silhouette score for data point *i*. *a(i)* is the average distance from the *i*-th data point to the other data points in the same cluster. *b(i)* is the smallest average distance from the *i*-th data point to data points in a different cluster, minimized over clusters.

2.2. Related Works

2.2.1. Supervised Learning for Predictive Maintenance

Many other researches have been conducted in the realm of predictive maintenance. Some examples include research on predicting health factors on heavy machinery [1]. Another common term in predictive maintenance is predicting the remaining useful life (RUL) of machines [2]. Predictive maintenance is also associated with predicting when failures will occur in a component [3]. In [10], Random Forest Algorithm and Random Undersampling with AdaBoost (RUSBoost) algorithm are used for analyzing the distribution transformer to determine when a transformer will likely to fail or need to be replaced.

2.2.2. Unsupervised Learning for Predictive Maintenance

In contrast to supervised algorithms, unsupervised algorithms operate on datasets without labeled output or target variables, aiming to discover inherent patterns, structures, or relationships within the data on their own. Fortunately, other research has been done in the realm of implementing an unsupervised learning algorithm with the goal of a model that can help with predictive maintenance.

In [4], a K-Means clustering algorithm is used to group key performance indicators into 5 clusters based on their degradation level, and the resulting clusters are used in a Hidden Markov Model (HMM) based classifier. In [5], an approach using the K-Means clustering algorithm is used to group time-series data using statistical information such as mean, and standard deviation of the time-series. In [6, 19], K-Means clustering is used for fault detection prior to implementing it as predictive maintenance. These researches show the potential of using unsupervised learning algorithms to group performance measurements of a machinery component in order to develop a data driven approach for predicting when maintenance will be necessary. In [11], in terms of classification accuracy, the implementation of K-Means clustering outperforms SVM on their dataset for implementing predictive maintenance for distribution system operators in increasing transformers' reliability . In [12], K-Means clustering method's advantages are the ease of its programming and the ability to provide a good trade-off result between achieved performance and computational complexity.

Table 1. Transformers and Feeders of Amuntai Main Substation

Transformer	Feeder
	Feeder-1
Transformer-1	Feeder-2
	Feeder-3
	Feeder-4
Transformer-3	Feeder-5
	Feeder-6

2.2.3. AC Current on Transformers and Feeders on the Electrical Substation

Transformers and feeders are vital components within electrical substations, playing essential roles in the transmission and distribution of electrical power. Transformers are key devices that efficiently adjust voltage levels, enabling the seamless transfer of electricity across the power grid. According to [7], these transformations are well-suited for AC (alternating current) systems, where the current undergoes periodic fluctuations, oscillating between positive and negative phases. This inherent characteristic of AC current aligns seamlessly with the operational needs of transformers and allows for the effective use of feeders circuitry that links transformers to various points in the power grid. The utilization of AC current, with its fluctuating nature, ensures the smooth compatibility and efficiency of transformers and feeders within electrical substations, contributing to the dependable and stable delivery of electricity to end-users.

2.3. Data Collection & Preparation

The data utilized in this study originates from the main substation in the Amuntai region, South Kalimantan. Acquired from this source, the dataset comprises performance measurements, specifically electrical currents (Ampere) generated by individual components at 30-minute intervals. The Amuntai Main Substation is composed of two transformers, with each transformer interconnecting to three feeders. Table 1. shows the encoded transformers with their respectively connected feeders.

It's important to note that the data is received in XLSX (Excel) file format, necessitating further processing before it can be effectively utilized for subsequent analyses and interpretations. For further analysis and processing, the data undergoes a transformation to the CSV (comma separated values) format. More importantly, the transformed data is considered a type of time series data, as it captures the temporal dimension of electrical currents over the designated intervals. This temporal aspect shows dynamic behavior of the electrical system, enabling patterns, trends, and anomalies that may not be apparent in static datasets. To make further processing easier, the data is divided into 2 distinct datasets: 1 for data relating to transformer 1, and 1 for data relating to transformer 3. Table 2 shows some samples of the data and their columns.

Table 2. Prepared Dataset Samples

Index	Date	Time	Trafo Value	Feeder-1 Value	Feeder-2 Value	Feeder-3 Value
0	01/06/2023	00:00:00	476	121	126	152
2	01/06/2023	00:30:00	470	116	124	149
4	01/06/2023	01:00:00	459	105	120	153
6	01/06/2023	01:30:00	450	115	124	148

The collected data ranges from recorded electrical current performance of components from June - August 2023. In total, 8832 rows of data are used which is further divided into 2 for each transformer.

2.4. Proposed Solution

As mentioned in [1], [2], and [3], a supervised learning predictive approach for classifying when maintenance is necessary have been successful. However, the challenge for these approaches is that supervised learning algorithms require labels / targets in order to be trained. The challenge faced when specifically requiring labels for training a model is, more often than not, the lack of available labels. Such is the case with the collected electrical current data for this research. When faced with the challenge of the lack of labels, a few options can be done: create pseudo-labels [13] which will require expert domain knowledge to know what and how to label, or use a machine learning algorithm that doesn't require labels

As mentioned, unsupervised learning algorithms, which don't require labels, have also been explored in developing a model for predictive maintenance [4, 5, 6, 11, 12]. A common approach is using K-Means clustering as the modeling algorithm. And, as shown in [11] and [12], the K-Means algorithm has significant advantages due to its simplicity and performance when compared to other models. Due to this, this research proposes the usage of K-Means clustering algorithm to cluster the electrical component's performance. In this way, the resulting clusters can give insights on when maintenance will be necessary. In particular, with regards to outlier measured performances.

The challenge, for this research, then becomes how to adapt the techniques for electrical substation components. According to [7], and as seen from the dataset, the Amuntai main electrical substation processes and produces electricity under an alternating current (AC) based system. Given its nature of fluctuating between positive and negative values, accurately assessing its performance becomes a nuanced challenge. To tackle this, this paper proposes an approach which involves employing the absolute z-score of the measured current performance. This methodology proves particularly beneficial when seeking to cluster and analyze the overall performance of AC currents, providing a standardized metric that facilitates the comparison and classification of diverse electrical behaviors.

Another challenge for this research is the combination of features to cluster the model. The collected data and the PLN documentation [7] informs an interconnection between the transformer component and the feeder components. However, correlation between the variables and their subsequent effects to the maintenance have not yet been explored. Therefore, This paper also proposes the analysis of combinations of features either between the transformer value and feeder value to find the best clustering performance. To that end, figure 1 provides a flow-chart on how this research is conducted to find a solution for a best model for predictive maintenance.

2.5. Experimental Design

2.5.1. Preprocessing Data

The aim of this step is to clean and pre-process the data. The data is prepared to be used as an input for the K-Means clustering model. This step includes first loading the data, cleaning the null / empty values, and removing any duplicate data. Afterward, the attributes for absolute z score values are created. Before the data is used, normalization is done to the data. Normalization is necessary in machine learning to ensure that features with different scales do not disproportionately influence the model, allowing for more effective and stable training.

2.5.2. Feature Combination Experiment

The aim for this experiment is to find the best feature combination for clustering the performance of each electrical component. As seen, for both transformers 1 & 3, and accounting only the absolute z-score value for each measured electrical current, a total of 15 combinations of features that can be used for clustering for each of the components. This iterative approach to feature selection not only aims to enhance the accuracy of clustering outcomes but also sheds light on the nuanced relationships within the electrical current data. The experiment is done by modeling a K-Means clustering model for each feature combination. The evaluation metric used to determine the quality of clustering in this experiment is the silhouette score.

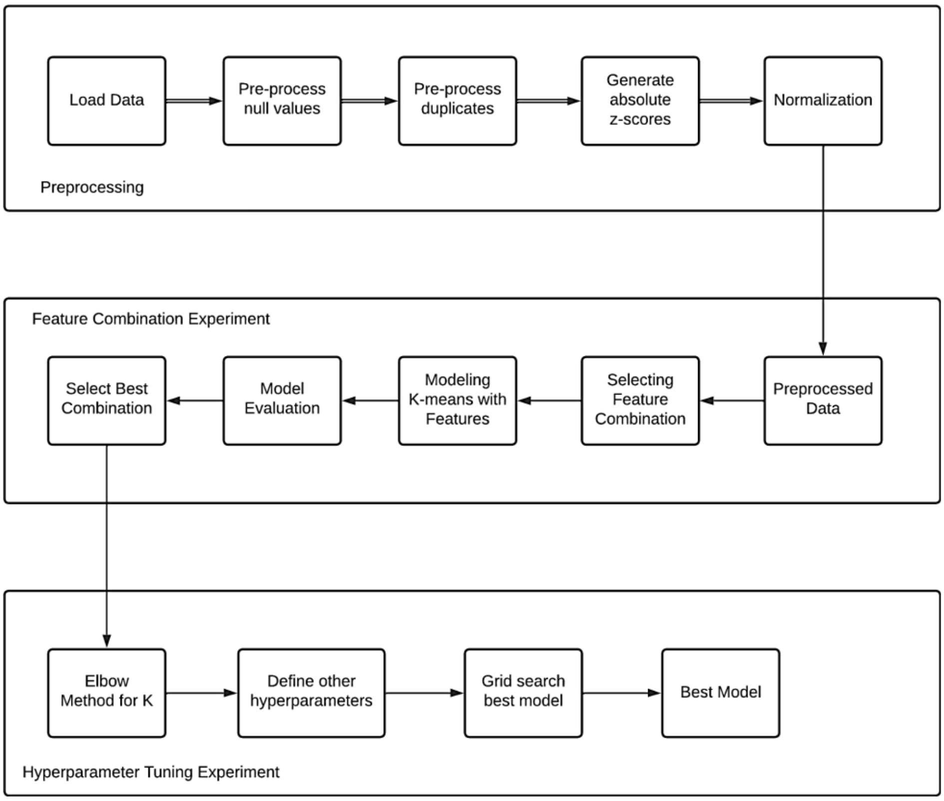

Figure 1. Flowchart of The Proposed Research Process

2.5.3. Hyperparameter Tuning Experiment

The aim for this experiment is to tune the K-Means model with the best parameters for the best clustering performance. The model that is fine-tuned in this experiment will also use the best feature combinations from the previous experiments. K-Means relies on parameters such as the number of clusters (K) and the initialization method, which greatly influence the quality of clustering results. The process typically involves experimenting with different values for K to identify the optimal number of clusters that best captures the inherent structure of the data. Additionally, fine-tuning the initialization method, which affects the starting positions of centroids, plays a vital role in mitigating sensitivity to the initial configuration and achieving more stable results. The hyperparameters that need to be tuned for the K-Means model can also be found on the Scikit-learn documentation [11]. This experiment first implements an elbow method calculation using the silhouette score as a performance measure to find the best values for K. Afterward, a grid search method is used for the remaining other hyperparameters. The scoring criteria used for this experiment, same as the other experiments, is silhouette score. This results in a model that maximizes the silhouette score for clustering given said hyperparameters.

3. RESULTS AND ANALYSIS

3.1. Preprocessing Result

For the pre-processing, the following steps are done to the data. All the steps are done in Python using common libraries for data processing such as Pandas, Matplotlib, and finally Scikit-learn for the modeling. All the recorded current values are loaded to a dataframe using the Pandas library. Null and duplicate data are then dropped from the dataset. From each of the data columns, corresponding to transformer value, and the 3 feeder values, 4 new columns are created denoting the absolute z score values of each of the data points. The columns are named as table 3.

Table 3. Newly Generated Columns

Column Name	Description
absolute_z_score_trafo	absolute z score of current transformer (1 & 3) value

Column Name	Description
absolute_z_score_feeder_1	absolute z score of current feeder 1 (for transformer 1) and feeder 4 (for transformer 3) value
absolute_z_score_feeder_2	absolute z score of current feeder 2 (for transformer 1) and feeder 5 (for transformer 3) value
absolute_z_score_feeder_3	absolute z score of current feeder 3 (for transformer 1) and feeder 6 (for transformer 3) value

The data is then scaled using Scikit-Learn MinMaxScaler. Because this is a clustering task for an unsupervised algorithm, all of the data is used for training the model.

3.2. Feature Combination Result

For the feature selection, all combinations of the 4 attributes are used for clustering. The evaluation metric used to determine the clustering quality is silhouette score. This experiment works by using the feature combinations to create a K-Means model and then recording the clustering performance. An initial model is created with K=3, and the other parameters are the default settings from Scikit-learn documentation. The experiment results are shown in table 4 for transformer 1 data and table 5 for transformer 3 data.

Table 4. Feature Selection Result for Transformer 1 Data

Selected Features				Silhouette Score
absolute_z_score_trafo	absolute_z_score_feeder_1	absolute_z_score_feeder_2	absolute_z_score_feeder_3	
√				0.5699891994
	√			0.6047394646
		√		0.6014615249
			√	0.5939623744
√	√			0.4812564749
√		√		0.4634812881
√			√	0.4248591017
	√	√		0.4855246771
	√		√	0.4558434172
		√	√	0.5407500046
√	√	√		0.383864566
√	√		√	0.3783910422
√		√	√	0.4266100734
	√	√	√	0.5046587295
√	√	√	√	0.3367990746

From the results in both table 4 and table 5, the highest silhouette score is achieved when only using singular attributes. This results in the analysis that even though the performance of the electrical components are interconnected, they are not necessarily correlated with each other. As, combination with other attributes for clustering results in the model's performance degrading. This leads to the belief that the maintenance of the components are supposed to be independent as well. The solution for this is then to build a separate model trained on each of the attributes representing the components. In total, 8 K-Means clustering models are trained. The next steps are then to tune this model in order to produce the best model for each of the electrical components in Amuntai main electrical substation.

Table 5. Feature Selection Result for Transformer 3 Data

Selected Features				Silhouette Score
absolute_z_score_trafo	absolute_z_score_feeder_1	absolute_z_score_feeder_2	absolute_z_score_feeder_3	
√				0.5910541623
	√			0.7583164349
		√		0.6049557159
			√	0.6206309254
√	√			0.3991837866
√		√		0.341657812
√			√	0.3928141464
	√	√		0.4633187672
	√		√	0.546677281
		√	√	0.4317529127
√	√	√		0.3373761362
√	√		√	0.3743768243
√		√	√	0.3197325048

Selected Features				Silhouette Score
absolute_z_score_trafo	absolute_z_score_feeder_1	absolute_z_score_feeder_2	absolute_z_score_feeder_3	
	√	√	√	0.4407082764
√	√	√	√	0.3586691358

3.3. Hyperparameter Tuning Results

Because K-Means is most sensitive to the number of K, the elbow method is used to first determine the best number of clusters for each electrical component. Afterwards, to further broaden the results, the number of K+1 and K-1 from the elbow method is also tested to see the effects on the silhouette score. From the elbow method experiments, the best cluster numbers for all of the components are around 3, 4, and 5 clusters. Therefore, this cluster number will be used in further hyperparameter tuning. The following hyperparameters, according to Scikit-learn K-Means model documentation is then used for hyperparameter tuning, 2 of the most sensitive parameter being the number of clusters and initiation method.

Table 6. List of Hyperparameters

Hyperparameter	Values
n_clusters	3, 4, 5
init	K-Means++, random
n_init	10, 15, 20
max_iter	300, 400, 500

From the hyperparameter tuning experiment, 8 best K-Means models representing clustering for electrical components evaluated by silhouette score are created. Table 7 shows the hyperparameters of these models.

Table 7. List of Hyperparameters

Electrical Component	Hyperparameter	Silhouette Score
Transformer 1	{'init': 'K-Means++', 'max_iter': 300, 'n_clusters': 4, 'n_init': 10}	0.5761
Transformer 3	{'init': 'K-Means++', 'max_iter': 300, 'n_clusters': 3, 'n_init': 15}	0.6182
Feeder 1	{'init': 'K-Means++', 'max_iter': 300, 'n_clusters': 3, 'n_init': 10}	0.6104
Feeder 4	{'init': 'K-Means++', 'max_iter': 300, 'n_clusters': 5, 'n_init': 10}	0.9203
Feeder 2	{'init': 'random', 'max_iter': 400, 'n_clusters': 4, 'n_init': 10}	0.6039
Feeder 5	{'init': 'K-Means++', 'max_iter': 400, 'n_clusters': 3, 'n_init': 15}	0.6050
Feeder 3	{'init': 'K-Means++', 'max_iter': 300, 'n_clusters': 4, 'n_init': 10}	0.5924
Feeder 6	{'init': 'K-Means++', 'max_iter': 300, 'n_clusters': 4, 'n_init': 15}	0.5880

The clustering results for each of the models is shown in figure 2 using a scatter plot. The figure plots the electrical current against the datetime with hue representing the clusters.

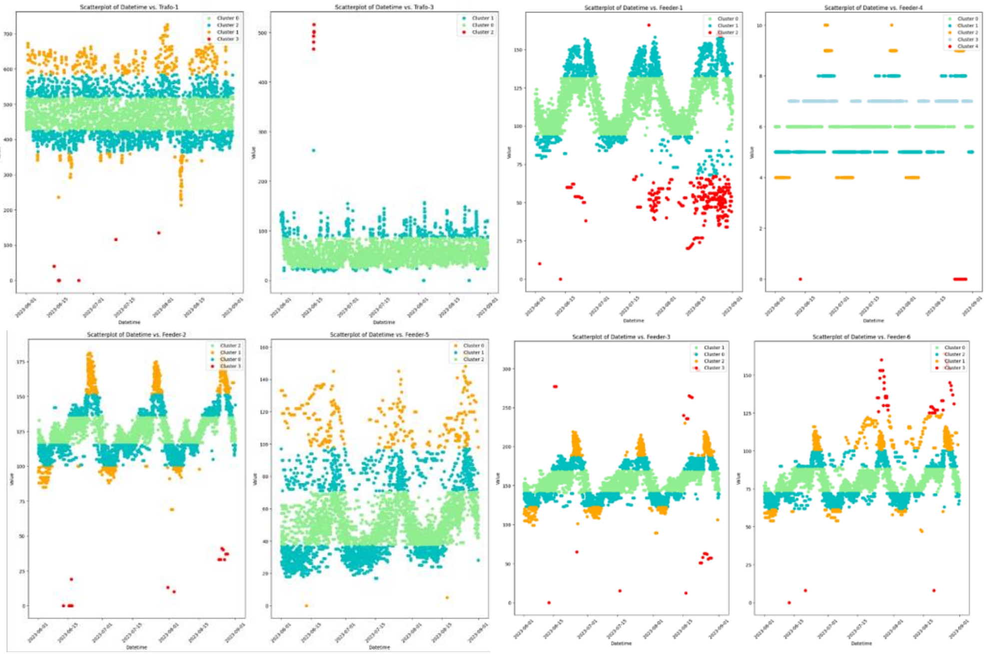

Figure 2. Clustering Results in Scatter Plot for Transformer 1&3 (top left), Feeder 1&4 (top right), Feeder 2 & 5 (bottom left), and Feeder 3 & 6 (bottom right)

From the clustering result, distinct clusters of performances can be observed. In particular, each electrical component is represented by a different model, and some even have different numbers of clusters relating to their performance. This clustering result can be helpful when determining anomalies of electrical components. This way, the cluster serves as a warning when anomalies are detected leading to predicting when maintenance should occur.

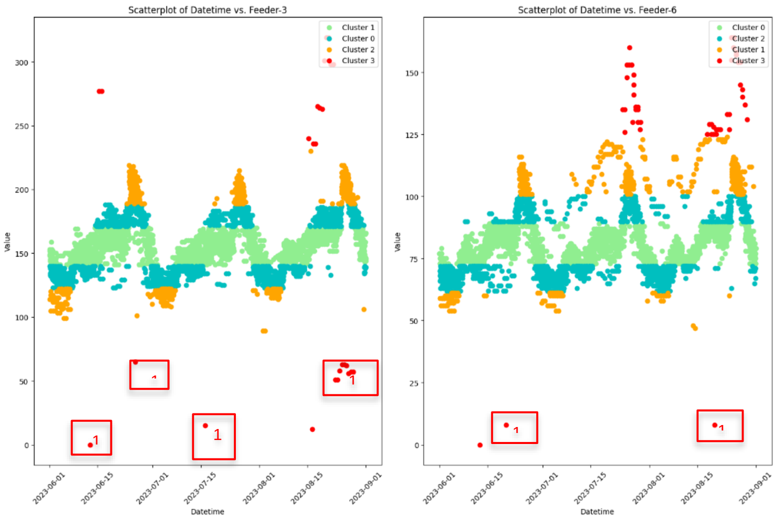

Figure 3. Comparison of the Model Prediction for Feeder-3 (left) and Feeder-6 (right) and the Power Outage Data

3.4. Comparisons with Actual Power Outage Data

In this section, we will present the comparison between our model prediction and the real-world data. As the research progresses, we collect a collection of data of reports regarding actual maintenance that occurs on a component. The comparison of our model prediction and the real-world case can be seen in Figure 3.

Based on the reports, there are several power outages that happened in June 2023 until August 2023 and each of the power outages has an effect on Feeder-3 and Feeder-6 performance. As seen on Figure 3, there is the visualization of our model for Feeder-3 and Feeder-6 and there are red boxes that represent the actual power outage. With the figure showing the comparison between our model's prediction and the power outage data, the model has successfully represented the status of the electrical substation component and predicted the problems occurring with the components.

4. CONCLUSION

This research's focus is to do a predictive maintenance to evaluate the performance of the transformers and the performance of the feeders. There are steps to achieve the research focus: (1) Preprocess the Electrical Components' Data, (2) Finding the best Feature Combination for Modelling, and (3) Hyperparameter Tuning on each Model .

The conclusion obtained from the results of the research that has been carried out is that from the feature selection we can claim that the performance of every feeder is not related to the performance of the connected transformer. With that result, we need to build 1 model for each 2 transformers and 6 feeders, which totals 8 models, to evaluate each of their performance. Afterwards, we do a hyperparameter tuning towards each model using the elbow method to obtain the optimal number of clusters for each model. The results of the hyperparameters vary in the range of 3 until 5 clusters. Subsequently, we choose silhouette score as the metric evaluation of each model. Generally, each model already has a silhouette score above 0.5, coming near to 1 which represents that the resulting cluster is already of good quality.

Finally, when comparing the clustering results with real world data, it can be concluded that the clusters are able to identify anomalies in the component's performance. This can lead to the usage of the clustering models of each component as an early prediction system before power outage occurs. Therefore achieving predictive maintenance. However, it is important to note that further experiments and actual on-field implementation are also required in order to further test the model's capabilities.

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