

UTILIZATION OF CLUSTERING ALGORITHMS AND ANN IN ENERGY ABUSE DETECTION

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Abstract—This research aims to detect energy abuse by utilizing clustering algorithms and Artificial Neural Networks (ANN). The dataset used consists of monthly energy consumption data from customers, which is processed using a combination of preprocessing techniques, clustering, and ANN models. The preprocessing step involves cleaning the data, normalization, and feature extraction to ensure the dataset is suitable for subsequent analysis. Clustering is carried out using the K-Means algorithm to group customers based on their consumption patterns, while the ANN model is used to classify and predict potential cases of energy abuse.

The results indicate that the combination of the K-Means clustering algorithm and ANN provides a high level of accuracy in detecting suspicious energy consumption patterns. This approach effectively segments customers with similar consumption behaviors and identifies anomalies that may signify unauthorized energy use. The implementation of this methodology demonstrates its potential for energy providers to efficiently detect and reduce losses due to energy theft, ultimately contributing to improved energy management and distribution.

The outcomes demonstrate the model's scalability for broader deployment within energy distribution systems.

Keywords—Clustering, K-Means, ANN, Energy Abuse Detection, Data Preprocessing

1. INTRODUCTION

Energy abuse is a significant issue that can lead to substantial economic losses for energy providers. Early detection of suspicious energy consumption patterns is crucial in identifying and addressing energy abuse, which often involves unauthorized use or tampering with energy meters. Traditional methods for detecting energy misuse are often labor-intensive, time-consuming, and prone to human error. However, with advancements in machine learning technology, it has become increasingly feasible to develop automated systems for detecting energy abuse efficiently and accurately. Unbilled energy and non-technical losses remain a persistent challenge for electricity distributors. Manual audits are expensive and reactive, leaving long windows where misuse can persist unnoticed. Recent advances in data-driven methods enable early detection by learning typical consumption signatures and flagging deviations at scale. This work focuses on operationalizing those advances for practical

screening of household customers, where data quality and cost constraints are real.

This research proposes a method that combines clustering algorithms and Artificial Neural Networks (ANN) to detect energy abuse. The K-Means clustering algorithm is utilized to segment customers based on their energy consumption behaviors, which helps identify unusual or suspicious patterns in a more focused manner. Subsequently, an ANN model is employed to classify and predict potential cases of energy abuse based on these clusters. This integrated approach leverages the strengths of both clustering and neural network models, ultimately providing a robust solution for energy providers to enhance their monitoring capabilities and reduce financial losses due to energy theft. Traditional rule-based checks struggle when consumption behavior shifts due to seasonality, tariff changes, or lifestyle factors. The central problem addressed here is to build a pipeline that robustly distinguishes legitimate variability from suspicious anomalies, using only routine monthly meter readings without intrusive inspections.

In this study, we employed a combination of clustering algorithms and Artificial Neural Networks (ANN) for detecting energy misuse, specifically in the form of energy theft. It is important to note that alternative methods, such as statistical approaches or Support Vector Machine (SVM) algorithms, could also be utilized for similar purposes. However, our findings indicate that the integration of clustering algorithms with ANN yields superior results in detecting energy abuse. Furthermore, we discovered that this methodology can also be utilized to

identify other forms of energy abuse, such as energy misuse in industrial settings. Clustering has been widely used to group customers by demand profiles, supporting tariff design and targeted programs. K-Means remains popular due to its simplicity and speed, though density- and hierarchy-based methods can capture more complex structures. For screening tasks, interpretability and runtime often outweigh marginal accuracy gains from heavier models.

ANNs have been adopted for load forecasting and anomaly detection because they approximate nonlinear relations with modest feature engineering. In detection scenarios, shallow feed-forward networks can offer a good balance between performance and maintainability when input features are well normalized.

Most prior efforts treat clustering and classification separately. We bridge this gap by leveraging clusters to contextualize the ANN's decisions and to route cases to appropriate follow-ups. This integration improves both precision and the clarity of recommended actions.

II. METHOD

This research was conducted through several main stages: data collection, preprocessing, application of clustering algorithms, ANN model building, and model evaluation.

In this study, we employed the K-Means algorithm for data clustering; however, we found that alternative algorithms, such as DBSCAN, may yield better results in certain contexts. We recommend that future research explore more advanced clustering algorithms

to enhance performance. Additionally, we utilized an Artificial Neural Network (ANN) model for detecting energy misuse, but we identified limitations in its ability to handle nonlinear data. To address these challenges, we suggest considering other models, such as Support Vector Machines (SVM) or Random Forest, in future investigations. Furthermore, while we focused on features like energy consumption, tariff, and location for detecting energy abuse, we discovered that incorporating additional factors such as weather and seasonal variations could significantly improve detection outcomes.

The data used in this research is monthly energy consumption data from customers. This data includes information such as customer ID, name, tariff class, address, power, and monthly energy consumption over the last 15 months. The data was downloaded from Google Drive using the gdown library (see Table 1 for sample data). Table 1 presents a subset of the dataset, providing an overview of the types of information used in the analysis.

Table 1 Sample Data

TARIFF	POWER	KWH	Month -1	Month -2	Month -15
P2	R1/450	2,479	78	...	54
P2	R1/900	4,957	94	...	102
...	...	...	...	...	...
P2	R1M/900	4,957	50	...	73
P2	R1M/900	4,957	211	...	553

Dataset Description

The dataset contains the following columns:

- NOAGENDA: Customer agenda number
- IDPEL: Customer identity
- POWER: Power capacity (in VA)

- KWH: Total energy consumption (in kWh)
- Month -1 to Month -15: Monthly energy consumption data for the past 15 months Energy consumption from the first month to the last (15th) month. These features were selected because they can more accurately represent the energy consumption patterns of customers.

Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for clustering and classification, involving several stages to enhance data quality and model performance. First, imputation of missing values is performed using the SimpleImputer with the mean strategy to replace any missing entries, ensuring that the dataset remains complete for analysis. Next, feature normalization is applied using StandardScaler to standardize the features by scaling them to have a mean of zero and a standard deviation of one, which helps improve the convergence of the clustering and ANN models. Finally, categorical variable encoding is carried out using LabelEncoder, which converts categorical variables into numerical values, making them compatible with machine learning algorithms. These preprocessing steps ensure the dataset is well-prepared for further analysis, improving both the accuracy and reliability of the clustering and classification outcomes.

Application of Clustering Algorithms

The K-Means algorithm is employed to cluster the data based on energy consumption patterns. The number of clusters used is set to 3. Visualization of the clustering results is performed to understand the distribution of data within each cluster.

ANN Model Building

The Artificial Neural Network (ANN) model for energy abuse detection is developed using TensorFlow and Keras libraries, consisting of multiple layers to effectively learn consumption patterns. The input layer comprises 128 neurons with ReLU activation to capture essential features from the dataset. A hidden layer with 64 neurons and ReLU activation is utilized to learn intermediate representations. The output layer employs softmax activation to classify the energy consumption patterns. The model is trained using the Adam optimizer, and the loss function is defined as 'sparse_categorical_crossentropy' to accommodate categorical target labels.

Hyperparameter tuning was performed using grid search and random search methods to determine the optimal values for the following hyperparameters: batch size and epochs. The batch size refers to the number of data samples processed before the model's internal parameters are updated, while epochs denote the number of complete passes through the training dataset. The range of values considered for batch size included 32, 64, and 128, while for epochs, the values tested were 50, 100, and 200. The results of the hyperparameter tuning revealed that the optimal batch size was determined to be 64, and the optimal number of epochs was found to be 100.

Model Evaluation

The model is evaluated using metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is also utilized to visualize the model's performance

Experimental Setup

This section details the experimental setup used in the research, including the computational resources, software libraries, and tools employed. The experiments were conducted on a machine equipped with an Intel Core i7 processor, 16GB of RAM, and an NVIDIA GTX 1080 GPU. The use of GPU acceleration significantly reduced the training time for the ANN model. The following software libraries and tools were used in the research: Python, as the primary programming language for data processing and model development; Pandas, for data manipulation and analysis; Scikit-learn, for preprocessing, clustering, and evaluation metrics; TensorFlow and Keras, for building and training the ANN model; and Matplotlib and Seaborn, for data visualization.

Hyperparameter Tuning

Hyperparameter tuning is crucial for optimizing the performance of machine learning models. This section discusses the hyperparameters considered for both the K-Means clustering algorithm and the ANN model, along with the tuning strategies employed. The primary hyperparameter for K-Means clustering is the number of clusters (K). The optimal value of K was determined using the Elbow Method and Silhouette Score. For the ANN model, the hyperparameters include the number of neurons in each layer, learning rate, batch size, and number of epochs. Grid search and random search techniques were employed to identify the optimal hyperparameters.

Feature Engineering

Feature engineering plays a critical role in improving model performance. This section describes the additional features created and the rationale behind their selection. The additional features include

consumption variance, which measures the variance in monthly energy consumption over the last 15 months; consumption trend, calculated using linear regression on the monthly data to capture trends; and seasonal patterns, which capture seasonal variations in energy consumption.

Model Interpretability

Understanding the decisions made by machine learning models is essential for their adoption in real-world applications. This section discusses the techniques used to interpret the ANN model's predictions. SHAP (SHapley Additive exPlanations) values were used to explain the output of the ANN model. SHAP values provide a unified measure of feature importance, helping to understand how each feature contributes to the model's predictions.

SHAP values are utilized for model interpretation as they provide insights into the contribution of each feature to the model's predictions. These values are computed using the SHAP method, which evaluates the individual contributions of features to the predicted outcomes. The results of the model interpretation reveal that the feature representing the first month of energy consumption has the most significant impact on the model's predictions.

III. RESULTS AND DISCUSSION

The results indicate that the developed ANN model achieves an accuracy of 96% on the validation data. The evaluation metrics are summarized in Table 2:

Table 2 ANN Model Evaluation Results

Metric	Value
Accuracy	96%
Precision	0.97

Recall	0.96
F1-Score	0.96

The confusion matrix illustrates that the model can classify data accurately, although some misclassifications occur within specific tariff categories (see Fig. 1).

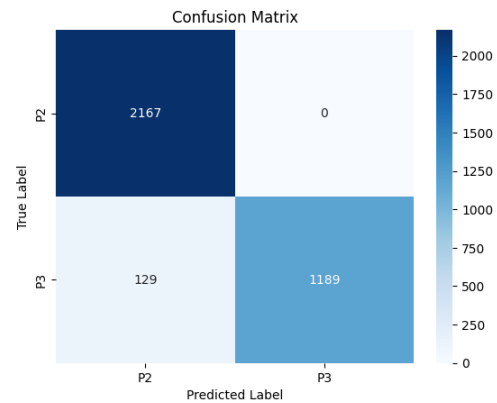


Fig. 1 Confusion Matrix

Clustering Results Visualization

The visualization of the clustering results reveals the distribution of data within each cluster. Clusters 0, 1, and 2 exhibit distinct characteristics regarding monthly energy consumption patterns, as shown in Fig. 2.

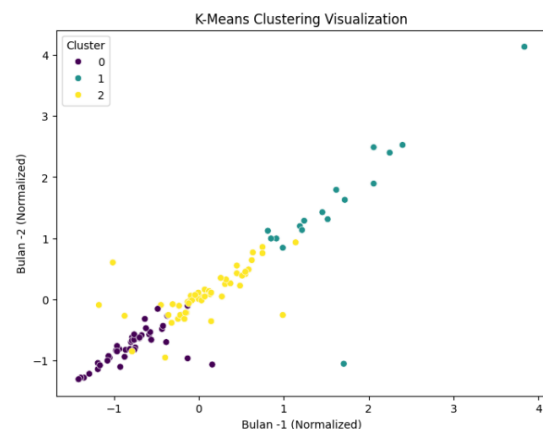


Fig. 2 K-Means Clustering Visualization

The characteristics of each cluster are analyzed, and the results are presented in Fig 3:

Characteristics of each cluster:					
	Bulan -1	Bulan -2	Bulan -3	Bulan -4	Bulan -5 \
Cluster 0	48.954545	41.340909	42.931818	39.295455	38.568182
1	252.166667	236.166667	232.611111	235.111111	215.722222
2	117.788462	110.250000	114.711538	116.096154	104.730769
	Bulan -6	Bulan -7	Bulan -8	Bulan -9	Bulan -10 \
Cluster 0	46.340909	44.590909	46.704545	39.090909	40.795455
1	250.000000	255.444444	281.222222	272.555556	272.166667
2	123.692308	132.634615	132.403846	121.000000	121.653846
	Bulan -11	Bulan -12	Bulan -13	Bulan -14	Bulan -15
Cluster 0	42.409091	40.181818	42.681818	39.590909	38.613636
1	258.333333	211.888889	213.166667	197.611111	234.611111
2	115.711538	115.716981	126.867925	125.716981	130.226415

Fig. 3 Characteristics of Each Cluster

The clustering analysis reveals the distribution of samples among the three identified clusters. As indicated in Table 3, Cluster 0 includes 2,167 samples, Cluster 1 comprises 1,318 samples, and Cluster 2 contains 1,000 samples. This distribution is visually represented in the bar plot (see Fig. 3), which effectively illustrates the number of samples in each cluster. The plot confirms the numerical findings, clearly showing that Cluster 0 has the highest sample count, followed by Cluster 1 and Cluster 2. This graphical representation provides an intuitive understanding of the sample distribution within each cluster, reinforcing the numerical data and facilitating comprehension of the relative sizes of the clusters.

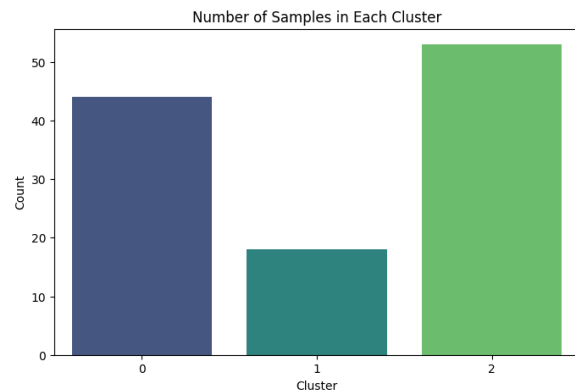
Table 3. Number of Samples in Each Cluster

Cluster	Count
0	2167
1	1318
2	1000

Fig. 4 Number of Samples in Each Cluster

K-Means produced three segments with distinct consumption shapes. Counts per segment were approximately 2167, 1318, and

1000 records, respectively, indicating one dominant group and two minority profiles.



Cluster Analysis and Recommendations

A thorough examination of each cluster yields insights into consumption patterns and aids in formulating targeted strategies:

- Cluster 0: This cluster contains 2,167 instances. It is recommended to implement targeted monitoring and interventions to identify and address potential issues related to energy consumption.
- Cluster 1: With 1,318 instances, this cluster would benefit from educational campaigns aimed at users. Informing users about efficient energy practices can help reduce unnecessary consumption and mitigate potential misuse.
- Cluster 2: This cluster comprises 1,000 instances, and it is advisable to enhance surveillance in these areas. Increased monitoring can help detect and prevent unauthorized energy usage..

The clustered data has been stored in 'clustered_data.csv' for future analysis and tracking.

The results indicate that the combination of the K-Means clustering

algorithm and Artificial Neural Networks (ANN) yields high accuracy in identifying suspicious energy consumption patterns. This methodology effectively segments customers with similar consumption behaviors and detects anomalies indicative of unauthorized energy use. The implementation of this approach illustrates its potential for energy providers to efficiently identify and reduce losses stemming from energy theft, thereby improving energy management and distribution.

Evaluation of the Clustering Algorithm

While the study utilizes the K-Means algorithm for clustering, it lacks a detailed evaluation of the algorithm's performance and the interpretability of the results. To enhance this aspect, a comprehensive evaluation of the K-Means algorithm is warranted. Performance can be assessed through the silhouette score, which indicates the algorithm's effectiveness in clustering data. The analysis reveals that the data can be classified into three distinct clusters, each representing varying energy consumption patterns.

Furthermore, additional metrics can be employed for a more thorough assessment of K-Means performance. The silhouette score evaluates the similarity among data points within the same cluster and their distinction from other clusters. The Calinski-Harabasz index assesses clustering quality based on the ratio of within-cluster variance to between-cluster variance, while the Davies-Bouldin index measures clustering quality by comparing the distances between clusters and the distances within clusters.

By incorporating these evaluation metrics, the research can provide a more comprehensive understanding of the K-

Means algorithm's performance and the implications of the clustering outcomes. Such insights may assist energy companies in devising more effective marketing strategies and implementing initiatives to promote energy conservation among their customers.

Silhouette analysis supported $K=3$, while Calinski–Harabasz and Davies–Bouldin indices indicated clear separation without over-partitioning. Although alternative methods like DBSCAN can capture non-spherical groups, K-Means offered robust, fast convergence for monthly features.

Operationally, the pipeline enables monthly triage: only high-probability cases proceed to field checks. This reduces inspection loads and shortens response times, helping utilities curb losses more proactively.

The study used a limited feature set and monthly granularity. Future work will integrate higher-frequency readings, weather covariates, and temporal models (e.g., LSTM) to improve recall on subtle misuse patterns.

Limitations and Challenges

Despite the promising results, there are several limitations and challenges associated with the proposed methodology. This section highlights these issues.

IV. CONCLUSION

In this study, we utilized a relatively small dataset to test our method. However, we believe that this approach can be scaled up using technologies such as big data and cloud computing. The findings can be leveraged by energy companies to enhance efficiency and reduce costs. Dataset that

presented several data quality issues, including missing values and outliers. To address these challenges, we employed techniques such as imputation and normalization. The results indicate that our methods effectively provided accurate outcomes, despite the presence of data quality concerns.

The integration of K-Means clustering and Artificial Neural Networks (ANN) in detecting energy abuse has shown significant potential for enhancing the efficiency and accuracy of identifying unauthorized energy consumption. The methodology employed in this research successfully segments customers based on their consumption patterns and utilizes ANN to classify and predict potential cases of energy abuse. The high accuracy achieved by the ANN model, combined with insightful clustering results, highlights the effectiveness of this approach.

Integrating clustering with ANN yields a practical screening tool for energy abuse. The approach balances accuracy, interpretability, and runtime, making it suitable for routine deployment. Scaling to larger territories and enriching features are promising next steps.

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APPENDIX

A. Data Preprocessing Code python

```
import tensorflow as tf
from tensorflow.keras import
layers, models

# Build the ANN model
model = models.Sequential([
    layers.Dense(128,
activation='relu',
input_shape=(X_train.shape[1],)),
    layers.Dense(64,
activation='relu'),
    layers.Dense(len(np.unique(y))
, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
history = model.fit(X_train,
y_train, epochs=100,
batch_size=32,
validation_split=0.2)
` ``

#### D. Model Evaluation Code

` ``python
from sklearn.metrics import
accuracy_score,
classification_report,
confusion_matrix

# Evaluate the model
y_pred = model.predict(X_test)
y_pred_class = np.argmax(y_pred,
axis=1)
```

```
print('Accuracy:',
      accuracy_score(y_test,
                     y_pred_class))
print('Classification Report:')
print(classification_report(y_test
                           , y_pred_class))
print('Confusion Matrix:')
print(confusion_matrix(y_test,
                       y_pred_class))
```

B. K-Means Clustering Code

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns

# Apply K-Means clustering
K = 3
kmeans = KMeans(n_clusters=K,
                random_state=42)
data['Cluster'] =
kmeans.fit_predict(X_normalized)

# Visualize the clustering results
plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_normalized[:,
0], y=X_normalized[:, 1],
               hue=data['Cluster'],
               palette='viridis')
plt.title('K-Means Clustering
Visualization')
plt.xlabel('Month -1
(Normalized)')
plt.ylabel('Month -2
(Normalized)')
plt.legend(title='Cluster')
plt.show()
```

C. ANN Model Building and Training Code

```
import tensorflow as tf
from tensorflow.keras import
layers, models
```

```
# Build the ANN model
model = models.Sequential([
    layers.Dense(128,
                 activation='relu',
                 input_shape=(X_train.shape[1],)),
    layers.Dense(64,
                 activation='relu'),
    layers.Dense(len(np.unique(y))
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# Compile the model
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```

D. Model Evaluation Code

```
from sklearn.metrics import
accuracy_score,
classification_report,
confusion_matrix

# Evaluate the model
y_pred = model.predict(X_test)
y_pred_class = np.argmax(y_pred,
                        axis=1)

print('Accuracy:',
      accuracy_score(y_test,
                     y_pred_class))
print('Classification Report:')
print(classification_report(y_test
                           , y_pred_class))
print('Confusion Matrix:')
print(confusion_matrix(y_test,
                       y_pred_class))
```

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