Report on the review and study of unsupervised methods for fault detection and clustering

18/06/2025

Author:
Masoud Hosseini

Reviewed by:
Prof. Dr. Cèsar F. Camon
Dr. Gabriel Zsembinszki
Prof. Dr. Luisa F. Cabeza

1. Introduction

In today's interconnected world, refrigeration systems serve as the lifeblood for countless industries and businesses, from preserving food and pharmaceuticals to powering data centres and providing essential climate control. Optimizing their performance and ensuring their sustainability, however, has always presented significant challenges.

In the field of artificial intelligence (AI) and refrigeration, moving towards unsupervised learning is a logical and smart step. These methods allow us to discover hidden patterns and unknown structures in unlabelled data, which is especially valuable when collecting labelled data is difficult or expensive.

Refrigeration systems play a vital role in various industries, but their efficiency and sustainability have always been a major challenge. Today, vast amounts of data are collected from various sensors in these systems; data that is a treasure trove of hidden information for optimization, failure prediction, and increased productivity. However, this data is often unlabelled, meaning that explicit information about "normal" or "failed" states is not available. This is where unsupervised learning methods come into play.

Unlike its supervised counterpart, which requires labelled data, unsupervised learning is able to extract hidden patterns, structures, and relationships directly from raw data. This approach allows us to gain deep insights into the performance of refrigeration systems, even when we have limited prior information. The aim of this report is to explore the key applications and potential of unsupervised methods in refrigeration system data analysis. From early anomaly detection and clustering of operational patterns to data dimensionality reduction and discovery of hidden relationships, these techniques will open the door to intelligence, increased efficiency, and reduced maintenance costs in refrigeration systems.

Early detection and prediction of failures in industrial systems, especially in critical equipment such as freezers with different setpoint settings (e.g. -26 and -22 °C), plays a significant role in increasing efficiency, reducing maintenance costs, preventing downtime, and increasing safety. The large volume of data generated by modern sensors provides unique opportunities for the application of automated methods based on machine learning.

This report examines the effectiveness of the K-Means clustering approach as an unsupervised method for identifying different performance and failure patterns in freezers with temperatures of -22 and -26 °C. The main goal is to discover hidden structures in sensor data and group them into meaningful clusters that can represent normal states or specific types of failures. These failures include: "No failure" (Class 0), "Blocked evaporator" (Class 1), "Full blocked condenser" (Class 2), "Fan condenser not working" (Class 3), and "Open door" (Class 4). Although K-Means is inherently an unsupervised algorithm, in this study we have used ground truth labels to assess the accuracy of the results and the interpretability of the discovered clusters. This approach gives our model a quasi-supervised nature in the evaluation phase, but it is emphasized that the main learning and clustering process is completely unlabeled.

2. Data and Preprocessing

The data used in this study were collected from various sensors of freezers with setpoints of -26 ºC and -22°C. These data include three key temperature characteristics: evaporator temperature (r1 s1), condenser temperature (r1 s4), and air temperature (r1 s5). The dataset includes samples from the "No failure" condition (Class 0) and four different failure types: "Blocked fvaporator" (Class 1), "Full blocked condenser" (Class 2), "Fan condenser not working" (Class 3), and "Open door" (Class 4). It should be noted that the distribution of samples between classes is unbalanced.

The data preprocessing steps to prepare for clustering are as follows:

- Loading and cleaning: Data was loaded from CSV files, time columns were converted to datetime format, and missing values were filled using linear interpolation.
- Resampling: Time series data was resampled from its original frequency to 5-minute intervals. This helps to smooth the data and reduce noise.
- Scaling: RobustScaler was used to standardize the range of feature values and increase the model's robustness to outliers that are common in sensor data. This method, unlike StandardScaler, is less affected by extreme values.
- Feature engineering: This step is crucial to extracting more meaningful information from the raw data:
  - Create sequences: The time series data is transformed into fixed-length sequences (timesteps). Each sequence represents the behaviour of the system over a specific time interval. These sequences are then "flattened" for input to the K-Means model.
  - Add rate of change: The difference between consecutive values for each feature is calculated and added to the data as new features. This allows the model to detect dynamic patterns and trends (such as sudden increases or decreases in temperature), which is very useful in identifying anomalies and failures.

3. Methodology (K-means clustering)

The K-means clustering algorithm is used to group the preprocessed data. K-means is an unsupervised method that aims to divide n observations into k clusters, such that each observation is assigned to the cluster that has the closest mean to it. This algorithm works by minimizing the sum of squares of the distances between the data points and the center of the corresponding cluster (Inertia).

- Selection of the number of clusters (n_clusters): Given that we know that there are 5 different states (0 to 4) in real data, n_clusters for K-means is set to 5. Although in completely unsupervised scenarios, determining the optimal K is a challenge and requires methods such as Elbow method or Silhouette analysis, in this study, we have acted based on prior knowledge of the number of classes.
- K-means feature (spherical clusters): K-means inherently seeks to identify clusters that are spherical in shape and have well-defined boundaries. If the

actual clusters in the feature space have irregular shapes, are elongated, or overlap a lot, K-means will have difficulty distinguishing them.

- Multiple runs (n_init): The model is run with 10 random initial values (n_init=10) to avoid getting stuck in local optima and achieve the best possible clustering.

4. Pseudo-supervised evaluation and clustering criteria

As mentioned earlier, K-means is an unsupervised algorithm and does not use any labels in the training phase. However, the actual labels present in the dataset are used to validate, interpret, and measure the performance of the discovered clusters. This evaluation process is quasi-supervised in nature and is as follows:

- For the purpose of this evaluation, the K-means model, particularly the configuration employing RobustScaler preprocessing, was applied to and assessed using the "Transition" data. This "Transition" data represents dynamic or transient operational states of the refrigeration systems, making it crucial for evaluating the model's robustness and its ability to detect anomalies and fault patterns under realistic, changing conditions. The reported metrics in Sections 5.1 and 5.2 are therefore reflective of the model's performance on this critical "Transition" dataset.
- Cluster-to-true-label mapping: After K-means has identified clusters, a "Dominant True Label" is determined for each cluster (Cluster ID). This is done by examining the true labels of the samples assigned to that cluster and selecting the most frequent label. In this way, each cluster predicted by K-means is "mapped" to one of the true labels (0 to 4).
- Classification metrics: To measure the performance of the model after mapping, common evaluation tools in supervised learning are used, including:
    - Confusion matrix: A visual representation of the number of true examples of each class assigned to each predicted (labelled) cluster.
    - Classification report: Provides metrics such as precision, recall, and F1-score for each class individually, as well as their average. It is emphasized that in this project, these metrics, especially precision and recall, are much more important than overall accuracy. The reason for this is the imbalanced data and the need to accurately assess the model's performance in identifying each of the failure classes (especially the minority classes). High accuracy on imbalanced data can be misleading and hide poor performance in the minority classes.
- Intrinsic clustering metrics:
    - Inertia: The sum of the squared distances of samples to the nearest cluster centre. A lower value indicates denser clusters.
    - Silhouette score: This metric (ranging from -1 to +1) evaluates the quality of clustering by measuring the degree of compactness and separation of clusters:
        - A value close to 1: indicates completely separate and dense clusters.

- A value close to 0: indicates overlap between clusters or samples lying on the boundary of clusters.
- A negative value: indicates incorrect assignment of samples to clusters (a sample is assigned to a cluster that is closer to another cluster).
- Dependence on the number of clusters: This criterion can be affected by the choice of K and in special cases (such as the presence of noise or irregular clusters) does not necessarily indicate the best K, but it is a useful criterion for assessing the separation of clusters and the validity of the assumption of cluster sphericity.

5. Results and analysis

The results of running the K-means model on the data of freezers with setpoints of -26 ºC and -22 ºC and their quasi-supervised evaluation are presented in the following subsections.

5.1 Freezer with setpoint -26 °C (SP=-26)

Evaluation metrics:

- Inertia (final): 20406.6267
- Average Silhouette score: 0.6068 (good value, indicating good separation and compactness of clusters).

Table 1. Evaluation results (clusters vs. true labels).

Class (True label)	Precision	Recall	F1-score	Support
0 (No failure)	0.8	1	0.89	845
1 (Blocked evaporator)	0.96	1	0.98	557
2 (Full blocked condenser)	1	0.76	0.86	845
3 (Fan condenser not working)	1	1	1	557
4 (Open door)	1	0.97	0.98	767
Accuracy			0.94	3571
Macro average	0.95	0.94	0.94	3571
Weighted average	0.95	0.94	0.93	3571

Analysis: In this scenario, K-means has shown excellent performance (accuracy: 0.94). In particular:

- Class 3 (broken condenser fan): With an F1-score of 1.00, the model was able to detect this failure perfectly.
- Classes 1 (blocked evaporator) and 4 (door left open): also performed brilliantly with F1-scores close to 1.00 (0.98 and 0.98, respectively).

- Class 0 (no failure): With a recall of 1.00 (all normal samples detected) and a precision of 0.80, it performs very well; this indicates that some samples from other classes are misclassified as "normal" (although very few).
- Class 2 (Completely blocked condenser): With precision 1.00 and recall 0.76, it shows that although the model correctly identified the predicted samples for this class, it was not able to identify all the real samples of this class (slightly low recall). Conclusion: At -26°C, the failures (especially Class 3) create distinct and separable sensor patterns that K-means is able to identify well. The high Silhouette score also confirms this good separation of clusters.

5.2 Freezer with setpoint -22 °C (SP=-22)

Evaluation metrics:

- Inertia (final): 13548.9014
- Average Silhouette score: 0.7021 (very good value, indicating excellent cluster separation and compactness).

Table 2. Evaluation results (clusters vs. true labels).

Class (True label)	Precision	Recall	F1-score	Support
0 (No failure)	0.86	1	0.93	557
1 (Blocked evaporator)	1	1	1	557
2 (Full blocked condenser)	0.97	1	0.98	254
3 (Fan condenser not working)	1	0.82	0.9	557
4 (Open door)	1	1	1	845
Accuracy			0.96	2770
Macro average	0.97	0.96	0.96	2770
Weighted average	0.97	0.96	0.96	2770

Analysis: This scenario also shows excellent performance (accuracy: 0.96) of K-means and generally shows the best results among all tests (at other temperatures).

Classes 1, 4: performed flawlessly with an F1-score of 1.00.

Class 0 (no failure): performed very strongly with an F1-score of 0.93.

Class 2: performed excellent with an F1-score of 0.98.

Class 3 (failed condenser fan): performed very well with an F1-score of 0.90 (precision 1.00 and recall 0.82). Although recall is slightly below ideal, it shows that a large proportion of the samples of this failure were detected and the full precision indicates a high accuracy in detecting this class. Conclusion: The freezer at -22 °C gave the best overall results, as confirmed by the highest Silhouette score (0.7021). This indicates clear and distinguishable differences in the sensor patterns in this condition.

6. Limitations and potential drawbacks (in this domain)

While K-means performed remarkably well in these two freezer scenarios, it is important to consider the general limitations of the method:

- Cluster shape dependency (spherical and discrete): K-means is designed to identify clusters with spherical shapes and high resolution. Its performance degrades if the actual clusters have irregular shapes or overlap. Fortunately, at -22 ºC and -26 ºC, these clusters appear to be sufficiently distinct and discrete.
- Sensitivity to the choice of the number of clusters (K): Although in this study K was adjusted based on prior knowledge of the number of actual classes, in fully unsupervised scenarios, determining the optimal K is itself a challenge and can significantly affect the quality of clustering.

7. Conclusions and next steps

This study demonstrated that the K-means clustering algorithm, as an unsupervised method, performs very robustly and reliably in effectively identifying and discriminating different types of failures in freezers at -22 ºC and -26 °C. This success is particularly promising in the detection of critical failures such as "failed condenser fan" (Class 3). The ability of K-means to identify distinct patterns in sensor data at these temperatures is a testament to the effectiveness of this approach in these specific situations.

Next steps and future perspectives:

Given the positive results in low-temperature freezers, an important and critical next step will be to extend this analysis to other refrigeration equipment, including freezers at other temperatures (e.g. -18 °C) and refrigerators (with setpoints of 0 ºC, 2 ºC and 4 °C). The goal at this stage is to understand the potential challenges in these environments and evaluate the model's performance in them. This step-by-step approach allows us to carefully consider the complexities of each equipment type and operating temperature and, if necessary, develop appropriate feature engineering or algorithm solutions. Analysing the results in other equipment will give us a more comprehensive view of the generalizability of this model or the need for more specialized approaches for each scenario.

8. Future steps and methodological enhancements

Given the promising results of the K-Means clustering algorithm in diagnosing refrigeration system faults, and to continuously improve model performance and accuracy, valuable guidelines for future research were proposed in a meeting with the supervisors. These guidelines clarify the future direction of the research as follows:

8.1 Investigating alternative K-means approaches and determining the optimal number of clusters

In the present study, the number of clusters (K) in K-means was determined based on prior knowledge of the number of failure classes. However, in completely unsupervised scenarios, determining the optimal K remains a challenge. In this regard, it was suggested that other K-means methods based on distributions or probabilistic distributions be investigated for a more comprehensive evaluation and to find the most optimal approach. These approaches, instead of focusing solely on geometric distance, consider the probability of a data point belonging to a particular cluster, and can be useful in modelling non-spherical clusters and managing data assignment uncertainty.

Furthermore, to determine the optimal number of clusters in unsupervised settings, the Elbow method and Silhouette analysis are currently being implemented and tested. These methods help evaluate clustering quality for different values of K. Gaussian mixture models (GMMs), which are inherently a type of probabilistic distribution-based clustering, have also been considered, and their implementation and testing codes are currently in progress. Comparing the performance of these approaches with the current method will provide deeper insight into the true nature of clusters in refrigeration system sensor data.

8.2 Development of ensemble models

To achieve more robust, stable, and resilient results against noise and data fluctuations, the importance of combining methods (ensemble models) was emphasized. By integrating the output of several base models, ensemble models typically provide better and more stable performance than a single model. In future steps, the feasibility and implementation of approaches such as consensus clustering will be considered. By combining the results of multiple independent clustering, these methods can create a final, more stable cluster structure that is less affected by initial choices or data noise.

8.3 A more detailed analysis of the impact of RobustScaler

Although RobustScaler was used in the data preprocessing stage to standardize feature values and increase the model's robustness against outliers, it was suggested that the impact of this scaler on the final clustering performance be investigated and analysed more systematically. This analysis could include comparing the clustering results using RobustScaler against other scaling methods (such as StandardScaler or MinMaxScaler) and examining the model's sensitivity to RobustScaler's potential parameters. The goal is to confirm the selection of RobustScaler as the most optimal preprocessing tool for this type of data and to gain a deeper understanding of its role in improving clustering quality.