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Transformer Condition Assessment using Fuzzy C-means Clustering Techniques

Key Words: *Clustering, data analysis, diagnostic, fuzzy C-means, insulating oil, maintenance, principal component analysis, transformers.*

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This paper introduces a transformer fleet monitoring solution to help the end user to group transformer assets and react accordingly to monitored situations.

Introduction

For proper transformer management, maintenance managers must react quickly to uncover faulty feedback from investigation information which should be part of the general policy of operating power networks. In a production site, there are often several transformers and generators that contribute to the production of electrical energy. The requirement of continuity of service, that is to say of the availability of electrical energy, depends on adequate responsiveness on the part of power plant managers. This means that planning, organization and execution of maintenance tasks must integrate all network management actions (load changes, various switchings, unplanned events, etc.). It is, therefore, necessary for the management system to take into account a certain amount of data useful for decision making at all levels of the maintenance management process. At the planning level, it is often important to be able to have a view of all the devices which are defective for an optimal organization of the various resources to be mobilized and of the periods of interruption. Some companies have set up a transformer selection organization for which maintenance actions must be programmed [1], [2]. For such a setup, the data from the diagnostic team must be interpreted and the transformers prioritized according to the actions to be performed as well as to other criteria related to the policy of the company. Knowledge on the reliability, aging, lifetime, and condition of the internal parts and insulation system of each equipment is important for general maintenance organization. In the case of fleet transformers, it is necessary to program the actions taking into account the urgency presented by the state of each unit.

Transformer management

Transformer management concerns all activities that enable transformers to fulfill their role in the production of electrical energy. It is operationalized around a maintenance management process consisting of 5 phases [3]:

- Planning
- Organization

- Execution
- Recording of data
- Optimization of maintenance

Each phase is important and allows the manager to follow the life of transformers and take important decisions ensuring power availability. It is a question of allowing the implementation of any of the maintenance strategies: TBCM (Time Based Condition Monitoring), CBM (Condition Based Maintenance), OLCM (On-Line Condition Monitoring), TBM (Time Based Maintenance) and RCM (Reliability Centered Maintenance). An assessment of the actual condition of each unit is often made. It consists of characterizing the cumulative wear of each equipment through the evaluation of the number of faults and failures, and the net future value of each transformer. All of these activities rely on electrical tests and oil analysis. References [2] and [3] give more details on the implementation of the transformer maintenance process. However, the examination of analysis results and the maintenance history, operations are used to identify which transformers need urgent action.

Considering all the data at hand, the present study proposes a classification system whereby this data is set and the groups to be analyzed are determined. This tool can be used at the three levels of transformer management as implemented in [1].

METHODOLOGY

The operational objective of this method is to identify from the data (population of transformers) made up from observations available at a given instant, groups of transformers which present similarities. The aim is to exploit hidden links in the data to make a classification.

As a first step, it is advisable to assess the importance of each characteristic in the data. In the field of pattern recognition and machine learning, the literature presents some feature selection tools. Using these tools, it is possible to classify and select subsets of characteristics according to their degree of relevance or importance as to user requirement. In unsupervised classification, feature selection is rather complex because of the lack of class labels which can guide the search for relevant information. Techniques such as unsupervised Graph Filter (Inf-FS) [4] [5] , Multi-Class Feature Selection (MCFS) [6] and Laplacian Score (LS) [7] still provide results that can be used to accelerate the classification process, reduce dimensionality and improve data understanding. Because of its simple implementation, the Laplacian Score technique is used in this work. The identification of the parameters that carry the most relevant information in class construction is obtained after sorting the LS values. Once the relevant characteristics are identified, the least important features can be removed before moving on to the second stage of the methodology.

For the second step, principal component analysis is used to identify a new observation structure. New variables are obtained, consisting of the linear combination of the starting observation variables. Depending on these new variables, which are in fact the main components, an observation space and the amount of information it carries are identified.

In the third step, unsupervised classification is applied through the Fuzzy C-means algorithm. Clusters are formed based on non-visible links in the data.

The fourth and last step is the interpretation of each cluster, according to the technical and economic criteria. The expertise of the managers is then used to prioritize the groups whose transformers require urgent action.

Laplacian Score (LS)

According to [8], the basic idea of LS is to evaluate the features according to their locality preserving power. So, let $\mathbf{X} \in \mathbb{R}^{n\times p}$ be the data matrix, where n is the number of instances and d is the number of features. $f_1, \dots, f_p$ denotes the p features, and $\mathbf{f}_1,\dots,\mathbf{f}_p$ are the corresponding feature's vectors, where $\mathbf{f}_i \in \mathbb{R}^n$ and $\mathbf{X} = (\mathbf{f}_1,\dots,\mathbf{f}_p)^T$. For the given n instances $x_1, \dots, x_n$, the pair-wise similarity among them can be presented as a symmetric matrix $\mathbf{K} \in \mathbb{R}^{n\times n}$. Let $\boldsymbol{G}$(V, E) denote the undirected graph constructed from **K**, where V is the vertex set, and E is the edge set. The i-th vertex of G corresponds to x_i, and there is an edge between each vertex pair (x_i, x_j), whose weights k_{ij} allows to build the affinity matrix of $\boldsymbol{G}$ called **K.** Let **d** denote the vector: $\mathbf{d} = (d_1, \dots, d_n)$, where $d_i = \sum_{j=1}^{n} k_{ij}$. The degree matrix **D** of the graph $\boldsymbol{G}$ is defined by: $\mathbf{D}_{ij} = d_i$ if $i = j$, and 0 otherwise. According to [7], d_i can be interpreted as an estimation of the density around x_i, the larger value of d_i.

So, Laplacian score select features that retain sample locality specified by an affinity matrix **K**, its corresponding degree matrix **D** and Laplacian matrix **L** defined as:

$$\mathbf{L} = \mathbf{D} - \mathbf{K} \qquad (1)$$

The Laplacian Score of the feature **f** is calculated in the following way:

$$L_{r\mathbf{f}} = \frac{\tilde{\mathbf{f}}^T \mathbf{L} \tilde{\mathbf{f}}}{\tilde{\mathbf{f}}^T \mathbf{D} \tilde{\mathbf{f}}} \qquad (2)$$

where $\tilde{f} = f - \frac{\mathbf{f^T D 1}}{\mathbf{1^T D 1}}$

Principal Component Analysis (PCA)

Let $X \in R^{n \times p}$ be a matrix containing n observations (instances). Each observation is described by p variables or parameters, and can thus be considered as a point in an observation space. The aim of PCA is to explore the links between the p variables and the similarities between the n observations. This tool allows construction of a Euclidean space consisting of principal components, a linear combination of the p initial variables with the goal of building up a Euclidean space with features most adaquately summarizing the data structure in this space. Indirectly, a reduction of the variable dimensionality is obtained. The principal components that constitute the axes of this space are obtained by calculating the vectors and eigenvalues of the correlation matrix $\mathbf{R}$.

$$\mathbf{R} = \frac{1}{p}\mathbf{X}^t\mathbf{X} \qquad (3)$$

Where $\mathbf{X}^t$ is the transpose of matrix $\mathbf{X}$.

The inertia of the data is evaluated by calculating the variance. For each variable, the ratio between the eigenvalues of $\mathbf{R}$ and the total number of variables are characterized, providing the amount of information carried by each principal component . The inertia is calculated by the following relation:

$$I_i = \frac{\lambda_i}{p} \qquad (4)$$

where, $\lambda_{i \in \{1,\ldots,p\}}$ are the eigenvalues of matrix $\mathbf{R}$.

Fuzzy C-means

Unsupervised classification consists in grouping data without the contribution of an expert. Clustering techniques are used to partition data into multiple groups so that the degree of association is strong within one group and low between different groups. Observations from a same group (called a cluster) are then closer to each other than those from other clusters, in terms of a criterion of (dis) similarity. In other words, any observation is assigned to the cluster for which it is closer to its center of gravity. The similarity criterion is generally based on distance. In the literature, however, there are several unsupervised classification methods that apply the coalescence technique [10] and [11]. For example, the fuzzy C-means technique uses fuzzy logic to define the degree of belonging to a class. For every group, each point is assigned a membership degree between 0 and 1. The membership values indicate the probability of each point to belong to the different groups.

Given a number of clusters C, the Fuzzy C-means technique will classify the $X = \{x_1,\ldots,x_n\}$ data into C fuzzy clusters by minimizing the following objective function with respect to fuzzy membership u_{ij} and cluster centroid c_j.

$$\Gamma_m(u,c) = \sum_{i=1}^{n}\sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, \quad 1 < m < \infty \qquad (5)$$

where

m: a weighting exponent that is called a "fuzzifier"

u_{ij} : membership degree of x_i to the cluster j

x_i : the ith observation with dimension d in the matrix data

c_j : is the cluster center j with dimension d

The membership degree u_{ij} is given by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|}\right)^{\frac{2}{m-1}}} \qquad (6)$$

and the cluster center by:

$$c_j = \frac{\sum_{i=1}^{n} u_{ij}^m x_i}{\sum_{i=1}^{n} u_{ij}^m} \qquad (7)$$

The Fuzzy C-means algorithm [12], [13], [14] and [15] can be summarized by the 5 following steps:

1- *Randomly initialize the cluster membership values,* u_{ij} *of* x_i *belonging to cluster* i *such that*

$$\sum_{i=1}^{C} \mu_{ij} = 1 \qquad (8)$$

2- *Calculate the cluster centers* c_j

3- *Update membership degree (eq. 5)*

4- *Calculate the objective function* $\Gamma_m(u,c)$ *(eq.4)*

5- *Repeat steps 2 to 4 until the convergence of algorithm.*

Convergence can be considered achieved if the relative value of the Γ criterion (3) falls below a predetermined small threshold or if the maximum number of prefixed iterations has been reached. It is possible to adjust the amount of fuzzy overlap when performing the fuzzy c-means clustering.

Application and results

It is supposed that during the maintenance process, the transformer managers have gathered data on some oil-filled transformers including some parameters and basic maintenance or oil treatment actions to be planned.

Description of the case under study

The data analyzed in this study are derived from the functional requirements of 33 oil-filled power transformers which were collected from the maintenance program of Rio Tinto Alcan's power station transformers (Chicoutimi, Canada). Table 1 lists the parameters used and their significance [16] [17] while Table 2 presents the transformers characteristics.

TABLE 1: PARAMETER SPECIFICATIONS

Parameters	Meaning	Diagnosis	Limits
Dielectric strength	Ability to withstand electrical stress without failure	Presence of sediment and conducting particles	> 70 kV/2.5mm (IEC 60156)
Water content	Water accelerates deterioration of both insulating oil and paper insulation	Presence of moisture - possible paper degradation (loss of mechanical strength)	30 ppm max (IEC 60814)
Acid number or Neutralization Number	Oil decomposition or oxidation products	Deterioration of oil with sludge	0.01mg KOH/g max (IEC 62021-1)
Interfacial Tension (IFT)	Tension at the interface between two liquids (oil and water)	Oil oxidation products	40mN/m (dynes/cm) (ISO 6295)
Oil colour	Is an indication of deterioration of the mineral insulating oil	Oil oxidation	02 ppm min
OQIN	Oil Quality Index	Oil condition, can help in making a decision to replace or reclaim oil in the transformer	1500 for a new oil
TDCG	Total Dissolved Combustible Gas	Alert for verification of each gas	Condition: 1: 720 ppm 2: 720 to1920 ppm 3: 1921 to 4630 ppm 4: > 4630 ppm
CO_2/CO	Carbon content of oil	Probable involvement of paper in the fault	< 3 or >10

TABLE 2. CHARACTERISTICS OF TRANSFORMERS

MANUFACTURER: CGE	
VOLTAGE	154 KV
POWER	30000KVA
YEAR OF COMMISIONING	1954
SITE OF OPERATION	CENTRALE SHIPSHAW ON THE SAGUENAY RIVER IN CANADA
EXPLOITATION	RIO TINTO ALCAN CANADA
DATA	1998

Results

Let $\mathbf{X} \in R^{n \times p}$ be the matrix containing n observations described by p variables composing the feature vector. In the case of this study, the following 8 parameters are used: TDCG, CO_2/CO, Dielectric strength, Water content, IFT, Acid number, Density, and Oil color, as shown in Table 1 above. The values of each of these parameters are recorded on the 33 transformers. Each observation (transformer) is considered as a point in a p dimensional space.

As previously stated, our methodology is applied in 4 steps:

First step: Identification of the relevance of each parameter in the data structure constitution in the space representation.

By applying the LS, it can be observed that, without affecting the structure of the data, it is possible to ignore three variables (Acidity, Density and Color of Oil).

Figures 1 and 2 present the data structure in the space consisting of the three first variables before and after applying LS, according to the results presented in Table 3 below. The two figures are almost identical, although three variables in the data matrix have been removed (bolded in Table 3).

TABLE 3. RESULTS OF LS APPLICATION

N°	Feature	L_{fr}
1	TDCG	6927.9
2	CO_2/CO	0.0000
3	Dielectric strength	0.2000
4	Water content	0.2000
5	IFT	0.0000
6	Acid Number	0.0000
7	Density	0.0000
8	Color	0.0000

Ranking	
1	TDCG
3	Dielectric strength
4	Water content
5	IFT
2	CO_2/CO
8	Color
6	Acid Number
7	Density

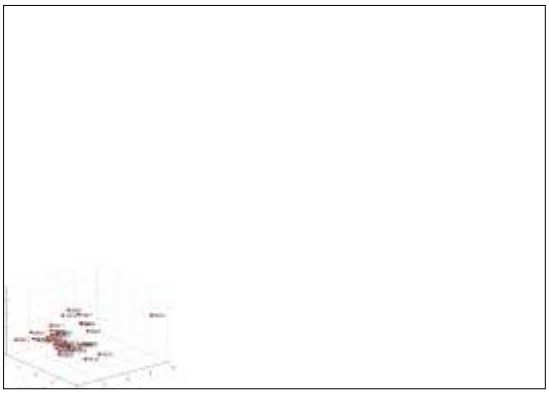

Figure 1. Data structure in the 3D space (three first variables), before applying LS.

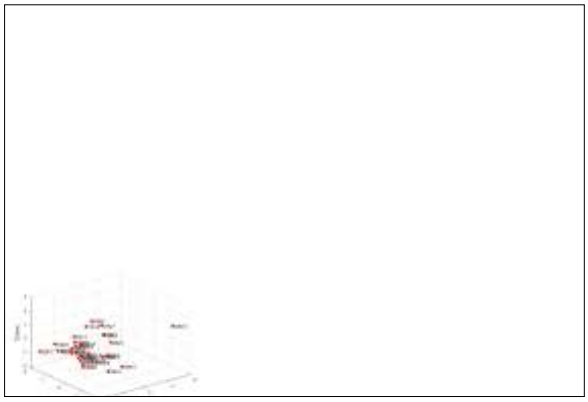

Figure 2. Data structure in the 3D space (three first variables), after applying LS.

Second step: Characterization of the classification or representation space.

PCA is applied to obtain the principal components that characterize the axes of the observation or representation space. After the application of the Laplacian score, the goal of the PCA is to identify the data representation space and the importance of each axis constituting this space.

Taking into account the variance of the data, this method allows the classes mainly responsible for this variance to be better distinguished.

Table 4 shows the eigenvalues corresponding to matrix **R** and the cumulative variances, which highlight the information contained in the observation space. Table 5 is derived from the calculation of correlation matrix **R** , according to Eq. 2.

TABLE 4. PRINCIPAL AXES, EIGENVALUES, EXPLAINED VARIANCE AND CUMULATIVE VARIANCES

Factor	Eigenvalues of R	Explained variances (%)	Cumulated variances (%)
1	2.7361	54.7214	54.6712
2	1.0356	20.7125	75.4339
3	0.6884	13.7679	89.2018
4	0.3421	6.8419	96.0437
5	0.1978	3.9563	100.0000

The first three factors account for 89.20% of the information in the data set (cumulated variances in Table 4). The projection of the initial variables in the space constituted by these three main factors allows the identification of the information that each

factor carries, and characterizes the new variables. This projection of the variables (Figure 3) is summarized in Table 5 below. Figure 3 shows the spatial distribution of each variable according to the first two principal components.

The application of the PCA shows that the 3 D space representative of the data to be analyzed consists in the axes carried by the water content (Axis 1), the TDCG (Axis 2), and the Dielectric strength (Axis 3).

TABLE 5.CORRELATION BETWEEN AXES AND VARIABLES

Variables	Axis1	Axis 2	Axis 3	Axis 4	Axis 5
TDCG	-0.2614	0.7448	-0.5626	0.2453	-0.0155
CO2/CO	0.5187	0.1080	0.2386	0.7524	-0.3104
Dielectric strength	-0.4732	0.2049	0.6134	0.3127	0.5100
Water content	0.5510	0.0102	-0.2528	0.0268	0.7948
IFT	-0.3676	-0.6257	-0.4317	0.5247	0.1079

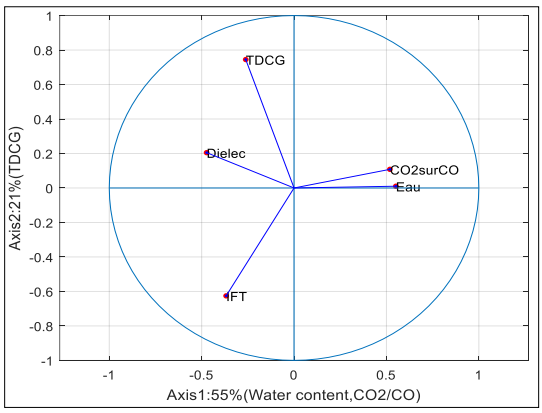

Figure 3. Correlation circle

Third step: Obtaining clusters

The number and validity of classes can be discussed through existing tools. In this study, the optimal class number is held through the Davies-Bouldin and silhouette indexes [18], [19] and [20] for the k-means algorithm and adopted for the fuzzy C-means algorithm applied here as a classification method.

Figure 4 shows the clustering obtained. The clusters are represented in the space identified from the PCA. It presents 4 clusters whose characteristics are analyzed in the procedure that follows.

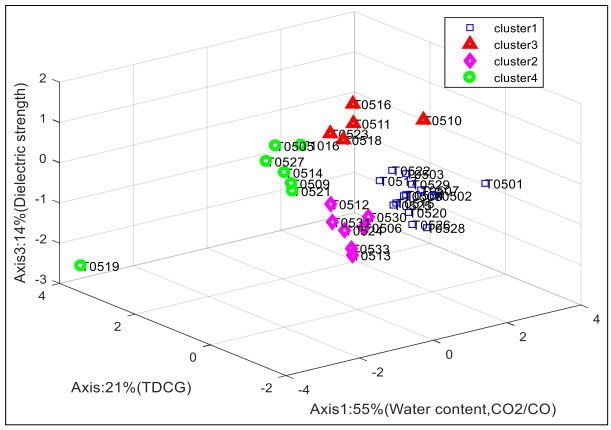

Figure 4. Clustering by fuzzy C-means

Fourth step: Clusters interpretation

The analysis results of Table 6 display the characteristics of each cluster.

Cluster 1: This cluster consists of transformers that have a doubtful quality of insulation, for which it is desirable to consider filtering action of the insulating oil.

Cluster 2: This group presents transformers whose oil quality and insulation are acceptable. However, an individual gas control should be programmed for most transformers. The state of this cluster is quite close to that of cluster 4.

Cluster3: The quality of oil and insulation of this group of transformers is questionable. The transformers whose maintenance actions include regeneration of oil belong to this group.

Cluster 4: The oil of these transformers is acceptable for insulation.

TABLE 6. CHARACTERISTICS OF EACH CLUSTER

Cluster	Trs	TDCG	Dielectric strength	Water content	**IFT**	**CO2/CO**
Cluster1	T0501	79,53	20	28	35,70	10.67
	T0502	807,00	25	29	36,40	10,39
	T0503	857.30	27	31	28,40	8,53
	T0504	946,00	23	35	28,20	7.16
	T0507	920,20	19	26	31,50	9,82
	T0508	975,40	18	28	28,20	7,76
	T0515	839,60	22	21	32,90	7,71
	T0517	1175	27	26	29,40	8,72
	T0520	962,80	25	30	35,40	8,15
	T0522	976,80	32	36	27,10	7,76
	T0525	938,30	23	24	32,70	7,57
	T0526	845,90	18	26	34,60	7,17
	T0528	908,90	14	32	32,90	7,30
	T0529	870,30	23	30	29,20	8,52
Cluster2	T0506	1023,50	23	16	35,50	5,93
	T0512	436,80	41	7,30	37,10	3,53
	T0513	1149,60	18	12	37,70	4,83
	T0524	934,70	32	13	39,10	5,09
	T0530	747,30	27	14	36,10	5,85
	T0531	919,50	35	12	37,80	4,63
	T0533	1044,40	30	27	36,5	3,00
Clus-ter3	T0510	946,00	18	37	14,50	10,38
	T0511	903,50	39	23	22,20	8,35
	T0516	1148,10	22	21	32,90	7,71
	T0518	1200	32	22	21,20	8,05

	T0523	1439,00	22	19	14,40	7,77
Cluster4	T0505	1039,2	60	6,50	34,10	6,57
	T0509	1095,00	51	11	35,90	5,25
	T0514	1167,70	51	11	33,30	5,41
	T0519	4369,9	50	6,2	36,60	3,87
	T0521	952,00	49	9,90	35,60	4,13
	T0527	1133,4	59	6,70	35,00	5,58
	T01016	827,10	55	8,20	33,11	6,78

Discussion and conclusion

The classification methods used in this contribution allow extracting non-obvious relationships from transformer maintenance data (Appendix 1). In the management of transformers, all the possible observations are not always available. The maintenance planner must implement an operating procedure to ensure continuity of service and power. It is desirable to be able to quickly identify at-risk transformers to plan appropriate actions. In the present study, Machine Learning techniques were presented in a four-step procedure as support to transformer management. A pseudo code is proposed in Appendix 2. The case presented provides a quick assessment of the condition of the transformers, especially as concerns the oil data. The starting parameters have been restricted to those which carry the most relevant information for the analysis (feature selection). PCA allows visualizing the observation space according to the variance of the data. The classification obtained by the Fuzzy C-means algorithm provides four groups presenting quite different characteristics. However, it is important to note the outlier character of the T0519 transformer, whose TDCG parameter requires special attention (degassing) or more extensive investigation. Maintenance actions can be scheduled for obtaining such results. The brainstorming provided by this method can be helpful. The expertise of the engineers must be used to better understand the maintenance information provided by each group. .

The constraints and limitations of this work may well depend on the quality of data. In order to ensure such quality, it is important to have a group of transformers with the same characteristics and operating under the same conditions. Otherwise, the interpretation of the classes may not be consistent because the limiting values of certain parameters depend on the characteristics of the transformers (power, voltage, type, technology, etc.).

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Appendix 1: Data table used

Equipment	TDCG	CO_2/CO	Dielectric Strength	Water content	IFT	Acid number	Density	Color
'T0501'	79,52	10,66	20	28	35,70	0,018	0,87	2
'T0502'	807	10,39	25	29	36,40	0,025	0,86	1,50
'T0503'	857,30	8,536	27	31	28,39	0,07	0,96	2
'T0504'	946	7,16	23	35	28,20	0,11	0,86	2
'T0505'	1039,20	6,57	60	6,50	34,09	0,04	0,87	2
'T0506'	1023,50	5,937	23	16	35,50	0,054	0,87	2
'T0507'	920,19	9,82	19	26	31,50	0,06	0,86	1,50
'T0508'	975,40	7,76	18	28	28,20	0,09	0,87	2
'T0509'	1095	5,25	51	11	35,90	0,050	0,87	2
'T0510'	946	10,38	18	37	14,50	0,032	0,86	2
'T0511'	903,50	8,35	39	23	22,20	0,014	0,87	2
'T0512'	436,80	3,53	41	7,30	37,09	0,032	0,87	2
'T0513'	1149,60	4,83	18	12	37,70	0,03	0,87	2
'T0514'	1167,70	5,41	51	11	33,29	0,04	0,87	2
'T0515'	839,60	7,71	22	21	32,90	0,05	0,87	2
'T0516'	1148,10	8,76	31	27	13,50	0,04	0,87	2
'T0517'	1175	8,72	27	26	29,39	0,057	0,87	2
'T0518'	1200	8,05	32	22	21,20	0,10	0,87	2
'T0519'	4369,90	3,87	50	6,19	36,59	0,04	0,87	2
'T0520'	962,80	8,15	25	30	35,40	0,03	0,87	2
'T0521'	951,99	4,13	49	9,89	35,59	0,02	0,87	2
'T0522'	976,80	7,76	32	36	27,10	0,079	0,87	2
'T0523'	1439	7,77	22	19	14,39	0,10	0,86	1,50
'T0524'	934,70	5,09	32	13	39,09	0,02	0,87	2
'T0525'	938,30	7,57	23	24	32,70	0,06	0,87	2,50
'T0526'	845,90	7,17	18	26	34,59	0,09	0,86	2
'T0527'	1133,40	5,58	59	6,69	35	0,02	0,87	2
'T0528'	908,90	7,30	14	32	32,90	0,04	0,87	2
'T0529'	870,30	8,52	23	30	29,20	0,07	0,86	2
'T0530'	747,30	5,85	27	14	36,09	0,05	0,87	2
'T0531'	919,50	4,63	35	12	37,79	0,03	0,87	2
'T0533'	1044,40	3,00	30	27	36,50	0,04	0,86	2
'T1016'	827,10	6,78	55	8,2	33,10	0,05	0,86	2,50

Appendix 2: Pseudo code

1. **Read Data File**
2. **Extract Variables** = {'TDCG', 'CO2surCO', 'Dielectric strength', 'WaterContent', 'IFT'}
3. **Compute Laplacian Score**

3.1 calculation of the affinity matrix K

for i = 1 to p,

for j = 1 to p,

$$k_{ij} = \frac{e^{\|x_i - x_j\|^2}}{t}$$

$$d_i = \sum_{j=1}^{n} k_{ij}$$

$\mathbf{D}_{ij} = d_i$ if i = j

else $\mathbf{D}_{ij} = 0$

end;

end;

3.2 Calculation of Laplacian Matrix

$$\mathbf{L} = \mathbf{D} - \mathbf{K}$$

3.3 calculation of Laplacian Score $L_{r\mathbf{f}}$

$$\tilde{f} = f - \frac{\mathbf{f}^{\mathbf{T}}\mathbf{D1}}{\mathbf{1}^{\mathbf{T}}\mathbf{D1}}$$

$$L_{r\mathbf{f}} = \frac{\tilde{f}^{\mathbf{T}}\mathbf{L}\tilde{f}}{\tilde{f}^{\mathbf{T}}\mathbf{D}\tilde{f}}$$

4. **Compute PCA**

4.1. Calculation of correlation matrix

$$\mathbf{R} = \frac{1}{p}\mathbf{X}^t\mathbf{X}$$

4.2. calculation of eigenvector of **R**

$$\mathbf{U} = \mathbf{XV\Lambda}^{1/2}$$

4.3. Sort and keep specific number of first component

4.4. calculate the inertia of each component

for i = 1 to p,

$$I_i = \frac{\lambda_i}{p}$$

5. **Compute Fuzzy C-means** [21]

5.1 Initialization of the membership matrix{Citation}

5.2 t = 0

5.3 Calculate the cluster center

Do:

For j = 1 until c do:

$$c_j(t) = \frac{\sum_{i=1}^{n} u_{ij}^m(t) x_i}{\sum_{i=1}^{n} u_{ij}^m(t)}$$

end;

5.4 Update the membership matrix:

For j = 1 until c do:

for i = 1 until n do:

$$u_{ij}(t+1) = \frac{1}{\sum_k^c \left(\frac{\|x_i - c_j(t)\|}{\|x_i - c_k(t)\|}\right)^{2/(m-1)}}$$

end;

end;

5.5 t= t+1; While $\|U(t+1) - U(t)\| \varepsilon$.