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Implementation and Comparison of Contemporary Data Clustering Techniques for a Multi-Compressor System: a Case Study

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Abstract: - This paper gives the implementation and deployment of fuzzy clustering algorithm applied to a process control data along with its comparison to various other clustering algorithms. In this paper, the analysis is carried out for the data as obtained from a multi-compressor system based on the factor of keeping the maximum weighted square error at the minimum level. Also, this paper consists of an algorithm, which groups the data according to fuzzy clustering, considering the intermediate values between zero and one. The paper also outlines the comparison among other clustering algorithms on the basis of various validation parameters there by telling us the importance of fuzzy clustering, which considers all the ambiguity in data to be a part of n- clusters, giving an extra attribute of membership function.

Key-Words: - Data clustering, Data clustering Algorithms, Data mining, Fuzzy Clustering, Multi-Compressor

1 Introduction

Multi-compressor systems are used for refrigeration, cooling and air-conditioning. These systems are quite different as compared to electrical or electronic systems because of these natural attributes like weight, inertia, force and torque requirements etc. As reported in literature there is trend to use computerized numerical techniques, which greatly reduce energy, time, cost etc and drastically enhances the efficiency of multi-compressor systems. The data is normally huge in size and vary in nature. Therefore data clustering is inevitable for giving an economic size to this big chunk of data [13, 16].

Data base controller depends upon selection and use of right kind of data. Data in itself has no meaning at all. The symbolic nature of data can be in the form of a graphical symbol, a numeric value, a textual description, an image, a signal or any other symbolic form. Raw data are numbers, characters, images or other outputs from devices to convert physical quantities into symbols, in a very broad sense. Such data are typically further processed by a human or input into a computer, stored and processed there, or transmitted (output) to another human or computer. Raw data is a relative term; data processing commonly occurs by stages, and the "processed data" from one stage may be considered the "raw data" of the next. Precisely, Data Clustering is a technique in which, the information that is logically similar is physically stored together [1]. The huge amount of data that is generated by any process contains important information that accumulates daily in databases and is not easy to extract. The clustered data gives us a better control efficiency and performance of our system rather than working with an unorganized scattered dataset. Precisely, Data Clustering is a technique in which, the information that is logically similar is physically stored together. Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters). Consequently, it is the user, which must supply this criterion, in such a way that the result of the clustering will suit their needs. In order to increase the efficiency in the database systems the numbers of disk accesses are to be minimized. In clustering the objects of similar properties are placed in one class of objects and a single access to the disk makes the entire class available [5, 7, 8]. Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters). At the very high end of the overall

taxonomy we envision two main categories of clustering, known as hierarchical and objective function-based clustering [2, 4, 6, 15].
In this paper, the clustering of quantitative data is considered. The analysis is carried out for the data as obtained from a multi-compressor system based on the factor of keeping the maximum weighted square error at the minimum level. This paper consists of an algorithm, which groups the data according to fuzzy clustering, considering the intermediate values between zero and one[10]. This paper carries the comparison among other clustering algorithms on the basis of various validation parameters there by telling us the importance of fuzzy clustering. Fuzzy clustering considers all the ambiguity in data to be a part of n- clusters, giving an extra attribute of membership function [3].

2 Multi Compressor System

This plant is used for making the food products. In this plant, temperature variations occur, so cooling is required from time to time. A robust controller is required, which can provide temperature stabilization and accurate cooling [12]. The important units of the system are engine, refrigerator and heat pump. These are shown below in figure 1. Systems having thermodynamic importance are divided into two groups. First, work developing systems which includes all types of engines producing power using thermal energy and second work-absorbing systems which include compressors, refrigerators and heat pumps etc. Source and sink contain infinite energy at constant temperature. Source temperature is always higher than the sink temperature.

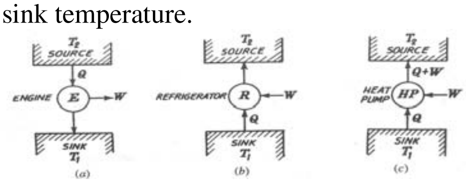

Fig. 1: Engine, Refrigerator and Heat pump

In case of the engine, for higher efficiency it is desired to get maximum amount of work W, with minimum supply of energy Q. The performance of an engine is taken into account by the ratio W/Q, which is known as efficiency (η) of the engine and is given as below.

$$\eta = W/Q \qquad (1)$$

In case of refrigerator, it is desired to maintain temperature $T_1<T_2$, where T_2 is the atmospheric temperature. For greater economy, the maximum Q must be taken from sink with the minimum amount of W, so that the performance of the refrigerator is taken into account by a ratio Q/W. The theoretical coefficient of performance (C.O.P.) is calculated as below.

$$\text{C.O.P.} = Q/W \qquad (2)$$

Also, Relative

$$\text{C.O.P.} = (\text{actual C.O.P./theoretical C.O.P}) \qquad (3)$$

The cycle used for refrigerator is also used for heat pump. The performance of the heat pump is taken into account by a ratio (Q+W)/W and it is known as energy performance ratio (E.P.R.). It is obtained as below.

$$\text{E.P.R.} = (1 + Q/W) \qquad (4)$$

Also,

$$\text{E.P.R.} = (\text{C.O.P.} + 1) \qquad (5)$$

The value of C.O.P. should be less than one or greater than one, which depends upon the type of the refrigeration system. The value of E.R.P. should always be greater than one. Figure 2 shows the multi-mode system with single compressor, which is used when numbers of loads at same temperatures are to be taken by the refrigerating plant.

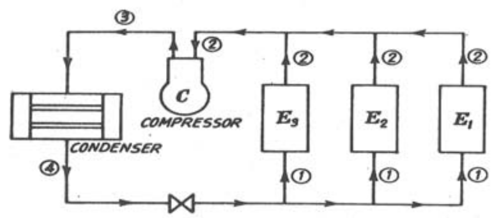

Fig. 2: Multimode systems with single compressor

The arrangement of multi-evaporators at different temperatures with back pressure valves is shown in figure 3 below. 1 is the condition of the refrigerant entering into the evaporator E_1 and leaving with condition 2.Then 8 is the condition of the refrigerant entering into the evaporator E_2 and leaving with condition 3.Then 7 is the condition of the refrigerant entering into the evaporator E_3 and leaving with condition 4.

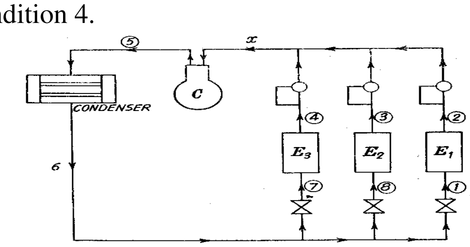

Fig. 3: Multi-evaporators at different temperatures with backpressure valves

The pressures of the refrigerants coming out of the evaporators and after leaving the back pressure valves is same and that is the suction pressure of the compressor. Table 1 as given below, provides the operational data taken over a particular period as a sample.

Table 1: Observation data for a single compressor in a multi-compressor system

S. No.	Suction pressure Kg/cm^2	Oil pressure Kg/cm^2	Delivery pressure Kg/cm^2	Current Amperes
1	3.6	5.6	10.2	120
2	3.7	5.7	11.2	128
3	3.8	6.0	11.6	133
4	3.6	5.6	12.4	136
5	3.5	5.6	12.0	142
6	2.9	4.26	11.6	156
7	2.8	4.25	10.8	176
8	2.6	5.8	10.4	190
9	2.4	5.9	9.9	200
10.	2.3	6.0	9.3	220

From the table above it is observed that while suction pressure of the compressor-system decreases current taken increases monotonically. However the two pressures viz. oil pressure and delivery pressure exhibit swing behavior.

3 Problem Formulation

Different approaches to clustering data as considered in this paper are described with the help of the hierarchy shown in figure 4. At the top level, there is a distinction between hierarchical and partitional approaches (hierarchical methods produce a nested series of partitions, while partitional methods produce only one).

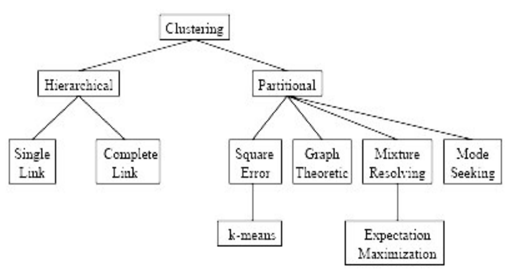

Fig. 4: Taxonomy of Clustering Approaches

Clustering techniques have been applied to data that is quantitative (numerical), qualitative (categorical), or a mixture of both. The data are typically observations of multi-compressor system as considered in this paper as a case study. Each observation consists of *n* measured variables, grouped into an *n*-dimensional row vector $x_k = [x_{k1}, x_{k2}, x_{k3}.............x_{kn}]^T, x_k \in R^n$. A set of *N* observations is denoted by $X = \{x_k \mid_{k=1,2,..........N}\}$ and is represented as an $N \times N$ matrix.

Data mining takes this evolutionary process beyond retrospective data access and navigation to prospective and proactive information delivery. Data mining is supported by three technologies viz. massive data collection, powerful multiprocessor computers and data mining algorithms. Here, in this application we have used a minimal methodology and a high-level approach to classifying the multi-compressor data. We have considered all the "variations" of each different algorithm used for solving each different formulation. We finally ended up with a very large family of clustering algorithms. We have considered two types of clustering techniques viz. parametric clustering and non-parametric clustering. Fuzzy clustering domains are shown in figure 5 below.

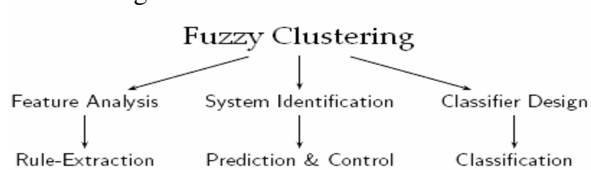

Fig. 5: Fuzzy clustering domains

The fuzzy data-clustering algorithm is used here. The relationships between the presented identification method and linear regression are exploited, allowing for the combination of fuzzy logic techniques with standard system identification tools. We have grouped m_j objects into c clusters. C = [c (1)… c(c)] is a set of prototypes or cluster centers: $c^{(i)} = \sum_{j=1}^{a} u_{ij}.m_j / \sum_{j=1}^{d} u_{ij}$ i =1, 2 . . . c. A cluster describes an equivalence class as $\left[c^{(i)}\right]_E = \{o : o \in E, E(c^{(i)}, o) = 1\}$. We have used following clustering algorithms.

3.1 Hard-c-Means clustering (k-mean clustering)

It is a powerful and most frequently used crisp clustering data mining method with standard Euclidean distance norm [11].

Let c be the number of clusters, the hard partitioning space given as

$$M_{hc} = \left\{ U \in V_{cd} : u_{ij} \in \{0,1\}, \forall (i,j); \sum_{i=1}^{c} u_{ij} = 1; 0 < \sum_{j=1}^{d} u_{ij} < d, \forall_i \right\} \ldots(6)$$

Clustering criterion (objective function, cost function) be

$$J_{hc}(M;U,C) = \sum_{i=1}^{c} \sum_{j=1}^{a} u_{ij} d_A^2 (m_{j,} c^{(i)}) \ldots\ldots\ldots\ldots.. (7)$$

Distance measure is

$$d_A^2(m_j, c^{(i)}) = \left\| m_j - c^{(i)} \right\|_A^2 = (m_j - c^{(i)})^T A (m_j - c^{(i)}) \ldots (8)$$

Hard-c-means clustering algorithm used in this work is described below.

3.1.1 Hard-c-Means Clustering Algorithm

This algorithm is given as below.

Step 1: Calculate centers of clusters; c-mean vectors as

$$c_l^{(i)} = \left(\sum_{j=1}^{d} u_{ij}^{(l-1)} . m_j \right) / \left(\sum_{j=1}^{d} u_{ij}^{(l-1)} \right), 1 \le i \le c. \ldots\ldots. (9)$$

Step 2: Update U (l): Reallocate cluster memberships to minimize squared errors by using the conditional

$$u_{ij}^{(l)} = \begin{cases} 1 \text{ if } d(m_{j,} c_i^{(l)}) = \min_{1 \le k \le c} d(m_j, c_k^{(l)}) \\ 0 \text{ otherwise.} \end{cases} \ldots.(10)$$

Fuzzy clustering algorithm used in this work is described below.

3. 2 Fuzzy Clustering

Fuzzy C-means clustering method is used with standard Euclidean distance norm [14]. It includes fuzzy partition space give as

$$M_{fc} = \left\{ U \in V_{cd} : u_{ij} \in [0,1], \forall (i,j); \sum_{i=1}^{c} u_{ij} = 1; 0 < \sum_{j=1}^{d} u_{ij} < d, \forall_i \right\} \ldots(11)$$

Fuzzy objective function is a least-square functional given as

$$J_{fc}(M;U,C) = \sum_{i=1}^{c} \sum_{j=1}^{d} (u_{ij})^w d_A^2(m_{j,} c^{(i)}), \quad w \in [1, \infty). \ldots (12)$$

Weighting factor considered are

- $w \to 1$: hard, crisp clustering.
- $w \to \infty : u_{ij} \to 1/c.$
- Typical values: 1.25 and 2.

The designed and implemented high-level partition fuzzy clustering algorithm is given below.

3. 2. 1 Fuzzy Clustering Algorithm

This algorithm is given as below.

Step 1: Select an initial fuzzy partition of the N objects into K clusters by selecting the N × K membership matrix U. An element uij of this matrix represents the grade of membership of object x_i in cluster c_j. Typically, $u_{ij} \in [0, 1]$

Step 2: Using U, find the value of a fuzzy criterion function, e.g., a weighted squared error criterion function, associated with the corresponding partition. Fuzzy criterion function is given in equation 13 below.

$$E^2(\mathrm{X,U}) = \sum_{i=1}^{N} \sum_{k=1}^{K_j} u_{ij} \left\| x_i - c_k \right\|^2, \ldots\ldots\ldots\ldots\ldots\ldots. (13)$$

where $c_k = \sum_{i=1}^{N} u_{ik} x_i$ is the k^th^ fuzzy cluster center.

Step 3: Repeat step 2 until entries in U does not change significantly.

The above algorithm is implemented with the data values of multi-compressor system. This dendogram is easiest and most effective way to represent clustering. The inputs in the form of suction pressure and current are taken and output as delivery pressure of the multi compressor system is utilized. The various values of these parameters are clustered using the fuzzy clustering algorithm where each data in a cluster has a particular membership function with another cluster such that the error criterion is reduced.

3.3 Gustafson-Kessel Clustering

Fuzzy Gustafson-Kessel clustering method uses squared Mahalanobis distance norm for the purpose of clustering. The Gustafson–Kessel (G–K) algorithm and the original adaptive fuzzy clustering (AFC) algorithm are special cases of a more general algorithm [9]. The Gustafson-Kessel clustering algorithm used in this paper is described below.

3.3.1 Gustafson-Kessel Clustering Algorithm

It is given as

$$J(B,U;X) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij})^m d^2(x_j, \beta_i) \ldots\ldots\ldots (14)$$

where $\mathrm{B} = (\beta_1, \ldots\ldots. \beta_c)$ is c-tuple of prototypes, $U=\{u_{ij}\}$ is the fuzzy partition matrix with u_{ij} the grade of membership of feature point x_j in cluster $i, X = \{x_1, x_2, \ldots\ldots x_n\}$ is the set of d-dimensional feature vectors, $d^2(x_j, \beta_i)$ is the distance between x_j and the prototype β_i, c is the number of clusters, and *n* is the number of feature vectors.

Thus

$$J(B,U;X) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij})^m (x_j - m_i)^T C_i^{-1} (x_j - m_i) \ldots (15)$$

where C_i denotes the convariance matrix of cluster *i*.

$$J(B,U;X) = d \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij})^m \ldots\ldots\ldots\ldots\ldots\ldots\ldots. (16)$$

$$d^2(x_j, \beta_i) = \rho_i^{1/d} \left| C_i \right|^{1/d} (x_j - m_i)^T C_i^{-1} (x_j - m_i) \ldots (17)$$

or

$$J(B,U;X)=\sum_{i=1}^{c}\sum_{j=1}^{b}(u_{ij})^{m}(x_j-m_i)^{T}C_i^{-1}A_i(x_j-m_i) \cdots\cdots (18)$$

subjected to $|A_i| = \rho_i$.

4 Simulations and Testing

The various clustering algorithms for the data of multi-compressor system have been simulated and tested. The results are shown below in each case.

4.1 K-means Clustering

The clustering plot is shown in figure 6 below

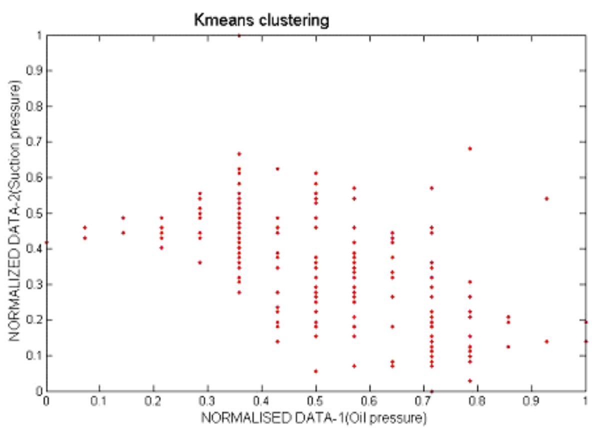

Fig. 6: K-means clustering plot with normalization of data

Various validity parameters have been calculated. In no way one parameter can be regarded as sufficient to approve or perfectly be regarded as a perfect index for the validity of clustering. Table 2 below, gives the validity parameters for this algorithm, in this case.

Table 2: Validity parameters for k-means

No of CLS	PC	CE	(SC)	(S)	(XB)	(DI)	(ADI)
2	1	-	1.074	0.002	3968	0.053	0.002
3	1	-	2.100	0.0014	Inf	0.083	0.0012
4	1	-	1.411	0.002	Inf	0.021	0.0101
5	1	-	1.123	0.01	Inf	0.040	0.0021
6	1	-	1.031	0.002	Inf	0.020	0.008
7	1	-	0.80	0.0013	Inf	0.028	0
8	1	-	0.629	0.0018	Inf	0.029	0
9	1	-	0.540	0.0015	Inf	0.037	0
10	1	-	0.658	0.0010	Inf	0.029	0

Here CLS: Cluster, PC: partition coefficient, CE: classification entropy, SC: partition index, S: separation index, XB: Xie and Beni's index, DI: Dunn's index and ADI: alternative Dunn index. The plot for variation of partition index (SC) with respect to number of clusters in k-means clustering as obtained here is shown below in figure 7 below.

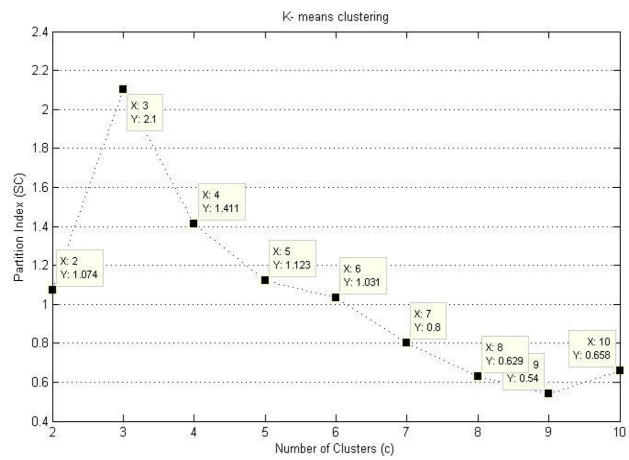

Fig.7: Variation of partition index with respect to number of clusters

4.2 Fuzzy C-Means Algorithm

The clustering plot is shown in figure 8 below.

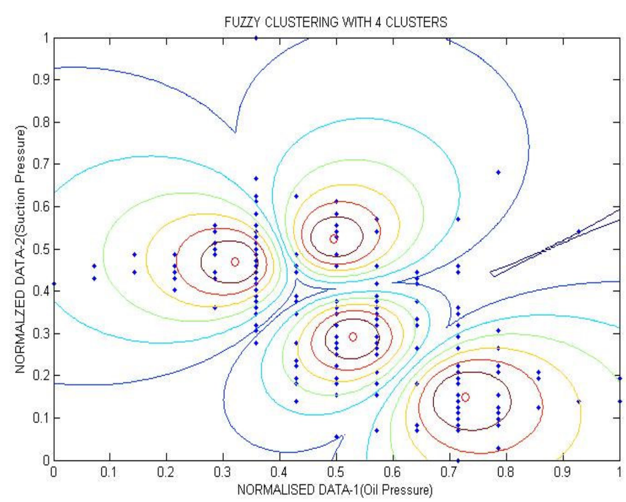

Fig.8: FCM clustering plot with normalization of data

Table 3 below, gives the validity parameters for this algorithm, in this case.

Table3: Validity parameters for Fuzzy clustering

No. of CLS	(PC)	(CE)	(SC)	(S)	(XB)	(DI)	(ADI)
2	0.814	0.303	1.787	0.003	4.247	0.016	0.0645
3	0.705	0.527	2.017	0.005	5.193	0.020	0.0050
4	0.639	0.696	1.829	0.004	3.367	0.019	0.0037
5	0.577	0.828	1.399	0.004	3.125	0.026	6.7162e-004
6	0.579	0.886	1.565	0.003	3.714	0.024	0.0011
7	0.569	0.928	1.181	0.002	3.266	0.027	0
8	0.588	0.921	1.101	0.002	3.010	0.027	0
9	0.581	0.962	1.130	0.003	3.255	0.0275	0

The plot showing the variation of partition index with respect to number of clusters in fuzzy clustering algorithm is shown below in figure 9 below.

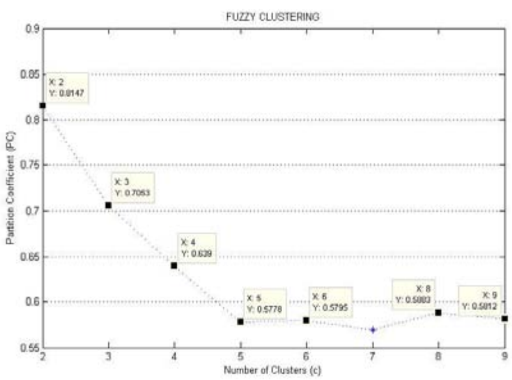

Fig.9: Variation of Partition coefficient with respect to number of clusters

4.3 Gustafson-Kessel Clustering Algorithm

The clustering plot is shown in figure 10 below.

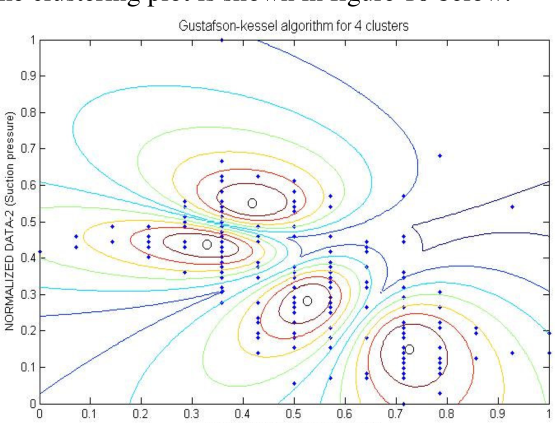

Fig.10: Gustafson-Kessel clustering plot with normalization of data

Table 4 below, gives the validity parameters for this algorithm, in this case.

Table 4: Validity parameters of Gustafson Kessel algorithm for clustering

No. of CLS	(PC)	(CE)	(SC)	(S)	(XB)	(DI)	(ADI)
2	0.801	0.324	1.845	0.003	4.085	0.0148	0.0249
3	0.715	0.512	1.982	0.005	5.602	0.0168	0.0085
4	0.660	0.659	1.621	0.004	2.635	0.0190	0.0018
5	0.615	0.765	1.311	0.003	4.334	0.0214	8.0667e-004
6	0.729	0.554	1.169	0.002	7.281	0.0192	3.1483e-013
7	0.803	0.398	0.860	0.002	10.91	0.0192	0
8	0.783	0.459	0.820	0.002	7.285	0.0192	0
9	0.898	0.202	0.334	0.001	8.620	0.0385	0

The plot showing the variation of partition index with respect to number of clusters Gustafson Kessel algorithm is shown below in figure 11 below.

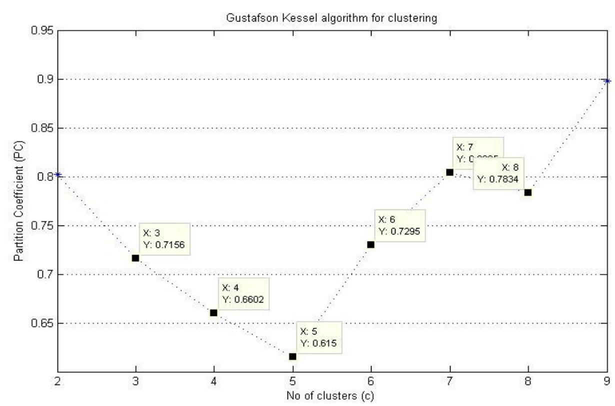

Fig.11: Variation of Partition coefficient with respect to number of clusters for

5 Results and Discussions

The results depend on the data being used. In this paper for the purpose of comparison of various contemporary data clustering algorithms, two pressure variables viz. oil pressure and suction pressure of multi-compressor system are considered. From the simulation and testing plots we infer that Kmeans finds a good solution for the clustering problem, when it is compared with fuzzy clustering algorithms. The only difference between them stands in the shape of the clusters. The Gustafson-

Kessel algorithm can finds the elongated clusters better, but as we increase the number of clusters we get straight lines. On the score of the values of the Partition Coefficient and Xie Index and Beni's Index, the fuzzy clustering has best results for this multi-compressor data sets. Table 5 below summarizes the data clustering performances of various considered data clustering algorithms in the case.

Table 5: Comparison of various data clustering techniques

Clustering Algorithms	(PC)	(CE)	(SC)	(S)	(XB)	(DI)	(ADI)
K-means	1	-	1.411	0.002	Inf	0.021	0.0101
Fuzzy Cluster	0.6390	0.6965	1.8297	0.0047	3.3675	0.0190	0.0037
Gustafson Kessel	0.6602	0.6597	1.6219	0.0042	2.6353	0.0190	0.0018

6 Conclusion

A partition clustering like the k-means algorithm cannot separate structures (patterns) properly, which have been easily achieved by fuzzy clustering. The single-link algorithm works well on this data but is computationally expensive. A hybrid approach may be used to exploit the desirable properties of both these algorithms. It increases the efficiency of the decision making task. Also in several applications involving large data sets, clustering is used to perform indexing, which helps in efficient decision making. Here, the fuzzy data clustering algorithm for the multi-compressor system enhances its controller's efficiency by 10-15%.

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