Segregation of Machines According to the Noise Emitted by Different Mechanical Methods by Hierarchical Clustering Method

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Abstract:- The main motivation of this work deals with the hearing system the most negative effects are caused by noise exposure and this may cause permanent deafness. This effect has very important influence on workers' health, so it is necessary to develop mathematical models and identification of similar noise producing machines. In this work a study of noise, emitted from different press machines of a press shop in West Bengal have been discussed. Different noise parameters such as L_{Aeq} (equivalent continuous Aweighted sound level), L_{AE} (sound exposure level), L_{AV} (average sound level) and TWA (Time weighted average level) are taken by a precision noise dosimeter (Model-4444). For this Johnson's Algorithm of Hierarchical clustering method is applied. Clustering is a popular data mining technique for partitioning a dataset into a set of clusters (i.e. segmentation). Hierarchical Clustering is a graph based algorithm that calculates the Euclidean distance of the different machines in terms of noise exposure parameters - L_{Aeq} (equivalent continuous A-weighted sound *level)*, *L*_{AE} (sound exposure level), *L*_{AV} (average sound level) and TWA (Time weighted average level). It forms the distance matrix. The matrix is then reduced step by step until all the machines are clustered. Then it constructs the dendrogram i.e. graphical representation of the hierarchical clustering thus formed. The dendrogram forms one cluster containing all the machines at some point of distance. The dendrogram is then cut following a threshold value that is set earlier. It leads to the segregation of machines into clusters. Johnson's algorithm has two components - Singlelink and Complete-link. In this paper, we have considered both the components leading to two different formations of clusters.

Keywords:- *Distance matrix, dendrogram, threshold value, Single-link, Complete-link.*

I. Introduction

Clustering is a popular data mining technique for partitioning a dataset into a set of clusters (i.e. segmentation). Hierarchical clustering algorithms can be classified into two categories namely Agglomerative and Divisive. Generally, agglomerative clustering can be applied with the help of clubbing of objects to form single cluster. Divisive clustering involves partitioning of the objects into clusters. In this paper, agglomerative clustering is applied on machines in such a way that all the machines club together to form the clusters. This process is repeated until a certain threshold value is obtained to the formation of certain number of clusters.

The machines are clustered according to the noise they produce and the data are collected from [4]. The experimental results have been shown in different Tables and finally with the help of two figures. In this work, total ten numbers of machines are used with the help of various relevant parameters. The data taken from the paper [4] is given as under:-

Table – I: Noise parameters for various mechanical machines

Mashina Truna /	т	T	T	TWA
Machine Type /	L _{Aeq}	L _{AV}	L _{AE}	
Sound Level	(dB)	(dB)	(dB)	(dB)
Power Press				
1(100 T)	98.2	128	98	73.4
Power Press				
2(100 T)	99.9	120.6	97.6	57.9
Power Press				
3(100 T)	111.5	126.5	108.5	59.4
Power Press				
4(100 T)	100.6	128.7	100.3	72.9
Power Press				
5(100 T)	98	117.5	97.2	55.5
Power Press				
6(100 T)	96.2	125.2	95.9	70
Power Press				
7(100 T)	98	127	97.7	71.9
Power Press				
1(150 T)	97.6	127.3	97.2	72.4
Power Press 1				
(25 T)	98.5	128.1	98.5	73.5
Grinding				
Machine - 1	91.6	117.1	91.5	59.8

II. Classification of machines

The available data shows that each machine has four dimensions. The machines are named as $1, 2, \dots 10$ as there are 10 machines. So, the data table becomes: -

M/C	L _{Aeq}	L _{AV}	L _{AE}	TWA
1	98.2	128	98	73.4
2	99.9	120.6	97.6	57.9
3	111.5	126.5	108.5	59.4
4	100.6	128.7	100.3	72.9
5	98	117.5	97.2	55.5
6	96.2	125.2	95.9	70
7	98	127	97.7	71.9
8	97.6	127.3	97.2	72.4
9	98.5	128.1	98.5	73.5
10	91.6	117.1	91.5	59.8

The logical distance from one machine to the other is calculated as

 $1-2 = \sqrt{(98.2-99.9)^2 + (128-120.6)^2} + (128-120.6)^2 + (12$

 $(98-97.6)^2 + (73.4-57.9)^2 \approx 17$

Similarly we can calculate the logical distance of each machine from the other. The logical distance of each machine from the other is given as an upper triangular matrix which is shown in TABLE – II.

Table – II: Logical distance between the machines – upper triangular matrix

2	1	M/ C
	0	1
0	17.2644	2
17.0420	22.0316	3
17.2740	3.4337	4
4.3749	20.7687	5
13.5702	5.2735	6
15.5106	1.8385	7
16.1428	1.5780	8
17.3891	<u>0.6000</u>	9
11.0436	19.7378	10

4		0	21.0848	7.7058	4.1725	4.5629	2.8931	21.5548
5			0	16.5671	18.9594 4.1725	19.5400 4.5629	20.9356 2.8931	
6				0	3.6510	3.7175	5.7193	17.9950 14.4972 9.5969
7					0	0998.0	2.1587	17.9950
8						0	2.0857	4
9							0	1
10								0

III. Single link

In the upper triangular matrix, logical distance of 1-9 is the minimum. So, we will cluster 1 and 9 together.In Single Link Clustering when we are considering how to populate the cells having index (AI, B), then the cell is to be populated by the minimum of the two.

Ex-Cell(AI, B) = Min((A,B), (B,I))

The minimum rule is applied in the next iterations of the Single Link.

Table – III: Clustering after 1st iteration

h	-	_							
M/C	1,9	2	3	4	5	6	7	8	10
1,9	0	17.2644	21.6880	2.8931	20.7687	5.2735	1.8385	1.5780	19.7378
2		0	17.0420 21.6880	19.3168 17.2740 2.8931	4.3749	22.5144 13.5702 5.2735	21.3399 15.5106 1.8385	22.1481 16.1428	21.5548 27.8124 11.0436 19.7378
3			0	19.3168	20.1532	22.5144	21.3399	22.1481	27.8124
4				0	21.0848 20.1532 4.3749	7.7058	4.1725	4.5629	21.5548
5					0	16.5671 7.7058	18.9594 4.1725	19.5400 4.5629	9.5969

6			0	3.6510	3.7175	14.4972
7				0	0.8660	17.9950
8					0	20.1321 17.9950 14.4972
10						0

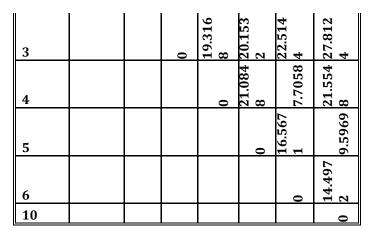
Now, the logical distance between 7 and 8 is minimum. So, we cluster 7 and 8 which is shown in TABLE – IV.

Table – IV: Clustering after 2nd iteration

M/C	1,9	2	3	4	5	6	7,8	10
1,9	0	17.264 4	21.688 0	2.8931	20.768 7	5.2735		17.995 0
2		0	17.042 0	0 0		13.570 2	15.510 6	11.043 6
3			0	19.316 8		22.514 4	21.339 9	27.812 4
4				0	21.084 20.153 8 2	7.7058	4.1725	1.554
5					0	16.567 1	18.959 4	2 9.5969 8
6						0	-	14.497 2
7,8							0	17.995 0
10								0

Now, the logical distance between 1,9 and 7,8 is minimum. So, we cluster 1,9,7,8 which is shown in TABLE – V.

-							
M/C	1,9,7, 8	2	3	4	5	6	10
1,9,7, 8	0	15.510 6	21.339 9	2.8931	18.959 4	3.6510	17.995 0
2		0	17.042 0	17.274 0	4.3749	13.570 2	11.043 6



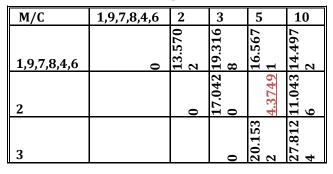
Now the logical distance between 1,9,7,8 and 4 is minimum. So, we cluster 1, 9,7,8,4.

Table –VI: Clustering after 4th iteration

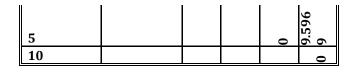
M/C	1,9,7,8,4	2	3	5	6	10
1,9,7,8,4	0	15.510 6	19.316 8	18.959 4	3.6510	17.995 0
2		0	17.042 0	4.3749	13.570 2	11.043 6
3			0	20.153 2	22.514 4	27.812 4
4				0	16.567 1	9.5969
5					0	14.497 2
10						0

Now the logical distance between 1,9,7,8,4 and 6 is minimum. So, we cluster 1,9,7,8,4,6.

Table – VII: Clustering after 5th iteration



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Now the logical distance is minimum between 2 and 5. So, we cluster 2, 5.

	1,9,7,8,4,			
M/C	6	2,5	3	10
1,9,7,8,4,		13.570	19.316	
6	0	2	8	14.4972
			17.042	
2,5		0	0	9.5969
3			0	27.8124
10				0

Table- VIII: Clustering after 6th iteration

We stop our iterations over here as our threshold value is taken as 5. That means we put the elements whose distance is less than or equal to five (<= 5) in the same cluster.

So we derive the clusters (1,9,7,8,4,6), (2,5), 3 and 10. Dendrogram is drawn for pictorial representation of the clustering thus formed.

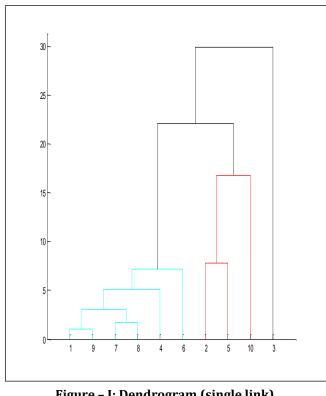


Figure - I: Dendrogram (single link)

IV. Complete link

We take our threshold value as 5. Similar to the Single Link Clustering; we start with the upper triangular matrix and move in similar fashion as the Single Link Clustering but when we are considering how to populate the cells having let us say A, I at the horizontal index, then the cell is to be populated by the maximum of the two.

Ex-Cell(AI, B) = Max((A, B), (B, I))

This is true for any cell.

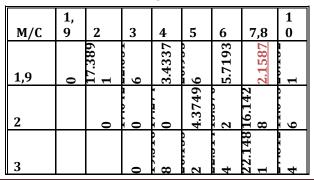
The cell 1, 9 has the minimum value. So 1 and 9 cluster together.

Table –	IX:	Clustering	after	1 st	iteration
rubic	1111	onustering	, uncer	-	nerution

M/C	1,9	2	3	4	5	6	7	8	10
1,9	0	11	9 I CO'77	3.4337	9	5.7193	2.1587	2.0857	zu.13z 1
2		0	0 0	0 1/	4.3749 6	2 2	9 01C'CI	8	9 6 1 0
3			0	01C.71	2 2	41 C.22	6 6	1 1	27.012 4
4					1 00-т 7	7.70584	4.1725		1.JJF
5						1 100.01	< C C - D	0	2 9.5969 8
6						0	3.6510 4	3.7175	2
7							0		00 00
8								0	10.20 14
10									0

Similarly, here (7,8) has the minimum value. So we cluster 7,8 together.

Table - X: Clustering after 2nd iteration



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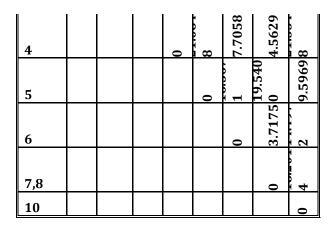


Table - XI: Clustering after 3rd iteration

M/C	1,9,7,8	2	3	4	5	6	10
1,9,7,8	0	17.3891	22.1481	4.5629	20.9356	5.7193	20.1321
2		0	17.0420 22.1481	17.2740 4.5629	4.3749	13.5702	11.0436
3			0	19.3168	20.1532	22.5144 13.5702 5.7193	21.5548 27.8124 11.0436 20.1321
4				0	21.0848 20.1532		21.5548
5					0	16.5671 7.7058	
6						0	14.4972 9.5969
10							0

Table – XII: Clustering after 4th iteration

M/C	1,9,7,8	2,5	3	4	6	10
		20.935 6	22.148 1	5629	5.7193	701
1,9,7,8	0	20. 6	22. 1	4.5	5.7	zu. 1
				084	67	C1
2,5		0	20.153 2	21.08 8	16.567 1	9 9
				16	14	71
3			0	19.316 8	22.514 4	4 4

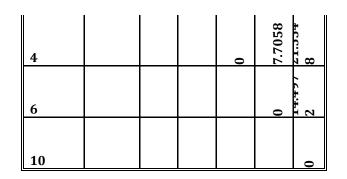
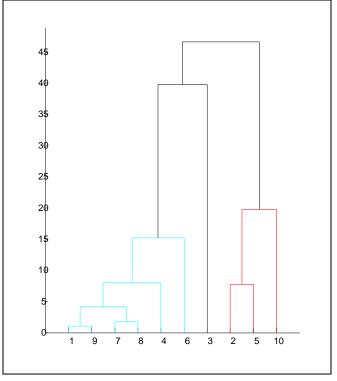


Table - XII: Clustering after 4th iteration

M/C	1,9,7,8,4	2,5	3	6	10
1,9,7,8,4	0	21.0848	22.1481	7.7058	21.5548
2,5		0	20.1532	16.5671	11.0436
3			0	22.5144	27.8124
6				0	14.4972
10					0

Finally, through this approach the clusters formed are: (1,9,7,8,4), (2,5), 3, 6, 10.

Dendrogram is drawn for representing the clustering pictorially.





IV. Conclusion

The machines are classified on the basis of similarity of the levels of noises they produce. We have used Johnson's algorithm to cluster machines. The process is done by

clubbing one machine with the other through the process of iteration. The entire data is taken from another paper which was written as a result of a detailed experiment in apress shop. So basically, we dealt with secondary data. Our result may be of particular importance to the press shop. This paper may be of particular importance to the press shop that might go for replacement of part of the machines those of which are producing similar levels of noise. After replacement of faulty parts of the machines, the damage to the ears of the workers may be reduced and it might lead to increase in productivity of each worker and more important is that environmental degradation may be reduced.

V. Relevance of the work

Using this clustering method, for identifying similar high noise-producing machines, we may plan for a better preventive maintenance for more noise exposure of machines. This will ensure better productivity of the workers in the shop floor.

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