

A STATISTICAL APPROACH FOR LANDFILL CLASSIFICATION IN SRI LANKA BASED ON WASTE CHARACTERISTICS

N.K. Wijewardane

Post Graduate Institute of Agriculture, University of Peradeniya, Sri Lanka

E-mail: nkw.pdn@gmail.com

Koide Takahiro

Institute for Environmental Science and Technology, Saitama University, Japan

Kawamoto Ken

Institute for Environmental Science and Technology, Saitama University, Japan

M.I.M. Mowjood

Department of Agricultural Engineering, Faculty of Agriculture, University of Peradeniya, Sri Lanka

E-mail: mowjood2010@gmail.com

G.B.B. Herath

Department of Civil Engineering, Faculty of Engineering, University of Peradeniya, Sri Lanka

Abstract

Several parameters have been used to characterize wastes in dumping sites. It is not possible to measure all the parameters and also those parameters are not equally important for management options which are decided on priority basis. In fact some parameters are closely related to other parameters. Therefore, parameters have to be clustered for classifying the wastes in dumping sites. A study was conducted to develop a statistical procedure using available tools to cluster landfills based on landfill waste characteristics. Five waste samples were collected from three landfills in the central province of Sri Lanka to compare the waste characteristics followed by the use of data to elaborate the clustering procedure. Correlation diagrams, principle component and cluster analysis have been applied for eight parameters; Moisture content, Ash content, Unit Volume mass, Lower heating value, Particle density < 2mm, Plasticity index, pH and Electrical Conductivity. Statistical analysis was able to extract two main principle components as primary, and secondary which accounted for 92.1 % of the total variability establishing two main classes which can be further improved to be more representative and precise with the increased number of samples subjected to the analysis.

Keywords: Waste characteristics, Landfill classification, Clustering

1. Introduction

Proper management of waste landfills mainly depends on 'waste characteristics' which are the physical, biological and chemical properties of buried waste affecting the behaviour of waste degradation and its effects on the environment. There are many parameters which have been widely used for waste characterization in waste landfills. These can be mainly divided into three categories as gas, leachate and waste characteristics. In gas CH_4 , CO_2 , nitrogen, oxygen, ammonia, sulfides, hydrogen, carbon monoxide, and nonmethane organic compounds (NMOCs) such as trichloroethylene, benzene, and vinyl chloride can be shown as main characteristics while pH, EC, heavy metals can be considered as characteristics common to waste and leachate. BOD, TDS, TS, TSS, microbial counts and activity can be distinguished as characteristics of leachate while composition, atterberg limits, ash content, particle densities, particle size distribution and calorific values can be considered as some of the main characteristics of waste (Tchobanoglous et al., 1993).

All the aforementioned factors do not have an equal relationship with the waste decomposition process which in turn decides the landfill management strategies. These are not equally weighted either and also some components may be mutually dependant and represent each other. For instance waste characteristics together with climatic factors such as temperature and rainfall mainly decide the waste decomposition and thus producing gas and leachate. This fact infers that solid waste characteristics are of paramount importance in deciding the landfill management.

Developing countries as Sri Lanka lacks the technical and financial capability to measure all these parameters for the decision of a suitable management strategy for each landfill. In such an effort for characterization of landfills it is essential to have minimum number of acceptable, crucial parameters to enhance the feasibility of decision making for a proper landfill management system.

A statistical approach could be adopted using the techniques such as correlations, principle component analysis (PCA) and to identify the mutual relationships among these parameters and thus to reduce the number of variables (characteristics) to a minimum number of parameters in which the vital components representing most of the variability can be extracted. Using the extracted parameters, clustering procedure can be used to detect possible classes of landfill to enable the application of a tailored management strategy for each class identified (Good, 1997; Marban and Sandgathe, 2006; SAS, 2008).

This research is mainly aimed to develop a methodology to classify landfills in Sri Lanka considering waste characteristics of dumpsites which utilizes different statistical procedures to depict the variation of different waste parameters, identify parameters of importance to classify landfills and thus to discover different categories of landfills. This will be of immense importance in establishment of tailored guidelines for landfill management later and thus to assist in converting the dumpsites in to well-established environmentally sound landfills.

2. Methodology

2.1 Site selection

Easily accessible three landfills in central province of Sri Lanka including one engineered landfill, were selected for sampling in this study. First site was 'Moonplains' engineered landfill site (N 6° 35', E 80° 48') which belongs to Nuwara-Eliya municipal council (MC) which receives approximately 22 t/day of waste. The second landfill selected was Gohagoda dumpsite (N 7° 18", E 80° 37') which receives 130 t/day of waste generated mainly by Kandy municipality. Third site is the Nawadewita dumpsite (N 7° 08", E 80° 34') which had been used by both Gampola Urban council (UC) and Udapalatha Pradeshiya Sabha (PS) and has been abandoned from April 2011. The amount of waste received during that functioning period was 3-5 t/day from the Udapalatha PS and 12-15 t/day from the Gampola UC.

2.2 Sampling

Waste sampling was done in December 2011. After preliminary investigation of each site sampling points were selected considering the demarcation of waste dumping duration. At each sampling point, waste samples each weighing 10-20 kg were obtained in to polythene bags and which were tied with an air trap to preserve moisture until it reaches the laboratory for further analysis. In Gohagoda dumpsite one sampling point was selected from the slope and a waste sample was obtained from the surface as deeper layer could not be reached due to the presence of excess polythene and high compactness. In Moonplains landfill two sampling points were selected representing old and fresh waste and waste sampling was done from surface in the fresh waste point and at 20 cm depth in the old waste point to avoid landfill cover. In Nawadewita dumpsite several locations were identified as shown in Figure 1. Samples were taken from old waste dumped area at surface one sample from top and one from bottom.

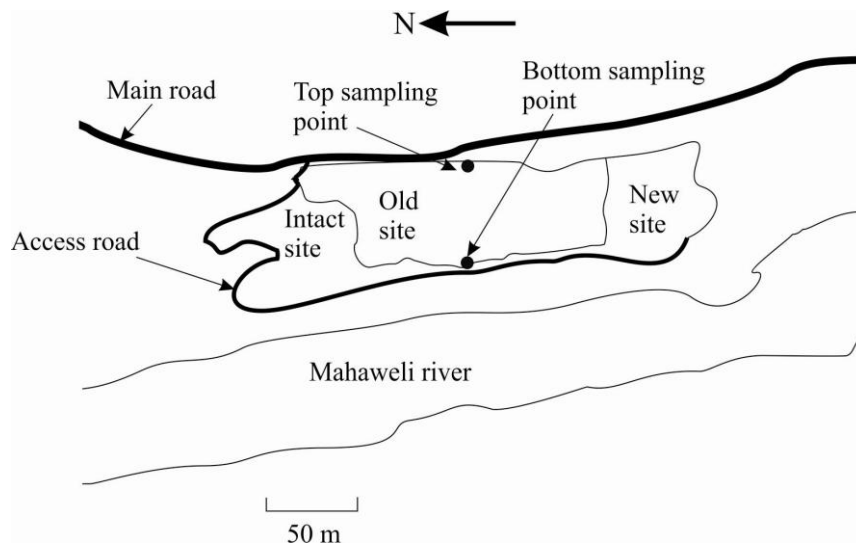


Figure 1: Map of Nawadewita dumpsite

Obtained samples were then transported to the geotechnical laboratory in the Faculty of Engineering, University of Peradeniya, Sri Lanka for further analysis of the waste characteristics.

2.3 Waste characterization

After bringing the samples to the laboratory waste samples were immediately prepared for the drying by mixing the sample on the floor with a shovel followed by composite sampling (Figure 2) and then a part of the sample containing approximately 5-10 kg, was selected for drying at 110 °C for 48 hours.

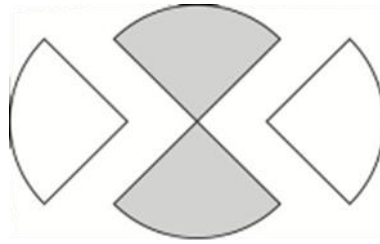


Figure 2: Conceptual diagram of divided sample into four segments

Bulk density and the moisture content were determined using the brought sample. The dried samples were then be categorized into different waste types such as Kitchen waste, Paper, Hard plastic, Soft plastic, Metal, Glass, Ceramic, Leather & Rubber, Textile, Grass & Wood, Rock, Cemented material, Aggregated soil and Others to obtain the composition of the waste followed by the determination of ash content of each category by ignition at 800 °C for two hours. Particle density of the samples were obtained according to the JIS A 1202 Japanese standards (Equivalent to ASTM D854-10) for the dried samples followed by the particle size distribution (JIS A 1204; Equivalent to ASTM D422-63). Raw parts of the samples were subjected to the analysis of pH, EC and liquid limit & plastic limit test according to the JIS A 1205 (Equivalent to ASTM D4318-10).

After the determination of ash content of the sample, combustible content (C) was calculated as follows:

$$C = 100 - M_w - A_{wet} \quad (1)$$

Where M_w is moisture content (%) and A_{wet} is the ash content (%) wet basis. Lower calorific value was calculated by proximity analysis as shown in Eq. 2 and 3 as explained by Watanabe (2000) and the reference values were obtained from a previous JICA report (2003):

$$H_{total} = \sum ((A(i) + V(i)) / (W \times H(i))) \quad (2)$$

$$H_{available} = H_{total} + 0.6 \times (\sum (M_{air}(i) + M_{ult}(i)) + 18/2 \text{ (hydrogen)}) / W \quad (3)$$

Where H_{total} is the total heat per unit mass of raw waste, $H_{available}$ is the available heat per unit mass, $A(i)$ is the ash content of i^{th} waste component, $V(i)$ is the volatile content of i^{th} waste component, $H(i)$ is the heat value of i^{th} waste component, $M_{air}(i)$ is the air dryable moisture content of i^{th} waste

component, $M_{ult}(i)$ is ultimately dryable moisture content of i^{th} waste component, 'hydrogen' is the mass of hydrogen and W is the total weight.

Ignition loss (Li) was calculated as follows:

$$Li = 100 - A_{<2mm} \quad (4)$$

Where $A_{<2mm}$ is the ash content (%) of the particles of size less than 2 mm diameter.

2.4 Data analysis

Waste characteristics data were compared using graphs drawn by MS Excel to grasp the possible variations of the waste features according to the different conditions of the landfills. Correlations among the basic parameters of waste were calculated to observe any relationships. Comparison of Eigen values used to identify possible principle factors and thus to identify main influential parameters which ultimately used for clustering to identify possible categories of landfills. SAS package was used as the software package for statistical analysis.

3. Results and Discussion

3.1 Preliminary analysis of waste characteristics

According to the Table 1 all the parameters are highly varying. In contrast to the Nuwara-Eliya old sample, the new waste has more moisture which may be due to the soil cover in the old site. This soil cover is 20 cm thick well-compacted causing less water to penetrate. In addition percentage ash, particle density, unit volume mass is lower in the Nuwara-Eliya new sample than the old sample which may be a result of decomposition of waste and the presence of soil in the old sample derived from the landfill cover. Especially ash content is higher in old sample due to the presence of these soils. Composition analysis also indicates this presence of extra soil by the increase in aggregated soil and residues. Moreover EC of the Nuwara-Eliya old sample is higher while pH is lower than the new sample which may be an indication of mobilization of acidic ions trapped in waste by decomposition. When comparing the surface samples of Nawadewita dumpsite top (UPS1) sample which was obtained from the upslope and bottom (UPS2) sample which was taken from downslope show significant variations in ash content, combustible content, ignition loss, pH and aggregated soil content which is a direct result of sliding and rolling waste dumped at the upslope (Wijewardane et al., 2012).

Figure 3 shows the average composition of waste for the analysed samples. It clearly shows that 57 % of landfill waste is soil (Residue (< 2mm) + Soil aggregates) in weight basis as the local authorities tend to cover waste with soil. Soft plastic content is the highest (7 %) of all the other waste components which is important to be addressed in landfill management.

Table 1: Comparison of waste characteristics

Parameter	Sample				
	NE Old	NE New	Gohagoda	UPS1	UPS2
Moisture content (%)	26	44	30	26	26
Ash content (%)	67	45	59	19	62
Combustible content (%)	6	9	11	57	14
Unit volume mass (kg m^{-3})	901	765	929	571	600
Lower heating value (kcal kg^{-1})	121	876	550	739	613
Particle density of < 10 mm (g cm^{-3})	2.16	1.72	2.49	2.61	2.59
pH	6.58	7.54	7.12	7.99	7.93
EC ($\mu\text{S cm}^{-1}$)	481	235	501	267	224
Ignition loss (%)	15	18	12	90	7
Particle density of < 2 mm (g cm^{-3})	2.4	2.0	2.2	2.3	2.3
Liquid limit (%)	65.3	39.3	-	58.0	42.1
Plastic limit (%)	56.5	32.1	-	57.6	41.8
Plasticity index	8.8	7.2	-	0.4	0.3
Waste composition (%)					
Kitchen waste	0.63	2.23	2.91	0.47	0.39
Paper	0.30	0.00	0.00	0.39	0.12
Hard plastic	0.04	1.23	0.15	1.62	0.70
Soft plastic	1.70	10.06	8.69	8.09	6.85
Metal	0.41	6.13	1.80	1.57	0.02
Glass	5.01	11.95	4.97	0.84	0.46
Ceramic	0.00	0.00	0.00	0.09	0.00
Leather & Rubber	0.00	1.27	0.00	0.06	0.09
Textile	0.01	0.90	0.57	3.14	4.33
Grass & wood	0.38	5.62	0.54	0.40	0.50
Rock	5.68	3.61	19.02	4.63	2.93
Cement	0.00	0.00	0.30	2.30	6.59
Aggregated soil (> 4.75 mm)	40.2	30.6	5.8	0.8	13.0
Others	0.17	0.34	0.42	1.70	0.00
Residue (2 - 4.75 mm)	21.1	10.6	11.6	10.3	15.4
Residue (< 2 mm)	24.2	15.4	43.4	62.5	47.5

* UPS1 – Nawadewita old top, UPS2 – Nawadewita old bottom, NE- Nuwara Eliya

Figure 4 shows the graphical comparison of the waste composition of the samples. According to the graph waste components are highly varying. Almost in each sample, soil account for most of its weight. Other components are highly depending on many socio-economic and management factors. According to Bandara et al. (2007) waste composition is mainly affected by average mean living standards or the average income of the people, climate, living habits, level of education, religious and cultural beliefs, and social and public attitudes. For an instance the glass content is higher in Nuwara

Eliya and Gohagoda (Kandy) samples due to the increased use of glass beverages by the floating population during vacation season. Thus the consumption pattern and the acceptance of different types of waste highly decide the landfill waste composition. Detailed studies are needed to grasp the exact variation of waste composition with those factors.

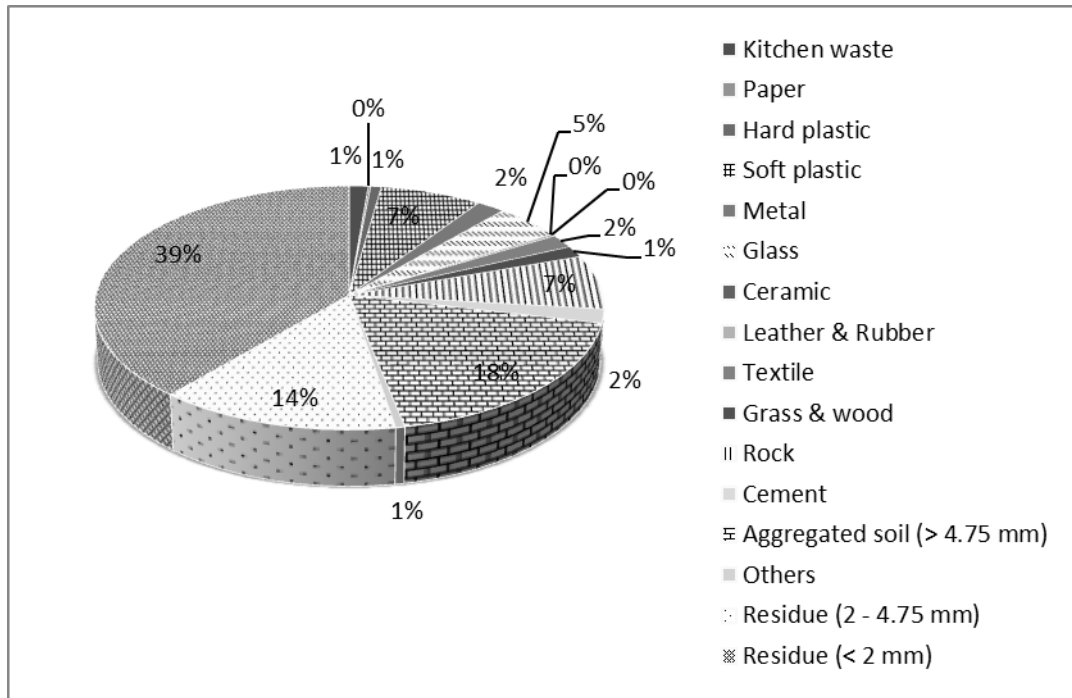


Figure 3: Average composition of landfill waste

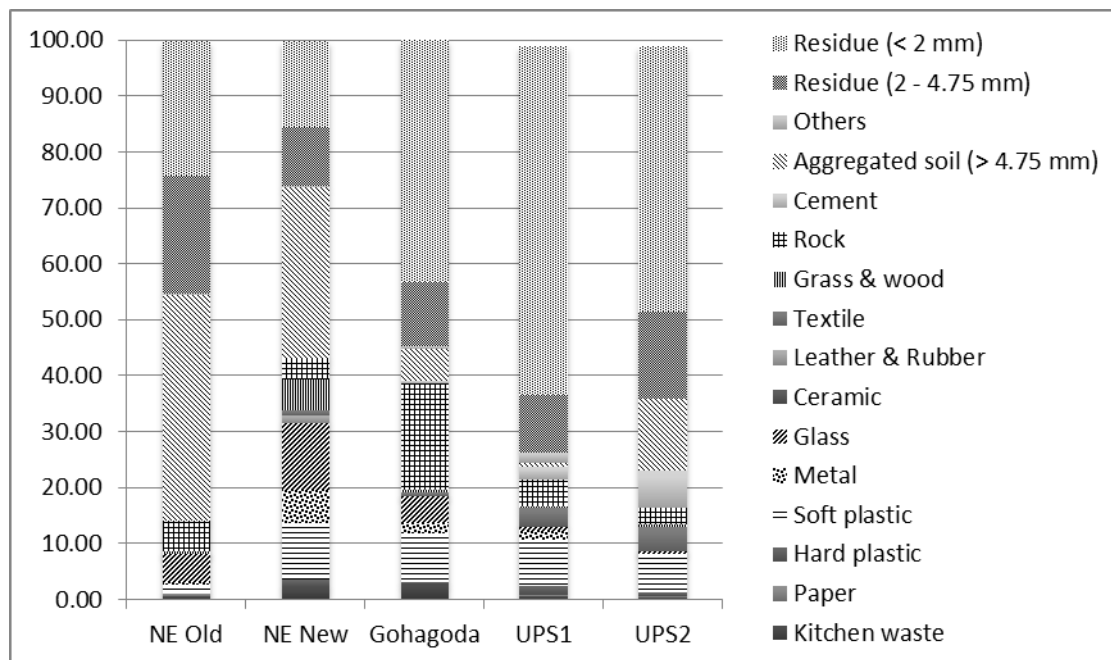


Figure 4: Comparison of landfill waste samples

3.2 Statistical analysis

Statistical analyses were performed for 8 selected parameters i.e. Electric conductivity (EC), Lower calorific value (LCV), pH, Ash content (AC), Unit volume mass (UV), Moisture content (MC), Particle density of < 2mm (PD2), Plasticity index (PI). Other waste composition data were not used for the statistical analysis to reduce the redundancy of variables otherwise the number of variables becomes considerably higher than the observations decreasing the accuracy of the analysis. Correlations of these 8 selected parameters were evaluated for their relationships and the developed correlation matrix is shown in Table 2.

Table 2: Correlation matrix of parameters

	<i>MC</i>	<i>AC</i>	<i>UV</i>	<i>LCV</i>	<i>pH</i>	<i>EC</i>	<i>PD2</i>	<i>PI</i>
<i>MC</i>	1.00							
<i>AC</i>	-0.10	1.00						
<i>UV</i>	0.18	0.61	1.00					
<i>LCV</i>	0.58	-0.64	-0.55	1.00				
<i>pH</i>	0.03	-0.64	-0.91	0.80	1.00			
<i>EC</i>	-0.29	0.49	0.87	-0.74	-0.86	1.00		
<i>PD2</i>	-0.97	0.17	-0.06	-0.74	-0.22	0.39	1.00	
<i>PI</i>	0.46	0.46	0.97	-0.44	-0.88	0.65	-0.24	1.00

According to the table 2 there is a strong negative correlation between moisture and particle density. This may be due to the increase in soil content which causes to reduce the moisture content of the samples. This is clearly depicted by table 1 where NE old and UPS1 and UPS2 samples have low moisture (< 26 %) and higher soil contents (> 60 %) compared to other samples. According to table 2, ash content is negatively correlated to lower calorific value due to reduction of combustible content with the increment of ash content. Unit volume mass and pH is negatively related. According to Alashty *et al.* (2011), application of municipal solid waste decreases the pH and increase EC in soil due to decomposition. This may be the same scenario caused the negative correlation between pH and EC.

Table 3 shows the Eigenvalues of the Correlation Matrix in the principle component analysis. The eigenvalues of first 2 factors accounts for 92.1 % of the total variability which clearly depicts the presence of two main principle components. Table 4 shows the factor pattern of these main components. According to the table it is clear that primary principle component account for 59.7 % of total variability of the parameters while secondary principle factor for 32.4 % which all together accounts for 92.1 % of the total variability.

Table 3: Eigenvalues of the Correlation Matrix

	<i>Eigenvalue</i>	<i>Difference</i>	<i>Proportion</i>	<i>Cumulative</i>
1	4.7777045	2.18770652	0.5972	0.5972
2	2.58999806	1.95770071	0.3237	0.921
3	0.63229735	0.63229735	0.079	1
4	0	0	0	1

Table 4: Factor pattern of principle component analysis

	<i>Primary principle factor</i>	<i>Secondary principle factor</i>
MC	-22	98
AC	69	6
UV	89	45
LCV	-92	39
PH	-98	-19
EC	95	-16
PD2	43	-90
PI	76	64
Variance explained (%)	59.72	32.37

To identify the exact parameters which have higher contributions to the principle components, correlation of parameters with each component was evaluated and the results obtained are shown in Table 5. According to the results obtained, primary principle factor is mainly influenced by the unit volume mass, pH, EC and plasticity index while secondary principle factor is affected by moisture content and particle density.

Table 5: Correlation of parameters with principle components

	<i>Primary principle factor</i>	<i>Secondary principle factor</i>
MC	0.10736	0.99421
AC	0.67152	-0.16848
UV	0.98861	0.13905
LCV	-0.74381	0.66694
PH	-0.98573	0.13452
EC	0.8466	-0.45839
PD2	0.11586	-0.99059
PI	0.92414	0.35818

The primary principle factor indicates the age of the sample as its main components i.e. UV, pH, EC and PI are clearly varying with the age of the samples which can be observed by comparing the NE Old and NE New samples in Table 1. Secondary principle component represent the degree of soil contamination in the samples as it is mainly influenced by the particle density. Using these main principle components cluster analysis was done and the results are shown in figure 7 as a dendrogram. UPS1 and UPS 2 samples are in a same cluster as they are obtained from the same site leading to have similar age and soil contamination level. The difference of the Gohagoda sample with all other samples in this analysis indicates that there should be other kind of factors to describe characters of the samples which could not be recognized due to the limitation of sample numbers. Hence the recommendation is to have higher number of observations. When this clustering procedure is applied with adequate number of samples obtained from the landfills representing whole country, better clusters can be obtained

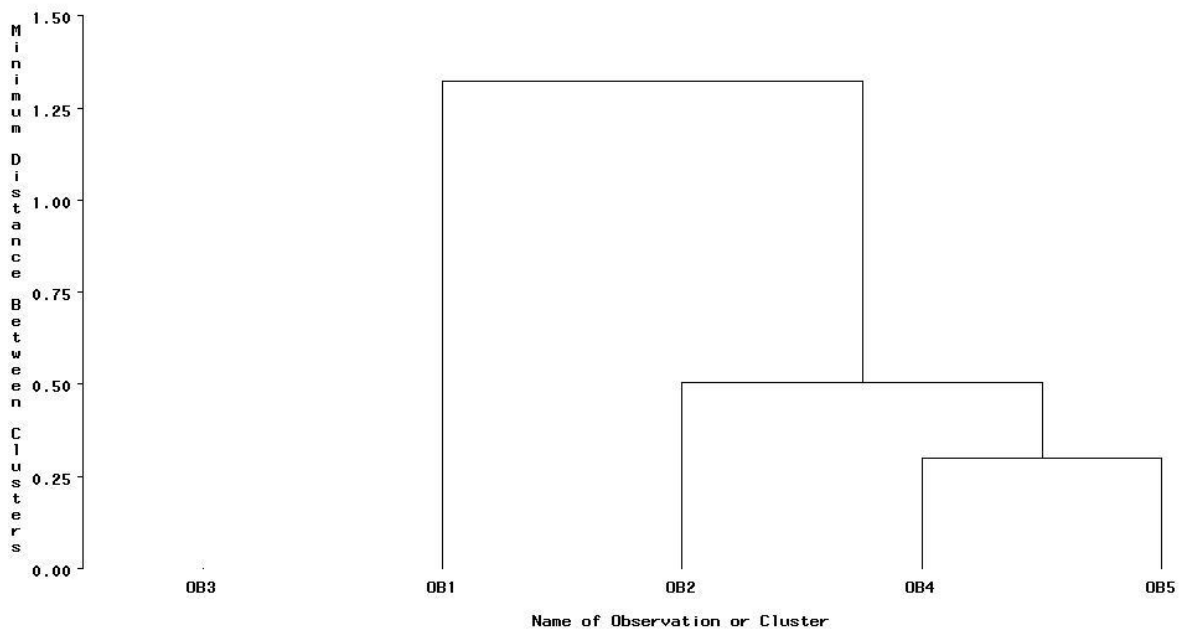


Figure 7: Dendrogram of sample clustering (OB1 –NE old, OB2 – NE new, OB3 – Gohagoda, OB4 – UPS 1, OB 5 – UPS 2)

4. Conclusions and Recommendations

The developed statistical procedure is well suited to categorize landfills in the country and to identify the influential parameters to be considered during such an effort to make the clusters. Nevertheless the available data is not enough for making rigid decisions on classification and need a comprehensive study to obtain more waste samples from all over the country which will lead to more accurate principle characteristics and a well-established classification system.

5. Acknowledgements

Authors thank all the members of the SATREPS project funded by Japanese International Cooperation Agency and Japan Science and Technology Agency which provided the financial support for this research and the gratitude should go to all the academic and non-academic staff of Environmental laboratory and Geotechnical laboratory of the Faculty of Engineering, University of Peradeniya, Sri Lanka for their support in the laboratory analysis.

References

- Alashty S. R., Bahmanyar M. A. and Sepanlou M.G. (2011). *Change of pH, organic carbon (OC), electrical conductivity (EC), nickel (Ni) and chrome (Cr) in soil and concentration of Ni and Cr in radish and lettuce plants as influenced by three year application of municipal compost*, African Journal of Agricultural Research, Vol. 6(16), pp. 3740-3746.
- Bandara N.J, Hettiaratchi J.P, Wirasinghe S.C, Pilapiiya S. (2007). *Relation of waste generation and composition to socio-economic factors: a case study*, Journal of Environmental Monitoring and Assessment, Vol. 135, No. 1-3.
- Good, I. J. (1977), —*The Botryology of Botryology*, in Classification and Clustering, ed. J. Van Ryzin, New York: Academic Press.
- JICA (2003), *The study on improvement of solid waste management in secondary cities in Sri Lanka*, KOKUSAI KOGYO CO., LTD.
- Marzban, C., S. Sandgate (2006), *Cluster analysis for verification of precipitation fields*. Wea. Forecasting, Vol. 21, No. 5, 824-838.
- SAS/STAT 9.2 user guide (2008).
- Tchobanoglous G., Theisen H. and Vigil S. (1993). *Integrated solid waste management*. Published by McGRAW-HILL.
- Watanabe N. (2000), *Proximate Analysis, Heat Measurement and Elemental Analysis of Waste*, Journal of the Japan Society of Waste Management Experts, Vol. 11, No.6.
- Wijewardane N.K., Koide Takahiro, M.I.M. Mowjood, Kawamoto Ken, L. C. Kurukulasuriya (2012). *Characteristics of municipal solid wastes from selected plots located at up-slope and down-slope of the dumping site: A case study in Udapalatha/Gampola*, in Proceedings of the International Symposium on Advances in Civil and Environmental Engineering Practices for Sustainable Development.