Invention Journal of Research Technology in Engineering & Management (IJRTEM)
ISSN: 2455-3689
www.Ijrtem. com Volume 3 Issue 6 ǁ September-October 2019 ǁ PP 27-34

Assessment of Food Waste Resources Recycling in Composting Process Using Multivariate Statistical Methods

[1,]Shu-Lung Kuo, [2,]Ching-Lin Ho

[1,2.] Department of Technology Management, Open University of Kaohsiung, Taiwan

ABSTRACT: *This study disseminated survey questionnaires, mostly to environmental protection-related personnel, public institutions, factories and units engaged in composting operations, and academic units and scholars endeavored in compost recycling to investigate the four most commonly used kitchen waste composting methods in Taiwan, and perform multivariate statistical analyses (i.e., factor analysis and cluster analysis) on the survey results to identify the characteristics, advantages, and disadvantages of the kitchen waste composting methods. The goal was to identify the major factors influencing the four composting methods and the relationships among these factors. The factor analysis showed two major factors of influence on the four composting methods, which were static composting factors and improved composting factors; the former exhibited stronger influence. The cluster analysis divided the four kitchen waste composting methods into four different groups, which successfully represented the differences among the kitchen waste composting methods currently employed in Taiwan. The analysis results revealed factors influencing current kitchen waste composting methods adopted in Taiwan which, combined with the multivariate statistical analyses on the questionnaire survey, can be used as reference for Taiwan's environmental protection agencies to formulate more stringent composting regulations and for compost businesses to improve waste management in the future.*

KEYWORDS: *compost recycling, kitchen waste, multivariate statistical analyses, factor analysis*

I. INTRODUCTION

In Taiwan, the government successfully launched a national-wide household food wastes recycling program in 2006, and more than 2,500 metric tons are collected daily. The food wastes typically comprise uneaten food and food preparation leftovers from residences, commercial establishments such as restaurants, institutional sources such as school cafeterias, and industrial sources such as factory lunchrooms (Zhang et al., 2007; Wang et al., 2015). Contents of food wastes include grains, fruits, vegetables, rice, noodles, breads, seafood, fish and meat, etc. Thus, the organic contents and the nutrients are of value to be recycled and composted (Zhang et al., 2007; Lin, 2008). Similar demands are also obvious in the major cities of the developing Asian countries, such as India, Korea, Hong Kong, Vietnam, Thailand, and China (Kumar et al., 2010; Lin et al., 2012).

Composting, which is increasingly used to treat organic household waste (Sundberg et al., 2004; Saldarriaga et al., 2014), is the most natural recycling method among various organic waste-disposal methods, because during composting, biological reactions mediate the self-cleaning of the environment (Tai and He, 2007; Lin et al., 2011). Composting is attractive and inexpensive method for treatment and biomass disposal of water hyacinth. However, the major disadvantage of water hyacinth composting is the high content of heavy metals in the final compost. Thus, composting, which causes little environmental pollution and facilitates the beneficial use of the end products, is a favorable option available for treating food wastes (Kim et al., 2008; Adamcova et al., 2015). In addition, composting is an automated process in the developed countries and monitoring is carried out by detectors and suitable equipment in the composting units, thereby the measurements indicating the actual exposure levels undergone by the workers. Nevertheless, operation is totally manual in the developing countries. Thus, the workers are placed on the upper level of the bed and turn it. Therefore, they are exposed to concentrations close to those corresponding to the equilibrium with air, which are much higher than those monitored by the measurement devices because the gaseous stream leaving the bed is rapidly diluted with the surrounding air prior to reaching the device. In addition, enzymatic activity was explored as a possible tool for composting process characterization (Mondini et al., 2004), and a high proportion of biodegradable matter may sustain high microbial activity (Gomez et al., 2006). Important enzymes involved in the composting process include the following: dehydrogenases, constituting an indicator of oxidation of simple organic sources of carbon and of respiratory activity of microorganisms, proteases, and ureases that participate in mineralization of nitrogen, and cellulases, which depolymerize cellulose and lipases, which are related to biodegradation of fats. Thus, enzymatic activities could apparently give interesting information on the rate of decomposition of organic matter and, therefore, on the product stability (Jurado et al., 2014; Voberkova et.al., 2017).

This study conducted a questionnaire survey on the most commonly used kitchen waste composting methods in Taiwan and performed multivariate statistical analyses (i.e., factor analysis and cluster analysis) to investigate the characteristics, advantages, and disadvantages of four kitchen waste composting methods. The goal was to identify the major factors influencing the four composting methods, the relationships among these factors, and the characteristics, advantages, and disadvantages of the kitchen waste composting methods.

II. METHODOLOGY

Kitchen Waste Composting Methods Selected: Currently, Taiwan mostly uses the following kitchen waste composting methods: aerated static-pile composting, traditional composting, machine-based kitchen waste composting, and aerobic reactor composting. Thus, this study researched and analyzed these composting methods.

Questionnaire Survey Content : This study used questionnaires to survey the four most commonly used kitchen waste composting methods in Taiwan and conducted multivariate statistical analyses (i.e., factor analysis and cluster analysis) on the survey results. The questionnaire survey employed both internal and external environmental assessment indicators. The internal environmental assessment indicators consisted of 10 indicators (i.e., maturity of the operating technology, supply source stability, human load size, stench severity, difficulty implementing a composting method, required processing time, nutrient utilization, fat content utilization, product stability, and product quality requirements), while the external environmental assessment indicators consisted of six indicators (i.e., market acceptance, operation and maintenance costs, required land size, extent of environmental quality improvement, market sales, and policy stability). Subsequently, this study utilized a 5-point Likert scale (Lin et al., 2011) to evaluate the influences of the 16 assessment indicators for each of the four kitchen waste composting methods. For instance, for “difficulty implementing a composting method”, this study divided it into five categories (i.e., extremely difficult (1 point), difficult (2 points), neither easy nor difficult (3 points), easy (4 points), and extremely easy (5 points)) to assess how difficult it was to implement the kitchen waste composting method.

Survey Questionnaire Content and Results: This study disseminated the survey questionnaires mostly to environmental protection-related personnel, public institutions, factories and units engaged in composting operations, and academic units and scholars endeavored in compost recycling to identify the current situation of converting kitchen waste into resources in Taiwan. Next, this study conducted factor analysis and cluster analysis on the survey results. A total of 74 questionnaires were sent out in April 2019, of which 60 valid questionnaires were returned in June 2019, posting a valid response rate of 81.1%. The questionnaire participants are listed as follows: (1) environmental protection-related personnel: primarily personnel and businesses working in environmental protection-related industries in Taiwan, who had a good understanding of, and concerns for, environmental protection-related issues (a total of 31 questionnaires were disseminated, of which 26 were returned, posting a valid response rate of 83.9%); (2) academic research institutions and scholars: mostly institutions, scholars, and professors from public or private colleges and universities engaged in kitchen waste recycling-related research (a total of 23 questionnaires were disseminated, of which 18 were returned, posting a valid response rate of 78.3%); and (3) public institutions as well as domestic factories and units engaged in composting operations (public and kitchen waste-related agencies) (a total of 20 questionnaires were disseminated, of which 16 were returned, posting a valid response rate of 80.0%). The survey results are shown in Table 1.

Table 1 This study’s questionnaire survey results

Questionnaire subject	Questionnaire situation		
	Number of questionnaires issued	Number of valid questionnaires recovered	Questionnaire recovery rate (%)
Personnel engaged in the environmental protection industry	31	26	83.9
Academic agencies and scholars	23	18	78.3
Public agencies and kitchen waste-related industries	20	16	80.0
Total	74	60	81.1

Multivariate Statistical Analyses—Factor analysis: For selecting the elements to be included in factor analysis, a minimum of 70% of the samples needs to have measurable levels of the element. In principle, factor analysis actually groups the elements whose concentrations fluctuate together from one sample to another and separates these elements into “factors” (Henry et al., 1984; Martinez et al., 2012). Factor analysis is used for source apportionment in environmental data, with the argument that those elements that fluctuate together have some common characteristics. Ideally, each extracted factor represents a source affecting the samples. Factor analysis has been performed using the statgraphics plus program package (Liu et al., 2003). The initial components were rotated using the varimax method to obtain final eigenvectors with more representatives of individual sources of variation. Although there are no well-defined rules on the number of factors to be retained, usually either factors that are meaningful or factors with eigenvalues larger than 1 are retained. In theory, irrelevant factors have zero eigenvalues and eigenvalues less than 1 indicate that factor contributes less than a single variable. The physical meaning of the factors must be interpreted by observing which elements or variables display high (≥0.25) loading within the factor. Loadings less than 0.25 in absolute value may be dominated by random errors.

Multivariate statistical analyses—cluster analysis: Cluster analysis is an exploratory data analysis tool for solving classification problems. Its objective is to sort cases into groups, or clusters, so that the degree of association is strong between members of the same cluster and weak between members of different clusters. Each cluster thus describes, in terms of the data collected, the class to which its members belong; and this description may be abstracted through use from the particular to the general class or type. Hierarchical agglomerative clustering is the most common approach as it provides intuitive similarity relationships between any one sample and the entire dataset. It is typically illustrated by a dendrogram (tree diagram) (McKenna 2003). The dendrogram provides a visual summary of the clustering processes, presenting a picture of the groups and their proximity, with a dramatic reduction in dimensionality of the original data. Additionally, cluster analysis helps in grouping objects (cases) into classes (clusters) on the basis of similarities within a class and dissimilarities between different classes. The class characteristics are not known in advance but maybe determined from the analysis. The results of CA help in interpreting the data and indicate patterns (Vega et al. 1998; Tobiszewski, et al., 2010).

III. RESULTS AND DISCUSSION

Factor model analysis selected for the four kitchen waste composting methods: This study performed orthogonal rotations by using the varimax rotation method to explain the characteristics of each factor. The analysis results showed two factors with an eigenvalue greater than 1 (Table 2), indicating that two factors could be chosen. The two common factors had an eigenvalue of 1.544 and 1.213, respectively, and a cumulative explained variance of 68.910%. Table 3 shows that KMO was 0.759 (> 0.5), which signified that subsequent factor analyses could be performed according to Kaiser. Additionally, the Bartlett's Test of Sphericity showed an approximate chi-square value (χ^2) of 143.301, achieving the significance level and indicating the presence of common factors in the population correlation matrices. Therefore, subsequent factor analyses could be carried out.

Table 2. Total variance for each of the four composting methods used by kitchen waste composting factories

Components	Initial eigenvalues	% of total variance	Cumulative variance %
1	1.544	38.589	38.589
2	1.213	30.321	68.910
3	0.744	19.361	88.271
4	0.469	11.729	100.000

Table 3. KMO and Bartlett test results for the four composting methods used by kitchen waste composting factories

Kaiser-Meyer-Olkin measure of sampling adequacy		0.759
Bartlett test of sphericity	Chi-square distribution	143.01
	Degree of freedom	6
	Significance	.000

Determining the factors : For components with an eigenvalue greater than 1, the number of their main factors could be determined. By having two main factors that underwent orthogonal rotation, a component matrix was obtained, which was subsequently used to determine the variance of each variable. Table 4 shows the different component matrices after the orthogonal rotations. By rotating the matrices, the characteristics of each variable were revealed. Additionally, the two factors could be used to show the differences between the four kitchen waste composting methods.

Table 4. Loading matrix of each factor employed by the four kitchen waste composting methods

Parameters	Factors	
	1	2
Aerated static-pile composting	0.816	0.295
Traditional composting	0.751	-0.289
Machine-based kitchen waste composting	-0.237	0.762
Aerobic reactor composting	0.409	0.744

Interpreting the factors: Table 4 shows that the four kitchen waste composting methods were influenced by two factors. These factors are described in detail below:

The First Factor: The first factor entailed aerated static-pile composting and traditional composting, which had a total variance of 38.589% (Table 2). Table 4 shows that aerated static-pile composting had the highest first factor loading degree (0.816), followed by traditional composting (0.751). Aerated static-pile composting involves installing a grating-shaped ventilation grill or ventilation ducts at the bottom of the compost and having an exhaust machine that pumps or emits gas to provide sufficient air. Sometimes, fillers such as sawdust are used to control compost porosity and moisture. The composting process lasts approximately three to four weeks, and extra heat from fermentation is released during this process. By setting the compost aside for four more weeks, the compost will decompose completely (Lin et al., 2016). Because composting mostly uses aerobic microbes to decompose organic matter, blowers or fan systems are normally used to provide them with sufficient air. In general, aeration systems use positive pressure (pressure-based ventilators) or negative pressure (vacuum-based ventilators) to achieve appropriate procedural control, where negative pressure enables the collection and processing of stench. In addition, aerated static-pile composting, pipes and pressurized or gas exchange method are used. The ventilation system and turning over of the material is used to forcefully provide oxygen. Therefore, aerated static-pile composting mainly uses a container to hold kitchen waste, and then mandatorily ventilates the composting material during the process.

In traditional composting, kitchen waste is accumulated in layers in a shaded and ventilated area. The pile is turned approximately once every one or two weeks. The turning over can be done with manual labor or with an excavator (Wang et al., 2015). The natural composting method of traditional composting requires large areas of land; the secondary turnover will produce stench, and the decomposition of the kitchen waste will require several months, which makes it unsuitable for Taiwan. Natural composting is also a static accumulation method without the use of forced ventilation. Thus, the microbes in traditional natural composting method require more time to decompose the compost material, and the compost quality will be poorer. Currently, traditional accumulation/piling method is used for composting leaves in parks or schools. Wooden boards and wire mesh are used to mark out an area or a large container is used. The leaves and green waste, microbe starter, and soil are placed inside layer by layer to induce natural decomposition. Although this method is slower, it is also simple and convenient.

The two aforementioned kitchen waste composting methods mainly focus on simply and conveniently or rapidly composting kitchen waste. If high compost quality is not required, then these two methods can provide fast and simple/convenient compost (Jurado et al., 2014). However, because composting characteristics are not strictly managed during these two types of processes, the quality of the compost product is harder to control. Thus, these two types of processing methods are composting in a static environment. Summarizing the above, this first factor can be called the static composting factor.

The second factor : The second factor is mainly composed of machine-based kitchen waste composting and aerobic reactor composting. The total variance quantity of this factor is shown in Table 2, which reaches 30.321%. Table 4 shows that in machine-based kitchen waste composting, the second factor has a higher loading degree (0.762), followed by aerobic reactor composting (0.744). Machine-based kitchen waste composting uses microbes to decompose organic matter into carbon dioxide and water vapor. After using rapid BIO (low, medium, and high temperature microbes) decomposition, the volume of the kitchen waste is reduced to 1/10 - 1/40 of the original volume and then discharged from the machine. The use of this method is simple and there is no need to add microbes or fermentation agent, which saves on cost. Machines can automatically operate and process waste rapidly.

The product after processing is also very environmentally friendly and can be mixed with 10~30 times of soil to be used as fertilizer, or be used as burnable trash without causing secondary public hazard. The residual after processing is ideal agricultural fertilizer (Voberkova et al., 2017). The resulting product from this process is not harmful to humans or the living environment, and does not smell. Machine-based kitchen waste composting has both biological decomposition/fermentation reaction and physical decomposition characteristics, which not only can decrease the acid hardening of the earth caused by chemical fertilizers (resulting in gradual barren soil), but can also produce high-value organic agricultural products and outstanding green environment. Aerobic reactor composting can be perceived as composting equipment. That is, materials are placed in a bioreactor for composting. Compost material is placed in a fixing tank and mechanically stirred and hydrated (Saldarriaga et al., 2014). Compared to aeration method or aerated static-pile composting, aerobic reactor composting can produce more stable product quality and is better for controlling odor. In addition, operating factors (feed/discharge method, aeration quantity) can be controlled in aerobic reactor composting with equipment components, and can be considered a piece of semi-automatic production equipment (because the entire production process needs to include the initial material adjustment and follow-up aging). Considering the land factor and secondary pollution, aerobic reactor composting equipment is the future trend. However, this method also requires more complex machine equipment and more labor to maintain the machines. Production can also be affected by machine equipment problems. The aforementioned two types of kitchen waste composting methods primarily focus on improving the disadvantages of the first factor in traditional composting (traditional composting and aerated static-pile composting) with operating technology. In summary, this second factor is called the "improved composting factors."

Characteristic analysis of the four types of kitchen waste composting methods: cluster analysis

Exploring the results of the cluster analysis: This study mainly uses two-stage cluster analysis. First, hierarchical clustering is used to obtain the rough clustering result. Non-hierarchical clustering (K-mean method) is then used to test different cluster numbers. Finally, four clusters are chosen to differentiate the differences among the four types of kitchen waste composting methods. Fig. 1 shows the relationship between the clusters and factors. Fig. 1 shows that the first cluster had the lowest first factor and second factor scores of the four clusters. This indicates that the first cluster is obviously disadvantaged in both factors. The second cluster had the second highest score in the first factor and the highest score in the second factor. This indicates that the second cluster has an advantage in both factors. The third cluster had the lowest score in the first factor and the third lowest score in the second factor. This indicates that the third cluster is disadvantaged in both factors. The fourth cluster had the highest first factor score and the second highest second factor score. This indicates that this cluster has an advantage in both factors.

The aforementioned analysis result shows that the second cluster and the fourth cluster scored in both the first factor and the second factor. Fig. 1 results show that the second cluster and the fourth cluster received more recognition in the first factor (static composting factors) and the second factor (improved composting factors) from respondents. These two clusters also had fewer negative selections. The factor scoring of the four clusters is used to obtain the impact results for the 16 original assessment indicators (10 types of internal environmental assessment indicators and six external environmental assessment indicators). This can help us understand how questionnaire respondents perceive the advantages and the disadvantages of the four types of kitchen waste composting methods. The result is shown in Table 5.

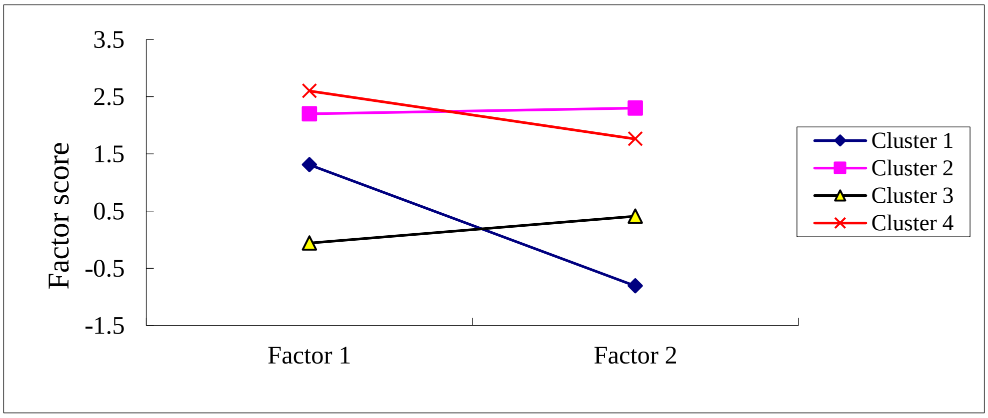

Figure 1. Correlation between clusters and factors

Table 5. Investigation analysis of the cluster variables of the four types of kitchen waste composting methods

Cluster / Processing method and level	The first cluster					The second cluster					The third cluster					The fourth cluster				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Traditional composting	30	18	27	66	3	54	183	93	12	0	144	93	27	0	0	21	102	114	114	24
Aerated static-pile composting	15	51	75	3	0	0	48	201	75	18	33	183	48	0	0	3	12	231	114	15
Aerobic reactor composting	21	84	36	3	0	0	0	78	240	24	18	84	144	18	0	0	18	180	156	21
Machine-based kitchen waste composting	51	45	48	0	0	0	0	12	195	135	0	12	90	135	27	12	78	216	69	0
Statistical result of various levels	117	198	186	72	3	54	231	384	522	177	195	372	309	153	27	36	210	741	453	60
Distribution of different levels	Primarily negative level					Primarily positive level, followed by normal level					Primarily negative level, followed by normal level					Primarily normal level, followed by positive level				
Total questionnaire statistical result	576					1368					1056					1500				

Analysis of cluster analysis results : The cluster analysis obtained clustering results. Table 5 shows the kitchen compost processing characteristics of various clusters. Here, we further analyze the clusters.

(1) The first cluster
Table 5 shows that this cluster had low scores for the two factors, especially for the second factor (improved composting factors). This cluster had almost no positive acceptance level (4 and 5) and only accounting for 0.52%; it only had a 12% positive level for the first factor (static composting factors). The first cluster had the highest negative proportion for the two factors out of the four clusters (accounting for 54.68%). This shows that the higher the negative proportion chosen for the two factors (1 and 2), the lower the positive proportion that will be chosen for the two factors. Overall, the sample size in this cluster is the smallest of the four clusters. Thus, this cluster is classified as “low acceptance compost processing factor cluster.”

The second cluster : Table 5 shows that this cluster had the highest proportion of positive level (4 and 5) in the second factor in the questionnaire survey, followed by normal level. However, this cluster had a very high quantity of negative level for traditional composting in the first factor. The second cluster also had the lowest negative level quantity in the first factor’s aerated static-pile composting processing out of the four clusters. This cluster’s second factor score is the highest of the four clusters, which shows that the second factor’s (improved composting factors) technology and environmental aspects are recognized by many respondents. In both the internal and external assessment indicators, its operating technology and various objective factors reached a high standard. Furthermore, this cluster’s first factor score is the second highest of all the clusters, which indicates that this cluster has a high level of recognition for the first factor’s (static composting factors) various assessment indicators. In this cluster, the higher the number of respondents who chose the positive level for the second factor, the higher the proportion of positive level will be for the first factor. Conversely, a higher proportion of respondents will choose the negative level for the first factor. This shows that this cluster has a certain proportion of respondents who chose positive and negative levels for the first factor. Therefore, this cluster can be classified as “cluster with high level of acceptance for improved composting factors.”

The third cluster : Table 5 shows that this cluster had a higher number of respondents who chose the negative level in the questionnaire survey. This cluster had the highest proportion of the first factor (static composting factors) with more defects and not being widely accepted out of the four clusters. The third cluster had the second highest proportion of the second factor (improved composting factors) with more defects and not being widely accepted out of the four clusters. Thus, Fig. 1 shows that this cluster had a lower factor score. Respondents of the questionnaire survey had a very low acceptance level regarding the first factor, but they had the second highest level of acceptance for the second factor out of the four clusters. This indicates that questionnaire respondents are not satisfied with current domestic compost processing methods and the overall environment. This cluster can be categorized as “cluster with low level of acceptance towards static accumulation compost processing factors.”

The fourth cluster : Table 5 shows that respondents mainly chose the normal level for this cluster. This cluster had the highest proportion of respondents who chose the second factor as having more advantage and being widely accepted out of the four clusters. Fig. 1 shows that this cluster had the highest first factor score and the second highest second factor score. This can be interpreted as this cluster’s questionnaire respondents having a more positive attitude towards the internal and external assessment indicators for the four types of kitchen waste processing methods in Taiwan, or having a neutral attitude (normal level) towards the internal and external assessment indicators. This cluster had a lower proportion of respondents who believe that there are more defects and it is not widely accepted. Overall, this cluster had a higher proportion of positive attitude towards internal and external assessment indicators. Thus, this cluster can be called “the cluster with a high level of acceptance towards compost processing.”

IV. CONCLUSION

This study conducted a comprehensive questionnaire survey regarding the internal and external environmental assessment indicators of the four main types of kitchen waste composting methods used in Taiwan. The subjects of the questionnaire survey are various public agencies and private sector vendors who currently engage in kitchen waste, vendors with mature composting technology, and domestic scholars who have conducted studies on kitchen waste. The questionnaire results and multivariate statistical analyses were used to explore the correlations among the four types of kitchen waste composting methods and among various clusters. Factor analysis in the multivariate statistical analyses shows two factors with an eigenvalue greater than 1: the first factor (static composting factors) and the second factor (improved composting factors). These two factors’ cumulative explained variance is 68.910%. Secondly, this study used non-hierarchical clustering (K-mean Method) to test different cluster numbers. The four types of kitchen waste composting methods can be divided into four types of clusters. The first is “low acceptance compost processing factor cluster”, the second is “cluster with high level of acceptance for improved composting factors”, the third is “cluster with low level of acceptance towards static accumulation compost processing factors”, and the fourth is “cluster with a high level of acceptance towards compost processing.” Summarizing the aforementioned analysis results, the factor assessment results for the four types of kitchen waste composting methods and the internal and external assessment indicator questionnaire survey results can serve as a reference for domestic composting operators when considering various kitchen waste composting methods. The results can also serve as a basis for managing and improving waste material for composting operators in the future.

REFERENCES

1. Adamcova, D.,Vaverkova, D. M., Hermanova, S., Voberkova, S. (2015). Ecotoxicity of Compost Containing Aliphatic-Aromatic Copolysters. Pol. J. Environ. Stud. 24, 1497.
2. Gomez, R.B., Lima, F.V., and Ferrer, A.S. (2006). The use of respiration indices in the composting process: A review. Waste Manage. 24, 37.
3. Henry, R.C., Lewis, C.W., Hopke, P.K., and Williamson, H.J. (1984). Review of receptor model fundamentals. Atmos. Environ., 18, 1507.
4. Jurado, M.M., Sua ´rez-Estrella, F., Vargas-Garcı ´a, M.C., Lo ´pez, M.J., Lo ´pez-Gonza ´lez, J.A., and Moreno, J. (2014). Evolution of enzymatic activities and carbon fractions throughout composting of plant waste. J. Environ. Manage. 133, 355.
5. Kim, J.D., Park, J.S., In, B.H., Kim, D., and Namkoong, W. (2008). Evaluation of pilot-scale in-vessel composting for food waste treatment. J. Hazard. Mater. 154, 272.
6. Kumar, M., Ou, Y.L., and Lin, J.G. (2010). Co-composting of green waste and food waste at low C/N ratio. Waste Manag. 30, 602.
7. Lin, C. (2008). A negative-pressure aeration system for composting food wastes. Bioresour. Technol. 99, 7651.

8. Lin, C., Sheu, D.S., Lin, T.C., Kao, C.M., and Grasso, D. (2012). Thermophilic biodegradation of diesel oil in food waste composting processes without bioaugmentation. Environ. Eng. Sci. 29, 117.
9. Lin, C., Wu, E.M.Y., Lee, C.N., and Kuo, S.L. (2011). Multivariate statistical factor and cluster analyses for selecting food waste optimal recycling methods. Environ. Eng. Sci. 28, 349.
10. Liu, C.W., Lin, K.H., Kuo, Y.M. (2003). Application of factor analysis in the assessment of groundwater quality in a blackfoot disease area in Taiwan. *Sci. Tot. Environ.* 313, 77.
11. Martinez, M.A., Caballero, P., Carrillo, O., Mendoza, A., Mejia, G.M. (2012). Chemical characterization and factor analysis of $PM_{2.5}$ in two sites of Monterrey, Mexico. Journal of the Air & Waste Management Association 62, 817-827.
12. McKenna, Jr. J.E. (2003). An enhanced cluster analysis program with bootstrap significance testing for ecological community analysis. Environmental Modeling & Softwar 18, 205-220.
13. Mondini, C., Fornasier, F., and Sinicco, T. (2004). Enzymatic activity as a parameter for the characterization of the composting process. Soil Biol. Biochem. 36, 1587.
14. Saldarriaga, J. F., Aguado, R., & Morales, G. E. (2014). Assessment of VOC Emissions from Municipal Solid Waste Composting. Environ Eng Sci 31(6), 300-307.
15. Sundberg, C., Smars, S., and Jonsson, H. (2004). Low pH as an inhibiting factor in the transition from mesophilic to thermophilic phase in composting. Bioresour. Technol. 95, 145.
16. Tai, H.S., and He, W.H. (2007). A novel composting process for plant wastes in Taiwan military barracks. Resour. Conserv. Recycling. 51, 408.
17. Tobiszewski, M.; Tsakovski, S.; Simeonov, V.; Namieśnik, J. (2010). Surface water quality assessment by the use of combination of multivariate statistical classification and expert information. Chemosphere 80, 740-746.
18. Voberkova, S., Vaverkova, M. D., & Adamcova, D. (2017). Enzyme Production During Composting of Aliphatic–Aromatic Copolyesters in Organic Wastes. Environ Eng Sci, 34(3), 177-184.
19. Wang, C.T., Lee, Y.C, and Liao, F.Y. (2015). Effect of Composting Parameters on the Power Performance of Solid Microbial Fuel Cells. Sustainability 7, 12634-12643.
20. Vega, M.; Pardo, R.; Barrado, E.; Deban, L. (1998). Assessment of seasonal and polluting effects on the qualityof river water by exploratory data analysis. Water Res. 32, 3581-592.
21. Zhang, Y., Li, W.W., Zeng, G.M., Tang, L., Feng, C.L., Huang, D.L., and Li, Y.P. (2009). Novel neural networkbased prediction model for quantifying hydroquinone in compost with biosensor measurements. Environ. Eng. Sci. 26, 1063.