International Journal of Applied Science and Engineering

Comparative study of eco-performance evaluation for municipal solid waste management practices

Hung-Yueh Lin [1], **Sandhya Rijal** [1, 2 *]

[1] *Department of Environmental Engineering and Management, Chaoyang University of Technology, Taichung 413310, Taiwan*
[2] *Department of Applied Chemistry, Chaoyang University of Technology, Taichung 413310, Taiwan*

ABSTRACT

In recent decades, eco-efficient waste management practices that incorporate economic and ecological considerations have been increasingly preferred by numerous municipal solid waste (MSW) authorities. Several approaches for evaluating the eco-efficiency of decision-making units (DMUs), i.e., MSW authorities, were previously reported. However, the typical one is often difficult to comprehend as pertinent. Hence, it might be imperative to compare efficiency results from different methods to generalize the decent eco-performance status of DMUs. This study thus used data envelopment analysis (DEA) and the Weighted Russell Directional Distance Model (WRDDM) to analyze the eco-efficiency level of MSW authorities. The relevant performance factors, including an undesirable output (UDO), as eco-indicators, are screened and selected. Three different DEA methods, considering UDO respectively as an input (for input-oriented DEA), a negative output (for input-oriented DEA), and a direction vector-dependent UDO (for WRDDM), have been applied for efficiency assessment. Furthermore, eco-efficiency analyses are followed by corresponding DMUs' rankings based on their respective efficiency scores by each method. A case study of 38 MSW authorities in Kaohsiung, Taiwan, demonstrates the distinct eco-efficiency outcomes from different DEA approaches. Applied methods revealed consistent findings for determining efficient and inefficient DMUs, but distinct efficiency scores for inefficient DMUs by varying methods influenced DMUs' rankings. The comparative analysis of ranking variation for inefficient DMUs across those methods suggested the WRDDM method with the least variation as the robust method for assessing eco-efficiency. Further exploration of an integrated approach that incorporates undesirable factors appropriately would enhance the reliability of performance evaluation.

Keywords: Eco-efficiency, Municipal solid waste, Data envelopment analysis, Weighted Russell directional distance model.

OPEN ACCESS

Received: December 16, 2022
Revised: June 28, 2023
Accepted: October 7, 2023

Corresponding Author:
Sandhya Rijal
sandhyarijal83@gmail.com/
s10832902@gm.cyut.edu.tw

Copyright: The Author(s). This is an open access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0), which permits unrestricted distribution provided the original author and source are cited.

Publisher:
Chaoyang University of Technology
ISSN: 1727-2394 (Print)
ISSN: 1727-7841 (Online)

1. INTRODUCTION

The circular economy model is gaining popularity as a critical component in advancing sustainable development (Bertanza et al., 2021). It is a production and consumption system that depends on the recycling, reuse, repair, remanufacturing, and sharing of products. The idea is now widely accepted as a crucial element in solving problems, including waste, pollution, resource depletion, and climate change. Ultimately, it calls for new business models with a shift in consumer behavior and circular production and resource allocation. Local governments should take the initiative and lead in this venture by incorporating more stakeholders, such as municipality-residents, municipality-business, and municipality-business-residents (Dagilienė et al., 2021).

Municipal solid waste (MSW) authorities play pivotal roles in directing and assisting the transition to a circular economy as these authorities are directly interwoven with local communities and can formulate local regulations and interventions for circular goods and services. In recent decades, MSW authorities globally prioritize managing MSW, however, current collection and disposal techniques practiced by many of those authorities are not ideal or economically viable due to several factors such as poor management and enforcement, regulatory disparities, lack of infrastructure, and high cost of waste recycling systems, etc. Consequently, it results in inefficient waste management (Taleb and Al Farooque, 2021). Thus, it is crucial to assess those authorities' performances for comprehending their current efficiency status and recommend possible benchmarks for productive performance.

Data envelopment analysis (DEA) is one of the simple-to-calculate performance analysis tools over more advanced alternatives (Ananda, 2018). Several previous studies have employed DEA for economic, environmental, as well as joint efficiency evaluation, termed as eco-efficiency. The prefix 'eco' stands for both environmental and economic performance, and thus determining eco-efficiency requires considering both environmental and economic factors (Molinos-Senante et al., 2018). The term "environmental factors" usually refers to undesired outcomes like pollution and waste, while the economic factors are associated with cost efficiency. Studies have also attempted varying approaches to integrate undesirable output (UDO) into the efficiency assessment models with the growing interest of public or governments' policies for improving those factors with adverse impacts. A few studies integrated UDO into the input-oriented DEA model by assuming it as a normal input (Korhonen and Luptacik, 2004; Romano and Molinos-Senante, 2020) while Koopmans (1951) suggested treating it as negative output in output-oriented DEA. Likewise, Seiford and Zhu (2002, 2005) performed linear transformation of bad output to model the pollutant (UDO) as a regular output while some integrated it into the DEA model by non-linear transformation using multiplicative inverse ratios (Lovell et al., 1995). In addition, another alternative DEA, known as Weighted Russell Directional Distance Model (WRDDM) is also used to integrate UDO into the efficiency evaluation model, based on the combination of directional distance function with a non-radial approach (Barros et al., 2012; Chen et al., 2014). This model can gauge performance in terms of increased desirable output (DO) and decreased UDO and inputs simultaneously, based on chosen directional vectors.

Although different oriented and non-oriented DEA models for efficiency evaluations are available, it still appears challenging to integrate undesirable variables into the performance evaluation functions. This could be due to the absence of a unified strategy that can effectively define such parameters and integrate various formulated models comprehensively. Eventually, data analysts and managers could be confounded in choosing a precise model. Thus, this study aims to analyze if any variation exists in the efficiency results of decision-making units (DMUs), i.e., MSW authorities, when UDO is incorporated differently in the production process with input-oriented and non-oriented DEA approaches. The findings of this study would assist in better understanding of the similarity or disparity among different selected models. For this, three approaches respectively, including two models with input-oriented radial DEA and one encompassing directional vector-dependent non-radial DEA, incorporating (i) UDO treated as a normal input (Romano and Molinos-Senante, 2020), (ii) UDO treated as a negative output, (Koopmans, 1951), and (iii) UDO with weak disposability assumption for WRDDM (Barros et al., 2012) have been examined.

Eco-efficiency evaluation methods incorporate various desirable and undesirable performance variables. Nevertheless, previous studies have no hints regarding most favorable method(s), to our knowledge, for incorporating those multi-dimensional variables for eco-efficiency evaluations. In order to fill such a gap in literature, it is crucial to analyze and gain a comprehensive understanding of the suitability of commonly used evaluation methods for efficiency analysis. Such an approach would aid in fair performance assessment of provided MSW authorities. Therefore, our study aims to contribute to the existing literature on waste-related performance assessment by analyzing and indicating the better method for incorporating desirable and undesirable factors. It thus would enhance the empirical understanding of the adopted DEA methods along with fair efficiency findings and provide useful insights for further research.

2. MATERIAL AND METHODS

2.1 MSW Problem

MSW authorities are presumably interested in collecting and recycling high-value waste, like paper, plastics, glass etc., while also trying to reduce undesired outputs like pollution or unsorted (mixed) waste and input factors, such as operational expenses. To attain their intended goals of circular economy and sustainability, effective waste management strategies should be adopted. Therefore, it is essential to examine their current management techniques and suggest precise benchmarks for inefficiency improvements.

2.2 Study Procedure

Fig.1. illustrates the overall research procedure of this study. Data related to the performance factors, known as input and output variables of MSW authorities, were collected from concerned authorities and relevant literature. Different approaches of the DEA method were then implemented with selected input and output factors to assess the eco-performance on waste management of DMUs. Both the desirable and undesirable factors were considered during the evaluation. Finally, the ranking of DMUs by following efficiency estimations of different DEA models facilitated in comparing and analyzing their respective

Lin and Rijal, International Journal of Applied Science and Engineering, 21(1), 2022363

efficiency status. Details of the overall procedures are explained below.

2.2.1 Input and Output Factors

Input and output (desirable and undesirable) factors can objectively represent the eco-efficiency levels of MSW authorities once progression of such factors is examined. The performance of each authority is determined based on input and undesirable factors involvement and targeted output achievement. These factors, after analysis, can be a reference for benchmark learning. Table 1 demonstrates the possible input and output factors associated with eco-efficient waste management.

The indicators of input and output factors and their corresponding definitions are based on the studies listed in the reference column of the table. The number of manpower used served as the input factor, whereas the annual amounts of recyclables and mixed waste served as the bases of DO and UDO factors, respectively. Input factors are subjectively invested by municipal authorities according to their policy objectives and some of them may be highly correlated to each other. For instance, Parthan et al. (2012) and Fernandez-Aracil et al. (2018) revealed strong correlation of capital value with the number of employed manpower. However, the data regarding cost or capital was

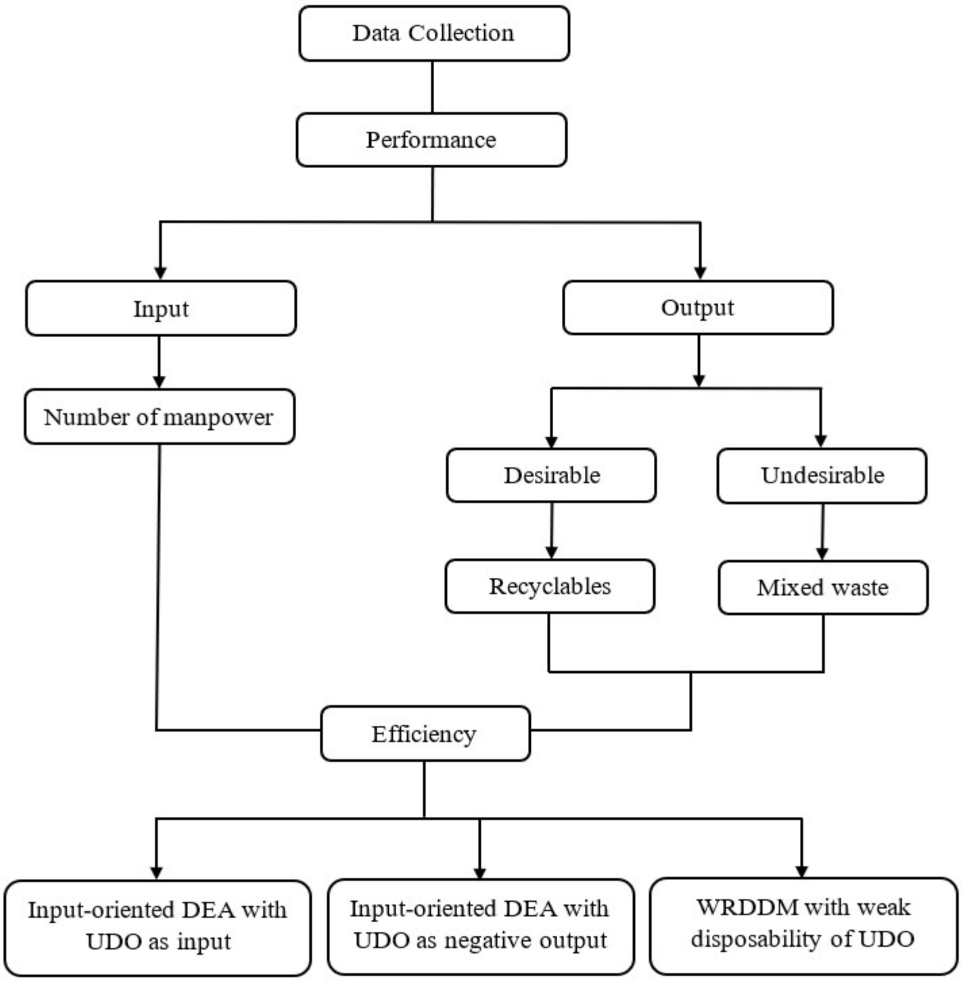

Fig.1. Research flow chart

Table1. Input and output factors of MSW authorities

Parameters	Inputs	Description	References
Input	Manpower involved (number)	Number of cleaning, clearing and disposing team	(Zhou et al., 2007; Wang and Feng, 2015)
DO	Selective or sorted waste collection (tons/year)	Amount of segregated waste collection or selective collection of recyclable materials	(Sarra et al., 2017; Lombardi et al., 2021)
UDO	Total quantity of unsorted/ mixed waste (tons/year)	Amount of mixed waste except recyclables collection	(Delgado-Antequera et al., 2021; Sala-Garrido et al., 2022)

not available from all municipal authorities in our case. Thus, the employed manpower has been selected as an input factor in this study. The amounts of recycled resources would contribute to the environment and economy and are required to be enhanced. Thus, it has been classified as a DO, while the quantity of mixed waste is an environmental cost which is accounted as an optimizable UDO (Wojcik et al., 2017; Lombardi et al., 2021).

2.2.2 DEA for Performance Evaluation

The DEA method is employed to analyze the eco-efficiency of DMUs via screened input and output (desirable and undesirable) factors. Those DMUs with the highest efficiency score can be used as benchmarks for other inefficient DMUs in the group. Among various models/approaches of DEA, this study used three different approaches to DEA and employed radial (classical Charnes, Cooper, and Rhodes, i.e., CCR model) and non-radial (WRDDM) models to incorporate the UDO in the efficiency evaluation procedures.

Based on radial DEA, an input-oriented CCR-DEA model with two different approaches for UDO inclusion were adopted, including (i) UDO was treated as a normal input in the production function, implying that both inputs and UDO are to be decreased (Korhonen and Luptacik, 2004; Romano and Molinos-Senante, 2020), and (ii) UDO was treated as negative output as suggested by Koopmans (1951). This model is characterized by adjusting all the variables to efficiency targets by the same proportion (Zhou et al., 2007), meaning that they provide a score of overall, i.e., global efficiency score (Zhou et al., 2012).

The equations for the input oriented CCR model, based on Charnes et al. (1978) are as follows.

$$Max\ \ h_o = \sum_{r=1}^{s} u_r Y_{ro} \tag{1.1}$$

$$\sum_{i=1}^{m} v_i X_{io} = 1 \tag{1.2}$$

$$\sum_{r=1}^{s} u_r Y_{rk} - \sum_{i=1}^{m} v_i X_{ik} \leq 0, k = 1, 2, \ldots, z \tag{1.3}$$

Where, o denotes the index of a DMU under evaluation; r refers to the index of output factors; s indicates the total number of output factors; u_r is the nonnegative weight assigned to output factor j; Y_{ro} represents the value of the DMU under evaluation on output factor r ; Y_{rk} represents the value of the DMU k on output factor r; i refers to the index of input factors; m indicates the total number of input factors; v_i is the nonnegative weight assigned to input factor i; X_{io} represents the value of the DMU under evaluation on input factor i ; X_{ik} represents the value of the DMU k on input factor i ; k indicates the index of total competitive DMUs (i.e., *DMU-1, 2,….., z)*. The variables in the above equations are constrained to be non-negative.

Equation 1.1 represents the objective function, which is to maximize the weighted sum of the DMU o's output factors. Equation 1.2. shows the sum of weighted input factors for the given DMU o to prevent unbounded solutions. Similarly, Equation 1.3 indicates that the weighted sum of each individual DMU's output factors (DO) should be less than or equal to the weighted sum of its input factors (including UDO that is also assumed as input). For each DMU, the above equations (Equation1.1-1.3) are applied to form a linear model to determine its efficiency. Thus, 'n' models must be established for the efficiencies of all DMUs. The CCR model evaluates the overall efficiency (OE).

In the non-radial DEA approach, such as WRDDM (Chen et al., 2010; Barros et al., 2012), global as well as individual inefficiency scores are obtained for each input, DO, and UDO. Based on non-radial models, (iii) UDO was considered as weakly disposable and employing constant returns to scale (CRS). The equations for non-radial DEA, i.e., WRDDM method as provided by Chen et al. (2014) are as follows.

Let us consider that municipalities produce a vector of desirable (good) outputs, $Y = (y_1, \ldots, y_M) \in R^{+M}$ using a set of inputs $X = (x_1, \ldots, x_N) \in R^{+N}$. During the production process, a set of undesirable (bad) outputs are also produced as $H = (h_1, \ldots, h_J) \in R^{+J}$. As a result, production technology is defined as follows.

$$T = \{(X, Y, H): X \text{ can produce } Y \text{ and } H\} \tag{2}$$

It is assumed that both DO and UDO are jointly produced as part of the production process, and bad outputs are weakly disposable (Färe et al., 2005), which require additional expense for their management. Thus, weak disposability of UDO is assumed.

WRDDM with weak disposability of UDO as indicated by Barros et al. (2012) is given by,

$$Max: W_X \sum_{n=1}^{N} T_n \beta_{no} + W_Y \sum_{m=1}^{M} T_m \beta_{mo} + W_H \sum_{j=1}^{J} T_j \beta_{jo} \tag{2.1}$$

$$\sum_{k=1}^{K} X_{nk} z_k + g_{Xn}\beta_{no} \leq X_{no} \qquad n = 1, \ldots, N \tag{2.2}$$

$$\sum_{k=1}^{K} Y_{mk} z_k - g_{Ym}\beta_{mo} \geq Y_{mo} \qquad m = 1, \ldots, M \tag{2.3}$$

$$\sum_{k=1}^{K} H_{jk} z_k + g_{Hj}\beta_{jo} = H_{jo} \qquad j = 1, \ldots, J \tag{2.4}$$

$$z_k \geq 0,\ k = 1, \ldots, K \tag{2.5}$$

Where, X, Y, and H indicate the indices for input, DO, and UDO respectively. N, M, J are respectively the total number of inputs, DO and UDO. W_X, W_Y and W_H are preset weights for total inputs, UDO, and DO respectively and their sum is normalized to unity. Equal prioritization is given to all parameters and the value is assumed to be 1/3 for each weight respectively, based on (Chen et al., 2014). $\beta_{no}, \beta_{mo}, \beta_{jo}$ are respectively the inefficiency associated with input, DO and UDO of DMU under evaluation. T_n, T_m, T_j are the respective normalized weight vectors associated with priorities given for individual input, DO and

UDO and are allocated based on the cardinal of each set of inputs, DOs, and UDOs, i.e., *1/N, 1/M,* and *1/J,* respectively (Chen et al., 2014; Delgado-Antequera et al., 2021). X_{nk} , Y_{mk}, and H_{jk} indicate respectively, the value of DMU k ($k=1,2,..,K$) on input factor n, DO factor m, and UDO factor j. g_{Xn}, g_{Ym}, and g_{Hj} refer to direction vector chosen by the analyzer for each input and output. z_k refers to the intensity vector that weights the DMUs to construct a production set.

Because the aim of the directional distance function in given equations is to maximize the generation of DO and minimize the use of input as well as the production of UDO, the direction vector can be written as (g_X, g_Y, g_H = $-X$, Y, $-H$) (Molinos-Senante et al., 2016).

2.2.3 Ranking DMUs for Comparative Analysis of Efficiency Results

Efficiency analysis of DMUs from varying approaches was followed by their corresponding ranking based on their respective efficiency scores in each model (Cooper et al., 2006; Cook and Zhu, 2014). As DEA assists in classifying DMUs into efficient and inefficient ones, in practice, it is often necessary to rank them individually based on their respective efficiency scores by each method to increase discrimination among inefficient DMUs. The rankings of DMUs reveal their relative position or status among all. This could aid in additional information for precise benchmarks. The ranking of DMUs with each examined method would provide a foundation for comparative analysis of a particular DMU's rank across the various DEA methods. Ultimately, it assists in understanding the efficiency assessment tendency of adopted DEA approaches.

3. CASE STUDY

3.1 Case Background

This study assessed 38 MSW authorities in Kaohsiung, a city in southern Taiwan. Data on current waste management activities were collected from the respective municipal offices (Table S1) and relevant literature. Performance parameters, including an input, DO, and UDO, were screened, and then selected based on the data availability and existing literature. The selected input and output factors, such as the number of labor forces as an input, the amounts of recyclables, and mixed waste as a DO and UDO, respectively formed the basis of eco-performance evaluation.

Eco-performance evaluation of DMUs was done using different approaches of DEA as discussed earlier. Ranking of the DMUs following efficiency results by various DEA models provided a basis for a comparative analysis of each DMU's performance status with distinct models. Ultimately, the appropriate discrimination of employed approaches could be established.

3.2 DEA Results for Classification of DMUs

Table 2 elucidates eco-efficiency outcomes, where the majority of the MSW authorities showed poor performances. This result suggests that the eco-performance of waste management sector was considerably unsatisfactory on average, which is in line with earlier research (Llanquileo-Melgarejo et al., 2021; Molinos-senante et al., 2022), who disclosed reduced efficiency estimates for the Chilean municipalities using non-parametric techniques. Only two MSW authorities, including K_{11} and K_{29}, are deemed overall efficient in all applied methods, while the remaining 36 are inefficient. This outcome indicates that the application of various DEA models does not influence the classification of DMUs as efficient or inefficient. The evaluation procedure was based on the provided performance indicators, including inputs and outputs (DO and UDO), and three DEA approaches were adopted to incorporate UDO in the DEA model. The first two approaches were based on an input-oriented CRS model, where UDO was incorporated as (i) input to be reduced and (ii) a negative output, and the third approach was based on directional distance function measure, indicating WRDDM (CRS) with UDO (iii) based on direction vector with weak disposability assumption.

3.3 Ranking of DMUs

Table 2 demonstrates DMUs' corresponding rankings obtained after efficiency analysis using different DEA approaches. It is found that only a few DMUs acquired identical ranks in two different applied models such as K_{34}, K_{37}, K_{38}, in model 1 and 3, K_8 and K_{36} in model 1 and 2 and K_3 in model 2 and 3 while none of the inefficient DMU acquired equivalent rank in all three applied models (Table 2). These findings infer that incorporating the same performance parameters with varying DEA models can also provide inconsistent efficiency scores for inefficient DMUs that characterize their respective ranks.

Regarding the assessment of mean ranking values and individual ranks of DMUs by each model (Table 2), almost 80% of DMUs with model 3 have ranking values that are proximal or equivalent (in many cases) with their mean ranks, followed by approximately 30% of DMUs in model 1, and 14% in model 2. Furthermore, the proximity between ranking ranges (maximal-minimal ranking) and individual ranking values is demonstrated by a higher number of DMUs (61%) with model 2, while relatively by a less number (21%) with model 3. These findings suggest that model 3 could offer a more robust approach to eco-efficiency analysis compared to other models.

3.4 Comparative Analysis of DMUs' Eco-efficiency Findings from Different Efficiency Analysis Approaches

Intriguingly, out of 38 total DMUs, Table 2 demonstrates two equivalents efficient DMUs (i.e., K_{11}, K_{29}) in all the adopted models and the remaining 36 as inefficient. This could reveal the consistent discriminating power of DEA methods for the best and worst performers, regardless of distinct approaches used for UDO inclusions. Nonetheless, prior studies reported contrasting outcomes for number of (in)efficient DMUs when two different statistical measures, including parametric SFA, i.e., stochastic frontier analysis and non-parametric DEA methods (Moutinho et al., 2020) as well as when both non-parametric measures, including DEA and FDH (free-disposal hull), (Kounetas et al., 2021) were employed. However, the ranking outcomes, as illustrated in the same table, vary for inefficient DMUs among different DEA models. A higher resemblance in ranking results is observed between model 3 (column 4) and mean ranking (column 6), with approximately 80% of DMUs having proximal values. Model 2 (column 3), on the other hand, shows the least number of DMUs (approximately 14%), having proximity in those ranking results. These outcomes suggest that model 3 might be a better fit for integrating UDO than the other two models.

Table 3 demonstrates the assessment of comparative ranking variations and classification of inefficient DMUs based on their corresponding ranks in each model. Each model provides a rank to each DMU after the DEA analysis.

Table 2. Results of DMU ranking after efficiency analysis

DMU	(Model-1) Ranking after UDO used as an input	(Model-2) Ranking after UDO used as a negative output	(Model-3) Ranking after UDO used as a weakly disposable vector with direction function	(From all models) Maximal-minimal ranking	Mean ranking
K_1	11	4	7	7	7
K_2	12	5	10	7	9
K_3	14	8	8	6	10
K_4	20	32	29	12	27
K_5	23	36	35	13	31
K_6	28	25	26	3	26
K_7	26	22	23	4	24
K_8	15	15	14	1	15
K_9	7	14	6	8	9
K_{10}	8	29	18	21	18
*K_{11}	1	1	1	0	1
K_{12}	19	11	13	8	14
K_{13}	31	24	27	7	27
K_{14}	32	30	33	3	32
K_{15}	6	7	3	4	5
K_{16}	29	19	22	10	23
K_{17}	27	20	24	7	24
K_{18}	18	10	17	8	15
K_{19}	36	26	34	10	32
K_{20}	9	16	12	7	12
K_{21}	3	28	9	25	13
K_{22}	30	31	32	2	31
K_{23}	21	34	31	13	29
K_{24}	4	27	11	23	14
K_{25}	24	12	20	12	19
K_{26}	10	3	4	7	6
K_{27}	33	18	28	15	26
K_{28}	25	13	19	12	19
*K_{29}	1	1	1	0	1
K_{30}	13	6	15	9	11
K_{31}	17	9	16	8	14
K_{32}	16	33	25	17	25
K_{33}	34	21	30	13	28
K_{34}	5	17	5	12	9
K_{35}	22	23	21	2	22
K_{36}	35	35	36	1	35
K_{37}	38	37	38	1	38
K_{38}	37	38	37	1	37

** Represents the efficient DMU.*

Lin and Rijal, International Journal of Applied Science and Engineering, 21(1), 2022363

For each inefficient DMU, three ranks from different models are obtained, and the maximal/minimal rank among them were marked as highest/lowest rank, respectively. The total number of DMUs that were marked as both highest and lowest, i.e., extreme ranks, for each model are listed in columns 2 and 3, respectively. The ranking variation for each model (column 4) is obtained by summing the number of DMUs in column 2 and 3 and dividing by the total inefficient DMUs (column 5), which were determined for a specific model after rankings. Each model consists of 36 inefficient DMUs (column 5), with varying ranks that are assigned by each model. The comparative analysis of three models for DMUs' ranking revealed model 2 as having the highest extreme values or inconsistent ranking scenario for inefficient DMUs. For instance, model 2 (column 3) depicts the maximum number of DMUs (21), with the top ranks, and 14 DMUs (column 2), with the lowest ranks of all. As a result, 35 DMUs in total with model 2 obtained extreme ranking values, which led it to exhibit the greatest ranking variation (97%), followed by model 1 and model 3 respectively. Model 3, on the other hand, demonstrates five DMUs (column 2) with the lowest and six DMUs (column 3) having top ranks, including 25 DMUs with normal rankings. Thus, it exhibits relatively minimal ranking variation (31%), implying that it would be the most robust and reliable of all.

Ultimately, the overall eco-efficiency and ranking findings infer that the varying models used for DMUs' efficiency evaluation do not influence the classification of a specific DMU to be efficient or inefficient. However, distinct scores, characterizing their performance levels, especially for inefficient DMUs with different models have affected their corresponding rankings. The probable reason for such anomalies could be the diversified way of incorporating UDO while formulating eco-efficiency formulae or models, which would ultimately influence determining their precise benchmarks.

Most of the eco-efficiency studies used a single non-parametric DEA model to assess the eco-efficiency of the concerned authorities (Delgado-Antequera et al., 2021; Sala-Garrido et al., 2022), and derived the performance status based on the determined single efficiency estimates. However, our study attempted to assess the eco-efficiency of DMUs by employing and examining multiple UDO inclusion approaches of DEA methods, revealing the pertinent approach among all with relevant eco-performance findings.

3.5 Limitations of the Study

Data related to preferable input and output factors are not readily available in all the cases. For instance, capital-related information was not available in our case, which may have an influence on the performances of MSW authorities. Additionally, this study utilized the CCR-DEA model assuming constant returns to scale for all MSW authorities. Future studies could explore the potential scale effects of those authorities by incorporating the BCC-DEA model as well. Furthermore, three specific DEA approaches were analyzed for the comparative study. Future research may examine and compare multiple existing evaluation models to gain a better comprehension of each method for fair analysis of waste-related eco-performances.

3.6 Policy Implications and Future Prospects

Our findings may assist solid waste management authorities in adopting appropriate performance evaluation methods, like WRDDM, to fairly address eco-challenges faced by them. This could further contribute to establishing reliable efficiency improvement targets for inefficient municipalities. In addition, the findings may serve as baseline for decision-makers and analysts for revising and updating existing waste-related protocols and guidelines.

Future studies may target selecting relevant performance factors based on the appropriate factor assessments and incorporate them for performance analysis with a suitable method. Additionally, the decent disposability assumption for each input and output factor can be emphasized during the DEA evaluation. The continuous monitoring and evaluation of waste management practices are recommended for all MSW authorities to identify potential areas for improvement and update regulations and policies accordingly.

4. CONCLUSION

This study has assessed the suitability of eco-efficiency evaluation methods by applying three commonly used DEA models for MSW authorities. Various oriented and non-oriented DEA methods demonstrated distinct efficiency estimates (scores) for the inefficient DMUs, providing valuable insights for the comparative analysis of applied models. Nevertheless, the classification of DMUs as efficient or inefficient was consistent among all models, indicating the equivalent effectiveness of adopted models. The non-radial and directional vector dependent 'WRDDM' method was analyzed as a better DEA approach for integrating both desirable and undesirable performance

Table 3. Classification based on DMUs' rankings with different models

Model	Number of DMUs with lowest rank	Number of DMUs with highest (top) rank	Percentage of ranking variation (%)	Total number of inefficient DMUs
Model-1	17	9	72	36
Model-2	14	21	97	36
Model-3	5	6	31	36

factors. This could be due to its non-oriented and directional vector-based features, offering a more robust efficiency comparison than the remaining input-oriented CCR models.

The ranking method that relied on the efficiency estimates of MSW authorities by each DEA method assisted in a comparative analysis of the incorporated DEA approaches. The proximity between individual ranking and the mean ranking values of MSW authorities, as well as the ranking variation among applied DEA models formed the basis for identifying a robust evaluation approach for waste-related eco-performances. Based on the comparative analysis, model 3, i.e., WRDDM, outperformed other models regarding the same. In contrast, highly varying or deviated ranking outcomes were revealed by model 2, indicating CCR model with negative UDO requires further investigation to accurately incorporate undesirable factors for fair eco-performance findings. Future research may focus on assessing multiple performance factors to determine their suitability for determining waste-related performances effectively.

REFERENCES

Ananda, J. 2018. Productivity implications of the water-energy-emissions nexus: An empirical analysis of the drinking water and wastewater sector. Journal of Cleaner Production, 196, 1097–1105.

Barros, C.P., Managi, S., Matousek, R. 2012. The technical efficiency of the Japanese banks: Non-radial directional performance measurement with undesirable output. Omega, 40, 1–8.

Bertanza, G., Mazzotti, S., Gómez, F.H., Nenci, M., Vaccari, M., Zetera, S.F. 2021. Implementation of circular economy in the management of municipal solid waste in an Italian medium-sized city: A 30-years lasting history. Waste Management, 126, 821–831.

Charnes, A., Copper, W.W., Rhodes, E. 1978. Measuring the efficiency of decision making units. European Journal of Operational Research. 2, 429–444.

Chen, P.C., Yu, M.M., Hang, C.C., Managi, S. 2014. Non-radial directional performance measurement with undesirable outputs. 57189, 1–36.

Cook, W.D., Zhu, J. 2014. DEA Cobb-Douglas frontier and cross-efficiency. Journal of the Operational Research Society, 65, 265–268.

Cooper, W.W., Huang, Z., Li, S., Zhu, J. 2006. Critique of Dmitruk and Koshevoy and of Bol plus expanded opportunities for efficiency and effectiveness evaluations with DEA. Journal of Productivity Analysis.

Dagilienė, L., Varaniūtė, V., Bruneckienė, J. 2021. Local governments' perspective on implementing the circular economy: A framework for future solutions. Journal of Cleaner Production, 310.

Delgado-Antequera, L., Gémar, G., Molinos-Senante, M., Gómez, T., Caballero, R., Sala-Garrido, R. 2021. Eco-efficiency assessment of municipal solid waste services: Influence of exogenous variables. Waste Management, 130, 136–146.

Färe, R., Grosskopf, S., Noh, D.W., Weber, W. 2005. Characteristics of a polluting technology: Theory and practice. Journal of Econometrics, 126, 469–492.

Fernandez-Aracil, P., Ortuno-Padilla, A., Melgajero-Moreno. J. 2018. Factors related to municipal costs of waste collection service in Spain. Journal of Cleaner Production, 175, 553–560.

Koopmans, T.C. 1951. An analysis of production as an efficient combination of activities. Activity Analysis of Production and Allocation.

Korhonen, P.J., Luptacik, M. 2004. Eco-efficiency analysis of power plants: An extension of data envelopment analysis. European Journal of Operational Research, 154, 437–446.

Kounetas, K.E., Polemis, M.L., Tzeremes, N.G. 2021. Measurement of eco-efficiency and convergence: Evidence from a non-parametric frontier analysis. European Journal of Operational Research, 291, 365–378.

Llanquileo-Melgarejo, P., Molinos-Senante, M., Romano, G., Carosi, L. 2021. Evaluation of the impact of separative collection and recycling of municipal solid waste on performance: An empirical application for Chile. Sustainability, 13, 1–15.

Lombardi, G.V., Gastaldi, M., Rapposelli, A., Romano, G. 2021. Assessing efficiency of urban waste services and the role of tariff in a circular economy perspective: An empirical application for Italian municipalities. Journal of Cleaner Production, 323, 129097.

Molinos-Senante, M., Maziotis, A., Sala-Garrido, R., Mocholi-Arce, M. 2023. The eco-efficiency of municipalities in the recycling of solid waste: A stochastic semi-parametric envelopment of data approach. Waste Management & Research, 41, 1036–1045.

Molinos-Senante, M., Mocholi-Arce, M., Sala-Garrido, R. 2016. Efficiency assessment of water and sewerage companies: A disaggregated approach accounting for service quality. Water Resources Management, 30, 4311–4328.

Moutinho, V., Madaleno, M., Macedo, P. 2020. The effect of urban air pollutants in Germany: Eco-efficiency analysis through fractional regression models applied after DEA and SFA efficiency predictions. Sustainable Cities and Society, 59.

Parthan, S.R., Milke, M.W., Wilson, D.C., Cocks, J.H. 2012. Cost function analysis for solid waste management: A developing country experience. Waste Management & Research, 30, 485–491, 2012.

Romano, G., Molinos-Senante, M. 2020. Factors affecting eco-efficiency of municipal waste services in Tuscan municipalities: An empirical investigation of different management models. Waste Management, 105, 384–394.

Sala-Garrido, R., Mocholi-Arce, M., Molinos-Senante, M., Maziotis, A. 2022. Measuring technical, environmental and eco-efficiency in municipal solid waste management in Chile. International Journal of Sustainable Engineering,

15, 71–85.
Sarra, A., Mazzocchitti, M., Rapposelli, A. 2017. Evaluating joint environmental and cost performance in municipal waste management systems through data envelopment analysis: Scale effects and policy implications. Ecological Indicators, 73, 756–771.
Seiford, L.M., Zhu, J. 2002. Modeling undesirable factors in efficiency evaluation. European Journal of Operational Research, 142, 16–20.
Seiford, L.M., Zhu, J. 2005. A response to comments on modeling undesirable factors in efficiency evaluation. European Journal of Operational Research, 161, 579–581.
Taleb, M.A., Al Farooque, O. 2021. Towards a circular economy for sustainable development: An application of full cost accounting to municipal waste recyclables. Journal of Cleaner Production, 280, 124047.
Wang, Z., Feng, C. 2015. A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: An application of global data envelopment analysis. Applied Energy, 147, 617–626.
Wojcik, V., Dyckhoff, H., Gutgesell, S. 2017. The desirable input of undesirable factors in data envelopment analysis. Annals of Operations Research, 259, 461–484.
Zhou, P., Ang, B.W., Wang, H. 2012. Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. European Journal of Operational Research, 221, 625–635.
Zhou, P., Poh, K.L., Ang, B.W. 2007. A non-radial DEA approach to measuring environmental performance. European Journal of Operational Research, 178, 1–9.

Lin and Rijal, International Journal of Applied Science and Engineering, 21(1), 2022363

SUPPORTING INFORMATION

Table S1. Data of performance parameters for 38 municipal authorities in Kaohsiung

District code	Year- 2019		
	Input Number of cleaning teams	UDO Total garbage removal (Metric tons/year)	DO Total recyclables (Metric tons/year)
K1	160	31229.4	43449.6
K2	168	32908.4	44354.8
K3	130	21462.0	31682.0
K4	57	4730.4	6307.2
K5	45	1073.1	1401.6
K6	76	9493.7	11541.3
K7	242	31645.5	39091.5
K8	219	30879.0	45289.2
K9	195	23644.7	41522.4
K10	59	4599.0	7767.2
K11	77	18308.4	27944.4
K12	350	60809.0	83147.0
K13	52	6825.5	8066.5
K14	38	4234.0	4745.0
K15	41	5409.3	10402.5
K16	47	6701.4	8015.4
K17	45	6022.5	7336.5
K18	71	14819.0	17118.5
K19	60	8541.0	8409.6
K20	52	5986.0	10074.0
K21	25	1635.2	3423.7
K22	24	2409.0	2847.0
K23	16	1160.7	1533.0
K24	21	1401.6	2890.8
K25	120	24936.8	26572.0
K26	362	62721.6	99309.2
K27	60	9314.8	10278.4
K28	43	8124.9	9351.3
K29	103	17702.5	43194.1
K30	52	11388.0	13286.0
K31	32	6540.8	7767.2
K32	17	1303.1	1865.2
K33	44	6570.0	7117.5
K34	49	4380.0	8869.5
K35	21	2555.0	3372.6
K36	10	386.9	386.9
K37	14	612.1	78.5
K38	14	470.9	76.7