Performance assessment for municipal solid waste collection in Taiwan

You-Ti Huang, Tze-Chin Pan, Jehng-Jung Kao*

Institute of Environmental Engineering, National Chiao Tung Univ., 1001 University Road, Hsinchu, 30039 Taiwan, ROC

ARTICLE INFO

ABSTRACT

Collecting municipal solid waste (MSW) is a major and expensive task for local waste management authorities, thus efficient MSW collection is a necessity. This study presents a procedure for developing an aggregate indicator (AI) to assess MSW collection efficiency based on multiple factors. The applicabilities of various key performance indicators (KPIs) are evaluated based on five selection criteria, and five KPIs are chosen to form the AI. The relative efficiencies of local MSW collection services are analyzed by the data envelopment analysis (DEA) method. A set of common weights for all five KPIs is then generated based on DEA results and four selection rules by modifying a previous approach. Finally, the proposed AI is applied to assess the MSW collection services provided by 307 local governments in Taiwan, and associated results are compared and discussed.

© 2010 Elsevier Ltd. All rights reserved.

1. Introduction

Municipal solid waste (MSW) management poses a daunting task for local authorities worldwide (Li and Huang, 2006; Fobil et al., 2006). MSW collection is an important and expensive public service worldwide and generally accounts for 75–80% of the MSW management budget (Simonetto and Borenstein, 2007; ROCEPA, 2010). The MSW collection service, provided by either the private or public sector, includes many activities and requires numerous collectors and equipment (García-Sánchez, 2008). The quantity of the MSW, the type of equipment, and the distances the MSW transported as well as the labor required, are all major factors with significant effects on MSW collection (Kao and Lin, 2002). Inefficient MSW collection can rapidly deplete resources and energy (Alam et al., 2008). MSW collection efficiency has thus attracted increasing attention and is also a major concern among many local environmental authorities worldwide. Several studies have assessed the performance of waste collection or management programs in different countries (e.g. Woodard et al., 2001; Worthington and Dollery, 2001; Sarkis and Dijkshoorn, 2007;

García-Sánchez, 2008), although these methods cannot be directly applied owing to special local features in Taiwan, including high population density, narrow local streets restricting entry to small collection vehicles, heavy traffic, and public rather than private sector MSW collection service. Therefore, this study explores a method of developing an aggregate indicator for assessing local MSW collection system performance.

To assess MSW collection efficiency, the two most common methods are questionnaire survey (e.g., Dajani et al., 1976; Shuhua et al., 2007; Ramzan et al., 2008; Lin et al., 2010) and key performance indicator (KPI) (e.g., Menezes et al., 2003; Australian Government, 2006; Tugnoli et al., 2008). Questionnaire surveys, although simple and useful, may produce subjective results because responses are influenced by the questions asked. Deciding which groups should be surveyed and how to implement the survey are also problematic. Although KPI is simple and generally easy to understand, it usually assesses only a single aspect or factor, and is thus inappropriate to assess the multi-dimensional MSW collection performance. Therefore, this study was initiated to explore an appropriate aggregate indicator (AI) for assessing the performance of the MSW collection services as provided by 307 local governments in Taiwan.

A typical AI, such as the Environmental Sustainability Index (Esty et al., 2005) or Water Quality Index (ODEQ, 2007), is composed of several indicators for assessing a multi-factor issue. Compared to multiple KPIs, an AI is easier to use and to communicate to the public. To establish an AI for assessing MSW collection, major KPIs must first be carefully selected for use as sub-indicators.

Selection criteria proposed in other areas (ICLEI et al., 1996; Spangenberg et al., 2002; Zhen and Routray, 2003; Alegre et al., 2006) include data availability, suitability, community values, indicator comparability, etc. However, these criteria, although useful, are not enough for selecting the KPIs for assessing the efficiency of MSW collection, and thus alternative criteria were explored in this study.

After KPIs are selected, the method of aggregating them into an AI must be determined. Currently, several methods are available to aggregate sub-indicators, such as Analytic Hierarchy Process (Saaty, 1987), Impact Assessment Analysis (Prë-Consultants, 2000), and Conjoint Analysis (Ülengin et al., 2001). However, these methods must use a questionnaire survey or collect personnel opinions from experts or related individuals, and thus the results obtained may be subjective. The data envelopment analysis (DEA) method (Charnes et al., 1978) can discriminate relative effectiveness of evaluated units based on multiple inputs and outputs, and the weights of sub-indicators are directly generated according to the indicator values themselves without external judgment. However, as indicated by Cook and Kress (1990); Ganley and Cubbin (1992) and Despotis (2005), DEA applies different weight sets to assess different evaluated units and is thus not directly comparable between evaluated units.

Therefore, Despotis (2005) modified the DEA and proposed a common weight (CW) method to derive a set of CWs for use as sub-indicators. However, the CW method generates different alternative CW sets, and it is hard to decide which one is the final CW set. Therefore, this study modified the CW method and proposed four rules for selecting the final CW set: distinguishability, absence of major KPI exclusion, similarity, and skewness. The final CW set was then used to establish AI and to assess the performance of the MSW collection services provided by 307 Taiwan local governments. Local governments can use the proposed AI to review the efficiencies of their MSW collection programs and to compare them with others. Any key collection factor with poor performance can be identified by the AI, from the KPIs begin assigned with a low weight, and thus the governments can effectively address the deficiencies of their collection programs.

Next, the procedure for selecting KPIs is detailed. The KPIs serve as the sub-indicators of the AI to be established. Next, the DEA method is descried, along with its application for determining the weight of each KPI for each evaluated local government. The enhanced CW method and the proposed procedure for selecting the final set of CWs are followed. Finally, the results are compared and discussed.

2. Selection of MSW collection KPIs

Various indicators were previously reported for assessing MSW collection performance (e.g. Quon et al., 1970; Kao et al., 1992; World Economic Forum, 2002; Australian Government, 2006), and thirty-two indicators were collected. An AI is composed of several KPIs. However, too many KPIs may increase the complexity and the cost of establishing an AI. The development of criteria for selecting a set of KPIs is needed. Similar to the requirements proposed for selecting KPIs for a water utility (Alegre et al., 2006) and the criteria proposed for selecting indicators to assess sustainable communities (ICLEI et al., 1996; Holden, 1998), this study uses the following five criteria to select MSW collection KPIs:

(1) Completeness: in order to evaluate and cover all essential aspects of MSW collection performance, KPIs should have at least one indicator from each major aspect for evaluating MSW collection performance, including collection cost, work load and time, collection distance, and vehicle usage.

(2) Applicability: KPIs should be able to respond to changes in MSW collection performance. For example, per collection vehicle failure rate can be used to evaluate the efficiency for maintaining collection vehicles, but cannot respond to the collection performance and thus should not be included. Thirteen of the collected indicators failed to meet this criterion and thus were excluded.

(3) Ability to measure results: the data for computing an indicator should be regularly available. Some data are available for some specific periods only and should not be used to establish an indicator before a decision is made to collect that data on a regular basis. Eleven indicators did not meet this criterion and were thus excluded.

(4) Similarity: to avoid duplicate assessment, this study computed the correlation coefficients (Pearson, 1987) among indicators to check their similarity. When the coefficient value is greater than 0.75, the similarity of two MSW collection indicators is regarded as high and one of these indicators will be eliminated based on the next criterion. Among remaining eight major indicators, the correlation coefficients for the quantity of MSW collected per collection vehicle (MQ-Veh) vs. the population served per collection vehicle (SP-Veh), the population served per collector (SP-Collector) vs. the quantity of MSW collected per collector (MQ-Collector), and the quantity of MSW collected per vehicle-mile (MQ-Mile) vs. the cost per vehicle-mile (Cost-Mile) were 0.782, 0.766, and 0.969, respectively. Since these three pairs of indicators are all regarded as similar indicators, the next selection criterion is thus applied further.

(5) Distinguishability: when two indicators are highly correlated, only one of them needs to be retained. To determine which one to select, the sum of the deviations, either positive or negative, to the average of all indicator values is used to determine the level of distinguishability. If the deviation sum is small, then it means that most values do not vary too much from each other and the distinguishability is thus low. An example figure for the indicator values vs. the corresponding ranks of all local governments is shown in Fig. 1, the indicator of the SP-Collector is more suitable to differentiate the rank than the indicator of the MQ-Collector, and thus the former is selected as a KPI.

According to these five criteria, five KPIs were selected:

(1) Cost-MQ: cost per unit volume of MSW collected;
(2) MQ-Time: quantity of MSW collected per unit collection time;
(3) MQ-Veh: the quantity of MSW collected per collection vehicle;
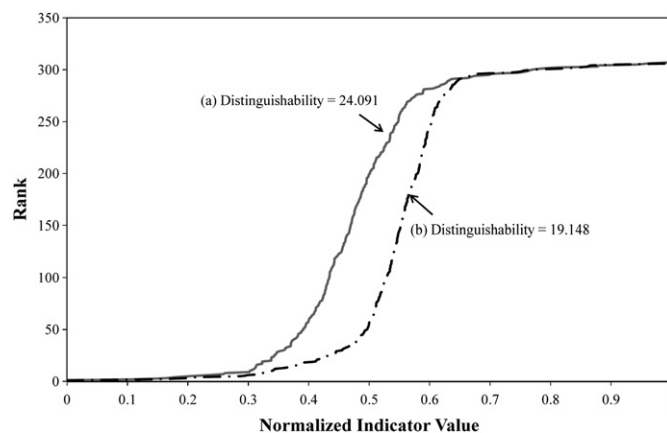

Fig. 1. Normalized indicator values vs. their ranks for two MSW collection indicators: (a) SP-Collector and (b) MQ-Collector.

(4) SP-Collector: the population served per collector; and
(5) MQ-Mile: the quantity of MSW collected per vehicle-mile.

Fig. 2 shows the five KPIs for each local government. KPI values are normalized to a range from 0 to 1. The darker the areas in the figure indicate better performance. Fig. 2(a) shows the Cost-MQ indicator values for all local governments. This indicator expresses the cost utility of a MSW collection system based on consumption of materials, energy, and resources. About 28% of all local governments whose scores are higher than 0.5, about NTD 4620 per ton annually, and the others may require improvement in resource planning and usage.

Fig. 2(b) shows the MQ-Time indicator values, which indicate the efficiency of time usage for MSW collection. An effective collection system is expected to collect a large quantity within a reasonably short time. The scores for most local governments on the West Coast of Taiwan exceed 0.5, about 2.9 tons collected per hour, which is substantially higher than those of East Coast governments. However, this is due to the fact that the population density in the West Coast of Taiwan is significantly higher than that in the East Coast and thus it must take longer time to collect MSW in the eastern regions.

Fig. 2(c) shows the MQ-Veh indicator values, which indicate the efficiency in using collection vehicles. Most MQ-Veh indicators for local governments on the West Coast of Taiwan are less than 0.3, about 1.8 tons per collection vehicle, which is significantly less than those for East Coast local governments. However, one reason for this situation is the uneven allocation of vehicles among local governments and the fairness of the vehicle allocation should be re-evaluated.

Fig. 2(d) shows the values obtained for the SP-Collector indicator, which reveals the collection efficiency of collectors in different local governments. Some local governments in the mid-south, northeast, and mid-west have high scores more than 0.7, about 1919 residents served per collector. Two possible reasons for the high scores are effective use of human resources or an insufficient number of collectors resulting in a high loading. Further analysis is needed to distinguish these two different types of performances.

Fig. 2(e) shows the values obtained for the MQ-Mile indicator, which indicate the collection routing efficiency of a MSW collection system. This KPI shows the effectiveness of collection routing plans. Approximately 40% of the local governments whose scores are less than 0.3, about 3446 tons per mile, and mostly are located on the East Coast. This indicator is substantially affected by the population density. Sparsely populated regions tend to have low scores for this KPI. Thus, comparisons should be made based on similar density.

The scores of the KPIs may significantly interfere with the operational environment of each local MSW collection system. For example, factors such as oil prices, labor costs and the expenditure of collection vehicles and equipment can significantly influence the COST-MQ indicator. Besides, population density, road density, traffic condition, and regional characteristics (e.g., area with popular tourist attraction) can change the score of the MQ-Time indicator. Other factors, such as management, routing, planning, can also alter the scores of KPIs. To analyze the differences among the KPI scores in detail these factors for MSW operational environment should be considered, although this lies beyond the scope of this study.

For each indicator, the performance rank order for each evaluated local government differs from those determined by other
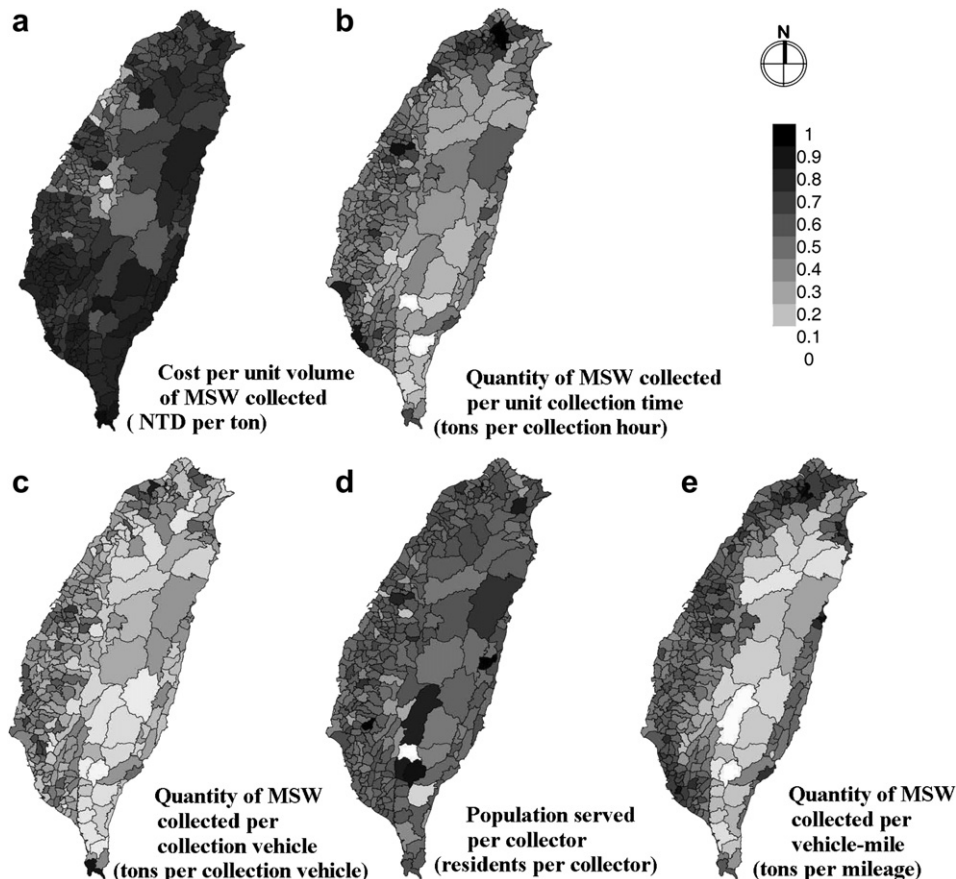

Fig. 2. The values of five MSW collection key performance indicators: (a) Cost-MQ, (b) MQ-Time, (c) MQ-Veh, (d) SP-Collector, and (e) MQ-Mile.

indicators, complicating the evaluation of overall performance from individual KPIs. Therefore, this study developed an approach to aggregate these five KPIs for this multi-factor MSW collection performance assessment problem.

3. The DEA method

After selecting the five KPIs, it needs to aggregate KPIs for assessing the MSW collection performance. The DEA method (Charnes et al., 1978) is frequently used to evaluate the efficiency among multiple inputs and outputs, and the weight set for each evaluated unit is determined based on the distance ratio to the efficiency frontier. The DEA efficiency frontier is defined as the collection of best achieved performances (Norman and Stoker, 1991). The line in the indicator space, along the upper edge of the region enclosing all performance indicator values is known as the efficiency frontier. The DEA input-oriented method is applied to generate initial weight sets for this study. The weights for KPIs are estimated by a linear programming model to the best advantage of each local government so as to maximize its relative efficiency. In this study, all the KPIs are considered as outputs and a dummy input (equal to one) is assumed (Ramanathan, 2006) for all local governments. Therefore, the modified linear model is formulated as follows.

$$E_k = \text{Maximum} \sum_{r=1}^{S} u_{rk} Y_{rk} \qquad (1a)$$

Subject to

$$\sum_{r=1}^{S} u_{rk} Y_{rj} \leq 1, \quad j \in C \qquad (1b)$$

$$u_{rk} \geq 0 \quad r \in S \qquad (1c)$$

$$Y_{rj} = [0, 1], \quad r \in S, j \in C \qquad (1d)$$

where E_k is the AI score for local government k; S is the set of the KPIs; u_{rk} are the weights of KPI r for local government k; Y_{rj} is the indicator value of KPI r for local government j; and C is the set of the 307 local governments.

Equation 1a is the objective function for optimizing a set of weights to maximize the total aggregate score (E_k) for the local government k. Each local government has its own weights to maximize their score, the value of the AI. Using the weight set determined for local government k, Equation 1b limits the AI score for each of the local governments to be less than or equal to 1. Equation 1c sets the lower bound of u_{rk} for all the weights to be determined. Equation 1d limits all indicator values to be between 0 and 1.

The DEA method can be applied to identify efficient local governments. When the AI score of a local government is equal to 1, it is regarded as an efficient unit. On the other hand, if the AI score of a local government is less than 1, it is inefficient, and there is at least one other local government with a performance better than it.

According to the result obtained using the DEA method, fourteen local governments are efficient, as marked A to N in Fig. 3. The weights for each local government are significantly different, and are not easy to rank and compare in the real world for assessing the MSW collection performance of all local governments. Furthermore, as shown in Fig. 3, all DEA-based efficient local governments have at least one KPI with a zero weight and thus cannot cover all KPIs. Therefore, this study modified the CW method proposed by Despotis (2005) to generate a CW set for assessing MSW collection performance, as described in the following section.

4. Enhanced CW method

Because each local government is assigned a different set of indicator weights in using the DEA method, it is not practical for assessing the performance of the MSW collection service. Therefore, this study modified the CW method proposed by Despotis (2005). However, Despotis (2005) did not mention how to select the final CW set from several alternative CW sets. This study thus proposed four selection rules for determining the final CW set. The CW method and the selection of the final CW set are described as follows.
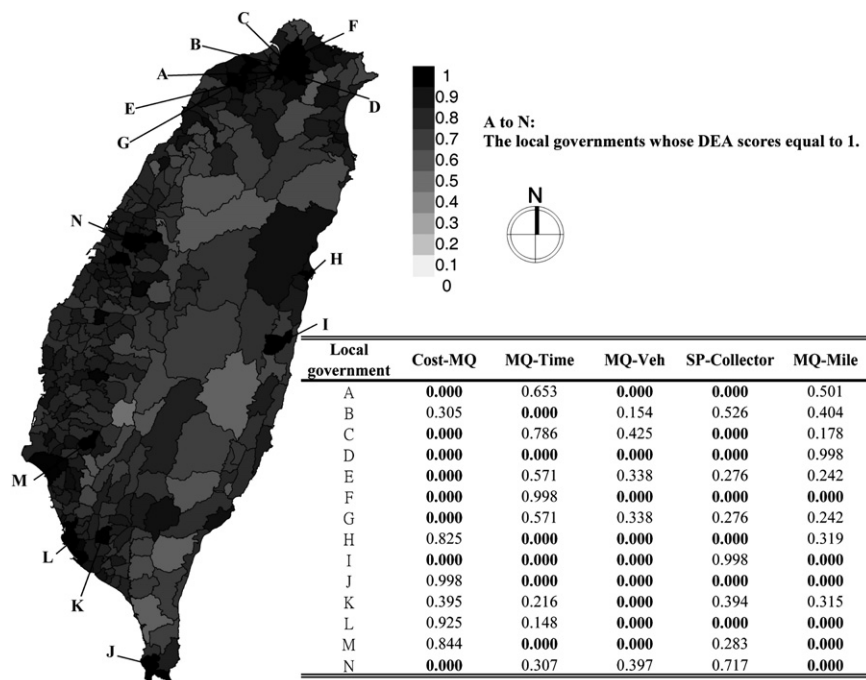

Local government	Cost-MQ	MQ-Time	MQ-Veh	SP-Collector	MQ-Mile
A	0.000	0.653	0.000	0.000	0.501
B	0.305	0.000	0.154	0.526	0.404
C	0.000	0.786	0.425	0.000	0.178
D	0.000	0.000	0.000	0.000	0.998
E	0.000	0.571	0.338	0.276	0.242
F	0.000	0.998	0.000	0.000	0.000
G	0.000	0.571	0.338	0.276	0.242
H	0.825	0.000	0.000	0.000	0.319
I	0.000	0.000	0.000	0.998	0.000
J	0.998	0.000	0.000	0.000	0.000
K	0.395	0.216	0.000	0.394	0.315
L	0.925	0.148	0.000	0.000	0.000
M	0.844	0.000	0.000	0.283	0.000
N	0.000	0.307	0.397	0.717	0.000

Fig. 3. The performance scores of all local governments determined by the DEA method.

Table 1
The weight sets determined by the CW method with different t values and their distinguishabilities and applicable selection rules.

No.	Cost-MQ	MQ-Time	MQ-Veh	P-Collector	MQ-Mile	Distinguishability	Rule[a]
CW1	0.325	0.000	0.254	0.529	0.160	20.974	(1)
CW2	0.195	0.000	0.455	0.567	0.000	21.112	(1)
CW3	0.001	0.000	0.489	0.574	0.265	28.759	(2)
CW4	0.000	0.000	0.478	0.600	0.258	28.425	(2)
CW5	0.000	0.000	0.476	0.602	0.259	28.395	(2)
CW6	0.030	0.000	0.425	0.601	0.296	27.891	(2)
CW7	0.127	0.086	0.209	0.672	0.363	27.133	(3)(4)
CW8	0.104	0.161	0.262	0.546	0.327	28.302	(3)(4)
CW9	0.118	0.169	0.236	0.542	0.342	28.280	(3)(4)
CW10	0.083	0.237	0.317	0.456	0.279	29.732	–
CW11	0.079	0.148	0.308	0.551	0.300	28.396	(3)(4)
CW12	0.000	0.105	0.452	0.569	0.217	29.067	(2)
CW13	0.000	0.236	0.315	0.458	0.281	29.696	(2)

[a] Selection Rules: (1) distinguishability, (2) no major KPI exclusion, (3) similarity, and (4) skewness.

4.1. CW method

Despotis (2005) proposed the following model to determine a CW set based on the result obtained from the DEA method.

$$G = \text{Minimum} \quad t \cdot \frac{1}{N} \cdot \sum_{j=1}^{N} d_j + (1-t) \cdot z \tag{2a}$$

Subject to

$$\sum_{r}^{S} w_r Y_{rj} + d_j = E_j, \quad j \in N \tag{2b}$$

$$d_j - z \leq 0, \quad j \in N \tag{2c}$$

$$w_r \geq 0, \quad r \in S \tag{2d}$$

$$d_j \geq 0, \quad j \in N \tag{2e}$$

$$z \geq 0 \tag{2f}$$

$$Y_{rj} = [0,1], \quad r \in S, j \in N \tag{2g}$$

where G is the minimal total distance between each pair of a DEA and a CW score; N is the number of local governments; the sum of $w_r Y_{rj}$ is the AI score for local government j; d_j is the difference between the AI scores obtained by the DEA method and the CW method for local government j; t is a prespecified constant between 0 and 1, as explained in the next paragraph; z is a nonnegative variable; w_r is the CW of KPI r; and E_j is the DEA score for the local government j.

The objective function, Equation 2a, is to minimize the total distance between each pair of DEA and the CW aggregative indicator scores. When t is set to be 1, then the distance is defined as the difference, d_j, between two AI scores (the L_1 norm distance) If t is set to be 0, then the distance is defined as the maximum of all d_j's (the L_∞ norm). A different value of t will derive a different set of CWs. Equation 2b is used to determine the difference d_j between two AI scores. Equation 2c is used to determine the maximum, z, of all d_j's, while t is set to be zero. Equation 2d limits w_r to being positive and greater than 0. Equations (2e) and (2f) set d_j and z to be positive. And Equation 2g sets Y_{rk} to be bounded in the interval of (0, 1).

Besides the L_1, L_∞ norms and various t, between 0 and 1, this study also applied a least square objective function to find another set of CWs based on the Euclidean distance (L_2). The objective function is listed as follows Equation (3).

$$\text{Minimum} \quad \left(\sum_{j=1}^{N} d_j^2 \right)^{\frac{1}{2}} \tag{3}$$

As listed in Table 1, thirteen alternative CW sets were generated. However, some of these sets are not appropriate. For example, the weights of some KPIs in some sets are zero and thus will exclude associated KPIs. Furthermore, the problem that must be resolved is selecting the final set to be used. Therefore, this study proposed four selection rules to resolve this problem, as explained in the following section.

4.2. Selection of final CW set

Four rules of distinguishability (IISD, 1999), absence of major KPI exclusion (Sustainable Measures, 2006), similarity (Spangenberg et al., 2002), and skewness (Azzalini, 1985) were used to select the final CW set.

(1) Distinguishability: this rule is similar to the one aforementioned for selecting KPIs. The distinguishabilities of CW1 and CW2, as shown in Table 1, were significantly lower than that of the others, and thus they were excluded.

(2) Absence of major KPI exclusion: for assessing the essential aspects of MSW collection performance, all KPIs should be considered. Therefore, if the weight of any KPI in a weight set is zero, then the weight set is not suitable to be used. Therefore,
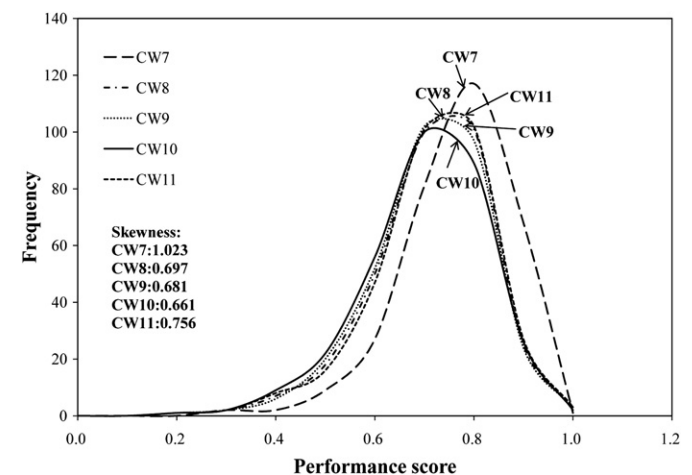
Fig. 4. The distributions of CW7-CW11 results and their coefficients of skewness.
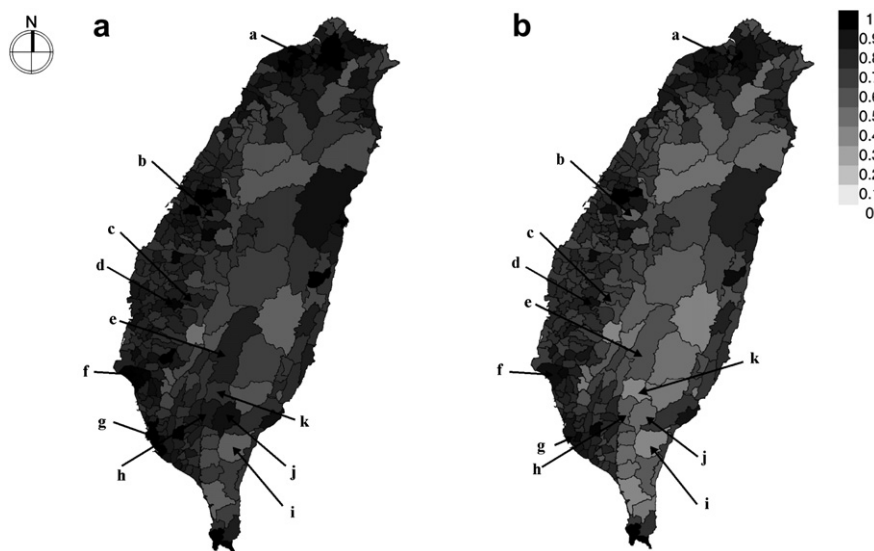
Fig. 5. MSW collection performance scores of 307 local governments in Taiwan: (a) the DEA method and (b) the CW method.

as listed in Table 1, six sets of CW3-CW6, CW12-CW13 were excluded.

(3) Similarity: to identify similar sets, the correlation coefficients of all sets are evaluated. If the correlation coefficient between two sets is greater than 0.95, the two sets are regarded as similar sets. The correlation coefficients of all pairwise comparisons for CW8-CW11 are all higher than 0.95, and a rule is thus needed to eliminate similar ones.

(4) Skewness: if two sets are highly correlated, then only one is retained. A distribution plot and the coefficient of skewness are prepared to check the skewness of the results obtained by two similar CW sets. If the frequency plot is close to a normal distribution, then its skewness coefficient will be small. In Fig. 4, two groups can be observed in the plot. One group consists of CW8-CW11, and the other one is CW7. The skewness coefficient of CW10 is the lowest, is thus selected as the final CW set.

Fig. 5 compares the aggregate performance indicator scores determined by the DEA method and the final CW set. Fig. 5(a) and (b) present the DEA and the CW results, respectively. The AI scores

Fig. 6. The accumulated percentages of the performance scores of all local governments.

determined by the CW method shown in Fig. 5(b) range from 0.4 to 1. Local governments with low AI scores need to examine their policy and planning of MSW collection to improve the poor performances.

The DEA method can evaluate relative efficiency, but the ranks determined by the DEA scores are not readily accepted by the local governments because the score of each local government is calculated based on a different weight set. On the other hand, the scores obtained by the CW method are comparable among local governments. By comparing the results obtained by both the DEA and the CW method, the performance scores of some local governments, as marked a to k in Fig. 5, are high according to the DEA method, but their performance scores are then reduced by the CW method because they have only one or few KPIs with good performance that lead to high DEA scores. The AI established by the CW method is more practicable than the one generated by the DEA method. With the DEA method, in addition to the different sets of weights assigned to KPIs for each local government, the assigned weights are frequently set to be extreme values, either 1 or 0. If the weight of any KPI is set to be zero, it indicates that the KPI is ignored, and such a situation should not happen for any selected KPI. The set of weights determined by the CW method and selection rules can overcome these problems when the performance scores determined by the set of weights are kept as close as possible to the DEA scores. Furthermore, as the accumulated percentages of performance scores shown in Fig. 6, the distinguishability of the CW result is superior to that for the DEA result.

5. Conclusion

Because MSW collection is the main expenditure in waste management, it is crucial to optimize MSW collection efficiency. This study proposed the following five criteria for selecting indexes for assessing the performance of MSW collection: completeness, applicability, ability to measure results, similarity, and distinguishability. Five KPIs, Cost-MQ, MQ-Time, Q-Veh, SP-Collector, and MQ-Mile, were then selected and used to establish an AI for evaluating MSW collection performance.

Although the DEA method is widely used to analyze AIs, it tends to generate different weights for evaluated local governments and does not enable comparisons among local governments. This study
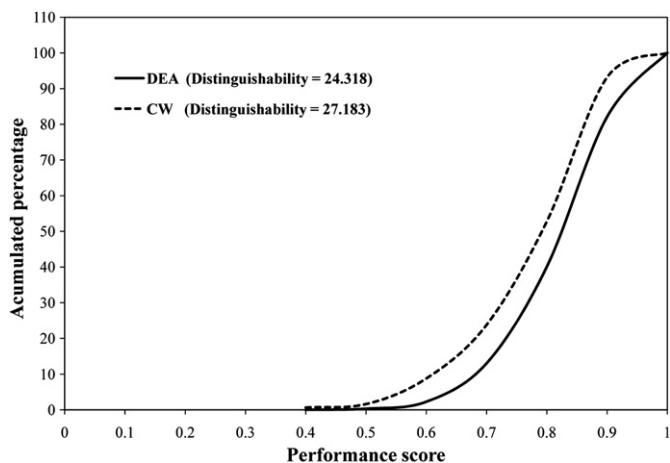
thus modified the CW method proposed by Despotis (2005) to overcome this problem. However, the issue of how to select the final weight set from multiple alternative CW sets remains a problem. Therefore, four rules of distinguishability, absence of major KPI exclusion, similarity, and skewness, were developed for selecting a proper CW set. The proposed procedure, including the index selection criteria and rules, was demonstrated in development of an AI to assess the MSW collection performance in 307 local governments in Taiwan.

The final AI scores were calculated by DEA scores and the CW set determined by the CW method. Each local government can assess its performance by comparing its indicator score with its own previous scores or with the scores of other local governments. Local governments with good scores can serve as exemplars for other local governments that wish to improve their MSW collection performances. The central government can also evaluate the AI and KPI scores to identify such exemplars and to promote good collection policies or programs, and it can also identify those with extremely poor performance and assist them in improving.

All study data were provided by the Environmental Protection Administration, Executive Yuan, R.O.C. Data validation, including accuracy and reliability, is important, although this issue was not explored because a procedure was generally implemented to validate the data before released. The sensitivity of efficiency scores relative to the data variation may significantly influence the reliability of performance assessment and thus should be evaluated. The Super-efficiency DEA sensitivity analysis approach (Zhu, 2001) was thus applied to evaluate the sensitivity. The result of the analysis shows that all local governments are inliers, and no outlier with an infeasible value was found. The sensitivity thus is regarded as insignificant in this study. The procedure is highly proposing for use in developing other aggregate indexes. Moreover, the proposed MSW collection AI may also be applicable in other countries if it is adjusted based on the local operational environment.

Acknowledgments

References

Alam, R., Chowdhury, M.A.I., Hasan, G.H.J., Karanjit, B., Shrestha, L.R., 2008. Generation, storage, collection and transportation of municipal solid waste – a case study in the city of Kathmandu, capital of Nepal. Waste Management 28, 1088–1097.

Alegre, H., Baptista, J.M., Cabrera Jr., F., Cubillo, E., Duarte, P., Hirner, W., Merkel, W., Parena, R., 2006. Performance Indicators for Water Supply Services, second ed. IWA Publishing, Madrid, Spain.

Australian Government, 2006. Productivity Commission Draft Report: Waste Management, Australian Government Productivity Commission. Australian Government: Australian.

Azzalini, A., 1985. A class of distributions which includes the normal ones. Scandinavian Journal of Statistics 12, 171–178.

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

Cook, W.D., Kress, M., 1990. Data envelopment model for aggregating preference ranking. Management Science 36 (11), 1302–1310.

Dajani, J.S., Vesilind, P.A., Hartman, G., 1976. Measuring the Effectiveness of Solid Waste Collection. Department of Civil Engineering, The Institute of Policy Sciences and Public Affairs Duke University, Durham, N.C., USA.

Despotis, D., 2005. A Reassessment of the human development index via data envelopment analysis. Journal of the Operational Research Society 56, 969–980.

Esty, D.C., Levy, M.A., Srebotnjak, T., Sherbinin, A.D., 2005. Environmental Sustainability Index: Benchmarking National Environmental Stewardship. Yale Center for Environmental Law and Policy, New Haven, Connecticut, USA. 2005.

Fobil, J.N., Armah, N.A., Hogarh, J.N., Carboo, D., 2006. The influence of institutions and organizations on urban waste collection systems: an analysis of waste collection system in Accra, Ghana (1985–2000). Journal of Environmental Management 86 (1), 262–271.

Ganley, J.A., Cubbin, S.A., 1992. Public sector efficiency measurement: applications of data envelopment analysis, North-Holland, Amsterdam, Netherlands, pp. 39–43.

Garcia-Sanchez, I.M., 2008. The performance of Spanish solid waste collection. Waste Management & Research 26 (4), 327–336.

Holden, M., 1998. Sustainable Seattle – Indicators of Sustainable Community. The Sustainable Seattle Indicators Task Team. Springer, Netherlands, Canada.

The International Council for Local Environmental Initiatives (ICLEI), The International Development Research Centre (IDRC), The United Nations Environment Programme (UNEP), 1996. The Local Agenda 21 Planning Guide. ICLEI, IDRC, UNEP, Toronto, Canada.

International Institute for Sustainable Development (IISD), 1999. Indicator for Sustainable Development: Theory, Method, Applications (Tokyo, Japan).

Kao, J.J., Lin, T.I., 2002. Shortest service location model for planning waste pickup locations. Journal of the Air & Waste Management Association 52, 585–592.

Kao, J.J., Liu, Y.I., Fang, M.H., 1992. The Research of Public Enterprise of Solid Waste Performance. National Chiao-Tung University, Institute of Environmental Engineering, Hsinchu, R.O.C.

Li, Y.P., Huang, G.H., 2006. An inexact two-stage mixed integer linear programming method for solid waste management in the city of Regina. Journal of Environmental Management 81, 188–209.

Lin, C.H., Wen, L.C., Tsai, Y.M., 2010. Applying decision-marking tools to national e-waste recycling policy: an example of analytic hierarchy process. Waste Management 30, 863–869.

Menezes, J., de Carvalho, J.C., Dias, E.B., Martins, A.L., 2003. The Need of a Network Approach in Household Waste Packages Collection: An Empirical Analysis in a Heterogenous Population Density Area.

Norman, M., Stoker, B., 1991. Data Envelopment Analysis: The Assessment of Performance. John Wiley & Son, New York, U.S.A.

Oregon Department of Environmental Quality (ODEQ), 2007. Oregon Water Quality Index Summary Report, Water Years 1997–2006. State of Oregon, Oregon, U.S.A.

Pearson, K., 1987. Mathematical Contributions to the Theory of Evolution. On the Law of Ancestral Heredity. In: Proceedings of the Royal Society of London. London, 1987, vol. 62, pp. 386–412.

Prë-Consultants, 2000. A Damage Oriented Method for Life Cycle Impact Assessment. The Eco-indicator 99, Netherlands. <http://www.pre.nl/eco-indicator99/ei99-reports.htm> (Oct. 13, 2009).

Quon, J.E., Asce, M., Martens, R.R., Tanaka, M., 1970. Efficiensy of refuse collection crews. Journal of the Sanitary Engineering Division 2, 437–453.

Ramanathan, R., 2006. Data envelopment analysis for weight derivation and aggregation in the analytic hierarchy process. Computers & Operations Research 33, 1289–1307.

Ramzan, N., Degenkolbe, S., Witt, W., 2008. Evaluating and improving environmental performance of HC's recovery system: a case study of distillation unit. Chemical Engineering Journal 140, 201–213.

ROCEPA, 2010. 2009 Yearbook of Environmental Statistics. Environmental Protection Administration, Executive Yuan, Taipei, R.O.C.

Saaty, R.W., 1987. The analytic hierarchy process: what it is and how it is used. Mathematical Modelling 9, 161–176.

Sarkis, J., Dijkshoorn, J., 2007. Relationships between solid waste management performance and environmental practice adoption in welsh small and medium-sized enterprises (SMEs). International Journal of Production Research 45 (21), 4989–5015.

Shuhua, H., Qingguo, M., Thjota, H., 2007. The analysis and demonstration of value engineering about the performance of science & technology inputs of local government. In: Proceedings of the 2nd International Conference on Production Innovation Management & the 3nd International Conference on Value Engineering, pp. 52–58 (Wuhan, Peoples R China).

Simonetto, E.O., Borenstein, D., 2007. A decision support system for the operational planning of solid waste collection. Waste Management 27, 1286–1297.

Spangenberg, J.H., Pfahl, S., Deller, K., 2002. Towards indicators for institutional sustainability: lessons from an analysis of agenda 21. Ecological Indicators 2, 61–77.

Sustainable Measures, 2006. Sustainable Community Indicator Checklist. http://www.sustainablemeasures.com/Indicators/ChecklistItself.html (accessed October 2007).

Tugnoli, A., Santarelli, F., Cozzani, V., 2008. An approach to quantitative sustainability assessment in the early stages of process design. Environmental Science & Technology 42, 4555–4562.

Ülengin, B., Ülengin, F., Güvenc, Ü, 2001. A multidimensional approach to urban quality of life: the case of istanbul. European Journal of Operational Research 130, 361–374.

Woodard, R., Harder, M.K., Bench, M., Philip, M., 2001. Evaluating the performance of a fortnightly collection of household waste separated into compostables, recyclates and refuse in the south of England. Resources Conservation & Recycling 31, 265–284.

World Economic Forum, 2002. Environmental Sustainability Index: Main Report. Global Leaders of Tomorrow Environmental Task Force. World Economic Forum. http://www.ciesin.columbia.edu/indicators/ESI (Nov. 1, 2010).

Worthington, A.C., Dollery, B.E., 2001. Measuring efficiency in local government: an analysis of new south Wales municipalities' domestic waste management function. Policy Studies Journal 29 (1), 232–249.

Zhen, L., Routray, J., 2003. Operational indicators for measuring agricultural sustainability in developing countries. Environmental Management 32 (1), 34–46.

Zhu, J., 2001. Super-efficiency and DEA sensitivity analysis. European Journal of Operational Research 129, 443–445.