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Research paper

Cost drivers and functions for municipal solid waste collection systems in Ghana

Alhassan Sulemana [1, 2] *, Emmanuel Amponsah Donkor [2], Sampson Oduro-Kwarteng [2]

[1] *Department of Environmental Science, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana*
[2] *Department of Civil Engineering, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana*
**Corresponding author E-mail: sulemanaalhassan@knust.edu.gh*

Abstract

The collection of municipal solid waste accounts for 60% to 80% of total management cost. This study determined the factors driving operating cost and developed cost functions for municipal solid waste collection systems in Ghana. Data on cost variables from seventy systems were used to estimate the parameters of log-linear cost functions. Results from the study led to the conclusion that quantity of waste collected, fuel consumed and distance travelled increase significantly and explain about 63.0% of the variation in operating cost. The amount of fuel consumed and quantity of waste collected varied significantly and explained about 67.4% of the variation in operating cost of systems from low waste generating sources. For high waste generating sources, the distance travelled, fuel consumed and quantity of waste collected significantly and better explained (85.4%) the variation in operating cost. This can be attributed to the fact that such systems are from places with better facilities. The cost function for high waste generating sources can comparatively better aid decision making in terms of operations, management, investment and policy actions. Cost-effective solid waste collection schemes should therefore consider efficient management of fuel consumed, quantity of waste generated and distance travelled.

Keywords: *Cost Drivers; Cost Function; Solid Waste Collection; Operating Cost; Fuel Consumed.*

1. Introduction

Municipal solid waste (MSW) management has become a major challenge with serious socio-economic and environmental implications, particularly for many developing countries [1, 2]. The situation is worsened by inadequate financing [3]. Annually, as stated by Hoornweg and Bhada-Tata [4], up to $205.4 billion is spent on MSW management and the costs in developing countries, where waste management is already the single largest budgetary item in most cities, are expected to increase five-fold by 2025. The cost of solid waste collection accounts for approximately 60% – 80% of total MSW management cost due to labour intensity and massive use of trucks [5], [6]. Reduction of MSW collection cost has become a major economic concern for managers in the waste management sector.

In response to the need for decisions concerning cost reduction, several studies have identified, assessed and modeled the factors driving MSW collection cost using cost functions [7], [8]. Cost function as defined by Parthan et al. [8] is used to broadly describe the relationship of cost to variables such as number and age of trucks, number of employees, frequency of collection and total tonnes collected. Different forms of cost function have been used by past studies to model MSW collection cost. Greco et al. [9] investigated the drivers of solid waste collection cost and found out that different waste types are significantly affected by population size and density, percentage of separate collection, percentage of home collection and private delivery. Their results also indicate that internal efficiency of management companies also significantly affects collection cost. A study by El-Hamouz [10] established labour and total collection cost as a function of number of houses. The effects of operational drivers such as distance travelled, quantity of waste collected, number of trips and fuel consumed on operating cost have rare been assessed.

Developing a cost function using scalar variables affecting cost of waste collection can describe the economies of scale effect [8]. Variables such as quantity of waste collected from different waste generating sources, segregated based on human population of the study areas can help describe the economies of scale effect of the collection systems. Cost functions for MSW collection systems can thus have managerial, policy and environmental implications. Inputs of the system for a given level of service that is cost-effective can be found using cost functions. They help in performance evaluations and future predictions in order to make informed investment decisions. Cost functions can also allow conclusions to be drawn concerning economies of scale. This study therefore determined the factors driving operating cost and developed cost functions for MSW collection systems in Ghana.

2. Methodology

2.1. Study area and data collection

The study was conducted in Ghana using seventy local authorities (representing MSW collection systems) from Ashanti Region, Brong Ahafo Region and Upper East Region (Figure 1). The seventy MSW collection systems represent Metropolitan, Municipal and District Assemblies (MMDAs). District Assemblies were considered as low generating sources of MSW (0.28 kg/capita) and have comparatively less population while Metropolitan/Municipal Assemblies were considered as high generating sources of MSW (0.52 kg/capita) [11]. The study used mean monthly data collected from 2016 operating year in the respective

MMDAs and Table 1 presents descriptive statistics on the sample. The data shows extensive variation in operating cost, quantity of waste collected, distance travelled, fuel consumed and number of trips made by collection trucks; the coefficient of variations are greater than one for all the variables, except operating cost for low generating sources.

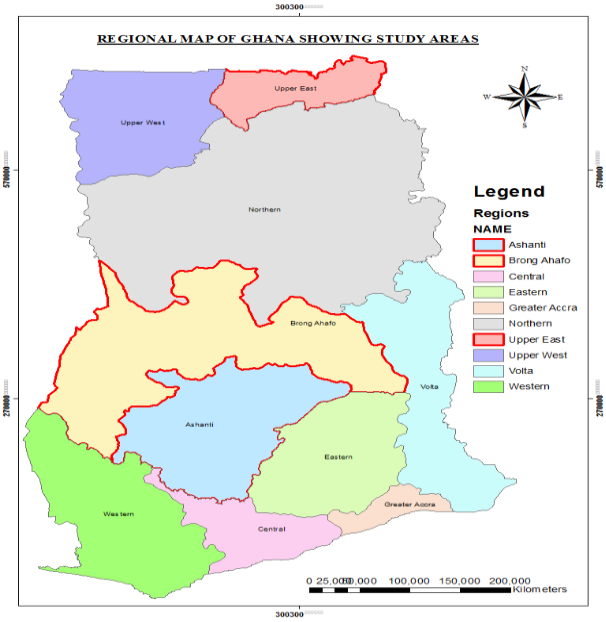

Fig. 1: Map of Ghana Showing Study Areas: Map Developed by Author Using ArcGIS Software

2.2. Specification of variable cost function

Empirical literature explaining variables that influence solid waste operating cost dates back to mid-1960s [12]. In econometric modeling of MSW collection systems, there is the need to specify a cost function and a method for estimating the parameters, for e.g. Saturation Curve Method, as stated in Dyson and Chang [13]; and Ordinary Least Squares Regression, as applied by Greco et al. [9]. The functional forms of the estimation methods include the linear, trans-log and log-linear models. Past studies show that the log-linear and trans-log functional forms have been more popular in modeling the cost of MSW management [12], [14]. Because the trans-log functional form requires a large sample size [15], the log-linear functional form, as presented in (1), was used in the study.

$$\ln OPC = \beta_0 + \beta_1 \ln Q + \beta_2 \ln F + \beta_3 \ln D + \beta_4 \ln T + \varepsilon \qquad (1)$$

Here, the operating cost (*OPC*) is measured in Ghana Cedi (currently, \$1.0 = GH₵4.7) and composed of staff remuneration cost, truck maintenance and repair costs, and energy and administration costs. *Q* represents the quantity of MSW collected by trucks and is measured in kilogram (kg). *F* is the fuel consumed by collection trucks and is measured in litres (l). *D* refers to the distance travelled in kilometers (km). *T* is the number of trips made by trucks in collecting waste from points of generation to disposal. The difference between the actual *OPC* and the predicted *OPC* is measured by ε (random error term). The parameters of the variables are represented by the ß terms which measure *OPC's* elasticities in terms of the predictor variables. Within the study's limitation of inadequate data, four variables affecting operating cost were used in establishing the cost functions (Table 1). It is expected that operating cost will increase with increasing quantity of waste collected, distance travelled and fuel consumed.

Table 1: Descriptive Statistics of the Variables on MSW Collection Systems with Coefficient of Variations in Parentheses

Variable	Description	Generalized Sources		Low Generating Sources		High Generating Sources	
		N	Mean	N	Mean	N	Mean
OPC	Operating cost (GH₵)	70	3259.90 (1.805)	54	2,749.53 (0.871)	16	3,259.95 (1.803)
Q	Quantity of waste collected ('000 kg)	70	438.59 (1.657)	54	383.90 (1.155)	16	438.79 (1.664)
D	Distance travelled (km)	70	1264.72 (2.491)	54	981.20 (1.152)	16	1,264.74 (2.489)
F	Fuel consumed (litres)	70	499.84 (2.475)	54	388.15 (1.169)	16	499.84 (2.473)
T	Number of trips	70	71.75 (1.608)	54	63.39 (1.166)	16	71.75 (1.606)

Source: Authors' analysis.

2.3. Estimation procedure and diagnostics

The specified cost function in (1) risks suffering from multicollinearity problems; all predictors (*lnQ*, *lnF*, *lnD* and *lnT*) are highly correlated (r = 0.745 – 0.996). Beigl et al. [16] in forecasting municipal solid waste generation in major European cities noted that inclusion of many variables in multiple regression models typically causes collinearity problems leading to ill-conditioned models. As a result, parameters of three models were estimated: Model 1, formulated in (1) involved all significant and insignificant variables. Model 2, as formulated in (2), used average cost (*OPC/Q*) as the dependent variable. The variables in (2) competed statistically to sequentially eliminate the variable that is least significant at each estimation state, on condition that its t-statistic is below 1.667 in absolute value. This resulted in the third model, Model 3.

$$\ln(OPC/Q) = \alpha_0 + \alpha_1 \ln Q + \alpha_2 \ln F + \alpha_3 \ln(D/Q) + \alpha_4 \ln T + \varepsilon \qquad (2)$$

This procedure makes sure that all variables in the model are significant at the 10% significance level. It only allows variables that are significant in the cost function and ensures improved precision with which the effects of the variables are estimated. Diagnostic checks of the models were conducted using normality test of residuals. The variables' order of importance was evaluated by considering the standardized beta coefficients (Std. Beta) of the variables with respect to their magnitude. Variables with higher values have more explanatory power. Condition Index (CI) and Variance Inflation Factor (VIF) were used to check for the degree of multicollinearity in the models. VIF more than 10 or CI greater than 30 indicated that severe multicollinearity problems exist.

3. Results and discussion

3.1. General cost function for MSW collection systems

Stepwise Regression, using Statistical Package for Social Sciences (Version 21) was used to estimate the parameters for models and also for conducting model diagnostics. Results for Model 1a (general cost function for MSW collection systems) are presented in Table 2. Overall, the generalized model was significant (p = 0.000), explains about 64.1% of the variation in operating cost but suffers from severe multicollinearity problems (highest VIF = 52.267 and final CI = 113.403). The results indicate that direct operating cost increases significantly with quantity of waste collected and fuel consumed whiles distance travelled and number of trips were insignificant, all at the 5% level. We observe from Model 1a that a 1% increase in each of quantity of waste collected and fuel consumed result in 0.336% and 0.404% increases in operating cost respectively. The resulting function can therefore be represented as (3).

$$\ln OPC = 3.679 + 0.336 \ln Q + 0.404 \ln F + \varepsilon \qquad (3)$$

Model 2a which considered average cost as the dependent variable was significant (p = 0.000), explains about 63.2% of the variation in average cost and also suffers from multicollinearity problems (Table 2). It however produced more explanatory variables as quantity of waste collected, fuel consumed and distance travelled were significant at the 5% level. The resulting cost function is presented as (4). From (4), a 1% increase in each of quantity of waste collected, fuel consumed and distance travelled, holding all other variables constant results in 0.427%, 0.395% and 0.043% increases in operating cost respectively.

$$\ln(OPC/Q) = 3.648 - 0.531\ln Q + 0.395\ln F + 0.043\ln(D/Q) + \varepsilon$$

$$\ln OPC = 3.648 + (1 - 0.531 - 0.043)\ln Q + 0.395\ln F + 0.043\ln D + \varepsilon$$

$$\ln OPC = 3.648 + 0.426\ln Q + 0.395\ln F + 0.043\ln D + \varepsilon \quad (4)$$

To eliminate the multicollinearity problems in Model 2a, the variables competed statistically to eliminate the insignificant variables to generate Model 3a (Table 2). The model is generally significant (p = 0.000) and explains 63.0% of the variation in average cost at the 10% level. The cost function for MSW collection systems from the study areas can therefore be represented as shown in (5). From the results, a 1% increase in quantity of waste collected, holding all other variables constant leads to 0.210% increase in operating cost at 10% significance level whiles 1% increase each in fuel consumed and distance travelled, holding other variables constant results in 0.383% and 0.045% increases in operating cost respectively at the 10% level. Considering standardized beta coefficients of the variables, fuel consumed has the highest explanatory power, followed by distance travelled and then quantity of waste collected respectively. The general cost function for MSW collection in the study areas is characterised by economies of scale as change in the input variables results in disproportionate change in the output variable.

$$\ln(OPC/Q) = 4.031 - 0.745\ln Q + 0.383\ln F + 0.045\ln(D/Q) + \varepsilon$$

$$\ln OPC = 4.031 + (1 - 0.745 - 0.045)\ln Q + 0.383\ln F + 0.045\ln D + \varepsilon$$

$$\ln OPC = 4.031 + 0.210\ln Q + 0.383\ln F + 0.045\ln D + \varepsilon \quad (5)$$

Table 2: Parameter Estimates and Model Utility Values for General MSW Collection Systems

Model	Model 1a	Model 2a	Model 3a
Dependent Variable:	ln(OPC)	ln(OPC/Q)	ln(OPC/Q)
N	70	70	70
Explanatory Variables:			
CONSTANT	3.679	3.648	4.031
ln(Q)	.336*	-.531*	-.745**
ln(F)	.404*	.395*	.383**
ln(D)	.130		
ln(D/Q)		.043*	.045**
ln(T)	-.246	-.232	
Model Utility			
R^2	.641	.632	.630
Adj R^2	.638	.629	.627
SEE	.42998	.42655	.42727
Highest VIF	52.267	53.470	8.456
Final Condition Index	113.403	109.641	44.672

* (Significant at 5% level) and ** (Significant at 10% level).
Source: Authors' analysis.

3.2. Cost function for low MSW generating sources

Results for low MSW generating sources are presented in Table 3. Overall, the model was significant (p = 0.000) and explains about 67.4% of the variation in average cost (Model 3b). Average cost of MSW collection significantly decreases with the quantity of waste collected but increases with the amount of fuel consumed by collection trucks at the 10% significance level. Distance travelled and number of trips were insignificant at the 10% level. The resulting cost function for MSW collection in low generating sources in the study areas can be represented as formulated in (6). We observe from (6) that, a 1% increase in quantity of waste collected and/or amount of fuel consumed results in less than proportionate (i.e. < 1%) increase in operating cost for MSW collection which indicates existence of economies of scale. Fuel consumed had a higher explanatory power than quantity of waste collected considering their standardized beta coefficients.

$$\ln(OPC/Q) = 5.091 - 0.819\ln Q + 0.280\ln F + \varepsilon$$

$$\ln OPC = 5.091 + (1 - 0.819)\ln Q + 0.280\ln F + \varepsilon$$

$$\ln OPC = 5.091 + 0.181\ln Q + 0.280\ln F + \varepsilon \quad (6)$$

Table 3: Parameter Estimates and Model Utility Values for Low and High MSW Generating Sources

Source	Low Generating			High Generating		
Model	Model 1b	Model 2b	Model 3b	Model 1c	Model 2c	Model 3c
Dependent Variable:	ln(OPC)	ln(OPC/Q)	ln(OPC/Q)	ln(OPC)	ln(OPC/Q)	ln(OPC/Q)
N	54	54	54	16	16	16
Explanatory Variables:						
CONSTANT	4.811	4.797	5.091	-1.685	5.528	5.653
ln(Q)	.292	-.641*	-.819**	-8.684E-007	3.391E-005*	3.477E-005**
ln(F)	.231*	.230*	.280**	.938*	.852	.333**
ln(D)	.065			.155*		
ln(D/Q)		.069			.870	.342**
ln(T)	-.128	-.127		-.101*	-.504	
Model Utility						
R^2	.371	.676	.674	.991	.856	.854
Adj R^2	.363	.672	.672	.990	.850	.850
SEE	.41181	.41027	.41014	.08066	.31762	.31824
Highest VIF	33.652	36.061	2.646	19.248	165.888	3.131
Final Condition Index	98.661	97.446	30.008	92.643	285.001	35.132

* (Significant at 5% level) and ** (Significant at 10% level).
Source: Authors' analysis.

3.3. Cost function for high MSW generating sources

Table 3 presents results of parameter estimates and model utility values for high MSW generating sources. The overall model (Model 3c) was significant (p = 0.000), and explains about 85.4% of the variation in average cost. As will be expected, the average cost for solid waste collection in high generating sources increases significantly with the quantity of waste collected, fuel consumed and distance travelled at the 10% level. The associated cost function is represented as (7). It can be observed from (7) that, a 1% increase in quantity of waste collected, holding all other variables constant, results in about 0.7% increase in operating cost, while fuel consumed and distance travelled, each increase by approximately 0.3%. Considering the standardized beta coefficients of the variables, quantity of waste collected had the highest explanatory power, followed by fuel consumed and then distance travelled. Parameter estimates of the variables suggest that high generation sources are characterised by economies of scale.

$$\ln(OPC/Q) = 5.653 + 0.0000348 \ln Q + 0.333 \ln F + 0.342 \ln(D/Q) + \varepsilon$$

$$\ln OPC = 5.653 + (1 + 0.0000348 - 0.342) \ln Q + 0.333 \ln F + 0.342 \ln D + \varepsilon$$

$$\ln OPC = 5.653 + 0.658 \ln Q + 0.333 \ln F + 0.342 \ln D + \varepsilon \tag{7}$$

Thus, the most important cost drivers for MSW collection in the study areas are fuel consumed, quantity of waste collected and distance travelled. An increase in each of these variables results in corresponding disproportionate increase in operating cost. This supports the hypothesis that the operating cost for solid waste collection increases with increasing levels of input variables and agrees with Parthan et al. [8]. The model for high MSW generating sources explains the variation in cost better than low generating sources. This can be attributed to the fact that places such as Municipals and Metropolitans generate high waste quantities and hence exhibit higher economies of scale. The cost function for high MSW generating sources can comparatively better aid decision making in terms of operational and management activities, investment and policy actions.

4. Conclusion

Within the study's limitations, such as absence of enough data, we conclude that cost drivers of operating cost that are most important for municipal solid waste collection in the study areas are amount of fuel consumed, quantity of waste collected and distances travelled by collection trucks. These identified drivers better explain variations in operating cost for high MSW generating sources than for low MSW generating sources. The conclusions from this study have operational, managerial, investment and policy implications related to effective cost control in solid waste collection. The development of cost-effective municipal solid waste collection schemes should therefore consider efficient management of fuel consumed, quantity of waste generated, and distances travelled by the collection trucks.

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