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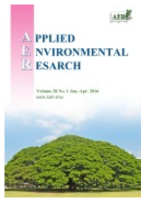

A Workforce and Truck Allocation Model in a Solid Waste Management System: A Case from Nigeria

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Abstract

The management of waste with the limited workforce and trucks is a complicated problem. Currently, there is insufficient evidence in literature on how this process could be optimised. In this article, two new models on genetic algorithm and differential evolution were developed to jointly optimise the cost and human reliability of a municipal solid waste (MSW). It optimised this system's benefit-cost and established the relationship between a MSW's workforce and truck allocation. Although prior research has revealed relationships among cost, workforce strength, and truck allocation activities, however, the nature of this relationship and the unique attribute of workers' reliability to influence the total operating cost and the benefit-cost ratio have not been thoroughly understood. A case study of a MSW agency in Nigeria was used to demonstrate the applicability of the proposed model. The results obtained showed preference to the differential evolution algorithm's results. This article contributes to MSW in the following ways: it presents a model to assign reliability to workforce in a MSW system based on evolutionary algorithms performance, and it optimises a MSW system's total operating cost and the benefit-cost ratio concurrently.

Keywords: Reliability; Operating cost; Benefit/cost; Meta-heuristics; Municipal solid waste

Introduction

In research regarding municipal solid waste (MSW), operating costs and benefit-cost analysis of diverse solid waste options are important concerns [1–4]. This is because they explain the daily expenses of managing MSW and the benefits in revenues of selling recyclables (plastic bottles, glass, steel and aluminium cans, newspapers and cardboards) from waste and compost [1, 4]. Monitoring the operating cost of MSW offers significant benefits to effectively control

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operation and maintenance costs [5]. It helps to detect and avoid partial separation of non-compostable, deficient maintenance practices on facilities and high composting cost weighed against commercial fertilizers [6–7]. In compliment, a MSW benefit-cost analysis promotes insight on how to determine the comparative labour cost and other operation parameters.

Despite the proliferation of studies on MSW [8–19], very little is known about how to determine this system's total operating costs when synchronized with its benefit-cost ratio [11, 13, 20]. This problem can be attributed to the several parameters that constitute its total operating cost, among which are workers expenses, truck cost and processing cost of recyclables [9, 21–22]. The cost of disposing waste at the dumpsite is another cost that contributes to this total operating cost. The direct and interactive effects of the total operating costs affect the performance of a waste disposal agency. As a result, quantifying these parameters in a deterministic optimisation model is essential.

However, as optimisation is sought for, a concurrent integration of the benefit-cost analysis of a solid waste process is compelling because the sustainability of a MSW project depends on this. Therefore, a deterministic expression concerning the benefit-cost ratio should be integrated into a MSW model. The outcome of a research in this direction would be useful to waste disposal managers for a deeper insight into budgetary decisions. Here, this article presents an explanation of the literature to guide scholars and practitioners towards developing models that will improve MSW systems.

A study was conducted by Pati et al. [23] to develop a multi-diversity model to reduce the total logistics costs for a waste system. The model served as an intervention tool to establish policy for inventory decisions. In another study by Zhou et al. [24], the value flow mathematics to optimise reverse logistics from the cost accounting perspective was established. With a case validation in the auto-recycling sector, the paper ascertained how an organization could optimise its operational costs. Furthermore, a linear programming model was used by Budak and Ustundag [25] to solve a reverse logistics problem in Turkey. The main focus of the study was to ascertain the number and positions of facilities while reducing operation cost. There is also a report by Xu et al. [26] on how to use a combined genetic algorithm and fuzzy chance-constrained programming approach to deal with uncertainty tracking in a MSW system. A model to analyse the waste management system in Zhongshan city of China was successfully tested and proved to be superior to the scheme practised in the system.

Yet in another research, a mixed-integer linear programming model was proposed by del Rosario Pérez-Salazar et al. [27] for MSW facility positioning problem. The proposed model was solved using genetic algorithm. To reduce the system's total cost, the model worked for the Polyethylene Terephthalate waste generation problem in Northern Mexico. Furthermore, a mixed-integer linear programme was used by Boonmee et al. [28] to reduce the financial influence of a MSW while maximizing the revenue obtainable from selling waste. The work further employed the differential and particle swarm optimisation to analyse the proposed model. The authors claimed the superiority of their model over the on-site and off-site parting models. A research group by Najm et al. [21] optimised the difference between the cost and benefits of a waste management system.

Their study concentrated on the issue of capacity and materials limitations while ensuring a balance between the amounts of wastes generated in a municipal and the amounts that enter a facility. Moreover, a linear programming model was developed by Schreiber and Yang [29] to optimise cost in a reverse logistics system, built on Beijing waste management system. The goal was to lessen the total cost and incorporate sustainable practices in consumption method and also analyse the production method. Mesjasz-Lech [30] proposed the concept of zero waste and argued for an adequate establishment of waste flows and facilities. Drawing from Poland as a case study, the argument for guidelines to control the flow of waste items was advanced.

Furthermore, the author analysed on reverse logistics to justify arguments using data in the year range from 2012 to 2016. Furthermore, the content analysis approach was used by Banguera et al. [31] on the diverse inverse and reverse logistic models to manage solid waste. With the key functions of gatekeeping, followed by collection, sorting and dumping analysed, the authors established their points. Besides, the analysis was extended to methodologies, mathematical methods, and designs and the articles reported in the 2010 to 2016 period were analysed.

In another article by Zitrický et al. [32], heuristics was introduced to optimise the collection and haulage activities in reverse logistics. Attention was drawn to a chosen kind of sorted waste. The goal of the article was to establish reserves of the present approach to waste colection. Furthermore, the article appraised alternatives to eradicate reserves and implement an effective collection and haulage system. Furthermore, Wang et al. [33] developed a grey-motivated decision-making trial and evaluation laboratory approach to examine the key barriers to effective electronic waste collection. The deficiency in tax preference was reported as the principal hindrance to attaining profitability and convenience for collectors and consumers, respectively.

Cumps demonstrated the use of a computer-based re-use model for e-waste activities [34]. The functional parts of the model include re-use establishment, diverse parts and the interface of the model. A case study is used to tackle how the model could be implemented. Moreover, a multiple-period bi-objective 0–1 integer programming framework was used by Shi et al. [35] to model a facility location problem where e-waste will be collected. The formulated problem was solved using three metaheuristics. The model was validated with a case study and the findings reveal that the local search heuristics is the most acceptable tool to find the Pareto outcomes for the problem. In a contribution by Hannan et al. [36], the best solutions for the collection of solid waste and route optimisation using particle swarm optimisation were established. Results from the analysis revealed that the capacitated vehicle routing problem model offers the most desired waste collection and routes. This was analysed from the context of waste collection efficiency, travel distance, tightness index and total waste. Greco et al. [37] examined the factors, which established the cost of waste collection. With data from the Italian municipalities, the findings reveal that economies of scale and cost drivers are different for all kinds of waste.

The literature on waste logistics optimisation exposes a gap as follows:

1. Waste logistics workers are discussed as significant constraints and are very crucial in optimum total operating cost development. But workers' reliability analysis was not considered in the literature.

2. Conventional procedures that are extensively discussed in the literature, particularly the gradient-oriented algorithms are largely local search approaches. They are frequently not comfortable to tackle demanding optimisation problems.

3. Models for operating costs of waste logistics optimisation exist but no research that has considered the optimisation of total operating cost where the benefit-cost ratio is concurrently considered with workers' reliability analysis.

4. Articles on natural selection are extremely restricted. Real-life waste logistics optimisation problems are extremely linear, unstable and extensive. To capture these characteristics, powerful methods of optimisation, including genetic algorithm, and differential evolution algorithm can

handle variables and constraints of industrial problems and add value to industrial practice.

The objective of this study is to use evolutionary algorithms to solve a deterministic optimisation model for solid waste management system by minimising the total operating costs while maximising the system's cost-benefit ratio. This is achieved by considering constraints that deal with fund budget and the system performance metrics. The optimal values for the performance metric are generated by using a genetic algorithm and differential evolution algorithm.

To confront the gap stated earlier, in this article, alongside considering the usual constraints, the workers' reliability, truck reliability and system's overall effectiveness were added. Particular constraints of Tavares et al. [9] and Najm et al. [21] are retained, however, the present article improves on their presentations and besides, bridges the gap identified above by introducing certain innovative variables as additions.

The novel aspects of this paper are as follows:

1. Reliability of the workers in the municipal management system – It is treated both in series and parallel concerning the reliability of workers. Furthermore, it incorporates the reliability of completing a particular solid waste task.

2. Reliability of the trucks in the municipal waste management system – It is imposed on the solid waste model as a constraint. This considers the expected workers' reliability for the solid waste task.

3. System's overall effectiveness constraints – It is a newly introduced constraint that considers the waste collection service overall effectiveness as depending on the waste system's availability, quality of service offered by the workers and the service efficiency generated.

The manner of organising the article is as follows: Section 2 presents the problem description. In section 3, the optimisation model is presented. In section 4, evolutionary algorithms are reported. In section 5, a case study is presented. The section also contains managerial implications. Finally, the concluding aspect is detailed in section 6.

Material and methods

1) Problem description

This is a need to design an optimal schedule plan for workforce and truck allocations for a community MSW. For example, the number of personnel, $i = \{1, \ldots, n\}$, the different locations $l = \{1, \ldots, L\}$, waste types, j $\{1, \ldots, n\}$, are parameters that vary in planning periods $t = \{1, \ldots, T\}$. These variations cause a change in the performance (service quality, reliability and availability) of a MSW. To generate optimal values for these parameters emphasis must be placed on fund availability as well as the population growth rate of a community. The consideration of the population growth rate is necessary to predict the expected amount of wastes that will be generated in a particular location. In the Nigerian situation, many factors are contributing to waste generation in the area of study. These include the increased number of tourists to the area. Since tourist centres and religious sites are highly improved in the study area, tourists exploit the facilities provided by the government such as stadium, zoological gardens to meet for a social and religious meeting during holidays and this affects the waste generation in the area. Also, several vehicle drivers from neighbouring states contribute to waste generation but are non-registered population. Thus, as the dynamics of this population is complicated to model, it is assumed that these are of negligible effects in our computations and not considered in the work. In terms of the system's effectiveness, the analysis of service quality, efficiency and availability are parameters which are required for an in-depth analysis of a MSW. In this paper, the idea of human reliability that was introduced to aid the effectiveness of the system argues that the workforce's activities influence the outcome of the system. The workforce reliability refers to the probability of the waste disposal agency's workforce actualizing particular tasks competently. The tasks are associated with the conduct of minor repairs on the trucks such as empowered by the total productive maintenance activities whereby the driver is equipped with the basic training and skills in the elementary truck repairs. Other tasks are truck operations, safety acts on vehicular usage and interactions with other workers. Furthermore, the workforce is viewed with the attribute of being available for use. It is assumed that family and social distractions influence the workforce to the least extent. Once the workforce reports at work it is assumed that the workforce is in a healthy condition. In summary, while the workforce availability evaluates the competence of the workforce to conduct waste disposal activities as planned, the workforce reliability evaluates the workforce's competence to actualize the planned waste disposal activities in a planned period without failure. Thus optimisation models are suitable for MSW parameters optimisation.

2) Optimisation model

Some of the assumptions that are made during the formulation of the proposed model are stated as follows:

- The performance of waste management systems varies from one location to another.
- The cost of waste collection is constant over a period.
- The expected workforce and trucks size are independent of one location to another.

2.1) Model's objective function

Cost of a municipal waste management system: In this article, the total cost of municipal waste management is taken as a function of workforce, truck and processing costs [9, 21]. The cost of municipal waste processing also covers the cost disposing of waste at a dumpsite (Z_1), Eq. 1.

Benefit-cost of a municipal waste management system: The benefit of operating a system plays a pivotal role in ensuring the sustainability of the system. When this factor is converted into monetary terms, it creates an opportunity to compare it with the cost of generating such benefit. This comparison is often carried out using the concept of benefit-cost ratio. This concept makes it possible for decision-makers to know the viability of different activities which an organisation is either planning or engaging in within a specific period. Thus, the expression for a waste management system's benefit-cost ratio is given as Eq. 2. This equation considers the revenue from the sales of recyclable waste and the total cost of solid waste collection. The average amounts of waste generated (Z_2) were considered and the issue of the fluctuation in the expected amounts of solid waste that will be collected at any period is assumed negligible.

$$Z_1 = \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{i=1}^{m}\sum_{j=1}^{n} c_{iljt}x_{iljt} + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{j=1}^{n} t_{ljt}d_{lj}u_{lj}v_{ljt} + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{j=1}^{n} v_{ljt}q_{lj}t_{ljt}\delta_{ljt} \quad \text{(Eq. 1)}$$

where x_{iljt} and c_{iljt} represent the number of workers and cost for solid waste activity i concerning solid waste j in location l at period t, respectively, δ_{ljt} represents the unit disposal cost of solid waste j in location l at period t, t_{ljt} represents the number of trips a truck makes for solid waste j in location l at period t, d_{lj} is the average distance travelled when transporting solid waste j in location l, u_{lj} is the unit transport cost per unit waste of type j at location l, v_{ljt} denotes the number of trucks for solid waste j in location l at period t and q_{lj} represents the average capacity of a solid waste type j truck in district l.

$$Z_2 = \frac{\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{j=1}^{n} P_{lt} w_{lj}\left(\delta_{ljt}^{1} + \chi_{lt}\delta_{ljt}^{2}\right)}{\sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{i=1}^{m}\sum_{j=1}^{n} c_{iljt}x_{iljt} + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{j=1}^{n} t_{ljt}d_{lj}u_{lj}v_{ljt} + \sum_{t=1}^{T}\sum_{l=1}^{L}\sum_{j=1}^{n} v_{ljt}q_{lj}t_{ljt}\delta_{ljt}} \qquad \text{(Eq. 2)}$$

where δ_{ljt}^{1} and δ_{ljt}^{2} denotes the unit charge of waste collected and the unit cost of sales of recyclable materials of waste *j* from location *l* at period *t*, respectively, x_{lt} the fraction of recyclable materials form collected wastes from location *l* at period *t*, w_{lj} represents the average amount of solid waste type *j* produced by an individual in district *l* and p_{lt} represents the population size of district *l* at period *t*.

2.2) Model's constraints

The proposed model constraints the performance on key performance indices (KPI) for system evaluation. This study modified the selected KPI to suit the problem that the study is concerned with. Details on the modified KPI are presented as follow:

Reliability of a municipal waste management system: The reliability of workers for a solid waste type *j* of a district is taken to be in series connections. The connection between the different solid waste type is considered as a parallel connection (Figure 1). Given that the reliability for workers and trucks in district *l* are expressed as Eq. 3 and 4. Given Eq. 3 and 4, the reliability of a district MSW is given as Eq. 5.

Given that workers are the most important elements in a MSW, the current study considered a situation where the expected workers' reliability for a district is greater than trucks' reliability (Eq. 3).

$$\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{t=1}^{T} R_{iljt}}{\sum_{j=1}^{n}\sum_{t=1}^{T} \bar{R}_{ljt}} \leq \lambda_l \qquad \text{(Eq. 3)}$$

where R_{iljt} represents the reliability of a worker for solid waste activity *i* concerning solid waste *j* in location *l* at period *t*, $\bar{R}_{ljt}$ represents the reliability of a truck for solid waste *j* in location *l* at period *t*, and λ_l represents the expected ratio between truck and workers sold waste management reliability in district *l* at period *t*.

Eq. 3 does not provide a clear picture of the reliability of completing a specific solid waste activity. This situation is addressed by Eq. 4. This trucks' reliability for a location is expressed as Eq. 5.

$$1-\prod_{j=1}^{n}\left(1-R_{iljt}\right) \geq \rho_{ilt} \qquad \forall i,l,t \qquad \text{(Eq. 4)}$$

$$1-\prod_{j=1}^{n}\left(1-\bar{R}_{ljt}\right) \geq \bar{\rho}_{lt} \qquad \forall l,t \qquad \text{(Eq. 5)}$$

where ρ_{lit} represents the expected worker's reliability for solid waste activity *i* in district *l* at period *t*, and $\bar{\rho}_{lt}$ represents the expected trucks' reliability in district *l* at period *t*.

System's collection efficiency constraints: The collection efficiency of a MSW is evaluated by considering the change in a location population [38] as well as the unit waste generated by an individual per period. Also, the population growth rate of a location is considered as a means of evaluating the predicted population of a location (Eq. 6). These parameters are used to predict the expected amount of wastes per period. By comparing the total waste collected with the predicted wastes in a location, the expected collection efficiency of a location is given as Eq. 7.

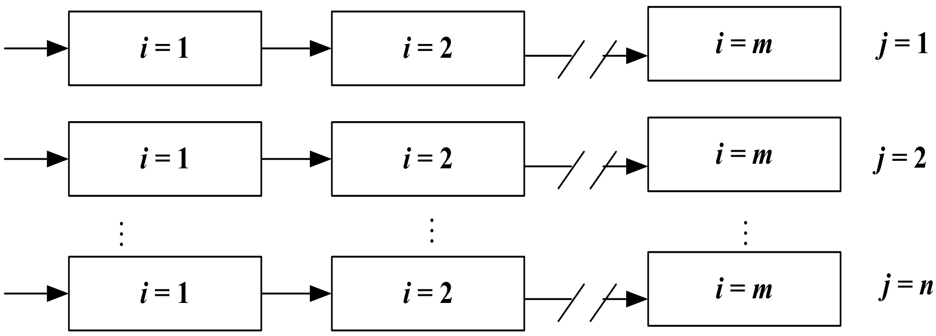

Figure 1 Reliability body diagram for series-parallel solid waste activities of a district.

To ensure load balancing for trucks, the contributions of trucks in each district are considered (Eq. 8). A similar approach is used for the workforce balancing between two adjacent districts. However, consideration is given to the number of trucks in each district (Eq. 9). However, the locations are ranked based on selected criteria such as population size, location criticality among others.

$$P_{lt} = \left(1+g_l\right)P_{lt-1} \quad \text{(Eq. 6)}$$

$$\frac{\sum_{j=1}^{N} v_{ljt} q_{lj} t_{ljt}}{\sum_{j=1}^{N} P_{lt} w_{lj}} \geq E_{lt} \qquad \forall l,t \quad \text{(Eq. 7)}$$

where g_l represents population growth rate for district l, E_{lt} represents the expected collection efficiency for the districts l at period t.

$$\frac{\sum_{j=1}^{n} v_{(l+1)jt}}{\sum_{j}^{n} v_{ljt}} \geq \eta^1_{(l,1+1)t} \qquad \forall l,t \quad \text{(Eq. 8)}$$

$$\frac{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{i(l+1)jt}}{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{iljt}} \geq \eta^2_{(l,l+1)t} \qquad \forall l,t \quad \text{(Eq. 9)}$$

where $\eta^1_{(l,l+1)t}$ is the expected ratio between the number of trucks in two adjacent districts for activity at period t and $\eta^2_{(l,l+1)t}$ denotes the expected ratio between the number of workers in two adjacent districts for activity at period t.

System's cost-benefit constraints: One approach of improving the cost-benefit ration value of a system is to reduce the cost of operating the system [21]. The current study constrained the expected workforce and transportation cost of a MSW using Eq. 10. Based on this equation, the expression for a MSW locational cost-benefit ratio is given as Eq. 11.

$$\sum_{i=1}^{m}\sum_{j=1}^{n} c_{iljt} x_{iljt} + \sum_{j=1}^{n} t_{ljt} d_{lj} u_{lj} v_{ljt} \leq T_{lt} \qquad \forall l,t \quad \text{(Eq. 10)}$$

$$\frac{\sum_{j=1}^{n} P_{lt} w_{lj}\left(\delta^1_{ljt} + \chi_{lt}\delta^2_{ljt}\right)}{\sum_{i=1}^{m}\sum_{j=1}^{n} c_{iljt} x_{iljt} + \sum_{j=1}^{n} t_{ljt} d_{lj} u_{lj} v_{ljt}} \qquad \forall l,t \quad \text{(Eq. 11)}$$

where T_{lt} represents the total operating cost of solid waste collection for location l at period t.

System's availability constraints: The availability of workers in a MSW for a location concerning other locations is expressed as Eq. 12. Similarly, truck availability for a location concerning other locations is expressed as Eq. 13. These equations are combined in obtaining the average availability of a MSW (Eq. 14).

$$A_{lt} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} \overline{a}_{iljt} x_{iljt}}{\sum_{i=1}^{m}\sum_{j=1}^{n} \overline{\overline{a}}_{iljt} x_{iljt}} \qquad \forall l,t \quad \text{(Eq. 12)}$$

$$A'_{lt} = \frac{\sum_{j=1}^{n} \bar{u}_{ljt} v_{ljt}}{\sum_{j=1}^{n} \bar{\bar{u}}_{ljt} v_{ljt}} \qquad \forall l,t \qquad \text{(Eq. 13)}$$

$$\frac{A_{lt} + A'_{lt}}{2} \geq \bar{A}_{lt} \qquad \forall l,t \qquad \text{(Eq. 14)}$$

where $\bar{a}_{iljt}$ and $\bar{\bar{a}}_{iljt}$ are the actual and expected availability of a worker for solid waste activity i concerning solid waste j in location l at period t, respectively, $\bar{u}_{ljt}$ and $\bar{\bar{u}}_{ljt}$ are the actual and expected availability of a truck for solid waste j in location l at period t, A_{lt} and A'_{lt} represent the workers' and trucks' availabilities for location l at period t, respectively and $\bar{A}_{lt}$ represents average workers-trucks' availability for location l at period t.

System's service quality constraints: The service quality of a MSW is evaluated based on the number of trips a truck makes within a period. These trips are compared with the expected amounts of trips per truck (Eq. 15).

$$\frac{\sum_{j=1}^{n} t_{ljt} v_{ljt}}{\sum_{j=1}^{n} \bar{T}_{ljt} v_{ljt}} \geq S_{lt} \qquad \forall l,t \qquad \text{(Eq. 15)}$$

where $\bar{T}_{ljt}$ denotes the expected number of trips for a truck used to transport solid waste j in location l at period t and S_{lt} the minimum expected service quality in location l at period t.

System's overall effectiveness constraints: A service system overall effectiveness is a function of the systems' availability, service quality and service efficiency [39]. Eq. 7, 14 and 15 are used to determine the overall effectiveness of a MSW (Eq. 16).

$$\frac{\sum_{j=1}^{n} v_{ljt} q_{lj} t_{ljt}}{\sum_{j=1}^{n} P_{lt} w_{lj}} * \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} \bar{\bar{a}}_{iljt} x_{iljt} \sum_{j=1}^{n} \bar{u}_{ljt} v_{ljt} + \sum_{j=1}^{n} \bar{\bar{u}}_{ljt} v_{ljt} \sum_{i=1}^{m}\sum_{j=1}^{n} \bar{a}_{iljt} x_{iljt}}{\sum_{i=1}^{m}\sum_{j=1}^{n} \bar{\bar{a}}_{iljt} x_{iljt} \sum_{j=1}^{n} \bar{\bar{u}}_{ljt} v_{ljt}} * \frac{\sum_{j=1}^{n} t_{ljt} v_{ljt}}{\sum_{j=1}^{n} \bar{T}_{ljt} v_{ljt}} \geq e_{lt} \qquad \text{(Eq. 16)}$$

where e_{lt} represents the expected overall effectiveness of district l at period t.

2.3) Non-negativity constraints

This article considered the workforce, number of trips made by a truck and number of trucks in a location as integer variables (Eq. 17). Eq. 18 gives the non-negativity constraints for workers and trucks availability while Eq. 19 represents the non-negativity constraints for workers and trucks reliability.

$$x_{iljt}, t_{ljt}, v_{ljt} \geq 1 \textit{ and } \text{integer} \qquad \text{(Eq. 17)}$$

$$a_{ijlt}, \bar{u}_{ljt} \geq 0 \qquad \text{(Eq. 18)}$$

$$0 \leq R_{iljt}, \bar{R}_{ljt} \leq 1 \qquad \text{(Eq. 19)}$$

3) Evolutionary Algorithms (EA)

Evolutionary computing is implemented to bring about solutions to some significantly complicated and challenging problems essential to gain flexibility and fit them with the objective goal together with a robust feature, using evolutionary algorithms (EA). The EAs, being a search and optimisation tool has the attractive attribute of being adaptable to solve the workforce and truck allocation problem. EA employs the concept of survival of the fittest as a mechanism for generating optimal or near-optimal solutions for numerical problems. This is achieved by ensuring the exploration and exploitation of the solution search space for a problem [40]. Thus, the individuals in a population serve as the potential solution to a problem are generated using a random mechanism (Eq. 20). This is possible by considering the variable limits in a problem.

$$z_g = z^l + Rnd\left(z^u - z^l\right) \quad \text{(Eq. 20)}$$

where Z_g denotes the value of a variable at generation g, Z^l and Z^u denote the variable lower and upper limits, respectively, and Rnd denotes a random variable with a range from 0 to 1 [40].

Eq. 1 is often used to generate the initial solution of the various metaheuristics that follows under EA. Some of the family members EA are genetic algorithm (GA), differential evolution (DE), evolutionary programming and among others. However, DE and GA have enjoyed significant applications as solutions methods for optimisation models [20, 39, 41-42]. In waste management domain, GA has been successfully used as solution methods for fuzzy-based recycling plant siting [20], logistic plant siting [41], conversion of waste digester to biogas [43] and supplier selection for the green environment [44]. These works have all followed the basic outline for applying any EA algorithm (See Algorithm 1).

The mutation operation of EA is used to generate mutant vectors by combining the individuals (parents) in a reproduction pool. For GA, two or more parents are combined to produce the offspring(s) for a current population [45], Eq. 21.

$$\begin{cases} z_{1,g+1} = 0.5\left(1+\gamma\right)z_g^{'} + 0.5\left(1-\gamma\right)z_g^{''} \\ z_{2,g+1} = 0.5\left(1-\gamma\right)z_g^{'} + 0.5\left(1+\gamma\right)z_g^{''} \end{cases} \quad \text{(Eq. 21)}$$

where Z_g' and $Z_g^{''}$ denote the first and second parents that are randomly selected from a reproduction pool, respectively, $Z_{1,g+1}$ and $Z_{2,g+1}$ denote the first and second offsprings, respectively that are generated during a GA mutation operation and γ denotes a constant random variable whose value is within the range of 0 to 1 [45].

A DE algorithm uses three or more parents to generate an offspring. It enforces a condition that none of the three parents must be the same as well as equal to the previous parent of the offspring to be produced [40]. Eq. 22 shows this condition. This algorithm uses Eq. 23 to create new offsprings.

$$z_g^q \neq z_g^1 \neq z_g^2 \neq z_g^3 \quad \text{(Eq. 22)}$$

$$z_{g+1}^q = z_g^1 + \beta\left(z_g^2 - z_g^3\right) \quad \text{(Eq. 23)}$$

where Z_{g+1}^q denotes the offspring generated at generation g+1, Z_g^1 , Z_g^2 , and Z_g^3 denote the first, second, and third offsprings that are randomly selected from a reproduction pool, respectively, and β denotes a constant random variable whose value is within the range of 0 to 1.

Algorithm 1 An outline for evolutionary algorithm implementation

Step 0:	⟶ Determine (population size, generation size, mutation rate, crossover rate)
	⟶ Create initial solution, define stoppage criteria
Step 1:	⟶ Perform mutation operation
Step 2:	⟶ Perform crossover operation
Step 3:	⟶ Perform selection operation
Step 4:	⟶ Create reproduction pool, check stoppage criteria

Offsprings that are produced during a mutation operation are considered during a crossover operation. This operation produces trial vectors. On one hand, a DE algorithm uses Eq. 24 to generate trial vector based on mutant and target vectors. On the other hand, GA uses a binary concept to modify a mutant vector (Eq. 25).

Currently, there are several selection approaches for EA implementation. For example, some authors have favoured the use of a tournament approach while others believe that an elitism approach is equally good for EA selection process. Elitism approach ensures that only the best individual survives to the next generation. This approach reduces the diversity in a reproduction pool [40].

It is interesting to state that to define the population of solution as in the definition of variables in z_g for the evolutionary algorithm, the number of workers, number of trucks, number of trips, workers' availability, trucks' availability, workers' reliability and trucks' reliability were considered. For more comprehensive analysis, the coordinates of locations, truck driving routes and choices of activities may be incorporated. However, as a research strategy, the later variables are omitted as they will bring in complications in analysis. Hence, it was decided to incorporate these variables at a next stage of analysis in a future paper engagement on the subject.

$$z(g+1) = \begin{cases} \breve{z}(g+1) & \textit{if } CR < Rnd_1 \textit{ and } \quad q = Rnd_2 \\ \bar{z}(g) & \textit{Otherwise} \end{cases} \qquad \text{(Eq. 24)}$$

$$\breve{z}_{g+1} = \begin{cases} z'_g + (0,1)\left(z^u - z'_g\right) & \hat{R} = 0 \\ z'_g + (0,1)\left(z'_g - z^s\right) & \hat{R} = 1 \end{cases} \qquad \text{(Eq. 25)}$$

Results and discussion

1) Case study

The study area relates to a municipality in Nigeria with one of the utmost population densities and an estimated area of 1,171 km^3, of which 77.46% is captured by urban centres. The population growth rate of the municipal is roughly 600,000 people per annum while the population density is 4,193 persons per km^2 in the urban areas of the municipal. The household waste generation rate is 1.2 kg per person per day. The case study agency serves roughly 2,000 industrial complexes, a growing intermediate class with towering purchasing power and an average of 15,000 commercial undertakings. The agency studied whose data was used to verify the model is a government agency located in the state capital but transports and receives waste at the closest sites to the collection centres all over the state. This agency is located in a highly industrialised municipal in Nigeria.

The municipal, described as a fast-growing city in Nigeria has about 22 million people that generate roughly 10,000 metric tons of waste daily (about 3.65 million tons per annum). The agency has four permanent collection sites (roughly 55.5 hectares in size) and each site receiving roughly 2,250 metric tons of waste daily. To complement the collection effort, the agency has four other temporary sites but all the sites are distributed within and outside the state capital according to the clusters of industries and settlements. However, the major sites were established in 28, 14 and 12 years ago with the oldest located in the state capital and receive roughly 40% of the total waste deposits in the state. However, the case data discussed in this article considered a major route from the centre of the city to the border of the neighbouring state as it is substantial because of the clusters of settlements and the industrial locations. It is, therefore, suitable to illustrate the working of the proposed model in this article. The time for waste collection is from 8 am to 4 pm daily (Monday to Friday).

During the application of the proposed model, a stationary haulage MSW was considered. The system is located in the southern part of Nigeria. The MSW does not segregate waste during its evacuation from designated dumpsites. The workers' reliabilities and availabilities limits are based on reference [46]. The salaries of workers that perform the same type of waste management activity are the same. Information on the number of trip per truck, efficiency and cost per distance travelled were obtained from the literature [47–48]. The average capacity of a fully-loaded tripper for waste collection is taken at 9 t, while its daily total load is 63 t [49]. The amounts of waste generated by a community in the study are 117,825 t month^{-1} [50–51]. The population of the selected locations are obtained from Figure 2. This study used the population of the locations to rank their importance. The average amount of waste generated per individual is taken as 0.035 t month^{-1} [52].

The mutation (40%) and crossover (30%) for the DE algorithm and the GA were the same. Similarly, the population (40) and generation sizes of the algorithm were also the same. The GA and DE algorithm used an elitism selection approach [40]. This study uses a weighted goal programming method to handle the bi-objective mentioned above. It assigned equal weight to both objectives. VB.net was used to program and implement these algorithms on a Windows 8 laptop with a memory of GB and processor of 2.5 GHz. The comparison of these algorithms' performance was based on their computation time and their solution quality (Figure 2). The results in Figure 2 showed that the DE algorithm is the most suitable algorithm for the proposed deterministic model for the MSW problem. This algorithm had about 0.9% improvement in its best solution when compared with the GA best solution. Also, the DE computation time (3,484.51 s) was less than that of the GA with about 0.43%.

This observation is consistent with reference [39] which identified the DE algorithm as a suitable solution method for a maintenance workforce. This solution method generated a total workforce, transportation and waste disposal cost of N35,056,099.50 ($1 = N 360) and a cost-benefit ratio of 1.10. The MSW performance concerning this algorithm is presented in Tables 2 to 4.

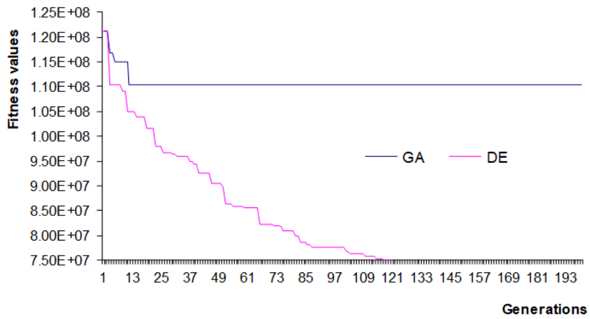

Figure 2 Fitness values for the meta-heuristics.

2) The workers' performance

In the case study, the dumpsites are situated in different parts of the study area, including the northern part, at the centre of the town and several other areas. However, for convenience, ease of coordination and adequate management of the dumpsites, the whole sites were segregated into two groups 1 and 2. The criterion for grouping is that sites that are close to one another are given one group while the rest forms the second group. The expected average number of Group 1 workers is the same for L1 and L5. The same attribute was observed for these locations when

Group 2 workers are analysed (Table 1). In this work, the terms “min”, “ave” and “max” are used as short forms for the minimum, average and maximum number of trucks among the selected solutions.

Furthermore, these locations have the same number of the expected average number of workers for L2, while L3 and L4 had the same values for this index (see Table 1). The expected minimum number of workers for Group workers is the same, while only L4 and L5 had the same number of expected minimum numbers of Group 1 workers (Table 1). The maximum number of Group 1 workers for L2 is twice the minimum number of its required minimum workers (Table 1), this also the same for L1 and L5 Group 2 workers. These locations (i.e. L1 and L5) have similar attributes for their Group 2 workers. Also, a pattern exists among Group 2 workers for L1, L2 and L5, see their average and minimum values, while L3 and L4 also displayed a similar pattern for its Group 2 workers.

The ratio between the required maximum and average workers for Group 1 is two. Furthermore, there is an alternating decreasing and increasing pattern among the Group 1 workers concerning the locations expected average and maximum values. This is also true for the expected maximum values for Group workers. The distributions of the total numbers of workers for the locations are presented in Figure 3.

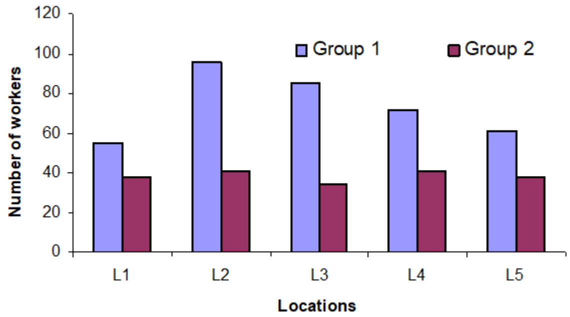

Figure 3 Distributions of the workers for the locations.

The total number of Group 1 workers for L2 was the maximum required by the system while the minimum values for these workers' group were in L1. However, the total number of Group 2 workers required for L1 and L4 are the same (38 workers), while L2 and L5 had the same total number of required workers (41 workers). The total required number of workers for L3 was the least (34 workers) for this group of workers (Figure 3).

Table 1 The summary of the selected workers' parameters for the different locations

	Group 1					**Group 2**				
	L1	L2	L3	L4	L5	L1	L2	L3	L4	L5
Avg	7	11	10	9	7	5	5	4	4	5
Max	9	16	15	12	14	6	8	5	7	6
Min	4	8	6	2	2	3	3	3	3	3
	Reliability					**Reliability**				
Avg	0.86	0.84	0.87	0.84	0.81	0.82	0.84	0.84	0.80	0.86
Max	0.98	0.94	0.97	0.97	0.86	0.92	0.96	0.89	0.90	0.95
Min	0.72	0.75	0.80	0.75	0.70	0.74	0.76	0.74	0.71	0.78
	Availability					**Availability**				
Avg	0.83	0.79	0.84	0.82	0.80	0.80	0.84	0.79	0.82	0.82
Max	1.10	1.05	1.20	0.97	1.16	1.06	1.21	1.25	1.13	1.12
Min	0.66	0.54	0.48	0.60	0.44	0.56	0.63	0.51	0.56	0.67

The expected average, maximum and minimum workers' reliabilities for the different workers' groups and location are more than 70%. However, Group 1 workers' reliabilities for the indices are all greater than that of the workers in Group 2 (Table 1). In terms of the average workers' reliabilities, all the locations had a value that was above 80%. For example, the reliabilities for Group 1 workers in L1 and Group 2 workers in L5 are the same (86%) while the workers in Groups 1 and 2 for L3 had the same reliabilities (84%). This latter value is the same for the workers in L3 concerning Group 2 workers (Table 1). Also, the expected maximum workers' reliabilities for L3 and L4 are the same based on the Group 1 results. L5 has the least expected maximum and minimum workers' reliabilities among Group 1 workers (Table 2). The minimum workers' reliabilities for Group 1 workers in L2 and L4 are the same while Group 2 workers have the same expected minimum reliabilities for L1 and L3 (71%). The expected least minimum reliabilities for Group 1 worker are less than Group 2 workers' reliabilities while Group 1 and higher average and maximum reliabilities than Group 2.

The system's expected workers' maximum availabilities for the workers' groups are very high, except for the workers in L4 for Group 1. To be more specific, Group 2 workers for L3 has the best-expected maximum workers' availability (1.25). Also, L3 workers' maximum availability is the best for the Group 2 workers. This is also true for the expected average workers' availabilities for this group of workers. There is an alternating increasing and decreasing pattern for this group expected average workers' availabilities (Table 1). A similar attribute was observed for expected maximum workers' availabilities in Groups 1 and 2. Furthermore, Group 1 average workers' availability in L3 is the same as that of Group 2 workers availabilities for L2 (0.84), while Group 2 average workers' availability for L4 and L5 are the same as that of Group 1 workers for L4 (Table 1). Another similarity in results is for the expected minimum workers' availabilities in Group 2 concerning L1 and L4 values. It should be noted that Group 2 average workers' reliabilities and availability for L2 are the same.

3) The trucks' performance

The information in Table 2 showed that the trucks in L1 are expected to make the lowest maximum number of trips. This location has the same number of expected average trips with L2 while L3 and L5 also have the same number of expected average trips (Table 2). The expected numbers of trips for L4 are the least among the locations (Table 2). None of the locations requires the expected number of minimum trucks increase in the following order expected minimum (11), average (14) and maximum (17).

There is an intercept between the expected maximum numbers of trucks for L5 and the expected minimum number of trucks for L3 (Table 2). Similarly, the expected average number of the truck for L2 is the same as the expected maximum number of trucks for L4 (Table 2). An interesting observation from Table 2 is that the number of trucks for L1 is greatly higher than for other locations. What this suggests is that we should add another location near L1 while greatly reducing the resource deployment and service levels to L4 that requires less than 50% number of trucks and at the same time the least number of trips. However, caution should be taken such that it does not affect the service requirements of the trucks for L4. The total number of trucks' distribution for the locations are presented in Figure 4. This figure also presents information on the total expected trips per truck. In terms of the total expected number of trucks, L1 and L5 had the maximum and minimum values, respectively. The interesting implication of this issue is that it is not advisable for the agency to spend extra cost on both locations since it may mean resource wastage. Also, the trucks in L3 and L1 are expected to make the maximum and minimum numbers of trips, respectively (Figure 4).

Table 2 The summary of the selected trucks' parameters for the different locations

	Trucks					Trips				
	L1	L2	L3	L4	L5	L1	L2	L3	L4	L5
Avg	38	19	20	15	14	10	10	11	9	11
Max	45	21	24	19	**17**	13	14	15	15	15
Min	33	18	**17**	13	11	7	8	7	4	6
	Reliability					Availability				
Avg	0.84	0.83	0.82	0.84	0.84	0.89	0.86	0.83	0.82	0.79
Max	0.90	0.93	0.94	0.98	0.96	1.18	1.32	1.08	1.19	1.31
Min	0.79	0.71	0.68	0.72	0.69	0.62	0.50	0.53	0.59	0.29

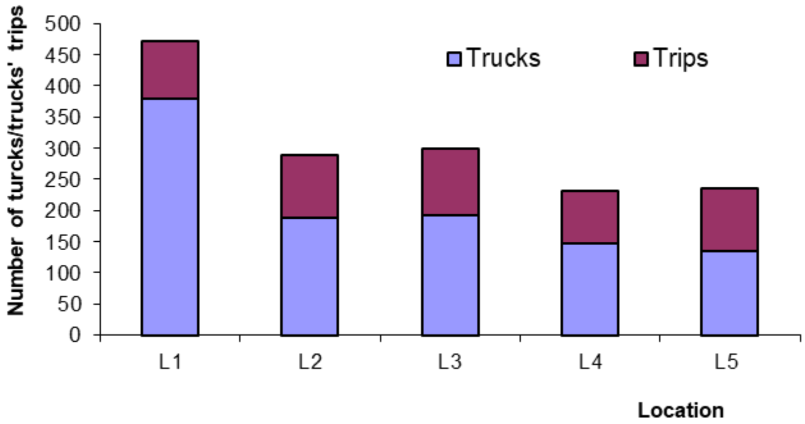

Figure 4 The locations' total number of trucks and the trucks' trips.

None of the locations considered has a minimum value of truck availability that is above 65%. The worst and best values are obtained from L5 and L1, respectively. L5 also had the worst expected maximum truck availability, while location L2 had the best results. However, it should be noted that these locations all had maximum truck availability values that are above 100% (Table 2). This was not true for the expected average truck availability. To be more precise, all the locations had values that are less than 90%, with L1 and L5 having the best and worst values, respectively (Table 2).

The performance of the trucks in term of their reliability showed that none of the locations had a level that was less than 65%. Their expected average trucks' reliability for the location is above 80%, with L1, L4 and L5 having the same values and L3 having the lowest value (Table 2). The maximum truck reliability for L4 was the best, while that of L1 was the least among the locations (Table 2). L1 has the best minimum truck reliability, while L3 had the lower minimum truck reliability when compared with other locations. However, the expected minimum amount of trips for L1 and L3 are the same while L4 has the lowest value (Table 2). The expected maximum numbers of trips for this location (i.e. L4) was the same for locations L3 and L5.

4) The system's performance

Based on Table 2 information, it can be seen that the expected average performance of the various locations service quality and effectiveness are above 100% for all the locations. The expected service quality for L3 had the highest average and maximum values for the systems, while L4 has the highest minimum service quality. The L2 had the lowest minimum and average service quality for the system. This implies that more consideration should be given to this location to meet the expectations of the system's clients. Also, there is a need to monitor the system quality of L5, this is because its average service quality is the lower among the various locations.

The system effectiveness shows that L2 had the best minimum value while that of L1 and L3 are the same. The minimum service of L5 shows that there is a need to monitor this location efficiency, availability and service quality. This poor result is reflected in the expected average value of the location's service effectiveness. The average service effectiveness for L3 has the best value while its maximum value is the same as that of L4 and L5 (Table 3), with L1 having the lower value for this index. Table 2 results showed that apart from the L2 minimum value, the other locations values are below unity. Likewise, none of the locations has a minimum service quality that is above unity (Table 3).

5) The system's expenses

Fund budgeting is an integral part of any decision-making process. It helps to create the necessary logistics for an organisation's operations. This amount is expected to vary from one activity to another. This attribute is rightly captured by the proposed deterministic model. For example, the average, maximum and minimum costs for the locations workforce and transportation costs are different. In term of the average, maximum and minimum workforce costs of the locations, Table 3 shows that L2 had the highest values.

The expected maximum cost for workers is the same for L3 and L5 (Table 4). L5 had the lowest workforce cost, while L1 had the lowest maximum workforce cost. This location minimum workforce cost is the same as that of L4. However, there was a difference between L1 and L4 transportation expenses (Table 4). It can be seen that L4 has the lowest minimum transportation cost while L5 and L4 have the lowest maximum and average transportation expenses, respectively (Table 4). The average and maximum transportation expenses for L1 are the highest for the systems.

Table 3 The summary of the selected system's performance for the different locations

	L1	L2	L3	L4	L5	L1	L2	L3	L4	L5
	Service quality					**Service effectiveness**				
Avg	1.41	1.19	1.62	1.31	1.29	1.15	1.24	1.34	1.05	1.26
Max	1.86	2.15	2.39	2.11	1.97	1.62	1.75	1.88	1.88	1.88
Min	0.72	0.61	0.69	0.81	0.71	0.88	1.00	0.88	0.50	0.75

Table 4 The summary workforce and transportation expenses (naira)

	L1	L2	L3	L4	L5
	Workforce costs				
Avg	371,001.06	521,501.49	479,501.37	451,501.29	385,001.10
Max	455,001.30	700,002.00	630,001.80	560,001.60	630,001.80
Min	245,000.70	385,001.10	315,000.90	245,000.70	210,000.60
	Transportation Expenses				
Avg	628,380.00	335,700.00	371,700.00	231,120.00	244,440.00
Max	865,800.00	453,600.00	486,000.00	513,000.00	351,000.00
Min	466,200.00	273,600.00	239,400.00	100,800.00	118,800.00

6) Management implications

The attempt made in this research is to close the gap existing between the theories guiding the joint consideration of workforce activities and the allocation of trucks for the collection of wastes. The implications are detailed subsequently:

• The structure proposed adds to how the waste manager can control the daily operating costs by adopting two different models, namely, genetic algorithm and differential evolution model. This is tied to the global goal of the waste agency to become more effective by searching for weaknesses, reducing them and pursuing the enhancements of the strengths of the system.

• The structure may help managers and chief executives of waste disposal agencies to gain increased insight and specify the strategic viewpoint of creative projects based on evolutionary algorithm structures.

• This research is a unique opportunity to open the door of a two-way interface between the workers' representatives (trade unions) and the representatives of the management (managers) who represents the concerns of the workers and management, correspondingly.

Conclusions

This research contributes to the solid waste management knowledge advancement through an open form representation of how the workforce activities and the truck allocation process exist. In this research, the mixed-integer programming model was utilised for the near-optimal solution for the solid waste workforce and the truck allocation problem. The contributed model is novel and was rigorously tested and found to be efficient and competent in functionality. Springing up from the diverse calculations and examination of data are the subsequent conclusions.

• The research established a deterministic optimisation model for solid waste management system reliability and cost optimisation and evolved an optimal solution for the related parameters using a differential evolution algorithm to demonstrate its robustness and superiority.

• The mixed-integer programming model showcases performance indices for reliability, availability, service quality, efficiency and effectiveness, and the number of trucks and expected trips for different locations in a community.

• Based on the outcomes of the computational time as well as the algorithms, the differential evolution algorithm performed better than the genetic algorithm.

In addition to the mentioned factors, certain interesting avenues are available for fruitful research endeavours. Extending the framework established in this research include:

• A system dynamics model may be formulated for the problem.

• The mathematics of the proposed model can be by-passed using predictive models such as an artificial neural network.

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