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Application of a Modified ACO Algorithm for Optimizing Routes and Externality Effect of Solid Waste Management

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Abstract

To improve solid waste management and maintain its sustainability, it is important to reduce both the solid waste operational cost which includes the monetary value of distances covered and the externality effects of solid waste management. Therefore, this paper presents an application of a modified Ant Colony System algorithm to a bi-objective model for solid waste management in the Shama District in the Western Region of Ghana. The objective is to optimize route lengths and externality effects of solid waste management. Data on route lengths and population of communities along the routes were collected from 20 communities in the Shama Distric. Externality effect was measured by considering the population of the communities along the routes, the cost of treating a common cold subject to the assumption of two percent of the population being affected by the externality effect. The implemented algorithm has demonstrated the bi-objective optimal solution of route length (km) and externality effect (GHS) of (11, 2100) achievable on the path $1 \rightarrow 3 \rightarrow 9 \rightarrow 12 \rightarrow 14 \rightarrow 20$, which respectively represents a path linking the following communities: Aboadze, Abuesi Assorko Essaman, Beposo, Bosomdo and Fawomanye. There is therefore the need to ensure that the communities involved are linked with good roads.

Keywords: Ant colony optimization; ant colony system algorithm; metaheuristic; bi-objective problem; externality effects; waste management.

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1. Introduction

Waste Management has become a very challenging global issue, especially, for developing countries. Researchers agree that urbanization, population growth and economic development bring about increase in waste generation (1, 2). The urban centers of various countries generate tremendous amount of waste from households, schools, market centers, open spaces, industrial areas, business premises, medical facilities and others. In 2016, solid waste generated globally was estimated around 2.01 billion tones amounting to a 0.74 kg per person per day. With the forecast of the rapid population growth, industrialization and urbanization, annual solid waste generation could increase, between 40% to 70% from 2016 level to 3.40 billion tones in 2050 if the trend should continue (2, 3).

Solid Waste Management refers to the collection, storage, transportation and final disposal of waste in an environmentally friendly manner. Solid Waste Management includes all activities that seek to minimize the health, environmental and aesthetic impact of solid waste. Solid Waste Management has become an essential aspect of health delivery. Effective waste management is a very important element in the health of a people thus managing it in an environmentally sustainable way is of paramount importance. Another issue closely related to health which results from unsustainable waste management practices is pollution of the environment, which consists essentially of solid waste.

Diseases such as cholera, typhoid, dysentery and malaria are all related to the practice of poor waste management. This can result in the loss of human resources needed in the development of the country [4]. As indicated in (5, 6) solid waste encapsulates rubbish, trash, junk, and garbage, subject to the type of material or regional terminology, and is the undesirable material from manufacturing processes or community or household activities." Waste produce are the outcome of human actions in life, and waste results at all points of manufacturing and growth. Solid waste occurs at every phase of human actions, from the point of production to the point of consumption. Of all the time, solid waste management has been a crucial environmental issue due to its bad effects on the community and environment if it is not effectively implemented. In Africa, several factors contribute to high rate of solid waste in the environment. These include the negligence of the local government authorities with the responsibility to manage solid waste, the issue of finance and poor commitment on the part of the citizens to deal with solid waste [8] as well as poor planning due to inadequate data [7]. Factors such as "poor service coverage, irregular sloid waste collection, solid waste spill over from bins, and the careless attitude of citizens towards indiscriminate disposal at unlawful places, and waste littering" have been attributed to the problems of solid waste generation in the developing countries [9]. This, to a very large extent, defines the unsustainable solid waste management phenomenon, and will aggravate without cutting edge management strategy (10, 11). In economic valuation of urban solid waste collection, the willingness of family aggregates to pay for the urban solid waste collection service has been established [12]. As underscored, families would be willing to pay for solid waste collection service subject to service improvement. This explains the crucial need to institute proactive measure to improve solid waste collection service delivery. A significant aspect of solid waste collection and transport is the operational scheduling and truck routing. As a result, drivers are scheduled for daily solid waste collection in their corresponding operational areas. Previous works showed that collection, transfer, and transport procedures are affected by poor collection plans, inappropriate bin collection structures, inadequate infrastructure, as well as small number of trucks available for waste collection. Routes taken by truck drivers are mostly left to their discretion and they do it with no respect for operational cost saving and environmental conservation resulting in an increase in costs of collection and transport, in addition to increase in environmental pollution. For effective waste collection and transport, scheduling must be done by considering a systematic routing using scientific methods which take into account cost reduction and environmental conservation (12, 13, 14). The performance indicators of solid waste collection include cost of operational activities, distance travelled by vehicles for haulage, quantities of waste collected, scheduling and routing of vehicles and number of waste truck trips, total operational cost of system, penalty, externality or social cost, labor hours, and number of containers collected. One cutting-edge approach to vehicle routing in solid waste management is the Ant Colony Optimization (ACO) algorithm. Ant Colony Optimization (ACO) techniques that have received wide application include the Ant System, the Max-min Ant System, and the Ant Colony System. Defined in (13, 14) Ant Colony Optimization (ACO) involves a colony of artificial ants which are concepts from the characteristics of real ants liaising in finding healthier resolutions to different discrete optimization problems. ACO has been described as one of the best new computational techniques for parameter optimization, and it overcomes several disadvantages of Artificial Neural Networks (ANN). ACO is quite effective and useful when the search space is large and complex, and requires a short computation time. The advantages of ACO are the contribution to computations, heuristic techniques, and positive feedback. Contributions to computations can effectively avoid premature convergence. Heuristic techniques can be used to find better potential solutions at the early stage, and positive feedback ensures the fast detection of better solutions (15, 16). Hence, ANNs with ACO provide a good approach for solving several types of optimization problems. Shortest Path network problems have been applied in areas such as routing in telecommunication networks, email and teleconference, transportation, garbage collection, delivery of goods, rail construction, social networks such as knowledge (skill) workers, control of infectious diseases and disaster evacuation (14, 16, 17, 18). It is indicated in [19, 20] that the popularly-known graph theory problems are shortest path problems with numerous applications. The crux of Shortest Path Problem (SPP) is to find the minimum distance between two points of a network. Shortest path problem is one of the most traditional optimization problems in transportation and logistics; and has earned a great deal of attention from researchers worldwide [21]. ACO has been applied to solve many single and bi-objective modelling problems in solid waste management (22, 23, 24, 25, 26, 27, 28, 29). However, among the various performance indicators, estimating the obnoxious effects of semi-obnoxious services have received little attention. A closer look shows that solid waste management is a potential semi-obnoxious service; while it improves general health of environment and human, it is also associated with harmful effect like pollution with its adverse health consequences. Thus, solid waste management service comes with both positive and negative (externality) impact. The positive impact is enjoyed by people who directly receive the service, while the negative impact or the externality effect is dispensed on people along the routes where the service delivery vehicles are routed. This externality effects exacerbate in the case of hazardous solid waste. It is strongly contended in this paper that sustainable solid waste management cannot be holistic unless it also focuses on mitigating the harmful effects of air contamination, pollution of water and land resources. To actualize this, most optimization problems involving semi-obnoxious services or products have to deal with maximizing the positive while at the same time minimizing the harmful effects of these services. A notable optimization approach has adopted the max-min objective functions. For instance, different classes of unconstrained and constrained minimization problems with max-min objective functions have been investigated [30].

Again, a fundamental relation was developed between resource allocation optimization problem and the notion of max-min fairness [31]. In this edition of optimizing a semi-obnoxious service, emphasis is placed on optimizing costs which include minimizing both the distance of the vehicle route networks and externality which is measured by the effect of air pollution. A critical factor in this context is the population density. Obviously, routes with higher population density may likely correlate with higher obnoxious effects resulting from air pollution in comparison to those with lower population densities.

In order to reduce the effect of environmental pollution, routes networks of the waste collection trucks will be selected by avoiding those connecting areas with comparatively higher human population while shortening the travel time to the dumping site to, respectively, reduce the harmful effect of gases that may be emitted on the people and service cost. ACO algorithms has seen little application in the light of optimizing semi-obnoxious services or products. A modified Ant Colony Systems was applied in a bi-objective study to simultaneously minimize distance and social cost of constructing a railway. This represents the case of a min-min objective function and has outperformed existing Ant System algorithms. So far, little is known about a bi-objective study within the context of simultaneously minimizing distance and pollution effects which measures externality.

The aim of this paper therefore, is to apply the modified Ant Colony System [16] in a bi-objective study to simultaneously optimize a solid waste collection route length and externality due to air pollution. This paper contributes to existing literature by integrating the effect of air pollution or externality in the ACO algorithm in a practical solid waste management system within the Shama District in the Western Region of Ghana.

In application sense, whereas the techniques for quantifying non-pollution-based social costs are clear, those for quantifying pollution-induced externality are unclear and non-existing. Therefore, a simple way of quantifying pollution-induced externality is presented. By providing an insight on how pollution effect can be measured, a foundation is laid for other alternative techniques of quantifying externality. The paper also provides additional information critical to appraise solid waste management policies subject to myriad performance indicators to inform optimal policy selection for sustainable solid waste management.

2. Materials and methods

Most optimization problems involving semi-obnoxious services or products have to deal with maximizing the good products while at the same time minimizing the harmful effects of these services, as presented. However, the focus in this paper is to minimize both distance and externality in a bi-objective model. A similar bi-objective problem was presented in a railway construction [16], where the focus was to minimize the distance of the railway network and social cost incurred due to the construction. In application sense, whereas the techniques for quantifying non-pollution-based social costs are clear, those for quantifying pollution-induced externality are unclear and non-existing.

This paper provides a simple way of quantifying pollution-induced externality, then applies the improved Ant

Colony System [16] to obtain optimal solution. The assumption underlying the bi-objective model is that routes with higher population densities are associated with greater externality effect than routes with lower population densities; only a given percentage of the population are affected by externality effects; also, externality effect is measured by the cost of treating the health effects of the externalities.

2.1. The optimization model

Suppose that G(U, A) is an undirected graph comprising of an indexed set of nodes, U, with n = |U| and a straddling set of edges (arcs), A, with m = |A|, where *n* and *m* are the number of nodes and edges respectively. Each arc is represented as a pair of nodes, thus from node *i* to node *j*, and denoted by (i, j). Let each arc be associated with two numbers; the distance (l_{ii}) and reduction of the effect of pollution on the population, (c_{ij}^{po}) experiencing it on the route linking node i to node j (waste bin collection points) and let the arcs represent the streets. The bi-objective problem is then given by

$$f_n(p); n = 1,2 \qquad (1)$$

where;

$$f_1(p) = \sum_{(i,j)\in A} I_{ij} w_{ij} \qquad (2)$$

$$f_2(p) = \sum_{(i,j)\in A} c_{ij}^{po} w_{ij} \qquad (3)$$

subject to $w_{ij} \in \{0,1\}, \forall\{i,j\} \in A$ where $i = 1,2,3,\dots,n-1$ and $j = 1,2,3,\dots,n$

w_{ij} = the decision variable, f_1 = the objective function for distance, f_2 = the objective function for reduction in the effect of the pollution and p = a path from the source to the destination. This implies that

$$f(p) = (f_1, f_2) \qquad (4)$$

2.2. Solution technique

The approach adopted in this study is the new weighted sum ratio min-max approach. This novel approach advanced is categorized under the posterior enunciation information method where a number of Pareto optimal solutions are offered to authorities to make a choice.

For the min-max technique, the mistakes of the objectives are weighted in the course of finding the solution and at the end, the minimum is carefully chosen as the best conciliatory solution. Here, the user is at a disadvantage because this user has no chance of getting any idea of the real margin of mistakes of the individual objectives, thus, making it difficult for this user to take the best decision. There is a situation where the user might at times have a condition in the form of a maximum of error in the solution. This is a problem which needs to be solved.

In an attempt to solve the problem, a new weighted sum ratio min-max approach has been adopted. Thus, under this approach, the objectives are weighted and summed throughout the process of finding the solution. The margin of mistakes of the distinct objectives in the solutions are then obtained for one to carefully pick the best solution [16].

The weighted sum of a bi-objective optimization problem to a single objective optimization problem is then given by;

$$f(p) = w_1 f_1(p) + w_2 f_2 \qquad (5)$$

subject to $p \in P, \sum_{i=1}^{2} \quad w_i = 1,\ w_i \geq 0,$ where $p =$ path generated and $P =$ the feasible Paths.

Therefore, the optimized function is given by;

$$f(p) = \sum_{i=1}^{2} \quad w_i f_i(p) \qquad (6)$$

subject to $p \in P, \sum_{i=1}^{2} \quad w_i = 1,\ w_i \geq 0,$

These objective functions are then normalized using the model;

$$f_i^{norm} = \frac{1}{(f_i)\ - min(f_i)} \qquad (7)$$

2.3 Ratio min-max approach

After the Pareto optimal solution has been found by using the weighted sum as the solution strategy, a post-optimality ratio min-max approach is then applied to support the course of finding a best result.

Assuming P is the set of Pareto optimal solutions, such that $p \epsilon P$ is a Pareto optimal route, the ratio min-max approach is defined as;

$$min[F(p)] = min[\left|\frac{F_i^*(p)}{f_i^*(p)} - 1\right| \ , \forall_i : p\epsilon \qquad (8)$$

where $F(p) =$ a measure of the maximum margin of mistake of the i^{th} objective function at the pareto optimal solution

$F_i^*(p) =$ the value of the i^{th} objective function at a Pareto optimal solution after the weighted sum optimization

$f_i^*(p) =$ unique optimal solution value of i^{th} objective function. The steps below describe the procedure for finding the best conciliation solution;

1. Calculate $f_i^*(p) =$, the unique optimal value of the i^{th} objective function for all $p \epsilon P$
2. Execute the weighted sum optimization with a set of generated weights.
3. Calculate $F_i^*(p) =$, the value of the i^{th} objective function for all $p \epsilon P$
4. Calculate the absolute values of the ratios $F_i^*(p) =$ to $f_i^*(p) =$ less one $\forall_i$ and $p \epsilon P$
5. Choose the maximum values of the result in the immediate previous step above, $\forall_i$ and $p \epsilon P$
6. Pick the minimum value in the immediate previous step above or the last step before this one.

This approach above helps in finding the margin of mistakes of the Pareto optimal of the objective functions values in relation to their ultimate ones to enable authorities to pick the best result.

2.4. The ant colony system algorithm

In this study, the problem to be solved belongs to the member of the Ant Colony Optimization (ACO) family. As a result, Ant Colony Optimization algorithm was employed in solving the problem since it is mainly designed to handle network problems. Ant colony optimization (ACO) involves a colony of artificial ants which are concepts from the characteristics of real ants liaising in finding healthier resolutions to different discrete optimization problems [23] in [32]. The similarities between real ants and artificial ants which are exploited in ACO include the use of:

i. a colony of cooperate individuals into finding an improved global result to the task under consideration;
ii. artificial pheromone trail for stigmaria interaction;
iii. a local move to find the shortest path between the origin (nest) and the destination (food site); and
iv. a probabilistic decision policy to move through adjacent nodes.

This ant colony system optimization algorithm (ACSO) is based on or originated from the lifestyle exhibited by ants in their pursuit of food. Here, the movement of the artificial ant from one node to the other say, from node *i* to node *j* follows stochastic process, which is indicated by the extent of the pheromones on the path. Below are the main steps followed in ant colony system optimization (ACSO) algorithm;

i. Set out parameters
ii. Initialize pheromone trails
iii. Calculate the heuristic information
iv. Use the stochastic state transition rule to build the ant solution
v. Update the local pheromone
vi. Search locally to improve the solution constructed by an ant
vii. Update the global pheromone information.

According to [22], the ant colony system optimization terminates when at least one of the conditions below has been satisfied;

i. a fixed number of solutions must be produced,
ii. a fixed CPU time had elapse, or
iii. a specified number of iterations do not give a better solution

Any artificial ant has a Tabu list which keeps all the nodes that had already been visited by the ant from the starting point to the end point. It also bans the ant from returning to a node that had already been visited. After obtaining a feasible result, the Tabu list of each ant which serves as a remote memory to the ant gets full.

- ***Initialization of pheromone trail***

A decent means to begin the pheromone trails is to set them to a value a little beyond the expected amount of pheromone deposited by the ants in one iteration. This is because if the initial pheromone values are too low, the search is quickly biased by the first tours generated by the ants, which in general leads toward the exploration of inferior zones of the search space. Also, if the initial pheromone values are too high, then many iterations are lost waiting until pheromone evaporation reduces enough pheromone values, making pheromone added by ants to start to bias the search [33]. In [26] initial pheromone was defined as;

$$\tau_{ij}(0) = \frac{1}{n} \tag{9}$$

Where n is the number of nodes

In [16], the inverse of the ratio of the weighted sum of the distance and social cost $(w_1 d_{ij} + w_2 A_{ij})$ connected by node *i* and node *j*, times one subtracted from the number of nodes, was used. This is given by;

$$\tau_{ij}(0) = \frac{1}{(n-1)\underline{L_{ij}}}, w_1, w_2 \epsilon w; 0 \leq w \leq 1 \tag{10}$$

- ***Heuristic information***

Heuristic techniques can be used to find better potential solutions at the early stage, and positive feedback ensures the fast detection of better solutions [34]. In [16] a modification of the heuristic information was made based on the heuristic information in [35], as the method does not offer the ant with an information on the nature of the route from source to the current node i. A new heuristic information which is based on the source node to the present node i plus node i to the next node j to solve this problem. This is given by

$$\eta_{ij} = w_1 \eta_{0j}^1 + w_2 \eta_{0j}^2 \tag{11}$$

where;

$$\eta_{0j}^1 = \frac{1}{\left(d_{0i} + d_{ij}\right)}, \eta_{0j}^2 = \frac{1}{\left(A_{0i} + A_{ij}\right)}, \ w_1, w_2 \in w \ \ and \ \ 0 \leq w \leq 1$$

d_{0i} is the total distance from the starting node to the current node i.

A_{0i} is the total social cost from the starting node to the current node i.

- ***Local pheromone update***

The reduction of the content of the pheromone trail deposited along a path created by an ant to make it unattractive to the next ants so as to broaden the scope of the search space is the actual reason for the local pheromone trail. It was however, contented that one must be cautious not to needlessly create routes that are not close to the optimum solution and also delay the search for the actual solution.

In view of this, another ratio method in his study to improve upon the present local pheromone update model provided in [36]. Kparib (2020), also, introduced another ratio method in his study to improve upon the present local pheromone update model provided in [Chen and Ting (2009)]. This is represented by;

$$\tau_{ij}(t+1) = (1-\rho)\frac{\tau_{ij}(t)}{L_{ij}} + \rho\,\tau_{ij}(0) \qquad (12)$$

where;

$L_{ij} = \sum \tau_{ij}(t)$,

$\rho \in [0, 1]$ is the pheromone evaporation rate.

- ***Global pheromone update***

In [37], a method was proposed to calculate the pheromone increment. The purpose of this global pheromone update is to basically raise the content of pheromone to routes which

have a greater possibility of becoming the finest route so that the search will be accelerated. As an alternative, an enhancement was proposed the model proposed in [16] by introducing the reverse of the evaporation rate of the pheromone trail, $\left(\frac{1}{\rho}\right)$, where, instead of the constant value used in the previous studies, the global pheromone update was completed based on the worth of the path, emphasizing the fact that the global update is applicable to only the global best solution (U_i) and the iteration best (I_{ij}). This enhanced global pheromone update is

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \frac{1}{\rho}\sum_{k=1}^{m}\Delta\tau_{ij}^{k} \qquad (13)$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{1}{\bar{L}} \bullet \frac{L^{k} - L_{ij}}{L^{k}}, \text{if } (i,j) \in U_i \text{ } or \text{ } I_i \\ 0, \text{otherwise} \end{cases} \qquad (14)$$

where;

L_{ij} = weighted sum of distance and social cost $(w_1 d_{ij} + w_2 A_{ij})$ of the edge (i, j)

L^{k} = weighted sum of distance and social cost of the k^{th} solution created by ant k

$\bar{L}$ = ratio of the weighted sum of the distance and social cost of the solutions.

- ***The probabilistic decision rule***

The probability decision rule proposed by Majid and Mohammad [38] was adopted for this study with the projected initial pheromone trail, heuristic information, local pheromone update trail and global pheromone trail update embedded in the expression below;

$$P_{ij}^{k}(t) = \begin{cases} 1, & \text{if } q \le q_0, \text{and } j = j^{*} \\ 0, & \text{if } q \le q_0, \text{and } j \ne j^{*} \\ \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum_{r \in N_i^k}[\tau_{ir}(t)]^{\alpha}[\eta_{ir}(t)]^{\beta}}, & \text{otherwise} \end{cases} \qquad (15)$$

j^{*} : yields $\text{argmax}_{r \in N_i^k}\left\{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}\right\}$ used to identify the unvisited node.

3. Results and Discussions

A total of 20 collection points representing routes linking 20 communities in the Shama District in the Western Region of Ghana was considered in the construction of the tour of the ants (vehicles).

The distances (in km) connecting each collection point (community) and the population of the community along the stretch of the routes were collected using google maps and projected figures according to Ghana's 2012 Population Census (Table 1).

The total cost of externality was estimated using the treatment cost of the common health-effect of waste evacuation and discharging activities. In this work, the basic health consequence was approximated to 'cold' or flu, which is a very common infection from unpleasant gases or stench from waste management activities. Though there are other harmful effects in the case of hazardous waste, the effect is limited to non-hazard wastes to simplify the cost evaluation process.

It is however important to note that the concept of cost estimation can be extended to hazardous waste once information about the cost of treating a known hazardous effect is available. In general, the treatment cost of an ailment covers both explicit cost (total cost of treatment plus transportation cost to health facility) and implicit cost (the monetary value of a time spent in treatment, which could have been spent for an economic gain). Since it is costly to estimate implicit cost, this paper limits itself to the explicit cost excluding the transportation cost to the health facility.

Table 1: Route distances, population and externality cost in the Shama District.

Nodes	Community	Population	Distance (km)	Total externality cost
0	Shama	24,000	0	0
1	Aboadze	18,000	2.4	3600
2	Abotar yie	400	3.6	80
3	Abuesi	28,000	2	5600
4	Aminano	980	1.2	196
5	Anopasu	460	3.4	92
6	Anto Aboso	700	2.5	140
7	Aruna Beach	530	2.5	106
8	Asem Asa	360	4	72
9	Assorko Essaman	9,000	2.7	1800
10	Ata na Ata	3000	3.3	600
11	Bedukrom	800	3.6	160
12	Beposo	5000	3.4	1000
13	Beposo Nkran	340	2.6	68
14	Bosomdo	260	3.2	52
15	Bronikrom	300	2.4	60
16	Daboase	1200	3.2	240
17	Dwomo	590	2.5	118
18	Epowano	150	2.7	30
19	Essumankrom	460	3	92
20	Fawomanye	320	1.2	64

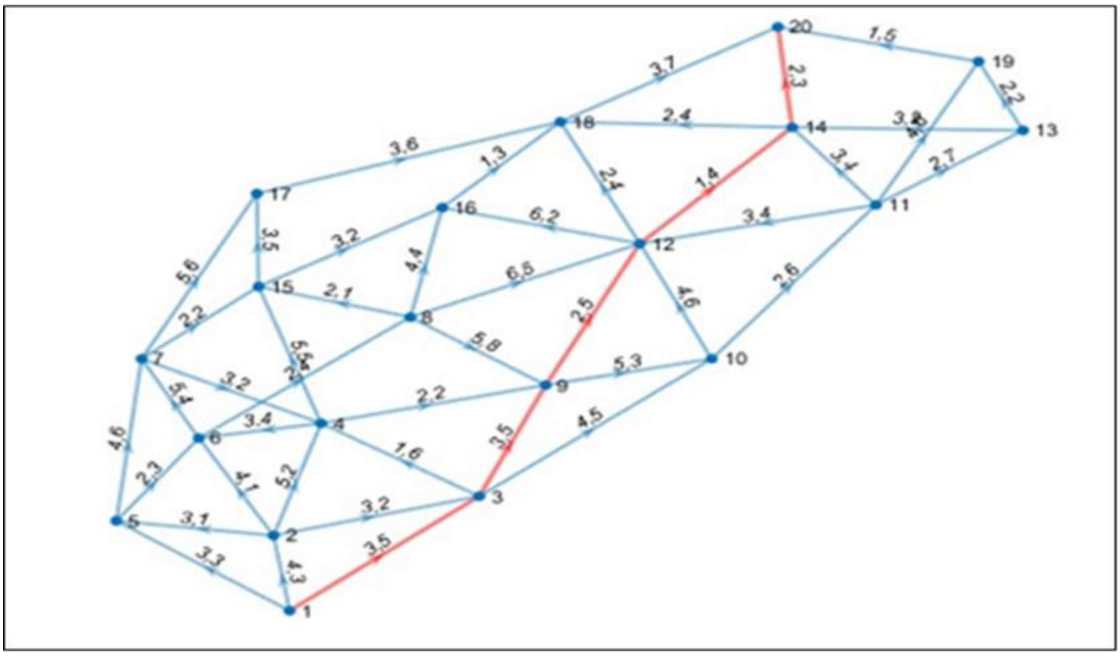

Figure 1: optimized route length and externality.

Therefore, treatment cost for a common cold in the Shama District was estimated using $C = pain\ killer\ price + \ decongestant\ price$**.** It was also assumed that only 2% of the total population (P) will be affected, hence total externality cost (in Ghana cedis) was estimated ($Externality\ cost\ = 0.2\ P\ C$**)** (Table 2).

Using the modified Ant Colony system algorithm [16], the optimal value as indicated in (6) is implemented and the result is displayed in Figure 1, which shows the waste collection points represented by the communities and the assigned distances between them.

The optimal (shortest) path is represented by $1 \to 3 \to 9 \to 12 \to 14 \to 20$ covering a total optimal distance of 11 km as well as an optimal externality cos of GHS 2, 200. A quick look shows that the path $1 \to 3 \to 10 \to 11 \to 14 \to 20$ has a total optimal route length of 12 km and a total optimal externality cost of GHS 2, 300. Similarly, the path, $1 \to 3 \to 10 \to 12 \to 14 \to 20$ is associated with an optimal externality cost of GHS 2, 300 and a total optimal distance of 14 km showing a better solution in terms of externality cost but a worse solution in terms of distance. Apart from the best optimal path, the next best path is $1 \to 3 \to 10 \to 11 \to 14 \to 20$ which gives the optimal bi-objective solution (12 km, GHS, 2300) in terms of route length and externality. This is followed by a bi-objective solution of (14 km, GHS 2300) associated with the path $1 \to 3 \to 10 \to 12 \to 14 \to 20$. This shows that the improved Ant System algorithm [16], in addition to its higher efficient performance in terms of time, meets the performance standard of a general ant colony algorithm which obtains a global optimal solution (14, 16, 21, 37) in comparison to other greedy-based or sub-optimal heuristic algorithms. Thus, the improve Ant Colony System algorithms is suitable for handling a bi-objective problem in respect of reduction in route lengths and optimality. The optimized bi-objective solution in respect of distance and externality is therefore, (12 km, GHS 2100). Although the ACS algorithm has demonstrated effectiveness and efficiency in handling a bi-objective involving reduction of waste management collection routes and associated effects of externality, the difficulty of its real application is tied with the estimation of externality. Using the cost of treating flu alone does not realistically represent the cost of externality, other measures may include transportation cost to health facilities, the lost opportunity in terms of time that could have been engaged in economic activities, etc. It is however very difficult to obtain a definite means of estimating such opportunity cost. Similarly, it will be very cumbersome to provide a single measure of transport cost to health facilities for all affected individuals given the sparsely geographic distribution of each individual location from a given health facility of various health facility. The solution therefore, depends on the measure of externality. However, if such measures can be obtained, the algorithm will be able to give a good estimate of the optimal solution.

4. Conclusion

A modified Ant Colony Metaheuristic optimization model has been applied to a bi-objective model for solid waste management to optimize route lengths and externality effects in the Shama district in the Western Region of Ghana. The implemented algorithm has demonstrated the bi-objective optimal solution of route length and externality effect of (11 km, GHS 2200) achievable on the path $1 \rightarrow 3 \rightarrow 9 \rightarrow 12 \rightarrow 14 \rightarrow 20$, which respectively represents a path

linking the following communities: Aboadze, Abuesi Assorko Essaman, Beposo, Bosomdo and Fawomanye. To improve solid waste management and maintain its sustainability, it is important to reduce both the solid waste operational cost which includes the monetary value of distances covered and the externality effects of solid waste management. This can be achieved as the bi-objective optimal results of this paper evinces. There is therefore the need to ensure that the communities involved are linked with good roads.

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