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CAPACITATED CLUSTERING AND COLLECTION OF SOLID WASTE IN KWADASO ESTATE, KUMASI

D. Otoo

Department of Mathematics, University of Energy and Natural Resources, Sunyani, Ghana

S. K. Amponsah

Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

C. Sebil

Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

ABSTRACT

The collection, transport and disposal of solid waste, which is a highly visible and important municipal service, involves a large expenditure but receives, scant attention. This problem is even more crucial for large cities in developing countries due to the hot weather. ***.*** *Solid waste management is a very pertinent issue facing municipal and local authorities in Ghana. Due to the population growth and the changing lifestyles of Ghanaians, the amounts of waste generated has increased drastically over the years. This paper presents cluster-first-route-second heuristic method to generate feasible solution to an extended Capacitated Arc Routing Problem (CARP) in Kwadaso, a suburb of Kumasi, Ghana. The proposed method was compared with existing schedules with respect to cost and distance travelled. The adoption of the proposed heuristic resulted in a reduction of 40% vehicle distance travelled per week.*

Keywords: Capacitated arc routing, Cluster-first-route-second, Waste management, Heuristic.

Contribution/ Originality

The study contributes in the existing literature in the area of solid waste collection and transportation; it uses new initial cluster point selection in the formulation and methodology. The study has provided the operators of the area a new way of collection in the form of flow chart for customer waste collection and thereby reducing total distance of collection and saving cost.

1. INTRODUCTION

Solid waste collection is one of the most difficult operational problems faced by almost all cities in Ghana. In most cities, solid waste collections are done in an arbitrary manner, which contributes to high solid waste collection cost.

Solid waste collection vehicles are assigned to zones without any scientific base, route construction being left to the discretion of the drivers. Every time a vehicle is filled up, it heads to the disposal site to unload and then returns to the zone assigned to the driver. This paper seeks to address the solid waste collection problem for Kwadaso sub-metropolitan area. Emphasis is placed on minimizing the total haulage cost/distance of solid waste.

2. RELATED WORKS

Many methods and algorithms have been used for optimizing the routing aspects of solid waste. Many papers have modelled the optimization problem of urban waste collection and transport as variants of the Arc Routing Problem (ARP) by Maniezzo [1]; Amponsah and Salhi [2] and Ghiani, et al. [3]. An Ant Colony System (ACS), a distributed algorithm inspired by the observation of real colonies of ants, has been presented by Dorigo, et al. [4], Dorigo and Gambardella [5] for the solution of Travelling Postman's Problem (TPP) and Ant Colony System (ACS) problems by Karadimas, et al. [6].

Viotti, et al. [7] introduced a Genetic Algorithm for solving the TSP.

Poser and Awad [8] developed a methodology based on real genetic algorithm for effectively solving the TSP in the field of solid waste routing system in large cities.

Some methods have been advanced for improving solid waste management system.

Prominent among these methods include vehicle routing and optimisation of solid waste collection routes by Mourão and Almeida [9]. Wang, et al. [10] proposed a model where waste collection, recycling and disposal are explicitly considered, but route design problem is solved only by considering the districts as the sources of demand, without analyzing collection routes inside each of the zones.

Agunwamba, et al. [11] intended to associate the demand to a set of points representing a set of streets, instead of considering in details the arcs of the network.

Arribas, et al. [12] applied a cluster first-route second approach, by executing a bin clustering method followed by a local search improvement.

Kim, et al. [13] developed a capacitated clustering-based algorithm to deal with real life waste collection problems. Ganesh and Narendran [14] provided an initial solution with k-means clustering methods and thereby accelerated convergence of the genetic algorithm to solve the vehicle routing problem with deliveries and pickups.

Amponsah and Salhi [2] used the Variable Neighbourhood Method to solve the solid waste collection problem, which exists in Kumasi by considering the effect of smell on the environment.

3. CASE STUDY

In this paper, Kwadaso Estate a sub metropolitan area in Kumasi was chosen as a case study. The area has approximately 590, 240 litre waste bins. We first clustered the entire area under consideration according to the capacity of the collecting vehicle and then used ant colony optimization to find the minimum route in the collection of the waste.

In a given cluster, a vehicle is assigned to collect all the waste bins in a day.

The population of the area under consideration is over 18,000 people and a production of about 4.2 tonnes of solid waste per day. Data was gathered from the Municipal authorities and the housing cooperation.

4. PROBLEM FORMULATION

The Capacitated Clustering Problem (CCP) is considered to have *n* waste collection bins, which are placed in front of their houses along the streets, d_i.

The *n* bins are then grouped to form *k* clusters according to the capacity of the vehicle assigned to a particular zone. Each cluster has $n_1, n_2, n_3, . . ., n_k$ bins with the condition that $\sum_{j=1}^{k} n_j = n$

where ***n*** is the total number of bins.

The problem is given with a set of

Customers: $r_1, r_2, r_3, . . ., r_n$

Distances: $d_1, d_2, d_3, . . ., d_n$

Demands: $q_1, q_2, q_3, . . ., q_n$

Capacity: Q

where $r_i \in R$ are the set of bins that are distributed along the road, with road distance (d_i)

Let X be a binary matrix, such that

$$x_{ij} = \begin{cases} 1, & \text{if bin } i \text{ is assigned to a cluster } j \\ 0, & \text{otherwise} \end{cases}$$

The objective is to find X, which minimizes

$$\sum_{j=1}^{k} \sum_{i=1}^{n} d_{ij} x_{ij} \qquad (2.1)$$

Subject to

$$\sum_{j=1}^{k} x_{ij} = 1, \; i = 1, 2, 3, \ldots, n \qquad (2.2)$$

$$\sum_{i=1}^{n} d_i x_{ij} \leq Q, \quad j = 1, 2, 3, \ldots, k \qquad (2.3)$$

where d_{ij} represents the closeness distance of bin *i* to the cluster *j*.

The objective function (2.1) seeks to minimize the total distance of bins to a cluster. Constraint (2.2) ensures that each bin *i* is assigned to only one cluster *j*. Constraint (2.3) stipulates that the total volume of waste in a cluster should not exceed the capacity *Q* of the vehicle assigned to the cluster.

5. ALGORITHM FOR THE PROPOSED WORK

In this paper, the CCP is solved using vertex-one centre algorithm, which includes capacity as one of the constraints for clustering the loads along road distances based on bin with minimum distance from the cluster centre.

6. VERTEX ONE- CENTRE CLUSTERING

The one centre algorithm assigns each point to a cluster whose centre is nearest by the use of a priority measure to select the waste bins for a cluster.

The bins are assigned to the nearest cluster based on maximum demand and minimum distance so the customer having larger demand are assigned to the cluster first and the customer with smaller demand can be easily packed in to other clusters. If bins are assigned based on distance alone, the number of clusters formed may not be optimal since customers with smaller demand may be assigned to a cluster before the customer with larger demand, which may lead to the formation of additional cluster.

7. VERTEX 1-CENTRE ALGORITHM

The major steps involved in the formation of the algorithm are described in the following section.

7.1. Calculate the Number of Clusters

It is calculated based on the demand (q_i) of the customer and capacity of cluster (Q) as

$$k = \sum_{i=1}^{n} \frac{d_i}{Q} \qquad (2.4)$$

7.2. Select Initial Centroids

The initial k centroids are selected by arranging the bins based on their demand in their non-increasing order $q_1 > q_2 > q_3 > . . . > q_n$. Then the first k bins with the highest loads becomes k centroids.

7.3. Assignment of the Bins

The distances between each requester to all the k centroids are found. We then group all the bins r_i to the closest centroid j. To find the appropriate centroid j for r_i, we calculate a priority value as,

$$\text{Priority: } P_i = \frac{d_{ij}}{q_i} \qquad (2.5)$$

This priority determines the r_i, which has the highest priority of having the centroid j. The selected r_i is assigned based on constraint (4). If constraint (4) is satisfied the selected r_i will be assigned to the next nearest centroid based on (5) and (4).

7.4. Convergence Criteria

The iterative procedure is repeated until there is no change in cluster formed.

8. PROBLEM DESCRIPTION

Capacitated Clustering Vehicle Routing Problem (CCVRP) deals with a single depot collection system servicing a set of customers by means of a homogeneous fleet of vehicles. The vehicles leave the depot empty, collect the waste of each customer to the dump site and return to the depot empty. The objective of the study is to find the set of vehicle routes servicing all the customers with the minimum total distance.

In CCVRP, each customer must be served exactly once. The area under study was clustered according the capacity of the vehicle, by the time the vehicle collects the load from the last bin in the cluster, the vehicle will be full and each customer in the cluster might have been served.

9. PROBLEM FORMULATION

Mathematically, CCVRP is described by a set of homogenous vehicles *V*, a set of bins *R*, and a complete directed graph *G*(*N*, *A*). The graph consists of (*n*+1) vertices where the bins are denoted by 1, 2, ..., *n* and the depot is represented by the vertex 0 with (*n* + 1) as the dumpsite. $A=\{(i,\ j):i,\ j\in N, i\neq j\}$ denote the set of arcs that represents connections between the depot and the customers and among the customers. No arc terminates at vertex O and no arc originates from vertex (*n* + 1), distance (d_{ij}) is associated with each arc (*i*, *j*).

Each vehicle has capacity *Q* and each bin (node) *i* is characterized by its direct distance and the pick up demand *qi*. Finally, *Q*, d_{ij}, and $q_i$are assumed to be non-negative integers. The CCVRP determines a set of paths (routes) such that:

(i) each vehicle travels exactly one route;

(ii) each customer is visited only once by one of the vehicles completely satisfying its demand and supply;

(iii) the load carried by a vehicle between any pair of adjacent bin on the route must not exceed its capacity; and

(iv) total distance given by the sum of the arcs belonging to these routes is minimal.

10. MATHEMATICAL FORMULATION FOR CCVRP

$$\text{Minimize } Z=\sum_{i\in N}\sum_{j\in N}\sum_{v\in V} d_{ij}x_{ijv} \qquad (3.6.1)$$

Subject to

$$\sum_{j\in N}\sum_{v\in V} x_{ijv}=1 \qquad \forall i\in R \qquad (3.6.2)$$

$$\sum_{i\in N}\sum_{v\in V} x_{ijv}=1 \qquad \forall j\in R \qquad (3.6.3)$$

$$\sum_{j\in N} x_{0jv}=1 \qquad \forall v\in V \qquad (3.6.4)$$

$$\sum_{i\in N} x_{ikv} = \sum_{j\in N} x_{kjv} \qquad \forall k \in R, v \in V \tag{3.6.5}$$

$$\sum_{i\in N} x_{i\,n+1\,v} = 1 \qquad \forall v \in V \tag{3.6.6}$$

$$\sum_{i\in R} q_i \left[\sum_{j\in N} x_{i\,j\,v} \right] \le Q \qquad \forall v \in V \tag{3.6.7}$$

$$x_{i\,j\,v} \in \{0,1\} \qquad \forall i,\, j \in N, \forall v \in V \tag{3.6.8}$$

Equation (3.6.1) ensures that the objective function aims at minimizing the total travel distance, Equations (3.6.2) and (3.6.3) guarantees that for each cluster, a customer is visited exactly once, equations (3.6.4), (3.6.5) and (3.6.6) ensure that each vehicle leaves the depot O, after arriving at the customer the vehicle leaves that customer again, and finally arrives at the dumpsite (n + 1). Equation (3.6.7) state that no vehicle is loaded more than its capacity and equation (3.6.8) are the binary constraints.

11. ACO ALGORITHM FOR OUR PROPOSED WORK

The construction of G = (N, A), where the set A fully connects the components N, is identical to the problem graph, that is the set of states of the problem corresponds to the set of all possible partial tours.

An initial solution is first obtained using the nearest-neighbour heuristic: start at the depot and then select the not yet visited closest feasible customer as the next customer to be visited.

Each artificial ant has a memory called tabu list. The tabu list forces the ant to make legal tours. It saves the cities already visited and forbids the ant to move already visited cities until a tour is completed.

After all cities are visited, the tabu list of each ant will be full. The shortest path found is computed and saved. Then, tabu lists are emptied. This process is iterated for a user-defined number of cycles.

Suppose there are n nodes and b_i is the number of ants at city i. Consider the following notation:

$K = \sum_{i=1}^{n} b_i$: Total number of ants

N : Set of customers to be visited

$tabu_k$: Tabu list of the k-th ant

$tabu_k(s)$: s-th customer visited by the *k*-th ant in the tour

τ_{ij} (t) : Intensity of trail on edge between customer *i* and customer *j* at time *t*

η_{ij} : Visibility of edge between customer *i* and customer *j*

η_{ij} is usually assumed as the inverse of the distance between customer *i* and customer *j* (d_{ij}) Thus,

$$\eta_{ij} = \frac{1}{d_{ij}}$$

After *K* artificial ants are randomly placed on customers, the first element of each ant's tabu list is set to be equal to its starting bins. Then, the ants move to unvisited customers. The probability of moving from customer *i* to customer *j* for the *k*-th ant is defined as: (p_{ij}^k)

$$p_{ij}^k = \begin{cases} \dfrac{[\tau_{ij}]^\alpha.[\eta_{ij}]^\beta}{\sum_{k \in \text{allowed}_k} [\tau_{ik}]^\alpha.[\eta_{ik}]^\beta}, & j \in \text{ allowed} \\ 0, & \text{otherwise} \end{cases}$$

where $allowed_k = \{N - tabu_k\}$, α and β are parameters that control the relative importance of pheromone trail versus visibility.

12. HEURISTIC INFORMATION

Generally, the ant approaches developed for solving TSP and VRP the visibility value between a pair of customers is the inverse of their distance, thus $\eta_{ij} = \dfrac{1}{d_{ij}}$.

13. INITIAL PHEROMONE TRIALS

In most of the ant colony based algorithms to VRP, initial pheromone trails τ_0 is set equal to the inverse of the best known route distances found for the particular problem. However, it was found that $\tau_0 = \dfrac{1}{n}$.

When the initial route is constructed, it is started at the depot and the customer with the highest φ_{0j} value is selected as the first customer to be visited. Then, the tour is constructed by selecting the not yet visited feasible customer with the highest φ_{ij} at each time.

14. ROUTE CONSTRUCTION PROCESS

It is assumed that the number of ants is equal to the number of customers, initially each ant is positioned at each customer. Then, each ant constructs its own tour by successively selecting a not yet visited feasible customer. The choice of the next customer to visit is based on proportional fitness (Roulette Wheel) in conjunction with the information of both the pheromone trails and the visibility of that choice given in equation $\varphi_{ij} = \tau_{ij}[\eta_{ij}]^{\beta}$, τ_{ij} denotes the amount of pheromone on arc (i, j) and β is power weighting parameter that weights the consistency of arc
(i , j).

15. PHEROMONE UPDATE

Our pheromone update consists of an improved ant system strategy. In this strategy our pheromone update rule is as follows: $\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \sum_{r=1}^{k} \Delta\tau_{ij}^{r} + \frac{Q}{L^k}$

where Q is a constant based on the number of nodes in the cluster , L^k is the length of tour of ant K and $\rho, 0 \le \rho \le 1$, is the evaporation factor, which determines the strength of an update.

16. DATA ANALYSIS AND RESULTS

The study seeks to find the minimum route in order to collect the garbage at Kwadaso estate in Kumasi. Kwadaso estate is a residential area built by state housing corporation, now state housing company. The site layout for the said area was obtained from state housing company and Geographic Information System (GIS) was used to obtain road distances linking adjacent node(s). Table 3.1 shows the load (number of 240 litre bins) on each node and Figure 4.2 shows the road distances between adjacent node(s) of the area under study.

Table-**3.1.** Node number and its corresponding load

Service points (nodes)	1	2	3	4	5	6	7	8	9
Load (q_i)	3	5	6	6	2	1	3	3	6

10	11	12	13	14	15	16	17	18	19
1	3	3	4	2	2	4	6	6	2

. . .

. . .

148	148	150	151	152	153	154	155	156	157
5	2	2	3	3	4	3	4	4	2

Table-3.2. Road distances between customer points

	1	**2**	**3**	**4**	**5**	**6**	**7**	**.**	**.**	**.**	**151**	**152**	**153**	**154**	**155**	**156**	**157**
1	0	56	inf	80	inf	inf	inf	.	.	.	inf	inf	inf	inf	inf	inf	inf

Continue

2	56	0	44	74	inf	inf	inf	. . .	inf	inf	inf	inf	inf	inf	inf
3	inf	44	0	inf	inf	inf	inf	. . .	inf	inf	inf	inf	inf	inf	inf
4	80	74	inf	0	53	inf	inf	. . .	inf	inf	inf	inf	inf	inf	inf
5	inf	inf	inf	53	0	44	inf	. . .	inf	inf	inf	inf	inf	inf	inf
6	inf	inf	inf	inf	44	0	35	. . .	inf	inf	inf	inf	inf	inf	inf
7	inf	inf	inf	Inf	inf	35	0	. . .	inf	inf	inf	inf	inf	inf	inf
.	.	..	.	.	.	.	.	. . . .	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	. . . .	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	. . . .	.	.	.	.	.	.	.
151	inf	inf	inf	inf	inf	inf	inf	. . .	0	44	inf	inf	inf	inf	inf
152	inf	inf	inf	inf	inf	inf	inf	. . .	44	0	56	inf	inf	inf	inf
153	inf	inf	inf	inf	inf	inf	inf	. . .	inf	56	0	50	inf	inf	inf
154	inf	inf	inf	inf	inf	inf	inf	. . .	inf	inf	50	0	35	inf	inf
155	inf	inf	inf	inf	inf	inf	inf	. . .	inf	inf	inf	35	0	30	inf
156	inf	inf	inf	inf	inf	inf	inf	. . .	inf	inf	inf	inf	30	0	25
157	inf	inf	inf	inf	inf	inf	inf	. .	inf	inf	inf	inf	inf	25	0

Table-3.3. All pair shortest path in metres (m) from table 3.2 by Floyd Warshall's Algorithm

	1	**2**	**3**	**4**	**5**	**6**	**7**	**. . . .**	**151**	**152**	**153**	**154**	**155**	**156**	**157**
1	0	56	100	80	133	177	212	. . . .	599.5	643.5	699.5	749.5	784.5	814.5	839.5
2	56	0	44	74	127	171	206	. . . .	593.5	637.5	693.5	743.5	778.5	808.5	833.5
3	100	44	0	118	171	215	250	. . . .	637.5	681.5	737.5	787.5	822.5	852.5	877.5
4	80	74	127	0	53	97	132	. . . .	519.5	563.5	619.5	669.5	704.5	734.5	759.5
5	133	127	171	53	0	44	79	. . . .	466.5	510.5	566.5	616.5	651.5	681.5	706.5
6	177	171	215	97	44	0	35	. . . .	422.5	466.5	522.5	572.5	607.5	637.5	662.5
7	212	206	250	132	79	35	0	. . . .	387.5	431.5	487.5	537.5	572.5	602.5	627.5
.	.	..	.	.	.	.	.	. . . .	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	. . . .	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	. . . .	.	.	.	.	.	.	.
151	599.5	599.5	599.5	599.5	599.5	599.5	599.5	. . . .	0	44	100	150	185	215	240
152	643.5	643.5	643.5	643.5	643.5	643.5	643.5	. . . .	44	0	56	106	141	171	196
153	699.5	699.5	699.5	699.5	699.5	699.5	699.5	. . . .	100	56	0	50	85	115	140
154	749.5	749.5	749.5	749.5	749.5	749.5	749.5	. . . .	150	106	50	0	35	65	90
155	784.5	784.5	784.5	784.5	784.5	784.5	784.5	. . . .	185	141	85	35	0	30	55
156	814.5	814.5	814.5	814.5	814.5	814.5	814.5	. . . .	215	171	115	65	30	0	25
157	839.5	839.5	839.5	839.5	839.5	839.5	839.5	. .	240	196	140	90	55	25	0

The results from Floyd Warshall's algorithm was used to cluster the area which has 588 garbage bins, based on the vehicles capacity (103 bins) using our proposed vertex one-centre algorithmand all road distances were measured (in metres) from the graph of scale 1:2.

17. RESULTS FROM VERTEX 1-CENTRE ALGORITHM

Table 4.4 Stable cluster Centres and their respective clusters

Cluster Centres = 128 6 48 31 146 106

cluster1 = 113 114 115 116 118 119 120 121 122 123 124 125 126 127 128
129 130 131 132 133 134 135 139 140

cluster2 = 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 25 29 30 37 38 39 40 57 58 59 60 61

cluster3 = 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 63 64 65 66 67 68 69 70 71 72 73 74 75 76

cluster4 = 19 20 21 22 23 24 26 27 28 31 32 33 34 35 36 78 79 80 81 82 83 62 77

cluster5 = 84 85 86 87 88 89 105 108 109 136 137 138 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157

cluster6 = 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 106 107 110 111 112 117 141

18. MODIFIED ACO (ASOPTION) RESULTS

Our modified AS option was then used on each of the clusters to find the minimum tour of each ant and then select the best ant tour. The result for each ant in a cluster is as shown in Tables 4.1.

Table 4.1 Ants tour length and the best ant tour for cluster 1

Distance_Covered_By_Ant =
431.4000
382.9333
495.1417
535.5250
412.0250
436.0167
435.3500
395.1417
447.2333
336.3292
377.7042
478.5167
537.7167
472.2667
562.3583
402.5375
453.9375
548.1583

476.1875
421.3667
579.4333
371.7500
527.0167
463.4375

Ant_Best_Tour = 116 → 118 → 119 → 122 → 128 → 129 → 134 → 135 → 139 → 140 → 132 → 133 → 131 → 130 → 127 → 126 → 125 → 124 → 123 → 114 → 113 → 115 → 120 → 121

By similar method the minimum route for cluster 2 through cluster 6 is as shown in Table 4.2.

Table-4.2. Ants route and the minimum distance for cluster 2 through cluster 6

Cluster number	Shortest ant route	Minimum distance (m)
2	3 → 2 → 1 → 4 → 5 → 6 → 7 → 8 → 10 → 11 → 9 → 30 → 37 → 39 → 40 → 38 → 29 → 25 → 14 → 13 → 12 → 16 → 17 → 15 → 18 → 61 → 60 → 59 → 58 → 57	805.2
3	56 → 55 → 54 → 53 → 52 → 51 → 50 → 49 → 48 → 63 → 64 → 70 → 69 → 68 → 67 → 71 → 66 → 65 → 72 → 76 → 75 → 74 → 73 → 44 → 45 → 46 → 47 → 43 → 42 → 41	952.7
4	77 → 78 → 79 → 80 → 81 → 82 → 83 → 34 → 35 → 36 → 26 → 27 →28 → 22 → 23 → 24 → 21 → 20 → 19 → 33 → 32 → 31 → 62	804
5	142 → 143 → 144 → 145 → 146 → 147 → 105 → 109 → 108 → 138 →137 → 136 → 150 → 151 → 152 → 148 → 149 → 84 → 86 → 87 → 88 → 89 → 85 → 153 → 154 → 155 → 156 → 157	737.7
6	90 → 91 → 92 → 93 → 94 → 95 → 96 → 110 → 111 → 112 → 97 → 98 → 99 → 100 → 101 → 102 → 103 → 104 → 107 → 106 → 117 → 141	547.3

19. CONCLUSIONS

The adoption of the proposed clustering heuristics decreased the number of vehicles required to complete the service in Kwadaso from 8 to 6. It enabled a cut back in the number of runs for trucks per day. Because of the shorter operational time and reduced runs for trucks, reductions in operational and labour cost were also reduced. The new decision procedures for scheduling of solid waste collection routes would go a long way in solving the problem of indiscriminate collection of waste by service providers, since it will reduce the collection cost, and increase the frequency of solid waste collection. Efficient routing of solid waste collection vehicles would reduce costs by reducing the labour expended in collection. The algorithm would provide optimal route, conserve energy, and reduce working hours and vehicle fuel consumption. The algorithm can be applied successfully applied to urban garbage management problem where door to door collection of waste is practiced.

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