Optimization of the Waste Collection Arc Routing Problem using the Physics-based Electromagnetism-Like Algorithm

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Abstract: The Philippine context of waste collection is removing waste from sources like households or common collection areas. Strategic planning of the collection routing is considered one of the methods to optimize performance and cost of service. This problem of effective routing may be mathematically formulated as a Vehicle Routing Problem (VRP). The study aims to build a VRP model to optimize the waste collection service in a specified area of Parang, Marikina City, by minimizing the cost function composed of fuel consumption and comparing each path's Greenhouse Gas Emission (GHG). The study examines the door-to-door waste collection service and the waste's transport to a depot. A physics-based Electromagnetism-like (EM-Like) Algorithm will be implemented to generate optimized paths. The road network will be translated into a directed, multigraph-based graph representation where arcs will serve as the road segments, and the nodes will correspond to street intersections and dead-ends. In order to get the spatial data, Geographic Information Systems (GIS) will be used to extract them from Open Street Map (OSM).

Key Words: vehicle routing problem, electromagnetism-like algorithm, mathematical optimization

1. INTRODUCTION

One of the problematic sectors that countries all over the world face includes Municipal Solid Waste (MSW) management (Diaz, 2017; The World Bank Group, 2018; EPA, 2020) because of its essentially complex characteristic (Kolekar et al., 2016), the rise of the rapid increase of waste amount due to development, and expensive management costs needed (Fernández-Aracil et al., 2018) both in developing and developed countries. Magalang (2014) asserts that these problems can be mirrored in the Philippines since the increase in population in the said country (Gatpolintan, 2021) rise in household consumption by 0.03 percent from the years 2019 to 2020 (The World Bank Group, 2021), and expansion of its urbanization with 0.13 percent from 2010 to 2015 (Philippine Statistics Authority, 2019) affects the volume and management of such sector. Waste collection is to be treated as a primary objective in planning sustainable waste management (World Bank Group, 2018) because the provision of significant collection coverage in urban and rural places should be satisfied first before investing in more sophisticated infrastructure. Negligence of this detail has been shown to undo waste treatment advantages as waste is not properly collected and disposed of. This implies the importance of a substantial waste collection service to enhance further the following levels of an MSW system. Several kinds of literature on collection route optimization have been written and conducted through the years (Villanueva, 2020), and this problem has been formulated as a Vehicle Routing Problem (VRP). In fact, according to Oduro- Kwarteng (2011), an efficient and effective solid waste collection can be done by system analysis and optimization of operations like planning the effective routing of vehicles involved in the service. Therefore, this study aims to transform the problem of waste collection optimization in Marikina City into a VRP model to optimize waste collection, minimize the cost function composed of fuel consumption, and compare the potential amount of emission emitted per arc. To get the optimal path of waste collection, the study will implement the physics-based EM-Like algorithm to find a solution to the routing problem. Each particle represents a possible solution, that is, one that is composed of a sequence of edges to be taken on the map. The said algorithm implements both the exploration and exploitation of the search space or the space of all possible configurations of edge and node sequences. During the first stages of the process, solutions are explored by permitting the movement of particles through the calculation of force and movement at the next iteration. Later on, better solutions are taken and exploited in a way to help the process converge into favorable value. The algorithm will be exploring a directed, multigraph-based representation of the road network, where arcs will correspond to the demand points and nodes will be the intersections and dead-ends. Antiparallel edges and directed lines will represent the one and two-way streets profile. Geographic Information Systems (GIS) will also be utilized to extract spatial data from Open Street Map (OSM) by generating formatted shapefile data such as the road network, service points, and intersections. The spatial data taken will only contain planar characteristics and is not fitting for 3D analysis. The road network information will not give the road restrictions and real-time road closures due to construction; however, it will contain traffic directions, road types, and street names.

2. METHODOLOGY

2.1 Geographic Information Systems

GIS is one of the tools that the study will utilize to obtain and process spatial data, including street segments, intersections/dead-ends, type of highway, and geometrical attributes like road length. The road network comprises 277 edges corresponding to a particular traffic direction and 106 nodes which signifies dead-ends and intersections. Figure 1 shows an instance of extracted spatial features in the study area.

2.2 MATLAB

The software MATLAB will be used to build the dual, multigraph-based representation of the road network. The purpose of this is to enable the algorithm's execution. It will also consist of importing the set of edge lists and nodes and generating initial feasible solutions.

Fig. 1. Geographical Map of Barangay Parang, Marikina City

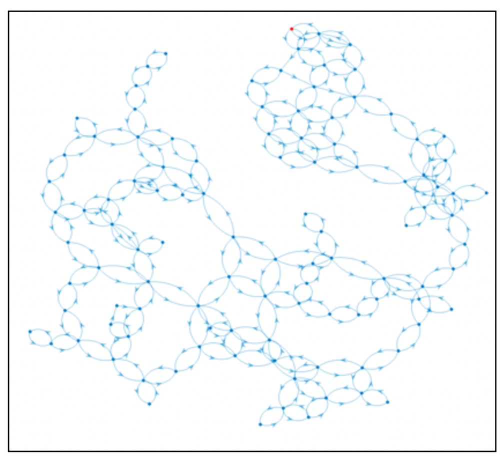

Fig. 2. Directed Mathematical Graph Representation of Parang, Marikina City Road Network.

The graph is also configured to be a connected one; a particular path along the graph can connect every pair of nodes. Figure 2 shows the directed, multigraph-based representation of the road network in Parang, Marikina City. The red node corresponds to the depot or the point where the waste collection will start. Each arc in the graph is associated with an arc cost related to fuel consumption and potential GHG emission. Ten partitions of the graph is initialized and five initial solutions are prepared. Each partition will serve as the component of each solution/particle in the EM-like algorithm.

2.3 Mathematical Models

The static emission model for network links (Wallace, 1998) will be utilized to identify potential emissions that may be presented for each arc. It is formulated as:

$$e_{ij}(x_{ij}) = 0.2038\tau_{ij}(x_{ij})\exp\left(\frac{0.7962 l_{ij}}{\tau_{ij}(x_{ij})}\right) \qquad \text{(Eq. 1)}$$

where:

$e_{ij}(x_{ij})$ = CO emission in grams per hour per vehicle

l_{ij} = link length (in kilometers) at an arc

x_{ij} = link-state variables at an arc

$\tau_{ij}(x_{ij})$ = travel time (in minutes) at an arc

On the other hand, the research aims to use the Comprehensive Modal Emissions Model (CMEM) to calculate the fuel consumption for every arc:

$$F(t, v, f) = \lambda k N_e V t + \lambda\gamma\beta v^3 t + \lambda\gamma\alpha d(\mu + f) \qquad \text{(Eq. 2)}$$

where:

F = Fuel consumption, liters

t, v = Vehicle traveling a distance d at a constant speed v in duration t

f = Carrying load

μ = Vehicle curb weight

λ = $\varepsilon/(\kappa\psi)$

γ = $1/(1000\epsilon\varpi)$

α = $g\sin(\phi) + gC_r\cos(\phi)$

β = $0.5 \times C_d A_f$

The other parameters used in the CMEM are listed in Table 1, which is based on vehicle JAC HFC1082KD. These values can be adjusted in the context of the waste collection trucks used in the Philippines.

Table 1. Parameters in the CMEM model of Vehicle Type: JAC HFC1082KD

Type	Notation	Description	Value
Vehicle-dependent	k	Engine friction factor (kJ/rev/ liter)	0.20
	N_e	Engine speed (rev /s)	38.33
	V	Engine displacement (liter)	4.70
	A_f	Frontal surface area (m^2)	5.03
	μ	Curb-weight (kg)	3850
	Q	Vehicle capacity (kg)	4460
	ε	Vehicle drive train efficiency	0.4
	ϖ	Efficiency parameter for diesel engines	0.9
Road-dependent	ϕ	Road angle	0
	C_r	Coefficient of rolling resistance	0.01
Other constants	ξ	Fuel-to-air mass ratio	1
	κ	Heating value of a typical diesel fuel (kJ/g)	44
	ψ	Conversion factor (g/liter)	737
	ρ	Air density (kg/m^3)	1.2041
	g	Gravitational constant (m/s^2)	9.81
	C_d	Coefficient of aerodynamic drag	0.7

2.3 Electromagnetism-like Algorithm

A typical population-based optimization algorithm requires a set of initial solutions, so the number of points in the population should be determined beforehand. In this study, the algorithm proceeds with the following steps:

1. ***Initialization***. The first step of the EM-like optimization is initialization, which is to generate m initial solutions called $\boldsymbol{x_i}$, where $i = 1,2,3, \ldots m$. In this study, $m = 5$. Each $\boldsymbol{x_i}$ is made up of a sequence of edges (i.e., an edge list) that starts from the waste depot and ends at the same point. Each of these solutions is treated as a charged particle, and it lies inside an $n-$dimensional space, which in this case $n = 10$. The physical representation of the dimension in this problem is that for each $\boldsymbol{x_i}$, which can be written $\boldsymbol{x_i} = \sum_{k=1}^{10} x_i^k$, each x_i^k refers to the component of the k^{th} solution. Every x_i^k refers to a partition of the graph that can be independently explored. This is where the algorithm will choose several paths to maximize the objective function. The objective function values are computed for each $\boldsymbol{x_i}$ and the $\boldsymbol{x_{best}}$ is accordingly defined per iteration, which is the particle with the best function value.

2. ***Charge Calculation.*** Next is to get the charge of each feasible solution. This value tells the ability of attraction or repulsion on the point $\boldsymbol{x_i}$, and is related to the objective function value of each particle by the equation:

$$q_i = \exp\left(-n\frac{f(x_i) - f(x_{best})}{\sum_{k=1}^{m}\left(f(x_k) - f(x_{best})\right)}\right), \quad \forall i \quad \text{(Eq. 3)}$$

where:

q_i = Charge of particle i

$f(\mathrm{x_i})$ = Objective function value of a particle i

$f(x_{best})$ = The best solution

$f(x_k)$ Objective function value of a particle k

n = Number of dimensions

m = Population size

3. ***Force Calculation.*** Next is to calculate the individual component forces between any pair of points x_i and x_j. For example, for particle i,

$$F_{ij}^1 = \begin{cases} \left(x_j^1 - x_i^1\right)\dfrac{q_i q_j}{\| x_j^1 - x_i^1 \|^2} & \text{if } f\left(x_j\right) < f\left(x_i\right) \\ \left(x_i^1 - x_j^1\right)\dfrac{q_i q_j}{\| x_j^1 - x_i^1 \|^2} & \text{if } f\left(x_i\right) \le f\left(x_j\right) \end{cases} \quad \text{(Eq. 4)}$$

where:

F_{ij}^1 = Force at particle i at the 1st component, due to particle j

x_j^1 = Position of particle j at the 1st component

x_i^1 = Position of particle i at the 1st component

q_i Charge of the particle i

q_j = Charge of the particle j

$|x_j^1 - x_i^1|^2$ = The distance between particle i and j

The reason why the denominator of Equation 4 is not raised to three as what is expected from the general form of Coulomb Force is that the term does not contribute toward total force significantly during the optimization and increases with population size. Therefore, it is eliminated for the sake of computational simplification. In fact, several modifications of the force component were implemented where the denominator is completely taken away (Siddique & Adeli, 2017). This procedure aims to ensure that all points move to the better points and to be far from the worse ones. The one with the better objective function value between pairs of particles will attract the other. The one with worse value repulses the other. After this, the particle's movement will be evaluated, which determines the direction and step length of movement.

4. ***Movement.*** This procedure aims to displace the particles in the population (except for the $\boldsymbol{x_{best}}$) according to the resultant force exerted on them, calculated previously. For instance, for component 1 of the i^{th} solution/particle, the new position according to the resultant force at the corresponding component is:

$$x_i^1 = \begin{cases} x_i^1 + \lambda\dfrac{F_i^1}{\| F^1 \|}\left(u_i - x_i^1\right) & \text{if } F_i^1 > 0 \\ x_i^1 + \lambda\dfrac{F_i^1}{\| F^1 \|}\left(x_i^1 - l_i\right) & \text{otherwise} \end{cases} \quad \text{(Eq. 5)}$$

where:

x_i^1 = Position of particle i at the 1st component

u_i = Upper boundary of search space, 1

l_i = Lower boundary of search space, 0

$\frac{F_i^1}{|F^1|}$ Normalized force vector at 1st component (retains direction)

λ = Random step length, [0,1]

5. ***Local Search.*** The algorithm will repeat iterations to generate new particles using the obtained movement in step 4. The best point $\boldsymbol{x_{best}}$ will not be moved from the previous iteration. For every iteration a comparison will be made: if $\boldsymbol{x_{best}}(iter+1)$ is better than $\boldsymbol{x_{best}}(iter-1)$ set the $\boldsymbol{x_{current\ best}} \rightarrow \boldsymbol{x_{best}}(iter = iter+1)$. On the other hand, if $\boldsymbol{x_{best}}(iter+1) = \boldsymbol{x_{best}}(iter-1)$ then retain the $\boldsymbol{x_{best}}$ in the next iteration and change all the positions of the particles.

3. RESULTS AND DISCUSSION

The EM-like algorithm was implemented in 10 iterations. These solutions are compared per iteration and each $\boldsymbol{x_{best}}, \boldsymbol{x_{worst}}$ is tabulated in Table 2 below.

Table 2. List of Best and Worst Objective function Values per Iterations.

variables	**Initial**	***Iterations***									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
best particle	4	5	5	4	1	1	2	2	3	3	3
best objective function value (least fuel consumption) [liters]	7.06	5.77	5.77	4.79	4.72	4.72	4.54	4.54	4.44	4.44	4.44
worst objective function value (highest fuel consumption) [liters]	12.08	7.76	11.37	9.30	8.66	9.93	6.01	8.24	6.74	5.82	9.54
worst particle	2	2	2	3	5	2	3	1	4	2	1

The solution gives a sequence of edges or pairs of nodes that show a valid path when traced on a geographical map. The column "initial" signifies the solution generated initially to start the algorithm. In Iteration 1, particle 5 displayed optimal values, so it is carried onto iteration 2, where it is still the best value despite all the particles around it changing position. The particles should be seen as dynamic variables. For example, iteration one treats particle one as best, while in iteration seven it is treated as the worst. This means that what matters is identifying a position vector composed of a set of components that will locate the place where minimum values are obtained. Moreover, the particles that contain information about a path and its charge that signifies the quality of the objective function on how well it can attract or repel better and worse solutions deliver significance in the exploration and exploitation of the search space. On the other hand, Table 3 shows the summary of the variables for each best particle per iteration.

Table 3. Summary of Variables for the Particle with the Best Objective Value.

best objective value characteristics											
Variables	***Initial***	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
length traveled [km]	19.85	17.47	17.47	18.07	16.95	16.95	17.97	17.97	15.37	15.37	15.37
service duration [hr]	2.26	2.15	2.15	2.04	0.98	0.98	1.58	1.58	1.20	1.20	1.20
number of edges covered	291	257	257	267	244	244	280	280	229	229	229
number of unique covered	175	172	172	169	162	162	169	169	158	158	158
accumulated GHG emission (Carbon Monoxide) [g/hr/vehicle]	32.16	30.17	30.17	29.06	15.83	15.83	23.40	23.40	18.05	18.05	18.05

There is a trade-off between minimizing fuel consumption like decreasing the distance taken. Although the best point holds the least fuel consumption, the number of edges or the streets covered are also fewer than the particle with the highest fuel consumption. The unique nodes covered in the same table tell us the number of unique arcs traveled throughout the service. It is preferable to have a greater amount of unique arcs serviced with a reasonable amount of repeating paths since the goal is to also cover all possible streets as much as possible. Figure 3 shows the changes per iteration of best objective function values vs. the mean. It can be seen that the best solution is slowly decreasing in value. This slow decrease in minimization may suggest the need to implement interventions to speed up the computational frame in getting converging solutions at a reasonable interval of steps.

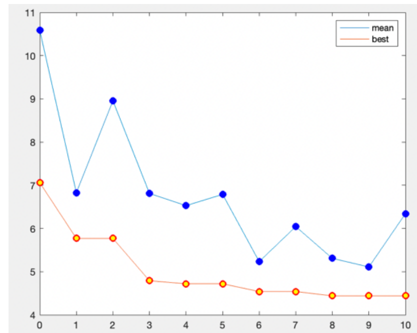

Fig. 3. Mean and Best Value Changes per Iteration from a Five-particle Population of Solution.

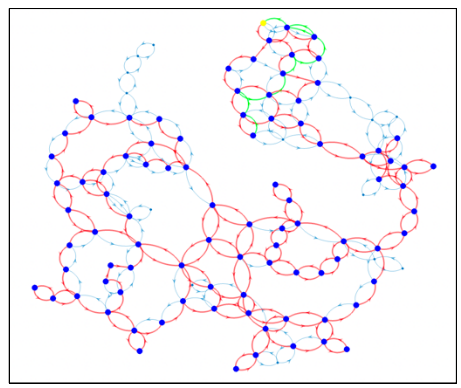

Fig. 4. Waste Collection Path that Optimizes the Fuel Consumption function.

Figure 4 presents the optimized path for a waste collection service that minimizes fuel consumption. The yellow node specifies the waste depot, while the red lines specify the movement of each component of the particle, that is, the feasible paths. On the other hand, the green path signifies the shortest path from the last node of the last component of the particle going back to the depot. The light blue lines are the ones not covered by the waste truck, as specified.

4. CONCLUSIONS

Throughout the iteration, the best objective function value is seen to be decreasing, which is preferred and converging towards a value close to 4. This means that the algorithm is moving and encourages other particles to move towards optimal locations. It is important to note that the particle being referred here is only a placeholder of possible values that will minimize the fuel consumption; thus, they are also seen to be constantly changing in value at each iteration. The generation of the initial solution can be further improved using efficiency-based path-scanning heuristics, clustering-based methods to locate the best pairs of nodes that will cover streets as much as possible, or employing guided search algorithms to make informed decisions on what node to take or leave. It is also recommended to evaluate the performance of the algorithm through the use of artificial landscapes like test functions. Future research on measuring Pareto-Optimality of solutions can also be done, especially for multi-objective situations like minimizing emissions and fuel consumption simultaneously, as there is a trade-off between choosing only one over the other.

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