A Logistics Planning Tool for E-Waste Collection: Streamlining Sustainability and Efficiency

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Abstract

We have developed a vehicle routing problem (VRP) optimization tool aimed at improving the efficiency of e-waste collection and logistics systems. Given the geospatial dispersion of electronic waste (e-waste), an effective reverse logistics system is crucial for successful recycling efforts. Our tool combines guided local search and k-opt algorithms to optimize travel routes for fleets of heterogeneous vehicles. To ensure accurate calculations, the tool utilizes the Open Street Map API, which provides actual road network data for calculating travel distances and time. Furthermore, we have incorporated a comprehensive emission model that accurately quantifies vehicular emissions. By doing so, we can generate optimized solutions with an average optimality gap of 2.2% compared to known best solutions of benchmark VRPs within a time limit of 30 seconds. It also generates an interactive map showing color-coded vehicle routes and collecting nodes' information. The effectiveness of the tool has been tested with real data from our industry partner. Out developed VRP optimization tool comes with a graphical user interface that can provide optimized routes and quantify—environmental emissions, actual travel distance, and cost within a reasonable amount of time. It has been released as an open-source software. The tool can potentially be utilized for minimizing carbon dioxide emissions from commercial vehicles to mitigate greenhouse gas impacts.

Keywords
Logistics, VRP, E-Waste, Recycling, Emission

1. Introduction
The global consumer electronics market is expected to expand by a compound annual growth rate (CAGR) of 8% through 2027 from its estimated value of over $1 trillion in 2020 (Wadhwani and Saha, 2021). As a result, an increase in electronic waste (e-waste) generation is expected in the coming years (Forti et al., 2020; Rahman et al., 2023). In 2019, 53.6 million metric tons of e-waste, defined by the Global E-waste Statistics Partnership (GESP) as "products with a battery or plug", was generated worldwide (Forti et al., 2020). Collecting and recycling e-waste is an attractive alternative to landfilling because it provides (1) environmental relief from the chemical hazards associated with untreated e-waste and (2) economic incentives associated with valuable raw material recovery (Forti et al., 2020; Nguyen et al., 2022).

A challenge to developing an e-waste recycling infrastructure is the establishment of a cost-effective collection and logistics system (Xu et al., 2021). There are three primary scenarios for collection and management (Forti et al., 2020) including (1) formal collection established by national legislation, (2) collection by commercial e-waste dealers and companies, and (3) collection by informal door-to-door buyers. Organized municipal or commercial e-waste collection at designated collection points is primarily seen in developed countries (Kumar et al., 2017), while informal collection mostly exists in developing countries. For example, in China, door-to-door collectors dominate the e-waste collection circuit due to the high collection costs of the formal systems (Xu et al., 2021, Salhofer et al., 2016). Therefore, minimizing collection costs is critical to the economic viability of e-waste recycling. The utilization of a decision support tool can be crucial for e-waste companies in achieving their business objectives by aiding in logistics planning. Recently, there has been a growing interest among researchers in decision support systems based on machine learning (Rahman et al., 2020; Rahman, Ghasemi, et al., 2021) and computer simulation (Lu et al., 2021; Rahman et al., 2022; Rahman & Zhou, 2018) due to their effectiveness and efficiency.

1.1 Objectives

This study aims to develop a logistics planning tool that can optimize the e-waste collection process for companies by improving travel distance, travel time, and vehicular emissions. To accomplish this, we will integrate the open street map (OSM) API into our tool, providing us with accurate travel route distances and road speeds, resulting in a more realistic solution. The tool will provide users with valuable information by calculating transportation costs, including fuel, driver salary, vehicle capital, and operational costs. This unique feature will be beneficial for companies seeking to reduce their logistics expenses. Furthermore, our tool will provide quick and reliable results, even for large-scale problems. We aim to maintain an average optimality gap of no more than 5% for the well-known benchmark problems, which should instill confidence in logistics planners who use our tool. Moreover, our objective is to release the tool's source code as open-source software, allowing other recycling companies to adapt it to their specific requirements.

2. Literature Review

E-waste collection is commonly modeled as some variant of the Vehicle Routing Problem (VRP), which deals with minimizing the total transit cost generated by a fleet of vehicles servicing the demand for a given commodity (Ralphs et al., 2003, Mar-Ortiz et al., 2011). Mixed-integer linear programming (MILP) is frequently used to solve small-scale VRPs. However, due to the relatively large size of vehicle routing problems and long computing time, heuristic and meta-heuristic approaches are often implemented to estimate optimized solutions (Akhtar et al., 2017).

While various heuristic approaches exist for solving the general Vehicle Routing Problems (VRPs), only a few studies have considered vehicle emissions as a primary or secondary objective. In 2010, Figliozzi introduced a model for the Emissions Vehicle Routing Problem (EVRP) (Figliozzi, 2010). Although the study considered static vehicle weights, it did not account for the added weight of collected goods along a route. This factor could significantly affect fuel consumption and emissions, leading to less accurate results. Additionally, the author did not report optimality gaps with existing benchmark studies, making it difficult to evaluate its performance.

Bektaş and Laporte proposed the "Pollution-Routing Problem" (PRP) and presented a model that calculated the emission rate from the fuel use rate through energy consumption (Bektaş and Laporte, 2011). However, the applicability of this approach is limited due to several factors. Firstly, the paper formulated the PRP as a MILP and used a CPLEX solver to solve the problem for a maximum of 20 nodes or customers. In real-world scenarios, there may be hundreds of customers, making this approach less practical. Additionally, the 15 and 20-node problems studied in the paper took more than three-hour to produce results. This is not practical for day-to-day planning, where waiting for three hours or longer to obtain an optimal solution is not feasible. Moreover, the model considered identical (homogeneous) vehicles in the fleet and equal demand for all customers. These assumptions are unrealistic, as vehicles in a fleet may vary in size, carrying capacity, and emission rates. Also, the demand for customers varies, which would affect the optimal routing of vehicles.

Kramer et al. (2015) utilized a metaheuristic optimal recursive algorithm to optimize speed and departure times for the PRP (Kramer et al., 2015). They minimized fuel consumption by finding optimal speeds for each arc between two customers and considered environmental cost proportional to fuel consumption. However, the study assumed a single optimal speed for a given travel arc, while travel speed can be variable depending on speed limitations and congestion effects. Additionally, they did not use real road networks to determine route distance.

Nowakowski et al. used a genetic algorithm heuristic to optimize travel distance (Nowakowski et al., 2017). They suggested that finding the best route in terms of distances traveled will decrease vehicle emissions as a secondary effect. This assumption is flawed because there are factors beyond travel distance that impact emissions. In another work, Malekkhouyan et al. used a Grasshopper Optimization Algorithm (GOA) to obtain the optimal collection routes (Malekkhouyan et al., 2021). Although the authors considered emissions in the objective function, their approach did not account for road speed variations or dynamic loads along the routes, which can significantly affect fuel consumption and emissions.

Overall, the above-mentioned previous works have several limitations that limit their practical applicability. In our methodology, described in Section 3, we attempt to overcome these limitations. Section 4.1 presents a comparison of our tool's results with the best-known solutions to existing benchmark problems, while Section 4.2 presents the results of a case study. Based on our industry partner's feedback, Section 4.3 discusses tool development, while Section 4.4 examines the limitations of our approach. Finally, Section 5 concludes the paper.

3. Methods

3.1 Vehicle Routing Optimization

Figure 1 shows the overall methodology to develop the vehicle route planning tool. This tool has two primary components – data preparation application and vehicle route optimizer. The address adder application takes input from an Excel file containing data on the list of collection nodes with addresses. Next, the application collects necessary data including longitudes and latitudes of the collection nodes, distance and travel time among the nodes, and road speed data connecting two nodes using OpenStreetMap (OSM) (Luxen and Vetter) and Google Maps API (Wang and Xu, 2011). Since a user can obtain data from the OSM for free, the application first tries to collect all necessary data from the OSM. If the application fails to find an address in the OSM, it will collect the missing data using Google Maps API. The collected data are processed to generate an origin-destination (OD) matrix and exported as a csv file.

The second component of the tool, the vehicle route optimizer takes input as the exported OD matrix file and an Excel file containing information on the vehicle fleet including capacity, vehicle mass, engine – efficiency, size, revolutions per minute (rpm), and vehicle frontal area. Section 3.2 describes the methodology for estimating fuel consumption and CO_2 emissions. We developed a Python library called PyEmission (Rahman and Nguyen, 2021) and utilized it to estimate vehicular emissions. The user can optimize travel distance, travel time, or CO_2 emissions. There are two distinct steps to optimizing the objective functions. In the first step, we used the guided local search (GLS) metaheuristic algorithm (Voudouris et al., 2010) to find the initial solution. We utilized the OR-tools (Perron, 2011) implementation of the GLS algorithm in our application. In the second step, we considered each of the sub-tours as traveling salesman problems (TSPs) and optimized them using the 2-opt algorithm (Helsgaun, 2006). The generated results are then exported as an interactive map using the Python Folium library (Journois et al., 2022). Besides, the tool creates a comma-separated values (CSV) file which contains the summary of the results.

3.2 Fuel Consumption and CO_2 Emission

There are several models to estimate vehicular emissions and fuel consumption. Examples of popular models include the running speed fuel consumption model (Bowyer et al., 1985), the instantaneous fuel consumption model (Bowyer et al., 1985, Kent et al., 1982), the four-mode elemental fuel consumption model (Akçelik, 1983), CMEM (**C**omprehensive **M**odal **E**mission **M**odel) (Barth and Boriboonsomsin, 2007, Barth et al., 2005), MEET (**M**ethodologies for **E**stimating air pollutant **E**missions from **T**ransport) (Hickman et al., 1999), COPERT (**Co**mputer **P**rogramme to estimate **E**missions from **R**oad **T**ransport) (Ntziachristos et al., 2009), and EMFAC (**Em**ission **Fac**tors) (CARB, 2007). Demir et al. (Demir et al., 2011) performed a comparative analysis and found that CMEM and the COPERT models generated more accurate results for medium to heavy-duty diesel trucks. In this study, we utilized the CMEM model to estimate fuel consumption and the corresponding CO_2 emission. This model has successfully been utilized in several recent studies (Rahman, Zhou, et al., 2021; Turkensteen, 2017; Rahman, Galvez, et al., 2021). There are primarily three modules in this model – engine power, engine speed, and fuel rate.

The requirement for engine power P_{engine} can be calculated using equation (1).

$$P_{engine} = \frac{v\left(Ma + \ Mgsin\theta + M\mu_{rr}gcos\theta + \frac{1}{2}\rho_a C_d A_f v^2\right)}{\eta_{pt}} + P_{acc}(t) \tag{1}$$

Fuel rate FR can be calculated using equation (2). Here engine speed N is interpolated between engine idle rpm and governing rpm using the speed of the vehicle.

$$FR = \frac{\phi}{\psi\rho}\left(kNV + \frac{P_{engine}}{1000 * \eta_{engine}}\right) \tag{2}$$

There is a direct correlation between fuel consumption and CO_2 emissions (EPA, 2008). Carbon dioxide emission rate E_{co2} (in g/s) can be calculated using equation (3).

$$E_{co2} = FR * f_{co2} \quad (3)$$

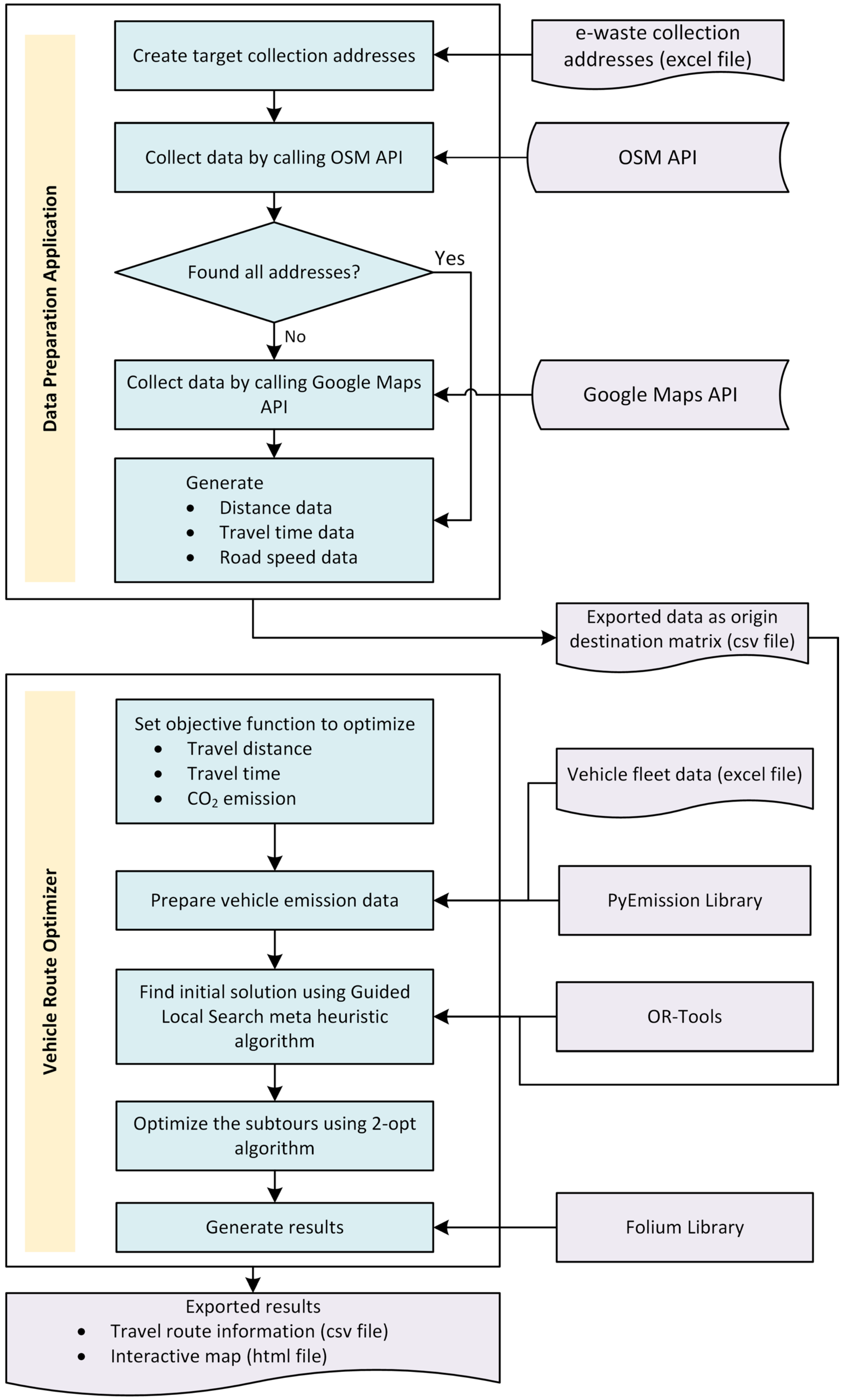


Figure 1. Overall framework for the vehicle route planning tool

The descriptions of the parameters and their commonly used values are provided in Table 1.

Table 1. Description of the parameters

Parameter	Description	Unit	Value Used
M	Mass of the vehicle with load	kg	User input
g	gravitational acceleration	m/s^2	9.81
θ	road grade or slope	$radian$	0
μ_{rr}	rolling resistance coefficient	-	0.07
ρ_a	ambient air density	kg/m^3	1.18
a	acceleration of the vehicle	m/s^2	0
C_d	aerodynamic drag coefficient	-	0.8
A_f	vehicle frontal area	m^2	User input
v	velocity of the vehicle	m/s	Model
η_{pt}	vehicle drivetrain efficiency	-	0.8
P_{acc}	power for running accessories	W	0
ϕ	fuel-to-air mass ratio	-	1/14.5
k	engine friction factor	-	0.2
V	engine displacement	L	User input
η_{engine}	engine efficiency	-	User input
ψ	fuel calorific value	KJ/g	45.5
ρ	fuel density	g/ml	0.846

3.3 Transportation Cost

For the calculation of transportation cost, we utilized equation (4) where C_{driver} is the wage rate of the drivers ($/hour), T_i is the travel time of vehicle i (hours), C_{fuel} is the price of fuel ($/gallon), F_i is the amount of fuel burnt for vehicle i (gallons), and V_i is the cost of vehicle i ($/day). The cost of vehicle is calculated considering different types of capital and operating costs including down payment, salvage value, insurances, taxes, and interests. Table 2 shows a sample data table of three vehicles where the user can input the required vehicle information using an excel file.

Table 2. Example vehicle fleet data used for the case study

Parameters	vehicle_1	vehicle_2	vehicle_3
Capacity (pallets)	20	50	35
Vehicle Weight (lbs)	15000	20000	16000
Engine Size (Liter)	8	10	9
Engine Efficiency	40%	40%	40%
Idle Engine RPM	600	600	600
Max Engine RPM	2200	2200	2200
Frontal Area (square meter)	5.5	5.5	5.5
Down Payment (USD)	4000	4000	4000
Average Life (years)	15	15	15
Salvage Value (USD)	5000	8000	6000
Monthly Other Costs	700	900	600

Once the total cost is known, the e-waste collection cost $C_{collection}$ ($/tonne) can be calculated using equation (5) where m_i is the mass (tonne) of e-waste collected by vehicle i.

$$C_{total} = C_{driver}\sum_{i=1}^{n} T_i + C_{fuel}\sum_{i=1}^{n} F_i + \sum_{i=1}^{n} V_i \tag{4}$$

$$C_{collection} = \frac{C_{total}}{\sum_{i=1}^{n} m_i} \tag{5}$$

3.4 Development of the Graphical User Interface

We developed an easy-to-use GUI for the route planning tool. This is a stand-alone application, platform agnostic, and requires no installation process – plug and play type. We used the PyQt library (Harwani, 2018), a Python binding of the cross-platform GUI toolkit Qt, for the development of the GUI. Figure 2 shows a snapshot of the GUI for the route optimizer application. The user will provide necessary information like the average weight of the collection pallets, objective function to minimize, OD matrix, vehicle fleet data, and a list of collection points to pick up and their corresponding load values in pallets. Figure 3 and Figure 4 show the snapshots of the sample excel files with information on vehicle fleet data and e-waste collection point addresses, respectively. The tool allows users to minimize CO_2 emissions, travel time, or travel distance separately.

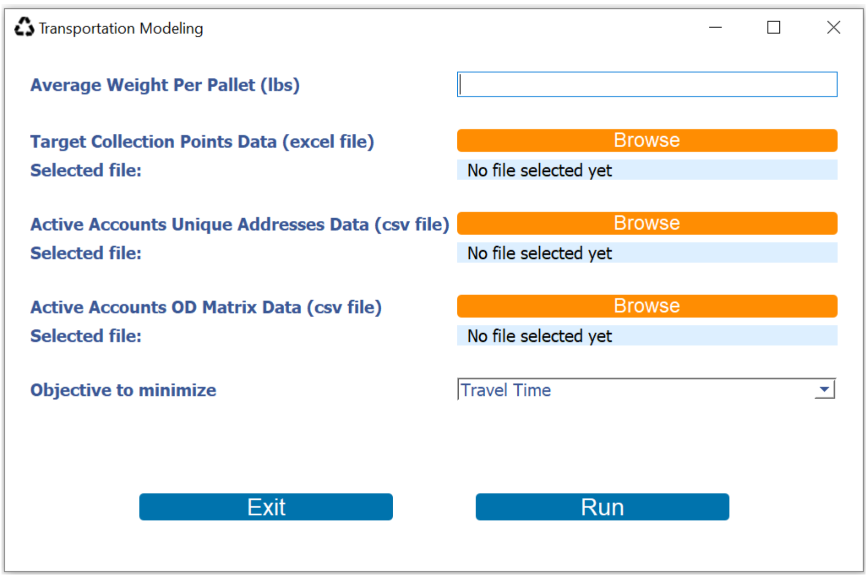
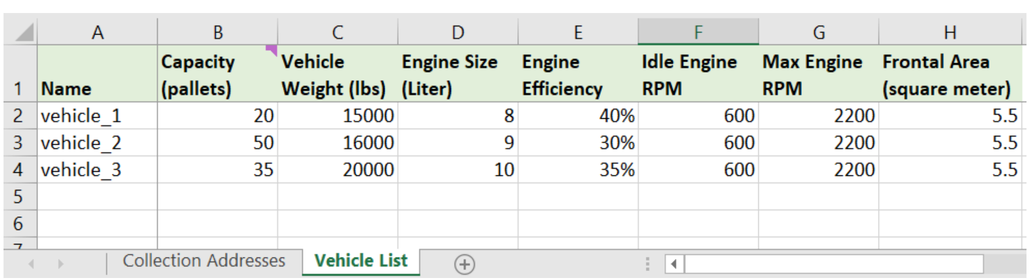


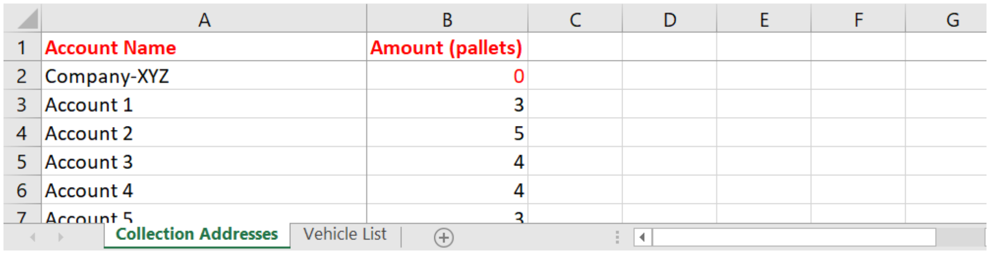
Figure 2: Snapshot of the route optimizer GUI



	A	B	C	D	E	F	G	H
1	Name	Capacity (pallets)	Vehicle Weight (lbs)	Engine Size (Liter)	Engine Efficiency	Idle Engine RPM	Max Engine RPM	Frontal Area (square meter)
2	vehicle_1	20	15000	8	40%	600	2200	5.5
3	vehicle_2	50	16000	9	30%	600	2200	5.5
4	vehicle_3	35	20000	10	35%	600	2200	5.5
5								
6								

Collection Addresses | Vehicle List

Figure 3. Snapshot of the Excel file with vehicle fleet data



	A	B	C	D	E	F	G
1	Account Name	Amount (pallets)					
2	Company-XYZ	0					
3	Account 1	3					
4	Account 2	5					
5	Account 3	4					
6	Account 4	4					
7	Account 5	3					

Collection Addresses | Vehicle List

Figure 4. Snapshot of the Excel file with a list of collection addresses

3.5 Case Study

To test the usefulness of our tool, we partnered with an electronic recycling company based in New York, USA to get their input and feedback. For data privacy, we describe the company as XYZ Recycler and use pseudo data for illustration purposes. A list of vehicles with different capacities and engine configurations was used (Table 2). There are 30 locations to collect e-wastes utilizing the available vehicles. The locations have different loads to be collected ranging from 1 to 7 pallets on average, and the pallets weigh 500 lbs.

4. Results and Discussion

4.1 Benchmark Problem Validation

For the validation purpose, we compared the results from our developed tool with the benchmark problems discussed by Christiansen et al. (Christiansen and Lysgaard, 2007). The problems are available in the VRP repository (VRP-REP, 2014). The dataset includes the number of customers with corresponding demands and the number of available vehicles with corresponding capacities. A customer is represented as a two-dimensional coordinate. The number of customers varies from 16 to 101 with varying total demand from 407 to 932. The number of vehicles varies from 5 to 10 with varying capacity from 35 to 400 for all the problems. Though our tool can get the actual distance from the real road network, we used Euclidian distances to compare solution quality with the best-known solutions for these benchmark problems.

Table 3 summarizes the performance of our route planning tool for the benchmark problems. We set the maximum runtime as 30 seconds. The optimizer application was run on a personal computer with an Intel Core i7 CPU (3.00 GHz), 32.0 GB RAM, and a 64-bit Windows operating system. The optimality gap of the solutions generated from our tool ranges from 0.19% to 7.79% with an average of 2.20%. By increasing the route optimizer runtime, the solution quality can be further improved for large-size problems like F-n72-k4 and F-n135-k7. From our literature review, it takes more than three hours for a commercial solver like CPLEX to obtain the global optimum solution for pollution routing problems with only 20 customers using exact algorithm in a standard desktop (Bektaş and Laporte, 2011). In contrast, our tool generated high-quality solutions within 30 seconds. This is promising for practical uses in industries for day-to-day logistics planning.

Table 3. Comparison of results with benchmark problems

Problem	Customers	Vehicles	Capacity	Best known	Our solution	Gap
A-n32-k5	31	5	100	784	797.45	1.72%
A-n33-k5	32	5	100	661	662.26	0.19%
A-n33-k6	32	6	100	742	744.26	0.30%
A-n34-k5	33	5	100	778	796.23	2.34%
A-n36-k5	35	5	100	799	810.37	1.42%
A-n37-k5	36	5	100	669	674.23	0.78%
A-n37-k6	36	6	100	949	974.7	2.71%
A-n38-k5	37	5	100	730	734.44	0.61%
A-n80-k10	79	10	100	1763	1,813.55	2.87%
F-n45-k4	44	4	2,010	724	731.31	1.01%

F-n72-k4	71	4	30,000	237	248.12	4.69%
F-n135-k7	134	7	2,210	1162	1,252.5	7.79%

4.2 Case Study Results

We set 30 seconds as the maximum runtime for the tool to find the solutions of the case study described in section 3.5. Figure 5 shows the routes of each of the vehicles, and the optimal sequence of the nodes to visit. Some related summary statistics include CO_2 emissions, fuel consumption, miles per gallon (MPG) value, capacity utilization, travel time, and travel distance. Here, emissions are set as the objective function to minimize. Out of a total of 98 pallets, vehicle 2 collects 50 pallets utilizing 100% of its capacity, and vehicle 3 collects 34 pallets utilizing 97% of its capacity. The remaining 14 pallets are collected by vehicle 1 utilizing 70% of its capacity. Overall, the three vehicles travel 561 miles in 14.5 hours burning 65.3 gallons of fuel and emitting 1,401 lbs of CO_2 to the environment. The average transportation cost is USD 44.1 per tonne. It should be noted that it is more common to denote transportation cost as 'USD/tonne/mile'. This metric can sometimes be misleading in our case. For example, for an optimized route, the total distance traveled by the collection vehicles is smaller than for an unoptimized route. Hence, the metric 'USD/tonne/mile' could be larger for an optimized route compared to the unoptimized route. Therefore, we chose the metric 'USD/tonne' over 'USD/tonne/mile'.

```
vehicle_1
=========
Route: ['Company-XYZ', 'Account 29', 'Account 14', 'Account 18', 'Account 4', 'Company-XYZ']
Travel distance      :  215.0 miles
Travel time          :  4.7 hours
Fuel burnt           :  20.1 gallons
CO2 emission         :  430.3 lbs
Miles per gallon     :  10.7
Collected amount     :  14 pallets
Capacity utilization :  70%

vehicle_2
=========
Route: ['Company-XYZ', 'Account 16', 'Account 5', 'Account 22', 'Account 6', 'Account 7',
'Account 8', 'Account 27', 'Account 10', 'Account 12', 'Account 19', 'Account 1', 'Account 2',
'Account 11', 'Account 9', 'Company-XYZ']
Travel distance      :  187.7 miles
Travel time          :  5.4 hours
Fuel burnt           :  25.9 gallons
CO2 emission         :  555.3 lbs
Miles per gallon     :  7.2
Collected amount     :  50 pallets
Capacity utilization :  100%

vehicle_3
=========
Route: ['Company-XYZ', 'Account 26', 'Account 25', 'Account 13', 'Account 20', 'Account 3',
'Account 28', 'Account 15', 'Account 17', 'Account 21', 'Company-XYZ']
Travel distance      :  158.3 miles
Travel time          :  4.4 hours
Fuel burnt           :  18.6 gallons
CO2 emission         :  398.5 lbs
Miles per gallon     :  8.5
Collected amount     :  34 pallets
Capacity utilization :  97%

Overall Summary
===============
Total distance          :  561 miles
Total time              :  14.5 hours
Total CO2               :  1,384 lbs
Total fuel              :  64.49 gallons
Overall MPG             :  8.7
Total collected amount  :  98 pallets
Unvisited account names :  None
Uncollected amount      :  0 pallets
Collection cost         :  44.1 $/tonne
```

Figure 5. Vehicle routes for optimizing CO_2 emissions.

In addition to minimizing emissions, we ran the tool by minimizing (1) travel time, and (2) travel distance. Table 4 displays the key results for all three objective functions. As per the table, no major difference among the performance metrics is observed regardless of the selected objective function. This is because of (1) a short planning horizon and (2) correlations among different objective functions. For example, if there is no major difference in speed limit among various routes, when the travel distance is minimized, travel time and emissions would be also minimized. Only when there is a difference between highway and town traffic, longer highway distance might yield shorter travel time than town traffic. Also, because of constant stop-and-go in town traffic conditions, there might be more emissions than highway travel. Regarding the short planning horizon, the results are for a day. Cumulatively, if we compare the results for yearly planning, the difference might be significant. For example, the daily difference in CO_2 emissions is 117 lbs between minimizing travel distance and emission. The yearly difference in CO_2 emissions becomes 30,420 lbs for the three collection vehicles assuming 5 working days in a week and 52 weeks in a year. For larger recycling companies with more collection vehicles, this emission difference would be even more substantial.

Table 4. Comparison of results for different objective functions

Performance metrics	**Objective Functions**		
	Emission	**Travel time**	**Travel distance**
Travel distance (miles)	561	551	544
Travel time (hours)	14.5	13.3	13.7
Fuel consumption (gallons)	64.49	68.4	69.96
CO_2 emission (lbs)	1384	1468	1501
Collection cost (USD)	44.1	41.6	41.7

Figure 6 shows a sample interactive plot of the vehicle routes in the GIS environment with travel directions generated by our tool. If the user clicks on any of the marker icons, it will show further details of that location including address, account number, and account name. The travel routes of each of the vehicles are color-coded. The user can also show or hide the travel routes on the map by selecting or deselecting vehicles located on the top right corner widget.

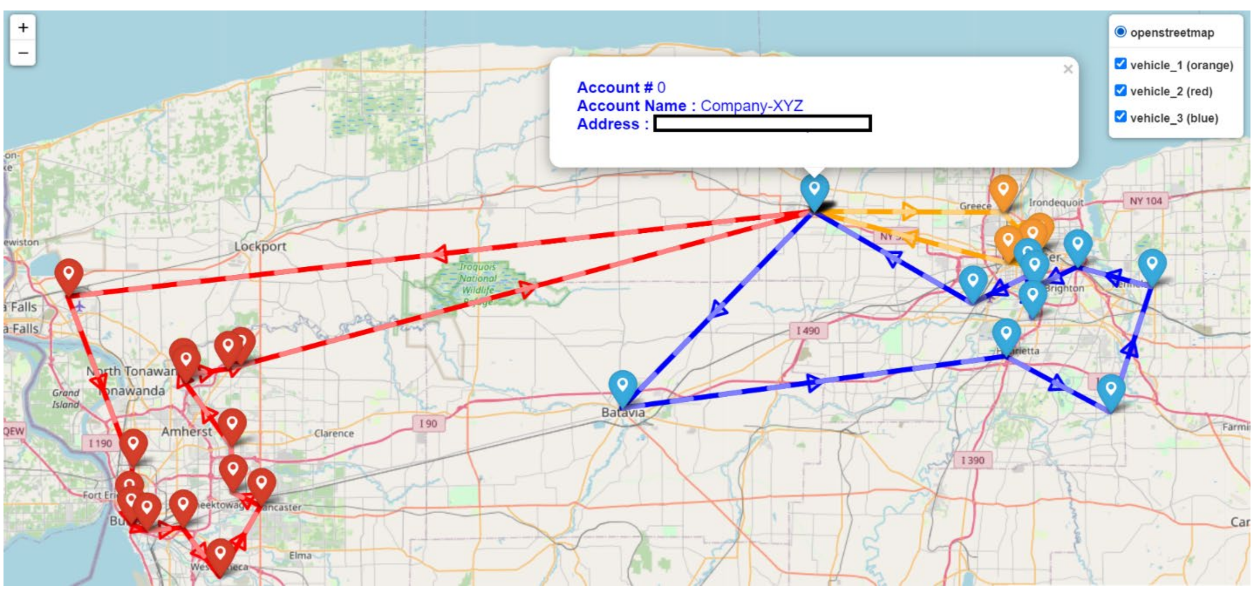


Figure 6. Interactive map showing optimized routes for different vehicles.

VRP can be formulated as a mixed-integer linear programming (MILP) problem and solved using commercial and non-commercial solvers. The primary advantage of this solution approach is that it guarantees the global optimum

solution. For a small-size problem, the computational time of the solvers to get the results is reasonable. But for a medium to large problem size, for example, 20 to hundreds of collection nodes, the solvers are not practical since it could take several weeks to months to get the results. It is very common for logistics companies to do their day-to-day logistics planning for a problem size consisting of hundreds of collection/delivery nodes. From a practical standpoint, industries need a good solution within minutes for their daily logistics planning. Our tool uses real road network data using OSM and Google API to capture the actual travel distance and time and then optimizes the travel route for vehicles with different capacities and configurations within minutes. The tool does not guarantee the global optimal solution but is very competitive for practical applications. The tool is released as an open-source software under the General Public License and is available at this GitHub repository:
https://github.com/IdahoLabResearch/CMAT.

4.3 Feedback from Industry Partner

During the development of this tool, we engaged with our industry partner to better understand the common practices and general requirements of the e-waste collection logistics process. Based on their feedback, we included different features in our tool like direct data input from Excel files, adding business account numbers and account names in addition to the addresses in the interactive map, color coding of different routes, adding clockwise or anti-clockwise directions to the individual routes, exporting summary results to external CSV files and so on. The logistics team tested our tool for their day-to-day uses. Although they agreed that the tool was easy to use and helpful, their daily operation does not require the same level of complexity. However, they were able to apply the tool for their quarterly/annual collection events where hundreds of addresses need to be covered and dozens of vehicles and trailers are utilized.

4.4 Limitations and Future Works

There are some limitations of our study. Firstly, our current route planning tool does not take real-time traffic data into account when calculating travel time and environmental emissions. The vehicular speed might get severely impacted due to traffic congestion and consequently, our tool can potentially underestimate the emissions and travel time. As part of future development, live traffic data can be integrated into the tool. Secondly, our tool currently lacks the capability to send routing directions directly to drivers' electronic devices such as tablets or phones. This feature would enhance convenience and usability for users. Another limitation worth mentioning is that the tool employs US units, including pounds, gallons, and miles, which might prove inconvenient for users outside of the United States. To make our tool more accessible globally, we aim to integrate equivalent SI units into the system.

5. Conclusion

The use of electrical and electronic devices is growing day by day and hence increasing the need for recycling. In this study, we developed a vehicle routing tool to help e-waste recycling companies establish a cost-effective collection and logistics system. The key features of the tool can be summarized below:

- The tool uses real road network data for calculating travel distance and travel time as opposed to other works where a straight line or Euclidian distance has been used. This feature makes the tool suitable for practical logistics applications.
- While most of the previous works utilized a constant factor for the calculation of emissions, we integrated a comprehensive emission model into the tool. The emission model considers vehicle mass, collected e-waste weight, road speed, and a wide range of vehicle attributes for accurately estimating emissions.
- The tool can generate results within minutes even for large-scale problems and the quality of the solutions is satisfactory. The average optimality gap we found for the well-known benchmark problems is only 2.2%, making the tool reliable.
- We tested the tool with real-world data from our partnering e-waste recycling company and included different features based on their feedback.
- The tool can calculate transportation costs by considering fuel costs, driver salary, vehicle capital, and operational costs. This is useful information for the users.
- One of the key features of this tool is the development of the graphical user interface. Logistics people can use the capability of the tool without any need for mathematical or programming knowledge. Previous works lack this feature.

The transportation sector is responsible for the largest share of greenhouse gas emissions. Our developed route planning tool can potentially be utilized for minimizing carbon dioxide emissions from commercial vehicles and hence mitigating greenhouse gas impacts. Though the tool has been developed primarily focusing on the e-waste recycling industry, we have released the source code as open source so that it can easily be adapted for other recycling industries as well.

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