An Adaptive Tabu Search Optimisation Algorithm for Solving E-Scooters Battery Swapping Problem

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Abstract

E-scooters have become a popular mode of transportation for first and last-mile excursions in recent years. Their usage as a short-distance public transit system is commonly regarded as an efficient solution to minimise carbon emissions while also being handy for individuals on the go. The need for charging, however, has become problematic as a result of the popularity of e-scooters because it effectively renders the scooter that is presently being charged inoperable. A relatively new method being used involves swapping batteries in e-scooters rather than transferring full scooters to be recharged, reducing out-of-service time to a few minutes rather than hours. To reduce trip distances and maximise fuel economy for battery swapping operators, a system for determining the most effective path to switch the e-scooters' batteries will be required. This paper aims to do this through the use of Tabu Search (TS) algorithm to determine the optimal number of battery swapping operators for an area and then to ascertain the most efficient routes for each operator. This method will then be compared to Simulated Annealing in order to determine which method is the most optimal for this scenario. The data used to evaluate this method was obtained from the 2019 Chicago pilot program . The results showed an adapted tabu search in the total distance travelled, leading to shorter charging trips comparing to simulated annealing.

Keywords: Micro-mobility; e-scooters; Freelancers; Tabu search; Assignment problem; Simulated Annealing

1 Introduction

With the rise in popularity of e-scooters, a new mode of transportation has emerged to finish the last-mile journey. This popular mode of transportation, however, faces its own set of challenges in order to improve and become more efficient. Some of these concerns include the necessity for e-scooters to be recharged, and their relatively hefty size, which can make it difficult for freelance chargers to carry multiples e-scooters home to recharge (Carey & Lienert, 2022). To address this, rechargeable batteries are rapidly becoming the standard. This implies that the people who charge these e-scooters may carry hundreds of batteries with their person at once and go on a path where they just need to replace the scooter's battery, saving time and effort. However, this procedure may be made more effective by optimising the route and cutting down on the distance the operators must drive, which will reduce the cost of fuel and the amount of time required (Masoud et al., 2019a; Almannaa et al., 2021a; Almannaa et al., 2021b). Using e-cargo bikes, which presently have a battery capacity of 20 and 40 batteries and have a range of around 30 kilometres, is one environmentally beneficial prospective option being investigated (Severengiz, et al., 2020). Reducing it as much as feasible might have a huge beneficial impact on the environment overall because the environmental footprint of recharging e-scooters is rather large—it accounts for 43% of the entire environmental impact of an e-scooter.

This problem is blatantly similar to the capacitated vehicle routeing problem, which is a derivation of the travelling salesman problem (Eksioglu, Vural & Reisman, 2009). The main notion is that a travelling salesperson must go from site to location selling their wares; the salesman aims to limit the overall distance traversed because it will take less time. The capacitated vehicle routeing challenge entails adding a capacity to both the vehicle travelling around and the destinations the vehicles arrive at. This means that the trucks must not only decrease the total distance of their routes, but also deliver the appropriate capacity of commodities at each point (Clarke & Wright, 1964; Mingozzi, 2005).

This study proposes a modified tabu search to handle this problem, as well as a comparison to Simulated Annealing, both of which will be done using Google.

2. Methodology

The implementation of the separate methods for optimizing the routes for the capacitated vehicle routing problem described in this paper can be split into five major components:

1. Cleaning and extraction of data.
2. Run the data through the Google OR-Tools API with the different methods provided (Tabu Search (TS), Simulated Annealing (SA)).
3. Compare and analyse the results.

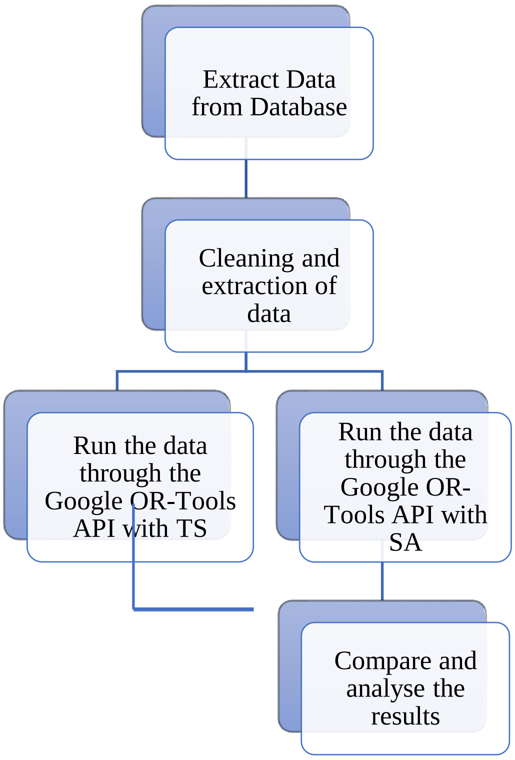

Fig. 1: Methodology Flowchart

1.1 Data Extraction

The E-Scooter Trips 2019 Chicago Pilot dataset (City of Chicago, 2020) is a large dataset that includes 710839 e-scooter trips with information on the trip's duration, location, and region. Only the e-position scooter's at the conclusion of the journey is necessary for our algorithm because that is likely the time when a scooter may need charging. The whole set of data will be cleaned by deleting any rows that have NaN values in the necessary fields, such as the End Community Area Number, End Centroid Latitude, and End Centroid Longitude. The data is initially divided into its many sections in order to assess the efficacy of the various route optimisation techniques under a variety of circumstances. This will generate several sub datasets that may be assessed, such as a dataset in Table 1 which is relevant data columns used for implementation.

Table 1: Relevant Columns Used for Implementation

Column Name	Description
Trip ID	A unique code used for identifying each trip
End Time	Timestamp of when the trip ended, rounded to the nearest hour
End Community Area Number	A number identifying the Community Area where the trip ended
End Community Area Name	The Community Area name where the trip ended
End Centroid Latitude	The Latitude of the centre of the trip end census tract
End Centroid Longitude	The Longitude of the centre of the trip end census tract

The pseudo-code for the data extraction can be seen below:

1. **Load** data as $\mathrm{Dataset}_{\mathrm{all}}$
2. **Remove** unnecessary rows with NaNs as values for relevant columns in *Dataset_{all}* as *Dataset_{cleaned}* **For** 'i' = number of community areas:
   3.1 **Extract** all rows and columns of community area 'i' in 'End Community Area Number' from $Dataset_{cleaned}$ as $Dataset_{Area_i}$
   3.2 **Find** *timestamp* t_{max} in '*End Time'* from $Dataset_{Area_i}$ with maximum number of rows
   3.3 **Extract** all rows and columns of timestamp t_{max} in '*End Time*' from $Dataset_{Area_i}$ as $Dataset_{Area_i}$
   3.4 **Extract** '*End Centroid Latitude*' and '*End Centroid Longitude*' columns from $Dataset_{Area_i}$ as $Dataset_{Area_i}$
   3.5 **Convert** $\mathrm{Dataset}_{\mathrm{Area_i}}$ from 'End Centroid Latitude' and 'End Centroid Longitude' to '*X*' and '*Y*' (Gerdan & Deakin, 1999)
3. **Output** $Dataset_{AreaXY_i}$ as the datasets to be used for evaluation in each algorithm

2.2 Adaptive Tabu Search

Tabu search is a metaheuristic optimisation algorithm designed to locate effective solutions to problems that are challenging to resolve using conventional optimisation methods. The algorithm operates by incrementally enhancing a solution to a problem by making little adjustments to the existing solution, while avoiding making the same modification more than once. This is accomplished by keeping track of "tabu" moves, or modifications that are prohibited from being made again during the current search.

The initial solution to the problem is used as the basis for the tabu search method, which iteratively refines the answer. The algorithm finds the optimal option that is not forbidden at each stage after evaluating the alternatives that may be made to the present solution. The algorithm may make a tabu move, albeit with a lower probability, if no such move can be located. The algorithm keeps going until it meets a predetermined stopping criterion, such the maximum number of iterations or an acceptable level of solution quality (Masoud et al., 2019b).

Pseudo-code for the general formulation of the Tabu Search algorithm can be seen below:

1. **Initialize** solution (i.e. in this case a set of routes determined by using the First Solution Strategy: "PATH_CHEAPEST_ARC" from Google OR-Tools). PATH_CHEAPEST_ARC starts from a route "start" node and iteratively connects to the next node that is the shortest distance away from it until it returns to the "start" node.
2. **Initialise** the Tabu List to be empty
3. **While** the stopping condition has not been met (for e.g. 1000 iterations):
   3.1 **Generate** a set of potential routes by making small changes to the current route (e.g. using 2-opt which is swapping the order of the locations of two e-scooters on a route)
   3.2 **Evaluate** each potential route to determine distance travelled
   3.3 **Choose** the best route with the smallest distance travelled that is currently not on the Tabu List
   3.4 **Update** the Tabu List by adding the current route onto it
   3.5 **If** stopping condition has not been met return to 3a and loop.
4. **If** the stopping condition has been met, output the current set of routes as the optimal solution

2.3 Simulated Annealing

A heuristic optimisation approach called Simulated Annealing employs randomisation to determine a function's global minimum or maximum. It is based on the idea of metallurgy's annealing process, in which a material is heated and then gradually cooled to improve its hardness and minimise flaws. In simulated annealing, an algorithm employs random motions to explore various places in the search space where the problem's solution is represented as a point (Kirkpatrick, Gelatt Jr. & Vecchi, 1983).

The algorithm evaluates a new solution at each step and determines whether to accept it based on how well it compares to the existing solution. It is always accepted if the new answer is superior. If it is worse, it is occasionally accepted with a probability based on how much worse it is and a metric known as the temperature. The algorithm becomes increasingly selective and converges on the best answer when the temperature is continuously lowered over time. The temperature schedule, which controls how rapidly the temperature drops and how selective the algorithm gets over time, is crucial to the effectiveness of simulated annealing. The algorithm can locate the global minimum and avoid getting caught in local minima with the aid of a well-designed temperature schedule.

Pseudo-code for the general formulation of the Simulated Annealing algorithm can be seen below:

1. **Initialize** solution (i.e. in this case a set of routes determined by using the First Solution Strategy: "PATH_CHEAPEST_ARC" from Google OR-Tools). PATH_CHEAPEST_ARC starts from a route "start" node and iteratively connects to the next node that is the shortest distance away from it until it returns to the "start" node.
2. **Initialize** 'temperature' variable
3. **While** the stopping condition has not been met (for e.g. 1000 iterations) and the temperature is above a minimum threshold:
   3.1 **Generate** a set of potential routes by performing local search from the current route
      3.1.1 **Select** a random route from the set of routes
      3.1.2 **Select** a random e-scooter from the route
      3.1.3 **Generate** a set of possible new routes by removing the selected e-scooter from the selected route and inserting it into each of the other routes

3.1.4 **Evaluate** each of the new routes based on distance and load capacity

3.1.5 **Select** the new route with the smallest distance travelled that still satisfies the load constraint

3.2 **If** the new route is an improvement over the previous route, update the set of routes with the new route

3.3 **Else if** the new route is not an improvement, accept the new route based on a probability equal to $e^{-\frac{\Delta}{T}}$, where Δ is the difference in distance between routes, and T is the temperature

3.4 **Decrease** the temperature based on a pre-defined cooling schedule

3.5 **If** stopping condition has not been met return to 3a and loop.

4. **If** the stopping condition has been met, output the current set of routes as the optimal solution

3. Results

The the comparison of SA and TA techniques has been included in Table 2. The highlighted values show which algorithm performed the best and produced the smallest distance for each respective area. The algorithm with the largest number of highlighted values is Tabu Search compared to simulated annealing.

Table 2: Comparison of SA and TA Performance

Area	Load	No. of Locations	SA	TS
7	31	5	5147	5147
8	32	6	6882	6882
9	84	8	12143	11759
10	15	3	1326	1326
11	53	11	12226	10231
13	30	5	2185	2185
14	44	8	4796	4796
15	453	34	45873	45613
16	32	8	7462	7462
17	525	36	49702	49404
18	364	26	42005	40851
19	18	4	2175	2175
20	22	3	1786	1786
21	322	23	37904	37857
22	40	4	4160	4160
24	40	7	7563	7563
25	40	6	8053	8053
45	35	4	3746	3746
67	65	6	12119	12119
76	45	3	3910	3910
All	377	58	111503	99878

Table 1 demonstrates that TS is performing better than SA. The e-scooter chargers frequently cover shorter distances using TS than SA. The overall distance covered by chargers using TS for 20 locations was 99878 km, which is less than 10.5% of the total distance covered by chargers using the SA approach. From Figure 2, Tabu search as a best solution, will sometimes have routes that surround other routes but never have multiple operators arriving at the same destination.

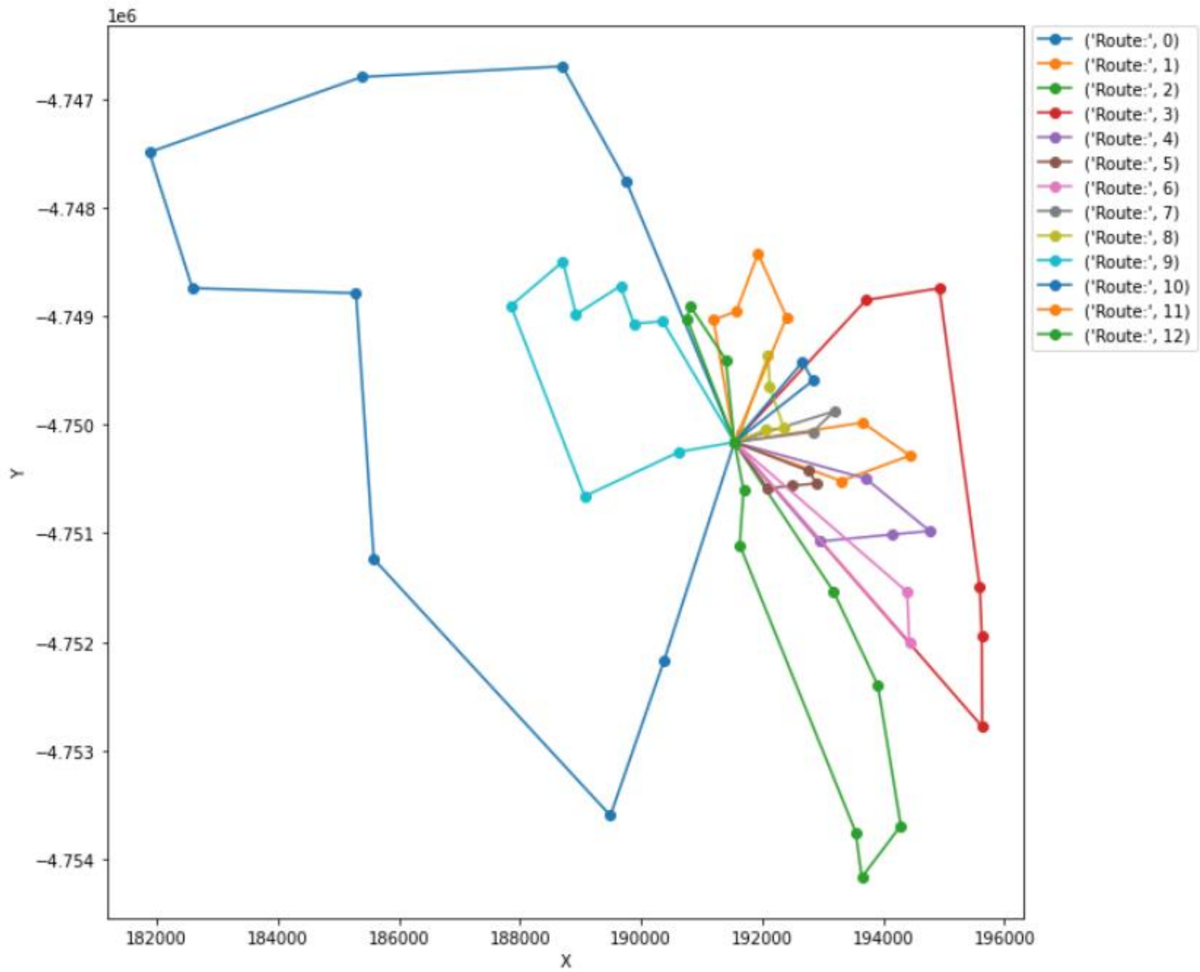

Fig. 2: Tabu Search for Chicago

4. Conclusion

E-scooters are frequently seen as an effective way to reduce carbon emissions while also being convenient for people on the go when used as a short-distance public transportation system. Instead of moving complete scooters to be recharged, e-scooters' batteries are swapped, decreasing out-of-service time to a few minutes rather than hours. A method for calculating the most effective way to exchange the batteries on e-scooters will be necessary to decrease travel lengths and maximise fuel economy for battery switching operators.

In this study, Simulated Annealing and Tabu Search were used to build, analyse, and compare a route optimisation method. The efficiency of the optimisation algorithms as a technique for optimising e-scooter battery charging routes was tested using an e-scooter trip dataset from the 2019 Chicago Pilot. The findings demonstrated that, in comparison to Simulated Annealing, which was somewhat inferior, Tabu Search was generally the best solution for many instances. The total distance travelled by chargers using the TS strategy for 20 sites was 99878 km, which was less than 10.5% of the total distance travelled by chargers using the SA approach.

References

Almannaa, et al. (2021a). A comparative analysis of e-scooter and e-bike usage patterns: Findings from the City of Austin, TX. *International Journal of Sustainable Trans-portation, 15*(7), 571-579.

Almannaa, et al. (2021b). Perception anal-ysis of E-scooter riders and non-riders in Riyadh, Saudi Arabia: Survey outputs. *Sustainability, 13*(2), 863.

Carey, N. & Lienert, P. (2022). “E-scooters fall head over wheels for battery swapping,” Reuters, p. 1, 25 March 2022.

City of Chicago, “E-Scooter Trips - 2019 Pilot,” 15 April 2020. [Online]. Available: https://data.cityofchicago.org/Transportation/E-Scooter-Trips-2019-Pilot/2kfw-zvte.

Clarke, G. & Wright, J. W. (1964). “Scheduling of Vehicles from a Central Depot to a Number of Delivery Points,” Operations Research, Vol. 12, no. 4, pp. 568-58.

Eksioglu, B., Vural, A. V. & Reisman, A. (2009). “The vehicle routing problem: A taxonomic review,” Computers and Industrial Engineering, vol. 57, no. 4, pp. 1472-1483.

Gerdan, G. P. & Deakin, R. E. (1999). “Transforming Cartesian coordinates X,Y,Z to Geographical coordinates φ, λ, h,” The Australian Surveyor, vol. 44, no. 1, pp. 55-63.

Kirkpatrick, S., Gelatt Jr., C. D. & Vecchi, M. P. (1983). “Optimization by Simulated Annealing,” Science, Vol. 220, No. 4598, pp. 671-680.

Masoud, et al. (2019a). Heuristic approaches to solve e-scooter assignment problem. IEEE Access, 7, 175093-175105.

___. (2019b). Optimal Assign-ment of e-scooter to Chargers. In 2019 IEEE Intelligent Transportation Systems Conference (ITSC) (pp. 4204-4209). IEEE.

Mingozzi, A. (2005). “The Multi-depot Periodic Vehicle Routing Problem,” in International Symposium on Abstraction, Reformulation, and Approximation, Berlin, 2005.

Severengiz, et al. (2020). “Life Cycle Assessment on the Mobility Service E-Scooter Sharing,” in IEEE European Technology and Engineering Managment Summit (E-TEMS), Dortmund, 2020.

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