Optimizing Multi-Truck Delivery Routes for Cost-Efficiency

Solving the Traveling Salesman Problem, Comparing Solutions of Clustering and Simulating Annealing

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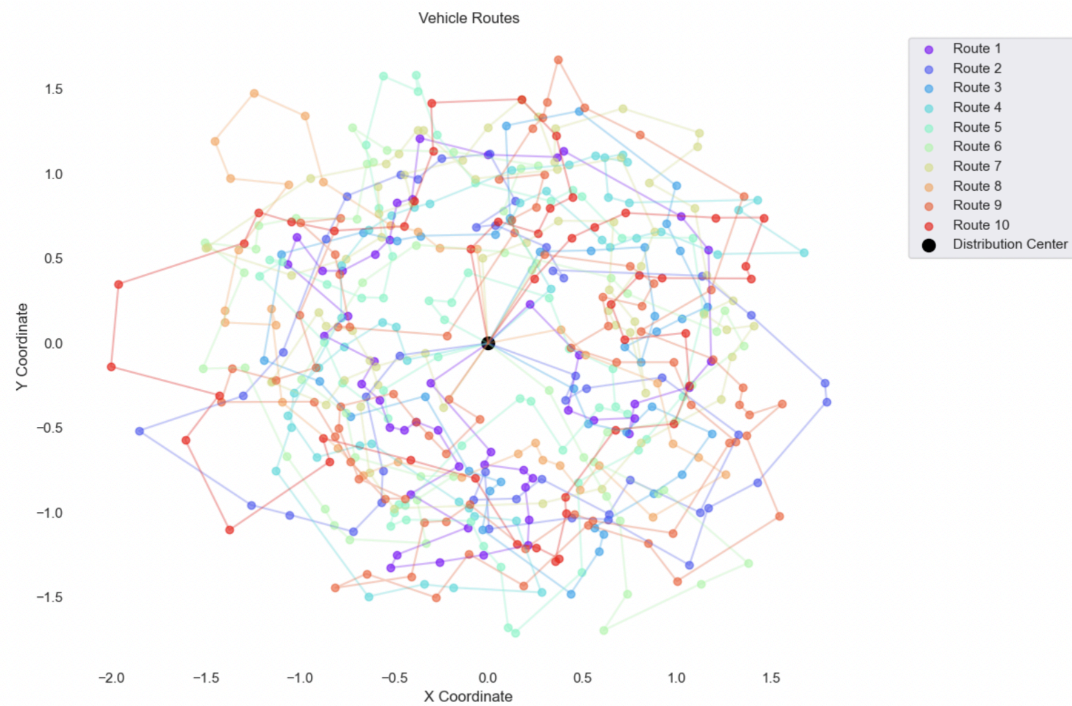
Overview:

This project addresses a real world logistics problem where there is an objective to minimize distance traveled, while minimizing costs to deliver packages at the same time. The problem at hand is to find the most optimal route for trucks to drive from a centralized distribution location, to drop-off locations, and back to the centralized distribution location. We will compare minimizing these by using two approaches, clustering and simulating annealing. Practical recommendations are provided on route planning, cost reduction, and the benefits of optimization-driven scheduling for logistics operations, supported by visualization of route paths and cost comparisons.

1. **Solve the problem that minimizes the total distance traveled using all 10 trucks. Do this once with the clustering methodology, and once with the 3-change simulated annealing methodology. Which of these 2 methodologies works best?**
    a. In our group's project, we chose to utilize simulated annealing (SA) over clustering methods for solving the Traveling Salesman Problem (TSP) due to its ability to navigate complex solution spaces and yield high-quality results. While clustering techniques can efficiently group locations and generate initial routes, they often fall short in optimizing the overall path, especially in scenarios with intricate routing constraints and varying distances.
    b. Simulated annealing allows for a more thorough exploration of global potential solutions, leveraging probabilistic acceptance criteria to escape local optima and approach a global solution over time. This adaptability is crucial for our specific requirements, where maintaining consistency in routes and minimizing total travel distance were important. Although SA is computationally intensive, the trade-off in time and resources was justified by the superior quality of the optimized routes it produced, ultimately leading to more effective and efficient delivery strategies for our logistics challenges.

Simulated Annealing Method

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All clusters completed at 15:58:20
Final total distance: 55.61
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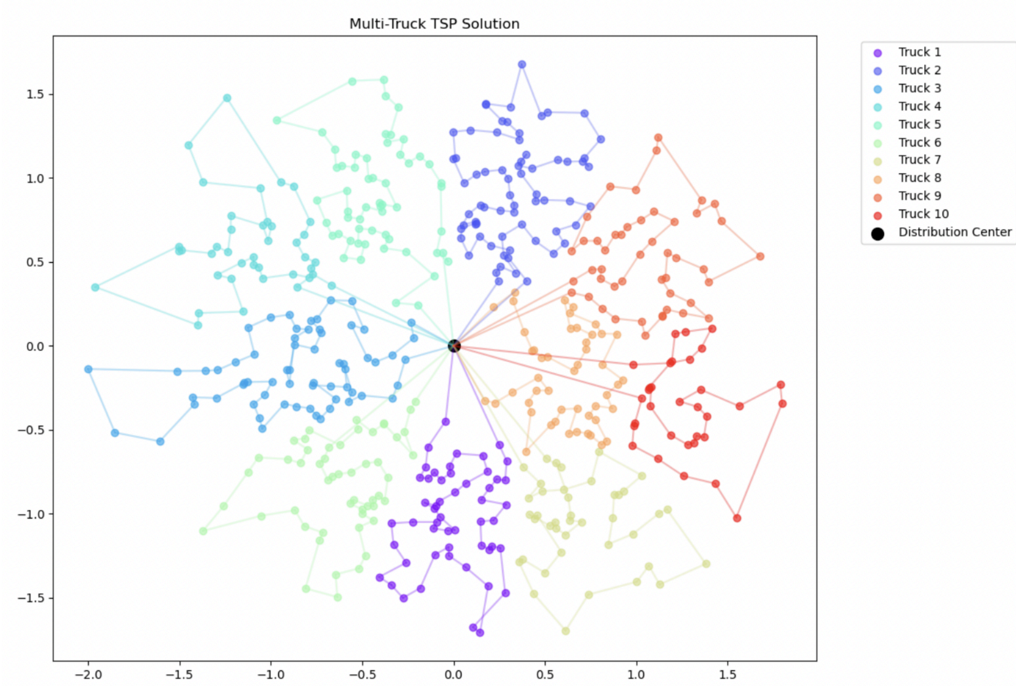
Clustering Method

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All clusters completed at 15:19:38
Final total distance: 68.18
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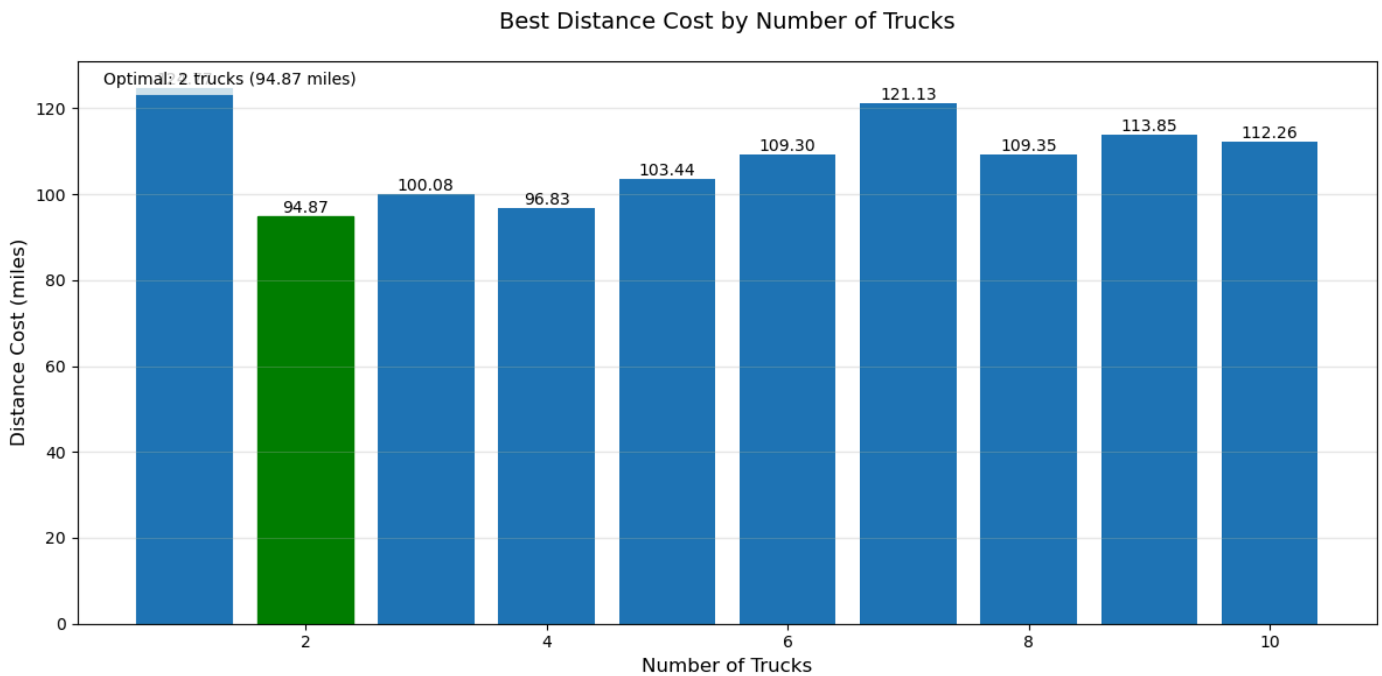
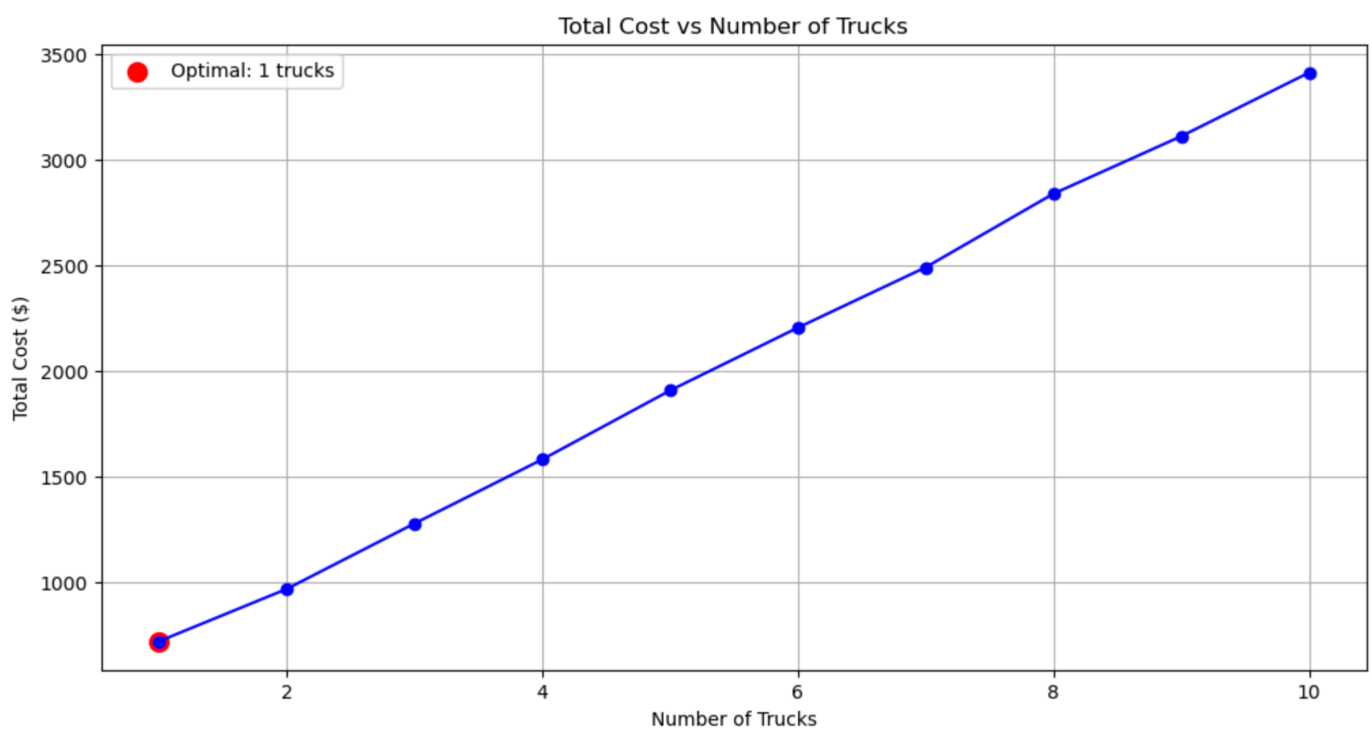
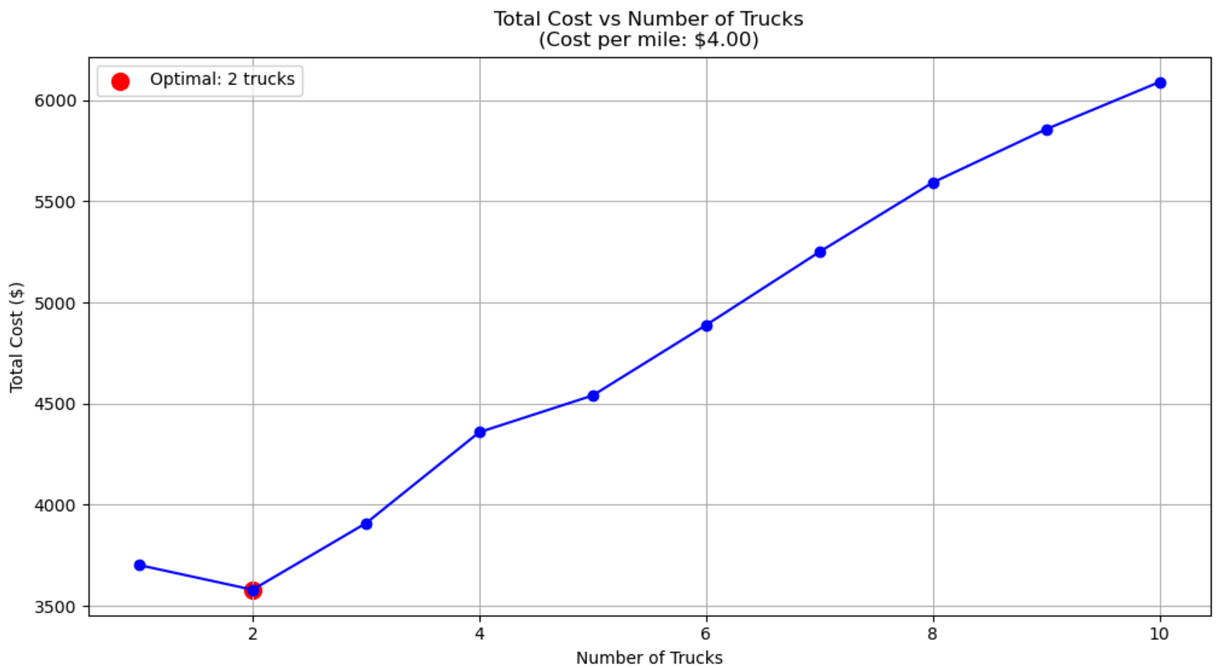
2. **For every mile traveled delivering packages it costs $1 for gasoline, labor, truck depreciation and so on. Additionally, every driver that works today gets an additional payment of $300, no matter how many packages they deliver. Additionally, any driver that works 10% more than the average driver gets overtime pay of 1.5x for every hour over the average. This does not apply if there is just 1 driver... How many trucks should you use to make your deliveries? To answer this question, pose the optimization problem from step one repeatedly for every possible number of trucks from 1-10. Use either the clustering or 3-change simulated annealing policy, whichever worked best in step 1.**
    a. For this question, the group decided to move forward with the 3-change simulated annealing policy, which was chosen in question one. The optimal amount of trucks needed, at 20,000 iterations, was two trucks. This was done by re-doing the TSP for each truck with these new cost constraints.
    b. Reasoning for 20,000 iterations:
        i. As the group decided to try out different variable costs and fixed costs (e.g. 100 FC + 5 VC, 300 FC + 8 VC), we found the computational intensity to be very time consuming. However, we noticed a pattern; as we were running the simulations, there was a pattern that two required trucks needed the lowest cost with the shortest distance required. These findings were to be ~$803 and ~95 miles for the day for locations1.
    c. Expectations:
        i. We would expect as the iterations increased, these results would be exacerbated. The optimal amount of iterations would probably be around 100,000-200,000 iterations.
    d. Drawbacks/Realistic Interpretation:
        i. These findings do not go without the group realizing that two trucks may not be optimal in a real world environment, where it may be very intense for two drivers to deliver all packages possible in one day. In the real world, there are many trucks sent out to deliver a mass amount of packages. However, for the problem at hand, we find our optimization solution for the business needs to be at two trucks.
        ii. If there were breakdowns or issues with one of the trucks, it would be impossible for the single truck to make all the deliveries on time. There is no leeway for any problems that may occur.


Best Distance Cost by Number of Trucks
Optimal: 2 trucks (94.87 miles)
94.87
100.08
96.83
103.44
109.30
121.13
109.35
113.85
112.26
Distance Cost (miles)
Number of Trucks


Total Cost vs Number of Trucks
Optimal: 1 trucks
Total Cost ($)
Number of Trucks



3. **Tomorrow there is a new set of packages that need to be delivered to a new set of locations. The locations are in the second csv file. You want to have some sort of consistency in the neighborhoods/routes that each truck travels to, so you're thinking about putting packages that need to be delivered close to yesterday on the same truck as yesterday, and then solving the TSP for each truck.**
    a. How much does this increase the total cost relative to completely starting over to solve the problem from scratch?
        i. Our group used the simulated annealing approach again, matching each new package with the closest package from yesterday's dataset, resulting in them being assigned to the same truck. Using this method, we calculated a total cost of $834.43 for the new packages. In contrast, our original simulated annealing approach, which utilized just two trucks, yielded a total cost of $829.66. The difference in total costs is negligible, leading us to conclude that maintaining consistency in routes is preferable.
    b. Should you have consistency in the routes, or is it worth it to start from scratch every day?
        i. Our group believes that starting from scratch daily is not justified. While optimizing routes each day may ensure the lowest possible costs and travel distances for deliveries, the advantages of consistent routes outweigh this benefit. Consistent routes are easier for drivers to remember, fostering greater comfort as they

navigate familiar areas daily. Additionally, these routes are simpler and quicker to compute, resulting in lower computation costs, which is crucial for effective logistical management, timely deliveries, and scheduling.

Consistent Routes	**Daily Optimized Routes**
Pros: ● Easier for the drivers to remember ● Computationally easier ● Does not require additional waiting for the code to be created	**Pros:** ● Most optimized solution ● Ensures everything is as cheap as possible for the business ● Adding new locations still ensures everything is as optimized as possible
Cons: ● If drivers are out, it can be difficult to incorporate their packages and routes into other drivers' routes ● If packages are based on yesterday's locations, one driver could be burdened with too many packages/locations and not get them delivered on time (uneven workload for drivers)	**Cons:** ● Optimization code takes too long to run, and time is of the essence when delivering packages ● Requires more computational power ● Logistically difficult ● Requires extra work on the drivers' part to adjust to new routes

c. **Should there be some penalty/cost for drastically changing routes on drivers?**

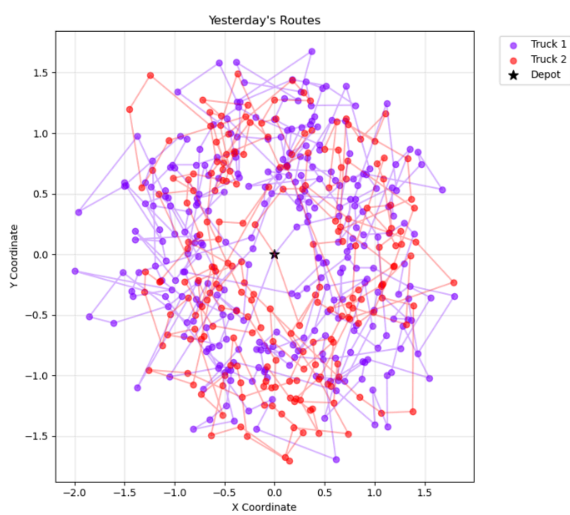
    i. There should be a penalty/cost for drastically changing routes on drivers. On a realistic level, drastic changes may make drivers more irritable and prone to mistakes. This can cause them to feel frustrated and decrease efficiency and quality deliveries. Mistakes in deliveries may also negatively affect customers receiving the packages and their opinions of the company. Additionally, drivers driving on unfamiliar roads may decrease their safety and confidence while driving.

ii. Our current optimizations reflect the optimal routes for an "ideal world." For example, this problem also only computes in straight-line distances and does not take into account other important variables like traffic levels, speed limits, and possible construction. The current constraints in our calculations do not penalize drastic changes in routes even though they can have drastic changes in real life.

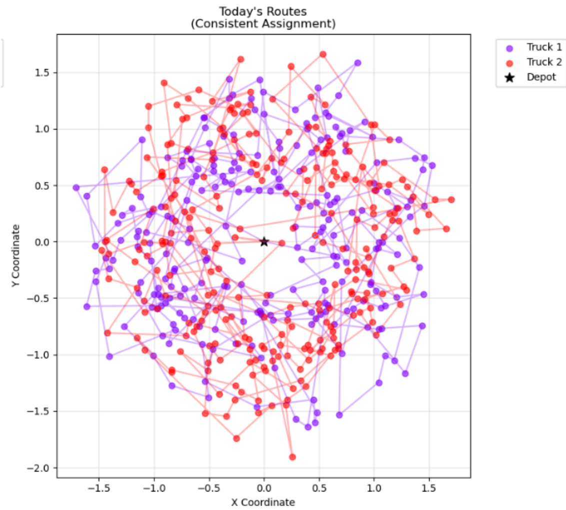
iii. To modify our optimization to better reflect the real-life consequences of drastic changes in routes, we would suggest adding a cost penalty function that increases with the magnitude of route changes. This will help minimize and prioritize total delivery distance and route changes.

Comparing Convenience Method and New Optimization with Simulated Annealing

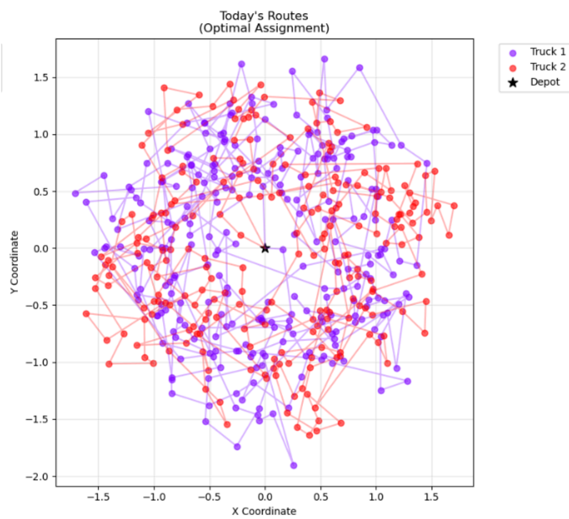
Route Comparison (two trucks, $300/truck, $1/mile)



Total cost: $842.21



Total cost: $834.23



Total cost: $829.66

4. **You work for a logistics company. Your boss has been manually sorting packages and scheduling routes. Your boss is tired of doing this and knows that you took a class that covers the TSP. Could you decrease costs by using optimization to plan delivery routes? Describe the advantages and disadvantages of this.**
    a. After thorough consideration, we believe that daily optimization for scheduling routes is not advisable due to the increased computational complexity that arises with a greater number of stops. This optimization approach exacerbates the common issue of overfitting, where the model becomes overly tailored to specific locations. As a result, when applied to

a new dataset, it leads to higher computational costs and complexity, underscoring the advantages of maintaining a more consistent, generalized route rather than re-running the optimization every day. Additionally, not executing the program on a daily basis could result in cost savings and reduce the time wasted during program execution, as well as minimize employee idle time. While optimization may be beneficial for initial route scheduling, its drawbacks outweigh the advantages of performing it daily.

Not Using Optimization	**Using Optimization**
Pros: ● Has been done in the past and is part of the company's current function ● Does not require additional waiting for computer to run	**Pros:** ● Reduces delivery costs ● Improves route efficiency
Cons: ● Tedious and tiring work ● Human error is a factor that could cause package misplacement	**Cons:** ● Computational power ● Time required for program to run ● Gets more complex as more stops are added

Conclusion:

In the context of this issue, we recommend conducting a simulating annealing method as it resulted in the superior optimized model. We chose a 3-change policy that resulted in two trucks needed. We found that maintaining consistency within routes is preferable, as the difference in costs is negligible. Creating new routes daily is not recommended, as it puts the drivers under severe mental pressure. Therefore, a policy will be created to prevent any drastic route changes. Optimization is a great way to plan delivery routes as it reduces delivery costs and improves route efficiency, but it can become increasingly complex and requires much computational power and time.

After examining industry trends and considering the insights gained from our coursework, we recommend exploring the use of machine learning as an alternative approach. Specifically, we suggest implementing a system that can automatically sort packages without requiring daily optimization. A prime example of a company that effectively utilizes this strategy is Amazon. By investing in advanced software capable of efficiently sorting and organizing packages, the company can achieve a more streamlined process rather than starting the optimization from scratch each day.

Machine learning has the potential to significantly reduce costs and enhance operational efficiency while also offering a reduced time investment compared to traditional optimization methods, such as the Traveling Salesman Problem (TSP). This approach not only minimizes the computational demands associated with daily route optimization but also allows for a more adaptive system that can learn and improve over time, ultimately benefiting the company in the long run.