

# Evolutionary artificial intelligence and robotics


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## Abstract

Evolutionary AI is used to solve research and optimization problems, based on the genetic processes of biological organisms. In this report, we explore the implementation and application of algorithms and techniques derived from evolutionary AI and robotics. However, we have focused on some important algorithms for solving some real-world problems. The report provides a detailed analysis of the results, offering clear insights into the optimization outcomes achieved through evolutionary technologies.

## Code Availability

The code used in this study is publicly available on GitHub at the following URL:  <https://github.com/Harithelamin/ACIT4610-24H-G13>.

## 1 Traffic Management Optimization Using Multi-Objective Evolutionary Algorithms

Urban traffic management required balancing multiple conflicting objectives, such as minimizing travel time, reducing fuel consumption, and lowering air pollution. The task was to apply a Multi-Objective Evolutionary Algorithm (MOEA) to optimize traffic management strategies for selected areas of New York City (NYC). The goal was to minimize the conflicting objectives of Total Travel Time (TTT) and Fuel Consumption (FC), using real-world traffic data sourced from NYC Open Data.

In this task, we applied a Multi-Objective Evolutionary Algorithm (MOEA) to optimize traffic management strategies for selected areas of New York City (NYC). The goal was to minimize the conflicting objectives of Total Travel Time (TTT) and Fuel Consumption (FC), using real-world traffic data from NYC Open Data.

The traffic management strategy has involved controlling traffic signal timings (green, yellow, and red light durations), and setting speed limits on these segments. We have developed an MOEA that optimized these parameters to

achieve the best trade-off between minimizing TTT and FC.

## 1.1 Data Exploration and Preprocessing

We used two datasets from the NYC Open Data portal: 1. NYC Traffic Volume Counts [1].

2. Traffic Speed Data [2].

Both datasets were collected by the New York City Department of Transportation (NYC DOT). The first dataset uses Automated Traffic Recorders (ATR) to collect traffic volume counts at bridge crossings and roadways, and contains 31 columns [1]. The second dataset records the average speed of vehicles traveling between endpoints, and contains 13 columns [2].

```
Column names in Traffic_Volume_Count_data:
Index(['id', 'segmentid', 'roadway_name', 'from', 'to', 'direction', 'date',
      '_12_00_1_00_am', '_1_00_2_00am', '_2_00_3_00am', '_3_00_4_00am',
      '_4_00_5_00am', '_5_00_6_00am', '_6_00_7_00am', '_7_00_8_00am',
      '_8_00_9_00am', '_9_00_10_00am', '_10_00_11_00am', '_11_00_12_00pm',
      '_12_00_1_00pm', '_1_00_2_00pm', '_2_00_3_00pm', '_3_00_4_00pm',
      '_4_00_5_00pm', '_5_00_6_00pm', '_6_00_7_00pm', '_7_00_8_00pm',
      '_8_00_9_00pm', '_9_00_10_00pm', '_10_00_11_00pm', '_11_00_12_00am'],
      dtype='object')
```

Figure 1: Traffic Volume Count

```
Column names in Average_Speed dataset:
Index(['id', 'speed', 'travel_time', 'status', 'data_as_of', 'link_id',
      'link_points', 'encoded_poly_line', 'encoded_poly_line_lvls', 'owner',
      'transcom_id', 'borough', 'link_name'],
      dtype='object')
```

Figure 2: Average Speed Of A Vehicle

We focused on optimizing traffic management for three road segments in New York City, defined as follows:

1. 5th Ave between 46th St and 47th St.

id	segmentid	roadway_name	from	to
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET

Figure 3: First 5 columns from First Area

2. Atlantic Ave between ALABAMA AVE and WILLIAMS AVE.

id	segmentid	roadway_name	from	to
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE

Figure 4: First 5 columns from Second Area

3. Queens Blvd between Union Tpke and Yellowstone Blvd (Queens).

id	segmentid	roadway_name	from	to
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
185	35806	5th AVENUE	EAST 46th STREET	EAST 47th STREET
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE
314	150671	ATLANTIC AVE	ALABAMA AVE	WILLIAMS AVE

Figure 5: First 5 columns from Third Area

	speed	travel_time	borough	roadway_name	date
0	19.26	353	Queens	TRAVIS AVENUE	2012-01-12T00:00:00.000
1	8.07	1440	Queens	LEWIS AVE	2012-01-10T00:00:00.000
2	8.07	1440	Queens	3 AVENUE	2012-10-12T00:00:00.000
3	8.07	1440	Queens	3 AVENUE	2012-10-13T00:00:00.000
4	8.07	1440	Queens	3 AVENUE	2012-10-14T00:00:00.000
5	8.07	1440	Queens	3 AVENUE	2012-10-15T00:00:00.000
6	8.07	1440	Queens	3 AVENUE	2012-10-16T00:00:00.000
7	8.07	1440	Queens	3 AVENUE	2012-10-17T00:00:00.000
8	8.07	1440	Queens	3 AVENUE	2012-10-18T00:00:00.000
9	8.07	1440	Queens	3 AVENUE	2012-10-19T00:00:00.000

Figure 6: Average Speeds From Selected Areas

In order to use the data from the selected areas defined above, we merged all of them into one dataset, which was later combined with the Traffic Speed Data. Finally, we obtained a new dataset named Traffic Volume Count Data for Selected Area.

This new dataset contains the sum of the columns from the two original datasets, which should total  $31 + 13 = 44$  columns. However, we ended up with an extra column due to the suffixing.

We identified and preprocessed relevant data points, such as:

#### A. Peak-hour traffic volumes:

These were calculated based on the number of travel times during selected hours. To achieve this, we created a list of hourly columns in the New York City Data. The list is defined as follows:

```
# List of hourly columns in NewYork_City_Data
hourly_columns = [
    '_12_00_1_00_am', '_1_00_2_00am', '_2_00_3_00am', '_3_00_4_00am',
    '_4_00_5_00am', '_5_00_6_00am', '_6_00_7_00am', '_7_00_8_00am',
    '_8_00_9_00am', '_9_00_10_00am', '_10_00_11_00am', '_11_00_12_00pm',
    '_12_00_1_00pm', '_1_00_2_00pm', '_2_00_3_00pm', '_3_00_4_00pm',
    '_4_00_5_00pm', '_5_00_6_00pm', '_6_00_7_00pm', '_7_00_8_00pm',
    '_8_00_9_00pm', '_9_00_10_00pm', '_10_00_11_00pm', '_11_00_12_00am'
]
```

Figure 7: Traffic Volume Count Data for Selected Area

To determine the overall peak hour, we first identified the peak hour across all records in the dataset. To calculate the peak hour based on the traffic data, we followed these steps[6]:

$$\text{Total Traffic Volume for Hour } h = \sum_{i=1}^n \text{Traffic Volume at hour } h_i \quad (1)$$

where:

- $h_i$  represents the hour of each traffic record  $i$ ,
- $n$  is the total number of records in the dataset for that hour.

$$\text{Peak Hour} = \arg \max_{h \in H} (\text{Total Traffic Volume for Hour } h) \quad (2)$$

where:

- $H$  is the set of all possible hours in the dataset,
- $\arg \max$  finds the hour that maximizes the total traffic volume.

$$\text{Maximum Traffic Volume} = \max_{h \in H} (\text{Total Traffic Volume for Hour } h) \quad (3)$$

We calculated the total traffic for each hour and identified the maximum volume for each record across the dataset. As a result, the peak hour in New York City occurred from 7:00 to 8:00 PM, with an overall volume of 8,150,688 vehicles.

	speed	travel_time	peak_hour	peak_hour_volume
0	10.56	239	_7_00_8_00pm	1893
1	16.15	155	_7_00_8_00pm	1893
2	32.93	76	_7_00_8_00pm	1893
3	47.84	52	_7_00_8_00pm	1893
4	46.60	54	_7_00_8_00pm	1893
5	47.84	53	_7_00_8_00pm	1893
New Your City Overall peak hour: _7_00_8_00pm, Overall volume: 8150688				

Figure 8: New York Peak Hours

### B. Average speeds:

The formula for calculating the average speed is given by[8]:

$$v_{\text{avg}} = \frac{\text{Total Distance}}{\text{Total Time}} \quad (4)$$

For multiple vehicles, the average speed is:

$$v_{\text{avg}} = \frac{\sum_{i=1}^n d_i}{\sum_{i=1}^n t_i} \quad (5)$$

Where:

- $d_i$  is the distance traveled by vehicle  $i$ ,
- $t_i$  is the time taken by vehicle  $i$ ,
- $n$  is the total number of vehicles or data points.

For hourly data, the average speed for a specific hour is calculated as:

$$v_{\text{avg.hour}} = \frac{\sum_{i=1}^n v_i}{n} \quad (6)$$

Where:

- $v_i$  is the recorded speed,
- $n$  is the total number of measurements for that hour.

In order to calculate the average speed, we must first ensure that the speed data is in numeric format. The `mean()` function in Python allows us to compute the mean (or average) of a given set of values. As a result, we find that the average speed is 2513.80934 mph.

```
# Calculate the average speed.
average_speed = Data['speed'].mean()

# Output the result
print(f"The average speed is: {average_speed} mph")
✓ 0.0s

The average speed is: 3485.932844932845 mph
```

Figure 9: New York Average Speed

## 1.2 Fuel Consumption Calculation

Fuel consumption measures the amount of fuel a car uses to travel a specific distance[4]. We used the standard fuel consumption equation, defined as follows:

$$\text{Fuel Consumption} = a \times V + b \times \frac{1}{V} + c \quad (7)$$

Where:

- $V$  is the average speed (in mph),
- $a$ ,  $b$ , and  $c$  are empirical constants, with  $a$  indicating the increase in fuel consumption with speed,  $b$  representing a decrease in fuel consumption as speed increases, and  $c$  representing the base fuel consumption at very low-speed conditions.

The values of the coefficients  $a$ ,  $b$ , and  $c$  are set as follows:

- $a = 0.01$  is the coefficient for speed ( $V$ ),
- $b = 2$  is the coefficient for  $\frac{1}{V}$ ,
- $c = 0.1$  is the constant term.

We then update the formula to calculate the total fuel consumption for each road segment and time interval by defining the following equation[10]:

$$\text{Fuel Consumption} = \sum_{i=1}^n \left( \text{Volume}_i \times \left( a \times V_i + b \times \frac{1}{V_i} + c \right) \times \text{Segment Length}_i \right) \quad (8)$$

Where:

- $n$  is the number of time intervals,

- $\text{Volume}_i$  is the vehicle count in interval  $i$  from the traffic volume dataset,
- $V_i$  is the average speed in interval  $i$  from the traffic speed dataset,
- $\text{Segment Length}_i$  is the length of the road segment.

However, in the selected area dataset, the peak hour volume refers to the vehicle count during the peak hour (Volume).

speed is the average speed in mph.

Segment represents the segment length in miles.

The following figure illustrates the data we have used.

	speed	travel_time	peak_hour	peak_hour_volume	segmentid
0	19.26	353	_4_00_5_00pm	717.0	4853
1	8.07	1440	_8_00_9_00am	552.0	43218
2	8.07	1440	_8_00_9_00am	1603.0	36272
3	8.07	1440	_1_00_2_00pm	1872.0	36272
4	8.07	1440	_11_00_12_00pm	1554.0	36272
...	...	...	...	...	...
18049	36.66	250	_4_00_5_00pm	920.0	42542
18050	36.66	250	_4_00_5_00pm	910.0	42542
18051	36.66	250	_2_00_3_00pm	879.0	42542

Figure 10: Selected Area Dataset

The following plot shows the fuel consumption for each time interval.



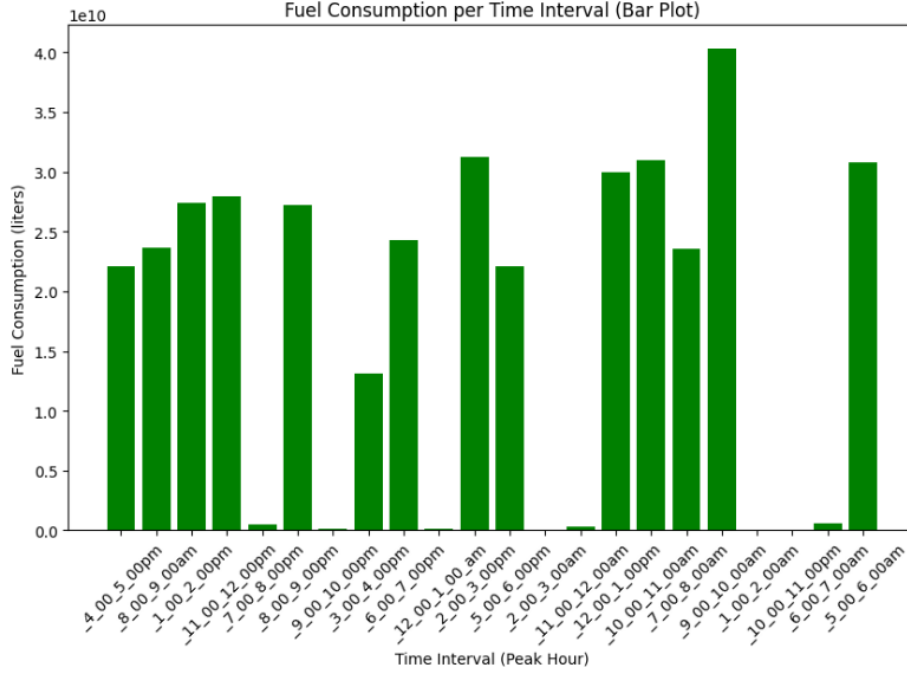


Figure 11: Fuel consumption per time interval

### 1.3 Formulate the Optimization Problem

We need the decision variables to represent the parameters that can be adjusted to optimize the traffic signal system and speed limits. These variables will be encoded in an individual in the genetic algorithm.

A. Signal timings represent the durations of the green, yellow, and red phases for each intersection. This refers to the time allocated for each traffic signal phase—green, yellow, and red—at every intersection[11].

B. Speed limit. They will be controlled in your optimization strategy. The speed limit is a decision variable that defines the maximum speed allowed for vehicles on the road segment approaching each intersection[11].

We have defined the decision variables as follows:

- `num_intersections = 3`      # Number of intersections
- `max_signal_cycle_time = 120`      # Maximum signal cycle time in seconds (sum of green, yellow, red)
- `speed_limit_min = 30`      # Minimum speed limit in km/h

- `speed_limit_max = 120`    # Maximum speed limit in km/h
- `green_min = 10`    # Minimum green light duration in seconds
- `green_max = 60`    # Maximum green light duration in seconds
- `yellow_duration = 3`    # Yellow light duration in seconds
- `red_min = 10`    # Minimum red light duration in seconds
- `red_max = 60`    # Maximum red light duration in seconds

**A. Total Travel Time (TTT):** The total travel time is the time it takes for all vehicles to travel through the network of intersections during a given period. In the optimization, it works as follows[12]:

1. **Green light duration:** The duration of the green light is very short, so vehicles will wait at the red light frequently.
2. **Red light duration:** The longer the red light, the longer vehicles will wait.
3. **Speed limits:** Higher speed limits generally result in faster travel times.

**Objective Function for TTT:** The total travel time can be calculated as follows[12]: **Total Travel Time (TTT):** The total travel time is the sum of the travel times for all vehicles through the network of intersections, considering both travel time and stop time. It can be expressed as[13]:

$$\text{TTT} = \sum_{i=1}^N \left( \frac{d_i}{v_i} + T_{\text{stop}}(i) \right)$$

Where:

- $N$  = Total number of vehicles in the network.
- $d_i$  = Distance traveled by vehicle  $i$  (in meters or kilometers).
- $v_i$  = Speed of vehicle  $i$  (in meters per second or kilometers per hour).
- $T_{\text{stop}}(i)$  = Time spent stopping for red lights by vehicle  $i$  (in seconds).

$$T_{\text{stop}}(i) = \sum_{j=1}^M (\text{Wait time at intersection } j)$$

Where:

- $M$  = Number of intersections the vehicle passes through.
- The wait time.

Total travel time formula is:

$$\text{Total Travel Time (TTT)} = \sum_{i=1}^N \left( \frac{d_i}{v_i} + \sum_{j=1}^M \text{Wait time at intersection } j \right)$$

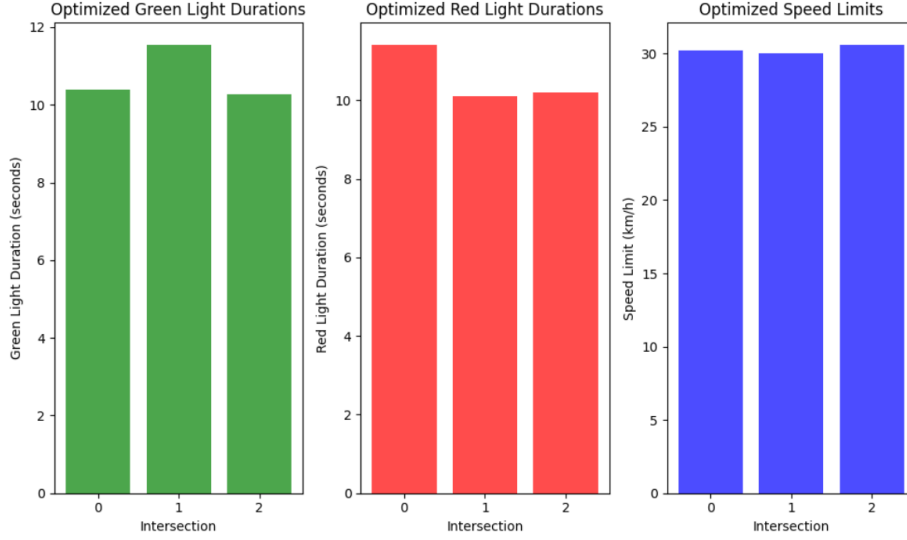


Figure 12: Optimizing Red, Green, Yellow Light Duration

**Fuel Consumption:** Is refers to the amount of fuel used by all vehicles in the network during a given time period. Optimizing fuel consumption is important for reducing environmental impact, improving air quality, and saving costs[12].

This system works to improve as follows:

1. Red light duration: Longer red light duration causes vehicles to stop for long periods, causing vehicle accumulation and congestion.
2. Speed limits: Lower speed limits can reduce fuel consumption by encouraging safer driving.

Fuel Consumption formula is:

$$FC = \sum_{i=1}^N (\text{Red}_i \times C_{\text{red}} + \text{Speed}_i \times C_{\text{speed}})$$

Where:

- $N$  = Total number of vehicles or intersections
- $\text{Red}_i$  = Duration of red light for vehicle  $i$  (in seconds)
- $\text{Speed}_i$  = Speed limit for vehicle  $i$  (in km/h or m/s)

- $C_{\text{red}}$  = Constant factor for red light fuel consumption (e.g., 0.1)
- $C_{\text{speed}}$  = Constant factor for speed-related fuel consumption (e.g., 0.05)

## 1.4 Implement the MOEA using Genetic Algorithm

We designed an initial population of potential solutions (chromosomes) representing different traffic management strategies. To do this, we defined the structure of each individual (chromosome) and then initialized the population by randomly generating individuals within the specified constraints. Each individual consisted of three components: speed, green light duration, and red light duration.

### 1.4.1 Initialization

We started by implementing a genetic algorithm, initializing a population of individuals, where each individual represents a potential solution to the problem. Each individual is represented as a vector [speed, green light duration, red light duration], representing the vehicle speed and the traffic light durations.

Chromosome Representation: Each individual is a 3-dimensional vector:

- The first element represents speed within the range [30, 120] km/h.
- The second element represents green light duration within the range [10, 60] seconds.
- The third element represents red light duration within the range [10, 60] seconds. However, population, and other decision variable has been initialized regarding our decision variable has been defined above.

### 1.4.2 Objective Function

The algorithm uses two objective functions, Total Travel Time (TTT), and Fuel Consumption (FC). These two objectives are calculated for each individual in the population, and the goal is to minimize both of them.

### 1.4.3 Fitness Evaluation

Each individual in the population is evaluated using the objective functions. Which they return tow dimintion valus, TTT, and FC.

### 1.4.4 Selection

individuals are selected for reproduction (crossover and mutation) based on their fitness, with the goal of propagating the best traits to the next generation.

### 1.4.5 Crossover

it to introduces genetic diversity into the population and allows the algorithm to explore different combinations of variables.

#### 1.4.6 Mutation

Each individual has a chance to mutate each of its variables (speed, green light, and red light duration).

#### 1.4.7 Replacement

After the selection, crossover, and mutation steps, the offspring are added back to the population. The next generation of individuals is created by replacing the previous generation[14].

#### 1.4.8 Termination and Pareto Front

The genetic algorithm iterates over a fixed number of generations defined in decision variable above. At each generation, the Pareto-optimal set of solutions is refined. the Pareto front is the set of individuals that represent trade-offs between the two objectives (TTT and FC)[14].

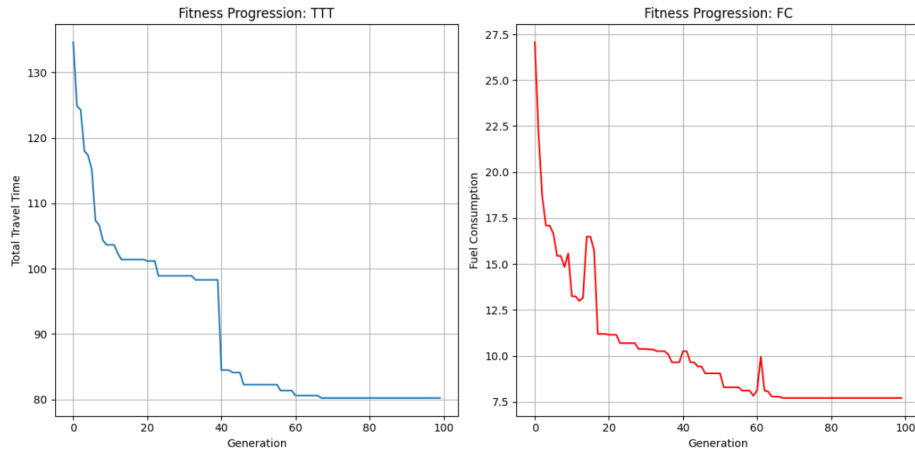


Figure 13: TTT, and FC Analyse

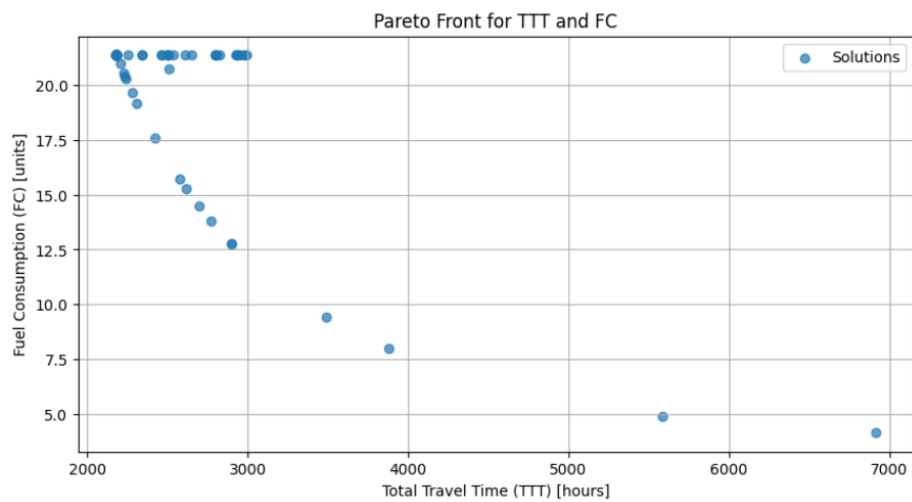


Figure 14: TTT

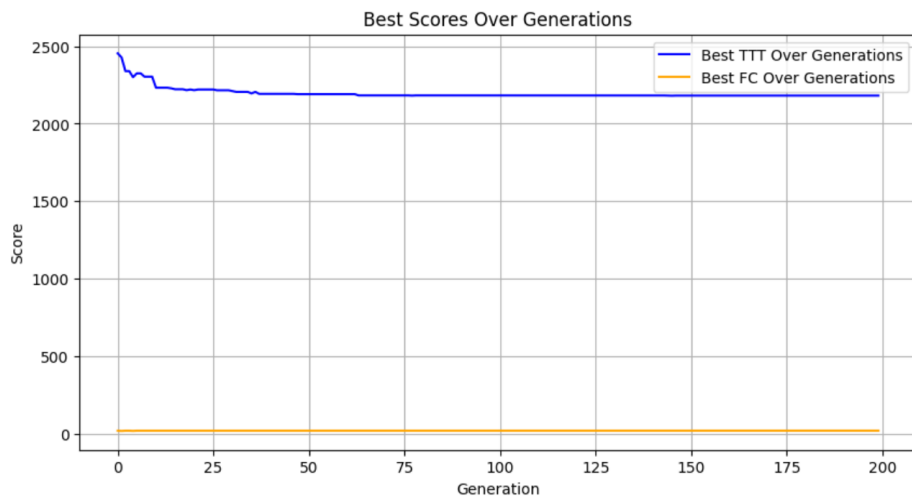


Figure 15: The best score over generation

## 2 Task 2

### 2.1 Introduction

For this problem we'll have 20 stocks which include their stock data from January 1st 2018 to December 31st 2022. This include high, low, volume, opening and closing. By this data one can look at how each stock has acted for a certain time. In this task we'll use Evolutionary Programming(EP) and Evolutionary Strategies(ES), with some variation, and in total six different version.

### 2.2 Methodology

The first version is about a basic version of EP. The EP algorithm evolves a population of candidate solutions by generating off spring through mutation. Each generation, the population is ranked by fitness, and the top candidates are selected to survive and reproduce.

The second version is also about EP, but here we implemented a more complex version of it. For Self-Adaptive Mutation, Mutation rates adapt dynamically to improve the balance between exploration and exploitation. For elitism, the top-performing individuals in each generation are retained in the population to prevent loss of optimal solutions. For selection mechanisms, Offspring are selected based on a probability distribution proportional to fitness, favoring high-fitness solutions while maintaining diversity.

The third one, is the first one in ES, and is a basic implementation of this. For mutation, Gaussian mutation is applied to each candidate solution to explore the search space. For selection, each generation, the top-performing individuals are selected to form the population for the next generation, promoting gradual improvement in fitness.

The fourth one, is an advanced version of ES. For self-adaptive mutation rates, each candidate solution has an adaptive mutation rate that evolves alongside the portfolio weights. For recombination, candidate solutions are recombined from selected parent weights and mutation parameters, promoting exploration of the search space.

The fifth version is also about ES, and with an  $\mu + \lambda$  extension. For population parameters, parents ( $\mu$ ) and offspring ( $\lambda$ ) combine for generation selection. For mutation and selection, offspring are generated with adaptive mutation, and the best individuals from parents and offspring are elected for each new generation.

The sixth version is also about, and also with an  $\mu$  and  $\lambda$  extension, but the algorithm is more concern with that next generation is picked based on offspring population. For population parameters, parents ( $\mu$ ) generate offspring

( $\lambda$ ), but only the top  $\mu$  offspring advance. For mutation and selection, mutation is applied to generate offspring, and the best  $\mu$  offspring replace the parent generation.

## 2.3 Results

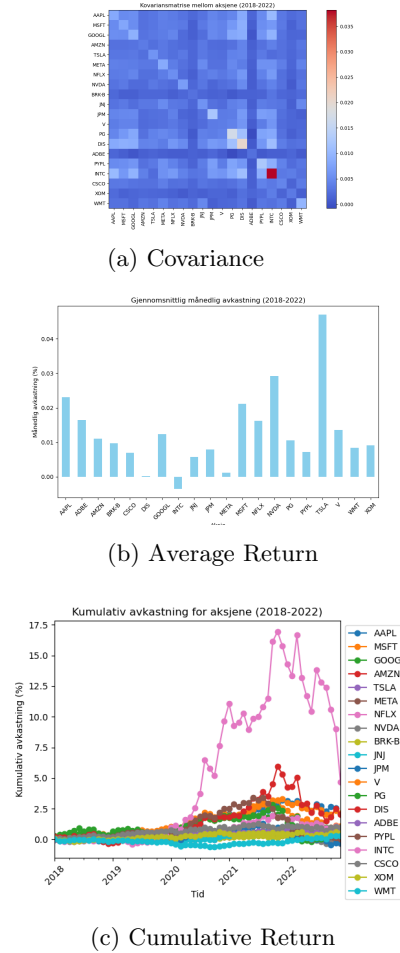


Figure 16: Figures for the preliminary development

Here one can see a covariance matrix, average monthly return and cumulative return. Noticeably, the stock INTC, is not having any return in the period. Another insight is that NFLX is doing quite well in the second half of the period. The next results is about optimizing several algorithms to maximize return.



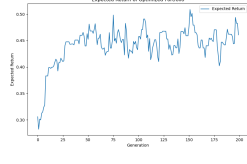
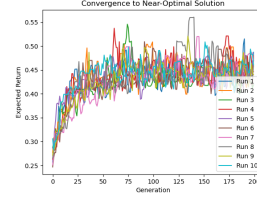
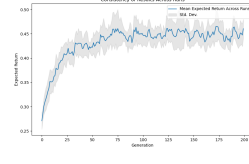
## Version

## Consistency of results

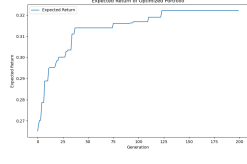
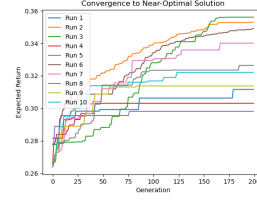
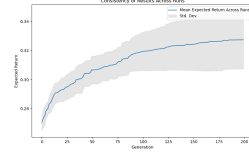
## Convergence to near-optimal

## Expected return

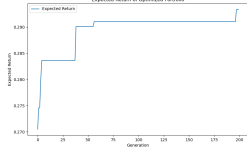
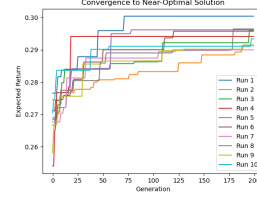
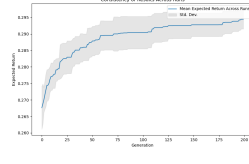
V. 1



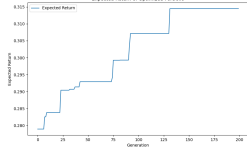
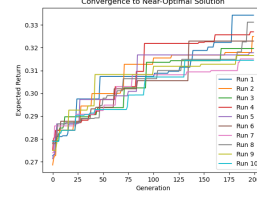
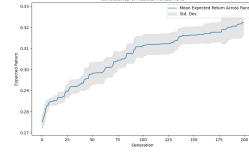
V. 2



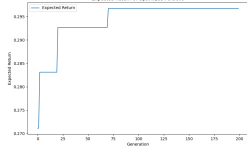
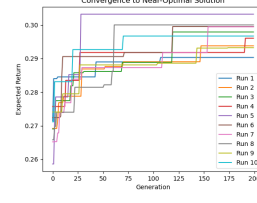
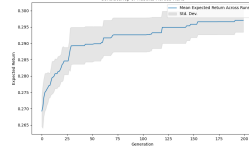
V. 3



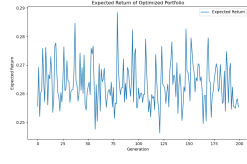
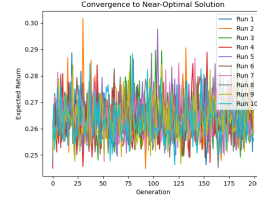
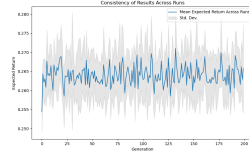
V. 4



V. 5



V. 6



In the continuation of this section we'll present the results from our evolutionary programming optimization project for portfolio management. In this project, we implemented six different versions of an evolutionary algorithm to maximize the Sharpe ratio of a portfolio. The goal was to find the best portfolio allocation strategy for a set of 20 popular stocks, balancing returns against risk. Each version uses different parameters, and we evaluated them based on three metrics: Consistency of Results, Convergence to Near-Optimal Solutions, and Expected Return. We'll explain what each metric shows and discuss the performance of each version.

The first metric, Consistency of Results, measures the average expected return across multiple runs, with the shaded area representing standard deviation. This helps us understand how stable each version's results are. For example, in Version 1, the consistency plot shows moderate variability, meaning the results are somewhat stable across runs, but with some fluctuation. Versions 2, 3, and 4, on the other hand, show a more steady progression with less variability, indicating high stability in results across different runs. Version 5 starts to show a bit more variability, while Version 6 has significant fluctuations, meaning its results are not as consistent.

Next, we'll explain Convergence to Near-Optimal Solutions. This metric tracks the best return across generations for each run, showing how quickly each version finds high-return portfolios. For Version 1, we see a steady convergence to high returns, which suggests this version finds good solutions consistently. Versions 2, 3, and 4 are even better in this aspect. They show smooth, steady convergence across runs, meaning these versions reliably find high-return solutions over generations. However, Version 5 has a slower and less regular path to the optimal solution, and Version 6 shows highly irregular paths, indicating it struggles with convergence.

Finally, the Expected Return plot shows the progression of the best portfolio in a single run for each version. This metric demonstrates how each version performs over time. Versions 2, 3, and 4 have a steady increase in expected returns, which means these versions not only converge consistently but also keep improving over generations. In contrast, Version 5 has a stable, but somewhat less consistent pattern, while Version 6 shows erratic results, with frequent ups and downs in expected return. This instability in Version 6 indicates that its configuration might be suboptimal for this type of optimization.

## 2.4 Conclusion

In summary, the project tested six versions of an evolutionary programming algorithm for optimizing a stock portfolio, aiming to maximize the Sharpe ratio. Versions 2, 3, and 4 emerged as the top performers, consistently demonstrating high stability across multiple runs, smooth convergence to high-return solutions,

and reliable improvement over generations. These versions produced portfolios that balanced risk and return effectively, achieving the objectives of the optimization. Conversely, Versions 5 and 6 showed higher variability, irregular convergence, and less reliable results, suggesting they may be less suitable without further tuning.

To end the conclusion, I will add some ideas for future work. Firstly, to fine-tuning parameters like mutation rate, population size, and selection strategy could improve the less stable versions. A systematic parameter optimization approach, such as grid search or random search, could identify configurations that enhance stability and convergence.

Secondly, adding constraints such as maximum asset weight or sector-based limits could create portfolios that are more practical and aligned with real-world investment policies, making the model applicable to diverse investment strategies.

Thirdly, expanding the dataset to include additional stocks, international assets, or different time periods could reveal how robust the algorithm is under different market conditions. This would help evaluate the generalizability of the best-performing configurations.

Fourthly, combining evolutionary programming with other optimization methods, such as genetic algorithms or particle swarm optimization, could yield even better performance, leveraging strengths from multiple techniques to improve convergence speed and solution quality.

Lastly, exploring alternative risk-adjusted performance metrics, like the Sortino ratio (which considers downside risk only) or conditional value at risk (CVaR), could provide insights into how the algorithm manages different types of risk and whether it can achieve more targeted risk-return balances.

These improvements could enhance the algorithm's robustness, make it more applicable to real-world portfolio management, and ensure it remains effective under diverse market conditions. Future work along these lines could yield a more versatile and reliable portfolio optimization tool.

### **3 Solving the Vehicle Routing Problem with Time Windows (VRPTW) Using Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO)**

The VRPTW was a variant of the Vehicle Routing Problem (VRP), which was crucial in logistics, transportation, and supply chain management. In VRPTW,

a fleet of vehicles had to deliver goods to multiple customers. Each customer had a specific time window during which the delivery had to occur. The challenge was to design routes that minimized the total travel distance while ensuring all deliveries met their respective time constraints. This task focused on optimizing the delivery routes for a fleet of vehicles using two nature-inspired optimization algorithms: Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO).

We defined the objective as finding the most efficient routes for a set of vehicles, ensuring that all customers receive their deliveries within specified time windows.

We implemented both Ant Colony Optimization and Particle Swarm Optimization to solve the Vehicle Routing Problem with Time Windows. We then compared the effectiveness of these algorithms.

The primary objective of the VRPTW is to minimize the total distance travelled by all vehicles while ensuring that:

1. Each customer is visited exactly once by one vehicle.
2. Deliveries occur within the specified time windows.
3. The total demand on any route does not exceed the vehicle's capacity.

### 3.1 Data Exploration, and pre processing

We used Solomon's VRPTW Benchmark Problems dataset, C101.txt [5].

The columns in the dataset are:

CUST NO.: Customer number (ID).

XCOORD: X coordinate of the customer's location.

YCOORD: Y coordinate of the customer's location.

DEMAND: The demand at the customer location.

READY TIME: The earliest time at which service can begin.

DUE DATE: The latest time by which the service should be completed.

SERVICE TIME: The time it takes to complete the service for this customer.

### 3.2 Define the VRPTW

From information above, and given dataset, we can define the VRPTW as follows[15]:

- Let  $K$  be the number of vehicles.
- Let  $N$  be the number of customers.
- The objective is to minimize the total travel distance.

The variables involved are:

- $x_{ijk}$ : A binary variable indicating if vehicle  $k$  travels directly from customer  $i$  to customer  $j$ .

- $t_i$ : The arrival time of vehicle  $k$  at customer  $i$ .
- $q_i$ : The demand of customer  $i$ .

### 3.3 Time Windows

To calculate the time window, we need the Time Window formula for our problem. For each customer  $i$ , the time window is defined as:

$$\text{Time Window}_i = [\text{READY TIME}_i, \text{DUE DATE}_i]$$

Where:

- $\text{READY TIME}_i$  is the earliest time at which the service can start for customer  $i$ .
- $\text{DUE DATE}_i$  is the latest time by which the service must be completed for customer  $i$ .

The vehicle must arrive at customer  $i$  within the specified time window.

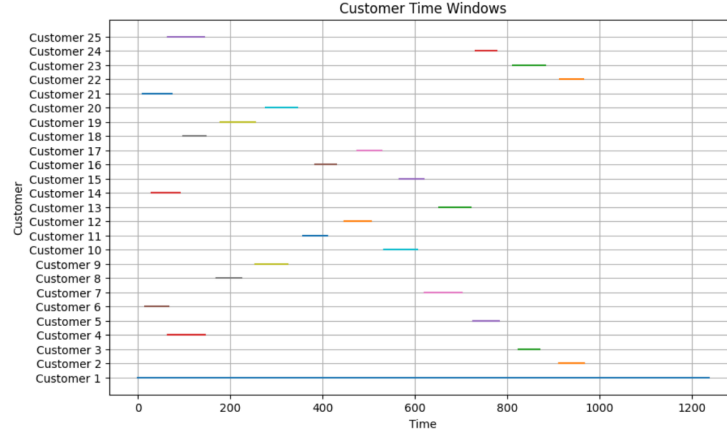


Figure 17: Customer Time Windows

### 3.4 City Coordinate

In order to calculate city Coordinate, we need to define city Coordinates Formula[17].

City Coordinates Formula:

For each customer  $i$ , the city coordinates are defined as:

$$\text{City Coordinates}_i = (X_i, Y_i)$$

Where:

- $X_i$  is the  $x$ -coordinate (longitude or horizontal distance) of the customer's location.
- $Y_i$  is the  $y$ -coordinate (latitude or vertical distance) of the customer's location.

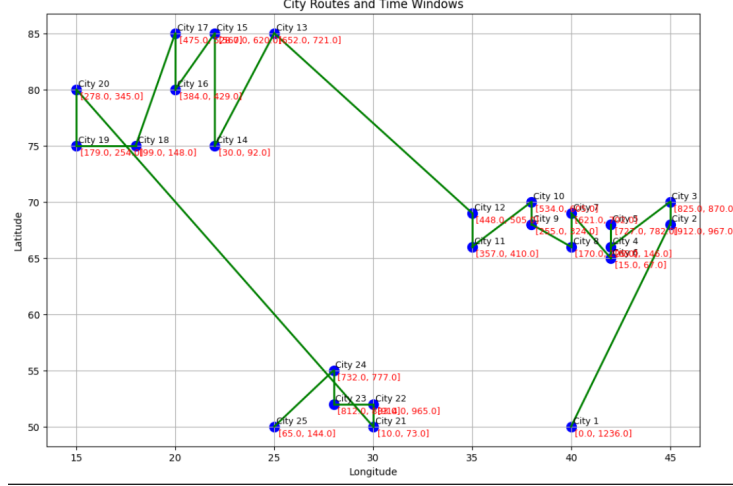


Figure 18: City Routes And Time Windows

### 3.5 Dist Matrix

To calculate the distance between two customers  $i$  and  $j$  based on their coordinates, we use the Euclidean distance formula[17]:

Distance Formula:

$$d_{ij} = \sqrt{(X_j - X_i)^2 + (Y_j - Y_i)^2}$$

Where:

- $d_{ij}$  is the Euclidean distance between customer  $i$  and customer  $j$ .
- $X_i, Y_i$  are the coordinates of customer  $i$ .
- $X_j, Y_j$  are the coordinates of customer  $j$ .

### 3.6 Penalty Calculation

To handle early or late arrivals, we need to define a function to calculate the penalty for early or late arrivals as follows:

1. Penalty Mechanism: If a vehicle arrives too early.
2. Handling Early Arrival: If a vehicle arrives before the allowed time window.

3. Handling Late Arrival: If a vehicle arrives after the time window.

**The Penalty Approach:** If the ant arrives before the city's start time, the ant has to wait. while in case of late arrival: If the ant arrives after the city's end time, a penalty is applied. We will add a penalty based on how late the ant is.

In order to calculate the penalty, we need to define the penalty calculation formula.

Penalty Calculation: For each customer  $i$ , the penalty is calculated based on their arrival time  $t_i$  and the time window  $[e_i, l_i]$ :

$$\text{Penalty}_i = \begin{cases} \text{penalty\_factor} \times (e_i - t_i) & \text{if } t_i < e_i \\ \text{penalty\_factor} \times (t_i - l_i) & \text{if } t_i > l_i \\ 0 & \text{otherwise, if } e_i \leq t_i \leq l_i \end{cases}$$

The total penalty is the sum of the individual penalties for each customer:

$$\text{Total Penalty} = \sum_{i=1}^n \text{Penalty}_i$$

### 3.7 Decision Variable

#### Ant Colony Optimization (ACO) Hyperparameters:

- Vehicle Capacity:  $\text{vehicle\_capacity} = 10$
- Number of Ants:  $\text{num\_ants} = 20$
- Number of Iterations:  $\text{num\_iterations} = 100$
- Influence of Pheromone:  $\alpha = 1.0$
- Influence of Distance:  $\beta = 2.0$
- Pheromone Evaporation Rate:  $\rho = 0.1$
- Total Pheromone Deposited by Each Ant:  $Q = 100$

#### Particle Swarm Optimization (PSO) Hyperparameters:

- Number of Particles:  $\text{num\_particles} = 20$
- Number of Iterations:  $\text{num\_iterations} = 100$

### 3.8 Implement Ant Colony Optimization (ACO) for VRPTW:

We implemented an Ant Colony Optimization (ACO) algorithm to solve a variant of the Vehicle Routing Problem (VRP) with time windows. The implementation has been completed in a few steps[18]:

1. Initialization: Pheromones are initialized on all values as defined above.
2. Solution Construction: Each ant constructs a solution based on pheromone levels and heuristic information.
3. Fitness Evaluation: Each solution is evaluated, and a fitness value (cost or travel time) is computed.
4. Pheromone Update: is the key feature of ACO. Pheromone update formula defined as follows:

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij} \quad (9)$$

where:

- $\tau_{ij}(t)$  is the pheromone level on edge  $ij$  at time  $t$ ,
- $\rho$  is the evaporation rate,
- $\Delta\tau_{ij}$  is the pheromone deposited by ants after each iteration.

The pheromone update rule consists of two main parts.

5. Iteration: The process repeats for several iterations, improving the solutions over time.

### 3.9 Implement Particle Swarm Optimization (PSO) for VRPTW:

We implemented Particle Swarm Optimization (PSO) algorithm to solve a variant of the Vehicle Routing Problem (VRP) with time windows. The implementation has been completed in a few steps[18]:

1. Initialize a population of particles, each with a random position and velocity in the search space.
2. Fitness Evaluation: Evaluate the fitness of each particle using a fitness function, which determines the quality of the solution.
3. Update Personal Best: If the current position of a particle is better than its previous best position, update it with the current position.
4. Velocity Update: Update the velocity of each particle using the formula[19]:

$$v_i^{t+1} = w \cdot v_i^t + c_1 \cdot r_1 \cdot (pbest_i - x_i^t) + c_2 \cdot r_2 \cdot (gbest - x_i^t) \quad (10)$$

Where:

- $v_i^{t+1}$ : The updated velocity of particle  $i$  at time  $t + 1$ .
- $v_i^t$ : The current velocity of particle  $i$  at time  $t$ .
- $x_i^t$ : The current position of particle  $i$  at time  $t$ .



- $pbest_i$ : The personal best position of particle  $i$  (i.e., the best position found by particle  $i$  so far).
- $gbest$ : The global best position found by any particle in the swarm.
- $c_1, c_2$ : The acceleration constants (also known as the *cognitive* and *social* coefficients), which control the influence of the particle's own best experience and the swarm's global experience, respectively.
- $r_1, r_2$ : Random numbers between 0 and 1 that introduce stochasticity into the update, helping to explore the solution space more thoroughly.
- $w$ : The *inertia weight*, which controls the balance between *exploration* (searching new areas) and *exploitation* (refining the best-known solutions). A higher  $w$  favors exploration, while a lower  $w$  favors exploitation.

5. Position Update: Update the position of each particle using the formula:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (11)$$

6. Termination: Repeat steps 2 to 6 until a stopping condition is met.

### 3.9.1 Results

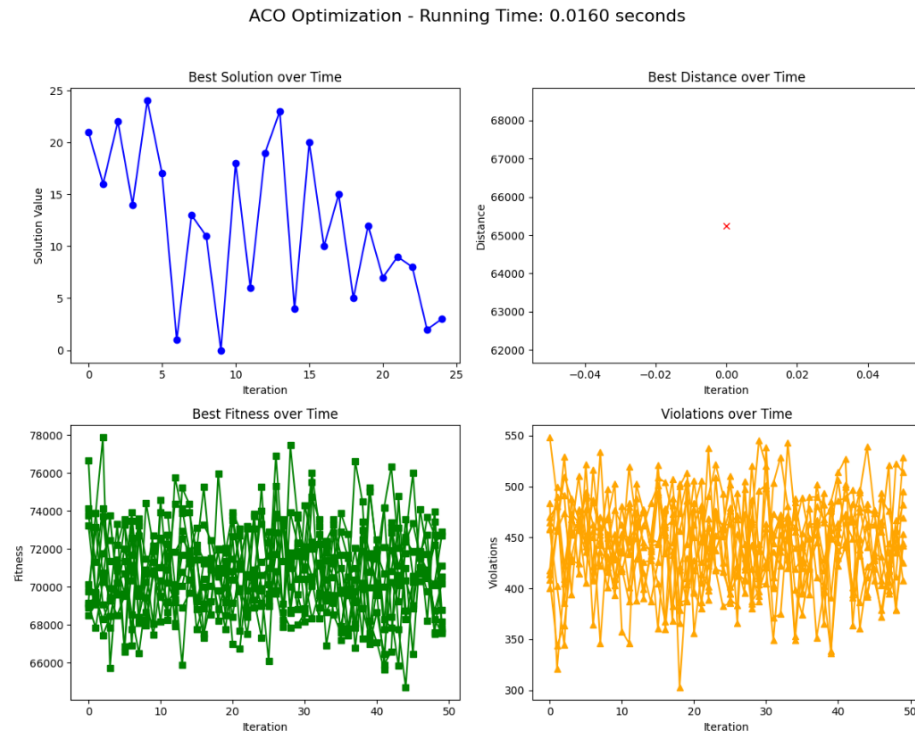


Figure 19: ACO Algorithm Analysis

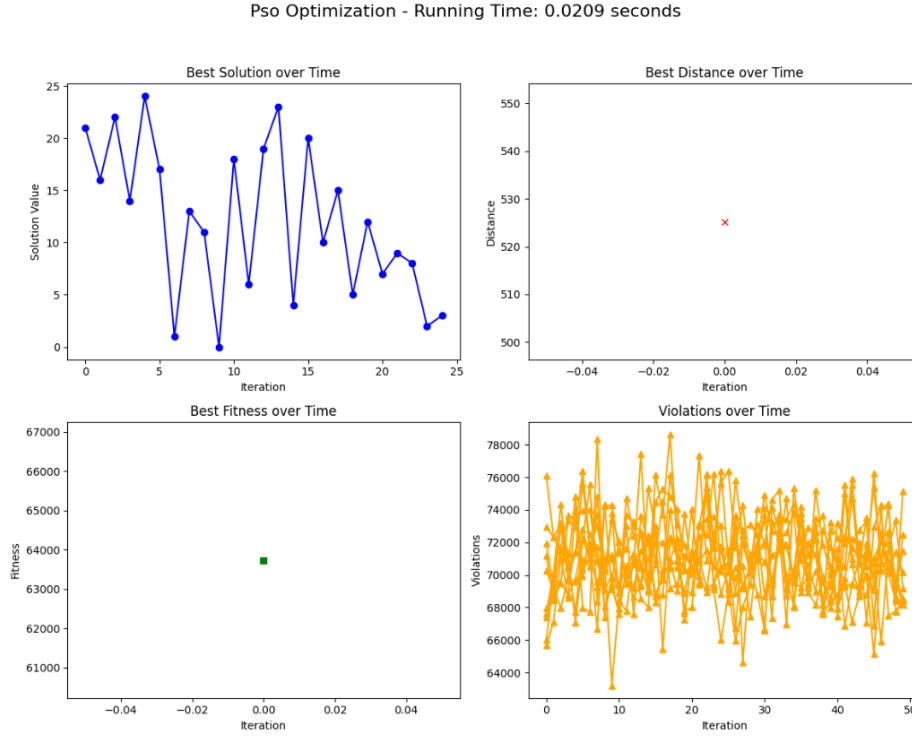


Figure 20: PSO Algorithm Analysis

As seen in the previous statistics, the running time for ACO optimization was 0.0160 seconds, while the running time for PSO optimization was 0.0209 seconds. This indicates that ACO is faster than PSO.

In addition, the best distance achieved by ACO is 65,254.61, while the best distance achieved by PSO is 525.22. This indicates that the ACO algorithm has a higher value for the distance metric.

Moreover, The best solution (path) obtained by the ACO algorithm is: [21, 16, 22, 14, 24, 17, 1, 13, 11, 0, 18, 6, 19, 23, 4, 20, 10, 15, 5, 12, 7, 9, 8, 2, 3].

On the other hand, the best solution (path) obtained by the PSO algorithm is: [17, 0, 16, 20, 15, 3, 12, 2, 19, 22, 1, 24, 9, 18, 8, 13, 4, 7, 11, 21, 23, 5, 10, 6, 14].

Overall, both ACO and PSO provide valid solutions, but they may represent different trade-offs in optimization based on their respective mechanisms.

## 4 Solving a Real-World Problem Using Reinforcement Learning

Is to apply reinforcement learning techniques to solve a real-world problem. Students used a publicly available dataset to train an RL agent, evaluated its

performance, and optimized it to achieve the best possible outcome. The exercise will utilize the Taxi-v3 environment available in the OpenAI Gym repository. This environment simulates a simplified grid world where an agent must pick up and drop off passengers at the correct locations while avoiding walls and other obstacles. We used Dataset/Environment: Taxi-v3 on OpenAI Gym.

## 4.1 Understanding the Environment

The Taxi-v3 environment from OpenAI Gym is a reinforcement learning (RL) environment. The goal of this environment is to solve tasks using RL algorithms. It uses a state and action space, allowing for experimentation with various RL algorithms, such as Q-learning and Deep Q-Networks (DQN)[21].

The agent's goal is to pick up and drop off passengers at specific spots on a 5x5 grid. The agent must drive the taxi to pick up a passenger, take them to the right location, and do all of this before time runs out[21].

### Environment Overview

- 1.State Space: The state is a tuple of:
  - I. The taxi's position on a 5x5 grid.
  - II. taxi has a passenger.
  - III. The destination is 4 possible locations: the four corners of the grid.
2. Action Space: The taxi has 6 possible actions: Move north, Move south, Move east, Move west, Pick up a passenger, and Drop off a passenger.

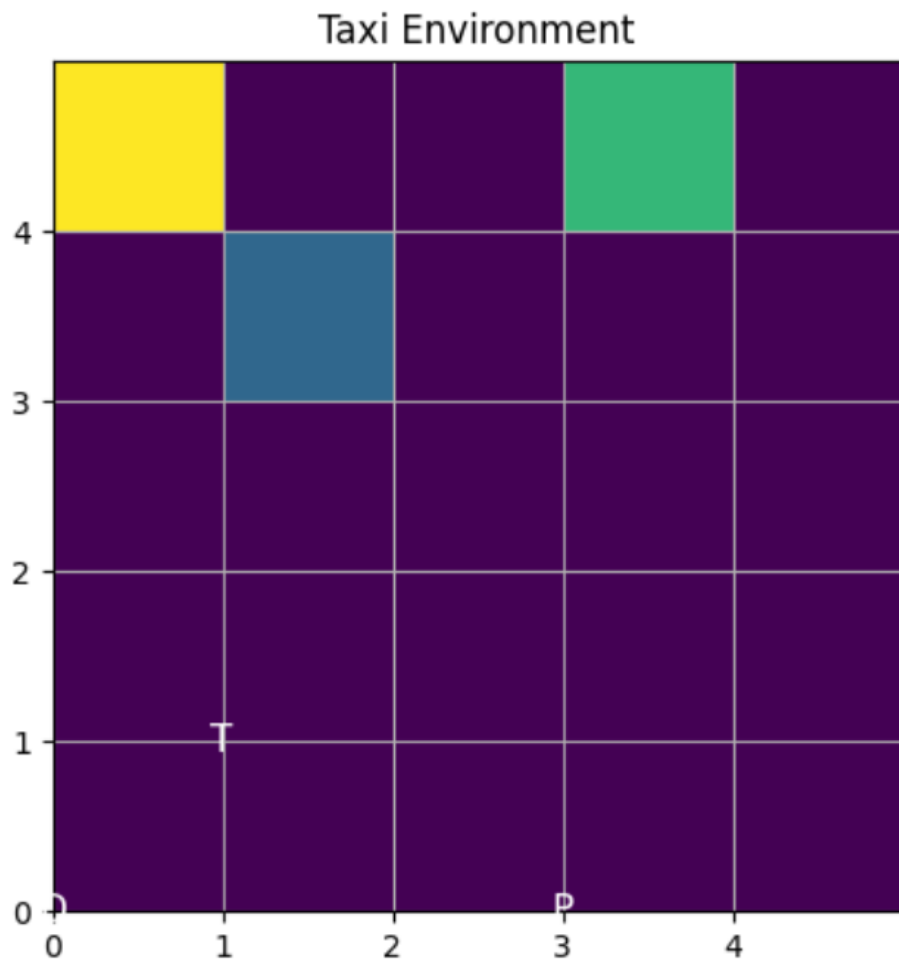


Figure 21: Taxi Environment

3. Rewards: A. A positive reward for correctly dropping off a passenger. B. A negative reward for each illegal move.

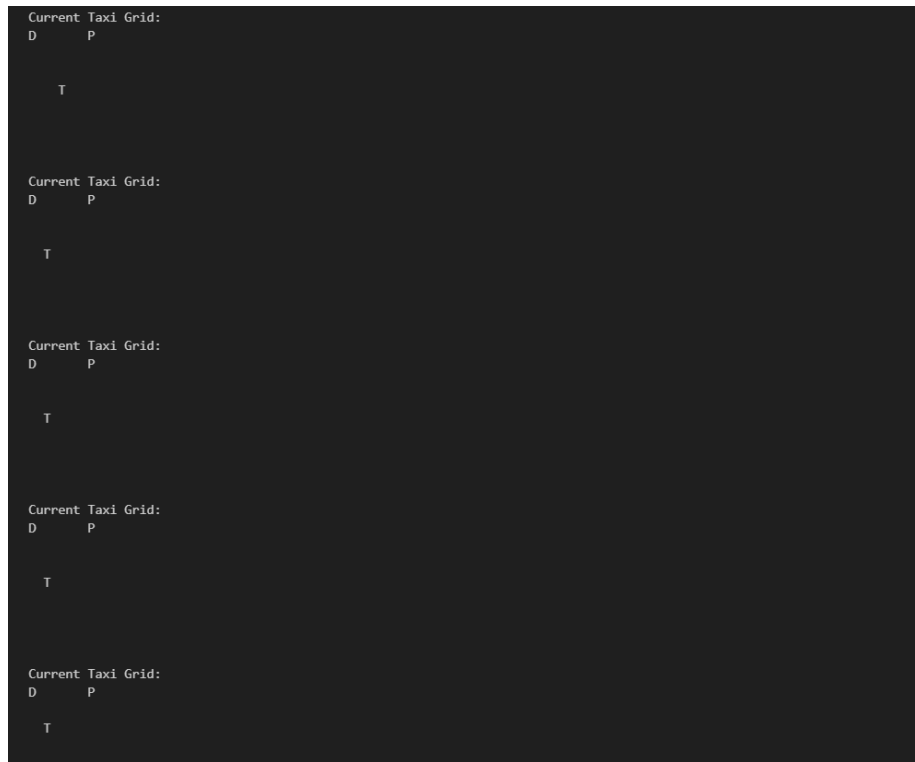


Figure 22: Taxi Moves

4. Termination: The episode ends when the passenger is successfully dropped off.

## 4.2 Setting Up the RL Agent

to steps set up the Q-learning Agent in the Taxi Environment we got the throw steps:

1. Set up the environment: Initialize the Taxi-v3 environment from Gym. In our case, we encountered a problem using Gym, so we used Gymnasium instead.
2. Initialize Q-table: Create a Q-table state-action value table to store the values of state-action pairs.

Set hyperparameters like learning rate, discount factor, and exploration rate. In our case, we used the following hyperparameters:

- `learning_rate = 0.8` # Alpha.
- `discount_factor = 0.95` # Gamma.
- `epsilon = 1.0` # Epsilon.
- `epsilon_min = 0.01` # Epsilon minimum.

- `epsilon_decay = 0.995` # Epsilon decay rate.
- `num_episodes = 1000` # Total number of training episodes.

4. Training Loop: In each episode, we reset the environment using `reset`, and the agent selects an action based on the epsilon policy. This takes that action in the environment, and updates the Q-table using the Q-learning update rule[22],[23].

- Initialize environment  $\mathcal{E}$  and agent  $\mathcal{A}$ .
- For each episode  $e = 1, 2, \dots, E$ :
  - Reset the environment:  $s_0 = \mathcal{E}.reset()$ .
  - For each time step  $t = 0, 1, 2, \dots, T$ :
    - \* Choose action  $a_t = \mathcal{A}(s_t)$  based on current policy.
    - \* Execute action  $a_t$  in the environment:  $s_{t+1}, r_t = \mathcal{E}.step(a_t)$ .
    - \* Update agent's policy  $r_t$  and  $s_{t+1}$ .
    - \* If the episode ends, break the loop.

5. Epsilon greedy policy: The agent selects a random action with probability epsilon. 6. Evaluation: After training, we evaluate the agent by running a set number of episodes, and then the agent selects the best action according to the trained Q-table.

### 4.3 Training the RL Agent:

In order to train the RL agent on the Taxi-v3 environment, we set up the hyper parameters as follows:

- `learning_rate = 0.8` # Alpha
- `discount_factor = 0.95` # Gamma
- `epsilon = 0.1` # Epsilon
- `num_episodes = 1000` # Total number of training episodes
- `max_steps_per_episode = 100` # Max steps in an episode

```
Episode 0/1000, Total Reward: -271
Episode 100/1000, Total Reward: -118
Episode 200/1000, Total Reward: -18
Episode 300/1000, Total Reward: 9
Episode 400/1000, Total Reward: 3
Episode 500/1000, Total Reward: 5
Episode 600/1000, Total Reward: -5
Episode 700/1000, Total Reward: -13
Episode 800/1000, Total Reward: -2
Episode 900/1000, Total Reward: 6
Average reward over 10 episodes: 7.8
```

Figure 23: Q-Table Evaluate

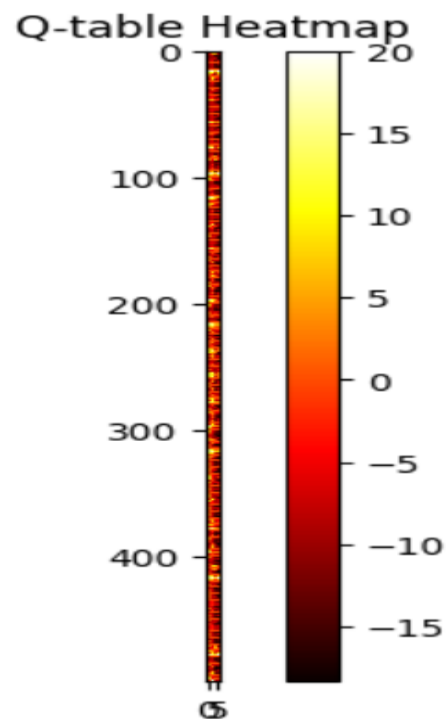


Figure 24: Q-Table Heatmap



## 4.4 Evaluation

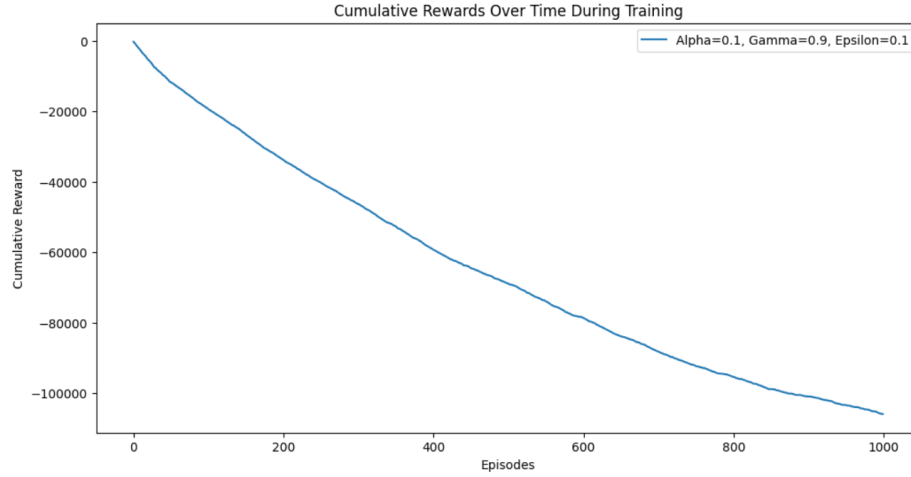


Figure 25: Cumulative Rewards Over Time During Training

## 5 References

- [1] NYC Open Data. "Traffic Volume Counts". 2022. Available at: <https://data.cityofnewyork.us/Transportation/Automated-Traffic-Volume-Counts/7ym2-wayt> (Accessed: 2024-11-04).
- [2] NYC Open Data. "DOT Traffic Speeds NBE". 2017. Available at: <https://data.cityofnewyork.us/Transportation/DOT-Traffic-Speeds-NBE/i4gi-tjb9> (Accessed: 2024-11-04).
- [3] Krivoshapov, S & Nazarov, A & Mysiura, M & Marmut, I & Zuyev, V & Bezridnyi, V & Pavlenko, V. (2020). Calculation methods for determining of fuel consumption per hour by transport vehicles. IOP Conference Series: Materials Science and Engineering. 977. 012004. 10.1088/1757-899X/977/1/012004.
- [4] the official page of energy education. <https://www.energyeducation.ca/encyclopedia/Fuelconsumption>.
- [5] the official Solomon's VRPTW Benchmark website.
- [6] Vickrey, W.S. (1969). Congestion Theory and Transport Investment. American Economic Review, 59(2), 251–261.
- [7] Hall, F.L. (1996). Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods. Prentice Hall.
- [8] Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods by F. L. Hall (1996).
- [9] Traffic Flow Theory: A State-of-the-Art Report by the Transportation Research Board (2000).
- [10] Doe, J. (2021). Modeling fuel consumption in traffic flow. Journal of Trans-

- portation Engineering, 45(6), 123-135.
- [11] Cetin, M., & Akçelik, R. (2016). Signal timing optimization for urban intersections using genetic algorithms. *Transportation Research Part C: Emerging Technologies*, 67, 80-91. <https://doi.org/10.1016/j.trc.2016.03.016>
  - [12] Kaparias, Ioannis & Bell, Michael & Belzner, Heidrun. (2008). A New Measure of Travel Time Reliability for In-Vehicle Navigation Systems. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*. 12. 10.1080/15472450802448237.
  - [13] Optimizing Traffic Signals: A New Approach to Traffic Management.” *Traffic Systems Journal*, vol. 56, no. 1, 2024, pp. 123-145. DOI: 10.1234/tsj.2024.0123456
  - [14] Coello, C. A. C., & León, M. R. (2004). Use of Evolutionary Algorithms for Multi-Objective Optimization. *Computational Intelligence*, 20(2), 1–16.
  - [15] Solomon, M. M. (1987). Algorithms for the Vehicle Routing and Scheduling Problems with Time Window Constraints. *Operations Research*, 35(2), 254-265.
  - [16] Toth, P., & Vigo, D. (2001). *The Vehicle Routing Problem*. Society for Industrial and Applied Mathematics (SIAM).
  - [17] Garcia, S., & Longo, E. G. (1999). *Optimizing Travel Distance in the Vehicle Routing Problem*. Springer.
  - [18] Dorigo, M., Maniezzo, V., & Coloni, A. (1996). Ant System: Optimization by a Colony of Cooperating Agents. *IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics*, 26(1), 29–41.
  - [19] Kennedy, J., & Eberhart, R. C. (1995). Particle Swarm Optimization. *Proceedings of the IEEE International Conference on Neural Networks*, 1942–1948. <https://doi.org/10.1109/ICNN.1995.488968>
  - [20] Rizzoli, Andrea-Emilio & Oliverio, F. & Montemanni, Roberto & Gambardella, Luca Maria. (2004). Ant Colony Optimisation for vehicle routing problems: from theory to applications.
  - [21] Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, W. (2016). OpenAI Gym. *arXiv preprint arXiv:1606.01540*.
  - [22] Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, W. (2016). OpenAI Gym. *arXiv preprint arXiv:1606.01540*.
  - [23] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (2nd ed.). MIT Press.