Evolutionary artificial intelligence and robotics

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November 2024

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: Trafic 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

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]:

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

where:

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

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

where:

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

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

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]:

$$v_{\text{avg}} = \frac{\text{Total Distance}}{\text{Total Time}} \tag{4}$$

For multiple vehicles, the average speed is:

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

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:

$$v_{\text{avg\_hour}} = \frac{\sum_{i=1}^{n} v_i}{n} \tag{6}$$

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.

```python
# 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:

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

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]:

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

Where:

- n is the number of time intervals,

- 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,
- 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.

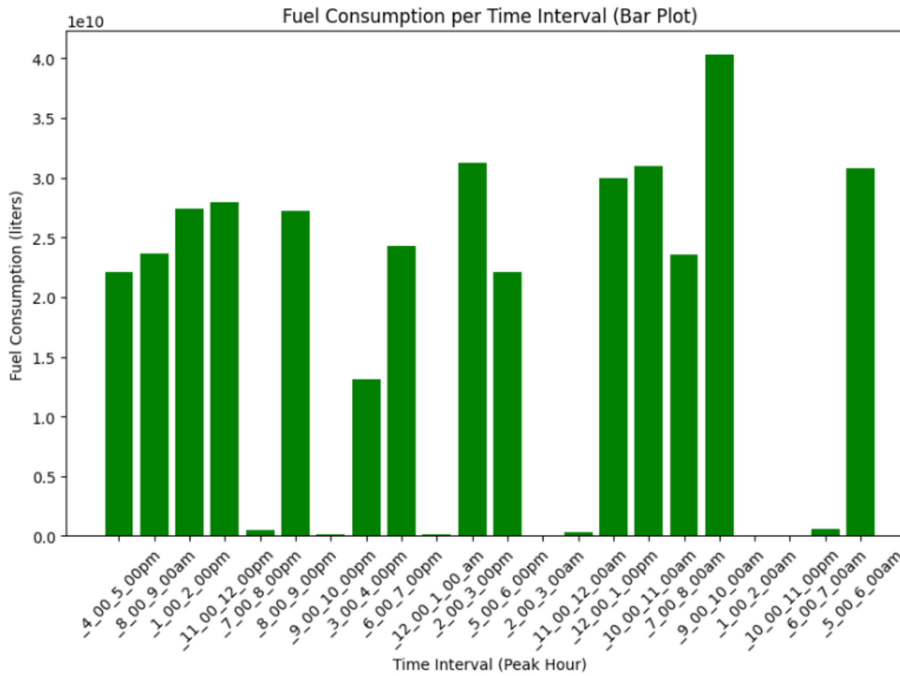

Figure 11: Fuel consumption per time interval

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:

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

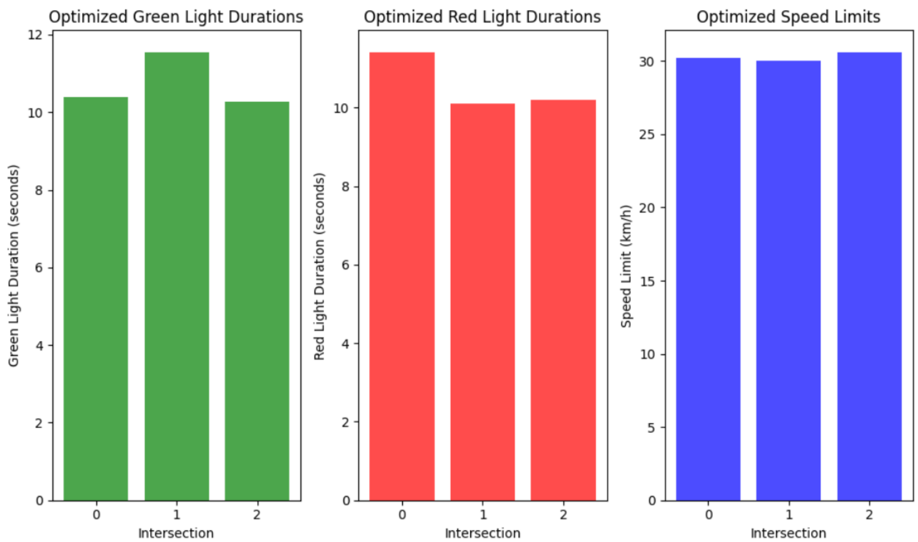

Figure 12: Optimizing Red,Green, Yellow Light Duration

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
- Red_i = Duration of red light for vehicle i (in seconds)
- Speed_i = Speed limit for vehicle i (in km/h or m/s)

- C_{red} = Constant factor for red light fuel consumption (e.g., 0.1)
- C_{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:
A. The first element represents speed within the range [30, 120] km/h.
B. The second element represents green light duration within the range [10, 60] seconds.
C. 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 decition 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].

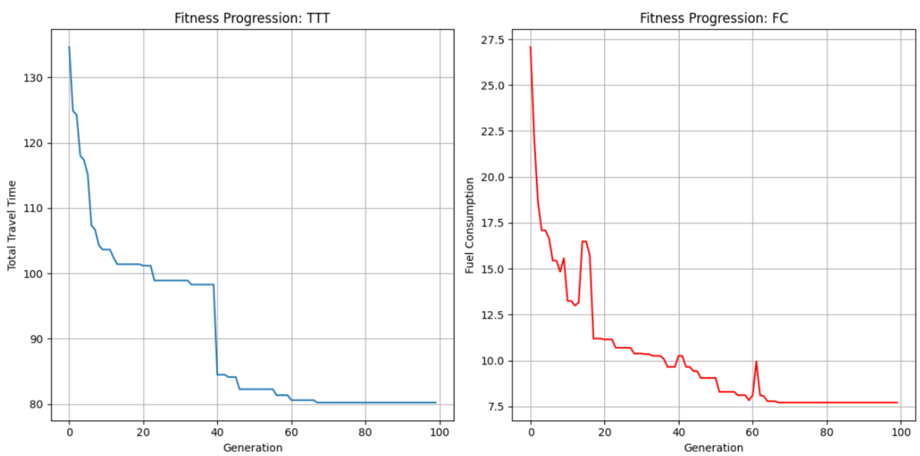

Figure 13: TTT, and FC Analyse

2 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

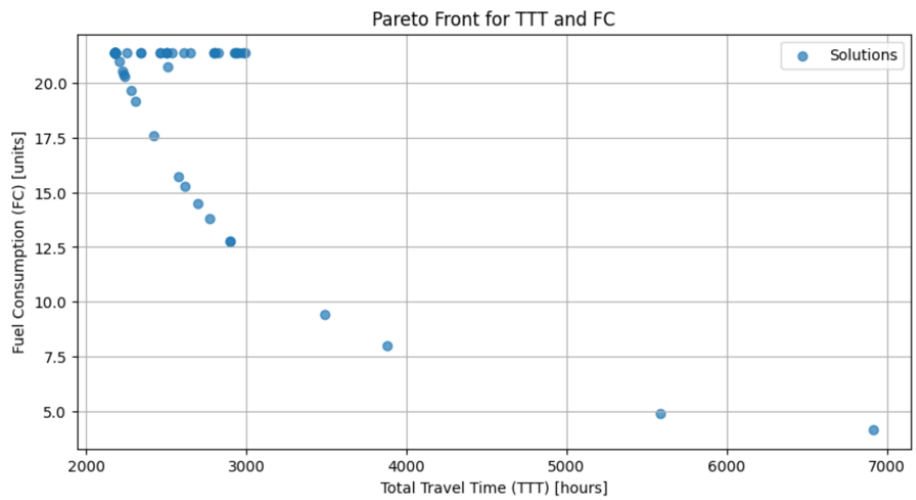

Figure 14: TTT

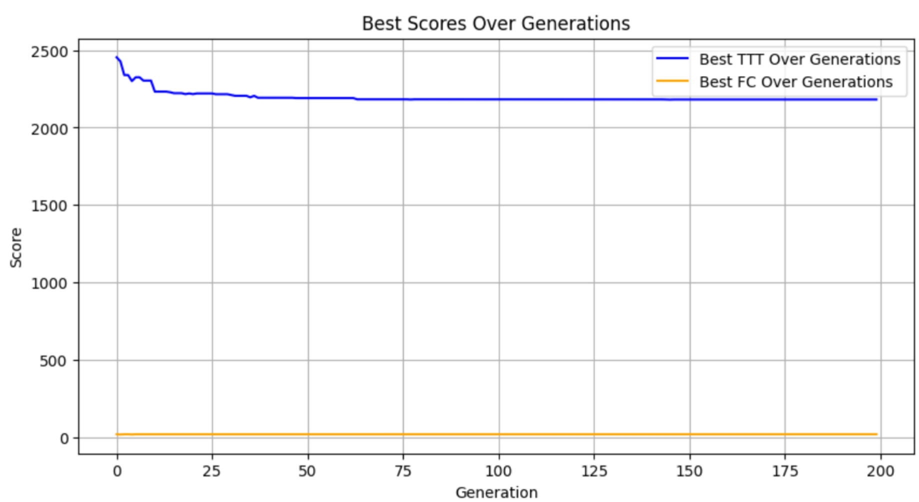

Figure 15: The best score over generation

walls and other obstacles. We used Dataset/Environment: Taxi-v3 on OpenAI Gym.

2.1 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: Ï. 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.

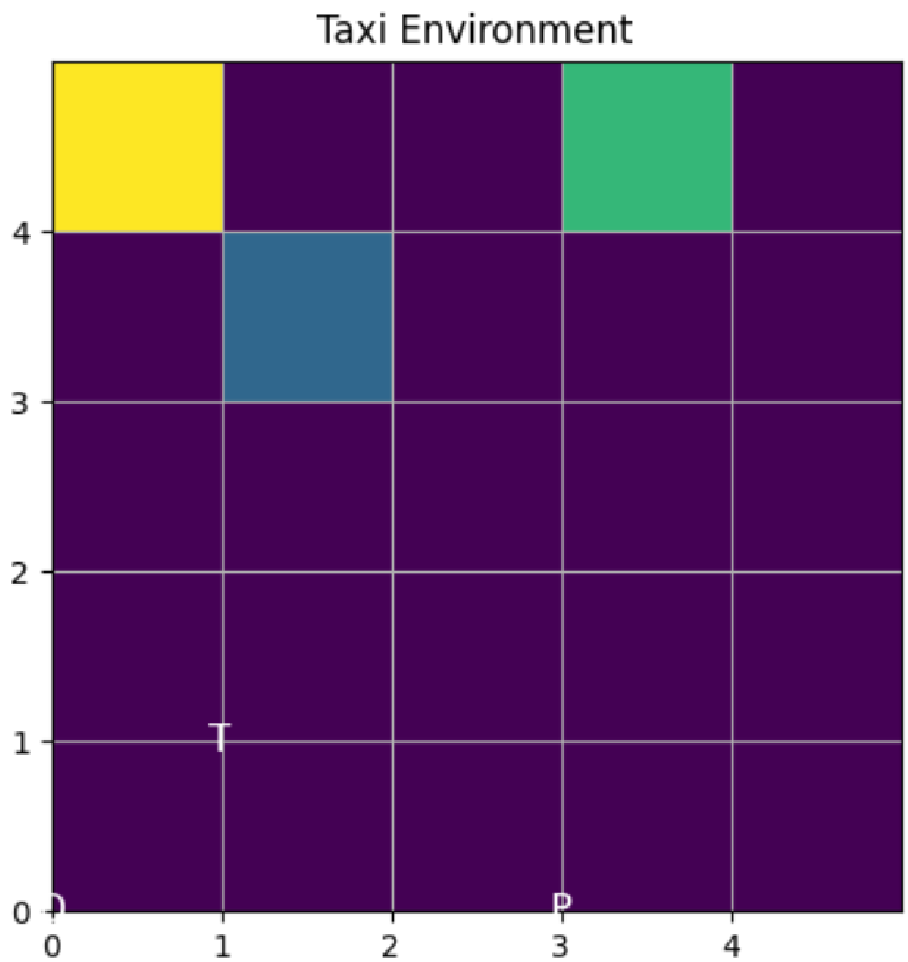

Figure 16: Taxi Environment

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

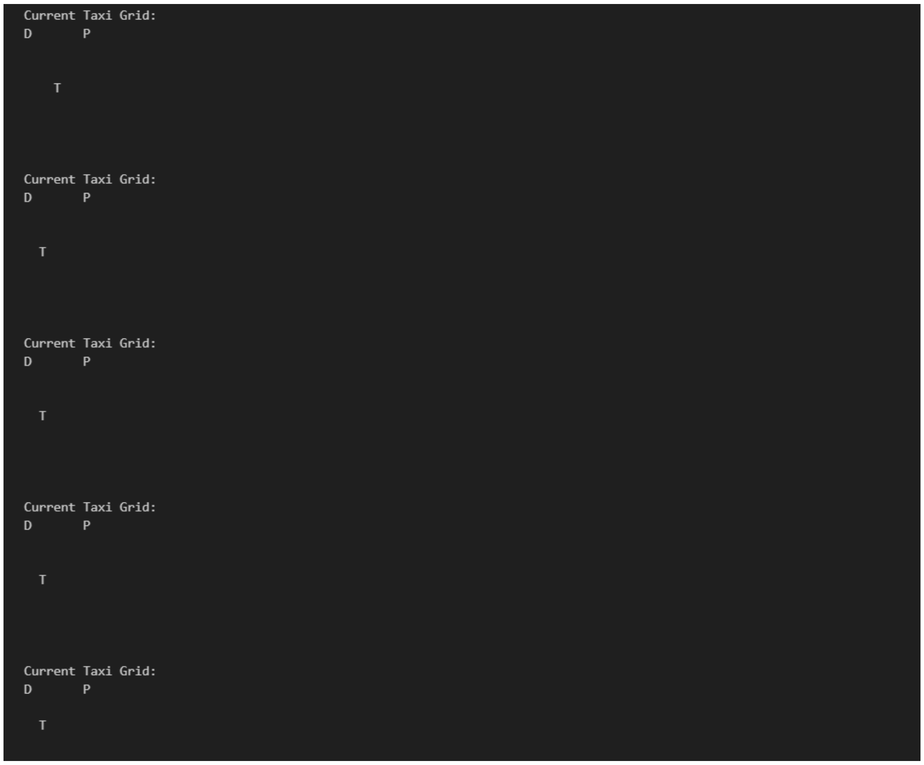

Figure 17: Taxi Moves

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

2.2 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 $e = 1, 2, \ldots, E$:
  - Reset the environment: $s_0 = \mathcal{E}.reset()$.
  - For each time step $t = 0, 1, 2, \ldots, T$:
    * 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 policyr_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.

2.3 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 18: Q-Table Evaluate

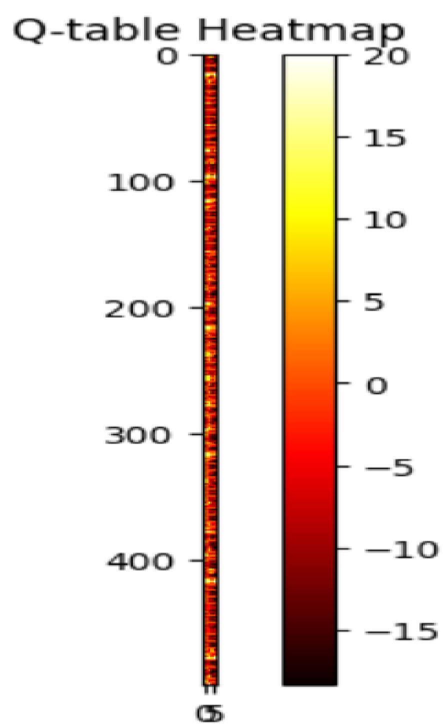

Figure 19: Q-Table Heatmap

2.4 Evaluation

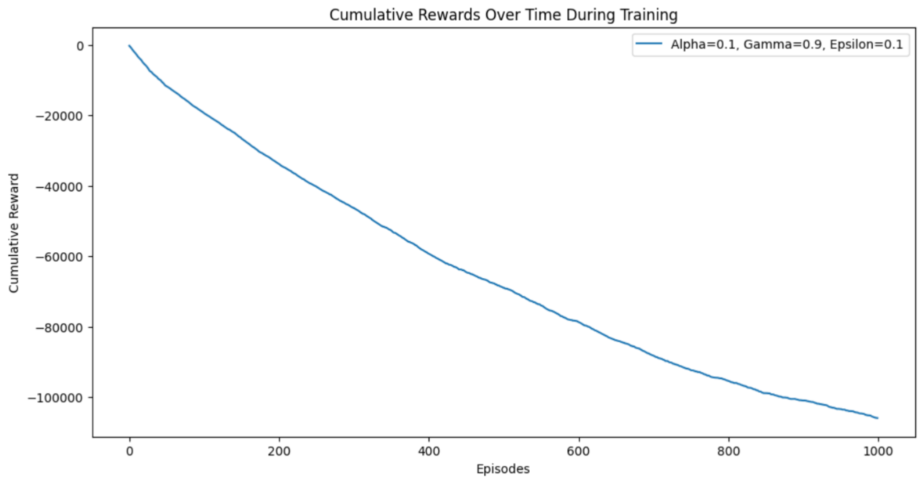

Figure 20: Cumulative Rewards Over Time During Training

3 Refrences

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