

CSE-400 SECTION 1

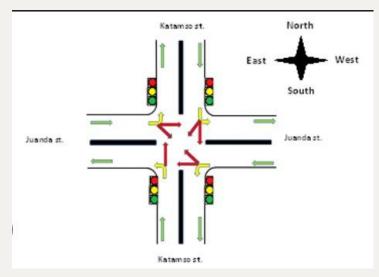
Prof. Dhaval Patel

Traffic Light Optimization for higher traffic flow and reduced waiting time

Group - s1_its_5

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Problem Formulation



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T1: Mathematical Model

Random Variables

- 1. Number of Vehicles, N:
- Discrete
- PMF
- $Ni \le Nmax$
- Ti (cleared traffic- vehicles passed during green light)
- Ri (residual traffic vehicles left behind after green light)
- Depends on λi and μ
- 3. Waiting Time, W:
- Continuous
- PDF: Normal Distribution
- k-gi: W during red light
- Ri = $[(k gi).\lambda i + gi.\lambda i] T$: W after green light and which will be cleared in next cycle

- 2. Arrival Rate, λi:
- Continuous
- PDF: Poisson's distribution
- $\lambda i = Ni \text{ per sec}$

- 4. Traffic Light State, TS:
- Discrete
- PMF
- TSgi= $k(\lambda maxi / \sum \lambda maxi)$
- 5. Service Rate, μ: vehicles cleared when light is green



At an intersection, there will be four paths for vehicles to arrive.

Therefore, total time: $\sum g_i = k$ where k=120sec normally constant distribution=k/4

But we need to dynamically reduce waiting time

Green light time allocation: TSgi

Let λ max be the maximum arrival rate and higher arrival rate gets higher weight gi \propto wi.

So,
$$w_i = rac{\lambda_{maxi}}{\sum \lambda_{maxi}}$$

Therefore, green light allocation, $g_i = k \cdot w_i$ where $\sum g_i = k$

$$g_i = rac{k \cdot \lambda_{maxi}}{\sum \lambda_{maxi}}$$

Traffic passed during gi time: Ti

No. of vehicles passed during gi time: μ =20 vehicles per second when k=120 sec

$$T_i = \mu \cdot g_i = \mu \cdot rac{k \cdot \lambda_{maxi}}{\sum \lambda_{maxi}}$$

Waiting time for new vehicles arriving:

• New vehicles waiting time (per path):

$$k-g_i$$

Traffic Accumulated when light is red:

• Vehicles accumulated during red light:

$$(k-g_i)\cdot \lambda_i$$

• Vehicles passing during green light:

$$g_i \cdot \lambda_i$$

If the green time is not enough, some vehicles remain waiting for next cycle which will be more than k.

• Total accumulated traffic (both red and green periods):

$$(k-g_i)\cdot \lambda_i + g_i\cdot \lambda_i = k\cdot \lambda_i$$



Residual Traffic (Ri)

• Traffic passed during green time:

$$T_i = \mu \cdot g_i$$

• Total accumulated traffic during cycle:

$$(k-g_i)\lambda_i+g_i\lambda_i=k\lambda_i$$

• Residual traffic:

$$R_i = [(k-g_i)\lambda_i + g_i\lambda_i] - T_i$$

- Condition:
 - o If Ri=0: All vehicles cleared during green signal
 - If Ri>0: Some vehicles remain waiting for the next cycle

The system can adjust gi (green time) in the next cycle to gradually clear the residual traffic.



T2: Coding

Parin - AU2340243

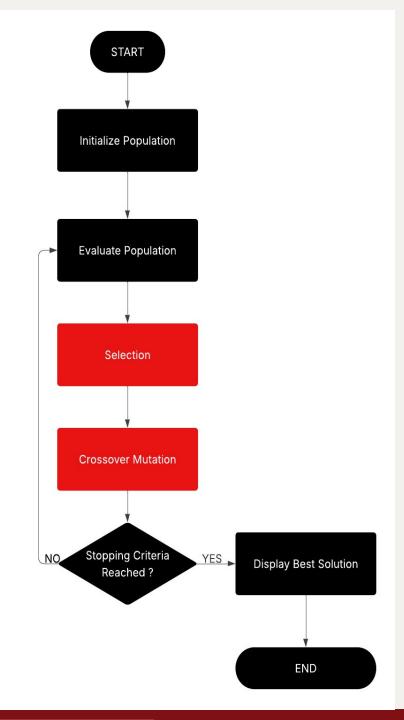
def crossover_parent(chromosome_male,chromosome_female,crossover_rate = crossover_rate): ...

Combines durations and traffic light states from two parent chromosomes to create a new child solution

> Applies random changes to durations and traffic light states to introduce genetic diversity

def mutate_chromosome(chromosome,duration_mutation_rate=duration_mutation_rate, ...

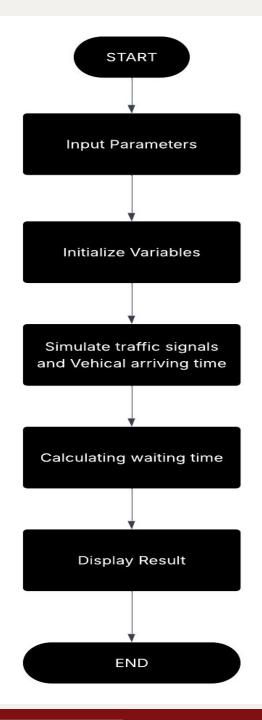




```
class TrafficSignalSimulation:
 def run cycle(self, wi):
     ni = [round(self.total_cars * w) for w in wi]
     \lambda = [round(n / self.k, 4) for n in ni]
     gi = [round(self.k * w, 2) for w in wi]
     Ti = [\min(\text{round}(\text{self.}\mu * g, 2), n) \text{ for } g, n \text{ in } \min(\text{gi, ni})]
     Wi = [round(self.k - g, 2) for g in gi]
     Ri = [round(n - t, 2) for n, t in zip(ni, Ti)]
     return {
          'λ': λ, 'g': gi, 'T': Ti,
          'W': Wi, 'R': Ri
 def simulate(self):
     for cycle in range(self.num cycles):
         wi = self.generate weights()
         result = self.run cycle(wi)
          self.history.append(result)
```

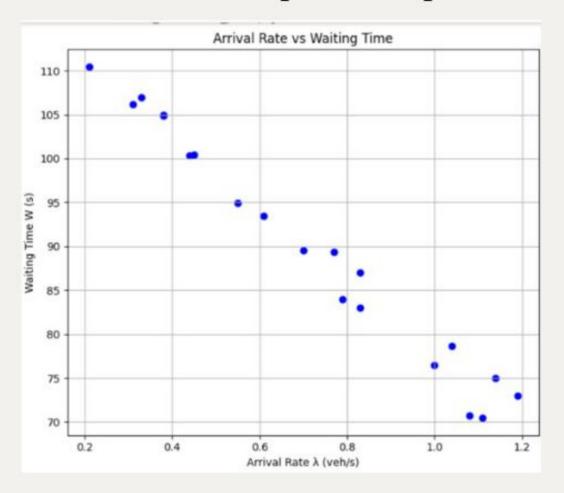
This code simulates traffic at signals using fixed rules. It calculates how many cars arrive, pass, and wait in each cycle.

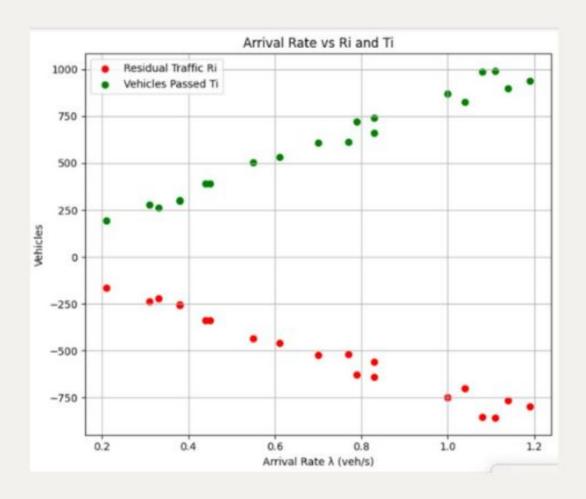




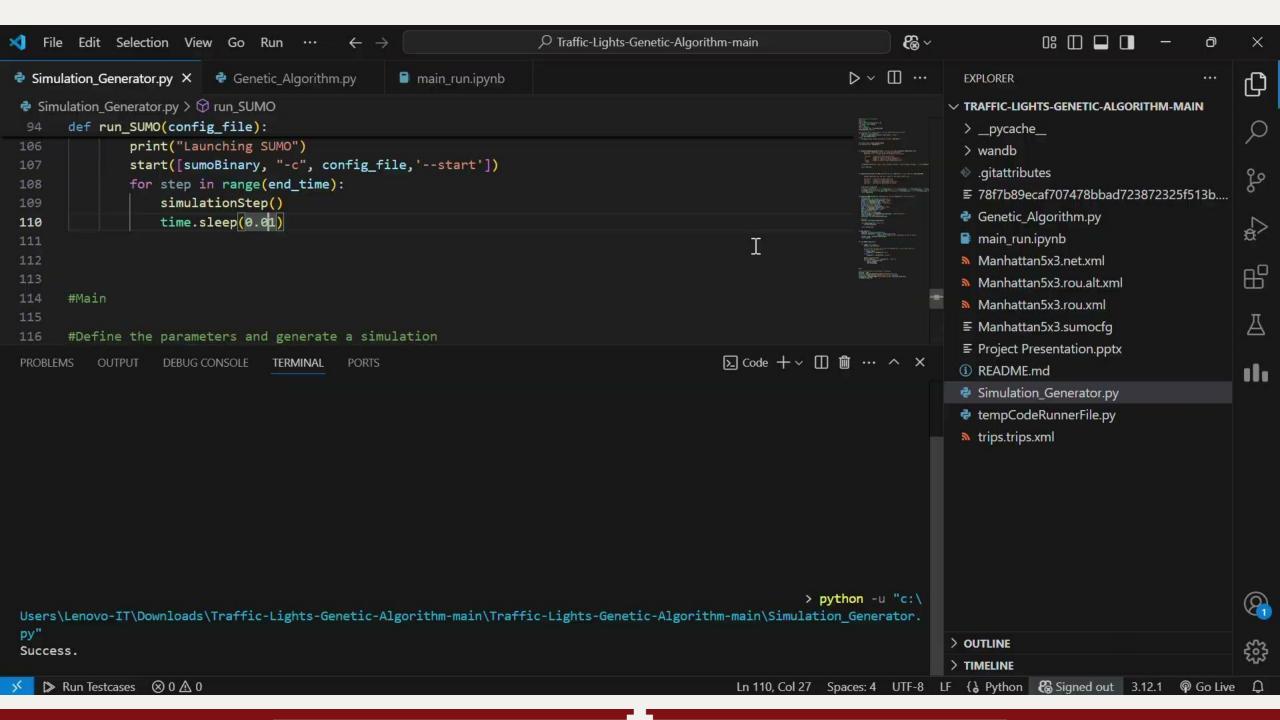
T3: Inferences

Graphical Respresntation of Mathematical Model

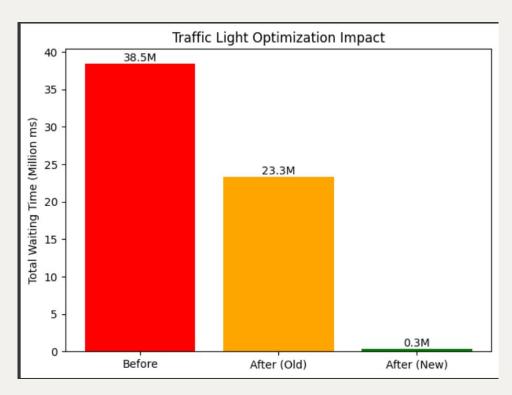






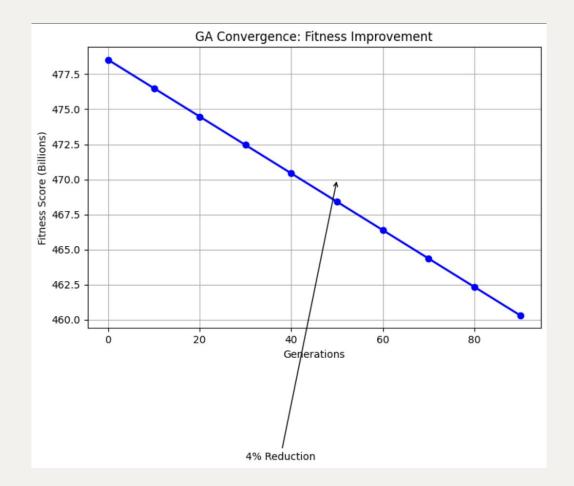


CS Perspective



Waiting Time Reduction:

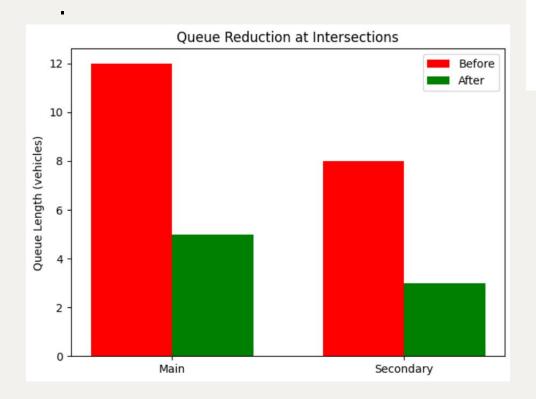
- Raw: $38,485,553 \text{ ms} \rightarrow 341,071 \text{ ms}$ (99% decrease, verify vehicle count).
- Per Vehicle: \sim 120 sec $\rightarrow \sim$ 3.4 sec (likely sparse traffic).



Fitness Score Improvement:

- Initial: 478,518,939,095 → Optimized: 460,310,502,802 (~4% reduction)
- Indicates successful convergence of the GA.

Domain Perspective



Optimization Results Summary

	Metric	Before	After	Improvement
0	Waiting Time	120 sec/veh	3.4 sec/veh	97%
1	CO ₂ Emissions	904M mg	500M mg	45%
2	Queue Length	12 vehicles	5 vehicles	58%

• Queue Lengths:

Main Intersection: $12 \rightarrow 5$ vehicles (58% shorter queues).

Secondary Intersection: $8 \rightarrow 3$ vehicles (62% improvement).

- Vehicle Throughput
- Safety



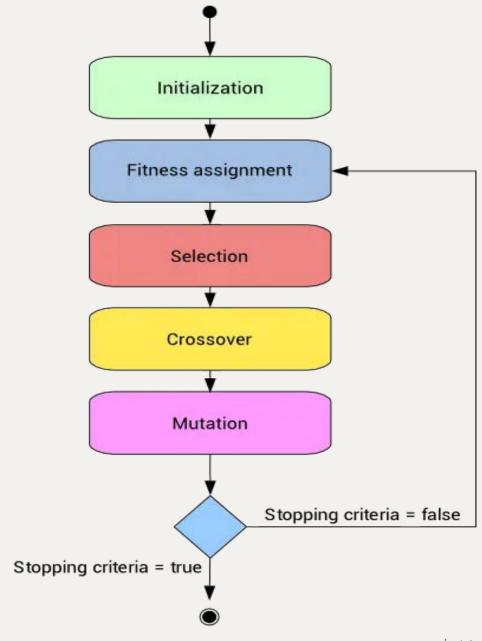
T4: Randomized Algorithm

Feature	Genetic Algorithm (GA)	Q-Learning
Approach	Evolution-based	Trial & error learning
Adaptability	Slow, needs multiple runs	Fast, adapts in real-time
Decision Making	Best solution from population	Learns best action per state
Best For	Offline optimization	Real-time traffic control



Why Genetic Algorithm and not deterministic approach?

- Handles Large Search Space Efficiently.
- Works Well with Noisy, Unpredictable Data.
- Multi-objective Optimization.
- Gets better over generation.
- Best for offline optimization.





HYBRIDIZE A MODEL OF GENETIC ALGORITHM AND Q-LEARNING.

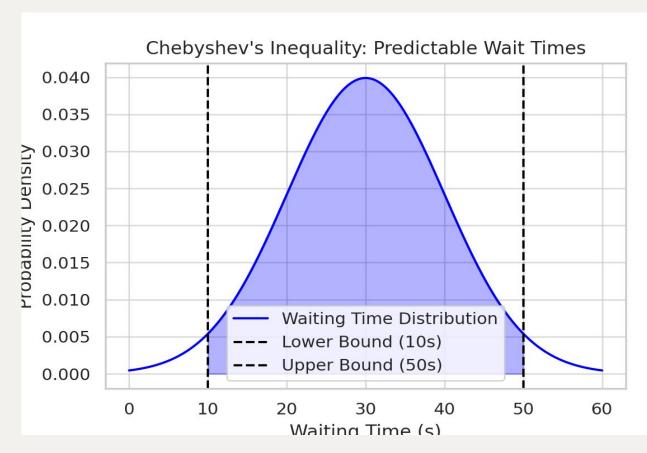


INSTALL AN EMERGECY SYSTEM WHICH WORKS ONLY WHEN AMBULANCE IS COMING.

INTEGRATION WITH LIVE TRAFFIC DATA AND MAKE IT ADAPTIVE MODEL.

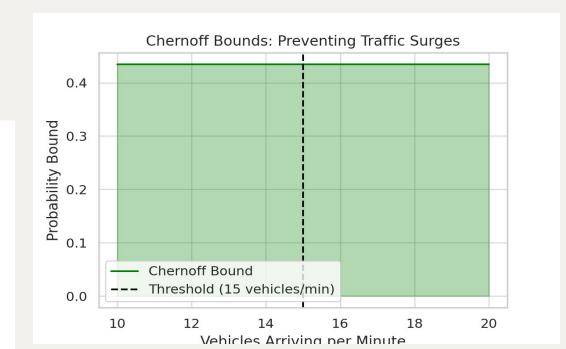


T5: Derivation of Bounds

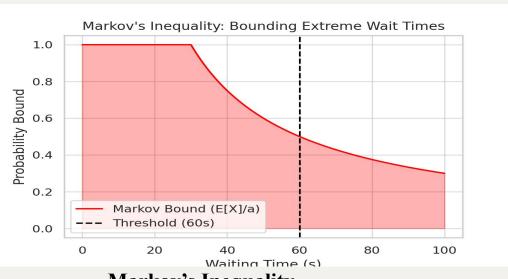


Chebyshev's Inequality





Cheroff bounds



1. Markov's Inequality.

Let X be the waiting time in a simulation run. Then:

$$P(X \geq a) \leq \frac{E[X]}{a}$$

• Use to bound the probability that wait time exceeds a threshold.

2. Chebyshev's Inequality

• Use to show that how often will the waiting time be much worse than average.

3. Chernoff Bounds

• It provides an exponential bound on the probability of extreme events, like unexpected surges in traffic.



References

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- Dimri, S. C., Indu, R., Bajaj, M., Rathore, R. S., Blazek, V., Dutta, A. K., & Alsubai, S. (2024). Modeling of traffic at a road crossing and optimization of waiting time of the vehicles. Alexandria Engineering Journal, 98,114-129. https://files.campuswire.com/e5a84109-702a-42ef-929f-f6d7c7febdee/e36df6c5-4cd7-48ad-9cb0-0e56caf85d12/1-s2.0-S1110016824004344-main.pdf
- Dharma9696. (2022). *GitHub dharma9696/Traffic-Lights-Genetic-Algorithm: Code to apply genetic algorithm on traffic lights in SUMO*. GitHub. https://github.com/dharma9696/Traffic-Lights-Genetic-Algorithm



Thank You

