

Traffic Signal Optimization using SLSQP and Projected Gradient Descent

A Delay Minimization Approach for a Four-Phase Intersection

Signal Crawlers

1 Problem Statement

The primary objective of this project is to optimize the allocation of green signal durations at a four-phase urban intersection in order to minimize total vehicular delay. With a fixed cycle length and predetermined lost time, each phase competes for a portion of the effective green time, and the overall efficiency of the intersection depends on how this limited resource is distributed. Because traffic arrival rates vary across phases, an equal distribution of green time is rarely optimal and can lead to excessive queues, longer delays, and uneven performance across approaches.

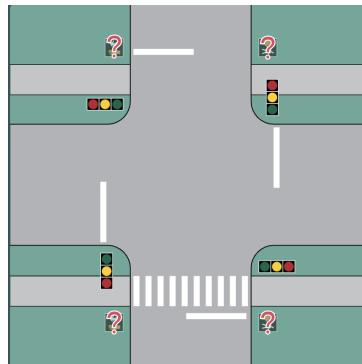


Figure 1: 4 – Way – intersection

To address this, the problem is formulated as a constrained nonlinear optimization task where the decision variables are the green times assigned to each phase. These green times must satisfy operational requirements such as minimum green durations, upper bounds, and a fixed total green constraint. The goal is to find a feasible set of green times that reduces congestion, balances service among approaches, and improves the overall performance of the intersection under realistic traffic demands.

2 Motivation

Efficient signal timings reduce delay, maintain stable queues, and improve throughput. When traffic arrivals vary across phases, equal green splits are inefficient and can lead to:

- Long queues at high-demand approaches,

- Poor vehicle discharge,
- Oversaturation,
- Unbalanced intersection performance.

Optimization provides a systematic method to match green times with traffic demand and minimize delay.

3 Mathematical Model

Objective Function The optimization seeks to minimize the sum of delays across all phases. Delay is modeled with Webster's uniform delay formula, which captures how insufficient green time sharply increases delay due to higher saturation levels. This makes the objective function smooth, differentiable, and suitable for gradient-based methods like SLSQP and PGD.

3.1 Delay Model

For phase i :

$$d_i = \frac{0.5C(1 - g_i/C)^2}{1 - X_i}, \quad X_i = \frac{\lambda_i}{s_i(g_i/C)}.$$

Total delay:

$$D(g) = \sum_{i=1}^4 \lambda_i d_i.$$

Non-Convexity via Hessian Analysis

Consider the total delay for a single phase:

$$D_i(g_i) = \lambda_i \frac{0.5C(1 - g_i/C)^2}{1 - X_i}, \quad X_i = \frac{\lambda_i}{s_i g_i / C}.$$

The first derivative with respect to g_i is:

$$\frac{dD_i}{dg_i} = \lambda_i \frac{(1 - g_i/C)(1 - X_i) + 0.5C(1 - g_i/C)^2 \frac{d(-X_i)}{dg_i}}{(1 - X_i)^2}.$$

The second derivative (Hessian in 1D) is:

$$\frac{d^2 D_i}{dg_i^2} = \text{complex function of } g_i, \lambda_i, s_i, C.$$

Observation: The second derivative changes sign for different values of g_i :

- For small g_i , $X_i = \lambda_i/(s_i g_i / C)$ becomes large, making $1 - X_i$ small and the denominator dominates, yielding $\frac{d^2 D_i}{dg_i^2} > 0$.
- For large g_i , X_i becomes small, and the quadratic numerator dominates, yielding $\frac{d^2 D_i}{dg_i^2} < 0$.

Thus, the second derivative is not always non-negative, implying the Hessian is not positive semi-definite. Therefore, the total delay function $D(g)$ is **non-convex**.

3.2 Variable Definitions

Variable	Definition	Units
λ_i	Arrival rate	veh/s
s_i	Saturation flow	veh/s
g_i	Green time for phase i	s
C	Cycle time	s
L	Lost time	s
X_i	Degree of saturation	—
d_i	Delay per vehicle	s

4 Constraints

The feasible region is defined by:

$$\begin{aligned} g_i &\geq g_{\min} = 5 \text{ s} \\ g_i &\leq g_{\max} = 0.8G_{\text{total}} \\ \sum_{i=1}^4 g_i &= G_{\text{total}} \end{aligned}$$

Projection onto this feasible set is performed using a bounded simplex projection.

5 Optimization Methods

we implemented two optimization methods for minimizing the total intersection delay. The first is Projected Gradient Descent (PGD), which manually updates the green splits using a numerical gradient and projects them onto the feasible region. The second is SLSQP from SciPy, which handles both equality and inequality constraints automatically for a more fast and efficient solution.

5.1 SLSQP

Correctness and Robustness of SLSQP SLSQP enforces equality and inequality constraints directly through a sequential quadratic programming framework. Its quasi-Newton updates result in fast and reliable convergence toward feasible green-time distributions. In this project, SLSQP consistently produced stable solutions under different initial conditions and proved effective for nonlinear delay minimization.

$$\min_g D(g) \quad \text{s.t. constraints on } g$$

5.2 Projected Gradient Descent (PGD)

Correctness and Robustness of PGD Projected Gradient Descent (PGD) updates the green times via gradient descent followed by projection onto the feasible region:

$$g_{k+1} = \Pi_{\mathcal{F}}(g_k - \alpha \nabla D(g_k)),$$

where $\Pi_{\mathcal{F}}$ denotes the projection onto the feasible set \mathcal{F} , and $D(g_k)$ is the total delay.

In PGD, the step size α_k is chosen to satisfy the **Armijo condition**:

$$f(x_k - \alpha_k \nabla f(x_k)) \leq f(x_k) - c \alpha_k \|\nabla f(x_k)\|^2,$$

where:

- x_k is the current iterate,
- $\nabla f(x_k)$ is the gradient at x_k ,
- α_k is the step size,
- $c \in (0, 1)$ is a small constant (e.g., $c = 10^{-4}$).

The step size is determined using **backtracking line search**:

$$\alpha_k \leftarrow \beta \alpha_k, \quad \text{until the Armijo condition is satisfied,}$$

where $\beta \in (0, 1)$ is the reduction factor, typically $\beta = 0.5$.

Although slower than SLSQP, PGD is transparent, easy to tune, and consistently converged to solutions close to SLSQP's, confirming the reliability of the optimal green times. It also serves as an independent cross-validation method.

6 Methodology

This study models a four-phase traffic intersection, optimizing green times to minimize total vehicle delay. Baseline equal green-time allocation is compared with two optimization methods: Sequential Least Squares Programming (SLSQP) and Projected Gradient Descent (PGD). Both methods respect cycle-time constraints and green-time bounds, with PGD projecting iterates onto the feasible set. Convergence and performance are evaluated through per-iteration delay, and results are visualized in terms of total delay, green-time allocation, and queue evolution.

1. Define arrival rates, saturation flows, and timing parameters.
2. Construct the total delay model using Webster's formula.
3. Initialize green times with equal splits.
4. Optimize green times using SLSQP for fast and reliable results.
5. Run PGD for independent verification and comparison.
6. Record iteration histories for convergence analysis.

7 Results and Discussion

Results, Plots, Discussion and Analysis Both SLSQP and PGD produced substantial delay reductions compared to the equal-split baseline. SLSQP converged quickly, while PGD displayed stable, gradual improvement. Visualizations confirm that optimized timings reduce queue lengths and distribute green times proportional to demand.

7.1 Delay Comparison

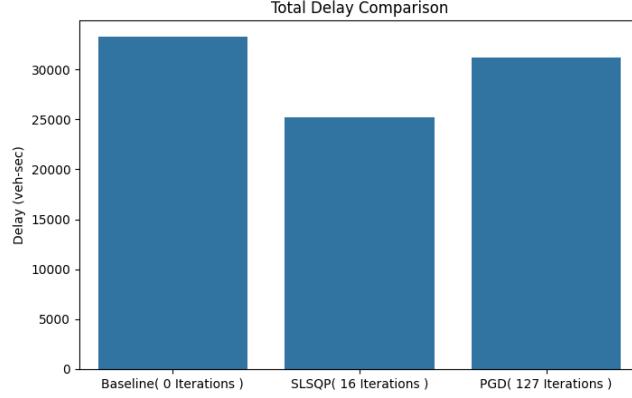


Figure 2: Delay comparison: Baseline vs SLSQP vs PGD

Total Delay Comparison This bar chart compares the total network delay across three scenarios: the baseline signal timing plan, the SLSQP optimization method, and the PGD optimization method. The results show that SLSQP achieves the lowest delay, significantly reducing overall congestion, while PGD also improves performance relative to the baseline but to a lesser extent. .

7.2 PGD Convergence

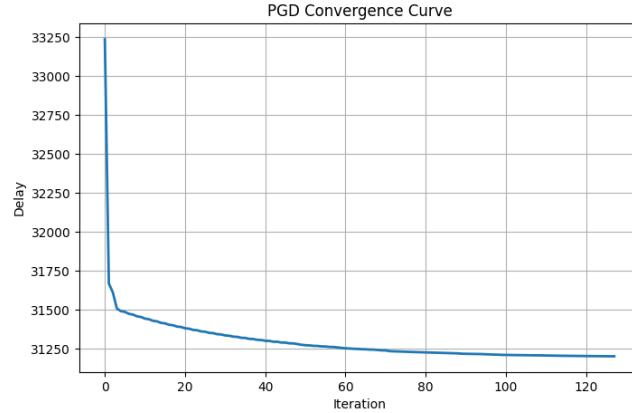


Figure 3: PGD convergence curve

PGD Convergence Curve This line plot shows the decrease in total delay as the PGD algorithm iteratively updates signal timings. The steep drop in the early iterations indicates rapid initial improvement, followed by gradual convergence toward a stable minimum, demonstrating the algorithm’s steady and consistent optimization behavior.

7.3 Optimized Green Times

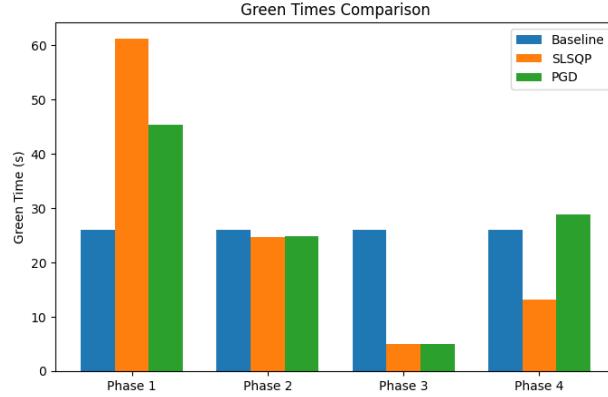


Figure 4: Optimized green-time distribution

Green Times Comparison

Green Times Comparison This grouped bar chart illustrates how green time allocations differ across four signal phases for the baseline, SLSQP, and PGD solutions. SLSQP heavily prioritizes Phase 1, while PGD distributes green times more evenly. Compared to both optimization methods, the baseline exhibits uniform phase lengths, highlighting the adaptive nature of the optimized timings.

7.4 Queue Simulation

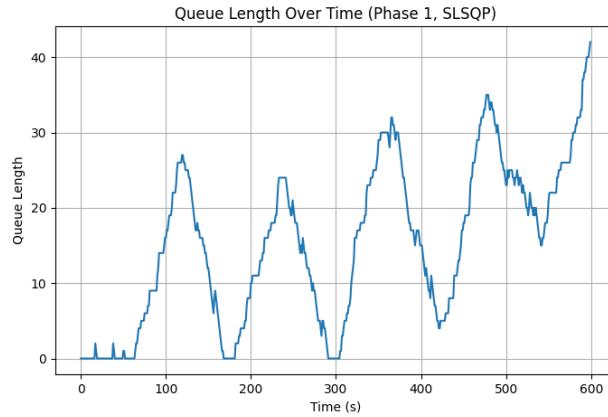


Figure 5: Queue simulation for optimized Phase 1

Queue Length Over Time (Phase 1, SLSQP) This time-series plot presents the evolution of queue length in Phase 1 under the SLSQP-optimized signal plan. Queue lengths fluctuate in response to varying traffic demand, with several peaks and dissipations, illustrating how the optimized green times respond dynamically to congestion patterns.

7.5 SLSQP Convergence

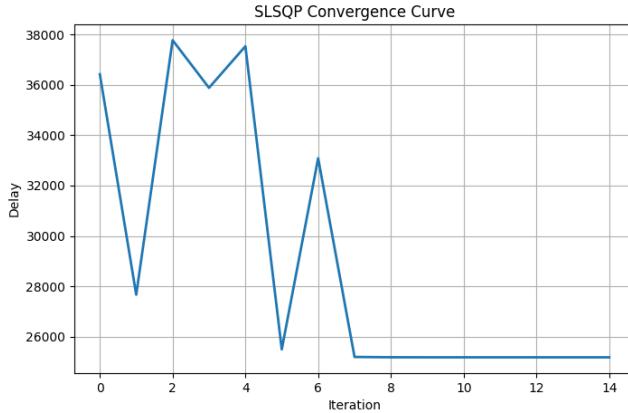


Figure 6: SLSQP delay convergence per iteration

SLSQP Convergence Curve This plot tracks total delay across SLSQP iterations, showing significant oscillations before converging to a stable minimum. The sharp reductions followed by fluctuations reflect the algorithm’s constrained search process, eventually yielding the lowest delay among all tested configurations.

8 Conclusion

The visualizations collectively demonstrate that optimization-based signal timing strategies provide clear improvements over the baseline traffic control plan. In particular, the SLSQP method achieves the greatest reduction in total delay, rapidly converging to an efficient solution while strategically reallocating green times across phases. This aggressive redistribution reduces congestion levels and leads to smoother traffic operations, as reflected in both the delay and queue length plots.

The PGD approach also enhances network performance, showing steady and stable convergence with moderate delay reduction. While its improvements are less pronounced than those of SLSQP, PGD maintains a more balanced distribution of green times, which may be beneficial in scenarios prioritizing fairness among phases. Overall, the results highlight the effectiveness of iterative optimization techniques in improving traffic efficiency and reducing system-wide delay.

9 Future Improvements

Several avenues can be explored to enhance the current traffic signal optimization framework:

- **Multi-Intersection Networks:** Extend the model to coordinated networks of intersections to minimize delays across a larger urban area.
- **Dynamic Traffic Patterns:** Incorporate time-varying arrival rates to optimize signals under peak and off-peak conditions.

- **Stochastic Modeling:** Account for randomness in vehicle arrivals and driver behavior to improve robustness.
- **Real-Time Implementation:** Integrate adaptive control strategies that update green times in real-time based on traffic sensors.
- **Pedestrian and Bicycle Considerations:** Include multimodal traffic and safety constraints for non-vehicular traffic.
- **Alternative Optimization Methods:** Explore metaheuristics such as genetic algorithms or particle swarm optimization for non-convex scenarios.

These improvements would make the framework more realistic, adaptable, and suitable for deployment in smart traffic management systems.