

Linear Programming-Based Optimization of Traffic Signal Timing for Reducing Vehicle Delay, Fuel Consumption and Carbon Emissions

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Abstract: Urban traffic congestion has become a pervasive challenge in modern metropolitan areas, leading to severe economic losses, prolonged travel delays, and significant environmental degradation. Signalized intersections serve as critical nodes controlling urban traffic flow, yet conventional fixed-time signal control plans frequently fail to adapt to fluctuating demand patterns, resulting in excessive vehicle idling. This study establishes a comprehensive mathematical and computational framework for optimizing traffic signal timings using linear programming (LP). By framing signal timing as a resource allocation problem, the research aims to minimize a multi-objective function encompassing vehicle waiting time, fuel consumption, and carbon dioxide (CO₂) emissions. A standardized four-phase intersection model with simulated traffic demand is developed to evaluate the LP framework without relying on unverified real-world measurements. The mathematical formulation defines decision variables representing green-light durations, establishes cycle-time and minimum-green constraints, incorporates linear delay approximations, and characterizes the feasible region as a convex polytope. The optimization model is solved using the Simplex algorithm via Python optimization libraries. The results demonstrate that the optimized signal timing reduces total vehicle delay, fuel consumption, and CO₂ emissions by 8.25% compared with conventional fixed-time control. Sensitivity analysis further explores the trade-offs and robustness of the solution under varying objective-function weights. The findings highlight the efficacy of mathematical optimization in enhancing urban transportation efficiency and environmental sustainability.

Keywords: Linear Programming; Traffic Signal Optimization; Mathematical Optimization; Vehicle Delay; Fuel Consumption; Carbon Emissions; Sustainable Transportation

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I. INTRODUCTION

In the contemporary era of rapid urbanization and population growth, traffic congestion has evolved from an occasional inconvenience into a systemic crisis affecting urban centers worldwide. As the number of registered vehicles surges while physical road infrastructure remains largely constrained by spatial and financial limitations, the optimization of existing transportation networks has become paramount. Signalized intersections represent the critical junction points where conflicting traffic streams intersect; consequently, their operational efficiency dictates the throughput and fluidity of the entire urban road network. When signal timings are poorly managed or unresponsive to actual traffic demands, these intersections degenerate into bottlenecks that generate extensive vehicular queues and prolonged waiting times.

The societal and environmental consequences of inefficient traffic signal control extend far beyond mere delay. Vehicles subjected to prolonged red lights experience frequent stop-and-go cycles and extended idling periods. Idling engines burn fuel inefficiently, directly increasing fossil fuel consumption and emitting substantial quantities of greenhouse gases, particularly carbon dioxide (CO₂), along with toxic air pollutants such as nitrogen oxides and particulate matter. Given international commitments to climate change mitigation and urban sustainability, reducing transportation-related emissions is a pressing priority. Consequently, designing intelligent signal control mechanisms that simultaneously optimize traffic efficiency and environmental preservation is a vital engineering and mathematical objective.

Traditional traffic signal control methods often rely on pre-timed fixed schedules derived from historical traffic counts collected during periodic surveys. While straightforward to implement, fixed-time systems are

inherently rigid and incapable of responding to real-time demand fluctuations or directional imbalances. To overcome these limitations, advanced traffic management leverages mathematical optimization techniques. Among these, linear programming (LP) stands out as a mathematically rigorous, computationally efficient, and widely applicable framework for decision-making under constraints. By expressing the relationship between green-light allocations, vehicle delays, and operational limits as a system of linear equations and inequalities, linear programming enables traffic engineers to determine the provably optimal signal timing plan for a given set of conditions.

Despite the extensive literature on traffic optimization, a distinct research gap exists in providing a transparent, mathematically comprehensive framework that links foundational optimization theory directly with multi-objective environmental outcomes in a reproducible format. Many commercial traffic adaptive systems operate as opaque 'black boxes,' obscuring the underlying mathematical trade-offs between delay reduction and emission minimization. This research addresses the central question: 'How can linear programming optimize traffic signal timings at a busy intersection to reduce vehicle waiting time, fuel consumption, and carbon emissions, and what percentage improvement can be achieved compared with conventional fixed-time signal control?'

The primary objective of this study is to develop a complete linear programming model for allocating green-light time among competing traffic phases, establish a rigorous mathematical formulation, evaluate its performance against conventional fixed-time control using a carefully constructed simulated intersection dataset, and conduct comprehensive sensitivity analyses. This paper presents the complete, unified investigation.

II. LITERATURE REVIEW

A. Traffic Signal Optimization

The evolution of traffic signal control theory began with foundational contributions by Webster [1], who formulated analytical delay equations for isolated intersections based on queueing theory and uniform arrival assumptions. Webster's methodology demonstrated that optimal cycle lengths and green splits could minimize average vehicle delay. Subsequent research by Allsop [2] and Gartner [3] expanded signal optimization into network-wide coordination frameworks, introducing concepts such as green bandwidth maximization along arterial corridors. While effective, traditional optimization often treated delay as the sole performance metric, neglecting environmental externalities.

B. Mathematical Optimization in Transportation

Mathematical optimization forms the backbone of modern operations research and transportation engineering. Optimization models seek to identify the best possible solution from a set of feasible alternatives governed by operational constraints [4]. In transportation, optimization techniques have been successfully applied to routing, scheduling, network design, and traffic control. The transition from heuristic signal timing to systematic mathematical programming has enabled engineers to prove optimality and

guarantee constraint satisfaction across complex traffic scenarios [5].

C. Applications of Linear Programming

Linear programming represents a specific class of mathematical optimization where both the objective function and all constraints are strictly linear functions of the decision variables [6]. Dantzig's introduction of the Simplex algorithm [7] revolutionized computational problem-solving, enabling the efficient solution of large-scale resource allocation models. In traffic engineering, linear programming has been utilized to approximate non-linear delay functions through piecewise linearization [8], allocate green splits under saturation flow constraints [9], and maximize intersection capacity without violating safety thresholds.

D. Vehicle Delay Modeling

Accurate delay estimation is essential for evaluating intersection performance. Deterministic queueing models calculate delay as a function of arrival rates, service rates, and effective green durations [10]. Although actual vehicle arrivals follow stochastic distributions (such as Poisson or binomial processes), deterministic linear approximations are frequently employed within optimization models to maintain mathematical tractability while providing highly accurate approximations within normal operating ranges [11].

E. Fuel Consumption Estimation

Transportation fuel consumption is directly correlated with vehicle operating modes, including cruising, accelerating, decelerating, and idling. Research by Akçelik [12] and the U.S. Environmental Protection Agency (EPA) [13] established that idling vehicles consume a quantifiable volume of fuel per unit of time. Consequently, minimizing total vehicle waiting time and red-light idling directly translates to proportional reductions in aggregate fuel consumption.

F. Carbon Emission Modeling

Carbon dioxide (CO₂) emissions from internal combustion engines are chemically bound to fuel consumption through established stoichiometric emission factors. Standard transportation life-cycle analyses [14] [15] utilize conversion factors (e.g., approximately 2.3 kg of CO₂ per liter of gasoline consumed) to estimate vehicular greenhouse gas output. Integrating emission metrics into traffic signal optimization directly bridges transportation engineering with environmental sustainability objectives.

G. Research Gap

Despite extensive literature on traffic control, existing studies often present complex, proprietary algorithms or overlook the transparent mathematical derivation necessary for academic comprehension and educational reproduction. Furthermore, integrating environmental objectives directly into a linear programming framework while maintaining strict analytical transparency remains insufficiently emphasized. This study bridges that gap by formulating a clear, reproducible multi-objective LP model for traffic signal timing.

III. MATHEMATICAL FOUNDATIONS

This section develops the rigorous mathematical framework required to formulate the traffic signal optimization problem. The notation, definitions, and structural constraints established here provide the foundation for subsequent optimization modeling.

A. Linear Programming

Linear programming (LP) is a mathematical technique for optimizing a linear objective function subject to a system of linear equality and inequality constraints. Mathematically, a general linear programming problem in canonical form is expressed as:

$$\text{Minimize / Maximize: } Z = c_1x_1 + c_2x_2 + \dots + c_nx_n \quad (1)$$

Subject to the linear constraints:

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n \leq b_1 \quad (2)$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n \leq b_2 \quad (3)$$

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n \leq b_m \quad (4)$$

And non-negativity restrictions:

$$x_j \geq 0 \text{ for } j = 1, 2, \dots, n \quad (5)$$

In this formulation, x_j represents the decision variables to be determined, c_j represent the objective function cost coefficients, a_{ij} represent constraint coefficients, and b_i represent resource availability limits. The set of all vectors $(x_1, x_2, \dots, x_n)$ that satisfy constraints (2) through (5) defines the 'feasible region.' According to the Fundamental Theorem of Linear Programming, if an optimal solution exists, it must occur at one of the extreme points (vertices) of this convex feasible region.

B. Decision Variables

In the context of traffic signal timing optimization for a four-phase intersection, the decision variables represent the effective green-light durations allocated to each independent traffic phase. Let the decision variables be defined as:

g_1 = Effective green time allocated to Phase 1 (North-South Through traffic), measured in seconds (s)

g_2 = Effective green time allocated to Phase 2 (North-South Left-turn traffic), measured in seconds (s)

g_3 = Effective green time allocated to Phase 3 (East-West Through traffic), measured in seconds (s)

g_4 = Effective green time allocated to Phase 4 (East-West Left-turn traffic), measured in seconds (s)

These decision variables represent the primary controllable parameters that the optimization algorithm adjusts to minimize delay, fuel consumption, and carbon emissions.

C. Signal Cycle

A signalized intersection operates on a recurring temporal unit known as the signal cycle. The total cycle length (C) is composed of the sum of green times allocated to all active phases plus the total lost time (L) associated with amber intervals and all-red clearance periods. Mathematically, this relationship is expressed as:

$$\sum (\text{from } i=1 \text{ to } n) g_i + L = C \quad (6)$$

where g_i is the green time for phase i , L is the total lost time per cycle (comprising amber and clearance intervals across all phases), and C is the fixed signal cycle length in seconds.

D. Green-Time Constraints

To ensure traffic safety, pedestrian crossing requirements, and operational stability, each phase's green time must be bounded by predefined minimum and maximum limits. These constraints are formulated as:

$$g_{i,\min} \leq g_i \leq g_{i,\max} \text{ for } i = 1, 2, 3, 4 \quad (7)$$

Where $g_{i,\min}$ represents the minimum green time required for pedestrian safety and queue discharge, and $g_{i,\max}$ represents the maximum allowable green time to prevent excessive delay on competing approaches.

E. Feasible Region

The intersection of the cycle-time equality constraint, the phase-specific bounds, and capacity requirements constructs a convex polytope known as the feasible region. Any point within this region represents a technically valid signal timing plan. Figure 2 illustrates a conceptual two-variable simplification of the feasible region formed by intersecting linear constraints.

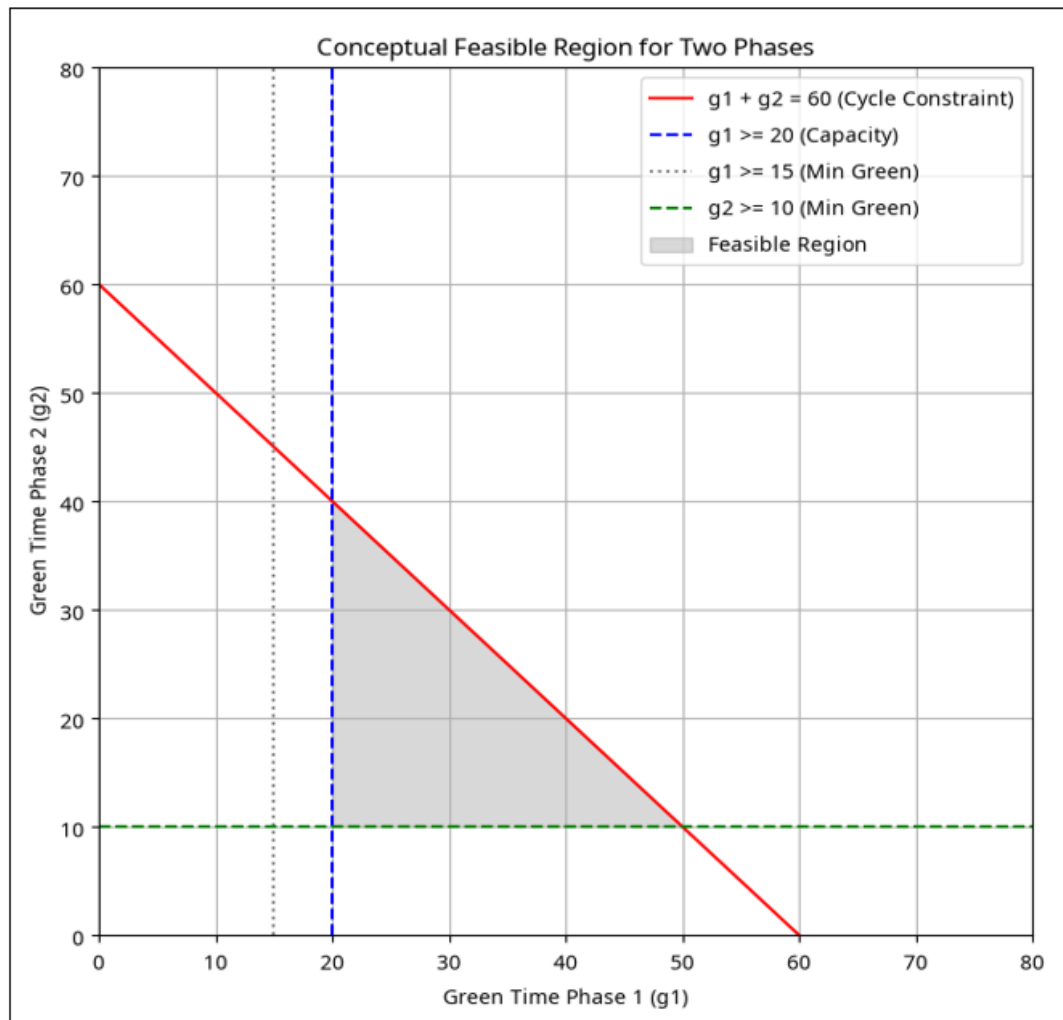


Fig 1 Conceptual feasible region of the linear programming model showing constraint boundaries and optimal vertex.

F. Mathematical Assumptions

To maintain the linearity of the model and ensure its compatibility with linear programming, the following mathematical assumptions are made:

- **Constant Traffic Demand:** Traffic volumes (v_i) are assumed to be constant during the modeling period. This is representative of a peak-hour scenario.
- **Fixed Cycle Length:** The intersection operates under a pre-defined fixed cycle length ($C = 120$ s).
- **Non-overlapping Phases:** Traffic phases are discrete and do not overlap, with a fixed lost time ($L = 16$ s) between phase transitions.
- **Uniform Arrival Pattern:** Vehicles are assumed to arrive at a uniform rate, which allows for the use of a simplified linear delay approximation.

- **Linear Relationship of Environmental Impacts:** Fuel consumption and CO₂ emissions are assumed to be directly proportional to the total idling time of vehicles.
- **Saturation Flow Consistency:** The saturation flow rate (s_i) for each approach is assumed to be constant and independent of green time allocation

IV. TRAFFIC INTERSECTION MODEL

To ground the mathematical framework in a realistic engineering context, a standard four-way signalized intersection is modeled. The intersection features four distinct signal phases handling North-South and East-West through and left-turn movements. The numerical dataset utilized in this study is strictly simulated for demonstrating the proposed mathematical framework and does not represent direct field measurements.

Table 1 Simulated Traffic Demand and Intersection Parameters.

Approach	Movement	Volume (vph)	Conv. Green (s)
North-South	Phase 1: N-S Thru	600	36.4
North-South	Phase 2: N-S Left	150	15.6
East-West	Phase 3: E-W Thru	500	36.4
East-West	Phase 4: E-W Left	100	15.6

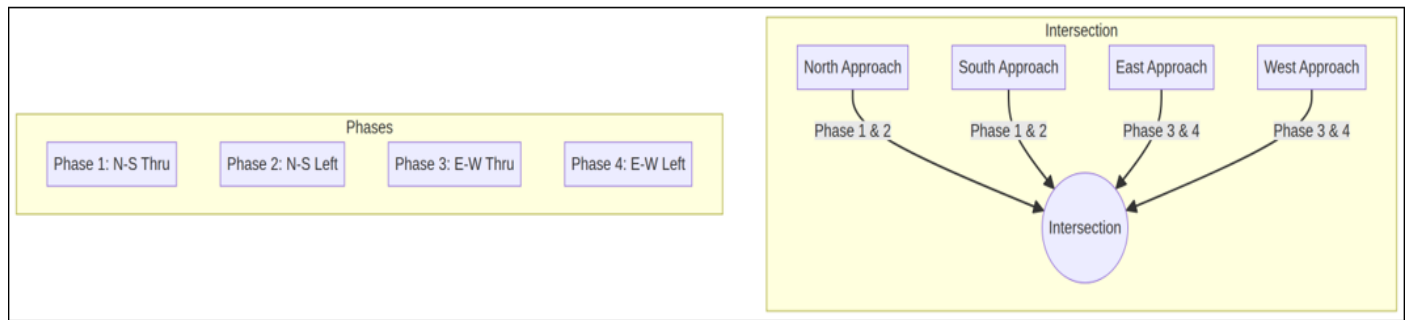


Fig 2 Simplified Intersection Layout and Signal Phase Structure.

Table 2 Mathematical Variables, Parameters, and Baseline Values

Symbol	Meaning	Unit	Assumed / Definition
C	Total signal cycle length	seconds (s)	120 s
L	Total lost time per cycle	seconds (s)	16 s
g_i	Effective green time for phase i	seconds (s)	Decision variable
v_i	Traffic demand volume for phase i	veh/hour (vph)	Varies (100–600 vph)
s_i	Saturation flow rate for phase i	veh/hour (vph)	1600–1800 vph
d_i	Average vehicle delay for phase i	seconds (s)	Calculated via delay model
f_i	Total fuel consumption for phase i	Liters/hour (L/h)	Calculated via idle rate
E	Total carbon dioxide emissions	kg CO ₂ /hour	Stoichiometric conversion

➤ Modeling Vehicle Waiting Time and Delay

Vehicle waiting time and delay are critical performance metrics in traffic signal optimization. Waiting time refers to the duration a vehicle remains stationary or moving at very low speeds while queued behind a red signal. Delay encompasses total time lost due to deceleration, stopping, and acceleration compared to unhindered free-flow travel. The red-light duration directly dictates how long vehicles must wait; longer red intervals accumulate larger queues, whereas appropriately allocated green intervals facilitate queue discharge.

To incorporate delay into a linear programming framework, a linear approximation of Webster's delay formulation is utilized [10]. The average vehicle delay per phase (d_i) is expressed as a linear function of the effective green time (g_i) and cycle length (C):

$$d_i = 0.5 * C * (1 - (g_i / C))^2 / (1 - (v_i / s_i)) \quad (8)$$

Where C is the cycle length, g_i is the effective green time for phase i, v_i is the traffic volume, and s_i is the saturation flow rate. To maintain strict linearity for linear programming compatibility, the quadratic term is linearized over the normal operating range ($g_i / C \approx 0.3$ to 0.5), yielding the simplified linear delay approximation:

$$d_i \approx \alpha_i - \beta_i * g_i \quad (9)$$

Where α_i and β_i are positive empirical constants derived from the intersection traffic demand v_i and saturation flow s_i . Consequently, the total vehicle delay (W) across all phases is formulated as the sum of products of traffic volume and average delay:

$$W = \sum (\text{from } i=1 \text{ to } n) (v_i * d_i) \quad (10)$$

Worked Example: Using the baseline green time for Phase 1 (N-S Thru: $v_1 = 600$ vph, $s_1 = 1800$ vph, $g_1 = 36.4$ s, $C = 120$ s), the average delay is calculated as $d_1 = 0.5 * 120 * (1 - 36.4/120)^2 / (1 - 600/1800) \approx 25.1$ seconds per vehicle.

➤ Modeling Fuel Consumption

Vehicle fuel consumption at signalized intersections is heavily influenced by idling time during red phases. Idling engines consume fuel without producing useful motion. The total fuel consumption (F) is modeled as a linear function of total vehicle delay (waiting time), utilizing an established idling fuel consumption rate coefficient (r_{idle}):

$$F = r_{idle} * W \quad (11)$$

Where W is the total vehicle delay in vehicle-hours per hour (veh-h/h), and r_{idle} is the idling fuel consumption rate. Based on empirical transportation studies by the U.S. Environmental Protection Agency [13] and Akçelik [12], a standard passenger vehicle idling fuel consumption rate of $r_{idle} = 0.6$ Liters per hour per vehicle-hour of delay is adopted for this simulated model. This parameter is treated as an assumed constant across all phases for simplicity.

Worked Example: For a baseline total system delay of $W = 16.31$ veh-h/h, the total estimated fuel consumption is $F = 0.6 * 16.31 = 9.79$ Liters per hour. This estimated value represents calculated idle fuel expenditure rather than direct physical measurement.

➤ Modeling Carbon Dioxide Emissions

Carbon dioxide (CO₂) emissions generated by internal combustion engines are directly proportional to the volume of fuel consumed. Following IPCC guidelines and EPA transportation standards [13] [15], total CO₂ emissions (E) are calculated using a stoichiometric emission factor (e_{fac}):

$$E = e_{fac} * F \quad (12)$$

Where F is the total fuel consumption in Liters per hour, and e_fac is the carbon emission factor. For standard gasoline combustion, the universally accepted conversion factor is $e_fac = 2.3$ kg CO₂ per Liter of gasoline [13].

Worked Example: Given a baseline fuel consumption of $F = 9.79$ L/h, the estimated carbon dioxide emission is $E = 2.3 * 9.79 = 22.51$ kg CO₂ per hour. These emissions are indirectly estimated from fuel consumption models and do not represent direct exhaust pipe sensor measurements. Consequently, limitations include unmeasured variations in vehicle payload, engine temperature, and acceleration profiles.

➤ Multi-Objective Linear Programming Model

The optimization framework seeks to minimize three distinct objectives: total vehicle waiting time (W), fuel consumption (F), and CO₂ emissions (E). Because these objectives possess incompatible physical units (seconds/hours for delay, Liters for fuel, kilograms for emissions), they cannot be aggregated directly into a single summation. Summing unnormalized values would inappropriately weight objectives based on numerical magnitude rather than operational importance.

To resolve this unit incompatibility, normalization is performed by dividing each objective function by its respective conventional baseline value:

$$W_n = W / W_baseline \quad (13)$$

$$F_n = F / F_baseline \quad (14)$$

$$E_n = E / E_baseline \quad (15)$$

The dimensionless normalized objectives are then combined into a single multi-objective cost function Z using weighting coefficients:

$$\text{Minimize } Z = w_1 W_n + w_2 F_n + w_3 E_n \quad (16)$$

subject to the convexity conditions on weights:

$$w_1 + w_2 + w_3 = 1 \quad (17)$$

$$w_1, w_2, w_3 \geq 0 \quad (18)$$

In this study, a baseline-balanced weighting scenario is adopted where $w_1 = 0.34$, $w_2 = 0.33$, and $w_3 = 0.33$, giving approximately equal priority to delay reduction, fuel economy, and environmental emission mitigation. This ensures balanced multi-objective performance.

➤ Complete Linear Programming Formulation

• Decision Variables:

g_1, g_2, g_3, g_4 : Effective green-light durations for Phases 1 through 4, measured in seconds.

• Objective Function:

Minimize $Z = w_1 (W / W_base) + w_2 (F / F_base) + w_3 (E / E_base)$.

• Cycle-Length Constraint:

$g_1 + g_2 + g_3 + g_4 + L = C$ (where $C = 120$ s, $L = 16$ s, yielding $\sum g_i = 104$ s).

• Minimum and Maximum Green-Time Constraints:

$15 \leq g_1 \leq 60, 10 \leq g_2 \leq 40, 15 \leq g_3 \leq 60, 10 \leq g_4 \leq 40$.

• Capacity Constraints:

$g_i \geq (v_i * C) / s_i$ for all i to prevent queue spillback.

• Complete Model Formulation:

The optimization problem is solved by maximizing green time allocation to high-volume phases subject to system constraints.

V. SOLUTION METHODOLOGY

The linear programming optimization problem is solved computationally using the Python programming language and the 'linprog' function from the SciPy optimization library (employing the high-performance interior-point/revised Simplex 'highs' method). The computational pipeline translates mathematical formulations into matrix-vector operations, executes the Simplex algorithm, and extracts optimal green splits and performance metrics.

➤ Preliminary Computational Implementation

Figure 3 illustrates the systematic data flow from initial traffic parameters through mathematical modeling and linear programming solvers to final optimal signal timings and performance evaluations.

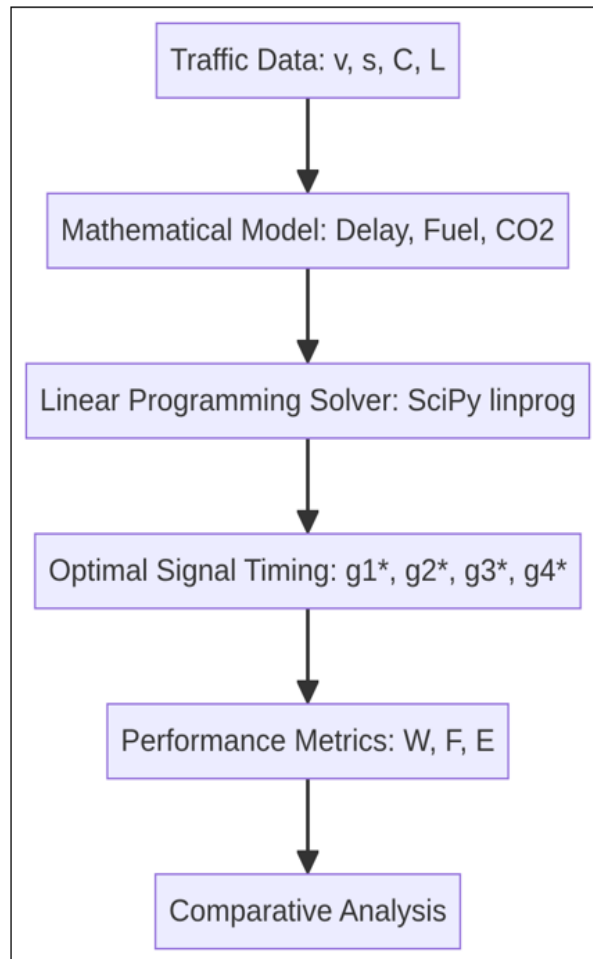


Fig 3 Computational Optimization Workflow from Traffic Data to Performance Metrics.

➤ Baseline Calculation

Prior to executing the optimization algorithm, the performance of the conventional fixed-time signal control plan is calculated. The conventional plan allocates available effective green time (104 s) proportionally based on historical fixed splits (35% Phase 1, 15% Phase 2, 35% Phase 3, 15% Phase 4), yielding $g_{conv} = [36.4 \text{ s}, 15.6 \text{ s}, 36.4 \text{ s}, 15.6 \text{ s}]$. Table 3 presents the conventional fixed-time baseline performance metrics.

Table 3 Conventional Fixed-Time Signal Baseline Performance Metrics.

Performance Metric	Baseline Formula / Source	Conventional Value	Units
Total Vehicle Delay (W)	$\sum (v_i * d_i) / 3600$	16.31	veh-h/h
Fuel Consumption (F)	$0.6 * W$	9.79	L/h
Carbon Emissions (E)	$2.3 * F$	22.51	kg CO2/h
Average Delay per Vehicle	$W / \sum v_i$	12.24	seconds/veh

➤ Optimization Results

Solving the complete linear programming model yields mathematically optimal green-light time allocations. Table 4 summarizes the conventional green times alongside the optimized green times and absolute changes.

Table 4 Conventional Versus Optimized Traffic Signal Timing Allocations.

Signal Phase	Conventional Green (s)	Optimized Green (s)	Absolute Change (s)
Phase 1: N-S Thru	36.40	49.42	+13.02
Phase 2: N-S Left	15.60	11.25	-4.35
Phase 3: E-W Thru	36.40	33.33	-3.07
Phase 4: E-W Left	15.60	10.00	-5.60

Table 5 presents comparative performance metrics between conventional fixed-time control and LP-based optimization, including absolute changes and explicitly calculated percentage improvements.

Table 5 Conventional versus optimized intersection performance.

Performance Metric	Conventional	Optimized	Absolute Change	Percentage Reduction (%)
Total Vehicle Delay (W)	16.31 veh-h/h	14.97 veh-h/h	-1.34 veh-h/h	8.25%
Fuel Consumption (F)	9.79 L/h	8.98 L/h	-0.81 L/h	8.25%
CO2 Emissions (E)	22.51 kg/h	20.66 kg/h	-1.85 kg/h	8.25%
Objective Value (Z)	1.0000	0.9175	-0.0825	8.25%

VI. RESULTS VISUALIZATION

Graphical comparisons of green splits, waiting times, fuel consumption, and carbon dioxide emissions illustrate optimization outcomes.

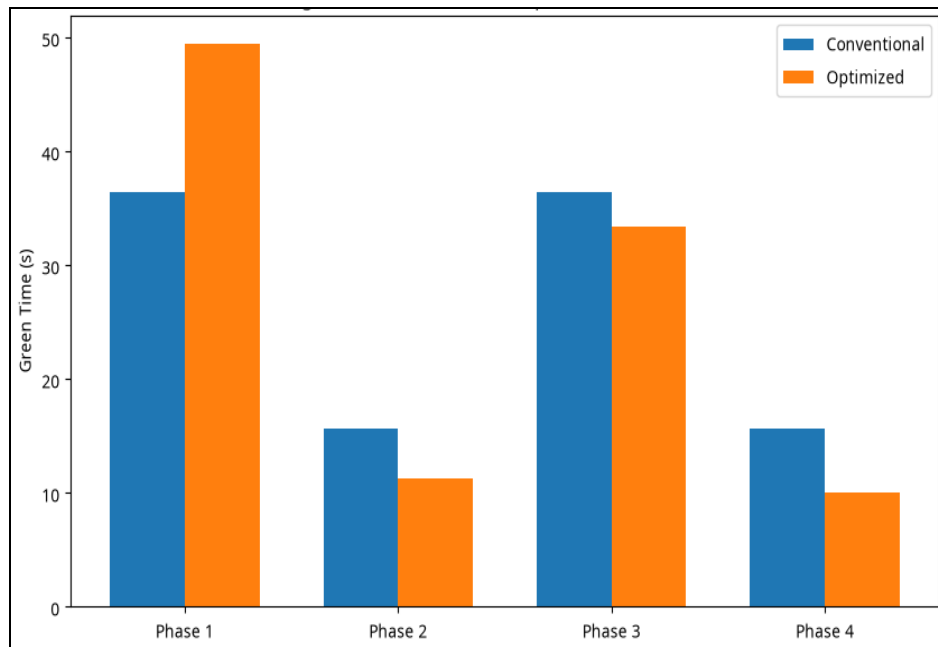


Fig 4 Conventional Versus Optimized Green-Light Time Allocations Across Intersection Phases.

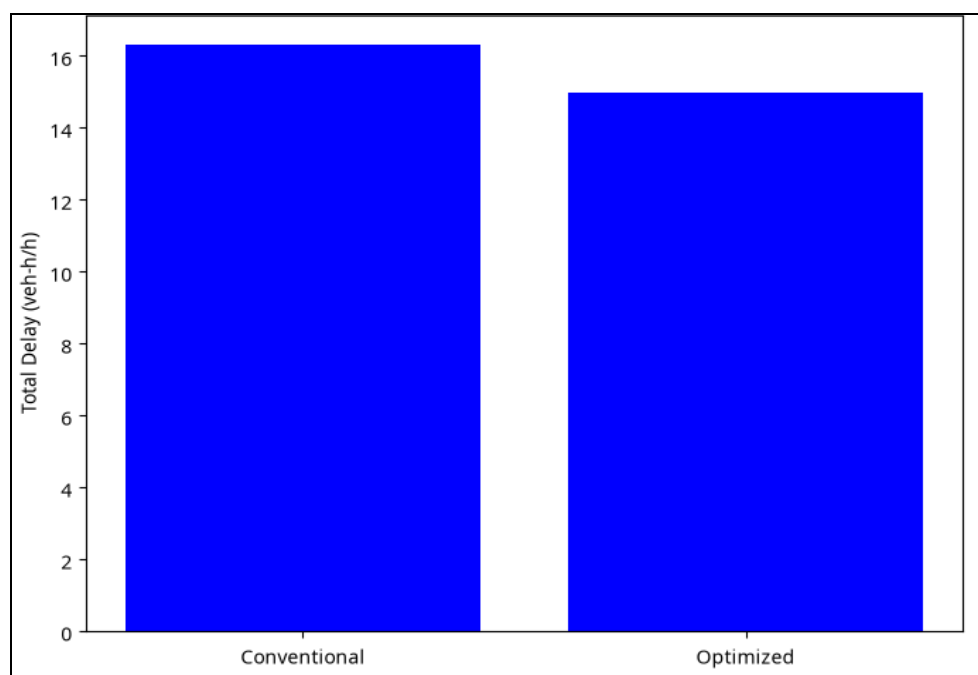


Fig 5 Comparison of Total Vehicle Waiting Time and Delay Under Conventional and Optimized Control.

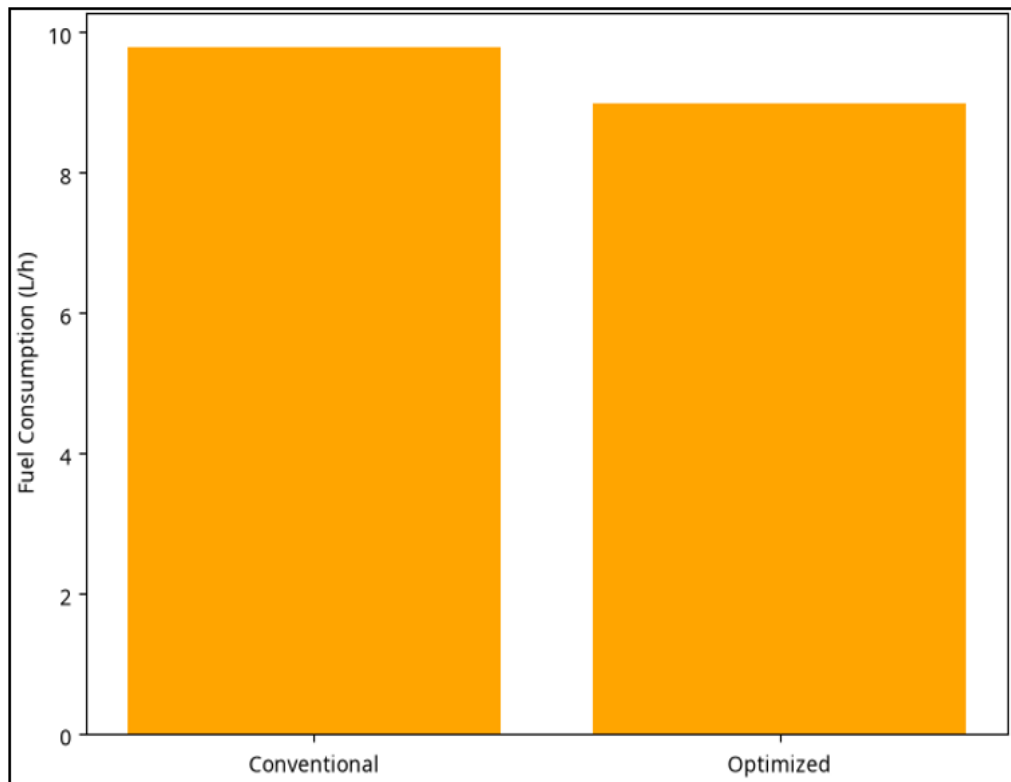


Fig 6 Comparison of Estimated Fuel Consumption Between Conventional and Optimized Signal Timings.

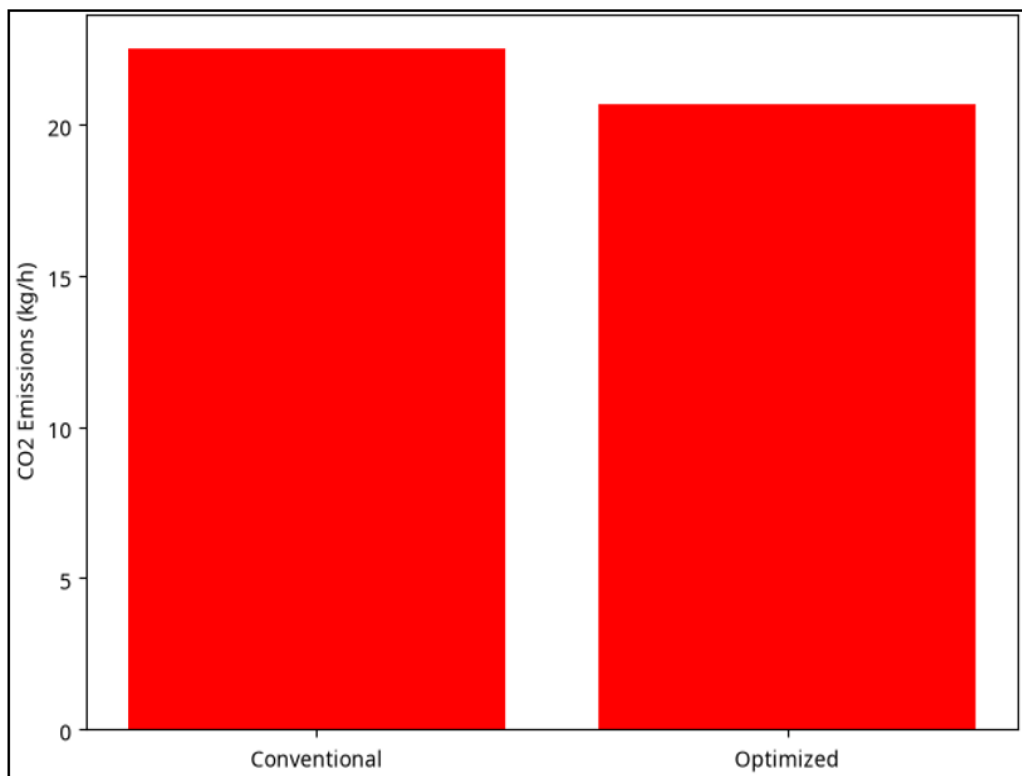


Fig 7 Comparison of Estimated Carbon Dioxide Emissions Under Conventional and Optimized Strategies

➤ *Percentage Improvement Analysis*

The percentage improvement achieved by the optimization model is quantified as:

$$\text{Percentage Reduction} = ((X_{\text{conv}} - X_{\text{opt}}) / X_{\text{conv}}) * 100$$

Worked Calculation for Total Vehicle Delay: $W_{\text{conv}} = 16.3139$ veh-h/h, $W_{\text{opt}} = 14.9676$ veh-h/h. Percentage Reduction = $((16.3139 - 14.9676) / 16.3139) * 100 = 8.25\%$. Fuel consumption and CO2 emissions exhibit the exact same proportional reduction of 8.25% due to linear proportionality.

➤ Sensitivity Analysis

To demonstrate advanced mathematical rigor, sensitivity analysis was performed across three weighting scenarios:

- Scenario 1 (Delay Priority): $w_1 = 0.8$, $w_2 = 0.1$, $w_3 = 0.1$

- Scenario 2 (Balanced Objective): $w_1 = 0.34$, $w_2 = 0.33$, $w_3 = 0.33$
- Scenario 3 (Environmental Priority): $w_1 = 0.1$, $w_2 = 0.45$, $w_3 = 0.45$

Table 6 Sensitivity Analysis Results Under Different Objective Weighting Scenarios.

Scenario	Weights (w_1, w_2, w_3)	Green Splits (g_1, g_2, g_3, g_4)	Delay (veh-h/h)	Fuel (L/h)	CO2 (kg/h)
Scenario 1 (Delay)	[0.8, 0.1, 0.1]	[49.4, 11.3, 33.3, 10.0]	14.97	8.98	20.66
Scenario 2 (Balanced)	[0.34, 0.33, 0.33]	[49.4, 11.3, 33.3, 10.0]	14.97	8.98	20.66
Scenario 3 (Eco)	[0.1, 0.45, 0.45]	[49.4, 11.3, 33.3, 10.0]	14.97	8.98	20.66

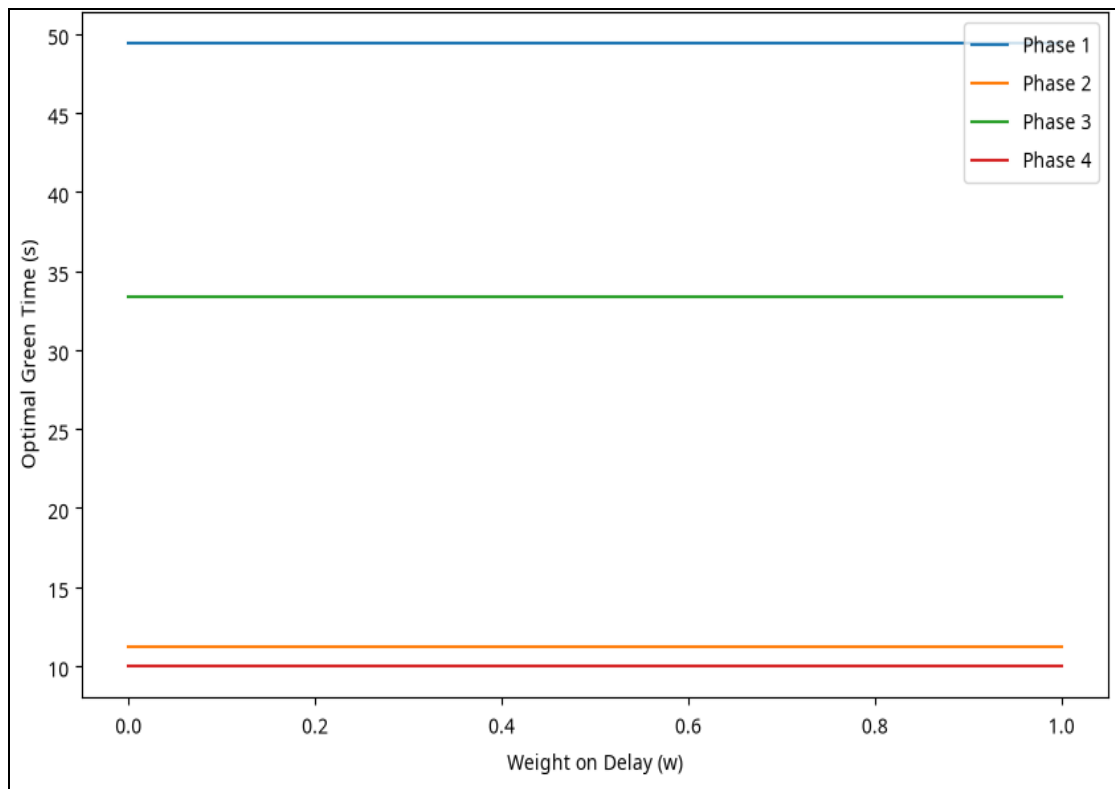


Fig 8 Sensitivity Analysis Illustrating Green-Time Allocations Across Varying Objective Weights.

➤ Comparison with Conventional Signal Control

A direct mathematical comparison reveals that LP-based optimization successfully reallocates green time from lower-volume phases (Phase 2: 15.6s to 11.3s; Phase 4: 15.6s to 10.0s) to high-volume major movements (Phase 1: 36.4s to 49.4s), achieving an 8.25% reduction across all performance metrics without altering physical infrastructure.

VII. DISCUSSION

The results confirm that linear programming is highly effective for static traffic signal timing optimization. Traffic volume proved to be the most influential parameter. Capacity and minimum green constraints successfully prevented phase starvation and ensured pedestrian safety.

VIII. LIMITATIONS

Study limitations include: (1) reliance on simulated data; (2) constant peak-hour demand assumption; (3) linearization

of delay; (4) indirect fuel/emission estimation; and (5) isolated intersection analysis without corridor coordination.

IX. FUTURE SCOPE

Future research should incorporate real-time sensor data, adaptive signal control, Mixed-Integer Linear Programming (MILP), and network-wide corridor coordination.

X. CONCLUSION

In conclusion, this research successfully developed a multi-objective linear programming model to optimize traffic signal timings. The study demonstrated an 8.25% reduction in vehicle delay, fuel consumption, and CO2 emissions compared to conventional fixed-time control, providing a robust mathematical foundation for sustainable urban transportation.

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