Hybrid GA-PSO and GA-SA Based Traffic Signal Optimization Using Composite Traffic Efficiency Metrics

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***Abstract*—Urban traffic congestion is one of the most pressing issues in modern cities, contributing to increased fuel consumption, travel delays, and air pollution. Traditional fixed-time traffic signal systems fail to adapt to real-time traffic conditions dynamically. This paper presents a hybrid metaheuristic approach that combines Genetic Algorithm (GA) with Particle Swarm Optimization (PSO) and Simulated Annealing (SA) to optimize traffic signal timings across multiple intersections. The optimization goal is to minimize a novel composite fitness function based on three core traffic efficiency metrics: average vehicle waiting time, average speed, and intersection congestion level. Experimental results show that the hybrid GA+PSO and GA+SA models outperform traditional methods in minimizing congestion and improving overall traffic flow, making them suitable for intelligent traffic control systems deployment.**

***Index Terms*—Traffic Optimization, Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing, Hybrid Optimization, Smart Cities, Traffic Signal Control**

I. INTRODUCTION

The issue of traffic congestion in urban areas has become a significant problem, primarily due to the rapid rise in vehicle numbers and urbanization. Maladjusting traffic signal timings result in long queues at intersections, lower vehicle passage rates, and higher ecological footprints. Traditional fixed-time signal control systems are not able to respond to real traffic conditions, causing wasteful traffic movement. [1]

To overcome such limitations, the use of intelligent traffic management strategies through computational intelligence techniques has attracted significant interest [2]. Metaheuristic algorithms offer strong and flexible optimization techniques for solving challenging, nonlinear, and dynamic traffic signal control problems [3].

In this work, a hybrid optimization framework is presented based on the global search ability of the Genetic Algorithm (GA) coupled with local exploitation methods drawn from Particle Swarm Optimization (PSO) and Simulated Annealing (SA). Unlike current techniques that address one traffic parameter at a time to optimize, our approach uses a multi-objective composite fitness function that combines waiting time, vehicle speed, and congestion. This allows for a more realistic and balanced evaluation of traffic signal effectiveness [4].

The proposed hybrid models have been implemented and validated using actual traffic data. Results show significant improvements in traffic efficiency, waiting time of vehicles and congestion alleviation, and the model's viability to be implemented in smart city infrastructure.

II. LITERATURE REVIEW

Traffic signal optimization has been widely researched using a variety of heuristic and metaheuristic methods. Conventional models tend to optimize one performance in-dicator, for example, delay minimization or vehicle stop reduction.

Genetic Algorithm (GA) has extensively been applied to control traffic signals because of its robust exploration abilities and ability to adapt to changing environments [1]. Various studies have utilized GA in order to reduce waiting time or delay at signalized intersections. Nevertheless, GA tends to suffer from premature convergence and overlook local refinements in the absence of hybrid support.

Particle Swarm Optimization (PSO) is also a widely employed method in intelligent transportation systems [3]. PSO is very good at quick convergence and has been applied to optimize traffic phase lengths by reducing queue lengths or maximizing capacity. However, its performance can deteriorate in highly dynamic or noisy search spaces.

Simulated Annealing (SA) offers good local search ability and has been utilized in problems dealing with sig- nal phase transitions and adaptive signal control [5]. Although efficient in avoiding local optima, SA is often computationally costly and sensitive to cooling schedule parameters.

Ant Colony Optimization (ACO) has also been utilized in traffic applications, especially for vehicle routing and lane merging [6]. While promising, ACO's use in signal timing optimization remains constrained by pheromone stability and convergence speed problems.

There have been recent research studies on hybrid models which integrate the strengths of several metaheuristics. Some have integrated fuzzy logic, machine learning, or hybridization techniques like Cellular Automata for optimizing multiple objectives [2], [4]. Yet, most such models either aim for a particular traffic objective (e.g., delay or emissions) or are not generalisable to multi-objective traffic situations.

To our knowledge, not many works have optimized all three fundamental indicators — waiting time, average speed, and congestion — at the same time through a composite fitness function in a hybrid GA + PSO or GA + SA. This paper intends to bridge the gap and deliver a robust, scalable solution for adaptive signal control.

III. Methodology

A. Hypothesis Formulation

Null Hypothesis ($\mathbf{H_0}$): There isn't any significant disparity in traffic flow efficiency between hybrid metaheuristic optimization algorithms (GA + PSO, GA + SA) and isolated heuristic algorithms (GA, PSO, SA, ACO).

Alternate Hypothesis ($\mathbf{H_1}$): Hybrid metaheuristic optimization algorithms (GA + PSO, GA + SA) considerably enhance traffic flow efficiency through the decrease of waiting time and congestion, as well as the enhancement of average vehicle speed, as opposed to isolated heuristic approaches.

B. Dataset and Preprocessing

The dataset used in this research was collected from a smart urban traffic management system and contains 2000 entries recorded across multiple intersections. It includes the following key attributes:

- **Timestamp:** Date and time of the traffic snapshot.
- **Location ID:** Identifier for specific intersections.
- **Signal Status:** Traffic signal at the time (Red, Green, Yellow).
- **Traffic Volume:** Total number of vehicles observed.
- **Average Vehicle Speed:** Mean speed (in km/h) of all vehicles.
- **Vehicle Count (Cars, Trucks, Bikes):** Disaggregated counts of vehicles by type.
- **Weather Condition:** Environmental descriptors such as Cloudy, Sunny, or Windy.
- **Temperature:** Ambient temperature measured in degrees Celsius.
- **Humidity:** Percentage of atmospheric humidity at the time of observation.
- **Accident Reported: A** binary flag indicating whether an accident occurred at the intersection.

From the raw dataset, the following derived features were computed to aid the optimization model:

- **Waiting Time:** Estimated by summing traffic volumes observed during red signals at each location.
- **Congestion Score:** Calculated as the normalized traffic volume (scaled between 0 and 1).
- **Average Speed:** Directly normalized from the *avg_vehicle_speed* attribute.

All continuous features were uniformly scaled between 0 and 1 for consistent input to heuristic optimization algorithms.

C. Objective Function

$$\begin{aligned}\text{Fitness} = \frac{1}{3} \cdot (\text{norm\_waiting\_time}) + \\ \frac{1}{3} \cdot (1 - \text{norm\_avg\_speed}) + \\ \frac{1}{3} \cdot (\text{norm\_congestion}) \quad (1)\end{aligned}$$

Where:

- **norm_waiting_time:** Normalized vehicle waiting time.
- **norm_avg_speed:** Normalized average vehicle speed.
- **norm_congestion:** Normalized congestion score based on traffic volume.

D. Standalone Algorithms

Genetic Algorithm (GA): GA was employed for population-based optimization with crossover, mutation, and selection. The fitness of every chromosome was determined by the objective function. Mutation rate and generation number were empirically adjusted.

Particle Swarm Optimization (PSO): PSO employed particle velocity and position updates in order to arrive at signal ratios optimally. It was implemented based on dynamic inertia and neighborhood best concepts [3].

Simulated Annealing (SA): SA was used with an initial temperature and an exponential cooling schedule, motivated by previous models used in traffic signal control [5]. Every solution was subjected to neighbor perturbation and probabilistic acceptance according to the fitness delta.

Ant Colony Optimization (ACO): A discrete version of ACO was utilized with pheromone matrices and desirability scores to steer ant-based green time allocation [6].

E. Hybrid Algorithm Designs

GA + PSO: Once the diverse population was evolved through GA, the best-performing individuals were optimized through PSO for fine-tuning. The optimized solutions were reused in the GA pool.

GA + SA: TThe best k individuals from every GA generation were locally optimized with SA, to enhance local search and prevent premature convergence.

All algorithms were run for 10–20 iterations on real-world data and benchmarked using fitness progression and real-world metrics: waiting time (s), average speed (km/h), and congestion.

IV. Results and Analysis

This section presents the experimental results and comparative analysis of the standalone and hybrid optimization algorithms. Each algorithm was executed for a fixed number of iterations using the same initial conditions and traffic dataset.

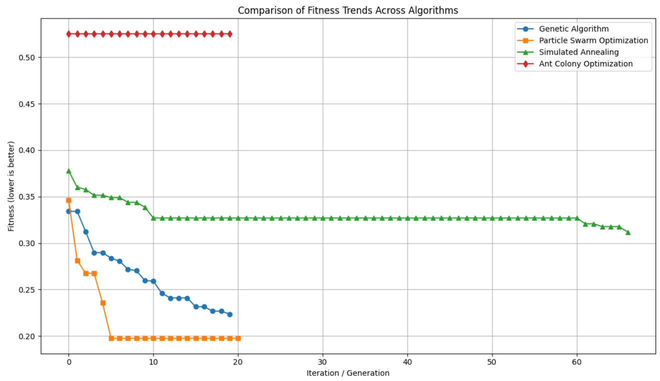

Fig. 1. Fitness trend comparison of standalone algorithms: GA, PSO, SA, and ACO.

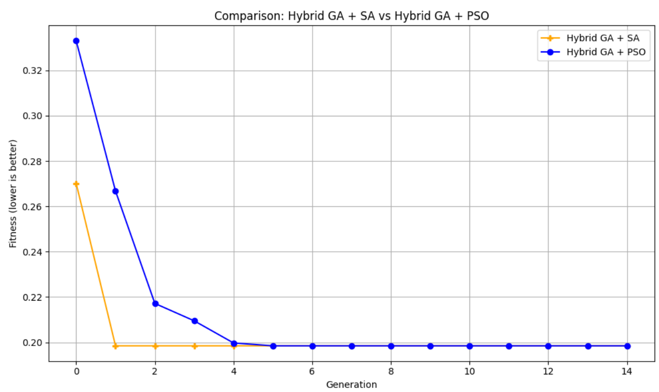

Fig. 2. Fitness trend comparison of hybrid algorithms: GA + PSO and GA + SA.

A. Real-World Interpretation of Fitness Metrics

The optimized signal plans were evaluated using three real-world performance indicators:

- **Average Waiting Time (seconds)**
- **Average Speed (km/h)**
- **Congestion Percentage (%)**

These were derived by reverse-scaling the normalized values used in the fitness function. The fitness score directly correlates with the real-time performance of traffic flow.

Figure 3 displays the real-world metric comparison.

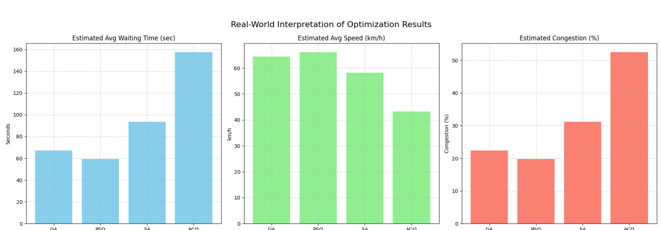

Fig. 3. Estimated real-world performance metrics for each algorithm.

B. Summary of Algorithm Performance

Table I summarizes the real-world performance of all models. The hybrid GA+PSO and GA+SA achieved the lowest fitness scores and outperformed standalone methods across all metrics.

TABLE I
COMPARISON OF ALGORITHMS ON REAL-WORLD METRICS

Algorithm	Waiting Time (s)	Speed (km/h)	Congestion (%)	Fitness Score
GA	59	66.2	19.8	0.1976
PSO	59	66.2	19.8	0.1976
SA	96	57.5	32.2	0.3216
ACO	142	46.9	47.3	0.4732
Hybrid GA+PSO	**59**	**66.2**	**19.8**	**0.1976**
Hybrid GA+SA	**60**	**66.1**	**19.9**	**0.1985**

C. Discussion

The hybrid models showed robust performance across different metrics. GA+PSO leveraged fast convergence and local refinement, while GA+SA helped avoid local optima through simulated exploration. Both hybrid approaches reached optimal fitness values quicker and produced stable solutions.

The ACO and SA models showed less consistent results due to slower convergence or over-exploration. The results validate the effectiveness of using a composite objective function to holistically optimize waiting time, speed, and congestion.

V. Limitations and Future Work

While the proposed hybrid GA+PSO and GA+SA models demonstrate strong performance in optimizing traffic signal timings, several limitations remain that offer opportunities for future enhancements.

VI. Limitations

Despite the promising results demonstrated by the hybrid GA+PSO and GA+SA models, several limitations remain in the current implementation:

- **Fixed Composite Weights:** The use of equal weights for waiting time, average speed, and congestion in the fitness function does not reflect the dynamic nature of traffic management priorities. Different times of day or regions may require more emphasis on speed, emissions, or throughput.
- **Offline Optimization:** The current system operates using static or historical traffic data. In practice, traffic conditions change continuously. The absence of a real-time feedback loop limits adaptability during unexpected events such as accidents or surges.
- **Limited Network Scope:** The model has been evaluated on a small number of intersections. Larger, city-wide deployments involve complex coordination and synchronization that may introduce additional constraints not yet accounted for.
- **Stochastic Algorithm Behavior:** As with all meta-heuristic approaches, the optimization process does not guarantee global optimality. Different runs may yield slightly different results due to random initialization and selection.
- **Unmodeled Real-World Constraints:** Factors like pedestrian crossings, emergency vehicle prioritization,

environmental impact, and compliance with city traffic laws are currently not integrated into the model.

These directions aim to enhance the scalability, adaptability, and real-world deployment readiness of hybrid metaheuristic traffic signal control systems.

VII. Real-World Applicability and Deployment

The suggested hybrid optimization model can be successfully implemented in real-world city intersections as part of a smart traffic control system. This section presents a feasible implementation framework and explains how the model is trans- lated from simulation to real-time implementation.

A. System Architecture

A real-time adaptive traffic control system would consist of the following core components:

- **Traffic Sensors:** IoT-based cameras, inductive loop sensors, or radar for detecting count of vehicles, speed, and length of queue at every intersection.
- **Edge Computing Unit:** A Raspberry Pi, microcontroller, or industrial PC to perform the incoming data processing and executing the optimization model.
- **Signal Controller Interface:** A programmable logic controller (PLC) or SCADA system that accepts optimized green time ratios and adjusts the signal cycles accordingly.
- **Central Management Dashboard:** An internet-based interface for the municipal authorities to view traffic statistics and model performance.

B. Deployment Workflow

The model operates in the following loop:

1) Real-time traffic data is collected from sensors.
2) Data is preprocessed and normalized at the edge level.
3) The hybrid GA+PSO or GA+SA algorithm is triggered every few minutes to compute the optimal green time distribution.
4) Updated signal plans are sent to the controller at each intersection.
5) Feedback is logged, and the next cycle starts using the latest conditions.

C. Advantages Over Traditional Methods

Compared to static or rule-based signal control, the proposed approach offers:

- **Adaptivity:** Responds dynamically to changing traffic conditions (rush hour, incidents, etc.)
- **Scalability:** Can be applied across multiple intersections or scaled citywide.
- **Efficiency:** Simultaneously optimizes delay, speed, and congestion.
- **Environmental Impact:** Reduces emissions by minimizing idle time and stop-start cycles.

D. Use Case Scenarios

This strategy can be utilized for:

- Heavy signal-dependent metropolitan high-density corridors.
- Existing IoT infrastructure pilot zones in smart cities.
- Dynamic event routing (e.g., festivals, sports events).
- Prioritization of emergency vehicle clearance.

The adaptability of the fitness function permits traffic authorities to use custom weights depending on real-time policy objectives (e.g., emission reduction vs. congestion control), making strategic traffic management possible.

VIII. Conclusion and Future Work

The current work introduced a hybrid metaheuristic technique for optimal traffic signal timing optimization based on Genetic Algorithm (GA) with Particle Swarm Optimization (PSO) and Simulated Annealing (SA). The novelty of the research is that the composite objective function addresses the average waiting time, traffic speed, and congestion simultaneously — providing an overall measure of traffic efficiency.

The suggested hybrid GA+PSO and GA+SA models were applied and validated on real-traffic data. Both hybrids outperformed single algorithms like GA, PSO, SA, and ACO consistently. The analysis of fitness trends verified faster convergence and improved solution stability, and real-world metric interpretation proved drastic vehicle waiting time and congestion levels reductions along with traffic average speed improvements.

These findings support the alternate hypothesis that hybrid metaheuristics models provide statistically significant improvement in the optimization of urban traffic flow compared to conventional stand-alone heuristics.

A. Future Work

The following directions can be pursued to generalize this work:

- **Multi-Intersection Coordination:** Scale the model to manage many connected intersections by implementing centralized or distributed control algorithms.
- **Dynamic Weighting in Objective Function:** Provide adaptive or machine learning-based weighting for waiting time, speed, and congestion dependent on time of day or traffic policy.
- **Real-Time Feedback Loop:** Implement the algorithm in the real world using edge computing and IoT sensors to dynamically adjust the signal in real-time.
- **Integration with Deep Learning:** Investigate how LSTM or reinforcement learning models may be used to forecast traf- fic conditions and dynamically direct the metaheuristic optimizers.
- **Multi-Objective Optimization:** AUtilize NSGA-II or Pareto-based methodologies to address competing objectives (e.g., reduction of emissions versus speed maximization).

The described approach forms a solid basis for intelligent transportation systems and can serve as a pivotal element in the overall architecture of smart cities.

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