Kufa Journal of Engineering
Vol. 15, No. 3, July 2024, P.P. 21-31
Article history: Received 20 January 2024, last revised 19 March 2024, Accepted 20 March 2024

MULTI-OBJECTIVE OPTIMIZATION OF TRAFFIC SIGNAL TIMINGS FOR MINIMIZING WAITING TIME, CO_2 EMISSIONS, AND FUEL CONSUMPTION AT INTERSECTIONS

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https://doi.org/10.30572/2018/KJE/150302

ABSTRACT

In this paper, we present an optimization strategy that uses Genetic Algorithms (GA) to reduce Waiting Time, CO_2 Emissions, and fuel consumption in a transportation network. The optimization process is performed through simulations using the well-known traffic simulation tool, SUMO (Simulation of Urban MObility). The main objective is to identify the most efficient traffic light timing plan. The proposed GA uses a binary encoding method for signal timing configurations and includes a fitness function to evaluate network performance regarding fuel consumption. The algorithm iteratively builds a set of signal-timing solutions over generations until it converges on the optimal solution. Empirical results show that the GA approach significantly reduces waiting time, reducing CO_2 emissions, and reducing fuel consumption compared to standard signal timing plans. This research makes a significant contribution to the domain of traffic management and provides valuable insights for policymakers and transportation planners looking to reduce the environmental footprint of urban transportation networks.

KEYWORDS

Genetic Algorithm, Optimization, Signal timing Optimization, SUMO.

1. INTRODUCTION

Traffic congestion in cities causes environmental issues like higher CO_2 emissions and fuel usage. Smart traffic signal management is key to solving these problems by making traffic flow better and reducing delays. Scientists have been working on using Genetic Algorithms (GAs) to improve how long cars wait at lights, reduce CO_2 emissions, and save fuel. The goal is to make a strong optimization system that can balance traffic efficiency with keeping the environment clean. GA is used because it can adapt signal timing and find solutions through evolution. Using the SUMO (Simulation of Urban MObility) software, simulations were run to test the effectiveness of the new optimization framework.

The paper's structure is as follows: In the subsequent section, we review state-of-the-art techniques in traffic signal optimization and their impact on waiting time, CO_2 emissions, and fuel consumption. This provides a comprehensive understanding of the current research landscape and identifies the gaps addressed by this study. The methodology section elaborates on the Genetic Algorithm and its implementation in the context of traffic signal control. The section on experimental results presents the outcomes of the simulations, including the reduction in waiting time, CO_2 emissions, and fuel consumption achieved through GA optimization. Finally, the conclusion summarizes the key findings, discusses their implications, and outlines potential avenues for future research.

1.1. Aim of the study

Through the use of Genetic Algorithms and the capabilities of SUMO, this research aims to contribute to the development of sustainable traffic signal control strategies that effectively reduce environmental impact while maintaining efficient traffic operations.

1.2. Background

Optimization algorithms and Artificial Intelligence (AI) techniques have emerged as powerful tools in the quest for more efficient traffic signal timing, with a specific focus on reducing CO_2 emissions and fuel consumption. Researchers have explored various approaches to tackle this challenge. Genetic algorithm-based approaches have been widely applied in traffic signal timing optimization. Researchers have demonstrated the effectiveness of these algorithms in achieving significant reductions in CO_2 emissions (Li et al., 2021). Deep reinforcement learning has also shown promise in optimizing traffic signal timings to minimize environmental impacts. A specific deep reinforcement learning approach designed to reduce CO_2 emissions in traffic signal control highlighted the potential of AI techniques in achieving substantial improvements in emission reduction (Li et al., 2020). To address the multi-objective nature of traffic signal timing optimization, researchers have developed models that consider both CO_2 emissions and travel time. These multi-objective optimization approaches provide decision-makers with flexible solutions that balance environmental concerns and traffic efficiency (Zhang et al., 2020). Enhancements to genetic algorithms have been explored to improve the coordination of signal timings and reduce CO_2 emissions. Fine-tuning the optimization process has led to more effective strategies for emission reduction (Ma et al., 2019). Dynamic programming-based models have been utilized to minimize CO_2 emissions at signalized intersections while maintaining efficient traffic operations, showcasing the potential of this approach in achieving environmentally conscious signal timing (Cui et al., 2018). Researchers have also focused on optimizing CO_2 emissions at isolated intersections through signal timing adjustments, emphasizing the importance of these adjustments in achieving substantial emission reductions (Wang et al., 2017). Comprehensive optimization models have been proposed that consider various factors, including traffic flow, road conditions, and CO_2 emissions, resulting in improved signal timings and reduced environmental impacts (Yu et al., 2016). Wang et al. as discussed by the authors proposed a multi-objective optimization approach for timing information control. This approach takes into account various factors including capacity for passing, and frequency of parking to construct a model. They employed a genetic algorithm to tackle this optimization problem (Xin, Liu., Bing, Wang. 2022).

In (Albool et al, 2023) the authors used simulator data of sixty-six drivers going through signalized intersections equipped with two different signal indication settings, namely, control and flashing green conditions, to study the correlation between the two treatments and fuel consumption The paper (JD Reddy et al, 2023) explores a sophisticated traffic management system leveraging AI and IoT technologies to enhance traffic flow efficiency and effectively handle diverse traffic situations. It describes the adaptation of traffic signals using data from cameras, sensors, and devices. However, it does not explicitly refer to AI-enabled traffic signals.

These diverse approaches illustrate the dynamic landscape of research and innovation in the field of traffic signal timing optimization with a strong focus on reducing CO_2 emissions and promoting environmentally conscious traffic management.

2. METHODOLOGY

2.1. Problem Statement

The study focuses on three main performance indicators in urban transportation systems: waiting time, CO_2 emissions, and fuel consumption. By optimizing routing and planning, the aim is to reduce waiting time at intersections and congestion along travel routes. This reduction in waiting time not only enhances overall system efficiency but also has a coordinated impact on fuel consumption and CO_2 emissions. Decreasing CO_2 emissions aligns with environmental sustainability goals and is closely linked to improvements in fuel efficiency. Additionally, optimizing fuel usage directly affects waiting time by reducing congestion and delays for commuters. These goals are interconnected, and improvements in one area can positively influence others. The optimization strategy aims to balance these objectives to ensure holistic enhancements in urban transportation system performance.

2.2. Genetic Algorithm (GA)

In our study, we compare the performance of the Genetic Algorithm (GA) proposed in this study with two other widely used optimization techniques: Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). PSO and ACO are chosen for comparison due to their effectiveness in solving multi-objective optimization problems, similar to the one addressed in this paper, as shown in Table 1 below:

Table 1. Comparison between GA, PSO, and ACO

Feature	GA	PSO	ACO
Strengths	Robust, versatile, good exploration & exploitation	Simple, efficient, good exploration	Effective for combinatorial problems
Weaknesses	Requires careful parameter tuning	May struggle with local optima, high-dimensional problems	Less scalable, prone to premature convergence

2.2.1. Justification for GA Choice

The intersection management problem, with its multi-objective nature of balancing waiting time, CO_2 emissions, and fuel consumption, demands a robust search technique. Genetic Algorithms (GAs) stand out due to their effectiveness in exploring diverse search spaces through crossover and mutation, while also exploiting promising areas via selection. This capability is crucial for attaining well-balanced solutions that address all objectives simultaneously. To address these challenges, a Genetic Algorithm implemented using the pyeasyga library is chosen as the primary optimization technique. GA is adept at navigating complex and multi-dimensional solution spaces, mimicking natural selection to iteratively enhance candidate solutions.

2.2.2. GA Configuration:

The *pyeasyga* library provided the framework for the GA implementation, with the following configuration:

- Population Size: Initial: 20, Best Performing: 50 (determined through experimentation)
- Number of Generations: Initial: 10, Best Performing: 30 (determined through experimentation)
- Selection Strategy: Tournament selection (default in *pyeasyga*)
- Crossover Probability: 0.7 (default in *pyeasyga*)
- Mutation Probability: 0.01 (default in *pyeasyga*)

This configuration was chosen based on common practices for GA optimization problems. Further experimentation with population size and number of generations revealed the settings that yielded the most effective results.

Algorithm 1: Genetic Algorithm for SUMO Simulation Parameter Optimization

Data: Initial population of parameter sets
Result: Optimal parameter set for SUMO simulation
while *stopping criterion not met* **do**
  Selection: **for** *each parameter set* **do**
    Evaluate fitness based on SUMO simulation results;
  Select individuals for the next generation using roulette wheel or tournament selection;
  Crossover: Generate offspring through crossover (e.g., one-point or two-point crossover);
  Mutation: Apply mutation operators (e.g., change a parameter value randomly);
  Replacement: Replace the old generation with the new generation;
  Termination: Check termination criteria (e.g., number of generations, convergence);
Output: Optimal parameter set for SUMO simulation

Fig. 1 Pseudocode representation of GA

2.3. Simulation Environment

The optimization process is carried out within the Simulation of Urban MObility (SUMO) framework, a versatile and realistic simulation tool designed for the evaluation of urban transportation scenarios.

2.3.1. Simulation Setup and Control Variables:

The SUMO microscopic traffic simulation platform was employed to model traffic flow at the intersection.

- Traffic Demand: A total of 500 vehicles were used to simulate traffic flow at the intersection.

- Route Choice: Fixed routes were employed for the vehicles within the simulation. These routes were created using the graphical network editor (NetEdit) included in SUMO.
- Traffic Light Settings:

Initial signal timings were set randomly. The initial configuration was:

default = [60, 'GGGGgrrrrrGGGGgrrrrr', 5, 'yyyyyrrrrryyyyyrrrrr', 60 'rrrrrGGGGgrrrrrGGGGg', 5, 'rrrrryyyyyrrrrryyyyy']

this provided a starting point for the GA optimization process.

2.3.2. Theoretical Basis for Junction Improvements:

GA-optimized signal timings aim to enhance traffic flow efficiency by implementing several strategies:

- Reduced cycle times: Optimization of red, yellow, and green phases aims to minimize the total cycle time, reducing vehicle waiting periods. This not only decreases CO_2 emissions but also lowers fuel consumption.
- Optimized green splits: Allocation of green time for each direction is adjusted based on traffic volume data to prioritize directions with higher vehicle flow.
- Phase optimization: Signal phases' sequence and duration are coordinated to minimize conflicts between turning movements, thereby reducing delays, and improving overall intersection throughput.

2.4. Fitness Function

A fundamental component of this methodology is the fitness function, which governs the GA's search for optimal solutions. The fitness function is formulated as the reciprocal of the total waiting time, CO_2 emissions, and fuel consumption derived from the simulation, as in equation (1). This formulation ensures the minimization of these factors.

$$fitness = \frac{1}{total\_value} \quad (1)$$

total_value represents the aggregate impact of waiting time, CO_2 emissions, and fuel consumption resulting from traffic signal timings.

2.5. Optimization Process

The GA iteratively generates and assesses candidate solutions by adjusting the parameters of urban mobility systems. Each candidate solution is rigorously evaluated within the SUMO environment, and the fitness value is determined based on the reciprocal of waiting time, CO_2 emissions, and fuel consumption. Selection, crossover, and mutation operators are employed to refine solutions across multiple generations.

2.6. Experimental Setup

To assess the methodology, realistic urban scenarios and mobility patterns are utilized for experimentation. Multiple optimization runs are conducted to explore the solution space and discern trade-offs between waiting time, CO_2 emissions, and fuel consumption.

2.7. Data Collection and Analysis

Performance data, including waiting times, CO_2 emissions, and fuel consumption, is systematically collected and subjected to rigorous statistical analysis. Graphical and statistical methods are used to assess the effectiveness of the GA-based optimization.

3. RESULTS & DISCUSSION

3.1. Results

In this simulation, we focus on an intersection where two roads meet Fig. 2, each having two lanes. The primary objective of this simulation is to reduce the CO_2 emissions at this specific intersection. To measure the effectiveness of our efforts, we compute the fitness value as the reciprocal of the total CO_2 emissions generated during the simulation. A lower fitness value signifies reduced emissions, signifying an improved solution.

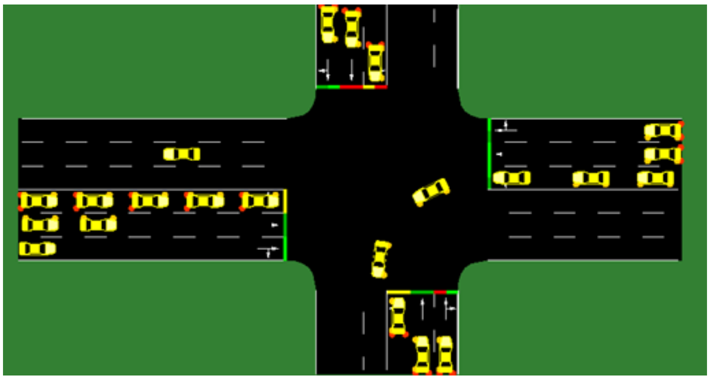

Fig. 2 The intersection considered

We conducted three experiments to evaluate the efficiency and performance of the proposed algorithm in an experimental simulation environment.

- Experiment 1: In the initial experiment, we conducted the simulation without integrating the genetic algorithm to obtain results under standard conditions.

- Experiment 2: In the second experiment, we focused on optimizing the total waiting time for all cars (in seconds) depending on the number of cars in the simulation.
- Experiment 3: In the third experiment, we focused on optimizing the total CO_2 emissions of all cars (in mg/s) depending on the number of cars in the simulation.
- Experiment 4: In the fourth experiment, we focused on optimizing the total fuel consumption of all cars (in mg/s) according to the number of cars in the simulation.

From the simulation outputs experiments to the same scenario before and after optimization, we note the following results in Table 2.

Table 2: Simulation results before and after optimization

Name	Experiment 1 Without optimization	Experiment 2 waiting time optimization	Experiment 3 CO_2 emission optimization	Experiment 4 Fuel optimization
Waiting time (s)	8.20	0.89	2.49	6.36
Total CO_2 (mg/s)	22683337.1	16043039,26	17216454.46	21068643.02
Total Fuel consumption mg/s	7235133،38	5117044,87	5491333.7	6720087.89

The simulation is executed over 200 generations with a population size of 20. During each generation, the genetic algorithm evaluates different traffic signal timing configurations to minimize not only CO_2 emissions but also waiting time and fuel consumption at the intersection.

In our study, we employed the *randomTrips.py* tool to generate trips continuously. The trip data includes various parameters such as departure speed, arrival speed, stop time, vehicle type (*DEFAULT_VEHTYPE*), and speed factor, which are crucial for our simulation analysis.

3.2. Discussion

From the results shown in Table 2, and after calculating the percentage for each experiment, we noticed the following:

1. Percentage Change from Experiment 1 to Experiment 2
   - Waiting Time ~ 89.63% reduction.
   - CO_2 Emission ~ 29.37%reduction.
   - Fuel Consumption ~29.18% reduction.
2. Percentage Change from Experiment 1 to Experiment 3

- Waiting Time ~ 69.39% reduction.

- CO_2 Emission ~ 23.98% reduction.
- Fuel Consumption ~ 23.97% reduction.

3. Percentage Change from Experiment 1 to Experiment 4

- Waiting Time ~ 22.44% reduction.
- CO_2 Emission ~ 7.11% reduction.
- Fuel Consumption ~ 7.09% reduction.

Compared to the baseline (Experiment 1), waiting times, CO_2 emissions, and fuel consumption all significantly decreased in Experiment 2 (Waiting Time Optimization) and Experiment 3 (CO_2 Emission Optimization).

Notable gains are also obtained from Experiment 4 (Fuel Optimization), albeit marginally less so than from Experiments 2 and 3.

In addition to identifying the best solution, the simulation records fitness values for all individuals in each generation. These fitness values provide insights into how well each individual performs in the task of minimizing waiting time, CO_2 emissions, and fuel consumption. These fitness values are then used to create a line plot that visualizes the performance of the population over the 200 generations, highlighting metrics such as:

- Overall Fitness: This reflects the general performance of the population in each generation regarding waiting time, CO_2 emissions, and fuel consumption.
- Elite Fitness: This indicates the fitness of the best-performing individual in each generation.
- Mean Fitness: This represents the average fitness of all individuals in a given generation.
- Standard Deviation: This shows how much the fitness values vary within the population in each generation.

The study analyzed the performance of a Genetic Algorithm in optimizing traffic signal timings to reduce CO_2 emissions, waiting time, and fuel consumption. The results showed that the GA consistently improved the quality of solutions over time. The mean fitness decreased, indicating enhanced solution quality, while elite fitness exhibited a declining trend, signifying the discovery of better solutions. The standard deviation also decreased, reflecting convergence towards a refined set of optimal solutions. These findings emphasize the effectiveness of the GA in optimizing traffic signal timings and reducing environmental impact. Visualizing these metrics over time provides a clear understanding of how the population's performance evolves and improves in terms of minimizing waiting time, CO_2 emissions, and fuel consumption at the intersection, aiding in the optimization of traffic signal timings.

The results for waiting time, CO_2 emission, and optimization are illustrated below:

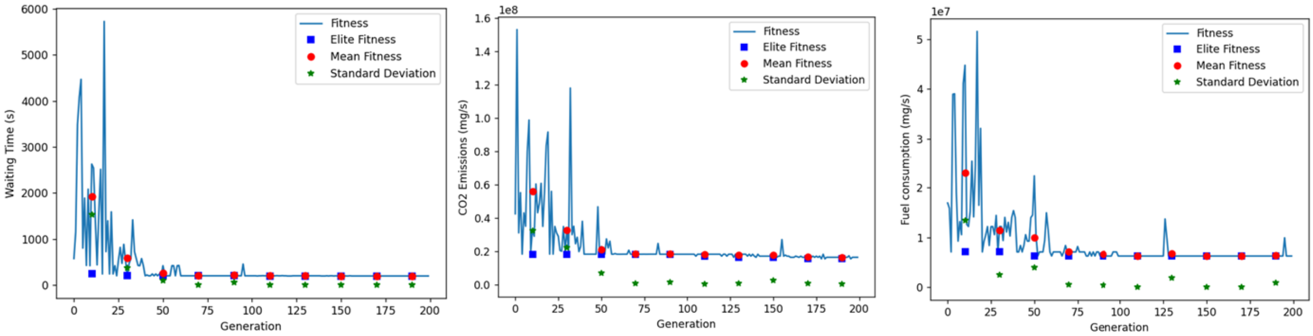

Fig. 3 Results of Waiting Time, CO_2 Emission, and Optimization Analysis

4. CONCLUSION

In this paper, we have presented a novel and comprehensive approach to optimizing traffic signal timings at intersections. By addressing multiple objectives, including the reduction of waiting time, CO_2 emissions, and fuel consumption, our research provides a versatile solution for enhancing traffic management while promoting environmental sustainability. Through an extensive simulation involving 200 generations and a population size of 20, we have successfully identified optimal signal timing configurations that strike a balance between these crucial goals.

Our study's findings are visualized through fitness metrics tracked over generations, offering insights into the evolutionary process of signal timing solutions. This multi-objective optimization framework has the potential to significantly improve urban traffic efficiency, making it more sustainable and less environmentally taxing.

As cities worldwide face growing challenges of congestion and environmental concerns, our approach provides a practical and data-driven methodology to enhance the performance of traffic signal systems. We hope this research serves as a valuable contribution to the ongoing efforts to create more efficient, eco-friendly urban transportation networks.

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