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Management of Traffic Light by Evolutionary algorithm

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ABSTRACT

Traffic congestion on main streets and intersections is caused by rapid urban expansion, increased automobile use, speeding, and a lack of driver awareness. One of the solution of reducing the congestion is the traffic lights. In this study, we optimized the traffic light timing by maximizing green light duration and minimizing red light duration, we developed an application to study timing at 16 intersections (64 traffic lights total). Each traffic light's initial red and green light values were randomly assigned. We implemented and compared two optimization methods within our application., genetic algorithm (GA) and Bio-inspired meta-heuristic, we selected the differential evolution (DE) algorithm from a suite of algorithms and compared its results to those of the genetic algorithm (GA). The DE method yielded better solutions, as shown in the tables and graphs.

Keywords: Traffic congestion, Traffic lights, Multiple intersection, Genetic algorithm, Bio-inspired meta-heuristic, Differential evolution algorithm.

INTRODUCTION

Among the upgrades to the standard of living for the largest number of people, access to personal motors has led to increased traffic and congestion on the roads. Thus, infrastructure is designed so that its capacity to move motors is in high demand and continuously expands, especially during peak hours (morning, noon, and evening). Not forgetting the delays that harm personal and professional lives. Drivers facing traffic jams are often subject to stress, noise, and nuisance. This phenomenon, widely recognized as a cause of health issues, also affects other elements such as energy loss, pollution, and the main congestion problem. Transport has visible terrific development and diversity, especially after the Industrial Revolution and the discovery of steam engines.

Traffic light optimization is a key element of modern urban transportation management, aiming to minimize congestion, reduce travel time, and improve flow. With growing cities and rising vehicle numbers, traditional fixed-time systems are inadequate for dynamic patterns. This has led to sophisticated approaches, with bio-inspired metaheuristic algorithms emerging as powerful optimization tools for traffic signal control.

Bio-inspired metaheuristics, inspired by natural phenomena and biological systems, apply nature-based principles to solve complex optimization problems. They are well-suited for traffic light optimization as they handle the multi-objective, nonlinear, and dynamic nature of traffic without requiring full mathematical models. Using probabilistic search, they explore solution spaces efficiently and adapt to changing conditions.

Nature-inspired methods for traffic signal timing have drawn significant attention from researchers and engineers over the past two decades. By mimicking evolutionary processes, swarm intelligence, and other natural mechanisms, these algorithms optimize multiple parameters, including cycle lengths, green times, phase sequences, and intersection coordination.

Traffic light optimization with bio-inspired metaheuristics aims to minimize vehicle delay, queue length, stops, fuel consumption, and emissions while maximizing throughput. Unlike traditional methods, these algorithms can escape local optima, handle uncertainty, and deliver near-optimal solutions within reasonable computation times for large-scale networks.

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RELATED WORK: BIO-INSPIRED MATAHEURISTIC ALGORITHMS

Several bio-inspired metaheuristic algorithms have been applied to traffic light optimization, each inspired by natural processes. The most prominent include:

Genetic Algorithm (GA): The most widely used, representing about 68% of implementations [5]. They have been effectively applied to reduce delays by optimizing cycle lengths and generating efficient traffic signal timing plans [6].

Ant Colony Optimization (ACO): Mimicking how ants find paths with pheromones, ACO has been applied to improve vehicle movements [7], accounting for about 17% of approaches [5].

Particle Swarm Optimization (PSO): Based on the social behavior of bird flocking or fish schooling, PSO has been applied in small to medium-scale networks [8], representing about 15% of uses [5].

Bat Algorithm (BAT): An Enhanced Bat Algorithm (EBAT) incorporates adaptive parameter tuning and guided exploration, improving execution time and convergence compared to other metaheuristics [10].

Other Algorithms: Additional methods include Differential Evolution (DE) [6], Simulated Annealing (SA) [11], Artificial Immune System (AIS), and Reinforcement Learning (RL) [12], [13].

Hybrid and Fuzzy Approaches: Some works combine algorithms with fuzzy logic for adaptive control. For example, type-2 fuzzy coordination allocates green times using gravity search algorithms to prevent queue overflow [9], [14].

These algorithms are well-suited for traffic light optimization, where traditional models struggle with randomness, non linearity, and complexity [15]. They have proven effective in optimizing green duration, cycle length, and phase sequences [16].

Table 1. Comparative Analysis of Intelligent Traffic Control Systems

Papers	Optimization Objectives	Validation and Comparison	Real-World Constraints Considered
Ibrokhimov et al. (2022) Italian National Conf. on Sensors	- Maximize throughput - Reduce average travel time - Address operational constraints	- Compared with related methods - Synthetic and real-world datasets	- Cyclic phase order - Min/max phase duration - Pedestrian safety - Vehicle starvation prevention
Bi et al. (2018) IEEE Trans. Intell. Transport. Syst.	- Alleviate traffic pressure - Prevent queue spillover - Enlarge green wave band	- Simulation validation - No detailed benchmarks	- Turning vehicles - Lane length limitations - Dynamic coordination - Traffic uncertainty
Kamran et al. (2017)	- Minimize average waiting time	- Real-world data validation - 3-phase vs 4-phase comparison	- Real-world data collection - Traffic light structure

IMPLEMENTATION AND APPLICATIONS APPROACHES

Implementing bio-inspired metaheuristics for traffic light optimization involves two parts: an optimization component that generates traffic light configurations and a simulation component that evaluates their effectiveness. This allows solutions to be tested virtually before real-world deployment.

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A. Simulation-Based Evaluation

Most implementations rely on traffic simulation platforms. The Simulation of Urban Mobility (SUMO) is widely used as a microscopic simulator to assess traffic light configurations under varying conditions [17]–[19], validating timing plans in virtual environments before real deployment [20].

Some works combine microscopic simulation with evolutionary algorithms for optimization. For instance, Semet et al. developed a system with memetic (genetic+gradient) calibration to adapt to current conditions and incorporated existing traffic light programs through an inoculation procedure [21].

B. Optimization Approaches

The optimization component typically focuses on adjusting various traffic signal parameters:

1. **Single Intersection Optimization:** Some approaches optimize traffic light phases at individual intersections. For example, Rida et al. used Ant Colony Optimization to dynamically plan and sequence phases, minimizing vehicle waiting time and maximizing flow [22].
2. **Multi-Intersection Coordination:** More advanced approaches address networks of intersections. Particle Swarm Optimization has been applied to improve traffic flow, achieving over 95% improvement after 80–90 iterations [23]. PSO is favored for its fast convergence, valuable in scenarios requiring immediate traffic light schedule updates [17], [24].
3. **Multi-Objective Optimization:** Many implementations address multiple objectives. For example, Zhang et al. proposed a hybrid constraint strategy with the NSGAIII framework (HCNSGA-III) to optimize capacity and delay, considering emissions for sustainable traffic [25].
4. **Environmental Considerations:** Some implementations specifically target environmental impacts. The micro artificial immune system (MAIS) algorithm has been developed to reduce pollution rates by optimizing vehicular flow, with simulations showing improvements in traffic flow, reduced waiting times, and decreased fuel consumption and environmental pollution [18].

C. Alternative Approaches and Enhancements

Several enhancements to traditional bio-inspired methods have been proposed:

1. **Hybrid Methods:** Hybrid approaches combine different metaheuristics. For example, variable neighborhood search with Tabu search has been used to synchronize intersections, incorporating memory structures for broader solution exploration [26].
2. **Surrogate Models:** To address the high computational demands of traffic simulations, surrogate models have been employed to approximate results quickly. Dissel et al. tested four surrogate models (Linear Regression, Multi-Layer Perceptron, Support Vector Regression, and Random Forest) alongside Differential Evolution to predict average speed and queue length [33].
3. **Decentralized Approaches:** Some implementations utilize decentralized, agent-based approaches where traffic signals operate autonomously based on local conditions. This self-organization principle can make solutions both efficient and adaptable to changing traffic patterns [27].
4. **Algorithm Modifications:** Researchers refine algorithms for better performance. The Hash-Table Multielement Genetic Algorithm (H-MEGA) improves upon earlier Multielement Genetic Algorithm (MEGA) and Particle Swarm Optimization implementations [28].

D. Practical Applications

The practical application of these approaches has shown promising results. Genetic Algorithms optimized traffic signal timing, with one study reporting 38.46% fewer losses than Webster's formula-based methods under high demand [19].

Recent work has shifted toward adaptive frameworks that design optimal strategies for unseen patterns with limited online simulations, leveraging prior knowledge from offline meta-datasets [29]. These approaches address the unpredictability that limits static models.

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The variety of implementation approaches reflects the complexity of traffic light optimization and the versatility of bio-inspired metaheuristics. From simple genetic algorithms [30] to advanced multi-objective frameworks, these methods continue evolving to meet modern urban traffic demands

PERFORMANCE AND COMPARATVE ANALYSIS

Performance evaluation is a critical aspect of traffic light optimization research, providing insights into the comparative effectiveness of different bio-inspired metaheuristic approaches. Studies consistently demonstrate that these algorithms significantly outperform traditional fixed-time and pre-timed traffic control methods across various performance metrics.

A. Performance Metrics and Evaluation

Traffic light optimization algorithms are evaluated with metrics such as delay, capacity, stops, fuel use, and impact. Simulation tools like Signalized Intersection Fuzzy-Real Control (SIFRC) and Simulation of Urban Mobility (SUMO) allow performance comparison before real-world deployment [31].

B. Comparative Analysis of Bio-inspired Algorithms

A review of metaheuristic traffic light control showed Genetic Algorithms (GA) as the most used method (68%), followed by Ant Colony Optimization (ACO, 17%) and Particle Swarm Optimization (PSO, 15%) [5], reflecting their effectiveness and adaptability.

GA has delivered strong results, particularly under high demand, outperforming Webster's formula with 38.46% fewer losses at high traffic, 37.41% at low, and 3.48% at medium levels [19], highlighting the value of bio-inspired methods as complexity rises.

Comparative studies note specific strengths: Differential Evolution (DE) converges faster, but GA often yields higherquality solutions, especially for delay reduction [25]. PSO converges quickly, making it suitable for cycle plans across multiple lights [25]. Hybrid approaches, such as HCNSGA-III (Hybrid Constraint Strategy with NSGA-III), improve multiobjective optimization, generating stronger Pareto sets for traffic indicators [25].

C. Recent Innovations and Performance Improvements

Recent research has focused on enhancing existing algorithms and developing new approaches to address limitations in execution time and convergence speed:

The Enhanced Bat Algorithm (EBAT) uses adaptive parameter tuning and guided exploration based on predicted congestion. In comparisons with seven metaheuristics, EBAT showed faster convergence and execution, making it suitable for real-time applications [10].

Hybrid methods combining fuzzy logic with real-time optimization also improved performance. One fuzzy-real method outperformed fixed-time by up to 50% and other approaches by 10%. Additionally, this hybrid approach achieved optimization responses 11 times faster than pure real-time methods without increasing intersection delay times [31].

Reinforcement learning is emerging as an alternative. A Deep Q-Network case study reduced emergency stops by 44.16%, showing machine learning's potential to ease congestion [32].

Overall, bio-inspired metaheuristics consistently outperform conventional traffic control. Their evolution, including hybrid and enhanced designs, shows strong potential for further optimizing urban traffic signals.

TRAFFIC CONTROL SIGNALS

Traffic Control Signals are devices placed along, beside, or above a roadway to guide, warn, and regulate the flow of traffic, which includes motor vehicles, motorcycles, bicycles, pedestrians, and other road users [1].

• **Red light:** A right turn can be made against a red light ONLY after you stop and yield to pedestrians and vehicles in your path. DO NOT turn if there is a sign posted for NO TURN ON RED.

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• **Yellow or Orange light:** signal warns that red is about to appear. You should stop if safe; if not, proceed cautiously and watch for vehicles entering the intersection.
• **Green light:** A green light means GO, but you must first let any vehicles, bicycles, or pedestrians remaining in the intersection get through before you move ahead.

Figure 1: Traffic Control Signals

INTERSECTIONS

An intersection is an at-grade junction where two or more traffic flows meet or cross. Intersections can be classified by the number of road segments, traffic controls, or lane design. The figure (2) shows the crossroads model commonly used in the literature for model validation.

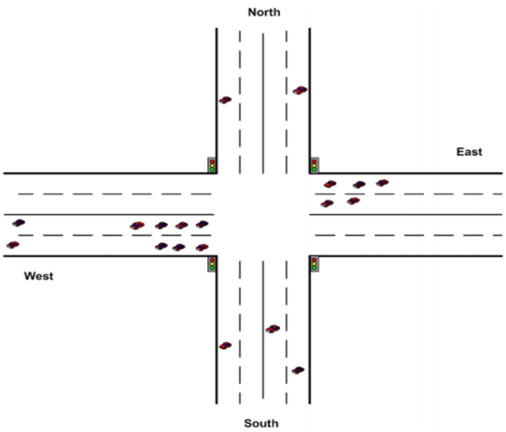

Figure 1: Intersections

OPTIMIZATION

Optimization refers to improving, maximizing, minimizing, or perfecting performance to yield the most favorable conditions. According to Kulkarni et al., it holds great significance in both human affairs and natural laws, reflecting the inherent tendency to achieve the best (minimum or maximum) outcome in a given situation [2].

1. **General optimization problem statement:** We can now express our optimization task in quantitative form. This mathematical expression of the design problem is called the basic optimization problem statement and can be written as follows:

$$(P)\begin{cases} \min f_{obj}(x) \\ x \in D \\ g_i(x) \leq 0 \quad 1 \leq i \leq n \\ h_j(x) = 0 \quad 1 \leq j \leq n \end{cases}$$

2. **Objectify function:** The objective function is the scalar quantity to be minimized, depending on the set of design variables. (Although stated as a minimization task, a function can be maximized by minimizing its negative).

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3. **Evolutionary algorithms:** Evolutionary Computation is a leading journal providing an international forum for exchanging information among researchers in both theoretical and practical aspects of computational systems inspired by nature, with emphasis on evolutionary models such as genetic algorithms, evolutionary strategies, classifier systems, evolutionary programming, and genetic programming [3].

GENETIC ALGORITHM (GA)

A genetic algorithm (GA) is a heuristic search method for solving optimization problems. It is a subset of evolutionary algorithms used in computation. GAs apply concepts of genetics and natural selection to provide solutions [4].

A. **Basics of Genetic algorithm(GA):**
- **Population:** This is a subset of all the probable solutions that can solve the given problem.
- **Chromosomes**: A chromosome is one of the solutions in the population.
- **Gene**: This is an element in a chromosome.
- **Fitness function:** This function uses a specific input to produce an improved output. The solution serves as the input, while the output represents solution suitability.

B. **GA operators:** After the evaluation of the initial population, it is necessary to make it evolve to generate a new one, this evolution and to ensure by three operators who are:
- **Selection**: Choice of the most suitable individuals.
- **Crossover**: Mixing by reproduction of the particularities of the chosen individuals.
- **Mutation:** Random alteration of the particularities of an individual.

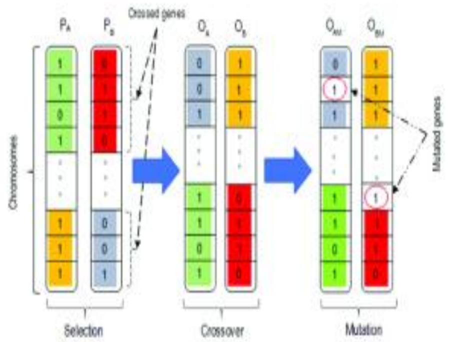

Figure 3: Genetic Algorithm Basics

DIFFERENTIAL EVOLUTION ALGORITHM(DE)

The Differential Evolution (DE) algorithm, proposed by Storn and Price, is a simple yet powerful population-based stochastic global search method. It has been successfully applied in fields such as mechanical engineering, communication, and pattern recognition. In DE, generations of test vector strategies are created, some suitable for solving a given problem. The algorithm evolves a population of NP D-dimensional vectors, called individuals, which encode candidate solutions:

$$X_i(G) = ((X_i(G))^1, \ldots, (X_i(G))^D), \quad i = 1, \ldots, NP.$$

Towards the global optimum, the initial population should better cover the entire research space by uniformly randomizing individuals within the search space limited by the prescribed minimum and maximum parameter limits.

$$X_{min} = (X_{\min 1}, \ldots, X_{\min D}), \; X_{max} = (X_{\max 1}, \ldots, X_{\max D})$$

For example, the initial value of the j-th parameter in the i-th individual at generation G = 0 is generated by:

$$x(i,0)_j = x_{\min j} + rand(0,1).(x_{\max j} - x_{\min j}), \qquad j = 1,2,\ldots,D$$

Where rand(0; 1) represents a uniformly distributed random variable in the range.

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A. Mutation Operation

After initialization, DE uses the mutation operation to produce a mutant vector $V_{i,G}$, associated with each individual $X_{i,G}$ (the so-called target vector) in the current population.

For each target vector $X_{i,G}$ at generation G, its corresponding mutant vector $V_{i,G} = \left(v_{i,G}^{1}, v_{i,G}^{2}, \dots, v_{i,G}^{D}\right)$ is generated using one of several mutation strategies. The five most frequently used mutation strategies implemented in DE codes are listed below:

1. **DE/rand/1**

$$V_{i,G} = X_{r1,G} + F\,.\left(X_{r2,G} - X_{r3,G}\right) \qquad (1)$$

2. **DE/best/1**

$$V_{i,G} = X_{best,G} + F\,.\left(X_{r1,G} - X_{r2,G}\right) \qquad (2)$$

3. **DE/rand-to-best/1:**

$$V_{i,G} = X_{i,G} + F\,.\left(X_{best,G} - X_{i,G}\right) + F\,.\left(X_{r1,G} - X_{r2,G}\right) \qquad (3)$$

4. **DE/best/2**

$$V_{i,G} = X_{best,G} + F\,.\left(X_{r1,G} - X_{r2,G}\right) + F\,.\left(X_{r3,G} - X_{r4,G}\right) \qquad (4)$$

5. **DE/rand/2**

$$V_{i,G} = X_{r1,G} + F\,.\left(X_{r2,G} - X_{r3,G}\right) + F\,.\left(X_{r4,G} - X_{r5,G}\right) \qquad (5)$$

Note: We have chosen the "DE/rand/1" mutation strategy in our application.

B. Crossover Operation

After the mutation phase, the crossover operation is applied to each pair of the target vector $X_{i,G}$ and its corresponding mutant vector $V_{i,G}$ to generate a trial vector $U_{i,G}$:

$$U_{i,G} = (U_{i,G}^{1}, U_{i,G}^{2}, \dots, U_{i,G}^{D} \qquad (6)$$

In the basic version, DE uses the binomial (uniform) crossover defined component-wise as:

$$U_{i,G}^{j} = \begin{cases} V_{i,G}^{j} \; if \; rand_j(0,1) \le CR \; or \; j = j_{rand} \\ X_{i,G}^{j} \; otherwise \,, j = 1,2,..,D \end{cases} \qquad (7)$$

where $rand_j(0,1)$ is a uniformly distributed random number in [0, 1] for the j-th component, CR is the crossover rate, and j_{rand} is a randomly chosen index in {1, . . . , D} to ensure at least one component is taken from the mutant vector.

C. Selection Operation

If any parameter of a new trial vector exceeds its bounds, it is reset uniformly at random within the allowed interval. The objective function is then evaluated for all trial vectors. A selection follows: the objective value $f\left(U_{i,G}\right)$ of each trial vector is compared with its target vector $f\left(X_{i,G}\right)$ The next generation vector is chosen as:

$$X_{i,G+1}^{j} = \begin{cases} U_{i,G}^{j} \; if \; f\left(U_{i,G}\right) \le f\left(X_{i,G}\right) \; or \; j = 1,2,\dots,D \\ X_{i,G}^{j} \; otherwise \end{cases} \qquad (8)$$

Thus, If the trial vector is at least as good as the target, it replaces it; otherwise, the target survives.

MODELIZATION AND REALIZATION

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Traffic Control Signals are devices placed along, beside, or above a roadway to guide, warn, and regulate the flow of traffic, which includes motor vehicles, motorcycles, bicycles, pedestrians, and other road users [1].

A. Problem Adaptation

The objective function of our problem is defined based on traffic conditions at an intersection. The objective function is defined by traffic conditions at an intersection. If any incoming lane (left, right, up, or down) has ≥ 50% of the total vehicles, traffic is considered congested, and the green light is extended by an adjustment factor $T \in [2,5]$.

The objective function is then expressed as:

$$f(t) = Time_{green} + \tau_i \qquad 2 < \tau_i < 5$$

If the lower lane alone reaches 50% of vehicles, localized congestion is identified, and a smaller adjustment $T \in [0,2]$ is applied, making the corresponding objective function:

$$f(t) = Time_{green} + \tau_i \qquad 0 < \tau_i < 2$$

B. Our Application

We have developed an application integrating Genetic Algorithm (GA) and Differential Evolution (DE) to address this optimization problem. The interface and implementation of the application are illustrated in Figure 4.

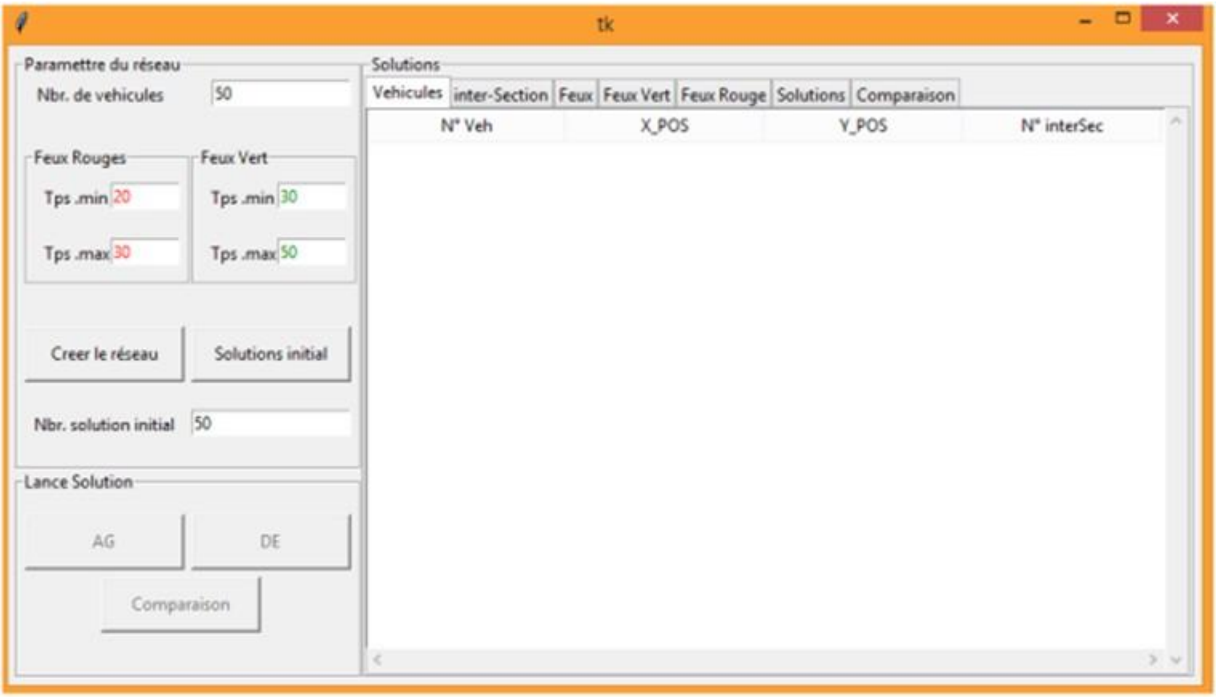

Figure 4: Main Interface

C. Testing

After the configuration in network section in figure(5) we:

1. create the network. as shown in the Figure 5.
2. Initialize solution randomly for :
   a. Red light:

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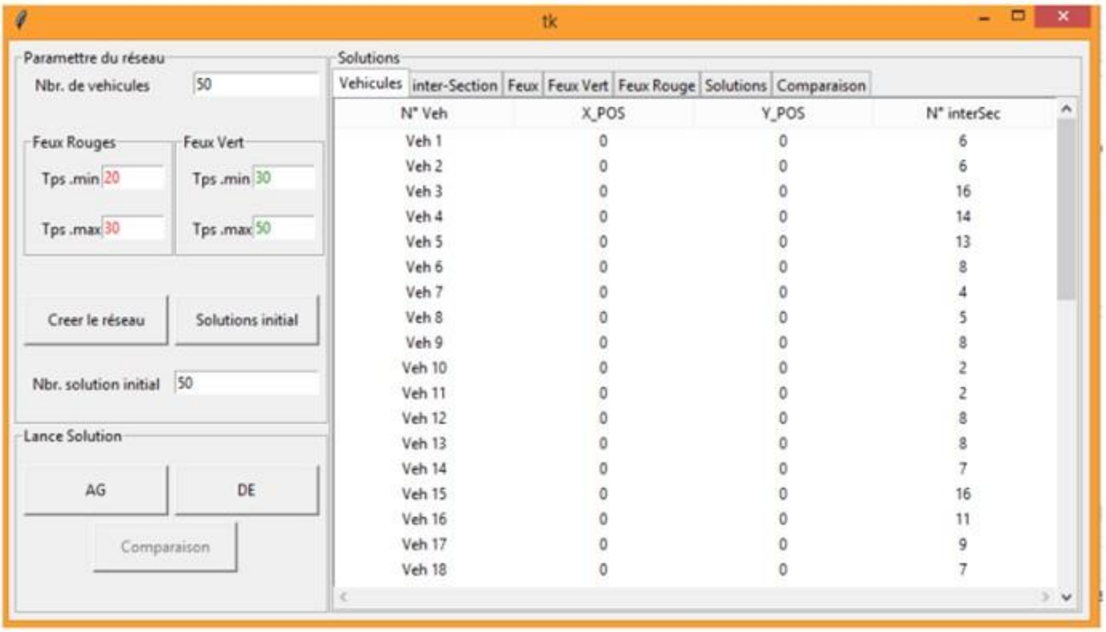

Figure 5:Network Creation

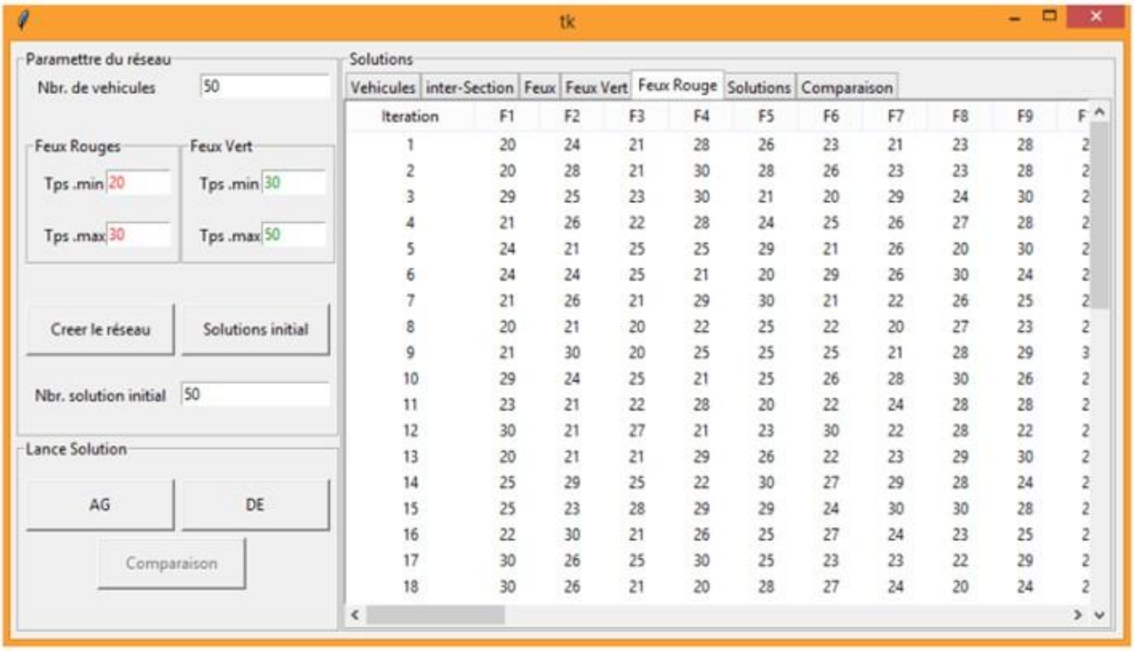

Figure 6: Red light initial solution

b. Green light

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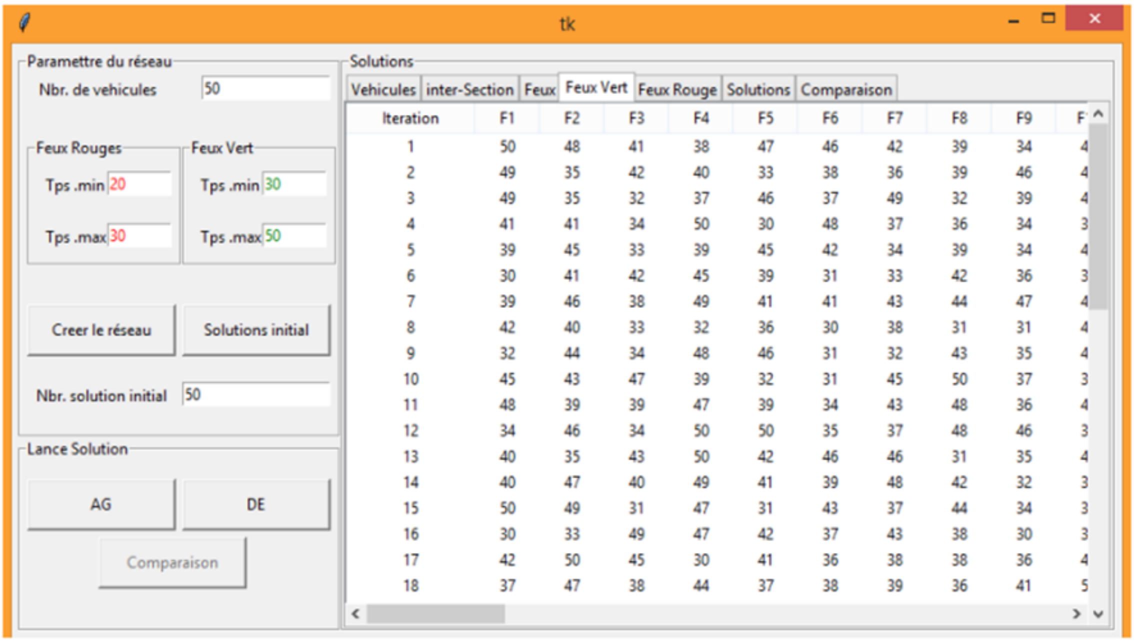

Figure 7: Green light initial solution

D. Comparison between GA and DE results

After running both algorithms, the results are shown in Figures 8 and 9.

The GA fitness for green lights is lower than DE, indicating that DE maximizes green light efficiency better. For red lights, DE fitness is lower than GA, meaning DE minimizes red light duration more effectively. Overall, the DE approach outperforms GA in optimizing traffic signal timing.

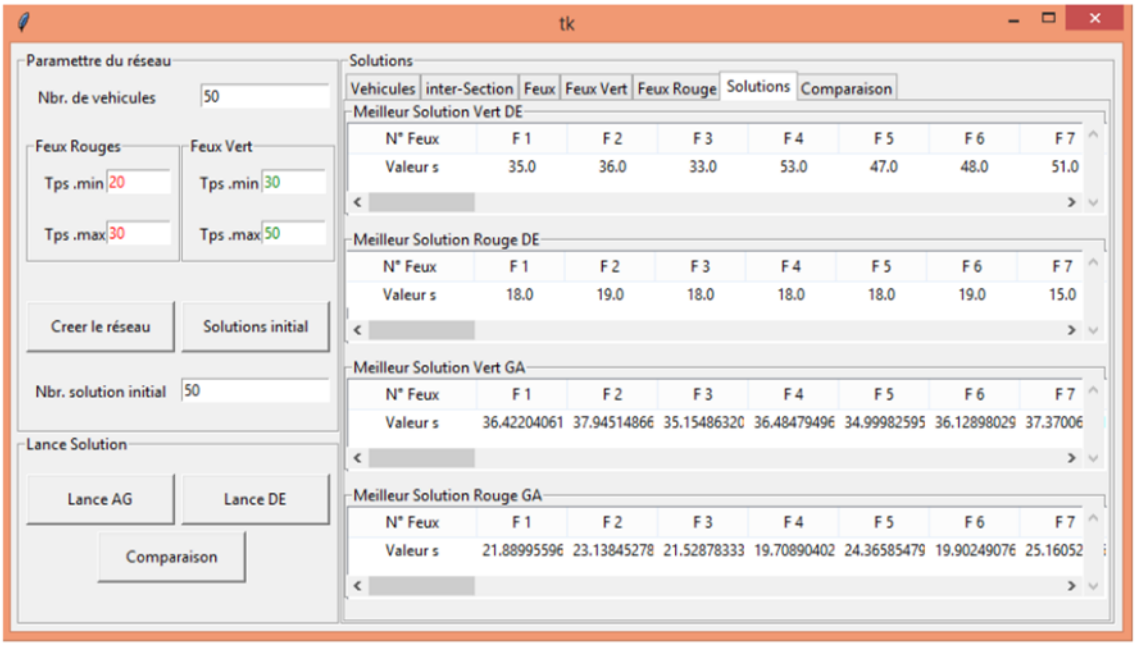

Figure 8. Last results of Green/Red for each algorithm

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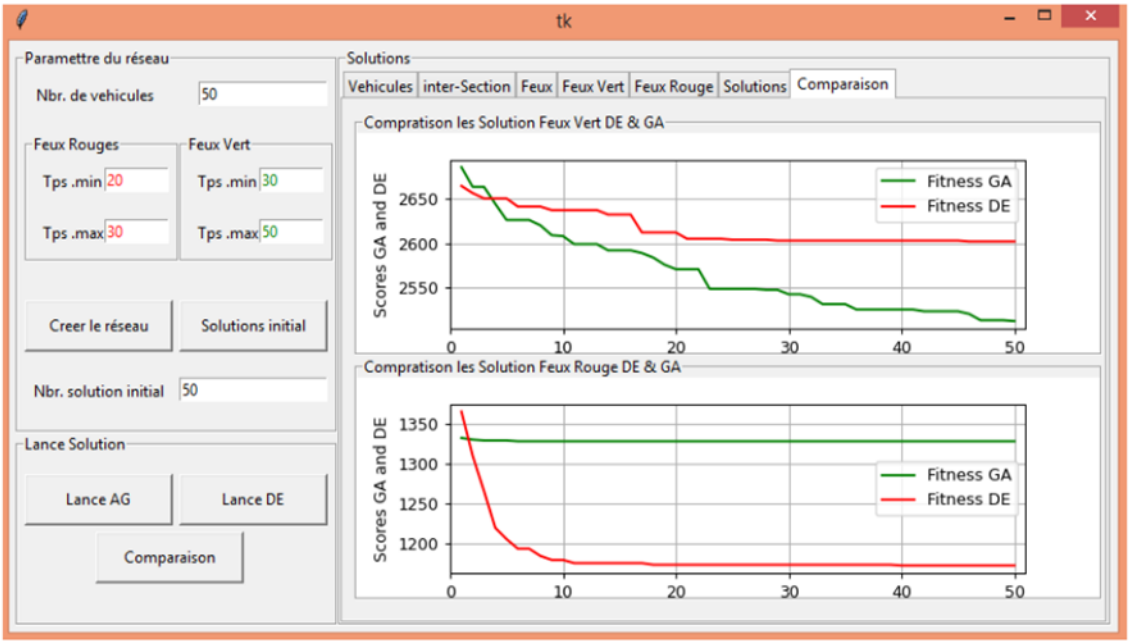

Figure 9: Charts Comparison between DE and GA fitness

CONCLUSION

The study that we have presented concerns the optimization of the signalization of the lights of several intersection which constitutes 16 Intersections with data on the state of each lane with the precision of vehicle flow the streets of this intersection generate an enormous congestion in traffic. At these intersections and then manage the traffic of vehicles in real time, so that this would be done according to the actual presence of vehicles in the different lanes.

According to previous studies on this subject, we have applied two meta-heuristic methods as a continuation of the projects proposed in the past years, after having good results for the optimization of this problem by the Genetic Algorithms (GA) and the differential evolution algorithm (DE), By changing the parameters of each method and discussing the results we find a good improvement about the signaling proposed by the state and the signaling found by each method, which confirms their effectiveness.

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