Traffic Light Optimization for Vehicles and Pedestrians through Evolution Strategies

Lucas de C. Gomes, *Student Member, IEEE*, and Luís Henrique M. K. Costa, *Senior Member, IEEE*
Universidade Federal do Rio de Janeiro - GTA/Poli/COPPE/UFRJ - Rio de Janeiro, Brazil
{gomes, luish}@gta.ufrj.br

***Abstract*—The optimization of urban traffic lights is a relevant problem. With the increasing occupation of urban pathways comes mobility deterioration: increasing delays, traffic jams and other consequential losses. Its relevance led to several proposals on traffic light optimization; the majority of them only consider vehicular traffic, to the detriment of pedestrians. Nonetheless, the longer pedestrians wait to cross, the riskier their behavior becomes, since they become more impatient. We tackle this problem through the optimization of traffic lights considering the average delays of both pedestrians and vehicles, by using microscopic traffic simulations. The problem is modeled on the basis of reference works of the area, and solved by an Evolution Strategy (ES). Several constraint handling methods are compared, including one proposed in this work, Two-Level Ranking (TLR), that aims to quickly find feasible solutions, which is important for real-time execution. The ES was able to find solutions that keep the pedestrian delays within the limits given by related work. Furthermore, in the evaluated scenario, a solution that satisfies the constraints is found, in average, at approximately 18.6 seconds with TLR, which is shorter than what other methods yield, allowing real-time operation.**

***Index Terms*—Traffic light optimization, evolution strategies, intelligent transportation systems.**

I. Introduction

The increasing amount of vehicles used daily in urban environments overloads pathways, leading to traffic jams, and economical, environmental and health-related consequences. The study conducted by INRIX Research, with data obtained from more than 200 cities, indicates severe losses of capital and time due to traffic jams [1]. For example, the United States freight transport sector loses US$ 74.5 billion per year due to traffic congestion. This problem is influenced by urban traffic lights, which regulate the traffic of vehicles and pedestrians. Therefore, their optimization has attracted the attention of academia, industry and governments, which pursue solutions for decades [2]–[5]. Most proposed approaches optimize vehicle-related metrics, such as mean travel time, fuel consumption, and pollutant emissions [6]. While these metrics are indeed important, the satisfaction of pedestrians is hardly considered. This is a limitation: the longer pedestrians have to wait, the more impatient they become, leading to riskier behaviors to cross faster and increasing the risk of accidents [7]–[9].

Related works employ analytical models and simulations, divided into microscopic, macroscopic, and mesoscopic approaches. Microscopic ones represent the individual behavior of each vehicle and pedestrian, with theoretical mobility models. Macroscopic models approximate the urban traffic dynamics by using fluid dynamics theory. Mesoscopic methods are intermediary solutions. Macroscopic models have, in general, lower execution times, albeit being less accurate. Microscopic ones offer greater accuracy at the cost of longer processing times. Therefore, a difficulty for solutions that employ microscopic approaches is reducing the optimization procedure time, in order to make it compatible with real-time operation for dynamic scenarios.

The problem we consider is the optimization of the allocation of times for traffic lights placed at intersections, in order to speed up the flow of vehicles and pedestrians. There are two ways of handling pedestrians at an intersection [10]. Two-Way Crossing (TWC) allows pedestrians and vehicles to simultaneously cross the pathways, as long as their trajectories do not conflict. Exclusive Pedestrian Phase (EPP) isolates vehicles from pedestrians, concentrating all the pedestrian traffic on one phase, which reduces the risk of accidents but tends to increase delays for both vehicles and pedestrians [11].

In this context, we implement an approach for traffic light optimization that considers the conflicting pedestrian and vehicle interests, using traffic simulations executed in the SUMO framework [12]. The problem is modeled as an optimization one, following traffic guidelines and green time threshold values obtained from related work [2], [7]–[11]. This model was used to solve the problem through an Evolution Strategy (ES) [13]. With this configuration, fitness evaluations (FEs) are microscopic traffic simulations, imposing a great computational cost. Thus, the ES employed here has received several adjustments, aiming to reduce the execution time and amounts of fitness evaluations and generations required to find an interesting solution, and to avoid premature convergence. Different constraint handling methods are compared to our proposal, Two-Level Ranking (TLR), which aims to quickly find feasible solutions. In the tested scenarios, TLR has been able to find solutions that satisfy the restrictions. Nevertheless, there are important performance differences between the techniques.TLR achieved the lowest execution time, finding a feasible solution on 18.6 s on average. Additionally, optimizing for pedestrian and vehicle traffic has reduced pollutant emissions and fuel consumption.

This work is organized as follows. Section II presents related work. Section III describes the problem modeling. Section IV discusses the adopted Evolution Strategy and relevant implementation decisions. Section V presents the evaluation scenario and the obtained results. Finally, Section VI concludes the paper and presents future work.

II. Related Work

Yang and Benekohal [2], [10] consider traffic light optimization for one intersection. They minimize the sum of average delays of each type of user of the urban pathways – vehicles or pedestrians. The weight given to the pedestrian average delay (called K) was varied between 0 and 3, with integer values. The phase durations attributed to the traffic lights were also integers and individually set to each lane of each street. Moreover, the optimization decides if an exclusive pedestrian phase (EPP) is added. The authors employ a Genetic Algorithm (GA) for the optimization. In order to verify which factors made an EPP an interesting choice, they have evaluated several configurations, varying K, the sizes of the queues at the beginning of the simulations, the amount of lanes in each direction, and the traffic density. The results indicate that higher K values discourage using EPPs, given that pedestrians already receive a more important role in the objective function. The authors conclude that EPP is more suitable for intense flows of pedestrians and vehicles that are perpendicular. The main shortcomings of this work are: the usage of integer variables for optimization, affecting its precision; the absence of other meta-heuristics or variations of the GA for comparison; and the small scenario with one intersection.

Gao *et al.* [14] perform an optimization which minimizes the total delays of pedestrians and vehicles. The authors have designed a macroscopic model for the movements of these individuals, which depends on two considerations: the proportions of vehicles and pedestrians that head to each direction at every street are known; and EPPs are disregarded. The model considers operation in time slots of an arbitrary duration. This modeling allows allocating predefined phases for time slots in the future. Two meta-heuristics are evaluated, and a local search mechanism was turned on and off in different runs of both algorithms, making a total of four candidates. To solve the problem for two optimization objectives, the authors employ the concept of Pareto dominance [15] to find the best solutions: for those, improving the value of one objective worsens the value of the other, and vice-versa. Nevertheless, the usage of time slots and a macroscopic approach limit the precision of the approach proposed by this work.

Although Ishaque and Noland [11] do not focus on traffic light optimization, they bring important observations. The authors have conducted microscopic traffic simulations, involving several types of vehicles and pedestrians. The evaluation scenario was composed of four intersections. In the experiments, the vehicle flow and the cycle durations at intersections were varied, and the duration of phases that involve pedestrians was kept constant. The adoption of one or two EPPs was also considered. Delays for each vehicle type and the pedestrian delays were analyzed, in order to seek measures that reduce them. The authors conclude that raising the cycle duration increases the vehicle throughput, until a limit value of 90 s. Considering only passenger cars, a 72 s cycle duration minimizes the delay. For pedestrians, however, the delay is minimized with a 45 s duration, indicating a conflict of interest between pedestrians and vehicles. The authors also observe that giving a weight of 2 to the pedestrian delay and putting more importance on vehicles that carry more passengers – such as buses and taxis – can shift the best configuration, so that its cycle duration assumes values ranging between 60 s and 72 s, representing a better compromise among the different interests in the scenario. This study simplifies, however, the behavior of pedestrians, considering that they always follow the traffic rules and that pedestrians do not interact with each other. As such, there is no limit on the number of pedestrians simultaneously crossing the street, which is unrealistic.

Vallyon *et al.* [7] evaluate interactions between pedestrians and traffic lights. They observe the behaviors of pedestrians in a New Zealand scenario, followed by the conduction of surveys with some of them, and conduct an evaluation through microscopic simulations and optimization. The observation of pedestrians and the surveys led to the conclusion that, the more populated a city is and the more traffic jams occur there, the greater the delay pedestrians suffer during commuting. They also tend to cross more often at red or blinking red lights, increasing risks. The evaluation via simulation and optimization considers six scenarios, with varying amounts of intersections. It was observed that optimizing by the per-person delay – assuming that each passenger car carries 1.4 people in average – leads to significant improvements of the pedestrian delays, ranging between 26% and 45%, in relation to the standard phase durations. The vehicular delay, with this optimization, has slightly increased in some scenarios, although it was reduced in others. Other measures, such as merging phases that allow similar vehicular movements or increasing the cycle durations, have also led to additional improvements for most scenarios.

The mentioned related work discusses several important characteristics of the problem. Nevertheless, each work has some limitations, discussed on their paragraphs. Our proposal aims to fill this gap by providing an optimization framework which operates with real values for the green times instead of integer values or time slots of arbitrary duration, which allows finer adjustments. Furthermore, our work contributes to the state of the art on optimization with microscopic simulations, by proposing a constraint handling method that finds feasible solutions in less time than other alternatives.

III. Problem Modeling

The problem we model is the optimization of traffic light timing schedules at intersections, to improve the traversal of land vehicles and pedestrians. The operation of traffic lights is characterized by the phases, the movements that they allow and their durations. Thus, the goal is: given queues of vehicles and pedestrians at approaches of one or more intersections, make those individuals leave the region as soon as possible. To simplify the problem, the phase orders for each intersection and the permissions given by each phase are immutable, excluding the combinatorial aspect from the optimization problem. Furthermore, no other vehicle or pedestrian enters the region of interest during the experiments. The objective function considers the delays of vehicles and pedestrians. Other relevant metrics are the amount of executed simulations and the run time for the optimization, so that it is possible to assess the viability of applying this approach to real-time traffic light control. The evaluated scenario assumes an exclusive pedestrian phase (EPP). Employing information extracted from related work [2], [7]–[11], we have designed the following optimization problem, considering TWC:

$$\text{minimize } f(T_{g,1},...,T_{g,i}) = \bar{D}_{car} + 2\ \bar{D}_{ped}, i \in [1, N_d] \quad (1)$$
$$\text{s.t. } Q_{car,i}, Q_{ped,i}, Q_x \in \mathbf{Z}^+, i \in [1, N_d] \quad (2)$$
$$0 \le max_{j=0}^{N_{ped}} D_{ped,j} \le 60 \text{ s} \quad (3)$$
$$0 < \sum_{i=1}^{N_d} (T_{g,i} + T_{y,i} + T_{endped,i}) \le 90\,\text{s} \quad (4)$$
$$3.2 + \frac{l_{cw,i}}{V_{ped}} + 0.27\ max_{i=1}^{N_d}(Q_{p,i}) \le T_{g,i} \quad (5)$$
$$1 \le T_{g,i} \quad (6)$$
$$D_x, T_x \in \mathbf{R}^+. \quad (7)$$

In this model, $\bar{D}_{car} = \sum_{j=1}^{N_{veh}} \frac{D_{car,j}}{N_{veh}}$ and $\bar{D}_{ped} = \sum_{j=1}^{N_{ped}} \frac{D_{ped,j}}{N_{ped}}$ correspond, respectively, to the mean delays of vehicles and pedestrians, produced by the traffic simulations. N_{veh} and N_{ped} are the amounts of vehicles and pedestrians in the simulation and $T_{g,i}$ is the green time for traffic light i. N_d is the amount of approaches in the intersection, which means the amount of streets which converge to it. $T_{y,i}$ is the yellow time for traffic light i; it is assumed to be equal to 3 s – a value frequently used in the related work [2], [10], [11], $T_{endped,i}$ is the duration in which the flashing red light for pedestrians is active, warning them that their phase is ending, employed in order to guarantee all pedestrians are on sidewalks. This value is assumed to be 5 s, duration given by SUMO in function of the intersection dimensions. $max_{j=0}^{N_{ped}} D_{ped,j}$ corresponds to the longest delay seen by a pedestrian during the simulation. $Q_{car,i}, Q_{ped,i}$ are the sizes of vehicle and pedestrian queues in the direction i; those are conditions given by the traffic simulation configuration; $l_{cw,i}$ represents the length of the crosswalk for direction i; and V_{ped} represents the speed of a walking pedestrian, equal to 1.2 m/s [10].

The objective function (Eq. 1) is the sum of the mean pedestrian and vehicle delays. $\bar{D}_{ped}$ receives weight 2, which is considered a good balance between pedestrians and vehicles [2], [10], [11]. Eq. 3 sets an upper bound for the maximum pedestrian delay – 60 s –, conceived by studies which aimed to produce a traffic safety manual for Germany [9]. This value is justified by information from other works. According to [11], pedestrians feel impatient after waiting 30 s. Furthermore, empirical observations [7], [8] suggest that, the longer pedestrians wait, the riskier their behavior becomes. Eq. 4 restricts the duration of a cycle. Cycles over 90 s should be avoided; this is a conclusion derived from the restriction over the maximum pedestrian delay [9]. Eq. 5 is the minimal green time for phases which allow the crossing of pedestrians, extracted from [10] and originated from the American *Highway Capacity Manual* (http://www.trb.org/publications/hcm6e.aspx). Eq. 6 sets an arbitrary minimum value for the green time of any traffic light; this is meant to prevent “frozen” simulations, in which the green time is zero for a direction with queued vehicles, preventing its conclusion. Eqs. 4, 5 and 6 are related to decision variables. Nevertheless, Eq. 3 concerns a simulation result – the maximum pedestrian delay. For cases in which an exclusive pedestrian phase is used, this model was adapted to:

$$\min f(T_{g,1},...,T_{g,i},T_{ped}) = \bar{D}_{car} + 2\ \bar{D}_{ped}, i \in [1, N_d] \quad (8)$$
$$\text{s.t. } Q_{car,i}, Q_{ped,i}, Q_x \in \mathbf{Z}^+, i \in [1, N_d] \quad (9)$$
$$0 \le max_{j=0}^{N_{ped}} D_{ped,j} \le 60 \text{ s} \quad (10)$$
$$0 < \sum_{i=1}^{N_d} (T_{g,i} + T_{y,i}) + T_{ped} + T_{endped} \le 90\,\text{s} \quad (11)$$
$$3.2 + \frac{l_{cw,i}}{V_{ped}} + 0.27\ max_{i=1}^{N_d}(Q_{p,i}) \le T_{ped} \quad (12)$$
$$1 \le T_{g,i} \quad (13)$$
$$D_x, T_x \in \mathbf{R}^+. \quad (14)$$

An additional variable in this model, T_{ped}, is related to the duration of the EPP. Also, T_{endped}, present at Eq. 11, does not have a direction index anymore: there is only one transition between a phase involving pedestrians and phases involving vehicles, differently from the TWC model. For multiple intersections, each additional intersection adds, to the decision variables, green times relative to their approaches with traffic lights, and additional cycle duration restrictions – 1 per additional intersection –, green times for pedestrians – 1 per phase that involves pedestrians in the additional intersection – and green times for any direction – 1 per approach. New intersections also add new queues on each approach.

IV. Employed Meta-Heuristic

Genetic Algorithms (GAs) are one of the most employed meta-heuristics for traffic light optimization [2], [4]–[6]. Nonetheless, Evolution Strategies (ESs) [13] were more efficient in initial evaluations; therefore they were chosen for the experiments. ESs are evolutionary algorithms which are similar to GAs, using crossover, mutation and survivor selection mechanisms. Nevertheless, they do not employ parent selection mechanisms, generating offspring from any pair of parents with equal probability, disregarding their fitness in this step. This provides larger variability.

The decision variables – green times – are coded as real values. This is different from what is performed in a part of the related work, which employs integer variables, offering less precise adjustments. The population is initialized randomly, using uniform distributions. It is typical for ESs to generate more offspring (λ) than the amount of parents (μ – also the population size). This, coupled with generational survivor selection mechanisms – that exclude the parents – accelerates the search and allows efficient exploration in promising regions. A recommended proportion is the value 7 [15], which was employed here – we have used $\mu = 20$ and $\lambda = 140$. Elitism is also employed, preserving the best individual from each generation, avoiding its loss by mutation, crossover or survivor selection. In order to generate offspring, the BLX-α *crossover* [16] was chosen. Given two parents p_1 e p_2, a child c is generated as follows:

$$c = p_1 + \beta(p_2 - p_1), \tag{15}$$

where $\beta \in U(-\alpha, 1 + \alpha)$: it is generated from a uniform distribution. α was set to 0.5 and the crossover probability to 0.8. Each operation generates one child.

Another feature which improves ESs performances are mutations with self-adaptive parameters. We employ a modified creep mutation [13]. It chooses, at each generation, the best parameter values, which depend on the objective function. A creep mutation adds perturbations over each decision variable, originated from a standard distribution; their mean values were kept as 0. The standard deviations for each dimension i, σ_i, are modified every generation. Standard deviations also compose individuals genotypes and undergo changes by the crossover procedure. Since those values are selected through survivor selection, the method is self-adaptive. Before the mutation step, they are also modified:

$$\sigma_i' = \sigma_i \times e^{\tau' N(0,1) + \tau N_i(0,1)}, \tag{16}$$

where σ_i is the standard deviation for dimension i, σ_i' is its next value, τ' is the global learning rate, which adjusts the perturbations for every dimension, τ is the individual learning rate, which adjusts the perturbations for a specific dimension, $N(0, 1)$ is a standard perturbation that assumes the same value for every dimension, and $N_i(0, 1)$ is an individual standard perturbation that applies to a specific dimension. With the computed standard deviation values, the variables of the new individual are mutated as follows:

$$x_i' = x_i + \sigma_i' \times N_i(0, 1). \tag{17}$$

The adopted values for τ' e τ are, respectively, $1/\sqrt(2n)$ and $1/\sqrt(2\sqrt(n))$ [13]. To avoid too small step sizes or too large ones, which could stagnate the algorithm, step sizes are confined between the bounds $\epsilon_0 = 10^{-5}$ and $\epsilon_{i,max}$ – equal to 60% of the search space length of variable i. Since the step sizes have the tendency to reduce over the algorithm execution, a high initial value for every variable was chosen, for broader exploration at the first generations: $\epsilon_{i,max}$. The mutation probability is 100%, given that the mutation is self-adaptive. We evaluate four constraint handling methods:

1) Penalty Method [15]: uses a penalty term based on the violations, calculated in function of the distance from the feasible region. Given decision variables $\mathbf{x}$, an objective function $f(\mathbf{x})$, a restriction in the form $g(\mathbf{x}) \leq 0$, and another restriction in the form $h(\mathbf{x}) = 0$, a new objective function $f_2(\mathbf{x})$ is created from the violations:

$$f_2(\mathbf{x}) = f(\mathbf{x}) + kP(\mathbf{x}), \tag{18}$$

$$P(\mathbf{x}) = max(0, g(\mathbf{x})) + max(0, (|h(\mathbf{x})| - \epsilon)), \tag{19}$$

which considers a linear scaling for the violation. More restrictions require additional penalty terms. We have used the value 3 for the weight k. This method was used alongside a generational survivor selection, preserving only the best offspring – it does not preserve the parents, with the exception of the individual preserved by elitism.

2) TS-R [17]: a modification of the tournament selection mechanism for survivor selection, which selects pairs of random individuals and preserves the best one in the pair for the next generation. It has three pairwise comparison rules:

- if the pair is composed of two feasible individuals, select the one with the best objective function value;
- if it is composed by a feasible and an infeasible individual, select the feasible one;
- if it is composed by two infeasible individuals, select the one with the lowest violation.

3) Stochastic Ranking [18]: specific for ESs. Performs survivor selection by using a ranking to select the individuals for the next population. The ranking only considers offspring and is ordered similarly to the bubble-sort algorithm, swapping adjacent individuals positions following a criterion to create an ordered list. The procedure iterates through the list for N iterations. The criterion for swapping is stochastic: it has a probability P_f of being a comparison by fitness and a probability $1 - P_f$ of being by violation. If both individuals are feasible, the comparison will be by fitness. Since P_f is typically lower than 1, this algorithm aims to keep a balanced proportion of feasible and infeasible solutions, to achieve solution quality without losing information from infeasible solutions. The parameters used are the same as [18]: $P_f = 0.45$ and $N = \lambda = 140$.

4) TLR (*Two-Level Ranking*): we propose an alternate ranking scheme for this problem. Given that ESs have high selective pressure, objective function evaluations are traffic simulations and that there is a restriction which depends on a simulation, TLR aims to quickly minimize the violations and fill the population with feasible solutions, in order to have a faster response for real-time scenarios. It works as follows:

- The λ children of a given generation are split into two lists: one contains N feasible solutions; the other contains the $\lambda - N$ infeasible ones;
- Both lists are sorted: the feasible solutions list is sorted by fitness (for minimization, ascending order of fitness values); the infeasible solution one is ordered by violation (ascending order of violation);
- Both sorted lists are used to compose the population of the next generation, of size $\mu < \lambda$. First, it is filled with the feasible solution list. If there are remaining slots, they are filled with the infeasible solution list.

For every constraint handling method, to further reduce the computational cost of the optimization, simulations were parallelized. Furthermore, elitism is guided by fitness if the penalty method is employed. Otherwise, a mechanism similar to TLR is used: the best feasible individual is added to the

Figure 1: Evaluation scenario (Figure produced by SUMO).

elite if any exists; otherwise the unfeasible one with the lowest violation composes the elite.

V. Performance Evaluation

Fig. 1 presents the simulation scenario. It is comparable in scale to related work: it has four intersections, each having four approaches with two-way traffic and sidewalks. The horizontal street at Fig. 1 has two lanes for vehicles for each direction, while the vertical ones only have one per direction. At every street, vehicles are allowed to go straight, turn left or turn right. Each intersection has four traffic lights, which follow the same phase sequence:

- For the directions east, south, west and north, one at a time, in this order:
  - Green – adjustable duration – then yellow – 3 s – for vehicles approaching from this direction;
- Exclusive Pedestrian Phase (EPP) – adjustable duration;
- No movements allowed (all-red phase) – 5 s.

EPP, as previously mentioned, interrupts all vehicle traffic. The all-red phase is used to clear the pathways of all pedestrians before allowing vehicles to move. Using EPPs increases the number of decision variables by 1 per intersection, in relation to TWC. Each intersection has 5 adjustable durations. Given that the scenario has four intersections, there is a total of 20 decision variables to adjust and 29 restrictions: 1 for the pedestrian maximum delay, 4 for the cycle durations, 20 for the minimal green time for vehicles and 4 for the minimal green time related to exclusive pedestrian phases.

Twenty-four vehicles enter the intersections from the horizontal street and 48 arrive from the vertical ones, for a total of 72 vehicles; their movements are uniformly distributed among the possible directions. Each vertical street has between 4 to 6 pedestrians, resulting in a total of 42. Their movements are also uniformly distributed among the possible directions.

As mentioned in Section IV, four constraint handling methods are evaluated: the penalty method – with weight $k = 3$ –, TS-R [17], Stochastic Ranking [18] and the proposed TLR. Each algorithm configuration is tested for 25 rounds. The stopping criteria for the rounds are the execution of 5000 FEs (Fitness Evaluations), which corresponds to 5000 traffic simulations, and the execution of 2100 FEs without any improvements on the objective function value. Given that the number of children generated at each generation (λ) is 140, 2100 FEs correspond to the evaluation steps of 15 generations, provided that all children are feasible. SUMO simulations employ several random components. To make them deterministic, avoiding influences from these random factors on the performance of ESs, the seed 23423 was used for its random number generator. Simulations complete when all vehicles and pedestrians fulfill their routes.

Tables I and II compare the performance of the four constraint handling methods. TS-R shows the worst overall results. It has the worst values for the best, worst, mean, and median values of the fitness, as well as the largest standard deviation for it, which indicates less consistency. Among the Penalty Method, TLR and SR, the difference in fitness value statistics is smaller, except for the standard deviation, where SR is closer to TS-R. Penalty, TLR, and SR have found the same values for the pedestrian delay statistics; those are higher than TS-R's, suggesting that better solutions cannot further reduce pedestrian delays without increasing vehicle delay. TS-R was the only method which did not find a feasible solution in all 25 rounds: no feasible solution was found at 7 of them. It also had the longest average run time. Regarding the time to find the first feasible solution, TLR yields significantly lower values for all statistics, suggesting it is an interesting option for optimizing traffic lights in real time or handling dynamic scenarios. Typical cycle durations for urban scenarios are between 60 s and 90 s[1], meaning that our approach would have spare time to enhance its feasible solutions in such environments before a new cycle starts.

Fig. 2 presents the evolution of the feasibility ratios – ratio of feasible solutions in the population – for the best rounds with each constraint handling method, over three metrics: fitness evaluations, generations, and execution time. This figure helps explaining the longer average execution time for TS-R: it has used a significantly higher amount of generations to fulfill the stopping criteria, which can be explained by the lower feasibility ratios it maintains during the entire execution. TS-R does not evaluate infeasible individuals and, since it maintains lower feasibility ratios, it runs for more generations. Nevertheless, the lower feasibility ratios do not allow the ES to leverage the parallel distribution of traffic simulations and harm the optimization. TS-R has lower feasibility ratios due to the random pair compositions of tournament selections, which can discard feasible solutions, whereas the other methods prioritize lowering the violations of the solutions they encounter. TLR and SR show similar evolution curves, however TLR finds the first feasible solution earlier, keeps a 100% feasibility ratio for longer, converges earlier and has a shorter execution time than SR. Penalty Method evolves differently, maintaining intermediate ratios during its execution. Figs. 3 and 4 compare the median and worst rounds, over the progress in fitness evaluations. They show similar tendencies, in comparison to Fig. 2, indicating these behaviors are consistent. Fig. 5 shows, for median rounds, the evolution of the fitness of the best solution. This value starts higher for the Penalty method, since its objective function has a violation term and random initial solutions. TS-R converges prematurely to a worse solution.

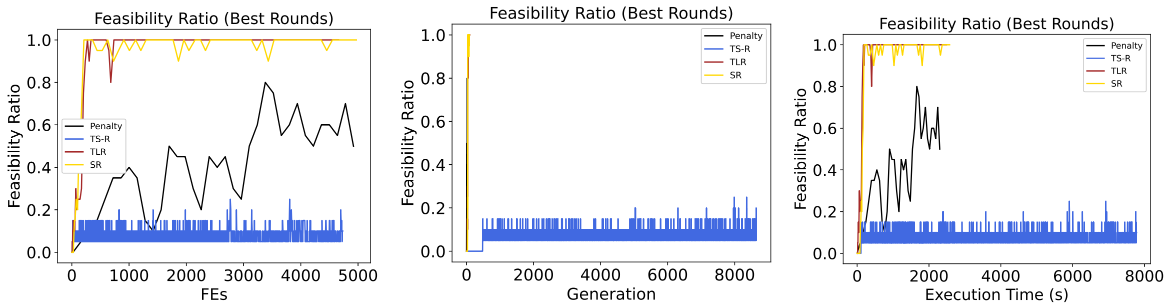
[1] https://nacto.org/publication/urban-street-design-guide/intersection-design-elements/traffic-signals/signal-cycle-lengths/

Method	Best Fitness	$D_{mean,car}$	$D_{mean,ped}$	$D_{max,ped}$	Worst Fitness	Mean Fitness	Median Fitness	Fitness St. Dev.
Penalty	168	122.94	22.53	59.76	195.97	179.245	178.171	7.353
TS-R	176.63	137.37	19.63	50.76	236.81	194.959	191.11	14.621
TLR	166.5	121.44	22.53	59.76	192.87	174.404	172.38	5.647
SR	167.28	122.22	22.53	59.76	221.81	178.792	174.38	12.453

Table I: For the tested constraint handling methods, fitness statistics and obtained delays – in seconds – of their best solutions.

Method	Feasible Rounds	Avg. Run Duration	$t_{1st,mean}$ (s)	$t_{1st,median}$ (s)	$t_{1st,stddev}$ (s)
Penalty	100%	41 min 5 s	114.611	91.896	52.589
TS-R	72%	55 min 27 s	171.309	110.187	198.429
TLR	100%	36 min 41 s	18.663	14.045	14.538
SR	100%	40 min 55 s	56.939	49.424	36.326

Table II: From left to right: proportions of feasible rounds, average run durations and statistics (means, medians and standard deviations) of the necessary time for reaching the first feasible solution, for each constraint handling method.



(a) With FEs.

(b) With generations.

(c) With execution time.

Figure 2: Evolution of feasibility ratios for each constraint handling method over the optimization process, for the best rounds. Three measures of the optimization progress are given: FEs, generations and execution time.

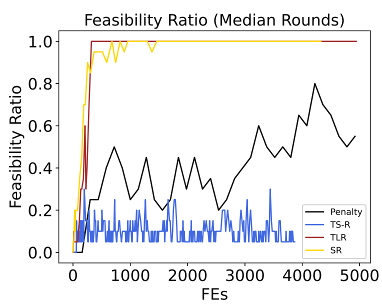


Figure 3: Evolution of feasibility ratios over the optimization process, for the median rounds with each method.

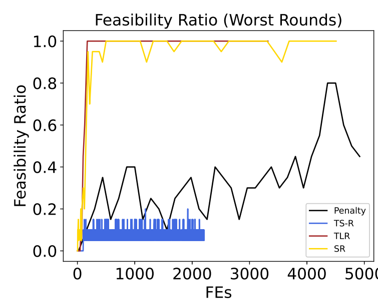


Figure 4: Evolution of feasibility ratios over the optimization process, for the worst rounds with each method.

The other methods have similar final fitness values, although SR and TLR improve fitness faster.

Fig. 6 shows another noteworthy result: although our proposal does not optimize for pollutant emissions or fuel consumption, these metrics have also been reduced. The chart shows the evolution of CO emissions from the best solution at each optimization step, for the best rounds of the four constraint handling methods. All methods find solutions that reduce emissions, in relation to the initial set of solutions – random solutions. TLR and SR present quicker reductions along the optimization. TLR has a slight advantage over SR during some moments of the optimization and for the final solution. We have also obtained the results for CO_2, particulate matters (PM_x), nitrogen oxides (NO_x), hydrocarbons and fuel consumption. They produce the same curves as CO but at different scales, thus are omitted here. The reductions in emissions and fuel consumption are a consequence of the minimization of the mean delay for vehicles.

VI. Conclusion

This work has proposed a framework for traffic light optimization, considering the conflict of interests between pedestrians and vehicles. Our proposal encompasses modeling an optimization problem and solving it through an Evolution Strategy (ES), a meta-heuristic. Microscopic traffic simulations are used to evaluate a given solution, by the mean pedestrian

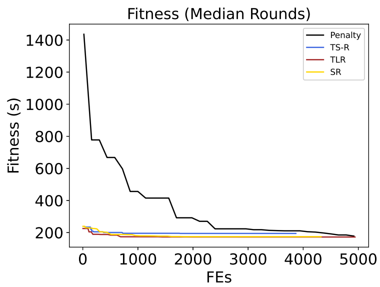


Figure 5: Evolution of fitness for the ES with each constraint handling method over the optimization process, for the median round with every constraint handling method.

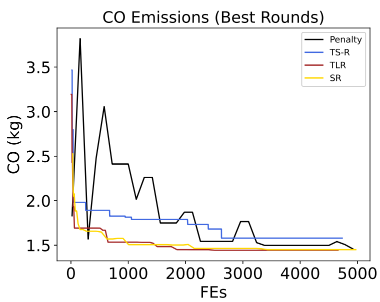


Figure 6: Evolution of carbon monoxide emissions during the optimization process, for the best rounds.

delay and mean vehicle delay values they yield. Given that the optimization problem has restrictions, we evaluate four constraint handling methods, including our proposal, TLR. The proposed optimization framework was able to find solutions that satisfy the constraints defined at the optimization problem, which were formulated based on data from related work. Notwithstanding, the methods have significant performance differences. TLR and SR achieved similar results for most metrics – notably best solution fitness, mean and median fitness. Nonetheless, TLR has a noteworthy advantage over all other methods: the required time to find the first feasible solution is significantly lower: the mean over all 25 rounds is 18.663 s, and the median is 14.045 s. These values are relevant to consider a real-time implementation or for handling dynamic scenarios, because they allow more frequent updates on the traffic light policy. Another interesting result from our proposal is the reduction of pollutant emissions and fuel consumption, which is a consequence of reducing the mean vehicle delay. In future work, we will expand the analysis with different topologies and traffic demands, optimize the phase sequence – a combinatorial optimization problem which was not handled by our proposal – and design a mathematical model that can approximate traffic simulation results, which would produce a significant optimization speed up.

Acknowledgement

This work was financed by CNPq, Coordenação de Aperfeiçoamento de Pessoal de Nível Superior Brasil (CAPES), Finance Code 001, FAPERJ, and Fundação de Amparo à Pesquisa do Estado de São Paulo (FAPESP) Grant 15/24494-8.

References

[1] T. Reed and J. Kidd, “INRIX 2018 Global Traffic Scorecard,” INRIX, Tech. Rep., Feb. 2019. [Online]. Available: https://inrix.com/
[2] Z. Yang and R. F. Benekohal, “Use of Genetic Algorithm for Phase Optimization at Intersections with Minimization of Vehicle and Pedestrian Delays,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2264, no. 1, pp. 54–64, Jan. 2011.
[3] J.-D. Schmöcker, S. Ahuja, and M. G. Bell, “Multi-objective signal control of urban junctions – Framework and a London case study,” *Transportation Research Part C: Emerging Technologies*, vol. 16, no. 4, pp. 454–470, Aug. 2008.
[4] W. Ma, D. Liao, Y. Liu, and H. K. Lo, “Optimization of pedestrian phase patterns and signal timings for isolated intersection,” *Transportation Research Part C: Emerging Technologies*, vol. 58, pp. 502–514, Sep. 2015. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0968090X14002460
[5] J. Sanchez-Medina, M. Galan-Moreno, and E. Rubio-Royo, “Traffic Signal Optimization in “La Almozara” District in Saragossa Under Congestion Conditions, Using Genetic Algorithms, Traffic Microsimulation, and Cluster Computing,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 11, no. 1, pp. 132–141, Mar. 2010. [Online]. Available: http://ieeexplore.ieee.org/document/5308324/
[6] J. Jin, X. Ma, and I. Kosonen, “A stochastic optimization framework for road traffic controls based on evolutionary algorithms and traffic simulation,” *Advances in Engineering Software*, vol. 114, pp. 348–360, Dec. 2017.
[7] C. Vallyon, S. Binder, and S. Hodgson, “Reducing Pedestrian Delays at Traffic Signals,” in *IPENZ Transportation Group Conference New Plymouth*, New Plymouth, New Zealand, Nov. 2008, p. 15.
[8] M. R. Virkler, “Pedestrian Compliance Effects on Signal Delay,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1636, no. 1, pp. 88–91, Jan. 1998. [Online]. Available: http://journals.sagepub.com/doi/10.3141/1636-14
[9] W. Brilon, “Traffic engineering and the new German highway capacity manual,” *Transportation Research Part A: Policy and Practice*, vol. 28, no. 6, pp. 469–481, Nov. 1994.
[10] Z. Yang, “Signal Timing Optimization Based on Minimizing Vehicle and Pedestrian Delay by Genetic Algorithm,” 2010, Dissertação de Mestrado, 2010, *University of Illinois at Urbana-Champaign*.
[11] M. M. Ishaque and R. B. Noland, “Multimodal Microsimulation of Vehicle and Pedestrian Signal Timings,” *Transportation Research Record*, p. 8, 2005.
[12] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner, “Microscopic Traffic Simulation using SUMO,” in *The 21st IEEE International Conference on Intelligent Transportation Systems*. IEEE, 2018. [Online]. Available: https://elib.dlr.de/124092/
[13] H.-G. Beyer and H.-P. Schwefel, “Evolution strategies – A comprehensive introduction,” *Natural Computing*, vol. 1, no. 1, pp. 3–52, Mar. 2002.
[14] K. Gao, Y. Zhang, Y. Zhang, R. Su, and P. N. Suganthan, “Meta-heuristics for bi-objective urban traffic light scheduling problems,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 7, pp. 2618–2629, 2019.
[15] A. Eiben and J. Smith, *Introduction to Evolutionary Computing*, ser. Natural Computing Series. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015.
[16] L. J. Eshelman and J. D. Schaffer, “Real-coded genetic algorithms and interval-schemata,” in *Foundations of Genetic Algorithms*, ser. Foundations of Genetic Algorithms, L. D. WHITLEY, Ed. Elsevier, 1993, vol. 2, pp. 187 – 202.
[17] K. Deb, “An efficient constraint handling method for genetic algorithms,” *Comput. Methods Appl. Mech. Engrg.*, p. 28, 2000.
[18] T. Runarsson and X. Yao, “Stochastic ranking for constrained evolutionary optimization,” *IEEE Transactions on Evolutionary Computation*, vol. 4, no. 3, pp. 284–294, 2000.