Expert Competitive Traffic Light Optimization with Evolutionary Algorithms

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Abstract: We present a complete system to optimize traffic lights green phases and temporal offsets based on a combination of microscopic simulation and black box, evolutionary algorithms. We also report the outcome of an AI versus experts comparison workshop conducted with our algorithm and seasoned experts from a specialized traffic engineering office. Experimental results indicate that the proposed algorithmic scheme significantly outperforms expert efforts. Our system entails a memetic (genetic+gradient) calibration module to adapt the Origin/Destination (O/D) matrix to current traffic conditions, an inoculation procedure to incorporate existing traffic light programs, genetic multi-objective optimization capabilities and sound metrics. Experiments are conducted over several real world datasets of operational sizes from the Paris outskirts and various other French urban areas. Our experimental outcome is threefold. First, we report the success of the memetic calibration module in adjusting the simulator's O/D matrix to a point with variation levels corresponding to recorded sensor data. Second, we confirm the ability of the system to obtain significant gains on that sound basis: gains ranging from 15% to 35% are consistently reached on both traffic jams reduction and pollutant emissions. Most importantly, we report the outcome of the comparison workshop: a formalized methodology followed by experts to manually optimize traffic lights, iterative experimental logs tracing the application of that methodology to two real world cases and comparable results obtained by the algorithm on the same cases. Results indicate that the AI module performs significantly better than experts in both speed and final solution quality.

1 INTRODUCTION

Urban planning is a daunting task. Traffic light optimization is one lever to improve the quality of life for all citizens: less traffic jams means more time, less stress and cleaner air. But the task is ludicrously difficult and infrastructure managers or specialized engineering offices need help to reduce the costs and increase the efficiency of traffic light plans design. Artificial Intelligence can help by providing computational support in exploring the space of possibilities.

Traffic engineers are usually equipped with sophisticated command and control systems that provide them with substantial data streams and action possibilities. They are also pressured to pursue various, varying and sometimes antagonistic objectives dictated by the needs of the local population, the particularities of their traffic network and political leadership or sustainable concerns. Making a smart an efficient mapping between complex objectives and complex decision variables with hidden relationships or correlations is precisely what evolutionary algorithms can offer. This artificial intelligence technique, coming from the fields of optimization and machine learning can indeed quickly and reliably figure out the right elements of solution necessary to achieve what the infrastructure engineers want.

In this paper, we present an integrated, global approach to help experts optimize traffic light settings on a sound, validated basis. It is organized as follows: after a brief literature review, we detail the various components of our system and then present experimental results on real-world benchmarks. Most importantly, we conclude with the report of a competitive comparison workshop between actual traffic experts and our algorithm in order to confirm the ability

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of this AI-based approach to outperform humans on this specific mathematical but very complex and subtle task.

2 LITERATURE REVIEW

Many attempts at optimizing traffic light settings with various flavors of evolutionary algorithms have been made, underlining both how promising the approach is and how important the problem has always been. Two early examples can be found in (Foy et al., ; Rouphail et al., 2000). As early as 1992 indeed, Foy, Benekohal and Goldberg (Foy et al.,) applied bit-string Genetic Algorithms to the optimization of signal timing and obtained consistent results in decreasing wait time on variants of a small test case with four junctions. In 2000, (Rouphail et al., 2000) tried to minimize queue lengths on a Chicago,IL test case with 9 signalized intersections using CORSIM and Transyt.

More recently, (Stevanovic et al., 2008) conducted a rigorous study with genetic algorithms searching a sophisticated, complete representation of traffic light plans tried against a traffic model run by microscopic simulator VISSIM. Experiments were conducted on two US benchmarks: Park City, UT and Albany, NY. One particular focus of the study was to see how optimizing parameters in sequence or all at once influenced final solution quality. Optimized plans were favorably compared to existing plans and to plans produced by SYNCHRO but with gains limited in amplitude.

(Sanchez-Medina et al., 2008) applied evolutionary algorithms to the traffic light optimization problem with a sophisticated gray-code based encoding of phases. Plan quality was evaluated with an ad hoc Cellular Automaton based microscopic simulator built after the Kraus car following model and run on a Beowulf cluster. Two rather large test cases and associated data were procured from the local councils of Saragossa and Santa Cruz de Tenerife and significant gains were obtained with respect to existing traffic light plans : around 10% on the first benchmark even though it had little traffic and therefore room for improvement and up to 30% on the second one although with very significant variance between solutions.

Very recently, (Péres et al., 2018), following several studies over preceding years (e.g. see (García-Nieto et al., 2011) or (García-Nieto et al., 2013)) tackled real-world cases with evolutionary algorithms with a particular focus on multiobjective optimization and sustainable concerns. Using SUMO, an open-source traffic simulator, as the objective function provider, they obtain large and consistent gains on three real-world benchmarks in Montevideo. They offer an interesting benchmark comparison of various classical Multi-Objective Evolutionary Algorithms applied to the problem and shed interesting light on edge prioritization.

Other studies worth citing (Hu et al., 2015; García-Nieto et al., 2011; Jin et al., 2017; Jin and Ma, 2014) make use of various computational techniques related to evolutionary algorithms such as Particle Swarm Optimization in varied operational contexts.

There are many ways in which traffic regulation can be approached with computational support. With the recent rise of global interest in Machine Learning, on can note observe an increasing number of attempts at using Reinforcement Learning to approach the problem with a more dynamic orientation (e.g. see (Chin et al., 2012; Fakultät, 2006; Marsetic et al., 2014; Salkham et al., 2008) and obtain very encouraging results with Q-learning, policy gradients or actor critic methods.

Most aforementioned approaches make use of microscopic simulation as the objective function provider. For any operational application to be considered or more generally, for any trust to be placed in the results, care must be taken that simulators and their models are realistic enough. To that end, calibration is necessary. Calibration is the problem of adjusting simulation parameter values so as to maximize the predictive capability of the simulator. Simulation parameters include physical variables (e.g. vehicle weights and length), behavioral and kinetic variables and, most importantly, demand modeling with O/D matrices and dynamic routing parameters. Calibration is absolutely critical but is often overlooked in studies that are focused on the main optimization problem that is difficult enough in itself. There is, however a significant but rather separate body of work on that issue. (Paz et al., 2015; Chu et al., 2003) for example, offer very interesting systematic methodologies to address all aspects of the calibration problem. Other approaches, such as (Toledo and Kolechkina, 2013), focus on specific calibration subproblems with adequate mathematical tooling.

Overall, although many traffic light optimization studies have been conducted, most of them, while offering interesting insight and convincing results, seem to be lacking in at least one aspect of this deceptively complex problem: validation benchmarks, particularly in early studies, are often small and/or unrealistic, simulators may have weak or no calibration and optimization sometimes lack essential aspects such as multi-objective capabilities or statistical validation of its results. We try to offer a comprehensive algorithmic proposal with at least one form of answer for all key aspects of the problem.

3 SYSTEM OUTLINE AND ALGORITHMS

3.1 Overview

Our system's purpose is to try to find optimal or near optimal values for traffic light plan settings. To that end, we follow the classical evolutionary black-box approach which consists in associating a genetic search engine with a simulator that provides objective function values. Having a well calibrated simulator is extremely important in such a context because by providing short term world evolution prediction for particular individuals to feed the objective function, the simulator is ultimately and almost entirely responsible for solution quality. That is the reason why, as outlined in figure 1, our system is composed of three main separate boxes whose underlying principles and implementation we detail below : simulator, optimizer and calibrator. The input data comes from the field (sensors providing flow or occupancy rate measurements and/or existing traffic light plans). The output is of course, a suggested near optimal traffic light plan for the input traffic model. More detailed design information, along with experimental validation of choices can be found in (Damay, 2015).

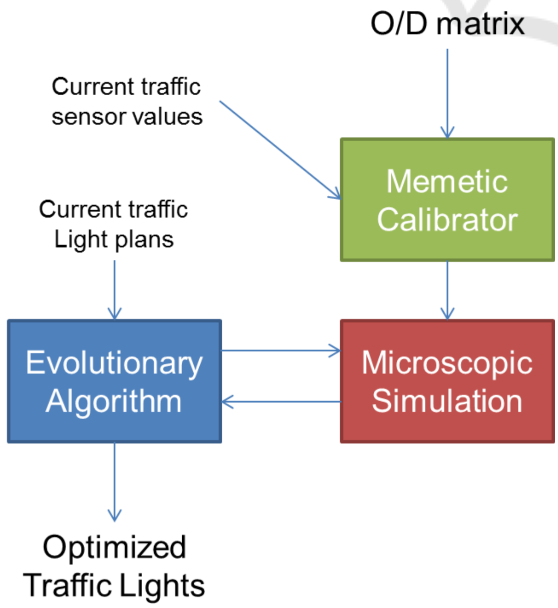

Figure 1: Global system architecture.

3.2 Genetic Search and Multi-objective Capabilities

Genetic and Evolutionary Algorithms (Goldberg, 1989; Eiben and Smith, 2003) are mathematical procedures created in the field of Artificial Intelligence to solve complex problems by following a biological metaphor with a few essential aspects : genetic encoding, random variations (mutation and crossover) and survival of the fittest. By using selection pressure to intelligently explore the spaces of possible solutions, engineers have created very powerful algorithms which can favorably solve very difficult real world problems. Evolutionary algorithms, besides being mathematically efficient, happen to have several practical advantages: they provide "anytime" solutions, are highly paralellisable, straightforward to implement, need very little information about the problem and can be hybridized naturally with specific algorithms or expert knowledge.

Another key advantage of evolutionary algorithms is that, being population based, they are naturally fit for multi-objective search in the Pareto sense. By that we mean the ability to provide the entire set of solutions, or a good approximation of that set, which are non Pareto-dominated. Practically, it means that the algorithm is able to identify in a single run all good solutions which represent interesting compromises for the decision maker facing antagonistic objectives (e.g. cost vs. engine power when considering a new car). Very well-known multi-objective variants of evolutionary algorithms such as NSGA-II (Deb et al., 2002), SPEA2 (Zitzler et al., 2001), IBEAx (Zitzler and Künzli, 2004) or MOEAD (Zhang and Li, 2007) can indeed provide that service very efficiently.

Traffic light plan design is a typical optimization problem : variables are green phases durations and temporal offsets, constraints are given by law or security considerations and limit the possible values for the variables and objective functions are straightforwardly given by traffic fluidity metrics (waiting time, timeloss, queue length, etc.) or pollutant emissions measurements (CO, CO2, NOx, PMx, HC, fuel consumption, noise, etc.). Experimenting directly in the field is of course impossible for obvious security and public relations reasons so one has to resort to mathematical models or simulators. Vehicular traffic being a very complex process with significant human and cognitive components, microscopic simulation is often the most reasonable option to be sure to take intricate interaction phenomena properly into account.

We therefore have a classical black-box setting, which we tackle straightforwardly with an evolutionary algorithm and simulator combination. So as not to reinvent the wheel and benefit from good implementation and out of the box parallel computing, we use the excellent DEAP library (Distributed Evolutionary Algorithms in Python (Fortin et al., 2012)).

Our particular choice of basis algorithm went to NSGA-II after an extensive experimental campaign with statistical significance testing for algorithmic variants, components and parameter settings. The fundamental multi-objective mechanism of NSGA-II uses a combination of crowding distance non-dominated sorting of its population to ensure diversity preserving and exploration in the Pareto sense. We use a traditional evolutionary sequence and the structure of our algorithm follows the NSGA-II basis, which we use in either mono-objective or multi-objective mode.

3.3 Problem Representation, Variation Operators, Metrics

We adopt a very straightforward solution encoding strategy. As detailed in figure 2, we just use vectors of integer values that represent, junction by junction successively, green phases durations and temporal offsets.

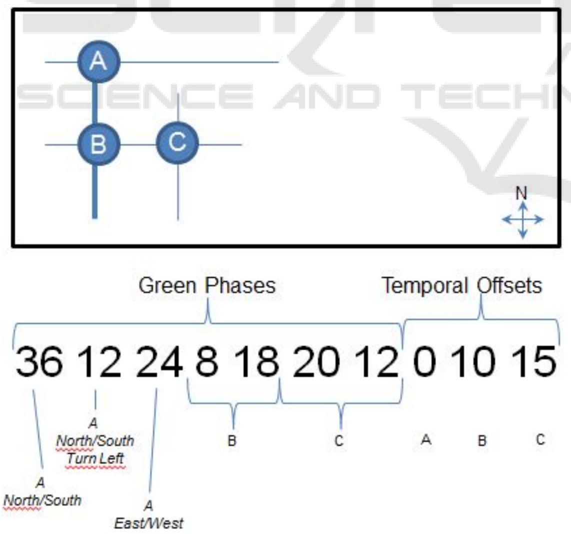

Figure 2: Problem representation. The small schematic zone above contains three junctions (A,B and C) situated along and aside a main axis of traffic. The corresponding genome encodes green phase durations for A's 3 phases and B and C's two phases as well as relative temporal offsets for all 3 junctions.

Variation operators work on that representation directly. Crossover is a classical two point scheme. Our mutation is a Gaussian variation whose standard deviation is controlled dynamically with a sigmoid swap scheme as introduced in (Semet and Schoenauer, 2006) and used in (Marceau Caron, 2014). This allows to tune the exploration/exploitation trade-off by controlling how "disruptive" the mutation radius (in our case the standard deviation of the Gaussian variation) shall be over the course of evolution:

$$\sigma_{mutation} = \begin{cases} \alpha & \text{if } t < t_0 \\ \beta + 2 \times (\alpha - \beta) \times \frac{1}{1+\exp^{\gamma(t-t_0)}} & \text{if } t \geq t_0 \end{cases}$$

Initialization finally, although not technically a variation operator, is, as outlined in (Semet and Schoenauer, 2006), an essential building block of the overall algorithm. We found that using an "inoculant", which means a heuristically built individual based on the existing traffic light plan was useful to achieve rapid early search, which is a particularly desirable trait in this fast paced operational context. The initial population is therefore built as a mix of inoculants varied with mutation and purely random individuals.

3.4 Microscopic Simulation and Calibration

3.4.1 Simulator

To substantiate the objective function, we use the open-source microscopic traffic simulator SUMO (Krajzewicz et al., 2012) developed by DLR. In their own words, taken from SUMO's homepage (http://http://sumo.sourceforge.net/) :

> "Simulation of Urban MObility", or "SUMO" for short, is an open source, microscopic, multi-modal traffic simulation. It allows to simulate how a given traffic demand which consists of single vehicles moves through a given road network. The simulation allows to address a large set of traffic management topics. It is purely microscopic: each vehicle is modeled explicitly, has an own route, and moves individually through the network.

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SUMO is a very powerful and versatile tool that provides rigorous traffic representation and easy integration with computational support algorithms. It is also very fast, which is particularly precious for population based stochastic search, which requires many computations of the objective function.

Our SUMO traffic model is an O/D matrix that is turned into individual routes by shortest path routing utilities provided with the software (*od2trips* and *duarouter*). Some attempts at dynamic equilibrium finding and routing optimization have also been found useful and were performed with the *duaIterate* script and the *Cadyts* external utility (Flotterod et al., 2011). Our GIS based road network was imported and adjusted, which is a long, tedious, but absolutely critical step for any realism to be achieved, with *netconvert* and *netedit*.

3.4.2 Memetic Calibration

One specificity of our algorithmic system is the calibrator module. Achieving realistic simulation is extremely important, both for fundamental solution quality and as a caution of trust for the end-user who wants guarantees about how well her field is modeled by the computer. To that end, much effort was spent in trying to procure the best possible O/D matrix. Beyond dynamic routing and calibration outlined above, specific R&D efforts were conducted to develop an optimization module for that purpose. Experiments, reported in (Damay, 2015) revealed that the best solution was an hybrid algorithm combining genetic search and a specific, state-of-the-art gradient algorithm. Such an hybrid is usually called a Memetic algorithm and typically tries to combine the benefits of global stochastic search with local optimization to refine the solution.

Uncharacteristically, this particular flavor uses gradient to optimize the starting point (either a zero or heuristically provided O/D matrix) and produce an inoculant for the genetic search that will find both local and global improvements. The genetic part of the calibrator is a standard $(\lambda + \mu)$ evolutionary scheme with Gaussian mutation. The gradient part is an extended version of the algorithm introduced in (Toledo and Kolechkina, 2013), which performs steepest descent on matrix coefficients in the error space. For both parts, error or fitness is measured by comparing obtained simulated counts with sensor history. Importantly, considered sensor values can either be averages or specific values. This allows to serve, at will, two functional purposes: aiming for robust values with good generalization ability or being as precisely close as possible to what is currently happening in the field.

4 EXPERIMENTAL RESULTS

4.1 Benchmarks

Validation experiments have been conducted on several real-world benchmarks corresponding to regulation zones of medium size, usually a well delimited neighborhood, portion of the dense center of a city. Our main test cases were :

- A portion of the downtown area in Rouen, with a mesh-like network of 10 signalized intersections
- A portion of the downtown area in Strasbourg, with 9 signalized junctions, one of them being shared with a tramway line with absolute priority
- A large linear portion of the immediate northern outskirts of Paris with three intersecting high speed axes of traffic which has 12 to 20 signalized intersections, depending on the instances.

A screen capture of the typical Rouen benchmark is given in figure 3 with sensors and O/D source/sinks. All benchmarks were complete with digitized road network, sensor data over several months and/or turning proportion studies and currently used traffic light plans.

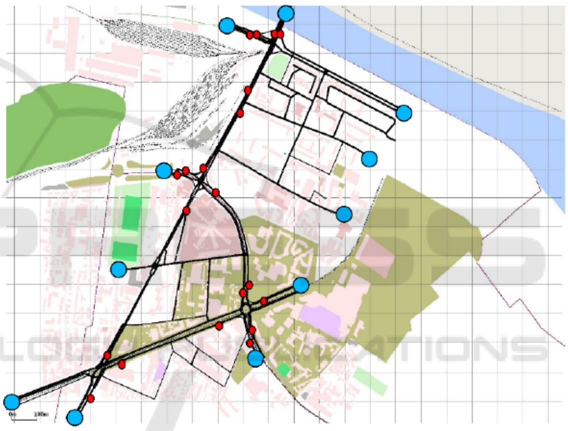

Figure 3: The downtown Rouen benchmark map. Blue dots represent O/D entry/exit points, red ones sensors.

4.2 Calibration Results

The first O/D matrix we used for the Rouen benchmark was constructed heuristically using a few measured flow rates and turning proportions studies. In order to refine it against historical sensor data, we defined a realism goal by computing statistics on a carefully chosen subset of sensors. We observed that within the considered morning peak hours, values for individual sensors varied within a plus or minus 30 % range over average values. We therefore set as an objective that the optimized O/D matrix should produce simulated counts, not only as close as possible to the average corresponding counts (for each sensor) on average (over all sensors) but that the average of variances for all sensors should be below the 30% limit as observed in the data. This simple criterion proved difficult to reach and only the memetic hybrid algorithm we proposed was able to reach that target with a 28% average variance. The heuristic matrix alone yielded $\tilde{6}0\%$ variance, gradient alone (as in (Toledo and Kolechkina, 2013)) yielded 41% and genetic search alone yielded 32%.

Figure 4 illustrates the result obtained by the memetic algorithm with a star diagram: each branch of the star shows a specific sensor and the point on that axis represents the obtained simulated count for that sensor on a normalized scale valued at 1 if simulated count exactly equals the average of historical sensor data. According to our criterion, points should therefore lie between 0.7 and 1.3 on all axes, which is represented by the blue and black circles respectively, the red circle representing the ideal solution. As can be seen in the figure, while correct on average over all sensors, our solution has room for improvement on several underused sensors.

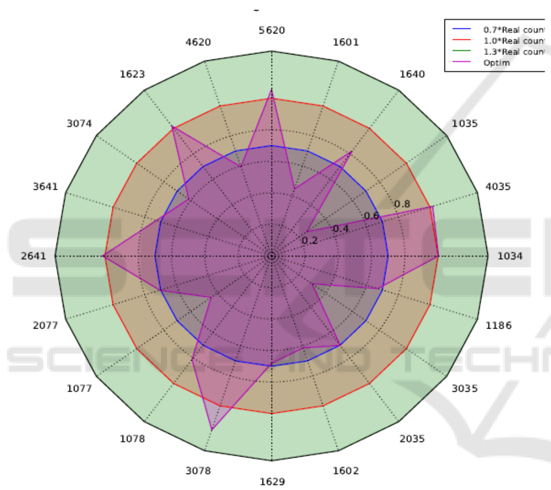

Figure 4: Calibration results star diagram. Each branch represents a sensor, whose simulated count should reach the red circle (normalized value of 1) corresponding to the average measured value. This solution, the best we obtained, corresponds to an average variance of 28%.

4.3 Optimization Results

4.3.1 Experimental Setup

In order to assess the ability to produce substantial and reliable gains, we follow the following experimental guidelines:

- All evolutionary algorithm run results are averaged over at least 11 random seeds
- All simulator runs are averaged over 10 random seeds, a value empirically determined to trigger sufficiently low variance
- Simulator runs usually have a warm-up time of 5 minutes and metric measuring time window of 20 minutes
- Algorithmic variants, components or parameter settings are chosen from using the **Wilcoxon signed test for statistical significance**

Typical parameter values are as follows: population size 12, mutation probability 0.5, crossover probability 0.25, 100 generations, minimum variable value 1, maximum 120, initial sigma value 10.

4.3.2 Mono-Objective Results

In the following section, we report results obtained on the Rouen benchmark. Similar results have been obtained on the other test zones. The main objective of traffic light optimization being to reduce traffic jams, mono-objective results are related to traffic fluidity metrics. Many possibilities exist to quantify this, we chose to use a weighted average of waiting time (total amount of time spent by vehicles under epsilon speed) and total number of processed vehicles so as to avoid solutions where traffic is prevented from entering the zone by over-saturating entry junctions.

Figure 5 illustrates the typical optimization curve we obtain on both morning and evening peak hours, with average and maximum gain (which means minimum metric value). Gains of up to 28% in waiting time are obtained for the morning peak at end of the run. One notices that variance is limited, making for a robust result and that, thanks to the anytime property of evolutionary algorithms, strong gains of 15 to 20 % can be obtained very quickly, as soon as generation 10. As one can see, the evening peak is much more difficult, maximum gain is only around 12% in that case.

4.3.3 Multi-objective Results

Thanks to the HBEFA and Harmonoise models provided with SUMO, one can pursue other objectives than traffic fluidity: pollutant emissions (CO, CO_2, NOx, PMx, HC, fuel consumption) and noise. Some of these objectives are correlated, some are antagonistic with varying degrees. See (Damay, 2015) for extensive analysis and experimental results on all objectives. For the sake of brevity and simplicity, we report results obtained on the illustrative waiting time / CO_2 couple. The top-right corner of figure 6 shows the evolution path followed by the population towards the Pareto front obtained at the end of the run, one clearly sees both a strong direction, aiming at the bottom left corner, and a maintained variety of choices along the front.

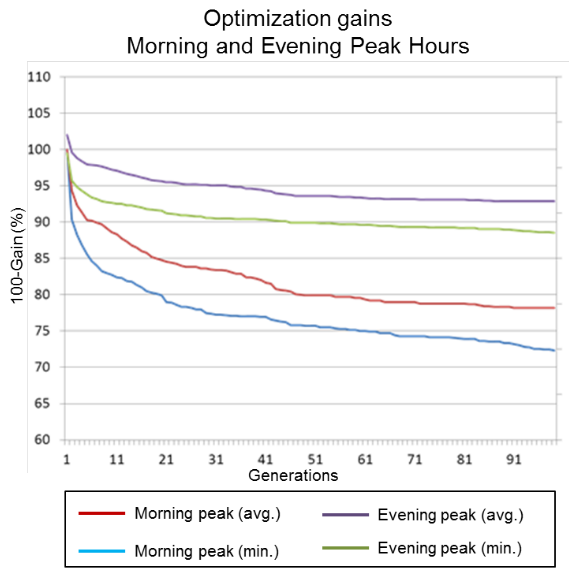

Figure 5: Mono-Objective (waiting time) results obtained on morning and evening peak hours.

Zooming in on the obtained Pareto front in figure 6, one can pick four distinct illustrative solutions A,B,C and D. A and B are extremal solutions, respectively excellent in waiting time and CO2. C and D offer two different compromises.

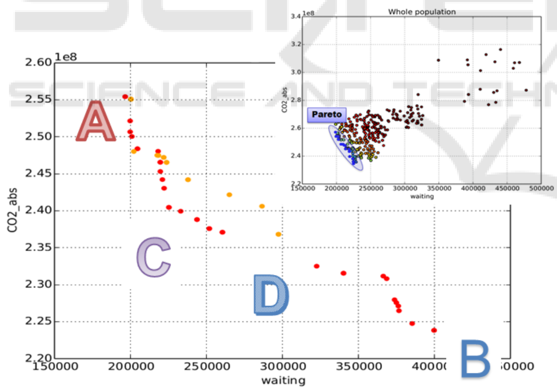

Figure 6: Zoom on the Pareto fronts. 4 representative points are chosen along it: 2 extremal ones (A and B) and 2 compromises (C and D).

Finally, one gives corresponding gain figures : up to 38% in waiting time (point A) and 24% in CO2 (point B). Point C has 32% gain in waiting time and 13% in CO2. Point D offers 16% and 18% respectively. One notices that optimizing seems to be significantly harder and that going from C to D for example has a huge cost in waiting time for a limited CO2 benefit.

4.3.4 Drawing Lessons with Reverse Engineering

A very interesting characteristic of straightforward black-box search, where one manipulates decision variables directly, is that the result can be interpreted immediately by experts, who can start an analysis process to try to understand why the settings proposed by the algorithm are efficient. This process, based on the fact that the outcome of the optimization algorithm is interesting in itself, can bring a lot of useful information by shedding light on the specifics of the field or by experimentally confirming counterintuitive ideas. All that can help improve or adjust heuristics and expert thinking. This reverse engineering process is not always easy or necessary but it is almost systematically informative. We give here a simple example of solution interpretation to illustrate both the surprisingly accurate ability of evolutionary search to detect opportunities in the objective function search landscape and the type of methodological conclusion one may draw from observing, a posteriori, building blocks of the optimized solutions.

Our example focuses on a specific junction in the benchmark. It is situated along an important axis of traffic and has three main successive phases in its traffic light plan. The first one is for the main north/south axis, going straight in both directions, the second phase is for vehicles turning left coming from that main axis and onto the perpendicular, secondary axis and the last phase is for the secondary axis, going straight. The initial, expert provided, traffic light plan had values, for the respective phases, of [29 12 21]. The optimized plan suggests [20 5 20]. By observing traffic, one quickly understands why. First and foremost, there is a significant loss of green time on the first phase : the light remains green long after all vehicles have been processed. Secondly, very few vehicles use the left turn phase. Finally, the flow of vehicles on the secondary axis is steady and properly handled. The algorithm has therefore managed to make the right decisions both by implicitly making these observations and by adequately sizing the corresponding changes.

The methodological conclusion for experts, which confirms what we have seen on other similar cases is that one of the most efficient optimization lever, as opposed to focusing on green splits, consists in reducing unnecessarily long green times to decrease cycle length so as to process more cycles and therefore more vehicles in a given time window. In our small example, saving 17 seconds of cycle length procures 3 additional full cycles over the metric measuring time window.

4.4 Additional Results

In order to further substantiate and illustrate the comparison between expert and algorithmically computed settings, we synthetically report below results obtained in other studies we conducted on strongly related traffic problems.

4.4.1 Traffic Conditions Classification

A critical problem in traffic regulation is to be able to identify the currently ongoing type of traffic episode in order to trigger the right plan in a portfolio of precomputed options. This is essential in order to avoid incorrect regulation, which means using a peak hour plan during off peak hours or vice-versa, and the ensuing consequences on waiting time and pollutant emissions.

As can be seen in figure 7, our algorithm, in that case a patented combination of optimization and machine learning, is able to produce a surprisingly compact and accurate decision tree which performs better than expert provided classification criteria based on field observation and experience. Estimated gains are indeed of 264 hours of incorrect regulation over regular work days in a year, which correspond to more than 10% of the total regulation time. Through reverse engineering analysis, this result also allowed to correct significant misconceptions about peak hours starting and end times.

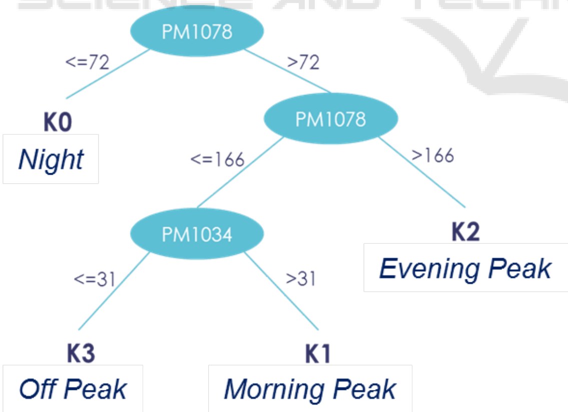

Figure 7: Compact and accurate algorithmically produced classification tree for traffic episode classification.

4.4.2 Adaptive Traffic Lights

Adaptive traffic lights are based on modern controllers that adjust their plans dynamically according to on-line sensor feedback. This form of dynamic regulation is very efficient when allowed by available equipment but rather difficult to parametrize properly.

In a separate preliminary study, publication pending, we proposed to genetically optimize such dynamic controllers based on decision trees. As a preliminary trial, we only optimized thresholds (on sensor data) and green phases adjustment values on an otherwise fixed tree. We intend to apply Genetic Programming on tree structure exploration in further work.

Experiments were conducted on a benchmark of three successive intersections with a three hours simulation time line enriched with three events (simulated accidents obstructing lanes for a certain duration at distinct timestamps) to assess the adaptive capacity of the dynamic controller. Comparisons, reported in figure 8 were made between a static plan, a dynamic plan whose weights and thresholds were set manually by an expert, and the genetically engineered plan. Results show that the expert tuned plan performs only slightly better than the static, non-adaptive plan, while the the decision tree with genetically optimized thresholds procures a very significant and promising gain of 34% in waiting time.

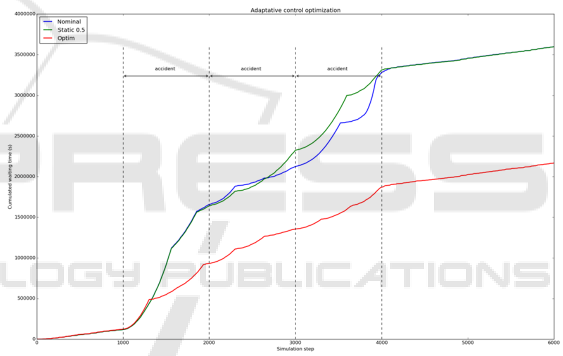

Figure 8: Results of the comparative benchmark for dynamical control: algorithmically optimized decision trees largely outperform expert provided trees. The x-axis shows simulation time steps, the y-axis total accumulated waiting time. The blue and green curve (top) show the static and expert plans respectively and the red curve (bottom) shows the results of the genetically optimized tree.

5 EXPERTS VERSUS ALGORITHMS

This section details the benchmarking experiment we conducted to compare the efficiency of traffic light setting efforts as they are usually performed by experts to those automatically obtained with our algorithm. We introduce the actual experts who commendably accepted to do this with us, outline their methodology and report comparative results on two test zones.

5.1 Meet the Experts

This work was conducted with three experts from CDVIA, a French traffic engineering office specialized in mobility, traffic analysis and optimization, measurement and modeling. Created in 1984 by Christian Isberie, M. Eng., it now employs a total of 35 engineers with several offices across the country. CDVIA works with town councils, cities, local communities or infrastructure managers to help them analyze, predict and design in all mobility related matters. CDVIA is particularly specialized in traffic flow modeling and regulation based on macro, micro or mesoscopic simulation. In constant search of innovative tools and approaches, CDVIA uses both cutting-edge technology and field-honed expertise to tackle large scale study cases such as the airport platform for Charles de Gaulle in Paris or the Conakry peninsula project for the Guinean ministry of transportation.

Christian Isbérie, M. Eng., CDVIA founder and traffic regulation expert has 35 years of experience in mobility engineering. After founding the company as a local, individual consulting business, he gradually modernized it and steered its growth into a full fledged engineering company with contracts all over the country. Besides management duties, he provides traffic-related expertise and encourages innovation as well as the adoption of modern technologies particularly in data collection and traffic simulation.

Benoit Berthelot, M. Eng., project manager, has 10 years of experience in mobility and traffic regulation related studies and has command over all aspects of CDVIA's business areas : field based traffic measurement, mobility modeling tools and urban traffic simulation.

Aurélien Varest, M. Eng., senior consultant, has 5 years of experience. He graduated with and M. Eng. from the National School of Geographical Science Engineers and obtained an additional M. Sc. in Urban Planning and Information Sciences from the City of Paris Engineering School. Specialized in traffic engineering and GIS based traffic simulation, he is also contributing to internal research and development efforts. He has conducted over 70 mobility studies for CDVIA so far.

5.2 Formalized Expert Methodology

The experts shared their methodology for optimizing traffic lights in a medium sized urban area with us. It was formalized through an extensive, procedure oriented discussion to produce this unique set of explicit steps that is most likely largely followed, more or less consciously, by numerous other experts. This knowledge is widely transverse but it is usually guarded or encapsulated by personal field-based expertise or intuition and oral tradition, leading to pitfalls such as subjectivity, variability or wishful thinking. The coarse grained methodology is as follows. Intricate details, specific principles or tools cannot be shared for obvious industrial secrecy reasons.

5.2.1 Preamble

We suppose that three aspects of the problem are kept constant: the infrastructure cannot be modified to achieve better traffic (e.g. by adding a lane), the type of ongoing traffic is considered unique and fixed (e.g. morning peak hours) and traffic light plans are considered static (no on-line adaptation in relation to sensors) and fixed in structure, which means that no changes are allowed besides green phase durations and relative temporal offsets (phases cannot be added or removed or see their order changed for example).

The methodology proceeds in four major steps, usually in the following order, although all steps are not systematically used and loops can be necessary : 1) Global Static Analysis, 2) Cycle Length Optimization, 3) Green Split Optimization, 4) Temporal Offsets and Junction Coordination.

5.2.2 Global Static Analysis

A global analysis is conducted for each individual flow controlled by a traffic light by comparing theoretical demand (vehicle flows pondered by the kind of movement (straight, turn left, etc.)) and flow capacity, which is a product of current corresponding green time and number of implicated lanes. The resulting vector provides a coarse grain analysis of which flows are in need of more green time and those who have too much. This step can also be used to provide a first heuristic traffic light plan based on making, at each intersection, green splits proportional to relative demands for each flow.

5.2.3 Cycle Length Optimization

If the considered junction is under capacity, shortening the cycle will help reduce queues and will increase fluidity. On the contrary, saturated junctions can benefit from longer cycle durations to prevent transmission of part of the queue from one cycle to the next. When modifying cycle length, care must be taken to keep green splits unmodified. In dense urban areas, shorter cycles are preferred, notably to facilitate pedestrian traffic.

5.2.4 Green Split Optimization

To adjust green split within an intersection, one usually goes through the following steps:

1. Check all lanes and order them by degree of congestion (queue length, number of unprocessed vehicles in one cycle, etc.)
2. Relate ordered lanes to existing green phases in the current plan
3. Identify phase couples with one “rich phase” (under capacity) phase and one “poor” phase (saturated) to move green time from the former to the latter without affecting cycle length.
4. Repeat previous step until no significant couple can be found

5.2.5 Temporal Offsets and Junction Coordination

To coordinate junctions with each other, the following principles are useful : cycle lengths should be homogenized, try to ensure that upstream junctions will not deliver more flow than downstream ones can handle, do not hesitate to limit output flow if necessary to preserve global fluidity even at the cost of a little local congestion. Finally, try to create green waves by :

1. Identifying major axes
2. Identifying main direction of traffic for the current conditions (can be opposite between morning and evening peak hours)
3. Compute corresponding temporal offsets by observing actual run times between junctions with the considered conditions (use simulation or sensor data) as opposed to theoretically calculated run times.

5.3 Experimental Setup and Results

The experts followed the methodology outlined above to try to increase traffic fluidity metrics (a combination of waiting time and total number of processed vehicles) as given by our simulator. They also used visual analysis and iterative trial and error to achieve the best possible result.

5.3.1 First Area

The first optimization session focused on a small trial zone made of two signalized intersections of medium complexity. It lasted for two hours and the experts produced a final gain of 13.68%.

Figure 9 gives, as an illustration of the tedious, iterative character of the methodology, the last trial and error steps followed by the experts to get to the best possible setting they could reach.

Step	Fitness	Gain (%)
Initial plan	112980	0
4s from phase N1 to phase N6	110228	2,43582935
6s from N1 to N6	116804	-3,38466985
5s N1 -> N6	110067	2,57833245
1s N4->N6 + 5s N1->N6	108296	4,14586653
Idem + 1s N4 ->N1	106523	5,71517083
Idem +2s N4 -> N1	108620	3,8590901
N* idem + 4s S6 -> S1	100766	10,810763
3s S6 -> S1	97552	13,6555143
5S S6 -> S1	100556	10,9966366
3s S1 -> S6	97651	13,5678881
1s S6 -> S1	97529	13,6758718

Figure 9: Sample of steps followed by experts on the small test case. The two junctions are named N (North) and S (South) respectively. Nk means phase number k of junction N.

In contrast, and as can be seen in figure 10 below, the algorithm managed to reach much better solutions, achieving a final gain of 23.9%. That level of gain is reached in 37 minutes on a regular laptop computer without parallel computing and the crossing point with experts in terms of gain amplitude (1̃3 percent) is reached after 2 minutes only.

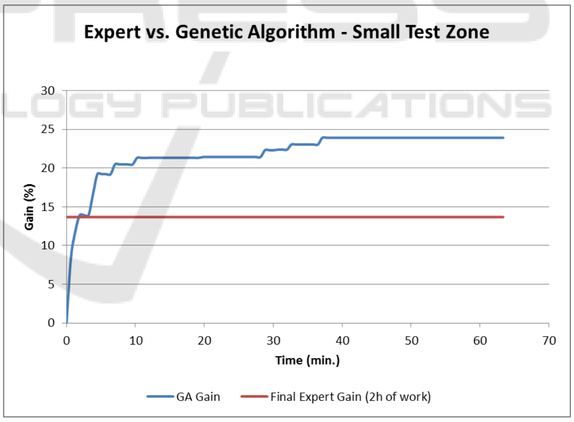

Figure 10: Gains obtained by the experts and the algorithm respectively, on the small test zone.

5.3.2 Second Area

In order to assess whether this result extended to cases of operational size and complexity, we organized a second session with a full-fledged zone extracted from a real world benchmark with 12 signalized intersections in the immediate northern outskirts of Paris. As can be seen in figure 11, it has one major north/south axis and two intersecting highways.

Experts tried very hard to manually optimize traffic on this zone under the arbitrage of the simulator.

Figure 11: Second testing area: a large portion of a dense urban area situated along a major traffic north/south axis with 12 signalized intersections and crossed by two highways.

The experiment lasted for 3 hours and 45 minutes and while the task proved very hard, the experts managed to achieve 7.08% gain.

Part of the analysis and of the numerous attempts they made is traced if figure 12 for illustrative purposes, notably to underline how rigged and counterintuitive the search space of this problem can be.

Step	Fitness	Gain (%)
Initial plan	762000	0
Identifying 3 saturated junctions: A,B,C	N/A	
8s A1->A2	766000	-0,52493438
6s B1->B2	783000	-2,75590551
7s C1->C2	790000	-3,67454068
4s A1/B1/C1 -> A2/B2/C2	782000	-2,62467192
2s idem	775000	-1,70603675
minus 1s on all radial phases A2/B2/C2	782000	-2,62467192
minus 2s on all radial phases A2/B2/C2	750000	1,57480315
minus 3s on all radial phases A2/B2/C3	734000	3,67454068
minus 4s on all radial phases A2/B2/C4	**708000**	**7,08661417**
minus 5s on all radial phases A2/B2/C5	720000	5,51181102
minus 6s on all radial phases A2/B2/C6	742000	2,62467192
Other unsuccesful attemps on A and B	N/A	

Figure 12: Sample of the steps followed by experts to try to optimize the large test zone.

Again in striking contrast (see figure 13), the genetic algorithm reached a final gain of 35.06 % in around 1h42. The crossing point with manual expert gain was reached in under 6 minutes.

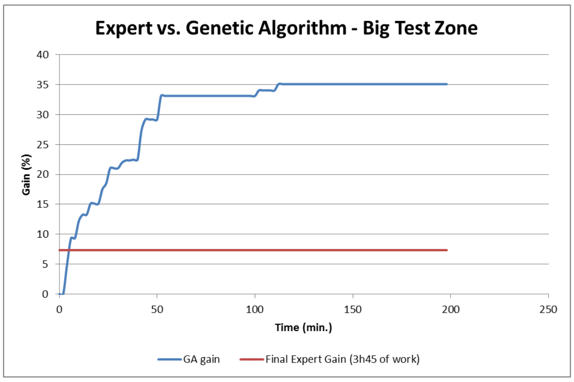

Figure 13: Gains obtained by the experts and the algorithm respectively, on the large test zone.

6 CONCLUSIONS

We introduced an algorithmic system based on evolutionary algorithms and calibrated microscopic simulation to optimize traffic light green phase durations and relative temporal offsets in order to reduce traffic jams and pollutant emissions simultaneously. Our experimental results are threefold. First, we report success of the calibration module to reach statistically realistic vehicle counts with respect to historical data. Secondly, we confirm the ability of the introduced system to consistently produce significant optimization gains on real-world benchmarks with respect to expert provided solutions. Finally, and most importantly, se report the results of a competitive comparison workshop between traffic engineering experts and our algorithm. The results indicate that the evolutionary algorithm performs substantially better in both speed and final solution quality.

While the results reported here suggest that AI based optimization modules perform significantly better than experts at these particular tasks, we firmly believe that there is much to gain from hybridizing expert knowledge with stochastic search algorithms. The former indeed have both precious insights and heuristics as well as an uncapturable ability to think globally. The latter, conversely, are uncannily apt at quickly figuring out the right numerical decisions. We sincerely think the future belongs to those who will know how to use both in synergy.

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