SIALAC Benchmark: On the design of adaptive algorithms for traffic lights problems

Florian Leprêtre, Cyril Fonlupt, Sébastien Verel, and Virginie Marion
Univ. Littoral Côte d'Opale
EA 4491 - LISIC - Laboratoire d'Informatique Signal et Image de la Côte d'Opale, F- 62228 Calais, France
florian.lepretre@univ-littoral.fr

ABSTRACT

Optimizing traffic lights in road intersections is a mandatory step to achieve sustainable mobility and efficient public transportation in modern cities. Several mono or multi-objective optimization methods exist to find the best traffic signals settings, such as evolutionary algorithms, fuzzy logic algorithms, or even particle swarm optimizations. However, they are generally dedicated to very specific traffic configurations. In this paper, we introduce the SIALAC benchmark bringing together about 24 real-world based study cases, and investigate fitness landscapes structure of these problem instances.

ACM Reference Format:
Florian Leprêtre, Cyril Fonlupt, Sébastien Verel, and Virginie Marion. 2018. SIALAC Benchmark: On the design of adaptive algorithms for traffic lights problems. In *GECCO '18 Companion: Genetic and Evolutionary Computation Conference Companion, July 15–19, 2018, Kyoto, Japan.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3205651.3205776

1 INTRODUCTION

Mobility represents an increasing challenge in modern cities. By 2030, United Nations accord to say that 60 percent of the world's population will live in urban areas [1]. This growing rate constantly requires cities to improve their travelers' mobility, by making a better use of their existing road infrastructure, which can be achieved by an accurate setting of traffic lights systems. Researching such settings would not only help to streamline urban traffic flows, but also to reduce travelers' individual carbon footprint and pollutant emissions. However, simulation of synthetic mobility plans constitutes a very costly and computationally expensive task.

Therefore, urban planners are usually restricted to optimize small and specific parts of the urban area. Most of the time in the literature, one specific optimization algorithm is used to solve one specific mobility problem [2, 3, 9, 10]. Thus algorithms' performances are difficult to compare, as they are often employed on heterogeneous mobility case studies. That points the lack of a general comparison tool for real-world mobility problems.

In this work, we introduce the *Scenario Investigations of Agents Localizations for Algorithm Conception* (SIALAC) Benchmark, bringing together 24 mobility scenarios. We experiment these case studies on the Calais city (76,402 inhabitants), France, and model the mobility of a simulated population on an area of 35 km^2. From a city planner point of view, such a benchmark could help to anticipate future evolution of cities. From a more fundamental perspective, SIALAC benchmark would promote the understanding of real-world mobility problems search space, in order to design suitable optimization algorithms.

GECCO '18 Companion, July 15–19, 2018, Kyoto, Japan

ACM ISBN 978-1-4503-5764-7/18/07.
https://doi.org/10.1145/3205651.3205776

2 FITNESS LANDSCAPE

From the point of view of local search algorithms, fitness landscape (FL) provides a metaphorical picture of the search space geometry (peaks, valley, plateaus, ...). Such an analysis brings as well a portrait of the problem structure with a set of metric features, in order to quantify and compare the search difficulty of different possible representations, local search operators, or objective functions.

More formally, a FL [11] is a triplet $(\mathcal{X}, \mathcal{N}, f)$ where $\mathcal{X}$ is the set of the potential solutions, $f : \mathcal{X} \to \mathbb{R}$ is the objective function of the optimization problem, and $\mathcal{N} : \mathcal{X} \to 2^{\mathcal{X}}$ is the neighborhood relation between solutions, which associates to each solution a set of neighboring solutions.

In optimization, the two main fitness landscape geometries are neutral ones dominated by plateaus, and multi-modal ones, dominated by local optima. For neutral geometries, features are computed during neutral random walks, and bring information about neutral networks, as graphs induced by the neighborhood relation on plateaus. For multi-modal geometries, the fitness distance correlation value [6], and the autocorrelation length [12] give a measure of the landscape ruggedness.

Although such analyses are well suited for black-box optimization problems, where an analytic definition of the fitness function is not required, only few works [8] have used FL on real-world problems. For a broader overview, see the review of Malan [7] on the existing FL analyzing methods.

3 PROPOSITION

3.1 Model and Case Studies

The considered simulation system in this work is the Multi-agent Transport Simulation, MATSim [5]. Mobility plans are synthesized from census data, and consist in a round trip between home and an activity (work, study, leisure). Thus, we define home and activity *clusters* inside the network, and distribute individuals' departure and arrival locations amongst these. Finally, individuals are assigned a random departure time between 7AM and 9AM. Activity durations are set to 4 hours.To run a simulation with traffic lights, MATSim microscopically simulates road intersections signal systems using fixed-time controls [4]. Traffic lights systems settings are modeled as in Armas *et. al* works [2].

SIALAC benchmark offers 24 different instances of mobility case studies in order to compare average travel duration of synthetic population flows. It takes into account 3 parameters, listed below.

Number of agents	$\{5, 10, 15, 20\} \times 10^3$
Home	{1 cluster, 4 clusters, uniform[1]}
Activity	{1 cluster, 4 clusters

3.2 Importance of a Variable

Intuitively, importance of a variable quantifies its ability to alter the fitness value of a solution. In the context of expensive black-box optimization problems, we assume a variable is important when the mutation of its value implies a large modification in the fitness value of the solution. More formally, let op_i be the local search operator that modifies the variable i of a solution. At a given threshold $\epsilon > 0$, the variable is important when $|f(op_i(x)) - f(x)| > \epsilon$. Importance of a variable can be estimated during a random walk that modifies one variable at each step. In that case, a random walk is a sequence of solutions $(x_1, x_2, \ldots, x_n)$ where for all $t \in [1, n-1]$, it exists i such as $x_{t+1} = op_i(x_t)$. The importance of a variable i is defined by the number of times that the difference of fitness between two successive solutions in the walk is important: $I_\epsilon(i) = \sharp\{x_t \ : \ t \in [1, n-1] \text{ and } |f(x_{t+1}) - f(x_t)| > \epsilon\}$.

4 EXPERIMENTS

SIALAC instances are run on the Calais city road network, on which we modeled 33 intersections with traffic lights. The fitness function f is given by the average trip duration to be minimized, which represents one of the main measures of congestion within the city from a planner perpective. In order to investigate fitness landscape structures, 20 random walks of 50 steps are performed on every instance : a randomly chosen traffic light system is mutated each step. A mutation is defined by an alteration of a signal system's cycle time, offset time, or green times – by adding or withdrawing a random amount of seconds to these durations. The choice of the used mutation operator depends on respective mutation rates [2].

Then, ruggedness of the landscapes can be estimated, using the autocorrelation of fitness. Although the lengths are short and indicate a rugged landscape, surprisingly from a planner expert perspective, the difficulty of underlying optimization problems are similar according to ruggedness. Indeed, the Fig. 1 shows examples of random walks on two different instances. The walks are similar for every instances. The fitness displays sudden rapid *jumps* upwards or downwards, which suggests to analyze the importance of variables across instances.

Figure 1 shows the absolute value of the normalized fitness values difference δ_t across all walks on all instances. All the differences δ are similar across the instances, but the tail of the distribution for high value of $|\delta_t|$ is large. This allows us to define a meaningful threshold for the importance metrics across the instances. The threshold ϵ is defined such that 10% of the $|\delta_t|$ are considered to be a significant difference.

[1]Uniform distribution will be the basic reference when no or few data are known about population distribution.

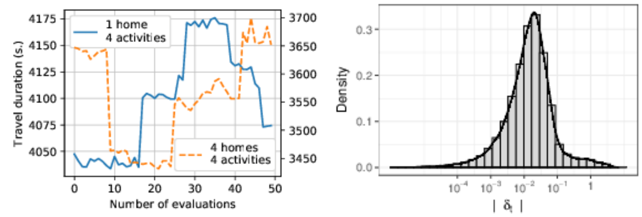

Figure 1: Example of random walks for 20000 **agents and 2 study cases (left). Distribution of** $|\delta_t|$ **where** $\delta_t = \hat{f}(x_{t+1}) - \hat{f}(x_t)$ **is the difference of normalized travel duration (right).**

5 DISCUSSION

These landscapes analyses, driven from various mobility benchmark instances, reveal that some variables of such a real world class of problem appears to be critical in an optimization perspective. That leads our future works to design adaptive optimization algorithms able to take advantage of these previous experiments.

ACKNOWLEDGMENT

Experiments presented in this paper were carried out using the CALCULCO computing platform, supported by SCOSI/ULCO (Service COmmun du Système d'Information de l'Université du Littoral Côte d'Opale).

We thank Calais city (France) for the data and its support.

REFERENCES

[1] 2016. The world's cities in 2016. United Nations, Department of Economic and Social Affairs.
[2] Rolando Armas, Hernán Aguirre, Saúl Zapotecas-Martínez, and Kiyoshi Tanaka. 2016. Traffic Signal Optimization: Minimizing Travel Time and Fuel Consumption. In *Artificial Evolution*. Springer, 29–43.
[3] K. Gao, Yicheng Zhang, A. Sadollah, and Rong Su. 2017. Improved artificial bee colony algorithm for solving urban traffic light scheduling problem. In *2017 IEEE Congress on Evolutionary Computation (CEC)*. 395–402.
[4] Dominik Grether. 2014. *Extension of a multi-agent transport simulation for traffic signal control and air transport systems*. Ph.D. Dissertation. Technische Universität Berlin, Fakultät V - Verkehrs- und Maschinensysteme.
[5] Andreas Horni, Kai Nagel, and Kay Axhausen (Eds.). 2016. *Multi-Agent Transport Simulation MATSim*. Ubiquity Press, London.
[6] T. Jones. 1995. *Evolutionary Algorithms, Fitness Landscapes and Search*. Ph.D. Dissertation. University of New Mexico, Albuquerque.
[7] KatherineM. Malan and AndriesP. Engelbrecht. 2014. Fitness Landscape Analysis for Metaheuristic Performance Prediction. In *Recent Advances in the Theory and Application of Fitness Landscapes*. Vol. 6. Springer, 103–132.
[8] Mathieu Muniglia, Sébastien Verel, Jean-Charles Le Pallec, and Jean-Michel Do. 2017. Massive asynchronous master-worker EA for nuclear reactor optimization: a fitness landscape perspective. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*. ACM, 295–296.
[9] S. M. Odeh, A. M. Mora, M. N. Moreno, and J. J. Merelo. 2015. A Hybrid Fuzzy Genetic Algorithm for an Adaptive Traffic Signal System. *Advances in Fuzzy Systems* 2015 (2015).
[10] J. J. Sanchez-Medina, M. J. Galan-Moreno, and E. Rubio-Royo. 2010. 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* 11, 1 (2010), 132–141.
[11] P. F. Stadler. 2002. Fitness Landscapes. In *Biological Evolution and Statistical Physics (LNP)*, Vol. 585. Springer, 187–207.
[12] E. D. Weinberger. 1990. Correlated and uncorrelatated fitness landscapes and how to tell the difference. In *Biological Cybernetics*. 63:325–336.