A Genetic Programming Approach for the Traffic Signal Control Problem with Epigenetic Modifications

Esteban Ricalde(✉) and Wolfgang Banzhaf

Memorial University of Newfoundland, St. John's, NL A1B 3X5, Canada
{ergl45,banzhaf}@mun.ca

Abstract. This paper presents a proof-of-concept for an Epigenetics-based modification of Genetic Programming (GP). The modification is tested with a traffic signal control problem under dynamic traffic conditions.

We describe the new algorithm and show first results. Experiments reveal that GP benefits from properties such as phenotype differentiation, memory consolidation within generations and environmentally-induced change in behavior provided by the epigenetic mechanism. The method can be extended to other dynamic environments.

Keywords: Genetic Programming · Epigenetic modification · Dynamic environments · Traffic signal control

1 Introduction

Because of the flexibility of its representation and its context independent methodology, GP can be used to generate solutions to problems in different areas of application in science and technology. However, in real world problems, the goal is often not fixed and can change during the evolutionary process. In a dynamic environment GP needs to be able to adapt to constant changes of the goal and fitness evaluation criteria. One approach to face these challenges is to generate variable locally adaptable solutions.

Biological evolution has different mechanisms to deal with environmental perturbations. Recently, Epigenetics, defined as phenotypic modifications without requiring changes in the nucleotide sequence (DNA), has been discovered to have important influences on the development of adaptation mechanisms at cellular, individual and species levels [13,16]. These imply a more active role for epigenetic mechanisms on the cellular, individual and species development.

In this paper an Epigenetics-based mechanism is presented and integrated into the Genetic Programming algorithm using a decision tree forest representation. A proof-of-concept in a dynamic environment is presented and future experiments are described.

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In this paper, the term decision tree is used in a loose sense. By decision tree we mean a tree that evaluates to an integer value with a conditional statement as the first node.

We use a traffic signal control problem as our testbed. Urban traffic network control is a complex nonlinear problem and traffic congestion affects daily life of millions of citizens. Furthermore, the rapid increment of metropolitan populations makes control of traffic signals a challenging task. Most of the traffic controller systems currently in use are pre-timed and cannot handle the dynamic nature of the problem. However, in the last decades, different adaptive methods have been implemented in simulated environments, reducing the delay during rush hours.

This paper is organized as follows: Sect. 2 describes one of the biological epigenetic mechanisms named DNA methylation and gives an overview of the different approaches followed to integrate epigenetic mechanisms into Evolutionary Computation. Section 3 introduces the Traffic Signal Control Problem and explores different Evolutionary Algorithm methods implemented for its solution. Section 4 describes the simulator and the traffic network used in this paper. Section 5 defines the chromosome representation and genetic operators used in the GP environment. Section 6 describes the epigenetic mechanism introduced in this paper. Section 7 provides details on the experimental configuration used. Results are presented and discussed in Sect. 8. Section 9 presents conclusions.

2 Epigenetics

Epigenetics is the study of cellular and physiological phenotypic trait variations that are caused by external or environmental factors affecting how cells read genes. This could be seen in contrast to the modifications caused by changes in the DNA sequence.

One of the clearly heritable mechanisms of Epigenetics is DNA methylation [16]. Methylated DNA has a methyl group (CH_3) attached to some of its bases. It is found in vertebrates, plants, and even in many invertebrates, fungi and bacteria [11]. A methyl group is normally attached to the cytosine (C) nucleotide. Methylated cytosine doesn't change its role in the genetic code. It is still paired with guanine. However, the methyl group affects protein transcription by binding with special proteins and preventing Ribonucleic acid (RNA) polymerase to work on it, or by interfering with the binding of regulatory factors to the gene control region. In other words, cytosine methylation is a mechanism to silence DNA sections. During development, methylation marks can change and the modified (methylated) DNA sequence is transferred from cell to cell during cell division.

Even though the importance of epigenetic inheritance in cell differentiation and memory processes has been recognized, its influence on macroscopic phenomena has been discovered only recently. Some examples are environmentally induced epigenetic modification of behavior [10], the influence of Epigenetics on memory consolidation within generations [5], the inherited propensity for learning [2], the role of Epigenetics in morphological differentiation (Honeybee reproductive queen differentiation mediated by royal jelly consumption [8]) and even species differentiation through morphological specializations (for instance phenotypic changes in the modern human brain and behavior compared to other hominids [13]).

The Evolutionary Algorithm (EA) community has recently started to consider the discoveries in the area of Epigenetics. Different approaches have been used to represent the phenotypic mechanism, but it has normally been implemented as extra optimization to accelerate the adaptation of the EA.

Tanev and Yuta [22] worked with a modification of the predator-prey pursuit problem. GP is used to define a set of stimulus-response rules to model the reactive behavior of predator agents. The implementation includes active and inactive histones in the representation and uses age-based predators moving through different life stages (birth, development, survival and death). An extra step called Epigenetic Learning (EL) is included in the fitness evaluation. EL is basically a hill climber acting through epi-mutations of the histone activation signals.

It was found that the probability of success is larger when the Epigenetic Learning mechanism is included. The authors ascribe the difference to the robustness gained with the representation by preserving the individuals from the destructive effects of crossover by silencing certain genetic combinations and explicitly activating them only when they are most likely to be expressed in corresponding beneficial phenotypic traits.

Fontana [6] used other multi-cellular morphogenic models for development with an integer number genetic representation controlled by a regulatory network with epigenetic activation and deactivation signals in different development phases. A two-dimensional cellular grid and a Genetic Algorithm running on the genome allow the model to generate predefined 2-dimensional shapes.

In [21], Sousa and Costa present an epi-genetically controlled agent system for Artificial Life. The agents wander around a 2D environment with walls and different attributes -temperature, light and food- that can vary over time. The goal of the agents is to survive and to reproduce.

The behavior of the agents is coded on binary strings. Activation of genes is controlled by methylation marks. An Evolutionary Algorithm controls the survival and reproduction of the different organisms. Several experiments were performed with different levels of epigenetic transfer between parents and offspring. The results show a significant improvement: Non epigenetic populations found it hard to thrive in dynamic environments, while epigenetic populations were able to regulate themselves under dynamic conditions.

Chikumbo et al. [3] proposed a Multi-Objective Evolutionary Algorithm with epigenetic silencing for the land use management problem. The goal of the farm was to reduce the environmental footprint whilst maintaining a viable farming business through land use and/or management option changes.

The chromosome encoded each paddock land use and the system emulated gene regulation with epigenetic silencing based in histone modification and RNA editing mechanisms. A Pareto front visualization tool was developed composing the 14 fitness criteria into 3 super-objectives. However, the approach was not compared against a classical Multi-Objective Evolutionary Algorithm. Therefore, the improvement of the epigenetic variation could not be estimated.

In 2014, the same authors [4] extended their previous work using a similar epigenetic based modification. The main modification is the use of Hyper Radial Visualization, 3D Modeling and Virtual Reality to reduce the 14 fitness functions and display the solutions in a understandable way to a group of experts. Again, the approach is not compared with a classical EA.

Turner et al. [23] used an Artificial Gene Regulation model with an epigenetic mechanism based on DNA methylation and chromatin modifications. The inclusion of epigenetic information gave the network the ability to allocate different genes to different tasks, effectively regulating gene expression according to the environment in which it was operating.

The goal of the model was to follow specific trajectories in a chaotic system (Chirikov's standard map). The network was evolved using a Genetic Algorithm. The epigenetic mechanism improved performance of the model in a dynamic system. With the ability to inactivate genes came the ability to increase the efficiency of the network. Hence, with each inactive gene for an objective, there was less computational effort required to complete a single iteration of the network simulation.

La Cava et al. [15] included an Epigenetic Hill Climber into the Linear Genetic Programming algorithm by the addition of a binary array equivalent in length to the genotype of each individual. This array, referred to as an epiline, indicated the active genes. The algorithm was used to solve different symbolic regression problems and performed better than the non-epigenetic one. Even when there was no statistically significant improvement in Mean Best Error, the authors reported improvements in effective program size and beneficial genetics (genetic operations that resulted in fitter offspring).

The same research group used a similar epigenetic mechanism in [14] to solve symbolic regression and program synthesis problems. Stack-based GP representations are used for both types of problems. The binary epiline is used to deactivate nodes. Epigenetic hill climber and epigenetic mutation variations are compared against a GP method were all the nodes are active. The epigenetic methods outperformed the GP baseline implementation in terms of fitness minimization, exact solutions, and program sizes.

3 Traffic Signal Control

Urban traffic network control is a complex nonlinear problem and traffic congestion affects daily life of millions of citizens. Furthermore, the rapid increment of metropolitan populations makes the control of the traffic signals a challenging task. Different traffic signal control methods have been implemented over time to try to reduce the negative effects of traffic congestion.

A basic fixed traffic signal has static phase lengths based on historical information for each intersection. However, traffic doesn't behave in the same way during different hours of the day. An engineer can analyze the behavior of the traffic during the day and define different phase lengths for specific intervals. This method is called pre-timed control. It presents an improvement over the fixed control depending on human expertise and the correct modeling of traffic conditions, but requires constant surveillance and constant update, but cannot adapt to sudden modifications in traffic behavior.

Actuated control or traffic-responsive control consists of phase length sets that are extended in response to vehicle detectors. Detection is used to provide information about traffic demand to the controller. Each phase length is determined by a detector input and corresponding controller parameters.

Different traffic units have been used in the literature to measure traffic: average car speed, average intersection delay, average queue length, total system delay, etc. Total system delay is defined as the sum of the stop time of all vehicles in the system for a defined interval of time.

Traffic-control systems are affected by many factors: infrastructure, vehicles, drivers, pedestrians, weather, seasonal effects, etc. Each factor has its own characteristics, which makes the entire traffic system a large complex nonlinear stochastic system which poses many interesting problems and challenges for researchers and engineers.

Wang [24] proposed a general "parallel" control model, where parallel implies parallel interactions between a real transportation system and its corresponding artificial or simulated counterpart. The approach consists of three steps: (1) generation of a simulated model; (2) analysis and evaluation by computational experiments; (3) control and management through parallel execution of the real and artificial system.

This general framework can be used with different simulation, control and learning algorithms, with the constant feedback of differences between real world events and simulated environments as one of its main benefits.

In [25], Zhang et al. proposed a real-time online urban traffic signal control approach using a multi-objective discrete differential evolution modification to optimize the light phase periods of a three-lane, single intersection road including left-turn phases. The authors compared their algorithm with a pre-timed controller using a Poisson distribution to regulate the traffic flow. The proposed approach behaved better in the single intersection problem.

Sánchez-Medina et al. [20] used a Cellular Automaton based traffic simulator and a Genetic Algorithm to simulate and optimize the traffic light phase periods of a section of Saragossa city. The section has seven intersections, 16 input nodes, 18 output nodes and 17 traffic signals. Individuals were represented as an array containing light phase periods of all traffic signals. Four different parameters were used as fitness function. The algorithm was tested with different traffic situations and limited results were obtained. The methodology does not provide a significant improvement for regular traffic conditions of the network; however, it increases the performance for more congested scenarios.

Nie et al. [18] used a two-dimensional Cellular Automaton and a $1 + \lambda$ Evolutionary Strategy to update the time parameters of CA rules in a 20×20 cell network. The authors performed experiments with different traffic densities and the results demonstrated a better performance of the evolutionary approach compared to previous work done with the same Cellular Automaton. However, the simulated environment was too rigid and was not able to represent all conditions of a real environment.

In [1], Braum and Kemper modified an open source area-wide traffic light signal optimizer, called BALANCE [7]. They replaced the hill-climbing algorithm used on the tactical level of BALANCE with a Genetic Algorithm. The chromosome representation used is similar to the one used in [20]; however, the optimization was done online with a real system. The architecture used is similar to the parallel control model defined in [24].

Several experiments were performed with the traffic network of Ingolstadt, Germany. The results demonstrated a better performance of the GA over the Hill Climber (HC) in almost all (different) traffic density tests. The authors conclude that as the network becomes larger and more complex, the evolutionary algorithm provides larger advantages. Once the system started operating in the real world, daily average delays were reduced by 21 % compared to the standard 10 % expected using the traditional HC algorithm of BALANCE.

In [19], Padmasiri and Ranasinghe used a GP and fuzzy logic hybrid approach to define a single fine-tuned fuzzy rule for a single intersection using a Poisson distribution to control the vehicle arrival rate under different traffic volume scenarios. The set of evolved rules use traffic parameters as input and decide to extend or terminate the current green lapse. The results present an improvement compared to previous work. However, solutions lack adaptability to changes in the traffic conditions and the method was tested only with a single intersection.

4 The Traffic Simulator

Microscopic traffic simulation models study individual elements of transportation systems, such as individual vehicle dynamics and individual traveler behavior. The model depends on random numbers to generate vehicles, to select routes and to determine the behavior of the system. In a microscopic simulator the dynamic variables of the model represent microscopic properties like the position and velocity of single vehicles.

Even though several commercial and open source simulators are available, we decided to create a microscopic model simulator in order to have full control of the environment. It allows the parallel execution of experiments in a multiprocessor environment, and to simulate different dynamic traffic conditions by the hour.

The simulator works in a similar way to the Cellular Automaton described in [12, 20], but operates in a two-dimensional environment. It can represent roads with multiple-lanes and two directions. An extra Object-Oriented layer was incorporated to update only the cells containing vehicles and to reduce simulation time. Instead of using a toroidally closed environment, the network entries are controlled by a Poisson distribution described in Sect. 4.2.

4.1 Traffic Network

The size of the network, its number of connections, geometry, number of lanes and type of intersections can be modified before running the simulator. For this paper, the experiments were performed in a 10 intersections network with 9 input/output nodes and 31 traffic signals. All the nodes are connected by two-lane bi-directional roads. The network is presented in Fig. 1.

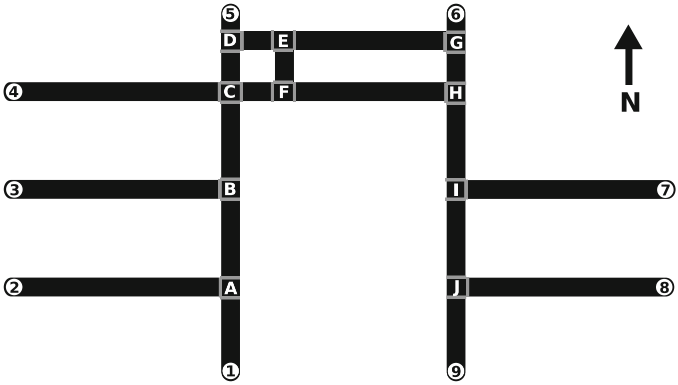

Fig. 1. Traffic network used for the experiment

4.2 Vehicle Insertion

The Poisson distribution correctly models arrival of vehicles, on one or multiple lanes [17]. The flexibility of the Poisson distribution allows the simulation of changes in the traffic densities. In order to simulate real-world similar conditions, the scenario simulates 16.5 h of traffic. The traffic densities change during the simulated day and each entry point to the network follows a different distribution.

The first hour is considered a training step where all the entries follow a standard Poisson distribution going from zero traffic conditions to the maximum saturation peak and declining again to zero traffic. During the remaining 15.5 h of the scenario, two traffic waves are executed. The first one initiates from south-west entries between 7 and 11 am. The second one from north-east entries between 4 and 7 pm. Figure 2 presents the probability distributions generated corresponding to the defined behavior for the network presented in Fig. 1.

Even when the complete scenario covers more than 16 h of traffic, each simulation runs only for one hour of traffic. A time window is used during the experiments. The window moves 5 min after each execution. Using this approach, the full scenario is covered with 200 simulations.

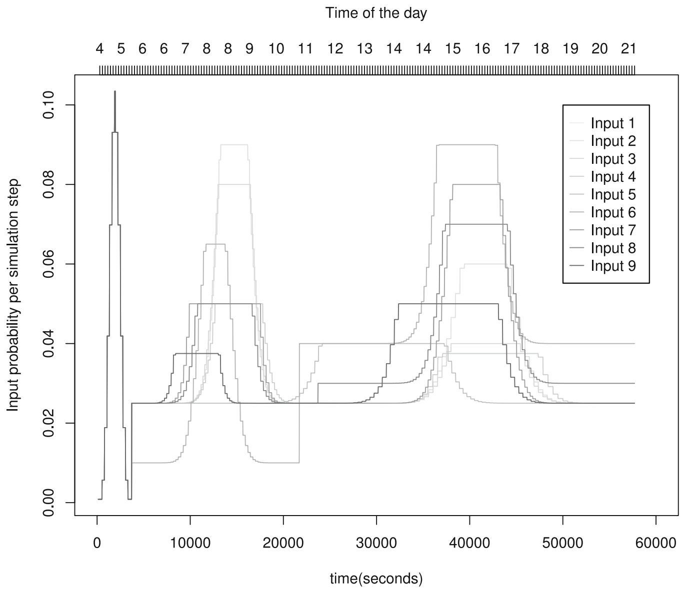

Fig. 2. Traffic input probability distributions

5 Representation

We used a forest of decision trees as the GP representation. Each decision tree is employed to evaluate a set of intersections with similar characteristics; i.e., same number of intersecting roads and equivalent proximity to entry points. For example, the network in Fig. 1 requires a forest of 4 decision trees: (E, F, H), (B, D, G, I), (A, J) and (C).

The terminal set is formed by integer numbers, between -10 and 10, and traffic parameters listed in Appendix A. The function set is formed by mathematical operators (addition, subtraction, multiplication and protected division), logical operators (conjunction, disjunction and negation), comparison operators (equal to, bigger than and smaller than), and a conditional operator.

During the simulation, a decision tree is executed for each intersection twice in every light cycle with current traffic parameters. The resulting integer number is added to the vertical green phase period, subtracted from the vertical red phase period, added to the horizontal red phase period and subtracted from the horizontal green phase period.

Figure 3 presents a single decision tree. This tree represents a human designed solution. The idea is to increase the mobility (increase the green phase in 1 s and reduce the red phase in 1 s) of the vertical or horizontal directions if the corresponding queue is larger than the opposite direction queue for more than 5 vehicles.

Two different crossover operations are available: Tree exchange and sub-tree exchange. The former occurs in 10 % of all crossover operations and exchanges

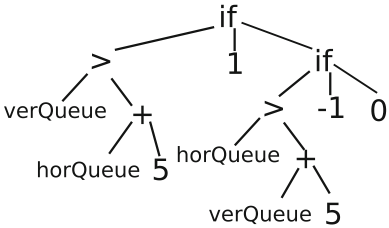

Fig. 3. Decision tree

one tree between two chromosomes. The trees exchanged are in the same position of the two different forests. The latter operator selects a random crossover point of a specific decision tree in both chromosomes and exchanges the two sub-trees selected only if both are of the same type; otherwise, it selects a new crossover point.

Two different mutation operations are available: New tree mutation and node mutation. The former occurs with a probability of 0.1 %, selects a random tree of the forest and replaces it with a newly generated tree. The latter replaces a single node with a node of the same type.

Strong typing is performed through evaluation of the selected points before the application of the reproduction operators. These GP parameters and those presented in Table 1 were selected based on a set of preliminary experiments.

6 The Epigenetic Mechanism

The epigenetic mechanism proposed is based in DNA methylation. Each conditional node is associated with an activation index in analogy to the concentration of methyl groups attached to cytosine nucleotides along the DNA structure. As in the biological counterpart, the evolutionary process of chromosomes is not affected by the activation index. However, during the evaluation step, if the activation index is smaller than an activation threshold, defined as 50 % for this experiment, the conditional node is ignored and the *else sub-tree* is executed, deactivating with that action the *conditional sub-tree* and the *then sub-tree*.

The activation indices are initialized randomly between 0 % and 100 % for the first generation. However, they are transferred to the offspring as part of the crossover operation in the same way methylated DNA is transferred between generations. The collection of activation indices is stored in an epigenetic vector for easy manipulation. The epigenetic vector is included as part of the chromosome, but it is not affected by the genetic operators.

Figure 4 presents the effect of the activation thresholds in a forest of decision trees. The branches in gray are inactive. This change modifies the behavior of the decision tree without modifying the chromosome.

Since methylation marks change during development, it was decided to modify the epigenetic vector during the simulation process using the following procedure: For each intersection that uses a tree expression the traffic balance, defined

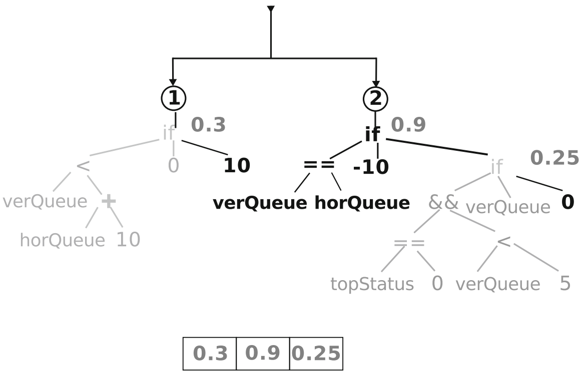

Fig. 4. Decision trees under influence of activation thresholds and epigenetic vector

as the difference between the traffic congestion in vertical directions and the traffic congestion in horizontal directions, is calculated using (1), where i represents an intersection evaluated through the tree expression e, and t represents the current time step.

$$B_{e_i}(t) = \text{verticalQueue}_{e_i}(t) - \text{horizontalQueue}_{e_i}(t) \tag{1}$$

Every 5 light cycles, a mean traffic balance of the interval is calculated per intersection with (2), where T is the number of time steps of the interval.

$$\overline{B}_{e_i} = \frac{\sum\limits_{t=1}^{T} B_{e_i}(t)}{T} \tag{2}$$

The interval mean is then compared to the last element of the time interval in order to get the adaptive factor of the expression as it is defined by (3).

$$\Lambda_{e_i} = |B_{e_i}(T) - \overline{B}_{e_i}| \tag{3}$$

The goal of the adaptive factor is to identify differences between the interval mean congestion levels and the current state for each intersection in the system. A large difference between the current congestion level and the mean behavior of the intersection indicates a change in the environment. In that case, a modification in the behavior of the intersection could help the system to adapt to this environmental change.

Therefore, the adaptive factor of the expression is used as a mutation probability to modify the activation indices of the expression tree. A mutation is performed on the local activation indices. This step is performed as an internal mutation during the simulation process for each intersection. The mechanism works in a similar way to the epigenetic mutation variations presented in [14] and has the purpose to adapt the intersection behavior to environmental changes.

The conceptual idea behind this process is to keep the system behavior stable under environmental perturbations, one of the roles of Epigenetics at the cellular level in Nature. At the end of the simulation, the final activation indices are stored in the epigenetic vector of the chromosome and transferred to the next generation.

7 Experiments

Five different algorithms were tested with the traffic network of Sect. 4: (1) a fixed static control, (2) an actuated control using a human designed fixed decision tree, (3) a pre-timed control evolved using a Genetic Algorithm (GA), (4) an actuated control using the GP representation described in Sect. 5 and (5) an actuated control using the GP representation including the epigenetic mechanism described in the previous section.

The baseline is a fixed control with synchronization of all the intersections. For this method, all the lights are synchronized and the lapses are fixed (15 s for the green light, 5 s for yellow light, 10 s for red light and 10 s for a left turn). The system behavior keeps static for the 16 h of traffic.

The decision tree of Fig. 3 is the human designed actuated control used for the second algorithm. In each simulation, the lights start with the fixed configuration used in the static method, but the decision tree is executed at each intersection twice every light cycle. Therefore, the lapses of each intersection can be modified depending on traffic conditions. The same decision tree is used for all intersections in every simulation.

A pre-timed control is evolved using a GA similar to those presented in [1,20]. The length of the lapses for each intersection in the system is stored as an integer chromosome. An online optimization approach is used with the GA for 200 generations to approximate an optimal pre-timed configuration for the 16.5 h of traffic as it is described in Sect. 4.2.

The GP actuated control and the GP actuated control including the epigenetic mechanism evolve a forest of decision trees (see Sects. 5 and 6) using an online approach.

During the evolution process each individual is evaluated with 20 independent simulation runs. Total system delay, defined in Sect. 3, is used as objective function.

For the fixed control and fixed tree actuated control, 20 independent simulation runs are effectuated for each of the 200 simulation configurations. The total system delay is calculated for each of them and the objective function is defined as the average total system delay of the 20 simulations.

The parameters employed for the Genetic Programming are presented in Table 1. A similar configuration in terms of population size, number of generations, selection method, mutation probability and crossover probability is used for the Genetic Algorithm.

Table 1. Summary of the configuration parameters for the Genetic Programming Model

Configuration parameters	Selected values
Population size	50 individuals
Number of generations	200
Mutation probability rate per node	5%
Crossover probability	80%
Initial size limit	5 levels
Maximum size limit	7 levels
Selection operator	Tournament selection with group size of 7 individuals
Elitism	1 individual

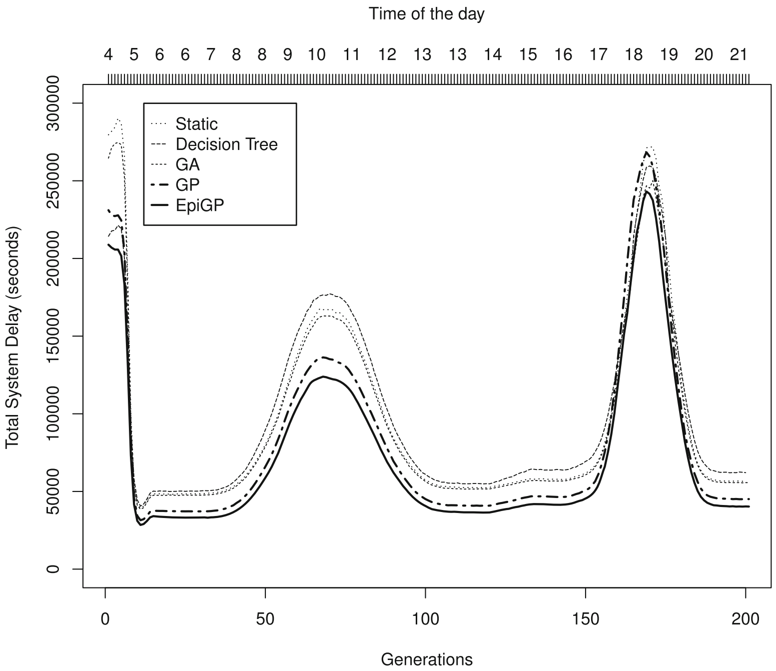

Fig. 5. Fitness curves of fixed control, tree actuated control, GA pre-timed control, GP and epigenetic modification of GP for the experiment

8 Results and Discussion

15 independent runs were performed for each algorithm. Figure 5 presents the comparison of the fitness obtained by the five methods. For GA, GP and the epigenetic modification of GP the fitness value of the best individual per generation is displayed.

Table 2. Vehicle waiting time differences of the four methods

Compared methods	Vehicle waiting time difference (seconds)	Relative difference with static method
Static - GA	13.85	3.33 %
Static - GP	61.82	14.91 %
Static - EpiGP	98.29	23.71 %
GP - GA	47.58	11.57 %
GA - EpiGP	84.45	20.37 %
GP - EpiGP	36.47	8.80 %

From the first generation, the learning curve of the evolutionary actuated control methods starts to provide better solutions than the fixed control approach for almost all evaluation steps. This behavior can be caused by the high variability of traffic densities used in the experiment. Further experiments should be performed with lower variability to analyze the behavior of the methods in more detail.

The epigenetic modification of GP has a lower delay than the standard GP algorithm for almost all the evaluation points. The difference between both methods is more drastic during rush hours. A possible explanation is the adaptive ability provided by the activation-deactivation of code of the epigenetic method during the simulation.

Table 2 presents pairwise comparisons of the vehicle waiting time for combinations of the methods. The second column indicates the difference of the average waiting time per vehicle for the different algorithms. The third column is that difference divided by the average vehicle waiting time of the pre-timed experiment.

It is noteworthy that the epigenetic modification outperformed the other four methods used in the experiments, providing an improvement of more than 20 % compared to the fixed control and the pre-timed control. However, an evaluation of the methods with different variability in traffic conditions needs to be conducted to provide a better understanding of the behavior of the methods. For now, this set of experiments is a proof-of-concept.

9 Conclusions and Future Work

The GP modification described in this paper is an epigenetic approach specifically designed to work on traffic signal control problems. A basic set of experiments was performed and the results demonstrate an increase in the performance compared to the basic GP method and other methods previously used.

Extensive experimentation is required to give statistical significance to the results. To achieve that, statistical tools should be used to perform analysis of the data generated by the independent runs. Scenarios of different sizes should be evaluated to analyze the behavior of the method under different circumstances. It would be ideal to acquire data from a real world network.

Furthermore, the modification needs to be compared against traditional methods used in Traffic Signal Control. An example of these methods is the green wave algorithm described in [9]. Because the architecture developed can be easily transformed into an online real-virtual parallel system as the one described in [24], it can be used in real world traffic optimization.

Moreover, the epigenetic modification can be used to solve other problems. Problems were some elements of the domain vary with the progression of time (dynamic environments) can benefit of the short term memory mechanism presented in this paper. The key elements to implement the epigenetic modification are: the identification of a variable independent to the objective function (traffic balance in our experiment) to calculate the adaptive factor, the insertion of activation indices in nodes of a specific type and the code activation-deactivation process described in Sect. 6.

A Traffic Parameteres

Traffic parameters included in the terminal set:

- **topStatus**: Status of the north-south direction light of the current intersection (returns 0 if the light is red, 1 if the light is yellow, 2 if the light is green and 3 if the turn left right is on).
- **bottomStatus**: Status of south-north direction light of the current intersection (same output configuration that topStatus).
- **leftStatus**: Status of west-east direction light of the current intersection (same output configuration that topStatus).
- **rightStatus**: Status of east-west direction light of the current intersection (same output configuration that topStatus).
- **verQueue**: Sum of the number of vehicles stopped in the north-south direction and the number of vehicles stopped in the south-north direction in the current intersection.
- **horQueue**: Sum of the number of vehicles stopped in the west-east direction and the number of vehicles stopped in the east-west direction of the current intersection.
- **1stTopNeighborQueue**: Number of vehicles stopped in the north-south direction of the first intersection in the north direction of the current crossing.
- **1stBottomNeighborQueue**: Number of vehicles stopped in the south-north direction of the first intersection in the south direction of the current crossing.
- **1stLeftNeighborQueue**: Number of vehicles stopped in the west-east direction of the first intersection in the west direction of the current crossing.
- **1stRightNeighborQueue**: Number of vehicles stopped in the east-west direction of the first intersection in the east direction of the current crossing.
- **2ndTopNeighborQueue**: Number of vehicles stopped in the north-south direction of the second intersection in the north direction of the current crossing.

– **2ndBottomNeighborQueue**: Number of vehicles stopped in the south-north direction of the second intersection in the south direction of the current crossing.
– **2ndLeftNeighborQueue**: Number of vehicles stopped in the west-east direction of the second intersection in the west direction of the current crossing.
– **2ndRightNeighborQueue**: Number of vehicles stopped in the east-west direction of the second intersection in the east direction of the current crossing.

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