EVOLUTION STRATEGIES COMPARED TO GENETIC ALGORITHMS IN FINDING OPTIMAL SIGNAL TIMING FOR OVERSATURATED TRANSPORTATION NETWORK

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Abstract: This paper compares the performance of Evolution Strategies (ES) with simple Genetic Algorithms (GAs) in finding optimal or near optimal signal timing in a small network of oversaturated intersections with turning movements. The challenge is to find the green times and the offsets in all intersections so that total vehicle-mile of the network is maximized. By incorporating ES or GA with the micro-simulation package, CORSIM, we have been able to find the near optimal signal timing for the above-mentioned network. The results of this study showed that both algorithms were able to find the near optimal signal timing in the network. For all populations tested in this study, GA yielded higher fitness values than ES. GA with a population size of 300, and selection pressure of 10% produced the highest fitness values. In GA for medium and large size populations, a lower selection pressure produced better results while for small size population a large selection pressure resulted in better fitness values. In ES for small size population, larger μ/λ yielded better results, for medium size population both μ/λ ratios produced similar results, and for large size population smaller μ/λ provided better results.

1 INTRODUCTION

Traffic congestion in major US metropolitan areas costs $87 billion dollars annually. These costs plus other negative effects of traffic congestion, calls for practical methods for managing congestion in transportation networks. Transportation supply management can effectively reduce congestion in a network by determining the optimal signal timing that provides maximum capacity. In this study, two different methods, ES and GAs, were used to find the optimal or near optimal signal timing for a transportation network consisting of nine oversaturated intersections with turning movements.

In the past 10 years, much research has been conducted to optimize signal timing in transportation networks. A few examples are: Abu-Lebdeh and Benekohal (2000) considered a two-way arterial consisting of several intersections and tried to manage the queues on this oversaturated arterial using Gas. Chang and Sun (2003) considered a network of 12 oversaturated and 13 undersaturated intersections and proposed the Maximal Progression Possibility method to minimize the delay and total number of stops in the network by choosing the most critical intersection and removing congestion from that. Girianna and Benekohal (2004) considered an oversaturated network consisting of 20 intersections with one-way streets and used GAs to solve the problem. Their algorithm was able to determine a common cycle for the network and coordinate the signals to remove congestion from the network. Sanchez Medina et al. (2008) used GA to determine optimal signal timing in two urban areas in Spain and in one of their case studies increased the fitness by 10% compared to the currently used signal timing.

Similar to GAs, Evolution Strategies (ES) are meta-heuristic approaches that start with a population of candidate answers and try to improve the fitness of the population over generations. Beyer and Schwefel (2002) explained different aspects of ES in their comprehensive introduction to ESs. ES have been used extensively as an optimization engine in a variety of scientific fields; however, we did not find any study using ES to optimize signal timing in transportation networks. This motivated us to compare ES with GAs in finding signal optimization solutions.

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In this study, ES and GAs were used to find the optimal or near optimal signal timing for a small size oversaturated transportation network. Different settings of GAs have been used and compared to different settings of ES and their benefits and drawbacks are discussed. The next sections discuss methodology, results and our conclusions.

2 METHODOLOGY

In this section, the problem statement and formulation, and the methodology to solve the problem are presented.

2.1 Signal Optimization Problem

In signal optimization the goal is to find signal timing such that a measure of effectiveness is optimized. In this study, we are trying to maximize total vehicle-mile in the network. The network is oversaturated meaning that the traffic demand in the network is more than the capacity. By signal timing, we mean green times for each movement at the intersection and the offsets. To study if ES and GAs are capable of solving the signal optimization problem, a simulated oversaturated transportation network is used. This symmetric network consists of nine intersections forming a rectangular grid as shown in Figure 1. The length of each street is 2000 ft (including the entry and exit links as well).

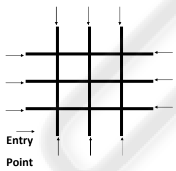

Figure 1: The schematic study network.

Traffic consists of only passenger cars; and they enter the system at nine entry points shown in Figure 1. At each entry point, the volume is 1000 passenger cars per hour per lane. It is assumed that 70% of vehicles go straight, 10% turn right, and the remaining 20% turn left. A fixed time signal timing plan is used. All streets are two-way with one approach lane per direction. At each intersection a 1000 ft long left turn pocket is assumed to avoid the through lane being blocked by the left turning vehicles. The traffic signal is assumed to have 4 phases, staring with left turn green arrows and continued by through traffic green for each direction.

ES or GAs determines the green times (consequently the cycle lengths) and the offset for each intersection to improve the total vehicle-mile travelled in the entire network.

2.2 Signal Optimization Problem Formulation

The problem could be formulated as an optimization problem where we try to maximize total vehicle-mile in the network. Vehicle-mile depends on the signal timing of each intersection. In this problem, the vehicles are moved in the network by CORSIM simulation model and the vehicle-mile travelled is tallied by software as well. We assumed that the left turn green times are between 7 and 15 seconds. A minimum of 20 seconds and a maximum of 80 seconds of green time are assumed for the through traffic. The signal optimization problem is formulated as follows:

$$
\begin{aligned}
& Max \quad v = f(g_{ki}, Off_i) \\
& s.t. \\
& 7 \le g_{1i}, g_{3i} \le 15 \\
& 20 \le g_{2i}, g_{4i} \le 80 \\
& 0 \le Off_i \le C_i \\
& C_i = g_{1i} + g_{2i} + g_{3i} + g_{4i} + 14 \\
& i = 1..9
\end{aligned}
$$

Where: $f(g_{ki}, Off_i)$: is the total vehicle-mile in the network, i: is the intersection index, g_{1i}, g_{3i}: are the left turn green times at intersection i, g_{2i}, g_{4i}: are the through traffic green times at intersection i, Off_i: is the offset at intersection i, C_i: is the cycle length at intersection i, and number 14: is the lost time at each intersection.

2.3 How the Problem is Solved

For signal timing problem, each individual consists of signal timing for the whole network, and the fitness function is the total vehicle-mile travelled in the entire network. The ES Algorithm used in this study uses three different recombination methods which are: global intermediary, local intermediary, and discrete recombination. Each time one of these recombination operators is chosen randomly with similar probabilities. In addition, a correlated mutation is used. For simple GA that is used, tournament selection with replacement, two-point crossover with probability of 0.85, and simple mutation with probability of 0.01 are used.

To solve the problem with ES, the initial population is randomly generated and the fitness of all individuals is evaluated (by CORSIM). Using recombination and mutation, the descendants are generated and their fitness is evaluated by CORSIM. Using selection operator, the parents for the next generation are selected and this process is continued until the termination criteria are met.

To solve the problem by GAs, the initial population is randomly generated and the fitness of all individuals is evaluated (by CORSIM). Then using selection operator, the mating pool is formed and the individuals are crossed over and mutated to form the next generation. The fitness of all individuals in the new generation is evaluated by CORSIM and this procedure is continued until the termination criteria are met.

The problem is solved using a PC with Pentium 4 CPU with clock time of 3.2 GHz, and memory of 1 GB. Each run of the algorithm that contains 9000 times fitness function evaluations takes around 8 hours of CPU time. For each setting, three different seeds are used: 12345701, 52345681, and 92345723 (unique numbers). For each seed, the fitness of each generation is the maximum fitness of the population in that generation and the average of these three fitness values is the reported fitness value.

3 RESULTS

We made both ES and GAs algorithms to evaluate the objective function 9000 times in order to get comparable results. In the following sections, details on fine tuning GA and ES will be presented and then the two methods will be compared.

3.1 Fine Tuning GA

In order to get good results from GAs, GA parameters were selected according to Goldberg et al. (1993). Three different population sizes were tested: 25, 75, and 300 corresponding to a small, medium size, and large population respectively. For all of these three population sizes, tournament selection with replacement with two different pressures was tested: 40%, and 10%. These selection pressures correspond to a high and a low selection pressure. The values of fitness function versus the number of fitness function evaluations are presented in Figure 2 separately for each population size.

For medium and large size populations (75 and 300 in case study), using a low selection pressure results in better fitness values. The reason is that a large selection pressure ends up selecting the best individuals over and over and does not let other individuals (that are less fit) to participate in generating the next population. The less fit individuals my pass some good genes and end up creating a descendant with a higher fitness value. In an extreme case, choosing a selection pressure of 100% forces the algorithm to choose the fittest individual of the population each time. This setting does not provide any good result and will be trapped in a local optimum. On the other hand, a very small selection pressure results in choosing parents almost randomly. This way of choosing parents does not pass the good genes to the next generation and does not result in a significant increase in fitness value.

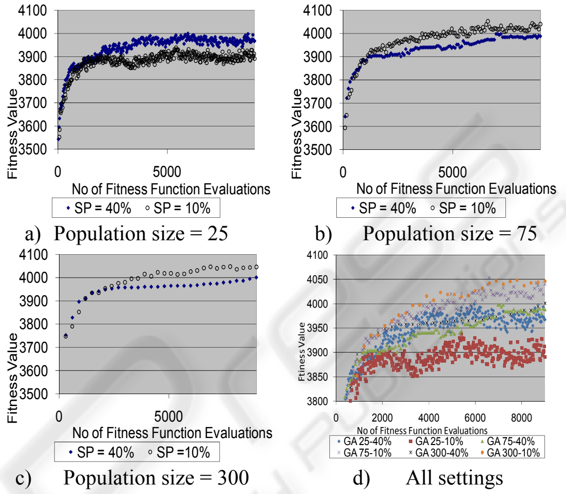

Figure 2: Effects of SP on the value of fitness function for different population sizes (*SP: Selection Pressure).

On the other hand, for a small population size, a higher selection pressure should be used. The reason is that when the population size is small (25 in this case) a relatively small selection pressure (10%) results in selecting only two individuals each time; and then selecting the fittest of the two as one of the parents. Figure 2 supports the above-mentioned statements. When the population size is equal to 25, setting selection pressure equal to 40% results in better fitness values compared to setting selection pressure equal to 10%. However, when the population size becomes 75 or 300, choosing a smaller selection pressure results in better fitness values. Based on Figure 2, GA setting that provided numerically better fitness values is GA 300-10%. This setting has been chosen as the best setting in GA.

3.2 Fine Tuning ES

Six different settings were tested to fine tune ES. These settings were chosen corresponding to the setting used for GA. These six settings are: ES10,25, ES4,25, ES30,75, ES7,75, ES120,300, and ES20,300 and correspond to GA25-40%, GA25-10%, GA75-40%, GA 75-10%, GA300-40%, and GA300-10% respectively. As presented in Figure 3, for small and medium size populations, large and small μ/λ ratios result in very similar fitness values.

However, when the population size is 300, similar to GA, a μ/λ ratio of 10% produces a faster increase in fitness value. Comparing different ES settings reveals that ES30,75, and ES7,75 produced numerically higher fitness values compared to the other settings tested in this study.

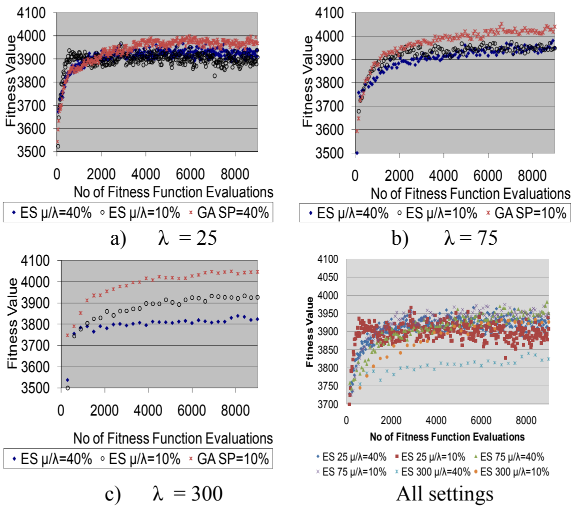

Figure 3: Effects of SP on the fitness value for different population sizes (*GA SP=10%: GA with SP=10%).

3.3 GA vs. ES

In Figure 3 for each ES population size, the corresponding best GA setting for that population size is plotted. This plot shows that for all three population sizes tested in this study, GA outperforms ES. For small population size (25) ES10,25 results in higher fitness values during the first 1000 fitness function evaluations, however, for the rest of fitness function evaluations GA 25-40% results in numerically higher fitness values. This observation shows that for small population sizes, ES may be able to find a good quality answer faster than GA. For mid-size and large size populations, GA with 10% selection pressure clearly produces higher fitness values than both tested settings of ES.

4 CONCLUSIONS

This paper compares the effectiveness of ES to GAs in solving signal optimization problem. Both algorithms were tested on a small transportation network of nine oversaturated intersections. We compared six different ES settings with six different GA settings and found out that both algorithms were capable of solving the signal optimization problem.

Findings of this study showed that, GA outperforms ES for all three different populations sizes tested. The setting that produced the highest fitness values was GA with 300 population size, 10% selection pressure, two-point crossover with probability of 85%, and simple mutation with probability of 1%. For small population size (25), for the first 1000 fitness function evaluations ES provided higher fitness values than GA. However, for the rest of fitness function evaluations (9000 total), GA outperformed ES.

In fine tuning GA, for medium size and large size population sizes, a low selection pressure (10%) resulted in higher fitness value due to providing enough diversity and conducting a more comprehensive search in the feasibility area. However, for a small population size, a large selection pressure (40%) provides higher fitness values compared to a low selection pressure (10%). Comparing the fitness values of different settings numerically indicates that GA with 300 population size and 10% selection pressure, outperforms all other GA settings.

In fine tuning ES, for 25 and 75 population sizes, both selection pressures, 40% and 10%, result in similar fitness values. For population size equal to 300, selecting a lower selection pressure provides higher fitness values. Comparing different ES settings revealed that ES 30,75 and ES 7,75 resulted in highest fitness values compared to the other settings.

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