

Genetic Algorithm Approach for Adaptive Offset Optimization for the Fluctuation of Traffic Flow

Sei Takahashi*, Hideo Nakamura*, Hiroshi Kazama† and Tomokazu Fujikura†

*College of Science and Technology, Nihon University, Funabashi-shi, Chiba 274-8501, JAPAN
Telephone: +81-47-469-5475, Fax: +81-47-467-9683, Email: {seitaka,nakamura}@ecs.cst.nihon-u.ac.jp

†Kyosan Electric Manufacturing Co., Ltd., Yokohama-shi, Kanagawa 230-0011, JAPAN
Telephone: +81-45-575-8862, Fax: +81-45-575-1844, Email: {h-kazama,t-fuji}@kyosan.co.jp

Abstract—This paper describes offset optimization for the fluctuations of traffic flow using a genetic algorithm (GA). An offset, which is the target of signal control parameters for this study, is difficult to optimize because of its variety of combinations. Traffic signal optimization using GAs has been investigated in previous studies. Most of them however, focused on signal control without considering the fluctuations of traffic flow. In a practical situation, the rate of flow changes as time passes, so that offset optimization considering these fluctuations of flow is required. As a case study, an urban traffic route in a city of the Chubu region in Japan, with twenty-one signalized intersections, was tested. To perform offset-optimization by a GA, offset values were represented in a chromosome having the same number of genes as the signals. Two different schemes are introduced into the GA-based program and evaluated in terms of average travel time. The results show that the offset optimization schemes used in this study were valuable for efficient signal control.

I. INTRODUCTION

THE traffic signal control has been recognized as an important means of solving various traffic problems such as traffic congestion. Many studies have been done on traffic signal control [1], [2]. Among the various signal control parameters, such as cycle length or green split, offset is one of the most important yet most difficult to optimize.

In a practical traffic situation, offset based on a very simple algorithm has been used for traffic signal control. However, the offset using this method is not guaranteed to be an optimum parameter. In addition, it takes an enormous time to test all offset patterns because of their variety of combinations. To find an optimal offset, a genetic algorithm (GA) [3], which is a search/optimization algorithm, is a valuable technique.

Traffic signal optimization using GAs has been investigated in previous studies [4], [5], [6]. However, most of these studies focused on signal control without considering the fluctuations of traffic flow. In a practical situation, the rate of flow changes as time passes, so that offset-optimization considering the fluctuations of flow is required.

In this study, we investigate adaptive offset optimization by a GA-based program designed to take into account the fluctuations of the traffic flow.

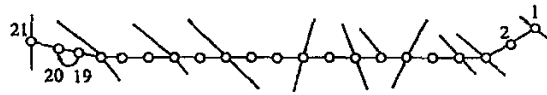


Fig. 1. The schematic diagram of the target route.

TABLE I
SIGNAL PARAMETERS FOR THE ROUTE.

Signal No.	1	2	3	4	5	6	7
Link [m]	0	215	295	500	450	300	650
Split [%]	67	75	56	54	75	75	69
Signal No.	8	9	10	11	12	13	14
Link [m]	500	405	450	495	430	370	530
Split [%]	68	57	63	62	76	68	62
Signal No.	15	16	17	18	19	20	21
Link [m]	495	430	370	530	400	100	350
Split [%]	62	76	68	62	71	71	50

II. TARGET ROUTE

As a target for computer simulation, an urban traffic route, with twenty-one signalized intersections in a city of the Chubu region in Japan, was selected. Figure 1 shows the schematic diagram of the target route. The route is 8,305 meters long, and consists of twenty-one signal intersections shown as circles in the Figure. The distance between the 19th and the 20th signals is short, so they are controlled together.

In this study, the parameter of offset is optimized for traffic signal control. The other parameters, cycle length and green split are fixed. The cycle length for all signals is 130 seconds, and the green splits and the link length between signals are displayed in Table I.

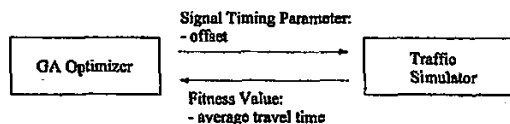


Fig. 2. Concept for GA-based program.

III. GENETIC ALGORITHM-BASED PROGRAM

A. Concept

In order to find a near-optimal offset, we make a genetic algorithm-based program. The genetic algorithm-based program consists of two main components: a GA optimizer and a traffic simulator. The concept for our GA-based program is shown in Figure 2. The GA optimizer produces randomly a certain number of individuals (offset) as the initial generation. Each individual offset is evaluated by the traffic simulator, which then returns a fitness value (average travel time) to the GA optimizer. The GA optimizer will evolve the next generation based on fitness values obtained from the traffic simulator. Evolution is continued until the specified number of generations is achieved.

B. Genetic Algorithm Optimizer

To perform offset-optimization, offset values have to be coded as a gene value of a chromosome. The basics of genetic algorithms use binary strings to represent solutions. In this study, integers from 0 to 99 are used as a gene value to code an offset value that is a percentage of a cycle length. Each chromosome has the same gene value for the offset values of the 19th and the 20th signals for the reason described in the section on the target route. An example of a chromosome representing an offset is shown below:

{15:93:7:86:34:53:87:51:65:83:6:33:38:17:1:12:92:79:29:29:0}

Table II shows the parameters for the GA optimizer. The size of chromosome is the number of signals in the route. A pair of mates is picked from the population by using roulette wheel selection, and crossover is performed with two-point crossover operation. The mutation rate is set at the high value of 0.5 because in a practical situation an optimized solution would have to converge rapidly. The number of generations is set at 250 because this is enough for the GA optimizer to find the individual having the best fitness value in an optimization trial.

C. Traffic Simulator

The traffic simulator is a part of the GA-based program for providing fitness values. In the simulator, vehicles are generated at the 1st intersection for an up flow and the 21st intersection for a down. For ease of analyzing traffic conditions, losses

TABLE II
PARAMETERS FOR THE GA OPTIMIZER.

Number of individuals	30
Size of chromosome	21
Crossover rate	0.8
Mutation rate	0.5
Number of generation	250

TABLE III
PARAMETERS FOR A VEHICLE.

Acceleration [m/s^2]	1.4
Deceleration [m/s^2]	1.7
Maximum speed [km/h]	60

of vehicles turning left or right are not taken into account in this simulator. A traffic flow level can be set as the degree of saturation for an up and down flow separately. The parameters for a vehicle are shown in Table III.

The fitness value provided from the simulator is a reciprocal number average travel time (ATT), the average of the travel time for all vehicles. The travel time for each vehicle includes the number of stops \times 30 seconds.

IV. SIMULATION RESULTS

Experimental adaptive offset optimization was performed by computer simulation. A GA-based program set at the parameters shown in table II, III was used. Using a Pentium III 863 MHz computer with 260 megabytes of RAM, the GA-based program took about 4.4 minutes of computation time for each trial of the GA.

It depends on the fluctuation of traffic flow whether the optimization step should be repeated. In a practical situation, however, traffic is measured every fifteen minutes. Therefore, the computation time for the GA-based program is enough to adapt in the field.

A. Non-Adaptive Offset Optimization

To verify the usefulness of the GA-based program mentioned above, non-adaptive offset control was tested. In this simulation, we made the assumption that the degree of saturation for both up and down flows was fixed at 20 %

We made ten trials of the GA, each of which was operated for 250 generations. The best and the worst fitness values (average travel time) resulting from the offset patterns optimized by the ten simulations are shown in table IV. The average travel time resulting from the offset pattern produced by the present method is also shown as comparative data. The present method,

TABLE IV
OPTIMIZED OFFSET BY GA-BASED PROGRAM.

Offset pattern	Average travel time [s]
GA-based program (best)	604
GA-based program (worst)	666
Present method	708

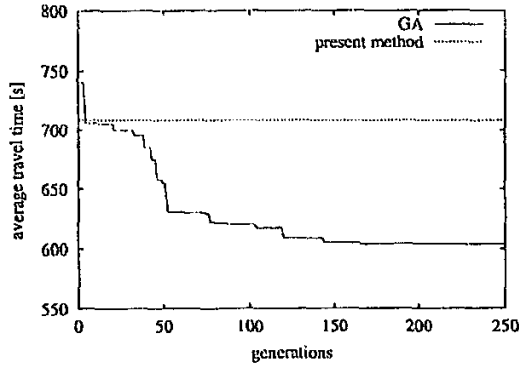


Fig. 3. Convergence of the GA-based program.

having a very simple algorithm, has been used to decide the offset of the target route. Even the worst result of the GA gives a shorter average travel time than the result achieved by the present method.

Figure 3 shows the convergence of the GA-based program in the best trial. The horizontal axis corresponds to generations and the vertical axis indicates average travel time representing the best solution for each generation of the GA. Even though the average travel time for the GA at the initial condition is higher than the one for the present method, the average travel times for the GAs are lower than that after passing several generations. Moreover, average travel times converge to 604 seconds around the 150th generation.

B. Adaptive Offset Optimization

In this subsection, we describe adaptive offset optimization. To evaluate adaptive offset control for fluctuations of traffic flow, the following simulations take the traffic condition where the traffic level changes from a low to a high level. The degree of saturation for the low and high traffic levels is U5D5 (up 5%, down 5%) and U25D5 (up 25%, down 5%) respectively. The purpose of the GA-based program is to find an optimized offset pattern for the new traffic level of U25D5 following the previous level of U5D5.

To find an offset optimized adaptively for the fluctuations of flow, two schemes are introduced into the GA-based program.

They are as follows:

Scheme 1: Including the offset pattern for a previous traffic level in the population of individuals at the initial generation of the GA-based program for a new traffic level.

Scheme 2: Considering a distance between the offsets for previous and new traffic levels as part of a fitness value.

1) *Scheme 1:* Scheme 1 includes the offset pattern for a previous traffic level in the population of individuals at the initial generation of the GA-based program. In this simulation, the previous traffic flow means the traffic level of U5D5. Before operating the GA for the traffic level of U25D5, the optimized offsets for U5D5 were worked out using the non-adaptive offset optimization technique. The best solution for U5D5 from the ten trials is as follows:

{87:71:16:42:66:50:15:10:31:58:86:2:38:67:79:71:98:24:53:53:89}

This was chosen as the offset pattern for the previous traffic level and was included in the population of individuals at the initial generation of the GA.

In scheme 1, ten trials of the GA were conducted. To verify the usefulness of scheme 1, further tests were also made using ten trials of the GA with non-adaptive offset optimization technique in which all initial individuals were produced randomly. The best offset patterns in each group of ten trials are as follows:

{82:76:13:42:53:50:11:10:35:58:85:6:33:57:79:71:0:24:47:47:84} (for scheme 1)

{20:13:50:70:95:92:41:56:59:80:12:39:62:82:7:25:30:55:74:74:9} (for all random)

Comparisons of the results of scheme 1 and of the random trials are summarized in Table V. The results are shown as the fitness values (average travel times [s]) for each optimized offset. The standard deviations (Stdev) are also calculated. Even though the best results for scheme 1 and the random trials are close, the average for scheme 1 is better. The result, namely that the standard deviation for scheme 1 is the small value of 2.4, shows that the GA using scheme 1 produces regular solutions of the best individual. This is the advantage of shorter trial times in real time signal optimization. The other advantage of using scheme 1 is that it does not lead to a situation producing a 'best' individual having a worse fitness value than that of an individual for a previous traffic level. In the case of using the all-random system, there are three best individuals having a worse fitness value in the ten trials.

To evaluate the offset control using the best offset optimized by scheme 1, the traffic simulator examined the effect of chang-

TABLE V
COMPARISON OF THE RESULTS.

	Best	Worst	Average	Stdev
Scheme 1	553.6	562.7	556.5	2.4
All random	557.5	603.3	579.8	15.2

ing or unchanging offset in the changing flow level from U5D5 to U25D5. The effect is measured by the transition of 'moving average travel time' (MATT), which is the average of travel times for vehicles that started in the past six cycles (780 [s]).

Figure 4 shows the transitions of MATT using the best offset optimized by scheme 1 and the all-random system. Each offset is the best solution in each of the ten GA trials. The previous flow level (U5D5) lasts for fifteen cycles, then the new flow level (U25D5) continues for thirty cycles. In the case of changing offset, the optimized offset for the new flow is set with the change of a traffic flow level.

In both results for offset changing, MATTs increase rapidly due to changing the offsets. After peaking, MATTs decrease and converge on the proper values. This behavior makes a loss time compared with the result for unchanging offset (shown as "Loss"). The MATT for scheme 1 converges with smaller loss time.

2) *Scheme 2*: Scheme 2 considers a distance between the offsets for previous and new traffic levels as part of a fitness value. As shown in Figure 4, a loss time can be expected with the change of an offset, therefore reduction of loss time should be considered. To find an optimal offset without a large loss, a distance between new and previous offsets was incorporated into a fitness value provided from the traffic simulator. The distance between the offsets can be a parameter to represent ease of changing offset. The distance between the offsets is determined as follows,

$$D_{\text{offsets}} = \sqrt{\sum_i (o_i^{\text{Prev}} - o_i^{\text{New}})^2} \quad (1)$$

where

$o_i^{\text{Prev}} = i_{th}$ offset value of a previous offset (U5D5)

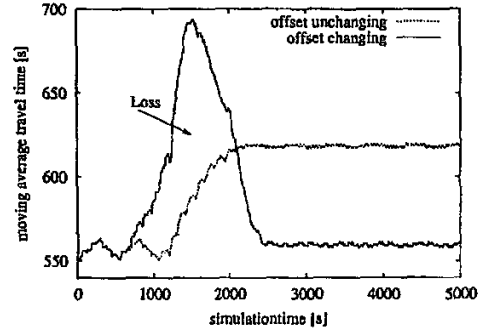
$o_i^{\text{New}} = i_{th}$ offset value of new offset (U25D5).

The fitness value to be maximized for the GA-based program is now given by the following equation:

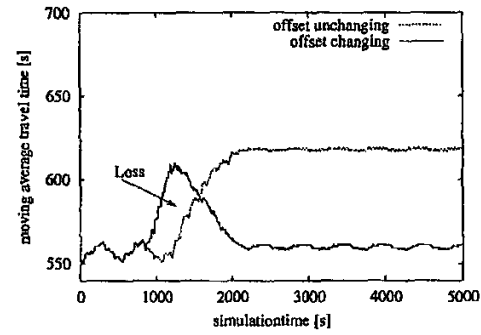
$$\text{Maximize} \quad \frac{1}{\text{ATT} + c_d \times D_{\text{offsets}}} \quad (2)$$

where

ATT = average travel time [s]



(a) all random



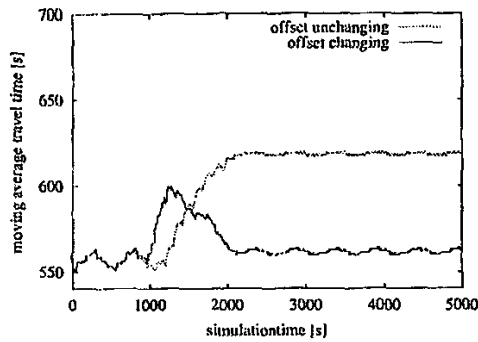
(b) Scheme 1

Fig. 4. Transitions of MATT using the best offset optimized by the scheme 1 and all random.

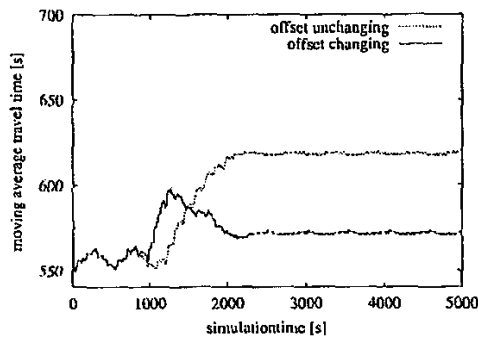
c_d = contribution rate of D_{offsets} to a fitness value

Four different c_d values were chosen, and ten optimization trials were carried out for each value. Each GA trial also adapted scheme 1. The typical results with ATT and D_{offsets} for the different c_d values are shown in Table VI.

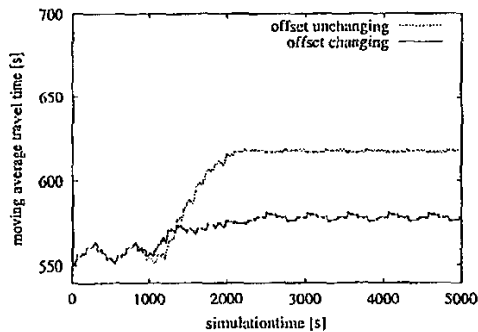
The effect of changing or unchanging offset was examined with the optimized offsets, providing the results in Table VI. The procedure for evaluation was the same as for scheme 1. The case of the c_d value of 0.0 corresponds to the result shown in Figure 4(b). Figure 5 indicates the transition of MATT for the offsets with different c_d values. As the c_d value increases, the loss can be reduced. Although the converged MATT for the c_d value of 2.0 grows slightly, the offset with small D_{offsets} values gives the more efficient control.



(a) $c_d = 0.5$



(b) $c_d = 1.0$



(c) $c_d = 2.0$

Fig. 5. Transition of MATTT for the offsets with different c_d values.

TABLE VI

TYPICAL RESULTS FOR DIFFERENT c_d VALUES.

c_d	0.0	0.5	1.0	2.0
ATT	559.5	562.0	571.5	578.5
D_{offsets}	100.51	13.45	8.66	6.86

V. CONCLUSIONS

In a practical situation with traffic flow conditions, the rate of flow changes as time passes. Therefore, it is important that an optimized offset considering these fluctuations of flow can be found within a useful time. In this study, we have investigated adaptive offset control using a GA-based program for traffic conditions where the traffic level changes from a low level to a high level. To achieve offset optimization in the fluctuation of flow, we introduced two schemes and evaluated them in terms of average travel time (ATT).

Scheme 1 includes the offset pattern for a previous traffic level in the population of individuals at the initial generation of the GA-based program. This scheme had the following principal merits.

- The average of the best ATT is good.
- Even solutions are produced.
- The loss time caused by changing offset is small.

Scheme 2 considers a distance between the offsets for previous and new traffic levels as part of a fitness value. This allows the GA-based program to produce the optimal offset having a small loss time when changing the offset.

The results in this study are for a target route with twenty-one signalized intersections under typical conditions of traffic flow. More research should be done to investigate other routes having different networks and various conditions of traffic flow.

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