Multi-objective Traffic Signal Timing Optimization Using Non-dominated Sorting Genetic Algorithm

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Abstract

The purpose of this paper is to investigate the application of Non- dominated Sorting Genetic Algorithm in solving the multi-objective signal timing optimization problem (MOSTOP). Three n-objective signal timing optimization problems with m-constraint, which cover both deterministic and stochastic traffic patterns, are defined and solved in this study. Mathematical approximations of the resulting Pareto Frontiers are presented to evaluate the trade-off among various objectives and thus provide the most appropriate alternatives for all potential situations of the intersection traffic signal design.

1 Introduction

In most real-world problems, several goals must be satisfied simultaneously in order to obtain the preferred solution. A common difficulty with the multi-objective optimization problem is the appearance of an objective conflict - none of the feasible solutions allow simultaneous optimality for all objectives. Signal timing planning is a typical multi-objective optimization problem, because for a signalized system, an optimal timing plan is usually required to meet four typical objectives (Leonard, 1998):

- minimizing delay;
- minimizing stops;
- minimizing fuel consumption;
- maximizing progression.

Current traffic signal optimization methods account for some of these objectives but not all. Most of previous work has focused on capturing a design cycle length and green time split which take into account only the minimization of system delay. Although single-objective optimization methods prevail in signal timing design, the optimized cycle lengths and green splits are subject to change caused by different single objective. While some computer tools account for multiple objectives to obtain the cycle length, this is accomplished by simply combining the objectives through a weighted sum into a single objective in nature. Therefore, their optimization strategies are still characterized as single-objective in nature. Obviously, the single-objective optimization provides an easy way to handle some applications with Pareto-frontier solutions. However, the weighting coefficients need to be assumed beforehand in this method. In addition, the weighting coefficients may not correspond accurately to the relative importance of the objectives or allow tradeoffs between the objectives to be expressed. In fact, we may not know this weighting, and decisions might only be truly informed if we first know all the Pareto-optimal solutions.

Many of the past research effort were conducted to examine various signal timing optimization methods with different single objective. For instance, Saka et al. (1986) investigated two innovative stochastic traffic signal optimization techniques on isolated intersections. The optimum cycle and green-phase lengths were determined by minimizing the average delay at the intersection within a given period of observation. Foy and Benekohal et al. (1992) implemented a genetic algorithm to generate optimal or near-optimal intersection traffic signal timing strategies which yield the smoothest traffic flow with the least average automobile delay. Park et al. (1999) developed a genetic algorithm-based signal optimization program which consists of a genetic algorithm (GA) optimizer and a mesoscopic traffic simulator to handle oversaturated signalized intersections. Abu-Lebdeh and Benekohal (2000) & Girianna and Benekohal (2001) proposed dynamic signal control optimization algorithms. Their algorithms were structured to find optimal control with robust queue management for oversaturated arterial and integrated multiple criteria into one objective function. All of these signal optimization research used only one objective function, but provided a basis for investigating the implementation of multi-objective optimiza-

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tion technologies in traffic signal timing design.

Some classical optimization methods are widely used in multi-objective optimization problem, such as the method of objective weighting, method of distance functions, and min-max formulation etc. They take advantage of some problem-specific knowledge and thus combine multiple objectives into one objective so that the resulting solution depends mainly on the underlying weight vector or demand level (Srinivas & Deb, 1994). As a result, the same problem have to be solved a number of times in different situations.

Since GAs search for the optimal solutions based on a population of points instead of a single point, multiple Pareto-optimal solutions can be found in a single run. Multi-objective GAs provide more efficient approaches for simultaneous multiple Pareto-optimal solutions, from which to choose the most appropriate solution in all possible situations.

This paper addresses multi-objective intersection signal timing design using GAs. First, an overview of some recent research on intersection signal timing design and multi-objective optimization is outlined, followed by a brief introduction to non-dominated sorting genetic algorithms- NSGA and NSGA II. Three problems of n-objective signal timing optimization with m-constraint, which cover both deterministic and stochastic traffic patterns using Webster delay formulation and Akçelik stops calculation function, are designed and solved by NSGA II. The experimental results are discussed, including some regression functions for Pareto-optimal solution set and trade-off evaluation.

2 Multi-objective Optimization Genetic Algorithms

To find an optimal solution, decision makers often need to consider multiple objectives. A common difficulty with multi-objective optimization is to balance different objective needs. Thus, a mathematically most favorable Pareto-optimum is the solution that offers that least objective conflict. Multi-objective problems are addressed to provide several Pareto optimal solutions, while decision makers are concerned with the selection of the most suitable solution from them. The search for several non-dominated solutions is computationally intensive and requires efficient methods and powerful computer are desirable.

A number of GA-based multi-objective optimization tools have been developed in recent years, including Multi-objective Optimization Genetic Algorithm - MOGA (Shaffer, 1985), Niched Pareto Genetic Algorithm - NPGA (Horn et.al, 1994) and Non-dominated Sorting Genetic Algorithms - NSGA (Srinivas et.al, 1994), Strength Pareto Evolutionary Algorithm - SPEA (Zitzler et.al, 2001), Pareto-Archived Evolutionary Strategy - PAES (Knowles et.al, 1999), and Non-dominated Sorting Genetic Algorithms II - NSGAII (Deb et.al, 2002) etc. All of these methods can be divided into two categories. The first category just converts a simple GA to a multi-objective GA by adding some new operators, such as MOGA, NPGA and NSGA. Nevertheless, these methods have been criticized due to their high computational complexity, non-elitist approach, and their needs for setting an arbitrary sharing parameter. This results in the development of some new elitist MOEAs, including PAES, SPEA and NSGA II (Deb et. al 2002). In some recent studies, NSGA II has been proved to be one of the very promising members of MOEAs (Deb et. al 2002 and D'Souza et. al 2002).

3 Non-dominated Sorting Genetic Algorithms

The idea underlying the non-dominated sorting method is that a ranking selection procedure is applied to strengthen the elite possible solutions and a niche method is implemented to maintain the stable subpopulations of the elite. NSGA differs from a simple genetic algorithm only in the selection operator. The crossover and mutation operator remain as normal. The population is ranked based on the individual's non-domination before performing a selection. In order to preserve the diversity of the population, a sharing method, proposed by Goldberg and Richardson (1987), is used to share these classified individuals by corresponding dummy fitness value. However, NSGA has been subjected to some criticism, as mentioned earlier. Deb et. al (2002) propose a upgraded elitist algorithms, named NSGA II. In NSGA II, there are several major innovations- a fast non-dominated sorting approach, a fast crowed distance estimation procedure and a simple crowed comparison operator etc., which alleviates all of these difficulties specifically. In the updated version, $O(MN^2)$ computational complexity can be achieved. The complexity is reduced by systematic book-keeping which increase the storage size to $O(N^2)$ from $O(N)$. The elitism is introduced by using $\lambda + \mu$ selection procedure and crowding factor is introduced to eliminate the need for sharing parameter. (Deb et. al 2002)

4 Multi-objective Traffic Signal Timing Optimization

The average delay and the number of stops per unit of time are considered vital in the evaluation of the traffic signal timing plan. However, none of the feasible solutions could accommodate the simultaneous optimum of these two objectives for an intersection with asymmetric traffic demand. A generic multi-objective traffic signal timing optimization problem for a two-phase control strategy can be formulated as:

$$\begin{aligned} &\text{minimize} \quad F(G) = [f_1(G), f_2(G)] \\ &\text{subject to} \\ &\qquad g_i^l \le G_i \le g_i^u \quad k = 1, 2 \end{aligned} \tag{1}$$

Where:
G- vector of effective green time for each phase i
g_i^l- lower bound of effective green for phase i
g_i^u- upper bound of effective green for phase i
$f_1(G)$- the first objective function with respect to delay
$f_2(G)$- the second objective function with respect to stops

The delay function based on Webster formula (Webster, 1958) and stop function based on Akçelik formula (Akçelik, 1981), which are widely used for calculating the corresponding performance index of delay and number of stops, are modified to represent the objective functions mentioned in equation (1):

$$f_1(G) = TD = \sum_{i=1}^{N} q_i d_i \tag{2}$$

Where:

$$\begin{aligned} d_i &= 0.9(D_{i1} + D_{i2}) \\ &= 0.9 \left\{ \frac{(1-\lambda_i)^2 (\sum_{i=1}^{n} g_i + L)}{2\left(1 - \frac{q_i}{s_i}\right)} + \frac{q_i}{2 s_i \lambda_i (\lambda_i s_i - q_i)} \right\} \end{aligned} \tag{3}$$

$$\lambda_i = \frac{g_i}{\sum_{i=1}^{N} g_i + L}$$

TD: total rate of delay
N: number of streams at an intersection
n: number of phases
q_i: mean arrival rate of vehicles in stream i
d_i: average delay in stream i
g_i: effective green time for phase i
s_i: saturation flow rate
L: lost time per cycle

$$f_2(G) = TS = \sum_{i=1}^{N} \frac{q_i (1-\lambda_i)(\sum_{i=1}^{n} g_i + L)}{(\sum_{i=1}^{n} g_i + L)\left(1 - \frac{q_i}{s_i}\right)} \tag{4}$$

Where:
TS: total number of stops
other variables are as defined previously

Because the cycle length will affect the intersection overall effective capacity, an additional constraint on minimum cycle length could be included in signal timing optimization, which is formulated as:

$$\left(3600 - nl \frac{3600}{(\sum_{i=1}^{n} g_i + L)} \right) - \sum_{i=1}^{n} q_i \ge 0 \tag{5}$$

Where:
l: lost time each phase
other variables are as defined previously

Three signal timing optimization problems are defined to cover both uniform and stochastic arrival pattern and to investigate the influence of Webster minimum cycle length constraint. In the modified Webster delay function (2) and (3), two delay terms are employed that $D1$ denotes the uniform delay and $D2$ represents the random or overflow delay. For problem F1 and F2, only $D1$ is involved in the first objective function $f_1(G)$; for problem F3, both delay terms are computed in $f_1(G)$. The first problem F1 seeks to minimize the average delay and the average number of stops per unit of time under uniform arrival pattern. The constraints, involved in F1, define the minimum green time and the upper bound for green phase. In case F1, the minimum cycle length constraint is ignored.

The problem F2 and F3, compared to F1, are reinforced by adding some cycle length constraint, which identifies the lower bound of design cycle length calculated by Webster's minimum cycle length function. The third problem F3, the most complex case, copes with a randomly distributed arrival with the Webster minimum cycle length constraint.

5 Experiment Design and Result Analysis

To investigate the application of NSGA II to traffic signal optimization, three signal design problems are defined to minimize average delay and the average number of stops, using the effective green time at each signal phase as the design variable. Such objective consideration is conflicting in traffic signal design, because minimizing delay leads to short cycle length while minimizing stops indicates long cycle length. These objectives are also non-commensurable. The average delay usually has large value, while the average number of stops is generally a small value. The designed scenario is a two-phase isolated intersection with permissive left turn. The critical flow ratios are 0.47 and 0.39; saturation flow is 1800 pcphpl. Table 1 shows the GA parameters used in these experiments as follows:

Parameter	Value	Parameter	Value
Population Size	150	No. of Functions	2
Chromosome Length	60	No. of Constrains	3
No. of Generation	300	No. of Binary-coded Variables	2
Selection Strategy	Tournament Selection	Lower limits on 1st variable	10
X-over on binary string	Single point X-over	Upper limits on 1st variable	120
Cross-over Probability	0.95	Lower limits on 2nd variable	10
Mutation Probability	0.008	Upper limits on 2nd variable	120

Table 1: GA parameters used in signal optimization

5.1 Optimization Problem1 — F1: Uniform traffic pattern without Webster cycle length constraint

Problem F1, which only includes uniform delay term $D1$ in the first objective function, is the simplest design case for intersections. It is observed that a clear frame of actual Pareto Frontiers is located in the generation 5. As the generation number grows, more Pareto Frontiers are discovered and a well-fitted third degree polynomial function is constructed to measure the tradeoff between the objective values of the average delay and number of stops per unit of time. In the meantime, a linear regression function is established to reflect the multiple Pareto-optimal solution space. Figure 1 - 3 show the variables and objective values at generation 1, 10 and 20 of problem F1.

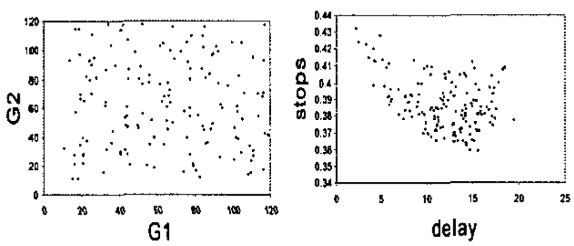

Figure 1: Population and objectives of generation 1 for problem F1

5.2 Optimization problem 2 — F2: Uniform traffic pattern with Webster minimum cycle length constraint

F2 involves a new minimum cycle length constraint in order to ensure the overall intersection effective capacity. The result shows that after 5 generations, there

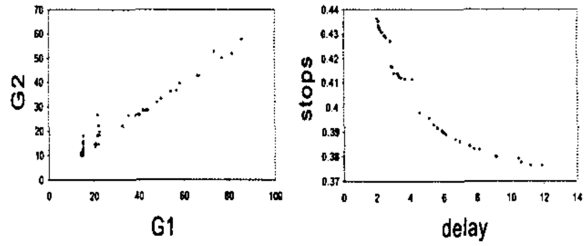

Figure 2: Population and objectives of generation 10 for problem F1

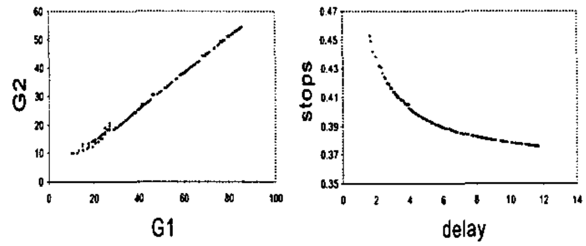

Figure 3: Population and objectives of generation 20 for problem F1

are still 8 ranks of non-dominated frontiers remaining in the population. Finally, a unique rank of frontier is achieved at generation 13. Figure 4 and 5 show the variables and objective values at generation 5 and 20 of problem F2.

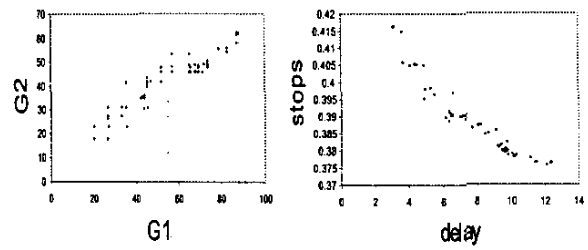

Figure 4: Population and objectives of generation 5 for problem F2

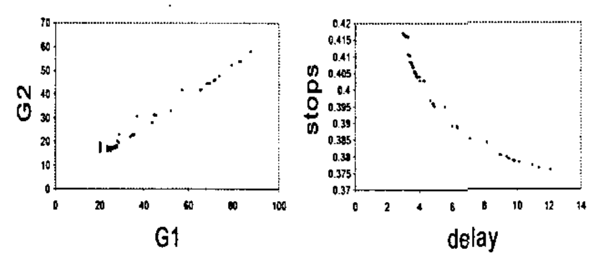

Figure 5: Population and objectives of generation 20 for problem F2

5.3 Optimization problem 3 — F3: Stochastic traffic pattern with Webster cycle length constraint

F3 describes a design problem with the consideration of random or overflow delay term in the first objective function. At the same time, minimum cycle length constraint is introduced to provide the adequate effective overall capacity.

F3 yields 8 ranks of non-dominated frontier in the population of generation 5. One unique rank of PF can be obtained at generation 11. It was found that all non-dominated solutions located along a certain straight line in the feasible solution space. Figure 6 and 7 show the variables and objective values at generation 5 and 20 of problem F3.

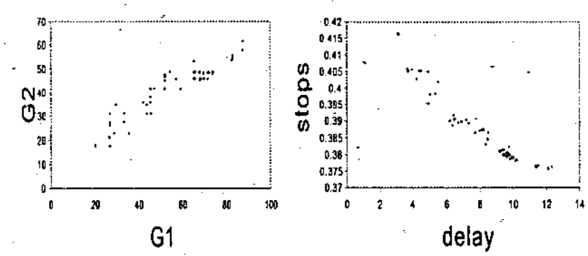

Figure 6: Population and objectives of generation 5 for problem F3

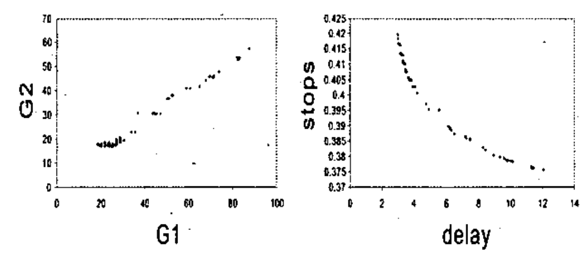

Figure 7: Population and objectives of generation 20 for problem F3

In order to evaluate the tradeoff between objectives, a set of well-fitted third degree polynomial regression functions are presented in Table 3. Additionally, it is observed that the Pareto-optimal design of variable and is positioned along a certain straight line in the feasible space and the corresponding regression functions are displayed in Table 2 as well. It's indicated that cycle length will take smaller value in problem F1 where Webster cycle length constraint is ignored; however, intersection overall capacity may not be able to handle the actual demand with too small cycle length.

Case	Pareto-optimal Solution g_1: green time 1 g_2:green time 2
F1	$g_2 = 0.6110g_1 + 1.7902$ $g_1 \in [10.00, 85.60]$
F2	$g_2 = 0.6249g_1 + 1.0311$ $g_1 \in [20.04, 88.63]$
F3	$g_2 = 0.6231g_1 + 1.3782$ $g_1 \in [20.23, 88.67]$

Table 2: Regression functions for Pareto-optimal solutions

Case	Trade-off function for objectives: x_1: delay and x_2: stops
F1	$x_2 = 10^{-5}(-15.383x_1^3+401.69x_1^2-3622.08x_1+$ 49394.79, $x_1 \in [1.66, 11.69]$
F2	$x_2 = 10^{-5}(-8.146x_1^3+237.05x_1^2-2453.80x_1+$ 46859.89, $x_1 \in [2.96, 12.10]$
F3	$x_2 = 10^{-5}(-7.447x_1^3+221.530x_1^2-2348.87x_1+$ 46670.21, $x_1 \in [2.97, 12.34]$

Table 3: Trade-off between multiple objectives

6 Conclusion

It can be concluded from the results of this study that the multi-objective genetic algorithm has potential use in intersection signal timing optimization. It has been demonstrated that NSGA II is efficient to solve multi-objective signal timing design problems under uniform and stochastic traffic arrival patterns. Further, the proposed Pareto-frontier regression functions provide an insight into the trade-off among multiple signal optimization objectives. It is also observed that the Pareto-optimal solution set is located along a certain straight line within feasible solution space, from which practitioners can easily select the most appropriate design for particular situations.

In addition, it shows that NSGA II can find a much better spread of optimal signal design plans on the true Pareto-optimal frontiers with high convergence speed. Therefore, the implementation of NSGA II in network signal control system should be investigated further. This will provide the network traffic signal control system with the ability to simultaneously optimize of multiple objectives and parameters.

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