Multiobjective Optimization of Optimum-Cycle-Length and Average-Delay-Time at a Specific Isolated Intersection in Konya-Turkey

Ali Tahir Karaşahin[1], Tahir Sağ[*2]

[1] Karabük University, Faculty of Engineering, Department of Mechatronics Engineering, KARABUK
[*2] Selçuk University, Faculty of Technology, Department of Computer Engineering, KONYA

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Abstract: Parallel to population growth, the number of vehicles in cities also increasing. The vehicle increase makes traffic management difficult. This situation leads to higher fuel consumption and emissions of CO2 and similar harmful emissions. Therefore, real-time optimization of traffic lights i.e. signalization can make traffic management more efficient. In this study, the duration of the signals at an intersection where the signal light in the center of Konya/Turkey is optimized by multi-objective optimization algorithms using optimum-cycle-length and average-delay-time as objectives. Four state-of-the-art algorithms are applied to this problem, which are named as Non-dominated Sorting Genetic Algorithm (NSGAII), Strength Pareto Evolutionary Algorithm (SPEA2), Indicator-Based Evolutionary Algorithm (IBEA) and Speed-constrained Multi-objective Particle Swarm Optimization (SMPSO). The dataset is obtained from Konya Metropolitan Municipality Transportation Traffic Planning Branch Directorate. The experimental results show that the optimum-cycle-time at signalized intersections can be determined by multi-objective optimization algorithms.

Konya-Türkiye'de Belirli Bir İzole Kavşakta Optimum Çevrim Uzunluğu ve Ortalama Gecikme Süresinin Çok Amaçlı Optimizasyonu

Anahtar Kelimeler
Trafik sinyalizasyonu,
Çok-amaçlı optimizasyon,
NSGA-II,
SPEA2,
IBEA

Öz: Nüfus artışına paralel olarak şehirlerdeki araç sayısı da artmaktadır. Artan araç sayısı trafik yönetimini zorlaştırmaktadır. Bu durum daha yüksek yakıt tüketimi ve CO2 emisyonu ve benzeri zararlı emisyonların salınımına yol açmaktadır. Bu nedenle, trafik ışıklarının gerçek zamanlı optimizasyonu, yani sinyalizasyon sistemi, trafik yönetimini daha verimli hale getirebilir. Bu çalışmada, Konya/Türkiye şehir merkezinde belirlenen bir sinyalizasyon kavşağında, bekleme süreleri çok amaçlı optimizasyon algoritmaları ile optimize edilmiştir. Optimum-döngü-uzunluğu ve ortalama bekleme süreleri amaç fonksiyonları olarak tanımlanmıştır. Literatürde bulunan en gelişmiş çok amaçlı optimizasyon algoritmalarından dördü bu problem için çalıştırıldı. Bu algoritmalar: Bastırılmamışlık Sıralamalı Genetik Algoritma II (NSGAII), Kuvvet Pareto Evrimsel Algoritması 2 (SPEA2), Gösterge Tabanlı Evrimsel Algoritma (IBEA) ve Hız Kısıtlamalı Çok Amaçlı Parçacık Sürü Optimizasyon (SMPSO) algoritmalarıdır. Kullanılan kavşağa ait veriler Konya Büyükşehir Belediyesi Ulaştırma Trafik Planlama Şube Müdürlüğü'nden elde edildi. Deneysel sonuçlar, sinyalize kavşaklarda optimum döngü süresinin çok amaçlı optimizasyon algoritmaları ile verimli bir şekilde belirlenebileceğini göstermektedir.

*İlgili Yazar, email: tahirsag@selcuk.edu.tr

1. Introduction

In recent years, researches on the application of information and communication technologies to various fields have an increasing interest. One example of these works is the development of smart city applications for solutions to rapid urbanization problems. One of the important parameters of smart city applications is smart transportation systems [1-4]. For intelligent transportation systems to respond to today's real problems in an adaptive way, control methods must be kept up to date. One of the important issues of Intelligent Transportation

Systems is traffic congestion due to rapid urbanization. Traffic congestion leads to lost times, increased fuel consumption and the release of harmful emissions such as CO2. It also gives drivers trouble and discomfort. Various methods to reduce traffic congestion with increasing urban populations are used, some of which are traffic lights, intersections and road capacities. However, green light times at intersections are fixed according to the estimated vehicle intensity, which is also called as fixed-time management. In this method, the duration of green light determined once does not change for 24 hours. Many efforts have been made to improve the efficiency of existing traffic management. Some of the smart city applications are aimed at the technological solution of traffic density at intersections. Therefore, the duration of the traffic lights should be optimized [5].

In addition to traditional techniques, there are also advanced traffic control techniques used in literature. Li et al. investigated the effect of a dynamic intersection control system and optimized signal times on the traffic network in smart cities and they proposed an auxiliary optimization framework for determining cycle-length. It is stated that the proposed model is successful as a result of the experimental results and real-world tests [6]. In a scenario solved by JACK that is an agent-based software for traffic management, Lowrie aimed to separate the vehicles from the intersection as soon as possible. She reported that traffic flow will be accelerated by reducing traffic congestion and traffic accidents owing to the proposed traffic management [7]. On the other hand, there are different studies in the literature to improve the average delay times at signalized intersections. In a master thesis at the department of transportation engineering, different calculation methods used in the capacity calculation at signalized intersections (Webster, Highway Capacity Manual, Australia Method, and Sidra intersection 3.2 programs) were explained [8]. The methods discussed were elaborated with examples at a specific intersection. It was stated that techniques such as ANN can produce faster and more reliable solutions to problems that cannot be expressed mathematically in transportation engineering. The rapid increase in the number of vehicles in traffic as a reflection of the increasing population and economic developments bring about other problems. As a result of the increase in the number of vehicles and traffic movements, traffic accidents also increase. In [9], traffic accidents in Turkey are modeled by ANNs and attention was drawn to what needs to be done in this regard. In the study given in [10], the optimum cycle length is calculated by using the Differential Evolution Algorithm. As a result of the study performed with the Australian method, different scenarios were developed and gains in signal times were obtained.

There are some similar studies in which the multi-objective optimization algorithms are used for this purpose. One of these is a signalization study which takes reference to Webster's method using multi-objective particle swarm optimization (MOPSO) algorithm [11]. In a study presented by Yanfang and Jianmin, it was stated that Webster's method can be move away from the optimum solution in the case of the oversaturated signalized intersection and they handled the problem as a multiobjective optimization to solve by using a fuzzy-logic-control [12]. In an alternative study to the Webster method, Zakariya and Rabia proposed two regression formulas for estimating the minimum delay optimal cycle length based on a time-dependent delay formula. They claimed that better results were obtained for optimum cycle length at high intersection flow rates compared to the Webster formula [13]. Estrada et al. presented a multi-objective system for traffic optimization (MOSTRO). In order to minimize the total length of the queues of vehicles waiting at each intersection, a traffic network model is introduced and the solution of this problem is modelled with linear programming. Compared to traditional methods, the proposed strategy has been shown to significantly reduce the number of vehicles accumulated at each link [14]. Chen proposed another multiobjective optimization control algorithm based on HCM delay function for traffic signal plans. It has been reported that the implemented model is effective in coordinated intersection management and reducing waiting times according to experimental results [15]. In another study, Cell Transmission Model and NSGAII were used together. The developed model has been claimed to be more advantageous than the Webster model [16]. Again, in a proposed study based on the NSGAII and Webster method, signaling times were similarly optimized [17]. Gao and Yang [17] stated that the most suitable solution for the traffic problem is to use the existing capacity efficiently. In order to achieve this, NSGA-II is applied to create a model for fixed-time signal control of unsaturated intersections by optimizing the variables cycle length and splits of intersections. The results were compared with the single-objective optimization method based on Webster method. The authors claimed that their approach was able to obtain better results for average vehicle delay and queue length.

In this study, the signalization process is handled as a multi-objective optimization problem. The focus here is to determine the signal duration times for a specific intersection in Konya-Turkey. Thus, the optimal values of optimum-cycle-length, intersection-flow-rate and average-delay-time are determined by multi-objective optimization algorithms (MOAs) with Webster's Delay model. To compare and achieve more fair results, NSGAII [18], SPEA2 [19], IBEA [20] and SMPSO [21] algorithms are applied to the problem. This study shows that the relationship between the optimum-cycle-length and intersection-flow-rate of the fixed-time signal intersection can be expressed by multi-objective optimization algorithms. In this way, a decision-support-system is established to assist in deciding the signal durations for a specific signalization system.

The rest of the paper is organized as follows. In section-2, material and methods are briefly explained. Section-2 also includes subsections about the definition of signalization plans as a multi-objective optimization problem, Webster's delay method and the concept of multi-objective optimization. The signal plans for real-time optimization of traffic lights are defined in the concept of optimization terminology. In section-3, experimental results are given. Finally, conclusions are presented in section-4.

2. Material and Method

The signalized intersection to be evaluated within the scope of this study is the "Lastik bus-stop" intersection in Konya, Turkey. The traffic volumes of signalized intersection operated in 4 phases are shown in Table 1. Saturated flow values of the Lastik bus-stop intersection were realized in May 2019 by manual counting method. The counting was done on Saturday, May 25, 2019, at the peak time of 18:00 - 18:15. These hours were preferred because the busiest day of the intersection specified during the week was Saturday. The hourly counting results specified in Table 1 were obtained by multiplying the 15-minute counting operation by four.

Table 1. Lastik bus-stop vehicle count values

Traffic Direction	Saturated flow value ($vehicle/hour$)
North	1900
East	1850
South	2075
West	1900

In this study, optimum-cycle-length and average-delay at fixed-time signalized-intersections are calculated by the aid of multi-objective optimization algorithms. Also, Webster (British) method is conducted as the calculation model. Non-dominated Sorting Genetic Algorithm (NSGAII), Strength Pareto Evolutionary Algorithm (SPEA2) and Indicator-Based Evolutionary Algorithm (IBEA) algorithms, which are widely used in the multi-objective optimization research field, are applied to the same problem. In order to evaluate the obtained outcomes by the algorithms, four performance indicators are employed, which are frequently used most commonly used methods for evaluation in the literature. These are Generational Distance (GD), Inverted Generational Distance (IGD), Spacing (SP) and Hypervolume (HV) performance criteria.

2.1. Webster's delay model

The methods used for optimizing signal durations at signalized intersections are classified as phase-based and motion-based methods. There are three widely used methods: Webster (British) [22], Highway Capacity Manual (HCM) [23] and Australia method [24]. In the Australian method, since the flows are evaluated separately instead of the phases, the dataset has to be suitable for this. Australia model is not preferred because our dataset created with manual vehicle count is based on phase order. In the HCM method, it gives importance to the critical flow ratios in the intersection. Since the focus of the study is not critical flows, the HCM model is also not preferred. In the Webster model, it focuses on optimum cycle length and the average delay of the intersection. In this study, the calculation approach of the Webster method is preferred to use since the calculations are considered as phase-based.

The number of vehicles passing through the signalized intersection depends on the green duration applied in all directions. The capacity of the intersection leg is calculated as in Eq. (1).

$$c = \frac{g * s}{D} \ vehicle/hour \tag{1}$$

where c denotes the capacity of the intersection leg. g is the effective green time in seconds. s is the saturated flow per unit of vehicle/hour. D is the cycle length in seconds. The effective green time is expressed as the time during which the green time flows saturated. In other words, it is the time that is found by subtracting the initial and final losses from the green time that appears. The effective green time is shown in Eq. (2).

$$g = G - l \tag{2}$$

where G is the appearing green time in seconds and l is the lost time in seconds. Lost time means the duration which is without traffic flow. After the red light is on, the required time to leave from the intersection safely for the last vehicle entering the intersection at the green light is defined as the lost times. In the Webster method, it is calculated by summing the difference of the yellow times between phase transitions to the red time at which all vehicles stop. It is calculated as in Eq. (3).

$$L = \sum (I - a) + \sum l \tag{3}$$

where I is the time among the green lights and a is the time of yellow light in seconds. l is the lost time in one phase. The optimum-cycle-length to minimize the time spent at an intersection is calculated by using Eq. (4).

$$D_o = \frac{(Q * L) + 5}{1 - Y} \tag{4}$$

where D_o shows the optimum-cycle-length in seconds. Q is a constant value between 1.2 and 1.5 according to intersection capacity. L is the total lost time and Y presents the sum of all intersection legs. It describes the degrees of saturation for the directions connected to an intersection. Y is expressed as dividing the instantaneous vehicle counts by the saturated flow value.

The average delay is the average time that elapses until leaving the intersection after joining the vehicle queue from the intersection leg. In the Webster model, Eq. (5) is used to calculate the average delays per vehicle.

$$w = \frac{D(1-\lambda)^2}{2(1-\lambda * x)} + \frac{x^2}{2q(1-x)} + 0{,}65\left(\frac{D}{q^2}\right)^{(1/3)} x^{(2+5\lambda)} \tag{5}$$

where w indicates the average delay per vehicle. λ is the ratio of green time to cycle time ($\lambda = g/D$). x is the saturation ratio. q shows the maximum flow value of intersection leg (vehicle/second) and D is the optimum-cycle-length in seconds. q is in the range of [200, 1800] in this study.

2.2. Multi-objective optimization problems

Many of the real-world problems include multiple conflicting objectives that need to be optimized simultaneously. When there are multiple objectives that are inversely proportional to each other, defined by the same decision variables, it may not always be possible to define them with a single function. Therefore, applying single-objective optimization algorithms to these problems often fails to achieve satisfactory results [25]. Multi-objective optimization problems are defined in Eq. (6).

$$\begin{aligned}
\text{Maximize/Minimize} \quad & y = f(x) = \{f_1(x), f_2(x), \dots, f_M(x)\} \\
\text{Subject to} \quad & g(x) = \{g_1(x), g_2(x), \dots, g_J(x)\} \leq 0 \\
& h(x) = \{h_1(x), h_2(x), \dots, h_K(x)\} = 0 \\
\text{where} \quad & x = \{x_1, x_2, \dots, x_N\} \in X \\
& y = \{y_1, y_2, \dots, y_N\} \in Y
\end{aligned} \tag{6}$$

where x is set of the decision variable and X is the parameter space, y is the objective, Y is the objective space, g(x) and h(x) is the constraints depend on the decision variables.

Unlike single-objective optimization seeking global optimum, multi-objective optimization usually does not produce a single optimal solution since it is not always possible to obtain a single decision vector for conflicting objectives. Thus, multi-objective optimization algorithms generally obtain a set of optimal solutions by using a technique that satisfies a balance among the objectives. The techniques depend on Pareto-Optimality are the most suitable algorithms to handle objectives separately and synchronously. According to the concept of Pareto-Optimality, an optimal solution is a solution that is not the worst in any of the objectives and is better than the others in at least one objective. It is also a solution that is not dominated by any other solution in the search space. This situation is mathematically defined as in Eq. (7).

$$\forall i: f_i(x) \leq f_i(y) \text{ and } \exists j: f_j(x) < f_j(y) \tag{7}$$

Such a solution is called as nondominated or Pareto-optimal solution, and the set of such optimal solutions is called the Pareto-Optimal Set [18, 26]. Evolutionary algorithms are very convenient to obtain a set of solutions owing to their population-based nature. So, several multi-objective evolutionary algorithms (MOEAs) have been presented to solve MOPs up to now. These algorithms are generally classified in three groups: (i) Pareto-dominance-based methods [18, 19, 27], (ii) decomposition-based methods [28-30], and (iii) performance indicator-based methods [31, 32].

In this study, four well-known multiobjective algorithms (NSGAII, SPEA-2, IBEA, and SMPSO) are chosen with respect to this classification. The algorithms in the first group distinguish and select candidate solutions according to Pareto dominance. In this category, NSGA-II and SPEA-2 are the most cited algorithms which have the principal strategies for selection and diversity. The second group algorithms decompose a MOP into a number of single-objective optimization problems to be solved collaboratively, such as MOEA/D, C-MOGA and NSGA-III. These are especially used to solve MOPs including more than three objectives, known as many-objective optimization problems. The algorithms in the third group adopt performance indicators of generated solutions as selection criteria in the environmental selection. The most prominent representative of this group is IBEA. In addition, SMPSO which one of the most successful swarm-intelligence-based multiobjective optimization algorithms is included in this study to improve the novelty.

2.2.1.Performance indicators

In recent years, many indicators have been proposed to compare the performance of MOEATs. The indicators are important to reflect the output quality of different algorithms and to carry out the necessary experimental work to compare various approaches. According to a study on performance indicators conducted in 2015, hypervolume (HV), generational distance (GD), epsilon indicator (ε), inverted generational distance (IGD) and spread indicator (SP) are the most used metrics in literature, respectively [33].

Four indicator values (HV, SP, GD, and IGD) are calculated in this paper. The descriptions and mathematical formulations are given below. P* is a set of points distributed uniformly along the true Pareto front (PF) in the objective space; Q is a set of the nondominated solutions obtained by an algorithm to search the PF.

Hypervolume (HV): HV measures the volume of the objective space that is weakly dominated by set Q. In order to calculate this volume, a bounded space has to be constructed by PF and a user-defined reference point [34].

$$HV = volume\left(\cup_{i=1}^{|Q|} v_i\right) \tag{8}$$

The larger the indicator value, the greater the size of the dominated area, the better front is obtained. For this reason, it uses normalized objective values. The best value for the indicator is one.

Spread (SP): Spread indicator measures the distribution of obtained set Q along PF [35]. There are two versions of the indicator. The first one is used for only two objectives, while the other one is generalized to be able to use for all multi-objective problems, which is named as the generalized spread and denoted as Δ. It is formulated as in Eq. (9).

$$\Delta = \frac{\sum_{i=1}^{n} d(e_i, Q) + \sum_{X \in S^*} |d(X,Q)| - \bar{d}}{\sum_{i=1}^{n} d(e_i, Q) + |P^*|.\bar{d}} \tag{9}$$

$$d(X,Q) = \min_{Y \in Q, Y \neq X} \|f(X) - f(Y)\|^2$$

$$\bar{d} = \frac{1}{|P^*|} \sum_{X \in P^*} d(X,Q)$$

Here, $(e_1, \ldots, e_n)$ shows the m extreme points in set P^*; $d(e_i, Q)$ indicates the minimum Euclid distance between e_i and the set Q; m is the number of the objective function. Δ is based on calculating the distance between two consecutive solutions closest to each other in the normalized objective space. It is desired to approximate zero.

General Distance (GD): GD is calculated as the average of the distance of the obtained nondominated solutions to the true Pareto surface [36]. The desired ideal value is zero. Mathematically, it is defined as in Eq. (10).

$$GD(Q, P^*) = \frac{\sqrt{\left(\sum_{p \in, P^*} d(p,Q)^2\right)}}{|P^*|} \tag{10}$$

Inverted General Distance (IGD): IGD measures the accuracy by calculating the average distances between Q and $\boldsymbol{P}^*$ [37]. The desired ideal value is zero. Mathematically, it is defined as in Eq. (11).

$$IGD(Q, P^*) = \frac{\sum_{p \in, P^*} d(p,Q)}{|P^*|} \tag{11}$$

where $d(p, Q)$ is the minimum Euclid distance between p and the set Q.

2.2.2. Descriptions of the algorithms

The short descriptions of the algorithms called NSGAII, SPEA2, IBEA and SMPSO are given in this section, respectively.

Nondominated Sorting Genetic Algorithm-II (NSGAII): NSGAII [18] is developed by Deb et al. in 1999, is the most well-known multi-objective optimization algorithm in the literature. It is the dominance-based technique that presents pioneering methods for exploration and exploitation such as fast sorting strategy and crowing distance method. The algorithm begins by generating a random population. The N-sized population is separated into fronts by use of a nondominated-sorting strategy. It means that all solutions are sorted according to Pareto-dominance and nondominated solutions are picked to the first front and this process is repeated for remaining solutions for the next front until no solutions remain in the population. The front level is used to select parent solutions as a rank in the binary tournament. When the ranks are equal, the crowding-distance method of promoting diversity is used. N-new solutions are generated by SBX crossover and polynomial mutation. At the end of each iteration, the 2N-sized population is obtained by combining current and new solutions. The best N solutions are picked to the next generation by using nondominated sorting. In this way, elitism is guaranteed.

Strength Pareto Evolutionary Algorithm 2 (SPEA2)**:** SPEA2 [19] is developed by Zitzler et al. in 2001. It is another popular multi-objective optimization algorithm depend on genetic algorithm. It is the improved version of SPEA, which was previously proposed by Zitzler. SPEA2 involves a fine-grained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method.

Indicator-based Evolutionary Algorithm (IBEA): IBEA was proposed by Zitzler and Künzli in 2004 [31]. It is based on a strategy that allows the arbitrary performance indicators to be used directly in the selection process. Thus, IBEA can be tailored to user preferences and does not need extra diversity protection methods such as fitness sharing. The algorithm performs binary tournaments for mating selection and removes the worst individuals iteratively. The authors placed two different versions of the algorithm named basic IBEA and adaptive IBEA in their paper.

Speed-constrained Multi-objective Particle Swarm Optimization (SMPSO): SMPSO was proposed by Nebro et al. in 2009 [38]. It is an adapted version of the PSO algorithm to multiobjective optimization. To enhance the search capability, SMPSO employs a novel strategy to limit the velocities of the candidate solutions. Besides this, the algorithm uses polynomial mutation as a turbulence factor and an external archive to store the nondominated solutions found during the search.

3. Results

In order to organize the signalization plans, optimum-cycle-length and average-delay are defined as two separate objective functions. The 1st objective function, which represents the optimum-cycle-length, is shown in Eq. (12).

$$D_o = \frac{(Q * L) + 5}{1 - Y} \tag{12}$$

The second objective function, which represents the average delay time, is seen in Eq. (13).

$$w = \frac{D(1-\lambda)^2}{2(1-\lambda * x)} + \frac{x^2}{2q(1-x)} + 0{,}65\left(\frac{D}{q^2}\right)^{(1/3)} x^{(2+5\lambda)} \tag{13}$$

In this study, NSGAII, SPEA2, IBEA, and SMPSO were run for a reference model established by Webster model which involves the calculations for optimum-cycle-length, intersection flow ratio and the average delay time per vehicle. The relations of optimum-cycle-length with intersection flow ratio and the average delay time are shown in Fig. (1) and Fig. (2), respectively. The selection task of one optimal solution from the Pareto-Optimal Set is fulfilled by a decision-maker since the optimum solutions will change according to the intersection vehicle counts, the current geometric plan of the intersection and past traffic habits. For this purpose, the Platypus framework [39] which was developed to solve multi-objective optimization problems is utilized to model the handled problem. Webster calculation method is inserted into the Platypus framework as an optimization problem. The results of performance indicators calculated with the outcomes obtained by the algorithms are given in tables. Further, the Pareto-front of the model used in the evaluation phase is shown in Fig. (3). All algorithms were run for 10 independent times under the same control parameter values, which population size is used as 100 and the number of iterations is taken as 100.

The extreme solutions in PFs obtained by the algorithms are given in Table-2, which contains two solutions (extreme-1 and extreme-2) in each row for an algorithm. Extreme-1 represents a solution that has the best value for f1 (optimum-cycle-length) and related f2 (average delay time), while extreme-2 is a solution that consists of the best f2 and related f1.

Table 2. The extreme solutions found by the algorithms

	Extreme-1		Extreme-2	
	best-f1	f2	best-f2	f1
NSGAII	30.04	12.65	12.64	37.16
SPEA2	32.80	22.47	12.84	40.18
IBEA	30.60	13.86	11.88	36.11
SMPSO	31.83	14.70	12.46	39.16

The comparative results of performance indicators are listed in the tables below. Furthermore, the relationship between the intersection flow ratio and the optimum-cycle-length is shown in Fig. (1).

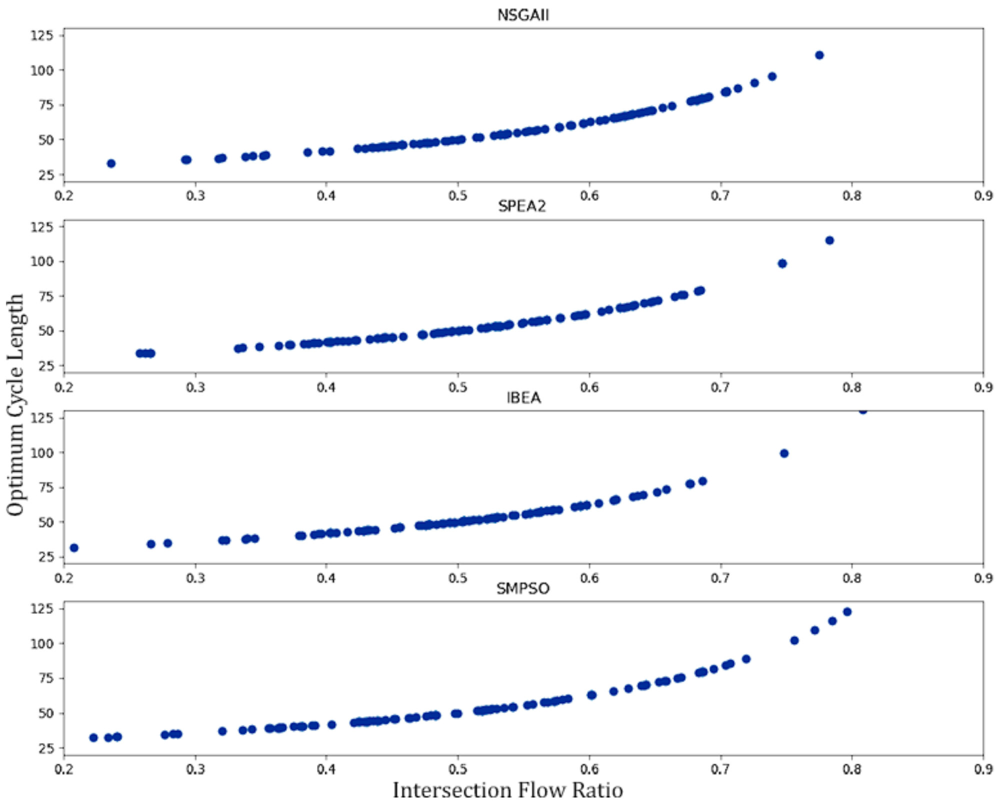

Figure 1. Relation between intersection flow ratio and optimum cycle length

The increase in the optimum-cycle-length due to the increase of the lost times as a result of the increase in the intersection flow ratio is seen in Fig. (1). The optimum-cycle-length is determined for the intersection where signalization should be established or signal durations should be updated after counting the vehicles. The determined signal duration is a parameter that will enable the intersection to operate efficiently. By means of this parameter, a signalization system can be mentioned where the signal time losses are minimized. According to the relationship between optimum-cycle-length and intersection flow ratio, optimum signalization durations are maintained. In this way, the applications performed in the form of trial and error will be disabled. The relation between the optimum-cycle-length and delay-time is shown in Fig. (2).

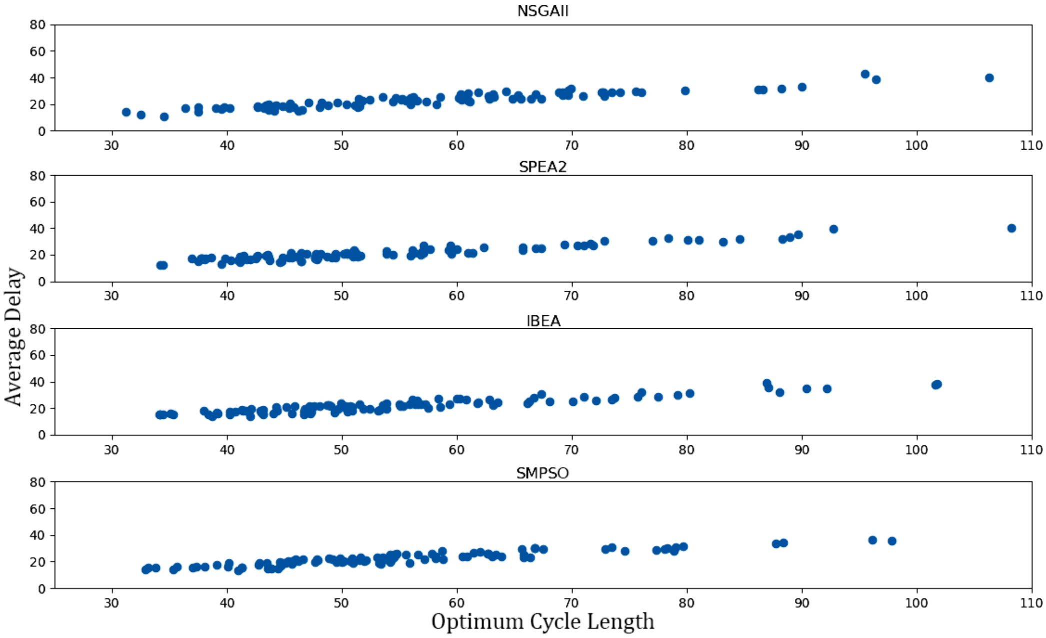

Figure 2. Relation between optimum cycle length and average delay time

When deciding the optimum-cycle-length at a fixed-time intersection, criteria other than the saturated flow values should be considered. One of these criteria is the average delay time per vehicle. The average delay time and cycle length are directly proportional to each other. In order to achieve a successfully operated signalization system, an approach in which there is no lost time or the lost time is minimized is required. With the approaches put forward in this study, signalization can be accomplished with multi-objective optimization. The focus in the multi-objective signal optimization approach is the relationship between the intersection flow ratio and the optimum-cycle-length, and the relationship between average delay and optimum-cycle-length.

Table-3 shows the HV results of the algorithms. It can be seen that NSGAII and IBEA were achieved the best result among the four algorithms. SP results are given in Table-4. The SMPSO algorithm for the SP metric, which is required to converge to zero for a good distribution on the Pareto front, obtained the best result. The results of the GD and IGD metrics comparing the accuracy of the obtained results are given in Table-5 and Table-6, respectively. IBEA has the most accurate values according to GD indicator, while SPEA-2 algorithm reached the most accurate values according to IGD indicator. Considering all results calculated with indicator values for each algorithm, it was seen that all four algorithms can find very close and effective outcomes. This is understood from the closeness of the values given in Table-2 and the similar distribution of Pareto-Optimal results obtained from algorithms shown in Fig. (1) and Fig. (2).

Table 3. The HV results for the signalization problem depend on Webster model

NSGAII	SPEA2	IBEA	SMPSO

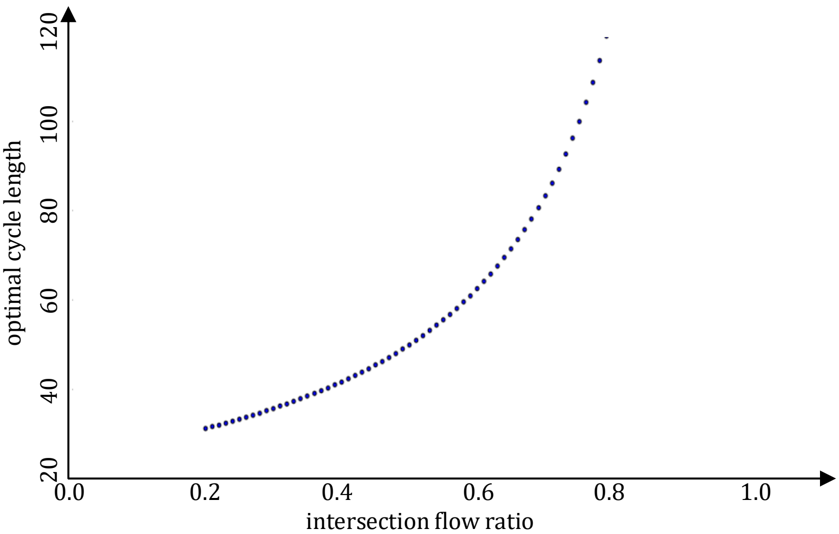

Figure 3. Pareto-front of the handled problem

mean	9.859E-01	9.853E-01	9.859E-01	9.857E-01
std	3.983E-05	2.225E-04	4.818E-05	1.715E-04

Table 4. The SP results for the signalization problem depend on Webster model

	NSGAII	SPEA2	IBEA	SMPSO
mean	3.647E-02	1.066E-01	4.214E-02	3.628E-02
std	7.742E-03	1.524E-02	1.287E-02	6.699E-03

Table 5. The GD results for the signalization problem depend on Webster model

	NSGAII	SPEA2	IBEA	SMPSO
mean	2.978E-04	2.991E-04	2.797E-04	4.165E-04
std	2.960E-05	1.426E-05	3.526E-05	5.367E-05

Table 6. The IGD results for the signalization problem depend on Webster model

	NSGAII	SPEA2	IBEA	SMPSO
mean	3.960E-01	2.909E-01	3.924E-01	3.878E-01
std	4.582E-03	1.048E-01	7.387E-03	8.723E-03

In order to test whether the indicator values calculated from the results obtained in the problem of determining the signal plans of the algorithms are statistically different from each other's values, Wilcoxon two-sided rank-sum test was applied in the 95% confidence interval and the results are given in Table 7-10. A p-value of less than 0.05 in the tables indicates that the results produced by an algorithm are statistically significantly different from the results of the algorithm compared. Significant differences are shown in the tables with a "+" sign. In summary, each of the state-of-the-art algorithms selected for use in this study has been seen to be successful algorithms that produce statistically significantly different results.

Table 7. Wilcoxon rank-sum test on HV indicator values of all algorithms

	SPEA2		IBEA		SMPSO	
	p	*h*	*p*	*h*	*p*	*h*
NSGAII	1.8267e-04	+	0.52050000	-	6.3864e-05	+
SPEA2			1.8267e-04	+	6.3864e-05	+
IBEA					6.3864e-05	+

Table 8. Wilcoxon rank-sum test on SP indicator values of all algorithms

	SPEA2		IBEA		SMPSO	
	p	*h*	*p*	*h*	*p*	*h*
NSGAII	1.8267e-04	+	0.3847000	-	6.3864e-05	+
SPEA2			1.8267e-04	+	6.3864e-05	+
IBEA					6.3864e-05	+

Table 9. Wilcoxon rank-sum test on GD indicator values of all algorithms

	SPEA2		IBEA		SMPSO	
	p	*h*	*p*	*h*	*p*	*h*
NSGAII	0.2567000	-	0.3447	-	1.8267e-04	+
SPEA2			0.9097	-	1.8267e-04	+
IBEA					1.8267e-04	+

Table 10. Wilcoxon rank-sum test on IGD indicator values of all algorithms

	SPEA2		IBEA		SMPSO	
	p	*h*	*p*	*h*	*p*	*h*

NSGAII	1.8267e-04	+	0.5205000	-	6.3864e-05	+
SPEA2			1.8267e-04	+	6.3864e-05	+
IBEA					6.3864e-05	+

4. Conclusions

In this study, optimum-cycle-length and average delay times per vehicle were calculated in a fixed time isolated signalized intersection control system. For this purpose, Webster's delay model is employed as the calculation method. This model was adapted to multi-objective optimization and signalization system is considered as an optimization problem. Four state-of-the-art multi-objective optimization algorithms NSGA-II, SPEA2, IBEA, and SMPSO were applied to the problem. In order to evaluate the results, four performance indicators were calculated, which are frequently used methods and called HV, SP, GD, and IGD. In terms of accuracy, the SPEA2 and IBEA algorithms showed relatively better results than the others. However, SMPSO algorithm achieved a better distribution on the Pareto front according to the SP metric. Besides these, NSGA-II and IBEA algorithms obtained the best results with respect to the HV metric that takes into account both criteria. On the other hand, all algorithms were able to find close and appropriate values for the signalization system. As a result, it has been shown that multi-objective optimization algorithms produce successful results in determining signal durations in isolated signalized intersections. By deciding the cycle length of signalized intersections with the mentioned algorithms, significant fuel savings and emissions of harmful gas emissions will be reduced.

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