Hindawi
Advances in Civil Engineering
Volume 2019, Article ID 1638618, 13 pages
https://doi.org/10.1155/2019/1638618

Research Article

A Multiobjective Bilevel Programming Model for Environmentally Friendly Traffic Signal Timings

Ozgur Baskan

Department of Civil Engineering, Faculty of Engineering, Pamukkale University, Denizli 20160, Turkey

Correspondence should be addressed to Ozgur Baskan; obaskan@pau.edu.tr

Received 6 July 2019; Accepted 23 August 2019; Published 20 October 2019

Academic Editor: Tayfun Dede

Copyright © 2019 Ozgur Baskan. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Rapid urbanization and mobility needs of road users increase traffic congestion and delay on urban road networks. Thus, local authorities aim to reduce users' total travel time through providing a balance between traffic volume and capacity. To do this, they optimize traffic signal timings, which is one of the most preferred methods, and thus they can increase the reserve capacity of a road network. However, more travel demand along with more reserve capacity leads to vehicle emissions problem which has become quite dangerous for road users, especially in developing countries. Therefore, this study presents a multiobjective bilevel programming model which considers both the maximization of reserve capacity of a road network and the minimization of vehicle emissions by aiming to achieve environmentally friendly signal timings. At the upper level, Pareto-optimal solutions of the proposed multiobjective model are found based on differential evolution algorithm framework by using the weighted sum method. Stochastic traffic assignment problem is presented at the lower level to evaluate the users' reactions. Two signalized road networks are chosen to show the effectiveness of the proposed model. The first one is a small network consisting two signalized intersections that are used to show the effect of the weighting factor on the proposed multiobjective model. The other road network with 96 O-D pairs and 9 signalized intersections is chosen as the second numerical application to investigate the performance of the proposed model on relatively large road networks. It is believed that results of this study may provide useful insights to local authorities who are responsible for regulating traffic operations with environmental awareness at the same time.

1. Introduction

Traffic congestion has become a serious problem worldwide especially in dense urban road networks and causes an increase in overall delay, which is the most significant effect of traffic congestion in a road network. As it is well known, major delays occurring in urban road networks arise from signalized intersections. In fact, a significant decrease in delay can be provided by optimizing signal timings at intersections. Conversely, applying improper signal timings leads to increase in total delay by reducing network's capacity. It is therefore a common method to optimize signal timings at intersections in order to increase the performance of a road network. The concept of reserve capacity has been widely used for a long time to optimize traffic signal timings. Reserve capacity can be defined as the maximization of the origin-destination (O-D) demand multiplier by means of ensuring that flow on each link in the network does not exceed its capacity. It means that how large a multiplier can be applied to the base travel demand matrix by optimizing traffic signal timings. On the contrary, O-D demand multiplier represents increasing travel demand that occurs as a result of growing population, changing land use pattern, etc. Besides, the concept of reserve capacity describes the border between applying physical improvements and optimizing signal timings to increase the performance of a road network. In other words, local authorities can manage a road network by optimizing traffic signal timings until travel demand reaches a certain level. This concept was taken into consideration with the study proposed by Webster and Cobbe [1]. Allsop [2] took this pioneer work a step further in order to provide an opportunity for intersections with complicated signal plans. Yagar [3, 4] proposed new methods for maximizing capacity at a signalized intersection by introducing different saturation flows from one stage to another in a cycle to overcome shortcomings in the study by Allsop [2]. While the reserve capacity has been successfully considered for signalized intersections, this concept has also been applied to roundabouts and priority junctions by Wong [5]. Considering a road network rather than a single intersection, Wong and Yang [6] aimed to maximize the reserve capacity of a signalized road network by using deterministic user equilibrium link flows. After that, Yang and Wang [7] explored the relationship between the reserve capacity maximization and travel cost minimization at a signalized road network. At the same year, Ziyou and Yifan [8] pointed out that the concept of reserve capacity and continuous network design problem must have been combined in order to reveal more realistic results for decision makers. Ge et al. [9] studied network's reserve capacity to reveal the impact of user information by using a bilevel programming model. Results showed that the relationship between reserve capacity and user information level depends on characteristics of a considered road network. Besides, a two-stage model to find optimal signal timings in the context of reserve capacity was proposed by Ceylan and Bell [10]. In view of network reliability, Chen et al. [11] developed a new index that examines the relationship between capacity and reliability of a signalized road network. Chiou [12] aimed to maximize the reserve capacity considering an explicit traffic model for a signalized road network. Furthermore, Chiou [13–16] investigated the concept of reserve capacity in the context of toll settings, expansions of link capacity, and minimizing of users' travel time. Similarly, Miandoabchi and Farahani [17] proposed a new framework which solves lane addition and street direction problems within the concept of reserve capacity. Chiou [18] attempted to maximize the reserve capacity of a road network by considering simultaneously the delay minimization problem. On the contrary, Wang et al. [19] extended the study conducted by [8], assuming drivers' decisions in the stochastic user equilibrium (SUE) manner. Baskan and Ozan [20] proposed a bilevel model based on the harmony search (HS) method to maximize the reserve capacity of a road network by taking equity issue into account. Recently, Baskan et al. [21] developed a biobjective bilevel programming model that simultaneously solves the reserve capacity maximization and delay minimization problems.

From another point of view, nowadays, many urban areas are faced with adverse environmental impacts such as noise and smog due to increasing travel demand. While noise can be prevented through enforcements and awareness of drivers, smog and its primary source vehicle emissions cannot be reduced in urban areas by such applications. As is known, significant emission reduction can be achieved by encouraging drivers to preserve their speed consistency. However, it is mostly not possible for drivers to maintain their speed constant due to traffic congestion and delay especially at intersections. Therefore, environmental effects arising from vehicle emissions should be taken into account in optimizing traffic signal timings. In this context, there are a limited number of studies concerning environmentally friendly signal timings in urban road networks. Kwak et al. [22] investigated the effect of use of proper signal timings on vehicular emissions at an arterial road. Results of a case study showed that the proposed approach produces better solution than that of the best solution produced by Synchro. Ferguson et al. [23] developed a new model considering vehicle emissions in order to fill the gap in the literature-related road network design. Results clearly showed that minimizing network overall delay may increase vehicle emissions. Lv et al. [24] drew attention to the fact that minimizing delay does not reduce vehicle emission-based pollutants. To fill this gap in the literature, they developed an optimization model considering both delay and vehicle emissions as objectives. Liao [25] proposed a signal optimization model which consists of fuel consumption based upon the vehicle movements. The performance of the fuel-based signal optimization model is compared with other signal optimization models through simulations. Results showed that the fuel-based model is able to reduce fuel consumption and CO_2 equivalent (CO_2e) emissions with respect to compared models. Similarly, a vehicle-based emission model has been developed by Chang et al. [26] in order to estimate CO_2e emissions using intelligent transportation systems (ITSs). Findings indicated that the proposed model is capable of estimating CO_2e emissions using different types of ITS. Zhang et al. [27] developed a biobjective programming model to find optimal signal timings for coordinated arterials by minimizing delay and traffic-related emissions. A simulation-based genetic algorithm is used to solve the proposed model. Li and Ge [28] proposed a multiobjective bilevel programming model that maximizes the reserve capacity of a road network and minimizes vehicle emissions by considering equity issue. However, contrary to this study, they considered deterministic user equilibrium traffic assignment at the lower level to represent users' reactions. Khalighi and Christofa [29] investigated the relationship between traffic congestion and vehicle emissions at a signalized intersection. Results revealed that the proposed real-time signal control system is able to optimize traffic signal timings by minimizing vehicle emissions. Stevanovic et al. [30] presented a new method to integrate safety, traffic emission, and signal timing optimization to achieve more reliable decisions when local authorities face a choice between mobility, safety, and environment. Yao et al. [31] remarked that signal timings not only affect the capacity of an intersection but also vehicle emissions. They developed single objective and biobjective optimization models considering different travel demand levels and found that a proper signal timing plan can reduce both delay and vehicle emissions at a signalized intersection. Recently, Li and Sun [32] developed a multiobjective optimization method for signal timing optimization and turning-lane assignment problems considering three important performance measures, namely, transportation efficiency, road safety, and fuel consumption. The proposed methodology clearly showed that significant positive impacts on these measures can be observed with combined optimization of turning-lane assignment and signal timings.

In the light of literature outlined, this study proposes a multiobjective bilevel programming model which considers both the maximization of reserve capacity of a road network and the minimization of vehicle emissions by aiming to achieve environmentally friendly signal timings. As it is well known, the reserve capacity can be utilized until the increasing travel demand reaches a certain level. On the contrary, this certain level of travel demand also causes significant increase on vehicle emissions in a road network. It indicates that only maximizing the reserve capacity rather than considering environmental effects does not mean that the road network can be managed effectively. Therefore, in this study, a multiobjective bilevel programming model has been developed to find Pareto-optimal solutions for these conflicting objectives. At the upper level, maximum O-D matrix multiplier and optimal signal timings are determined based on differential evolution algorithm frameworks, while the lower level is presented as an SUE assignment problem to evaluate users' reactions.

The remainder of this study is organized as follows. Section 2 is about statement of the problem. Solution algorithms are explained in detail in Section 3. The experimental evaluation of the proposed model is given in Section 4. Conclusions and future directions are provided in Section 5.

2. Statement of the Problem

The mutual interaction between two players, namely, local authority and road users, can be presented as a bilevel programming model. In this study, it is supposed that the local authority seeks to provide a sustainable traffic management through the maximization of the reserve capacity in a road network and the minimization of vehicle emissions. On the contrary, road users aim to minimize their own travel cost and to complete their travels within the shortest travel time. Therefore, road users are interested in neither maximizing the reserve capacity of a road network nor minimizing the total amount of vehicle emissions. The trade-off between the reserve capacity maximization and vehicle emission minimization can be investigated by defining a multiobjective bilevel programming model. At the upper level, reserve capacity maximization and vehicle emission minimization problems are simultaneously solved while SUE traffic assignment is performed at the lower level. The equilibrium link flows are determined by the path flow estimator (PFE) which is a logit-based SUE assignment tool [33]. The most important advantage of the PFE tool is that it does not involve path enumeration [21]. Considering a road network with a set of O-D pairs K, a set of links A, a set of paths D, a set of nodes N, and a set of intersections I, the problem can be formulated as

$$\max_{\boldsymbol{\xi},\mathbf{x}^*} \quad \psi, \tag{1}$$

$$\min_{\psi,\boldsymbol{\xi},\mathbf{x}^*} \quad \mathrm{E} = \sum_{a\in A} x_a^* e_{ai}, \tag{2}$$

subject to

$$x_a^*(\psi,\boldsymbol{\xi}) \le p_a Q_a(\boldsymbol{\xi}, s_a), \tag{3}$$

$$\mathbf{G}_i\boldsymbol{\xi}_i \ge \mathbf{b}_i, \tag{4}$$

where ψ is the O-D matrix multiplier, e_{ai} is the amount of vehicle emissions on link a for vehicle class i, and x_a^* is the equilibrium link flow on link a. Equation (3) represents the link capacity constraint in which s_a is the saturation flow, Q_a is the capacity, and p_a is the saturation flow rate. $\boldsymbol{\xi}_i$ is a vector of signal timings and matrices, $\mathbf{G}_i$ and $\mathbf{b}_i$ are depended on signal timing specification for signalized intersection $i \in I$ (see for details [34]). E is the total amount of vehicle emissions in a road network which can be determined using a mesoscopic emission estimation model proposed by Behnke and Kirschstein [35]. According to their study, the amount of vehicle emissions (in kg CO_2e) on link a for vehicle class i can be formulated as

$$e_{ai} = e\cdot l_a \cdot \left(d_{\mathrm{ai}}^{\mathrm{fix}} + d_{\mathrm{ai}}^{\mathrm{load}}\left(m_i^t + \mathrm{cap}_i\right)\right), \tag{5}$$

where e is the coefficient for diesel fuel, l_a is the length of link a (i.e. travel distance), d_{ai}^{fix} is the load-independent emission factor, d_{ai}^{load} is the load-dependent emission factor, m_i^t is the tare weight, and cap_i is the load capacity for vehicle class i. cap_i is taken between 0 and maxcap_i, which is the maximum load of vehicle class i. Emission factors dependent on load can be calculated as

$$d_{ai}^{\mathrm{fix}} = \frac{r_i^{\mathrm{idle}}}{v_{ai}} + \alpha_{ai}\cdot\frac{1}{2000}\cdot\frac{c_i^{\mathrm{air}}}{3.6^3}\cdot\rho\cdot A_i\cdot v_{ai}^2, \tag{6}$$

$$d_{ai}^{\mathrm{load}} = \alpha_{ai}\cdot\left(\frac{c_i^{\mathrm{roll}}}{3.6}\cdot g\cdot + \frac{0.504}{2\cdot 3600\cdot 3.6^2}\cdot n_{ai}^{\mathrm{acc}}\cdot v_{ai}^2\right). \tag{7}$$

Here, r_i^{idle} is the minimum fuel consumption of vehicle class i, v_{ai} is average speed of vehicle class i on link a, c_i^{air} is the air resistance coefficient of vehicle class i, ρ is the density of air, A_i is the surface area of vehicle class i, c_i^{roll} is the rolling resistance coefficient of vehicle class i, g is the gravitational acceleration, n_{ai}^{acc} is the expected number of accelerations per km on link a, and α_{ai} represents the amount of fuel consumption per hour to provide one KW of energy, and α_{ai} is defined as

$$\alpha_{ai} = \frac{r_i^{\mathrm{full}} - r_i^{\mathrm{idle}}}{P_i\cdot\left(0.88 - 0.72\cdot\exp\left(-0.077\cdot v_{ai}^{1.41}\right)\right)}, \tag{8}$$

where r_i^{full} and P_i are the maximum fuel consumption and rated power of engines in vehicles of class i, respectively.

The equilibrium link flows are needed to determine the total amount of vehicle emissions given in equation (2) in a road network. Thus, SUE link flows can be determined by solving traffic assignment problem given in equation [36].

$$\min_{\mathbf{x}} z(\mathbf{x}) = -\psi\mathbf{q}^{\mathrm{T}}\boldsymbol{\mu}(\mathbf{x}) + \mathbf{x}^{\mathrm{T}}\mathbf{t}(\mathbf{x}) - \sum_{a\in A}\int_0^{x_a} t_a(w)\mathrm{d}w, \tag{9}$$

where $\mathbf{q}$ is the vector of travel demand, $\mathbf{t}(\mathbf{x})$ represents a vector of link travel times for the given vector of link flows, and $\boldsymbol{\mu}$ is the vector of expected minimum O-D costs. The proposed multiobjective bilevel programming model aims to maximize the reserve capacity and to minimize vehicle emissions in a road network. It is clear that these objectives are involved in an interaction, and it should be emphasized that one solution may not be existed for all objectives in case a multiobjective problem exists. Therefore, multiple objectives in a given optimization problem require finding well-known Pareto-optimal solutions. A solution for a multiobjective optimization problem is called Pareto-optimal if an objective function can only be improved by degrading some of the other objective function values. Therefore, the proper solution for a multiobjective problem can be provided by Pareto-optimal solutions using the weighted sum method. Before applying the weighted sum method, both objective functions have to be done unitless so that they can be directly added, that is,

$$f_1 = \frac{\psi^*}{\psi}, \tag{10}$$

$$f_2 = \frac{\mathrm{E}}{E^*}, \tag{11}$$

where ψ^* and E^* represent upper and lower limits of objective functions given in equations (1) and (2). Since the objective functions are furthermore unitless, the weighted sum method can be applied to find the Pareto-optimal solutions of reserve capacity maximization and vehicle minimization problems subject to equations (3), (4), and (9) as given below:

$$\min f\left(\psi, \boldsymbol{\xi}, \mathbf{x}^*\right) = \lambda f_1 + (1-\lambda) f_2, \tag{12}$$

where λ represents the weighting factor that is specified to find the Pareto-optimal solutions between two objective functions, namely, f_1 and f_2. The reserve capacity is maximized when a larger value of λ is used by the local authority. Conversely, the minimization of vehicle emissions is taken much more into account for smaller values of λ.

3. Solution Algorithms

The differential evolution- (DE-) based solution algorithm has been introduced to solve the proposed multiobjective bilevel programming model by considering environmental issues. DE optimization algorithm developed by Storn and Price [37] is referred to as one of the most powerful metaheuristic methods [38, 39]. Its solution process is consists four fundamental steps, namely, initialization, mutation, crossover, and selection. As it is well known, few parameters are needed in DE to control the solution process. The first one is the number of population (NP) that represents the population size as used in all population-based metaheuristic methods. The solution vectors stored in the population are called *target vectors*. The second one is the mutation factor (F) used to create the mutant vector, and the last control parameter is the crossover rate (CR) that provides a probabilistic choice between the mutant and target vectors to generate the so-called *trial vectors* (see [37] for details).

It is clear that the maximum value of O-D multiplier, ψ^* and the minimum value of the total amount of vehicle emissions, E^* should be determined for solving the multiobjective model given in equation (12). For this purpose, both problems are solved separately by using the bilevel programming model within the DE framework. The maximization of the O-D multiplier and the minimization of the amount of vehicle emissions are handled at the upper level, while equilibrium link flows are obtained by means of solving SUE assignment problem at the lower level.

3.1. Maximization of Road Network's Capacity. Considering that DE is a minimization algorithm, equation (1) should be reformulated as a minimization problem as given in equation (13) subject to equations (3), (4), and (9) to maximize the reserve capacity of a road network.

$$\min Z\left(\psi, \mathbf{x}^* \boldsymbol{\xi}\right) = \frac{1}{\psi} + \sigma\left[\max\left(\sum_{a\in A}\left(x_a^*\left(\psi, \boldsymbol{\xi}\right) - Q_a\left(\boldsymbol{\xi}, s_a\right)\right), 0\right)\right], \tag{13}$$

where σ is a penalty weighting factor. The right side of equation (13) is the penalty function that ensures link flows do not exceed their capacities. Pseudocode and solution steps for the reserve capacity maximization problem are given below in the line with the DE framework. Before starting Step 1, upper/lower bounds for cycle time for each signalized intersection and possible bounds for O-D multiplier are specified. Similarly, DE parameters and road network parameters, namely, saturation flows, free-flow travel times, and O-D demand matrix are initialized.

Step 1. Solution vectors (i.e., target vectors), $\boldsymbol{\Delta}_u$ ($u = 1, 2, \ldots, \mathrm{NP}$), which include O-D multipliers, cycle times, and stage green timings generated randomly considering their upper and lower bounds. The generation of the decision variables can be formulated as

$$\psi_u = \mathrm{rand}[0,1] \times \left(\psi_u^{\max} - \psi_u^{\min}\right) + \psi_u^{\min}, \quad u = 1, 2, \ldots, \mathrm{NP}, \tag{14}$$

$$c_{u,i} = \mathrm{int}\left[\mathrm{rand}[0,1] \times \left(c_{u,i}^{\max} - c_{u,i}^{\min}\right) + c_{u,i}^{\min}\right], \quad i = 1, 2, \ldots, N, \tag{15}$$

$$\Upsilon_{u,i,j} = \mathrm{int}\left[\mathrm{rand}[0,1] \times \left(c_{u,i} - \Upsilon_{u,i,j}^{\min}\right) + \Upsilon_{u,i,j}^{\min}\right], \quad i = 1, 2, \ldots, N,\ j = 1, 2, \ldots, z_n, \tag{16}$$

where $c_{u,i}$ is the cycle time for i^{th} signalized intersection for u^{th} target vector, $c_{u,i}^{\max}$ and $c_{u,i}^{\min}$ are its upper/lower bounds, $\Upsilon_{u,i,j}$ and $\Upsilon_{u,i,j}^{\min}$ are the j^{th} stage green and minimum green times of intersection i for u^{th} target vector, z_n is the number of stages at i^{th} intersection, and N is the number of intersections in a road network. It should be emphasized that the stage green timings generated according to equation (16) may not satisfy the condition in which the sum of all green and intergreen times should be equal to the cycle time.

Therefore, the stage green timings should be revised according to equation.

$$\Upsilon_{u,i,j} = \text{int}\left[\Upsilon_{u,i,j}^{\min} + \frac{\Upsilon_{u,i,j}}{\sum_{j=1}^{z_n}\Upsilon_{u,i,j}}\left[c_{u,i} - z_i \times \left(I + \Upsilon_{u,i,j}^{\min}\right)\right]\right], \tag{17}$$

subject to

$$\sum_{j=1}^{z_n}\Upsilon_{u,i,j} + I = c_{u,i}, \tag{18}$$

where I is the intergreen time. At this stage, the SUE link flows are needed to calculate the value of objective function given in (13). For this purpose, the PFE algorithm is used based on the logit route choice model. The details of the PFE algorithm are not provided to facilitate the presentation of the main contributions without loss of generality (see [33] for details).

Step 2. After creating the initial population, DE operators (mutation, crossover, and selection) are applied to each target vector in order to improve its solution quality. Thus, the solution vectors in the population may find an optimal/near-optimal solution through iterations for a given optimization problem. The mutation process is carried out by using three randomly selected solution vectors which should be different from each other [37]. A mutant vector, Φ_u^{iter} (iter = 1, 2, . . . , maxiter), for the u^{th} target vector $\mathbf{\Delta}_u^{\text{iter}}$, is created as

$$\Phi_u^{\text{iter}} = \Delta_{r0}^{\text{iter}} + F\cdot\left(\Delta_{r1}^{\text{iter}} - \Delta_{r2}^{\text{iter}}\right), \tag{19}$$

where $r0$, $r1$, and $r2$ are indices of the selected target vectors which should be different from the u^{th} target vector.

Step 3. Crossover is conducted by using u^{th} target and mutant vectors. Each member of the trial vector, $\beta_{u,i}^{\text{iter}}$, from the u^{th} target or the mutant vectors by using probabilistic choice with CR as given in the following equation:

$$\mathrm{B}_u^{\text{iter}} = \beta_{u,i}^{\text{iter}} = \begin{cases} \phi_{u,i}^{\text{iter}}, & \text{if}\left(\text{rand}(0,1) \le \text{CR or } i = i_{\text{rand}}\right), \\ \delta_{u,i}^{\text{iter}}, & \text{otherwise},\ i = 1, 2, \ldots, \text{ND}, \end{cases} \tag{20}$$

where ND represents the number of decision variables. The statement $i = i_{\text{rand}}$ ensures that the u^{th} target and the trial vectors are different from each other in any case.

Step 4. Corresponding SUE link flows should be calculated for u^{th} trial vector by solving traffic assignment problem before applying the last step of DE. At this step, u^{th} target vector, $\mathbf{\Delta}_u^{\text{iter}}$, is replaced with the u^{th} trial vector, $\mathrm{B}_u^{\text{iter}}$, if the trial vector provides lower objective function value as shown in equation (21). The DE optimization framework is terminated when the maximum number of iterations (maxiter) is reached.

$$\mathbf{\Delta}_u^{\text{iter}+1} = \begin{cases} \mathrm{B}_u^{\text{iter}}, & \text{if } Z\left(\mathbf{x}^*\left(\mathrm{B}_u^{\text{iter}}\right)\right) \le Z\left(\mathbf{x}^*\left(\mathbf{\Delta}_u^{\text{iter}}\right)\right), \\ \mathbf{\Delta}_u^{\text{iter}}, & \text{otherwise}. \end{cases} \tag{21}$$

3.2. Minimization of Total Amount of Vehicle Emissions. A bilevel programming model to minimize the total amount of vehicle emissions is explained based on the four-step DE framework. Algorithm 1 represents the main steps of the proposed model similar to Algorithm 2. Before applying Step 1, the upper and lower bounds for signal timing variables are specified. Similarly, DE parameters and road network parameters, namely, saturation flows, free-flow travel times, and O-D demand matrix are initialized. It should be emphasized that O-D demand matrix multiplier is taken as 1 in Algorithm 1. It means that the base travel demand is considered while the total amount of vehicle emissions, E^*, is minimized for a road network.

Step 1. Target vectors, T_u $(u = 1, 2, \ldots, \text{NP})$, include cycle times and stage green timings generated randomly considering their upper and lower bounds. The generation of the decision variables is formulated based on equations (15) and (18) similar to Algorithm 2. SUE link flows are determined by the PFE algorithm, and the corresponding objective function value for each target vector is calculated as given in equation (2).

Step 2. At this step, the mutation operator is performed and a mutant vector, $\mathbf{\Phi}_u^{\text{iter}}$, (iter = 1, 2, . . . , maxiter), for the u^{th} target vector, $\mathrm{T}_u^{\text{iter}}$, is created as

$$\mathbf{\Phi}_u^{\text{iter}} = \mathrm{T}_{r0}^{\text{iter}} + F\cdot\left(\mathrm{T}_{r1}^{\text{iter}} - \mathrm{T}_{r2}^{\text{iter}}\right). \tag{22}$$

Step 3. At this step, u^{th} trial vector, $\mathrm{B}_u^{\text{iter}}$, is generated from u^{th} target vector, $\mathrm{T}_u^{\text{iter}}$, and mutant vector, $\mathbf{\Phi}_u^{\text{iter}}$. Each member of the trial vector, $\beta_{u,i}^{\text{iter}}$, is created as given in the following equation:

$$\mathrm{B}_u^{\text{iter}} = \beta_{u,i}^{\text{iter}} = \begin{cases} \phi_{u,i}^{\text{iter}}, & \text{if}\left(\text{rand}(0,1) \le \text{CR or } i = i_{\text{rand}}\right), \\ \tau_{u,i}^{\text{iter}}, & \text{otherwise},\ i = 1, 2, \ldots, \text{ND}. \end{cases} \tag{23}$$

Step 4. At the beginning of this step, equilibrium link flows are calculated for u^{th} trial vector by solving SUE assignment problem. Finally, u^{th} target vector, $\mathrm{T}_u^{\text{iter}}$, is replaced with the u^{th} trial vector, $\mathrm{B}_u^{\text{iter}}$, if the trial vector provides lower objective function value as shown in equation (24). The DE process is terminated in case the maximum number of iterations (maxiter) is reached.

$$\mathrm{T}_u^{iter+1} = \begin{cases} \mathrm{B}_u^{\text{iter}}, & \text{if } Z\left(\mathbf{x}^*\left(\mathrm{B}_u^{\text{iter}}\right)\right) \le Z\left(\mathbf{x}^*\left(\mathrm{T}_u^{\text{iter}}\right)\right), \\ \mathrm{T}_u^{\text{iter}}, & \text{otherwise}. \end{cases} \tag{24}$$

After the values of ψ^* and E^* are determined by applying Algorithms 1 and 2, the reserve capacity maximization and vehicle emission minimization problems can be simultaneously handled to find the Pareto-optimal solutions. To do

```
for u ⟵ 1 to NP do
  for i ⟵ 1 to ND do
    Generate cycle time c_i for i^th intersection considering its upper and lower bounds
    Generate green timings for i^th intersection between minimum green time and c_i
    Revise stage green times of i^th intersection providing signal timing constraints
    Determine SUE flows for the u^th target vector
    Determine objective function value given in equation (2) for u^th target vector
for iter ⟵ 1 to maxiter do
  for u ⟵ 1 to NP do
    Perform mutation to the u^th target vector to create a mutant vector
    for i ⟵ 1 to ND do
      Perform crossover to obtain the i^th decision variable of u^th trial vector
      Revise cycle times considering their upper and lower bounds
      Revise stage green times providing signal timing constraints
    Determine SUE flows for the u^th trial vector
    Determine objective function value given in equation (2) for the u^th trial vector
    Include u^th trial vector to the population instead of u^th target vector if it provides lower objective function value
print optimal/near optimal signal timings
```

ALGORITHM 1: Pseudocode for the minimization of vehicle emissions.

```
for u ⟵ 1 to NP do
Generate O-D matrix multiplier as ψ ∈ {ψ^min, ..., ψ^max} for the u^th target vector
  for i ⟵ 1 to N do
    Generate cycle time c_i for i^th intersection considering its upper and lower bounds
    Generate green timings for i^th intersection between minimum green time and c_i
    Revise stage green times of i^th intersection providing signal timing constraints
    Determine SUE flows for the u^th target vector
    Determine objective function value given in equation (13) for u^th target vector
for iter ⟵ 1 to maxiter do
  for u ⟵ 1 to NP do
    Perform mutation to the u^th target vector
    for i ⟵ 1 to ND do
      Perform crossover to obtain the i^th decision variable of u^th trial vector
      Revise cycle times considering related constraints
      Revise O-D matrix multiplier considering their upper and lower bounds
      Revise stage green times providing signal timing constraints
  Determine SUE flows for the u^th trial vector
  Determine objective function value given in equation (13) for the u^th trial vector
  Include u^th trial vector to the population instead of u^th target vector if it provides lower objective function value
print optimal/near optimal signal timings and maximum O-D matrix multiplier, ψ
```

ALGORITHM 2: Pseudocode for the maximization of reserve capacity.

this, a multiobjective bilevel programming model given in equation (12) subject to equations (3), (4), and (9) is solved by using Algorithm 3 based on the DE framework by taking weighting factor λ into account.

4. Numerical Applications

The applicability of the proposed algorithms is demonstrated by using two signalized test networks in this section. First network called Test Network-1 is used to reveal the effect of the weighting factor in solving the multiobjective optimization problem given in equation (12). A road network called Test Network-2 is chosen as the second numerical application to investigate the performance of the proposed algorithms on relatively large networks.

4.1. Test Network-1. The first test network taken from [21] is a small road network which has 2 signalized intersections and 8 links. Layout, stage plans, and revised layout for the PFE are given in Figures 1 and 2, respectively.

The free-flow travel time, t_a^0, and saturation flow, s_a, for link $a \in A$ are set to 20 sec and 1800 veh/hr, respectively. It is assumed that there is one O-D pair as shown in Figure 1, and travel demand for this O-D pair is taken as 1500 veh/hr. The intergreen time, I, is chosen as 5 sec. Upper and lower

Specify the weighing factor $\lambda \in (0,1)$
Initialize the values of ψ^* and E^* to calculate functions f_1 and f_2 given in equation (10) and (11)
for $u \longleftarrow 1$ to NP **do**
Generate O-D matrix multiplier as $\psi \in \{\psi^{\min}, \ldots, \psi^{\max}\}$ for the u^{th} target vector
  for $i \longleftarrow 1$ to N **do**
    Generate cycle time c_i for i^{th} intersection considering its upper and lower bounds
    Generate green timings for i^{th} intersection between minimum green time and c_i
    Revise stage green times of i^{th} intersection providing signal timing constraints
    Determine SUE flows for the u^{th} target vector
    Determine objective function value given in equation (12)
    for u^{th} target vector subject to equations (3) and (4) and equation (9)
for iter $\longleftarrow 1$ to maxiter **do**
  for $u \longleftarrow 1$ to NP **do**
    Perform mutation to the u^{th} target vector to create a mutant vector
  for $i \longleftarrow 1$ to ND **do**
    Perform crossover to obtain the i^{th} decision variable of u^{th} trial vector
    Revise cycle times considering related constraints
    Revise O-D matrix multiplier considering their upper and lower bounds
    Revise stage green times providing signal timing constraints
  Determine SUE flows for the u^{th} trial vector
  Determine objective function value given in equation (12)
  for u^{th} trial vector subject to equations (3), (4), equation (9)
  Include u^{th} trial vector to the population instead of u^{th} target vector if it provides lower objective function value based on the rule given in equation (24)
print optimal/near-optimal signal timings and maximum O-D matrix multiplier, ψ

Algorithm 3: Pseudocode for the multiobjective bilevel programming model.

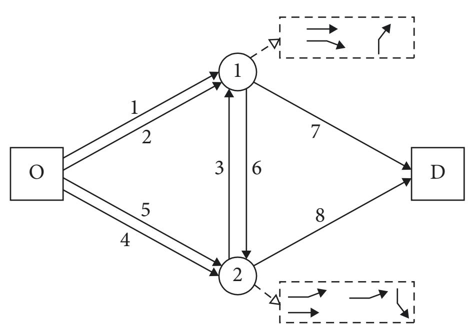


Figure 1: Test Network-1.

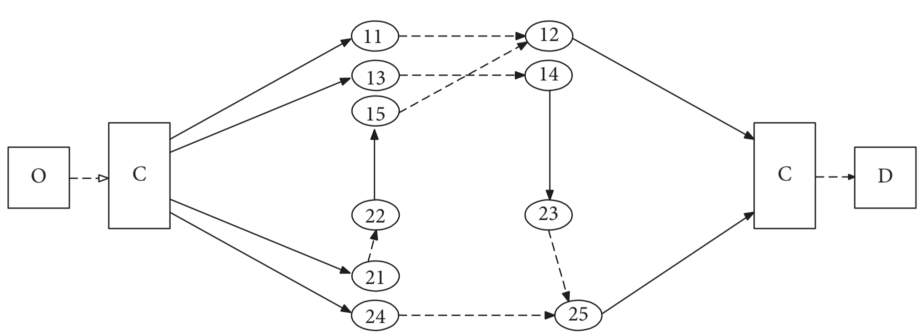


Figure 2: Test Network-1 revised for the PFE algorithm.

bounds for cycle time c_i for i^{th} intersection are set to 30 and 100 sec, respectively, in keeping with previous studies [21, 40]. $\Upsilon_{i,j}$ is set as being between minimum green time and c_i where minimum stage green time is selected as 7 sec. Please note that all intersections in Test Network-1 are isolated. On the contrary, it is clear that the values of control parameters of DE optimization algorithm have an impact on solution quality. In this context, the ranges for F and CR are recommended as [0.5, 1.0] and [0.8, 1.0] by [37], Storn and, Price, respectively. In addition, there are quite a few numbers of studies in the literature for setting of DE parameters in last decades. The recent study by [21] recommends that the value of 0.8 can be used for F and CR. In their study, a comparative sensitivity analysis has been performed and the parameter combination of $F = \mathrm{CR} = 0.8$ has been resulted in the lowest mean objective function and standard deviation values. Therefore, this parameter combination is selected for all numerical applications in this study. The population size, NP, is selected as 15 considering the number of decision variables, and the maxiter is set to 200 for all algorithms for Test Network-1 (see [21] for details). Note that the average computational time of each iteration of the Algorithm 2 for 30 independent runs, using PC with Intel Core i7 2.10 GHz, 8 GB RAM, was about 7.5 seconds of CPU. To maximize the reserve capacity of Test Network-1, the objective function in equation (13) subject to equations (3) and (4) and equation (9) was minimized by executing Algorithm 2. The best objective function value was found as 0.4680 after 200 iterations, that is, the O-D demand matrix for Test Network-1 can be increased by about 2.14 times as shown in Figure 3. In this case, link flows do not exceed their capacities although the travel demand was increased more than two times. Degree of saturation for links 1 and 4 is 100% that means flows on those links equal their capacities. Flows on other links in Test Network-1 are less than their capacities with the degree of saturation of 98%. In addition, optimal cycle time was found to be 100 sec, which is equally distributed to the stages in each intersection in Test Network-1. It should be emphasized that decision makers do not take the amount of vehicle emissions in the network into account in case they aim to maximize the network's reserve capacity.

On the contrary, the total amount of vehicle emissions represented in equation (2) subject to equations (4) and (9) was minimized for Test Network-1 by using Algorithm 1. The convergence graph is given in Figure 4. The objective function value was found to be about 145.25 after 200 iterations. The optimized signal timings are given in Table 1. The all parameters needed for the mesoscopic emission model were selected similarly as in [35] for small vehicle class.

Once the values of ψ^* and E^* are determined by applying Algorithms 1 and 2, the reserve capacity maximization and vehicle emission minimization problems can be simultaneously solved using equation (12) by applying Algorithm 3. The Ψ, E, and corresponding function values for different weighting factors are given in Table 2. As can be seen in Table 2, the network's reserve capacity cannot be increased when the weighting factor varies between 0 and 0.3 since local authorities try to minimize the total amount of vehicle emissions in the network and they are unwilling to increase the base travel demand in the network. In this case, f_1 is equivalent to ψ^* since ψ is 1.0 which represents the base O-D demand. On the contrary, the value of f_2 equals 1.0 since the value of E is equivalent to E*. This means that local authority totally concentrates on minimization of vehicle emissions by

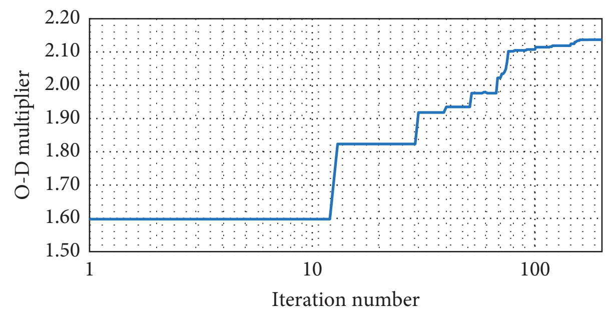


Figure 3: Convergence graph of the Algorithm 2 for Test Network-1.

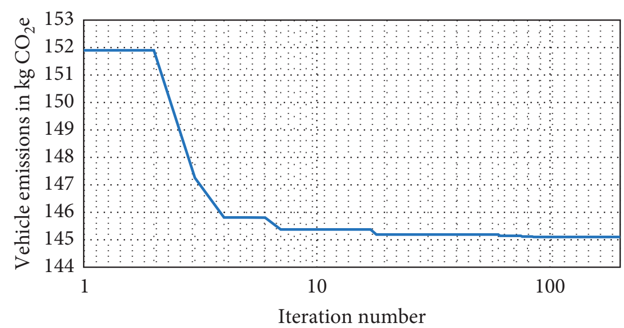


Figure 4: Convergence graph of the Algorithm 1 for Test Network-1.

Table 1: Optimal signal timings for E^* in Test Network-1.

Cycle time (sec) c_i	Green timing (sec) $\Upsilon_{i,1}$	Green timing (sec) $\Upsilon_{i,2}$
90	58	22
68	40	18

Table 2: The ψ, E, and corresponding function values for Test Network-1.

λ	ψ	E	f_1	f_2	f
0.0	1.000	145.25	2.137	1.000	1.000
0.1	1.000	145.25	2.137	1.000	1.114
0.2	1.000	145.25	2.137	1.000	1.227
0.3	1.000	145.25	2.137	1.000	1.341
0.4	1.121	164.47	1.906	1.132	1.442
0.5	1.353	200.03	1.579	1.377	1.478
0.6	1.372	206.00	1.557	1.418	1.501
0.7	1.606	356.78	1.331	2.456	1.668
0.8	1.811	421.37	1.180	2.901	1.524
0.9	2.000	515.20	1.068	3.546	1.316
1.0	2.137	674.15	1.000	4.641	1.000

optimizing traffic signal timings instead of increasing network's reserve capacity. Conversely, in case the weighting factor is equivalent to 1.0, local authority is not interested in minimizing vehicle emissions and tries to maximize the network's reserve capacity.

In this context, Figure 5 represents Pareto-optimal solutions for f_1 and f_2 with various values of weighting factor λ.

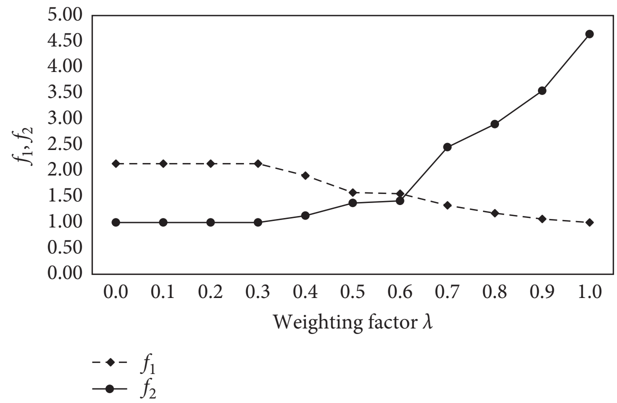


FIGURE 5: Solutions of f_1 and f_2 with various values of weighting factor λ for Test Network-1.

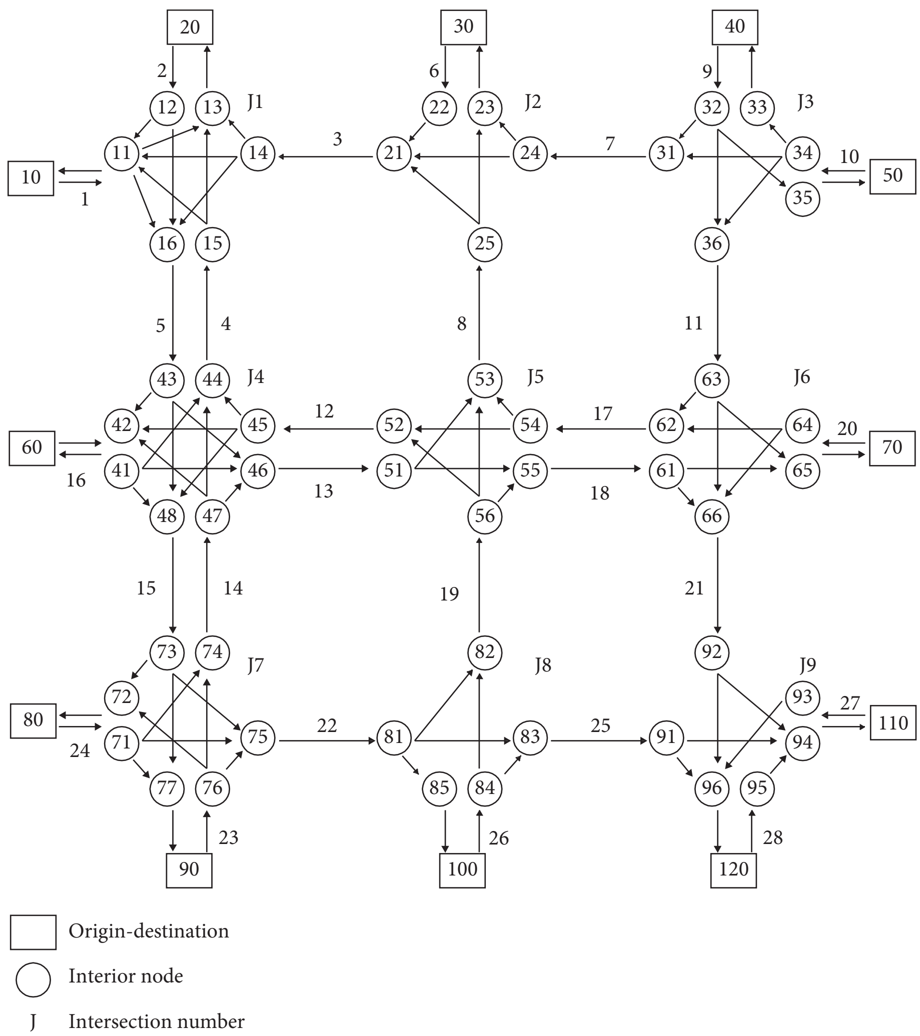


FIGURE 6: Test Network-2 and its representation for the PFE algorithm.

It can be clearly seen that the value of f_1 decreases when the weighting factor varies between 0.0 and 1.0. This result means at the same time that the O-D demand multiplier increases since local authority pays more attention to maximize the reserve capacity of the network.

Conversely, the value of f_2 increases as the weighting factor increases from 0.0 to 1.0. On the contrary, the total amount of vehicle emissions, E, has a decreasing trend when the weighting factor varies from 1.0 to 0.0 as can be seen in Table 2 since local authority focuses attention on minimizing vehicle emissions in the network instead of maximizing the reserve capacity. In addition to these results, there is no change in f_1 and f_2 until the weighting factor is increased to 0.3. On the contrary, as the weighting factor continues to increase, the value of f_1 begins to decrease and the value of f_2 begins to increase. The value of f_1 shows almost a linear decrease while the weighting factor increases from 0.3 to 1.0. However, the value of f_2 increases significantly especially after the weighting factor's value reached to the value of 0.6 as shown in Figure 5. Thus, after this point, increasing the network's reserve capacity leads to significant increase in the total amount of vehicle emissions in the network.

4.2. Test Network-2. Test Network-2 previously proposed by Gartner et al. [41] and Jovanovic et al. [42] is selected as the second numerical application to show the effectiveness of the proposed algorithm on relatively large networks. Test Network-2 revised for this numerical application consisting 96 O-D pairs, 9 signalized intersections, and 28 links as shown in Figure 6.

Interior nodes are presented to indicate how the PFE algorithm works to solve SUE traffic assignment problem. Each intersection is operated by two stages as can be seen in Figure 7. The minimum stage green time, $\Upsilon_{i,j}^{\min}$, is set to 7 sec and the minimum and maximum cycle times for each intersection are taken as 30 and 120 sec, respectively. In addition, the intergreen time between successive stages is set to 5 sec and the minimum and maximum values of the O-D matrix multiplier are selected as 1 and 3, respectively. The saturation flow is taken as 1800 veh/hr. Table 3 presents link-related data for Test Network-2. The free-flow travel times of the entrance links (1, 2, 6, etc.) in the network are assumed to be 1 sec. O-D demand matrix is assumed as given in Table 4.

The population size, NP, is set to 60 considering the number of decision variables, and the maxiter for all algorithms is set to 300. Note that the average computational time of each iteration of Algorithm 2 for 15 independent runs was about 41 sec of CPU. To maximize the reserve capacity of Test Network-2, the objective function in equation (13) subject to equations (3), (4), and (9) was minimized by executing Algorithm 2. The maximum O-D matrix multiplier, ψ^*, was found as 1.24 for Test Network-2. Furthermore, E^* was determined as 1248 by using Algorithm 1. The Ψ, E, and corresponding function values for different weighting factors are given in Table 5.

Similar to the analysis performed for Test Network-1, local authority aims to minimize the total amount of vehicle emissions in the network, and travel demand increase is not permitted until the weighting factor reached to the value of 0.3. However, in case the weighting factor varies from 0.3 to 1.0, local authority focuses on the maximization of network's reserve capacity more than the minimization of vehicle emissions. Figure 8 represents Pareto-optimal solutions for f_1 and f_2 with various values of weighting factor λ for Test Network-2. The value of f_1 decreases when weighting factor increases from 0.3 to 1.0. On the contrary, the value of f_2 significantly increases especially after the value of weighting

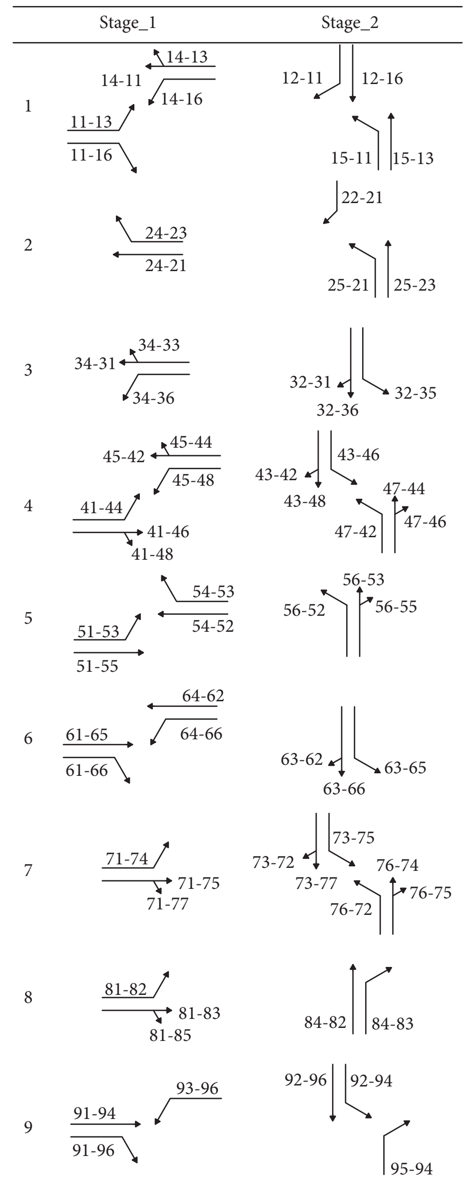


Figure 7: Stage plans for Test Network-2.

Table 3: Link-related data for Test Network-2.

Link number	Link length l_a (km)	Free-flow travel time t_a^0 (sec)
3	0.183	13.18
4	0.305	21.96
5	0.305	21.96
7	0.244	17.57
8	0.305	21.96
11	0.305	21.96
12	0.183	13.18
13	0.183	13.18
14	0.168	12.10
15	0.168	12.10
17	0.244	17.57
18	0.244	17.57
19	0.168	12.10
21	0.168	12.10
22	0.183	13.18
25	0.244	17.57

Table 4: O-D demand matrix for Test Network-2 (veh/hr).

O/D	10	20	30	40	50	60	70	80	90	100	110	120
10	—	100	100	—	—	100	100	100	100	100	100	100
20	60	—	60	—	—	60	60	60	60	60	60	60
30	60	60	—	—	—	60	60	60	60	60	60	60
40	60	60	60	—	60	60	60	60	60	60	60	60
50	40	40	40	40	—	40	40	40	40	40	40	40
60	50	50	50	—	—	—	50	50	50	50	50	50
70	70	70	70	—	—	70	—	70	70	70	70	70
80	110	110	110	—	—	110	110	—	110	110	110	110
90	90	90	90	—	—	90	90	90	—	90	90	90
100	30	30	30	—	—	30	30	30	30	—	30	30
110	—	—	—	—	—	—	—	—	—	—	—	45
120	—	—	—	—	—	—	—	—	—	—	69	—

Table 5: The ψ, E, and corresponding function values for Test Network-2.

λ	ψ	E	f_1	f_2	f
0.0	1.00	1248	1.240	1.000	1.000
0.1	1.00	1248	1.240	1.000	1.024
0.2	1.00	1248	1.240	1.000	1.048
0.3	1.00	1248	1.240	1.000	1.072
0.4	1.03	1290	1.203	1.034	1.101
0.5	1.04	1300	1.192	1.042	1.117
0.6	1.11	1350	1.119	1.082	1.104
0.7	1.17	1470	1.062	1.178	1.097
0.8	1.18	1620	1.047	1.298	1.097
0.9	1.21	1734	1.026	1.389	1.062
1.0	1.24	1872	1.000	1.499	1.000

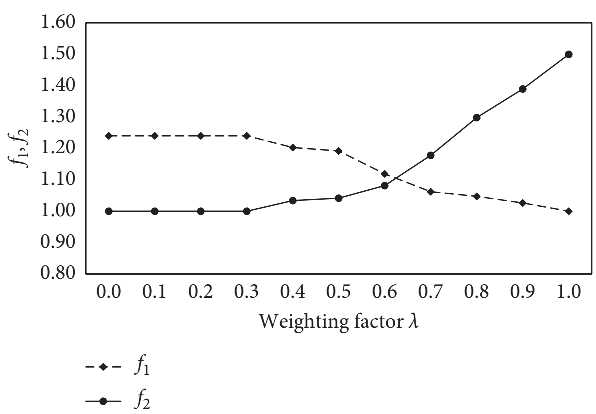


Figure 8: Solutions of f_1 and f_2 with various values of weighting factor λ for Test Network-2.

factor equals 0.6. This result is compatible with the results of the analysis performed for Test Network-1.

In case the weighting factor is equivalent to the value of 0.0, only the minimization of vehicle emissions is taken into account by local authority. Conversely, the maximization of network's reserve capacity is considered instead of the minimization of vehicle emissions in case weighting factor λ equals 1.0. The total amount of vehicle emissions has reached the value of 1872 in kg CO_2e as shown in Table 5 in case the O-D travel demand matrix has increased 24%. It should be pointed out that link flows do not exceed their capacities although the maximum demand multiplier has been applied to the O-D matrix. Optimized signal timings for Test Network-2 for weighting factor $\lambda = 0.6$ are given in Table 6 since this value is assumed as a critical point.

Table 6: Optimal signal timings for Test Network-2 for weighting factor $\lambda = 0.6$.

Cycle time (sec) c_i	Green timing (sec) $\Upsilon_{i,1}$	Green timing (sec) $\Upsilon_{i,2}$
45	20	15
51	16	25
36	14	12
81	24	47
75	37	28
40	16	14
74	25	39
74	50	14
30	10	10

5. Conclusions and Future Directions

This study presents a multiobjective bilevel programming model that considers the maximization of reserve capacity of a road network and the minimization of vehicle emissions by aiming to achieve environmentally friendly signal timings. A weighted sum method is introduced to find the Pareto-optimal solutions of the proposed multiobjective problem based on differential evolution algorithm framework. Two road networks are considered in order to show the applicability of the proposed model. Test Network-1 is used to reveal the effect of the weighting factor in solving the multiobjective optimization problem. It is found that the O-D demand matrix for Test Network-1 can be increased by about 2.14 times without links exceeding their capacities. According to the results of the Pareto-optimal analysis, it should be emphasized that the total amount of vehicle emissions significantly increases especially after the value of the weighting factor equals 0.6. In other words, increasing the network's reserve capacity leads to significantly increasing the amount of vehicle emissions in the network after this point. Test Network-2 is selected as the second numerical application to show the effectiveness of the proposed algorithm on relatively large networks. Results show that the total amount of vehicle emissions is found as the value of 1872 in case the O-D matrix is increased 24%. Pareto-optimal analysis reveals that the results for Test Network-2 are compatible with those of Test Network-1.

In conclusion, results obtained from the Pareto-optimal analysis may give a good opportunity to authorities to provide a balance between two conflicting objectives, namely, reserve capacity maximization and vehicle emissions minimization. In addition, results also show that the proposed multiobjective model may be a useful tool to provide sustainable signal timings considering environmental issues. In future studies, an application on a realistic road network is necessary to validate the results of the proposed model even though the findings for the two test networks give some new insights.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] F. V. Webster and B. M. Cobbe, *Traffic Signal*, Road Research Technical Paper No. 56, HMSO, London, UK, 1966.

[2] R. E. Allsop, "Estimating the traffic capacity of a signalized road junction," *Transportation Research*, vol. 6, no. 3, pp. 245–255, 1972.

[3] S. Yagar, "Capacity of a signalized road junction: critique and extensions," *Transportation Research*, vol. 8, no. 2, pp. 137–147, 1974.

[4] S. Yagar, "Addressing errors and omissions in paper on intersection capacity maximization," *Transportation Research Part B: Methodological*, vol. 19, no. 1, pp. 81–84, 1985.

[5] S. C. Wong, "On the reserve capacities of priority junctions and roundabouts," *Transportation Research Part B: Methodological*, vol. 30, no. 6, pp. 441–453, 1996.

[6] S. C. Wong and H. Yang, "Reserve capacity of a signal-controlled road network," *Transportation Research Part B: Methodological*, vol. 31, no. 5, pp. 397–402, 1997.

[7] H. Yang and J. Y. T. Wang, "Travel time minimization versus reserve capacity maximization in the network design problem," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1783, no. 1, pp. 17–26, 2002.

[8] G. Ziyou and S. Yifan, "A reserve capacity model of optimal signal control with user-equilibrium route choice," *Transportation Research Part B: Methodological*, vol. 36, no. 4, pp. 313–323, 2002.

[9] Y. E. Ge, H. M. Zhang, and W. H. K. Lam, "Network reserve capacity under influence of traveler information," *Journal of Transportation Engineering*, vol. 129, no. 3, pp. 262–270, 2003.

[10] H. Ceylan and M. G. H. Bell, "Reserve capacity for a road network under optimized fixed time traffic signal control," *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, vol. 8, no. 2, pp. 87–99, 2004.

[11] A. Chen, P. Chootinan, and S. C. Wong, "New reserve capacity model of signal-controlled road network," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1964, pp. 35–41, 2006.

[12] S.-W. Chiou, "Reserve capacity of signal-controlled road network," *Applied Mathematics and Computation*, vol. 190, no. 2, pp. 1602–1611, 2007.

[13] S.-W. Chiou, "An efficient search algorithm for road network optimization," *Applied Mathematics and Computation*, vol. 201, no. 1-2, pp. 128–137, 2008.

[14] S.-W. Chiou, "A hybrid approach for optimal design of signalized road network," *Applied Mathematical Modelling*, vol. 32, no. 2, pp. 195–207, 2008.

[15] S.-W. Chiou, "Optimization of limited network capacity with toll settings," *Information Sciences*, vol. 179, no. 1-2, pp. 109–119, 2009.

[16] S.-W. Chiou, "Optimization for signal setting problems using non-smooth techniques," *Information Sciences*, vol. 179, no. 17, pp. 2985–2996, 2009.

[17] E. Miandoabchi and R. Z. Farahani, "Optimizing reserve capacity of urban road networks in a discrete network design problem," *Advances in Engineering Software*, vol. 42, no. 12, pp. 1041–1050, 2011.

[18] S.-W. Chiou, "Optimal signal-setting for road network with maximum capacity," *Information Sciences*, vol. 273, pp. 287–303, 2014.

[19] J. Wang, W. Deng, and J. Zhao, "Road network reserve capacity with stochastic user equilibrium," *Transport*, vol. 30, no. 1, pp. 103–116, 2015.

[20] O. Baskan and C. Ozan, "Reserve capacity model for optimizing traffic signal timings with an equity constraint," *Highway Engineering*, Wiley-Blackwell, Hoboken, NJ, USA, 2017.

[21] O. Baskan, H. Ceylan, and C. Ozan, "A simultaneous solution for reserve capacity maximization and delay minimization problems in signalized road networks," *Journal of Advanced Transportation*, vol. 2019, Article ID 6203137, 18 pages, 2019.

[22] J. Kwak, B. Park, and J. Lee, "Evaluating the impacts of urban corridor traffic signal optimization on vehicle emissions and fuel consumption," *Transportation Planning and Technology*, vol. 35, no. 2, pp. 145–160, 2012.

[23] E. M. Ferguson, J. Duthie, and S. Travis Waller, "Comparing delay minimization and emissions minimization in the network design problem," *Computer-Aided Civil and Infrastructure Engineering*, vol. 27, no. 4, pp. 288–302, 2012.

[24] J. Lv, Y. Zhang, and J. Zietsman, "Investigating emission reduction benefit from intersection signal optimization," *Journal of Intelligent Transportation Systems*, vol. 17, no. 3, pp. 200–209, 2013.

[25] T.-Y. Liao, "A fuel-based signal optimization model," *Transportation Research Part D: Transport and Environment*, vol. 23, pp. 1–8, 2013.

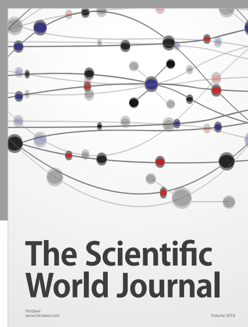
[26] X. Chang, B. Y. Chen, Q. Li, X. Cui, L. Tang, and C. Liu, "Estimating real-time traffic carbon dioxide emissions based on intelligent transportation system technologies," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, no. 1, pp. 469–479, 2013.

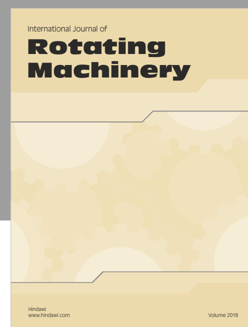
[27] L. Zhang, Y. Yin, and S. Chen, "Robust signal timing optimization with environmental concerns," *Transportation Research Part C: Emerging Technologies*, vol. 29, pp. 55–71, 2013.

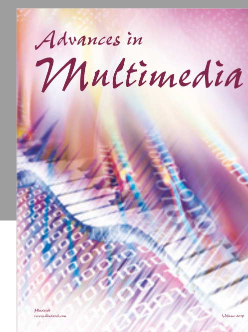
[28] Z.-C. Li and X.-Y. Ge, "Traffic signal timing problems with environmental and equity considerations," *Journal of Advanced Transportation*, vol. 48, no. 8, pp. 1066–1086, 2014.

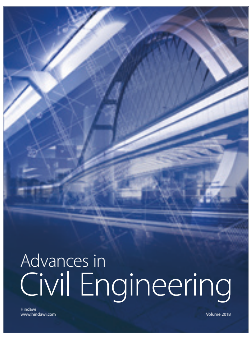
[29] F. Khalighi and E. Christofa, "Emission-based signal timing optimization for isolated intersections," *Transportation*

Research Record: Journal of the Transportation Research Board, vol. 2487, no. 1, pp. 1–14, 2015.
[30] A. Stevanovic, J. Stevanovic, J. So, and M. Ostojic, "Multi-criteria optimization of traffic signals: mobility, safety, and environment," *Transportation Research Part C: Emerging Technologies*, vol. 55, pp. 46–68, 2015.
[31] R. Yao, X. Wang, H. Xu, and L. Lian, "Emission factor calibration and signal timing optimisation for isolated intersections," *IET Intelligent Transport Systems*, vol. 12, no. 2, pp. 158–167, 2018.
[32] X. Li and J.-Q. Sun, "Turning-lane and signal optimization at intersections with multiple objectives," *Engineering Optimization*, vol. 51, no. 3, pp. 484–502, 2019.
[33] M. G. H. Bell and C. M. Shield, "A log-linear model for path flow estimation," in *Proceedings of the 4th International Conference on the Applications of Advanced Technologies in Transportation Engineering*, Y. J. Stephanedes and F. Filippi, Eds., pp. 695–699, Capri, Italy, June 1995.
[34] R. E. Allsop, "Evolving application of mathematical optimisation in design and operation of individual signal-controlled road junctions," in *Mathematics in Transport and Planning and Control*, J. D. Griffiths, Ed., pp. 1–24, Clarendon Press, Oxford, UK, 1992.
[35] M. Behnke and T. Kirschstein, "The impact of path selection on GHG emissions in city logistics," *Transportation Research Part E: Logistics and Transportation Review*, vol. 106, pp. 320–336, 2017.
[36] M. G. H. Bell and Y. Iida, *Transportation Network Analysis*, John Wiley & Sons, Chichester, UK, 1997.
[37] R. Storn and K. Price, "Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341–359, 1997.
[38] P. Civicioglu and E. Besdok, "A conceptual comparison of the Cuckoo-search, particle swarm optimization, differential evolution and artificial bee colony algorithms," *Artificial Intelligence Review*, vol. 39, no. 4, pp. 315–346, 2013.
[39] A. Deb, J. S. Roy, and B. Gupta, "Performance comparison of differential evolution, particle swarm optimization and genetic algorithm in the design of circularly polarized microstrip antennas," *IEEE Transactions on Antennas and Propagation*, vol. 62, no. 8, pp. 3920–3928, 2014.
[40] M. Dell'Orco, O. Baskan, and M. Marinelli, "A Harmony Search algorithm approach for optimizing traffic signal timings," *Promet—Traffic & Transportation*, vol. 25, no. 4, pp. 349–358, 2013.
[41] N. H. Gartner, J. D. C. Little, and H. Gabbay, "Optimization of traffic signal settings by mixed-integer linear programming," *Transportation Science*, vol. 9, no. 4, pp. 321–343, 1975.
[42] A. Jovanovic, M. Nikolic, and D. Teodorovic, "Area-wide urban traffic control: a bee colony optimization approach," *Transportation Research Part C: Emerging Technologies*, vol. 77, pp. 329–350, 2017.









Hindawi

Submit your manuscripts at
www.hindawi.com