An Improved Differential Evolution Algorithm for Coordinated Signalized Networks

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Abstract

The optimization of traffic signal timings can be considered as one of mostly used traffic management methods, controlling vehicle movements in order to decrease congestion. Thus, some indirect benefits can be gained by improving safety, and decreasing pollution and fuel consumption. As known, traffic signal setting is a prominent example of optimization field since it includes multi-objectives. Optimization of traffic signal timings is very difficult issue especially in coordinated signalized networks due to offset term. Especially in last two decades, meta-heuristic methods have been used by scientists rather than using exact methods to optimize signal timings due to difficulty of the problem. Additionally, although meta-heuristic methods are able to solve this problem without guarantee to achieve to a global solution, the performances of newly developed methods should be investigated to provide better solutions in particular with less computational effort. In this study, an improved differential evolution algorithm is proposed with two improvement strategies to optimize traffic signal timings in coordinated signalized networks. The performance comparison of improved and classical differential evolution methods has been conducted on a simple road network. Results showed that improved version outperforms the classical differential evolution algorithm in terms of objective function value and computational effort.

Keywords: *traffic signal timings, offset term, coordinated signalized networks, differential evolution algorithm,*

1 Introduction

Traffic signal control can be considered as one of the effective ways of traffic management in urban roads. In fact, one of the subjects of traffic signal control is optimization of traffic signal timings. It is clear that this is a prominent example of multi-objective optimization problems because of including different direct and indirect objectives. Some valuable methods to solve this multi-objective problem have been proposed for decades for signalized road networks. Although the solution of this problem is relatively easy for an isolated networks, it is very difficult issue for the Coordinated Signalized Networks (CSN) due to its components, namely "offset" and "common cycle time". For the CSN, TRANSYT is firstly proposed by Robertson (1969) and it is one of the most useful program in which a Performance Index (PI) is computed for a given signal timing and staging plan. It also allows to optimize signal timings for coordinated networks. PI can be presented in a different forms but its general form used in TRANSYT is the sum of a weighted linear combination of estimated delay and number of stops.

In the literature, different methods have been developed for solving signal timing optimization problem. Wong (1995) proposed some mathematical expressions for the derivatives of PI with respect to control variables. Results showed that the proposed expressions are needed less computational effort in comparison to numerical differentiation. One year later from this study, Wong (1996) enhanced an approach using group-based control variables in the context of Area Traffic Control (ATC) without considering traffic assignment procedure. About 10% improvements has been performed in comparison to the stage-based method used in TRANSYT. However, to overcome some disadvantages of this method by means of computational effort, parallel computing technique has been proposed by Wong (1997). Heydecker (1996) developed a decomposition approach to solve signal timings optimization problem without considering coordination between intersections. Afterwards, Wong et al. (2002) proposed a time-dependent TRANSYT model for improving the performance index. Girianna and

Benekohal (2002) presented two different Genetic Algorithm (GA) techniques for oversaturated signalized networks. On the other hand, as a pioneer study, Ceylan (2006) combined GA and Hill Climbing (HC) methods, and proposed an approach to decrease the search space through subsequent solution steps to solve the ATC problem. Another study related to meta-heuristic methods proposed by Chen and Xu (2006) aimed to solve traffic signal timings optimization problem by using Particle Swarm Optimization (PSO) algorithm. Chiou (2007a) presented a hybrid algorithm for the ATC problem by considering multi-objectives. Similarly, Chiou (2007b) presented an algorithm based on Quasi-Newton method to solve the ATC problem. Dan and Xiaohong (2008) developed an improved GA to determine optimal solution for the ATC problem for coordinated signalized networks. Zhang et al. (2009) presented a real-time signal control method based on discrete differential evolution algorithm by considering multi-objectives. Li (2011) presented a model to solve signal optimization problem for an arterial for oversaturated road networks considering queues between intersections. Liu and Chang (2011) further developed an arterial signal optimization model which considers queues on links and their interactions between lane groups.
He et al. (2012) developed a mathematical model to perform arterial traffic signal control, aiming to provide dynamical progression based on the probe information. Jones et al. (2013) drew the attention interdependency of signal controls and traffic flows in determining robust signal timings. On the other hand, Hu and Liu (2013) developed an arterial signal optimization model by considering vehicle-actuated signal coordination. Similarly, Maher et al. (2013) dealt with optimizing signal timings for the ATC by using cross-entropy method. Zhang et al. (2013) determined signal timings by introducing a bi-objective optimization model for coordinated signalized networks by considering environmental issues. Dell'Orco et al. (2013) and (2014) presented Harmony Search and Artificial Bee Colony algorithms for coordinated signalized networks, respectively. In the first study, they took the users' reactions for each candidate signal timing plan into account by solving stochastic traffic assignment whereas fixed set of link flows were considered in the second study. Bi et al. (2014) used fuzzy logic to solve traffic signal control problem for road networks. Cesme and Furth (2014) suggested an approach for traffic signal control called self-organizing signals based on actuated control. He et al. (2014) addressed in their study the conflicting issues between actuated-coordination and multimodal priority control. Ozan et al. (2015) combined Reinforcement Learning (RL) algorithm with TRANSYT-7F to optimize signal timings in CSN and to minimize the PI. Baskan and Ozan (2015) proposed a heuristic solution algorithm based on classical Differential Evolution (DE) for solving signalized road network design problem with link capacity expansions using bi-level programming. Gangi et al. (2016) suggested two steps approach for signal traffic control where the first step refers to each single junction optimization, the second to network coordination. Zhang et al. (2016) attempted to synchronize signalized long arterials and grid networks along the line of bandwidth maximization. Li et al. (2016) proposed a set of algorithms to design signal timing plans via deep RL. Dogan and Akgungor (2016) developed a fuzzy logic based method in order to optimize signal timings at an isolated four-leg intersection. Recently, continuous RL algorithms were applied to optimize traffic signal controllers in a traffic network by Aslani et al. (2017). Yu et al. (2017) proposed a convex programming approach to optimize signal timings for both vehicular and pedestrian traffic at an isolated intersection. Jovanovic´ et al. (2017) developed a new method based on Bee Colony Optimization (BCO) technique for optimizing traffic signal timings at the area-wide urban traffic control system.
The literature reveals that researchers preferred the use of meta-heuristic methods rather than using exact methods to solve different types of signal optimization problems by means of aiming different objectives. Additionally, although the heuristics methods existed are able to achieve good results in optimizing signal timings, their improved versions need to be investigated to provide better results. In this study, Improved Differential Evolution (IDE) algorithm is compared with the classical DE in optimizing traffic signal timings with fixed link flows in a coordinated signalized network. The remaining content of this paper is organized as follows. Problem formulation is provided in Section 2. The solution algorithm which contains classical DE and IDE methods is given in Section 3. Numerical applications are presented in Section 4. Conclusions and future directions are given in the last section.

2 Problem Formulation

As mentioned above, we aim to optimize traffic signal timings in coordinated signalized networks without solving traffic assignment problem. This means that we used fixed set of link flows for each candidate signal timing plan to determine the PI given in Eq. (1) by considering its constraints presented in Eq. (2). Our aim is to minimize the PI, which is generally expressed as the sum of delay and number of stops in a road network in TRANSYT-7F. In this study, we have used total operating cost as a measure of the effectiveness which is one of the several objective functions provided in TRANSYT-7F.

$$\min_{\boldsymbol{\psi},\mathbf{q}} PI = \sum_{a \in L} \left[w_a^d \cdot d_a\left(\psi\right) + K \cdot w_a^s \cdot S_a\left(\psi\right) \right] \tag{1}$$

s.t.

$$\boldsymbol{\psi}\left(c,\boldsymbol{\theta},\boldsymbol{\varphi}\right)\in\boldsymbol{\Omega}_0;\;\begin{cases} c_{\min}\le c\le c_{\max} \\ 0\le\theta\le c \\ \varphi_{\min}\le\varphi\le c \\ \sum_{i=1}^{z}\left(\varphi+I\right)_i=c \end{cases} \tag{2}$$

where d_a is delay on link a, $a\in L$, w_a^d is link-specific factor for delay d on link a, K is stop penalty factor, S_a is stops on link a per second, w_a^s is link-specific factor for stop S on link a, $\mathbf{q}$ is a vector of fixed set of link flows, $\boldsymbol{\psi}$ is a vector of signal setting parameters, c is network cycle time (sec), θ is offset time (sec), φ is stage green time (sec), $\boldsymbol{\Omega}_0$ is feasible region for signal timings, I is intergreen time (sec), and z is number of stages at each signalized intersection in a given road network. Additionally, the relation given Eq. (3) is used in order to provide the green timings constraints (Ceylan and Bell, 2004). The advantage of this relation is that it ensures the sum of the green times of each stage will be equal to the network cycle time.

$$\varphi_i=\varphi_{\min,i}+\frac{\varphi_i}{\sum_{k=1}^{z}\varphi_k}\left(c-\sum_{k=1}^{z}I_k-\sum_{k=1}^{z}\varphi_{\min,k}\right)\qquad i=1,2,\ldots,z \tag{3}$$

where φ_i is the green time (sec) for stage i, and $\varphi_{\min,i}$ the minimum green time for stage i.

3 Solution Algorithm

The DE algorithm is proposed as a strong and easy applicable algorithm by Storn and Price (1995). It guides the initial solution vectors towards to vicinity of the global or near-global optimum solution by means of a repeated cycle of mutation, crossover, and selection (Liu et al., 2010). The DE takes the advantage of two parameters in the solution process apart from the number of populations (NP). One of them is the mutation factor (F), which is used to obtain mutant vector from selected three solution vectors in the population and recommended to set between 0.5-1 by Storn and Price (1995). The second one is the crossover rate (CR) which represents the probability of consideration of the mutant vector. The recommended range of CR by Storn and Price (1995) is [0.8, 1]. The steps of the classical DE can be summarized within the context of signal timings in order to provide the brevity of the paper.

Initialization: At generation t, the initial population ($\boldsymbol{\psi}^t$) is randomly created with signal timings providing lower and upper bounds shown in Eq. (4). Taking the created decision variables with the fixed link flows into account for each solution vector (i.e. target vector) in the population, the objective function values ($PI^{j,t}$) are calculated using TRANSYT-7F traffic model as given in Eq. (1).

$$\boldsymbol{\psi}^t\left(c,\boldsymbol{\theta},\boldsymbol{\varphi}\right)=\begin{array}{c} \begin{array}{llllll} \varphi_{11} & \varphi_{12} & \qquad\qquad\qquad & \theta_1 & \theta_2 & \qquad c_1 \end{array} \\ \left[\begin{array}{l} \psi_1^{1,t},\psi_2^{1,t},\ldots\ldots\ldots\ldots,\psi_{i-2}^{1,t},\psi_{i-1}^{1,t},\ldots\ldots,\psi_i^{1,t} \\ \psi_1^{2,t},\psi_2^{2,t},\ldots\ldots\ldots\ldots,\psi_{i-2}^{2,t},\psi_{i-1}^{2,t},\ldots\ldots,\psi_i^{2,t} \\ \cdots\quad\cdots\qquad\qquad\cdots\quad\cdots\qquad\cdots \\ \cdots\quad\cdots\qquad\qquad\cdots\quad\cdots\qquad\cdots \\ \cdots\quad\cdots\qquad\qquad\cdots\quad\cdots\qquad\cdots \\ \psi_1^{j-1,t},\psi_2^{j-1,t},\ldots\ldots\ldots,\psi_{i-2}^{j-1,t},\psi_{i-1}^{j-1,t},\ldots\ldots,\psi_i^{j-1,t} \\ \psi_1^{j,t},\psi_2^{j,t},\ldots\ldots\ldots\ldots,\psi_{i-2}^{j,t},\psi_{i-1}^{j,t},\ldots\ldots,\psi_i^{j,t} \end{array}\right]_{NP*n} \end{array}\Rightarrow\begin{bmatrix} PI^{1,t}(\boldsymbol{\psi}^{1,t},\mathbf{q}) \\ PI^{2,t}(\boldsymbol{\psi}^{2,t},\mathbf{q}) \\ \cdots \\ \cdots \\ \cdots \\ PI^{j-1,t}(\boldsymbol{\psi}^{j-1,t},\mathbf{q}) \\ PI^{j,t}(\boldsymbol{\psi}^{j,t},\mathbf{q}) \end{bmatrix} \tag{4}$$

where $j\in\{1,2,\ldots,NP\}$, $i\in\{1,2,\ldots,n\}$ and n is the number of decision variables.

Mutation: This process is done by adding the weighted difference vector between two solution vectors to a third vector in the population. Mutant vector, $\mathbf{m}^t$, is determined as given in Eq. (5).

$$m_i^{j,t} = \psi_i^{1,t} + F(\psi_i^{2,t} - \psi_i^{3,t}) \tag{5}$$

where $\psi_i^{1,t}$, $\psi_i^{2,t}$ and $\psi_i^{3,t}$ are selected vectors in the population, and $\psi_i^{1,t} \neq \psi_i^{2,t} \neq \psi_i^{3,t}$.

Crossover: In order to create trial vector by combining the mutant and target vectors, the crossover mechanism is utilized. The vector created by using crossover operator is called trial vector ($\mathbf{r}^t$) and it can be determined as given in Eq. (6).

$$r_i^{j,t} = \begin{cases} m_i^{j,t}, & \text{if rand } (0,1) \leq CR \quad \text{or } i = i_{rand} \\ \psi_i^{j,t}, & \text{otherwise} \end{cases} \tag{6}$$

The crossover rate, CR, is compared with the randomly generated value between 0-1. If CR is greater, the trial vector is created from the mutant vector otherwise from the target vector. In addition, the statement, $i = i_{rand}$, where i_{rand} is the randomly selected integer number in the range [1, *n*], ensures that at least one member of the trial vector is taken from the mutant vector to make the trial vector different from the target vector at each generation.

Selection: After executing this step, each generation is completed. Firstly, the objective function value of each trial vector is calculated by using Eq. (1). After then the trial vector is compared with the target vector according to their objective function values and the best one gains to enter to the next generation as shown in Eq. (7).

$$\boldsymbol{\psi}^{t+1} = \begin{cases} \mathbf{r}^t, & \text{if } PI(\mathbf{r}^t) < PI(\boldsymbol{\psi}^t) \\ \boldsymbol{\psi}^t, & \text{otherwise} \end{cases} \tag{7}$$

3.1 Improved Differential Evolution (IDE) Algorithm

In spite of the fact that the classical DE algorithm is recognized as one of the powerful meta-heuristic algorithms, probably better solutions in optimizing traffic signal timings can be attained by improving it in different ways. Baskan and Ceylan (2014) developed a DE based algorithm with local search and mutation operators in order to solve continuous network design problem. Taking the solid performance of this method into account, we aimed to investigate its performance in optimizing traffic signal timings in coordinated signalized networks. For this purpose, we combined the Improved Differential Evolution (IDE) algorithm and TRANSYT-7F traffic model. The IDE algorithm has two improvements in respect to classical DE as given below:

Improvement 1: More than one mutation strategies are simultaneously taken into account by means of a parameter called Mutation Strategy Selection Rate (MSSR). If the MSSR is greater than the random number generated between 0-1, the classical mutation strategy is used as shown in Eq. (8). Otherwise, the second mutation strategy, in which the best solution vector found in the previous generation is considered, is used to obtain a mutant vector.

$$m_i^{j,t} = \begin{cases} \psi_i^{1,t} + F(\psi_i^{2,t} - \psi_i^{3,t}), & \text{if rand } (0,1) < \text{MSSR} \\ \psi_i^{1,t} + F(\psi_i^{best,t-1} - \psi_i^{2,t}), & \text{otherwise} \end{cases} \tag{8}$$

The proposed mutation strategy brings two novelties: (*i*) the MSSR allows of using two different strategies simultaneously, (*ii*) it considers the best solution vector at each generation with the probability of (1-*MSSR*). Thus, the proposed algorithm may have the potential to achieve faster to global or near global optimum solution of a given optimization problem. The value of the MSSR is taken between 0.9 and 1 according to the Baskan and Ceylan (2014).

Improvement 2: The second improvement strategy is the addition of a local search to the end of the each generation. In this process, $\mathbf{dx}^t$ is generated from the range of (γ_1^t, γ_2^t) as shown in Eq. (9). This range is selected according to the upper and lower bounds of the signal timings constraints given in Eq. (2). Following this, it is added to the vector of best solution and then the candidate vector (**cv**) is created as can be seen in Eq. (10). If the candidate vector's fitness function value is better than that of the best solution, it is replaced with the best solution in the population. Otherwise, $\mathbf{dx}^t$ vector is subtracted from the vector of the best solution in order to search possible better solutions in other direction. Once the local search is ended, the vector of $\mathbf{dx}^t$ is multiplied with a number of 0.9 to reduce the search space around the best solution step by step as given in Eq. (11). The flowchart of the developed meta-heuristic solution algorithm is given in Fig. 1.

$$\mathbf{dx}^{t} = rand\ (\gamma_1, \gamma_2) \tag{9}$$

$$\mathbf{y}^{cv,t} = \mathbf{y}^{best,t} \pm \mathbf{dx}^{t} \tag{10}$$

$$\mathbf{dx}^{t+1} = \mathbf{dx}^{t} * 0.9 \tag{11}$$

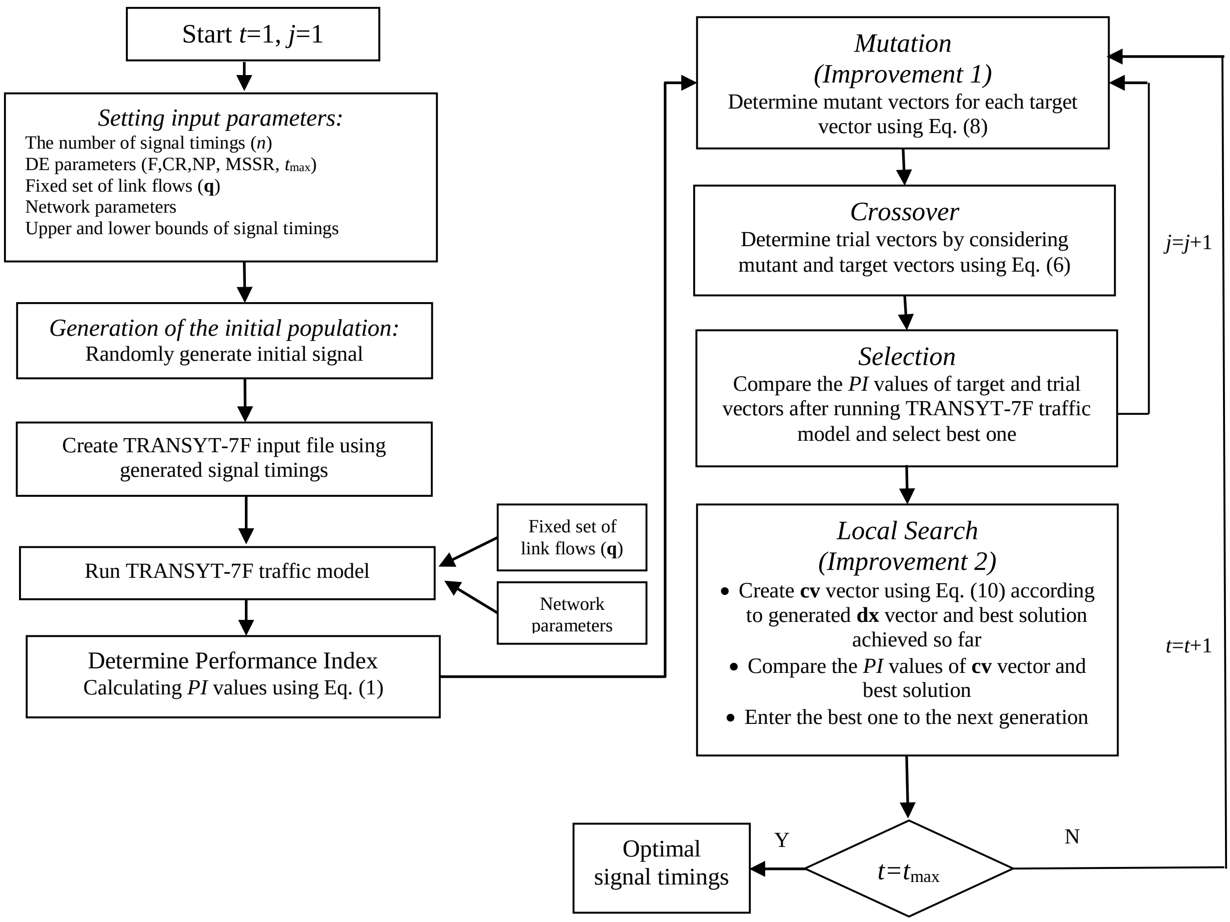

Figure 1. The flowchart of the developed meta-heuristic solution algorithm

4 Numerical Application

In this section, **D**ifferential **E**volution **TRANS**YT-7F (DETRANS) and **I**mproved **D**ifferential **E**volution **TRANS**YT-7F (IDETRANS) models are compared. These models include two parts: (*i*) meta-heuristic algorithm: DE and IDE algorithms; (*ii*) TRANSYT-7F traffic model. The meta-heuristic algorithm optimizes traffic signal timings while TRANSYT-7F is used to determine network PI for a given signal timing plan. The performance comparison of DETRANS and IDETRANS has been conducted by solving a two-junction network (Ceylan, 2002). The basic layout of the two-junction network and stage plans are given in Figs. 2 and 3. This network includes 8 links and 7 signal setting variables at two signal-controlled junctions. Saturation flow and free-flow travel time of all links are 1800 veh/h and 20 sec, respectively. The fixed set of link flows is given in Table 1.

Table 1. Fixed set of link flows (Ceylan, 2002)

Link flows in veh/h					
q_1	q_2	q_3	q_4	q_5	q_6
615.00	45.00	225.00	615.00	225.00	45.00

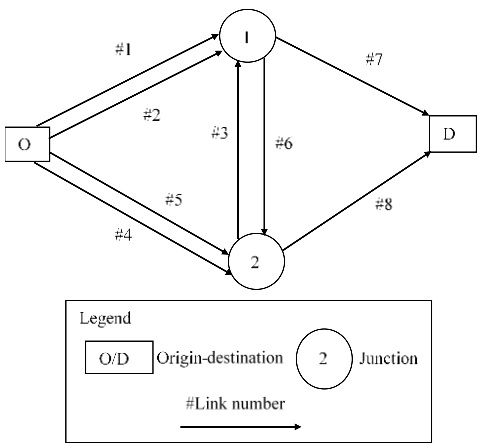

Figure 2. Two-junction network (Ceylan, 2002)

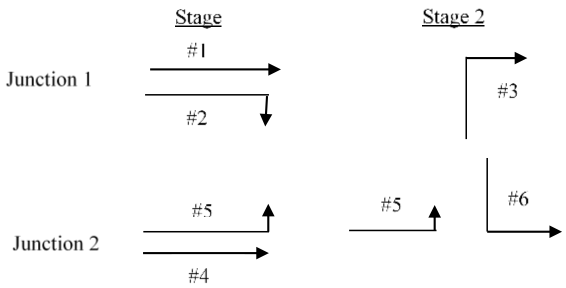

Figure 3. Representation of signal stages (Ceylan, 2002)

The constraints for signal timing variables are set: $36 \le c \le 120$; $0 \le \theta \le c$; $\varphi_{\min} = 7$; $I_{1-2} = I_{2-1} = 5$. The developed models are executed with the following DE parameters: crossover rate (CR) is 0.8, mutation factor (F) is 0.8, population size (NP) is 15, and maximum generation number ($t_{\max}$) is 150. The total computation times for the number of maximum generations in DETRANS and IDETRANS models took about 43 and 53 minutes, respectively. Convergence graphs of both models are given in Figure 4. They show totally different trends even though both models are initiated at the same initial PI value as 20.07. While the PI was found as 18.01 at the 115th generation in the DETRANS model, it was determined as 16.40 at the 15th generation in IDETRANS. In other words, the improvement rates for DETRANS and IDETRANS models are about 11% and 22% according to the initial PI value, respectively. Although the computation time of the IDETRANS model considering maximum number of generation was a bit more than that of the DETRANS, it reaches to its best PI value only after 15th generation. This result shows that the IDETRANS outperforms the DETRANS in terms of both objective function value and computational effort. Additionally, the common cycle times are obtained as 61 and 69 seconds for both models as can be seen in Table 2.

Table 2. The results for fixed set of link flows

Model	**Performance Index** (PI)	**Cycle Time** c (s)	**Junction number**	**Duration of stages** (sec) **Stage 1** φ_{11}	**Stage 2** φ_{12}	**Offsets** (sec) θ
DETRANS	18.01	61	1	40	21	0
			2	41	20	61
IDETRANS	16.40	69	1	48	21	0
			2	52	17	33

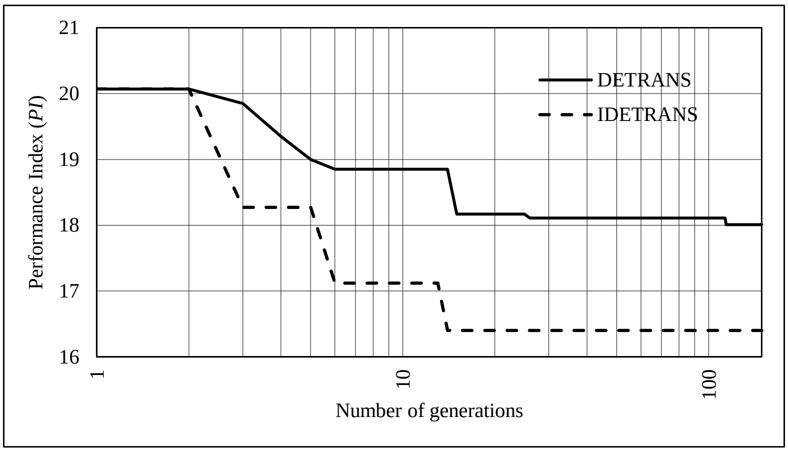

Figure 4. The convergence of DETRANS and IDETRANS for the two-junction network

5 Conclusions

This study deals with optimizing traffic signal timings in coordinated signalized networks. For this purpose, IDETRANS model is developed by means of combining IDE algorithm and TRANSYT-7F traffic model. In order to compare the performance of IDETRANS and DETRANS models, they are applied on a small road network. IDETRANS model is able to improve PI about 22% according to its initial value while the DETRANS improves only about 11%. As a result, IDETRANS may be alternative for optimizing traffic signal timings in coordinated signalized networks. Further study should be on testing IDETRANS on real city networks.

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