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نماذج تقدير التأخير للتقاطعات ذات الإشارات باستخدام خوارزمية التطور التفاضلي

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الخلاصة

ويعتبر التأخير معلما هاما في تحسين إشارات الحركة وتحديد مستوى الخدمة في تقاطع إشارة، نظرا لأنه يعكس مباشرة وقت السفر المفقود واستهلاك الوقود. ولذلك فإن التقدير الدقيق للتأخير مسألة هامة. والغرض من هذه الدراسة هو تطوير نماذج تأخير جديدة مع معلمات المدخلات أقل باستخدام واحدة من التقنيات الذكية الاصطناعية. في هذا البحث تم تطوير ثلاثة أنواع من نماذج تقدير تأخر التطور التفاضلي، أي الخطية، الأسي، التربيعي، باستخدام أسلوب التطور التفاضلي. وعند وضع نماذج التأخير، تم النظر في النسبة الخضراء (g / C الفعالة الخضراء إلى طول الدورة) ودرجة التشبع ($x = v / c$؛ الحجم إلى السعة). تغير الأول من 0.35 إلى 0.60، وتراوحت الثانية بين 0.7 إلى 1.4. تمت مقارنة مخرجات النموذج تحليليا لنماذج التأخير (HCM) والأسترالي (Akçelik). أوضحت نتائج الدراسة أن قيم الأخطاء التربيعية R^2 ومتوسط الخطأ التربيعي ومتوسط الخطأ المطلق لنماذج تخمين التأخير هي على التوالي: 0.97 و207.98 و12.12 كانت أفضل من نماذج التأخير التحليلي ونماذج النماذج الأخرى. ونتيجة لذلك، يمكن استخدام النموذج التربيعي لنموذج (DEDEM) كنموذج تقدير بديل للتأخير، ويمكن استخدام نهج المعادلات التفاضلية كخوارزمية نموذجية أيضا.

Delay estimation models for signalized intersections using differential evolution algorithm

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ABSTRACT

Delay is an important parameter in the optimization of traffic signals and the determination of the level of service (LOS) of a signalized intersection since it directly reflects the lost travel time and fuel consumption. The accurate estimation of delay is, therefore, an important issue. The purpose of this study is to develop new delay models with less input parameters by using one of the artificial intelligent techniques. In this research, three types of differential evolution delay estimation models (DEDEM), i.e. linear, exponential and quadratic, were developed using differential evolution (DE) approach. In developing of the delay models, the green ratio (g/C effective green to cycle length) and the degree of saturation (x=v/c; volume to capacity) were considered. The first one changed from 0.35 to 0.60, the second one varied between 0.7 and 1.4. The model outputs were compared analytically to the HCM and Australian (Akçelik) delay models. The study results illustrated that R2, Mean Square Error (MSE) and Mean Absolute Error (MAE) values of DEDEMquadratic, which are 0.97, 207.98, 12.12 respectively, were better than analytical delay models and other types models. As a result, the quadratic form of DEDEM model can be used as an alternative estimation model for delay, and DE approach can be utilized as a model-fitting algorithm as well.

INTRODUCTION

Estimating vehicle delay at signalized intersections is an important issue into which the researchers have been putting effort for years. Delay is one of the major parameters, which are used for estimating the LOS of an intersection. Generally, delay minimization constitutes a significant parameter for the entire transportation systems, while operating parameters for signals are determined. Therefore, the delay should be calculated as accurately as possible, in order to minimize error for optimum operation of the signal systems.

Delay concept was endeavored for the first time by traffic engineers and researches about 50 years ago. Various analytical models have been developed with different assumptions. Webster (Webster, 1958), HCM (Highway Capacity Manual, 2000), and Akçelik (Akçelik, 1981) delay models are some of the commonly used models. In these models, delay basically consists of uniform and random components. While the uniform component of the delay results from the interruption of traffic flow by traffic signals at intersections, its random component is caused by the fluctuation in vehicle arrivals. Although the Webster model is known as one of the oldest models in the literature, it is not useful and efficient for oversaturated flow. HCM model is a time dependent delay model, which has been improved over the years. The Australian delay model, which is also known as the Akçelik delay model, was derived using the coordinate transformation technique. This model is different from other time dependent delay models with minimum degree of saturation parameter

x_0. The Akçelik delay model predicts zero overflow delay when the degree of saturation is smaller than x_0. Dion *et al*. (2004) defined five delay models for signalized intersection: deterministic queuing model, shock wave delay model, steady-state stochastic delay model, time-dependent stochastic delay model, and, finally, microscopic simulation delay model. Dion *et al*. (2004) has shown that there is coherence among all analytical models. Wang *et al*. (2015) compared the delay estimation models for signalized intersections. Four different commonly adopted models, which are deterministic queuing, Webster, highway capacity manual (HCM) 2000, and Shanghai adjusted models, were compared using field data observed from three signalized intersections in Shanghai. The results indicate that the HCM 2000 model and Shanghai adjusted model perform similarly and satisfactorily under various v/c ratios, while the deterministic queuing model has better performance when the v/c ratio is extremely high, but the Webster model is mostly inadequate at coordinated signalized intersections.

Previous studies about estimation of delay methods showed that there were a lot of parameters like degree of saturation, capacity, queue lengths, and so on affecting delay. Selecting of important and more effective parameters is a crucial step for more accurate estimation. Also, in the estimating of delay, not only using correct parameters but also employing feasible and influential methods is a major requirement. Researches illustrated that there were some deficiencies in analytical methods, and some novel algorithms should be utilized to solve equations that were proposed for delay.

So as to overtake the deficiencies in the prevalent delay models, researchers focused on new methods and intelligent algorithms like differential evolution algorithm (DEA), genetic algorithm (GA), particle swarm optimization (PSO), fuzzy-logics (FL), and so forth. Atalay (2004) compared some analytical delay models with artificial intelligence methods and noticed that ANFIS closely estimated vehicle delay to observed delay values. Another comparative study among the HCM, Akçelik, neuro-fuzzy, and artificial neural network delay models was performed by Murat (Murat, 2006), and his research results illustrated that the neuro-fuzzy model gave the best performance compared to the other models.

The differential evolution (DE) algorithm, proposed by Storn and Price (1995), is a fast and simple technique that performs well on a wide variety of engineering optimization problems. DE has only three or four operational parameters and can be coded in about 20 lines of pseudo-code. Various applications in traffic and transportation engineering, such as traffic signal control, delay estimation, road design, and routing and scheduling of transport, have been studied by utilizing DE algorithm. Ceylan (2013) applied DE algorithm for optimal design of signal controlled road networks and showed that results outperformed the GA and HS-based models in terms of the network performance when the proposed model was compared to two previous works done using Genetic-Algorithms (GAs) and Harmony-Search (HS) based models. In another application of DE, Yunrui *et al*. (2014) examined traffic signal control with DE and then indicated that DE is efficient to decide the parameters of the system, and results are good enough in terms of reduction of the delay, queue length, and parking rate. Feng-Tse Lin (2010) used DE for the transportation problem, and results showed that it was as efficient as genetic algorithms in solving transportation problems. Akgüngör and Korkmaz (2015) analyzed and modelled the relationship between stopped and control delays by employing DE algorithm. The results of this study revealed that the conversion ratio cannot be accepted to be constant, usually taken as 0.76 for practical purposes since it is dependent on changing operation and traffic conditions.

There are some studies purposing to minimize the amount of delay by optimizing the traffic signal control of an intersection via DE algorithm in the literature. However, this study directly focusses on the estimation of delay unlike previous studies. This study aims at pioneering similar studies in the future. This research has two objectives, ; the first is to develop new, simple and practical delay models adhered adhering to two parameters that are green ratio (g/C) and degree of saturation (x = v/c; volume to capacity ratio) employing DE, and to evaluate the performance of the proposed models against to existing analytical models. Secondly, the study aimed at investigating the applicability and efficiency of DE in delay estimation.

This paper is organized as follows. Section 2 explains the steps of DE in detail. Section 3 presents the delay models developed by using the algorithm given in Section 2 and compares the performance of the developed models to against existing ones. Finally, the conclusion is discussed in the last section.

MATERIALS AND METHODS

Differential evolution algorithm

DE is an efficient and powerful population-based stochastic search technique for solving engineering optimization problems such as non-differentiable, non-continuous, non-linear, and multi-dimensional problems. It was developed to optimize parameters with real values and functions. If the problem is non-linear, multi-dimensional or it has many local minima, DE can give approximate results in such cases.

DE has a basic architecture consisting of four stages, presented in Figure 1.

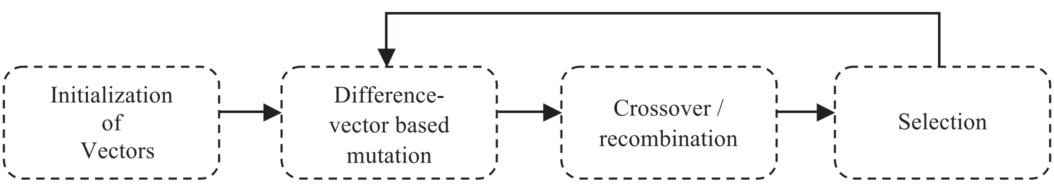

Fig. 1. Main stages of the DE algorithm.

Initialization step

Lower and upper bounds for each parameter are defined. And then, uniformly distributed random numbers between 0 and 1 are generated, defined in Eq (1) below:

$$X_{j,i}^{(0)} = X_j^{min} + rand_j(0,1) \,.\, (X_j^{max} - X_j^{min}), \tag{1}$$

where X_j^{max} and X_j^{min} are the upper and lower bounds of the jth parameter, i = 1... Np (number of population) and j = 1…D (number of parameters in fitness function).

Mutation

In order to expand the search space, the mutation step is applied after the initialization. Three selected chromosomes from the population are employed to create the mutant vector defined by the following equation. The mutation factor (F) is a constant ranging from 0 to 2.

$$X_i'^{(G)} = X_a^{(G)} + F(X_b^{(G)} - X_c^{(G)}), \qquad i=1\ldots Np \tag{2}$$

in which $X_i'^{(G)}$ is the mutant vector, $X_a^{(G)}$ is the base vector, G is the generation number, F is the scaling constant, and $X_b^{(G)}$ and $X_c^{(G)}$ are random vectors to produce the difference vector.

DE offers several variants or strategies for optimization illustrated by DE/x/y/z. Here, x refers to the vector employed to create mutant vectors, y is the number of difference vectors used in the mutation process and z is the crossover scheme utilized in the crossover operation. Below are four of the well-known mutation vectors in the literature.

DE/rand/1/bin: $V_{i,g} = X_{r0,g} + F(X_{r1,g} - X_{r2,g})$ (3)

DE/best/1/bin: $V_{i,g} = X_{best,g} + F(X_{r1,g} - X_{r2,g})$ (4)

DE/rand-to-best/2/bin: $V_{i,g} = X_{i,g} + K\left(X_{best,g} - X_{i,g}\right) + F\left(X_{r1,g} - X_{r2,g} + X_{r3,g} - X_{r4,g}\right)$ (5)

DE/target-to-best/1/bin: $V_{i,g} = K(X_{best,g} - X_{i,g}) + F(X_{r1,g} - X_{r2,g})$ (6)

where $X_{best,g}$ is the best fitness in population and *K* is randomly chosen within the range [0, 1].

Crossover

In this step, the major objective is crossing over the mutant and target vectors. The trial vectors (X_i'') are generated by mixing mutant and target vectors according to the chosen probability distribution.

$$X_i''^{(G)} = \begin{cases} X_i'^{(G)} \; if \; rand_j(0,1) \le C_r \; or \; j = j_{rand} \\ X_i^{(G)} \qquad\qquad otherwise \end{cases} \tag{7}$$

where C_r is the crossover probability between 0 and 1, $rand_j$ is a uniform random number generator, and j_{rand} is a randomly chosen trial parameter, which is taken from the mutant to ensure that the trial does not duplicate $X_i^{(G)}$.

Selection

The final step of DE is the selection operation which is used to choose the better population between trial and target vector for minimization of the fitness function. If the trial vector has a better value than the target vector, then it is transferred in the next generation instead of target vector. Otherwise, the target vector retains its place for next generation. The equation is defined as follows.

$$X_i^{(G+1)} = \begin{cases} X_i''^{(G)} \ if \ f\left(X_i''^{(G)}\right) \le f\left(X_i^{(G)}\right), i = 1 \ldots Np \\ X_i^{(G)} \quad\quad\quad\quad\quad\quad\quad\quad otherwise \end{cases} \tag{8}$$

There are three control parameters which are F, Cr , and population size (Np) in DE. Storn and Price (1995) suggested optimal value range for these parameters.

F = [0.5-1]; Cr = [0.8-1]; Np ≈ 4.D -10. D

Initial algorithm parameters are needed to be initialized. These parameters include number of population (NP) members, number of parameters of the objective function (D), crossover probability (CR) constant from interval [0, 1], maximum number of iterations (itermax), vector of lower bounds and vector of upper bounds of initial population (XVmin and XVmax), strategy, refresh, and DE-step size (F) from interval [0.5-1].

Flow chart of DE is shown in Figure 2 as below:

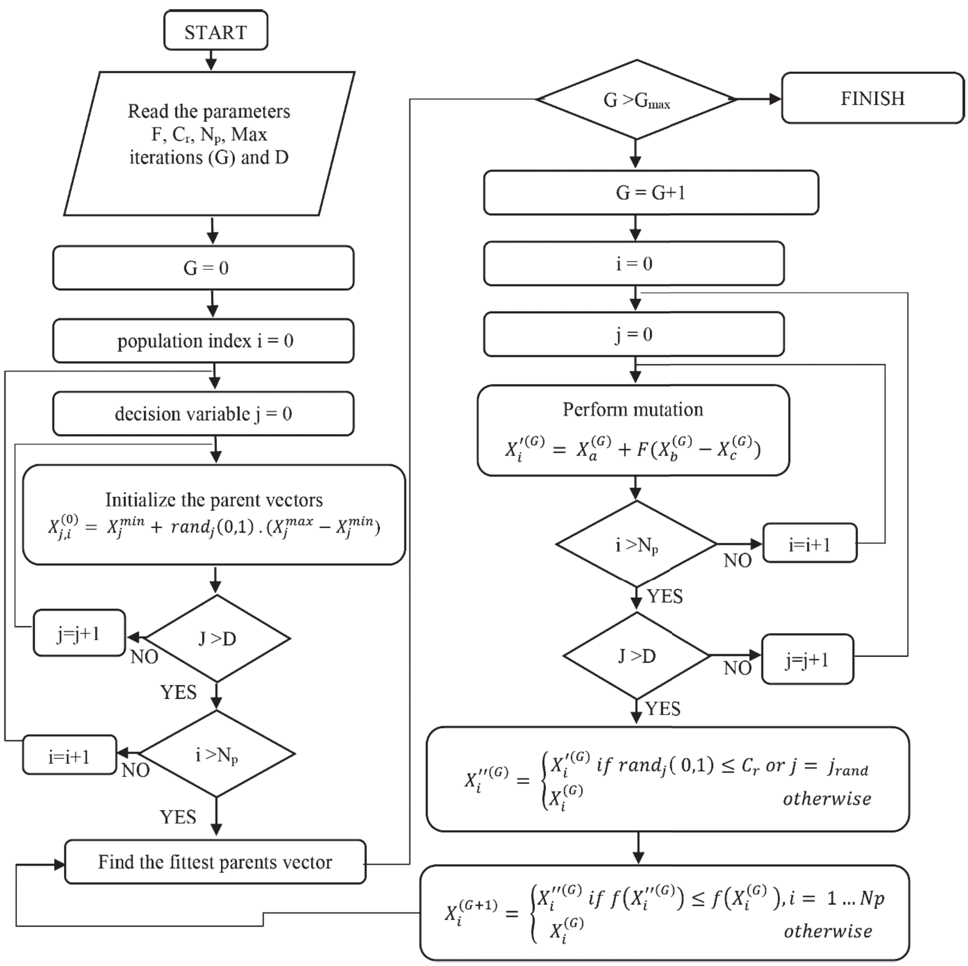

Fig. 2. Diagram of the DE algorithm

Mutation, crossover and selection stages used in DE are the same as operators in GA. Unlike GA, each operator is not applied to the entire population one by one. While GA works based on probability distribution function, DE uses a mutation process based on differences of randomly selected vectors. Thus, used using this simple mutation process improves the performance of the algorithm and makes it more robust. Finding the true global minimum regardless of the initial parameter values, fast convergence, and using a few control parameters are major advantages of this algorithm. Other significant properties are being simple, fast, easy to use, and very easily adaptable for integer and discrete optimization.

Development of models

Delay estimation is a comprehensive subject and has been gradually improving by including new solution methods for years. In order to solve delay equations and overtake deficiencies in previous studies, different heuristic methods like genetic algorithm, fuzzy-logic, particle swarm optimization, and so on have been experimented. DE is one of them and has a lot of advantages to in solve solving equations. To be more practical, the most effective parameters and DE algorithm have been used. As reference values to evaluate the performance of models, simulation results have been utilized. So as to obtain delay values according to input parameters, a simulation program (CORSIM) has been preferred in this study.

Simulation and experimental design

TSIS-CORSIM is a microscopic traffic simulation software package for signal systems, highway systems, freeway systems, or a combined combination of the three of them. CORSIM (CORridor SIMulation) consists of an integrated set of two microscopic simulation models that represent the entire traffic environment. NETSIM represents traffic on urban streets. FRESIM represents traffic on highways and freeways. Microscopic simulation models the movements of individual vehicles, which include the influences of geometric conditions, control conditions, and driver behavior. This simulation program is one of the commonly used software programs as Synchro Traffic and VISSIM in the traffic engineering studies. Sun and Elefteriadou (2010) investigated the implementation of a lane-changing model based on driver behavior. They proposed a lane-changing model and compared the performance of the proposed model with the original lane-changing model embedded in CORSIM. Sun et al. (2013) used CORSIM and VISSIM simulation programs to compare their performance for urban street network. It is showed shown that each simulator has its particular advantage in replicating real traffic. The CORSIM simulation program has been utilized in this study since it has a lot of advantages as being practical, less costly, quickly obtained obtaining results, and including several measures of effectiveness. A lot of indicators as fuel consumption, delay, vehicle emission, and so on have been obtained via CORSIM; however, delay times especially as total delay, control delay, and queue delay have been examined, and simulated delay values have been used as comparison values for other models. Thus, the delay values for different traffic and control conditions have been practically got from CORSIM.

The intersection shown in Figure 3 was simulated on TRAF-NETSIM, which is the network simulation model of CORSIM. Every link in the intersection consisted of one line and controlled by pre-timed controller. The E-W links were considered major approaches, while the N-S links were considered minor approaches. The intersection was operated with on two phases. In a pre-timed controller, the cycle length was between 60 and 150 seconds, and also yellow and red intervals were 2 and 1 seconds for all approaches respectively, The green ratio ranged from 0.35 to 0.60 for major approaches. Therefore, the displayed green times were set according with to this green ratio in major and minor approaches. A start-up lost time of 2 seconds, a mean discharge headway of 2 seconds and a free flow speed of 30 mph (48.3 km/h) were used in the simulation runs.

Saturation flow varied between 1500 and 1800 vph. The degree of saturation for major approaches ranged from 0.7 to 1.4 and also is also considered a constant value as at 0.7 for minor approaches. Entry link volumes were between 600 vph and 1400 vph in major approaches, 300 vph and 800 vph in minor approaches as well. The percentage of trucks and carpools for all links was given as 15% and 10 %, respectively.

In this experiment, the duration of each simulation run was 15 minutes, and, for each entry link volume, 10 simulation runs with different random seed numbers, which NETSIM uses to generate varying driver and vehicle characteristics, were made. The random seed numbers were not varied from one degree of saturation to the other, and kept constant during multiple runs to obtain identical traffic movements.

Delay time for each link in major approaches in accordance with different traffic situations has been obtained from CORSIM simulation output. Since there are different delay types as overall delay, and control and queue delay in output of simulation, the overall delay value of each link has been preferred. For each traffic condition, the average of 10 simulations was determined and, therefore, a total of 253 delay data were obtained from major approaches.

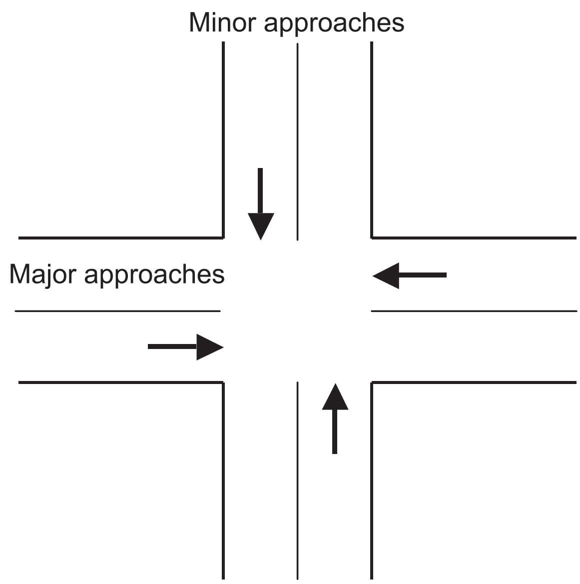

Fig. 3. The simulated intersection.

Differential evolution delay estimation model

The differential evolution operates in accordance with selection rules, which are described by the theories and statutes of evolutionary genetics. The model endeavors to reach the fittest model, which is close to the observed parameters values. To provide the fittest model, the DE works with the operations that are executed based on fitness evolution. The fitness points out the beneficence of the design model, and thus, the objective function is a reasonable selection in the fitness measure. The three forms of the DEDEM model look for the fit members by minimizing the Sum of Squared Errors (SSE).

The linear form of DEDEM can be written as follows:

$$\mathrm{DEDEM}_{\mathrm{Linear}} = w_1 * x_1 + w_2 * x_2 + w_3 \tag{9}$$

The exponential form of DEDEM can be expressed as follows:

$$\mathrm{DEDEM}_{\mathrm{Exponential}} = w_1 * x_1^{w_2} * x_2^{w_3} \tag{10}$$

The quadratic form of DEDEM can be formed as follows:

$$\mathrm{DEDEM}_{\mathrm{Quadratic}} = w_1 * x_1 + w_2 * x_2 + w_3 * x_1 * x_2 + w_4 * x_1^2 + w_5 * x_2^2 + w_6 \tag{11}$$

where X_1, X_2 are the green ratio (g/C) and degree of saturation (x=v/c), respectively, and wi are the corresponding weighting factors.

The fitness function (i.e., minimum sum of squared errors), F (x), gets the following form:

$$MinF(x) = \sum_{n=1}^{m} (D_{Simulated} - D_{Estimated})^2 \tag{12}$$

where $D_{simulated}$ and $D_{estimated}$ are the simulated and estimated delay values, and m is the numbers of input data. Based on previous study, Mallipeddi *et al.* (2011) suggested that convenient values of DE parameters can be chosen between 4D and 10D for NP, 0.9-1 for CR, and 0.4-0.95 for F. Hence, the user specified parameters in Table 1 are selected for the DEDEM model.

Table 1. Parameters of DE

Population size (NpNP)	50
Crossover rate(CR)	0.95
Scaling factor (F)	0.95
Mutation strategies	DE/best/1/exp
Max. Number number of iterations	200

Some different parameters' values among the above ranges were applied and then it was noticed that there is no significant impact to estimate the weighting values of the model except the time catching the value. When CR and F values especially are closer to their upper bounds, the algorithm can find the weighting values in early iterations. Additionally, although the 0.95 value of CR is not a common choice, this value is the best to optimize our equations, because of the fact that input variables of our problem have a wide range of values and are discrete values. Therefore, in our study, the optimum parameters, which are shown in Table 1, were preferred for DE.

After application of the linear, exponential, and quadratic forms of the DEDEM model, Eqs. (13-15) given below are obtained:.

$$\mathrm{DEDEM}_{\mathrm{Linear}} = 42.449 * x_1 + 314.158 * x_2 - 241.530 \quad (13)$$

$$\mathrm{DEDEM}_{\mathrm{Exponential}} = 82.780 * x_1^{0.081} * x_2^{3.14} \quad (14)$$

$$\mathrm{DEDEM}_{\mathrm{Quadratic}} = -187.166 * x_1 - 380.230 * x_2 + 131.533 * x_1 * x_2 + 43.717 * x_1^2 + 288.718 * x_2^2 + 183.946 \quad (15)$$

209 pieces of data taken from CORSIM, a microscopic traffic simulation program, are used to predict weighting values of DEDEM model, and the remaining 44 pieces of data are used to test the model results. The output of training and test data are compared with the analytical methods and DEDEM model using mean absolute error (MAE), mean square error (MSE), and R^2 defined by Eqs. (16-18), and the results are illustrated in Tables 2 and 3. The simulated and estimated values are graphically presented in Figures (4-8).

$$MSE = {}^{1}/_{m} \sum_{n=1}^{m} (D_{Simulated} - D_{Estimated})^2 \quad (16)$$

$$MAE = {}^{1}/_{m} \sum_{n=1}^{m} |(D_{Simulated} - D_{Estimated})| \quad (17)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n} (Co_{Observed} - Co_{estimated})^2}{\sum_{i=1}^{n} (Co_{Observed} - Co_{mean})} \right] \quad (18)$$

As seen from Tables 2 and 3, when the performances of existing and proposed models are compared to each other, test R^2 values obtained by means of test data, are 0.95, 0.97, 0.93, 0.96, and 0.97 for HCM, Akçelik and linear, exponential, and quadratic forms of DEDEM models, respectively. The Quadratic DEDEM model has the best result according to MAE, MSE, and R^2 values. It is more compatible with Akçelik's analytical model. Moreover, quadratic model is closer to simulated values as demonstrated in Figure 9. Thus, the proposed quadratic delay model can be used as an alternative model to estimate delay at signalized intersections.

Table 2. Analytical methods statistics of training and test data for comparison

	HCM			Akçelik		
	MAE	MSE	R^2	MAE	MSE	R^2
Train	17.01	440.01	0.96	15.24	357.38	0.98
Test	16.90	428.87	0.95	13.20	269.08	0.97

Table 3. DEDEM model statistics of training and test data for comparison

	Linear			Exponential			Quadratic		
	MAE	MSE	R^2	MAE	MSE	R^2	MAE	MSE	R^2
Train	19.06	574.38	0.95	13.04	252.24	0.96	11.90	207.60	0.97
Test	21.97	773.92	0.93	13.02	250.96	0.96	12.12	207.98	0.97

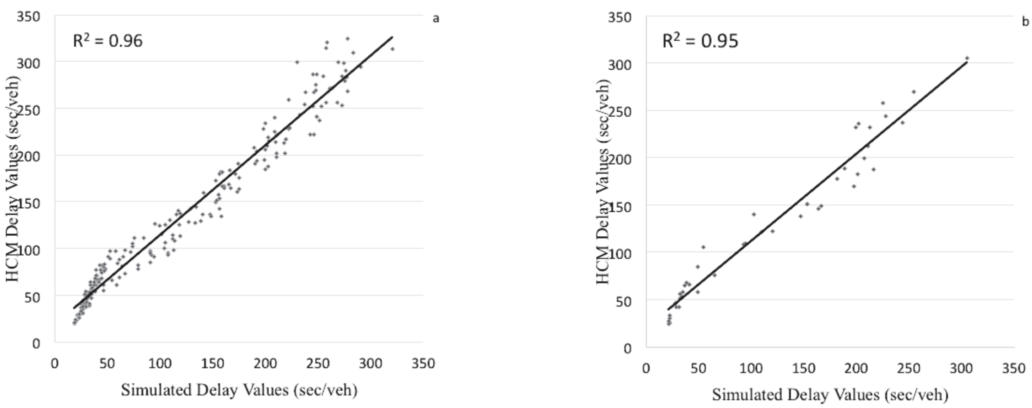

Fig. 4. R^2 results of (a) training and (b) testing data for the HCM model

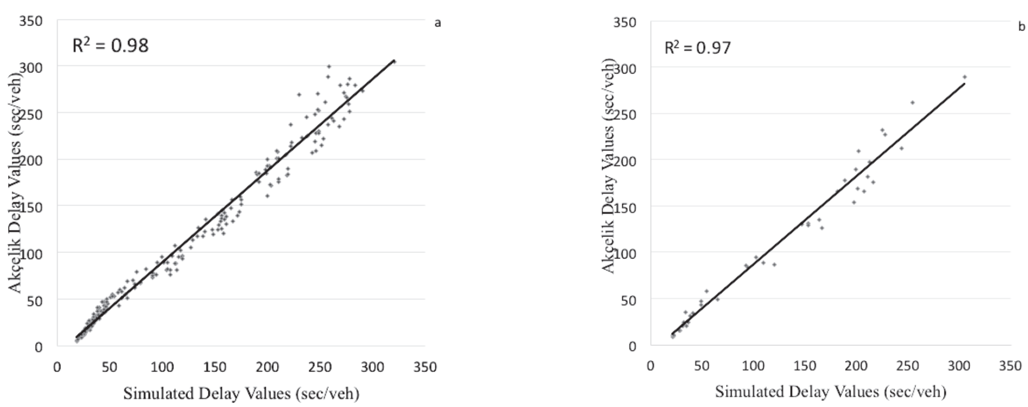

Fig. 5. R^2 results of (a) training and (b) testing data for the Akçelik model

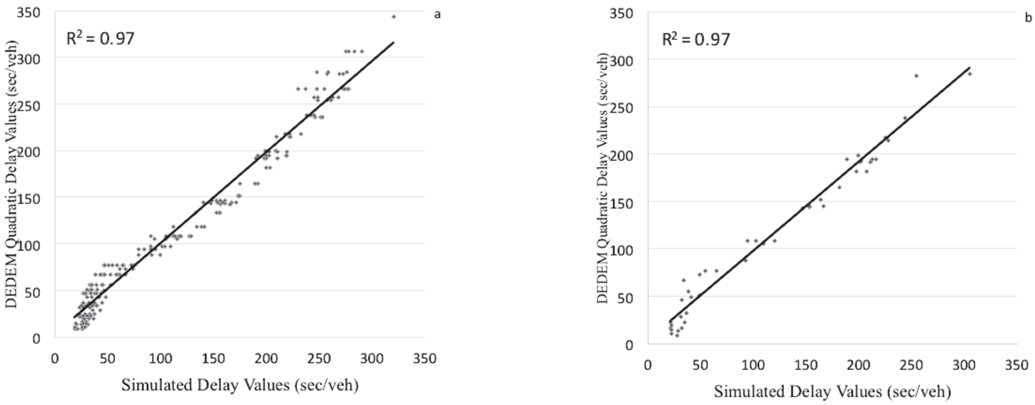

Fig. 6. R^2 results of (a) training and (b) testing data for the $DEDEM_{Linear}$ model

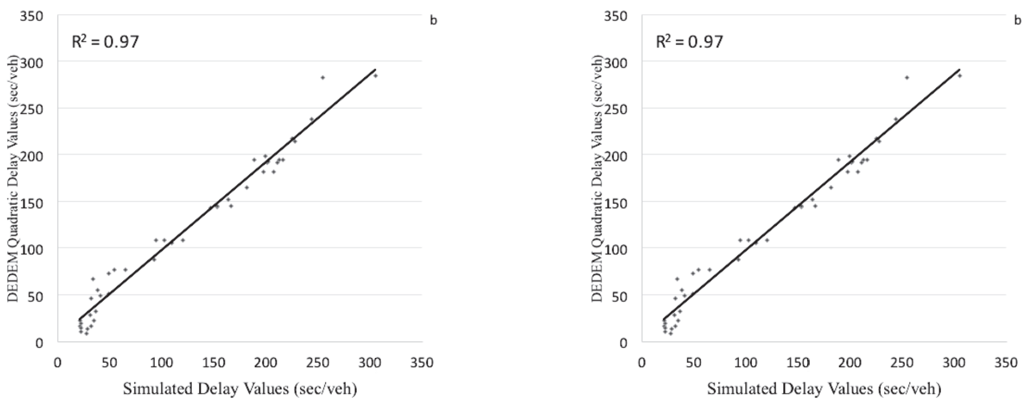

Fig. 7. R^2 results of (a) training and (b) testing data for the $DEDEM_{Exp}$. model.

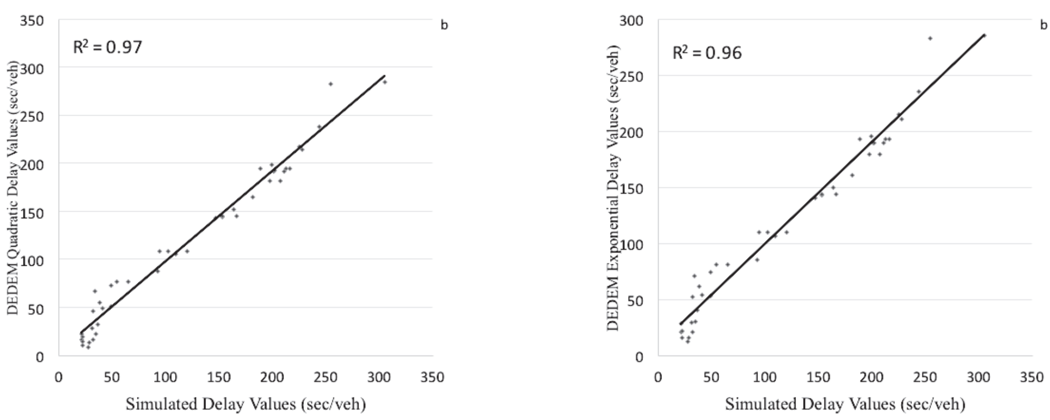

Fig. 8. R^2 results of (a) training and (b) testing data for the $DEDEM_{Quad}$. model.

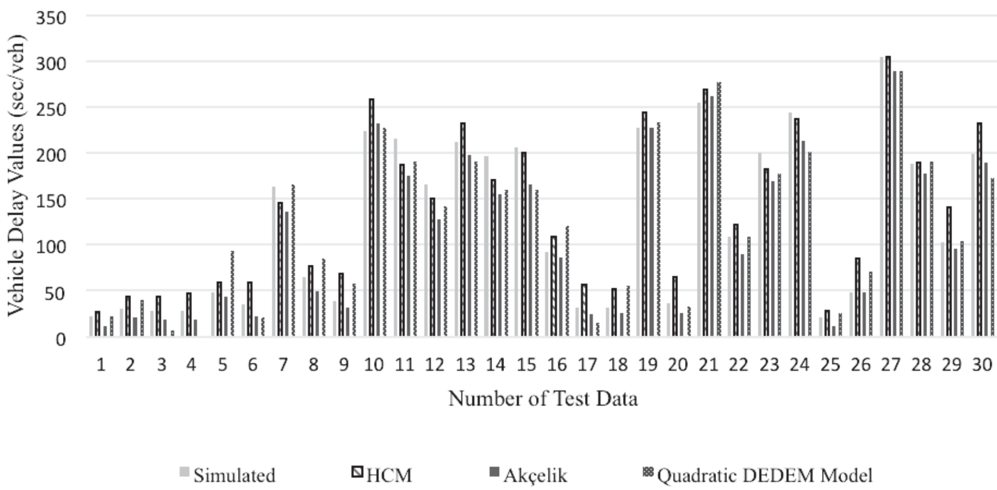

Fig. 9. Comparison of the predicted and analytical models for test data

CONCLUSIONS

In this study, a new delay estimation model with less parameters but more efficient at signalized intersections was proposed. The proposed model was developed with two parameters, a green ratio (g/C) and a degree of saturation (x=v/c), by using DE algorithm in three forms of DEDEM model, that is, linear, exponential, and quadratic. The results obtained were compared with error measurements such as MSE, MAE, and the R^2 to determine models' feasibility. The linear DEDEM model showed low performance when it was compared to other forms. The success of the exponential DEDEM model was not as well good as the quadratic form. The quadratic form of the model is capable of predicting the vehicle delay more closely in terms of relative errors between simulated and estimated values. The test values of MAE for linear, exponential and quadratic forms of DEDEM models were 21.97, 13.02 and 12.12 respectively. Similarly, the lowest value of MSE belonged to the quadratic form with 207.98. Additionally, a comparative study was performed between proposed and existing analytical delay models. Comparative results showed that the performance of the Akçelik's delay model was better than that of the HCM model. The values of MAE and MSE for Akçelik's model was were 13.20 and 269.08, respectively. The quadratic model form especially had more reliable statistics from other model forms and analytical models. The quadratic model yielded to estimates, very close to the simulated delay values as seen from Fig. 9. The quadratic model showed the best performance in terms of evaluation criteria and has shown to be an optimum one. As a result, the quadratic form of DEDEM model can be used as an alternative estimation model for delay, and DE approach could be utilized as a model-fitting algorithm as well. Therefore, it was noticed that the intersection delay could be calculated with less and easily obtained parameters and its results are quite acceptable when compared with those of other studies. As a next step in future studies, the proposed delay model may be expanded by incorporating other variables that are effective on delay or developing various new delay estimation models. The delay models in this research were developed for pre-timed traffic signals. Further studies should be performed for vehicle actuated signal controls. Finally, future research associated with more field data could better specify the performance of the delay model developed in the research.

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