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Travel Time Modelling of Urban Roads By Application of Coyote Optimization-based Machine Learning Method

A. Golroo * , A. H. Fani, H. Naseri

Department of Civil and Environmental Engineering, Amirkabir University of Technology, Tehran, Iran.

ABSTRACT: Travel time prediction as an essential issue has been scrutinized in recent decades. To this end, various techniques are applied to estimate travel duration in dynamic networks and intelligent transportation systems. Accordingly, in this investigation, the prediction of travel time is considered by machine learning techniques. Initially, the experimental test is planned, and the travel time effective parameters are spotted. Subsequently, with the assistance of the floating car method, and My-tracks application, the data are collected in six elected roads. After data preparation, stop delay, grades, and the number of the lane are determined as the most effective travel time criteria. In this study, a novel machine learning technique based on the coyote optimization algorithm is introduced, and its precision is compared with five conventional regression models. Drawing on results, the accuracy of the coyote optimization algorithm-based machine learning technique is more than that of other prediction methods. The coefficient of determination of the introduced machine learning technique for training and testing data is equal to 0.746 and 0.724, respectively. Furthermore, coyote optimization algorithm-based machine learning estimates 73% of testing data with an error of fewer than 20 seconds. .

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1- Introduction

Travel time prediction is one of the essential parts of informing drivers. This system helps travelers to select an appropriate path, which leads to traveling duration reduction [1]. Accordingly, various machine learning techniques, including regressions, decision trees, artificial neural networks, time series, have been applied to estimate the travel time duration and to reduce the traffic in the pavement networks.

Sil et al. [2] stated that geometric characteristics of roads and the number of lanes significantly impact the vehicle's speed, and accordingly, they have to be considered in travel time prediction [2]. Vilarinho et al. [3] analyzed the influences of traffic lights on travel duration, and the results indicated that stop delay is a vital criterion in order to evaluate the travel time.

As can be seen from the above references, the novel machine learning techniques have not received enough attention in this field. Regarding the literature, essential parameters may not be considered in a model simultaneously—accordingly; a new machine learning method was introduced in this study. Moreover, various parameters are scrutinized, and the most important criteria are taken into consideration in the prediction model.

*Corresponding author's email: agolroo@aut.ac.ir

2- Methodology

2- 1- Data collection

The data were collected based on the floating car method, and this method is applied according to the procedure presented in NCHRP Handbook [4]. In this regard, Mytacks application is utilized so as to collecting data and saving them. The case study comprises nine sections, and each section is approximately 1 km.

2- 2- Parameter selection

Initially, stop delay, the number of lanes, availability of adjacent parking, grade, the number of speed bumps are taken into consideration as effective parameters. The enter method is used to analyze these parameters. The results show that stop delay, grade, and the number of lanes are the most critical parameters, and accordingly, they are applied to generate prediction models.

2- 3- Modeling

The coyote optimization algorithm-based machine learning algorithm (COA) is introduced in this investigation. That is to say, by virtue of the coyote optimization algorithm, a novel machine learning technique is developed. To this end, the coyote optimization algorithm is adjusted to solve integer programming. Afterward, the mean absolute error is set the objective function of the optimization algorithm.

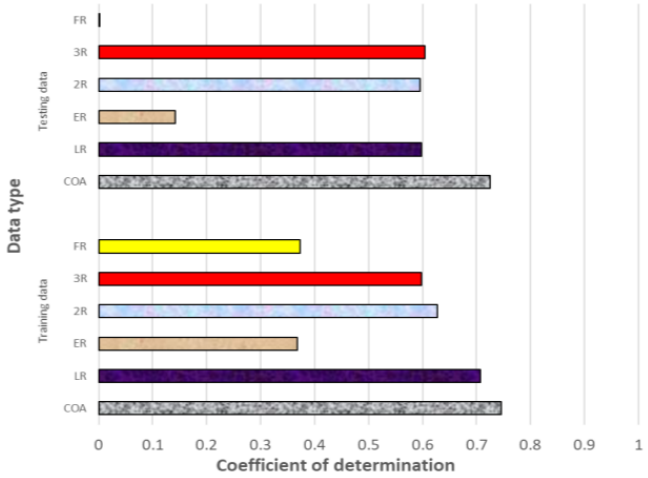

Fig. 1.The coefficient of determination

Eight thousand various modes are considered for each input. Consequently, the model is run ten times, the formula containing the lowest mean absolute error is considered the prediction model.

The introduced model is compared with five conventional regression models, including linear regression, fractional regression, exponential regression (ER), 2nd polynomial regression (2R), and 3rd polynomial regression (3R). Mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), coefficient of determination, and the percentage of data which their error is fewer than 20 seconds (E20s) are applied to compare the introduced model (COA) with five conventional regression models. The equation travel time prediction presented by COA, LR, ER, 2R, 3R, and FR is indicated in Eq. (1) to (6).

$$COA-Time(s/km) = (0.7\times\sqrt[3]{3}\times StopDelay)^2 + (0.7\times\sqrt{6}\times\sqrt{Lane})^2 + (0.8\times Grade^2)^2 + (0.7\times\sqrt[3]{3}\times StopDelay)^3 + (0.7\times\sqrt{6}\times\sqrt{Lane})^3 + (0.8\times Grade^2)^3 + 3.587401 \quad (1)$$

$$LR-Time(s/km) = (1.3688\times StopDelay) + (10.1461\times Lane) + (14.3076\times Grade) + 13.3413 \quad (2)$$

$$ER-Time(s/km) = (0.0001\times\exp(StopDelay)) + (0.4291\times\exp(Lane)) + (4.9904\times\exp(Grade)) + 34.0197 \quad (3)$$

$$2R-Time(s/km) = (0.0598\times StopDelay^2) + (1.8666\times Lane^2) + (8.7428\times Grade^2) + 24.7024 \quad (4)$$

$$3R-Time(s/km) = (0.0005\times StopDelay^3) + (0.2976\times Lane^3) + (4.1589\times Grade^3) + 38.4088 \quad (5)$$

$$FR-Time(s/km) = (-92.8259\times\frac{StopDelay}{Lane\times Grade}) + 59.9815 \quad (6)$$

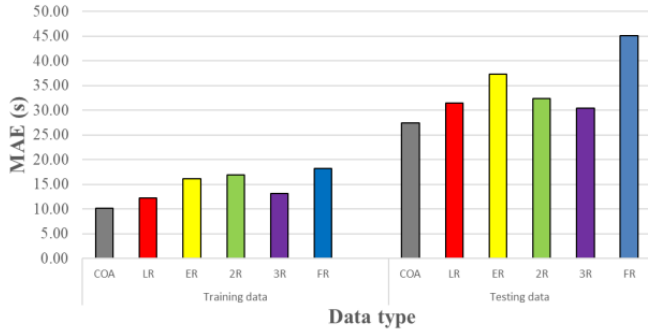

Fig. 2. The mean absolute error

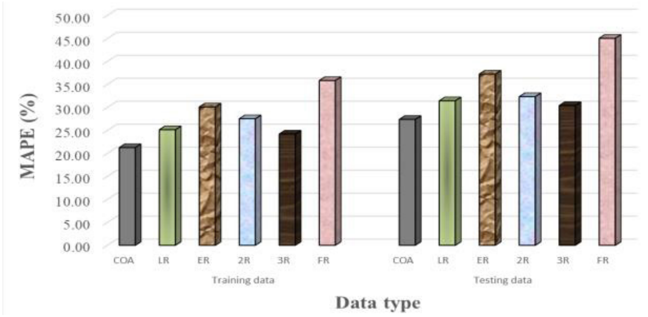

Fig. 3. The mean absolute percentage error

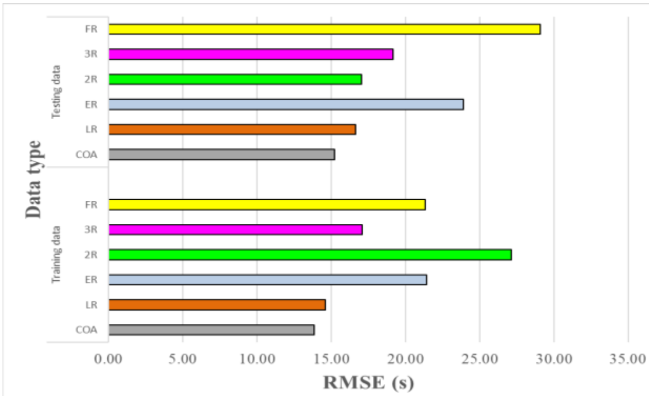

Fig. 4.The root mean square error

Results and discussions

Figure 1 displays the coefficient of determination related to the prediction models. Figures 2 and 3 illustrate the MAE and MAPE of estimation algorithms, respectively. The RMSE and E20s results are indicated in Figures 4 and 5 in the order mentioned.

3- Conclusions

As can be seen, the accuracy of COA is considerably better than that of other models for both testing and training data. Moreover, the introduced model is highly qualified to estimate travel time with high accuracy.

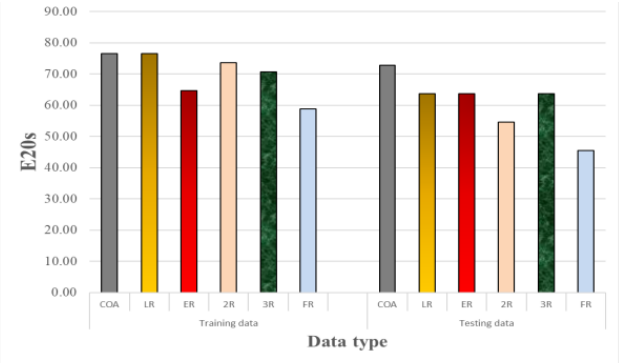

Fig. 5. The percentage of data which their error is fewer than 20 seconds

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