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Machine learning-based multi-target regression to effectively predict turning movements at signalized intersections

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ABSTRACT

Effective prediction of turning movement counts at intersections through efficient and accurate methods is essential and needed for various applications. Commonly predictive methods require extensive data collection, calibration, and modeling efforts to estimate turning movements. In this study, three models were proposed to estimate turning movements at signalized intersections using approach volumes. Two sets of data from the United States and Canada were obtained to develop and test the proposed models. Machine learning-based regression models, including random forest regressor (RFR) and multioutput regressor (MOR) in addition to an artificial neural network (ANN) model, were developed and trained to analyze the relationship between approach volumes and corresponding turning movements. Multiple evaluation measurements were utilized to compare the models. All models produced satisfactory results. The RFR regression model outperformed the MOR model. However, the ANN model had the best performance when compared to the other models. The proposed models provide traffic engineers and planners with reliable and fast methods to estimate turning movements.

1. Introduction

Carrying out a detailed count of all vehicles moving through an intersection is defined as a turning movement count. Turning movement counts are essential for any type of analysis needed in the areas of planning, design, management, and control of road networks. They are used for traffic impact studies, traffic operations analyses, intersection geometric design, signal timing design, signal coordination analysis, capacity analysis, and different transportation planning applications (Alibabai and Mahmassani, 2008; Cascetta et al., 1993). They are also needed for carrying out any traffic simulation analysis (Shaaban and Ghanim, 2018; Shaaban et al., 2019). Many reliable and widely used techniques are used by transportation agencies and traffic engineers to collect traffic counts (Shirazi and Morris, 2016; Tageldin et al., 2015). The selection of a specific method depends highly on the purpose of the study and the anticipated level of effectiveness. Most of the agencies start their projects by collecting traffic volumes in the form of approach volumes and turning movement counts.

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Once the volumes are collected, they are often analyzed and used as inputs for the next stage, where traffic performance is assessed using different methodologies.

The counts for the approach volumes in one direction are simple and usually fully automated. They can be collected using pneumatic tubes for relatively short time intervals, which might last for days or hours. They can also be collected using sensors if traffic data is needed for long time intervals that can reach months. Unlike approach volumes, where there is only one origin and one destination for every vehicle, vehicles at a typical four-legged intersection have one origin and multiple possible destinations. Therefore, it is generally costly and not practical to use pneumatic tubes or sensors for every turning movement at each approach to obtain the turning movements at all approaches. This makes the previous methods more applicable to only counting approach volumes and makes turning movement counts rely on other methods and techniques. Accordingly, the most common and cost-effective way to collect these types of counts is the manual count method. This method requires one observer or more, depending on the size of the intersection, to be present during the whole duration to count the vehicles using handheld electronic boards. Observers must receive some training, and the duration is usually less than 12 hours due to the observers' involvement. This method is the oldest method used to count vehicles at intersections. The method requires extensive manpower, and human errors might exist. While other methods can reduce the need for manpower such as video imaging and Bluetooth readers, these methods are expensive and require special equipment and installation specifications (Ghanim and Shaaban, 2019; Zaki et al., 2014).

Furthermore, it is often required to estimate future traffic based on census data or origin–destination (OD) matrix for future intersection turning movements. These could be either existing intersections with new demand segments or proposed ones. Extensive computational software processes are often required to distribute traffic through the network and then estimate turning movements at different intersections. This approach requires extensive data as a start to feed the transportation networks using transportation packages, such as Visum or TransCAD before outcomes are available. If computer-based models are not available, then turning movements can be estimated through an iterative process such as the use of Turns5 in the Florida Department of Transportation. In this case, turning movements are estimated based on approach volumes and assumed initial turning movements before traffic is balanced, which may not be reliable.

In summary, obtaining effective turning movement counts at intersections is essential and needed for different applications. Turning movement counts can be collected manually, but the process is tedious, expensive, and time-consuming. Furthermore, turning movement counts are needed for many planning applications such as future improvements to an intersection or even proposed new intersections that do not exist. In most of these cases, traffic volumes are available from transportation planning models or other forecasting procedures. These models can estimate both the approaches and turning volumes based on the traffic assignment on the road network. However, there is always a need for efficient and accurate methods to estimate turning movements at intersections from approach volumes. These methods need to be cost-effective while easy to use and maintain. The purpose of this study is to utilize different state-of-the-art machine learning (ML) techniques to effectively estimate turning movement counts from approach volumes.

There have been previous works attempting to address the need for turning movements estimates with minimal required data. Lin and Rasp (1983) used the total entering and leaving counts to estimate the maximum likelihood of turning movements. Schaefer (1988) assumed initial turning movements before they go through an iterative process of adjusting the turning movements and adjusting the inbound and outbound approach volumes. Martin and Bell (1992) proposed an algorithm to estimate turning movements using linear programming similar to estimating water and electricity flows. In their algorithm, they used a set of assumptions such as the constrained upper and lower flows, weighted links, and flow measuring detectors. Wu and Thnay (2001) proposed an OD-based method, where the existing OD traffic demand matrix is estimated based on observed turning movements and link flow. This existing OD is later used to estimate a future one. Finally, the future OD matrix is used to assign traffic to the transportation network. Gholami and Tian (2016) used the stop bar traffic detection data to estimate turning movements.

In the authors' previous study (Ghanim and Shaaban, 2018), an artificial neural network (ANN) approach was used to estimate turning movements at signalized intersections. While turning movements are important to meet different objectives when performing traffic engineering studies, the common practice involves either assuming initial values for turning movements that go through an iterative balancing process or the use of extensive data to model transportation networks before turning movements can be found. All these methods require a set of assumptions and relatively expensive collected data before developing appropriate estimates for turning movements. Thus, a model that can estimate turning movements based only on the simplest available information such as approach volumes is needed. This study is a follow-up to the authors' previous research (Ghanim and Shaaban, 2018). The study aims to create a simple and precise method to estimate turning movements at signalized intersections from approach volumes by testing two ML algorithms including random forest regressor (RFR) and multioutput regressor (MOR). RFR is an ensemble learning model that combines multiple decision tree models to obtain better regression results (Breiman, 2001; Geurts et al., 2006). MOR uses multiple single-target regression models for each output. In general, MOR extends regression models that do not have support for multi-target regression (Pedregosa et al., 2011). In this study, RFR, MOR, and ANN were investigated to predict turning movement counts.

Recently, ML algorithms have been utilized in multiple intelligent transportation applications. Charouh et al. (2019) used a set of ML algorithms to optimize different operations for detecting moving vehicles. Jahangiri and Rakha (2015) performed a supervised classification to predict transportation methods using mobile sensing data. This study used different ML methods such as random forests which achieved high effectiveness. Tsiligkaridis and Paschalidis (2017) studied traffic congestion detection caused by different events such as lane closures and vehicle crashes. In this study, ML methods were applied for anomaly detection. Also, ML models were used to study car following movements, especially in autonomous cars. Yang et al. (2018) proposed a hybrid approach to combine ML and kinematic models to enhance the car following in abnormal contexts. Aksjonov et al. (2018b) used ML to detect driver distraction. They proposed a model that considered driver behavior and speed maintenance. ML models were also used in traffic safety assessment (Cai et al., 2019) and to detect drivers' risky behaviors that lead to severe crashes (Aksjonov et al., 2018a; Gwak et al., 2018; Iranitalab and Khattak, 2017). Fang et al. (2018) developed an ML algorithm to assess driving safety based on the drivers' profiles and traffic records including violations and crashes. Lai et al. (2018) reported that ML algorithms are useful in behavior analysis. Müller et al. (2018) evaluated the driver behavior using random forest. The random forest model was used to predict crashes and their severity. Heyns et al. (2019) studied the impact of traffic density on drivers' performance. ML methods were also used in transportation sharing (Zhou et al., 2019), real-time speed prediction (Julio et al., 2016), and crowd and flow estimation (Liu et al., 2019; Nagao et al., 2018).

2. Methods

2.1. ML-based multi-target regression models for predicting turning movements

This study aims to develop and evaluate turning movement estimation models for signalized intersections using ML-based multi-target regression. The advantages of such models are tangible when limited traffic data or turning movement counts are observed. In particular, the developed models can produce reliable and effective turning movements when only approach volumes are available (either actual volume counts or projected ones). Most of the methods that are currently used in practice require information or assumed initial turning movements beyond the approach volumes. The multi-target regression models express the underlying relationship between approach volumes and corresponding turning movements. Once the turning movement models are developed, estimating turning movements volumes from approach volumes becomes viable and practical, eliminating the need of assuming initial turning movements. The use of such models becomes also practical when dealing with planning data or newly proposed intersections.

At a typical four-legged signalized intersections, there are three possible movements for any approach inbound traffic, right, through, and left. Accordingly, 12 movements need to be estimated. Given the fact that there are only four inbound volumes and four outbound volumes, this means that there are only eight continuity equations that can be used to estimate turning movements (inbound and outbound volumes for each approach). Therefore, many possible turning movement combinations can be made to maintain the continuity conditions. A graphical presentation of four-legged intersections and the possible turning movements are demonstrated in Fig. 1.

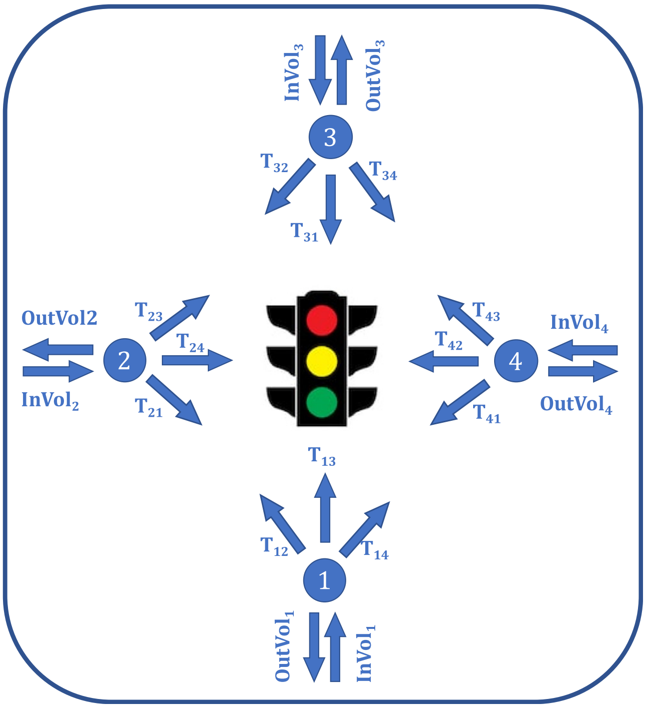


Fig. 1. Graphical illustration of turning movements at a four-legged signalized Intersection.

In Fig. 1, the $InVol_i$ and $OutVol_i$ represent the directional traffic flow that is entering and leaving the intersection through approach i, respectively. T_{ij} is the proportion of traffic flow that is entering the intersection from approach i and leaves through approach j. Turning movements can also be expressed using the T_{ij} expression. By taking Approach 1 as an example, the following expression can be written as: $InVol_1 = T_{12} + T_{13} + T_{14}$, where T_{12}, T_{13}, T_{14} are the left, through, and right turning movements from approach 1. While $OutVol_1 = T_{21} + T_{31} + T_{41}$, where T_{21} is the approach 2 right turn, T_{31} is approach 3 through movement, and T_{41} is approach 4 left movement. Moreover, $\sum_{i=1}^{4} InVol_i = \sum_{i=1}^{4} OutVol_i$.

2.2. Turning movements and data description

The initial turning movement counts used to develop the proposed models in this study were collected from 847 intersections (3,388 approaches assuming four approaches per intersection) between 2010 and 2014. All intersections are located in Palm Beach County, Florida, United States (PBC, 2021). The turning movement counts covered the two typical peak periods, morning and evening peaks, which are typically used to perform traffic operational analysis. The data included 691 four-leg intersections and 156 three-leg intersections. The data were structured in the form of a systematic database that can be used to prepare further data analysis and modeling. The database contained 4,175 hour records. Each record included three movements per approach since u-turns were combined with left turns. A summary of the number of hours per intersection type per year is shown in Table 1.

Another database that included 16,700 records was developed based on the 4,175 hour records multiplied by four approaches. In this database, turning movements per approach per intersection were treated as one independent record. This database was adopted since the objective was to predict the directional turning movements (i.e., turning movement per approach). To develop a generalized and systematic model, the missing fourth approach for three-leg intersections was assumed to exist with zero turning movements and zero downstream and upstream approach demand. A summary of the hourly traffic demand is shown in Table 2.

The records structure in the final database represents the outputs (i.e., approach turning movements), which requires the use of input vectors to estimate the approach turning movements. Since the study aims to predict turning movements using only approach volumes, the inbound and outbound traffic per approach was used, with a total of eight input vectors (i.e., inbound and outbound traffic for the northbound, southbound, eastbound, and westbound directions).

Table 1
Number of hours per intersection type per year.

	Three-Leg Intersections		Four-Leg Intersections		Total
Peak-Hour	AM	PM	AM	PM	
Year 1	72	73	405	442	992
Year 2	82	84	345	369	880
Year 3	60	60	360	400	880
Year 4	74	73	371	364	882
Year 5	48	50	212	231	541
Total	336	340	1693	1806	4175

Table 2
Hourly traffic volume data per intersection type.

Three-Leg Intersections		NB	SB	EB	WB	Total
		AM Peak Period				
	Average	494	620	902	582	2,598
	Std. Dev.	557	559	936	549	1,124
	Maximum	2,508	2,287	4,043	2,337	6,854
		PM Peak Period				
	Average	566	583	654	897	2,699
	Std. Dev.	593	542	637	893	1,181
	Maximum	2295	2646	2,863	3,805	7,260
Four-Leg Intersections		AM Peak Period				
	Average	670	757	1,210	789	3,423
	Std. Dev.	544	596	900	533	1,497
	Maximum	2,784	2,825	4,190	2,908	7,848
		PM Peak Period				
	Average	801	742	924	1,199	3,667
	Std. Dev.	616	576	657	882	1,644
	Maximum	2,870	2,851	2,863	5,387	8,949

For any given approach turning movement, the input vectors are arranged systematically. The first vector is the approach inbound traffic volume, the second vector is the approach outbound traffic. This trend continued in a clockwise direction. Therefore, the third and fourth input vectors were the inbound and outbound traffic volumes at the approach to the left of the targeted approach, respectively. For instance, to find the northbound turning movements, the input vectors are the inbound and outbound traffic through the south approach, inbound and outbound traffic through the west approach, inbound and outbound traffic through the north approach, inbound and outbound traffic through the east approach, respectively. In the case of any missing approach or turning movement (i.e., three-leg intersections, one-way traffic, or restricted movement), a value of zero was used to compensate for any missing or restricted movements. The final database used to develop all the models contained 16,700 records with 11 fields (eight inputs and three outputs).

A correlation matrix between the input data attributes and the output variables was developed as shown in Fig. 2. The figure uses the colors dark-red and blue for positive and negative correlations, respectively. The figure shows multiple interesting relationships that could have a powerful impact on RFR regression results. For example, the output 'Through' is correlated positively with the input 'In' and negatively with the input 'OutLeft'. The outputs 'U + Left' and 'Right' have less correlation polarity than the 'Through' direction. However, they still have some positive and negative correlations. Table 3 lists the inputs and output movement variables.

To use the turning movement counts to train the multi-target regression models, the inbound and outbound traffic volumes for each approach were calculated. The proposed multi-target regression models considered the turning movements as dependent variables and the approach in-traffic and out-traffic as independent variables. For each recorded hour, a record was created for the four approaches of the intersection. For example, the northbound turning movements were assumed to be a function of the inbound and outbound traffic of the south approach itself, the left-hand approach (i.e., west approach), the opposing approach (i.e., the north approach), and the right-hand approach (i.e., east approach). By referring to Fig. 1, this relationship can be mathematically expressed using Equation (1):

$$\begin{bmatrix} NBL = T_{12} \\ NBT = T_{13} \\ NBR = T_{14} \end{bmatrix} = f(P_1, A_1, P_4, A_4, P_3, A_3, P_2, A_2) \tag{1}$$

where NBL, NBT, and NBR were the northbound left, through, and right turning volumes, respectively. A value of zero was assumed for approaches that do not exist such as in the case of one-way roads or three-leg intersections. Furthermore, u-turns were combined with the left turning movements since they can use the left-turn phase at the same time. Thus, T_{ii} for different approaches in the T matrix were considered zeros. Table 3 shows the variables utilized for training the multi-target regression models, along with their description.

2.3. Multi-target regression models

The multi-target regression models are used to predict the turning movements at signalized intersections using the process shown in Fig. 3. In this process, two different ML methodologies for multi-target regression, RFR and MOR, were utilized.

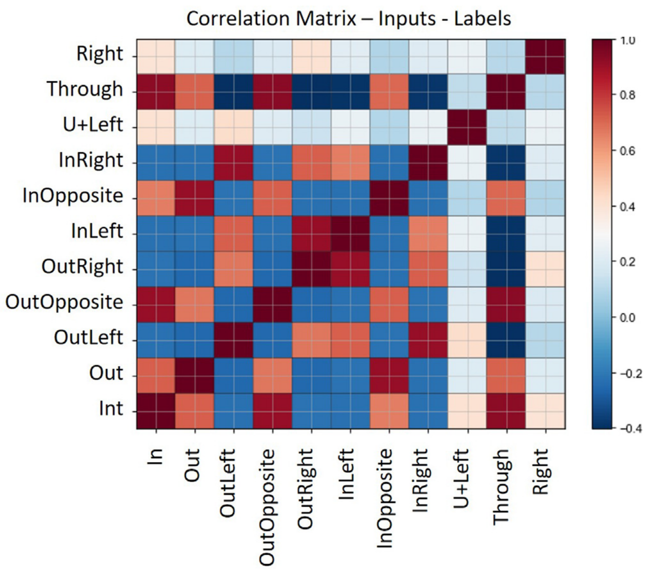
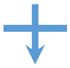
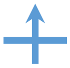
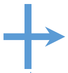
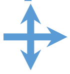


Fig. 2. Visualization of the correlation matrix between input and output variables.

Table 3
Input and output variables for the ANN model.

Variable	Sign Input Variables	Description*
In		Inbound traffic volume for the approach, *veh/hr*
Out		Outbound traffic volume for the approach, *veh/hr*
OutLeft		Left approach outbound traffic volume, *veh/hr*
OutOpposite		Opposing approach outbound traffic volume, *veh/hr*
OutRight		Right approach outbound traffic volume, *veh/hr*
InLeft		Left approach inbound traffic volume, *veh/hr*
InOpposite		Opposing approach inbound traffic volume, *veh/hr*
InRight		Right approach inbound traffic volume, *veh/hr*
Output Variables U + Left		Approach left-turn traffic volume (NBL), *veh/hr*
Through		Approach through traffic volume (NBT), *veh/hr*
Right		Approach right-turn traffic volume (NBR), *veh/hr*

* The northbound direction was used as a reference.

2.3.1. Random forest regressor

Recently, ensemble learning models gain increasing research attention in different areas (Falamarzi et al., 2018). These models generate multiple bootstrap samples of the input dataset and aggregate the final results (Breiman, 2001; Geurts et al., 2006). A random forest is an ensemble method that performs classification and regression tasks. It uses multiple decision trees with two additional features, namely, bagging and random subspace method (RSM). The bagging method involves training each decision tree on a different data sample where sampling is done with replacement. More specifically, bagging is an optimization algorithm that improves the prediction based on the multiple bootstrap samples. RSM aims to reduce the correlation between the ensemble regressors by using random samples of features for training instead of the whole feature set (Hua et al., 2016; Toran Pour et al., 2017). The learning average is used to improve the prediction and control over-fitting.

RFR was used in different applications (Breiman, 2001; Geurts et al., 2006). RFR is implemented in three main phases including bagging, RSM, and voting. In the bagging phase, the algorithm creates multiple trees for a number of bootstrap samples from the training dataset. Unlike decision trees, RFR split the tree nodes based on the best features. Those features are selected from a subset of randomly created predictors for each node. Then, a majority voting technique is applied to compute the final decision. Specifically, it computes the average of the various output predictions (Santur et al., 2016; Sharma et al., 2018).

For evaluation purposes, the RFR algorithm predicts out-of-bags (OOB) or the data that are not included in the bootstrap sample. The error rate is calculated by comparing the real OOB with RFR predictions. Multiple attributes control the learning process of the RFR such as the number of decision trees in the forest and the depth of each tree. Increasing the number of trees decreases the error rate (Genuer et al., 2010; Rodriguez-Galiano et al., 2012).

2.3.2. Multioutput regressor

On the other hand, MOR uses multiple single-target regression models for each output. Simply, MOR extends regression models that do not have support for multi-target regression (Pedregosa et al., 2011). Within the MOR, the gradient boosting regression (GBR) algorithm is used. Multiple research works proposed various versions of GBRs such as gradient boosting machine (Friedman, 2001), functional gradient boosting (Mason et al., 1999), multiple additive regression trees (Friedman

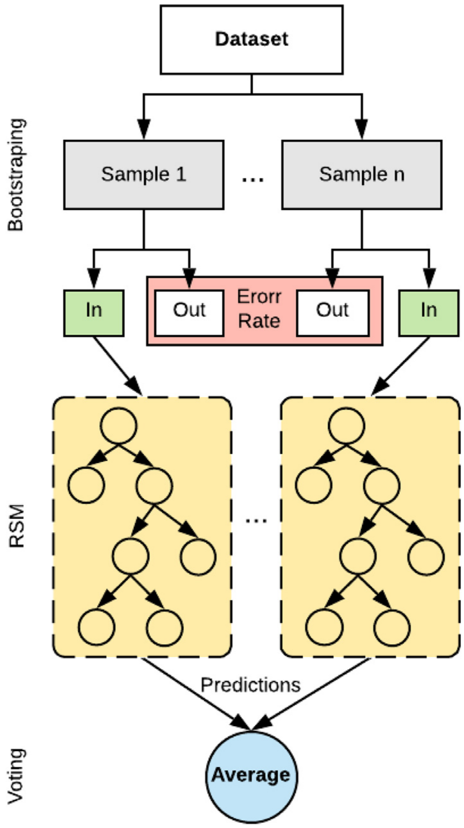


Fig. 3. Prediction process for the dataset.

and Meulman, 2003), and boosted regression trees (Elith et al., 2008). The gradient boosting trains a regression tree on the negative gradient of the loss function. GBR combines multiple "weak learners", regressors, into one strong regressor. For simplicity, it can be explained to minimize the learning error iteratively in the least-squares regression. Where GBR trains the prediction model $F_t(x) = \hat{y}$ by minimizing the mean squared error (MSE) which equals $\frac{1}{n}\sum_i(\hat{y}_i - y_i)^2$. At each iteration of the gradient boosting process, GBR updates the weak models F_t adding a new estimator as in Equation (2) below.

$$F_{t+1}(x) = F_t(x) + h(x) = y \tag{2}$$

Each $F_{t+1}(x)$ tries to improve the regression performance of its predecessor F_t. GBR works as a gradient descent algorithm and uses different loss functions as the residual function $y - F_t(x)$. In this case, the squared error loss function is computed as $\frac{1}{2}(y - F_t(x))^2$.

2.3.3. Artificial neural network

A feed-forward ANN was implemented to regress the turning movement counts. Fig. 4 shows the ANN architecture. It consists of an input layer that feeds the features into the hidden layer. The features are fully connected to one hidden layer that calculates the network bias and weights and sums the final output at the output layer. The weights of the hidden neurons are calculated based on the weights of the connected features in addition to bias as shown in examples (a1 and a2) in Eqs. (3)–(5). Eq. (5) shows the calculation of the output regression value. This ANN can be represented in matrices for the hidden and output layers as described in Eqs. (6) and (7).

$$a1 = x1^{\star}w11 + x2^{*}w12 + x3^{*}w13 + b1 \tag{3}$$

$$a2 = x1^{*}w21 + x2^{*}w22 + x3^{*}w23 + b2 \tag{4}$$

$$o = a1^{\star}w31 + a2^{\star}w32 + b3 \tag{5}$$

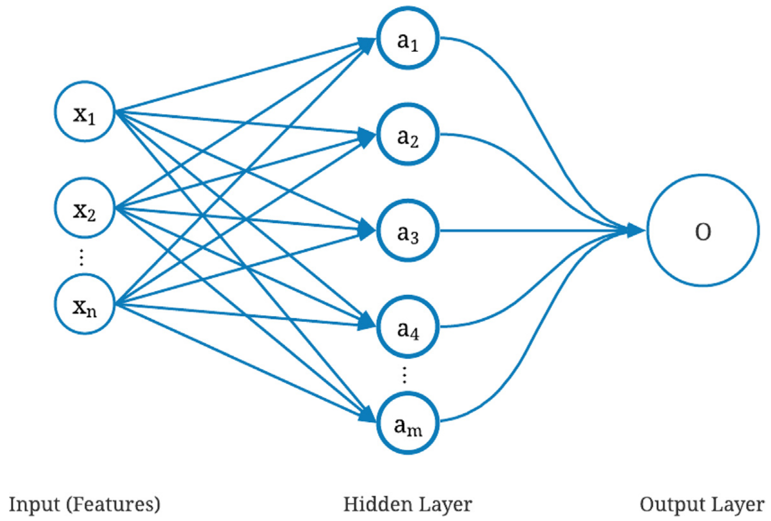


Fig. 4. Architecture of the implemented ANN.

$$[x_1 \quad x_2]\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix} = \begin{bmatrix} x_1w_{11} + x_2w_{21} \\ x_1w_{12} + x_2w_{22} \\ x_1w_{13} + x_2w_{23} \end{bmatrix}' = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix}' \tag{6}$$

$$\begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix}' \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = h_1 + h_2 + h_3 = y \tag{7}$$

The output is computed as the element-wise dot product of the input features and a kernel of weights matrix. Then, the output is activated by Rectified Linear Units (ReLU) activation function as in Eq. (8).

$$ReLU(z) = \left\{ \begin{matrix} z & z > 0 \\ 0 & z <= 0 \end{matrix} \right\} \tag{8}$$

ReLU is important to avoid the vanishing gradient problem. It requires less computation resources in comparison to other activation functions such Sigmoid and tanh, due to its simple mathematical operations.

3. Analysis

3.1. Multi-target regression training and validation

In this section, the ML training and evaluation of the proposed multi-target regression models are described. Python was used to implement, train, and evaluate the models. Cross-validation was used to evaluate the multi-target ML methods. Cross-validation is a resampling process that splits the dataset into K equal subsets. K was defined as 10. The cross-validation iteratively trains the model 10 times using different testing sub-set. In each fold iteration, the sub-sets are randomly selected to assure space independence. The multi-target regression models and ANN use the training for fitting purposes. The regression performance is calculated as an average of the performances of the trained models across the 10-folds. The performance scores show the quality of the created multi-target regression models to estimate turning movements for sites not used in the training process. The input records of the 10-folds were randomized before being fed to the regression models so that the training process is generalized and unbiased. This step assures that the multi-target regression models can be applied for cases that have not been represented in the input records.

3.2. Multi-target regression models

After the multi-target regression models and neural network were trained, the observed and predicted turning movements were compared for the K = 10 cross-validation. For the validity of the trained models, different measures of effectiveness (MOEs) were calculated for each data group. These MOEs are namely the mean square error (MSE), the coefficient of determination (R^2), the root mean square error (RMSE), and the mean absolute percentage error (MAPE), as defined in Eqs. (9) to (12) (Chicco et al., 2021).

$$MSE = \frac{\sum (y_{out} - y)^2}{N} \tag{9}$$

$$R^2 = 1 - \frac{\sum (y_{out} - y)^2}{\sum \left(\bar{y} - y\right)^2} \tag{10}$$

$$RMSE = \sqrt[2]{\frac{\sum (y_{out} - y)^2}{N}} \tag{11}$$

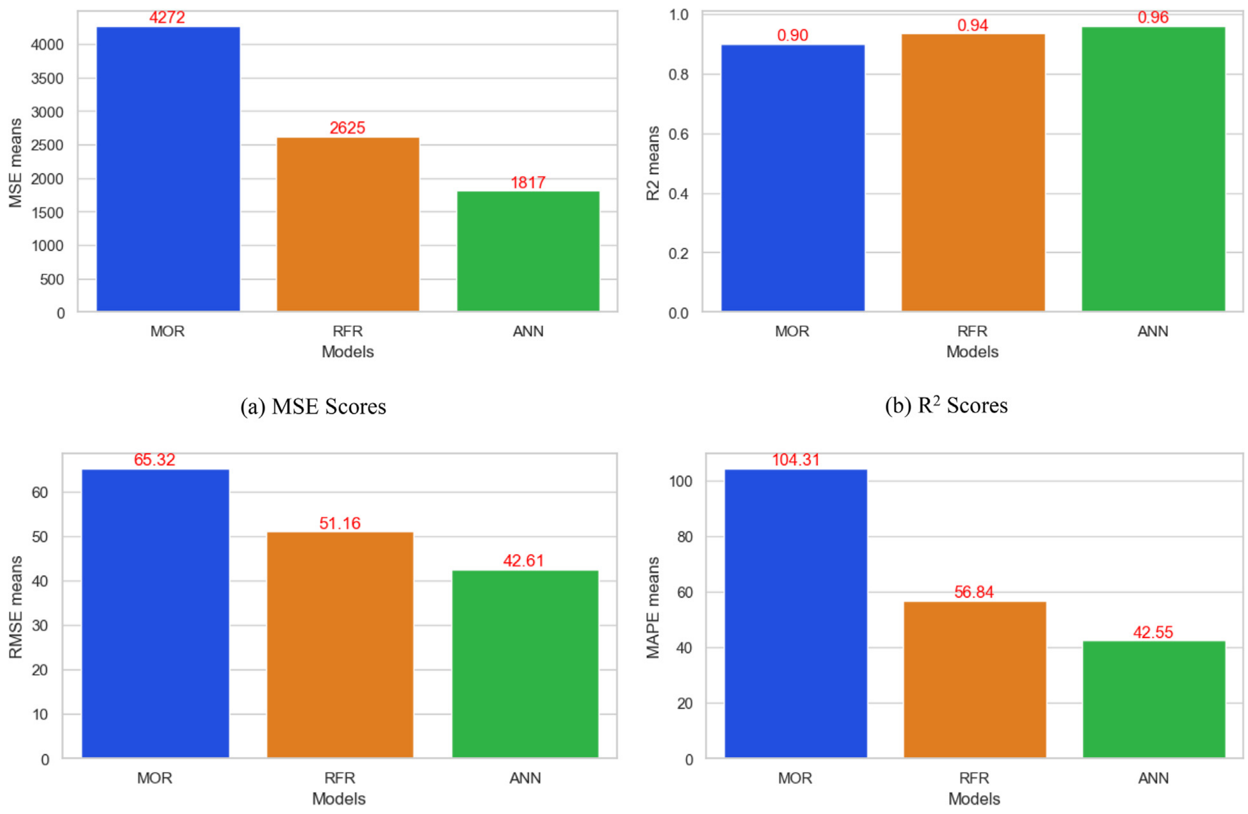
$$MAPE = \frac{1}{N} \sum_{1}^{N} \left| \frac{y - y_{out}}{y} \right| \tag{12}$$

where y is the observed value, $\bar{y}$ is mean of observed values, y_{out} is the predicted output, and N is the number of observations.

Table 4 summarizes the cross-validation results and lists the evaluation results for the utilized multi-target regression models and the ANN with the employed MOEs. In the case of the R^2 measure, a high score indicates high performance. The trained multi-target regression models and ANN were tested to estimate the turning movements at the validation/testing sub-set of unseen sites that were not used in the model training. The results in the table show that all developed models can provide reliable turning movement estimates.

Table 4
MOEs results for the different models.

Model	MSE	R^2	RMSE	MAPE
MOR	4095	0.902	65.3	104.3
RFR	2577	0.937	51.2	56.8
ANN	1796	0.962	42.6	42.5



(a) MSE Scores

(b) R^2 Scores

(c) RMSE Scores

(d) MAPE Scores

Fig. 5. Summary of the MOEs results.

Table 5
MOEs results per movement type for the different models.

	Model	MSE	R^2	RMSE	MAPE
Left Target	MOR	3837	0.91	62	112
	RFR	2458	0.94	50	61
	ANN	1610	0.96	40	47
Through Target	MOR	4182	0.91	65	107
	RFR	2759	0.94	52	54
	ANN	1847	0.96	42.9	42.7
Right Target	MOR	4270	0.89	65	109
	RFR	2516	0.94	50	62
	ANN	1935	0.96	43.8	37.9

Fig. 5 visualizes the results according to each measure of the MOEs. The figure compares the performances of the utilized multi-target regression models and the ANN. The ANN had the best performance across the different measures. It had less error than the regression models. For example, the ANN had around 800 and 2600 less error values in the MSE. Moreover, ANN also had better performance in comparison to RFR and MOR with 2.5 percent and 6 percent, respectively. On the other hand, the RFR regression model outperformed the MOR model. The RFR resulted in 2484 and 2625 with around 40 percent better than the MOR. For R^2, the score comes constant with the MSE result. RFR is the best with 0.937 in cross-validation. On the other hand, the MOR is 3 and 4 percent lower than the RFR. In the same fashion, the RFR model achieved around 50 in the RMSE better than the MOR with around 15. Finally, the MAPE measure also shows consistent results showing the superiority of using RFR over MOR.

The results of the proposed multi-target regression models were studied for the different movement types. The observed and predicted values for each type of movement were compared. Table 5 lists the evaluation results for the 'Left' output target. Training the ANN at the cross-validation mode achieved the best results. It scored 0.962 with 2.2 and around 10 percent better than its RFR and MOR at the cross-validation testing. The same table shows the results for the 'Through' output target. The ANN had the best results consistently with the other tables. It had the highest R^2 scores and lowest error scores in the other measures. The cross-validation R^2 is 0.937 and 0.902 for the RFR and MOR, respectively. In terms of the other measures, MSE for example, the performance of the ANN outperformed the RFR and MOR. Finally, Table 5 lists the 'Right' evaluation scores. The RFR with cross-validation comes in second place with 0.937 after the ANN with 0.956, which was consistent with the previous results. The overall evaluating process shows that the ANN produced the best regression results compared to the traditional RFR and MOR.

3.3. Evaluating the proposed multi-target regression models using another dataset

The proposed multi-target regression models were tested using another turning movement dataset collected from the city of Edmonton, Canada. The utilized dataset has around 12,000 records of balanced distribution over the day with 6168 (49.4 percent) and 6312 (50.6 percent) for the AM and PM periods, respectively. Fig. 6 shows that the 'Through' class is approximately 54 percent of the collected data followed by around 25 percent and 21 percent for the 'Left' and 'Right' turns, respectively. The statistical analysis of the correlation among the different data features was conducted. Fig. 7 shows

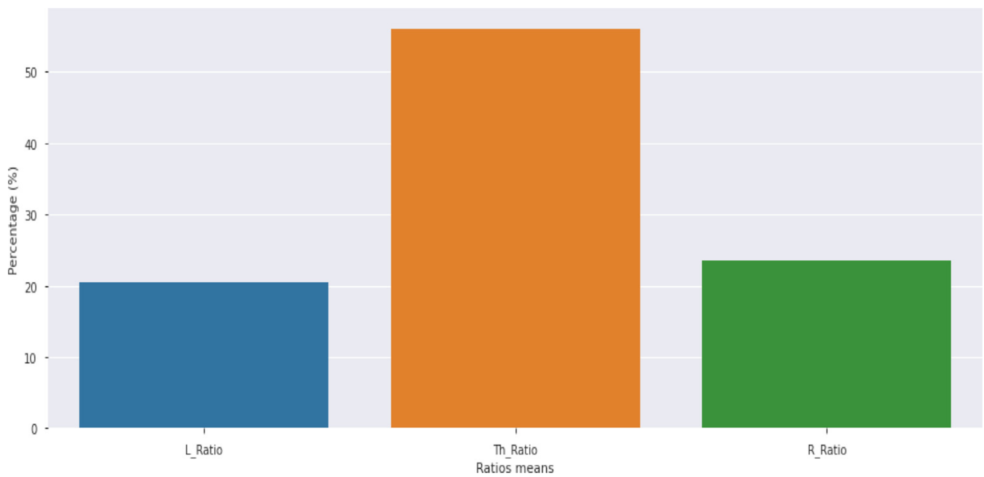


Fig. 6. MOEs results for the second dataset.

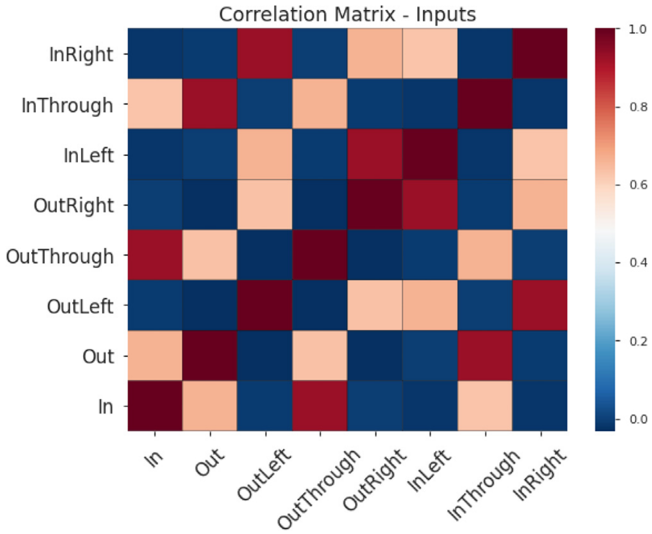


Fig. 7. Visualization of the correlation matrix for the second dataset.

Table 6
MOEs results for the second dataset.

Model	MSE	R^2	RMSE	MAPE
MOR	2126	0.89	46.1	59.6
RFR	1681	0.90	41.0	67.4
ANN	1514	0.92	38.9	59.6

Table 7
MOEs results per movement type for the second dataset.

	Model	MSE	R^2	RMSE	MAPE
Left Target	MOR	1868	0.83	43	131
	RFR	1617	0.85	40	100
	ANN	1148	0.89	33	77
Through Target	MOR	2560	0.98	50	98
	RFR	1827	0.99	42	33.4
	ANN	2189	0.99	46.8	30.7
Right Target	MOR	1952	0.84	44	96.5
	RFR	1600	0.87	40	67.7
	ANN	1204	0.88	34.7	70.6

that there are many positive and negative correlations among the feature set. For example, the 'InRight' has a positive correlation with 'OutLeft' and a negative score with 'Out' and 'OutRight'. The 'Out' data are positively correlated with 'InThrough' and negatively with 'OutLeft'. More useful correlation insights can be seen in the correlation matrix shown in Fig. 7.

Table 6 lists the evaluation results for the multi-target regression models with the employed MOEs on the second dataset. The results show consistent performance with the other dataset. Similarly, ANN had the best results with 1514, 92, 38.9, and 59.6 for the MSE, R^2, RMSE, and MAPE. More detailed performance evaluation results are listed in Table 7.

4. Conclusion

Multi-target regression models were used to provide a reliable estimate of turning movements at signalized intersections using only approach volumes. Real-life turning movement data were collected from signalized intersections within the United States and Canada. Three ML-based regression models, including MOR, RFR, and ANN were trained to analyze the relationship between approach volumes and the corresponding turning movements. Multiple evaluation measurements were computed including the MSE, RMSE, MAPE, and R^2. All models produced good results. However, the testing results showed that ANN had better performance in predicting turning movements. In summary, the methods tested provide a reliable and effective model that can be used for turning movement estimation when limited data are available.

The value of this research is highlighted when compared to the other methods used in practice. Most of the existing methods rely on assumed initial turning volumes that go through an iteration process of adjustments and balancing, or through an extensive process of modeling transportation planning data. The outcome of this study provides traffic engineers and transportation planners with a straightforward and easy-to-use method to estimate turning movements based on approach volumes only.

It should be noted that only peak-hour volumes were used in the analysis based on the available data. Nonetheless, peak hour volumes are often used to perform operational analysis, optimization, and designs at signalized intersections. Peak hours are also used to perform transportation studies such as traffic impact studies. It is recommended to expand the scope of this research to cover additional cases. For instance, developing models for non-signalized intersections and roundabouts and considering the functional classifications of the intersecting roads can have potential benefits for practitioners.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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