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Modeling and Prediction of Freight Delivery for Blocked and Unblocked Conditions Using Machine Learning Techniques

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Abstract

Freight deliveries on signalized city road are recognized as lane obstructions throughout delivery. Traffic jamming associated with urban freight deliveries has gained increasing attention recently. As traffic engineers and planners are tasked with finding solutions to accomplish comprehensive demand more sustainably with restricted road capacity. The goal of this research is to evaluate the model for quantifying the capacity and delay effect of a freight delivery on a signalized city road in Ahmedabad. The all or nothing model similar to the procedure used in the highway capacity manual (HCM2010). The persistence is to provide an understanding of the use of these tools for analysis of urban freight delivery policy. The present study covers delay and vehicle capacity estimation that can account for the changeable locality of deliveries, duration, and different impact on different lane groups. To predict the vehicle capacity and delay estimation, machine learning models, Support vector machine and Artificial neural network was utilized. Result shows excellent agreement between experimental and predicted observations.

Keywords: Freight delivery; Ahmedabad; Machine learning; Support vector machine; Artificial neural network

1. Introduction

Freight deliveries on signalized city road are renowned as lane obstructions throughout the distribution route. Traffic congestion associated with urban freight deliveries has gained increasing responsiveness in recent years. Traffic engineers and planners are tasked to find solutions to accomplish comprehensive demand with more sustainably with restricted road capacity. Emerging conversation of policies to shift deliveries to off hours is proposed to improve the effects on traffic jamming conditions. A significant combination of the effects of heavy vehicles in the traffic tributary was published in NCFRP Report 31 (Dowling et al., 2014). The report gives precise information about the impact of trucks on mid-block arterials speeds and suggests improved methods for computing truck-passenger car equivalent factors for capacity analysis of signalized crossings.

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Nomenclature

AR	red time
C	cycle length
Cdl	revised lane group capacity
Csr	capacity of shared right turn lane
Ct	capacity of through lane
ddl	delay time with freight delivery
Er	equivalent no of through cars for a protected right turn
G	effective green time
lt	phase lost time
Nsr	no of lane in the shared right turn lane
Nt	no of lane in the through lane
Pr	proportion of the right turning vehicle in the shared lane
Ssr	saturation flow rate for the shared right lane
Ssr,dl	average saturation rate for shared right turn lane
St	saturation flow rate of a through lane
T	duration of analysis period
td	duration of blockage
v	vehicle arrival rate
Vdl	revised vehicle arrival rate
Y	yellow time

These methods do not justify obstructions caused by parked trucks. Keegan and Gonzales (2016) discussed the problem of city freight deliveries in city areas such as obstructive traffic, which reduces street capacity and delays on vehicles. To deal with the problem, researchers applied All or Nothing model and Kinematic wave theory to calculate the effect of freight deliveries on traffic for suitable policies. Benekohal and Zhao (2000) conducted study on passenger car equivalents concept that has been used to justify the contrary effects of heavy vehicles on traffic flow operations. Heavy vehicles, owing to their size and lower acceleration/ deceleration capabilities, may harmfully affect traffic performance at crossings. Holguín-Veras et al., (2006) investigated policies to inspire the plan of deliveries in city areas during off-peak hours. The study covers the essential conditions required for receivers and carriers to agree for off-hour deliveries, and the helpfulness of other policies to foster such change in competitive markets. Holguín-Veras (2008) discussed the importance of motivation for off-hour delivery programs to reduce traffic congestion. Most of the analysis focuses on experiences from the viewpoint of agencies or the delivery drivers, who can travel at a advanced speed during minor traffic periods. Crainic et al. (2004) discussed the task to assure receiver an off-hour deliveries schedule, which in many cases require disbursing an employee of a store to stay after consistent business hours or make superior arrangement for the delivery to be completed in the absence of someone to receive the delivery. Holguín-Veras et al. (2016) studied the properties of the agent interactions at the core of supply chains, and recognizes the serious role played by the receivers of supplies in responsible when and how deliveries are made. The results show that RLC programs could bring welfares to large city areas, reducing freight vehicle-miles-traveled and congestion levels. In another study, Yannis et al. (2006) investigate the effects of the acceptance of restrictions in vehicle movements related with urban delivery operations on traffic. The conclusions recommend that restricting delivery to specific types of businesses during rush hours can lead to optimistic traffic and environmental effects.) have examined data on city freight deliveries and parking areas in the direction of an optimized city freight transportation system and developed new check-in based mobile parking system for freight vehicles, to recognize and enhance freight delivery processes.

With the advancement of computing technologies, it became possible to utilize machine learning models for classification, prediction and forecasting of data, Vakharia et al. (2017). In present scenario, it is possible to form machine learning models for bigger and complex data sets to assist decision makers to know the real time scenario and estimation of the data. For transportation applications, it is possible to assess the behavior of individual drivers for improving traffic congestion problem and at the same time to predict the flow of traffic after some hours, if past data is available. Yang et al (2014) have studied the application of a robust learning method, Support Vector Machine (SVM) in identifying delivery stops using Global Positioning System (GPS) data. Period of a stop, the distance from a stop to the center of the town, and the distance to a stop's closest major blockage are extracted as a three structures used in the SVM model. Mrówczyńska et al. (2017) discussed in detail the application of artificial intelligence techniques for prediction of road freight transportation. Authors applied double exponential smoothing (HM),double exponential smoothing supported by artificial immune system and Bayesian network to predict the volume of freight and the results are encouraging to use machine learning models for freight applications.

After literature review and need of assessment of traffic conditions in smart cities, it is envisaged that utilization of machine learning models for predicting and validation for capacity and delay time with freight delivery for blocked as well as the unblocked street were not studied in detail. In present study, All or Nothing model which is developed by highway capacity manual 2010 was used for experimental study. After the calculation of position and delay time, machine learning techniques such as Artificial neural network and Support vector machine was employed for prediction and validation of experimental data. The flowchart depicting the methodology used in present study is shown in Fig.1.

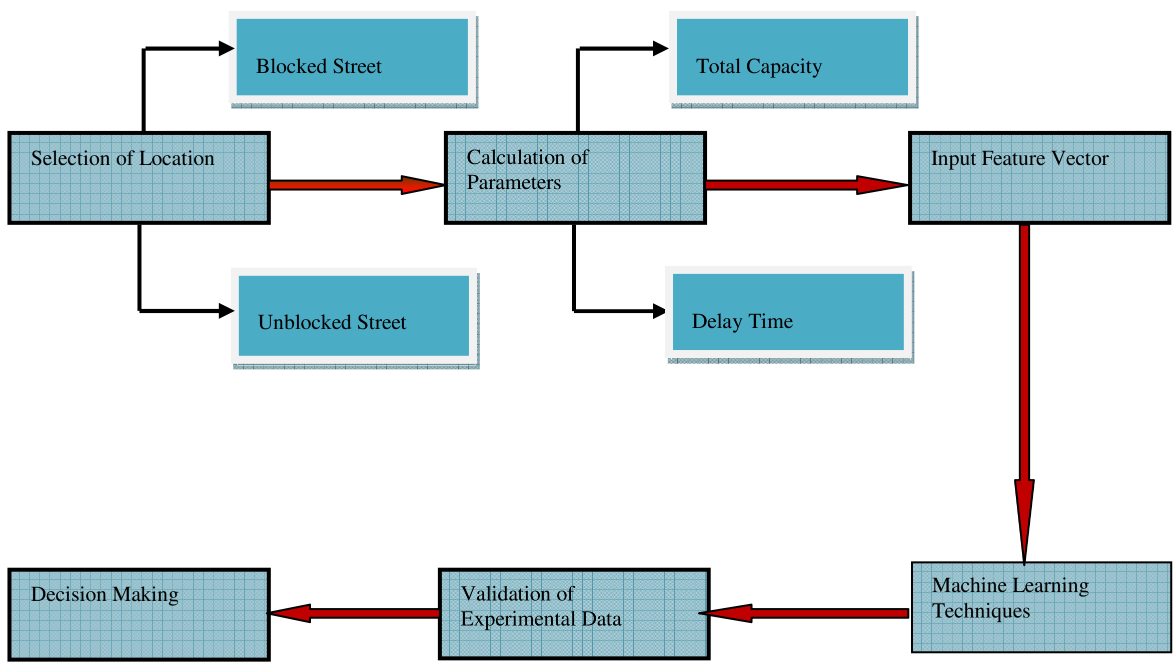

Fig.1. Flowchart depicting methodology used for prediction using machine learning techniques.

2. Machine learning techniques

Machine learning represents sets of algorithms in which patterns are identified in the supplied data. Broadly machine learning techniques are classified in to supervised learning methods in which labeled data is needed for classification or regression, unsupervised learning in which unlabeled data is used and semi-supervised learning in which both labeled and unlabelled data is used. Artificial Neural Network (ANN), Support Vector Machine (SVM),Random forest are some of the widely used algorithms used in various applications like fault diagnosis Vinay et al. (2015),Rotor fault identification, Singh and Kumar (2015),EEG signal, Upadhyay et al. (2015) etc. Artificial Neural Network (ANN) is a computational model and it works like the way human brain processes the information with the aid of neurons. ANN usually consists of inputs which are multiplied by weights where weights denote the strength of signal and the computation is done by a mathematical function which denotes the activation of neuron. By adjusting the weights of a neuron we can able to obtain desired output for a pre-specified inputs, Vakharia et al. (2016).Support Vector Machine is a type of supervised learning algorithm mainly used for classification and regression. The formulation of SVM is based on the principle of structural risk minimization. For binary classification problem, the aim is to maximize margin between the separating planes. The maximum margin which separates the hyperplanes can be used to classify data sets into the classes consider. Due to better generalization capability, SVM as an algorithm is of great interest for academic and industrial societies, Vakharia et al., (2017).

3. Experiments conducted

Ahmedabad is one of the fastest growing city in India. Since last one decade industrial as well as commercial development takes place rapidly, so addressing the traffic congestion was one of the essential factor for optimum utilization of transport capacity besides improving economic performance, mobility and conservational sustainability for the benefit for the citizen. The present study addresses the problem of urban freight deliveries in urban areas blocking traffic, which reduces street capacity and imposes delays on vehicles. The study covers three major intersections of Ahmedabad city which starts from Kalupur market, Kalupur railway station to Sarangpur junction. Out of which two intersection junction is facing heavy traffic and blocked entirely due to the freight delivery. Kalupur railway station is unblocked road because no freight delivery takes place on this road. In the study conducted, authors followed All or Nothing model, which is described in highway capacity manual ( ) for calculations related to unblocked street and blocked street with freight delivery. Table 1 and Table 2 shows the total capacity and delay time calculated for blocked and unblocked street.

The saturation flow rate for the shared right lane is given by

$$Ssr = St/(1 + \mathrm{Pr}(Er - 1)) \tag{1}$$

Each road group's capacity is measured recognized on the saturation flow rate and signal to phase. For a pretimed traffic signal, the capability of the through the lane, and the capacity of the shared right-turn lane are given by HCM manual 2010

$$Ct = StNtg/C \tag{2}$$

The capacity of the Shared right turn lane is given by

$$Csr = Ssr\ Nsr\ g\ /C \tag{3}$$

The control delay at the intersection is calculated for each lane group

$$d= (0.5c(1\text{-}g/C)^{\wedge}2)/(1\text{-}((\min\ \{1,v/c)\ g)/C)) \tag{4}$$

Capacity with freight delivery based on All or Nothing model is calculated as

$$Ssr,dl=Ssr(1\text{-}\ td/T) \tag{5}$$

The capacity of the shared right turn lane is calculated as

$$Csr,dl=Ssr,dl\ g/C \tag{6}$$

Delay with freight delivery based on All or Nothing model is calculated as ddl=0.5 (C(1-g/C)^2)/(1-min {1,vdl/cdl} g/C) (7)

Table 1 Total capacity and delay time values for blocked location

No	Blocked location	Capacity (Veh/hr)		Total capacity	Delay time(sec)
		Through lane	Shared right turn lane		
1	Kalupur market	914	646	1560	17
2	Sarangpur junction	914	646	1560	17
3	Bapunagar junction	923	653	1576	16
4	Naranpura junction	933	660	1593	15.5

Table 2 Total capacity and delay time values for Unblocked location

S.No.	Unblocked location	Capacity (Veh/hr)		Total capacity	Delay time(sec)
		Through lane	Shared right turn lane		
1	Kalupur railway station	969	821	1790	14
2	Indira bridge	984	835	1819	12
3	Shahibaug juction	973	825	1798	13
4	Isanpur junction	968	821	1789	14

Table 3 Prediction result using ANN and SVM for freight delivery

Conditions	Correlation coefficient	Root mean square error (RMSE)	Mean absolute error (MAE)
Blocked capacity	SVM = 0.9928 ANN = 0.9994	SVM = 3.2 ANN = 0.647	SVM = 1.6383 ANN = 0.5343
Blocked delay time	SVM = 0.9944 ANN = 0.9994	SVM = 3.2272 ANN = 0.647	SVM = 1.6383 ANN = 0.5343
Unblocked capacity	SVM = 0.9921 ANN = 0.9995	SVM = 2.4375 ANN = 0.4256	SVM = 1.797 ANN = 0.2766
Unblocked delay	SVM = 1 ANN = 1	SVM = 0.0059 ANN = 0.0028	SVM = 0.0039 ANN = 0.0018

4. Results and Discussion

The study used ALL or Nothing model for calculating capacity and delayed time for unblocked street and blocked the street with freight delivery. It is observed that the capacity of the road was decreased with blocked street with freight delivery and delay time is also increased. The capacity of the unblocked street is more compared to the blocked street. Machine learning techniques such as SVM and ANN were used to predict the capacity and delay for blocked and unblocked conditions. Parameters such as Correlation coefficient, root mean square error and absolute error were used for analyzing the prediction capability of machine learning techniques. Correlation coefficient refers to a numerical relationship between two variables that can be measured either on ordinal or continuous scales. Correlation does not imply interconnection; rather it proposes an association between two variables. The Correlation coefficient designates the strength of a relationship and its value is between -1 to +1.For blocked capacity and delay time ANN given high value of Correlation coefficient as compare to SVM. Similar observation was revealed for unblocked capacity and delay as seen from Table 4.Root Mean Square Error (RMSE) measures the differences between values predicted by a machine learning model and the observed values. In other words, it measures the quality of the fit between the actual data and the predicted model. For prediction model, ideal RMSE should be minimum. From Table 4,it is observed that SVM gives high RMSE as compare to ANN for all the four cases considered.Mean absolute error (MAE) is a measure of the difference between two continuous variables. For analyzing the prediction capability of machine learning model, MAE should be as low as possible. From Table 4,it is clear that ANN gives low value of MAE for all the cases i.e. Blocked capacity, Blocked delay time, Unblocked capacity and Unblocked delay considered in present study. From the results obtained ANN gives better prediction as compare to SVM as evident from all the three parameters i.e. Correlation coefficient, RMSE and MAE.

5. Conclusion

In the present study, freight deliveries for blocked and unblocked street in Ahmedabad district was calculated at different locations. Total capacity and delay time were calculated at specified locations considering the HCM manual with All or Nothing model. Machine learning techniques such as SVM and ANN were used to predict the parameters calculated experimentally. To evaluate the efficacy of machine learning model three parameters Correlation coefficient, Root means square error and Mean absolute error were utilized. It was observed that for all the four cases considered ANN gives better result as compared to SVM for all the three parameters. Proposed methodology will be useful for prediction of online freight delivery in real scenario.

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