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MACHINE LEARNING APPROACHES FOR TRAFFIC FORECASTING ON BLOCKED STREETS: A STUDY WITH MICROSIMULATION MODELS

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Abstract:
Freight deliveries on city roads with traffic signals often cause lane blockages, worsening urban traffic congestion. This issue has garnered increased attention as traffic engineers and urban planners seek sustainable ways to manage growing demand within the limits of existing road capacities. This study aims to assess a model designed to quantify the impact of freight deliverieson road capacity and delays on signalized streets in Ahmedabad. The model is based on methodologies similar to those outlined in the Highway Capacity Manual (HCM2010). The research explores how these analytical tools can be utilized in developing urban freight delivery policies. It examines delay estimation and vehicle capacity by considering various factors such asdelivery locations and times, and their effects on different lanes. Machine learning techniques, including Support Vector Machines and Artificial Neural Networks, were employed to forecast vehicle capacity and estimate delays. The results demonstrate a strong alignment between the predicted outcomes and actual data.

Keywords: Freight Delivery, Machine Learning, Support Vector Machine, Artificial Neural Network, Microsimulation model.

1. Introduction

Freight deliveries on city roads with traffic signals are well-known for causing lane blockagesalong their routes. Recently, the issue of traffic congestion resulting from these urban freight operations has gained significant attention. Traffic engineers and urban planners face the challenge of finding sustainable solutions to accommodate increasing demand while dealing with the limitations of road capacity. There is a growing focus on implementing policies to shift deliveries to off-peak hours to reduce their negative impact on traffic congestion. A prominent study on the effects of heavy vehicles on traffic networks is detailed in NCFRP Report 31 by Dowling and colleagues (2014), which offers valuable insights into how trucks influence mid-block arterial speeds and introduces improved methods for calculating truck-to- passenger car equivalent factors, aimed at refining capacity analysis for signalizedintersections.

Nevertheless, these strategies do not fully address the issues caused by parked trucks blocking lanes. Keegan and Gonzales (2016) highlighted the challenges that freight deliveries present in urban environments, including disruptions to traffic flow, reduced street capacity, and increased vehicle delays. To tackle these challenges, researchers have employed the 'All-or-Nothing' model and

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Kinematic wave theory to assess the impact of freight deliveries on traffic and to develop appropriate policies. Benekohal and Zhao (2000) explored the use of passenger car equivalents tomeasure the varying effects of heavy vehicles on traffic flow, noting that the size and slower acceleration and deceleration of heavy vehicles can significantly impair traffic performance at intersections.
In 2006, Holguín-Veras and his team conducted an extensive study on policies to promote off- peak deliveries in urban areas. Their research examined the conditions required for establishing agreements between receivers and carriers for off-hour deliveries and evaluated the effectivenessof various policies in encouraging these changes, particularly in competitive markets. Holguín- Veras reiterated in 2008 the importance of incentivizing off-hour deliveries to alleviate traffic congestion, focusing on the benefits to governmental agencies and delivery drivers who experiencereduced congestion during off-peak periods.
Crainic and his team (2004) addressed the challenge of ensuring compliance with off-hour delivery schedules, which often requires store staff to be available for proper acceptance and handling. This situation demands that recipients either stay available after business hours or make prior arrangements for deliveries when no designated receiver is present.
Holguín-Veras et al. (2016) further explored supply chain interactions, emphasizing the significantrole of supply receivers in influencing delivery timing and methods. Their findings suggested that Residential Loading Zone (RLC) programs could offer substantial benefits for large urban areas by reducing freight vehicle miles traveled and easing congestion. Yannis et al. (2006) investigatedthe effects of restricting vehicle movements related to urban deliveries, concluding that limiting deliveries to certain business types during peak hours could improve both traffic conditions and the environment. Additionally, research aimed at optimizing urban freight transportation systems proposed a mobile check-in-based parking system to enhance delivery efficiency.

Advancements in computing technologies have made machine learning models increasingly valuable for data classification, prediction, and forecasting, as noted by Vakharia et al. (2017). These models can now handle larger and more complex datasets, providing real-time insights anddata estimates. In transportation applications, these models analyze individual driver behavior to address traffic congestion and predict future traffic flow based on historical data. Yang et al. (2014)investigated the use of Support Vector Machines (SVM) for identifying delivery stops using GPSdata, considering factors such as stop duration, distance to town centers, and proximity.

Mrówczyńska et al. (2017) conducted an extensive study on applying artificial intelligence techniques to forecast road freight transportation. Their research examined several methods, including double exponential smoothing, enhanced double exponential smoothing with artificial immune system support, and Bayesian networks for predicting freight volumes. The findings were promising and highlighted the potential of machine learning models in freight transportation applications.

Upon reviewing existing literature and recognizing the need to assess traffic conditions in smart cities, it became clear that there was a significant research gap regarding the use of machine learning models

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to predict and verify capacity and delay times for freight deliveries on both obstructed and unobstructed streets. This study addresses this gap by conducting an experimentalanalysis using the 'All-or-Nothing' model from the Highway Capacity Manual (2010). After calculating positions and delay times, we applied machine learning techniques, specificallyArtificial Neural Networks (ANN) and Support Vector Machines (SVM), to predict and validate the experimental results. The detailed methodology used in this study is illustrated in Figure 1.

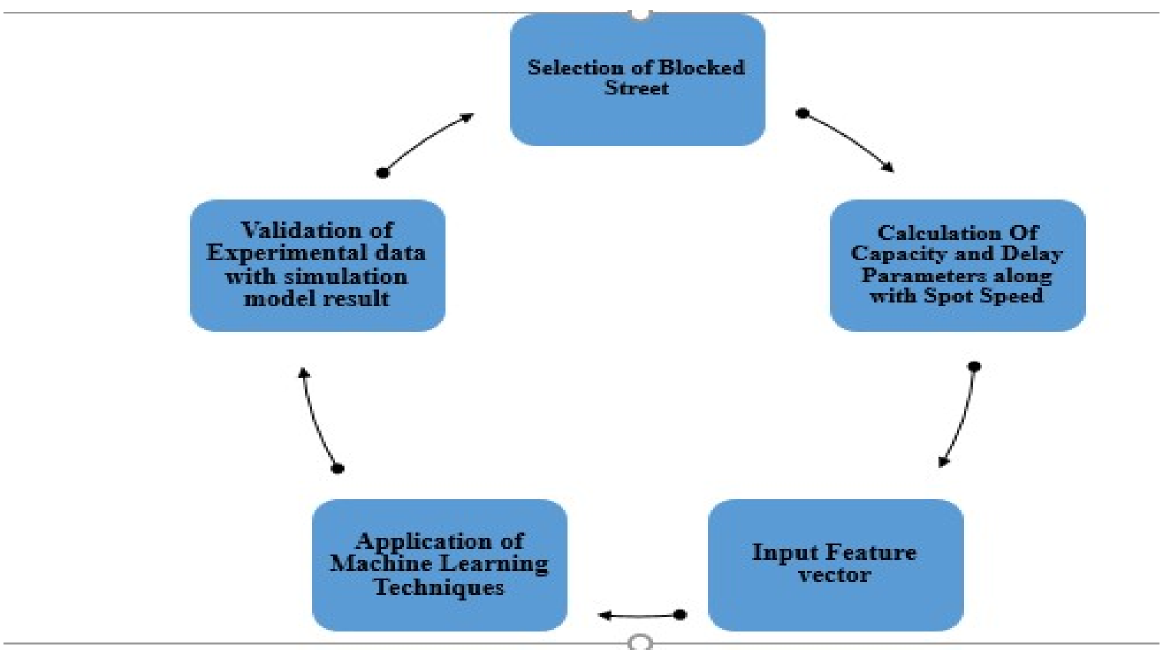

Figure 1: Flowchart depicting the methodology used for prediction with machine learningtechniques.

2 Machine Learning Techniques

Machine learning encompasses a variety of algorithms designed to identify patterns withindatasets. These algorithms are typically categorized into three main types: supervised learning, which requires labeled data for tasks such as classification and regression; unsupervised learning,which analyzes data without labels; and semi-supervised learning, which integrates both labeled and unlabeled data. Common algorithms include Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest, which are utilized in various applications such as fault diagnosis (Vinay et al., 2015), rotor fault detection (Singh and Kumar, 2015), and EEG signalanalysis (Upadhyay et al., 2015).

Artificial Neural Networks (ANN) are computational models inspired by the brain's structure, consisting of multiple layers of interconnected neurons. Each input passes through these neurons, where weights represent the strength of the signals and activation functions drive the computations.By modifying these weights, ANNs can generate specific outputs from given inputs (Vakharia et al., 2016).

Support Vector Machines (SVM) are supervised learning algorithms primarily used for classification

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http://magellanes.com/

and regression tasks. They work on the principle of structural risk minimization andaim to maximize the margin between different classes in binary classification. This approach helpsSVMs effectively separate data into distinct groups. Their strong generalization capabilities makeSVMs widely used in both research and practical applications (Vakharia et al., 2017).

3 Experiments Conducted

In the last decade, Ahmedabad has emerged as one of India's rapidly expanding cities, marked by notable growth in both industrial and commercial sectors. This expansion has intensified the challenge of managing traffic congestion, which is crucial not only for enhancing transportation capacity but also for boosting economic performance, mobility, and environmental sustainability, thereby benefiting the city's residents. This study addresses the issue of urban freight deliveries in Ahmedabad, which frequently lead to traffic obstructions, diminishing street capacity and increasing vehicle delays.
The research focuses on three key intersections in Ahmedabad: Kalupur Fruit Market, Kalupur Chokha Bajar, and Maninagar Railway Station, as well as other locations such as Bapunagar Cross Road, Jai Hind Char Rasta, and Ratanpole. Among these, two intersections face severe congestion mainly due to freight deliveries. The study utilizes the 'All or Nothing' model from the Highway Capacity Manual to evaluate both unobstructed and obstructed streets. The findings, including metrics on total capacity and delay times for both types of streets, are detailed in Tables 1 and 2.

The saturation flow rate for the shared right lane is determined by...

$$Ssr = St / (1 + Pr(Er - 1)) \quad (1)$$

Where, Ssr = Saturated flow rate for the shared right, St = Saturated Flow rate for through lane,Pr = proportion of the right-turning vehicle in the shared lane.

Each road group's capacity is established by considering variables like the saturation flow rate and signal timing. When dealing with a pre-timed traffic signal, the capacity for both the through laneand the shared right-turn lane can be referenced in the 2010 edition of the Highway Capacity Manual.

$$Ct = StNtg/C \quad (2)$$

Where Ct = Capacity of through lane, C = Cycle Length, Nt = Number of lane in the through lane,G = Green Time

The capacity of the shared right-turn lane is determined as follows:

$$Csr = SsrNsrg/C \quad (3)$$

Ssr=saturation flow rate for the shared right lane, Nsr = Number of lanes through the shared rightturn

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lane.

The calculation of control delay at the intersection is conducted separately for Each lane group.

d=(0.5c(1-g/C) ^2)/(1-((min {1, v/c)g)/C)) .... (4)

Where d= Delay time.

The calculation of capacity in the presence of freight delivery, using the All or Nothing model, isas follows:

Ssr, dl=Ssr(1-td/T)..-(5)

Where, T = Duration of analysis Period, Ssr, dl = Average Saturated rate for shared right turn lane/The capacity of the shared right-turn lane is determined as follows:

Csr, dl=Ssr, dl/C..(6)

Where, Csr, dl = Capacity of shared right turn lane.

The Calculation of delay in the context of freight delivery, utilizing the all-or-nothing model is determined 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(veh/hr)	Delay time(sec)
		Through lane	Shared right turn lane		
1	Kalupur Fruit Market	913	645	1558	15.95
2	Kalupur Chokha Bajar	837	592	1429	16.34
3	Maninagar Railway Station	814	575	1389	16.74
4	Bapunagar Cross Road	796	563	1359	17.15
5	Jai Hind Char Rasta Maninagar	772	546	1318	17.58
6	Ratanpole	756	534	1290	17.91

Table 2: - Spot Speed for Different Location

Sr. No.	Location	Speed(km/hr)
1	Kalupur fruit market	32.15
2	Kalupur Chokha bazar)	31.35
3	Maninagar railway station	31.32
4	Bapunagar road	31.27

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5	Jay hind char Rasta (Maninagar)	31.2
6	Ratanpole Junction	31.16

Table 3: Prediction result using ANN and SVM for Freight Delivery

Conditions	Correlation Coefficient	Root Mean Square error (RMSE)	Mean Absoluteerror (MAE)
Blocked Capacity	SVM = 0.9930 ANN = 0.9996	SVM = 3.2 ANN = 0.649	SVM = 1.6386 ANN = 0.5346
Blocked delay time	SVM = 0.9946 ANN = 0.9996	SVM = 3.2274 ANN = 0.647	SVM = 16385 ANN = 0.5343

4. Results and Discussion

In this study, the 'All or Nothing' model was employed to assess the capacity and delay times for streets with and without freight obstructions. The findings indicate a significant reduction in road capacity when streets are blocked by freight deliveries, resulting in increased delays. Clearly, unobstructed streets have superior capacity compared to those affected by freight.

To enhance the accuracy of capacity and delay predictions for both types of conditions, machine learning methods were applied, specifically Support Vector Machines (SVM) and Artificial Neural Networks (ANN). These techniques were evaluated using metrics such as the Correlation Coefficient, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to determine theireffectiveness.

The Correlation Coefficient measures the strength of the relationship between two variables, whichcan be ordinal or continuous, but it does not establish causation. It ranges from -1 to +1, with values closer to +1 indicating a stronger association. In this study, the ANN model showed a notably higher Correlation Coefficient compared to the SVM model when analyzing blocked capacity and delay times, a trend that persisted throughout the analysis.

Table 4 provides additional details on unblocked capacity and delay times. RMSE is an important metric for assessing the accuracy of model predictions compared to actual observed values, with lower RMSE values indicating a closer fit between predicted and real data. As shown in Table 3, the SVM model consistently recorded higher RMSE values than the ANN model across all cases studied. MAE evaluates the average deviation between predicted and actual values, with lower MAE values signifying better prediction accuracy. Table 4 demonstrates that the ANN model consistently achieved lower MAE values for all cases—Blocked Capacity, Blocked Delay Time, Unblocked Capacity, and Unblocked Delay—indicating superior performance.

In summary, the results show that the ANN model outperforms the SVM model in terms of all three key metrics: Correlation Coefficient, RMSE, and MAE.

5. Conclusion

This research focused on assessing the impact of freight deliveries on both obstructed and unobstructed streets within the Ahmedabad district. The study involved several locations where the

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total capacity and delay times were precisely calculated using methods from the Highway Capacity Manual (HCM) and the 'All or Nothing' model. To enhance the accuracy of these calculations, machine learning techniques, namely Support Vector Machines (SVM) and ArtificialNeural Networks (ANN), were utilized to predict experimental parameters. The performance of these models was assessed using three key metrics: Correlation Coefficient, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

The findings consistently showed that the ANN model surpassed the SVM model in all four scenarios assessed. This conclusion was based on a comprehensive evaluation of the three criticalmetrics: Correlation Coefficient, RMSE, and MAE. The methodology proposed in this study offerssignificant insights and practical applications for forecasting freight deliveries in real-world environments.

References

1. Benekohal, R. F., and Zhao, W. ,2000. Delay-based passenger car equivalents for trucks at signalized intersections.Transportation Research Part A: Policyand Practice34.6,437-457.
2. Crainic, T.G.Ricciardi, N. and Storchi, G. 2004. Advanced freight transportation system for congested urban areas. Transportation Research Part C, Emerging Technologies 12.2, 119-137.
3. Dowling, R., List, G., Yang, B., Witzke, E., Flannery, A., 2014. Incorporating truckanalysis in to the Highway Capacity Manual. DOI: https://doi.org/10.17226/22311.
4. Holguín-Veras, J., Wang,Q.,Xu,N.,Ozbay,K., Cetin,M.,Polimeni,J.,2006.The impacts of time of day pricing on the behavior of freight carriers in a congested urban area: Implications to road pricing. Transportation Research Part A: Policyand Practice40 (9),744-766.
5. Holguín-Veras, J.,2008. Necessary conditions for off-hour deliveries and the effectiveness of urban freight road pricing and alternative financial policies in competitive markets. TransportationResearch Part A: Policyand Practice42,392-413.
6. Holguín-Veras, J., Sánchez-Díaz, I. and Browne, M. ,2016. Sustainable Urban Freight Systems and Freight Demand Management. Transportation Research Procedia 12,40-52.
7. Keegan, A. and Gonzales, E. ,2016. Evaluating Capacity and Delay for Signalized Arterials with Freight Deliveries. Transportation Research Procedia15,161-175.
8. Manual, H. (2010) HCM 2010 Highway Capacity Manual. National Academy of Sciences. Mrazovic, P. Eravci B, Larriba Pey, J.L. Ferhatosmanoglu, H. Matskin M. 2017 Understanding and Predicting Trends in Urban Freight Transport. 18th IEEE International Conference on Mobile Data Management DOI:10.1109/MDM.2017.26.
9. Singh, S. and Kumar, N.,2015. Rotor Faults Diagnosis using Artificial Neural Networks and Support Vector Machines. International Journal of Acoustics and Vibrations 20.4,153-159.
10. Upadhyaya,R., Manglick,A., Reddy, D.K.,Padhy, P.K.,Kankar, P.K.,2015. Channel optimization and nonlinear feature extraction for Electroencephalogram signals classification. Computers and Electrical Engineering.45,222-234.
11. Vinay, V., Kumar, G.V., Kumar, K.P.2015. Application of chi square feature ranking technique and random forest classifier for fault classification of bearing faults. In Proceedings of the 22th International Congress on Sound and Vibration, Florence,Italy12–16.

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Volume 06 Issue 2
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ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

12.Vakharia,V, GuptaV.K., and KankarP.K., 2016. Bearing Fault Diagnosis Using Feature Ranking Methods and Fault Identification Algorithms. ProcediaEngineering.144,343-350.
13. Vakharia,V, GuptaK, and KankarP, 2017. Efficient fault diagnosis of ball bearing using ReliefFand Random Forest classifier. Journal of the Brazilian Society of Mechanical Sciences and Engineering 39.8, 2969–2982.
14. Yang, X.,Sun,Z.,Ban,X.J.,Veras,J.H.,2014.Urban Freight Delivery Stop Identification with GPS Data Transportation Research Record: Journal of the Transportation Research Board 2411 (December),55–61.
15. Yannis, G., Golias, J. and Antoniou, C. (2006) Effects of urban delivery restrictions on traffic movements, Transportation Planning and Technology29.4,295-311.