Comparative study of statistical and machine learning methods for streetcar incident duration analysis

Siying Zhu[a,*]

[a] *Department of Civil and Environmental Engineering, National University of Singapore, Singapore 117576*

Abstract

This study aims to investigate and identify the contributing factors to long-duration streetcar incident delay, where contingency plan could be activated. For comparative study, the performance of eight statistical and machine learning methods, including logistic regression model, Bayesian logit regression model, classification and regression tree model, K-nearest neighbours model, random forest model, gradient boosting model and artificial neural network model, have been compared and analysed based on the Toronto streetcar incident dataset in 2019 with 11418 streetcar incident records. The comparative study results show that the random forest method has the best performance, whose marginal effect analysis further demonstrates that the most significant contributing factors to streetcar incident delay duration are the morning peak period, the streetcar incidents types including mechanical failure, held by, diversion and late leaving the garage, as well as the month and weekday. The result of the paper could provide policy implication on timely streetcar incident clearance and contingency plan implementation.

Keywords: Streetcar incident, long-duration delay, comparative study, statistical and machine learning methods, marginal effect analysis

1. Introduction

Streetcar, which is considered as an efficient solution to alleviate traffic congestion, operates on tracks along public urban streets and on segregated rights-of-way (Nguyen-

*Corresponding author.

Email address: SIYING001@e.ntu.edu.sg (Siying Zhu)

Phuoc et al., 2017). As an efficient, energy-saving, and environmentally friendly urban public transportation mode, the utilisation rate of modern streetcar system has been rapidly growing worldwide over the years (Wang et al., 2015). Nevertheless, streetcar incidents, caused by various reasons such as mechanical failure and emergency services, could result in a temporary reduction in streetcar capacity.

Various lengths of streetcar delays have significantly different impacts on the general traffic condition, public transit ridership and individual commuter's travel time (Leung et al., 2020). For the streetcar incident delays with long duration, great disruption to passengers can be incurred, in spite of their low likelihood of occurrence. Thereby, it is essential for the traffic management authorities to effectively respond and implement the management strategies to clear the long-duration streetcar incidents in a timely manner. In many mega-cities around the world, contingency plans have been designed by the transportation agencies based on the estimated delay time or level of emergence. For instance, in Singapore, bus-bridging service should be activated when metro delay is expected to exceed 30 minutes (Tan et al., 2020). In this paper, similar to the case of Singapore metro system, we define the streetcar delays longer than 30 minutes as significant or long-duration delays. To enable the timely clearance of long-duration streetcar incidents or the implementation of the contingency plan, it is necessary analyse the impact factors to streetcar incident delay duration systematically.

1.1. Relevant studies

Many researchers have focused on the traffic incident duration analysis, where various parametric and non-parametric models have been applied. For the metro incident delay duration analysis, accelerated failure time (AFT) approaches have been commonly applied, where Weng et al. (2014) focused on the subway operation incidents; Louie et al. (2017) considered the causal and non-causal contributing factors to metro delay specifically; Weng et al. (2015, 2019) have further proposed maximum likelihood regression tree with AFT model in each leaf node. In addition, ordered logit model (Lu et al., 2021), binary probit model (Volovski et al., 2021), random parameter proportional hazard model

(Agbelie and Libnao, 2018), multinomial logit model (Juan et al., 2019), linear regression models with interaction effects between outdoor track distance and weather condition (Diab and Shalaby, 2020), neural network model (Yaghini et al., 2013), network topology analysis (Wang et al., 2020) have also been applied for the metro delay duration prediction. However, even though numerous studies have been conducted to model the delay due to metro incidents, there are very limited research on streetcar incident delay. Leung et al. (2020) has utilised the streetcar incident data to test the performance of the proposed fuzzy logic-based model, but the descriptive statistics and interpretability of streetcar incident delay model has not been catered for.

1.2. Objectives and contributions

This paper aims to analyse the streetcar incident dataset and identify the contributing factors to long-duration delay. For comparative study, the performance of eight statistical and machine learning methods are compared and analysed. The result of the paper could provide policy implication on streetcar incident mitigation.

The remainder of the paper is organised as follows: Section 2 illustrates data collection process and the descriptive statistics of the streetcar incident duration dataset. Section 3 shows various research methodologies, i.e., statistical and machine learning methods for streetcar incident delay analysis. Section 4 discusses the results of the comparative study. Lastly, Section 5 draws the conclusion of the study, addresses the study's limitation and potential future work directions.

2. Data Collection and Descriptive Analysis

Streetcar operation incident data were collected from the open-source database published by Toronto Transit Commission[1]. 11418 streetcar incident records in 2019 have been utilised to develop and test the streetcar incident delay model. The distribution of the streetcar delay time has also been plotted in Figure 1, where the blue line denotes

[1]Data source: *https://ckan0.cf.opendata.inter.prod-toronto.ca/tr/dataset/ttc-streetcar-delay-data*

the streetcar delay time as 30 minutes. 93% of the streetcar incidents lasted less than 30 minutes, while 7% of them were longer than 30 minutes. As mentioned in the previous section, similar to the case of Singapore metro system, the streetcar incident delays longer than 30 minutes are identified as significant or long-duration delays, and the descriptive statistics of the streetcar incident delay dataset has been summarised in Table 1. Note that since the proportion of long-duration streetcar incidents is relatively low, to tackle the class imbalance issue, Synthetic Minority Over-sampling Technique (SMOTE) (Chawla et al., 2002) is further applied to resample the dataset for modelling.

The distribution of streetcar delay with different incident types has also been illustrated with a boxplot (Figure 2). The band in the middle of each box indicates the 50th percentile or the median of the streetcar incident delay duration corresponding to each incident type; the top and bottom of each box represent the 75^{th} (Q_3) and 25^{th} (Q_1) of the streetcar delay duration, respectively; and the length of each box is denoted as the interquartile range (IQR). In addition, the upper whisker is located at the smaller of the maximal of the streetcar delay duration and $Q_3 + 1.5 \cdot IQR$; the lower whisker is at the larger of the minimal of the streetcar delay duration and $Q_1 - 1.5 \cdot IQR$; and the streetcar incidents whose duration falls out of the two whiskers are considered as outliers in the boxplot. Observing Figure 2, it is identified that streetcar diversion issue tends to cause streetcar incidents with longer duration.

3. Research Methodology

In this study, the target variable is the occurrence of long-duration streetcar incident delay, thus classification is the most suitable data mining functionality to be applied. The set of explanatory variables can be defined as $X = \{Month, Day, Time, Incident\}$. For comparative study, eight statistical and machine learning methods, including logistic regression model, Bayesian logit regression model, classification and regression tree model, K-nearest neighbours model, random forest model, gradient boosting model and artificial neural network model, are utilised and executed in R programming language.

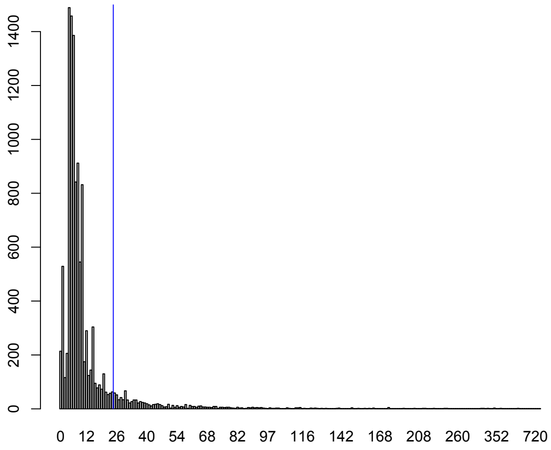

Figure 1: Distribution of the streetcar delay time (minutes)

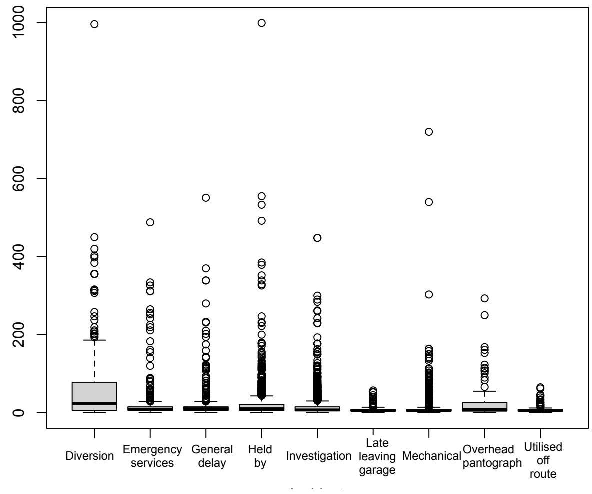

Figure 2: Streetcar delay duration by incident types (minutes)

Table 1: Descriptive statistics

Variable	Values	Delay time				Total	Percent
		≤30min	%	>30min	%		
Delay	≤30min	-	-	-	-	10610	93%
	>30min	-	-	-	-	808	7%
Month	Jan	1398	94%	97	6%	1495	13%
	Feb	1171	92%	107	8%	1278	11%
	Mar	1054	93%	78	7%	1132	10%
	Apr	821	94%	56	6%	877	8%
	May	780	92%	66	8%	846	7%
	Jun	786	90%	85	10%	871	8%
	Jul	792	93%	62	7%	854	7%
	Aug	700	92%	62	8%	762	7%
	Sep	713	90%	80	10%	793	7%
	Oct	842	93%	68	7%	910	8%
	Nov	747	94%	51	6%	798	7%
	Dec	750	94%	52	6%	802	7%
Day	Monday	1530	94%	102	6%	1632	14%
	Tuesday	1585	93%	117	7%	1702	15%
	Wednesday	1445	93%	116	7%	1561	14%
	Thursday	1625	93%	117	7%	1742	15%
	Friday	1547	92%	132	8%	1679	15%
	Saturday	1545	94%	105	6%	1650	14%
	Sunday	1333	92%	119	8%	1452	13%
Time	Morning peak	1652	96%	72	4%	1724	15%
	Evening peak	1701	92%	147	8%	1848	16%
	Non-peak	7257	92%	589	8%	7846	69%
Incident	General delay	984	95%	49	5%	1033	9%
	Diversion	115	59%	81	41%	196	2%
	Emergency services	630	92%	54	8%	684	6%
	Held by	1377	83%	283	17%	1660	14%
	Investigation	1741	90%	195	10%	1936	17%
	Late leaving garage	597	99%	5	1%	602	5%
	Mechanical	4685	98%	116	2%	4801	42%
	Overhead pantograph	75	81%	18	19%	93	1%
	Utilised off route	406	98%	7	2%	413	4%

In the following subsections, brief illustration of each classifier is presented.

3.1. Logistic Regression & Bayesian Logit Regression

As a commonly used statistical model, logistic regression method applies the logistic function (as shown in Eq.1) to determine the probability of different classes of the target variable (Kleinbaum and Klein, 2010). In this study, the streetcar incident duration model is a binary classification model, such that the target variable could be represented by a dummy variable, where 1 indicates long-duration streetcar incident and 0 denotes the others; and other streetcar incident contributing factors serve as the explanatory variables.

$$p = \frac{e^{(\beta_0+\beta_1 x_1+...+\beta_n x_n)}}{1+e^{(\beta_0+\beta_1 x_1+...+\beta_n x_n)}} \tag{1}$$

Different from the logistic regression model which estimates fix values for the coefficients ($\beta_0, \beta_1, ..., \beta_n$), Bayesian logit regression further takes into account the uncertainty of coefficients based on the posterior probability distribution (Haq et al., 2020; Train, 2009), as shown in Eq.2:

$$p(\beta|y) = \frac{p(y|\beta)p(\beta)}{p(y)}, \tag{2}$$

where β denotes the vector of estimated parameters; y denotes the set of observed target variables on delay duration for all streetcar incident records; $p(\beta|y)$ denotes the posterior distribution of β; $p(y|\beta)$ represents the likelihood function; $p(\beta)$ indicates the prior information on the parameters; and $p(y)$ denotes the marginal probability distribution of y over β, calculated by Eq.3:

$$p(y) = \int p(y, \beta) d_\beta \tag{3}$$

3.2. Classification and Regression Tree

The classification and regression tree (CART) algorithm enables the classification of streetcar incident delay by selecting the explanatory variable that achieves the 'best' split in the decision tree. In this study, the classification tree aims to maximise the purity level or impurity reduction $\Delta G(N)$ at each node N in the tree:

$$\Delta G(N) = G(N) - \frac{m(N_L)}{m(N)} \cdot G(N_L) - \frac{m(N_R)}{m(N)} \cdot G(N_R), \tag{4}$$

where N denotes a parent node, N_R and N_L denote the two child nodes of N; and $m(N)$, $m(N_L)$, $m(N_R)$ indicate the number of streetcar incident records at the three nodes, respectively. G denotes the impurity measure function, hereby represented by the Gini index, which is defined as follows:

$$G(N) = 1 - \sum_j [p(j|N)]^2, \tag{5}$$

where j denotes the class of the response variable, i.e., the streetcar incident delay duration category; $p(j|N)$ represents the probability that a streetcar incident belongs to class j, provided it exists in the node N.

To maximise the purity level of leaf node, the data could be recursively partitioned such that the classification tree is saturated, resulting in the overfitting issue. Therefore, the saturated tree is further pruned via cross-validation to obtain simpler tree with better cross-validated performance (Chang and Chien, 2013; Therneau et al., 2019).

3.3. K-Nearest Neighbours

As a non-parametric statistical method, K-Nearest Neighbours (KNN) algorithm conducts the classification task by extracting k closest data records to the observation of interest (Cover and Hart, 1967). In this paper, similar to (Iranitalab and Khattak, 2017), the distance D_{ij} between two observations i and j in the dataset is determined with the Euclidean distance, as shown in Eq.6:

$$D_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2}, \tag{6}$$

where p denotes the dimension of the feature vectors; and x_{ik} and x_{jk} indicate the value of the k^{th} feature of observations i and j, respectively.

3.4. Random Forest and Gradient Boosting

Random forest model and gradient boosting model are both ensemble learning models, where many based learners or individual trees are fitted, and the final predictor aggregates across them. In the gradient boosting algorithm, each base tree learner learns from the fitting error from the previous iteration, and the sequential process continues until the best fitted model is derived (Zheng et al., 2018; Friedman, 2001). On the other hand, different from the gradient boosting algorithm that generates base learners in sequence, random forest algorithm models the individual base learners with bootstrapped data samples in parallel way. In other words, only a random subset of features are utilised at splitting nodes of the individual trees, such that the diversity among base learners can be guaranteed (Zhang and Haghani, 2015; Breiman, 2001).

3.5. Artificial Neural Network

The artificial neural network model consists of an assembly of artificial neurons or inter-connected nodes and weighted links (as shown in Figure 3), attempting to simulate the way the human brain that contains a network of neurons learns and extracts information (Schmidhuber, 2015; Ripley, 2007). In this paper, the input neurons receive the streetcar incident delay data, which could be further transmitted to hidden layer neurons via weighted connections that indicate their relative importance. In the end, weighted sum of the inputs is applied to the activation function to determine the response (Kumar et al., 2015), i.e. streetcar incident delay duration classification.

4. Results and Discussions

In this section, we compare the results from different statistical and machine learning models, then the marginal effect analysis is conducted based on the best fitted model to illustrate the impacts of various contributing factors to streetcar incident delay duration.

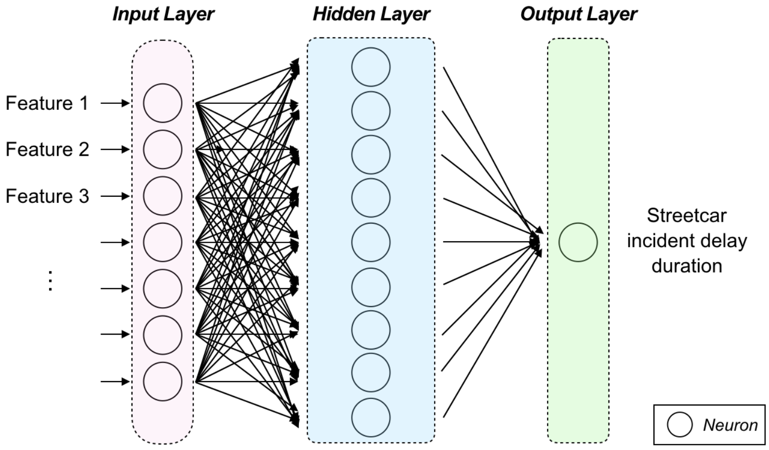

Figure 3: Artificial neural network structure illustration

4.1. Results of different models

In this paper, we perform three-fold cross validation on the training set (80% of the dataset) to tune the parameters, and the remaining 20% of streetcar incident records serve as the test data. The performance of the models described in Section 3 are summarised in Table 2, where various performance evaluation matrices including accuracy, sensitivity, specificity and AUC value are demonstrated for comparative study, and the best metrics among these models are highlighted in bold. Observing the results on the test set, random forest has the best performance, followed by gradient boosting model, demonstrating that the ensemble learning methods make better predictions than the single base model, i.e., CART model in this case. On the other hand, logistic regression model has the worst performance, while the Bayesian logit model that applies the Bayes theorem to derive the posterior probability distribution of parameters has better performance than it.

The computational costs (in seconds) of the models are also shown in Table 2. All models are implemented on a personal computer with Intel Core i5 CPU 2.3 GHz, 8 GB RAM and MacOS 10.14, and the software configuration is R 4.1.0. The LR model demonstrates the shortest computation cost, whereas the RF model with the best performance needs the highest running time. On account of the large streetcar dataset with 11418 incident delay records, the RF model's running time, which is less than 3 minutes, is hereby considered as acceptable.

Table 2: Results of different models

Model	Training				Test				Computation cost(in seconds)
	Accuracy	Sensitivity	Specificity	AUC	Accuracy	Sensitivity	Specificity	AUC	
LR	0.655	0.794	0.513	0.654	0.664	0.808	0.515	0.661	**0.296**
BLR	0.694	0.680	0.707	0.753	0.689	0.690	0.689	0.753	40.513
KNN	0.751	0.756	0.747	0.841	0.776	0.797	0.755	0.776	31.513
RF	**0.884**	**0.896**	**0.872**	**0.939**	**0.886**	**0.897**	**0.875**	**0.886**	160.001
GBM	0.846	0.872	0.820	0.927	0.858	0.888	0.826	0.857	16.394
NN	0.780	0.764	0.796	0.865	0.782	0.758	0.806	0.782	36.252
CART	0.760	0.860	0.659	0.817	0.765	0.870	0.656	0.763	2.295
SVM	0.833	0.855	0.811	0.833	0.844	0.867	0.819	0.843	30.471

*The parameter settings of machine learning models are listed as follows: KNN(k=5), RF(no. of variables randomly sampled at each split=16), GBM(no. of trees=150, max no. of nodes per tree=3, learning rate=0.1, min no. of observations in terminal nodes=10), NN(no. of units in hidden layer=5, decay=10^{-4}), CART(complexity parameter=0.02938355), SVM(cost=10, kernel='radial').

4.2. Marginal effect analysis

After comparing the results of the models in the previous section, random forest has the best performance. Thereby, we further conduct the marginal effect analysis of the model (as shown in Eqn.7, modified based on Yu et al. (2021)) in this section to illustrate the positive and negative impacts of the contributing factors on the streetcar incident delay:

$$M_j = \frac{1}{n} \cdot \sum_{i=1}^{n} (O_i|_{x_{ij}=1} - O_i|_{x_{ij}=0}), \tag{7}$$

where M_j denotes marginal effect of the j-th explanatory variable of streetcar incident dataset; n denotes the total number of streetcar incident records; x_{ij} indicates the j-th explanatory variable of streetcar incident record i; $O_i|_{x_{ij}=1}$ and $O_i|_{x_{ij}=0}$ represent the output values associated with streetcar incident i given $x_{ij} = 1$ and $x_{ij} = 0$, respectively. Note that all the explanatory variables (month, day, time, incident type) utilised in this study are categorical/nominal variables, which are expressed as dummy variables for marginal effect analysis. Since they are all analysed in the same scale, data normalisation or standardisation has not been conducted. The marginal effects of the top ten features to the streetcar incident delay are depicted in Table 3:

The results show that the streetcar incidents including mechanical failure and late leaving the garage tend to decrease the likelihood of significant streetcar delay, and it could be more feasible for the streetcar to catch up with the schedule. On the other hand,

Table 3: Marginal effect of the top ten features

No.	Variable	Marginal effect
1	Incident (Mechanical)	-0.363
2	Month (Apr)	-0.187
3	Incident (Held by)	0.138
4	Time (Morning peak)	-0.111
5	Day (Thursday)	-0.072
6	Incident (Diversion)	0.069
7	Incident (Late leaving garage)	-0.052
8	Month (Nov)	-0.049
9	Month (Oct)	-0.049
10	Month (May)	-0.047

the streetcar incident tends to be with long-duration when the streetcar is held by, for instance, at control points by the transit agencies or due to unexpected event. In addition, the incident – diversion is also more likely to incur significant streetcar delay, which could be explained by the fact that diversion is due to construction or repair, and it usually lasts several days, affecting streetcars' normal navigation pattern through the traffic. It is also identified that when the streetcar incident occurs during the morning peak, the likelihood of significant incident delay decreases. This could be explained by the impact of night-time inspection and maintenance to avoid conflicts with the passenger service before the morning peak, hence reducing the possibility of major malfunction of streetcars in the morning. In addition, Thursday, as a typical workday, is identified to reduce the probability of significant streetcar incident delay. Lastly, the months April, May, October and November are identified to decrease the probability of significant streetcar incident delay, which could be attributed to the relatively mild weather condition.

Figure 4 further demonstrates the marginal effects of streetcar incident types. Apart from the incident types described in Table 3, streetcar utilised off route, general delay and overhead pantograph issue are found to decrease the likelihood of significant streetcar incident delay, while the investigation and emergency services are more likely to incur significant streetcar incident delay.

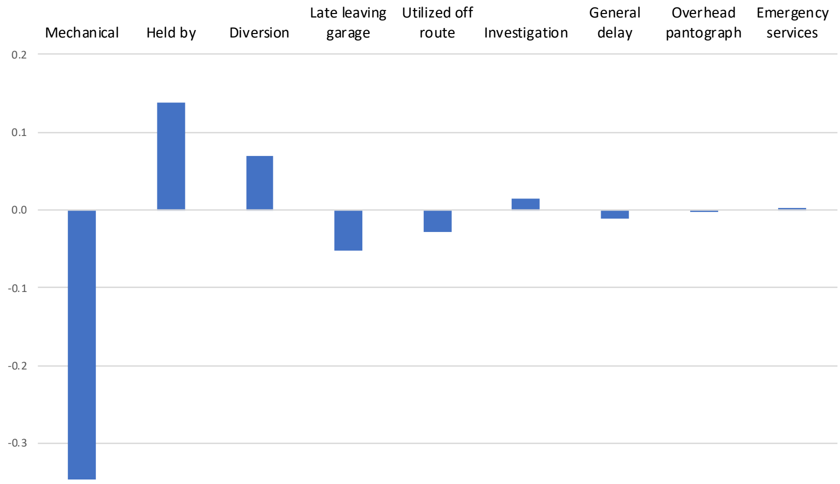

Figure 4: Marginal effects of streetcar incident types

5. Conclusions

Long-duration streetcar incidents have a significant impact on general traffic condition, public transit ridership and individual commuter's travel time, in which case the incident mitigation contingency plans need to be activated. This paper has conducted a comparative study with various statistical and machine learning methods for streetcar incident duration analysis, such that the contributing factors to long-duration streetcar incident delay have been identified.

The comparative study results show that the random forest method has the best performance, demonstrating the effectiveness of the ensemble learning method. Marginal effect analysis has been further conducted based on the random forest model to depict the positive and negative effects of various contributing factors on the occurrence of long-duration streetcar incident delay. Apart from the effects of month and weekday, the most significant contributing factors show that the morning peak period and the streetcar incident types including mechanical failure and late leaving the garage tend to reduce the likelihood of significant streetcar delay. On the other hand, the streetcar incident types held by and diversion are more likely to cause long-duration streetcar delay. For the other streetcar incident types, we have also observed that utilised off route, general delay and overhead pantograph issue are less likely to incur long-duration streetcar incident delay, while the investigation and emergency services tend to increase the likelihood of significant streetcar incident delay.

The result of the paper could provide policy implication on timely streetcar incident clearance and contingency plan implementation. In the future research, we will explore more advanced statistical and machine learning methods to further investigate the streetcar incident delay.

References

Agbelie, B., Libnao, K., 2018. Unobserved heterogeneity analysis of rail transit incident delays. Transportation Research Part A: Policy and Practice 117, 39–43.

Breiman, L., 2001. Random forests. Machine Learning 45, 5–32.

Chang, L.Y., Chien, J.T., 2013. Analysis of driver injury severity in truck-involved accidents using a non-parametric classification tree model. Safety Science 51, 17–22.

Chawla, N.V., Bowyer, K.W., Hall, L.O., Kegelmeyer, W.P., 2002. Smote: synthetic minority over-sampling technique. Journal of Artificial Intelligence Research 16, 321–357.

Cover, T., Hart, P., 1967. Nearest neighbor pattern classification. IEEE Transactions on Information Theory 13, 21–27.

Diab, E., Shalaby, A., 2020. Metro transit system resilience: Understanding the impacts of outdoor tracks and weather conditions on metro system interruptions. International Journal of Sustainable Transportation 14, 657–670.

Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Annals of Statistics , 1189–1232.

Haq, M.T., Zlatkovic, M., Ksaibati, K., 2020. Assessment of tire failure related crashes and injury severity on a mountainous freeway: Bayesian binary logit approach. Accident Analysis & Prevention 145, 105693.

Iranitalab, A., Khattak, A., 2017. Comparison of four statistical and machine learning methods for crash severity prediction. Accident Analysis & Prevention 108, 27–36.

Juan, L., Yesheng, F., Jian, H., 2019. Analysis of subway delay based on data mining, in: 2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), IEEE. pp. 254–258.

Kleinbaum, D.G., Klein, M., 2010. Introduction to logistic regression, in: Logistic Regression. Springer, pp. 1–39.

Kumar, K., Parida, M., Katiyar, V.K., 2015. Short term traffic flow prediction in heterogeneous condition using artificial neural network. Transport 30, 397–405.

Leung, C.K., Elias, J.D., Minuk, S.M., de Jesus, A.R.R., Cuzzocrea, A., 2020. An innovative fuzzy logic-based machine learning algorithm for supporting predictive analytics on big transportation data, in: 2020 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), IEEE. pp. 1–8.

Louie, J., Shalaby, A., Habib, K.N., 2017. Modelling the impact of causal and non-causal factors on disruption duration for toronto's subway system: An exploratory investigation using hazard modelling. Accident Analysis & Prevention 98, 232–240.

Lu, J., Ma, X., Xing, Y., 2021. Risk factors affecting the severity of disruptions in metro operation in shanghai, 2013-2016. Journal of Transportation Safety & Security 13, 69–92.

Nguyen-Phuoc, D.Q., Currie, G., De Gruyter, C., Young, W., 2017. Net impacts of streetcar operations on traffic congestion in melbourne, australia. Transportation Research Record 2648, 1–9.

Ripley, B.D., 2007. Pattern recognition and neural networks. Cambridge University Press.

Schmidhuber, J., 2015. Deep learning in neural networks: An overview. Neural Networks 61, 85–117.

Tan, Z., Xu, M., Meng, Q., Li, Z.C., 2020. Evacuating metro passengers via the urban bus system under uncertain disruption recovery time and heterogeneous risk-taking behaviour. Transportation Research Part C: Emerging Technologies 119, 102761.

Therneau, T.M., Atkinson, E.J., et al., 2019. An introduction to recursive partitioning using the RPART routines. Technical Report. Technical report Mayo Foundation.

Train, K.E., 2009. Discrete choice methods with simulation. Cambridge university press.

Volovski, M., Ieronymaki, E.S., Cao, C., O'Loughlin, J.P., 2021. Subway station dwell time prediction and user-induced delay. Transportmetrica A: Transport Science 17, 521–539.

Wang, B., Wang, W., Hu, X., Li, X., 2015. A segmented signal progression model for the modern streetcar system. Discrete Dynamics in Nature and Society 2015.

Wang, Z., Ma, W., Chan, A., 2020. Exploring the relationships between the topological characteristics of subway networks and service disruption impact. Sustainability 12, 3960.

Weng, J., Feng, L., Du, G., Xiong, H., 2019. Maximum likelihood regression tree with two-variable splitting scheme for subway incident delay. Transportmetrica A: Transport Science 15, 1061–1080.

Weng, J., Zheng, Y., Qu, X., Yan, X., 2015. Development of a maximum likelihood regression tree-based model for predicting subway incident delay. Transportation Research Part C: Emerging Technologies 57, 30–41.

Weng, J., Zheng, Y., Yan, X., Meng, Q., 2014. Development of a subway operation incident delay model using accelerated failure time approaches. Accident Analysis & Prevention 73, 12–19.

Yaghini, M., Khoshraftar, M.M., Seyedabadi, M., 2013. Railway passenger train delay prediction via neural network model. Journal of Advanced Transportation 47, 355–368.

Yu, H., Li, Z., Zhang, G., Liu, P., Ma, T., 2021. Fusion convolutional neural network-based interpretation of unobserved heterogeneous factors in driver injury severity outcomes in single-vehicle crashes. Analytic Methods in Accident Research 30, 100157.

Zhang, Y., Haghani, A., 2015. A gradient boosting method to improve travel time prediction. Transportation Research Part C: Emerging Technologies 58, 308–324.

Zheng, Z., Lu, P., Lantz, B., 2018. Commercial truck crash injury severity analysis using gradient boosting data mining model. Journal of Safety Research 65, 115–124.