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Data-driven evaluation model of safety risks at signalised intersection

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Abstract

Near future safety risk evaluation is a critical step towards adaptive traffic safe operation at a smart intersection. This paper proposes a data-driven model that can quickly evaluate simulated safety risks for use in adaptive operational interventions. A traffic micro-simulation model was utilised to generate conflicts-based data for developing the machine learning model. Conflict indicators including time to collision, TTC, and post encroachment time, PET, were used to identify safety risk. Supervise learning models such as linear regression and machine learning models including random forest and extreme Gradient Boosting (XGBoost) were employed to evaluate risk indices for adaptive operations. In total, 9 models were trained, and XGBoost were found to outperform the other algorithms with 0.87 of the overall accuracy. The findings of this study contribute to the development of edge computing traffic operation system accounting safety.

1. Introduction

Road safety is one of the critical global public health challenges influencing urban health. Traffic crashes caused 1.35 million deaths and over 50 million injuries in 2016 (World Health Organization, 2019a), which also caused a significant economic burden, costing 3% of GPD on average for most countries (World Health Organization, 2019b). Although there are lots of efforts made tacking the road safety issue, the sustainable development goal (SDG) indicator for road traffic mortality revealed that the progress has stalled or trends in wrong directions. Understanding potential crash risk in the transport system fully is a first step to enhance traffic safety.

Urban roadway intersections are given significant attention when developing safe transport system, due to complex traffic conflicting movements inside the intersection area. In order to manage the intersecting traffic flow, various traffic signs and signal control systems were developed. Safety management and traffic operations are the two distinct but interrelated aspects in traffic management systems. Operational aspects aimed for efficient traffic through minimising delays, travel time and queue length etc. Meanwhile, safety management aspect involved identifying safety prone zone or develop counter solutions to mitigate injuries and fatalities. Nevertheless, traffic crashes could breakdown traffic flow causing serious delays. Cooperating both safety and operations management becomes the key to success.

Following the advancements in connected vehicles technologies (CVs), research that focused on real-time safety risk using high-resolution data have received significant attention (Ghoul and Sayed, 2021; Hu et al., 2020). However, obtaining insight of real-time risk may still be insufficient for the management systems to optimise and diverge traffic flow in advance. In order to allow sufficient time for the transport management network to redirect traffic flow away from the safety prone intersection, forecasting near future safety risk and optimising adaptive signal phasing for safety across network is needed.

Consequently, this paper aims to develop a near future safety risk evaluation model at an actuated intersection and explore the effect of signal control phasing to the near future safety risk. The objective is to develop a data-driven model that can quickly evaluate safety risks for use in real-time operational interventions, such as signal phase reconfigurations and timing adjustments, variable speed limits, etc. A traffic micro-simulation model was utilised to generate conflicts database for training the models. Conflict indicators including time to collision and post encroachment time were used to measure safety risk, then machine learning models were developed to evaluate risk indices for real-time operations. The developed model aims to address the research questions about how signal control phasing influence near future conflicts frequency and how can such information be evaluated and utilised in a timely manner. This research is among first attempts towards adaptive traffic operation at a smart intersection accounting near future safety.

2. Literature review

Modelling safety risk at signalised intersection falls into two categories, which are conflict-based and collision-based. Collision-based model utilises the historical crash report while conflict-based model measure risk using Surrogate Safety Measures (SSMs) approach. Common SSMs indicators includes: Post-Encroachment Time, PET (Cooper, 1984), Time to Collision, TTC (Hayward, 1972) and Modified Time to Collision, MTTC (Ozbay, 2008) etc. Apart from using field measured collision and conflict data, approaches utilizing microsimulation software is an alternative to assess safety performance. Following sections will review the state-of-the-art research from the above three aspects.

2.1 Collision-based safety evaluation model

Considerable research has been conducted in modelling real-time collision risk (Khattak et al., 2021; Kidando et al., 2021; Wang et al., 2020; Yuan et al., 2020; Yuan and Abdel-Aty, 2018). These studies demonstrate the use of crash data to evaluate safety risk and predict crash occurrence from traffic state variables. Nonetheless, only a few studies have explored the temporal effect on the traffic state data. Yuan and Abdel-Aty (2018) investigated the effect of utilising traffic data up to 20 minutes prior the targeted crash or non-crash event through 5 model, including a full model and 4 time slice model for each 5 minutes slice. Meanwhile, Yuan et al. (2020) further investigate the temporal effects of traffic state data on real-time risk at signal cycle level. The result demonstrates the potential using current traffic state data to predict safety risk after longer period. Despite the efforts made in utilizing crash data in assessing safety performance, there are concerns, including long data collection time (Hu et al., 2022; Yang et al., 2021b), inconsistency or under reports (Wood et al., 2016) and lack of insight into fail mechanisms behind an accident (Tarko and Lizarazo, 2021).

2.2 Conflict-based safety evaluation model

Contrarily, assessing traffic conflicts overcome concerns of using crash data. Traffic conflicts happens more often than collision, which provides a more comprehensive insight to the dangerous movement that leads to collision. Essa and Sayed (2019) developed a fully Bayesian models to evaluate real time rear-end conflict frequency per traffic cycle of a signalized intersections. Despite conflict frequency, Guo et al. (2020) proposed a Bayesian Tobit models to evaluate real-time rear-end conflict rate SPFs, which remove the vagueness of using conflict frequency as a measurement of risk level due to inconsistent cycle length. Yang et al. (2021a) proposed a functional data analysis approach to investigate the signal cycle safety risk at the movement level, meanwhile Hu et al. (2022) examined the internal relationship between traffic states variables and traffic conflicts through a lane-based real-time safety evaluation model. These studies demonstrated the application of traffic conflicts in real-time vehicle-based safety risk evaluation.

2.3 Simulation-based safety evaluation model

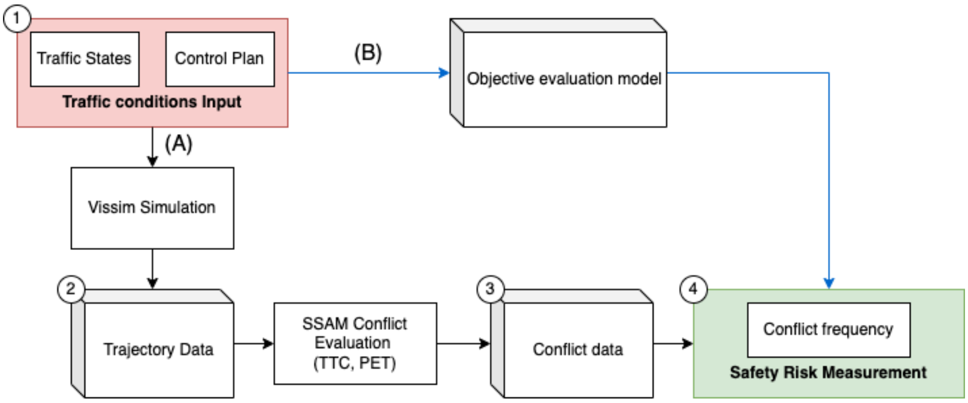
Apart from utilising historical or field measured data, traffic simulation is an alternative safety performance modelling approach found in previous studies (Katrakazas and Quddus, 2018; Ozbay, 2008; Rong Fan et al., 2013; Salim et al., 2007; Shahdah et al., 2015; Sobhani et al., 2013). It provides an easy and effective way to gather data compared to the other two data sources (Mahmud et al., 2019). Furthermore, it offers the ability to proactively evaluate safety performance of a conceptual design, such as modifying geometry or signal control system, before the actual implementation. However, there are concerns about whether simulated conflicts can reasonably estimate traffic conflicts in real world. Huang et al. (2013) and Rong Fan et al. (2013) proposed a two-stage calibration approach and evaluate the method through comparing the simulated conflicts to the field measured conflicts extracted from video analysis. The result shows that calibration could improve goodness-of-fit between simulated and field measured conflicts to certain extend. Later, Guo et al. (2021) proposed an extreme value theory based approach to calibrate microsimulation model for safety evaluation. The study demonstrates to match field measured conflicts with extreme value distributed simulated conflicts, revealing potential application of simulation-based safety evaluation model.

In summary, crash data recorded the direct cause of injuries and fatalities while conflicts data corresponds to the potential crash or near-miss events. Besides, frequently happened traffic conflicts is believed to provide a better clue to the unsafe situation. Efforts had been found in building connection between conflicts and crashed events to support conflicts as a surrogate of crash data. For the data source, historical, field-measured and microsimulation are the common approach observed in literatures. Previous literatures attempt to assess real-time safety risk at an intersection with crashed and conflicts data. The proposed model aims to contribute to forecast near future risk to allow sufficient time for the traffic management system to react in traffic operations to redirect flow away from safety prone intersections

3. Methodology

With the objective to explore the effect of signal control operations and traffic volumes and speeds, microsimulation approach is believed to be the best fit as it can evaluate safety performance without the physical implementation. Apart from the time intensive simulation, Figure 1 path (A), this paper aims to develop a data-driven model, Figure 1 path (B), that can quickly evaluate safety risks for use in real-time operational interventions. Following sections will discuss the methodology in term of data sources, safety risk criteria, and objective model design and evaluation.

Figure 1 Methodology schematic diagram



3.1 Conflict data preparation

Considering the aim to investigate the effects of signal control phasing to near future conflict frequency. Microsimulation approach is utilised to generate conflicts data. Microscopic simulation model Vissim, published by the PTV Group, is a mature software often being utilised by previous researches (Guo et al., 2021; Huang et al., 2013; Katrakazas and Quddus, 2018; Rong Fan et al., 2013; Shahdah et al., 2015; Sobhani et al., 2013). With the attention given in SSMs approaches, multiple researches were also found to utilise microsimulation technologies with Surrogate Safety Assessment Model (SSAM) (Guo et al., 2021, 2019; Huang et al., 2013; Katrakazas and Quddus, 2018; Rong Fan et al., 2013; Shahdah et al., 2015). The SSAM is a SSMs assessment applicant published by the Federal Highway Administration (FHWA) of the United State. As shown in Figure 1 path (A), 1 hour simulation is run for each traffic conditions input set, and the conflict data is collected from evaluation of SSAM. After that, the conflict frequency data is pre-processed for the prediction modelling.

3.2 Conflict indicator

The SSAM utilise TTC and PET to determine conflicts occurrence. TTC described the instant of time required for two vehicles to collide if there is no changes of speeds and paths (Hayward, 1972), while PET represent the time difference between the moment of the first vehicle passes out of the potential collision area and the moment of arrival at the potential collision point by the following vehicle (Cooper, 1984). Despite TTC have been frequently used to evaluated rear-end conflicts in previous studies, there are limitations for using TTC as the single indicator to evaluate safety (Mahmud et al., 2019; Vogel, 2003). Calculation of TTC assumed vehicles are in constant speed which ignored potential conflicts due to different in acceleration or deceleration. Meanwhile, PET is only useful for transversal trajectories cases. As a result, considering both TTC and PET complement each other. Regarding to the selection of indicator threshold, different threshold values have been used in previous studies. Mahmud et al. (2019) and Johnsson et al. (2021) suggested that threshold of TTC is usually ranged from 1.5s to 4s while PET is ranged from 1s to 5s. Threfore, considering nature of both indicators, the threshold value of 1.5s and 4s is selectd for TTC and PET respectively.

3.3 Objective model algorithm and evaluation

3.3.1 Machine learning method

Considering the objective model is a regression type problem. The linear regression method is first utilised to estimate relationship between traffic stats, signal control operations and resulted conflict frequency. Apart from traditional statistical method, different machine learning algorithms were found to be utilised in previous traffic safety studies (Hu et al., 2022; Huang et al., 2016; Kidando et al., 2021; Mafi et al., 2018; Zhang et al., 2020). In this study, random forest (RF) and extreme Gradient Boosting (XGBoost) were chosen as the candidate algorithms. Both RF and XGBoost are ensemble machine-learning algorithm, which combines multiple week decision trees to improve accuracy (Kidando et al., 2021; Mafi et al., 2018).
RF used the bagging techniques to improve prediction power and model efficiency (Mafi et al., 2018). According to the author, prediction outcome of a RF regressor is calculated by averaging result from the decision trees, which helps controlling the issue of overfitting. On the other hand, XGBoost is a widely recognised scalable tree boosting system giving state-of-the-art results across different research area, for example, hazard risk prediction or store sales prediction (Chen and Guestrin, 2016). It is noted that all of the mentioned methods is implemented using the scikit-learn package in python (Pedregosa et al., 2011).

3.3.2 Hyperparameter tunning and model selection

The k-fold cross-validation procedures (k=10) is utilised to estimate the model performance when predicting unseen sample. It is believed to be less bias compared to the single train-test split technique. Each of the folds is given an opportunity to be used as a held back test sample while the rest are used as training sample. The performance of the fitted models is evaluated through root mean square error (RMSE) and coefficient of determination (R^2). Besides, each machine learning algorithm includes various choice of hyperparameters which could affect algorithm behaviour. In order to discover a suitable set of hyperparameters in feasible amount of time, the grid search techniques are used, combined with k-fold cross-validation, to evaluate each distinct set of model hyperparameters. Below table summaries the tunned hyperparameters and corresponding value range observed to be suitable for the datasets.

Table 1 Description of tunned hyperparameters

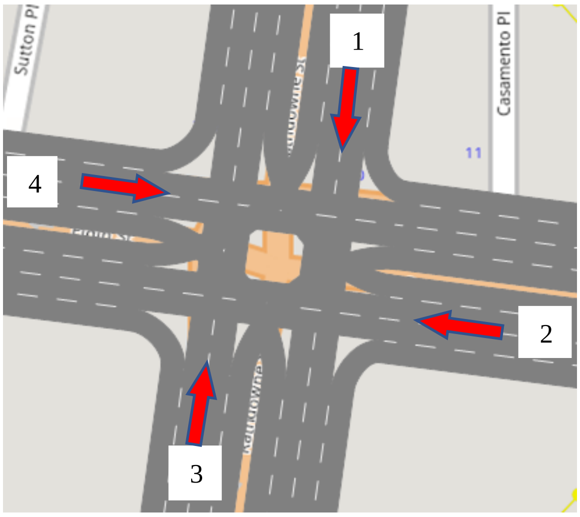
RF		**XGB**	
Description	**Observed suitable values**	**Description**	**Observed suitable values**
Number of estimators	500, 1000	Number of estimators	300, 500
Subsample ratio of features to train each base estimator	0.7, 1	Learning rate	0.1, 0.3, 0.5
Number of features to consider when looking for the best split	sqrt, log2	Maximum depth of a tree	4, 6, 8, 10
Maximum depth of the tree	8, None	Subsample ratio of the training instances	0.5, 0.7
Minimum number of samples required to split an internal node	0.5, 1	Subsample ratio of columns when constructing each tree	0.5, 0.7, 1
Minimum number of samples required to be at a leaf node	0.3, 0.5, 1	Subsample ratio of columns for each level	0.5, 0.7, 1
Criterion	squared loss, poisson,	Minimum sum of instance weight needed in a child	3, 5, 7
		Objective	poisson, tweedie, squared loss

4. Data and result

To produce the required “labelled” data for supervised learning, conflicts data is first simulated by microsimulation software, VISSIM (PTV Vissim, 2021), then processed against volume and operational features for machine learning models. Following sections will present the simulated conflict data and resulted prediction model.

4.1 Simulated conflict data

Figure 2 Simulation model numbering notation



The simulation model was developed based on real world intersection located in Carlton, Melbourne, Australia with actuator signal timing. From Figure 2, Approach 1 and 3 (North-south movement) is defined as the major approach while approach 2 and 4 (East-west movement) is defined as the minor approach. Considering the threshold value of 1.5s and 4s is selected for TTC and PET respectively, 60 simulations run for each scenario is chosen to limit the error of the simulated conflicts into 5% level (Shahdah et al., 2015). Thus, 60 × 1hour simulation is run for each traffic conditions input set, then the conflicts frequency data is collected from averaging the result of simulation runs. Table 2 present the descriptive statistics of the dependent variable. In short, there are 3 dependent variables to represent 3 types of averaged conflicts frequency. For instance, "rear_end" denotes number of rear end conflicts within the 60 minutes period. Remaining dependent variables are similarly defined, with "crossing" and "lane_change" correspond to conflicts due to crossing and lane change movement respectively. It is observed that rear end conflict is the major type founded within the intersection area. On the other hand, Table 3 explained the description of explanatory variables (E. V.) including traffic states and signal operation parameters. For this study, traffic states parameters are approach-based, for example "traffic_vol_1" denotes traffic volume of approach 1. Meanwhile, signal operation parameters are direction-based, "Max_Green_NS" denotes maximum green time of north-south (approach 1 and 3) direction movement etc. In summary, over 1600 scenarios were simulated and used for machine learning model training.

Table 2 Descriptive statistics of dependent variables

Name	Min	Max	Mean	Std
rear_end	0	392.15	59.8399	57.1078
crossing	0	2.1667	0.3702	0.4065
lane_change	0	18.9167	3.5106	3.2607

Table 3 Definitions of explanatory variables

E. V.	Description	Unit	Range
traffic_vol	Number of vehicles, at each approach, for the next 60 minutes: traffic_vol_(1, 2, 3, 4)	veh/hour	[0,700]
percent_RT	Percentage of right turn vehicles at each approach: percent_RT_(1, 2, 3, 4)	%	[0,40]
percent_LT	Percentage of left turn vehicles at each approach: percent_LT_(1, 2, 3, 4)	%	[0,40]
Speed_lim	Speed limit for each direction: Speed_lim_(1, 2) for NS and EW direction respectively	km/h	40, 50, 60, 70, 80
Max_Gap	Through and left turn movement maximum gap time: Max_Gap_(NS, EW)	s	2, 2.5, 3, 3.5, 4
Min_Green	Through and left turn movement minimum green time: Min_Green_(NS, EW)	s	[6,14]
Max_Green	Through and left turn movement maximum green time: Max_Green_(NS, EW)	s	[30,50]
Max_Gap_RT	Right turn movement maximum gap time: Max_Gap_(NS, EW)_RT	s	2, 2.5, 3, 3.5, 4
Min_Green_RT	Right turn movement minimum green time: Min_Green_(NS, EW)_RT	s	[3,9]
Max_Green_RT	Right turn movement maximum green time: Max_Green_(NS, EW)_RT	s	[11,19]
Amber	Amber duration: Amber_(NS, EW)	s	3, 3.5, 4
Red	Minimum Red duration: Red_(NS, EW)	s	2.5, 3, 3.5

4.2 Result of machine learning model

Machine learning algorithms including linear regression (LR), random forest (RF) and extreme gradient boosting (XGB) were employed to estimate conflict frequency. In total, 9 models were selected for all dependent variables. Table 4 summaries individual model RMSE and R^2 scoures aginst the test datasets, which are not involved in hypermater tunning process.

Table 4 Results of prediction models

Conflict Type	Testing set accuracy, R^2 (RMSE)		
	Linear Regression	Random Forest	XGBoost
Rear end	0.6961 (31.4355)	0.7787 (28.3150)	0.8917 (17.9747)
Crossing	0.6470 (0.2353)	0.8202 (0.1727)	0.8711 (0.1435)
Lane change	0.7068 (1.6276)	0.8116 (1.3962)	0.8763 (1.1162)

From the resulted model, it is observed that the accuracy ranking, from high to low, appears to be XGBoost, random forest and linear regression across all conflicts type. XGBoost models is obviously outperform the other two algorithms in term of lower RMSE and higher R^2 scoures criteria aginst unseen input. More specifically, rear end model results indicated XGBoost R^2 scored 14% and 25% higher than random forest and linear regression respectively. Meanwhile, crossing model results revealed XGBoost R^2 scored 6% and 30% higher than random forest and linear regression respectively. For the lane change model, XGBoost outperform random forest and linear regression with 8% and 21% R^2 boost. Although linear regression model has a relative low accuracy, it still achieved a high overall accuracy (0.64 - 0.70). It may because conflicts frequency was a relatively simple measurement of safety risk, which only account for probability.

4.3 Model interpretation and feature importance

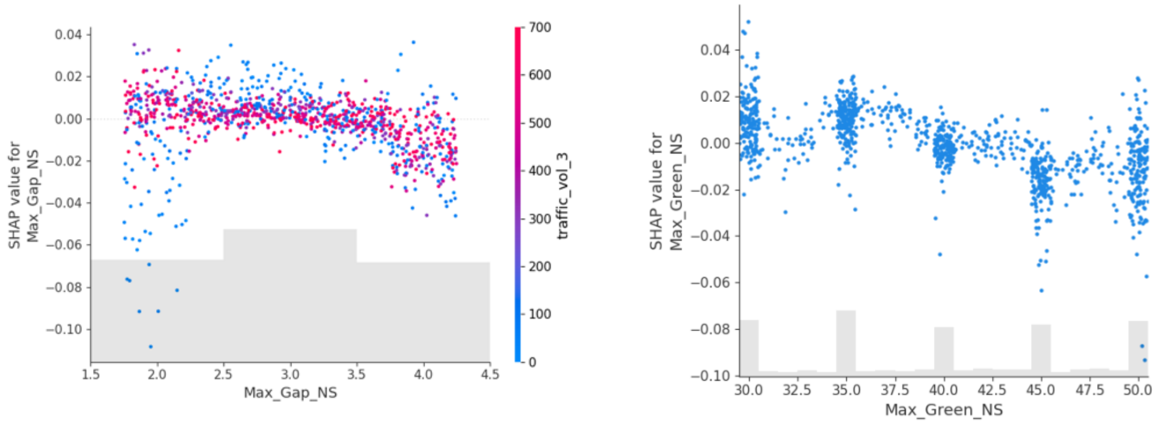
Interpreting the output of the prediction model is a critical step to understand model performance. It provides insight into how the model may improve, and how each feature contributes to the prediction process (Kavzoglu and Teke, 2022). Since from the previous sections, XGBoost was found to outperform the other two algorithms, following interpretation focused on the XGBoost model result. There are serval approaches to interpret tree-based model, such as reporting the decision path (Lundberg et al., 2019). However, these methods are unhelpful for complex models, including RF and XGBoost, which are ensemble trees algorithm. Thus, Lundberg et al. (2019) proposed a SHAP (SHapley Additive exPlanations) based tree explainer compute optimal explanations for complex tree model. Meanwhile, the SHAP approach is implemented based on game theory to compute explanations of model predictions (Lundberg and Lee, 2017). In general, analysing SHAP values can determine how the feature contribute, positively or negatively, to the predictions. Furthermore, SHAP value can be computed on individual observation level. In other words, the SHAP based tree explainer enables both local and global interpretation. Following section discussed the interpretation of XGBoost model with the SHAP based tree explainer.

4.3.1 Feature importance and interoperability of rear end conflict model

Figure 3 Rear end conflict model global explanation summary

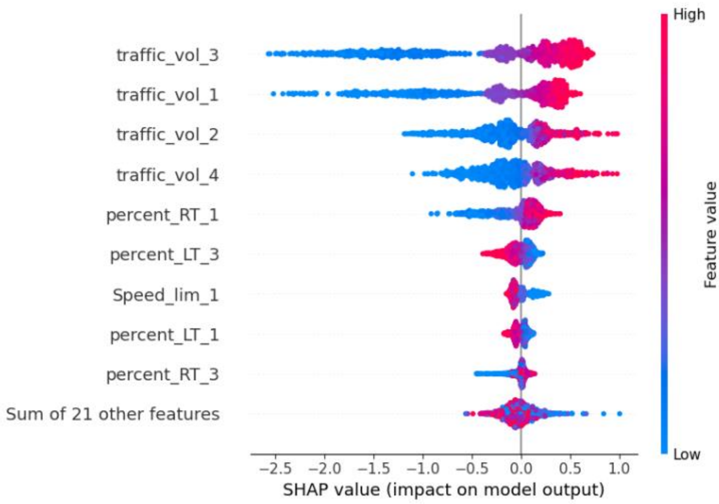
Results in Figure 3 indicates that traffic volume variables are the most important features affecting the prediction for rear end conflict frequency in the following 1-hour period. A significant positive relationship (SHAP value increased with feature values) between traffic volume and rear end conflict frequency is observed. It may because rear end conflicts are mainly caused by traffic stop-and-go, which were not well captured by turning flow and signal timing parameters. Essa and Sayed, (2018) reported that shock wave parameters, caused by stop-and-go situation, have a significant effect on rear end conflicts frequency at signalized intersection. Despite importance of traffic volume variables dominates at global level, there are interesting interaction observed at local level. Figure 4, left, shows that longer gap time of the major approach tends to reduce frequency of rear end conflict. However, such effect weaker under low traffic volume situation (dispersed blue dot), which red and blue coloured dots corresponds to high and low traffic volume scenario respectively. It may because longer gap time allows more extension of green time for a dense vehicle pattern, thus frequency of stop-and-go cycle decreased and resulting in lower rear end frequency. Meanwhile, Figure 4, right, reveals that extending major approach maximum green time tends to reduce rear end conflict risk to certain extent. For the tested range, 45 seconds of maximum green time seems to be an appropriate choice for safter rear end risk in near feature.

Figure 4 Local SHAP interaction of, major approach maximum gap time (left), major approach minimum green time (right)



4.3.2 Feature importance and interoperability of crossing conflict model

Figure 5 Crossing conflict model global explanation summary



Results in Figure 5 shows that major approach traffic volume are the most important features for crossing conflict model. Nevertheless, significance of turning percentage increase compared to rear end model. It is expected as in a left-hand driving environment, right turning flow which cross over opposing flow is the main cause of crossing conflict. In term of local explanations, Figure 6 shows that left and right turn percentage is inversely and directly related to crossing conflicts frequency respectively. It may because increasing left turn percentage implies relatively less demand in through or right turn flow, thus the probability of crossing conflict decreased. Furthermore, it is noted that significance of turning percentage is emphasized by major traffic flow volume, indicated by Figure 6 coloured distribution. For the signal related parameters, Figure 7 shows that increasing maximum gap time for dedicated right turn duration reduced crossing conflicts risk. It may because longer gap time for right turn benefit in extending dedicate right turn flow, thus reducing cross flow risk. Furthermore, it is spotted that certain value (6 second) of minimum green right turn duration in minor approach give safer conflict risk performance for the tested scenarios (Figure 8, left). Contrarily, increasing minimum green right turn duration in major approach achieved similar effect (Figure 8, right).

Figure 6 Local SHAP interaction of T4 major approach turning percentage, left turn (left), right turn (right)

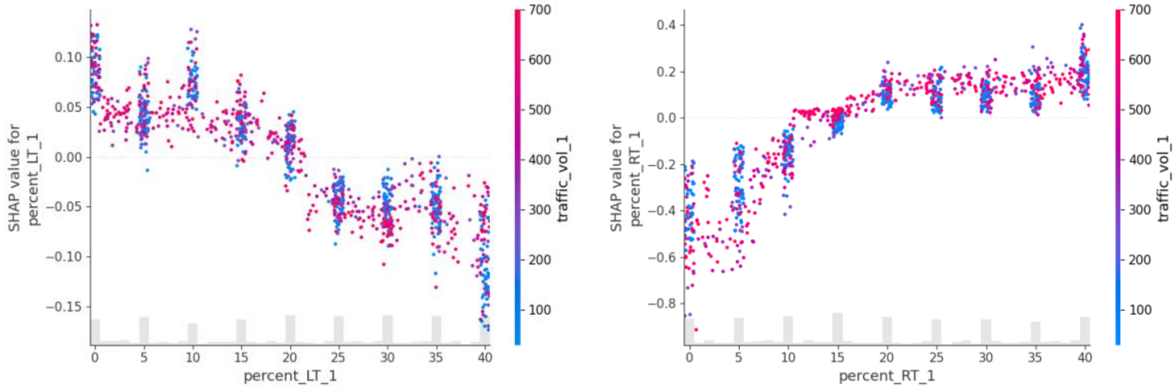


Figure 7 Local SHAP interaction of major approach maximum right turns gap time

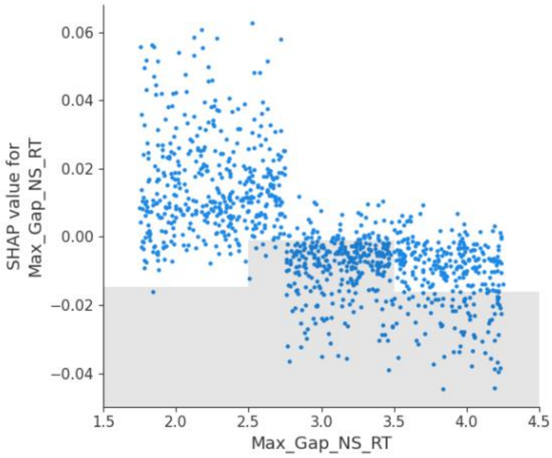
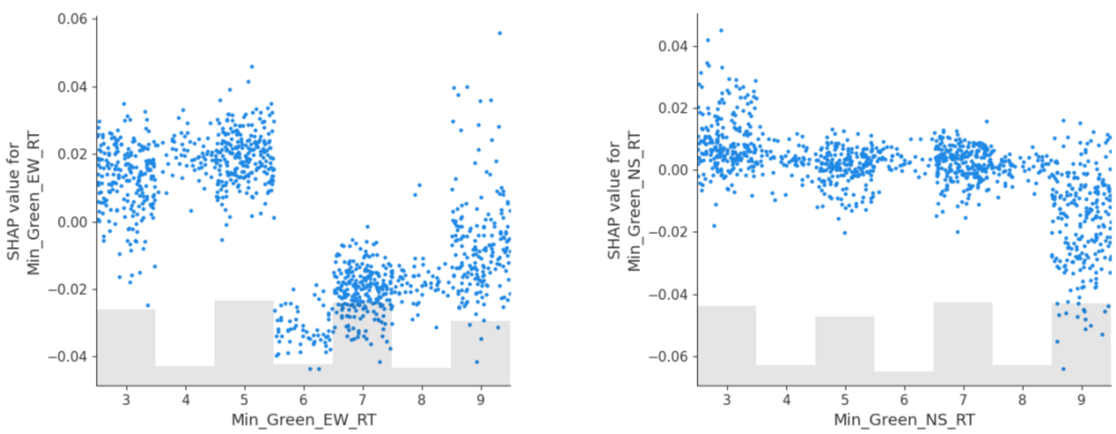
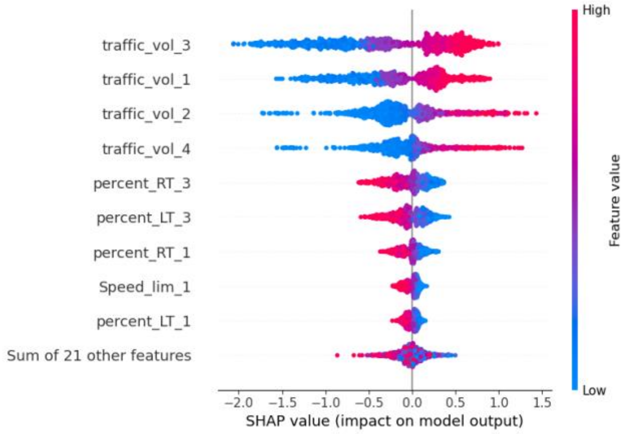


Figure 8 Local SHAP interaction of minimum right turn green time, minor approach (left), major approach (right)



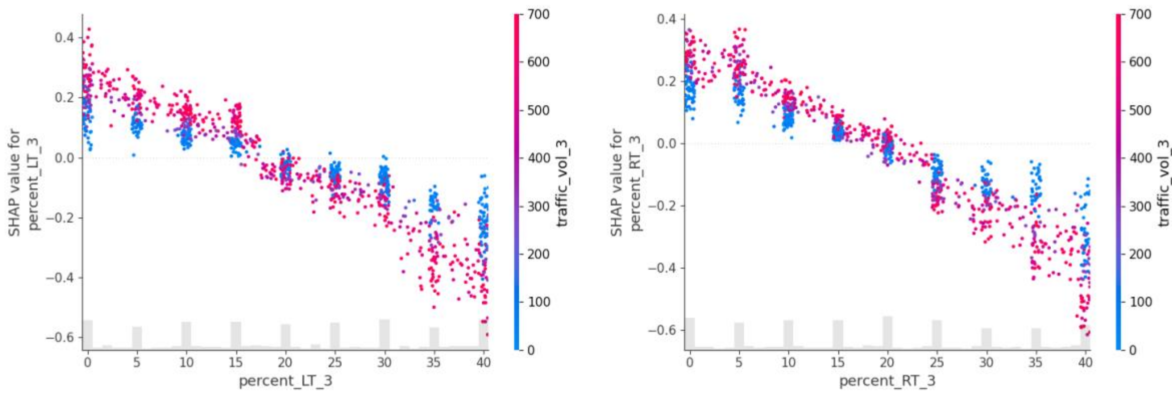
4.3.3 Feature importance and interoperability of lane change conflict model

Figure 9 Lane change model global explanation summary



Lastly, Figure 9 shows that traffic volume variables are the most important features affecting the prediction for lane change conflict frequency. According to the definition in SSAM, lane change conflicts is defined when the conflicts angle is between 85° and 30°. Thus, lane change conflicts are treated as the intermediate between crossing and rear end conflicts, which corresponds to situation when conflicts angle over 85° and below 30° respectively. For the local explanations, both left turn and right turn percentage variables for all approaches was found to be negatively related to lane change conflicts frequency across all time intervals. Figures 10 were an example from approach 3.

Figure 10 Local SHAP interaction of major approach turning percentage, left turn (left), right turn (right)



5. Conclusion and recommendation

This paper proposed a data-driven model that can quickly evaluate safety risks for use in real-time operational interventions. Microsimulation approaches were utilized to generate conflict-based data. Conflict indicators including time to collision, TTC, and post encroachment time, PET, were used to identify safety risk. Three type of conflicts frequency, including rear end, crossing and lane change, within 1 hour period were defined as the dependent variables. Machine learning algorithms, including linear regression, random forest and extreme Gradient Boosting (XGBoost) were employed to develop the objective models. The resulted models show that XGBoost model outperform other two algorithms in term of coefficient of determination (R^2) with satisfactory score. The main conclusion drawn from interpretation of the XGBoost model are as follow:

1. Traffic volume variables are the most important features that have a positive relationship for all conflict frequency types.
2. Significance of turning percentage variable in crossing conflict model increased. Local explanations reveal that left and right turn percentage is inversely and directly related to crossing conflicts frequency respectively.
3. Serval signal timing parameters including maximum gap time, maximum green time and minimum green time were found to have interesting local interaction with estimated conflicts frequency.

The result clearly show that signal timing parameters has relativity weak impact when compared to traffic demand parameters. However, when considering certain level of traffic demand, especially in low demand cases, parameters including maximum gap time, maximum green time and minimum green time were observed to have local impact on model output. In other words, assuming a situation of off-peak hour, it may be possible to reduce conflict incidents through adaptive signal duration. Besides, the proposed model show that it is feasible to evaluate safety performance from unseen scenario in moment, compared to hourly microsimulation process, with satisfactory accuracy. As a result, it can contribute towards the safety aspect of an adaptive traffic operation system.

Although the XGBoost models achieved satisfactory accuracy, there are limitations to this research. Firstly, conflicts frequency was used as a measurement of safety risk. Conflicts frequency describe probability of conflicts occurrence without accounting severity. Therefore, global significance of traffic volume variables is relatively high compared to other features. In other words, impact from other parameters on safety risk may not be fully discovered. A safety risk measurement that considers both probability and severity is needed for further research. Secondly, driving decision parameters of the simulation model were not calibrate with real-world conflicts data. Thus, the evaluation model is only a proactive safety evaluation of a conceptual signal control system. Further calibration on driving behaviour parameters is needed before real world application. Lastly, the proposed model focused on single intersection, which vehicles were assumed from far upstream. In this situation, lane selection behaviour due to change in travel direction may not be captured.

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