TEXAS A&M UNIVERSITY

Countermeasure Selection Using Near-Miss Data to Support Vision Zero in Bellevue (WA)

PREPARED FOR

Vision Zero Design Sandbox Competition, Institute of Transportation Engineers

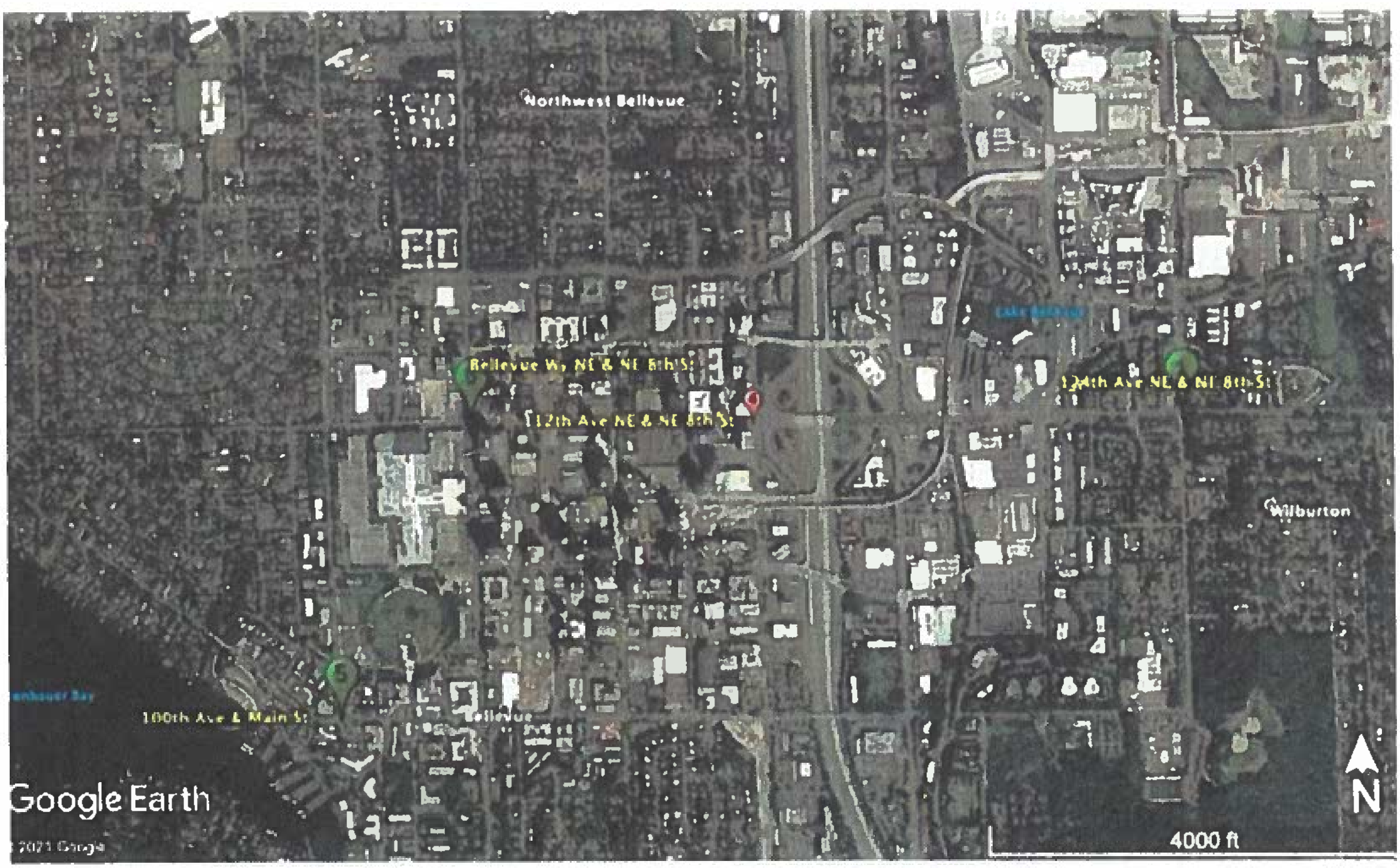
April 15, 2021

PREPARED BY

AggieVision

Ashraf, Sruthi
Guo, "Sky" Xiaoyu*
Li, Zihao
Ma, Chaolun
Xiao, Xiao
Zhang, Cheng

Ph.D. Students,
Civil Engineering and Environmental Engineering,
Texas A&M University, College Station
* Lead author



1. Introduction

With the availability of innovative technologies and big data, it is time that we rethink about the conventional ways of crash data assessment. Previous approaches focused on historic data to recommend countermeasures, but such reactive approach might not be relevant anymore given the dynamic changes in the field of transportation. Vision Zero cannot be achieved if the safety researchers only examine crash data after its occurrence. Therefore, this project aims to leverage the near-miss data to provide a proactive solution for safety management and to support Vision Zero.

The project team received data from six different intersections in Bellevue, Washington as a part of ITE Vision Zero Sandbox Competition. The data includes safety related events (i.e., conflicts) based on traffic video processed and analyzed using Transoft Solutions' video-based road safety solutions. These conflicts are further categorized into critical and non-critical ones based on their Post-Encroachment Time (PET). Critical conflict is when PET is smaller than 2 seconds. Non-critical conflict has a PET value equal to or larger than 2 seconds but smaller than 10 seconds. Any event with a PET larger than 10 seconds is not defined as a conflict. The objective of this effort is to make use of the automated conflict data collected through innovative technologies to gain new insights into safety problems and to select low-cost countermeasures at the given intersections.

This project compares insights from a newly proposed approach based on conflict level data and intersection level data to conventional approaches. It evaluates the effectiveness of proposed solutions based on both approaches. It also checks the constructability and transferability of countermeasure selections. A brief flowchart on the methodology adopted to screen and analyze the study intersections and to recommend and compare countermeasures is provided below (refer **Figure 1**).

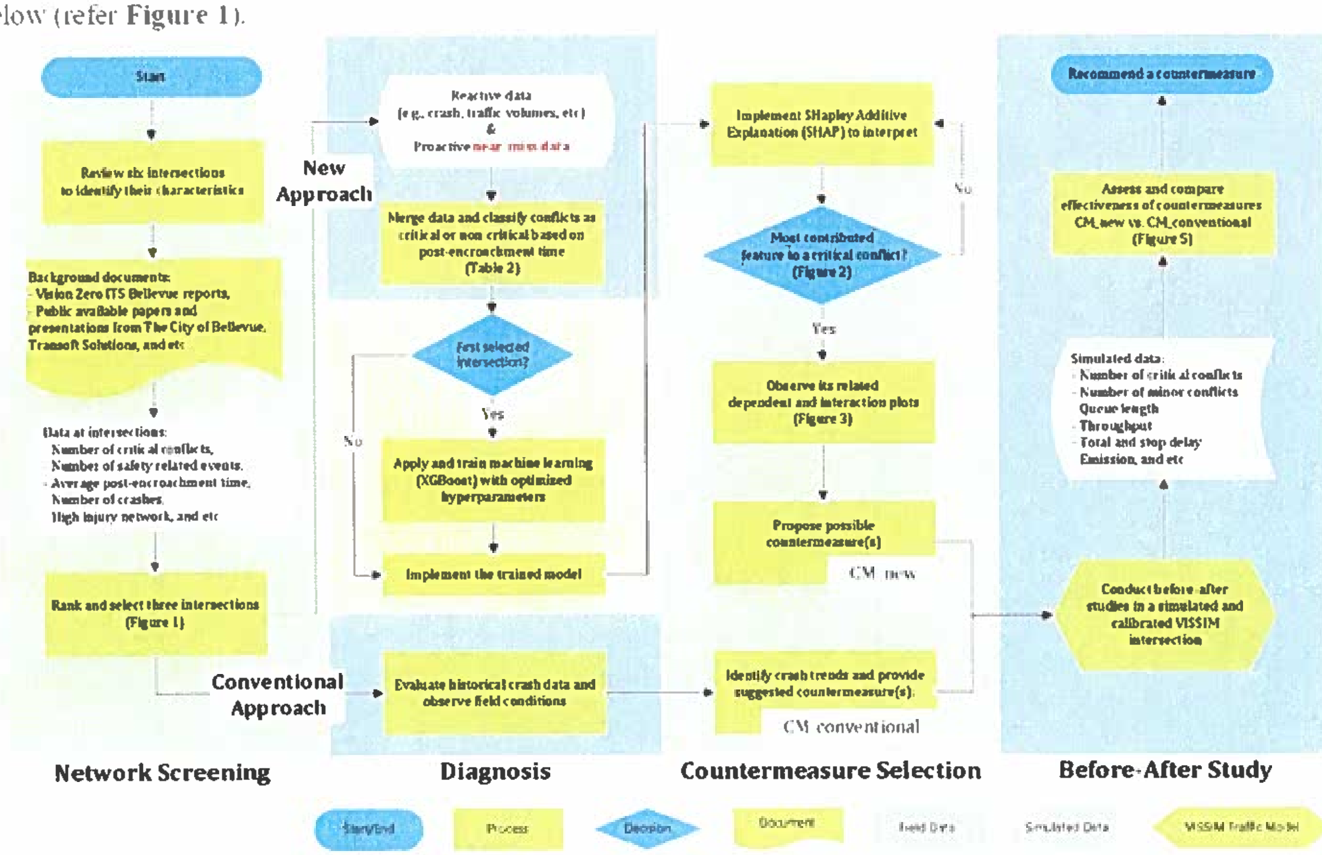


Figure 1: Methodology of the project

2. Screening and Selection of Intersections

Reviewing and ranking the available sites (i.e., network screening) is the first step to prioritize the sites based on the potential for reducing crashes, and to identify the high-risk locations[1]. This is an important step because any inefficient use of limited resources and investments can result in additional loss of lives. The assigned six intersections have already been shortlisted by the City of Bellevue, Washington, based on geographic location, land uses, population density, road geometry and conflict data. All of them belonged to the City's High Injury Network from 2014 to 2018. Their detailed information is listed in **Table 1**. To better serve the purpose of this study (i.e., constructability and transferability of a new and proactive approach for countermeasure selections), the team selected the following three intersections: **(1)** 124th Avenue NE & NE 8th Street, **(2)** 100th Avenue & Main Street, and **(3)** Bellevue Way NE & NE 8th Street for further analyses.

Table 1: Study Intersections - Crash and Conflict Data

	Intersection Name	Number of Crashes (#)	Number of Conflicts (#)	Number of Critical Conflicts (#)	Number of Pedestrian Conflicts (#)	Average PET (s)
★	124th Avenue NE & NE 8th Street	19	31,616	1,811	3,419	6.28
	116th Avenue NE & Northup Way	7	1,966	518	146	2.09
	148th Avenue SE & SE 22nd Street	24	16,962	541	833	6.50
	112th Avenue NE & NE 8th Street	40	21,303	248	2,250	6.80
★	100th Avenue & Main Street	1	9,840	151	1,825	6.64
★	Bellevue Way NE & NE 8th Street	23	29,507	105	13,293	6.96

Note: Number of crashes is collected from 2017 to 2019; Number of conflicts, critical conflicts, pedestrian conflicts, and average PET are based on the entire duration provided by Transoft Solutions; PET stands for Post-Encroachment Time

Conventionally, crash and traffic related data (e.g., crash frequency, AADT, crash rate, and etc.) are analyzed when prioritizing intersections. Following that convention, intersections 112th Avenue NE & NE 8th Street and 148th Avenue SE & SE 22nd Street will be prioritized over other sites. However, to better explore countermeasure selection with near-miss data, the team first ranked the intersections based on the number of conflicts. With a total of 31,616 conflicts and 1,811 critical conflicts (i.e., 5.7% of total conflicts), 124th Avenue NE & NE 8th Street is identified as the first intersection to study. This intersection was widely studied in City of Bellevue's Vision Zero related reports as well[2,3,4].

Beyond evaluating the constructability of new approach, another project objective is to ensure that the proposed approach has transferability and adaptability to an intersection with some common characteristics - Bellevue Way NE & NE 8th Street, or to an intersection with dissimilarities - 100th Avenue & Main Street. Like 124th Avenue NE & NE 8th Street, the intersection, Bellevue Way NE & NE 8th Street, also have a large number of conflicts (i.e., 29,507). Both intersections also have similar numbers of reported crashes. However, Bellevue Way NE & NE 8th Street has only a smaller percentage conflicts as critical conflicts (i.e., 0.4%), but has higher number of pedestrian conflicts (i.e.,13,293). Hence, Bellevue Way NE & NE 8th Street is indeed a good candidate to test the transferability of the proposed approach.

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[1] AASHTO. (2010). Highway Safety Manual (1st edition). American Association of State Highways and Transportation Officials Transportation Project Board of the National Academies

[2] City of Bellevue. (2020). Video-based Network-wide Conflict Analysis to Support Vision Zero in Bellevue (WA) United States. https://bellevuewa.gov/sites/default/files/media/pdf_document/2020/VZ-ITS-Bellevue-Report-1-web.pdf

[3] Samara, L., Chung, C., Loewenherz, F., Akers, D., & Budnick, N. (2020). Networkwide Traffic Data and Safety Analysis in Bellevue (WA). 27th ITS World Congress, 1-8. https://bellevuewa.gov/sites/default/files/media/pdf_document/2020/ITS-World-Congress-Paper-20354.pdf

[4] Samara, L., St-Aubin, P., Loewenherz, F., Budnick, N., & Miranda-Moreno, L. (2020). Video-based Network-wide Surrogate Safety Analysis to Support a Proactive Network Screening Using Connected Cameras: Case Study in the City of Bellevue (WA) United 2 States 3. 100th Annual Meeting Transportation Project Board, 1–21

Compared to the above two intersections, 100th Avenue & Main Street, has fewer number of conflicts and critical conflicts. This intersection has only one crash reported in 3 years (2017 to 2019), while 124th Avenue NE & NE 8th Street documented 19 crashes during the same period. Therefore, 100th Avenue and Main Street is an intersection that would challenge how well the new approach with near-miss data transfers and adapts itself.

It is worth mentioning that the intersection, 116th Avenue NE & Northup Way is not considered because the average PET value is extremely low (i.e., 2.09 seconds, whereas the average of the rest is 6.64 seconds). Moreover, the percentage of critical conflict is very high (i.e., 26.3%, whereas the largest among the rest is 5.7%). Being dubious about the completeness of the conflict data, this intersection is avoided from further consideration.

3. Conventional Approach

This section briefly presents the conventional approach for intersection diagnosis and countermeasure selection.

3.1 Historical crash data and field observations

After prioritizing the study sites based on measurable goals and thresholds for selection, next step is to identify contributing factors (i.e., diagnosis) and potential countermeasures (i.e., countermeasure selection)[5]. In this section, one of the study sites (i.e., 124th Avenue NE & NE 8th Street) is evaluated with historical crash counts, crash types and field observations using the conventional approach.

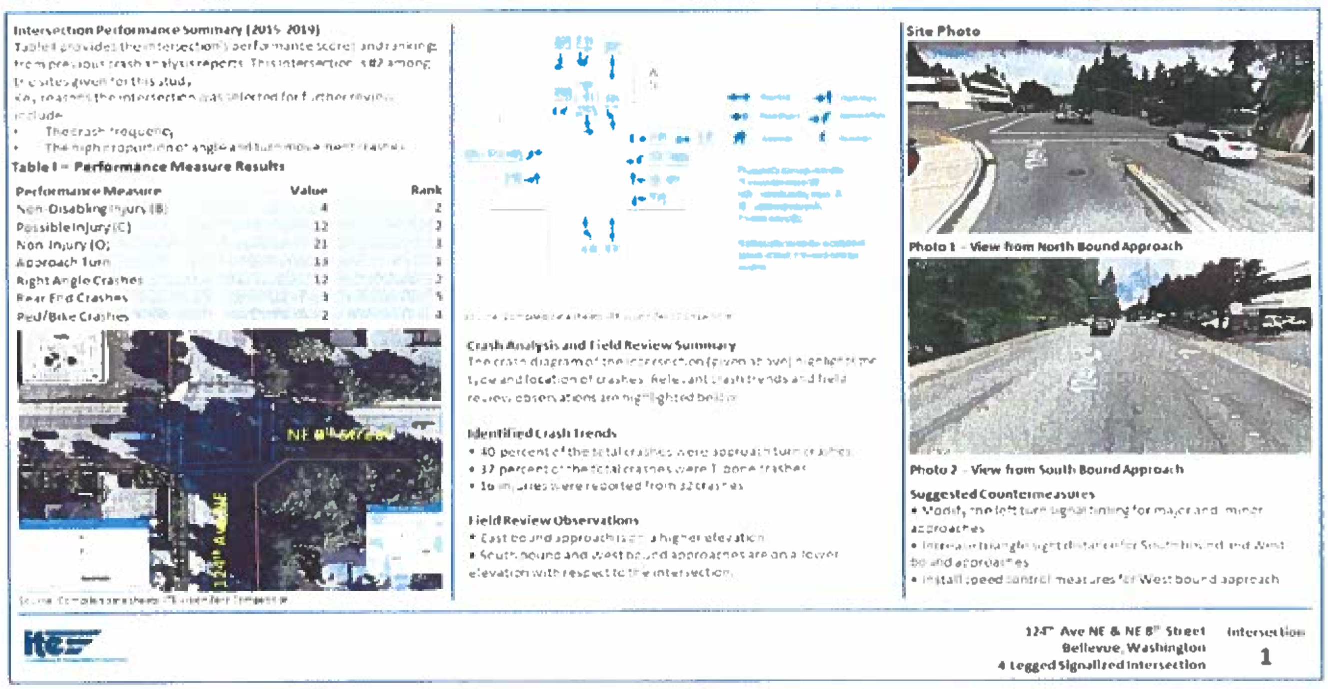


Figure 2: Summary of the conventional approach to select countermeasures

This signalized intersection is in an urban setting surrounded by multi-family dwellings and office spaces. A total of 32 crashes occurred at this intersection in 5 years (2015-2019). However, no fatal or severe injury crashes is reported at this location. Among the reported injuries, 11 percent were non-disabling injuries (B), 32 percent were possible injuries (C) and 57 percent were non-injury crashes (O). 78 percent of crashes reported at this location involved either approach

[5] AASHTO (2010) Highway Safety Manual (1st edition). American Association of State Highways and Transportation Officials Transportation Project Board of the National Academies

turn movements (predominantly left turns) or through movements (right angle crashes). Currently, the signal phasing for the left turning drivers along the East-West corridor (NE 8th St) is protected-permissive. Additionally, the North-South corridor does not have any dedicated left turn phasing but permissive. Speed limits for west bound and east bound approaches are 30 mph and 35 mph respectively. However, the mean and mean speed of both legs are similar. A detailed crash summary sheet for this intersection is illustrated in **Figure 2** above.

3.2 Proposed countermeasure

One of the suggested countermeasures would be adding protected left turn phases at northbound and southbound approaches. In fact, that countermeasure was temporally installed at 124th Avenue NE & NE 8th Street from September 19th to 25th, 2019 for seven days to conduct a before-after study. Details of the before-after study is documented in the Conflict Analysis Report[6].

4. New and Proactive Approach

There are many limitations for conventional approaches. For instance, it is a reactive approach as it is based on historical data. There is a lack of transferability and adaptability as the process must be changed for every site. This is the motivation to explore a new approach using proactive data such as near-miss data for selecting countermeasures. This new approach includes three steps: (1) Data integration with transitional safety data and near-miss data; (2) Critical conflict classification using machine learning technique; and (3) Model interpretation and countermeasure selection. The first two steps fall into the diagnosis process, and the last step belongs the countermeasure selection process of the road safety management process.

4.1 Data Integration with traditional safety data and near-miss data

Data integration of traditional safety data and near-miss data is the first step in this proposed approach. Traditional safety data is site related data - such as number of crashes, traffic volume, etc. Near-miss data is the video-based conflict related data. The proposed approach is a machine learning based classification model that categorizes the given conflict data as critical and non-critical conflicts. Therefore, it is necessary that the two data sources mentioned above are integrated at a conflict event level. **Table 2** on Page 6 shows descriptive statistics of this integration for the intersection 124th Ave NE & NE 8th Street. The project team classified conflicts as critical conflicts when PET is smaller than 2 seconds, and non-critical conflicts otherwise. According to this definition, 124th Ave NE & NE 8th Street has 2,647 critical conflicts and 16,652 non-critical conflicts.

4.2 Critical conflict classification using machine learning model

After a meticulous effort for data preparation and integration, the project team applied and trained a machine learning model with optimized hyperparameter to predict the critical and non-critical conflicts for the first intersection (i.e., 124th Ave NE & NE 8th Street). This well-trained model is then applied to the second and third intersection for verifying the transferability and adaptability of the proposed approach.

Machine learning models have shown their superiority in transportation safety project in predicting crashes and surrogate measures, such as conflicts and time-to-collision measures. Machine learning techniques could outperform conventional statistical modeling, especially when dealing with rich but imbalanced data. In this study, among the three selected intersections (i.e., 124th Avenue NE & NE 8th Street, Bellevue Way NE & NE 8th Street, and 100th Avenue

[6] City of Bellevue. (2020). Video-based Network-wide Conflict Analysis to Support Vision Zero in Bellevue (WA) United States https://bellevuewa.gov/sites/default/files/media/pdf_document/2020/VZ-ITS-Bellevue-Report-1-web.pdf

& Main Street), the critical conflicts only account for 5.73%, 0.36% and 1.53% of the total conflicts. XGBoost classifier is a general tree boosting algorithm well known for its ability to handle imbalanced data with high computational efficiency. Therefore, XGBoost classifier is adopted to predict critical conflicts in this study.

Table 2: Descriptive Statistics Summary of Features

Category	Road User Arrived	West	East	North	South
Movement	First	Left turn: 659 (3.79%) Through: 2,452 (14.12%) Right turn: 59 (0.34%) Crosswalk: 424 (2.44%)	Left turn: 2,673 (15.39%) Through: 2,763 (15.91%) Right turn: 36 (0.21%) Crosswalk: 432 (2.49%)	Left turn: 808 (4.65%) Through: 2,223 (12.80%) Right turn: 485 (2.79%) Crosswalk: 415 (2.39%)	Left turn: 1,544 (8.89%) Through: 1,902 (10.95%) Right turn: 412 (2.37%) Crosswalk: 78 (0.45%)
	Second	Left turn: 1,779 (10.24%) Through: 2,762 (15.91%) Right turn: 314 (1.81%) Crosswalk: 170 (0.98%)	Left turn: 864 (4.98%) Through: 1,790 (10.31%) Right turn: 96 (0.55%) Crosswalk: 165 (0.95%)	Left turn: 1,493 (8.60%) Through: 803 (4.62%) Right turn: 871 (5.02%) Crosswalk: 258 (1.49%)	Left turn: 2,838 (16.34%) Through: 1,924 (11.08%) Right turn: 1,132 (6.52%) Crosswalk: 106 (0.61%)

Category	Road User Arrived	Minimum	Maximum	Mean	Standard Deviation
Median Travel Speed (mph)	First	0.06	82.93	20.16	12.41
	Second	0.06	65.49	12.72	6.99
Conflict Speed (mph)	First	0.06	65.52	22.77	11.21
	Second	0.00	68.57	16.30	6.40
15-min Traffic Volumes	First	0	277	71.51	67.38
	Second	0	277	60.27	65.40
Vehicle Type	First	Car: 15,528 (89.42%), Bus: 196 (1.13%) Truck: 269 (1.55%)		Pedestrian: 1,349 (7.77%), Motorcycle: 14 (0.08%), Bicycle: 9 (0.05%)	
	Second	Car: 16,178 (93.16%), Bus: 136 (0.78%) Truck: 319 (1.84%)		Pedestrian: 699 (4.03%), Motorcycle: 19 (0.11%), Bicycle: 14 (0.08%)	

Conflict	Observation
Day/Period/Hour Conflict Occurred	Weekday: 16,264 (84.27%); Weekend: 3,035 (15.73%)
	Peak: 14,120 (73.16%); Off-Peak: 5,179 (26.84%)
	AM peak: 12,922 (66.96%); PM peak: 6,377 (33.04%)
Conflict Type	Critical Conflict, $PET < 2$: 2,647 (13.72%); Non-critical Conflict, $2 \leq PET < 10$: 16,652 (86.28%)

Note: PET = Post-Encroachment Time. The above statistics is for the intersection *124th Ave NE & NE 8th Street*, collected from September 13th to 19th, 2019

First, the model trains a tree by calculating each sample's predicted values and the corresponding differences with the true value using the training set's features and targets. When training other trees in the next step, this residual is taken as the goal, and the algorithm will stop once the total tree number reaches the pre-set limits or when the error of the verification set reaches the threshold. Finally, each tree's output sample value is added, which is the sample's final predicted value. Thus, the parameter 'scale_pos_weight' within the XGBoost Classifier is modified to adjust the weight of the two classes - critical and non-critical conflicts and to force the model to take care of the minority group and solve problems because of an imbalanced data. This value is defined as the ratio of the binary classes and hence different for each intersection. The classifier was implemented with optimized hyperparameter values in Python 3.8 using the "xgboost" function within the package "XGBoost". The tuning parameter values and the estimator numbers are selected based on 10-fold cross-validation of the training dataset. The values used are - learning rate=0.05, maximum depth=5, minimum child weight=5, gamma=0.3, regularized alpha=0.25, and regularized lambda =1.

This study considers selectivity (i.e., percentage of correctly identified critical conflicts out of total critical conflicts) to evaluate the prediction capability of the model. We are interested in how accurate the model performed with the critical conflicts category as it is the most important indicator from a safety perspective.

$$Selectivity = \frac{Number\ of\ correctly\ identified\ critical\ conflicts}{Number\ of\ critical\ conflicts} \tag{1}$$

For the intersection 124[th] Ave NE & NE 8[th] Street, the selectivity is 86.49%. That is, if there are 10 conflicts identified as critical ones from few hundreds of conflicts, about 8 or 9 out of those ten are correctly identified as critical conflicts. This indicates that the applied XGBoost classifier performed well. It is worth mentioning that selectivity is different from accuracy and is a better measure for this study, because high accuracy may only be a result of well predicted non-critical conflicts (i.e., majority group) and not indicative of the accuracy of critical conflicts (i.e., minority group).

4.2 Model interpretation and countermeasure selection

The new approach demonstrated that it differentiates critical conflicts from non-critical ones well. Shapley additive explanation values (SHAP) are used in this step to find the most important features (attributes) that determine critical conflicts. SHAP is a widely used interpreter of the results from the machine learning technique. A feature's importance is determined by calculating each single feature's contribution to the total features. For instance, for 124[th] Ave NE & NE 8[th] Street, **Figure 3** illustrates the value and ranking of features by their average impact.

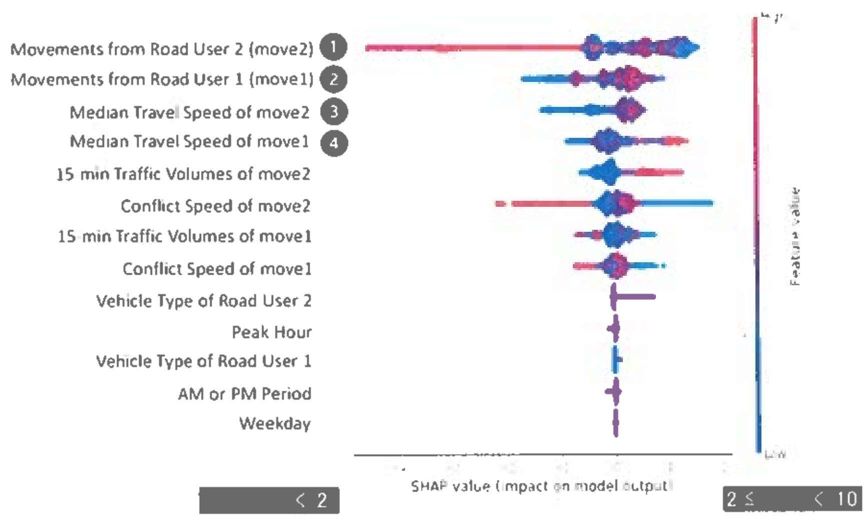
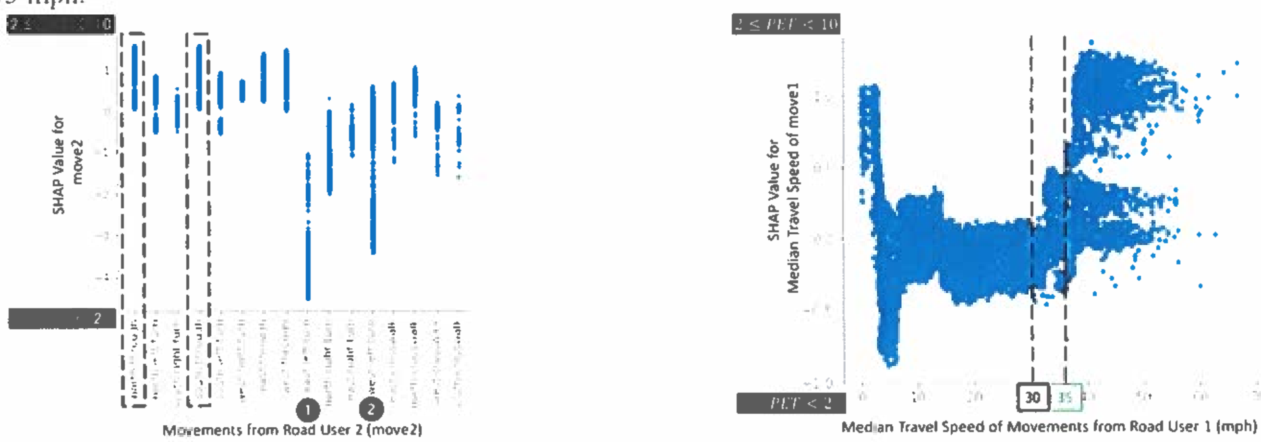


Figure 3: Shapley additive explanations value of features (ranked by average impact)

The type of movement made by Road User 2 and Road User 1 contributes the most in the classification of conflict data for the intersection 124[th] Ave NE & NE 8[th] Street. Additional to the ranking, it is observed that a high feature value for movement by road user 2 (i.e., red in first line) indicates a critical conflict (i.e., PET<2). However, the observation for move2 does not hold for move1. This means that a conflict is more likely to be a critical conflict, when the conflict is associated with the movement made by Road User 2 when that person arrives first (move2). To explore which type of move2 contributes most to critical conflicts, a dependence plot (**Figure 4(a)**) is developed. The movements, east left turn and west left turn are determined as the most conflict contributing ones. It is interesting to note that, among the movements, north through and south through, are the least contributing to critical conflicts. But, when south through or north through are the movements made by Road User 2 who arrived first, it results in a conflict with north left turn or south left turn. These movement pairs were the ones selected as the base for proposing countermeasure selection in

Section 3.2 using the conventional approach. However, these movements are important to conflict events, but not very crucial to critical conflicts. This demonstrates the detailing with which machine learning results can be interpreted and how beneficial the new approach can be.

Median Travel Speed of move2 and move1 are ranked as 3rd and 4th most important factors in categorizing conflicts as critical and non-critical at the intersection 124th Ave NE & NE 8th Street. From line 3 and 4 of **Figure 3** (especially line 4 - Median Travel Speed of move1), it is seen that regardless of move2 or move1, a low feature value (i.e., blue) is towards the critical conflict (i.e., PET<2). That is, the slower the median travel speed of a movement is, the more likely that the conflict to be a critical one. To better understand how median travel speed contributes to critical conflicts, the Median Travel Speed for move1 is explored using dependence plot (**Figure 4(b)**) with the corresponding conflict speed of move1. It agrees with the general trend - it is more likely to be a critical conflict when median travel speed is low (i.e., 5-10 mph). It is also noted that it is more likely to be a non-critical conflict when median travel speed is more than 35 mph.



(a) Dependence plot for movements which Road User 2 arrived first

(b) Dependence plot for median travel speed of movements which Road User 1 arrived first

Figure 4: Dependence plots for important features

In summary, from the ranking of feature importance (**Figure 3**) and dependence plots (**Figure 4**), the project team observes the following trends for 124th Ave NE & NE 8th Street:

1. The conflict is more likely to be a critical conflict when it is associated with the movement by which Road User 2 arrived first (move2); and this movement is the most contributing feature to critical conflicts.
2. Among all movements by which Road User 2 arrived first, east left turn and west left turn are the most contributing ones to critical conflicts.
3. Regardless of the movements, the slower the median travel speed of a movement is, the more likely the conflict to be a critical one.
4. When median travel speed is more than 35 mph for Road User 1, a conflict is more likely to be non-critical.

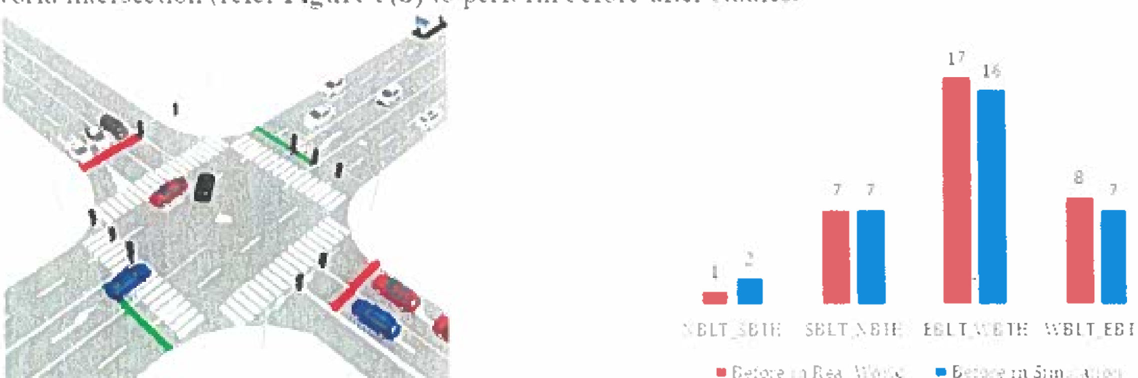
With these, the project team examined the available countermeasure(s). Based on remarks 1, 3 and 4, the team focuses on median travel speed for Road User 1. This is a direct measure based on Remark 3 and 4, and indirect measure based on Remark 1. Because the conflict often happens at the right of way, the movement by which Road User 2 arrived first is associated with the travel speed of Road User 1. Based on Remark 2, the team targets west through and east through movements for Road User 1, which are the dominant pairs for east left turn and west left turn movements for Road User 2

Thus, the team evaluated the countermeasure(s) related travel speeds along with the current travel speeds reported in the westbound (i.e., 30 mph) and eastbound (i.e., 35 mph) approaches of the intersection 124th Ave NE & NE 8th Street. An imbalanced speed limit compliance is observed at the undivided westbound and eastbound arterial road. Therefore, referring to Remarks 3 and 4, the team suggests setting 35 mph as the speed limit on both westbound and eastbound approaches.

5. Assessment and Comparison of Proposed Countermeasures

According to Conventional Approach, adding protected left turn movements for northbound and southbound (i.e., CM_{conv}) is suggested as the countermeasure for the intersection124th Ave NE & NE 8th Street. Based on the previous section, New and Proactive Approach, increasing the speed limit of westbound from 30 mph to 35 mph (i.e., CM_{new}) is proposed. In this section, the project team will conduct a simulation based before-after study with calibrated intersection details to assess and compare CM_{conv} and CM_{new}.

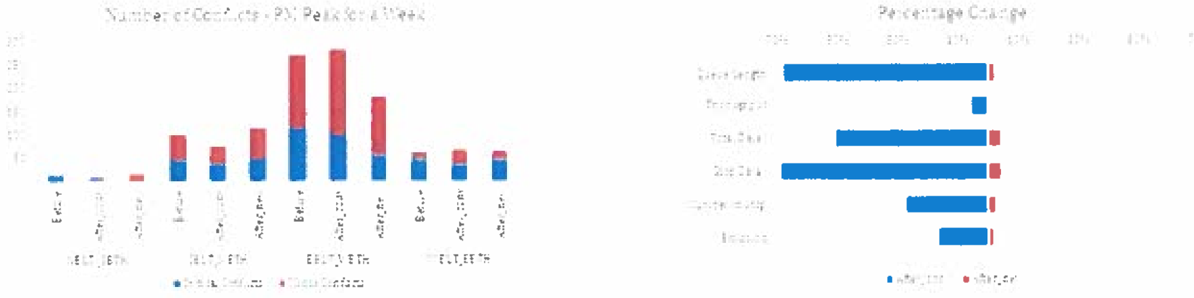
The comparison is conducted for the intersection 124th Ave NE & NE 8th Street. A simulated intersection is developed using microscopic traffic simulation software, VISSIM. The traffic and conflict conditions are simulated for PM peak during the week of September 13th to 19th, 2019. A calibration process is conducted for the VISSIM intersection by matching the travel speed distributions, throughput and more based on the real-world data. Although conflicts or numbers of conflicts are not direct outputs from VISSIM, such conflicts exist in simulation program as shown in **Figure 5(a)**. Thus, the project team postprocessed the vehicle trajectory output to capture the conflicts at the intersection. Considering both CM_{conv} and CM_{new} are associated with conflicts between left turn and through movements, the team focused on four movement pairs for evaluation: northbound left turn and southbound through (NBLT_SBTH), southbound left turn and northbound through (SBLT_NBTH), eastbound left turn and westbound through (EBLT_WBTH), westbound left turn and eastbound through (WBLT_EBTH). To make sure that the postprocessed critical conflicts correctly represent the real-world data, a round of calibration has been completed on the yielding behaviors of left turning vehicles at each of the four approaches. The simulated intersection reflected the real-world intersection (refer **Figure 5(b)** to perform before-after studies.



(a) Example of Conflict in Simulation (b) Calibration of Critical Conflicts – a PM peak

Figure 5: VISSIM simulated and calibrated intersection

Two before-after studies are completed: **(1)** Before vs After_conv, which is with and without CM_{conv}; **(2)** Before vs After_new, which is with and without CM_{new}. To compare the effectiveness of the two countermeasures quantitively, numbers of conflicts (i.e., critical conflicts with $PET < 2$ seconds, minor conflicts with $2 \leq PET < 5$ seconds) for all pairs are examined in **Figure 6(a)**. It demonstrates that, CM_{conv} decreases the numbers of conflicts for movement pairs on south and north (e.g., -8 [-17.4%] for SBLT_NBTH) approaches, whereas CM_{new} decreases the conflict numbers for pairs on west and east (e.g., -56 [50.5%] for EBLT_WBTH) approaches. Hence, from a safety perspective, both proposed countermeasures improve safety.



(a) (b)

Figure 6: Quantitative and qualitative assessments of countermeasures from two approaches

In addition to safety, traffic and environmental impacts of countermeasures are also very important. The project team measured average queue length, total throughput, total delay, stop delay, total number of stops, and emission/fuel consumption to compare the effectiveness of countermeasures. A comparison of the percentage changes of indicators for After_conv and After_new, are illustrated in **Figure 6(b)** above. Because CM_{conv} proposed protected left turn phases for south and north (i.e., minor roads) approaches in the timing plan, the countermeasure brought negative traffic impacts to west and east (i.e., major road) approaches to some extent. Moreover, the north bound through movement suffered due to spill back because of the shorter left turn lane. All traffic performance indicators have negative impact when CM_{conv} is implemented, especially average queue length and stop delay (i.e., both increase by more than 60%). On the other hand, CM_{new} has positive impacts on emission values. From the comparisons of the quantitative and qualitative assessments, the team concludes that both countermeasures brought safety improvements, but CM_{new} has positive impacts on traffic and emissions compared to conventional solutions.

6. Transferability and Adaptability

Through sections 4 and 5, the team demonstrates the constructability of the new approach to select a countermeasure and evaluates its effectiveness by a before-after study, using the intersection 124^{th} Ave NE & NE 8^{th} Street. In addition to that, a comparison is conducted to showcase how effective the conventional and the newly proposed crash /conflict countermeasures are. As mentioned in section 4, after obtaining a well-trained XGBoost machine learning model using the first intersection, other intersections can easily be modeled using the trained model with minimum effort. That means, only less time is needed to be spend on the Diagnosis process once the model is ready. However, such transferability can only be achieved when the selectivity of the machine learning model at the new intersection is within the acceptable limits. In this study, for intersection 124^{th} Ave NE & NE 8^{th} Street, the selectivity is 86.49% (details are explained in section 2). When the trained model is directly applied to Bellevue Way NE & NE 8^{th} Street and 100^{th} Avenue & Main Street, the selectivity is 74.13%; and 72.72% respectively. These selectivity percentages are acceptable in this case, because (1) the trained model is not optimized for these two intersections. Therefore, a slight decrease can be allowed. (2) Bellevue Way NE & NE 8^{th} Street intersection is selected as it shares some common characteristics with intersection 1. 100^{th} Avenue & Main Street intersection is selected as it has many dissimilarities with intersection 1 (details are documented in section 2). Therefore, a decrease in selectivity with respect to the sites is expected. Overall, the percentage of selectivity is above 70% when the trained model is applied to another similar or different intersection. Therefore, the project team believes that the new approach has transferability and adaptability, which the conventional approaches lack.

7. Conclusions

This project made use of near-miss data to select conflict countermeasures – a new approach and compared it with the conventional approaches. The safety improvement and traffic impact of the suggested countermeasures were evaluated based on the transferability and adaptability across intersections. Although some road safety management processes, such as economic appraisal (e.g., cost-benefit analysis), are not included in this project due to time and budget constraints, the project has successfully introduced and presented the new approach pertaining to the first three steps of safety management process - Network Screening, Diagnosis, and Countermeasure Selection. This new approach is found to provide safety improvement and traffic improvement based on several indicators. Moreover, they seem to have good transferability and adaptability for new sites. Therefore, a machine learning approach combined with simulation-based analysis can be considered as a better and proactive solution for countermeasure selection to support Vision Zero in Bellevue.

The project team would like to thank ITE and its Consultants Council for supporting the ITE Vision Zero Sandbox Competition. We express our gratitude to City of Bellevue and Transport Solutions (ITS) Inc. for providing us the data.