1. Description of Proposed Research

2.1. Project title: Work Zone Delay modeling using Big Data and Machine Learning

2.2. Research Abstract (Approx. 200 words):

Please include: Research problem to be addressed and its significance, objectives, and proposed methodology. This section will be used to recruit reviewers; it differs from section 7.2. (Public Project Overview) and must clearly summarize the research proposed.

Managing traffic through work zones is a complex task that involves minimizing traffic delays without exposing workers to excessive risks. One aspect to effective traffic management through work zones involves predicting anticipated delays, understanding their causes, and proactively mitigating those causes. Unlike smooth traffic flow, predicting travel times and delays through interrupted traffic conditions like work zones is a more challenging task. This is particularly true when managing traffic through multiple work zones, which is the case along the 700km Trans Mountain corridor between Edmonton and Vancouver managed by Intellitraffik (a division of ATS Traffic). To ensure that delay due to construction activity does not exceed thresholds set by BCMoTI, the project team currently monitors travel time using probe vehicle data (e.g. Google) that is transmitted to the REFLEKTAR cloud-based platform in real-time via Cellular and GPS signals. The difference between current and baseline travel time is then used to estimate delay. Although such estimates are reliable, lapses in GPS and Cell coverage result in erroneous estimates due to current travel time estimates being heavily reliant on historic data. To overcome these challenges, this research project aims to develop statistical and deep learning models capable of providing more reliable travel time (and delays) predictions at work zones with poor coverage. The model will be trained, tested, and validated using big data collected at work zones with reliable GPS and Cell signal and will integrate wok zone characteristics, traffic, temporal, and weather information. The models will then be used to estimate delay at locations with poor coverage and their performance will assessed using field collected data.

2.3. Background and review of relevant prior work (minimum 500 words):

The US Federal Highway Administration once estimated that work zones account for 24% of nonrecurrent traffic congestion resulting in 482million vehicle hours of delay (FHWA 2004). Despite that, the majority of existing research modelling delay at work zones has been limited to parametric and simulation studies. Only recently have there been a few studies attempting to forecast mobility at work zones using statistical and machine learning techniques. In fact, the lack of travel time prediction models for work zones, has led most transportation agencies across North America to use simulation tools developed to model freeway travel times, to predict work zone impacts and to select optimal design and deployment strategies(Berthaume, Jackson et al. 2018).

Du, Chien et al. (2017) developed a model to predict the speed reduction/delay caused by an expected work zone with lane closures on New Jersey freeways. The model integrated a neural network (NN) which was fed capacity information from a support vector machine (SVM) model. The model was developed to predict spatiotemporal delays using multiple variables including road geometry, number of lane closures, work zone length, upstream traffic volume, truck percentage, and average upstream speed and work zone duration. The authors found that the predicted work zone speed was accurate and within a narrow band offsetting the INRIX reported speed.

Wen (2018) attempted simulating work zone travel time in a connected vehicle environment. The author developed the simulation model using travel demand data from a single work zone in NY state. Sixteen variables were extracted from the simulation results to explore travel time estimation and prediction. For the travel time analysis, four types of models were constructed, including linear regression, multivariate adaptive regression splines (MARS), stepwise regression and elastic net.

Kamyab, Remias et al. (2020) utilized historical lane closure information and used supervised machine learning algorithms to forecast spatio-temporal mobility for future lane closures. The research focused on situations where hourly traffic volume is not available. Modelling data was collected at 1,160 work zones on Michigan interstates between 2014 and 2017. To retrieve a mobility profile for historic observations, the authors used probe vehicle data. The profiles were then used to apply random forest, XGBoost, and artificial neural network (ANN) classification algorithms. Mobility prediction was done by placing speed observations in 20mph bins. The results showed that the ANN model outperformed the other models by reaching up to 85% accuracy. One issue with this study is that the prediction assumes continuous availability of real time probe vehicle traffic data, which is not the case at locations where lapses in GPS signal and cell coverage exist. The study also placed speed data into wide 20mph bins which makes a significant difference when the concern is predicting delay such as in this study.

The Smart Work Zone Deployment Initiative in collaboration with the Center for Transportation Research in Austin Texas recently published a report summarizing efforts to develop machine learning (ML) models to the prediction of work-zone traffic impacts including local speed and traffic volume changes and corridor-level travel time increases (Liu, Westerfield Ross et al. 2021). The research used data collected on a 20.4 mile section of the I-35 in Austin, Texas where smart work-zone trailers (SWZTs) were placed. Predictive models combined SWZT point speed and volume data with INRIX segment-level speed data. The researchers implemented artificial neural networks (ANNs) to forecast speed and volume changes for planned closures. The researchers also analyzed the performance of three short-term travel-time prediction (STTTP) techniques. This included a time series analysis model and two types of ANNs. The study found that, on average, the new models outperformed traditional approaches by up to 50 percent during the peak period travel time prediction, however, the study noted that performance was not as reliable when predicting travel times when work zones were present. The study concluded that the results were promising with ML models consistently outperforming the traditional approaches.

Other studies attempted modelling and prediction of other work zone features. This includes work zone capacity (Bian and Ozbay 2019, Mashhadi, Farhadmanesh et al. 2021), speeds (Wang, Liu et al. 2016), and safety (Yang, Ozbay et al. 2015, Sekuła, Vander Laan et al. 2018, Hou, Chen et al. 2020).

Although the body of research attempting to model work zone delays has grown in the past four years, more work is required to develop a robust delay prediction model. To that end, the proposed research builds on limited previous studies in this area by: (i) developing a model that uses work zone characteristics, temporal, spatial and weather variable to predict travel time, and the associated delay, through work zone using field collected data as opposed to simulations (ii) attempting to predict the delay without the use of existing probe vehicle data, which resembles situations where such data is not available due to lapses in GPS signal and cell coverage (iii) understanding the impacts of several different factors including geometric road features, the spatial proximity of a work zone to other work zones, temporal variables, and weather conditions on work zone delay.

2.4. General objective of the research project broken down into sub-objectives, activities, themes, or subprojects, as applicable:

As noted in the previous section, this project aims investigate the relationship between work zone characteristics and delay while also developing a travel time prediction model that is independent of probe vehicle data. The model will be developed using traffic data collected along a 700km travel corridor between Edmonton, AB and Vancouver, BC. Work under this project has been split into two primary objectives:

- The ***first objective*** will involve investigating the relationship between work zone design/layout and delays through a work zone. To achieve this a logistic model that incorporates work zone characteristics, traffic volumes and temporal variables will be developed. Sensing technology (i.e. LiDAR, imagery, and traffic counters) will be used to collect field data and estimate traffic conditions. The objective is split into the following subobjectives
    - **Obj 1.1** Data collection, assembly, and cleaning.
    - Under this subobjective the intern will collaborate with ATS Traffic and BCMoTI to obtain access to the collected probe vehicle data. The intern will then begin cleaning the big dataset which includes over a year of 5-minute travel time observations at all active work zones along the 700km corridor. Data cleaning will involve removing duplicate observations, filtering data based on work zone site ID, aggregating delay observations on a wider time interval, and writing the codes and scripts required to attach work zone attributes and other features including traffic volumes to the work zone travel time data.

- The Intern will also work with ATS Traffic personnel and coordinate installing traffic monitoring and speed measurement devices at a selection of work zones to collect ground truth vehicle travel time information for the model validation conducted under Objective 2. This will involve using a combination of traffic counters and on-site cameras and sensors. The sensors will be installed early on in the project and the data will be used in validating the prediction models developed under objective 2.
- **Obj 1.2** Literature review of factors impacting work zone delay
- While working on data collection, assembly and cleaning the intern will also lead conducting the literature review of the relationships between different variables and work zone delays. This will help the intern develop a deeper understanding about the variables that have been found to have direct or in-direct impacts on travel time through work zones in preparation for Obj 1.3.
- **Obj 1.3** Exploratory data analysis
- Under this stage the intern will run exploratory analysis between the different variables in the compiled dataset. This will involve obtaining descriptive statistics, running correlation tests, and visually exploring the descriptive plots. This will help capture trends in the data, while also identifying missing information, testing model assumptions, and applying any required transformations.
- The variables considered in the exploratory analysis will include closure length (i.e. how long the work zone extends), closure start time, closure duration, percentage of lanes closed, closure direction, closure location, day-of-week index, time-of day, typical travel speed, proximity to the closest work zone, weather conditions, road geometry (i.e. grades and slopes), and traffic volume. It is worth noting here that, traffic volume will be obtained from permanent traffic counters installed by BC MoTI along its highway network. For each work zone, information captured by the traffic counter nearest to the location of the work zone will be used. For a road segments geometric attributes including slopes and grades this information will be extracted from LiDAR and photogrammetric scans of the work zones that will be obtained by ATS traffic using third part services. In the situation that the LiDAR scans cannot be collected, profile elevation information will be extracted from google earth.
- **Obj 1.4** Logistic model development and analysis
- After identifying the most appropriate modelling techniques and the underlying trends in the data, Interns will work on getting familiar with the most appropriate statistical software package and programming language to build the logistic models. The collected data will then be used to develop logistic models. After developing the models, these models will be used to identify the variables with the statistically significant impacts on delay. The analysis will also help explore the sensitivity of the relationships between statistically significant variables and the work zone travel time (delay). This will help identify the variables that would be most effective to use in the delay prediction models. This assessment will also provide insights to ATS traffic on the design that could result in more efficient traffic flow through a work zone.

- The ***second objective*** of this work is to develop a statistical machine learning model capable of predicting work zone delays based on the characteristics of the work zone and other variables related to operating conditions. The model will be capable of predicting travel times at work zones without the reliance on probe vehicle data. The objective is split into the following subobjectives
  - **Obj 2.1** Field data transfer and assembly
  - **Obj 2.2** Literature review of methods
  - Interns will work on conducting a thorough literature review of the tools and techniques that have been used in the past to predict work zone delays while documenting the advantages and disadvantages of each method. The interns will also assess the applicability of each technique to the existing dataset. This will provide the interns with information on the most appropriate model structure including the neural network architecture and the hyperparameters.
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- **Obj 2.3** NN Model development
- After identifying the most appropriate modelling techniques, interns will then get familiar with the most appropriate programming language to design and train the machine learning models. The data assembled under Objective 1 will then be used to build and train an Artificial Neural Network to predict delays.
- Artificial neural networks (ANNs) are robust statistical models that work on establishing a logical model consisting of inter-connective neurons. Neural Networks (NN) have been used to solve complex modeling challenges including regression and classification problems. In nonlinear regression problems the Deep Neural Network adopts a Multi-Layer Perceptron (MLP) structure and consist of an input layer, an output layer and several hidden layers. Within each of the hidden layers several neurons compute a weighted sum of input values to generate outputs, as illustrated in Figure 1. In supervised learning the NN learns the weights between neurons that result in the minimizing the differences between the predictions and the estimates.
- The DNN will work on predicting a dependent variable (*y*), travel time through a work zone, based on multiple independent variables (***X***), which represent the work zone characteristics and other variables with perceived impacts on travel time. To train the neural network a back propagation and stochastic gradient descent will be adopted to minimize the least squares loss function. This will involve assigning random initial weights to input data. The weights are then subsequently updated based on a comparison between predicted response values and the training data. Model training will be carried out until the predefined number of epochs is achieved or the loss obtained on the validation data is satisfactory.
- It is worth noting here that only data collected at work zones where reliable GPS and Cell coverage exists will be used to build the prediction model. Interns will then work on splitting the collected dataset into three subsets. The first subset (training data) will be used to develop the models. The second subset (validation data) will be used to fine tune the test model parameters based on the validation outputs. Finally, the third subset (test data) will be used by the intern to evaluate the performance of the model and the accuracy of the predictions.
- **Obj 2.4** Result Comparison and Model Evaluation
- Once the neural network is trained, Afshin will be assisted by Ali (intern 3) in testing it initially using data collected at work zones with reliable GPS and cell coverage that was not used to develop the neural network. After evaluating performance using this dataset, he will then use the NN to predict travel time at locations with limited GPS and cell coverage. At those locations the project team will also collect field observations of travel time. Field observations will be collected using conventional tools including the stalker data collector and miovision scout and will be cleaned and transferred from site by intern 3. Model performance will be evaluated by comparing travel time observations predicted using the model and those obtained in the field. Depending on the prediction accuracy part of the field data might also be used to retrain the NN to improve performance. Finally, the level of accuracy achieved using the prediction model will be compared to that of the probe vehicle data obtained from Google where lapses in GPS and cell coverage are experienced (i.e. current practice). This could include locations studies as part of the project and other work zones set up on other highways or in other environments.
- **Obj 2.6** Manuscript and Final Report Preparation

2.5. References:

Berthaume, A., et al. (2018). "Validating the Performance of the FHWA Work Zone Model Version 1.0: A Case Study along I-91 in Springfield, Massachusetts." 2672(16): 46-56.

Bian, Z. and K. J. T. r. r. Ozbay (2019). "Estimating uncertainty of work zone capacity using neural network models." 2673(2): 49-59.

Du, B., et al. (2017). "Predicting freeway work zone delays and costs with a hybrid machine-learning model." 2017.

FHWA (2004). Making Work Zones Work Better.

Hou, G., et al. (2020). "Study of work zone traffic safety under adverse driving conditions with a microscopic traffic simulation approach." 145: 105698.

Kamyab, M., et al. (2020). "Machine Learning Approach to Forecast Work Zone Mobility using Probe Vehicle Data." 2674(9): 157-167.

Liu, H., et al. (2021). Using Smart Work Zone Trailer Data to Evaluate and Predict Lane Closure Impacts with a Consideration of Work Intensity.

Mashhadi, A. H., et al. (2021). "Review of Methods for Estimating Construction Work Zone Capacity." 03611981211002202.

Sekuła, P., et al. (2018). "Predicting work zone collision probabilities via clustering: application in optimal deployment of highway response teams." 2018.

Transport Canada (2006). The Cost of Urban Congestion in Canada.

Wang, H., et al. (2016). "A novel work zone short-term vehicle-type specific traffic speed prediction model through the hybrid EMD–ARIMA framework." 4(3): 159-186.

Wen, X. (2018). "A work zone simulation model for travel time prediction in a connected vehicle environment."

Yang, H., et al. (2015). "Work zone safety analysis and modeling: a state-of-the-art review." 16(4): 387-396.