Transportation Research Record

Short-term traffic prediction under non-recurrent incident conditions integrating data-driven models and traffic simulation

--Manuscript Draft--

Full Title:	Short-term traffic prediction under non-recurrent incident conditions integrating data-driven models and traffic simulation
Abstract:	Predicting the traffic condition in urban networks is a priority for all traffic management centers around the world. This becomes very challenging especially when the network is affected by traffic incidents which vary in both time and space. Although data-driven machine learning (ML) modeling can be considered as an ideal tool for short-term traffic predictions, its performance is severely degraded when little historical traffic information is available under non-recurrent incident conditions. This paper addresses this challenge by integrating both data-driven and traffic simulation modeling. Instead of directly predicting the traffic states using limited historical data, we apply data-driven models to reinforce the traffic microsimulation. More explicitly, we employ ML models to predict origin-destination (OD) demand flows based on historical day-to-day demand flows. The traffic simulation uses the freshly reported incident information and the predicted OD demand flows obtained from ML models to forecast the future traffic states under non-recurrent incident conditions. Since accurate OD flows cannot directly measured in large-scale areas, we propose an OD demand rolling-horizon estimation problem to estimate demand flows based on the most recent measured link volumes. Results show that Decision Tree method outperforms other ML models in OD demand flow prediction. Finally, we showcase the capability of the proposed data-driven enforced traffic simulation platform for incident impact analysis in a real –life sub-network from Sydney, Australia.
Manuscript Classifications:	Data and Information Technology; Freeway Operations AHB20; Incident Management; Operations and Traffic Management; Freeway Operations AHB20; Incident Management
Manuscript Number:	20-01059
Article Type:	Presentation
Order of Authors:	Sajjad Shafiei
	Adriana-Simona Mihăiță
	Hoang Nguyen
	Christopher Bentley
	Chen Cai

Short-term traffic prediction under non-recurrent incident conditions integrating data-driven models and traffic simulation

Sajjad Shafiei
(corresponding author)
Transport Analytics Group
DATA61| CSIRO, Sydney, Australia
Email: sajjad.shafiei@data61.csiro.au

Adriana-Simona Mihăiţă
University of Technology Sydney, Australia
Email: adriana-simona.mihaita@uts.edu.au

Hoang Nguyen
Transport Analytics Group
DATA61| CSIRO, Sydney, Australia
Email: hoang.nguyen@data61.csiro.au

Christopher D B Bentley
Transport Analytics Group
DATA61| CSIRO, Sydney, Australia
Email: christopher.bentley@data61.csiro.au

Chen Cai
Transport Analytics Group
DATA61| CSIRO, Sydney, Australia
Email: chen.cai@data61.csiro.au

Total words: 6,700 words + 3 tables x 250 = 7,450

Submitted for Presentation only in the Transportation Research Board

August 2019

ABSTRACT

Predicting the traffic condition in urban networks is a priority for all traffic management centers around the world. This becomes very challenging especially when the network is affected by traffic incidents which vary in both time and space. Although data-driven machine learning (ML) modeling can be considered as an ideal tool for short-term traffic predictions, its performance is severely degraded when little historical traffic information is available under non-recurrent incident conditions. This paper addresses this challenge by integrating both data-driven and traffic simulation modeling. Instead of directly predicting the traffic states using limited historical data, we apply data-driven models to reinforce the traffic microsimulation. More explicitly, we employ ML models to predict origin-destination (OD) demand flows based on historical day-to-day demand flows. The traffic simulation uses the freshly reported incident information and the predicted OD demand flows obtained from ML models to forecast the future traffic states under non-recurrent incident conditions. Since accurate OD flows cannot directly measured in large-scale areas, we propose an OD demand rolling-horizon estimation problem to estimate demand flows based on the most recent measured link volumes. Results show that Decision Tree method outperforms other ML models in OD demand flow prediction. Finally, we showcase the capability of the proposed data-driven enforced traffic simulation platform for incident impact analysis in a real –life sub-network from Sydney, Australia.

Keywords: *demand estimation and prediction, micro-simulation, incident impact management*

INTRODUCTION

Short-term traffic forecasting is a necessary step for efficient network operations and is an integral part of Intelligent Transportation System (ITS) applications. The abundance and recent increase of various traffic data sources have led many researchers and data scientists to employ a wide range of data-driven models to predict future traffic conditions. There are various parametric and non-parametric methods for the short-term forecast of speed (*1*, *2*), travel time (*3–5*), and traffic volume (*6*, *7*), which offer a prediction in the range of a few minutes to a few hours into the future. However, two challenges are highlighted in the previous studies as the main critical limitations of the majority of data-driven models (*8*). Firstly, the majority of data-driven forecasting models have been applied to freeways or arterial corridors rather than regular urban networks. The complex spatial configuration of all network connections and the dynamics of the travel demand makes the traffic forecasting in urban networks very challenging, particularly for large suburban networks. Secondly, an important challenge is the wide variability of traffic incidents that can occur at different times of the day, rarely in the same location or with the same severity. These incidents can range from temporary lane closures due to car breakdowns and small-scale accidents to more complicated ones such as sudden weather changes and train system breakdowns. All these varying characteristics of traffic disruptions increase the complexity of forecasting and make it almost impossible to find similar patterns in any historical dataset. To address this issue, some studies focus only on a particular type of incidents (*9*) or for example on highway lane closures due to roadway reconstruction projects (*10*, *11*). However, in most cases, there is limited recorded data for each particular type of incident, and thus, forecasting traffic measurements such as traffic volume, speed, or travel time can result in inaccurate outcomes.
On a parallel research track, an approach to predict the traffic state incorporating incidents is using reliable traffic assignment models (*12–14*). In these models, each traveler attempts to minimize his/her travel time/cost and their decision will impact the other travelers' decisions to move in the network (*15*). By considering this essential principle, the intricate traveler route decisions can be modeled in the traffic network. Moreover, the propagation of traffic along the network is replicated by traffic flow theories that determine the traffic flows and the associated travel times on network links (*16*). However, the traffic assignment models require several demand and supply inputs which should be predicted as well for operational applications (*17*).
In this paper, instead of directly predicting the link traffic features using only historical data, we use data-driven models to reinforce a traffic micro-simulation by providing the required inputs. In our proposed framework, once an incident is categorized as severe by an Al-engine (*18*), a summary of incident characteristics such as the location and the number of affected lanes is transferred to the traffic simulation. Moreover, a machine learning method predicts short-term OD demand flows and feeds them to the traffic simulator. With knowledge of the

incident information and predicted OD demand flows, the simulator applies traffic flow principles to predict the traffic state under non-recurrent incident conditions.

We make the assumption that network commuters hardly cancel their short-term trips even if affected by disruptions. This assumption holds particularly for morning peak hours in which a large proportion of trips like home-to-work or home-to-education still need to continue. The travelers mainly respond to a new prevailing bad network condition by updating/changing their route trips. Such behavioral phenomena can be modeled accurately in traffic simulations. We propose a rolling horizon bi-level optimization model to keep the traffic simulation model calibrated based on the most recent measured traffic data. To summarize, we present our main contributions for this paper as:

- A dynamic OD estimation problem is formulated and solved to keep the traffic simulation updated based on the most recent measured traffic data. The estimated day-to-day OD flows are archived for the OD demand prediction module.
- Several machine learning models are deployed for OD demand prediction to reinforce the traffic simulator.
- A prototype for an integrated incident management platform is developed to make use of data-driven and dynamic traffic simulation modelling.
- The impacts of traffic incidents are investigated for a real application in an urban sub-network.

The rest of the paper is organized as follow: Section 2 describes the methodology applied over a real sub-network in Sydney, Australia and Section 3 showcases the results. Finally, Section 4 provides the concluding remarks and outlines some research extensions for future studies.

METHODOLOGY

1.1. Incident management platform

In this section, we explain the general data flow used for building an operational incident management platform tailored to the needs of the Traffic Management Center in Sydney, Australia. Figure 1 presents the proposed incident impact analysis platform using integrated data-driven and traffic simulation models. The methodological diagram treats the cases of recurrent versus non-recurrent incidents differently, by triggering various modules detailed here below.

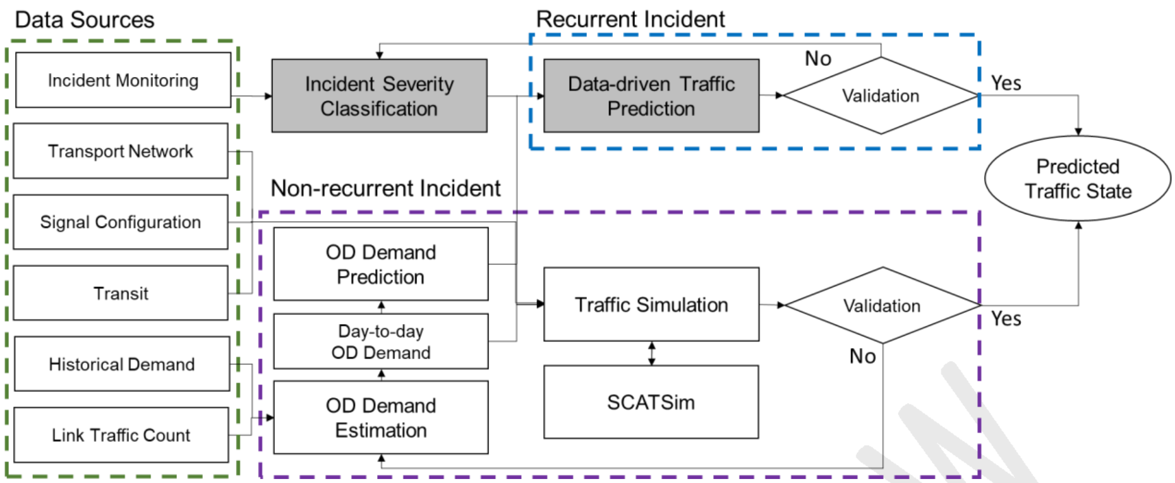

Figure 1. Data-driven and simulation platform for incident impact analysis. The gray modules are beyond the scope of this paper.

Our proposed framework is based on various data types including:

- **measured link traffic count**: Link traffic counts are essential inputs for the OD demand estimation module as well as to validate the framework's output.
- **supply/demand data:** which contains the primary information of the links of the network, public transport lines and their frequency, and signal configuration. This data is exported and used to construct the simulation model once offline.
- **incident data logs**: includes the incident location ([x,y] coordinates), the number of affected lanes, the start time of the incident, the incident duration and more details about the incident severity.

By having such information, the proposed framework predicts traffic state in two streams of recurrent and non-recurrent conditions using the following modules:

- ***Incident severity classification***: This module includes raw data processing and uses machine learning techniques to classify reported incidents into severe and non-severe. When an incident is categorized as a severe incident, its data is transferred to the traffic simulation model for further impact analysis. For non-severe incidents, the data-driven traffic model is used for short traffic prediction, This module is not a focus of this study and readers can refer to our previous work (*18*).
- ***Data-driven traffic prediction***: This module is based on our previous study (*19*) which proposed a deep learning methodology for travel speed prediction involving feature generation, model development, and model deployment. The proposed neural network model is used for recurrent incident conditions.
- ***OD demand estimation***: the purpose of this module is to adjust a-priori demand data by using link traffic observations. We estimate the OD flows through a bilevel optimization

framework in which the a-priori demand flow is updated based on the latest measured traffic in several links of the network.

- ***OD demand prediction***: The demand prediction model will forecast the OD trip flows for short time intervals into the future (up to an hour ahead) by using the OD demand flows obtained by the OD demand estimation module.
- ***Traffic simulation***: is used to understand the allocation of the predicted OD demand flows with consideration of the freshly reported incident information. The outputs of the traffic microsimulation are: travel times, link traffic volumes, delay and so on.
- ***SCATSIM***: is a simulator plug-in which responds to the simulated traffic state by changing: a) the total cycle times inside each SCATS-controlled intersection, b) the ratio of the cycle time assigned to each phase and c) the offset between adjacent signal controls. As a result, the real-life SCATS control logic is applied to the simulated vehicles in the simulator which offers a realistic replication of real-world traffic control conditions.
- ***Validation***: the inputs of the simulation model are regulated by the updated traffic measurements observed consistently from the network at each time-interval, in order to ensure the predicted results reflect the actual real-life conditions. If the error between the predicted and the corresponding observed values is less than an acceptable threshold defined in NSW traffic modelling guidelines (*20*), then we accept the outputs of the platform as the final predicted traffic state.

1.2.Demand estimation and prediction

The success of the traffic simulation relies on the quality of this fundamental input and how well it captures the travelers' movement in the city from one-time interval to another. Accurate demand flow information is difficult to obtain directly and normally it is estimated based on link traffic measurements (*21*). The main objective of the OD demand estimation problem is to minimize the error between the simulated and the observed traffic measurements. Many studies apply a bi-level optimization formulation where demand flows are estimated in the upper-level and the feedback of estimated demand in the network is evaluated by a lower-level traffic assignment model (*22*). Some relevant works for dynamic OD estimation problems are conducted in the literature such as a) using advanced traffic surveillance data to improve the accuracy of estimated OD flows (*23*), b) proposing methodological enhancements to deal with nonlinearity problem in congested networks (*24*, *25*), and c) applying simultaneous adjustment of supply and demand parameters to consider the complex interactions of demand and supply components (*26*).

Dynamic OD demand estimation based on traffic measurements is often performed offline for planning and operational applications. However, the offline procedure is not sufficient for real-time traffic management applications. The offline demand flow estimation problem requires measured traffic data, while in the real-time applications, the model should be able to predict the traffic data actively for the near future. Offline dynamic OD estimation provides a reliable initial OD demand for online applications to estimate the OD flows within a reasonable computational time (*27*).

The OD demand estimation problem is expressed as a system of equations in which the unknown parameters are OD flows and each equation represents the observed link flow. In this study, we used a bi-level optimization problem in which the OD demand flows are estimated by solving the system of equations in the upper level, and the estimated OD demands are evaluated in the lower level. In addition to reducing the Euclidean distance between simulated and observed traffic data, the objective function seeks to keep the estimated demand as close as possible to the initial demand. In this way the solution does not explore the local optima far from the initial demand flows. Our optimization OD demand estimation problem is mathematically expressed as follows:

$$\min \ \mathrm{F(X)} = \omega . \sum_{i=1}^{I} \sum_{t=0}^{T} \mathrm{f}(\hat{x}_i^t, x_i^t) + (1-\omega) . \sum_{a=1}^{A} \sum_{t=0}^{T} \mathrm{f}(\hat{y}_a^t, y_a^t)$$
$$y_a^t = \sum_{\tau=1}^{t} \sum_{i=1}^{I} p_{a,i}^{\tau,t}(X) x_i^{\tau} \tag{1}$$

where each parameter is explained here below:

f	Euclidean distance function,
a	Link index, a ϵ [1,A], A is the total number of observed links in the network
t,τ	Time index t, τ ϵ [1,T], T is the total number of modeling discrete times,
i	OD pair index *i* ϵ [1,I], I is the total number of OD pairs in the network,
$\hat{x}_i^t$	Estimated demand flow for an OD pair *i* ϵ I at time *t*,
x_i^t	Initial demand flow for an OD pair *i* ϵ I at time *t*,
$\hat{X}$	Estimated demand vector, $\hat{X} = [\hat{x}_1^1 , \ \hat{x}_2^1, \hat{x}_3^1, \dots, \hat{x}_I^1, \ \dots, \hat{x}_{I-1}^T, \hat{x}_I^T]$
$\hat{y}_a^t$	Estimated link flow in link *a* at time *t* ϵ T,
y_a^t	Observed link flow in link *a* at time *t* ϵ T,
$p_{a,i}^{\tau,t}$	Assignment proportion of x_i^t that passes through a link *a* during time period τ,
ω	Reliability weight for the demand deviation.

To solve the problem in Eq.(1, the partial derivative of function F with respect to the demand flow for the OD pair η at time h (x_η^h $h \in [0, T], \eta \in I$) is determined as follows:

$$\frac{\partial F}{\partial x_\eta^h} = \frac{\partial}{\partial x_\eta^h} \left(\omega \sum_{t=1}^{T} \sum_{i \in I} (x_i^t - \hat{x}_i^t)^2 + (1-\omega) \sum_{a=1}^{A} \sum_{t=1}^{T} (y_a^t - \hat{y}_a^t)^2 \right) \tag{2}$$

$$= 2\omega\left(x_\eta^h - \hat{x}_\eta^h\right) + 2(1-\omega)\left(\sum_{a=1}^{M}\sum_{\tau=h}^{T} p_{a,\eta}^{\tau,h}(X^*)(\sum_{t=1}^{\tau}\sum_{i\in I} p_{a,i}^{\tau,t}(X^*)x_i^t - \hat{y}_a^\tau)\right)$$

In addition to determining of the gradient, we also need to calculate the step size (λ). To do so, the sub-optimization problem in Eq.3 is solved in each iteration:

$$\min_{\lambda} F(X + \frac{\partial F}{\partial x}\lambda) \tag{3}$$

We use the golden section algorithm, as a line search minimization solution for solving the sub-optimization problem defined in Eq.(3. The algorithm includes the following steps:

Step 1: if $\lambda^* \in [0,1], \zeta = 0,\ \varrho = 1,\ \lambda_1 = \psi,\ \lambda_2 = 1 - \psi$ where $\psi = \frac{\sqrt{5}-1}{2}$

Step 2: if $F(X + \frac{\partial F}{\partial x}\lambda_1) > F(X + \frac{\partial F}{\partial x}\lambda_2)$

$\zeta = \lambda_2\,, \lambda_2 = \lambda_1, \varrho = \varrho, \lambda_1 = \psi$

if $F(X + \frac{\partial F}{\partial x}\lambda_1) < F(X + \frac{\partial F}{\partial x}\lambda_2)$

$\zeta = \zeta\,, \varrho = \lambda_1, \lambda_1 = \lambda_2,\ \lambda_2 = \varrho - \psi$

Step 3: if $\zeta - \varrho < \varepsilon$ then: $\lambda^* = \frac{\zeta+\varrho}{2}$; otherwise, go to, step 2.

With the knowledge of the gradient $\left(\frac{\partial F}{\partial x_\eta^\tau}\right)$ and the step size (λ), the demand flow ($\hat{x}_\eta^\tau$) is then updated as:

$$\hat{x}_\eta^\tau = x_\eta^\tau + \lambda \frac{\partial F}{\partial x_\eta^h} x_\eta^\tau \tag{4}$$

The proposed OD demand estimation model is performed in two stages. First, we execute the procedure offline to estimate OD demands for a typical weekday. In this stage, an initial static OD demand obtained from the strategic model is used to estimate sixteen 15-minute OD demand matrices for a 4-hour simulation during peak hours. Second, the time-dependent OD demand matrices estimated from the first stage are adjusted in a rolling-horizon estimation procedure based on the most recent observed traffic counts. As a result, the simulation model is kept updated in real-time using the newly observed data. Moreover, the estimated OD demand flows are archived for different days of the week. The archived demand is considered as a reliable training demand set for any demand prediction module. Let the current time be '*t*'. Then, the demand prediction model has to predict demand flow for the next time intervals ($\tilde{x}_i^{t+1}$) given the value of the '*m+1*' previous demand flow values ($\hat{x}_i^{t-m}$, …, $\hat{x}_i^{t-1}$, $\hat{x}_i^t$). Thus, the prediction model is expressed as:

$$\tilde{x}_i^t = \mathrm{P}(\hat{x}_i^t, \hat{x}_i^{t-1}, \ldots, \hat{x}_i^{t-m}, t) \tag{5}$$

For building this OD demand prediction module, we use different predictors which are presented in the next sections.

1.3. Data-driven models

In this section, we provide a brief description of various algorithms that we used for demand flow prediction, among which we cite: support vector machines (SVM), decision trees (DT), and autoregressive moving average (ARMA).

Support Vector Machines

Support vector machines (SVM) in statistical learning theory have been widely applied for solving classification and regression problems (*28*). In general, SVM is a well-established prediction method in complex systems which can deal with noisy databases (*29*). The SVM model is formulated as a constrained optimization problem specified in Eq.(6). The problem consists of two conflicting objectives: minimizing the Euclidean distance of ω to increase the margin and reducing the instance margin violations (ξ_i). Constant *C* makes a balance between the two objective terms. A small value for hyper-parameter *C* allows a higher generalization ability while a big *C* value enforces serious penalty to limit instances (in our application demand flow x_i^t) that violate the determined margin.

$$\begin{gathered}\underset{\varpi, b}{minimize} \;\; 0.5\, \varpi^T . \varpi + C \sum_{i=1} \xi_i \\ \text{so that:} \\ \xi_i = \begin{cases} |\varpi . \Gamma(x_i^t) + b - x_i^t| - \varepsilon & |\varpi . \Gamma(x_i^t) + b - x_i^t| \geq \varepsilon \\ 0 & |\varpi . \Gamma(x_i^t) + b - x_i^t| < \varepsilon \end{cases} \;, \forall i\end{gathered} \tag{6}$$

where Γ is a transformation function that can be replaced with a kernel function. Different kernel functions such as linear, polynomial, Gaussian radial basis function (RBF), and Sigmoid are commonly used in SVM modelling (*28*). Regardless of the kernel functions used, the main goal is to estimate the value of coefficients of ϖ and b in the Eq.(6. To do this, the parameters C, ε, and ξ should first be defined. Once they are determined, there will be a global optimal solution found for the convex Problem Eq.(6 to obtain ϖ and b values. In Section 2.2, we explore different values to find the best combination for our application.

Decision Trees

Decision Trees (DT) are versatile non-parametric supervised ML algorithms that are capable of fitting complex datasets. Decision Trees are considered as white box models because their decisions are intuitive and easy to interpret. This algorithm is also widely used in both classification and regression (*28*). The following cost function is minimized to determine the subsets and their thresholds:

$$J = \frac{m_{left}}{m} G_{left} + \frac{m_{right}}{m} G_{right}$$

$$G = 1 - \sum_{k=1}^{n} {p_k}^2 \quad (7)$$

$$\begin{cases} G_{left/right} & \text{the impurity measurement of the left/right subset,} \\ m_{left/right} & \text{the number of examples in the left/right subset.} \end{cases}$$

where p_k is the ratio of subset k among the training data. If all training instances belong to the same subset then the impurity measurement would equal to zero (*G*=0). In this study, the Classification and Regression Tree (CART) algorithm is employed (*30*). The algorithm splits various instances into several subsets and defines a threshold. The CART algorithm investigates greedily for the optimum split thresholds from the top level and continues the process to lower levels. The algorithm stops splitting once it reaches the maximum depth for the decision (regression) tree, or the impurity measurements are not reduced by splitting the instances.

ARMA

We used the ARIMA model as a traditional time series model only for the demand prediction (not for the incident classification). The ARMA-family models include an autoregressive (AR) and a moving average (MA) part. The models predict the main variable for one or more discrete time intervals by using the time-lagged values. Therefore, the historical variation of the variable along with subtle time series dynamics is handled. The ARMA model with "p autoregressive terms" and "q moving-average terms" takes the following form:

$$\phi(L)x_i^t = \theta(L)\epsilon^t + \delta \quad (8)$$

where ϕ(L) and θ(L) are respectively the autoregressive operator on variables and the autoregressive operator on residuals, L is the backshift (lag) operator ($Lx_i^t = x_i^{t-1}$), ϵ_t represents the residuals between the real and the estimated variable at time t, and δ is a constant. θ(L) and ϕ(L) can be presented as a polynomial relationship in the lag operator, defined as:

$$\theta(L) = 1 - \theta_1 L - \cdots - \theta_q L^q,$$
$$\phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p \tag{9}$$

Consequently, if Eq.(9) is replaced in Eq.(8), we have:

$$\left(1 - \phi_1 L - \cdots - \phi_p L^p\right) x_i^t = (1 - \theta_1 L - \cdots - \theta_q L^q)\epsilon^t + \delta \tag{10}$$

Producing an ARMA model requires defining parameters p and q in order to specify θ(L) and ϕ(L). Identification of p and q terms involves investigating a tentative formulation for the model as a starting point. After the general model is specified, the θ(L) and ϕ(L) are estimated using the least-squares method.

NUMERICAL RESULTS

1.4. Study Area

In this study, we evaluate the proposed framework models for one of the major subnetworks in Sydney, stretching alongside the Victoria Road corridor form CBD to western city (see Figure 2). The subnetwork includes 1,310 links and 428 nodes. The General Transit Feed Specification (GTFS) data is used to import public transport information such as bus time schedules, lines, and bus stop data. There are 81 signalized intersections with the adaptive SCATS control system running. The link traffic counts obtained from the SCATS detectors are aggregated in 15-min time-intervals. Most of the SCATS signals are located throughout the main corridor and near the Sydney CBD. The simulation is conducted for 4-h morning peak hours from 6:00 to 10:00 a.m. using an AIMSUN microscopic model. AIMSUN is a discrete-event simulation tool established based on car-following and lane-changing models (*31*). Therefore, detailed traffic phenomena such as congestion propagation and dissipation of queues are simulated over time. We used a modified multinomial logit model as an advanced stochastic route choice model (*31*). Maximum five shortest paths are calculated using Dijkstra's label-setting algorithm. The probability of choosing a path k is then calculated according to a utility function of each path.

In Sydney, the signal controls are working with SCATS to reduce delay and make the transport system more efficient. Signal configurations such as signal group, phases and detector IDs are set in the model based on the SCATS configuration. Since the SCATS signals are adaptive and the adjacent signals are synchronized, it is very challenging to model such a complex system. To deal with this issue, we integrate our traffic simulator with SCATS using SCATSIM plug-in architecture (*32*). As a result, the real-life adaptive SCATS control logic is applied to the simulated vehicles in our AIMSUN microsimulation model.

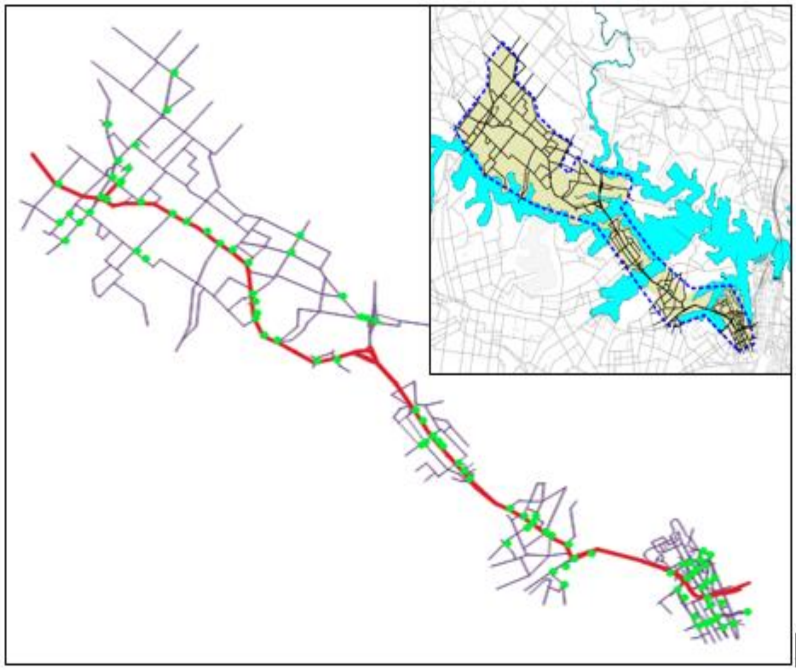

Figure 2. Victoria corridor sub-network. Green points show signals equipped with SCATS count detectors (measured traffic data). Red line demonstrates the main Victoria corridor.

1.5.Demand estimation and prediction

The initial demand used in our study was obtained from the Sydney strategic model received from Transport for NSW, Australia. The extracted demand for the subnetwork contains 1,262 non-zero origin and destination pairs and around 150,000 travelers who are commuting in the area during 4-h morning peak hours working days. The total number of travelers suffers daily changes and declines to less than 100,000 on weekends. We select October 2017 because the traffic count data and incident data are available for almost every day of the month. To compare day-to-day traffic changes, we plotted the overall traffic counts pattern for all days in October in Figure 3. We observe that during morning peak hours, the traffic flow can reach almost 40,000 vehicles per every 15-min time interval compared to weekend when this number can be counted in the 20,000s. This indicated almost twice motorists travelling daily during working week, increasing the traffic congestion along the Victoria Road Corridor. From Figure 3, we selected Thursday 12th October as a typical weekday.

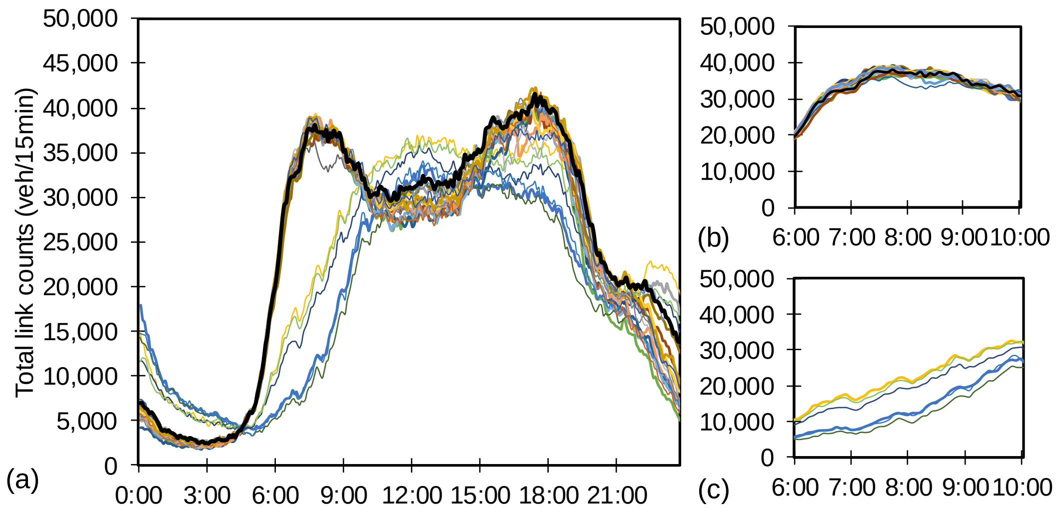

Figure 3. (a) Total 24-hour link counts obtained from loop detectors in the Victoria area in different days within a month, morning peak hours in (b) weekdays and (c) weekends.

We conduct our OD estimation process in two stages. At the first stage, we estimate time-dependent OD demand matrices based on the selected typical weekday link count and a-priori demand data. A priori static OD demand obtained from the strategic model is time-sliced into sixteen 15-minute OD demand matrices for a 4-hour simulation during peak period. Then, the bilevel optimization problem formulated in Eq.(1 is iteratively solved for the whole 4-hour morning peak period. This stage is done once in an offline manner and demand flows at different time intervals are estimated. The only parameter in Eq.(1 that must be set before executing the OD estimation problem is the demand reliability weight, which influences the accuracy of results. Previous studies proposed ranges based on the accuracy of the initial demand, the size of the network, and the simulation time window(*33*, *34*). After various tests, we set this parameter to 0.95 for this case study.

We next execute our proposed OD estimation in a 15-min rolling-horizon procedure. In other words, the time-dependent OD demand matrices estimated from the first stage are adjusted every 15-min time interval based on the most recent observed traffic counts. Note that the input OD matrices for the second stage are more reliable than the inputs to the previous stage since they have already been adjusted. We increase the reliability weight (ω) value from 0.95 to 0.99. Adding higher weight for demand deviation also helps us to avoid overfitting the simulation model based on possible noisy count data. The microsimulation is executed for four hours morning peak with a 15-min network warm-up (5:45- 6:00 AM). We used the coefficient of determination (R^2), mean absolute error (MAE) and GEH (*35*) as the common goodness of fit criteria to evaluate the simulation results based on link traffic volumes.

$$R^2 = 1 - \frac{\sum_{a=1}^{A} (\hat{y}_a^{\tau} - y_a^{\tau})^2}{\sum_{a=1}^{A} \left(\hat{y}_a^{\tau} - (\frac{1}{A} \sum_{a=1}^{A} y_a^{\tau}) \right)^2}$$

$$MAE = \frac{1}{A} \sum_{a=1}^{A} |\hat{y}_a^{\tau} - y_a^{\tau}| \qquad (12)$$

$$GEH_a = \sqrt{\frac{2(\hat{y}_a^{\tau} - y_a^{\tau})^2}{(\hat{y}_a^{\tau} + y_a^{\tau})}}$$

Table 1 presents how the accuracy of the simulated traffic volumes increases through the two-stage OD estimation applications. Results show that MAE improves about 42% and 27% respectively after implementing OD demand estimation process at first and second stages. In general, a GEH value under 5 is regarded as a good fit, between 5 and 10 implies the measurement site needs further investigation, and a value greater than 10 implies a significant error (*35*). As can be seen, at the end of the OD estimation process, all links among 252 observed links have GEH less than 10 and almost 90% of links have GEH<5. Similar work is conducted for other days of October 2017 to archive day-to-day OD demand matrices. Figure 4 displays day-to-day variation in the estimated demand. The scatter plots in Figure 5 show the simulated and observed traffic flows after OD estimation applications.

Table 1. The goodness of fit before and after the OD estimation.

OD matrices	No. links GEH<5	No. links GEH<10	MAE (veh/h)	R2	Regression line
Before OD estimation	189	243	97	0.97	Y=0.98X
After OD estimation stage 1	228	251	56	0.99	Y=1.00X
After OD estimation stage 2	231	252	41	0.99	Y=1.00X

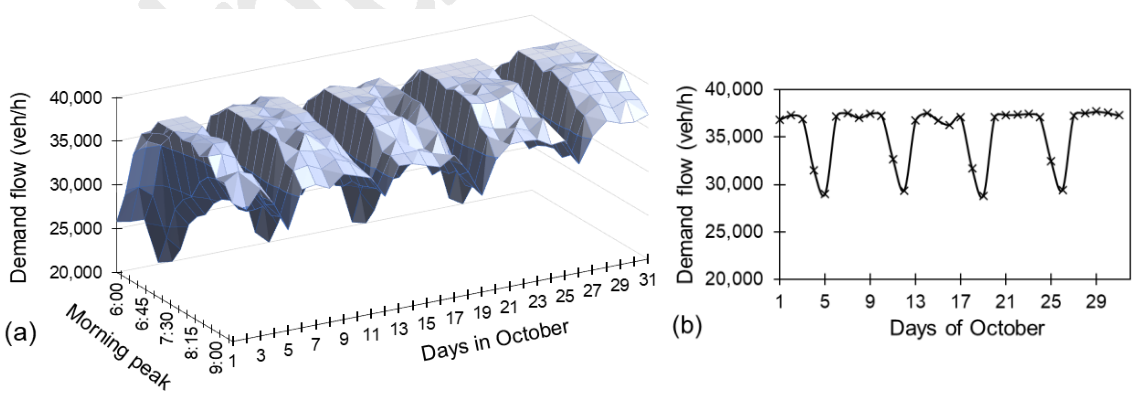

Figure 4. Day-to-day total estimated demand flow profiles: (a) in a 3D, (b) in 2D plotting.

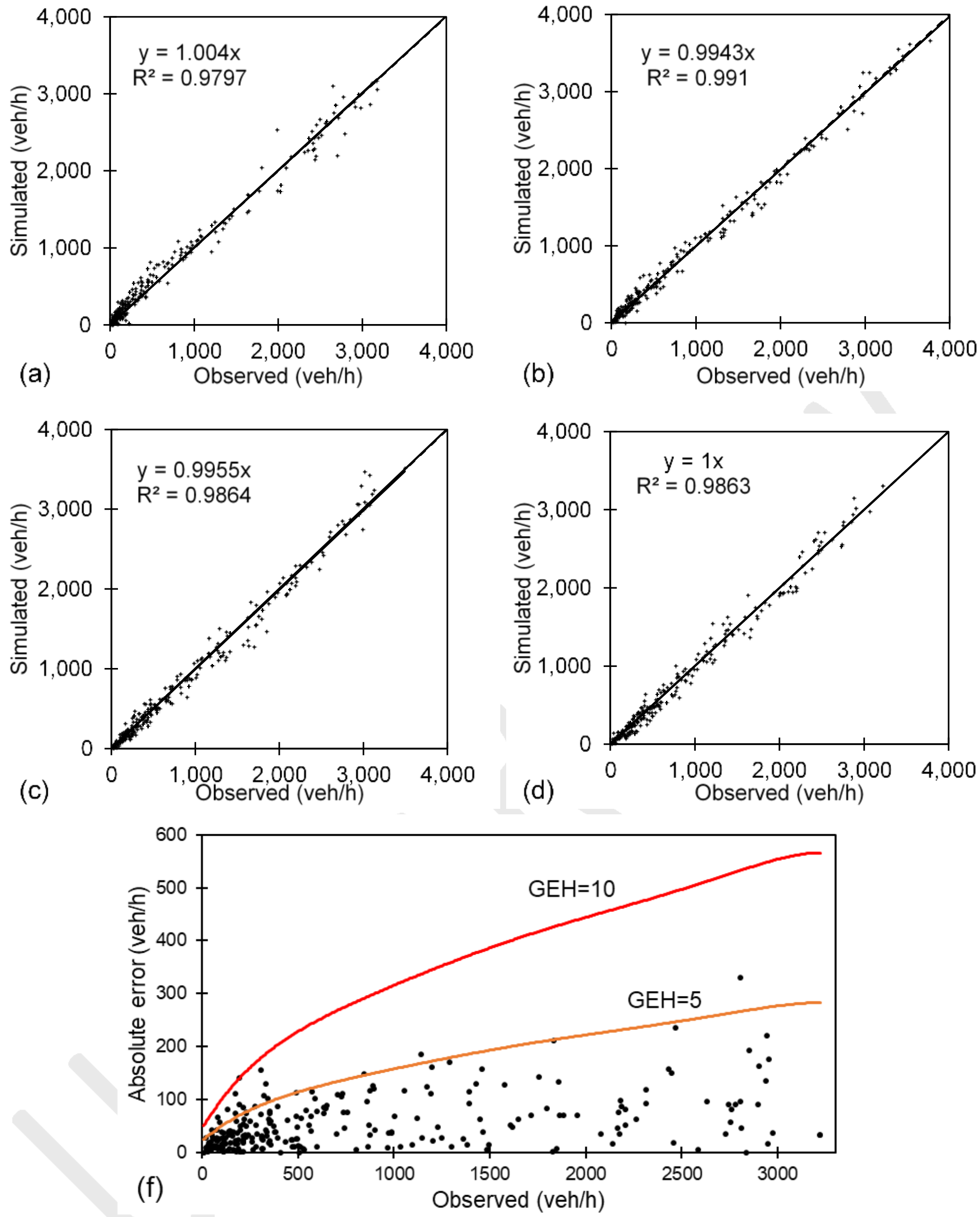

Figure 5. Simulated versus observed traffic flows after the rolling horizon OD estimation (a) 6:00-7:00 am, (b)7:00-8:00 am, (c) 8:00-9:00 am and (d) 9:00-10:00 am (f) Absolute flow errors vs observed flows.

The estimated OD demand matrices were archived and used for the demand prediction model. As mentioned earlier, there are 1,262 OD pairs with various demand profiles in the study network. The OD flows vary from few trips between local OD pairs to hundreds of trips between two ends of the main corridor. Therefore, it is necessary to consider an ML model for each OD pair trained on previous historical OD pairs. We consider the corresponding OD flow values from the 5 previous working days. There is a tradeoff between the size of the database and the accuracy of the prediction. More historical data may be useful, but it increases the computation time, especially for real-time forecasting.

The features we consider for our models are: three time-lagged demand data (x_i^{t-2}, x_i^{t-1}, x_i^{t}), the time interval of the prediction (*t*) and the flow direction (inbound and outbound). We adopt DT, SVR, and the traditional ARMA models for predicting the OD flows for the next 15, 30, 45 and 60min. The experiments were conducted in Scikit tool and Stat Python libraries (*30*). The results of each approach are presented in

Table 2 and evaluated against the total error and MAE.

As a baseline approach, we assume that we do not have any model to predict the demand. Therefore, the latest demand flow is considered for the next time intervals. As can be seen, by extending the prediction time intervals (from 15 min to 60 min), the prediction error grows quickly (from 1.37 to 1.85). First, we investigate the performance of the decision tree model. The maximum depth of the decision tree is one of the most important parameters that affect the prediction accuracy. Therefore, we chose three different values for this parameter to investigate the sensitivity of the model (maximum depth of 2, 5 or unconstrained). When the constraint is too strict (e.g., max depth=2), the predictor is too simplistic to predict the traffic demand accurately. In contrast, with no constraint (no max depth), the prediction error increases showing the predictor overfitted to the training data. This result demonstrates that the optimum depth of the tree is a critical parameter, which can be optimized. Next, the performance of the SVM model is explored by using different kernel functions. We tried several combinations (the radial basis function (RBF), the sigmoid function, and the linear function) and compared the results through a cross-validation approach. As can be seen, the first two models fail to predict the demand flows successfully and the error is higher than the baseline (e.g. 1.47 and 1.71 to 1.37). The best result for SVM prediction was obtained when using the Linear kernel (with critical parameter of C=0.1), for a 45min prediction in the future. This seems to perform similarly to predictions for the next 15 or 60min time-interval. However, overall, the accuracy results for SVM are significantly worse than those of DT prediction. Lastly, we present the results of the ARMA model, for which we need to determine the *p* and *q* parameters. Defining various parameters for each OD pair requires a vast amount of modelling effort. This process would be extremely computationally intensive if we need to execute the demand forecasting for any incidents that may arrive in the road network. As a result, we consider the specifications of a unique model for all OD demands and estimate the factors of each OD pair. To identify *p* and *q*, we test various combinations of these parameters on all OD demand series ((1,0,0,), (2,0,0) and (0,0,1)). Overall, the performance of the traditional AR and MA models show a medium level of accuracy compared to the others and the MAE errors are similar to those of SVM only for a 45min prediction.

Overall, we can conclude that DTs are outperforming all other models and represent our final choice for conducting the rest of the experiments presented in this paper.

Table 2. Predicted demand using different predictors.

Predictor	Prediction window							
	15 min		30 min		45 min		60 min	
	Total error	MAE	Total error	MAE	Total error	MAE	Total error	MAE
Baseline	1283	1.37	2785	1.49	4519	1.61	6953	1.85
DTs								
Max=2	762	0.81	2785	0.79	2278	0.81	3077	0.82
Max=5	606	0.65	1152	0.61	1743	0.62	2533	0.68
unconstraint	660	0.70	1216	0.65	1816	0.65	2645	0.70
SVM								
RBF (C=0.1)	1381	1.47	2613	1.40	3738	1.33	4797	1.28
Sigmoid (C=0.1)	1592	1.71	3017	1.67	4519	1.54	5545	1.48
Linear (C=0.1)	832	0.89	1676	0.89	2462	0.87	3327	0.89
Linear (C=1.0)	852	0.91	1693	0.90	2490	0.89	3376	0.90
ARMA								
(1,0,0)	869	0.93	1652	0.88	2459	0.87	3377	0.90
(2,0,0)	883	0.94	1678	0.90	2517	0.89	3509	0.93
(0,0,1)	1009	1.08	1876	1.00	2762	0.98	3864	1.03

1.6.Incident impact analysis:

For evaluating the potential of our proposed framework, we consider a real reported incident along the Victoria Rd with characteristics showcased in Table 3 (as received from the real-life incident stream in the Traffic Management Centre - TMC). The incident took place at 7:58 AM on the 11th of October 2017 and affected the traffic in both directions.

Table 3. CMCS incident data example

(X, Y)	(9684462, 4425168)
Date	11/10/2017
Start Time Plain	7:58:19 AM
End Time Plain	8:23:00 AM
Incident Description	Accident: Accident
Location Description	VICTORIA RD PARK AVE DRUMMOYNE 2047 CANADA BAY (LGA) NSW
Direction	BOTH DIRECTIONS
Affected Lanes	ALL LANES
Sector ID	ICMT
Inc Source	ICEMS INCIDENT AND ISENTRY
Operator	----
ICEMS Street	VICTORIA RD
ICEMS Suburb	DRUMMOYNE
UBD Ref	235 A/4
ed duration	25
rowid	A6C4B8F8-5617-4E12-B170-973234EA31B0

First, the accident information is imported into the simulation platform. The corresponding affected link IDs from the traffic simulation are determined based on the accident location. For example, according to the presented data, the accident impacts both travel directions, and thus, two affected sections are selected. Then, an incident scenario containing the number of blocked lanes, start time and incident duration is generated. Next, the Decision-Tree demand prediction module is triggered to forecast the travel demand starting from 8:00 AM for the next hour. Subsequently, the simulation model is executed with consideration of the developed incident scenario. Since the incident is located in a crucial link, we explore the impact of the incident duration by analyzing the total travel time in the network and the extra delay it caused in next hour.

Figure 6 (a) shows the location of the car accident. The accident took place in the main road and according to the reported data it impacted all lanes in both directions. No further details about how the accident affected the area exist in the database. Therefore, different interpretations of affected lanes can be considered. For example, the accident may have physically blocked all the lanes or it caused some speed reduction for crossing vehicles. Since it is unlikely that for half an hour all lanes are fully blocked in two directions, we assume only two lanes were blocked and vehicles could slowly cross the accident area with some lane changing near the accident. We executed the simulation based on the above assumption and the simulated speed and delay ratio are plotted for two different location points along the corridor: point A taken near the accident location and point B towards west, 1,600 meters away from the accident. Figure 6 (b) and (c) show the severe drop in the speed near the incident location (Point A) and consequently, the delay/travel time ratio increases significantly at this point. The impact of the accident can be observed upstream with a time lag and less severity. Next, we compare the simulated travel time obtained for the eastbound/westbound directions along the entire Victoria Rd corridor in two scenarios: with the reported incident and without the incident (this would be regular travel times in normal conditions) in Figure 6 (d) and (e). One can observe that the reported incident at 07: 58AM induces an increase of almost 12 min on the eastbound direction (from 36-48 min) and 13 minutes in the westbound direction (from 22 to 35 minutes).

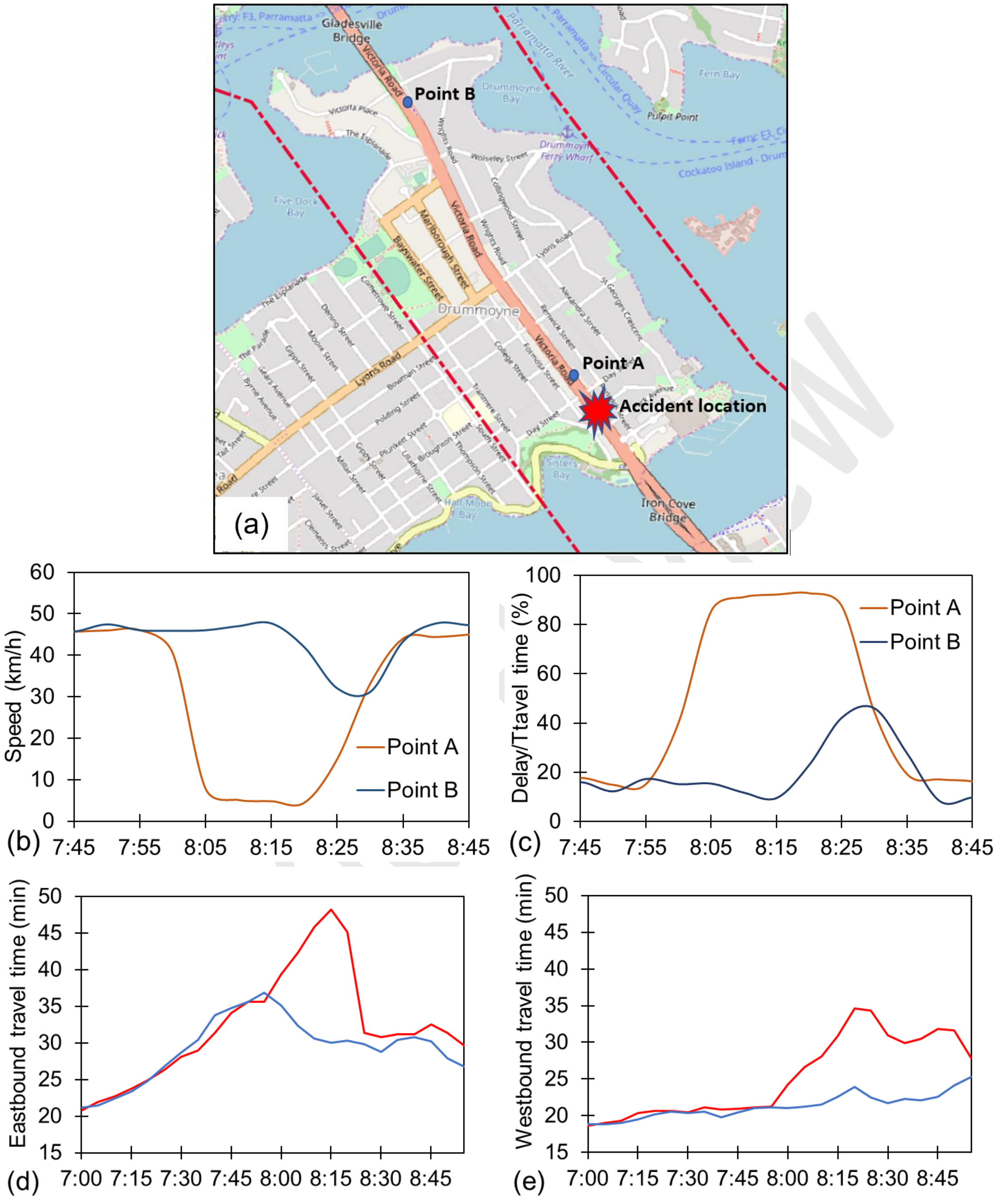

Figure 6. (a) Accident location, (b) speed (c) delay ratio profiles for Point A and B. Journey times with (red) and without (blue) the incident: (d) Eastbound, (e) Westbound.

CONCLUSION

Managing an incident situation effectively is one of the critical challenges that TMCs deal with on a daily basis. Methodological advances in both data-driven and computer-based simulation modeling provide a unique opportunity to predict traffic conditions accurately in real-time. This paper presented a generic framework for incident management proposed for use in the TMC of Sydney, Australia, by using integrated data-driven and traffic simulation models. We first introduced a generic demand estimation and prediction model which provides the essential input for the traffic simulation model to forecast the traffic features under non-recurrent incident conditions.

The proposed approach initially calibrates the traffic model based on the most recent observed link traffic count and then uses them for demand prediction for the next time-interval. A bi-level dynamic OD demand estimation problem was formulated and solved iteratively. Thereafter, we showcased that Decision Trees outperformed the baseline, SVM and ARMA models in terms of prediction accuracy. Finally, we investigated an incident's impact by making use of the proposed framework outputting the predicted travel time/delay along the affected corridor. Several limitations exist for this study that will be addressed in our future work:

- We assumed that travellers respond to the bad traffic conditions by changing routes in peak hours. However, for critical traffic disruptions, we should consider mode shifting and trip cancelation in short-term traffic forecasting.
- Although the current simulation network provides the commuters with some re-routing options, the selected area has limited major parallel routes to consider strategic re-route choices of travellers under severe incident conditions. We plan to expand our simulation modelling to larger subnetwork areas.
- For the real-time incident impact application, incident time duration should be predicted based on the incident features. Another AI-engine will be added to the incident management platform to provide an incident duration estimation for the traffic simulator when an incident occurs. This estimation can be updated with more incident data.
- In order for our proposed modelling framework to be used for real-life traffic management operations, it requires exact details of the incident location (inside intersection or not, beginning and ending of road link), the length of the affected incident area and exact number of blocked lanes. This can be challenging for operational centres to provide in real-time.
- The performance of the simulation results should be evaluated based on complementary measured traffic data including travel time, flow and queue length.

- The traffic model includes private cars and buses. The other types of traffic modes such as taxi, freight and active modes can be exclusively considered in the model. This will help us to replicate the simulated congestion more accurately.

ACKNOWLEDGEMENT

The work presented in this paper is partially funded by the New South Wales Premier's Innovation Initiative. The authors of this work are grateful for the work and support of the Traffic Management Centre from Transport for New South Wales Australia. Data61 is funded by Australian Federal Government through Commonwealth Scientific and Industrial Research Organization.

AUTHOR CONTRIBUTIONS

S. S. designed and performed the research, A-S. M. contributed to direction, and A-S. M., H. N., C. B. and C. C. reviewed and contributed to the manuscript.

REFERENCES

1. Yao, B., C. Chen, Q. Cao, L. Jin, M. Zhang, H. Zhu, and B. Yu. Short-Term Traffic Speed Prediction for an Urban Corridor. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 32, No. 2, 2017, pp. 154–169.
2. Xu, D., Y. Wang, P. Peng, S. Beilun, Z. Deng, and H. Guo. Real-Time Road Traffic State Prediction Based on Kernel-KNN. *Transportmetrica A: Transport Science*, Vol. 9935, 2018, pp. 1–15.
3. Zhang, Y., and Y. Liu. Traffic Forecasting Using Least Squares Support Vector Machines. *Transportmetrica*, Vol. 5, No. 3, 2009, pp. 193–213.
4. Wang, D., F. Fu, X. Luo, S. Jin, and D. Ma. Travel Time Estimation Method for Urban Road Based on Traffic Stream Directions. *Transportmetrica A: Transport Science*, Vol. 12, No. 6, 2016, pp. 479–503.
5. Oh, S., Y. J. Byon, K. Jang, and H. Yeo. Short-Term Travel-Time Prediction on Highway: A Review of the Data-Driven Approach. *Transport Reviews*, Vol. 35, No. 1, 2015, pp. 4–32.
6. Vlahogianni, E. I., M. G. Karlaftis, and J. C. Golias. Spatio-Temporal Short-Term Urban Traffic Volume Forecasting Using Genetically Optimized Modular Networks. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 22, No. 5, 2007, pp. 317–325.
7. Polson, N. G., and V. O. Sokolov. Deep Learning for Short-Term Traffic Flow Prediction. *Transportation Research Part C: Emerging Technologies*, Vol. 79, No. 6, 2017, pp. 1–17.
8. Vlahogianni, E. I., M. G. Karlaftis, and J. C. Golias. Short-Term Traffic Forecasting: Where We Are and Where We're Going. *Transportation Research Part C: Emerging Technologies*, Vol. 43, No. 5, 2014, pp. 3–19.
9. Karim, A., and H. Adeli. Radial Basis Function Neural Network for Work Zone Capacity and Queue Estimation. *Journal of Transportation Engineering*, Vol. 129, No. 5, 2003, pp. 494–503.
10. Levin, M. W., S. D. Boyles, J. Duthie, and C. M. Pool. Demand Profiling for Dynamic Traffic Assignment by Integrating Departure Time Choice and Trip Distribution. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 31, No. 2, 2016, pp. 86–99.

11. Du, B., S. Chien, J. Lee, and L. Spasovic. Predicting Freeway Work Zone Delays and Costs with a Hybrid Machine-Learning Model. *Journal of Advanced Transportation*, Vol. 2017, No. 2017, pp. 1–8.
12. Oh, S., Y. J. Byon, K. Jang, and H. Yeo. Short-Term Travel-Time Prediction on Highway: A Review on Model-Based Approach. *KSCE Journal of Civil Engineering*, Vol. 22, No. 1, 2018, pp. 298–310.
13. Hawas, Y. E. A Microscopic Simulation Model for Incident Modeling in Urban Networks. *Transportation Planning and Technology*, Vol. 30, No. 2–3, 2007, pp. 289–309.
14. Li, X., W. H. K. Lam, H. Shao, and Z. Gao. Dynamic Modelling of Traffic Incident Impacts on Network Reliability. *Transportmetrica A: Transport Science*, Vol. 11, No. 9, 2015, pp. 856–872.
15. Ziliaskopoulos, A. K. Foundations of Dynamic Traffic Assignment : The Past , the Present and the Future. *Networks and Spatial Economics*, Vol. 1, No. 3, 2001, pp. 233–265.
16. Cascetta, E. *Transportation Systems Analysis: Models and Applications*. Springer Science & Business Media. Vol. 29, 2009.
17. Balakrishna, R., D. Morgan, Q. Yang, and H. Slavin. Comparison of Simulation-Based Dynamic Traffic Assignment Approaches for Planning and Operations Management. 91st Annual Meeting of the Transportation Research Board, Washington, DC. 2012.
18. Nguyen, H., C. Cai, and F. Chen. Automatic Classification of Traffic Incident's Severity Using Machine Learning Approaches. *IET Intelligent Transport Systems*, Vol. 11, No. 10, 2017, pp. 615–623.
19. Nguyen, H., C. Bentley, L. M. Kieu, Y. Fu, and C. Cai. Deep Learning System for Travel Speed Predictions on Multiple Arterial Road Segments. *Transportation Research Record*, Vol 2673, Issue 4, 2019, p. 03-6.
20. Morgan, C. J., and M. Veysey. *Traffic Modelling Guidelines*. vol. 1, no. February. 2013.
21. Iqbal, M. S., C. F. Choudhury, P. Wang, and M. C. González. Development of Origin–Destination Matrices Using Mobile Phone Call Data. *Transportation Research Part C: Emerging Technologies*, Vol. 40, 2014, pp. 63–74.
22. Antoniou, C., J. Barceló, M. Breen, M. Bullejos, J. Casas, E. Cipriani, B. Ciuffo, T. Djukic, S. Hoogendoorn, and V. Marzano. Towards a Generic Benchmarking Platform for Origin–Destination Flows Estimation/Updating Algorithms: Design, Demonstration and Validation. *Transportation Research Part C: Emerging Technologies*, Vol. 66, 2016, pp. 79–98.
23. Rao, W., Y. J. Wu, J. Xia, J. Ou, and R. Kluger. Feredri. *Transportation Research Part C: Emerging Technologies*, Vol. 95, No. July, 2018, pp. 29–46.
24. Frederix, R., F. Viti, and C. M. J. Tampère. Dynamic Origin–Destination Estimation in Congested Networks: Theoretical Findings and Implications in Practice. *Transportmetrica*, Vol. 9935, No. July 2015, 2011, pp. 1–20.
25. Shafiei, S., M. Saberi, A. Zockaie, and M. Sarvi. A Sensitivity-Based Linear Approximation Method to Estimate Time-Dependent Origin-Destination Demand in Congested Networks. *Transportation Research Record*, Vol. 2669, 2017, pp. 72–79.
26. Omrani, R., and L. Kattan. Demand and Supply Calibration of Dynamic Traffic Assignment Models. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2283, No. 1, 2012, pp. 100–112.
27. Zhou, X., and H. S. Mahmassani. A Structural State Space Model for Real-Time Traffic Origin-Destination Demand Estimation and Prediction in a Day-to-Day Learning Framework. *Transportation Research Part B: Methodological*, Vol. 41, No. 8, 2007, pp. 823–840.
28. Geron, A. *Hands-on MachineLearning with Scikit-Learn & Tensorflow*. O'Reilly Media, 2015.
29. Wu, C. H., C. C. Wei, D. C. Su, M. H. Chang, and J. M. Ho. Travel Time Prediction with

Support Vector Regression. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, Vol. 2, 2003, pp. 1438–1442.

30. Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, and V. Dubourg. Scikit-Learn: Machine Learning in Python. *Journal of machine learning research*, Vol. 12, No. Oct, 2011, pp. 2825–2830.
31. TSS-Transport Simulation System. Aimsun 8 Dynamic Simulators Users ' Manual. No. July, 2013.
32. SCATSIM. https://www.aldridgetrafficcontrollers.com.au/products/scats-urban-traffic-control/simulation.
33. Verbas, İ. Ö., H. S. Mahmassani, and K. Zhang. Time-Dependent Origin-Destination Demand Estimation. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2263, No. 1, 2011, pp. 45–56.
34. Shafiei, S., Z. Gu, and M. Saberi. Calibration and Validation of a Simulation-Based Dynamic Traffic Assignment Model for a Large-Scale Congested Network. *Simulation Modelling Practice and Theory*, Vol. 86, 2018, pp. 169–186.
35. TfL. Traffic Modelling Guidelines TfL Traffic Manager and Network Performance Best Practice. Vol. Version 3., 2010, p. 184.