

Road incident and traffic monitoring in low latency environment for intelligent decision making

John Worrall^{1*}

1. Department of Transport and Main Roads, 313 Adelaide Street, Brisbane, Queensland, Australia,
+61 7 30665549, john.a.worrall@tmr.qld.gov.au

Abstract

Department of Transport and Main Roads (TMR) in Queensland has developed multiple automated processes for analysing transport network performance data from multiple disparate sources in a low latency environment, to support improved network monitoring, incident management and decision making.

Traditionally network managers have relied upon heterogenous systems that burden users with the task of relating and reacting to information, to minimising network congestion and mitigate the impacts of incident. However, given the steady increase in frequency of incidents and growth of separate data sources, there are rising challenges in delivering accurate decision making in a timely manner, and opportunities in improving services through automating processes.

We have developed a real-time road traffic monitoring system that incorporates probe data, traffic sensors and crowd sourced incident data to effectively analyse and report road network abnormalities, supporting improved decision making. Results from our test case show viable low latency analysis based on real time and historic patterns, performing optimally across several different datasets.

Keywords:

Real-time, Big data, Probe vehicle data, Serverless, Micro services

1.1 Introduction

A core service of transport network operators is incident management, involving the monitoring, detection, verification and response to unplanned events that impact the safe and efficient operations of the network. This service is critical in environments of significant traffic demand, where any reduction in network capacity can have considerable impact to the overall operation of the network. In these conditions, timely detection of events is essential to minimising the impacts of these unplanned events.

Traditional road traffic data sources such as loops, tubes and CCTV camera images have

significant challenges in coverage, cost, accuracy and integrations across systems in real time. There are several challenges associated with these data sources ([Wang et al., 2015](#)), such as;

- cost associated with deployment and maintenance of associated devices,
- the infeasibility to install the technologies densely enough to provided complete road network coverage, and
- weather conditions impacting data collection.

With advancements in collection of probe vehicle data (PVD) there exist opportunities to supplement traditional road data systems and provided further confidence in information provided to road managers.

PVD (such as HERE) in combination with traditional traffic devices has shown to perform traffic metric identification (average flow speed and travel time) at a small spatial-temporal scale ([Bickel et al., 2007](#)). This data has already seen uptake for use in historical travel time reporting and performance analysis, as well as recently for real time travel time publication. However further real time monitoring of PVD data for statistical performance abnormality identification also demonstrates benefit for incident detection.

Identifying an incident as quickly as possible is very important, especially for enacting response, network management to mitigate impacts, and encouraging detours. Probe data can be a source of information for; 1) identification of outliers for incident detection or as 2) validation of incidents prompted by traditional device detection systems. Papers, ([Sethi et al., 1995](#)) and ([Thomas & Hefeez, 1998](#)) investigate velocity change of probe vehicles to detect an incident, concluding that the detection accuracy was acceptable. However, ([Pei et al., 2017](#)) highlighted system architecture and algorithms being critical to effectively provide reliable and rapid traffic information.

Cloud computing improves system performance with its ability to processing large scale data streams in real time and in parallel ([Schneider et al., 2009](#)). The micro serverless environment (such as lambda, s3 and RDS in AWS) is especially useful due to its flexibility in connections across systems and adaptability to computing resources required ([Kleiminger et al., 2011](#)). This study will investigate feasibility of cloud computing within DTMR, particularly micro serverless architecture in combining PVD, crowd source and traditional devices to more accurately estimate traffic metrics and reporting in real time.

2.1 Aim

The project has three main objectives to better leverage the increasingly available crowd

sourced data for real time traffic management decisions and enhanced transport network management. The project specifically has three main objectives with regards to filling the gap within the department by developing data analytics and data integration capabilities to leverage increasingly available crowd sourced data for better real time traffic management decisions and enhance transport services in road networks. This goal will be attained by achieving the following aims:

- 1) **Traffic demand and abnormality detection:** Develop travel time profiles based on PVD, estimating and ranking travel time of routes in a travel time dashboard to identify performance abnormalities (indicating a potential incident).
- 2) **Automatic incident correlation and verification:** Develop methodologies for integrating traditional incident management data (SIMs) with PVD and crowd source data for validation and earlier incident responses.
- 3) **Hybrid implementation for traffic management:** Integrated approaches 1) and 2) for both traffic monitoring and early detecting of incidents to support improved network monitoring, incident detection, and decision making.

At the completion of the project, the department expects to gain new knowledge in real time traffic analytics and intelligent decision making for optimised network management, as well as greater understanding about the potential opportunities of new server and data management technologies.

3.1 Methodology

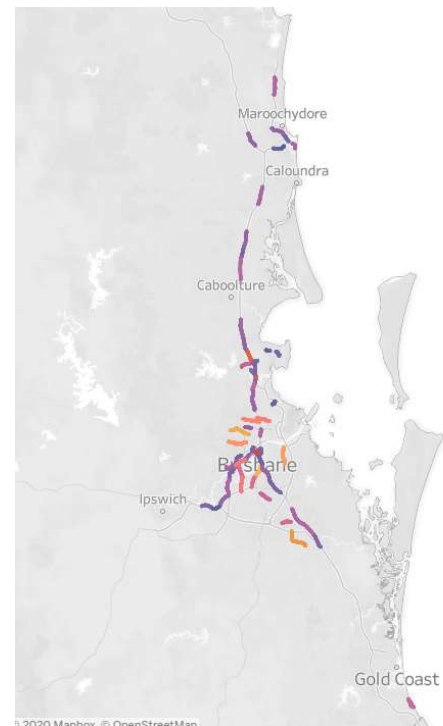
In the following section we summarise the methodologies and issues involved in integration of datasets and technique implemented through cloud computing technology for real time traffic monitoring and earlier incident detection information.

Study Site

The study uses data for South East Queensland, with focus on state-controlled roads around Brisbane and Gold Coast areas.

Raw Data

Vehicle probe speeds - Probe dataset (HERE) is accessible via an API for near real-time flow speed data.



SIMS Incidents – Information of logged incidents by Transport Management Centres, provided via Transmax STREAMS Gateway.

Traffic devices – Near real-time measures such as flow, occupancy, speed and level of services from loop detectors, provided via Transmax STREAMS Gateway.

Crowd source events – Waze alert feeds from incident live feed, through the Connected Citizen Partnership program.

QLDTraffic events – Traveller information for road conditions, including incidents, hazards, closures, roadworks and special events, published by Transport Management Centres and other sources.

Passenger Transport – GTFS real-time bus routes, via TransLink Open Data API.

Weather data - hourly weather data was obtained from OpenWeatherMap, and used to extract the following records: Temperature, Visibility, Precipitation, Weather Description

Temporal data - Information about the hour of the day if the observed day is weekday, weekend or holiday.

3.2 Application - Traffic Demand and Abnormality Detection

Previously PVD metrics relied on a proof of concept, the ‘TMR Travel Time dashboard’ (based on Google data), an extension of work developed by Transport for NSW. This relied on a single probe data source with a limited rolling history, and was provided ‘as a service’ meaning with limited ability for TMR to modify or integrate. Recognising the weakness of this system we proposed an improved algorithm, using an alternative data source, developed in an open way to be more easily integrated with future works.

3.2.1 Methods

For this application we utilised cloud computing (AWS), particularly the services lambda, S3, glue, Athena, RDS and Tableau.

Route Data Pre-processing

Representing time travel along route segment are several links and their associated sample speeds (derived travel time). Pre-processing route calculations were determined with routing API and buffer search capability, providing the API with a densified route and a maximum distance.

Real-time processing and storage

The HERE flow API was fetched in parallel to determine real-time speeds for selected routes only. Applying corridor functionality of the API rather than the bounding-box API to determine all flow links potentially used by the route. If successful, verification with custom map matching

algorithm then takes a shortlist and determines the actual links, their directions, and what parts of them, are used by the route.

The aggregation of route travel time is then built (via Athena, serverless interactive query service) and loaded (RDS, Postgres database). Statistical metrics of routes within database are calculated and stored. Both current routes travel time and statistical metrics are readied for visualisation in dashboard. See the described process in diagram 2 below.

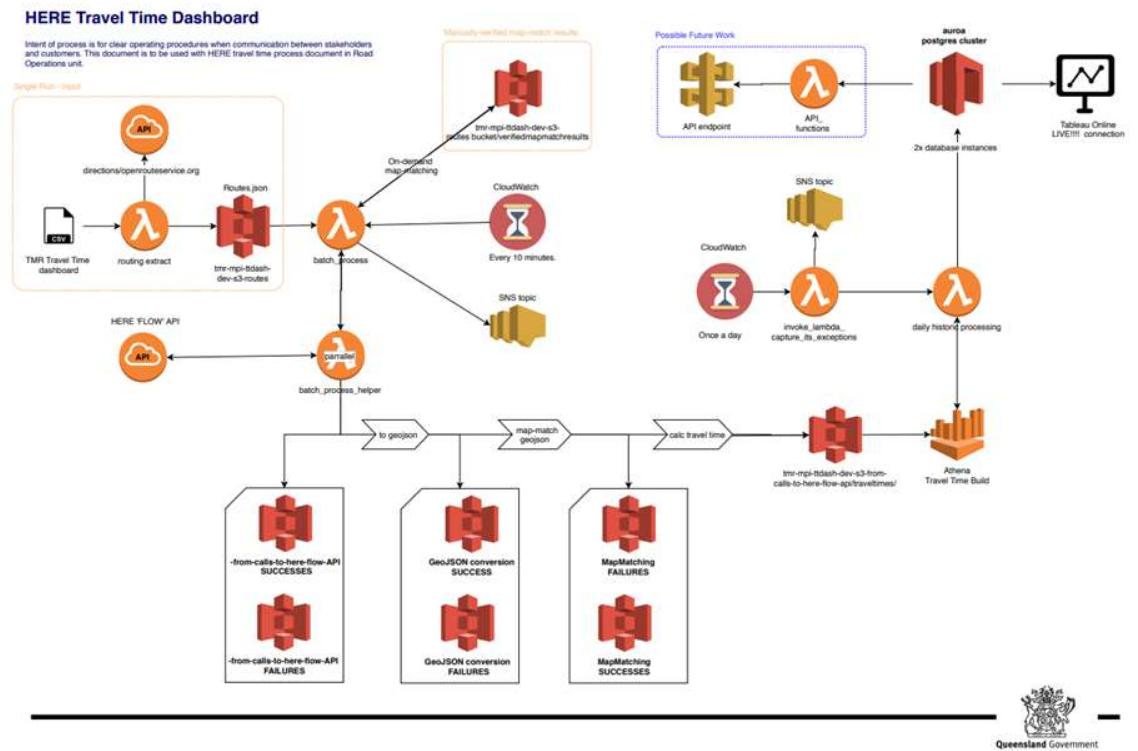


Figure 2. Microservices architecture

Architecture diagram of services lambda, S3, Athena and RDS.

Rank	Route Name	
1	PacMtwy_SB12_Reedy_to_Tallebudgera	
2	HamiltonRd_Webster_to_Sandgate_EB	
3	SouthportBurleigh_SB1_Smith_to_Cotlew	
4	GoldCoastHwy11A_EB_OlsenAve_to_Nort..	
5	GoldCoastHwy11A_EB_CCDr_to_OlsenAve	
6	HamiltonRd_Sandgate_to_Webster_WB	
7	CHTowersRD/RRR_to_Willows	
8	BCC_QWB_GeorgeSt	
9	PacMtwy SB5 Days to HobbsIsland	

Route Name:

PacMtwy_SB12_Reedy_to_Tallebudgera

Time of Last Refresh:

2019/04/17 11:21:04

Avg. Current Travel Time Minutes:

7.34

Avg. Historic Travel Time Minutes:

3.38

Travel Time Delta (absolute):

3.954

Rank:

1

Figure 3. Top 10 underperforming routes by travel time.

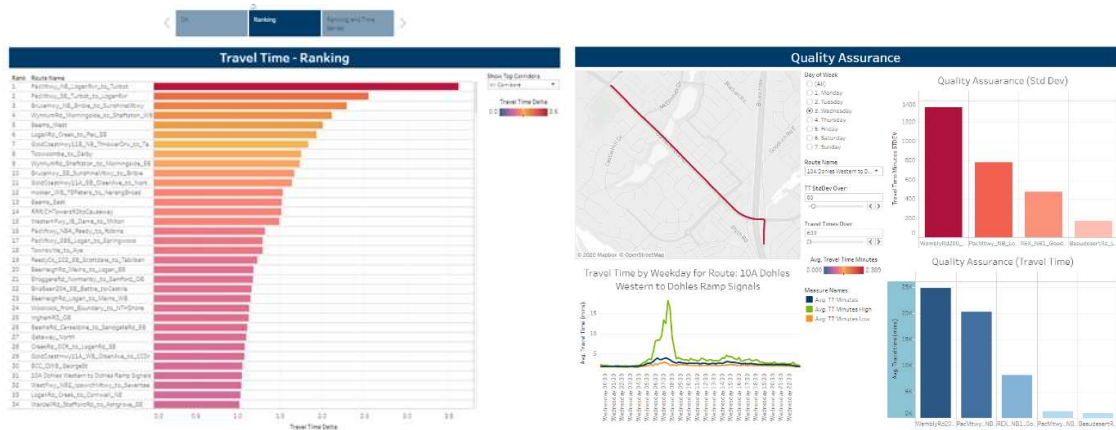


Figure 4. Route ranking (left), Quality assurances metrics (right)

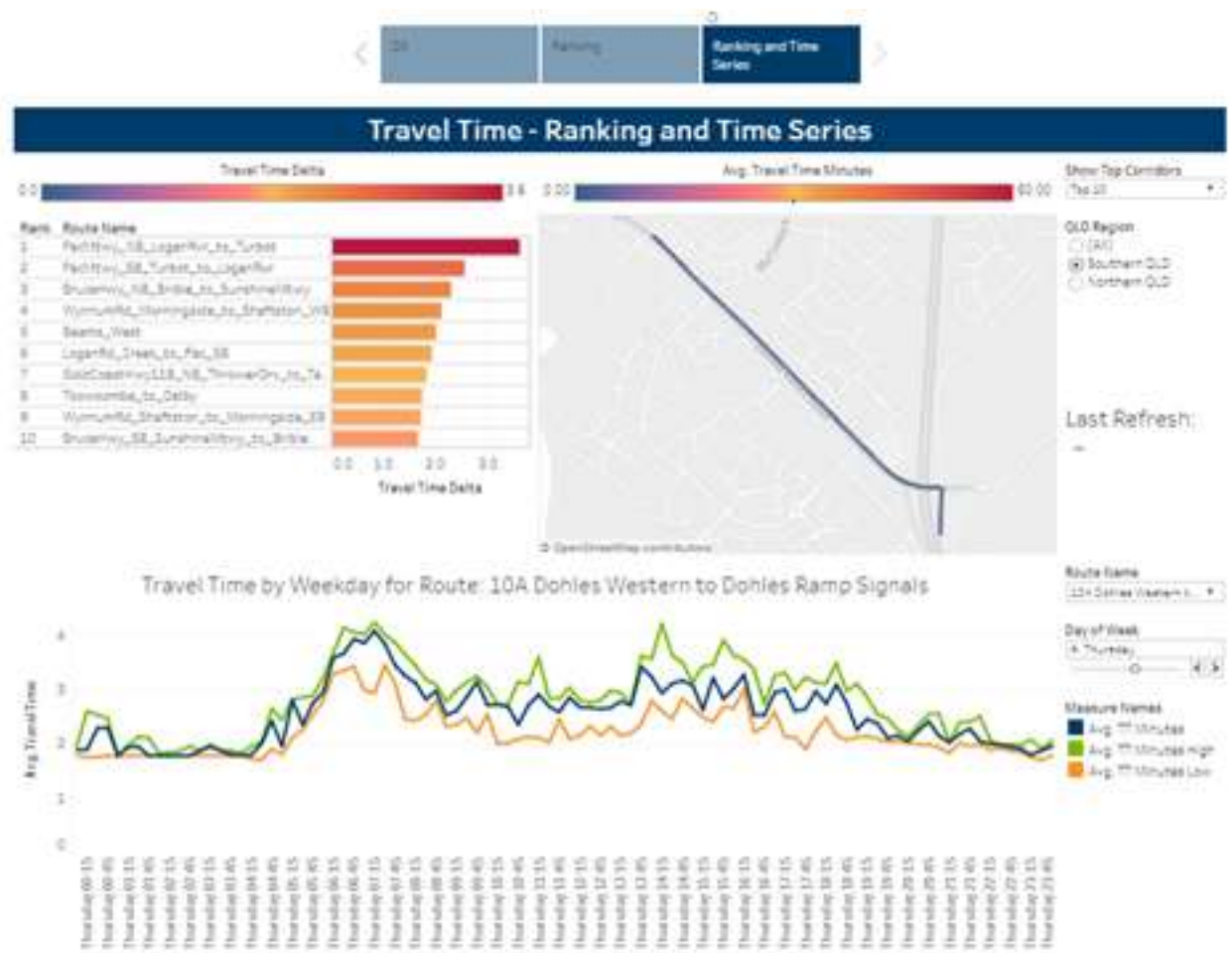


Figure 5. Travel time ranking metrics

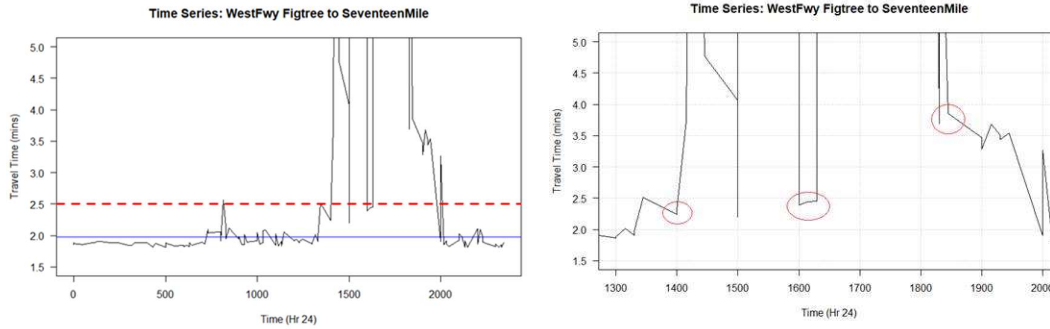


Figure 6. Historic time series analysis of incident on Western Freeway, March 18th
(left -24hrs profile, right – during time of impact)

3.2.2 Results - Travel Time Dashboard

The developed dashboard is an open real-time integrated micro serverless system consuming vehicle probe speed data (HERE) via an API. It monitors a selection of 350 key routes within south east Queensland for outliers and ranks based on statistical metrics.

The resultant dashboard above, displays worst performing routes ranked (figure 3) and historic timeseries statistical metrics (figure 5, bottom) for a given locality (figure 5, top right) in real time.

The quality of the data sources directly determines the quality of the output metrics, since processing algorithm follows the “garbage in and garbage out” theorem. When displaying the travel time abnormalities we integrated the dynamically driven Quality Assurance GUI (figure 4, right). This tool can be used to further investigate specific feeds from probe vehicle data that show statistical abnormality.

A subsequent outcome in developing a platform that identifies route abnormalities is the ability for playback of historic incidents/route performance for debriefing and the storage of this data source for future predictive works. Figure 6 quantifies traffic breakdown (due to multi vehicle incident) which otherwise would be reliant on adhoc reports.

3.3.1 Application - Automatic incident correlation and verification

Automatic incident detection systems have existed for many years, however many of the established algorithms rely on loop detectors and these algorithms work with mixed success. Recently there has been renewed interest in incident detection algorithms partly because of the availability of new sensors and data sources, one of these sources is vehicle probes.

3.3.1 Methods

Our next case study builds on the previous research, with low latency analyse of multiple traffic data sources, that includes; reported incidents via SIMS, inductive loops (via STREAMS), vehicle probe speed data (HERE), crowd source (WAZE) and public transport (GTFS) for public disruptions mitigation. The application is developed using pervious microservices lambda, S3, glue, Athena, RDS and the libraries React, D3 and deck.gl.

Real-time storage and processing

The SIMS incident data reported from Transmax API is monitored for in progress incidents, if a priority incident is detected the corresponding feeds are triggered to detect for correlation. Business rules for priority events are easily customisable, so as to allow processing on only events of interest. Figure 8 shows reported incident location with the speed of nearby roads and associated variables and events.

Inferring Incidents impacts on passenger transport

Given the live feeds of bus and their schedule routes, we investigate the probability of affected passenger transport services based on the condition of an incident, shown be below (figure 7, left). The incident and bus information are continuously monitored and updated as feed changes.

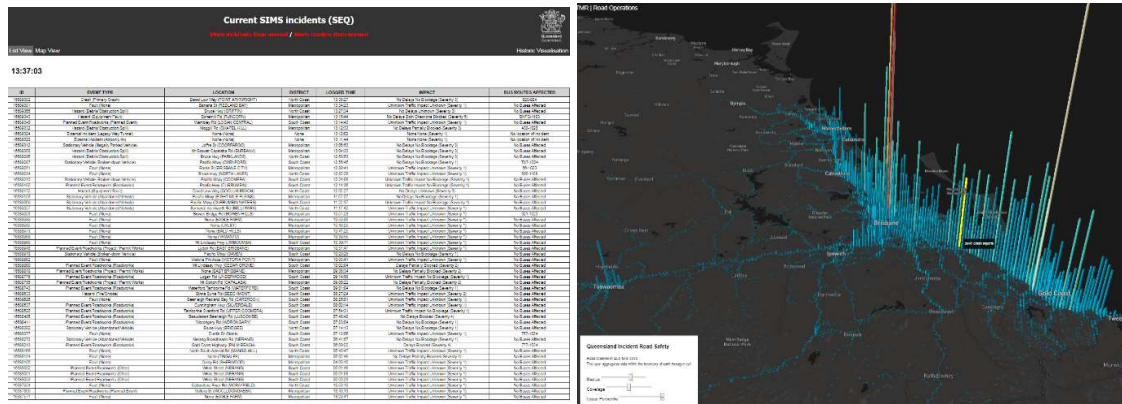


Figure 7. Incidents and possible PT effect (left), visual data analysis exploratory tool (right)

3.3.2 Results - Integration of probe sources

The verification of incidents and the additional valid related information can be extended to applications in the analysis exploratory tool (figure 7, right) and performance indicators (figure 8, left).

The primary objective of correlating other traffic data sources (Qld Traffic, Waze, Streams etc) for increase confidence is displayed in figure 8. The current architecture improved on previous system of storing link performances and provides a dynamic output in real-time reporting associated events and variables.

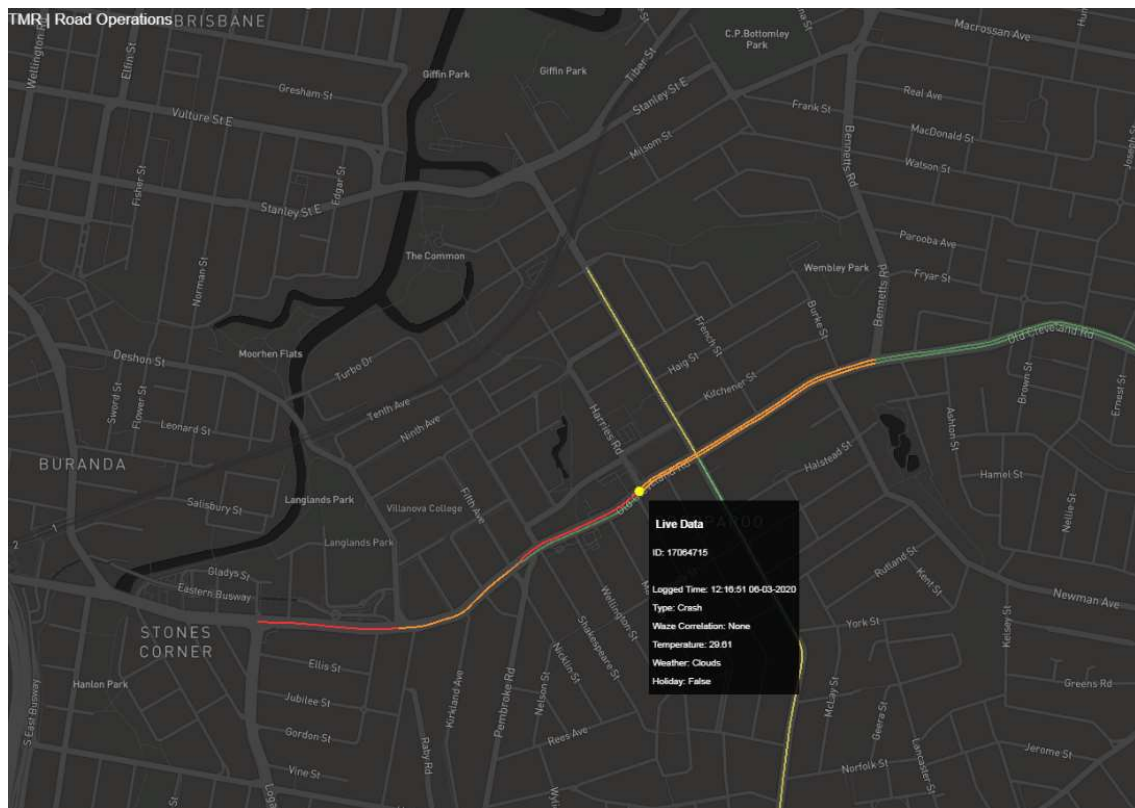


Figure 8. Real-time priority feed correlation

3.4.1 Results - Integration of probe sources

Data fusion and integration is the gathering of different kinds of information together into a procedure yielding a single model of related events. Among the different methods that exist in combining data from different sources, the current process and display is in its infancy. With a focus of proofing the concept and ability of integrating built systems within a TMR ecosystem and providing lessons learnt. Below figure 9, shows the platform of event integration.



Figure 9. Real-time incidents performance metrics

4.1 Conclusions

There is a growing number of both ITS assets and alternative data sources to provide sophisticated applications that can enhance traditional systems and be automated to processed in many real-world domains. This is one of several studies by TMR that is investigating cloud computing, having proven this architecture as cost effective compared to traditional on premises services and of sufficiently low latency, with the benefit of improved accessibility.

Microservices architecture

Microservices were adopted to provide an interoperable medium on diverse data generation and processing components in a uniform, scalable manner in the developed framework. Along with successfully proving the capabilities of real time functionality and integration of decoupled systems, there is a clear financial and operational benefit when compared to on premises infrastructure or monolithic applications.

The current serverless computing infrastructure supports 3,500 writes and 5,500 reads per second with theoretically unlimited store objects. For future works, opportunities exist to investigate scaling read/writes exceeding previous limits using various design considerations in streaming services (i.e Kinesis).

Data fusion

Further to proving the capabilities of cloud computing as a viable non-homogenous real time processing architecture, our primary objectives of road incidents and traffic anomalies detections was met.

Results from traffic demand and abnormality detection shows the implementation in ranking worst performing travel times from probe dataset along with historic performance for both review and as a data source for future models.

The outcomes from the automatic incident correlation and verification study depicted in the result section show clear validation of metrics through correlations of ingested data source in real time, supporting earlier intelligent decision making.

Finally, due to previously describe microservices architecture both objectives could be easily integrated for a better traffic management reporting system.

In addition to the study deliverables and outcomes, the project highlights the requirement in supporting current projects within Road Operations, such as data fusion methods (map matching) and PVD in the understanding of roadworks dynamics. There are also several opportunities for future works in incident predictions and other novel machine learning algorithms.

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