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Dealing with latency effects in travel time prediction on motorways

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ABSTRACT

Real-time traffic information is now a crucial part of operating a road network. The quality, accuracy and reliability of such information is critical to the road operators and users. Real-time travel time prediction methods using Automatic Number Plate Recognition cameras or Bluetooth/Wi-Fi readers that use matching algorithms to generate travel times in real-time can be vulnerable to an inherent latency issue. Measured travel times are based on vehicles that have already completed the journey and may not be representative for users about to commence that same journey. The aim of this research was to identify the latency in travel time prediction, quantify its effect, and develop a model to remove it. Datasets for the M50 motorway in Dublin, Ireland, were used to conduct the analysis. The results show that real-time travel times can be more accurately predicted when combined with historical travel time information. The approach was found to be valid and achievable and the developed tool can predict and inform both road operators and users during regular periods of congestion. The project also identified other data sources, such as real-time Automated Incident Detection (AID) loop data, incident and weather data, that can further enhance the predicted travel time calculation.

1. Introduction

Road network operators are increasingly encouraged to provide high-quality and timely traffic information to the road user, as part of their operational responsibilities. This is to support the management and operation of the road network in as efficient and safe manner as possible [1,2]. The need to advise road users of current and future traffic conditions has become progressively more important as the general population has become more information literate [3,4]. This approach to enabling the road user has been encouraged legislatively in recent years by the European Commission through various Intelligent Transport System (ITS) Directives [5]. These ITS Directives typically require real-time, safety and traffic-related information held by road authorities to be published for free, so that third parties can then create added value for users.

Travel times are considered an important performance indicator for both the road user and the road operator [5]. Not only can they provide useful pre-trip or on-trip information to the driver as an indicator of how traffic is performing ahead of them or on their planned route, but travel times also allow the road operator to assess and review the current performance of the road network in real-time. Even free third-party web applications such as Google Maps can provide both user and operator with a useful spatial summary of a network's current traffic status through a simple graphical heat map [6–8] and many other traffic information providers use this approach.

Previous research has acknowledged the importance of the use of both historical and real-time data as a means of travel time prediction. A common theme is the use of real-time data fused with historical data to provide more accurate predictions [2,9,10–14]. Other studies, however, focused on using only real-time data in the case of bus Automatic Vehicle Location (AVL) data [15], loop data [1], ANPR data [16], weather data [17], loop and ANPR data [16], speed and flow data [18], Bluetooth data [19], traffic and weather data [20], and multiple sourced data [21–23].

All the above studies applied algorithms to specific road sections, i.e. data (real-time and/or historical) was collected for a specific road section, and travel time was predicted for the same road section. In the case of historical data, many studies utilised either one or a combination of data sources. Some applied the historical average travel time for a specific time of day, week, month and year [19,22,23], all of which concluded that this was an inferior predictive model in comparison to the other techniques tested. Others [16,20,24] utilised simple linear regression of real-time and historical data inputs with mainly positive results. Prediction errors for linear regression models ranged from 5% [24] to 10% [25] and others concluded that linear regression methods were as good as non-linear methods in most cases [26].

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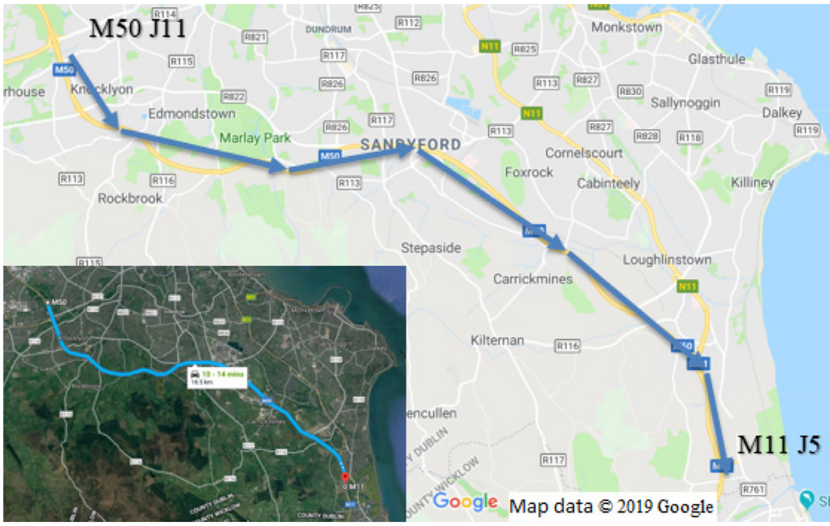

Fig. 1. Study road section Junction 11 on M50 to Junction 5 on M11.

Many studies used K-Nearest Neighbour (KNN) [2,15,19,21,23,26] as a means of analysing historical data to identify similar patterns in real-time data. Most studies concluded that its use improved travel time prediction. However, other research [26] revealed that KNN is only sometimes better than linear regression for short-term prediction. Some studies [19,23] found much clearer improvement of KNN over Linear Regression. A number of reviewed studies [11,19,22,25] proposed the Kalman Filter algorithm to predict travel times and others [5,10,12,26] proposed neural networks.

The utilisation of ANPR-based travel times with both historical and real-time data was only fully explored by two studies [16,27]. Only one paper [9] made an explicit reference to the underlying latency issue with ANPR-based travel time calculation. This however was only an observation and the proposed prediction model examined alternative data sources to ANPR.

Real-time travel time prediction methods for travel times displayed on VMS which use Automatic Number Plate Recognition (ANPR) cameras or Bluetooth/Wi-Fi readers, can be vulnerable to an inherent latency issue. Measured travel times are based on vehicles that have already completed the journey and are therefore not necessarily representative for users about to commence that same journey. A driver about to commence a trip observes the displayed travel time on the VMS before they commence their journey. They assume that the travel time displayed will be the time it will take them to make the journey. The travel time displayed by the VMS at that moment may or may not be correct for that particular driver because it will have been based on the travel times experienced by drivers who have already made the journey. The first aim of the research was to investigate discrepancies between the travel time displayed on roadside VMS and the actual travel time the same driver experiences for the trip. The second objective was to identify and measure the differences, or in other words the latency, using available historical travel time data and other available datasets. Finally, the research developed a model to remove the effect of latency, using historical travel time data, to enhance the accuracy of travel times displayed on VMS.

2. Materials and methods

A section of motorway that exhibits all the attributes of the latency effect in relation to travel times, and that would offer the opportunity for daily validation of the analysis using a Dashcam survey was selected for the analysis. The section is between the M11 Junction 5 and M50 Junction 11 (see Fig. 1). Generally, the morning northbound journeys are likely to be at free-flow, particularly during the summer months. However, for the afternoon southbound journeys – particularly south of Carrickmines (see Fig. 1) congestion is evident on this section during weekdays, even during the summer months. It is therefore a good candidate route to observe fluctuations and patterns in the displayed travel times, when compared with travel times experienced.

2.1. Data

A number of TII datasets were evaluated for use in the analysis on the M50 motorway corridor around Dublin. They include historical travel time data, automatic incident detection (AID) loop data, real-time weather data and real-time incident data. An important element when assembling the data was to source both real-time and historical data.

Travel time data is held in two data sources within TII [28]. Firstly, the Journey Time Management System (JTMS), located in the Motorway Traffic Control Centre (MTCC) server room, contains processed travel time data where a 5-min average travel time for each link is recorded. The JTMS processes the data collected directly from the roadside ANPR cameras. The JTMS gathers and collates an average journey time for a single journey time link based on all vehicle number plates that pass by and are matched at both the start and end point of that link by roadside ANPR cameras. This processing is all done in real-time with the JTMS calculating the average journey time every 5 min. Outliers are individual vehicles that are deemed to be travelling considerably slower (e.g. farm vehicles) or faster (e.g. emergency vehicles) than the general traffic to the extent that their speeds would be seen to skew the average travel time. The JTMS designer designated the outlier criteria of a slow moving vehicle as less than 60% of the median travel time and greater than 210% for a fast moving vehicle. Outlier travel times are removed. The JTMS then accumulates the resultant average journey time for each travel time link. This total time is then assigned to a travel time route which is then sent to the ATMS for further processing. The important point here is that the resultant journey times calculated by the JTMS are, by all intents and purposes, the raw data by which further analysis can be achieved. The JTMS does not display or publish the averaged times; it is merely a real-time repository for the current calculated travel times.

Secondly, the live real-time data is then passed to the Active Traffic Management System (ATMS). Further post-processing (i.e. capping travel times to the speed limit) is carried out in order to disseminate the information to users. This dataset comprises the journey times that were prepared for display on roadside VMS and the TII Traffic website and App. Each record is a travel time for pre-selected route sections with an origin and a destination. It should be noted that these travel time route sections are an aggregation of the shorter travel time links calculated by the JTMS. Each record therefore comprises the aggregated travel time

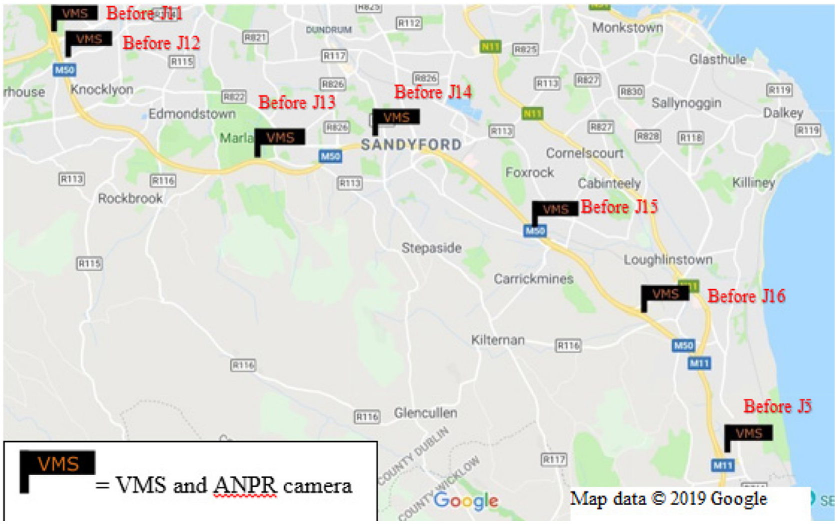

Fig. 2. Locations of VMS along test route.

every 5 min for each travel time route section. These data are recorded within the ATMS database.

Inductive loops have been installed approximately every 500 m along the entirety of the M50 and log data every 20 s. The loops have been deployed in every lane and in both directions. They were primarily deployed as part of a proposed AID (Automatic Incident Detection) system. This system receives inputs from each pair of loops in real-time that provide data on the current speed, occupancy and flow of the passing traffic. The AID algorithm within the ATMS then interprets these data to deduce whether a pattern (e.g. slower moving platoons of vehicles) is occurring. If the physical distance between the two loops is known, then the speed of the object can be easily deduced (speed = distance /time). In addition to speed, the gap/headway in time between successive vehicles can be measured as well as the traffic flow (i.e. number of vehicles passing in a defined time-period). It is these measurements, when analysed in real-time, that can help identify significant changes in traffic behaviour.

A record of each reported incident is logged by the MTCC, on behalf of TII, on the Incident Management System (IMS). The information is particularly useful when undertaking an analysis of the post-event handling of an incident by the MTCC. The data is retrievable from the IMS server on request. The system has limitations, mainly due to the free-text journalistic style of reporting, and the restriction to certain geographical regions or corridors. Unfortunately, after review of the available data, it was considered that it was insufficiently complete to provide a reliable data source for this research.

The last set of data used in the analysis was from a series of Dashcam recordings using a Nextbase® 612 GW Dashcam [29] for a typical vehicle commute along the selected study route section were carried out in both the northbound and southbound directions between 16th May 2018 and 12th July 2018.

The recordings were used to:

1. Identify the displayed clock time and message text displayed on a roadside Variable Message Sign (VMS) when passing by along the route. It is important to note that when there are no incidents the message text would generally default to displaying estimated travel times. This would be overwritten by incident or safety messages as and when they occur.
2. Identify any incidents/diversions undertaken along the route journey that may have affected the total travel time to the indicated destination.
3. Identify the clock time as the vehicle reached the indicated destination.

The locations of the VMS signs are presented in Fig. 2. Analysis of the recordings were used to verify the latency issue and validate the prediction algorithm.

A software package, Replay 3 software, provided by Nextbase®, allows the video of the journey to be viewed in sequence along with timestamp and location/mapping information. Each video is split into an individual one-minute file, but the entire journey can still be viewed seamlessly using the Replay 3 software. In addition to the expected video and audio information, each MP4 file is encoded with additional data that includes direction of travel, speed in km/h, acceleration in x and y direction, GPS location and timestamp (in GMT).

2.2. Identifying the latency period using the ATMS data

The research relies on a number of distinct travel times and they are each defined here.

- Actual (Experienced) Travel Time – this is the travel time experienced in reality by an individual or set of vehicles travelling from the origin (VMS sign) to the destination indicated.
- Displayed Travel Time – this is the calculated travel time to the destination and displayed to the vehicle as it passes the VMS.
- Historical Travel Time – this is the historical record of the displayed travel time (see above) for that specific same time.
- Estimated Travel Time – this is an estimate of the Actual Travel Time.

One of the key objectives was to try to identify how much the displayed travel time on the VMS as a driver enters the test section of road is different to the actual travel time the driver will experience by the time they reach the end of the section. The difference is referred to as a lag/latency. Knowing this, the historical data can be cross-referenced to identify a better estimate of the displayed travel time on the VMS when taking into account the time lag/latency. This will then help reduce the difference between the displayed travel time on the VMS and travel times drivers experience by using the historical data to predict the current travel time more accurately.

Fig. 3 below shows an underlying weekly trend (with the travel time dipping to free flow times every weekend). The free-flow travel time was calculated to be 10.4 min i.e. the time it would take to travel the section at the speed limit. This travel time increases typically to 20–30 min during peak times. However, there were a number of periods where the travel time exceeded 50 min, in one instance peaking close to 70 min. Further checking of the data indicated that a traffic incident had occurred.

It was expected that the displayed travel time on the VMS and the travel times experienced by drivers were identical outside of peak times

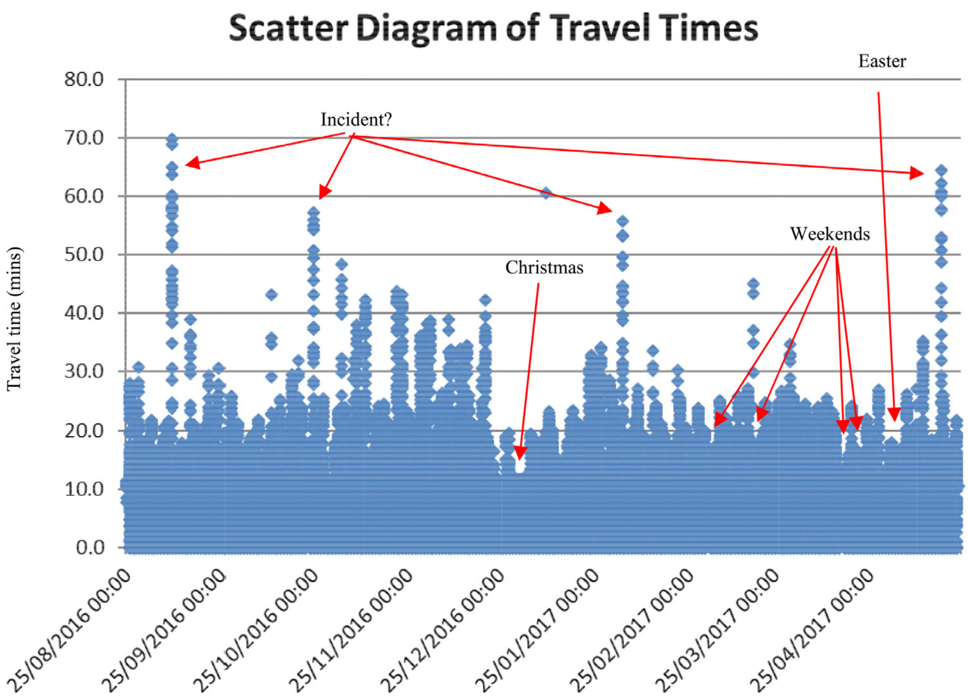

Fig. 3. Scatter plot of travel times over 9 month period.

because drivers could drive at speeds that were unimpeded by congestion or delays. However, during the transition from congestion to free-flow (and vice versa) it was expected the displayed and experienced travel times could differ significantly due to changes in traffic levels. This difference is known as the latency period.

Two methods were considered for establishing how this latency period could be calculated:

Latency Period Method LPM 1 (LPM1): Given that the displayed travel time at time (t) is recorded for vehicles that have already completed the travel time section within the last 5 min, then this travel time is assumed to be the travel time for vehicles that started the journey 5 min previously, i.e. at time t – 5. Therefore, the experienced travel time at time t is equivalent and connected to the historical travel time at t + 5. In this scenario, the latency period is assumed to be equal to 5 min.

Latency Period Method 2 (LPM2): The travel time that is displayed on the VMS when the vehicle reaches the destination is the travel time that ideally should be displayed when it starts the journey. This obviously cannot be done in real-time. However, the historical travel time data can be used to establish historically what the VMS was displaying at the time when the vehicle has already reached the destination (i.e. the latency period). Then by effectively looking ahead in time in the historical data one can establish a good estimate of the typical journey travel time at the point which the vehicle arrives at its destination. The question is at which time do we sample the historical journey time? The sample has to be taken from a travel time already completed at the time which it must be displayed. For the LPM2 method, the travel time of the vehicles when they have reached the destination is looked at, and this point in time (i.e. the latency period) is effectively the time it takes the vehicle to travel from the origin (VMS). The best estimate for this latency period is therefore the displayed travel time.

A preliminary analysis of the historical data for the test section indicates that the delay during the evening peak-hour is around 10 min longer than the free-flow travel time i.e. the travel time increases from ~10 min to ~20 min. This suggests looking at travel times of vehicles up to 20 min in the future i.e. referencing the historical travel time of the vehicles as soon as they complete the entire study route section. This would imply that the experienced travel time at time t is equivalent and connected to the historical travel time at time t + TT, where TT is the displayed Travel Time at time t. In this scenario, the latency period is assumed to be equal to the displayed travel time. On this basis, the displayed travel time at time (t) was paired with the displayed travel time at time (t + 5) for LPM1 and the displayed travel time at time (t+TT) for LPM2.

2.3. Historical pattern identification in the ATMS data

The displayed and experienced travel times for each 5-min interval were used as the basis for interpreting historical patterns in the travel time data. The analysis of 77,000 travel time comparisons (each 5 min interval) from 25th August 2016 to 24th May 2017 sought out instances where the displayed travel time was over- or under-estimated at specific times of day, weekday, month, etc. Differences were used to illustrate the lag/latency enabling the historical travel time data to be compared with the probe vehicle data (Dashcam survey) and to establish whether LPM1 or LPM2 would be the best method of calculating the latency period. Experienced travel time data were then compared with the average of the historical data and linear regression was used to examine displayed travel times with historical travel time with the LPM1 or LPM2 added.

Identifying particular day types was necessary as the ATMS data analysis showed that traffic behaves very differently depending on the day of the week, the month, public holiday, etc. Anecdotal evidence suggests that even weekdays can be different from each other. Mondays tend to have lower traffic volumes than other days in the week, (perhaps due to people taking long weekends). Fridays, on the other-hand appear to have higher traffic volumes, with the evening peak starting much earlier in the day.

As a final output of this analysis phase it was expected that the analysis would produce a set of linear models that could be applied to the current measured travel times. These models, depending upon the day type, would reference historical data that matches the same day type and provide a more accurate journey time estimate.

In the model, the actual travel time (TT_a) is an estimate of the actual travel time and is expressed as a function of the known measurements i.e. displayed travel time (TT_d) and the historical travel time (TT_h), as

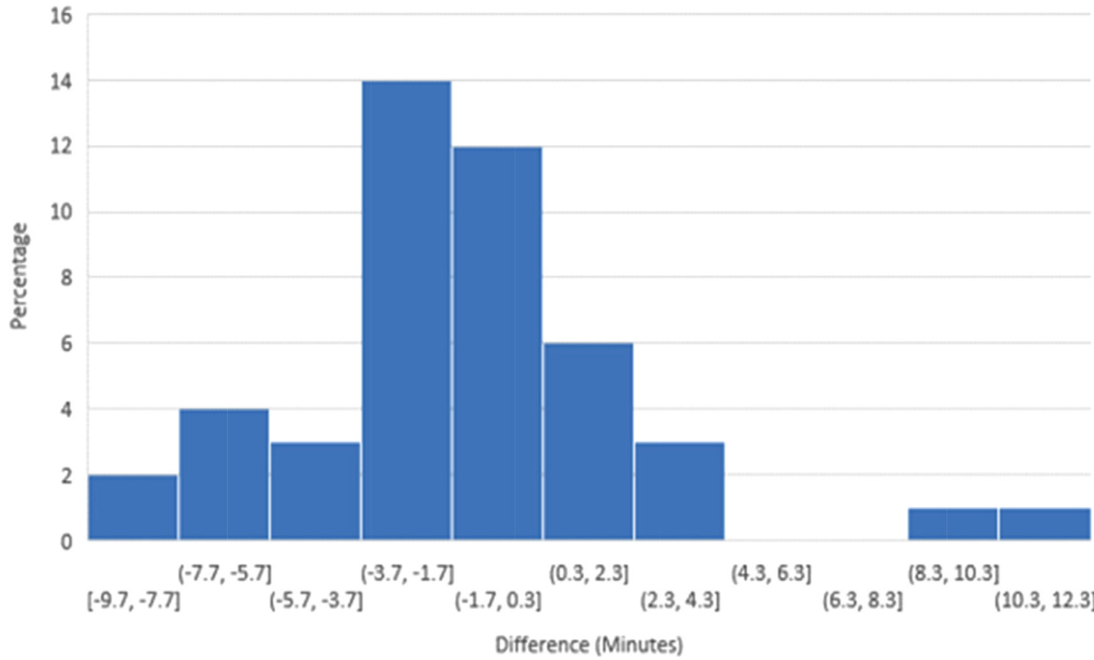

Fig. 4. Distribution of difference between displayed and experienced travel times.

follows:

$$TT_a = \beta_1 + \beta_2 TT_d + \beta_3 TT_h \quad (1)$$

where β_1, β_2 and β_3 are regression constants.

2.4. AID inductive loop data analysis

Loop data provides a potentially useful set of feedback parameters to the existing ANPR-based travel time estimator in that they provide spot-speed or spot-flow measurements in real-time every 500 m. This allows the travel time estimating algorithm to be alerted to queuing by the AID loops several minutes before the JTMS notices any increases in travel time. Similarly, the same principle would work for when queuing dissipates. The AID algorithm interprets these data to deduce whether a pattern (e.g. slower moving platoons of vehicles) is occurring. These triggers can be used to improve the travel time predictions.

3. Results and discussion

3.1. Probe vehicle Dashcam survey results

The primary purpose of the Dashcam survey was to log the displayed travel time on the VMS as the probe vehicle passed it. This displayed travel time was the time the VMS predicted the trip would take to the end of the test section. The displayed travel times are then compared later to the travel time the driver actually experienced. The survey demonstrated that as congestion increases the displayed travel time is underestimated when compared with the experienced travel time. Similarly, when congestion begins to subside, the displayed travel time is overestimated when compared with the experienced travel time. Fig. 4 below illustrates the results of the Probe Vehicle Dashcam survey from twenty-three separate journeys undertaken with a range of departure times between 13:45 pm and 22:57 pm, mostly on weekdays.

Disparities ranged from an underestimate of −9.7 min (−36.9% error) and an overestimate of 11.5 min (+41.8% error) in the southbound direction. The average disparity was an underestimate of −1.5 min (−7.5% error). The analysis of the individual journeys along the study route revealed an average travel time of 19:11 min ranging from 11:04 min to 40:41 min. However, the spread of travel times is much wider (up to 30 min) with a standard deviation of around 6:20 min.

By comparison, the equivalent northbound journey time was an average of 12:55 min ranging from 11:38 min to 14:50 min. The spread of travel times is very narrow, no more than 3 min with a standard deviation of 50 s. This confirms, as was experienced, that there was no discernible congestion on the northbound section for the periods analysed.

3.2. Historical travel time data analysis results

Fig. 5, based on 9 months data, clearly identifies a regular increase in travel times southbound between 16:30 and 19:30 on weekdays with the travel time rising from a free-flow of 10.4 min to a maximum of around 20 min. A mini-morning peak is also evident between 7:30 and 9:30. Further analysis showed that Monday and Friday profiles shared many characteristics but there were marked differences. Travel time on Mondays was 17 min compared with 23 min on Friday with the peak occurring 30 min earlier on Fridays but finishing about the same time as on Mondays. Data from Tuesdays indicated consistently higher congestion than other mid-week days with the peak travel time running at 22 min compared with 19–20 min on other days.

3.3. Latency measurement

Fig. 6 demonstrates the differences between displayed travel times and those calculated on the basis of applying LPM1 and LPM2. It shows that, on-average, when using LPM1 the difference between the displayed travel time and the historical travel time for the same time of day, but five minutes in the future, does not change by more than 1 min, even at its greatest peak.

When observing LPM2 the difference between the displayed and historical travel times for the same time, but at the current travel time value in the future, suggests differences of as much as 3 min. This observation is consistent with the probe vehicle Dashcam results presented earlier where the majority of discrepancies range between −5 and +5 min. Some larger discrepancies exist but closer examination found that the majority of these occurred when the VMS signs were showing DELAYS or LONG DELAYS messages – not the actual travel time. In these instances,

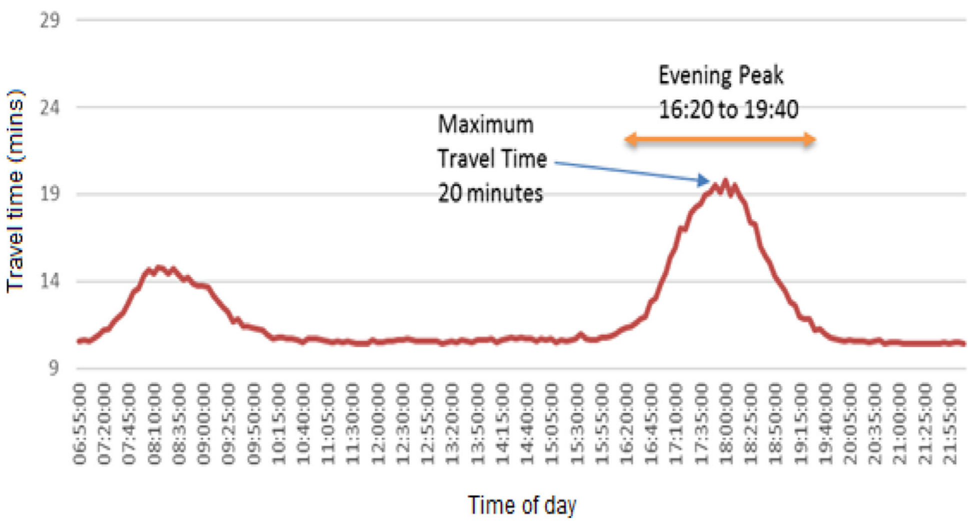

Fig. 5. Travel time distribution during weekdays.

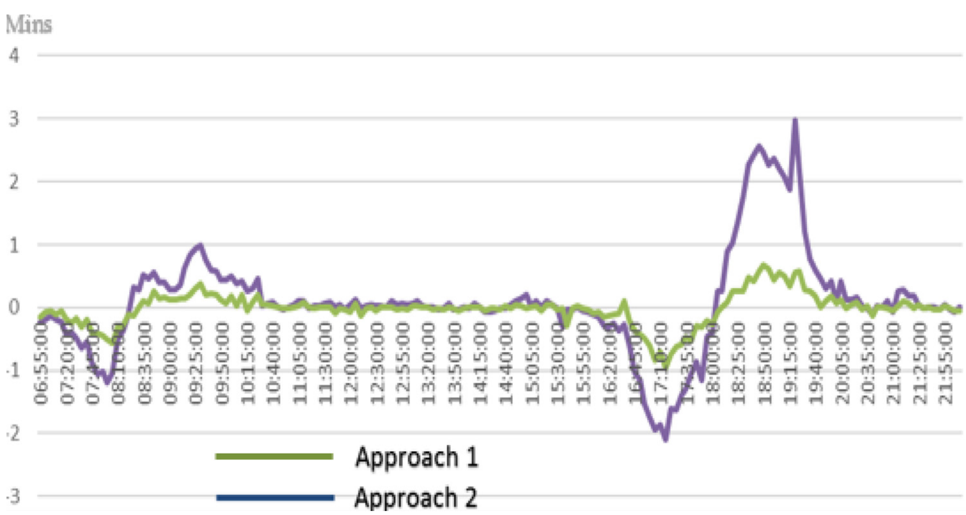

Fig. 6. Latency periods measured using approaches 1 and 2.

the lower threshold was chosen and this may have skewed the results. To eliminate this discrepancy, when all Dashcam-surveyed travel times displaying DELAYS or LONG DELAYS or a safety message are removed, the range is between −3.8 to 2.4 min. The range of differences for LPM2 is −2.1 to +3.0 min. This demonstrates a stronger correlation between LPM2 and the Dashcam survey results. Matching the current time to the current time + current travel time in the historical travel time data closely offers a comparative travel time that reduces the observed latency effect.

The final step in the analysis was to apply linear regression where actual travel time is calculated as a function of the displayed and the historical travel times as indicated earlier in Eq. (1). For weekday data, the linear regression equation is presented as Eq. (2) below.

$$TT_a = 0.54 + 0.65TT_d + 0.33TT_h \quad (2)$$

The R^2 value of 0.7 demonstrates a reasonable fit and further examination of the results found that, while it was useful in predicting free-flow travel times, it was much less accurate in delivering accurate predictions for the evening peak period. At least half of the observations were in the free-flow range, so the regression may have been weighted significantly in that regard. The detailed regression model results are presented in Table A.1 in the Appendix.

As latency is not an issue for trips conducted in free-flow conditions, a further regression analysis was conducted on the evening peak-hour data only (8228 observations) for the time period 16:00 to 19:30, producing the linear regression equation in Eq. (3). The R^2 rises marginally to 0.71 with the model not demonstrating a major improvement on the former one. The detailed regression model results are presented in Table A.2 in the Appendix.

$$TT_a = -1.75 + 0.67TT_d + 0.43TT_h \quad (3)$$

While the coefficients of the two models are different, the R^2 values are quite close indicating that the percentage variation in TT_a can be explained by the two models to a similar degree. A more significant increase in R^2 value was expected for the evening peak model but the level of congestion can vary significantly day to day and this may be influencing the outcome.

To test the model, Eq. (3) was applied to the Dashcam Survey data as this recorded both the displayed time (TT_d), and the actual experienced travel time (TT_a). Only the Dashcam Survey observations in the modelled time period (16:00 to 19:30) were considered and when a travel time message was displayed on the VMS. The test calculated the estimated travel time (based on the above formula) and compared this with the actual recorded travel time. A comparison was also made between the displayed and actual travel times. The results are presented in Table 1.

Estimated travel time tends to be underestimated by an average of 1.25 min while the displayed travel time overestimates by an average of 1.65 min. The estimation/predictive model has improved the estimation but there is certainly scope to obtain more accurate estimations if other factors can be taken into account. The data used was from August 2016 to May 2017. It is likely that travel times were much higher and the evening peak probably wider since then (except during the lockdown period associated with Covid-19, from March - June 2020, when traffic levels were very low). Annual average daily traffic in 2016 at different points along the section ranged from 48,624 to 110,213. Traffic in 2017

Table 1
Comparison between modelled and actual travel times.

Time	TT_d (min)	TT_a (min)	TT_h (min)	Estimated (min)	Actual vs estimated (min)	Actual vs displayed (min)
17:25	23.00	19.82	17.90	21.36	−1.54	−3.18
17:08	25.00	22.28	19.13	23.23	−0.94	−2.72
17:01	20.00	17.77	14.50	17.89	−0.12	−2.23
17:04	19.00	17.65	15.40	17.60	0.05	−1.35
17:06	18.00	17.02	15.40	16.93	0.08	−0.98
17:04	20.00	21.33	15.40	18.27	3.06	1.33
17:24	19.00	16.20	17.90	18.68	−2.48	−2.80
17:32	22.00	23.22	18.50	20.95	2.27	1.22
17:05	21.00	18.60	15.40	18.94	−0.34	−2.40
17:10	25.00	24.75	15.90	21.84	2.91	−0.25
17:01	19.00	19.33	14.50	17.22	2.12	0.33
17:04	22.00	21.40	15.40	19.61	1.79	−0.60
17:04	19.00	21.07	19.00	19.15	1.92	2.07
				Total	8.78	−11.57
				Average	1.25	−1.65

increased by 2–3% with traffic in 2018 increasing by 1–2% on 2017 levels.

The results indicate significant differences between weekdays, as mentioned previously. Equally, seasonal effects will all have an effect on travel time. It is therefore worth considering the future development of a library of historical travel time profiles based on different months.

3.4. Discussion

Considering the above observations and findings, there is significant potential for an enhanced travel time prediction system. Road authorities, such as TII, are obligated, through EU directives, to provide accurate information to the road user for reasons of traffic safety and efficiency. New methods of travel time calculation (e.g. using roadside Bluetooth and Wi-Fi readers) may still have the same form of inherent latency as described in this project. Even the longer-term likely removal of roadside VMS, through the imminent advent of in-car information systems (as required by C-ITS), will not remove the need to inform road users with accurate data. The media will change but the core information will remain the same.

Previous research has identified that travel times can be influenced and/or derived from a multitude of other datasets (e.g. inductive loops, weather, incidents, etc.). The primary purpose of this project was to identify how the latency effect can be measured and how it can be removed so as to improve the travel time estimation. This was achieved for the study route section. The methods used could be easily applied on other routes.

4. Conclusions

Motorway travel time latency in VMS information provision was shown to exist and be measurable. The analysis was carried out at a location known to have a significant daily peak congestion period. The historical ATMS travel time dataset provided sufficient information to deduce and measure the latency effect. The developed prediction model produced a moderate but identifiable improvement on travel time estimation in comparison to the currently calculated (and displayed) travel time. However more detailed data analysis revealed distinct differences in travel time profiles for historical data depending on time of day, day of week, and month. Finally, the research confirmed that an accurate means of travel time prediction has been shown as a crucial and important indicator for road operator and road user alike. The method developed in the research could be easily transferred to other networks.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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Appendix

Tables A.1 and A.2.

Table A1
Linear regression model results for weekdays.

Summary output						
Regression statistics						
Multiple R	0.835189573					
R square	0.697541623					
Adjusted R square	0.697502259					
Standard error	2.573972252					
Observations	15,370					
ANOVA						
	df	***SS***	***MS***	***F***	***Significance F***	
Regression	2	234801.75	117400.87	17719.995	0	
Residual	15,367	101811.49	6.6253332			
Total	15,369	336613.24				
	Coefficients	***Standard error***	***t Stat***	***P-value***	***Lower 95%***	***Upper 95%***
Intercept	0.537127083	0.1000406	5.3690926	8.03E−08	0.341035724	0.7332184
TT_d	0.647452268	0.004532	142.86114	0	0.638568935	0.6563356
$TT_h - t + 1$	0.329904747	0.0081847	40.293862	0	0.313856338	0.3459532

Table A2
Linear regression model results for the evening peak period.

Summary output						
Regression statistics						
Multiple R	0.84738635					
R square	0.718063626					
Adjusted Rsquare	0.71799507					
Standard error	3.125999397					
Observations	8228					
ANOVA						
	df	***SS***	***MS***	***F***	***Significance F***	
Regression	2	204703.61	102351.81	10474.124	0	
Residual	8225	80373.649	9.7718722			
Total	8227	285077.26				
	Coefficients	***Standard error***	***t Stat***	***P-value***	***Lower 95%***	***Upper 95%***
Intercept	−1.752820853	0.17442	−10.049429	1.26E−23	−2.09472799	−1.4109137
TT_d	0.672738817	0.0058251	115.49022	0	0.661320206	0.6841573
$TT_h - t + 1$	0.427252266	0.0124801	34.234657	2.96E-240	0.402788101	0.4517164

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