A Personalised Online Travel Time Prediction Model

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***Abstract*— Congestion slows road traffic and this has become a prominent urban road traffic problem. For commuters about to travel, or on route, accurate travel forecasts enable them to choose the right routes in a timely manner to avoid travel delays. In this paper, a personalised online travel time prediction model is proposed. The novelty of the work is threefold. First, commuters' travel status according to their movement status, OD (origin-destination) status and plan status can be identified. Second, a traffic data critical factor evaluator system is proposed to extract critical factors from raw traffic data that can predict travel time episodically. Third, travel information can be personalised to the individual commuter's current travel status. The evaluation of the proposed model is conducted with a Google Android mobile application prototype and traffic data from the city of Enschede. The results suggest that the model can provide commuters with accurate travel time prediction (>93%) by leveraging machine learning techniques such as a M5 tree model.**

Keywords- Traffic data processing, travel time prediction, VRI system application

I. INTRODUCTION

Congestion slows the normal urban road traffic flow. This has financial and environmental costs [3]. A long travel time can frustrate commuters, e.g. road rage can occur which could further disrupt daily commuters. Reducing traffic congestion is one of the main challenges to be addressed by researchers and multiple countries' local, transportation, authorities. One of the approaches that could reduce urban congestion and improve traffic flow is to allow daily commuters to proactively and flexibly manage their trip. To achieve this, the expected travel time to reach destinations should be known in time. However, travel time prediction is becoming more and more complex because there are multiple causes that could impact the traffic prediction results e.g. planned or ad-hoc road works, social-events, e.g. concerts, road traffic flow in and out of city and etc. In addition, travel time prediction results cannot be presented in a one size fit all approach because commuters can have different prediction information requirements, e.g., en-route vs. pre-planned, short-term prediction such as 2 minutes or 1000m ahead vs. long-term prediction such as 60 minutes ahead.

Existing travel information used by urban road traffic management systems are mainly retrieved from various traffic monitoring infrastructures. For example, according to the U.S. DOT highway administration[1], monitoring systems can be road surface invasive detectors such as inductive loop (ILD) and two-axis fluxgate magnetometer. They can also be non-invasive road surface detectors such as microwave radar, infrared and ultrasonic. Furthermore, there are special purpose detectors for specific transport modes such as selective vehicle detection [15]. One of the benefits of using these devices is that it enables a broader range of data exploitation in a bid to view road traffic status from different perspectives. However, the deluge of traffic data from these devices also brings a universal challenge, that is, which set of data from the available data can be used to produce a better prediction result according to users' specific prediction requirements. This will be even more complex when the prediction requirements are episodic i.e., offering prediction information to commuters customised to situations and commuter preferences. This involves further challenges 1) how to make the prediction more accurate when the situation has changed and 2) how to adapt the prediction to the commuter's changing preferences.

In this work, a POTTP (Personalised Online Travel Time Prediction) model is proposed. It aims to personalise road traffic prediction information according to individual commuter's live travel status and current urban road traffic status. More specifically, the model:

1. Can identify commuters in terms of their travel status.

2. Can identify and combine critical factors that can contribute to a better travel time prediction accuracy.

3. Personalises prediction information with a prediction lead time to individual commuters according to their travel status or conditions.

The paper is organised as follows. In section II, the related works on travel time prediction are reviewed. A POTTP model is proposed in Section III. The effectiveness of proposed model is evaluated in section IV. Section V concludes the paper.

II. RELATED WORK

Predicting travel time for individual commuters involves two essential processes, one is to understand a commuter's situation and the other is to understand current traffic situation. In this section related works of these two processes are surveyed.

Personal travel information are important to understand commuter's demand about travel prediction information. That said it is not easy for devices on roadways to collect a commuter's personal travel information such as origin and

[1] http://ops.fhwa.dot.gov/

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destination. In recent years, personal mobile devices are becoming more capable, they are often equipped with different types of sensors e.g. accelerometer and GPS. As a result, personal mobile devices have emerged to be a critical experimental tool in the research field of personal travel behaviours. In [19], mobile phone GPS data are sent to a central server to investigate the automatic travel mode detection. Mobile devices can also be attached to a mobile vehicle such as in [11], both mobile phones and floating car data are used to study the population distribution and travel flow in a city. In most mobility pattern studies a common objective is to provide information to support decision-making in urban management, which hardly can benefit individual commuters directly. For works focusing on individual user mobility such as in [1] individual historical travel information is recorded and visualised but no further travel information obtained from data fusion and processing are offered. In [8], the question of "what travel information do commuters exactly want?" is investigated and it is found that time is tangible and measurable and has tended to be the core elements of provision in most travel information services. In the route planning studies such as [22] and [16], travel times are presumably to be accurate and planned routes often depend on the current travel time required and can be less optimal in the future. In this work, a new approach is proposed to adapt the predicted travel time with personalised prediction lead time to individual commuters according to individual's current travel status.

For urban transport management, a number of work focused on empirical studies in terms of speed, flow rate, vehicle density [17][2][23], and many other factors such as past traffic level, time, traffic count survey [10] from urban sites, traffic speed, traffic volumes, occupancy [26][6]. Spatiotemporal factors analysis is also seen in some research work such as in [24] where the bottlenecks in urban networks were predicted in a weekly manner. Traffic monitoring system data are essential inputs to understand commuters travel patterns, how these patterns change over time and how to change such patterns at some point so that congestions can be alleviated. Different traffic monitoring solutions are proposed by transport science community by using these such as in [7] and [18]. For example, adding more lanes to roadways and streets. This solution, at first glance, seems to be reasonable. In [20], it is argued that this strategy is futile in a long run as it is likely to lead more congestion and more pollution. In the meanwhile, governments have employed different traffic monitoring and incident reporting systems such as acoustic tracking systems, microwave radar sensors and inductive loop detectors (ILD). Less expensive traffic monitoring and incident detection systems are also massively deployed by transport authority worldwide such as video cameras. However, data from traffic monitoring sensors are normally not ready for direct use for different use requirements. Occasionally these data are not even reliable for direct use, e.g. the official stats showed that 50% of the IDLs and 30% of the video cameras are defective [14]. Hence, a further data processing including filtering and fusion is required to reduce data errors. Data mining approaches are often used to address this issue. In the scenario of studying group mobility, decision tress [21] and neural networks [9] [26] [27] are most frequently used approaches to predict the travel time/speed. However, the prediction results from these studies are often presented at system or group level, e.g. travel patterns as defined in [6] and [25]. In this work, a traffic data critical factors evaluator system is provided which can extract the critical factors that can be used to more accurately predict the travel time from raw traffic data. In addition, the proposed system is also aiming to provide low level results targeting at individual commuters.

III. POTTP MODEL

A. Model Overview

The prosed POTTP (personalised online travel time prediction) model consists of three systems (see Figure 1):

- Commuter identification system,
- Traffic data critical factors evaluator system and
- Travel information personalisation system.

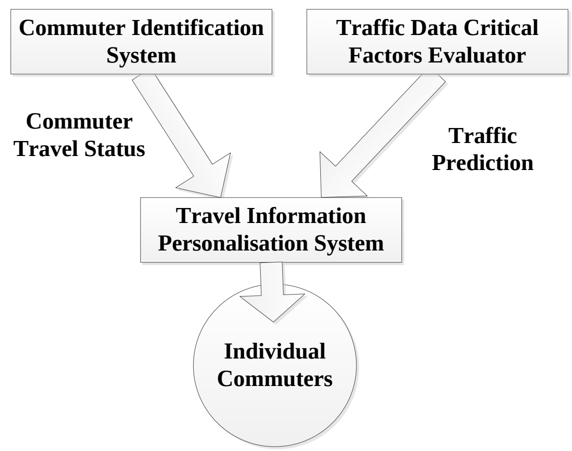

Figure 1 POTTP Architecture

In the commuter identification system, commuters are identified in terms of current travel status. The corresponding travel information will be tailored according to the commuters' characteristics. An evaluation method is crucial to determine the quality of generated travel time prediction results. The critical factors that can have a significant impact on the prediction accuracy will be determined. Personalisation is performed so that travel time prediction with a prediction lead time can be adapted based on individual commuters travel status.

B. Commuter Identification System

It is important to understand commuters' travel conditions so that the required travel information can be adapted to them. Two common characteristics are well identified in other work they are time and space. In this work, commuter travel status is defined in terms of temporal and spatial characteristics (see Figure 2). Two types of travel status are defined in terms of spatial characteristics, i.e. movement status and OD (origin-destination) status. A Movement status can be either static or moving, and an OD status can be either near destination, far from destination or in the middle of a trip. A plan status is also defined in terms of temporal characteristics of a trip. The plan can be to travel in long future, short future and medium future, the specific time length definition depends on a commuter's trip patterns and other spatial related status.

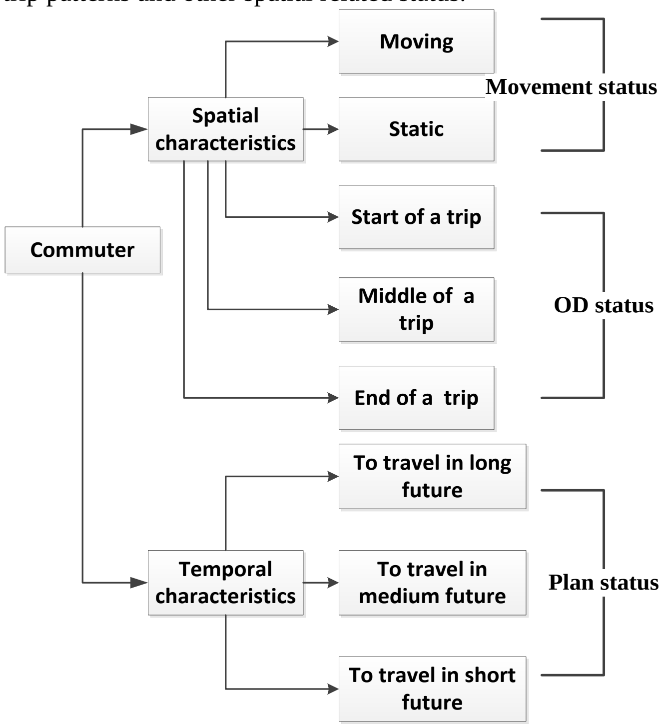

Figure 2 Identifying commuters in terms of spatial and temporal characteristics

1) Movement Status Quantification

A movement status can be determined by a combination of sensors on mobile devices, in this work, both GPS and accelerometer are used. The former is used to determine a commuter's horizontal travel distance and the latter is used to detect the vertical travel distance. The travel distance D thus can be induced by:

$$D = f(t) = \sqrt[2]{(\frac{1}{2} \times g \times t^2)^2 + (V_{GPS} \times t)^2}, \tag{1}$$

where *t* is the travel time, *V* is the GPS detected velocity, *g* is the accelerometer detected gravity. The movement status in therefore can be defined in a derivative form as following equation.

$$M = \frac{\Delta D}{\Delta t} \geq 1: \text{Moving? Static} \tag{2}$$

2) OD Status Quantification

The OD status can be determined by three parameters, the origin location *O*, the destination location *D* and the current location *L*. This information can be obtained either through user manual input or mobile device auto detection. For the user manual input approach as used by most sat-nav applications, commuters are asked to input the origin and destination and the application will draw up a direction map. For the auto detection approach, no user input is required; the application automatically monitors a commuter's daily travel routes and will generate some personal routes based on the trip frequency such as in [7]. In this work, the OD status can be quantified as:

$$OD = \begin{cases} \left(0, \frac{|O-D|}{3}\right) & \rightarrow Trip_{start} \\ \left[\frac{|O-D|}{3}, \frac{2 \times |O-D|}{3}\right] & \rightarrow Trip_{middle} \\ \left(\frac{2 \times |O-D|}{3}, |O-D|\right) & \rightarrow Trip_{end} \end{cases} \tag{3}$$

3) Plan Status Quantification

An accurate travel plan status can be determined by commuters themselves as there will be ad hoc travel plans which are caused by many factors either from commuters themselves or physical environment such as weather conditions. And there can also be new plan during a trip when a commuter is in a static movement status. The plan status eventually can be a trigger for travel information retrieval. In the proposed model, commuters are assumed to make travel plan queries to the system in order to move better. The system will record each query time. Hence, if the time difference between each query time is defined by *t*, then a collection of *t*, $T = \{t_0, \ldots, t_n\}$can be obtained from a commuter's *n* queries. The plan status can be quantified as:

$$t_q = \begin{cases} \left(argmin(T), \frac{argmedian(T)}{3}\right) & \rightarrow Short \\ \left[\frac{argmedian(T)}{3}, \frac{2 \times argmedian(T)}{3}\right] & \rightarrow Medium \\ \left(\frac{2 \times argmedian(T)}{3}, argmax(T)\right) & \rightarrow long \end{cases} \tag{4}$$

C. Traffic Data Critical Factors Evaluator System

The proposed model can be applied for supervised machine learning driven traffic prediction systems where model matching is used to match the current state to a past equivalent state and to reuse as the sequence for later states for the current equivalent state as the predicted set of future state. Here, a critical factor evaluation is proposed based on PE (prediction effectiveness) function to improve the prediction precision. With the expected accuracy and time for prediction, PE is able to find out the critical factors and data training size that impact the prediction accuracy. This can be achieved with the following equation,

$$PE(S_i) = Sort\left(\left(\frac{Tr_A - (1 - A_i)}{Tr_T - T_i + Tr_A - (1 - A_i)}\right)^2 \times \omega_A \times \left(\frac{Tr_T - T_i}{Tr_T - T_i + Tr_A - (1 - A_i)}\right)^2 \times \omega_T\right) \tag{5}$$

where *A* denotes accuracy for a training set, Tr_A is the expected accuracy error and Tr_T is the expected time, A_i is the actual accuracy and T_i is the actual prediction time, ω_A denotes the overall importance of accuracy in evaluation and ω_T denotes the overall importance of time in evaluation and $\omega_A + \omega_T = 1$.

D. *Travel Information Personalistion System*

The travel information in this work is defined as the travel time expected to travel from current locations to expected destinations. This information are offered with a lead time which can be termed as short, medium and long lead time in corresponding to the a commuter's plan status.

The corresponding lead time for each travel status is quantified in terms of corresponding quantity measurements (see Figure 3). E.g. the near destination in OD status will correspond to a short lead time. A special case here is for static movement, since a static movement can trigger a commuter further travel plan which could be either travel within short, medium or long time, and therefore will require any type of lead time.

The problem of adapting the personalised travel information to a commuter can boil down to a fundamental question, i.e. which lead time should be used in different situations? This question is addressed with a lead time evaluator which scores the importance of lead time type corresponding to a commuter's spatial and temporal status. The score calculation is based on the following formula.

$$Score_l = \sum Char \tag{6}$$

where l is lead time type, $Char$ is spatial and termporal characters, the value is 1 if there is and 0 otherwise. The lead time type can be determined from selecting the ones with highest scores.

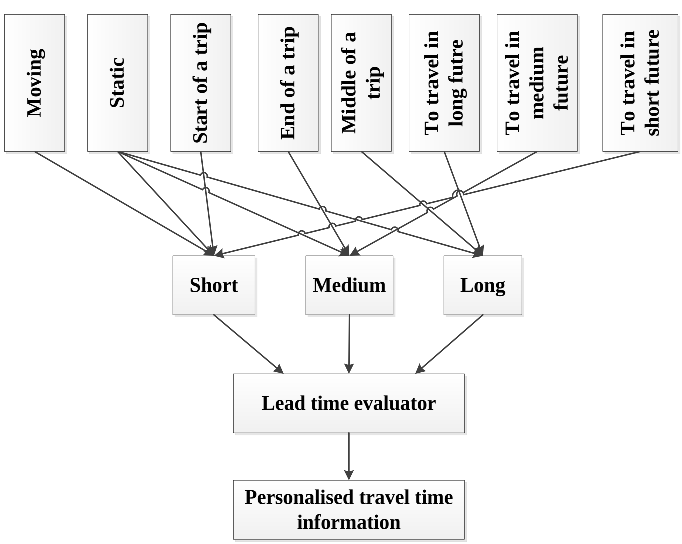

Figure 3 travel information personalisation workflow

IV. POTTP VALIDATION AND EVALUATION

There are two sets of experiments here to verify the proposed model. The first experiment is to validate the travel statues detection which is carried out by integrating the proposed commuter identification system to an Android prototype application. The second experiment is to assess and demonstrate the capability of proposed POTTP model on travel time prediction and on handling identified commuters. A semi-simulation based approach is used, and this is carried out by laying out a set of predefined commuters with different travel conditions and simulating their trips with traffic data from the city of Enschede Netherland.

A. *Travel Status Detection Validation*

The approach used here is to validate the proposed commuter identification mythology with an existing mobile application. The plan status mainly driven by users can be implemented via a variety of user input interfaces in most mobile front ends and hence is not validated in this experiment. This is done by implementing the proposed system with a developed Google Android mobile prototype application on top of the application introduced in [7] (see Figure 4). The application prototype supports 1) detailed frequent trip detection. 2) GPS and accelerometer data access, which are envisioned to be critical to realise the proposed system, the former will allow live OD status detection and the latter can be used for both live movement status detection and live commuter location.

A two-month long experiment has been carried out with 50 monitored daily trips. For the movement status, i.e. static is defined as motorised movement has been stopped for more than one minute and otherwise moving. During experiment, both movement status and trip of original and destination are recorded in a diary for each trip. The results (see Table 1) of this experiment include the Recorded Trip vs. Detected Trip and Recorded Movement vs. Detected Movement. The results suggest that 86% of the OD can be correctly identified based upon the identified trip and 92% of the movement statues are correctly detected throughout all trips.

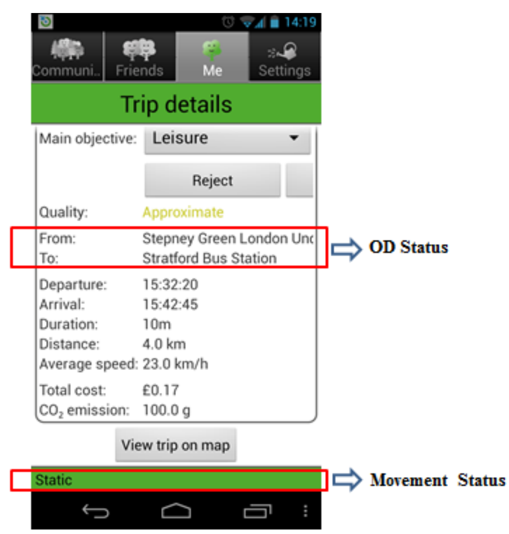

Figure 4 Detected frequent trip detail with an Android App

Table 1 Results of travel status experiment

	Recorded Trip vs. Detected Trip	Recorded Movement vs. Detected Movement
True Cases	43/50	398/432
False Cases	7/50	34/432

B. Travel Time Prediction Evaluation

1) Traffic data for fusion and processing Settings

The traffic data including IDL and traffic lights data from a city centre intersection (8 directions) in the city of Enschede Netherland are used. The data cover from 2010-01-01 00:00:00 to 2011-06-22 23:55:00 and they are collected in every five minutes. In this setting, four types of data for analysis are defined:

Factor 1: Day of the week
Factor 2: Green light counts within 5 minutes
Factor 3: Occupational level for long loop within 5 minutes
Factor 4: Occupational level for short loop within 5 minutes

Given there is no evidence on which of these factors are more important to predict the travel time passing through the studied intersection, there are 15 possibilities, i.e. unique combinations of these factors obtained from sum of binomial coefficients $C_4^1 + C_4^2 + C_4^3 + C_4^4$. Training data sizes are predefined as at latest 60%, 70%, 80% and 90% of the whole data set respectively for each possible combination, the rest of data are used for verifying prediction results. For training accuracy, a prediction error of 1.00 second is allowed, i.e. predictions are accurate if the result is within one second deviation from verifying data values.

2) Commuter Settings

18 commuters are predefined in corresponding to 18 types, which can be derived from defined commuter classes (see Figure 2), i.e. $C_2^1 \times C_3^1 \times C_3^1$. All these commuters are assumed to pass through the selected intersection from different directions in order to reach their destinations.
These commuters are randomly deployed in 8 directions of the intersection and their travel lead time preferences (i.e. plan status) are calibrated with traffic data. The prediction lead time hence is defined as 60 minutes (long), 30 minutes (medium) and 5 minutes (short) and this time interval definition also applies to travel information personalisation process.

3) Prediction with M5' Tree Model

In this experiment, the decision tree technique called M5 model tree [12] is used for data fusion and processing. This choice is based upon the observation that model tree is an excellent alternative of other machine learning techniques such as artificial neural network in prediction applications [5]. In addition, tree model also exhibits unique advantage in presenting more human readable rule based results (see Table 2).

4) Prediction Experiment 1

This experiment tries to find out the critical factors that can lead to high accuracy of a travel information forecast. It is assumed that a more powerful computer will generate the forecast results quicker, and hence, in this experiment the importance of accuracy is set to be absolute and with the expected accuracy of over 90%.

The results from the data processing and fusion suggest that factor 2 and 4 are of most important factors influence the accuracy of forecast in all eight directions. It is also found that the highest forecast accuracy can be achieved in varied training size depending on the direction being tested (see Table 3).

Table 2 M5' Tree Model generated travel time rules

Rule: 1

IF green_count > 1.5 and long_occupation <= 1.5

THEN travel_time=-

2.9258*green_count+3.6188*long_occupation + 17.7814

Rule: 2

IF green_count <= 2.5 and long_occupation <= 0.5

THEN travel_time = -0.0036 * green_count + 0.0030 *

long_occupation + 18.0313

Table 3 Highest forecast accuracy with training size in eight directions

Direction	Training size with the prediction accuracy >90% (%)	Accuracy (%)
1	80	95.07
2	80	94.72
3	80	93.49
4	80	94.37
5	90	93.47
6	60	93.61
7	60	93.91
8	70	96.58

5) Prediction Experiment 2

The experiment here is to assess how accurate the POTTP can provide the required travel information according to different prediction lead time requirement. This is done by furthering experiment 1.

Each of the direction in studied intersection is allocated at least one commuter and the eighteen commuters are reallocated to each direction for ten times. During the experimental queries, the results can be obtained within seconds. Also, from the test results, it can be found that by average the personalised travel information prediction accuracy can achieve 94.49% with a standard deviation of 1.66 % in ten tests. As a result, the provided travel information can be viewed as stable and accurate.

V. Conclusion

In this paper, a personalised online travel time prediction model is presented. The model aims to addresses the urban road traffic issue an individual commuter level. It is able to offer predicted travel time for commuters according to their current travel statues. This is done by identifying commuters' prediction lead time requirements according to their movement status, OD status and plan status. In addition, the model identifies the critical prediction factors that can lead to high prediction accuracy based upon a proposed prediction effectiveness function. The personalised prediction eventually occurs when the obtained high accurate prediction results with prediction lead times are applied to individual commuters. The proposed model is validated and evaluated using a Google Android mobile application prototype and traffic data from Enschede city. The results suggest that the proposed commuter status identification system is valid. A commuter's travel status can be monitored with existing application with a decent accuracy (⩾86%) in terms of OD status and movement status. The experiment results also show that via traffic data critical factor evaluator, it is able to produce high accurate personalised prediction results (>93%) by leveraging existing machine learning techniques such as M5 tree model.

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