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A Review of Travel Time Estimation and Forecasting for Advanced Traveler Information Systems

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Abstract

Providing on line travel time information to commuters has become an important issue for Advanced Traveler Information Systems and Route Guidance Systems in the past years, due to the increasing traffic volume and congestion in the road networks. Travel time is one of the most useful traffic variables because it is more intuitive than other traffic variables such as flow, occupancy or density, and is useful for travelers in decision making.

The aim of this paper is to present a global view of the literature on the modeling of travel time, introducing crucial concepts and giving a thorough classification of the existing techniques. Most of the attention will focus on travel time estimation and travel time prediction, which are generally not presented together. The main goals of these models, the study areas and methodologies used to carry out these tasks will be further explored and categorized.

1 Introduction

In recent years, the technological advances have enabled the collection and diffusion of real-time traffic information and this, in combination with the growing traffic volume and congestion, has triggered an increasing interest in traffic modeling [31]. These models and algorithms enable a more efficient traffic management and also provide the commuters with the necessary tools for decision making [70].

While variables such as flow, occupancy and speed are very useful in Advanced Traffic Management Systems (ATMS), travel time measures are more popular in Advanced Traveler Information Systems (ATIS), because they are highly intuitive for both engineers and users and can be easily understood by non experts [46].

Travel time is defined as the total time for a vehicle to travel from one point to another over a specified route, taking into account the stops, queuing delay and intersection delay [134]. The modeling of this traffic variable is a recurrent research topic and there are a vast number of algorithms and applications whose main goal is obtaining travel time in the past and current [11, 108, 110] or future timestamps [31, 36, 70, 120].

Indeed, two of the main issues concerning travel time are the prediction and estimation of this traffic variable, which are frequently confused terms in the literature [72].

The main difference between travel time prediction and estimation is the dynamicity. Estimation algorithms are more or less complex calculations of travel times of trajectories that have already ended, using other traffic variables or incomplete data captured during the trip. In prediction algorithms, a time variable is included and the objective is to use the current and past data to forecast the travel time in future time intervals [72]. Prediction models are more useful for ATIS because they enable decision making but evidently, predicting travel times for future time intervals incorporates higher uncertainty and demands more complex models. On the contrary, estimation models are not directly useful for ATIS but are necessary for validation purposes and as a baseline for many prediction models.

In practice, the two concepts are closely related and in some cases estimation and prediction algorithms can even have the same formulae [71, 131], but with clearly different objectives. Despite these differences, the two approaches to travel time have similar difficulties due to the highly dynamic and nonlinear nature of traffic processes [70] and the influence of many exogenous factors such as demands, weather, roadway conditions or traffic conditions [127], that are usually difficult to model.

The remainder of this paper is organized as follows. We will first introduce some critical concepts in the topic of travel time prediction and estimation in Section 2. Next, in Section 3, travel time estimation will be introduced and an extensive categorization of the methodologies used in the literature will be described. In Section 4, the most recurrent topic regarding travel time will be approached: travel time prediction. Finally, some conclusions and insights will be presented in Section 5.

2 Basic Concepts in Travel Time Modeling

When modeling travel time, there are three basic concepts that are present in all investigations and should be approached beforehand. First of all, modeling travel time requires the acquisition of a large quantity of data and it is necessary to have some knowledge of the different types of data that can be used for each purpose. A second important factor regarding travel time is the location in which the model is situated, because the different characteristics of each study site have a clear influence in the modeling process [117]. Finally, since we will generally be dealing with temporal data, the treatment of the variable time is also influential and should be studied in advance.

2.1 Data Sources

Recent progress in advanced technologies for intelligent transportation systems have enabled the extraction of traffic information from many different sources and in multiple formats [31]. At the same time, advances in computer science and modeling have introduced methods and tools to accurately manage and simulate these traffic variables [2, 39, 122].

Simulated or real, traffic data sources are classified into two main groups [69, 120]: point detectors and interval detectors. This classification is based on the ability of the different sensors to directly obtain travel time [108].

2.1.1 Point detectors

This type of detectors are set in fixed points of the road and capture traffic variables in those specific points. They accurately represent the traffic state in the target points but have problems in capturing area wide traffic dynamics [16]. They can further be classified into intrusive and non-intrusive sensors, where the first type of detectors are directly placed on or beneath the pavement, whereas the latter type are situated in the surroundings of the road but not directly on the asphalt [61].

The most conventional point detectors are the intrusive inductive loop sensors [16, 70, 127]. They consist of a set of square inductive loops buried in the road that generate a magnetic field and are able to sense the passing of vehicles [61].

These sensors provide accurate data and are not affected by external factors, but their installation is expensive and complicated. For this reason, in the recent years, non intrusive devices are gaining approval because of their low installation cost and their high accuracy. Some of the most common non intrusive point detectors are video image detection methods, that use image processing methods to obtain vehicle counts and speeds at specific points of the road. The main drawback of non-intrusive detectors is that they are usually susceptible to external factors such as weather, and that they precise periodic maintenance [61].

2.1.2 Interval detectors

Interval detectors measure travel time between two points directly by using active floating vehicles, passive probe vehicles or automatic vehicle identification techniques (AVI) [120]. Floating and probe vehicles are generally equipped with cell-phones or Global Positioning Systems and send location, direction and speed information every few seconds [61]. On the contrary, AVI systems can be of various types, from manual surveys [91] to automatic toll collection systems [33] or video cameras in combination with license plate matching techniques [114]. These AVI detectors detect and identify the vehicles in the beginning and end of the study segment and calculate travel time from this data.

This type of data collection promises high accuracy and high quality description of the traffic situation [69]. However, there are some practical inconveniences to using interval detectors. These issues, which will be explained in Section 3.2, are the main reason why, in the literature, point detectors are more frequently used than interval detectors. In any case, in the last few years different techniques have been introduced in the models to permit the introduction of interval detector data for a better description of the real traffic situation [11, 58, 69, 135].

2.2 Study Site

The characteristics of the area in which the model is situated clearly influence it and, in fact, one of the drawbacks of travel time models is that many of them are site specific [72] and not easily transferable to other areas.

Most of the travel time models in the literature are set in freeway or highway segments because the acquisition of data and the construction of the model in these roads is simpler than in other road types [117]. The length of the segment may vary from less than 15 km in most cases [70, 127, 131] to more than 50 km [119, 120].

On the contrary, research on urban and arterial road segments is not so abundant because traffic sensors are not always available in these sites. However, interest in this type of areas is gaining strength as sensors are developed and placed in more roads [11, 91, 134]. Moreover, traffic in urban sites is more complex and factors such as signal and intersection delays must be taken into account [123].

Another crucial fact related to the study site is that since travel time depends on the origin and destination, and given the huge number of possible combinations of origins and destinations in a road network, ATIS normally use methods that calculate travel time information at link or section level [12]. A section can be defined as the distance between two intersections in the urban environments, the distance between two entry and exit ramps in highways or the distance between two detectors, in general cases. The travel time of a whole trajectory is obtained as the sum of the travel times of the links or sections that constitute it. As exceptions, there are a few articles that construct their models for pre-defined complete trajectories instead of dividing the study site into links [8, 60] but this becomes unfeasible when modeling a big road network.

Finally, there are very few models that are evaluated in an entire network because travel time modeling for a whole road network is more challenging than modeling a road segment. Most researchers limit their study to a limited number of links or trajectories.

2.3 Treatment of the temporal variable

The treatment of the temporal variable is a fact to be taken into account in this type of dynamic applications. In travel time modeling, data is not usually presented in its continuous form, but aggregated and simplified in a certain way to facilitate the modeling process. Because of this, the authors generally refer to discrete time intervals and not continuous time instants. The aggregation technique can vary depending on the type of detectors used in the study and the arrival pace of the data.

Point detectors sense the passing of vehicles continuously but the data is generally not presented in this raw form. The sensors sort and aggregate the data into discrete time intervals of a predefined length and so the data from the vehicles that traverse the sensor in the same time interval are averaged. Furthermore, a balance must be found between the too high variability that short time aggregation introduce and the too smooth data that long time aggregations generate. Typically the data is averaged between 1 and 5 minute intervals [31, 36, 70, 120, 131, 134] but in some papers shorter 10, 20 or 30 second intervals [24, 28, 135] or longer 15 minute aggregation intervals [37] are also used.

Interval detectors offer more possibilities because they measure area wide variables such as travel time, which is the variable of interest in this case. On the one hand, with AVI interval detectors, travel time is available each time a vehicle arrives to the destination point. In most cases, an aggregation similar to that used for point detectors is applied and the travel times of vehicles arriving in the time interval are averaged [8, 58, 69, 134]. This aggregation is a solution for applications where the most recent data is required in real time but, it is not the best way to represent the traffic because the grouped vehicles may have started their trip at very different times and useful information might be lost. An aggregation based on departure time represents the traffic situation more adequately than an arrival based aggregation but, in the case of AVI detectors, it can not be calculated in real time, because the data is not available until the vehicles arrive to the destination point. This is called the time delay problem and will be further commented in Section 4.5.

On the other hand, in the case of probe vehicles provided with GPS detectors, the position and the speed of the vehicles is available every few seconds [92] and this provides more freedom and eliminates some of the inconveniences found when working with AVI detectors. Both arrival time and departure time based aggregations are possible in an on line fashion by using the position and speed in an adequate manner. Furthermore, in some specific cases, when the sample of probe vehicles is not very big, no aggregation is done and the time intervals are defined using the arrival time of each probe vehicle to the destination [119].

3 Travel time estimation

Travel time estimation consists in calculating travel times of already completed trips based on other quantities or traffic variables which are somehow related to travel time [72]. It can be said that travel time estimation is a descriptive task that is not directly useful for ATIS because the input data is not available until the time interval or the vehicle trajectories are over. However, estimation algorithms are essential to obtain statistics on the performance of new traffic measures [71] and as a baseline to calculate input data [113] and validation data [70] for more complex travel time prediction algorithms.

The general objective of the researchers is to obtain the mean travel time because it gives an overall view of the traffic situation in a given time interval. For this purpose, in the literature, the true mean travel time of a given segment for the vehicles that depart in time interval $[t-l,t]$ is defined by:

$$TT_{[t-l,t]} = \frac{L}{\bar{v}_{space,[t-l,t]}} \tag{1}$$

where L is the length of the study segment and $\bar{v}_{space,[t-l,t]}$ is the space mean speed of vehicles departing in the time interval $[t-l,t]$. Since L is generally well known, the modeling of space mean speed and travel time are essentially equivalent.

The space mean speed is defined as the division of the total distance traveled by all the vehicles that depart in time interval $[t-l,t]$ with the total time of travel of all these vehicles. It is important to note that the space mean speed is an area wide variable that is used to describe the velocity in the whole road section and not only a specific point in the road.

This formulation poses different problems to all the traffic data detectors that have been presented in the previous section and is not directly calculable in most real world situations. Point detectors are only able to capture data in specific locations of the study segment and since the space mean speed is a section wide variable, the data from these detectors is not sufficient to calculate Equation 1. Among the interval detectors the main problem is that in real situations, it is not usually possible to track all the vehicles, which is necessary to explicitly calculate equation 1, and only a sample of the whole data will be available [55].

So, since the mean travel time for vehicles departing at a certain time interval can not be calculated directly, approximation or estimation schemes will have to be presented.

3.1 Travel Time Estimation from Point Detectors

For many years, double or single inductive loop detectors have been the most widely used detectors [102] and therefore the vast majority of the travel time estimation algorithms from point detectors use this type of sensors. However, most point detectors, intrusive or non intrusive, provide the same type of data and the algorithms that will be presented next could be applied equivalently for point detectors other than loop detectors [61].

There are two types of loop detectors. The first type are called single loop detectors and consist of a single induction loop that is able to detect the passing of big metallic objects, in this case vehicles. These detectors output variables such as flow (number of passing vehicles/hour) and occupancy (% of the time that the detector is occupied) [38], often aggregated in specific time intervals as explained before. The second type of inductive detectors are called double loop detectors. As the name indicates, the double loop detectors consist of a pair of detectors set very close to each other and that are able to sense the passing of vehicles. This pair of sensors is capable of obtaining flow and occupancy but they can also collect speed at the point where the detectors are situated as well as vehicle lengths, by using the travel time of the vehicles between the two sensors [45]. The speed captured by double loop detectors is called point mean speed and is conceptually different to the space mean speed mentioned previously because it is not an area wide variable and is only valid to describe the mean speed at a specific point of the road.

3.1.1 Single Loop Detectors

As we have explained above, single loop detectors are able to capture flow and the occupancy of the detector and obtaining travel time estimates from these traffic variables is a complex task. Therefore, a few approaches have been presented in the literature and they can be divided into two classes: traffic theory based methodologies and data based methodologies such as machine learning or statistical techniques.

The first class of techniques apply relations between traffic variables, obtained from traffic flow theory, to extract travel time values from flow data [76, 84, 116, 130]. Different traffic dynamics approaches are introduced, essentially based on flow conservation equations. The main idea is to estimate traffic density (vehicles/km) using the difference in cumulative vehicle arrivals and cumulative vehicle departures in the target link in different ways. Finally, using the density (k) and flow (q), space mean speed can be obtained using the following identity [26]:

$$\bar{v}_{space} = q/k \tag{2}$$

On the contrary, in data based methods, models and equations from traffic theory are ignored and diverse statistical and machine learning methods are used to create new structures that relate flow, occupancy and travel time using the data as a baseline.

One of the most recurrent and successful data based models are artificial neural networks. These models are inspired in the structure and functional aspects of the biological networks that neurons form in the brain and are able to construct complex non-linear relations between the input and the output variables. Because of this, they have been extensively used in many classification and regression problems in different application fields. A wide variety of different neural structures have been used to find the best relation between occupancy, flow and travel time or space mean speed, from fuzzy neural networks [87] to Multilayer Perceptron, radial basis neural networks and probabilistic networks [56].

More statistical models such as polynomial regression models are also used in the literature [99,100] where occupancy, flow and speed are related generally with linear and quadratic relations.

Finally, more unusual approaches use time series modeling techniques such as calculating the cross correlation function between flow and travel times series [26].

It can be seen that the references for direct estimation of travel time from single loop detectors are not very numerous and are very sparse and distinct from each other. The main reason for this is that the majority of the researchers have focused their attention in imitating double loop detectors by estimating point mean speed using data from single loop detectors, instead of estimating travel time. Although these algorithms do not directly obtain travel time values, which are of interest in this paper, they can be helpful for obtaining travel time measurements if used in combination with other estimation methods that will be presented in latter sections. Therefore, the most exploited methodologies for point mean speed estimation from single loop detectors will be commented briefly in the following paragraphs.

The most conventional method for point mean speed estimation is a traffic theory model based on the identity in Equation 2. Since density can not be obtained directly from loop detectors, the main idea consists in using occupancy values (o) to approximate this traffic variable and the following formulation is obtained:

$$\bar{v}_{space} = \frac{q}{o \cdot g} \tag{3}$$

where g is the inverse of the average effective vehicle length in the target study period [38]. The effective length for each vehicle is calculated by summing the vehicle length and the detection zone length [45]. This methodology is denominated the g-factor approach and since vehicle length can not be obtained directly from single loop detectors, different techniques have been presented to approximate it adequately.

In the simplest case, g, and therefore vehicle length, is assumed to be constant over all the time intervals [20] but certain studies observe that this approach gives biased estimates in some cases [41,45,93]. Since vehicle length is not directly collected by single loop detectors, they have tried to find suitable approximations of g. Some proposals for obtaining more reliable values of g are presented in [20,26,118].

The second point mean speed estimation method that deserves a mention is Bayesian filtering. It is assumed that vehicle speed (v_k) is a random variable that is not observable from the sensors and two equations are defined:

State Equation: $v_k = F(v_{k-1}) + B(u_{k-1}) + r_n$

Measurement Equation: $y_k = H(v_k) + w_n$

where u_k is the control vector that is not taken into consideration in many approaches, y_k is the observed variable that is available from the traffic sensors and r_n and w_n are the model and measurement noises. In the case of point mean speed estimation from single loop detectors, it is typical to use equation 3 and its variations to define functions F, B and H [25,38,126].

The Kalman filters are widely used to solve these dynamic state-space model iteratively and a variety of Kalman filters exist depending on the linearity of the equations involved. The downside of the Kalman filters is the assumption of the normality of the variables involved. However, new methodologies such as Particle Filters provide alternatives to this condition [125].

These two methodologies estimate point mean speed, which is the variable captured by double loop detectors, and not travel time, which is the variable of interest in this case. Consequently, one of the travel time estimation methods that will be presented in the next section for double detectors would have to be applied in order to obtain travel time values.

A summary of all the methodologies presented for travel time and point speed estimation using data from single loop detectors is present in Table 1 including the advantages and disadvantages of each of the proposals.

Table 1: Travel Time Estimation Methods with Single Loop Detectors

Estimated variable	Method Type	Methods	Advantages	Disadvantages
Travel Time or Space Mean Speed	Traffic Theory based methods	Flow conservation equations and traffic dynamics	Realistic theoretical relations are applied	Expertise on traffic theory models is necessary
	Statistical and machine learning methods	-Polynomial Regression methods -Cross Correlation functions -Artificial Neural Networks	Underlying structures in the data can be found	A lot of good quality data is needed
Point Speed	g-factor approaches	-Constant g -Non-constant g	Simplicity	Another estimation method is necessary to obtain travel time
	Bayesian filtering	-Kalman filters -Particle Filters	Better results in congested states	

3.1.2 Double Loop Detectors

These loop detectors are able to capture flow, occupancy and speed at the point where the detector is situated. Speed is more easily related to travel time and therefore, it is generally simpler to estimate travel time from double loop detectors than single loop detectors. However, the speed captured by double loop detectors is only valid for a specific point and it is not always reliable to assume that it can represent the whole study site [23]. Because of this, very different approaches have been proposed to extend the data to the whole target site, which is usually a road segment, and provide travel time estimations.

The first and most common approach consists in extending the speeds of the captured points to the whole study site by using combinations of speeds from various detectors and interpolation schemes. As we have explained previously, the road is usually divided into smaller links, and although there are certain articles that present different divisions [23], normally each link is defined as the road length between two detectors. The detector at the beginning of the link is called the upstream detector while the one at the end of the link is denominated the downstream detector.

The main objective is to estimate the travel time for each link and then, the travel time for longer routes is obtained by summing the traversing times of the links that constitute the trajectory. This type of travel time calculations are denominated "Trajectory methods" [71].

Two types of "Trajectory methods" will be differenced: the static methods and the dynamic methods. The static methods collect the data from all the detectors situated in the trajectory of interest at the departure time and assume that the measurements from the detectors will remain constant throughout the trip. On the contrary, other authors present dynamic methods where the most recent available data, the data captured by each detector at the arrival time to that specific detector, is used as input. Since the arrival time to each detector is unknown a priori and must be estimated, more complex iterative methods must be introduced [23, 71], but these models are more realistic.

Both in static and dynamic "Trajectory methods", it is necessary to decide how the speed collected from the sensors will be expanded so that it represents a whole link. The most simple way is by using "Piece-wise Constant methods", where the speed captured in one of the detectors that delimit the link will represent the whole link [71, 103]. More complex approaches combine speeds from both upstream and downstream detectors in the link or even use speeds from neighboring links [23, 71, 103, 108].

All these "Trajectory methods" are widely used and present similar good performances in free flow conditions. However, they demand a dense spacing of the detectors and they do not provide very good solutions in congested situations, although the dynamic methods combining data from more that one detector perform slightly better [103].

Apart from the point speed interpolation and combination methods, there has been some interest in trying to use double loop detectors as if they were interval detectors by using vehicle re-identification, which attempts to find a signature that uniquely identifies each vehicle at two consecutive detectors. On the contrary of interval detectors such as AVI detectors, it is not so easy to uniquely identify vehicles using data from loop detectors and because of this, various techniques have been developed.

Since vehicle lengths can be obtained from dual detectors, one way of acquiring a vehicle signature can be by using this length. However, vehicle lengths are not unique and different solutions have been searched to convert them to unique signatures [19, 22]. A second approach to obtain unique signatures is presented in [1, 106] where it can be seen that some special dual detector manufacturers are incorporating the ability to monitor and output vehicle inductance values such as maximum magnitude of inductance, length and shape of the metal mass of the vehicle. This vector of information is used as a signature to match vehicles arriving to the upstream and downstream detectors and different methods have been applied to find the best match. A last methodology for unique re-identification can be found in [77], where vehicle platoons are created and re-identified using flow and volume. This last approach only uses flow data and therefore could also be applied in the case of single loop detectors.

This re-identification approach has some advantages compared to AVI interval detection [19]. First, the identification of the vehicles is anonymous and does not invade the privacy of the drivers. Second, there is no need of active population participation since all vehicles can be identified with the loop detectors and no special device has to be installed in the vehicles. Finally, these systems have more capacity to detect incidents, because not only travel time is observable but also spot speeds which give additional information. However, double loop detectors usually only provide aggregates of speed, flow and volume and since individual vehicle data may not be available, these contributions are not very popular for real world applications [102, 116].

Finally, less common approaches for travel time estimation from double loop detectors are traffic flow approaches based on different relations between traffic variables [21, 113] and statistical and machine learning models such as simple Bayesian estimators, feed forward neural networks [91] and Markov chains [127].

A summary of all the presented methodologies for travel time estimation from double loop detector data is provided in Table 2 with the advantages and disadvantages of each method.

Table 2: Travel Time Estimation Methods with Double Loop Detectors

Estimated variable	Method type	Methods	Advantages	Disadvantages
Travel time or Space Mean Speed	Point Speed Interpolation and Combination methods	-Static in time methods -Iterative methods	Simplicity	Inaccurate in congested and transition state conditions
	Vehicle Re-identification methods	-Re-identification using length -Re-identification using vehicle inductance values - Re-identification using volume and flow	Travel time is obtained directly	The necessary input data is not always available
	Traffic Theory based method	-Traffic identities using flow, occupancy and point speed	More complex and realistic relations are applied	Expertise on traffic theory models is necessary
	Statistical and Machine Learning methods	-Artificial Neural Networks -Markov Chains -Simple Bayes Estimators	No expertise in traffic theory is needed and good results are obtained	A lot of data is needed and the quality of the data conditions the precision

3.2 Travel Time Estimation with Interval Detectors

Interval detectors are more recent than point detectors, and in the past few years research on the use of these sensors has flourished considerably. The reason is that interval detectors provide travel time data directly and offer more possibilities for ATIS. However, travel time from all the vehicles is generally not available and because of this, most of the effort is focused on estimating the minimum number of detected vehicles needed to obtain a reliable picture of the traffic situation.

For this purpose, some statistical approaches are presented in which the authors frequently assume a normal probability distribution for travel time/speed [94, 98], mean travel time/speed [105, 112] or mean error [12, 55] and extract the minimum vehicle sample size by using reliability concepts [105] and constructing confidence intervals.

Although it is proved in [7] that the Gaussian distribution is not always the most adequate, and a possible improvement is presented for non Gaussian travel times, the cited techniques that use normality are widely accepted and directly used in the case of links and small road segments. Nevertheless, they are not directly applicable and must be slightly extended in the case of a whole network [7, 105].

In general, the minimum percentage of vehicles needed varies depending on the permitted error, the level of congestion and the characteristics of the study area, and it is not possible to give a unique minimum sample value for all situations because each case has to be studied independently. However, the minimum sample size needed for accurate representation of traffic is generally quite large and difficult to obtain in real situations.

3.2.1 GPS provided Probe Vehicles

Probe vehicles equipped with GPS systems are able to collect position, speed and time stamp data every few seconds [66] and this introduces a wide range of new possibilities into travel time estimation. Probe vehicles are able to provide all the data needed to calculate the space mean speed because the vehicles can be tracked at all times, but in real situations, it is usually impossible to track all the vehicles in a traffic network.

Given this situation, the main objective of the research is generally to estimate travel time from a reduced probe vehicle sample. In the past few years some examples of this type of estimation have been published and the increase in GPS enabled devices promises more interest in this type of models in the near future.

A couple of different statistical approaches are available in [92] and [34]. In these approaches a Bayesian prior conjugate scheme and a weighted average with historical data are used to generalize the observations obtained from an insufficient vehicle sample to the whole traffic.

Another approximation is the use of fuzzy logic [63, 66], that is an extension of regular set theory, in which each element is associated to a fuzzy set with a degree of membership. The objective is to assign the individual trajectories of probe vehicles to different fuzzy driving patterns and fuzzy traffic situations and to derive the mean travel time of the whole population from this information.

It is quite common to use bus or taxi fleets as probe vehicles because these vehicles cover a large part of the traffic network and the fleet sample is quite big [34, 92].

3.2.2 AVI detectors

Another type of interval detectors that have gained popularity in the past few years are the AVI detectors. We recall that these detectors identify the vehicles at the beginning and end of the study section and infer travel time values from this data. Some of these detectors, such as license plate matching video cameras or closed toll highways, are able to collect the travel times of all the vehicles that travel in the surveilled section. However, in many cases, the detectors only capture the travel times of a sample of the whole traffic population and this sample is not always sufficiently large.

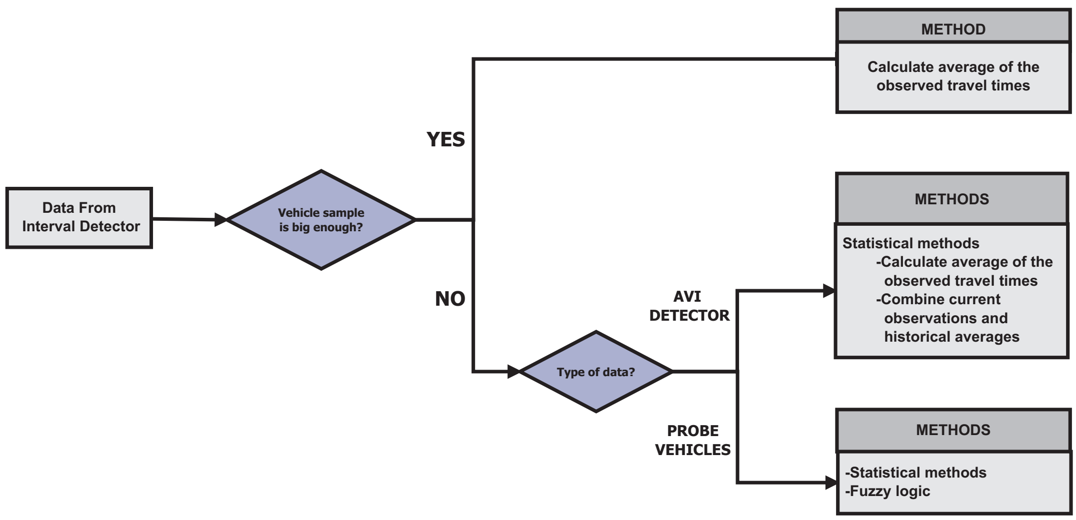

Figure 1: Travel Time Estimation from Interval Detectors

In the second case, for example when using electronic toll collection tags or roadside beacons, the travel time must be extrapolated to the whole population. The solutions are a series of statistical methods that vary from simple averaging of the valid travel time records as in the TransGuide system [109] to more complex approaches that combine current, historical and estimations from the previous time intervals in different manners [78, 81, 110].

Furthermore, even when the sample of detected vehicles is big enough, when using data from AVI detectors there is a problem that arises, unlike with GPS enabled vehicles and a large part of the research attention is focused on finding solutions to this problem. This obstacle is the difficulty in differentiating noisy and unusual data from valid data. Extremely short and long observations should be eliminated from the data base to obtain more reliable estimations, but the identification of non valid data is not always immediate [86]. Because of this, some effort is put into filtering these erroneous or invalid registers such as travel times of vehicles that stop midway, duplicate entries, and observations of vehicles that travel faster than permitted [29, 78, 86, 102, 109, 110].

3.3 Estimation with Fusion of Different Data Sources

Most of the studies in the literature use only one kind of detector data as input to the model and not many studies combine different sources of data. However, lately, fusion of different type of sensors has been introduced into the travel time estimation field to increase reliability of travel time estimates [14] and to reduce sensing costs [35].

Although in the literature the term "data fusion" is used with various meanings, we will focus on data fusion from different types of traffic sensors, also denominated multi-sensor data fusion.

We will distinguish between two distinct types of fusion algorithms. The first type directly accepts input data from different sources and constructs a unique estimation model. The second type of fusion consists in constructing an estimation model for each data source by using one of the methods presented in the previous sections and finally fusing these estimates by different techniques. A graphical example of these two fusion methodologies can be seen in Figure 2.

In the first type of fusion, the direct fusion of data from different sources, methodologies such as neural networks, state space models or traffic theory based models are proposed in the travel time estimation literature.

Artificial neural networks have already been mentioned in the previous sections and used for different purposes. Regarding travel time or space mean speed estimation from different sources, in [3, 11, 68], feed forward neural networks are built with some of the input nodes corresponding to data from loop detectors and the remainder of input nodes corresponding to data obtained from probe vehicles.

Another way of fusing data from different sensors consists of a state space model similar to the presented in Section 3.1 but adapted to a multi-sensor case.

Three different types of adaptations to the multi-sensor case are observed in the literature and the first one is present in [16] and [82]. In this occasion, the control vector (u_k) in the state equation is obtained with data from loop detectors and on the contrary, the observations present in the measurement equation (y_k) are travel times or speeds obtained with the help of GPS enabled probe vehicles. The second adaptation is introduced in [3] where the information from all sources is introduced in a multivariate measurement equation in a state space system. The third type of adaptation is also introduced in [3] and is denominated the SCAAT Kalman filter. In this case the

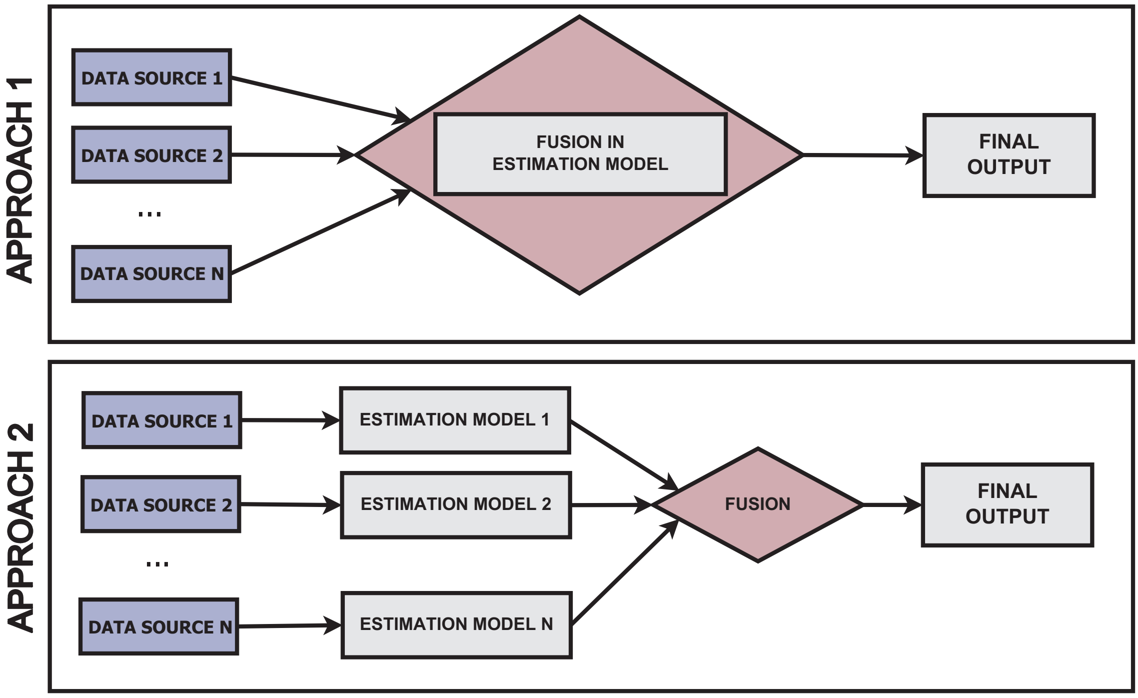

Figure 2: Travel Time Estimation from Different Data Sources

state space equation only uses the last piece of available data from all sensors. Therefore, in each step only one sensor is used and the state space model is reduced to the case of one sensor.

Finally, models based on traffic theory are not so common when the data is provided by different sources, because it is not easy to find models that accept inputs from various sensors [18]. Some isolated and distinct cases can be seen in [80], where shock wave theory is used to better estimate travel time in a urban stretch from AVI cameras and probe vehicles data; in [45], where a g-factor approach is used to combine data from single and double loop detectors and in [18], where the Moskowitz formula from kinematic wave theory is applied fusing data from loop detectors and GPS provided mobile phones.

The second type of fusion algorithms estimate travel time separately for each available sensor and then fuse these estimations using linear combinations, evidential theory or fuzzy theory.

The first way to combine estimations from different sensors is by weighted linear combination or weighted average. The weights can be calculated in different manners, but they are usually built by measuring the reliability of the estimations from each individual source and giving more weight to the most reliable sources. Some ideas for calculating these weights are proposed in [3, 14, 15].

Another methodology that is often used for fusion of estimators is evidential theory or Dempster-Shafer theory, and several attempts to apply this theory to estimation of travel time can be seen in [32, 33, 101]. Evidential theory is a generalization of Bayesian probability theory and it permits the treatment of ignorance, which is not contemplated in Bayesian theory. In the first step, the target variable must be discretized into a set of states $\{\omega_1, \omega_2, ..., \omega_n\}$ because evidential theory is only applicable to discrete variables. Next, each of the possible states or combination of states is assigned a credibility measurement on the basis of a belief function (m_i), defined differently for each source i and that indicates the credibility or degree of trust that the source has for each possible output. Different methods have been proposed to calculate these mass functions in [32, 33, 101].

Once the mass functions for each data source are well defined, Demster-Shafer theory provides a simple formula that permits the fusion of two sources of information based on the orthogonal sum of the belief functions.

A last typical approach in data fusion is the use of fuzzy set theory which allows the introduction of vagueness into the model [57]. However, in travel time estimation, this methodology is only used in [101].

3.4 Comments about the study site

To finish with the section about travel time estimation, some comments about the study site or location of the model must be made. Most of the models presented in these sections are built for highways, expressways or motorways. In essence, roads without intersections or programmed delays [74].

However, there are some authors that refer to estimation of travel time in urban roads [80, 92], where signalized and non signalized intersections are present. In these cases some authors calculate the travel time using a unique model, chosen from the ones presented in the previous sections, that calculates the sum of the cruising time and the intersection delay directly in a single model [87, 92]. On the contrary, there are other approaches that attempt to estimate travel time by modeling the cruising time and the intersection delay separately and then summing both components [11, 74]:

$$TT = T_{cruise} + T_{delay}$$

Generally, the cruise travel time is obtained with models similar to those introduced in the previous sections, and the intersection delay is calculated using delay formulas and queuing theory approaches.

4 Travel Time Prediction

The objective of the travel time prediction models is to obtain the travel time for a given departure time in the future using the traffic and contextual data available in the moment together with data from the past. Similar to estimation methods, the predictive models have to deal with the non-linear nature of traffic but in addition, they are no longer static in time and they must handle the dynamicity [72].

In the past few years the need for traffic predictions has become indispensable due to the increasing congestion in the road networks. It has been extensively proved that traffic prediction is beneficial for ATIS [120] because it provides the necessary *pre-route* and *in-route* information to schedule and choose the most adequate trajectories in each situation. Moreover, travel time has been qualified as the most suitable traffic variable for ATIS due to its high comprehensibility and intuitiveness [46].

Because of this, the prediction of this traffic variable has become a very recurrent topic in the literature of intelligent transportation systems and a vast portfolio of different methods have been presented for this goal [46]. A couple of reviews on short-term traffic prediction have been presented in the past [46, 117] but, since this paper is focused on ATIS, we will restrain the review to the variable travel time and discard the prediction of other traffic variables.

Before presenting a general taxonomy for the existing methods for travel time prediction, some clarifications must be made for better understanding.

Firstly, same as in estimation of travel time, most of the authors concentrate in the prediction of mean travel time as opposed to individual travel times. A few remote cases provide confidence intervals [65, 114] or probability distributions [36, 50] for the mean travel time but in general the authors focus on estimating a single mean value.

The second important factor to take into account is the prediction horizon concept. This refers to how far in the future the predictions are made. In general, the authors have focused their attention in short term prediction, which considers the predictions up to one hour in the future [46]. The cases where travel time is predicted for further than one hour in the future are almost non existent [59, 104] because it is difficult that these type of predictions are robust enough to be used in ATIS.

Finally, as explained in Section 2.3 the time variable is usually divided into discrete intervals, and therefore we will be referring to time intervals of length Δt instead of continuous time stamps. The time interval lengths vary from a few seconds [28] to 15 minutes [59, 128], and the prediction horizon is generally defined as the number of time steps into the future (k).

Taking into account all these factors, a typical travel time predictive model can be formulated as:

$$TT_i(t+k) = f(X(t), Y_1(1), ..., Y_{t-1}(t-1)) \tag{4}$$

where, t and $t+k$ are the number of time intervals of length Δt from the beginning of the study period and $TT_i(t+k)$ is the travel time on link i of vehicles departing at time interval $t+k$. $X(t)$ is the set of explicative variables observed at the time interval the prediction is made (t) and the set of explicative information collected in the past is expressed by $\{Y_1(1), \ldots, Y_{t-1}(t-1)\}$, starting from the first time interval until time interval $t-1$. Finally, f is the function that relates the explicative variables with the target variable.

Once a general notation for travel time prediction models is given, a taxonomy of these will be presented in the next sections. This taxonomy is schematically represented in Figure 3. The models will be classified depending on the technique used to construct the function f defined in equation 4. Estimation methods presented in the previous section are more dependent of the specific characteristics of each data source and because of this, the classification has been given based on data sources. However, the data source or typology of the input data is not so relevant in prediction methods because the data can be translated from one format to another using estimation methods. Because of this, it is interesting to categorize the prediction methods based on the type of model applied and not on the data source. Anyhow, some comments about the input data will be addressed in the last part of the section.

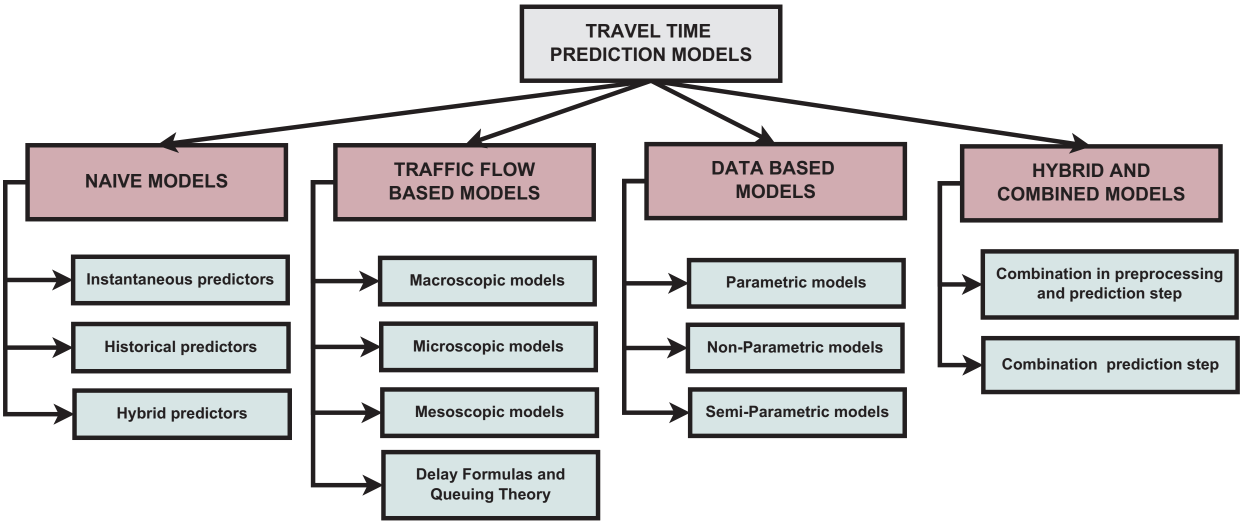

Figure 3: Travel Time Prediction Models Taxonomy

4.1 Naive Models

As the name indicates, these are the most simple and ad hoc travel time prediction methods. They do not need any training or estimation of parameters and are very simple and fast. Nevertheless, they make some very restrictive assumptions that are not fulfilled in many situations [72]. They are mainly used in commercial ATIS because of their simplicity [48, 81, 109] but in the scientific literature they are usually only used as a baseline for comparison with other more complex methods. These methods are divided into instantaneous, historical and hybrid methods, and a summary including advantages and drawbacks is available in Table 3.

Table 3: Naive Travel Time Prediction Methods

Method type	Methods	Advantages	Disadvantages
Instantaneous	Instantaneous predictors	-Simplicity -Can give good results for short prediction horizons	-Assumptions are rarely fulfilled -Weak when the prediction horizon increases
Historical	Historical predictors	-Simplicity -Can give good results for long prediction horizons	-Similarity with past conditions is required -Not good for non-recurrent congestion
Combination methods	-Exponential Filtering -Switch Models	-The assumptions are not so strong	-The weight assigned to each predictor must be chosen manually

4.1.1 Instantaneous Predictors

The first type of naive predictors are the so called "Instantaneous Predictors". These forecasting models assume that the traffic conditions in the time when the prediction is made will remain constant until the departure time in the future [46]. This can be formulated as:

$$TT(t+k) = TT(t)$$

where t is the time interval where the prediction is made.

Since estimation methods calculate the travel time of current or past journeys, in essence, any estimation method presented in the previous section could be used as an "Instantaneous Predictor" by outputting the most up-to-date travel time estimation. The most used estimation methods are the static combination and extrapolation methods presented in Section 3.1.2, because these methods do not suffer from the time delay problem.

The assumption that the traffic state will not suffer any changes becomes more and more erroneous as the prediction time horizon increases and therefore, these predictors are only reliable when the prediction is done for the near future and the traffic remains sufficiently constant [97].

4.1.2 Historical Predictors

The second type of naive predictors are the historical predictors that assume that the travel time at a certain time interval is very similar to the travel times collected at the same time in the past. The most recurrent method is to simply average all the historical travel times collected in the given time interval [97]. Slightly more complex methods further reduce the historical set by filtering by weekday, month or any other characteristic [48, 120] or weight the historical average according to the similarity of the current situation with the historical profile [48].

These methods depend greatly on the similarity in traffic conditions between current and past days and this not always occurs, especially in non-recurrent congestion situations. However, historical estimators are generally more accurate for long term prediction than the instantaneous predictors [97].

4.1.3 Hybrid methods

This third type of models combine historical and instantaneous methods in a simple way and with no need for parameter estimation. A first example is the exponential smoothing technique used in [121] and expressed as:

$$TT(t+k) = \alpha T_h + (1-\alpha) T_i$$

where α is a manually specified parameter, T_h is the historical prediction and T_i is the instantaneous prediction.

A second approach can be seen in [97] where a switch model between the two naive predictors is applied. The instantaneous predictor is applied for short term prediction while the historical predictor is applied for longer term prediction.

4.2 Traffic Theory Based Models

Traffic theory based approaches usually focus on recreating the traffic conditions in the future time intervals and then deriving travel times from the predicted traffic state and variables [72]. The most recurrent use of traffic theory based models in travel time prediction is done by using simulation tools. These simulation models can be divided into three main categories: macroscopic,

Table 4: Traffic Flow Based Travel Time Prediction Methods

Method type	Simulators	Advantages	Disadvantages
Macroscopic Simulation Models	-EMME -METANET	Good for prediction in big networks of different order	-Travel time is not obtained directly -Individual details are overlooked
Microscopic Simulation Models	-CORSIM -PARAMICS -INTEGRATION	Very detailed information can be obtained	-Computationally intensive -O-D matrices must be predicted
Mesoscopic Simulation Models	-CONTRAM -DynaMIT -DynaSMART	-Faster than microscopic models -More detailed than macroscopic models	They inherit some of the disadvantages of microscopic and macroscopic models
Delay Formulas and Queuing theory		Good for specific situations (intersections, congestion etc.)	Not very used for ATIS

microscopic and mesoscopic simulation [46]. Moreover, apart from simulation models, there are some other traffic theory based methods that must be taken into account and are more suitable for specific situations of delay and congestion: delay formulas and queue theory.

Traffic theory based models are specially advantageous for ATMS because they give very detailed information about the location and causes of delays on a road network, and they provide means for decision making in route construction and management [46]. Furthermore, they allow the representation and inclusion of crucial components in traffic modeling such as traffic lights, intersections, lanes etc. In addition, they also provide useful information for ATIS and are widely used in these systems.

The main drawback of these models is that they are in general computationally very intensive and furthermore, a high knowledge of traffic theory is necessary for their application. More specific information about each type of traffic theory based method can be looked up in Table 4.

4.2.1 Macroscopic Simulation Models

Macroscopic simulation, also called continuous flow simulation, applies equations from fluid flow theory to model the traffic by simulating aggregated traffic variables such as flow, density and mean speed in the future time intervals.

There are many equations and general relations between traffic variables that can be used for macroscopic simulation and they are categorized based on the order of the mathematical equation. These models do not generally output travel time values and therefore, these will have to be inferred using estimation methods as the ones presented in Section 3 [6, 24]. Some examples of macroscopic simulator softwares are EMME [44] and METANET [88].

The use of macroscopic models for travel time prediction is not very common in the literature because these models are mainly used for prediction of other traffic variables.

4.2.2 Microscopic Simulation Models

There are different ways to represent the distribution of traffic in a traffic network. Two typical ways are Origin-Destination (O-D) matrices, which represent the traffic flow from every possible origin to every destination, or turning volumes that represent the percentage of the traffic that turns in each direction in an intersection. Microscopic models take predictions of these O-D matrices or turning volumes as input and simulate trajectories of individual vehicles in the future time intervals, taking into account factors such as interactions between vehicles, driver behavior, lane changing, etc. [72].

Some of the models used in microscopic simulation are car-following models and cellular automaton models. The first are time-continuous ordinary differential equations which represent the behavior and trajectory of each vehicle depending on the vehicle in front. On the contrary, the second are simpler models that discretize the time and study road into small cells and move the vehicles along the cells by following some predefined rules for lane-changing and acceleration, among other factors.

As opposed to the macroscopic models, in these cases, travel times can be derived directly [72] but there is an additional task of predicting O-D matrices or turning volumes which can be done with methods similar to the ones that will be presented for travel time prediction in the next sections [75, 79].

Some microscopic simulation softwares are CORSIM [39], PARAMICS [122], and INTEGRATION [2].

4.2.3 Mesoscopic Simulation Models

These models combine the features of microscopic and macroscopic simulations models. They simulate individual vehicles, but describe their behavior and interactions based on general macroscopic relationships [46]. They are mostly used in cases of large networks where the microscopic simulation of all the vehicles is unfeasible.

Some examples of mesoscopic simulators are CONTRAM [111], which groups the vehicles into platoons and assigns the same behavior to the whole platoon , DynaMIT [4], that divides the road into cells and assigns a behavior to each cell and DynaSMART [54], where the vehicles are represented individually but the speed in each link is determined by a macroscopic speed-density function.

In this case, the prediction of O-D matrices or turning volumes is also necessary as we can see in [49].

4.2.4 Delay formulas and Queuing Theory

To finish with traffic theory based travel time prediction models, delay formulas and queue theory [132] must be mentioned. They are basically estimation methods equal to the ones mentioned in section 3.4, but they become predictive methods when the input variables are predicted values and not direct measurements.

These models are mostly used for delay prediction in urban roads in more specific situations of congestion or signalized intersections. They are widely used for optimization of signal timing and traffic management in general [30], but are not so recurrent in travel time prediction for ATIS. The reason is that they only represent specific situations and they must be used in combination with another method that predicts the cruising time for the rest of the link [74].

4.3 Data Based Models

In data based models, the function that relates the explicative variables with the target variable (f) is not obtained from traffic theory identities and relations, but instead, the structure of this function is determined either by the researcher or by the data itself by using statistical and machine learning techniques [72]. Moreover, in either case, the rest of the parameters that will fully determine the model are found by using the data.

The main advantage of these methods is that expertise in traffic theory is not required. The downsides are that usually a lot of data is needed, which is not always available, and that the models are very linked to the data and consequently to a certain study site [72]. Because of this, they are not always successfully transferable to other sites.

An outline of these methods is present in Table 5, where the advantages and disadvantages of each method are underlined.

Table 5: Data Based Travel Time Prediction Methods

Method type	Methods	Advantages	Disadvantages
Parametric models	-Linear Regression -Bayes Nets -Time Series Models	Visual and easy to understand	Too simple structures may not represent the data well
Non Parametric models	-Neural Networks -Decision Trees -Support Vector Regression	Underlying complex, nonlinear structures can be found	A lot of data is needed
Semi Parametric models	-Varying Coefficient Models	-Not so simple as parametric models -Valid for situations where non parametric models suffer from the curse of dimensionality	Structure is somewhat predefined and may not represent the data well

4.3.1 Parametric Models

In these models the ensemble of parameters that must be estimated is predefined and set in a finite dimensional space [42]. In the case of travel time prediction, this means that the structure of f is fully predetermined by the researcher but however, some parameters will be determined using the data.

The most typical parametric model is the linear regression where the target variable is a linear function of the explanatory or input variables:

$$TT = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n \tag{5}$$

The use of different sets of input variables and different techniques to estimate these parameters $(\beta_0, \beta_1, ...\beta_n)$ define the different linear regression models. Some possible input variables are traffic observations from current and past time intervals [5, 83] or more elaborate inputs such as historical and instantaneous predictors [31]. Adding context information such as the departure moment, the weekday and the weather can also be beneficial [5]. In travel time prediction, the parameter learning techniques can also vary from the common least squares approach [5, 83] to more complex entropy minimization methods [31].

The next type of parametric models are the Bayes Nets. In some cases, the conditional independences between variables, and therefore, the structure of the graph are pre-specified by an expert or by the researcher. However, as in all parametric models, a set of real valued parameters have to be estimated from the data to fully determine the model. The most simple example is the Naive Bayes model [62, 129] where it is assumed that the explanatory variables are conditionally independent, given the target variable. In some other more complex cases, the structure of the graph is not pre-specified and it is constructed by using the data [52].

A third type of parametric models for travel time prediction are time series models. Among all the existing time series models, the most common are the state space models that have been mentioned in previous sections. In the case of travel time prediction, the most typical model corresponds to the following equations:

State Equation: $TT(t+1) = \Phi_t TT(t) + w_t$

Measurement Equation: $Y(t) = TT(t) + v_t$

where TT is the hidden travel time variable to predict, Y corresponds to the travel time observations collected by the traffic sensors and w_t and v_t are white noise errors with zero mean. When linearity and normality conditions are fulfilled or assumed, this model can be solved by using a regular Kalman filter [8, 13, 60, 124]. In addition, some enhancements to this state space model are presented in [134] and [115] where the travel times of neighboring links are also taken into account when predicting travel time for a certain link.

Another type of time series models, which can also be formulated as a state space model, are ARMA models which are a combination of autoregressive (AR) and moving average (MA) models. The general formulation of an ARMA(p,q) model is:

$$TT_t - \sum_{i=1}^{p} \phi_i TT_{t-i} = Z_t + \sum_{j=1}^{q} \theta_j Z_{t-j} \tag{6}$$

where the target variable TT_t, in our case travel time at departure time interval t, is represented as a linear function of this same variable in previous time intervals ($TT_{t-1}, ..., TT_{t-p}$) and a set of white noise variables ($Z_t, ...Z_{t-q}$). The parameters of the ARMA model ($\phi_1, .., \phi_p, \theta_1, ..., \theta_q$) can be estimated with different methods [123]. An improvement of this approach is applied in [37], where a seasonal component is added to the ARMA model, obtaining a structure denominated SARIMA model.

Finally, a more unusual time series methodology is the use of non linear time series [53].

4.3.2 Non-Parametric models

In this case, the structure of the model is not predefined and therefore the shape of f is also obtained from the data. Consequently the term non-parametric does not mean that there are no parameters to be estimated, but on the contrary, it means that the number and typology of the parameters is unknown a priori and possibly infinite [46].

There are many methodologies for non parametric regression, and the most typical and recurrent in the literature of travel time prediction is the use of artificial neural networks. Many different types of neural networks have been applied for travel time prediction from regular multilayer feed forward neural networks [5, 9, 51, 65, 83, 90, 119] to more complex spectral basis neural networks [89], counter propagation networks [27], generalized regression networks [56] and recurrent neural networks [28, 70, 85]. Different input variables are used in each case depending on the availability. The training of the neural networks is commonly done by different variations of the back propagation algorithm [5, 9, 70, 89], although depending on the network type, other types of techniques might be preferable [27, 70].

Another option for travel time prediction is using regression trees [5, 83]. In travel time prediction, regression trees are trained by using top-down iterative methods, where at each iteration a set of new branches of the tree are created by choosing the explanatory variable that best divides the dataset. The choice of the explanatory variable and the division thresholds is done by using a pre-specified criterion for example the Gini Impurity or the Information Gain.

A third non parametric approach that gives very accurate results are the local regression models. The main idea of these methods is to choose a set of historical data instances which have similar characteristics to the current situation and then obtain the prediction by using a model constructed with these chosen data points [83]. Different types of local regression models appear depending on the type of technique used to fit the model to the selected historical data points [17, 83, 107]

Finally, a couple of researchers [104, 120] have used Support Vector Regression (SVR) techniques to find travel time in the future. This approach consists on mapping the input dataset into a higher dimensional space with the help of a kernel function and finding the flattest linear function that relates these modified input vectors and the target variable with an error smaller than a predefined ϵ. This linear function is mapped again into the initial space to obtain a final non linear function that is used to predict travel time. Some of the most common kernel functions used in travel time prediction are radial basis kernels and linear kernels [120].

4.3.3 Semi-Parametric models

This last case is a combination of parametric and non parametric regression schemes. The idea is to loosen some of the strong assumptions of the parametric model to obtain a more flexible structure [96]. There are many types of semi-parametric models but, in the case of travel time prediction, semi-parametric models are presented in the form of varying coefficient regression models [43]. Travel time is defined as a linear function of the naive historical (T_h) and instantaneous predictors (T_i), but the parameters vary depending on the departure time interval (t) and prediction horizon (Δ) [40, 95, 97, 131]:

$$TT(t, \Delta) = \alpha(t, \Delta)T_h + \beta(t, \Delta)T_i \tag{7}$$

In this approach, the structure of f is defined as a linear function with respect to T_h and T_i, which corresponds to a parametric model. However, the parameters α and β are defined as smooth functions of departure time and prediction horizon and have previously unknown structures, which corresponds to non-parametric models.

A enhancement of this method is presented in [50], where a log-linear regression model with varying coefficient is applied. The logarithm of the target variable is approached with a varying linear combination of the logarithms of the explanatory variables.

4.4 Combined or hybrid models

The last type of models are denominated hybrid models or combination models because they combine several models of the same or different type. The objective is to enhance the performance of each of the participant models.

As we can see in Figure 4, we will define two different types of combinations. The first initially uses a method for preprocessing the data and then applies a second method to perform the predictions. The second type of combination directly fuses a number of methods in the prediction phase.

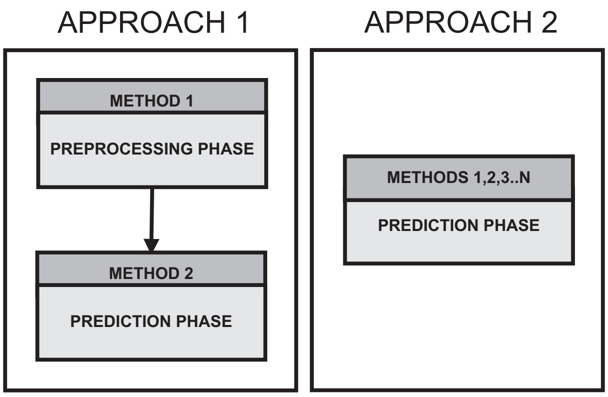

Figure 4: Travel Time Prediction with Hybrid Methods

4.4.1 Combination in preprocessing and prediction step

This type of combination consists in the consecutive use of two methods. A first method, generally data based, is applied to pre-process and simplify the input data. Then, a second method is used to obtain the predictive travel time values.

The typical approaches are clustering [64, 135], principal component analysis [28] or other methods such as rough set theory [10] in order to reduce the number of features and obtain a new and simplified set of input data. These new input vectors are later introduced in models such as neural networks [64, 135] or support vector regression [10] to calculate the predictions.

4.4.2 Combination in prediction step

This second type of combination fuses several methods in the prediction step in order to obtain more reliable predictions.

A first typical example is the use of meta-models. In this case, several models of the same type are combined by methodologies such as boosting [67], bagging [104] or Bayesian combination

[47, 114]. Some examples for travel time prediction can be seen with combinations of decision trees [104] and neural networks [47, 67].

A second strategy is the introduction of traffic theory identities or queue theory equations in the data based state-space equations to include theoretical traffic dynamics into the model [73].

Finally, a third approach is to use another data based method in the training process of a neural network. In [70, 73] extended Kalman filters are used to train neural networks. Moreover, in [56, 133] radial basis neural networks are used and these neural networks make use of clustering or other data based methods in the training phase to obtain the centers of the hidden nodes.

4.5 Comments about the input data

To finish with this section, some comments about the input data in the predictive models are necessary.

To begin with, it is important to note that most of the predictive models accept historical traffic data, current traffic data or both from a certain type of sensors situated in the target segment, as well as characteristics of the departure such as time, day of the week or month. However, the inclusion of contextual information such as weather [9, 59, 104] or data from nearby locations [129, 134] does not appear so much in the research papers and it is only approached in a few cases.

Furthermore, most of the predictive models only accept input from one type of sensor, and data fusion schemes are hardly available in the literature. A few existing examples can be found, but they are generally very simple combinations [48, 58, 69] or neural network models [64, 119].

Finally, it is important to note that the time delay problem introduced in Section 2.3 and present mostly when using AVI detectors, must really be taken into account in predictive models. When using data from AVI detectors, data is only available when the vehicles finish the trajectory and therefore, if the most recent data is used in an on line manner, the difference in the departure times of vehicles used for prediction and vehicles that will receive the prediction might be very large, especially in congested situations. A few solutions for this problem are presented in [69, 70].

5 Concluding Remarks

Travel time is a useful traffic variable, especially for ATIS, which are generally oriented to non expert users. The modeling of this traffic variable has been a recurrent topic in the scientific literature because of its utility. However, the only reviews available for this topic are restricted to predictive models. Furthermore, these reviews do not focus their attention on travel time but survey the predictive models for all the traffic variables.

In this review on the construction of travel time models, an extensive survey of all the necessary concepts when modeling travel time is done and a complete and innovative taxonomy of the existing methods for estimation and prediction of travel time is presented.

Although numerous methods exist for travel time modeling, further research is necessary to enhance their applicability in ATIS. First, it is observed that most of the methods are restricted to short road segments, usually highways or freeway stretches and not many authors refer to methods extended to whole road networks or urban roads. In second place, very few methods are able to incorporate data from different types of sensors, and in real situations the data available from a unique type of sensors might not be sufficient to represent the traffic state adequately. Finally, many of the presented methods give precise outputs in free flow conditions or even recurrent congestion, but are not so reliable in non-recurrent congestion, where the traffic state changes abruptly and erratically. These aspects are crucial to enhance the quality of an ATIS system and should be studied in future research.

To finish, it is important to note that it is difficult to choose a specific method that is reliable for all situations because many of the presented methods are site specific and not easily transferred to other zones. Therefore, a deep study must be done in each site to decide which is the most adequate model and adaptive or combined models should be taken into consideration to better adjust to the changing traffic situation.

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