



An adaptive information fusion model to predict the short-term link travel time distribution in dynamic traffic networks

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ABSTRACT

As intelligent transportation systems (ITS) approach the realm of widespread deployment, there is an increasing need to robustly capture the variability of link travel time in real-time to generate reliable predictions of real-time traffic conditions. This study proposes an adaptive information fusion model to predict the short-term link travel time distribution by iteratively combining past information on link travel time on the current day with the real-time link travel time information available at discrete time points. The past link travel time information is represented as a discrete distribution. The real-time link travel time is represented as a range, and is characterized using information quality in terms of information accuracy and time delay. A nonlinear programming formulation is used to specify the adaptive information fusion model to update the short-term link travel time distribution by focusing on information quality. The model adapts good information by weighing it higher while shielding the effects of bad information by reducing its weight. Numerical experiments suggest that the proposed model adequately represents the short-term link travel time distribution in terms of accuracy and robustness, while ensuring consistency with ambient traffic flow conditions. Further, they illustrate that the mean of a representative short-term travel time distribution is not necessarily a good tracking indicator of the actual (ground truth) time-dependent travel time on that link. Parametric sensitivity analysis illustrates that information accuracy significantly influences the model, and dominates the effects of time delay and the consistency constraint parameter. The proposed information fusion model bridges key methodological gaps in the ITS deployment context related to information fusion and the need for short-term travel time distributions.

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1. Introduction

In recent years, the increased deployment of advanced technologies such as video image processing, automatic vehicle identification, and non-intrusive sensor systems, under the aegis of intelligent transportation systems (ITS), is enabling system operators and individual travelers to access real-time traffic data from multiple sources. In parallel, a whole range of algorithms and methodologies have been proposed to estimate the real-time traffic network state and predict future conditions by leveraging the available data from multiple sources in conjunction with models of traffic flow dynamics and traveler behavior. They enable the transportation system operators to more effectively deploy dynamic traffic management and/or service systems through the development of innovative and novel solution strategies, while providing travelers capabilities for making informed real-time travel decisions. Examples of such ITS application domains include dynamic congestion pricing, real-time route guidance, vehicle-to-vehicle (V2V) communication networks, and collaborative freight systems.

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While traffic data from multiple sources can be beneficial in the ITS context, a key issue is the variability in the quality of real-time data from these sources (Kothuri et al., 2008). This variability arises due to sensor errors, sensor failures, and the type and extent of sensor deployment for different road facility types (Peeta and Anastassopoulos, 2002). The inferior data quality at different time instances and/or on different road facilities in turn affects the accuracy of the traffic information estimated by processing the sensor data. In this paper, we differentiate between data and information by defining information to be processed data. More precisely, we focus on link travel time as the information obtained by processing raw data for ITS applications. Recent field experiments (Kothuri et al., 2008; Tam and Lam, 2007) highlight the limitations of most existing link travel time estimation or prediction methods vis-à-vis the degree of accuracy. For example, inaccurate link travel time information to travelers can cause them to experience worse trip conditions than if no information were provided to them (Kothuri et al., 2008). Hence, there is a need to develop a methodology to estimate/predict link travel time information that is sensitive to the quality of data.

While data quality directly influences information accuracy, the dynamic nature of real-time traffic conditions is another dimension that significantly affects the quality of the predicted real-time traffic information. It manifests in terms of the time gap between when data is collected and when it is used to generate traffic information, and is labeled as the time delay. That is, in addition to the historical link travel time information (up to the current day), the data collected on the current day is used to estimate current conditions or predict future conditions. Hence, larger time delays in the context of dynamic traffic networks can imply that the corresponding data may be less representative of the current traffic conditions. For the same reason, it is more meaningful to predict traffic conditions for the near-term future (short-term) rather than for the medium- or longer-term future in a given time horizon of interest. In this paper, we focus on predicting the short-term link travel time information by characterizing real-time link travel time information in terms of information quality which is represented through information accuracy and time delay.

The third dimension related to real-time information prediction for ITS applications is the effect of stochasticity inherent to dynamic traffic networks. Randomness arising in the context of the supply, demand, and performance elements of the dynamic traffic network, has led to an increasing focus on the reliability of link travel time (Dong and Mahmassani, 2009; Hollander and Liu, 2008; Kaparias et al., 2008; Rakha et al., 2006), rather than on predicting a single measure of link travel time (such as the mean travel time). This issue has also found resonance in practice as ITS technologies, leveraged through novel and/or more refined solution paradigms, are approaching the realm of widespread deployment. To address it, some studies in recent years (Rakha et al., 2006) have sought to capture the variability of travel time by estimating its variance. However, without assumptions on the link travel time distribution, even this capability provides only a limited ability (van Lint et al., 2008) to exploit the stochastic characteristics of dynamic link travel times for developing a new generation of robust solution strategies that can explicitly incorporate such characteristics. Consequently, there is a need to predict dynamic link travel time distributions. For reasons discussed in the previous paragraph, this implies the need for short-term link travel time distributions. However, the existing literature primarily focuses on long-term link travel time distributions which capture the daily or seasonal variability in link travel time (Hollander and Liu, 2008; Anantharam, 1998). Other studies (He et al., 2002) suggest that normal or log-normal distributions are not representative of short-term link travel time distributions. This study seeks to develop an information fusion model that combines past and real-time traffic information to predict discrete short-term link travel time distributions for use in various ITS application domains, for links equipped with detectors.

The remainder of this paper is organized as follows. The next section briefly reviews previous literature on forecasting models and data fusion techniques for predicting the short-term link travel times. Then, some preliminaries, including notation and definitions, are discussed for the information fusion model to predict the short-term link travel time distribution. The associated mathematical formulation is presented in next section. This is followed by the description of the experimental setup of the numerical experiments, and the associated results. The final section provides some concluding comments.

2. Literature review

Past literature on the estimation of the short-term link travel time distribution is sparse. He et al. (2002) analyze the temporal and spatial short-term link travel time distribution using simulated travel time data. They conclude that due to the complexity associated with real-world travel time distributions, histograms representing empirical distributions based on sampled data may provide a robust mechanism to describe the short-term link travel time distributions. However, they do not specify a rigorous method to generate such histograms. Fei et al. (2011) propose a Bayesian inference-based dynamic linear model for predicting route travel time by combining an *a priori* known initial distribution and real-time traffic information. They predict the *a posteriori* route travel time distribution in terms of the variation of travel time around its historical median. Hence, determining short-term link travel time distributions is not a focus of their study, nor is information quality considered. A few past studies (Dany and McBean, 1984; Polus, 1979) focus on addressing the long-term link travel time distribution, and suggest that it could be represented using the normal or log-normal distribution. However, long-term link travel time distributions do not capture the variability of the link travel time in the short-term (He et al., 2002). The proposed study is among the first to analytically address the determination of the short-term link travel time distributions.

While there are few studies on modeling link travel time distributions, there is an extensive literature on short-term link travel time prediction (Vlahogianni et al., 2004; Lin et al., 2005; Krishnan and Polak, 2008). Since our study uses both past and real-time information, we will briefly review the literature on short-term link travel time prediction that uses data fusion techniques. These studies are broadly categorized into parametric and non-parametric models (Vlahogianni et al., 2004).

Non-parametric models, such as artificial neural network techniques (Park et al., 1999; Dia and Berkum, 2001; van Lint, 2006) and k -nearest neighbor algorithms (Smith et al., 2002; Clark, 2003; Bajwa et al., 2005), have been used to predict short-term link travel times by fusing historical and real time data (Smith et al., 2002). However, these models are better-suited to predict link travel time as a discrete value than a discrete distribution. In addition, though these models can deal with imprecise data, they usually do not account for data errors related to time delay, a key issue for operational strategies for dynamic traffic networks. Therefore, they have limitations in modeling the short-term link travel time distributions proposed in this study.

Parametric models have also been used to predict the short-term link travel time. They include regression models (linear, nonlinear, local weighted regression model, etc.) (Zhang and Rice, 2003; Wunderlich et al., 2000; Wu et al., 2003), autoregressive integrated moving average (ARIMA) family of models (Oda, 1990; Yang, 2005), and Kalman filter models (van Lint, 2008; Chen and Chien, 2001; Yang et al., 2004; Chien and Kuchipudi, 2003; Nanthawicit et al., 2003). These studies either integrate real-time and historical data, or combine data from multiple sources such as probe vehicles, loop detectors, automatic vehicle identification, and other traffic detectors. However, parametric models primarily explore the functional linkages between the output and input factors, which is not meaningful in the context of determining the discrete short-term link travel time distribution. Further, they are sensitive to data quality, and typically cannot deal with data sets with missing values or poor accuracy (Vlahogianni et al., 2004; Tu, 1996), which are possible in the context of the current study. Therefore, parametric models have gaps relative to modeling short-term link travel time distributions.

In summary, existing short-term link travel time prediction models using data fusion techniques are either insufficient or have limitations in predicting the short-term link travel time distributions. To address these methodological gaps, this study develops an information fusion model which determines the short-term link travel time distribution by combining past information on link travel time on the current day represented as a discrete distribution with the real-time link travel time information incorporating information quality represented by time delay and information accuracy. The long-term historical link travel time distribution is used as an initial solution for the distribution of the past link travel time information on the current day. The short-term link travel time distribution provides a mathematical tool to analyze link travel time reliability, and hence can significantly aid operational strategies for dynamic traffic networks in ITS application domains such as real-time route guidance, dynamic congestion pricing, and stochastic routing.

3. Preliminaries

This section introduces the notation and definitions associated with the formulation of the information fusion model. The road traffic network is represented as a directed graph $G(N, A)$, where the nodes correspond to intersections and the arcs correspond to road links. Let N be the set of all nodes and A be the set of all links. The notation includes: (i) a, b, c, d, e : indices for links, (ii) i, j, k, g : indices for link travel time states, (iii) r : superscript representing real-time information, (iv) h : superscript representing past information on the current day, (v) β : superscript representing long-term historical information, and (vi) f : superscript representing information fusion. Other notation will be defined when first introduced.

The time duration of interest is divided into time intervals $t = 1, \dots, T$. The study considers the actual (ground truth or field) travel time on link a for time interval t , $c_a(t)$, as a random variable whose short-term variability is represented by a time-dependent discrete distribution (histogram) $\varphi(c_a(t))$, implying various states (denoted by discrete travel time ranges which need not be uniform) with associated probabilities. Thereby, the random variable $c_a(t)$ has the possible set of states $\{s_a^i(t) = [l_a^i(t), u_a^i(t)]\}_{i=1}^{I_a^t}$, where $l_a^i(t)$ and $u_a^i(t)$ denote the lower and upper bound values of the travel time range corresponding to state i , respectively, and I_a^t is the number of states of the discrete travel time distribution for link a for time interval t . Each travel time state i for link a at time t is associated with probability $p_a^i(t)$.

3.1. Long-term link travel time distribution

The discrete long-term historical travel time distribution $\varphi^\beta(c_a)$ for a link is obtained from the historical data for the link travel time c_a for the network. The corresponding probability mass function (or histogram) is as follows:

$$\varphi^\beta(c_a) = [s_a^{\beta i}, p_a^{\beta i}]_{i=1}^{I_a^\beta}, \quad a \in A, \quad (1)$$

$$s_a^{\beta i} = [l_a^{\beta i}, u_a^{\beta i}].$$

Based on the definition of the travel time state, the link travel time in each state i obeys a continuous uniform distribution. Correspondingly, the long-term historical mean and variance of the link travel time can be calculated using (2)–(4):

$$E(c_a^i) = \frac{u_a^{\beta i} + l_a^{\beta i}}{2}, \quad (2)$$

$$E(c_a) = \sum_{i=1}^{I_a^{\beta}} p_a^{\beta i} E(c_a^i), \quad (3)$$

$$\sigma_a = \sqrt{\sum_{i=1}^{I_a^{\beta}} \int_{l_a^{\beta i}}^{u_a^{\beta i}} (x - E(c_a))^2 p_a^{\beta i} dx}. \quad (4)$$

The long-term historical distribution can be updated over a longer time period (day-to-day, weekly, monthly, etc.) which would depend on the requirements of the problem being addressed.

3.2. Real-time link travel time information

Based on the discussion on information quality in Section 1, the real-time link travel time is represented in this study by an estimated travel time range, $c_a^r(t) = [l_a^r(t), u_a^r(t)]$, rather than a single value, and is obtained by processing the raw data. The information representing the real-time link travel time consists of three components: (i) $c_a^r(t)$, (ii) a time-dependent probability $p_a^r(t)$ representing the information accuracy, and (iii) a scalar value Δt representing the time delay.

Information accuracy $p_a^r(t)$ is defined as the conditional probability that the estimated real-time link travel time range belongs to state i given that the actual link travel time $c_a(t)$ belongs to state i .

$$p_a^r(t) = p(c_a^r(t) \in s_a^i(t) | c_a(t) \in s_a^i(t)), \quad i = 1, \dots, I_a^r. \quad (5)$$

Without loss of generality, we assume that the probability that the estimated real-time link travel time range is not in state i given that the actual link travel time $c_a(t)$ belongs to state i , is uniformly distributed among all the remaining states j :

$$p(c_a^r(t) \in s_a^j(t) | c_a(t) \in s_a^i(t), j \neq i) = \frac{1 - p_a^r(t)}{I_a^r - 1}. \quad (6)$$

This assumption does not restrict the proposed information fusion methodology, described in Section 4.2.2. In practice, one can obtain the distribution from field data, and then the probabilities represented by Eq. (6) can be obtained using that distribution.

Following up on the definition earlier, the time delay (Δt) is the time interval between the time stamp at which link travel time data is collected and the time stamp at which the real-time link travel time information is generated.

4. Information fusion model

This study proposes an information fusion model that analytically integrates the long-term historical and past link travel time distributions with real-time link travel time information as part of an adaptive process to dynamically update the short-term link travel time distribution. This section first presents the methodology as an adaptive process, followed by a detailed mathematical exposition of the information fusion model.

4.1. Adaptive process to generate short-term link travel time distribution

The time-dependent short-term link travel time distribution is generated through an adaptive update process over time on a given day at the discrete time intervals when real-time travel time information becomes available based on sampling detector data for a link. We label the short-term distribution available up to the current time interval on a given day as the past link travel time distribution. The long-term historical link travel time distribution is the starting point on a given day to determine the short-term distribution, and as such, represents the initial past link travel time distribution for that day. When the real-time link travel time information is available for a time interval, it is combined with the past link travel time distribution to obtain the updated short-term distribution. The updated short-term distribution then becomes the past link travel time distribution for future time intervals. This process continues iteratively over time for the duration of interest on that day during the time intervals that new real-time link travel time information becomes available. The information fusion model is used to determine the weights used to combine the past link travel time distribution and the real-time information. These weights are determined so as to minimize the uncertainty associated with determining the actual short-term link travel time distribution. That is, the proposed information fusion model identifies weights in each update process so that the occurrence of travel time states not reinforced by the real-time travel time information can be avoided or reduced in the predicted short-term travel time distribution. Mathematically, this idea is realized by minimizing Shannon's information entropy (Shannon, 1948), which is a measure of the uncertainty associated with a random variable in information theory.

4.2. Information fusion model formulation

The first step in developing the information fusion model is to relate the real-time travel time range to the states of the discrete distribution of the past link travel time. This is followed by a conceptual discussion of the mechanism to fuse them. Finally, a nonlinear programming formulation is proposed for the information fusion model that determines the associated weights. Since each fusion (update) process represents a time step over a time interval (t), the rest of this section does not include t in the mathematical exposition for analytical convenience.

4.2.1. Relating past and real-time information

The complexity for the proposed information fusion arises because the past link travel time information is represented as a discrete distribution while the real-time travel time information is provided as a travel time range associated with the information quality. Thereby, from the perspective of the information format, the proposed problem is to fuse a discrete distribution and a confidence interval with time delay.

Fig. 1 illustrates the six possible cases that represent the relationship between the past travel time states and the real-time travel time range on a link. Cases 1–3 represent situations when the real-time travel time range is fully covered by the states of the past travel time distribution. Cases 4–6 represent situations where some or all of the real-time travel time range is not contained in the set of past travel time states.

From an analytical standpoint of the information fusion procedure, Case 1 represents the most straightforward situation as the real-time travel time range is covered by exactly one or more of the past travel time states:

$$\varphi(c_a^r) = [l_a^r, u_a^r]; \quad l_a^r = l_a^{hi}, \quad \text{and} \quad u_a^r = u_a^{hj}, \quad \forall i, j \in I_a, \quad a \in A. \quad (7)$$

This is because it is consistent with the methodology to be discussed in Section 4.2.2 for the information fusion step. Hence, a key conceptual step in relating the past and real-time information is the mapping of the other five cases to Case 1. As will be illustrated in Section 4.2.4, for Cases 2 and 3, this is done by introducing additional states in the past travel time distribution such that the relevant boundaries of the newly introduced states coincide with those of the real-time travel time range; that is, they map to Case 1.

For Cases 4–6, one or more boundaries of the real-time travel time range are outside the set of states of the past travel time distribution. From a real-world perspective, it implies that a new outlier for the relevant link travel time is observed, which has not been historically observed based on a substantial database of previously-collected data. In these situations, an additional step is performed so that they become similar to Cases 2 and 3, and then they are mapped to Case 1. In this step, new states are added to the past travel time distribution so that their relevant boundaries coincide with those of the travel time range that are not previously covered by the states of the past travel time distribution. Then, they become conceptually similar to Cases 2 and 3, and can be mapped to Case 1. A key difference from Cases 2 and 3 is that, before the fusion step, the newly added states have zero probabilities in the past travel time distribution. This is again consistent with the real-world because new outliers do not entail the same weight in updating the likelihoods of travel time values as those that have been observed over a longer history. More broadly, over a long period of time, the likelihood of Cases 4–6 is substantially reduced

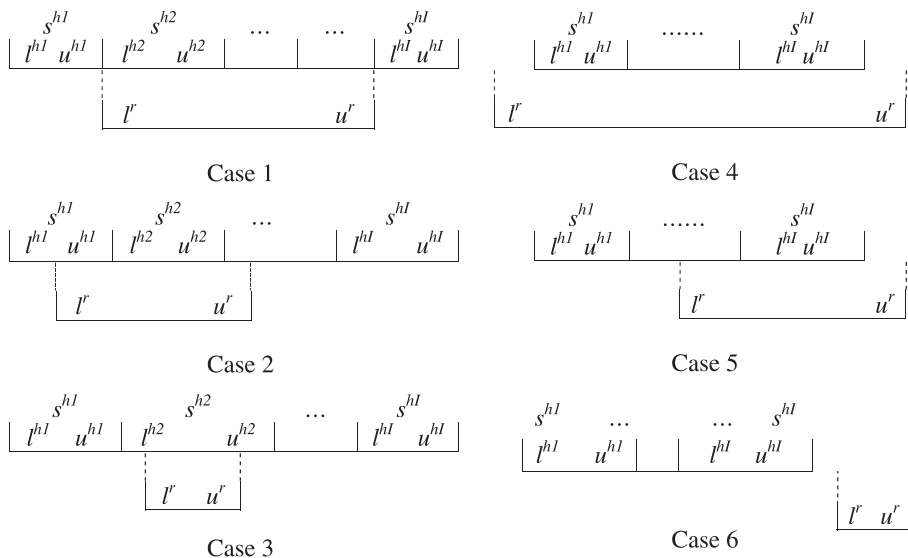


Fig. 1. Relating past travel time distribution and real-time travel time information.

as the database of travel times becomes more comprehensive. Hence, the proposed methodology for information fusion is synergistic with real-world applicability.

4.2.2. Information fusion methodology

Based on the discussion heretofore, the information fusion methodology and the model formulation will be illustrated first for Case 1. Later, the mapping of Cases 2 or 3 to Case 1 is illustrated along with how the formulation for Case 1 can be adapted for them. The key concept of the proposed information fusion methodology is that once the boundaries of the real-time travel time range coincide with those of the relevant states in the past travel time distribution, the probability of each state i of the short-term link travel time distribution for link a , p_a^i , is obtained by combining the past state probability p_a^{hi} and the real-time posterior travel time state probability q_a^i , which is derived from the accuracy of the real-time travel time information, p_a^r . This idea is illustrated in Fig. 2.

Mathematically, the information fusion methodology is represented by the following equations:

$$p_a^i = x_a^i p_a^{hi} + (1 - x_a^i) q_a^i \quad \forall i \in I_a, \quad a \in A, \quad (8)$$

$$\begin{aligned} q_a^i &= p(c_a \in s_a^i | c_a^r \in s_a^i) = \frac{p(c_a \in s_a^i, c_a^r \in s_a^i)}{p(c_a^r \in s_a^i)} = \frac{p(c_a^r \in s_a^i | c_a \in s_a^i) p(c_a \in s_a^i)}{p(c_a^r \in s_a^i | c_a \in s_a^i, j \neq i) p(c_a \in s_a^i, j \neq i) + p(c_a^r \in s_a^i | c_a \in s_a^i) p(c_a \in s_a^i)} \\ &= \frac{p_a^r p_a^{hi}}{p_a^r + p_a^{hi}}, \quad a \in A, \end{aligned} \quad (9)$$

$$\begin{aligned} p_a^r &= p(c_a^r \in s_a^i | c_a \in s_a^i, j \neq i) p(c_a \in s_a^i, j \neq i) = \sum_{j \neq i} p(c_a^r \in s_a^i | c_a \in s_a^j) p(c_a \in s_a^j) = \sum_{j \neq i} \frac{1 - p_a^r}{I_a - 1} p(c_a \in s_a^j) \\ &= \frac{1 - p_a^r}{I_a - 1} \sum_{j \neq i} p(c_a \in s_a^j) = \frac{1 - p_a^r}{I_a - 1} (1 - p_a^{hi}). \end{aligned} \quad (10)$$

Here q_a^i , the real-time posterior state probability, is the probability that the actual travel time is in state i given that the real-time travel time range estimates it to be in state i . Eqs. (6) and (9) are used in the derivation of q_a^i .

Eq. (8) is a convex combination which is a standard information fusion technique used for travel time estimation. Eqs. (8)–(10) illustrate that p_a^i can be obtained using mostly known quantities and parameters (p_a^{hi} , p_a^r , and I_a). The only unknowns are the weights x_a^i . Most studies in this domain typically assign fixed empirical values for the weights independent of the evolving dynamic traffic conditions. The information fusion model developed in this study proposes a nonlinear programming formulation to determine the optimal weights so as to minimize the uncertainty associated with determining the actual short-term link travel time distribution, represented using Shannon's information entropy (Shannon, 1948).

The determination of the weights is also linked across links, by relating the weights x_a^i to information quality in terms of the real-time information accuracy and time delay, as shown in Eq. (11). The weight of the past travel time distribution for link a for state i , x_a^i , is assumed to be directly proportional to the real-time information time delay, Δt_a , and inversely proportional to the variability in link travel time, σ_a , and the accuracy of real-time information, p_a^r .

$$x_a^i \propto \frac{\Delta t_a}{\sigma_a p_a^r}. \quad (11)$$

These assumptions are consistent with the role played by each variable of the RHS of Eq. (11). The information fusion among different links is unified by assuming that all links possess the same closed-form expressions represented by Eq. (11), and manifests as constraint (18) in the formulation M1 discussed in Section 4.2.3.

Another aspect to address is that the information fusion formulation should update the short-term link travel time distribution in a consistent manner; that is, the distribution should not be oversensitive to single instances of real-time information measurements or fluctuate wildly from one time step to the next. To address this issue, as illustrated in Fig. 3, the study considers the probability of each travel time state i on a link, p_a^i , as a random variable, whose variation obeys a normal distribution with the mean equal to the long-term historical probability of the travel time state, p_a^{hi} , and the variance θ_a^i

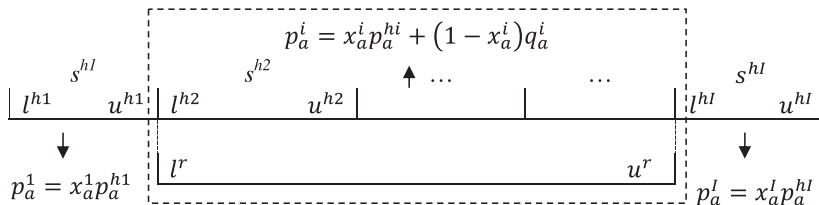


Fig. 2. Information fusion for Case 1.

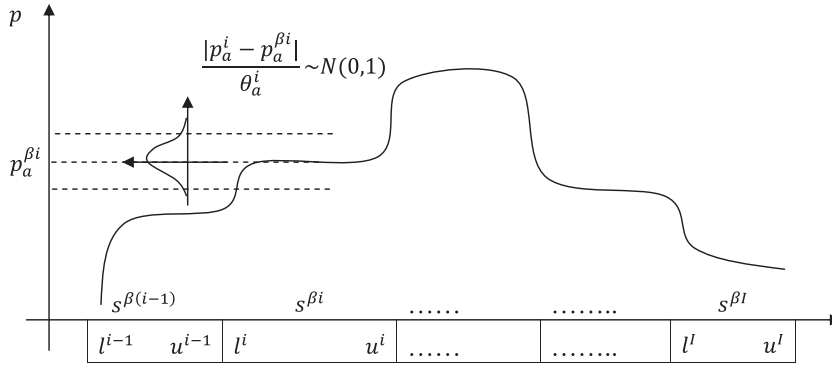


Fig. 3. Mechanism to ensure consistency in the update of the travel time distribution.

obtained from the collected sets of past data.¹ The range of the adjustment through the information fusion formulation in a time step is designed to be within a confidence interval with the significance level² α . It is equal to $P\left(\frac{|p_a^i - p_a^{\beta i}|}{\theta_a^i} \leq z_{\frac{\alpha}{2}}\right) = 1 - \alpha$. Labeled the consistency constraint, it is represented as Constraint (19) in formulation M1. It is expressed as follows:

$$\frac{|p_a^i - p_a^{\beta i}|}{\theta_a^i} \leq z_{\frac{\alpha}{2}}, \quad \forall i \in I_a, \quad a \in A. \quad (12)$$

Without loss of generality, the aforementioned distribution can have another form rather than a normal distribution, depending on the characteristics of the data for the links of a specific network.

4.2.3. Nonlinear programming formulation

We assign indices $g_a = \min\{i | s_a^i \in [l_a^r, u_a^r]\}$ and $k_a = \max\{i | s_a^i \in [l_a^r, u_a^r]\}$ for links in Case 1. Using the past link travel time distribution and real-time link travel time information (c_a^h and c_a^r) as input parameters, the information fusion model is formulated as the nonlinear program M1.

$$\text{M1} \quad \min \sum_{a=1}^A \sum_{i=1}^{I_a} (-p_a^i \log p_a^i), \quad (13)$$

$$\text{s.t.} \quad p_a^i = x_a^i p_a^{hi} + (1 - x_a^i) q_a^i, \quad \forall i \in [g_a, k_a], \quad a \in A, \quad (14)$$

$$p_a^i = x_a^i p_a^{hi}, \quad \forall i \notin [g_a, k_a], \quad i \in I_a, \quad a \in A, \quad (15)$$

$$x_a^i \geq 0, \quad \forall i \in [g_a, k_a], \quad a \in A, \quad (16)$$

$$x_a^i \leq 1, \quad \forall i \in [g_a, k_a], \quad a \in A, \quad (17)$$

$$x_a^i - x_b^{i'} \geq 0, \quad \forall \frac{\Delta t_a}{\sigma_a p_a^{hi}} \geq \frac{\Delta t_b}{\sigma_b p_b^{hi}}, \quad i \in [g_a, k_a], \quad i' \in [g_b, k_b], \quad a \neq b \in A, \quad (18)$$

$$|p_a^i - p_a^{\beta i}| / \theta_a^i \leq z_{\alpha/2}, \quad \forall i \in I_a, \quad a \in A, \quad (19)$$

$$\sum_{i=1}^{I_a} p_a^i = 1, \quad \forall a \in A, \quad (20)$$

$$p_a^i \geq 0, \quad i \in I_a, \quad \forall a \in A. \quad (21)$$

The nonlinear program M1 has a concave objective function and linear constraints. x_a^i and p_a^i are the decision variables. The objective function (13) is based on Shannon's information entropy. It aims to minimize the uncertainty associated with determining the actual short-term link travel time distributions. Constraints (14) and (15) update the probabilities of link travel time states that are, respectively, covered or not covered by the real-time link travel time information. Constraints (16) and (17) ensure that the probabilities of all link travel time states updated by the information fusion formulation satisfy the basic properties of probability. Constraint (18) illustrates the linkage of the information fusion among different links as discussed earlier; links with better real-time information have smaller weights for past travel time distributions, and vice versa. Constraint (19) ensures consistency of the update process, as discussed previously. Constraints (20) and (21) ensure the basic properties of probability.

¹ We briefly introduce the process as follows: Collect multiple sets of historical data. Each data set provides one value for the probability of a travel time state, and multiple sets of historical data provide a sample set of the probability of a travel time state. Then, calculate the sample mean and variance of the probability of the travel time state.

² Consider the hypothesis, $H_0: E(p_a^i) = (p_a^{\beta i})$, $H_1: E(p_a^i) \neq p_a^{\beta i}$. The significance level is the maximum probability of rejecting H_0 when H_0 is true.

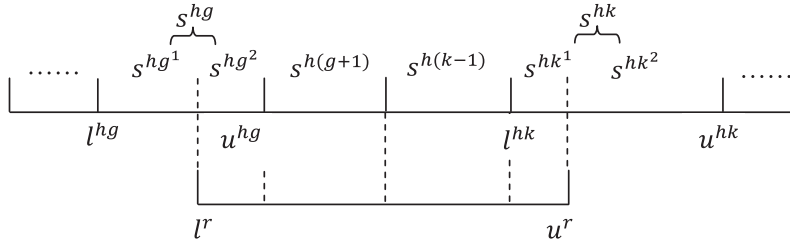


Fig. 4. Method for converting Case 2 to Case 1.

The nonlinear program M1 is characterized by a concave objective function and a set of linear constraints that define a compact convex feasible region. Hence, it belongs to the class of concave minimization problems. While this problem is NP-hard (Pardalos and Schnitger, 1988), the existence of an optimal solution has been proved by Hoffman (1981). In addition, as one of the oldest and best-studied problems in global optimization, this problem has been extensively addressed in the literature. Many algorithms, such as the pure cutting plane, partitioning, branch-and-bound algorithms and some approximate algorithms have been proposed (see Benson, 1985; Falk and Hoffman, 1986; Pardalos and Rosen, 1986; Porembski, 2004 and many references therein) to address moderate- and large-sized problems in this context. In this study, we use the commercial software GAMS and its CONOPT solver to solve the problem for the numerical experiments discussed in Section 5.

4.2.4. Converting Case 2 or Case 3 to Case 1

In situations that correspond to Cases 2 or 3 in Fig. 1, as discussed earlier, new states are created such that the associated boundaries in the past travel time distribution coincide with the relevant boundaries of the real-time travel time range. It is illustrated for Case 2 in Fig. 4. The real-time travel time range is decomposed into several sub-ranges such that the real-time information can be represented by the distribution in Eq. (22):

$$\varphi(c_a^r) = [[l_a^r, u_a^r], p_a^r] = \left\{ [[l_a^{hg}, u_a^{hg}], p_a^{hg}], [[l_a^{h(g+1)}, u_a^{h(g+1)}], p_a^{h(g+1)}], \dots, [[l_a^{hk}, u_a^{hk}], p_a^{hk}] \right\}, \quad (22)$$

where $g = \{i | l_a^r \in s_a^i\}$, $k = \{i | u_a^r \in s_a^i\}$. Based on the assumption stated earlier that c_a^h follows a uniform distribution within each state, we further decompose the corresponding past state at the lower end $[[l_a^{hg}, u_a^{hg}], p_a^{hg}]$ into two states:

$$(g^1) : \left[[l_a^{hg}, l_a^r], p_a^{hg} \frac{l_a^r - l_a^{hg}}{u_a^{hg} - l_a^{hg}} \right], \quad (23)$$

$$(g^2) : \left[[l_a^r, u_a^{hg}], p_a^{hg} \frac{u_a^{hg} - l_a^r}{u_a^{hg} - l_a^{hg}} \right]. \quad (24)$$

The newly-created state is $g^1 : [l_a^{hg}, l_a^r] = [l_a^{hg^1}, l_a^r]$. The past travel time distribution state at the other end $[[l_a^{hk}, u_a^{hk}], p_a^{hk}]$ is decomposed into the two states below:

$$(k^1) : \left[[l_a^{hk}, u_a^r], p_a^{hk} \frac{u_a^r - l_a^{hk}}{u_a^{hk} - l_a^{hk}} \right], \quad (25)$$

$$(k^2) : \left[[u_a^r, u_a^{hk}], p_a^{hk} \frac{u_a^{hk} - u_a^r}{u_a^{hk} - l_a^{hk}} \right]. \quad (26)$$

Hence, for Case 2, minor modifications include changing the state set I_a to $I_a' = \{I_a \setminus \{g_a, k_a\}\} \cup \{g_a^1, g_a^2, k_a^1, k_a^2\}$ and correspondingly modifying the associated probabilities. In this manner, Case 2 is mapped to Case 1, and the formulation M1 can then be applied. Similar procedures can be used for Cases 3–6 to map them to Case 1.

5. Numerical experiments

The performance of the proposed information fusion model is investigated using numerical experiments. This section describes the experimental setup and discusses the numerical results. As field data is not available, the DYNASMART simulator is used to generate the traffic data for analyzing the performance of the information fusion model. Hence, the link travel times and the associated distributions in each time interval in the simulation are, respectively, assumed to represent the actual link travel times and the associated distributions for analyzing the capabilities of the information fusion model. In the real-world, the actual travel times (and, consequently, the distributions) may not be known as the raw detector data may not be accurate (detector errors) or representative of the true value (variability in vehicle speeds). The ability of the information

fusion model to predict the actual short-term link travel time distribution is analyzed in terms of accuracy, consistency, and robustness. The sensitivity of the model to time delay and the consistency constraint parameter α is examined.

5.1. Experimental setup

The study network is the Borman Expressway network in northwest Indiana (shown in Fig. 5), which consists of a 16 mile segment of I-80/94, the I-90 toll freeway, I-65, and the surrounding arterials. The network has 197 nodes and 458 links. While the simulation is performed for the entire Borman Expressway network, the link travel time data for the 19 links enclosed by the dotted lines in Fig. 5 is used to analyze the performance of the information fusion model.

The DYNASMART simulator is used to simulate the dynamic traffic conditions on the Borman Expressway network for a 90-min duration on each day of a 55-day period using origin–destination demand that is randomly generated for each day based on pre-specified demand distributions. The link travel time data for the 19 links is collected for the 90-min duration. The data for the first 50 days is used to generate the long-term historical link travel time distribution for each link. Travel time data from one among the remaining 5 days is randomly used to provide real-time information for each link every 2 min from time point 30 min to time point 70 min (the start-up and end effects are excluded) for various experiments; that is, each experiment uses data from one among those 5 days.

Using the GAMS/CONOPT solver on a computer with configuration: 4.0 GB RAM, Intel(R) Core(TM)i3 (64-bit) M330@2.13 GHz processor, it takes 0.05 s execution time, on average, to solve the nonlinear information fusion formulation and update the short-term travel time distribution in a time step for the 19-link study area.

The long-term historical link travel time distributions and the real-time link travel time information are synthetically generated from the simulated data as described hereafter.

5.2. Generation of long-term distribution and real-time information

To generate the synthetic long-term link travel time distribution composed of the travel time states and their probabilities as defined in Section 3.1, the study clusters the simulated link travel time data into different travel time states by dividing the range of this travel time data (the interval between the minimum and maximum travel time) using a time interval of a fixed length. The probability of each state is estimated as the ratio of the number of travel time data points that fall within a travel time state to all the travel time data points obtained from the simulation data for the first 50 days. Travel time states can vary across individual links.

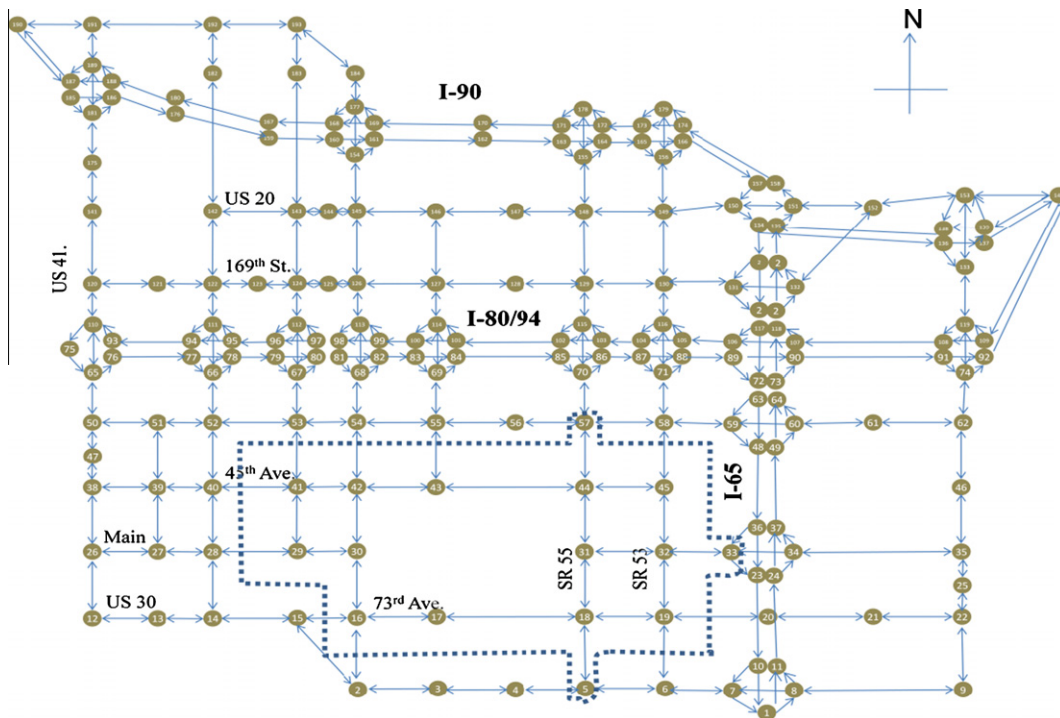


Fig. 5. Borman Expressway network.

The real-time information, represented using a travel time range $[l_a^r, u_a^r]$, time delay (Δt_a) and information accuracy (p_a^r), as discussed in Section 3.2, is generated synthetically as follows. For any time t for link a , the time delay (Δt_a) and information accuracy (p_a^r) are first randomly generated. As stated earlier, the simulated data is assumed to represent the actual travel time value for time t for link a . Correspondingly, the travel time state including the actual travel value is considered as the actual travel time state. The travel time range $[l_a^r, u_a^r]$ is determined using a set of steps based on replicating two random scenarios that can occur in the real world: (i) the range contains the actual travel time value, and (ii) the range does not contain the actual travel time value. More specifically, a random value v is used to simulate these two scenarios. If $v < p_a^r$, a real-time travel time interval $[l_a^r, u_a^r]$ covering the actual travel time value at time $(t - \Delta t_a)$ is generated using the travel time states in the previous short-term distribution as a benchmark for the collected raw field data. If $v > p_a^r$, a real-time travel time interval $[l_a^r, u_a^r]$ outside the actual travel time state is generated.

5.3. Performance evaluation

5.3.1. Accuracy

Accuracy manifests as the ability of the predicted short-term link travel time distribution to approach the actual short-term link travel time distribution. It is examined by tracking the predicted short-term link travel time distribution across different time steps for a day.

For the purpose of deriving insights from the experiments, an issue in this context is the quantification of the actual short-term link travel time distribution using the simulated data. While the predicted short-term distribution is obtained using the information fusion model, and accounts for information quality in terms of information accuracy and time delay, the “actual” short-term distribution is based on using the simulated data directly. Hence, an interesting question arises as to what would represent the actual short-term distribution for the experiments. There are two factors that trade-off in the determination of this distribution. First, data from a small time duration may not have sufficient data point to provide a stable distribution. Second, if data over a large time duration were used, it may not be representative of the short-term distribution in the near

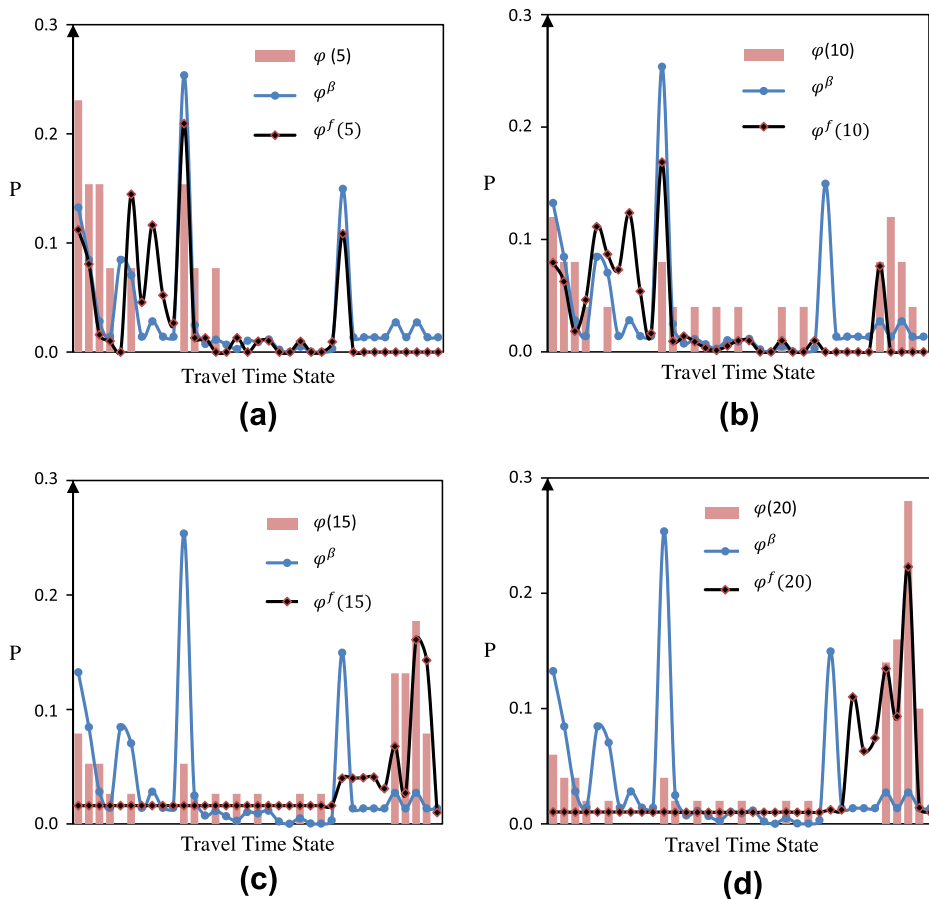


Fig. 6. Travel time distributions on a link. $\varphi(*)$: Actual link travel time distribution from time step 1 up to time step $*$; φ^β : Long-term historical link travel time distribution; $\varphi^f(*)$: Short-term link travel time distribution in time step $*$.

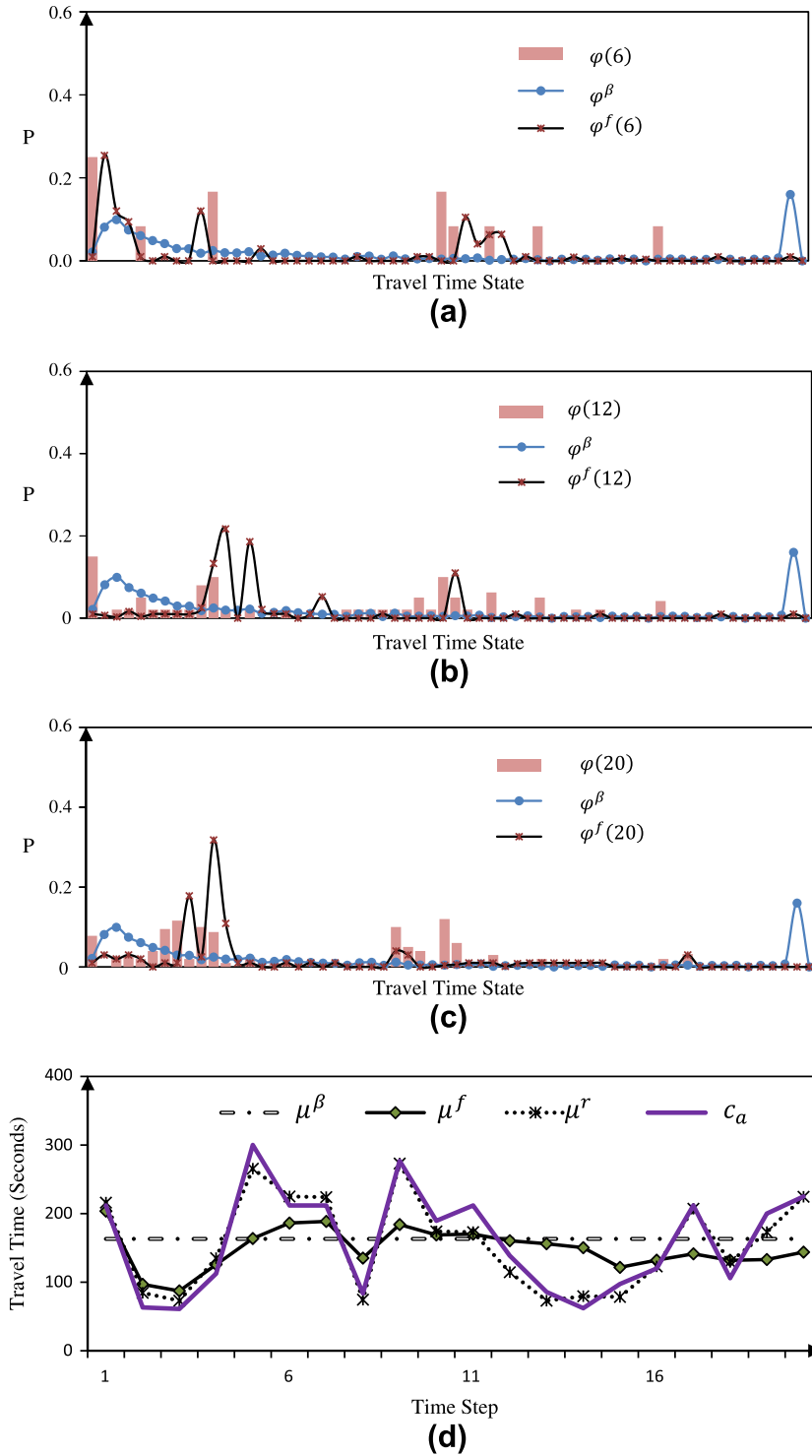


Fig. 7. The results when the consistency constraint is considered.

term depending on the dynamics of traffic flow conditions. Hence, accuracy is analyzed here (Fig. 6) in terms of how well the predicted short-term distribution captures the trend of the “actual” short-term distribution.

Fig. 6 compares the probability mass functions of the long-term historical and actual travel time distributions at different time steps for a randomly selected link with the corresponding short-term travel time distributions. The x-axis represents various discrete travel time states, with the states further from the origin implying higher travel time ranges. While the

actual travel time distribution is shown as a histogram, the other two are illustrated as continuous lines that join the corresponding discrete points for visual convenience when comparing the three distributions.

In Fig. 6, the long-term historical distribution is aggregated over the time period from 30 min to 70 min over data from the 50 days; hence, it does not change within a day. The actual travel time distribution is time-dependent (as illustrated by $\varphi(5)$, $\varphi(10)$, $\varphi(15)$, and $\varphi(20)$). As discussed in Section 5.1, there are 20 time steps from time point 30 min to time point 70 min based on the availability of real-time information every 2 min. Hence, $\varphi(5)$ represents the actual distribution based on the link data available from the 30th minute up to the 40th minute for the current day, and $\varphi(10)$ represents the actual distribution based on data available from the 30th minute up to the 50th minute, and so on. The $\varphi(\cdot)$ characteristics in the figure indicate that the link is relatively uncongested up to the 40th minute, but congestion steadily increases from

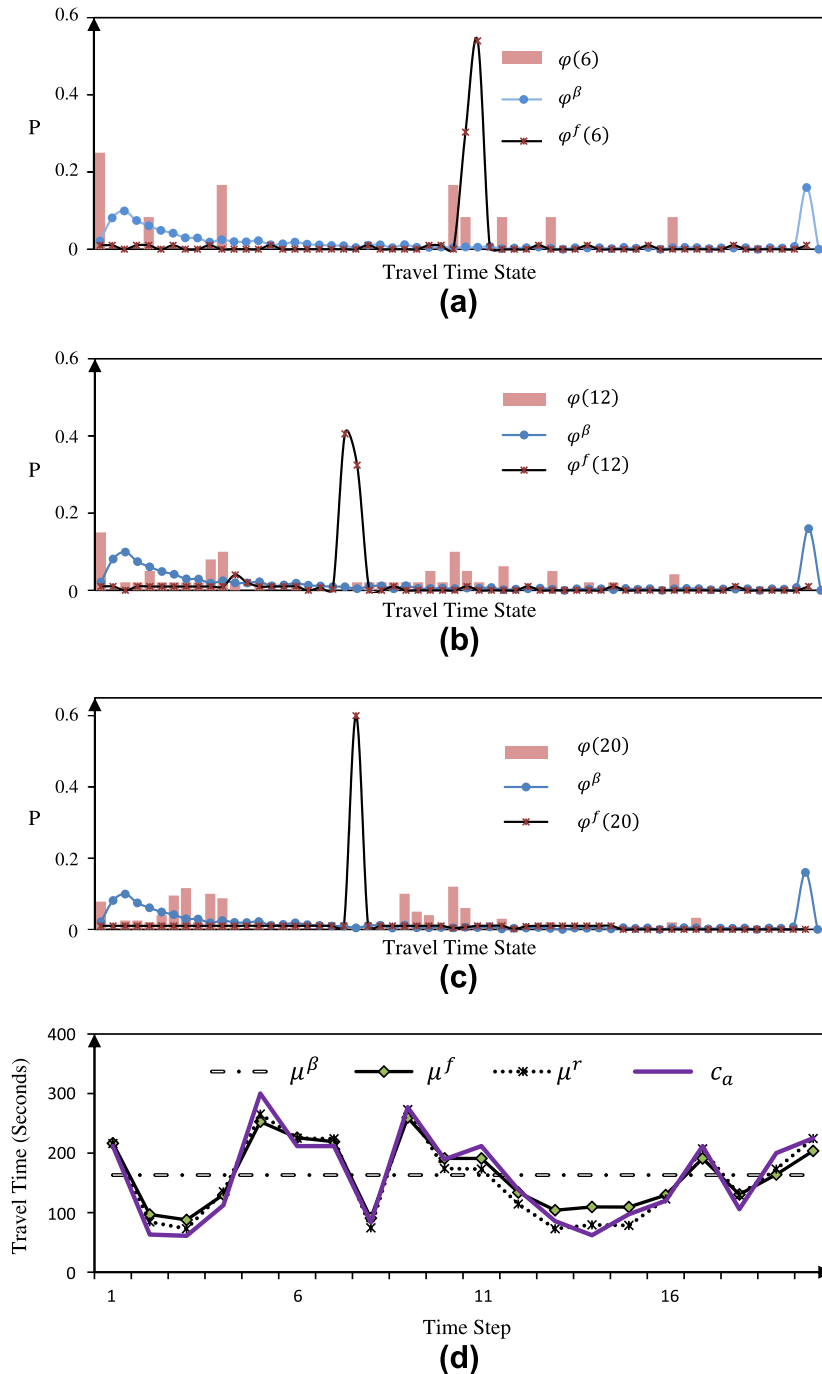


Fig. 8. The results when the consistency constraint is not considered.

thereon, implying significant time-dependency for the link traffic conditions. The predicted short-term link travel time distribution $\phi^f(\cdot)$ has the long-term historical distribution as its initial solution at time point 30 min.

The first key observation from Fig. 6 is that the long-term historical travel time distribution ϕ^β is not representative of the actual travel time distribution at different time points, which is consistent with the conclusions of past studies.

Second, the information fusion model enables the predicted short-term link travel time distribution $\phi^f(\cdot)$ to track the time-dependent actual travel time distribution with increasing accuracy over time on that day. For example, as illustrated in Fig. 6a, the short-term link travel time distribution at the 40th minute, $\phi^f(5)$, is closer to the long-term historical link travel time distribution. Consistent with the logic of the information fusion model, since the long-term historical distribution represents the “initial solution,” the predicted distribution is initially closer to it. By the 50th minute, as indicated by $\phi^f(10)$ in Fig. 6b, the predicted short-term distribution starts shifting away from the historical distribution as illustrated by its tempering down of the spikes present in the historical distribution. Fig. 6c and d illustrate that $\phi^f(15)$, and $\phi^f(20)$, respectively, capture the skew to the right in $\phi(15)$ and $\phi(20)$, and with increasing accuracy. Hence, the information fusion model is able to adaptively modify the short-term link travel time distribution to capture the variation in the actual short-term link travel time distribution over time.

In Fig. 6, the difference between $\phi^f(5)$ and $\phi(5)$ is because the update process starts from a long-term historical travel time distribution, and may not be representative of the historical conditions in the vicinity of the 30th minute. It suggests two factors that can potentially enhance the accuracy of the proposed information fusion model in the context of real-world implementation. First, the accuracy can be enhanced if more real-time information with short time delay and high information accuracy is available, especially during periods of significant transitions in the traffic state. Second, choosing a more representative initial solution for the update process can aid the information fusion model to more accurately capture the actual travel time distribution in fewer time steps. In addition, if the link travel time characteristics change significantly over the long-term, it is preferable to use the near-term historical data as part of the initial solution. Hence, another role of the information fusion model for practitioners is its ability to provide reference points to examine the efficiency of the historical travel time distributions in terms of the level and time period of aggregation.

5.3.2. Consistency

Consistency manifests as the need to ensure that the predicted short-term link travel time distribution will not vary significantly in a short time period, which is representative of typical real-world traffic conditions. That is, while the actual

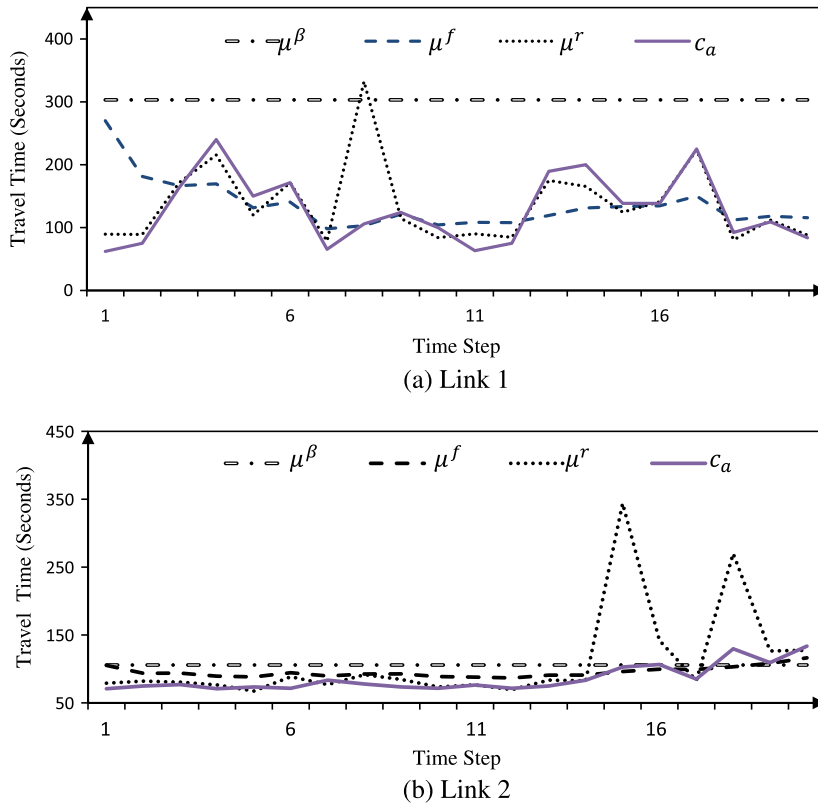


Fig. 9. Mean values of travel time distributions for different links μ^f : the mean of the predicted short-term travel time distribution in each time step; μ^β : the mean of the long-term travel time distribution; μ^r : the mean of the real-time travel time information range at each time step.

travel times may fluctuate in a small time interval, their effect on the distribution is more tempered and manifests over a longer time period. Hence, consistency refers to the ability of information fusion model to ensure that the predicted short-term link travel time distribution varies in a consistent manner during the update time steps. As discussed in Section 4.2.2, the consistency constraint (12) mitigates the impact of a single data point of real-time information in each update process. In the numerical experiments to analyze the ability of the information fusion model to ensure consistency (Constraint (19)), to avoid interactions related the impact of the information quality, good information with small time delay and high information accuracy is provided in these experiments.

Figs. 7 and 8 illustrate the results for the cases where the consistency constraint is considered and not considered in the information fusion model, respectively. A comparison of the figures indicates that Constraint (19) enables the predicted short-term travel time distribution ($\varphi^f(6)$, $\varphi^f(12)$ and $\varphi^f(20)$) to accumulate the variability in the travel time across time steps and approach the actual short-term travel time distribution in a consistent manner, as illustrated through Fig. 7a–c. By contrast, when the consistency constraint is not considered, variability in travel times across time steps is reflected in the predicted short-term distribution through shifting spikes in Fig. 8a–c, implying that significant variability is captured rather immediately though the distribution itself is not stable. The consistency characteristic makes the information fusion model more sensitive to significant non-recurrent traffic events, such as a traffic accident with significant impact on traffic conditions over a period of time, rather than an occasional non-severe traffic incident whose effects dissipate in a short time duration. Hence, the predicted short-term link travel time distribution is useful in real-world situations where its benefits are more meaningful.

Figs. 7d and 8d compare the mean of the predicted short-term travel time distribution μ^f with the actual travel time value c_a in each time step; μ^β represents the mean of the long-term travel time distribution and μ^r represents the mean of the real-time travel time information range. They indicate that a consistently predicted short-term travel time distribution may not have a mean that tracks the fluctuation of the actual travel time value well since this distribution seeks to represent the travel time variation in the time interval of interest in a consistent manner. Hence, unlike existing methods to predict a single short-term travel time value, a methodology to predict the short-term travel time distribution should be more sensitive to repetitive travel time states rather than a single travel time spike. When the consistency constraint is removed, the mean of the short-term distribution closely tracks the actual travel time value, as shown in Fig. 8d. However, this is at the expense of obtaining a fluctuating short-term distribution that is additionally not representative of the actual distribution.

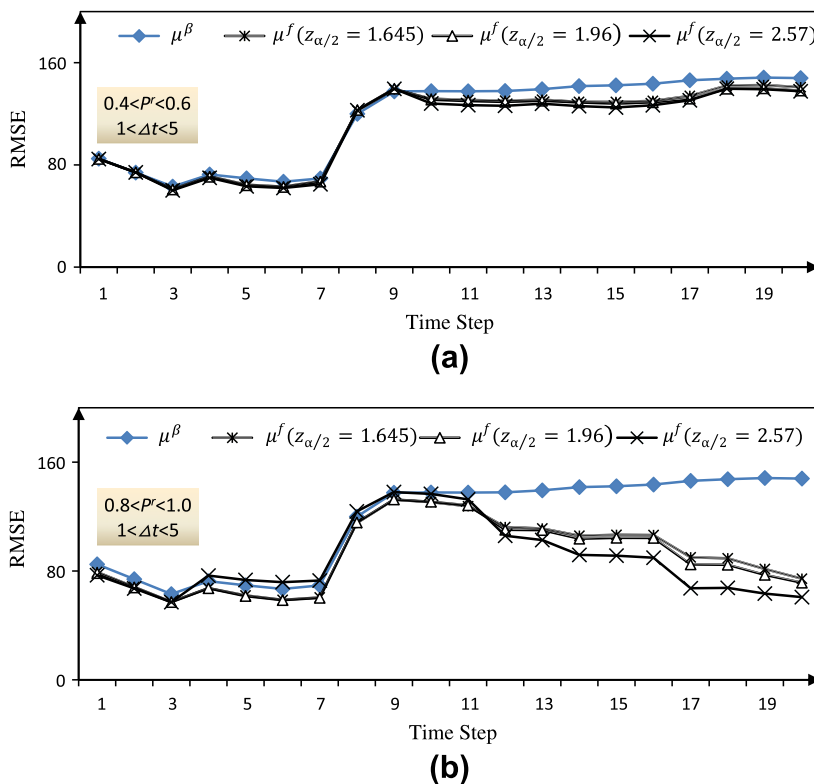


Fig. 10. Sensitivity analysis for significance level. μ^f : the mean of the predicted short-term travel time distribution in each time step.

5.3.3. Robustness

Robustness indicates the extent to which the information fusion model enables the predicted short-term link travel time distribution to be shielded from the effects of inferior real-time information in terms of information accuracy. Fig. 9 illustrates instances where the mean of the real-time link travel time information is far from the actual link travel time, such as in time step 8 for Link 1 in Fig. 9a, and in time steps 15 and 18 for Link 2 in Fig. 9b. While Section 5.3.2 indicates that the mean of the predicted travel time distribution may not be representative of the performance of the predicted travel time distribution, Fig. 9 is able to demonstrate the robustness of the proposed information fusion model because it shows that the mean of the predicted distribution is not significantly influenced by the spikes that indicate inaccurate real-time information. That is, in such instances, it provides a negligible weight for the real-time information during the update process. Thereby, the information fusion model is able to weaken the impact of the inaccurate real-time information in an individual time step so that the short-term travel time distribution prediction is not worsened by occasional inferior real-time travel time information. Hence, the information fusion model is robust to inaccuracies in real-time information. More broadly, Section 4.2.2 illustrates that if the accuracy of the real-time travel time information, p_a^r , is low, the corresponding information receives a low weight during the update process.

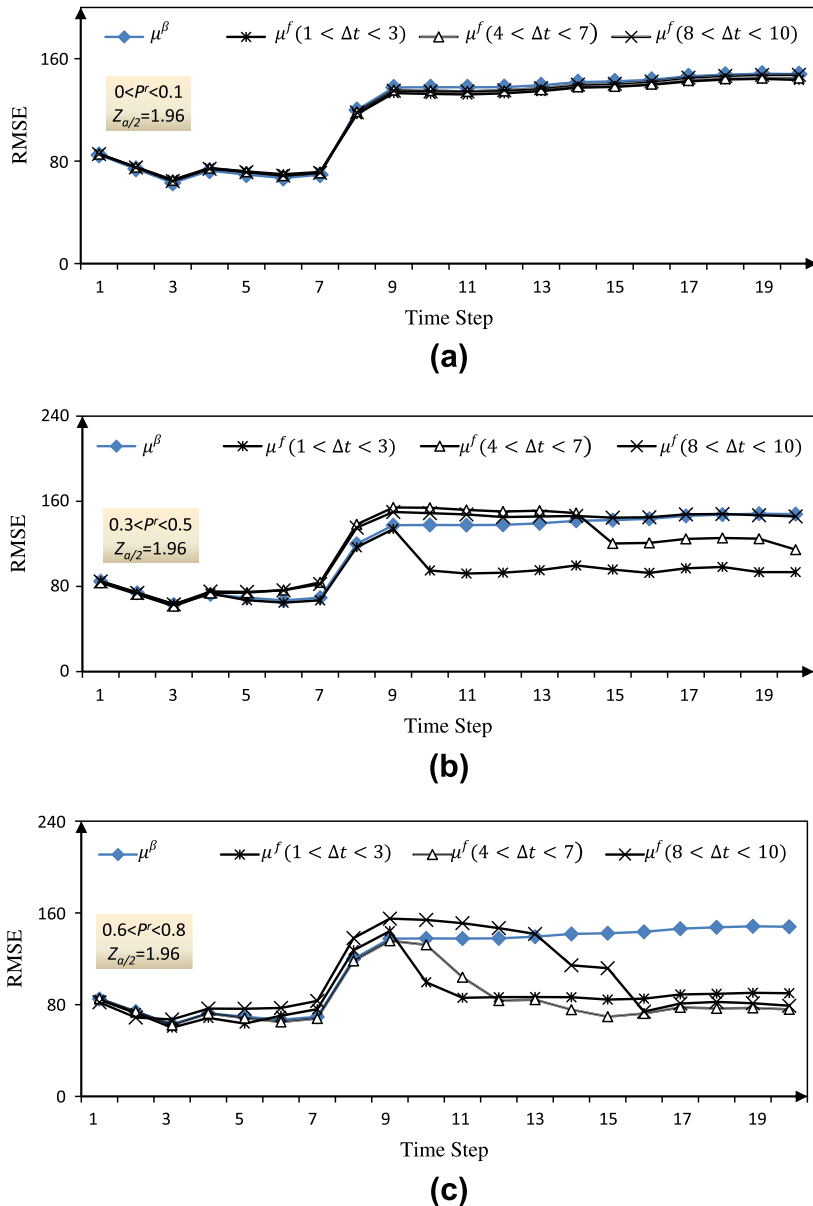


Fig. 11. Sensitivity analysis for time delay. μ^f : the mean of the predicted short-term travel time distribution in each time step.

5.4. Parametric sensitivity analysis of the information fusion model

Sensitivity analyses are conducted for the information fusion model for the parameters α (consistency constraint significance level) and Δt (time delay), under different levels of information accuracy p_a^r . They seek to analyze the effect of these parameters on the behavior of the information fusion model. The root mean square error (RMSE) in Eq. (27) is used as the measure to study the model behavior; $|A|$ denotes the number of links in the study network, and the superscript for μ_a can be β or f . A smaller RMSE value indicates a better estimation of the actual travel times, on average, across all links in the network.

$$RMSE = \sqrt{\frac{\sum_a (\mu_a^r(t) - c_a(t))^2}{|A|}} \quad (27)$$

5.4.1. Sensitivity analysis for significance level

The sensitivity of the significance level α in the information fusion model is analyzed for a fixed time delay range ($1 < \Delta t < 5$ min) under two different information accuracy ranges ($0.4 < p^r < 0.6$ and $0.8 < p^r < 1$). The significance levels analyzed include $\alpha = 0.01, 0.05$, and 0.1 (with corresponding $z_{\alpha/2} = 2.57, 1.96$, and 1.645 , respectively). The results in Fig. 10 illustrate that a higher significance level improves the performance of the proposed information fusion model, but only under higher information accuracy levels. This is indicated in Fig. 10b where the scenarios with higher significance levels result in lower RMSE values for $0.8 < p^r < 1$. By contrast, as shown in Fig. 10a, the significance level has little influence on the performance of the proposed information fusion model under lower information accuracy levels ($0.4 < p^r < 0.6$). These observations indicate that the significance level is important to the proposed information fusion model primarily under high levels of information accuracy. They are consistent with the motivation for introducing the consistency constraint in the formulation for the information fusion model.

5.4.2. Sensitivity analysis for time delay

The sensitivity of the time delay in the information fusion model is explored for the significance level $\alpha = 0.05$ ($z_{\alpha/2} = 1.96$) under three different information accuracy ranges $0 < p^r < 0.1$, $0.3 < p^r < 0.5$, and $0.6 < p^r < 0.8$. Three ranges of time delay, $1 < \Delta t < 3$ min, $4 < \Delta t < 7$ min, and $8 < \Delta t < 10$ min, are analyzed. Fig. 11a illustrates that under low information accuracy, the mean of the short-term travel time distribution μ^f has an RMSE similar to that of the mean of the long-term historical travel time distribution μ^β . However, as information accuracy increases (Fig. 11b and c), μ^f performs better than μ^β . Fig. 11b and c also illustrate that shorter time delays produce more accurate estimations; the RMSE values for μ^f with time delay range $1 < \Delta t < 3$ are typically less than those for $4 < \Delta t < 7$ min or $8 < \Delta t < 10$ min. In summary, the results suggest that the proposed information fusion model is more sensitive to time delay as information accuracy increases. This is consistent with the real-world, in that information with long time delay may not as relevant in predicting the short-term traffic conditions.

6. Concluding comments

Under the auspices of intelligent transportation systems, fixed sensors (such as loop detectors and non-intrusive sensors) and mobile ones (such as probe vehicles and vehicles under V2V) are being increasingly deployed in vehicular traffic networks. The resulting extensive real-time travel time data as well as processed traffic information enables transportation system operators to develop robust traffic management strategies and empowers travelers to make more informed travel decisions. In this context, existing efforts to predict the real-time traffic conditions focus primarily on determining a single value of time-dependent travel time (typically, the mean value), or more recently, the variance in addition to the mean. While the variance can, to some extent, reflect the variability of the dynamic link travel time, it cannot provide detailed characteristics of the dynamic link travel time without assumptions on the underlying distribution. Hence, there is a methodological need to identify these characteristics to develop a new generation of real-time traffic control strategies that are commensurate with, and can leverage, the capabilities afforded by the technological advances. Examples of such real-time strategies include dynamic congestion pricing, reliable route guidance, and V2V traffic networks. They entail methodological capabilities such as k -reliable routes and stochastic shortest paths to factor the inherent randomness in such dynamic networks, which entails predicting the short-term link travel time distributions.

This study seeks to predict the short-term link travel time distribution, which specifies the probability of all feasible link travel time states based on the recently-observed traffic conditions on the current day. Such distributions aid traffic management practice by providing valuable information about the short-term traffic conditions and its variability. The shape and skew in the distribution indicate the level of traffic congestion; if the distribution mainly consists of travel time states with high/low values of travel time, it indicates congested/uncongested traffic conditions. Further, the distributions can capture transience in traffic conditions, as illustrated by Fig. 6a–d which progressively illustrate increase in congestion levels with time. The shape of the distribution can also be used to interpret the reliability in link travel time; if it is relatively well-spread/sharp, it indicates a high/low uncertainty in the link travel time in the corresponding time interval.

The ability to generate such detailed stochastic information on link travel time variability enables the development of more advanced methodologies that explicitly consider the detailed stochastic features of the travel time. For example, in the context of dynamic congestion pricing, the ability to obtain the probability of a possible link travel time state in the near-term future enables the determination of more robust pricing strategies. In the context of stochastic routing, the short-term link travel time distribution can be used to treat reliability in a more explicit manner. That is, it can provide the ability to determine the k th reliable shortest path for a specific origin–destination pair. The short-term link travel time distribution can also aid in Monte Carlo simulation based approaches in which possible scenarios of the link travel time can be sampled.

The proposed study models the short-term link travel time variability as a stochastic time-dependent random variable with a discrete distribution, and characterizes real-time link travel time information as a travel time range with information quality represented by information accuracy and time delay. The methodology predicts the short-term link travel time distribution by using the real-time travel time information to update the past travel time distribution. The associated information fusion model is a nonlinear programming formulation (M1), in which information accuracy and time delay are used to weigh the impact of real-time information in each update process. In addition, a consistency constraint is introduced to limit the effect of a single real-time information data point so that the short-term travel time distribution reflects the effects of multiple data points rather than any single instance.

The numerical experiments illustrate that the information fusion model can ensure accuracy, consistency, and robustness while predicting the short-term link travel time distribution. Further, it shields the effects of bad information and is sensitive to good information. The consistency constraint ensures that the predicted distribution approaches the actual distribution in a consistent manner. More importantly, the results suggest that a representative short-term travel time distribution may not have a mean close to the actual travel time during the update process as the distribution is reflective of multiple events rather than a single instance. This aspect highlights a key difference between the proposed methodology to determine the short-term travel time distribution and existing methods in the literature to predict a single travel time value. Sensitivity analyses indicate that information accuracy dominates the effect of time delay and significance level.

There are some potential future research directions based on this study. First, the proposed fusion methodology can be extended to address the case where the format of the real-time link travel time information is a discrete distribution. Thereby, two distributions (past travel time distribution and real-time travel time information distribution) can be fused to predict the short-term travel time distribution. Second, the real-time information can be differentiated by vehicle classes in the information fusion model to aid in problems that require such categorization. Third, in an implementation context, how can the information fusion model be adaptively re-started with new “initial” distributions at time points with significant traffic state transitions?

In general, this study provides a methodology to fuse information from multiple sources, characterized as a discrete distribution or a confidence interval with uncertain errors. Hence, the proposed methodology is not limited to predicting short-term travel time distributions, and can be extended to predict the distributions of other traffic parameters such as traffic flow or speed, and beyond that, parameters in other application domains outside of the transportation field.

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