USING LINK TRAVEL TIME COVARIANCE INFORMATION TO PREDICT DYNAMIC JOURNEY TIMES IN STOCHASTIC ROAD NETWORKS

H.W. HO [a], William H.K. LAM [b] and Mei Lam TAM [c]
[a,b,c] *Department of Civil and Environmental Engineering,*
The Hong Kong Polytechnic University, HKSAR, China
[b] *Research Institute for Sustainable Urban Development,*
The Hong Kong Polytechnic University, HKSAR, China
Email: cehwho@polyu.edu.hk[a], cehklam@polyu.edu.hk[b], trptam@polyu.edu.hk[c]

ABSTRACT

Journey time prediction is a crucial component in advanced traveler information systems for helping travelers in making their travel decisions. This paper investigates the journey time prediction problem in road network with stochastic journey times and link flows. The proposed prediction framework consists of two sub-modules. The first one is a reliability-based dynamic traffic assignment model to establish a database for the historical traffic conditions, while the other sub-module, which is a multi-level k-NN model for predicting journey times based on the historical records in the database. A Sioux Falls road network example is used to demonstrate the accuracy, efficiency and robustness of the proposed framework for the journey time prediction problem in stochastic network with uncertainties.

Keywords: Journey time prediction, effective path journey time, dynamic traffic assignment, travel time covariance, k-nearest neighborhood

1. INTRODUCTION

In the recent decades, due to the advancement of communication technologies and related infrastructures, intelligent transportation system (ITS) is gaining its concerns among traffic engineers, researchers and general public. Among the various deployed ITSs around the world, advanced traveler information systems (ATIS), which provides necessary information (e.g., travel/journey time, waiting time, parking spaces, etc.) for travelers in making their travel decisions (e.g., mode choice, route choice, departure time choice, etc.), is the most commonly implemented system. Journey time (travel time), among the various information provided by ATIS, is most crucial for travelers in assessing the road traffic network conditions and making their choices to avoid unnecessary delay (Liu and Ma, 2009). Concerning journey times, estimation, which the journey time is calculated after the trip is finished, and prediction, which the journey time is calculated before or during the trip, are the two main issues that are commonly considered (Wei and Lee, 2007; Shao et al., 2017). For travelers, predicted journey times are more useful as they are the journey times that travelers are going to experience. However, given the intrinsically uncertain nature of journey time, predicting an accurate and reliable journey time has long been a challenging task for traffic engineers especially for highly congested and stochastic road network such as Hong Kong.

Substantial numbers of journey time prediction studies have been focused on data-driven approaches (e.g., regression models, neural networks, Kalman filtering, etc.) due to the advancement of technologies for the ease of data collections for model setups (Oh et al., 2015). Accuracy of the data-driven approaches heavily depends on the amount of data used for training and, thus, it is more suitable for scenarios with single or few paths as more effort could be put on collecting data for each path (Wei and Lee, 2007). For network-wide journey time predictions, as there are numerous OD pairs/paths, it is common that some of the paths have very few, or even no, observed journey time data. In such cases, flow-based models (Hu et al., 2012) are more advantageous than the data-driven approaches. Thus, this paper proposed a network-wide journey time prediction (NJTP) framework based on observed journey times and link flows. The dynamic flow model adopted in this NJTP framework has taken into account the covariance of the link travel times, which is difficult to be replicated by the data driven approaches and is not considered in the current flow-based prediction models. The proposed NJTP framework consists of two sub-modules: i) journey time estimation sub-module, which consists of a reliability-based dynamic traffic assignment dynamic (RDTA) model to estimate the past traffic conditions for establishing the database, and ii) journey time prediction sub-module, which is a multi-level k-nearest neighborhood (k-NN) approach for predicting the current demand and link travel time multipliers of the RDTA model from the database. With these multipliers and the RDTA model, the short-term future journey times can be predicted for the whole network with uncertainties in journey times and link flows.

The remaining of this paper is organized as follows. Model formulations and the corresponding solution algorithms of this framework will be proposed in Section 2. Section 3 then depicts the results of the numerical example for Sioux Falls road network. Lastly, conclusions and further studies will be given in Section 4.

2. MODEL FORMULATIONS AND SOLUTION ALGORITHMS

In this study, the proposed framework for NJTP is shown in Figure 1. In this study, two major sources of data, link flows and path journey times are collected and used for the journey time prediction. Link flows, which are usually collected by loop detectors and/or camera with image processing software, are assumed to be available 24/7 for the selected subset of links in the monitored network. On the other hand, path journey time in this study could be collected through various technologies, such as automatic vehicle identification (AVI), global positioning system, etc. Owing to the uncertainties of travel conditions, there is will be a variation in path journey times and, thus, the observed path journey times will be represented in mean and standard deviation (SD). The observed link flows, mean and SD of path journey time will then be used in journey time estimation sub-module (section 2.1), journey time prediction sub-module (section 2.2) and stored in the database for future use.

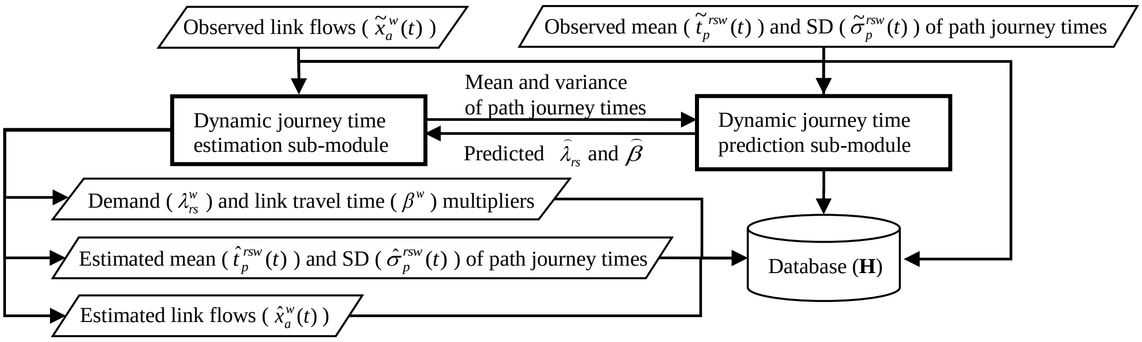

Figure 1. Framework for network-wide journey time prediction (NJTP)

The journey time estimation sub-module is required to estimate the journey times of the unobserved OD pairs. The estimation sub-modules will gives: i) Demand and link travel time multipliers that define the RDTA model in the estimation sub-module; ii) Estimated mean and SD of path journey times of unobserved OD pairs, and; iii) Estimated link flows of the unobserved links. All these estimated data will be stored in the database (**H**) with the observed data. To predict path journey times, the proposed journey time prediction sub-module will first search through the database for finding days with similar travel conditions based on the link flows and path journey times. Then, the past demand and link travel time multipliers will be used to predict the current multiplies. Lastly the predicted multipliers will then be applied to the RDTA model for predicting path journey time between different OD pairs. For effective presentation of key ideas without loss of generality, the four assumptions considered in Tang et al. (2016) on stochastic network are also adopted in this paper

2.1 Dynamic Journey Time Estimation Sub-module

In this paper, the dynamic journey time estimation model introduced in Tang et al. (2016) is adopted. For effective presentation, this paper will introduced again the key ideas, while for others details readers could be referred to Tang et al. (2016). In this section, the variables and relations are defined within the same day *w*. Consider a network *G* = (*N*,*A*) with set of nodes *N* and set of links *A*. In this study, a linear form of link travel time function is adopted and link travel time for link *a* on day *w* in time interval *k* ($T_a^w(k)$) is defined in Equation (1) below.

$$T_a^w(k) = T_a^f + \omega_a \frac{x_a^w(k)}{C_a} \tag{1}$$

where T_a^f is the free-flow travel time of link *a*, ω_a is the congestion-dependent coefficient, $x_a^w(k)$ is the link flow on link *a* at the beginning of time interval *k* on day *w* and, C_a is the capacity of link *a*. To incorporate the road supply uncertainty, T_a^f and C_a are random variables and, similar to previous studies (Tang et al., 2016), T_a^f and $1/C_a$ are assumed to be independent random variables with mean taken as μ_a^T and μ_a^C respectively. With Equation (1) and the assumption of SD of link travel time (Tang et al., 2016), the mean and SD of stochastic link travel time of link *a* at the end of time interval *k* on day *w* could be defined as $t_a^w(k) = \mu_a^T + \omega_a \mu_a^C x_a^w(k)$ and $\sigma_a^w(k) = \beta^w t_a^w(k)$ respectively. Note that β^w is the non-negative multiplier between the mean and variance of the link travel time on day *w*. Consider a path *p* within the set of path P_{rs} between OD pair (r,s) that passes sets of links $\{a_1, a_2, ..., a_m\}$ and nodes $\{r, 1, ..., m\text{-}1, s\}$. The path journey time of this path *p* at the end of time interval *k* on day *w* ($T_p^{rsw}(k)$) will then follows a multivariate normal distribution with mean ($t_p^{rsw}(k)$) and SD ($\sigma_p^{rsw}(k)$) defined in Equations (2) and (3) respectively.

$$t_p^{rsw}(k) = \sum_{a\ on\ path\ p} \sum_{l(\geq k)\in T_d} t_a^w(l) \delta_{apk}^{rsw}(l) \tag{2}$$

$$\sigma_p^{rsw}(k) = \sqrt{\left(\sum_{a\ on\ path\ p} \sum_{l(\geq k)\in T_d} \sigma_a^w(l) \delta_{apk}^{rsw}(l) \right)^2 + 2 \sum_{1\leq i\leq j\leq m} \text{cov}(t_{a_i}, t_{a_j})} \tag{3}$$

$$\text{cov}(t_{a_i}^w(k_1), t_{a_j}^w(k_2)) = \theta \exp(-|\text{order}(a_i) - \text{order}(a_j)|) \sigma_{a_i}^w(k_1) \sigma_{a_j}^w(k_2) \tag{4}$$

where T_d is the set of departure time intervals considered. $\delta_{apk}^{rsw}(l) = 1$ if trips on the path *p* of OD pair (*r*,*s*) entering the network at interval *k* on day *w* and arrive link *a* at interval *l*, otherwise $\delta_{apk}^{rsw}(l) = 0$. In this paper, as only spatial correlation of link travel times is considered, the covariance between travel time for link a_i and a_j on same path *p* on day *w* ($\text{cov}(t_{a_i}^w, t_{a_j}^w)$) is defined in Equation (4). In Equation (4), $\text{order}(a_i)$ refers to the ordinal number of link a_i in path *p*, while θ is a coefficient that indicates whether the link travel times are positively correlated ($\theta > 0$), negative correlated ($\theta < 0$) or not correlated ($\theta = 0$). Under the scenario of stochastic path journey time, with mean and variance defined in Equations (2) and (3), travelers will consider a desired probability for on-time arrival in make their departure time and route choice. The effective path journey time for path *p* of OD pair (*r*,*s*) at the end of time interval *k* on day *w* with a given probability α ($\eta_p^{rsw,\alpha}(k)$) is defined in Equation (5).

$$\eta_p^{rsw,\alpha}(k) = t_p^{rsw}(k) + Z_\alpha \sigma_p^{rsw}(k) \tag{5}$$

where Z_α is the inverse of the cumulative distribution function of standard normal distribution at α confidence level (e.g., $\alpha = 95\%$ for $Z_\alpha = 1.64$) and could be determined based on the trip purpose of travelers. The dynamic user equilibrium condition adopted in this paper will then be based on this effective path journey time and is defined in Equation (6)

$$\eta_p^{rsw,\alpha}(k) \begin{cases} = \pi^{rsw,\alpha}(k), & \text{if} \quad f_p^{rsw}(k) > 0 \\ \geq \pi^{rsw,\alpha}(k), & \text{if} \quad f_p^{rsw}(k) = 0 \end{cases} \tag{6}$$

$$D^{rsw}(k) = \lambda_{rs}^w d^{rsw}(k) \tag{7}$$

where $f_p^{rsw}(k)$ is the flow on path *p* between OD pair (*r*,*s*) at the beginning of time interval *k* on day *w*, $\pi^{rsw,\alpha}(k)$ is the minimum effective path journey time between OD pair (*r*,*s*) with probability α at the end of time interval *k* on day *w*. On the demand side, the demand for OD pair (*r*,*s*) at the beginning of time interval *k* on day *w* ($D^{rsw}(k)$) adopted in this paper is assumed to be proportional to the corresponding prior OD demand ($d^{rsw}(k)$) and is defined in Equation (7). Note that λ_{rs}^{w} is the demand multiplier for OD pair (*r*,*s*) on day *w*. With the above definitions, the path flow assignment constraints, flow conservation and propagation equations, definitional constraints and non-negativity conditions, the RDTA problem will be setup and solved as the same as that in Tang et al. (2016).

In this study, a bilevel formulation is adopted to estimate the OD path journey time with observed path journey times and link flows as inputs. The lower-level model is a RDTA model for finding the equilibrium path flows and, thus, the effective path journey times, based on the demand (λ_{rs}^{w}) and link travel time (β^{w}) multipliers determined in the upper-level model. The lower-level model is formulated as a variational inequality (VI) problem for finding a flow pattern $\mathbf{f}^{w^*} \in \mathbf{F}^{w}$ such that Equation (8) is satisfied.

$$\sum_{k\in T_d}\sum_{p\in P_{rs}}\eta^{rsw,\alpha}(k)\left[f_p^{rsw}(k)-f_p^{rsw*}(k)\right]\geq 0,\quad \forall \mathbf{f}^{w}\in\mathbf{F}^{w} \tag{8}$$

where $\mathbf{F}^{w}$ is a closed convex set defined by $\mathbf{F}^{w}=\{\mathbf{f}^{w}\geq 0:\sum_{p\in P_{rs}} f_p^{rsw}(k)=D^{rsw}(k),\forall rs\in R,k\in T_d\}$. The estimated mean path journey times, SD of path journey times and link flows from the lower-level model are feedback to the upper-level model for matching the observed values. The upper-level model is formulated as a generalized least square problem for finding the optimal λ_{rs}^{w} and β that minimize the difference between the estimated and observed mean and SD of path journey times. Apart from the boundary constraints for λ_{rs}^{w} and β, this generalized least square problem will also included a constraint to ensure the estimated link flows are reasonably close to the observed values. The formulation and solution algorithm of this generalized least square problem could be found in Tang et al. (2016).

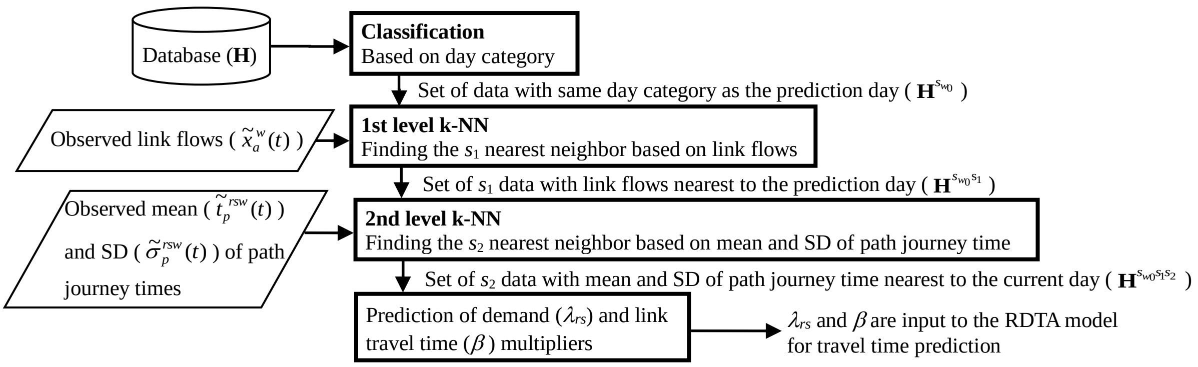

Figure 2. Framework for multi-level k-NN approach for journey time prediction

2.2 Dynamic Journey Time Prediction Sub-module

In this study, the dynamic journey time prediction sub-module aims to predict a time-dependent path journey time of all OD pairs within the monitored network for future time intervals (e.g., every 1 minutes for the next hour). The multi-level k-NN approach, which is similar to that in Tak et al. (2014), will be adopted to predict that future OD path journey times from observed and estimated link flows/path journey times. The framework for the multi-level k-NN approach adopted in this paper is shown in Figure 2. To predict future path journey times, the database will first be classified into different day categories of which records with same day category as the prediction day will be used in the further steps. In this study, 2 different day categories (i.e., Weekdays and Weekends) are considered based on the distinct travel and demand patterns on these days. This classification step will help to sort out records with similar travel/demand patterns and substantially reduce the records to be evaluated in the subsequent steps to enhance the efficiency of the proposed prediction framework. With the set of s_{w_0} records having the same day category as the prediction day ($\mathbf{H}^{s_{w_0}}$), link flows are considered in the first level of k-NN for finding a set of s_1 records ($\mathbf{H}^{s_{w_0}s_1}$) that is closest the current situation. Mean and SD of path journey times are not adopted in the first level of k-NN screening, as it is relatively difficult to collect (observe) all path journey times of any OD pair for evaluating a correct mean and SD that are used to find records with similar travel conditions. On the other hand, link flows, which could be collected in high accuracy, are more suitable for this first stage screening. The distance measure for finding s_1 nearest neighbors is defined in Equation (9).

$$\varpi_1(w) = \sum_{a \in \tilde{A}} \sum_{t \in T_o} \left[\tilde{x}_a^{w_0}(t) - \hat{x}_a^{w}(t) \right]^2 \tag{9}$$

where w_0 is the superscript denotes the prediction day; $\tilde{x}_a^w$ and $\hat{x}_a^w$ are respectively the observed and estimated on link a at the beginning of observed time interval t on day w; $\tilde{A}$ and T_o are respectively the set of observed links and time intervals. The s_{w_0} records in $\mathbf{H}^{s_{w_0}}$ are then sorted based on $\varpi_1(w)$ and the s_1 records of smallest $\varpi_1(w)$ are chosen to form a new set of records $\mathbf{H}^{s_{w_0}s_1}$ to input to the second level k-NN screening. In the second level k-NN screening, apart from the mean and SD of observed path journey time, the number of observations is also considered in the evaluation of the distance between neighbors. The reason of including the number of observations is to eliminate records in $\mathbf{H}^{s_{w_0}s_1}$ with mean and SD of path journey times that are match with the observed values by random. The distance measure adopted in the second level k-NN for finding s_2 nearest neighbors is defined in Equation (10).

$$\varpi_2(w) = \frac{\kappa_t}{\tilde{\varpi}_t} \sum_{rs \in R} \sum_{p \in \tilde{P}_{rs}} \sum_{t \in T_o} \left[\tilde{t}_p^{rsw_0}(t) - \hat{t}_p^{rsw}(t) \right]^2 + \frac{\kappa_\sigma}{\tilde{\varpi}_\sigma} \sum_{rs \in R} \sum_{p \in \tilde{P}_{rs}} \sum_{t \in T_o} \left[\tilde{\sigma}_p^{rsw_0}(t) - \hat{\sigma}_p^{rsw}(t) \right]^2 + \frac{\kappa_M}{\tilde{\varpi}_M} \left[\tilde{\varpi}_M - \sum_{rs \in R} \sum_{p \in \tilde{P}_{rs}} \sum_{t \in T_o} M_p^{rsw}(t) \right] \tag{10}$$

$$\tilde{\varpi}_t = \max \left\{ \sum_{rs \in R} \sum_{p \in \tilde{P}_{rs}} \sum_{t \in T_o} \left[\tilde{t}_p^{rsw_0}(t) - \hat{t}_p^{rsw}(t) \right]^2, \ \forall w \in W^{s_{w_0}s_1} \right\} \tag{11}$$

$$\tilde{\varpi}_\sigma = \max \left\{ \sum_{rs \in R} \sum_{p \in \tilde{P}_{rs}} \sum_{t \in T_o} \left[\tilde{\sigma}_p^{rsw_0}(t) - \hat{\sigma}_p^{rsw}(t) \right]^2, \ \forall w \in W^{s_{w_0}s_1} \right\} \tag{12}$$

$$\tilde{\varpi}_M = \max \left\{ \sum_{rs \in R} \sum_{p \in \tilde{P}_{rs}} \sum_{t \in T_o} M_p^{rsw}(t), \ \forall w \in W^{s_{w_0}s_1} \right\} \tag{13}$$

where $\hat{t}_p^{rsw}$ and $\hat{\sigma}_p^{rsw}$ ($\tilde{t}_p^{rsw}$ and $\tilde{\sigma}_p^{rsw}$) are respectively the estimated (observed) mean and SD of path journey time on path p between OD pair (r,s) at the end of time interval t on day w; $M_p^{rsw}(t)$ denotes the number of observed path journey time on path p of OD pair (r,s) at the end of observed time interval t on day w; R and $\tilde{P}_{rs}$ are respectively the set of OD pairs and observed paths between (r,s); $W^{s_{w_0}s_1}$ denotes the set of day of the records in set $\mathbf{H}^{s_{w_0}s_1}$; κ_t, κ_σ and κ_N respectively define the weight of mean path journey time, SD of path journey time and number of observations. As the three quantities are of different scales, each of these quantities in the distance equation (Equation 10) is converted into a scale free scalar between 0 (closest to the quantities in the prediction day) and 1 (furthest to the quantities in the prediction day). Equations (11) ~ (13) respectively defines the maximum distance in mean path journey time, maximum distance in SD of path journey time and maximum number of observations among all the records in $\mathbf{H}^{s_{w_0}s_1}$. These quantities are used in Equation (10) for defining the scale-free distance $\varpi_2(w)$. The s_1 records in $\mathbf{H}^{s_{w_0}s_1}$ are then sorted based on $\varpi_2(w)$ and the s_2 records with smallest $\varpi_2(w)$ are chosen to form a new set of records ($\mathbf{H}^{s_{w_0}s_1s_2}$) for predicting the demand and link travel time multipliers. With the set of records in $\mathbf{H}^{s_{w_0}s_1s_2}$, the predicted demand and link travel time multipliers are defined in Equations (14).

$$\hat{\lambda}_{rs} = \sum_{i \in s_2} \tilde{\kappa}_i \lambda_{rs}^i, \quad \forall rs \in R \quad \text{and} \quad \hat{\beta} = \sum_{i \in s_2} \tilde{\kappa}_i \beta^i \tag{14}$$

where $\hat{\lambda}_{rs}$ is the predicted demand multiplier for OD pair (r,s), $\hat{\beta}$ is the predicted link travel time multiplier. $\tilde{\kappa}_i = [\varpi_2(i)]^{-1} / \sum_{j \in s_2} [\varpi_2(j)]^{-1}$ defines the weight in combining the demand and link travel time multipliers in $\mathbf{H}^{s_{w0} s_1 s_2}$ for predicting the multipliers in future time intervals. The weight $\tilde{\kappa}_i$ is defined such that records that are similar to the prediction day have higher weight. Lastly, the predicted multipliers ($\hat{\lambda}_{rs}$ and $\hat{\beta}$) are input to the RDTA model (Equations 6~8) in the estimation sub-module for finding the mean ($t_p^{rsw_0}(k)$) and SD ($\sigma_p^{rsw_0}(k)$) of path journey time for the future time intervals. As the major part of computations in this prediction sub-module is sorting the records in $\mathbf{H}^{s_{w0}}$ and $\mathbf{H}^{s_{w0} s_1}$ based on the distance measures (ϖ_1 and ϖ_2), efficient sorting algorithms (e.g., bubble sort, mergesort) are adopted in the 1st and 2nd level k-NN algorithm.

3. NUMERICAL EXAMPLES

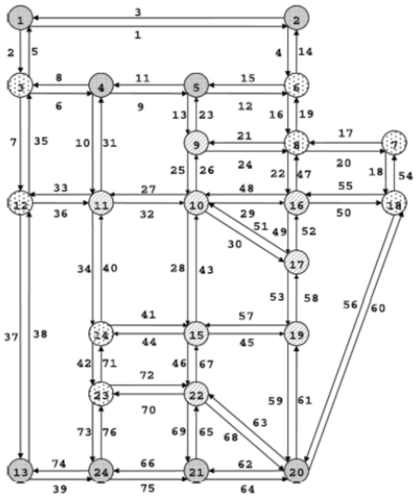

Figure 3. Sioux Falls road network

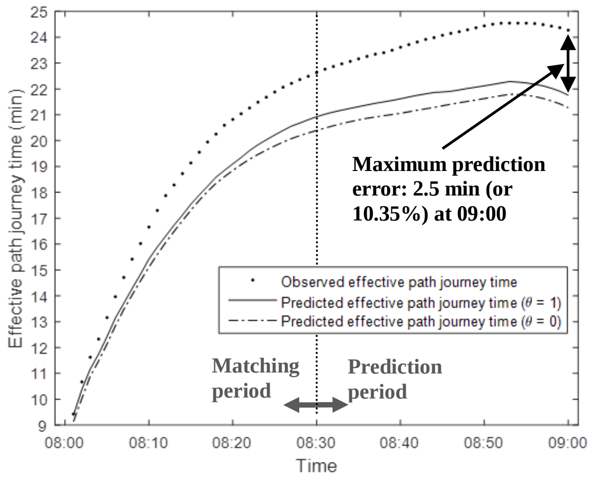

Figure 4. Observed and predicted effective path journey times of a path between OD pair (13,1) for Scenario A

In this paper, the Sioux Falls road network is adopted to demonstrate the effectiveness and efficiency of the proposed NJTP framework. Figure 3 shows the Sioux Falls road network which consists of 24 nodes, 76 links and 48 OD pairs (Origin nodes: 1, 4, 2 and 5, Destination nodes: 13, 20, 21 and 24; Origin nodes: 13, 20, 21 and 24, Destination nodes: 1, 2, 4 and 5; Origin nodes: 3, 12, 14 and 23, Destination nodes: 6, 7, 8 and 18). The link travel times are considered to be positively correlated in path journey times and the corresponding coefficient (θ) is taken as unity. The study period in this example is Tuesday (Weekday) 08:00~09:00 with the link flows and path journey times in the first 30 minutes (i.e. 08:00 ~ 08:30) used to match the records in the database while the prediction period is the last 30 minutes (i.e., 08:31 ~ 09:00). The time-dependent OD demands between these OD pairs ($d^{rsw}(k)$) have adopted a quadratic functional form with a maximum demand of 26 pcu/min at 08:30. The demand multipliers on day w (λ_{rs}^w) are randomly chosen from normal distributions with mean equals to 1.0 and SD equals to 0.3 (Wang et al., 2015) to mimic the day-to-day uncertainty. Between these OD pairs, 192 paths are initially generated for evaluation. The free flow travel time of the road network is taken as the same in Wang et al. (2015) while the link capacity is taken as 30 pcu/min in this study. Similar to the demand multipliers, the link travel time multiplier on day w (β^w) is randomly chosen from normal distributions with mean equals to 0.25 and SD equals to 0.025 to mimic the uncertainty of link travel time variance. Among the links and paths considered in this example, link flows of 24 links and path journey times of 48 paths are chosen as the observed quantities in the prediction framework. In this numerical example, 250 records for Weekday 08:00 ~ 09:00 are generated, which are based on the same distribution of λ_{rs}^{w} and β^{w} as defined above, to form the database used in the prediction framework. As the observed flows and path journey times are generated by the RDTA model in this example, the number of observed path journey time ($M_{p}^{rsw}(t)$) is not considered in the evaluation and the corresponding weight is taken as zero (i.e,. κ_M = 0). Calibrations are carried out for the other weights in Equation (10) based on the generated database and the optimal weights adopted in this numerical example are κ_t = 0.60 and κ_σ = 0.40. In this example, the numbers of nearest neighbor are also calibrated to improve the prediction accuracy and the optimal value for s_1 and s_2 are both found to be 18. To quantify the accuracy of the proposed NJTP framework, the following Root Mean Squared Errors (RMSEs) are adopted (Equations 15).

$$\left(RMSE_{\mu}, RMSE_{\sigma}\right)=\left(\sqrt{\frac{1}{N_{\tilde{P}}N_{\hat{T}}}\sum_{rs\in R}\sum_{p\in\tilde{P}_{rs}}\sum_{k\in\hat{T}}\left(\tilde{t}_{p}^{rsw_0}(k)-t_{p}^{rsw_0}(k)\right)^{2}}, \sqrt{\frac{1}{N_{\tilde{P}}N_{\hat{T}}}\sum_{rs\in R}\sum_{p\in\tilde{P}_{rs}}\sum_{k\in\hat{T}}\left(\tilde{\sigma}_{p}^{rsw_0}(k)-\sigma_{p}^{rsw_0}(k)\right)^{2}}\right) \quad (15)$$

where N_{OD}, $N_{\tilde{P}}$ and $N_{\hat{T}}$ are respectively the number of OD pairs, observed paths and predicted time intervals; $\hat{T}$ denotes the time intervals for journey time prediction. The proposed NJTP framework is then solved with desktop computer (Intel Pentium G620 @ 2.60GHz, RAM 8G) giving a computational time of 28 seconds for the prediction of a 30-minute period. The results of this scenario (Scenario A) are shown in Table 1 (2nd ~ 4th column).

Table 1. RMSEs for proposed NJTP framework

	Scenario A			20 scenarios [a]			Scenario A without link travel time covariance [b] (i.e. θ = 0)
Prediction period	5 minutes	15 minutes	30 minutes	5 minutes	15 minutes	30 minutes	
RMSE$_\mu$	0.6733	0.6836	0.7199	0.6798	0.6901	0.6855	0.7431
RMSE$_\sigma$	0.2025	0.2047	0.2174	0.4618	0.4642	0.4569	0.6855

[a] RMSEs for 20 scenarios is taken as the average of RMSE from each scenarios.
[b] RMSEs for 5-minute prediction period is chosen as it is the most accurate prediction among the 3 prediction periods considered. Similar level of accuracy could also be found in the 15- and 30-minute prediction periods.

In this scenario, the RMSE of mean path journey time are respectively 0.6733 minutes (40.40 second), 0.6836 minutes (41.02 second) and 0.7199 minutes (43.19 second) for 5-minute, 15-minute and 30-minute prediction periods. Such errors are relatively small as compared to the range of mean path journey time in this scenario (10.7 ~ 33.1 minutes). Similar level of accuracy could also be found in the prediction of SD of path journey time, which is between 3.0 ~ 9.1 minutes, with RMSEs ranging from 0.2025 minutes (12.15 second) to 0.2174 minutes (13.04 second). Figure 4 shows the observed and predicted effective path journey times (at 90% confident level) for a path between OD pair (13,1) in Scenario A. This path is chosen as it gives the largest percentage error of predicted effective path journey times among the all the paths considered in this scenario. Despite the predicted effective path journey times for this path are always under predicted (Figure 4), the proposed prediction framework has over-predictions on effective path journey times for other paths. In Figure 4, the maximum prediction error of effective path journey time is 2.5 minutes (10.35%) at 09:00, while the minimum is 1.74 minutes (7.64%) at 08:31. Considering the 5,760 effective path journey time predictions (192 paths with 1 prediction per minute of each path for period 08:31 ~ 09:00) in Scenario A, 83.9% of predictions have errors less than 5%, while 16.1% of predictions have errors between 5% and 10%. Only 2 predictions of effective path journey time have error slightly over 10% (i.e., 10.35% and 10.09%).

To test for the impact of link travel time covariance on effective path journey time prediction, Scenario A is repeated with θ in Equation (4) taken as zero and the corresponding RMSEs for the prediction period of 5 minutes are shown in the last column of Table 1. Comparing the results in the last column to that of the 5-minute prediction period of Scenario A, it could be seen that without considering the link travel time covariance, the prediction accuracy decreases, especially in predicting the SD of path journey times. Similar results could also be found in Figure 4 as the line for $\theta = 0$ has a larger difference from the observed effective path journey time as compared to that for $\theta = 1$. To demonstrate the robustness of the proposed prediction framework, predictions are repeated for 20 different scenarios and similar level of prediction accuracy is obtained (5th ~ 7th column of Table 1). For the average RMSEs of 30-minute prediction period of the 20 scenarios case (7th column of Table 1), it could be seen that there is a decrease as compared to that of the 5- and/or 15-minute prediction period (5th and 6th column of Table 1). These results suggested that the accuracy of the proposed prediction framework is independent of the prediction period and could be explained by the use of RDTA model in path journey time predictions. Accuracy of such dynamic flow-based prediction model depends on the accuracy of the estimated input parameters (i.e., demand and link travel time multipliers) and their impacts on the journey time predictions at different time periods.

4. CONCLUSION

In this study, a network-wide journey time prediction (NJTP) framework with consideration of link travel time covariance is proposed for dynamic journey time prediction based on path journey times and link flows observed in congested road network with uncertainties. The proposed prediction framework consists of two sub-modules: journey time estimation and journey time prediction sub-modules. The journey time estimation sub-module aims to estimate the link flows, path journey times and flow model multipliers (i.e., demand and link travel time multipliers) from the observed quantities for establishing the database used in the prediction sub-module. The journey time prediction sub-module is formulated as a multi-level k-NN model using two different day categories, observed link flows, observed mean path journey times and observed SD of path journey times to screen and sort the records in the database. Similar records are selected for predicting model multipliers that used in the reliability-based dynamic traffic assignment model for predicting path journey times. The Sioux Falls road network is adopted as the numerical example and it is shown that the proposed framework is accurate, efficient and robust in travel time prediction in medium-size road network. Future research will be focused on the real-world implementation of this proposed NJTP framework together with empirical validation.

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