TERP: Time-event-dependent Route Planning in
Stochastic Multi-modal Transportation Networks
with Bike Sharing System
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Abstract—Advanced traveler information systems (ATIS) provide travelers with public transportation information to improve the quality of individual life and alleviate congestion as well as air pollution. However, existing works haven’t fully incorporated bike sharing systems within ATIS, providing no interaction with other modalities nor taking bike stocks into account. In addition, the uncertainty of traffic conditions and multi-modal routing makes it challenging to accurately estimate the travel time. In this paper, we leverage large-scale historical data collected in London and construct a multi-modal transportation network including bus, tube, public bikes and walking. We solve the modalities aggregation problem by practically modeling the travel time, arrival time, bike stock and transfer time between different transport modalities. Furthermore, we propose TERP, a time-event-dependent route planner that optimizes both trip duration and reliability. We conduct experiments on extensive real-world data with over 23 million arrival records and 15 million stock records on more than 10000 stations from Transport for London platform (TfL). The results validate 14.91% reduction of actual total trip duration and 56.28% improvement in terms of route reliability in rush hours comparing with TfL.

Index Terms—Multi-modal transport, Bike sharing system, Dynamic stochastic networks, Optimal routing problem.

I. INTRODUCTION

Increasing concerns are being raised about serious traffic problems nowadays, such as congestion, which is doing major damage to the city’s economy as well as aggravating air pollution [1], [2]. Therefore, providing effective public transport services has become a key challenge for the urban sustainable development [3], [4], among which, bike sharing systems (BSS) recently attracted considerable attention all over the world [5]. Considered as one of the most effective public transportations to alleviate congestion, 1100 bike sharing systems are now in active operation world wide and the total number of sharing bikes hits an estimated number of 2 million by the end of 2016 [6].

Although various works have been done in the field of multi-modal transportation network, in terms of transportation mode, cycling is either ignored [7], [8] or regarded as private mode that commuters travel with their own bikes [9]. Popular route planners, such as Google Maps and Transport for London (TfL), regard BSS as an independent part and do not take them into consideration when providing multi-modal pre-trip advisories. Moreover, no multi-modal transportation research has incorporated the stock of bikes in stations, which fluctuates intensively according to the commuter-mobility and may exert great influence on one’s travel plans.

In multi-modal transport networks, BSS offers an environmentally friendly solution for the ”last-mile” connection and helps to bridge the gap between existing modalities [10], [11]. By integrating with other modalities, BSS also acts as an important complement to cover congested road segments and would discourage the use of motor vehicles for short-distance trips [12], [13]. Thus, providing practical multi-modal transportation route recommendation with BSS helps to encourage commuters to switch to public transportation and save travel time, reduce traffic congestion, conserve energy consumption and enhance traffic safety.

With the observations mentioned above, we are motivated to provide a practical route planner in large-scale multi-modal transportation network with BSS. However, several challenges need to be addressed.

Firstly, it is required to deal with uncertain and stochastic characteristics of urban traffic and extract the key parameters such as the expected time-dependent travel time and arrival time from numerous historical data, while most of the researches assume that travel times are deterministic or determine the coefficients heuristically. Moreover, few works have dug into the specific transfer time related to different modalities [14], [15].

Secondly, difficulties exist with the incorporation of BSS. Different from any other modes of transportation, cycling trips do not have fixed lines or routes yet are limited to predetermined departure and arrival bike stations. In addition, the uncertain stock may severely affect the hire and return of bikes and needs to be characterized in the model. Thus a new design of the multi-modal system should be provided to take both cycling links and bike stock into consideration.

In order to address the aforementioned challenges, we estimate the distribution of actual vehicle arrival, travel time and bike stock based on the historical data. Then we leverage necessary transfer links and pre-computed bike paths related to the origin and destination as well as precisely define the state-based transfer time to form the multi-modal transportation network with BSS.

The main contributions of this paper are summarized as follows:
1) We extend the traditional multi-modal network to incorporate the effects of public bike services by pre-adding the possible links and extracting the availability and returnability of bikes in each station. To the best of our knowledge, this is the first work to leverage complete large-scale BSS and further take the time-dependent stock distribution into account when routing.

2) We present a general framework that models the uncertain public transport condition and with the parameters of which, we introduce a directed multi-edge graph by novelty combining time-expanded and time-dependent network to construct the stochastic time-event-dependent transportation network. Meanwhile, we dynamically update the parameters with user reports. Then we propose our real-time route planner TERP—with a multi-criteria algorithm which solves the travel time aggregation problem among different transportation modes and optimizes both total travel time and reliability of the route advised with not more than 3 transfers.

3) We build the stochastic transportation network for London with both static transport information and numerous historical arrival data crawled from TfL. Then we evaluate the system based on our collected datasets at both system and algorithm level. The results confirm the quality of returned routes and accuracy of expected total trip time in comparison with other state-of-the-art route planners.

The rest of the paper is organized as follows. In Section III, we present an overview of the architecture of our system and briefly describe the datasets used in our work. In Section IV, we present the modeling of arrival time, travel time, and also the availability and returnability of public bikes. Then we introduce the stochastic time-event-dependent multi-modal transportation network and illustrate the routing algorithm adopted in Section V. We evaluate the proposal method in Section VI. Related works are discussed in Section II, and Section VIII concludes the paper.

II. RELATED WORKS

In recent years, efforts have been devoted to investigating route planning in multi-modal transport network [16]–[21]. [7] proposed an object-oriented model and an agent-based approach to heuristically improve the scalability and flexibility. [22] improved the method by applying a label-correcting algorithm to find best transfer location. However, BSS, which constitute an increasingly important part in urban transportation, are not taken into consideration in these multi-modal networks, nor are the bike stocks in stations.

With regard to the stochastic travel time, time-expended network and time-dependent network are widely used in such scenarios [14], [23]. [9] proposed a modified time-expanded super-network based on a static time schedule, but the size of this kind of graph can be very large and costs hours of computation. [24] built a stochastic time-dependent network that optimize minimum upper bounds of travel times, but assumes transfer times to be deterministic. In addition, few works have dug into the transfer time related to different modalities nor leveraged real-world data to model both the travel time and waiting time in public transportation network.

As for the routing algorithms, Dijkstra’s algorithm is one of the most commonly used solution [25], but the runtime of Dijkstra’s algorithm is too high for real-time applications. Much effort has been devoted to bi-directional search [26], [27] and the goal-directed search such as ALT algorithm [28] which can be well adapted to our work. Multi-objective optimization problems need to generate all non-dominated alternative solutions during the search processes. However, ALT returns only one result while there could be several shortest paths, thus the algorithm is not capable of dealing with several minimization criteria and need to be extended when applied in our framework.

Recently researches have focused on the extension of route planning algorithms to take reliability into account. Sun et al [29] proposed a modified algorithm considering the largest deviation of the arrival time on each node. B. Chen et al [30] aggregate travel time and uncertainty as travel time budget to ensure a certain level of on-time arrival probability. However, both of these algorithms do not fit to our need as their target of routing is different from us. The former aims at finding a solution close to a target time and the travel time budget in the latter work does not reflect the real travel time thus the route recommended is not necessarily the shortest path.

To the best of our knowledge, this is the first work to leverage complete large-scale BSS and take the availability and returnability of bikes into account when routing. Furthermore, due to the practical aggregation of different modes and precise computation of various transfers, our work provides a novel model different from these designs.

III. SYSTEM DESCRIPTION

In this section, we take an overview of the structure of TERP, and introduce the real-world datasets crawled from Transport for London API1.

A. Network Structure

Figure 1 depicts the structure of TERP. Public transport information are combined with OpenStreetMap2 (OSM) road networks to construct the network graph, then arrival time and bike stocks crawled from TfL are leveraged to model the edge weight of the time-event-dependent network. In addition, users are encouraged to report real-time arrival time and bike stocks, then the edge weight can be updated incrementally with the consideration of new reports. By providing a pair of origin and destination (O-D pair) coordinates and the departure time, a user can acquire a multi-modal route with least expected travel time and high reliability.

B. Dataset Description

TfL supports the majority of public transport in London, where more than 31 million journeys are made a day [31], and through TfL we crawled the static transport information

1https://api.tfl.gov.uk/

2https://www.openstreetmap.org/
and historical data from February 15th to April 25th in 2017, including more than 23 million bus and tube arrival records on over 10000 stations along 600 lines and more than 15 million stock records on over 750 bike stations. As in most developed cities, buses and tubes are the most common public transportation in London, while BSS is also adopted.

- **Public Transport Information** The transport information includes the stations and lines of buses and tubes, the expected schedules of arrivals on each bus station, as well as the distribution and capacities of stations in BSS.

- **Road Network from OSM** While the lines are represented as paths between stations in our model, it is necessary to have a higher level of details when cycling and walking are considered. To this end, the fine-grained data structure of OSM can be used to refine pre-added links. We exploit both walking and cycling networks to identify the road segments which do not fit for cycling and walking are considered. To this end, the fine-grained data structure of OSM can be used to refine pre-added links. We exploit both walking and cycling networks to identify the road segments which do not fit for cycling such as stairs and narrow walking paths.

- **Arrival Data** We crawl the historical arrival data to characterize the changing traffic condition. According to the historical data, arrivals in rush hours are more scattered and uncertain but still relative to the static timetable. Therefore, it is significant to make use of both the schedules and arrival data to model the real timetable and travel time.

- **Stock Data** Each row of the collected data includes a record of stock in the station. The average bike stock percentage distribution after rush hours of BSS in London based on the crawled historical data is represented in Figure 3. Each dot stands for a bike station in London with its color representing the percentage of the bike stock. As we can see from the figure, the bike stock distribution varies both geographically and temporally, and cases exist that bikes are unavailable or unreturnable for certain stations in peak hours. Therefore, we utilize the historical stock data to model the availability and returnability of stations in different time intervals.

IV. PUBLIC TRANSPORTATION MODELING

Considering the stochastic traffic, we need to extract the real-time key information, namely the arrival and travel time, as well as the bike stock based on the crawled datasets and update them dynamically with information reported by users. Different from existing works which mostly utilize the static schedule or do not take bike stock into consideration in multi-modal transport network, we confront the schedules to historical data for more accurate arrival time and travel time, and estimate the availability and returnability of public bikes under certain confidence level in different time intervals.

A. Bus Arrival Time Modeling

We use the expected arrival time $B_{l,i,k}^j$, namely the $j^{th}$ arrival of line $l$ on station $i$, to divide the historical arrivals into time intervals. For a record of arrival $A_{l,i,k}^j$, it falls into interval $j$ when Eq. (1) is satisfied. The $n$ days of arrival time on station $i$ along line $l$ towards the next station $k$ in time interval $j$ can be fit into a normal distribution as in Eq. (2). The mean and the variance are regarded as the expected arrival time and the criterion for reliability evaluation respectively, which can be updated incrementally when new arrival times are reported by users as Eq. (3) and Eq. (4).

$$\frac{B_{l,i,k}^{j-1} + B_{l,i,k}^j}{2} \leq A_{l,i,k}^j < \frac{B_{l,i,k}^j + B_{l,i,k}^{j+1}}{2} \quad (1)$$

$$A_{l,i,k}^j \sim N\left(\hat{\mu}_{l,i,k}^j, (\hat{\sigma}_{l,i,k}^j)^2\right) \quad (2)$$

$$\hat{\mu}_{l,i,k,n+1}^j = \frac{1}{n+1} \left(\hat{A}_{l,i,k,\text{reported}}^j + n\hat{\mu}_{l,i,k,n}^j\right) \quad (3)$$

$$\hat{\mu}_{l,i,k,n+1}^j = n\left((\hat{\mu}_{l,i,k,n}^j)^2 + (\hat{\mu}_{l,i,k,\text{reported}}^j - \hat{\mu}_{l,i,k,n}^j)^2\right) \quad (4)$$

B. Tube Arrival Time Modeling

No direct tube schedule is available on TfL, but the total runs of a certain line on each day is determined and can be set as the cluster number for corresponding tube line. Therefore we adopt K-means clustering on each line and station to estimate the tube arrival time as Eq. (5). With consideration of outliers, we divide a day into intervals with the core point of each cluster and then calculate and update the mean and variance just in the way we deal with the bus arrival time.

$$SSE = \sum_{m=1}^{n} \sum_{A_{l,i,k}^j \in C_m} \text{dist}\left(A_{l,i,k}^j, c_m\right) \quad (5)$$

C. Travel Time Modeling

For departures $A_{l,i,k}^j$ aggregated in interval $j$, we extract all the reasonable arrivals on the next station along line $l$ and calculate the travel time of trips with the same departure stop $i$, arrival stop $k$, vehicle ID $v$ and departure interval $j$ in Eq. (6). Similarly to the departure, the travel time can also be fit into a normal distribution.

$$T_{l,i,k,v}^j = A_{l,i,k}^v - A_{l,i,k}^j \quad (6)$$

D. Bike Stock Modeling

Compared to previous works [5], [32], this is a simplification of bike stock prediction as only whether the user will be able to hire or return a bike is addressed. We use 5 minutes as a time interval and accumulate historical stock data for each station within each interval in different days. Then we
identify the confidence interval of $n$ days of stock samples in time interval $j$ at station $i$ with upper limit $I^U_{i,j}$, lower limit $I^L_{i,j}$ and confidence level $\alpha$ as shown in Eq. (7). When receiving real-time information such as bike stock, broken bikes or unserviceable stations, we recalculate the bike stock distribution and update the confidence interval.

$$P \left\{ I^L_{i,j} \leq \mu \leq I^U_{i,j} \right\} = 1 - \alpha$$

(7)

Then the availability $\alpha^i_j$ and returnability $r^i_j$ of station $i$ in interval $j$ are defined in Eq. (8) to determine if the station is reachable in routing where $\beta_1$ and $\beta_2$ are the stock percentage coefficients and $Cap_i$ denotes the capacity of $i$.

$$\left\{ \begin{array}{ll}
\alpha^i_j = 0 & \text{if } \frac{I^L_{i,j}}{Cap_i} < \beta_1 \\
r^i_j = 0 & \text{if } \frac{I^U_{i,j}}{Cap_i} > \beta_2 \\
\alpha^i_j = 1, r^i_j = 1 & \text{otherwise}
\end{array} \right.$$  

(8)

V. ROUTE PLANNING

With networks constructed in the previous section, we need to design the overall network structure and obtain accurate weight for corresponding links. However, existing networks are not sufficient to depict the stochastic multi-modal transport network with BSS, because each considered modality has its own properties in terms of possible transfer and travel time and requires special handling to connect to others. Therefore we are motivated to unify the description of different transport modes and design a novel method to construct the stochastic multi-modal transport network. Then suitable routing algorithm should be adopted to precisely handle the real-time transfers. Existing works do not have enough adaptability to our usage scenarios, as the incorporation of modalities ends in a large number of possible connections and the algorithm need to deal with the edge selection and weight determination. Thus we design a state-based multi-criteria ALT algorithm to determine the accurate weight of links and optimize both travel time and reliability.

A. Multi-modal Transit Network

We indentify reasonable locations to insert transfer links and connect the uni-networks. Then a directed multi-edge graph is devised to depict the stochastic network and assign accurate weight according to different transfer modes.

1) Transfer links: Walking paths are always involved to connect different networks as transfer links. The weight of a certain walking path is associated with the distance between the start and end node through the walking network in OSM and a set walking speed of 5 km/h based on common values.

2) The combination of different modes: Each of the unimodal graphs, $G_b, G_t, G_c, G_w$, denoting bus, tube, cycling and walking graph respectively, is constitutive of nodes, edges and label sets $G_i = (V_i, E_i, \Sigma_i)$. With links needed for transfers incorporated, the multi-modal transport graph can be represented as the union of all unimodal graph: $G_m = (V_m, E_m, \Sigma_m)$, where $V_m = V_b \cup V_t \cup V_c \cup V_w$, $\Sigma_m = \Sigma_b \cup \Sigma_t \cup \Sigma_c \cup \Sigma_w$, $E_m = E_b \cup E_t \cup E_c \cup E_w \cup E_{links}$. It should also be noted that commuters are able to choose whether or not to add public bikes according to their own conditions.

First, we insert walking links from each station to its neighbors within a distance of 200 meters to enable transfers between two close stations. Then we assign nearby bike stations to each bus and tube station, and add bike paths between bike stations where their corresponding bus or tube stations are connected by a transport line. Thus it helps to cover gridlocked road sections during peak hours with cycling. The weight of a certain bike path is calculated with the cycling network in OSM and a reasonable cycling speed of 12 km/h.

Given the O-D pair, we connect them with their neighbor stations by walking paths. In order to cover the last kilometer, we search for bus and tube stations as well as their nearby bike stations with a reasonable riding distance, which we set as 2km as default, away from the O-D pair’s nearby bike stations, and concatenate them with cycling paths.

Figure 4 shows the schematic representation of the connected transportation modes. Every two public transport network are connected through foot network. For example, when transferring from bus line $l_1$ to tube line $l_4$, commuters can either walk from station $n_{14}$ to $n_{12}$ or walk to bike station $n_5$, cycling to $n_{16}$ and then walk to $n_{12}$.

3) Stochastic time-event-dependent transportation network: We devise a directed multi-edge graph that integrates the time-expanded and time-dependent networks, the substructure of which is depicted in Figure 5. Commuters arrive at station $i$ at time $t$ by line $l_1$ of mode $m$. Multiple edges are aggregated connecting with the next station $k$ and each event node denotes departure events with different departure time, modes or lines to $k$. Each edge includes the source node, destination...
node, mode, line, arrival time, arrival variance, weight and weight variance. We assume that walking and cycling are only involved with distance and the variance is set to be zero.

The edge selection and weight determination constitute the core of the routing which can be basically formulated as Eq. (9). $w_{i,k}$ represents the accurate weight from node $i$ to node $k$, the minimum sum of the transfer time $T_i(A_{1,i,k})$ from $i$ to transfer node and the travel time $T_{l,i,k}^j$ from transfer node to $k$.

$$w_{i,k} = \min \left( T_i(A_{1,i,k}^j) + T_{l,i,k}^j \right) \tag{9}$$

Then we further illustrate how we compute the state-based transfer time: when commuters arrive at station $i$ by line $l_1$ at time $t$ towards station $k$, how we determine the transfer time for different lines and arrival time.

4) Bus and tube: There are two kinds of transfers after a bus or tube trip: line transfers and transferring to walk. The waiting time for the expected arrival $A_{1,i,k}^j$ is shown in (10).

$$T_i(A_{1,i,k}^j) = A_{1,i,k}^j - t, \quad A_{1,i,k}^j \geq t \tag{10}$$

Three conditions are considered as in (11). Firstly, when no transfer was made, we leverage the travel time corresponding to the arrival time as weight of the edge. Secondly, when transferring to line $l_2$, the sum of the travel time and waiting time for the upcoming vehicle is computed as real travel time. Thirdly, travelers get off the vehicle and the travel time associated with distance of the trip is regarded as the edge weight.

$$\begin{align*}
\arg\min \{ & T_i(A_{1,i,k}^j) \} \\
T_{l_1,i,k}^j & \text{ if } l_2 = l_1 \\
\arg\min \{ & T_i(A_{1,i,k}^j) \} + \min \{ T_i(A_{l_2,i,k}^j) \} \\
T_{l_2,i,k}^j & \text{ if } l_2 \neq l_1 \\
T_i & \text{ if } m_2 = \text{walk}
\end{align*} \tag{11}$$

5) Cycling: The possible waiting time for cycling is concerned with the bike stock when renting or returning the bike at station $i$ at time $t$, and the routing algorithm will then evaluate the sum of the waiting time and travel time of each mode to decide whether to wait for a bike or transfer to other transport modes.

First we inquire the availability $a_{t,i}^j$ at the arrival time. When a bike is not available at the station, the least waiting time $T_{a,t,i}^j$ is formulated as (12). And the least waiting time to give back the bike can be calculated in a similar way.

$$\begin{align*}
T_{a,t,i}^j & = \min \{ t' - t | a_{t,i}^j = 1, t' \geq t \} \\
T_{r,t,i}^j & = \min \{ t' - t | r_{t,i}^j = 1, t' \geq t \} \\
T_{a,t,i}^j & = 0 \\
T_{r,t,i}^j & = 0 \text{ otherwise}
\end{align*} \tag{12}$$

The bike network is only connected to walking network which stands for the return of a bike, then only the returnability needs to be dealt with.

$$\begin{align*}
T_i + T_{a_i}^j & \text{ if } m_2 = \text{walk} \\
T_i & \text{ if } m_2 = \text{bike}
\end{align*} \tag{13}$$

6) Walking: With walking network connected to all other networks, three conditions are considered. Similar to bike network, the availability need to be noted when transferring to cycling.

$$\begin{align*}
T_i & \text{ if } m_2 = \text{walk} \\
T_i + T_{a_i}^j & \text{ if } m_2 = \text{bike} \\
\arg\min \{ & T_i(A_{1,i,k}^j) \} + \min \{ T_i(A_{l_2,i,k}^j) \} \\
T_{l_2,i,k}^j & \text{ otherwise}
\end{align*} \tag{14}$$

So far, we’ve completed the walkthrough of all transfers, thus the final weight of the edges will be computed as (9).

B. Routing strategy

When the stochastic time-event-dependent transportation network is constructed, a routing strategy should be adopted to obtain the optimal route. Commonly used algorithms, such as ALT algorithm [33], only minimize one criterion and need to be adapted to our network to precisely aggregate the travel time. Thus we extend ALT algorithm to a state-based multi-criteria algorithm that is able to calculate accurate link weight and generate the route with least travel time within the mode transfer number constraint, while reliability is also considered. We select a set of landmarks with MaxCover [33].
The algorithm can be adapted to the time-event-dependent networks by calculating the minimum weight of the arcs.

We construct a multi-dimensional label $L_u$ for each node $u$, consisting of the accumulated travel time $dist[u]$, the variance $V[u]$, the line $l_p[u]$, the mode $m_p[u]$ taken from the previous node $prev[u]$ and the number of transfers $trans[u]$. Given the arrival time on $u$, the algorithm obtains the time-event-weighted average of the next feasible arc from $u$ by methods in Section V-A3 with parameters in $L_u$.

Algorithm 1 shows the steps to get the desired path with the input of departure time, origin and destination. We choose node $u$ with minimum key, namely the sum of accumulated distance and potential cost to the destination, from the priority queue and check if the transfer number exceeds the limit when arriving at $u$. The two optimization objectives can then be determined as in line 12 and 13. Subsequently, line 17 turns the predecessors of each node into an array to maintain those with same accumulated travel time to store multiple paths. When the algorithm ends, we keep track of all the non-dominated paths and retrieve the path with highest reliability, that is to say, the recommended route is the path with highest reliability in those with least travel time. It should also be noted that the travel time is accurate to minute.

It should be noted that time-dependent multi-criteria shortest path problem is polynomially solvable, and the ALT-based algorithm is practically faster because of the precalculations of the key and the reduction of the search space.

### VI. Experiment

#### A. Experimental Setup

We randomly select 100 trip instances of which the start and end points are located in the whole city with an air line distance from 2km to 10km. Then we conduct experiments on these instances in both peak and off-peak hours with transfer number constraint set as 3 and collect the optimal results returned by different route planners.

#### B. Ground Truth

In order to guarantee the effectiveness of obtaining the ground truth for a large number of trip instances and eliminate the influence of personal random error when gathering the real data as far as possible, when a certain route is returned from a route planner, we track the real arrivals and the stock of stations in the optimal route and compute the truth-value of the total travel time of each route with 7 days of historical data as ground truth.

#### C. Performance Metrics

We utilize the 7-day ground-truth of the trip duration and calculate their mean value $t_{i,j,k}$, the Mean Relative Error (MRE) and variance $v_{i,j,k}$ as metrics to verify the ability to provide least trip duration and higher reliability with higher estimation accuracy. The $MRE(r_i, s_j, c_k)$ for route $r_i$ returned by $s_j$ in $n$ days on condition $c_k$, namely in peak or off-peak periods, is computed as follows.

$$MRE(r_i, s_j, c_k) = \frac{\sum_{d=1}^{n} |t_d(r_i, s_j, c_k) - t_d(r_i, s_j, c_k)|}{t_d(r_i, s_j, c_k)}$$

### D. Experiment Baselines

We conduct comparisons among different route planners. At systems level, we choose TFL and Google Maps, which are time-dependent systems and widely used in London. As for algorithms, we conduct experiments on the network that we construct with different multi-criteria routing algorithms. The algorithms proposed by S. Sun et al [29] and B. Chen et al [30] are chosen as baselines considering they are also solution to the stochastic routing problem. The former minimizes the
largest difference between the actual arriving time and the desired arrival time in dynamic stochastic networks, and in the latter research, the $\alpha$-reliable path is determined by minimizing the travel time budget required to ensure a certain level of on-time arrival probability.

E. Experimental Results

1) The ability to provide routes with least expected time: The total trip duration is the criterion that commuters care most about. In this subpart, we utilize the mean trip duration of each route to test the performance.

a) Comparison with different routing systems: Figure 6 presents the average truth-value of the trip duration of routes returned by TERP, TERP without BSS, TfL and Google Maps in peak and off-peak hours, sorted by the air line distance of each instance. As can be seen from Figure 6a, TERP, the only planner with BSS outperforms the others by leveraging cycling to cover long-distance walk and congested road segments thus reduce the total trip duration by 14.72%, 14.91% and 16.35% on average respectively. Meanwhile, cases exists that all systems return the same route when the departure and destination are both located near tube stations and quite exempt from congestion or when no bike stations are around or no bikes are available. For results in off peak periods, cycling is adopted less compared with routes in rush hours, especially in long-distance trips. In this case, TERP still achieves improvement of 8.20%, 12.88% and 14.25% respectively.

b) Comparison with different routing algorithms: Figure 7 depicts the comparison among the algorithms proposed by S. Sun et al, B. Chen et al and the Multi-criteria Routing Algorithm in this paper. While the other two algorithms combine trip duration and reliability as one label, our algorithm recommends routes with least trip duration and higher reliability and provides routes with total duration 11.51% and 7.13% less in peak periods and 11.23% and 8.98% less in off-peak periods than the other two algorithms. For trip instances with shorter distance, the three algorithms tend to only choose riding bikes thus results in the same trip duration especially in peak periods.

2) The ability to provide routes with higher reliability: In this part, we calculate the 7-day variance of real trip durations of routes returned by different systems and algorithms to verify if the trip duration fluctuates too much.

a) Comparison with different routing systems: TERP outperforms system without BSS, TfL and Google Maps in terms of route reliability with a reduction of trip duration variance by 43.19%, 56.28% and 57.53% in peak hours and 38.14%, 38.26%, 44.92% in off-peak hours as shown in 8a. Incorporating BSS reduces the risk of long-time congestion and waiting, thus provides routes with higher reliability.

b) Comparison with different routing algorithms: The comparison on the ability to provide routes with higher reliability between three algorithms is shown in 8b. It can be learned that outliers exist in the results of the other two algorithms because they reckon without the stock of bikes in the stations and may result in large delays when no bike can be rent or returned.

3) The accuracy of the expected travel time: We calculate the MRE of each route based on the estimated and truth-value of trip durations in 7 days so as to verify the accuracy of different systems in this part.

a) Comparison with different routing systems: The result in figure 9a shows that in rush hours, the MRE of our system is remarkable fewer than the other three systems by 21.66%, 52.50% and 54.27% respectively and 13.97%, 61.58%, 62.36% in off-peak periods. When cycling is adopted as the only mode of transportation, the estimation error is regarded as 0 if the bike is available and returnable in corresponding stations.

b) Comparison with different routing algorithms: At algorithm level, our multi-criteria routing algorithm yields significant decreases by 19.83% and 12.04% in peak periods and 18.63% and 14.29% in off-peak periods. As can be seen from Figure 9b, there are more cases that the other two algorithms select cycling as the only modality when MRE is regarded as 0. However, our algorithm deals with the travel
time aggregation property better when combining different modes of transportations and reaches overall higher accuracy of total trip duration estimation.

4) Case study: Finally, we illustrate the optimal routes of an trip instance in order to show the validity of the proposed route planner in Figure 10. When querying TfL and Google Maps, the two route planners both recommend to take bus 12 in peak and off peak periods as in Figure 10b. The proposed planner without BSS returns the same results in off peak periods but suggests to take tube first in order to avoid the congested roads in rush hours as shown in Figure 10a. Figure 10c and 10d show the impact of bike stocks. The proposed route planner with BSS returns routes in peak periods that suggests to rent a bike to cover the congested road segments and return the bike at a reasonable station which is at the boarder of the congestion charge area of London in this case. In addition, with the consideration of the number of bikes parked in the stations, the planner chooses the available and returnable bike stations with shortest distance.

VII. DISCUSSION

In this part, we provide some insights into the practical application of our proposed framework, and provide directions for future work.

A. Application in Other Sharing Systems

It is learned that there can be more than one sharing system in the same city [34], including bike sharing systems and car sharing systems. TfL didn’t provide the detailed distribution of other sharing systems but it should be noted that our proposed framework can also be applicable since the structure of sharing systems are similar and the scale of others is much smaller than the bike sharing system that TfL provides. However, the use of sharing cars may lead to the congestion problem and thus effect the estimation of traveling time. Therefore, we need to further incorporate the congestion management and improve the proposed framework for application in car sharing systems in the future [35].

B. Real-time information in Practical Application

Though only historical records are used to predict the probable traffic condition in our framework, more attention should be paid to real-time information, which reflects the fact of road condition, in practical application. The proposed system enables operators to incorporate real-time information to provide better recommendation. For example, real-time bus GPS can be uploaded to calculate waiting and traveling time more accurately along with historical road speed, which can also be updated with data newly uploaded. In addition, the effectiveness of real-time transmission and analysis of massive IoT Data and concurrent processing capacity of the server should also be considered in our future work [36], [37].

VIII. CONCLUSION

In this paper, we extract the travel time, arrival time and bike stock distribution from the real-world historical data and construct a stochastic time-event-dependent multi-modal transportation network with bike sharing system for London. Then we present TERP, a practical real-time route planner that optimizes multiple criteria and can effectively deal with uncertainty of urban traffic. Extensive experiments based on large-scale real world data proves that TERP outperforms other route planners and algorithms and validates 14.91% reduction of trip duration, 56.28% improvement in routes reliability and 52.50% decrease in prediction error comparing with TfL in rush hours. It helps to improve the quality of travel for commuters and may encourage them to switch to public transportation, especially to bike sharing system. In addition, the results also validate the great improvement in terms of trip duration and reliability in congested area when incorporating BSS and therefore suggest the significant importance of BSS in multi-modal transport network.
REFERENCES


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