Handoff Time Estimation Model for Vehicular Communications

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Abstract –A good understanding of the behaviour of the traffic of a mobile network is essential for an efficient planning and management of the mobile network's scarce bandwidth resources. In this paper, we propose a probabilistic approach, called Handoff Time Estimation MODel (HTEMOD), to estimate the time window when a user will perform handoffs along his/her movement/path to a destination. We derive the probability distribution function of time taken to transit each road segment along the path, using a sample of users that is selected according to navigation zone characteristics, current data on road segments, and current behaviour of users on the road segment. We evaluate our model via simulations, and compare it with the model proposed in [1]. Regardless of the given probability value to obtain a time window, the road segment density and the number of road segments to handoff, HTEMOD provides a better accuracy and good duration of predicted time window when handoff will occur. Whilst the proposed HTEMOD model can be applied to any type of user equipment, its efficiency becomes more appealing in the context of vehicles (i.e., for the support of road to vehicles communications - RVC) or highly mobile nodes travelling in urban areas constrained by predefined roads and whose velocities are also restricted according to speed limits, level of congestion in roads, and traffic control mechanisms (e.g., stop signs and traffic lights).

I. INTRODUCTION

In mobile communications, successful handoffs are only possible if sufficient resources can be granted to the ongoing IP session by the new network access point. Otherwise, the session will be prematurely terminated or dropped due to insufficient available resources at the new cell. Recent contributions about bandwidth management [1-4], in cellular networks, have focused on bandwidth reservation. They estimate the arrival times of a user in each neighboring cell or in the next cell to be visited according to the user's predicted path; then, they perform bandwidth reservation before the arrival of the user. However, for better resource utilization, it is important that bandwidth reservation, in a cell, is not made a long time before the arrival of the user into the cell.

In this paper, we propose a probabilistic approach, called Handoff Time Estimation Model (HTEMOD), which estimates the time windows when a user will perform handoffs along his/her movement path to a destination. More specifically, HTEMOD estimates the time windows when the user arrives in each cell along the path to a destination, and when he/she leaves the cell. HTEMOD computes the probability distribution of time taken to transit a road segment (i.e., a road portion between two road intersections) according to the navigation zone characteristics, current data on road segments and current behavior of users on the road segment. We use this probability distribution to compute the PDF (Probability Distribution Function) of time taken to transit a road segment or to reach a handoff point (i.e., intersection between a cell border and a road segment). The PDF of time taken to reach a handoff point after traversing many road segments is obtained from the convolution of the PDFs of time taken to transit these road segments and the PDF of time taken to reach this handoff point. To set the desired level of accuracy, we use the inverse function of the PDF of time taken to reach a handoff point, after traversing a number of road segments, to compute the lower and upper bound values of the time taken to reach the handoff point.

In our proposed approach, we assume that the path of a mobile user is known in advance; e.g., using the schemes described in [5, 6] to predict the path a user will use to reach his/her destination. Unlike certain existing contributions [1, 2, 7-9] which determine the user speed based on the average historical travel speed or connection duration to a cell or location at two consecutive epochs and select, from within a given time window, the stop duration at road junction randomly, HTEMOD (1) takes into account the variation of users' velocity as a time function; and (2) develops a scheme to estimate the user's stop duration at the road junction with a STOP sign according to the road segment density. Among existing research work which estimate the handoff time [1, 2, 4, 9], there are certain research work [2, 4, 9] which limit their mobility prediction to the neighboring cells while HTEMOD (3) predicts a user's mobility along the user's entire path to a particular destination. Wee *et al.*[1] proposed a handoff time estimation along user's path to destination. But, they use all the previous users to compute the PDF. A major difference with HTEMOD is the selection mode of population to compute the PDF. HTEMOD selects the population (4) according to the characteristics of the navigation zone. Also, HTEMOD uses (5) more recent users' movement characteristics to improve the prediction accuracy.

The remainder of this paper is organized as follows. Section II presents some related work. Section III describes the proposed HTEMOD approach. Section IV reports some simulation results and discusses the performance of HTEMOD. Finally, Section V concludes the paper, highlighting some future research work.

II. RELATED WORK

Effective bandwidth management in cellular mobile networks makes use of information about the movement of mobile users [10, 11]. Recent years have seen a considerable amount of work done on developing mobility prediction schemes [1-9, 12]. Existing contributions rely on the availability of prior information on the user's mobility behavior; most of these contributions [7, 8, 12] are limited to predicting the user's future path without estimating times when the user performs handoffs along his/her movement/path to a destination and also heavily rely on historical data. A few contributions [1, 2, 9] had focused on estimating the times when a user performs handoffs towards the destination. Lu, *et al.*[9] proposed a mobility model to estimate handoff times with the user speed randomly chosen from within the range [36, 90]

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km/h. If a mobile user chooses to go straight or turn right at an intersection, he/she will stop with a probability of 0.5 for a random time between 0 and 30 seconds due to a red traffic light. If the user chooses to turn left or around, he/she will stop for a random time between 0 and 60 seconds due to the traffic signal. This model [9] does not take into account the users' behaviors and does not consider different types of roads. Madhavi *et al.*[2] proposed a handoff time prediction scheme based on the location information at two consecutive epochs. Indeed, they instruct the base stations (BSs) to estimate the speeds and moving directions of mobile users and to compute the probability that a mobile will enter a neighboring cell based on his velocity and the road-map information stored in the BSs. The scheme does not take into account the variation of velocity and traffic signalling; furthermore, it is limited to the prediction of the entrance time into next cell. Wee-Seng, *et al.*[1] introduced a predictive bandwidth reservation scheme using mobile positioning and road topology information. To estimate the time that a user of a mobile station will take to transit his/her path to a destination, they use the probability density function of the time taken by the previous users to transit each road segment which forms this path to the destination. The choice of the population to compute the probability does not help increasing the accuracy of the probability density function. Indeed, the probability density function will be more accurate if the population selection is based on the density of the road which describes the users' behaviors on the road.

All in all, existing contributions have one or more of the following limitations in predicting the entrance/exit times of a user into/out of cells to a destination: (1) additional equipment are required [2, 9]; (2) increase of data traffic due to mobility data transmission between users and network backbone [8]; (3) prediction is limited to the next cell [2, 4, 9] ; (4) an inefficient estimation of stop duration (i.e., random choice) at the road junctions and users' speed (not a function of time) [1, 2, 7-9]; (5) use of old road traffic data that does not necessarily help producing an accurate view of the network state [1]; and (6) PDF population selection does not take into account the navigation zone type and road density. In this paper, we propose a scheme that proposes solutions to these limitations.

III. PROPOSED MODEL

The objective of HTEMOD is to estimate the time window when a user will perform handoffs along the predicted path to a destination.The output of HTEMOD, for a given user, is an *n*-tuple: $\Omega = \left\langle \left(t_1^l, t_1^u, c_1\right), \left(t_2^l, t_2^u, c_2\right), ..., \left(t_n^l, t_n^u, c_n\right) \right\rangle$

where t_i^l and t_i^u denote the lower and upper bound values of the estimated time when the user will reach cell i and C_1 ... C_n represent the cells the user is predicted to travel across towards the destination. HTEMOD maintains a database that includes the road topology within cells. We refer to a road between two adjacent junctions as a road segment, and identify each segment using an ordered junction pair (i.e., $s_{a\to b} \neq s_{b\to a}$). A junction is an intersection of roads (e.g., T-junction) or the intersection of a road and the border of a cell, called handoff point. For a road without intersection (e.g., highway), we partition the road into virtual road segments according to a given length l_s. A path to a destination is formed by a set of roads segments $\eta = \left(s_1, ..., s_i, ..., s_\eta\right)$. It shall be mentioned that the size of each road segment (in square meters) and the approximate coordinates of each junction are stored in the database; all these coordinates could be extracted from existing digital road maps previously designed for GPS-based navigational devices. The characteristics of each segment are also stored: length, number of lanes, presence of traffic light at the junction, and priority level at the junction [11]. In addition to the road topology information, the database stores information about each user location (road segment ID), his acceleration/deceleration, his maximum velocity, and statistical data of time taken to transit road segments. Note that user's mobility information is related to a given road segment. When he/she leaves from this navigation zone, his/her mobility information can be deleted.

Our handoff time estimation function is based on a PDF of time that will be taken to transit the rest of road segments forming the path to the destination. To compute this PDF, we select the population of probability based on the density of road segments (in opposition to existing contributions [1, 2, 9]). We use the density of a road segment as a criterion because it has a dependency relationship with the followings: (1) current road traffic state; (2) current users' behaviors on the road segment; (3) navigation zone type; and (4) time of the day. According to the density value (relative to the threshold values d_t^1 and d_t^2 where $d_t^1 < d_t^2$, denoting the low and high value limits representing a medium level of roads congestion), we select a specific type of population. The density is calculated by the following formula:

$$d_s(t) = \frac{n_s(t)}{s_s} \tag{1}$$

where $n_s(t)$ and s_s denote the number of users in the area of road segment s at time t and the size of the area s in square meters, respectively. $n_s(t)$ is computed using user location data; collected and stored in the database.

For density values lower than the threshold value d_t^1, the population of PDF of time that will be taken by a user to transit a road segment S (element of the rest of the road segments forming the path to the destination) is formed by the set of his/her movement characteristics (e.g., acceleration, deceleration and maximum velocity) on each past road segments which are located in the same navigation zone as S. Using this past movement characteristics, the length of S and the rule of physics in term of element motion (Equations 2 and 3), we compute the time to transit S (Equations 4 and 5). Based on [11] , we simplify the velocity function, as shown in Fig. 1. In Fig. 1(a), $[t_0 : t_1]$ represents the acceleration phase, $[t_1 : t_2]$ represents the constant velocity phase, and $[t_2 : t_3]$ represents the deceleration phase. The three phases can occur in a road segment. v_m denotes the maximum velocity that the user travels at during the constant phase. Each phase is associated with a corresponding road length, as shown in Fig. 1(b), which should be computed in order to obtain the transition time of the entire road segment.

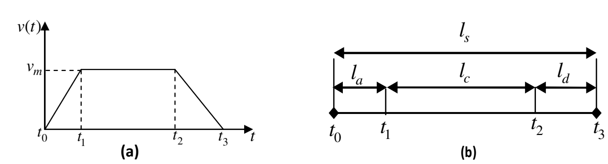


Fig. 1: (a) Simplified velocity function and (b) Association between time and length of a road segment portion.

In Fig. 1(b), l_s, l_a, l_c and l_d denote the length of road segment S which is stored into the database, the length of the road segment portion during the acceleration phase, the length of the road segment portion during the constant velocity phase and the length of the road segment portion during the deceleration phase, respectively. We compute the average velocity, using Equation 2, as follows:

$$\bar{v}=\frac{1}{\Delta t}\int_{0}^{\Delta t}(\sigma t+v_i)\,dt=\frac{\sigma}{2}\Delta t+v_i \qquad (2)$$

where σ and v_i denote the acceleration/deceleration and the initial velocity, respectively. The traveled distance during this epoch is computed as follows:

$$l=\bar{v}\times\Delta t=\frac{\sigma}{2}(\Delta t)^2+v_i\Delta t \qquad (3)$$

We estimate the time taken to transit segment S as follows:

$$\Delta t_s=\Delta t_a+\Delta t_c+\Delta t_d \qquad (4)$$

If the user does not stop due to any road traffic signs, the estimated time to transit segment S is defined as follows:

$$\Delta t_s=\frac{l_s}{v_m} \qquad (5)$$

For density value $d_s(t)$ where $d_t^1 \le d_s(t) \le d_t^2$, the population of PDF of time that will be taken by a user to transit a road segment S is formed by the set of last movement characteristics of users who are currently on S. These last movement characteristics can be sampled on their current segments S or their more recent past segments (S adjacent roads segments). We apply the same equations as above to estimate the time that each population element takes to transit S. For density values bigger than d_t^2, the population of PDF of time that will be taken by a user to transit a road segment S is formed by users who have already transited S and are currently located on the S adjacent roads segments (A, B and C in Fig. 2). In this case, we directly use their time taken to transit S.

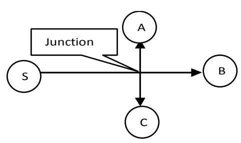


Fig.2: Illustration of the adjacent segments of the studied road segment.

After estimating the times taken by each element of the selected population to transit each road segment *Si* forming the rest of the path to the destination, we compute the probability distribution of these times on *Si* as follows:

$$p_i=P(\Delta T_s=\Delta t_s^i)=\frac{n_i}{n_{po}} \qquad (6)$$

where n_i denotes the number of elements in the selected population on *Si*, who have the same $\Delta t_s=\Delta t_s^i$ (Equations 4 and 5). n_{po} denotes the total number of elements in the selected population. The PDF of time taken to transit each road segment *Si* forming the rest path to the destination is given by the following equation:

$$F_{\Delta T_S}(\Delta t_s^i)=P(\Delta T_s\le\Delta t_s^i)=\sum_{j=1}^{i}p_j \qquad (7)$$

Note that the PDF of time taken to transit a path to destination (set of road segment *Si*) is obtained from the convolution of the PDF of time taken to transit each road segment *Si*. For example, if the path consists of road segment *A* followed by road segment *B* and then *C*, the convolution of the corresponding PDF is then defined as follows:

$$F_{\Delta t_\eta}(\Delta t_\eta)=F_{\Delta t_A}(\Delta t_A)\otimes F_{\Delta t_B}(\Delta t_B)\otimes F_{\Delta t_C}(\Delta t_C) \qquad (8)$$

where $F_{\Delta t_\eta}(\Delta t_\eta)$ denotes the PDF of the time taken to transit path η. So, we exploit this theory (Equation 8) to compute the PDF of time taken to transit a path to a given handoff point along the user path to a destination (Fig. 3).

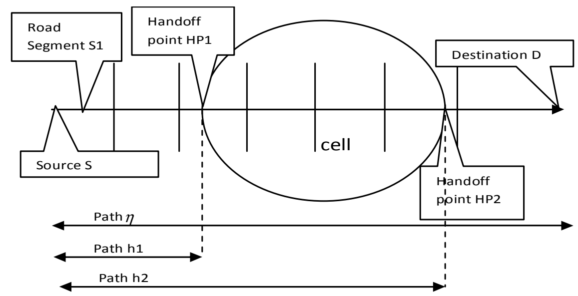


Fig. 3: Illustration of the paths to handoff points.

Our goal is to estimate the time windows during which a user will likely perform handoffs to the destination. For each handoff point, we select two values of probabilities δ_L and δ_U that determine the earliest time Δt_η^l and latest time Δt_η^u to enter the new cell (i.e., perform handoff), respectively. Based on Equation 8 and the properties of PDF, we obtain the following:

$$\forall\delta_U,\delta_L\in[0;1],F_{\Delta T_\eta}^{-1}(\delta_U)=\Delta t_\eta^u \quad and \quad F_{\Delta T_\eta}^{-1}(1-\delta_L)=\Delta t_\eta^l \qquad (9)$$

In our approach, we take into account the stop signs at the road junction along the path to the destination when $d_s(t)\le d_t^2$ (Equation 1). If $d_s(t)>d_t^2$, then the stop duration is included in the time taken to transit the road segment. If $d_s(t)<d_t^1$, we compute the stop duration for the road junction *j* (at the end of road segment *Sj*) as follows:

$$\Delta t_j=\frac{\sum_{\omega=1}^{n}\omega\Delta t_\omega}{\sum_{\omega=1}^{n}\omega} \qquad (10)$$

with $n\le j-1$ where n, ω and Δt_ω denote the number of road junctions already crossed and located in the same navigation zone as *Sj*, a weight of road junction ω and the stop duration at the road junction ω. This mechanism allows giving more weight to the more recent STOP duration. If $d_t^1\le d_s(t)\le d_t^2$, the average of the last stop duration of users who have already crossed the road junction *j* (according to Fig. 2, there are users located in segments A, B and C). The stop duration between current location and the handoff point HP*i* can be obtained as follows:

$$\Delta t_{STOP}^i=\sum_{j=1}^{k}\Delta t_j \qquad (11)$$

where $k\le i-1$ denotes the number of road junctions between the current location and the handoff point HP*i*. The stop duration along the rest of the path to handoff point HPi is added to the predicted time taken to transit it (Equation 9). This action does not modify the PDF. We obtain:

$$t_i^l = t_0 + \Delta t_\eta^l + \Delta t_{STOP}^i \quad and \quad t_i^u = t_0 + \Delta t_\eta^u + \Delta t_{STOP}^i \qquad (12)$$

where t_0 denotes the initial time of estimation.

IV. Performance Evaluation

Having described details of our proposed HTEMOD scheme, we now direct our focus to evaluating its performance. The performance evaluation relies on computer simulation, using a program developed in JAVA. Note that HTEMOD focuses on the handoff time estimation in contrast to the bandwidth management; hence it is appropriated to evaluate HTEMOD performance in terms of handoff time accuracy and time window duration. This accuracy may be used by the bandwidth management models; those models may evaluate their performances in terms of handoff call dropping, new call blocking and efficient use of available bandwidth. Table I lists up the values of the parameters used in the simulations, envisioning a highly realistic scenario.

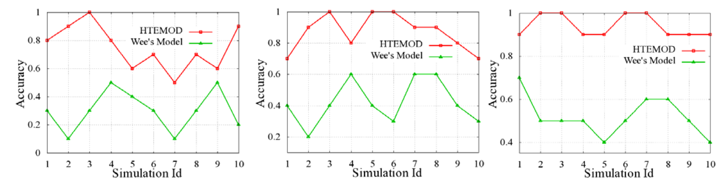
Table I: Simulation parameters.

Parameter	Value
s_s	1.5 $10^3 m^2$ (300m x 5m)
Cars	$15m^2$ (5m x 3m)
d_t^1	3.3 $10^{-3} car/m^2$ (about 5 cars on the road segment)
d_t^2	3.3 $10^{-2} car/m^2$ (about 50 cars on the road segment)
l_s	300m
v_m	random selection between 4 and 8m/s (28 and 33m/s for highway)
α	random selection between 0.3m/s^2 and 0.7m/s^2 (0m/s^2 for highway)
β	random selection between -0.9m/s^2 and -0.5m/s^2 (0m/s^2 for highway)
$\delta_L = \delta_U$	Between 0.5 and 0.7
Δt_j	random selection between 1 and 5sec. and 0sec. for highway

We assume that the handoff occurs at the end of the fifth road segment for each simulation run except where the number of road segments/junctions before the handoff is used as performance metric. Note that δ_L and δ_U are design parameters whose optimal values are best determined empirically. A general rule of thumb is to set a value that is within the range of 0.5 and 0.7 [1]. We have considered the impact of δ_L and δ_U only in the scenarios of Fig. 4 and Fig. 5. In the other scenarios, we set $\delta_L = \delta_U = 0.7$. In Fig. 4, Fig. 5, and Fig. 6(c) $d_s(t) \le d_t^1$, the prediction accuracy is computed as follows:

$$A_d = \frac{n_{bp}}{n_{tp}}$$

where n_{bp} and n_{tp} denote the number of good estimates and the total number of estimates, respectively. A good estimate occurs when the real time of arrival into cell is within the predicted time window. Note that one simulation is composed by ten estimates (tests). We compare our model with that proposed in [1]; referred to as Wee's model. According to Wee's model, they evaluate the probability distribution using the previous users on the path as probability population in contrast to HTEMOD which selects the probability population depending on the road density. In the worst case, HTEMOD probability population is less than Wee's model; Wee's model requires larger database storage space than HTEMOD. However, HTEMOD uses more recent data of probability population; this data is closer to the considered user behaviour; nevertheless, HTEMOD is more complex than Wee's model due to HTEMOD population selection based on road segment density and stop consideration.

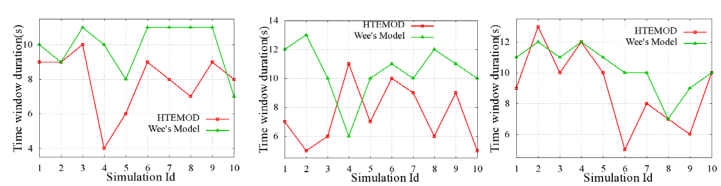


(a) $\delta_L = \delta_U = 0.5$ (b) $\delta_L = \delta_U = 0.6$ (c) $\delta_L = \delta_U = 0.7$

Fig.4: Prediction accuracy for different values of δ_L and δ_U

Fig. 4 highlights the impact of δ_L and δ_U on the prediction accuracy of HTEMOD and Wee's model. HTEMOD's accuracy reaches an average of 75% versus 30% for model [1] when $\delta_L = \delta_U$ =0.5, 87% versus 42% for model [1] when $\delta_L = \delta_U$ =0.6 and 94% versus 52% for model [1] when $\delta_L = \delta_U$ =0.7. According to the graphs (a), (b) and (c), the values of δ_L and δ_U affect both schemes. However, the accuracy of HTEMOD remains always better than that of model [1]. This is due to our selection method of the sample population. The graphs (a), (b) and (c) show that regardless of the simulation ID, the accuracy of HTEMOD exceeds 50% when $\delta_L = \delta_U$ =0.5, 70% when $\delta_L = \delta_U$ =0.6, and 90% when $\delta_L = \delta_U$ =0.7.

Fig. 5 shows the impact of δ_L and δ_U on the predicted time window duration. According to Fig. 5, δ_L and δ_U impacts the size of the time window. For $\delta_L = \delta_U$ =0.5, the average predicted time window duration is 7.9 sec for HTEMOD versus 9.9 sec for model [1]. When $\delta_L = \delta_U$ =0.6, the average predicted time window duration reaches 7.5 sec for HTEMOD versus 10.5 sec for model[1]. For $\delta_L = \delta_U$ =0.7, it reaches 9 sec for HTEMOD versus 10.3 for model [1].

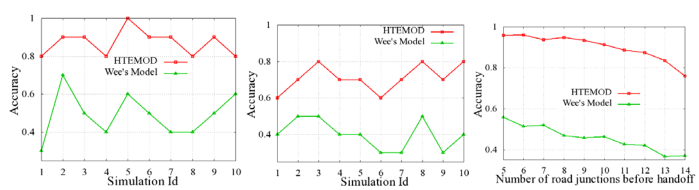


(a) $\delta_L = \delta_U = 0.5$ (b) $\delta_L = \delta_U = 0.6$ (c) $\delta_L = \delta_U = 0.7$

Fig.5: Predicted time window duration

Regardless the values of δ_L and δ_U , HTEMOD provides a lower time window duration compared to model[1]. This is due to the fact that HTEMOD takes into account the characteristic of user's movement which represents the current behavior of user; user's movement is more realistic (the variation of users' velocity as a time function and scheme to estimate the user's stop duration at road junction). Note that it rarely happens that model[1] provides shorter time window duration compared to HTEMOD. This happens when HTEMOD requires a larger time window to ensure that the handoff will be performed in the predicted time window.

Fig. 6(a) shows the prediction accuracy of the two models when the road segment density is between d_t^1 and d_t^2 ($d_t^1 \leq d_s(t) \leq d_t^2$). From this figure, it becomes apparent that HTEMOD is more efficient as it exhibits an average accuracy of 85% versus 49% for model [1]. Fig. 6(b) plots the accuracy of the two models when the road segment density is higher than d_t^2 ($d_s(t) \geq d_t^2$). The accuracy average of HTEMOD exceeds 71% versus 40% for model [1]. With HTEMOD, there is a significant performance improvement compared to model [1]. According to Figs. 6(a) and 6(b), the HTEMOD performance degrades when the density increases; when density is high HTEMOD exhibits a performance similar to model [1]. Also, density affects HTEMOD more than model [1] because model [1] ignores density. Nevertheless, regardless density, HTEMOD provides a better performance compared to model [1]. Fig. 6(c) shows the impact of the number of road segments/junctions before the handoff occurs on the prediction accuracy. From the figure, the performance of HTEMOD decreases slowly (<5%) unlike model [1] (<10%) before 10 road junctions; knowing the average size of cell coverage, HTEMOD ensures QoS over a long distance. The rapid drop in the performance of HTEMOD after 10 road junctions is indeed attributable to the increase in the selected population when the number of road segments increases. However, it remains higher than 70% when the number of road junction exceeds 14.



(a) medium density (b) high density (c) low density

Fig.6: Accuracy for different values of density

V. Concluding Remarks

In this paper, we proposed a probabilistic approach, called Handoff Time Estimation Model (HTEMOD), which estimates the time window when a user will perform handoffs along his/her movement path to a destination. We computed the PDF using a selected population based on the density of the road segment which describes navigation zone characteristics and more recent users' movement characteristics. We evaluated our model via simulations and compared it against Wee's model [1]. Regardless of the given probability value to obtain a time window, the road segment density and the number of road segments before handoff, HTEMOD provided a better accuracy and a better predicted time window duration. This good performance is essentially thanks to our method to select the population of PDF of time taken to transit roads segments and the technique to estimate the STOP duration at the road junction. From the simulations, it has also become apparent that the road segment density affected the performance of HTEMOD more than Wee's model [1] as the latter does not take into account density in its prediction. Nevertheless, the performance of HTEMOD remained better. In the future, we plan to propose a scheme to estimate resource availability at a cell based on HTEMOD.

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