# Time-distance Accessibility of Public Transport considering In-vehicle Crowding based on Smart card data

Minhyuck Lee, Inwoo Jeon, Chulmin Jun [1]

Dept. of Geoinformatics, University of Seoul.
{lmhll123, yugo123, cmjun}@uos.ac.kr

**Abstract.** In this study, we propose the time-distance accessibility of public transport considering in-vehicle crowding. It is an indicator that measures how easy to reach other areas by travel times. The time-distance includes not only general factors such as in-vehicle time, out-of-vehicle time, and transfer penalties but also feelings of exhaustion due to in-vehicle crowding level. The crowding was computed by smart card data. We analyzed the accessibility of public transport in the Seoul city by using the proposed index.

**Keywords.** Public transport, Accessibility, Time-distance, Smart card, Crowding

## 1. Introduction

The time-distance accessibility is an indicator that measures how easy to reach other areas by travel times (Lee et al. 2014). The time-distance of public transport includes in-vehicle time, out-of-vehicle time. It may include psychological burden caused by transfer called transfer penalty. Some studies have shown that passengers experience longer travel time than their actual travel time if the crowding level in a vehicle is high (Wardman & Whelan 2011, Tirachini et al. 2013, Jenelius 2018).

In this study, we propose the time-distance accessibility of public transport considering in-vehicle crowding. As the automated fare collection system was introduced and the use of smart cards became common, the calculation of the number of passengers in a vehicle became easier. We computed

[1] Corresponding author

LBS 2019
15th Conference on Location Based Services
Vienna, 11–13 November 2019

Published in "Adjunct Proceedings of the 15th International Conference on Location Based Services (LBS 2019)", edited by Georg Gartner and Haosheng Huang, LBS 2019, 11–13 November 2019, Vienna, Austria.

This contribution underwent double-blind peer review based on the paper.
https://doi.org/10.34726/lbs2019.40 

crowding level of each vehicle using smart card data, and analyzed the time-distance accessibility of public transport in the Seoul city.

## 2. Methodology

The time-distance accessibility considering in-vehicle crowding is defined as Eq. 1. The $A_i$ is a accessibility of zone $i$, $T^*_{ij}$ is a relative time-distance from zone $i$ to $j$, $n$ is the total number of zones.

$$A_i = -\sum_{j(j\neq i)}^{n} T^*_{ij} \qquad \text{Eq. 1}$$

The time-distance $T_{ij}$ is composed of the sum of the total in-vehicle time $T^{In}_{ij}$, total walking time $T^{Walk}_{ij}$, total waiting time $T^{Wait}_{ij}$, and total transfer penalty $T^{P}_{ij}$. The total transfer penalty is calculated by multiplying the number of transfers by the time value of the psychological burden.

$$T_{ij} = T^{In}_{ij} + T^{Walk}_{ij} + T^{Wait}_{ij} + T^{P}_{ij} \qquad \text{Eq. 2}$$

The relative time-distance $T^*_{ij}$ is the deviation of $T_{ij}$ from the average time-distance $\bar{T}_{X^k}$ of all $(o,d)$ pairs within the same distance class with $(i,j)$. The $(o,d)$ set $X^k$ is classified by the integer distance class $k$ calculated by rounding off the distance function $\ell(o,d)$.

$$T^*_{ij} = T_{ij} - \bar{T}_{X^k}, \quad (i,j) \in X^k \qquad \text{Eq. 3}$$

$$X^k = \{(o,d) \mid \lfloor \ell(o,d) + 0.5 \rfloor = k\}, \qquad k \in \mathbb{Z} \qquad \text{Eq. 4}$$

If the relative time-distance from zone $i$ to $j$ is negative, it means that the travel time of $(i,j)$ is faster than the average travel time of same distance class. Therefore, the smaller the relative time-distance, the higher the accessibility.

The total in-vehicle time $T^{In}_{ij}$ including crowding is shown in Eq. 5. It is calculated by multiplying an in-vehicle time $t^{In}_{ij,m}$ for each route by a time multiplier $\beta^{In}_{ij,m}$ according to the crowding level of that route $m$.

$$T^{In}_{ij} = \sum\nolimits_m \left(\beta^{In}_{ij,m} \times t^{In}_{ij,m}\right) \qquad \text{Eq. 5}$$

**Table 1.** An example of smart card data.

| Card_ID | Boarding_time | Boarding_Stop_ID | Arrival_time | Arrival_Stop_ID | Route_ID | Vehicle_ID |
|---|---|---|---|---|---|---|
| 1 | 07:00 | 100 | 07:20 | 200 | 1000 | 1 |
| 2 | 07:10 | 100 | 07:30 | 200 | 1000 | 2 |
| 3 | 07:00 | 100 | 08:00 | 500 | 1000 | 1 |

The crowding level is calculated using smart card data. The smart card data store records of individual passengers such as boarding / arrival time, station and vehicle. The *table 1* is an example of smart card data. Passengers 1 and 2 arrived at station 200 using route 1000 and passenger 2 used the next vehicle of passenger 1. Also, passengers 1 and 3 used the same vehicle, and passenger 3 stayed longer in that vehicle.

The occupancy of each vehicle can be calculated, and dividing by the capacity can calculate the crowding level. However, unlike the occupancy of bus, the calculation of occupancy of subway is complex. This is because the tagging of smart card in the subway takes place on platforms, not on vehicles. We are currently studying a methodology for estimating the occupancy of subway.

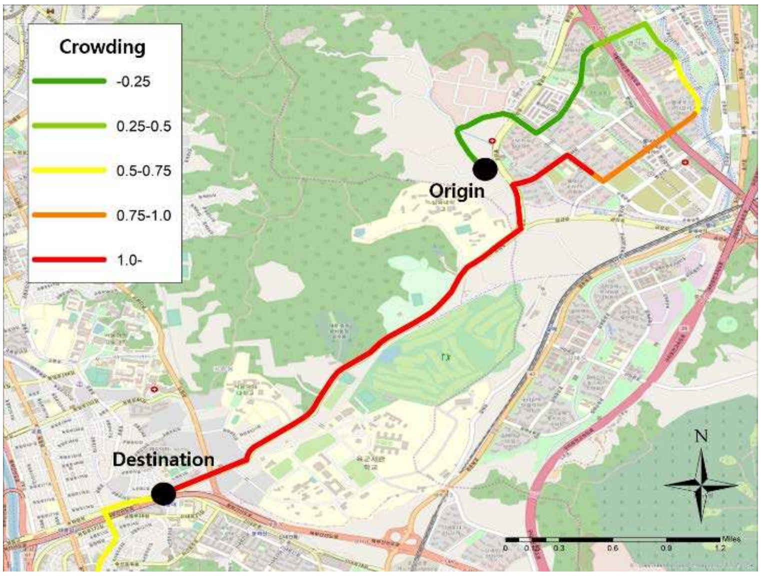


**Figure 1.** The crowding in a specific bus route at the morning peak in Seoul city.

## 3. Results

Due to the limitation of estimating the number of passengers in a train, we analyzed the time-distance accessibility in Seoul city which does not reflected in-vehicle crowding. The time-distance of $(o, d)$ is the minimum travel time, and the penalty for a transfer is 5 minutes. We analyzed about 120 million all-to-all public transport route.

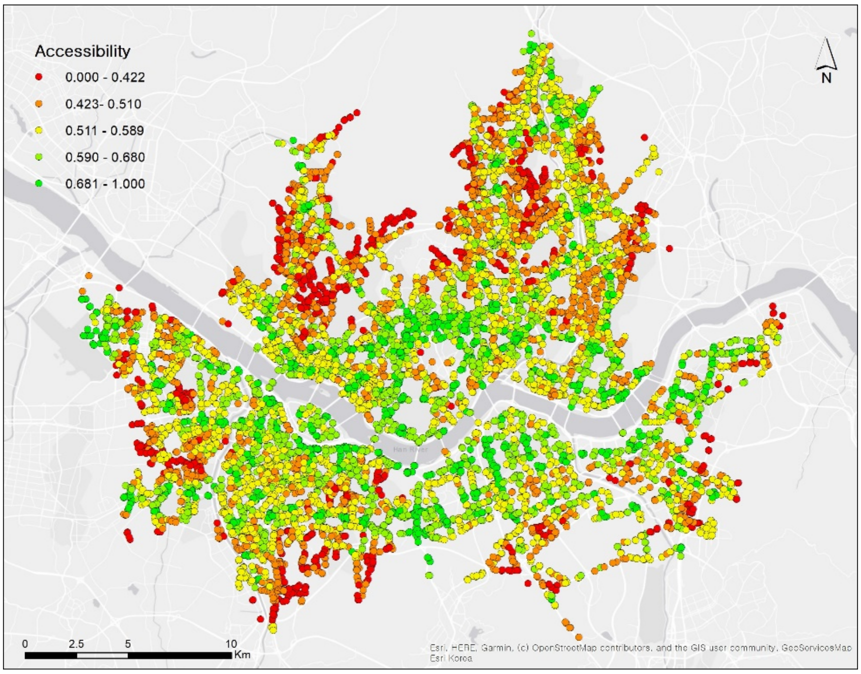


**Figure 2.** The time-distance accessibility of each transit stops in Seoul city.

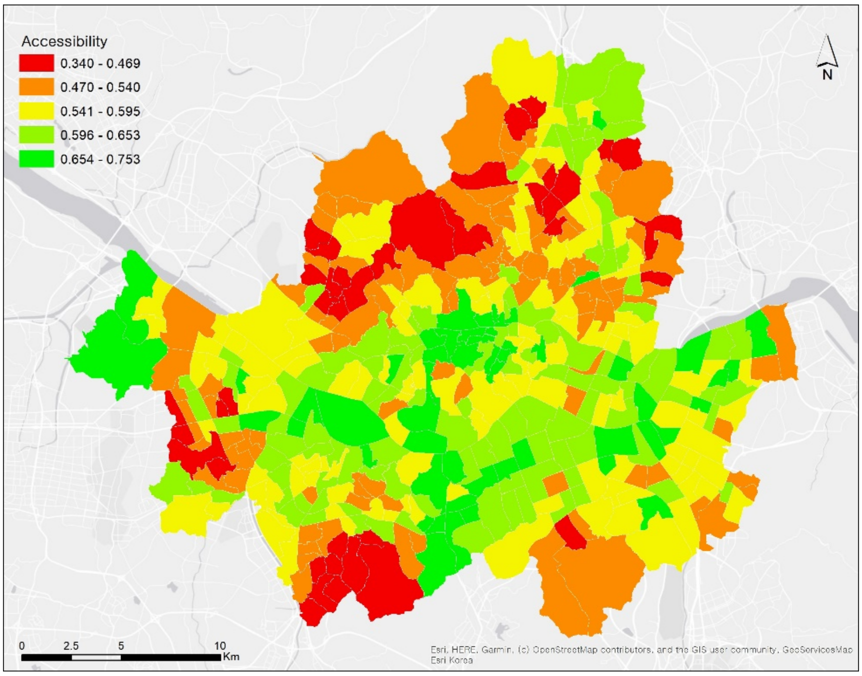


**Figure 3.** The time-distance accessibility of each administrative areas in Seoul city.

The *figure 2* shows the accessibility of each transit stops. The accessibility was normalized between 0 and 1. Thus, a stop that can be quickly moved to all other stops has accessibility close to 1. High accessibility appeared in the major urban centers and subway influential areas. Highly accessible stops were formed along the subway lines. Low accessibility was mostly analyed in the northern areas rather than the southern areas. In particular, accessibility was poor in areas with low land prices. The *figure 3* shows the accessibility of public transport by administrative district.

## 4. Conclusions

In this study, we proposed the concept of time-distance accessibility index that contains the in-vehicle crowding based on the smart card data. It is possible to analyze the accessibility based on the travel time experienced by the passengers. In future work, we plan to estimate the number of passengers in a subway, and consider GIS data such as population and land use.

## Acknowledgement

This work was supported by Road Traffic Authority grant funded by the Korea government (KNPA) (No.Police-L-00002-01-201, Development of signal control system for autonomous driving based on AI)

## References

Lee, K., Park, J. S., & Jeong, M. S. (2014). Accessibility Changes in the Metropolitan Seoul Subway System: Time-distance Algorithms based on the T-card Big Data and an Accessibility Measurement Model for Un-fixed Transportation Networks. Journal of the Economic Geographical Society of Korea, 17.

Wardman, M., & Whelan, G. (2011). Twenty years of rail crowding valuation studies: evidence and lessons from British experience. Transport reviews, 31(3), 379-398.

Tirachini, A., Hensher, D. A., & Rose, J. M. (2013). Crowding in public transport systems: effects on users, operation and implications for the estimation of demand. Transportation research part A: policy and practice, 53, 36-52.

Jenelius, E. (2018). Public transport experienced service reliability: Integrating travel time and travel conditions. Transportation Research Part A: Policy and Practice, 117, 275-291.