A review on route choice behavior and volume control of passengers in urban rail transit network

Jiamin Zhang

College of transportation, Shandong University of science and technology, Qingdao 266590, China

^zjmsunrise@126.com

Abstract. The Urban Rail Transit (URT) network possesses the features of multi-route and big volume of passengers. To study the route choice behavior and volume control of passengers is a bridge to match the capacity supply and passenger demand in URT network. It’s also a crucial problem proposed by the networked operation of URT. We analyze systematically the effect factors of passengers’ route choice behavior and related research on passenger volume control in URT network, as well as the updated representation of URT network and nature of passenger demand. Then we set up the integrated calculation formula for general travel cost in URT network. Afterwards, we summarize the classical research method for route choice behavior, including its main study procedure, the search and identify method for effective routes, logit model, probability distribution model, multi-agent simulation and calculation of the match probability by using big data e.g. AFC data. Importantly, we propose the framework for joint comprehensive prediction of passenger route choice behavior and volume control in URT network based on big data, which displays the mind map of passenger-flow-based prediction control and intelligent decision for future study. This review has great theoretical and practical meanings in improving the service efficiency and quality of URT, so as to balance the load of each line and station in URT network, as well as to reduce or eliminate the passenger waiting time for those being left behind because of congestion.

1. Introduction

Up till the end of year 2018, there have been 35 cities running the urban rail transit (abbreviated as URT) with 185 lines and the length in total has reached 5761.4 km in China; moreover, the number of the city with a networked URT system which has more than 4 URT lines in operation and more than 3 transfer URT stations is 16, occupying 45.7% of the total number of URT cities [1]. To study the route choice behavior and volume control of passengers is a bridge to match the capacity supply and passenger demand in URT network. In the condition of networked operation, quantitative analysis of the URT passengers’ route choice behavior is the foundation of both knowing the distribution of passengers accurately and clearing the ticket income. What’s more, it can also lay the basis for determination of passengers’ choice of transfer stations, identifying the key routes and big passenger flow, guiding the passengers’ route plan, so as to make a sound scheme for evacuation of the big passenger flow and headway time of the trains in the URT network.
It’s a critical problem to construct a route choice behavior model which can dynamically adapt to the time-variant URT system [2]. The route choice problem in URT network is based on the same OD pairs, and the passengers decide comprehensively their transfer station according to the train operation plan and their own travel experiences, so as to form the travel route in URT, which is also the typical problem raised by the networked operation of URT in the real world [3]. In nature the route choice problem also belongs to the passenger assignment problem, which means that the passenger assignment is the aggregated results of the route choice for all of the passengers [4]. The necessity for passenger flow control in URT network lies in the assurance of the order and security of the URT stations and lines, so as to improve the service level of the whole URT network. We review the academic outcomes related to the route choice behavior and volume control of the passengers in the URT network. Importantly, we propose the joint framework for the comprehensive prediction of the passenger route choice behavior and scheme of volume control in the URT network, which displays the mind map of passenger-flow-based prediction control and intelligent decision for future study further. The purpose of our work is to enhance the URT operation efficiency and quality, as well as to balance the load of the lines and stations, and to reduce or eliminate the waiting time of the left behind passengers in the URT network.

Section 2 analyzes the effect factors of passengers’ route choice behavior in URT network. In section 3 we discuss the nature of UTR passengers and propose to adopt the randomly switching topologies to represent the URT network under different passenger load. We summarize the research methods for passenger route choice behavior in section 4. Section 5 analyzes the related research on passenger volume control in URT network, and proposes the framework for joint comprehensive prediction of passenger route choice behavior and volume control in URT network based on big data. We conclude this review in section 6.

2. Effect factors of passengers’ route choice behavior in URT network

So far most of the Chinese URT ticket systems adopt the single price or metered price (the ticket price increases with the number of stations or kilometers) mechanism. In the conditions of same OD and ticket mechanism, the cost of the passenger is similar no matter which route he/she chooses in the URT network. So indifferent to the conventional route choice behavior, the influence of the price mechanism can be neglected in the URT network. Generally, the effect factors of passengers’ route choice behavior in URT network are as following:

En route time consists of train running time and stationary time. (2) Transfer time [5], composed of walking and waiting time for transfer. (3) Number of transfers, usually we use the penalty coefficient to describe the passengers’ perception towards the transfer time and number of transfers. (4) Congestion degree, which can be represented by the maximum section train load percentage. Usually we use the additional cost coefficient to describe quantitatively the passengers’ perception towards the congestion which can be found in section 3. (5) Reliability of travel time, which is the probability of the passengers’ completion their journey within the predefined time and related to the congestion degree of the stations and the passenger volume. At peak hours it’s likely for the passengers to fail on board the train at the first time resulted in being left behind. (6) Attribute of the passengers, [6] divided the passengers into the familiar type & unfamiliar type according to their acquaintance degree to the URT network and endowed the perception of each kind of passengers towards the travel time with a variable, and [7] introduced the average passenger volume at the peak hours to describe the URT network knowledge. (7) Network structure. (8) Train’s stop pattern [8].

[7] studied the unconventional effect factors of the route choice behavior, e.g. the angular cost, where the angle is formed by a straight line from the initial point of a segment to the final trip destination and another straight line from the initial point of the segment itself, e.g. the angle \( \theta_1 \) and \( \theta_2 \) in Fig.1. In Fig.1, let \( a_r \) denote the angular cost, the calculation method of \( a_r \) is expressed as formula (1).

\[
a_r = \alpha \cdot \theta
\]
3. Nature of URT passenger demand and updated representation of URT network

3.1. Nature of URT passenger demand

The main technique feature of URT is its rail mode, while its service form belongs to urban public passenger transport, in nature which is the kind of public transportation. The trip of URT passenger possesses a sense of self-organization and stochastics. However, its operation mode approximates to the national railroad, which means that the operators can make the train operation plan according to the principle of system optimum, so as to decide the passenger route to a greater extent. On the other hand, considering the various characteristics of traffic flow, we can divide them into the kinds of weak-controllable-autonomous traffic and strong-controllable-organized traffic. So the feature of the URT passenger flow belongs to something in between.

3.2. Updated representation of URT network by randomly time-switching topologies

Transportation network features should be considered as a prerequisite while studying the passenger route choice behavior. To a certain degree the URT network is similar to the public transport network, and some of the research methods (e.g., graph theory [9] of the latter one can be applied to the former one with some limitations (e.g., overlap features of the lines in the public transport network). [10] Proposed three-layer structure to represent the URT network, which is the planning network layer, infrastructure network layer and travel network layer respectively. In nature the modern URT system has the features of CPS (Cyber-Physical-System). So we should adopt the technique to represent the URT network from planning as a craft to planning as a social science, abiding by the philosophy of Colin Buchanan [11], from perspective of society—technique. With the changes of passenger demand, in order to grasp the distribution of passenger flow in URT network accurately, it’s necessary to describe the passenger route choice behavior in more details, e.g., the impact of morning-peak & evening-peak of passenger flows on their route choice behavior. Considering the time-variance property of the URT network passenger load, e.g., the congestion status at peak hours and the uncrowded condition at off-peak hours, we suggest to adopt the randomly time-switching topologies to update the URT network representation under different passenger load.

4. Integrated function for calculation of general travel cost in URT network

For simulation of passenger choice behavior, each route is endowed with a general cost, which reflects the comprehensive travel cost for the passenger’s route choice. Considering the effect factors in section 1, we set up the integrated function for calculation of general travel cost in URT network as formula (2).
Where $C_R$ denotes the general cost of route $R$, $t^n_{ij}$ the real running time between station $i$ and $j$ in $n$th section. $Y^n_{ij}$ Denotes the additional time cost coefficient induced by congestion within the running time between station $i$ and $j$ in $n$th section, namely the function of congestion degree. When the volume of the passenger flow is more than the allowable overcrowded load, the passenger transfer would fail and the passengers have to be left behind on the platform and wait for the next train. So the calculation method of $Y^n_{ij}$ is as formula (3).

$$
Y^n_{ij} = \begin{cases} 
\frac{x^n_{ij} - z}{z}A & z < x^n_{ij} < C \\
\frac{C - z}{z}A + \frac{x^n_{ij} - C}{C}B & x^n_{ij} > C 
\end{cases}
$$

Where $x^n_{ij}$ denotes the passenger volume between station $i$ and $j$ in $n$th section, $z$ the number of train seats, $C$ the maximum volume of passengers that can be carried by the train, $B$ the additional cost for over congestion, $t_k$ the dwell time at station $k$, $i$, $j$ and $k$ the sequence number of the station, $M_R$ the number of passenger transfers on route $R$, $t_{mw}$ the average walking time of passengers at transfer station $m$ on route $R$, $t_a$ the waiting time at transfer station $m$, $a$, the angular cost of route $R$, $\alpha, \beta$ the parameters that can be calibrated by questionnaire through regression analysis, $\gamma$ the waiting coefficient at transfer station that is related to the train arrival distribution, $\lambda$ the time transformation coefficient.

5. Classical research methods for passenger route choice behavior in URT network

5.1. Main procedure for study of route choice behavior in URT network
[12] Verified the effectiveness of route choice behavior by using the cumulative prospect theory, and the result shows it is closer to the reality than that of the expected-utility-based method. [13] Used $C_{logit}$ model to analyze the impact of the passenger transfer perception, train congestion degree, network topology and socio-demographichs on the route choice behavior. From perspective of the passenger travel, in fact the passenger route consists of a series of on board procedure and possible transfer procedure. The passenger route choice behavior can be understood as the probability of each effective route chosen by the passengers, whose main procedure is as following: representation of URT network $\rightarrow$ calculation of general travel cost (comprehensive travel impedance) for passengers $\rightarrow$ calculation of possible feasible routes and choice of effective routes $\rightarrow$ calculation of the probability of each effective route chosen by the passengers. [14] assumed that there were $K$ (usually $K \leq 5$ [15]) effective routes between certain OD pair, and proposed that the route choice strategy of passengers would not be more than the maximum endurable variance of the established travel time according to portfolio theory

5.2. Effective route
Usually we assume that there is one segment at most between any adjacent station points in the URT network when studying the route choice behavior, neglecting the multi-parallel-segment condition (e.g., Beijing Sihui east station to Sihui station). Also we would consider only several effective routes between
the OD pairs in URT network, instead of all of the routes. The criteria for judging the effective routes include the operating time, the limitation of the transfer numbers, and the threshold of the general travel cost. The search methods for effective routes include k gradually short path search algorithm, Dial algorithm, depth-first or breadth-first graph ergodicity algorithm [16-18]. The key factors that affect the efficiency of the algorithms lie in the threshold of the effective routes, which can be set by using the absolute value or relative value method.

5.3. Logit model and its improved form

[19] Adopted the multi-logit model to describe the route choice problem and tested it on the large scale transport network. In general logit model is the mostly used method to study the chosen probability in urban transport, which uses the discrete choice theory to obtain the preferences of passenger route choice. Most of the existing literatures also use the logit model or its improved form to study the route choice behavior in URT network. Let K denote the number of effective routes between station r and s in OD pairs, \( C^k_{rs} \), the estimated value of general travel cost of kth effective route between station r and s in OD pairs, \( p^k_{rs} \) the chosen probability of kth effective route between station r and s in OD pairs, \( c_{min} \) the minimum general travel cost in all of the effective routes, \( \theta \) the parameter related to the variance for describing the stochastic degree, \( \xi_{rs}^k \) the random error item with \( \text{var}(\xi_{rs}^k) = \frac{\pi^2}{6} \vartheta \). The conventional logit model usually results in some unreasonable consequences, in practice its improved form is used as formula (4).

\[
p^k_{rs} = \frac{\exp(-\theta C^k_{rs} / c_{min})}{\sum_{k=1}^{K} \exp(-\theta C^k_{rs} / c_{min})}, \quad \forall k \in K
\]

For the calibration of logit parameters, one method is based on RP/SP questionnaire survey, another method is based on AFC data [20, 21]. In view of the collection cost for questionnaire and AFC data, in the future research it’s feasible to adopt the ant colony algorithm to simulate the passengers [22] so as to simulate the route choice behavior in URT network. Any OD pairs may have multiple routes, and some of the routes may share common segments, which means the existence of common segments among the OD pairs in URT network, so it’s likely to form the relevant routes, instead of being independent mutually. However, most of the existing literatures adopting the logit model for route choice behaviour study haven’t taken into account of the relevance among the routes, which would affect the accuracy of the results. We suggest adopting the C-logit or path size logit model [23, 24] when studying the route choice behavior in practice, so as not to ignore the route relevance in URT network.

5.4. Probability distribution based on normal distribution

[25] Proposed the Probit model, and it was firstly applied probability distribution on the route. [26] Used Monte Carlo simulation to sample randomly the stages of travel procedures, and solved approximately the chosen probability of each route by frequency statistics. [27] Calculated the passenger proportion on each route based on the real distribution of travel time. [28] Proposed two-stage route choice method for impedance layering based on normal probability distribution (the model of normal probability distribution is represented as formula (5)), whose principle is to determine the proportion of passenger assignment by calculating the utility value of the passengers undertaken by each route. The more utility value of the passenger assignment on the feasible route is, the more proportion of the passenger assignment is. In general, the passenger assignment utility on the route relates to such a degree, as that
the comprehensive travel impedance surpass its counterpart on the shortest route. The more the comprehensive travel impedance surpass its counterpart on the shortest route, the less the utility for the passenger assignment on the route, which results in the less proportion OD shares. Based on the proportion of initial route choice, considering the proportion of initial route choice amended by the number of transfers on different routes, we can reflect the passenger route choice behavior more accurately.

\[
\begin{align*}
  x &= \frac{C_i - C_{\text{min}}}{\min\{C_{\text{min}} \times f, f_{\text{max}}\}} \\
  S_i &= e^{\frac{(x-a)^2}{2\sigma^2}} \\
  p_i &= \frac{S_i}{\sum S_i}
\end{align*}
\]

In formula (5) where \(x\) denotes the degree that the comprehensive travel impedance (or general travel cost) surpass its counterpart on the shortest route, \(C_i\), the comprehensive travel impedance of route \(i\), \(C_{\text{min}}\) the comprehensive travel impedance of the shortest route, \(f\) a percentage, \(f_{\text{max}}\) the threshold of the effective route, \(S_i\), the utility value for route \(i\) participating in passenger assignment, \(a\) the \(x\) value when the probability get the maximum expectation value, \(e\) the logs base, \(\sigma\) a constant value, and usually the smaller \(\sigma\) is, it indicates that the passenger has more sensitivity degree towards general travel cost which can be estimated by passenger survey.

5.5. Multi-agent simulation

With the development of artificial intelligence and technique of software design, multi-agent modelling has become the main stream in system simulation. The agent can be regarded as the improvement of the object-oriented technique, which provides the best mode for description of the intelligent entity and has the features of self-governance, sociality, responsiveness, activity, etc. [10] studied the passenger route choice behavior from the perspective of interaction between the passenger and the network operation, as well as the adaptive evolution of the complex system, and they abstract three main agents, which are passenger agent, train agent and network agent respectively. They also built the relationship graph of the agents, and then simulated the system operation procedure by using the multi-agent simulation tool. However, they haven’t described further the behavior rule and decision mechanism of some agents (e.g., train agent, network agent).

5.6. Calculation of the match probability by using big data e.g. AFC data

[29] Used the AFC (Automatic Fare Collection) data to study how to make the incentive mechanism in order to induce the passenger travel behavior. AFC data record the OD spatial-temporal information of each passenger. Aiding by the data mining technology, we can get the detailed travel information of each passenger. With this background, combining with the timetable, [30-35] calculated the match probability to quantize the match degree between each likely time-space extended travel path and the realized travel path, and then each record of AFC data was matched randomly to certain time-space extended travel path by using the roulette method. [36] Studied the route choice behavior of subway passengers from AFC data and calibrated the parameters with Bayes method. The above mentioned studies show that the difference gap of results obtained by using AFC data and the logic model is very small, which proves the feasibility and validity of the application of AFC data for route matching.
5.7. Summary of the classical methods for route choice in URT network
So far the classical methods for route choice in URT network have been analyzed in details, and we can summarize their characteristics, adaptability and key points in Table 1.

| Classical methods for route choice | Characteristics, adaptability and key points | Literature lists |
|-----------------------------------|---------------------------------------------|-----------------|
| Logic model and its improved form | A disaggregate, more mature method. Parameters need to be calibrated and validated with data survey from questionnaire, AFC data or simulation. It’s complex when dealing with the relevance among the routes in URT network. | [19-24] |
| Probability distribution based on normal distribution | A method based on statistics of travel time or utility value. Depending on the proportion of initial route choice to a large extent, and reflecting the passenger route choice behavior more accurately. | [25-27] |
| Multi-agent simulation | A method based on artificial intelligence and software design. Besides to abstract the agents and define their logic relationship, also it’s key to define the behavior rule and decision mechanism for agents. | [10] |
| Calculation of the match probability by using big data e.g. AFC data | A method based on big data and data mining, deep learning as well as Bayes theory. Combined with the timetable, it’s more likely to get more precise results. | [29-36] |

6. Framework for joint comprehensive prediction of passenger route choice behavior and volume control in URT network based on big data

6.1. Related research on passenger volume control in URT network
When the capacity can’t sufficiently meet the passenger demand, it’s necessary to control the passenger volume. Particularly, it’s a typical phenomenon in the operation of China URT at peak hours. Usually the rule for passenger flow control is as following: firstly we control the passenger flow on platform by intercepting them in the station hall; with the volume of passengers in the station hall approximating the security limit, it has to control the passenger flow outside of the station. When the passenger flow within the station is crowded, we should first control the passengers’ entering the station. If the passenger volume keeps increasing, then we have to adopt some control measures on its nearby transfer stations. [37, 38] proposed the linear mathematical models for super-volume passenger control adaptable to single station, and the calculation method for the parameters of the collaborative flow-limiting based on priority for two stations, respectively. [39-41] proposed the method of passenger organization (e.g., control of total volume and control of each class of passenger flow) for single station under various passenger demand, and the scheme of passenger volume collaborative control for multi-station on single line at peak hours (e.g., strategy of passenger organization at some station, strategy of passenger flow control in certain section, strategy of transportation organization control on the whole line). [42, 43] put forward the framework and model for passenger flow control with multi-station coordination in subway networks. In general, the items for making the scheme of passenger flow control involve the trigger indicator of passenger flow control and the control threshold, control station/ time period/volume, normal passenger flow control/ temporal passenger flow control. However, the existing related literatures couldn’t yet fully support the theory and practice for multi-station coordinated passenger flow control in URT network.
6.2. Framework for joint comprehensive prediction of passenger route choice behavior and volume control in URT network based on big data

The new era belongs to big data and intelligence for human beings, and the rail industry is being transformed towards digitalization/intelligentization, which means the big data has penetrated into the rail industry. The big data related to train operation and passenger organization comes from GPS, GIS, Mobile Phones, AFC and train operation control system, etc. Especially using GPS is more reliable for reporting accurate location, trip time, and trip duration [44]. These big data can be used to passenger flow forecast, rescheduling of trains, route choice behavior study [36], making the scheme of passenger flow control. Based on big data, we propose the framework for joint comprehensive prediction of passenger route choice behavior and volume control in URT network as illustrated in Fig. 2, which displays the mind map of passenger-flow-based prediction control and intelligent decision for future further study.

Figure 2. Framework for joint comprehensive prediction of passenger route choice behavior and Volume control in URT network based on big data

7. Conclusion

The route choice behavior study can be the foundation for passenger flow control, both of which are to build the safe and well-organized environment for passengers and train operation. At the same time, we also should pay more attention to the intelligent design and service of URT stations and the integrated transport hubs, so as to realize the coordination development among the different mode of public transport, especially for the collaborative connection between the bus and URT aiming at guidance and collecting/distributing efficiently. Taking advantage of the big data and its process technique, we can forecast and analyze the passenger demand more precisely. Considering the dynamics of the passengers, we use the randomly time-switching topologies to represent the URT network, based on which we
propose the framework for joint comprehensive prediction of passenger route choice behavior and volume control in URT network, combining with the related mathematical model and simulation technique. The inherent principle of this framework is much closer to the real operation scenario of URT network and it will be instrumental in improving the matching degree between the capacity supply and the passenger demand, as well as the total service level of URT.

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