Citation: CHEN Xianlong, ZHANG Hua, CHEN Xiaohong, ZHANG Tianran, MA Yilin. Urban Activity Models Based on Spatiotemporal Inference [J]. Urban Transport of China, 2023 (1).

Urban Activity Models Based on Spatiotemporal Inference

CHEN Xianlong[1,2], ZHANG Hua[3], CHEN Xiaohong[1], ZHANG Tianran[4], MA Yilin[5]

1. Key Laboratory of Road and Traffic Engineering of the Ministry of Education, Tongji University, Shanghai 201804, China;
2. Guangzhou Transport Planning Research Institute Co., Ltd., Guangzhou Guangdong 510030, China;
3. National Maglev Transportation Engineering R&D Center and Urban Mobility Institute, Tongji University, Shanghai 201804, China;
4. Shanghai Urban Planning & Design Research Institute, Shanghai 200040, China;
5. Beijing Transport Institute, Beijing 100073, China

Abstract: Based on reviewing the limitations of existing transportation models, such as over-dependence on mathematical optimization solutions and insufficient analysis of actual travel activities, as well as the lack of connection between current and future modeling situations, this paper proposes model improvements using big data methods. The paper presents an extended demographic spatiotemporal inference model, including a base-year population synthesis module, a demographic development module, and a job-housing transition module, which achieves the spatiotemporal continuation of individual attributes and the result of travel demand associated with urban characteristics. The activity simulator designed in the paper includes multiple sub-modules, such as travel chain generation, destination selection, individual activity organization, and family member activity coordination, to simulate travel activities based on individual attributes and urban activity patterns. Empirical studies demonstrate that introducing individual attributes and urban activity patterns based on big data enhances the casual inference ability of travel activities, avoids large-scale computation of mathematical optimization solutions, and generates consistent modeling results in line with urban realities. This approach also achieves the inheritance of the present in the future and reflects the continuity of urban development. **DOI:** 10.13813/j.cn11-5141/u.2023.0107-en

Keywords: transportation model; spatiotemporal inference; travel chain; activity model; demographic inference model; activity simulator

0 Introduction

Transport model is the most important quantitative analysis tool for transport planning research. Since the 1950s, combined with the advancement and application of computer technology, transport modeling theory and technology continue to develop. Chronologically, the Four-step model (FSM) [1–2], the Tour-based model (TBM) [3], the Activity-based model (ABM) and Agent-based model (AgBM) [4] lead to improvement of interpretability as well detailed level for modelling. In practical, the existing transport model is in the parallel development stage of theories and methods of the above-mentioned multiple models, and the accuracy of the model generally does not meet the requirement [6], which also makes the transport model widely criticized [5]. The main reason of such problems is the inevitable flaws among the data base and theoretical methods. In terms of data, the analysis method, relying on sample surveys and statistics, for revealing the overall characteristics of urban transport is incomplete. The theoretical approach, whether FSM, TBM, ABM or AgBM, the intrinsic of them is a solution based on optimization theory, which the travel activity is interpreted as a mathematically optimal solution to a given constraint rather than as a causal relationship. In addition, the existing transport demand modelling method has separate trip generator for each characteristic year, however, as cities enter the era of stock development and urban growth becomes increasingly stable, the disconnection between the current situation and future is clearly detrimental to the accuracy of the transport model.

With the widespread application of location-based services such as cellular signal, the acquisition of the OD matrix for job-housing is now a fundamental function, and technical methods for the exploration of spatio-temporal travel behavior are becoming progressively more mature, making it feasible to trace the changing dynamics of individual job-housing in urban. The large-scale as well as long-period spatio-temporal location data in transport demand modelling also provide new possibility for the exploration of characteristics of job-housing and travel activities ranging from individual to urban-wide. Furthermore, the introduction of indicators such as job and housing in the transport model can directly enhance the causal inference of travel activities; establishing a link between the present and the future can increase the ‘memory’ of the urban in the transport model, which enabling better evolution of the present situation of the urban and improving the interpretability level of the urban in the transport model.

Received: 2022-08-09

Accordingly, this paper proposes a modeling approach driven by urban operational data with large-scale individual-level continuous spatio-temporal Location, travel characteristic survey as the core. Firstly, an extended spatio-temporal population evolution model is used to reproduce the linkages of urban's job-housing location in base year, to forecast recent population attribute structures and population-employment migration, and to simulate and forecast the dynamic spatio-temporal movement of individual-level travel activities. Secondly, the employment features, travel activity matrix and characteristics of the population are integrated to establish an activity simulator to model and predict urban activities and trips according to individual attributes and urban activity patterns. It enables transport models to propagate traveler activity in time and space. The established urban activity model based on spatio-temporal evolution, by tracking the socio-demographic attributes and job-housing changes of travelling individuals, and on the basis of analysis and classification of massive individual activity patterns, allows to simulate and propagate of urban activities as a whole.

1 Literature review

Since the Detroit Metropolitan Area Traffic Study (DMATS) [7] and Chicago Area Transport Study (CATS) [8] in the 1950s, the FSM has been widely applied in travel demand forecasting as a typical representative of the aggregate model. However, the aggregation feature of the FSM always faces theoretically criticisms, including independency of each individuals' trips and lack of consideration of the association among family members' activities; The model takes the traffic analysis zone (TAZ) and its centroids as the origin and destination of trip, it leads to a rough spatial resolution; The one-hour unit of analysis for traffic assignment results is in difficulty on accurately modelling the dynamic process of road network state variation, referred as insufficiency of time resolution. In order to overcome the limitations of FSM, the TBM and the ABM theories have been proposed in academia since the late 1970s, and the TBM model usually serves as an important component of ABM in later applications. Hasnine et al [9] summarized the ABM research from 1995–2020, and categorized it into seven types and giving associated definitions. Based on activity-based model theory, many activity simulators have been developed, including DAYSIM [10], CEMDAP [11], CARLA [12], STARCHILD [13], ALBATROSS [14], TASHA [15], FEATHERS [16], and ActivitySim [17].

From the analysis of travel activities, each stage of the FSM directly answers a fundamental question: what to do (trip generation), where the destination is (trip distribution), which mode of transport to use (mode split), which route to choose (trip assignment), and the choices of travel times (time of day). Compared with applying single-purpose trips in FSM, the TBM using trip chain during working process. And ABM (AgBM) adds more information of attributes including socio-economic and job-housing. In terms of activity interpretability, the detail level of ABM ranks at the top, followed by TBM and FSM serves as the last one. The core of the progress of TBM and ABM over FSM is the introduction of more individual attributes and activity pattern, but there is no intrinsic difference in the analysis of travel activity itself (Table 1).

Consistency in the resolution of activities results in the problems that exist in FSM to be remained in TBM and ABM. For example, the trip distribution calculation in the FSM is based on a gravity model that generates attraction and generalized cost matrices; the parameter calibration is predicated on a generalized cost impedance distribution. The result of trip distribution is rather merely mathematical optimal solutions under given conditions, than a correlation analysis or causal inference. In other words, it close to the guesswork by mathematical calculations under partially defined terms. In fact, there is a certain causal relationship between origins and destinations. To demonstrate, if someone lives in TAZ i and works in TAZ j, a work trip from i to j will be generated. Although the ABM model establishes a correspondence between residence and workplace through population synthesis and location choice model, instead of being a result of successive selection of individual in time dimension, its theoretical foundation still relies on optimal solution by feature indicators. The available data resource has changed currently. With consecutive spatio-temporal data on individuals coming from cellular signal and other LBS data, researchers can track the continuous evolution of different individual spatial migrations, particularly housing and job location choices, which devotes to significant enhancement on the ability of modelling on activity patterns by individual attributes, and improvement on the interpretability of transport models.

Moreover, the travel demand for each feature year supported by the established transport model theory is mutually independent. However, the urban in practice is a continuously evolving system and the inertia of the established system has a huge impact on the evolution. There is a strong correlation and predictable stability between urban attributes and human activities in different years (i.e., urban activity patterns), as evidenced by stability of living place, stability of workplace, stability of destinations for activities and stability of urban spaces (e.g., transport hubs, commercial centers at all levels, community living circles, etc.). These characteristics lead to the inheritance of transport models for the base year (status quo) being particularly important, especially for the cities stepping into a relatively stable development, the status quo of current transport operations has a decisive influence on near-term traffic forecasts. In addition, urban activities have statistical stability and randomness; For example, 0.1% of people may be sick in terms of statistical stability, while when it comes to an individual, it shows randomness or occasionality. And some patients will choose to visit the same hospital, which indicates groups stability. LBS data resources such as cellular signaling provide supports for studying individual stability and urban activity patterns. The survey and modelling analysis, which targets people who have moved and re-chosen their job and workplace, allows for propagated simulations of urban change. Therefore, more comprehensive research of individual attributes and urban activity patterns and scientific spatio-temporal evolution modelling will devote to high-quality copy of urban travel activities, and lead to their continuity in time and space.

Tab.1 The analytical processes of travel activities using different transportation models

Model	FSM	TBM	ABM (AgBM)
Working process	− Trip generation (by trip purpose) − Trip distribution (destination choice) − mode split (Mode choice) − Choice of travel time (Time of day) − Traffic assignment (route choice)	− Trip generation (by trip chain) − Destination choice − Mode choice − Time of day − Traffic assignment	− Population synthesis − Residence location choice − Job location choice − Activity generation (including destination choice, time of day, model choice) − Traffic assignment
Differences	——	From trip purpose to trip chain	Adding individual attributes such as residence location and workplace location, etc.

In summary, the existing transportation planning model theory supported by small sample survey data has limitations in explaining urban travel activities, and the introduction of big data resources will bring new changes and help to understand the continuity of urban activity evolution in a more comprehensive way. Meanwhile, bringing individual attributes and urban activity mode results will further enhance the causal inference of the traffic models for modelling travel behavior.

2 Activity-based model design based on spatio-temporal evolution

2.1 Model design

The design idea of urban activity model by spatio-temporal evolution is as follows: according to the urban population structure data of the base year, an extended spatio-temporal evolution model of population is established to get the evolution of urban population from current to future (near-term). Then building an activity analysis model by the original trip chain to get the list of activities of all travelers in each characteristic year, which allows for stimulating urban activities.

As shown in Figure 1. The model consists of two parts. The first one is an extended population spatio-temporal evolution model. By serving attributes of household and individual which from HTS as seeds, this model serves population and job-housing OD matrices collected by census and internet location database as the main input, then attributes of household and individual for each base year can be simulated through the base year population synthesis model. Those attributes of characteristic year can also be predicted when combing the population evolution model and job-housing change model with above ones, which is a foundation for future succession to the current situation. The second part is the activity simulator based on individual attribute and urban activity mode. It uses LBS data such as HTS and cellular signal to build original trip chain database and combines attributes of family and individual to initialize individual trip chain through probability sampling model. Meanwhile, according to trip chain, individual attributes and urban activity mode, the simulator contributes to travel destination choice as well as activity time initialization. Further step, relying on activity rescheduling and synchronization of travel activity list of family members, it could eventually get individual-level activities list.

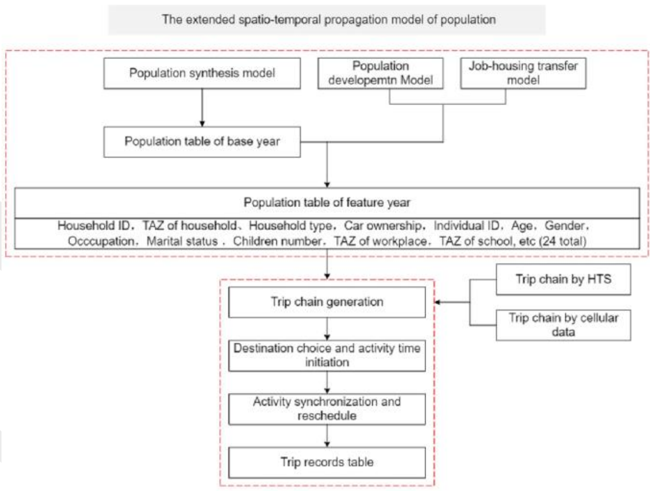


Fig.1 Urban activity model framework based on spatiotemporal inference

Activity simulator based on individual attributes and urban activity pattern

2.2 The extended spatio-temporal evolution model of population

The foundation of the extended spatio-temporal evolution model of population is current job-housing connection and population spatial distribution in urban area. It applies population synthesis model of base year [18–19] to simulate same year's family and individual table, and used probability sampling model, based on existing workplace OD matrix, to assign workplace for commuters, and to complete the initialization for individual as well as workplace attributes; The population evolution model, through the base year individual attributes, applies the life cycle and fertility model and the population migration model to forecast the natural and mechanical growth of the population. In addition, by using relevant parameter and model, the job-housing transfer model predicts the behavior of household and individual in moving and job alternation, and ultimately lead to evolution of population, employment and job-housing connection in time and space (see Figure 2). Unlike conventional population synthesis models that only consider the spatial distribution of the population, the extended spatio-temporal population evolution model introduces information on individual workplace (place of education), further specifies spatial location of individual commuting and school commuting. It is an extended population evolution model with both temporal and spatial information. The model consists of three parts, main function of each part is followed.

1) Base year population synthesis model: The population size and spatial distribution are decided by population census and LBS data; General population and spatial distribution of employment rely on economic census and LBS data; the model establishes the spatial association of job-housing based on LBS data and serves the HTS as seed data. It also applies PopulationSim [20] for population synthesis and sets information database of household and individual. Nonetheless, applying random sampling model based on job-housing OD matrix, it settles to workplace for employment population, and builds individual job-housing connection database, which also contributes to adding individual job-housing message to the personal database.

2) Population evolution model: Setting life cycle and fertility model to forecast the natural population growth; and building population immigration model to forecast mechanical growth of the population. The two model together can achieve prediction of future population.

3) Job-housing transition model: Based on the survey data of the relocation characteristics of residence and workplace, the probability sampling-based residence choice model and workplace choice model are set up to track the spatial location changes of residence and workplace, and finally to forecast the shifts of the spatial relationship between job and housing.

The base year population synthesis model is the foundation of the whole work and serves as the main input of the population evolution model and the job-housing transition model. meanwhile, they form an interactive model system. The extended spatio-temporal population evolution model forecasts the relationship between population, employment and job-housing from the present to the future while providing continuity in the evolution of the spatio-temporal population distribution. In addition, the spatial location information of individual travel activities is further clarified by the added attributes of population in job and housing.

2.3 Activity simulator based on travel attributes and urban activity patterns

The structure of the activity simulator model based on individual attributes and urban activity patterns is shown in Figure 3. Different from conventional transport planning model, the proposed model applies probability sampling by urban activity patterns, and its working mechanism is to provide information on the location of commuting and school activities according to the home address and workplace (school location) of traveler. There is no iterative feedback process in the main structure of the model presented in this paper, mainly because instead of travel impedance, the certain travel activity normally only be related to individual attributes. The advantage of the model is better use of the individual attributes and the spatial activity characteristics of the present urban state. There two challenges of this model: 1) first, it requires high data completeness and quality; 2) second, the key data source is the base year data, although some compensations are made by the extended spatio-temporal population deduction model, there are still large uncertainties in the urban activity prediction for medium- and long-term.

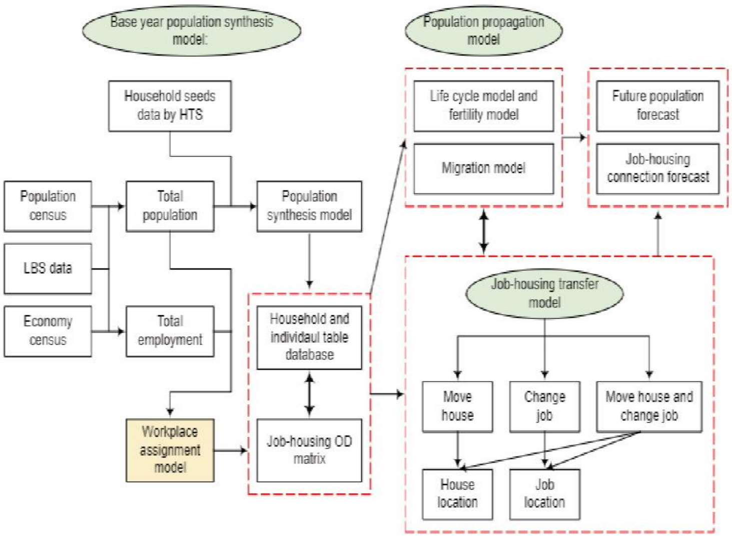


Fig.2 Structure of the extended demographic spatiotemporal inference model

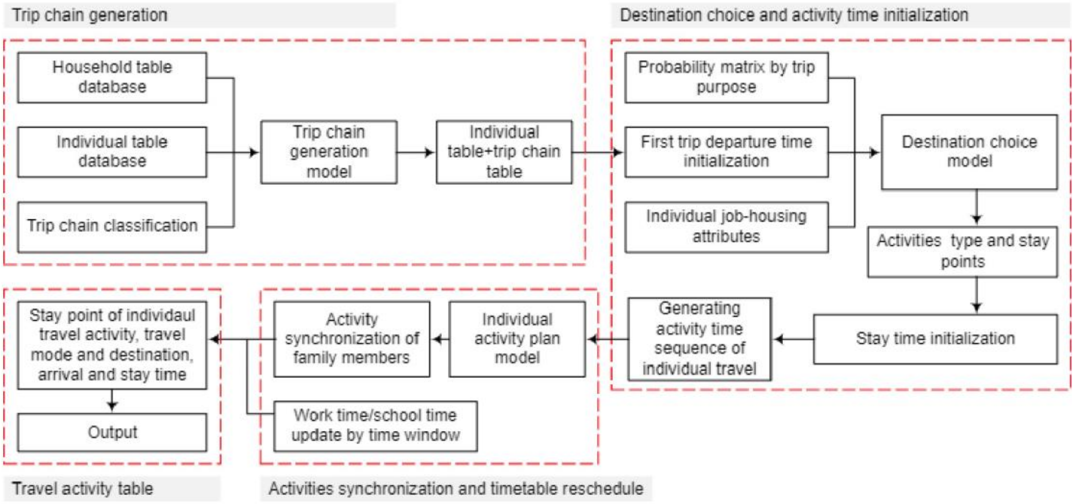


Fig.3 Structure of the activity simulator based on individual attributes and urban activity patterns

3 Database and key models

3.1 Database foundation

Making conventional data resources as the foundation, the urban activity model by spatio-temporal derivation relies more on multi-sources data, including the population and employment distribution, the OD matrix of job-housing, as well as the activity matrix of different travel purposes and the distribution of stay time of activity location, which all come from cellular signal data. The travel purpose activity matrix consists of four stay points[21], which are home (H), work/school (W/S), daily life (L) and others (O). These stay points are two-by-two combined to indicate 13 categories of travel purpose, namely Home to Work (HW), Work to Home (WH), Home to Life (HL), Life to Home (LH), Home to Other (HO), Other to Home (OH), Work to Life (WL), Life to Home (LW), Work to Other (WO), Other to Work (OW), Life to Other (LO), Other to Life (OL), and Other to Other(OO). In addition, the travel mode preferences of different types of individuals get from the HTS are also key input for the model, and Table 2 provides a description of the main data sources and applications.

3.2 The random sampling-based workplace assignment model

The random sampling-based workplace assignment model involves obtaining a workplace list M_i of the employed people in TAZ *i* from the urban job-housing OD matrix, with the object in the list being the TAZ number. For example, if there are five employed people in a TAZ, three of whom work in TAZ 1 and two in TAZ 2, then the list is [1, 1, 1, 2, 2], and the workplace of the working population in TAZ *i* are allocated by random sampling without replacement to implement the association between the job-housing OD matrix and the population attributes. Different from the conventional workplace choice model through utility maximization, this random sampling model is supported by real urban job-housing OD matrix which has become a well-established module in LBS data analysis such as cellular signal.

Tab.2 Data demand table

Data name	Data form	purpose
Household and individual attributes	Household type, car ownership, number of school children	Initializing individual travel activity purpose chains and synchronizing of family members' travel activities
OD Matrix of job-housing	Matrix of connections between employment population and job by TAZ	Initializing work pace of extended spatio-temporal population evolution model
OD Matrix of travel activities	13 travel purposes; divided into 5 periods: early morning, AM peak, mid-day, PM Peak and overnight	Calculating the probability of non-commuting trip destinations
Distribution of stay time.	Distribution of stay time in three categories: Home (H), Life (L) and Other (O)	Initializing stay time
Matrix of other network indicators	Distance between paired OD point; network indicators matrix for different transport modes and time including travel time, bus accessibility and urban rail accessibility, etc.	Determining travel time and manage time budgets

3.3 A trip chain generation model integrating location and HTS data.

The generation and integration of trip chain is crucial for simplifying activity-based model. Firstly, the presence of a certain proportion of unreported trips in the HTS data, with the almost complete absence of night trips, leave fault in the trip chain collected directly from the HTS data. The trip chain obtained from LBS data have problem in accuracy due to the use of fuzzy addresses, and LBS data also face difficulty on coving young children, which refers to be unable to identify school trip. For the case study in this paper, 45 trip chains were created based on HTS data and 78 trip chains were formed from LBS data, with a trip volume share of more than 0.05% as a constraint. For different types of individuals, integrating trip chain of cellular signal and residence, the travel activity characteristics are classified according to primary and secondary school students, university students, employed people, unemployed active people (unemployed adults aged <65 years) and non-active people (aged 65–75 years, >75 years). For students and non-active people, trip chain from HTS is used as seed bank; For the employed and unemployed active people, considering the advantages of cellular signal data for active people activity analysis, a 1:1 mix of trip chain of HTS and cellular signal data was used to build a seed bank. The steps of the trip chain generation model are shown in Figure 4.

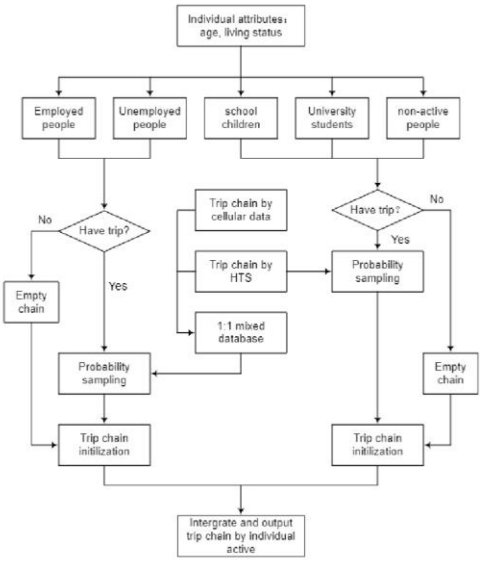


Fig.4 Framework of the travel chain generation model

3.4 Destination choice model-based on urban activity patterns.

The activity information related to individual attributes, such as the location data of residence, workplace and school, is already identified in the individual attributes, but the other two types of destinations—life activity destinations and other activity destinations—are defined by probability sampling methods. The probability sampling method corresponds to the assumption that the stability of urban activities is accepted. For example, the number of customers in a shopping mall is 20,000 a day, which is relatively constant, but the sources of the 20,000 are modeled by probability sampling using the base year spatial distribution of customer sources. The model inputs include living trip matrix in five time periods: early morning, AM peak, mid-day, PM peak and overnight, and other trip matrix. The corresponding assumption is that the choice of trip destinations for the same type of activity in the same region is similar. The probability sampling model is calculated as follows.

Step 1: According to trip purpose, selecting the row $P_{m,\,i}$ in origin TZA i from trip distribution probability matrix P_m.

Step 2: Constraint of being accessible within the departure time budget, the TAZ with this trip purpose is treated as the targeted TAZ sequence X, and get a probability list subset $P'_{m,i}$;

Step 3: Normalize the subset of probability list $P'_{m,i}$ to get a new probability list U, $\sum U= 1$;

Step 4: Based on list U, number the target TAZ in sequence X, conduct probability sampling, obtain target TAZ numbers as the destination TAZ. End of procedure.

3.5 Individual activity plan model of multi-purpose travel under dual constraints of time budget and timing window

The result of travel activity generation is a sequence of multi-purpose travel activities containing the departure time of the trip and the stay time of the activity. The following constraint mechanisms are considered in the individual activity organization model (Figure 5). 1) Only 24 hours a day, i.e., the activities in the trip destination chain need to be completed within 24 hours. an 18-hour deadline for the activity completion is set for the case study in this paper. 2) The departure time of school activities is completely fixed to ensure no late arrival. 3) Non-flexible work commuting hours is constrained by working timing window. This paper categories the work into four major types: 10 hours a day, 12 hours a day, 3 shifts a day and flexible working hours, and sets the activity timing window as a constraint accordingly. 4) There is an on-the-way time constraint between two activity stay points.

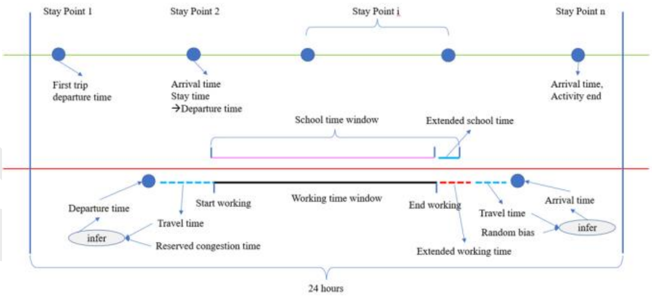


Fig.5 Schematic diagram of activity plan and schedule window

The activity time updating process is as follow.

1) Subtracting the initial trip departure time $T_{last,arr}$ from the last trip arrival time $T_{0,dep}$ to get the total active time $T_{active,total}$. If the total active time is within 18 hours, then the activity sequence is not updated, otherwise the next step;

2) Deciding working trip chain, if not, move to the next step; if yes, determine whether the total working time $T_{work\text{-}time,total}$ is ≤ 12 h, if more than 12 hours then discount by equal proportion of the segment and update the working time, next step

3) If the new overall calculated active time $T'_{active,total}$ is still greater than 18 hours, then scale the non-working activity stay time by an equal proportion and keep the single activity stay time $T_{staytime,i} \geq 15$ min, update the non-working residence time, next step;

4) Output the activity time sequence and the process ends.

3.6 Synergy model of family members' activities by timing window synchronization

Synergistic family member activity window matching is primarily for children who need to be picked up and dropped off at school. These children are categorized into three group by age: boarders, round-trip pickup and one-way pickup; the family members responsible for picking up and dropping off are determined by followings: the structure of family members (full-time mothers, retired people under 75 years old, single parents) and the location relationship of the residence-school-workplace. The process is shown in Figure 6.

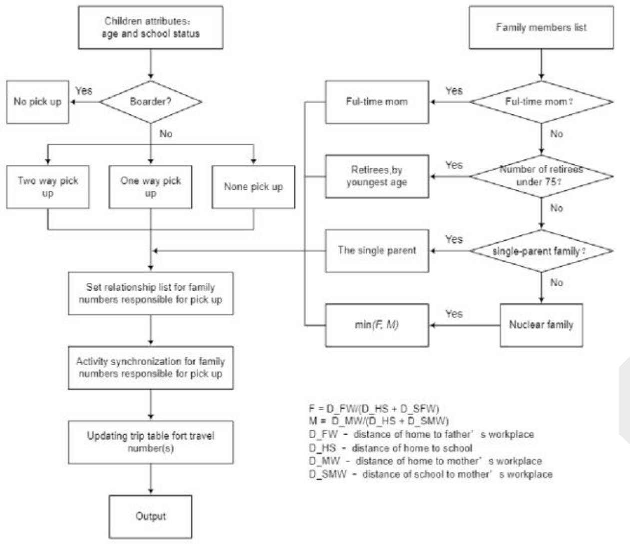


Fig.6 Framework of family member activities coordination model based on schedule window synchronization

4 Case study

This paper choices Huangpu District, in Guangzhou in China, as the empirical case, and the base year of the study is 2020. The study case contains approximately 460,000 households of 1,239,000 people, of which 681,000 are male and 648,000 are female, and about 807,000 are employed. According to the extended spatio-temporal population projection model, 79,796 people (5.9% of the population) will move over the next five years; 82,643 people (10.2% of the population) will change jobs; and 32,549 people (2.5% of the population) will both move and change jobs. In view of the percentage of people changing residence and job, the evolution of the urban is a comparatively stable process, with the state of the base year having a decisive impact on the recent urban.

4.1 Characteristic of Transport demand

The activity simulator is run to calculate activity simulations for all households and individuals, resulting in 3,691,345 trip record data, the indicators for each characteristic of the simulation results are followed:

1) Travel purpose

The composition of trip purposes (see Table 3) shows that activity ending in non-stable other types of stay points is about 17.9%, and trips related to stable stay point account for approximately 82.1%. It reflects the assumption that trip activity is stable, and the urban is a holistically stable plus partially stochastic evolutionary system.

2) Travel time

The distribution of travel times by trip purpose is shown in Figure 7. In the morning peak hour, the largest proportion of work trips are made from the home, accounting for about 25%; in the evening peak hour, the highest proportion of trips are made from work to other types of locations and from work to home, with the former even exceeding the latter; another local temporal peak appears around 1:00 am, which is difficult to describe in the existing four-stage model. The continuous spatio-temporal data supports the modelling of travel activity across days, enabling the analysis of 24-hour travel activity all day long.

Tab.3 Composition of travel purposes

Trip purpose	Work	School	Life	Other	Go home	Total
Trips/day	829,942	216,337	706,025	659,559	1,279,482	3,691,345
Proportion(%)	22.48	5.86	19.13	17.87	34.66	100.0

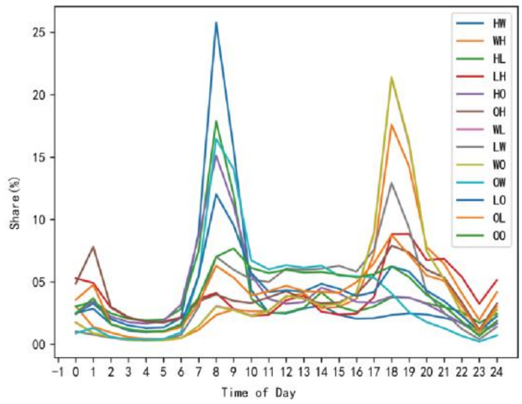


Fig.7 Distribution of travel time by travel purpose

4.2 Spatial distribution of trip activities

Commuting activity dominates urban travel activity, with a greater proportion during peak hours, and is directly related to the job-occupancy OD matrix, which facilitates testing. Therefore, this paper analyses the results of the activity-based model by spatio-temporal evolution, using trips from home to work as examples, and comparing them with the conventional model. Although the distribution of trips for different travel distances is similar between the two models (see Figure 8), a comparison of Figure 9a and Figure 9b shows that the OD matrices of the two models are significantly different, as the OD matrix of the spatio-temporal based urban activity model is more discrete, and the gravity model presents a more regular clustering feature.

As Figure 10 demonstrates, there is a strong linear correlation between PA matrix of the TAZ home to work trip and the LBS-based job-housing OD matrix, with few outliers, which is virtually unfeasible in conventional transport planning modelling schemes. It also reflects the inheritance of individual attributes in a spatio-temporal based urban activity model, which provides a better interpretation and a more causal logic to travel activity. The distribution of trip length distribution in conventional models like the gravity model can approximate to constraint condition, but the spatial distribution of travel activity is somewhat dubious.

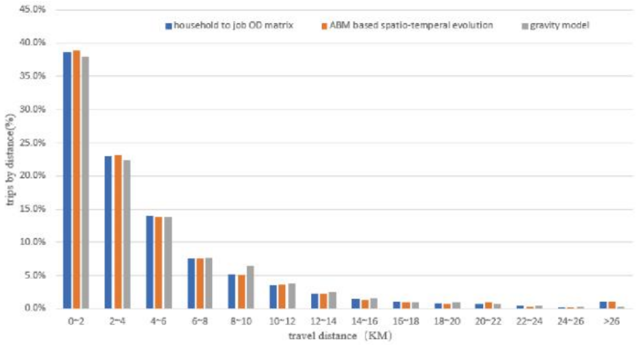


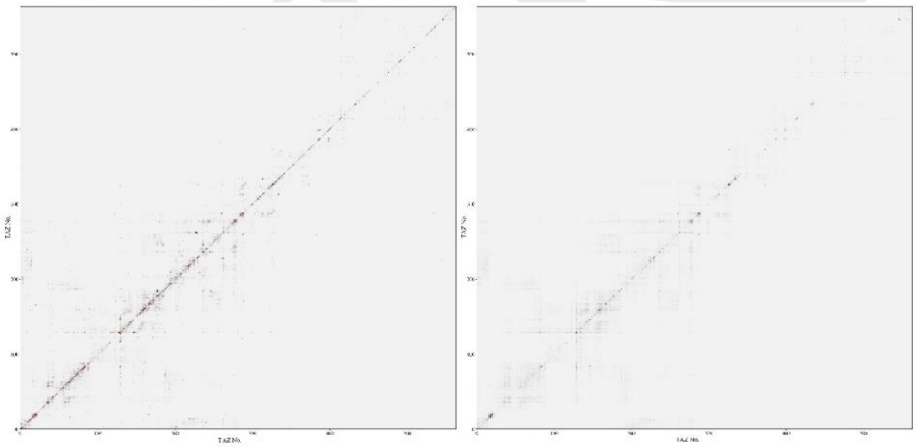
Fig.8 Comparison of travel distance distribution for home-based commuting OD matrix and job-housing OD matrix between two models

4.3 Model running efficiency.

The proposed urban activity model based on spatio-temporal evolution is far superior than similar models in efficiency. Including 460,000 households and 1,329,000 people, the case study applies ubuntu 20.04 server version with 46 threads (10,000 households thread^{-1}) running synchronously and using the activity simulator to simulate travel activity. Finally, a total of 3,690,000 full-day travel records is collected with approximately 63 min running, and maximum memory consumption does not exceed 30 G.

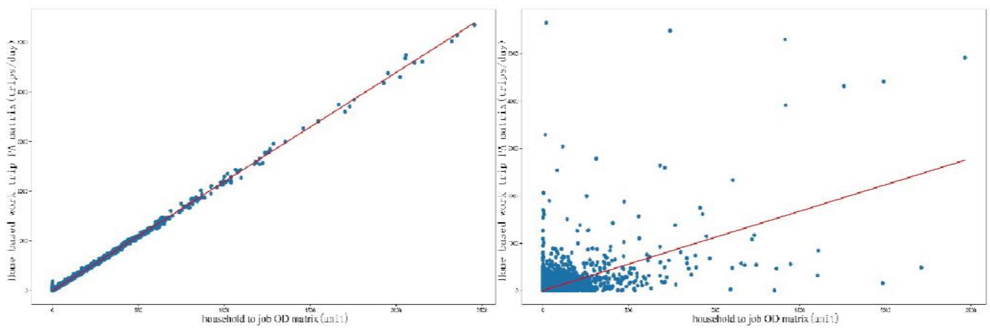
5 Conclusion and summary

The urban activity model based on spatio-temporal evolution put forward in this paper aims to integrating individual attributes into the travel activity analysis and simulation process. In the activity simulation process, it also takes the stable residence, workplace, school place of individual and travel stay point in stable life of urban space into account. Compared to FSM, existing travel chain models and activity models that use partially known terms to model the relationship between individuals and activity stay point by mathematical optimization, proposed method enhances the causal inference capability of travel activity analysis, which is the intrinsic difference.



(a) ABM base spatio-temporal inference (b) Gravity model

Fig.9 Comparison of contour lines of home-based commuting OD matrix



(a) ABM base spatio-temporal inference (b) Gravity model

Fig.10 The correlation of home-based commuting PA matrix and job-housing OD matrix

Furthermore, on the basis of identifying individual stable stay points such as job-housing location and living stay point, individual non-stable activities are analyzed by continuous spatio-temporal location data, and the stochastic nature of individuals is found to be stable in groups at the urban level. The use of “individual stochastic and group stable” activity characteristics of the rule of other types of travel destination choice, allowing various travel activities is no longer brute mathematical optimization match, but truly inherited the genes of urban travel activities.

Empirical research has also proven that urban activity models based on spatiotemporal inference have better explanatory power in terms of spatial distribution of travel activities compared to traditional transportation models.

It should be noted that, according to the extended population spatio-temporal derivation model, this paper focuses on the trip chain generation model, and the destination choice model by individual travel attributes couple with urban activity patterns, which refers to the trip distribution model, while no additional explanation is given for the mode segmentation model. This is because after addressing the two key issues of trip generation and trip distribution, the segmentation model can still use traditional discrete behavioural choice models or machine learning methods such as neural networks and decision trees. It also reflects the feasibility of urban activity models by spatio-temporal derivation.

The proposed model still needs improvement in two aspects. First, the model requires a high degree of data continuity and spatio-temporal granularity, therefore, the data processing techniques and modeling processes need to be more standardized and modularized. Second, evolution forecast and activity simulation are mostly driven by the base year. Although the model can forecast annual evolutionary, its ability to adapts to sudden intervention strategies and external factors leaves much to be desired, thus simulation forecasting capabilities for the medium to long term may lack adaptability. Finally, it is important to emphasize that as Chinese cities move from incremental planning to stock planning, the external boundaries and internal structures of urbans are stabilizing, and urban development will be in a phase of partial regeneration and dynamic re-equilibration. Within this development context, the spatio-temporal urban activity model coupled with the increasing abundance of multi-source data, can provide a better analysis of the status quo and recent development of urbans, especially for the prediction of travel demand for the improvement of existing infrastructure and optimization of travel services.

References

[1] BOYCE D, WILIAMS H. Forecasting urban travel: past, present and future [M]. Northampton, Massachusetts: Edward Elgar Publishing Limited, 2015.

[2] MEYER M D, MILLER E J. Urban transportation planning (second edition) [M]. New York: McGraw-Hill, 2001: 656.

[3] CASTIGLIONE J, BRADLEY M, GLIEBE J.Activity-based travel demand models: a primer [R]. Washington: Transportation Research Board, 2015.

[4] ABAR S, THEODOROPOULOS G K, LEMARINIER P, et al. Agent based modelling and simulation tools: a review of the state-ofart software [J]. Computer science review, 2017, 24: 13–33.

[5] CHEN X L. A review on urban transportation models in China [J]. Urban transport of China, 2016, 14 (2): 17–21.

[6] KITAMURA R. An evaluation of activity-based travel analysis [J]. Transportation, 1988, 15 (1–2): 9–34.

[7] CARROLL J D. Detroit metropolitan area traffic study part II: future traffic and a long range expressway plan [R]. Detroit: Michigan State Highway Department, 1956.

[8] CARROLL J D. Chicago area transportation study final report volume III: transportation plan [R]. Chicago, Illinois: Chicago Area Transportation Study, 1962.

[9] HASNINE M S, NURUL HABIB K N. Tourbased mode choice modelling as the core of an activity-based travel demand modelling framework: a review of state-of-the-art [J].Transport reviews, 2021, 41 (1): 5–26.

[10] BOWMAN J L, BRADLEY M. Sound cast activity-based travel forecasting model for PSRC: featuring DAYSIM—the person day activity and travel simulator [R]. Seattle: Puget Sound Regional Council, 2014.

[11] PINJARI A R, ELURU N, SRINIVASAN S, et al. Cemdap: modeling and microsimulation frameworks, software development, and verification [DB/CD]. Washington DC: TRB, 2008–01–13.

[12] JONES P, DIX M C, CLARKE M I, et al.Understanding travel behaviour [M]. Aldershot: Gower, 1983.

[13] BHAT C R, GUO J Y, SRINIVASAN S, et al. Comprehensive econometric microsimulator for daily activity-travel patterns [J]. Transportation research record: journal of the transportation research board, 2004, 1894 (1): 57–66.

[14] ARENTZE T, HOFMAN F, van MOURIK H, et al. ALBATROSS: multiagent, rule-based model of activity pattern decisions [J].Transportation research record: journal of the transportation research board, 2000, 1706 (1): 136–144.

[15] MILLER E J, ROORDA M J, CARRASCO J A. A tour-based model of travel mode choice [J]. Transportation, 2005, 32 (4): 399–422.

[16] BAQUERI S F A, ADNAN M, KOCHAN B, et al. Activity-based model for mediumsized cities considering external activity–travel: enhancing FEATHERS framework [J]. Future generation computer systems, 2019, 96: 51–63.

[17] FREEDMAN J, HENSLE D. ActivitySim: an advanced activity-based travel demand model built by and for users [R]. Dartmouth: Resource Systems Group, 2022.

[18] YE X, KONDURI K C, PENDYALA R M, et al. Methodology to match distributions of both household and person attributes in generation of synthetic populations [DB/CD].Washington DC: TRB, 2009-01-11.

[19] MÜLLER K, AXHAUSEN K W. Population synthesis for microsimulation: state of the art [DB/CD]. Washington DC: TRB, 2011-01-23.

[20] PAUL B M, DOYLE J, STABLER B, et al.Multi-level population synthesis using entropy maximization-based simultaneous list balancing [DB/CD]. Washington DC: TRB, 2018-01-07.

[21] CHEN X L, CHEN X H. Study on a simplified activity-based model framework based on stability of travelers [J]. Journal of South China University of Technology (natural science edition), 2021, 49 (2): 59–67.

