EVALUATE THE FEASIBILITY OF IMPLEMENTING ACTIVITYSIM ACTIVITY-BASED MODEL FOR VIETNAMESE MUNICIPALITIES IN TERM OF THE AVAILABLE INPUT DATA SOURCES

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Abstract - Activity-based modeling (ABM) has emerged as a promising approach in urban travel demand forecasting, addressing the limitations of traditional models that have dominated the field for over 50 years. ABM offers a powerful framework for simulating traffic at the city scale, enabling a deeper understanding of the complex behavior of urban transportation systems under various scenarios. This paper concisely overviews recent advancements and challenges associated with applying activity-based models in travel demand forecasting. Additionally, the article explores the operational process of the ActivitySIM model, a specific ABM tool for traffic demand forecasting, by detailing the required input data and parameters. The potential for deploying this technology in Ho Chi Minh City was analyzed to highlight relevant data sources. Furthermore, the paper discusses potential solutions to improve data accuracy and enhance the consistency of ABMs across multiple days of the week, addressing critical challenges in implementing these models effectively.

Keywords - Activity-based model; ActivitySIM; Travel Demand Forecast

1. Introduction

The growing concern about urban traffic issues, along with information technology development, has led to more advanced models of traffic demand management. While the 4-step model has been widely used in traffic demand forecasting, it suffers from several limitations.

- The model often aggregates data spatially, demographically, and temporally, which can lead to inaccuracies. The model divides the study area into traffic analysis zones (TAZs) and assumes that all individuals within a zone behave similarly. It may not account for variations in travel behavior within different parts of a city or among different population groups [1].

- The model's sequential process means that decisions made in earlier steps (like trip generation) are not influenced by choices made in later steps (such as route choice). This can result in a lack of feedback and interaction between steps, leading to less accurate forecasts [1].

- The model typically assumes that travel behavior and trip generation factors remain stable over time, which is often not the case. Changes in land use, economic conditions, and transportation policies can significantly alter travel patterns [2].

The model simplifies complex travel behaviors into basic categories, which can overlook the nuances of why and how people travel. For instance, it might not accurately capture trip chaining (making multiple stops in one trip) or the impact of emerging travel options like ride-sharing [3].

- The model is lack of real-time adaptability. It is not well-suited for real-time traffic management or for adapting to sudden changes in travel patterns [4].

Activity-based modeling emerges as an alternative to the 4-step model and overcomes this traditional approach's inherent theoretical and practical limitations [5, 6]. The extensive advantages of activity-based models (ABM) compared to 4-step models have been discussed [7], and their importance in the analysis of travel demand has also been extensively documented [8-11]. A comparison of these 2 models is presented in Table 1 [12].

Table 1. *Comparison between 4-step model and ABM*

Four-step model	**ABM**	**Objective**
Model based on trips	Model based on activities	Traffic Demand Forecast
Trip generation	Activity generation and scheduling.	The location of the trips generated and the types of activities that individuals engage in.
Trip distribution	Destination of tour and trip choice.	The places individuals traveled to.
Mode choice Network assignment	Tour and trip time of day; Tour and trip mode choice; Network assignment.	Time individuals traveled and duration of each activity; Types of modes individuals chose; Routes individuals used and the travel time.

Activity-based models are advanced transportation planning tools that simulate travel behavior at the individual level by considering the complex interdependencies between activity participation, travel behavior, and land use. Analyzing sequences of daily activity or patterns set in time and space constraints can examine how people conduct their activities and model them to address traffic problems. ABMs have become increasingly popular in transportation planning as they offer better accuracy in predicting travel behavior, evaluating policy scenarios, and assessing the impacts of land use changes.

ABMs can be categorized into three main approaches: constraints-based models, utility-maximizing models, and computational process models (CPMs)

Utility-maximizing models focus on individual decision-making to maximize utility, using econometric methods (e.g., logit, probit, and hazard-based models) to assess the impact of factors like income, demographics, costs, and travel time [13]. Logit models are used for mode and destination choices, while hazard-based models generate activity schedules [14]. Though these models assume rational behavior, real-life decisions aren't always rational, limiting predictive accuracy. CPMs use rule-based simulations (e.g., decision trees, neural networks, fuzzy logic) to model activity sequencing and scheduling. They capture complex behaviors, including social norms and habits, that utility-maximizing models miss. However, CPM rules can be challenging to interpret and validate.

Utility-maximizing models are flexible for policy analysis but require extensive data and assumptions. CPMs are efficient at modeling complex behavior but are harder to interpret and may lack precision. Both models have complementary strengths and limitations.

MatSIM (Multi-Agent Transport Simulation), 2005 and FEATHERS (Forecasting Evolutionary Activity-Travel of Household and their Environmental Repercussions), are 2 typical examples for utility-maximizing models. MatSIM uses an evolutionary approach to generate travel patterns by iterating traffic simulations and updating schedules until equilibrium is reached. It can run continuously or on a second-by-second basis [15, 16]. FEATHERS, designed for Flanders, Belgium, forecasts activity-travel sequences to estimate emissions, energy consumption, and exposure[17]. ALBATROSS (A Learning Based Transportation Oriented Simulation System), 2000 and ADAPTS (Agent-based Dynamic Activity Planning and Travel Scheduling) 2009. ALBATROSS is a multi-agent CPM that uses predictive algorithms to estimate various activity details while considering multiple constraints. It is comprehensive but does not simulate route choice [18-20]. ADAPTS creates activities from survey data and arranges them using scheduling rules, treating activity planning as dynamic events and eliminating fixed planning sequences [21-23].

Other approaches, such as time-space prism techniques and agent-based methods, can complement activity-based models. Time-space prisms represent geographical and temporal constraints on activities, while agent-based methods allow agents to adapt and interact within dynamic environments. These techniques enhance models by capturing complex behaviors and providing insights into travel demand but may require more data and computational resources for implementation and validation. Many of the above mentioned models that improved in this direction are ALBATROSS, FEATHERS, MATSim, TRANSIMS, and most recently is SimMobilitiy [24], POLARIS [25], ActivitySim Model (2022) [26]. The latest and updated version of the ActivitySim Model has just been implemented in 2022.

Despite significant advancements, ABMs still struggle to accurately reflect behavioral realism. Solutions include improving primary data accuracy, enhancing ABM consistency across different days, and integrating demand and supply to address uncertainty. There are also opportunities to test the spatial transferability of ABMs to new regions and to expand their use in transportation policy-making. Recent progress in activity-based travel demand modeling includes the emergence of big data sources such as cell phone data, smart card data, GPS data, social media data, and multi-day travel datasets [27].

One challenge is that data collection in developing countries can be more complex and time-consuming than in developed countries. Data availability and quality regarding transportation infrastructure, such as road networks, public transportation routes, and schedules, are often inadequate. Access to data may be limited or of lower quality, making calibration and validation of the models that generate meaningful results more complex; furthermore, even when available data may be collected at different scales or methods, it is difficult to combine or compare across different sources. Another challenge is the lack of expertise and resources to develop and apply ABMs. ABMs are more complex than traditional traffic demand models, making them more challenging to implement and comprehend. Developing and calibrating ABMs require significant technical expertise and resources, which may not be accessible in many developing countries.

Moreover, ABMs may be challenging to communicate to policymakers and stakeholders who are more familiar with traditional models. Finally, cultural and social factors can also affect the accuracy of activity-based models in developing countries. Travel behavior in developing countries is often shaped by cultural and contextual factors that may not be adequately captured by ABMs, such as social norms, informal transport systems, and the role of the informal economy.

Given the advantages of ActivitySim open model: open source, which can be replicated and modified for different urban contexts, real-time adaptability; this paper provides an overview of how the ActivitySim Model works to generate a fully replicable travel demand model and focuses on the detailed analysis of the procedure of collecting, processing, and validating data. Our aim to motivate governments of developing countries, including Vietnam, to consider developing ABM models for their cities.

2. ActivitySim Model

ActivitySim is an open-source software platform designed for activity-based travel behavior modeling. The ActivitySim project aims to develop and maintain cutting-edge, publicly available, open-source software for free public distribution according to optimal software development methodologies (The open-source is available online at https://github.com/ActivitySim). ActivitySim was developed and maintained by a collaboration of Metropolitan Planning Organizations (MPOs), which aims to establish a unified set of modeling tools and processes to improve collaboration and exchange innovative ideas between MPOs.

2.1. Inputs

ActivitySim requires two primary input datasets; one set is related to geography (NETWORK DATA), and the other is related to the synthetic population (OBSERVED DATA) (Figure 1).

Zone system along with transportation network and land use data is the baseline input data for the model. Traffic Analysis Zones (TAZs) are the most common type of zone system unit in transportation models. They are compact, adjacent geographic regions that signify the origins and destinations of trips in a travel demand model.

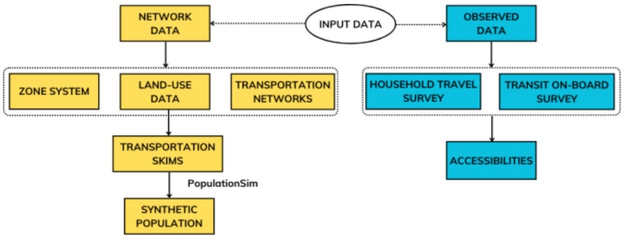

Figure 1. *Input for ActivitySIM model*

The traffic analysis zone (TAZ)-level geographic data has three components: 1) Land use data; 2) Travel impedances matrix between zones, taking into account mode of travel and time of day; 3) A table of aggregate utility measurements for each user-defined region. These impedance matrices and utility measurements are known as Skims and Accessibility.

The land use data includes zone-level residential characteristics (housing density and population characteristics), employment characteristics, and various land utilization metrics. In projects that use ActivitySim for modeling, land use data is taken from government zoning and planning records, national census and demographic data, existing GIS databases (e.g., OpenStreetMap), etc.

Transportation Skims are pre-calculated metrics representing the cost or travel time between origin-destination (OD) pairs. Skims are simply matrices or summaries of travel times, travel costs, distances, and other measures (congestion levels, transit access and egress times, number of transfers, etc.) of travel impedance between various traffic analysis zones (TAZs). There are some types of skims in Activitysim:

- Auto Skim is a matrix of zone-to-zone travel times, distances, and costs (including tolls, parking fees, fuel costs, etc.) for private vehicle trips. It can include free-flow travel time (without congestion) and congested travel time (during peak periods);

- Transit skim is a matrix of zone-to-zone travel times (in-vehicle time, waiting time, walking time (to/from transit), etc.), costs (including transit fares, parking fees, etc.);

- Non-motorized skims: a matrix for trips by walking or biking.

For other ABMs, Transportation Skims are usually created using a traffic assignment model, but ActivitySim cannot. ActivitySim requires OpenMatrix (OMX) skim data. Skims or other transportation network graphics can determine accessibility. Mode-specific indicators of network facilities, including job centers, retail outlets, and transit hubs, are used to derive these metrics. Accessibility metrics can range from simple counts of facilities along a shortest path distance or trip time to more complex composite utilities derived from a discrete choice model.

The second set of ActivitySim input data is the synthetic population. The synthetic population data consists of individuals and their characteristics and the households and household characteristics into which the individuals are organized.

2.2. The functioning process

ActivitySim primarily relies on discrete choice models and the notion of random utility maximization [28]. Decision-makers in the model system are households and persons. Population synthesis methods like PopulationSim generate decision-makers for each simulation year. Following discrete-choice models, decision-makers choose one option from a probability-distributed list. Logit-form models that account for the decision-maker and possibilities are used to calculate the probability distribution. The decision-making unit is essential to model estimation and implementation and is specified for each model.

An ActivitySim run comprises a sequence of model stages that are executed in order. The initial stage in the sequence is the generation of accessibility. These are the accessibility of origin zones for private vehicles, transit, and non-motorized mobility, which are utilized to impact vehicle ownership and trip frequency.

The accessibility model calculates cumulative (zonal) measurements of accessibility that the subsequent models utilize. The accessibility measure is a log sum of destination choices, where the level-of-service variable is limited to a specific mode or set of modes, and the size term is limited to a given employment variable. The equation is displayed below [29].

$$A_i = \ln\left[\sum_{j=1}^{I} S_j \times \exp\left(-\gamma c_{ij}\right)\right] \tag{1}$$

where: A_i is to the accessibility of the origin. TAZ_i;

S_j is the size of destination TAZ_j;

γ is a parameter represents the degree of responsiveness to changes in travel costs;

C_{ij} is the overall cost of travel from origin TAZ_i to destination TAZ_j, expressed as a generalized cost including time and cost. This cost is calculated by considering both the time and monetary expenses involved in the journey.

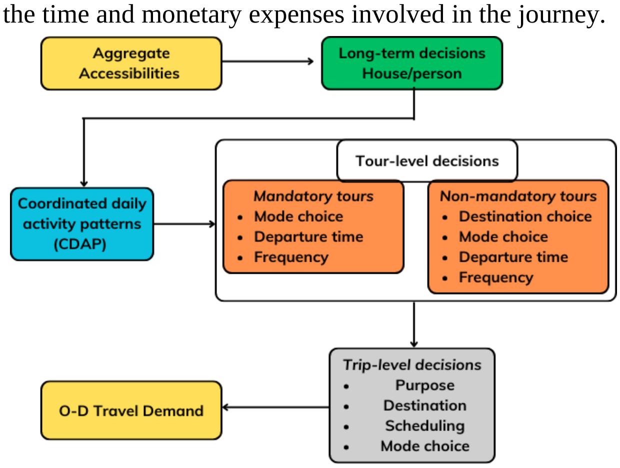

Figure 2. *ActivitySim model flow*

Figure 2 shows four clusters of models: long-term decisions, coordinated daily activity patterns, tour-level decisions, and trip-level decisions.

- *Long-term choice models*: ActivitySim's three long-term choice models - job location, school site, and auto-ownership - simulate decisions that are not made daily but strongly influence them.

- *Coordinated Daily Activity Patterns*: The CDAP phase models the group decision-making process for individual household members who aim to optimize the utility of their collective daily activities. CDAP considers mandatory and optional journeys, optimizing individual utility. The current maximization approach estimates all household member combinations, which takes the longest in ActivitySim.

- *Tour-level decisions*: Tours are continuous journeys without stopping. Trips to and from work and school are mandatory, while others are voluntary. The user-defined configuration file lists optional tour options, including a destination choice model. Long-term decision models estimate mandatory tour options. Each tour category has model phases for predicting transportation mode, departure time, and frequency.

- *Trip-level decisions*: A tour may have different modes for different trip legs, hence mode choice must be made at the trip and tour levels. Trip departure and arrival estimates. Other trip features emerge from its journeys.

2.3. Outputs

Trip lists are collected into origin-destination matrices by term, departure date, and mode of transportation. The transport network receives these matrices. The model system is iterated twice with a 100% sample size to converge and generate skims from high traffic congestion.

3. Analysis of Application Prospects – Case Study: Ho Chi Minh City

Ho Chi Minh City (HCMC), Vietnam's economic hub, is rapidly urbanizing, causing traffic congestion and pollutants. The local administration is developing policies and programs to change people's travel patterns and control travel demand efficiently. Addressing this difficulty requires a travel demand forecasting model that uses individual activities. HCMC is a metropolitan area located in the southern region of Vietnam. It has a monocentric structure, meaning it has a single dominant center. The city center is the primary hub for both the people and the traffic network [30]. The study area of HCMC spans 2,061 square kilometers and is home to 8.99 million people as of 2019. It is organized into 317 wards across 24 districts. The 24 districts are categorized into three distinct types: central business districts (CBD), recently developed districts (NDD), and rural districts (RA). The Central Business District (CBD), which comprises 13 districts, accommodates almost 50% of the population. It is distinguished by its tall buildings, commercial complexes, historical sites, top-notch hospitals, and educational institutions, among other amenities. The six districts of NDD have recently founded districts, having been established within the past 25 years, and have significant rates of urbanization. Over 75% of the total area of HCMC is comprised of rural districts [31].

A large-scale household travel survey, the "Data Collection Survey on Railways in Major Cities in Vietnam" (METROS Study), was conducted in HCMC and some surrounding provinces from January to April 2014. After screening for HCMC residents and travelers, 1,208 schedules of 46,197 individuals were observed [10].

There is no empirical evidence of developing an activity-based model for HCMC. However, Linh et al. transferred the theory of travel behavior and decision-making to adapt FEATHERS (developed for Flanders, Belgium) [9] for HCMC. This study examined the similarities and differences in activity and travel behavior between Flanders and HCMC to evaluate the transferability of FEATHERS to HCMC using one-day travel survey data. Initial tasks included assessing data inventories and analyzing temporal and spatial activity patterns to identify key differences. HCMC lacks high-quality data compared to previous transfers. However, METROS activity patterns are less complex and align with FEATHERS without major changes. The location and transport mode choice models are the least transferable. Future work will focus on implementing a work-based sub-tour model, recalibrating sub-models with HCMC data, and rebuilding the transport mode choice model to include motorbikes. The location choice model for HCMC will be developed based on existing land use data, considering activity type, mobility, accessibility, and time availability.

Future research will prioritize the implementation of a work-based sub-tour model, which primarily consists of individual travel goals and relies on workplace land use patterns. Personal and family characteristics affect activity and travel behavior in both datasets. Therefore, it is necessary to adjust all models using HCMC data. The transport mode choice will be reconstructed with a new set of options and distinct properties tailored for motorcyclists. The location choice model for HCMC will be developed using current land use data. This model will consider many factors, such as activity type, individuals' mobility, accessibility, and time availability at the tour and stop modeling levels.

The above analyses show that the data for ActivitySIM-based ABM development is insufficient. To create a comprehensive dataset and provide a full range of Transportation Skims for ActivitySim requires a huge effort by the government and people of HCMC as well as other cities of Vietnam.

In addition, new data sources (call detail records – CDR, Smart card systems with on- and off-boarding information, GPS data, Social media data) that record human movements, including information about movement tracks and activities performed are well suited to activity-based models. These large datasets for analyzing travel needs have been introduced. In the new era of travel demand modeling, dynamic time-series data delivered from new devices need to process large, and as a result, manage observations for days, weeks, and even months.

Based on an in-depth and critical review of the literature, there are still challenges in extracting the right information and integrating it appropriately into travel demand models. In particular, the extraction of personal characteristics and trip information such as the purpose of the trip and the mode of transportation remain open issues because these big data sources provide a spatio-temporal trace of the behaviors of the person making the trip.

4. Disscusion and Conclusion

Both ABMs overall as well as ActivitySim require detailed information on travel behavior and individual characteristics, which may be unavailable in many developing countries.

To overcome the challenges of applying ABMs in developing countries, researchers may need to be creative in data collection and model design approaches. This could involve using alternative data sources and innovative methods such as smartphone apps, GPS tracking, and social media. Future research could focus on developing simplified versions of activity-based models that are more computationally efficient and require fewer data inputs. It should be adapted to the local context by incorporating context-specific parameters. In addition, it could be focused on integrating activity-based models with other models, such as land-use models (UrbanSim), traffic simulation models (PTV VISUM), and emissions models, to provide a more comprehensive picture of the transportation system. Collaboration between researchers and local stakeholders, including policymakers and community members, can also help ensure that models are relevant and helpful in addressing real-world challenges.

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