Activity-Based Model: Requisite for a New Travel Demand Forecasting Approach for India

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1 Introduction

Travel behavior in developing countries has been substantially varying in recent years with growing vehicle ownership and the introduction of new modes. Modeling commuters' travel pattern is important for planners and decision-makers for the selection and implementation of the right mix of policies toward the creation of a sustainable travel environment. The traditional aggregated methods fail to estimate travel demand accurately for developing countries particularly due to heterogeneity in terms of income, religion, nature of jobs, family structure and size, culture, travel modes, and traffic flows which result in varied and complex travel environment. Thus, there is a need for a disaggregated realistic travel demand model for efficient travel demand forecasts for developing countries within budget and time constraints. However, till date in India, the traditional four-stage modeling approach has been being used for the estimation of travel demand in most cases.

The progress in behavioral research has helped to identify several shortcomings in the traditional four-stage model such as lack of integrity among various sub-models, interdependency between the four steps, strong aggregate nature both in time and space and lack of behavioral realism. In addition, in the early 1990s, the introduction of the concept of "travel as derived demand" [1] has brought a paradigm shift in travel behavior analysis which has led to the growth of ABMs. During the last two decades, the research and application of ABMs in different developed countries have advanced significantly, whereas very little research has been taken up in developing countries. Additionally, a country like India, where population density and diversity are very high, requires a comprehensive framework to understand the travel pattern of

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individuals for better travel demand management. This paper is an attempt to establish the need for the formulation of an integrated land use-transportation modeling framework for India through an intense conjectural study on existing travel demand models in India and different ABMs developed across the globe. The rest of the paper has been divided into four sections. The first section details the concept and evolution of activity-based models that have been adopted in other countries to identify limitations and applicability in the Indian context followed by the comparative analysis between the four-stage model and ABMs. The next phase involves critical analysis of earlier travel demand modeling studies in India to identify gaps and future direction of research followed by the description of the present Indian urban transportation scenario to establish the need for a new transport demand modeling approach. Finally, the paper has been concluded with a proposed activity-based modeling framework for India.

2 Appraisals of Different Activity-Based Models

In 1990, for the successful implementation of Clean Air Act Amendments in the USA, the application of traditional aggregate models was found to be inadequate for the accurate forecast of mobile emission. This led to the development of disaggregate ABMs to address the limitations of traditional models. In addition, strategies such as teleworking, congesting pricing, and ridesharing require a disaggregate travel demand model for precise assessment. Thus, since the last decade, ABMs are quite popular in many countries across the globe. The concept, component, and computational evolution of ABMs are narrated in detail in the subsequent sections.

2.1 Concept of Activity-Based Model

ABMs have been adopted with an aim to address the limitations of the four-stage models. In the early 1970s, Chapin has argued that instead of traveling aimlessly people travel to perform an activity [1, 2] and the choice of place to perform the activity is responsible for the creation of spatial patterns [3]. Hence, instead of relying on normative location theories, identification of activity patterns should be considered. As per Chapin, four reasons has been identified behind the willingness to take part in an activity such as propensity (people tend to deviate from their choices due to several factors such as lifecycle, health, etc.), opportunity (the favorable environment to perform an activity which is created by physical and spatial characteristics), situation (whether the state of the art of the surrounding environment is suitable for performance of an activity or not), and environmental context [1]. To perform the selected activities commuters choose travel options based on their socio-economic conditions, lifestyle and awareness of available options and constraints. Thus, the aim of ABMs is to predict the sequence of trip chains and all the attributes associated with each trip such as where, when, for how long by individuals under several constraints imposed by the travel environment, institution, other household members, and limited resource (time and budget). The concept of constraints, which limits the choices of an individual, was detailed out by Hägerstrand (1970). In his research, the constraints are broadly divided into three categories such as.

- Capability constraints: for biological reasons, e.g., time requirement for eating, sleeping
- Coupling constraints: performance of a joint activity when, where, for how long, and with whom
- Authority constraints: control of an administrative authority or law on an individual or group [4].

2.2 Activity-Based Model Components

The ABMs are composed of two sub-models such as activity generation and activity scheduling [5]. The activity generation model predicts the aspiration of an individual to participate in activities (i.e., activity demand). Then, the travel, which is conducted to perform the activity, is scheduled considering all the constraints (i.e., activity scheduling). Even after intense research in this field, research on activity generation remains relatively neglected in comparison with activity scheduling. During the initial era of the ABMs, an econometric modeling approach has been adopted which is mostly based on the utility maximization principle. These models act on the basis of determination of the probability of a decision while different choice alternatives are available. It has been found that different logit models (i.e., multinomial logit (MNL) models, nested logit (NL) models) are popular for econometric modeling approaches [5–9]. Though this modeling technique is capable of analyzing the casual relationships among various hypotheses, due to unrealistic assumption of utility maximization behavior (i.e., all commuters are rational and have complete information regarding travel time, cost, and availability of all the available alternative modes), it often fails to capture the actual decision-making processes with adequate accuracy. Computational process models (CPMs) have been developed with an aim to address some behavioral assumptions of econometric models and are based on the condition-action rules (if–then) principle along with the ability to model the interdependent decisions [10]. Based on the modeling approaches, CPM can be further categorized as weak CPM and strong CPM. A weak CPM can be defined as the model consisting of heuristic decision rules with assumptions of unbounded rationality (e.g., utility maximization principle) at the individual level [11–14]. A strong CPM is based only on decision rules and there is no assumption related to unbounded rationality [15–19]. Though there is no comparative analysis has been conducted between econometric based and computational process-based ABMs, several comparative analysis has been conducted for mode choice analysis and it has been proved that decision rule-based algorithms such as decision tree, random forest decision tree, and neural networks have been performed (i.e., level of prediction accuracy) better than logit models [20–22].

3 Comparison Between Activity-Based Models and Four-Stage Models

The activity-based modeling concept, in which activity participation is the focus point, has been developed with an aim to address the limitations of four-step models. Most of the ABMs have concentrated on the analysis of destination and mode choice, and very few models have included route choice [23]. However, like the four-stage models, ABMs also generate time-dependent OD matrices which can be further processed for the route choice model. In the overall travel demand modeling framework, there is hardly any difference between the four-stag model and ABMs. But, certain properties associated with ABMs such as integrity, allowance for complex dependencies, higher resolution, and disaggregate nature make ABMs more efficient and policy-sensitive than the traditional four-stage model. The disaggregated ABMs maintain both intra-person and inter-person integrity within a household. Intra-person integrity has been achieved by considering different constraints (institutional, temporal, spatial, and spatio-temporal) during the scheduling of activity sequences. Inter-person integrity within a household has been gained by including coordination among individuals' daily activity-travel patterns (DATPs) at the household level, joint travel to perform joint activities, drop-off and pick-up decisions, and allocation of household maintenance work. Besides, to improved integrity, ABMs have enhanced the interdependencies among different sub-models through checks on the interrelationship among various component of DATPs, consistency in modal choice during a tour, compatibility between activity-travel generation, the state of the travel environment and travel time, and interconnection between out-of-home activities and in-home activities [3]. A higher spatial and temporal resolution are also embedded within ABMs, which make these models more policy-sensitive and efficient tools for travel demand management.

In recent years, new technology platforms such as Google Maps, Google traffic, etc., have made it easier to get real-time information on the congestion status of urban roads. This influences travelers to shift their time of travel as per their convenience and most likely to non-peak-hours or to decide against joint tours if commuters have to pass through congested areas to pick-up or drop-off the second traveler. The emergence of telecommuters has also led to a change in travel patterns in urban areas. A study in California found that telecommuters distribute their trips, over the day and avoid peak-period travel (by 60%). In this way, telecommuters have also reduced the total distance traveled and freeway miles by 70%, and 90%, respectively [24]. The changing travel pattern requires us to analyze the travel demand for the whole day instead of peak hours only. As the rebound effect of teleworkers has not been included within the traditional travel demand modeling frameworks, these frameworks are unable to estimate the impact of teleworking on the urban travel environment [25]. Thus, there is a need to develop a modeling framework based on what-if relationships that would determine the effect of change in activity schedule.

The increasing usage of smartphones, mobile computing, and other ICTs has also reduced the difference between activities and travel episodes and also encourages multitasking during travel [26, 27]. This is also changing the way people plan their activities. Thus, the impact of real-time travel data on the travel choice of the individual also needs to be incorporated into the travel demand forecast.

Next, the introduction of ridesourcing services (i.e., OLA/UBER) has also brought a remarkable change in the urban transportation system during the last decade. The concept of ridesourcing has evolved from the idea of shared mobility. Shared mobility encompasses a wide range of services from public transportation, shuttles, and taxis to real-time on-demand ride services [28]. The growing popularity of on-demand shared modes suggests the necessity to develop an efficient demand estimation model. The demand estimation through traditional four-stage models has led to disequilibrium conditions since demand is dependent on the temporal and spatial variation in the availability of these shared modes, i.e., people may change their mode choice if the waiting time for shared modes is more than a certain threshold value. In this regard, individuals' multi-modal multi-activity trip chains must be considered to help policymakers to reduce the demand–supply gap and the application of ABMs in this context is appropriate to deal with commuters daily multi-modal multi-activity trip chains [29].

During the last two decades, several ABMs have been developed in different countries and some of these models have been able to address all the major issues related to the traditional four-step models. However, there are several limitations and issues associated with existing ABMs that need to be addressed. To reduce the computational and data burden of ABMs, a synthetic population is used for simulation which is again developed based on sample population characteristics, which result in a fair amount of uncertainty in the prediction. Uncertainty also results from inappropriate inputs in the models and from several studies, it has been found that with an increase of sample size, uncertainty associated with the model is reduced. However, in most cases, computational run time increases at an exponential rate with an increase in sample size [30]. Thus, there is a need for a tradeoff between sample size and the number of model runs (computational time). Most of the currents models simulate activity-travel patterns for a single day of the week (preferably any working day), which gives an unrealistic prediction of travel demand due to lack of integrity across all the days of the week (especially working days and holidays). Though recently, developed ABMs include the influence of travel attributes, socio-economic characteristics on the individuals, and households' choice, but the psychological factors and imperfect nonlinear perceptions are not considered. These attitudinal attributes are important components of behavioral models. In this context, hybrid choice models might be a solution to this, which demands further research before reaching to a conclusion. Though further research is required to address the limitations associated with ABMs, it has been already established by the large number of literature that ABMs gives a more realistic and accurate prediction than the traditional four-stage model.

4 Changes in Travel Behavior of Indian Citizens: Progress in Travel Demand Modeling Approach

In India, 31.2% of the population (377 million) lives in urban areas [31] and the urban economy contributes almost 60% of the country's GDP. However, most of the cities (i.e., 78% of the 5 million-plus cities) suffer from the lack of organized transportation facilities and only a few cities have deployed mass rapid transit systems [32]. During the last two decades, the share of public transportation at the city-level has also declined (between 1994 to 2007 from 69 to 38% for 4 million-plus cities) [32]. Therefore, to cope with the poor public transportation facilities, the number of registered vehicles (mostly two-wheelers) has increased from 55 million in 2001 to 142 million by 2011 and is estimated to be 195.6 million in 2016. Urban road infrastructure has failed to keep pace with this increased demand leading to severe congestion, pollution, traffic accidents and fatalities, longer trip lengths, and a higher per-capita trip rate [33]. Various policies have been recommended to deal with these transportation externalities [34, 35] but a precise assessment of the impact of policy using the existing conventional modeling framework is an arduous task for transportation planners and decision-makers.

Urban transport-related issues are mostly addressed in National Urban Transportation Policies [36], Comprehensive Mobility Plans (CMP), and Master Plan of different cities, which usually focuses on a long-term vision to create a suitable travel environment for people and goods in a city and recommends the appropriate strategies and investment initiatives to meet the vision [36]. Understanding of travel behavior and prediction of future demand of citizens is inevitable to suggest appropriate strategy and policy control the aggregate phenomena such as congestion, land use patterns, and emissions. However, these policies instead of affecting the aggregate phenomena directly, affect them indirectly through the behavior of individuals. Moreover, the travel demand modeling technique is not mentioned in several cities' CMPs and in many cities, there is no CMP. Till date in India, all the CMPs have been based on four-stage transportation demand models (trip generation, trip distribution, mode choice, and network assignment) in which the effect of long-term choices (household and work location choice), vehicle ownership in future, and the effect of transportation on the environment is ignored [37–42]. The travel demand approach and software used for transportation demand prediction in the top 20 populous cities of India have been listed in Table 1 which shows that there is no complete integrated land use-transportation model that has been developed for India till date. In addition, freight and passenger demand are estimated separately, which creates further

Table 1 Transportation demand modeling approach in CMPs of different Indian cities

Sl. No	City	Travel demand model approach	Software used
1	Mumbai	Standard four-stage travel demand modeling approach	EMME
2	Delhi	Not mentioned	
3	Bangalore	Traditional four-stage integrated land use transport transportation model	CUBE
4	Hyderabad	Traditional four-stage model	Not mentioned
5	Ahmedabad	Not mentioned	
6	Chennai	A four-stage model with combined trip distribution and modal split phase using a conventional doubly constrained gravity model	CUBE
7	Kolkata	Not available	
8	Surat	Not mentioned	
9	Pune	Conventional 4-stage transport model	CUBE
10	Jaipur	Conventional 4-stage transport model	CUBE 5.0
11	Lucknow	A conventional 4-stage transport model	CUBE 5.0
12	Kanpur	Conventional 4-stage transport model	CUBE
13	Nagpur	Conventional 4-stage transport model	CUBE
14	Indore	Not mentioned	
15	Thane	Not mentioned	
16	Bhopal	Not available	
17	Visakhapatnam	Conventional 4-stage transport model	Not mentioned
18	Pimpri and Chinchwad	Conventional 4-stage transport model	Not mentioned
19	Patna	Conventional 4-stage transport model	Not mentioned
20	Vadodara	Not available	

incomprehension for network analysis. The existing models fail to reflect behavioral realism and do not consider any interrelationships among trips performed by an individual on the same day or even among the trips belonging from the same tour, dependencies among different household members, and different choice facets (e.g., trip choice and mode choice).

During the last decade, India has also witnessed the same changes arising out of new information communication technology (ICT) platforms similar to developed countries. Additionally, the introduction of ridesourcing services, telecommuting, and the government investments in "smart city program," "National Electric Mobility Mission Plan 2020," Make in India, "Automotive Mission Plan 2026," etc., have been contributing toward the creation of a more dynamic and flexible travel environment which would be more challenging for the transport modeler. Thus, to cope with the changing travel pattern of Indian citizens, there is a need for the development of a comprehensive framework (integrated land use-transportation modeling framework), which would be based on disaggregated activity-based modeling framework including the characteristics of land use and built environment, household and individual socio-economic characteristics, travel attributes, impacts of households interaction, joint tours, modal switching, and multiple activities in one tour [43].

In recent years, the formulation of ABMs has been studied in different Indian cities, which have been discussed here briefly to understand their scope and limitations. In Mumbai Metropolitan Region, trip chaining behavior has been analyzed with the help of activity-travel survey data [43, 44] using NL model based on the random utility theory. This has been used to classify the trip chains into three categories, namely simple (two trips and one activity in-between), complex (all trip chains with at least one activity), and open chains (missing information) for two trip purposes, i.e., work and non-work. This simple classification has limited ability to predict the complex travel pattern and behavioral mechanism of commuters and the subsequent impact of different policy interventions. In another recent study in Thiruvananthapuram urban area, an activity-based mode choice model has been developed by using a MNL, which has explored only single activity [45]. Out-of-home activity participation behavior of "*non-student-non-workers*"(retired, homemakers, and unemployed) in Bangalore was analyzed for maintenance and discretionary activities [46]. The outcome of this research was to determine the frequency of stops for two types of activities for different age groups and genders. An activity-based mode choice model was also developed for rural areas in Ernakulam district of Kerala, India [47]. To ensure the applicability of this model for urban areas in India demands further research. In short, till date, there is a lack of comprehensive activity-based demand modeling structure in India as either existing models suffer from assumptions associated with the estimation techniques or are limited to a specific group of commuters.

The main challenge in the formulation of ABM is its data-intensive nature. While no national travel survey is conducted by the government in India, the socio-economic heterogeneity of the population demands more sample size than developed countries. Therefore, the collection of this huge amount of data considering the limited budget and time at regular intervals is the biggest hindrance to the adoption of ABMs in India. But, in recent years, advancement in information and communications technologies (ICTs) has led to the increased use of intelligent transport system (ITS), mobile app-based transportation services, open-source databases, and Web services which could be accessed through custom APIs such as Google API for Google maps and traffic Web services which have provided the opportunities for transportation planners, urban planners, and decision-makers to access an enormous amount of data, which can bring down the cost of development and implementation of ABMs. Therefore, the hassles related to data collection are going to diminish in the near future. The analysis of travel behavior for a wide range of heterogeneous population is a big data analytics problem which could be solved more efficiently with shorter computational time using machine learning algorithms [20, 22, 48–52]. These algorithms for ABMs in the context of India are yet to be explored.

Due to socio-economic heterogeneity, context-specific policy adoption and differences in cultural values make the transferability of models developed in other countries to India uncertain. In India, the residential choice is a household-level decision rather than an individual's or earning member's decision. Thus, the residential choice is pre-decided, and in most cases, rental accommodation is preferred over a change in permanent accommodation. In addition, affordability, ethnicity, religion, and other social aspect play a major role in residential location choice, which is quite different than in developed countries. The recent trend also shows the younger generation to prefer on-demand services since it reduces the burden to pay for, maintain, and drive a car. This along with the adoption of electric vehicles necessitates the prediction of vehicle ownership and shared mobility demand. Finally, delivery systems for goods and services ordered online are instrumental in changing the activity and travel patterns of consumers. This necessitates the estimation of trips and modes used for last-mile delivery services within the activity-based travel demand modeling framework. As discussed earlier, real-time information regarding traffic conditions of route and cancelation of activity during travel also need to be considered. Another important component of the ABMs is population synthesis. The attributes used for Census data collection in India are different from other countries which demand the formulation of a fresh population synthesis model for India. Micro-simulation of activity patterns of a synthetic population with high resolution in regards to space and time can also be applied to establish a dynamic exposure assessment model for air pollution.

In Fig. 1, a comprehensive integrated land use modeling framework has been suggested which includes different sub-models that are required together to predict travel demand in the Indian context. The overall framework is an amalgamation of six major models such as population synthesis model, location choice model, vehicle ownership model, activity-based travel demand model, auxiliary model, and emission model. The activity-based travel demand model can be further divided into three components such as activity generation, activity scheduling, and traffic assignment. For the creation of a synthetic population, the household survey format must include the variables mentioned in the Census of India. The suitable activity-travel diary for India would be designed in such a way that it will be affordable and user-friendly. The booklet format which is common for space–time data collection is not encouraged in the Indian context due to budget constraints. In addition, survey methods used in developed countries will not work here due to low literacy rates and poor access to the internet. To predict the travel demand, the residential and work location of the synthesized population for the forecasted year must be known. The choice of new residence depends on the availability of housing, price, proximity to the workplace, and other infrastructures. To forecast the vehicle ownership status, stated preference survey will be conducted to know the willingness to purchase and what type of vehicle will be purchased (e.g., electric vehicle). Besides, a simulator would be part of the framework that will estimate the demand for services provided by various transportation network companies (i.e., Ola/Uber/Shuttle) at different times of the day across a city and the availability of supply for the same. This will help to establish a demand–supply equilibrium with fleet size optimization [28]. Also, the

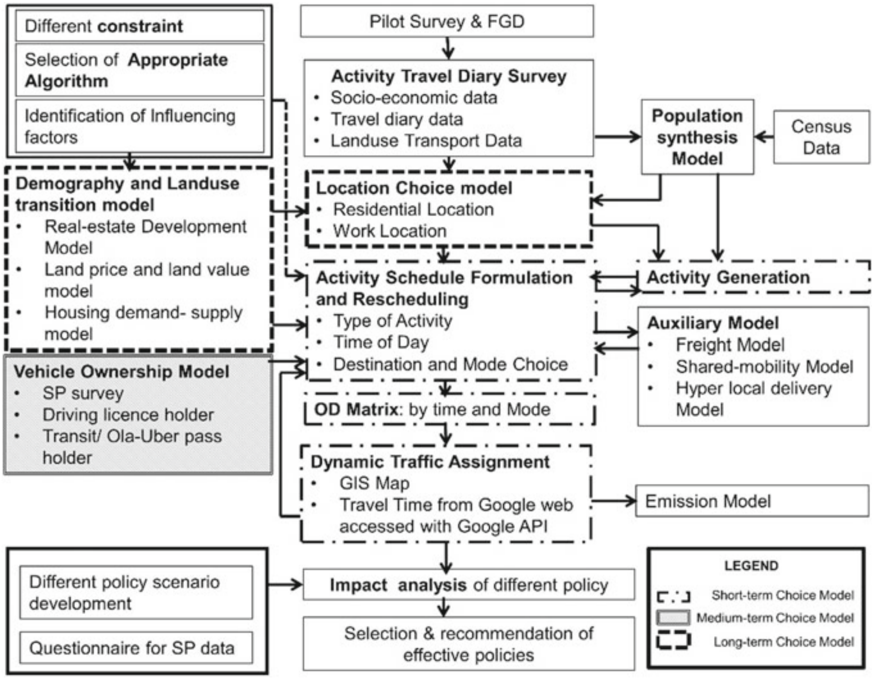

Fig. 1 Framework of integrated land use-transportation and activity-based demand model for India

demand generated for last-mile delivery services will be estimated. All the generated demand from the auxiliary models will be included in the network assignment to get the real network condition which will assist in determining the travel time more accurately. In addition, travel time between any two points within the study area for a particular time of a day will be collected from the Google Website accessed by using Google API. The output of this travel time will be used for the scheduling of activities generated by the synthetic population. The sampled households can be categorized into several "similar activities generating groups" by using unsupervised learning techniques. After that, each synthesized household can be labeled to any determined category based on their socio-economic characteristics (household size, number of job earners, income, type of jobs, number of students, age and gender of a household member, transit pass holder, and so on). After the generation of the activity list performed by the households, the activity schedule will be prepared for each person considering the household interaction effects, availability of different modes, travel time, cost of travel, and other constraints. This stage is the most critical and activity scheduling, network assignment, and auxiliary models are highly interconnected. After the allocation of travel routes and modes to a traveler to perform an activity, network load and auxiliary models will be updated. Thus, there will be continuous to and fro checks among activity scheduling, auxiliary model, and network assignment. After the allocation of activities for every synthesized household, the output from the demand model can be utilized to estimate emission caused by every kind of activity and travel distinctly. In addition, it can assist to analyze the impact of any policy related to transportation demand management to reach the right mix of policies.

5 Conclusion

This paper presents a comparative analysis between four-stage and activity-based travel demand models and identifies the scope of future research on developing integrated land use-transportation models in the Indian context. This research is also helpful in understanding the need for ABMs in India and the formulation of a simple yet efficient ABM-based travel demand modeling framework considering the constraints related to cost, time, and availability of data. The discussion also touches upon the computational complexity of ABMs where a new modeling approach is proposed on what-if relationships to determine the effect of change in the activity schedule. This research also deliberated on the changing travel environment and how an ABM can reflect the travel behavior more accurately and efficiently than the traditional four-stage model. Since no activity-based travel demand modeling framework has been constructed for India due to difficulties in data collection and computational challenges, this research has also provided insights to make use of publicly shared databases and Web services. The need for integrating long-term choices such as residential location choice and car ownership has also been considered while developing the modeling framework. This new activity-based integrated land use-transportation modeling framework would be capable of assisting the policymakers to reach the right combination of policies toward the fulfillment of a particular vision.

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