National and Industrial Transportation System Demand Simulation, Agent-Based Models, And Complexity Science

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Abstract

Planning and designing future additions and changes to current transportation systems require a detailed understanding of its current use and demand. From that foundational basis, hypothetical "what if" questions can then be carefully posed regarding changes or additions to the incumbent transportation system, informing critical investment, planning, and management decisions. Modern advancements in computational tools derived from complexity science, in particular Agent-Based Models (ABM), provide a framework for projecting the characteristics of demand in transportation systems. The tools developed under this framework are applied through computationally efficient combinatorial mathematics and validated against vast amounts of available data, thus yielding deeper understanding of macro- and micro-characteristics of transportation demand. The application of these tools yields demand characteristics by modal preference, geographic distribution, economic strata, pricing, and demographic parameters. The resulting demand characteristics can account for time-dependent (time of day, season of year) and even weather-dependent properties. The results provide a priori knowledge of choices travelers or shippers will likely make among different modes. The results also provide a marketing and sales test bed to guide pricing strategy, service policies, and market identification for individual businesses within the transportation ecosystem. An approach for leveraging the advancements in ABM with existing transportation demand models is suggested.

Introduction

"What If"
- New business models
- New markets
- New policies

The current transportation system is continually evolving with the addition of new services, new surface vehicle and aircraft profiles, new routes, new business models, as well as changing requirements and demand of the people utilizing the system. The cost of introducing additions and changes to infrastructure is high enough to justify careful planning in advance of the large capital and labor investments typical in this arena. Furthermore, we must be able to vet detailed plans without disrupting the current operational system. These are critical issues for many companies and government agencies involved in planning and introducing new or expanded transportation offerings.

The best planning methodology requires beginning with a clear quantitative understanding of the *current* existing transportation systems in use. From that foundation, we then need a way to hypothetically *add or change* specific features of the transportation system or service, and subsequently analyze the impacts of those additions and/or changes versus the incumbent system. This requirement provokes the need for new “bottoms-up” in addition to existing “top-down” approaches.

The tools used heretofore have tended to be “top-down” approaches based on averages and variances of large quantities of bulk data, data compression schemes that result in the loss of information that often turns out to be critical when describing complex human economic and logistical systems such as transportation networks and markets. This loss of information is particularly misleading when the statistics in question deviate substantially from the classic Gaussian “bell curve,” and this happens in the statistics of transportation which is often characterized by highly skewed curves called “power laws.” We advocate keeping all of our information and generating our statistics one data element at a time.

Drawing from Complexity Science and computational modeling, together with modern fast computers, tools can now be built making possible a true “bottom-up” approach to quantitatively understanding our transportation systems. In particular, using computational “agents” in the form of Agent-Based Modeling (ABM), we can simulate *all* of the millions of longer distance trips made each day. This mission-by-mission approach generates statistics one trip at a time, bottom up, with none of the data loss inherent in top-down bulk averages, variances, etc.

From this high-fidelity foundation of the current system, new additions or changes can be introduced to an operational model of the incumbent transportation system. Detailed hypothetical “what if” questions can now be carefully posed, and their results quantitatively analyzed in the form of changes in revenue, profit, modal preference, market share, etc. This is the information necessary to guide companies and governments, informing their investment decisions, infrastructure planning, capacity modeling, and advertising campaigns, for example. The day-to-day application of such tools in marketing and sales can inform market, product, and service decisions by service delivery managers.

This paper describes our approach to ABM for the purpose of building detailed computational models of our current transportation system, for use in industrial and governmental analyses. Our ABM approach provides an interactive “software laboratory” for understanding the current system, and more importantly, as a platform for posing a rich variety of “what if” questions helping to vet alternative designs for our national transportation system as well as providing a tool for business entities designing and operating a transportation offering within that system.

A Most Complex Machine

Transportation Systems

- Internal economies
- Internal sociologies
- Internal governments

The modern networked transportation system is one of the most complex “machines” ever built, with millions of users and moving parts. It is a machine that contains an internal economy, an internal sociology, and an internal government. Understanding the dynamics of such a system has long occupied the boundary between art and science, relying on a combination of rigorous analysis and heuristics. Traditional analytical efforts have centered on certain aspects of the system's operations considered singly, such as the economics of consumer choice, resource scheduling, route planning, or maintenance. In particular, the supply or demand side of the equation is usually approached while holding the other variable fixed because of the inherent complexity involved in understanding a system in which the two are free to adapt to each other.

In these types of analyses, decomposition or separation of the components often involves the loss of critical information. In addition, traditional top-down analytical efforts may not only lose information by decomposition, but by assumptions about the nature of dependency between input and output variables. For instance, a composition of many processes described by Gaussian distributions (bell curves) is going to produce an output similarly distributed. It is now known that many systems that display far-from-equilibrium or adaptive behavior tend to be described by unusual statistics, displaying "fat tails" and other behaviors. The solution is to understand systems from the bottom up, composing "atomic" interactions in full generality and learning the systemic dependencies from the emergent dynamics. Until recently, this scenario has been the subject of fiction, far too computationally intensive to be practical.

Complexity Science

System Thinking

- Massive interdependencies
- Computational efficiencies
- Role of simulation

In the last twenty years, a new set of approaches has emerged, combining elements of rigorous analytics and heuristics under the umbrella of "complexity science" and introducing a new form of experimentation that uses computer simulation to perform experiments difficult or impossible to set up in the real world. Advancements in complexity science have shifted the way scientists think. This shift has led not so much to a new field of science as it has to a new set of approaches to solving hard, real-world problems. Traditional science applies linear and separable cause-and-effect reasoning: if one knows all the factors that go into creating a situation, one can predict the outcome. These traditional approaches rely on decomposition of the system into parts and re-composition of the parts into the whole. These "top-down" approaches serve well in hierarchical systems with well-defined causal relationships between the components. However, traditional approaches work poorly in situations with widely varying, dynamic, and numerous causal relationships between distributed (versus hierarchical) components.

By contrast in complex, distributed systems (those made up of many autonomous, simultaneously interacting parts), patterns of behavior emerge, often with unpredictable or unexpected outcomes. Real-world emergent behavior is exhibited in systems ranging from biological ecologies and immune systems to economies and organizations where the dynamics are dominated by network effects. The goal of complexity science is to understand how distributed systems adapt to changes, learn efficiently, and optimize their behavior.

Complex Systems

- Adapt
- Learn
- Optimize

Complexity science spans many disciplines, including physics, computer science, biology, and systems theory. Applications from the science have profound implications for solving real-world problems. The solutions have sufficient specificity to be scientifically and commercially valuable and sufficient generality to be useful in a wide spectrum of strategic planning. In particular, the technique of using agent-based models (ABMs) to simulate the behavior of complex systems "*in silico*" has proven to be extremely useful. This paper reviews the advancements in agent-based modeling (ABM) of complex systems and applications of ABM tools to the challenges of modeling demand in transportation systems.

Agent-Based Modeling

Agent-based models (ABMs) provide a new and powerful approach to understanding the behavior of heterogeneous networked systems, such as transportation networks. ABMs leverage increasingly cheap and powerful computation with advances in software, particularly object-oriented languages such as Java and C#, to build sophisticated simulations with a high degree of interactivity. ABMs provide a platform for bottom-up computation in that they are built around the notion of "agents," computational entities that act on their own behalf by local rules and properties. Originally developed to understand ecological phenomena such as flocking and foraging, exhibited by swarms of organisms, ABMs have found fertile ground in their application to complex human-engineered systems such as transportation networks.

Agents

- Biological Systems Origins
- Genetic, learning behaviors
- Interactive

In agent-based modeling, systems are modeled as collections of autonomous decision-making entities, called agents. Each agent individually assesses its situation and makes decisions based upon a set of rules. Agents may execute various behaviors appropriate for the system they represent – for example, traveling, producing, or selling. Repetitive, competitive interactions between agents are a feature of ABM computational tools. The development of inexpensive and abundant power of computers and software has led to the ability to explore dynamics that are out of the reach of purely analytical, traditional mathematical methods.

Agent-based modeling realistically simulates a system because it emulates the manner in which the human world really operates. This is because an agent-based model (ABM) captures the notion of "subjectivity," allowing dynamics to be generated based on an agent's point of view. Traditional statistical methods are not readily adapted to systems with many points of view, let alone many *changing* points of view. At the simplest level, an ABM consists of a system of agents and the relationships between them. Even a simple model can exhibit complex behavior patterns and provide valuable information about the dynamics of the real-world system that it emulates (1,2).

For an ABM to be an effective planning, prediction, and analysis tool, large quantities of data are required to calibrate the model. Until recently, access to data has been a significant drawback, but we now live in a rapidly emerging Age of Data. This happy confluence of computational power and increasingly available data has led to a surge in the efficacy of agent-based modeling approaches.

Agent-Based Modeling and Transport Science

There have been a variety of efforts to develop and apply modeling and simulation tools to understand transportation modal preference and demand at local and national levels. These models have historically relied on advancements in computational power as well as theoretical insights for their progress. The approaches cited below summarize a few key examples.

Early Demand Models

- TRANSIMS
- TSAM
- JetSim (DayJet)

TRANSIMS Model: The first large-scale effort to apply ABM techniques to human transportation dynamics was the TRANSIMS project at Los Alamos National Laboratory, beginning in 1991 as a research project and now available as open-source software. (4) The TRANSIMS program produced a collection of analytical processes (integrated simulation and modeling tools, databases, and case studies) that addressed critical limitations in traditional modeling techniques for metropolitan ground transportation analyses. The TRANSIMS program was predicated on the concept that robust and realistic analyses must capture both the complex nature of individual traveler activity and the collective interaction of these activities within the transportation system itself. To do this, TRANSIMS modeled the surface transportation of an entire metropolitan area on a trip-by-trip basis, generating statistics from the bottom up by creating computational "agents" that set out to accomplish certain tasks using resources available to them. TRANSIMS has achieved considerable success in modeling large metropolitan areas and is now being used by municipal planning agencies.

TSAM Model: As a part of the NASA SATS (Small Aircraft Transportation System) research project and using some of the techniques pioneered in the TRANSIMS research effort, a group of researchers at NASA Langley and Virginia Tech produced an ABM to simulate mode choice for long-distance travel (between metropolitan areas, rather than internal to them as in the TRANSIMS case) and to generate statistics on a trip-by-trip basis, using publicly available data (5,6,7). The model works in batch mode, accumulating travel statistics for a given configuration of options, and was used to predict the future penetration of VLJ (very light jet) air-taxi type services into the

US airspace. Like TRANSIMS, TSAM uses ABM techniques to generate individual trips. TSAM addressed the entire USA on a county-by-county level of resolution and gave a well-informed answer to the outstanding question of the scale of overall demand for air-taxi type services.

DayJet "JetSim" Model: DayJet Corporation pioneered the PSOD (per-seat-on-demand) jet taxi service, using a high resolution ABM to understand their market niche before formulating the service offering in the marketplace. This ABM was inspired by both the TSAM and the TRANSIMS models and built upon their successes. Like both of those models, JetSim modeled a subset of trips (business trips in the Southeast 11 states) on a per-trip basis. JetSim improved on the previous models in using higher resolution demographic data. These data included subpopulation characteristics such as industry and job type numbers and income data. In addition, dividing the region into "squares" of 1/8th arc-degree on each side, rather than using larger and non-uniform regions such as counties as in the TSAM model generated higher resolution geographic data. In addition, JetSim was built to run in interruptible rather than batch mode so that parameters could be changed on the fly, rendering experimentation faster and more intuitive. JetSim also used highly optimized sampling methods so that it was able to simulate several thousand trips per second.

Moving Beyond Traditional Approaches to Demand Generation

Traditional approaches to demand generation have generally relied upon statistical averaging techniques and macroscopic modeling techniques such as differential equations. Averages are obtained from public and private surveys, such as "x% of the US population travels frequently on business." A "travel law," similar in form to Newton's Law of Gravitation, predicts that the travel between two population centers is given by $T(p_1, p_s, d) = C\frac{p_1 p_2}{d^\alpha}$, where the p's represent the populations and d is the distance between them (Chapman, 1979). This law works reasonably well for large population concentrations and does a good job of predicting the average trip for the average traveler.

However, the usefulness of this approach is diminished when one considers questions including:

- Where does the demand originate (by nine-digit zip code, for example), and destinate?
- What is the elasticity of total demand to price, convenience, and personal preference?
- How does travel get apportioned among different modes, including new modes?
- Are there "tipping points" in travel behavior?
- How much demand can actually be fulfilled by a profitable business?
- What is the time-dependence of demand, including seasonal variations?

Generative Statistics
And The NextGen AeroSciences Mission-Based Approach

NextGen AeroSciences
ABM Demand Model

- Geographic fidelity
- Business case performance
- Interactive, intuitive "software lab"

At NextGen AeroSciences, we have built upon the previous agent-based demand model work discussed here. Like TSAM and TRANSIMS, our travel models are built on "generative statistics," building up statistics one simulated trip (mission) at a time using ABMs. In addition, the NextGen AeroSciences model incorporates mission-based planning. Rather than assuming that the existing deployment of resources (trains, planes, and automobiles) effectively represents true consumer demand, we analyzed consumer preferences free of transportation constraints to learn what people might do in an ideal world, not a world filtered through the constraints of existing transportation logistics. After testing this hypothesis to see if it reproduced the statistics of existing mode choice, we then felt confident to extend this to new transportation offerings with different constraints than existing choices.

NextGen AeroSciences has custom-built an easily configurable simulator, to support modeling not readily accomplished in previous tools. The configurable simulator allows for real-time experimentation including business case analysis that simulates the interaction between demand and a new source of demand fulfillment (on-demand air taxis, for instance). The business model is comprised of the actual business structure of an enterprise (deployment, maintenance, deadheads, scheduling optimization, unplanned operations, profitability, etc.) required to fulfill the demand. If the TSAM model can be viewed as a "pitching machine" that characterizes demand, the NextGen AeroSciences model is an integrated pitching and batting machine that optimizes the coupled performance problem. We have connected the entire "food chain" of a transportation system, spanning the distance from personal preference all the way to the optimized behavior of a complex economic and logistical fulfillment network.

Since our system is agent-based, it provides a seamless link from individual preferences all the way through to system performance. Since transportation decisions for the most part ultimately rest on individuals, this provides a means by which marketing and sales strategies can be tested in the "silicon laboratory". Examples of variables that can be tested include pricing, geographic and demographic market selection, incentive structures, and different kinds of service offerings such as different aircraft models.

The NextGen AeroSciences ABM
– Interactive, Graphical "Software Laboratory"

Employing the theory discussed above, we have constructed an interactive "Software Laboratory" for simulating the national transportation system at a geographic granularity of 0.1-arc degrees surface element (about 6 nm by 5 nm at mid-latitudes). Hence the geography of the contiguous 48 states is divided up into approximately 80,000 "squares," each with its own demographics: population, income distribution, propensity to travel, *etc*.

Using data from the US Department of Transportation and other sources, our ABM acts like a kind of "digital terrarium" simulating the larger features of the national transportation system for trips longer than 100 miles. Modes of travel include automobiles, scheduled airlines, charter airlines, and in some cases, trains as well. As described above, the ABM machinery is "bottom up," one trip or "mission" at a time. The ABM computes travel expenses as well as evaluating the cost of time spent traveling according to the person's demographics –"time is money".

Modal Preference Demand Modeling

- **Value of time**
- **Proximity**
- **Frequency, convenience**

An example of a mission might be a businesswoman living in Santa Cruz, CA, needing to attend a meeting in Bakersfield the following day from 1 to 3pm. A real person might compare the time and expenses of driving versus flying, and might even consider chartering a plane. Depending on the value of the businessperson's time, he or she will choose a preferred mode of transport. The NextGen AeroSciences model does likewise, as its corresponding software "agent" also evaluates its own travel options. All these individual missions, all taken together, summed up, constitute the aggregate usage of the national transportation system.

The model generates large numbers (millions) of missions stochastically, according to the demographics, the "gravity" travel laws, and the available choices. Although each individual mission is fictitious, the aggregate of all the missions generated by the ABM is statistically valid as evidenced by calibration against real-world statistics. In fact, various parameters in the ABM are specifically tuned to ensure fidelity at the macro level. This tuning effectively improves the physical validity of the rules by which the agents operate. This calibration is an essential part of constructing the NextGen AeroSciences ABM.

Our NextGen AeroSciences ABM displays this "digital terrarium" interactively, graphically on geographical maps, as well as textually as specific detailed itineraries, including travel to the airport, waiting, meals, possible overnights en route, etc. The user can slow the ABM down to show each mission, one at a time. Or the user can speed up the ABM to display emerging statistics on the screen from simulating approximately 10,000 missions per second, even to as many as one million missions per minute.

However, the real value of the NextGen AeroSciences ABM is its "what if" facility. For example, the user can introduce a new "species" into the "digital terrarium" in the form of a new transportation service, perhaps an on-demand air service serving a specific set of less-utilized airports. Once this additional "what if" mode of travel is properly specified, the ABM can be (re-)run to determine, mission by mission, summed up over millions of missions, the expected market share of this new "species" of travel option. This facility can be used to design a new offering into an existing travel market. The tools can also be used as a control panel to tactically "fly" the new service offering, such as timing price changes, promotions, optimizing sales resources, etc.

As mentioned above, the ABM is interactive and graphical. The user can visualize the alternate choices of candidate modes of travel for each mission, on a geographical map, as well as displaying the minute-by-minute itineraries in textual form. An advantage of the availability of this detail is confirming that the model is in fact performing in a plausible manner. If desired, the user may probe into any mission to see in detail why the agent made any specific transportation decision, and then compare that decision with what a real person would likely have chosen. This graphical user interface makes the NextGen AeroSciences ABM quite transparent, hence providing important (micro) justification for its macro results.

Conclusion

Results

- Geographic demand locations
- Economic demand drivers
- Stimulated modal choices
- Substitution modal choices
- Travel patterns

Many research investigators desire to understand the current national transportation system in detail, towards the goal of making recommendations for changes to the system – all without disrupting the system to perform various "what if" experiments in it. Given this desire, agent-based computational modeling offers an efficacious tool for improving our national transportation system. The NextGen AeroSciences ABM is specifically targeted for this genre of use.

The approach offers tools to answer questions that have been previously very difficult to approach, such as:

- At what price point will how many travelers choose which mode from which destination to another?
- What travel patterns will emerge as a result of a new modal choice and how can this information be used for targeted advertizing and promotion?
- How many travelers might choose to connect between a small airport and a large hub to link an on-demand flight segment with a scheduled air carrier segment?

The ABM-based approach, in continual improvement by NextGen AeroSciences, offers industrial users a tool for day-to-day focusing of sales and marketing resources and product policy management. The approach offers government users a tool for infrastructure strategy assessment and for informing policy decisions across transportation modes. As data sources and computing power grow, these approaches will continue to improve in capability and fidelity.

***About the Authors:**

Drs. Sawhill, Herriot, and Holmes have joined with William Van Valkenberg, Esq., in founding NextGen AeroSciences, LLC. The company derives its technical foundation from their contributions in basic and applied research in the complexity and network sciences, computationally efficient combinatorial mathematics, and in air transportation system innovation (including developments at the Santa Fe Institute, Bios Group, and NASA). The advancements of the 1990s led to Complex Adaptive Systems studies, Agent Based Models, and high-efficiency combinatorial mathematics, with widespread applications in communications, computing, economics, biology, chemistry, policy, social systems, and other fields including transportation. They led in the innovations in automated, real-time logistics management systems for the first per-seat, on-demand air carrier (DayJet Corporation). The application of these tools to the DayJet per-seat, on-demand air carrier between 2001 and 2008 resulted in the first fully automated, integrated aircraft fleet management system for assigning passengers and pilots to aircraft, managing maintenance and training cycles, optimizing for disruptions, and providing full regulatory compliance in near real time. NextGen AeroSciences, LLC sees powerful opportunities to apply these tools to a variety of transportation system challenges, including transportation modal preference demand generation and satisfaction modeling.

References

(1) *Agent-Based Models and Generative Social Science*, Epstein, J., Princeton University Press, 2007
(2) *Agent-Based modeling: Methods and techniques for simulating human systems*, Bonabeau, E., PNAS:May 14, 2002 vol. 99, no. Suppl 3, pp. **7280-7287**
(3) Book: *Tourism and Transport, Modes, networks, and flows*: Duval, D.T., Channel View Publications, 2007
(4) White Paper: *A Vision for the TRANSIMS Open Source Community*, Wunderlich, K., Vasudevan, M., and Roberts, D., Federal Highway Administration Report, http://74.125.155.132/search?q=cache:xEr9q2WVODQJ:transims-opensource.org/index.php%3Foption%3Dcom_docman%26task%3Ddoc_view%26gid%3D68+transims+community+vision&cd=1&hl=en&ct=clnk&gl=us&client=safari
(5) Baik, H., and Trani, A.A., http://www.atsl.cee.vt.edu/Publications/2005_A_Transportation_Systems_Analysis_Model_TSAM_to_study_the_impact_of_the_Small_Aircraft_Transportation_System_SATS.pdf
(6) *American Travel Survey*, Bureau of Transportation Statistics, http://www.bts.gov/publications/1995_american_travel_survey/index.Html, 1995.
(7) *Department of Transportation DB1B Database*, Bureau of Transportation Statistics (BTS), http://www.transtats.bts.gov/DatabaseInfo.asp?DB_ID=125&DB_URL

