Analyzing the Potential for High-speed Rail as Part of the Multimodal Transportation System in the United States' Midwest Corridor

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ABSTRACT
With increasing demand and rising fuel costs, both travel time and cost of current intercity passenger transportation modes are becoming increasingly relevant. Around the world, high-speed rail (HSR) is seen as a way to alleviate demand on highways and at airports. Ridership is the critical element in determining the viability of a large capital, long-term transportation investment. This paper provides a systematic, consistent methodology for analyzing systemwide modal ridership with and without a proposed HSR network and analyzes the potential for high-speed rail as part of the existing multimodal transportation system in a region in terms of ridership. Considerations of capital investment (e.g., network design and HSR speed), along with exogenous demographic, technological, economic, and policy trends in the long-term, are used to project ridership over time. This study represents an important step toward a consistent, comprehensive economic analysis of HSR in the United States.

1. INTRODUCTION
Vehicle-miles traveled on interstates in the United States (US) increased 20% from the Interstate Highway System (IHS) completion in 1991 to 2009. Over 30% of these vehicle-miles traveled are under congested conditions, an estimated average increase of 35% more time per person since the completion of the IHS despite a 50% increase in urban interstate lane-miles. The total cost of travel time and fuel cost is estimated to

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be over $78 billion a year or about $713 per auto commuter [1]. The National Surface Transportation Policy and Revenue Commission estimates that an annual investment of over $130 billion is needed for improvements and maintenance to accommodate these trends [2].

Similar to the IHS, airports in the United States are facing increasing economic loss as a result of increasing demand. Departures from commercial airports have more than doubled since 1975 [1]. The total 2007 cost of delays from congestion was estimated to be $31.2 billion dollars, $16.7 billion of which was attributed to passenger travel delay [3]. Furthermore, the Federal Aviation Administration predicts 3% demand growth per year and the cost of meeting this capacity through new airports and current airport improvements to be $30-60 billion over the next twenty years.

Other countries are mitigating the transportation system risks of increasing demand by investing in electrified high-speed rail (HSR) (high-speed defined as speeds 125 mph or higher). In Europe, there are currently about 6,600 km (4,100 miles) in operation, 2,500 km (1,500 miles) under construction, and 8,700 km (5,400 miles) planned [4, 5]. China alone has constructed over 9,600km (6,000 miles) of HSR lines and plans a total of 16,000km (10,000 miles). The plan is expected to cost well over $300 billion [6]. The fastest operating passenger rail route in the United States (average speed of greater than 125 kph (~80 mph) and top speed of about 240 kph (~150 mph)) is the Amtrak Acela Express line connecting Boston to Washington D.C. This accounts for only 456 miles of the 21,178 miles of Amtrak routes, but over 10% of the total ridership.

Proponents see HSR in the United States as a viable option to shift ridership away from the current intercity transportation modes (road, air, and Amtrak), thereby reducing demand and demand-related problems across the entire system. Since HSR can be electrified, it may also be resistant to volatile petroleum prices that are characteristic of both personal vehicle and commercial air modes.

From the opposing perspective and considering the current ridership levels on existing intercity rail (Amtrak), it may seem difficult to reason the high ridership projections based on a non-US experience without rigorous analysis and justification in the US context. This is especially true when considering the vastness of the IHS and the current cost for the road user. If ridership, and therefore revenue, is not sufficient to offset the cost of HSR, then the government is forced to subsidize the project. Amtrak is currently subsidized with about $1.5 billion annually from federal, state, and local budgets. However, as the proponents of HSR point out this is low in magnitude compared to $122 billion and $45 billion total government expenditures for highways and air modes, respectively [1].

Motivated by the aforementioned strategic perspectives, this initial study seeks to understand the role of the commonly-used criterion in the current discourse, ridership, to analyze the long-term and systemwide ridership of a proposed HSR network in the context of the existing multimodal transportation system in a region. This study aims to develop a formal, systematic methodology to enable policymakers and planners to make informed decisions when evaluating the introduction of an alternative mode in an existing transportation network. Key elements of the proposed methodology are the capabilities to predict ridership and capture comprehensive systemwide impacts.

The ridership prediction includes considerations of modal accessibility and multimodal network performance. It is projected over the long-term by determining the ridership sensitivity to economic, demographic, and technological trends. Hence, the study provides policymakers and planners an ability to more robustly perform the systemwide impact analysis of a HSR option in a specific geographical region under the plausible long-term evolution of the ambient and relevant factors. Experiments are presented to illustrate the capability of the systematic methodology.

2. LITERATURE REVIEW

While much of the European research related to HSR focuses on estimating elasticity given the existing rail network, due to the uncertainty with respect to network design, technology, etc. most of the policy and research focus for HSR in the United States have been on demand and revenue forecasting. Direct comparisons of experiences in other countries may be misleading due to variables which include, but are not limited to, demographics, geography, and cultural norms. A study by the America 2050 planning group investigates the potential HSR demand of US corridors based on criteria such as city and metropolitan area population size, distance, GDP, and existing intra-city transit systems [7]. However, it does not consider the existing intercity transportation network which has significant implications for both ridership and the resulting impacts.

Others study the competition between the air and rail modes in great detail, but largely ignore the potential competitive, complementary, and other implications associated with the road network [8, 9]. A study on HSR ridership for California [10] estimated between 7-8% HSR ridership in the interregional markets; it suggests that 6% of automobile traffic, 33% of commercial air, and 27% of conventional rail was diverted to HSR. These ridership numbers were projected using a two-step nested logit model for determining ridership on both the egress and main modes by considering time, cost, trip length, station-specific constants, and level-of-service (LOS) variables. However, Brownstone et al. found several methodological issues with the study including: (i) arbitrary division of trips into long and short trips resulting in estimation discontinuity, (ii) absence of an airport/station choice model, (iii) incorrect use of a nested logit model (given choice-based data) in lieu of a multinomial logit model for the main mode choice model, and (iv) over use of station-specific variables [11]. These findings were corroborated by an independent peer review panel [12].

Joshi (2010) uses a door-to-door travel framework and a multinomial logit model based on time and cost for several different income classes and trip purposes to estimate ridership on an on-demand air service (ODAS) introduced to the existing intercity transportation network [13]. The proposed study uses this door-to-door travel framework, which includes the full cost of a trip with time and cost of access egress and primary travel modes, as a building block, and addresses the HSR ridership problem based on coefficients for the variables (total time and cost) in the utility function calibrated by Ashiabor et al. [14] derived from the 1995 American Travel Survey [15], the last nationwide, long-trip survey conducted by the United States DOT, along with a stated preference survey to estimate the ridership for HSR [16]. These three studies overcome

some of the methodological issues discussed above by specifically avoiding the division of long and short trips by only considering intercity trips, correctly using a multinomial logit model for the main mode choice, and avoiding station specific variables for calibration. A station choice model is incorporated into this study's model to further address the issues highlighted by Brownstone et al. [11] and Koppelman et al. [12].

In summary, the proposed study integrates demand and supply side characteristics to analyze the ridership potential of HSR in the context of the existing multimodal transportation system. It explicitly addresses many issues identified in previous HSR studies. A key contribution is that unlike previous studies which predict ridership under a specific scenario, the proposed methodology can forecast informed HSR ridership scenarios based on various design considerations and dynamic exogenous factors by incorporating changes to the existing multimodal network characteristics over time.

The remainder of the paper is organized as follows. The methodology section describes the data and articulates the methodology which is used to represent the multimodal network, predict future scenarios, and determine ridership. The validation section validates the methodology by demonstrating its ability to "predict" ridership in the multimodal network retroactively by comparing to past data. It also illustrates the ability to capture ridership trends related to dynamic exogenous factors. The discussion details the experimental scenario tested for prediction analysis. The conclusion briefly discusses the results obtained from the experiments, comments on the build and no-build scenarios, and presents possibilities for future work based on this study.

3. METHODOLOGY

As illustrated in Figure 1, the conceptual framework for the proposed methodology contains three primary models: (i) the traditional Four-Step Travel Demand (FSTD) Model, (ii) the State of "World" (SOW) model, and (iii) Impact Assessment Model. Although other demand planning models exist for passenger rail, the FSTD model was chosen for demand planning consistency across all modes. Due to the need for dynamic data and route information to accurately account for congestion, travel time is considered static and, thus, this study considers demand shifts, but not congestion effects explicitly. Demand is dynamic in that the demand is a function of exogenous variables which change during the study period.

The study region (shown later in Figure 3) includes Ohio, Indiana, Michigan, Illinois, Wisconsin, and Minnesota, the primary footprint of the proposed Midwest High Speed Rail Association (MWHSRA) Chicago-Hub HSR plan, disaggregated at the county-level; however, this methodology is extendable to any geographic area at any level where sufficient data exists. For instance, areas of influence serviced by stations could be used granted the necessary area-to-area demand data is available. The existing air, road, and Amtrak modes, as well as the proposed HSR mode, are used to develop multimodal composite networks (that is, networks consisting of multiple modes). The performance (time and cost) for a particular year of travel between each county on these composite networks depends on economic, technological, policy, and demographic factors included in the State of "World" (SOW) Model. A utility function is proposed for each individual mode based on time and cost for several income classes

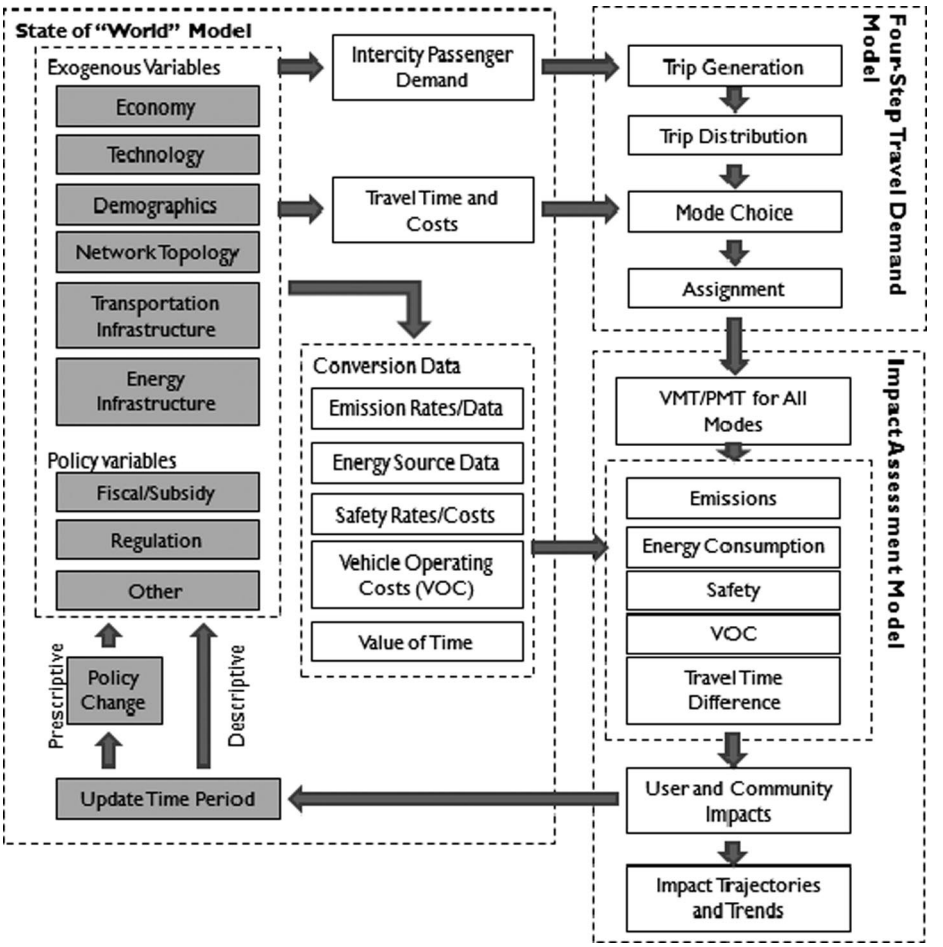

Figure 1. LUCIM conceptual framework (grayed boxes represent variables which change over time)

and travel purpose (business or non-business). The total ridership on each utility maximizing modal path for each county pair and income class is distributed using a multinomial logit model. This process is conducted for each year of analysis, and the various trends of variables in the SOW will impact the modal ridership distribution in the transportation system. The modeling framework is called the Long-term User and Community Impact Model (LUCIM). The inherent modular nature allows different data sources, data trends, and parameters to be replaced and tested with more reliable and/or up-to-date data or be altered to investigate the effects of disruptive events and innovations on the multimodal transportation system. Table 1 highlights the restrictive assumptions characteristic of the model proposed in this study along with the primary

limiting assumptions that were made in order to conduct experiments. The experimental assumptions are modular in that they can be relaxed provided better data are available.

Table 1. Important restrictive assumptions characteristic of the proposed methodology and modular assumptions chosen for the experiments

Model assumptions (restrictive)	**Implication**
Four-step Travel Demand	+ Provides a consistent travel demand process across all modes - Constrains demand and mode choice format
Maximum Utility Paths	+ Effective for discrete choice mode choice model - Cannot account for specific route choices on a mode
Congestion effects neglected	* Result of data availability + Reduces computational burden + Congestion due to mode shifts may be prove to be small based on results considering intercity trips are a small portion of total trips and the shift is relatively small
No land-use changes	* Result of data availability - New stations may change economic activity, population, and intercity travel patterns.
Dedicated HSR dedicated lines.	+ Speeds which make HSR competitive likely necessitate - Current HSR policy involves increasing current Amtrak speeds
No induced demand	* Result of data availability - The current methodology does not consider induced demand as a result of modal shift. Such secondary effects may be significant.
Experimental assumptions (modular)	**Implication**
Modal Costs	Assume only fuel costs in road mode; fare structures taken from literature
Speed	180 mph average speed used for comparison with MWHSRA and advanced HSR systems worldwide (sensitivity analysis performed)
EIA fuel price trends	High gasoline prices predicted in this particular outlook; no feedback to prices
BTS fuel eff. trends	Simple growth regression; assumes no disruptive technologies or policies
Multinomial Logit	Limits single modal alternative with single route; No combined road, air, train trips
Alternative-specific constant	*Result of data availability

Experimental assumptions (modular)	Implication
	Limits analysis to time and cost (i.e., treats frequency, comfort, etc. implicitly)
County-to-county demand	*Result of data availability Counties may be an arbitrary area designation. Area of influence may be more appropriate in the station context.
Six-state boundary	Reduces computation time without sacrificing many trips. Some trips may originate or terminate outside the experimental six-state boundary.

Note: For restrictive assumptions (+) designates a benefit of assumption, (-) designates a limitation in assumption, and (*) designates assumption made based on available relevant data.

The rest of this section describes the SOW and FSTD models and the data used for their calibration and validation. Consistent with the objectives of this study as, the Impacts Assessment Model in LUCIM is not used in this paper.

3.1 State of "World" (SOW) Model

3.1.1 Economic, Technological, and Demographic Exogenous Variables

Economic variables include the income of travelers, transportation fuel price fluctuations/trends, and fare structure changes (air and rail modes). The Energy Information Agency (EIA) publishes motor gasoline, airplane fuel (JetA), and electricity price trends each year under low, reference, and high scenarios [17]. The study uses the reference EIA projections for JetA and motor gasoline, shown in Figure 2, in LUCIM. In the figure, the lines to the left of the dashed vertical line are actual prices. The trends to the right are EIA projections from 2012 to 2035 and further regression after 2035.

While in reality there exist operating and maintenance costs, we assume the vehicle mode choice decision is only based on the immediate cost of travel (i.e., fuel cost). Toll

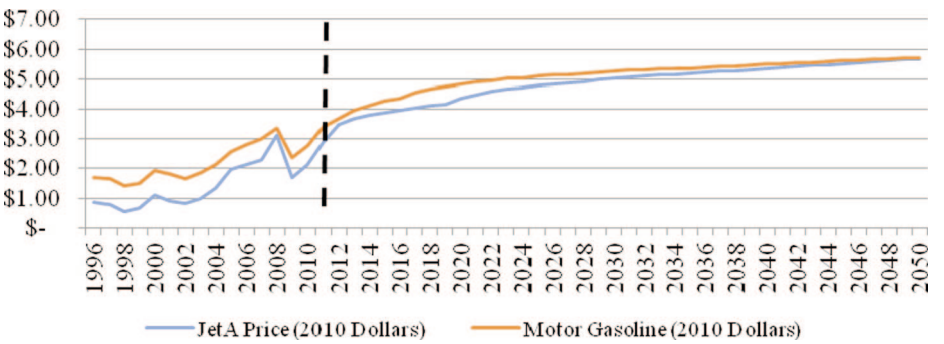

Figure 2. Petroleum product pvrices by year

and congestion pricing can be easily incorporated in the cost structure, but this particular analysis ignores these currently potential, but unimplemented policies. To address the study objectives, the function for fare price is dependent on both distance and fuel costs. All operational considerations are considered constant in the planning context. Amtrak fares are based on a regression of the actual fares of various legs in the region coupled with Amtrak-published data on total revenue and per-mile revenue [18]. Air fares are computed using a function based on great circle distance and JetA fuel prices as part of a concurrent study by Purdue University and NASA [19]. The HSR fare function is generated based on a study that analyzes the fixed and variable costs of HSR. As fare structure for HSR, and other modes, are developed, more appropriate market-based pricing mechanisms can be seamlessly incorporated in this part of the model. The HSR fare taken from literature does not explicitly incorporate the price of electricity [8]. In summary, the round-trip fare and cost functions used in this study are:

Personal Vehicle	$c_{iji}^{PV,y} = \frac{p_{Gas}^{y}}{mpg^{y}} \cdot \left(2 \cdot d_{ij}^{m}\right)$
Amtrak	$c_{iji}^{Amtrak,y} = \$21.52 + 0.2017 \cdot \left(2 \cdot d_{ij}^{m}\right)$
Commercial Air	$c_{iji}^{Air,y} = f\left(d_{ij}^{GC}, p_{JetA}^{y}\right)$
HSR	$c_{iji}^{HSR,y} = \$47.03 + 0.2560 \cdot \left(2 \cdot d_{ij}^{m}\right)$

where $c_{iji}^{m,y}$ is the travel cost for a round-trip from origin station i to destination station j on mode m in year y, d_{ij}^{m} is the one-way distance from i to j on mode m, d_{ij}^{GC} is the one-way great circle distance, mpg^{y} is the miles per gallon in year y, and p_{Gas}^{y} and p_{JetA}^{y} are the prices of a gallon of fuel for motor vehicle and JetA fuel, respectively. Access and egress modes are accounted for in the composite networks later in this section. Hence, the functions are for modal legs of a trip not representative of the total trip cost. Because the fare structure of a new mode and the price responses in the other modes remains largely uncertain, alternative functions for travel cost can be seamlessly integrated in the model.

An important technology variable used for input in this particular study is fuel efficiency trends for personal vehicle, commercial air, and Amtrak modes (HSR assumed constant). Fleet-wide fuel efficiency and emission trends can be generated from data published by the Bureau of Transportation Statistics (BTS) [1]. The fuel efficiency of personal vehicles and commercial air have generally increased, which may make these modes more attractive in terms of travel cost over time.

The demography of the region directly impacts the demand between each origin and destination in the network though population trends. For instance, as population increases the demand increases proportionally. The United States Census Bureau's County Intercensal Estimates from 2000 to 2010 are used to extrapolate county population trends [20]. Although some shifts in populations across counties is captured, in this study it is assumed there is no population or economic activity which may potentially agglomerate near the new HSR stations over time. This assumption may

potentially underestimate passenger rail ridership and would require more detailed economic activity models.

3.1.2 Network Topology and Transportation Infrastructure

The road network for the six-state region is constructed using link distances and connectivity from the National Transportation Atlas Data from 2010 for highways and major arterials [21]. An average intercity travel speed of 55 miles per hour is assumed. Road congestion, and resulting travel time, remain static over time for several reasons. This particular analysis considers the planning context at a high level of aggregation. Dynamic traffic conditions, scheduling, etc. at a level much more disaggregated than the county-level considered in this analysis are required to accurately estimate such congestion effects. Furthermore, intra-county and short trips (under 50 miles), which account for over 90% of miles traveled, will likely not be affected significantly by the introduction of HSR. Thus, total demand can be captured, but potential congestion relief in interregional and local level would require further investigation.

In addition to airports in the study region, SLO and CVG are included because of the proximity to the study region. The 2010 flight segment data from the Air Carrier Statistics database was used to construct the air network connectivity and estimate the average link travel time (22). Amtrak route guides available on the Amtrak website provide connectivity, distance, and fare information (23). Amtrak has an average speed of 45 miles per hour in the Chicago area. The proposed HSR network is created as a dedicated rail system from the MWHSRA Vision with an average train speed of 180 mph, which is similar to the fastest average speeds of newly-built HSR systems around the world and the speed proposed by the MWHSRA (24). Sensitivity analysis with respect to average speed is conducted in this study.

3.2 Four-Step Travel Demand (FSTD) Model

3.2.1 Trip generation and distribution

Criticisms of the four-step model are well documented and include ignorance in the activity patterns and schedules of individuals, variables constraints which impact choice and choice set, and the linkages between the two [25, 26]. Acknowledging these limitations, the trip generation and distribution stages account for differences in business and non-business trips and the gravity model includes an impedance term between each county pair, income class, and trip purpose thereby treating factors other than population (e.g., employment) implicitly and do not evolve with time in this study.

The projections for the inter-county demand used to calibrate the trip generation and distribution steps of the FSTD Model are obtained from the Transportation Systems Analysis Model (TSAM) model. Data were provided for origin and destination county-to-county demand in years 2002 and 2025. The TSAM model uses data from the 1995 National Travel Survey along with gravity models to predict county-to-county demand across the United States [27]. Since the proposed study only uses demand in the six-state study region, the analysis is performed only for trips which both originate and end within the region. Hence, travel on the infrastructure where either the origin, destination, or both counties are outside of the region, is excluded. The study also

excludes intra-county travel such as most commuting or small personal trips (grocery, appointments, etc.). This is appropriate for the evaluation of HSR as an intercity transportation mode; HSR is not expected to draw ridership from intra-county trips.

A gravity model is used to interpolate and extrapolate demand in between and beyond the TSAM demand for 2002 and 2025. Carrothers (1956) presents the fundamental form of the gravity model which reasons that the number of interactions (demand, in our case) is directly correlated with the population of two centers and inversely proportional with the distance between them and other frictional factors [28]. This reasoning has been applied to modal trip distribution and travel demand specifically [29]. The model used to estimate county-to-county demand in this study takes the following form:

$$D_{ij}^{y} = I_{ij} \frac{Pop_i^y \cdot Pop_j^y}{GCD_{ij}}$$

where D_{ij}^{y} is the travel demand from county i to county j for year y, I_{ij} is the impedance between counties i and j, GCD_{ij} is the great circle distance between counties i and j, and Pop_i^y and Pop_j^y are the population of counties i and j at year y, respectively. The impedance is unique for each county pair and represents the relative attractiveness or difficulty for interaction. The projected population of the individual counties (Pop_i^y) for the period 2000-2010 is available from the United States Census estimates. A regression for each county was used to extrapolate this population before and after the available U.S. Census estimates. In this way, county population growth is included as an explicit variable in analysis. This allows an opportunity to study potential population agglomeration effects near stations and land use changes which may prove to be significant in the long-term.

3.2.2 Mode choice

3.2.2.1 Utility and discrete choice model

To estimate mode choice, the utility of modal paths is computed for the travelers. Capon et al. (2003) found that out of intercity mode choice utility functions used in previous studies in evaluating road, train, and air modes 100% include travel time and cost, 60% include frequency, and 40% include accessibility as important factors [30]. The proposed study includes time and cost as variable components of modal utility from year to year. Furthermore, the sensitivities of time and cost will change based on the income level and trip purpose (business or non-business). Accessibility is incorporated explicitly in the door-to-door framework which includes road network access and egress at modal facilities (rail stations and airports). The following commonly-used utility function is used to compute the relevant utilities:

$$U_{ij}^{m} = \beta_m + \beta_c^{s,p} \cdot \text{total cost (\$)}_{ij}^{m} + \beta_t^{s,p} \cdot \text{total time(hr)}_{ij}^{m} + \varepsilon_{ij}^{m}$$

where U_{ij}^{m} is the utility for a trip on mode m from origin county i to destination county j, β_m is the alternative-specific constant (ASC), $\beta_c^{s,p}$ and $\beta_t^{s,p}$ are the coefficients for time and cost, respectively, for income class s and trip purpose p, and ε_{ij}^{m} is the estimation

error resulting from unobserved factors for a trip from county i to j on mode m. The ASC describes the average utility of various level-service (LOS) features of the mode that are not specifically addressed in this analysis such as comfort, safety, etc. [31]. Frequency is incorporated implicitly in the ASCs for each mode as it remains constant throughout this analysis; this study focuses on the planning and not the operational context. The same ASC for commercial air was used for the HSR system in this study. There is similarity between commercial air and the proposed HSR modes in terms of frequency, comfort and other LOS characteristics. There is room for improvement in this particular assumption especially in testing LOS characteristics explicitly. The value of β_m is calibrated in a similar fashion to incremental logit models where a known ridership proportion at some time is used to calibrate the model and the variable aspects of the utility are changed to determine the change in ridership [32]. A regional mode-specific survey is desirable to provide accurate time and cost sensitivities. As there has been no specific HSR survey for the Midwest corridor, we use values for five income levels and two trip purposes (business and non-business) for the entire United States derived from the 1995 American Travel Survey [15] in previous literature [14, 16] for the maximum transferability. These values were originally estimated for a nested logit model, but can be used for a multinomial logit in our case where there is only one route choice per mode choice [33]. It is important to note that alternative models (e.g. nested and mixed logit model) or additional variables (e.g. treating frequency and comfort explicitly) can be incorporated provided the coefficients are available. The 1995 American Travel Survey was the last large-scale survey for long trips (more than 50 miles) conducted by the BTS. The model choice for this study was chosen due to the current availability of appropriate and relevant data.

3.2.2.2 Composite networks

Personal vehicle travel can be represented by an individual mode (road) network. A path-based algorithm is used to determine the maximum utility road path for each county pair in the study region by factoring the travel time and cost on each link. However, travel by commercial air or passenger rail requires the road infrastructure to access and egress their modal infrastructures. Hence, a composite network is used to merge these modes. Additionally, a station choice model is introduced by searching nearby stations or airports in order to determine route alternatives that could ensure the maximum utility for the traveler.

The procedure for finding the maximum utility path in the commercial air and rail composite networks has three main steps. First, the four closest stations to the origin and the four closest stations to the destination are identified to incorporate aspects of station selection that have been neglected in previous studies [11]. Four is an arbitrary number; however, it was chosen to reflect the viable options for station access points. For instance, even in Chicago (Cook County, IL), the number of viable airports/stations to choose from for regional travel is rather limited. Second, the maximum utility path between each viable origin and destination station is found in the individual modal network. The access and egress road utility and the modal utility for each path are combined, resulting in a total of sixteen path alternatives. Third, of the sixteen alternatives, the path with the maximum total utility is selected as representative path for the modal alternative. This procedure ensures a single modal alternative for each

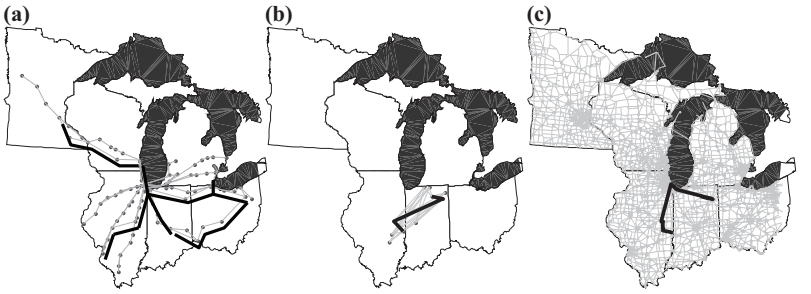

Figure 3. (a) rail network in study region (Amtrak in gray, HSR in black); (b) maximum utility rail paths (showing connectivity, not geographic path) for stations near Edgar County, IL and Kosciusko County, IN; (c) maximum total utility path between origin and destination county

county pair, reduces computational time, and has been show to return the actual maximum total utility path despite the simplification from a viable shortest path procedure. For the rail composite network is that the Amtrak network and the HSR network are combined into one rail network with some unique and some shared stations based on the MWHSRA network. In the study experiments, for the case with no HSR, the HSR network is simply removed. For example, Figure 3(c) shows the maximum utility path for Edgar County, IL and Kosciusko County, IN has three legs by rail, Crawfordsville-Lafayette via Amtrak and Lafayette-Gary-Fort Wayne via HSR. The maximum utility path does not have the most adjacent rail station for either origin or destination county due to the gain in total utility by driving to the HSR station. This illustrates the need for the station choice in the model.

Composite networks with combined road, passenger rail, and commercial air are excluded in this analysis due to the structure of the mode choice model. Using passenger rail as an access mode to the commercial air mode is not a likely action considering trips with both origin and destinations limited to the six-state region. Still, as a result the model may underestimate total passenger rail ridership. Furthermore, only the maximum utility path for each mode (road, passenger train, and commercial air) is used in the discrete choice model. This assumption implies that the user focus is on the mode choice and not a route choice, and is consistent with our study objective of tracking modal ridership versus specific route ridership. A multinomial logit (MNL) model is used to determine the ridership distribution on each mode, as follows:

$$P_{ij}^{m} = \frac{\exp\left(U_{ij}^{m}\right)}{\sum_{k} \exp\left(U_{ij}^{k}\right)}$$

where P_{ij}^{m} is the probability of choosing mode m on a trip from county i to county j.

3.2.3 Trip assignment

To analyze the impacts of the HSR mode, it is necessary to determine the total passenger-miles traveled (PMT) per mode.

$$R_{ij}^{m} = P_{ij}^{m} \cdot D_{ij} \qquad PMT_{ij}^{m} = R_{ij}^{m} \cdot d_{ij}^{m}$$

where R_{ij}^{m} is the total number of travelers who choose mode m from county i to county j and PMT_{ij}^{m} is the total passenger-miles traveled on mode m from county i to county j. The total system miles traveled on each mode is the sum of the PMT_{ij}^{m} values over all county pairs ij on mode m. Using this information the systemwide modal ridership and the corresponding user and community impacts can be determined. The model currently does not factor potential capacity constraints, but the ridership changes resulting from the experiments and the load factors of both train and air modes are small enough that capacity issues may not be particularly relevant in the planning context. Expanding the model to include capacity constraints to fully analyze congestion effects in specific contexts represents a future objective.

4. LUCIM VALIDATION

Experiments are conducted to estimate the ridership levels for personal vehicle, Amtrak, and commercial air within the six-state region from 1996 to 2011. These are compared to the actual data collected for this time period. This validation of the model using data from previous years would provide reassurance on the robustness of future ridership predictions. Instead of the projections described in the methodology, the actual population, fuel efficiency, and fuel costs for motor gasoline and JetA fuel during this time period are used in the analysis. This enables the investigation of the capability of the model to capture ridership trends due to exogenous factors, namely rising (or falling) fuel costs. The comparison of model trends and observed trends due to fuel price fluctuation addresses the model's ability to predict ridership responses to economic stimuli over the long-term.

4.1 Systemwide Validation

A primary objective of this study is to predict systemwide modal ridership for personal vehicle, intercity passenger rail, and commercial air. The ridership share, combined with total passenger-miles traveled on each mode, is a critical element in determining impacts and assessing alternative strategies in the multimodal transportation system. Figure 4 shows the LUCIM-predictions of past ridership shares based on actual fuel prices and fuel efficiency. Data for modal ridership distribution for intercity travel for demand completely contained in the six-state region are not readily available for all years. However, the 2001 National Household Travel Survey (NHTS) provides very similar data at an aggregate level over all modes [34]. This database defines intercity travel in terms of roundtrips of 50 miles or more between origins and destinations at the zip code-level. Based on this data, filters for the origin and destination states have been used to bound the raw data to demand within the study region. By doing so, the mode choice for the bounded, intercity trips from NHTS provides sufficient data to compare observed and LUCIM-predicted modal ridership share for validation at a regional aggregate level.

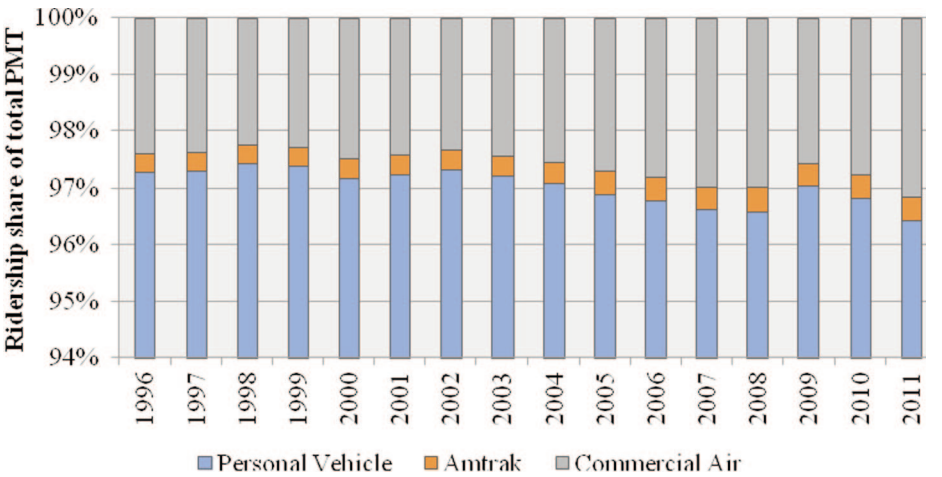

Figure 4. LUCIM ridership predictions for 1996 to 2011 based observed population, fuel efficiency, and fuel price

Table 2: Comparison between observed and LUCIM-predicted PMT in the study region

Mode	Ridership share of total PMT	
	2001 NHTS	2001 LUCIM Predictions
Personal Vehicle	97.00	97.21
Commercial Air	2.62	2.44
Amtrak	0.38	0.35

Table 2 compares the observed versus predicted modal shares based on observed exogenous variables such as county population, fuel efficiency, and fuel cost in 2001. The LUCIM modal shares for 2001 closely predict the actual ridership distribution based on PMT in the six-state region. This validates the ability of the model to reasonably capture the modal ridership share for the systemwide transportation network.

4.2 Trend Validation

Another goal of the study is to capture the long-term trends as a result of changes in exogenous and policy factors. The lack of disaggregate data for the study region requires validation of trends based on a comparison of regional LUCIM results to observed nationwide data over time. This is done by tracking the ridership changes in passenger train over time. HSR will likely have much different characteristics from Amtrak, but since no HSR currently exists in the study region validation against HSR is impossible. Figure 5 compares the observed nationwide Amtrak PMT with LUCIM predictions for the six-state study region.

While they are not directly comparable due to the different levels of aggregation, the trends correlate well. There are inflection points at 2008 and 2009 due to gasoline price

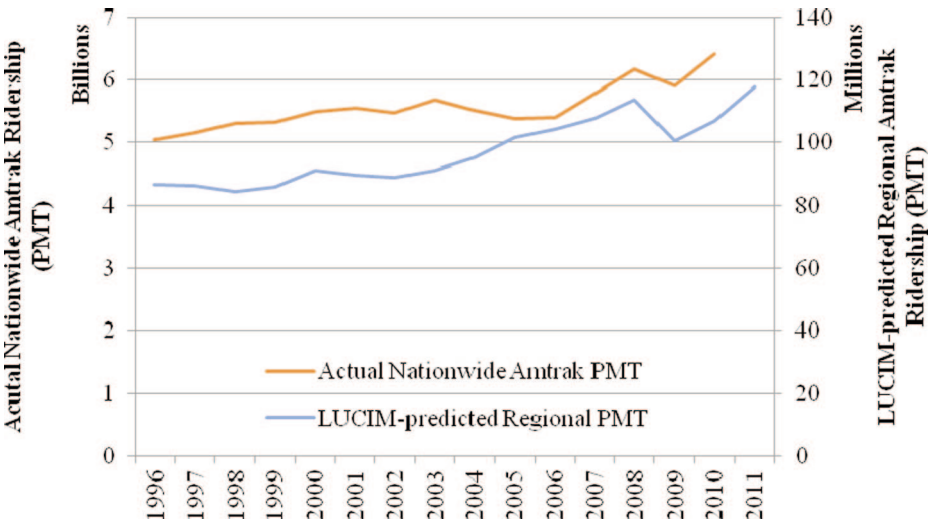

Figure 5. Comparison of actual nationwide Amtrak PMT trend versus LUCIM-predicted trend for the study region

fluctuation for both the actual PMT and LUCIM-predicted PMT as it is the only exogenous variable which is not monotonic in this validation experiment. Hence, LUCIM can robustly capture trends in train ridership over time due to intercity traveler sensitivity to county population, fuel efficiency, and fuel cost (shown in Figure 2).

4.3 Validation Limitations

The results illustrate that aggregate and trend comparisons between LUCIM predictions and actual data suggest robust predictive power for LUCIM in the context of the study objectives to determine the systemwide ridership distribution across modes for intercity passenger travel over the long-term. In that sense, the validation process achieves its objectives, and indicates that LUCIM can aid in analyzing the viability of a proposed HSR system in the Midwest corridor. Also, due to the focus on systemwide analysis, link-level and route ridership are outside the scope of the current study.

5. EXPERIMENTS

Two experiments were conducted to compare various HSR scenarios. First, an Amtrak-only scenario without HSR (no-build) is used as a baseline case for comparison with the second experiment where HSR is introduced with an alternative-specific constant (ASC) identical to commercial air travel. This may be a meaningful preliminary experiment considering the planned expansion of service and frequency for HSR. The two scenarios show the ridership shifts for all modes in the multimodal transportation network. Sensitivity analysis of HSR ridership is performed to illustrate the capabilities of the model to test important design considerations. All experiments cover the period 2012 to 2050, with the baseline demographic, economic, and technological trends discussed in the methodology.

5.1 2012-2050 No-Build Scenario

The first experiment assumes that no HSR is built from 2012 to 2050. Figure 6 shows the ridership distribution in PMT during this period. There is a strong shift from the road mode to the air mode due to rising fuel prices dominating the increase in fuel efficiency of passenger vehicles. This is due to the greater fuel price sensitivity in travel cost than for the air mode. A large shift to the air mode may magnify the issues arising from the current air capacity problems. Ridership by personal vehicle increases due to lower cost of travel as fuel efficiency continues to increase and fuel price increases level off. The rail mode ridership share reaches a maximum of 0.56% in 2029. This is a 30% increase from 2011 and 50% increase in passenger-miles traveled; however, the ridership share remains small in comparison to the other intercity modes.

Figure 7 illustrates the ridership growth in the commercial air and passenger rail mode in relation to the rising cost of fuel (Figure 2) and improved fuel efficiency. Ridership on Amtrak lines grew 6.5% from FY2010 to FY 2011 and 2.7% for just the first six months of FY 2012. The results from LUCIM show sustained growth in passenger rail and air modes due to rising fuel costs.

5.2 2012 - 2050 High-Speed Rail with Commercial Air Alternative-Specific Constants

On a dedicated HSR line, frequency of service would be higher and riders would potentially enjoy similar levels of comfort and safety as airlines. Therefore, an ASC for the HSR system that is identical to that for the commercial air mode can provide some preliminary insights into the shifts in ridership to HSR, shown in Figure 8.

The majority of the total rail ridership is in the Amtrak mode. This is a result of Amtrak use as a feeder to the HSR system (See Figure 3(c)). The total rail ridership

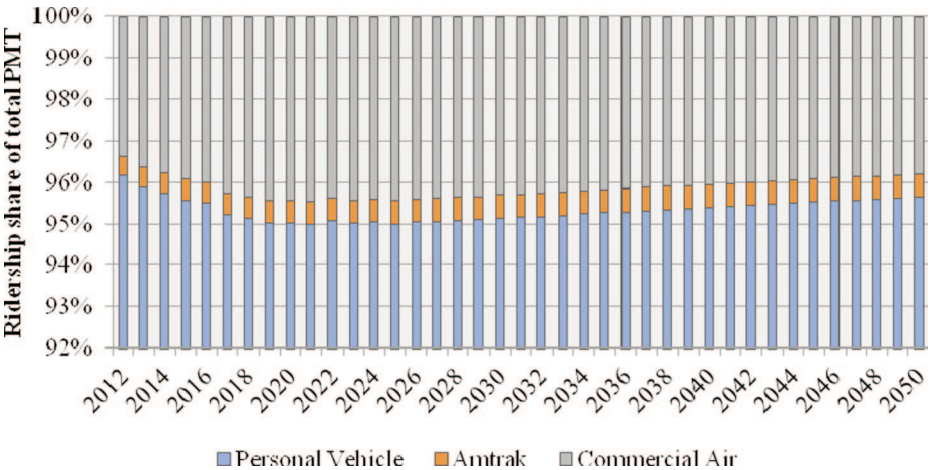

Figure 6. Ridership share of Midwest corridor intercity travel market (No HSR) (34.5 billion system-wide PMT in 2012 and 51.1 billion system-wide PMT in 2050)

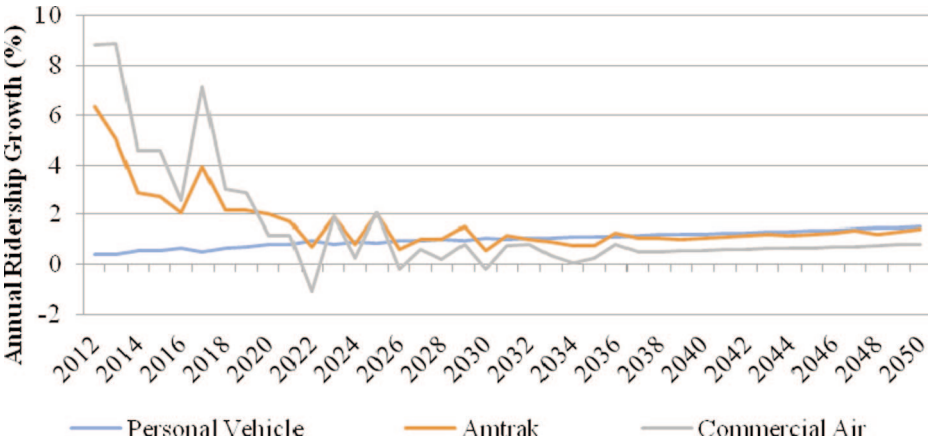

Figure 7. Modal ridership growth as a function of time (No HSR)

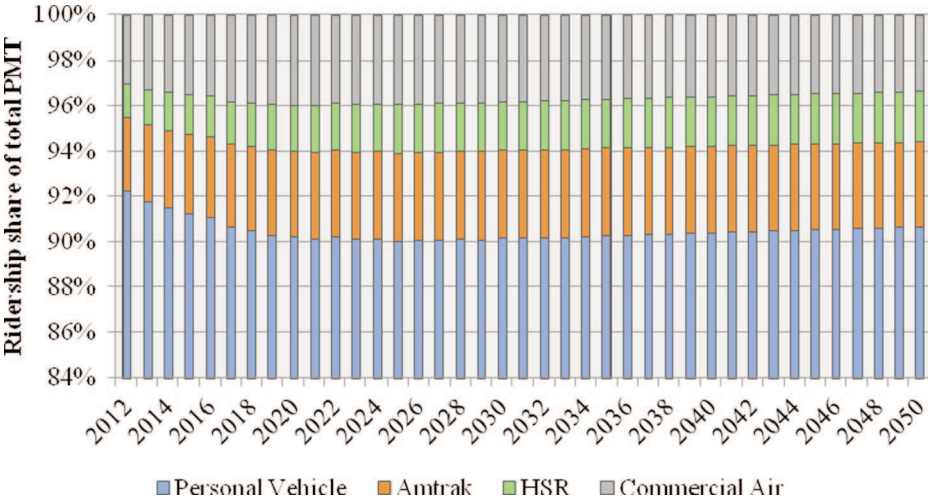

Figure 8. Ridership share of Midwest corridor intercity travel market for HSR with commercial air LOS characteristics (35.4 billion system-wide PMT in 2012 and 52.4 billion system-wide PMT in 2050)

peaks in 2029 at 6.0% of the total intercity PMT with 3.9% from Amtrak lines and 2.1% from HSR. Furthermore, most of the additional ridership is from a shift from the road mode compared to the commercial air mode. Figure 9 shows the sensitivity of the HSR ridership with respect to the average HSR design speed.

Based on the experimental assumptions in the LUCIM model, the long-run HSR average speed elasticity of ridership decreases from 1.15 between 110 and 120 mph to 0.49 between 210 and 220 mph. In terms of modal shift, ridership share of HSR is

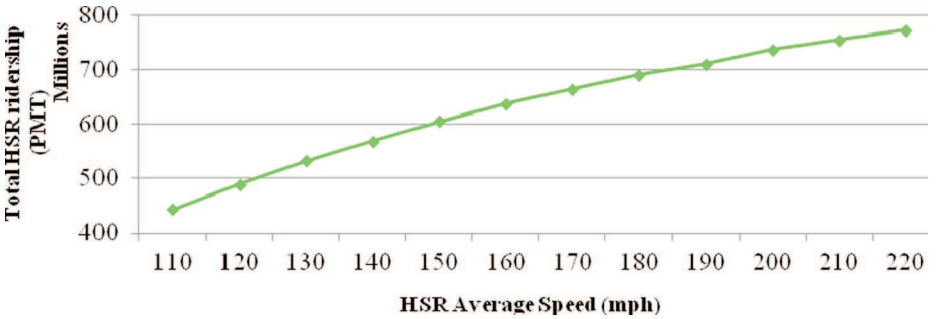

Figure 9. HSR ridership (PMT) as a function of HSR average speed in the year 2030

approximately 0.09% per 10 mph increase; as expected, these have decreasing returns to ridership due to constant connections, access, and egress times. Exploration of such design variables is critical to the HSR planning process.

6. CONCLUSIONS

Much of the current uncertainty and debate regarding the potential for HSR as a viable alternative in the multimodal transportation network is based on ridership. This study develops a systematic model (LUCIM) which provides robust predictions of long-term modal ridership shares due to sensitivities to economic, demographic, and technological trends. The methodology overcomes several gaps which have been identified in previous HSR ridership forecasts [10, 11, 12]. The model is validated against actual data at a systemwide level and reasonably captures ridership responses to evolving exogenous stimuli such as fuel prices. This provides planners and policymakers with a robust, systematic methodology for analyzing the viability of a proposed HSR network over the long term.

Experimental results show that if operational characteristics were improved to match that of air service in terms of frequency, comfort, etc., HSR has the potential to see ridership on the order of 50 to 60 million riders annually. MWHSRA predicted ridership of 35 and 44 million annually for 130 mph and 160 mph average speeds, respectively. The LUCIM-predicted 6% market share of intercity travel in the Midwest is a little lower than the 7-8% ridership shift predicted in the California HSR study [10]. Considering the difference in underlying assumptions in the models, study areas, and the inherent error in prediction in the long-term, these results are surprisingly similar. The projected ridership is at a level high enough to warrant future research in HSR in the Midwest corridor. Furthermore, the results demonstrate that there will be a continual ridership shift to passenger train as fuel costs increase for the alternative modes in the long-run until there reaches a point when vehicle efficiency can offset these costs. This, along with the average HSR speed sensitivity analysis, shows the capabilities of the model with respect to important HSR design considerations (e.g., average speed, fare price, projections in exogenous variables). This could provide important insight in future comprehensive analysis of cost, revenue, and resulting societal impacts.

Several gaps remain (see Table 1) but could be addressed in future research by extending the proposed methodology. A more detailed utility function incorporated in the proposed methodology could give insight into additional design factors such as comfort and safety. Also, incorporating induced demand and congestion effects are important next steps to forecast how the intercity transportation system would evolve after incorporation of a new mode like HSR.

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REFERENCES

[1] Bureau of Transportation Statistics (BTS) (2011). *National Transportation Statistics*. United States Department of Transportation, Washington, D.C., 2011

[2] National Surface Transportation Policy and Revenue Study Commission (NSTPRSC) (2007). *Final Report of the National Surface Transportation Policy and Revenue Study Commission—Transportation for Tomorrow*. Volume II, Chap. 4, December 2007

[3] Ball, M., Barnhart, C., Dresner M., Hansen, M., Neels, K., Odoni, A., Peterson, E., Sherry, L., Trani, A. and Zou, B. (2010). *Total Delay Impact Study - A Comprehensive Assessment of the Costs and Impacts of Flight Delay in the United States*. Prepared for the Federal Aviation Administration (FAA) Air Traffic Organization Strategy and Performance Business Unit by the National Center of Excellence for Aviation Operations Research (NEXTOR), October, 2010

[4] International Union of Railroads (UIC) (2011). *High Speed lines in the World*. <http://www.uic.org/IMG/pdf/20111101_a1_high_speed_lines_in_the_world.pdf> (May 30, 2012)

[5] Campos, J. and De Rus, G. (2009). Some stylized facts about high-speed rail: A review of HSR experiences around the world. *Transport Policy*, 16(1), 19–28.

[6] Amos, P., Bullock, D. and Sondhi, J. (2010). *High-Speed Rail - The Fast Track to Economic Development?* World Bank, Beijing, China, July 2010

[7] Hagler, Y. and Todorovich, P. (2011). *High Speed Rail in America*. Report by America 2050, January, 2011

[8] Adler, N., Nash, C. and Pels, E. (2008). *High-Speed Rail & Air Transport Competition*. Prepared as Tinbergen Institute Discussion Paper, TI 2008-103/3, Amsterdam, Netherlands, 2008

[9] Dobruszkes, F. (2011). High-speed rail and air transport competition in Western Europe: A supply-oriented perspective. Transport Policy, 18(6), 870–879.

[10] Cambridge Systematics, Inc. (CS) (2007). *Bay Area/California High-Speed Rail Ridership and Revenue Forecasting Study*. Prepared for Metropolitan Transportation Commission and the California High-Speed Rail Authority, 2007

[11] Brownstone, D., Hansen, M. and Madanat, S. (2010). *Review of "Bay Area/California High-Speed Rail Ridership and Revenue Forecasting Study*. Research Report UCB-ITS-RR-2010-1, 2010. Prepared at the request of the California Senate Transportation and Housing Committee and Submitted to the California High Speed Rail Authority, June 30, 2010

[12] Koppelman, F., Axhausen, K., Charlton, B., Miller E. and Small, K. (2011). *Independent Peer Review of the California High-Speed Rail Ridership and Revenue Forecasting Process*. Final Report to the California High-Speed Rail Authority. July 22, 2011

[13] Joshi, A. (2010). *An integrated framework to study the interaction between on-demand air service and existing regional transportation system*. M.S. thesis, Purdue University, West Lafayette, IN 2010.

[14] Ashiabor, S., Baik, H. and Trani, A. (2007). *Logit Models for Forecasting Nationwide Intercity Travel Demand in the United States. In Transportation Research Record: Journal of the Transportation Research Board,* Transportation Research Board of the National Academies, Washington, D.C., 2007, 1–12.

[15] Bureau of Transportation Statistics (BTS) (1995). *1995 National Travel Survey.* United States Department of Transportation, Washington, D.C., 1995

[16] Baik, H., Trani, A., Hinze, N., Swingle, H., Ashiabor, S. and Seshadri, A. (2008). *Forecasting Model for Air Taxi, Commercial Airline, and Automobile Demand in the United States. In Transportation Research Record: Journal of the Transportation Research Board*, 08-2052,Transportation Research Board of the National Academies, Washington, D.C., 2008, 9–20.

[17] United States Energy Information Administration (EIA) (2011). *Annual Energy Outlook 2011.* Report, Department of Energy, Washington, D.C. March 2011

[18] Amtrak (2011a) *Monthly Performance Report for September 2011.* Washington D.C., November 2, 2011

[19] Moolchandani, K., Agusdinata, D.B, Mane, M., DeLaurentis, D.A and Crossley. W.A. (2012). Airline Competition in Duopoly Market and its Impact on Environmental Emissions. *12th AIAA Aviation Technology, Integration, and Operations (ATIO) Conference,* Indianapolis, IN, USA, 2012.

[20] United States Census Bureau (USCB) (2011). *County Intercensal Estimates (2000-2010).* United States Department of Commerce, Washington, D.C., December 2011

[21] Bureau of Transportation Statistics (BTS) (2010a). *National Transportation Atlas Database.* United States Department of Transportation, Washington D.C., 2010

[22] Bureau of Transportation Statistics (BTS) (2010b). *Air Carrier Statistics Database*. United States Department of Transportation, T-100 and Form 41 Traffic, Washington D.C., 2010

[23] Amtrak (2012). *Route Guides*. Website database with downloadable route guides, <http://www.amtrak.com/servlet/ContentServer?c=Page&pagename=am%2FLayout&p=1237405732511&cid=1241337978894> (Retrieved May 31, 2012)

[24] AECOM and Economic Development Research Group (EDRG) (2011). *The Economic Impacts of High Speed Rail: Transforming the Midwest*. Technical report prepared for Midwest High Speed Rail Association, May 2001

[25] United States Department of Transportation (USDOT) (1997). *Activity-based Travel Forecasting Conference Proceedings*. US Department of Transportation, Washington, DC, Report DOT-T-97-17.

[26] McNally, M. G. and W. W. Recker (1986). *On the Formation of Household Travel/Activity Patterns*. Institute of Transportation Studies, University of California, Irvine, CA. USDOT Final Report.

[27] Trani, A., Baik, H.,Swingle, H. and Ashiabor, S. (2003). "Integrated Model for Studying Small Aircraft Transportation System." In *Transportation Research Record: Journal of the Transportation Research Board,* 1850, 1–10.

[28] Carrothers, G.A.P (1956). An Historical Review of the Gravity and Potential Concepts of Human Interaction. *Journal of the American Institute of Planners*, 22(2), 94–102.

[29] Alcaly, R. (1967). Aggregation and Gravity Models: Some Empirical Evidence. *Journal Regional Sciences*, 7(1), 61–73.

[30] Capon, P., Longo, G. and Santorini, F. (2003). Rail vs. air transport for medium range trips. *ICTS, Nova Gorica*, 1–11.

[31] Koppelman, F. and Bhat, C. (2006). *A Self Instructing Course in Mode Choice Modeling: Multinomial and Nested Logit Models.* Prepared for United States Department of Transportation Federal Transit Authority, Washington, D.C., January 31, 2006

[32] Dehghani, Y. and Harvey, R. (1994). Fully Incremental Model for Transit Ridership Forecasting: Seattle Experience. In *Transportation Research Record: Journal of the Transportation Research Board*, Transportation Research Board of the National Academies, Washington, D.C., 1452, 52–61.

[33] Brownstone, D. and Small, K. (1989). Efficient Estimation of Nested Logit Models. *Journal of Business & Economic Statistics*, 7(1), 67–74.

[34] United States Department of Transportation (USDOT) (2005). *2001 National Household Travel Survey - Version 4.0.* USDOT, <http://nhts.ornl.gov/download.shtml#2001>, July 2005

[35] Amtrak (2011b). *Amtrak Ridership Rolls-Up Best Ever Records.* Press Release ATK-11-133, Washington D.C., October 13, 2011