Development of a High-Speed Rail Model to Study Current and Future High-Speed Rail Corridors in the United States

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Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Master of Science
In
Civil Engineering

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May 31, 2011
Blacksburg, VA

Keywords: Logit Model, High-Speed Rail, High-Speed Train, Box Cox, Amtrak, American Travel Survey

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ABSTRACT

A model that can be used to analyze both current and future high-speed rail corridors is presented in this work. This model has been integrated into the Transportation Systems Analysis Model (TSAM). The TSAM is a model used to predict travel demand between any two locations in the United States, at the county level. The purpose of this work is to develop tools that will create the necessary input data for TSAM, and to update the model to incorporate passenger rail as a viable mode of transportation. This work develops a train dynamics model that can be used to calculate the travel time and energy consumption of multiple high-speed train types while traveling between stations. The work also explores multiple options to determine the best method of improving the calibration and implementation of the model in TSAM. For the mode choice model, a standard C logit model is used to calibrate the mode choice model. The utility equation for the logit model uses the decision variables of travel time and travel cost for each mode. A modified utility equation is explored; the travel time is broken into an in-vehicle and out-of-vehicle time in an attempt to improve the model, however the test determines that there is no benefit to the modification. In addition to the C-logit model, a Box-Cox transformation is applied to both variables in the utility equation. This transformation removes some of the linear assumptions of the logit model and thus improves the performance of the model. The calibration results are implemented in TSAM, where both existing and projected high-speed train corridors are modeled. The projected corridors use the planned alignment for modeling. The TSAM model is executed for the cases of existing train network and projected corridors. The model results show the sensitivity of travel demand by modeling the future corridors with varying travel speeds and travel costs. The TSAM model shows the mode shift that occurs because of the introduction of high-speed rail.

Acknowledgements

I would like to first thank Dr. Antonio Trani for giving me the opportunity to conduct this research and work toward receiving my degree. This work would not have been possible without all of his guidance and assistance. I would also like to thank Dr. Montasir Abbas and Dr. Gerardo Flintsch for serving on the committee and providing valuable input and information.

I want to extend a special thank you to Nicolas Hinze for all of his assistance in helping with the development of the computer modeling code. I also want to mention all of the new friends I have made, both in the Air Transportation Systems Lab and the Civil Engineering Graduate Program; thanks for all of the good times and memories.

Finally, I would like to parents and grandparents for everything they have done to provide me an opportunity to complete this work. I would not have been in this position without all of their support and guidance.

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Introduction

History of American Railroad

The development and implementation of the railroad played an important role in the shaping of the United States. The use of a railroad network for carrying both passengers and freight helped spur the development of the United States at a critical point in its existence. The earliest records indicate that the first tracks, approximately three miles long, were placed in Quincy, Massachusetts. The first cars to operate on this line were pulled by horses.[1]

Several different carriage powering alternatives were tested in the early years of rail. The use of horses for power, either attaching them directly to the car for pulling or placing the horse on a belt that drives the wheels, was the most prevalent. As well, designer began experimenting with wind power by attaching a sail to the train car; this design was tested but ultimately failed. However, the most important development for the railroad was the use of the steam engine to develop a powered car. The development of the steam engine and even the locomotive had begun long before the placement of the first rail track; the first steam engine arrived in the U.S. in 1753. The advent of the steam powered locomotive engine allowed the movement of more people and freight at a much higher efficiency. The steam engine created an opportunity for people to utilize the train as a viable, dependable mode of transportation. Individuals and corporations alike began to operate businesses on the rail lines; one of the first railroad companies to launch was the Baltimore and Ohio (B&O) railroad that ran west from Baltimore into Virginia (present day West Virginia).[1]

Another important event in the history of U.S. rail was the completion of the First Transcontinental Railroad which opened a link between the east and west coasts. The line was completed on May 10, 1869 at Promontory Summit, Utah. Although rail operations were already developing heavily, particularly on the east coast, this was an important event because travel across the country became much quicker and safer. At the time of the completion of the Transcontinental Railroad, there was approximately 50,000 miles of rail track in the United States. The completion marked an important point as it began to connect the entire nation, effectively making the country smaller. The United States' desire to increase the amount of rail network and the amount of goods transported continued to grow after the connection of the coasts; this allowed rail operations to flourish into the next century.[1]

It was during the 1920's that rail had its greatest peak. The network had approximately 254,000 miles of track and it captured almost all interstate traffic at the time. However, the decline of rail would be soon to follow. The amount of track mileage began shrinking as companies were starting to struggle to make profits and thus began abandoning unprofitable lines. This was due in large part to the development of the automobile, which was becoming increasing popular and efficient during this time. The railroad industries last blow came with World War II. Passenger and freight traffic continued to decline as rail was quickly losing popularity. The creation of the Interstate Highway System and the improvement of the airplane further increased competition and aided in the decline. It is known that passenger traffic declined from 770 million to 298 million between 1946-1964.[2]

Rail also lost the governmental mail contract in 1960's, which was a major source of revenue for the industry. Governmental regulations were another obstacle as rails were not permitted to abandon routes, cancel passengers, lay off workers or change freight rates without ICC approval.[2] Rail continued to struggle until the deregulation of the industry in 1980, which did help companies to begin to profit again. However, in the early days there were numerous different companies that operated on the rail, but a large portion were either out of business or on the verge of collapse before deregulation. The deregulation allowed the formation of some of the large notable freight companies today such as Norfolk Southern and CSX.

A boost to passenger rail came with the passage of the Rail Passenger Service Act on May 1, 1971, which effectively created the federally funded and controlled rail service

Amtrak. The act allowed the federally controlled Amtrak to operate over mostly private freight tracks, except for the Northeast Corridor (NEC), where the federal government owns most of the track. The passage of the law also required two things of existing rail companies, “one time payments, which would eventually total $190 million (from 13 railroads), and/or equipment… In exchange railroads received Amtrak Common Stock.” In total Amtrak received 300 locomotives and 1200 cars.[3] Amtrak has continued to grow, despite being underfunded and unprofitable, having reached 25 million passengers in 2007. Amtrak captures a large number of its riders in the Northeast Corridor region.

High-Speed Rail Operations Around the World

The following sections discuss some of the countries that are leading the way in the development and use of high-speed rail. Although high-speed passenger rail is barely seen in the United States, it is a driving force and desired commodity in many other countries around the world. This section is by no means all inclusive; other countries such as Italy, Spain, Germany, India, etc. are either investigating or already using high-speed rail on a large scale. Spain, despite is relatively small land mass and low population, currently has the second largest high-speed rail network in the world.

Japan

Japan is considered to be the world leader in terms of high-speed rail technology and its operation. Japan began operating the world’s first high-speed rail network in 1964 using the Shinkansen trains, known as the bullet trains. The first line connected Tokyo, Nagoya, Kyoto, and Osaka. The trains initially ran at 200 km/h, but with technological advances, they can currently operate at 300 km/hr. The Shinkansen network is currently operating a series of different “lines” through multiple cities. The network has grown to 1,528 miles of track and serves the islands of Kyushu and Honshu; it connects to several major cities on each island. The network itself extends from Aomori to Kagoshima. One of the design features of the network is that there are no at-grade crossings and the track is fenced off; trespassing is heavily protected by law. These safeguards enable safe high-speed operations because the trains are not operating on the same lines as the slower freight cars and there are no concerns about vehicles or pedestrians on the track.

The network operates trains in three different categories. The Nozomi is the highest/fastest category because it stops only at very important stations, thus producing the shortest overall travel time. The second category is the Hikari which stops more frequently than the Nozomi. Due to the additional stops, the Hikari takes about 30 minutes of additional time to travel between Osaka and Tokyo. The last category is the Kodama which is the slowest category because the train stops at every station along the route.

There have been many different versions of the trains on the Shinkansen network. The inaugural train was the Shinkansen Series 0. This train was typically 12 cars long and operated at speeds around 220 km/hr. Later versions include the 100 series, 300 series, 500 series, and 700 series. Each train featured consumer upgrades and/or upgraded technology that allowed for faster travel and/or better passenger accommodations. More information is widely available about each of the different series of trains. The newest train is the Shinkansen Series N700 which is capable of traveling 300 km/hr. This train is unique for the Shinkansen in that it has a tilting mechanism that allows it to tilt one degree during turns; this allows the train to travel 270 km/hr through turns with a design radius of 2,500 meters.[4] Another notable improvement is that the N700 Series was also able to increase its acceleration performance by 30% vs. older Shinkansen trains.

France

The French high-speed train network is known as the TGV (Train à Grande Vitesse), which stands for high-speed train. The project was launched in the late 1960’s with the first prototype, the TGV 001, being tested in the early 1970’s. Only one TGV 001 was built as it was used for research and testing of brakes, aerodynamics, traction, etc. The TGV 001 was powered by a gas turbine and set a world speed record at the time at 318 km/hr. The oil crisis in 1974 led the developers to begin working on an electric powered train. One thing to note is that the trains are designed to be able to operate on the existing rail network; this allows the trains to connect with many different cities without adding additional construction costs associated with a new track. As well, it allowed “high-speed” sections to be built as funding became available. The ultimate goal is to have protected high-speed sections with no at-grade crossings for long distance travel and then have the trains run on existing track to connect to various cities.[5]

The first line opened to passenger service on September 27, 1981 between Paris and Lyon. The network was incredibly successful as it captured most of the air traffic along the route and was able to pay for itself within 10 years. This initial success led to the development of the large TGV network that exists today. Today, the current TGV network is approximately 1250 miles and another 400 miles is currently being built.[6] This is despite the fact that there are only 18 TGV stations outside of Paris on the six active lines, which shows the network is currently running only city-city travel.[6] The TGV network also connects with many of France’s neighboring countries such as Switzerland, Germany, Belgium, etc.

The rolling stock of the TGV has also evolved. There are currently 7 types of trains (depending on classification) that are operating on the network. They vary by length of cars, type of vehicle (single deck or double deck), and seating capacity. The newest of the trains is the TGV POS (Paris-Ostfrankreich-Süddeutschland : Paris-Eastern France-Southern Germany), which was developed in 2005 and reaches a top speed of 320 km/hr. One major achievement for the TGV was setting the World Speed Record for conventional trains. A modified train, named the V150, reached a speed of 574.85 km/hr. on a section of track between Paris and Strasbourg. The train however was unable to break the top speed record of 581 km/hr. held by a Magnetic Levitation Train.[7]

China

China is one of the relative newcomers to the high-speed rail market but perhaps they have the most aggressive goals thus far. China had a very poor performing rail network before it began its series of “Speed-Up” campaigns that began in April 1997 and concluded in April 2004. This campaign upgraded 7,700 km of existing track, allowing trains to reach 160 km/hr. on the new track.[8] China has continued to expand its network; there was approximately 78,000 km of track in 2010. This is currently the largest rail network in the world. However, China is continuing to expand its network; they have set an expansion goal of 110,000 km of track by 2012 and 120,000 km in 2020. Of this proposed expansion, 13,000 km will be for high-speed line (220 mph).[9] The Chinese network is planned to be a network that comprises of both high-speed lines and moderate speed regional lines. This will allow them to connect a large portion of their county with rail service while reducing overall costs because the expensive high-speed track will be placed only along busy corridors. China is making large strides with their rail program; it will be important for the United States to monitor and learn from their project. This will provide insight into whether or not high-speed rail can be successful in the United States because there are similarities between the Chinese project and the proposed projects in the U.S.

Description of Transportation Systems Analysis Model (TSAM)

The Transportation Systems Analysis Model (TSAM) is a nationwide intercity transportation planning model that utilizes the traditional four-step planning process. It is used to predict the travel demand from any one location to any other location in the United States at the county level. The model was developed as a joint effort between the Virginia Tech Air Transportation Systems Lab (ATSL) and NASA Langley Research Center. Later versions of the model have been used by the Federal Aviation Administration (FAA). The model uses the 1995 American Travel Survey (ATS) as the basis of the travel choice behavior in the United States.; a more detailed description of ATS can be found below or on the internet. The model also uses other data sets such as Woods & Poole socioeconomic data, Airline Origin and Destination Survey (DB1B), etc. A description of the inputs and modeling process of TSAM can be found in another work.[10]

The model currently focuses on two modes of transportation, automobile and air (commercial, general aviation, cargo, air taxi). This work will show the development of a package that will allow passenger train to be included as another viable mode of transportation in the model.

Literature Review

Available Rail Planning/ Analysis Software

There are currently several rail planning software packages that are commercially available. Each package offers a different array of tools and calculations; some are used for planning purposes while others specialize in existing network analysis. A description of a few different commercial packages is available below.

Rail Traffic Controller

Rail Traffic Controller (RTC) is a software package developed by Berkeley Simulation for the purpose of modeling trains and their interactions on a rail network. This software works to emulate and improve the role of a human dispatcher on a network. It can provide the capacity of a network while accounting for delays and re-routing of trains due to their interactions. It is typically used for the purposes of developing operating plans, determining locations of bottlenecks, verifying or determining schedule changes and finding the impact of new trains on a network.

The software includes a vehicle dynamics model that considers different equipment types, track conditions and constraints, and terrain variations. The software produces time-distance diagrams, train performance profiles, timetables, etc. As well, it produces an animation of the traffic flow across the network. This software is commonly employed by rail analysts in industry. The source of this information as well as additional information can be found at http://www.berkeleysimulation.com/home.html.[11]

RAILSIM

RAILSIM is a model that is developed by SYSTRA Consulting for the purposes of existing network analysis of vehicle, network, and energy supply performance. The package offers multiple modules, each performing a different calculation or simulation. The Train Performance Calculator is the rail vehicle dynamics model. The inputs are the track territory to be simulated, train composition, train schedule, and stopping pattern; the track territory includes the track length, grades, curves, and speed requirements/restrictions in different areas. The output includes trip times and energy consumption, as well as possible alternatives such as stopping pattern alternatives, rolling stock alternatives, station dell time alternatives, and rail alignment alternatives.

Other modules include the RAILSIM Editor, which handles the network construction in the form of a database, the Network Simulator, which is the full model simulation of a network, the Load Flow Analyzer, which is the tool for all electrical calculations (predicted consumption costs, grid capacity, demand, and regenerative braking effects). Others include the Headway Calculator, which is useful in determining if the network is operating at capacity, the Safe Breaking Calculator, which determines the necessary "worst case" braking distance for different trains, and Control Line Generator, which is used to analyze and test train control systems. This package provides many tools that are useful in analyzing current networks and testing different scenarios with regards to train types, network schedules, and control systems.

The package has been implemented on projects such as the Northeast Corridor (NEC) Energy Usage and Capacity Study, Caltrain "Baby Bullet" Express Train Service, LACMTA Westside Extension Transit Corridor Project, etc. For example, in Northeast Corridor Energy Usage and Capacity Study, RAILSIM was used to ensure that all agencies running trains on the NEC were paying their share of the utility bills. As well, field tests were conducted on motor efficiency, which led Amtrak to implement regenerative braking. The source of this information is www.railsim.com.[12] More information about the software and other case studies can be found on the website.

TransCAD

TransCAD is a software package that was developed by Caliper Corporation for the purpose of modeling, analyzing, and displaying transportation data. It claims to be the first and only Geographic Information Systems (GIS) software that has been customized for use by transportation professionals. The software offers a GIS engine, mapping and analysis tools that have been customized for transportation projects, and multiple calculation modules that perform the calculations and analysis of the transportation data, examples are travel demand forecasting, public transit modeling, path routing, etc.

The network analysis models are used to solve transportation network problems. This model contains shortest path routines, traveling salesman models, and network partitioning. The planning and demand model has tools that analyze the phases of the four step planning process. This model can handle trip generation, trip attraction, mode split analysis, and traffic assignment. Other models are available such as a logistics model, site location and land management, and a transit model.

The transit model allows for shortest path problems as well as determining the attributes of the path. It also allows multi-modal network integration, such as connecting a pedestrian network to the transit network. The model can predict the number of passengers that will utilize the network, based on factors such as user determined transit fares, surrounding population, level of service, etc.

The benefit of using TransCAD is that provides powerful visualization tools that can be used to display the results of the analysis that has been conducted. For example, if calculating flows on streets in a network, TransCAD allows for a GIS type map that will color the roads based on the traffic flow. This is very beneficial because the visual presentation of the analysis allows for easy understanding of the situation, can help spot an error quickly, or can it can be instrumental in the presentation of work to a client or non-technical audience. The source of this information and additional information can be found at http://www.caliper.com/tcovu.htm.[13]

Trip Distribution Modeling

Trip distribution is typically the second step in the traditional four-step transportation planning process. It relies on the results of the trip generation phase, which determines how many trips are produced in and attracted to each study area or zone. The distribution phase takes the trip generation results and produces a matrix of the number of trips that occur between each origin and each destination in the study area. For example, this matrix provides that there are X trips traveling from zone 1 to zone 2 or there are X trips traveling from household 3 to grocery store 5, depending on the level which the study area has been divided. There are multiple model types that have been used for modeling such as growth factor models, gravity models and opportunity models.[14] The most common model by far is the gravity model.

The transportation gravity model is based on Newton's Law of Gravitation, which states "there is a power of gravity pertaining to all bodies, proportional to the several quantities of matter which they contain, and the force of gravity towards several equal particles of any body is inversely as the square of the distance of places from the particles." [14] The formulation is widely available and can be seen elsewhere.[14] The transportation planning gravity model is loosely based on Newton's Law in that is distributes trips based on the distance between the zones/regions and the "friction" of travel between the origin and destination zone. The most common formulation of the gravity model is:

$$V_{ij} = O_i \frac{D_j F_{ij}}{\sum_j D_j F_{ij}} \text{ .... (1)}$$

Where:

$V_{ij} =$ Trips going from zone i to zone j

$O_i =$ Trip productions from zone i

$D_j =$ Trip attractions to zone j

$F_{ij} =$ friction factor for travel from zone i to zone j

This model distributes the trips based on the "friction" of travel to a given zone relative to the "friction" of traveling to all zones. The friction factor is typically a function of distance between zones, travel time, socioeconomic characteristics, etc.

The model is also often modified in order to achieve a better fit with the use of a K-factor. The new model formulation is:

$$V_{ij} = O_i \frac{D_j F_{ij} K_{ij}}{\sum_j D_j F_{ij} K_{ij}} \text{ .... (2)}$$

Where:

$V_{ij} =$ Trips going from zone i to zone j

$O_i =$ Trip productions from zone i

$D_j =$ Trip attractions to zone j

$F_{ij} =$ friction factor for travel from zone i to zone j

$K_{ij} =$ specific zone − to − zone adjustment factor

This change to the gravity model allows more degrees of freedom and ideally a more realistic/accurate trip distribution. This formulation uses the F factor as an exclusive function of travel time between zones. The K factor is then used as an adjustment factor to account for factors that are not explicitly modeled, such as socioeconomic factors. This is the trip generation formulation that is utilized in the TSAM Model.[10]

Other models have been used, though far less commonly, for trip distribution modeling, one such model is the Fratar model. The Fratar model is a typical growth factor model; it assumes that future trips can be calculated by adjusting base year trips with growth factors that represent the zone or household. The weakness of this method is that it does not account for changes in the transportation network or land use characteristics that changes users behavior; this implies that future projections only vary by a factor from the base year.[15].

Mode Split Modeling

Mode split is traditionally the third step in the transportation planning process. Although this step is sometimes called mode choice, it is more accurate to refer to it as mode split because there may be certain situations where users only have one available mode, thus there is no choice. Mode split analysis involves "predicting the number of trips from each origin to each destination which will use each mode of transportation."[16] For example, it predicts the number of trips from zone 1 to zone 2 by mode of car given the demand from zone 1 to zone 2 and the utility (attractiveness) of the car mode relative to the utility of all other modes. The typical inputs to the mode split analysis are characteristics about both the transportation system and the users.[16] Characteristics of the transportation system can include travel time, travel cost, time of day, capacity limitations, etc. Items such as income level, trip purpose, gender, age, employment status, personal preferences, etc. are all characteristics of the users that can affect the mode choice split.[17]

The two variations of the transportation planning models with respect to mode choice are trip end and the trip interchange models. Trip end models are some of the first transportation planning models that were developed; in these models, the four steps of the typical planning process are ordered slightly different than the common models today. Trip end models follow the order of trip generation, mode split, trip distribution, and traffic assignment. The advantages of this structure is that it preserves characteristics of trip makers and it can be very accurate in special case, such as short term analysis, areas of little congestion and areas were public transport is available in similar ways throughout the study area.[17] Some of the problems that apply to trip end models are that they try to assign modes before trip destinations have been determined. Based on the formulation of the model, which relies on the relationships between the various modes and the economic and social characteristics of the users, future changes to the system will not be reflected in the mode split. As well, these models are not transferrable from region to region because of the reliance on relationships instead of system characteristics.[14]

Trip interchange models are the newer and most frequently used planning models; the four steps are executed in the order of trip generation, trip distribution, mode split, and traffic assignment.[15] Trip Interchange models have the advantage in that travel modes of choice are assigned after trip destinations have been determined, therefore the model can use characteristics of the modes as well as relevant socioeconomic characteristics to determine the mode split.[17] The model is sensitive to specific changes in the system such as time or cost changes. As well, a small dataset is sufficient for calibration. Some of the disadvantages are that the model uses tradeoffs between modes to determine the split, which can lead to problems such as the independence of irrelevant alternatives if not corrected.

The most common model for mode split analysis is the multinomial logit model. This model uses a utility function for each mode (based on characteristics such as travel time and cost) that determines the benefit the user gets from each mode. The probability of the user choosing that mode is then typically a ratio of the utility of the given mode relative to the utility of all the other available modes.[16]. The common formulation of the logit model is:

$$P(i) = \frac{e^{U_i}}{\sum_{i=1}^{i} e^{U_i}} \text{ .... (3)}$$

where:

$P(i) \;=\;$ probability of selecting mode i

$U(i) \;=\;$ Utility of mode i (usually expressed as a function of factors that affect mode split)

Logit models are commonly employed in different types of mode split research. Poorzahedy, Tabatabaee, Kermanshah, Aashtiani, and Toobaei [18] conducted research on developing a model that will determine whether or not a city has the necessary characteristics to require a high investment transportation system, as compared to the average city. The purpose of the work is to use city specific data (GDP, political system, etc.) to predict whether or not the city has HSR. Once the model is calibrated, it can be apply to a new city to determine if that new city will invest in high-speed rail, as would the average city. The work examines the calibration of a logit model with two different methods; maximum log likelihood and non-linear least squares regression. The results of the effort show that non-linear regression tends to be more accurate in its average prediction but it produces a higher standard deviation than maximum likelihood. Maximum log likelihood was found to be more stable and produce a lower standard deviation which makes it better suited for applications where certain data or inputs might be missing because it would be affected less by the missing data.

Yao, Morikawa, Kurauchi, and Tokida [19] have examined the demand for a planned high-speed rail system in Japan using a forecasting model. A nested logit mode choice model is calibrated with a combination of revealed preference (RP) and stated preference (SP) data. SP data is typically survey type data where the users state what their choice or plan would be if they faced a certain situation or decision. RP data is typically field measured data where users actually choices are monitored and collected without the users directly knowing of the measurement. By these definitions, RP data is typically more accurate because it shows the actual choices that users make in a situation, however it is often difficult and very expensive to collect. SP data is easier to collect however, it is less reliable because the user's actual choice to a situation will not always match their stated choice. This work created two logit models, one for SP and one for RP, and then combined the models to calculate the maximum log likelihood. The results found that the combination of RP and SP provided more realistic results than by using only SP data. While a model with exclusively RP data is preferred, it is difficult to obtain therefore the RP and SP data model provides a reasonable substitute.

Chen, Mao, Yang, and Zhang [20] verified that there is benefit in acquiring RP data. This work looks at a nest logit model to determine passenger travel behavior on a dedicated high-speed rail line in China. The researchers collected both SP and RP data about users of the rail line and then use maximum likelihood to estimate the parameters of the model. Their nested logit model consists of two levels, the first level is the passenger's travel time preference and the second is the choice between the three travel modes available. The model also accounts for some socioeconomic factors as well. The researchers found that is valuable to know the passenger's actual travel behavior when trying to study the effects of introducing a new mode of transportation.

The work of Mandel, Gaudry, and Rothengatter [21] proposes the use of Box Cox transformations for the purpose of improving the logit model prediction rate. The transformations can be applied to any variable that contains all positive values. The benefit of the box cox transformation is that it eliminates some of the unrealistic assumptions behind the logit model such as equal cross elasticities of demand, exclusion of complementarity among alternatives, a symmetrical response curve, and the assumption that "coefficients for the constants and for the variables common to all alternatives are under identified, which means that, for these variables, only differences with respect to an arbitrarily chosen reference can be identified."[21] The formulation of the box cox transformation is:

$$X_{kjn}^{(\lambda_{kj})} = \begin{cases} \frac{(X_{kjn}^{\lambda_{kj}} - 1)}{\lambda_{kj}} & if \quad \lambda_{kj} \neq 0, \\ \ln X_{kjn} & if \quad \lambda_{kj} = 0 \end{cases} \quad \ldots\ldots\ldots\ldots (4)$$

Once the transformation has been applied, the utility equations for each of the alternatives can be formulated. Then the logit model can be executed and calibrated using methods such as log likelihood maximization. The probability equation for a given mode, after applying the transformation is

$$P(i)_n = \frac{exp\left(\beta_i X_i + \sum_{k=1}^{K} \beta_{ki} X_{kin}^{\lambda_{kj}}\right)}{\sum_{j \in C_n} exp\left(\beta_i X_i + \sum_{k=1}^{K} \beta_{ki} X_{kin}^{\lambda_{kj}}\right)} \quad \ldots\ldots\ldots\ldots (5)$$

This transformation removes some of the "linear" assumptions of the logit model and adds degrees of freedom so that the model is better able to adapt and provide a better fit to the data. This is illustrated in Figure 1; the figure shows that the response curve of the linear logit is symmetrical whereas the Box-Cox curve can be calibrated to be non-symmetrical, as well as having varying degrees of slope. This is beneficial for improved modeling; an example would be the response to a change in price of long distance flights. The curve may have a small or flat slope because travelers do not have any other practical options, in this case, a linear logit curve may overestimate the response curve because it is constrained to be symmetrical.

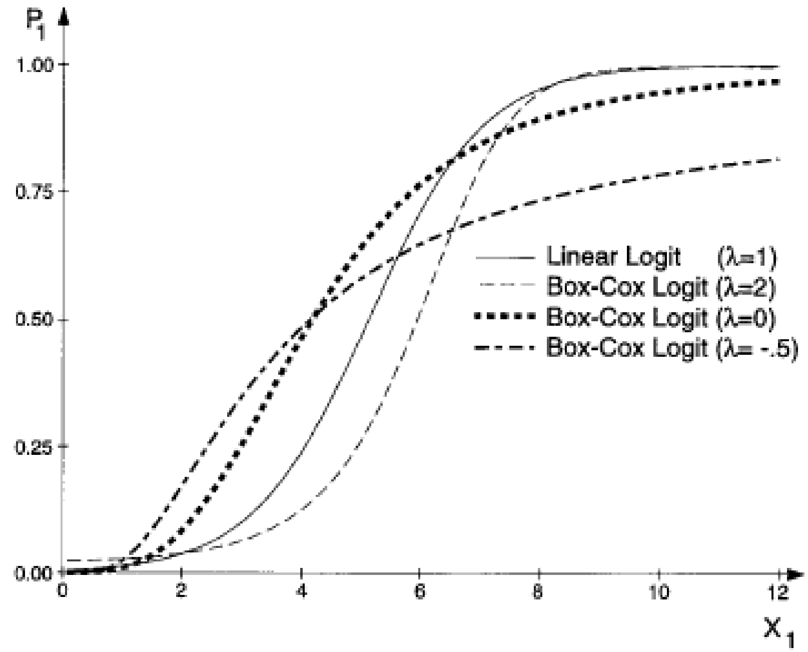

Figure 1 - Comparison of Linear and Box- Cox Logit Response Curves [21]

Problem Description

The purpose of this research is to develop tools that can be integrated into the TSAM model and used to analyze both current and projected future high-speed rail corridors. The TSAM model uses 1995 as the base year so the updated model should be able to accurately predict the train trips from the year 1995 forward. As well, many new high-speed rail lines have been proposed and are in the planning stage. The TSAM model needs to be able to accurately predict the intermediate/long range trips that will be taken on the projected corridors. However the model will not be capable of making ridership projections since TSAM only models “intercity trips”; an intercity trip is defined as a trip that has a one-way route travel distance of 100 miles or greater.

The model needs to be able to calculate the travel times and travel costs of both the current and future corridors. The time and cost values will be used to develop a new calibration that will include train as a mode choice option. As well, a future work will likely focus on developing a life-cycle cost analysis for high-speed passenger trains that will be used to make more accurate travel cost predictions. Therefore the model also needs to be able to determine the energy consumption associated with the trains because this will be a large portion of the operating costs.

Methodology

Train Dynamics Model

<u>Method</u>

A Matlab script is developed for use in calculating travel time and energy consumption calculations of current and future high-speed rail corridors. The primary calculation in the script is the calculation of travel times between stations. The velocity profile is calculated as either a two or three phase profile, depending on the input parameters. Figure 2 below shows a sample of three phase profile, which includes an acceleration, cruise and deceleration phase. Figure 3 shows a sample two phase profile, which includes only the acceleration and deceleration phases. The inputs are the distance between stations, the type of train to be modeled, maximum desired cruising speed, deceleration rate, and the integration time step.

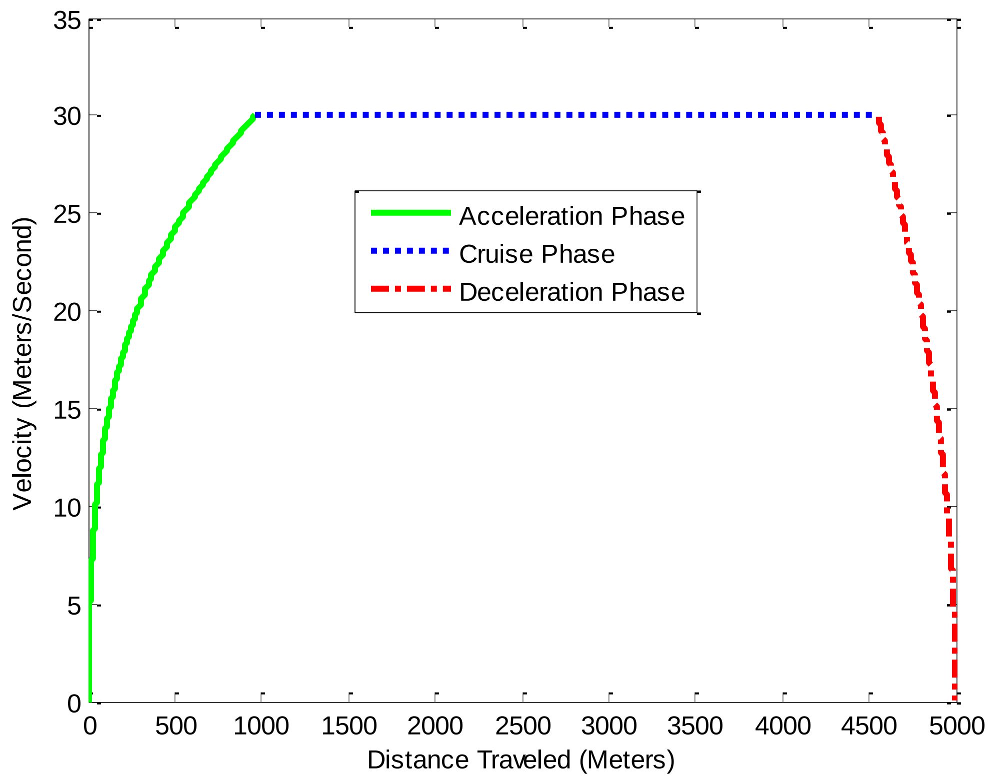

Figure 2 - Sample Three Phase Velocity Profile

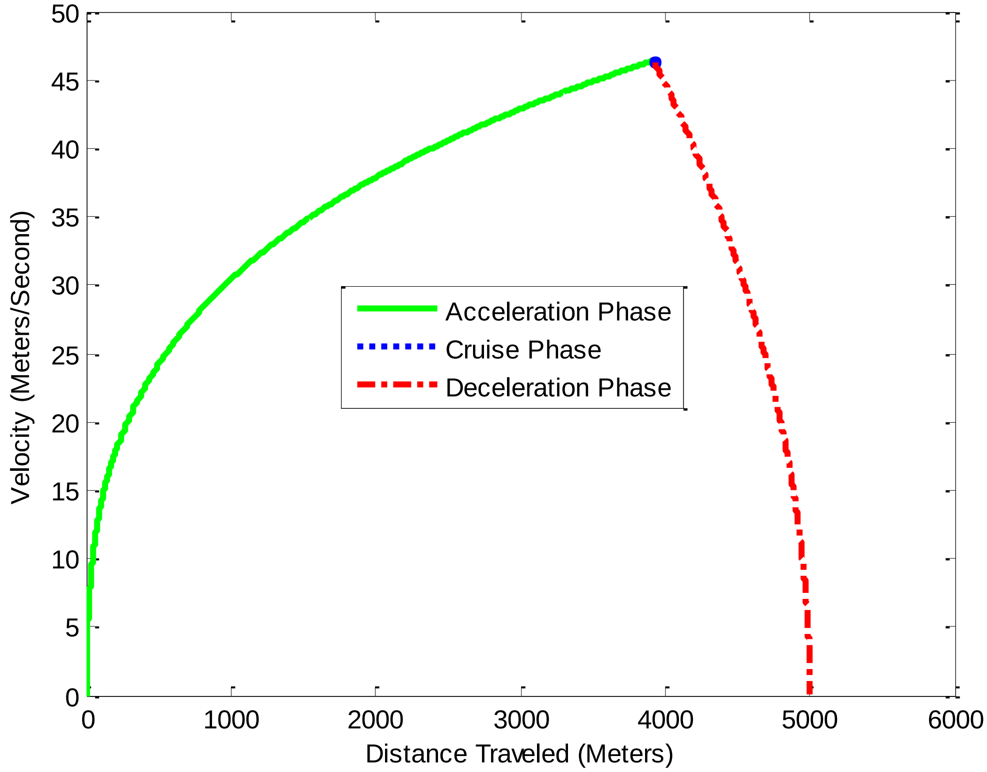

Figure 3 - Sample Two Phase Velocity Profile

The maximum desired cruising speed is an input because it may be practical to limit the cruising speed to a chosen value. This could be the case because of either the tradeoff between cruising speed and energy consumption or due to track/technological constraints that prevent the train from reaching a higher speed. For example, if a train is traveling between stations that are ten kilometers apart, it would not be practical, or actually occur in real world operations, for the train to accelerate as long as possible and then immediately begin deceleration; in this scenario, the train would burn more energy but not provide significant time savings versus a train that "cruised" part of the segment. This is because energy is consumed at a much higher rate while accelerating vs. cruising operation (steady state). The deceleration rate is input as a constant value. This provides a simple yet realistic model of a train's deceleration characteristics. The maximum deceleration rates will likely vary with train type; no train specific information was found that would allow for a more accurate model of train deceleration.

The integration time step is included as an input because the script uses a numerical integration approach to calculate the velocity profile. This is chosen over a differential equation method because the distance between stations and the input desired speed will vary between different O-D pairs, thus an iterative process would be needed to determine the profile. In the code, at each time step, three items are calculated; the current speed of the train, total distance traveled, and the distance required for the train to stop at its current speed. After these calculations, it is then verified that there is ample distance for the train to be able to stop at the next station. This works by taking the cumulative distance traveled by the train, at the given time step, and the distance required for the train to stop at that time step, based on the current velocity of the train, and ensuring that the sum of the two distances is less than the distance between stations.

Essentially, the code ensures that the train will be able to accelerate and a come to a stop at the next train station. For example, if the distance between stations is 5 kilometers and the maximum desired cruising speed is set to 75 m/s, the train cannot reach 75 m/s and come to a stop in 5 kilometers. Therefore within the code, the train accelerates as long as possible and then decelerates, while still ensuring that is can come to a stop at the next station. This example, which is a two-phase profile, is seen in Figure 3.

Model Equations

The code utilizes Newton's second law of motion, $F = ma$. This fundamental equation is used to calculate the acceleration of the vehicle at each time step. The mass is dependent upon the type and length of train that is modeled, which will be discussed later. The tractive effort is calculated as:

$$TE = \text{minimum}\left(\frac{k1 * \nu * P}{V}, 1000000\right) \quad \ldots\ldots\ldots\ldots \text{(6)}$$

Where:

$K1 = 745.7$, conversion factor (horsepower to Newtons)

$\nu = 0.75$, engine efficiency factor(unitless)

$P =$ Power (horsepower)

$V = \text{Velocity}\ (\frac{m}{s})$

The tractive effort calculation uses the minimum of the calculated function value and 1,000,000 Newtons because the function approaches infinity as the velocity gets close to 0. Although the actual tractive effort would be finite, the minimum function ensures that the equation can be used for modeling ant that at low speeds, the tractive effort is small enough so that the wheels should not slip.

The resistive forces acting on the train, rolling resistance, aerodynamic resistance, etc. are calculated with the use of the Davis Equation. The Davis Equation integrates all of the resistive forces into one equation, which is a function of velocity. The formula that is used for the modeled Japanese Shinkansen trains is:

$$R = A + B * V + C * V^2 \quad \ldots\ldots\ldots\ldots \text{(7)}$$

Where:

$R = \text{Resistance (Newtons)}$

$A = \text{train specific coefficient (N)}$

$B = \text{train specific coefficient}\ (\frac{\text{N} * \text{s}}{\text{m}})$

$C = \text{train specific coefficient}\ (\frac{\text{N} * \text{s}^2}{\text{m}^2})$

$V = \text{Velocity}\ (\frac{\text{m}}{\text{s}})$ Source: [22]

"Coefficients A and B of the Davis Equation include the mechanical resistances and are thus mass related. … At higher speeds, the CV^2 term becomes dominant since it can be said to relate to the aerodynamic resistance."[22] Table 1 shows the major resistance contributors to each of the three coefficients. A more detailed description and illustration of some of the different forces listed in Table 1 can be found in another work.[23]

Table 1 - Forces Contributing to the Coefficients of the Davis Equation [24]

A	B	C
Journal Resistance	Flange Friction	Head-end Wind Pressure
Rolling Resistance	Flange Impact	Skin Friction on Side of Train
Track Resistance	Rolling Resistance – Wheel/Rail	Rear Drag
	Wave Action of the Rail	Turbulence Between Cars
		Yaw Angle of Wind Tunnels

The equation is useful for modeling purposes because it allows the resistance of different train types to be calculated easily by simply inputting three train specific coefficients. The Davis Equation is a commonly used equation thus the coefficients for different train types are typically available.

The TGV trains are modeled with a modified version of the Davis Equation. The coefficients are calculated as functions of the rolling stock characteristics.[22] The parameters are calculated using the following formulas:

$A = 0.00001\left[\lambda M\left(\sqrt{\frac{10000}{m}}\right)\right]$ ………..... (8)

$BV = (3.6\ x\ 10 - 7)MV,$ assumes good quality track, modern rolling stock on bogies with roller bearings ………..... (9)

$CV^2 = 0.1296\ [k_1 S(V^2) + k_2 pL(V^2)]$ ………..... (10)

Where:

$M =$ total train mass (Kg)

$m =$ Mass per axle (kg)

$\lambda =$ dimensionless parameter,

$0.9 < \lambda < 1.5,$ lower value for modern stock, higher values for non − homogeneous freight trains

$V =$ Velocity (m/s)

$p =$ partial perimeter of rolling sock down to rail level (m), common values about 10m

$L =$ train length (m)

$k1 =$ parameter that depends on shape of train, front and rear. Varies between $20 \text{ x } 10 - 4$ for conventional rolling stock to $9 \text{ x } 10 - 4$ for TGV Stock

$S =$ front surface cross $-$ sectional area (m2), commonly 10m2

$k2 =$ parameter depending on condition of surface, pL; varies between $30 \text{ x } 10 - 6$ for conventional stock to $20 \text{ x } 10 - 6$ for TGV stock

Train Types

The code models four different types of high-speed trains; the Japanese Shinkansen Series 100, Japanese Shinkansen Series 200, French TGV-R, and the French TGV-D. The train characteristics and coefficients for the Shinkansen Trains can be seen in Table 2 and the information for the TGV Trains is located in Table 3. The source of coefficients for both train types is [22].

Table 2 - Model Coefficients for Shinkansen Trains

Shinkansen Trains			
	Parameters	**Series 100**	**Series 200**
Train Characteristics	Mass (kg)	886,000	712,000
	Capacity	1,285	720
Tractive Coefficients	Power (horsepower)	15,900	15,900
	Engine Efficiency Factor	0.75	0.75
Resistive Coefficients	A (Newtons)	11060	8202
	B $(\frac{Newtons*seconds}{meters})$	109.44	105.56
	C $(\frac{Newtons*seconds*seconds}{meters*meters})$	15.6168	11.9322

Table 3 - Model Coefficients for TGV Trains

TGV Trains			
	Parameters	**Series 100**	**Series 200**
Train Characteristics	Mass (kg)	416,000	424,000
	Capacity	377	545
Tractive Coefficients	Power (hp)	11,800	11,800
	Engine Efficiency Factor	0.75	0.75
Resistive Coefficients	λ	0.9	0.9
	# of axles	24	24
	Mass / axle	17,333	17,667
	k1	0.0009	0.0009
	S	10	10
	k2	20×10^{-6}	20×10^{-6}
	p	10	10
	L	200	200

Energy Consumption

The code that is used to calculate the velocity profile is also used to calculate the energy consumption. The energy consumption rate is calculated by multiplying the tractive effort at each time step by the current velocity; in this script, the units are Joules/second. Next, the total energy consumption (Joules) is found by using linear interpolation between time step intervals; the energy consumption is calculated as the length of the interval (timestep) multiplied by the average between the energy consumption rate at the current timestep and energy consumption rate at the previous timestep; essentially it uses linear interpolation between time steps to develop the total energy consumption. The total energy consumption is then tracked throughout the entire distance profile. Once the total energy consumption of the train has been calculated, the units are converted so that a series of factors can be applied, these factors account for efficiency losses in the train and the electrical grid. This allows for the determination of the total raw potential energy that is used by the train.

The first factor is an efficiency factor for the pantograph on the train. The pantograph is the device on the top of the train that contacts the electrical wires and channels the electricity to the engine. At the time of this research, no empirical measurements about the energy loss in the pantograph could be found. Thus, it was assumed for the calculations that the pantograph is 95% efficient.

The other factor is used to account for losses in the generation of electricity and its transmission through the electrical grid. In order to make meaningful energy consumption comparisons across different modes of travel, the total raw potential of each mode must be measured. The loss factor is calculated by the National Renewable Energy Laboratory and it accounts for transmission and distribution losses, as well as pre-combustion effects, which includes extraction, processing and transportation of the fuel source (coal, natural gas, etc.).[25] There are some important assumptions in the development of the energy factor; the assumptions are illustrated in Figure 4, Table 4, and Table 5.

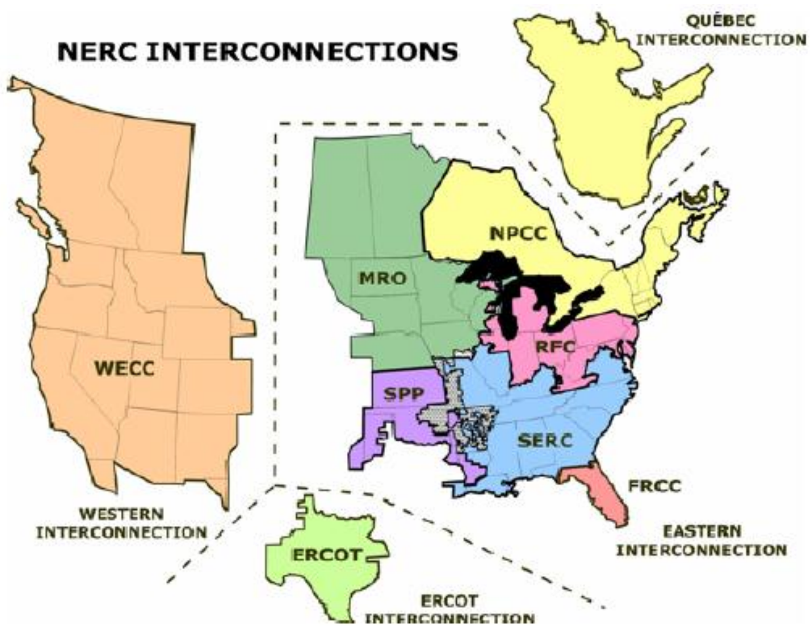

Figure 4 - U.S. Energy Regions used for Consumption Calculations [25]

Table 4 - Energy Generation Percentages for Energy Production Methods [25]

Energy Type	National %	Eastern %	Western %	ERTOC %	Alaska %	Hawaii %
Bituminous Coal	27.8	34.3	13.1	0.0	0.0	0.0
Subbituminous Coal	19.8	19.6	19.8	21.4	9.9	13.1
Lignite Coal	2.3	1.4	0	14.8	0.0	0.0
Natural Gas	18.3	12.7	27.4	49.4	55.5	1.5
Petroleum Fuels	2.8	3.6	0.5	0.5	11.5	77.4
Other Fossil Fuels	0.2	0.2	0.3	0.2	0.0	0.2
Nuclear	19.9	23.0	9.9	12.4	0.0	0.0
Hydro	6.8	3.4	24.6	0.3	23.0	0.8
Renewable Fuels	1.5	1.7	1.3	0.2	0.1	4.2
Geothermal	0.4	0.0	2.1	0.0	0.0	1.9
Wind	0.4	0.1	1.0	0.9	0.0	0.1
Solar (PV)	0.0	0.0	0.1	0.0	0.0	0.0
Fossil Fuel Total	71.2	71.8	60.9	86.2	76.9	93.1
Renewable (Non Hydro)	2.2	1.8	4.6	1.1	0.1	6.1

Table 5 - Source Energy Factors for Delivered Electricity (Kilowatt-hours of source energy per Kilowatt- hours of delivered electricity) [25]

Energy Type	National	Eastern	Western	ERCOT	Alaska	Hawaii
T & D Losses	9.9%	9.6%	8.4%	16.1%	12.9%	8.9%
Fossil Fuel Energy *	2.500	2.528	2.074	3.168	3.368	3.611
Non Renewable Energy **	3.188	3.321	2.415	3.630	3.386	3.653
Renewable Energy ***	0.177	0.122	0.480	0.029	0.264	0.368
Total Energy	3.365	3.443	2.894	3.658	3.650	4.022
* Fossil Fuel Energy includes all coal, natural gas, petroleum fuels, and other fossil fuels **Non Renewable Energy includes Fossil Fuel Energy and nuclear energy ***Renewable Energy includes hydro, renewable fuels, geothermal , wind and solar PV						

Figure 4 shows that North America is divided into regions for the purpose of determining specific energy factors. Table 4 shows the different fuel source types and the percentage of energy that they produce in each of the regions. It is important to note that there are significant differences in the fuel source percentages across the regions. This shows why each region was segregated but also shows there are underlying assumptions in using these factors. If the energy production characteristics of a region change then the energy factors would need to be recalculated. Ensuring that the fuel source breakdown is applicable to the region of study is critical for accurately determining energy consumption and making comparisons across modes. The difference is illustrated in that the Hawaii region uses 77% petroleum fuels and no nuclear fuels while the Eastern region uses only 2.8% petroleum fuels and 23% nuclear fuels. Ensuring accurate fuel source breakdown will become increasingly more important in the event that this script is expanded to model emissions.

Table 5 shows the energy conversion factors for each of the regions in Figure 4 and the overall national average. The factors in the table represent the kilowatt-hours of source energy consumed per kilowatt-hours of delivered electricity. The disadvantage of this method, using a single factor to account for multiple sources of energy loss and determine final energy consumption, is that the factor is highly dependent upon a number of assumptions and any changes in the assumptions will affect the accuracy of the calculations. However, the advantage is that it provides flexibility in being able to easily model energy consumption and its losses in different regions of North America. This is highly beneficial because the focus of this work is not the energy consumption analysis so this method allows for a quick, accurate measure of energy consumption without having to develop complex algorithms or make determinations about each of the types of losses individually.

Another feature included in the model is energy regeneration by the train. Energy regeneration is becoming a common feature on modern railways and automobiles alike. The most commonly used method is regenerative brakes. This method works by changing the connections in the motor so that the motor of the vehicle is converted to a generator. This allows the motor to convert the kinetic energy of the train to electrical current which can be passed into some other device on the train that is currently drawing power, some type of energy storage system (battery bank, compressed air tank, flywheel, etc.) or the current can be fed back into the electrical grid, if the train is connected to the grid and has the necessary equipment.

While regenerative braking does capture a portion of the energy consumed, it should be noted that it is limited in its application. It is only able to capture a small portion of the energy used to accelerate the vehicle and the vehicles still require the use of mechanical brakes. Regenerative braking “force” is related to the speed of the vehicle since the resistance of the motor (generator) is the braking force; at lower speeds, there is less braking force therefore mechanical brakes are required to be able to bring the vehicle to a stop. As well, in emergency situations, more braking force is needed than the maximum force that can be supplied by the regenerative brake therefore the regenerative brakes cannot be the only braking system installed.

At the time of this publication, only empirical studies on the amount of energy regenerated by regenerative braking were found. No method of modeling energy regeneration is available unless electrical grid modeling is also included in a model. The studies vary but estimate that the percentage of energy regenerated varies between 5-20% of the total energy consumed. However, these studies were mostly conducted on electrical subways and smaller trains therefore the approximation may not directly apply. As well, the studies do not provide any information about the speeds the vehicles were traveling and the travel distance over which the analysis occurred. The best measurement comes from an analysis of the Acela Express regenerative braking system.[26] This work conducted field measurements on the Acela train and found that the average energy recovery ratio was 7.65%. This work however does not provide the travel speeds of the trains. Therefore, this model has conservatively assumes that 5% of total energy consumption of the rail vehicle can be recaptured. This should be used with caution because the energy regeneration occurs only during the braking phase therefore this number can vary largely with the distance between stops. An example would be a train that runs for 3 hours consecutively (between stops); this train is likely to recover only a very small portion of the total energy consumed. This is because the great majority of the energy consumed would be used during the cruise phase, therefore only a small portion of the total energy could be recovered. Therefore, the energy regeneration would need to be more thoroughly examined in order to make detailed assessments or comparisons.

Figures C2, C3, and C4 below show sample graphical output from the model; the figures represent a Shinkansen 100 series train traveling 20,000 meters at a maximum cruising speed of 50 m/s. The deceleration rate in this trip is 1 meter/second. Figure 5 shows the train's tractive effort rate vs. time. It shows that the greatest tractive effort generated by the engine is at the beginning of acceleration; note that per the calculation, the tractive effort is capped at a maximum value to prevent wheel slip. The tractive effort produced by the motor decreases as the speed of the vehicle increases and then reaches "steady state" during the cruise phase.

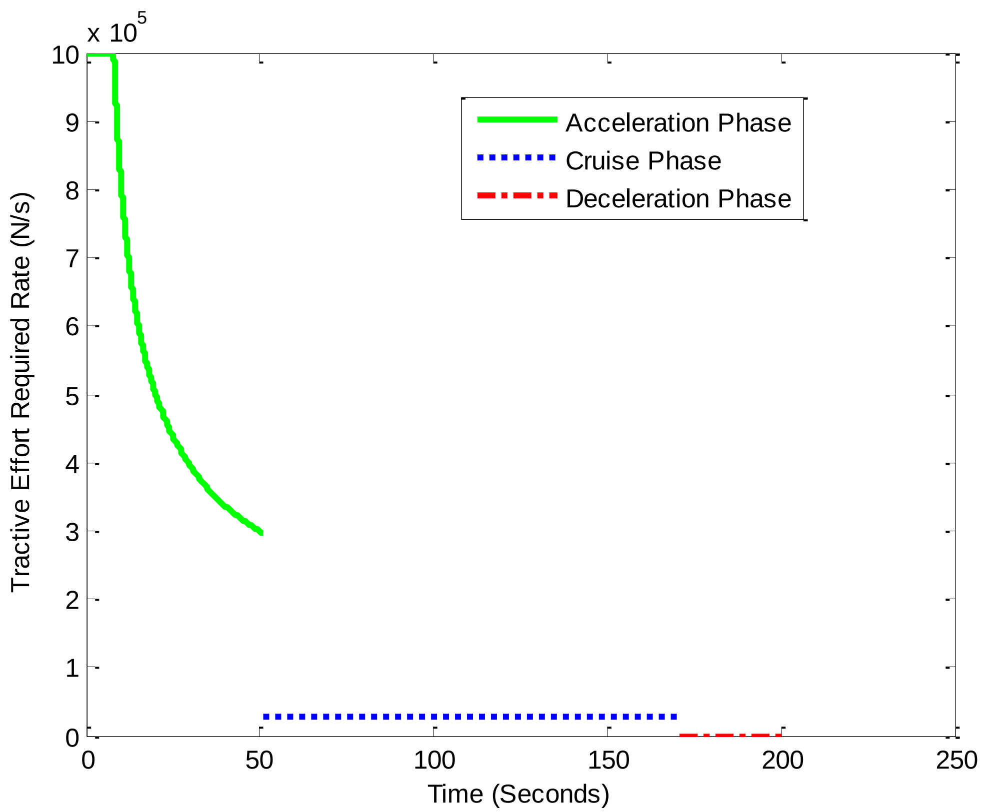

Figure 5 - Vehicle Tractive Effort Rate vs. Time

Figure 6 shows the train's energy consumption rate vs. time. It should be noted that the energy consumption rate is also greatest at the beginning of acceleration and that the rate decreases slightly during the acceleration phase, although it is not visible in Figure 6. Once the vehicle reaches cruising speed, the energy consumption drops significantly therefore showing the advantages in keeping a vehicle in steady state (cruise) mode as much as possible. One important detail is that the energy created by regenerative breaking is not modeled in Figure 6 because it is modeled as a percentage of total energy consumed during acceleration and cruise. However, the regenerated energy is shown in Figure 7.

Figure 7 shows the cumulative energy consumed by the train vs. time. It is important to highlight that while the train spends most of the time in cruise mode, the majority of the consumed energy is used during acceleration. Obviously, this will not always hold true, particularly on long trips with no stops, however it does highlight the importance of trying to reduce energy consumption by attempting to minimize stops and perhaps using a lower cruise speed, particularly on short distance segments. In addition to the graphical output, the numeric values of total travel time between stations, total energy consumed by the train, total energy consumed per passenger (based on train capacity and load factor), total raw potential energy consumed by the train, and the total raw potential energy consumed per passenger.

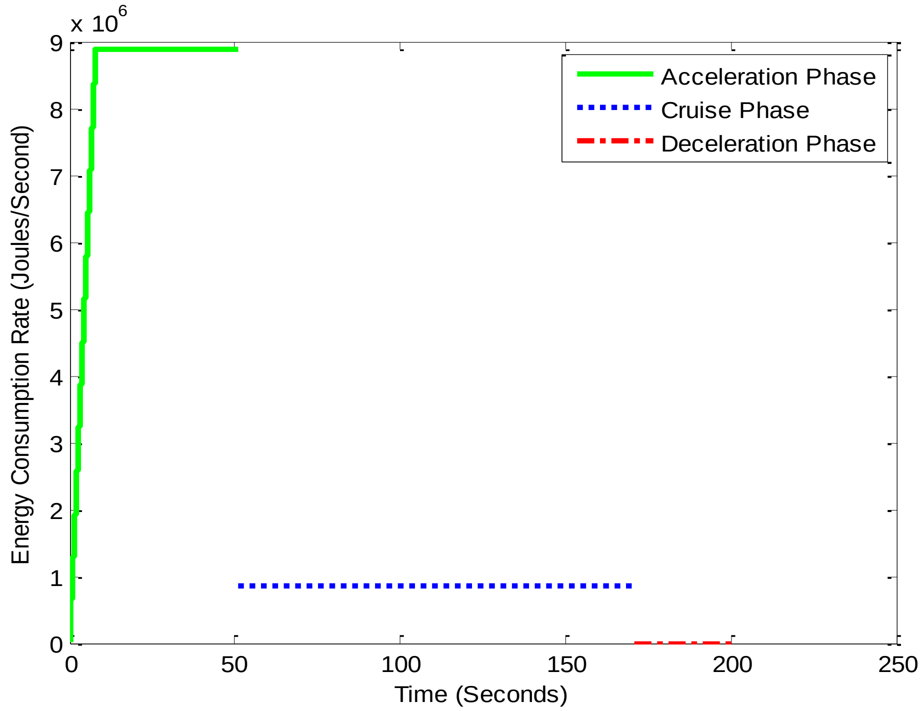

Figure 6 - Vehicle Energy Consumption Rate vs. Time

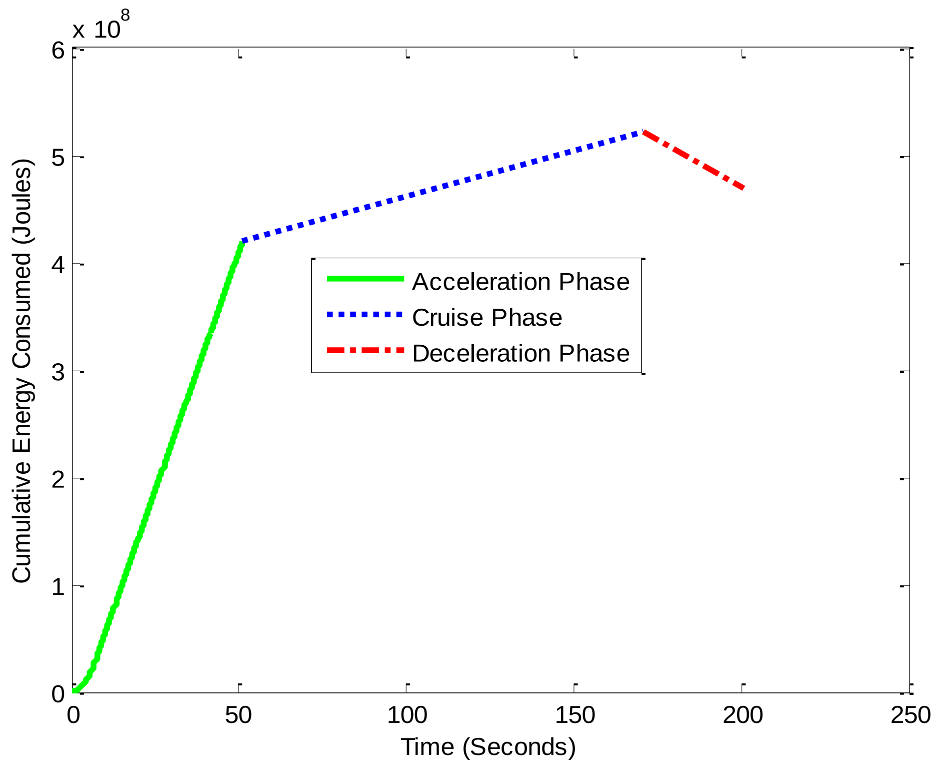

Figure 7 - Vehicle Cumulative Energy Consumed vs. Time

Description of American Travel Survey (ATS) Data Set

The American Travel Survey (ATS) is a survey of approximately 80,000 randomly selected households in the United States; the data was collected about trips that actually occurred, therefore providing revealed preference (RP) data. It collected information about all intercity trips, longer than 100 miles, which were taken by household members. The survey was collected to capture information about the approximately 1 billion person trips that occurred in 1995. The data in the survey is applied a weight factor, which is discussed later, so it can be scaled up to represent the 1 billion trips.

For modeling purposes, the ATS data has been separated into groups by income category and also trip purpose. There are 5 income groups and 2 trip purpose categories, the trip purposes are business and non-business. The income categories are shown in Table 6. This effectively creates 10 separate models for the data. This segmentation of data is based on previous analyses in the development in TSAM that showed there are distinct differences in the behavior of people in each of the different groups.

Table 6 - TSAM Income Category Divisions - $(1995)

Income Category	Income Range
Category 1	< $25,000
Category 2	$25,000 - $50,000
Category 3	$50,000 - $75,000
Category 4	$75,000 - $125,000
Category 5	> $125,000

Mode Split Analysis - C Logit Model

The first model to be analyzed for mode split modeling is the C logit model. This is one of the most commonly employed models for mode split analysis; information on this model is widely available. The model utilizes a utility function that uses data about a specific mode as well as socioeconomic data about the users to capture the benefit that the user obtains from the mode. The probability of choosing a given mode is calculated as:

$P(i) = \frac{e^{U_i}}{\sum_{i=1}^{i} e^{U_i}}$ ………..... (11)

$U_i = \text{Utility of mode i}$

$P(i) = \text{Probability of choosing mode i}$

For this first attempt to calibrate a C logit model, only data for automobile and commercial air is used, thus since there are only two modes available, the mode with a probability greater than 0.5 is the mode that the model "chooses" for the corresponding trip. The model is calibrated by using the log likelihood maximization. Log likelihood maximization is a commonly used statistical technique that is used to determine the best statistical fit to the data. Information about log likelihood maximization is widely available, more information could be found in a choice theory modeling textbook or the internet.

The C-logit model calibrations that follow have been executed using the program "Mixed Logit Estimation for Cross-Sectional Data using Maximum Simulated Likelihood" written by Kenneth E. Train. This code is publicly available at the website http://elsa.berkeley.edu/~train/software.html.[27] The code has been set up to run as a standard fixed coefficient logit model. The code is executed in the software Gauss, Version 9.0. The first model is calibrated using the ATS data, only automobile and air transportation modes. The utility functions of this initial model are:

$U_{auto} = \alpha_{travel\ time} * Travel\ Time_{auto} + \alpha_{cost} * Travel\ Cost_{auto}$ ………..... (12)

$U_{air} = \alpha_{travel\ time} * Travel\ Time_{air} + \alpha_{cost} * Travel\ Cost_{air}$ ………..... (13)

The number of observations for each of the 10 different categories is listed in Table 7. It should be noted that for the Business Groups, any trip over 700 miles one way has been filtered out of the analysis; this is because there are few data points in the longer range trips and thus the distribution becomes inconsistent and unreliable. The calibration is conducted using both weighted and un-weighted data. The results of these calibrations are shown in Table 8 and Table 9.

Table 7 - Number of ATS Observations in Each Trip Purpose / Income Group Category

Trip Purpose/ Income Category	# of Data Points
Business 1	8663
Business 2	27868
Business 3	20919
Business 4	12135
Business 5	3336
Non Business 1	40736
Non Business 2	84178
Non Business 3	51347
Non Business 4	24217
Non Business 5	18072

C- Logit Model - Comparison of Weighted vs. Un-weighted Data:

Table 8 - Summary of Coefficients for Un-Weighted ATS Data

	Travel Time	Travel Cost	TT Std. Error	TC Std. Error	Ratio TT/TC	Correct Prediction (%)
Business 1	-0.02657	-0.00902	0.00392	0.00209	2.94524	92.27
Business 2	-0.03692	-0.00861	0.00264	0.00013	4.28838	91.86
Business 3	-0.05406	-0.00585	0.00231	0.00009	9.24248	84.22
Business 4	-0.07446	-0.00571	0.00318	-0.00571	13.04691	85.09
Business 5	-0.10249	-0.00226	0.00608	0.00206	45.28120	80.88
Non-Business 1	-0.04332	-0.00978	0.00118	0.00008	4.43198	92.20
Non-Business 2	-0.04955	-0.01053	0.00081	0.00006	4.70408	93.10
Non-Business 3	-0.05038	-0.00970	0.00106	0.00007	5.19496	91.29
Non-Business 4	-0.06011	-0.00922	0.00180	0.00010	6.51934	90.72
Non-Business 5	-0.07029	-0.00746	0.00423	0.00017	9.41740	88.08

Table 9 - Summary of Coefficients for Weighted ATS Data

	Travel Time	Travel Cost	TT Std. Error	TC Std. Error	Ratio TT/TC	Correct Prediction (%)
Business 1	-0.04436	-0.00951	0.00859	0.00046	4.466481	92.31
Business 2	-0.01595	-0.00970	0.00513	0.00257	1.64321	91.83
Business 3	-0.05638	-0.00529	0.00527	0.00194	10.66700	84.29
Business 4	-0.05842	-0.00662	0.00550	0.00203	8.82330	84.17
Business 5	-0.08360	-0.00361	0.01844	0.00336	23.17834	80.21
Non-Business 1	-0.04690	-0.01132	0.00263	0.00020	4.14298	92.11
Non-Business 2	-0.04783	-0.01173	0.00162	0.00014	4.07639	92.91
Non-Business 3	-0.04813	-0.01061	0.00228	0.00016	4.53747	91.08
Non-Business 4	-0.05497	-0.00882	0.00189	0.00011	6.23295	90.56
Non Business 5	-0.06162	-0.00744	0.00957	0.00039	8.27910	87.70

Table 8 and Table 9 show the travel time and travel cost coefficients for un-weighted and weighted ATS data respectively. The un-weighted data represents the raw number of trips collected during the survey; the weighted data is data that has been multiplied by a scaling factor so that the total number of trips is 1 billion. The tables also show the standard error that is associated with each coefficient. The important item to notice is the Ratio – TT/TC column, which shows the ratio of the travel time coefficient to the travel cost coefficient. This column states how important travel time is relative to travel cost for users in the respective income group; for example, in Table 8, users in income group 2 consider travel time to be 4.29 times more important than travel cost. The last column of both tables shows the percentage of predictions that the model estimates correctly. The model predictions were compared with the actual ATS data choices to determine the percentage of choices that the model predicted correctly.

Table 8 shows that the ratio of TT/TC is monotonically increasing from low-income groups to high-income groups in both the business and non-business categories. While the ratio for non-business trips in Table 9 is similar to that of Table 8, there is considerable difference between the business group ratios of the figures. The ratios for the business group - weighted data are no longer monotonically increasing, and they have changed significantly from their counterparts in the un-weighed data. This indicates one of the shortcomings of the ATS data; the method that was used to determine weighting factors. It is known intuitively and from multiple studies that users in higher income groups value travel time more than travel cost relative to lower income groups; this is because they tend to have more discretionary income and are able to pay additional costs for a travel time benefit. The weighted coefficient values contradict this fact by implying that users in income group 1 value time more than users in group 2.

Improvement of C- Logit Coefficient Optimization

In the preceding tables, Table 8 and Table 9, the model was calibrated using all of the ATS data and then the percentage of correct predictions was determined. The correct predictions in that case is somewhat biased because the model has already been calibrated against the data. In an effort to add validity to the model, the calibration is improved by randomly selecting approximately 2/3 of the data for calibration and the remaining data for the validation. This will allow analysis on data that the model is not calibrated against, thus providing a more realistic measure of how well the model can predict trips. The randomization of the data is accomplished by entering the data in Excel and assigning a random number between 0 and 1 to each data point, then any data with a random number less than 0.65 is used for calibration and any above 0.65 is used for validation. Table 10 and Table 11 below summarize the results.

Table 10 - Summary of Coefficients for Random Portion of Un-Weighted Data

	Travel Time	Travel Cost	TT Std. Error	TC Std. Error	Ratio – TT/TC	Correct Prediction (%)
Business 1	-0.02407	-0.00888	0.00482	0.00026	2.70996	93.02
Business 2	-0.03930	-0.00862	0.00333	0.00016	4.56462	91.75
Business 3	-0.05675	-0.00584	0.00292	0.00011	9.71945	83.91
Business 4	-0.07433	-0.00571	0.00396	0.00015	13.02549	84.96
Business 5	-0.10129	-0.00229	0.00760	0.00026	44.30826	81.00
Non-Business 1	-0.04415	-0.00977	0.00150	0.00010	4.51727	92.33
Non-Business 2	-0.04950	-0.01051	0.00100	0.00008	4.70893	93.01
Non-Business 3	-0.05044	-0.00978	0.00132	0.00009	5.15678	91.14
Non-Business 4	-0.05894	-0.00904	0.00221	0.00012	6.51690	91.48
Non Business 5	-0.06513	-0.00727	0.00499	0.00020	8.96423	88.29

Table 11 - Summary of Coefficients for Random Portion of Weighted ATS Data

	Travel Time	Travel Cost	TT Std. Error	TC Std. Error	Ratio – TT/TC	Correct Prediction (%)
Business 1	-0.04078	-0.00901	0.01079	0.00056	4.52679	93.18
Business 2	-0.03155	-0.00881	0.00726	0.00284	3.57929	91.76
Business 3	-0.05740	-0.00600	0.00484	0.00020	9.57084	83.83
Business 4	-0.06194	-0.00637	0.01284	0.00060	9.72681	84.04
Business 5	-0.06949	-0.00375	0.02141	0.00045	18.55323	79.71
Non-Business 1	-0.04604	-0.01113	0.00336	0.0025	4.13467	92.16
Non-Business 2	-0.04645	-0.01165	0.00210	0.00018	3.98789	92.80
Non-Business 3	-0.05013	-0.01092	0.00218	0.00018	4.59039	90.93
Non-Business 4	-0.05571	-0.01054	0.00349	0.00025	5.28771	90.60
Non-Business 5	-0.05638	-0.00729	0.01091	0.00452	7.73349	87.48

Table 10 and Table 11 show that the coefficients for each income/trip purpose group, as well as the travel time/travel cost ratios, did not change significantly because of the use of the random portion of data for validation approach. The important result is that the new model still predicts the mode choice well; the correct prediction percentages of the new model are similar to those from the previous calibration. This adds validity because the new model, using “unseen” data, is able to predict equally as well as the original model, which was calibrated against all of the data. The travel time/travel cost ratios of the business group for the weighted data have improved; they are closer to monotonically increasing but they still do not match expectations or the previous model. This is likely due to the ATS weight factors which are discussed below.

Skepticism of ATS Weight Factors

Again the ATS data was collected in 1995 and recorded data for 550,000 intercity trips that were taken in the U.S. The weighting factors were applied so that the data set could be scaled up to the estimated 1 billion intercity trips that occurred that year. The weighting factors are assigned by dividing the data into groups based on multiple socioeconomic factors of the surveyed user and then determining how many people/households in the U.S. had similar characteristics. It is assumed that everyone within each socioeconomic group will make travel decisions in a similar manner; based on surveyed users in the socioeconomic group. However, in the ATS data, not all origin-destination pairs had numerous observations; some pairs had only one observation. Thus, when these data points receive their weight, a small number of choices has a large effect on the model, and if the user made a choice that is not necessarily in line with their income group/ trip purpose/length etc., then this data will greatly skew the results.

For example, there is only 1 record for travel from Nashville to Atlanta. The surveyed user chose to drive for this trip, despite the fact that most travelers chose to fly this trip, so the result is that when the weight factor is applied, the model determines that the majority of users drive between this origin-destination pair when in actuality, it is the opposite. This is what causes the irregularities in the coefficients of the weighed data.

Based on the discussed issues, it appears that it would be beneficial to continue the analysis using the un-weighted data. However, the specific details of the ATS's method to determine the weight factors are not published, therefore we must assume that the method is without flaws. In order to drop the weights from further analysis, we must test to see if the distributions of the trips vs. distance for the un-weighted and weighted variables are equivalent. If the distributions prove to be equivalent, this will imply that the weight factors are used only to scale up the total number of trips instead of potentially being used as a correction factor for the distribution of nationwide trips. It is possible that the weights are used to change the distribution because some areas/income groups/origin-destination pairs may not have been representatively sampled therefore an adjustment is necessary to represent the "true distribution".

Analysis of ATS Weight Factor Effect

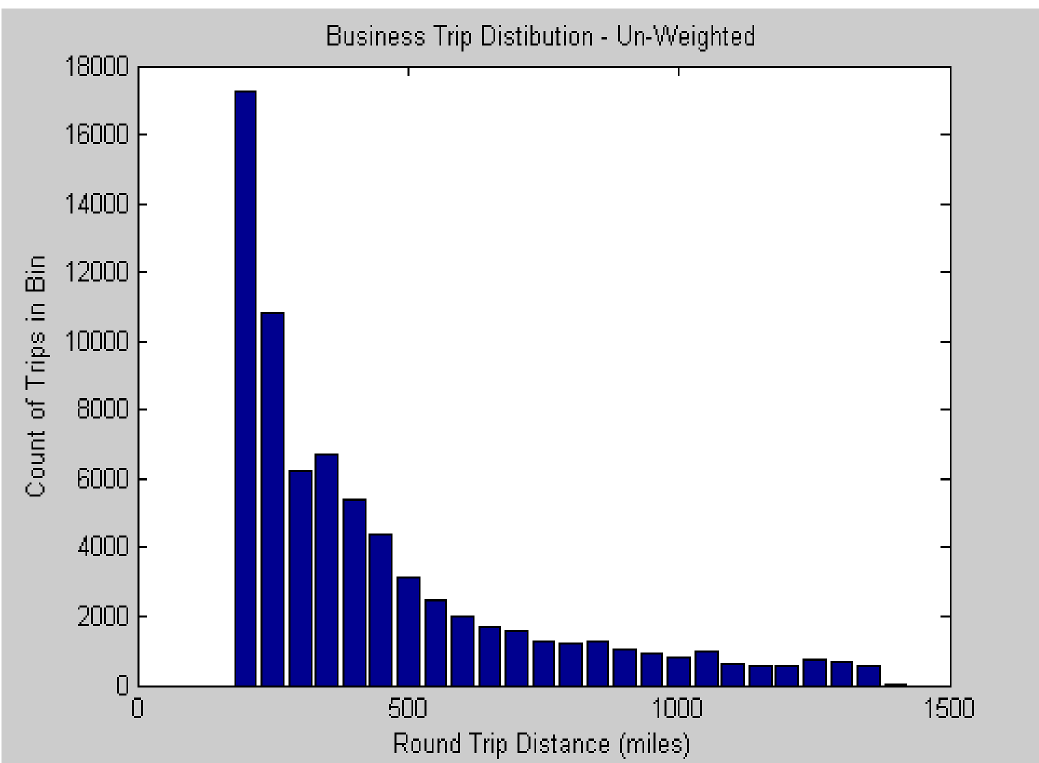

Figure 8 - Business Trip Distribution of Un-Weighted ATS Data

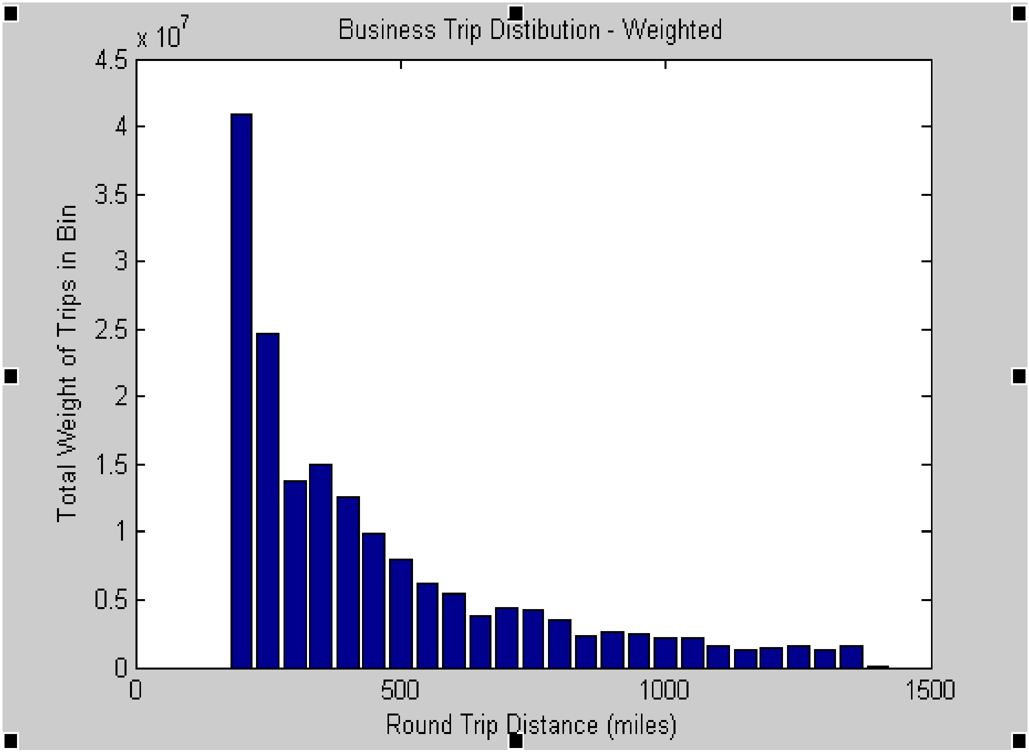

Figure 9 - Business Trip Distribution Weighted Data

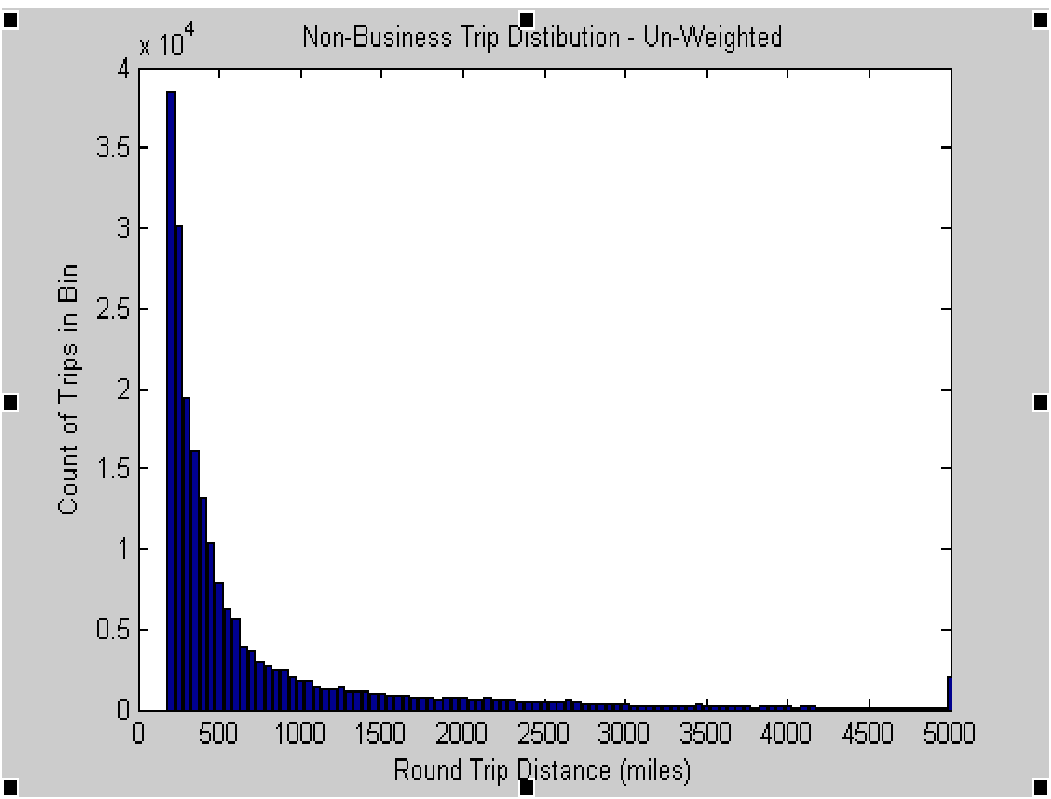

Figure 10 - Non Business Trip Distribution of Un-Weighted Data

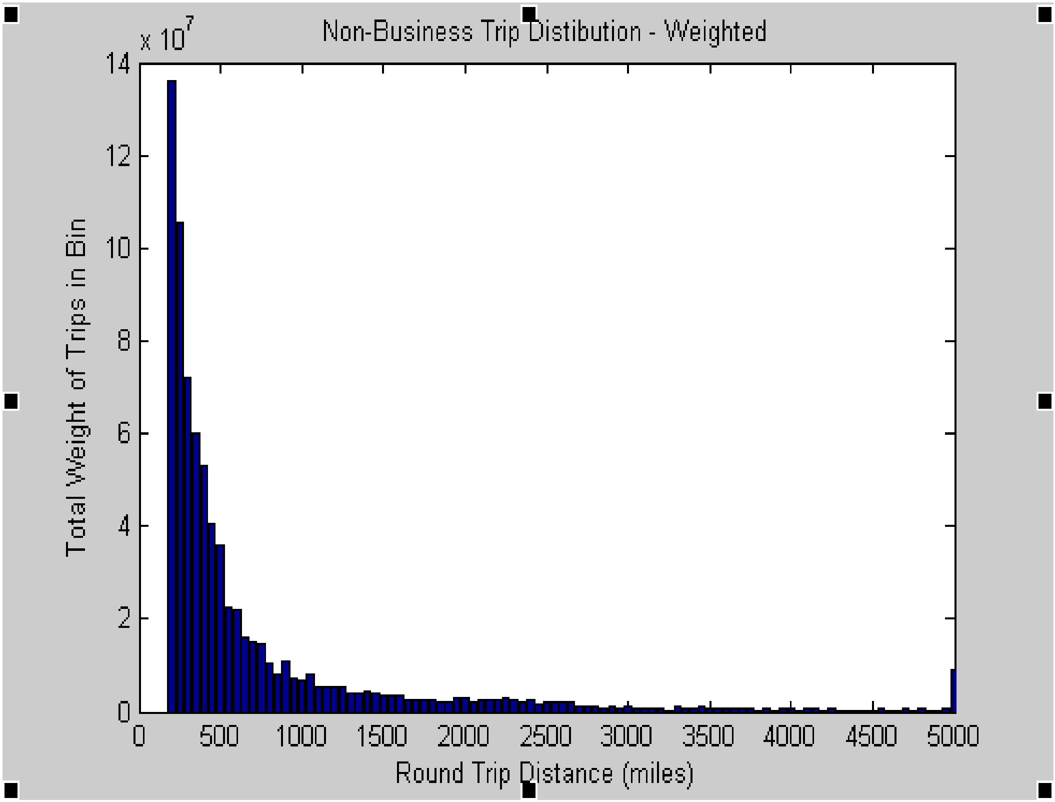

Figure 11 - Non Business Trip Distribution of Weighted Data

A visual comparison of Figure 8 vs. Figure 9 and Figure 10 vs. Figure 11 seems to indicate that the distribution of trips in unchanged by applying the ATS weight factor. The figures shown above are generated by binning data in 50 mile intervals. Note that trips in the Business data group that exceeded 700 miles one way were filtered out due to scarcity of data points for long-range trips.

Two different tests, Chi Square and Kolmogorov-Smirnov, are shown below to test the hypothesis that the distributions are equivalent. The Chi Square test is executed first; the formulation for the test is:

$$X^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad \text{............ (14)}$$

where:

X^2 = Pearson's cumulative test statistic; asymptotically approaches χ^2 distribution.

O_i = an observed frequency.

E_i = expected (theoretical) frequency, asserted by the null hypothesis.

n = the number of cells in the table.

If the X^2 is greater than the critical value, which can be found by using the degrees of freedom, desired confidence, and a widely available Chi Square table, then you reject the null hypothesis.

In this case, the null hypothesis is: H_o: Un-weighted Distribution = Weighted Distribution and H_1: Un-weighted Distribution ≠ Weighted Distribution. For this test, the values of the weighted distribution are treated as the expected value and the un-weighted values are the observed frequency. The degrees of freedom are calculated as the number of bins - 1. The results for the business and non-business group tests are:

Business Test:
X^2 = 560.1
Critical X^2 = 36.4 (degrees of freedom = 24; assuming 95% confidence (α=0.05))
560.1 > 36.4 thus reject H_o

Non Business Test:
X^2 = 2154.4
Critical X^2 = 124 (degrees of freedom = 96; assuming 95% confidence (α=0.05))
2154.4 > 124 thus reject H_o

The results show that for both comparisons, the samples are not from the same distribution, which would prevent the dropping of the weight factors. In order to validate the results, the two sample Kolmogorov-Smirnov test was calculated. The two sample Kolmogorov-Smirnov test is a non-parametric test that can be used to determine if two samples have the same distribution. The advantage of this test is it is non-parametric; this implies that the distribution type is not specified by the test. The formulation of the test is:

$D_{n,n'} = sup_x \left| F_{1,n}(x) - F_{2,n'}(x) \right|$ ………..... (15)

$F_{1,n}$ and $F_{2,n'}$ are the empirical distribution functions of the sample.

The Null Hypothesis is rejected at level α if:

$\sqrt{\frac{nn'}{n+n'}} D_{n,n'} > K_\alpha$ ………..... (16)

The critical K_α can be calculated as:

$K_\alpha = c(\alpha)\sqrt{\frac{n_1 + n_2}{n_1 n_2}}$ ………..... (17)

Where:

Table 12 - Parameters for Kolmogorov-Smirnov Test

α	0.1	0.05	0.025	0.01	0.005	0.001
c(α)	1.22	1.36	1.48	1.63	1.75	1.95

In Table 12, α represents the confidence level. More information about the data in Table 12 is available at www.soest.hawaii.edu/wessel/courses/gg313/Critical_KS.pdf.[28] The test results for each group are:

Business Test:

Test Value = 6.4526

Critical Value= 0.0050

6.4526 > 0.0050 thus reject H_o

Non Business Test:

Test Value = 13.13

Critical Value = 0.0029

13.13 > 0.0029 thus reject H_o

The results of both the business and non-business tests show that the distributions are not the same in either case. This validates the results of the Chi Square test and determines that the distribution is statistically different by applying the weight factor. Therefore the weighting factors will continue to be applied in the model.

Model Comparison Metric

The results of the statistical tests prove the original hypothesis, which states that the distributions are the same, is false. Based on the results, all analyses will use the weight factors. As well, direct comparison of the two models shows that they perform similarly. This comparison is accomplished with the % Correct metric; the calibrations are optimized using log likelihood values but log likelihood is not easy to interpret and generally does not allow for comparisons across models, therefore the % Correct metric is developed in order to provide an easily interpretable comparison metric. In the initial model, since there are only two alternatives, it is assumed that the alternative with the highest probability is the one that is "predicted" by the model. This prediction is then compared to the actual choice that the user made. Then the percentage of the total trips that are predicted correctly are calculated and used as the metric. This method is not the most precise, however it provides a quick, easy way to compare the different models.

Table 13 - Comparison of Un-Weighted vs. Weighted Model Predictions

	% Correct (Un-weighted)	% Correct (Weighted)
Business 1	93.7	93.8
Business 2	92.1	91.2
Business 3	85.7	83.5
Business 4	85.0	82.1
Business 5	79.8	83.7
Non-Business 1	91.9	92.8
Non-Business 2	93.1	93.1
Non-Business 3	91.5	92.0
Non-Business 4	88.5	89.1
Non-Business 5	85.1	86.2

Table 13 shows the percentage of correct predictions for the weighted and un-weighted models for each of the 10 different categories. It is shown that there is not a significant difference in how the percentage of correct predictions changes, in most cases the weighted model predicts more trips correctly than the un-weighted. So, although it has been shown that there are some flaws with the ATS weight factors, we will continue to use them for the remaining analysis.

C- Logit Model - Utility Function Variation

In a search to try to achieve a better overall fit from the model, it is postulated that breaking the total travel time into in-vehicle time and out-of-vehicle time will improve the model. The theory is that a traveler may perceive out of vehicle time or “idle” time more negatively than in-vehicle time. If true, then for example, if a traveler faces a choice between using a private automobile or a bus system to take a trip, with both modes having equal travel time, the traveler will be more likely to choose the automobile because there will not as much out-of-vehicle time (transfer time, time waiting on bus to arrive, security processing time, etc.). This example is assuming that the mode choice decision is based solely on travel time but it illustrates the difference between in vehicle and out of vehicle travel time. The utility functions for this modification are:

$$U_{auto} = \alpha_{in\ veh.time} * In - Veh.Time_{auto} + \alpha_{out\ veh.time} * Out\ Veh.Time_{auto} + \alpha_{cost} * Travel\ Cost_{auto} \quad \ldots\ldots\ldots\ldots (18)$$

$$U_{air} = \alpha_{in\ veh.time} * In - Veh.Time_{air} + \alpha_{out\ veh.time} * Out\ Veh.Time_{air} + \alpha_{cost} * Travel\ Cost_{air} \quad \ldots\ldots\ldots\ldots (19)$$

For the automobile mode, the in-vehicle time is defined as the county to county driving time and the out-of-vehicle time is defined as any forced lodging time; it is assumed that access/egress time for the automobile is 0. For the airplane mode, the in-vehicle time is defined as the access/egress times to airport and the airport-airport flight time. The out-of-vehicle time is the schedule delay, inbound processing time, outbound processing time, and any forced lodging time. The results are shown in Table 14 and Table 15.

Table 14 - Utility Equation Coefficients for Two Variable Formulation

	TT Coefficient	TC Coefficient	% Correct
Business 1	-0.0349	-0.0089	93.7
Business 2	-0.0379	-0.0088	92.1
Business 3	-0.0619	-0.0088	85.7
Business 4	-0.0841	-0.0057	85.0
Business 5	-0.0101	-0.0024	79.8
Non-Business 1	-0.0423	-0.0099	91.9
Non-Business 2	-0.0493	-0.0106	93.1
Non-Business 3	-0.0507	-0.0097	91.5
Non-Business 4	-0.0595	-0.0092	88.5
Non-Business 5	-0.0717	-0.0075	85.1

Table 15 - Utility Equation Coefficients for Three Variable Formulation

	In Vehicle TT Coefficient	Out- Vehicle TT Coefficient	TC Coefficient	% Correct
Business 1	0.0982	-0.1486	-0.0620	93.5
Business 2	0.0872	-0.1542	-0.0060	91.9
Business 3	-0.0161	-0.1068	-0.0048	85.8
Business 4	-0.1099	-0.0573	-0.0064	85.0
Business 5	-0.1687	-0.0266	-0.0041	79.7
Non-Business 1	-0.1630	0.0571	-0.0121	91.8
Non-Business 2	-0.1352	0.0244	-0.0122	93.1
Non-Business 3	-0.1446	0.0332	-0.0116	91.4
Non-Business 4	-0.1689	0.0429	-0.0116	90.3
Non-Business 5	-0.1957	0.0517	-0.0103	87.5

Table 14 provides the results of the calibration using the original, two variable utility equation. It shows the coefficients of the variables as well as the % Correct for each trip purpose/income group. Table 15 shows the results of the calibration using the three-variable utility equation. A comparison of the percent correct metric between the two tables shows that there is no significant difference in the two models, which implies that there is no benefit in using the modified utility equations. Practically, this implies that the users did not change their mode choice based on the out- vehicle time; they appear to base their decision solely on the overall travel time. A closer look at Table 15 also shows there is a problem with using the modified utility equation; some of the variable coefficients are positive. For example, the In-Vehicle TT coefficient for Business 1 group would imply that if the In-Vehicle travel time is increased for a given mode, then that mode would have a higher utility, which would make the user more likely to choose that mode. Obviously, if the travel time is increased for a mode, then it would be less favorable to the user therefore these coefficients would go against conventional logic. For this reason, the original two-variable utility equation formulation will be used.

Validation of C Logit Coefficient Optimization Code

Table 16 - Validation of C-logit Optimization Code

Simulations	Initial Values	Travel Time Coefficient	Travel Cost Coefficient	Function Value	Convergence
100	-0.01,-0.01	-0.01594	-0.00970	-15459802	Yes
100	-0.1,-0.1	-0.01594	-0.00970	-15459801	Yes
100	-0.5,-0.5	-0.01594	-0.00970	-15459801	Yes
100	-0.01,-0.5	-0.01594	-0.00970	-15459801	Yes
100	-0.1,-0.01	-0.01594	-0.00970	-15459801	Yes
250	-0.01,-0.01	-0.01594	-0.00970	-15459802	Yes
250	-0.1,-0.1	-0.01594	-0.00970	-15459802	Yes
250	-0.5,-0.5	-0.01594	-0.00970	-15459802	Yes
250	-0.01,-0.5	-0.01594	-0.00970	-15459802	Yes
250	-0.1,-0.01	-0.01594	-0.00970	-15459802	Yes
1000	-0.01,-0.01	-0.01594	-0.00970	-15459802	Yes
1000	-0.1,-0.1	-0.01594	-0.00970	-15459801	Yes
1000	-0.5,-0.5	-0.01594	-0.00970	-15459801	Yes
1000	-0.01,-0.5	-0.01594	-0.00970	-15459801	Yes
1000	-0.1,-0.01	-0.01594	-0.00970	-15459801	Yes

A simple test is conducted to verify the consistency and robustness of the C-logit optimization code that is used. The purpose is to ensure that the code produces consistent results and that is it not susceptible to be influenced by the starting values or being caught in a local optimum point. Table 16 above shows the results of the test. The income group 2, business purpose data is utilized for the test. The code is run with different combinations of starting values for the coefficients and # of simulations. Table 16 shows that the same travel time and travel cost coefficients are produced regardless of initial parameters; as well, the log likelihood function converges to the same value. Although there is generally no guarantee that the results produced are globally optimal, the results show that the model is robust and consistent in its optimization methods, at least for the purposes of this analysis.

Logit Model Improvement - Box Cox Transformation

In an effort to find a better modeling fit, as well maintaining consistency with the TSAM model, the box cox transformation is applied. The transformation is applied to both the travel time and travel cost variables of all modes. The new utility equations for use in the logit model are as follows:

$$U_{Auto} = \alpha_{TT} \frac{(TT_{Auto}^{\lambda_{TT\ Auto}} - 1)}{\lambda_{TT\ Auto}} + \alpha_{TC} \frac{(TC_{Auto}^{\lambda_{TC\ Auto}} - 1)}{\lambda_{TC\ Auto}} \quad \ldots\ldots\ldots\ldots (20)$$

$$U_{Air} = \alpha_{TT} \frac{(TT_{Air}^{\lambda_{TT\ Air}} - 1)}{\lambda_{TT\ Air}} + \alpha_{TC} \frac{(TC_{Air}^{\lambda_{TC\ Air}} - 1)}{\lambda_{TC\ Air}} \quad \ldots\ldots\ldots\ldots (21)$$

$$U_{Train} = \alpha_{TT} \frac{(TT_{Train}^{\lambda_{TT\ Train}} - 1)}{\lambda_{TT\ Train}} + \alpha_{TC} \frac{(TC_{Train}^{\lambda_{TC\ Train}} - 1)}{\lambda_{TC\ Train}} \quad \ldots\ldots\ldots\ldots (22)$$

Where:

TT_i = Travel Time of mode i for given trip

TC_i = Travel Cost of mode i for given trip

α_{TT} = Travel Time Coefficient
α_{TC} = Travel Cost Coefficient
λ_{TT_i} = Box Cox Travel Time (TT) Coefficient specific to mode i
λ_{TC_i} = Box Cox Travel Cost (TC) Coefficient specific to mode i

After the Box Cox transformation is applied, the new utility equations are used in the logit model to make the predictions. The calibration of the box cox model for each trip purpose/income group is accomplished using Microsoft Excel 2010 Solver. The GRG nonlinear solver was used with a convergence of 0.0001. The option of “Require Bounds on Variables” is also selected. The coefficients are bounded during the calibration; the bounds for each coefficient can be seen in Table 17. The bounds are necessary because otherwise the coefficients will take values that lead to errors in the mathematical calculations. As well, if the λ values become very large, it will effectively eliminate the effect of the variable because the response curve will either become flat or vertical.

Table 17 - Calibration Bounds for Box-Cox Coefficients

Coefficient		Lower Bound	Upper Bound
Travel Time	α	-10	-0.000001
	λ Auto	-2	1
	λ Air	-2	1
	λ Train	-2	1
Travel Cost	α	-10	-0.000001
	λ Auto	-2	1
	λ Air	-2	1
	λ Train	-2	1

Existing Train Network - Station to Station Travel Time and Cost

TSAM currently has rail network data that is representative of the rail network in the United States in 1995. It includes 464 Amtrak Rail Stations (please see Appendix B, Table 35 for the full station list), the track distance between stations, and the calculated schedule delay for travel between each station-station pair. This network was developed in an earlier work.[29] This data is used as the basis for development of the station-station travel time and travel cost matrices.

The first step is to develop baseline station-station travel time and travel cost matrices, the time and cost values will be representative of service conditions in 1995; this is accomplished using regression equations. The regression data is collected from Amtrak's website, www.Amtrak.com, using randomly selected origin-destination pairs across the United States. It is known that Amtrak's level of service (travel speed) has not changed significantly for a large number of years, the northeast corridor is the exception but a separate regression analysis is used for that corridor, therefore the travel times presented on the website are representative of the travel times in 1995.

Although train technology has greatly improved since 1995, the limiting factor for travel time is typically the track design. Amtrak currently operates older, outdated train technology, however improving the rolling stock will provide minimal travel time benefit until the track design is improved and the track is rebuilt to allow for faster travel times. For the collected travel cost data, the cost is representative of either coach or business class (lowest available); also, a lodging room on the train is not included. The travel cost data is collected in 2011 $'s however it is adjusted for inflation within the TSAM model. The curves are shown below in Figure 12 and Figure 13.

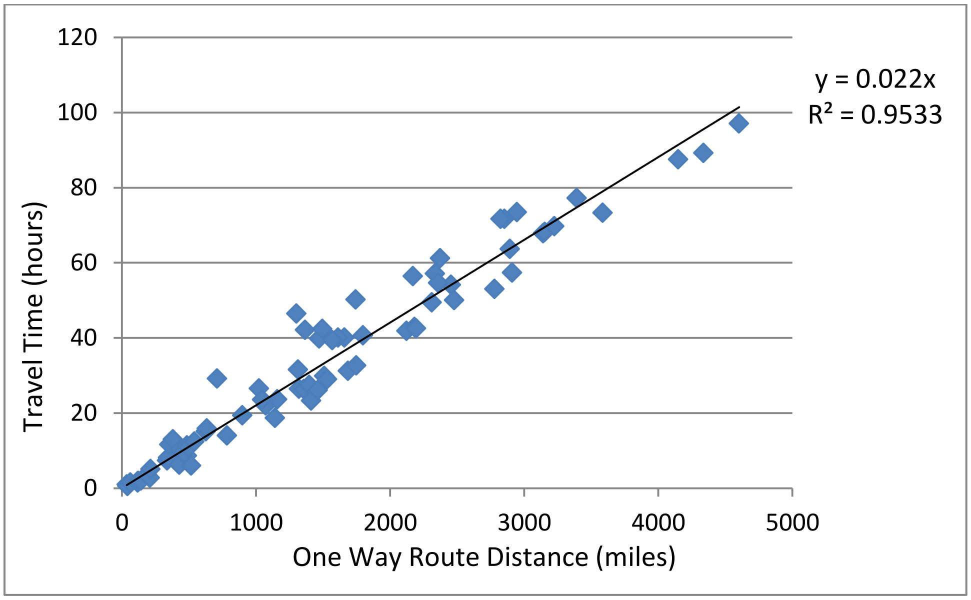

Figure 12 - Nationwide Train Travel Time Regression Curve

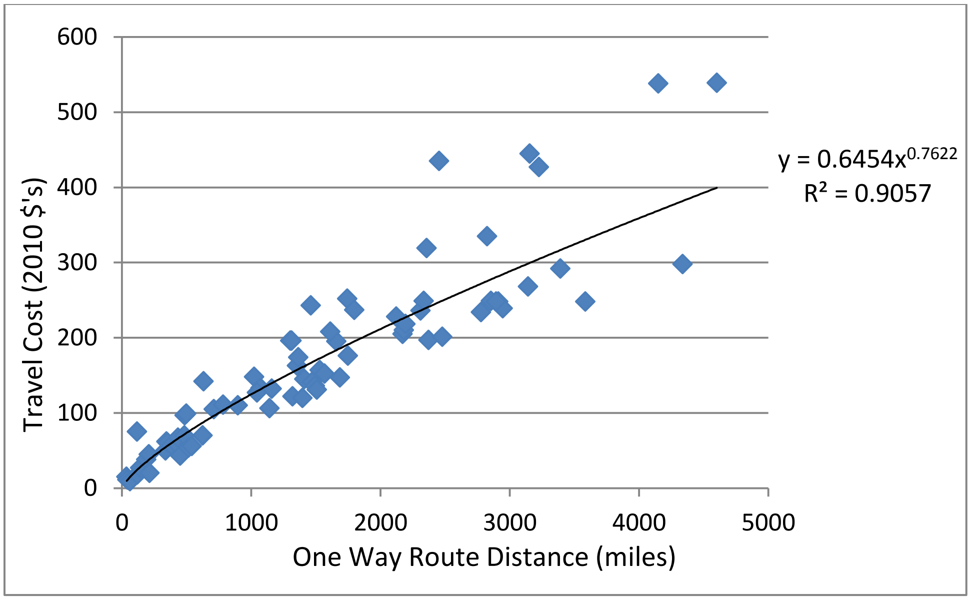

Figure 13 - Nationwide Train Travel Cost Regression Curve

Figure 12 shows the travel time vs. distance for Amtrak across the continental United States. A linear regression equation is fitted to the data; the intercept is fixed to 0 so that the curve is applicable at any distance. The equation of the line is

Travel Time (hours) =0.022 * Travel Distance (miles) ………... (23)

The R^2= 0.9533; this indicates that the regression line is a very good fit to the data. Figure 13 shows the travel cost vs. distance for the same data set. A power function is selected to represent the cost curve. The equation is

Travel Cost ($) =0.6454* Travel Distance (miles) ^ 0.7622. ………... (24)

The R^2 = 0.9057, which does not provide as good a fit as the travel time function, but it is still a very reasonable approximation of the data.

As mentioned, the northeast corridor (NEC) line is handled separately because the service conditions there are significantly different than those on the other parts of the network. It is important to note that for the implementation in TSAM, there are two regression curves for the NEC line, this is because the Acela train service was initiated in 2001 therefore the curves for the years 1995-2000 represent service conditions of Amtrak's Northeast regional service and curves for years 2001 and forward represent service conditions of the Acela Express train. The regional service trains continued operation after the Acela line was introduced, they even maintain steady ridership because of similar travel times and lower costs than Acela service; however they are not modeled in TSAM after 2001. For future TSAM improvements, it may be beneficial to develop some type of route choice model for train ridership so that both the Acela and the regional service are included in the model.

The regression curves for the regional service can be found in Appendix A, Figure 40 and Figure 41. The regression curves for the Acela express can be found in Appendix A, Figure 42 and Figure 43. Data for both cases are collected in the same manner as for the nationwide regression that is discussed above. Again, all cost data was collected in 2010 $'s but the TSAM model accounts for inflation.

Future High-Speed Rail Corridor Modeling

Alignments

The primary purpose of this work is to incorporate the train mode as an option in TSAM. This includes modeling of both the existing and future networks. At the time of this work, there are multiple potential high-speed rail corridors that have been proposed. Many of the technical details are still undetermined (exact alignments, train set type, station location, etc.). However, there are planned alignments that will be used for modeling. This work has incorporated twelve of the proposed high-speed rail corridors into the TSAM model; several corridors are located in the northeast U.S. and will be joined, however they are modeled separately to provide flexibility for analysis. It is worth noting that the issue of high-speed rail in America has become a large political issue due to fears of cost and profitability, several states have declined federal funding for high-speed rail, so it will be important to watch both the ongoing planning studies as well as the political landscape to determine if/how the projected corridors may change.

Table 18 shows each of the projected corridors that are modeled in TSAM as well as a list of the major cities that are expected to be served by the corridor. Note that the city names that are in italics and underlined are not currently modeled in TSAM. There are no current Amtrak stations in those cities therefore when the station list is expanded, these cities will need to be included. It is unlikely that the cities in Canada can be included because the ATS data set is based on travel in the United States only.

Table 18 - Major Cities Along Proposed High-Speed Rail Corridors

Proposed Corridors	Major Cities Served by Each Corridor								
California	San Francisco, CA	San Jose, CA	Sacramento, CA	Merced, CA	Fresno, CA	Bakersfield, CA	Los Angeles, CA	Riverside, CA	San Diego, CA
Northeast Corridor	Boston, MA	New Haven, CT	New York, NY	Philadelphia, PA	Baltimore, MD	Washington, DC			
Pacific Northwest	*Vancouver, BC*	Seattle, WA	Tacoma, WA	Portland, OR	Eugene, OR				
Florida	Tampa, FL	Orlando, FL	Miami, FL						
Chicago Hub	Pontiac, MI	Detroit, MI	Kalamazoo, MI	Chicago, IL	St. Louis, MO	Kansas City, MO	*Iowa City, IA*	Omaha, NE	
Southeast	Charlotte, NC	Greensboro, NC	Raleigh, NC	Richmond, VA	Washington, DC				
Empire	New York, NY	Albany, NY	Rochester, NY	Buffalo, NY	Niagara Falls, NY				
Northern New England	*Montreal, QC*	Albany, NY	Springfield, MA	New Haven, CT	Boston, MA	*Portland, ME*			
Keystone	Philadelphia, PA	Harrisburg, PA	Pittsburgh, PA						
South Central	*Tulsa, OK*	Oklahoma City, OK	Dallas, TX	Fort Worth, TX	Austin, TX	San Antonio, TX	Texarkana, AR	Little Rock, AR	
Gulf Coast	Atlanta, GA	Birmingham, AL	Meridian, AL	New Orleans, LA	Houston, TX	Biloxi, MS	Mobile, AL		
Vermont	St. Albans, VT	Montpelier, VT	Northfield, MA	Springfield, MA	New Haven, CT				

In addition to the stations listed in Table 18, there are additional stations that are modeled for each corridor; the list of stations modeled for each corridor can be seen in Appendix A. The additional stations are selected by looking at each projected route and determining what existing Amtrak stations are nearby. Since the detailed alignment of each corridor has not been finalized, an attempt is made to determine what additional stations would be included for each route. No specific criteria was used for the selection process, if the station was close to the route and/or located in a fairly well populated area then it was selected. It is known that the alignments will try to pass through as many heavily populated areas as possible because this will produce higher potential ridership. This station selection process will also need to be updated as more details about the corridors emerge.

Train Station to Train Station Travel Time and Cost – Future Corridors

The travel time and cost values are determined by using fixed coefficients. The travel time is calculated using the overall average travel speed (including stops) and the travel cost is determined by a fixed price per mile for each corridor. The corridors are still in the planning stage so detailed cost data or travel speed information is not currently available. Using fixed values allows for sensitivity runs using different travel speeds and costs which will show the sensitivity of travelers to both metrics. The train dynamics model can be used to calculate travel times, however because of the network connectivity issue in the model (discussed in Recommendations section), it will likely not provide any improved accuracy because the number of stops and distance between intermediate stops is not currently available in TSAM. Once the network connectivity issue is addressed and the speed restrictions on each corridor have been determined, the train dynamics model will be able to accurately determine the travel time between stations on the network. However, as the model stands now, the connectivity between stations is not modeled.

It is important to point out that there are multiple modeled stations along each corridor that belong to the same greater metropolitan region. For example, looking at the California Corridor, there are multiple stations that lie within the Los Angeles area; Los

Angeles, Irvine, Anaheim, Glendale, etc. It is obvious that not all of these stations will fall along the high-speed line, however since the final alignment is not yet known, all of the stations are included so that for modeling purposes, the maximum potential ridership for the greater Los Angeles area will have access to train. It is assumed that once the high-speed line has been built, the existing train network will be improved so that there can be quick access from the outlying stations, such as Pomona, to the stations along the high-speed line. As well, the TSAM model is interested in only intercity trips, therefore any trip with a one way distance less than 100 miles is removed from consideration, so for example, the model would not be estimating trips from Pomona to Irvine.

In TSAM, the train network is represented as a distance between each O-D station pair; the number and location of stops between each O-D pair is not included. This inhibits the ability to utilize the dynamics model because the number and location of each stop is important because stops can have a large effect on travel time because of the additional time caused by deceleration, stop time at each station, and acceleration back to travel speed. As well, the track design of each corridor has yet to be determined; therefore information about potential speed restrictions caused by the track design is needed to accurately calculate travel times. If the maximum speed in the dynamics model is not restricted, the vehicles will accelerate and travel at maximum possible speed; this is unrealistic because there will potentially be speed restrictions on each route due to curve radii, grades, and at grade crossings.

County to Train Station Travel Time and Cost – TSAM

The TSAM model predicts travel demand at the county level. Woods and Poole socioeconomic data is used in the trip generation and trip distribution phases of the model. This data is also used to determine the population centroid of each county; this centroid is used for the purposes of determining travel time between O-D pairs. The calculated driving times between O-D pairs are from county centroid to county centroid.

In order for TSAM to be able to predict train ridership, the full travel time between O-D pairs must be known. Trips that are designated as air or train trips are actually multi-modal trips in most cases; the method of access to and egress from the stations are handled by some other form of transportation, mainly automobile. Thus, the travel times for these trips include several components such as access, processing (origin station), processing (destination station), schedule delay, and egress time. For each county, the rail station that is the shortest driving distance away from the county centroid is considered to the rail station for the corresponding county; thus all train users either originate or end their trips in the given county will come through the assigned rail station for that county.

Once each county has been assigned to the closest rail station, the access and egress times to the rail stations are calculated using Microsoft MapPoint. This is accomplished by using the latitude-longitude coordinates of both the population centroid of a given county and the train station. The latitude-longitude coordinates of the train stations were developed in a previous effort, [29] ,and are currently available in TSAM. As well, for the projected driving time for all years, a congested driving time is calculated. This driving time utilizes Travel Time Indices (TTI) to account for congestion, mostly around cities and large urban areas, while driving. The adjustment of travel times due to the TTI indices is handled within TSAM.

Additional Time and Cost Components – TSAM

In addition to accounting for congestion penalties for travel times, several other factors are included in the total travel time and cost values. The first additional component is the schedule delay. Schedule delay is defined as the time difference between the desired time of departure and the actual time of departure. Schedule delay typically only applies to public transportation modes such as commercial air and train; the schedule for an automobile trip is zero because it is assumed that the traveler can access their automobile and begin their trip at any time they desire. For example, a traveler taking a trip by train may desire to leave at 1 pm, however the closest train departure time may be 2 pm, therefore there is a delay associated with the train mode because the user cannot depart at their desired time. The formula to calculate the schedule delay is:

$$S.D. = \frac{T}{4f} \text{ ………..... (25)}$$

Where:

$S.D. =$ schedule delay (hours)

$T =$ daily service period (hours)

$f =$ daily service frequency

The schedule delay for the existing nationwide network in the year 1995 is already incorporated into TSAM. However, the schedule delay for the Acela Express service, which is modeled starting in the year 2001, has to be calculated. The service frequency of the Acela express is found by using Amtrak's published time tables, which can be found at Amtrak's website, www.amtrak.com.[30] Table 19 shows a matrix of the service frequency for the Acela Express train for each of the 16 stations of the Original Northeast Corridor; the underlined values represent a trip that is traveling Southbound. The service frequency for this corridor is based on typical weekday operation. Table 20 shows the corresponding schedule delay for the NEC.

Table 19 - Acela Express Train Daily Service Frequency

FREQUENCY	STM	NHV	NLC	WIL	WAS	BWI	BAL	RTE	BOS	NWK	TRE	MET	NYP	PHL	PVD	BBY
STM	0	8	2	9	9	8	9	8	8	9	1	1	9	9	8	9
NHV	9	0	2	9	9	8	9	8	8	9	1	1	9	9	8	9
NLC	1	1	0	1	1	1	1	2	2	1	1	1	1	1	2	1
WIL	8	8	2	0	9	8	9	9	9	9	1	4	9	9	9	9
WAS	8	8	2	9	0	4	9	9	9	9	1	4	9	9	9	9
BWI	4	4	2	4	8	0	8	4	4	4	1	4	4	4	4	8
BAL	8	8	2	9	9	8	0	9	9	9	1	4	9	9	9	9
RTE	9	9	1	9	9	8	9	0	10	9	1	1	10	9	10	10
BOS	9	9	1	9	9	8	9	10	0	9	1	1	10	9	10	10
NWK	8	8	2	9	9	8	9	9	9	0	1	1	9	9	9	9
TRE	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
MET	4	4	2	1	1	1	1	4	4	4	1	0	4	1	4	1
NYP	8	8	2	9	9	8	9	10	10	9	1	1	0	9	10	10
PHL	8	8	2	9	9	8	9	9	9	9	9	4	9	0	9	9
PVD	9	9	1	9	9	8	9	10	10	9	1	1	10	9	0	10
BBY	8	8	2	9	9	4	9	10	10	9	1	4	10	9	10	0

Table 20 - Acela Express Train Schedule Delay (hours)

		Destinations															
Schedule Delay (hours)		**STM**	**NHV**	**NLC**	**WIL**	**WAS**	**BWI**	**BAL**	**RTE**	**BOS**	**NWK**	**TRE**	**MET**	**NYP**	**PHL**	**PVD**	**BBY**
	STM	0.000	0.594	2.375	0.528	0.528	0.594	0.528	0.594	0.594	0.528	4.750	4.750	0.528	0.528	0.594	0.528
	NHV	0.528	0.000	2.375	0.528	0.528	0.594	0.528	0.594	0.594	0.528	4.750	4.750	0.528	0.528	0.594	0.528
	NLC	4.750	4.750	0.000	4.750	4.750	4.750	4.750	2.375	2.375	4.750	4.750	4.750	4.750	4.750	2.375	4.750
	WIL	0.594	0.594	2.375	0.000	0.528	0.594	0.528	0.528	0.528	0.528	4.750	1.188	0.528	0.528	0.528	0.528
	WAS	0.594	0.594	2.375	0.528	0.000	1.188	0.528	0.528	0.528	0.528	4.750	1.188	0.528	0.528	0.528	0.528
	BWI	1.188	1.188	2.375	1.188	0.594	0.000	0.594	1.188	1.188	1.188	4.750	1.188	1.188	1.188	1.188	0.594
	BAL	0.594	0.594	2.375	0.528	0.528	0.594	0.000	0.528	0.528	0.528	4.750	1.188	0.528	0.528	0.528	0.528
Origins	**RTE**	0.528	0.528	4.750	0.528	0.528	0.594	0.528	0.000	0.475	0.528	4.750	4.750	0.475	0.528	0.475	0.475
	BOS	0.528	0.528	4.750	0.528	0.528	0.594	0.528	0.475	0.000	0.528	4.750	4.750	0.475	0.528	0.475	0.475
	NWK	0.594	0.594	2.375	0.528	0.528	0.594	0.528	0.528	0.528	0.000	4.750	4.750	0.528	0.528	0.528	0.528
	TRE	4.750	4.750	4.750	4.750	4.750	4.750	4.750	4.750	4.750	4.750	0.000	4.750	4.750	4.750	4.750	4.750
	MET	1.188	1.188	2.375	4.750	4.750	4.750	4.750	1.188	1.188	1.188	4.750	0.000	1.188	4.750	1.188	4.750
	NYP	0.594	0.594	2.375	0.528	0.528	0.594	0.528	0.475	0.475	0.528	4.750	4.750	0.000	0.528	0.475	0.475
	PHL	0.594	0.594	2.375	0.528	0.528	0.594	0.528	0.528	0.528	0.528	0.528	1.188	0.528	0.000	0.528	0.528
	PVD	0.528	0.528	4.750	0.528	0.528	0.594	0.528	0.475	0.475	0.528	4.750	4.750	0.475	0.528	0.000	0.475
	BBY	0.594	0.594	2.375	0.528	0.528	1.188	0.528	0.475	0.475	0.528	4.750	1.188	0.475	0.528	0.475	0.000

The next addition relates to the time spent at the origin and destination stations. When a user takes a train, there will be a certain time period that is devoted to purchasing a ticket, check in, boarding/un-boarding, security checkpoints, etc. For the TSAM model, the processing time at the origin station is assumed to be 20 minutes. This assumption will need to be periodically examined to ensure it is realistic; potential increased security and congestion at train stations would greatly increase the processing time. The processing time at the destination station is assumed to be 10 minutes; this accounts for time spent unloading and departing the train. In addition to processing time, a waiting time at both origin and destination stations is assigned. The waiting time for both stations is assumed to be 10 minutes. The waiting time at the origin station accounts for passengers arriving early to the station so that they do not miss their train. The waiting time at the destination station accounts for passengers waiting for a connecting trip; either by connecting taxicab, bus, or time spent loading personal automobile and exiting the station.

Finally, the TSAM model accounts for lodging times and costs for trips that are too long to complete in one day; if the round trip travel time exceeds the maximum daily travel time, then the lodging times and costs are included. The maximum daily travel time is assumed to be 8 hours for business trips and 10 hours for non-business trips; although this is a user option in the TSAM model. The time penalty is implemented as a ramp function, the time penalty for each trip length is shown in Appendix A, Table 49. Although the ramp function may seem unrealistic, it makes sense for modeling purposes because having a step function could cause drastic shifts for trips from the same area. For example, if a step function were implemented, a trip from one location may have no lodging time included, whereas a trip that originates only a few miles away would have a full night of lodging time included. This would make the model inconsistent because users who trips begin and/or end only a few miles apart will likely make similar travel decisions.

The lodging costs are assigned based on trip purpose and income group. It is assumed that travelers in higher income groups will stay at more expensive hotels, as well it is assumed that business travelers will spend more on lodging than non-business travelers. The lodging cost values are based on average lodging costs in the year 2000 and then are scaled by inflation to match the given year. The lodging costs are shown in Table 21.

Table 21 - TSAM Lodging Costs - $(2000)

	Business	Non-Business
Income Group 1	70	50
Income Group 2	80	60
Income Group 3	90	70
Income Group 4	100	80
Income Group 5	120	90

Results

Test of Train Dynamics Model

In order to demonstrate the train dynamics model as well as compare the different train sets that are modeled, a test run along the Northeast Corridor has been analyzed. Two different scenarios are considered; the first scenario examines stops at all 16 stations that are modeled on the corridor, see Table 24, the second scenario considers stops only in the cities of Boston MA, New York NY, Philadelphia PA, Baltimore MD, and Washington DC. The first scenario matches current Amtrak operations, the Acela Train stops at nearly every station along the route. The second scenario models the type of operations that are commonly seen in Europe; the high-speed trains stop only in the large cities and commuter trains are used to get passengers into smaller areas.

For both scenarios, stops at stations are modeled as a stop and go only; the time that would be required for passengers to board/depart the train is not included. As well, the route is assumed to flat for the entire trip; the detailed gradients of the track are not available. For both the full NEC route and the major city route, three different scenarios are included; the first scenario limits the maximum train speed to 50 m/s (112 mph), the second scenario limits the maximum train speed to 70 m/s (157 mph), and the last scenario allows the train to travel at its maximum possible speed. Although it is unlikely that there would ever be a scenario that the train could travel at its maximum speed with no restrictions, this will help demonstrate the differences between the train sets and will show how the travel speed and number of stops can affect the travel time and energy consumption.

Table 22 - Comparison of Trainset Performance on Original Northeast Corridor Route

		Shinkansen-100	Shinkansen-200	TGV-R	TGV-D
Max Speed = 50 m/s	**Travel Time (hrs.)**	4.77	4.73	4.69	4.69
	Energy Use (KW-hrs.)	52993	41993	25199	25442
Max Speed = 70 m/s	**Travel Time (hrs.)**	3.77	3.66	3.58	3.58
	Energy Use (KW-hrs.)	86911	70303	42444	42814
Max Speed = Unrestricted	**Travel Time (hrs.)**	3.69	3.4	3.15	3.16
	Energy Use (KW-hrs.)	91914	84695	57950	58190

Table 23 - Comparison of Trainset Performance on Original Northeast Corridor Route (Stops at Major Cities Only)

		Shinkansen-100	Shinkansen-200	TGV-R	TGV-D
Max Speed = 50 m/s	**Travel Time (hrs.)**	4.54	4.53	4.52	4.52
	Energy Use (KW-hrs.)	43905	34400	20751	20908
Max Speed = 70 m/s	**Travel Time (hrs.)**	3.35	3.32	3.29	3.29
	Energy Use (KW-hrs.)	74353	58506	35159	35379
Max Speed = Unrestricted	**Travel Time (hrs.)**	3.22	2.93	2.69	2.7
	Energy Use (KW-hrs.)	80116	73938	51030	51113

Table 22 shows the travel times and energy consumptions for each of the three scenarios for the full NEC analysis; Table 23 shows the results for the Major NEC Cities Analysis. The charts show how each of the different train sets perform in different scenarios; notice that the two TGV trains perform similarly for all the scenarios. It is obvious from looking at the charts that as the travel speed increases, the travel time decreases and the energy use increases. Also, as expected, reducing the number of stops on the trip will cause the travel time and energy consumption both to decrease.

It is important to note that a significant amount of energy is saved by reducing the number of stops. This is due to the fact that the train uses energy at a much higher rate for acceleration when compared to a cruise (steady state) condition. This demonstrates the importance of proper planning for the future corridor alignments and station locations. Adding additional stations along a corridor will provide better access to customers, in turn increasing potential ridership, however there will be an associated travel time and energy consumption penalty. The station location process will need to be optimized to maximize ridership while minimizing costs associated with energy consumption and station operation and maintenance, especially given the financial climate and the political scrutiny of high-speed rail.

NEC Corridor Model

The initial TSAM attempt is to calibrate and apply a mode choice model with three 3 possible modes of transportation (commercial air, auto, and rail) for the Northeast Corridor (NEC) region only. This is the Amtrak line that runs between Boston, MA and Washington, DC. The NEC is chosen for several reasons. First, the NEC is the only section that has true high-speed rail; the NEC is not considered to have high speed operations when compared to train's operating speeds around the world, however when compared to the other sections of the United States network, it provides the fastest service. The average operating speed in the NEC is approximately 85 mph.

The NEC also has the highest number of passengers, with approximately 11 million users in 2010.[31] Finally, the ATS is sparse with train records, but approximately half of the train records are recorded in the NEC, therefore this provides the best possible corridor for a calibration.

Table 24 shows a list of the 16 Amtrak stations that are along the NEC route and are included in this model. These stations are served by the Acela Express Train (Amtrak's high-speed train).

Table 24 - Amtrak Stations Served in Northeast Corridor

Amtrak Station Code	City	State
BOS	Boston	MA
BBY	Boston	MA
RTE	Westwood	MA
PVD	Providence	RI
NLC	New London	CT
NHV	New Haven	CT
STM	Stamford	CT
NYP	New York	NY
NWK	Newark	NJ
MET	Iselin	NJ
TRE	Trenton	NJ
PHL	Philadelphia	PA
WIL	Wilmington	DE
BAL	Baltimore	MD
BWI	Baltimore	MD
WAS	Washington	DC

For modeling purposes, the ATS train records are analyzed to determine what distance users are willing to travel to access a train station. This analysis aids in determining a "buffer distance". The buffer distance will determine the buffer zone; only counties that are within the buffer distance from one of the NEC stations will be considered. Therefore only trips that originate and end within the buffer zone will be considered to have access to train. Table 25 shows the analysis of driving distance to the station for both rail and airport stations.

Table 25 - ATS's Reported Driving Distance to Station - Northeast Corridor Only

Air		Rail	
Distance (miles)	% of Records	Distance (miles)	% of Records
100	91.89	100	92.33
150	95.95	150	96
200	97.35	200	97.48

From Table 25, it can be seen that a buffer distance of 150 miles will capture approximately 96% of the records where the users chose air and also 96% of records where rail was selected. Selecting a 150 mile distance allows the model to capture the majority of the ATS records while still passing the sanity check; it is obvious, particularly for a corridor model, that users of both air and rail are not going to drive very long distances in order to access another mode of transportation. For a corridor model where the study area is relatively small, users driving any further than 150 miles to an air/train station would defy conventional logic because taking an automobile for the full trip would be cheaper and likely faster, given the processing and delay times at congested stations and airports.

The resulting NEC corridor studied is shown by Figure 14. This shows the 16 selected Amtrak stations and the area of analysis of the corridor. Counties that are colored purple (shaded) form the corridor area of analysis. These counties are within 150 miles (great circle distance) of at least one NEC train station.

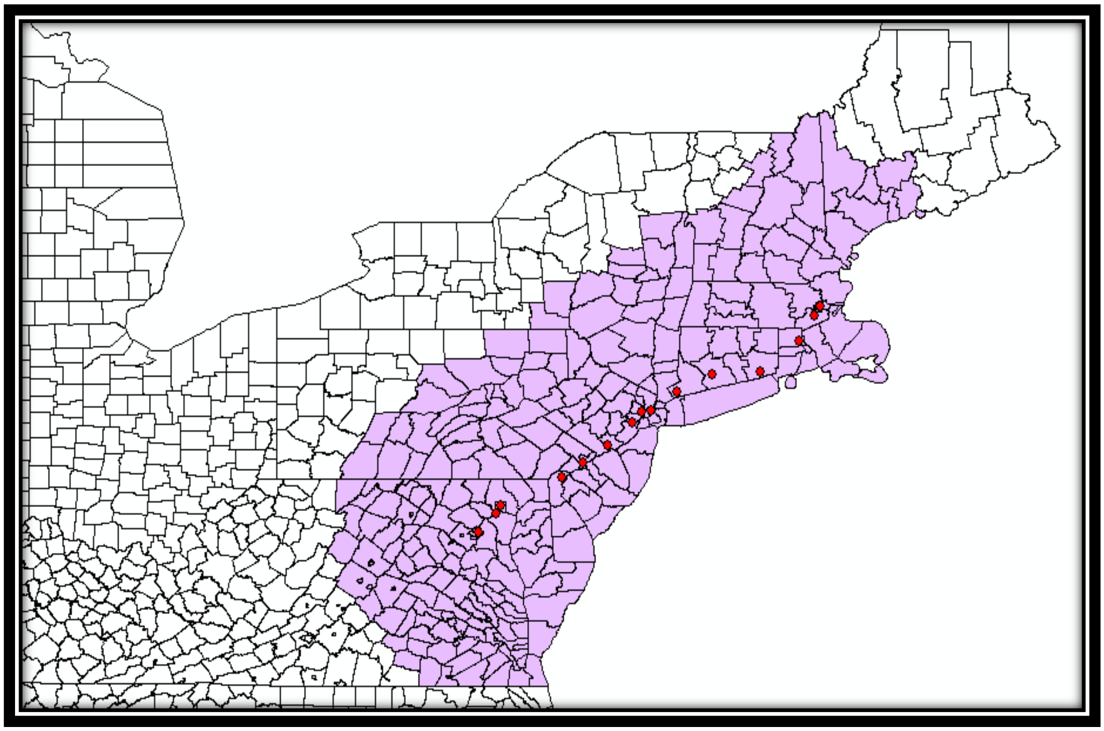

Figure 14 - Northeast Corridor Model Analysis Area

Using this corridor above, the relevant ATS records are selected and a Box Cox calibration is completed. The number of records, as well as the number of trips (number of records * weight factor) for each group is shown in Table 26.

Table 26 - Breakdown of ATS Records in Northeast Corridor Model

	# of Records	# of Trips
Business 1	340	638,322
Business 2	1,413	3,051,578
Business 3	2,488	4,587,556
Business 4	1,750	4,444,444
Business 5	495	1,220,500
Total	6,486	13,942,400
Non Business 1	2,105	5,403,227
Non Business 2	5,492	17,556,728
Non Business 3	5,665	21,203,213
Non Business 4	3,538	14,959,048
Non Business 5	852	3,756,022
Total	17,652	62,878,238
Grand Total	24,138	76,820,638

Analysis of the calibration shows that there are problems with this attempt. One major problem, and likely a contributor to the other issues, is the small number of records in each group. Table 26 indicates that there are likely too few records for a corridor type of analysis, especially in the Business 1, Business 5, and Non Business 5 groups. Compounding the problem is that each record in not always associated with a different household therefore there are even fewer household represented in each group; each household provided multiple trip records therefore the decision making of each household is heavily represented in the dataset. This can lead to bias because each household is likely to travel the same way for all trips, even if that travel decision goes against conventional logic. This effect is likely illustrated in Figure 15 and Figure 16.

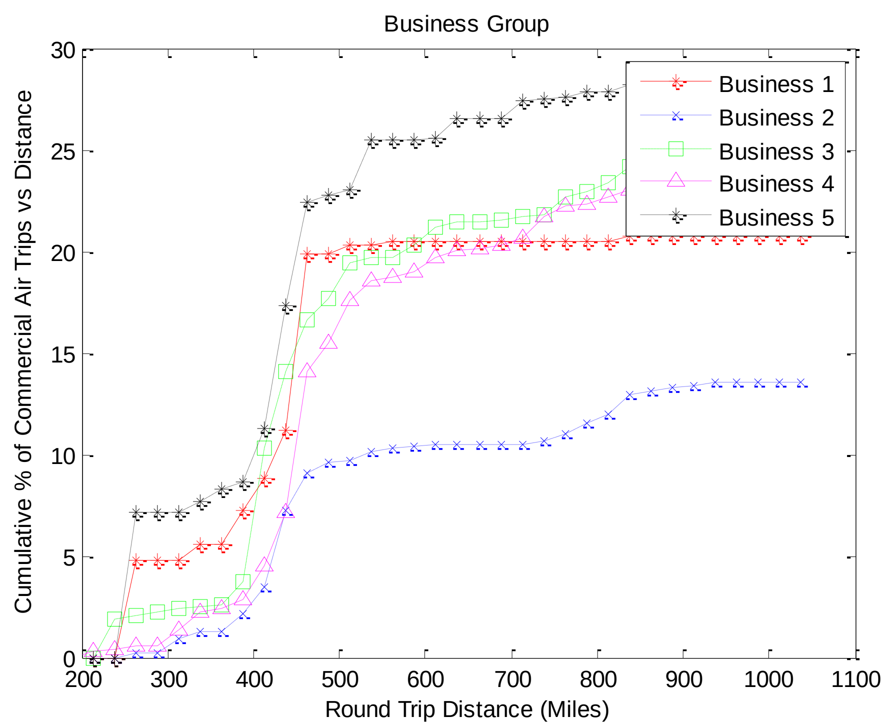

Figure 15 - Cumulative Percentage of Commercial Air Trips by Distance - Business Trips - Northeast Corridor Model Only

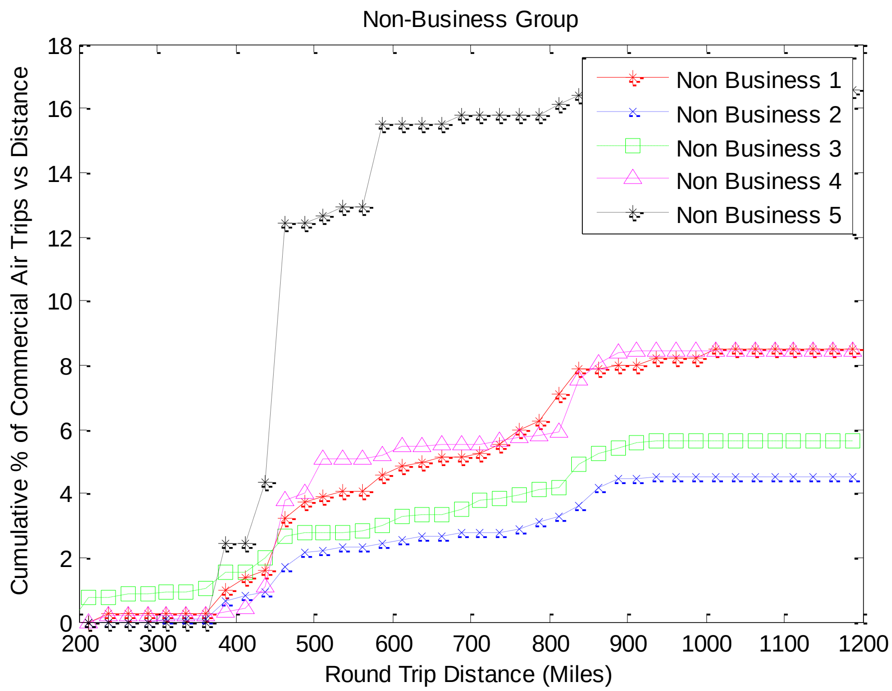

Figure 16 - Cumulative Percentage of Commercial Air Trips by Distance - Non-Business Trips - Northeast Corridor Model Only

Figure 15 shows the cumulative percentage of trips by airplane over distance for the business trips. Figure 16 shows the same data except for the non-business trips. The results show that the number of train trips in 1995 is much smaller than the trips taken by either airplane or automobile; therefore the percentage of air trips by distance is examined to ensure the results are sensible. It is expected that as the income level increases, the percentage of total trips by airplane will be higher because the users will have more disposable income, which will allow them to spend additional money for airline tickets in order to reduce their travel time. However, Figure 15 and Figure 16 show that the results do not meet this expectation.

Examining Figure 15, we expect the Business 5 group to have the largest percentage of airs trips, with the percentages decreasing as the income level decreases. However, Figure 15 shows that the Business 3 group has a larger percentage of airs trips than Business 4 group. The order of Business groups 1 and 2 is also reversed.   The same type of problem occurs in the Non Business group which is seen in Figure 16. The Non Business 1 group has the second highest percentage of trips by air which is highly unexpected.

The conclusion from these results is that the projections from a "corridor" model have too much inconsistency and thus cannot be trusted. This is based on the inconsistencies of Figure 15 and Figure 16 above as well as the knowledge of the ATS data set. The ATS data set is relatively sparse and the corridor type analysis does not capture a large number of records so thus the results are likely biased and cannot be used for making projections. The next effort will calibrate the model for the entire continental U.S. (entire ATS data set), since the ATS dataset was sampled to represent overall travel in the U.S., not for use in specific corridors.

Nationwide Calibration Results

The corridor type model proves to be inconsistent so the next effort is to calibrate a nationwide model. The nationwide model uses the box- cox transformation and is calibrated for the year 1995, since that is the year of the ATS data. The results of the calibration of the Box Cox model vs. the ATS can be seen in Table 27 below, the detailed calibration results and the calibration coefficients can be seen in Appendix A, Table 50. The calibration is conducted using the bounds that are listed in Table 17.

Table 27 - Nationwide Mode Choice Calibration vs. ATS Data

	Business		Non – Business		Total	
	ATS	**Calibration**	**ATS**	**Calibration**	**ATS**	**Calibration**
Automobile	154,079,520	154,036,233	706,195,897	706,316,064	860,275,417	860,352,297
Commercial Air	66,050,944	66,227,697	88,742,525	88,486,227	154,793,470	154,713,924
Train	1,359,012	1,225,546	3,890,824	4,026,956	5,249,836	5,252,501
Total	221,489,476	221,489,476	798,829,247	798,829,247	1,020,318,723	1,020,318,723

The calibration results show that the calibrated model matches the ATS data set very well. The results show that using the coefficients calibrated by the model, the projected train trips are over estimated by 0.05% compared to ATS, the projected automobile trips are over estimated by 0.05% and the projected commercial air trips are underestimated by 0.05%. There is larger deviation when looking at only one income/trip purpose group, for example the Non Business 1 model over estimates auto trips by 0.04%, under estimates commercial air trips by 0.78% and over projects rail trips by 4.10% however as a whole, the model matches the ATS data set very well. The coefficients from this calibration are used as input in the TSAM model for the mode choice application.

Nationwide Mode Choice Results – 1995

The first TSAM runs are conducted for the year 1995. This will provide a basis of comparison between the calibration results for 1995 and the TSAM model results. As well, it will point out potential errors in the model because if the model results differ significantly from the calibration results, then there is a problem with the application. The results of the TSAM 1995 run using the calibration coefficients are shown in Table 28. The results show that while the 1995 TSAM run does not match the ATS dataset exactly, it matches fairly well. The difference likely lies within the modeling methods of TSAM. TSAM is still under development, work is continually being done to improve the model, however one of the main challenges is that the origin and destinations of the trips in the ATS dataset are not publicly available. This forces TSAM to attempt to determine these origins and destinations, as well as trying to determine the routes of the trips and the corresponding travel times and costs. Although there are still issues with the TSAM model that are being examined, incorporating the train mode has slightly improved the mode choice results so while it is not perfect, it does provide a benefit to the model.

Table 28 - TSAM Mode Choice Results – 1995

	Business	Non-Business	Total
Automobile	151,615,285	703,216,195	854,831,840
Commercial Air	68,939,830	92,799,526	161,739,356
Train	934,309	2,813,462	3,747,771
Total	221,489,424	798,829,183	1,020,318,967

Nationwide Mode Choice Results – 2011

The year 2011 is chosen to analyze the travel effects of adding high-speed rail in the United States. At the time of this work, The TSAM model is capable of projecting to the year 2040, however the year 2011 is chosen because all of the supporting data will be actual recorded data instead of projected data (GDP, inflation rates, Travel Time congestion factors, etc.). As well, it will help policymakers understand the effects that high-speed rail provided that it would be implemented today.

The first scenario that is examined is the case of running the year 2011 with no future corridors modeled; only the existing train network is modeled. This will provide a baseline case which can be compared to the other cases to determine the ridership effects of adding high-speed rail. Again, the existing network models Amtrak's Acela express in the northeast corridor and the slower nationwide service everywhere else. The results of the baseline scenario are shown in Table 29. It should be mentioned that the 150 mile buffer distance that is implemented in the NEC model does not apply to the nationwide model. For the mode choice application, any trip is considered to have access to train as long as it is within 4 hours driving time of a station.

Table 29 - TSAM Mode Choice Results - 2011 - Existing Train Network

	Business	Non-Business	Total
Automobile	194,845,891	840,364,729	1,035,210,620
Commercial Air	90,025,826	136,293,632	226,319,458
Train	1,382,200	5,539,859	6,922,059
Total	286,253,917	982,198,220	1,268,452,137

For the modeling of the high-speed rail corridors, multiple variations of train travel time and travel cost have been examined. The different scenarios are defined below, and results are presented. Detailed results for each calibration can be found in Appendix A.

Table 30 - TSAM Mode Choice Results – High-Speed Rail Modeling Scenario Descriptions

Scenario 1	Average Train Speed = Planned Speeds Train Travel Cost = $0.20/mile
Scenario 2	Average Train Speed = 153 mph for All Projected Corridors Train Travel Cost = $0.20/mile
Scenario 3	Average Train Speed = Planned Speeds Train Travel Cost = $0.40/mile
Scenario 4	Average Train Speed = 153 mph for All Projected Corridors Train Travel Cost = $0.40/mile

Table 30 gives the definition of the four scenarios that are used to model the high-speed rail corridors. The first scenario is created using a train travel cost of $0.20/mile and the train travel speed is the current projected average speed for each corridor. The projected speed for each corridor can be found in the appendix in Table 48. The results of this run are shown below in Table 31. Table 32 provides the results for scenario 2, Table 33 provides the results for scenario 3, and Table 34 provides the results for scenario 4.

Table 31 - TSAM Mode Choice Results - 2011 – Scenario 1

	Business	Non-Business	Total
Automobile	191,959,423	837,600,478	1,029,559,901
Commercial Air	89,379,072	136,097,659	225,476,731
Train	4,915,422	8,500,083	13,415,505
Total	286,253,917	982,198,220	1,268,452,137

Table 32 - TSAM Mode Choice Results - 2011 – Scenario 2

	Business	Non-Business	Total
Automobile	190,896,275	836,429,030	1,027,325,305
Commercial Air	89,019,997	136,017,426	225,037,423
Train	6,337,645	9,751,764	16,089,409
Total	286,253,917	982,198,220	1,268,452,137

Table 33 - TSAM Mode Choice Results - 2011 – Scenario 3

	Business	Non-Business	Total
Automobile	193,608,715	839,612,037	1,033,220,752
Commercial Air	89,705,159	136,243,647	225,948,806
Train	2,940,043	6,342,536	9,282,579
Total	286,253,917	982,198,220	1,268,452,137

Table 34 - TSAM Mode Choice Results - 2011 – Scenario 4

	Business	Non-Business	Total
Automobile	192,960,036	839,073,538	1,032,033,574
Commercial Air	89,479,744	136,206,738	225,686,482
Train	3,814,137	6,917,944	10,732,081
Total	286,253,917	982,198,220	1,268,452,137

The results show that the number of trips by each mode is sensitive to both the travel time and travel cost. Comparing Table 31 and Table 32 shows the sensitivity of the model to travel speed. Increasing the speed from the planned speeds (Table 48) to 153 mph average speed for all corridors produces approximately 2.67 million addition trips by train. It is also shown that approximately 2.2 million of these trips were previously conducted by automobile. As well, the sensitivity to travel cost is illustrated by comparing Table 31 and Table 33. Increasing the train's travel cost from $0.20/mile to $0.40/mile leads to a decrease in total train trips of approximately 4.2 million trips. These effects are illustrated in Figure 17, Figure 18, and Figure 19. These figures show the total trips for automobile, commercial air and train respectively. The predictions using the existing network are also shown for comparison; the speed on the x-axis does not apply to the existing network, the regression curves are used.

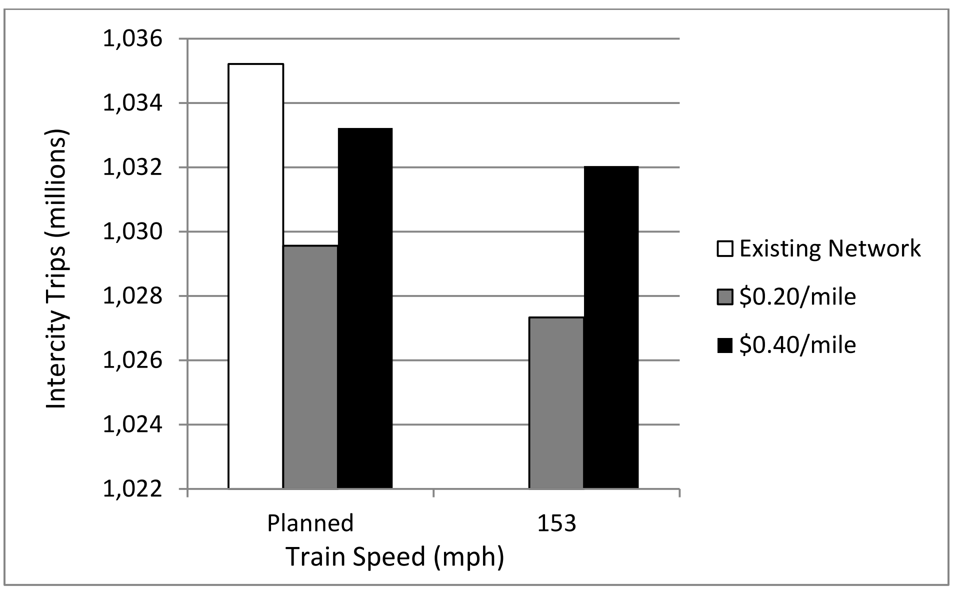

Figure 17 - TSAM Mode Choice Results - 2011 - Total Automobile Trips

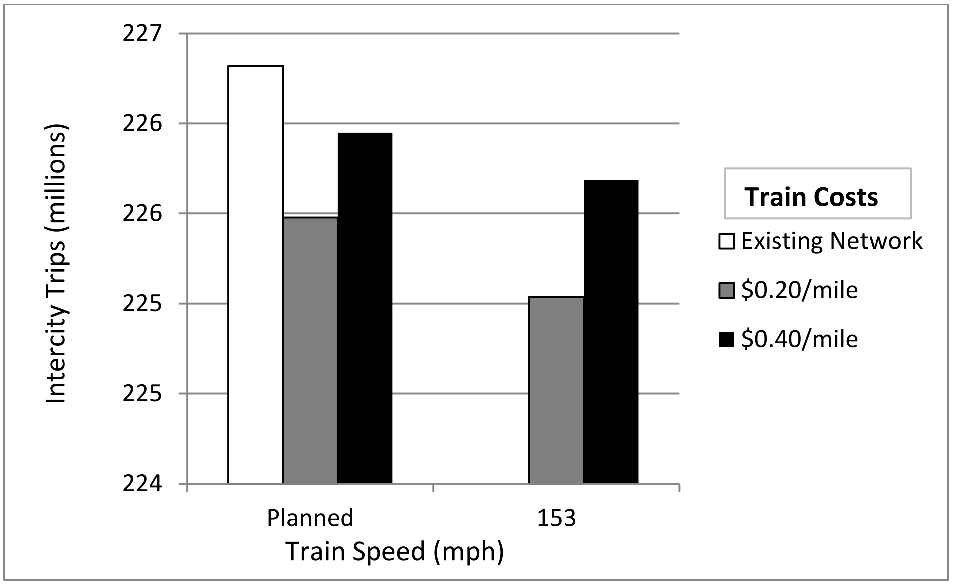

Figure 18 - TSAM Mode Choice Results - 2011 - Total Commercial Air Trips

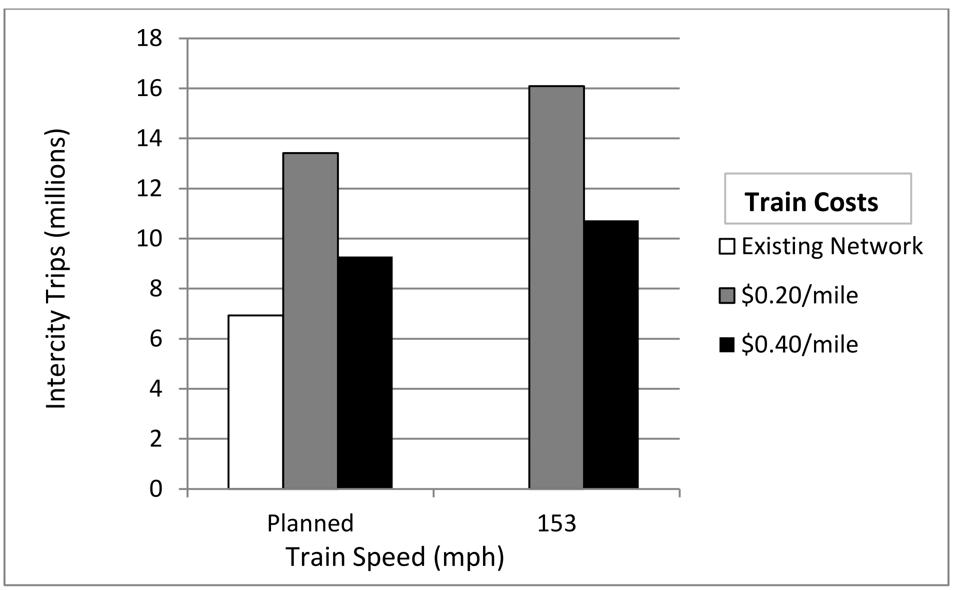

Figure 19 - TSAM Mode Choice Results - 2011 - Total Train Trips

These comparisons show that the TSAM model is capable of making predictions for high-speed rail corridors because it is sensitive to both travel time and travel cost. It should be noted that the results of the four scenarios could also be compared to the baseline case to determine the overall mode shift that would be caused by the introduction of high-speed rail. It also should be noted that all four of the scenarios presented above modeled all of the proposed corridors. It is possible to determine the effect of each proposed corridor individually if needed; a TSAM run could be executed with only the desired corridor turned on and then the results could be compared to the baseline case.

Nationwide Mode Choice Results – 2020

In addition to modeling high-speed rail in the year 2011, results for the years 2020 and 2030 have also been presented. For both years, the same scenarios listed in Table 30 have been calculated. This shows the projected intercity ridership data and modal shift effects caused by the different high-speed rail scenarios. As well, the "existing network" case for each year is presented; this represents the actual network in place in the U.S. in the year 2011, no high speed rail. This provides ridership results for the case of no implementation of high speed rail. The results for the future years are based on the current (2011) projections of population growth, economic growth, inflation index, etc. therefore they will be sensitive to any changes in those items. The 2020 results are shown in Figure 20, Figure 21, and Figure 22.

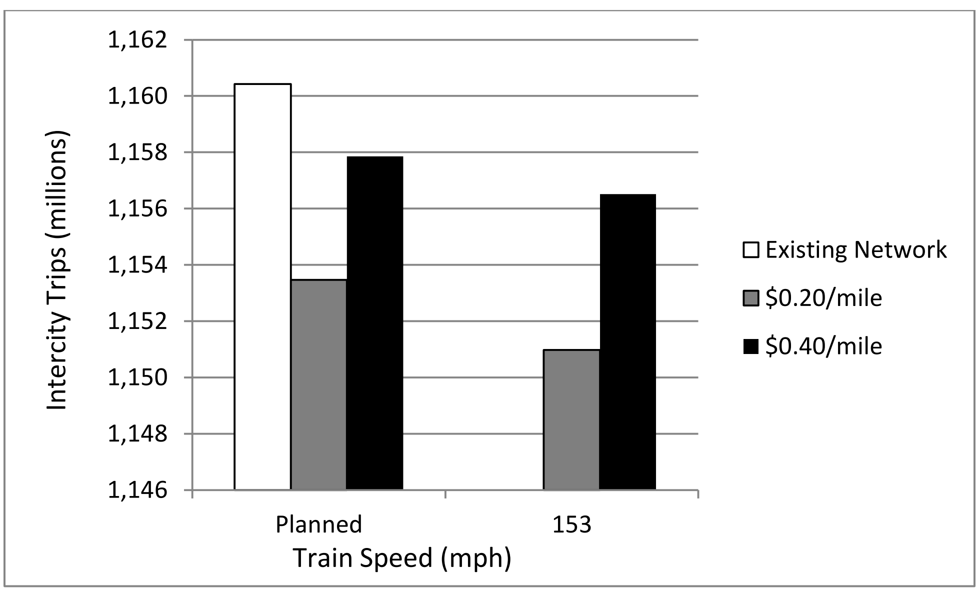

Figure 20 - TSAM Mode Choice Results - 2020 - Total Automobile Trips

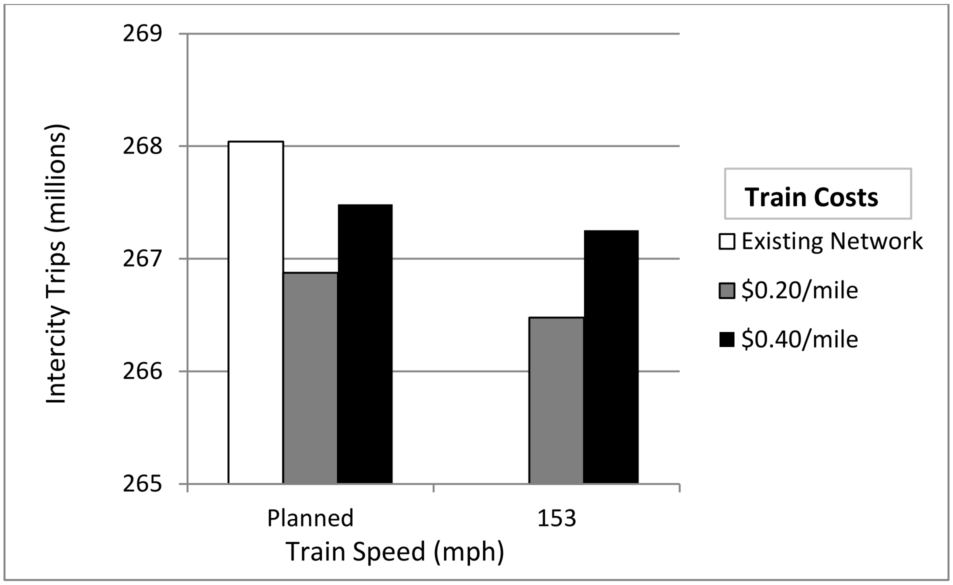

Figure 21 - TSAM Mode Choice Results - 2020 - Total Commercial Air Trips

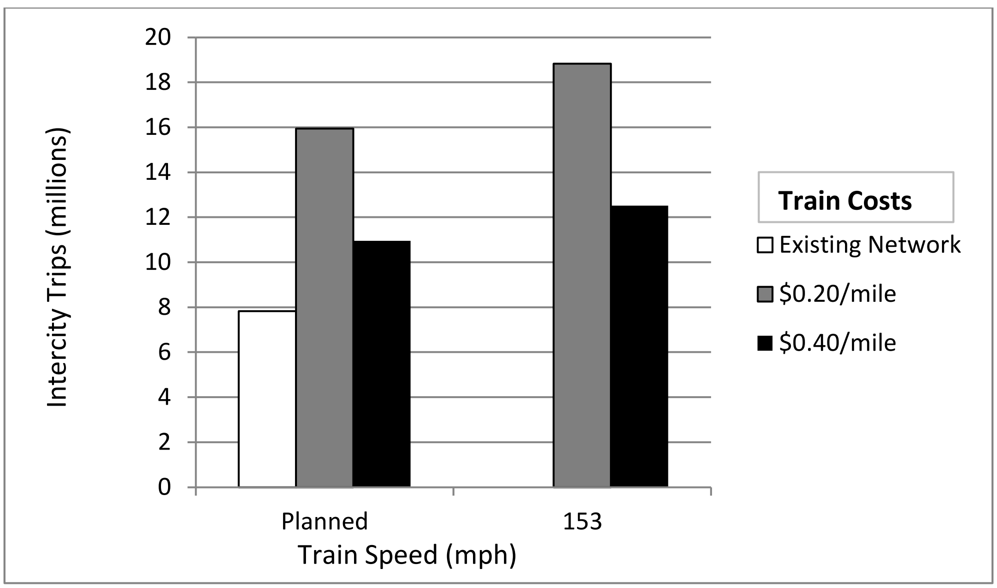

Figure 22 - TSAM Mode Choice Results - 2020 - Total Train Trips

Nationwide Mode Choice Results - 2030

The results for the year 2030 are presented in Figure 23, Figure 24, and Figure 25.

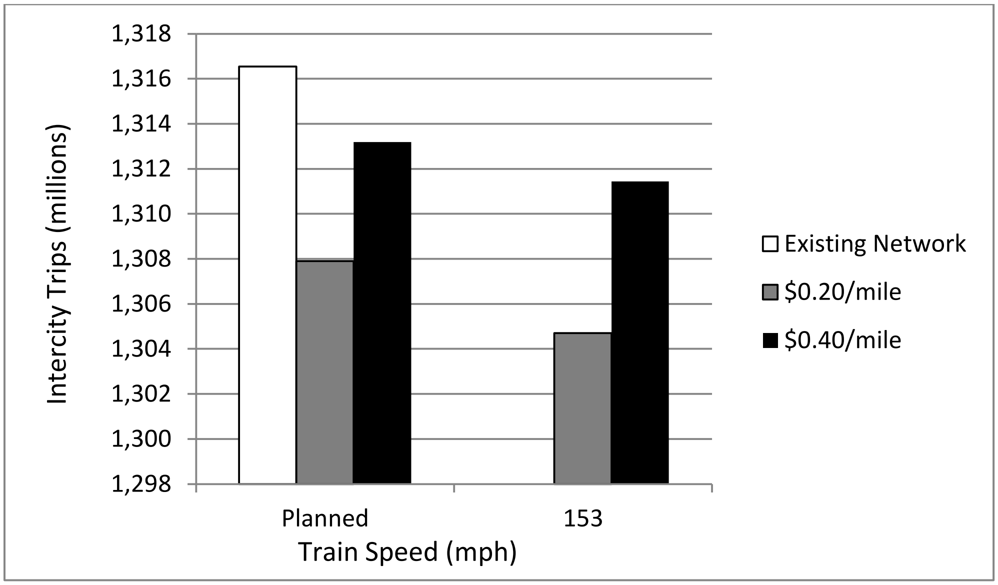

Figure 23 - TSAM Mode Choice Results - 2030 - Total Automobile Trips

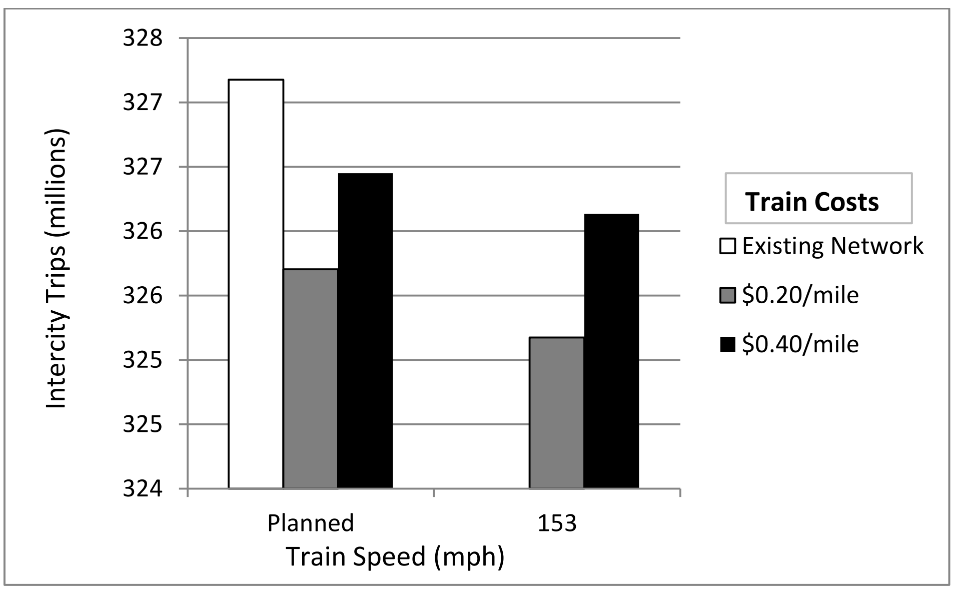

Figure 24 - TSAM Mode Choice Results - 2030 - Total Commercial Air Trips

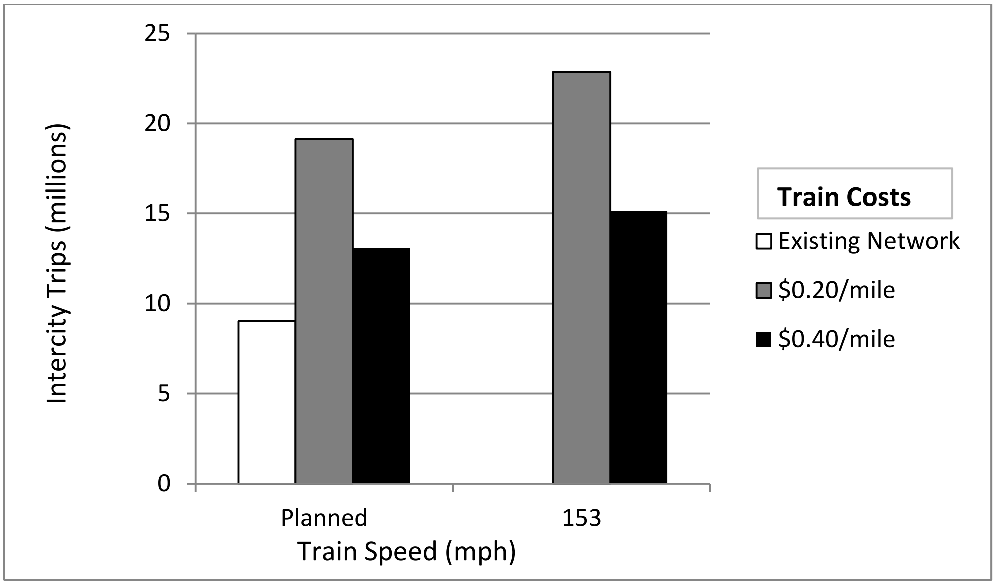

Figure 25 - TSAM Mode Choice Results - 2030 - Total Train Trips

Summary and Conclusions

This thesis developed a high-speed rail model which has been integrated into TSAM and can now be used to analyze traveler behavior on the basis of three possible modes of travel (automobile, air, and train). The work examined the use of the standard logit model for mode choice modeling. Several variations of the calibration procedure were tested, such as using the full data set for calibration or using some of the data for calibration and the rest for validation; Maximum log likelihood was used for optimization of the calibration attempts. The results from all of the different methods were reasonably good, however knowledge about the limitations of the logit model and the goal of an improved model led to the implementation of a box cox transformation. The box cox transformation, which removes many of the linear assumptions of the standard logit model, is applied to all of the decision variables.

The trip generation, trip distribution and the mode choice modules in TSAM have been updated to include train trips; the process of updating the trip generation and trip distribution modules are part of another work, therefore it is not discussed in this thesis. The mode choice calibration, using the box cox transformation and optimizing for maximum log likelihood, matches the base data very well and is used within TSAM for the mode choice application.

A train vehicle dynamics model has been developed that can be utilized to calculate travel times and energy consumption. The dynamics model includes four possible train types since the standards for high-speed rail (rolling stock type, train length, track design guidelines, etc.) in the United States have yet to be determined. The dynamics model is also capable of calculating the energy consumption of the vehicle and could eventually be expanded to calculate emissions. The dynamics model is tested for a sample run between Boston, Massachusetts and Washington, DC. Two scenarios are examined, the first case has the train stop at all 16 stations along the route, and the second case stops at only the 5 major cities; each train is run for three different speeds for each scenario. The results show the tradeoffs between travel time and energy consumption; obviously the energy consumption increases at faster speeds and also increases because of additional stops. As well, the capacity of each trainset can be used to determine the energy consumption per passenger; which may also be used for a benefit/cost analysis. This model will help policymakers determine the number of stations and desired travel speeds by analyzing the benefit/cost ratio of the travel time/energy consumption cost. Since energy consumption is likely to be an important factor for decision making, the energy consumption per passenger could be used to help determine the best trainset for each corridor; there will be a balance between having enough capacity for ridership while minimizing the total energy consumption.

The existing nationwide train network and some of the proposed high-speed rail corridors have been added to the TSAM model. Since many of the proposed high-speed corridors are still in the planning stage, the current planned alignments have been used for the model. Each corridor has determined the major cities that will likely be served, therefore existing Amtrak stations in those cities, as well as existing stations that may potentially be served by the corridor, have been modeled as the stations serviced by the corridor. The updates provide the capability for TSAM to model three modes of transportation; automobile, commercial air, and train (both current network and proposed corridors). This allows TSAM to predict the number of intercity trips for all modes on the existing network, as well as determine the modal shift effects that will be caused by the introduction of high-speed rail service.

The modal shift effect caused by the introduction of high-speed rail is illustrated in the results. The results show that if the proposed train corridors were functioning in 2011, operating at the proposed speeds and having a passenger cost of $0.20/mile, there are approximately 5.5 million more trips taken by train compared to the existing network; approximately 850,000 of these additional train trips would be diverted from commercial air. It can be seen that of the trips that are diverted to high-speed rail, approximately 15-20% of those diverted trips would have chosen commercial air; the diverted trips is found by comparing the train trips in a given scenario to the train trips on the existing network. While the trips diverted from commercial air to train is relatively small compared to the total number of trips taken, it would provide some congestion relief to the airports that are along the corridors by reducing the number of annual passengers. This could potentially allow airports to reduce flights between cities that are served by the high-speed rail corridors, commonly regional flights, and provide more operating capacity for the longer range flights. This would be beneficial to the NextGEN Airspace improvement project, because the airspace could be optimized for the longer range flights. The high-speed rail corridors could also potentially reduce congestion on the highway network, specifically major roads; however a more detailed study would be necessary to test this hypothesis.

It is important to point out that the model is not capable of producing train ridership estimates because it only considers intercity trips, defined as greater than 100 mile one way route distance. However it is useful because it can estimate the impact that high-speed rail will have on the other modes of transportation, air and automobile. The effect of introducing high speed rail will be important for planners and policymakers because many airports are operating near or above their capacity and the condition of the nation’s road network continues to deteriorate. As travel demand will likely continue to grow, this model will allow policymakers to determine what benefits high-speed rail will offer and whether it will be a better transportation investment going forward as compared to building additional roads and/or airports.

Recommendations

This work has developed tools and updated TSAM to model high-speed rail. However, there are improvements that would be beneficial to the model, some of which will be necessary as more information about the high-speed rail corridors becomes available. The improvements are:

1. Improving more complex/accurate methods of calculating energy consumption.
2. Developing a modeling mechanism for train energy regeneration.
3. Adding additional train types to the dynamics model / adding the U.S. trainset to the model once the standards have been determined.
4. Implementing a link-node style train network in TSAM.
5. Updating the train station list in TSAM

For the first improvement, the current method of calculating energy consumption provides a quick and easy way to model energy consumption, however it is dependent upon a large number of assumptions. The method is assuming that the energy sources of a region retain the same proportions as those listed in the report. As energy sources vary and continue to shift toward renewable energies, the current method of modeling energy consumption will no longer be valid, unless there is a new report that provides the energy source information. The factors that are used are only valid for the energy source proportions that are detailed in the report. While the energy consumption modeling is suitable for planning, a more accurate method of calculation would be necessary to make detailed energy comparisons between trains or across modes. As well, if the model is expanded to include emissions, detailed energy consumption information would be necessary for accurate emission totals.

The second improvement would to be to develop algorithms that could be implemented in the dynamics model and calculate energy regeneration. As mentioned in this paper, energy regeneration is currently modeled as a fixed percentage of the total energy consumed by the train. However, it is obvious to see that this percentage will change significantly as the trip distances change. Since the amount of energy regenerated is a function of the velocity of the train prior to braking, the energy regeneration capability is limited. The current modeling method is likely more accurate for short range trips. It can be seen that for a very long trip where the train is in “cruise” mode for a large period of time, the majority of consumed energy cannot be recaptured, thus the longer the trip, the lower the percentage of total energy consumed that can be regenerated.

The third improvement would be to include more types of train sets in the dynamics model. The trains included in the model are some of the original high-speed trains that were in operation. Currently, they are either nearing the end of their life cycle or already out of service. These trains are still applicable for modeling because at the time of publication of this work, the United States has not set the standards for the type of train set that will be operating on the proposed high-speed lines. While there have been technological improvements over the currently modeled train sets, the United States certainly will not be operating trains at the speeds of the European and Asian countries, at least initially, due to technological limits on the current U.S. rail network (curve radii, at grade crossings, terrain issues, etc.). Therefore the included train sets provide a good starting point for modeling high-speed trains in the United States but eventually the rail network may be improved/developed to the point that some of the newer train types would be able to achieve a time savings compared to the older trains therefore modeling additional trains will be necessary as advancements are made.

The fourth improvement involves updating the station list and applying the correct station list to the corresponding years in TSAM. The currently available station list contains 464 stations that were determined to be in the Amtrak network in 1995. At the time of this work, there are 526 stations that are serviced by Amtrak. The station list needs to be updated for each year to represent the stations that would have been active in the corresponding year. This would provide more accurate ridership numbers because the station list for each year would then be consistent with the actual network of the corresponding year. As well, selected stations from the list of 464 are used to model the projected future corridors. The projected corridors have determined the major cities that will be served however, they have not determined the location and number of stations that will be on the routes, therefore Amtrak stations that are in the major cities are currently used to model the projected routes. Once the location and number of stations have been determined, the station list will need to be updated to include the new and/or relocated stations. This will be very important for ridership projections because the location of a station within a city will have an effect on the amount of potential riders.

The fifth improvement, which may provide the greatest benefit to the TSAM model, is to model the train network as a link-node type network. A network analysis was conducted in an earlier work, [29], to determine the shortest path between stations. This analysis provided the track distance between each origin-destination station pair. However, this analysis will need to be redone when the station list is updated. The model would benefit by representing the network as a link-node type network instead of simply using the distance between each origin-destination station pair. As currently modeled, a trip between any two-station pairs is only represented by a track distance; there is no information about how many stations are traveled through during the trip. This limits the model because the travel time between stations can only be based on an average travel speed, including stops at stations. If the network is modeled as a link-node type network, the travel time calculations could be greatly improved because the number of stops and length of each segment could be calculated as well as calculating the exact speed of the train on each segment between stops. This would provide better time calculations, particularly on trips that travel through two or more corridors because the travel speed could be calculated for each segment instead of simply an average speed for the entire trip.

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Appendix A – Additional Information

Complete List of Amtrak Stations Available in TSAM

Table 35 shows the full list of modeled stations that are currently included in TSAM. The stations are representative of Amtrak stations that were in service in 1995.

Table 35 - Full List of Modeled Train Stations Available in TSAM

Amtrak Station Code	City	State	Longitude	Latitude
ABQ	ALBUQUERQUE	NM	-106.650	35.083
ADM	ARDMORE	OK	-97.125	34.172
AKO	AKRON	OH	-81.516	41.081
AKY	ASHLAND	KY	-82.639	38.481
ALB	RENSSELAER	NY	-73.741	42.642
ALC	ALLIANCE	OH	-81.096	40.922
ALD	ALDERSON	WV	-80.645	37.724
ALI	ALBION	MI	-84.756	42.247
ALN	ALTON	IL	-90.135	38.904
ALP	ALPINE	TX	-103.660	30.357
ALT	ALTOONA	PA	-78.401	40.515
ALX	ALEXANDRIA	VA	-77.063	38.806
ALY	ALBANY	OR	-123.100	44.631
AMM	AMHERST	MA	-72.512	42.375
AMS	AMSTERDAM	NY	-74.210	42.947
ANA	ANAHEIM	CA	-117.880	33.804
ARB	ANN ARBOR	MI	-83.744	42.288
ARK	ARKADELPHIA	AR	-93.052	34.114
ARN	AUBURN	CA	-121.080	38.904
ATL	ATLANTA	GA	-84.392	33.800
ATN	ANNISTON	AL	-85.832	33.649
ATR	ATMORE	AL	-87.487	31.024
AUS	AUSTIN	TX	-97.756	30.269
BAL	BALTIMORE	MD	-76.617	39.308
BAM	BANGOR	MI	-86.112	42.314
BAR	BARSTOW	CA	-117.030	34.905
BAS	BAY ST. LOUIS	MS	-89.337	30.307
BBY	BOSTON	MA	-71.076	42.347
BEL	BELLINGHAM	WA	-122.510	48.720
BEN	BENSON	AZ	-110.290	31.968
BER	KENSINGTON	CT	-72.766	41.636
BFD	BAKERSFIELD	CA	-119.020	35.371
BFX	BUFALO	NY	-78.875	42.878

BHM	BIRMINGHAM	AL	-86.807	33.512
BIX	BILOXI	MS	-88.891	30.399
BKY	BERKELEY	CA	-122.300	37.868
BLF	BELLOWS FALLS	VT	-72.445	43.136
BMM	BIRMINGHAM	MI	-83.195	42.546
BMT	BEAUMONT	TX	-94.123	30.077
BNC	BURLINGTON	NC	-79.436	36.094
BNG	BINGEN	WA	-121.470	45.715
BNL	NORMAL	IL	-88.984	40.508
BOS	BOSTON	MA	-71.055	42.352
BRA	BRATTLEBORO	VT	-72.550	42.839
BRH	BROOKHAVEN	MS	-90.442	31.579
BRL	BURLINGTON	IA	-91.102	40.806
BRO	BROWNING	MT	-113.010	48.533
BRP	BRIDGEPORT	CT	-73.187	41.177
BTL	BATTLE CREEK	MI	-85.186	42.317
BWI	BALTIMORE	MD	-76.693	39.190
BYN	BRYAN	OH	-84.553	41.480
CAM	CAMDEN	SC	-80.626	34.247
CBR	CLEBURNE	TX	-97.382	32.348
CBS	COLUMBUS	WI	-89.012	43.341
CDL	CARBONDALE	IL	-89.216	37.724
CEN	CENTRALIA	IL	-89.136	38.528
CHI	CHICAGO	IL	-87.639	41.879
CHM	CHAMPAIGN	IL	-88.241	40.116
CHS	N. CHARLESTON	SC	-79.999	32.876
CHW	CHARLESTON	WV	-81.647	38.352
CIC	CHICO	CA	-121.840	39.723
CIN	CINCINNATI	OH	-84.537	39.102
CIP	CHIPLEY	FL	-85.538	30.781
CLA	CLAREMONT	NH	-72.379	43.369
CLB	COLUMBIA	SC	-81.041	33.994
CLE	CLEVELAND	OH	-81.698	41.504
CLF	CLIFTON FORGE	VA	-79.836	37.812
CLP	CULPEPPER	VA	-77.993	38.473
CLT	CHARLOTTE	NC	-80.824	35.241
CMO	CHEMULT	OR	-121.780	43.217
COC	CORCORAN	CA	-119.560	36.098
COI	CONNERSVILLE	IN	-85.134	39.646
COV	CONNELLSVILLE	PA	-79.593	40.018
COX	COLFAX	CA	-120.950	39.099

CRF	CRAWFORDSVILLE	IN	-86.899	40.044
CRN	CRESTON	IA	-94.361	41.057
CRT	CROTON-ON-HUDSON	NY	-73.884	41.193
CRV	CARLINVILLE	IL	-89.889	39.279
CSN	CLEMSON	SC	-82.833	34.691
CSV	CRESTVIEW	FL	-86.569	30.758
CTL	CENTRALIA	WA	-122.950	46.717
CUM	CUMBERLAND	MD	-78.758	39.651
CUT	CUT BANK	MT	-112.330	48.637
CVS	CHARLOTTESVILE	VA	-78.492	38.032
CYN	CARY	NC	-78.780	35.788
DAL	DALLAS	TX	-96.807	32.776
DAN	DANVILLE	VA	-79.384	36.584
DAV	DAVIS	CA	-121.740	38.544
DDG	DODGE CITY	KS	-100.020	37.753
DEM	DEMING	NM	-107.760	32.271
DEN	DENVER	CO	-105.000	39.753
DER	DEARBORN	MI	-83.201	42.313
DET	DETROIT	MI	-83.072	42.368
DFB	DEERFIELD BEACH	FL	-80.121	26.318
DIL	DILLON	SC	-79.372	34.418
DLB	DELRAY BEACH	FL	-80.093	26.455
DLD	DELAND	FL	-81.352	29.017
DLK	DETROIT LAKES	MN	-95.846	46.819
DNC	DURHAM	NC	-78.907	35.997
DNK	DENMARK	SC	-81.143	33.326
DOA	DOWAGIAC	MI	-86.109	41.981
DRD	DURAND	MI	-83.982	42.910
DRT	DEL RIO	TX	-100.900	29.363
DUN	DUNSMUIR	CA	-122.270	41.211
DVL	DEVILS LAKE	ND	-98.861	48.111
DWT	DWIGHT	IL	-88.428	41.092
DYE	DYER	IN	-87.518	41.499
EDM	EDMONDS	WA	-122.380	47.811
EFG	EFFINGHAM	IL	-88.546	39.119
EKH	ELKHART	IN	-85.971	41.681
ELK	ELKO	NV	-115.750	40.837
ELP	EL PASO	TX	-106.490	31.758
ELY	ELYRIA	OH	-82.097	41.370
EMY	EMERYVILLE	CA	-122.290	37.841

EPH	EPHRATA	WA	-119.550	47.321
ESM	ESSEX	MT	-113.610	48.281
ESX	ESSEX JUNCTION	VT	-73.110	44.493
EUG	EUGENE	OR	-123.090	44.055
EVR	EVERETT	WA	-122.220	47.979
FAR	FARGO	ND	-96.785	46.881
FAY	FAYETTEVILLE	NC	-78.885	35.055
FBG	FREDERICKSBURG	VA	-77.457	38.299
FED	FORT EDWARD	NY	-73.580	43.270
FHV	FAIR HAVEN	VT	-73.262	43.591
FLG	FLAGSTAFF	AZ	-111.650	35.198
FLN	FLINT	MI	-83.655	43.014
FLO	FLORENCE	SC	-79.757	34.199
FMD	FORT MADISON	IA	-91.333	40.623
FMG	FORT MORGAN	CO	-103.800	40.247
FNO	FRESNO	CA	-119.780	36.739
FOS	FOSTORIA	OH	-83.414	41.153
FRA	FRAMINGHAM	MA	-71.418	42.277
FTC	TICONDEROGA	NY	-73.391	43.853
FTL	FORT LAUDERDALE	FL	-80.170	26.120
FTN	FULTON	KY	-88.888	36.523
FTW	FORT WORTH	TX	-97.324	32.749
FUL	FULLERTON	CA	-117.920	33.869
GAS	GASTONIA	NC	-81.164	35.268
GBB	GALESBURG	IL	-90.364	40.944
GCK	GARDEN CITY	KS	-100.870	37.965
GDL	GLENDALE	CA	-118.260	34.124
GFK	GRAND FORKS	ND	-97.110	47.919
GFV	DEARBORN	MI	-83.242	42.305
GGW	GLASCOW	MT	-106.630	48.195
GJT	GRAND JUNCTION	CO	-108.570	39.065
GLE	GAINESVILLE	TX	-97.140	33.624
GLN	GLENVIEW	IL	-87.805	42.074
GLP	GALLUP	NM	-108.740	35.529
GLY	GILROY	CA	-121.570	37.006
GNB	GREENSBURG	PA	-79.547	40.305
GNS	GAINESVILLE	GA	-83.827	34.284
GPK	EAST GLACIER PARK	MT	-113.220	48.444
GRA	GRANBY	CO	-105.930	40.084
GRI	GREEN RIVER	UT	-110.160	38.992
GRO	GREENSBORO	NC	-79.831	36.061

GRR	GRAND RAPIDS	MI	-85.679	42.956
GRV	GREENVILLE	SC	-82.414	34.857
GSC	GLENWOOD SPRINGS	CO	-107.320	39.548
GUF	GULFPORT	MS	-89.095	30.369
GVB	GROVER BEACH	CA	-120.630	35.122
GWD	GREENWOOD	MS	-90.176	33.518
GZZ	GLENS FALLS	NY	-73.648	43.312
HAM	HAMLET	NC	-79.698	34.883
HAR	HARRISBURG	PA	-76.878	40.262
HAS	HASTINGS	NE	-98.387	40.584
HAV	HAVRE	MT	-109.680	48.554
HAZ	HAZELHURST	MS	-90.394	31.863
HBG	HATTIESBURG	MS	-89.286	31.327
HEM	HERMANN	MO	-91.433	38.707
HER	HELPER	UT	-110.850	39.688
HFD	HARTFORD	CT	-72.682	41.768
HFY	HARPERS FERRY	WV	-77.734	39.325
HGD	HUNTINGDON	PA	-78.012	40.483
HIN	HINTON	WV	-80.889	37.677
HLD	HOLDREGE	NE	-99.371	40.436
HMD	HAMMOND	LA	-90.464	30.512
HMI	HAMMOND	IN	-87.509	41.693
HMN	HAMILTON	OH	-84.560	39.395
HMW	HOMEWOOD	IL	-87.669	41.562
HNF	HANFORD	CA	-119.650	36.326
HOL	HOLLYWOOD	FL	-80.169	26.011
HOM	HOLLAND	MI	-86.098	42.789
HOS	HOUSTON	TX	-95.367	29.767
HPT	HIGH POINT	NC	-80.006	35.958
HUD	HUDSON	NY	-73.798	42.253
HUN	HUNTINGTON	WV	-82.441	38.415
HUT	HUTCHINSON	KS	-97.930	38.056
IDP	INDEPENDENCE	MO	-94.429	39.087
IND	INDIANAPOLIS	IN	-86.160	39.762
IRV	IRVINE	CA	-117.760	33.675
JAN	JACKSON	MS	-90.191	32.301
JAX	JACKSONVILLE	FL	-81.725	30.367
JEF	JEFFERSON CITY	MO	-92.170	38.579
JOL	JOLIET	IL	-88.079	41.525
JSP	JESUP	GA	-81.882	31.606
JST	JOHNSTOWN	PA	-78.922	40.330

JXN	JACKSON	MI	-84.400	42.248
KAL	KALAMAZOO	MI	-85.584	42.295
KAN	KANNAPOLIS	NC	-80.622	35.501
KCY	KANSAS CITY	MO	-94.584	39.086
KEL	KELSO	WA	-122.910	46.143
KFS	KLAMATH FALLS	OR	-121.770	42.226
KGC	KING CITY	CA	-121.130	36.204
KIN	WEST KINGSTON	RI	-71.562	41.484
KIS	KISSIMMEE	FL	-81.405	28.293
KKI	KANKAKEE	IL	-87.866	41.119
KNG	KINGMAN	AZ	-114.050	35.188
KTR	KINGSTREE	SC	-79.829	33.664
KWD	KIRKWOOD	MO	-90.408	38.581
LAB	LATROBE	PA	-79.385	40.318
LAF	LAFAYETTE	IN	-86.895	40.421
LAJ	LA JUNTA	CO	-103.540	37.988
LAK	LAKELAND	FL	-81.952	28.046
LAP	LA PLATA	MO	-92.485	40.031
LAU	LAUREL	MS	-89.128	31.692
LAX	LOS ANGELES	CA	-118.240	34.056
LCH	LAKE CHARLES	LA	-93.215	30.238
LCN	LINCOLN	IL	-89.363	40.148
LDB	LORDSBURG	NM	-108.710	32.351
LEC	LAKE CITY	FL	-82.651	30.197
LEE	LEES SUMMIT	MO	-94.378	38.913
LEW	LEWISTOWN	PA	-77.579	40.589
LFT	LAFAYETTE	LA	-92.015	30.227
LIB	LIBBY	MT	-115.550	48.395
LMR	LAMAR	CO	-102.620	38.090
LMY	LAMY	NM	-105.880	35.477
LNC	LANCASTER	PA	-76.308	40.054
LNK	LINCOLN	NE	-96.711	40.815
LNS	EAST LANSING	MI	-84.494	42.719
LPE	LAPEER	MI	-83.306	43.050
LRC	LAWRENCE	KS	-95.232	38.972
LRK	LITTLE ROCK	AR	-92.286	34.750
LSE	LA CROSSE	WI	-91.248	43.834
LSV	LAS VEGAS	NM	-105.210	35.593
LVW	LONGVIEW	TX	-94.725	32.496
LYH	LYNCHBURG	VA	-79.157	37.407
MAL	MALTA	MT	-107.870	48.360

MAT	MATTOON	IL	-88.376	39.482
MAY	MAYSVILLE	KY	-83.771	38.652
MCB	MCCOMB	MS	-90.453	31.249
MCD	MERCED	CA	-120.480	37.307
MCG	MCGREGOR	TX	-97.402	31.438
MCI	MICHIGAN CITY	IN	-86.905	41.721
MCK	MCCOOK	NE	-100.630	40.198
MDN	MERIDEN	CT	-72.801	41.539
MDO	MADISON	FL	-83.413	30.459
MDR	MADERA	CA	-120.020	36.975
MDT	MENDOTA	IL	-89.117	41.550
MEI	MERIDIAN	MS	-88.696	32.364
MEM	MEMPHIS	TN	-90.059	35.132
MET	ISELIN	NJ	-74.328	40.568
MHL	MARSHALL	TX	-94.367	32.551
MIA	MIAMI	FL	-80.258	25.850
MIN	MINEOLA	TX	-95.490	32.662
MKA	MILWAUKEE	WI	-87.946	42.954
MKE	MILWAUKEE	WI	-87.916	43.034
MNG	MONTGOMERY	WV	-81.324	38.181
MOD	MODESTO	CA	-120.910	37.668
MOE	MOBILE	AL	-88.038	30.690
MOT	MINOT	ND	-101.300	48.236
MPR	MONTPELIER	VT	-72.609	44.257
MRB	MARTINSBURG	WV	-77.962	39.458
MRC	MARICOPA	AZ	-112.050	33.058
MSP	ST. PAUL	MN	-93.186	44.963
MSS	MANASSAS	VA	-77.474	38.750
MTP	MOUNT PLEASANT	IA	-91.551	40.971
MTZ	MARTINEZ	CA	-122.140	38.020
MVN	MALVERN	AR	-92.812	34.366
MVW	MOUNT VERNON	WA	-122.330	48.436
MYS	MYSTIC	CT	-71.960	41.349
NBM	NEW BUFFALO	MI	-86.740	41.788
NBN	NEWBERN	TN	-89.263	36.112
NCR	NEW CARROLLTON	MD	-76.864	38.953
NDL	NEEDLES	CA	-114.600	34.840
NEW	NEWTON	KS	-97.345	38.047
NFL	NIAGARA FALLS	NY	-79.031	43.114
NHV	NEW HAVEN	CT	-72.926	41.299
NIB	NEW IBERIA	LA	-91.824	30.008

NLC	NEW LONDON	CT	-72.094	41.354
NLS	NILES	MI	-86.254	41.837
NOL	NEW ORLEANS	LA	-90.080	29.947
NOR	NORMAN	OK	-97.442	35.220
NPI	NAPPANEE	IN	-86.001	41.441
NPV	NAPERVILLE	IL	-88.145	41.780
NWK	NEWARK	NJ	-74.165	40.734
NYP	NEW YORK	NY	-73.992	40.750
OAC	OAKLAND	CA	-122.190	37.755
OKC	OKLAHOMA CITY	OK	-97.513	35.466
OKE	OKEECHOBEE	FL	-80.830	27.251
OLW	OLYMPIA	WA	-122.800	46.991
OMA	OMAHA	NE	-95.927	41.250
ONA	ONTARIO	CA	-117.650	34.062
ORC	OREGON CITY	OR	-122.600	45.365
ORL	ORLANDO	FL	-81.382	28.526
OSB	OLD SAYBROOK	CT	-72.376	41.301
OSC	OSCEOLA	IA	-93.766	41.037
OSD	OCEANSIDE	CA	-117.380	33.193
OTM	OTTUMWA	IA	-92.416	41.020
OXN	OXNARD	CA	-119.170	34.199
PAG	PASCAGOULA	MS	-88.559	30.367
PAK	PALATKA	FL	-81.641	29.649
PAO	PAOLI	PA	-75.484	40.042
PBF	POPLAR BLUFF	MO	-90.393	36.754
PCT	PRINCETON	IL	-89.462	41.387
PDX	PORTLAND	OR	-122.680	45.529
PGH	PITTSBURGH	PA	-79.993	40.445
PHL	PHILADELPHIA	PA	-75.183	39.955
PIC	PICAYUNE	MS	-89.680	30.525
PIT	PITTSFIELD	MA	-73.256	42.450
PLB	PLATTSBURGH	NY	-73.447	44.697
PNS	PENSACOLA	FL	-87.204	30.418
PNT	PONTIAC	MI	-83.294	42.636
POG	PORTAGE	WI	-89.469	43.547
POH	PORT HENRY	NY	-73.462	44.033
PON	PONTIAC	IL	-88.636	40.879
POS	POMONA	CA	-117.750	34.059
POU	POUGHKEEPSIE	NY	-73.939	41.706
PRB	PASO ROBLES	CA	-120.690	35.623
PRC	PRINCE	WV	-81.054	37.859

PRK	PORT KENT	NY	-73.444	44.578
PRO	PROVO	UT	-111.660	40.226
PSC	PASCO	WA	-119.080	46.234
PSN	PALM SPRINGS	CA	-116.550	33.896
PTB	ETTRICK	VA	-77.429	37.242
PTH	PORT HURON	MI	-82.442	42.961
PUR	PURCELL	OK	-97.356	35.012
PVD	PROVIDENCE	RI	-71.416	41.826
PVL	PAULS VALLEY	OK	-97.219	34.741
QAN	QUNATICO	VA	-77.293	38.522
RAT	RATON	NM	-104.440	36.901
RDD	REDDING	CA	-122.390	40.583
RDW	RED WING	MN	-92.542	44.565
REN	RENSSELAER	IN	-87.154	40.943
RGH	RALEIGH	NC	-78.644	35.774
RHI	RHINECLIFF	NY	-73.952	41.921
RIC	RICHMOND	CA	-122.350	37.936
RIV	RIVERSIDE	CA	-117.370	33.977
RKV	ROCKVILLE	MD	-77.147	39.085
RLN	ROCKLIN	CA	-121.240	38.792
RMT	ROCKY MOUNT	NC	-77.798	35.938
RNO	RENO	NV	-119.810	39.529
ROC	ROCHESTER	NY	-77.610	43.163
ROM	ROME	NY	-75.451	43.199
ROY	ROYAL OAK	MI	-83.148	42.489
RPH	RANDOLPH	VT	-72.666	43.923
RSP	ROUSES POINT	NY	-73.371	44.995
RSV	ROSEVILLE	CA	-121.280	38.751
RTE	WESTWOOD	MA	-71.150	42.208
RUD	RUTLAND	VT	-72.982	43.607
RUG	RUGBY	ND	-99.998	48.369
RVR	RICHMOND	VA	-77.497	37.614
SAB	ST. ALBANS	VT	-73.086	44.811
SAC	SACRAMENTO	CA	-121.500	38.584
SAL	SALISBURY	NC	-80.457	35.673
SAN	SAN DIEGO	CA	-117.170	32.716
SAR	SARATOGA SPRINGS	NY	-73.810	43.082
SAS	SAN ANTONIO	TX	-98.478	29.419
SAT	SANTA MARIA	CA	-120.420	34.951
SAV	SAVANNAH	GA	-81.144	32.079
SBA	SANTA BARBARA	CA	-119.690	34.414

SBG	SEBRING	FL	-81.435	27.497
SBY	SHELBY	MT	-111.850	48.505
SCD	ST. CLOUD	MN	-94.148	45.567
SCH	SCHRIVER	LA	-90.813	29.747
SDL	SLIDELL	LA	-89.782	30.278
SDY	SCHENECTADY	NY	-73.943	42.815
SEA	SEATTLE	WA	-122.330	47.599
SED	SEDALIA	MO	-93.228	38.712
SFD	SANFORD	FL	-81.289	28.806
SIM	SIMI VALLEY	CA	-118.690	34.270
SJC	SAN JOSE	CA	-121.900	37.331
SJM	ST. JOSEPH	MI	-86.487	42.107
SKN	STOCKTON	CA	-121.280	37.946
SKY	SANDUSKY	OH	-82.712	41.440
SLC	SALT LAKE CITY	UT	-111.900	40.762
SLM	SALEM	OR	-123.030	44.932
SLO	SAN LUIS OBISPO	CA	-120.650	35.277
SLV	SOLVANG	CA	-120.140	34.596
SMC	SAN MARCOS	TX	-97.936	29.879
SMT	SUMMIT	IL	-87.813	41.792
SNA	SANTA ANA	CA	-117.860	33.753
SNB	SAN BERNARDINO	CA	-117.310	34.104
SNC	LEE HALL	CA	-117.660	33.501
SND	SANDERSON	TX	-102.400	30.140
SNS	SALINAS	CA	-121.660	36.679
SOB	SOUTH BEND	IN	-86.289	41.679
SOD	SODA SPRINGS	CA	-120.370	39.324
SOL	SOLANA BEACH	CA	-117.270	32.992
SOP	SOUTHERN PINES	NC	-79.392	35.174
SPB	SPARTANBURG	SC	-81.936	34.954
SPG	SPRINGFIELD	MA	-72.594	42.106
SPI	SPRINGFIELD	IL	-89.652	39.802
SPK	SPOKANE	WA	-117.410	47.657
SPL	STAPLES	MN	-94.795	46.355
SPM	SOUTH SHORE	KY	-82.964	38.721
SPR	SPARKS	NV	-119.750	39.542
SPT	SANDPOINT	ID	-116.610	48.252
SPX	SPARKS	NV	-119.760	39.534
SSM	SELMA	NC	-78.281	35.532
STA	STAUNTON	VA	-79.073	38.148
STL	ST. LOUIS	MO	-90.205	38.624

STM	STAMFORD	CT	-73.543	41.046
STN	STANLEY	ND	-102.390	48.319
SUI	SUISUN	CA	-122.040	38.243
SVT	STURTEVANT	WI	-87.905	42.700
SYR	SYRACUSE	NY	-76.152	43.086
TAC	TACOMA	WA	-122.420	47.242
TAY	TAYLOR	TX	-97.409	30.567
TCA	TOCCOA	GA	-83.331	34.579
TCL	TUSCALOOSA	AL	-87.560	33.192
THN	THURMOND	WV	-81.078	37.957
TLH	TALLAHASSEE	FL	-84.290	30.433
TOH	TOMAH	WI	-90.504	43.986
TOL	TOLEDO	OH	-83.541	41.638
TOP	TOPEKA	KS	-95.665	39.051
TPA	TAMPA	FL	-82.451	27.952
TPL	TEMPLE	TX	-97.345	31.095
TRE	TRENTON	NJ	-74.755	40.218
TRI	TRINIDAD	CO	-104.510	37.173
TRK	DENAIR	CA	-120.800	37.530
TRU	TRUCKEE	CA	-120.180	39.328
TUK	TUKWILA	WA	-122.240	47.453
TUS	TUCSON	AZ	-110.970	32.223
TXA	TEXARKANA	AR	-94.042	33.420
TYR	TYRONE	PA	-78.241	40.670
UCA	UTICA	NY	-75.224	43.104
VAN	VANCOUVER	WA	-122.680	45.630
VRV	VICTORVILLE	CA	-117.290	34.537
WAB	WATERBURY	VT	-72.752	44.335
WAC	WASCO	CA	-119.330	35.594
WAH	WASHINGTON	MO	-91.012	38.561
WAR	WARRENSBURG	MO	-93.740	38.763
WAS	WASHINGTON	DC	-77.006	38.897
WDL	WISCONSIN DELLS	WI	-89.775	43.625
WEN	WENATCHEE	WA	-120.310	47.422
WFH	WHITEFISH	MT	-114.340	48.414
WGL	WEST GLACIER	MT	-113.970	48.499
WHL	WHITEHALL	NY	-73.403	43.555
WIH	WISHRAM	WA	-120.970	45.657
WIL	WILMINGTON	DE	-75.552	39.737
WIN	WINONA	MN	-91.642	44.045
WIP	FRASER	CO	-105.820	39.949

WLN	WILSON	NC	-77.908	35.723
WLO	WINSLOW	AZ	-110.690	35.021
WLY	WESTERLY	RI	-71.831	41.381
WMA	WILLIAMS	AZ	-112.190	35.249
WNM	WINDSOR	VT	-72.385	43.480
WNN	WINNEMUCCA	NV	-117.730	40.970
WNR	WALNUT RIDGE	AR	-90.956	36.068
WOR	WORCHESTER	MA	-71.793	42.261
WPB	WEST PALM BEACH	FL	-80.062	26.712
WPK	WINTER PARK	FL	-81.352	28.597
WPT	WOLF POINT	MT	-105.640	48.091
WRJ	WHITE RIVER JUNCTION	VT	-72.318	43.649
WSP	WESTPORT	NY	-73.453	44.187
WSS	WHITE SULPHUR SPRING	WV	-80.306	37.785
WTH	WINTER HAVEN	FL	-81.734	28.002
WTI	WATERLOO	IN	-85.025	41.432
WTN	WILLISTON	ND	-103.620	48.143
YAZ	YAZOO CITY	MS	-90.415	32.848
YEM	YEMASSEE	SC	-80.847	32.688
YNY	YONKERS	NY	-73.903	40.936
YTO	YOUNGSTOWN	OH	-80.657	41.102
YUM	YUMA	AZ	-114.620	32.722

Proposed High-Speed Rail Corridor Layouts and Stations

California

The information presented in Figure 26 shows the proposed layout of the California corridor. Table 36 gives list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 26 is http://www.fra.dot.gov/rpd/downloads/California_Corridors_102910.pdf

Figure 26 - Planned Alignment of California High-Speed Rail Corridor

Table 36 - Modeled Train Stations for California High-Speed Rail Corridor

Station Code	California Station	Station Code	California Station
ANA	ANAHEIM	ONA	ONTARIO
BKY	BERKELEY	POS	POMONA
DAV	DAVIS	PRB	PASO ROBLES
EMY	EMERYVILLE	RIC	RICHMOND
FNO	FRESNO	RIV	RIVERSIDE
FUL	FULLERTON	RLN	ROCKLIN
GDL	GLENDALE	RSV	ROSEVILLE
IRV	IRVINE	SAC	SACRAMENTO
LAX	LOS ANGELES	SAN	SAN DIEGO
MCD	MERCED	SJC	SAN JOSE
OAC	OAKLAND	SNA	SANTA ANA

Pacific Northwest

Figure 27 shows the proposed layout of the Pacific Northwest corridor. Table 37 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 27 is http://www.fra.dot.gov/rpd/passenger/645.shtml

Figure 27 - Planned Alignment of Pacific Northwest High-Speed Rail Corridor

Table 37 - Modeled Train Stations for Pacific Northwest High-Speed Rail Corridor

Station Code	Oregon Station
ALY	ALBANY
EUG	EUGENE
ORG	OREGON CITY
SLM	SALEM

Station Code	Washington Station
BEL	BELLINGHAM
CTL	CENTRALIA
EDM	EDMONDS
EVR	EVERETT
KEL	KELSO
MVW	MOUNT VERNON
OLW	OLYMPIA
SEA	SEATTLE
TAC	TACOMA
TUK	TUKWILA

Florida

Figure 28 shows the proposed layout of the Florida corridor. Table 38 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 28 is http://www.fra.dot.gov/rpd/downloads/Tampa_Orlando_Miami_FINAL_1027.pdf

Figure 28 - Planned Alignment of Florida High-Speed Rail Corridor

Table 38 - Modeled Train Stations for Florida High-Speed Rail Corridor

Station Code	Florida Stations
DFB	DEERFIELD BEACH
DLB	DELRAY BEACH
FTL	FORT LAUDERDALE
HOL	HOLLYWOOD
KIS	KISSIMMEE
LAK	LAKELAND
MIA	MIAMI

Station Code	Florida Stations
ORL	ORLANDO
SFD	SANFORD
TPA	TAMPA
WPB	WEST PALM BEACH
WPK	WINTER PARK
WTH	WINTER HAVEN

Chicago Hub

The information presented in Figure 29, Figure 30, and Figure 31 shows the proposed layout of the Chicago Hub corridor. Table 39 and Table 40 provide a list of the stations that are modeled in TSAM to represent the corridor. The sources of Figure 29, Figure 30, and Figure 31 are
http://www.fra.dot.gov/rpd/downloads/Detroit_Chicago_FINAL_1027.pdf
http://www.fra.dot.gov/rpd/downloads/Kansas%20City_St%20Louis_Chicago_FINAL_1029.pdf
http://www.fra.dot.gov/rpd/downloads/Omaha_Iowa%20City_Chicago_FINAL.pdf

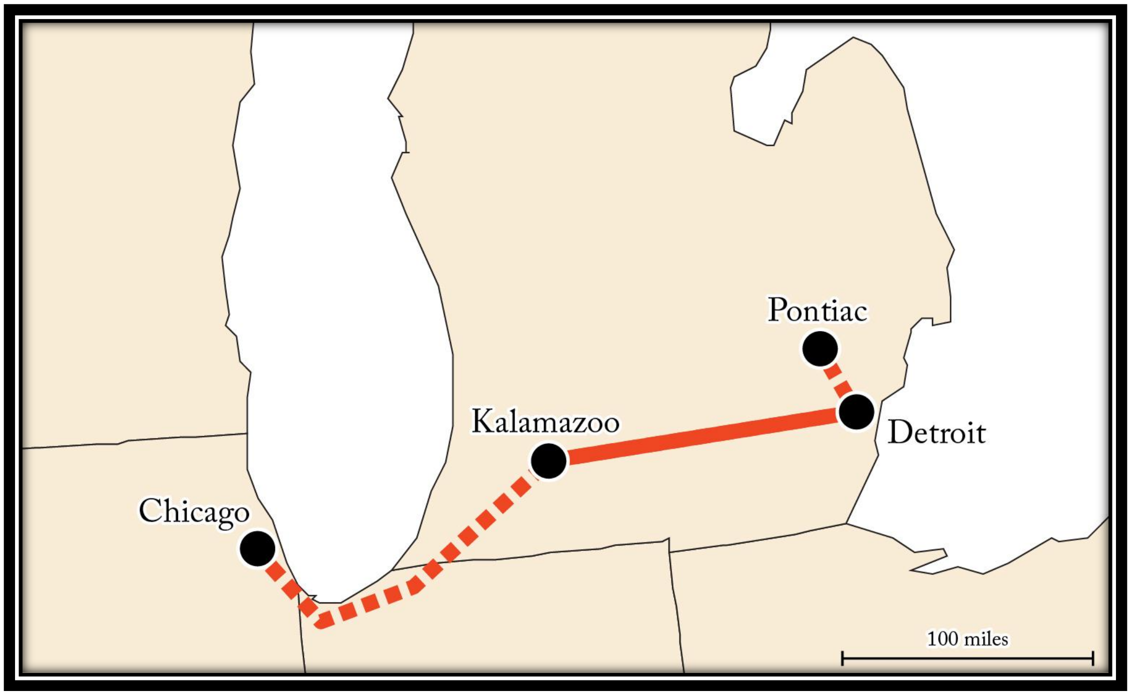

Figure 29 - Planned Alignment of Chicago Hub High-Speed Rail Corridor - part 1

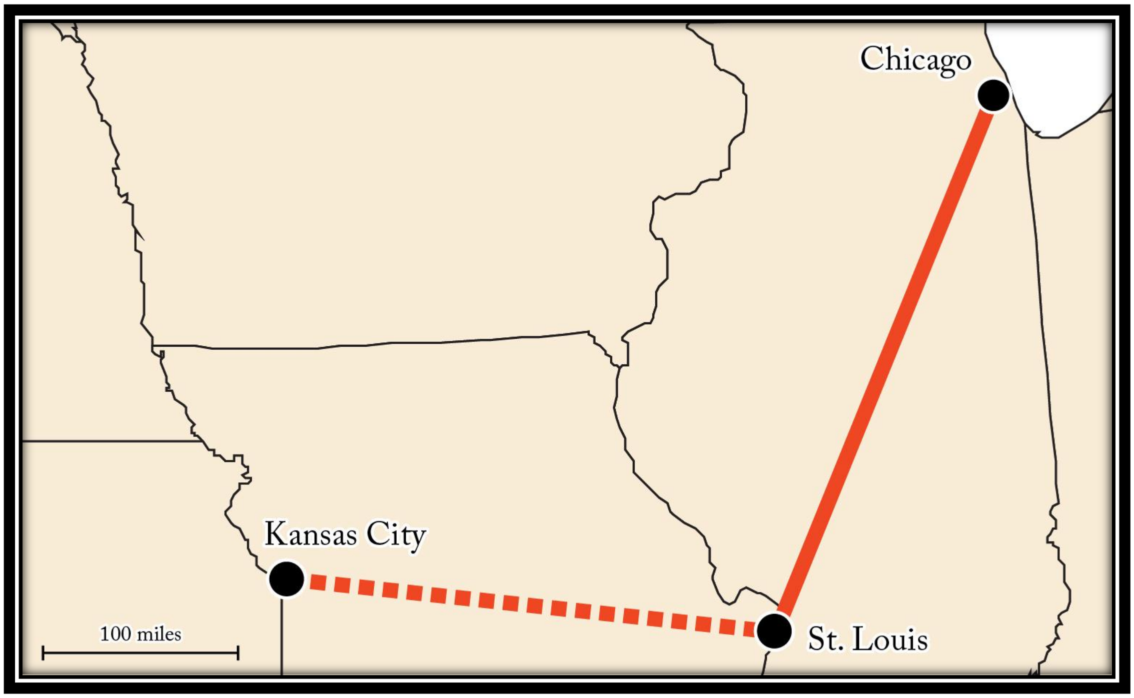

Figure 30 - Planned Alignment of Chicago Hub High-Speed Rail Corridor - part 2

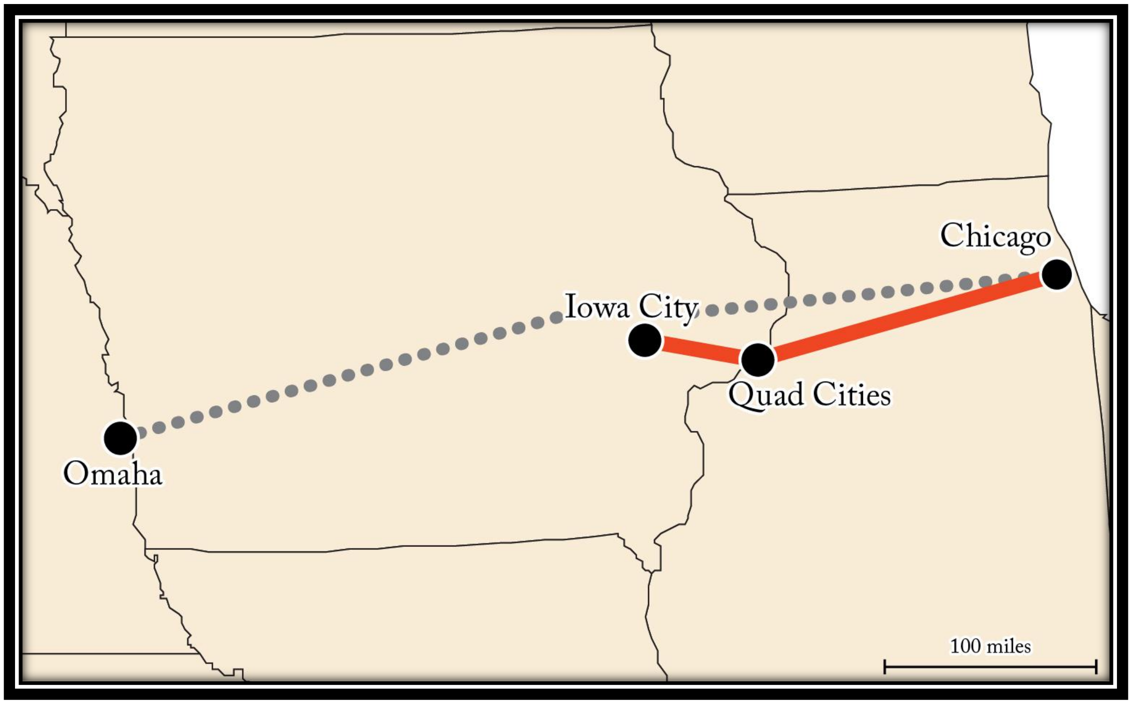

Figure 31 - Planned Alignment of Chicago Hub High-Speed Rail Corridor - part 3

Table 39 - Modeled Train Stations for Chicago Hub High-Speed Rail Corridor – p. 1

Station Code	Illinois Stations
ALN	ALTON
BNL	NORMAL
CHI	CHICAGO
CRV	CARLINVILLE
DWT	DWIGHT
JOL	JOLIET
LCN	LINCOLN
NPV	NAPERVILLE
PON	PONTIAC
SMT	SUMMIT
SPI	SPRINGFIELD

Station Code	Michigan Stations
ALI	ALBION
ARB	ANN ARBOR
BAM	BANGOR
BMM	BIRMINGHAM
BTL	BATTLE CREEK
DET	DETROIT
JXN	JACKSON
KAL	KALAMAZOO
NBM	NEW BUFFALO
PNT	PONTIAC
ROY	ROYAL OAK
SJM	ST. JOSEPH

Table 40 - Modeled Train Stations for Chicago Hub High-Speed Rail Corridor – p. 2

Station Code	Missouri Stations
IDP	INDEPENDENCE
KCY	KANSAS CITY
KWD	KIRKWOOD
STL	ST. LOUIS

Station Code	Iowa Stations
No Stations	

Station Code	Nebraska Stations
OMA	OMAHA

Station Code	Indiana Stations
DYE	DYER
HMI	HAMMOND
MCI	MICHIGAN CITY

Southeast

The information presented in Figure 32 shows the proposed layout of the Southeast corridor. Table 41 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 32 is http://www.fra.dot.gov/rpd/downloads/Charlotte_Raleigh_Richmond_DC_FINAL_1027.pdf

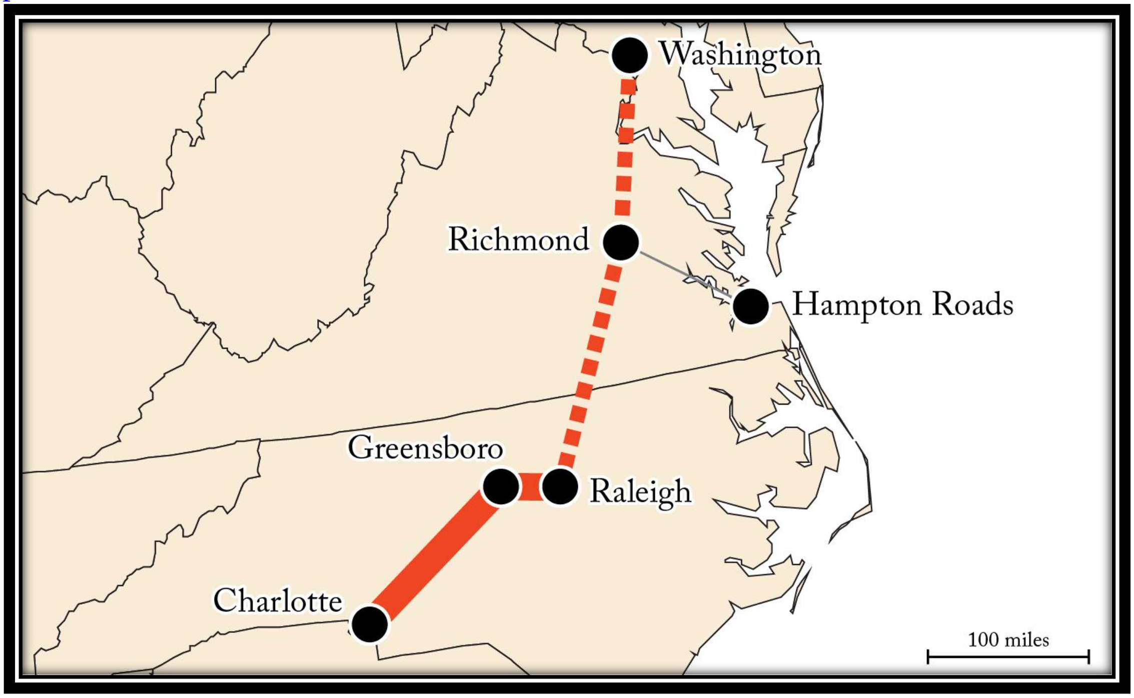

Figure 32 - Planned Alignment of Southeast High-Speed Rail Corridor

Table 41 - Modeled Train Stations for Southeast High-Speed Rail Corridor

Station Code	North Carolina Stations
BNC	BURLINGTON
CLT	CHARLOTTE
CYN	CARY
DNC	DURHAM
GRO	GREENSBORO
HPT	HIGH POINT
KAN	KANNAPOLIS
RGH	RALEIGH
SAL	SALISBURG

Station Code	Virginia Stations
ALX	ALEXANDRIA
FBG	FREDERICKSBURG
MSS	MANASSAS
PTB	ETTRICK
QAN	QUNATICO
RVR	RICHMOND

Station Code	D.C. Stations
WAS	WASHINGTON

Empire

The information presented in Figure 33 shows the proposed layout of the Empire corridor. Table 42 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 33 is http://www.fra.dot.gov/rpd/passenger/653.shtml

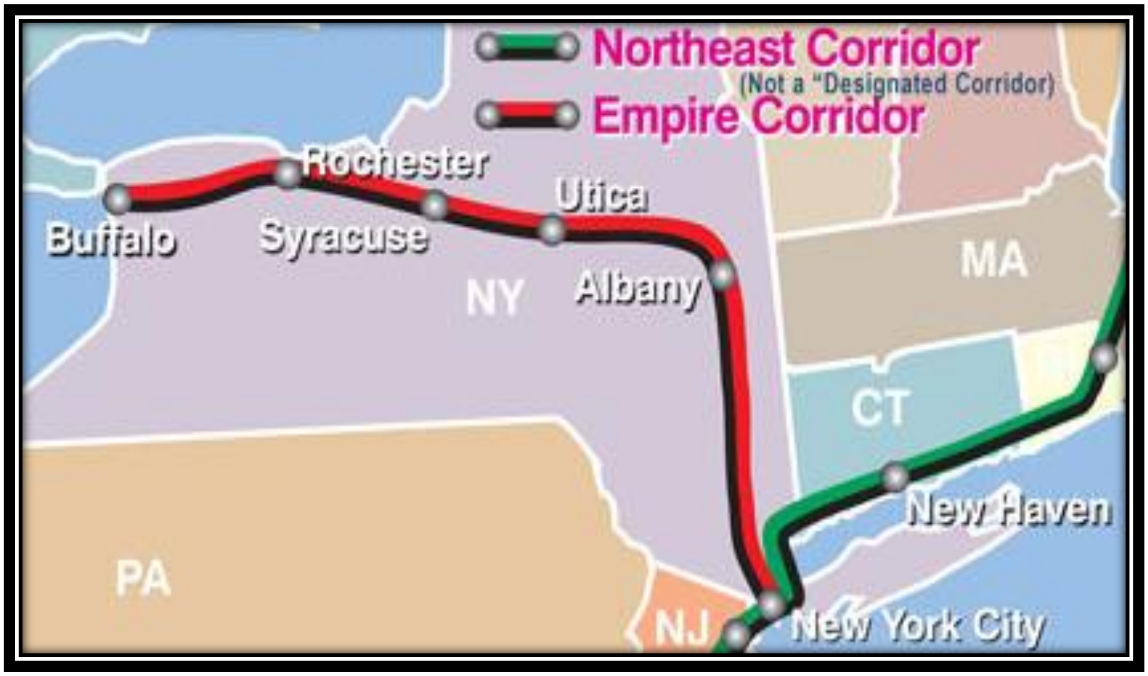

Figure 33 - Planned Alignment of Empire High-Speed Rail Corridor

Table 42 - Modeled Train Stations for Empire High-Speed Rail Corridor

Station Code	New York Stations
ALB	RENSSELAER
AMS	AMSTERDAM
BFX	BUFFALO
HUD	HUDSON
NFL	NIAGARA FALLS
NYP	NEW YORK
POU	POUGHKEEPSIE
RHI	RHINECLIFF
ROC	ROCHESTER
ROM	ROME
SDY	SCHENECTADY
SYR	SYRACUSE
UCA	UTICA
YNY	YONKERS

Northern New England

The information presented in Figure 34 shows the proposed layout of the Northern New England corridor. Table 43 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 34 is http://www.fra.dot.gov/rpd/passenger/654.shtml

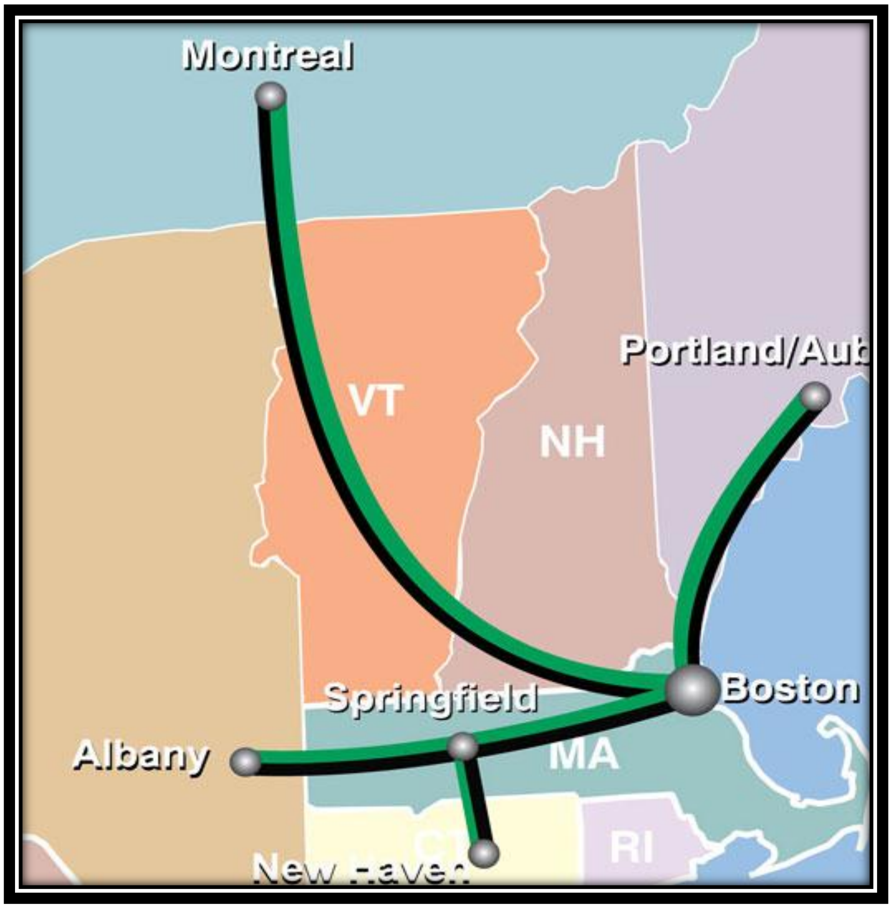

Figure 34 - Planned Alignment of Northern New England High-Speed Rail Corridor

Table 43 - Modeled Train Stations for Northern New England High-Speed Rail Corridor

Station Code	New York Stations
ALB	RENSSELAER
FED	FORT EDWARD
FTC	TICONDEROGA
GZZ	GLENS FALL
PLB	PLATTSBURGH
POH	PORT HENRY
PRK	PORT KENT
RSP	ROUSES POINT
WHL	WHITEHALL
WSP	WESTPORT

Station Code	Massachusetts Stations
BBY	BOSTON
FRA	FRAMINGHAM
SPG	SPRINGFIELD
WOR	WORCHESTER

Station Code	Connecticut Stations
BER	KENSINGTON
HFD	HARTFORD
MDN	MERIDEN
NHV	NEW HAVEN

Keystone

The information presented in Figure 35 shows the proposed layout of the Keystone corridor. Table 44 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 35 is http://www.fra.dot.gov/rpd/passenger/652.shtml

Figure 35 - Planned Alignment of High-Speed Rail Corridor

Table 44 - Modeled Train Stations for Keystone High-Speed Rail Corridor

Station Code	**Pennsylvania Stations**
COV	CONNELLSVILLE
GNB	GREENSBURG
HAR	HARRISBURG
LAB	LATROBE
PAO	PAOLI
PGH	PITTSBURGH
PHL	PHILADELPHIA

South Central

The information presented in Figure 36 shows the proposed layout of the South Central corridor. Table 45 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 36 is http://www.fra.dot.gov/rpd/passenger/647.shtml

Figure 36 - Planned Alignment of South Central High-Speed Rail Corridor

Table 45 - Modeled Train Stations for South Central High-Speed Rail Corridor

Station Code	Oklahoma Stations
ADM	ADRMORE
NOR	NORMAN
OKC	OKLAHOMA CITY
PUR	PURCELL
PVL	PAULS VALLEY

Station Code	Arkansas Stations
ARK	ARKADELPHIA
LRK	LITTLE ROCK
MVN	MALVERN
TXA	TEXARKANA

Station Code	Texas Stations
AUS	AUSTIN
CBR	CLEBURNE
DAL	DALLAS
FTW	FORT WORTH
GLE	GAINESVILLE
MCG	MCGREGOR
SAS	SAN ANTONIO
SMC	SAN MARCOS
TAY	TAYLOR
TPL	TEMPLE

Gulf Coast

The information presented in Figure 37 shows the proposed layout of the Gulf Coast corridor. Table 46 gives a list of the stations that are modeled in TSAM to represent the corridor. The source of Figure 37 is http://www.fra.dot.gov/rpd/passenger/649.shtml

Figure 37 - Planned Alignment of Gulf Coast High-Speed Rail Corridor

Table 46 - Modeled Train Stations for Gulf Coast High-Speed Rail Corridor

Station Code	Mississippi Stations
BIX	BILOXI
HBG	HATTIESBURG
LAU	LAUREL
MEI	MERIDIAN
PIC	PICAYUNE

Station Code	Louisiana Stations
LCH	LAKE CHARLES
LFT	LAFAYETTE
NOL	NEW ORLEANS

Station Code	Georgia Stations
ATL	Atlanta

Station Code	Alabama Stations
ATN	ANNISTON
BHM	BIRMINGHAM
MOE	MOBILE
TCL	TUSCALOOSA

Station Code	Texas Stations
BMT	BEAUMONT
HOS	HOUSTON

Vermont Route

The information presented in Figure 38 shows the proposed layout of the Vermont corridor. Table 47 gives a list of the stations that are modeled in TSAM to represent the corridor. The image shown represents the entire northeast area. The Vermont line is considered the route that runs between St. Albans, VT and New Haven, CT. The source of Figure 38 is
http://www.fra.dot.gov/rpd/downloads/Northeast_Region_FINAL_1027.pdf

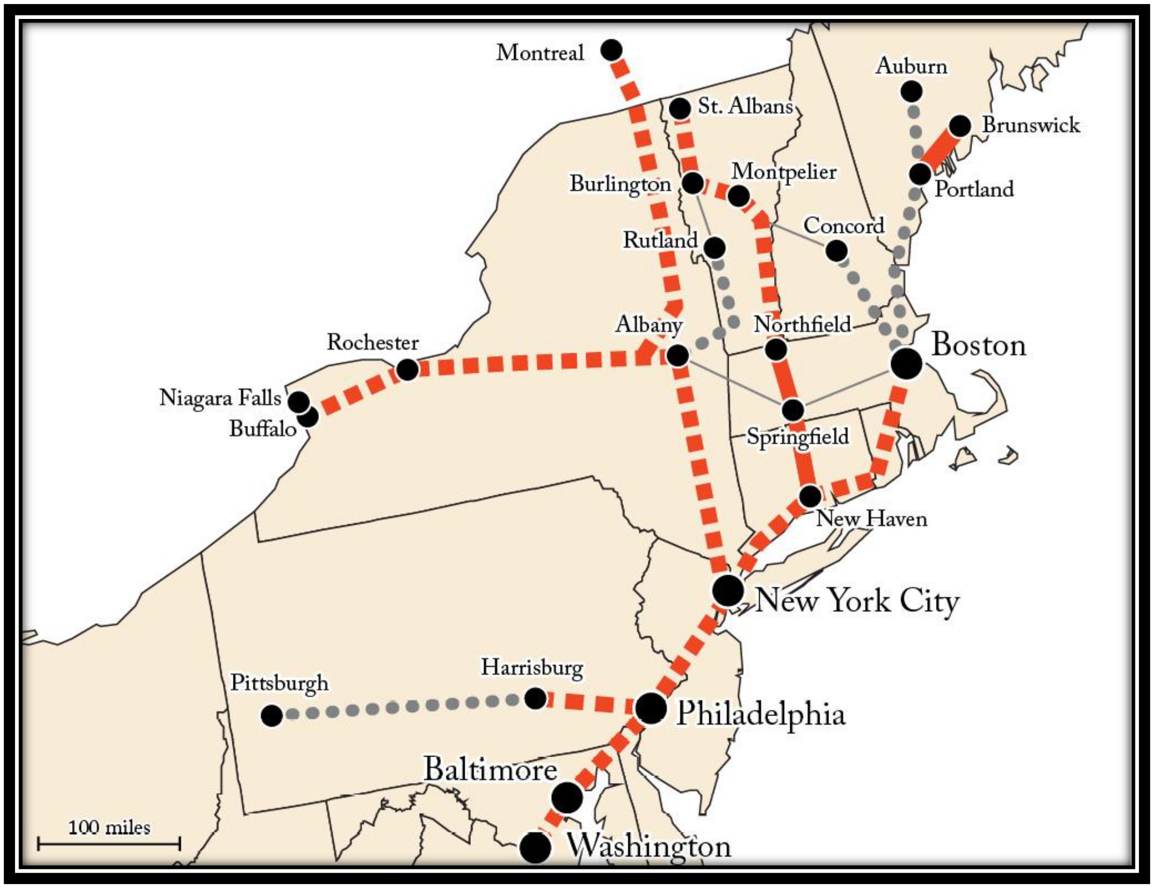

Figure 38 - Planned Alignment of Vermont High-Speed Rail Corridor

Table 47 - Modeled Train Stations for Vermont High-Speed Rail Corridor

Station Code	Vermont Stations
BLF	BELLOWS FALLS
BRA	BRATTLEBORO
ESX	ESSEX JUNCTION
MPR	MONTPELIER
RPH	RANDOLPH
SAB	ST. ALBANS
WAB	WATERBURY
WNM	WINDSOR
WRJ	WHITE RIVER JUNCTION

Station Code	Massachusetts Stations
AMM	AMHERST
SPG	SPRINGFIELD

Station Code	Connecticut Stations
BER	KENSINGTON
HFD	HARTFORD
MDN	MERIDEN
NHV	NEW HAVEN

Original Northeast Corridor

Figure 39 shows the proposed layout of the Original Northeast corridor. Table 24 gives a list of the stations that are modeled in TSAM to represent the corridor. The image shown represents the entire northeast area. The Original Northeast Corridor line is considered the route that runs between Boston, MA and Washington, DC. The source of Figure 39 is http://www.fra.dot.gov/rpd/downloads/Northeast_Region_FINAL_1027.pdf

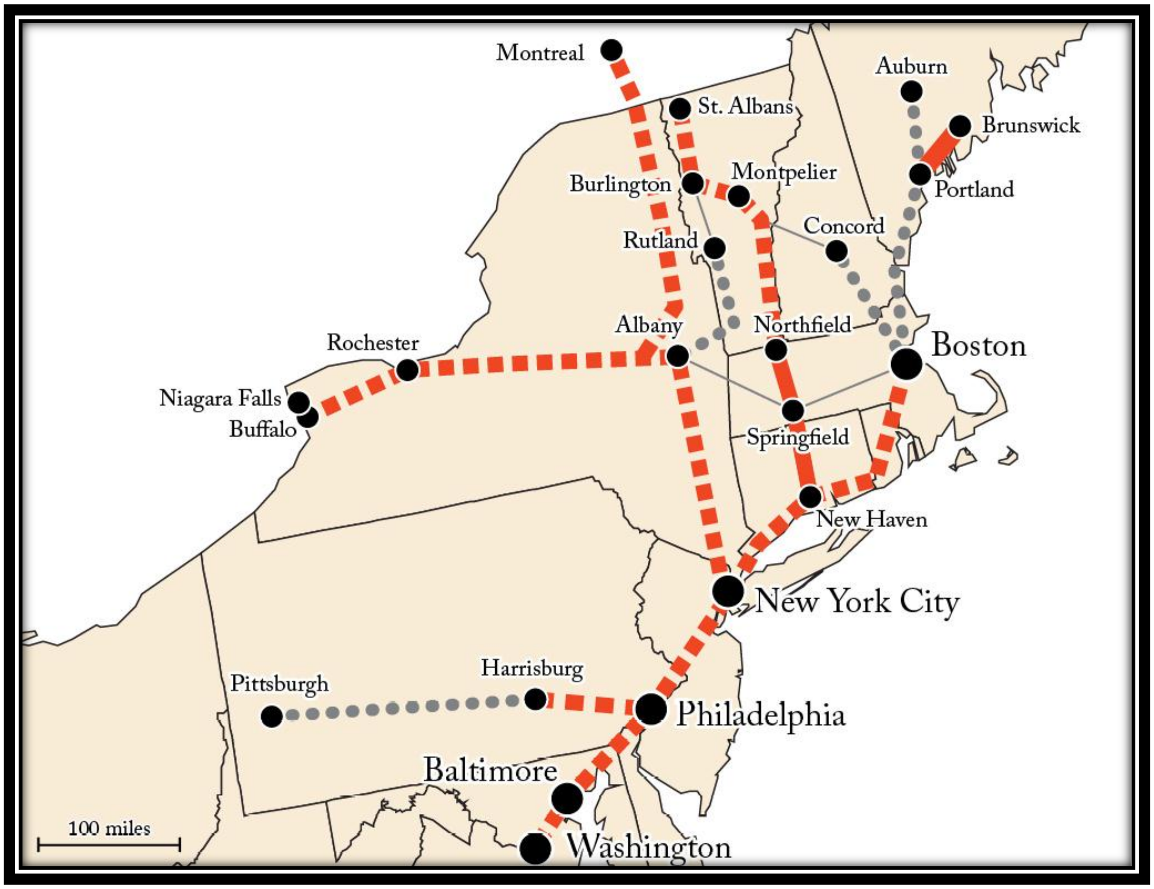

Figure 39 - Planned Alignment of Original Northeast Corridor

Proposed High-Speed Rail Corridors Modeling Assumptions

Table 48 shows the assumptions that go into the modeling of the high-speed rail corridors. The max planned speed is known for all corridors, however average travel speed is necessary for modeling. Based on information from planning studies, it is assumed that the average travel speed for each corridor will be approximately 70% of the maximum travel speed. This assumption is applied to each corridor in order to develop the average speed.

Table 48 – High-Speed Rail Corridor Modeling Assumptions

	Max Speed (mph)	Average/Max Speed	Average Speed (mph)	Train Frequency (all-all)
Original NEC	170	0.7	119	8
California	220	0.7	153	8
Pacific Northwest	150	0.7	105	8
Florida	168	0.7	118	8
Chicago Hub	110	0.7	77	8
Southeast	110	0.7	77	8
Empire	110	0.7	77	8
Northern New England	110	0.7	77	8
Keystone	110	0.7	77	8
South Central	150	0.7	105	8
Gulf Coast	150	0.7	105	8
NEC Northern	110	0.7	77	8

Nationwide Train Travel Time and Travel Cost Regression Curves

Figure 40 shows the travel time regression that is used to model the northeast region service that operates in the Northeast Corridor. This regional service was in place before the Acela service and continues to operate today, however for the purpose of TSAM, the regional service is modeled only from 1995 – 2000. Figure 41 shows the travel time regression curve for the regional service.

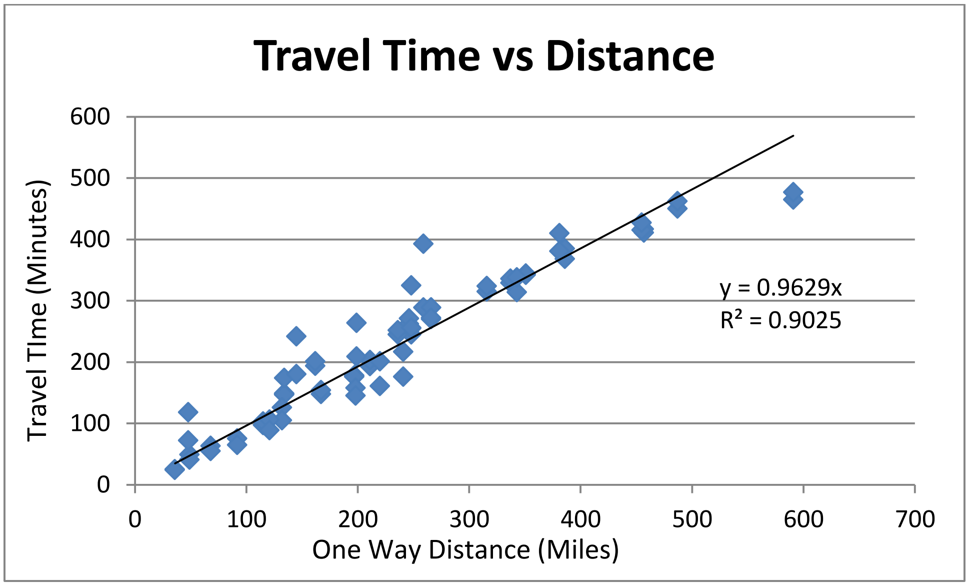

Figure 40 - Northeast Corridor Regional Service Travel Time Regression Curve

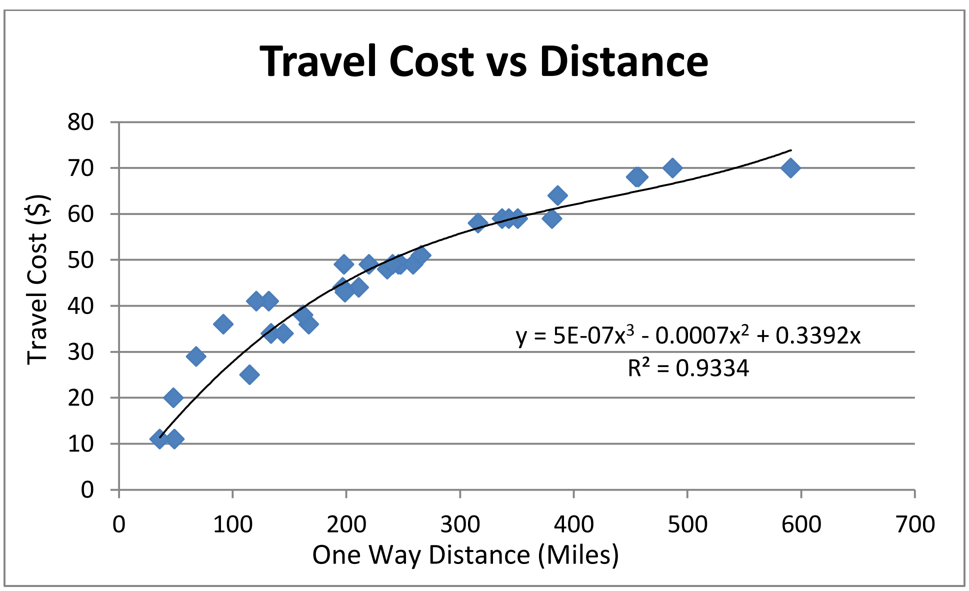

Figure 41 - Northeast Corridor Regional Service Travel Cost Regression Curve

Figure 42 shows the regression analysis that is used to determine the curve that will be used to estimate the travel time of the Acela Express train. A linear curve is found to be the best fit; the line is set to have an intercept of 0 so that the equation is valid for all distances.

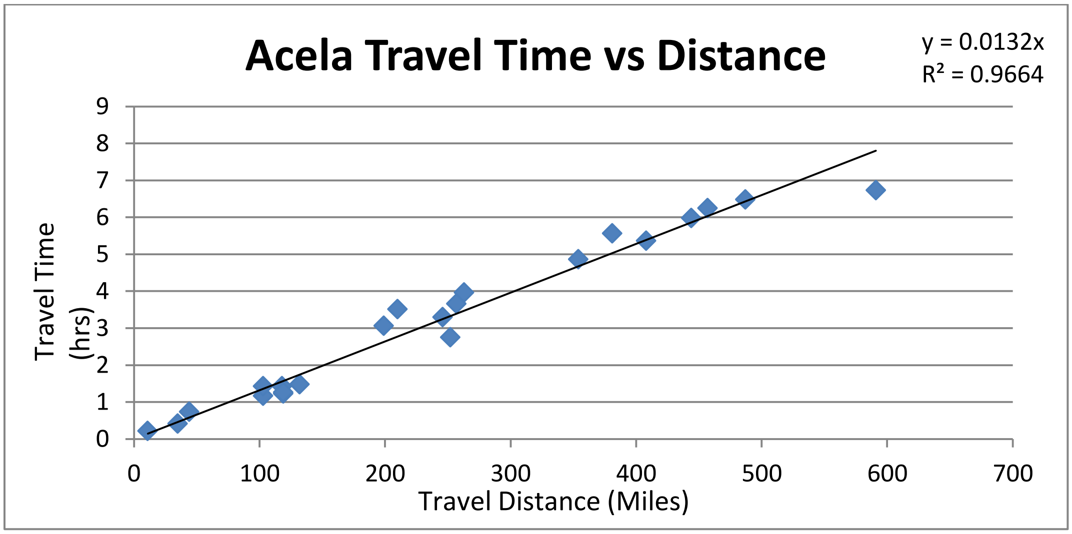

Figure 42 - Acela Express Travel Time Regression Curve

Figure 43 shows the regression analysis that is used to determine the curve that will be used to estimate the travel cost of the Acela Express train. A third order polynomial is found to be the best fit. The equation of the line and the R^2 value is shown on the chart.

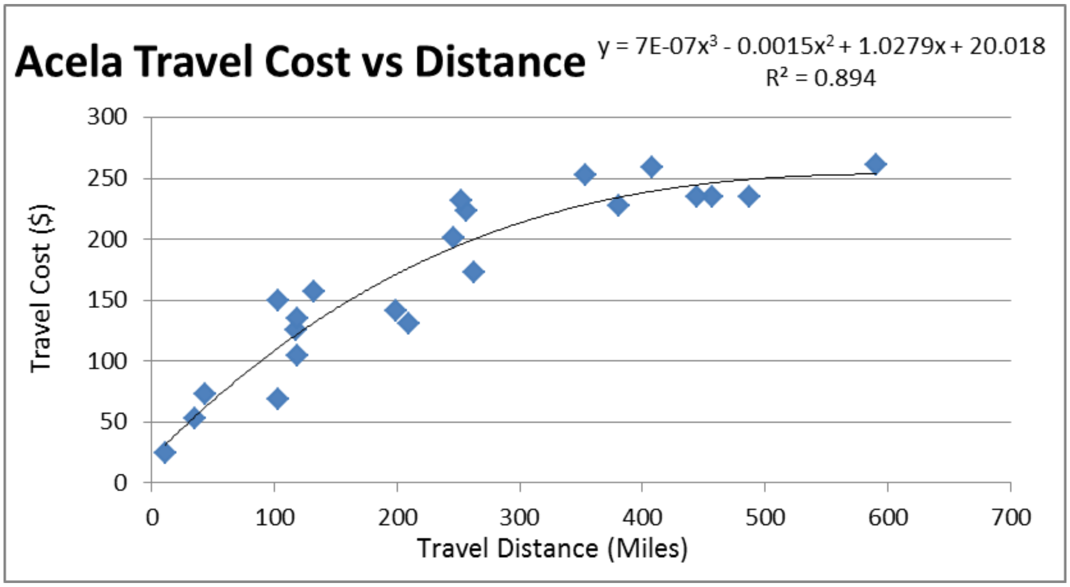

Figure 43 - Acela Express Travel Cost Regression Curve

TSAM Lodging Time Penalty

Table 49 shows the forced stay time for business trips for all three modes depending on the round trip travel time. Note that there is no penalty for a trip shorter than 8 hours and the penalty for any trip greater than 16 hours is one day. Also note that for the time penalty, a day is defined as 24 hours – maximum daily travel time. For business trips, the max daily travel time is 8 hours therefore 1 day for the time penalty is considered 16 hours.

Table 49 - TSAM Lodging Time Penalty

Round Trip Time (hours)	Forced Stay (days)
0-8	0
8.5	0.0625
9	0.125
9.5	0.1875
10	0.25
10.5	0.3125
11	0.375
11.5	0.4375
12	0.5
12.5	0.5625
13	0.625
13.5	0.6875
14	0.75
14.5	0.8125
15	0.875
15.5	0.9375
16-30	1

Nationwide Mode Choice Calibration Detailed Results

Table 50 shows the numerical results of the mode choice calibration vs. the ATS Data Set

Table 50 - Nationwide Mode Choice Calibration - Detailed Results

	Automobile Round Trips in 1995					
	Business		Non-Business		Total	
Income Group	ATS	MC Calibration	ATS	MC Calibration	ATS	MC Calibration
<$28K	20,622,164	20,621,335	116,841,938	116,886,483	137,464,102	137,507,818
$28K - $56K	60,876,508	60,877,756	275,542,934	275,572,874	336,419,442	336,450,630
$56K -$85K	41,574,747	41,597,008	196,951,658	196,958,161	238,526,405	238,555,169
$85K - $141K	24,864,575	24,815,150	94,753,296	94,792,815	119,617,871	119,607,965
> $141K	6,141,526	6,124,985	22,106,071	22,105,730	28,247,597	28,230,715
Total	154,079,520	154,036,233	706,195,897	706,316,064	860,275,417	860,352,297

	Commercial Airline Round Trips in 1995					
	Business		Non-Business		Total	
Income Group	ATS	MC Calibration	ATS	MC Calibration	ATS	MC Calibration
<$28K	3,175,263	3,176,078	11,459,457	11,370,037	14,634,720	14,546,116
$28K - $56K	12,418,753	12,417,255	25,870,251	25,802,691	38,289,004	38,219,945
$56K -$85K	21,694,421	21,775,791	25,447,773	25,395,711	47,142,195	47,171,502
$85K - $141K	18,116,856	18,189,458	16,276,410	16,227,008	34,393,266	34,416,466
> $141K	10,645,650	10,669,115	9,688,634	9,690,781	20,334,285	20,359,896
Total	66,050,944	66,227,697	88,742,525	88,486,227	154,793,470	154,713,924

	Rail Round Trips in 1995					
	Business		Non-Business		Total	
Income Group	ATS	MC Calibration	ATS	MC Calibration	ATS	MC Calibration
<$28K	119,571	119,585	1,093,836	1,138,710	1,213,407	1,258,295
$28K - $56K	187,641	187,892	1,319,615	1,357,236	1,507,256	1,545,127
$56K -$85K	567,381	463,751	736,508	782,068	1,303,889	1,245,818
$85K - $141K	332,881	309,704	614,586	624,469	947,467	934,173
> $141K	151,538	144,614	126,279	124,473	277,816	269,087
Total	1,359,012	1,225,546	3,890,824	4,026,956	5,249,836	5,252,501

	All US Continental Round Trips in 1995					
	Business		Non-Business		Total	
Income Group	ATS	MC Calibration	ATS	MC Calibration	ATS	MC Calibration
<$28K	23,916,998	23,916,998	129,395,231	129,395,231	153,312,229	153,312,229
$28K - $56K	73,482,902	73,482,902	302,732,800	302,732,800	376,215,703	376,215,703
$56K -$85K	63,836,550	63,836,550	223,135,940	223,135,940	286,972,489	286,972,489
$85K - $141K	43,314,312	43,314,312	111,644,292	111,644,292	154,958,604	154,958,604
> $141K	16,938,714	16,938,714	31,920,984	31,920,984	48,859,698	48,859,698
Total	221,489,476	221,489,476	798,829,247	798,829,247	1,020,318,723	1,020,318,723

Table 51 - Nationwide Mode Choice Calibration - Calibration Coefficients

		Business 1	Business 2	Business 3	Business 4	Business 5	Non Business 1	Non Business 2	Non Business 3	Non Business 4	Non Business 5
Travel Time	α	-2.4120	-2.7832	-3.8096	-4.2348	-5.4205	-2.6295	-4.8889	-5.3026	-2.4363	-10.0000
	λ Auto	-0.0843	-0.1064	-0.2048	-0.1776	-0.2864	-0.0551	-0.2275	-0.2072	-0.1233	-0.3266
	λ Air	-2.0000	-1.9998	-0.4806	-0.4826	-0.5713	-2.0000	-2.0000	-0.3308	-2.0000	-0.6033
	λ Rail	-2.0000	-2.0000	-0.2952	-2.0000	-2.0000	-1.0536	-2.0000	-0.3326	0.0284	-0.4883
Travel Cost	α	-1.0380	-1.1731	-0.3948	-0.4807	-0.4076	-1.3780	-2.4729	-0.7692	-3.2027	-0.4241
	λ Auto	-2.0000	-2.0000	-2.0000	-1.3857	-2.0000	-2.0000	-2.0000	-2.0000	-0.2890	-2.0000
	λ Air	0.0501	0.0309	0.0979	0.1089	0.0771	0.0269	-0.0801	0.0220	-0.1004	0.3181
	λ Rail	0.2000	0.1976	0.1872	0.4475	0.4714	0.0995	0.0302	0.1452	-0.2902	0.3781
% Correct Pred.		89.2516	90.6294	86.4111	86.9497	86.0287	92.0932	92.9178	91.7465	90.5294	89.0610
% Correct Pred. (Weighted)		89.3311	89.9967	84.3039	85.9545	86.5231	92.2698	93.2527	92.1802	91.2045	87.3042

TSAM Mode Choice Application Detailed Results

Baseline Case

Table 52 below provides the detailed results for the baseline 2011 TSAM run. This run models only the existing train corridors using the time and cost curves that are presented.

Table 52 - TSAM Mode Choice Detailed Results - Baseline Case

	Automobile Trips		
Income Group	Business	Non Business	**Total**
<$28K	18,302,061	101,988,905	120,290,966
$28K - $56K	69,095,049	300,736,295	369,831,344
$56K -$85K	58,692,340	263,065,428	321,757,768
$85K - $141K	38,384,766	136,906,056	175,290,822
> $141K	10,371,675	37,668,045	48,039,720
Total	194,845,891	840,364,729	1,035,210,620

	CA Trips		
Income Group	Business	Non Business	**Total**
<$28K	2,871,546	13,075,518	15,947,064
$28K - $56K	13,636,714	35,914,522	49,551,236
$56K -$85K	29,533,071	43,218,409	72,751,480
$85K - $141K	26,576,778	29,556,003	56,132,781
> $141K	17,407,717	14,529,180	31,936,897
Total	90,025,826	136,293,632	226,319,458

	Train Trips		
Income Group	Business	Non Business	**Total**
<$28K	54,346	1,156,826	1,211,172
$28K - $56K	91,542	1,827,457	1,918,999
$56K -$85K	717,496	1,041,833	1,759,329
$85K - $141K	334,846	1,364,335	1,699,181
> $141K	183,970	149,408	333,378
Total	1,382,200	5,539,859	6,922,059

	Total Trips		
Income Group	Business	Non Business	**Total**
<$28K	21,227,953	116,221,249	137,449,202
$28K - $56K	82,823,305	338,478,274	421,301,579
$56K -$85K	88,942,907	307,325,670	396,268,577
$85K - $141K	65,296,390	167,826,394	233,122,784
> $141K	27,963,362	52,346,633	80,309,995
Total	286,253,917	982,198,220	1,268,452,137

Scenario 1

Table 53 below provides the detailed results for the baseline 2011 TSAM run. This run models the future corridors with a travel cost of $0.20/mile and uses the planned average travel speeds.

Table 53 - TSAM Mode Choice Detailed Results - Scenario 1

	Automobile Trips		
Income Group	Business	Non Business	**Total**
<$28K	18,239,582	101,735,837	119,975,419
$28K - $56K	68,896,646	300,240,084	369,136,730
$56K -$85K	57,953,303	262,274,095	320,227,398
$85K - $141K	37,066,725	135,839,942	172,906,667
> $141K	9,803,167	37,510,520	47,313,687
Total	191,959,423	837,600,478	1,029,559,901

	CA Trips		
Income Group	Business	Non Business	**Total**
<$28K	2,868,760	13,058,616	15,927,376
$28K - $56K	13,620,185	35,882,506	49,502,691
$56K -$85K	29,428,061	43,170,634	72,598,695
$85K - $141K	26,310,657	29,469,043	55,779,700
> $141K	17,151,409	14,516,860	31,668,269
Total	89,379,072	136,097,659	225,476,731

	Train Trips		
Income Group	Business	Non Business	**Total**
<$28K	119,611	1,426,796	1,546,407
$28K - $56K	306,474	2,355,684	2,662,158
$56K -$85K	1,561,543	1,880,941	3,442,484
$85K - $141K	1,919,008	2,517,409	4,436,417
> $141K	1,008,786	319,253	1,328,039
Total	4,915,422	8,500,083	13,415,505

	Total Trips		
Income Group	Business	Non Business	**Total**
<$28K	21,227,953	116,221,249	137,449,202
$28K - $56K	82,823,305	338,478,274	421,301,579
$56K -$85K	88,942,907	307,325,670	396,268,577
$85K - $141K	65,296,390	167,826,394	233,122,784
> $141K	27,963,362	52,346,633	80,309,995
Total	286,253,917	982,198,220	1,268,452,137

<u>Scenario 2</u>

Table 54 below provides the detailed results for the baseline 2011 TSAM run. This run models the future corridors with a travel cost of $0.20/mile and an average travel speed of 153 mph for all projected corridors.

Table 54 - TSAM Mode Choice Detailed Results - Scenario 2

	Automobile Trips		
Income Group	Business	Non Business	**Total**
<$28K	18,218,175	101,668,029	119,886,204
$28K - $56K	68,802,074	300,098,999	368,901,073
$56K -$85K	57,848,047	261,919,127	319,767,174
$85K - $141K	36,432,980	135,360,294	171,793,274
> $141K	9,594,999	37,382,581	46,977,580
Total	190,896,275	836,429,030	1,027,325,305

	CA Trips		
Income Group	Business	Non Business	**Total**
<$28K	2,866,819	13,054,034	15,920,853
$28K - $56K	13,608,690	35,873,817	49,482,507
$56K -$85K	29,383,703	43,152,126	72,535,829
$85K - $141K	26,137,748	29,431,226	55,568,974
> $141K	17,023,037	14,506,223	31,529,260
Total	89,019,997	136,017,426	225,037,423

	Train Trips		
Income Group	Business	Non Business	**Total**
<$28K	142,959	1,499,186	1,642,145
$28K - $56K	412,541	2,505,458	2,917,999
$56K -$85K	1,711,157	2,254,417	3,965,574
$85K - $141K	2,725,662	3,034,874	5,760,536
> $141K	1,345,326	457,829	1,803,155
Total	6,337,645	9,751,764	16,089,409

	Total Trips		
Income Group	Business	Non Business	**Total**
<$28K	21,227,953	116,221,249	137,449,202
$28K - $56K	82,823,305	338,478,274	421,301,579
$56K -$85K	88,942,907	307,325,670	396,268,577
$85K - $141K	65,296,390	167,826,394	233,122,784
> $141K	27,963,362	52,346,633	80,309,995
Total	286,253,917	982,198,220	1,268,452,137

Scenario 3

Table 55 below provides the detailed results for the baseline 2011 TSAM run. This run models the future corridors with a travel cost of $0.40/mile and uses the planned average travel speeds.

Table 55 - TSAM Mode Choice Detailed Results - Scenario 3

	Automobile Trips		
Income Group	Business	Non Business	**Total**
<$28K	18,283,232	101,981,756	120,264,988
$28K - $56K	69,012,616	300,697,631	369,710,247
$56K -$85K	58,662,603	262,815,277	321,477,880
$85K - $141K	37,624,234	136,457,795	174,082,029
> $141K	10,026,030	37,659,578	47,685,608
Total	193,608,715	839,612,037	1,033,220,752

	CA Trips		
Income Group	Business	Non Business	**Total**
<$28K	2,871,216	13,076,122	15,947,338
$28K - $56K	13,629,045	35,911,787	49,540,832
$56K -$85K	29,555,223	43,207,277	72,762,500
$85K - $141K	26,405,373	29,517,339	55,922,712
> $141K	17,244,302	14,531,122	31,775,424
Total	89,705,159	136,243,647	225,948,806

	Train Trips		
Income Group	Business	Non Business	**Total**
<$28K	73,505	1,163,371	1,236,876
$28K - $56K	181,644	1,868,856	2,050,500
$56K -$85K	725,081	1,303,116	2,028,197
$85K - $141K	1,266,783	1,851,260	3,118,043
> $141K	693,030	155,933	848,963
Total	2,940,043	6,342,536	9,282,579

	Total Trips		
Income Group	Business	Non Business	**Total**
<$28K	21,227,953	116,221,249	137,449,202
$28K - $56K	82,823,305	338,478,274	421,301,579
$56K -$85K	88,942,907	307,325,670	396,268,577
$85K - $141K	65,296,390	167,826,394	233,122,784
> $141K	27,963,362	52,346,633	80,309,995
Total	286,253,917	982,198,220	1,268,452,137

Scenario 4

Table 54 below provides the detailed results for the baseline 2011 TSAM run. This run models the future corridors with a travel cost of $0.20/mile and an average travel speed of 153 mph for all projected corridors.

Table 56 - TSAM Mode Choice Detailed Results - Scenario 4

	Automobile Trips		
Income Group	Business	Non Business	**Total**
<$28K	18,275,646	101,950,557	120,226,203
$28K - $56K	68,968,974	300,636,896	369,605,870
$56K -$85K	58,649,639	262,661,167	321,310,806
$85K - $141K	37,193,281	136,189,317	173,382,598
> $141K	9,872,496	37,635,601	47,508,097
Total	192,960,036	839,073,538	1,032,033,574

	CA Trips		
Income Group	Business	Non Business	**Total**
<$28K	2,870,578	13,074,009	15,944,587
$28K - $56K	13,623,309	35,907,990	49,531,299
$56K -$85K	29,551,717	43,199,706	72,751,423
$85K - $141K	26,283,131	29,495,339	55,778,470
> $141K	17,151,009	14,529,694	31,680,703
Total	89,479,744	136,206,738	225,686,482

	Train Trips		
Income Group	Business	Non Business	**Total**
<$28K	81,729	1,196,683	1,278,412
$28K - $56K	231,022	1,933,388	2,164,410
$56K -$85K	741,551	1,464,797	2,206,348
$85K - $141K	1,819,978	2,141,738	3,961,716
> $141K	939,857	181,338	1,121,195
Total	3,814,137	6,917,944	10,732,081

	Total Trips		
Income Group	Business	Non Business	**Total**
<$28K	21,227,953	116,221,249	137,449,202
$28K - $56K	82,823,305	338,478,274	421,301,579
$56K -$85K	88,942,907	307,325,670	396,268,577
$85K - $141K	65,296,390	167,826,394	233,122,784
> $141K	27,963,362	52,346,633	80,309,995
Total	286,253,917	982,198,220	1,268,452,137

Appendix B – Source Code

Train Dynamics Model - Matlab Code

Primary File

```
% This script contains high speed train coefficients and calls the
function
% train_profile_function.

stat_dist   =input('The distance(meters) between train stations = ');
train_model =input('\n Enter the number of the train to be modeled. \n
\n 1. Shinkansen Series 100  \n 2. Shinkansen Series 200 \n 3. French
TGV-R \n 4. French TGV-D \n = ');
des_speed   =input('\n The maximum desired cruising speed (m/s) = ');
decel_rate  =input('\n The constant deceleration rate (m/s) for this
train(Enter as positive number) = ');
time_step   =input('\n The time step used in acceleration and
deceleration calcs. = ');



%This function assigns the various coefficents of the desired train to
be
%modeled.
[Resistive_Coefficients,Tractive_Coefficients,mass,capacity]=Train_Coef
ficients(train_model);

%This if state is necessary because if the TGV is to be modeled, the
%resistive coefficents are calculated differently thus there is a
seperate
%function for the calcs.
if train_model==3 || train_model==4
    Resistive_Coefficients=TGV_Resistance(mass);
end

load_factor =0.8;  %This is the percentage of the train capacity that
is occupied. Used for energy consumption/passenger.

Acceleration_cut_off =0.02; %Units are m/(s*s). This value is used such
that when the acceleration at a given time step is less than the
Acceleration_cut_off value, the train is effectively considered to be
at top speed, thus ending the acceleration phase.

Energy_Regeneration_Factor =0.1; %This factor estimates the percentage
of total energy expended during acceleration and cruise that can be
recovered with regenerative braking. The current value of 10% is
estimated based on several literature papers.

[Velocity_Maximum,Total_Energy_Consumption,Total_Travel_Time]
=train_profile_function(stat_dist,des_speed,decel_rate,time_step,mass,R
esistive_Coefficients,Tractive_Coefficients,Acceleration_cut_off,Energy
_Regeneration_Factor);
```

```
[Total_Energy_Consumption_KWh,Total_Raw_Energy_Consumption_KWh]
=Energy_Conversion(Total_Energy_Consumption);

Total_Energy_Consumption_KWh_per_passenger
=Total_Energy_Consumption_KWh/(capacity*load_factor);
Total_Raw_Energy_Consumption_KWh_per_passenger
=Total_Raw_Energy_Consumption_KWh/(capacity*load_factor);

fprintf('\n The maximum speed achieved between stations is %f
meters/second',Velocity_Maximum)
fprintf('\n The total travel time between stations is %f seconds
\n',Total_Travel_Time)
fprintf('\n The total energy consumed by the train is %f
Joules',Total_Energy_Consumption)
fprintf('\n The total energy consumed by the train is %f Kilowatt-
Hours',Total_Energy_Consumption_KWh)
fprintf('\n The total energy consumed per passeneger is %f Kilowatt-
Hours \n',Total_Energy_Consumption_KWh_per_passenger)
fprintf('\n The total raw energy consumed to power train is %f
Kilowatt-Hours',Total_Raw_Energy_Consumption_KWh)
fprintf('\n The total raw energy consumed per passenger is %f Kilowatt-
Hours \n ',Total_Raw_Energy_Consumption_KWh_per_passenger)
```

Train Profile Function

```
%This function calculates the 3-phase profile of a high speed train and
%outputs the maximum velocity achieved, total energy consumption and
the
%total travel time, as well as multiple plots.  The inputs for this
%function are located in file train_profile_function_caller.m. The
%functions resistive_force.m and tractive_effort.m are also needed.

function
[Velocity_Maximum,Total_Energy_Consumption,Total_Travel_Time]=train_pro
file_function(stat_dist,des_speed,decel_rate,time_step,mass,Resistive_C
oefficients,Tractive_Coefficients,Acceleration_cut_off,Energy_Regenerat
ion_Factor)

%Initializes variables so that the logical tests will operate.
Acceleration_current =1;
Distance_2_phase     =0;
Velocity_Maximum     =0;

%Initial velocity and position set to 0.  All others also initially set
to 0 (allows the logical tests to run). The preallocation size changes
based on the time step that the preallocation won't be unnecessarily
large.
Acceleration         =zeros(1,10000/time_step);
Velocity_accel_phase =zeros(1,10000/time_step);
Position_accel_phase =zeros(1,10000/time_step);
Time_vector_accel    =zeros(1,10000/time_step);

Energy_consumption_rate_vector_accel       =zeros(1,10000/time_step);
Energy_consumption_vector_cumulative_accel =zeros(1,10000/time_step);

Tractive_effort_accel =zeros(1,10000/time_step);
Resistance_accel      =zeros(1,10000/time_step);

int=(time_step/time_step); % this converts the chosen time step into an
integer for variable storage purposes


    while (Velocity_Maximum<des_speed) &&
(Acceleration_current>Acceleration_cut_off) &&
(Distance_2_phase<stat_dist)  % This command continues the acceleration
phase as long as the train speed is less than the desired cruise speed
, the rate of change of acceleration is less than the Acceleration Cut
off Value (at that point, the train has effectively reach top
speed),and the stat_dist is less than the desired distance.

    Tractive_effort_accel(int)
=tractive_effort(Velocity_accel_phase(int),Tractive_Coefficients);
%Calculates the tractive effort vector for the acceleration phase;
Velocity in m/s
    Resistance_accel(int)
=resistive_force(Velocity_accel_phase(int),Resistive_Coefficients);
%Calculates the resistive effort vector for the acceleration phase;
Velocity in m/s
```

```
    Acceleration(int+1)         =(Tractive_effort_accel(int)-
Resistance_accel(int))/mass;      % Calculates the acceleration rate
vector during the acceleration phase, Acceleration in m/(s*s)
    Velocity_accel_phase(int+1) =((Acceleration
(int+1)*time_step)+Velocity_accel_phase(int)); % Calculates the train
velocity for each time step during the acceleration phase and stores as
a vector, Velocity in m/s
    Position_accel_phase(int+1)
=((((Velocity_accel_phase(int+1)+Velocity_accel_phase(int))/2)*time_ste
p)+Position_accel_phase(int)); %Calculates the train position for each
time step during the acceleration phase and stores as a vector,
Position in m.

    Velocity_Maximum         =Velocity_accel_phase(int+1); % pulls out
current velocity value and stores as a scalar for use in the comparison
statement above.
    Acceleration_current     =abs(Acceleration(int+1));    % This
stores the absolute value of last value of acceleration for use in the
comparison statement above. The purpose is that once the accelration
drops below the criteria above, then the train has essentianly hit
maximum speed and then must enter the cruise or deceleration phase.
    Accel_time               =int*time_step;  % Calculates the time
elasped during the acceleration phase.
    Time_vector_accel(int+1) =int*time_step;  % Stores a vector of time
values from the acceleration phase for plotting purposes.

    Energy_consumption_rate_vector_accel(int+1)
=tractive_effort(Velocity_accel_phase(int+1),Tractive_Coefficients)*Vel
ocity_accel_phase(int+1); %calculates the rate of energy consumption at
each time step in the acceleration phase.
    Energy_consumption_vector_cumulative_accel(int+1)
=((Energy_consumption_rate_vector_accel(int)+Energy_consumption_rate_ve
ctor_accel(int+1))/2)*time_step+(Energy_consumption_vector_cumulative_a
ccel(int)); %computes the cumulative energy consumed for each time step
during the acceleration phase.
    Energy_consumption_cumulative_end_of_accel
=Energy_consumption_vector_cumulative_accel(int+1); %Finds the total
energy consumed during the acceleration phase.

    int =int+(time_step/time_step); % Counter function, allows for
progression of calculations.

    Distance_end_of_accel =Position_accel_phase(int); % Finds the
distance covered by the train during the acceleration phase.



    %This phase calculates the distance needed for deceleration
assumming a
    %constant rate decel.  Note that distance_end_of_decel is only
distance
    %for deceleration phase. It is not tied to the acceleration
distance at
    %this point because the train may have a cruise phase which will
fall
```

```
    %in between.

    Decel_time            =Velocity_Maximum/decel_rate; % The time
elasped during the deceleration phase
    Distance_end_of_decel =(-(Velocity_Maximum^2)/(2*-decel_rate))+ 0;
%Finds total distance traveled during deceleration phase using constant
deceleration equation.

    Distance_2_phase =Distance_end_of_accel+Distance_end_of_decel; %
The total distance required for the acceleration and deceleration
phases. Used in logical test above such once the distance required for
the train to accelerate to the current value of velocity and then
decelerate exceeds the distance between stations, then the loops ends
and the maximum velocity possible for that station length can be found.
    Time_2_phase     =Accel_time+Decel_time; % Time required for the
train to accelerate and decelerate.

    end

    if Velocity_Maximum<des_speed %Provides message that train didn't
reach the desired speed for that calculation.
        fprintf('\n NOTE: The train never reaches the desired cruising
speed!\n The speed is either unattainable or unreachable for the given
station length! \n')
    end


    %Preallocate decel_distance_vector for speed.
    decel_distance_vector =zeros(1,round(Decel_time/time_step));
    decel_velocity_vector =zeros(1,round(Decel_time/time_step));
    Time_vector_decel     =zeros(1,round(Decel_time/time_step));

    %initialize velocity_vector element 1 to cruise velocity for
    %calculations and plotting.
    decel_velocity_vector(1)=Velocity_Maximum;

    int=(time_step/time_step); % this converts the chosen time step
into an integer for variable storage purposes

    timer=0;

    while timer<Decel_time %this loop fills out the distance profile
vector of the train during the deceleration phase.  It is independent
of distances from acceleration at this point. It is not included in the
while statement above for speed.
      decel_distance_vector(int+1) =0.5*-
decel_rate*(timer)^2+Velocity_Maximum*(timer)+0; % calculates vector of
distances at eact time step.  The j/time_step converts each time step
to an integer for variable storage.
      decel_velocity_vector(int+1) =(-
decel_rate*(timer))+Velocity_Maximum;
      Time_vector_decel(int+1)     =(timer);

      timer =int*time_step;
      int   =int+1;
```

```
    end


    %This if-else statement determines if the train will have a cruise
segment,
    %based on the while statement above. Then depending on whether or
not
    %there is a cruise segment, cruise time and distance are computed.
    if (Distance_2_phase<stat_dist)

        Cruise_dist =stat_dist-Distance_2_phase;  %Determines how much
distance is available for cruise segment.
        Cruise_time =Cruise_dist/Velocity_Maximum;%Determines time
required for cruise segment based on cruising speed,  the cruising
speed is the speed of the train at the end of the acceleration phase.

        Total_Travel_Time =Cruise_time+Time_2_phase; % total Travel
time for all 3 phases.

        Tractive_effort_cruise_rate
=resistive_force(Velocity_Maximum,Resistive_Coefficients); % The
tractive effort of the train during the cruise segment, this will be a
constant value. This is the tractive effort required because the train
isn't accelerating thus tractive effort only needs to equal resistance.
        Energy_consumption_end_of_cruise
=Tractive_effort_cruise_rate*Velocity_Maximum*Cruise_time; % Calculates
the total energy consumed during the cruise phase.
        Tractive_effort_used_rate_vector
=[Tractive_effort_cruise_rate,Tractive_effort_cruise_rate]; %2 element
vector of tractive effort rate during cruise. Used for plotting.



        %calculate the position and time at the start of deceleration
phase
        Position_start_decel =Distance_end_of_accel+Cruise_dist;
        Time_start_decel     =Accel_time+Cruise_time;

    else  % if there is no cruise segment, then the values are
calculated accordingly. Although there is no cruise segment if this
section is activated, the values are calculated for plotting purposes,
so that no if statements are necessary in the plotting section.
        Total_Travel_Time    =Time_2_phase;
        Position_start_decel =Distance_end_of_accel;
        Time_start_decel     =Accel_time;
        Cruise_time          =0;

        Tractive_effort_cruise_rate       =0;
        Tractive_effort_used_rate_vector
=[Tractive_effort_cruise_rate,Tractive_effort_cruise_rate];
        Energy_consumption_end_of_cruise  =0;
    end

    % Calculate the vectors for cruise and deceleration phases so that
they
```

```
    % can be plotted.  The vectors are all 2 elements because the
cruise
    % and deceleration phases occur at constant rates.
    Cruise_time_vector     =[Accel_time, Time_start_decel];
    Cruise_position_vector
=[Distance_end_of_accel,Position_start_decel];
    Cruise_velocity_vector =[Velocity_Maximum, Velocity_Maximum];

    Decel_time_vector     =Time_vector_decel+Time_start_decel;
    Decel_position_vector =decel_distance_vector+Position_start_decel;

    %calculate the energy consumption vectors for cruise and decel so
they
    %can be plotted
    Energy_consumption_vector_cumulative_cruise
=[Energy_consumption_cumulative_end_of_accel,
Energy_consumption_cumulative_end_of_accel+Energy_consumption_end_of_cr
uise];
    Energy_consumption_vector_cumulative_decel
=[Energy_consumption_vector_cumulative_cruise(2),
Energy_consumption_vector_cumulative_cruise(2)-
(Energy_consumption_vector_cumulative_cruise(2)*Energy_Regeneration_Fac
tor)];

    %Find the last non-zero element in the acceleration phase
variables.
    %this is necessary because the arrays are preallocated and without
    %modification, the plot will plot all elements of the arrays,
including the zeros,
    %which is incorrect for the graph.

    Last_element_position_accel =find(Position_accel_phase,1,'last');
    Last_element_velocity_accel =find(Velocity_accel_phase,1,'last');
    Last_element_time_accel     =find(Time_vector_accel,1,'last');
    Last_element_energy_accel
=find(Energy_consumption_vector_cumulative_accel,1,'last');
    Last_element_tractive_accel =find(Tractive_effort_accel,1,'last');



Tractive_effort_accel(Last_element_tractive_accel+1)=Tractive_effort_ac
cel(Last_element_tractive_accel); % this function makes the tractive
effort vector the same length as the time vector for plotting purposes.


Total_Energy_Consumption=Energy_consumption_vector_cumulative_decel(2);

    %------------------------------------------------------------------
----
    %The remaining commands generate the various plots that are
produced.

    %This series of commands plots the velocity vs distance profile for
the
    %train.
```

```
    figure

plot(Position_accel_phase(1:Last_element_position_accel),Velocity_accel
_phase(1:Last_element_velocity_accel),'-g')
    hold on
    plot(Cruise_position_vector,Cruise_velocity_vector,'-b')
    plot(Decel_position_vector,decel_velocity_vector,'-r')
    xlabel('Distance Traveled (Meters)')
    ylabel('Velocity (Meters/Second)')
    title('High Speed Train Velocity vs Distance Profile')
    legend('Acceleration Phase','Cruise Phase','Deceleration Phase')
    hold off


    %This series of commands plots the position vs time profile of the
    %train.
    figure

plot(Time_vector_accel(1:Last_element_time_accel),Position_accel_phase(
1:Last_element_position_accel),'-g')
    hold on
    plot(Cruise_time_vector,Cruise_position_vector,'-b')
    plot(Decel_time_vector,Decel_position_vector,'-r')
    xlabel('Time (Seconds)')
    ylabel('Distance Traveled (Meters)')
    title('High Speed Train Distance Traveled vs Time')
    legend('Acceleration Phase','Cruise Phase','Deceleration Phase')
    hold off


    %This series of commands plots the energy consumption rate vs time
    %profile of the train.
    figure

plot(Time_vector_accel(2:Last_element_time_accel),Energy_consumption_ra
te_vector_accel(2:Last_element_energy_accel),'-g')
    hold on

plot(Cruise_time_vector,[(Energy_consumption_end_of_cruise/Cruise_time)
,(Energy_consumption_end_of_cruise/Cruise_time)],'-b')% the second
vector is the energy consumption rate for the cruise segment.
    plot(Decel_time_vector,zeros(1,numel(Decel_time_vector)),'-r') %
assume no energy is consumed during the deceleration operation
    xlabel('Time (Seconds)')
    ylabel('Energy Consumption Rate (Joules/Second)')
    title('High Speed Train Energy Consumption Rate vs Time')
    legend('Acceleration Phase','Cruise Phase','Deceleration Phase')
    hold off


    %This series of commands plots the cumulative energy consumed vs
time profile of
    %the train
    figure
```

```
plot(Time_vector_accel(1:Last_element_time_accel),Energy_consumption_ve
ctor_cumulative_accel(1:Last_element_energy_accel),'-g')
    hold on

plot(Cruise_time_vector,Energy_consumption_vector_cumulative_cruise,'-
b')

plot([Decel_time_vector(1),Decel_time_vector(numel(Decel_time_vector))]
,Energy_consumption_vector_cumulative_decel,'-r')
    xlabel('Time (Seconds)')
    ylabel('Cumulative Energy Consumed (Joules)')
    title('High Speed Train Energy Consumed vs Time')
    legend('Acceleration Phase','Cruise Phase','Deceleration Phase')
    hold off

    %This series of commands plots the tractive force uses vs time for
the
    %train.
    figure

plot(Time_vector_accel(1:Last_element_time_accel),Tractive_effort_accel
(1:Last_element_tractive_accel+1),'-g');
    hold on
    plot(Cruise_time_vector,Tractive_effort_used_rate_vector,'-b')
    plot([Time_start_decel, Total_Travel_Time],[0 0],'-r')
    xlabel('Time (Seconds)')
    ylabel('Tractive Effort Required Rate (N/s)')
    title('High Speed Train Tractive Effort Required Rate vs Time')
    legend('Acceleration Phase','Cruise Phase','Deceleration Phase')
    hold off
```

Resistive Force Function

```
%This function returns the resistive forces of a high speed train from
the
%input of velocity(m/s).
function
[Resistive_Force]=resistive_force(Velocity,Resistive_Coefficients)
%High Speed Train resistance coefficients.
A = Resistive_Coefficients(1);
B = Resistive_Coefficients(2);
C = Resistive_Coefficients(3);

Resistive_Force=(A+B*Velocity+C*Velocity^2);
```

Tractive Effort Function

```
%This function returns the tractive effort of a high speed train from
the
%input of velocity(m/s).
function
[Tractive_Effort]=tractive_effort(Velocity,Tractive_Coefficients)
%Coefficients for calculation of tractive effort.
k1 = Tractive_Coefficients(1);     % conversion factor from HP to
Newtons (Newton m/s)
P  = Tractive_Coefficients(2);     % horsepower (Hp)
nu = Tractive_Coefficients(3);     % engine efficiency (dim)

Tractive_Effort=min(((k1.*nu.*P)/Velocity),1e6);
```

TGV Resistance Function

```
%This function calcuates the resistive coefficents of the French TGV.
All
%information was taken from the paper "A Review of Methods to Measure
and
%Calculate Train Resistances" by Rochard and Schmid.

%Note that the length, mass, power, and capacity comes from the paper
%"Efficiency Comparisons of the Typical High Speed Trains of the in the
%World" by Shoji

function [Resistive_Coefficients]=TGV_Resistance(mass)

Lambda          =0.9;                   %The value for lambda should be
between 0.9 and 1.5.  The lower values are similar to the high speed
TGV stock.
Number_of_axles =24;                    %This is important because the
calculation of resistive coefficents require mass per axle. Currently
asssumed.
Mass_per_axle   =mass/Number_of_axles;

k1 =(9*10^-4);  % A parameter that depends on shape of train.(Value
listed is for TGV
S  =10;         %Front surface cross sectional area (m^2).
```

```
k2 =(20*10^-6); %Parameter that depends on condition of surface, pL.
p  =10;         %Partial perimeter of rolling stock down to rail level.
L  =200;        %Length of train (m).

%these are the equations listed in the paper.  Each equation has been
%multiplied by 1000 to convert the coefficents from kiloNewtons to
Netwons.
A =(0.00001*(Lambda*mass*(sqrt(10000/Mass_per_axle))))*1000;
B =((3.6*10^-7)*mass)*1000;
C =(0.1296*((k1*S)+k2*p*L))*1000;

Resistive_Coefficients=[A B C];
```

Station to Station Input File Creator

Primary File

```
%This file will create the S2S travel time and S2S travel cost
%matrices.

%This file needs the functions: Train_Station_Index Finder,
%Schedule_Delay_Calculator

%Travel Cost Equation Values.  A cost analysis was conducted on Mar.
23,
%2011 for travel on March 9, 2011 on the Amtrak Network Nationwide.
Coach
%class with no room.
clear all;
clc;




for i=2010 %:1:2011

global TrainStation_List
Desired_Year         = i; %this is the data year that the files are
created for.
Cost_Year            = 2000; %This should always be 2000 to be
consistent with TSAM.  TSAM needs all input cost in 2000 $'s. So the
created table of S2S costs for 1995, or 1996, or 1997, etc. should all
be in 2000 $'s.
Regression_Cost_Year = 2010; % THIS HAS TO BE =2010 UNLESS NEW
REGRESSION CURVES ARE DEVELOPED. This is the year of the cost data that
was used to develop regression curves. All curves were developed in
2010 $'s unless noted otherwise.


Very_High_Time_and_Cost='YES'; %If this is yes, the TT and TC are set
to very high values for all O-D pairs. This is used to effectively
elimnate the train mode but still use the 3 mode calibrated
coefficients.
Year_Start_High_Speed_Service=2010; %This needs to be year of high
speed initialization for all corridors. If corridors start in different
years, then enter value for each initial year parameter below.

Output_Save_Directory='C:\Users\avandyke\Desktop\S2S_Matlab_Input_Files
\';

disp(['Year:',num2str(Desired_Year)])
%---------------------------------------------------------
%This section is used to determine what projected corridor lines are
%included in the model.  Variables should be 'YES' if the corridor is
to be
```

```
%modeled.  Descriptions of the corridors can be found below. The
initial
%year variables are the first year that the given corridor is to be
%modeled. These variable should not be less than 2011.

Original_NEC_Route           = 'YES'; %this applies only for future
corridor, after year 2010. the route is already modeled for 2001-2010.
California_Route             = 'YES';
Pacific_Northwest_Route      = 'YES';
Florida_Route                = 'YES';
Chicago_Hub_Route            = 'YES';
Southeast_Route              = 'YES';
Empire_Route                 = 'YES';
Northern_New_England_Route = 'YES';
Keystone_Route               = 'YES';
South_Central_Route          = 'YES';
Gulf_Coast_Route             = 'YES';
Vermont_Route                = 'YES';
Cumulative_NEC_Route         = 'No'; %IF Cumulative_NEC_Route= YES, this
will combine and overwrite the Original_NEC_Route, Empire_Route,
Northern_New_England_Route, Keystone_Route, and Northern_NEC_Route.
Turn off these corridors to speed the code.

%Initial year of service for each high speed corridor.
Original_NEC_Route_Initial_Year          =
Year_Start_High_Speed_Service; %This implies the year that the NEC
corridor gets updated (higher speeds).
California_Route_Initial_Year            =
Year_Start_High_Speed_Service;
Pacific_Northwest_Route_Initial_Year     =
Year_Start_High_Speed_Service;
Florida_Route_Initial_Year               =
Year_Start_High_Speed_Service;
Chicago_Hub_Route_Initial_Year           =
Year_Start_High_Speed_Service;
Southeast_Route_Initial_Year             =
Year_Start_High_Speed_Service;
Empire_Route_Initial_Year                =
Year_Start_High_Speed_Service;
Northern_New_England_Route_Initial_Year =
Year_Start_High_Speed_Service;
Keystone_Route_Initial_Year              =
Year_Start_High_Speed_Service;
South_Central_Route_Initial_Year         =
Year_Start_High_Speed_Service;
Gulf_Coast_Route_Initial_Year            =
Year_Start_High_Speed_Service;
Vermont_Route_Initial_Year               =
Year_Start_High_Speed_Service;
Cumulative_NEC_Route_Initial_Year        =
Year_Start_High_Speed_Service;



%If Acela_Cost_XXXXXX_Route = 'YES' then that corridor is modeled with
```

```
%the existing Amtrak Acela Cost curve. Otherwise, Cost is currently
based on $/mile.
%When new cost function is developed,the code in the double for loop
below
%will have to be changed.

%This needs to be in 2010 dollars because Regression_Cost_Year = 2010

Acela_Cost_Original_NEC_Route         = 'YES';
Acela_Cost_California_Route           = 'YES';
Acela_Cost_Pacific_Northwest_Route    = 'YES';
Acela_Cost_Florida_Route              = 'YES';
Acela_Cost_Chicago_Hub_Route          = 'YES';
Acela_Cost_Southeast_Route            = 'YES';
Acela_Cost_Empire_Route               = 'YES';
Acela_Cost_Northern_New_England_Route = 'YES';
Acela_Cost_Keystone_Route             = 'YES';
Acela_Cost_South_Central_Route        = 'YES';
Acela_Cost_Gulf_Coast_Route           = 'YES';
Acela_Cost_Vermont_Route              = 'YES';
Acela_Cost_Cumulative_NEC_Route       = 'YES';


Original_NEC_Route_Average_Cost        = 0.60; %This applies only after
high speed rail corridors are turned on.
California_Route_Average_Cost          = 0.60;
Pacific_Northwest_Route_Average_Cost   = 0.60;
Florida_Route_Average_Cost             = 0.60;
Chicago_Hub_Route_Average_Cost         = 0.60;
Southeast_Route_Average_Cost           = 0.60;
Empire_Route_Average_Cost              = 0.60;
Northern_New_England_Route_Average_Cost= 0.60;
Keystone_Route_Average_Cost            = 0.60;
South_Central_Route_Average_Cost       = 0.60;
Gulf_Coast_Route_Average_Cost          = 0.60;
Vermont_Route_Average_Cost             = 0.60;
Cumulative_NEC_Route_Average_Cost      = 0.60;

%Travel Time is currently based on an average speed across the
corridor.
%This speed is the average speed including stops.  When new time
functions
%are developed, the code in the double for loop below will have to be
%changed. The speed is presented in miles/hr.
Original_NEC_Route_Average_Speed        = 175; %Planned Value = 119.
%This applies only after high speed rail corridors are turned on.
California_Route_Average_Speed          = 175; %Planned Value = 153
Pacific_Northwest_Route_Average_Speed   = 175; %Planned Value = 105
Florida_Route_Average_Speed             = 175; %Planned Value = 118
Chicago_Hub_Route_Average_Speed         = 175;  %Planned Value = 77
Southeast_Route_Average_Speed           = 175;  %Planned Value = 77
Empire_Route_Average_Speed              = 175;  %Planned Value = 77
Northern_New_England_Route_Average_Speed= 175;  %Planned Value = 77
Keystone_Route_Average_Speed            = 175;  %Planned Value = 77
South_Central_Route_Average_Speed       = 175; %Planned Value = 105
Gulf_Coast_Route_Average_Speed          = 175; %Planned Value = 105
```

```
Vermont_Route_Average_Speed             = 175;  %Planned Value = 77
Cumulative_NEC_Route_Average_Speed      = 175; %Planned Value = 100

%------------------------------------------------------

load('C:\Users\avandyke\Documents\TSAM_GUI_VB_2005\bin\data\mode_choice
\input\TrainStation_List.mat') %This file containts the Amtrak
"TrainStation_List"
load('C:\Users\avandyke\Documents\TSAM_GUI_VB_2005\bin\data\mode_choice
\input\PCEP_Index.mat') %This is the inflation index
load('C:\Users\avandyke\Documents\TSAM_GUI_VB_2005\bin\data\mode_choice
\input\S2S_Train_ScheduleDelay_HSR.mat') %This loads the original
schedule delay values from TSAM. IT is assumed this is the scheule
delay unless changes are made in the code below.
load('C:\Users\avandyke\Documents\TSAM_GUI_VB_2005\bin\data\mode_choice
\input\S2S_Train_Distance_HSR'); %This is the original matrix of
distance between stations. This is the original data and is assumed to
be correct unless specific changes have been noted below.

[~,Number_Stations_Total_Network] = size(TrainStation_List);
Station_Index       = 1:Number_Stations_Total_Network;

S2S_Train_ScheduleDelay=S2S_Train_ScheduleDelay_HSR;
clear S2S_Train_ScheduleDelay_HSR

S2S_Train_Distance=S2S_Train_Distance_HSR(Station_Index,
Station_Index); %this renames the distance matrix.
clear S2S_Train_Distance_HSR


if strcmp(Very_High_Time_and_Cost,'YES')==1
    S2S_Train_TravelTime=S2S_Train_Distance .* 10; %This means the S2S
travel speed is  1/10 mph.
    S2S_Train_TravelCost=S2S_Train_Distance .* 5000; %This means the
S2S travel cost is  5000 $/mi.
else
    %-------------------------------------------------------------------
--
    %ORIGINAL NEC
    %-------------------------------------------------------------------
--
    %The code in this section is used to identify the 16 NEC station's
index
    %numbers. This is the original NEC corridor route,  It is modeled
between
    %2001 and XXXX.

    Station_Abbreviation_List =
{'STM','NHV','NLC','WIL','WAS','BWI','BAL','RTE','BOS','NWK','TRE','MET
','NYP','PHL','PVD','BBY'}; %Stations in the NEC. The file
Train_Station_ID_Finder. m can be used to find these codes based on the
desired city.
    %The Station Abbreviation List is representative of Stamford CT,
New Haven
```

```
    %CT, New London CT, Wilmington DE, Washington DC, Baltimore MD
(airport),
    %Baltimore MD, Westwood MA, Boston MA, Newark NJ, Trenton NJ,
Metropark NJ,
    %New York NY, Phidelphia PA, and Providence RI.

    [~,Number_Stations]        =size(Station_Abbreviation_List);
    Original_NEC_Station_Index =zeros(1,Number_Stations);

    for a=1:1:Number_Stations

Original_NEC_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbr
eviation_List{1,a});
    end

    if strcmp(Original_NEC_Route,'YES')==1 &&
Original_NEC_Route_Initial_Year <= Desired_Year
        Train_Frequency      = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Original_NEC_Station_Index,Original_NEC_Station
_Index)=Schedule_Delay; %Updates the main S2S schedule delay with the
delay calculated for stations listed above.

        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end

    clear a
    clear Station_Abbreviation_List
    clear Number_Stations
    %-------------------------------------------------------------------
---



    %-------------------------------------------------------------------
---
    %CALIFORNIA ROUTE
    %-------------------------------------------------------------------
---
    %The code in this section is used to identify the station index
    %numbers of the California Corridor.
    if strcmp(California_Route,'YES')==1 &&
California_Route_Initial_Year <= Desired_Year
        Station_Abbreviation_List =
{'SJC','SAC','MCD','FNO','BFD','LAX','RIV','SAN','ANA','DAV','EMY','FUL
```

```
','GDL','IRV','OAC','ONA','POS','PRB','RIC','RLN','RSV','SNA'}; %Major
stations end at 'SAN'
        %The Station Abbreviation List is representative of San Jose,
Sacramento,
        %Merced, Fresno, Bakersfield, Los Angeles, Riverside, and San
Diego. All
        %stations are in CA.  Other Stations listed are non-major
stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are
        %located.
        [~,Number_Stations]         = size(Station_Abbreviation_List);
        California_Station_Index    = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

California_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbrev
iation_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay        =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(California_Station_Index,California_Station_Ind
ex)=Schedule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end

    %------------------------------------------------------------------
--

    %------------------------------------------------------------------
--
    %PACIFIC NORTHWEST ROUTE
    %------------------------------------------------------------------
--
    %The code in this section is used to identify the station index
    %numbers of the Pacific Northwest Route.
    if strcmp(Pacific_Northwest_Route,'YES')==1 &&
Pacific_Northwest_Route_Initial_Year <= Desired_Year
```

```
        Station_Abbreviation_List =
{'SEA','TAC','PDX','EUG','ALY','ORC','SLM','BEL','CTL','EDM','EVR','KEL
','MVW','OLW','TUK'};
        %The Station Abbreviation List is representative of Seattle WA,
Tacoma WA,
        %Portland OR, and Eugene OR. Other Stations listed are non-
major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are
        %located.

        [~,Number_Stations]                 =
size(Station_Abbreviation_List);
        Pacific_Northwest_Station_Index    = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Pacific_Northwest_Station_Index(1,a)=Train_Station_Index_Finder(Station
_Abbreviation_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Pacific_Northwest_Station_Index,Pacific_Northwe
st_Station_Index)=Schedule_Delay; %Updates the main S2S schedule delay
with the delay calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end

    %-------------------------------------------------------------------
-

    %-------------------------------------------------------------------
-
    %FLORIDA ROUTE
    %-------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Florida Route.
```

```
    if strcmp(Florida_Route,'YES')==1 && Florida_Route_Initial_Year <=
Desired_Year
        Station_Abbreviation_List =
{'TPA','ORL','MIA','DFB','DLB','FTL','HOL','KIS','LAK','SFD','WPB','WPK
','WTH'};
        %The Station Abbreviation List is representative of Tampa,
Orlando, Miami. Other Stations listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are
        %located.

        [~,Number_Stations]   = size(Station_Abbreviation_List);
        Florida_Station_Index = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Florida_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbreviat
ion_List{1,a});
        end

        Train_Frequency      = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Florida_Station_Index,Florida_Station_Index)=Sc
hedule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %------------------------------------------------------------------
-


    %------------------------------------------------------------------
-
    %CHICAGO ROUTE
    %------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Chicago Route.

    if strcmp(Chicago_Hub_Route,'YES')==1 &&
Chicago_Hub_Route_Initial_Year <= Desired_Year
```

```
        Station_Abbreviation_List =
{'CHI','KCY','STL','OMA','DET','PNT','ALN','BNL','CRV','DWT','JOL','LCN
','NPV','PON','SMT','SPI','IDP','KWD','DYE','HMI','MCI','ALI','ARB','BA
M','BMM','BTL','JXN','KAL','NBM','ROY','SJM'};
        %The Station Abbreviation List is representative of Chicago,
Kansas City, St. Louis, Omaha NE, Detroit, Pontiac MI. Other Stations
listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.
        %located.

        [~,Number_Stations]        = size(Station_Abbreviation_List);
        Chicago_Hub_Station_Index  = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Chicago_Hub_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbre
viation_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay        =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Chicago_Hub_Station_Index,Chicago_Hub_Station_I
ndex)=Schedule_Delay; %Updates the main S2S schedule delay with the
delay calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %-----------------------------------------------------------------
-



    %-----------------------------------------------------------------
-
    %SOUTHEAST ROUTE
    %-----------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Southeast Route. Other Stations listed are non-
major stations, see
    %Projected Rail Corridor Data sheet to see where other stations.
```

```
    if strcmp(Southeast_Route,'YES')==1 && Southeast_Route_Initial_Year
<= Desired_Year
        Station_Abbreviation_List =
{'CLT','GRO','RGH','RVR','WAS','BNC','CYN','DNC','HPT','KAN','SAL','ALX
','FBG','MSS','PTB','QAN'};
        %The Station Abbreviation List is representative of Charlotte
NC,
        %Greensboro NC, Raleigh NC, Richmond VA, and Washington DC.
Other Stations listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.

        [~,Number_Stations]        = size(Station_Abbreviation_List);
        Southeast_Station_Index    = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Southeast_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbrevi
ation_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay        =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Southeast_Station_Index,Southeast_Station_Index
)=Schedule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %------------------------------------------------------------------
-


    %------------------------------------------------------------------
-
    %EMPIRE ROUTE
    %------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Empire Route.
    if strcmp(Empire_Route,'YES')==1 && Empire_Route_Initial_Year <=
Desired_Year
```

```
        Station_Abbreviation_List =
{'NYP','ROC','BFX','NFL','ALB','AMS','HUD','POU','RHI','ROM','SDY','SYR
','UCA','YNY'};
        %The Station Abbreviation List is representative of New York
NY, Rochester
        %NY, Buffalo NY, ,Niagara Falls NY and Rensselaer NY(Albany).
Other Stations listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.

        [~,Number_Stations]     = size(Station_Abbreviation_List);
        Empire_Station_Index    = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Empire_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbreviati
on_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay        =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Empire_Station_Index,Empire_Station_Index)=Sche
dule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %------------------------------------------------------------------
-


    %------------------------------------------------------------------
-
    %NORTHERN NEW ENGLAND
    %------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Empire Route.
    if strcmp(Northern_New_England_Route,'YES')==1 &&
Northern_New_England_Route_Initial_Year <= Desired_Year
        Station_Abbreviation_List =
{'ALB','SPG','NHV','BOS','FED','FTC','GZZ','PLB','POH','PRK','RSP','WHL
','WSP','FRA','WOR','BER','HFD','MDN'};
```

```
        %The Station Abbreviation List is representative of Rensselaer
NY (Albany),
        %Springfield MA, New Haven CT, Boston MA. Other Stations listed
are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.

        [~,Number_Stations]                    =
size(Station_Abbreviation_List);
        Northern_New_England_Station_Index    =
zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Northern_New_England_Station_Index(1,a)=Train_Station_Index_Finder(Stat
ion_Abbreviation_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Northern_New_England_Station_Index,Northern_New
_England_Station_Index)=Schedule_Delay; %Updates the main S2S schedule
delay with the delay calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %-------------------------------------------------------------------
-


    %-------------------------------------------------------------------
-
    %KEYSTONE ROUTE
    %The code in this section is used to identify the station index
    %numbers of the Empire Route.
    if strcmp(Keystone_Route,'YES')==1 && Keystone_Route_Initial_Year
<= Desired_Year
        Station_Abbreviation_List =
{'PHL','HAR','PGH','COV','GNB','LAB','PAO'};
        %The Station Abbreviation List is representative of
Philadelphia PA,
        %Harrisburg PA, Pittsburgh PA. Other Stations listed are non-
major stations, see
```

```
        %Projected Rail Corridor Data sheet to see where other stations
are.

        [~,Number_Stations]    = size(Station_Abbreviation_List);
        Keystone_Station_Index = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Keystone_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbrevia
tion_List{1,a});
        end

        Train_Frequency      = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Keystone_Station_Index,Keystone_Station_Index)=
Schedule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %------------------------------------------------------------------
-


    %------------------------------------------------------------------
-
    %SOUTH CENTRAL ROUTE
    %------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Empire Route.
    if strcmp(South_Central_Route,'YES')==1 &&
South_Central_Route_Initial_Year <= Desired_Year
        Station_Abbreviation_List =
{'OKC','AUS','DAL','FTW','SAS','LRK','TXA','ADM','NOR','PUR','PVL','CBR
','GLE','MCG','SMC','TAY','TPL','ARK','MVN'};
        %The Station Abbreviation List is representative of Oklahoma
City, Austin TX, Dallas, Ft. Worth TX, San Antonio, Little Rock AR, and
Texarkana AR . Other Stations listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.
```

```
        [~,Number_Stations]          = size(Station_Abbreviation_List);
        South_Central_Station_Index = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

South_Central_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abb
reviation_List{1,a});
        end

        Train_Frequency      = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(South_Central_Station_Index,South_Central_Stati
on_Index)=Schedule_Delay; %Updates the main S2S schedule delay with the
delay calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %------------------------------------------------------------------
-



    %------------------------------------------------------------------
-
    %GULF COAST ROUTE
    %------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the Empire Route.
    if strcmp(Gulf_Coast_Route,'YES')==1 &&
Gulf_Coast_Route_Initial_Year <= Desired_Year
        Station_Abbreviation_List =
{'ATL','BHM','MOE','BIX','MEI','NOL','HOS','ATN','TCL','HBG','LAU','PIC
','LCH','LFT','BMT'};
        %The Station Abbreviation List is representative of Atlanta,
Birmingham AL, Mobile AL, Biloxi MS, Meridian MS, New Orleans, Houston
TX . Other Stations listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.

        [~,Number_Stations]     = size(Station_Abbreviation_List);
        Gulf_Coast_Station_Index = zeros(1,Number_Stations);
```

```
        for a=1:1:Number_Stations

Gulf_Coast_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbrev
iation_List{1,a});
        end

        Train_Frequency      = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Gulf_Coast_Station_Index,Gulf_Coast_Station_Ind
ex)=Schedule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %-------------------------------------------------------------------
-



    %-------------------------------------------------------------------
-
    %Vermont ROUTE
    %-------------------------------------------------------------------
-
    %The code in this section is used to identify the station index
    %numbers of the NEC Northern ROute. This route goes from New Haven
CT to
    %St. Albans VT.
    if strcmp(Vermont_Route,'YES')==1 && Vermont_Route_Initial_Year <=
Desired_Year
        Station_Abbreviation_List =
{'MPR','SAB','SPG','HFD','NHV','BLF','BRA','ESX','RPH','WAB','WNM','WRJ
','AMM','BER','MDN'};
        %The Station Abbreviation List is representative of Montpelier
VT, St. Albans VT, Springfield MA, Hartford CT, New Haven CT. Other
Stations listed are non-major stations, see
        %Projected Rail Corridor Data sheet to see where other stations
are.

        [~,Number_Stations]    = size(Station_Abbreviation_List);
        Vermont_Station_Index = zeros(1,Number_Stations);
```

```
        for a=1:1:Number_Stations

Vermont_Station_Index(1,a)=Train_Station_Index_Finder(Station_Abbreviat
ion_List{1,a});
        end

        Train_Frequency      = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay       =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Vermont_Station_Index,Vermont_Station_Index)=Sc
hedule_Delay; %Updates the main S2S schedule delay with the delay
calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end
    %------------------------------------------------------------------
-


    %------------------------------------------------------------------
-
    %CUMULATIVE NEC ROUTE
    %------------------------------------------------------------------
--
    %- This route combines all of the NEC routes in one
    %so that the average speed between all the stations are improved.
    if strcmp(Cumulative_NEC_Route,'YES')==1 &&
Cumulative_NEC_Route_Initial_Year <= Desired_Year
        Station_Abbreviation_List =
{'STM','NHV','NLC','WIL','WAS','BWI','BAL',...

'RTE','BOS','NWK','TRE','MET','NYP','PHL','PVD','ROC','BFX',...

'NFL','ALB','AMS','HUD','POU','RHI','ROM','SDY','SYR','UCA','YNY',...
            'SPG','FED','FTC','GZZ','PLB','POH','PRK','RSP',...

'WHL','WSP','FRA','WOR','BER','HFD','MDN','HAR','PGH','COV',...

'GNB','LAB','PAO','MPR','SAB','SPG','HFD','BLF','BRA','ESX',...
            'RPH','WAB','WNM','WRJ','AMM','BER','MDN'};
        %The Station Abbreviation List is representative of all
stations that
        %are in the various NEC Corridors.
```

```
        [~,Number_Stations]     = size(Station_Abbreviation_List);
        Cumulative_NEC_Station_Index = zeros(1,Number_Stations);

        for a=1:1:Number_Stations

Cumulative_NEC_Station_Index(1,a)=Train_Station_Index_Finder(Station_Ab
breviation_List{1,a});
        end

        Train_Frequency       = ones(Number_Stations,Number_Stations)*8;
%This is assigning the frequency of train between all possible
combinations of stations above to be 6 trains. Once an actual schedule
is developed, then a new matrix can be created.
        Train_Service_Period = 18; %The service period of trains. This
is used for the calculation of schedule delay.
        Schedule_Delay        =
Schedule_Delay_Calculator(Train_Frequency,Train_Service_Period);
%Schedule delay for stations listed above.


S2S_Train_ScheduleDelay(Cumulative_NEC_Station_Index,Cumulative_NEC_Sta
tion_Index)=Schedule_Delay; %Updates the main S2S schedule delay with
the delay calculated for stations listed above.

        clear a
        clear Station_Abbreviation_List
        clear Number_Stations
        clear Train_Frequency
        clear Train_Service_Period
        clear Schedule_Delay
    end

    %disp('All Index Creation is Complete, Calculations of Time and
Cost is occuring now')


    %-------------------------------------------------------------------
---
    %Nationwide Regression Coefficients  Currently valid for 1995-2040.
This curve is used as baseline.  Other routes have been modified below.
    %-------------------------------------------------------------------
---
    % A power function was fit for the Travel Cost regression.

    %y=A*x^B.   R^2 = 0.9057 for this analysis.
    A=0.6454;  %A=0.6454 for original nationwide regression analysis
    B=0.7622;  %B=0.7622 for original nationwide regression analysis
    Cost_Factor=1; % Factor=1 for original regression. If ~=1 then a
trial value is used. This factor will increase each cost by the factor
value.

    %A linear function was fit for the Travel Time
regression.(Intercept was
    %set to 0)
```

```
    %y=C*x
    C=0.022; %C=0.022 for original regression of nationwide times.  If
C~=0.022, then it is a trial of a different time.
    %-----------------------------------------------------------------------
----

    %-----------------------------------------------------------------------
----
    %NORTHEAST CORRIDOR REGRESSION COEFFICIENTS
    %-----------------------------------------------------------------------
----

    %-----------------------------------------
    % YEARS 1995-2000

    %A 3rd order polynomial function was fit for the Travel Cost in the
NEC
    %regions.  The intercept was fixed at 0.
    %y=G*X^3 + H*X^2 + I *X
    G=2E-7;
    H=-0.0006;
    I=0.4439;

    %A linear function was fit for Travel Time in the NEC. Intercept
was fit to 0.
    %y=J*x
    J=0.9629; %This regression was done using minutes therefore in the
equation below, it is divided by 60
    %-----------------------------------------

    %-----------------------------------------
    %YEARS 2001-2010  Acela Travel Time and Cost Curves
    %A 3rd order polynomial function was fit for the Travel Cost in the
NEC
    %(years 2001-2010)
    %y=G*X^3 + H*X^2 + I *X
    M=7E-7;
    N=-0.0015;
    P=1.0279;
    Q=20.018;

    %A linear function was fit for Travel Time in the NEC  (years 2001-
2010).

    R=0.0132;  %This regression was done using hours.
    %-----------------------------------------------------------------------
---

    Inflation_Factor=PCEP_Index((Cost_Year-
1994),2)/PCEP_Index((Regression_Cost_Year-1994),2); %This finds the
inflation factor to convert costs from the Cost Year to the Desired
Year.

    S2S_Train_TravelTime =
zeros(Number_Stations_Total_Network,Number_Stations_Total_Network);
```

```
    S2S_Train_TravelCost =
zeros(Number_Stations_Total_Network,Number_Stations_Total_Network);


    if (Desired_Year>2000 && Desired_Year
<Year_Start_High_Speed_Service) || strcmp(Original_NEC_Route,'YES')==0
%2011 is currently the cutoff because it is hoped that the projected
high speed corridors will be modeled in year 2011. If the Original NEC
HSR route is not modeled, this will revert the schedule delay to that
of the Acela service instead of the regional service.

load('C:\Users\avandyke\Desktop\S2S_Matlab_Input_Files_NEW\S2S_Train_Sc
heduleDelay_NEC_Acela_2001_Forward.mat'); %The stations are in the
order of
{'STM','NHV','NLC','WIL','WAS','BWI','BAL','RTE','BOS','NWK','TRE','MET
','NYP','PHL','PVD','BBY'}. This is the schedule delay of Acela based
on the service frequency in the year 2010.

S2S_Train_ScheduleDelay(Original_NEC_Station_Index,Original_NEC_Station
_Index)=S2S_Train_ScheduleDelay_NEC_Acela_2001_Forward;
        clear S2S_Train_ScheduleDelay_NEC_Acela_2001_Forward
    end


    for e=1:1:Number_Stations_Total_Network

        if mod(e,100)==0

disp([num2str(e),'/',num2str(Number_Stations_Total_Network),' Stations
Processed'])
        end

        for f=1:1:Number_Stations_Total_Network

            if S2S_Train_Distance(e,f)<=0
                S2S_Train_TravelTime(e,f) = 0;
                S2S_Train_TravelCost(e,f) = 0;

            else
                %these two lines calculated based on the nationwide
cost
                %regression. Then if the station pair belongs to one of
the
                %corridors then it is overwritten with new values.
                S2S_Train_TravelTime(e,f) =
(C*S2S_Train_Distance(e,f)); %hrs
                S2S_Train_TravelCost(e,f) =
max(25,((A*(S2S_Train_Distance(e,f))^B)*Cost_Factor))*Inflation_Factor;
% A minimum of 25 dollars is assigned to cost because regression curve
produces negative values for short distances. The $30 is valid for 2011
and it is adjusted for inflation for the desired year.
```

```
                if max(e==Original_NEC_Station_Index(1,:))==1 &&
max(f==Original_NEC_Station_Index(1,:)) %This line determines if both
the origin and destination station are stations in the NEC.  If so, the
NEC cost and time functions are used.

                    if Desired_Year<=2000
                        S2S_Train_TravelTime(e,f) =
(J*S2S_Train_Distance(e,f))/60;
                        S2S_Train_TravelCost(e,f) =
max(25,((G*(S2S_Train_Distance(e,f)^3))+(H*(S2S_Train_Distance(e,f)^2))
+(I*(S2S_Train_Distance(e,f)))))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.

                    elseif Desired_Year>=2001 &&
Desired_Year<Year_Start_High_Speed_Service
                        S2S_Train_TravelTime(e,f) =
(R*S2S_Train_Distance(e,f));
                        S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.

                    elseif strcmp(Original_NEC_Route,'YES')==1 &&
Original_NEC_Route_Initial_Year <= Desired_Year
                        if max(e==Original_NEC_Station_Index(1,:))==1
&& max(f==Original_NEC_Station_Index(1,:)) %This line determines if
both the origin and destination station are stations in the corridor.
                            S2S_Train_TravelTime(e,f) =
(1/Original_NEC_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                            if
strcmp(Acela_Cost_Original_NEC_Route,'YES')==1
                                S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                            else
                                S2S_Train_TravelCost(e,f) =
max(25,Original_NEC_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflati
on_Factor; % $.  A minimum of 25 dollars is assigned to cost. The cost
is in 2010 $ and then adjusted back to inflation.

                            end
                        end

                    else %if the updated high speed rail corridor is
not modeled, then use time and cost data is developed using the Acela
train
                        S2S_Train_TravelTime(e,f) =
(R*S2S_Train_Distance(e,f));
```

```
                        S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.

                    end %if Desired_Year<=2000
                end %max(e==Original_NEC_Station_Index(1,:))==1 &&
max(f==Original_NEC_Station_Index(1,:))

                if strcmp(California_Route,'YES')==1 &&
California_Route_Initial_Year <= Desired_Year %determines if California
route is modeled for current year.
                    if max(e==California_Station_Index(1,:))==1 &&
max(f==California_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/California_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_California_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,California_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation
_Factor; % $.  A minimum of 25 dollars is assigned to cost. The cost is
in 2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==California_Station_Index(1,:))==1 &&
max(f==California_Station_Index(1,:))
                end %strcmp(California_Route,'YES')==1 &&
California_Route_Initial_Year <= Desired_Year

                if strcmp(Pacific_Northwest_Route,'YES')==1 &&
Pacific_Northwest_Route_Initial_Year <= Desired_Year
                    if max(e==Pacific_Northwest_Station_Index(1,:))==1
&& max(f==Pacific_Northwest_Station_Index(1,:)) %This line determines
if both the origin and destination station are stations in the
corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Pacific_Northwest_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if
strcmp(Acela_Cost_Pacific_Northwest_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
```

```
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Pacific_Northwest_Route_Average_Cost*S2S_Train_Distance(e,f))*In
flation_Factor; % $.  A minimum of 25 dollars is assigned to cost. The
cost is in 2010 $ and then adjusted back to inflation.
                        end

                    end
%max(e==Pacific_Northwest_Station_Index(1,:))==1 &&
max(f==Pacific_Northwest_Station_Index(1,:))
                end %strcmp(Pacific_Northwest_Route,'YES')==1 &&
Pacific_Northwest_Route_Initial_Year <= Desired_Year

                if strcmp(Florida_Route,'YES')==1 &&
Florida_Route_Initial_Year <= Desired_Year
                    if max(e==Florida_Station_Index(1,:))==1 &&
max(f==Florida_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Florida_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_Florida_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Florida_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation_Fa
ctor; % $.  A minimum of 25 dollars is assigned to cost. The cost is in
2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Florida_Station_Index(1,:))==1 &&
max(f==Florida_Station_Index(1,:))
                end %strcmp(Florida_Route,'YES')==1 &&
Florida_Route_Initial_Year <= Desired_Year

                if strcmp(Chicago_Hub_Route,'YES')==1 &&
Chicago_Hub_Route_Initial_Year <= Desired_Year
                    if max(e==Chicago_Hub_Station_Index(1,:))==1 &&
max(f==Chicago_Hub_Station_Index(1,:)) %This line determines if both
the origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Chicago_Hub_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if
strcmp(Acela_Cost_Chicago_Hub_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
```

```
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Chicago_Hub_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflatio
n_Factor; % $.  A minimum of 25 dollars is assigned to cost. The cost
is in 2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Chicago_Hub_Station_Index(1,:))==1 &&
max(f==Chicago_Hub_Station_Index(1,:))
                end %strcmp(Chicago_Hub_Route,'YES')==1 &&
Chicago_Hub_Route_Initial_Year <= Desired_Year

                if strcmp(Southeast_Route,'YES')==1 &&
Southeast_Route_Initial_Year <= Desired_Year
                    if max(e==Southeast_Station_Index(1,:))==1 &&
max(f==Southeast_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Southeast_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_Southeast_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Southeast_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation_
Factor; % $.  A minimum of 25 dollars is assigned to cost. The cost is
in 2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Southeast_Station_Index(1,:))==1 &&
max(f==Southeast_Station_Index(1,:))
                end %strcmp(Southeast_Route,'YES')==1 &&
Southeast_Route_Initial_Year <= Desired_Year

                if strcmp(Empire_Route,'YES')==1 &&
Empire_Route_Initial_Year <= Desired_Year
                    if max(e==Empire_Station_Index(1,:))==1 &&
max(f==Empire_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Empire_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_Empire_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
```

```
                            S2S_Train_TravelCost(e,f) =
max(25,Empire_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation_Fac
tor; % $.  A minimum of 25 dollars is assigned to cost. The cost is in
2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Empire_Station_Index(1,:))==1 &&
max(f==Empire_Station_Index(1,:))
                end %strcmp(Empire_Route,'YES')==1 &&
Empire_Route_Initial_Year <= Desired_Year

                if strcmp(Northern_New_England_Route,'YES')==1 &&
Northern_New_England_Route_Initial_Year <= Desired_Year
                    if
max(e==Northern_New_England_Station_Index(1,:))==1 &&
max(f==Northern_New_England_Station_Index(1,:)) %This line determines
if both the origin and destination station are stations in the
corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Northern_New_England_Route_Average_Speed)*S2S_Train_Distance(e,f);
%hrs


                        if
strcmp(Acela_Cost_Northern_New_England_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Northern_New_England_Route_Average_Cost*S2S_Train_Distance(e,f))
*Inflation_Factor; % $.  A minimum of 25 dollars is assigned to cost.
The cost is in 2010 $ and then adjusted back to inflation.
                        end


                    end
%max(e==Northern_New_England_Station_Index(1,:))==1 &&
max(f==Northern_New_England_Station_Index(1,:))
                end %strcmp(Northern_New_England_Route,'YES')==1 &&
Northern_New_England_Route_Initial_Year <= Desired_Year

                if strcmp(Keystone_Route,'YES')==1 &&
Keystone_Route_Initial_Year <= Desired_Year
                    if max(e==Keystone_Station_Index(1,:))==1 &&
max(f==Keystone_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Keystone_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_Keystone_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
```

```
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Keystone_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation_F
actor; % $.  A minimum of 25 dollars is assigned to cost. The cost is
in 2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Keystone_Station_Index(1,:))==1 &&
max(f==Keystone_Station_Index(1,:))
                end %strcmp(Keystone_Route,'YES')==1 &&
Keystone_Route_Initial_Year <= Desired_Year

                if strcmp(South_Central_Route,'YES')==1 &&
South_Central_Route_Initial_Year <= Desired_Year
                    if max(e==South_Central_Station_Index(1,:))==1 &&
max(f==South_Central_Station_Index(1,:)) %This line determines if both
the origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/South_Central_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if
strcmp(Acela_Cost_South_Central_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,South_Central_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflat
ion_Factor; % $.  A minimum of 25 dollars is assigned to cost. The cost
is in 2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==South_Central_Station_Index(1,:))==1 &&
max(f==South_Central_Station_Index(1,:))
                end %strcmp(South_Central_Route,'YES')==1 &&
South_Central_Route_Initial_Year <= Desired_Year

                if strcmp(Gulf_Coast_Route,'YES')==1 &&
Gulf_Coast_Route_Initial_Year <= Desired_Year
                    if max(e==Gulf_Coast_Station_Index(1,:))==1 &&
max(f==Gulf_Coast_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Gulf_Coast_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_Gulf_Coast_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
```

```
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Gulf_Coast_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation
_Factor; % $.  A minimum of 25 dollars is assigned to cost. The cost is
in 2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Gulf_Coast_Station_Index(1,:))==1 &&
max(f==Gulf_Coast_Station_Index(1,:))
                end %strcmp(Gulf_Coast_Route,'YES')==1 &&
Gulf_Coast_Route_Initial_Year <= Desired_Year

                if strcmp(Vermont_Route,'YES')==1 &&
Vermont_Route_Initial_Year <= Desired_Year
                    if max(e==Vermont_Station_Index(1,:))==1 &&
max(f==Vermont_Station_Index(1,:)) %This line determines if both the
origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Vermont_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if strcmp(Acela_Cost_Vermont_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Vermont_Route_Average_Cost*S2S_Train_Distance(e,f))*Inflation_Fa
ctor; % $.  A minimum of 25 dollars is assigned to cost. The cost is in
2010 $ and then adjusted back to inflation.
                        end

                    end %max(e==Vermont_Station_Index(1,:))==1 &&
max(f==Vermont_Station_Index(1,:))
                end %strcmp(Vermont_Route,'YES')==1 &&
Vermont_Route_Initial_Year <= Desired_Year

                if strcmp(Cumulative_NEC_Route,'YES')==1 &&
Cumulative_NEC_Route_Initial_Year <= Desired_Year
                    if max(e==Cumulative_NEC_Station_Index(1,:))==1 &&
max(f==Cumulative_NEC_Station_Index(1,:)) %This line determines if both
the origin and destination station are stations in the corridor.
                        S2S_Train_TravelTime(e,f) =
(1/Cumulative_NEC_Route_Average_Speed)*S2S_Train_Distance(e,f); %hrs

                        if
strcmp(Acela_Cost_Cumulative_NEC_Route,'YES')==1
                            S2S_Train_TravelCost(e,f) =
max(25,((M*(S2S_Train_Distance(e,f)^3))+(N*(S2S_Train_Distance(e,f)^2))
+(P*(S2S_Train_Distance(e,f))+Q)))*Inflation_Factor; % A minimum of 25
dollars is assigned to cost because regression curve produces negative
```

```
values for short distances. The $30 is valid for 2011 and it is
adjusted for inflation for the desired year.
                        else
                            S2S_Train_TravelCost(e,f) =
max(25,Cumulative_NEC_Route_Average_Cost*S2S_Train_Distance(e,f))*Infla
tion_Factor; % $.  A minimum of 25 dollars is assigned to cost. The
cost is in 2010 $ and then adjusted back to inflation.
                        end

                    end%
                end




            end % if S2S_Train_Distance(e,f)<=0
        end % for f=1:1:Number_Stations_Total_Network
    end %e=1:1:Number_Stations_Total_Network


end %strcmp(Very_High_Time_and_Cost,'YES')==1

save([Output_Save_Directory,'S2S_Train_Distance_',num2str(Desired_Year)
,'.mat'],'S2S_Train_Distance')
save([Output_Save_Directory,'S2S_Train_TravelTime_',num2str(Desired_Yea
r),'.mat'],'S2S_Train_TravelTime')
save([Output_Save_Directory,'S2S_Train_TravelCost_',num2str(Desired_Yea
r),'.mat'],'S2S_Train_TravelCost')
save([Output_Save_Directory,'S2S_Train_ScheduleDelay_',num2str(Desired_
Year),'.mat'],'S2S_Train_ScheduleDelay')
clear A
clear B
clear C
clear c
clear d
clear e
clear f
clear F
clear all


end
```

Train Station Index Finder Function

```
 %This file finds the index number of a rail station.  The city name is
used
%for the station, name must be entered in all caps.

function [Station_Index]=Train_Station_Index_Finder(Train_Station_Code)
global TrainStation_List
%load('C:\Users\Alex\Desktop\TrainStation_List.mat')
```

```
Station_Index=0;

for i=1:1:464
    if strcmp(TrainStation_List(1,i).Station_ID,Train_Station_Code)==1
        Station_Index=i;
    end
end
```

Schedule Delay Calculator Function

```
%This file calculates the schedule delay for service between stations.
function
[Schedule_Delay]=Schedule_Delay_Calculator(Train_Frequency,Train_Servic
e_Period)
Schedule_Delay=Train_Service_Period./(Train_Frequency .* 4);
```