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1. Introduction

Corridor congestion presents a particularly vexing problem to many states. While the investments required to remove “bottlenecks” are frequently local, the implications of a free-flowing highway network are clearly statewide, if not national. Departments of Transportation are often faced with investing scarce resources in infrastructure that benefits adjacent or even remote regions, but provides little economic benefit to the state itself. As a result, diversion and economic analysis is becoming an increasing important part of state highway planner’s toolkit – and an increasingly critical item for accurate forecasts. This case study is devoted to illustrating the state-of-art methodologies for making such forecasts.

1.1 Project Background

Two prior studies sponsored by the Commonwealth of Virginia analyzed the relationship between highway freight traffic and rail intermodal service, along a North-South corridor focused particularly on Interstate 81. Rail intermodal is a cooperative service where trucks pick up and deliver their shipments, but the truck trailer (or container) is carried between cities by rail, thus reducing the number of trucks that have to travel by highway. The two studies were motivated by rising projections of highway congestion, by truck traffic growth exceeding what the highways were designed to handle, and by the perceived concern for safety among citizens whose automobiles share the road with commercial vehicles.

Interstate 81 in the Commonwealth of Virginia is a critical artery in the nation’s highway network. It serves as a primary corridor for tourism and local economic activity, and as a vital conduit for through freight providers connecting the growing industrial south to the consuming markets of the Northeast. On Interstate Highway 81 at most times of day, about every third vehicle is a truck, and this is about double what the road was designed for. Motorists who share the road with commercial trucks often will feel unsafe and blame the larger vehicles for their concern, even when the trucks are carefully driven.

Freight traffic crosses metropolitan and state boundaries, and that individual pieces – like particular highway corridors – are interdependent parts of a larger statewide and national network. Traffic shifts in a locality will be created by investments and actions in other regions and other states, and conversely investments made locally will produce statewide and nationwide benefits. Evaluation of freight traffic patterns on a national scale is of paramount importance to statewide freight planning.

1.2 Study Background

Reebie Associates conducted two further studies for the Commonwealth of Virginia: (a) The Northeast – Southeast – Midwest Corridor Marketing Study, and (b) The Impact of Tolls on Freight Movement for I-81 in Virginia. The first study served to demonstrate the use of a statewide cross-elasticity highway-to-rail diversion model, whose results were used to design a suitable rail intermodal service and determine the extent to which public rail investment would be effective in mitigating the effect of increased traffic levels due to economic growth. The second study served to illustrate how existing tools could be put together to evaluate the traffic impact of tolling, or other infrastructure changes that might cause substantial truck routing changes to occur.

The marketing study sought to determine (1) the marketplace demand for improved intermodal service in the corridor; (2) service offerings that could generate the greatest diversion benefits to the corridor; and (3) level of public investment in rail intermodal that would materially impact the level of highway commercial traffic for I-81.

The tolling study consisted of two distinct elements that were designed to extract qualitative and quantitative results: (1) a series of interviews and surveys of motor carriers operating nationally, and along the I-81 corridor; (2) application of a customized diversion model that would reflect the decision logic of motor carriers operating in the corridor, and serve as a proxy for the thousands of routing decisions made by truckers of all sizes, everyday.

1.3 Demonstration of Methodologies

At the core of these study was the methodology that quantified the potential for truck diversions from I-81 with various service levels and designs of rail intermodal service, rates of tolling, and to scale the potential economic impact of these diversions on Virginia's industrial base. Two similar but not identical methodologies were used. In the marketing study, a cross-elasticity based diversion model was used to determine the extent to which new intermodal technologies and public investment in rail infrastructure could successfully divert truck traffic off the I-81. In the tolling study, an impedance-based routing model was used to determine to what extent truckers would divert from the I-81 if truck tolls were imposed. In the remainder of this case study, the two methodologies will be demonstrated in turn.

2. Methodology: Highway-Rail Diversion Model

A diversion model basically addresses the following question: if any of the attributes of the transportation services provided changes, to what extent will the traffic level and mode shares change? Attributes of a transportation system include such factors as cost, level-of-service, transit time, reliability, and other factors.

A general diversion model has three constituent parts: a cost model, to inform the cost of transportation using different modes; a market or traffic model, constructed from current traffic data, to determine where the markets are and how the goods are moving; and an elasticity model, for defining how these markets and costs (therefore prices) will change as the transportation system is modified through capital investment or new operating strategy. Figure 1 is a simplified diagram of the structure of the model used in the Virginia study.

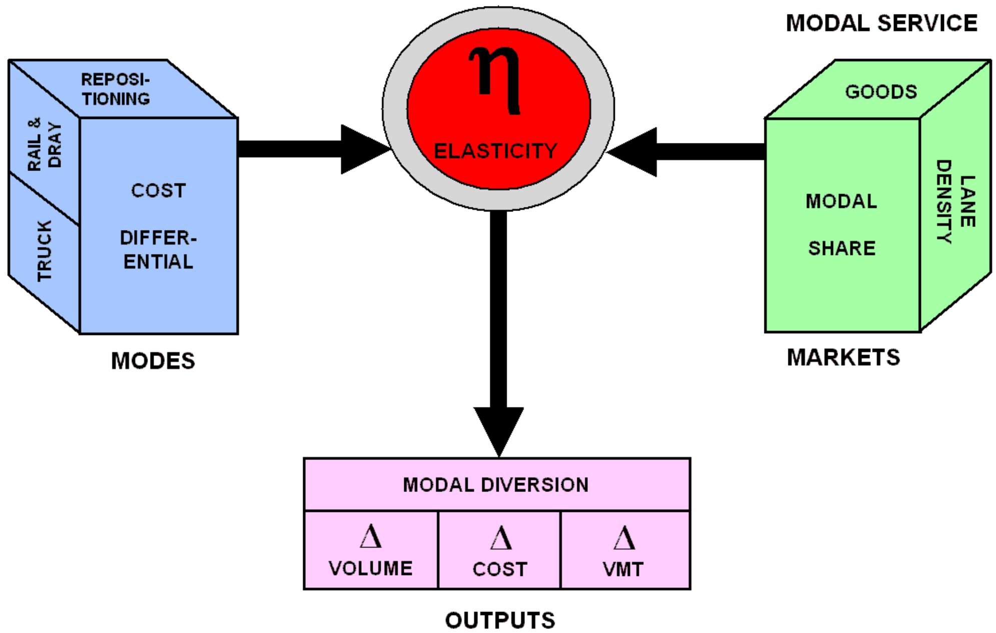


Figure 1: The three main constituent parts of a modal diversion model

The cost model could be a simple cost allocation model that represents the carrier cost of operations, or a total logistics model which takes into account of the shipper's full logistics costs incurred through the value-of-inventory-in-transit, stockout risk, and other such service reliability related factors. The market model could be a simple one that reflects or estimates the current traffic pattern and is not dependent on transportation infrastructure capacity and availability of cheap transportation, or it could be a land-use economic model which takes into account induced demands, differential growth and other important factors that can affect model market share. The elasticity model could be a simple linear regression that works well only for incremental changes, or it could be an elaborate, multi-dimensional econometric model that accurately reproduces the effect of demand changes for any range of price and service alterations. In this section, the simple methodology will be demonstrated through a set of illustrative examples. In the Virginia study, the methodologies used by Reebie Associates were generally more complicated, but in many cases it was simply a better disaggregation into more strata using input data gathered from multiple sources.

In the following sections, the three steps to constructing a diversion model will be described and illustrated in turn:

1. **Establishing the Current Traffic Pattern:** Constructing a database of current origin-destination commodity flows, by mode, to serve as the base case of how the traffic is

currently flowing. In the Virginia case, Reebie Associates' Transearch data was used as the primary source for the commodity flow database, and the data was supplemented with loop count and other traffic data supplied by the Virginia Department of Transportation.

2. **Forecasting Transportation Price Impact of Infrastructure Investment:** Building a generalized cost model for all modes affected by the infrastructure project, which will drive the elasticity model. In the Virginia case, Reebie Associates' proprietary CostLine family of models were used to determine the cost changes available from new intermodal technologies such as ExpressWay®; operating plan analysis was used to determine level-of-service changes from upgrade of Norfolk Southern's two main lines, which was translated into cost savings for the shippers using a logistics model.

3. **Applying the Cross-Elasticity Model:** The cross-elasticity model translates changes in prices of transportation services to the changes in demand and therefore traffic level. At the heart of the elasticity model is a matrix of cross-elasticities (η), which is calibrated from historical time-series cost and traffic data. In the Virginia case, Reebie Associates used the proven Reebie Diversion Model which had been previously calibrated against an extensive array of proprietary transportation carrier data, and other publicly available data.

2.1 Establishing the Current Traffic Pattern

A good starting point for a diversion model is always the current traffic pattern. Unless the infrastructure changes proposed are radically different from that existed previously, an incremental forecast will almost always be better than a theoretical construct based on trip generation and gravity attraction models. One example of a radical change in infrastructure would be the construction of a new bridge across a river, which has previously only had ferry crossings. In a case like that, the possibility of induced traffic and changing land-use pattern must be considered. However, for general-purpose statewide planning, such as constructing by-passes around small urban areas, widening existing highways with high levels of congestion, and construction of small-scale new links, incremental modeling based on cross-elasticities (see 2.2) is likely to suffice.

For the Virginia study, the current traffic pattern was culled from multiple sources. For national traffic levels, Reebie Associates' Transearch database was used. Reebie's TRANSEARCH Data is a model of freight flows, and contains origin, destination, mode, and commodity detail at a US county-to-county level. To augment that data, Virginia Department of Transportation supplied loop-count data in terms of Annual Average Daily Truck Traffic (AADTT), and Transearch data was calibrated against the empirical traffic counts. This provided a validation of Transearch data (which is economically and tonnage-based), against a well-grounded, vehicle-based direct empirical observation.

2.1.1 Unit Conversion: Tons per Truck, Dollars per Ton

The difficulty in generating such calibration typically involves a question of units. Economic and trade data is dollar based, while Transearch reports volumes in terms of tons, and loop-count data is in terms of vehicles. It is not sufficient to simply use an average value for dollars-per-ton, and tons-per-truck for obvious reasons such as different values of different commodities, and different types of vehicles that carry dramatically different volumes of goods. This problem can be overcome by using translation tables at a finer degree of disaggregation than a population average.

For example, many automatic loop counters are now capable of distinguishing between different classes of trucks. Some commodities are generally carried only in specific type of trucks with specific weight limits (such as sand, gravel, and lumber trucks). Thus, a more intelligent translation between number of vehicles and tons can be obtained from a translation matrix such as the following table:

Commodity	Light Truck	Class 8+
Sand	0	80,000
Gravel	0	80,000
Lumber	0	80,000
Iron	0	70,000
Others, NEC*	20,000	60,000
* Not elsewhere classified		

Table 1: Average weight in lbs per truck for example commodities and truck types

Since sand, gravel, lumber and iron do not travel in light trucks, it is safe to assign a "zero" value. When this table is applied to an existing database of commodity flows by equipment type, any records showing a sand and gravel flow by light truck will drop out. This is intentional, since such records are likely nonsensical and should be eradicated. Sand, gravel and lumber tend to weight out before they cube out, thus the maximum permitted weight of 80,000 lbs is assigned. The other commodities are lighter, and an average of 60,000 lbs is assigned. Practitioners can expand this matrix to as many dimensions and as many different commodity types as there is data available, to produce a comprehensive translation table.

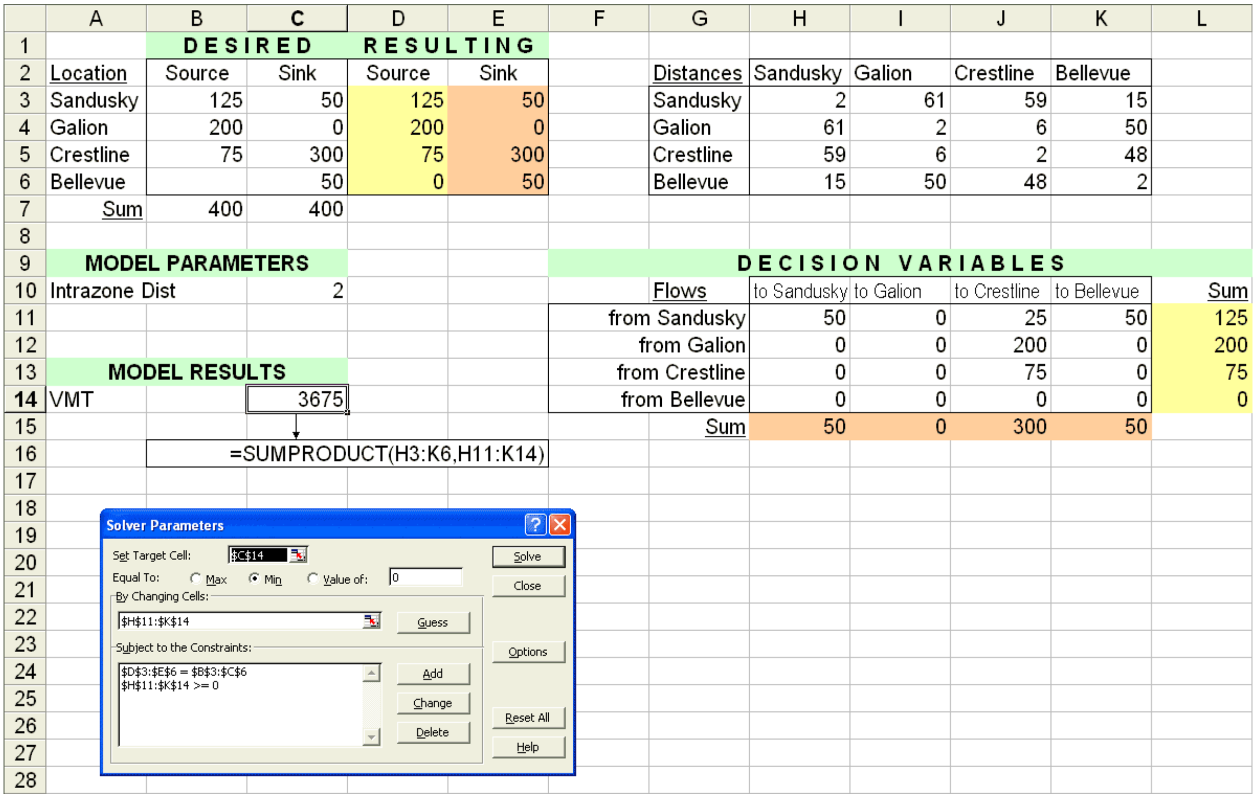
State DOTs often have this type of data available to them through intercept surveys. Weight station data, for example, could be used to compile one such table provided that at the time of weighing, the driver is asked to fill out a report on what commodity the truck is carrying. If commodity information is unavailable due to privacy concerns, even the equipment type alone could be used to make a weigh translation table. It is important to distinguish beyond FHWA truck classes when collecting information about equipment type. For example, dry vans tend to be lighter and are less likely to carry the maximum weight when compared to aggregate trucks and chemical tankers – even though both may be Class 8 trucks.

2.1.2 Using a Mileage Minimizing Model

This section examines ways to generate market data from theoretical constructs when appropriate data is not available. These methods are not generally recommended for actual analysis; if used, the results from the models should be checked with empirical data sources.

Figure 2 demonstrates a simple demand-supply equilibrium model, constructed on the principle of mileage minimization. This model take as inputs the sources and sinks of a single commodity, and calculates the traffic flows that are implied by the most efficient use of the commodity. Implicitly this model assumes a closed system (i.e. all demands are satisfied by local supplies), and that global optimization is possible.

For example, for poultry, the sources would be chicken farms, frozen poultry warehouses, etc., and the sinks would be grocery stores, restaurants, markets, or a factory that produces canned chicken soup. In a sense, the sinks draw chickens from the sources, and the sources will attempt to satisfy the demand while incurring minimum transportation distances (and by implication, costs).



	A	B	C	D	E	F	G	H	I	J	K	L
1		DESIRED		RESULTING								
2	Location	Source	Sink	Source	Sink		Distances	Sandusky	Galion	Crestline	Bellevue	
3	Sandusky	125	50	125	50		Sandusky	2	61	59	15	
4	Galion	200	0	200	0		Galion	61	2	6	50	
5	Crestline	75	300	75	300		Crestline	59	6	2	48	
6	Bellevue		50	0	50		Bellevue	15	50	48	2	
7	Sum	400	400									
8												
9	MODEL PARAMETERS					DECISION VARIABLES						
10	Intrazone Dist		2				Flows	to Sandusky	to Galion	to Crestline	to Bellevue	Sum
11							from Sandusky	50	0	25	50	125
12							from Galion	0	0	200	0	200
13	MODEL RESULTS						from Crestline	0	0	75	0	75
14	VMT		3675				from Bellevue	0	0	0	0	0
15							Sum	50	0	300	50	
16		=SUMPRODUCT(H3:K6,H11:K14)										

Figure 2: Developing a mileage-minimizing model with Excel® Solver

In this model, you enter the units of poultry (birds, pounds, or tons) that each town is capable of supplying in a given time period, and enter the demand. Set up the distance matrix, and ensure the decision variable matrix is empty. The simple optimization model has two constraints: the supply-demand constraint (that the flows have to sum up to the right demand and supply totals), and the positive flow constraint (chickens should not flow from the stores back to the chicken coops). These constraints are shown in the Solver dialog box in Figure 2. The objective function is to minimize VMT, which is the sum of all mileages incurred in chicken distribution – the sum product of the two matrices shown, mileage matrix and flow matrix. Solving the linear program will populate the Decision Variables matrix with answers shown above, representing the least-VMT way of fulfilling all demands from all available supplies.

The drawback of this type of modeling is that it is very data intensive, and does not make use of real traffic data. Relating market flow data to empirically observed traffic data is not trivial, since flows would still have to be assigned to specific routes to allow it to be matched to point-check traffic data (such as data from loop counts and checkers). Another problem is that modeling must be conducted for each individual commodity. Since the model is commodity specific, this model runs into trouble when there are substitutable commodities being produced and consumed whose precise production and consumption patterns are not known. (Chicken feed is one such example; chickens can be fed corn, ground mussel shells, and other types of chicken feed depending on their nutritional needs and the price of commodities.) However, without a large scale shipper survey, a mileage-minimizing, geographical-equilibrium model might be one of the best way to generate market data required for strategic studies in a reasonably short timespan.

2.1.3 ***Using a Gravity Model***

The gravity model is another commonly used method to generate some point-to-point flow data when individual market data is not available but some point-check data and some measure of industrial activity is available for each node. The theory is that commercial activity falls off with the square of the distance (or the journey time – in some cases that metric works better). The gravity model takes the following general form:

$$\text{Projected Flow } (P_{12}) = \frac{\text{Gravity Constant } (k) * \text{Node 1 Activity } (A_1) * \text{Node 2 Activity } (A_2)}{\text{Square of Distance Node1-Node2 } (D^2)}$$

There are two parameters that are generally customizable in this model. The Gravity Constant (k) is simply a number that converts measures of economic activity and distance to flow in terms of tonnage. Another variable is the exponent to which the distance is raised. In this example, we will use a simple gravity model where the exponent is fixed at two – the classic inverse square model.

Figure 3 demonstrates how one such model could be set-up in an Excel spreadsheet. There are a number of ways to calibrate this model – by using observed link-flow data, the Gravity Constant resulting in the best-fit could be found. The goodness-of-fit could be determined using regression methods, or a simpler method such as one demonstrated, where the minimum log square difference between the observed and projected are found.

	A	B	C	D	E	F	G	H	I
1	**Location**	**Distance**	**Activity**		**PROJECTED FLOWS**				
2	Boston		3297201			Boston	Providence	New Haven	Stamford
3	Providence	50	1125639		Providence	190452			
4	New Haven	102	522279		New Haven	9562	7249		
5	Stamford	41	332835		Stamford	3780	2350	13266	
6	New York	40	8712607		New York	67883	37569	88974	232508
7									
8	Segment Flows								
9	**From**	**To**	**Observed**	**Projected**	**Ln. Sq. Diff.**		=C16*C3*C5/(SUM(B4:B5)^2)		
10	Boston	Providence	159000	190452	20.71				
11	Providence	New Haven	24300	16811	17.84				
12	New Haven	Stamford	21700	19396	15.48				
13	Stamford	New York	427100	426934	10.23				
14									
15	**MODEL PARAMETERS**								
16	Gravity Model Constant		0.000128287						
17	Model Fit			64.27					

Figure 3: Calibrating a simple inverse-square gravity model

For a detailed treatment of using the gravity model, consult any standard urban transportation planning textbook[1]. In general, the use of gravity model in freight planning is not recommended, partly because of the problem of substitutable commodities mentioned earlier (see 2.1.2), as well as the lack of detailed link-flow data on a commodity-by-commodity basis that could be used to calibrate one such model. In essence, although loop-count data is very useful in determining truck volumes, it is not generally possible to determine what the truck is carrying by observing them roadside. However, knowing the commodity being carried is key in link truck movements to economic activity in a model such as ones demonstrated in this section.

2.2 Transportation Cost Models

Another necessary prerequisite to a diversion model is a transportation cost model. Transportation cost models are used in estimating the cost impact to transportation carriers given certain infrastructure improvements (or other changes, such as imposition of tolls or changes in labor regulations). The cost model is needed to drive the elasticity model, since the price of transportation services after the infrastructure changes is unknown at the time of the study. In a deregulated environment, the cost of service is a good proxy for the price.

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[1] For example: *George E. Gray, Lester A. Hoel*, Public Transportation: Planning, Operations & Management; *Michael Meyer, Eric Miller*, Urban Transportation Planning.

For the Virginia study, Reebie's CostLine family of cost models were used to generate carrier cost estimates. CostLine is a cost allocation model. Based on analysis of URCS (Uniform Rail Costing System), ATT (American Trucking Trends), other industry standard cost reports, proprietary data exchange data from affiliated carriers, and independent research, the model provides detailed insight about the costs of carrier operations. Diversions are in general based on a cost differential (or changes in the existing cost differential) between one mode and another, thus having a good cost model is critical to having meaningful results in a diversionary analysis.

CostLine is a proprietary model. For demonstration purposes, a general cost allocation methodology will be covered in this section. State DOTs and other governmental organizations may calibrate their own cost models based on this methodology and with appropriate data.

2.2.1 Data Sources for a Cost Allocation Model

There are two general approaches to building a cost model. A cost allocation model takes as its input historical shipment accounting records, along with detailed information on how much money was spent on each item, as well as related cost factors such as mileage travelled, fuel cost. For example, typical machine readable data from carriers or other sources might look something like this:

Origin	Dest	Rate	Mile	Labor	Fuel	O/H	Hrs	Trct'r	Trl'r	Cost	Profit
Newark, NJ	Brighton, MA	$335	221	$125.97	$99.45	$15.47	4.3	$53.92	$17.39	$312.21	$22.79
Bridgeport, CT	Pawtucket, RI	$195	126	$71.82	$56.70	$8.82	2.4	$29.50	$9.52	$176.36	$18.64
Harrisburg, PA	Dorchester, MA	$550	398	$226.86	$179.10	$27.86	7.6	$94.79	$30.58	$559.18	-$9.18
Scranton, PA	New London, CT	$330	230	$131.10	$103.50	$16.10	4.4	$54.16	$17.47	$322.34	$7.66
Worcester, MA	Schenectady, NY	$235	147	$83.79	$66.15	$10.29	2.7	$33.61	$10.84	$204.68	$30.32

Table 2: Hypothetical carrier data exchange accounting information relating to five shipments

This data is typically contained in a file with proprietary data formats. . File formats are likely to be specific to each carrier, although in the railroad industry there are some common standards. Smaller files can be manipulated in Excel, while a proprietary database product or statistical analysis package is recommended for model construction and curve fitting.

Using such proprietary data, it is possible to construct a percentage breakdown of costs based on the sampled shipments. When calculating percentages, it is important to note that the correct cost attribution percentages are based on the weighted average of all costs, and not the average of the percentages in each record. To obtain the chart below (Figure 4), sum up each of the cost categories in the columns (labor, fuel, overhead, etc.) and divide each of the sums by the sum of the rates (i.e., carrier price, or cost to the shipper).

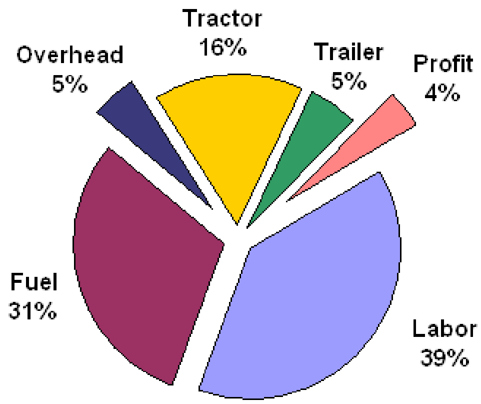


Figure 4: Cost breakdown report based on the five-shipment sample shown in Table 2

The basic methodology for cost allocation assumes that certain types of costs can be related to certain types of activities and units of production. Based on the cost breakdown shown, it is possible to project how each of these cost elements may change when infrastructure is upgraded. If congestion mitigation is planned for I-95 in Connecticut, it could reduce fuel costs by eliminating stop-go conditions, labor costs through increased staff utilization (unless the trucker is being paid by the mile), and it could decrease allocated amortization costs for the tractor and trailer by increasing utilization. However, it might not change the overhead and profit cost categories.

Supposing that transportation engineers have determined that reconstruction of a certain intersection would allow trucks that use it to by-pass the congestion instead of sitting in stop-go traffic for 10 minutes, it would reduce the trip time by 0.16 hours, and through factoring the numbers in Table 2, the cost saving can be calculated.

2.2.2 Cost Functions and Causal Models

Some carriers will have already developed cost models for their own operations. In fact, developing cost models is very much a part of a carrier's core business. When the shipper calls up a carrier for a quote, smart carriers ought to check both their cost and pricing models before they respond with a bid. The pricing model ensures their price is competitive, and the costing model ensures that the shipment will bring a net contribution to the company.

During the Virginia study, some survey work was carried out and a number of truck carriers chose to divulge their cost functions in addition to stating preferences with respect to tolls. One carrier stated that they used a formula of $20 per hour plus 45 cents per mile to assess their operating costs. Owner-operators, whose tractors and drivers are essentially leased to the carrier as a service package, stated that they were willing to work for between $1.00 and $1.25 per mile. These are very simple cost functions and can be used as rules of thumb when calibrating cost models. They will also serve well in measuring the dollar impact of transportation infrastructure changes that may result in temporary delays during construction, or permanent congestion relief with reduced trip times, once the project is completed.

Some carriers have more sophisticated cost models that do not measure operations purely in terms of mileage and trip time. Some cost models will take into account such factors as tractor, trailer, and driver utilization; some will factor in the effect of overtime; other integrated pricing and costing models will attribute capital amortization and overhead differently depending on the pricing strategy. There are also operations simulation models that combine costing, scheduling, and dispatching functions. Usually, in a diversion study, such operational details are not required and an accurate cost attribution model will suffice.

2.2.3 Total Logistics Cost Models

In addition to shipper's rates, shippers also incur costs in terms of inventory-in-transit, warehouse rent, risk of stockout, and other logistics-related expenses. These will not be captured by a transportation carrier costing model. However, they may affect the efficacy of diversion schemes. For instance, shippers that have time-critical inventory or high-value inventory will always demand high-service transportation (both in terms of time and reliability), even if the out-of-pocket costs might be higher than a slower, less reliable mode. A logistics model is necessary to accurately capture the service implication of diversion and shippers' reactions.

Total logistics cost models are generally described with the conceptual formula given in the following paragraph, which includes all the cost associated with getting the product to market from the shipper's perspective. All of those costs have a potential to affect diversion behaviour, although in terms of tonnage, perishable and time-sensitive goods make up generally a small percentage of total truck traffic.

Total Logistics Cost =

Transportation Cost +	Inventory-in-Transit Cost +
Stockout Risk +	Warehousing Cost +
Loss & Damage Risk +	Delay/Perishability Risk +
… …	

In the Virginia study, the effect of the value of inventory-in-transit was ignored for a variety of reasons. The cost of inventory-in-transit is mainly driven by the 95th percentile trip time and not the average trip time; in other words, a slower and more reliable service may result in lower total logistics costs than a faster and more variable one. Given the magnitude of delays typically incurred by avoiding I-81 (about 0.5-2.5 hours), this value is typically not recaptureable by the shipper. Distribution center and small package traffic that are typically most valuable and time-sensitive, generally have sufficient slack time to absorb the delay without compromising other processes in the logistics chain. For the minority of cases where the delay would result in disruption, it is generally possible to re-engineer the distribution chain, absorb the costs, or pass the costs to the customer. Thus, the value-of-inventory is unlikely to affect diversion behavior or truck operating costs significantly.

Total logistics cost models are well documented elsewhere, and are outside the scope of this case study. Interested readers are referred to the appropriate texts[2] and other NCHRP publications. The total logistics cost is of particular importance when dealing with air cargo or other highly time-sensitive transportation issues.

2.2.4 ***Final Word of Warning***

As a final word of advice, it should be made clear that cost breakdowns can be drastically different for different lengths of haul, different commodities, for different geographic areas, and other factors. Trucks operating in the New York area, for example, has a much higher time-component of costs compared to the rest of the U.S. Short-haul truckers have much higher operating costs in relation to terminal time than trip time, and some have asset utilization issues. All these small differences can affect transportation costs substantially, and therefore a cost analysis makes much more sense when it is coupled to a specific market, or a segment of markets such as a length-of-haul bracket.

In this NCHRP Report, a number of sample cost breakdowns are given and they are reasonably reflective of current industry state-of-practice. However, Figure 4 is genuinely derived from a total sample of five shipments shown. Figures 5 and 6 shown below are derived from a specific CostLine run for a specific market. Using these numbers for general analysis of transportation costs can lead to unexpected results. Transportation planners must calibrate their own cost model based on the data available and the region in question. Frequently, developing a relationship with local transportation providers can yield much useful information through surveys, as was found during the Virginia case study experience.

2.2.5 ***Reebie's CostLine Model as Applied to Virginia Case Study***

Reebie's COSTLINE® products are used to calculate the shipment costs of U.S. and Canadian freight carriers. COSTLINE analyses typically reveal comparative advantages between modes and carriers, as well as providing informed bargaining and systematic benchmarking of transport profit margins to users. Other generic cost models could also be used. The following costing

[2] See Paul O. Roberts, *The Translog Shipper Cost Model*, MIT Center for Transportation Studies Report No.81-1, Massachusetts Institute of Technology, Cambridge, Mass. (June, 1981); Association of American Railroads, "Overview" from *The Intermodal Competition Model*, -- User's Reference Manual, and standard textbooks such as Marvin L. Manheim, Fundamentals of Transportation Systems Analysis, MIT Press.

chartswere generated for the purposes of the Virginia study, which may be helpful for other government practitioners developing internal cost models:

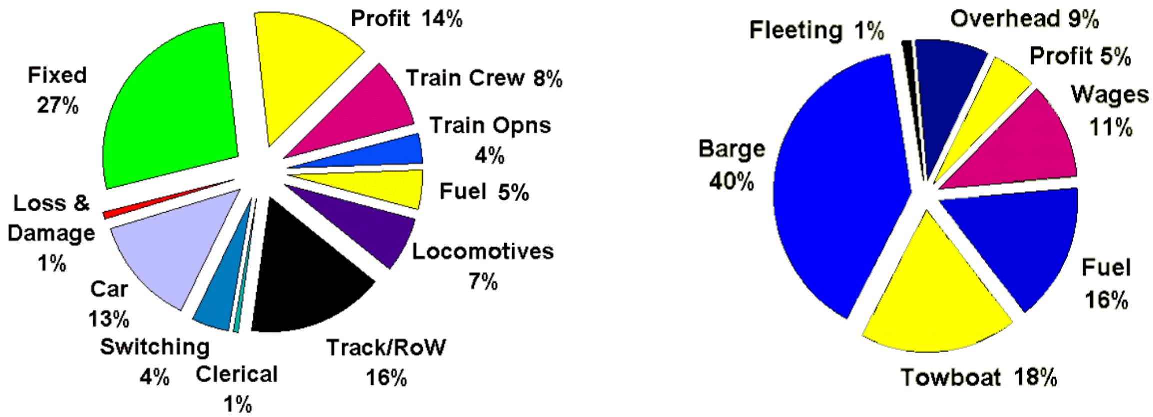


Figure 5 & 6: Cost Breakdown Reports from Reebie's CostLine Rail Cost Allocation Model (RCAM) and Barge Cost Analysis Model (BCAM)

2.3 Defining Cross Elasticities

The econometric concept of *cross elasticity of demand* is defined as:

> The relative response of a change in the demand to a change in the price of another good. The cross elasticity of demand is percentage change in the demand for one good due to a percentage change in the price of another good. This notion of elasticity captures the other prices demand determinant.

In the context of transportation planning, the cross elasticities are used to determine to what extent the demand for one type of transportation service changes when the price of another service is changed. For example, in a simple case, a coefficient of cross-elasticity might measure how much additional rail traffic we would expect if the price of truck transportation increased by 1%. In this case, we expect the demand for rail transportation to increase when the price for truck transportation increases, because rail and truck transportation are substitutable goods; the logistics manager has the choice of moving one given load of freight by either rail or truck, and not both (except in the case of intermodal services).

In its simplest form, a cross-elasticity matrix is a two-dimensional table, such as the one shown below:

Elasticities	Carload	Intermodal	Truck
Carload	-0.40	0.10	0.05
Intermodal		-0.70	0.30
Truck			-0.50

Table 3: Example elasticities and cross-elasticities for three common freight transportation modes

This table can be interpreted in this way: if the price of carload services increase by 1%, the demand for carload service will decrease by 0.4%, while the demand for intermodal service will increase by 0.1% and the demand for trucking will increase by 0.05% (see Row 1). If the price of intermodal service were to increase by 1%, the demand will be down by 0.7%, while truck demand will be up by 0.3%.

This table therefore suggests that the carload business is not as price sensitive as the intermodal business, and that truck is a reasonable substitute for intermodal while it is a poor substitute for carload. Also, note that the numbers do not (and should not) add up: because these are percentages of total demand, if 100,000 tons annually were diverted from carload to intermodal, carload traffic might experience a 0.01% loss while intermodal might report a 0.08% gain.

Another reason is that the tonnages lost by one mode might not be exactly equal the tonnages gained by another, because geographic shifts may occur. If the price for transportation service increases, the marketplace on the whole may choose to consume less transportation as plants are shut down or output were decreased. This type of relationship would be captured in an input-output table or by computing cross-elasticities for apparently unrelated goods such as the cost of rail transportation and electricity. The relationship becomes clear when it is revealed that the price of rail transportation contributes substantially to the cost of generating electricity at coal-fired power plants.

Cross-elasticities are a good way of predicting marginal market share changes, but may not be a good way of predicting drastic changes. Economic research has shown that cross-elasticities in transportation can depend on a variety of factors, including the base traffic level and price level. For example, a 1% reduction in air fares between two major metropolitan areas may not be noticed – resulting in a mere 0.1% increase in passengers and an elasticity of 0.10, while a 10%-off sale may result in a 3% increase in demand and therefore an elasticity of 0.30. There may be private tables of elasticities and cross-elasticities available, based on decades of historical econometric data to cover many permutations of traffic level, base price level, and magnitude of change. Just as disaggregation of sampled data into many strata will enhance the accuracy and predictive power of a traffic flow model (see 2.1), disaggregation of elasticities based on these variables will also improve its predicting power.

2.3.1 *Historical Price and Demand Data for Calibrating Elasticities*

In the Virginia Study, the Reebie Highway-Rail Diversion Model was used, which was calibrated using extensive historical price and demand data stretching back a number of years that were obtained from public sources, cost models, as well as proprietary carrier data exchange. The following section is an exposition of how a gross calibration could be done by a planner with access to suitable empirical data.

In general, the data needed to calibrate a simple elasticity model is not extensive, but extensive data is required to calibrate a model that accurately reflects actual conditions. The elasticity model measures the relationships in price/demand changes, thus at minimum a time-series record of price and demand would be needed. If a cross-elasticity model were needed, the historical price-demand data would be required for at least two modes. In this example, such a simple data series would be used to illustrate the generally accepted econometric methodology. The data series for rail and truck average prices between a particular origin and destination might look something like this, in its simplest form:

	Price (¢/ton-mile)	
Week	Rail	Truck
1	0.79	1.30
2	0.63	2.73
3	0.85	1.40
4	1.05	2.85
5	0.89	2.95
6	0.94	1.66
7	0.97	1.29
8	1.08	1.43
9	1.05	1.44
10	1.00	1.33

	Traffic (loads/wk)	
Week	Rail	Truck
1	1320	400
2	1340	380
3	1270	390
4	1280	370
5	1350	365
6	1300	340
7	1320	440
8	1270	450
9	1270	430
10	1280	450

**Table 4: Historical price and traffic data example
for rail and truck over a ten-week period, for a single O/D pair**

To calibrate a large model, time-series data for a single O/D (origin-destination) pair would not be sufficient. Also, being able to predict the mode shift in a single O/D based on historical data for that O/D might not be very useful. Ideally, the model should predict mode change for all possible O/D's based on historical data for a number of sample O/D's. To accomplish this, time-series datasets could be aggregated by commodity classification, length-of-haul, equipment type, operating methods, TL/LTL, and a variety of other dimensions. This enables the model to predict mode shifts in O/D's lacking historical data, by assuming that another O/D with similar length-of-haul and commodity characteristics might have similar elasticities.

In this simple methodology, the traffic data (loads carried per week) is used as a proxy for demand (loads that would be carried per week if capacity were available, and that the prices were right). In general, this is a good approximation, since capacity will tend to expand to cater to available demand as price is driven towards marginal cost in a competitive market. However, it is important to bear in mind that demand is really a demand function, which changes with variables such as price, capacity available, and other extraneous factors. This aspect of demand becomes important when a very large capital investment is being considered, with its consequential impact on available capacity, economic development (and hence 'induced' demand), and shifts in land-use patterns.

2.3.2 Survey Data as a Basis for Calibrating Elasticity Models

Technically, by using historical time-series data to calibrate demand models is usually referred to as the *Revealed Preferences*. The preferences are revealed because shippers have let their preferences be known to the world through past actions. This method is usually considered more reliable, if suitable data can be obtained. However, it is subject to certain pitfalls (discussed in section 2.3.4).

An alternative method for populating an elasticity model is by calibrating parameters based on surveys. This is termed the *Stated Preferences* method, because the shippers state their preferences in usually an inconsequential way. Thus, it is subject to a number of obvious problems: some shippers will say one thing, then do another; other shippers simply don't know because they don't have experience in utilizing the mode or with the specific situation and policy scenario. The ramifications of a policy change is not always immediately evident, even with experienced traffic managers.

However, in some cases, stated preferences methods are the only tool in which demand can be ascertained. For example, when introducing a new mode, calibration by historical data is impossible since the mode has yet to be designed and constructed. In general, elasticity models are not suitable for large-scale changes anyway, and thus do not usually cause a problem. Other methods (logit models, economic development models, gravity models, comparative methods) are available for forecasting demand due to a new mode or large scale infrastructure changes.

In terms of the Virginia marketing study, since highway or rail capacity expansion is essentially an incremental change, and prior data and elasticity estimates for highway-rail diversion is generally available, the stated preference method was not used. The survey work focused on a marketing orientation with the main aim being the gathering of intelligence rather than the pooling of massive amounts of data for the purposes of calibrating an elasticity model. Although the ExpressWay® service recommended in the report is technically a new mode in this market, revealed preference techniques were perfectly adequate for this task.

A detailed design process for a stated preferences survey will be covered elsewhere in this handbook, in another case study.

2.3.3 Calculating Elasticities

The elasticity of demand is calculated using the following formula:

$$\textbf{Elasticity} = \frac{\text{Percentage Change in } \textbf{Demand}}{\text{Percentage Change in } \textbf{Price}}$$

Using the data from Table 4, an Microsoft® Excel chart can easily be constructed to calculate the percentage change for each mode. To obtain cross elasticities from such a dataset, use Excel's Trendline function to find the line of best fit between a percentage change of demand data series, and a % change in price data series, as demonstrated below.

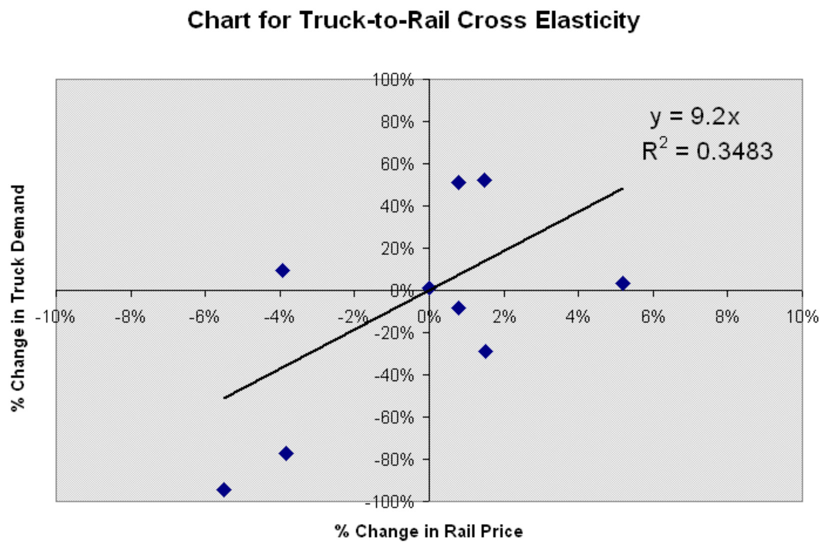


Figure 7: Calibrating cross elasticities

The equation of line-of-best-fit is shown on the chart, and suggests a relationship between the percentage change in truck demand and the percentage change in rail price. The gradient of the line of best fit (shown on chart as 9.2) is the cross-elasticity of demand. According to the test dataset, a 1% increase in the price of rail transportation will cause a 9.2% increase in truck demand. The R^2 variable is a number between –1 and 1 that gives information as to how good the line of best fit is. It is a measure of the predictive power of the equation. The value of 0.3483 shown means that rail price (through the equation y = 9.2x) is able to explain approximately 35% of the variation in truck demand. If the R^2 is too low, then further disaggregation is needed – to explicitly bring out the (yet unknown) variables that may affect truck demand.

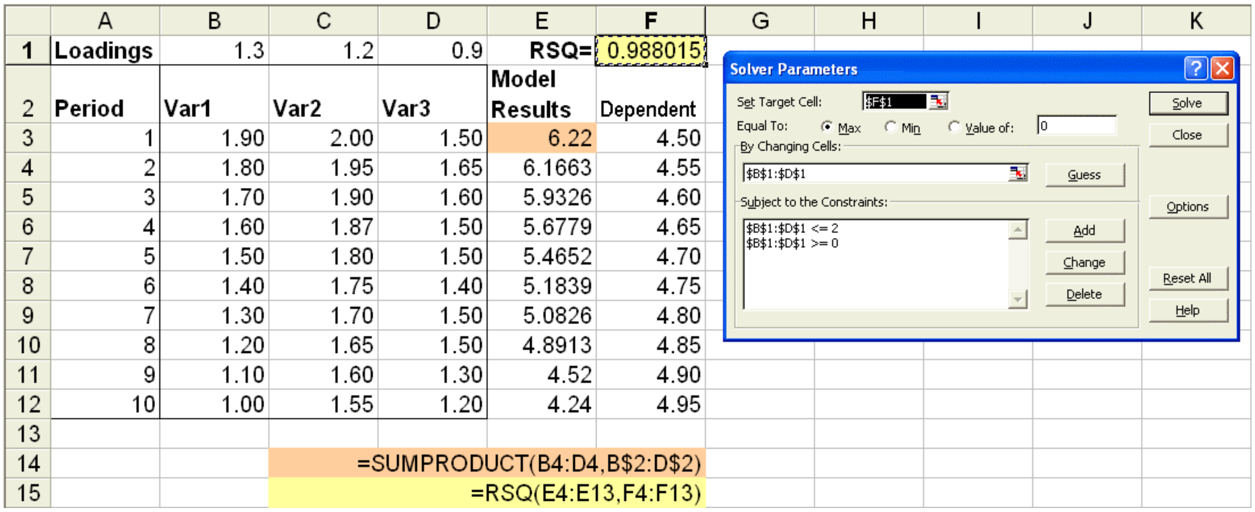
2.3.4 Analysis of Variance

Analysis of Variance (or ANOVA) is a method of dealing with multiple regressions efficiently. Its main application to the calculation of cross-elasticities is for finding multiple factors that contribute to the changes in demand. ANOVA techniques are covered in standard statistical analysis texts as well as software manuals for such statistical analysis packages as SPSS, SAS, JMP, and others.

There are a number of reasons why transportation demands may change, and some of these are independent of the price of transportation. During the grain harvest season, grain transportation needs are driven by the demand for grain and world grain prices, and not by the price of transportation. Thus, attempts to use such historical data to calibrate an elasticity model may result in counterintuitive findings – for example, even though carload railroad prices may increase throughout the harvest season, the demand nevertheless increases. This suggests that railroads have pricing power in that market; if grain prices are high, transportation costs is a small percentage of delivered cost and thus farmers are more concerned with getting product to market than with the increasing price of rail transportation. Calibration of cross-elasticities is best done using dataset that is not muddled by extraneous factors such as a surge in demand of the good being transported.

The effect of these extraneous factors can be subtracted out during the calibration process, if time-series data for the factor is available. To use ANOVA-type methods to find elasticities and subtract out the effects of the extraneous factors, generally a list of "% Change" is calculated for all variables (e.g. fuel price, truck price, rail price, latent transportation demand, etc.), similar to example shown in Table 5. These columns are then selected as explanatory variables and % change in truck demand is the dependent variable. This method has the advantage of finding the elasticity of demand for truck simultaneously with the cross-elasticity of rail-truck demand.

Without access to statistical analysis packages, it is usually possible to approximate the analysis in a less rigourous way using Excel's statistical functions and Solver. To create a multiple-regression model, put each of the variables in a column, and reserve the top row for loadings on each variable. Set up a column for model results, which equals to the sumproduct of each cell in a given row and the top row. To find the model of best fit, create a cell containing an expression for R^2 for data series "model results", and data series "dependent variable." Populate the model with reasonable initial values, and use Solver to maximize the R^2 cell by changing the loadings. A spreadsheet example of this method is shown in Figure 8.



	A	B	C	D	E	F
1	Loadings	1.3	1.2	0.9	RSQ=	0.988015
2	Period	Var1	Var2	Var3	Model Results	Dependent
3	1	1.90	2.00	1.50	6.22	4.50
4	2	1.80	1.95	1.65	6.1663	4.55
5	3	1.70	1.90	1.60	5.9326	4.60
6	4	1.60	1.87	1.50	5.6779	4.65
7	5	1.50	1.80	1.50	5.4652	4.70
8	6	1.40	1.75	1.40	5.1839	4.75
9	7	1.30	1.70	1.50	5.0826	4.80
10	8	1.20	1.65	1.50	4.8913	4.85
11	9	1.10	1.60	1.30	4.52	4.90
12	10	1.00	1.55	1.20	4.24	4.95
13						
14			=SUMPRODUCT(B4:D4,B$2:D$2)			
15			=RSQ(E4:E13,F4:F13)			

Figure 8: Using Microsoft® Excel Solver to approximate a multiple regression for finding cross-elasticities

2.3.5 <u>Applying the Demand Elasticities and Cross-Elasticities</u>

Using one of the methods shown above, a table of elasticities can be constructed. Using the definition of elasticity (see 2.3), forecasting demand is simply a matter of multiplying out the current traffic base by the appropriate elasticities. In the following section, we will discuss a short example to make a differential forecast based on current traffic pattern, a discounted rail rate, and the imposition of highway tolls.

Figure 9 shows a cross-elasticity matrix and a demand model set up in Microsoft Excel. The elasticity matrix has price on the vertical (y-) axis, and demand on the horizontal (x-) axis. The rail-rail demand elasticity is shown as –0.55 – in other words, a 1% increase in rail price will result in a 0.55% decrease in rail demand. The rail-highway demand cross-elasticity is shown as 0.20 – when rail price is increased by 1%, highway demand will increase by 0.20%. The elasticity matrix was previously calibrated using a methodology similar to that described in section 2.3.3.

	A	B	C	D	E	F	G	H	I	J	K	L
1	BEFORE						AFTER					
2			Rail		Highway		Rail			Highway		
3	O/D Pair	Mileage	Rate	Traffic	Rate	Traffic	Rate	Inc%	Demand	Rate	Inc%	Demand
4	BOS-NYP	216	$89	3,940	$86	12,460	$79	-11%	4,548	$96	12%	10,323
5	BOS-NHV	137	$79	570	$55	6,130	$69	-13%	693	$65	18%	4,559
6	BOS-PHL	312	$86	1,080	$125	5,720	$79	-8%	1,267	$145	16%	4,480
7	BOS-BAL	407	$89	710	$163	2,390	$84	-6%	802	$183	12%	1,997
8	BOS-WAS	448	$99	1,450	$179	3,050	$89	-10%	1,660	$199	11%	2,552
9	NHV-PHL	176	$69	320	$70	1,280	$69	0%	375	$85	21%	950
10	NHV-BAL	271	$74	280	$108	820	$74	0%	311	$123	14%	683
11	NHV-WAS	312	$89	400	$125	1,090	$89	0%	438	$140	12%	931
12												
13						=(G8-C8)/C8						
14												
15	Elasticity Matrix		Demand			=D9+D9*(H9*C17)+D9*(K9*C18)						
16			Rail	Highway								
17	Price	Rail	-0.55	0.28					=F6+F6*(H6*D17)+F6*(K6*D18)			
18		Highway	0.80	-1.21								

Figure 9: Cross-elasticity demand model set up in a spreadsheet using Microsoft Excel

To assess the new demand after the changes take place, each component of demand changes must be assessed separately. By lowering rail rates, demand for rail service would increase, and demand for highway service would decrease. By increasing highway costs through tolls, demand for rail service would further increase, and highway demand will be further surpressed. Those are four components of demand changes that must be calculated separately. First, calculate the change in rail demand due to the decreased rail rates using the following formula, by applying the definition of demand elasticity:

$$\begin{array}{c}\text{Change in Rail}\\\text{Demand due to}\\\text{Rail Rate Cut}\\(\Delta R_{\text{Rail}})\end{array} = \begin{array}{c}\text{Prior Rail}\\\text{Traffic}\\(R_{before})\end{array} * \begin{array}{c}\text{Percentage}\\\text{Rail Fare}\\\text{Change}\\(\Delta Rf\%)\end{array} * \begin{array}{c}\text{Rail-Rail}\\\text{Demand}\\\text{Elasticity}\\(\eta RR)\end{array}$$

The portions relevant to this calculation are shown in red. Next, calculate the change in rail demand due to the increased highway costs, using a similar formula, but instead employing the rail-highway cross-elasticity. To enumerate the forecasted demand due to both highway cost and rail fare impacts, simply sum up the changes and apply the changes to the current (observed) traffic levels:

$$\begin{array}{c}\text{Rail Demand}\\\text{after Hwy \& Rail}\\\text{Cost Changes}\\(R_{after})\end{array} = \begin{array}{c}\text{Prior Rail}\\\text{Traffic}\\(R_{before})\end{array} + \begin{array}{c}\text{Rail Rate}\\\text{Demand}\\\text{Change}\\(\Delta R_{\text{Rail}})\end{array} + \begin{array}{c}\text{Hwy Cost}\\\text{Demand}\\\text{Change}\\(\Delta R_{\text{Hwy}})\end{array}$$

This concludes our discussion of cross-elasticity models and its application. In the following section, how Reebie Associates applied this type of diversion model – which is the basis of the Reebie Diversion Model – in the Virginia I-81 marketing study, will be examined.

2.4 How the Elasticity Model was Applied in the Virginia Study

Reebie's quantification of the potential shifts of freight traffic from highway to rail intermodal service was centered on an evaluation of specific individual traffic lanes (one origin linked to one destination). Lanes were selected based on projections for improved intermodal service resulting from theoretical investments in infrastructure, the volumes of highway traffic and the potential of such traffic to contribute to intermodal train volumes, and the likelihood that diversions would be successful.

The assessment of potential rail intermodal gains from these candidate lanes employed a series of tools and techniques, developed by Reebie and used in ICC and STB proceedings to assess the potential traffic gains from rail network investment. This assessment involved weighing competitive alternatives against the rail intermodal offerings brought to market by changes in rail operating cost. The relative changes in modal shares that would result from the changes in costs and service arising from the benefits of proposed investments was calculated on a lane-by-lane basis. Current modal shares was examined and then correlated those to the underlying changes in the rail carriers' estimated operating costs. Service competition was also examined to assure that the new intermodal service offering would meet or exceed market standards.

Recognizing that rail-truck intermodal traffic increasingly operates between hub centers (usually located in or near major metropolitan areas), the study methodology took into account that intermodal facilities located in some cities could economically be used to reach other metropolitan markets outside of those immediate areas, even some distance from the terminal. Such a long "reach" would require the use of an extended dray, but this was not uncommon, particularly as part of a long rail line-haul movement.

The elasticity model that underlies Reebie's Diversion Model, implicitly accounts for the whole range of distribution cost and service considerations necessary for customers to use intermodal over highway service. The diversions resulting from the model was chacked against total train volumes, including base load volumes and rail-to-rail diversions, to ensure the adequacy of traffic levels to sustain dependable rail service.

The relationship of intermodal/highway cost and share was interpreted in terms of elasticity, meaning that a change in cost for a mode would produce a corresponding change in its market share. Based on that association, the cross-elasticity analysis was used to predict diversions across modes. Specifically, the elasticity measurement was a statistical coefficient by which one can quantify the effect of change in the intermodal cost on the demand for highway service.

Transportation researchers routinely apply discrete choice models to measure elasticity in mode selection. The analysis adopted modal share as the dependent variable, since share supplies a comparable measure of modal activity for business areas differing in traffic volume. To estimate elasticity where the variable is modal share, the model must restrict results to values between 0% and 100%, in effect estimating the probability of customers selecting intermodal transportation over highway, given some independent attribute. The selected attribute is the difference in average cost between intermodal and highway. In sum, the model measures the elasticity of intermodal share with respect to the difference between highway and intermodal costs, following a logit design. The model predicted, with some measure of reliability, how intermodal share will change when operating costs are changed.

For those O-D pairs passing the service and cost hurdles, diversions were determined in four steps:

1. Categorize lane density;
2. Calculate the change in differential between old rail costs versus highway and new rail costs versus highway;
3. Multiply the change in differential by the relevant coefficient from the market share model; and
4. Apply the multiplied differentials to present intermodal market share, yielding the new intermodal share of the market and the volume diverted.

This last step produces an estimate of rail intermodal diversions from highway. In applying the diversion model to individual lanes, however, a limited set of modifications is required.

First, recognizing that there were practical limits on the volumes of traffic that can move via intermodal service, the intermodal market share was capped at 90%. No traffic was diverted in lanes where the current share already exceeded the cap.[3]

Second, intermodal share gains was generally capped at a 15% increase, except up to a 20% increase in the backhaul direction of each lane was allowed. This better balances backhaul with headhaul diversions, where the available volume is higher. The cap reflects expert judgment as to the outer limit of diversions likely to occur in a three-year time frame, absent significant technological innovation.

Third, where current rail intermodal market share is below 4%, a floor value based on truck types of between .005 and 6.0 % was substituted, incorporating the results developed from previous shipper and motor carrier surveys and interviews, and other research materials. This practice of "seeding" traffic volume is consistent with generally accepted methodologies and reflects a conservative procedure even in light density lanes.

Intermodal market penetration is a function of two primary factors: (1) relative length of haul and (2) concentration of volume in traffic lanes. As the distance between the origin and the destination increases and lane volume (density) grows, intermodal service becomes more

[3] This is a standard feature of the model, and has been supported in previous analyses including those conducted for STB filings and has been supported by discussions with rail intermodal marketing executives.

competitive relative to highway, and its cost advantage increases (See Figure 6). A statistical interpretation of this principle underlies the Reebie Associates' Diversion Model that was employed to estimate the diversion of traffic to rail intermodal for the selected corridors.

Reebie's quantification of the potential shifts of freight traffic from highway to rail intermodal service is centered on an evaluation of specific individual traffic lanes (one origin linked to one destination). The lanes were selected based on projections for improved intermodal service resulting from hypothetical investments in infrastructure, the volumes of highway traffic and the potential of such traffic to contribute to intermodal train volumes, and the likelihood that diversions would be successful.

3. Using an Off-the-Shelf Highway Routing Model

In the Virginia Toll Study, Reebie analysts applied a shortest-path model developed by the Oak Ridge National Laboratory to determine the likely impact on traffic patterns. The Oak Ridge Model (ORM) takes as its input an origin-destination traffic flow matrix and routes traffic by the shortest path based on fixed impedances that are dependent on link type (i.e. interstates, U.S. highways, and secondary routes). This type of model logic is identical to that employed by many motor carriers, as indicated in the Virginia Survey results.

ORNL offers the ORM in a variety of tabulations that are usable by users with different levels of technical sophistication. For the purposes of the Virginia Study, a special tabulation of the ORM was used, which translated origin-destination information directly into shortest path. This method is cumbersome and is not recommended for running shortest-path models.

The dataset that underlie ORM are downloadable from the Center for Transportation Analysis, ORNL at the web address: *http://www-cta.ornl.gov/transnet/Index.html*. The dataset downloaded, which includes impedances for route segments, can be manipulated with a custom program to generate shortest paths, or with a commercial GIS package such as ArcInfo and TransCAD.

For the Virginia study, the model assumed that the U.S. Interstate network is operating at or close to its original design speed, and therefore does not address the effects of highway congestion. This may be a factor in determining the likelihood that an alternative route is preferred. The most significant choke point (leading to highways periodically operating at speeds lower than 60% of design speed) affecting I-81 routing alternatives is congestion along I-95. To adjust travel time for motor carriers using an alternative I-95 routing, this was accounted for as an explicit added cost in the model, the I-95 surcharge.

The ORM model was calibrated to produce routing under three scenarios: (1) the base scenario, involving the use of I-81; (2) diversion through a northwesterly route (mostly a combination of I-

64 and I-79), with Virginia portion of I-81 unavailable; (3) diversion through a southeasterly route (i.e. I-95), with I-81 unavailable. A sample of the routings produced by ORM were compared to results using ALK Technologies' PC*Miler® software[4]. In the study, the "next-best" routings were explicitly defined based on survey input from truck operators. Again, this illustrates the importance of gaining feedback from actual users through surveys and focus groups, as logically shortest routing is not necessarily the one preferred by most operators, and therefore not the one that would absorb the impacts of diversions.

3.1 Solving the Shortest Path Problem

There are, in general, two ways to think of a shortest path problem. It can be considered as a network problem, but it can also be formulated as a linear program (and solved using an optimization tool, such as Excel's Solver, or more advanced tools such as XPressMP, SAS/LP amongst others). The network problem approach tends to use an intelligent 'mouse' which crawls around the network, making decisions at nodes according to a predetermined set of rules, and tracing out the shortest path. The linear programming approach tends to evaluate all possible routes, calculate the sum of all impedances exhaustively, and finding the path of least resistance.

3.2 Making a Routing Decision

There are many ways to construct a decision model. The decision model determine which path a vehicle would follow, given the generalized costs for all available paths. Typically, the industry standard practice is to use a logit model [5], shown in Figure 11. The logit model is defined by the following equation:

$$P(Z) = \frac{expZ}{1 + expZ}.$$

Applied to transportation, this is simply a way of allocating traffic between two modes, or between two paths. If P(Z) on the vertical axis represented the probability that a given vehicle will take path A, while Z represents the difference in generalized costs between paths A and B, looking up the graph reveals that if the cost were the same, the probability of taking path A

[4] While several commercial products are available to calculate miles, we selected the widely used PC Miler® product from ALK because it provides a decidedly commercial vehicle (truck) bias, and is easily customizable for route preferences. Many Internet based products do not readily distinguish between designated or preferred truck routes and passenger vehicle corridors. The PC Miler® product provides this feature, and is thus consistent with the basic ORM logic.

[5] A more mathematical and in-depth treatment of logit models is available here: J.S. Cramer, The origin and development of the logit model, August 2003, Cambridge University Press, Cambridge, England. *http://publishing.cambridge.org/resources/0521815886/212298*

would be 0.5 – in other words, 50% of all traffic will take path A, and another 50% will take path B. This is intuitively obvious.

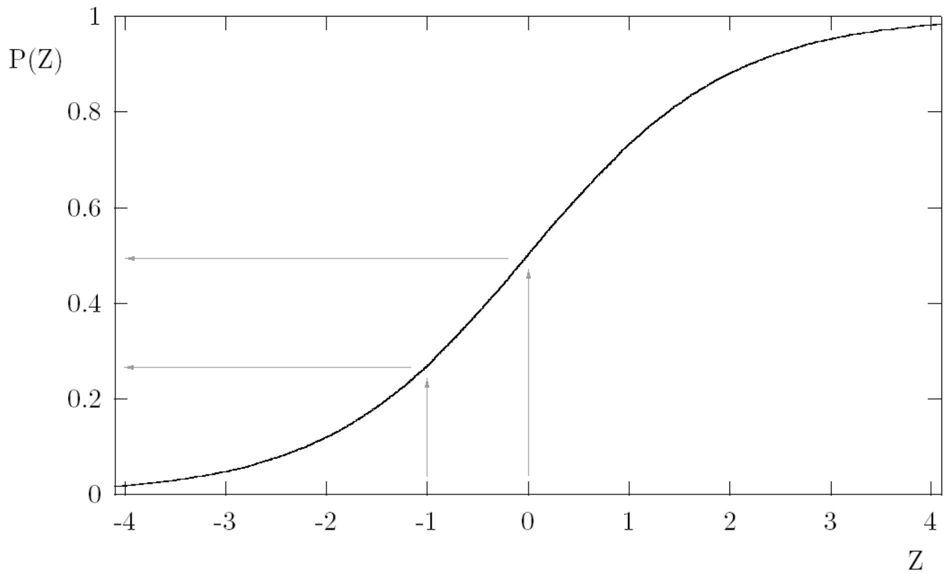


Figure 11: Generic shape of a logistic distribution

3.3 Routing Decision Model in the Virginia Study

In the Virginia study, the traffic diversion model assumed that the trucking industry behaves in an economically rational manner. Regardless of external factors such as: scenery, family visitation, gradients, and personal preferences, the trucker will always take the cheapest route (having accounted for the full cost of labor, equipment, fuel, congestion, and tolls). The decision variable is thus binary for a given level of toll. This methodology is consistent with motor carrier operating practice. It corresponds to the deterministic limiting case of the logit model demonstrated above[6].

For a sufficiently large sample of market data and well-calibrated cost and service data, the limiting case can be used. Mode share is calculated from a large number of lanes each with slightly different service attributes and costs, and thereforethe abruptness of the binary model will even out. The binary model fails where there are many shipments traveling between very similar origins and destinations where the costs and service attributes are very similar between

6 See Ben-Akiva and Lerman, Discrete Choice Analysis (MIT Press, 1985), p.70 for a detailed discussion on the logit model and the limiting cases.

competing modes – in this case, the binary model will always select the (marginally) cheaper routing, when in reality the traffic will tend to distribute itself over both routes according to variables that are not explicitly accounted for in the cost model.

3.3.1 Cost Model Detail

In the study, Reebie's Truck Cost Analysis Model (TCAM) was used to estimate the marginal cost of transportation per mile for each equipment type, using all origin-destination flows. This cost function was then further disaggregated into labor (mileage dependent) and equipment life-cycle cost (time dependent) using the carrier survey data discussed separately. We chose not to address differences in cost functions due to: (1) How the operators are being paid, employee versus owner-operators, (2) Fuel costs due to different terrain and operating characteristics, because we believe labor costs and time-dependent fuel costs (tractor idling time) are good proxies for the aforementioned effects. In general, the cost functions amounted to about 40-50 cents per mile for labor, and about $15-$30 per hour for equipment and fuel, depending on the type of rig and speeds operated.

The likely congestion on I-95 through Washington D.C. is considered a significant economic cost to truckers. In addition, I-95 boasts a large number of tolls, all of which change the economics of truck operation. To calculate the impact of this congestion on motor carrier routing choice, we utilized data from VDOT's I-95 Roadside Survey (conducted in October of 2002) to estimate the volume of trucks moving on the highway that could be impacted by highway congestion. Out of the average 12,228 Class 8+ trucks traveling on I-95 per day in 2002, 4,453 (36%) passed Dumfries, VA (a suburban location just outside Washington, D.C.) during the morning or evening rush hours (defined as 6am-10am and 3pm-7pm). Using an average delay of 45 minutes estimated based on motor carrier interviews, and average equipment & fuel cost of $27.50 per hour (based on earlier TCAM data and 2002 fuel prices), this delay results in a per-shipment cost increase of $7.43. In addition, between Washington D.C. and New York City, trucks must pay approximately $10.50 in highway tolls.[7] Allocating this cost over the 300 miles of I-95 in the Northeast, this results in a surcharge for trucks accessing the Northeast from the South of about 6 cents per-mile. This surcharge was applied to all flows that reflected I-95 mileage in the Northeast either for the primary or alternative routes. With the congestion and I-95 toll adjustments in place, we initiated a process of calculating potential diversions based on the application of various toll levels to I-81 in Virginia.

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[7] I-95 Toll locations were developed from ALK's PC Miler product, and from secondary source data including the following: http://www.usastar.com/i95/tolls.htm; http://www.state.nj.us/turnpike; http://www.mdroads.com/routes/is095.html.

3.3.2 The Resulting Traffic Routing Model

The result of the model is a database detailing origin, destination, commodity, equipment type, tonnage, loads, shortest path miles, diversion penalty miles, I-81 miles, toll cost, congestion cost, diversion fuel, equipment, and labor cost, as well as the driver's best economic routing decision at different levels of toll, and its implication on I-81 loads and VMT. In reality, at least some drivers are likely to make decisions based on qualitative factors, especially when traffic levels are low. However, the likely impact of these variables is modest as such decisions are generally irregular, or spontaneous. Motor carriers expressed a distinct preference for economic routes that become familiar to regular drivers and thus improve safety and performance.

At peak season, the opportunity cost of the equipment increases, and far more trucks are likely to take the toll road than the "average" equipment cost per-hour used in this survey would predict. Independent and small-company drivers, knowing that they have a return load waiting and a demanding customer, are likely to absorb the cost of a faster toll road. On the other hand, when traffic levels are low, more diversions would occur. Over the long run however, the impact of these seasonal variances is diminished, and traffic levels will average out at the levels predicted by the economically driven binary model.

4. Lessons Learned

- Transportation modeling can be said to be a combination of art and science. No single methodology will be suitable for two different studies, because the goals of the study, the data availability, and the policy questions that the studies are trying to answer may be different. This chapter serves to demonstrate example methodologies that can be adapted by State DOT analysts for use in their own studies, or in creating scope-of-work for external consultants.

- In general, transportation modeling relies heavily on statistical analysis and regression curve-fitting. A specialized computerized statistical package can greatly simplify the process of turning data into information and arguments that can be used to support policy decisions, but analysts familiar with statistical principles could conduct most processes on a small scale on a standard spreadsheet. Regression curve-fitting and statistical tests are covered in standard college-level mathematics manuals, as well as more specialized texts.

- Calibrating a transportation demand modal-diversion model comprises three-steps: establishing the current traffic pattern, establishing the cost functions of the competing models, and defining cross-elasticities. Once the model is calibrated, the model is applied to different policy scenarios by translating the impact of infrastructure investment into traffic, cost, and service-level changes – which in turn is translated to changes in transportation demand using elasticity matrices.

- Highway routing models are similar to modal-diversion models. Instead of diversion amongst different modes, the diversion occurs instead between competing highway routes. It is commonly accepted practice for freight transportation to assume that the truckers would on average take the shortest route after taking into account of factors such as trip time, cost, and external factors such as congestion and risk. Historical cost data, market demand data, coupled with decision rules on route preference, can be used to predict traffic volumes on each route.