

Transferability of an Intermodal Freight Transportation Forecasting Model to Major Florida Seaports

By

Dr. Jack Klodzinski, Ph.D.*

Transportation Systems Research Engineer and ITS Lab Manager
Department of Civil and Environmental Engineering
University of Central Florida
P.O. Box 162450
Orlando, Florida 32816-2450
Phone (407) 823-4552
Fax (407) 823-3315
E-mail: jklozdzin@mail.ucf.edu

and

Dr. Haitham M. Al-Deek, Ph.D., P.E.

Associate Professor
Associate Director of CATSS for ITS Programs, and
Director of Transportation Systems Institute (TSI)
Department of Civil and Environmental Engineering
University of Central Florida
P.O. Box 162450
Orlando, Florida 32816-2450
Phone (407) 823-2988
Fax (407) 823-3315
E-mail: haldeek@mail.ucf.edu

Submitted for Presentation and Publication
July 31st, 2002
Transportation Research Board
82nd Annual Meeting

4,738 Words in text, 2 Tables and 5 Figures
Total Word Count: 6,488

* Corresponding Author

ABSTRACT

Seaports are important economic generators and identifying necessary infrastructure improvements is essential to accommodate potential growth at these intermodal facilities. The ability for heavy trucks to access the port's freight terminals is one such operational improvement that needs to be addressed. The freight activity from Florida's major seaports generates over 10,000 trucks per day. Providing efficient accessibility to the freight terminals and storage facilities at ports can be accomplished by identifying needed improvements in transportation operations and developing truck trip generation models to forecast truck trips in and out of the ports. In July 2001, an Artificial Neural Network (ANN) model using back propagation techniques to simulate the transportation of freight by heavy trucks generated from an intermodal activity center such as a seaport was developed successfully. The general methodology for developing this model was applied to the Port of Tampa and Port Canaveral in Florida to test the transferability of this ANN modeling technique. From daily vessel freight data, models for both ports were developed successfully and validated at the 95% confidence level with data collected from the field. The validated models were executed for short term forecasts of truck trips at both ports. The Port of Tampa was forecasted to have a 0.31% average annual decrease in heavy trucks, attributed to the decreasing trend in bulk commodity shipments. Port Canaveral was forecasted to have a 5.07% average annual increase, which correlated to historical trends and future estimates for freight activity.

Key words: Artificial Neural Networks, intermodal, freight transportation modeling, truck trip generation.

INTRODUCTION

Freight transportation is an essential component for the growth of any global economy. The United States' total waterborne commerce in short tons for year 2000 was almost 2.5 billion and the State of Florida's freight activity contributes a significant portion to the nation's total (1). Florida's foreign and domestic waterborne commerce totals over 125 million short tons annually. Florida is ranked 6th in the nation in terms of total short tons but economically, Florida's almost 74 billion in annual international trade (including waterborne commerce) accounted for 3.8% of the nation's total in year 2000 (2). Florida has 1,197 statute miles of coastline and eleven active seaports handling waterborne trade. Among Florida's seaports, the Port of Tampa and Port Canaveral are in the top 100 ports for the nation in total waterborne commerce (short tons).

In order for Florida to experience continued growth, utilize potential new global markets and open new trade corridors for increasing foreign commerce, the seaports must be able to accommodate increases in freight traffic. To do this, it is important to address necessary improvements required to the infrastructure of the seaport's transportation operations. Port access roads must have the capacity and geometric designs to accommodate the freight motor carriers, which are an important mode of transport for the mobility of freight (3). The ability to accurately measure and forecast the heavy truck volumes on these access roads is essential for engineers and planners to recommend improvements so growth is not inhibited.

Currently, transportation planning has some deficiency with the ability to model freight movements and the relationship to heavy truck trips at a seaport. Trip generation models are useful tools for evaluating such data. In 2001, a truck trip generation model for the Port Everglades in Fort Lauderdale, Florida was successfully developed and implemented for short term forecasting using vessel freight data as input to the model (4,5). To determine the broad application of this methodology, two other seaports with different site specific characteristics were selected to test the transferability. The site specific characteristics include the freight activity and the access roads.

LITERATURE REVIEW

Balbach and Tadi investigated the use of regression for building a truck trip generation model for computing truck trip rates using several land use categories and levels of activities as independent variables (6). In 1998, a regional freight study was conducted in the Tampa Bay area that included investigation of freight movement characteristics and patterns and identified a set of priorities and improvements (7). Al-Deek compared the use of Neural Networks to Multiple Regression Analysis for application to freight modeling (8,9).

From this research, Al-Deek developed a methodology for using Artificial Neural Network (ANN) modeling with the application of backpropagation to use freight data for computing daily truck volumes generated by seaport vessel freight activity (4,8,9). Neural Networks is a collection of nodes connected by communication channels, which carry numerical data (weights). The nodes are grouped together to form layers. These layers include an input layer which feeds the model information, an output layer which is the desired product from the modeling and there may also be hidden layers. Hidden layers are additional layers where processing is done utilizing the weights. This is how Neural Networks can compute highly nonlinear and complex problems.

The backpropagation is a method in which the network is trained. An error is produced at the end of a series of calculations and then backpropagated through the network adjusting the weights as it passes through the layers. Calculations are initiated by the model again and this iterative process continues until the error produced is less than a preset tolerance. The MatLab computer software was used to build and execute the model by establishing relationships between daily vessel freight data and heavy truck volumes for both the inbound and outbound directions. This methodology was selected for testing its application of accurately generating current and forecasted daily truck volumes at two other significantly different Florida seaports.

SITE OVERVIEWS

Port Everglades, the port used to develop the methodology for truck trip generation has significant petroleum imports and containerized cargo activity. Cement and aggregate were also found to affect the selection of the independent variables for modeling and were also considered significant in this respect. Port Everglades has three roads for truck traffic to access the areas of freight activity. The Port of Tampa and Port Canaveral, the two seaports selected for the transferability testing, have somewhat different site characteristics than Port Everglades.

The Port of Tampa is Florida's largest tonnage port and ranked 17th in the nation for total tonnage (1). The majority of Tampa's commodities are considered bulk freight. These include phosphate and related products, which account for approximately 50% of Tampa's total tonnage. The port also handles a significant amount of petroleum imports but does not have any significant containerized cargo traffic, especially compared to Port Everglades. Port of Tampa has three main freight activity centers with five access roads; Hooker's Point (20th Street, 22nd Street, Causeway Boulevard), Port Sutton (Port Sutton Road), and Pendola Point (Pendola Point Road). Figure 1 shows the Port of Tampa and indicates the access roads by stars.

Port Canaveral, which handles 4.2 million short tons annually, is a smaller port in terms of total tonnage when compared to Port Everglades and the Port of Tampa. Annually, Port Everglades handles over 22 million short tons and the Port of Tampa handles over 46 million short tons (1). Port Canaveral however is unique because of its location to the Kennedy Space Center; it is considered quadramodal (transportation by surface, sea, air, and space). Port Canaveral has two freight activity centers, the north and south freight terminals. Each has its own access roads. The south terminal is accessed by George King Boulevard and the north terminal is accessed by Grouper Road. Figure 2 is a map of Port Canaveral and indicates the access roads by stars.

DATA COLLECTION

Vessel freight data and heavy truck volumes on the access roads to the port were required for building the ANN truck trip generation models for the Port of Tampa and Port Canaveral. The vessel freight data was obtained from the port authorities. The truck volumes were collected from selected locations around the ports.

The vessel freight data included activity date, commodity description, quantity, and import/export. The quantity indicated the amount by unit of measure (barrels, measured board feet, board feet, each, short tons). The Tampa Port Authority provided 4915 daily vessel freight records from March through December of year 2000. The Canaveral Port

Authority provided 273 daily vessel freight records from August 2001 through April 15, 2002.

Field truck volumes were collected on the access roads for both ports. Daily vehicle class and volume data was collected using roadside vehicle classification devices and air tubes. One day of data is a 24-hour period from midnight (12:00 AM) to 11:59 PM. Data was collected for both inbound and outbound directions.

The data collection period for the Port of Tampa was from June 1st through December 16th in year 2000. Due to periodic equipment malfunctions and frequent tube damage, comprehensive data for all five access roads was difficult to obtain. From the data collection period, after filtration of unusable data including holidays and unusually high or low volumes, 68 days of inbound and 66 days of outbound truck volumes were concluded.

The data collection period for Port Canaveral was from September 20th 2001 through the end of March 2002. Due to similar equipment problems, not all days of data collection were successful and unusually high or low volumes were excluded because they were considered outliers. From the data collection period, 70 days of inbound and 56 days of outbound truck volumes were concluded.

TRANSFERABILITY EVALUATION

Independent and Dependent Variables

From the collected data for the ANN truck trip generation models for the Port of Tampa and Port Canaveral, the specific variables were identified. The independent variables include the vessel freight data and any significant day of the week variables. The dependent variables, the desired model output, are the daily inbound and outbound truck volumes.

In order to have a model that can be used to perform short term forecasting of the truck volumes, the selection of independent variables for the ANN model was done with the application of a regression analysis (4). This analysis determines the significance of each proposed defined independent variable so the variables that negatively affect the output are not selected. The defined variable includes the type of variable and method by which its value is determined including the unit of measure. A freight variable must not have a negative coefficient or a coefficient cannot be almost equal to zero to be selected. Furthermore, if an independent variable was found to have an extremely high positive coefficient value (i.e. 3,000 or more) it can significantly reduce the contribution of the other variables. This may also not be a good variable for selection.

The tested vessel freight variables included commodities identified by unit type (barrels, measured board feet, board feet, short tons, each), by total tonnage, and storage duration. A storage variable (lead or lag) considers a time period of inactivity for the freight. A lead storage variable considers the freight shipped the indicated number of days after (+) the desired date of model output (truck volume). A lag storage variable considers the freight shipped the indicated number of days before (-) the desired date of model output (truck volume). These independent vessel freight variables were also separated by import or export.

Due to the insignificance of containerized cargo shipments at both ports, they were converted to tons when possible or excluded from the analysis. The Port of Tampa's high bulk tonnage shipments and their storage duration made it difficult to determine appropriate variables. Through discussions with port tenants, some determination on the transportation frequency of certain bulk commodities provided more information. The phosphate products and citrus pellets were delivered on a regular schedule and therefore a monthly total was

calculated for these commodities and distributed equally over each day of the corresponding month. These commodities were included with the daily exported tons variables. It was also found that the commodities measured in barrels provided a better variable if converted to short tons (conversion factor was provided by the port authority) and also totaled monthly and distributed equally over each day of the corresponding month. This was appropriate due to the high quantity of these commodities transported by vessel in a single shipment. One vessel shipment can generate trucks through the next shipment. It was also determined that the imported total tonnage for a previous seven days will generate trucks on the eighth day.

Similar difficulties were encountered with Port Canaveral. However, due to the infrequency and irregularity of most vessel shipments at this port, it was difficult to apply any storage variables. Interviews were conducted with port tenant operators to determine turn around time of a vessel shipment for the significant commodities. These included lumber, cement products, bulk aggregate and slag, petroleum, salt and seasonal citrus products. Port Canaveral has sufficient storage capacity for accommodating most vessel shipments thus allowing the accumulation of inventory from the vessel shipments. Therefore, each shipment was distributed equally over the number of days determined by the turn around time for each commodity type, which was provided by the tenant operators. Some commodities had no activity for a weekend day and therefore those days were excluded from the total number of days for distribution from the turn around time. Also, it was found that the imported independent variable performed better with the petroleum products converted from barrels to short tons (conversion factor was provided by the port authority).

To determine if a day of the week variable may be important, the daily truck volumes from both ports were statistically analyzed. A Kolmogorov-Smirnov (K-S) test for normality was done on the daily truck data (5,10). Once the data was determined to be normally distributed, a Scheffe's statistical test was conducted on the daily truck volumes between each day of the week (11).

For both the Port of Tampa and Port Canaveral, at the 95% confidence level, there was no significant difference between weekdays (Monday through Friday). However, there was a significant difference between a weekday and a weekend day. This concluded the significance in the day of the week for model development. For the day of the week variables, a "1" or "0" was selected for the input value. A "1" indicated recognition of that day (Saturday or Sunday) and a "0" indicated that the value of the variable was null. To indicate a Monday-Friday, both weekend variables were coded as "0".

The variables and their unit of measure concluded for the Port of Tampa ANN model were (5):

Independent Variables:

- Imported Tonnage-Sum of Last 7 days (Short Tons)
- Daily Imported Barrels (Short Tons) note: calculated from a monthly average
- Daily Exported Tonnage (+3) (Short Tons)
- Daily Exported Tonnage (+1) (Short Tons) note: phosphate products and citrus pellets calculated from a monthly average
- Saturday (Sat)
- Sunday (Sun)

Dependent Variables:

- Inbound Trucks (Trucks/day)
- Outbound Trucks (Trucks/day)

The variables and their unit of measure concluded for the Port Canaveral ANN model were (10):

Independent Variables:

- Daily Imported Lumber (BDFT)
- Daily Imported Tonnage (Short Tons)
- Daily Exported Tonnage (Short Tons)
- Saturday (Sat)
- Sunday (Sun)

Dependent Variables:

- Inbound Trucks (Trucks/day)
- Outbound Trucks (Trucks/day)

Calibration and Validation

Separate ANN truck trip generation models for inbound and outbound daily truck volumes were developed for each port. The MatLab computer program was used to formulate and train the models using the application of Backpropagation Neural Networks (BPN). It was found that both models produced more accurate results when developed with a hidden layer. Figure 3 displays the structures of both developed models. Both the inbound and outbound models are executed simultaneously to produce results during one model run but do not influence the performance of each other.

The available data for each port were separated into two sets of records, one for calibration (training) and one for validation. A record included the date and the corresponding independent and dependent variables. The calibration process used both independent and dependent variables to train the model. The calibration data is displayed in Table 1. For validation, the independent variables were used as input to the calibrated model and the dependent variables (truck volumes) output from the model were statistically compared to the corresponding field truck volumes of the same date.

The Port of Tampa calibration data was comprised of 46 records for the inbound model and 44 records for the outbound model. The validation data included 22 records for the inbound model and 22 records for the outbound model. The Port Canaveral calibration data had 46 records for the inbound model and 35 records for the outbound model. The validation data included 24 records for the inbound model and 21 records for the outbound model.

The truck volume validation data is displayed in Table 2. A K-S Normality Test was performed on the difference between the model and actual truck volumes to confirm the distributions were normal. Then, a Scheffe's paired t-test was applied at the 95% confidence level (5,10,11). The results for the Tampa model (p-value for inbound trucks was 0.555 and p-value for outbound trucks was 0.913) showed no significant difference between the model output and the actual field truck volumes. The results for the Canaveral model (p-value for inbound trucks was 0.375 and the p-value for the outbound trucks was 0.248) were also good. No significant difference was found between the model output and the actual field truck volumes. Figure 4 is a graphical comparison of the validation data for both port models.

A sensitivity analysis was performed with the Tampa and Canaveral ANN models to determine the models' ability to forecast. The quantitative independent variables (vessel

freight data) were increased 50% for both models. The Tampa ANN model produced an average increase for inbound and outbound truck volumes of 32%. The Canaveral ANN model showed an average increase for inbound and outbound truck volumes of 33%. These results indicated that both models' outputs were sensitive to variations of the models' input, yet the relationship is non-linear. This confirmed the potential of the models for use in forecasting truck volumes at the ports.

FORECASTING

To show useful application of the developed models, a short term forecast of the expected truck volumes in five years was completed. In order to execute the model, some estimates of the future vessel freight activity were required. Historical data for both ports was obtained and an Auto Regression Integrated Moving Average (ARIMA) time series model was developed for each port to produce short-term forecasts of the freight vessel data (3,4,5,12). The historical data was separated into the same independent variables and units of measure as the validated ANN models. Due to limitations of the forecasting models, monthly vessel freight data totals were used in the forecasting and then a daily distribution was calculated from the historical data and applied to each corresponding month for the five year forecast.

The historical data available for the Port of Tampa ranged from January 1992 through December 2000 (5). The forecasted variables were Imported Tonnage, Exported Tonnage, and Barrels (commodities with a unit of measure as barrels). Once the forecast for the barrels was completed, the conversion factor (provided by the port authority) was applied for calculating short tons. The forecasted years were 2001 through 2005. The trends produced for the freight data for the five year forecast show the imported tons are expected to decrease by 25%, the exported tons are expected to decrease by 36%, but the imported barrels are expected to increase by 16%. From historical statistics records of total annual tonnage for the Port of Tampa recorded by the Navigation Data Center, these trends are considered to be an accurate representation (1).

The historical data available for Port Canaveral ranged from October 1994 through August 2001 (10). The forecasted variables were Imported Tonnage, Exported Tonnage, and Lumber (measured in short tons). Once the forecast for the Lumber was completed, the conversion factor (provided by the port authority) was applied for calculating the BDFT (board feet) unit of measure. The forecasted years were 2002 through 2006. The trends produced for the freight data for the five year forecast show the imported tons are expected to increase by 27%, the imported Lumber are expected to increase by 39%, and the exported tons are expected to increase by 8.5%. The historical statistics records for Port Canaveral from the Navigation Data Center show that Port Canaveral has experienced an annual growth between 1997 and 2000 of as much as 20% for a single year (1). This provides evidence that the forecasted trends are representative of future expected freight movements.

The daily forecasted vessel freight data for the Port of Tampa was input to the validated ANN truck trip generation model. The trend of forecasted inbound and outbound daily truck volumes showed a 0.31% average annual decrease over the five year period. Figure 5 includes a graph displaying the inbound and outbound truck volumes from the current year 2000 through the forecasted year 2005 for the Port of Tampa.

The daily forecasted vessel freight data for Port Canaveral was input to the validated ANN truck trip generation model. The trends produced from the results of the forecasted truck volumes showed an average annual increase of 5.07%. Figure 5 includes a graph

showing the trend of forecasted truck volumes for Port Canaveral. The fluctuations in truck volumes displayed in the figure indicate the model has successfully captured the seasonal freight trends at the port.

CONCLUSIONS

The methodology for modeling the transportation of freight by heavy trucks generated from an intermodal activity center such as a seaport was successfully tested on six Florida seaports with different characteristics. In addition to the Port of Tampa and Port Canaveral detailed herein, the truck activity for the ports at Everglades, Palm Beach, Jacksonville, and Miami were also been successfully modeled (3,4,5,10). This modeling application utilized vessel freight data (model input) to determine the daily number of inbound and outbound trucks. To evaluate the model's effectiveness as a useful tool, the heavy truck traffic at the Port of Tampa and Port Canaveral was successfully simulated.

During model development, consideration was given to the number of independent (model input) variables selected. It was desired to minimize this quantity for ease in execution of the models. Regression analysis was conducted to identify the best variables for both models. All commodities with the unit of measure as short tons except Lumber for Port Canaveral were concluded to be most appropriate.

Both models were successfully validated at the 95% confidence level using truck volume data collected from field locations around the ports. In order to determine the value of the developed models, they were applied to each port for determining a five-year forecast of expected daily truck volumes. For the Port of Tampa, the expected number of truck trips for year 2005 was estimated between 3270 and 3470 trucks per day. This is slightly lower than the current average of 3750 trucks per day. Port Canaveral is expected to have significant growth. The average daily truck trips were forecasted to be between 450 and 720 trucks per day compared to a current average of 350 trucks per day. Port Canaveral has significant variation in truck volumes from month to month due to the high seasonal activity with citrus exports that contributed significantly to this.

There are a number of applications these models can be used for. The daily number of trucks can be used for application to traffic simulation and assignment (planning) models that require the percent of trucks on the roads connecting to a special generator such as a seaport. Heavy trucks make up 26% of the total traffic on the Port of Tampa's access roads during the peak hour and are 10% of the total traffic on Port Canaveral's access roads. This is valuable information for accurately modeling a road network that would include the access roads of an intermodal facility such as these seaports.

Planning applications for future freight growth can be used not only at a seaport but may also be adjusted for application to a specific freight terminal or individual pier location. Private industry could use the models for determining the number of trucks necessary to transport/accommodate current or future cargo shipments. This can assess the economic impact of a facilities operation by determining the number of trucks required for hire or purchase to service customers for the imported or exported freight shipments. This may also provide capabilities for calculating the viability of using other modes of transport based on the assessment of the cost for transportation of the cargo by truck compared to the expected time for transportation of the shipment. The shipment of products has increased considerably in the last few years and could continue (13). These simulation models and the methodology

for developing them can prove to be useful tools for evaluating and accommodating future growth in freight transportation domestically and internationally.

REFERENCES

1. Navigation Data Center, Army Corps of Engineers, "Waterborne Commerce of the US", <http://www.iwr.usace.army.mil/ndc/wcusnat100.pdf>, accessed May 2002.
2. Florida Ports Statistics, Florida Ports Council, "% of Total U.S. Trade (2000)", <http://www.flaports.org/Section3.htm>, accessed May 2002.
3. Al-Deek, H. M., G. Johnson, A. Mohamed, and A. El-Maghraby. *Truck Trip Generation Models for Seaports with Container/Trailer Operation*, Journal of the Transportation Research Board 1719, TRB, National Research Council, Washington D.C., 2000, pp.1-9.
4. Al-Deek, H. M., *Using Vessel Freight Data to Forecast Heavy Truck Movements at Seaports*, forthcoming in the Journal of the Transportation Research Board, November/December 2002.
5. Al-Deek, H. M., J. Klodzinski, A. Jujare, A. El-Helw. *Development of a Statewide Model For Heavy Truck Freight Movement On External Road Networks Connecting With Florida Ports, Phase II*, Final report, Contract No. BB-869. Florida Department of Transportation, Tallahassee, Florida, July 2001, pp. 1-241.
6. Balbach, P., and R. R. Tadi. Truck Trip Generation Characteristics of Nonresidential Land Uses. ITE journal, Vol. 64, 1994, pp. 43-47.
7. Florida Department of Transportation, *Tampa Bay Regional Freight Movement Study*. Final report prepared for the Florida Statewide Model Task Force, 1998.
8. Al-Deek, H. M., Comparison of Two Approaches for Modeling Freight Movement at Seaports, ASCE Journal of Computing in Civil Engineering, Vol. 15, No. 4, pp. 309-319, October 2001.
9. Al-Deek, H. M., Which Method is Better for Developing Freight Planning Models at Seaports: Neural Networks or Multiple Regression? Journal of the Transportation Research Board 1763, pp. 90-97, December 2001.
10. Al-Deek, H. M., J. Klodzinski, A. El-Helw, P. Sarvareddy, and E. Emam. *Development of a Statewide Model For Heavy Truck Freight Movement On External Road Networks Connecting With Florida Ports, Phase III*, Final report, Contract No. BC-355. Florida Department of Transportation, Tallahassee, Florida, July 2002, pp. 1-282.
11. Pankratz, Alan. *Forecasting with Dynamic Regression Models*. John Wiley and Sons Inc., New York, 1991.
12. Mendenhall, W. and T. Sincich. *Statistics for Engineering and Sciences*. Prentice Hall, New York, N.Y., 1994.
13. United States Postal Service, "Financial Statements 2001, Operating Statistics" <http://www.usps.com/history/anrpt01/financial/opstats2.htm>, accessed July 2002.

LIST OF TABLES

TABLE 1 ANN Model Calibration Data

TABLE 2 ANN Model Daily Truck Volume Validation Data

LIST OF FIGURES

FIGURE 1 Port of Tampa Area Map

FIGURE 2 Port Canaveral Area Map

FIGURE 3 Artificial Neural Network Model Structures

FIGURE 4 ANN Model Validation Results

FIGURE 5 Short Term Forecast of Daily Truck Volumes for Port of Tampa and Port Canaveral

TABLE 1 ANN Model Calibration Data

PORT OF TAMPA

INBOUND					OUTBOUND				
Date*	Imported Barrels ¹	Imported Tonnage	Exported Tonnage (+3)	Trucks	Date*	Imported Barrels ¹	Imported Tonnage	Exported Tonnage (+1)	Trucks
070500	27222	402951	30381	3780	080100	28021.2	391459.0	17018.1	3889
070600	27222	326198	33181	3691	080200	28021.2	361855.0	17018.1	4004
070700	27222	300464	30381	4221	080300	28021.2	408750.0	17018.1	3747
071800	27222	302908	30381	4516	080600	28021.2	315637.0	19818.1	1364
072000	27222	297858	31781	4542	080800	28021.2	279080.0	17018.1	3946
072100	27222	325550	30381	4191	081000	28021.2	207329.0	17018.1	3697
072500	27222	330560	30381	4346	090600	40924.3	163896.0	28529.5	3756
072600	27222	352224	58902	4707	090700	40924.3	207661.0	28577.5	3949
072700	27222	355546	30381	4342	090900	40924.3	257678.0	49705.5	1765
072800	27222	347102	31781	4236	091500	40924.3	219486.0	28274.5	4311
072900	27222	370437	17018	2177	091600	40924.3	179050.0	28274.5	2020
073000	27222	368035	17018	1588	092600	40924.3	411820.0	29802.5	4032
080400	28021	357032	19818	4078	092800	40924.3	366955.0	31794.5	4159
082500	28021	276934	17018	3950	100100	43953.9	352840.0	33511.0	1452
082700	28021	214940	17018	1181	100200	43953.9	259775.0	33511.0	4231
090500	40924	118305	28578	4271	100300	43953.9	270003.0	33950.0	4104
090600	40924	163896	28327	4383	100500	43953.9	359221.0	33928.6	3899
090800	40924	217243	28275	4348	100600	43953.9	334549.0	33511.0	3792
090900	40924	257678	32492	2258	100700	43953.9	338542.0	34096.0	1881
091100	40924	204299	28275	4191	101200	43953.9	217324.0	34966.0	3481
091200	40924	244690	28275	4233	101500	43953.9	274916.0	63407.0	1413
091400	40924	224004	28275	4517	101600	43953.9	243066.0	33610.0	3562
091600	40924	179050	28329	2047	101800	43953.9	297777.0	33511.0	3469
091700	40924	191113	32475	1667	101900	43953.9	289605.0	59399.0	3369
091900	40924	178517	28275	4222	102000	43953.9	293668.0	34426.0	3071
092000	40924	146675	29269	3961	102300	43953.9	224187.0	34095.5	4034
092100	40924	147800	28275	3867	102400	43953.9	174667.0	33748.0	4168
092200	40924	177983	30256	3526	102500	43953.9	269086.0	33511.0	4098
092800	40924	366955	38784	4249	102600	43953.9	306475.0	33647.3	4148
092900	40924	371103	33511	4213	102700	43953.9	355998.0	34379.0	4123
100100	43954	352840	33950	1666	102800	43953.9	395593.0	34911.0	1811
100200	43954	259775	33511	4183	102900	43953.9	395947.0	33543.0	1444
100400	43954	359317	33511	4113	103000	43953.9	376691.0	36311.0	3783
100500	43954	359221	34096	4113	110100	43987.8	372074.0	32710.9	4178
100600	43954	334549	35320	4087	110200	43987.8	286660.0	32724.1	4083
101000	43954	273251	34966	4166	110800	43987.8	336385.2	32710.9	3926
101100	43954	188047	34911	3842	110900	43987.8	346385.2	51595.9	4126
102400	43954	174667	33647	4388	111000	43987.8	334248.2	45480.9	3460
102500	43954	269086	34379	4257	111100	43987.8	310496.0	33458.9	1751
102600	43954	306475	34911	4299	111200	43987.8	299484.0	32710.9	1270
102700	43954	355998	33543	4274	111500	43987.8	290780.8	32710.9	3820
103100	43954	426685	32724	4438	111600	43987.8	336179.8	32710.9	3562
110100	43988	372074	33234	4272	111700	43987.8	341243.8	33388.9	3737
110200	43988	286660	32711	4232	111800	43987.8	322050.8	35993.9	1796
110800	43988	336385	45481	4111					
110900	43988	346385	33459	4213					

* (mm/dd/yy)

¹ measured in Short Tons

Note: Shaded records indicate weekends

PORT CANAVERAL

INBOUND					OUTBOUND				
Date*	Imported BDFT	Imported Tons	Exported Tons	Trucks	Date*	Imported BDFT	Imported Tons	Exported Tons	Trucks
100600	0	3757.872	0	139	092901	0	3136.872	0	46
100700	0	361.872	0	39	101101	187657	5284.720	28	318
101101	187657	5284.720	28	355	101401	0	1250.928	0	59
101301	0	2487.928	236	112	101501	187657	3214.928	236	310
101501	187657	3214.928	236	364	101701	187657	2566.296	236	326
101901	187657	5885.296	264	352	110101	239882	6798.992	485	343
102001	0	5727.296	248	116	110301	0	3112.992	201	89
102101	0	1465.296	0	66	110401	0	2182.992	0	54
102201	187657	5885.296	28	286	110601	266190	4725.552	227	318
102301	187657	5886.296	28	295	110701	266190	4772.552	238	307
110301	0	3112.992	201	114	110801	266190	4772.552	227	360
110401	0	2182.992	0	76	110901	266190	3702.704	227	347
110601	266190	4725.552	227	338	112101	266190	6116.128	0	339
110701	266190	4772.552	238	374	120101	0	6555.440	132	133
112901	225000	8304.008	172	359	120201	0	2197.440	0	66
113001	225000	7749.272	172	310	120801	0	3217.328	543	117
120101	0	6555.440	132	128	120901	0	2267.328	0	82
120201	0	2197.440	0	88	121301	316595	6534.328	584	333
120301	225000	4438.928	504	302	121401	316595	6609.328	210	291
120401	38106	4438.928	504	274	123001	0	1904.616	0	80
120801	0	3217.328	543	101	010502	0	4923.488	501	79
121001	38106	6535.328	584	283	010602	0	1480.080	0	27
121601	0	2634.328	0	58	011402	140140	6283.272	550	194
121701	316595	6870.328	209	300	020502	215929	6817.200	179	354
010502	0	4923.488	501	127	030602	441720	8810.000	941	510
010602	0	1480.080	0	84	031902	411793	9115.736	812	475
010702	418629	5781.080	147	370	032002	411793	9871.736	812	477
010802	418629	5781.080	147	364	032102	419958	9802.384	266	490
010902	418629	4613.080	490	392	032502	419958	9926.032	244	488
011002	418629	6525.080	491	396	032602	419958	9925.032	244	457
011102	418629	6829.080	549	411	032702	419958	9925.032	244	439
011202	0	5283.272	523	142	032802	397665	7349.032	244	448
011302	0	2388.272	12	58	032902	397665	7530.536	244	446
012002	0	2769.984	4	89	033002	0	4932.736	244	192
020502	215929	6817.200	179	284	033102	0	2318.736	0	82
020702	215929	7209.656	876	291					
030602	441720	8810.000	941	539					
030702	441720	8201.000	1186	477					
030802	441720	7807.544	1146	499					
032002	411793	9871.736	812	501					
032102	419958	9802.384	266	512					
032702	419958	9925.032	244	438					
032802	397665	7349.032	244	481					
032902	397665	7530.536	244	475					
033002	0	4932.736	244	211					
033102	0	2318.736	0	89					

TABLE 2 ANN Model Daily Truck Volume Validation Data

INBOUND			OUTBOUND		
Date*	Actual	Model	Date*	Actual	Model
PORT OF TAMPA					
71700	4298	4259	80400	3612	3787
71900	4451	4218	80500	1667	1723
72300	1723	1724	80700	3575	3754
72400	4331	4259	80900	3298	3686
80500	2204	2065	90500	3508	3695
81200	2294	1829	90800	3888	4202
90700	4429	4366	91400	4596	4279
91000	1834	1818	91700	1109	1146
91300	4361	4342	92700	4165	4015
91800	4018	4302	92900	4291	4367
92600	4102	4188	93000	1612	1619
92700	3941	4104	100400	3930	4011
93000	2309	2258	101000	4480	3677
100300	4059	4207	101100	4606	4118
102300	4286	4359	101400	1545	1727
103000	4101	4173	101700	3387	3550
110300	4230	4209	103100	4274	4326
110400	2280	2259	110300	4004	3989
110700	4055	4185	110400	2015	2030
111000	2089	2049	110700	3834	3825
111800	2002	2099	111400	3768	3632
111900	1700	2443	111900	1300	1444
PORT CANAVERAL					
092901	71	95	102101	61	64
093001	49	47	102201	221	310
102601	331	328	102301	257	310
102701	94	139	102601	290	342
102801	70	62	102801	48	59
102901	354	332	102901	333	312
103001	346	332	103001	310	312
103101	373	340	103101	339	305
112601	316	372	112701	298	354
121801	340	374	112801	350	357
121901	327	381	112901	326	363
122001	309	381	113001	329	356
122101	301	381	121501	109	124
122801	378	329	121601	58	81
122901	152	121	121701	340	384
123001	93	78	121801	384	384
011802	388	343	122601	306	242
011902	158	130	122701	290	245
012102	358	398	122801	308	253
020802	253	301	122901	119	137
021102	234	292	031802	493	488
031802	510	434			
032502	476	470			
032602	461	470			

* (mm/dd/yy)

Note: Shaded records indicate weekends

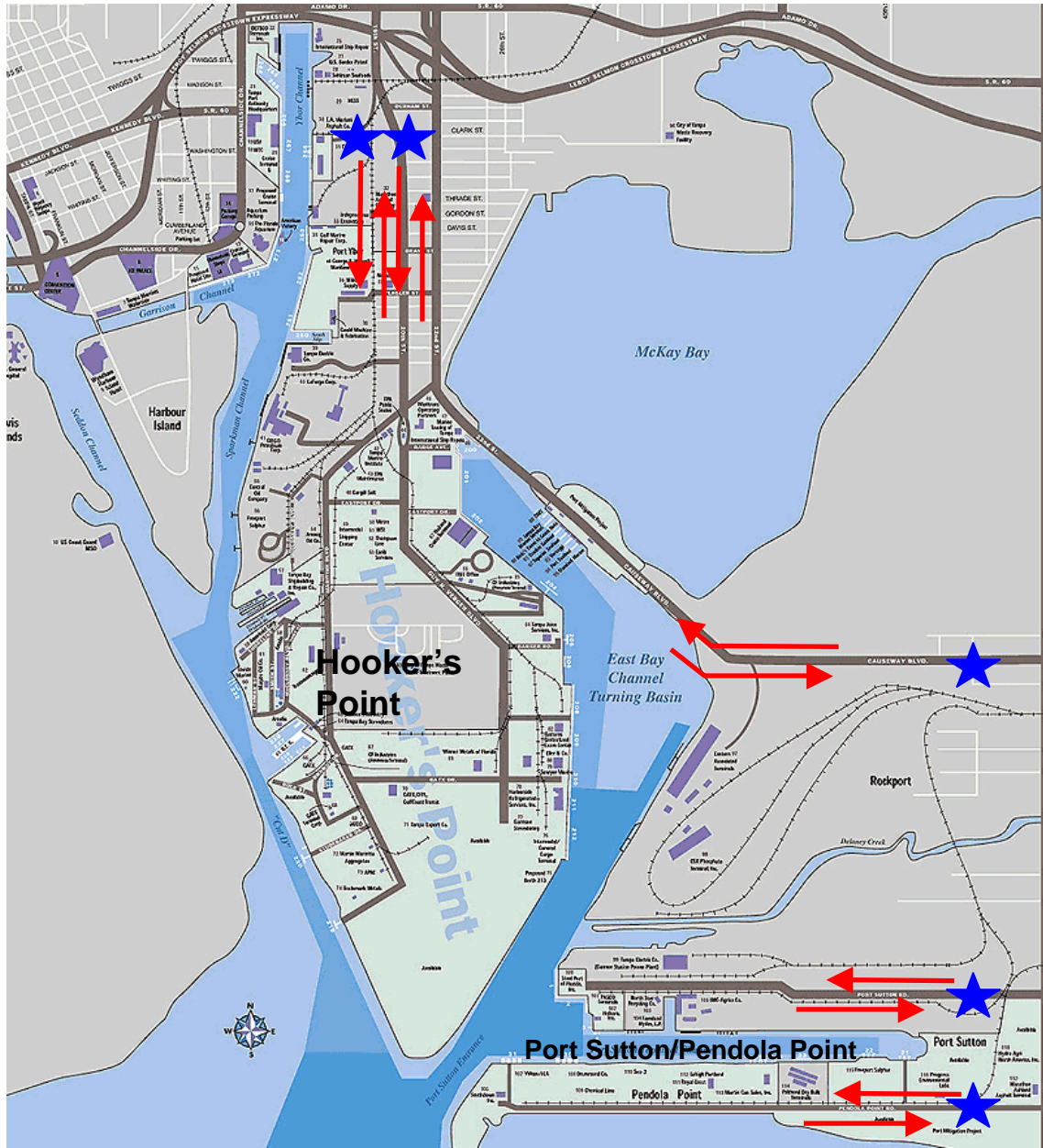


FIGURE 1 Port of Tampa Area Map

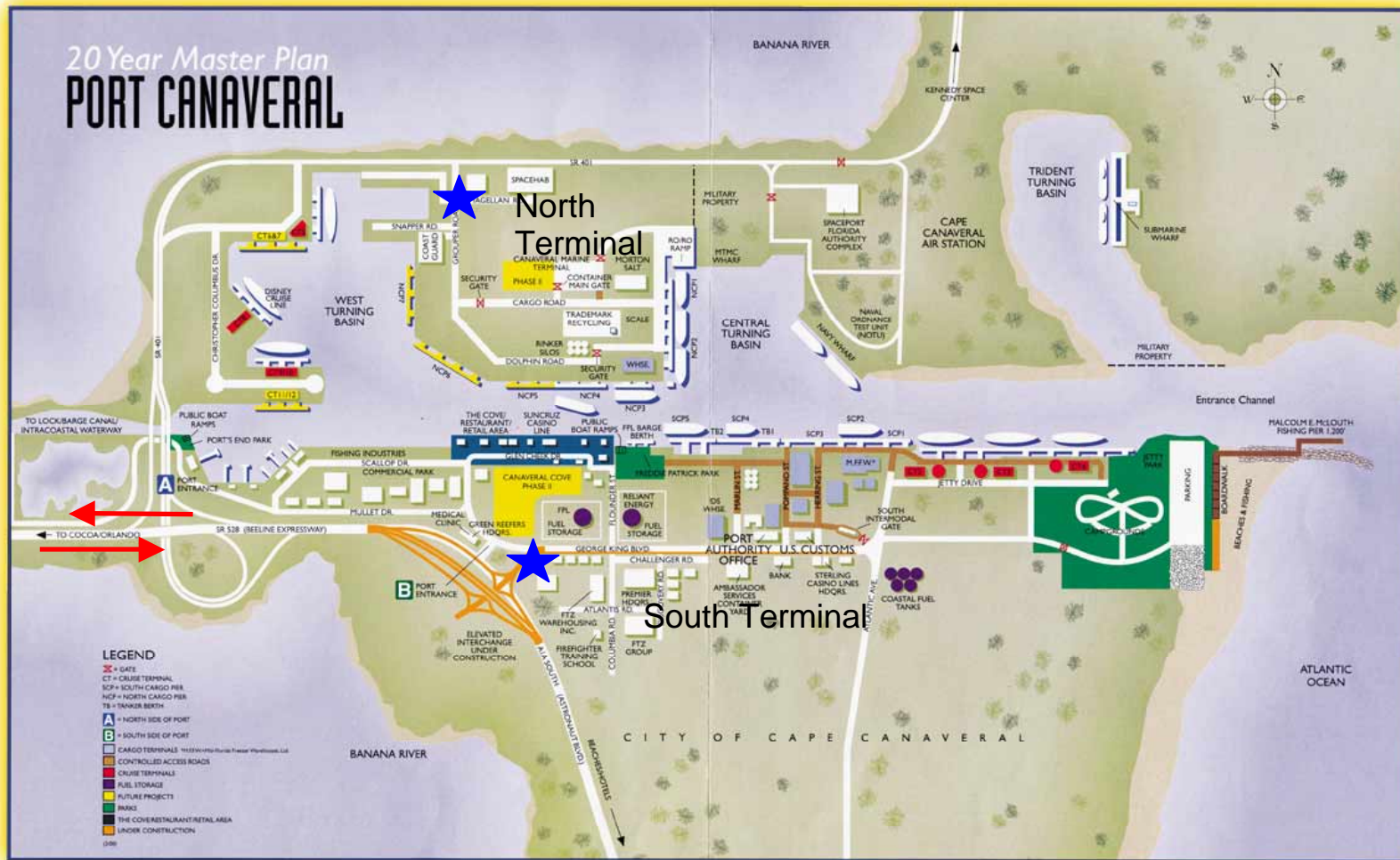


FIGURE 2 Port Canaveral Area Map

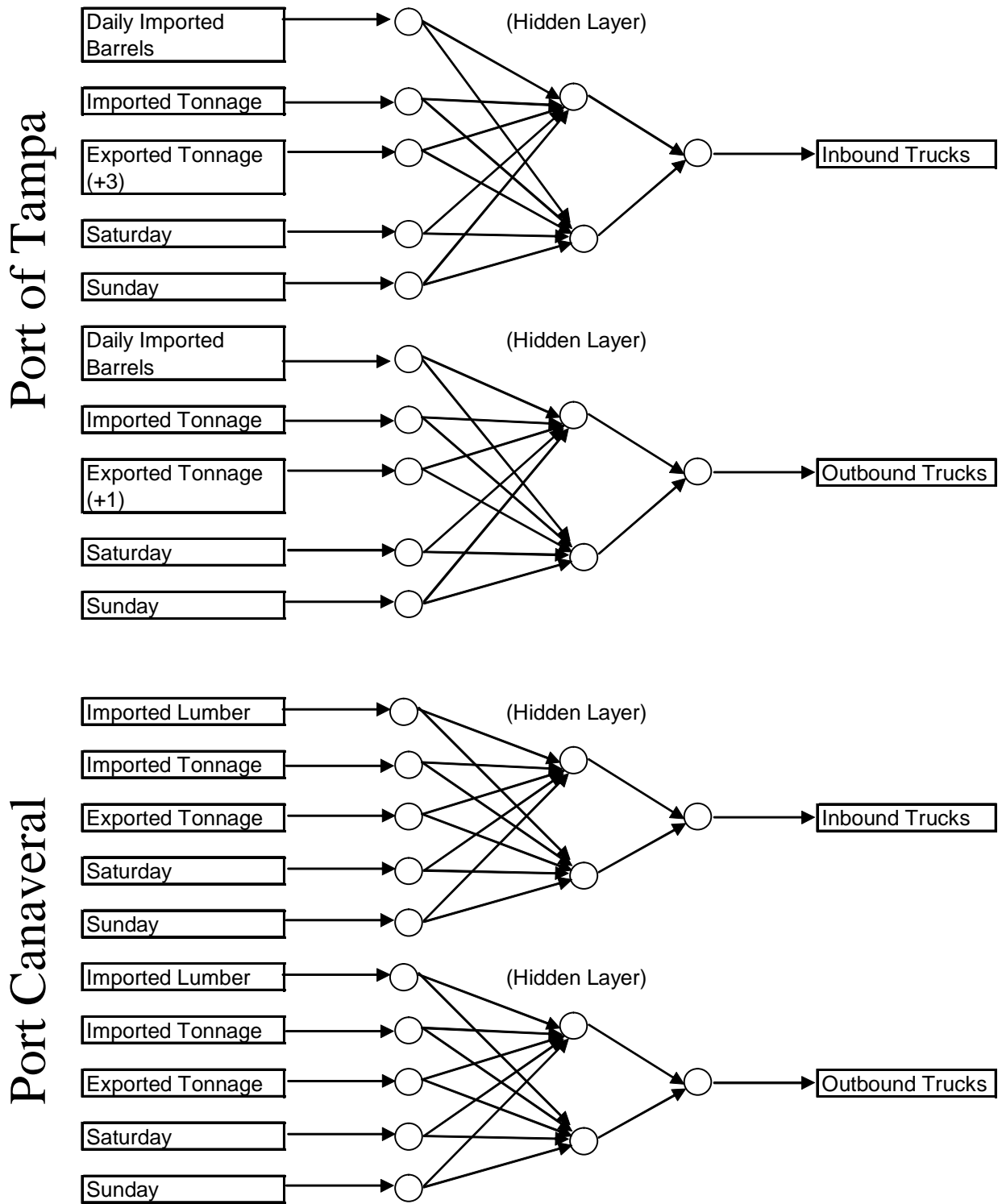
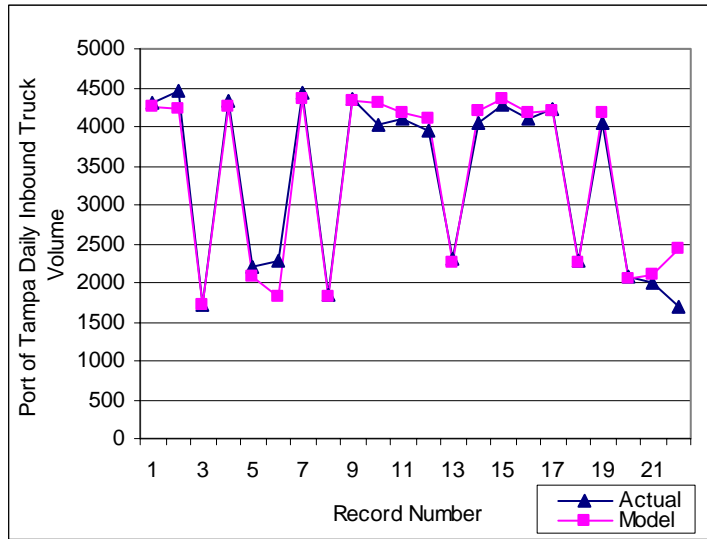
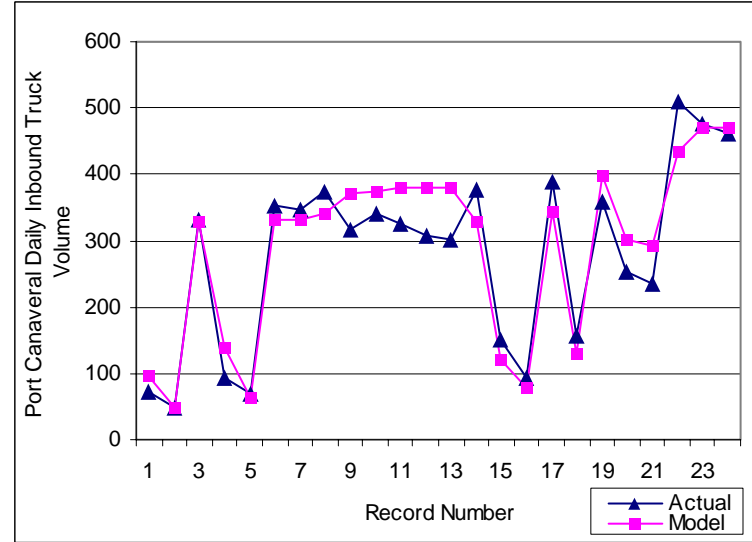


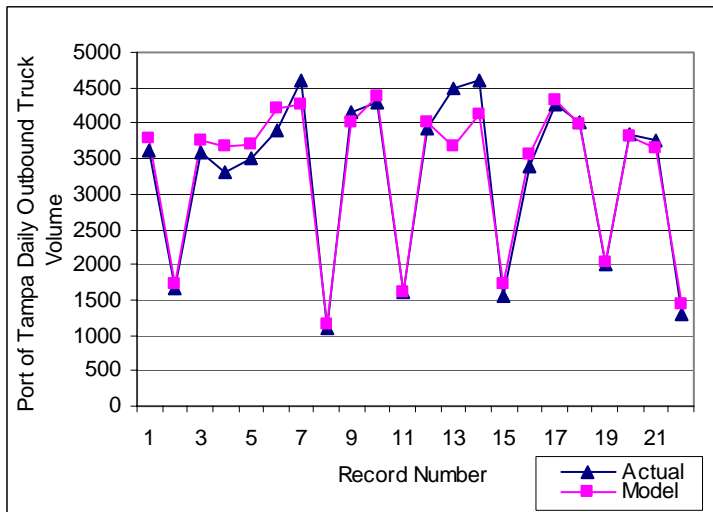
FIGURE 3 Artificial Neural Network Model Structures



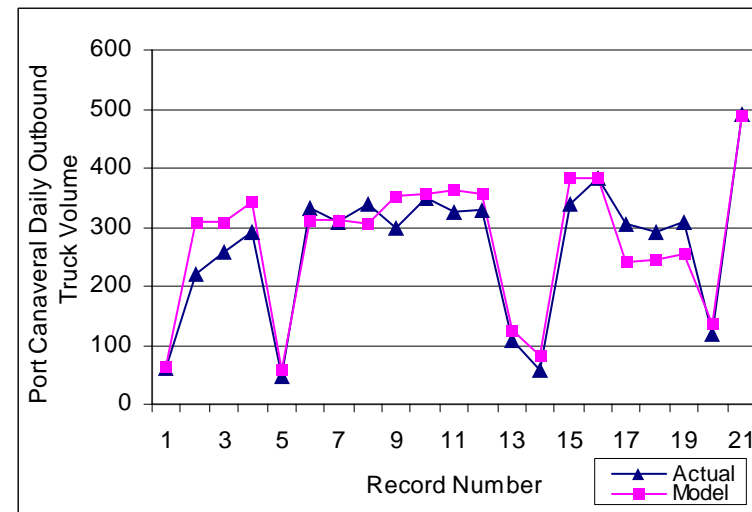
Port of Tampa Inbound Trucks



Port Canaveral Inbound Trucks

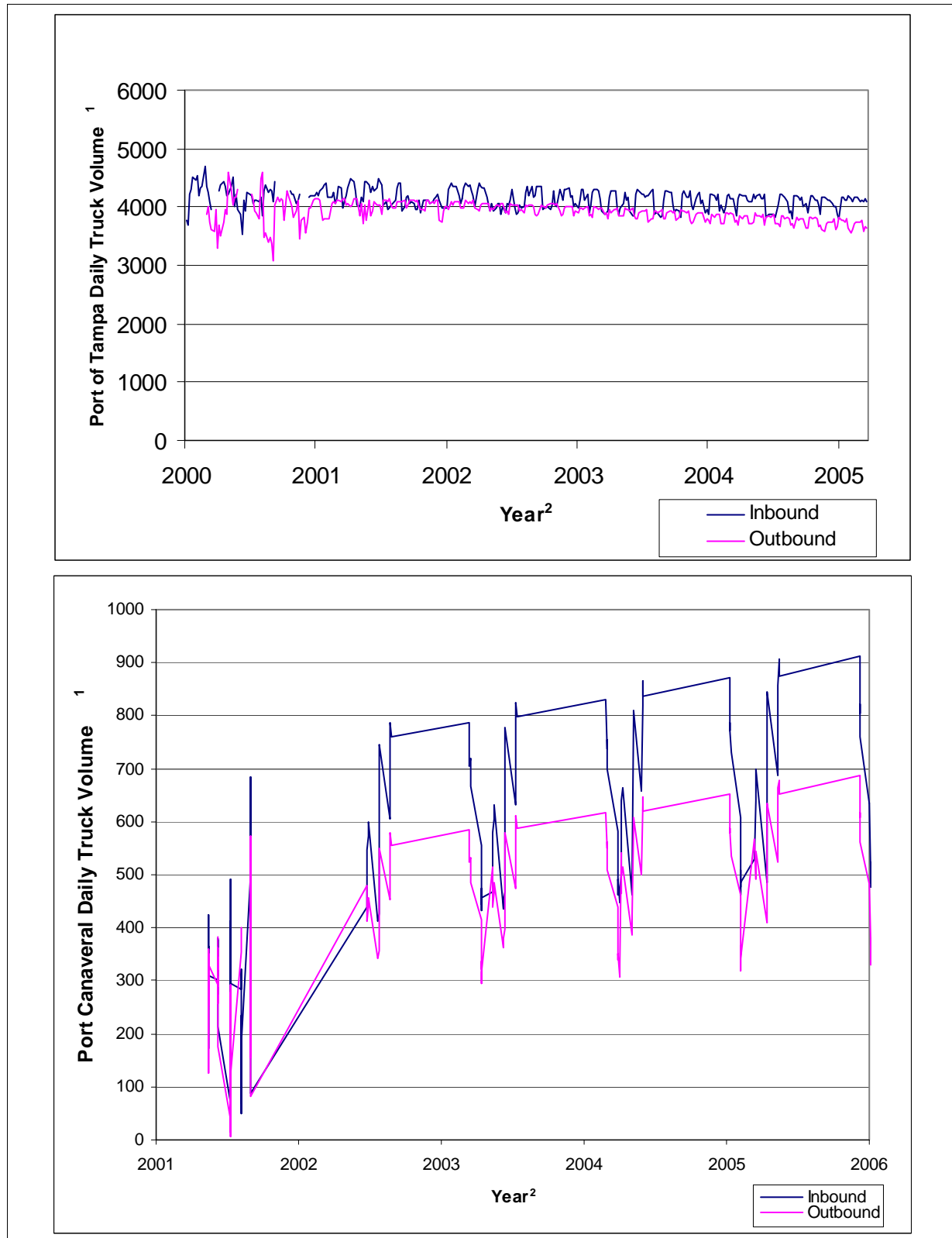


Port of Tampa Outbound Trucks



Port Canaveral Outbound Trucks

FIGURE 4 ANN Model Validation Results



¹excludes weekends

²annual counts using one week from each month of the year

FIGURE 5 Short Term Forecast of Daily Truck Volumes for Port of Tampa and Port Canaveral