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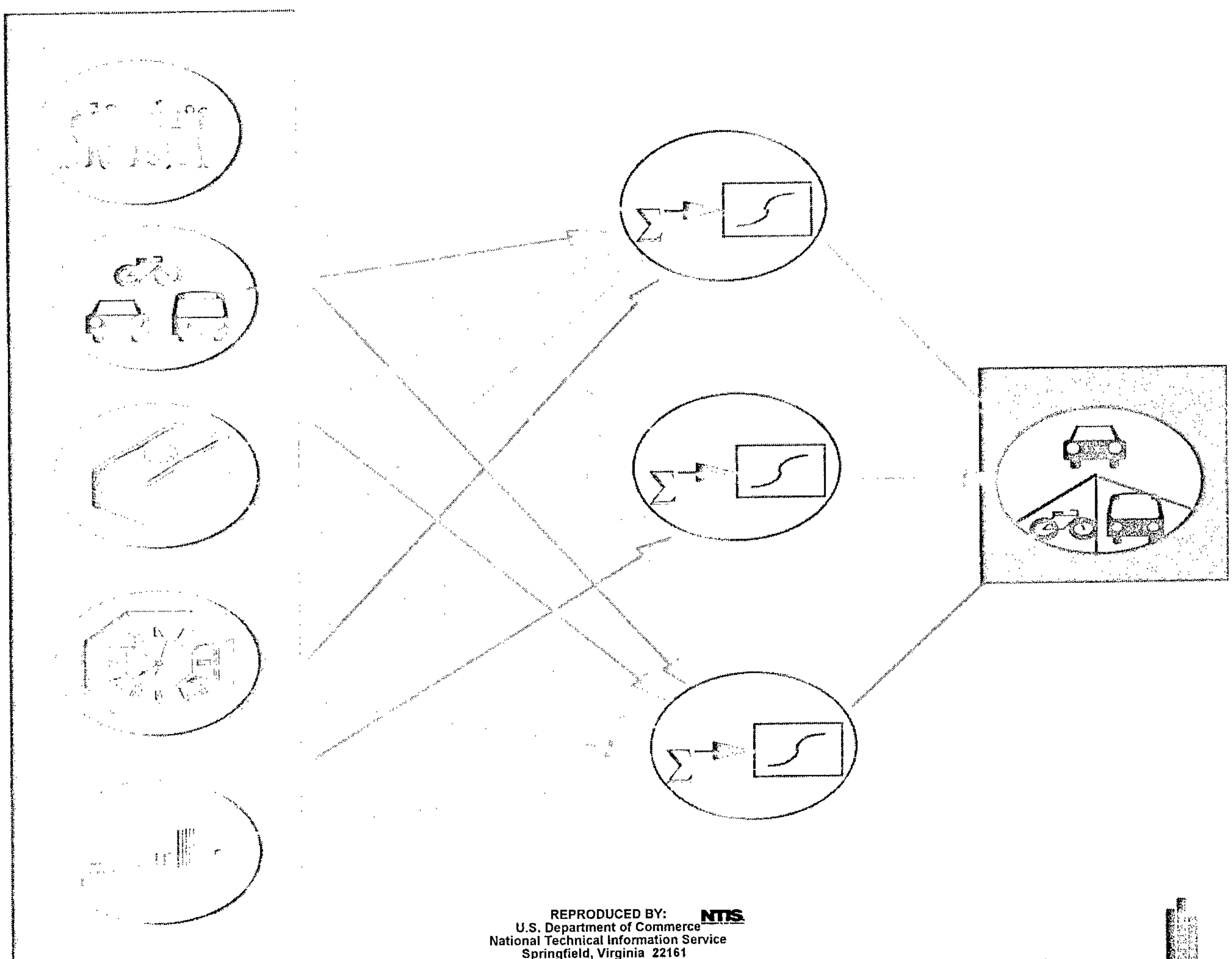
Neural Network Application for Predicting the Impact of Trip Reduction Strategies



CUTR

Neural Network Application for Predicting The Impact of Trip Reduction Strategies

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Acknowledgements

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NEURAL NETWORK APPLICATION

FOR PREDICTING THE IMPACT OF TRIP REDUCTION STRATEGIES

Background

Rising traffic congestion and air quality problems contributed to federal, state, and regional efforts to reduce vehicle emissions by requiring large employers to develop programs to reduce vehicle trips. In areas with the worst air pollution, the program's goal was to reduce driving—and pollution—by increasing the average number of employees in vehicles commuting to work (that is, average vehicle ridership or AVR). Employers were targeted by these regulations as employer policies such as work location, work schedule, and parking policies strongly influence transportation mode choice decisions made by employees.

In several of the major urban areas of the country (such as Los Angeles, Phoenix, Seattle), large employers with 100 or more employees were required by federal, state or local regulation to submit detailed plans for influencing employee travel behavior in order to reduce air pollution and/or traffic congestion. Over the years, these metropolitan areas collected a large amount of data from these companies. Information was obtained that described different company site characteristics and the alternative modes of transportation available to the employees. The data also included information on the types of financial and non-financial incentives employers offered to employees. Employers provided information on work schedules and alternative work arrangements such as telecommuting and compressed work weeks. They also collected information from employees on the different modes of transportation selected by the employees and estimated the site's AVR.

Though areas such as Los Angeles had thousands of employer plans submitted under these regulations, the regulators have had limited success in developing models to predict changes in AVR. Part of the reason for this rests with the complexity of the data. The Los Angeles area database, for example, includes 62 different incentives that employers can select to increase AVR in their work sites. Some incentives are offered by relatively few employers. Even when condensing the incentives into 28 categories, the plans represented about 1,500 different combinations of incentives.

At the same time, the current models (such as the FHWA TDM Model) are based on disaggregate data collected through relatively small samples of employers but augmented by employee surveys. Specifically, model predictions were not compared with actual results for any data that had not been used in the model building process.

Project Objective

Under this Florida Department of Transportation (FDOT) Research Idea project, the project team of the Center for Urban Transportation Research (CUTR) and the Department of Computer Science and Engineering at the University of South Florida applied neural network technology to predict the impacts of various trip reduction strategies on changes in commute behavior.

In the early 1990s, COMSIS, a transportation consulting firm, was hired by the South Coast Air Quality Management District (SCAQMD) in the Los Angeles area to develop a linear model to predict AVR. They attempted to use the several thousand employer trip reduction plans to build the model. However, the model did not perform to the satisfaction of COMSIS. SCAQMD agreed to build a model using a data set developed by ARB for the California Air Resources Board (CARB) by COMSIS. The CARB model is a logit based model that used the results of surveys from only 45 employers. However, it also included data from nearly 2,500 employees. Disaggregate employee data was not part of the AQMD data structure.

Neural networks were selected because they can uncover the hidden relationships in the data from employers and the resulting change in average vehicle ridership (AVR). The performance and selection of the best model were based on comparing neural network output to actual AVR observations. The neural network training (or learning) process allows the neural network model to predict the correct response to combinations of input data values not previously seen by the network. The benefits of developing such a model are to streamline development of trip reduction plans for employers, increase effectiveness of those plans, and provide a basis for consistent review by the regulating agencies. It should also improve efficiency by reducing regulatory staff time in the review of employer/developer trip reduction plans.

Project Overview

This project executive summary describes neural network models, highlights the efforts to build a model to predict changes in AVR, summarizes the development of the application, compares the neural network model performance with other analytical approaches, and summarizes the results of the field test. The reader should review the four technical memoranda prepared as part of this project for more information.

Technical memorandum #1, "Regional Trip Reduction Databases," reports on the present state of trip reduction data management and analysis. Model inputs and outputs are identified by reviewing several trip reduction ordinances. The technical memorandum also reviews previous attempts to develop a model including the TDM Model developed for FHWA, the California Air Resources Board TDM Model, and the TDM Cost-Effectiveness Model developed for Pleasanton, California.

Technical memorandum #2, "A Primer on Neural Networks in Transportation: Concepts and Applications," discusses neural network capabilities for data analysis, forecasting, and model building and contrasting this approach with other methods. Various applications of artificial neural networks (ANN) in the transportation industry are identified. The technical memorandum concludes that the strength of ANN models of learning by comparing known inputs and resulting outputs for a large number of examples should lend itself to this application.

Technical memorandum #3, "Neural Network Application for Predicting Impact of Trip Reduction Strategies: Application Development," reviews the process for compiling the data, the identification of model inputs and outputs from the data, and the building and testing of the neural network model. This step also includes building alternative models using regression and discriminant analysis to measure relative ANN performance. These models are also compared with the FHWA's TDM Model. The ANN model built only with data from SCAQMD is validated using a separate data set and evaluated based on the model's ability to classify the change in AVR within an acceptable range. This technical memorandum concludes that it is feasible to build a model that predicts changes in AVR based on the employer site characteristics and strategies used.

Technical memorandum #4, "Neural Network Application for Predicting Impact of Trip Reduction Strategies: Field Testing," summarizes the steps taken to validate the model using data from other sites. During this phase of the project, CUTR selected field test sites and established a memorandum of understanding for the development and use of existing employer trip reduction plan data from the test sites. The research team collected and interpreted data from Phoenix and Tucson areas. The result is a model built on data from Los Angeles and Tucson that performed well when tested with data from Phoenix, suggesting that the model is transferable from one site to another.

Given a sufficient amount of data, locally-developed models can be expected to perform better than a model based on data from a cross section of the country. However, the need for transferability is of particular importance to states such as Florida where employers are not required to submit trip reduction plans. The need for a single model also increases in the areas of the country with the worst air pollution. The Employee Commute Options (ECO) requirement in the Clean Air Act Amendments of 1990 required large employers in these areas to submit trip reduction plans on an annual basis. However, ECO was made voluntary in late 1995. These plans would have been the source of data that would have allowed many large urban areas to develop their own model or calibrate a national model.

What are Neural Networks?

Artificial neural networks (ANN), synonymous with neural networks, represent a form of computer intelligence and operate similarly to the human brain, but on a very reduced scale. Artificial neural networks are being used today to predict results by learning from existing input and resulting output data in science, engineering, medicine, banking, management, marketing, manufacturing, and sports wagering.

To develop or "train" the model, the data set is usually divided into two groups--one group for training the network and another group for testing how well the network has learned. A third independent data set is often reserved for validation. Each training set of data is presented to the network. If the output of the network differs from the correct output, the weights of individual network nodes are changed. Training a neural network requires many cycles until the cumulative errors of all training sets are below an acceptable level, as pre-defined by the neural network builder. The lower this number the better the network is able to duplicate the associations between inputs and outputs in the training data. It is expected that once the network is able to duplicate the associations between inputs and outputs in the training data, it will be able to produce correct outputs for input data not specifically included previously as part of the training data. The training set of data uses an independent test data set against which to test predictions on a regular basis. Training is halted when the test performance begins to degrade. Otherwise, the model may overfit the data. Overfitting the training data occurs when the neural network produces a nonlinear model that fits the training data perfectly, but fits the test data very poorly.

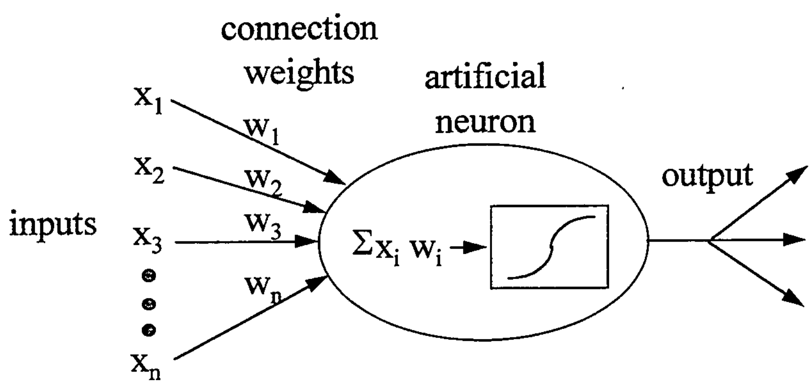

Figure 1 – Typical Artificial Neuron

Training a network using back propagation (the method used in this project) consists of finding the correct number of computational units in the network with the correct numerical values of the weights that connect these units so that the associations between input and output in an existing data set can be duplicated by the network. Since each neuron implements a non-linear mapping between its inputs and output neural networks are capable of learning non-linear relationships that may exist in the data. This makes neural networks adaptable and especially useful in environments where the relationships between inputs and outputs change over time.

Comparison of Neural Networks to Other Modeling Techniques

Neural networks deal with a broad range of problems. Artificial neural networks are known to be good at classification, evaluation, optimization, decision-making, pattern recognition, behavior trend prediction, image analysis, filtering, and modeling control systems.

There are some significant differences between expert systems and neural networks. Expert systems require that the relationships between the input data and the conclusions to be derived from that data be established before the expert system is built. The neural network needs the data from which it can uncover the relationships, while the expert system needs the expert who has already learned those relationships. Another important difference can be found in the encoding of the data. Expert systems encode their knowledge in terms of rules, object descriptions, and procedures. After training, neural networks encode their knowledge of relationships in terms of weight values and in the interconnection between the neurons.

Updating the knowledge in the system is another area where neural networks and expert systems differ. If the problem domain changes and new knowledge is required, this knowledge must be obtained from the human expert and carefully crafted into the already-existing software knowledge structures of the expert system. A neural network would need input that reflects the changes in the problem domain with the corresponding conclusions that can be drawn from the data in order to retrain itself.

There are other machine learning techniques in addition to neural networks and expert systems. Neural networks form a category of learning techniques called "connectionist." This term emphasizes the dependency of neural networks on the connectivity of a large number of computational units. Other machine learning techniques rely on the manipulation of symbols used to create rules similar to the "IF-THEN" rules used widely in expert systems and are grouped under the category of "symbolic" learning techniques. One of the main differences between neural networks and these other symbolic learning techniques is in the form of the knowledge that they learn from the data presented to them.

Another important difference is in the range of problem domains that they can effectively deal with. Symbolic learning methods deal mostly with classification problems. The assignment of a class label to an object or situation based on the specific values of a set of parameters. The neural network models can learn not only to classify data into different categories but to predict the numerical value of outputs (such as level-of-service classification based on volume to capacity ratios or average travel speeds), learn to interpret a visual image, etc.

Probably the most important similarity between neural networks and symbolic learning methods is that they both require a set of representative data from the problem domain in order to learn the relationships that exist between inputs and outputs. There is a need for explicit knowledge of these relationships as long as training and testing data exist.

There are also differences between neural networks and linear regression modeling. Linear regression modeling uses a strictly linear combination of independent variables. Neural networks, on the other hand, provide weights that represent non-linear functions of the input variables. For example, the ANN models are trained to predict deterioration based on various samples of pavement condition data (inputs) that correspond to pavement roughness coefficients (outputs). In another example, Coy and others[1] showed that neural networks outperformed linear regression models, using both linear and non-linear functions of the independent variables in predicting returns for Initial Public Offerings.

ALTERNATIVE MODELING PROCEDURES

To provide an indication of the relative ability of the neural networks to predict changes in AVR, and to show the reduction in data needed to conduct this analysis, three methods of alternative modeling were developed. The first was a standard *linear regression analysis*. This was used to compare nonlinear capabilities of the neural network with linear predictions of linear regression. The second method was a *linear discriminant analysis*, which was used to show the relative ability of the neural network to classify observations into ranges correctly. The SCAQMD data was converted into inputs to the FHWA TDM Model to compare the neural network with this commonly-used analytical tool for predicting results of trip reduction strategies.

A validation data set was created to test each model's effectiveness in predicting results. Random sampling created the validation data set from the full set of SCAQMD data. After data cleaning had been completed, 432 total observations remained for validation purposes. A total of 9,096 observations were used for training and testing the model. For comparison to regression and discriminant models, testing using virtually any size data set would have been possible. However, because of the extremely labor-intensive process of developing FHWA TDM Model estimates from the SCAQMD data (see below), the size of the initial validation data set was limited to the 432 observations.

[1] S. Coy et al. "Using Neural Networks to Predict the Degree of Underpricing of an Initial Public Offering," *in Proceedings* of 3rd International Conference on AII Applications on Wall Street, New York City: June 6-9, 1995, 223-231.

Regression Analysis

An independent model was first created by means of factor analysis and stepwise regression to provide a baseline of comparison of the ability of the neural network model to predict changes in AVR correctly. Initial regressions suffered from multicollinearity within the data. Since many independent variables were intercorrelated, a possibility exists that the coefficients resulting from model runs would not fully reflect the effects of each of the independent variables. The initial approach to eliminating the effects of the multicollinearity was to run a factor analysis.

Generally, factor analysis is used as a data reduction technique. The analytical procedure involves creating uncorrelated (orthogonal) combinations of the initial dependent variables. In common practice, the purpose of the analysis is to reduce a mass of variables to a reasonable number of elements (for example, 10) that the analyst can understand and explain. The stepwise regression was set to accept variables that significantly improved the model at an 85 percent confidence level. When the analysis had been completed, the factors were then reconverted into the original component independent variables. The conversion was made by multiplying the coefficients assigned by the regression model to the factors by the matrix of the factor loadings of the original variables. The resulting equations predicted the change in AVR. Linear and factor analyses were built using Statistical Analysis System (SAS).

An alternative approach to reducing multicollinearity is to examine intercorrelations between the variables and to eliminate variables until no highly intercorrelated combinations remain. Therefore, a correlation matrix of the variables was prepared, and policy-oriented variables with correlations more than 0.20 were eliminated from further estimations. This process also combined incentives into "incentive groups" as described earlier. Other variables (such as site descriptors, percentages of employees using modes or in various jobs, etc.) remained in the model.

The variable set was reduced to a total of 77 "reasonably uncorrelated" variables from the original set through examination of the correlation matrix. These variables were then used to produce both new neural network models and revised regression and discriminant (see below) models. Stepwise procedures were used to build both the regression and discriminant models, and the neural net variable selection procedures were used for creating the neural net input set.

Discriminant Analysis

Comparing the neural network model's performance against a categorical prediction modeling procedure was logical because CUTR already determined that models would be evaluated based on their ability to classify observations into categories. The usual choice in transportation demand problems is to conduct a logit analysis. However, discriminant procedures, while methodologically less rigorous, provide the same types of results and are much simpler to develop. The approach to the discriminant analysis model-building was similar to the approach to the building of the regression model and used the same version of SAS, a statistical software package.

Typically, the evaluation of a discriminant model is done by determining the percentage of observations correctly classified in an independent test data set. In practice, the results from test data sets tend closely to mirror the results from the data sets used to build the models. The size of the initial test data set (432 observations) was such that evaluation of classification patterns for anything but the overall sample was impractical. Results were reported for both the test data set and for the base (or training) data set. These results were reported because it is important to know not only overall how well the model classifies results, but also whether there were any *patterns* of misclassification.

FHWA TDM Model

Testing the neural network model's performance against an existing trip reduction analytical tool was a sensible next step. The FHWA TDM Model was selected because it was the most commonly used tool available. The FHWA TDM Model uses a logit pivot point procedure to estimate how changes in travel time or cost would affect mode shares. This model handles strategies other than changes in time or cost as a system of look-up factors. The effectiveness of employer-based strategies is function of the TDM strategies used and employer participation in carrying out those strategies.

The FHWA TDM Model requires that data be entered into the model that define the starting conditions, including employer/site data on trips and modal split from site surveys. The primary inputs are either trip tables from the regional model or the mode split of an area or employer. The next step gives the user flexibility to relate special conditions that may not properly reflect the starting data inputs. At this point, the user specifies the TDM strategies to be applied. The Model allows testing of any individual strategy, or as many as the user desires in combination. The FHWA TDM Model separates TDM strategies into two groups: Area-wide Strategies or Employer-Based Strategies. Area-wide strategies are incentives provided by the public sector (such as high occupancy vehicle facility). Employer-based strategies are TDM strategies funded and/or carried out by individual businesses (such as transit-pass subsidies).

The approach to evaluating the FHWA TDM Model was to use a sample randomly extracted from the SCAQMD data set to compare models. The SCAQMD data corresponding to the descriptions for each level had to be converted into a form acceptable for input into the TDM Model to compare the neural net model with the FHWA TDM Model. Many of the SCAQMD data fields could be easily converted into inputs for the FHWA TDM Model. A notable exception was how much time spent on the trip reduction program by the employee transportation coordinator. Generally, SCAQMD data had to be aggregated for inclusion into the FHWA TDM Model. For the Employer Support Programs input screen, data for input were extracted for the carpool program, including; regional-based matching, employer-based matching, preferential parking for carpools, flextime for ridersharers and guaranteed ride home. After entering the levels of effort, employer's incentive programs were keyed in.

There are some caveats associated with this comparison of FHWA TDM Model's performance. The data needs of the FHWA TDM Model and the models built for this project are very different. First, COMSIS did not build the FHWA TDM Model on the type of data used to build the neural net model. Second, the data available to the FHWA TDM Model developers was very limited at the time. The neural network model has the benefit of more data.

MODEL - BUILDING ACTIVITIES

Overview of Neural Network Model Building

In the first phase of model-building, initial efforts were based on drawing comparisons between the results of the models built from the SCAQMD database and the FHWA TDM Model. Because the data conversion from SCAQMD format to TDM Model format is labor-intensive, analysis was limited to comparing results on 432 records. Phase II involved creating a new, larger validation set that would permit more detailed comparisons and rebuilding the models. Phase III involved a shift from the original factor-analytic approach to regression (and discriminant) models to one where correlated variables were removed to allow for some level of data reduction in the linear models. This also allowed for additional confidence that multicollinearity was not affecting the neural network models. The fourth phase varied a range of neural network settings in an attempt to best understand how the neural networks could work with the data available.

The type of neural network selected to predict the change in AVR was a multi-layer, fully-connected, feed forward type. Neural network model builders have applied these types of networks successfully for prediction and classification problems in a variety of fields.

The neural network development package selected for this project is named PREDICT and is sold by NeuralWare, Inc. CUTR used Microsoft's Excel to interface with the training data and show results after training the network. Microsoft's database program, Access, also was used to manipulate the data before training the network. PREDICT simplifies the different aspects of the neural network training process by allowing the network builder to select many parameters that can affect the performance of the final model.

Data Used for Model Building

The data selected for building a neural network is usually divided in three sets – the training set, test set, and validation set. *Training* is a process that uses one of several learning techniques to modify the weights in an orderly fashion. The *training set* of data is a list paired input and desired output patterns used in supervised training. The training set is used to change the weights and the number of units in the network. All of the information the network needs to learn must be in the training set. The inputs can be numbers or symbols.

PREDICT uses 70 percent of the data as the training set and 30 percent as the test set, although the network builder can change these values to any other proportions.

The *test set* is an extract of the training set used while building the model to prevent overfitting. Overfitting the training data can occur when the neural network produces a nonlinear model that fits the training data perfectly, but fits the test data very poorly. The goal is to fit the training and test data with about the same overall error. Therefore, the test data set is used to analyze the model's ability to interpolate the train/test data regularly during training. Training is halted when the test performance starts to degrade.

The *validation set* is independent of the train/test set and typifies the data that will be seen by the model in the outside world. The neural network software does not use the validation set in building the model.

The SCAQMD database includes 62 different incentives that employers can select to increase AVR in their work sites. One neural network was built where all 62 incentives were grouped into one category. Subsequent networks were built using more limited incentive groups. As mentioned earlier, 9,096 were used to build the networks and 432 to validate the networks after they were built. Initially, the network parameter settings were tested to find optimal configuration for network performance.

Criteria for Evaluating Model Performance

The SCAQMD data contained many observations (more than 500) where employers had either a very large increase or very large decrease in AVR. Nevertheless, the vast majority (almost 90 percent) of the data falls near -0.10 to +0.20 change in AVR. Models built on prediction error minimization criteria may force their predictions to the middle of the range (that is, predict little or no change in AVR). This approach causes the models to have much more accuracy in the middle ranges of AVR change than with the outliers (that is, large changes in AVR). Preferably, a model should interpolate well over the entire range of the input values. The neural network software manual contains an example of exactly this type of situation:

"Is the linear regression line shown in Figure [2] a good solution to this problem? The answer depends on how the model is used. The objective of linear regression is to minimize the sum squared error of the difference between the estimated and actual outputs. If that is what is required by system objectives, this model does that. However, if the purpose of the model is to interpolate well over the entire range of the input space, this model fails." (Neuralware documentation, 1995)[2].

To get a more comprehensive evaluation of the network's effectiveness, it was determined that an examination of the network's ability to correctly classify each prediction into a *range* (or a category) of AVR change would be conducted. The ranges were developed by partitioning the data into equal sized groups based on the number of plans that fell within each range (that is, the value of the dependent variable). (See Table 1.)

In effect, the evaluation centers on the model's ability to predict whether a given combination of site characteristics and incentives will produce a large increase in AVR, a small increase, virtually no increase, a small decrease, or a large decrease in AVR. Models were evaluated both through comparison of R (linear correlation) values of predicted and actual change in AVR and by their ability to classify an observation into the correct group or into an adjacent group. This was termed "acceptable" (as opposed to "correct") classification. (See Tables 2 & 3.)

[1] Neuralware documentation "NeuralWorks Predict Manual" Introduction 1-8, Building a Neural Net Model. NeuralWare, Inc., 1995

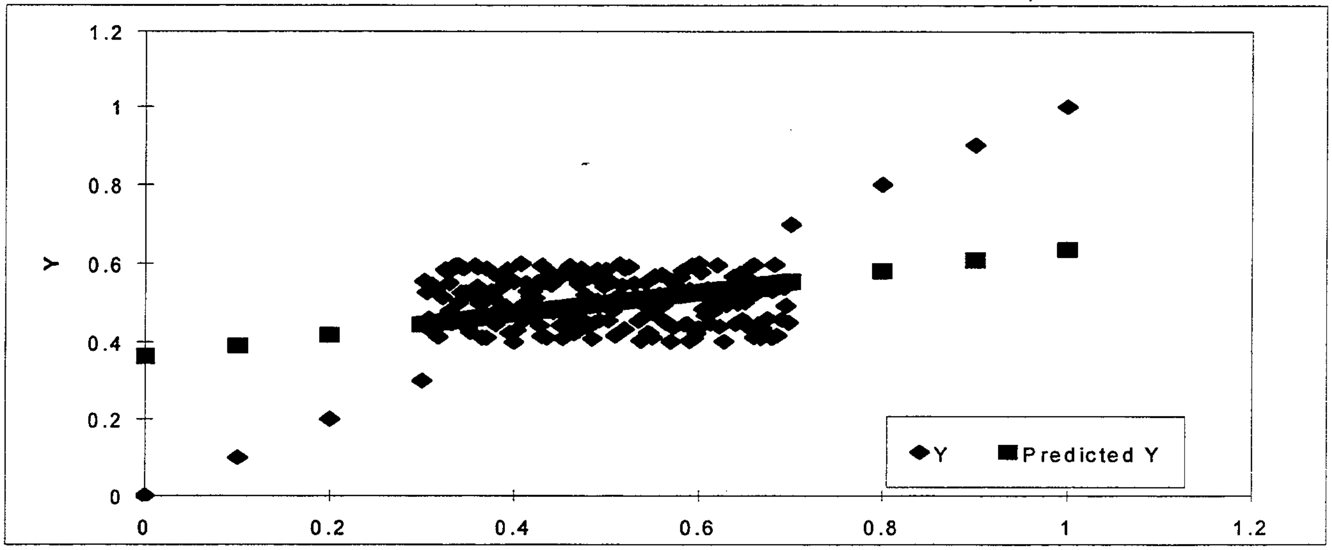

Figure 2 – Scatter plot and linear regression line for data with a single input (x –axis) and single output (y-axis)

Results of Alternative Modeling Procedures

After the neural network was built with only SCAQMD data, its performance was compared with the FHWA TDM Model and the alternative modeling procedures.

While it may appear that the alternative models are in some respects outperforming the neural networks, it should be kept in mind that the neural network built at this stage used fewer variables. This feature would contribute to one of the project's primary objectives-reducing the costs of developing and implementing plans to reduce vehicle trips by streamlining the plan development and review process. The neural network model contains only 17 input variables, compared with the full range of data (178 variables) used by the discriminant and regression approaches.

For the neural network, the models were developed using the default variable selection setting and a root mean power error evaluation function.

This analysis showed that the linear approaches clearly outperformed the FHWA TDM Model. Also, these results provide an initial baseline against which to compare the neural network models to be developed.

Tables 4 & 5 compare the results of the models using full data and a factor-analysis approach to models using an approach containing only uncorrelated variables in predicting into acceptable ranges.

Clearly, the factor approach and the use of potentially correlated variables had not significantly improved the performance of the regression or discriminant models. The neural network performed consistently with performance in the prior phase where variable selection had been applied.

The discriminant procedure could produce more accurate predictions for observations with negative changes in AVR (classification levels 1 and 2) and for those with the largest positive increases (classification level 7). While the discriminant analysis actually did a better job of classification, it is incapable of producing the types of results required by the likely users of this product. Users are most likely to need an exact (even if not necessarily 100 percent reliable) estimate of trip reductions that cannot be achieved by a classification approach.

The neural network performed better in the middle ranges. Overall, classification rates within the validation set remained close enough for their differences to be of questionable significance. However, it began to appear as if the linear procedures were possibly outperforming the neural networks.

Table 1

AVR Change Range Categories for Model Evaluation

AVR change category	Change in AVR category range	Acceptable range for model evaluation
Large decrease	-0.08 or less	Cl. 1: Any change less than -0.03
Moderate decrease	-0.03 to -0.079	Cl. 2: Any decrease
Small decrease	0 to –0.029	Cl. 3: Any change less than +0.03
Neutral	0 to 0.029	Cl. 4: >-0.03, <0.06
Small increase	0.03 to 0.059	Cl. 5: >0.00, <0.12
Moderate increase	0.06 to 0.119	Cl. 6: Any change more than +0.03
Large increase	0.12 or more	Cl. 7: Any change more than +0.06

Table 2

Acceptable Range Classification by Model for TDM Validation Data Set (N=432)

MODEL	Percent
Neural network	53.1
Discriminant	54.6
Regression	49.1
FHWA TDM Model	39.6

Table 3

Linear correlation of prediction and actual output

TDM Model Validation Set (N=432)

MODEL	R
Neural network	0.441
Regression	0.541
FHWA TDM Model	0.032

This led to Phase IV, where it was decided to examine the impacts of changing parameters on the neural network software, hoping to improve network performance. The fourth phase was an attempt to vary a range of neural network settings in attempting best to understand how the neural networks could work with the data available. Many settings ("data noise level", the appropriate variable selection level, comprehensiveness of network searches and tolerances) do not have clearly evident optimal settings.

The appropriateness of the settings is based on the character of the data, and to some extent can best be evaluated only through trial and error. The fourth phase reports the results of these attempts and the conclusion drawn on the most appropriate model built.

Final Model Building Results Using Only the SCAQMD Data

Having determined all of the parameters that would be used for the model, the final step was to rebuild the model using the parameters outlined above to conduct a final test against the TDM model's performance (using all data except the 432 observations to train the network).

The new settings were applied to the 9,096 observations that were not part of the TDM model data set, and that model was tested against the 432 observations that were the TDM model data set. The linear regression and discriminant models were also rerun, using the uncorrelated data set developed earlier. The results are outlined in the tables below:

Again, the models built were clearly superior to the alternative of using the FHWA TDM Model. As to correct classification, the neural network was superior to the regression procedure in classifying results into the proper ranges to regression, although the correlation of predicted to actual results was lower. For reasons described earlier, the correlation values are not necessarily the most appropriate way to evaluate the model's performance.

Table 4

Acceptable Classification by Models Using Full Data Set

Model	R	Overall acceptable classification	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Neural	0.33	52%	39%	24%	40%	76%	89%	65%	23%
Regression	0.52	56%	63%	50%	54%	71%	74%	52%	27%
Discriminant	N/A	53%	53%	55%	53%	59%	61%	56%	40%

This approach had the anticipated impact of improving predictive performance among the outlying categories of AVR change, but reduced the network's ability to classify observations in the middle of the range. Overall performance was consistent with networks built earlier.

Given the neural network's ability to predict change at about the same level as a linear regression, and its ability to do so more efficiently (using 18-20 variables as inputs compared with 33 for the linear regression), it was determined that the best performing neural network should be used. This was the *moderately noisy* model, which had a R-value of 0.36 and used 17 variables to make its predictions.

Table 5

Acceptable Classification by Models Using Uncorrelated Data Set

Model	Inputs	R	Overall acceptable classification	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Neural	19	.33	53%	44%	31%	46%	78%	86%	60%	23%
Regress.	33	.49	55%	47%	32%	43%	73%	86%	65%	33%
Discrim.	21	na	56%	54%	46%	65%	74%	68%	46%	35%

Table 6

Acceptable Range Correct Classification by Final Models for TDM Model Validation Data Set (N=432)

MODEL	Inputs	Percent
Neural network	16	54.2
Discriminant	23	58.1
Regression	31	50.2
FHWA TDM Model	N/A	39.6

Table 7

Linear Correlation of Prediction and Actual Output TDM Model Validation Data Set (N=432)

MODEL	R
Neural network	0.312
Regression	0.544
FHWA TDM Model	0.032

The neural network was, therefore, deemed to be the superior model built, although admittedly it was somewhat less able to outperform the linear procedures than initially anticipated. None of the models had a significant change in the number of variables they used to make their predictions, although the identity of those variables did change some from model to model. As a final step in model building, a neural network-based classification approach was tested. The best result obtained was with a network with only superficial data transformation and no hidden units. The superficial data transformation creates just one transform (for example the hyperbolic tangent function) per input field and is used when there is a large number of input variables.

FIELD TESTING ANN MODEL

Approach to Field Testing the Model

The approach to evaluating the transferability of the ANN model was to use the Los Angeles-based ANN model to predict change in AVR using data from another city (that is, Tucson and Phoenix). However, the Los Angeles-based ANN model did not perform as well with the data from other cities as it did with data used from Los Angeles as a validation set (that is, Los Angeles data that wasn't used to build the Los Angeles-based ANN model). (See technical memorandum #3 for a description of the model building process.)

The project team hypothesized that other variables not included in the data set could explain the differences between the urban areas. For example, Los Angeles' population density is about 5 times higher than Phoenix and Tucson. Higher densities can provide for transit service with lower headways thus offering more opportunities for commuters. The project team added the MSA population density factor as an additional variable to the data set.

With this additional data, another round of model building began. Various combinations of the models were built with data from two of the cities and validated with the data from the remaining city. The final data set consisted of nearly 7,000 records with 48 fields from which to select variables. The data included 29 incentive fields. The data contained 5,001 employer plans from Los Angeles and 1,103 employer plans from Tucson that were used to build the new ANN model. Another 878 employer plans from Phoenix were used to validate the model.

The final ANN model (Los Angeles-Tucson) was actually built as three sequential ANN models. All the variables were made available to build the first model to predict change in AVR. The second model was built to explain the residual value (that is, actual AVR change less predicted AVR from the first model) using only the combined incentive groups (for example, any guaranteed ride home, financial incentives, etc.). The third model uses the individual incentives (for example, higher cost of driving alone) to explain the residual from the second model. The final predicted value of AVR change is the sum of these three models.

The Los Angeles-Tucson based model performed the best in predicting change in AVR (see Table 8). The results of this task show that, based on the data from these three cities, the ANN model is transferable. More observations were acceptably classified in the validation sets than in the ANN modeling data set. Only at the large increase in AVR range did the validation data under perform the base model. This was partially due to the few employer records from Phoenix in that category.

Though there were nearly 7,000 trip reduction plans used to build and validate the model, there are two points that should be made: (1) some incentives are offered by relatively few employers (see Table 9) and (2) many combinations of the plans illustrate the challenge in finding the "best" plan. Only "marketing incentives" was included by more than half of the filed plans. The plans also represent 1,163 different combinations of incentives when marketing activities were considered to be only present or absent. If the number of marketing activities is considered then there were about 1,500 combinations of incentives. This situation may have had a tendency to reduce the ability of the ANN model to detect any significant change based on the presence or absence of any given incentive.

Model Incentives

Picking the right input variables is critical to model development. A good subset of variables can substantially improve the performance of the neural network model. The challenge is finding ways to pick good subsets of variables to predict the change in average vehicle ridership (AVR).

The neural network software uses a genetic algorithm that selects the variables. This algorithm is looking for sets of inputs (for example, site characteristics and incentives) that act in a synergistic manner as good predictors of the output (that is, change in AVR) rather predicting the impact of every potential variable. The algorithm begins with a population of random variable sets of limited size. As the algorithm progresses, the size of these variable sets will tend to increase if the problem requires larger data sets.

The idea of discarding potentially substantial number of variables is sometimes hard to accept. However, there are plausible reasons for their exclusion by the algorithm.

It might seem unrealistic that only five TDM incentives can impact employee choice of how to commute. Where are the marketing programs? What about having an Employee Transportation Coordinator in place? For several reasons, some incentives that might seem effective, or even absolutely necessary, may not appear as options in the software.

Some incentives, particularly marketing materials and having Employee Transportation Coordinators (ETCs) in place, were common to virtually all companies in the database. This situation made it impossible for any modeling procedure to determine where marketing worked and where it did not, and, therefore, seemed to have an unpredictable impact on AVR. ETCs and focused marketing materials are key elements of any TDM program. This fact is one reason why ETCs and marketing materials were common to all of the employer plan submissions that were analyzed. It is essential that marketing materials and ETCs be put in place to support ongoing TDM programs, to improve awareness and understanding of any of the other incentives (from the list of five that are included in the model) that might be provided in an employer's trip reduction program.

Some incentives (such as facility improvements) may have been offered by so few companies that it was impossible to accurately determine their impact. Rather than provide an extremely unreliable estimate of the impact of that incentive, more data needs to collected and analyzed before providing an estimate.

The amount of financial subsidy provided is another area where the nature of the data we were using to build our model hampered our efforts to provide an estimate. The extent of financial incentives offered by companies was effectively constrained by the tax code (that is, employers were less likely to offer more than the nontaxable amount allowed by the Internal Revenue Service. At the time of the plan submittal, transit subsidies were limited to $15 to $21 per month for all plans prior to 1993 and any vanpool subsidy was subject to tax. Hence, the model only specifies a generic "subsidy," and gives no estimate of the impact of increasing the amount of the incentive. It is assumed that when variable indicating a financial subsidy is offered that it is at least $15 to $20 per month per employee using the incentive. Subsidies offered for multiple modes (for example; transit, vanpool, etc.) could be expected to make a larger impact than the same subsidy for a single mode.

Table 8

Final Model Performance vs. Validation Data

Model	Inputs	Overall acceptable classification	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Train and Test Data Set (LA – Tucson)	13	49%	31%	15%	27%	67%	91%	78%	33%
Validation Data Set (Phoenix)	13	58%	43%	25%	63%	95%	87%	25%	2%

Table 9 shows the number of plans with a given incentive from the data used to build the model and validate the model. Data from Los Angeles and Tucson were used to build the model. Data from Phoenix was used to validate the model. Those variables included in the final model are shown in the last column as Included and those that were available for selection but not included are shown with Excluded.

Table 10 summarizes the common data fields available from each city. The data was reformatted for the three cities (for example, impedance categories were reduced from 10 ranges to 5 ranges to correspond to the categories used in Phoenix and Tucson). The last column in the table indicates which fields were used to build the ANN model based on the availability of the data from each city and the ability to combine data fields (for example, guaranteed ride home programs using taxis and guaranteed ride home programs using fleet vehicles). For a complete description of the data elements available in the LA data set, please refer to technical memorandum #3.

TECHNOLOGY TRANSFER

Software

Trip reduction software (CUTR AVR) was developed as the result of this project. Using the software:

- Employers and developers can reduce the costs for developing and implementing plans to reduce vehicle trips by streamlining the plan development and review process.
- Public agencies could improve efficiency by reducing staff time in the review of employer/developer trip reduction plans.
- Analysts in public agencies can develop consistent interpretations of trip reduction plans.
- Though the model was never intended to be an integral part of the transportation planning modeling process (for example, TRANPLAN), it can be used to evaluate impacts of TDM on vehicle trips at the large employer level and sub-area basis.

The delivery of TDM programs and services are typically aimed at the large employer. This ANN model is based on the impacts of large employers (more than 100 employees).

The impact of a regional TDM program is largely a function of its success in encouraging employers to offer incentives and promote alternatives to the single occupant vehicle. The software requires information about the current mode split. (see Figure 11.)

Table 9

Frequency of Incentives

Incentive	No. of Plans with Incentive	No. of Plans without Incentive	Final Model
Rideshare matching	3,644	3,336	Included
Guaranteed ride home	3,486	3,494	Included
Alternative mode subsidies	3,227	3,744	Included
Compressed work week	1,769	5,211	Included
High parking costs for SOV	76	6,904	Included
Marketing	4,459	2,521	Excluded
Preferential parking	2,721	4,259	Excluded
Other services	2,655	4,325	Excluded
Bike racks and lockers	2,620	4,360	Excluded
Flexible work arrangements	1,914	5,066	Excluded
Showers & clothing lockers	1,554	5,426	Excluded
Telecommuting	1,058	5,922	Excluded
Cafeteria, ATMs, post office, etc.	1,019	5,961	Excluded
Other on-site services	920	6,060	Excluded
Free meals	771	6,209	Excluded
Other compressed work week	675	6,305	Excluded
Child care service	597	6,383	Excluded
Walk to work subsidies	454	6,526	Excluded
Catalog points	354	6,626	Excluded
Service (unspecified)	320	6,660	Excluded
Gift certificates	304	6,676	Excluded
Auto services	221	6,759	Excluded
Additional time off with pay	153	6,827	Excluded
Other non-financial incentives	127	6,853	Excluded
Other facility improvements	117	6,863	Excluded
Other parking strategies	116	6,864	Excluded
Company vanpools	98	6,882	Excluded
Facility improvements	33	6,947	Excluded
Prize drawings	0	6,980	Excluded

Table 10

Common Data Elements

DATA ELEMENT	Phoenix	Tucson	Los Angeles	Data Used to Build ANN Model
Plan Sequence Indicator	na	Excluded	Excluded	
Drive alone percentage	Excluded	Excluded	Excluded	Included
Motorcycle percentage	Excluded	na	Excluded	Excluded
2-Person carpool pct.	Excluded	Excluded	Excluded	Excluded
3-Person carpool pct.	Excluded	Excluded	Excluded	Included
4-Person carpool pct.	Excluded	Excluded	Excluded	Excluded
5-Person carpool pct.	Excluded	Excluded	Excluded	Excluded
6+ Person carpool pct.	na	na	Excluded	Excluded
Vanpool percentage	Excluded	Excluded	Excluded	Excluded
Buspool percentage	na	na	Excluded	
Transit	Excluded	Excluded	Excluded	Included
Walk	Excluded	Excluded	Excluded	Excluded
Bicycle	Excluded	Excluded	Excluded	Included
Telecommute	na	na	Excluded	
Current AVR	Excluded	Excluded	Excluded	Included
Target AVR	na	na	Excluded	
Standard Industrial Classification (SIC)	Excluded	Excluded	Excluded	
No. of employees on site	Excluded	Excluded	Excluded	Included
No. of employees arriving between 6 and 10 a.m.	Excluded	Excluded	Excluded	Excluded
Percent of administrative employees	na	na	Excluded	
Percent of professional employees	na	na	Excluded	
Percent of technical employees	Excluded	Excluded	Excluded	
Percent of clerical employees	na	na	Excluded	
Percent of skilled workers	na	na	Excluded	
Percent of service workers	na	na	Excluded	
Percent of sales employees	na	na	Excluded	
Percent of semi-skilled employees	na	na	Excluded	
Percent of job – other	na	na	Excluded	
Percent of job – other 1	na	na	Excluded	
Percent of job – other 2	na	na	Excluded	
Percent of job – other 3	na	na	Excluded	
Percent of job – other 4	na	na	Excluded	
Presence of employee transportation coordinator	Excluded	Excluded	Excluded	
Number of bus routes	Excluded	Excluded	Excluded	
Availability of bike paths	na	na	Excluded	
Pct of employees w/5 min commute	na	na	Excluded	Excluded

DATA ELEMENT	Phoenix	Tucson	Los Angeles	Data Used to Build ANN Model
Pct of employees w/5 to 10 min commute	na	na	Excluded	Excluded
Pct of employees w/10 to15 min. commute	Excluded	Excluded	Excluded	Excluded
Pct of employees w/15 to 20 min. commute	na	na	Excluded	Excluded
Pct of employees w/20 to 30 min. commute	na	na	Excluded	Excluded
Pct of employees w/30 to 40 min. commute	Excluded	Excluded	Excluded	Excluded
Pct of employees w/40 to 60 min. commute	na	na	Excluded	Included
Pct of employees w/60 to 90 min. commute	na	na	Excluded	Included
Pct of employees w/90 to 120 min. commute	na	na	Excluded	Included
Pct of employees w/120+ min. commute	na	na	Excluded	Included
Facility Improvements (unknown)	Excluded	Excluded	Excluded	Excluded
Other facility improvements	na	na	Excluded	Excluded
Preferential parking	na	na	Excluded	Excluded
Bike racks & lockers	na	na	Excluded	Excluded
Showers & clothing lockers	na	na	Excluded	Excluded
Rideshare match – employer based	na	na	Excluded	
Carpool subsidies	na	na	Excluded	
Introductory transit passes or subsidies	Excluded	na	Excluded	
Other subsidies	na	na	Excluded	
Walk to work subsidies	Excluded	na	Excluded	Excluded
Auto services (Fuel, Oil, Tune-up)	Excluded	na	Excluded	Excluded
Gift certificates	Excluded	na	Excluded	Excluded
Free meals	Excluded	na	Excluded	Excluded
Other non-financial incentives	na	na	Excluded	Excluded
Catalog points	Excluded	Excluded	Excluded	Excluded
Additional time off with pay	Excluded	Excluded	Excluded	Excluded
Higher parking costs for SOV	Excluded	Excluded	Excluded	Included
Other parking strategies	na	Excluded	Excluded	Excluded
Other compressed work week	Excluded	Excluded	Excluded	Excluded
Other services	Excluded	Excluded	Excluded	Excluded
Prize drawings	na	Excluded	Excluded	Excluded
Service (unspecified)	Excluded	Excluded	Excluded	Excluded
Company owned/leased vanpools	Excluded	Excluded	Excluded	Excluded
Child care service	na	Excluded	Excluded	Excluded
Other on-site services	Excluded	Excluded	Excluded	Excluded
Cafeteria, ATMs, Postal, etc.	Excluded	Excluded	Excluded	Excluded
Unspecified (Other)	na	Excluded	Excluded	
Any type of Guaranteed Ride Home	Excluded	Excluded	Excluded	Included
Any type of Alternative Work Hours Program	Excluded	Excluded	Excluded	Excluded
Number of Marketing Activities	Excluded	Excluded	Excluded	Excluded

DATA ELEMENT	Phoenix	Tucson	Los Angeles	Data Used to Build ANN Model
In-house or regional ridematching system	Excluded	Excluded	Excluded	Included
Any type of Telecommuting Program	Excluded	Excluded	Excluded	Excluded
Any type of Compressed Work Week program	Excluded	Excluded	Excluded	Included
Any type of Financial Incentive/Disincentive	Excluded	Excluded	Excluded	Included
Percentage of parking reserved for pools	na	na	Excluded	

Included = included in the final model. Excluded = excluded in the final model. Impedance values are grouped as a single variable representing the percent of employees commuting over 40 minutes one-way to work.

One of the features contained in the software is the ability to evaluate the impact of multiple employers (currently up to 100) and combine the results of 2 or more employer profiles. This feature will help regional agencies such as a transportation management organization evaluate the impact of the program in a particular area or multiple employer sites.

At the same time, the data necessary to run the model in a sub-area mode is not readily available. As explained in an earlier technical memorandum, Florida employers are not required to submit trip reduction plans so the data on number of large employers with given strategies is currently unknown. However, as part of the mobility management process, regional commuter assistance programs could be requested to collect the data on a larger scale.

Sample Trip Reduction Plans

In addition, sample plans based on the model were developed to allow employers and others to estimate changes in AVR based on different mixes of key variables (for example, employees at site, current mode split, etc.). Partially as a result of meeting with the Arizona trip reduction program staff, CUTR focused efforts on designing the output for sample trip reduction plans as stand-alone guidance documents for employers and developers with these pre-selected attributes.

Though the model was developed to predict the absolute change in AVR, the Arizona TDM staff recommended that the results also be presented in other formats. As the attached sheets show, CUTR added the Vehicle-Employee Ratio (VER) that shows the number of vehicles per 100 employees. Also at the suggestion of the Arizona TRP staff, CUTR estimated the number of vehicles reduced for that employer. For example, a reduction in VER of 10 vehicles per 100 employees would result in 25 fewer vehicles or parking spaces for a company with 250 employees.

Based on several input screens, including incentives offered by the employer, the software produces the following output. The software estimates the change in AVR and the number of vehicle trips removed per 100 employees. The user can modify the conditions or develop another "profile" of strategies to test.

Additional Research

On a more basic level, the ANN model uses employer plans (for example, existence of subsidies) to assess commuter behavior (change in mode used). Subsequent research into the impacts of employer-provided incentives on individual commute decisions and/or the use of actual revealed preference data (not aggregated to the employer level) could strengthen the model. Another FDOT Research Idea project, Market-Based Approach to Trip Reduction, has collected data from Miami, Tampa, and Jacksonville commuters using a fractional fractorial experimental design to assess commuter willingness to use alternative modes (drive alone, carpool, vanpool and transit) given the presence of various incentives. This other research project should also provide insight into the transferability of logit models between cities.

Table 11

Employee Commute Information

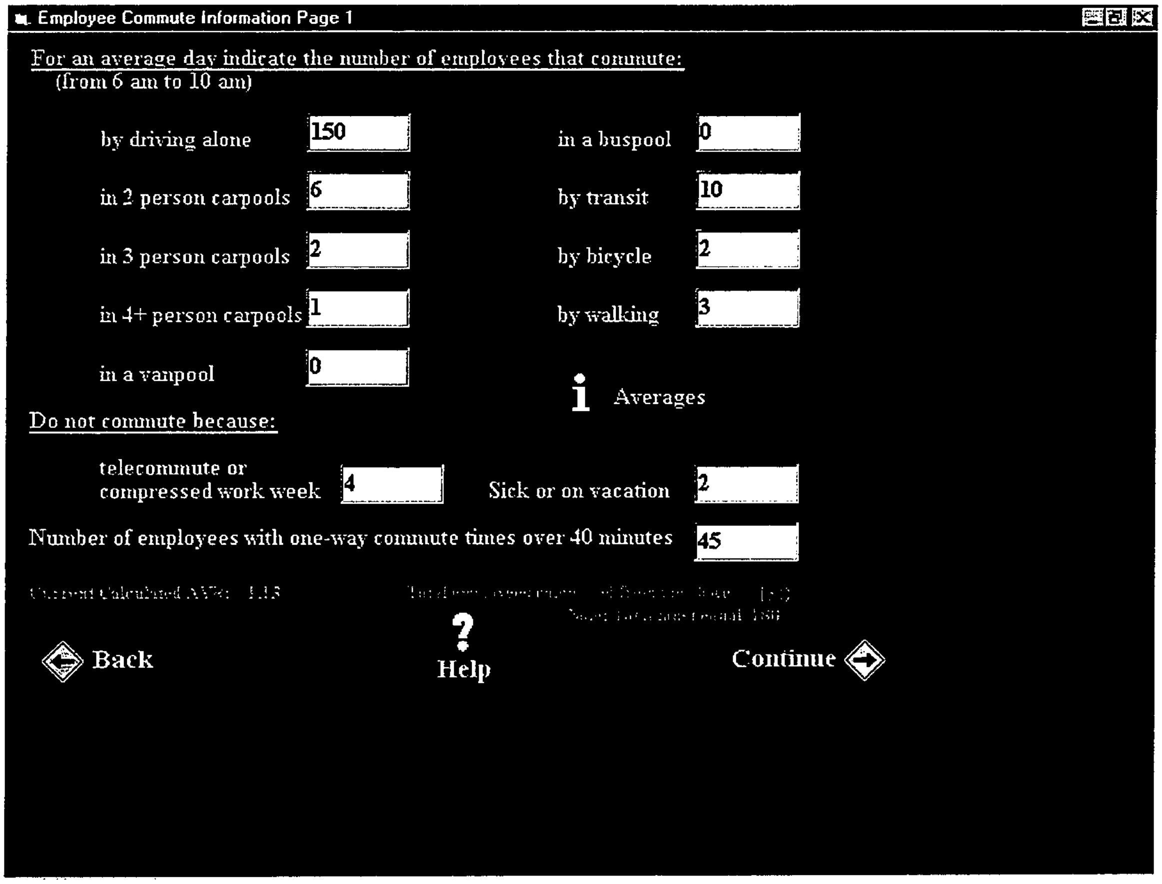

Table 13 shows that the same change in AVR can measure different impacts on vehicle travel and parking depending on the initial AVR. For example, an increase of AVR by 0.06 from 1.10 to 1.16 would convert to a reduction in 5 vehicles per 100 people. However, the same increase in AVR from 1.50 to 1.56 would mean only a reduction of 3 vehicles per 100 people. Therefore, the final stand-alone document of sample trip reduction plans should reflect changes in AVR, VER for several different starting AVR levels (for example; 1.10, 1.50 and 1.90).

Table 12

AVR Calculations

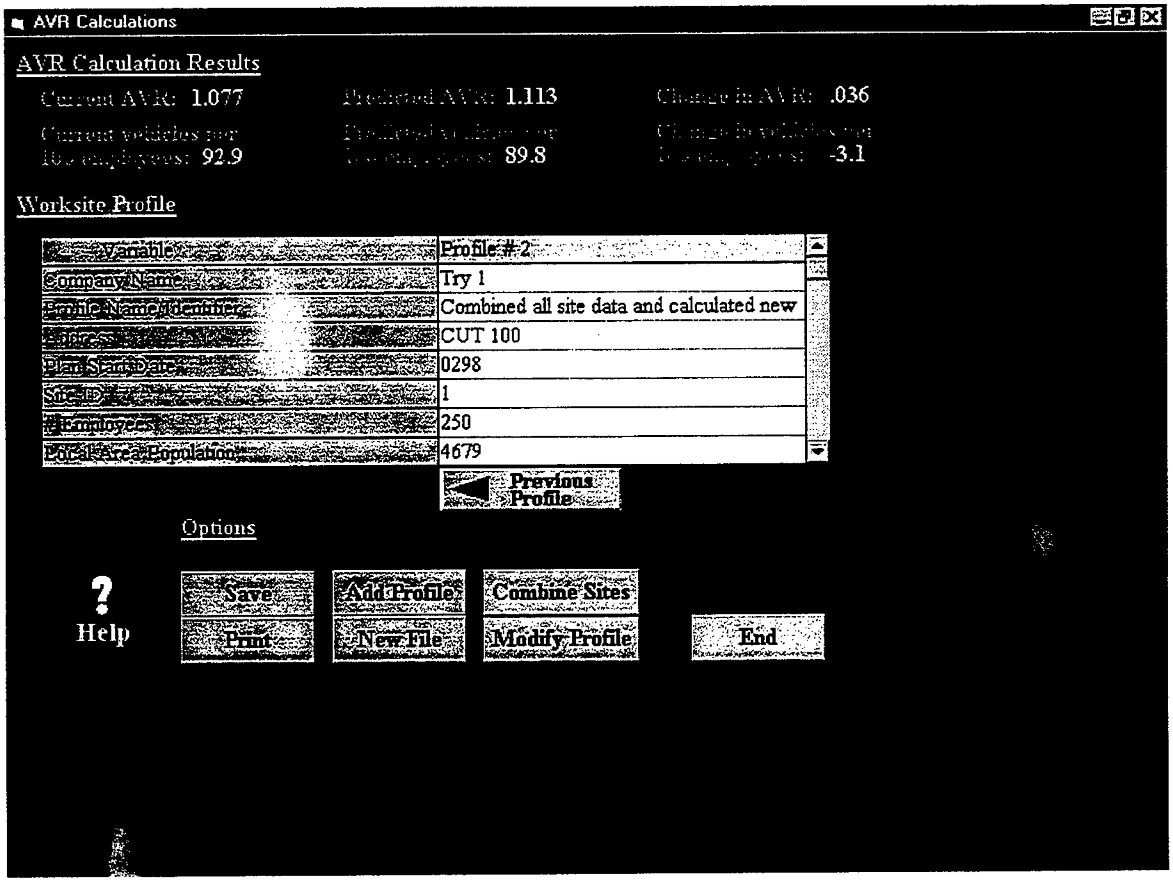

Table 13

Changes in AVR vs. Vehicles Per Employee Ratio

		CHANGE IN AVR				
AVR	VER	-0.08	-0.03	0	0.03	0.06
1.10	91	98	93	91	88	86
1.50	67	70	68	67	65	64

Future research projects could seek to adapt the ANN trip reduction model to transportation planning process in a similar manner to the FHWA TDM Model. The FHWA TDM Model, a pivot point logit model, modifies trip tables based on assumptions of individual strategies including employer participation based on size of the employer and regulatory environment. In the short term, the ANN model could use the output of the mode split model to estimate current AVR. Assuming a mix of employer sizes and a proportional distribution of the reduction among zones, the model can calculate the number of vehicle trips reduced at the zonal level. Additional research could be undertaken to evaluate the impacts of these assumptions. Assessing other means of gathering data to take advantage of the model's sensitivity to variables such as the current AVR, the share of employees with long distance commutes and employer size could include combining commercial databases and geographic information systems.

The ANN model does have limitations. One of the limitations of the ANN model is the lack of information on impacts of small employer programs. The data used to develop the ANN model is limited to large employment sites due to the regulatory requirements in Los Angeles, Phoenix, and Tucson only applying to large employers. Another limitation is the use of dummy variables rather than discrete values. For example, the impact of financial incentives was based on whether incentives were offered, not the amount of the incentive due to inconsistent reporting of the incentive (amount, number of employees, etc.). In general, the federal taxcode effectively limited the tax-free amount of transit subsidies to $15 to $21 per month in the late 1980's and early 1990s. In 1992, the tax code was changed to allow employers to provide up to $60 per month tax-free to employees for transit and vanpool subsidies.

CONCLUSIONS

Based on this project, the ANN model has proven to predict an acceptable range of changes in AVR and has proven to be transferable to another site.

- The final products (software and sample plans) should be applicable to Florida.
- Furthermore, the ANN model outperformed other analysis tools and is easier to use as evaluated by TDM professionals.
- Finally, the model provides a basis for helping transportation planners assess the impacts of employer-based TDM strategies on vehicle trips.