WORKSITE TRIP REDUCTION MODEL (WTRM) AND MANUAL

PROBLEM STATEMENT

Today's transportation professionals and others often use Institute of Transportation Engineers' (ITE) Trip Generation Manual and the Parking Generation Manual to estimate future traffic volumes to base off-site transportation improvements or identify parking requirements. Planners may use these same resources to evaluate the impacts of land use or zoning changes on the transportation system. According to ITE, one of the many issues facing users of this trip generation data is determining whether specific transportation demand management programs and transit services can reduce site trip generation by predictable amounts.

OBJECTIVES

The objective of this project is to develop a Worksite Trip Reduction Model and accompanying manual that will estimate the impacts of various combinations of transportation demand management (TDM) strategies in reducing vehicle trips.

FINDINGS AND CONCLUSIONS

This project used several thousand worksite trip reduction plans to build the model. The data came from Los Angeles, Tucson, and several urban areas in the state of Washington; in all of the areas, employers had been under trip reduction requirements for many years. Employers were required to submit plans to reach particular objectives, such as a reducing the levels of single occupant vehicle (SOV) use. The data consisted of worksite modal characteristics aggregated at the employer level and a listing of incentives and amenities offered by employers. The Los Angeles data contained the most data; the Tucson and Washington datasets were considerably smaller. Data quality control problems reduced the size of the data in each area and eliminated or restricted some potentially useful variables (e.g., dollar values of some incentives). For performance evaluation, the datasets were divided into two disjoint sets: the "training/testing set," which was used to build the models, and the "validation set," which was used as an unseen data to evaluate the models. The dependent variable chosen was the change in vehicle trip rate (VTR) (e.g., reduction of 4.5 vehicles per 100 employees). VTR correlates closely with the goals of TDM—to reduce trips, decrease air pollution, and decrease the need for parking—and is generally proportional to the desired result. Alternative dependent variables such as SOV share or average vehicle ridership (AVR) have disadvantages. SOV share misses the benefits of moving from one non-SOV mode to another where the switch may actual reducing traffic but not affect SOV share (e.g., carpool to transit). The reduction in vehicle trips is distorted when using AVR as the dependent variable due to the non-liner relationship between AVR and vehicle trips.

Two approaches were used for the model-building process: linear statistical regression models and non-linear neural networks. The linear statistical regression models were used as a benchmark for the validity and accuracy of the neural net models. The linear statistical regression models minimize the sum of the error between the real and predicted data, learning simple linear relationships between the worksite characteristics, incentives and the dependant variable "change in VTR," while the neural networks learn more complex non-linear relationships. Sometimes linear regression methods were used to determine which variables the neural net would use to build its models.

Several phases were followed to build the models. Models were built for each of the three datasets using a variety of approaches for handling the data, including variable selection, grouping of incentives, and the treatment of outliers. Models were also built after combining the data from the three urban areas into a single dataset. Assuming that the transportation industry was most interested in a model that predicted when large reductions could be achieved, the model performance objective was focused on predicting the change equally well across the range of the changes in VTR.

No single variable selection technique, data handling method, or modeling approach yielded the best-fitting model for all urban areas. In many cases, there was no significant performance difference between the top models, so the recommended model for some datasets had to be decided by using the F-value measure, which incorporated two other metrics: Recall, which gave a measure of the completeness of the model, and Precision, which gave a measure of the correctness of the model.

The best model for each city also was not the model that used data only from that city. Before combining the Los Angeles dataset with the others, the preferred model was the one built on the grouped incentives data with records with “no incentives” removed. After combining the datasets, the neural network model built with no variable selection performed better for Los Angeles than the model built with only data from Los Angeles. For Tucson data, a neural network model built on the equally sampled (i.e., each dataset contributes equally) data performed better than the previously selected neural network model built on the full sample (i.e., all valid records from the dataset) with ungrouped incentives data. The best model for the Washington data was the linear forced enter regression model built on full sample with ungrouped incentive data.

The generalized models for any urban area were built on the combined training datasets and equally sampled training datasets. The models built using equally sampled datasets were not biased towards any dataset. Overall, the best generalized model for any location was the neural net model built on equally sampled data based on three performance measures: (1) accuracy across the moderate range of change in VTR, (2) accuracy on full range of change in VTR, and (3) the R-square between the actual Delta_VTR and the predicted Delta_VTR (go to http://www.nctr.usf.edu/worksite). Overall, the neural net models performed better than the linear regression models, possibly because the neural network program can move beyond simple linear regression, which tries to minimize the error between the predicted and actual datasets. The neural network models in many situations could learn the non-linear relationships among various combinations of strategies. Some neural network models performed worse than the linear models, perhaps due to over-fitting the training data and reducing the neural net’s power to generalize unseen validation data.

BENEFITS

The developed model will allow transportation engineers, local planners, developers, employers, and TDM professionals to easily input various programs, incentives, disincentives, and worksite characteristics to obtain predictions about the change in vehicle trips from the input mix of tactics. The manual and model will (1) save the stakeholders time and money, (2) allow for a quick assessment of different worksite-based transportation demand management strategies on traffic volumes and parking impacts, (3) allow for assessment of parking needs in new developments (and potentially reduce the cost of parking construction), (4) enable informed decision-making regarding the types of services and programs employers and developers could offer employees, residents and tenants to decrease onsite traffic congestion and reduce their need for parking, and (5) contribute to improved air quality resulting from reduced vehicle traffic and vehicle miles traveled.

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