Journal of Transportation Management

Volume 21 | Issue 3 Article 9

10-1-2010

# Full Issue (21.2A, Fall 2010)

Journal of Transportation Management Editors

# Journal of Transportation Management

Vol. 21 No. 2 A
Fall 2010



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# Journal of Transportation Management



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ISSN# 1058-6199

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## Editorial Policy

The primary purpose of the JTM is to publish managerial and policy articles that are relevant to academics, policymakers, and practitioners in the transportation, logistics and supply chain fields. Acceptable articles could include conceptual, theoretical, legal, case, and applied research that contributes to better understanding and management of transportation and logistics. Saying that, our policy requires that articles be of interest to both academics and practitioners, and that they specifically address the managerial or policy implications of the subject matter. Articles that are strictly theoretical in nature, with no direct application to transportation and logistics activities, or to related policy matters, would be inappropriate for the *JTM*. Articles related to any and all types of organizations, and of local to global scope, will be considered for publication.
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Submissions from practitioners, attorneys or policymakers, co-authoring with academicians, are particularly encouraged in order to increase the interaction between groups. Authors considering the submission of an article to the *JTM* are encouraged to contact the editor for help in determining relevance of the topic and material.

The Editor information is: Dr. John C. Taylor, Associate Professor of Supply Chain Management, Department of Marketing and Supply Chain Management, School of Business, Wayne State University, Detroit, MI 48202. Office Phone: 313 577-4525. Cell Phone: 517 719-075. Fax: 313 577-5486. Email: taylorjohn@wayne.edu

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*Revised September 15, 2010*

# From the Editor...

This issue of the *Journal of Transportation Management* is dedicated to Dr. Donald J. Bowersox, a pioneer in the discipline of logistics and supply chain management. Don Bowersox started his career at Michigan State University in the early 1960's and went on to hold the John H. McConnell Chair in Business Administration, before additionally serving as Dean of the Eli Broad Graduate School of Management at MSU. Dr. Bowersox was a visionary leader that thousands of academics and practioners were inspired by and this discipline and profession will sorely miss him. For me personally, and many other Michigan State Ph.D. students, Dr. Bowersox was a life changing force that encouraged us to excel in what we did while moving the discipline forward. Those of us that were his students will try to carry on his mission and live up to his high expectations, however, the profession has lost an irreplaceable leader who gave his life to the field he loved.

At the *Journal*, we are continuing to make a number of changes that will improve the visibility of JTM, and improve its position in the supply chain publishing world. These include registering and updating journal information with several publishing guides, placing the journal content with the EBSCO, Gale and JSTOR databases faculty have access to, registering the journal with Google Scholar, and placing abstracts of all past journal articles on an open area of the DNA Journal web page. We are in the process of uploading all past issues to these various sites. Full journal article PDF's continue to be available to subscribers on the web page at www.deltanualpha.org with password: dna4education.

This issue of the *Journal* contains five articles on various aspects of transportation management, with three focusing on freight and logistics management, and two focusing on passenger transportation. The first freight related article focuses on truckload carrier management and investigates the relationship between various operating efficiency measures and financial success. The second article offers managerial guidelines for the use of artificial neural network software for use in transportation decision-making. The last logistics related article focuses on Air Force Logistics Readiness Officers and investigates the types of analytical tools that are of most use to logistics officers, with implications for military and industrial logistics education. The fourth article addresses benchmarking and evaluation of the efficiency of urban paratransit systems in the U.S. The final article examines passenger trip patterns in Akure, Nigeria.

I look forward to continuing my service as Editor of the *Journal*, and hope to hear from you our readers; with questions, comments and article submissions.

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# THE RELATIONSHIP BETWEEN MEASURES OF OPERATIONS EFFICIENCY AND FINANCIAL SUCCESS OF TRUCKLOAD MOTOR CARRIERS: AN EMPIRICAL ANALYSIS

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## ABSTRACT

This research paper examines the statistical relationship between day to day performance and efficiency measures and financial performance in the motor carrier industry. Key findings are that carriers with more miles per tractor per year, a larger average length of haul, more revenue per mile, and more revenue per tractor per week tend to perform better financially as measured in three separate models by operating ratio, return on assets, or return on equity. Unexpectedly, for the eight publicly traded carriers included in the analysis, there was a negative relationship between empty mile percentage and financial performance, indicating that carriers with a higher empty mile percentage have better financial performance. Possible explanations for these counterintuitive results could be due to a focus on better customer service or driver satisfaction causing slight increases in empty miles. Therefore the increased costs resulting from empty miles could be offset by higher revenue or decreased costs in other aspects of the operation. These results suggest that managers should focus not on minimizing empty miles but rather on keeping them within an acceptable range.

## INTRODUCTION

A commonly accepted measure of financial stability and general business health for a motor carrier is the operating ratio (OR). Operating ratio is defined as the ratio of operating expenses to operating revenue, and as such, a lower operating ratio signifies better profit margin for the firm (Coyle et. al, 2004). While operating ratio is an acceptable measure for evaluating motor carriers, it isn't necessarily the most effective tool for managers to measure the efficiency of a firm's day to day operations. For this reason, managers and dispatchers of motor carriers often rely on other measures such as average length of haul, empty mile percentage and revenue per mile to evaluate and manage day to day operations. The goal of most motor carriers is to increase length of haul and revenue per mile, while decreasing the empty mile percentage.

This study evaluated the statistical relationship between managerial measures of performance in daily operations and operating ratio. Specifically, a linear regression was conducted with operating ratio as the dependent variable and various managerial measures of performance as the independent variables. Return on assets (ROA) and return on equity (ROE) are also commonly used to measure a firm's performance, so two secondary analyses were conducted using return on assets as the dependent variable in one and using return on equity as the dependent variable in the other. While the relationship between operating ratio, return on assets, or return on equity and these explanatory variables seems fairly straightforward, an examination of the data resulted in some surprising and even counter-intuitive results. Potential reasons for these results, managerial implications, and directions for future research are also explored.

## FINANCIAL AND PERFORMANCE METRICS

The operating ratio is a measure of the general financial health of a firm but does not indicate any kind of operating efficiency. It is a ratio calculated as operating expenses divided by operating revenue, and was used by the Interstate Commerce

Commission to set motor carrier rates from 1935 until 1978. Questions about the rationale for using this measure as a standard have been raised by many authors. Wilson (1966) showed that the Interstate Commerce Commission's regulatory standard of 93 percent operating ratio translated into a 21 percent return on capital, while the railroads were regulated based on the rate of return standard and restricted to a 6 percent return on capital. This would mean that the two different standards would allow motor carriers to earn a much higher return than railroads were allowed to earn. Wilson argued that both types of transportation providers should be held to the same standards.

Nevel and Miklius (1968) showed "that the output which minimizes the operating ratio neither maximizes the profits of the firm nor is the optimum output from the point of view of society." They go on to say that the operating ratio is an ambiguous and possibly meaningless criterion. Their rationale was that a firm could have a "reasonable" operating ratio and still be earning either a large or small return. There does not have to be a correlation between the two measures despite the fact that one may exist. Due to these and other concerns, the ICC switched from an operating ratio standard to a return on equity standard in 1978 (Giordano, 1989), but even today, 20 years after deregulation, the operating ratio is still regularly reported as a standard, and carriers, such as Knight Transportation, who regularly report below average operating ratios are widely considered to be better managed. This is contrary to the financial evaluation of most other business, where return on assets and return on equity are considered more important than operating profit margin, the inverse of operating ratio. Despite this issue, with the data used in this study, there is a strong correlation between both operating ratio and return on assets (-0.87) and operating ratio and return on equity (-0.60).

Besides measures of financial performance, there are a variety of performance metrics used by motor carriers to manage day to day operations, yet minimal research has been done with regards to their impact on measures of financial success. Baker (1989) examined the relationship between traditional measures of carrier performance and survivability of LTL firms after de-regulation. He defined the measures of success as operating ratio, average length of haul, average weight per load, percentage of LTL traffic, and rate per hundredweight. Baker found that operating ratio had an inverse relationship to survival and length of haul had a positive relationship with survival, as would be expected, but he found no strong relationships with the other measures of success.

Corsi, Barnard, and Gibney (2002) examined at the relationship between financial performance and safety ratings in the motor carrier industry. They defined measures of financial performance as being the operating ratio and return on assets. Results for general freight carriers revealed that carriers with satisfactory carrier reviews had lower operating ratios than carriers with non-satisfactory carrier reviews. However there was no significant relationship between financial performance and specific safety ratings. They also defined carrier operating characteristics as gross revenue, total ton-miles, average weight per load, average length of haul, and driver's wages and looked for relationships between these measures and safety ratings. For these measures, they found no significant relationship with satisfactory/non-satisfactory carrier reviews. However, a positive correlation between average length of haul and driver safety ratings and a negative correlation between driver's wages and both vehicle and driver safety ratings was found.

Cottrell (2008) wrote a descriptive paper on performance metrics uses by carriers based on surveys with Frozen Food Express, US Xpress, and USA Truck. Three measures that were reported as very important to the industry were operating ratio, average length of haul, and an empty miles factor. Other commonly used metrics reported by Cottrell were equipment utilization rate, revenue per loaded mile, and shipments per business day. Examples of measures of equipment utilization are loads per tractor per week and miles per tractor per week. Other metrics commonly reported by carriers in annual reports are revenue per load, revenue per tractor per week, and revenue per mile. The independent variables for the current study were selected based on those performance metrics which are "very important" to the literature and those which are commonly reported.

The studies reviewed found that operating ratio is commonly used to evaluate the financial performance of carriers, yet its importance as a measure of financial performance has been called into question. Managers rely on performance metrics to run business operations, presumably, with the intention of improving the financial performance of the firm, yet there has been little or no research examining how these managerial performance metrics relate to measures of financial performance. This paper seeks to fill this gap in the literature.

## DATA

ACT Research (2010) collects and reports operational metrics for publicly traded truckload carriers. The data is obtained from the annual reports of said carriers. Based on the data available and commonly used carrier performance metrics, six potential metrics were identified as potentially related to operating ratio and commonly measured by carriers: miles per tractor per year (MTY), average length of haul (ALH), empty mile percentage (EMP), revenue per mile (RM), revenue per tractor per week (RTW), and loads per tractor per week (LTW). Because average length of haul and loads per tractor per week were highly correlated (-0.89) only one of these metrics was used in the regression analysis. Because average length of haul is more commonly reported and available for more carriers in more years, it was used as an independent variable rather than loads per tractor per week. This resulted in five performance measures used as independent variables in the final model. Information for JB Hunt was reported incorrectly by ACT Research for some years; therefore, data for that carrier was obtained directly from annual reports submitted to the Securities and Exchange Commission (JB Hunt, 2005-2010).

Complete information was available for seven carriers from 1999-2009. However, data was available on some carriers from 1990-2009, and the particular model used for analysis did not require a balanced panel. Including all carriers for all years in which data was available resulted in 119 usable observations, rather than 77, and eight carriers in the final sample. These additional observations alleviated a problem with too few degrees of freedom which arose when the model was estimated using only 77 observations. While the eight carriers included in the sample represent a relatively small proportion of total truckload carriers, they represent a disproportionately large percentage of the revenue for this highly fragmented industry as detailed in Table 1 (US Census Bureau, 2010).

**TABLE 1**
**SIZE OF SAMPLE RELATIVE TO INDUSTRY***

| | 2002 | 2007 |
|---|---|---|
| Number of Carriers in Sample | 8 | 8 |
| Number of Carriers in Industry | 30,043 | 0,759 |
| Percent of Industry Carriers Represented by Sample | 0.03 | 0.03 |
| Revenue of Sample ($M) | 5,909 | 9,013 |
| Revenue of Industry ($M) | 65,030 | 3,385 |
| Percent of Industry Revenue Represented by Sample | 8.63 | 13.86 |

*Source: (US Census Bureau, 2010)
Industry defined as general freight trucking long-distance truckload (NAICS code 484121)

For revenue per mile and revenue per tractor per week, each observation was divided by the implicit price deflator to convert all monetary observations into 2005 dollars (Bureau of Economic Analysis, 2010). Each carrier's average value of each variable as well as the entire sample's average values of each variable are reported in Table 2. Table 2 also reports the years for which each carrier's observations were included in the final sample.

Some correlation between the independent variables was found, but the highest correlation coefficient was 0.65, and all estimated coefficients were significant in the final model, so this was assumed not to be a significant factor in the analysis. However this could be the cause of the lower significance of some estimated coefficients in the model with return on equity as the dependent variable. The correlation matrix is reported in Table 3. Both

**TABLE 2**
**AVERAGE VALUES OF VARIABLES LISTED BY CARRIER**

| Carrier | OR | ROA | ROE | MTY | ALH | EMP | RM | RTW |
|---|---|---|---|---|---|---|---|---|
| Celadon Trucking (1994-2009) | 94.77 | 1.8 | 2.7 | 109,097 | 1052 | 9.0 | $ 1.34 | $ 2,794 |
| Covenant Transport (1992-2009) | 94.91 | 1.7 | 10.0 | 135,268 | 1306 | 7.6 | $ 1.32 | $ 3,435 |
| J B Hunt (2004-2009) | 89.79 | 6.3 | 10.1 | 94,564 | 518 | 11.9 | $ 1.76 | $ 3,320 |
| Knight Transportation (1994-2009) | 83.25 | 10.7 | 16.2 | 113,438 | 519 | 11.0 | $ 1.46 | $ 2,959 |
| Marten Transport (1999-2009) | 93.42 | 7.7 | 22.1 | 111,823 | 947 | 7.2 | $ 1.64 | $ 3,149 |
| PAM Transportation (1990-2009) | 94.02 | 3.6 | 7.5 | 120,545 | 761 | 6.1 | $ 1.33 | $ 3,250 |
| USA Truck (1994-2009) | 93.94 | 3.2 | 6.4 | 119,716 | 845 | 9.8 | $ 1.36 | $ 3,048 |
| Werner Enterprises (1994-2009) | 91.61 | 4.8 | 8.4 | 122,570 | 689 | 10.9 | $ 1.39 | $ 3,288 |
| Overall Average | 91.97 | 5.0 | 10.4 | 115,877 | 830 | 9.2 | $ 1.45 | $ 3,155 |

OR = Operating Ratio
ROA = Return on Assets
ROE = Return on Equity
MTY = Miles per Tractor per Year
ALH = Average Length of Haul
EMP = Empty Mile Percentage
RM = Revenue per Mile
RTW = Revenue per Tractor per Week

**TABLE 3**
**CORRELATION MATRIX OF INDEPENDENT VARIABLES**

| | MTY | ALH | EMP | RM | RTW |
|---|---|---|---|---|---|
| Miles Per Tractor Per Year | 1 | | | | |
| Average Length of Haul | 0.561479 | 1 | | | |
| Empty Mile Percentage | -0.53802 | -0.56472 | 1 | | |
| Revenue Per Mile | -0.30121 | -0.11134 | 0.165601 | 1 | |
| Revenue/Tractor Per Week | 0.652937 | 0.449323 | -0.44288 | 0.287514 | 1 |

the correlation matrix and average variable values per carrier were very similar for both the complete data set used and the balanced data set from 1999-2009, further justifying the inclusion of the additional observations available back to 1990.

## STATISTICAL MODEL

Analysis was conducted via a regression analysis using SHAZAM. The dependent variable was operating ratio and independent variables were miles per tractor, average length of haul, empty mile percentage, revenue per mile, and revenue per tractor per week. Firm specific dummy variables, Fi, for all carriers except Werner Enterprises were included to control for differences between firms, and year specific dummy variables, Yj, for all years except 2009 were included to control for any differences between years that were not accounted for by converting the monetary values into 2005 dollars. An intercept term was also included in the final model. This resulted in Equation 1 which was the final model estimated. The only change between this and the alternate models is that return on assets and return on equity are substituted for operating ratio in the two alternate models estimated. These substitutions are shown in Equation 2 and Equation 3.

Due to autocorrelation of most of the included variables, estimation by ordinary least squares was not feasible, so a pooled cross section model available in SHAZAM was used for analysis. This is a generalized least squares estimation that allows for autocorrelation, cross-sectional heteroskedasticity and cross-sectional independence. This model also allows for unbalanced panels. Tests for the assumptions of heteroskedasticity and independence were conducted using the balanced panel data from 1999-2009. There were no statistical differences between the estimated coefficients from a model using this balanced panel and one using the full data set, but there was a lack of degrees of freedom from the balanced panel which resulted in higher standard errors. Furthermore, estimating the model using the full data set resulted in superior goodness of fit measures. An iterative procedure was used to improve the estimates. See Whistler et al. (2004) for details of the Pool command in SHAZAM.

### Hypotheses

Hypotheses for the study were developed based on the managerial measures of performance selected for inclusion as independent variables in the final models and the three measures of firm financial performance selected as dependent variables. Increased miles per tractor per year, an increase in average length of haul, and a decrease in empty mile percentage, should all correspond to better asset utilization and less non-revenue-generating time between shipments. This should result in lower operating costs without a corresponding decrease in operating revenue. If operating costs are reduced while operating revenue remains the same, and there is no change in assets or owners' equity, return on both assets and equity should increase. Based on this logic the following three sets of hypotheses were developed:

H1A: There is a negative relationship between miles per tractor per year and operating ratio.
H1B: There is a positive relationship between miles per tractor per year and return on assets.
H1C: There is a positive relationship between miles per tractor per year and return on equity.

1 $$OR = \alpha + \sum \beta_i F_i + \sum \beta_j Y_j + \beta_{MTY} MTY + \beta_{ALH} ALH + \beta_{EMP} EMP + \beta_{RM} RM + \beta_{RTW} RTW$$

2 $$ROA = \alpha + \sum \beta_i F_i + \sum \beta_j Y_j + \beta_{MTY} MTY + \beta_{ALH} ALH + \beta_{EMP} EMP + \beta_{RM} RM + \beta_{RTW} RTW$$

3 $$ROE = \alpha + \sum \beta_i F_i + \sum \beta_j Y_j + \beta_{MTY} MTY + \beta_{ALH} ALH + \beta_{EMP} EMP + \beta_{RM} RM + \beta_{RTW} RTW$$

H2A: There is a negative relationship between average length of haul and operating ratio.
H2B: There is a positive relationship between average length of haul and return on assets.
H2C: There is a positive relationship between average length of haul and return on equity.

H3A: There is a positive relationship between empty mile percentage and operating ratio.
H3B: There is a negative relationship between empty mile percentage and return on assets.
H3C: There is a negative relationship between empty mile percentage and return on equity.

Increasing revenue per mile or revenue per tractor per week should increase total revenue without a corresponding increase in operating costs, leading to a decrease in operating ratio. This should also lead to an increase in return on assets and equity, provided there is no change in either assets or owners' equity. This results in the following hypotheses:

H4A: There is a negative relationship between revenue per mile and operating ratio.
H4B: There is a positive relationship between revenue per mile and return on assets.
H4C: There is a positive relationship between revenue per mile and return on equity.

H5A: There is a negative relationship between revenue per tractor per week and operating ratio.
H5B: There is a positive relationship between revenue per tractor per week and return on assets.
H5C: There is a positive relationship between revenue per tractor per week and return on equity.

## RESULTS

The final models as previously discussed were estimated to test the five Hypotheses for each of the three models. These models resulted in estimates, which each had a fairly high Buse R2, which is a goodness of fit measure for generalized least squares models (Buse, 1973). Final estimated coefficients of the primary variables and goodness of fit measures of all three final models are reported in Table 4, and the full estimation results are shown in Appendix 1.

Estimated coefficients of the dummy variables confirm what is relatively apparent from an examination of the descriptive variables. Knight Transportation and JB Hunt have lower operating ratios and higher returns on assets and equity than Werner Enterprises; Werner Enterprises, Celadon Trucking Services, Marten Transport, and PAM Transportation Services have very similar operating ratios, returns on assets, and returns on equity;

**TABLE 4**
**ESTIMATED COEFFICIENTS**

| Variable Name | Estimated Coefficient OR Model | Estimated Coefficient ROA Model | Estimated Coefficient ROE Model |
|---|---|---|---|
| Miles per Tractor per Year | -0.00011* | 0.00014* | 0.00034* |
| Average Length of Haul | -0.00606* | 0.00844* | 0.02341* |
| Empty Mile Percentage | -0.66082* | 0.76696* | 1.53090** |
| Revenue per Mile | -5.19430* | 4.86520* | 10.56200 |
| Revenue per Tractor per Week | -0.00203** | 0.00214** | 0.00644** |
| Buse R2 | 0.8876 | 0.8858 | 0.7620 |
| Buse Raw Moment R2 | 0.9997 | 0.9788 | 0.9130 |

* Indicates significance at the 0.05 level
** Indicates significance at the 0.10 level

and Covenant Transport and USA Truck have higher operating ratios and lower returns on assets than Werner Enterprises, however USA Truck has a similar return on equity to Werner while Covenant Transport has a lower return on equity.

With regards to the impact of different years on the carrier's operating ratio, the operating ratio tended to be at the same level as in 2009 in 1992-1993, 1996, and 2000-2007; lower than 2009 levels in 1994-1995 and 1997-1999; and higher than 2009 levels in 1990, 1991, and 2008. Return on assets was lower than 2009 levels in 1990-1991, 1996, 2000-2001, and 2008 and not statistically different than 2009 levels for all other years. Return on equity was lower than 2009 levels in 1990-1991, 1996, 2001, and 2008. These periods of higher operating ratios and lower returns correspond fairly well to the July 1990 – March 1991 recession and the December 2007 – June 2009 recession. The March 2001 – November 2001 recession and 1996 near recession did not appear to increase operating ratios to levels above those of 2009 but did reduce returns on assets and equity.

Based on the results of the analysis, Hypotheses 1A-C, 2A-C, and 4A-B are strongly supported, and Hypothesis 4C is rejected. Increasing miles per tractor per year and average length of haul correlates to a lower operating ratio, higher return on assets, and higher return on equity. Increasing revenue per mile does correlate to a decrease in operating ratio and increase in return on assets but does not appear to correlate to any type of change in return on equity. While the coefficient is not significant, it is in the direction hypothesized (positive). The reason for this odd result is most likely due to the lower explanatory power of the ROE model (R2 = 0.76) compared to the OR and ROA models (R2 = 0.89). Hypotheses 5A-C are marginally supported. An increase in revenue per tractor per week does correlate with a lower operating ratio, higher return on assets, and higher return on equity. However, Hypotheses 3A-C are all rejected. Not only are these hypotheses rejected, but the estimated coefficients are significant in the opposite direction of that hypothesized. An increase in empty mile percentage correlates to a decrease in operating ratio, an increase in return on assets, and an increase in return on equity.

## DISCUSSION AND IMPLICATIONS

These results, as reported in Table 3 are rather esoteric but can easily be translated into a form that managers of motor carriers could find useful. The estimated coefficient of miles per tractor per year is 0.000108, indicating that, on average, increasing miles per tractor per year by 1 unit and holding everything else constant should increase operating ratio by 0.000108, increase return on assets by 0.00014, and increase return on equity by 0.000336. When the scale of this result is increased by a factor of 1,000, it can be seen that an increase of 1,000 miles per tractor per year should result in a 0.108 point increase in operating ratio, a 0.140 point increase in return on assets, and a 0.336 point increase in return on equity. A similar process can be employed on the remaining independent variables to show the impact on the dependent variables resulting from changes to them. Increasing the average length of haul by 100 miles should result in a 0.605 point reduction in operating ratio, a 0.844 point increase in return on assets, and a 2.341 point increase in return on equity. An increase of $0.10 per mile should result in a 0.519 point reduction in operating ratio and a 0.486 point increase in return on assets. Finally, an increase of $100 per tractor per week should result in a 0.203 point reduction in operating ratio, a 0.214 point increase in return on assets, and a 0.644 point increase in return on equity.

The estimated coefficient of empty mile percentage in the operating ratio model is negative and highly significant. This indicates that carriers with more empty miles tend to have lower operating ratios and thus higher profit margins. Specifically, a one percent increase in empty mile percentage (e.g. going from four to five percent empty miles) should result in a 0.661 point reduction in operating ratio. Furthermore, a one percent increase in empty mile percentage should result in a 0.767 point increase in return on assets and a 1.53 point increase in return on equity. These results seem counter-intuitive, but there are many potential explanations for them.

One potential reason for the inverse relationship between empty mile percentage and operating ratio could be that carriers with more empty miles are providing better customer service by being willing to drive additional empty miles in order to pick up a customer's load. Such a carrier would gain customer loyalty and, and as a result, be able to demand higher revenue per mile. However, looking at Table 1 makes it clear that Knight Transportation, with the lowest average operating ratio and one of the highest average rates of return, does not have the highest revenue per mile, so better customer service may only be part of the explanation.

An additional possible explanation for the apparent benefit of increased empty miles might be that the better performing carriers acquire more empty miles in an attempt to get their driver's home more often. This could result in more content and happier drivers, and having happier drivers might contribute to a reduction in driver turnover. Since it has been estimated that the cost to hire a driver is between $3,000 and $12,000 (Richard et al., 1994; Isidore, 1996), a reduction in driver turnover could result in a significant reduction in operating costs. However, with drivers not being paid for empty miles, it is possible that a shorter time between loads and more time home wouldn't provide enough benefit to the driver to offset his/her dissatisfaction with having excessive empty miles.

## CONCLUSION

For the most part, this study confirms a correlation between commonly used measures of effectiveness in motor carriers and three commonly used measure of financial performance in motor carriers. The one surprising exception was the relationship between empty mile percentage and financial performance. The results of the study indicate that, among the eight publicly traded truckload motor carriers included, an increase in empty miles is related to a decrease in operating ratio, a corresponding increase in profit margin, an increase in return on assets, and an increase in return on equity. Possible reasons for this could be better customer service resulting in an increase in revenue that offsets the additional costs associated with more empty miles, lower driver turnover resulting from drivers being happier due to more loads and more time home, or some combination of these.

This result indicates that managers of carriers should not focus heavily on decreasing empty miles as long as they remain below a certain level. None of the carriers in this sample had more than 13.6 percent empty miles or less than 4 percent empty miles, so the results of this analysis may only hold true within this relatively narrow range. It may certainly be the case that an empty mile percentage higher than 13.6 percent would lead to a significant increase in operating ratio and decrease in returns. However, the results of this study do seem to indicate that carriers need not worry excessively about keeping a low empty mile percentage at the expense of customer or driver satisfaction.

The results of this study should not be used as justification for carriers to increase their empty miles without reason or discard empty miles as a performance metric because there is clearly some additional factor(s) involved in the relationship that has not been accounted for in this study. Whatever the reason for the relationship between empty miles and measures of financial performance may be, this study shows that carriers with good financial performance are somehow able to overcome and even offset the additional costs of increased empty miles. This indicates that motor carrier managers should attempt to keep their empty mile percentage within an acceptable range rather than trying to keep it as low as possible.

## REFERENCES

ACT Research (2010), "Publicly Traded Truckload Carriers Database," [On-line]. Available: http://www.actresearch.net/. Created: 05/18/10, Accessed: 06/28/10.

Baker, Jace A. (1989), "Measures of Effectiveness for LTL Motor Carriers," *Transportation Journal*, 29(2): 47-53.

Bureau of Economic Analysis (2010), "Table 1.1.9 Implicit Price Deflators for Gross Domestic Product," [On-line]. Available: http://www.bea.gov/. Created: 08/27/10, Accessed: 09/08/10.

Buse, A. (1973), "Goodness of Fit in Generalized Least Squares Estimation," *The American Statistician*, 27(3): 106-108.

Corsi, Thomas M., Barnard, Richard, and James Gibney (2002), "Motor Carrier Industry Profile: Linkages Between Financial and Safety Performance Among Carriers in Major Industry Segments," [On-line]. Available: http://ai.volpe.dot.gov/carrierresearchresults/pdfs/financialsafety_mcips.pdf. Created: 07/25/02, Accessed: 09/02/10.

Cottrell, Wayne D. (2008), "Performance Metrics Used by Freight Transport Providers," [On-line]. Available: http://leonard.csusb.edu/research/documents/1011FinalReport.pdf. Created: 09/30/08, Accessed: 08/16/10.

Coyle, John J., Bardi, Edward J., and Robert A. Novack (2004), *Transportation*, 6th ed., Cincinnati, OK: South-Western College Publishing.

Giordano, James (1989), "A Trucker's Dilemma: Managerial Behavior Under an Operating-Ratio Standard," *Managerial and Decision Economics*, 10(3): 241-251.

Isidore, Chris (1996), "Dissatisfied Truckers Cost Sector Billions" *Journal of Commerce*, 407(28): 663

JB Hunt (2005-2010), "Annual Report," [On-line]. Available: http://www.sec.gov. Created: 03/11/05, 03/10/06, 02/28/07, 02/29/08, 02/27/09, and 02/26/10, Accessed: 09/10/10.

Nevel, R. and W. Miklius (1968), "The Operating Ratio as a Regulatory Standard," *Transportation Journal*, 8(2): 15-18.

Richard, Michael D., LeMay, Stephen A., Taylor, G. Stephen, and Gregory B. Turner (1994), "A Canonical Correlation Analysis of Extrinsic Satisfaction in a Transportation Setting," *The Logistics and Transportation Review*, 30(4): 327-338.

US Census Bureau (2010), "Detailed Statistics," [On-line]. Available: http://factfinder.census,gov. Created: 08/29/10, Accessed: 07/13/11.

Whistler, Diana, White, Kenneth J., Wong, S. Donna, and David Bates (2004), *Shazam Econometrics Software*: User's Reference Manual Version 10, Vancouver: Northwest Econometrics, Ltd.

Wilson, George W. (1966), "The I.C.C Profit Criteria – Rail vs. Truck," *Transportation Journal*, 6(1): 17-19.

## APPENDIX 1
## FULL ESTIMATION RESULTS

| | Estimated Coefficient: | | |
|---|---|---|---|
| Variable Name | OR Model | ROA Model | ROE Model |
| Constant | 131.13000* | -37.52600* | -94.95800* |
| Celadon Trucking Services | 1.06270 | -3.04910 | -5.13480 |
| Covenant Transport | 6.00350* | -9.69590* | -17.09700* |
| J B Hunt | -4.35610* | 6.94390* | 26.69500* |
| Knight Transportation | -10.56100* | 7.31510* | 13.80500* |
| Marten Transport | 0.01505 | -0.63418 | 0.65063 |
| PAM Transportation Services | -0.09433 | 0.99695 | 3.96460 |
| USA Truck | 1.53470* | -2.20620* | -2.25060 |
| 1990 | 10.86600* | -22.65600* | -77.91000* |
| 1991 | 6.77600* | -16.66000* | -60.88300* |
| 1992 | 0.62539 | -1.85370 | 30.03100 |
| 1993 | -1.10570 | -1.32160 | 20.64400 |
| 1994 | -3.47250* | -1.17010 | -5.30550 |
| 1995 | -2.78660* | -0.71414 | -3.96980 |
| 1996 | -0.60214 | -2.78390* | -10.76600* |
| 1997 | -2.55300* | -0.34976 | -4.06440 |
| 1998 | -3.48060* | -0.45585 | -3.26450 |
| 1999 | -2.25350* | -1.29600 | -2.94250 |
| 2000 | 0.32259 | -2.19710* | -5.39820 |
| 2001 | 0.80194 | -2.85830* | -7.52380* |
| 2002 | -0.78241 | -0.89149 | -4.75730 |
| 2003 | -1.08870 | -0.75707 | -4.08850 |
| 2004 | -0.99857 | -0.55248 | -3.35250 |
| 2005 | -0.93789 | -0.02315 | -1.76810 |
| 2006 | -0.81417 | -0.02873 | -2.99260 |
| 2007 | 0.93360 | -1.14120 | -3.42490 |
| 2008 | 2.30030* | -2.99610* | -4.92870** |
| Miles Per Tractor Per Year | -0.00011* | 0.00014** | 0.00034* |
| Average Length of Haul | -0.00606* | 0.00844* | 0.02341* |
| Empty Mile Percentage | -0.66082* | 0.76696** | 1.53090** |
| Revenue Per Mile | -5.1943* | 4.86520* | 10.56200 |
| Revenue Per Tractor Per Week | -0.00203** | 0.00214** | 0.00644** |
| Buse R2 | 0.8876 | 0.8858 | 0.7620 |

*Indicates significance at the 0.05 level **Indicates significance at the 0.10 level

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# USING ARTIFICIAL NEURAL NETWORKS FOR TRANSPORT DECISIONS: MANAGERIAL GUIDELINES

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## ABSTRACT

One information technology that may be considered by transportation managers, and which is included in the portfolio of technologies that encompass TMS, is artificial neural networks (ANNs). These artificially intelligent computer decision support software provide solutions by finding and recognizing complex patterns in data. ANNs have been used successfully by transportation managers to forecast transportation demand, estimate future transport costs, schedule vehicles and shipments, route vehicles and classify carriers for selection. Artificial neural networks excel in transportation decision environments that are dynamic, complex and unstructured. This article introduces ANNs to transport managers by describing ANN technological capabilities, reporting the current status of transportation neural network applications, presenting ANN applications that offer significant potential for future development and offering managerial guidelines for ANN development.

## INTRODUCTION

In today's intensely competitive and dynamic global market, serviced by complex, global supply chains, improving the quality of transportation management decisions will result in significant increases in corporate profitability and customer service performance (Holcomb and Manrodt, 2007). As the largest logistics cost component, representing 62.8 percent of U.S. total logistics costs in 2010 (Wilson, 2011), transportation can affect profits significantly. Additionally, transportation management decisions affect the length and variability of material and finished goods delivery leadtimes which directly impacts operational and customer service performance.

Improving transportation management decision quality in the current complex, turbulent supply chain environment is a substantial challenge. It is not surprising that many transportation managers in recent years have adopted transportation management systems (TMS) (Griffis and Goldsby, 2007). These systems are information technologies used to plan and execute transportation operations (Coyle, et al., 2009).

One information technology that may be considered by transportation managers to be included in the portfolio of technologies that encompass TMS is artificial neural networks (ANNs). These artificially intelligent computer decision support software provide solutions by finding and recognizing complex patterns in data. Based on a computing model similar to the underlying structure of the human brain, ANNs share the brain's ability to learn or adapt in response to external inputs. When exposed to data, ANNs discover previously unknown relationships in the data (Kamruzzaman et al., 2006; Smith and Gupta, 2000).

ANNs have been used successfully by transportation managers to make decisions in a number of critical decisions areas including: transport demand forecasting, transportation cost estimation, vehicle and shipment scheduling, vehicle routing and carrier classification and selection. In addition, when faced with challenging decision environments, transport managers who utilized ANNs were rewarded with excellent results (Duliba, 1990). For example, Victory Shipping Company employed an ANN to route leased container shipments from Shanghai, China to global destinations using a myriad of databases. The ANN reduced costs and achieved 100 percent on-time delivery (Lau et al., 2004). Also, by using an ANN to select containers to inspect, Chinese customs inspectors were able to maintain the same level of security while decreasing the number of container inspections to only 30 percent of the pre-ANN total (Hua, Li and Tao, 2006).

This article introduces ANNs to transport managers by describing ANN technological capabilities, reporting the current status of transportation neural network applications, presenting ANN applications that offer significant potential for future development and offering managerial guidelines for ANN development.

## ANN TECHNOLOGICAL CAPABILITIES

Artificial neural networks are capable of performing several generic tasks that transport managers perform. These generic tasks involve interpreting, predicting, diagnosing, designing, planning, monitoring, repairing and controlling

When transport managers must perform any of these generic tasks in a very challenging decision environment, ANN technology may be very useful. Specifically, artificial neural networks excel in transportation decision environments that are: (1) dynamic- involving data that is incomplete, non-linear and/or rapidly changing (e.g. forecasting demand for transportation (Nijkamp, Reggianni and Tsang, 2004)); (2) complex- involving numerous alternatives, large amounts of data and many variables (e.g. designing routes for pickup and delivery (Ghaziri and Osman, 2006)); and (3) unstructured- involving variables that are both quantitative and qualitative (e.g. selecting a third party transportation partner). In contrast, traditional TMS decision support tools such as linear regression, mathematical optimization and linear programming are better suited to transport decision environments where: (1) data is linear, less dynamic and more complete and (2) there are fewer variables that are all quantitative in nature.

ANNs excel in very challenging transportation decision environments because they possess the following capabilities:

- **Reaches conclusions in problem domains that are not well understood**: enables managers to solve problems when no exact model of the underlying process exists (e.g. using an ANN to forecast European inter-regional truck freight flows for food and chemicals (Nijkamp et al., 2004));

- **Rapid knowledge acquisition**: enables managers to leverage numerous, large, existing databases to solve problems (e.g. an ANN was used to forecast VLCC freight rates for 3, 6, 9 and 12 month periods using numerous large databases involving: demand for oil transport, crude oil pricing, time charter rates, and crude oil production among others (Lyridis et al., 2004));

- **Rapid processing and response**: enables managers to receive decision support quickly despite the dynamic, complex, unstructured nature of the data and problem environment (e.g. an ANN is being used to control a gasoline engine fuel-air ratio between cycles to decrease $NO_2$ emissions (Editor, The Engineer, 2004)); and

- **Learns from previous applications**: enables managers to receive better solutions over time (e.g. an ANN learns and makes better decisions over time as it schedules daily assignments of inland barges to pusher tugs at a loading port and provides decision support to dispatchers when changes are necessary (Vukadinovic et al., 1997)).

## TABLE 1
## GENERIC TASKS PERFORMED BY ARTIFICIAL NEURAL NETWORKS

| Task | Definition | Potential Application |
|---|---|---|
| **Interpreting(classifying)** | Infer situation description from observations | Classifying carriers for consideration in a carrier selection decision |
| **Predicting (forecasting, estimating)** | Infer likely consequences of given situations | Forecasting transportation demand in a dynamic market |
| **Diagnosing** | Infer malfunctions from observations | Diagnosing vehicle malfunctions from vehicle operating data |
| **Designing** | Configure objects under constraints | Designing facility locations (network design) and optimizing routes |
| **Planning** | Designing actions | Optimizing scheduling of vehicle arrivals/loading at facilities |
| **Monitoring** | Compare observations to plan vulnerabilities | Monitoring vehicle/pipeline operations |
| **Repairing** | Prescribe malfunction remedies and plans to implement remedies | Prescribing vehicle repairs that are timely and cost effective |
| **Controlling** | Interpret, predict, repair and monitor system behavior | Controlling engine performance for improved energy use |

### ANN Advantages and Disadvantages

The application of ANN technology to transportation management decision making may result in significant improvements in transportation effectiveness and efficiency when compared to traditional TMS mathematical tools. Examples of potential improvements include the following:

- **More effective decisions**: In complex operating environments, ANNs can provide better scheduling and routing of shipments (Schwardt and Dethloff, 2005) and better monitoring of operations (Rahmat et al., 2010);

- **Faster response**: In complex operating environments, ANNs can prescribe flight corrections in seconds to help pilots land aircraft during in-flight emergencies (Corder, 2004);

- **Improved accuracy**: In unstructured environments, ANNs can provide more accurate transport demand forecasts (Nam et al., 1995), more accurate price forecasts (Lyridis et al., 2004) and more accurate cost estimates (Williams, 2002); and

- **More efficient decisions**: In dynamic environments, ANNs can design more cost efficient loading schedules (Zeng and Yang, 2009).

There are some drawbacks to developing and using neural networks. Some disadvantages of ANNs are as follows (Kamruzzaman et al., 2006; Bigus, 1996):

- **No explanation of solution**: ANNs will not provide an explanation of the functional relationships among the variables involved;

- **Large data preparation effort**: 50 to 75 percent of development time is spent accessing, cleansing and coding data for use by the ANN; and

- **Training ANNs can be challenging**: Usually, an ANN is trained for a specific problem and for some complex problems might require hundreds of iterations before it is sufficiently trained.

Despite these drawbacks, ANN development for use in transportation management has grown in the last two decades.

## ANN TRANSPORTATION APPLICATIONS

In the past twenty years, numerous ANNs have been developed and used to improve transportation management decisions. In fact, ANNs have been applied effectively to numerous transportation areas including: transport planning, operations, operations support, international transportation, transport equipment manufacturing, infrastructure development, transport energy and security. Table 2 provides a list of several recent ANN applications.

### Current Applications

The leading transportation management category for ANN applications is transport operations. The primary focus of operations applications has involved vehicle or shipment scheduling and routing. Transport operations support ANNs have been primarily developed to monitor vehicle operations, detect vehicle operational malfunctions and support vehicle repair. Transport planning and international transport ANNs have focused on forecasting applications in three areas: (1) transport demand forecasts (e.g. global, country, regional, local, and modal); (2) transport rate forecasts (e.g. freight rates, monetary exchange rates); and (3) transport project cost forecasts (e.g. long-term construction projects such as roads, building, and bridges). Transport equipment manufacturing ANNs have supported various aspects of vehicle production while transport infrastructure development ANNs have focused on forecasting costs. Transport energy ANNs have been developed to forecast fuel demand/consumption and improve vehicle energy use. Finally, transport security applications have addressed border, transport asset and shipment security.

### Future Applications

There are many significant opportunities to utilize ANN technology to improve transportation effectiveness and efficiency given the dynamic, complex, and unstructured decision environment often facing transportation managers. Table 1 provides a potential transportation application for each generic task. In addition, the following set of more detailed applications is provided to illustrate the significant opportunities for future ANN development.

*Fuel Price Forecaster:* An ANN may be developed to forecast future gasoline or diesel fuel prices to help transportation managers develop fuel procurement strategies and serve as an input to transportation planning. The neural network could analyze data such as: global fuel consumption patterns, fuel production and inventory levels, fuel production capacities, risk of supply shortage due to global events/disasters, and pricing data to predict future fuel prices. A fuel price forecast ANN could enable managers to develop effective and efficient transport plans.

*Global Route Assessor*: An ANN may be developed to assess a proposed global shipment route to determine if it is viable. Factors considered could include likely leadtime length and variability; expected vehicle operating costs; and likely risk factors such as natural disasters, piracy, terrorism, and political unrest among others. A global route assessment ANN could enable managers to select global routes that are efficient and sustainable.

**TABLE 2**
**CURRENT TRANSPORTATION APPLICATIONS**

| Category | Transportation Neural Networks |
|---|---|
| **Transport Planning** | Predicts global requirements for logistics expenditures (Bowersox et al. 2003<br>Predicts individual country logistics expenditures (Rodriques et al. 2005)<br>Predicts regional Europe road food & chemical commodity freight flows (Nijkamp et al. 2004)<br>Predicts oil tanker(VLCC) spot freight rates for specific routes (Lyridis et al. 2004)<br>Predicts short-term traffic flow for Hong Kong to improve city planning (Lam et al. 2006)<br>Predicts vehicle travel time on a congested 17 mile 2 lane highway (Innamaa, 2005) |
| **Transport Operations** | Schedules vessels to optimize port capacity utilization (Lokuge and Alahakoon, 2007)<br>Predicts unexpected events to improve aircraft container loading/scheduling (Lau et al. 2004)<br>Schedules daily assignment of barges to pusher tugs at the port (Vukadinovic et al. 1997)<br>Designs routes for pickup delivery from customers from 1 site (Ghaziri and Osman, 2006)<br>Designs vehicle routes among a fixed set of bus stops (Creput and Koukam, 2007)<br>Designs routes from 1 location to multiple customers (Schwardt and Dethloff, 2005)<br>Identifies facility locations and assigns customers to a specific facility (Aras et al. 2006)<br>Prescribes flight correction to help pilot land aircraft during in-flight emergency (Corder, 2004)<br>Helps simulation model schedule container loading at terminals (Zeng and Yang, 2009)<br>Controls isolated road intersection traffic light changes & traffic flow (Teodorovic et al. 2006)<br>Improves outcomes of a shipper negotiation with a freight forwarder (Rau et al. 2006) |
| **Transport Operations Support** | Predicts part failures and provides inspection schedules for aging aircraft (Luxhoj et al. 1997)<br>Detects railcar bearing defects from shock impulse data (Editor, 1996)<br>Improves monitoring of solid particles flow in a pipeline (Rahmat et al. 2010)<br>Monitors oil platform leak detection systems on submerged oil transfer lines (Harrold, 1998)<br>Predicts vehicle downtime (Wang, Chen and Bell, 2005)<br>Predicts bus equipment part failure rates and resulting repair costs (Bellandi et al. 1998) |
| **International Transport** | Identifies critical customer services desired by ocean freight shippers (Durvasula et al. 2007)<br>Identifies import shipments to inspect for Chinese custom inspectors (Hua, Li and Tao, 2006)<br>Predicts daily exchange rates for US dollar with Euro and Canadian dollar (Jamal, 2005)<br>Predicts airline passenger traffic for flights between US and S. Korea (Nam et al. 1995)<br>Predicts Thailand's rice export quantity (Co and Boosarawongse, 2007)<br>Estimates political risks/predicts cost of intl construction projects (Al-Tabtabai and Alex, 2000) |
| **Transport Equipment Manufacturing** | Monitors quality of principal components used in auto body assembly (Jang and Yang, 2001)<br>Estimates unit manufacturing cost of a new type of auto disk brakes (Cavalieri et al. 2004)<br>Identifies 3D weld seams in ship blocks during hull assembly process (Yoo and Na, 2003) |
| **Transportation Infrastructure Development** | Predicts pavement stress from truck radial-ply & bias-ply tires-FHA study (DeGaspari, 1999)<br>Predicts completed cost of competitively bid highway projects for NJ DOT (Williams, 2002)<br>Predicts state DOT highway construction project costs and duration (Hassanein, 2006) |
| **Transport Energy** | Forecasts global consumption of non-fossil fuel energy (Ermis et al. 2007)<br>Forecasts national transport energy demand (Murat and Ceylan, 2006)<br>Predicts fuel consumption of a Boeing 757 aircraft (Stolzer and Halford, 2007)<br>Controls gas engine fuel-air ratio between cycles to decrease $NO_2$ emissions (Editor, 2004) |
| **Transport Security** | Designs packaging for products in transit to minimize shock damage (Somchai et al. 2000)<br>Detects explosives in baggage staged for loading onto aircraft (Glatzer, 1992)<br>Predicts induced voltage on gas pipeline from nearby transmission lines (Al-Alawi et al.2005) |

*Carrier Selector:* An ANN may be developed to analyze alternative transportation providers and classify potential providers to aid transportation managers in the selection of a carrier. The ANN could analyze a wide range of data pertaining to the carrier evaluation including: customer service and cost goals, prices, service capabilities for moving and storing products, quality of service provided, level of information technology, management experience and capabilities, cultural fit and financial stability among others. A carrier selection ANN could enable managers to select an efficient and effective carrier.

*Global Production Site Selector:* An ANN could be developed to analyze alternative plant site locations to support transportation managers in determining optimum production site locations. The ANN could analyze data regarding the following areas to aid managers in site selection: material source and market locations, labor and transportation availability and cost, import-export tariffs, monetary exchange rates, government risk, government policies and taxation, labor quality, trends in foreign investment, and energy utility support among others. A global production site selection ANN could enable managers to select optimum sites.

## ANN MANAGERIAL IMPLICATIONS AND DEVELOPMENT GUIDELINES

This section provides guidelines to assist transportation managers in ANN development. The ANN development process consists of five stages: project planning, application selection, design, development and implementation.

### Project Planning

A project plan should be developed to formalize the project and guide the development team through the remaining stages of the development process. A project plan should include a description of the project goals, resources required, benefits, development stages, costs, and time schedule. Large projects should have a champion and be fully supported by top management.

The resources required to develop a neural network should be identified and their availability and cost determined. Typical resources include: a knowledge engineer, experienced supply chain managers, problem domain data and appropriate hardware and software.

A productivity analysis should be performed to determine the expected return on investment for the selected application. The initial application should yield easily demonstrated, measurable and quantifiable benefits such as faster decision response time, lower error rates, or more effective and efficient transportation decisions.

### Application Selection

A potential ANN application should have the following characteristics (Kamruzzaman et al., 2006; Bigus, 1996):

- Problem area data are non-linear;
- Problem area knowledge is incomplete;
- Problem area knowledge is uncertain (dynamic/ever-changing);
- Problem area data are large and involves many variables;
- Problem area variables are quantitative and qualitative;
- Problem area variable relationships are not well-defined;
- Applying regression, mathematical optimization and linear programming provides unsatisfactory solutions; and
- Applying expert systems or case based reasoning provides unsatisfactory solutions.

In addition, the goal of the ANN application should be to perform one of the generic tasks listed in Table 1 such as predicting (e.g. forecasting tank truck demand).

## Design

A major aspect of ANN design involves selecting an ANN model that fits the specific application selected in the previous step. Three of the better known ANN models that are useful for transportation ANN development are: multilayered feedforward model (MF), optimization model, and self-organizing model (SO) (Smith and Gupta, 2000).

An overwhelming majority of transportation ANNs have been developed utilizing an MF model with a backpropagation learning rule. MF has broad applicability to many generic transportation tasks including: classifying, predicting, and modeling non-linear functions pertaining to diagnosing, designing, and monitoring among others.

The MF model consists of a multi-layered network of artificial neurons plus an adjustment algorithm (see Figure 1). The primary building block of the MF ANN is the artificial neuron (see Figure 2). Each neuron receives weighted inputs and sums them. Then, the summed value is fed to the neuron's on-off switch. If the summed value is greater than the threshold value, the neuron fires ... sending a weighted output to succeeding neurons in the network. However, if the summed value is less than the threshold value, the neuron does not fire.

As an example, if the MF ANN depicted in Figure 1 was being developed to forecast U.S. tank truck demand for 2012, transport managers would feed a series of weighted inputs (e.g. data from previous years such as demand for oil transport, crude oil production, crude oil prices) into the neural network. Some neurons would fire providing weighted outputs to other neurons. Some of the neurons receiving the weighted output would fire, others would not. Ultimately, actual outputs (demand forecasts for previous years) would be determined and compared to the desired outputs (actual demand in previous years) given the specific set of inputs. An error signal (forecast error) would be generated and fed through an adjustment algorithm which is used to train the ANN. The adjustment algorithm would direct the ANN to adjust some neuron weights and threshold values so that during the next iteration, the forecasts would be closer to the actual demands (learning). After much iteration, the ANN error signal (forecast error) would be small enough to be acceptable to management. At that point, the ANN has been trained and can be used to forecast tank truck demand for 2012 (Behara et al., 2002; Bigus, 1996).

A second model is principally used to solve optimization problems. As a result, the optimization model (e.g. Hopfield) is very useful in designing, planning, and control tasks. Like the MF model, the optimization model involves a set of inputs and known outputs and supervised learning (training).

A third model involves a self-organizing neural network. SO models are primarily used as a clustering technique. Therefore, SO models are developed to perform classification tasks. The primary difference between the SO model and models discussed previously is that learning is unsupervised because the desired outputs are unknown. The SO model identifies previously unknown patterns in data. Potential applications include identifying new transport market segments or new vehicle routes.

Another major aspect of ANN design involves the selection of a neural network software development tool. Software development tools include: (1) computer languages such as C or C++, that allow significant design flexibility but result in long development time and (2) specialized neural network software development tools that allow rapid prototyping, facilitate ANN training and provide a platform for operations but limit design flexibility to a degree. There are many software development tools available commercially. Table 3 displays a sample of available tools that range in price from thousands of dollars to zero. Some software providers offer free downloads of sample packages so that

FIGURE 1
ARTIFICIAL NEURAL NETWORK

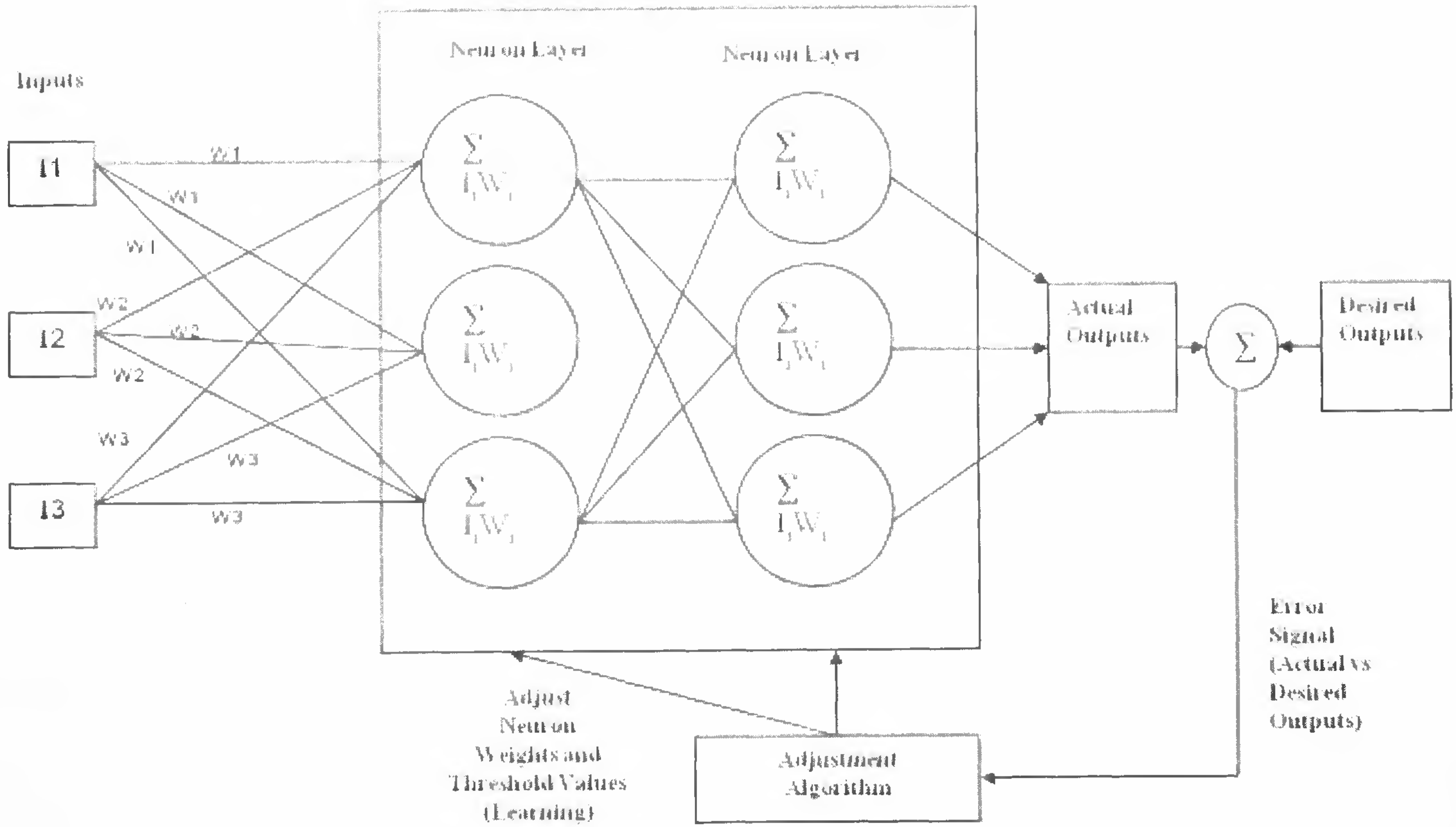

FIGURE 2
ARTIFICIAL NEURON

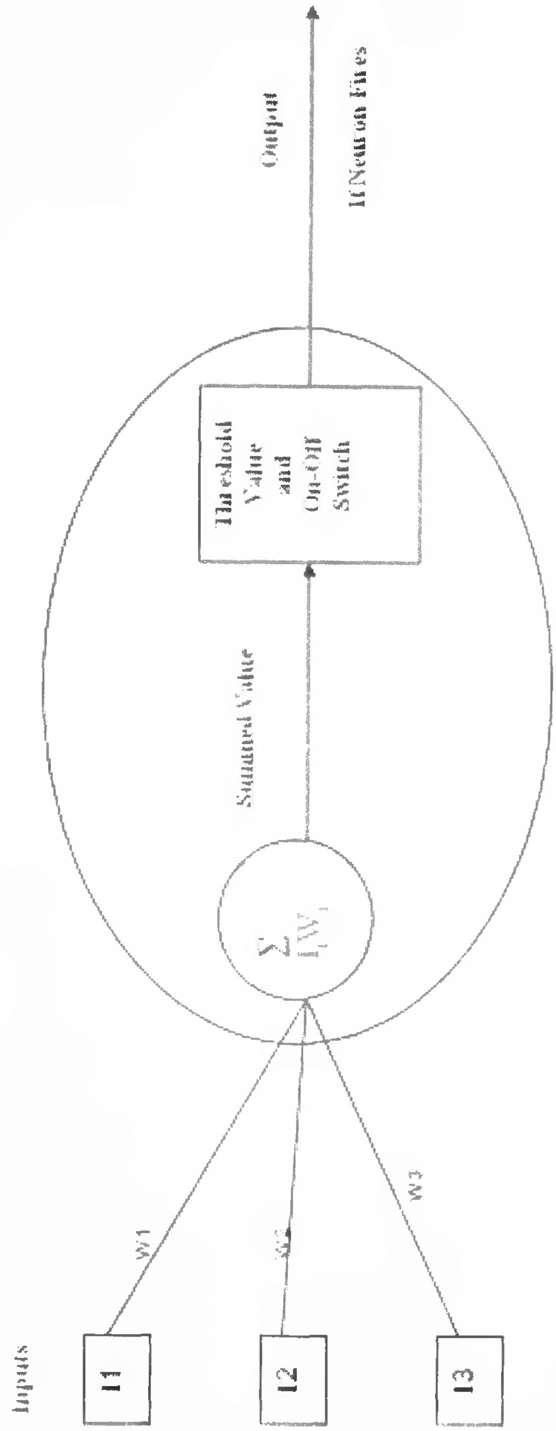

**TABLE 3**
**REPRESENTATIVE ARTIFICIAL NEURAL NETWORK DEVELOPMENT TOOLS**

| Company/E-Mail | Software Name | Price as of 7/20/11 | Generic Tasks |
|---|---|---|---|
| Alyuda www.contacts@alyuda.com | Neuro Intelligence | $497-$4,970 | Classification, prediction, function modeling |
| California Scientific sales@calsci.com | BrainMaker Professional | $795 | Classification, prediction, network design |
| NeuraWare www.neuralware.com | NeuralWorks Professional II/+ | $2,495-$4,995 | Classification, prediction, function modeling |
| NeuroDimension, Inc. www.info@nd.com | NeuroSolutions | $295- $2,495 | Classification, prediction, qulaity control |
| NeuroXL support@neuroxl.com | PredictorClusterizer | $49.95and up | Classification, prediction, pattern recognition |
| Palisade www.sales@palisade.com | NeuralTools Standard | $495 | Classification, prediction, control |
| Peltarion www.info@peltarion.com | Synapse | $1,419 | Classification, prediction, function modeling |
| Runtime Software Support europe@runtime.org | Pythya | Free | Classification, prediction |
| Statsoft info@statsoft.com | Statistica Neural Networks | varies | Classification, prediction, monitoring, control |
| The Mathworks www.mathworks.com | Neural Network Toolbox | varies | Classification, prediction, function modeling |
| Ward Systems Group, Inc. sales@wardsystems.com | AI Trilogy | $1,395 | Classification, prediction, function modeling, optimization |

potential users can interact with the tool prior to purchase.

**Development**

Once an application has been identified and an ANN model and software development tool selected, ANN development can start. Two critical aspects of ANN development involve data preparation and network training.

*Data preparation* There are two basic data preparation tasks to perform. The first task is to cleanse the data of inaccurate values, missing data or other inconsistencies. The second task is data representation. Most neural networks accept input values in the range of 0 to 1 or -1 to +1. Therefore, data representation must fit these parameters (Kamruzzaman et al., 2006; Bigus, 1996).

Most data can be classified as one of three types: continuous numeric values, discrete numeric values or symbolic values (Kamruzzaman et al., 2006; Bigus, 1996). For continuous numeric values, the most common representation approach is data scaling. For example, data that has a range of values from 0 to 100 can be linearly scaled from 0.0 to 1.0 so that .3 represents a value of 30. For discrete numeric and symbolic values, the most common representation codes are one-of-N codes, binary codes and thermometer codes.

- One-of-N codes are used most often and represent each distinct discrete value. For example, (air, rail, truck) can be represented as air=001, rail=010, and truck=100. One-of-N codes are easy to use and easy for ANN to understand.

- Binary codes are used to represent discrete variables. For example, yes/no can be represented as yes=1, n=0.

- Thermometer codes are used most often when discrete values are related. For example, excellent, good, fair and poor customer service performance can be represented by the following: excellent=1111, good=1110, fair=1100, and poor=1000. Using these codes ensures that the neural network recognizes that excellent is similar to good but excellent is not similar to poor.

Many software development tools are capable of interfacing with common spreadsheet and database programs. For example, Microsoft Excel and Access can facilitate initial data processing.

*ANN training.* Most ANNs require some form of supervised training. The amount of training required varies widely depending on the number of variables involved, the number of data patterns to learn (problem complexity), and the level of solution accuracy desired. For most ANNs, training begins with ANN weights initialized to small random values. Next, training control parameters are set. Then, training data patterns are fed through the ANN, one after another. Knowledge engineers monitor ANN output error and adjust weights to reduce output errors. In most cases, knowledge engineers should train the ANN with a subset of data patterns (examples) and then test the ANN performance with a separate smaller subset. Alternating between training and test data patterns ensures good generalization for the ANN application area.

Successful training (small error signal) depends, to a large extent, on how the training control parameters (learning rate, momentum, error tolerance) are set and troubleshooting. First, knowledge engineers must set learning rates to control the magnitude of weight adjustments prescribed by the adjustment algorithm. A large learning rate, to make major corrections, is acceptable early in the training process. However, it is beneficial to lower the learning rate as the training progresses to fine-tune the ANN. Remember, the ANN goal is not to have a perfect answer to each training data pattern but to be able to accurately generalize to data patterns that have not been seen before.

Second, a momentum parameter must be set to control oscillation of the weight values. This parameter dampens oscillation by averaging the output error of several previous training iterations. As a result, the ANN weighted adjustments are less likely to be driven back and forth in alternate directions based on a single training experience.

Third, an error tolerance level must be set to create an acceptable accuracy goal for the ANN. When ANN outputs are less than or equal to the error tolerance levels set, ANN training has been completed. For ANN, with a range of outputs from 0.0 to 1.0, a learning tolerance level of 0.1 is commonly used. Accepting output solutions at .10 or .90 avoids pushing the ANN weight values to extremes to reach extreme outputs approaching 0.0 or 1.0 which might paralyze the ANN.

If training progress stalls, these troubleshooting actions should be considered:

- If the error signal falls quickly then stays flat or oscillates up or down, add some random noise to the weights or reset the weights to new random values and start over;

- If the learning tolerance level is not reached after many iterations, add more neurons or neuron layers to boost the computational power; and

- If the learning tolerance level is not reached after many iterations, check key variables for improper data scaling or coding and use a domain expert to check for missing key variables

**Implementation**

The fully developed transportation ANN should be validated in the field. A field test will ascertain performance regarding user interface, corporate information systems interface, and decision support effectiveness and efficiency.

ANN maintenance is a necessary, on-going task. Primary maintenance activities include: adding new variables based on new experiences, deleting obsolete variables, and retraining the ANN, when necessary.

Training must be provided to transportation managers regarding the ANNs purpose, capabilities, and operational instructions. Potential ANN users should be involved early in the development effort to facilitate a smooth deployment transition.

## CONCLUSION

In today's highly competitive and volatile global marketplace, transportation managers must make more effective and efficient decisions if corporate profitability goals are to be achieved. Artificial neural networks may provide significant improvements in many transportation management decision environments that are dynamic, complex and unstructured. Transportation ANNs can result in faster, more accurate, more effective, and less expensive decisions. As a result, transportation managers should focus some of their TMS decision support efforts and resources on understanding ANN technology and developing appropriate applications to improve transportation management decision making.

## REFERENCES


Al-Alawi, S., Al-Badi, A. and Ellithy, K. (2005), "An Artificial Neural Network Model for Predicting Gas Pipeline Induced Voltage Caused by Power Lines Under Fault Conditions," *Compel*, 24(1): 69-81.

Al-Tabtabai, H. and Alex., A. (2000), "Modeling the Cost of Political Risk in International Construction Projects," *Project Management Journal*, 31(3): 4-13.

Aras, N., Ozkisacik, K. C. and Altinel, I. K. (2006), "Solving the Uncapacitated Multi-facility Weber Problem by Vector Quantification and Self-organizing Maps," *The Journal of the Operational Research Society*, 57(1): 82-93.

Behara, R., Fisher, W. and Lemmink, J. (2002), "Modelling and Evaluating Service Quality Measurement using Neural Networks," *International Journal of Operations & Production Management*, 22(9/10): 1162-1186.

Bellandi, G., Dulmin, R. and Mininno, V. (1998), "Failure Rate Neural Analysis in the Transport Sector," *International Journal of Operations & Production Management*, 18(8): 778-793.

Bigus, J. (1996), *Data Mining with Neural Networks*, New York, NY: McGraw-Hill Companies, Inc.

Bowersox, D. J. Calantone R. J. and Rodriques, A. M. (2003), "Estimation of Global Logistics expenditures Using Neural Networks," *Journal of Business Logistics*, 24(2): 21-36.

Cavalieri, S., Maccarrone, P. and Pinto R. (2004), "Parametric vs Neural Network Models for the Estimation of Production Costs: A Case Study in the Automotive Industry," *International Journal of Production Economics*, 91(2): 165-177.

Co, H. C. and Boosarawongse, R. (2007), "Forecasting Thailand's Rice Export: Statistical Techniques vs. Artificial Neural Networks," *Computers & Industrial Engineering*, 53(4): 610-627.

Corder, M. (2004), "Crippled but not Crashed," *Scientific American*, 291(2): 94-95.

Coyle, J., Langley, Jr., C., Gibson, B., Novack, R. and Bardi, E., (2009), *Supply Chain Management: A Logistics Perspective,* 8th Edition, Mason, OH: South-Western College Publishing.

Creput, J. and Koukam, A. (2007), "Transport Clustering and Routing as a Visual Meshing Process," *Journal of Information & Optimization Sciences*, 28(4): 573-601.

DeGaspari, J. (1999), "Measuring the Effect of Rubber on the Road," *Mechanical Engineering*, 121(10): "p.12"

Duliba, K. (1990), "Contrasting Neural Nets with Regression in Predicting Performance in the Transportation Industry," *NYU Working Paper Series*, IS-90(17): 1-17.

Durvasula, S., Lysonski, S. and Mehta, S. (2007), "Competitive Positioning in International Logistics: Identifying a System of Attributes Through Neural Networks and Decision Trees," *Journal of Global Marketing*, 20(1): 75-89.

Editor. (2004), "More Brain Power to Your Engine," *The Engineer*, April(16): "p.12"

Editor. (1996), "New Defective Bearing Detection Techniques," *Railway Age*, 197(3): 69-71.

Ermis, K., Midilli, A, Dincer, I and Rosen, M. A. (2007), "Artificial Neural Network Analysis of World Green Energy Use," *Energy Policy*, 35(3): 1731-1743.

Ghaziri, H. and Osman, I. (2006), "Self-organizing Feature Maps for the Vehicle Routing Problem with Backhauls," *Journal of Scheduling*, 9(2): 97-114.

Glatzer, H. (1992), "Neural Networks Take on Real-world Problems," *Computerworld*, 26(32): "p.21"

Griffis, S. and T. Goldsby (2007), "Transportation Management Systems: An Exploration of Progress and Future Prospects," *Journal of Transportation Management*, 18(1): 18-32.

Harrold, D. (1998), "Do You Know What's Leaking?," *Control Engineering*, 45(10): 81-82.

Hassanein, A. (2006), "Conceptual Planning of Highway Construction Projects," *AACE International Transactions*, PS171-177.

Holcomb, M. and K. Manrodt (2007), "The Changing State of Transportation," *Journal of Transportation Management*, 18(2): 17-37.

Hua, Z., Li, S. and Tao, Z. (2006), "A Rule-based Risk Decision-making Approach and its Application in China's Customs Inspection Decision," *Journal of the Operational Research Society*, 57(1): 1313-1322.

Innamaa, S. (2005), "Short-term Prediction of Travel Time Using Neural Networks on an Interurban Highway," *Transportation*, 32(6): 649-669.

Jamal, A. M. (2005), "The Neural Network and Exchange Rate Modeling," *International Journal of Management*, 22(1): 28-32.

Jang, K. and Yang, K. (2001), "Improving Principal Component Analysis (PCA) in Automotive Body Assembly Using Artificial Neural Networks," *Journal of Manufacturing Systems*, 20(3): 188-198.

Kamruzzaman, J., Begg, R. and Sarker, R. [Ed.] (2006), *Artificial Neural Networks in Finance and Manufacturing*, Hershey, PA: Idea Group Publishers.

Lam, W., Tang, Y.F., Chan, K. S. and Tam, M. (2006), "Short-term Hourly Traffic Forecasts Using Hong Kong Annual Traffic Census," *Transportation*, 33(1): 291-310.

Lau, H., Choy, K. L., Lau, P., Tsui, W. T. and Choy, L. C. (2004), "An Intelligent Logistics Support System for Enhancing the Airfreight Forwarding Business," *Expert Systems*, 21(5): 253-268.

Lokuge, P. and Alahakoon, D. (2007), "Improving the Adaptability in Automated Vessel Scheduling in Container Ports Using Intelligent Software Agents," *European Journal of Operational Research*, 177(3): 1985-2015.

Luxhoj, T., Williams, T., P. and Shyur, H. (1997), "Comparison of Regression and Neural Network Models for Prediction of Inspection Profiles of Aging Aircraft," *IIE Transactions*, 29(2): 91-102.

Lyridis, D., Zacharioudakis, P., Mitrou, P. and Mylonas, A. (2004), "Forecasting Tanker Market Using Artificial Neural Networks," *Maritime Economics & Logistics*, 6(1): 93-108.

Murat, Y. S. and Ceylan, H. (2006), "Use of Artificial Neural Networks for Transport Energy Demand Modeling," *Energy Policy*, 34(17): 3165-3172.

Nam, K. and Schaefer,T. (1995), "Forecasting International Airline Passenger Traffic Using Neural Networks," *Logistics and Transportation Review*, 31(3): 239-252.

Nijkamp, P., Reggianni, A. and Tsang, W. F. (2004), "Comparative Modeling of Interregional Transport Flows: Applications to Multi-modal European Freight Transport," *European Journal of Operational Research,* 155(3): 584-602.

Rahmat, M., Sabit, H. and Rahim, A. (2010), "Application of Neural Network and Electrodynamic Sensor as Flow Pattern Identifier," *Sensor Review*, 30(2): 137-141.

Rau, H., Tsai, M., Chen, C. and Shiang, W. (2006), "Learning-based Automated Negotiation Between Shipper and Forwarder," *Computers & Industrial Engineering*, 51(3): 464-481.

Rodriques, A. M., Bowersox, D. J. and Calantone, R. J.,(2005), "Estimation of Global and National Logistics expenditures: 2002 Data Update," *Journal of Business Logistics*, 26(2): 1-16.

Schwardt, M. and Dethloff, J. (2005), "Solving a Continuous Location Routing Problem by Use of a Self-organizing Map," *International Journal of Physical Distribution & Logistics Management*, 35(6): 390-409.

Smith, K. and Gupta, J. (2000), "Neural Networks in Business: Techniques and Applications for the Operations Researcher," *Computers & Operations Research*, 27(11-12): 1023-1044.

Somchai, C., Lye, S. and Yeong, H. (2000), "An Integrated Design Approach for Protective Packaging," *Integrated Manufacturing Systems*, 11(5): 321-330.

Stolzer, A. and Halford, C. (2007), "Data Mining Methods Applied to Flight Operations Quality Assurance Data: A Comparison to Standard Statistical Methods," *Journal of Air Transportation*, 12(1): 6-25.

Teodorovic, D., Varadarajan, V., Popovic, J., Chinnaswamy, M. R. and Ramaraj, S. (2006), "Dynamic Programming—Neural Network Real-time Traffic Adaptive Signal Control Algorithm, *Annals of Operations Research*, 143(1): 123-131.

Vukadinovic, K., Teodorovic, D. and Pavkovic, G. (1997), " A Neural Network Approach to the Vessel Dispatching Problem," *European Journal of Operational Research*, 102(3): 473-488.

Wang, W., Chen, H. and Bell, M. (2005), "Vehicle Breakdown Duration Modeling," *Journal of Transportation and Statistics*, 8(1): 75-84.

Williams, T. (2002), "Predicting Completed Project Cost Using Bidding Data," *Construction Management and Economics*, 20(3): 225-235.

Wilson, R. (2011), "22nd Annual State of Logistics Report: Navigating through the Recovery," Lombard, IL: Council of Supply Chain Management Professionals.

Yoo, W. S. and Na, S. J. (2003), "Determination of 3-D Weld Seams in Ship Blocks Using a Laser Vision Sensor and a Neural Network," *Journal of Manufacturing Systems*, 22(4): 340-347.

Zeng, Q. and Yang, Z. (2009), "Integrating Simulation and Optimization to Schedule Loading Operations in Container Terminals," *Computers & Operations Research*, 36(6): 1935-1944.

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# ANALYTICAL TECHNIQUES AND THE AIR FORCE LOGISTICS READINESS OFFICER

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## ABSTRACT

As the Air Force implements the Expeditionary Combat Support System (ECSS), it is imperative that Air Force logisticians competently analyze logistics data. This exploratory study sought to determine which analytical skills are useful for Logistics Readiness Officers (LROs), as reported by active-duty LROs and their supervisors. The research question was answered through a comprehensive literature review and the use of survey methodology. Analysis of survey responses found that Forecasting, Graphical Statistics and Descriptive Statistics are the analytical techniques valued most. The survey also identified a potential gap between perceived usefulness and competence levels. These findings were similar to what has been found in the civilian sector.

## INTRODUCTION

In 2002, three separate Air Force logistics-related officer career fields (Supply, Transportation, and Logistics Plans) merged to form the new Logistics Readiness Officer (LRO) career field. In the past, logistics officers were "stove-piped" by design. That is, assignments during their career would primarily focus on applying their specialized knowledge to one of the aforementioned logistics categories. Today, the logistics readiness officer may perform duties in any of the previously mentioned positions in addition to managing acquisition and wholesale logistics, support agreements, war reserve materiel management, or base-level fuels operations.

Along with the career field merger, LROs have also adapted to an increasingly expeditionary force. The ongoing military actions in Iraq and Afghanistan have ensured that today's LRO is far more likely to deploy than their pre-9/11 predecessors. As such, new training for LROs has focused more on training the logistician technically than on educating the logistician academically.

In 2010, the Air Force plans to establish initial operating capability for the Expeditionary Combat Support System, an enterprise resource planning system that will be used extensively by Air Force logisticians. As logistics information becomes more readily available to logistics managers and practitioners, it will be imperative that Air Force logisticians are equipped with a set of analytical tools to make the best possible use of the information available.

The focus of this research is to specifically determine which analytical tools are the most useful for the active-duty Air Force LROs in the ranks of 2nd Lieutenant (O-1), 1st Lieutenant (O-2), Captain (O-3), Major (O-4), and Lieutenant Colonel (O-5). While previous research has examined the value of statistics training in the commercial logistics industry (Parker, Kent and Brown, 2001) and the perceived training transfer of LRO technical school (Hobbs, 2005), no specific academic research has been published regarding analytical skills needed by the LRO.

## LITERATURE REVIEW

### AF LRO Training

In 2002, the release of the first-ever LRO Career Field Education and Training Plan (CFETP) accompanied the creation of the LRO career field. The CFETP was intended to guide the way in which LROs received training. Both the 2002 CFETP and its 2005 update state it is the document used to "plan, manage and control training" within the career field (Department of the Air Force, 2002; 2005).

As the Air Force continued to adapt to the ever-changing expeditionary and fiscal environment, the Air Force transformation office (HQ AF/A4I) compared the different curriculums offered to the Logistics Readiness career field. Study recommendations included the continued development of a sustainment curriculum portfolio for the LRO career field (Department of the Air Force, 2007). The portfolio consists of several AFIT online courses including Enterprise Resource Planning and Activity-Based Costing.

### Industry Training Literature

Academic literature has shown that knowledge of statistics is perceived to be valuable within business schools (Parker, Pettitjohn and Keillor, 1999) and among leaders of the transportation and logistics industry (Parker, Kent and Brown, 2001). Parker, Pettitjohn and Keillor (1999) found that at least 90% of undergraduate business schools required either one or two statistics classes, some of which were taught at the graduate level (Parker, Pettitjohn and Keillor, 1999).

Parker, Kent and Brown (2001) found that 86% of logistics and transportation executives considered statistics to be either supportive or critical to their operations. Furthermore, they found that there were five statistics techniques in particular that were considered most important: Probability, Sampling, Averages, Graphics, and Quality. These techniques considered important by industry leaders were different from those that were most commonly taught at the university level – descriptive statistics, probability distribution, hypothesis testing, and tables and charts (Parker, Pettitjohn and Keillor, 1999).

What should be done with this disconnect between what universities teach and what industry leaders consider important? One recommendation proposed by Parker, Kent and Brown (2001) was for education and industry leaders to communicate with one another to ensure that education providers are teaching the statistics techniques that are needed by industry. A second option would be for academics to proactively survey industry needs on their own and then modify their program curriculum to assure needs are being served.

### The Importance of Analysis Within the Organization

Davenport (2007) studied 32 organizations that had made a commitment to quantitative, fact-based analysis including Amazon, Netflix and the Boston Red Sox. Three common traits of these successful organizations include widespread use of modeling and optimization, an enterprise approach, and senior executive advocates. Davenport points out that an organization wishing to compete on analytics must be willing to invest significantly in technology, accumulate massive stores of data and formulate company-wide strategies for managing data. As the Air Force invests significantly in technology and data storage through the Expeditionary Combat Support System (ECSS), it is especially important that it also formulates these strategies for managing data. Davenport (2007) notes that as an organization that competes on analytics, employees will require extensive training.

They need to know what data are available and all the ways the information can be analyzed; and they must learn to recognize such peculiarities and shortcomings as missing data, duplication, and quality problems (Davenport 2007).

The following methodology works toward the purpose of examining the analytical knowledge needs of Air Force LROs and communicating these needs to those Air Force leaders who can guide career development.

## METHODOLOGY

### Procedures

Though no previous study has explored analytical skills and the LRO, many elements of the research are similar to those used by Parker, Kent and Brown (2001). Research began by identifying specific analytical skills which may be useful for the LRO. Items used by Parker, Kent, and Brown (2001) in their survey were included in a bank of potentially useful analytical skills for the LRO. A list of other statistics tools and a short description of each technique was compiled by consulting several statistics textbooks (Dixon and Massey, 1983; Devore and Peck, 2001; Field, 2005; and McClave, Benson, and Sincich, 2005).

Additionally, several quantitative and management textbooks were referenced to include other quantitative analytical techniques not categorized as statistics (Makridakis, Wheelwright, and Hyndman, 2003; Banks et al., 2005; Ragsdale, 2007). A list of 20 analytical tools was compiled from these sources along with a 4- to 16- word description of each technique (Table 1).

Two surveys were then developed. The first survey was designed to be answered by active-duty LROs in grades O1-O5. The second survey was designed to be answered by their supervisors. Both surveys were made up of four sections. The first collected basic demographic information, such as rank, major command (MAJCOM), and deployment history. The second section asked respondents to gauge their own degree of familiarity with each of the 20 analytical techniques. For LROs, the third section asked respondents to mark each of the analytical techniques they believe to be useful in their current position. For supervisors of LROs, the third section asked respondents to mark each of the analytical techniques they believe to be useful for the LROs they currently supervise. The fourth section asked respondents to assign a score on a scale of 1-10 for each analytical technique based on how useful they believed the technique is in the LRO position they fill or supervise (0=Not Familiar with the Technique; 1=Not At All Useful; 10=Absolutely Necessary to Perform Duties). For all sections of the survey which asked about analytical techniques, the 4- to 16- word description of each technique was written next to the technique name.

Each 65-item survey was developed with the guidance of an experienced academic professional familiar with survey-building procedures. The surveys were approved by the sponsoring office, converted into a web-based format and pilot tested among a small group of logistics officers for the purpose of gathering feedback. The first survey was developed for LROs to report which techniques they believed would be useful in the positions in which they are currently assigned. The second survey was developed for supervisors of LROs to report which analytical techniques they believed were important for the LROs who work for them.

A list of active-duty LROs in grades O1-O5, excluding those in student and special duty status, was obtained from the Air Force Personnel Center (AFPC). A similar list of LRO supervisors was not available due to computer system limitations. A survey invitation along with a link to the web-based survey was emailed to the 1,485 LROs. To gather data for the second survey, LROs were asked in their survey invitation to forward a copy of the invitation to their supervisors. After approximately 2 weeks, a follow-up email was sent to LROs requesting that they complete the survey.

## TABLE 1
## ANALYTICAL TECHNIQUES WITH DESCRIPTIONS

| Title | Description |
|---|---|
| **Descriptive Statistics** | utilizing numerical and graphical methods to observe patterns, gather information and present information in a convenient form |
| **Probability** | logically determining likelihood of events |
| **Statistical Sampling** | proper data handling techniques |
| **Estimating** | parameters based on empirical data |
| **Variation** | measuring how data is dispersed |
| **Averages** | determining an expected value |
| **Graphical Statistics** | understanding pie charts, bar charts and histograms |
| **Hypothesis Testing** | a method for using sample data to decide between two competing claims about a population characteristic |
| **Regression** | explaining an output variable based on one or more inde pendent variables |
| **Time-Series** | observing trends and seasonality in viewing data in a time series |
| **Forecasting** | predicting future output values based on past trends or future independent variables |
| **Quality** | quantitatively assessing the quality of a good or service (e.g. Six Sigma) |
| **Student's T-tests** | comparing means between two groups |
| **Analysis of Variance (ANOVA)** | comparing means between three or more groups |
| **Other Multivariate Techniques** | comparing means multiple differences between groups |
| **Decision Analysis** | methods of evaluating alternatives based on selected criteria |
| **Linear Programming** | creating and solving optimization problems with linear objective functions and linear constraints |
| **Simulation Techniques** | imitating a real-world process or system over time |
| **Queuing Theory** | the study of waiting lines |
| **Critical Path Method (CPM) / Program Evaluation and Review Technique (PERT)** | developing and managing project schedules |

### Participants

Invitations were sent to 1,484 LROs, and, excluding Out-of-Office messages which specified that the respondent would return prior to the survey close date, 220 undeliverable, full mailbox, or invalid email address messages were received. Of the 1,264 LROs who had the opportunity to respond to the survey, 494 participated (excluding duplicate entries) for a response rate of 39.1%. The population size of LRO supervisors is unknown, but responses were received from a total of 85 participants.

Using methods described by Armstrong and Overton (1977), the researcher analyzed responses to both surveys for non-response bias. Armstrong and Overton (1977) propose that non-respondents are likely to respond most similarly to those who are last to return their completed surveys. The final wave of responses (N=124, 25%) from the first survey was compared with the first 370 responses. Likewise, responses from the last group of LRO supervisors to respond (N=28, 33%) were compared with the first group. For both surveys, no significant differences exist between mean responses of several selected items, and no non-response bias is believed to exist.

### Methods

Percentages and mean score values for each technique were calculated, then differences were examined using the Wilcoxon rank-sum test for non-parametric independent samples. Because the data collected for these surveys is neither continuous nor normally distributed and because comparisons made for this research are between different groups of respondents, non-parametric independent sample tests are the appropriate method of analysis for measuring differences in these surveys (Field, 2005). JMP© statistical software calculated the rank sums and returned a significance value ($0<a<1$). Differences between means were considered significant at the 95% level ($a<.05$).

## ANALYSIS OF RESULTS

All survey participants were asked to identify which of the 20 analytical skills they believed to be useful for their current position. Responses varied from 70.4% who identified Forecasting as a useful technique to only 10.5% who identified Student's T-tests as being useful. 5.7% of LROs believe that none of the listed techniques are useful. Most respondents identified Forecasting, Descriptive Statistics, Graphical Statistics, Averages, Quality, Probability, Time-Series and Decision Analysis as useful tools in their present position (Table 2).

**TABLE 2**
**ALL LROS – PERCENT BELIEVE USEFUL**

| Technique | % Believe Useful |
|---|---|
| Forecasting | 70.4% |
| Descriptive | 70.0% |
| Graphics | 68.8% |
| Averages | 56.9% |
| Quality | 53.6% |
| Probability | 53.0% |
| Time Series | 51.4% |
| Decision A | 50.4% |
| Estimating | 45.5% |
| Sampling | 42.7% |
| Variation | 34.4% |
| CPM | 34.4% |
| Simulation | 32.0% |
| Hypothesis Test | 22.7% |
| Regression | 20.2% |
| Queuing | 17.0% |
| LP | 15.4% |
| Other Multi V | 12.8% |
| ANOVA | 12.6% |
| Student T | 10.5% |
| None Apply | 5.7% |

After identifying which techniques were useful in their present position, LROs assigned each technique a score from 1-10, (1 = Not at all Useful; 10 = absolutely necessary to perform duties). LROs gave the highest ratings to Graphical Statistics (7.44), Descriptive Statistics (6.77) and Forecasting (6.48) followed by Decision Analysis (6.05), Averages (6.02) and Quality (6.01). Results are listed in Table 3.

**TABLE 3**
**ALL LROs – MEAN SCORES**

| Technique | Mean Score |
|---|---|
| Graphics | 7.44 |
| Descriptive | 6.77 |
| Forecasting | 6.48 |
| Decision A | 6.05 |
| Averages | 6.02 |
| Quality | 6.01 |
| Time Series | 5.61 |
| Probability | 5.60 |
| CPM | 5.29 |
| Estimating | 5.24 |
| Sampling | 5.15 |
| Simulation | 4.67 |
| Variation | 4.53 |
| Hypothesis T | 4.17 |
| Regression | 3.85 |
| LP | 3.76 |
| Queuing | 3.49 |
| Other Multi V | 3.27 |
| ANOVA | 3.20 |

**LRO's Views of Important Analytical Skills**

An analysis was conducted based on company and field grade ranks. Second Lieutenants, 1st Lieutenants and Captains are Company Grade Officers (CGOs); Majors and Lieutenant Colonels are Field Grade Officers (FGOs). Of the LROs who responded to the survey, 272 (55.1%) are CGOs and 222 (44.9%) are FGOs (Table 4).

When asked to score each of the techniques, as shown in Table 4, both CGOs and FGOs rated Graphical Statistics, Descriptive Statistics and Forecasting as the most useful of the given analytical techniques to performing their duties. CGOs tended to score each individual technique higher than FGOs. Differences exist between perceived value of Probability, Simulation, Regression, ANOVA and Student's T-Test techniques. In each case, CGOs valued the technique higher than FGOs. Table 5 shows mean values for each category.

Further analysis was conducted to determine if LROs used analytical techniques differently based on their job classification. Data showed that 55.8% (829 of 1,485) of active-duty LROs are assigned to a Logistics Readiness Squadron, Aerial Port Squadron, Air Mobility Squadron or Contingency Response Wing. Respondents filling those operational positions equaled 56.7% (280 of 494). Responses of Operational LROs compared to others are shown in Table 6. Most respondents in both groups considered Forecasting, Descriptive Statistics, Graphics and Averages useful in their present position.

Some minor differences appear to exist between the two groups. In general, personnel assigned to an LRS or APS tend to score each technique higher. No significant differences exist between the highest scored items for both groups—Descriptive Statistics, Graphical Statistics and Forecasting. Higher scores from LROs assigned to an LRS or APS are statistically significant for Quality, Time Series, Critical Path Method, Simulation, Regression and Linear Programming (Table 7).

Company grade LROs are more likely to be assigned to operational units than field grade officers, and FGOs are more likely to be assigned to a staff position than CGOs. To compare the effect of the types of units to which LROs are assigned, we compare FGOs assigned to operational units

**TABLE 4**
**COMPARISON OF PERCENTAGES (CGO/FGO)**

| Technique | All LROs - % Believe Useful | CGO - % Believe Useful | FGO - % Believe Useful |
|---|---|---|---|
| Forecasting | 70.4% | 70.96% | 69.82% |
| Descriptive | 70.0% | 67.28% | 73.42% |
| Graphics | 68.8% | 65.81% | 72.52% |
| Averages | 56.9% | 57.35% | 56.31% |
| Quality | 53.6% | 58.46% | 47.75% |
| Probability | 53.0% | 58.46% | 46.40% |
| Time Series | 51.4% | 52.57% | 50.00% |
| Decision A | 50.4% | 49.26% | 51.80% |
| Estimating | 45.5% | 43.75% | 47.75% |
| Sampling | 42.7% | 44.85% | 40.09% |
| Variation | 34.4% | 34.19% | 34.68% |
| CPM | 34.4% | 34.19% | 34.68% |
| Simulation | 32.0% | 34.93% | 28.38% |
| Hypothesis Test | 22.7% | 24.26% | 20.72% |
| Regression | 20.2% | 20.22% | 20.27% |
| Queuing | 17.0% | 16.91% | 17.12% |
| LP | 15.4% | 13.97% | 17.12% |
| Other Multi V | 12.8% | 13.24% | 12.16% |
| ANOVA | 12.6% | 12.87% | 12.16% |
| Student T | 10.5% | 11.40% | 9.46% |
| None Apply | 5.7% | 4.78% | 6.76% |

(N = 76) with all other FGOs (N=146) (Table 8). The analytical technique valued by most FGOs assigned to operational positions is Graphics. The technique valued by most other FGOs is Forecasting.

An analysis of the mean scores marked by FGOs revealed no major differences between operational and non-operational FGOs' perceptions of usefulness for the techniques. Field grade LROs assigned to an operational unit gave higher scores to both Quality and Queuing Theory. The differences were slightly significant at the 90% level (a=.10) (Table 9).

Further exploratory analysis was conducted comparing responses of LROs assigned to the Air Staff and all others. Air staff duties of budgeting and establishing policy may be thought of as more analytically intensive; however, responses from LROs assigned to the Air Staff did not differ significantly from all other LROs.

Additionally, analysis was conducted to compare responses of wholesale logistics LROs (those assigned to Air Force Materiel Command or the Defense Logistics Agency) with all other LROs.

**TABLE 5**
**COMPARISON OF MEAN SCORES (CGO/FGO)**

| Technique | All LROs Mean Score | CGO Mean Score | FGO Mean Score | a |
|---|---|---|---|---|
| Graphics | 7.44 | 7.10 | 7.86 | .000 |
| Descriptive | 6.77 | 6.63 | 6.93 | .078 |
| Forecasting | 6.48 | 6.62 | 6.31 | .310 |
| Decision A | 6.05 | 6.03 | 6.06 | .631 |
| Averages | 6.02 | 5.92 | 6.15 | .081 |
| Quality 6 | .01 | 6.22 | 5.74 | .092 |
| Time Series | 5.61 | 5.82 | 5.36 | .126 |
| Probability | 5.60 | 5.91 | 5.21 | .006 |
| CPM | 5.29 | 5.46 | 5.10 | .283 |
| Estimating | 5.24 | 5.34 | 5.11 | .395 |
| Sampling | 5.15 | 5.27 | 5.00 | .325 |
| Simulation | 4.67 | 5.09 | 4.19 | .001 |
| Variation | 4.53 | 4.55 | 4.50 | .605 |
| Hypothesis T | 4.17 | 4.55 | 3.73 | .001 |
| Regression | 3.85 | 4.11 | 3.57 | .026 |
| LP_ Score | 3.76 | 3.85 | 3.65 | .371 |
| Queuing | 3.49 | 3.64 | 3.31 | .263 |
| Other Multi V | 3.27 | 3.49 | 3.01 | .027 |
| ANOVA | 3.20 | 3.45 | 2.90 | .016 |
| Student T | 3.19 | 3.47 | 2.87 | .013 |

It was hypothesized that LRO duties within these two organizations may require greater usage of quality-related statistics for comparing reliability rates or greater usage of the critical path method for program management. No significant differences, however, were found.

A final exploratory analysis was conducted to compare responses of Installation Deployment Officers (IDOs) with all other LROs. One responsibility of an IDO is to manage the structure of the deployment processing line, a duty which might be assisted by Simulation, Queuing Theory or the Critical Path Method. Exploratory analysis revealed no statistically significant differences between IDOs and non-IDOs in their scoring of any of the 20 techniques.

**Supervisors' Views of Analytical Skills**

As a group, LROs believed that Graphical Statistics, Descriptive Statistics and Forecasting were the most useful analytical techniques in performing their duties. A sample of LRO Supervisors (N=88) responded with which analytical skills they believed to be useful for the LROs under their supervision or command. Overall, a greater percentage of supervisors tended to consider the techniques useful compared with LROs. Descriptive Statistics are considered useful by 81.8% of su-

**TABLE 6**
**COMPARISONS OF PERCENTAGES (LRS/APS VS. ALL OTHERS)**

| Technique | All LROs - % Believe Useful | LRS/APS - % Believe Useful | All Others - % Believe Useful |
|---|---|---|---|
| Forecasting | 70.4% | 69.6% | 71.5% |
| Descriptive | 70.0% | 71.4% | 68.2% |
| Graphics | 68.8% | 71.1% | 65.9% |
| Averages | 56.9% | 58.9% | 54.2% |
| Quality | 53.6% | 57.9% | 48.1% |
| Probability | 53.0% | 55.7% | 49.5% |
| Time Series | 51.4% | 55.7% | 45.8% |
| Decision A | 50.4% | 50.0% | 50.9% |
| Estimating | 45.5% | 42.9% | 49.1% |
| Sampling | 42.7% | 43.2% | 42.1% |
| Variation | 34.4% | 32.5% | 36.9% |
| CPM | 34.4% | 36.1% | 32.2% |
| Simulation | 32.0% | 34.6% | 28.5% |
| Hypothesis Test | 22.7% | 23.9% | 21.0% |
| Regression | 20.2% | 19.3% | 21.5% |
| Queuing | 17.0% | 16.8% | 17.3% |
| LP | 15.4% | 14.3% | 16.8% |
| Other Multi V | 12.8% | 13.9% | 11.2% |
| ANOVA | 12.6% | 12.1% | 13.1% |
| Student T | 10.5% | 8.9% | 12.6% |
| None Apply | 5.7% | 3.6% | 8.4% |

pervisors compared with 70.0% of LROs. While Graphical Statistics are considered useful by 78.4% of supervisors compared with 68.8% of LROs (Table 10).

An analysis of the mean scores assigned to each technique revealed a continued trend of supervisors valuing these analytical techniques more than the LROs they supervise. Descriptive and Graphical Statistics were scored higher by supervisors at a statistically significant level (a=.02 and a =.04 respectively). These two techniques, however, receive the highest scores from both LROs and their supervisors. Variation (a=.085) and Queuing Theory (a =.081) are two other techniques in which supervisors' higher scores are statistically significant (Table 11).

**Summary of Analysis**

Though some differences exist as to the relative importance of several techniques, results from this study indicate that LROs and their supervisors agree that Descriptive Statistics, Graphical Statistics and Forecasting are the most important techniques. On the whole, supervisors of LROs believe the techniques are more important for LROs

**TABLE 7**
**COMPARISONS OF MEAN SCORES (LRS/APS VS. ALL OTHERS)**

| Technique | Total Mean Score | LRS/APS Mean Score | All Others Mean Score | a |
|---|---|---|---|---|
| Graphics | 7.44 | 7.50 | 7.39 | .347 |
| Descriptive | 6.77 | 6.92 | 6.63 | .849 |
| Forecasting | 6.48 | 6.84 | 6.16 | .138 |
| Decision A | 6.05 | 6.29 | 5.82 | .150 |
| Averages | 6.02 | 6.14 | 5.91 | .966 |
| Quality | 6.01 | 6.50 | 5.55 | .001 |
| Time Series | 5.61 | 6.11 | 5.16 | .029 |
| Probability | 5.60 | 5.92 | 5.29 | .066 |
| CPM | 5.29 | 5.87 | 4.78 | .001 |
| Estimating | 5.24 | 5.16 | 5.31 | .324 |
| Sampling | 5.15 | 5.28 | 5.02 | .369 |
| Simulation | 4.67 | 5.15 | 4.22 | .001 |
| Variation | 4.53 | 4.67 | 4.40 | .180 |
| Hypothesis T | 4.17 | 4.59 | 3.77 | .002 |
| Regression | 3.85 | 4.18 | 3.55 | .006 |
| LP | 3.76 | 4.19 | 3.37 | .002 |
| Queuing | 3.49 | 4.06 | 3.00 | .000 |
| Other Multi V | 3.27 | 3.78 | 2.81 | .000 |
| ANOVA | 3.20 | 3.67 | 2.77 | .000 |
| Student T | 3.19 | 3.66 | 2.75 | .000 |

than LROs believe themselves. CGOs value these analytical techniques more than FGOs for conducting their own duties.

Responses were surprisingly similar across ranks and organizations. No major differences existed between which techniques LROs and their supervisors believed to be important, though a greater percentage of supervisors tend to believe the techniques are useful. Descriptive and Graphical Statistics are very useful and relatively non-complex analytical tools. Viewing outputs from logistics information systems or explaining monthly metrics are two common ways for an LRO to use Descriptive and Graphical Statistics.

One surprising result from the survey was the high importance placed on Forecasting. In the Parker, Ken, Brown (2001) study, Forecasting was perceived to be less important than either Sampling or Quality. CGOs in our research consistently rated Forecasting in the top three most important techniques along with Descriptive and Graphical Statistics. Forecasting techniques can be more quantitatively rigorous than the other two, incorporating elements of Descriptive and Graphical Statistics as well as Regression, Linear Programming, Time-Series, Estimating, and Student's T-tests. Respondent's low assessment of these sub-components of Forecasting may indicate a gap between user competence and perceived usefulness.

**TABLE 8**
**COMPARISON OF PERCENTAGES (OPERATIONAL FGOs VS ALL OTHER FGOs)**

| Technique | All FGOs - % Believe Useful | Operational FGOs - % Believe Useful | All Other FGOs - % Believe Useful |
|---|---|---|---|
| Graphics | 73% | 80% | 68% |
| Descriptive | 73% | 78% | 71% |
| Forecasting | 70% | 62% | 74% |
| Averages | 56% | 58% | 55% |
| Time Series | 50% | 51% | 49% |
| Quality | 48% | 47% | 48% |
| Decision A | 52% | 46% | 55% |
| Estimating | 48% | 43% | 50% |
| Probability | 46% | 42% | 49% |
| Sampling | 40% | 42% | 39% |
| CPM | 35% | 34% | 35% |
| Variation | 35% | 30% | 37% |
| Simulation | 28% | 24% | 31% |
| Hypothesis Test | 21% | 18% | 22% |
| Regression | 20% | 13% | 24% |
| Queuing | 17% | 13% | 19% |
| LP | 17% | 12% | 20% |
| ANOVA | 12% | 11% | 13% |
| Other Multi V | 12% | 11% | 13% |
| Student T | 9% | 4% | 12% |
| None Apply | 7% | 3% | 9% |

## IMPLICATIONS, FUTURE RESEARCH AND LIMITATIONS

The research suggests a number of implications. Presently, there is no adequate quantitatively based training available to teach Forecasting techniques to all LROs. A 3-month graduate-level Forecasting course is taught in-residence at AFIT. The in-resident requirement precludes participation for most LROs. An online Forecasting familiarity course is also taught through AFIT On-line. The short (1 Continuous Learning Point credit) course is directed at informing students of the Enterprise Architecture (EA) more than teaching them how to use forecasting techniques. A more rigorous and quantitatively oriented Forecasting course could be developed and made available to all interested Air Force logisticians through either AFIT On-line or the Defense Acquisition University.

While this research was focused on DoD, and the Air Force in particular, it is felt that the results could be applicable to the logistician in the private sector also. The general functions of logistics are common regardless of the specific sector or industry in question, and the quantitative skills necessary to perform these functions efficiently would more than likely not differ significantly.

**TABLE 9**
**COMPARISON OF MEAN SCORES (OPERATIONAL FGOs VS. ALL OTHER FGOs)**

| Technique | Mean Score - All FGOs | Mean Score - Operational FGOs | Mean Score - All Other FGOs | a |
|---|---|---|---|---|
| Graphics | 7.86 | 8.20 | 7.67 | .773 |
| Descriptive | 6.93 | 7.31 | 6.72 | .306 |
| Forecasting | 6.31 | 6.31 | 6.31 | .648 |
| Averages | 6.15 | 6.09 | 6.18 | .495 |
| Decision A | 6.06 | 6.26 | 5.95 | .645 |
| Quality | 5.74 | 6.28 | 5.45 | .082 |
| Time Series | 5.36 | 5.50 | 5.29 | .664 |
| Probability | 5.21 | 5.32 | 5.15 | .690 |
| Estimating | 5.11 | 4.85 | 5.26 | .294 |
| CPM | 5.10 | 4.83 | 5.25 | .334 |
| Sampling | 5.00 | 4.97 | 5.02 | .965 |
| Variation | 4.50 | 4.45 | 4.53 | .832 |
| Simulation | 4.19 | 3.86 | 4.37 | .339 |
| Hypothesis T | 3.73 | 3.70 | 3.75 | .701 |
| LP | 3.65 | 3.74 | 3.59 | .428 |
| Regression | 3.57 | 3.49 | 3.61 | .839 |
| Queuing | 3.31 | 3.67 | 3.11 | .089 |
| Other Multi V | 3.01 | 3.21 | 2.90 | .217 |
| ANOVA | 2.90 | 3.11 | 2.78 | .229 |
| Student T | 2.87 | 2.98 | 2.79 | .397 |

## Future Research

An exploratory study assessing demand for more quantitatively oriented online courses (Linear Programming, Simulation, Basic Statistics, Forecasting, and Regression) through either AFIT Online or the Defense Acquisition University could be useful. Identification of these courses would provide justification for course implementation, which provides the foundation for the analytical techniques required by LROs.

The types of analytical techniques considered for this study are of the "building block" variety. Future research could inquire about other techniques such as cost-benefit analysis or technical skills related to analysis (e.g. ability to query the Global Transportation Network; ability to use Microsoft Excel®'s built-in Solver software).

## Limitations

This study focused on active duty United States Air Force officers. Their responses are from a military perspective where mission accomplishment is the goal with limited consideration for profit and return on investment. Responses from private sector organizations may weigh techniques used in finance and accounting more heavily. Additionally, the results may not be portable to other military services due their respective missions.

**TABLE 10**
**COMPARISON OF PERCENTAGES**
**(LROs VS. SUPERVISORS)**

| Technique | LROs - % Believe Useful | Supervisors - % Believe Useful |
|---|---|---|
| Descriptive | 70.0% | 81.8% |
| Graphics | 68.8% | 78.4% |
| Forecasting | 70.4% | 68.2% |
| Averages | 56.9% | 63.6% |
| Quality | 53.6% | 60.2% |
| Probability | 53.0% | 54.5% |
| Estimating | 45.5% | 53.4% |
| Decision A | 50.4% | 52.3% |
| Time Series | 51.4% | 50.0% |
| Sampling | 42.7% | 48.9% |
| Variation | 34.4% | 47.7% |
| CPM | 34.4% | 45.5% |
| Hypothesis Test | 22.7% | 30.7% |
| Simulation | 32.0% | 27.3% |
| Queuing | 17.0% | 26.1% |
| Regression | 20.2% | 23.9% |
| LP | 15.4% | 21.6% |
| ANOVA | 12.6% | 20.5% |
| Other Multi V | 12.8% | 19.3% |
| Student T | 10.5% | 14.8% |
| None Apply | 5.7% | 9.1% |

## Conclusion

The overall purpose of this research was to determine which analytical techniques LROs and their supervisors believe are important in conducting LRO duties. Forecasting, Graphical Statistics and Descriptive Statistics are considered by both LROs and their supervisors to be the most important techniques. Given the reported importance of Forecasting, LROs may benefit from having the opportunity to learn quantitatively based Forecasting techniques.

With the upcoming implementation of ECSS, analytical skills are an increasingly necessary tool for Air Force logisticians. Coupled with leadership ability, LROs will be able to use these skills to lead the equipping and sustainment of our nation's warfighters.

*The authors would like to thank Jodi Tinney (jodi.tinney.ctr@afit.edu), Research Assistant, for her work in editing and formatting the manuscript for this study. The views expressed in this article are those of the authors and do not reflect the official policy or position of the Air Force, Department of Defense, or U.S. Government.

TABLE 11

COMPARISON OF MEAN SCORES (LROs VS. SUPERVISORS)

| Technique | Mean Score LROs | Mean Score Supervisors | a |
|---|---|---|---|
| Graphics | 7.44 | 8.19 | .021 |
| Descriptive | 6.77 | 7.41 | .047 |
| Forecasting | 6.48 | 6.30 | .418 |
| Averages | 6.02 | 6.29 | .319 |
| Decision A | 6.05 | 6.28 | .600 |
| Quality | 6.01 | 6.17 | .672 |
| CPM | 5.29 | 5.87 | .126 |
| Time Series | 5.61 | 5.75 | .628 |
| Probability | 5.60 | 5.73 | .643 |
| Estimating | 5.24 | 5.63 | .195 |
| Sampling | 5.15 | 5.40 | .425 |
| Variation | 4.53 | 5.10 | .085 |
| Hypothesis T | 4.17 | 4.41 | .613 |
| Simulation | 4.67 | 4.30 | .314 |
| Queuing | 3.49 | 4.08 | .081 |
| LP | 3.76 | 3.90 | .793 |
| Regression | 3.85 | 3.68 | .540 |
| Other Multi V | 3.27 | 3.47 | .746 |
| ANOVA | 3.20 | 3.46 | .637 |
| Student T | 3.19 | 3.28 | .831 |

## Bibliography


Armstrong, J. Scott and Terry S. Overton (1977), "Estimating Non-response Bias in Mail Surveys," Journal of Marketing Research, 14(3): 396-402.

Banks, Jerry, Carson II, John S., Nelson, Barry L., and David M. Nicol (2005), Discrete-Event System Simulation, 4th ed., Upper Saddle River, NJ: Pearson Prentice Hall.

Davenport, Thomas H. and Jeanne G. Harris (2007), Competing on Analytics: The New Science of Winning, Boston, MA: Harvard Business School Press.

Department of the Air Force (2002), 21RX Logistics Readiness Officer, Career Field Education and Training Plan. Washington DC: HQ USAF/ILGX.

Department of the Air Force (2005), 21RX Logistics Readiness Officer, Career Field Education and Training Plan. Washington DC: HQ USAF/ILGF.

Department of the Air Force (2007), "Logistics Training Curriculum, Training Needs Assessment," [On-line]. Available: https://acc.dau.mil/getattachment.aspx?id=32016&pname=file&aid=6017. Accessed: 3 August 2007

Devore, Jay and Roxy Peck (2001), Statistics: The Exploration and Analysis of Data, Pacific Grove, CA: Duxbury.

Dixon, Wilfrid J. and Frank J. Massey, Jr. (1983), Introduction to Statistical Analysis, 4th ed., New York, NY: McGraw-Hill.

Dunn, Grover (2007), "AF Logistics Transformation (eLog21)," Presentation from Logistics Officer Association Conference, Washington DC.

Field, Andy (2005), Discovering Statistics Using SPSS. London: Sage.

Hobbs, Sarah E. (2005), Assessing Influences on Perceived Training Transfer: An Investigation of Perceptions of Air Force Logistics Readiness Officer Technical School Graduates. MS thesis, AFIT/GLM/ENV/05M-1. Department of Systems and Engineering Management, Air Force Institute of Technology (AU), Wright-Patterson AFB, OH.

Makridakis, Spyros, Wheelwright, Steven C., and Rob J. Hyndman (2003), Forecasting: Methods and Application, 3rd ed., New York, NY: John Wiley & Sons Inc.

McClave, James T., Benson, George, P. and Terry Sincich (2005), Statistics for Business and Economics, Upper Saddle River, NJ: Pearson Prentice Hall.

Parker, R. Stephen, Pettijohn, Charles E., and Bruce D. Keillor (1999), "The Nature and Role of Statistics in the Business School Curriculum," Journal of Education for Business, 75(1): 51-54.

Parker, R. Stephen, Kent, John L., and Thomas S. Brown (2001), "The Perceived Importance of Statistics in the Logistics and Transportation Industry," Journal of Education for Business, 76(4): 185-188.

Ragsdale, Cliff T. (2007), Spreadsheet Modeling & Decision Analysis, 5th ed., Mason, OH: Thomson/South-Western.

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# BENCHMARKING AND EVALUATING THE COMPARATIVE EFFICIENCY OF URBAN PARATRANSIT SYSTEMS IN THE UNITED STATES: A DATA ENVELOPMENT ANALYSIS APPROACH

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## ABSTRACT

The Americans with Disabilities Act (ADA) of 1990 encouraged public transit authorities to reassess the way they serve aging populations and physically-handicapped individuals requiring door-to-door services. As the demand for paratransit services rose dramatically the last few years due to a growing number of aging baby-boomers and injured Iraq-Afghanistan War veterans, many public transit authorities have been faced with the dilemma of meeting the growing demand while controlling costs in times of ongoing budget crises. To help public transit authorities better cope with such a dilemma, this paper evaluates the comparative operating efficiency of 75 selected paratransit agencies in the United States using data envelopment analysis (DEA) and then identifies the best-practice paratransit systems. Lagging paratransit agencies can use such systems as benchmark reference points to evaluate their performance against other systems. Finally this paper develops a profile of both efficient and inefficient paratransit agencies to discern a host of factors influencing the operating efficiency of paratransit systems.

## INTRODUCTION

The Americans with Disabilities Act (ADA) of 1990 required each public transit agency operating a fixed route system to provide physically or mentally disabled individuals with paratransit services that are comparable to the level of services provided to the general public without disabilities (ADA Paratransit Handbook, 1992). This service requirement includes door-to-door pickup/delivery services with a fare scheme comparable to regular transit. Due to the rapid growth of aging baby boomers and disabled Iraq-Afghanistan War veterans, the demand for paratransit services is expected to rise substantially over the next few decades. In response to the increased demand for paratransit services, public transit authorities have attempted to incorporate paratransit services as an integral part of the mass-transit system. Paratransit services aim to increase the mobility in an area where existing mass-transit systems fail to satisfy the regional demand and/or the specific needs of users with disabilities (mostly handicapped or elderly people) for public transportation (Tuydes and Ozen, 2009). In general, paratransit services refer to pre-scheduled, demand-responsive public transportation services that provide curb-to-curb access for people who are unable to use fixed-route mass transit services due to their mental or physical disabilities. These disabilities include:

- Passengers who are unable to get on, ride, or get off an accessible public transit vehicle without others' help;
- Passengers who are unable to get an accessible public transit vehicle because it does not have a lift;
- Passengers who are unable to get around bus stops or subway stations on their own due to their physical or cognitive handicaps.

The important benefits of paratransit services are to: (1) increase travel choices; (2) improve mobility; (3) enhance community environments; (4) impose a market discipline on public transportation; (5) make poor neighborhoods more accessible; and (6) help stimulate advanced transportation technologies (Cervero, 1997). In contrast with the fixed route/schedule based public transportation system, paratransit is more expensive on a per-passenger basis due to its customized service requirements for user-specified origin/destination and time.

According to the American Public Transit Association (APTA), the total operating expense of paratransit services in the United States surpassed \$1.2 billion with a meager \$173 million collected in fares (American Public Transit Association, 2009). APTA also reported that paratransit ridership made up 2% of mass transit ridership nationwide but 13% of operating costs in 2008 (Kern, 2009). As such, controlling paratransit operating costs as well as meeting service demand remains the greatest challenge for public transit authorities and paratransit service providers.

Considering the significant impact of paratransit services on public well-being and government budgets, a growing number of regional and local government officials have attempted to find ways to improve paratransit services, while better utilizing resources (e.g., drivers, dispatchers, maintenance crews, vehicles, equipment, depots) required for paratransit services under tight budget constraints. These attempts include the assessment of past and current paratransit service quality in terms of their efficiency (e.g., greater access to paratransit services, less waiting time for paratransit services).

Since the paratransit service efficiency may hinge on the community setting (i.e., the density of housing development, urban sprawl) and municipal size, a majority of the published literature regarding public services (Kain, 1967; Real Estate Research Corporation, 1974; Ladd, 1992 and 1994; Rosen, 1992; Carruthers and Ulfarsson, 2003; Moore et al., 2005; Garcia-Sanchez 2006; O'Sullivan, 2007) has focused on the discussions of appropriate municipal size and its potential impact on the efficiency of public services such as paratransit services. For example, in densely populated urban areas, distances paratransit vehicles must travel are short, but heavy traffic can cause delays, whereas sparsely populated suburban areas may involve longer travel times.

Moore et al. (2005) argued that larger urban cities were not efficient in the provision of local public services due to public sector unionism and layers of the bureaucracy which led to decreasing returns to scale in the provision of public services. On the contrary, others such as Ladd (1992 and 1994) and Rosen (1992) contended that increasing or constant returns to scale were common for making public service delivery in large cities due to dense population settlement and good road/transportation infrastructure networks. Their rationale is that costs be spread over a large population, which usually minimizes per capita tax liabilities, despite the fact that too large of a jurisdiction in terms of population or a jurisdiction growing too quickly or with too much population density can lead to decreasing returns to scale (Carruthers and Ulfarsson, 2003; Garcia-Sanchez, 2006; O'Sullivan, 2007). In particular, Ladd (1992 and 1994) observed that metro counties exceeding a population density of 250 per square mile tended to experience diseconomies of scales for providing public safety protection. Similarly, O'Sullivan (2007) found that an upper limit of a total population of 100,000 could be a cutoff point before diseconomies appeared for some local public goods like police, fire, and schools.

In contrast with the large urban metropolitan setting, sparsely populated suburban areas pose challenges for offering adequate paratransit services because dispersed populations limit access to paratransit services. Also, limited financial resources, communication gaps, and a lack of skilled drivers in suburban or satellite city areas may compound the problem of delivering paratransit services to their residents. Thus, the small satellite city setting can adversely influence the efficiency of paratransit services.

## RELEVANT LITERATURE

Despite a growing interest in paratransit services among the general public, the published literature evaluating the efficiency of paratransit services has been scant. However, some attempts have been made to assess the efficiency of paratransit services from financial or administrative perspectives. For instance, Jackson (1982) compared the real costs of service provided by major subsidized paratransit operations to that of for profit private-sector run operations in the New England region. He discovered that cost figures per passenger trip by non-profit and publicly-owned paratransit services were seriously underestimated and did not truly reflect the actual costs or the cost-efficiency of paratransit services provided.

From a different perspective, Bower (1991) investigated the impact of an automated paratransit routing/scheduling system called COMSIS on the operating cost and service quality of paratransit services. As expected, COMSIS turned out to be useful for reducing scheduling errors, reducing the cost of generating schedules, and identifying traffic patterns. Thus, Bower (1991) concluded that COMSIS improved the overall efficiency of paratransit service quality. Similarly, Chira-Chavala and Venter (1997) analyzed the impact of automated vehicle and passenger scheduling methods on the operating costs of paratransit systems. They found that such methods lowered unit paratransit transportation cost by 13%.

Further extending the earlier works of Chira-Chavala and Venter (1997), Pagano et al. (2002) assessed the impact of the computer-assisted scheduling and dispatching (CASD) systems on the service quality of paratransit services in central Illinois. They found that CASD systems allowed passengers to experience less riding time and greater on-time services at both pickups and drop-offs and subsequently enhanced their overall satisfaction with the paratransit services. On the other hand, the use of CASD to promote higher vehicle productivity resulted in slightly longer ride times. In addition, callers to the system experienced being put on hold more often. Overall, they concluded that the quality of service was positively affected by the implementation of the CASD system.

More recently, Fu et al. (2007) evaluated efficiency levels of individual paratransit systems in Canada with the specific objective of identifying the most efficient paratransit systems and the sources of their efficiency using data envelopment analysis (DEA). Through identification of the most efficient paratransit systems along with the key influencing factors such as automated scheduling methods, they developed new paratransit service policies and operational strategies for improved resource utilization and quality of services. In order to improve the efficiency of paratransit vehicle schedules, Shioda et al. (2008) proposed a computerized tool including a data mining technique that developed paratransit performance metrics reflecting the interests of paratransit stakeholders such as passengers, drivers, and municipal governments.

These performance metrics include: number of passengers per vehicle per hour, dead-heading time, passenger wait time, passenger ride time, and degree of zigzagging. This computerized tool turned out to be useful for improving the overall paratransit service quality. Though not directly tied to paratransit services, Paquette et al. (2009) conceptualized and defined quality of services in dial-a-ride operations intended for people with limited mobility. In particular, they identified various service dimensions and attributes used to measure quality of services in dial-a-ride operations. Most recently, Min (2010) developed a profile of paratransit riders and identified the key determinants of paratransit service quality.

As discussed above, a majority of these prior studies focused on the efficiency of particular paratransit systems (e.g., automated paratransit scheduling and routing) in terms of their cost saving opportunities and service deliveries. However, none of these prior studies but Fu et al. (2007) attempted to evaluate the relative efficiency of paratransit services in comparison to other public transit systems. Fu et al. (2007) employed DEA to create an overall ranking of cities according to their provision of paratransit services, yet their sample size is relatively small in assessing overall city service performances. In fact, their evaluation of paratransit services used a sample of 32 cities in Canada. Their analysis also only used three inputs (total number of paratransit employees, total fuel expenses, and total number of vehicles used for paratransit services) and a single output measurement (revenue vehicle kilometers) to benchmark paratransit services among 32 Canadian cities. Despite such shortcomings, their study is the only one to date that has attempted to measure the comparative efficiency of municipalities relative to other comparable communities with respect to paratransit services. Indeed, studies measuring paratransit service efficiency are still lacking, although there are a significant number of studies that develop benchmarks for other public services (e.g., Nolan et al., 2001; Magd and Curry, 2003; Northcott and Llewellyn, 2005; Wynn-Williams, 2005; Braadbaart, 2007; Vagnoni and Maran, 2008).

Considering the paucity of paratransit service benchmarking studies, this paper is intended to measure the relative efficiencies of 75 U.S. paratransit systems in terms of their capability to minimize paratransit costs, while handling a certain volume of paratransit service requests under multiple inputs and outputs. In addition, this paper identifies which exogenous variables, such as population size, resident profiles, housing density, and local weather conditions significantly impact the relative paratransit service efficiency of these cities.

## THE DEVELOPMENT OF THE DATA ENVELOPMENT ANALYSIS MODEL

As a way of comparatively assessing and benchmarking the efficiencies of paratransit systems, this paper proposes a data envelopment analysis (DEA) model with an input-oriented ratio form under both constant returns to scale (CRS) and varying returns to scale (VRS). In general, DEA is referred to as a linear programming (non-parametric) technique that converts multiple incommensurable inputs and outputs of each decision-making unit (DMU) into a scalar measure of operational efficiency, relative to its competing DMUs. Herein, DMUs refer to the collection of private firms, non-profit organizations, departments, administrative units, and groups with the same (or similar) goals, functions, standards and market segments. DEA can be employed for measuring the comparative efficiency of any entity including paratransit systems, which has inputs and outputs and is homogeneous with peer entities in an analysis. Therefore, DEA can be applied to the wide variety of DMUs such as paratransit systems in a certain municipality without much restriction as long as DMUs satisfy the basic requirements of inputs and outputs summarized in Table 1.

DEA is designed to identify the best practice DMU without *a priori* knowledge of which inputs and outputs are most important in determining an efficiency measure (i.e., score) and assessing the extent of inefficiency for all other DMUs that are not regarded as the best practice DMUs (e.g., Charnes et al., 1978). Since DEA provides a relative measure, it differentiates between inefficient and efficient DMUs relative to each other. Due to its capability to discern inefficient DMUs from efficient DMUs, DEA can be useful for developing benchmark standards (e.g., Min et al., 2008). The proposed DEA model can be mathematically expressed as (Charnes, et al., 1978; Fare et al., 1994; Nolan et al., 2001):

Solving the above equations, the efficiency of a DMU (*jp*) is maximized subject to the efficiencies of all DMUs in the set with an upper bound of 1 (Min and Lambert, 2006). DEA solves a linear program for each DMU in order to calculate a relative efficiency score that measures how well each DMU uses its inputs to produce its output

$$\text{Maximize Efficiency score } (jp) = \frac{\sum_{r=1}^{t} u_r y_{rjp}}{\sum_{i=1}^{m} v_i x_{ijp}} \qquad (1)$$

$$\text{Subject to} \quad \frac{\sum_{r=1}^{t} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad j = 1, \ldots, n, \qquad (2)$$

$$u_r, v_i \geq \varepsilon, \qquad \forall r \text{ and } i, \qquad (3)$$

where

= amount of output $r$ produced by DMU $j$,

$x_{ij}$ = amount of input $i$ used by DMU $j$,

$u_r$ = the weight given to output $r$,

$v_i$ = the weight given to input $i$,

$n$ = the number of DMUs,

$t$ = the number of outputs,

$m$ = the number of inputs,

$\varepsilon$ = a small positive number.

when compared to the "best" DMU, which produces the greatest output using the least amount of input. Often the best DMU is a composite and may not necessarily exist, yet all DMUs are compared against the performance of this best DMU. A score of 1.0 indicates that a DMU is efficient (or matches the composite producer/DMU), whereas a score less than 1.0 indicates inefficiency (Anderson et al., 1999). A DMU with a score of 1.0 is on the frontier of a plane which relates inputs and outputs where those with a score of less than 1.0 are on the interior of the frontier.

From the paratransit system perspective, an efficiency score represents a system's ability to transform a set of inputs (given resources) into a set of outputs. Herein, the paratransit systems that were evaluated under study represent mostly city owned public/non-profit ones. For our analysis, we make the conservative assumption that the paratransit system is provided with constant returns to scale because efficiency scores based on variable returns to scale tend to raise or inflate the scores (Garcia-Sanchez, 2006).

The DEA analysis is conducted by applying the above equations to actual data of regional paratransit systems serving 75 municipalities in the US. From these data sets, two different sets of DEA scores were calculated and then regressed against a set of independent (environmental) variables using Tobit regression which expresses observed responses in terms of latent variables. In general, Tobit regression is intended for analyzing continuous data that are censored, or bounded at a limiting value. The Tobit regression model is well suited to measure the transformed efficiency such as DEA efficiency scores, when dependent variables have sensible partial effects over a wide range of independent variables (see, e.g., Amemiya, 1985; Breen, 1996; Wooldridge, 2006 for details of Tobit regression analyses).

In general, a Tobit regression model assumes that the dependent variable has its value clustered at a limiting value, usually zero. But, in our model, the dependent variable is right censored and the model can be written in terms of the underlying or the latent variable that is mathematically expressed as:

where å$_i$ ~ N(0,ó²). In our sample, we observe y (=y*) only, when y$_i$* < c (right censored). The values of Y are censored to the right at 1, and thus we need to estimate

$$E(y_i \mid y_i < c, x_i) = E(y_i \mid \varepsilon_i \leq c - x_i \beta_i)$$

The probability that å$_i$ d" c is

$$\Phi\left[\frac{c}{\sigma}\right] = \int_{-\infty}^{c/\sigma} \frac{1}{\sqrt{2\pi}} \exp(-t^2/2)\,dt$$

The expected value is

$$E(y_i \mid y_i < c, x_i) = x_i'\beta - \sigma \frac{\phi(c)}{\Phi(c)}$$

$$= x_i'\beta - \sigma \hat{\lambda}_i(c), \text{ where } c = \frac{c - x_i'\beta}{\sigma}$$

**TABLE 1**
**INPUT AND OUTPUT VARIABLES IN THE DEA MODEL**

| Variables used in Data Envelopment Analysis | Mean | Standard Deviation |
|---|---|---|
| **Outputs:** | | |
| 1 Total amount of annual fare received | $1,724,745 | $2,299,117 |
| 2. Annual revenue vehicle hours (in thousands) | 377.9149 | 293.7305 |
| 3. Annual revenue vehicle miles (in thousands) | 5,947.493 | 5,148.653 |
| **Inputs:** | | |
| 1. Number of vehicles used | 259.96 | 286.5005 |
| 2. Operating expenses | $20,757,960 | $23,080,150 |
| 3. Annual passenger miles (in thousands) | 7,068.223 | 5,067.616 |
| 4. Annual unlinked trips (in thousands) | 771.908 | 481.0856 |
| **Variables used in Tobit Regression** | **Mean** | **Standard Deviation** |
| **Dependent variables:** | | |
| 1. VRS efficiency score | 0.8127927 | 0.17754198 |
| 2. CRS efficiency score | 0.672887 | 0.179733 |
| **Independent variables:** | | |
| 1. Density-traffic congestion index | .0007 | 1.00069 |
| 2. Median household income | $47,258.253 | $6,171.40548 |
| 3. Percentage of residents below the poverty line | 11.764121.8% | 2.3246412% |
| 4. Percentage of population aged 65 or older and disabled population | 28.959463% | 4.3153984% |
| 5. Average January temperature | 38.929 | 14.8864 |
| Average July temperature | 76.020 | 6.4709 |
| 6. Annual precipitation in inches | 35.3439 | 14.00035 |

Thus, the Tobit model accounts for truncation. A regression of the observed '*y*' values on '*x* will lead to an unbiased estimate of â (or the independent variables).

## DEA INPUT-OUTPUT MEASURES AND RELATED VARIABLES

Columns 3 and 4 in Table 2 shows the DEA efficiency scores of the 75 paratransit systems in terms of their total amount of annual fare revenues, annual revenue vehicle hours, and annual revenue vehicle miles given the following inputs (US National Transit Database, 2005):

- The Number of Vehicles Used by the Paratransit System. Since the number of vehicles used for paratransit services represents resources invested in the paratransit system and indicates how well these resources are utilized for paratransit operations, this measure should be regarded as an input.

- Operating Expenses. These expenses incur in carrying out the paratransit authority's day to day operations. They include driver payroll, employee benefits, pension contributions, depreciation of equipment, utilities, and vehicle repair and maintenance costs. Since these expenses can affect the paratransit authority's revenues and their subsequent service offerings, they will be regarded as one of the inputs.

● Annual Passenger Miles Driven. Route miles or a related measure have been frequently used as a way to evaluate the efficiency of mass transit systems (Viton, 1997; Nolan et al., 2001). Indeed, annual passenger miles driven by the paratransit vehicle can reflect the utilization rate of that vehicle and the subsequent paratransit efficiency. As such, we viewed annual passenger miles driven as the input.

● Annual Unlinked Trips. An annual unlinked trip refers to the number of trips made by paratransit riders on a paratransit vehicle each year, regarding each transfer between public bus routes or between bus and rail/subway as an individual trip (www.statemaster.com/.../trn_pub_tra_ann_unl_pas_tri_percap-**unlinked-passenger-trips**-per-capita). Since paratransit riders are counted each time they board paratransit vehicles no matter how many vehicles they use to make a trip from their origin to destination, annual unlinked trips should be regarded as an input regardless of whether an individual fare is collected for each leg of trip.

Both CRS (constant returns to scale where inputs are assumed to be infixed proportions, e.g., each bus has the same operating expense) and VRS (variable returns to scale, e.g., operating expenses are allowed to vary per bus) efficiency scores were then used as dependent variables in a Tobit regression and regressed against the following independent variables, which are also used to identify factors significantly influencing the paratransit efficiency.

● Density-Congestion Index. Since traffic congestion increases vehicle travel time, it can cause the delay of paratransit services and thus increase fuel consumption of the paratransit vehicles. If this is correct, we can expect an inverse relationship between the extent of traffic congestion and average paratransit operating efficiency in terms of paratransit vehicle run times and utilization, everything else held constant. On the other hand, greater population and housing density decrease commuting time for drivers. If this is correct, then we can expect a positive relationship between density and paratransit efficiency, everything held constant. It should be noted that this index is not readily available from the published sources. As a surrogate measure, we developed this index by combining the distance-weighed population/housing density with a percentage of residents who spent 30 minutes or more for their daily commutes through factor analyses.

● Median Household Income. This is used as a proxy for a municipality's ability to adequately fund a paratransit system. In other words, we made a premise that higher income cities, *ceteris paribus*, can afford to better support their paratransit systems because they have better tax bases and greater financial resources (Lambert and Meyer, 2008).

● Percentage of Household below the Poverty Line. Min (2010) discovered that a vast majority (more than 80% of his surveyed respondents) of the paratransit riders were people who were well below the federal poverty threshold (annual income less than \$10,830 for one-person household; \$14,570 for two-person household). That is to say, the paratransit system has become an important means of transportation for low-income people who cannot afford to use other more expensive means of transportation. As discussed above, since the concentration of low-income residents can influence the utilization of paratransit services, a percentage of the households below the poverty line in the municipality may be used as a proxy for the municipality's ability to better utilize the paratransit services and its subsequent paratransit operating efficiency.

● Percentage of Population aged 65 or older and Disabled Population aged 5 or older in the Municipality. Min (2010) found that nearly half

## TABLE 2.
## EFFICIENCY SCORES OF PARATRANSIT SERVICES IN MAJOR U.S. MUNICIPALITEIS USING DEA

**DEA Efficiency Scores**

| No. City | Input- oriented variable return to scale (VRS) efficiency | Input-oriented constant-to return scale (CRS) efficiency | RTS Score | Input-Oriented RTS |
|---|---|---|---|---|
| 1 Allentown, PA | 0.73711 | 0.51211 | 0.57795 | Increasing |
| 2 Atlanta, GA | 0.96707 | 0.75047 | 0.51930 | Increasing |
| 3 Austin, TX | 0.74393 | 0.58357 | 0.40614 | Increasing |
| 4 Baltimore, MD | 0.79504 | 0.78890 | 0.89731 | Increasing |
| 5 Barnstable Town, MA | 1.00000 | 0.64835 | 0.40305 | Increasing |
| 6 Boston, MA | 0.96480 | 0.75929 | 2.21786 | Increasing |
| 7 Bremerton, WA | 0.71403 | 0.38818 | 0.31503 | Increasing |
| 8 Charlotte, NC | 1.00000 | 0.60358 | 0.38518 | Increasing |
| 9 Chicago, IL CTA | 1.00000 | 0.59768 | 3.11619 | Increasing |
| 10 Chicago, IL Pace | 1.00000 | 0.67708 | 2.99027 | Decreasing |
| 11 Cleveland, OH Laketran | 0.84862 | 0.53270 | 0.37114 | Increasing |
| 12 Cleveland, OH GCRTA | 0.71273 | 0.51671 | 0.44178 | Increasing |
| 13 Dallas, TX ATC/VANCOM | 0.73426 | 0.70944 | 1.21076 | Decreasing |
| 14 Dallas, TX Fort Worth | 1.00000 | 0.83730 | 0.33127 | Increasing |
| 15 Daytona Beach, FL | 1.00000 | 0.82222 | 0.75489 | Increasing |
| 16 Denver, CO | 0.66524 | 0.64624 | 1.23626 | Decreasing |
| 17 Detroit, MI | 1.00000 | 1.00000 | 1.00000 | Constant |
| 18 Flint, MI | 0.58047 | 0.55732 | 0.75478 | Increasing |
| 19 Florence, SC | 1.00000 | 1.00000 | 1.00000 | Constant |
| 20 Grand Rapids, MI | 0.81879 | 0.44402 | 0.44572 | Increasing |
| 21 Hartford, CT | 0.61661 | 0.52206 | 0.69368 | Increasing |
| 22 Honolulu, HI | 0.50435 | 0.49820 | 0.90571 | Increasing |
| 23 Houston, TX | 0.88308 | 0.60071 | 2.10770 | Decreasing |
| 24 Indianapolis, IN | 0.98281 | 0.62199 | 0.45404 | Increasing |
| 25 Jacksonville, FL | 1.00000 | 1.00000 | 1.00000 | Constant |
| 26 Kansas City, MO | 0.76288 | 0.33157 | 0.32894 | Increasing |
| 27 Kennewick, WA | 0.58204 | 0.40949 | 0.38195 | Increasing |
| 28 Lancaster, PA | 0.95469 | 0.51862 | 0.34182 | Increasing |
| 29 Lansing, MI | 0.77687 | 0.53058 | 0.40638 | Increasing |
| 30 Las Vegas, NV | 0.59370 | 0.59342 | 0.98963 | Increasing |
| 31 Leominster, MA | 0.66914 | 0.65845 | 0.94434 | Increasing |
| 32 Los Angeles, CA Access | 1.00000 | 0.71126 | 3.11116 | Decreasing |
| 33 Los Angeles, CA LA DOT | 0.49739 | 0.49569 | 0.81620 | Increasing |
| 34 Los Angeles, CA LACMTA | 0.40586 | 0.40466 | 0.92469 | Increasing |
| 35 Los Angeles, CA OCTA | 0.78857 | 0.69069 | 1.60731 | Decreasing |

| | | | | |
|---|---|---|---|---|
| 36 Louisville, KY | 1.00000 | 1.00000 | 1.00000 | Constant |
| 37 Madison, WI | 1.00000 | 0.47732 | 0.31115 | Increasing |
| 38 Miami, FL Advanced Trans | 1.00000 | 0.85629 | 1.88899 | Decreasing |
| 39 Miami, FL Board of County | 1.00000 | 0.95648 | 1.50529 | Decreasing |
| 40 Miami, FL Broward County | 1.00000 | 0.81280 | 2.11858 | Decreasing |
| 41 Milwaukee, WI | 0.48061 | 0.44533 | 1.20009 | Decreasing |
| 42 Minneapolis, MN Mobility | 0.78736 | 0.72561 | 1.39856 | Decreasing |
| 43 Minneapolis, MN Metro Tran | 0.46856 | 0.41717 | 0.82278 | Increasing |
| 44 New York, NY American Tran | 0.94294 | 0.93000 | 1.21959 | Decreasing |
| 45 New York, NY Atlantic Tran | 1.00000 | 0.96411 | 1.73681 | Decreasing |
| 46 New York, NY MTA | 1.00000 | 0.80962 | 0.65197 | Increasing |
| 47 New York, NY NYCT | 1.00000 | 1.00000 | 1.00000 | Constant |
| 48 New York, NY NJ Transit | 0.71872 | 0.67501 | 1.39505 | Decreasing |
| 49 Orlando, FL | 0.81430 | 0.80970 | 1.04221 | Decreasing |
| 50 Palm Bay, FL | 0.71780 | 0.67084 | 0.91940 | Increasing |
| 51 Philadelphia Delaware Count | 0.75081 | 0.74918 | 1.02637 | Decreasing |
| 52 Philadelphia SEPTA | 1.00000 | 0.72521 | 2.88384 | Decreasing |
| 53 Phoenix, AZ | 0.74895 | 0.72349 | 0.79450 | Increasing |
| 54 Pittsburgh, PA | 1.00000 | 0.61521 | 2.73780 | Decreasing |
| 55 Port Huron, MI | 1.00000 | 0.84664 | 0.38497 | Increasing |
| 56 Portland, OR | 0.54401 | 0.52130 | 1.27007 | Decreasing |
| 57 Providence, RI | 0.67493 | 0.67251 | 0.90932 | Increasing |
| 58 Riverside, CA | 0.65850 | 0.61469 | 0.52816 | Increasing |
| 59 Sacramento, CA | 1.00000 | 0.72908 | 0.44889 | Increasing |
| 60 Salt Lake City, UT | 0.73903 | 0.68685 | 0.75275 | Increasing |
| 61 San Antonio, TX | 0.60450 | 0.60441 | 0.93101 | Increasing |
| 62 San Diego, CA | 0.61210 | 0.48058 | 0.59563 | Increasing |
| 63 San Francisco, CA Vanc. | 0.68373 | 0.68129 | 1.04545 | Decreasing |
| 64 San Francisco, CA ATC | 0.52083 | 0.41320 | 1.36381 | Decreasing |
| 65 San Fran., CA San Mateo Cty | 0.97428 | 0.75300 | 0.50291 | Increasing |
| 66 San Jose, CA | 0.59798 | 0.59246 | 1.26706 | Decreasing |
| 67 Seattle, WA King County Metro | 0.58737 | 0.46390 | 2.00364 | Decreasing |
| 68 Seattle, WA Pierce | 0.77437 | 0.51806 | 0.41023 | Increasing |
| 69 Spokane, WA | 0.71290 | 0.48830 | 0.43658 | Increasing |
| 70 Springfield, MA | 0.85733 | 0.58661 | 0.52775 | Increasing |
| 71 St. Louis, MO | 0.85103 | 0.84853 | 0.52873 | Increasing |
| 72 Tucson, AZ | 0.83643 | 0.63902 | 0.54830 | Increasing |
| 73 Wash., DC Montgomery Cty | 1.00000 | 1.00000 | 1.00000 | Constant |
| 74 Washington, DC WMATA | 1.00000 | 1.00000 | 1.00000 | Constant |
| 75 Wichita, KS | 1.00000 | 1.00000 | 1.00000 | Constant |

## TABLE 3
## A SUMMARY OF RESULTS FROM THE TOBIT REGRESSION ANALYSES

| Predictors | Model 1 | Model 2 |
|---|---|---|
| | **Dependent Variable: CRS Efficiency Score** | **Dependent Variable: VRS Efficiency Score** |
| Density-traffic congestion index | 0.0695518** (p=0.000) | 0.0536784* (p=0.075) |
| % of senior or disabled population | 0.0111974**(p=0.016) | 0.0194661** (p=0.008) |
| Average temperature | 0.0364899* (p=0.070) | 0.051167 (p=0.860) |
| Intercept | 0.3561404* (p=0.070) | 0.3032459 (p=0.150) |
| Log-Likelihood Ratio | 14.102 | -18.186 |
| Pseudo $r^2$ | 0.28 | 0.27 |

**Note:** *Statistically significant at á = 0.10
**Statistically significant at á = 0.05

of his surveyed paratransit riders were senior citizens. Also, given that paratransit services are intended for physically and mentally handicapped individuals, it makes sense that we consider the potential relationship between the paratransit operating efficiency and its users' profiles in terms of senior citizenship and disability status.

- Average January and July Temperatures. Since extreme temperatures can lead to sub-optimal provision of certain municipal services such as paratransit services, it is regarded as an explanatory or environmental variable (Ladd, 1992; Moore et al., 2005; Garcia-Sanchez, 2006).

- Annual Precipitation in Inches. Holding other things constant, the greater the precipitation, the slower the average paratransit service response time and the more difficult it is to complete a greater number of vehicle runs (Moore et al., 2005). In particular, during winter times, snow removal could delay passenger pickup/delivery processes and subsequently increase vehicle travel times. In other words, large precipitation may lead to lower paratransit efficiency scores.

## RESULTS AND DISCUSSION

These six independent variables were examined to see if they significantly affected the paratransit efficiency. As a paratransit efficiency measure, we considered both CRS and VRS efficiency scores. In other words, both CRS and VRS efficiency scores were used as dependent variables. The initial results of a Tobit regression model show that median household income, percentage of household below the poverty line, and annual precipitation did not significantly influence either CRS or VRS efficiency. On the other hand, the final results of a Tobit regression analysis recapitulated in Table 3 shows that the density-congestion index, percentage of senior citizens and disabled population, and temperature turned out to be significant independent variables ($p < .10$) for either Model 1 (with CRS efficiency) or Model 2 (with VRS efficiency). Correlation coefficients of these independent variables summarized in Table 3 indicates that the traffic congestion index, percentage of senior citizens and disabled population, and temperature positively influence paratransit efficiency.

To elaborate, the more densely settled the area and the more congested the traffic, the better the paratransit efficiency. This finding is somewhat surprising in that we expected an inverse relationship between density-congestion and paratransit efficiency. This unexpected result may be explained by the fact that a congested area happens to be the downtown area where many paratransit riders are concentrated and thus pickup/drop-offs of those riders require short vehicle miles. In other words, the more dense the rider population, the higher the efficiency score for a municipality's paratransit systems. This tendency has been observed by earlier urban economics studies conducted by Kvalseth and Deems (1979) and Lambert and Meyer (2006, 2008). Steele (1993) also suggested that population clusters could improve the quality of public services such as paratransit services.

The percentage of the population 65 years or older combined with the percentage of the population 5 years and over who report at least one disability is a good predictor of paratransit efficiency. Temperature works well in Model 1, but not in Model 2.

Table 2 shows both CRS and VRS efficiency scores in terms of total amount of annual fare revenues, annual revenue vehicle hours, and annual revenue vehicle miles for the municipality as the outputs. These output variables measure how well paratransit vehicles were utilized in generating revenues. The best performing municipalities with respect to both CRS and VRS efficiency scores are Detroit, Michigan; Florence, South Carolina; Jacksonville, Florida; Louisville, Kentucky; New York, New York; Washington, DC; and Wichita, Kansas. This result is somewhat surprising in that none of these cities are known to be either retirement communities or magnets for senior citizens. However, it should be noted that with an exception of Washington DC, most of these cities such as Detroit, Florence, Jacksonville, Louisville, and New York have relatively large percentages of senior citizens over 65 years old and persons with disabilities (e.g., 29.10% for Detroit; 33.64% for Florence; 29.72% for Jacksonville; 30.86% for Louisville; 31.13% for New York). In contrast, Los Angeles, California; Milwaukee, Wisconsin; Minneapolis, Minnesota performed poorly by registering the CRS and VRS efficiency scores below 0.50. As expected, these cities have relatively low percentages of senior citizens and persons with disabilities (e.g., 27.70% for Los Angeles; 27.84% for Milwaukee; 22.29% for Minneapolis).

In order to achieve efficiency, a paratransit system probably needs a critical number of threshold number or percentage of clients to serve, so perhaps a threshold of 30% of the population being 65 years or older and/or disabled is necessary for efficient operations and economies of scale. Also, we found that many west-coast cities such as Portland, Oregon; San Francisco, California; San Jose, California; San Diego, California; Seattle, Washington tended to perform poorly as compared to east-coast cities such as New York, New York; Boston, Massachusetts; Miami, Florida, which typically had more senior citizens on average than other cities.

## CONCLUSIONS AND IMPLICATIONS

This paper is one of the first to comprehensively measure and benchmark the comparative efficiency of paratransit systems in U.S. municipalities using DEA analysis, while identifying the factors (e.g., city size, resident income) most influential for paratransit service efficiency. DEA is a technique that helps public policy makers identify lagging paratransit systems with respect to various performance standards (e.g., vehicle utilization, return-on-investment of financial resources) and then highlight the specific aspects of paratransit performances that should be strengthened to further improve their efficiency. In all the DEA models tested, the greater the extent of density-congestion of a city, the more efficient the paratransit operation. However, we found that the overall size of a city has no bearing on the paratransit efficiency. Congruent with O'Sullivan's assertion (2007), mega cities exceeding populations of several million, such as Los Angeles, San Francisco, San Diego, and Seattle, did not produce high efficiency scores for their paratransit systems in terms of both CRS and VRS efficiencies.

On the other hand, mega cities such as New York and Detroit were considered to be benchmarks for others to meet. Thus, the economies of scale alone did not seem to dictate the paratransit efficiency. Especially, an intriguing observation that we made is the full efficiency of the Detroit paratransit system which endured a series of more severe budget cuts. Somewhat ironically, its lack of resources created a sense of urgency for their better utilization and then might have helped the paratransit authority streamline its operations.

Also, the findings of the Tobit regression models suggest that cities with densely populated downtown areas, less geographically dispersed, and East Coast/Midwestern cities with greater percentages of senior citizens and persons with disabilities tend to be more efficient in offering paratransit services than the other cities such as those on the West Coast. As noted earlier, more dense development usually accompanies economies of scale in providing public services to a certain extent (Hirsch, 1973 and 1984; Ladd, 1992 and 1994; Carruthers and Ulfarsson, 2003; O'Sullivan, 2007; Rosen, 1992; Garcia-Sanchez, 2006). Examples of public policies to encourage dense development within a city include: establishment of urban growth boundaries; assessment of higher impact fees for the development of remote neighborhoods; limitation of building permits only to existing neighborhoods or areas next to existing neighborhoods ("fill-in" development); and enactment of zoning laws which forbid new development until certain population densities are achieved in existing areas or neighborhoods of the cities.

When it comes to multiple paratransit systems in a given city, the cities with multiple paratransit systems tended to perform poorly. For example, Los Angeles, Minneapolis, San Francisco, Seattle, and Cleveland with multiple paratransit systems registered DEA efficiency scores well below 1. The only exception is the New York metro area which has five different paratransit systems, but other than the New Jersey transit system all four performed relatively well. The possible rationale being that, despite its separate paratransit systems, its unified government often shares resources among themselves. Another case in point is that benchmark cities such as Detroit, Florence, Jacksonville, Louisville, and Wichita have single paratransit systems. Perhaps, single paratransit authority or unified city governments are meant to attain paratransit efficiency by reducing paratransit service duplications and exploiting economies of scale.

For public policy purposes, and when it comes allocating resources, federal and state governments should reward and develop those paratransit systems that have large target populations (around 30% or more elderly and disabled) and that serve densely settled areas (a population per square mile of at least 7,000 on average). More emphasis nowadays seems to be placed on encouraging city planners and local governments to develop less sprawled and denser urban environments which can increase the efficiency of some public services including paratransit services. Therefore, federal and state governments should sustain policies that encourage denser local development to enhance the efficiency of paratransit services.

Regarding lagging paratransit systems whose financial and human resources were not fully utilized, public policy makers need to consider either outsourcing their operations to private companies or streamlining their operations by creating a separate taskforce that can dedicate its efforts to the continuous improvement of paratransit efficiency.

**Acknowledgments:** This research was funded by the University Transportation Center (UTC) at the University of Detroit-Mercy and the U.S. Department of Transportation. The authors would like to thank Mr. James Gee, General Manager of the *Toledo Area Regional Transit Authority (TARTA)* and Mr. Jon R. Elston, Director of the *Toledo Area Regional Para-transit Service (TARPS)* for providing valuable insights into this study.

## REFERENCES

ADA Paratransit Handbook (1992), *American with Disabilities Act of 1990: US Department of Transportation Paratransit Handbook.* Chicago, IL: Commerce Clearing House.

Amemiya, T. (1985), Chapter 10, the Tobit model in *Advanced Econometrics.*
Cambridge, MA: Harvard University Press.

American Public Transit Association (2009), *2009 Public Transportation Fact Book*, 60th edition, Washington DC: American Public Transit Association.

Anderson, D.R., Sweeny, D.J. and Williams, T.A. (1999), *Contemporary Management Science with Spreadsheets.* Cincinnati, OH: South-Western Publishing.

Bower, D.J. (1991), "Automated Paratransit Routing and Scheduling using a Highway Network Model," *Transportation Research Record: Journal of the Transportation Research Board*, 1292: 15-23.

Braadbaart, O. (2007), "Collaborative Benchmarking, Transparency, and Performance: Evidence from the Netherlands Water supply Industry," *Benchmarking: an International Journal*, 14(6): 677-692.

Breen, R. (1996), *Regression Models: Censored, Sample-Selected, or Truncated Data.* Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-111, Thousand Oaks, California: Sage Publications.

Carruthers J. I. and Ulfarsson, G F., (2003), "Urban Sprawl and the Cost of Public Services" *Environment and Planning B: Planning and Design,* 30(4): 503 – 522

Cervero, R. (1997), *Paratransit in America: Redefining Mass Transportation.* West Port, CT: Praeger Publishers.

Charnes, A., Cooper, W.W., and Rhodes, E. (1978), "Measuring the Efficiency of Decision Making Units," *European Journal of Operational Research*, 2 (6): 429-444.

Chira-Chavala, T. and Venter, C. (1997), "Cost and Productivity Impacts of a 'Smart' Paratransit System," *Transportation Research Record: Journal of the Transportation Research Board*, 1571: 81-87.

Fare, R., Grosskopf, S, and Knox Lovell, C.A. (1994), *Production Frontiers,* Boston, MA: Cambridge University Press.

Fu, L., Yang, J., and Casello, J. (2007), "Quantifying Technical Efficiency of Paratransit Systems by Data Envelopment Analysis Method," *Transportation Research Record: Journal of the Transportation Research Board*, 2034: 115-122.

Garcia-Sanchez, I.M. (2006), "The Efficiency Measurement in Spanish Local Government: The Case of Municipal Water Services," *Review of Policy Research*, 23(2): 355-371.

Hirsch, W.Z., (1973), *Urban Economic Analysis,* New York, NY: McGraw-Hill Publishers.

Hirsch, W.Z., (1984), *Urban Economics,* New York, NY: Macmillan Publishing.

Jackson, R. (1982), "The Cost and Quality of Paratransit Service for the Elderly and Handicapped," *Transportation Quarterly*, 36(4): 527-540.

Kain, J.F. (1967), *Urban Form and the Costs of Urban Services*, Cambridge, MA: Mimeographed. M.I.T. - Harvard Joint Center for Urban Studies.

Kern, R. (2009), "Cities Paratransit Services Face Cutbacks, Fare increases," *USA Today*, http://www.usatoday.com/news/nation/2009-03-31-dialaride_N.htm, Accessed: *10/21/09.*

Kvalseth, T.O., and Deems, J.M. (1979), "Statistical Models of the Demand for Emergency Medical Services in an Urban Area," *American Journal of Public Health*, 69 (3): 250-255.

Ladd, H.F. (1992), "Population Growth, Density and the Costs of Providing Public Services," *Urban Studies*, 29(2): 273-295.

Ladd, H.F. (1994), "Fiscal Impacts of Local Population Growth: A Conceptual and Empirical Analysis," *Regional Science and Urban Economics*, 24: 661-686.

Lambert, T.E. and Meyer, P.B. (2008), "New and Fringe Residential Development and Emergency Medical Services Response Times in the United States," *State and Local Government Review*, 40(2): 115-124.

Lambert, T.E. and Meyer, P.B. (2006), "Ex-urban Sprawl as a Factor in Traffic Fatalities and EMS Response Times in the Southeastern United States," *Journal of Economic Issues*, 40(4): 941-953.

Magd, H. and Curry, A. (2003), "Benchmarking: Achieving Best Value in Public Sector Organizations," *Benchmarking: an International Journal*, 10(3): 261-286.

Min, H. (2010), "Evaluating the Service Quality of Paratransit Systems; an Exploratory Study of the Toledo Regional Transit Authority," *International Journal of Logistics Systems and Management*, in press.

Min, H. and Lambert, T.E. (2006), "Evaluating the Comparative Efficiency of Eleven States' Highway Expenditures," *Journal of Transportation Management*, 17(2): 46-62.

Min, H., Min, H., Joo, S-J., and Kim, J. (2008), "A Data Envelopment Analysis for Establishing the Financial Benchmark of Korean Hotels," *International Journal of Services and Operations Management*, 4(2): 201-217.

Moore, A., Nolan, J., and Segal, G.F. (2005), "Putting Out the Trash: Measuring Municipal Service Efficiency in U.S. Cities," *Urban Affairs Review*, 41(2): 237-259.

Nolan, J.F., P.C. Ritchie, and Rowcroft, J.R. (2001), "Measuring Efficiency in the Public Sector using Nonparametric Frontier Estimators: a Study of Transit Agencies in the USA," *Applied Economics*, 33: 913-922.

Northcott, D. and Llewellyn, S. (2005), "Benchmarking in UK health: a Gap between Policy and Practice?," *Benchmarking: an International Journal*, 12(5): 419-435.

Pagano, A.M., Metaxatos, P., and King, M. (2002), "Effect of Computer-assisted Scheduling and Dispatching Systems on Paratransit Service Quality," *Transportation Research Record: Journal of the Transportation Research Board*, 1791: 51-58.

Paquette, J., Cordeau, J-F., and Laporte, G. (2009), "Quality of Service in Dial-a-Ride Operations," *Computers and Industrial Engineering*, 56(4): 1721-1734.

O'Sullivan, A. (2007), *Urban Economics*, 6th Edition, New York, NY: McGraw-Hill Publishers.

Real Estate Research Corporation (1974), *The Costs of Sprawl: Literature Review and Bibliography*, Washington, DC: U.S. GPO.

Rosen, H. (1992), *Public Finance*, Third Edition, Boston, MA: Irwin Publishers.

Shioda, R., Shea, M., and Fu, L. (2008), "Performance Metrics and Data Mining for Assessing Schedule Qualities in Paratransit," *Transportation Research Record: Journal of the Transportation Research Board*, 2072: 139-147.

Steele, S.B. (1993), *Emergency Dispatching: A Medical Communicator's Guide*, Englewood Cliffs: NJ Prentice Hall.

Tuydes, H. and Ozen, M. (2009), "Scenario-based Semi-disaggregate Market Share Estimation for Proposed Paratransit Systems for Philippi Region," Greece. Presented at the *88th Annual Transportation Research Board Meeting*, Paper #09-2624, Washington, DC.

US National Transit Database (2005), http://www.ntdprogram.gov/ntdprogram/. Accessed: *4/4/10*.

Vagnoni, E. and Maran, L. (2008), "Public Sector Benchmarking: an Application to Italian Health District Activity Plans," *Benchmarking: an International Journal,* 15(3): 193-211.

Viton, P.A. (1997), "Technical Efficiency for Multi-mode Bus Transit: Product Frontier Analysis," *Transportation Research Part B*, 31 (1): 23-39.

Wooldridge, J.M. (2006), *Introductory Econometrics: A Modern Approach*, 3rd edition, Mason, Ohio: Thomson South-Western.

Wynn-Williams, K.L.H. (2005), "Performance Assessment and Benchmarking in the Public sector; an Example from New Zealand," *Benchmarking: an International Journal*, 12(5): 482-492.

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# TRIP PATTERNS IN AKURE, NIGERIA: A LAND-USE ANALYTICAL APPROACH

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**Nigerian Federal University of Technology**

## ABSTRACT

Data on trips in land use parcels of Akure, a developing capital city in Nigeria, were collected and analyzed. Distance of each land use area from the central business district (CBD) was found to have played a significant role in trip attraction to it, while residential density was a major determinant of trip generation. Average numbers of daily work trips generated per capita ranged between 0.97 and 2.0, which compares with 0.8 to 2 specified in literature for developing cities. Total daily trips per capita for Akure-Nigeria (2.56) is higher than that of Mumbai-India (1.81), Chennai-India (2.08), and Harare-Zimbabwe(2.19). Availability, convenience, cost and promptness were found to be the major determinants of modal choice in the study area.

## INTRODUCTION

Extensive research has hitherto been carried out on travel characteristics and behaviour in many cities but mainly in cities of the developed world. However, attempts have been made to extend the research to cities of developing countries. Some of the authors that have conducted research in this regard are: Maunder (1984), Fouracre and Maunder (1987), Fouracre and Turner (1992), Astrop (1996), Mbara and Maunder (1997), Howe and Bryceson (2000), Cervero (2000), Sung et.al (2001), among others. Cities of the developing world that have been considered include Delhi, Jaipur, Patna, Pune and Vadodera in India; Harare in Zimbabwe; Dar Es Salaam and Morogoro in Tanzania; Nairobi and Eldoret in Kenya; Johannesburg in South Africa and Kumasi in Ghana among others.

The authors analyzed the effects of income, public transport systems, travel cost, city structure, household structure, location, trip length, and demography on travel behavior. This research is aimed at assessing the relationship between land use and trip patterns in Akure with a view to determining the modal split and reasons for choice of modes. Emphases have been placed on the influence of land use on the pattern of trips without undermining the importance of other socio-economic factors. Trips undertaken to places of vocation were considered as work trips while shopping, leisure, religious activity- related trips, and those made while visiting friends and relations were considered to be recreational trips. The findings of this research will provide a rational basis for transportation planning in the study area and other similar cities.

The Akure metropolis is the capital city of Ondo State, Nigeria. It is located in the northern part of the state around latitude $7^0$ $15^1$ North and longitude $5^0$ $15^1$ East and has an area of approximately 30.02 square kilometers. Its population was estimated at 353,211 according to 2006 census. This consisted of 175,495 (49.68%) males and 177,716 (50.32%) females who are mainly civil servants, traders and peasant farmers. The town was not planned ab-initio and as a result there are minimal functional relationships between the various land use areas. This disaggregated location of land use coupled with the morphological linearity of the town, its sparingly developed road network and ineffective traffic management, often create a chaotic pattern on major roads and large demands on public transport during rush hour. This large demand exerts a great strain on available facilities and because of institutional and funding constraints, conventional transit systems are not presently available. Hence some unconventional para-transit public transport modes like motorcycles (okada) and private vehicles not registered as taxis known as "Kabu-kabu" act as supplements. The road pattern in Akure metropolis is shown in Figure 1.

## METHODS

Data on intra city travel behaviour were collected in five residential land use areas of Akure metropolis namely: low, medium and high density residential; commercial (which is interspersed with residential buildings akin to that of high density residential); and military zone. The data were collected through intensive home and road side interviews. Figure 2 shows the major land use areas of Akure metropolis.

The home interview was conducted using a comprehensive two-part questionnaire. The first part collected information on socio-economic characteristic of households, while the second part obtained information on weekly trips made by household members. The data include: household size, sex, age and marital status of respondents. Others are nature of employment, household income, vehicle ownership, origin and destination of trips, modes of transport used in making trips, factors affecting choice of mode, frequency of trips within the week among others. For the survey, trip chains are disaggregated into direct single journeys.

Considering the population in the residential area of Akure (which is about 80% of the entire populace), a sample size of 1 in 10 (10%) was adopted, as suggested by Bureau of Public Road (1954), O' Flaherty (1974) and Salter (1989). Every 10th household on each street was interviewed in all the land use areas considered. The administered questionnaires were sorted and the information obtained analyzed.

## RESULTS AND DISCUSSION

Figures 3 and 4 illustrate the total number of daily work and recreational trips generated and attracted by each land use area. The high density residential area generated the highest number of daily work trips of 10,920 while the military zone generated the lowest (236). This indicates that higher density areas generate higher work trips. This trend is also similar for recreational trips except that the volume generated by the medium density residential (8,236) zones is higher than that of high density residential areas (4,560).

**FIGURE 1**
**MAP OF AKURE, NIGERIA SHOWING ROAD PATTERNS**

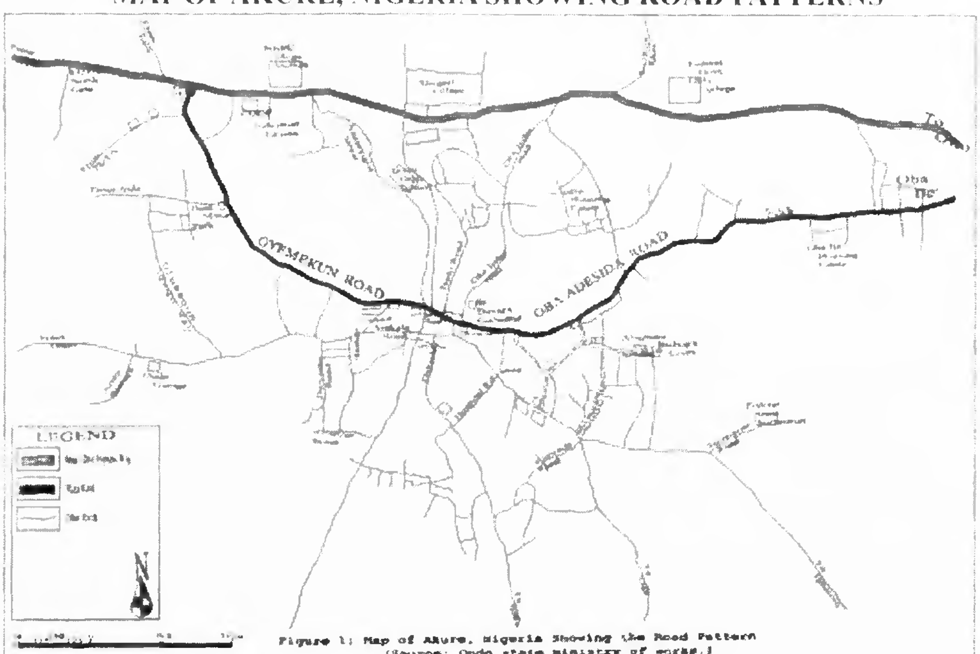
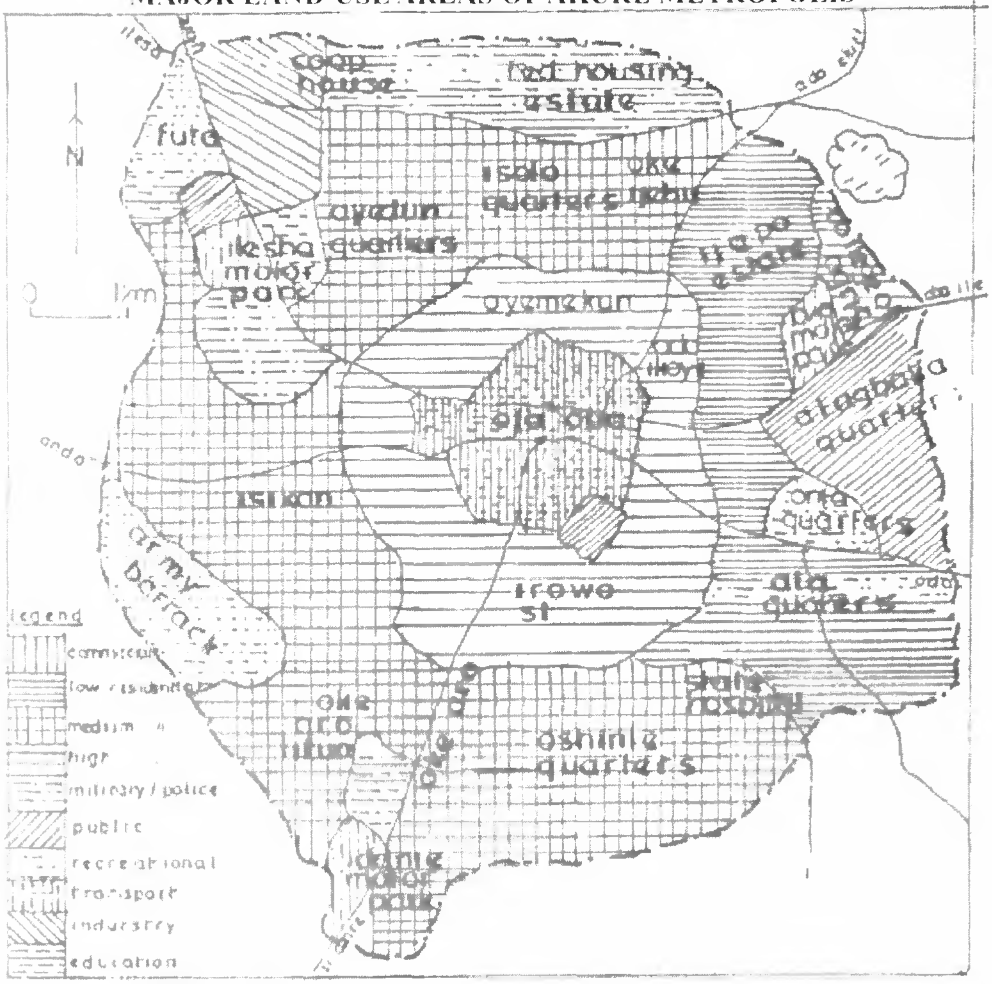


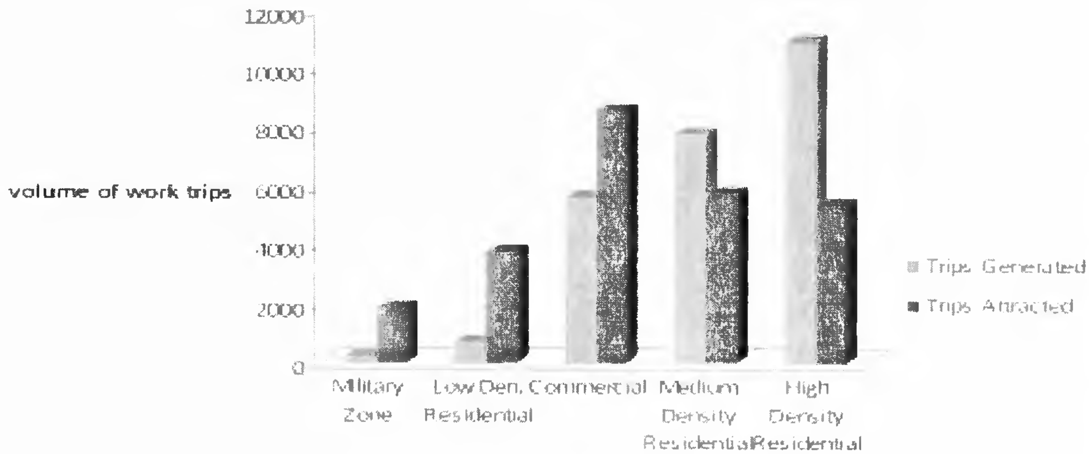
**FIGURE 2**
**MAJOR LAND-USE AREAS OF AKURE METROPOLIS**




The high volume of recreational trips generated by the medium density residential areas may be attributed to the fact that residents of the zone have the highest number of cars in the study areas . This further tends to suggest that many of those who make recreational trips do so with their personal cars. The use of private cars for recreational trips is not necessarily more economical but more convenient. The low volume of work and recreational trips generated by the military zone is not necessarily due to its residential density but because most of the socio-economic activities are confined within the barracks. These complexes are equipped with facilities like schools, health centres, mini-markets and religious worship centres, thus revealing their 'urban village' characteristic.

Distance of each land use area from the central business district (CBD) was found to have played a dominant role in trip attraction to it. The commercial zone attracted the highest volume of daily work and recreational trips of 8,590 and 7,982 respectively, possibly due to the fact that the Central Business District (CBD) is an integral part of this zone. The CBD is where most trips in the metropolis terminate for various business transactions, and commuters change or access modes of transport to other parts of the metropolis. The central market is located in this zone alongside shopping and relaxation centres. The military zone also attracted the lowest volumes of work and recreational trips (1,836 and 766 respectively) due to the fact that the zone is the farthest from the

**FIGURE 3**
**WORK TRIP GENERATION AND ATTRACTION**




CBD and operates like an urban village as earlier explained.

The numbers of daily work and recreational trips generated per capita for each land-use area are shown in Table 1. The average number of daily work trips generated per capita ranged from 0.97 to 2.0, which compares favourably with the range of 0.8 to 2 specified by Fouracre and Turner (1992) for developing cities. The average numbers of daily recreational trips per capita ranged from 0.67 to 1.92. These values indicate that recreational trips are not necessarily made daily. The medium density residential zone generated the highest number of daily recreational trips per capita, perhaps due to the fact that the zone has the highest number of cars in the study area, as earlier explained.

The ownership of a vehicle undoubtedly increases the propensity to make trips, particularly for discretionary journeys. The total daily trips per capita, for Akure, Nigeria are obviously higher than the values of 1.81, 2.08 and 2.19 for Mumbai-India, Chennai- India and Harare- Zimbabwe. The value for Harare was obtained by projecting that given by Palmer et.al (1996) and Mbara et.al (1997) using a growth rate of 5 %, while the values for Mumbai and Chennai were obtained by projecting those given by the Indian Ministry of Urban Affairs and Employment (1996) using the specified growth rates of 4.6% and 6.9% respectively.

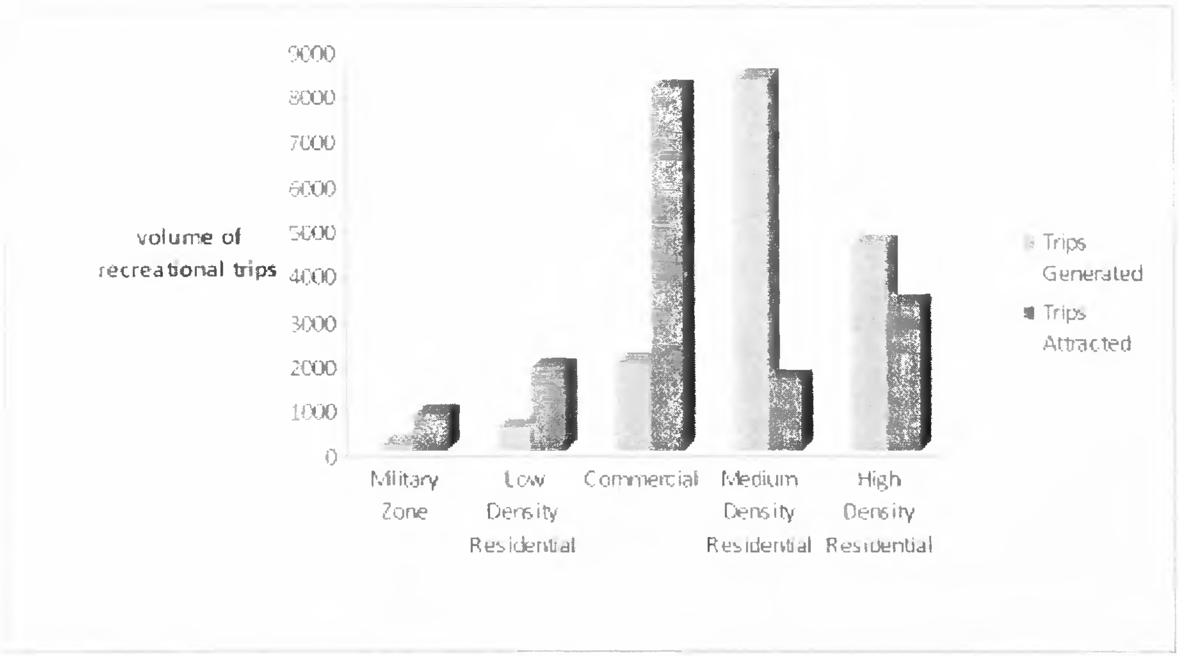
A comparison of mean car ownership rates (per household) between Akure- Nigeria, Accra-Ghana, and Pune- India has been made. The average number of cars per household in Akure (0.24) is lower than that in Accra (1.24) and Pune (0.63). The values for Accra and Pune were projected from those given by Palmer et.al (1996) using a growth rate of 5 %.

Figure 5 shows the proportion of work trips generated by mode in the study area. On the average, 55% of the trips were undertaken by taxi cabs while 20%, 10%, 9% and 6% were undertaken by private cars, mini buses, motorcycles and walking respectively. This shows that 74% of work trips in the metropolis are undertaken by para-transit modes. The proportion of recreational trips generated by mode in the land-use areas considered is given in Figure 6. On the average, 44% of the trips were undertaken by taxi cabs while 29%, 11%, 10% and 6% were undertaken by private cars, mini buses, motorcycles, and walking respectively. This

## TABLE 1
## CAR OWNERSHIP OF HOUSEHOLDS AND DAILY TRIPS PER CAPITA

| Land-use Area | No of Households Sampled | Number of Cars | Number of Cars per Household | Daily Recreational Trips per Capita | Daily Work Trips per Capita | Total Daily Trips per Capita |
|---|---|---|---|---|---|---|
| Low Density Residential | 120 | 72 | 0.60 | 0.67 | 0.97 | 1.64 |
| Medium Density Residential | 497 | 99 | 0.20 | 1.92 | 1.74 | 3.62 |
| High Density Residential | 420 | 73 | 0.17 | 0.91 | 2.00 | 2.91 |
| Commercial | 248 | 40 | 0.16 | 0.72 | 1.90 | 2.62 |
| Military zone | 23 | 18 | 0.78 | 0.68 | 1.29 | 1.97 |
| Average | | | 0.24 | 0.98 | 1.58 | 2.56 |

## FIGURE 4
## RECREATIONAL TRIP GENERATION AND ATTRACTION



shows that 65 % of recreational trips in the metropolis are undertaken by para-transit modes.

Figure 7 illustrates the factors affecting commuters' choice of para-transit modes for work trips in the study area. The factors considered include cost, speed, availability, absence of alternatives, comfort and convenience. The analyses revealed that the majority of those who patronize taxi cabs do so because they are readily available and convenient. Reasons adduced by commuters for patronizing motorcycles are that they are the only available alternative along their routes and that they are convenient and faster especially during the rush hours. Those who patronize mini buses do so because they are cheaper.
Figure 8 illustrates the effect of monthly income on choice of mode in the study area. It was observed that medium and high income earners (greater than $300 per month in Nigerian context) mostly make use of their private cars, while low income earners (less than $300 per month) mostly make use of taxi cabs. However, low income earners receiving less than $50 per month resort mainly to walking.

## CONCLUSION

This study on the pattern of trips in Akure Nigeria is one of the attempts to extend research on travel characteristics and behaviour to cities of the developing world. The findings show that distance of each land use area from the central business district plays a dominant role in work trip attraction to it while trip generation by the land-use areas increased with residential density. The low volume of work and recreational trips generated and attracted by the military zone is due to the fact that socio-economic activities are confined within the barracks. These complexes are equipped with

**FIGURE 5**
**PROPORTION OF WORK TRIPS GENERATED BY MODE**

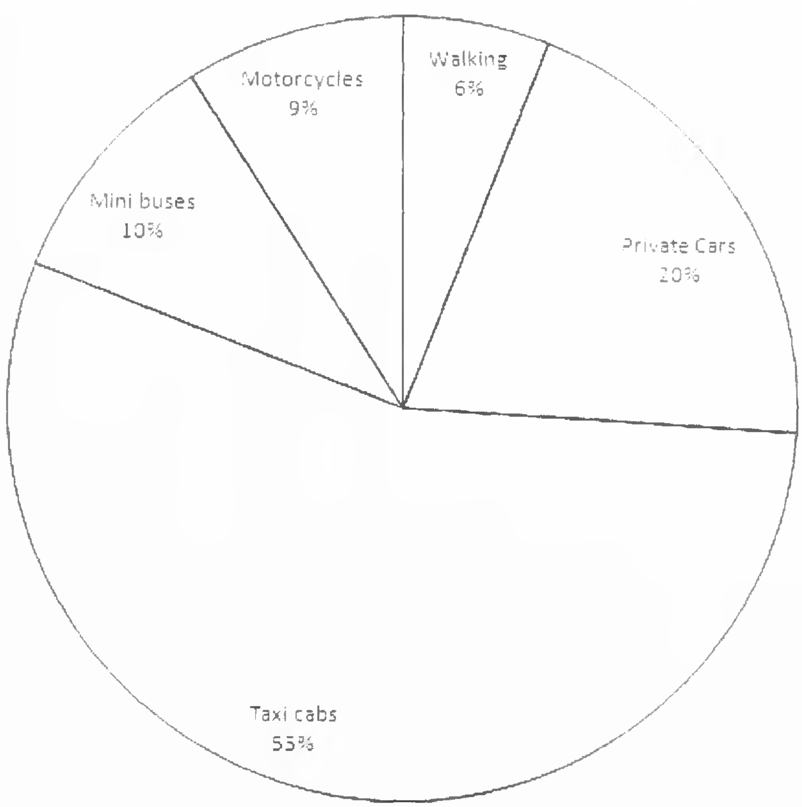


**FIGURE 6**
**PROPORTION OF RECREATIONAL TRIPS GENERATED BY MODE**

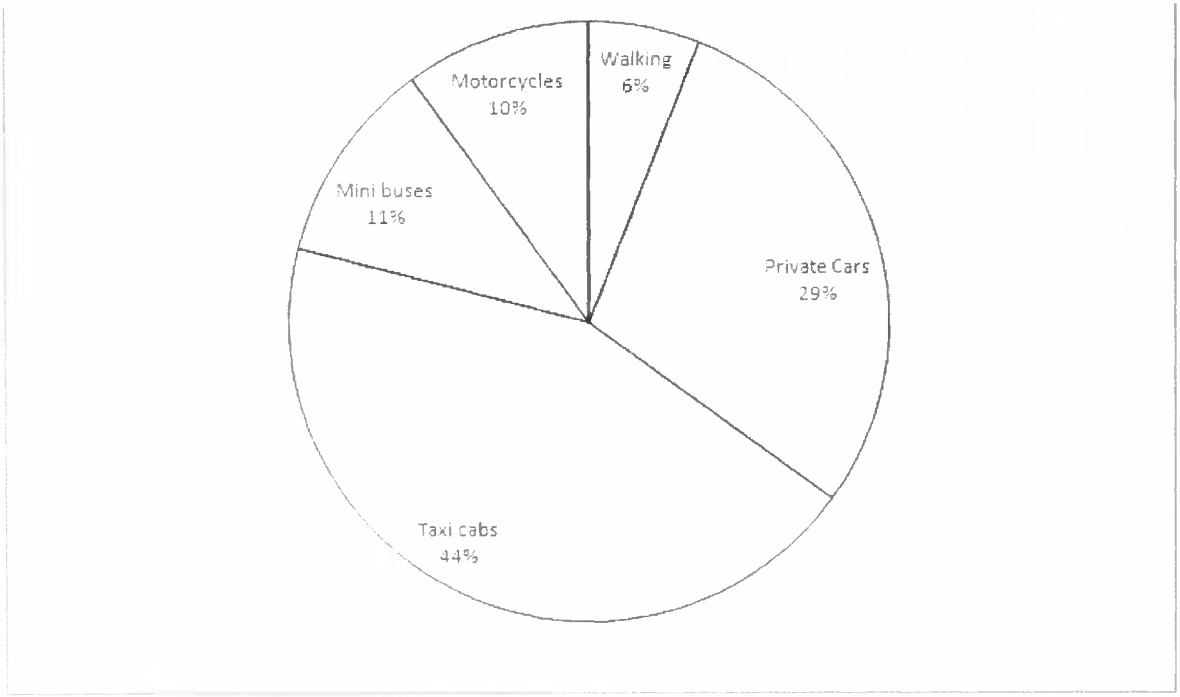



**FIGURE 7**
**FACTORS AFFECTING CHOICE OF WORK TRIP PARA-TRANSIT MODES**

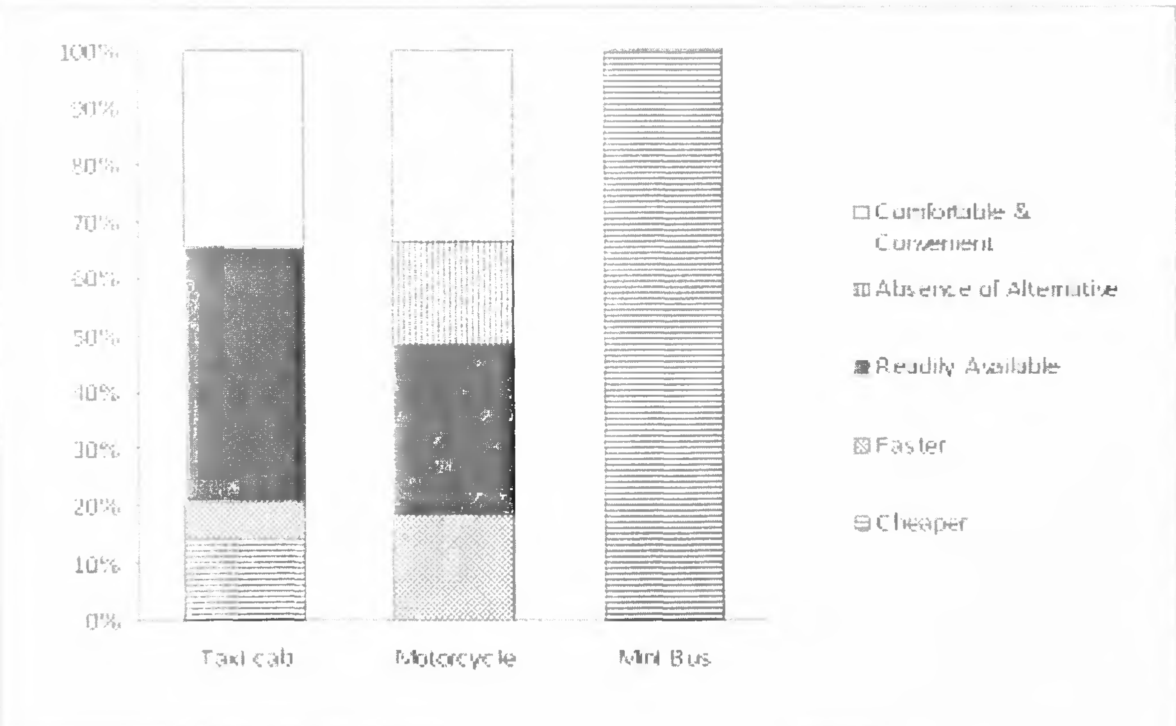
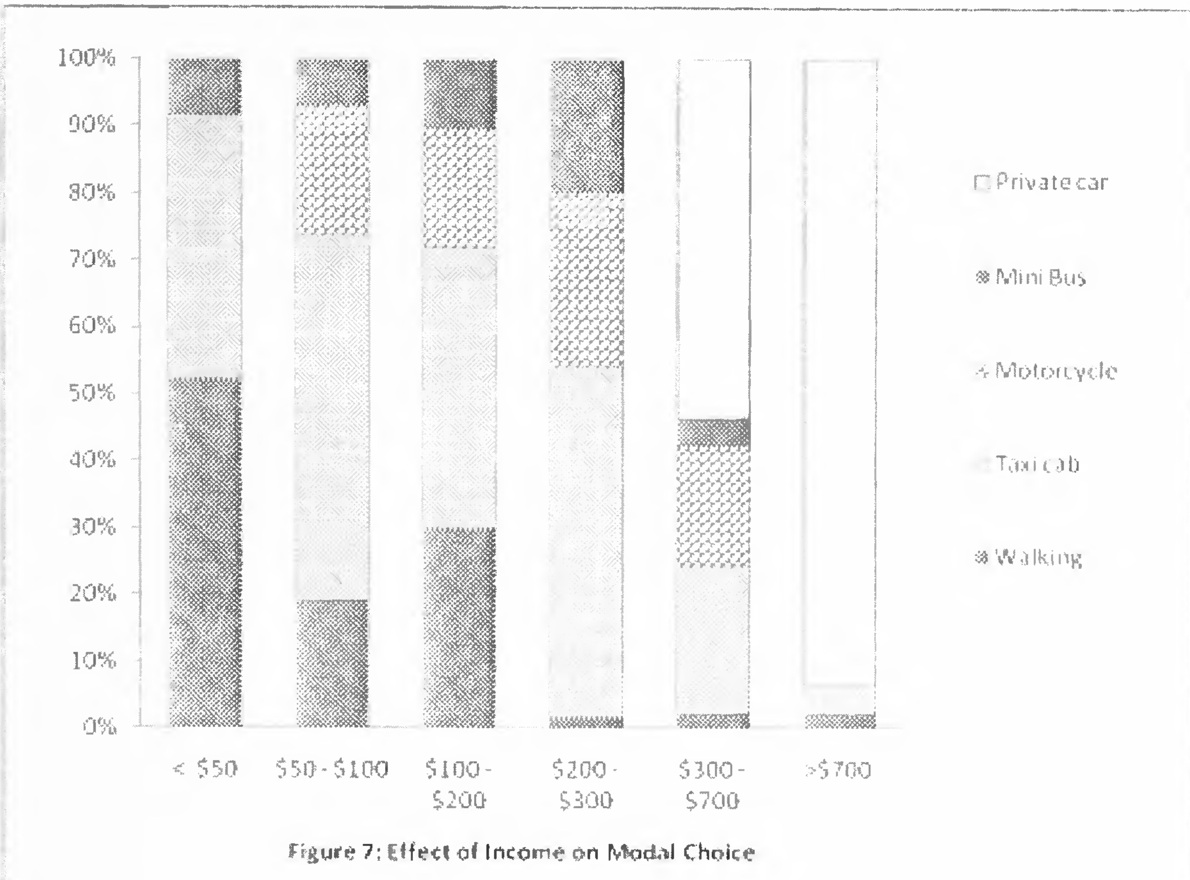


**FIGURE 8**
**THE EFFECT OF INCOME ON MODAL CHOICE**




necessary facilities. The range of work trips generated per capita in Akure compares favourably with that specified by Fouracre and Turner (1992) for developing cities, while the average daily trips generated per capita in the study area is higher than those for Mumbai- India, Chennai-India and Harare- Zimbabwe.

It has also been established that ownership of a vehicle increases the propensity to make trips, particularly for discretionary journeys. Para-transit modal choice in the study area has been found to depend on availability, convenience, cost and promptness. The fact that a higher proportion of trips in the study area were undertaken by modes other than private vehicles underscores the dominance of public para-transit. As such improvement of service delivery by the modes and creation of an enabling environment for their operations should be prioritized.

The findings of this study could be used by planners in developing nations and possibly UN and other economic development agencies in forecasting intra-city trips and providing facilities to accommodate them. It could also be a basis for conducting similar studies in developing cities of the world.

## REFERENCES


Astrop A. (1996), "The Urban Travel Behaviour and Constraints of Low Income Households and Females in Pune, India," *Women's Travel Issues: Proceedings from the Second National Conference.* Available: www.fhwa.dot.gov/ohim/womens/wtipage.htm

Bureau of Public Roads (1954), "Conducting a Home Interview: Origin and Destination Survey, " *Procedure Manual 2B, U.S. Public Administration Services.*

Cervero R. (2000), "Informal Transport in the Developing World," *United Nations Centre for Human Settlements (Habitat)*, Nairobi.

Fouracre P. R. and Maunder D. A. C. (1987), "Travel Demand Characteristics in Three Medium-Sized Indian Cities," *TRRL Research Report R1,* Crowthorn, Berkshire, RGII 6AU.

Fouracre P. and Turner J. (1992), "Travel Characteristics in Developing Cities," *Proceedings of the 6th World Conference on Transport Research*, Lyon.

Howe J. and Bryceson D. (2000), "Poverty and Urban Transport in East Africa," *Topic Review; Paper Prepared for the World Bank Urban Transport Strategy Review.* Available: http://www.worldbank.org/transport.

Indian Ministry of Urban Affairs and Employment (1996), "Report of the Working Group on Urban Transport," Government of India, New Delhi.

Maunder D. A. C. (1984), "Trip Rates and Travel Patterns in Delhi, India," *TRRL Research Report1*, Transport and Road Research Laboratory, Crowthorne, Berkshine.

Mbara T. C. and Maunder D. A. C. (1997), "Travel Characteristics of Urban Households in Harare, Zimbabwe," *8th IFAC Symposium on Transportation Systems,* Chania, Crete.

O'flaherty C. A. (1974), *Highways and Traffic,* 2nd Edition, London: Edward Arnold.

Palmer C., A. Astrop, M. Babu and D.A.C. Maunder (1996), "Understanding the Travel Behaviour and Constraints of Low Income Households in Pune, India," *Unpublished Project Report PR/OSC/109/96, TRL.*

Salter R. J. (1989), "Highway Traffic Analysis and Design," *Hempshire: Macmillan.*

Sung H. H., Morrison A. M., Hong G. S., and O' Leary J. T. (2001), "The Effects of Household and Trip Characteristics on Trip Types: A Consumer Behavioural Approach for Segmenting the U.S Domestic Leisure Market," *Travel Market Journal of Hospitality and Tourism Research,* 25(1): 46-68.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y = c + ax + bx
y = a + 1x + 2x + 3x + ax

2. References within the text should include the author's last name and year of publication enclosed in parentheses, e.g. (Wilson, 2004; Manrodt and Rutner, 2004). For more than one cite in the same location, references should be in chronological order. For more than one cite in the same year, alphabetize by author name, such as (Wilson, 2001; Mandrodt, 2002; Rutner, 2002; Wilson, 2003). If practical, place the citation just ahead of a punctuation mark. If the author's name is used within the text sentence, just place the year of publication in parentheses, e.g., "According to Manrodt and Rutner (2003) ...,". For multiple authors, use up to three names in the citation. With four or more authors, use the lead author and et al., (Wilson et al., 2004). References from the Internet should contain the site name, author/organization if available, date the page/site was created, date page/site was accessed, and complete web addresses sufficient to find the cited work.

3. Endnotes may be used when necessary. Create endnotes in 10-point font and place them in a separate section at the end of the text before References. (1, 2, etc.). Note: Endnotes should be explanatory in nature and not for reference purposes. Endnotes should NOT be created in Microsoft Insert Footnotes/Endnotes system. The Endnotes section should be titled in 12 point, uppercase and bolded.

4. All references should be in block style. Hanging indents are not to be used.

5. Appendices follow the body of the text and references and each should be headed by a title of APPENDIX (#) in caps and 12 Point, and bolded.

6. The list of references cited in the manuscript should immediately follow the body of the text in alphabetical order, with the lead author's surname first and the year of publication following all author names. The Reference Section should be headed with REFERENCES in caps, bolded, and in 12 point font. Work by the same author with the same year of publication should be distinguished by lower case

letters after the date (e.g., 1996a). For author names that repeat, in the same order, in subsequent cites, substitute a .5 inch underline for each name that repeats. Authors' initials should have a space between the initials, e.g., Smith, Jr., H. E., Timon, III., P. S. R., etc. A blank line should separate each reference in the list. Do not number references.

7. All references to journals, books, etc., are *italicized,* NOT underlined. Examples are as follows:

**Journal Article:**
Pohlen, Terrance L. (2003), "A Framework for Evaluating Supply Chain Performance," *Journal of Transportation Management,* 14(2): 1-21.

**Book Chapter:**
Manrodt, Karl (2003), "Drivers of Logistics Excellence: Implications for Carriers," In J. W. Wilson (Ed.), *Logistics and Transportation Research Yearbook 2003* (pp. 126-154) Englewood Cliffs, NJ: Prentice-Hall, Inc.

**Book:**
Coyle, John J., Bardi, Edward J., and Novack, RobertA. (2004), *Transportation,* 6th ed., Cincinnati, OH: South-Western College Publishing.

**Website:**
Wilson, J. W. (2003), "Adapting to the Threat of Global Terrorism: Reinventing Your Supply Chain," [On-line]. Available: http//:georgiasouthern.edu/coba/centers/lit/threat.doc. Created: 11/01/02, Accessed: 11/12/03.

**MANUSCRIPT SAMPLE**

**A FRAMEWORK FOR EVALUATING SUPPLY CHAIN PERFORMANCE**

Terrance L. Pohlen, University of North Texas

**ABSTRACT**

Managers require measures spanning multiple enterprises to increase supply chain competitiveness and to increase the value delivered to the end-customer. Despite the need for supply chain metrics, there is little evidence that any firms are successfully measuring and evaluating inter-firm performance. Existing measures continue to capture intrafirm performance and focus on traditional measures. The lack of a framework to simultaneously measure and translate inter-firm performance into value creation has largely contributed to this situation. This article presents a framework that overcomes these shortcomings by measuring performance across multiple firms and translating supply chain performance into shareholder value.

**INTRODUCTION**

The ability to measure supply chain performance remains an elusive goal for managers in most companies. Few have implemented supply chain management or have visibility of performance across multiple companies (Supply Chain Solutions, 1998; Keeler et al., 1999; Simatupang and

Sridharan, 2002). Supply chain management itself lacks a widely accepted definition (Akkermans, 1999), and many managers substitute the term for logistics or supplier management (Lambert and Pohlen, 2001). As a result, performance measurement tends to be functionally or internally focused and does not capture supply chain performance (Gilmour, 1999; *Supply Chain Management,* 200 I) . At best, existing measures only capture how immediate upstream suppliers and downstream customers drive performance within a single firm.

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Table 1 about here

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**Developing and Costing Performance Measures**

ABC is a technique for assigning the direct and indirect resources of a firm to the activities consuming the resources and subsequently tracing the cost of performing these activities to the products, customers, or supply chains consuming the activities (La Londe and Pohlen, 1996). An activity-based approach increases costing accuracy by using multiple drivers to assign costs whereas traditional cost accounting frequently relies on a very limited number of allocation bases.

$$y = a^2 - 2ax + x^2$$

**REFERENCES**

Manrodt, Karl (2003), "Drivers of Logistics Excellence: Implications for Carriers," In I. W. Wilson (Ed.), *Logistics and Transportation Yearbook 2003* (pp. 126-154) Englewood Cliffs, NJ: Prentice-Hall, Inc.

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*Revised August 30, 2011*
*Dr. John C. Taylor, Editor*

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