CONSTANTINE PORPHYROGENETUS INTERNATIONAL ASSOCIATION

Journal of Management Sciences and Regional Development
Issue 4, July 2002
Correspondence: ikarkazis@aegean.gr

http://www.stt.aegean.gr/geopolab/GEOPOL%20PROFILE.htm
ISSN 1107-9819
Editor-in-Chief: Arie Reichel

PERFORMANCE AND SCENARIO ANALYSIS OF THE WICHITA TRANSIT DEPARTMENT

Danaipong Chetchotsak & Mark J. Kaiser

Department of Industrial and Manufacturing Engineering
Wichita State University
Wichita, USA

Abstract. The performance of the Wichita Transit Department during 1994-1996 is assessed relative to a peer group of transit systems in the United States with a fleet size of 30-200 buses serving a base population of 200,000-500,000. A Data Envelopment Analysis (DEA) model is used to compute efficiency and effectiveness measures, and the results of the DEA model are compared against traditional measures and an alternative DEA model. Spearman's rank correlation test indicates general consistency among the efficiency measures of the three models, and Wichita Transit is shown to be efficient but ineffective relative to its peer group. The performance measures are then examined over a three-year period, 1994-1996, and scenario analysis is developed for a more comprehensive view of the system. A system performance metric is introduced and suggests that Wichita Transit can be improved by reducing its annual service hours 12%.

1. INTRODUCTION

Partial measures of transit performance such as cost efficiency and service utilization are normally used to monitor transit systems and assess performance between agencies (Obeng *et al.* (1992)). Efficiency measures indicate how well a transit agency uses its resources to provide the service, while effectiveness indicates how well the agencies service is consumed by the user group (Fielding (1992)). The cost efficiency and service utilization performance values are single-input/single-output measures defined as

$$\text{Cost Efficiency} = \frac{\text{Annual Service Hours}}{\text{Annual Operating Expenses}},$$

$$\text{Service Utilization} = \frac{\text{Annual Ridership}}{\text{Annual Service Hours}}.$$

Federal and local agencies in the U.S. tend to be primarily concerned with the cost efficiency values, since public transportation is normally viewed in terms of a service provider to underprivileged portions (the captive rider) of the population (Fielding (1992)). Single-input/single-output measures typically fail to accurately describe the overall system performance, however, and although they are meaningful gross measures, they are also subject to significant uncertainty due to the data reporting flexibility in generally accepted accounting practices.

The purpose of this paper is to assess the performance of the Wichita Transit Department relative to "similar" transit agencies in the United States. The model can also be viewed in a general systems perspective which can be suitably adjusted (depending on the quality and quantity of the data) for other transit agencies in different regions of the world. A Data Envelopment Analysis (DEA) model introduced by Chu *et al.* (1992) is used to assess the performance of a group of similar transit agencies, and a model is developed which incorporates the DEA efficiency and effectiveness measures. Chu's model forms the basis of this analysis but is modified to account for the nature of the available data and the assessment of model results deemed most useful for decision analysis at Wichita Transit. The DEA model is used to assess the performance of transit agencies which provide two modes of service: bus and demand response service. Demand response in the U.S. provides service on demand[1] (initiated from a phone call), while bus service operates on a fixed route and time schedule.

The DEA model is described in Section 2, and the database, peer group, and model adjustments are described in Section 3. Section 4 presents computational results for the DEA model and a comparison of alternative models for the year 1995. A three-year examination period, 1994-1996, is also analyzed for the peer group. A dynamic environment is developed for Wichita Transit which incorporates elements of scenario analysis in Section 5, and a brief summary in Section 6 concludes the paper.

[1] Demand response service is required by federal law to be provided for persons with disabilities who are not able to use the fixed route service (Federal Transit Administration (1995)).

2. MATHEMATICAL MODEL OF TRANSIT PERFORMANCE

2.1 The DEA Model

The basic DEA model formulation is well-known and for background information the reader is referred to Charnes *et al.* (1981) and Coelli *et al.* (1998). Following the notation of Charnes *et al.* (1981), the observation on the input and output vector for each of j = 1,2...,n Decision Making Units (DMUs) are presented in the form

$$X_j = \begin{pmatrix} x_{1j} \\ x_{2j} \\ \vdots \\ x_{ij} \\ \vdots \\ x_{mj} \end{pmatrix}, \quad Y_j = \begin{pmatrix} y_{1j} \\ y_{2j} \\ \vdots \\ y_{rj} \\ \vdots \\ y_{mj} \end{pmatrix}, \qquad (1)$$

where $x_{ij} > 0$ represents the observed value of the i^{th} input and $y_{rj} > 0$ represents the observed value of the r^{th} output for DMU j. Assuming constant returns to scale, the efficiency of a DMU k is determined from the set of j = 1,...,n units. The mathematical model, referred to as Program h_k, is presented as:

Program h_k:

$$\max \quad h_k = \frac{\sum_{r=1}^{s} \beta_r y_{rk}}{\sum_{i=1}^{m} \upsilon_i x_{ik}}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} \beta_r y_{rj}}{\sum_{i=1}^{m} \upsilon_i x_{ij}} \leq 1, \qquad j = 1,2,\ldots,n, \qquad (2)$$

$$\upsilon_i \geq \varepsilon > 0 \qquad i = 1,2,\ldots,m,$$

$$\beta_r \geq \varepsilon > 0 \qquad r = 1,2,\ldots,s.$$

The values of β_r and v_i are determined using the following criteria: Choose positive values of β_r and v_i so as to maximize the relative efficiency of the k^{th} DMU subject to the constraint that each of the n agencies, using the same value of β_r and v_i, has a relative efficiency that does not exceed one. In the same manner, the optimal efficiency of the k^{th} DMU is examined. A value of h_k =1 indicates that the k^{th} DMU is efficient while if h_k <1, the DMU is inefficient.

Program h_k is readily transformed and solved as a linear program, referred to as Program g_k:

Program g_k:

$$
\begin{aligned}
\max \quad & g_k = \sum_{r=1}^{s} \beta_r y_{rk} & & \\
s.t \quad & -\sum_{r=1}^{s} \beta_r y_{rj} + \sum_{i=1}^{m} \upsilon_i x_{ij} \geq 0 & & j = 1,2,\ldots,n, \\
& \sum_{i=1}^{m} \upsilon_i x_{ik} = 1 & & \\
& \beta_r \geq \varepsilon & & r = 1,2,\ldots,n, \\
& \upsilon_i \geq \varepsilon & & i = 1,2,\ldots,n,
\end{aligned}
\tag{3}
$$

A DEA model structure was adapted by Chu *et al.* (1992) to assess the efficiency and effectiveness of transit performance. This model serves as the basis of our analysis and is referred to, appropriately enough, as Chu's model. Transit agencies provide two primary modes of service – bus service and demand response service – and measures of efficiency and effectiveness of the service are developed using multiple-input and multiple-output system variables. The multivariable nature of DEA modeling is believed to provide a more accurate assessment of performance indicators over the traditional measures as previously described. Following the form of Program g_k, Program p_k and Program q_k are used to measure the relative efficiency and effectiveness of the k^{th} transit agency, respectively, and are defined with respect to the following variable sets.

2.2 Relative Efficiency Model

The relative efficiency model evaluates how efficient a transit agency is in producing its service. The annual service hours for bus service and demand response is selected to measure the output produced, while the annual total operating expense is used to measure the input consumed. The relative efficiency of the k^{th} transit agency can be measured using the Program p_k and the following variable sets. Specifically,

Program p_k:

$$
\begin{aligned}
Y_j &= \begin{pmatrix} \text{Annual service hours for demand response } (SHRDR_j) \\ \text{Annual service hours for bus service } (SHRBS_j) \end{pmatrix} \\
X_j &= \left(\text{Annual total operating expense } (TOPR_j)\right)
\end{aligned}
\tag{4}
$$

2.3 Relative Effectiveness Model

The relative effectiveness model measures the consumption of the transit service. The annual ridership for the bus service is used to measure the transit output consumed, while the annual service hours and socioeconomic variables that reflect the supply and demand characteristics of public transit consumption (Chu *et al.* (1992), Webster *et al.* (1980), and Yu (1988)), serve as the input X_j. The annual ridership and service hour for demand response is not included in the model because such service operates only upon passenger demand. The Program q_k variable set, which specifies the relative effectiveness model, is given as follows:

Program q_k:

$$Y_j = \left(\text{Annual ridership for bus service } (RIDEBS_j)\right)$$

$$X_j = \begin{pmatrix} \text{Annual service hours for bus service } (SHRBS_j) \\ \text{Urbanized area population density } (UZADEN_j) \\ \text{Portion of households without automobiles } (PNOVEH_j) \\ \text{Annual financial assistance } (AFA_j) \end{pmatrix} \quad (5)$$

3. DATA SOURCES, MODEL SELECTION, AND FACTOR ADJUSTMENT

In 1995 there were 467 transit agencies in the U.S. that reported statistical information to the Federal Transit Administration (FTA), U.S. Department of Transportation. The agencies ranged in size from the small (under 10 buses) to large (more than 1,000 buses) serving base populations from under 50,000 to over 1 million (FTA (1995)). To compare Wichita Transit to "similar" transit agencies, a peer group was defined as a system with a fleet of 30-200 buses serving a base population of 200,000-500,000. The population sample that falls within this spectrum and the number of service vehicles for this peer group are given in Table 1. The Federal Transit Administration (1995) provides operating characteristics for the transit systems, while the U.S. Census Bureau provides data for the socioeconomic variables associated with the cities. The data required for the DEA models are gathered from these sources.

Although the peer group and base populations cannot be considered homogeneous, the selection criteria was such that returns to scale within the peer group was considered negligible. This assumption dictated the choice of the specific DEA model applied (CCR as opposed to the BCC model) and appears to be reasonable on the basis of the restricted-size peer group. To perform DEA analysis, some criteria must be employed to select the peer group, while at the same time it is recognized that the range of the resultant values is subsequently based on this (arbitrary) selection. Since DEA measures are *sample-size dependent*, caution must therefore be exercised in the application and interpretation of the results[2].

In a DEA model, the efficient frontier is computed based on the data set of the selected input and output variables, and then the efficiency/effectiveness of a DMU is evaluated relative to the frontier. The frontier surface is developed from the variables and should therefore reflect the essential characteristics of the measures employed. In this regard, the variables included in the DEA model were pre-screened and adjusted to provide for more robust and accurate performance indicators. The variable PNOVEH for instance was found to have a very low correlation with ridership, and even though its removal may result in information loss, it simplifies the formulation and is dropped from the model. The exclusion of this factor is primarily a subjective judgment call. Additional socioeconomic variables such as population, total personal income, and the fraction of the population

[2] If returns to scale was considered to be a significant factor for the peer group, then it would be more appropriate to use the BCC model.

below the poverty line are also excluded from the effectiveness model since total personal income is highly correlated to the population level, and the portion of the population below the poverty line is strongly negatively correlated to total personal income. Inclusion of these variables would create multicollinearity which is believed to bias the effectiveness measure.

The input vector for the relative effectiveness model is thus modified as follows:

$$X_j = \begin{pmatrix} \text{Annual service hours for bus service } (SHRBS_j) \\ \text{Urbanized area population density } (UZADEN_j) \\ \text{Annual financial assistance } (AFA_j) \end{pmatrix} \quad (6)$$

4. COMPUTATIONAL RESULTS AND DISCUSSION

To determine the relative performance for the 16 transit agencies that comprise the peer group in review, the Programs p_k and q_k are solved using the data shown in Table 2 and Table 3.

The results of the computation, the efficiency and effectiveness measures, are shown in Fig. 1 with each agency identified by number. The right vertical and upper horizontal axis of Fig. 1 describes the efficient frontier; i.e., points that fall on the right vertical axis are (optimally) effective while transit agencies that fall on the upper horizontal axis are (optimally) efficient. The upper right-hand corner point of the graph would represent an agency that is both efficient and effective, and it is clear that no transit agency falls within this classification, although sub-optimality is obtained by a subset of agencies. Oklahoma City-COTPA, Fresno-FAX, Birmingham-Max, St. Petersburg-PSTA, and Bakersfield-GET are effective but inefficient, while Colorado Springs Transit and Wichita Transit are efficient but ineffective. The remaining transit agencies fall somewhere off the efficient frontier, and their distance from the boundary can be used as a measure of inefficiency or ineffectiveness relative to the peer group.

4.1 Traditional Cost Efficiency and Service Utilization Measures

Traditional measures for transit performance have been defined in terms of cost efficiency and service utilization. Cost efficiency and service utilization are single-input/single-output measures and can be considered to serve as a proxy for transit efficiency and effectiveness, respectively. In this paper, cost efficiency is computed as the ratio of the *weighted* sum of annual service hours for bus and demand response service to the annual total operating expense. Motivation for using a weighted measure arises from an examination of the cost data in the National Transit database. The cost per hour to provide one vehicle of bus service is normally higher than the cost to provide one vehicle for demand response, which makes intuitive sense because of the different physical size of the vehicles used to provide the service (bus versus van). The difference between the cost per hour of these two services depends upon the specific agency, however, and the cost allocation methods employed, maintenance programs utilized, etc. and the weight factors 2 and 1 are chosen to indicate that running one vehicle of bus service for an hour is "equivalent" to running one vehicle of the demand response for two hours. This value was obtained as the average cost ratio over the peer group. Weight factor ratios 3:1 or 4:1 represent extreme (outlier) values and might also be applied to compute cost efficiency, but the subsequent rankings of the transit agencies would likely change[3].

The comparison between the relative efficiency computed through the DEA model and cost efficiency is shown in Table 4. Spearman's rank correlation (Bhattacharyya *et al.* (1977)) is used to determine the degree of association between the two measures and a rank correlation coefficient value of 0.99 was obtained. This indicates that the two measures rate a particular agency almost identically.

The service utilization is determined using only bus service data and is also given in Table 4 relative to the effectiveness measures computed using DEA. The rank correlation coefficient between service utilization and relative effectiveness is 0.61, which indicates that several contradictory results between the models are present; e.g., compared to Lexington-Fayette-LexTran, St. Petersburg-PSTA has a comparable service utilization value but the DEA model indicates that St. Petersburg-PSTA is significantly more effective. To account for the discrepancy in this case, observe that the service utilization measure does not take population density and level of financial assistance into consideration. A transit agency that has a low ridership per hour but provides the service in a low-density area, or an agency that receives a smaller amount of funding could therefore be considered effective. St. Petersburg-PSTA has a high ridership per population density and a high ridership per financial assistance and is more effective than Lexington-Fayette-LexTran, even though the service utilization values are comparable. It is clear that the service utilization measure, although conceptually simple and easy to compute, may introduce significant "omission" bias into the analysis due to the exclusion of factors that help explain utilization.

There are many other ways error can permeate the analysis. As discussed earlier, the manner in which data is reported to the Federal Government is subject to the interpretation of the financial/general manager of the agency, and thus, is subject to bias. The data reporting strategies of a specific agency is outside the control of the analyst, however, and when averaged over the agencies in the study, is believed to be insignificant. Another more subtle means error can enter the analysis is through the inclusion of irrelevant explanatory variables as discussed next.

4.2 Comparison with Chu's Model

In Chu's relative efficiency model, each of the expenses classified by functional area (operations, maintenance, general/administration) were used as the input vector X_j, while the base model considered here applies only the annual total expense as shown in expression (4). Although the reduction of the expense category to total expenses reduces the amount of information available from the model, the aggregate expense is the primary consideration of the decision maker and is the main focus of his/her analysis. If additional agency data can be ascertained (such as average age of operating fleet, number of service personnel, etc.), then a strong argument can be made for using disaggregated expense data. In the relative effectiveness model, Chu also included the portion of households without automobiles, which for the peer group in this study is considered an irrelevant variable.

The distinction between the base model and Chu's DEA model results are sometimes significantly different, as depicted in Table 4. For the relative efficiency and effectiveness measures, the rank correlation coefficient is 0.59 and 0.53, respectively, which again indicates a large number of contradictions between the model formulations. For example,

---

[3] This suggests one of the disadvantages of this measure when dealing with multiple input/output variables.

Colorado Springs Transit is efficient in the base model while Chu's model indicates a lower efficiency. The reason for the discrepancy may be due to the fact that Colorado Springs Transit provides a high level of service hours for demand response (relative to bus service), whereas Chu did not include the annual service hour for demand response service as an input measure. Another example which exhibits discrepancy is the efficiency value of Birmingham-Max. The base model indicates that Birmingham-Max is slightly less efficient than Toledo-TARTA, while Chu's model indicates a much higher efficiency value. Chu's model result seems to be unreasonable in this instance because Birmingham-Max has a higher cost per hour than Toledo-TARTA, and so Birmingham-Max should be less efficient. Discrepancy with the effectiveness measures are also present (e.g., Birmingham-Max and St. Petersburg-PSTA) and can be analyzed on a case-by-case basis.

In general, the discrepancy in these examples suggest that the inclusion of irrelevant variables or the omission of relevant variables would affect the ability of the DEA model to accurately describe the numerical values of the performance measures. The sensitivity of the model results to the structural aspects of the model (model selection, variable set, parameter values) is not surprising, however, and is a common feature in modeling endeavors.

4.3 Time-Series Performance Monitoring

Time-series assessment of the transit agencies allows management to monitor efficiency and effectiveness measures over time. The performance of the transit agencies in the peer group in this study is observed over a three year period, 1994-1996. The input and output variables are checked for consistency using correlation analysis and the relative efficiency and effectiveness is computed using the base DEA model. The relative efficiency and effectiveness measures for the peer group from 1994-1996 is depicted in Fig. 2 and 3.

In Fig. 4 the performance dynamic for the peer group agencies in the Midwest is depicted. The relative effectiveness for Fort Worth Transit and Omaha-TA during 1996 increased significantly from the previous year. Colorado Springs Transit and Wichita Transit remained efficient for three consecutive years, whereas Oklahoma City-COTPA stayed effective during this time frame. Most performance values improved in one measure at the expense of the other; e.g., Oklahoma City-COTPA has been effective for three years but increasingly inefficient; for Tulsa-MTA, the efficiency has improved at the expense of the effectiveness. Lincoln-StarTRAN actually did worse in both dimensions during the three year period.

4.4 Duality Interpretation

Since Wichita Transit is ineffective, the input/output vector that will position the agency on the frontier boundary ($\hat{X}_k, \hat{Y}_k$) with unit effectiveness can be determined in the following manner. Using the notation of Winston (1993), the points on the efficient frontier $\hat{X}_k$ and $\hat{Y}_k$ are expressed as:

$$\hat{X}_k = \sum_{j=1}^{n} |\lambda_j| \cdot X_j \tag{7}$$

and,

$$\hat{Y}_k = \sum_{j=1}^{n} \left|\lambda_j\right| \cdot Y_j, \tag{8}$$

where k indicates the agency being computed and λ_j represents the Dual Price[4] (Lagrange Multiplier) for constraint j in Program q_k. The absolute value sign $\left|\lambda_j\right|$ ensures that $\hat{X}_k$ and $\hat{Y}_k$ are formed as positive linear combinations of the input and output variables.

First, obtain the original input and output vector for Wichita Transit; e.g., Y_8 and X_8 are as follows:

$$Y_8 = (2276.01), \quad X_8 = \begin{pmatrix} 124.93 \\ 4263.52 \\ 2709.30 \end{pmatrix}.$$

Next, obtain X_j, Y_j, and λ_j for $j = 1,\ldots n$ from Program q_8 and substitute in eqn (7) and eqn (8):

$$\hat{Y}_8 = (2330.06), \quad \hat{X}_8 = \begin{pmatrix} 69.65 \\ 2308.10 \\ 881.62 \end{pmatrix}.$$

Notice that $\hat{Y}_8 > Y_8$ and $\hat{X}_8 < X_8$ which indicates the extent Wichita Transit is ineffective relative to the peer group. Movement to the frontier is accomplished by *artificial* adjustment to the input and output vector. Specifically, the analysis suggests that the annual ridership should be "increased" 2.4%, while the annual service hour and funding should be "reduced" 44.2% and 45%, respectively. The population density cannot be affected directly by the transit agency and is thus not considered. The population density could be described as a non-discretionary variable in the model (see Banker and Morey (1986)), although this is not pursued. For additional discussion on the relationship between the DEA measures, the reader is referred to Thannassoulis *et al.* (1995). Using the values $\hat{X}_8$ and $\hat{Y}_8$ in Program q_8 will allow Wichita Transit to be "effective."

The duality interpretation is interesting since it indicates how the agency is ineffective relative to its peer group, but it does not provide a diagnostic to improve the system. In fact, it is clear that the duality interpretation of the variables does *not* provide useful policy suggestions since (1) population density is out of the agency's control and (2) reducing the annual service hours for bus service would have an impact on related variables such as the

---

[4] Alternatively, λ_j can be obtained from solving the dual form of Program g_k which is given as:

Program d_k:

$$min = \varphi_k + \varepsilon \sum_{r=1}^{s} \alpha_r + \varepsilon \sum_{i=1}^{m} \gamma_r$$

$$\begin{aligned}
s.t. \quad & -\sum_{j=1}^{n} y_{rj}\lambda_j + \alpha_r \geq y_{rk} && r = 1, 2, \ldots, s \\
& \sum_{j=1}^{n} x_{ij}\lambda_j + x_{ik}\varphi_k + \gamma_i && i = 1, 2, \ldots, m \\
& \lambda_j \leq 0 && j = 1, 2, \ldots, n \\
& \alpha_r \leq 0 && r = 1, 2, \ldots, s \\
& \gamma_i \leq 0 && i = 1, 2, \ldots, m \\
& \varphi_k \ urs &&
\end{aligned}$$

annual operating expense and ridership. This leads to a consideration of scenario analysis to develop prescriptive/interpretive measures to improve the transit agency.

5. SCENARIO ANALYSIS

Scenario analysis allows the impact of parameter variations on the system and the interrelationship between efficiency and effectiveness measures to be better understood. The efficiency and effectiveness measures are combined into an additive value function to reflect the overall performance of the transit agency, and then the impact of a reduction of service hour on the overall performance is examined.

5.1 Impact of Service Hour Reduction on the System Parameters

The impact of a reduction in service hours on the system are examined. As service hours are reduced, we would expect

(1) operating expenses to decline,
(2) annual ridership to decrease according to service level elasticity, and
(3) annual financial assistance to decline.

The functional forms describing each of these relationships are estimated as follows.

1. *Reduction in the annual total operating expense* ($TOPR_8$). The relationship between annual total operating expense and service hour for bus service during 1992-1998 is approximated with a linear function:

$$TOPR_8 = 2{,}969{,}574 + 18.49 \cdot SHRBS_8 \quad (9)$$
$$(10.10) \qquad (7.16)$$
$$\bar{R}^2 = 0.89$$

(e.g., the average cost to provide an hour for the bus service of Wichita Transit would be \$18.5.) The adjusted $\bar{R}^2$ value is high due to the small sample size, and the t-statistics shown in parenthesis indicate that the variables are statistically significant.

2. *Reduction in the annual ridership for bus service* ($RIDEBS_8$). Service hour reduction will decrease ridership according to the service level elasticity e which has been estimated through regression to be 0.54 (Chetchotsak and Kaiser (1999)). The impact on ridership due to a reduction in service hour is thus expressed as:

$$RIDEBS_8{}' = RIDEBS_8 \cdot (1 - \gamma \cdot e) \quad (10)$$

where,

$RIDEBS_8{}'$ = annual bus ridership after service hour reduction
γ = percent reduction of service hour for bus service
e = service level elasticity.

The value of γ is defined by the user.

3. *Decline in the annual financial assistance* (AFA_8). The level of funds required for operation will decrease with the reduction in the operating expenses, and is expressed as

$$AFA_8 = TOPR_8 - FREVBS - \alpha \tag{11}$$

where,

$FREVBS$ = fare revenue for bus service
α = fare revenue for demand response service.

The value of α is assumed to be constant while $FREVBS$ depends on the annual bus ridership and is expressed as

$$FREVBS = f \cdot RIDEBS_8{}' \tag{12}$$

where f represents the estimated fare revenue for bus service per passenger. The value of f is estimated using the ratio of the annual fare revenue for bus service to the annual ridership during 1995 ($f = 0.5$).

5.2 Impact of Service Hour Reduction on the DEA Measures

Under the assumption of a static operating environment over the short run, there will be no change in the input and output variables for the other transit agencies in the peer group. For a system which undergoes a reduction in service hours, Programs p_8 and q_8 are solved sequentially. Fig. 5 illustrates the result of the DEA model and the relationship between efficiency and effectiveness as a function of a reduction in service hours. Notice that in the range between 0-12% reduction of service hours, the effectiveness values increase linearly while the efficiency values remain constant. Beyond a 12% service hour reduction, the efficiency values decrease while effectiveness increases nonlinearly. Extrapolating the results of this analysis beyond say, a 30 percent service hour reduction, would be meaningless since the value for service level elasticity would no longer remain valid.

To determine the level of service hour reduction that yields the maximum overall performance, the efficiency and effectiveness values are combined as a weighted sum

$$\text{Overall Performance} = \omega \cdot \text{Efficiency} + (1-\omega) \cdot \text{Effectiveness} \tag{13}$$

where ω is a weighting factor, $0 \le \omega \le 1$. Transit operators normally use effectiveness as the primary measure of operational success, whereas federal, state, and local agencies have generally paid more attention to the efficiency measure (Fielding (1987)). For Wichita Transit, an appropriate weight factor is expected to lie within the interval (0.5, 0.9). Fig. 6 demonstrates the impact on the overall performance due to the service hour reduction with different preference weights. For ω ranging between (0.5,0.9), a 12% service hour reduction would yield the maximum overall performance. For $\omega \le 0.5$, the overall performance is an increasing function of service hour reduction.

6. CONCLUSION

Quantitative models developed for the economic and performance components of transit agency assessment are beholden to a variety of input assumptions, to input parameters and their ranges of uncertainty, and to the quality and quantity of data used in the models. In this paper, a DEA model is used to measure the efficiency and effectiveness of Wichita Transit relative to a peer group under the assumption that constant returns to scale is an accurate approximation for the members of the sample set. The results of the model analysis were compared with traditional single-input/single-output measures and a DEA model originally proposed by Chu. Spearman's rank correlation test indicated that for the efficiency measure the base model yielded consistent results with the traditional measure but not with Chu's model; for the utilization measure the three measures yield contradictory results. Performance measures are quite sensitive to the selection of the decision variables as well as the peer group size, and as usual, caution should be exercised in interpreting the model results. The "best" models can be considered to be the most consistent and robust with respect to minor parameter variation.

Wichita Transit is efficient in providing transit service but ineffective in having its service consumed. The overall performance of the agency can be improved by analyzing the trade off between efficiency and effectiveness and determining a suitable level of input and output for the agency. Scenario analysis suggests that reducing the annual service hours for bus service 12% would yield the maximum value of the overall performance. Time-series performance monitoring also shows that Wichita Transit has improved its effectiveness while remaining efficient over the time period 1994-1996.

Acknowledgement-The authors would like to thank Mr. Stan Zienkewicz, Wichita Transit, for his assistance in providing the data for this study. The authors would also like to acknowledge the helpful and insightful comments of the reviewers of the manuscript, as well as the careful editorial assistance provided by Prof. Zilla Sinuary-Stern.

References

[1] Obeng K., Assar N., and Benjamin J., (1992), "Total Factor Productivity in Transit System: 1983-1988", Transportation Research, 26(6), 447-455.

[2] Fielding G.J., (1992), "Transit Performance Evaluation in the USA", Transportation Research, 26(6), 483-491.

[3] Chu X., Fielding G. J. and Lamar B. W., (1992), "Measuring Transit Performance using Data Envelopment Analysis", Transportation Research, 26(3), 223-230.

[4] Charnes A., Cooper W. W. and Rhodes E., (1981), "Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through", Management Science, 27(6), 688-697.

[5] Coelli T., Rao D.S. P., and Battese G. E., (1998), An Introduction to Efficiency and Productivity Analysis, 1st ed., Kluwer Academic, Dordrecht, The Netherlands.

[6] Federal Transit Administration, U.S. Department of Transportation, (1995), National Transit Database, http://www.fta.dot.gov/ntl/

[7] Webster F. V. and Bly P.H. (Eds.), (1980), The demand for public transport: Report of the International Collaborative Study of factors affecting public transport patronage, Transportation and Road Research Laboratory, Crownthone, England.

[8] Yu J.C., (1988), Incorporating Exogenous Effect on Transit Performance in The Section 15 Data Base, Salt Lake City: University of Utah, Department of Civil Engineering, Final Report, UMTA-UT-11-0004.

[9] The U.S. Census Bureau, http://www.census.gov/, (8/20/99).

[10] Bhattacharyya G.K. and Johnson R.A., (1977), Statistical Concepts and Methods, 1st ed., John Wiley & Son, New York.

[11] Winston W.L., (1993), Operations Research: Applications and Algorithms, 2nd ed., Duxbury Press, Belmont, California.

[12] Banker R.D. and Morey R.C., (1986), "Efficiency Analysis for Exogenously Fixed Inputs and Outputs", Operations Research, 34(4), 513-521.

[13] Thannassoulis E., Boussofiane A., and Dyson R.G., (1995), "Exploring Output Quality Targets in The Provision of Perinatal Care in England using Data Envelopment Analysis", Eur. J. Opnl. Res. 80, 588-607.

[14] Fielding G.J., (1987), Managing Public Transit Strategically, 1st ed., Jossey-Bass, San Francisco.

[15] Chetchotsak D. and Kaiser M. J., (1999), Forecasting Model and Scenario Analysis for Wichita Transit Ridership, preprint.

Table 1 City Population and Number of Service Vehicles for the Peer Group

Transit Agency	City Population[1]	Number of Service Vehicles[2]	
		Demand response	Bus Service
1. Fort Worth-The T	473,617	65	109
2. Oklahoma City-COTPA	466,153	43	57
3. Albuquerque-Sun Tran	417,772	29	104
4. Fresno-FAX	392,789	19	74
5. Tulsa-MTA	376,040	46	66
6. Omaha-TA	359,929	16	119
7. Colorado Springs Transit	336,771	50	40
8. Wichita-MTA	320,007	15	43
9. Toledo-TARTA	311,841	12	147
10. Birmingham-Max	261,470	15	78
11. Raleigh-CAT	239,078	9	39
12. Lexington-Fayette-LexTran	238,125	14	34
13. St. Petersburg-PSTA	237,787	73	103
14. Rochester-RTS	223,242	17	177
15. Lincoln- StarTRAN	207,115	39	48
16. Bakersfield-GET	201,548	6	54

Source: *1. U.S.Census Bureau (1995)*
2.Federal Transit Administration, Department of Transportation (1995)

Table 2 Model Data for Efficiency Measure

Transit Agency	Input	Output	
	Operating Expenses ($)	Annual Service Hours for Bus Service	Annual Service Hours for Demand Response
1. Fort Worth-The T	22,030,552	11,138,686	3,974,930
2. Oklahoma City-COTPA	9,795,587	4,049,474	1,670,854
3. Albuquerque-Sun Tran	16,872,657	10,906,109	2,681,825
4. Fresno-FAX	16,081,507	7,942,628	3,439,070
5. Tulsa-MTA	10,016,472	4,572,603	1,607,141
6. Omaha-TA	13,386,195	8,147,846	2,475,530
7. Colorado Springs Transit	6,902,238	4,117,026	804,000
8. Wichita-MTA	5,418,577	3,421,862	1,096,180
9. Toledo-TARTA	16,294,968	10,560,050	2,526,146
10. Birmingham-Max	12,478,671	6,340,041	2,649,726
11. Raleigh-CAT	6,619,993	2,966,316	1,129,077
12. Lexington-Fayette-LexTran	4,310,415	1,895,452	706,679
13. St. Petersburg-PSTA	26,223,143	14,891,306	4,145,330
14. Rochester-RTS	31,067,192	18,100,239	8,128,004
15. Lincoln- StarTRAN	5,158,441	2,990,087	1,034,746
16. Bakersfield-GET	7,923,341	3,289,584	1,416,230

Source: Federal Transit Administration, Department of Transportation (1995)

Table 3 Model Data for Effectiveness Measure

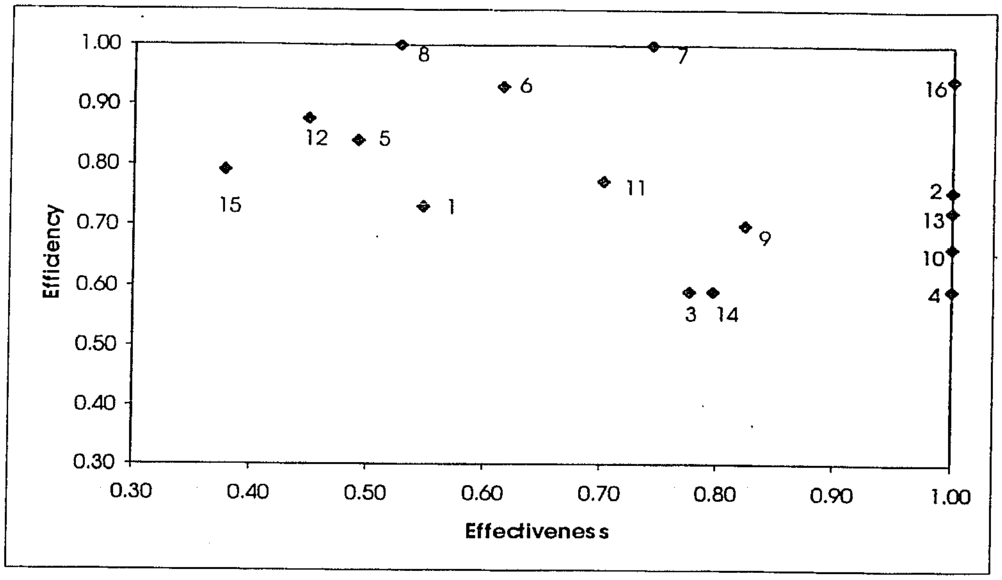
Transit Agency	Input			Output
	Annual Service Hour (Bus Service)	Annual Financial Assistance ($)	Population Density (per s.q. mile)	Annual Ridership (Bus Service)
1. Fort Worth-The T	354,428	5,788,961	1,685	5,576,686
2. Oklahoma City-COTPA	159,625	7,908,693	766	3,674,008
3. Albuquerque-Sun Tran	221,804	14,106,661	3,160	6,419,422
4. Fresno-FAX	219,706	11,731,682	3,964	8,552,797
5. Tulsa-MTA	176,896	8,017,173	2,049	2,896,197
6. Omaha-TA	287,703	2,719,272	3,578	4,962,598
7. Colorado Springs Transit	133,188	5,686,227	1,838	3,727,948
8. Wichita-MTA	124,928	4,263,523	2,709	2,276,010
9. Toledo-TARTA	264,149	4,013,506	3,970	4,650,478
10. Birmingham-Max	191,322	9,070,226	1,761	5,798,328
11. Raleigh-CAT	116,847	5,215,644	2,714	3,426,414
12. Lexington-Fayette-LexTran	81,356	3,582,548	837	1,490,364
13. St. Petersburg-PSTA	442,769	4,865,785	4,017	8,042,042
14. Rochester-RTS	422,467	21,509,436	6,236	13,607,538
15. Lincoln- StarTRAN	93,089	4,186,373	3,272	1,317,819
16. Bakersfield-GET	172,380	5,795,893	2,196	5,824,439

Source: Federal Transit Administration, Department of Transportation (1995)

Table 4 Computational Efficiency and Effectiveness

Transit Agency	Efficiency Measures			Effectiveness Measures		
	Base Model	Chu's Model	Cost Efficiency	Base Model	Chu's Model	Service Utilization
1. Fort Worth-The T	0.732	0.620	0.038	0.548	1.000	15.734
2. Oklahoma City-COTPA	0.726	0.797	0.037	1.000	1.000	23.016
3. Albuquerque-Sun Tran	0.589	0.590	0.030	0.777	0.736	28.942
4. Fresno-FAX	0.592	0.652	0.030	1.000	1.000	38.928
5. Tulsa-MTA	0.841	0.941	0.044	0.492	0.489	16.372
6. Omaha-TA	0.932	0.923	0.045	0.616	0.576	17.249
7. Colorado Springs Transit	1.000	0.602	0.053	0.743	0.735	27.990
8. Wichita-MTA	1.000	1.000	0.051	0.528	0.503	18.219
9. Toledo-TARTA	0.703	0.644	0.034	0.823	0.506	17.606
10. Birmingham-Max	0.665	0.817	0.033	1.000	0.887	30.307
11. Raleigh-CAT	0.774	0.854	0.040	0.701	0.758	29.324
12. Lexington-Fayette-LexTran	0.877	1.000	0.046	0.449	0.584	18.319
13. St. Petersburg-PSTA	0.758	0.772	0.039	1.000	0.569	18.163
14. Rochester-RTS	0.589	0.738	0.029	0.797	0.860	32.210
15. Lincoln- StarTRAN	0.790	0.826	0.041	0.378	0.375	14.157
16. Bakersfield-GET	0.943	1.000	0.046	1.000	1.000	33.788

Fig. 1 Efficiency and Effectiveness Values for the Peer Group



1. Fort Worth Transit
2. Oklahoma City-COTPA
3. Albuquerque-Sun Tran
4. Fresno-FAX
5. Tulsa-MTA
6. Omaha-TA
7. Colorado Springs Transit
8. Wichita Transit
9. Toledo-TARTA
10. Birmingham-Max
11. Raleigh-CAT
12. Lexington-Fayette-LexTran
13. St. Petersburg-PSTA
14. Rochester-RTS
15. Lincoln- StarTRAN
16. Bakersfield-GET

Fig. 2 Dynamic Efficiency Measure for the Peer Group (1994-1996)

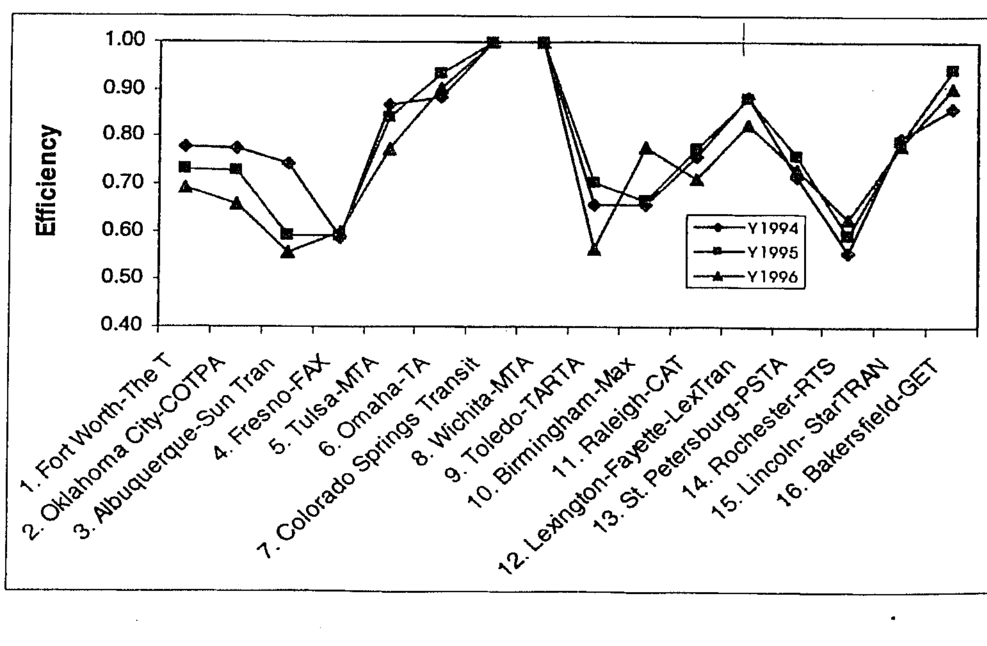


Fig. 3 Dynamic Effectiveness Measure for the Peer Group (1994-1996)

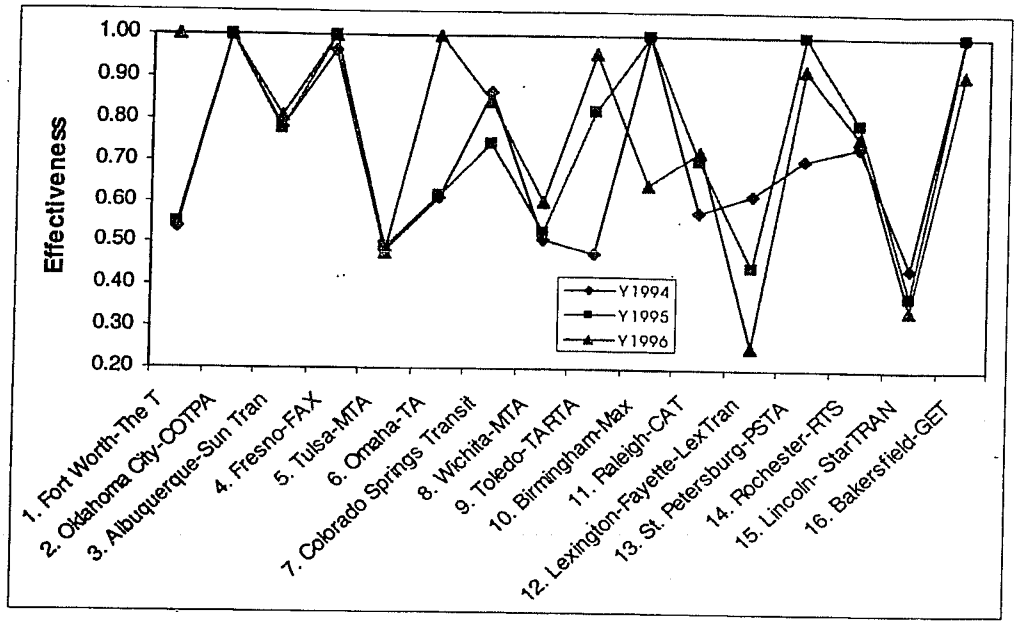
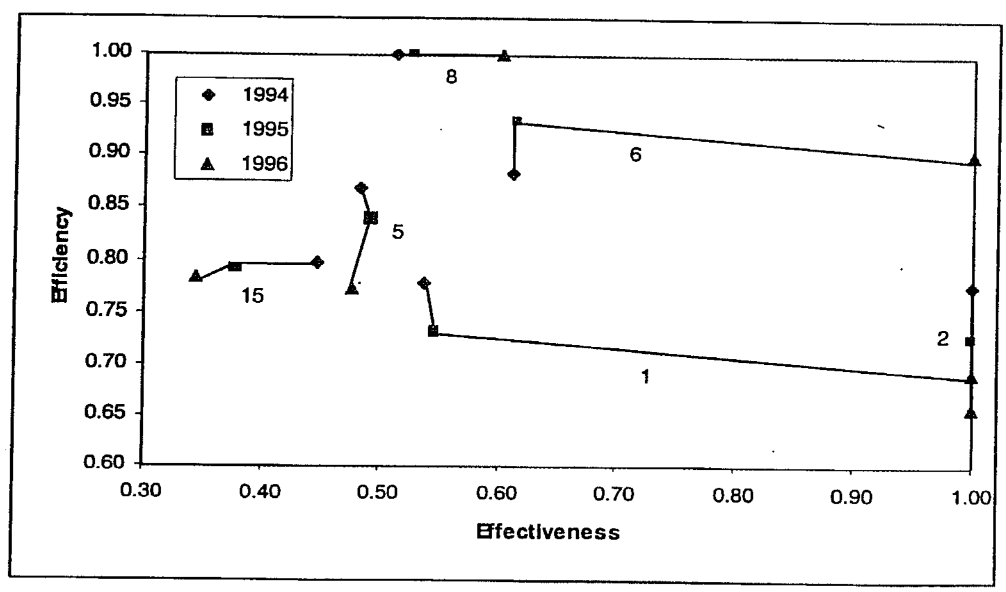


Fig. 4 Performance Dynamics for Selected Transit Agencies in the Midwest



1. Fort Worth Transit
2. Oklahoma City-COTPA
5. Tulsa-MTA
6. Omaha-TA
8. Wichita Transit
15. Lincoln- StarTRAN

Fig. 5 Wichita Transit's Relative Efficiency and Effectiveness as a Function of Service Hour Reduction

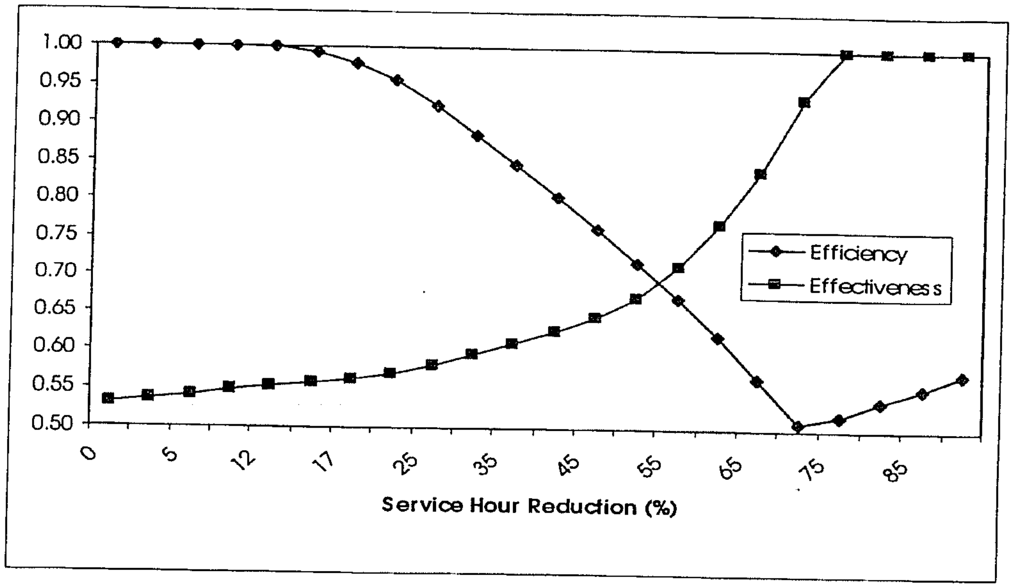


Fig. 6 Weighted Performance Metric for Wichita Transit as a Function of Service Hour Reduction