LOW COST DEMAND FORECASTING USING EXISTING PUBLIC TRANSPORT PATRONAGE DATA

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Abstract:

Increased concern with improving the efficiency of urban transport via low cost managment techniques has naturally focused more attention on the role of public transport. However, the development of demand forecasting methodologies appropriate to this scale of planning activity has not kept pace with the changing emphasis.

This paper describes the development of a simple time series model of public transport patronage, based on ticket sales records, that can provide useful forecasting information. The fare and service elasticities produced from this model directly provide changes. The potential for future use in a sketch planning role is considerable, given the ease and low cost of model development.

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INTRODUCTION: THE NEED FOR LOW COST FORECASTING METHODOLOGIES

Over the past decade, there have been a number of major changes in public perception of and response to urban transport problems. There has been widespread concern with and rejection of the large scale and primarily road oriented investment proposals universally recommended by the transport plans that have been undertaken in every major Australian city. There has been an associated growth in awareness of environmental and "quality of life" issues as a reaction to urban traffic congestion. Rising fuel prices associated with political changes in supplier nations have triggered considerable alarm about future price and supply stability, and the future of private personal mobility.

In response to the emergence of problems of this type there has been a reassessment of the nature of transport planning solution strategies. Increasing attention has been paid to improving the efficiency of the transport system and coping with short term or localised problems by transport management techniques rather than by large scale new investment. Naturally, this new direction has focused more attention on the role of and possibilities for public transport, which has a natural and major role to play in this context.

At a time of decreasing fund availability, rapidly escalating public transport deficits, and the need for improved and extended public transport services as part of transport efficiency improving strategies, the inability to properly evaluate proposed policies is disastrous. However, while the need for efficient management and more careful husbanding of investment resources has grown, the switch in scale of planning activity from long term, urban wide to localised, short term problems and solutions has left us largely without appropriate techniques for impact assessment or evaluation. The forecasting technology developed for large scale urban transport planning is simply inappropriate in this new context. Further, reaction to the past generation of transport plans has led to a disaffection with even the concept of forecasting. Consequently, there has been a marked reluctance to invest in the development and necessary understanding of methodologies that would be more appropriate to a lower level of planning and investment. Finally, many existing forecasting techniques, however contextually applicable they might be, are often too relatively expensive for use with low cost transport system improvement strategies.

There is, therefore, a considerable need for a forecasting methodology that can be used in the context of small scale planning activity, which is inexpensive and flexible in its application, and readily understood without extensive and expensive training. Some objectives that might be set for such a methodology include the following:

- it must be applicable at a range of geographic levels
- it should be able to be developed/updated using readily available data sources
- it should be applicable without the use of expensive and specialised computer software
- it must be able to be easily understood by perhaps untrained practitioners, who will still be aware of its limitations, and can interpret results accordingly
- it must be robust, in that it can predict the direction and order of magnitude of change, but not necessarily accurate in a detailed way.

A number of methodologies that might be employed in this context are briefly reviewed below, and one technique that fulfils the objectives set is examined in detail. The most urgent need for such a methodology is in the prediction of changes in public transport patronage as a result of operating policy changes affecting the extent, service and fare levels of public transport services. It is in this context that the remainder of the paper is placed, although it is recognized that other types of forecasting methodologies are urgently needed to predict other types of impact.

SOME POSSIBLE APPROACHES

Forecasting the future demand for travel requires the use of a model. Models used for travel demand forecasting generally have a formal mathematical structure, but the concept of a model is quite generally a postulate about behaviour being a (fixed) response to the influence of a set of stimuli. Both the functional form and the specification of mathematical models of population relationships are estimated using sample data from the present. A useful if simplistic model typology can be established, based on the type of data used for estimation. Models from either of the two categories discussed below can be of use in the context established in this paper, and depend only on the type and scale of the problem for their relevance.

MODELS BASED ON CROSS SECTIONAL DATA

Cross-sectional data is data collected at one point in time from a (hopefully representative) cross-section of the population. The household surveys used for the development of the past generation of urban transport planning models are examples of this type of data. Most models of travel behaviour are based on data of this type. Because it is collected at one point in time, dynamic aspects of choice can not be represented by models based upon it. Rather, variation in behaviours represented by such models derive from variations in behaviour within the sample with respect to a given stimulus. Because large samples are usually necessary to capture the range of such variation in the population, data collection is expensive, and therefore not frequently repeated for updating purposes.

Data bases of this type have been collected for all major Australian cities at some point in the last 15 years, and in some cases more than once. With only a few exceptions, they have been used for the development of aggregate models of travel behaviour. These are not relevant for our purposes as they do not incorporate the behavioural influences relevant to the small or short term issues increasingly the focus of concern. However, the same type of data can be used for the development of individual choice or "disaggregate" models of travel behaviour, which correct to a large extent the shortcomings in the traditional aggregate modelling procedures. Unlike their predecessors, individual choice model (ICM's) are directly applicable to the problem at hand; ways in which they might be used are explained briefly below.

Sketch Planning Applications of Individual Choice Models

Individual choice models can be developed for single choices, such as choice of mode, or for related choices where the outcome of one choice influences the second, such as choice of mode and destination. Limiting the remaining discussion to models of single choices, but emphasising that multiple choice models are often more plausible and as readily developed, the familiar multinomial logit model form (not the only one possible) may be written as

$$P_{tm} = \exp(U_{tm}) \Big/ \sum_{k \in A} \exp(U_{tk})$$

where P_{tm} = probability that individual t chooses alternative m from the set A of available alternatives

$U_{tm,k}$ = utility of choices m,k for individual t, defined as

$$U_{tm} = \sum_{\ell} \beta_{\ell} X_{t\ell m}$$

where $X_{t\ell m}$ = level of the ℓ^{th} attribute describing choice m for individual t

β_{ℓ} = parameters expressing the relative importance of each attribute in the utility function.

Models of this type are ideally suited to the prediction of the impacts of policy changes in fare or service level on patronage, and for low cost application for this purpose, (Manheim et al, 1980). It is of course necessary to have available previously developed models of mode choice. These can then be applied at different levels of sophistication depending on data availability and the requirements of the particular study.

The level of sophistication and accuracy of the application depend on the level of *aggregation* that the individual probabilities are applied at. At the highest extreme, individual choice probabilities would be computed for every member of the population affected by the proposed policy, using individual attribute levels and previously estimated model parameters to compute individual utility functions for each alternative. At the other end of the scale, average utility functions can be computed using average attribute levels for the population as a whole. The level of accuracy that can be obtained depends upon the nature of the data available about the affected population.

If a household survey of the affected population exists that contains the data necessary to construct individual utility functions, the first technique, of either full or sample enumeration, can be easily used. Computer analysis is necessary, but only to facilitate handling large amounts of data, not because of mathematical complexity.

Most usually, much more limited data will be available, but as the utility functions of most mode choice models do not contain a large number of socioeconomic variables, it is quite common to find that Census Data is all that is necessary for application. In this case, a form of market segmentation procedure can be used, with models applied to each segment defined either geographically or over socioeconomic groups. At this level of application, the minimal calculations necessary can be done using no more than a pocket calculator and a few pages of worksheets.

However, while these approaches are theoretically and conceptually appealing, require only limited data for application, and are computationally inexpensive, the basic ingredient does not yet exist in all Australian cities. That ingredient is a previously calibrated set of individual choice models. While this situation is gradually changing, the techniques outlined cannot yet be universally applicable.

MODELS BASED ON TIME SERIES DATA

Time series data is data about a single situation that has been collected over time. As such, it contains within it information about the dynamic processes at work during the time period, and hence information about the changes, expected in response to changes in the travel environment. The most important examples of this type of data are the patronage records kept by public transport operating authorities. Because time series data spans changes in service levels and prices, models based on it can provide vital information about past responses to such changes. More importantly this can be used to indicate the likely response to planned changes in operating or fare policies at any scale. This is precisely the information that we have been looking for; means by which it can be extracted from the data and used in prediction are developed below.

A Time Series Model

Suppose there exist periodic observations over a continuous time period of patronage on a particular mode. (This may be at any level; system-wide for all ticket types or by route and particular category of ticket). It is postulated that variations in patronage over time are in response to variations in the level of factors influencing patronage. These will include a range of influences on both passenger demand and service supply; this latter group will include such policy variables as *fare* and *quantity* of service provided. It is these variables that are manipulated in policy determination and their influence which is of concern.

Patronage over time is postulated to be a linear function of the effects of such influences:

$$Y_t = \Sigma \beta_k X_{kt} + \varepsilon_t$$

where Y_t = patronage level at period t

X_{kt} = level of the kth influence at period t

β_k = effect of the kth influence

ε_t = a component unexplained by the relationship.

The model coefficients, β_k, are readily estimable using multiple regression analysis. The estimated model can be of major importance in forecasting future patronage levels and operating revenues; an example of such an application is the London Transport Executive Fare Model and Scenario Model, developed for this purpose (Fairhurst and Mawford (1977), Fairhurst and Smith (1977)). For our purposes, however, another aspect of the model is of more importance. This is the estimate of the *elasticities*[1] of the explanatory variables, obtained directly from the model via the relationship below. If the model is properly specified to include measures of fare level and service provided, elasticity estimates for both will be available. An estimate of the patronage effects of any policy changes is immediately obtainable:

$$Q_2 = \frac{Q_1[(X_1+X_2) + E_D^x(X_1-X_2)]}{[(X_1+X_2) - E_D^x(X_1-X_2)]}$$

The power of this technique is obvious, but depends for its realisation on the ability to develop stable models at a sufficiently local level to be of use at the scale it is suggested is necessary. In the following, a study is reported that demonstrates that this can easily be achieved.

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[1] "Elasticity" is defined as the percentage change in quantity demanded in response to a small change in the level of the explanatory variable, and is expressed as:

$$E_D^x = \frac{\partial Q}{\partial X}\frac{X}{Q}$$

This is a *point* elasticity, defined at a point on the demand curve. For appreciable changes in X or Q, an *arc* elasticity should be defined:

$$\text{Arc } E_D^x = \frac{Q_2-Q_1}{X_1-X_2}\frac{X_1+X_2}{Q_2+Q_1}$$

A MELBOURNE CASE STUDY

A time series analysis was undertaken for the financial years 1972-1976, of the patronage records of M. & M.T.B. tram, bus and Preston Depot tram services, and for the private bus services. This is reported in detail elsewhere (Singleton, 1977). For the purposes of this example, only the models for the Metropolitan and Preston Depot tram services are reported.

Data

Data used in the analysis consisted of four weekly summaries of patronage by ticket denomination. A major cause of fluctuations in patronage are the seasonal effects of time of year, the incidence of school and work holidays, and climatic conditions. Their effect can be included by using "dummy" explanatory variables, but these lack sensitivity and have no causal interpretation. In this study the variables were included directly.

Income effects over the period were attempted to be captured through the use of a measure of disposable income from ABS quarterly statistics, deflated by the Melbourne CPI available from the same source. The influence of motoring cost increases was felt to be important, and an attempt was made to capture this by using the motor cost component of the CPI, deflated by the CPI. Fare for each ticket denomination was similarly deflated, to account for the declining real cost over the period. Only one fare rise was included in the period, that of 15th August, 1975.

Variations in the supply of services will have an obvious influence on patronage levels; these occur through scheduling changes as part of policy alterations, or through service disruptions from strike activity. Both influences were included, but because of the manner in which operating records are kept, it was impossible to accurately measure service kilometres run. These were estimated by using vehicle service hours and an assumed operating speed. Strikes were measured as quarter days of service lost during the period, and the service kilometres variables adjusted to exclude the running time lost during strikes.

In a time series analysis, time itself is an important influence, particularly on public transport patronage. Using time in the model proxies for all those excluded influences which affect patronage consistently over time. Its use is complicated by the fact that many included variables are themselves heavily correlated with time, and its inclusion may lead to high degrees of multicolinearity and the associated loss of precision in the parameter estimates. However, its exclusion when it might otherwise by a significant influence will force correlated variables to "pick up" its influence, resulting in biased estimates for parameters of those variables. Our concern is with estimates of elasticities; loss of precision in parameter estimates is not of concern, but biased estimates are. Time was included in all models for this reason.

The Models

The linear model postulated takes the form:

$$Y_t = aA_t + bB_t + cC_t + dD_t + eE_t + fF_t + gG_t + hH_t + jJ_t + \text{constant}$$

where
- Y_t = the patronage level at period t
- E_t = the mean winter temperature in period t
- C_t = the number of working days in period t
- B_t = the number of school holidays in period t
- G_t = the fare ÷ C.P.I. for period t
- J_t = the Motor Costs Index ÷ C.P.I. for period t
- F_t = the vehicle kilometres run in period t, adjusted for days lost due to strikes
- A_t = time
- H_t = Household Disposable Income ÷ C.P.I. for period t
- D_t = number of quarter days lost due to strikes.

This additive form is directly suited to multiple regression analysis, but multiplicative forms may be tested and analysed by the same estimation procedure via the use of a logarithmic transform on all variables. This was carried out, but the additive formulation was found to give the best results, and was used throughout.

Price and service elasticities of demand may be computed from the linear model with relative ease, as the un-normalised regression coefficients of explanatory variables are their partial differentials with respect to the dependent variable, patronage. As dynamic effects over the long-term may have shifted the demand curve, these "elasticities" may not be true elasticities in the classical micro-economic sense. It was felt that within the 4-year period studied major shifts in the demand curve were unlikely to have occurred, and that the elasticities would be good estimates of true elasticities.

Model results are presented for all Melbourne and Preston Depot M. & M.T.B. tram services in Tables 1-3. Where possible, separate models were estimated for each available ticket category, a measure of trip length; because of overlap between certain categories, some had to be grouped for analytical purposes.

Tables 1 and 2 give the variable coefficients and their t-statistics when significantly different from 0 at greater than the 10% level. Where no coefficient is given, the model reported was estimated without that variable. As a general rule, models were estimated with the full set of variables found from previous analyses to be of relevance. This was done to avoid possibly biased coefficients from excluded but relevant variables, even though significant multicolinearity may have been introduced by so doing. As previously discussed, for the calculation of level-of-service variable elasticities we are less concerned with the precision

Table 1: Model Coefficients and t-Statistics All-Melbourne Tram

EXPLANATORY VARIABLES

MODEL	Time (A)	Days of School Holidays (B)	No. of Work Days in Period (C)	No. of Quarter Days of Service Lost in Strikes (D)	Winter Temp (E)	Vehicle KM Run (Adj. for strikes) (F)	Fare ÷ CPI (G)	Disp. Inc. ÷ CPI (H)	Motor Costs ÷ CPI (J)	Pens. Valid Dummy
All Tram Sales	N.S.	-20.6 (-4.7)	148.5 (3.0)	-105.6 (-5.5)	-86.6 (-5.3)	3.4 (4.0)	-223 (-6.7)	-22.8 (-1.9)	-6686 (4.73)	N.A.
Child 1 Section	1.0 (3.7)	-2.2 (-5.6)	5.6 (1.8)	-2.8 (-1.6)	N.S.	N.S.	-1366 (-2.2)	N.S.	-343 (-1.7)	N.A.
Pensioner 1 Section	0.2 (N.S.)	-0.45 (-3.2)	-1.4 (N.S.)	-3.6 (-5.5)	-3.8 (-6.9)	0.14 (4.7)	-1240 (-5.8)	1.7 (3.8)	-158 (-2.5)	-39.8 (-8.7)
Adult 1 + Child 2 & 3	3.2 (5.4)	-3.7 (-5.9)	33.5 (40.6)	-18.4 (-6.4)	-18.1 (-7.5)	0.86 (6.6)	-1619 (-2.0)	-8.3 (-4.3)	-2051 (-7.5)	N.A.
Adult City	-3.5 (-3.8)	-3.8 (-3.9)	14.4 (N.S.)	-14.7 (-3.3)	-5.9 (N.S.)	0.31 (N.S.)	-7996 (-6.2)	4.0 (N.S.)	-765 (-1.8)	N.A.
Pensioner 2 & 3 Section	0.28 (N.S.)	-0.54 (-3.2)	-3.0 (N.S.)	-3.7 (-4.8)	-3.2 (-4.9)	0.18 (5.2)	-1242 (-5.2)	0.75 (N.S.)	-119 (N.S.)	-36.9 (-6.8)
Adult 2 & City +1 Concession	N.S.	-5.7 (-5.0)	31.2 (2.5)	19.8 (-3.4)	-22.9 (-5.4)	0.77 (3.0)	-4905 (-6.3)	-11.6 (-3.5)	1755 (-4.9)	N.A.
Adult 3 Section	N.S.	-2.2 (-4.3)	10.8 (1.9)	-13.6 (-6.2)	-10.0 (-5.3)	0.52 (5.3)	-1297 (-4.6)	-3.3 (-2.2)	-778 (-4.9)	N.A.
Adult 4 & 5 Section	N.S.	-2.0 (-3.6)	20.1 (3.1)	-11.8 (-4.8)	-13.1 (-6.1)	0.38 (3.4)	-1345 (-5.1)	-4.6 (-2.8)	-1127 (-6.3)	N.A.
Adult 6+ Section	N.S.	-0.66 (-1.7)	10.1 (2.3)	-6.7 (-4.1)	-6.4 (-4.4)	0.22 (2.9)	-387.8 (-2.5)	-1.8 (N.S.)	-303 (-2.5)	N.A.

Note: (a) (N.S.): variable coefficient computed but not significant at the 10% level

(b) N.S. : variable not included in estimated model

(c) N.A. : variable not applicable to estimated model

Table 2: Model Coefficients and t-Statistics
Preston Depot Tram

MODEL	EXPLANATORY VARIABLES Time (A)	Days of School Holidays (B)	No. of Work Days in Period (C)	No. of Quarters Days of Service Lost in Strikes (D)	Winter Temp (E)	Vehicle KM Run (Adj for strikes) (F)	Fare ÷ CPI (G)	Disp. Inc. ÷ CPI (H)	Motor Costs ÷ CPI (J)	Pens. Valid. Dummy
All Sales	-2.8 (-3.5)	-1.82 (-3.0)	15.9 (2.6)	-18.0 (-6.5)	-13.3 (-5.0)	4.9 (20.8)	-1799 (-6.3)	N.S	-598.5 (-1.9)	N.A
Child 1 Section	0.1 (1.9)	-0.08 (N.S.)	1.5 (3.4)	N.S.	-0.58 (-2.6)	N.S	-18.8 (-2.4)	-0.17 (N.S.)	-37.0 (N.S.)	N.A
Pensioner 1 Section	-0.07 (N.S.)	-0.15 (-3.1)	0.64 (1.7)	-0.27 (N.S.)	-0.39 (-1.9)	N.S	-262 (-3.4)	0.47 (3.2)	42.2 (1.8)	-5.0 (-3.0)
Adult 1 + Child 2 & 3	0.56 (2.3)	-0.47 (-2.0)	7.8 (4.1)	N.S.	-2.6 (-2.7)	N.S	-279 (N.S.)	-2.6 (3.6)	-135 (N.S.)	N.A.
Adult City	-1.7 (-3.7)	-1.1 (-2.4)	7.4 (1.7)	-3.13 (N.S.)	-0.69 (N.S.)	-0.009 (N.S.)	-2681 (N.S.)	4.2 (3.0)	410 (1.9)	N.A.
Pensioner 2 & 3 Section	N.S.	-0.15 (-3.1)	N.S.	N.S.	-0.49 (-2.6)	0.03 (1.7)	-240 (-3.1)	N.S.	32.2 (N.S.)	-4.9 (-3.9)
Adult 2 & & City +1 Concession	-0.5 (-1.8)	-1.1 (-4.2)	9.7 (4.5)	N.S.	-2.5 (-2.4)	N.S.	-595 (-2.3)	N.S.	N.S.	N.A
Adult 3 Section	N.S.	-0.55 (-4.3)	5.0 (4.7)	N.S.	-1.2 (-2.3)	N.S	N.S.	-0.46 (-1.7)	N.S.	N.A.
Adult 4 & 5 Section	N.S	-0.62 (-4.0)	6.2 (5.0)	N.S	-1.7 (-2.7)	N.S.	-136 (-1.7)	-0.86 (-1.8)	-37.6 (N.S.)	N.A.
Adult 6+ Section	0.19 (2.3)	-0.20 (-2.1)	3.7 (4.8)	N.S.	-1.2 (-3.0)	N.S.	N.S	-0.51 (-1.7)	N.S.	N.A

Note: (a) (N.S.): variable coefficient computed but not significant at the 10% level
(b) N.S. : variable not included in estimated model
(c) N.A. : variable not applicable to estimated model

Table 3: Elasticity values, Melbourne and Preston

MODEL	MELBOURNE			PRESTON		
	Fare Elasticity	Service Elasticity	Model Adjusted R^2	Fare Elasticity	Service Elasticity	Model Adjusted R^2
Total Sales	-0.37	0.83	0.84	-0.58	1.09	0.94
Child 1 Section	-0.19	N.A.	0.54	-0.23	N.A.	0.37
Pensioner 1 Section	-0.22	1.16	0.93	-0.38	N.A.	0.67
Adult 1 + Child 2 & 3	-0.07	1.02	0.93	-0.13	N.A.	0.47
Adult City	-0.65	0.67	0.77	-0.93	N.A.	0.40
Pensioner 2 & 3	-0.36	1.36	0.92	-0.51	0.18	0.66
Adult 2 & City + 1 Concession	-0.39	0.85	0.83	-0.38	N.A	0.46
Adult 3 Section	-0.26	1.17	0.84	N.A.	N.A.	0.51
Adult 4 & 5 Section	-0.29	0.73	0.82	-0.23	N.A.	0.53
Adult 6 - 9 Section	-0.20	0.90	0.67	N.A.	N.A.	0.43

Note: N.A.: elasticity not computed for "not significant" variables of the estimate than with freedom from bias. Models estimated on less than the full set of variables were admitted only after detailed inspection of relevant parameters and their elasticities.

In general, it can be observed that while both groups of models perform reasonably well in terms of explained variance and parameter significance, those for the Preston Depot are less robust than for all Melbourne services. This is an expected; the higher the level of disaggregation the greater will be the variance, and the explanatory power of a fixed set of variables will be reduced. A similar effect is observable within each group, between models for total sales and sales of each ticket denomination.

With the exception of the Motor Costs ÷ C.P.I. variables, all the significant variables have the expected sign. The motor costs variable would be expected to take a positive sign, implying that as the cost of motoring increased relative to the general costs of living (and to the cost of public transport), the use of public transport would increase. However a negative sign was consistently recorded, which indicates that the variable is proxying for some other effect. For this reason, it was included, so as to avoid bias due to the exclusion of relevant influences, as already discussed.

The disposable income variable in general takes a negative sign, which is consistent with expectations, as rising incomes will tend to imply a lessening of dependence on transit. However, there are certain models tabulated in which this variable assumes a positive sign; these are in the Adult City section and Pensioner sales segments, where increased disposable incomes may be indicative of increased retail activity (especially applicable to the City section ticket sales).

The influence of school holidays, number of work days in the four weekly period, and the effect of strikes are all significant and have the expected sign for metropolitan services. The influence of strikes and service level changes for the Preston Depot are masked by the greater variability in observations that occurs at this lower level of aggregation. The Pensioner Validity dummy variable was included to take account of the fact that this class of concession was not available in peak hours until after January 1974.

In the two sets of models presented here, no evidence of a significant lag effect of response to changes in explanatory variables (such as the fare rise) was found. In analysing bus patronage data (not reported here), the effect of the introduction of a new service was found to be spread over four periods. The lack of such a lag structure should be viewed somewhat sceptically; analysis using weekly data over a longer period spanning more changes would be useful in examining the possible nature of such an effect in more detail.

For metropolitan-wide service, but not for the Preston Depot, vehicle kilometres run was consistently an important influence, with a positive elasticity close to 1. This variable was adjusted to exclude the influence of strikes, but it is not necessarily an accurate measure of the level of service provided as it is estimated rather than actual service kilometres that are used. However, the magnitude of the elasticity estimate does indicate that service changes may be a significant policy variable and that this type of analysis is successful in capturing its influence. This points to the need for the maintenance of this accurate service records if the potential benefits of the approach are to be realised.

The fare variable is consistently negative as expected, and produces elasticity estimates which are typically of the expected order of -0.3, though they vary widely for different classes of user and for different trip lengths. This fact reinforces the need for disaggregation by user type and journey length in the development and application of models of this type.

For the Adult sales group, price elasticities are seen to decrease with increasing trip length. This behaviour is in accordance with prior expectations, as short trips may be substituted for by walking, whereas longer trips are less amenable to a "walk" alternative and are generally for the more necessary trip purposes. City section sales are seen to be particularly sensitive, probably for the same reason. Pensioner concession sales are relatively less price sensitive and the results indicate a general increase in elasticity with journey length. There are two possible explanations for the difference between this result and that observed for the Adult sales segment; firstly, older people are less likely to substitute walking for short trips on public transport and secondly the increases in the cost of the more expensive, longer trips may render them too costly for relatively low-income pensioners.

CONCLUSIONS

Two techniques for obtaining forecasts of the direction and magnitude of response to public transport operating policy changes have been presented, based on the type of data used. While both are flexible and inexpensive, it is clear that the existence of patronage records over time provides a resource that is admirably suited to the development of time series patronage models. Depending on the quality of the records kept, it is clear that the information provided by such models can be used for forecasting in a way that meets all the requirements for such methodologies that were previously postulated.

Geographic disaggregation can be undertaken within the data limits set by the patronage records, to ensure that local variations in response to significant variables are allowed for. Models can be readily developed and continually updated to ensure that they are always relevant to particular planning contexts. Development requires the use of readily available regression packages, operable without great technical expertise; application of the results does not require computer technology at all. While some theoretical knowledge is necessary for model development, to avoid pitfalls in application of regression analysis, the developed model and its output are readily interpretable by anyone with only limited mathematical training. Finally, so long as policy changes are not too far outside the environment within which the models were developed, they are robust and predict with a reasonable degree of accuracy.

These are extremely beneficial attributes, and are readily experiencable. However, they are not free; there is a cost, albeit small, in ensuring that they can be achieved. This is the cost associated with ensuring that patronage data is recorded in a form suitable for analysis in the way described above. An ideal set of patronage or ticket sales records would consist simply of weekly ticket sales by fare category, and by line, route or depot depending on what is the smallest practical level of geographic disaggregation. All public transport operating authorities have this information for accounting purposes; sometimes its detail is lost by recording at a more aggregate level. Only a small and relatively inexpensive change in recording procedures would be necessary to ensure that high quality data and the basis for a flexible and inexpensive forecasting methodology is obtained. In the current climate of growing concern with efficient transport systems management the returns to such an investment will be substantial.

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