Predictive Building Maintenance Funding Model

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Abstract

Predicting maintenance funding for government building portfolios is an issue which has received widespread attention in the last two decades. Research in the field, however, has failed to achieve a commonly accepted method in which maintenance funds may be predicted. The goal of this study is to formulate a mathematical model to predict the level of maintenance required for public buildings in the Perth metropolitan area, as managed by the Department of Housing and Works (DHW).

The study seeks to derive separate prediction models for the top five clients in the DHW portfolio which collectively represent 78% and 91% of the building portfolio by value and volume respectively. The predictions will then be used to assess the level of allocated funding provided by the Department of Treasury and Finance. The preliminary findings thus far outline a useful model has been developed to predict the level of maintenance funds for the Department of Education (Primary Schools), the largest client in the portfolio. This paper further discusses the importance of including qualitative variables in such a model and seeks to accomplish this.

1. Introduction

During 2007 the Department of Housing and Works (DHW) sponsored a CEED project completed by Tinapple (2007) to understand and develop a predictive building funding model which addressed the maintenance expenditure on buildings owned by the Government of Western Australia. The study focused on a small portfolio of fifty primary schools in the Perth metropolitan area, which covered their 50 year age span.

A model was developed using life cycle costing theories and the work by Bromilow (1985). Tinapple's findings suggest that maintenance costs level out at about $4000 per classroom (2.2% of replacement value) after twenty years, which confirms the pattern exhibited in the Bromilow model.

This year the DHW has extended initial study and is seeking to develop a model to include other clients and classifications of buildings within the facility portfolio. The model developed by Tinapple is centred around a plant value methodology whereas the model to be developed in this study will be distinctively different in that it will be based on a multiple regression model (formula-based methodology). This approach will consider factors believed to influence a building's maintenance needs.

The goal of this research is to predict maintenance expenditure of buildings for the short and medium term horizons. The model will also be used to present to the Department of Treasury recommendations for budget allocations for the facility portfolio.

2. Issues and Challenges

A routine upkeep of assets within a portfolio in the form of maintenance or renewal is a necessary prerequisite towards ensuring the successful provision of services by respective clients. A deficient maintenance program or failure to fulfil the maintenance requirements of the portfolio results in (a) backlog of deferred maintenance, (b) increased costs due to breakdowns and (c) the risk in failure to deliver safety and other level of service expectations. Coupled with the added issue of competing for funds usually set aside for capital expenditures and new projects, it is difficult for facility portfolio managers to justify spending to the Department of Treasury.

The DHW has developed a database over the past fourteen years to track expenditures related to maintenance and capital expenditures (Breakdown Repairs, Planned Maintenance, Routine Maintenance, and Minor Works). The figures below outlines the pattern of these expenditures over the last ten years for the Department of Education and Training (Primary Schools) which represents over 53% and 80% of the facility portfolio by value and volume respectively.

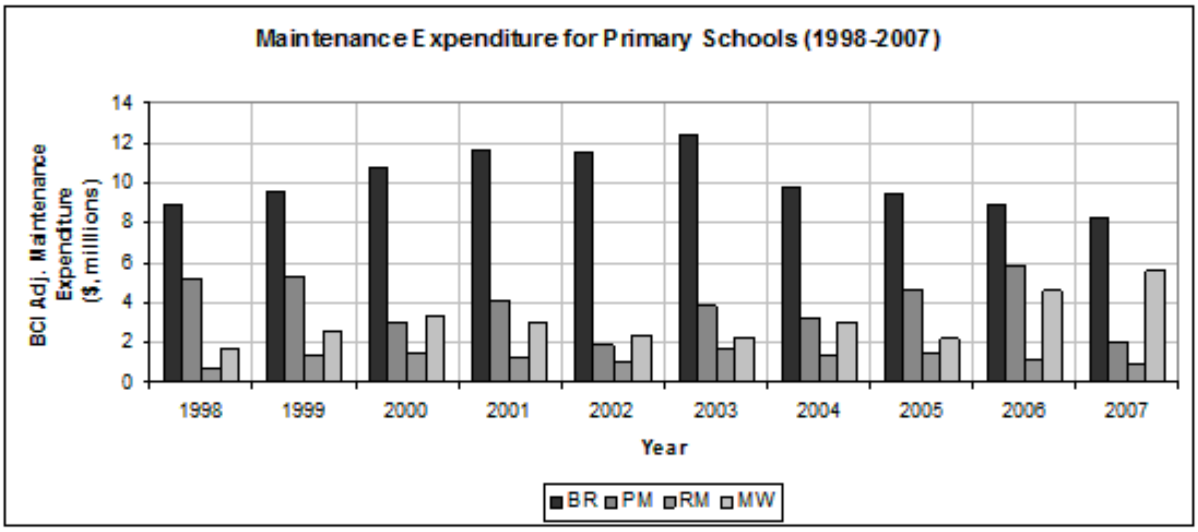

Figure 1 Pattern of expenditures for primary schools in sample data set (1998-2007).

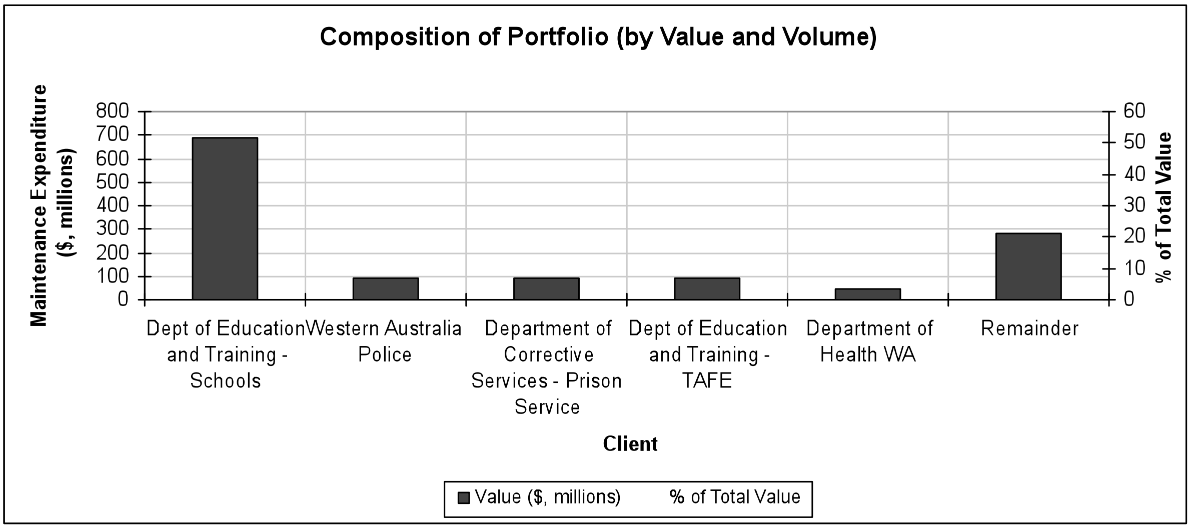

Figure 2 Compostion of portfolio (by Value and %) for clients during 1999-2007

The challenge with estimating maintenance levels for current and future years is that there is no commonly accepted method or model to evaluate and measure maintenance requirements. As a result this permeates to Treasury and makes it that much more difficult to justify a budget request, especially when the dollar amount suggested may be subjective.

As outlined by Tolk (2007) there are four common methods for developing models to estimate a maintenance budget. They are namely,

i. Plant value methodologies,
ii. Formula-based methodologies,
iii. Life-cycle cost methodologies, and
iv. Condition assessment methodologies.

The purpose of this research is to develop a formula-based model to evaluate maintenance needs based on historical data captured in the DHW data warehouse. Through invoices and condition assessments, data is recorded into the warehouse manually. A caution although with the data is that it has its limitations in the sense that it may be incomplete, inconsistently grouped, or incorrectly aggregated.

3. Data Mining

Data mining within the building maintenance context is the extracting of data records in order to find patterns in the data, which as a result may be converted into useful knowledge. As outlined by Reffat, Gero, and Peng (2004), organisations can use data mining to allow proactive maintenance to occur based on the knowledge and patterns extracted from past maintenance records.

Despite the increases in the availability in data and sophistication of data warehouses data may not be used (or stored) properly due to:

- Project managers not having the time available to analyse computerised data.
- Complexity of the data analysis process is beyond the capabilities of the managers and the relative simple building maintenance systems.

- There is no well defined automated mechanism to extract, process and analyse the data systematically and routinely to summarise results so that they are on the agenda of the next maintenance meeting.

Through the use of COGNOS Impromptu, a data extraction tool, the data from the DHW data warehouse is processed as shown below schematically.

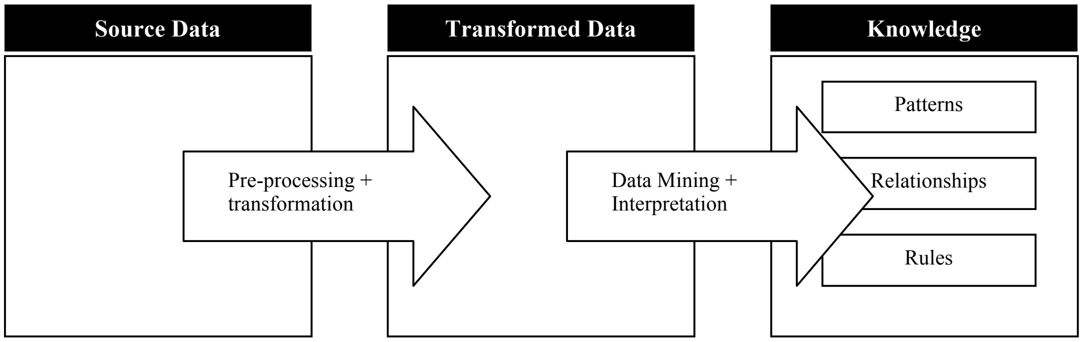

Figure 3 Schematic representation outlining how raw data is converted into knowledge (Reffat et al.).

4. Econometric Modelling

4.1 Data Set

As background research, panel data was collected for the top five clients within the DHW building portfolio. These top five clients represent 78% and 91% of the portfolio by value and volume respectively. The analysis first centred on primary schools in the Perth metropolitan area, which included the majority of schools analysed by Tinapple (2007).

4.2 Panel Data Approach

The data extracted from the data warehouse is in the form of panel data as the data available for empirical analysis has both cross-sections (specific building or site) and time (1998-2007) constituents.

Panel data is very informative and gives the ability to track changes in expenditure over time for a set of buildings in the portfolio of government assets. The data set for the primary school model is the largest with five variables, ten time periods and over 203 cross sections, leading to over 2000 observations.

Estimation of a linear regression model is included as a comparison to show that the fixed effects regression model is a far better predictor of the variables that influence maintenance.

5. Model Development

5.1 Parameters

5.1.1 Quantitative Variables

It is important to select those variables which are readily available within the data warehouse. A review of the data warehouse has unveiled that the following variables listed below may be suitable quantitative parameters in a model that explains maintenance expenditure[1].

i. AVAL – Aggregate maintenance expenditure adjusted to the building cost index (BCI),
ii. AGEY – Age of the building in years,
iii. WO – The number of work orders,
iv. AREA – The approximate area of the building subject to maintenance in m^2,
v. T – The time period in which maintenance work occurred.

Note that the aggregate maintenance expenditure (AVAL) is a summation of the four individual maintenance categories, they are namely,

i. BR – Breakdown Repairs (unplanned maintenance)
ii. RM – Routine maintenance (planned maintenance)
iii. PM – Planned maintenance (planned maintenance)
iv. MW – Minor Works (capital improvements)

5.1.2 Qualitative Variables

In the context of this research, it is believed that the inclusion of various qualitative parameters in the model will be beneficial towards making informative conclusions as to the possible reasons behind the breakdown of maintenance expenditure for certain buildings over others. The qualitative variables considered for use in the extended model are listed below.

i. Geographic Region (West, North, South)
ii. Historic Designation (Cultural Heritage listed buildings)
iii. Population (Student population for schools)
iv. Socio-Economic Region (as quoted by the ABS)
v. Distance to CBD/Coast (Radius bands)
vi. Building/Facility Type (Architectural building style)

5.2 Model Specification

A number of functional forms for the multiple regression model were considered (e.g. linear, semi-log, double-log, square root and reciprocal), however the double-log regression model was selected as it was the most statistically significant and robust of all models based on the results provided by the econometrics software LIMDEP. The models specified below are estimated using the traditional ordinary least-squares (OLS) method

Specifically, the following linear model is estimated:

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[1] Based on literature review.

$$Log(AVAL_{i,t}) = \alpha + Log(AGEY_{i,t}) + Log(WO_{i,t}) + Log(AREA_{i,t}) + T_{i,t} + \mu_{i,t} \qquad (1)$$

Where,
α – represents a constant
$\mu_{i,t}$ – represents the stochastic error term

A common method to take into account the 'individuality' of each building (cross-section unit) is to allow the coefficients and the constant term to vary for each building. This is known as a fixed effects (regression) model (FEM), and this model is estimated as:

$$\begin{aligned} Log(AVAL_{i,t}) &= \alpha_1 + \alpha_2 D_{2i} + \alpha_3 D_{3i} + \ldots + \alpha_n D_{ni} + Log(AGEY_{i,t}) + Log(WO_{i,t}) \\ &+ Log(AREA_{i,t}) + T_{i,t} + \gamma_1 (D_{2i} Log(AGEY_{it})) + \gamma_2 (D_{2i} Log(WO_{it})) + \gamma_3 (D_{2i} Log(AREA_{it})) \\ &+ \gamma_4 (D_{2i} T_{it}) + \gamma_5 (D_{3i} Log(AGEY_{it})) + \gamma_6 (D_{3i} Log(WO_{it})) + \gamma_7 (D_{3i} Log(AREA_{it})) \\ &+ \gamma_8 (D_{3i} T_{it}) + \ldots + \gamma_n (D_{ni} Log(AGEY_{it})) + \gamma_{n+1} (D_{ni} Log(WO_{it})) + \gamma_{n+2} (D_{ni} Log(AREA_{it})) \\ &+ \gamma_{n+3} (D_{ni} T_{it}) + \mu_{i,t} \end{aligned} \qquad (2)$$

Where,
D_{ji} - represents dummy variables for each building
$\alpha_j D_{ji}$ - represents the differential intercepts
$\gamma_j(D_{ji} Log(X_{it}))$ - represents the differential slope coefficients

This model allows us to determine group effects within each client. That is for example, larger primary schools are likely to exhibit on average higher maintenance costs.

Note – The models explained above (1) and (2) are predictions for the quantitative variables.

5.3 Forecasting

On the basis of this study, the student postulates that maintenance expenditure for government buildings may be explained by a single-equation regression model. By extrapolating the predictions given by this model we can use the model to forecast the maintenance expenditure of the facility portfolio into the future.

6. Results (Preliminary)

The table below summarises the estimated parameters for the linear, log-log and log-log (fixed effects) models respectively. As expected the age of the building (AGEY) and the size of the building (AREA) heavily influence maintenance expenditure as explained by large t-ratios. Also, it is believed that area (AREA) and the volume of work orders (WO) are somewhat correlated due to a small t-ratio obtained for work orders. On average, a 1% increase in the number of work orders will result in a 1% increase in the level of maintenance expenditure.

The validity and strength of the model is indicated by the adjusted R^2 value. As shown in the table, this value improves significantly for the log-log (fixed effects) when compared to the standard linear regression model. As the number of observations is large the improvement in R^2 values from 0.467 to 0.511 is highly significant indicating the fixed effects model is further superior to the log-log regression model.

	Linear		Log-Log		Log-Log (Fixed Effects)	
X	Coeff.	Std.Err.	Coeff.	Std.Err.	Coeff.	Std.Err.
Constant	9755.18	1.491	30.16	4.667	-	-
T	2163.77	5.024	0.018	4.494	0.021	5.421
AGEY	54.15	1.106	-3.132	-3.600	-0.406	-
AREA	0.312	0.117	0.04	0.870	0.304	-
WO	418.767	23.841	0.894	36.600	0.992	29.014
Adjusted R^2	0.275		0.467		0.511	

Table 1 Table outlining the estimated variables for the three regression models.

The values of estimated variables are also shown in the table and as such are used to predict maintenance expenditure. The figure overleaf outlines the predictions given by the models and is compared to the actual expenditures over the 1998-2007 period. The curves predict that, on average, maintenance expenditure is expected to cost between $80,000 to $100,000 per year. It appears that the log-log (fixed effects) model fits the data reasonably well whilst smoothing out large fluctuations, especially in the case of years 2003 and 2006 where there was a provision of extra funds for the budgets of particular schools.

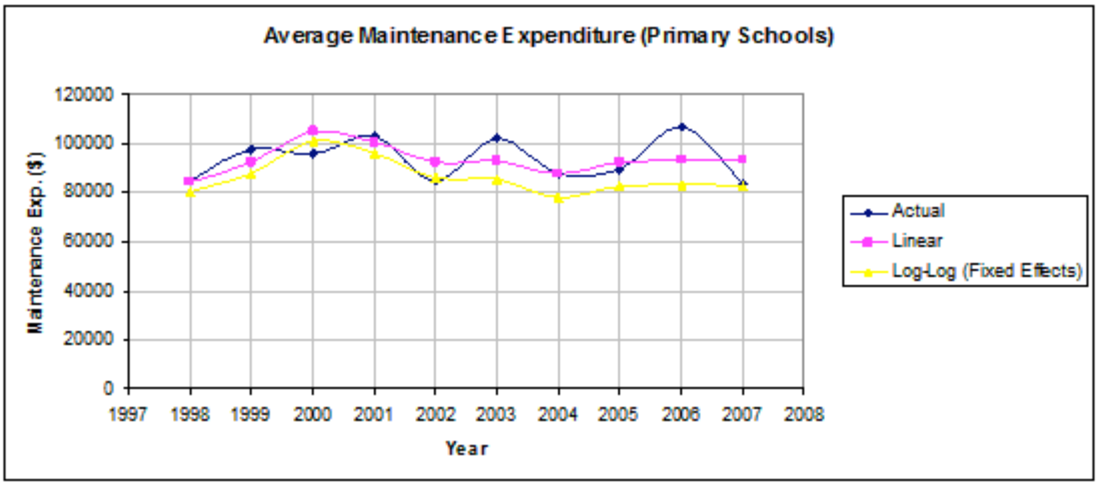

Figure 4 Curves outlining Average Maintenance Expenditure for Primary Schools as depicted by the linear and log-log (fixed effects) models.

Similar average maintenance curves for the other top five clients are expected to be included in the study. Forecasts for the top five clients will be provided in the dissertation and the effect they have on the portfolio and the Treasury budget will be outlined.

7 Conclusion

There has been much discussion into the study of formulating a method to determine the level of public funding required for the maintenance of government over recent years, although no commonly accepted method or model has been considered. Although there has been previous studies to determine a mathematical model to predict maintenance funding, current literature suggests that there has not been any previous work which considers as many quantitative and qualitative factors (variables) as this study.

The research conducted in this study is extensive in that qualitative variables are considered within the predictive model and therefore the notion of whether qualitative factors significantly influence maintenance funding may be addressed. It is long believed that the qualitative attributes mentioned previously have a similar if not greater effect on maintenance expenditure as the quantitative predictors, and it is the scope of this study to prove this.

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