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Published in:
Building and Environment

DOI:
[10.1016/S0360-1323\(97\)00013-9](https://doi.org/10.1016/S0360-1323(97)00013-9)

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Recommended citation(APA):
Li, H., Li, V., & Skitmore, M. (1997). Comparative study of analytical rental model and statistical models for predicting house rental levels. *Building and Environment*, 32(5), 389-395. [https://doi.org/10.1016/S0360-1323\(97\)00013-9](https://doi.org/10.1016/S0360-1323(97)00013-9)

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Comparative study of analytical rental model and statistical models for predicting house rental levels

Abstract. The need for a house rental model in Townsville, Australia is addressed. Models developed for predicting house rental levels are described. An analytical model is built upon a priori selected variables and parameters of rental levels. Regression models are generated to provide a comparison to the analytical model. Issues in model development and performance evaluation are discussed. A comparison of the models indicates that the analytical model performs better than the regression models.

1. INTRODUCTION

Townsville is the second largest city in Queensland, Australia. It has a population of about 120,000. In the housing rental market of Townsville, approximately 10% of households are private tenants and 12% are public tenants. The large percentage of tenants is due to the nearby army base and James Cook University which provide a constant supply of short-term inhabitants. On the other hand, Townsville tenants do not normally stay in one location for a long period, as neither military personnel nor university students will stay permanently at one place. The average period of residency is two years for tenants. These characteristics make tenancy an important force in Townsville's housing market.

In the Australian housing rental market, it has been widely observed that many landlords either have a biased expectation of the level of rental price, or have little knowledge of setting a proper rent. Conversely, many tenants do not have sufficient knowledge to determine analytically whether the rent is appropriate. Potential conflicts spawn between landlords and tenants when disagreements on such matters arise.

To achieve a steady rental market for tenancy, benefits of both landlords and tenants must be satisfied. In order to satisfy these two "opposing" parties, it is necessary to provide analytical ways to objectively measure rents for a specific period of time. For this purpose, this paper investigates factors that significantly influence the rental prices and, on that basis, establishes quantitative models to justify rental levels for houses in Townsville. We firstly analyse important factors affecting house rental levels based on 90 housing examples collected from three suburbs in Townsville. These three suburbs are Garbutt, Cranbrook, and Annandale, houses in these suburbs represent different location, different number of bedrooms, and different area weighting effects which will be described later.

The research presented in this paper was conducted in the following manner. Firstly, the 90 housing examples collected from three suburbs were randomly divided into a calibration sample (75) and a holdout sample (15). The calibration sample was used to develop rental models, and the holdout sample was used to validate the models. An analytical rental model and its variables and parameters were then described. Regression

models were developed to provide a comparison to the analytical model. The predictive accuracy of the rental models was analysed and tested upon the holdout sample to reveal the relative strengths and weaknesses of the models. The emphasis of this study, however, is on the forecasting methods and their performance in predicting house rental levels.

The paper is organised as follows. First, the methodology employed to represent and collect housing examples is explained in Section 2. Section 3 describes important factors used in formulating rental models and how rental models are developed. Section 4 finally analyses the performance and accuracy of the models. Conclusions and a summary are given as the last section.

2. HOUSE EXAMPLES

The sample was made up of 90 housing examples. Examples were obtained from houses in three different suburbs in Townsville during August to September 1994. Table 1 shows an example of the house examples represented in attribute-value pairs. The first three attributes of the example were used to record the *rent*, *area* and *number of bedrooms* of a house. The rest of the attributes were used to characterise the quality index of the house. Values of quality attributes were measured in linguistic terms using "*absolutely poor, very poor, poor, fairly poor, undecided, fairly good, good, very good, and absolutely good*". These terms were interpreted and evaluated using an angular fuzzy set model as illustrated in Fig. 1. The examples collected for the research project are listed in the Appendix.

Angular fuzzy sets use a semicircle on the right-hand side of the vertical axis to represent the quality values in a universe of discourse. The angle between a straight line from the centre of the circle and the horizontal line represents a particular quality value. Fig 1 shows how the quality values from *Absolutely Poor* (0.00) to *Absolutely Good* (2.00) are represented.

Using the angular set model, a particular linguistic term can be quantified into a non-negative value between 0.00 to 2.00. For example, the *cooling facilities are fairly good* can be interpreted as the quality index of cooling facilities is 1.25. 90 house examples were collected from three suburbs through site visits and interviews. In order to reveal the effect of area difference, examples were grouped according to suburb, which resulted in three groups, and each group had 30 examples.

3. MODELS

An analytical rental model and linear regression models were developed to model the rental data. The analytical model integrates important rental factors and parameters into a formula. In order to find predictive results with high accuracy to compare with the analytical model, normal regression and the Jackknife method [2] are used. The Jackknife method is an evolved form of regression analysis. It leaves out one example at a time to generate a regression model, and then uses the example to test the regression model. Thus, for a testing sample size of n (where n is the number of holdout examples),

the Jackknife method has to generate n regression models in order to make n forecasts. The Jackknife method will be further described in Section 3.3. Among the 30 housing examples collected from each suburb, 25 examples are used to develop the analytical model and the normal regression model, five to test the predicting accuracy of the models. Therefore, there are 75 examples in total for calibrating the analytical model and the regression models, and 15 examples for final validating of the models. Accuracy was measured in terms of bias and consistency. Bias indicates the difference between the mean levels of actual and forecast values, whereas consistency shows the dispersion of actual and forecast values around the mean and the regression models, and 15 examples for final validating of the models.

Accuracy was measured in terms of bias and consistency. Bias indicates the difference between the mean levels of actual and forecast values, whereas consistency shows the dispersion of actual and forecast values around the mean.

3.1. Analytical rental model

A number of professionals in the real estate market have helped us to identify important factors for modelling the rental level of a house. Specifically, Ferrari [3] of Ferrari Real Estate pointed out that *location* and *number of bedrooms* are two important factors that influence house rental levels. Stephens [4] of Ray White Real Estate indicated that *inflation* is another factor that should be considered in order to determine the appropriate rental levels. As a result of extensive discussions with professionals in the real estate market and a literature survey, five factors were determined for formulating the analytical rental model. They are:

- (1) average rent per bedroom
- (2) number of bedrooms
- (3) quality index
- (4) area weighting (location)
- (5) inflation correction.

The analytical model is then proposed as expressed in equation (1):

$$R = R P m \times (N B m - 1) \times Q I \times A W \times (1 + I R) \quad (1)$$

where

R = rent of house

$R P m$ = average rent per bedroom

$N B m$ = number of bedrooms

$Q I$ = quality index of house

$A W$ = area weighting

$(1 + I R)$ = inflation correction.

The following subsections describe each of the factors included in the analytical model.

3.1.1. *Quality index QI* . The quality index is a subjective evaluation of the quality of a house in the rental market. The index is the average of values of quality attributes in a house example. For instance, the quality index of the house example in Table 1 is calculated as 1.03.

3.1.2. *Average rent per bedroom RPm and area weighting AW* . Earlier, it has been described that house examples were classified into three groups. In order to obtain average rent per room RPm and area weighting AW , we first calculated the rent per room for each house example (rpm). For example, if the total rent is A\$180, and the number of bedrooms is 3, then the rent per bedroom is A\$180/3 = A\$60. The average rent per bedroom in group j ($LRPM_j$) is a weighted average of the rent per bedroom, as indicated in equation (2):

$$LRPM_j = \frac{\sum_{i=1}^n rpm_i QI_i}{\sum_{i=1}^n QI_i} \quad (2)$$

where

$LRPM_j$ = average rent per bedroom in group j
 rpm_i = rent per bedroom for house i of group j
 QI_i = quality index for house i of group j
 n = total number of house examples in group j .

The values of average rent per bedroom for the three groups, i.e. $LRPM_1$, $LRPM_2$, $LRPM_3$, were calculated as A\$46.7, A\$50.3, A\$58.3 in Garbutt, Cranbrook and Annandale, respectively. The average rent per bedroom for the whole area RPm was calculated as the average of these three values, this being A\$51.8, as indicated in equation (3):

$$RPm = (46.7+50.3+58.3)/3 = A\$51.8 \quad (3)$$

The area weighting AW for each suburb was calculated as the ratio of the rent per bedroom in a specific suburb j , $LRPM_j$, over the average rent per bedroom for the whole area, RPm . The results are listed in Table 2. Values of AW show that Annandale has the highest area weighting, indicating that it is the most expensive area among the three suburbs, Cranbrook is less expensive, and Garbutt has the lowest rental level. The value of AW is calculated based on $LRPM$.

3.1.3. *Inflation correction (1+IR)*. The inflation correction (1+IR) is a parameter included to adjust for the effect of inflation. It is applicable only in two instances, otherwise (1+IR) should be set as 1. The first instance is when the rental model is used to estimate the rental change into the future. Assuming the inflation rate in the coming year to be the same as in this year, the rent value should be increased by the increment of the inflation rate. For example, if the present rent is A\$180, and the

current inflation rate is 2.5%, then the rent for the next year would be likely to be $180 \times (1+0.025) = \text{A\$}184.5$. The second instance is in a situation where the house examples were collected in a previous year. Thus the average rent per bedroom APm , which is deduced from the house examples, should be adjusted by the inflation correction using the current inflation rate.

3.2. Regression model

Using the same variables identified for the analytical model (excluding the inflation rate IR and the constant Rpm , as we identified from experiments that their effects are minor in the regression models), the normal regression model was produced on the 75 housing examples as in equation (4):

$$R = -227.39 + 124.21Q + 160.49AW + 48.53(NBm-1) \quad (4)$$

This model has a relative accuracy R of 0.9244 and a standard error SE of 14.8976, indicating a good accuracy of the regression line in modelling the 75 housing examples.

3.3. Jackknife method

The Jackknife method can be viewed as an evolved form of regression analysis. It utilises as many examples as possible to generate regression models for *ex ante* forecasting tasks, in which forecasts are made beyond the available data scope [5]. To explain the Jackknife method, let us denote by n the total number of housing examples, and m the size of the holdout sample. In forecasting the rent of holdout example i ($1 \leq i \leq m$), $n-1$ examples (holdout example i is excluded) are used to run the regression. After the regression, the generated model is then used to predict the rental level of house i . This process continues until all holdout examples are selected. The Jackknife method is applied to the 15 holdout housing examples, the process can be outlined in the following stepwise procedure.

Step 1. Take the first of the 15 holdout examples, i.e. holdout example $i=1$.

Step 2. Regress on examples excluding holdout example i to generate the regression model.

Step 3. Forecast on holdout example i .

Step 4. Select the next holdout example and go to Step 2, until all 15 examples have been selected.

For the purpose of comparison, results generated by the Jackknife method are presented in Table 4 in the next section. Analyses and comparisons of the models are conducted also in the next section.

4. PREDICTIVE RESULTS AND PERFORMANCE OF MODELS

The analytical model and the regression based models were assessed on the 15 holdout examples. Results of the assessment from the analytical model are listed in Table 3. For each house example, the actual rent is listed in column 2, columns 3 to 5 give values of parameters needed for the analytical model to calculate the estimated rent, results from the analytical model are given in column 6. The error and its percentage are listed in columns 7 and 8, respectively. The mean error M , calculated as the average of individual error rates, and standard deviation SD are also listed.

Table 4 gives details of results from the Jackknife method. Columns 2 to 9 list values of parameters of the linear template of the rental model: $R = a + b \times QI + c \times AW + d \times (NBm-1)$. Column 9 gives the predicted rent R .

In Table 5, predictive results from the normal regression model are compared to those of the Jackknife method. The standard deviations of the assessment results show that results from the normal regression model are slightly better than those from the Jackknife method. However, the difference is very minor.

4.1. Forecast accuracy

The predicted results of the models, along with the error rates and standard deviations, provide the basis for accuracy evaluation. Since all models are tested on the holdout sample, their performance can be directly compared. The error rates and the standard deviations are important measures of accuracy. The analytical model has the lowest value of standard deviation, indicating that the analytical model outperforms the regression based models.

For comparability purposes, actual and predicted rental levels on holdout housing samples are plotted in Fig 2. A visual inspection reveals that all models give reasonable results, but the analytical model is more accurate than other models.

5. CONCLUDING REMARKS AND DISCUSSION

In this paper, we explored major factors affecting the rental level of a house, and then developed an analytical model and regression based models to assess and estimate housing rental levels. The rental models were analysed and tested on a number of house examples collected from three suburbs in Townsville, Australia.

Of interest is the discovery that the rental level of a house has no strong link with its market value, contrary to the common belief that rent is in proportion to the market value of the house. The analytical model highlights that location and quality index are the most important rental factors. The location effect is expressed in the model through the area weighting factor. The quality index is calculated from a number of quality attributes.

The angular fuzzy set model is employed to interpret and quantify linguistic values of the attributes.

The proposed analytical rental model still has limitations. Firstly, in evaluating the quality index, we did not consider the difference of typicality in the quality attributes. Typical attributes may outperform atypical ones and may have a more significant contribution to the quality index. Our next step is to normalise these attributes to reflect the typicality. Secondly, the number of housing examples used in this study is relatively small. In order to ensure the appropriateness of the analytical rental model, further research is needed to test the analytical model on housing examples from other suburbs.

A comparison of the analytical model with regression based models indicates that the analytical model performs well in predicting house rental levels. The analytical model gave the best performance in all testing examples. The normal regression model gave the second best results in testing and performed better than the Jackknife method.

It is interesting to note that the models developed in this study are area independent, it is reasonable to expect these models to be applicable for predicting housing rental levels in other areas.

Acknowledgements

The authors wish to thank many real estate agents in Townsville for providing information and data used in this research.

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APPENDIX

Suburb	RT	BDMS	CLI	SHP	PK	SEC	PRIV	APP	LSC	ODL	SER
Garbutt	120	3	0.75	0.75	0.75	1.00	1.25	1.00	1.00	0.75	1.00
Garbutt	160	3	1.00	0.75	1.00	1.00	1.50	1.25	1.00	1.00	1.00
Garbutt	140	3	1.00	0.75	1.25	1.00	1.25	1.50	1.00	1.00	1.25
Garbutt	140	3	1.25	0.75	1.00	1.00	1.00	1.25	1.00	1.25	1.00
Garbutt	130	3	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00
Garbutt	180	3	1.50	0.75	1.50	1.25	1.50	1.50	1.00	1.25	1.25
Garbutt	150	3	0.75	0.75	1.25	1.00	1.25	1.50	0.75	1.25	1.00
Garbutt	175	3	1.50	0.75	1.25	1.25	1.50	1.50	1.00	1.00	1.00
Garbutt	160	3	1.25	0.75	1.00	1.25	1.50	1.25	0.75	1.00	1.00
Garbutt	175	3	1.50	0.75	1.50	1.50	1.50	1.50	1.00	1.25	1.00
Garbutt	122	3	1.00	0.75	1.00	1.00	1.00	0.50	0.75	1.00	1.00
Garbutt	150	3	1.25	0.75	1.25	1.50	1.50	1.25	1.00	1.00	1.00
Garbutt	160	3	1.00	0.75	1.25	1.50	1.50	1.50	1.00	0.75	1.00
Garbutt	125	3	1.25	0.75	1.00	1.25	1.50	1.00	0.75	1.00	1.00
Garbutt	80	2	0.75	0.75	1.00	0.75	0.75	0.75	0.75	1.00	1.00
Garbutt	90	2	0.75	0.75	1.00	1.00	1.00	1.25	0.75	0.75	1.00
Garbutt	135	3	1.00	0.75	1.00	1.25	1.25	1.00	1.00	1.00	1.00
Garbutt	140	3	1.25	0.75	1.25	1.00	1.00	1.25	0.75	1.00	1.00
Garbutt	75	2	0.50	0.75	1.00	1.00	1.00	1.25	0.75	0.75	1.00
Garbutt	130	3	1.00	0.75	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Garbutt	140	3	1.00	0.75	1.25	1.50	1.00	1.25	0.75	0.75	1.00
Garbutt	80	2	1.25	0.75	0.75	0.75	0.75	0.75	0.75	1.00	0.75
Garbutt	90	2	1.25	0.75	1.00	1.25	1.00	1.00	0.75	1.00	1.00
Garbutt	135	3	1.00	0.75	1.25	0.75	1.25	1.00	1.25	0.75	1.00
Garbutt	110	3	0.75	0.75	0.75	1.00	0.75	0.75	1.25	1.00	0.75
Garbutt	160	3	1.00	0.75	1.25	1.50	1.50	1.50	1.00	0.75	1.00
Garbutt	145	3	1.00	0.75	1.00	1.00	1.25	1.00	0.75	1.00	1.00
Garbutt	100	3	1.25	1.25	1.25	1.25	1.25	1.50	1.25	1.00	1.00
Garbutt	170	3	1.00	0.75	1.25	1.00	1.25	1.00	1.00	1.00	1.00
Garbutt	90	2	0.75	0.75	0.75	1.00	1.25	1.00	1.00	0.75	1.00
Cranbrook	175	3	1.00	1.25	1.00	1.25	1.25	1.25	1.00	1.00	1.25
Cranbrook	180	3	1.25	1.25	1.25	1.00	1.25	1.25	1.25	1.00	1.25
Cranbrook	160	3	1.00	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00
Cranbrook	170	3	1.25	1.25	1.00	1.00	1.00	1.00	1.50	1.25	1.00
Cranbrook	130	3	0.75	1.25	0.75	0.75	0.75	0.75	1.00	0.75	1.00
Cranbrook	145	3	1.25	1.25	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Cranbrook	160	3	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	1.00
Cranbrook	175	3	1.50	1.25	1.00	1.00	1.00	1.00	1.00	1.25	1.00
Cranbrook	145	3	1.00	1.25	0.75	1.00	1.00	1.00	1.00	0.75	1.00
Cranbrook	II 0	2	1.25	1.25	1.25	1.25	1.00	1.00	1.25	1.25	1.25
Cranbrook	160	3	1.25	1.25	1.00	1.00	1.00	1.00	1.00	0.75	1.00
Cranbrook	155	3	1.50	1.25	1.00	1.25	1.00	1.00	0.75	0.75	1.00
Cranbrook	145	3	1.00	1.25	0.75	1.00	1.25	1.00	0.75	0.75	1.00
Cranbrook	100	2	1.50	1.25	1.00	1.25	1.00	1.00	0.75	1.00	1.00
Cranbrook	180	3	1.50	1.25	1.25	1.25	1.00	1.25	1.25	1.25	1.00
Cranbrook	160	3	1.25	1.25	1.00	1.25	1.00	1.00	0.75	1.00	1.00
Cranbrook	150	3	1.00	1.25	1.25	1.00	0.75	1.00	0.75	0.75	1.00
Cranbrook	95	2	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00	1.00
Cranbrook	160	3	1.25	1.25	1.00	1.25	1.00	1.00	0.75	1.00	1.00
Cranbrook	165	3	1.50	1.25	1.25	0.75	0.75	1.00	0.75	1.00	1.00
Cranbrook	155	3	1.00	1.25	1.00	1.00	0.75	1.00	0.75	0.75	1.00
Cranbrook	165	3	1.25	1.25	1.25	1.25	1.00	1.00	0.75	1.00	1.00
Cranbrook	140	3	0.75	1.25	1.25	1.25	1.00	1.00	0.75	0.75	1.00
Cranbrook	160	3	1.25	1.25	1.25	1.00	1.25	1.00	1.00	1.00	1.00
Cranbrook	145	3	0.75	1.25	1.00	1.25	1.00	1.00	0.75	1.00	1.00
Cranbrook	180	3	1.25	1.25	1.25	1.00	1.00	1.00	1.25	1.25	1.00
Cranbrook	185	3	1.25	1.25	1.00	1.25	1.00	1.00	1.25	1.25	1.25
Cranbrook	120	2	1.50	1.25	1.50	1.50	1.25	1.00	1.25	1.25	1.25

Suburb	RT	BDMS	CLI	SHP	PK	SEC	PRIV	APP	LSC	ODL	SER
Cranbrook	165	3	1.00	1.25	1.00	1.00	1.25	1.00	1.00	1.00	1.00
Cranbrook	170	3	1.00	1.25	1.00	1.00	1.00	1.25	1.25	1.25	1.00
Annadale	175	3	1.25	1.25	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Annadale	180	3	1.00	1.25	1.25	1.00	1.00	1.25	1.00	0.75	1.00
Annadale	180	3	1.00	1.25	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Annadale	160	3	1.25	1.25	1.00	1.00	0.75	1.00	0.75	1.00	1.00
Annadale	125	2	1.00	1.25	0.75	1.00	1.00	1.00	0.75	0.75	1.00
Annadale	175	3	1.25	1.25	1.00	1.00	0.75	1.00	0.75	1.00	1.00
Annadale	200	3	1.50	1.25	1.25	1.00	1.00	1.00	1.00	1.00	1.00
Annadale	180	3	1.50	1.25	1.00	1.00	0.75	1.00	0.75	1.00	1.00
Annadale	115	2	0.75	1.25	1.00	1.00	0.75	1.00	0.75	1.00	1.00
Annadale	180	3	1.50	1.25	1.25	1.00	0.75	1.00	1.00	0.75	1.00
Annadale	170	3	1.25	1.25	1.00	1.00	1.00	1.00	0.75	1.00	1.00
Annadale	180	3	1.25	1.25	1.00	1.00	0.75	1.00	1.00	0.75	1.00
Annadale	140	2	1.50	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.00
Annadale	170	3	1.25	1.25	1.00	1.00	0.75	1.00	1.00	1.00	1.00
Annadale	175	3	1.25	1.25	1.25	1.00	0.75	0.75	0.75	0.75	1.00
Annadale	180	3	1.00	1.25	1.00	1.00	1.00	0.75	1.00	1.00	1.00
Annadale	135	2	1.25	1.25	1.00	1.00	0.75	1.00	0.75	0.75	1.00
Annadale	170	3	1.25	1.25	0.75	1.00	1.00	0.75	1.00	1.00	1.00
Annadale	170	3	0.75	1.25	1.00	1.25	0.75	1.00	0.75	1.00	1.00
Annadale	175	3	1.00	1.25	1.00	1.00	0.75	1.25	1.00	0.75	1.00
Annadale	145	2	1.50	1.25	1.25	1.00	1.25	1.00	1.00	1.00	1.00
Annadale	170	3	1.25	1.25	1.00	1.00	0.75	1.00	1.00	0.75	1.00
Annadale	140	2	1.25	1.25	1.25	1.25	1.00	0.75	1.00	1.25	1.00
Annadale	175	3	1.00	1.25	1.00	1.00	0.75	1.00	1.25	1.00	1.00
Annadale	180	3	1.00	1.25	1.25	1.00	0.75	0.75	1.00	1.00	1.00
Annadale	200	3	1.25	1.25	1.25	1.25	1.00	1.00	1.25	1.25	1.00
Annadale	195	3	1.25	1.25	1.25	1.00	1.00	1.00	1.00	1.25	1.00
Annadale	150	2	1.50	1.25	1.25	1.25	1.00	1.25	1.00	1.25	1.00
Annadale	210	3	1.50	1.25	1.25	1.25	1.00	1.25	1.25	1.25	1.00
Annadale	190	3	1.00	1.25	1.00	1.00	1.50	1.25	0.75	1.00	1.00

RT =rent for house; BDMS =number of bedrooms; CL =cooling facilities; SHP =access to shops; PK =parking facilities; SEC= security; PRIV =privacy; APP =dwelling appearance;LSC =landscaping; ODL =outdoor lighting; SER = supporting services.

Table 1: A house example

Attributes	Values
Rent of house	A\$170 per week
Suburb	Cranbrook
Number of bedrooms	3
<i>Attributes for evaluating quality index</i>	
Cooling facilities	Fairly good
Parking facilities	Poor
Security	Undecided
Privacy	Good
Dwelling appearance	Fairly poor
Landscaping	Poor
Outdoor lighting	Very poor
Supporting services	Good

Table 2: Values of area weighting

Average rent per bedroom	Area weighting	(AW)
$LRPM_1$ (Garbutt)	A\$46.7	0.90
$LRPM_2$ (Cranbrook)	A\$50.3	0.97
$LRPM_3$ (Annandale)	A\$58.3	1.13
APm	A\$51.8	

Table 3: Assessment results from analytical model

1	2	3	4	5	6	7	8
Suburb	Actual rent	AW	NBm	QI	Analytical model	Error	Error(%)
Garbutt	160	0.90	3	1.13	158.04	-1.96	-1.22
	145	0.90	3	0.96	134.27	-10.73	-7.40
	100	0.90	2	1.05	97.90	-2.10	-2.10
	170	0.90	3	1.23	172.03	2.03	1.19
	90	0.90	2	0.92	85.78	-4.22	-4.69
Cranbrook	180	0.97	3	1.15	173.35	-6.65	-3.70
	185	0.97	3	1.16	174.86	-10.14	-5.48
	120	0.97	2	1.30	130.64	10.64	8.87
	165	0.97	3	1.06	159.78	-5.22	-3.16
	170	0.97	3	1.12	168.83	-1.17	-0.69
Annandale	200	1.13	3	1.18	207.21	7.21	3.61
	195	1.13	3	1.10	193.16	-1.84	-0.94
	150	1.13	2	1.20	140.48	-9.52	-6.35
	210	1.13	3	1.22	214.23	4.23	2.02
	190	1.13	3	1.09	191.41	1.41	0.74
		Mean				-1.87	-1.29
		Standard deviation				6.33	4.29

Table 4: Details of assessment results from the Jackknife method

Suburb	2 Actual rent	3 AW	4 NBm	5 QI	6 a	7 h	8 c	9 d	10 Predict (R)
Garbutt	160	0.90	3	1.13	-215.49	108.63	162.53	49.91	153.36
	145	0.90	3	0.96	-217.21	110.04	162.87	49.83	134.67
	100	0.90	2	1.05	-221.09	122.44	153.50	50.42	96.04
	170	0.90	3	1.23	-219.26	110.03	165.14	49.60	163.90
	90	0.90	2	0.92	-219.46	110.55	163.22	50.57	79.71
Cranbrook	180	0.97	3	1.15	-214.37	107.79	162.37	49.81	166.71
	185	0.97	3	1.16	-213.69	107.05	162.46	49.80	167.67
	120	0.97	2	1.30	-217.81	114.53	160.85	49.83	136.93
	165	0.97	3	1.06	-215.61	109.20	162.12	49.85	157.09
	170	0.97	3	1.12	-215.13	108.72	162.10	49.88	163.63
Annandale	200	1.13	3	1.18	-213.81	108.52	160.99	49.90	195.96
	195	1.13	3	1.10	-213.91	108.81	160.81	49.87	187.24
	150	1.13	2	1.20	-214.93	108.15	161.51	50.11	1476.47
	210	1.13	3	1.22	-211.92	107.36	160.34	49.86	199.96
	190	1.13	3	1.09	-214.53	109.08	161.13	49.90	186.24

Table 5: Error rates of results from the normal regression model and the Jackknife method

Suburb	Actual	Normal regression model			Jackknife method		
	Actual rent	Normal regression	Error	Error(%)	Jackknife method	Error	Error(%)
Garbutt	160	154.47	-5.53	-3.35	153.36	-6.64	-4.15
	145	133.36	-11.64	-8.03	134.67	-10.33	-7.12
	100	96.01	-3.89	-3.99	96.04	-3.86	-3.86
	170	166.89	-3.11	-1.83	163.90	-6.10	-3.59
	90	79.86	-10.15	-11.27	79.71	-10.19	-11.32
Cranbrook	180	168.19	-11.81	-6.56	166.71	-13.29	-7.38
	185	169.43	-15.57	-8.42	167.67	-17.33	-9.37
	120	138.23	18.29	15.24	136.93	16.93	14.11
	165	157.01	-7.99	-4.84	157.09	-7.91	-4.79
	170	164.46	-5.54	-3.26	163.63	-6.37	-3.75
Annandale	200	197.60	-2.41	-1.20	195.96	-4.04	-2.02
	195	187.66	-7.34	-3.77	187.24	-7.80	-4.00
	150	151.55	1.55	1.03	147.47	-2.53	-1.69
	210	202.56	-7.44	-3.54	199.96	-10.04	-4.78
	190	186.42	-3.81	-2.01	186.24	-3.58	-1.88
	Mean		-3.10	-3.06		-6.21	-3.71
	Standard deviation		9.03	5.95		9.56	6.59

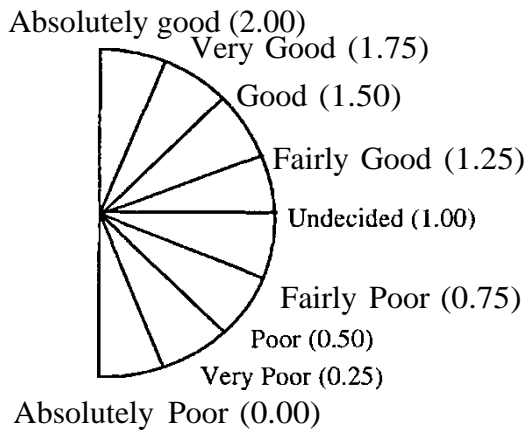


Fig 1: Angular fuzzy set models for qualitative values

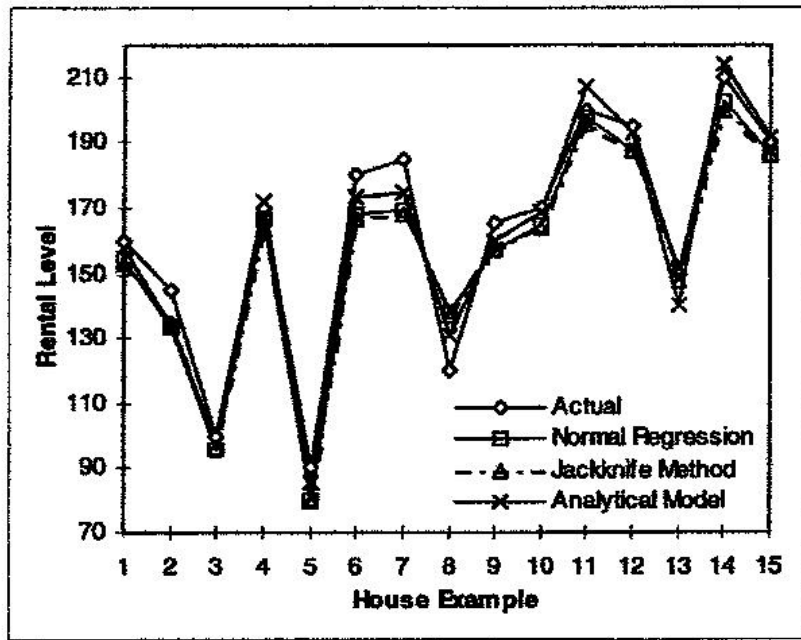


Fig 2: Comparison of actual and predicted rental results