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REFINEMENT OF STOREY ENCLOSURE FORECASTING METHOD

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Abstract

Previous researches have suggested that there is only little improvement in the accuracy of building forecasts as design develops. It has been criticized that established conventional forecasting methods also lack measures of their own performance. An early stage price forecasting model, the Storey Enclosure Method developed by James in 1954, uses some physical measurements of buildings to estimate building prices. Although James' Storey Enclosure Method (JSEM) is not a widely used model in practice, the model has been proved empirically, if rather crudely, to be a better model than other commonly used models. This paper describes some preliminary research to refine JSEM using regression techniques. Advanced features of the proposed model include the use of cross validation for reliability analysis that simulates how forecasts are produced in practice and a dual stepwise selection strategy that enhances the chance of identifying the best model. To precisely judge the performance of models, this paper suggests using bias and consistency with parametric and non-parametric statistical inferences.

Keywords: Cost Modelling, Forecasting Techniques, Regression Analysis

INTRODUCTION

Project cost planning and control is a core subject in commercial management from the client's perspective. In the design development stage of a project, cost planning and control is an iterative process for forecasting a building price based on available drawings and specifications (costing a design) and revising drawings and specifications to ensure the building price falls within the limit of a predetermined sum (designing to a cost). Design decisions made in the process are crucial to the success of the project as they are very cost sensitive during the design development, and especially before the detailed design stage. Changes to design decisions in the later design or execution stages can lead to redundancies. Thus, producing an accurate forecast of cost is essential. In this regard, the use of the right cost model is a fundamental concern.

One of the pioneer models, the James' Storey Enclosure Model (JSEM), developed by James in 1954, takes into account the effect of physical shape on building prices. James was able to show that his model outperforms two conventional forecasting models, floor area and cube models, although the comparison criteria used were quite crude. By simplifying the formula representing JSEM, it is possible to develop JSEM further by adopting a regression methodology. This paper describes some preliminary research concerning this development.

EARLY DESIGN STAGE COST MODELS: A REVIEW

The first recorded building price forecasting model is the cube model, invented about 200 years ago. In contrast, the more widely used floor area model was developed around 1920 (Skitmore et al. 1990). These two models are mainly used in the early design stage (from the inception to sketch design according to the RIBA outline plan of work). In the later design stage, practicing forecasters measure more items and quantities to produce forecasts.

The choice of model, or a combination of models, to use is a trade-off between forecasting accuracy and time availability or adequacy of available forecasting information (Taylor 1984). However, empirical studies of forecasting accuracy indicate that very little improvement in the overall accuracy can be obtained by simply increasing the level of detail and complexity of quantity-based models (Ashworth and Skitmore 1983; Ross 1983; Morrison 1984; Beeston 1987). Also, as practicing forecasters rarely monitor the performance of their forecasts produced in a project cycle (Morrison 1983; Bowen and Edwards 1985), the assumption that forecasting accuracy depends on the level of detail of forecast is not tested at all in practice.

Brandon (1982) has pointed out the need to focus research for cost modelling on its theory development. In response, a few comprehensive reviews have been done on grouping and classifying cost models (Raftery 1984; Beeston 1987; Newton 1990; Skitmore and Patchell 1990). Newton (1990) classified nine descriptive primitives for cost modelling studies; they are (1) data, (2) units, (3) usage, (4) approach, (5) application, (6) model, (7) technique, (8) assumptions and (9) uncertainty. With regard to the technique of cost models, ten types were classified; (1) Dynamic programming, (2) Expert system, (3) Functional dependency, (4) Linear programming, (5) Manual, (6) Monte Carlo simulation, (7) Networks, (8) Parametric modelling, (9) Probability analysis and (10) Regression analysis. Despite the vast development of newer techniques for constructing cost models, only manual techniques such as floor area and quantity based models are widely used today. This is evidenced by the results of surveys on the use of forecasting techniques by practitioners from Nigeria (Akintoye et al. 1992), South Africa (Bowen and Edwards 1998), and United Kingdom (Fortune and Lees 1996; Fortune and Hinks 1998).

JAMES' STOREY ENCLOSURE METHOD (JSEM)

James (1954) proposed a single rate forecasting model which takes into account the various important aspects of design that are ignored in the two other conventional single rate forecasting models – the floor area and cube models. It measures all the enclosure areas for a building. It considers (measures) the (1) shape of a building (elevation area), (2) vertical positioning of the floor area in a building (number of floor above and below ground floor level), (3) storey height of building and overall building height (roof area, as it affects the ratios of (i) floor and roof areas to elevation area, and (ii) roof area to elevation area), and (4) extra cost of sinking usable floor area below ground level (basement wall area). Rather than simply summing up areas of enclosure components to a total as the base quantity for the model, weightings are assigned prescriptively to components to produce the base quantity. The assigned weighting to each component is shown in Table 1.

Table 1: Weightings assigned to individual components

Component	Weighting
HORIZONTAL ELEMENT	
Ground Floor	2
Upper Floors	2 + (0.15 x No. of Floor above Ground)
Roof	1
Floors below Ground	2
VERTICAL ELEMENT	
Elevations	1
Basement Walls	2.5

Based on the above weightings, JSEM can be represented by Equation (1),

$$P = \left(\sum_{i=0}^{n} (2 + 0.15i) f_i + \sum_{i=0}^{n} p_i s_i + 2\sum_{j=0}^{m} f'_j + 2.5\sum_{j=0}^{m} p'_j s'_j + r \right) \cdot R \qquad \text{Eq. (1)}$$

in which P is the forecasted price; f_i the floor area, p_i the perimeter of elevation and s_i the storey height at i no. of storeys above ground; n the total no. of storeys above ground level; f'_j the floor area, p'_j the perimeter of basement wall and s'_j the storey height at j no. of storeys below ground level; m the total no. of floors below ground; r roof area; and R the unit rate for the model.

In James' study, the forecasting accuracy for JSEM was examined against the floor area and cube models based on 86 tenders for four types of building. The study was able to show that forecasts produced by JSEM were nearer to the actual tender prices than the other two models and the range of price variation was reduced accordingly. These results turn out to be statistically significant (chi-square 5.99, 2df) which suggest that JSEM and floor area model is better than the cube model (Skitmore, 1991). Despite the better performance demonstrated by James, JSEM remains primarily in textbooks of cost planning (Cartlidge and Mehrtens 1982; Seeley, 1996; Ashworth 1999; Ferry at el. 1999). The result from a survey on the use of cost forecasting models in UK revealed that less than 2% of its respondents (practitioners) made use of JSEM and the cube model to provide strategic cost advice to their clients (Fortune and Lee 1989). In contrast, a more recently conducted survey in South Africa, surprisingly, found that 27% of the respondents (practitioners) used the storey enclosure method in practice (Bowen and Edwards 1998). Those two surveys provide the only evidence of the real life application of the storey enclosure method.

The unpopularity of the model is said to be because: (1) the weightings are not derived empirically by proven data (Wilderness Group 1964; Ashworth 1999); (2) there is insufficient historical data support (Wilderness Group 1964; Seeley 1996); (3) the use of relatively complex calculations (as compared with floor area or cube models) (Seeley 1996). Having identified these hurdles on the use of JSEM, the research described in this paper adopted a regression methodology to refine JSEM as it was considered to be the most sophisticated conventional single rate method available at early design stage (Skitmore et al. 1990) that has considerable potential for further development by statistical means (Skitmore and Marston 1999).

SIMPLIFICATION OF JSEM

To make a cost model useful and applicable, it must be general enough to accommodate variations that do not validate the assumptions, and specific enough to reflect cost significant factors; simple enough to be understood by practicing forecasters and intricate enough to model reality. Although the data in James' study are mainly from low-rise buildings (below 3 storeys) such as houses, and medium rise (3 to 10 storeys) buildings such as schools and industrial buildings, JSEM can be also be applied to high-rise buildings (higher than 10 storeys). However, the direct application of JSEM's equation for high rise buildings results produces too many variables as the higher the building, the more the number of variables have to be created.

This huge number of variables can be significantly reduced if the reasonable assumption is made that the floor area at each level is approximately the same. Of course, care has to be taken to exclude buildings with changing floor sizes at different levels as this will violate the assumption.

Under this assumption then, Eq. (1) for a building comprising a basement, a podium and a tower is simplified to Eq. (2), as follows:

$$P = \begin{bmatrix} \left(2 - \frac{0.15}{2}\right) af_p + \frac{0.15}{2} a^2 f_p + \left(2 - \frac{0.15}{2}\right) bf_t + \frac{0.15}{2} b^2 f_t + 0.15abf_t \\ + r + (a+b) p_{pt} s_{pt} + 2mf_b + 2.5mp_b s_b \end{bmatrix} \cdot R \qquad \text{Eq. (2)}$$

in which *a* is the storey number for the podium; *b* the storey number for the tower; f_p the average floor area per storey for floors at podium level; f_t the average floor area per storey for floors at tower level; p_{pt} the average perimeter of podium and tower; s_{pt} the average storey height of podium; *m* the storey number for the basement; f_b the average floor area per storey for floors at basement level; and p_b the average perimeter of the basement; and s_b the average storey height of the basement.

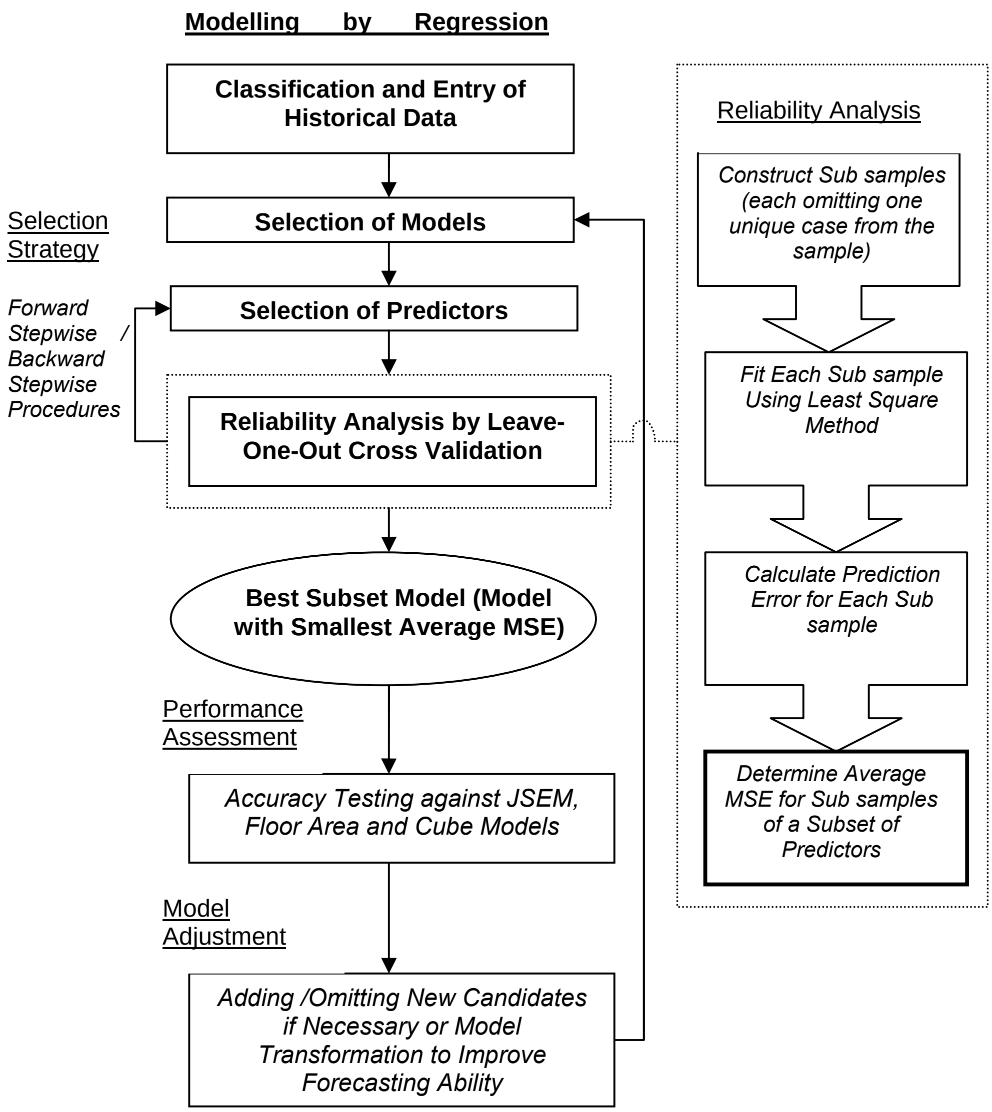
REFINEMENT METHODOLOGY

In JSEM, building prices are assumed to be proportioned to floor area, roof area and elevation area, etc. However, as their exact relationship is determined arbitrarily, it is possible that (1) JSEM may have included some irrelevant predicting variables or excluded some significant predicting variables and (2) the relationship between the building prices and the predicting variables is not the same as what has been assumed. Referring to Eq. (2), it is clear that these problems may be resolved statistically by the use of a regression technique. If regression analysis is applied, these problems concern the determination of the subset of variables and the set of coefficients for the variables that give the best forecast. Eq. (2) can be considered as a hypothetical model that consists of a number of independent variables (predictors) such as af_pR, bf_tR and rR, etc., and the dependent variable (response), *P*. Let all the predictors be V_i, and the corresponding coefficients be β_i where $i = 1, 2, \ldots, k$, the building price model becomes:

$$P = \beta_0 + \beta_1 V_1 + \beta_2 V_2 + \cdots + \beta_k V_k = \beta_0 + \sum_{i=1}^{k} \beta_i V_i \qquad \text{Eq. (3)}$$

Thus, the regressed model for JSEM (RJSEM) is the model comprising the (most important or most valid) subset of predictors from V_1 to V_k with the corresponding coefficients that gives the least mean square error (MSQ) in prediction. Figure 1 shows the framework of the regression approach used. The regression analysis goes through four typical stages: (1) classification and entry of historical data; (2) selection of models; (3) selection of predictors; and (4) reliability analysis. Several specific features on the modelling approach are highlighted in the following sections.

Figure 1: Research Framework to Produce RJSEM



Selection Strategy

The all-possible regressions procedure (fitting all combinations of variables) was used instead of any other variables selection strategy whenever practicable as it was the only way to guarantee a successful search for the best subset model. However, a full analysis of all subsets is a very time-consuming exercise especially if the interaction terms are included as candidates. To ensure the selection of the best subset model, a dual stepwise procedure (a combination of forward stepwise and backward stepwise) was used. The selection objective is to minimize the average MSQ in fitting of the cross validated models. In the forward stepwise procedure, forward regression is first applied by entering one candidate at a time. When no candidate entering into the model can further reduce the average MSQ, the forward regression ends. A subset of predictors is selected which produces the minimal average MSQ. Then, backward regression is followed. Candidates in the subset selected by forward regression are eliminated one at a time until no candidate being eliminated from the model can further reduce the average MSQ. Forward regression starts again and then backward regression follows until average MSQ cannot be further reduced and a minimum average MSQ is determined. The best subset model deduced from the forward stepwise procedure is compared with that from the backward stepwise procedure. Of course, if they are the same, the chance that the subset model is the best one becomes very high.

Reliability Analysis

In classical statistical inference, a model is validated using *ex ante* (out of sample) forecasts. However, the lack of available data in the construction of cost forecasting models always caused a limitation to its application. For this research a resampling method, cross validation, was used to select variables and evaluate the models. Cross validation is a compromise method that keeps the integrity of the inference when the same data are used for selection and validation of statistical models and so is kind of *ex post* forecast, i.e. test data are within sample but not used in model fitting. It is different from split sample validation that the latter uses only a single sub sample (the validation set) to estimate the error. This distinction is particularly important because cross-validation is proved to be markedly superior for small data sets (Goutte 1997). For predictive applications, the cross validation method has the most intuitive appeal as, with the non-time series data of this nature, each error value can be thought of as a real error that may arise in the 'real world' practice of forecasting. In this regard, the “leave-one-out” cross validation is the most suitable approach. The accuracy of statistical inference in leave-one-out method is preserved by dividing a sample containing *n* cases of data into *n* exploratory sub samples (each containing *n* - 1 cases by omitting one case without repeat from the original *n*-case sample), which each is used to select a statistical model, and the *n* omitted cases, which each is used to validate the selected model from an exploratory sub sample excluding itself. An average MSQ is deduced from *n* models for each subset of candidates. The MSQs from different subsets of candidates are compared and the one with the smallest MSQ is the best subset model.

Performance Measurement

To assess the performance of the best subset model, their prediction results were compared with those obtained from other conventional models, JSEM, floor area and cube models. Practitioners use the percentage error of a prediction, i.e.

(predicted price – actual tender price) / actual tender price x 100%, to measure how close a prediction is made relative to the actual tender price. To compare the performance of models based on a group of observations, two widely established measures as described in the methodology section, bias and consistency, were used. Bias and consistency of models are represented by the mean and standard deviation of percentage errors respectively. The higher the mean, the more bias the model; and the higher the standard deviation, the less consistent the model. The magnitude of these two measures of models alone cannot confidently distinguish whether a model is better or worse than the others. To tell the significance of bias, the models are tested against mean zero using *t* statistics. The *t*-test is well-known for its robustness even the distribution is departed from normality. The use of inference tests for consistency is more complicated.

Variances of percentage errors, as measures of consistency, are compared using both parametric and non-parametric inference. The former type of statistics is more powerful and is preferred if the assumption of normality of percentage error distribution is valid. The variances of percentage errors from forecasts of different models are compared first in a whole group (by Bartlett's test (for parametric, i.e. satisfying the normality assumption) and Kruskal-Wallis test (non-parametric, i.e. not satisfying the normality assumption)) and then in pairs (by Multiple *F*-test (parametric) and Multiple Mann -Whitney-Wilcoxon tests (non-parametric)). Figure 2 shows an algorithm designed for the comparisons.

Model Adjustment

The best subset models selected from forward stepwise and backward stepwise procedures are not necessarily the same. This divergence is easily caused by multicollinearity, i.e., the strong correlations among predictors. One typical strategy to avoid the multicollinearity and produce a suitable model from the two procedures is to combine or remove predictors that are strongly correlated to each other. This can be easily implemented by the use of correlation tables. However, this strategy is not considered to be appropriate for the modelling exercise in this study because many of the selected predictors are interaction terms that are likely to be strong correlated with the primary variables. Moreover, since the future use of the best model is for prediction rather than understanding how predictors in the model impact the response, good models with the problem of multicollinearity still produce accurate predictions. Therefore, except that variables are very highly correlated (> 0.95) or predictors have similar values to each other in principle, they will not be deleted simply because their correlation is high (say, > 0.7). Since if the cross validated average MSQs of the best models generated from the two procedures are different, there always exists a better one, the one with a smaller average MSQ. To prevent a less significant candidate, acting as an offending variable, entering into a model prior to a more significant candidate (or a more significant candidate is eliminated from the model prior to a less significant candidate), an algorithm to exclude offending variables was set up if divergence occurred. This involved four steps: 1) excluding a candidate in turn prior to modelling by regression, 2) modelling with forward stepwise and backward stepwise procedures, 3) choosing the model with the smallest MSQ and 4) comparing it with the MSQ (the smaller one from forward stepwise or backward stepwise) from the model including the excluded candidates. Step 1 shall be repeated (i.e. excluding the second, third or more candidates prior to modelling) if the forward stepwise and backward stepwise cannot produce an agreeable best model or a model's MSQ is higher than the MSQ from the set of candidates that contains the excluded candidate(s). This procedure for excluding candidates stops when forward and backward stepwise procedures produce the same model (subset of predictors) with the smallest MSQ.

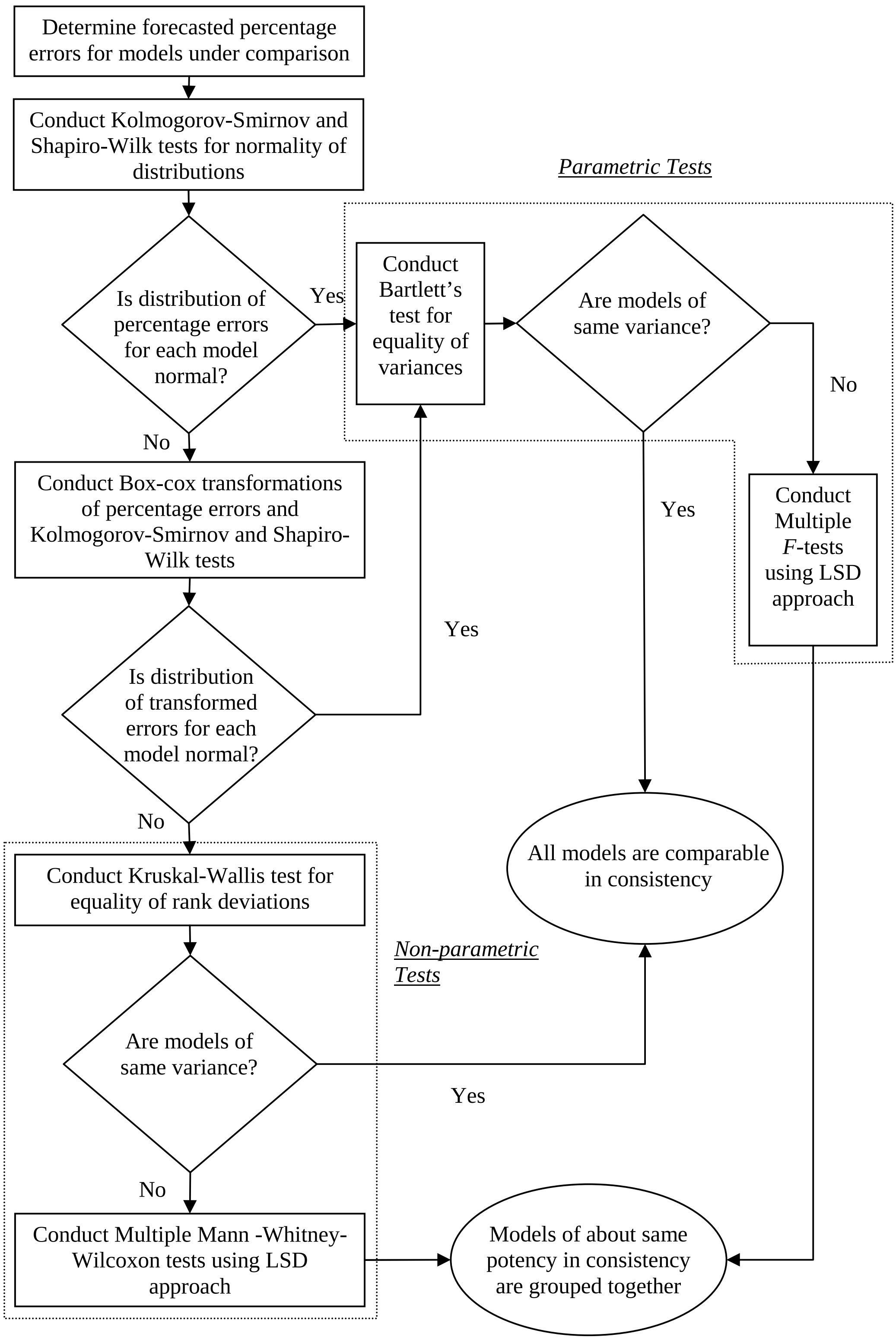
The use of cross validation is a non-parametric approach for determining the best subset of predictors and therefore does not have to fulfil the assumptions of homoscedasticity and normality of predictors as required in parametric regression. Because of this, the use of transformation strategies for variables in this study was limited to the circumstances where the original data suggested a model that is non-linear in either the regression coefficients or the original variables or to linearise the regression coefficients.

CONCLUSIONS AND FUTHER WORK

This paper explains a systematic approach to refine JSEM. This involves 1) the transformation of JSEM to fit a linear modelling requirement, 2) the use of regression methodology for modelling, 3) the use of bias, consistency and average MSE for performance assessment. A dual selection strategy containing forward stepwise and backward stepwise procedures was proposed to enhance the chance of identifying the best sub-set model. The proposed regressed model, RJSEM, is creditable and reliable as the use of leave-one-out cross validation approach to produce a model is very similar to the way a forecast is produced from historical data in practice, which often involves the use of all suitable and available historical project data (including prices and figures for identified variables) and the data of a new project (figures for identified variables only).

Data have been collected from a large quantity surveying practice in Hong Kong which are classified according to the types of buildings: (1) office; (2) private housing; (3) nursing home and (4) primary and secondary school. Analysis of the data using the refinement approach proposed in this paper has been carried out. Generally, the regressed models show improvement in consistency although their effects are not significant in every type of building. Surprisingly, the more widely accepted floor area model is underperformed in the category of private housing. The results of this analysis will be published in the near future.

Figure 2: Algorithm for Comparing Variances of Percentage Errors



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