VARIATIONS IN IMPLEMENTING SCM TO MINIMIZE SBJECTIVITY AND A FUTURE DIRECTION FOR MALAYSIA

ROHANA ABDUL RAHMAN

ABSTRACT

The Sales Comparison Method (SCM) is the most widely used method of property va luation, residential properties in particular. With transaction data becoming more and more accessible, the trend will continue. However, SCM is criticized for its subjectivity with inconsistent prediction. The main contributor of subjectivity is informal implementation procedure of the method.Variants of SCM have emerged focusing on implementation details with subjectivity minimized or eliminated. The grid adjustment method has formalized the procedure with optimal or non-optimal route. Spatial autoregressive error model formalized the procedure in addition to estimating the spatial error dependence in a dataset. There are methods that focused on weighting of comparables only. This paper reviews SCM and its variation of implementation, discuss their strengths and weaknesses and recommends modifying the grid adjustment methodas a new implementation procedure of SCM for the country that may minimizes subjectivity.

Keywords: property valuation, grid adjustment method, spatial autoregressive models, automated valuation.

INTRODUCTION

The Sales Comparison Method (SCM) is the most widely used method of property valuation world-wide including Malaysia, especially for residential properties(Pagourtzi et al., 2003). The method is regarded as one that produces the most reliable predicted value of a subject property compared to other methods of valuation, especially when records of recently sold properties are of quality, abundant and easily accessible.The use of SCM for commercial properties (office and retail) has started to attract valuation communities(Dunse and Jones, 1998, Gardiner and Henneberry, 1989, Sayer and Moohan, 2007, Tu et al., 2004). Unpopularity of the method in the past due to insufficient transaction records no longer hold and will continue to be untrue in the future. As the economy grows, the supply of commercial properties will also grow and the level of transaction is expected to increase as well. With proper record keeping of transaction records by the Department of Valuation and Property Services, SCM has a great potential to dominate the valuation of commercial properties in the near future. Thus, SCM will continue to be the main method of property valuation until proven irrelevant and taken over by another innovation.

A major critic of SCM is its subjectivity(Colwell et al., 1983, Gau et al., 1992, Gau et al., 1994, Isakson, 1986, Lipscomb and Gray, 1990, Vandell, 1991, You and Chang, 2009).The procedure for implementing SCM is informal requiring input based on the experience of valuers. Malaysia is no exception. The method requires comparables to be selected to be closest to the subject property requiring the least adjustment for term of sale, time, location, neighborhood, accessibility, tenure, restriction of interest, land use zoning and structural differences. Generally, adjustments made are not supported by analysis of relevant data. Indicated values of comparables are reconciled using simple average which violates the concept of comparability. The process seems to employ too much art; it is largely accepted that a process to produce quantitative prediction of property values ought to be primarily a science work with formal and precise methodology rather than dominated by an art(Vandell, 1991).

SCM has evolved and variants of it in terms of implementation details exist that eliminate or minimize subjectivity (Colwell et al., 1983, Gau et al., 1992, Gau et al., 1994, Isakson, 1986, Pace and Gilley, 1998, Vandell, 1991, You and Chang, 2009). This paper reviews these variations, discusses their strengths and weaknesses with the aim to familiarize Malaysian valuation communities with other better variants of SCM implementationsand recommend adirection of SCM for the country. The composition of the paper is as follows. The next section reviews the theorySCM and followed by a section that presents the Malaysian Valuation Standard (MVS) and *AmalanSistemPenilaian* (ASP)that regulate the practice of SCM in the country. The subsequent section discusses variations in implementing SCM. This is followed by discussions on all methods presented and a recommendation ofthe SCM direction for Malaysia. The paper concludes by highlighting the important points.

THE THEORY OF SALES COMPARISON METHOD

SCM has become one of the famous methods to predictthe market value of a property since early 1900. Like other economic commodity, the price of a property is also determined by its supply and demand at the time of transaction. The higher the demand, the higher the price of that property will be. The demand of each property will depend on the satisfaction on the characteristic of each property; a purchaser will only buy if he or she issatisfied with the characteristics offers(Lancaster, 1965).As such, SCM is variations on hedonic-type measurementswhich determines the value of aproduct as the sum of the value of the various components that contribute to its characteristics(Rosen, 1974). SCMuses transaction price of a property value in order to value the same type of property. Since no two properties are the same in their characteristics, one need to compare the subject property with a similar comparable property by adjusting either adding or subtracting from the comparable property in order to arrive at the price. The adjustment is made to reflect the dissimilarity of the subject property compared to the comparable property. Several comparable properties are required to obtain a reasonably accurate prediction.

The theory of SCM leaves out implementation details. Jurisdictions interested in SCM should further develop regulations detailing the selection, adjustment and weighting of comparable properties. Subjectivity or objectivity in the predicted values of properties utilizing SCM depends entirely on the implementation procedure.Valuers in Malaysia are guided by the Malaysian Valuation Standard (MVS) and *AmalanSistemPenilaian* (ASP) in implementing SCM.

MVS AND ASP

The Board of Valuers, Appraisers and Estate Agents Malaysia published the MVS to ensure that property valuations are carried out with a high level of integrity and professional competence. MVS requires the comparables used in arriving at the value of the subject property must be of similar properties. The comparables used must be stated in the valuation report with important information such as identification of the properties, date of the transactions, consideration of the transactions, a brief description of the properties, etc. that is valuable in analyzing the differences between the comparables and subject property. The valuer should also have regard to any prior transaction of the subject property within two years of the valuation. MVS also allows the opinion of other expert to be used in the valuation process apart from that of the valuer.

The Valuation and Property Services Department of Malaysia has published the ASP that further interpreted MVS for the benefit of government valuers. ASP dictates that a priori, a valuer has to investigate and verify sales data to avoid extraordinary circumstances or factors exist in cases of forced sales, special purchaser or non-arm's length transaction. Having done that a valuer can commence the selection of comparables. The requirement of comparable properties is that they are similar or identical to the subject property and the method works best if the comparable properties are identical. Otherwise, comparables should have similar characteristics with the subject property such as term of sale, time, location, proximity, accessibility, tenure, restriction of interest, land use and physical conditions which include size, shape and topography. Adjustments are needed for dissimilar characteristics where each adjustment must not exceed 30%. Adjustments for differences may be made to the total property price, to a common unit price, or to a mix of both, but the unit prices used must be consistently applied to the comparable properties. The adjustment is positive if the subject property is superior to the comparable and negative if the subject property is inferior compared to the comparable.

Adjustments must be supported by data evidence and market research (Section 11, Clause 1, Part No 3a in ASP (ASP, 2006), and justification is needed if an adjustment exceeds the specified limit. However, comparables with many adjustment factors are not considered as good comparables. Adjustment made must follow combination of sequential and cumulative ways, where the first adjustment must be made to the term of sale, followed by time to represent the market value, and then only adjustments of other factors will be made. Adjustment for size must consider the optimum size for that vicinity of the subject property. Various analytical techniques, quantitative and qualitative, may be used to identify and measure adjustments. The use of MRA to obtain accurate and justified property values by mathematical and statistical mean is also one of the possibilities, Clause 11, Section 6 in ASP (ASP, 2006). A minimum of three comparables are required to perform a valuation. Although the ASP is meant to assist government valuers, it is also used by private valuers.

VARIANTS OF SALES COMPARISON METHOD

A number of different implementation procedures of SCM to eliminate subjectivity have been proposed. We describe the grid adjustment method, spatial autoregressive error model and methods focusing on reconciliation of comparable valuesin the following subsections. The grid adjustment is further subdivided into non-optimal and optimal methods.

Grid Adjustment Method

The Grid Adjustment Method (GAM) resulted from continuous effort to substantially reduce subjectivity in the traditional SCM (Colwell et al., 1983, Gau et al., 1992, Vandell, 1991). The method focuses on key issues in the selection, adjustment and weighting of comparables with Colwell et al. (1983) provided the foundations of the method. The three basic methods of GAM as presented byColwell et al. (1983)are Additive Dollar Adjustment Method (ADAM), Additive Percentage Adjustment Method (APAM), and Multiplicative Percentage Adjustment Method (MPAM). The choice of the adjustment method depends entirely on the form of the hedonic functional model used. We focus on ADAM only because it is the most common adjustment of GAM used with the linear form of functional model.

The fundamental equations of ADAM GAM are:

$$y_i^c = y_0^c + \sum_{j=1}^{m} b_j\left(x_j^s - x_j^c\right) \tag{1}$$

$$y = \sum_{i=1}^{k} w_i y_i^c \tag{2}$$

$$\sum_{i=1}^{k} w_i = 1 \tag{3}$$

where y_i^c and y_0^c are the indicated and observed values of comparable i, respectively;$b_j$is the adjustment factor for property characteristic j;x_j^s and $x_j^c$are the j^{th} characteristic of subject and comparable properties, respectively;$w_i$is the weight of comparable i; y is the predicted value of the subject property; and k is the number of comparables.

The non-optimal and optimal options available for implementing ADAM GAM (how comparables are selected, adjusted and weighted) are described in the following subsections.

Non-Optimal Method

Comparables can be selected from a list of transaction records (candidate comparables) in several different ways. All methods aim at getting comparables most similar (least dissimilar) to the subject property. Two most popular methods are theuse ofMahalonobis and Minkowsky metrics. The expression forMahalonobismetric is:

$$\delta_{ij} = \sqrt{\left(\mathbf{x}_i - \mathbf{x}_j\right)\mathbf{C}^{-1}\left(\mathbf{x}_i - \mathbf{x}_j\right)^{\mathrm{T}}} \tag{4}$$

whereδ_{ij} is the Mahalonobis distance between property i and j; **x** is the vector of characteristics of property i and j; and **C** is the variance-covariance matrix of the characteristics. The expression forMinkowsky metric is(Todora and Whiterell, 2002).

$$\xi_j = \sum_{i=1}^{m} p_i \left[\frac{|(x_i^s - x_i^c)|}{x_i^s} \times 100\right]; \text{ for } j = 1, 2, 3, \ldots, n \quad (5)$$

where x_i^s is the value of i^{th} characteristic of the subject property; x_i^c is the value of i^{th} characteristic of a comparable; p_i is weight of i^{th} characteristic; m is the number of property characteristics; n is the number of candidate comparables and $|(x_i^s - x_i^c)|$ denotes the absolute value of the difference of the i^{th} value of the subject and a comparable characteristic. The weight p_i can be taken to be the percentage of the absolute value of the correlation coefficient between candidate comparable values, **y**, and each of m property characteristics. A small value ofMahalanobis orMinlowsky metric means small dissimilarity between the candidate comparable and subject property.

Candidate comparables with Mahalanobis or Minkowsky metric are ranked where a comparable with the smallest measure at the top of the list and a comparable with the biggest measure at the bottom of the list. The required k comparables can be taken from the top $k$of the Mahalonobis or Minkowsky ranked list.

The differences in values of the k selected comparables and the subject properties must be adjusted (Equation 1).Two different ways in which adjustment factors can be determined are by Ordinary Least Squares (OLS) regression andPaired Data Analysis (PDA) of candidate comparables(Lipscomb and Gray, 1995). The coefficients of OLS regression are the easiest way to obtain adjustment factors although it has been subject to a critic that the diverse candidate comparables degrade the accuracy of the estimated coefficient(Lentz and Wang, 1998).PDA requires a pair of comparables to be selected where all of their characteristics are the same except for one in which the adjustment factor is sought (primary characteristic). The difference in value of the paired comparables is said to be due to the difference in the primary characteristic.There is no established standard for the minimum number of pairs required for an adjustment factor but it is customary to base it on at least three pairs. If perfect pairs cannot be found, additional adjustments are required for characteristics not matched to correct the value of one of the pair. Additional adjustment values can come from other paired data, cost data, survey data or even OLS estimates.

Indicated value of each of the k comparables is determined after applying the adjustments(Equation 1). They are called indicated values because they represent values indicant of the subject property.

The final predicted value of the subject property is determined by appropriate weighting of indicated values of the k comparables. It is a process often referred to as the reconciliation of indicated values of comparables. Several different weighting strategies exist and they are based on comparability; how comparable is a comparable property(Colwell et al., 1983).

Optimal Method of Minimum Variance

Vandell(1991)argued that comparable selection of GAM based on distance metric such as theMahalanobis metric measures only nearness of the array of characteristics of comparables and a subject. Comparable selection is not affected by how much difference various characteristic adjustments of the sales price or the degree of confidence one has in the magnitude of each adjustment factor. The use of distance metric ignores important property characteristics and can be biased.

Vandell(1991)presented an optimal comparable selection and weighting based on minimization of variances. First, variances of expected values of comparables are minimized to determine candidate comparables. This is the same as minimizing the variance of indicated values of comparables of Equation (1);the variance is dependent only on the variance of the estimated adjustment factor of the j^{th} characteristic and the variance of the observed market value of the comparable.

The variances of the indicated value of comparables are calculated and the comparables are then ranked according to the magnitude of the variance; comparable with the smallest variance at the top of the list while comparable with the biggest variance at the bottom of the list. The comparable selection based on the minimum variance is consistent with the conventional selection of those comparables; comparables in which a valuer has the greatest degree of confidence in terms of smallest variance.

Second, the variance of the predicted value of the subject property is minimized in order to determine the weight ofcomparables.Minimizing the variance of predicted value through the optimal selection of weights is formulated as the constrained minimization problem.

Optimal Method of Minimum Coefficient of Variation

Gauet al. (1992,1994) proposed an optimal comparable selection and weighting based on minimum coefficient of variation (the standard deviation of the predicted value divided by the predicted value). The objective is to select non-negative weights that provide the least variation on a per dollar basis of the predicted value. Minimizing the coefficient of variation through the optimal selection of non-negative comparable weights is also formulated as the constrained minimization problem.

This approach is analogous to the concept of mean-variance efficient frontier found in finance (investment analysis and portfolio management); it is dimensionless and represents relative dispersion. The selected comparables provide not only minimum variance predicted value but also lowest expected return (accuracy per dollar) among predicted values. It may not be the best and optimal weighting of comparables in terms of the most accurate predicted value, but provide optimal trade-off between the magnitude of the predicted value and the magnitude of its variance (its accuracy).

Spatial AutoregressiveError Model

Spatial dependence exists in property data and it can be accounted for by the Spatialautoregressive Error Model (SEM). Anselin(1988),LeSage and Pace(2009) and Pace and Gilley(1998)showedthat SEM is a generalized GAM. GAM is a restricted SEM by combining GAM with OLS where the spatial dependence parameter, λ, of GAM and OLS are 1 and 0, respectively. This was achieved by combining and manipulating the observable errors of GAM and OLS.

This means that combining the OLS and GAM estimators produce SEM that can estimate spatial dependence parameter λ and not assuming it to be 1 or 0 as in the case of GAM and OLS, respectively.SEM should yield less correlated errors which could make the estimate of coefficientsmore efficient than onefrom GAM and OLS. This also meansthat SEM manages to obtain better performance estimator than GAM and OLS individually.

Weighting of Comparables

Isakson (1986) and You and Chang (2009) focused on weighting of candidate comparables in the attempt to decrease subjectivity. Both methods use transaction records of the entire database as candidate comparables,(Isakson, 1986) suggested using the nearest neighbor technique where the final predicted value of the subject property is calculated as the weighted average of actual (observed) transacted prices of candidate comparable properties. The technique eliminates the need to perform adjustments on the transacted prices of the comparables. It selects comparables and design weights for them using the Mahalonobis metric

You and Chang (2009) proposed a weight regression model to reconcile comparable values after performing the adjustments to the comparables. The variables are the transformed attributes of transactions.The dependent variable is the sales weight of a transaction and the independent variables are the price type, proximity of transaction date, in the neighborhood or otherwise, total gross adjustment, number of adjustment, distance to comparable 1, and distance to comparable 2 of the transaction, The model is calibrated using candidate comparables and the subject property is predicted using the estimated coefficients. The difficult task in the method is transforming existing transaction records into the required form.

THE PROPOSED PROCEDURE

The proposed implementation of SCM compliments and enforces MVS and ASP, the two standards and regulations that guide property valuation in Malaysia. The proposed implementation focuses on provisions in the ASP that (i) require quantitative analysis of data, and (ii) using MRA method to obtain accurate and justified values in adjusting comparables. These provisions are given less attention by valuers. We present the proposed procedure in the following three subsections following the three major issues in SCM.

Selecting Comparables

The selection of comparables begins with determining candidate comparables. The required *k*comparables will be selected from the determined candidate comparables and the remainder will be used to determine the adjustment factors. The criteria used in identifying candidate comparables is property type such as one storey linked, two storey semi-detached, two-and-half storey detached, etc. The candidate comparables are searched in the same neighborhood (*taman*) as the subject property failing which the search area is extended to its neighboring areas of first order contiguity. If necessary, the search area is extended to higher order contiguity (second, third, and so on). The minimum number of candidate comparables to be found is $m + 1 + k$ where m is the number of property characteristics (attributes) and k is the number of comparables to be selected.

After n candidate comparables are found, their similarities to the subject property is determined using Minkowsky metric. The Minkowsky metric for each of the n candidate comparables, ξ_j, is calculated using the expression (Todora & Whiterell, 2002).

$$\xi_j = \sum_{i=1}^{m} p_i \left[\frac{|(x_i^s - x_i^c)|}{x_i^s} \times 100\right]; \text{ for } j = 1, 2, 3, \ldots, n \tag{1}$$

where x_i^s is the value of i^{th} characteristic of the subject property; x_i^c is the value of i^{th} characteristic of a candidate comparable; p_i is weight of i^{th} characteristic; m is the number of property characteristics; n is the number of candidate comparables and

$|(x_i^s - x_i^c)|$ denotes the absolute value of the difference of the i^{th} value of the subject and a comparable characteristic. The weight p_i can be taken to be the percentage of the absolute value of the correlation between candidate comparable values, **y**, and each of *m* property characteristics, given as

$$p_i = \frac{|r_{y,x_i}|}{\sum_{i=1}^{m} r_{y,x_i}} \times 100 \text{ ; for } i = 1, 2, 3, \ldots, m \tag{2}$$

where r_{y,x_i} is the Pearson's correlation coefficient between candidate comparable values **y** and the i^{th} property characteristic. The Pearson's correlation coefficients can be obtained from the expression

$$r_{y,x_i} = \frac{n\sum_{j=1}^{n} x_j y_j - \left(\sum_{j=1}^{n} x_j\right)\left(\sum_{j=1}^{n} y_j\right)}{\sqrt{\left[n\sum_{j=1}^{n} x_j^2 - \left(\sum_{j=1}^{n} x_j\right)^2\right]\left[n\sum_{j=1}^{n} y_j^2 - \left(\sum_{j=1}^{n} y_j\right)^2\right]}} \text{ ; for } i = 1, 2, 3, \ldots, m \tag{3}$$

where y_j is the j^{th} element of candidate comparable values; x_j is the j^{th} element of i^{th} property characteristic; *m* is the number of property characteristics and *n* is the number of candidate comparables.

The coefficients of correlations between candidate comparable values *y* and all property characteristics are used as the basis of weight in the Minkowky metric.

A small value of Minkowsky metric means large similarity (small dissimilarity) between the comparable and subject property and a large value means small similarity (large dissimilarity) between the two properties. The candidate comparables are then ranked using values of Minkowsky metric with the smallest value at the top and largest value at the bottom. The top *k*comparables from the ranked list are taken to be the required *k* comparable properties for being the most similar to the subject property. It is also guaranteed that the k selected comparables require the least adjustment among all candidate comparables.

There may be situations that one of more candidate comparables that is identical to the subject; they have exactly the same characteristic values as the subject property. This may happen when the subject and concerned candidate comparables are located in the same row of terraced houses, barring renovations. The identical candidate comparables will be selected as comparables for having Minkowsky metric of zero. It is possible that all $k$comparables are identical to the subject if there are at least k identical candidate comparables.

Adjusting Comparable Values

The values of the k selected comparables must be adjusted for the differences between them and the subject property if the comparables are not identical. The differences in the values are due several factors, quantifiable and non-quantifiable. The quantifiable factors can be obtained by analyzing the transaction records of the same property type as the subject property. The estimated coefficient of an OLS regression of the remaining candidate comparables are used as the adjustment factors. The estimated coefficients are obtained using the expression:

$$\hat{\mathbf{b}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y} \tag{4}$$

where $\hat{\mathbf{b}}$ is a $(m + 1, 1)$ vector of estimated coefficients, $\mathbf{X}$ is a $(n \tilde{\ } k, m+1)$ matrix of characteristics of candidate comparables with ones in the first column, $\mathbf{y}$ is a $(n \tilde{\ } k, 1)$ vector of values of candidate comparables, n is the number of candidate comparables; k is the number of comparables; and m is the number of property characteristics.

The first element of $\hat{\mathbf{b}}$ is the intercept while the rest of the elements represent the estimated relationships between property characteristics and property values. These relationships are taken to be the adjustment factors. Thus for *m* property characteristics, we have *m* adjustment factors

$$f_i = \hat{b}_{1+i}; \text{ for} i = 1, 2, 3, \ldots, m \quad (5)$$

The adjustment for each of the *k*comparables, δ_j, is calculated using the expression

$$\delta_j = \sum_{i=1}^{m} f_i (x_i^s - x_i^j); \text{ for} j = 1, 2, 3, \ldots, k \quad (6)$$

wherex_i^s is the value of i^{th} characteristic of the subject property; x_i^j is the value of i^{th} characteristic of the j^{th} comparable; f_i is the adjustment factor for the i^{th} characteristic and *k* is the number of comparables. The indicated value for each of the comparables, v_i, is calculated using

$$v_i = y_i^c + \delta_i \quad (7)$$

wherey_i^c is the value of the i^{th} comparable and δ_i is its adjustment. Identical comparable properties receive zero correction because $x_i^s - x_i^j$ in Equation (6) equals zero.

The OLS regression is used in determining the adjustment factors because of its strong mathematical and statistical bases; OLS being the BLUE (Best Linear Unbiased Estimator)(Lentz & Wang, 1998). We choose to use $n \tilde{} k$ candidate comparables in the OLS regression because these properties represent properties that are most similar to the subject property and thus the coefficients are more likely to be equal to the subject; the concept of the economic principle of substitution is upheld. The use of all properties in a region of interest that are of the same type as the subject property is ruled out because this would degrade the accuracy of adjustment coefficients; dissimilarity increases as the distance between two properties increases. It is for this reason that the searching for candidate comparables starts from the neighborhood of the subject property and extending to higher order contiguity neighborhoods only if necessary.

As indicated earlier, it is possible that one or more comparable properties are identical to the subject property; it is a situation that valuers are aiming at. Comparable properties that are identical to the subject property receive zero corrections. Comparables that are not identical to the subject receive positive or negative corrections. The adjusted value of a comparable is called an indicated value because it represents a value indicant of the subject property. For many situations the indicative values from the *k*comparables are not the same due to unaccounted and unquantifiable factors.

Weighting of Comparables

So far the procedure has produced k indicated values of the subject property from the k selected comparables and these indicated values should be the same. The different indicated values must be reconciled using the expression

$$\hat{y}^s = \sum_{i=1}^{k} w_i v_i \tag{8}$$

such that

$$\sum_{i=1}^{k} w_i = 1 \tag{9}$$

where$\hat{y}^s$ is the predicted value of the subject property; v_i is the indicted value from the i^{th} comparable; k is the number of comparables and w_i is the weight for the i^{th} comparable.

The weighting scheme used is that a comparable with the most comparability receives the largest weight and a comparable with the least comparability receives the smallest weight. The weighting scheme of squared adjustments that satisfies the criterion is used and the weight w_i of comparable *i* is given as

$$w_i = \frac{\sum_{p=1}^{k}\sum_{j=1}^{m}\left[\hat{b}_j(x_j^s - x_{p,j}^c)\right]^2 - \sum_{j=1}^{m}\left[\hat{b}_j(x_j^s - x_{i,j}^c)\right]^2}{(n-1)\sum_{p=1}^{k}\sum_{j=1}^{m}\left[\hat{b}_j(x_j^s - x_{p,j}^c)\right]^2}; \text{ for} i = 1, 2, 3, \ldots, k \qquad (10)$$

where$\sum_{p=1}^{k}\sum_{j=1}^{m}\left[\hat{b}_j(x_j^s - x_{p,j}^c)\right]^2$is the sum of squared values of all adjustments made for all comparables; $\sum_{j=1}^{m}\left[\hat{b}_j(x_j^s - x_{i,j}^c)\right]^2$ is the sum of squared of all adjustments made for the i^{th} comparable; *k* is the number of comparables and *m* is the number of property characteristics.

If all *k*comparables are identical to the subject property, Equation (10) breaks down because both terms in the numerator are zero and the denominator is also zero. In such a case, the reconciliation process is a simple average. The equation makes sense when there is at least one comparable that is not identical.

AN EMPIRICAL EXAMPLE

The use the proposed SCM implementation to predict the value of a single storey linked house is demonstrated. The six characteristics of the house are land area (LA), main floor area (MFA), ancillary floor area (AFA), number of bedrooms (BED), category of cost (COS), and position (POS) and, thus the minimum number of candidate comparables to be determined is seven. Table 1 shows 14 transaction records in a neighborhood and the first transaction (house No. 1) is taken to the subject property and the remainder to be candidate comparables. The transacted prices and characteristic values of the candidate comparables are used to calculate the Pearson's correlation coefficients to be utilized as the basis of weights in the calculation of Minkowsky metrics (Table 2). The ranked Minkowsky metrics of the candidate comparables are then determined (Table 3). The three selected comparables are property No. 5, 4 and 3. OLS regression of the rest of the candidate comparables provides the adjustment factors for the house characteristic (Figure 1). Table 4 shows the adjustment and reconciliation of the comparables giving the predicted value of RM70,000.

Table 1 Transaction records of single storey houses in a neighborhood

House ID	LA	MFA	AFA	BED	COS	POS	Price (RM)
1	97.0	47.38	18.59	2	1	1	65,000
2	97.0	47.38	4.87	3	1	1	65,000
3	97.0	47.38	18.5	3	1	1	69,000
4	97.0	47.38	18.605	3	1	1	70,000
5	97.0	47.38	18.605	3	1	1	71,000
6	121.0	47.38	14.86	3	1	1	75,000
7	145.0	80.38	19.35	3	1	2	100,000
8	143.0	87.75	10.03	3	4	1	118,000
9	143.0	87.75	16.37	3	4	1	120,000
10	143.0	87.75	16.55	3	4	1	120,000
11	163.504	87.75	16.526	3	4	1	125,000
12	163.504	87.75	16.526	4	4	1	125,000
13	143.0	87.75	32.916	4	4	1	128,000
14	143.0	85.31	11.16	4	4	1	139,000

Table 2 Weighting of house characteristics

Characteristic	Coefficient	Absolute Difference	Weight (%)
LA	0.9173	0.2530	25.2997
MFA	0.9669	0.2667	26.6673
AFA	0.1410	0.0389	3.8888
BED	0.6516	0.1797	17.9717
COS	0.9415	0.2597	25.9682

POS	0.0074	0.0020	0.2042

Table 3 Ranking of candidate comparables according to Minkowsky metrics

House ID	Minkowsky Metric	Ranked
1	-	-
2	0.171018000	5
3	0.060119012	3
4	0.059958971	1
5	0.059958971	1
6	0.119963437	4
7	0.255539479	6
8	0.492170194	10
9	0.463864614	8
10	0.463377581	7
11	0.484944465	9
12	0.514908054	13
13	0.505642743	11
14	0.510617887	12

REGRESSION MODEL: ORDINARY LEAST SQUARES
Estimation and Diagnostics

Dataset	:	Single storey houses
Model Form	:	Linear
DependantVar	:	Price
Independent Var	:	LA, MFA, AFA, BED, COS, POS
NumObs	:	10
NumVar	:	7
Degrees of Freedom	:	3
R-squared	:	1.000
Adj R-squared	:	1.000
Sigma-squared	:	564261.9
F-Statistic	:	4565.111 Probability : 0.0000

Variable	Coefficient	Std Error	t-Statistic	Probability
Intercept	17021.8	1898.625	8.965	0.003
LA	244.5	15.214	14.760	0.001
MFA	-8124.7	281.393	-28.873	0.000
AFA	444.1	29.563	15.022	0.001
BED	223.7	483.234	0.463	0.675

COS	122579.4	3715.448	32.992	0.000
POS	285820.7	9017.074	31.698	0.000

Figure 1 Summary of the OLS regression

Table 4 Adjustment and reconciliation of comparables

House ID	Transacted Value (RM)	Total Adjustment (RM)	Indicated Value (RM)	Weight	Weighted Value (RM)	Predicted Value (RM)
5	71,000	-230.45029	70,769.55	0.33503	23,710.42	69,789.63 round-up to 70,000
3	69,000	-183.82126	68,816.79	0.32992	22,703.83	
4	70,000	-230.45029	69,769.55	0.33503	23,375.38	

The subject house was transacted at RM65,000 giving a prediction error of RM5,000. Upon examining the characteristic values of this house, it was found that they are more similar to houses No. 4 and 5 that was transacted at RM70,000 and RM71,000, respectively. The only difference is that it has two bedrooms instead of three. The OLS regression dictate RM223.7 per bedroom and based on this factor, the subject house should be transacted at a little less than the average price of house No. 4 and 5 which should round-off to RM70,000. The predicted price of the subject house is more reasonable than the transacted price.

Cross validation of the transacted prices of Table 1 produces prediction accuracy measures shown in Table 5. All measures are significantly high indicating the ability of the procedure to provide accurate property values.

Table 5 Cross validation statistics

Median Ratio	Coeff of Dispersion	Prediction <10%Error	RMSE	Hit Rate
1.0	5.4	92.86%	9400.79	14.29%

Accuracy Assessment

Table 5 Accuracy Assessment for Double Storey Terrace House Bandar MahkotaCheras

YEAR	R-square	Adjusted R-square	LA	MFA	AFA	COD	PRD	RMSE	hit	10% Range	20% Range	Total Data
2004	53.8%	53.3%	495.2423 (0.000)		2357.46 (0.000)	10.92	1.07659	55033.7382	8	71%	90%	174
2005	57.4%	56.4%	526.71 (0.000)	1324.74 (0.000)		11.141	0.97138	33849.6977	2	61%	91%	88
2006	72.2%	71.9%	462.55 (0.000)	1400.12 (0.000)		6.9735	0.9635	19953.4709	16	71%	97%	232
2007	65.9%	65.8%	437.16 (0.000)			6.177	1.07854	19954.732	2	89.10%	96%	413
2008	61.4%	61.0%	623.73 (0.000)	1022.16 (0.000)	1107.90 (0.02)	10.646	1.09769	37176.9693	4	66%	87%	287
2009	82.3%	82.0%	228.21 (0.000)	2368.32 (0.000)	4296.50 (0.01)	11.87	1.13402	134255.277	4	54%	87%	233

Accuracy assessment is done for double storey terrace house in Bandar MahkotaCheras. The result shown that the model recommended is more than acceptable as R squared for all years is more than 50%. The coefficient of dispersion (COD) calculated less than 15 is associated with good appraisal uniformity and and price related differential (PRD), statistics measuring assessment comply with International Association of Assessing Officers (IAAO, 2009). 10% range of value compared to transaction price agree with Fradie Mac criterion for evaluating automated valuation model whereby Fredie mac AVM specify at least 50% of predictions must be within 10% of actual market price (Fredie Mac,). We believe this finding can be acceptable to the Valuation

Department and finally the model can be recommended to the Board of Valuers, Estate Agent and Appraisal Malaysia.

DISCUSSIONS

MVS and ASP that regulate the implementation of SCM in the country contain largely informal and qualitativeprocedure that makes quantitative analysis unnecessary. The request for data evidence and market research supported adjustments was seldom complied by valuers. The suggestion using MRA for more accurate and justified values was never taken up either. Informal and qualitative analysis lead to subjectivity.MVS and ASP should have adopted a formalized implementation procedure of selecting, adjusting, and reconciling comparables in total so that every valuer will have to go through the same route and thus, ensuring objectivity.

Lipscomb and Gray (1995) argued that OLS and PDA used in GAM differ in two fundamental respects. First is the number of comparables used and whether or not the comparables are paired. PDA requires pairs of comparables matched in every respect except for the primary characteristic. However, getting a perfect matched pair is difficult; it is a common practice to obtain a minimum of three pairs for each adjustment factor.OLS does not require matched pair making comparable selection simpler and useable comparables more readily available. The minimum number of comparables required is two more than the number of independent variables. Additional comparables add extra information and therefore increase the accuracy of adjustment factors. Second, is in the way they account for differences in characteristics other than the one that the adjustment factor is desired. PDA does it by matching pairs of properties as closely as possible on all determinants of selling price except the primary characteristic. Additional adjustments are usually required to correct for leftover differences in a matched pair. PDA does not put constraint on how values of additional adjustments can be obtained; they may come from other paired data, cost data, survey data or OLS regression. In contrast, OLS uses estimated coefficients to account for characteristics that affect values. OLS decompose comparable prices into components due to all characteristics including the one that adjustment factor is desired. It uses dataset in the OLS to determine coefficients without any outside information. Thus, if comparables available to PDA and OLS are limited to paired comparables, and values for additional adjustments of PDA are obtained from OLS regression of the paired comparables, then OLS and PDA method of determining adjustment values are equivalent.

The use of OLS in GAM, however, was often criticized for various reasons(Lentz and Wang, 1998). One of the major issues was the accuracy of the estimated coefficients arising from diverse comparables. OLS uses all available comparables in the estimation which makes the accuracy of estimation inferior to PDA that uses few comparables which closely match the subject property. If OLS can restrict itself to regress enough comparables that closely match the subject property, the accuracy of estimation should be closed to PDA. This concept is consistent with the well accepted working principles of traditional SCM that a minimum number of comparables which closely resemble the subject property be used.

Comparable selectionprocess based on the minimum variance among the adjusted value of comparables is consistent with the traditional SCM; the fewest number of adjustments, the smallest adjustments and the adjustments in which the appraiser has the greatest confidence(Vandell, 1991).In deciding comparable weights, the approach selects a set of comparables that gives the minimum variance of the predicted value. This resulted in a predicted value having the least variance (the most accurate predicted value). The results require solving constrained minimization problem which is quite difficult to comprehend.

The optimal approach byGauet al. (1992,1994) selects a set of comparables that gives the minimum variation on per dollar of predicted value. Like in the method of minimum variance, constrained minimization problem is utilized which leads to complexity of the method.

The reduced mathematical sophistication of SEM in relation to the minimum variance and minimum coefficient of variation methods is the strength of SEM. However, SEM deals only with error dependence. There exist other kinds of spatial dependence among property prices and characteristics in which SEM ignores, such as price dependence. Price dependence is quite dominant in property modeling and leaving it untreated could be misleading. SEM also deviates from the usual line of thought of valuers in implementing SCM (selecting, adjusting and weighting of comparables).

Isakson (1986) and You and Chang (2009)focused on weighting of comparable values only with Isakson (1986)ignoring comparable selection task and You and Chang ignoring both comparable selection and adjustment tasks. Using the entire transactions in a database as candidate comparables adds diversity and degrades the accuracy of prediction.You and Chang (2009) further require transaction records to coded and recorded in a way that is entirely foreign to valuers.

GAM employing either OLS or PDA represents non-optimal ways of eliminating or reducing subjectivity. The underlying theories are relatively easy and they can readily be understood by most existing valuation professionals. Adopting them in lieu of the conventional SCM has found some success in the USA with majority favoring PDA to OLS(Lentz and Wang, 1998).The approaches byVandell, (1991) and Gauet al. (1992,1994)represent optimal methods based on rigorous mathematical and statistical formulations. The underlying theories are relatively harder to understand and the computations are more complex compared to GAM. Thus the methods fail to attract the attention of valuation professionals as the most viable method to replace the conventional SCM.

We see potentials in these developments that could benefit the Malaysian valuation profession; a new technique to replace the existing SCM procedure that would eliminate or reduce subjectivity. The best option is thenon-optimal GAM which could be modified and refined to suitcurrent practices in Malaysia. This is because non-optimal GAM is the easiest to comprehend and can adapt other techniques well. We should go for OLS regression of candidate comparable comprising property of the same type and neighborhood of the subject for determining adjustment factors. Comparable selection should be based on these candidate comparables as well.The optimal minimum variance and minimum coefficient of variation methods are not favored because experiences have shown that they fail to attract the attention of valuers.

The propose implementation with empirical example show that the model can complement and enforce existing MVS and ASP that call for data supported adjustments and using mathematical and statistical methods to obtain accurate and justified adjustment values. The proposed implementation is also in line with current practices of finding comparables that they should be of the same property type as the subject.The proposed procedure also can realized Automated Valuation for Malaysia valuation practice. The practice of property valuation in Malaysia has remained a human-intensive task although similar practices in the several advanced countries have move to automated valuations. Human-intensive property valuations are slow and prone to mistakes and most importantly cannot meet the current demand for fast and accurate valuation (Downie & Robson, 2007).

The demand for fast valuation can be seen from several examples: clients should know the amount of stamp duty incurred when submitting the application at counters instead of having have to wait for a number of days; bank is providing an excellent service if its officers can advise clients of the maximum amount that they can borrow, and having greater chances of being approved, at the time of application instead of having the applications rejected one week later; an educated buyer would like to know if the asking price of a property by a seller is actually the current market value of the property; an engineering consultant can prepare an accurate compensation list rapidly instead of inaccurate list that take months to prepare. There are many other situations that automated valuations are useful and in demand, especially in providing an initial accurate estimate of the value of property.Automated valuations are not meant to replace valuation professionals; they are tools to aid valuation tasks (Bahjat-Abbas, Carron, & Johnstove, 2005; Mitropoulos, Wu, & Kohansky, 2007).

A formal implementation procedure is proposed so that automated valuations may be implemented and subjective predictions eliminated. A limited accuracy assessments show the procedure is capable of providing accurate prediction. It is recommended that extensive study of the procedure is carried out to look at several other issues such as outliers in transaction records, insignificant adjustment factors (regression coefficients), insufficient candidate comparable, etc.

CONCLUSION

MVS and ASPare the references for the implementation details the SCM practiced in Malaysia. The absence of precise rules of how comparables should be selected, adjusted, and weighted in the two references to be the main contributors for subjectivity in SCM prediction.MVS and ASP allow discretion of valuers in every characteristic to be adjusted; requiring the adjustment to be reasonable and with a maximum absolute adjustment value of 30% give too much freedom for valuers to come up with an adjustment value backed only by his or her experience. We have to disallow valuers experiences to enter in the primary prediction processes; all adjustments must be based on quantitative analysis of market data. Personal experience of the valuers may be allowed as the very last and ending prediction process, if really necessary.

We presented several variations of SCM implementations that come under several different names with one common objective, i.e., to remove or reduce subjectivity.Any one of them could be adopted to replace the current SCM implementation. Optimal technique such as the minimum variance, minimum coefficient of variation, and SEMare the most rigorous. However, after considering institutionalissues, we recommend modifying non-optimal GAM where candidate comparables comprise properties of the same type and neighborhood as the subject, and adjustment factors are determined by OLS regression of the candidate comparables.This proposed implementation procedure is in line with current practices that also compliments and enforcing existingMVS and ASP. The proposed implementation also can enable automated valuation to be realized in Malaysia. Automated valuations and objective predictions are not possible with the current procedure of SCM due to its informal nature. The proposed procedure formalizes the three major activities of SCM (selecting, adjusting and weighting of comparables) providing precise rules how they must be carried out. By prescribing to a set of rules, subjectivity is eliminated and automated valuations become possible

The most important issue in a property valuation procedure is the ability of the procedure to provide accurate prediction of property values. A limited prediction accuracy assessments show relatively high prediction capability of the proposed procedure signifying a high potential of it to be adopted. It is recommended that extensive study of the procedure is carried out to resolve other issues and ascertain its merit.

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