COMPARISON OF MASS APPRAISAL MODELS FOR EFFECTIVE PREDICTION OF PROPERTY VALUES

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Abstract

There are a number of models that are used for mass appraisal of properties. However, the choice of a model is predicated on a number of criteria. Notable among these is to compare models predictive accuracies relative to the property market context where appraisal is undertaken or being contemplated. This study focuses on comparing predictive accuracies of mass appraisal models with a dataset of 3494 single-family property transactions in the city of Cape Town, South Africa, from 2012 - 2014. Five mass appraisal models including back propagation (BP) trained artificial neural networks, multiple regression model, M5P trees, support vector machine optimise with sequential minimal optimisation and additive nonparametric regression were used for the simulations. Waikato Environment for Knowledge Analysis (WEKA) explorer; an open source data mining software was used to pre-processed property data to normalised values and model property prices. The analysis shows that BP trained artificial neural networks (BP-ANNs) and M5P trees utilised in this study predicted better results with root mean squared error and mean absolute error within the acceptable threshold of 5%. But M5P trees demonstrate distinctiveness in predicted results between normalised and absolute values which require further examination. The other three mass appraisal models including multiple regression model, additive nonparametric regression and support vector machines with sequential minimal optimisation predicted results with RMSE that are higher than 5% acceptable threshold. Furthermore, contextual application of results with other studies reveal that BP-ANNs and M5P trees do not have power of universal acceptability because of varied results in other context. Therefore these models are particularly relevant to mortgage lenders, valuation offices, etc. in South Africa, but should the scope be extended to other context, application should be based on the property market features.

KEY WORDS: Mass appraisal models, Predictions, Accuracy, Market values, Properties

1.0 Introduction and study background

Mass appraisal is the estimation of values on large numbers of properties at a specified time period through application of standardised techniques (d'Amato & Kauko, 2008: 280). Inherent in this definition is the fact that standard techniques including statistical and machine learning tools are used in assessment of market values of a number of properties, than the usual conventional pricing manual models (comparison, cost and investment). Although, these models could as well be used in the ascertainment of market values of a number of properties, their benefits are profound when used for single appraisal of property (McCluskey, Deddis, Marris, McBurney & Borst, 1997: 453). Again, using conventional assessment models escalate valuation errors due to valuers subjective judgment over a number of properties (Adair & McGreal, 1988: 18); increase time of assessment; additional cost and professional responsibilities (Wiltshaw, 1995: 160). According to Thompson (2008: 26-28) the manual conventional pricing techniques was used in the 30s to capture property information and quickly ascribing values for large numbers of properties. But increase development in the USA property sector coupled with availability of more computers with capabilities of handling extensive data in the 60's and 70's led to emergence of computer computations such as multiple regression model (MRM).

This technique has capability of modelling relationship between myriads of properties independent and dependent variables thereby predicting market values of properties. However, despite its capabilities, the study of Peterson & Flanagan (2009: 147) reports that MRM is exposed to pricing errors owing to the way mean are extrapolated from large samples causing significant sampling errors. Additionally, Isakson (2001: 425) opine that important appraisal tools such as MRM can produce enormous errors swiftly as they yield significant results. These mistakes arise from convolutions and data requirements of MRM such as imprecise applications, inaccurate conclusion and unsubstantiated clarifications of results which can be committed during mass appraisal of properties. The need to mitigate

limitations of MRM in the assessment of properties has led to the introduction of other models including additive nonparametric regression (ANR), M5P trees, support vector machines (SVMs), fuzzy logic (FL), expert systems (ES) and BP trained artificial neural networks (BP-ANNs). These models all have proving capabilities of effectiveness in different fields. Their application into the field of mass appraisal of properties spans a period of one to three decades. However since their introduction, it appears the dominant use of these models is confined only to the property markets of developed countries as suggested in literatures (Zurada, Levitan & Guan, 2011; McCluskey, McCord, Davis, Haran & McIlhatton, 2013).

Although there are variations in property market contextual settings of different countries, a restriction should not be placed on uniform application of model(s) without testing its effectiveness on other geographical context. The guidance notes on international mass appraisal and related tax policy (IAAO, 2014); and international valuation standards (IVSC, 2005) should however support appraisal undertaken in any country. Additionally, there is need to measure market efficiency and maturity relative to a particular geographical context where appraisal is undertaken or being contemplated. The study of d'Amato & Kauko (2008: 281) argued that designing a methodology for mass appraisal is very important to emerging markets than well-established ones. The markets in the developed countries including USA, UK etc. are fully established and thus have mass appraisal models fully embedded into their appraisal practice. But this is not the case in emerging markets which have not fully introduced these models into their appraisal practice. For instance a number of emerging markets in Africa imposed value based ad valorem taxes on properties. Mortgage lenders interest on ascertainment of current values of mortgage backed securities have also escalated; more so dissolved companies distribute resources among shareholders and creditors; sharing of assets among dissolved couples married in the community of properties are among issues that should resonate the need for automating the appraisal process.

However there exist conflicting results in the appraisal process about which model predict values that reflects market price that is acceptable to property tax payers and administrators, mortgage lender, etc. Sometimes literature search does not provide a simple way of determining models predictive accuracies without empirically testing a range of models or algorithms.

Therefore this study becomes relevant as it represents a first attempt of comparing predictive accuracies of different mass appraisal models in an emerging market of South Africa. This will particularly bring to context each model in the light of the property market dynamics of both emerging and developed economies. This study is organised into five sections namely section two reviews literature on single and mass appraisal models; section three compares predictive accuracies of different mass appraisal models; section four contains the empirical analysis of mass appraisal models and finally, section five deals with the implications of research and conclusion.

2.0 Single and mass appraisal models

The main distinction between single and mass appraisal models is in term of scale otherwise both appraisal models are used for all categories of appraisal (McCluskey, *et al.,* 1997: 453). Single appraisal models are suitable for appraisal of few numbers of properties. This is a situation in which an appraiser/valuer manually analyse each property's dependent and independent attributes to arrive at the market value. Adequate pricing in this case is influenced by property market dynamics (interest rates, gazumping etc.) which the appraiser/valuer must have vast knowledge of in fixing prices. Single appraisal models have the limitations of subjectivity, delay in reporting if size of properties is large and sometimes accuracy arising from enormous responsibility of manual computations.

Single appraisal models have being in used by appraisal/valuers for a very long time until limitations mentioned earlier were observed. Consequent upon this are what led to emergence of models that have less subjectivity and capacity to handle mass appraisal of properties (McGreal, Adair, McBurney & Petterson, 1998: 57). The next few paragraphs briefly explain the underlining philosophies behind these models.

2.1 Comparison/market approach

This model operates under the premise that requires comparison between properties that are sited in same vicinity with adjustment made on observable differences in designs, number and arrangement of rooms, topography, location of the property etc. Adjustment of these constituent elements involves intuition by appraisers/valuers which is the reason why an appraisal/valuation prepared by two or more experts may sometimes have conflicting value estimates. Therefore, care must be taken by valuers when subjectively dealing with attributes that constitute market values, particularly, if sufficient numbers of properties to compare with are unavailable.

How does market approach works? As an illustration suppose it is required to ascertain the market value of a five bedroom duplex located at Pretorius Street, Hatfield with external dimensions of 16 meters by 24 meters. There are three comparable duplexes located within 200 metres radius that were recently sold. The Duplexes A, B and C have external dimensions – 400m^2, 350m^2 and 390m^2 respectively. These comparable properties were sold for R1,560,000.00, R1,800,000.00 and R1,400,000.00. In fixing value for the subject property, the appraiser/valuer is concern with the property that was recently sold, age, design etc. in selecting a suitable comparable to estimate the amount sold per square metre. This is reflected in the formula:

$$Market\ value\ per\ square\ metre = \frac{Market\ value\ of\ property}{External\ dimensions\ of\ property} \quad (2.1)$$

Let us assume the appraiser/valuer after careful analysis of all factors responsible for market value determination selected duplex A, the market value per square metre is R3,900. This value is therefore used to estimate the market value of the subject property as follows: 384m^2 @ R3,900 = R1,497,600.00.

2.2 Investment/income approach

This method relies on income from properties to estimate market value. Income from properties are capitalised with appropriate years purchase yield to arrive at the market value in a property submarket where comparison is difficult. Difficulty in comparing two or more properties arises due to their heterogeneous nature. Although, appraisers/valuers make adjustment for differences between subject properties with comparable properties, this is only possible if differences are minimal, but difficult if differences are profound (Adair & McGreal, 1988: 18). The best approach for an appraiser/valuer is to capitalise the rental income passing on properties within the submarket with an appropriate yield to arrive at the market value. Again, comparison approach cannot be completely ruled out of the investment method. This is because the yield that is use in capitalising rental income of subject property is a product of previous rental and sale values of properties within the immediate precinct of the submarket. Mathematically, this is demonstrated in the following formula:

$$capitalisation\ yield = \frac{Net\ rental\ income}{Capital\ or\ market\ value}\ x\ \frac{100}{1} \quad (2.2)$$

Net income is the rent passing on a recently sold comparable property, while capital value is the actual amount the property sold for in the market. For instance if a comparable 4 bedroom duplex in Hillcrest, Brooklyn, Pretoria let for R12,000.00 per month (R144,000.00 per annum) was recently sold for R1,800,000,000, utilising comparison approach will give a capitalisation rate of 8%. This rate is applied to subject property (a duplex in the same vicinity as comparable property) with say a rental income of R150,000,00 per annum. The differences in rental values might be the result of observable variances between comparable and subject property. Utilising capitalisation rate of 8% in perpetuity will give a market value of R1,875,000,00. The assessment of capitalisation rate via comparison method appears to be a good tool of assessment because it is predicated on the flow of rental income from property which is paid to reflect potential income of the property over its useful life.

2.3 Cost/contractor's approach

This is also known as depreciated replacement cost (DRC) method. The central idea of cost method is to assess market value from current cost of construction making provision for depreciation. It is a method that is based on an estimate of replacement cost of property value having regards to constituent elements that contribute to determination of value such as land and improvement. Cost method provides at a glance what a property worth after a split is made between cost of land and improvements. According to Zhang & Chen (2009: 255) the rationale behind cost approach is that a client(s) should not pay more for an existing property than what a comparable land and property provides in the market. How does cost approach work? The current costs of construction of building, less depreciation at certain rate per cent, add the value of land. Mathematically this is represented in the following equation as used by Zhang & Chen:

$$C_v = \pi LQ(LV + RCN - PQ_D) \quad (2.3)$$

where *LV* is land value, *RCN* is the replacement cost of the new property, PQ_D is the qualitative element of location and time. The capital value is given as C_v. This is adjusted by property appraiser/valuer after careful assessment of the market conditions M_t^c to arrive at an acceptable market value (MV), given in the form:

$$MV = M_t^c \; x \; C_v$$

Traditionally the class of special purpose properties that are valued with cost approach are hospitals, purpose built schools, police station, stadium, museum, mosque, church etc. In using cost approach, current rate of construction per meter square is obtain from local builder/quantity surveyors to apply to the dimension of subject property. The method does not support usage on income producing properties because there exist market for them. However, despite the underlying philosophy cost approach can be used in the assessment of market values for all land that has improvement on it.

2.4 M5P trees

According to Zurada, *et al.,* (2011: 357) M5P trees are normal decision trees with linear regression models at the leaves that based its decision on predictions when observations have reached the leaf. It was originally formulated as model tree by Quinlan (1992) as a technique for dealing with continuous class learning problems. Model trees incorporate a conventional decision tree with linear regression functions at the leaves. But Wang & Witten (1997: 4) observe that handling enumerated attributes and missing value are not clearly defined in Quinlan's idea. This led to their proposition for an improvement to earlier work particularly as it concerns real-world datasets. In their modification and clarification of how this might effectively be utilised with real-world data, M5P was introduced. M5P regression

algorithm is developed by Wang & Witten (1997) to process data different from model tree, essentially, in the selection of attributes. It is an improvement to classical model (M5) trees (Quinlan, 1992) in that M5P utilises attributes that predict or forecast results different from the normal theoretic metrics that classical model tree utilises.

In 1999 the study of Holmes, Hall and Frank modify this algorithm to generate rule from datasets. Holmes, *et al.,* (1999: 7-8) reports that M5P apply separate and conquer method to create sequence for its numeric predictions which is accentuated through one rule off reading approach. Effective implementation of M5P is a three pronged approach namely splitting the initial tree, pruning the tree and smoothing the tree (Wang & Witten, 1997: 2-3). The first approach requires a splitting criterion which treats standard deviation as a measure of error at each node of the class values. By testing attributes of each node, important attributes that have potential of maximising reduction of error is selected. The equation used in calculating standard deviation reduction (SDR) is given as:

$$SDR = sd(T) - \sum_i \frac{|T_i|}{|T|} X\ sd\ (T) \qquad (2.5)$$

where T represents a set of training instances that reach the node with a set of attributes used for every training case, T_i are subsets that result after splitting the instances that touch the node according to the selected attribute.

The second approach is pruning the likely error that might ensue from each node of the test data. In this stage, a difference between predicted and actual values is averaged for each of the training instances that reach the node. Though this sometime falls below the expected error for unexplained cases, they are compensated by multiplying a factor (*P'*) as follows:

$$P' = \frac{(n+v)}{(n-v)}$$

where *n* is the number of training instances that touch the node and *v* is the number of model parameters that signifies the class value at that node.

Finally, the third approach in building M5P trees is smoothing process that compensates for severe discontinuities that often occur between nearby leaves at the node of the pruned trees. The smoothing process is given in the formula:

$$P' = \frac{np + km}{n + k} \qquad (2$$

where p'denotes the estimated values that move up to the higher node, *p* depicts the predicted values that move to the node from below, *m* is the model predicted value at this node, *n* is the total number of training instances that reach the node from below and *k* is a constant which usually has a value of 15. The purpose of smoothing is to enhance accuracy of predictions.

M5P has over the years become a very useful model in predictions. The real estate and valuation profession has also taken advantage of this data mining tool in prediction of property values. Specifically, few studies involving M5P in mass appraisal of properties are Graczylk, Lasota & Trawiński (2009) and Zurada, Levitan & Guan (2011). Graczylk *et al.,* (2009) used three (3) different data mining tools for six different algorithms. The study found M5P to perform well in prediction of property values in Poland. Again using different scenarios, the study of Zurada *et al.,* (2011) found M5P to predict well in all scenarios. This reveals that M5P is a promising model in mass appraisal of properties.

2.5 Support vector machines (SVM)

There are several mass appraisal models that are designed with abilities to recognised patterns among variables. Support vector machine (SVM) is a creation of Vapnik (1995) as one of the tools that solve pattern recognition by not necessarily

having to solve a more herculean task immediately. Zurada, Levitan & Guan (2011: 361) opine that SVM achieve this through changing nonlinear input data space to a high dimensional feature space to form a nonlinear classifier in the former elements space. This is referred to as maximum boundary hyperplane that gives a higher split-up to decision classes in the former feature space. Furthermore the higher edge hyperplane that has the closest training instances is referred to as support vector. SVM is applied to the case of classification and regression. In the case of regression approximation, $y \in R$ a linear function is constructed in the feature space so that training cases do not extend beyond an error matrix of 0. This is represented as a quadratic programming problem which reflects the chosen kernels as follows:

$$y = b + \sum a_i y_i K(x(v), x), \quad (2$$

where kernel function is given as *K(x(v),x)*. Several kernels exist in practice, however, the choice of kernel lies with the objective of the appraiser. The appraiser's decision on kernel function is what informed the overall outcome. For classification case, Zurada *et al.,* (2011: 361) gave an example of an input/attribute space x with unknown distribution *R(x,y),* in which y is a binary number having two values 1, 0. The binary decision classes is separated with a hyperplane as represented in equation:

$$y = w \cdot x + w_0, \quad (2.9)$$

where *x* is the input vector, w is the weight vectors, and *y* is the output target data. According to Cui & Curry (2005) the separating hyperplane is represented in the following equation:

$$y = b + \sum a_i y_i x(i) \cdot x, \quad (2.10)$$

in which y_i is output of training instance represented as $x(i)$, parameters b and a_i are determined by training algorithm and test case is *x*. The study of Shevade,

Keerthi, Bhuttacharyya & Murthy (2000: 1188) reports that SVM has the capability of enhanced speed and easy to operate during computational procedures. The easy computation and speed operations are compelling forces to its utilisation by machine learning and programming community. But the study of Zurada *et al.,* (2011: 362) reports that despite its versatility initial acceptability was inhibited by the training algorithm-quadratic programming (QP) solver until this was overcome through a series of disintegrating large quadratic programming problem into small sets and subsets. But a notable breakthrough on its training algorithm came through the work of Platt (1998) who introduced sequential minimal optimisation (SMO) to optimise SVM without QP algorithm. SMO has capability of reducing the problem into sub-problem with analytical answer. According to Platt (1998: 41) the extent of memory needed for SMO is linear which boost its ability to handle large training datasets. Thus SMO avoid large matrix calculation scaling at any place between linear and quadratic in training set size for various investigation problems. This feature makes it considerably different from a standard projected conjugate gradient (PCG) algorithm because PCG scale anywhere between linear and cubic in size of training set.

Its use in mass appraisal is relatively new. For instance, Lam, Yu & Lam (2009: 215) reports that this model has been applied with plausible results in pattern recognition, regression valuation and predictions. In effect their study with datasets of 4143 and 21 previous property transactions in Hong Kong and Nanjing, Mainland China respectively show that a combination of entropy and SVM demonstrates high performance in predicting property prices. Most recently the study of Wang & Hong (2015) proposed a combination of minimal description length principle (MDLP) binning and SVM to improve its classification of residential prices. Four (4) different kernel functions with varied parameters were built in their study and concluded that linear kernel is found fit for dataset. Again the study of Zurada, Levitan & Guan (2011) used SVM-SMO with good performance indices for mass appraisal of properties in

Louisville, Kentucky. In this study we used support vector machines with sequential minimal optimisation regression (SVM-SMO) to predict property prices.

2.6 Multiple regression model (MRM)

This model can handle many factors/characteristics affecting values of properties (Mark & Goldberg, 1988: 91; Isakson, 2001: 424). The model usually takes the following form:

$$Y = a + b_1x_1 + b_2x_2 \dots b_nx_n + \varepsilon \qquad (2.11)$$

where Y is property sale price, a depicts a constant term, $b_1b_2 \dots b_n$ are regression coefficients that show influence of independent variables $x_1, x_2, \dots, x_n$ on the property selling price. This model has over the years been a dominant appraisal model in the developed economies, but its application to the South African property market is limited in scope (Boshoff & de Kock, 2013: 9). Nonetheless, the method has been widely criticised because of its intrinsic methodology like functional form specification, nonlinearity, multicolinearity and heteroskedascity (Mark & Goldberg, 1988: 90; Do & Grudnitski, 1992: 38; Worzala, Lenk & Silva, 1995: 185).

2.7 Additive nonparametric regression (ANR)

This model is designed to ameliorate challenges faced by MRA in mass appraisal of properties. While MRA is rigid in handling functionality, ANR is flexible in the choice of functional form of regression through the smoothing splines it introduces. Again, ANR is built to handle nonlinear relationship between variables which in most MRA assessment result in prediction errors. Lin and Mohan (2011:226) report that its major objective is to modify the linear function b_ix_i of the independent variables by an unexpressed nonlinear simple function to secure equation 2.12:

$$Y = b_0 + \sum_{i=1}^{p} f_i(X_i) + e \qquad (2.12)$$

Where Y is the property sale price, X_i is a set of property independent attributes; f_i is the nonlinear smooth functions which is arbitrary and having an unlimited shapes. In ANR, the independent variables make little contribution to the response which need not be rigid to the inputs. In practice, the specific regression curve this should take is not foreknown because ANR has the ability to give a form of regression curve that is flexible (Lin & Mohan, 2011: 226). Also, penalised splines are used to model effect of continuous covariate and time trend while spatial order is used within the framework to specify intercepts of the discrete spatial effects.

2.8 Artificial neural networks (ANNs)

This model as an aspect of Artificial Intelligence (AI) was designed to also handle the shortcomings of both conventional method and multiple regression analysis (MRA) (Do & Grudnitski, 1992: 38; Tay & Ho, 1992: 534-535; Worzala *et al.*, 1995: 185). However, the working of ANNs is unique because of its ability to mimic the human brain. The human brain has the cognitive ability to learn from experience and apply the knowledge to solve problems. Like the human brain; ANNs is designed with such ability of learning from history of previous property transactions and model relationship that exist between them. Although, ANNs use similar variables with MRA when predicting property values, they are highly "adaptive and generally nonlinear" (Bishop, 1995: 16). Their ability to deal with nonlinear data makes it possible for them to solve problems in a property environment characterised by complex, noisy, sometimes imprecise data and partial information (Do & Grudnitski, 1992: 38).

For a typical mass property appraisal as shown in Figure 2.1, the input node is supplied with linear and nonlinear property data x_o, x_1, x_2, x_3,…x_n and corresponding

weights w_0, w_1, w_2, w_3,…w_n. Tay and Ho (1992:532) reports that processing starts by multiplying each input variable with its corresponding weight as follows: $x_0(w_0)$; $x_1(w_1)$; … $x_n(w_n)$. The actual net input *S* is the ∑ (summation) of all products of property input variables and their corresponding weights as $x_1w_1 + x_2w_2 + x_3w_3 \ldots x_nw_n + b(x_0(w_0)) = s$. The summing junction and transformation via sigmoid activation function is done at hidden node of the network. After these operations, the results are presented in the last node. It is at the last output node that estimated/predicted sales price or market values are presented. This is usually compared with actual sale/market price of properties to determine models capability using test statistics.

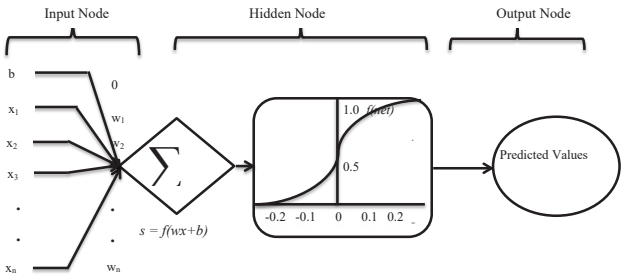

Figure 2.1: A typical operation of ANNs with BP training algorithm

Several algorithms are used for its training-back propagation, Levenberg-Marquardt, quasi newton and conjugate gradient descent. But the most widely used training algorithm is back propagation (BP) otherwise known as gradient descent search algorithm. This method designed by Rumelhart, Hinton & Williams (1986) utilises the

analogy of forward and where necessary backward pass. Backward pass can however, be activated only if the results are not in harmony with actual market price of property resulting into a Root Square Mean Error of over 1.000. Again the essence of backward pass is for the network to correct errors to a minimum of 0.001. Where a minimum error of 0.001 is not achieved it raises concerns to experts because results realised might be fraught with errors.

The gradient steep descent method has been blamed for network's inability to sometimes minimise errors and reach optimum. The study of Yacim & Boshoff (Forthcoming) notes that other fields of study that uses artificial neural networks modelling has since been able to deal with culpability of gradient descent back propagation through development of hybrid models and utilise cuckoo search algorithm which has been found to optimise the network faster and search for weights from global space and train with Levenberg-Marquardt. Alternatively the study also reports that training can thus be undertaken using back propagation but network should be optimise with cuckoo search algorithm to enhance its predictive capabilities.

2.9 Expert systems (ES)

This model has it origin from artificial intelligence to expand the rule based system in mass appraisal of properties (Rayburn & Tosh, 1995: 431). While ANNs is flexible, ES is rigid to certain rules set by an expert. Like the ANNs, they are designed to copy thought processes of human beings in solving complex problems through set rules. But unlike ANNs, expert systems do not generalise nor instruct "itself" through history of previous transaction involving properties but work rigidly under set rules. The implication of this, is when a transaction has reach optimal level in the market that require prompt execution of sales, ES will not execute until the set limit by an expert has reach before execution.

For an optimal performance of ES, the expert must readily be available to ensure accuracy in execution of this model for mass appraisal of properties. Indeed, Rayburn & Tosh (1995: 431) reports that ES are really not artificial intelligence since they cannot generalise or correct abnormality except to the extent of the set rules. If there are no specific rules on how a task could be executed, expert systems would give incomplete results. For instance in a property market such as Hatfield, South Africa where dynamics and volatility of property market is very profound utilising expert systems requires high knowledge and understanding by valuers who will conditioned the systems to irregular condition of the market. In Hatfield there is high prevalence of gazumping elicited by choice location. Consequently, if the set condition necessitates selling of a detached house for say R1,500,000,00 at Hatfield, Pretoria once negotiations between market participants reaches the target, expert systems will execute sale notwithstanding further negotiations that might surpassed the set target..

Further literature search reveals that its empirical application in the field of property valuation was first executed by Boyle (1984: 281). Boyles study was criticised by Gronow & Scott (1986: 395-397) to be MRA in disguise rather than a true ES because of the way model was statistically developed with analysis of past sales. ES involves modelling the proficiency of a valuer and then exerts that model to comparable sales evidence in order to appraise value in a similar approach as a human valuer. Gronow and Scott (1986: 396) note that ES normally operates "rule based" reasoning akin to "IF, THEN" …. Example of its rule based reasoning operation is: "IF the property is in a good state of repair, THEN do not request for an outgoing fee."

The study of McCluskey & Anand (1999: 232) gave additional insight into it's used. McCluskey *et al*., used 412 sample properties by dividing into two sets of data, ⅓ as hold out samples and ⅔ for training to estimate property values. Also Kilpatrick (2011) did a study with ES and found it very useful in mass appraisal properties, particularly when small data set is used.

2.10 Fuzzy logic (FL)

Another mass appraisal model designed to handle vagueness of variables is **fuzzy logic (FL)**. This model was introduced by Zadeh (1965) to represent similitude which an object shares with another using a function whose values with other memberships are in a range of $0 < m < 1$. Fuzzy logic operates using fuzzy-rule based systems (FRBSs), which is a crucial step in its operation. Set rules are designed in the form "if" a particular state of affair occurs, "then" the result will be …. In the real world, solving a problem relating to property appraisal will require a valuation expert setting rules that might follow the pattern:

- "If" the property is located in a high density area with variables that marginally influences consumer preference, "then" the property value will be low.
- "If" the property is cited in low density vicinity with variables that appeal to consumer preference, "then" the property value will be high.

In the above set rules, location and other key variables are germane to determination of property values. Quite naturally, in any given appraisal assignment, experts usually put this into consideration. Mathematically, "if" and "then" rule format for FRBSs is set out in the following equation:

$$if\ x_1\ is\ P_1 and \ldots and\ x_n\ is\ P_n, then\ y_1 = m_1 \cdot x_1 + \cdots + m_n \cdot x_n + m_o \qquad (2.13)$$

where x_1 are sets of input property attributes, P_1specify meanings of fuzzy sets, $m_1$are coefficients of the equation and $y_1$is the target variable. According to Gonzalez (2008: 185) the output of fuzzy system is calculated as a weighted average of the distinct rule outputs with the corresponding degree between inputs and the previous portion of each rule.

Fuzzy logic model will reduce appraisal/valuers subjectivity and increase precision having regard to the model's ability to handle large number of properties with noisy variables. But fuzzy logic does not train itself as ANN does, how can this model

determine fuzzy set and rules? Combining fuzzy logic with ANNs or Genetic Algorithm (GA) will aid in its training phases (Cordón, Harrera, Hoffmann & Magdalena, 2001: 86).

3.0 Comparison of performance and predictive accuracies of mass appraisal models

The objective of comparing two or more items should be with the purpose of discovering the best among several options. Consequently, the goal of comparison in this study is to discover a model(s) that generate minimal errors between actual and predicted value of properties. However, while it is acceptable to verify models performance within a given location, a lot of clog might follow similar assessment should this be done among different geographical contextual settings if the property market dynamics are not considered. d' Amato & Kauko (2008: 290) notes that in most African countries a substantial portion of land do not have formal recognition leading to paucity and unreliable real estate data in the economy. Therefore appropriate application of mass appraisal models in this region must be based on the type of information that is available. According to Grover (2016: 196) mass appraisal can only be carried out provided relevant and reliable data on transaction prices and property attributes are available. Interestingly the South African property market offers viable real estate information that makes model application a possibility. But what criteria should be used for comparing models? Kryvobokov (2004: 221) proposed five criteria for evaluating a model for land valuation in Ukraine. These criteria are: (i) clearness of method; (ii) measurability of the result; (iii) relevance of the result; (iv) market orientation of the methods; and (v) simplicity rather than accuracy of the method.

With this understanding, d' Amato & Kauko (2008: 293-294) extended the scope and proposed nine criteria for selecting suitable mass appraisal model(s). These are grouped under institutional and methodological criteria as follows: a. *institutional criteria,* (i) suitability of methodology to the property market context; (ii) specific

path-dependence; b. *methodological criteria,* (i) accuracy of independent valuations; external or out-sample validation; (ii) conceptual soundness; (iii) analysis of valuation variation; (iv) internal consistency of the model structure/predictions; internal or in-sample validation; (v) nature of the adjustment; (vi) reliability and robustness of the model; and (vii) feasibility. In effect the criteria advocated by d' Amato & Kauko (2008: 293-294) has direct relationship with the objective of this current study and hence will form the basis for our assessment of models. However, there are considerable studies that compare the predictive accuracies of different mass appraisal models. Most of these studies compare the performance of MRM with ANNs in different geographical locations. Accordingly, ANN models performed better than MRM in Tay & Ho (1992: 536) in Singapore; Do & Grudnitski (1992) in San Diego, USA; Brondino & Silva (1999) in Sao Carlos, Brazil. Again, Nguyen & Cripps (2001) in Tennessee, USA; Limsombunchai, Gan & Lee (2004) in Christchurch, New Zealand; Mora-Esperanza (2004) in Madrid, Spain; Peterson & Flanagan (2009) in Wake County, NC, Raleigh-Cary Metropolitan Statistical Area; Selim (2009) in Turkey; Meelun, Whittal & Evans (2011) in Cape Town, South Africa; and Nǔňez, Caridad & Ray (2013) in South of Spain all found ANNs to outperformed MRM in mass appraisal. But the study of Worzala, Lenk & Silva (1995); Lenk, Worzala & Silva (1997) in Fort Collin, Colorado, USA, found conflicting results that do not support ANNs superiority over MRM. The study of Lin & Chen (2011) in Taipei city, Taiwan utilises ANNs and Support Vector Regression (SVR) for mass appraisal predictions and found that SVR performed better than ANNs. However, observations made from literature suggest that size of datasets might have a direct effect on model performance. For instance, Nguyen & Cripps (2001: 333) reports that MRM outperform ANNs when dataset is small but a good network configuration will enhance ANNs performance. It is noteworthy to stretch that despite the geographical context of the property markets in most of these studies, ANNs consistently performs better than MRM. The goal of this current study is to attempt a comparison of predictive performance of five mass appraisal models including ANNs, SVM-SMO, ANR, MRM & M5P trees in an emerging

market. The main motivation is to see if capabilities of models that work well in developed market could be replicated in an emerging market of South Africa. More recently, there are limited studies on comparison with more number of models than the usual traditional comparison of MRM and ANNs. Graczyk, Lasota & Trawiński (2009) evaluates the effectiveness of ANNs, radial basis function neural networks (RBNN), M5P trees, M5Rules, MRM and SVM in Poland. The study found that all models predicted results that area plausible. Zurada, Levitan & Guan (2011) compares the performance of MRA, ANNs, additive regression (AR), M5P trees, support vector machines with sequential minimal optimisation (SVM-SMO), radial basis function neural networks (RBNN) and memory-based reasoning (MBR) in Louisville, Kentucky, USA. The results show that non-traditional regression models (AR, M5P trees, SVM-SMO) outperformed other models in all five simulated experiment, particularly with homogenous data, while artificial intelligence (AI) models (ANNs, RBNN and MBR) performs better with less homogenous datasets.

In Amherst, New York, Lin & Mohan (2011) compares performance of three mass appraisal models including MRM, ANNs and additive nonparametric regression (ANR) and found that ANN models consistently outperforms MRM and ANR models in both training and testing/validation datasets. Also, McCluskey, Davis, Haran, McCord & McIlhatton (2012) in Lisburn, Northern Ireland investigated the predictive abilities of ANNs and three regression functions (OLS, semi-log and log-log) and found the three regression models to outperformed ANN models. In another study, McCluskey, McCord, Davis, Haran & McIlhatton (2013) compares the predictive accuracies of different mass appraisal models namely: (i) MRM, (ii) simultaneous autoregressive models (SAR), (iii) geographically weighted regression (GWR) and (iv) ANNs, it was found that GWR outperformed all other models. Furthermore, a notable feature in the last four studies that relatively utilises more number of models reveals that absolute datasets were used in their simulations; however, this study employed both absolute and normalised datasets to avoid over-fitting and observe relationship and interpretation of market values.

4.0 IMPLEMENTATION AND RESULTS

4.1 IMPLEMENTATION

This study utilises a datasets of 3494 single-family residential properties that were sold between 2012 and 2014. The datasets was supplied by city valuation office, the city of Cape Town, South Africa. This dataset became suitable for analysis after it was cleansed from default and incomplete transactions. The analysis was implemented using an open source machine learning software: Waikato Environment for Knowledge Analysis (WEKA) explorer. The data was first pre-processed to CSV in excel and a further pre-processing to normalised values suitable for ANNs analysis was implemented in WEKA. The simulations were effected with five mass appraisal models, namely back propagation trained artificial neural networks (BP-ANNs), M5P trees, support vector machine simulated with sequential minimal optimisation (SVM-SMO), additive nonparametric regression (ANR) and multiple regression model (MRM).

Analysis was carried out using both absolute and normalised values in order to observe differences if any between predicted results. The root mean squared error (RMSE), coefficient of determination (COD), root relative squared error (RRSE), mean absolute error (MAE) and relative absolute error (RAE) were used to compare the predictive capabilities of models. These tools are briefly summarised in the following equations:

$$RMSE = \sqrt{\sum_i (\hat{y}_i - y_i)^2/n}, \quad (4.1)$$

$$MAE = \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{n} \quad (4.2)$$

$$RRSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2}}, where\ \overline{y} = \frac{\sum_{i=1}^{n} y_i}{n} \quad (4.3)$$

$$RAE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{\sum_{i=1}^{n}|y_i - \overline{y}|} \quad (4.4)$$

$$COD = 1 - \frac{\sum_{i-1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i-1}^{n}(y_i - \overline{y}_i)^2} \quad (4.5)$$

where *n* is number of properties evaluated, y_i is actual price for which properties were sold and $\hat{y}_i$ is the predicted price of properties. COD is the square correlation coefficient (COC) between independent and dependent variables. In assessing models predictive performance, this study utilised the root mean squared error of less than or equal to 5% as reported in Nguyen & Cripps (2001: 332-333) and Ogisi (2006: 20) as acceptable good fit for most investors.

In this analysis, 16 variables in all were used for our simulations. These included an output (target) variable (property sales price) and 15 input variables including living area, number of stories, main area, terrace-balcony, basement, carport, garages, swimming pool, actual number of bedroom and servant quarters. Others are property view, condition, building styles, traffic noise and security. These last five variables have dummy variables formed, which, for ease of analysis were coded into binary scale.

4.2 EXPERMIENTAL RESULTS AND DISCUSSIONS

This section deals with analysis of normalised and absolute property datasets using all models. The South African official currency (Rand) is the property selling price. This is used for all absolute values predicted with mass appraisal models as shown in Table 4.1.

Table 4.1: Predicted results of mass appraisal models

MEASUREMENT	MRM	M5P	SVM-SMO	ANR	BP-ANNs
COD a. Normalised Values b. Absolute values	0.3443	0.5328 0.4272	0.3249	0.3424	0.7085
RMSE a. Normalised values b. Absolute values	0.052936510 82**	0.044934129 74**	0.0563388759 9**	0.053136638 30**	0.0353 24354 67
MAE a. Normalised Values b. Absolute Values	0.031 21399 68**	0.0273 19630 05**	0.0283 195381 7**	0.032 22084 15**	0.0236 16260 11
RAE% a. Normalised values b. Absolute values	81**	71** 74**	74**	83**	61
RRSE% a. Normalised values b. Absolute values	80**	68** 75**	86**	81**	54

**Significantly more than BP-ANN @ α = 0.05

1 USD = 15 Rand

The results reveal a significant performance of BP-ANNs over other mass appraisal models. BP-ANNs predicted a lower RAE and RRSE errors between actual and predicted values of properties. In effect, the results show that BP-ANNs has a RAE 20% lower than MRM; 10% lower than M5P trees; 13% lower than SVM-SMO and 23% lower than ANR. Again the RRSE estimates show a significant lower error rate

when compared with other models. The BP-ANNs has RRSE that is 26% lower than MRM; 14% lower than M5P trees; 32% lower than SVM-SMO and 27% lower than ANR. The RMSE and MAE of BP-ANNs are significantly lower than all other mass appraisal models in this study. Figure 4.1 reveals the RMSE and MAE of all mass appraisal models used in this study.

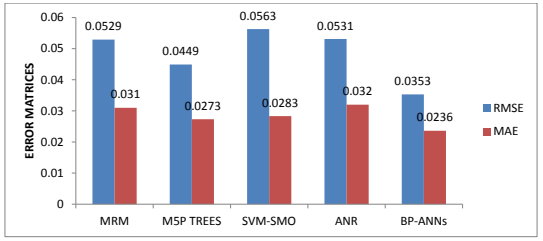

Figure 4.1: Performance of different mass appraisal models

Results in Figure 4.1 shows that BP trained ANNs (BP-ANNs) and M5P trees have RMSE of 0.0353 and 0.0449 respectively. These models predicted results that are within the acceptable threshold of less than or equal to 5%. Results also show that other models (MRM, SVM-SMO and ANR) utilised in this study predicted results that have RMSE above the acceptable threshold of 5%. Specifically, MRM, SVM-SMO and ANR predicted results with RMSE of 0.0529, 0.0563 and 0.0531 respectively.

Furthermore, Figure 4.2 reveals the results of all models in terms of their R^2 or COD. The COD provides correlation that exists between input and target variables towards the determination of market values in this analysis.

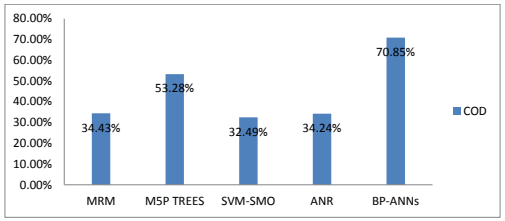

Figure 4.2: Coefficient of determination (COD) of all mass appraisal models

A cursory look at Figure 4.2 reveals that BP trained ANNs and M5P trees have goodness of fits that are above 50%. Consequently, this explains that there is a strong relationship between variables used for this analysis. Perhaps the South African property market context shows that these two models are particularly suitable for mass appraisal of properties in the region. This result however, should not be construed to mean that other models used in this analysis are not useful for mass appraisal. These two models (BP-ANNs and M5P trees) are feasible, reliable and consistently performed well in the light of the criteria set out by d' Amato & Kauko (2008: 293-294). However, to generally support models suitability, we reflect on the contextual perspective of studies undertaken in a developed market environment in relation to this study. Accordingly, the studies of Lin & Mohan (2011: 236); Zurada *et al* (2011) in the USA; McCluskey *et al* (2013) in the UK and Graczyk *et al* (2009) in Poland are cases for consideration.

In the USA, the study of Lin & Mohan (2011: 236) utilised ANNs, ANR and MRM on 33,342 dataset divided into 80% training and 20% cross-validation for 2009 transactions, while Zurada *et al* (2011) used MRM, SVM-SMO, ANR, M5P trees, ANNs, RBNN and MBR on 16,366 dataset for transactions between 2003 - 2007. Lin & Mohan (2011: 228) used 10 property variables including property price, living area, parcel (main area) size, depth of parcel, age of building, number of bedroom, number of baths, number of fireplace, building style with 12 dummy created and neighbourhood with 66 dummy created. Zurada *et al* (2011: 356) used 8 variables

including sale price, presence of central air, number of baths, lot type (main area), construction type, garage type, wall type, basement type, basement code and garage type. These were increased to 18 on account of dummy variables created from some of the variables. While few of the variables used are similar with current study there is great dissimilarities among variables. For instance, in this current study there are variables such as living area, number of stories, terrace-balcony, carport, swimming pool, servant quarters, property view, condition, traffic noise and security, previous studies in the USA under consideration did not utilised them. In terms of models performance, ANNs consistently predicted lower estimation errors than ANR and MRM in the study of Lin & Mohan (2011: 236). In ranking models performance in Lin & Mohan, these models stood as ANNs (1); ANR (2) and MRM (3). Also the models performance in Zurada *et al* (2011) shows that ANR, SVM-SMO and M5P trees outperformed all other models with homogenous data but when heterogeneous data was used ANNs, RBNN, MBR performed better. Interestingly this current study and Lin & Mohan found that ANNs outperformed other models while Zurada *et al* (2011) found that M5P trees have good performance. But MRM did not perform well in the three studies.

We also compare results of this current study with McCluskey *et al* (2013) in the UK. The models used are MRM, SAR, GWR and ANNs on a dataset of 2694 properties for 2002 and 2004 transactions. The adjusted sale price, size of property, garage, number of storey, age of property, property type, average travel time to work, class of property, type of glazing, number of bedroom and location are variables used for analysis. Again although there are dissimilarities among variables used with the current study, two models namely (1) MRM and (2) ANNs are similar in both studies. Comparing their results show that GWR which was not used in our study outperformed other models. ANNs only performed well in relations to predictive accuracy but not favoured because of its black box nature. Again, the study of Graczyk *et al* (2009) in Poland used ANNs, RBNN, M5P trees, M5Rules, SVM and MRM on a dataset of 1098 properties for 2001 and 2002 transactions. Five variables

namely: area of plot, number of storey, age of building, floor on which property is located and property selling price were used in their analysis. Three data mining tools including KEEL, WEKA and RapidMiner were used for simulations. Results reveal that apart from ANNs implemented in RapidMiner, all models predicted estimates within the acceptable threshold of less than or equal to 5% RMSE (see Figure 4 in Graczyk *et al* (2009: 806)). Therefore comparing results of this current study with previous studies of Graczyk *et al* (2009); Lin & Mohan (2011); Zurada *et al* (2011) and McCluskey *et al* (2013) might not be with the context of similar property market but universal performance of model on any geographical setting.

While it appears that performance of some models such as BP-ANNs and M5P trees are good in this current study, this can safely be compared with studies of Lin & Mohan for ANNs and Zurada *et al*. for M5P trees in the USA; and Graczyk *et al*. for ANNs and M5P trees in Poland. But results of this current study cannot be safely compared with model performance of ANNs in the UK study. This generally shows that a model that work well in a particular geographical context might not work well in another, therefore it is difficult to demonstrate superiority of one mass appraisal model over others, especially when they are applied to different context. Furthermore, a notable distinction was observed in the predicted results of M5P trees between absolute and normalised datasets as shown in the R^2 or COD, RAE and RRSE. In all simulations carried out in this study other mass appraisal models yielded consistencies in the predicted results between absolute and normalised datasets but M5P trees revealed otherwise. This development makes it grim to support and interpret results for application within the appraisal community; therefore, further examination of M5P trees is needed for acceptability despite its high predictive capabilities.

5.0 IMPLICATION OF FINDINGS AND CONCLUSION

This study is a first attempt at comparing a variety of mass appraisal models in the South African property market context. Since property appraisers/valuers in

emerging markets of developing countries are being commissioned by mortgage institutions, local tax authorities etc. to assess the market values of large number of properties, a study like this has become very imperative to demonstrate the usefulness of these models so as to better appreciate a paradigm of a model suitable for the South African property market. Several simulations were carried out utilising MRM, M5P trees, ANR, BP-ANNs and SVM-SMO. The results predicted by each model show a superiority of BP-ANNs over all other models tested. Specifically the RMSE of BP-ANN in this study is 0.0353. This is closely followed by M5P trees with a RMSE of 0.0449. These two models (BP-ANNs and M5P trees) predicted market values of properties that are less than 5% threshold acceptable to the appraisal community.

Surprisingly, M5P trees predicted a higher COD of 53% when simulated with normalised dataset than a COD of 43% when simulated with absolute dataset in this analysis. It might be that to achieve optimal result, there is a need to change absolute to normalised datasets when using the technique, hence, the need for caution when utilising M5P trees for mass appraisal of properties. To evaluate the usefulness of these two models we compare results with property market geographical context of USA, UK and Poland. Results of previous studies from USA and Poland reveals usefulness of ANNs and M5P trees for mass appraisal but study from UK did not support results of the present study. Thus the results show that the property market context exerts great influence on the predictive ability of a model. But with the proving accuracy of ANNs in the USA, Poland and South Africa, the model is particularly useful in mass appraisal of properties.

Therefore, findings of this research have shown that for effective predictability and defensibility of mass appraisal estimate, the BP-ANNs is favoured for used by the appraisal community. ANNs has demonstrated consistency in the South African, USA and Poland property markets. However, this result does not suggest that other mass appraisal models are not useful because when used in the property market context of other regions these models are found to be useful. Furthermore, it is noteworthy that any region that contemplates the introduction of a mass appraisal model into

their appraisal process, should visit the criteria advocated by d'Amato & Kauko (2008: 294) and in addition several models should be tested until a model that matches the local property market context is established.

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34

UNDERGRADUATE REAL ESTATE EDUCATION IN ZIMBABWE: A COMPARATIVE STUDY

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ABSTRACT

Purpose The aim of this study was to establish if there is a national consensus on the real estate body of knowledge in Zimbabwe and to benchmark Zimbabwean property programmes with similar RICS curricula in Africa.

Design/methods followed/approach Purposive sampling was used to choose participating institutions. Relevant documents were obtained from either websites of selected institutions or requested by email from relevant officials.

Findings The study established that while real estate curricula in Zimbabwe are diverse in nature, they do exhibit a number of similarities. Property programmes in Zimbabwe also compare well with RICS accredited curricula in Africa but there were notable variations on names of programmes, number courses covered and course credits.

Research limitations/impli ations This study was limited to real estate programmes which are offered up to Honours degree level in Zimbabwe and similar RICS accredited programmes which are offered in Africa. Results might be different if one is to consider all RICS accredited real estate programmes. Data was obtained only from document analysis and internet survey, a more detailed results could have been obtained through key informant interviews, questioner survey or focus group discussions.

Practi al implications Results of this study can be used to standardise real estate education curricula in Africa.

Originality/ Value of work Though research on real estate education improved over the past years, this study is the first to consider Zimbabwean curricula in detail.

KEYWORDS: ***Real estate, comparison, progress, curriculum, consistency, diversity.***