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Research Paper Traditional and Mass (Advanced) Valuation Methods

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Research Paper - Traditional and Mass (Advanced) Valuation Methods

Automated Valuation Models (AVMs): Machine Learning, namely Mass (Advanced) Valuation Methods and Algorithms

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He has extensive experience in asset management, and his research focuses on digital transformation in the valuation sector by pioneering new technology and techniques. He is developing algorithms (mathematical models) for Automated Valuation Models (AVMs) based on Big Data, Artificial Intelligence – AI: Artificial Neural Network and Machine Learning.

Executive Summary

Digitalisation is becoming increasingly common within the valuation sector. Thus, it is vital to understand how traditional valuation methods are being replaced by machine learning technology, namely mass (advanced) valuation methods.

According to Soni and Sadiq (2015: 100), real estate markets are popular with investors, who are keen to identify a fast way to play the market or to hedge against existing volatile portfolios. Therefore, an accurate prediction of house price is essential to prospective home owners, developers, investors, valuers, tax assessors, mortgage lenders and insurers.

Demirci, O (2021) stated that the fluctuation and the relationship between value, worth, and risk remain unchanged in the current market. This means that the increased use of Automated Valuation Models (AVMs) requires a discussion of the machine learning technology, namely mass (advanced) valuation methods, which are the fundamental basis of the algorithms used within the valuation sector.

This Research Paper will investigate both the statistical and modern methods of valuation and their application to the real estate valuation.

In particular, it will look at the main limitations of the traditional valuation methods in respect to their accuracy, consistency and speed (Jahanshiri, 2011; Wang & Wolverton, 2012; Adetiloye & Eke, 2014). Moreover, these methods will be compared against mass (advanced) valuation methods, when there is a need to value a group of properties. Indeed, with the increasing volume of transactions and changing marketplace of real estate, mass (advanced) valuation has been widely adopted in many countries for different purposes, including assessment of property tax (Osborn, 2014).

Introduction

The concept of Market Value (VPS 4, RICS Valuation – Global Standards (2020) is central to the functioning of the real estate sector. However, there are opposing arguments into what drives Market Value and whether it includes all variant data (Mooya, 2016). In simpler terms, as argued by Tretton (2007: 508), "data is the key", as data drives the quality in valuation. Good quality data is essential; otherwise, subjective opinion will dominate the valuation process.

In recent years, the traditional method of valuation has been slowly replaced by mass (advanced) valuation methods, a form of machine learning. Sevgen and Tanrivermis (2020: 303) argued that individual and traditional valuations with large data sets are "a waste of time".

Instead, the data can be incorporated into developed models to undertake the valuation process. According to Sevgen and Tanrivermis (2020: 303), "machine learning is the branch of artificial intelligence that determines the connection between an input data and its results within an algorithm." This can be used to build applications that learn from data and improve their accuracy over time, without being programmed to do so.

As defined by Erdem (2017), valuation can be categorised into traditional, statistical and modern methods.

The traditional methods are the three approaches (VPS 5) and five methods of traditional valuation.

The traditional approaches are market (Baum & Crosby, 2014), cost (Osborn, 2014) and income (Baum et al., 2017).

The traditional methods are comparative (McCluskey et at., 1997), (Scarrett, 2008; Isaac & O'Leary, 2013), (Wyatt, 2013), investment (Scarrett & Osborn, 2014; Wyatt, 2013), profit (Baum et al., 2017), (Pagourtzi et al. 2003), cost (Scarrett & Osborn, 2014), (Scarrett, 2008) and residual (Millington, 2013), (Pagourtzi et al., 2003).

Statistical methods include the hedonic model. Both (Court, 1939; Rosen, 1974) places the hedonic pricing model into standard economic theory and focuses specifically on the statistical model, cluster analysis, option-pricing methods.

The modern methods can be considered as a machine learning, also known as mass (advanced) valuation methods. The advanced valuation methods are classified as artificial neural networks (ANN), fuzzy logic, support-vector machine (SVM), radio frequency machine learning systems (RFMLS) and spatial analysis methods.

According to Zeicu et al. (2017: 244), advanced valuation methods are used by specialist valuers for immediate and palpable advantages, including the automation of the valuation process and existence of control for the results achieved. The main disadvantage is the complexity of applying the suggested solutions, requiring a team of specialists from different fields – programmers, statisticians, mathematicians, valuers, market analysts – to develop and operate systems of this nature and scale.

This paper will discuss both the statistical and modern methods, focusing on the hedonic model, artificial neural network (ANN) and fuzzy logic. These are accepted as forms of artificial intelligence and Advanced Valuation, which form the basis of the Automated Valuation Models (AVMs). According to Pagourtzi et al., ANN provides "possible solutions to many problems in real estate valuation" (2003:394).

Demirci, O (2021:5) stated that AVMs are mathematically generated statistical models that undertake a pre-set calculation depending on the type of data input. In other words, as expressed by Zeicu et al. (2017: 245), they are mathematical software that calculates Market Value based on location analysis, market conditions and real estate characteristics of market information previously collected.

According to Demirci, O (2021:4), AVMs ensure valuations' objectivity and facilitate quality control, reduce costs and permit the use of larger, more representative samples; therefore, they increase accuracy and speed.

Past research (McCluskey et al. (1997), (Scarrett, 2008); (Isaac & O'Leary, 2013); (Wyatt, 2013), (Millington, 2013) has indicated that value will reflect various characteristics of a property, such as size, location and number of bedrooms.

In this regard, a robust model can be formed to calculate the value automatically (Kauko & d'Amato, 2009). Mass valuation is the process of valuing a group of properties with a set date, data and standardised method (SMARP, 2013), by accessing an extensive database of accurate property information (i.e. the sale price, date of transaction, size and location).

Tretton argues that "a creation of a single Government-wide data warehouse of all property and transaction information would have the additional benefits of enabling sharing of accurate and consistent data and of removing the burden of joining up information from the citizen." (2007: 509). This would also eliminate misconceptions as the accuracy of the data would not be questioned and it would increase collaboration amongst stakeholders.

Kok et al.'s study (2017) reveals that AVMs produce much faster results at a lower cost while having an absolute error of ~9%; much lower than traditional forms. Moreover, Machine Learning, as a form of Mass (Advanced) Valuation Method, has been shown to replicate the decision-making process. This was achieved by studying and comparing larger datasets, based on the variables identified.

Mass (Advanced) Valuation Methods - Hedonic Models

Hedonic models are used in consumer and market research (Hirschman and Holbrook, 1982), tax assessment (Berry & Bednarz, 1975), computers (White et al., 2004), calculation of consumer price indices (Moulton, 1996), car valuation (Cowling & Cubbin, 1972) and housing (Court, 1939; Bartik, 1987; Goodman, 1998; Robert & Shapiro, 2003).

Rosen (1974) places the hedonic model into standard economic theory, being inspired by Houthakker (1952), Becker (1965), Lancaster (1966) and Muth (1966). This provides 'bid functions', maximising consumers, and 'offer functions', maximising producers, which is a vital tool of the model. As argued by Herath & Maier (2010), Rosen estimates a set of hedonic prices by observing price and property characteristics.

As stated by Hargrave (2020), hedonic pricing is a model that produces price according to the property itself; the internal characteristics, and the surrounding environment; external factors. Hedonic pricing requires a substantial degree of model specification, data collection and statistical expertise.

Hedonic Model Application to Real Estate Valuation

As stated by Hargrave (2020) and Pagourtzi et al. (2003: 396), the hedonic model provides a framework for the analysis of individual features which do not have an observable market price. The price of a building or piece of land is determined by the characteristics of both the property itself and its surrounding environment (Ge, 2009 and Ong, 2013).

The hedonic pricing model relies on market prices, i.e. requiring comprehensive, available and reliable data sets. According to Hargrave (2020), the model is also used to estimate the weighting for each factor affecting the market price of the property. When running this type of model, if non-environmental factors are controlled, any remaining discrepancies in price will represent differences in the property's external surroundings.

Court (1939) is known as the hedonic pricing model's pioneer and underlines how weighting factors can justify price. In his analysis, Court (1939) addressed the limitations of non-observable values. As agreed by Janseen et al. (2001), the traditional use of the hedonic model in housing shows heavy reliance of price on non-observable values, e.g. the air quality, airport noise, commuter access and neighbourhood amenities.

A classical hedonic equation is:

$$\boldsymbol{R = f\,(P, N, L, C, t)}$$

Thus, the expected price is the characteristics X times $\underline{\beta}$, where represents a vector of marginal price. The hedonic model analyses various weighting factors.

Where:

R = *Rent or Price*

P = *Property related attributes*

N = *Neighbourhood characteristics*

L = *Location variables*

C = *Contract conditions*

t = *Time*

$$VALUE = X\beta + \varepsilon$$

The hedonic model analyses various weighting factors. According to Malpezzi (2003), these are mainly age, construction, floor area, rooms, type, cateogry and features.

In the traditional hedonic regression model, the asset is broken down into related weighting factors that impact the price (Millington, 2013). In his study on the Turkish housing market, Selim (2011) used type of house, type of building, number of rooms, size, and other structural weighting factors such as water system, pool, natural gas. He identified 46 weighting factors in total.

Kok et al. (2017) developed an automated valuation model (AVM) with the use of hedonic regression. Kok et al. 's study (2017) reveals that this AVM produced much faster results at a lower cost while having an absolute error of ~9%, much lower than traditional forms.

Moreover, Kok concludes that machine learning, as a form of mass (advanced) valuation method, replicated the decision-making process. It was achieved by studying and comparing larger datasets, based on the weighting factors identified.

The hedonic pricing model has many advantages, including estimating values based on concrete choices, mainly when applied to property markets with readily available, accurate data. Simultaneously, the method is flexible enough to be adapted to relationships among other external factors.

Hedonic pricing also has significant drawbacks, including its ability only to capture consumers' willingness to pay for what they perceive to be the differences and their resulting consequences.

Statistical Model

According to Zeicu et al. (2017: 244), statistics is defined as "collecting, classifying, synthesizing, organising, analysing and interpreting numerical information". Zeicu et al. (2017: 244) also states that "the study of information was always positioned at the core of the valuation process, the tools required for rigorous analysis and interpretation of numerical data gave rise to expectations in terms of obtaining a more 'statistical' overall to conclude the valuation. Therefore, the profession has evolved into the direction in which valuers are expected to have a solid knowledge of statistics, statistical models and automated valuation models (AVMs)".

The statistical applications are classified into two categories: descriptive statistics and inferential statistics. Descriptive statistics involves scales of synthesising data to describe a data sample, graphs, scales and charts. Inferential statistics consist of using the sample data to formulate options about a population represented by that sample. It includes the result prediction and structure detection underlying the cause-effect relationship, estimating the core tendency and dispersion of the current but unknown population.

Demirci, O. (2021:3) stated that the concept of digitalisation has rapidly integrated into many sectors. This has led to rapid development of statistical software valuers can use, providing a user-friendly interface and marginal price value of 9% (Webb,1999). Zeicu et al. (2017: 244) argued that as operating systems have begun to predominate graphical interfaces, statistical programs such as SPSS, Minitab, SAS and R have become more user-friendly, mostly as it is no longer necessary for the user to write programming codes.

Statistical Model Application to Real Estate Valuation

Statistical models are a type of automated valuation model (AVM); mathematical software that produces an estimate of Market Value, based on the location analysis, market conditions and real estate features of market information previously collected. According to Zeicu et al. (2017: 244), the statistical model is used by specialist valuers for immediate advantages including the automation of the valuation process and the existence of the control methods for the results achieved.

According to Zeicu et al. (2017: 245), "AVMs credibility and accuracy of results depend on the quality and the quantity of the data used in the valuation, experience and trained of the staff that designs develop the model. AVMs are a complex process that requires close cooperation between the valuers, real estate market analysts, statisticians and software developers."

Statistical models use big data analytics, in addition to historical data and characteristics. Therefore, to construct a more sophisticated model, the statistical model requires greater access to data (Kauko & d'Amato, 2009).

A statistical model is a group of probability distributions (Cox, 1990). It can be univariate or multivariate. Univariate means that there is a single response or outcome variable (y), and multivariate means the modelling distribution has two or more response or outcome variables (y1, y2,…). The statistical model is largely represented in a linear model.

$$yi = \beta 0 + \beta 1xi + \beta 2zi + ei$$

if we assume ei ~ N (0, σ2), the family is a set of normal distributions indexed by β0, β1, β2, σ.

Multiple regression analysis (MRA) is one of the statistical methods used to predict a value and describe the dependent variable (effecting: weighting factors). It is also based on two or more relevant attributes (namely independent variables – causing: weighting factors) (Zurada et al., 2011). One of the key advantages of this model is simplicity. However, in this method, the main disadvantage is determining the dependant variables to minimise the risk or error in the calculation (Almy et al., 2018).

Zeicu et al. (2017: 245) suggested the following steps to build an automated valuation model of this standard:

1. Identifying the subject real estate.
2. Establishing extraordinary assumptions, hypothetical and limiting conditions.
3. Data management and data quality analysis.
4. Sample stratification (if it was not built by stratified sampling).
5. Establishing the model specifications.
6. Model calibration.
7. Model testing and quality assurance.
8. Model validation.
9. Application of the model.
10. Regular verification of the model accuracy.

Cluster Analysis

Cluster analysis focuses on clustering properties into bands according to factors such as location.

In this model, the main issue is assuming that all properties within such a cluster (group) are similar (Greiner and Thomas, 2012). De Nadai and Lepri (2018) studied several Italian urban markets with the use of cluster analysis and found that the vitality and walkability of the neighbourhood generated up to 20% of the property's total value.

Cluster Analysis Application to Real Estate Valuation

According to a Becoming Human: Artificial Intelligence (2021), property similarity to another is a crucial attribute to the cluster analysis. Clustering can help identify to which larger category of properties a given property belongs, and which features influence belonging in this category. One can then use the average from this category to get an indication of the price.

The first is the measurement of how far a property within a particular cluster is away from another property within the same group. This is done by calculating the 'average Euclidean distance' of one property 'i' to all other properties with the same cluster.

$$a(i) = \frac{1}{|C_i| - 1} \sum_{j \in C_i, i \neq j} d(i, j)$$

The second measurement is to see how well a property in a particular cluster fits with all other properties within a so-called 'neighbouring cluster'. A neighbouring cluster is a cluster which, on average, is closest. The assessment is done by calculating the 'average distance' of an individual property to all other properties of a neighbouring cluster.

$$b(i) = \min_{k \neq i} \frac{1}{|C_k|} \sum_{j \in C_k} d(i, j)$$

The last step is then to compare these measurements. The silhouette score is defined for a particular property as the difference between the average distance to a neighbouring cluster and the average distance within its own group. The number is standardised by dividing the difference by the maximum of a(i) and b(i).

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}, \text{ if } |C_i| > 1$$

Through this standardisation, the silhouette score will be between -1 and 1. To assess how well the clustering fits not only one property, but the entirety, the silhouette score is calculated for all properties and then averaged to determine value.

Option-Pricing Method

The option pricing formula was developed by Black and Scholes (1973). In a study conducted by Robert and Achour (1984), it was identified that there was a close similarity between fixed land options and call options on common stock in the market. They used this similarity to suggest ways in which fixed land options might be valued and analysed.

Option Pricing Method Application to Real Estate Valuation

According to Brown and Achour (1984), an option is a form of financial instrument in common use in real property transactions. According to Napthens (2019) “option agreements are entered into between landowners and developers and essentially grant the developer an option to purchase the land by exercising the right at any time during an agreed ‘option period’ in return for an ‘option fee’. Option agreements are used where a developer is interested in purchasing the land for residential and/or commercial development and the developer would ordinarily use the option period to apply for and secure the necessary planning permissions required to proceed with their development. The right to exercise the option lies with the developer”.

Option-pricing methods are traditionally used for corporate projects or financial returns. They have also been applied to the real estate market as it has become more commoditised given the prominence of real estate as an asset class for investment (Oppenheimer, 2002).

As stated by Brown and Achour (1984), there are several uses for option pricing models:

1. Guide transactors: negotiate option prices between themselves.
2. Construct ‘synthetic’ prices: If no market price is available, the model can estimate price, established by the market.
3. Market behaviour: investigating the efficiency.

Kummer and Schwatz (1980) introduced the Black-Sholes formula into the urban economics literature, each variable (weighting factor) with an interpretation appropriate to land options.

The formula is:

$$W = SN(d_1) - Xe^{-rT}N(d_2)$$

$$\text{where } d_1 = (\ln(S/X) + (r + \tfrac{1}{2}\sigma^2)T)/\sigma\sqrt{T}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

And N(.) indicates the cumulative standard normal density function.

The variables in the formula are:

W – the price of the fixed option

S – the current market value of the property

X – fixed purchase price

T – term to the expiration of the option

r – the risk-free rate of interest

o – standard deviation of the continuous (logarithmic) rate of return on the property.

A critique of this model, however, was the potential weakness in using a discount factor based on personal judgement and expectation.

Artificial Neural Network (ANN)

It is widely acknowledged that real estate valuation is subjective, requiring human intervention and feelings (Benjamin et al., 2004). The value is not always intrinsic and could be based on intangible variables (weighting factors) which cannot be computerised (Benjamin et al., 2004). The predecessors, discussed above, are not able to address these intangible variables efficiently.

Artificial neural network (ANN) forms the base of deep learning a subdivision of machine learning where the algorithms are inspired by the structure of the human brain (Peterson & Flanagan, 2009). Neural networks take in data and train themselves to recognise the patterns in this data to predict the output for a new set of similar data. Thus, ANN is classed as a form of artificial intelligence and an Advanced Valuation Method. According to Pagourtzi et al., ANN provides “possible solutions to many problems in real estate valuation” (2003:394).

According to Tabales et al., “ANN models were introduced by (McCulloch and Pitts, 1943) as an alternative to algorithmic programming” (2013:32).

Artificial Neural Network Application to Real Estate Valuation

One of the distinctive characteristics of ANN is that it can be trained. Indeed, property prices can be valued by training the ANN from a very large data set. The data can be processed through the three distinctive layers of ANN (input, hidden and output) to accurately complete the valuation process.

First, there is the input layer which receives the input. The output layer predicts the final output value. In between exists the hidden layers which perform most of the computations required by the network. The inputs are what the ANN learns from to produce the desired output.

Pagourtzi et al. (2003: 390) illustrated three components of the ANN to be the input layer, hidden layers, also known as the “black box.” and the output measure(s) layer (property value estimation).

Neural networks are made up of layers of neurons. Neurons are ‘things’ that hold a number, specifically between 0 and 1 (e.g., 0.1). There are 784 neurons in the input layer, each one of these neurons hold a number that represents the ‘grey-scale value’ of the corresponding input data, also known as the ‘activation’. The grey-scale value will activate (0.1 to 1) based on the input data.

The output layer has only 10 neurons each representing one of 10 digits (0,1,2…). The activation in these neurons represents how much does the system think the given data corresponds with the given digit. Therefore, activations in one layer determine the activations of the next layer.

As ANN is an information processing mechanism, the heart of the method is in the hidden layer. This is the key to its success in providing accurate valuations. There are two processes within the hidden layer. These are the transformation and the weighted summation functions, relating the input data value (which may include size, age, bathrooms, garages) to the output layer (the sales price).

$$(X, *0.8 + X_3 * 0.2) + B_1 > \text{Activation Function}$$

The propagation neural network model is used in the weighting summation function:

$$Y_j = \sum_j^n X_i W_{ij}, \qquad Y_T = \frac{1}{1+e^{-y}}.$$

Where:

Xi = The input values

Wij = Weights assigned to the input values for each of the j hidden layer nodes.

The transformation function then relates the summation value(s) of the hidden layers to the output variable value or Yj. According to Pagourtzi et al., “this transformation function can be of many different forms: linear functions, linear threshold functions, step linear functions, sigmoid functions and Gaussian functions. Most software products utilise a regular sigmoid transformation function” (2003: 395).

The sigmoid function S(x) (also known as the logistic curve) σ : indicates that very negative inputs will end up close to (0) and very positive inputs will end up close to (1). This then just steadily increases around input (0). All sigmoid functions have the property that they map the entire number line into a small range such as between (0) and (1), or (-1) and (1), so one use of a sigmoid function is to convert a real value into one that can be interpreted as a probability.

Borst (1992) and Trippi & Turban (1993) argued that the sigmoid transformation function is preferred due to its nonlinearity, continuity, monotonicity, and continual differentiability properties.

The success of ANN relies on the sophistication of the underlying technology. Lasota et al. (2015) applied a methodology using uniformed zones within a Polish metropolitan area. In Lasota et al.’s method, each zone reflected specific characteristics influencing value. The study concluded that this automated model was useful at predicting prices accurately compared to traditional methods.

Furthermore, a study conducted by Tay & Ho (1992) in Singapore revealed that the ANN model only had an average error of 3.9%. Several other authors (Do & Grudnitski, 1992., Evans et al., 1992., Pi-Ying, 2011) also noted that the ANN model is more accurate. However, this could be expected given the sophistication of ANN networks, allowing for a higher amount of data to be used in modelling (Do & Grudnitski, 1992., Evans et al., 1992., Pi- Ying, 2011).

Despite a steady improvement over the past decade, earlier work into this methodology in real-estate valuation found numerous issues with their valuations' speed and accuracy (Cechin et al., 2000; Wilson et al., 2002). These models rely on access to public records which provide the data needed for an accurate valuation, which are not always available to the broader public.

Demirci, O (2021) stated that the data could be segregated in a tribal network; therefore, the AVM will not provide an accurate value without quality data. The data is also known as big data analytics and offers a range of weighting factors, including previous sales values, property size, number of rooms, home-quality attributes such as granite worktops, new kitchen, and air conditioning (Kok et al., 2017).

Spatial Analysis Methods

The spatial analysis method is another advanced valuation method and a form of machine learning. This method can enhance analytical capabilities of location measurement and access variables when applied to the GIS (Geographic Information Systems) (Anselin and Getis, 1992; Griffith, 1993; Zhang and Griffith, 1993; Levine, 1996). The method can provide additional data on a given neighbourhood by Kriging techniques, variography (Dubin, 1992; Panatier, 1996) and autocorrelation analysis (Cressie, 1992; Odland, 1988).

The GIS framework can provide a three-dimensional visual aid on a given location, attached to value. This method investigates TINs (Triangulated Irregular Networks) to provide the basis for measuring location effects (Wyatt, 1995).

TINs represent a continuous surface consisting entirely of triangular facets, used mainly as a Discrete Global Grid in primary elevation modelling. LaRose (1988) demonstrated that TINs have the potential to predict residential property values and provide better results when produced on a global scale.

According to McClusky et al. (2000: 162) "The method specifically models the spatial distribution of house price with the objective of developing location adjustment factors which are based on the development of surface response techniques such as inverse distance weighting and universal kriging. The results generated from the surfaces created are then calibrated within Multiple Regression Analysis (MRA)."

Fuzzy Logic

The methodology of fuzzy logic, an advanced valuation method and a form of machine learning, was first introduced by Zahed (1965). The traditional logic only applies two possible outputs, 0 < m <1, which can be represented as true (1) and false (0).

Fuzzy logic can also have 'the inbetweeners'. This can be represented as 'partially' true (0.6) or 'mostly' false (0.3). The physical properties are not required to work the system as it is determined by Linguistic rules, which are easy to combine with human interaction or command.

Fuzzy Logic Application to Real Estate Valuation

According to a study conducted by Guidice et al. (2017), fuzzy logic will allow operators and investors to improve their investment decisions in terms of quality, reducing the risk arising from the uncertainties of inputs.

As stated by Guidice et al. (2017), fuzzy logic allows for representation mathematically, through a calculation system, of judgements without exact and univocal definition.

The deterministic statement “the value of this input is X” is replaced by the possibilistic assertation “the value of this input is approximately -X”. It assumes, therefore, that uncertainty presents possibilistic character rather than probabilistic, and that uncertainty could depend on the perception of eligibility for an individual event, rather than from its degree of statistical confidence.

Conclusion

As argued by Demirci (2021) it is widely acknowledged that there are numerous limitations to traditional valuation, when there is a need to value a group of properties. The main limitations of the traditional valuation methods are accuracy, consistency and speed (Jahanshiri, 2011; Wang & Wolverton, 2012; Adetiloye & Eke, 2014).

These disadvantages can be resolved by the adoption of automated valuation models (AVMs) in real estate valuation processes. With the increasing volume of transactions and changing marketplace of real estate, mass (advanced) valuation are becoming more widely adopted.

Due to the complexity of mass (advanced) valuation methods, namely, machine learning technology, the models are evolving through a path that enhances the integration of artificial intelligence (AI). AI enables the use of big data and provides accurate, efficient valuations and interactions of various systems. These modern methods are increasingly linked with AI systems. As computer technology develops, it allows machine learning and, in turn, AI to learn repetitive tasks. This may further reduce the need for human intervention.

References

Abidoye, R. B., & Chan, A. P. (2017). Valuers’ receptiveness to the application of artificial intelligence in property valuation. Pacific Rim Property Research Journal, 23(2), 175-193.

Adetiloye, K. A., & Eke, P. O. (2014). A review of real estate valuation and optimal pricing techniques. Asian Economic and Financial Review, 4(12), 1878-1893.

Almy, R., Horbas, J., Cusack, M., & Gloudemans, R. (2018). The valuation of residential property using regression analysis. Computer Assisted Mass Appraisal: An International Review.

Anselin, L. & Getis, A. (1992). Spatial statistical analysis and geographic information systems. The Annals of Regional Science, Vol. 26, pp. 19-33.

Bartik, T. J. (1987). The estimation of demand parameters in hedonic price models. Journal of Political Economy, Vol. 95 No. 11, pp.81-88.

Baum, A. E., & Crosby, N. (2014). Property investment appraisal. London: John Wiley & Sons.

Baum, A., Mackmin, D., & Nunnington, N. (2017). The income approach to property valuation. London: Routledge.

Becker, G. S. (1965). A theory of the allocation of time. The Economic Journal, Vol. 75 No. 299, pp. 493-517.

Benjamin, J., Guttery, R., & Sirmans, C. F. (2004). Mass appraisal: an introduction to multiple regression analysis for real estate valuation. Journal of Real Estate Practice and Education, 7(1), 65-77.

Berry, B. J. L. & R.S. Bednarz, (1975). A hedonic model of prices and assessments for single-family homes: does the assessor follow the market or the market follow the assessor? Land Economics, Vol. 51 No 1, pp. 21-40.

Brano, G. L. U. M. A. C., & François, D. R. (2018). Real estate and land property automated valuation systems: A taxonomy and conceptual model (No. 2018-09). LISER.

Brown, R. L., & Anchour, D. (1984) The Pricing of Land Options. Urban Studies (21) 317-323

Cechin, A., Souto, A., & Gonzalez, M. A. (2000, November). Real estate value at Porto Alegre city using artificial neural networks. In Proceedings. Vol. 1. Sixth Brazilian Symposium on Neural Networks (pp. 237-242). IEEE.

Clarke, H. R., & Reed, W. J. (1988). A stochastic analysis of land development timing and property valuation. Regional Science and Urban Economics, 18(3), 357-381.

Court, A, T. (1939). Hedonic price indexes with automobile examples. The dynamics of the automobile demand, New York, General Motors.

Cowling, K. & Cubbin, J. (1972). Hedonic Price Indexes for United Kingdom Cars. The Economic Journal, Vol. 82 No. 327, pp. 963-978.

Cox, D. R. (1990). Role of Models in Statistical Analysis. Statistical Science, Vol. 5, pp. 169-174.

Cressie, N. (1992). REML estimation in empirical Bays smoothing of census undercount. Survey Methodol, Vol. 18, pp. 75-94.

Demetriou, D. (2018). Automating the land valuation process carried out in land consolidation schemes. Land use policy, 75, 21-32.

Demirci, O. (2021). The Digital Transformation of the Valuation Sector in the World of Algorithms. London: Property Elite.

De Nadai, M., & Lepri, B. (2018, October). The economic value of neighborhoods: predicting real estate prices from the urban environment. In 2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA) (pp. 323-330). IEEE.

Do, A. Q., & Grudnitski, G. (1992). A neural network approach to residential property appraisal. The Real Estate Appraiser, 58(3), 38-45.

Erdem, N. (2017). Toplu (Kume) Degerleme Uygulama Ornekleri ve Ulkemiz Icin Onerileri. TMMOB Harita ve Kadastro Muhendisleri Odasi, 16. Turkiye Harita Bilimsel ve Teknik Kurultayi: Ankara.

Evans, A., James, H., & Collins, A. (1992). Artificial Neural Networks: An Application to Residential Valuation in the UK. University of Portsmouth, Department of Economics.

García, N., Gámez, M., & Alfaro, E. (2008). ANN+ GIS: An automated system for property valuation. Neurocomputing, 71(4-6), pp. 733-742.

Ge Janet, X. (2009). Determinants of house prices in New Zealand. Pacific Rim Property Research Journal, 15(1), 90-121.

Giudice, D. V., Paola, D. P. & Cantisani, B. G. (2017). Valuation of Real Estate Investments through Fuzzy Logic. Buildings, 7(26), pp. 18-22.

Goodman, A. C. (1998). Andrew Court and the invention of hedonic price analysis. Journal of Urban Economics, Vol. 44, pp. 291-298.

Greiner, M., & Thomas, M. (2012). Mass appraisal of residential real estate portfolios with stratified sampling: A case study. Journal of Real Estate Portfolio Management, 18(3), 305-321.

Griffith, T. L. (1993). Monitoring and Performance: A Comparison of Computer and Supervisor Monitoring. Journal of Applied Social Psychology, Vol. 23 No. 7, pp. 549-572.

Herath, S. K. & Maier, G. (2010). The hedonic price method in real estate and housing market research. A review of the literature. Institute for Regional Development and Environmental. Vienna, Austria: University of Economics and Business. pp. 1-21.

Hirschman, E. C. & Holbrook, M. B. (1982). Hedonic consumption: emerging concepts, methods and propositions. The Journal of Marketing, Vol. 46 No. 3, pp. 92-101.

Houthakker, H. S. (1952). Compensated changes in quantities and qualities consumed. The Review of Economic Studies, Vol. 19 No.3, pp. 155-164.

Isaac, D., & O'Leary, J. (2013). Property valuation techniques. London: Macmillan International Higher Education.

Jahanshiri, E., Buyong, T., & Shariff, A. R. M. (2011). A review of property mass valuation models. Pertanika Journal of Science & Technology, 19(1), 23-30.

Janseen, C., Soederberg, B. and Zhou, J. (2001). Robust estimation of hedonic models of price and income for investment property. Journal of Geographical Information Systems, Vol. 7 No.2, pp. 107-24.

Kauko, T., & d'Amato, M. (Eds.). (2009). Mass appraisal methods: An international perspective for property valuers. London: John Wiley & Sons.

Kok, N., Koponen, E. L., & Martínez-Barbosa, C. A. (2017). Big data in real estate? From manual appraisal to automated valuation. The Journal of Portfolio Management, 43(6), 202-211.

Lancaster, K. J. (1966). A new approach to consumer theory. The Journal of Political Economy, Vol. 74 No.2, pp. 132-157.

LaRose, T. A. (1988), "Global response surface analysis used to update appraisals in a computer assisted mass appraisal environment", paper presented at World Congress III of Computer Assisted Valuation and Land Information Systems, Cambridge, MA.

Lasota, T., Sawiłow, E., Trawiσski, B., Roman, M., Marczuk, P., & Popowicz, P. (2015, March). A method for merging similar zones to improve intelligent models for real estate appraisal. In Asian Conference on Intelligent Information and Database Systems (pp. 472-483). Springer, Cham.

Levine, R. (1996). Financial Development and Economic Growth: Views and Agenda. World Bank: Washington, D. C.

Malpezzi, S. (2003), Hedonic pricing models: A selective and applied review. In: T. O'Sullivan and K. Gibb (Eds) Housing Economics and Public Policy, 67-89. Malden, MA: Blackwell Science.

McCluskey, W. & Borst, R. (1997). An evaluation of MRA, comparable sales analysis and ANNs for the mass appraisal of residential properties in North Ireland. Assessment Journal, Vol. 4 No. 1, pp. 47-55.

McCluskey, W., Deddis, W., Mannis, A., McBurney, D. &Borst R. (1997). Interactive application of computer assisted mass appraisal and geographic information systems. Journal of Property Valuation & Investment, Vol. 15 No. 5, pp. 448-65.

Millington, A. (2013). An introduction to property valuation. London: Taylor & Francis.

Mooya, M. M. (2016). Real Estate Valuation Theory. Berlin: Springer Books.

Moulton, B. R. (1996). Bias in the consumer price index: what is the

Mousa, A. A., & Saadeh, M. (2010). Automatic valuation of Jordanian estates using a genetically-optimised artificial neural network approach. WSEAS Transactions on Systems, 9, 905-916.

Muth, R. F. (1996). 'Household production and consumer demand functions. Econometrica, Vol. 34 No. 3, pp. 699-708. Odland J (1988) Spatial Autocorrelation. Sage, Newbury Park: California.

Ong, T. (2013). Factors affecting the price of housing in Malaysia. Available on the Internet:< http://www. globalbizresearch. com/images/files/73848_JEIEJB_% 20Tze% 20San, 20.

Oppenheimer, P. H. (2002). A critique of using real options pricing models in valuing real estate projects and contracts. Briefings in Real Estate Finance: An International Journal, 2(3), 221-233.

Osborn, S. (2014). Property Valuation-the Five Methods. London: Taylor & Francis Limited.

Pagourtzi, E., Assimakopoulos, V., Hatzichristos, T. & French., N. (2003). Real Estate Appraisal: A Review of Valuation Methods. Journal of Property Investment & Finance, Vol. 21 No. 4, pp. 383-401.

Panatier, Y. (1996). 'Software for Spatial Datat Analysis in 2D', Variowin., New York: Springer-Verlag.

Peterson, S., & Flanagan, A. (2009). Neural network hedonic pricing models in mass real estate appraisal. Journal of real estate research, 31(2), 147-164.

Pi-ying, L. (2011). Analysis of the mass appraisal model by using artificial neural network in Kaohsiung city. Journal of Modern Accounting and Auditing, 7(10), 1080.

Robert C. F. & M. D. Shapiro, (2003). Scanner data and price indexes. University of Chicago Press, pp. 25, 341.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. Journal of Political Economy, Vol. 82 No.1, pp. 34-55.

Sayce, S., Smith, J., Cooper, R., & Venmore-Rowland, P. (2009). Real Estate Appraisal: from value to worth. London: John Wiley & Sons.

Scarrett, D. (2008). Property valuation: The five methods. London: Routledge.

Scarrett, D. & Osborn, S (2014). Property Valuation: The five methods. 3rd Ed. London: Routledge.

Selim, S. (2011). Determinants of house prices in Turkey: A hedonic regression model. Üniversitesi Dergisi, 9(1), 65-76.

Sevgen, C. S. & Tanrivermis, A. Y. (2020). Mass Appraisal with a Machine Learning Algorithm: Random Forest Regression. Ankara: Bilisim Teknolojileri Dergisi, Vol. 13 No.3, pp. 301-311.

SMARP. (2013). Standard on Mass Appraisal of Real Property. Missouri: International Association of Assessing Officers.

Soni, A. K. & Sadiq, A. A. (2015). Real Estate Valuation Using Artificial Neural Network International Journal of Science, Technology and Management. 5(4), 99-105.

Tabales, J. M. N., Ocerin, J. M. C. Y., & Francisco, J. R. C. (2013). Artificial neural networks for predicting real estate prices. Revista De Metodos Cuantitativos Para La Economia Y La Empresa, 15, 29-44.

Wang, K., & Wolverton, M. L. (Eds.). (2012). Real estate valuation theory (Vol. 8). Berlin: Springer Science & Business Media.

Wang, D., & Li, V. J. (2019). Mass Appraisal Models of Real Estate in the 21st Century: A Systematic Literature Review. Sustainability, 11(24), 7006.

White, A. G., Abel, J. R., Berndt, E. R. & C. W. Monroe, (2004), 'Hedonic price indexes for personal computer operating systems and productivity suites', NBER Working Paper Series, Working Paper 10427.

Wilson, I. D., Paris, S. D., Ware, J. A., & Jenkins, D. H. (2002). Residential property price time series forecasting with neural networks. In Applications and Innovations in Intelligent Systems IX (pp. 17-28), London: Springer.

Worzala, E., Lenk, M., & Silva, A. (1995). An exploration of neural networks and its application to real estate valuation. Journal of Real Estate Research, 10(2), 185-201.

Wyatt, P. J. (1995). Using a GIS for property valuation. Journal of Property Valuation and Investment, Vol. 14, No. 1, pp. 67-79.

Wyatt, P. J. (2013). Property valuation. London: John Wiley & Sons.

Zurada, J., Levitan, A., & Guan, J. (2011). A comparison of regression and artificial intelligence methods in a mass appraisal context. Journal of Real Estate Research, 33(3), 349-387.

Zeicu, S., Onose, D., Ortelecan, M. & Palamariu, M. (2017) Statistical Modelling Applied in Real Estate Valuation. University of Alba Iulia (22) 243-252.

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