A Survey on Application of Artificial Intelligence in Real Estate Industry

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Abstract

This paper will discuss the use of Artificial Intelligence (AI) in real estate industry. Today, besides Multiple Regression Analysis (MRA) models the use of AI systems for real estate valuation becomes better alternative. These AI systems for real estate valuation are more recent and becoming practical. Even if there are a number of artificial intelligent systems, Artificial Neural Networks (ANN) and Expert Systems (ES) are the ones presently applied for real estate valuation. Thus this paper will examine the current trends of ANN and ES and considers suitable applications in real estate valuation. In addition, prediction capability comparison between ANN and MRA will be presented by considering different case studies since both use statistical analysis and data modelling. Furthermore, common characteristic of ANN and ES will be compared. Beside ANN and ES, this paper will also discuss the application of hybrid systems for real estate valuation which mitigate the limitations and take advantage of the opportunities to produce systems that are more powerful than those that could be built with single intelligent systems.

Keywords: Real Estate Valuation, Artificial Intelligence, Artificial Neural Networks, Expert Systems, Hybrid Systems

Introduction

An accurate and fast prediction of the real estate value is important to prospective homeowners, developers, investors, appraisers, tax assessors and other real estate market participants, such as, mortgage lenders and insurers. Real estate valuation based on traditional approaches such as cost and sale comparison approach lacks an accepted standard and a certification process. Therefore, the availability of a real estate value prediction model helps to fill up an important information gap and improve the efficiency of the real estate market [5].

Over the last two decades there has been a proliferation of empirical studies analyzing residential real estate values. The use of computer for real estate valuation began in the early 1980s, coinciding with the development of information systems technology. Subsequently, different statistical techniques were incorporated to process market data, among which the method of MRA proved especially relevant [14]. MRA models are the most popular quantitative technique in real estate valuation. It has been applied in various residential real estate valuations to assist appraiser in statistical analysis and complement the traditional sales comparison approach. MRA methods have experienced criticism from the academic and practitioner community. MRA has often produced serious problems for real estate valuation that primarily result from multicolinearity issues in the independent variables and from the inclusion of "outlier" properties in the sample. Moreover, nonlinearity within the data may make multiple regressions an inadequate model for a market that requires precise and fast responses.

Nowadays, besides MRA models the use of AI systems for real estate valuation becomes better alternative. Using AI systems for real estate valuation is more recent and becoming practical. Since then there have been numerous experiences, and the creation of new models is on the increase. Even if there are a number of AI systems, ANN and ES are presently applied for real estate valuation.

Artificial Neural Network

An Artificial Neural Network (ANN), also called a Neural Network, is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. There is no precise agreed definition amongst researchers as to what an ANN is, but most would agree that it involves a network of relatively simple processing elements, where the global behaviour is determined by the connections between the processing elements and element parameters. The original inspiration for the technique was from examination of bioelectrical networks in the brain formed by neurons and their synapses. In an ANN model, simple nodes (called variously "neurons", "neurodes", "processing elements (PEs)" or "units") are connected together to form a network of nodes hence the term "neural network".

ANNs usually have several layers. The first layer is called the input layer, the last one the output layer. The intermediate layers (if any) are called the hidden layers which can not be inspected from the outside. Example of simple ANN structure is shown in Figure 1.

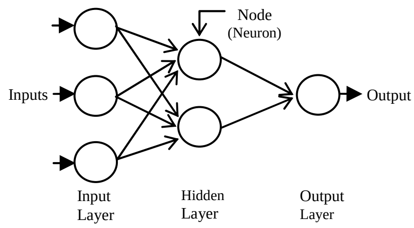

Figure 1 - Simple example of ANN

The information to be analyzed is fed to the neurons of the first layer and then propagated to the neurons of the second layer for future processing. The result of this processing is then propagated to the next layer and so on until the last layer. Each unit receives some information from other units or from the external world and processes this information, which will be converted into the output of the unit.

Depending on the desired functionality and problem area, neurons can be structured in a number of different architecture. In general it is possible to distinguish three main types of network architecture: single-layer feedforward networks, multi-layer feedforward networks and recurrent networks [1].

The learning process of the ANN can be likened to the way a child learns to recognize patterns, shapes and sounds, and discerns among them. In real neurons the synaptic strengths may, under certain circumstances, be modified so that the behaviour of each neuron can change or adapt to its particular stimulus input. In artificial neurons the equivalent of this is the modification of the weight values. ANNs never work the first time round. Thus, they need to “learn”. With standard learning algorithms an ANN learns through an iterative process of weight adjustment. The type of learning is defined by the way in which the weights are modified. The three main learning paradigms are: 1) supervised learning, 2) unsupervised learning, and 3) reinforcement learning [1]. Finally, testing can be done either from randomly selected learning set or from a set of observations immediately following the learning set.

Implementation of ANN for Real Estate Valuation

ANNs are often used for a statistical analysis and data modelling, in which their role is perceived as an alternative to standard nonlinear regression or cluster analysis techniques. Thus, they are typically used in problems that may be couched in terms of classification or forecasting. Forecasting is primarily a quantitative process using numerical data from the past to forecast the future. Since real estate valuation is forecasting process ANNs can be used for real estate valuation [17].

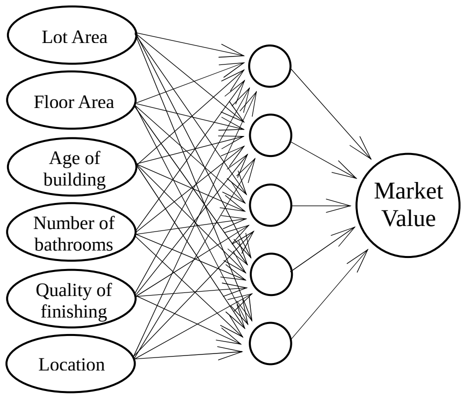

Figure 2 - Simple model of ANN for Real Estate Valuation

Different researches show that ANNs for real estate valuation usually work in the range of 10 to 50 variables [14]. It features an input layer with the same number of neurons, likewise the second hidden layer (although this can vary between half and double the number of variables), and an output layer containing a single neuron. Feedforward ANNs are most commonly trained using a back-propagation algorithm for training and have been widely used for several civil engineering applications [4]. Indeed feedforward /back-propagation network models are the most common form of ANN models used for real estate valuation. The majority of ANNs designed for real estate valuation is similar in structure with the structure in Figure 2. ANN algorithms typically begin with randomly determined or equal default weights for each of the nodes in each of the hidden layer(s). In each model-training, each real estate attribute is entered into the model, the network sums and transforms the values of the input variables into the predicted output value(s). The model then compares the ANN’s estimated price to the actual price. If a discrepancy exists, then the software works backwards to adjust the hidden layer weights to minimize the prediction error. These adjustments are similar in nature to the adaptive estimation techniques used in MRA for real estate valuation. While training, ANN models repeat these steps as the data for each new real estate are added, always adjusting the hidden layer weights to minimize the total prediction error. ANN stops training when it reaches a preset internal error threshold, either the software’s default error level or the researcher’s pre-designated error threshold. Such a threshold is needed because without one, an ANN would effectively memorize, or “over-train” on the training data, and its predictive ability towards a new real estate would significantly deteriorate.

Case-Studies of Real Estate Valuation Based on ANN

Effort to apply ANN technology to the valuation of real estate is dated from the early 1990s. Frequently these studies are in the form of comparative analysis, with researchers contrasting the findings and perceived efficiency of ANN models with more tried and tested statistical methods. Given the potential difficulties associated with regression modelling, namely functional form and non-linearity of variables, ANNs have found a measure of insightful appeal [13].

Table 1 – ANN vs. MRA Performance comparisons

Researchers	**Data**	**Place**	**ANN vs. MRA**
Do et al. [2]	105	----	ANN 2× accurate
Tay et al. [19]	833	Singapore	ANN 1.92× accurate
Evans et al. [3]	34	England & Wales	ANN better accuracy

The studies shown in Table 1 generally support the superiority of ANN over MRA in predictive ability. There are also studies showing the superiority of MRA over ANN while other studies show inconclusive results. For example *Worzala et al.* adopt a contrary position and cast some doubt upon the role of neural networks compared with MRA models, suggesting that caution is needed when working with neural networks. In undertaking analysis at varying levels of investigation and utilizing different neural network shells, the error magnitude for individual properties was found in some cases to be very significant and clearly not acceptable for a professional appraisal [20]. Other researchers *McGreal et al.* also adopts a more sceptical approach to the potential merits of neural networks within the valuation process and in this respect agrees with the cautionary tone expressed by *Worzala et al.* with reference to the position taken by other researchers [13].

Different recent researches show that neural networks are found to perform better than MRA when either the number of groups or the number of variables increases and also when the classification tasks tends to become complex [9]. Similarly study on real estate valuation gives a plausible explanation why previous studies have obtained varied results when comparing MRA and ANN predictive performance for real estate values. The predictive performance depends on the evaluation criteria used in combination with the training size and model specification. Fluctuation in the ANN model's performance may be due to the larger number of parameter settings chosen via experimentation and dependent on training sample size [15]. Also due to lack of some environmental attributes relationship between real estate attributes and real estate price is non-linear, thus it could be the cause of the poor performance of the MRA models. Conversely, the ANN model can overcome some of the problems related to the data patterns and the underlying assumption of the MRA model. As a result, the model yields a better prediction result when compares with MRA model [11].

In conclusion, if one provides sufficient data training size and appropriate ANN parameters, then ANN performs better than MRA.

Pros and Cons of ANN for Real Estate Valuation

The most advantageous property of ANN is its adaptability, which allows the neural network to perform well even when the environment or the system being controlled varies over time. Thus using ANNs for real estate valuation is advantageous because it has time dependent attributes. ANNs learn system behaviour by using system input-output data and do not require update when input changes. The learning and generalization capabilities of ANNs enable it to more effectively address nonlinear, time variant problems, even under uncertain or erroneous attributes of real estate valuation. Thus, ANNs can solve problems that either unsolved or inefficiently solved by traditional real estate valuation techniques. It can also develop solutions to meet a pre-specified accuracy.

A major disadvantage of ANN is their lack of transparency. The internal structure of the network is hidden and may not be easy to duplicate, even using the same data inputs. This leads to lack of accountability because the system's intermediate steps can not be checked [9]. Furthermore it is difficult to determine the proper size and structure of ANN which determines the value of real estates.

Expert System

ES has a wide base of knowledge in restricted domain, and uses complex inferential reasoning to perform tasks which a human expert could do. It encompasses several different components such as a knowledge base, inference mechanisms, explanation facility, etc. All these different components interact together in simulating the problem solving process by acknowledged expert of a domain. They are based on knowledge to solve problems that would normally require a human expert. The knowledge is collected from human experts and secondary knowledge resources, such as books, and is represented in some form, often using logic or production rules. The system includes a reasoning mechanism as well as heuristics for making choices and navigating around the search space of possible solutions. It also includes a mechanism for passing information to and from the user.

ES has four major architectural components with individuals in various roles. These are The Knowledge Base, Working Storage, Inference Engine, and User Interface. In ES model, knowledge can be represented and stored in the knowledge base in various forms. For example, one of the most commonly used ways to represent knowledge is rule-based reasoning, in the form of IF-THEN rules. But using rule-based reasoning in real estate valuation could be difficult to implement because rules would be based on observations of the market, which is a dynamic entity. Thus, the rules would likely have to be updated frequently after studying market data. An alternative of rule-based reasoning is Case-Based Reasoning (CBR). A CBR solves new problems by adapting solutions that were used to solve old problems. It is most useful in knowledge domains where precedence-based reasoning is appropriate. Domains such as medical diagnosis and audit commonly use CBR. Nowadays, real estate valuation lends itself well to CBR. Since the method to be followed is the market data approach, the case library will consist of descriptions of all kinds of real estates previously sold [6].

Implementation of CBR for Real Estate Valuation

CBR is built on the premise that humans use an analogical or experiential reasoning approach to learn and to solve complex problems. It involves two primary steps: (1) find those cases in storage that have solved problems similar to the current problem, and (2) adapt the previous solution(s) to fit the current problem context. Figure 3 shows nominal process of CBR.

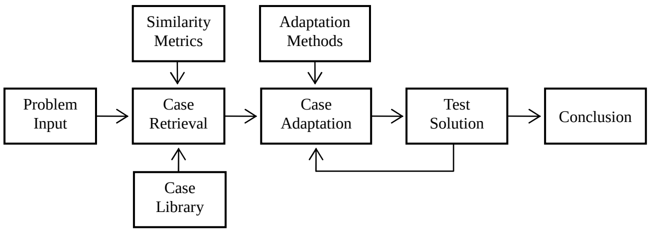

Figure 3 – Nominal process in CBR

Initially the expert will provide the heuristic knowledge necessary to adapt or adjust the values from the real estate properties in the case library that are the most similar in terms of characteristics or features to the real estate being appraised. To determine the solution it is necessary to follow the following four major steps:

Step 1: Problem Input

The cases to be represented in the real estate valuation model consist of the descriptions of real estates sold during a specific period of time in a certain geographic area. Even when the elements of comparison may vary somewhat from appraiser to appraiser and from market to market, a set of elements of comparison should be chosen such as area in square unit, number of bedrooms, number of bathrooms, age of the house, location, architectural style of the house, date of sale, type of HVAC equipment, type of garage, lot size, etc.

Step 2: Case Retrieval

In this step, three real estates that are similar to the subject property will be retrieved since real estate appraisers choose only three comparable properties to be adjusted and included in their valuation [6]. Valuation of real estate based on CBR is particularly interested in the global best matches with prior sales records. In the real estate valuation model, the best-match algorithm takes the target case, computes a similarity metric between the target case and each case in memory and retrieves the best matches from memory.

Step 3: Case Adaptation

Once the best cases in memory are identified, they are retrieved from memory to become the official comparable properties. Then, the adaptation phase begins. This phase applies adjustments to the sale price of comparables to get a better indication of the value of the subject property.

Probably the best understood adaptation technique is one called parameterized solutions. The parameter to be adapted is determined by the differences between the subject property and it's comparable from the case library. When a case is retrieved for an input situation, the old and new problem descriptions are compared along the specified parameters. The differences are then used to modify the solution parameters in the appropriate directions. In real estate valuation, the comparison parameters are used to determine what adjustments are needed to "adapt" the sale price of each comparable to the features of the subject property. Thus, the solution parameters are the sale prices of the comparables.

Step 4: Test Solution and Conclusion

Once all adjustments are obtained, they are added or subtracted, as appropriate, from the sale price of the corresponding comparable property. In this way, an adjusted value, which better reflects the value of the subject property, is produced for each one of the three comparables. Then, the new solution is tested and, if successful, added to the case library. If, however, the test fails, then the adaptation process must be revised or a new set of case must be retrieved.

Case-Studies of Real Estate Valuation Based on CBR

Gonzalez et al. verified the ability of CBR for real estate valuation. The case library contains multiple listing service manual with description of 107 sample of single-family residential real estates sold during a period of about five months in the area of Deltona, FL. The prototype number of elements of comparison was only 12. However, their CBR model appraise values were fairly consistent and close to the list prices. If more features are included for each real estate, a better differentiation between real estates can be made. Therefore, it is concluded that the values appraised would be more precise [6].

Based on the study done on residential apartments in Bangkok, Thailand, *Pacharavanich et al.* concluded that, CBR real estate valuation system has potential to become a viable commercial tool for the valuation of residential real estate in Bangkok. Appraisers also confirm that the CBR model is easy to use, its usefulness and confidence for the conclusion. Confidence in the conclusions provided by the artificial intelligence systems reflects attitudes that users can have towards the system after using it in training or for problem solving [16].

Pros and Cons of CBR for Real Estate Valuation

In real estate valuation sales comparison approach is mostly used among other approaches. Traditionally in sales comparison approach collection and retrieval of data on sales of similar properties and adjustment of the sales data are performed either manually or using non intelligent systems which makes the process tedious. On the other hand in CBR the system search for the most similar properties from library, retrieve it and make the adjustment easily. This takes a very short time to finalize the valuation process, leads to cost reduction. The accuracy of the appraised value is higher in CBR systems because it is easier to find the best match for the subject property. Also it reduces the required number of expertise significantly for real estate valuation. Since these systems are based on knowledge it can provide an accessible, available alternative that can be used as a training tool for beginners. As concluded by the above two case studies using CBR systems results in decreased costs for appraisers, reduced downtime and increased quality and throughput.

The knowledge may be internally consistent but inaccurate, due to either expert error or misunderstanding at the acquisition stage. Thus it is not an easy task to develop complete, consistent and correct knowledge bases. Some tool support is available, and usage of a structured approach can alleviate the problem. Therefore the appraised value may be incorrect due to the internal error of the system. Furthermore it requires a number of similar subject properties already stored in the case library to reach on the best match since the CBR system for real estate valuation is more dependent on the case library.

Characteristics Comparisons of ANN and ES

Even if ANN and ES use different approaches they have some common characteristics which can be used to compare them [10]. ANN has various advantages and disadvantages compared with ES. From functional and application standpoints, each approach can be equally feasible, although in cases one may have an overall advantage over the other. As we already discussed. ANN and ES follow two quite different approaches to evaluate the real estate. They have different properties, advantages and disadvantage with regard to this application. ANN is based on numeric computations and algorithms, while ES is based on symbolic and heuristic reasoning. ANN has capabilities of association, memorization, error-tolerance, self-adaptation, and multiple complex pattern processing. On the other hand, they cannot explain their own reasoning behaviours and cannot adapt new environment (those not made available previously in training the networks). Whereas ES has the ability to explain their reasoning behaviours and can adapt new environment using knowledge bases. ES has obvious knowledge representation forms that make knowledge easy to manage. However, self-learning is still a problem and computation time can be lengthy depending on the size of the domain and the range of cases that must be realized. But ANN can analyze a large number of cases quickly to provide accurate responses. Though, validation of the content of ANN (i.e., the determination of the completeness and consistency of the representation) is relatively more difficult than ES.

Table 2 – Characteristics of comparisons of AAN and ES

Characteristics	ANN	ES
Approach	Numeric	Symbolic
Reasoning	Associative	Logical
Operations	Biological-Like	Mechanical
Feedback to user	None	Reasoning Path
Processing Approach	Parallel	Sequential
System	Self-Organizing	Closed
Knowledge	Many examples	Expert
Self Learning	Inherent	None
Fault tolerance	Tolerant	Not
Maintenance	Easy	Difficult
Adaptability to changes	Adaptive and Flexible	Requires programming
Learning Capacity	High	None

Characteristics comparison between, ANN and ES is shown in Table 2. The different characteristics of these systems suggest that they can enhance each other to provide solutions that neither of the system alone can deliver nor lead to good solutions with less system complexity. Because of these reason integrating or combining of two or more intelligent systems become a primary concern for researchers and practitioners. In the following section the use of integrating these systems is presented in detail.

Hybrid of ANN and ES

The development of information systems based on the combination of two or more intelligent systems has been a solution to overcome the limitations presented by individual intelligent systems [8]. In the past decade, the amount of research and development involving hybrid intelligent systems has increased rapidly. Initial work addressed the integration of ANN and ES [21].

ES and ANN are well established as useful technologies that can complement each other in powerful hybrid systems [7]. These integrated systems can also involve database and other technologies to produce the best solutions to complex problems. Due to their fundamentals natures, ANN and ES have a natural synergism that can be exploited to produce powerful computing systems. It becomes more efficient and effective computing systems, making up for deficiencies in the conventional approaches. A hybrid approach which integrates ES and ANN has promising results to solve problems in a fashion more consistent with human intelligence. Interesting areas of research and development include the use of ANN in situations where ES have previously been used, development of application models and guidelines when best to use hybrid systems, and further work on creating development tools and environments.

Case-Study of Real Estate Valuation Based on Hybrid Systems

In recent years there has been an explosive growth in the successful use of hybrid intelligent systems in many diverse areas. There are few ongoing researches on hybrid intelligent systems which have been developed for real estate valuation. For example a study shows the performance of an integrated model named "Geo-Information Neural System" (GINS) which is developed as an alternative for use in the valuation of single-residential real estate. This system integrates a Geographic Information System (GIS) technique with ANN modelling [18]. GIS is utilized for location distance measurements, spatial queries and thematic mapping whilst ANN is employed to replicate the way the human brain might process data by learning relationships, in this case the one existing between property characteristics such as physical and location attributes and sales price. The results indicate that GINS provides an efficient tool that provides superior residential real estate valuations, while accuracy is improved by minimizing the influence of subjective judgments. The other example of hybrid system uses the hybrid of ANN and genetic algorithms in association with a nearest neighbour algorithm for mass valuation of real estate [12]. Though ANN and genetic algorithms have relatively poor levels of model transparency, the ability to objectively select and retrieve comparables based on an integrated nearest neighbour algorithm provides a solid foundation on which a transparent mass appraisal system can be developed. Optimum weights for the real estate attributes have been derived from information inherent within the data, thus negating the need to solely rely on subjective domain knowledge to determine these. The application of enhanced distance metrics such as mean, coefficient of variation and significant mean clearly improve weight determination with specific regard to categorical variables.

As of my knowledge there is no hybrid of ANN and ES system which is developed for real estate valuation. However using hybrid of ANN and ES is very promising for real estate valuation as explained in this paper.

Conclusion

Real estate valuation is no longer a traditional business that relies only on expert opinions of value. The profession is now facing greater transformation in the valuation process and methodology, along with innovations in information technology. Technology is having profound effect on the profession, as well as influence on the real estate valuation process, largely pressured by the needs of today's clients who demand quick, easy and more objective process to arrive at the opinion of value. The needs somehow motivate dependency on intelligent valuation system that allows clients to get faster and accurate value.

As shown in the case studies of this paper ANN and ES systems are already used successfully for real estate valuation. Different researcher's comparison result shows that ANN gives better accuracy than MRA. However there are few studies showing the superiority of MRA over ANN while other studies reached on an inconclusive result.

Hybrid systems mitigate the limitations and take advantage of the opportunities to produce systems that are more powerful than those that could be built with single intelligent systems. The hybrid systems represent a range of building blocks that may eventually allow simulating human-like intelligence. Two successful hybrid systems developed for real estate valuation is presented in this paper. These hybrid systems demonstrate their feasibility and advantages for single and mass real estate valuation. Thus it is recommendable to use hybrid systems for real estate valuation because it can reduce significantly the time and cost required to value a real estate, while enhancing the accuracy of value estimates.

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