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Using Expert Systems and Artificial Intelligence For Real Estate Forecasting

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Abstract: This paper examines the use of expert systems and artificial intelligence, (in particular the application of neural networks) to real estate forecasting. While there is a great deal of literature about the use of artificial intelligence for mass appraisal, there is relatively little work on how it can be applied in real estate forecasting. This paper examines the current uses of artificial intelligence, particularly neural networks, in the business-forecasting field and considers suitable applications in real estate. The paper also considers the broader issue of expert systems and how a better system can lead to better results. Some real estate data are used as simple case studies to demonstrate their use.

Introduction:

Over the last few decades there have been significant changes to the methods of forecasting available to analysts and practitioners. Complex methods have become available for routine use and complex econometric models are often suggested as the solution to forecasting problems. However some researchers suggest that the use of better systems rather than better forecasting techniques would lead to better overall forecasts. This idea was strongly supported by the work of Makridakis et al. (1982). This research involved forecasting 1001 different time series using 24 different methods. They concluded that more sophisticated methods may produce no better results from simple ones. These are highlighted in the following quote from their conclusions.

> *"If the forecasting user can discriminate in his choice of methods depending upon the type of data (yearly, quarterly, monthly), the type of series (macro, micro, etc.) and the time horizon of forecasting, then he or she could do considerably better than using a single method across all situations - assuming, of course, that the results of the present study can be generalized.... Even though further research will be necessary to provide us with more specific reasons as to why this is happening, a hypothesis may be advanced at this point stating that statistically sophisticated methods do not do better than simple methods (such as deseasonalized exponential smoothing) when there is considerable randomness in the data.... Finally, it seems that seasonal patterns can be predicted equally well by both simple and statistically sophisticated methods."*

One implication of this is that forecasting systems with simple artificial intelligence (AI) and expert systems (ES) may produce better outcomes and be more efficient than those use a single, (and often more complex and sophisticated) model (DeLurgio, 1998). This paper examines some of the uses of expert systems and artificial intelligence within business and how they are being applied to real estate problems.

One particular aspect that is considered is the advantages of these systems as a learning tool for inexperienced real estate practitioners. An example is used to show how an expert system for residential valuations might work.

What are expert systems and artificial intelligence?

The field of artificial intelligence (AI) has developed rapidly as computing power has increased. Artificial intelligence refers to the ability to perform the intelligent functions of the human brain. In particular some forms of reasoning, some learning and general improvement over time. The uses of AI are varied with the major uses so far being in the computing and robotics area. They form an integral part in modern optical character and speech recognition software, are broadly used in robotics and have very wide spread applications through the military. The use of AI is now extending into the social sciences including business studies. The use of artificial neural networks (ANN) and genetic algorithms are becoming more wide spread particularly in the fields of market research and forecasting.

Expert systems may be considered to be a subset of AI. DeLurgio (1998) makes a clear distinction between conventional program systems (CPS) and expert systems (ES). He maintains that CPS involves the researcher wanting to create a system that deals with interesting and difficult tasks without regard to whether these are similar to those used by humans i.e. it does not matter how the job gets done, as long as it does. The ES tries to gain an understanding of how humans solve problems and then uses the computer to explain and predict their behavior. In practice many systems contain elements of both. So that many systems have some aspects of expert systems but often rely on some of the basic number crunching abilities of a CPS. This will increasingly become the trend in real estate applications where hybrid techniques will become more prominent (McCluskey, 1999). The emergence of expert or partly expert systems is important for educators in nearly all fields. The advantages of ES include the ability to provide expert advice to non-experts, assist experts to solve problems and to act as a teaching tool for non-experts (DeLurgio, 1998). For educators the final issue is very beneficial. A well-constructed ES can form a valuable teaching and training tool.

The use of artificial intelligence for forecasting

The most used AI technique is probably artificial neural networks (ANN). The concept of the ANN is that of a learning algorithm similar to the function of the human brain. They work by a series of interconnected neurons in a similar manner to the working of the brain. However even with the largest modern computers it is estimated that an ANN with 10 million interconnections would have a neuron structure somewhat smaller than a cockroach. (De Lurgio, 1998). The process of using the ANN for forecasting is largely the same as for other forecasting methods such as multiple regression. As a results these two techniques are very often compared. In each case there is input data which is used to model output data. They each use a series of coefficients in the modeling process and each attempt to minimize error terms in a similar manner. The standard methods of hold out samples are also commonly used in both as a measure of the forecasting ability. The internal process of the ANN is however more complex and less easy to reproduce and explain. It functions as a “black box” to a much larger extent than for traditional statistical methods. On the other hand, people with no background in the method seem to be able to make better predictions using ANN’s. This sets a dangerous precedent and it is probable the use of ANN’s will be over-sold and they will be used in situations where more conventional methods are probably superior. As a result, dangerous conclusions and recommendations will be made by people who use ANN’s badly. Notwithstanding this ANN’s have been well researched in business fields in recent years. For a basic time series situation Kuo et al. (1996) found that neural networks produced lower errors than Box-Jenkins and regression procedures. Denton (1995) found ANN to be superior for causal forecasting to regression. There are numerous examples of where ANN’s have been used for business forecasting. These include forecasting of electricity consumption (Nizami et al., 1995), airline passengers (Man et al 1995), company audits (Lanard et al (1995), bank failures (Tam, 1992), bankruptcies (Fletcher, 1993), stocks and bonds (Desai, 1998, Li, 1994), futures and financial markets (Meade, 1995, Kaastra et al, 1995, Mangasarian, 1995, Kuan et al, 1995, Grudnitski et al, 1993). In most cases researchers have found that ANN’s can produce forecasts with lower overall errors than with conventional methods such as regression.

The use of artificial intelligence for real estate forecasting

Forecasting is a major issue in most aspects of real estate practice. Valuation and appraisal are forecasting. Property development relies on forecasting of expected costs and returns. Property and facilities managers use forecasts of supply and demand as well as of costs and returns. Funds and investment managers rely on forecasts of value now and in the future through forecasts of growth and economic activity. With all this forecasting being relied upon it is somewhat surprising that the uses of AI and ES are primarily restricted to mass appraisal, however this is less surprising when an analysis of the use suggests that most of this would fit better into the description of conventional program systems. Early attempts at "automating" or "computer assisting" valuation go back as far as the late 1970's when sufficient computing power became available (Eckert, 1993, Jensen, 1984). The use of expert systems and artificial intelligence techniques for residential valuation has been suggested in the literature for over a decade. Methods such as rule-based reasoning (Scott et al. 1989, Nawawi et al. 1997), case-based reasoning (O'Roarty et al. 1997), and neural network (Borst 1995, Do et al. 1992, Evans et al. 1993, James, 1996, Jensen 1990, Lenk et al., McClusky et al. 1996, Rayburn, 1995, Rossini 1997, Tay and Ho 1994, Worzala 1995) have all been suggested as means of approaching mass appraisal and to some extent valuation generally. In general the emphasis has been on data mining from a large property transaction database. There are a wide variety of methods that can be used for data mining but these can be classified into nine groups; classification, regression, discovery of associations, discovery of sequential patterns, temporal modeling, deviation detection, dependency modeling, clustering and characteristic rule discovery (McCluskey and Anand, 1999).

The use of AI through neural networks is not well researched in other aspects of property. Kershaw et al (1999) compared the results of neural networks to those using regression to develop time series indices for residential data. Neural networks were found to be useful (but no better) for estimating a hedonic price index based on cross sectional transaction data but were found to be quite useful when dealing with time series data e.g. median prices. Other examples of the use of neural networks have been in the property development/ building fields including models for the demand for residential construction (Hua, 1996) and cost estimation. (De la Garza,1995).

Using of artificial intelligence and expert systems in real estate practice

The discussion so far has focused around neural networks and data mining techniques for forecasting. Forecasting is primarily a quantitative process using numerical data from the past to forecast the future. Expert systems are an ideal method for dealing with many other problems as well. One of these is qualitative forecasting. This is typically used for new products and in situations where there is no long-term series that might assist in giving a forecast. Expert systems can assist in the use of methods such as sales-force composites, surveys of customers and populations, jury of executive opinion and the Delphi method (Wilson et al, 1998). There are numerous other areas within real estate practice where expert systems could be usefully employed. Some examples are

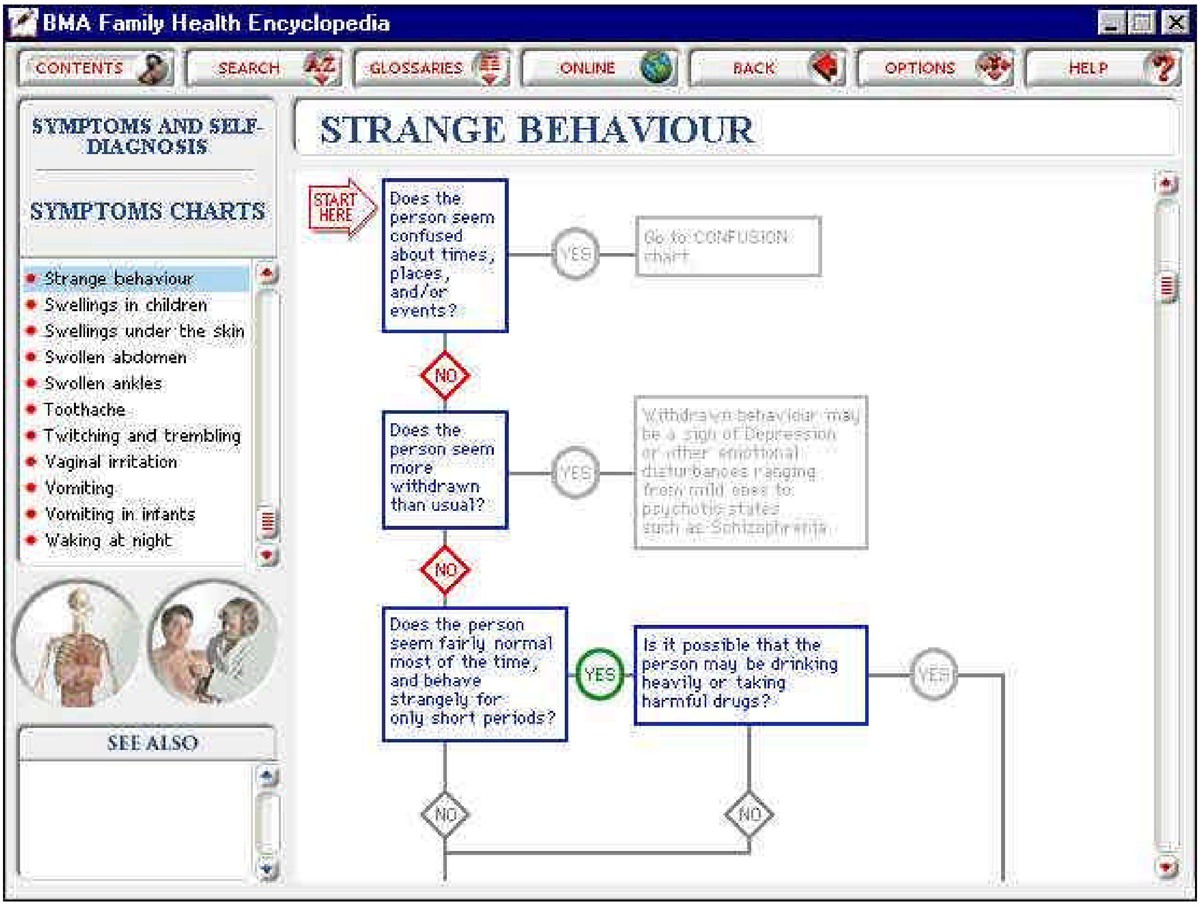
- the preparation of real estate documentation such as leases, contracts and forms. Expert systems can help the user prepare better documents by guiding them through the process and brining attention to issues that might other wise have been missed, as well as improving phrasing and structure.
- the costing of buildings and development projects. This requires a combination of data mining and rule based methods (or case based reasoning) to bring together the expert knowledge of quantity surveying, engineering and construction with current cost estimates.
- computing assistance with specialised as well as general computer software.
- preparation of reports and property descriptions
- property and facilities management problems where the ES can be used by both clients and property managers to streamline the solution to some problems

One of the obvious issues with each of these is that they are useful for the novice and can therefore assist in the teaching and training process until the user becomes and expert themselves.

Example of a common rule based expert system

Many useful expert systems use a rule-based approach where a set of rules are established and the user effectively moves from a starting point to some answer or output by answering a set of questions. Each next question is dependent upon the last answer or series of answers. There are many thousands of examples of such systems, and they are now widely used. shows a simple rule based system from the British Medial Association Family Health Encyclopedia (1997). Listed as interactive diagnostic charts, the program used a flow chart metaphor to assist the user to self-diagnose problems. The example in shows only the first of a large number of rule-based questions that eventually lead the user to a simple home remedy or advice to seek further expert help. More complex versions of this type of program are routinely used by the medical profession for education and training and as a continuous and updated reference.

Figure 1 - Example of a simple expert system (British Medial Association Family Health Encyclopedia)



An example of a residential valuation system

Valuation systems that are being proposed are usually more in the CPS rather than the ES mould. Most are probably better termed as automated or computer assisted valuation tools. The simplest use purely rule-based systems, sometimes implementing cost based methodologies. Future expert systems that utilise artificial intelligence, are likely to use hybrid techniques (McCluskey, 1999). The example discussed here had its foundation in 1992 (Rossini et al., 1992) with the design of a basic computer assisted appraisal system using Microsoft Windows. Since then it has progressed but is still clearly a “half way system” between CPS and ES, with future developments being in the ES area. The system uses a series of steps that the developers believe to automate a sound residential valuation practice with expert inputs and advice but with the option to override the system at any stage. Preliminary research using the (somewhat awkward) prototype system suggest that the accuracy of such a system would more than match the industry standards for **normal individual residential valuations**. (Rossini, 1999).

The system uses a seven-step process

Step 1. Collect and input details of the subject property.

Step 2. Find **"appropriate"** sales from the market place - using search and filter systems from the monthly updated sales database.

Step 3. Model the market using sales from Step 2. Test for any relationships and find the coefficients.

Step 4. Establish major value determinants and adjustments from the model in Step 3.

Step 5. Find **"appropriate"** number of the most comparable sales - using expert knowledge and value determinants from Step 4.

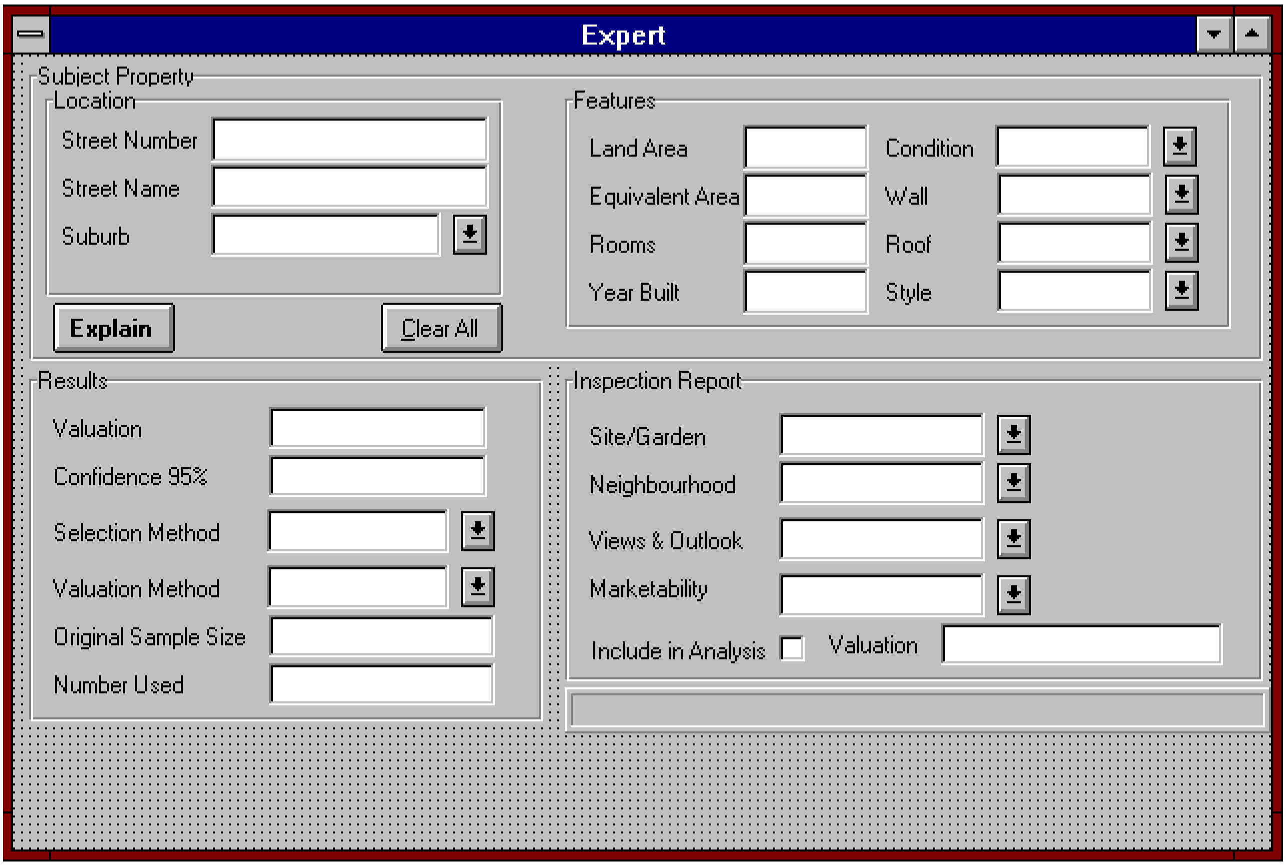
Step 6. Make adjustments to the most comparable sales to allow for differences between the subject and sale properties.

Step 7. Estimate value based on adjusted prices and relative comparability of each sale - using a weighted mean approach.

Step 1

The first step is to collect data about the subject property. For advanced or experienced users this data can be input directly. For the novice user or trainees, there is a rule-based system to allow for the user to be guided to the inputs. The prototype-input screen is shown as Figure 2. In the basic prototype this screen is used to input data, select methods and output the answer. The system will work with or without the data listed in the inspection report. This enable a valuation based on the "features" which are listed on the state valuation list however the result is less accurate in many locations.

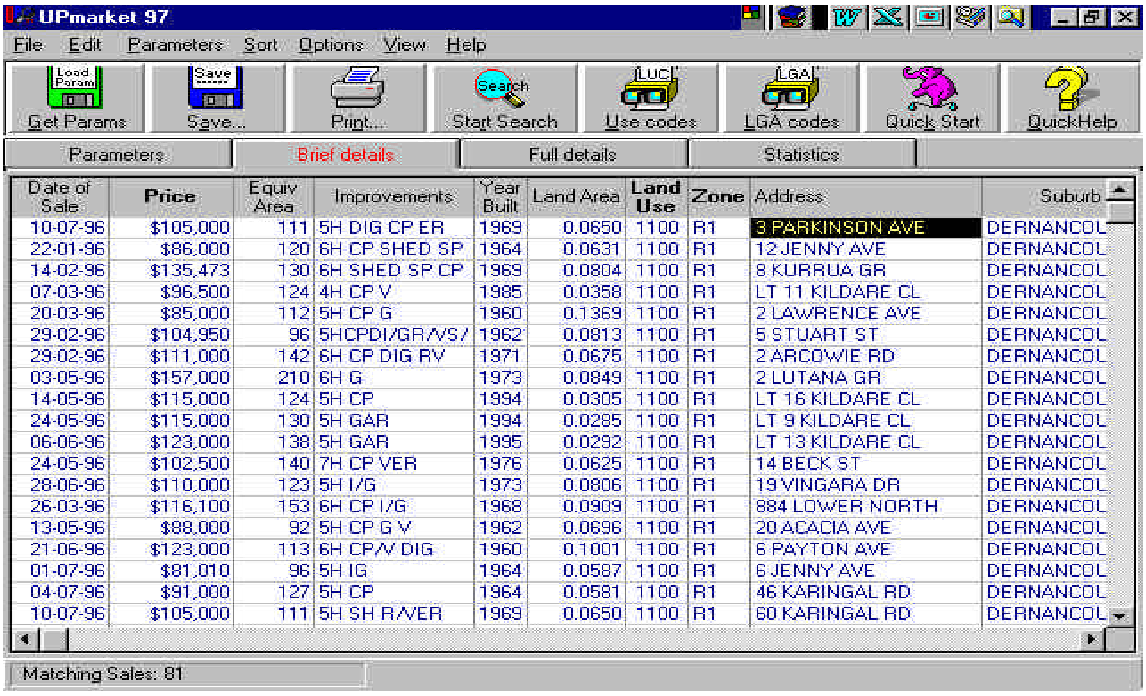
Figure 2 - Step 1 of the Valuation System - inputting the data



Step 2

The second step involves collecting sales data from the sales database. The data is updated monthly and the system utilises an existing search and filter system together with expert knowledge of the appropriate parameters to select the most sales set. These parameters can be over ridden by the user and the next version of the system will remember what parameters were effective in each location.

Figure 3 - Step 2 of the Valuation System - collecting sales data



Date of Sale	Price	Equiv Area	Improvements	Year Built	Land Area	Land Use	Zone	Address	Suburb
10-07-96	$105,000	111	5H DIG CP ER	1969	0.0650	1100	R1	3 PARKINSON AVE	DERNANCOL
22-01-96	$86,000	120	6H CP SHED SP	1964	0.0631	1100	R1	12 JENNY AVE	DERNANCOL
14-02-96	$135,473	130	6H SHED SP CP	1969	0.0804	1100	R1	8 KURRUA GR	DERNANCOL
07-03-96	$96,500	124	4H CP V	1985	0.0358	1100	R1	LT 11 KILDARE CL	DERNANCOL
20-03-96	$85,000	112	5H CP G	1960	0.1369	1100	R1	2 LAWRENCE AVE	DERNANCOL
29-02-96	$104,950	96	5HCPDI/GR/VS/	1962	0.0813	1100	R1	5 STUART ST	DERNANCOL
29-02-96	$111,000	142	6H CP DIG RV	1971	0.0675	1100	R1	2 ARCOWIE RD	DERNANCOL
03-05-96	$157,000	210	6H G	1973	0.0849	1100	R1	2 LUTANA GR	DERNANCOL
14-05-96	$115,000	124	5H CP	1994	0.0305	1100	R1	LT 16 KILDARE CL	DERNANCOL
24-05-96	$115,000	130	5H GAR	1994	0.0285	1100	R1	LT 9 KILDARE CL	DERNANCOL
06-06-96	$123,000	138	5H GAR	1995	0.0292	1100	R1	LT 13 KILDARE CL	DERNANCOL
24-05-96	$102,500	140	7H CP VER	1976	0.0625	1100	R1	14 BECK ST	DERNANCOL
28-06-96	$110,000	123	5H I/G	1973	0.0806	1100	R1	19 VINGARA DR	DERNANCOL
26-03-96	$116,100	153	6H CP I/G	1968	0.0909	1100	R1	884 LOWER NORTH	DERNANCOL
13-05-96	$88,000	92	5H CP G V	1962	0.0696	1100	R1	20 ACACIA AVE	DERNANCOL
21-06-96	$123,000	113	6H CP/V DIG	1960	0.1001	1100	R1	6 PAYTON AVE	DERNANCOL
01-07-96	$81,010	96	5H IG	1964	0.0587	1100	R1	6 JENNY AVE	DERNANCOL
04-07-96	$91,000	127	5H CP	1964	0.0581	1100	R1	46 KARINGAL RD	DERNANCOL
10-07-96	$105,000	111	5H SH R/VER	1969	0.0650	1100	R1	60 KARINGAL RD	DERNANCOL

Step 3

The third step is to analyse the market data. In this example an additive regression model is used. The system allows for a variety of different models that include logged regression models and various neural network models with genetic algorithms. The model building process is based on expert knowledge with standard tests being used for model validity. In Figure 3 only the land area, building area, building age and a style dummy variable are used. With different data, different appropriate models are found depending upon the location and the physical and economic environment.

Figure 4 - Step 3 of the Valuation System - modeling the data

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.986244
R Square	0.972677
Adjusted R Square	0.968774
Standard Error	5527.687
Observations	33

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regression	4	3.05E+10	7.61E+09	249.198	1.89E-21
Residual	28	8.56E+08	30555325		
Total	32	3.13E+10			

	Coefficients	*andard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-2627631	288667.5	-9.10262	7.35E-10	-3218940	-2036322
Land Area	690987.6	52798.42	13.08728	1.87E-13	582834.8	799140.4
Equiv Area	599.8755	32.88361	18.24239	4.46E-17	532.5164	667.2346
Year built	1327.624	146.5606	9.058533	8.15E-10	1027.408	1627.841
Conventional	-4750.27	2475.67	-1.91878	0.065259	-9821.46	320.9122

Step 4

Figure 5 - Step 4 of the Valuation System - quantifying the adjustments

Major Value Determinants
Land Area
Equivalent Building Area
Year of Construction
Building Style

Value Adjustments			
Land Area	$	69	Per Sq Metre
Equiv Area	$	600	Per Sq Metre
Year built	$	1,328	Per Year
Conventional	-$	4,750	If Conventional

The model of the market data is used as the basis for the adjustments for the system. This example using an additive regression model uses an additive adjustment method although other methods are available. The user can override the adjustments. In Figure 5 there is no adjustment for date of sale because the model of the market did not find any measurable impact of time on prices. If the user believes that there has been a very recent increase in prices then a suitable adjustment can be made.

Step 5

The next stage involves selecting the most comparable sales. This process uses a combination of expert knowledge and nearest neighbour techniques. The system attempts to find an appropriate number of comparable sales. This involves establishing the "jump" in a comparability rating eg if there are three quite comparable sales but the fourth sale is much less comparable, then only three will be selected. As with all parts of the system, the user can override the automatic system and select the most comparable sales.

Figure 6 - Step 5 of the Valuation System – select the most comparable sales

Address	SUBJECT	13 ACACIA AVE	1 CHERINGAR BLV	DRANGE GROVE C	1A TURNER TCE	47 BALMORAL RD	17 KARRI DR
Sale Price	**?????**	**$106,500**	**$116,500**	**$127,000**	**$108,000**	**$114,000**	**$113,000**
Land Area	**728**	**796**	**637**	**719**	**581**	**729**	**637**
Equiv Area	**143**	**136**	**136**	**136**	**145**	**148**	**150**
Year built	**1962**	**1960**	**1973**	**1984**	**1971**	**1965**	**1963**
Sale Date	Now	11-07-97	26-06-97	23-07-97	28-02-97	03-07-97	12-05-97
Zone	R1	R1	R1	R1	R1	R1	R1
Wall	BRICK	BRICK	BRICK	BRICK	BRICK	BRICK	BRICK
Roof	TILED	TILED	TILED	TILED	TILED	TILED	TILED
Style	CONVENL	CONVENL	CONVENL	CONVENL	CONVENL	CONVENL	CONVENL
Rooms	6	5	5	6	6	5	6
Condition	8	6	7	8	7	7	7
Improvements	6H DCP V	5H B/GAR CP	5H CP	6H CP	6H CP	5H CP SH R/R	6H CP V SP

Step 6

Step 6 utilises all the information collected to this point, to adjust the most comparable sales using the appropriate method and the selected adjustment factors. Figure 7 shows how these adjustments are made using the additive adjustment method used in this example.

Figure 7 - Step 6 of the Valuation System - applying the adjustments

Address	SUBJECT	13 ACACIA AVE	1 CHERINGAR BLVD	ORANGE GROVE C	1A TURNER TCE	47 BALMORAL RD	17 KARRI DR
Sale Price	**?????**	**$106,500**	**$116,500**	**$127,000**	**$108,000**	**$114,000**	**$113,000**
Land Area	728	796	637	719	581	729	637
Equiv Area	143	136	136	136	145	148	150
Year built	1962	1960	1973	1984	1971	1965	1963

Adjustments							
Sale Price		$106,500	$116,500	$127,000	$108,000	$114,000	$113,000
Land Area		-4692	6279	621	10143	-69	6279
Equiv Area		4200	4200	4200	-1200	-3000	-4200
Year built		2656	-14608	-29216	-11952	-3984	-1328
Adjusted Sale Price		**$108,664**	**$112,371**	**$102,605**	**$104,991**	**$106,947**	**$113,751**

Step 7

The final step involves weighting the adjusted sales prices on the basis of comparability and calculating a weighted average. A mathematical "nearness" calculation is uses to estimate these weights but expert knowledge and a rule-based system will assist the user to override these with what may well be more appropriate subjective value. This can be particularly useful when trying to allow for some aspects of comparability that are difficult to quantify. For example if the subject property has an outstanding view, then sales with a similar view may be considered most comparable since other more quantifiable factors are likely to be adjusted for.

Figure 8 - Step 7 of the Valuation System - weighting the adjusted sales and estimating a value

Adjusted Sale Price	**$108,656**	**$112,383**	**$102,613**	**$105,009**	**$106,949**	**$113,761**
Comparability Weight	20.4%	9.4%	6.9%	10.1%	33.4%	19.9%
Weighted Mean Value	**$108,666**					

Throughout the process the system will offer advice about the appropriateness of the outcomes. In some situations the system will not ever provide suitable outcomes and the user will be advised of this.

This system is designed overall to take the user through the valuation process. Users should become better at valuation through the process. One of the major advantages of the system, and a probable reason for its inherent accuracy compared to manual valuations, is the requirement for the user to follow all the steps. Using this system the user must consciously decide to take a shortcut such as ignoring recent sales and what this implies about the market place.

Conclusion

This paper has examined some of the current issues regarding the use of expert systems and artificial intelligence for practitioners in the real estate industry. The use of AI and ES have been suggested for a wider range of uses than is currently being research to any great extent. An important concept of the use of ES is that it is the overall system that is important rather than the reliance on new and "better" techniques. A valuation system that is approaching an expert system as examined as an example of how a system can work and how it can be used as a useful tool in teaching and training.

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