Artificial Neural networks and Computer Assisted Mass Appraisal

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Abstract

Artificial Neural Networks still have a limited application in CAMA setting. The reasons are partly (and wrongly) due to 'econometric' concerns, and partly (and justifiably) due to 'political' concerns. This article suggests that ANN could be used more widely and extended to data-poor environments.

This article has two objectives:

1) To illustrate one application of ANN to the Taipei residential market by the method of back-propagation. The study is based on 5528 sales and 11315 auction sales of homes in Taipei city and Taipei County.

2) To briefly illustrate – on Taipei markets again - how satisfactory results can also be obtained in an 'information' poor environment;

Keywords: artificial neural network (ANN), Computer Mass Appraisal.

Introduction

Artificial Neural Network (ANN) procedures are scions of a large family of computer programming techniques described as soft computing. The other members of the family include: expert systems, fuzzy logic, genetic algorithms, genetic programming and other evolutionary systems.
Soft programming options have become popular in the ‘hard sciences’ circles but their application to property issues are still limited with the exception – in the last 15 years – for artificial neural network treatments of mass appraisal, mortgage lending or property pricing trends. Still ANN is still very far from being mainstreamed in property research or teaching.

This article illustrates the use of artificial neural network (ANN) technology to real estate appraisal for the city of Taipei (Taiwan). It then discusses the various merits and demerits of this technique for the purpose of mass appraisal in a information-rich market and then, briefly, evokes how the same instrument could be applied to information-poor mass valuation situations.

2. Literature Review

Mass appraisal usually relies on multiple regression analysis and various other forms of ‘hedonic analysis’ approaches. The methodology has been in place for over 40 years now and is widely applied in various countries and large cities. Notably – to keep the comparison close to home – Hong Kong has been using various MRA based mass appraisal for over 20 years (Yu Shi Ming and Kevin Siu, 2003)

Multiple regression analysis (MRA) is still widely used despite its econometric and statistical weaknesses. These weaknesses are well recognised and some of them have been corrected through various refinements and adjustments *(references to insert here).* However basic issues of multicolinearity, spatial discontinuities, non-normality of most variables, inclusion of outliers, non linearities and the choice of aposite functional forms are still a handicap in using MRA for mass appraisal (Brunson et al., 1994; Do and Grudnitski, 1992 and a*dditional references to add here).*

Various non-parametric solutions have been applied to reduce MRA-Hedonic treatments restrictions. For example Pace (1995), Anglin (1996), Gencay (1996), Thorsnes (1998), Pavlov (2000), Clapp (2004) and Okmyung(2004). Recently this approach has been also applied to the Taipei residential market: Lin, V.C.C & Huang, Chiu C.Y (2005)

Some studies have demonstrated the superiority of ANN over MRA in predicting housing values (Tsukuda and Baba, 1990; Do and Grudnitski, 1992; Tay and Ho, 1997/1992; and Huang, Dorsey and Boose, 1994;). Other studies (Allen and Zumwalt ,1994; and Worzala, Lenk and Silva, 1995), however, have noted that ANN was not necessarily superior.

The Do and Grudnitski (1992) article concludes that a neural network model performs better than a multiple regression model for estimating the value of U.S. residential property. Eight attributes were used as independent variables (age, number of bedrooms, number of bathrooms, tool square footage, number of garages, number of fireplaces, number of stories, and lot size) and the selling price was used as the dependent variable. Their neural network model was formed with three nodes in the hidden layer. W.J.McCluskey, K. Dyson, S. Anand and D. McFall (1997) also indicate that neural networks provide superior predicative ability in comparison to the multiple regression in Northern Ireland. Results of their research are summarized in Table 1.

It is important to note that the Do and Grudnitski (1992) neural network model resulted in having almost twice the number of predicted values within 5% of the actual sales price than their regression model had predicted (40% vs. 20%) on a test sample of 105 houses. Moreover, the mean absolute error resulted from their neural network model was much lower the mean absolute error from their regression model (6.9% vs. 11.3%). These results led the researchers to conclude that the neural network model was superior to the multiple regression model. Tay and Ho (1992) compared the performances of neural networks and traditional regression analysis using a very large sample of data from residential apartment properties in Singapore. They reported a neural network mean absolute error of 3.9% and a regression mean absolute error of 7.5% when analyzing their entire sample. The results significantly improved for both models (-.2% and 0%, respectively) when data that was considered to be outliers was removed.

Evans et al. (1991) tested neural networks for accuracy in valuation when estimating residential property prices in England and Wales. They investigated the effects on the average prediction error when outliers in both the training data and the test data were removed. They concluded that when outliers are removed from the data sets, neural network models work well to value property. The average absolute error for their neural network models ranged between 5% and 7%.

Not all studies have reported successful or favorable results from the use of neural networks. Allen and Zumwalt (1994) review a number of these studies and present an example of what can occur when different neural network models are used for predicting stock price movements. They conclude that optimal neural network models depend upon the specific data sets and time periods involved. In addition, they found that the same data combined with different model settings (e.g., model tolerance, number of hidden nodes, number of hidden layers, etc.) can produce opposite results. Thus, they strongly recommend caution during the development and use of neural network models in finance-related fields.

This condemnation by inference is unwarranted. Allen and Zumwalt review ANN predictions of stock prices movements. However, stock prices movements are known to be random walks. Random walks, by their nature, can't have predictive structures. In contrast with the pricing of equity shares, the pricing of residential properties is structurally determined by a measurable number of indicators. Otherwise why should we worry about valuation models at all?

Finally, it should also be noted that the reported literature examples (see table 1) were too small to provide robust results from training runs. By contrast, one of our Taipei market treatment is based on over 16 000 transactions. A large population size is essential to ANN particularly when the spatial correlation issues can be reduced by subdividing the sample is homogenous sub-markets.

Table 1. Summary of literature Results

Authors	Sample time/Country	Sample	Results (MAPE)
Do & Grudnitsk	1992 /U.S.	105 residential properties	1. ANN (6.9%) 2. MRA (11.3%)
Tay & Ho 1997	1991/Singapore	Training Sample 833 Test Sample 222 Total 1055	1. ANN (3.9%) 2. MRA (7.5%)
Evans	1992 /England & Wales	34	ANN1 3.48% ANN2 5.03%
McCbuskey	1997 /Northern Ireland	Training Sample 378 Test Sample 138 Total 416	ANN1 15. 7% ANN2 7.75%
Stanley McGreal, A lastair Belfast Dylan McBurney & David Patterson 1998	1992-1993 /England	1992-1994 1026	ANN 10% ANN 15%
Lenk at al.	1997/		ANN 15%
Worzala (1995)	1993-1994/ US	Training ample 217 Test Sample 71 Total 288	ANN 13.2%
Borst 1992	1992 /US	Training Sample 137 Test Sample 43 Total 180	ANN1 8.7% ANN2 12.4%
Allan Din Martin Hoesli & Andre' Bender (2001)	1978-1992/ Switzerland	285	ANN1 11% ANN2 15%

Note: ANN means artificial neural network, MRA means multiple regression analysis

3. Methodology and Data

3-1 The concept of neural network system

A neural network system is an artificial intelligence model that replicates the human brain's learning process. The brain's neurons are the basic processing units that receive signals from and send signals to many nervous system channels throughout the human body. When the body senses an input experience, the nervous system carries many messages describing the input to the brain. The brain's neurons interpret the information form these inputs by passing the information through synapses that combine and transform the data. A response is ultimately created when the information processing is complete. Through repetition of stimuli and feedback of responses, the brain learns the optimal processing and response to the stimuli. The brain's actual leaning path is still somewhat of a chemical mystery; what is known is that learning does occur and reoccur through the repetition of the input stimuli and the output response(s).

Artificial neural networks were developed utilizing this `black box' concept. Just as a human brain learns with repetition of similar stimuli, a neural network trains itself with historical pairs of input and output data. Neural networks usually operate without an a priori theory that guides or restricts the relationship between the inputs and the outputs. The ultimate accuracy of the predicted output response, rather than the description of the specific path(s) or relationship(s) between the inputs and the output response, is the goal of the model.

In an artificial neural network, nodes are used to represent the brain's neurons and these nodes are connected to each other in layers of processing. Exhibit 1 illustrates the three types of layers of nodes: the input layer, the hidden layer or layers (representing the synapses) and the output layer. The input layer contains data from the measures of explanatory or independent variables. The data is passed through the nodes of the hidden layer(s) to the output layer, which represent the dependent variables(s). A nonlinear transfer function assigns weights to the information as it passes through the hidden layer nodes, mimicking the transformation of information as it passes through the brain's synapses. The goal of the artificial neural network model is that the effect of these the relationship that really exists between the input independent variables and the output, or dependent variable(s).

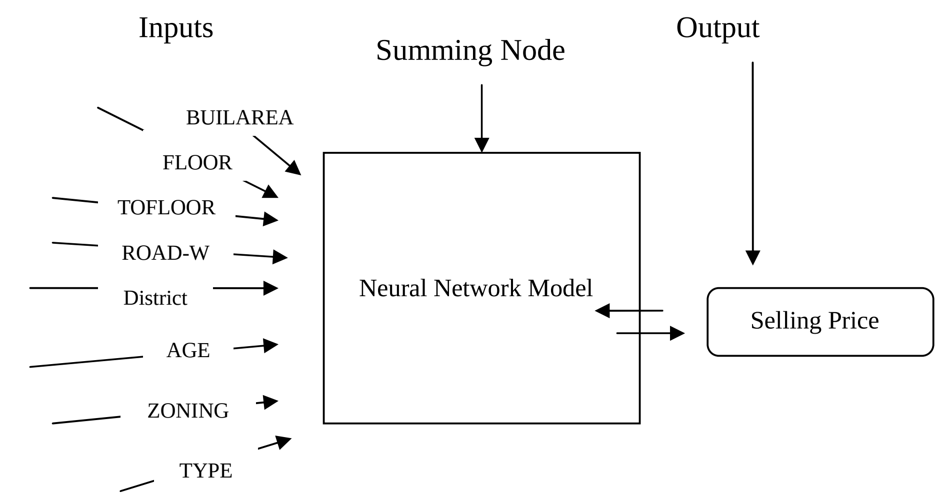


Figure 1. The processing elements of artificial neural network in selling price model..

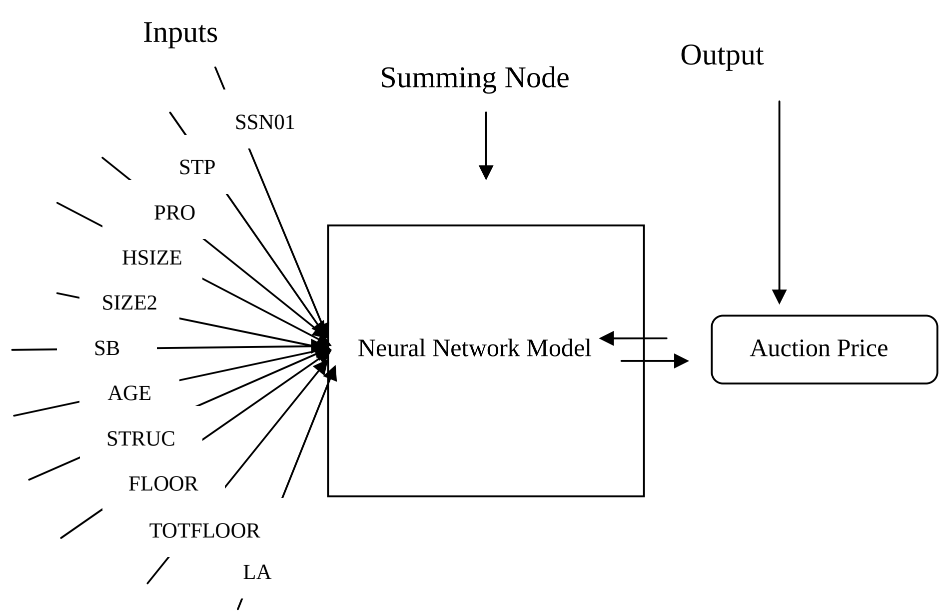


Figure 2. The processing elements of artificial neural network in auction price model..

3-2 ANN model specification

This method of error correction is usually referred to as back-propagation. The objective of the neural network is to find the set of weights for the explanatory variables and minimize the error between the neural network output and the actual data (Allen and Zumwalt, 1994).

Three criteria were used for comparing the performance of the different models: (1) the mean absolute error between the predicted and actual selling price of the samples, including: RMSE, MAPE , and (2) Assessment Ratio in the sample whose ratio was chose to the actual selling price and (3) Hit Ratio in the sample between the predated and selling price of the sample. The best model for predicting actual sales prices was determined to be the one that resulted in the lowest mean absolute percentage error and/or the highest percentage of predicted sales price with absolute error below 5% of the actual sales price.

The data model with a smaller MAPE is deemed superior. This error measurement attempts to produce a single number that represents the total error for all properties. This error measurement fails, however, to provide information as to how the error deviates between the properties. For example, if a model provides extremely accurate results for 90% of the properties tested while providing horribly inaccurate results for 10% of the properties tested, the MAPE value for this model may be comparable to another model with unacceptable results (*i.e.*, a large standard deviation in error, but with a comparable MAPE). The MAPE is defined as (2).

1. Root Mean Squared Errors(RMSE) is defined as:

$$RMSE = \sqrt{\sum_{i=1}^{n} e_i^2 / n} \qquad e_i = y_i - \hat{y}_i \tag{1}$$

2. Mean Absolute Percentage Errors(MAPE) is defined as:

$$MAPE = \frac{\sum_{i=1}^{n} |e_t / y_t|}{n} * 100\% \qquad (y_t \neq 0) \quad e_t = y_t - \hat{y}_t \tag{2}$$

3. Assessment Ratio(AS-Ratio) is defined as:

$$AS \quad Ratio = \hat{y} / y \tag{3}$$

4. Hit Ratio is defined as:

$$Hit\ Ratio\ Range = y - y(\alpha) \leq \hat{y} \leq y + y(\alpha) \tag{4}$$

Y : Selling Price of sample

α : confidence level at 5%、10%、20%

$$Hit \quad Ratio = \frac{n}{N} \times 100\% \tag{5}$$

n : No. of Hit Ratio

N : Total samples

3-3 Data

In this paper, we study the possibility of using artificial neural networks to construct real estate pricing models. We built two model : (1) The data used in this study is from the Brief information Brochure Concerning Real Estate Transaction Prices in Major Urban Areas of Republic of China. The sample consisted of 5288 residential properties sold in the Taipei city and Taipei County from 2001 to 2003, and (2) the data used form Enforcement court of Republic of China. The sample consisted of 11315 residential properties in Taipei City and Taipei County from 2001 to 2003. For each of the analyses, the relevant data set was separated into two separate samples. One data set (the training sample) was used to train both the neural network models and create the regression models, and the other data set (the test sample) was used to test the models' performance.

The variable-set were as follows: price, age, type, building structure, no. of floor, land zoning, land area, building floor area, selling price. (see Table 2) The sample was divided on a 2:1 basis between training data and testing data. This resulted in two cases. Case one was transaction price model. Case two was auction housing price model.

Table 2. Variables Description

Variables	Symbol	Mean		
● Selling Price		2001	2002	2003
1. Building Type (dummies)	TYPE	0.481	0.550	0.508
2. Building Structure (dummies)	STRUC	0.046	0.076	0.079
3. No. of Floor	TOTFLOR	6.507	6.696	6.947
4. Floor level	FLOOR	5.260	5.741	5.668
5. Land Zoning	ZONZING	0.117	0.163	0.170
6. Land Area (per ping)	LANDAREA	29.486	28.565	28.269
7. Total Building Floor Area (per ping)	BUILAREA	106.383	105.806	106.145
8. Building Age (years)	AGE			
9. Selling Price	PRICE	636.37	635.56	621.32
● Auction Price				
1.Freguency of Action	SSN01	3.094	2.955	2.695
2.Action price	STP	511.901	489.746	495.090
3.Transation promise (dummies)	PRO	-	-	-
4.Building Area	HSIZE	32.238	31.327	31.412
5.Land Area	SIZE2	26.549	26.733	25.443
6.Building Type (dummies)	SB	-	-	-
7.Building Age (years)	AGE	16.170	15.951	17.402
8.Building structure (dummies)	STRUC	-	-	-
9.No. of Floor	FLOOR	4.168	4.457	4.496
10.Total Number of Floor	TOTFLOOR	7.695	8.037	8.2763
11.Administrative District (dummies)	LA	-	-	-

Table 3. Neural Network Structure in selling price model

	Taipei City				Taipei County			
	Training sample	Test sample	Hidden Layer	Learning Cycle	Training sample	Test sample	Hidden Layer	Learning Cycle
2001	500	215	5	750	600	215	4	400
2002	1088	388	5	750	600	266	4	400
2003	700	352	5	500	600	289	4	400

Table 4. Neural Network Structure in auction price model

	Taipei City				Taipei County			
	Training sample	Test sample	Hidden Layer	Learning Cycle	Training sample	Test sample	Hidden Layer	Learning Cycle
2001	422	227	3	1000	1123	605	3	1000
2002	734	395	3	1000	2212	947	3	1000
2003	805	433	3	1000	2218	1194	3	1000

5. Empirical Results

Significantly different experiences were encountered with each of the neural network packages used. A neural network application has been overtrained' when instead of learning the training set, the model actually 'memorizes' the training set. While an 'overtrained' model performs well with the training set, it performs poorly when it is used to predict the test data set. While the computer run time for all of the multiple regression models could be measured in seconds, the running times for the neural networks varied from thirty seconds to several hours. The length of processing time was directly related to the threshold chosen during the development of the model for the acceptable level of individual house error during training of the neural network.

The neural network results that are reported in this paper are the 'best' results that were obtained after many different trails. The 'best' results were defined as the model that predicted the highest percentage of houses with average absolute errors below 5%. The problem was to determine the optimal number of hidden layers and the optimal number of nodes to use in each hidden layer for each of the models for each of the cases. The only method available to do this is through trial and error.

The results of the test for the percentage of properties within less than a 15% MAPE are presented in Table 5. The best performing ANN occurred in 2003 at Taipei City. (using the MAPE evaluation criterion.) Table 6 was the performance of the auction house in Taipei market. The results were better than the selling price model.

Table 5. Comparison of Predictive Power of each in selling price model

		RMSE	MAPE	AS Ratio Mean	AS Ratio Covariance	Hit Ratio		
						5%	10%	20%
2001	T.C.	115.04	0.149	1.019	0.206	22%	45%	72%
	T.H.	57.51	0.136	1.035	0.170	24%	48%	76%
2002	T.C.	123.58	0.168	1.053	0.207	17%	36%	66%
	T.H.	55.06	0.138	1.037	0.170	23%	45%	77%
2003	T.C.	116.60	0.157	0.975	0.206	19%	38%	69%
	T.H.	53.34	0.130	1.019	0.164	25%	47%	78%

Note: T.C.=Taipei City, T.H.=Taipei County

Table 6. Comparison of Predictive Power of each in auction price model

		RMSE	MAPE	AS Ratio Mean	AS Ratio Covariance	Hit Ratio 5%	10%	20%
2001	T.C.	44.59	0.057	1.018	0.071	58%	85%	99%
	T.H.	73.74	0.285	1.151	0.385	37%	61%	73%
2002	T.C.	43.47	0.068	1.00	0.082	38%	82%	99%
	T.H.	80.79	0.181	1.043	0.318	33%	59%	76%
2003	T.C.	67.97	0.083	0.984	0.101	33%	64%	97%
	T.H.	71.42	0.168	1.022	0.293	33%	60%	78%

Note: T.C.=Taipei City, T.H.=Taipei County

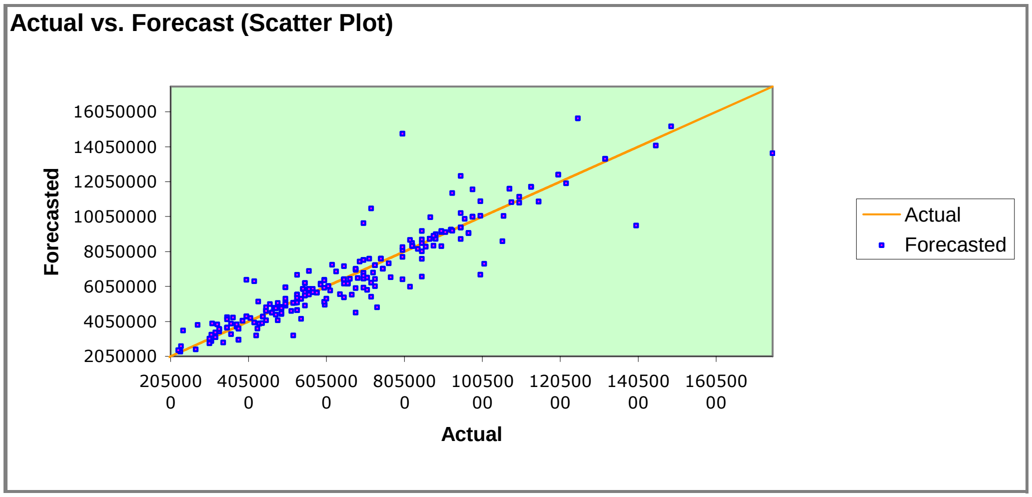
6. Taipei again

Independently, one of the author (Fischer) - mostly interested in the efficiency aspect of ANN treatments - ran a very `economical' ANN analysis on a much smaller set of Taipei apartment prices (300 data points).

The information – readily available from public sources – provides selling prices and characteristics of 300 Taipei high rise apartments. The characteristics available are floor areas, structure age and location variables: kilometric distances to the following urban features or services (main roads, parks, schools, sewage farm, car park, power station, subway station (MRT) and hospitals.

These variables are available and do not require additional treatments. Most of the distance variables are eminently collinear, but no effort was invested in trying to reduce their numbers in this first 'quick and dirty' analysis. The outcome of this treatment was surprisingly satisfactory in view the limited number of observations (300 units) despite the fact that, unfortunately, two crucial information are not provided: storey level and view. It could not be ascertained whether these information will be collected in the future.

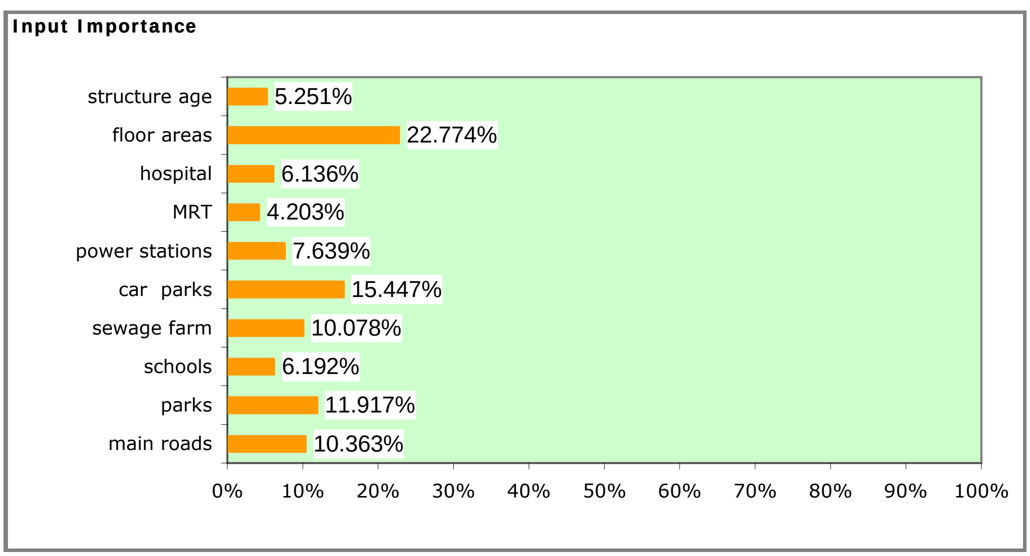
The results are depicted below (the axis of the scatter diagram are in Taiwan dollars).



Summary

	Training set	Test set
# of rows:	250	51
CCR:	n/a	n/a
Average AE:	447988.8008	1044668.153
Average MSE:	5.35862E+11	3.41622E+12
Tolerance type:	Relative	Relative
Tolerance:	10%	30%
# of Good forecasts:	202 (81%)	46 (90%)
# of Bad forecasts:	48 (19%)	5 (10%)

RSquared: 0.8504
Correlation: 0.9311



However, a drawback of ANN can be observed in the above graph of the inputs' relative importance: no signs are attached the calculated weights. Thus the interpretation of the relative weight requires the simultaneous running of a multiple regression. The task is not a major imposition on the analyst since - the ANN program used here being Excel based - it takes only a few more clicks to generate the regression results summarised below.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.852576576
R Square	0.726886817
Adjusted R Square	0.71740372
Standard Error	1396462.878
Observations	299

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	10	1.49477E+15	1.49477E+14	76.65078673	3.68818E-75
Residual	288	5.61631E+14	1.95011E+12		
Total	298	2.0564E+15			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*
Intercept	1356470.555	533125.0255	2.544376066	0.01146955	307153.8963
main roads	-18382.41233	196385.677	-0.09360363	0.92548911	-404916.0631
parks	-2580.594678	1950.915384	-1.322760946	0.186964239	-6420.459465
schools	3398.863493	1727.594106	1.967397018	0.050096984	-1.451984444
sewage farm	1048.830727	325.9720804	3.217547731	0.001440436	407.2402601
car parks	-476.2222712	320.0013512	-1.488188314	0.137795344	-1106.060926
power stations	-842.7575507	279.74186	-3.012625821	0.002820055	-1393.355965
MRT	-375.3003611	161.6763855	-2.321305984	0.020968282	-693.5178833
hospital	-116.872124	270.4214557	-0.432185101	0.665930294	-649.1257696
floor areas	47419.64415	1862.888372	25.45490372	1.10422E-75	43753.03743
structure age	-36913.982	18657.7533	-1.978479477	0.048827262	-73636.87141

We can now confirm that the signs are intuitively satisfactory and when they are not (for example distance to parks) the coefficients are not significant. The intriguing result here is that the distance to subways stations is highly significant and negative. This fact may not be so intriguing in Taipei where metro station have a tendency to attract a large number of noisy commercial activities.

These results were later much improved by reducing the number of distance variables however – the exercise merely demonstrates that even with a small data base and few critical variables we can obtain satisfactory results. The whole procedure took a few minutes to run (once the data are provided), it did not require heavy thinking about functional forms and mostly, it did not violate any statistical rule (contrary to MRA that commonly violate most of the sacrosanct statistical recommendations).

This attempt was not meant to demonstrate the 'superiority' of ANN treatments as such, but it was designed as the first step in a more policy oriented research to generate economical data based on property self-appraisal as advocated by Fischer (2002). Self-appraisal by homeowners can be administered through simple questionnaires on estimated values and a maximum of probably 10 structural information about the property. This information is well known by the property owner and then the appraising authorities simply need to match this structural information with simple location information based on homogeneous housing sectors. Mapping the property data can also be greatly simplified by the use of aerial photography and confirmed by hand-held GPS plotting and photography of every property.

In such a 'light and cheap' surveying and valuing system, the ANN calculations would then be used mostly to check and validate the results compiled from the households' self-valuation questionnaires. The full data would be used as the 'training' database and the weights would then be used then verify smaller sample of valuations. Random in-vivo inspection would complete this economical mass-appraisal system.

It is submitted that this 'light and cheap' approach is a reasonable alternative to the 'heavy duty' traditional mass surveying and appraising that has been promoted by international institutions (notably the World Bank) in their laudable efforts to promote market value based property taxation.

5. Conclusions

This research investigated the merits of applying neural network technology to the problem of real estate appraisal. Significant problems were also encountered during the development and implementation of the neural network models.

Furthermore, the results found in this research could be a function of the specific data characteristics of the sample used. It may be possible that neural networks will do a much better job than multiple regression if the nonlinear relationships between the variables are greater. Especially, no matter what the RMSE, MAPE ,AS Ratio & Hit Ratio, the performance of Taipei county was better than Taipei city.

Therefore, continued research in this area is important and necessary before the final verdict on the use of neural networks in real estate appraisal can be decided.

Finally, it is necessary when applying the neural network technology to real estate appraisal. This warning is primarily due to two experiences. First, Proper settings for the models are not obvious and it takes several iterations to find the set of parameters that best fit an application. Second, even when the same model (same number of hidden layers and same number of hidden layers) with the same data was re-estimated with the same software, exact results are not replicated. This is due to the fact the every time the neural network model initiates training, the software randomly generates the initial weights for each of the nodes in the hidden layer. Hence, the ANN is recommended when there is sufficient sample data set/ or when there is no theoretical basis for the data specification. The first appearance of ANN models in the property valuation field was not well received. The often quoted criticism was that ANN was un-competitive with multiple regression treatments and much too fiddly. (Worzala, Lenk and Silva,). And the article concluded that 'Any appraiser that uses this new technology should do so with caution'. This conclusion was reached despite the fact that the observed performance of ANN was (marginally) better than the results of multiple regressions applied to the same data set.

The main demerits of ANN were listed as:

- ANN is difficult to use and is sensitive to data fiddling;
- ANN processes are black boxes: their lack of computational transparency precludes full understanding and control;
- The ANN results are not consistent when different computational packages are used;
- Results can be inconsistent between runs of the same software model;
- Computations are can have very long run times.

These criticisms though formulated over 10 years ago are still partly true. However it should now be recognized that:

- Simple and transparent ANN models are now available and are even now offered as Excel macro add-ins;
- The computational processes have been improved and standardized to a greater extent;
- The available software are more user friendly and time efficient;
- The coefficient variability between runs is not such a major issue and is not significantly different from the variability resulting from adding or deleting variables in traditional multiple regression models.

ANN applications to mass appraisal however may still have `political demerits' mostly because of their relative opacity and the difficulties any tax administrator would have to explain the results to their disgruntled taxpayers. This issue should not be neglected however, the same cognitive barrier has handicapped (and probably still does…) the application of MRA to mass appraisal and did not preclude is widespread usage.

Finally we submit that ANN can be used to facilitate the implementation of questionnaire based economical mass appraisal systems in information-poor market conditions.

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