

Geo-Information Neural System For Single-Property Valuation

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Abstract

An Automated Valuation Model (AVM) named Geo-Information Neural System (GINS) is developed as an integrating technology in the valuation of single-property. GINS integrates Geographical Information System (GIS) technique and computing intelligent Artificial Neural Networks (ANN). It covers the establishment of a GIS database management system, GIS location measurements, spatial queries and thematic mapping. 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. A sample of 100 sales of detached houses in Damansara Heights, Kuala Lumpur is trained. The model is built on a GIS platform, which will allow for GINS automation as well as the conduct of interactive valuations. A graphical user interface is developed for seamless integration and user interaction. The results indicate that GINS provides an efficient AVM tool that provides superior residential property valuations, while accuracy is improved by minimising the influence of subjective judgements. The technique may be used to check valuations generated by more traditional methods as well as further improve the overall quality of single-property valuations.

Keywords: single-property valuation; automated valuation model; geographic information system; artificial neural networks.

Introduction

The purpose of this paper is to demonstrate the potential of computer modelling artificial neural network and GIS to improve the accuracy of value estimation for residential property. Property 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 and communication technology. Technological progress is continuing at a rapid pace and leading to a wide range of new applications.

Technology is having profound effect on the profession, as well as influence on the property 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 automated valuation that allows clients to get faster and better results. Advancement in information technology changes how the process is carried out and leads to more analytical applications within the valuation profession.

Regression analysis and other advanced statistical techniques have been used to automate valuation with varying degrees of success (Wyatt, 1996). Automated valuation modelling (AVM) is one of the new techniques in assessing single-property value (Waller, 1999; Robbins, 2001). Based on computing model, it is recognised as a new valuation tool in the 21st century (Waller *et al*, 2001). AVM is able to carry out automated valuation process, either in personal computers or more integrated systems such as on-line over wide area network and the internet. Robbins (1998) reported the advantages of AVM in property valuation process; "AVMs are used to reduce the time and costs associated with loan underwriting and help the valuer prepare more accurate and supportable valuation. The objective should not be to replace the valuer

but rather to increase the valuer's efficiency in rendering an opinion of value."

Among the AVM techniques are statistical-based hedonic pricing models such as multiple regression (MRA) and price-time indexing and artificial intelligence-based such as artificial neural networks (ANN), expert systems and case-based reasoning (Waller *et al*, 2001). Empirical analyses show that these techniques have proven their successes in producing reasonably and acceptable valuation of single-property. MRA is the most popular quantitative technique in property valuation. It has been applied in various residential property valuations to assist valuer in statistical analysis and complement the traditional sales comparison approach.

An alternative to multiple regressions is intelligent-based ANN. Similar to MRA, ANN models the relationships between property attributes and sales price. The main difference is in its structure. ANNs are distributed arrays of highly interconnected processing elements. Each connection has an associated strength or weight. Processing at each node involves a weighted sum of each connection forming a single input to a non-linear transfer function. The output from each node becomes the input to successive nodes (Lewis, 1999). Many empirical researches have approved that ANN is unique by its model structure and algorithms that are not only intelligent, but can emulate comparison approach and can be applied to prediction and regression tasks in valuation analysis.

A number of renowned valuation firms have adopted more advanced database systems and analytical techniques such as Geographic Information System (GIS) that allow for not only easy, but more efficient and effective management of spatial data (Almond *et al*, 1997). This is true as the greater availability of data today leads to a new set of methods for analysing properties. The ability to apply more advanced tools to analyse data allows for that

quicker response. Those methods tend to be based on quantitative analysis as well as GIS (Mattson-Teig, 2000). GIS uses digital technology, which combines hardware and software to meet user needs in handling spatial data to produce graphical output. GIS-based automated appraisal systems – on desktop computers and over the internet will inevitably and profoundly change the appraisal industry (Castle, 1998).

In this paper, we highlight how ANN and GIS technology provide the valuation profession with new technique. The aim is to present the development of an AVM named Geo-Information Neural System (GINS). The following section reviews the relevant research in the literature about a new quantitative method in single-property valuation using GIS technology and ANN computing model. Data and methodology for the development of GINS are described in Section 3 and GINS implementations in single-property valuation are discussed in Section 4. We conclude the paper by summarising the results and conclusion.

Automated Valuation Model (AVM)

Valuation is the process of assigning a value to a property at the date of valuation for specific purposes. Valuation exists as a field because there is uncertainty on the part of potential buyers, sellers, investors and others. This stems in part from the complex nature of the product (the real estate itself), and from the uninformed, imperfect, complex nature of the real estate market (Kinnard Jr., 2001).

The sales comparison approach is the most common method in single-property valuation especially for residential (Ismail, 1997). It is a method of estimating the market value of a subject property by analysis of sales of similar properties. Market value is the estimated amount for which a property should exchange on the date of valuation between a willing buyer and a willing seller in an arm's length

transaction after proper marketing wherein the parties had each acted knowledgeably, prudently and without compulsion (International Valuation Standard, 2003).

The philosophy is based on the existence of direct relationships between market value of a subject property and selling prices of comparison properties in the market represent competitive investment alternatives. Valuation factors such as physical characteristics, location, quality and other economic factors are considered in the comparable analysis. These factors affect the supply and demand of property and expressed in valuation models. In practice, valuers often rely on past transaction data to arrive at a market value. Adjustments are made for any differences using comparison unit and become the basis for comparison. Using AVM, valuers can produce valuations that take into account more economic factors than usually are considered in conventional single-property valuations.

AVM is a computer program that utilise relevant property information to calculate a value for a specific property. The sales comparison models in AVM generally have the following form:

$$Y = f(X_1, X_2, X_3, X_4, X_5, \dots, X_n) \quad [1]$$

where Y is estimated sale price; f is 'a function of' and $(X_1, X_2, X_3, \dots, X_n)$ are location and property characteristics. Models can be in the form of additive, multiplicative or hybrid. ANN modelling may be used to calibrate the models.

Traditionally, automated valuation is commonly used to estimate the value of residential property in computer-assisted mass-appraisal (CAMA), mostly for statutory purposes such as rating and taxation (O'Rourke, 1998; Rossini, 1999). However, AVMs are now getting wide acceptance as an alternative to estimate the value of single-property (Robbins, 2001; Waller *et al.*, 2001). The important aspects of AVM are quantitative-based analysis, consistency,

speed, ease of use and reasonable accuracy (Valentine, 1999). Although AVM may not provide the most accurate estimate of an individual property value, it may provide better indication and objective justification of the value.

Artificial Neural Networks

Artificial Neural Network (ANN) is a system of a massively distributed parallel processing

that has a natural propensity for storing experiential knowledge (Gopal, 1998). An ANN is composed of a set of nodes and a number of interconnected processing elements. ANNs use learning algorithms to model knowledge and save this knowledge in weighted connections, mimicking the function of a human brain (Turban and Aronson, 2001). The nodes generally have three layers: input nodes, hidden nodes and an output node. Figure 1 shows a generic model of an ANN.

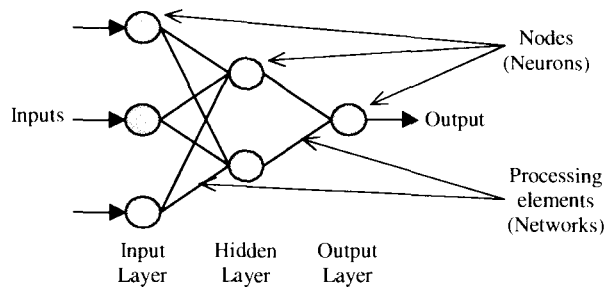


Figure 1: A generic ANN model

The most popular ANN model used in prediction and regression tasks is Multi-layer Perceptron (MLP) with Feed-forward Back-error Propagation (BP) type of learning algorithm, or simply as MLP-BP. The model has three layers interconnected to each other's nodes by the networks (Figure 1). Input nodes receive independent variables while hidden nodes run the learning process before passing on to output node (a dependent variable) for prediction. Each network carries weights (w_1 , w_2 , w_3). These weighted connections act as coefficients to the input

nodes. The hidden nodes (sum of the weighted inputs) compute network output (feed-forward) through a non-linear activation function, determining the difference (error) to the expected output (actual output). This error is distributed among the connections weights (back-propagation) in order to progressively reduce the error. These steps are repeated for many cycles in the learning phase until the desired error level is obtained and the system has achieved desired accuracy. The network is then verified with new data to verify the generalisation capability.

Figure 2 illustrates the MLP-BP model.

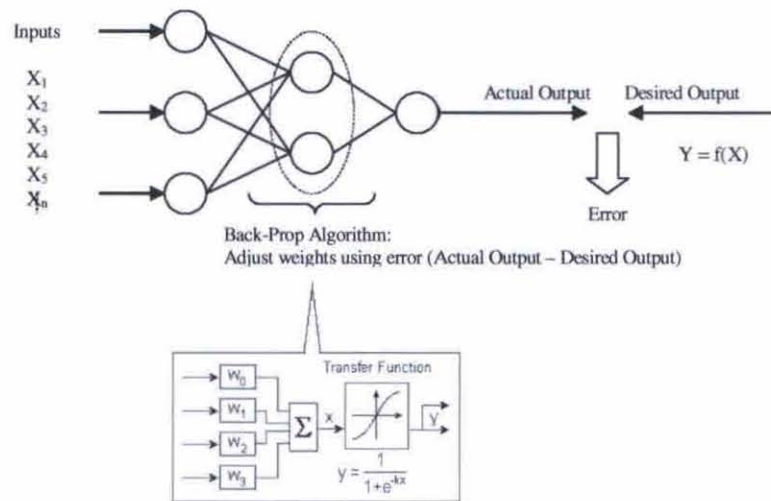


Figure 2: ANN MLP-BP model

ANN's back-error propagation learning algorithm has been investigated quite extensively to model residential property value by many researchers. For examples, refer to Borst, 1992; Evans *et al.*, 1992; Do and Grudnitski, 1992; Tay and Ho, 1992; Worzala *et al.*, 1995; McCluskey *et al.*, 1997; Kwon and Kirby, 1997; McGreal *et al.*, 1998.

Integration with Geographic Information System

Environmental Systems Research Institute (ESRI) (1990) defines Geographic Information System (GIS) as an organised collection of computer hardware, software, geographic data and personnel designed to efficiently capture, store, update, manipulate, analyse and display all forms of geographically referenced information. Previous studies have acknowledged that property valuations benefited from the application of GIS in many forms (see Longley *et al.*, 1993; Fung *et al.*,

1995; Rodriguez *et al.*, 1995; Wyatt, 1995; Wyatt, 1996; Wyatt, 1997; McCluskey *et al.*, 1997; Thrall, 1998; and Castle, 2000).

One of the GIS's significant applications is property location analysis in comparison approach. For example, Rodriguez *et al.* (1995) studied on the application of GIS "shortest path" algorithm to analyse the effect of location on property value. They concluded that, "distance variables are easily produced with GIS such as the shortest-path algorithm that produces a superior distance variable relative to the traditionally used straight-line distance variable and has significant relationship with residential sales prices. The GIS created variables expedite analysis within or outside the GIS environment."

According to Thurston (2002), the integration of ANN modelling in GIS can be applied in many applications to improve decision making process. Experimental studies have been

carried out on the integration of ANN model and GIS system in property valuation (Brondino and Silva, 1999; Moon and Hagishima, 2001; and Hall and Morgan, 2001).

For example, Hall and Morgan (2001) developed an automated valuation system named Spatial Aspect-Computer-Assisted Valuation Decision Support Tool. This software integrates GIS and ANN modelling. Sales of 181 residential properties in Turks & Caicos Islands, Central America were used as sample study. Attributes of property were trained and tested in ANN to get the predictive function. GIS was utilised for spatial analysis and visualisation. Property location factor was analysed in GIS to measure accessibility, while comparison analysis was carried out spatially to produce graphical outputs. Visualisations of raster-format spatial distribution of property prices and elevation models that shows parcel contours and the neighbourhood boundaries

were produced. The ANN predictive function was then integrated with GIS location to determine a property value.

Data and Model Design

The first step in AVM modelling is data collection. Property specific data were acquired from the government's Department of Valuation & Property Services. Sales of 138 detached properties were gathered and thoroughly analysed to select the most recent transactions and good data. Spatial data that consists of digital map of property parcels and building footprints were acquired from the GIS Unit of Kuala Lumpur City Hall. Data were categorised as either qualitative or quantitative and edited in GIS MapInfo Professional. Qualitative data were coded to a numeric form. Table 1 shows the data types and its representation used in this analysis.

Table 1: Data Representation

Attributes	Data Types	Value (Min – Max)	Representation
Selling price (RM mil)	Continuous numeric	1.50 – 5.65	Numeric
Lot area (sqm)	Continuous numeric	441.0 – 1275.3	Numeric
Building MFA (sqm)	Continuous numeric	158.5 – 568.7	Numeric
Building AFA (sqm)	Continuous numeric	22.0 – 380.0	Numeric
Building age	Continuous numeric	2 – 35	Numeric
Number of storey	Discrete numeric	2, 3	Numeric
Number of bedroom	Discrete numeric	3, 4, 5, 6	Numeric
Repair condition	Categorical	Good, Average	One-of-N code
Finishes quality	Categorical	Good, Average	One-of-N code
Distance to exit points (km)	Continuous numeric	0.1 – 5.0	Numeric
Distance to commercials (km)	Continuous numeric	0.05 – 3.5	Numeric
Distance to schools (km)	Continuous numeric	0.05 – 3.5	Numeric

The construction of ANN valuation model begins with learning process in Tiberius Neural Data Mining, a proprietary ANN software. Figure 3 illustrates a neural network model to property valuation in the study. Input training and testing datasets that are stored in Microsoft Access are called and form an

ANN MLP-BP structure. ANN learning computes the prediction output and is adjusted by an error term with the required output to minimise mean absolute error (MAE), the same way to reduce root mean squared error (RMSE) or E_2 (Figure 4).

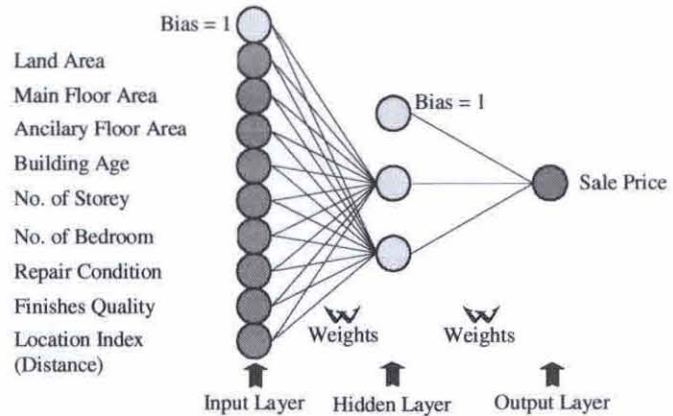


Figure 3: ANN property valuation model

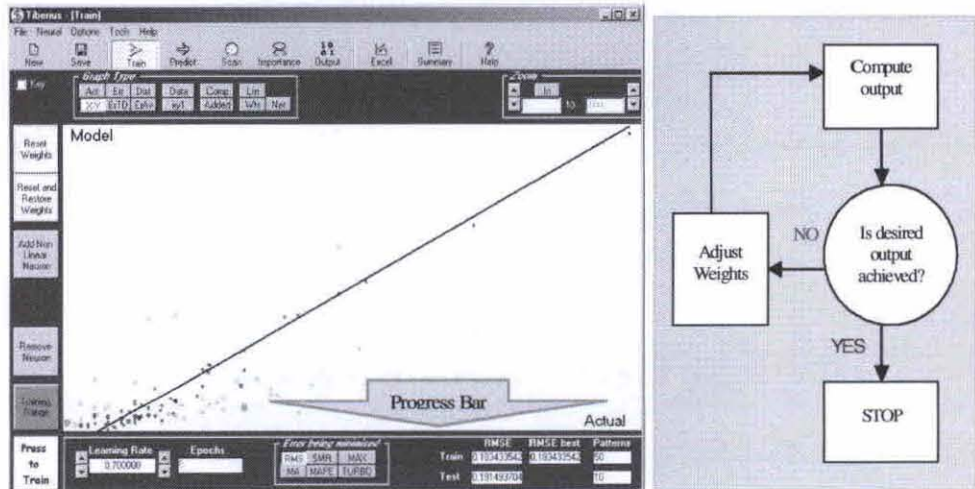


Figure 4: ANN learning in Tiberius

As the training run, Tiberius identifies the factors that contribute the most to the inputs

in relation to sale prices and show the results when the desired output is obtained (Figure 5).

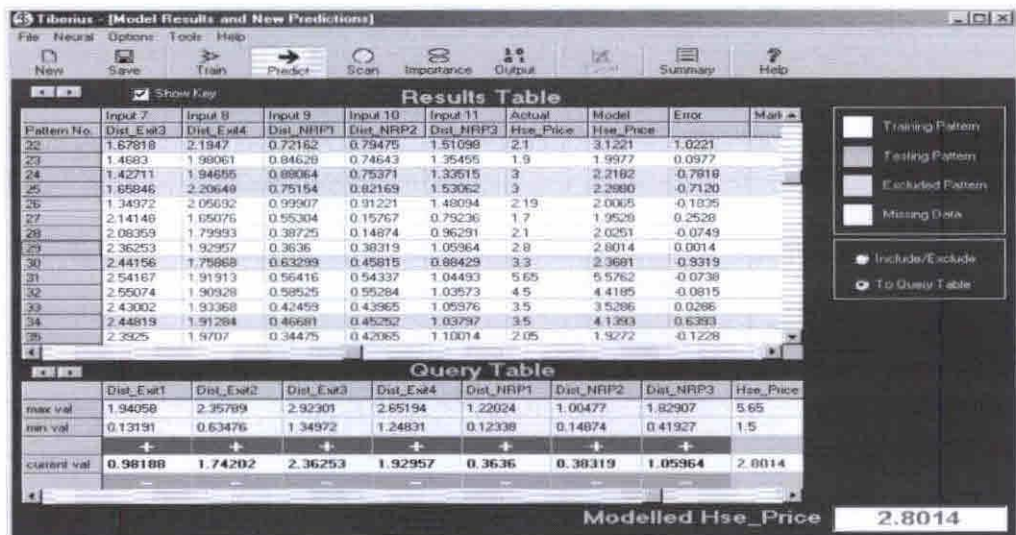


Figure 5: ANN learning result and predictive model

The location value analysis provides a means of adjusting for location in econometric modelling. Distance measurement functions are utilised based on the *shortest straight line* algorithm in MapInfo. In this study, we use

accessibility and proximity factors to measure distances from a property to value influence centres such as commercial centres and main exit points of the neighbourhood. Figure 6 exhibits the main exit points as applied in the study.

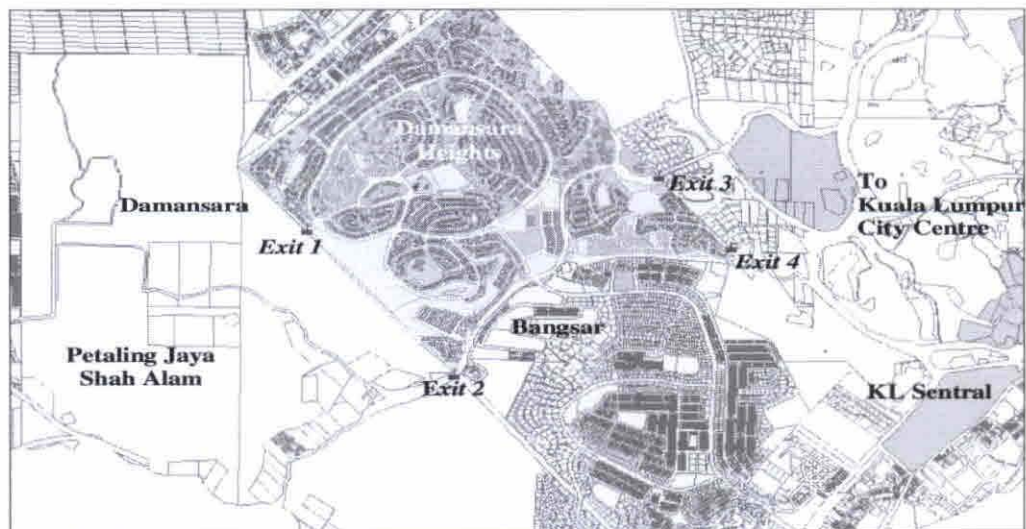


Figure 6: Main exits of Damansara Heights

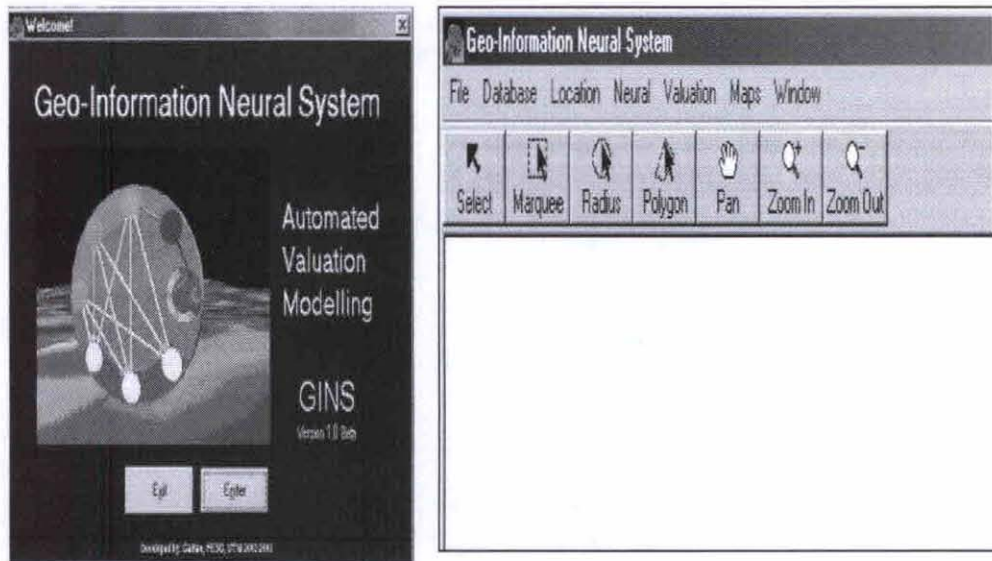


Figure 8: GINS MDI forms

Property attributes in Microsoft Access that can read by Tiberius are written out from MapInfo. Tiberius enables the construction of non-linear regression model and uses its back-propagation algorithm in multi-layer perceptron for the construction of predictive modelling. Spatial layer is created in MapInfo street file together with parcel and building layers which are previously geocoded. Property location indexes are built in MapInfo to measure shortest path distance for each property to all street segments to account for accessibility and proximity. The indexes are then sent to Tiberius for modelling with other property attributes. The program runs several training and testing to develop a function that yields the prediction of sale price as a function of all property attributes. The “goodness-of-

fit” model is run using the subset of variables that proves significant after adjustment of response coding to correct any error term.

Once the model is developed in Tiberius, the coefficients of ANN prediction model could be applied to tables in MapInfo. Call function is built in VB program that could be accessed from within the proprietary valuation engine that is GINS. User can either click at a particular property or comparable properties in the spatial layer or enter property specific attributes under valuation pull-down menu. Clicking evaluate, the system multiplies the values entered by their respective coefficients and add in the model constant term and return the market value of the subject property. Figure 9 illustrates the valuation process in GINS.



Figure 9: Valuation process in GINS

Results

The ANN predictive model is verified with new property data. The experiment indicates favourable prediction results with the actual

property prices of detached houses. Minimum and maximum errors are 1% and 11% respectively, while median error is 5% and 6% (Table 2).

Table 2: Results of ANN predictive modelling

No.	ANN Model Output (RM mil)	Actual Property Prices (RM mil)	Value Difference (RM mil)	Error (%)
1	1.947	2.100	-0.153	7.86
2	2.193	2.030	0.163	7.43
3	2.538	2.480	0.058	2.29
4	2.071	2.000	0.071	3.43
5	1.776	1.750	0.018	1.02
6	2.205	2.300	-0.095	4.31
7	1.788	1.680	0.108	6.04
8	2.895	1.100	-0.206	10.87
9	2.334	2.180	0.154	6.59
10	1.807	1.900	-0.093	5.15

Therefore, from this perspective, ANN valuation model in this study gave a reasonable and acceptable value of property.

Conclusion

The model demonstrates the potential of GIS and ANN as emerging tools in acquiring and

analysing spatial and attributes data. The model application can significantly reduce time and cost required to value a property, while enhancing the accuracy of value estimates. The automated valuation system product consists of a shell built around a valuation engine, which allows users to

perform specific tasks and obtain desired outputs. This shell can be customised to meet special user needs and to adapt to changing data conditions. Nevertheless, the valuation core remains relatively stable and will require alteration only when enhancements are added (Robbins, 1998).

The establishment of GINS can change the way property valuation services perform today by acquiring its competitive edge. GINS can possibly become an IT-intruder that is able to compete with other quantitative tools, thus bringing an alternative or improvement in the valuation profession and the real estate industry.

Although the results from this study seem appealing in enhancing valuation technique, there are still concerns need to be further research in future studies. For instance, GINS conceptual model can be improved for other application domain and can be enhanced to meet current market and user needs. Hence the future study will try to identify more variables to be added in ANN valuation model, i.e. economy and socio-economic factors.

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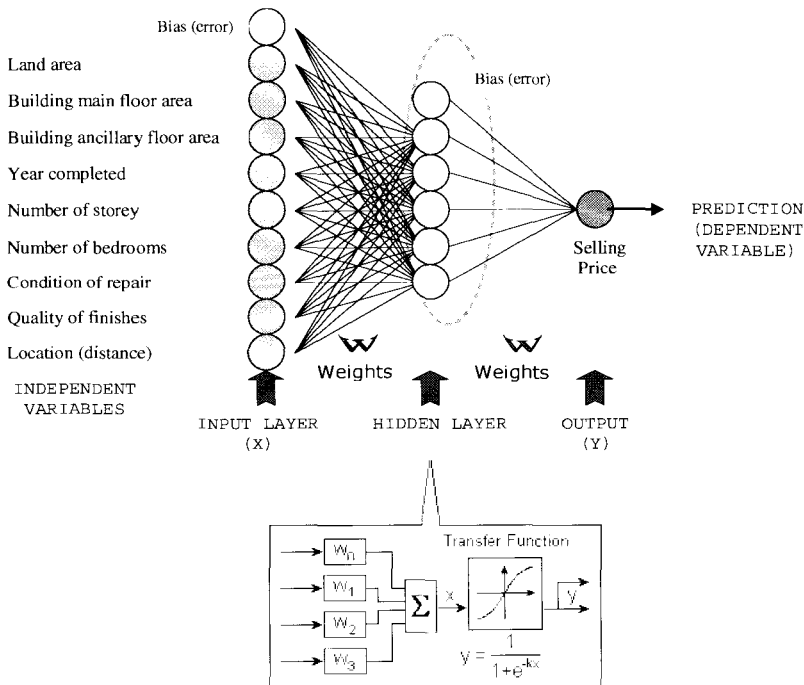
Appendix A: GINS Summary

Neural Network Structure

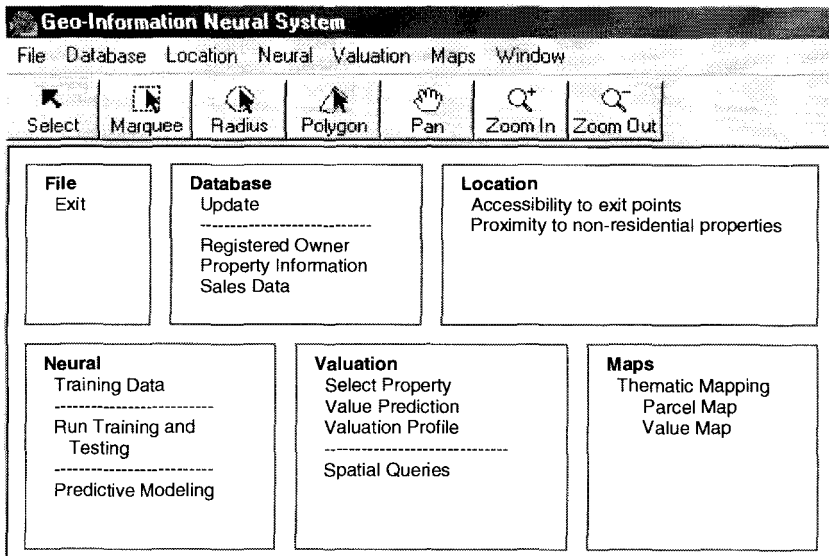
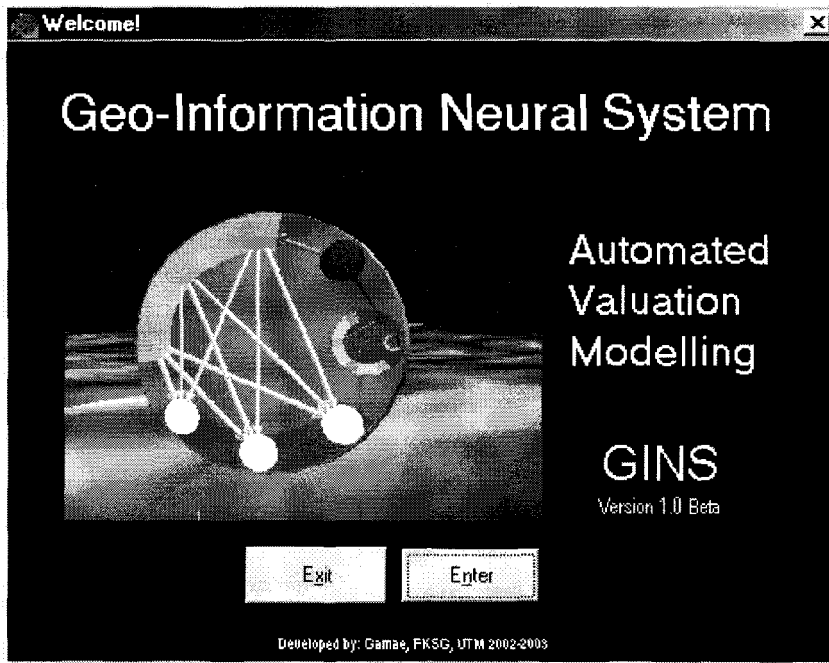
<i>Architecture</i>	: 3-layer perceptron fully interconnected neurons
<i>Algorithm</i>	: Back-error Propagation
<i>Objective</i>	: To predict selling price of a house within 10% error of estimation
<i>Target</i>	: Actual selling prices of houses in training dataset
<i>Output</i>	: Estimated selling price of a house
<i>Dataset</i>	: 100 sales data of detached houses in Damansara Heights, Kuala Lumpur
<i>Dataset Date</i>	: 3-year from 2001 – 2003
<i>Dataset Ratio</i>	: Training > Testing > Validation (80:10:10)

How it works?

- ◆ Uses Sales Comparison Approach: Property Value = Comparisons ± Adjustments
- ◆ ANN adds the intelligent factor into data analysis.
- ◆ Non-linear processing through hidden layer using summation and activation function.
- ◆ Algorithm:
 - o Pass training data through network.
 - o Adjust network weights to reduce error.
 - o Validate network with out-of-sample data.
 - o Use network to predict real data.



Guides on how to use GINS to value a property



Step-by-step Guide

1. Browse through the entire menu (Database; Location; Neural; Valuation; Maps) in the main interface to see the drop-down sub-menu functions.
2. Use icons to manipulate the graphic features.
3. Click on *Database* menu to browse the attributes and spatial data of sales and property information.
4. Click on *Location* menu to see the spatial analysis of property location. The location is calculated based on MapInfo 'straight line distance' algorithm of the following criteria:
 - o *Accessibility* measures distances from a property to four exit points of Damansara Heights.
 - o *Proximity* measures distances from a property to nearby commercials and schools.
 - o The distances values then feed into neural networks database.
5. Click on *Neural* menu to begin artificial neural networks modeling process.
 - o User determines the desired target (say, error of estimation < 10%).
 - o Open the database and selects property variables for inputs and output.
 - o Determine the neural networks structure – hidden layer.
 - o Begins *Training* on the property physical and location data and simultaneously *Testing* the network through the progresses.
 - o User retains the best network (*Predictive Modeling*) based on the progress charts windows and save as weight file to pass on to Valuation.
6. *Valuation* menu is the core in GINS that performs valuation procedure.
 - o User can make *Spatial Queries* (SQL) based on specific requirements.
 - o User *Select Property* to value.
 - o The system will generate a subject property value through *Value Prediction*.
 - o Alternatively, user can enter property inputs in *Value Prediction*.
 - o *Valuation Profile* shows the estimated value of the subject property and related summary.
7. Click on the *Maps* menu to view the graphical visualisation of thematic maps of distribution of values.

Benefits of GINS to Single-Property Valuation

1. Improved replication of valuations and decreased subjectivity.
2. Greater reduction in required time to process valuations (greater automation).
3. Incorporate existing spatial data and spatial analysis.
4. GIS visualisation and exploration.