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A spatially based artificial neural network mass valuation model for land consolidation

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Abstract
Land consolidation, which aims to promote sustainable development of rural areas, involves the reorganization of space through land reallocation, both in terms of ownership and land parcel boundaries. Land reallocation, which is the core part of such schemes, is based on land values because each landowner is entitled to receive a property with approximately the same land value after land consolidation. Therefore, land value, which in the case of Cyprus is the market value, is a critical parameter, and hence it should be reliable, accurate, and fairly valued. However, the conventional land valuation process has some weaknesses. It is carried out manually and empirically by a five-member Land Valuation Committee, which visits every unique parcel in the consolidated area to assign a market value. As a result, it is time consuming and hence costly. Moreover, the outcomes can be inconsistent across valuators for whom, in the case of such a mass appraisal procedure, it is hard to analytically calculate the scores for a series of land valuation factors and compare all of these for hundreds of land parcels using a manual process. A solution to these shortcomings is the use of automated valuation models. In this context, this paper presents the development, implementation, and evaluation of an artificial neural network automated valuation model combined with a geographical information system applied in a land consolidation case study area in Cyprus. The model has been tested for quality assurance based on international standards. The evaluation showed that a sample of 15% of the selected land parcel values provided by the Land Valuation Committee is adequate for appraising the land values of all parcels in the land consolidation area with a high or acceptable accuracy, reliability, and consistency. Consequently, the automated valuation model is highly efficient compared to the conventional land valuation method since it may reduce time and resources used by up to 80%. Although the new process is based partly on the Land Valuation Committee sample, which inherently carries inconsistencies, it is systematic, analytical, and standardized, hence enhancing transparency. The comparison of artificial neural networks with similar linear and nonlinear models applied to the same case study area showed that it is capable of producing better results than the former and similar outcomes to the latter.

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Keywords
Land consolidation, mass land valuation, automated valuation model, geographical information system, neural networks

Introduction

Land consolidation is a multipurpose land management approach, which mainly aims toward the sustainable development of rural areas (FAO, 2003a). The process involves the reorganization of space through land reallocation, both in terms of ownership and land parcel boundaries. In addition, it provides the necessary infrastructure for rural development, i.e. road and irrigation networks in the case of agricultural-oriented projects. Land reallocation (Demetriou et al., 2012) is the core part of such a scheme, which aims to balance agricultural efficiency, costs of infrastructure, environmental impacts, and the landowners' preferences. Land reallocation is based on land value because each landowner should receive a holding (consisting of a defined maximum number of land parcels) with approximately the same land value after land consolidation. If this value exceeds the original value, then the landowner must pay the extra cost to the Land Consolidation Corporation and vice versa. Therefore, land value is a critical parameter (FAO, 2003b) in land consolidation and hence it should represent a reliable, accurate, and fair measure so as to increase the acceptance of the land reallocation plan by landowners. This value can be the market value or the agronomic value. In contrast to other countries, the market value is utilized in Cyprus because land has broader development prospects and hence it is attractive to both farmers and nonfarmers.

In Cyprus, land valuation is a mass appraisal process carried out manually and empirically by a five member Land Valuation Committee (LVC). It aims to assign the market value of each land parcel and its contents, i.e. the farmstead, wells, etc. by employing the sales comparison method, which is based on comparison with similar sales transactions that have occurred in the area concerned. Demetriou (2016a) have shown that this manual conventional process faces some problems. In particular, the comparison of land parcel characteristics is mainly a result of an empirical analysis and subjective human judgment, which means the potential presence of inconsistencies across valuators, similar land parcels, and the regions of the study area and is not the outcome of a robust, standardized analysis using appropriate tools such as a geographical information system (GIS). As a result the process is not fully transparent and can lead to unfairness and bias against landowners. In this respect, FAO (2002) emphasizes that the critical point of valuation is not the valuation method followed, but the method of analysis utilized; hence, if analysis is successful and accurate (e.g. through a GIS), then it will be reflected in the method of valuation. Moreover, the process is not analytical because it does not split the problem into smaller elements or parts, i.e. it does not use land factor scores for estimating the land value. In addition, it is not systematic, i.e. it does not involve a standard set of steps to reach the outcome, i.e. the land value, and it is not based on recognized standards. Furthermore, it is time consuming and hence costly because the process is undertaken manually by inspecting all parcels so the process may take several weeks.

In order to overcome the aforementioned deficiencies, Demetriou (2016a) have proposed a new framework for mass appraisal (e.g. IAAO, 2013a; Kilpatrick, 2011; Kontrimas and Verikas, 2011) using automated valuation models (AVMs) (Downie and Robson, 2007; Schulz et al., 2013). AVMs are mathematically based computer software programs that are able to estimate the value (usually the market value) of various types of properties based on a market analysis of a specified area and the characteristics of a certain group of properties stored in appropriate databases for a given point in time (IAAO, 2003). The core process in developing AVMs is calibration where various methods have been used to date, including multiple regression analysis (MRA), which is the most traditional and popular method employed (e.g. Eckert, 2006; Milla et al., 2005; Schulz et al., 2013).

In addition, several studies have included a spatial component, i.e. GIS (Bastian et al., 2002; Hamilton and Morgan, 2010; Higgs et al., 1992; Iman, 1999; Longley et al., 1994; Wyatt, 1997; Zeng and Zhou, 2001), introducing new concepts such as spatial autocorrelation and spatial heterogeneity and have resulted in new modified versions of MRA, e.g. spatial lag model, spatial error model, general spatial model, and geographically weighted regression (Jahanshiri et al., 2011). Furthermore, the utilization of artificial intelligence (AI) techniques as an alternative calibration approach instead of MRA, e.g. artificial neural networks (ANNs) (Garcia et al., 2008; Kathman, 1993; Nguyen and Cripps, 2001; Pao, 2008), expert systems (Kilpatrick, 2011), and case-based reasoning (Gonzalez and Laureano-Ortiz, 1992) have arisen during the last two decades. Moreover, newer methods such as agent-based models (Breen et al., 2009) and genetic algorithms have also been applied in the area of land valuation more recently (Ahn et al., 2012). Among the AI techniques, ANNs (Fausett, 1994), which attempt to simulate the functioning of the human brain, have been the most widely used for valuation during the last decade (Garcia et al., 2008; Kathman, 1993; Kontrimas and Verikas, 2011). Various studies have shown that the accuracy of an ANN is comparable and sometimes better than standard calibration techniques such as MRA (e.g. Brooks and Tsolacos, 2003; Do and Grudnitski, 1992; Hua, 1996).

In this context, the literature about land valuation in land consolidation areas is very rare. The work of Yomralioglu et al. (2007) and similar studies produced in earlier years refer to urban land consolidation (i.e. land readjustment) based on a raster GIS (instead of a vector GIS employed in this study). In particular, they applied a type of suitability analysis that tried to estimate a nominal asset value instead of a real monetary value and the performance of the method is lacking in terms of quality assurance. A recent related study by the Demetriou (2016b) developed two hedonic price models based on a linear and a nonlinear regression analysis combined with GIS. The models have been tested for quality assurance based on international standards. The evaluation showed that the best results were produced by the nonlinear model, which is highly efficient compared to conventional land valuation methods since it may considerably reduce the time and resources required and it provides transparency. A question raised is how ANNs will perform compared to the linear and nonlinear models. Therefore, the aim of this research is to develop, implement, and test an ANN AVM model for a case study land consolidation area in Cyprus using international standards (defined by the International Association of Assessing Officers (IAAOs)) to compare the results with those obtained by utilizing a linear and a nonlinear function. The basic research questions that are clearly answered within the text are as follows: (i) which land valuation factors are important in the land valuation process and do they vary depending on the calibration method used? (ii) what is the quality of the outcomes based on international standards? (iii) what is an adequate land parcel sample size provided by the LVC that will ensure that the ANN model will automatically appraise the rest of the parcels within acceptable international quality measures? (iv) which of the three methods (linear, nonlinear, and ANN) perform the best? and (vi) what are the benefits of applying this ANN model over the other methods tested here?

The next section of the paper deals with the development and quality assurance of AVMs, which is then followed by a short background regarding the use of ANNs in developing an AVM in the subsequent section. "Case study" section presents the land consolidation case study area followed by the development of the ANN land valuation model in terms of specification and calibration in the case study area ("The spatially based ANN mass valuation model for land consolidation" section) and the evaluation of the model outputs based on testing and quality assurance tests defined by the IAAO ("Models testing and quality assurance" section). The final section provides conclusions and recommendations for further research.

The development and quality assurance of AVMs

The development process of AVMs

AVMs are part of broader systems called computer-assisted mass appraisal (Eckert, 2006; Gallagher et al., 2006), which are used for automated mass valuation by public authorities in several countries, including Cyprus (Pashoulis, 2011). The IAAO (2003) has defined standards and specifications for the development process of AVMs, which involves three basic steps: (i) model specification, (ii) model calibration, and (iii) model testing and quality assurance (IAAO, 2013b). Model specification first involves the definition of the valuation method, i.e. cost, sales comparison, and income approach (Wyatt, 2013), which is transformed in a mathematical formula categorized as additive, multiplicative, and hybrid (IAAO, 2003). The second aspect of model specification is the selection of independent variables that will be included in the model as predictors of the market value. Calibration is the process of testing the model structure to estimate the variable coefficients/parameters using a different dataset employed for testing the performance of the model by utilizing ratio studies (IAAO, 2013b). In essence, specification and calibration are a combined iterative process that continues until the model performance metrics are satisfied. The last step, i.e. model testing and quality assurance, aims to quantify model performance by employing a property sample (called a holdout sample) that has not been used in model calibration, so as to ensure that it fulfills the relevant accuracy and reliability standards before it is used.

Model testing and quality assurance

Model testing and quality assurance are carried out using ratio studies and involve four basic measures: (i) appraisal level (mean, median, weighted mean) representing accuracy; (ii) variability-uniformity (coefficient of dispersion (COD)), reflecting consistency; (iii) reliability (confidence interval); and (iv) vertical inequities (price-related differential (PRD), price-related bias (PRB)), also reflecting both accuracy and consistency. All the acceptable numerical limits of the above metrics, which are discussed below, are defined by the international standards (IAAO, 2013b).

In particular, the appraisal level aims to calculate how close predictions are to real market values by employing primary measures of central tendency. While ideally the desired level is 1.0, i.e. the appraisal value equals the market value, an appraisal level between 0.90 and 1.10 is considered acceptable for any type of property for certain confidence intervals. The second metric, i.e. variability-uniformity, is measured by the COD; for the vacant land (the closest category to agricultural land that is not exclusively involved in the standards) the COD should be between 5.0 and 25.0. The next metric, i.e. reliability, which reflects the degree of confidence that can be placed in a calculated statistic for a sample of appraised properties, should be between 0.9 and 1.10 for any type of property. In contrast to the COD, which is a "horizontal" metric, vertical inequities, which provide evidence of the accuracy of appraised individual properties, can be measured by an index called the PRD. The latter is calculated by dividing the mean ratio by the weighted mean ratio and ideally should be between 0.98 and 1.03. Measures significantly above or lower than 1.0 show regressivity, i.e. low-value properties are appraised at a greater percentage market value than high-value properties, or progressivity, i.e. low-value properties are appraised at smaller percentages, respectively.

In addition, IAAO (2013b) recommends that a statistical test for PRB should be carried out, because it provides a more meaningful and easily interpreted index than PRD. PRBs for which the 95% confidence interval falls outside the range of −0.10 to +0.10 indicates unacceptable vertical inequities. Furthermore, the root mean squared error (RMSE, equation (1)) and the mean absolute percentage error (MAPE, equation (2)) have also been used. The former measures the discrepancies between the predicted values and the actual observations while the latter measures scaled discrepancies. Such measures have also been used in other case studies (Ahn et al., 2012; Schulz et al., 2013). Moreover, in order to measure how the error deviates, the absolute percentage error (equation (3)) is estimated, which is called the forecasting error (FE) as outlined in Nguyen and Cripps (2001). All these three metrics, which reflect the accuracy of the predictions, can be calculated as follows

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - A_i)^2}{n}} \tag{1}$$

$$MAPE = \frac{\left(\sum_{i=1}^{n} \left| \frac{(P_i - A_i)}{A_i} \times 100 \right| \right)}{n} \tag{2}$$

$$FE = \left| \frac{(P_i - A_i)}{A_i} \times 100 \right| \tag{3}$$

where P_i and A_i are the predicted and actual values (i.e. the LVC values), respectively, of land parcel i in the set of n parcels.

The use of ANNs for developing an AVM

The employment of AI methods for valuations began after 1990. In particular, ANNs (Fausett, 1994) have been the most widely used AI technique for valuation during this period (Garcia et al., 2008; Kathman, 1993; Kontrimas and Verikas, 2011) as an alternative to the MRA model. ANNs attempt to loosely simulate the functioning of the human brain, i.e. the way human brain cells or natural neurons produce a certain activity as a reaction to inputs from other brain cells or sense organs and the output can be transported through other neurons (Kathman, 1993). In technical terms, ANNs are nonconventional computer programs that are typically organized in three layers, i.e. input, hidden, and output layers as illustrated in Figure 1. Layers are made up of a number of interconnected "nodes" which contain an "activation function." Patterns are presented to the network via the "input layer," which communicates to one or more "hidden layers" where the actual processing is done via a system of weighted "connections." The hidden layers then link to an "output layer" where the answer is provided as the output. ANNs contain some form of "learning rule" which modifies the weights of the connections according to the input patterns that iteratively change. In a sense, ANNs learn by example as they ingest new information and process it based on previous training examples.

The wider use of ANNs and the relatively straightforward procedure has motivated some statistical software companies to include the process in their packages in a user friendly environment, e.g. in the IBM SPSS Statistics 21 software, which is employed in this research. The most significant strength of ANNs is the fact that they may represent any kind of relation between the dependent and independent variables, including linear and nonlinear

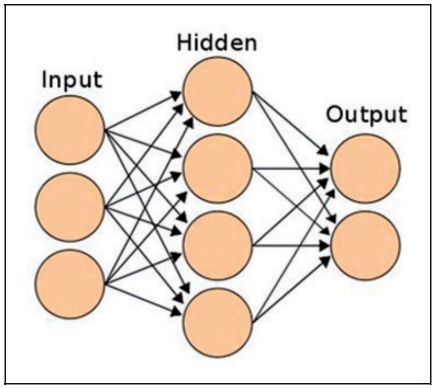

Figure 1. The structure of a typical ANN.
ANN: artificial neural network.

functions or even completely unknown and complicated models (Garcia et al., 2008; IAAO, 2003). In addition, MRA has a rigid model structure and a set of assumptions that need to be met so that the results will be reliable. Various studies have shown that the accuracy of an ANN is comparable and sometimes better than standard calibration techniques such as MRA (Brooks and Tsolacos, 2003; Do and Grudnitski, 1992; Hua, 1996; Nguyen and Cripps, 2001) while some older studies support the superiority of MRA over ANNs (Warzala et al., 1995).

On the other hand, some of the weaknesses of ANNs are the fact that they work more or less as a "black box" regarding the process in the hidden layer and it requires a minimum background in data structure and analysis. In addition, the optimum solution is achieved after trying several combinations of model structure parameters, i.e. number of neurons, number of hidden layers, training set, etc. assuming that there are sufficient sales data available for training (Kathman, 1993). Furthermore, some studies have found that the ANN performance depends on the sample size. Namely, James (1996) have pointed out that ANNs are appropriate for small datasets while Nguyen and Cripps (2001) found that ANNs are superior when a moderate to large sample size is used. However, it should be noted that most of these ANN weaknesses have been overcome since new software such as the IBM SPSS 21 Neural Network module minimizes the demands on the users, providing automatic procedures for architecture selection (number of units in the hidden layers), weight initialization, and the type of training through optimization algorithms. Specifically, the aforementioned software uses the simulated annealing (SA) method.

Case study

The study area

Choirokoitia is a village in the Larnaca District of Cyprus, which is located southwest of Larnaca town (Figure 2(a)). The village is built on a hill with an average elevation of 230 m, and the land consolidation area is located northwest of the village (Figure 2(b)) in lowlands with limited hills. The land consolidation area is included in an agricultural zone but on the eastern side, it almost coincides with the main road (F112) (Figure 2(b)) that connects some of the mountainous villages of the district with the main motorway connecting the two largest cities of Cyprus (A1). The land consolidation area has an extent of 266 ha and involves 488 land parcels (Figure 3). The land use is mainly citrus,

Figure 2. (a) The location of Choirokoitia village on the map of Cyprus and; (b) a more detailed map with the approximate location of the land consolidation area.

Figure 3. The land consolidation case study area.

olives, various fruit trees, and cereals. The majority of land parcels are dry while some are irrigated through individual wells or a network connected with a water reservoir.

The conventional land valuation process

Land valuation in land consolidation areas in Cyprus (Demetriou, 2016a) is a mass appraisal process undertaken by the LVC that consists of five members: a valuator from the Land and Surveys Department, an agriculturalist from the Land Consolidation Department, an officer of the District Administration, and two landowners who are directly elected by the entitled landowners of the particular consolidation project. The basic principle of land valuation is that the value of the property should reflect the market value at which the property can be sold at that time by a willing seller. Therefore, the LVC employs the sales comparison method to specify land values, although in most cases there is not an adequate number of comparable sales transaction within land consolidation areas. In practice, the LVC initially analyzes the available sales transactions within the land consolidation area for the last few years and tries to define a range of minimum and maximum land values by comparing the physical and legal characteristics of the land parcels with those parcels for which a sale value is available.

Then, the five members of the LVC visit every unique parcel within the consolidated area to carry out this comparison process to set the land values. The land valuation in the study area was carried out periodically from October 2008 until February 2009. The highest land value is €35,000 per decare (1000 m^2) while the lowest has been set to €2000. Land values were grouped in the official LV map into 26 categories. An example of a land valuation map which is reclassified into 17 categories with an interval of €2000 is shown in Figure 4. It should be noted that the LVC separately valued any constructions included within the land, i.e. a house, a farmstead, a well, a fence, and any isolated trees included in the land, e.g. large olive and carob trees. In addition, the LVC added a standard extra value to irrigated land parcels and to land parcels that included an organized plantation, e.g. an orchard with citrus fruits or olives.

Land valuation factors

All of the available data for land valuation were stored in a GIS. These data were used to extract parcel-based information regarding 14 land valuation factors, grouped into four categories (Wyatt, 1996): (i) *physical attributes*, (ii) *legal factors*, (iii) *locational characteristics*, and (iv) *economic conditions*. Each category includes the following factors regarding each parcel with the variable's name within parentheses:

(i) *physical attributes* are size (*size*) in square meters, shape (*shape*) measured using the parcel shape index *PSI* (Demetriou et al., 2013), mean slope (*slope*) measured in percentage, mean elevation from sea level (*elevation*) in meters, aspect (*aspect*) measured clockwise in degrees (i.e. 0 north, 90 east, 180 south, and so on), the existence of a stream (*stream*) and soil type (*soil*) provided by the Geological Survey Department, which involves two types: Skeletic-calcaric-REGOSOLS and calcaric-lithic-LEPTOSOLS represented by the letter "A" and calcaric-CAMBISOLS and calcaric-REGOSOLS represented by the letter "B."

(ii) *Legal factors* involve the existence of irrigation rights (*irrigation*) for a parcel.

(iii) *Locational characteristics* are access through a registered road (*access1*), access through a registered pathway (*access2*), the distance from residential zones (*zone*), the distance

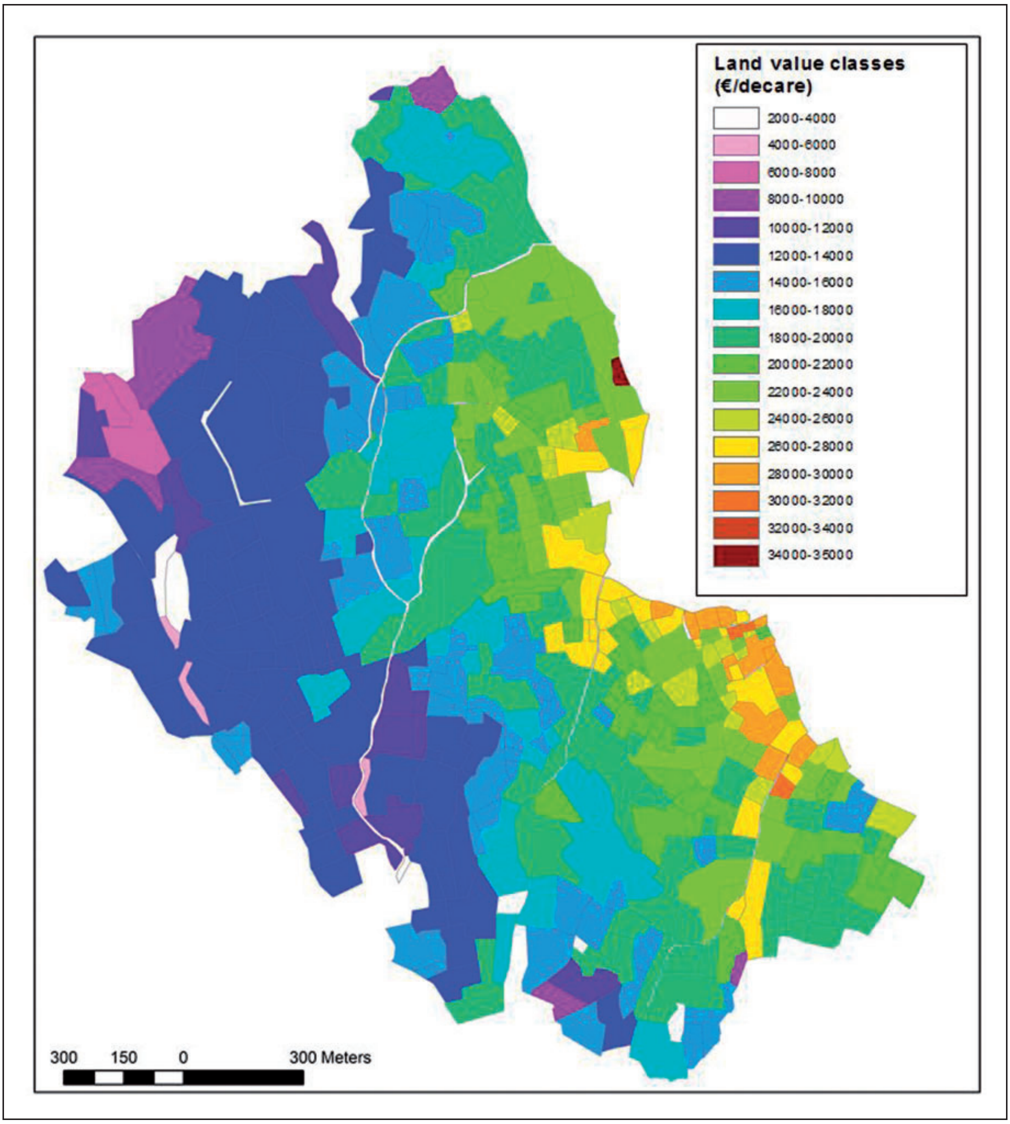

Figure 4. The land valuation map produced by the LVC. LVC: Land Valuation Committee.

from the main road that connects the neighborhood villages with the motorway (*main_road*), and the existence of a sea view (*sea_view*).

(iv) *Economic conditions* are land use/productivity (*land_use*) for the agricultural economic potential of a parcel, which is reflected by the expected net revenue per decare for various crops as provided by the Agricultural Department of Cyprus.

For the current study, it should be noted that the socioeconomic factors were considered constant because land valuation was carried out during a short period of time; hence the prevailing relevant conditions were indeed stable. The detailed definition of each factor associated with each thematic map is provided in Demetriou (2016a). The dependent variable, i.e. the market land value, is measured in Euros per decare. It is also worthwhile to note that the LVC has taken the following six land valuation factors from among the 14 noted above into account: the distance from residential zones, access through a registered road, access through a pathway, slope, the availability of irrigation, and the size of parcels.

The spatially based ANN mass valuation model for land consolidation

The use of samples provided by the LVC

Since sales transactions within the consolidated area were not sufficient to predict and compare the outcome of land values (Demetriou, 2016a), three sample sizes, i.e. 10, 15 and 20% of the values of land parcels assigned by the LVC, are used here because these were the only available data. Further to these reasons, the use of samples provided by the LVC is associated with additional grounds: (i) it is compulsory by legislation that the LVC should carry out the process so constitutionally it cannot be ignored; (ii) the main stakeholders involved in land consolidation schemes, i.e. authorities and landowners, directly participate in the valuation process suggesting good planning practice. However, clearly, the quality of the outputs is linked with the quality of the inputs, i.e. the use of these samples will have inconsistencies and inaccuracies due to the subjective nature of the conventional process, which will be propagated and bias the outputs of the models. However, these weaknesses are counterbalanced by the following facts: (i) the basic input of the models is not only the sample but also the scores calculated for each valuation factor, which are inherently very accurate; (ii) it is much better to use a sample of land values between 10 and 20% rather than using the whole population, i.e. 100% of the sample as the final outcome of the valuation; (iii) in practical terms, the application of the models will involve asking the LVC to value a representative sample of the parcels, e.g. 50–100 out of 500, and hence the LVC will pay more attention. It will be easier for them to compare this smaller number of parcels rather than comparing hundreds of parcels as per the conventional process. Therefore, the LVC samples can be considered suitable for the purpose of this research.

In terms of sample selection, the stratified sampling method was used, i.e. the population of parcels was divided into separate groups based on their attributes, called strata, and then a random sample was drawn from each group to adequately represent all features across the whole population. In this manner, all the parcels having the min, max, and mean score of all the continuous land valuation factors were selected and then parcels were chosen randomly to geographically cover the whole case study area. Similarly, for categorical factors (i.e. those that take a binary value), parcels were selected proportionally based on the frequency of each score (i.e. 0 or 1) and then randomly in order to ensure a location-based balance.

It is also noted that the samples used for the ANN models in this study, i.e. 10, 15, and 20%, are exactly the same as those employed in the linear and nonlinear models (Demetriou, 2016b) so that the results will be comparable. By default the ANN process in SPSS splits each sample into a training and testing data set.

Building the ANN model

After the automated extraction of scores for the 14 land valuation factors of the case study area was undertaken using ArcGIS 10.2, the results were then passed to the IBM SPSS 21.0 software for building the ANN model to predict the land values of the parcels. IBM SPSS 21 (IBM, 2011) provides two ANN procedures employed for predictive applications, namely the multilayer perception (MLP) and the radial basis function, which are supervised networks that aim to minimize the prediction error of the outputs (Fausett, 1994). The MLP gave better results and has therefore been used in this research. The MLP approach accepts any type of variable (interval, ordinal, nominal) as inputs and uses a series of default ANN parameters: number of generations, assignment of partitions, subsampling for initialization of synaptic weights, subsampling for automatic architecture selection, the parameters of the SA algorithm used in weight initialization, and automatic architecture selection. In addition, the results may be influenced by the order of the variables in the factor and covariate lists, due to the different pattern of initial values assigned when the variable order is changed. Therefore, different variable orders were tried in order to assess the stability of a given solution. Furthermore, parameters regarding *variables*, *partitions*, *architecture*, and *training* were set to the software default values.

In particular, scale-dependent variables and covariates are rescaled through standardization or normalization by default in SPSS to improve network training. In our case, variables have been rescaled via a standardized method, i.e. subtract the mean and divide by the standard deviation. Partitioning involves the subdivision of the active dataset into *training*, *testing*, and *holdout* samples. The training sample comprises some percentage of cases in the dataset used to train the ANN in order to obtain a model. The testing sample is an independent set of data records used to track errors during training in order to prevent overtraining. Network training will generally be more efficient if the testing sample is smaller than the training sample. The holdout sample is another independent set of data records used to assess the final ANN. Specifically, the error for the holdout sample gives an ‘‘honest’’ estimate of the predictive ability of the model because the holdout cases were not used to build the model. The relative ratio of cases assigned to each sample of partitioning can be done either randomly or defined by the user as in our case, to ensure consistency in the comparison of the outputs with MRA models. In terms of architecture, which involves the structure of the network, it can be specified either automatically by the system to find the ‘‘best’’ one, or defined by the user.

There are four basic architecture parameters: the number of hidden layers (one or two for the MLP), the number of units in each hidden layer, and the activation function (hyperbolic tangent or sigmoid) that links the weighted sums of units in a layer to the value of units in the succeeding layer. Similarly, for the output layer, an activation function should be specified. Custom architecture selection gives user control over the hidden and output layers and can be most useful when the user knows in advance what architecture to use, which was not the case in this research. Once the architecture is defined, two training parameters need to be specified: the type of network training, which determines how the networks process the records and the optimization algorithm employed to estimate the synaptic weights. Three training types are available: *batch*, *online*, and *mini-batch*. The former is the default and is used here. Two optimization algorithms are available: scaled conjugate gradient, which is not available for online or mini-batch training and is the default for batch training; and gradient descent, which can be used with all three training types. In general, the default values were accepted unless the network ran into problems with estimation. After defining the parameters, the system was run and a series of output tables and graphs is then provided. Further details on how to build an ANN can be found in the SPSS manual (IBM, 2011).

Running the ANN models

Similarly to the linear and nonlinear analysis, we ran a different ANN for each of the three samples. The subdivision of each sample in terms of training, testing, and holdout is

Table 1. The subdivision of each sample in training, testing, and holdout.

		Sample 1		Sample 2		Sample 3	
		N	Percent	N	Percent	N	Percent
Sample	Training	34	7.0	51	10.5	68	14.0
	Testing	15	3.1	22	4.5	29	6.0
	Holdout	438	89.9	414	85.0	390	80.1
Valid		487	100.0	487	100.0	487	100.0
Total		487		487		487	

Table 2. Network information for each sample.

			Sample1	Sample2	Sample3
Input layer	Factors	1	Stream	Access2	Access2
		2	Access1	Access1	Access1
	Covariates	1	Slope	Irrigation	Irrigation
		2	Zone	Size	Size
		3	Size	Slope	Aspect
		4		Zone	Slope
		5			Zone
	Number of units[a]		7	9	10
	Rescaling method for covariates		Standardized	Standardized	
Hidden layer(s)	Number of hidden layers		1	1	1
	Number of units in hidden layer 1[a]		3	3	4
	Activation function		Hyperbolic tangent	Hyperbolic tangent	
Output layer	Dependent variables	1	Value_Area		
	Number of units		1	1	1
	Rescaling method for scale dependents		Standardized	Standardized	Standardized
	Activation function		Identity	Identity	Identity
	Error function		Sum of Squares	Sum of Squares	Sum of Squares

[a]Excluding the bias unit.

indicated in Table 1. In order to produce results that are comparable with those produced by the linear and nonlinear functions, the sum of the training and testing samples constitutes the sum of the full sample used in each of those three cases. Moreover, it should be noted that various trials and combinations of the 14 variables were carried out and it was found that the best result produced by the set of variables was by the final linear model. Furthermore, the parameters for the best trials (since many combinations of variables were used) are shown for each sample in Table 2. An example of the structure of the ANN for sample-2 is illustrated in Figure 5.

A summary of the model outputs for each sample, including various types of errors used to assess the performance of the ANN (IBM, 2011), is provided in Table 3. It can be seen

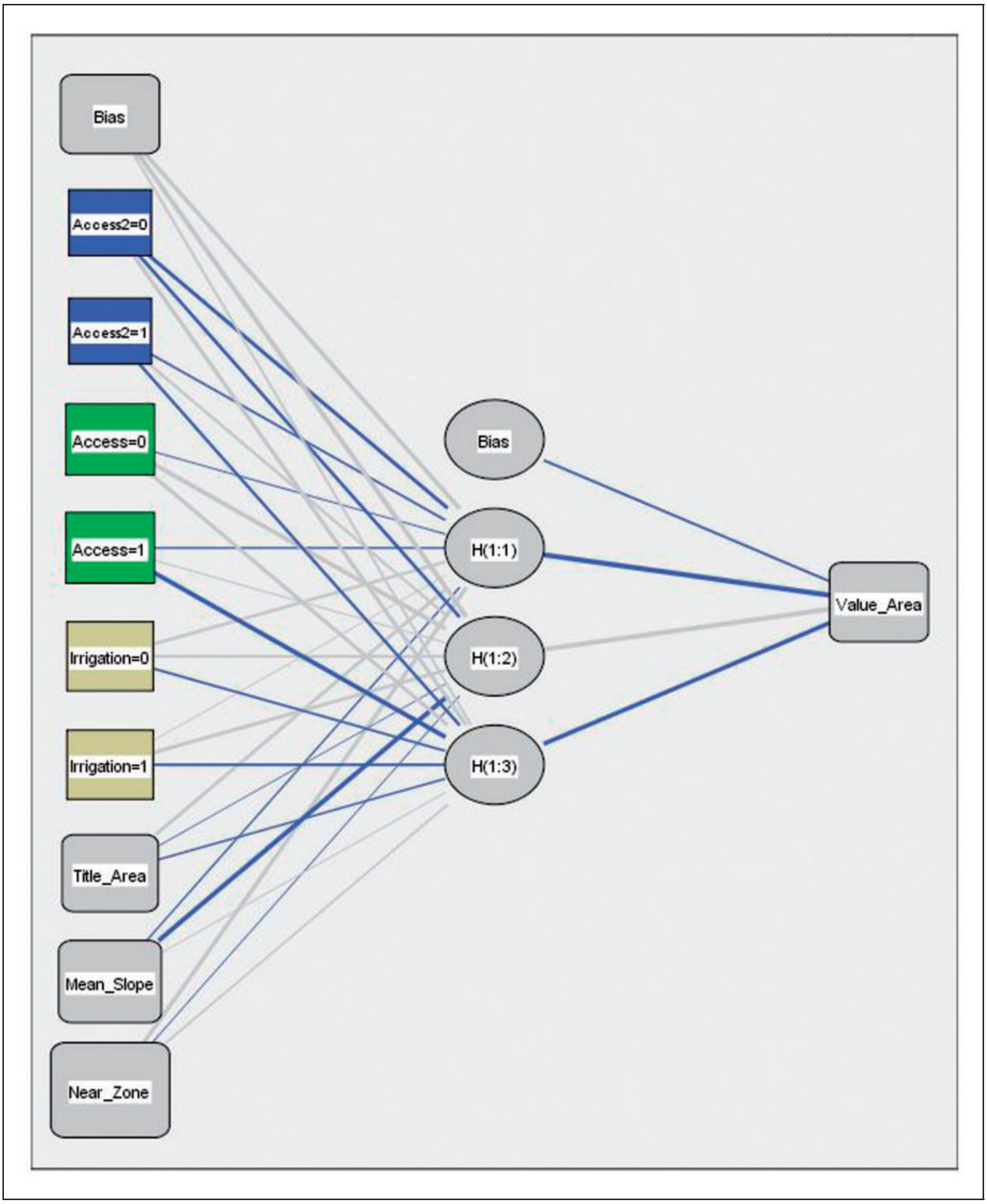

Figure 5. A graphical representation of the structure of the ANN for sample 2.

that the average overall relative errors are fairly close across the training, testing, and holdout partitions for the three samples. Results for samples 2 and 3 give us some confidence that the model is not overtrained and that the error in future cases will be close to the error reported. However, the difference between the average overall relative error of the training and testing data (for samples 2 and 3), and the error of the holdout sample, may occur because of using small samples to predict land values, which were inevitable based on the research aim. Thus, the results for samples 2 and 3 are very close and

Table 3. A summary of ANN model errors for each sample.

		Sample1	Sample2	Sample3
Training	Sum of squares error	3.294	4.088	5.091
	Relative error	.200	.164	.152
	Stopping rule used	One consecutive step(s) with no decrease in error[a]	One consecutive step(s) with no decrease in error[a]	One consecutive step(s) with no decrease in error[a]
	Training time	0:00:00.01	0:00:00.02	0:00:00.02
Testing	Sum of squares error	.486	1.903	2.629
	Relative error	.101	.186	.159
Holdout	Relative error	.289	.221	.233
Dependent variable: Value_Area.				

ANN: artificial neural network.
[a]Error computations are based on the testing sample.

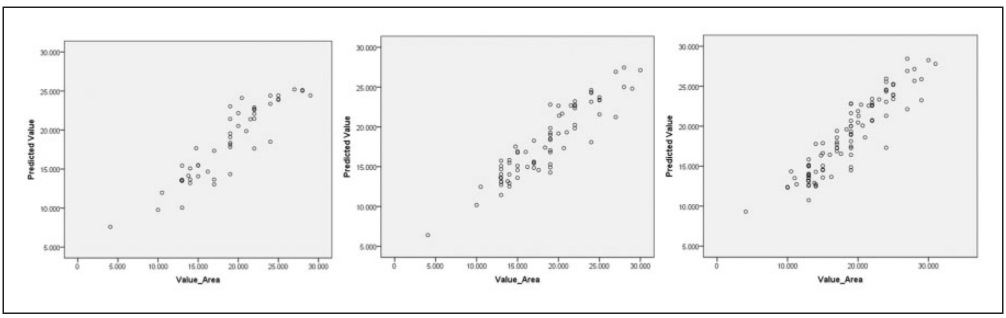

Figure 6. The performance of the ANN for the three samples, respectively (predicted against real land values).
ANN: artificial neural network.

perform best since only around 23% of predictions in the holdout sample can be considered as incorrect. In addition, model performance has been very good since in both cases, i.e. for samples 2 and 3, the explained variance (one minus the relative error for the holdout sample) equals 0.779 and 0.776, respectively. This finding is shown graphically in scatterplots (Figure 6) of the predicted against the LVC land values. Trials to increase both training and testing samples against the holdout sample showed that relative errors may fall to around 15%.

The predicted values are shown in Figure 6 and the points that are close to the diagonal represent the ideal result. Moreover, the correlation coefficient for each sample also justifies this finding, i.e. 0.844, 0.888, and 0.892 for each sample, respectively.

Furthermore, plots of the residuals shown in Figure 7 indicate that there is no visible pattern between the residuals and the predicted values and that there is a proportional spread of residuals over the whole range of predicted values.

Table 4 and Figure 8 show the importance and normalized importance of each predictor variable in determining each ANN, which helps us to answer research question (i). In particular, the results show that for all three samples, the most important valuation factor

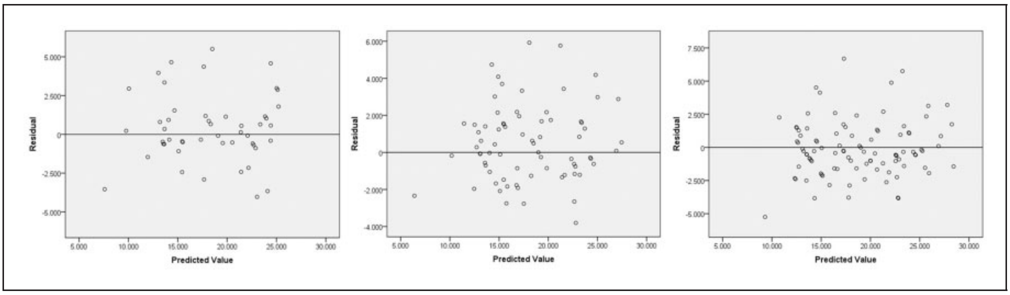

Figure 7. The residual for the three samples, respectively.

Table 4. The importance of independent variables for each sample.

Sample 1			Sample 2			Sample 3		
Variable	Importance	Normalized Importance	Variable	Importance	Normalized Importance	Variable	Importance	Normalized Importance
Stream	.063	15.2%	Access2	.033	8.2%	Access2	.058	14.4%
Access1	.048	11.6%	Access1	.092	23.2%	Access1	.071	17.6%
Slope	.316	76.7%	Irrigation	.071	18.0%	Irrigation	.065	16.2%
Zone	.412	100.0%	Size	.170	42.8%	Size	.147	36.7%
Size	.162	39.2%	Slope	.236	59.3%	Aspect	.096	23.9%
			Zone	.398	100.0%	Slope	.161	40.1%
						Zone	.402	100.0%

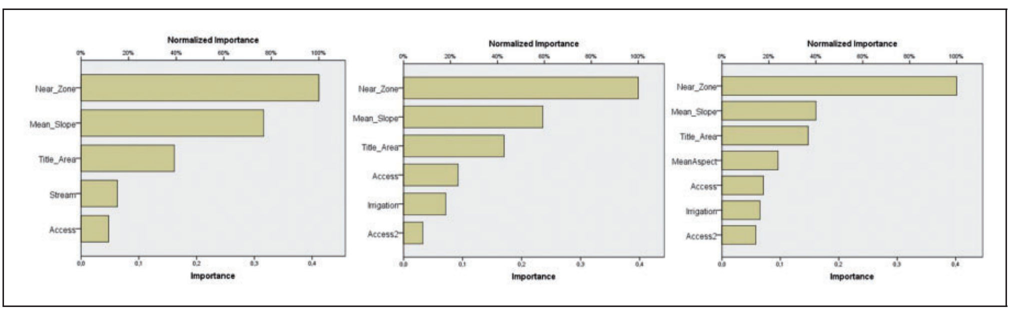

Figure 8. The normalized importance of variables of the three samples.

is the distance from residential zones, followed by the mean slope of the parcel, the size of the parcel, access1, and then the other factors. These outcomes are quite reasonable and, in general, close to the valuation considerations set up by the LVC, which originally assigned the sample land values. It is worth noting that the ranking of the most important factors resulting from the linear and the nonlinear model is slightly different in each case because of the different underlying assumptions of each method. In addition, the ranking of factor priority is very reasonable in practice because it generally fits to those of the LVC.

After model specification and validation, testing and quality assurance then follows.

Table 5. Testing and quality assurance for the ANN model.

	Appraisal level				
	Mean	Median	W. mean	RMSE	MAPE
Sample 1	1.035	1.019	1	2746.98	13.86
Sample 2	1.028	1.00	0.99	2398.62	11.71
Sample 3	1.057	1.019	1.02	2421.17	12.29
	Uniformity	Vertical inequalities			
	COD	PRD	PRB		
Sample 1	13.29	1.03	−0.046		
Sample 2	11.38	1.03	−0.07		
Sample 3	11.43	1.03	−0.046		
	Reliability				
	95% (mean)	95% CI (median)	FE< = 10%	10%>FE< = 20%	FE > 20%
Sample 1	1.00–1.07	0.99–1.05	50.23	33.79	15.98
Sample 2	1.00–1.06	0.97–1.04	58.45	29.95	11.59
Sample 3	1.02–1.09	0.98–1.05	60.77	28.21	11.03

ANN: artificial neural network; COD: coefficient of dispersion; FE: forecasting error; MAPE: mean absolute percentage error; PRB: price-related bias; PRD: price-related differential; RMSE: root mean squared error.

Models testing and quality assurance

Based on the evaluation metrics noted earlier in "Model testing and quality assurance" section, the results for the three different sample sizes produced by the ANN model are presented in Table 5. The outputs from the linear and nonlinear models are presented in Demetriou (2016b) so a direct comparison is possible.

The results show that all of the appraisal level statistics, i.e. the three main measures of central tendency for all samples are within the acceptable IAAO range, namely between 0.9 and 1.10 while the best was obtained for sample 2. The linear and nonlinear models present very similar values, slightly higher, than those of the ANN. Furthermore, the 95% confidence interval estimates for the mean and the median prove that the relevant standard has been met since all measures fall within the range 0.9–1.10 for all three models, suggesting reliability evidence. In addition, the COD is within the noted standard range of vacant land, ranging from 11.21 to 13.83, which is quite far from the highest acceptable value, i.e. 25, and very close to the maximum acceptable for residential properties of 10.0, which confirms that our results are very good. The COD is improved as the sample increases and the best value is achieved for the nonlinear model for sample 3 and similarly for the ANN model for both sample 2 and sample 3. The linear model gives slightly higher values.

The PRD is almost the same for all three models and samples and within the acceptable range, although it is closer to the maximum limit provided by the IAAO (2013a, 2013b). This potentially shows a slight regressive tendency, i.e. low-value properties are appraised at a greater percentage market value than high-value properties. Similarly, the estimated PRB is within the acceptable limits, showing a trend toward the lower one. The RMSE and MAPE decrease as the sample increases for all models with the exception of the ANN in sample 3. However, the decrease in all cases is very slight between sample 2 and sample 3 for all models, suggesting that no significant performance improvement can be achieved if the sample increased more than 15%. The smallest RMSE has been achieved by the nonlinear model in sample 3 while the smallest MAPE is obtained by the ANN model in sample 2.

Similarly, the percentage of FE for 10% increases with sample size providing, however, only a slight improvement between sample 2 and sample 3. The maximum FE of 10% is achieved almost equally (around 62%) by both the nonlinear and ANN models in sample 3 with very close results for sample 2. Similarly, for an FE of 20%, the maximum is achieved again by both the nonlinear and ANN models (with a value around 29%), meaning that 90% of the predictions have a difference from actual values of less than 20%, which is an acceptable inaccuracy for the purposes of land consolidation. The above outputs provide answers to research question (ii) and also suggest that an ANN can produce better results than the linear model and similar outputs with the nonlinear model (i.e. research question (iv)).

Despite the inconsistencies and inaccuracies within the LVC samples that could lead to biased outputs in the models, the preceding evaluation metrics confirm that the models are able to sufficiently predict land values of the holdout sample, irrespective of whether this sample inherently has the noted shortcomings. In essence, this evaluation refers to the "internal accuracy" of the models, i.e. their ability to predict the holdout sample and not to the "external accuracy," i.e. the accuracy of land values compared to the real market values. These statements mean that if the model is given accurate and reliable samples as inputs, then the outputs will also be of a similar quality.

Focusing on the explanation of the evaluation results, which answers research question (iii), it seems that the most beneficial are those of sample 2, since it is possible, with only 15% of the sample from the LVC (i.e. 73 land parcels), to automatically assign values to the rest of the land parcels (i.e. 414 land parcels) in the case study area with an FE accuracy of 10% for around 60% of the whole population of land values. Therefore, the AVM can adequately predict the land values based on the 15% sample provided by the LVC. If we consider these results in terms of the efficiency of the method, the AVM could carry out the site work of the LVC by employing around 80% less resources. In other words, the LVC would need to carry out only five site valuation visits in order to assign land values to only 73 parcels, instead of the 25 days needed to assess all of the 488 land parcels of the consolidated area. These figures suggest a proportional reduction of both time and costs.

Further to these time and cost savings, the quality of land valuation is enhanced since the AVM comprises 14 land valuation factors rather than the six currently taken into account by the LVC, suggesting a more integrated consideration of the process. With respect to this, the precise calculation and comparison of variable scores indicate a consistency that would be difficult to achieve by the LVC using the traditional method. In addition, the reliability of outputs, which is checked through international standards, and the potential for an analytical explanation of the outputs through this standardized modeling process provide transparency, which is required for such planning processes. These last two paragraphs have provided a concise answer to research question (vi).

Conclusions

This paper showed that the AVM developed in this research is considerably more efficient, systematic, and analytical than the traditional empirical process followed by the LVC in terms of time, costs, reliability, consistency, and transparency. In particular, the AVM can carry out the site work of the LVC by employing around 80% less resources with confirmed reliability and consistency based on international standards. Therefore, the authorities involved in land consolidation schemes should consider introducing AVMs combined with the adoption of international appraisal standards. The combination and even the full integration of these methods with a GIS is currently common good practice for land valuation. The ANN method used showed very good performance, which was better than the linear MRA but similar to the nonlinear MRA. The weaknesses of ANNs, which have been reported in various studies in the past regarding defining its structure, the selection of the training set, and the level of training, have been overcome by new software since they provide specific high level optimization algorithms. Thus, the use of ANNs is easy and clear, with a minimum background knowledge required. In addition, the power of ANNs is that they may capture any relationship between independent and dependent variables without the need to satisfy underlying assumptions that are often the case with statistical approaches. To these older-related studies, these findings add another positive indication that ANNs can be successfully employed for real estate valuation.

The contribution of this research is both scientific and practical. In terms of the former, it extends the knowledge about an important and still very limited area of research, i.e. land valuation of agricultural land for a powerful planning approach, i.e. land consolidation, which is applied in almost all EU countries and in several other countries around the world. The innovation of this research is the application, testing, and validation of a popular AI technique, i.e. an ANN combined with GIS, for automating and considerably improving a currently inefficient process. Thus, in terms of the latter, the model may have practical full implementation in Cyprus and in other countries with benefits noted above compared to the conventional process. In particular, in the case of Cyprus, the model can be used both by the Land Consolidation Department for the relevant schemes, especially after the current need for revaluating several schemes due to the considerable changes of land prices as a result of the financial crisis of the last decade; and by the Land and Surveys Department as a generic AVM for automating mass valuation of agricultural land in the context of the next comprehensive revised mass valuation program. Furthermore, the aim is to further extend this research to develop an integrated land valuation system within a GIS.

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