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Predicting Property Price Index Using Artificial Intelligence Techniques: Evidence From Hong Kong

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Abstract

Purpose - Booms and bubbles are inevitable in the real estate industry. Loss of profits, bankruptcy and economic slowdown are indicators of the adverse effects of fluctuations in property prices. Models providing a reliable forecast of property prices are vital for mitigating the effects of these variations. Hence, this study investigates the use of artificial intelligence (AI) for the prediction of property price index (PPI).

Design/Methodology/Approach - Information on the variables that influence property prices was collected from reliable sources in Hong Kong. The data were fitted to an autoregressive integrated moving average (ARIMA), artificial neural network (ANN) and support vector machine (SVM) models. Subsequently, the developed models were used to generate out-of-sample predictions of property prices.

Findings - Based on prediction evaluation metrics, it was revealed that the ANN model outperformed the SVM and ARIMA models. It was also found that interest rate, unemployment rate and household size are the three most significant variables that could influence the prices of properties in the study area.

Practical implications - The findings of this study provide useful information to stakeholders for policy formation and strategies for real estate investments and sustained growth of the property market.

Originality / Value of work – The application of the SVM model in the prediction of PPI in the study area is lacking. This study evaluates its performance in relation to ANN and ARIMA.

Keywords: artificial neural network (ANN), autoregressive integrated moving average (ARIMA), support vector machine (SVM), property price index, Hong Kong, prediction

Paper type - Research paper

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Introduction

The real estate sector plays a vital role in the economy of any nation. Several investigators suggest that a strong link exists between the property market and the economy (Pholphirul & Rukumnuaykit, 2009; Jiang *et al.*, 2013). At the microeconomic level, stakeholders are motivated to invest in real estate assets for three main reasons: (i) hedge against inflation, (ii) regular flow of future income and (iii) durability, among other qualities (Shapiro *et al.*, 2012). However, the real estate market (cycle) usually experience booms and bubbles (Malpezzi & Wachter, 2005). These booms and bubbles are commonly triggered due to the interplay between macroeconomic variables and property prices (Quigley, 2001). Booms and bubbles could have an effect on the portfolio of real estate investors (Crowe *et al.*, 2013). For instance, changes in the socioeconomic environment (such as the 2007 global financial crisis and the 1997 Asian financial crisis) were linked to activities in the real estate sector (Mera & Renaud, 2000; Jiang *et al.*, 2013). To reduce the uncertainty associated with such fluctuations, it is important to develop models that can produce reliable predictions of property price index (PPI).

Previous research has shown that traditional approaches (i.e. regression-based models) can be used for property price prediction. However, there is a need to identify new methods which provide reliable predictions. This is because accurate and reliable prediction of smooth changes in house prices could help to achieve economic growth (Ge & Lam, 2002). Most properties markets around the world are not immune from property price bubbles (Case & Shiller, 2003), and Hong Kong is not an exception. Hong Kong property market has experienced a number of bubbles and bursts over the decades (Teng *et al.*, 2013). Hui *et al.* (2011) reported that bubbles exist in residential mass and residential properties in Hong Kong, which could have devastating impact on housing prices stability and government policies. Therefore, the present paper evaluates the efficacy of using AI techniques for modeling and predicting of PPI in Hong Kong. This was achieved by (i) identification of macroeconomic indicators that influence the prices of properties; (ii) collection of relevant data relating to identified macroeconomic indicators and PPI; (iii) fitting the collected data into three modeling techniques (artificial neural network [ANN], support vector machine [SVM] and autoregressive integrated moving average [ARIMA]), (iv) comparison of the predictive accuracy of the three models to establish the most reliable; and (v) assessment of the influence of the macroeconomic variables considered in this study on property prices.

The ARIMA model was chosen as a benchmark model for evaluating the efficacy of the AI techniques for several reasons. First, previous research has shown that the ARIMA model is useful for prediction of building tender price index; construction investment; prices of agricultural commodities and gross domestic product, among others (see Brandt & Bessler, 1983; Goh & Teo, 2000; Abeysinghe & Rajaguru, 2004). Second, as suggested in Hyndman and Athanasopoulos (2014), predictive performance is one of the justifications for the application of complex algorithms. Therefore, the performance of the AI techniques was compared with the ARIMA model which was proven useful in previous studies. The results of the present study would be a useful tool for individuals and corporate real estate investors for decision making and also government authorities in policies formation and future economic planning in Hong Kong, and by extension, other similar property markets around the world. The remaining part of this paper is divided into four sections. The first section presents the review of the literature and this is followed by the description of the data and the research methodology adopted for this study. The third section presents the results and discussion of this study, while the last section concludes this paper.

Literature Review

Property price determinants

The price of a property is usually influenced by both macroeconomic (attributes that pertains to the social and economic situation of the property market) and microeconomic (i.e. structural, neighbourhood and locational attributes) factors in different property markets around the world (Lam *et al.*, 2008). Hence, previous property price prediction studies have either focused on analysing microeconomic or macroeconomic factors. Since PPI is the focus of this study, therefore, this study is based on the later.

Scholars have investigated the influence of microeconomic variables on property prices around the world. For instance, Tse and Love (2000) found that dwelling unit estate-type and the availability of car park significantly influence property prices positively, while the proximity to a shopping centre and cemetery view in an apartment do negatively affect property prices. Chau *et al.* (2004) reported that balcony and landscaped view contribute significantly to property price determination, suggesting that an apartment in Hong Kong with a balcony and landscaped view would command a higher price. Another study conducted by Hui *et al.* (2007) found that sea view and better air positively influence property price in Hong Kong.

On the other hand, Glindro *et al.* (2011) investigated the macroeconomic determinants of property prices in nine Asia-pacific property markets. The study revealed that generally, land supply, real construction cost and mortgage rates have a significant impact on property prices. In Hong Kong, Cheng and Fung (2015) study revealed that per-capita gross domestic product and export were found to be positively related to property prices. The econometric analysis of property prices in Hong Kong conducted by Tse *et al.* (1996) showed that speculations, population growth, real interest rate and the stock market activities are the significant determinants of property prices. Land supply, loan-to-value ratio and stamp duty were found to be the major determinants of property prices in Hong Kong by Craig and Hua (2011).

In terms of variables that determine home ownership which is linked to property prices, unemployment rate, interest rate and household size are the main determinants of property ownership in Hong Kong (Jayantha, 2012). There is a mix in the findings of studies that focused on property price determinants and this could be attributed to the composite nature of real estate properties (Rosen, 1974), and because the prices of properties are determined by their location (Li *et al.*, 2011). This is due to the socioeconomic, legal, environmental and cultural peculiarities across property markets around the world (Pagourtzi *et al.*, 2003). Table I contains the list of macroeconomic variables that have been used in previous studies and that are considered in the present study.

Table I: List of variables from the literature

Variable	Studies
Property price index	Ge and Lam (2002), Ge and Runeson (2004), Li *et al.* (2009), Chiarazzo *et al.* (2014), Tan *et al.* (2017)
Population	Tse *et al.* (1996) Ge and Lam (2002), Plakandaras *et al.* (2015), Tan *et al.* (2017)
Real GDP	Ge and Lam (2002), Ge and Runeson (2004), Lin and Chen (2011), Plakandaras *et al.* (2015), Tan *et al.* (2017)
Domestic export	Yan *et al.* (2007)
Domestic import	Yan *et al.* (2007)
Household size	Ge and Runeson (2004), Jayantha (2012)
Household income	Wilson *et al.* (2002), Ge and Lam (2002), Ge and Runeson (2004), Li *et al.* (2009)
Household stock	Wilson *et al.* (2002), Ge and Lam (2002), Chiarazzo *et al.* (2014)
Interest rate	Tse *et al.* (1996), Wilson *et al.* (2002), Ge and Lam (2002), Ge and Runeson (2004), Li *et al.* (2009), Jayantha (2012), Plakandaras *et al.* (2015), Tan *et al.* (2017)
Inflation rate (CPI)	Ge and Lam (2002), Li *et al.* (2009), Lin and Chen (2011), Plakandaras *et al.* (2015), Tan *et al.* (2017)
Unemployment rate	Ge and Lam (2002), Ge and Runeson (2004), Jayantha (2012), Chiarazzo *et al.* (2014), Plakandaras *et al.* (2015)

Property price modeling

Modeling and predicting of property prices have a long history (Haas, 1922; Wallace, 1926). Prediction-oriented research are meant to satisfy several purposes: (i) evaluation of practical relevance of theories, (ii) serve as a tool for assessing the impact of changes in policy on predicted variables (i.e. scenario prediction) and (iii) serve as a tool for estimating changes in future volume of predicted variable, among others (Ogunlana *et al.*, 2003; Shmueli & Koppius, 2011). The need for accurate predictions has led to the application of various techniques to property price prediction. Early studies applied regression-based models, such as ARIMA to property price prediction (see McGough & Tsolacos, 1995). Recent empirical evidence has shown that nonlinear models (e.g. ANN) provide more reliable predictions (see Abidoye & Chan, 2016a). This could be attributed to the underlying nonlinear relationship between property prices and its determinants (Cechin *et al.*, 2000; Lin & Mohan, 2011).

Borst (1991) study is one of the first to apply a nonlinear technique (i.e. ANN) to property price prediction. Subsequently, other studies have shown that ANN models provide reliable predictions of property price (Abidoye & Chan, 2016a), since it can handle the nonlinear relationship between property prices and property attributes; it is user-friendly; it can handle outliers and it is objective; among others (Tay & Ho, 1992; Paliwal & Kumar, 2009). ANN models are classified as a "black-box" approach because the effect of the input variables on the output variable is 'unknown' (Limsombunchai *et al.*, 2004). Getting stuck in local optima affects the predictive performance of the ANN model (Gorr, 1994). Developing algorithms which address the local optima problem associated with the ANN model is of particular interest in the field of AI.

On the other hand, the SVM model always converges to global optima. This is one of the main advantages of the SVM model when compared to the ANN model (Lu *et al.*, 2011). The SVM technique was initially proposed by Vapnik (1995) and its industrial context has made it suitable for handling real-world problems (Smola & Schölkopf, 2004). Although SVM has been applied in wine taste preference (Cortez *et al.*, 2009), credit scoring (Huang *et al.*, 2007), radial distribution system (Thukaram *et al.*, 2005) and banking financial strength (Öğüt *et al.*, 2012), among other areas, its application in PPI prediction has been limited. Hence, the study reported in this paper sets out to address this gap in the existing literature. As stated earlier, the ARIMA model was also applied in this study. The comparison of the predictive performance of the ARIMA with those of the SVM and ANN models serve as a rationale for the application of complex AI algorithm to PPI prediction.

The ARIMA technique is suitable for modeling time series data and it is used for the modeling and prediction of PPI. ARIMA model represents an autoregressive moving average (ARMA) model with autoregressive (p), differencing order (d) and moving average (q), and it takes the form of p,d,q (Yan *et al.*, 2007). The time series data used for the implementation of ARIMA model needs to be stationary before the development of ARIMA models and this is when the statistical properties of the data, such as mean, variance, autocorrelation, etc. are constant over time (Lam & Oshodi, 2016).

Lin and Chen (2011) compared the accuracy performance of ANN and SVM in the Taiwan real estate market context. The authors found that the SVM technique outperformed the ANN technique in terms of a lower mean absolute percentage error (MAPE) and higher coefficient of determination (r^2) values. Kontrimas and Verikas (2011) investigated the predictive accuracy of SVM, ANN and MR for real estate mass appraisal. The SVM technique was reported to have outperformed MR and ANN, and this was attributed to the ability of SVM to attain a global minimum of the cost function during data training when compared with ANN.

The Shanghai PPI was forecasted by Xie and Hu (2007) by examining the predictive accuracy of ARIMA, ANN and SVM. ANN and SVM were found to be better than ARIMA in predicting property prices accurately. The ANN technique was found to be better for short-term prediction, while SVM outperformed ANN in terms of accuracy for long-term prediction. This indicates that ANN and SVM are both useful techniques for PPI prediction.

Previous studies conducted in Hong Kong (Wong *et al.*, 2002; Ge & Runeson, 2004; Lam *et al.*, 2008) have reported the accurate and reliable quality of the ANN technique in predicting property prices. Lam *et al.* (2009) adopted the ANN and SVM techniques in addition to the regression model, for property valuation in Hong Kong. Yiu *et al.* (2013) demonstrated the use of Phillips, Shi and Yu (PSY) method to detect bubbles in the property market in Hong Kong. The study found that the 2011 bubble experienced in Hong Kong could be attributed to demand pressure for medium sized apartment by small sized property owners. Tan *et al.* (2017) also investigated the forecasting performance of grey models for property price indices in Hong Kong, and reported that grey models is a good tool to forecast property prices indices in Hong Kong. However, investigations into the performance of ANN been benchmarked with the SVM machine learning approach and ARIMA econometric approach in Hong Kong is limited, especially for the prediction of PPI. SVM possess theoretical advantages over ANN, such as the absence of local minima in the learning phase and has outperformed the ANN technique in several real-world applications (Cortez *et al.*, 2009), while ARIMA has been argued to be a good technique to predict time series data (Crawford & Fratantoni, 2003). Therefore, this study aims to establish and compare the predictive accuracy of AI and econometric techniques (ANN, ARIMA and SVM) in PPI prediction.

Research Method

Data

The variables used for this study were retrieved from previous studies (see Table I). The data comprises of 10 independent variables (that have been commonly used in previous studies in the study area) and one dependent variable (PPI). There are four main sources of PPI in Hong Kong: (1) the Rating and Valuation Department; (2) Jones Lang LaSalle; (3) FPDSavills; and (4) Centa-City (Chau *et al.*, 2005). However, the indices of the Rating and Valuation Department was adopted in this study due to its long history and wide coverage (Chau *et al.*, 2005). The construction of the PPI is transaction-based. The actual price data recorded during property transactions are measures in relation to the rateable value of the subject property. Chau *et al.* (2005) and the Technical Notes published by the Rating and Valuation Department of Hong Kong can be referred to for more details about Hong Kong PPI. Quarterly time-series data were collected from different government organizations in Hong Kong. The data were extracted from the various publications (monthly and quarterly) that were published online on the websites of different organisations which are available on a free of charge basis. The list of the variables, code, definitions and their sources are presented in Table II.

Table II: Sources of the data

Variable	Code	Definition	Source
Dependent variable			
Property price index	PPI	A measure of private domestic units' price changes with quality kept at a constant	The Hong Kong Rating and Valuation Department
Independent variables			
Population	POP	The total number of people residing in Hong Kong including usual and mobile residents	The Hong Kong Census and Statistics Department
Real gross domestic product	GDP	The total value of production of all resident producing units in Hong Kong in a specific period	The Hong Kong Census and Statistics Department
Domestic export	EXP	Domestic exports are the natural produce of Hong Kong or the products of a manufacturing process in Hong Kong which has changed permanently the shape, nature, form or utility of the basic materials used in manufacturing	The Hong Kong Census and Statistics Department
Domestic import	IMP	Goods which have been produced or manufactured in places outside the jurisdiction of Hong Kong and brought into Hong Kong for domestic use or for subsequent re-export	The Hong Kong Census and Statistics Department
Household size	HH_S	Consist of a group of persons who live together and make common provision for essentials for living	General Household Survey
Household income	HH_I	The median monthly household income of domestic households with four members, regardless of their household composition in Hong Kong Dollars	The Hong Kong Census and Statistics Department
Household stock	HH_SK	The total number of domestic households in Hong Kong	The Hong Kong Rating and Valuation Department
Interest rate	INT	The best lending rate in Hong Kong Dollars	Hong Kong Monetary Authority
Inflation rate (CPI)	INF	The measure of the changes over time in the price level of consumer goods and services generally purchased by households	The Hong Kong Census and Statistics Department
Unemployment rate	UMP	The proportion of unemployed persons in the labour force	The Hong Kong Census and Statistics Department

The collected data for this study covered the period of 1985Q1 to 2016Q3, this resulted in a sample size of 127 observations. The frequency distribution of the variables is presented in Table III. The time-series plot of PPI for Hong Kong is presented in Figure 1. The graph shows the decline in PPI between 1997 and 2003 and a steady upward trend since 2004. The Asian financial crisis in 1997 and the severe acute respiratory syndrome virus outbreak in Hong Kong in 2003 could be linked to the fluctuations in property prices in those periods (Lai *et al.*, 2006). It is evident that the PPI data exhibits cyclical behaviour (i.e. booms and bubbles). However, the need to accurately predict property price cannot be overemphasized, so as to strategically plan for property price booms or bubbles.

Table III: Frequency distribution of the variables

Variables	Unit of measurement	Mean	Standard deviation	Minimum	Maximum
Property price index	Price index	113.21	72.28	17.60	305.20
Population	Numeric	6,504,355.11	583,337.79	5,456,200.00	7,374,900.00
Real gross domestic product	HK$	324,528,149,606.29	148,206,799,602.22	67,087,000,000.00	646,163,000,000.00
Domestic export	HK$	151,528,842,519.71	91,096,900,167.65	17,717,000,000.00	328,457,000,000.00
Domestic import	HK$	164,598,354,330.70	103,994,594,973.82	18,000,000,000.00	377,507,333,333.00
Household size	Numeric	3.22	.26	2.90	3.70
Household income	HK$	18,059.84	6,883.83	5,000.00	31,900.00
Household stock	Numeric	1,990,098.42	335,408.22	1,402,900.00	2,505,700.00
Interest rate	Numeric	7.02	1.91	5.00	11.44
Inflation rate	Numeric	70.92	19.24	32.00	103.23
Unemployment rate	Numeric	125,443.30	67,055.74	27,000.00	296,500.00

Note: HK$ is Hong Kong Dollars which is Hong Kong's currency

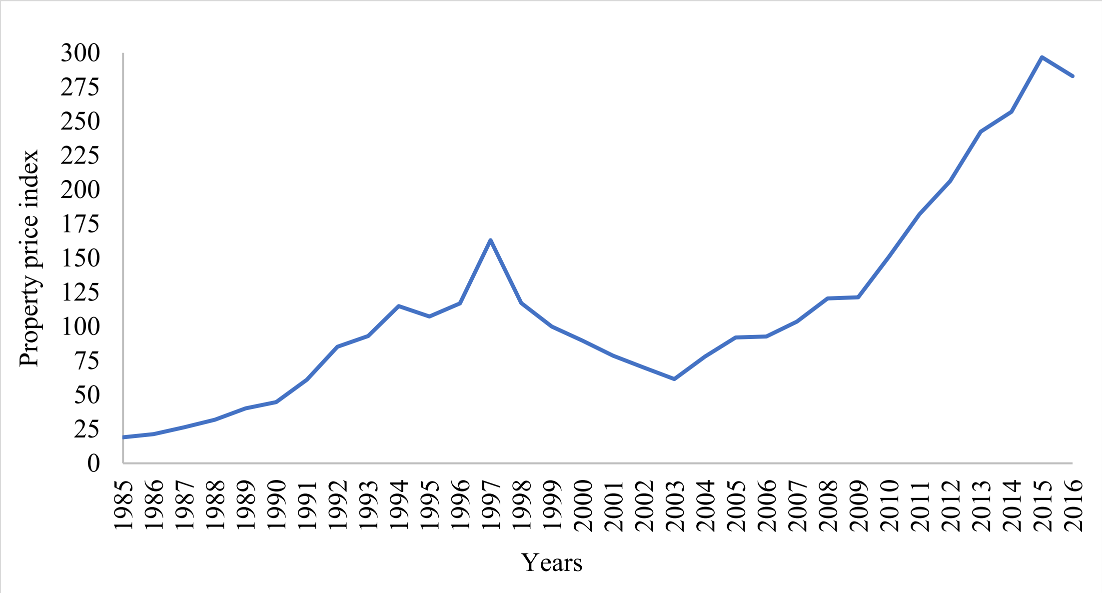

Figure 1: The trend of Hong Kong property price index

The study area

The Hong Kong property market is a unique market in the world. The reasons are; it is a densely populated environment (Hui *et al.*, 2007), most of its residential properties are high-rise (Choy *et al.*, 2007), making it the number one city with the highest number of skyscrapers in the world (The WorldAtlas, 2017). Also, the number of public housing represents a large proportion of housing units available in the property market of Hong Kong. This makes Hong Kong one of the largest suppliers of public housing in the world (Delang & Lung, 2010). In addition, Hong Kong's property prices are extremely volatile resulting in highest property prices and it been among the most expensive cities in the world over the years (Knight Frank, 2016).

The peculiarity of the Hong Kong property market could be attributed to the small and densely populated nature of the city (Hui *et al.*, 2007). Of the 1,106.34sqm total land area of Hong Kong, only 25% have been developed for human habitation, while most of the rest are being kept as country parks and nature reserves (Hong Kong Government, 2017). The return of investment on real estates in Hong Kong has been the highest among other cities of the world (Cervero & Murakami, 2009). This has attracted the interest of both the local and international investors to monitor the property price movements in Hong Kong with keen interest. Hence, this study would provide such investors more insight into this topic.

Models specification

The ARIMA Model

For time series prediction problems (such as property price index prediction), ARIMA models have been proven to be reliable for use in such cases (Fan *et al.*, 2010). Time series data must be transformed into stationary form prior to the application of the ARMA model (Pagourtzi *et al.*, 2003). This econometric technique was developed by Box and Jenkins (1976). Since then, the technique has been applied in property price prediction (McGough & Tsolacos, 1995; Tse, 1997; Hepşen & Vatansever, 2011). The process of applying ARIMA involves some steps which are; testing for the stationarity of the data which can be achieved by conducting the unit root test, if the data is not stationary, the next step is transforming the data by differencing, then the plotting of the autocorrelation function (ACF) and partial autocorrelation function (PACF) in order to select the model to be applied in the prediction (based on corrected Akaike's information criterion (AICc)) and then the forecast can be conducted. Hyndman and Athanasopoulos (2014) can be referred to for a detailed process of applying ARIMA for prediction problems.

The Eviews 9.5 software was used for the development of the ARIMA model. The default Automatic ARIMA prediction algorithm of the software was adopted. By this, the default parameters of the software in terms of the autoregressive (RA), moving average (MA) in addition to their seasonal process were used, while the number of differencing was put at 2.

Although the ANN and SVM techniques do not require the data stationary test, however, the Augmented Dickey-Fuller (ADF) test was conducted on the data in order to test for the unit root for the ARIMA model. The first order differencing show that the data is stationary, except for household income and inflation rate variables. This warranted a 2nd order differencing of the data which led to the rejection of the hypothesis that there is a unit root in the data at 5 per cent level of significance (see Table IV). Consequently, after the iteration of 100 ARIMA models, ARIMA (2,3)(1,0) with the lowest AIC value of 5.7422 was chosen in this study to predict the property prices.

Table IV: Results of the ADF unit root test

Variables	ADF unit root test					
	Level		1st difference		2nd difference	
	t-stat	*p-value*	*t*-stat	*p-value*	*t*-stat	*p-value*
PPI	2.128642	0.9920	-5.805815	0.0000	-4.056971	0.0000
POP	2.396644	0.9960	-1.825989	0.0647	-16.59364	0.0000
GDP	2.767501	0.9986	-1.710386	0.0826	-6.988867	0.0000
EXP	2.905345	0.9991	-2.981579	0.0031	-8.014895	0.0000
IMP	2.843122	0.9989	-4.395330	0.0000	-7.989221	0.0000
HH_S	-2.457840	0.0141	-12.10560	0.0000	-8.072142	0.0000
HH_I	1.141052	0.9339	-1.154295	0.2254	-8.269212	0.0000
HH_SK	2.825810	0.9988	-1.734958	0.0785	-17.75055	0.0000
INT	-0.920439	0.3159	-7.478325	0.0000	-6.079143	0.0000
IFR	0.954682	0.9092	-1.522735	0.1195	-7.318993	0.0000
UMP	-0.286599	0.5808	-4.988550	0.0000	-12.67337	0.0000

The ANN and SVM Models

The operation of the ANN technique is built on the interaction of neurons that mimics the human brain neurons (Mora-Esperanza, 2004). The ANN model is constructed on the basis of a network architecture that usually consists of three layers, namely input, hidden and output layers (Zhang *et al.*, 1998). The explanatory variables of the factor to be examined are entered into the model at the input layer. The weight factors of the input variables are processed at the hidden layer through an activation function, while the output value is obtained at the output layer. A three-layer network is commonly adopted in previous related studies. This is because one hidden layer is sufficient for ANN to produce excellent outputs (Masters, 1993). A detailed explanation of the process of fitting an ANN model can be found in Kaastra and Boyd (1996). Also, the predictions from an ANN model is dependent on the initial weights. In this study, an ensemble of neural network model was applied and the average of individual predictions was calculated to address this problem (Hastie *et al.*, 2009).

The SVM is a machine learning technique used for classification and regression tasks. SVM is based on the nonlinear mapping and transformation of the input variables into a high *m*-dimensional feature space. The risk minimisation of the SVM technique ensures the minimisation of the mean square error and an upper bound on the expected risk, as against the empirical risk minimisation that minimises the error of only the training data (Xie & Hu, 2007). The performance of SVM involves the linear separation of hyperplane of the set of support vector points in the feature space. The transformation that occurs is based on a kernel function, and the Gaussian (RBF) kernel is commonly adopted in previous studies because it uses fewer parameters when compared with others like the polynomial (Cortez, 2010). The three parameters of SVM are error cost C, the width of tube ε and the kernel function γ. A detailed explanation of the process of fitting an SVM model can be found in Smola and Schölkopf (2004). However, Pagourtzi *et al.* (2003) presented an overview of the application of these techniques in addition to other approaches.

The ANN and SVM models were developed using the R programming software and rminer package (R CoreTeam, 2016). The R codes were used to implement the development of the models. For the ANN model, the number of input neurons represent the number of the independent variables (10), while the output variable is the dependent variable (PPI). The grid search algorithm was used to optimize and identify the best hyperparameters for the ANN and SVM model. The number of neurons in the hidden layer was the hyperparameter for the ANN model. The backpropagation multilayer perceptron ensemble (mlpe) algorithm was adopted in the training of the ANN model. In the same vein, the hyperparameters of the SVM model were c, γ and ε.

Predictive Accuracy of the Developed Models

The evaluation of the models required the splitting of the available data set into two sets, i.e. for the training and the testing of the models. There is no rules for the splitting ratio of modeling data in the literature (Cechin *et al.*, 2000). The ratio of 90:10, 85:15, 80:20 have been adopted in previous studies (see, Abidoye & Chan, 2017b). Hence, the analyst's discretion is needed in determining the splitting ratio (Abidoye, 2017). The training of the models was conducted by using the data of 1985Q1 to 2012Q4 (112 observations). While a holdout sample of data of 2013Q1 and 2016Q3 (15 observations) were used for the testing of the models. The small sample size of the data could be attributed to the fact that it is a quarterly time-series data, as against the cross-sectional data mostly used in similar previous studies. Also, it should be noted that a small holdout sample could be used for the testing of the models (Zhang *et al.*, 1998). The sample size covers a period of 27 years and this size is within the range obtainable in the literature (see, for instance, Ge & Runeson, 2004; Ahmed *et al.*, 2014; Morano *et al.*, 2015). In addition, it has been established that AI techniques could function excellently with a small sample size (see Rossini, 1997; Zhang *et al.*, 1998).

The predictive accuracy of the models was tested by adopting the accuracy metrics, namely r^2, mean absolute error (MAE), normalized mean absolute error (NMAE) and the root means square error (RMSE) that are widely adopted in the literature (Makridakis *et al.*, 1998; McCluskey *et al.*, 2013; Oliveira *et al.*, 2017), and have been proven to be good measures of the predictive accuracy of models (Hyndman & Koehler, 2006). Moreover, it is suggested that these performance metrics would be easily interpreted by stakeholders. These metrics quantify the error between the actual (expected) and forecasted values under consideration. An MAE, NMAE and RMSE values close to 0 signifies a good model, suggesting an accurate model (Lin & Mohan, 2011), while an r^2 value that tends toward 1 depicts a better model fit. The expressions for the calculation of the accuracy metrics, i.e. r^2, MAE, NMAE and RMSE, found in the literature (Limsombunchai *et al.*, 2004; Lin & Mohan, 2011; Zurada *et al.*, 2011; Oliveira *et al.*, 2017) are presented in Equations 1 to 4, respectively. It should be noted that the same data set (i.e. the number of independent variables) were used for the development of the models so as to permit an objective basis of comparison. Also, all the variables incorporated into the models had 5 time lags. This is because previous studies have adopted a similar number of lags and it has produced excellent results (see, for instance, Tetlock, 2007; Oliveira *et al.*, 2017).

$$r^2 = 1 - \frac{\sum_{i=1}^{n} \left(P_i - \hat{P}_i\right)^2}{\sum_{i=1}^{n} \left(P_i - \overline{P}\right)^2} \qquad (1)$$

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1} \left(P_i - \hat{P}_i\right) \qquad (2)$$

$$\mathrm{NMAE} = \frac{\mathrm{MAE}}{P_H - P_L} \qquad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(P_i - \hat{P}_i\right)^2} \qquad (4)$$

Where P_i is the actual property value, $\hat{P}_i$ is estimated/predicted property value from the model, $\overline{P}$ is the sample mean of the property values, P_H is the biggest target value, P_L is the lowest target value and n is the number of observations.

Results and discussion

The results shown in Table V depicts that the SVM model produced a higher r^2 of 0.94 compared with the ones generated by the ANN and ARIMA models which are 0.92 and 0.73, respectively. This indicates that the variables included in the SVM model could explain 94% variations in the changes in property prices in Hong Kong, while the variables in the ANN model could explain 92% of such changes and that of the ARIMA model is 73%. The r^2 indicator only explains the variations between the independent variables and the dependent variable (Sincich, 1996), hence, the performance of the models is to be evaluated based on other indicators – MAE, NMAE and RMSE.

Table V: Predictive performance indicator of the developed models

Year	Actual value	Forecast value		
		ANN	ARIMA	SVM
2013Q1	237.5	234.05	239.42	227.60
2013Q2	241.2	244.81	251.58	235.75
2013Q3	245.6	242.22	256.36	236.43
2013Q4	245.2	248.06	257.61	241.07
2014Q1	244.2	245.24	260.96	241.73
2014Q2	247.6	244.12	266.07	242.61
2014Q3	261.3	251.40	265.05	247.67
2014Q4	274.3	272.33	265.74	261.19
2015Q1	289.2	283.45	266.38	267.18
2015Q2	299.2	298.39	268.34	272.50
2015Q3	305.2	304.76	262.64	272.74
2015Q4	293.6	308.01	256.75	272.37
2016Q1	274.7	284.63	254.77	261.17
2016Q2	275.2	262.35	253.57	251.80
2016Q3	288.4	279.84	248.60	262.10
	r^2	0.92	0.73	0.94
	RMSE	7.01	23.35	17.78

MAE	5.49	19.83	15.23
NMAE	0.08	0.29	0.23

Based on the MAE, NMAE and RMSE values generated by the models, the ANN model appears to possess a higher satisfactory predictive accuracy, when compared with the SVM and ARIMA models. This is because ANN generated the MAE value of 5.49, NMAE value of 0.08 and RMSE value of 7.01, which are closer to 0, as against the values of 15.23, 0.23 and 17.78, respectively, produced by the SVM model. These values are more encouraging when compared with that of the ARIMA model that generated the MAE value of 19.83, NMAE value of 0.29 and RMSE value of 23.35. The result could be interpreted to mean that the ANN model could forecast better than the ARIMA and SVM models, based on the predictive accuracy that the models generated. This result corroborates the findings of Lim *et al.* (2016) that found that the ANN technique generated a high predictive accuracy of condominium price index (CPI) in Singapore when compared with the performance of ARIMA and MRA. Also, Cortez *et al.* (2009) found that ANN is better than the SVM technique for predictions, while the SVM technique could outperform the ANN technique when used for classification tasks.

In another context, Zhao *et al.* (2014) reported that the SVM technique possesses a higher predictive accuracy in predicting property prices when compared with the ANN technique. Also, Lam *et al.* (2009) found the SVM approach to be better when compared with ANN in property valuation. Whereas, the study of McGough and Tsolacos (1995) found the performance of ARIMA to be satisfactory for retail and office rental value prediction. However, the study did not benchmark this performance with any other technique. However, Crawford and Fratantoni (2003) reported that the ARIMA model did not outperform other prediction techniques, while Tse (1997) suggested that the ARIMA techniques should be combined with others for prediction purpose. Nevertheless, the findings of this study corroborate that results of Xie and Hu (2007) that reported that the ANN and SVM models outperformed the ARIMA models in terms of predictive accuracy of PPI. This substantiates the fact that AI techniques could be more suitable for solving real-world problems, probably because econometric techniques cannot handle the nonlinear relationship that exists between economic variables (Lee *et al.*, 1993; Marwala, 2013).

The ANN technique has been established to be a better substitute to the traditional approaches, especially the hedonic pricing model (HPM) in a number of studies (see Abidoye & Chan, 2017a). The studies that compared the predictive performance of the three models (ANN, ARIMA and SVM) that are considered in this study are rather limited, particularly in the real estate domain. Therefore, the mix in the results of studies conducted to establish the predictive accuracy of the techniques (especially the AI techniques – ANN and SVM) could be attributed to the difference in the characteristics of the study areas, preferences of the researcher and the quality of the data set used (Powe *et al.*, 1995). Also, the type of data (time series, cross-sectional and panel) used could be responsible for the difference in results of property price prediction studies. For instance, Lam *et al.* (2009) used panel data, Kontrimas and Verikas (2011) used cross-sectional data, while this study adopted time series data. This buttress the fact that no model can address all the property price prediction real-world problems (Pagourtzi *et al.*, 2007).

In order to further evaluate the predictive accuracy of the models, the property price (holdout sample) forecasted by the ANN, ARIMA and SVM models were compared (by plotting their values) with the actual PPI. The plot shown in Figure 2 shows that the forecasts of the ANN model are closer in value to the actual PPI than the forecasts of ARIMA and SVM. In almost all the instances of the data points on each line shown in Figure 2, those of the ARIMA and SVM prices are farther to the actual PPI when compared with the predicted prices of ANN that are closer to the actual PPI.

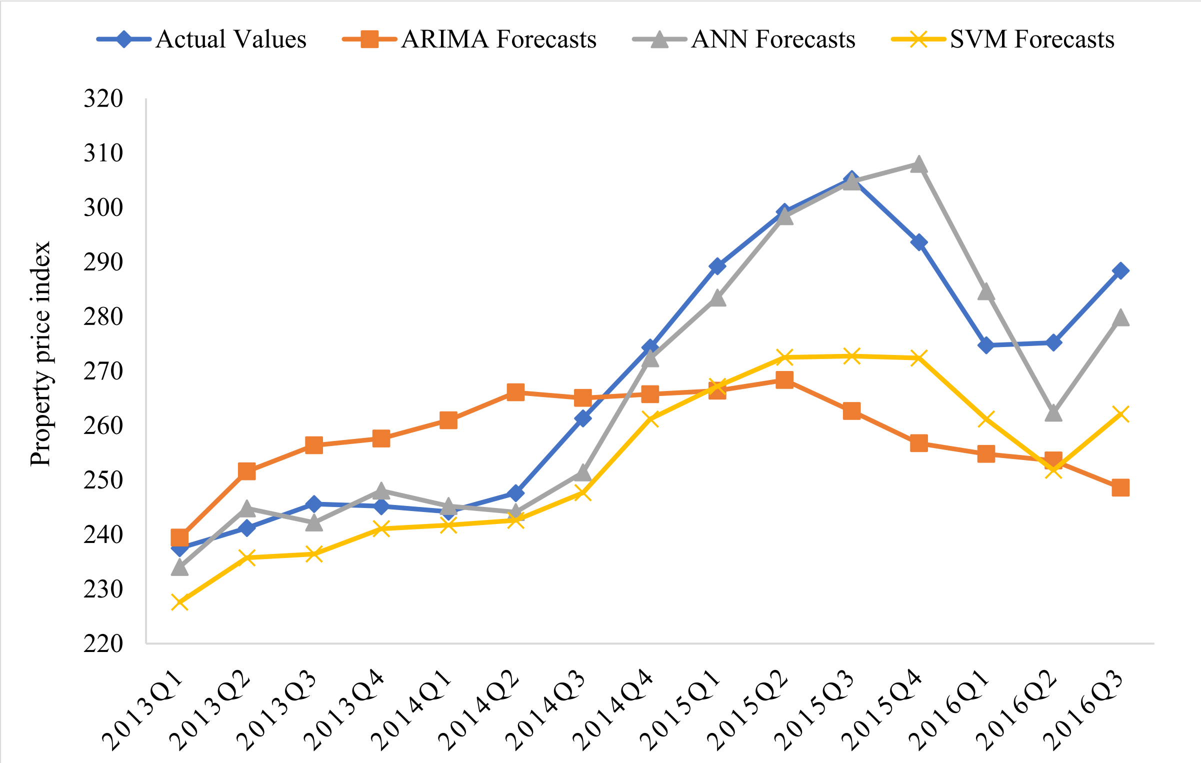

Figure 2: Comparison of the actual property prices and the predicted values of ANN, ARIMA and SVM

It is also evident from Figure 2 that the forecasts generated by both ANN and SVM were a bit more accurate when the trend in property prices was gradual, i.e. between 2013Q1 and 2014Q2. However, when sudden accelerated changes in properties prices were experienced between 2014Q3 and 2016Q1, the ANN forecasts were still more accurate compared with actual PPI, whereas the SVM forecasts were far from being accurate. On the other hand, it is evident that the forecasts from the ARIMA model did not follow these patterns as the trends of its forecasts are quite steady and far from actual property prices throughout the period. It may be safe to suggest that the ARIMA model could not handle the sudden changes in PPI. This may be responsible for the large values of the error metrics during this period (i.e. 2015Q1-2016Q3). This suggests that AI prediction techniques are better tools for property price prediction (Masías *et al.*, 2016). However, it should be noted that the encouraging performance of the AI techniques reported in this study does not negate the importance of the econometric technique (ARIMA), as all techniques possess their strengths and weaknesses (Abidoye & Chan, 2016b), and also contains some unique and peculiar additional information that is useful for different stakeholders (Diebold & Mariano, 1995).

The influence (sensitivity analysis) of the variables considered in this study (see Table VI) was evaluated so as to establish the importance of each independent variable in predicting property prices. This was performed by considering the RMSE of the ANN model (because it generated the best results) without one of the variables and comparing it with the RMSE of the model when all variables are included. This generates an error ratio for each variable which is ranked in establishing the most important variable. This approach has been adopted in previous studies (see, for instance, Tabales *et al.*, 2013; Morano *et al.*, 2015). The result of the sensitivity analysis is presented in Table VI.

Table VI: Importance of the macroeconomic variables to property price index

Variable	Ratio	Order of importance
Interest rate	7.0141098	1
Unemployment rate	7.0141087	2
Household size	7.0141086	3
Inflation rate	7.0141073	4
Domestic export	7.0141068	5
Real gross domestic product	7.0141063	6
Household income	7.0141040	7
Population	7.0140991	8
Household stock	7.0140963	9
Domestic import	7.0140910	10

The interest rate, unemployment rate and household size were found to be the three most significant variables that influence property price in Hong Kong. This implies that changes in these variables have the largest impact on property prices in Hong Kong. Coincidentally, these three variables were found to be critically significant to homeownership rates in Hong Kong as reported by Jayantha (2012). All these suggest that interest rate, unemployment rates and household size should be accorded more attention by property market policymakers in Hong Kong in order to ensure that properties are more affordable to either be owned or rented. Also, real estate investors should pay more attention to the movement in these three variables as they could have an impact on their investment portfolios. Domestic import has the least impact on PPI in Hong Kong.

Conclusion

The uncertainties that could occur in the real estate industry in the form of booms and bubbles warranted this study. This study investigated the efficacy of using the ANN, ARIMA and SVM techniques toward achieving an accurate and reliable property price prediction that could aid strategic planning and decision making in the real estate industry. Data comprising 127 observations that cover the period between 1985Q1 and 2016Q3 were collected from different government departments in Hong Kong. The observations of the collected data that were recorded between 1985Q1 and 2012Q4 were used for the training of the models, while the rest 15 observations (2013Q1 – 2016Q3) were used for the testing of the models.

An evaluation of the forecasts generated by the models shows that the ANN model outperformed both the ARIMA and SVM models in terms of predictive accuracy. This is evident with the ANN model generating MAE, NMAE and RMSE values closer to 0, compared with those of ARIMA and SVM. This implies that the ANN technique is more reliable for adoption by different real estate stakeholders in predicting property prices and for the formation of real estate related policies. The findings reported in this study has several implications. First, relevant stakeholders need to monitor the changes in interest rates, unemployment rates and household size. For example, government can use this information for properties prices control in order to make properties more affordable. Second, globalization has increased the volume of cross-border property transactions. Property investors and their advisers can use information provided by these variables in making investment decisions relating to real estate.

With more data available, the predictive accuracy of the models considered in this study could be tested by using varying data splitting ratio to establish their performance for short, medium- and long-term predictions. The need to accurately predict property prices cannot be overemphasized, therefore, the result of this study shows that the ANN model could be used as a decision support tool for the prediction of PPI.

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