KKU ENGINEERING JOURNAL July – September 2015;42(3):243-249 Research Article

KKU Engineering Journal

https://www.tci-thaijo.org/index.php/kkuenj/index

A comparison of regression analysis for predicting the daily number of anxiety-related outpatient visits with different time series data mining

Jaree Thongkam[1)], Vatinee Sukmak*[2)] and Weerayut Mayusiri[3)]

[1)]Faculty of Informatics, Mahasarakham University, MahaSarakham, Thailand, 44150.
[2)]Faculty of Nursing, Mahasarakham University, MahaSarakham, Thailand, 44150.
[3)]Prasrimahabhodi Psychiatric Hospital, Ubonratchathani, Thailand, 34000

Received February 2015
Accepted April 2015

Abstract

This study aimed to develop and evaluate different models to forecast the daily number of anxiety-relatedpatients seeking to visit the outpatient department in Prasrimahabhodi Psychiatric Hospital. The authors developed and tested four different models of outpatient visits using total daily counts of anxiety-related patient visits to outpatient at Prasrimahabhodi Psychiatric Hospital, Thailand from January 2011 to December 2013.Multi-Layer Perceptron Regression (MLPR), Radial basis function Regression (RBFR), and Support Vector Regression (SVR) were compared with the traditional statistical tool of Linear Regression (LR). The sliding window method was used to prepare the dataset for the number of anxiety-related outpatient visits forecasting process. The performances of the models were compared in terms of the mean absolute error (MAE) and root mean square error (RMSE). The performance comparison showed that the SVR exhibited a slightly better performance. The SVR also showed highly stable. The outcome of the study can be of use for planning staff arrangement and material resources distribution.

Keywords : Support vector machine, Artificial neural network, Time series, Anxiety-related outpatient visits

1. Introduction

The anxiety-related or disorders clinic is a multidisciplinary specialty clinic that provides evaluation and treatment for individuals with all types of anxiety disorders, including generalized anxiety disorder, panic disorder, social anxiety disorder or social phobia, specific phobias, post-traumatic stress disorder, obsessive compulsive disorder, and other types of anxiety symptoms. Anxiety disorders are common mental disorders and a serious mental illness. Anxiety disorders affected approximately 40 million American adults age 18 years and older (about 18%) in 2004, and nearly 29% of the U.S. population will experience an anxiety disorder at some point in their lives [1-3]. In Thailand the prevalence of anxiety disorders was approximately 16.4% in 2004 [4].

Prior studies have documented an increasing trend in outpatient visits for the treatment of anxiety disorders [5-7]. The rate of outpatient treatment for anxiety disorders increased from 0.43 visits per 100 persons in 1987 to 0.83 in 1999 [7]. Specifically, prevalence rates of anxiety disorders are generally higher in women across age groups [5]. However, prevalence rates for men are higher than women of the same age in the 16-19, 30-34, and 45-49 year old groups in the UK [8] and in the 45-54 and 65+ year old groups in Australia [9].

To make a strategic decision for the health care administrators, forecasting the number of anxiety-related outpatient visits plays an important role. If more accurate forecasts are obtained, it would help the health care administration effectively manage operation and distribute resources. Forecasting outpatient visits is absolutely necessary in order to arrange human resources and planning of future events.

In the literature, time series study has been wildly applied in several domains, such as economic and medical data analysis. For example,Adinaro et al. [10] performed the Box-Jenkins method to forecast anxiety-related visits to a New Jersey emergency department after September 11, 2001. Among the popular techniques are the artificial neural network (ANN) and support vector machine (SVM)[11-12]. For instance, a new fuzzy time series method which is based on weighted-transitional matrix was employedto predict patient visits to outpatient clinic by Cheng et al. [13]. Kam et al. [14] used average, univariate seasonal auto-regressive integrated moving average and multivariate whereas Jones et al. [15] employed seasonal autoregressive integrated moving average, time series regression, exponential smoothing, and ANN to forecast the daily patient numbers in the emergency department. Akande et al. [16] and Samudin et al. [17] compared the performance of time series forecasting using SVM and ANN. It was found that SVM outperformed ANN models.

*Corresponding author: Tel: +6686 457 0361
Email address: vsukmak@gmail.com
doi: 10.14456/kkuenj.2015.26

In this paper, we used MLPR, RBFR, and SVR for prediction of the daily number of anxiety-related outpatient visits and compared it with linear regression according to mean absolute error (MAE) and root mean square error (RMSE).

This paper is structured as follows: Section 2 briefly presentstime series techniques used in this study. In section 3, the experimental design and dataset are highlighted. Section 4 shows the experimental results. Finally, discussion and conclusion are given in sections 5.

2. Time series techniques

In this section, we present four models of time series techniques: Linear Regression (LR), Multi-Layer Perceptron Regression (MLPR), Radial basis function Regression (RBFR), and Support Vector Regression (SVR).

2.1 Linear regression

Linear Regression (LR) [18] is a traditional method for building the forecasting modeling using the relationship between class attributes *y* and one or more non-class attribute denoted *X*. It uses the M5 (attribute selection) method for selecting the attribute to build forecasting models. The M5 method steps through the attributes removing the one with the smallest standardized coefficient until no improvement is observed in the estimate of the error given by the Akaike information criterion [19]. Time series processes are often described by *multiple linear regression* (MLR) models of the form in Equation 1:

$$Y_i = \sum_{j=1}^{k} B_j X_{ij} + \varepsilon_i \tag{1}$$

where $Y_i$is the number of independent attributes, B_j is a regression coefficient, X_{ij} is the *j*value for the observation *i* and ε_i refers to the residual error.

2.2 Multi-layer perceptron regression

Multi-Layer Perceptron Regression (MLPR) network is a front forward neural network model and the most widely used in time series prediction [20]. It consists of three layers: input, hidden and output layers. Each layer has one or more neurons. Moreover, bias neurons are connected to the hidden and output layers. The computation of this MLPR is presented in Equation 2.

$$Y_j = f(\textstyle\sum_i w_{ij} X_{ij}) \tag{2}$$

where Y_j is the output of node *j*, *f(.)* is the transfer function, w_{ij} the connection weight between node *j* and node *i* in the lower layer and X_i the input signal from the node *i* in the lower layer. Several researchers have employed MLPR to predict the future trend [21-22].

2.3 Radial basis function regression

Radial Basis Function Regression (RBFR) is a feed forward neural network for the hidden layer [23]. The RBFR has three layers. The input layer is made up of source nodes. The hidden layer has a variable number of neurons. Each neuron consists of a radial basis function centered on a point with as many dimensions as there are predictor variables. The output layer is a linear combination of radial basis functions of the inputs and neuron parameters. The RBFR are calculated in Equation 3.

$$f(x_1, x_2, ..., x_m) = g(w_o + \sum_{i=1}^{b} w_i \exp(-\sum_{j=1}^{m} \frac{a_j^2 (x_j - c_{i,j})^2}{2\sigma_{i,j}^2})) \tag{3}$$

where$x_1, x_2, \ldots, x_m$ refers to the vector of attribute values for the relevant record s.*g(.)* refers to the activation function, w_i refers to the weight for each basis function, *b* refers to the number of basis functions, a_j^2refers to the weight of the j[th] attribute, and c_i and σ_i^2 refer to the basis function centers and variances respectively. The RBFR is powerful and easy to use. Also, the RBFR is not suffering from local minima in the same way as MLPR [24-25]. Many researchers have investigated the capability of neural networks for forecasting time series data. For example,Yilmaz and Kaynar [24] compared the performance of regression models including MLPR, RBFR and adaptive neuro-fuzzy inference system (ANFIS) to predict the swell potential of clayey soils. Their results displayed that the RBFR superior to MLPR and ANFIS.

2.4 Support vector regression

Support Vector Regression (SVR) [26] provides both linear and non-linear regression in a feature space. It contains all the main features that characterize maximum margin algorithm: a non-linear function is learned by a linear learning machine mapping into high dimensional kernel induced feature space. The process of analysis involves the sequential optimization of an error functions epsilon-SVR. Moreover, SVR provides five types of kernel (ϕ) including normalized Poly; pre-computed and matrix; personal VII universal; Gaussian radial basis function; and String. The most frequently used function is epsilon-SVR with Gaussian radial basis function [12]. The epsilon-SVR is shown in Equation 4 while radial basis function is displayed in Equation 5.

$$f(x) = \min \frac{1}{2} w^t w + C \sum_{i=1}^{n} \xi_i + \sum_{i=1}^{n} \xi_i \tag{4}$$

where *w* is the weight vector; *C* is the regularization factor which has value more than 0; ξ is the slack variables.

$$\phi = \exp(-\gamma * \left| X_i - x_j \right|^2) \tag{5}$$

where γ is kernel parameters, X_i and x_j refer to vectors of an inner product in the feature space. Many researchers have used this technique because it localized and finite response across the entire range of the real x-axis. For instance, Kandananond [12] compared SVR with ANN using stationary and non-stationary. Their result showed that SVR outperforms the ANN for non-stationary cases.

3. Methodology

3.1 Data set description

The data sets of hospital outpatient clinic visits for anxiety-related were obtained from the Prasrimahabhodi Psychiatric Hospital database. It is a large database of psychiatric patients in the northeast of Thailand. This study employed the summed numbers of patient visits to the outpatient clinic each day, excluding their identities (names and hospital numbers or identification information). The study has been approved by the Research Ethics Committee of Prasrimahabhodi Psychiatric hospital. The data also underwent several stages of quality checks to delete duplicated records and correct errant attribute coding.

Outpatient records of visitors with a primary diagnosis of anxiety disorders (ICD-10 diagnosis code F40-F48) diagnosed by an experienced psychiatrist were identified and retrieved from the IT department.We performed a retrospective analysis of computerized records for daily outpatient anxiety disorders visits from 2011 to 2013. We selected 3 years to provide a daily time series to enable us to detect any effect on the daily basis of anxiety complaints.

The daily number of anxiety-related patients visiting the outpatient was employed as a dependent variable, whereas sex and age were employed as independent variables. The age-based groups were divided into four categories: till 19, 20 to 39, 40 to 59 and above 60 due to age differences in the prevalence of anxiety disorders [1]. The number of patients visiting the outpatient per day was calculated by counting the number of visiting patients from 8.00 a.m. to 4.00 p.m. Holidays including public holidays, Saturday and Sunday were omitted from the analyses. This is because outpatient treatments are all closed on holidays, on weekends and at nights. The original dataset contained 3,390 visiting cases. We excluded 10 patients who came at the weekends. The remaining 3,380 patients comprised the study sample, and represented 99.70% of the usable patient records from the original sample.

Table 1 The number of anxiety-related outpatient visits by sex and age groups in 2011-2013

Description	Number of visitors	% of visitors	Average /day
Total	3,380		4.68
Sex			
Male	976	28.88	1.35
Female	2,404	71.12	3.33
Agegroup			
<20 years (P1)	219	6.48	0.30
20-39 years (P2)	890	26.33	1.23
40-59 years (P3)	1,530	45.27	2.12
≥ 60 years (P4)	720	21.30	1.00
Unknown	21	0.62	-

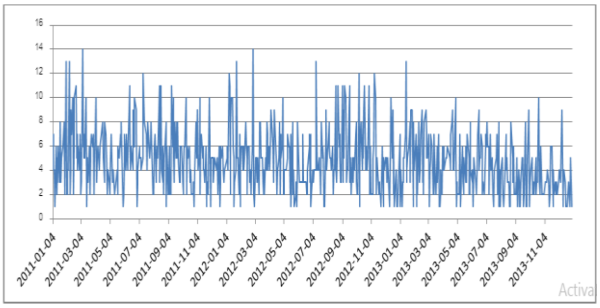

Figure 1 Time plots of daily anxiety-related patients visiting to outpatient department at Prasrimahabhodi Psychiatric Hospital (1/1/2011-31/12/2013)

Table 1 depicts that the majority patient was between 40-59 years of age (45.27%) and female (71.12%). The age of the patients ranged from 5.89 to 91.32 years, with a mean age of 46.90 years.

Figure 1 illustrates plots of the daily number of outpatient visits for anxiety-related patients atPrasrimahabhodi Psychiatric Hospital from January 1, 2011 to December 31, 2013. The total number of anxiety-related patients who visited the outpatient department during that period was 3,380, with an annual average of 1,121.67 or approximately 4.68 cases ranging from 1 to 14 patients per day. The time plot indicates an annual variation with a maximum in March and the evidence of a declining trend in 2013.

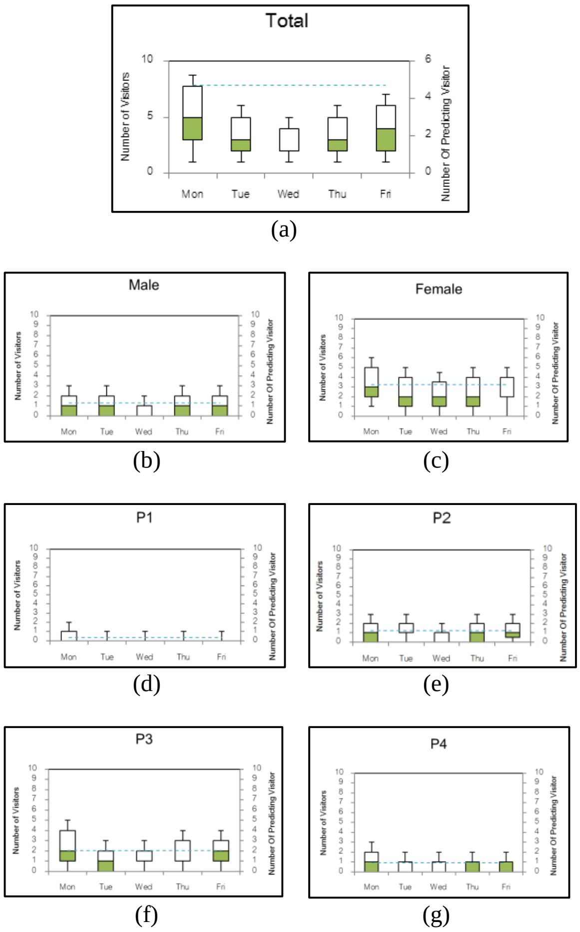

Figure 2 Box plots of male, female , P1, P2, P3, P4 and total anxiety visits by day of the week

Figure 2 presents that the box plots of data showed higher patient visits on Mondays and Fridays and lower visits on Wednesdays. However, there was little variation in daily visits for P1 and P4 groups.

3.2 Experimental design

WEKA version 3.7.10 [19] was utilized as a time series tool to evaluate the performance of the different forecasting models. This is because the WEKA program offers a well-defined framework for experimenters. In order to evaluate the performance of the anxiety-related outpatient daily visits predicting models, the experimental process is displayed in Figure 3.

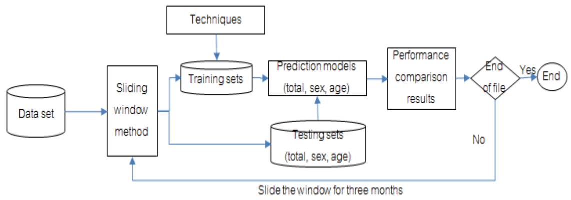

Figure 3 The experimental process

3.3 Sliding windows for dataset preparation

In order to reduce bias associate with the sampling of the training data due to the unequal of the number of working days in each week (public holidays and customs), we adopted a sliding window approach to handle with unequal sampling. The sliding window method is exploited to divide the dataset into subsets for estimating the performance of a predictive model [27-28].One sliding window consists of window size (training set) and step size (test set). In each iteration the training set size is fixed to a window, while the test set size is equal to a ratio except for the last iteration.

In this paper, the experiment used the anxiety-related outpatient daily visits data for the past three years (2011-2013). The whole dataset was divided into twelve quarters. Each quarter contained three months data. In each validation, four quarters were used for training data. Meanwhile, one quarter was used for testing data. In each iteration, the sliding window moved rightwards by one quarter while removed one quarter at the beginning of the windows (Figure 4). A major advantage of the sliding window is their requirement for less memory because only a small window of data is stored. Sliding window technique was also proven able to capture patterns from temporal data [29].

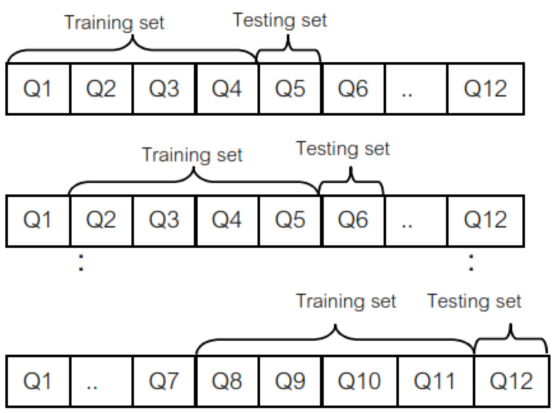

Figure 4 The sliding window method

3.4 Performance measurements

In this study, we used two different performances. The first is the mean absolute error (MAE) or the mean of average error criteria. MAE is calculated by taking the absolute value of the difference between the estimated forecast and the actual value at the same time so that the negative values do not cancel the positive values. Lower value of mean absolute error is indicative of good performance. Equation 6 presents the formula for the MAE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | t_i - y_i | \qquad (6)$$

where y_i refers to the forecasting value while t_i refers to the actual value.

Second is the root mean square error (RMSE) criterion. RMSE measures the average magnitude of the errorand represents the relative scale of the forecasting error between the forecasted value, which is a series attribute, and the actual values. The use of RMSE is very common and it makes an excellent general purpose error metric for numerical predictions. Smaller values of RMSE imply a superior performance of the model. RMSE is calculated in Equation 7.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{K} (t-y)^2}{K}} \qquad (7)$$

where K refers to the number observations: t refers the actual value: y refers to the forecasting value. Therefore, the generalization error of each round of the MAE and RMSE is used to present the overall performance of each technique in building the models.

The generalization performance of the model was also evaluated. It is measured as the distance between the error on the training set and the test set and is averaged over the entire set of possible training data that can be generated after each iteration of the learning process.

3.5 Parameter setting

In order to demonstrate the performance of the prediction models, the default parameters of each technique are defined as follows. LR uses the MS method for attribute selection in building the model eliminating co-linear attributes and setting the ridge value to 1.0E-8.MLPRuses two functions for the hidden layers, one thread, one spool size, 0.01 ridge, one seed and 1.0E-6 tolerance. RBFR uses two functions for the hidden layers, one thread, one spool size, a scale per unit, one seed and 1.0E-6 tolerance. SVR was set up by using1.0E-12 epsilon,0.001 of the epsilon parameter of the epsilon insensitive loss function;250007 cache size, 1 of cost parameter (*C*), 0.001 tolerances of termination criteria, Gaussianradial basis function for kernel, 0.01 gamma, one seed for random number generator and usesvariant1.

4. Experimental result

Table 2 and 3illustrate statistical performance measures of MAEs and RMSEs of the four models for total, male, female, age under 20 years (P1), age between 20 and 39 (P2), age between 40 and 59 (P3) and age from 60 years (P4) groups.

4.1 Performance criteria

4.1.1 Mean absolute error

The total, male, female, age under 20 years (P1), age between 20 and 39 (P2), age between 40 and 59 (P3) and age from 60 years (P4) models generated from LR, MLPR, RBFR and SVR are displayed, and the MAE average of the forecasting models is shown in Table 2.

Table 2 demonstrates that that SVR, MLPR, RBFR and LR have the best performance (denoted in bold) on age under 20 years group. Besides, SVR outperformed LR, MLPR and

Table 2 A comparison of MAE of the four models for forecasting daily anxiety-related outpatient visits

Models	LR		MLPR		RBFR		SVR	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Total	1.91±0.09	2.33±0.68	2.14±0.24	2.38±0.56	2.06±0.22	2.60±0.83	1.89±0.08	1.96±0.31
Male	1.00±0.06	**1.21±0.37**	1.28±0.20	1.26±0.31	1.06±0.11	1.49±0.57	0.96±0.05	1.00±0.11
Female	1.60±0.06	1.98±0.43	2.06±0.32	2.54±0.87	1.72±0.12	2.58±1.21	1.57±0.06	1.53±0.33
P1	**0.44±0.06**	1.65±2.70	**0.60±0.10**	**0.63±0.20**	**0.46±0.10**	**1.22±0.59**	**0.33±0.06**	**0.24±*0.10***
P2	0.89±0.05	3.89±6.25	1.33±0.29	1.76±0.44	1.05±0.12	2.34±1.11	0.86±0.05	0.90±0.15
P3	1.23±0.05	4.51±7.54	1.95±0.30	2.09±0.57	1.32±0.06	2.47±1.31	1.23±0.05	1.19±0.22
P4	0.84±0.03	4.21±7.76	1.38±0.26	1.60±0.61	0.96±0.08	2.74±1.44	0.82±*0.02*	0.81±0.16
Average	1.13	2.83	1.53	1.75	1.23	2.2	1.09	1.09

Table 3 A comparison of RMSE of the four models for forecasting daily anxiety-related outpatient visits

Models	LR		MLPR		RBFR		SVR	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
Total	2.44±0.11	2.81±0.69	2.81±0.42	3.01±0.85	2.57±0.20	3.13±0.87	2.48±0.13	2.39±0.47
Male	1.25±0.06	**1.51±0.43**	1.75±0.42	1.71±0.54	1.32±0.10	1.79±0.72	1.30±0.06	1.24±0.17
Female	2.00±0.09	2.34±0.52	2.75±0.66	3.24±1.12	2.11±0.10	3.02±1.39	2.06±0.10	1.96±0.48
P1	**0.55±0.05**	1.98±3.27	**0.89±0.17**	**0.92±0.30**	**0.59±0.08**	**1.55±0.61**	**0.64±0.08**	**0.48±*0.13***
P2	1.10±0.05	4.66±7.65	1.79±0.53	2.29±0.83	1.30±0.11	3.01±1.20	1.14±0.06	1.13±0.16
P3	1.54±0.06	5.52±9.25	2.62±0.53	2.93±1.04	1.69±0.08	3.14±1.47	1.57±0.06	1.48±0.28
P4	1.04±*0.04*	5.09±9.44	1.91±0.48	2.20±0.96	1.19±0.10	3.49±1.52	1.06±*0.04*	1.02±0.20
Average	**1.42**	3.41	2.08	2.33	1.54	2.73	1.46	**1.39**

RBFR with average MAE 1.09 in both training and testing, while MLPR produced corresponding values of 1.53 and 1.75. We can see that SVR had good performance in predicting the daily numbers of anxiety-related patients visiting the outpatient department. The SVR models for P1, P2 and P4 performed better in the daily prediction of patient visits, with a MAE of 0.33, 0.86 and 0.82 for training and 0.24, 0.90 and 0.81 for testing, respectively. Also, it was found that there is a slight difference between the MLPR and RBFR methods. Furthermore, SVR is 8.84% and 2.81% better than MLPR and RBFR in terms of MAE for training data and 8.39% and 14.10 better for testing, respectively. The percent of difference between MAE of training and testing for LR, MLPR, RBFR and SVR are 13.23%, 1.71%, 7.55% and 0.0%, respectively. As seen, the errors of training and test sets for SVR models are the same. This result indicated that SVR has the lowest over-fitting problem and is highly stable.

4.1.2 Root mean square error

The total, male, female, age under 20 years (P1), age between 20 and 39 (P2), age between 40 and 59 (P3) and age from 60 years (P4) models generated from MLPR, RBFR, SVR and LR are displayed and the RMSE average of the forecasting models is shown in Table 3.

Table 3 indicates that SVR, MLPR, RBFR and have the best performance (denoted in bold) on age under 20 years group. However, LR showed better performance than SVR, MLPR and RBFR in terms of RMSE for training data with average RMSE of 1.42 while SVR showed better performance than MLPR, RBFR and LR in terms of RMSE for testing data with average RMSE of 1.39. Also, the LR models for P1, P2, P3 and P4 performed better in the daily prediction of patient visits, with a RMSE of 0.55, 1.10, 1.54 and 1.04 for training while SVR performed better with a RMSE of 0.48, 1.13, 1.48 and 1.02 for testing, respectively. Furthermore, SVR is 9.54% and 1.23% better than MLPR and RBFR in term of RMSE for training data and 9.53% and 13.59% better for testing, respectively. The percent of difference between RMSE of training and testing for LR, MLPR, RBFR and SVR are 12.16%, 1.53%, 7.27% and -0.43%, respectively. As can be seen, the errors of training and test sets for SVR models are very close. This result indicated that SVR has the lowest over-fitting problem and is highly stable. This displays that SVR has good performance in predicting the daily numbers of anxiety disorder patients visiting at the outpatient department.

4.2 The forecasting of daily anxiety-related outpatient visits

In this section, we applied SVR to forecast the number of outpatient visits at Prasrimahabhodi Psychiatric Hospital. The SVR models were applied to male, female, P1, P2, P3, P4 and total patient visits using data of Q8-11 (Oct. 2012–Sep. 2013)of the sliding window to train and data of Q12 (Oct.-Dec. 2013) to test. The forecasting results are illustrated in Figure 5.

Figure 5 presents the observed and predicted time series for male, female, P1, P2, P3, P4 and total patient visits. The plots of observed and predicted daily anxity related visits are well aligned with each for total, female, P2 and P3 patient groups. Besides, the predicted value of SVR model is lower than the actual value for male and P4 patient groups.

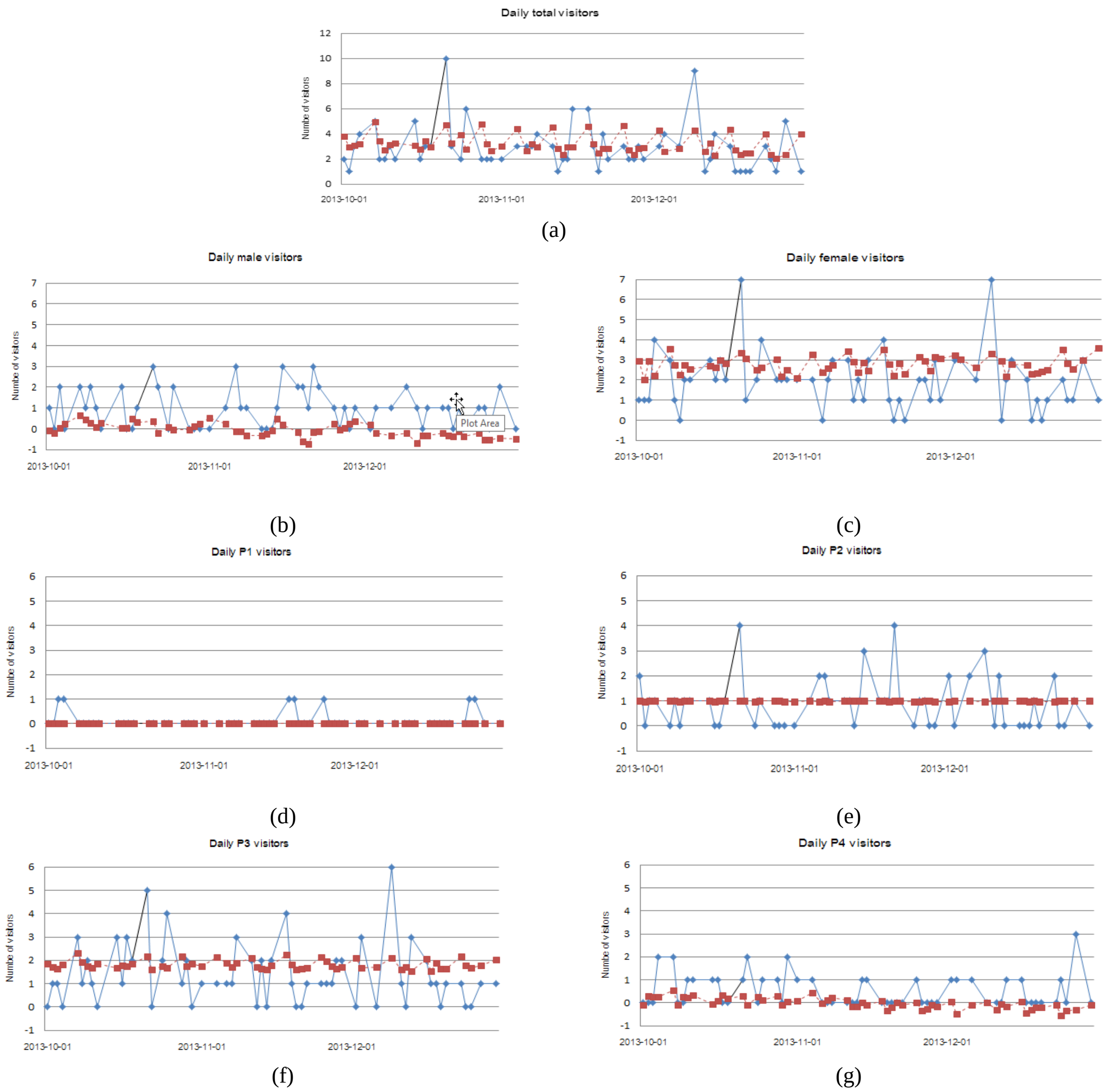

Figure 5 Observed and predicted daily anxiety patient visits at outpatient department by patient categories, October 1, 2013 to December 30, 2013 using SMR model

5. Discussion and conclusion

In this study, four models are developed to forecast the number of anxiety-related patients visiting the outpatient department per day: LR, MLPR, RBFR and SVR. As is shown in the results, the predicting performance of SVR models achieved a better performance as compared to ANN and LR in term of MAE and RMSE. These findings are *congruent* with those of *previous studies* that SVR outperformed ANN models [16-17].This might be an indication the SVR model can create a suitable hyper-plan which makes the model robust with regard to outliers or extreme value.

We found that SVR has the lowest over-fitting problem and highly stable while LR has the highest over-fitting problem when evaluated with MAE and RMSE. Our results confirm previous findings by Akande el at. [16] and Zhao and Magoules [30], reporting that SVR has a *stable* predictive performance and less over-fitting problem. This may be due to the fact that SVR uses the search techniques which eliminate kernel evaluations producing negligible contribution to the decision function output. Therefore, it leads to computational efficiency. In addition, SVR performs the regularization in the reproducing kernel Hilbert space yielding a stable model [31].

The daily patient visits are typically elevated on Mondays and Fridays, exhibiting a 5-day cycle. The present study also showed that outpatient visits have decreased in 2013. This is because the locus of care moves away from tertiary hospitals toward general hospitals, and even the community and the patient’s home.

In conclusion, as the result of our comparison of the four constructed prediction models, it was determined that the SVR model was the most appropriate for predicting the daily number of anxiety-related patients visiting the outpatient department. The findings of this study showed that sex and age information should be considered when attempting to predict the daily number of anxiety-related patients. The proposed prediction model can be used to forecast the daily patient in outpatient and preparing for staff allocations and material resources. Further research could be in the areas of using SVR to develop the application for forecasting patient visiting the hospital.

6. Acknowledgement

The authors would like to express their sincere gratitude to Prasrimahabhodi Psychiatric Hospital for providing data and to the Faculty of Informatics, Mahasarakham University for its funding this research.

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