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Time Series Forecasting in Anxiety Disorders of Outpatient Visits using Data Mining

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Abstract

This study aims to forecast the number of anxiety disorders patients who would be seeking treatment at an outpatient clinic in 2011 by comparing two Artificial Neural Network (ANN) models and selecting the most powerful model. Data were collected from the Prasrimahabhodi Psychiatric Hospital database. In order to develop a forecasting model, we used 4 years of data from January 2007 to December 2010 to construct the demand forecast model, whereas those from the following year (January to December 2011) were used to evaluate the model. Forecasted models were constructed with two ANN models: Radial Basis Function (RBF) and Multi-Layer Perceptron networks (MLP). The forecast accuracies for the models were evaluated via Mean Absolute Percentage Error (MAPE). The RBF was selected as the final model. The results demonstrated that monthly anxiety disorders patient visits can be predicted with good accuracy using the RBF model technique in time series analysis since the MAPE is below 20%. The majority of patients was female, married, farmers, aged between 40-59 years old and diagnosed with other anxiety disorders (F41). An average of one hundred and fifty patients of all ages attended each month at outpatient services with the highest being 244 and the lowest 76. The forecast cases exceeded the actual clinical cases in the 20-39 age groups. Accurate forecasting of outpatient visits can play a significant role in the management of a health care system.

Keywords: *Radial basis function, Multi-layer perceptron networks, Anxiety disorders*

1. Introduction

Anxiety disorders were classified into six broad categories: traumatic stress disorder, panic disorder, generalized anxiety disorder Obsessive-compulsive disorder, phobias and other anxiety disorders (1). Anxiety disorders are common mental disorders affecting the U.S. population. Approximately 18.9 million people in 2004, 21.4 million in 2009,or nearly 29% of the population, will experience anxiety disorders at some point in their lives (2-4), especially generalized anxiety disorder (about 18%) (5). In Thailand the prevalence of anxiety disorders was approximately 16.4% in 2004 (6). The negative impact of anxiety disorders with respect to several chronic physical and mental illnesses has been well documented. These illnesses include cancer, hypertension, chronic pain, asthma, cardiac disease and depression (7-9). A significant amount of productivity and economic loss is attributable to anxiety disorders and related comorbidity. Several studies of patients with anxiety disorders have shown that the disorders have a deleterious effect on role impairment, work productivity, health-related quality of life (10), and increased utilization of healthcare resources (9, 11).

Anxiety disorders are the most common psychological disturbances that lead people to seek mental health services. Prior studies have documented an increasing trend in outpatient visits for the treatment of anxiety disorders (12-14). The rate of outpatient treatment for anxiety disorders increased from 0.43 visits per 100 persons in 1987 to 0.83 in 1999 (14). Specifically, prevalence rates of anxiety disorders are generally higher in women across age groups (12, 15). 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 (16) and in the 45-54 and 65+ year-old groups in Australia (17). Furthermore, anxiety disorders were associated with education and patients with public insurance (4).

The outpatient unit in a hospital is an important part of its organization. A forecast of outpatient visits is absolutely necessary in order to manage the hospital, arrange human and material resources, and control finances reasonably well (18). Moreover, knowing the number of outpatient visits can help health care administrators in decision-making and planning for future events. Forecasting is the foundation for greater and better utilization of resources and increased levels of outpatient care. In general, an outpatient visit forecasting system can play the role of a decision support system for management. It can improve the overall performance of a department resulting in greater productivity and more patient satisfaction.

It is obvious that forecasting activities play an important role in many areas of an institute. The traditional time series method can predict problems arising from a new trend but fail to forecast the problems with linguistic data. Besides, the traditional time series method requires more historical data and the data must be in normal distribution. Recently, it has been observed that the data mining approach to time series analysis and forecasting is often more powerful and more flexible than classic statistical techniques such as regression, autoregressive integrated moving average (ARIMA) and artificial intelligence (AI) techniques such as artificial neural networks (ANNs), fuzzy logic and genetic algorithms (GAs).

ANNs in data mining are a popular technique for forecasting in time series and have been successfully used in forecasting complex problems. Although ANNs can be time consuming, they provide low error rate models. Also, a major advantage of ANNs is their ability to model both linear and nonlinear relationships. Several research studies have compared the capability of ANN with conventional techniques in the field of medicine (19-21). For instance, Guan, Huang and Zhou (21) used ANN and ARIMA to forecast the incidence of hepatitis A. Their result showed ANN superior to ARIMA. Furthermore, ANN models are better in terms of their ability to handle non-linear problems.

In this current study, ANN models: radial basis function (RBF) and multi-layer perceptron networks (MLP) were compared to determine an optimum model. Then, the final model was applied to the anxiety disorders data in order to forecast the number of outpatients with anxiety disorders to the year 2011. If we could forecast the number more accurately, it would help the health care administration effectively manage operations and resource distribution.

2. Methods

2.1 Data source

The Prasrimahabhodi Psychiatric Hospital is a 550-bed tertiary health care institution located in Northeast Thailand. It, one of seventeen mental hospitals, belongs to the Thai Department of Mental Health under the Public Health Ministry. In the present study, the data analyzed were obtained from the hospital's internal database. It is a large database of psychiatric patients in the northeast region of Thailand. This study employed the summed numbers of patient visits to the outpatient clinic per month, excluding their identities (names and hospital numbers or identification information). The study has also been approved by the Research Ethics Committee of Prasrimahabhodi Psychiatric hospital. The data then underwent several stages of quality checks to delete duplicated records and correct errant variable 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. Patients were included in the anxiety disorders group if their diagnosis met the inclusion criterion as shown in Table 1.

Table 1. ICD-10 codes and descriptors for anxietydisordersvisits

ICD-10 code	ICD-10 Descriptors
F40	Phobic anxiety disorders
F41	Other anxiety disorders
F42	Obsessive-compulsive disorder
F43	Reaction to severe stress, and adjustment disorders
F44	Dissociative [conversion] disorders
F45	Somatoform disorders
F48	Other neurotic disorders

2.2 Sample

We performed a retrospective analysis of computerized records for outpatient anxiety disorders visits from 2007 to 2011. We selected 5 years to provide a sufficiently long time series to enable us to detect any effect on monthly rates of anxiety complaints. The original dataset contained 9,160 visiting cases. All data sets were used.

2.3 Data analysis

The number of outpatient anxiety disorders visits was analyzed over time by age and sex due to several missing values in other demographic variables. For this study, we used ANN to forecast the number of outpatient visits at Prasrimahabhodi Psychiatric Hospital**.** The monthly observations are between 01 January 2007 and 31 December 2011. The hold out method was utilized to divide data into triaging and test sets. The advantage of this method is that it is usually preferable to the residual method and waste less time to compute (22). The complete analysis data were divided into two sub-data sets: the training dataset (2007/1/1-2010/12/31) so the time series include 7,921 observations; and the testing data set (2011/1/1-2011/12/31) so the time series include 1,239 observations. Each month on the prediction of 2011 was evaluated.

We examined different techniques of ANNs (RBF and MLP networks) to obtain more accurate out sample predictions. In the next section, brief information about ANNs is presented.

2.4 Modeling technique

Artificial neural networks

ANNs are a computational tool inspired by the way the biological nervous systems, such as the brain and process information. They consist of a processing elements set (called neurons) and the connection between the neurons. This technique provides an efficient model for modeling complex input-output relationships which learn directed from data during modeled (23-25). The basic architecture of ANNs consists of the input, hidden and output layers.

The input layer is a layer that introduces the data into the network. The hidden layer performs the internal calculation of the neural network model and the data are processed. The output layer performs the summation of all the input weighted with a linear output that the results of given input are produced.The most commonly used ANN methods are radial basis function and multi-layer perceptron networks. Both the RBF and MLP networks are normally employed in the same kind of application (nonlinear mapping approximation and pattern recognition), however, their internal calculation structures are different. They can use in both classification and regression problems (26). In this paper we used them for regression problem.

Radial basis function network

The RBF network for regression (RBFregressor) is becoming an increasingly popular ANN with diverse applications such as computer science and engineering (27). It is a feed-forward neural network to the linear output layer (28). The RBF network has three layers. The input layer is made up of source nodes. The hidden layer is connected directly to all of the nodes in the input layer. The output layer is a linear combination of radial basis functions of the inputs and neuron parameters.The relationship between the output y_{t+1} and the inputs y_1, y_2, y_3.. , y_t are calculated in Equation 1.

$$y_{t+1} = \alpha_0 + \sum_{j=1}^{q} \alpha_j g(\beta_{ij} + \sum \beta_{ij} y_{t-i+1}) + \varepsilon \quad (1)$$

where α_j (j=0,1,2…,q) and β_{ij} (i = 0,1,2…,p; j=1,2,3…,q) are the model parameters called connection weights, p is the number of input nodes and q is the number of hidden nodes. Yu et al. (29) pointed out that the RBF network has the advantages of an easy design and is less time consuming for training the model. For example, Magudeeswaran and Suganya-devi (24)compared the performance of modified radial basis function network and other neural networks to predict the blood glucose level for the diabetes patients. The experimental results displayed that the modified RBF obtained better results than other neural networks.

Multi-layer perceptron network

The MLP network for regression (MLPregressor) is a front forward neural network model and the most widely used in time series prediction. It can use from one hidden layer to multiple layers. Each hidden layer is fully connected to the succeeding layer. The computation of this MLP is presented in Equation 2.

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

Where Y_j is the output of node j, 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. The *f()* is the transfer function. It trains a multilayer perceptron with one hidden layer (30). To date, MLP has been widely employed to predict the future trend in the fields of medical and biological sciences (20, 26). For example, Memarian and Balasundram (31) compared the predictive performance of the MLP and RBF for forecasting suspended sediment discharge at the Langat River, Malaysia using time series of daily water discharge as the input data. The results demonstrated that MLP has slightly better output than the RBF network model in predicting suspended sediment discharge.

2.5 Model evaluation

In order to decide the model with higher accuracy in a fitted series value, the Mean Absolute Percentage Error (MAPE) was calculated. MAPE is the average of the absolute values of the percentage of the forecast errors. The formula for calculating MAPE is given as:

$$MAPE = \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \frac{100\%}{n} \quad (3)$$

where A_t is the actual value (target), F_t is the forecasting value (network output) and n is number of events. MAPE represents the relative scale of the forecasting error between the forecasted value, which is a series variable, and the actual values; the smaller the error, the more accurate the forecast is. A MAPE of 0% denotes a perfect fit of the model. If the MAPE is less than 20% it can be regarded as having good accuracy. A MAPE of less than 30% is considered as reasonably good while a MAPE of more than 30% can be regarded as an inaccurate forecast (32, 33). The model finally selected was then applied to the research data to forecast the number of outpatient anxiety disorders visits.

3. Results

3.1 Sample characteristics

The characteristics of anxiety disorders outpatients are presented in Table

2. Subjects included 9,160 anxiety disorders patients who were seeking treatment at an outpatient clinic between January 2007 and December 2011. Mean patient age was 46.12 years (±15.55). The majority of patients was aged between 40-59 years old (45.64%), female (71.26%), married (72.06%), farmer (60.88%) and had a primary education level (68.37%). Six thousand, one hundred and sixteen individuals (66.77%) were diagnosed with other anxiety disorders (F41). Approximately 30% were also diagnosed with reaction to severe stress, and adjustment disorders (F43).

Table 2. Patient descriptions

Characteristics	**n**	**%**
Sex		
Male	2,632	28.73
Female	6,527	71.26
Age		
< 20 years	586	6.40
20- 39 years	2,604	28.43
40 -59 years	4,181	45.64
≥ 60 years	1,739	18.98
Marital status		
Single	1,343	14.66
Married	6,601	72.06
Divorced	809	8.83
Widowed	214	2.34
Unknown	169	1.84
Educational status		
No schooling	142	1.55
Primary level	6,263	68.37
Secondary level	1,646	17.97
Occupational level	292	3.19
Higher education level	684	7.47
Unknown	133	1.45
Occupational status		
Farmer	5,577	60.88
Worker	69	0.75
Business owner	647	7.06
Civil servant	99	1.08
Monk	112	1.22
Professional	18	0.20
Unknown	2,638	28.80
Primary diagnosis		
F40	54	0.59

Table 2. Patient descriptions (continued.)

Characteristics	n	%
F41	6,116	66.77
F42	40	0.44
F43	2,790	30.46
F44	37	0.40
F45	120	1.31
F48	3	0.03

3.2 Construction and validation of models

In order to compare the adequacy and performance of the constructed model, the MAPE was calculated. Table 3 presents that the average MAPE of the all patients for the RBF (Total) was 15.59 and 38.39 for the MLP, respectively. The experimental result shows that RBF models can forecast with the lowest MAPE (8.83%) the number of patientsaged 40-59 who had visits in December 2011. However, MLP models give the highest MAPE (512.38%) for forecasting the number of patients aged lower than 20 who had visits in February 2011. This is due to the fact that anxiety disorders visits represent a relatively small percentage of patients aged 20 or lower. From model comparison, the RBF method was chosen in order to forecast the number of outpatient visits with anxiety disorders.

Table 3. MAPE comparison between RBF and MLP models

Month	RBF							MLP						
	Total	Male	Female	P1	P2	P3	P4	Total	Male	Female	P1	P2	P3	P4
Jun.	17.81	21.10	16.20	73.98	35.23	26.83	38.98	29.03	36.92	49.84	420.74	70.36	27.75	38.49
Feb.	17.71	22.40	15.83	57.99	35.67	30.36	41.30	30.73	34.89	45.39	512.38	69.89	22.14	40.30
Mar.	16.24	23.36	16.08	58.73	30.20	33.43	43.46	32.97	25.37	42.72	402.87	64.07	26.95	43.77
Apr.	17.39	24.81	17.40	52.94	32.63	34.92	44.33	36.95	28.25	35.26	396.74	40.93	26.43	48.39
May.	15.69	25.22	14.73	50.00	22.86	35.45	49.02	35.35	38.41	22.52	225.13	45.28	31.78	47.44
Jun.	11.33	28.18	11.25	41.17	24.94	38.59	47.65	38.60	38.08	29.49	90.18	48.43	26.37	33.23
July.	12.46	27.11	11.76	46.09	24.62	38.47	48.57	38.98	41.55	30.55	48.68	54.85	29.09	34.86
Aus.	15.06	26.23	13.52	54.57	26.62	36.61	47.55	38.37	42.22	41.19	49.21	28.89	37.41	39.88
Sep.	16.59	21.03	16.79	60.09	27.20	32.92	48.47	38.74	43.58	22.79	175.83	28.75	42.08	39.58
Oct.	18.21	15.56	16.60	68.87	25.91	29.46	44.70	54.50	23.08	25.60	511.83	16.21	36.15	52.04
Nov.	16.16	21.22	20.23	64.95	23.45	28.90	59.32	23.23	52.66	18.93	130.51	24.19	43.61	22.23
Dec.	12.42	16.01	10.61	112.08	16.44	8.83	57.79	63.20	59.91	36.59	27.61	46.65	160.10	34.70
Avg.	15.59	22.69	15.08	61.79	27.15	31.23	47.59	38.39	38.74	33.40	249.31	44.88	42.49	39.58
Std.	2.23	3.83	2.71	17.57	5.30	7.67	5.74	10.38	10.16	9.57	179.74	17.17	36.04	7.65

3.3 Forecasting the number of outpatient visits

In the implementation, the number of anxiety disorders visits in the outpatient clinic at Prasrimahabhodi Psychiatric Hospital was forecasted by using the RBF method. The monthly figures are between 01 January 2007 and 31 December 2011. A graph of the time series can be seen in Figure 1. The lowest outpatient visits could be seen at the end of the year 2011, and they slightly increased with a dramatic fluctuation during 2008-2009. Visual inspection of this group shows a definite peak in the number of anxiety disorders patients in October 2008, 2009 and again in October 2010. Besides, the graph shows a dramatic decrease in the number of anxiety disorders patients in November every year. On an average, there were about 152 monthly anxiety disorders patient visits during the period January 2007 to December 2011. The number of anxiety disorders outpatients was the highest at 244 persons in October 2008 and the lowest in December 2011 with 76 persons.

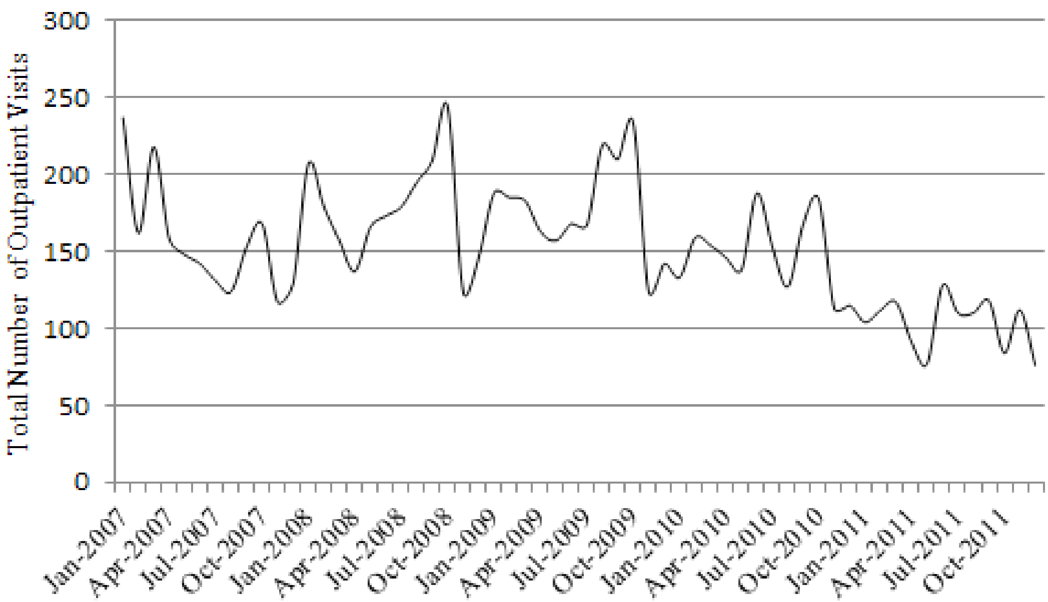


Figure 1. The trend in the number of anxiety patient between 2007 and 2011

In order to show the forecast results visually, the actual values and the forecast obtained from the RBF model are shown in Figure 2-4. According to Figure 2, the model shows there being a relatively high number of anxiety disorders patients in June and September, and a low number in May and October as well as at the end of the year. The model of forecast cases versus actual clinical anxiety disorders cases gives a MAPE of 15.59%. The forecasted number of cases exceeded the actual cast in the first half of the year. The model also forecasted cases with lower errors against real cases in the middle of the year.

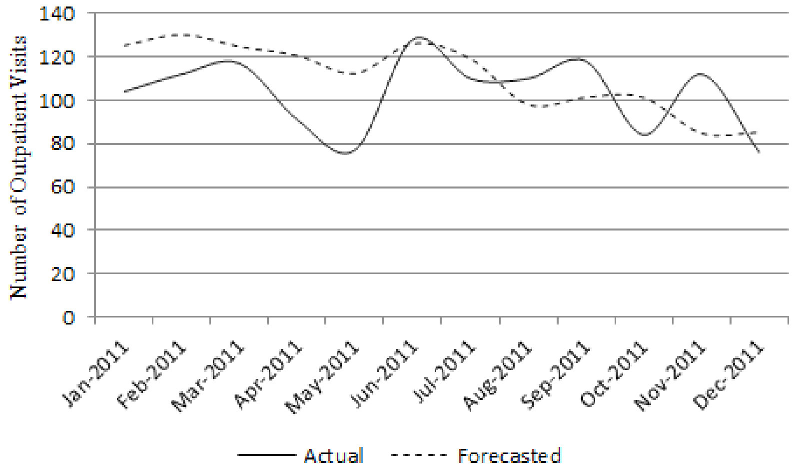


Figure 2. The graph of the actual and the forecast values

We next consider forecast results for two groups: male and female. Figure 3 illustrates that actual clinical cases exceeded the forecasted cases in males while the actual cases exceeded the forecasted cases in females from the middle of April until the end of the year. The models also forecasted cases with lower errors against real cases in the first half of the year for male and in the middle of the year for female. The average of MAPE value is 18.88%. The optimal model of forecast cases versus actual clinical female cases gives a MAPE of 15.08.

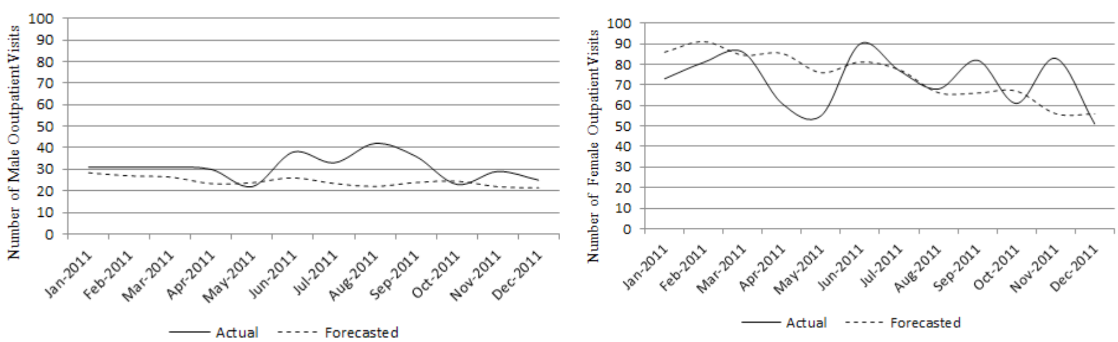
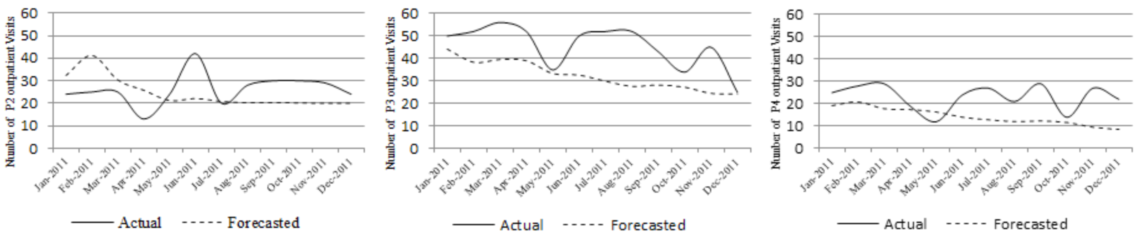


Figure 3. Comparison between actual values and forecasted values by sex

The third application was to predict the number of outpatient anxiety disorders visits by age. We excluded patients under 20 years of age due to the small number of patients. The estimated number of anxiety disorders outpatient was greatest in the 40-59 age group. However, the number of anxiety disorders outpatient visits in the 40-59 age group has decreased slightly while the numbers remained the same in the 20-39 and older age groups. The actual cases exceeded the forecast cases in the 40-59 age group (P3) and the older age group (P4). On the other hand, our model forecasted cases above the actual cases in the 20-39 age group (P2) at the beginning of the year. The monthly forecasting P2, P3 and P4 patients were 24.55, 32.46 and 14.40, respectively. The averages of MAPE of models of P2, P3 and P4 are 27.15 %, 31.23%, and 47.59%, respectively. The average of MAPE of all models is 35.32%.



P2 P3 P4

Figure 4. Comparison between forecasted values vs. actual values by ranges of age

4. Discussions

The use of forecasting methods in healthcare settings is very helpful in developing hypotheses to explain and predict the dynamics of the observed phenomena and subsequently in the establishment of a schedule for human resources and improved patient care. In this study, the number of outpatient visits at Prasrimahabhodi Psychiatric Hospital is forecasted by using the radial basis function network. The results indicated a strong agreement between model predictions and actual values.

During the study period, the high monthly variations were noted. We found that women outnumber men at the outpatient anxiety clinic. This is consistent with previous reports that prevalence rates of anxiety disorders are generally higher in women across age groups (12, 14). However, the age group with the highest number of anxiety disorders outpatient group was 40-59 with an average of 152.66 persons per month. This may be due to the fact that women in their 40s and 50s, often stretched already by work and home stresses, suffer from fatigue, sleep problems, hot flashes, and other symptoms that can directly contribute to problems with mood and emotion.

In the present study we found that the highest outpatient visits were in October every year. One possible explanation is that the maximum number of patients was farmers. The farmers become stressed with their traditional farm work due to financial pressure, physically heavy work and a long work hour, especially in harvesting time. It was also noted that the number of anxiety disorders outpatient cases gradually decreased from 2010 to 2011. This may be explained by the fact that Prasrimahabhodi Psychiatric Hospital is a tertiary referral hospital; patients should be referred from primary and secondary care hospital. Therefore, anxiety disorders patient must first seek treatment from primary care.

Fluctuations occurred in the number of outpatient visits throughout the analysis year. These fluctuations, which created an over-forecasting in females and an under-forecasting in males, relative to the observed values, had significant effects on the forecasting of future patient numbers.

In addition, the forecast number of visitors was lower than the actual for the male, 40-59 and over 60 age groups. One possible explanation is that the number of observations has trended lower and that would make the model predict a lower than actual value. However, the models' forecasting accuracy shows the RBF models have the average of MAPE of less than 20% except in the age groups, thereby suggesting a good degree of accuracy.

According to the results above, the conducted model is reliable and accurate. Once a satisfactory model has been obtained, it can be used to forecast expected numbers of cases for a given number of future time intervals. Some limitations of this study need to be taken into account when interpreting the results. First, the fitted models using the number of anxiety disorders outpatient during 2007-2010 to predict patients in 2011 assumes that past anxiety disorders outpatient patterns are identical to future patterns, so if the patterns are different, the estimated error will be greater and the forecast will be less accurate. Second, the interval of outpatient visit is monthly, so we could not analyze it daily in order to get higher predictive precision.

5. Acknowledgements

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6. References

(1) American Psychiatric. Association Diagnostic and Statistical Manual of Mental Disorders : DSM-5. American Psychiatric Publishing. Washington; 2013, 189-233.

(2) Kessler R, Berglund P, Demler O, Jin R, Merikangas K, Walters E. Lifetime prevalence and age-of-onset distributions of DSM IV disorder in the National Comorbidity Survey Replication. Archives of General Psychiatry. 2005;62:593-600.

(3) Kessler RC, Chiu WT, Demler O, Walters EE. Prevalence, severity and comorbidity of 12 month DSM IV disorders in the National comorbidity survey replication. Archivesof General Psychiatry. 2005;62:617-20.

(4) Wu X, Song Z. Multi-step prediction of chaotic time-series with intermittent failures based on the generalized nonlinear filtering methods. Applied Mathematics and Computation. 2013;219:8584-94.

(5) Bunevicius R, Liaugaudaite V, Peceliuniene J, Raskauskiene N, Bunevicius A, Mickuviene N. Factors affecting the presence of depression, anxiety disorders, and suicidal ideation in patients attending primary health care service in Lithuania. Prim Health Care. 2014;32(1):24-9.

(6) CureResearch.com. Statistics by Country for Anxiety Disorders. 2010 [cited 30 May 2014]; Available from: http://www.cureresearch.com/a/anxiety/stats-country.htm

(7) Roy-Byrne P, Davidson K, Kessler R, Asmundson G, Goodwin R, Kubzansky L, et al. Anxiety disorders and comorbid medical illness. General Hospital Psychiatry. 2008;30: 208-25.

(8) Strine T, Mokdad A, Balluz L, Gonzalez O, Crider R, Berry J, et al. Depression and anxiety in the United States: finding from the 2006 behavioral risk factor surveillance system. Psychiatric Services. 2008;59:1383-90.

(9) Sareen J, Jacobi F, Cox B, Belik S, Clara I, Stein M. Disability and poor quality of life associated with comorbid anxiety disorders and physical conditions. Arch Intern Med. 2006;166:2109-16.

(10) Revicki D, Travers K, Wyrwich K, Svedsäter H, Locklear J, Mattera M, et al. Humanistic and economic burden of generalized anxiety disorder in North America and Europe. Affective Disorders. 2011; 140:103-12.

(11) Bereza B, Machado M, Einarson T. Systematic review and quality assessment of economic evaluations and quality-of-life studies related to generalized anxiety disorder. Clinical Therapeutics. 2009;31: 1279-80.

(12) Olfson M, Marcus S, Wan G, Geissler E. National trends in the outpatient treatment of anxiety disorders. Clinical Psychiatry. 2004;65:1166-73.

(13) Smith R, Larkin G, Southwick S. Trends in U.S. emergency department visits for anxiety-related mental health conditions 1992-2001. Clinical Psychiatry. 2008; 69: 286-94.

(14) Larkin G, Claassen C, Emond J, Pelletier A, Camargo C. Trends in U.S. emergency department visits for mental health conditions, 1992 to 2001. Psychiatric Services. 2005; 56: 671-7.

(15) McLean C, Asnaani A, Litz B, Hofmann S. Gender differences in anxiety disorders: prevalence, course of illness, comorbidity and burden of illness. Psychiatr Research. 2011;45(8):1027-35.

(16) Singleton N, Bumpstead R, O'Brien M, Lee A, Meltzer H. Psychiatric morbidity among adults living in private households, 2000. International Review of Psychiatry. 2003;15: 65-73.

(17) Hunt C, ISSAKIDIS C, ANDREWS G. DSM-IV generalized anxiety disorder in the Australian National Survey of Mental Health and Well-Being. Psychological Medicine. 2002;32:649-59.

(18) Hadavandi E, Shavandi H, Ghanbari A, Abbasian-Naghneh S. Developing a hybrid artificial intelligence model for outpatient visits forecasting in hospitals. Applied Soft Computing. 2012;12: 700-11.

(19) Catto J, Linkens D, Abbod M, Chen M, Burton J, Feeley K, et al. Artificial intelligence in predicting bladder cancer outcome: a comparison of neuro-fuzzy modeling and artificial neural networks. Clinical Cancer Research. 2003;9:4172-17.

(20) Hadavandi E, Hadavandi E, Shavandi H, Ghanbari A, Abbasian -Naghneh S. Developing a hybrid artificial intelligence model for outpatient visit forcasting in hospitals. Applied Soft Computing. 2012;12:700-11.

(21) Guan P, Huang DS, Zhou BS. Forecasting model for the incidence of hepatitis: A based on artificial neural network. World Journal of Gastroenterology. 2004;10(24): 3579-82.

(22) Liu H, Motoda H. Feature extraction construction and selection: a data mining perspective. Massachusetts: Kluwer Academic Publishers; 1998.

(23) Zounemat-kermania M, Kisib O, Rajaeec T. Performance of radial basis and LM-feed forward artificial neural networks for predicting daily watershed runoff. Applied Soft Computing. 2013;13:4633-44.

(24) Magudeeswaran G, Suganyadevi D. Forecast of Diabetes using Modified Radial basis Functional Neural Networks. the Proceedings on Research Trends in Computer Technologies; 2013;2013;35-9.

(25) Kourentzes N, Barrow DK, Crone SF. Neural network ensemble operators for time series forecasting. Expert Systems with Applications. 2014;41:4235-44.

(26) Yilmaz I, Kaynar O. Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. Expert Systems with Applications. 2011; 38(5):5958–66.

(27) Oludolapo OA, Jimoh AA, Kholopane PA. Comparing performance of MLP and RBF neural network models for predicting South Africa's energy consumptio. Energy in Southern Africa. 2012;23:40-6.

(28) Poggio T, Girosi F. A Theory of Networks for Approximation and Learning; 1989.

(29) Yu H, Xie T, Paszezynski S. Wilamowski BM Advantages of Radial Basis Function Networks for Dynamics System Design. IEEE Transcations of Industrial Electronics; 2011;5438-50.

(30) Witten IH, Frank E, Trigg L, Hall M, Holmes G, Cunningham SJ. Weka: Practical machine learning tools and techniques with java implementations. International Workshop: Emerging Knowledge Engineering and Connectionist -Based Information Systems. 1999;192-6.

(31) Memarian H, Balasun SK. Comparison between Multi-Layer Perceptron and Radial Basis Function Networks for Sediment Load Estimation in a Tropical Watershed. Water Resource and Protection. 2012;4:870-6.

(32) Lewis C. Demand Forecasting and Inventory Control. Cornwall England: Woodhead publishing limited; 1997.

(33) Mukhopadhyay SK. Production Planning and control- Text and Cases. 2nd ed. New Delhi, Asoke K. Ghush: Phi learning private limited; 2007.