ISSN: 2349-9141

Available online at http://www.ijirr.com

International Journal of Information Research and Review
Vol. 2, Issue, 07, pp. 900-903, July, 2015

OPEN ACCESS JOURNAL

Full Length Research Article

PREDICTION ANALYSIS ON ECG ELECTRODE AND CONNECTA BD NEEDS FOR TEACHING HOSPITAL IN INDONESIA

[1]Indrabayu, [2,*]Andi Triska Muliana and [3]Amil A. Ilham

Informatics Study Program, Electrical Department, Engineering Faculty, Hasanuddin University Makassar, Indonesia

***Corresponding Author**

Received 24th June 2015; Published 31st July 2015

Abstract

Hospital logistics procurement planning for consumable materials and tools with the accurate prediction system can support the logistics management to determine safety stock, so that the problem of stock out and overstock can be reduced. This paper aims to compare the quantitative method consisting of Moving Average (MA) method, Back propagation Artificial Neural Network (BP-ANN) method and qualitative methods of hospital management for the usage prediction of ECG Electrodes and Connect a BD. The used data set is divided into training data, test data and validation data. ECG Electrodes prediction results shows RMSE value of Moving Average method, Neural Network and qualitative methods of hospital management are 4.8855, 2.5470 and 29.2718, respectively. Meanwhile, the RMSE value for Connect a BD is 2.5021, 2.4817 and 6.4031. The prediction results show that ANN-BP is better than MA for ECG Electrodes and Connect a BD.

Keywords: Predictions, Consumables Materials and Tools, Teaching Hospital, Artificial Neural Networks, Back propagation, Biomedical Engineering

To cite this paper Dr. Viswa Kumar, R., Dr. Chandra Mohan, V. Dr. Chuhitha, S. and Dr. Umapallavi, 2015. A study of serum cholinesterase levels in organo phosphorous poisoning, *International Journal of Information Research and Review.* Vol. 2, Issue, 07, pp. 900-903, July, 2015.

INTRODUCTION

Activities of public health services are supported by the specific needs organization, such as medical personnel, infrastructures, medicines/medical equipment and materials. Consumable Materials and Tools (CMT) is only for single treatment, for one patient and cannot be reused or recycled (Manjit, 2001). Every hospital installation offers various types of services include outpatient installation, Intensive Care Unit (ICU), emergency room, pharmacy, inpatient care, surgical installation, obgyn installation, radiology installation, and laboratories where the entire installations cannot be separated from CMT usage. CMT unavailability would hamper the entire health care process in hospital, lowering service quality and decrease the trust and customer satisfaction. A well logistics inventory management is one key to the success of the hospital services because of inventory sufficient quantities can be assured. There are two key considerations in supply management, i.e. diversity of stocks in inventory and the appropriate stock amount to assure safety stock and optimize over stock. The supply management influences other layer and sub layer of management in order to achieve the hospital goals effectively and efficiently, including financial affairs as well as maintaining the trust and good customer services (Qingkui, 2009).

The purpose of supply management is to streamlining the supply budget management and constantly fulfills customer needs when demanded with sufficient quantity and quality (Yan, 2010). Efficiency in procurement management can prevent overstock, stock out, death stock and chain problem due to overstock, expiry of goods (Adeyemi, 2010). Supply management in health services such as hospitals is quite different as supply management in manufacturing industry. The number of patients and cases are naturally stochastic that lead to indefinite number of CMT that need to be purchased from time to time. This issue is worsen with the compulsory of long and complicated tendering process for every procurement. IT-party support in supply chain engineering for the logistics supply and supported by appropriate and accurate predictions techniques become major issues in supply chain management (Rachmania, 2013). Therefore, the prediction technique using certain method of artificial intelligence and data mining for predicting CMT can help logistics management as an innovative strategy in hospital service particularly at supply chain management (Tsumoto, 2011). Forecasting techniques can be classified in four categories: 1) qualitative approach2) *time series* forecasting, 3) *causals forecasting* method and 4) simulation (Saha, 2014).

Prediction using qualitative measurement is derived logically and systematically by considering personal opinion, expert opinion, market research and other approaches (Muliana, 2015). The concept of prediction by comparing the quantitative and qualitative methods have been carried out, then the statistical approach versus artificial intelligence on rainfall prediction is a unique strategy in advance because it shows interesting results to be applied to the data non-stationary (Indrabayu, 2013). So in this study tried to apply that approach to the CMT prediction. This paper uses artificial intelligence method, BP-ANN, to predict future CMT usage as a reference to set safe rate of supply items that will be ordered compared with the statistic method – MA and the qualitative prediction results from the hospital management.

Artificial Neural Network

Artificial neural network is a computational technique adapted from the work ability of the human neural system which able to recognize a various patterns. For instance, human scan recognizea wide variety of objects because it has been storing information such as shape, color, sound and other patternsonthe object at the first point. The smallest part of the human brain that processes these information are billions amount of neurons. Based on the analogy of the human brain system, BP-ANN has a processing unit called neuron, weights (*w*) as the combined value which will be accumulated with the input value, input data (*x*), activation function (*z*) and the output value (*y*), wherein the activation function used for adjusting output provided by the neurons. The architecture of BP-ANN is shown in Figure 1.

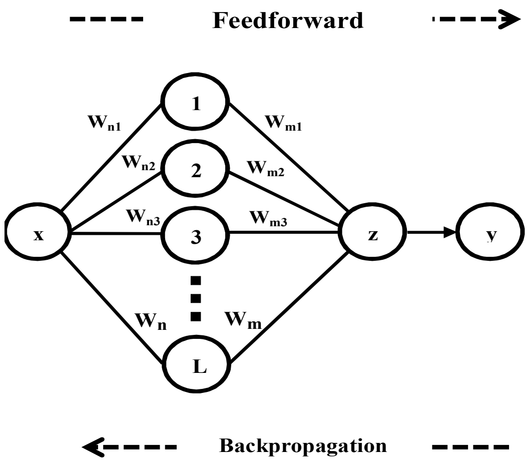

Figure 1. BP-ANN Architecture

Training algorithm in BP-ANN consists of two phases. First, the input pattern given to the input layer. Then, the network sends out the input pattern to the first hidden layer, and forwarded to the next hidden layer until output value generated by the output layer. Second, if the output value differs from the desired output value, an error will be counted and then propagated back from the output layer and return to the input layer. During the propagation process, its weight will be modified. The BP-ANN training process on three types of layers, i.e. input layer, hidden layer and output layer with *i, j* and *k* index of each layer. Input signal propagated forward from left to right, while the error signal *(e)* propagated back from right to left. Symbols w_{ij} stands for weights connection from input layer to hidden layer.w_{jk} symbolizes hidden layer's weight to k neurons in output layer. At the beginning of the BP-ANN training process, all the weights in the hidden layer and output layer are initialized, and then enable the use of activation function as below.

$$v = \sum_{i=1}^{n} x_i \cdot w_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

where, *n* is the number of data input, *x* is the input value and *w* is the weight input. Activation function used is binary sigmoid with the following formula.

$$= \frac{1}{1+e^{-v}} - 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

Error signal propagation begins from the output layer and move back to hidden layer.
The weights are updated when error propagated back through BP-ANN. Error signals in k neurons at p iteration formulated as follows.

$$e_k(p) = y_{dk}(p) - y_k(p) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

Where $y_{dk}(p)$ is the output value for the target of k neuron and $y_k(p)$ is a newly acquired output by k neuron in the output layer. To update weights (Δw) on the connection between hidden layer to output layer is as follows.

$$w_{jk}(p+1) = w_{jk}(p) + \Delta w_{jk}(p) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

$$w_{jk}(p) = \eta \times y_j(p) \times \delta_k(p) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5)}$$

Where η is the learning rate, δ_k is the error gradient on k neuron in output layer at p iteration. To calculate the error gradient in hidden layer is as follows.

$$\delta_j(p) = y_j(p) \times [1 - y_j(p)] + \sum_{k=1}^{1} \delta_k(p).w_{jk}(p) \quad \ldots\ldots\ldots \text{(6)}$$

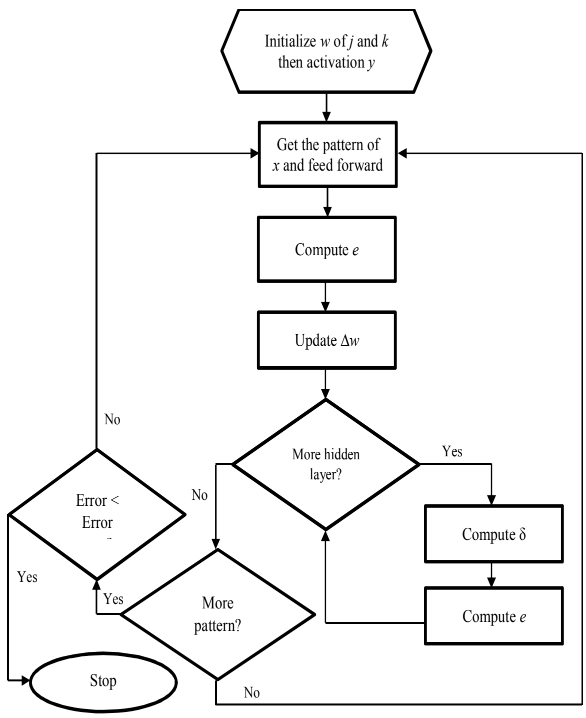

Figure 2. BP-ANN Training Flowchart

Moving Average

Moving average is forecasting techniques based on the moving average of the past values, for example moving average used per week, per month or per year. This method is simple and easy to implement method of forecasting time series. The MA formula is used as follows (Lee, 2012).

$$MA = \sum_{i=1}^{n} \left[\frac{x_i}{n}\right] (7)$$

where *n* is the moving average period and $\sum_{i=1}^{n} x_i$ is the number of observed values for *n* period.

MATERIALS AND METHODS

With many installations provided by the hospital management in supporting public health service improvement such as outpatient installation, inpatient, ICU, emergency room, pharmacy unit, laboratory, surgical installation, obgyn installation and radiological installation, then all of it affects the level of patient visits and directly affects the change movement of CMT usage in the hospital. Usage movement in this case is an increase or decrease usage of each item. Classification of usage movement according to the hospital management is divided into *fastmove*, *slowmove* and *deathstock*. *Fastmove* is an item usage with high movement level due to the excessive number of requests towards a certain item during a time period and the opposite is *slowmove*. While *deathstock* is a condition where items are available without any demand for over a time period and any prior information.

Prediction of Hospital CMT logistics using MA and BP-ANN use two samples, explicitly ECG Electrodes and Connect a BD. ECG electrodes is one of CMT type used for cardio examination. Connect a BD is used as an infuse connector for more than one infuse on a patient. ECG electrodes and Connect a BD are included in the *fast moves* category that needed to be prioritized item due to the high movement rate of its use. Based on the two mentioned examples, CMT usage prediction in hospitals is urgently needed to assist logistics management in planning the CMT logistics procurement to anticipate future *stock out, overstock* and obsolescence events *(expired)* due to *over stock*. Prediction phase, following is the general stages overview of conducted research:

In this paper, the data parameter used is the daily data usage for each CMT for 3 months with 120 total data obtained from Hospital XYZ. The obtained data is then divided into 90 prediction data for MA method. Whilst for the Artificial Neural Networks method, data division is split into 90 training data. Data validation is 30 for both methods. The predictions system design of CMT prediction using MA method use 90-day movement for each CMT item prediction. Number of inputs 1, *hidden layer* used is 10, the output result is 1. Learning rate of 0.1 and the activation function using binary sigmoid *(logsig)* with a target error of 10^{-5} and maximum iteration is *set* to 500 times. In the training and testing process, the data that has been sorted is then inputted into system of the two methods used. From input data, the system will be trained to recognize patterns and parameters movement. Therefore, when testing time, the system already learn previous data to generate future predictions. The results obtained from the training and testing prediction system are evaluated afterwards. Generated model from prediction system with BP-ANN method is optimized mathematically during the training and testing, while the statistical evaluation conducted by using RMSE values according to the following equation.

$$RMSE = \sqrt{\frac{\sum(Actual\ CMT - Prediction\ CMT)^2}{N}} \quad (8)$$

where N is the number of data.

RESULTS AND DISCUSSION

The prediction results using MA and BP-ANN are shown in Figure 4 and 5 for the usage prediction of CMT ECG Electrodes and Connecta BD, respectively.

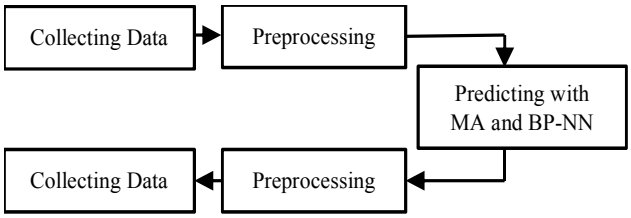

Figure 3. BP-ANN Training Flowchart

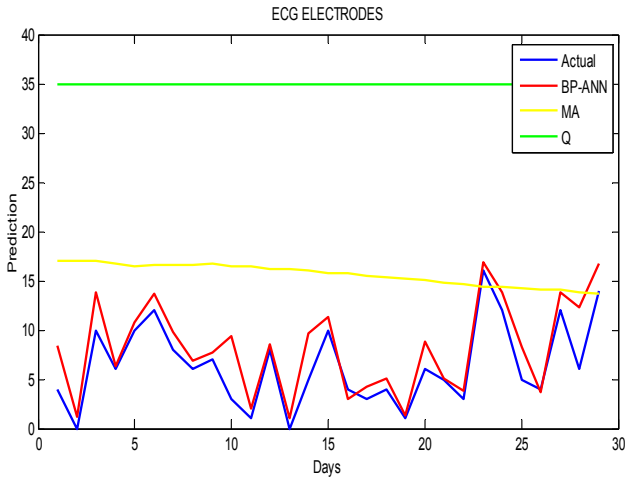

Figure 4. Prediction Results Comparison of CMT ECG Electrodes in April 2014 With MA, BP-ANN, Qualitative (Q) and the actual data usage

The prediction results were obtained by comparing the BP-ANN method, the MA time series method and qualitative methods of the hospital management, overall prediction for 30 days of April is shown in Figure 4. Based on these images, the prediction using MA time series method generate prediction value of average usage range from 16 and 17 use items every day. Meanwhile, hospital management predictions with qualitative forecasting method produce constant predictive value for 35 ECG electrodes item during the month. On the other hand, the prediction results by using BP-ANN are very close to the predicted item usage per day. Figure 5 shows the predictive value for the Connect a BD item usage.

From the graph presented, the best prediction is generated by BP-ANN method with the usage patterns mainly resemble and close to the actual consumption. As for the use of MA method produces average prediction value range for 22 for each item usage per day with the movement parameter of early 3 months usage. In contrast, the qualitative prediction of hospital management produce predictions that goes far beyond the actual usage during April. Thus, causing *overstock* due to large amounts of ordering compared to the consumption level in the period.

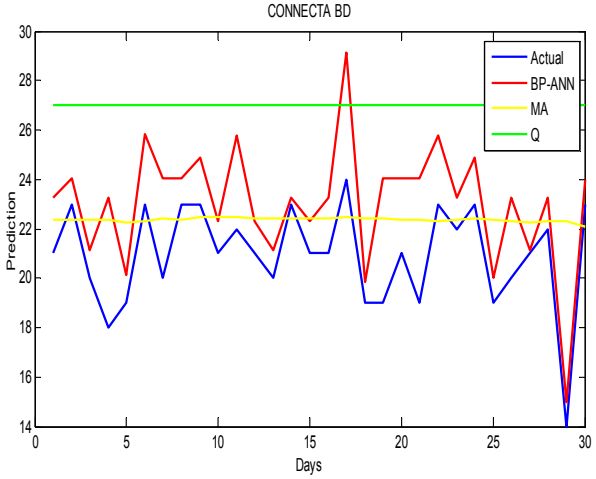

Figure 5. Prediction Results Comparison of CMT Connect a BD in April 2014 With MA, BP-ANN, Qualitative (Q) and the actual data usage

Table 1. RMSE Comparison table of CMT Prediction Results with BP-ANN, MA and Hospital Management Prediction (Qualitative)

CMT	RMSE		
	Qualitative	MA	BP-ANN
ECG Electrodes	29.2718	4.8855	2.547
Connecta BD	6.4031	2.5021	2.4817

The use of quantitative methods to predict April 2014 consumption by MA showed better results than the use of qualitative methods. From the obtained results, this method is able to meet the most of hospital demands without stock out. However, on certain days, stock out cases occurred in MA prediction. Therefore this method cannot be used as the best method, nevertheless it is better than the qualitative method. Based on Figure 4 and 5, MA method cannot generate prediction patterns that resembles the prediction trend of actual consumption because the MA prediction method is not performing training process of historical data so there is no learning process to identify consumption trends.

Based on the obtained results, RMSE of the actual and prediction comparison for ECG Electrodes and Connect a BD using BP-ANN, MA and qualitative methods as shown in Table 1, the forecasting method using BP-ANN is the preferred method for accurate prediction of ECG electrodes and Connect a BD usage compared with the MA and qualitative methods. It is indicated by the small BP-ANN RMSE value compared to the other methods. Accurate method selection will be the right strategy, innovative and efficient for hospital supply chain management.

REFERENCES

Adeyemi, S., L., Salami, A., O., 2010, "Inventory Management: A Tool of Optimizing Resource in a Manufacturing Industry A Case of Coca-Cola Bottling Company, Ilorin Plant", *J Soc Sci.*, 23(2), pp. 135-142.

Indrabayu., *et al*. 2013, "Statistic Approach versus Artificial Intelligence for Rainfall Prediction Based on Data Series", vol. 5, no. 2, pp. 1962-1969.

Jarrett P.G. An analysis of international health care logistics: the benefits and implications of implementing just-in-time systems in the health care industry. Leadership in Health Services.2006; 19: 1-10.

Lee, I, W., Chen, K, H., Chen, Tsung, Hao., Liu, C, C., 2012, "A Comparative Study on the Forecast of Fresh Foof Sales Using Logistic Regression, Moving Average and BPNN Methods", vol. 20, no.2, pp. 142-152.

Manjit, K., Sarah, H. 2001. Medical supplies and equipment for primary health care: A practical resource for procurement and management. United Kingdom: Dunns.

Muliana, A., T. 2015. The Consumables Prediction of Teaching Hospital Using Moving Average Method. PoliteknikNegri Ujung Pandang - BBPPKI Cooperation National Conference (SNKI). 2015.11, 06, In Press.

Qingkui, C. and Junhu, R. 2009. Study on the Demand Forecasting of Hospital Stocks Based on Data Mining and BP Neural Networks. Electronic Commerce and Business Intelligence, 284-289.

Rachmania, N. I. and Basri, M. H. 2013. Pharmaceutical Inventory Management Issues in Hospital Supply Chains. Scientific and Academic Publishing.2013; 3: 1-5.

Saha, C., Lam, S. S. and Boldrin, W. 2014. Demand Forecasting for Server Manufacturing Using Neural Networks. In: Proceeding of the 2014 Industrial and System Engineering Research Conference.

Tsumoto, Shusaku. Hirano, Shoji. Abde, Hidenao, 2011. Temporal Data Mining in History Data of Hospital Information Systems.

Yan, Wen, Zixian, Liu, Junlan, Liu, 2010. "Logistic Mode Reenginering of Hospital Material Based on JIT Theory", pp. 1039-1042.

****