Forecasting Fuzzy Delphi and Hybrid intelligent system for ERP Architecture through the Scientific Private Cloud

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ABSTRACT
To enhance the competitive advantage in a constantly changing environment, the manager of a company must make the right decision at the right time based on the information at hand. The Enterprise Resource Planning System (ERP) integrates the management of internal and external information across the organization (finance / accounting, manufacturing, sales and service, customer relationship management, etc.). How to use the information resources of the ERP and how to exercise effective information resources are currently pressing issues. This research proposes an intelligent hybrid sales forecasting system based on Fuzzy Delphi Method, fuzzy clustering and Back-propagation (BP) Neural Networks with adaptive learning rate in ERP architecture (Delphi-FCBPN-ERP). We utilize SPC (Scientific Private Cloud) was to reduce the time computation of the proposed model. This cloud computing platform will allow improved the execution time of parallel neural networks proposed in our model. Experimental results show that the proposed approach is superior then the traditional approaches.

Keywords
Enterprise Resource Planning (ERP), fuzzy Delphi, Sales forecasting, fuzzy clustering, fuzzy system, back propagation network, Hybrid intelligence approach.

1. INTRODUCTION
Sales forecasting, which has been investigated by various researchers, is a very complicated environment. Control and evaluation of future sales still seem concerned both researchers and policy makers and managers of companies. Obtaining effective sales forecasts in advance can help decision makers to calculate production and material costs, determine also the sales price, strategic Operations Management, etc.

Computers have been used for decades by enterprises involved in production, sales and distribution aiming towards to optimize the allocation of resources, improve the productivity of the company by enhancing their management efficiency. In recent years, there has been a strong tendency of companies to use centralized management systems like Enterprise resource planning (ERP). ERP systems offer a comprehensive and simplified process managements and extensive functional coverage. The sales management module is an important element business management of ERP.

Hybrid intelligent system denotes a system that utilizes a parallel combination of methods and techniques from artificial intelligence can solve non-linear prediction, this article proposes an integration of a hybrid system (Delphi-FCBPN-ERP) within the architecture of ERP to improve and extend the management sales module to provide sales forecasts and meet the needs of decision makers of the company.

Tabaa and Medouri [2] proposed a novel implementation of cloud computing platform SPC (Scientific Private Cloud) which offer a highly scalable data intensive distributed computing to perform complex tasks on massive amounts of data such as clustering, matrix computation, data mining, information extraction, etc.

The rest of the paper is organized as follows. Section 2 is the literature review. Section 3 describes the construction and role of each component of the proposed sale forecasting system Delphi-FCBPN-ERP Section 4 describes the sample selection and data analysis. Finally, section 5 provides conclusions.

2. LITERATURE AND RELATED RESEARCH
Enterprise Resource Planning (ERP) is a standard of a complete set of enterprise management system.It emphasizes integration of the flow of information relating to the major functions of the firm [6]. There are four typical modules of ERP, and the sales management is one of the most important modules. Sales management is highly relevant to today's business world; it directly impacts the working rate and quality of the enterprise and the quality of business management. Therefore, Integrate sales forecasting system with the module of the sales management has become an urgent project for many companies that implement ERP systems.

Attariuas, Bouhorma and el Fallahi [7] propose hybrid sales forecasting system based on fuzzy clustering and Back-propagation (BP) Neural Networks with adaptive learning rate (FCBPN).The experimental results show that the proposed model outperforms the previous and traditional approaches (BPN, FNN , WES, KGFS). Therefore, it is a very promising solution for industrial forecasting.

A Hybrid Intelligent Clustering Forecasting System was proposed by Kyong and Han (2001)[5]. It was based on Change Point Detection and Artificial Neural Networks. The basic concept of proposed model is to obtain significant intervals by change point detection. They found out that the proposed models are more accurate and convergent than the traditional neural network model (BPN).

Recently, some researchers have shown that the use of the hybridization between fuzzy logic and GAs leading to genetic fuzzy systems (GFSs) (Cordón, Herrera, Hoffmann, & Magdalena (2001) [8]) has more accurate and efficient results than the traditional intelligent systems. Casillas, & MartínezLópez (2009) [10], MartínezLópez & Casillas (2009) [9], utilized GFS in various case Management. They have all obtained good results.

Hadavandi, Shavandi and Ghanbari (2011) [4] proposed a novel sales forecasting approach by the integration of genetic fuzzy systems (GFS) and data clustering to construct a sales forecasting expert system. They use GFS to extract the whole knowledge base of the fuzzy system for sales forecasting problems. Experimental results show that the proposed approach outperforms the other previous approaches.

This paper proposes an intelligent hybrid sales forecasting system Delphi-FCBPN-ERP sales forecast based on architecture of ERP through Fuzzy Delphi, fuzzy clustering and Back-propagation (BP) Neural Networks with adaptive learning rate (FCBPN) for sales forecasting in packaging industry.

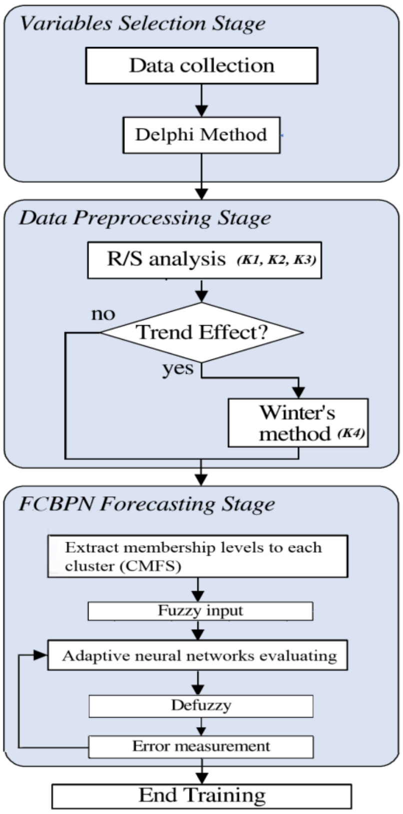

Figure 1: The architecture of Delphi-FCBPN-ERP.

3. DEVELOPMENT OF THE DELPHI-FCBPN-ERP MODEL

Basically, the proposed system is composed of: (1) Stage of data collection: Data collection will be implemented from the fields (attributes) existing at the interfaces (Tables the database) of the ERP. Collection of Key factors that influence sales be made using the Fuzzy Delphi method through experts judgments; (2) Stage of Data preprocessing: Use Rescaled Range Analysis (R/S) to evaluate the effects of trend. Winter's Exponential Smoothing method will be utilized to take the trend effect into consideration. (3) Stage of learning by FCBPN: We use hybrid sales forecasting system based on fuzzy Delphi, fuzzy clustering and Back-propagation (BP) Neural Networks with adaptive learning rate (FCBPN).

3.1 Stage of data collection

The data for this study come from an industrial company that manufactures packaging in Tangier from 2001 to 2009. Amount of monthly sales is seen as an objective of the forecasting model. The target company manages its information system using ERP called OpenERP.

3.1.1 The collection of attributes affecting sales

Data collection will be implemented from the fields (attributes) existing at the interfaces (Tables the database) of the ERP.

As ERP data base, there is a strong dependence between the modules of sale management with other modules such as (accounting, inventory management, production management, product management). The collection of attributes affecting sales will be based on the attributes of the Sales Management module and modules that have a direct dependence with the sales management module.

3.1.2 Fuzzy Delphi Method to select the factors affecting sales

The Delphi Method was first developed by Dalkey and Helmer (1963) in corporation and has been widely applied in many management areas, e.g. forecasting, public policy analysis, and project planning.

ssThe principle of the Delphi method is the submission of a group of experts in several rounds of questionnaires. After each round, a synthesis anonymous of response with experts' arguments is given to them. The experts were then asked to revise their earlier answers in light of these elements. It is usually found as a result of this process (which can be repeated several times if necessary), the differences fade and responses converge towards the "best" answer.

The FDM was used to choose the main factors, which would influence the PCB product sales quantity from all possible factors that were collected from the questionnaires in this research. The procedures of FDM are listed as follows:

1. Collect all possible factors from ERP database, which may affect the monthly sales from the domain experts. This is the first questionnaire survey.

2. Conduct the second questionnaire and ask domain experts select assign a fuzzy number ranged from 1 to 5 to each factor. The fuzzy number represents the significance to the sales.

3. Fuzzify the second questionnaires that are returned by the domain experts and determine the following indices:

a. Pessimistic (Minimum) index

$$\ell_A = \frac{\ell_{A1} + \ell_{A2} + \cdots + \ell_{An}}{n}$$

Where l_{Ai} means the pessimistic index of the ith expert and n is the number of the experts.

b. Optimiste (Maximum) index

$$u_A = \frac{u_{A1} + u_{A2} + \cdots + u_{An}}{n}$$

Where u_{Ai} means the pessimistic index of the ith expert.

a. Average (Most appropriate) index. For each interval $l_{Ai}+u_{Ai}$, calculate the midpoint, $m_{Ai}=(l_{Ai}+u_{Ai})/2$, then find $\mu_A=(m_{A1} \times m_{A2} \ldots \times m_{An})^{1/n}$ Therefore, the fuzzy number $A=(\mu,\sigma^R,\sigma^L)$, which represents the mean, right width, and left width, respectively, for an asymmetric bell shaped function that can be determined through the above indices:

$$\sigma^{R} = \frac{\ell_A - \mu_A}{3}$$

$$\sigma^{L} = \frac{u_A - \mu_A}{3}$$

4. Finalize the significance number of each factor in the questionnaire according to the index generated in step 3.

5. Repeat 3 to 4.

6. Use the following formulas as the stopping criteria to confirm that all experts have the consentaneous significance number of each factor.

$$\delta(\bar{A},\bar{B}) = \int_{\alpha=0}^{1} \delta(\bar{A}[\alpha],\bar{B}[\alpha])d\alpha$$

$$= \frac{1}{2}(\beta_2 - \beta_1)\int_{\alpha=0}^{1} (|\bar{A}[\alpha]^L - \bar{B}[\alpha]^L|) + (|\bar{A}[\alpha]^U - \bar{B}[\alpha]^u|)d\alpha$$

3.2 Data preprocessing stage

Based on Delphi method, the key factors that influence sales are (K1, K2, K3) (see Table 1): When the seasonal and trend variation is present in the time series data, the accuracy of forecasting will be influenced. R/S analysis will be utilized to detect if there is this kind of effects of serious data. If the effects are observed, Winter's exponential smoothing will be used to take the effects of seasonality and trend into consideration.

Table 1: Description of input forecasting model.

Input	Description
K_1	Manufacturing consumer index
N_1	Normalized manufacturing consumer index
K_2	Offers competitive index
N_2	Normalized offers competitive index
K_3	packaging total production value Index
N_3	Normalized packaging total production value Index
K_4	Preprocessed historical data (WES)
N_4	Normalized preprocessed historical data (WES)

3.2.1 R/S analysis (Rescaled Range Analysis)

For eliminating possible trend influence, the rescaled range analysis, invented by Hurst (Hurst, Black, & Simaika, 1965), is used to study records in time or a series of observations in different time. Hurst spent his lifetime studying the Nile and the problems related to water storage. The problem is to determine the design of an ideal reservoir on the basis of the given record of observed discharges from the lake. The R/S analysis will be introduced as follows:

Consider the XZ{x1, x2,., xn}, xi is the sales amount in period i, and compute MN where

$$M_N = \frac{1}{N}\sum_{i=1}^{t} X_i$$

The standard deviation S is defined as

$$S = \sqrt{\frac{\sum_{i=1}^{N}(X_i - M_N)^2}{N}}$$

For each point i in the time series, we compute

$$X(t,N) = \sum_{t=1}^{t} X_i - M_N$$

$$R = \max_{1\le t\le N} X(t,N) - \min_{1\le t\le N} X(t,N)$$

We computed the H coefficient as

$$H = \mathrm{Ln}\left(\frac{R}{S}\right)/\mathrm{Ln}(aN)$$, here a=1

When 0<H<0.5, the self-similar correlations at all time scales are anti-persistent, i.e. increases at any time are more likely to be followed by decreases over all later time scales. When H=0.5, the self-similar correlations are uncorrelated. When 0.5<H<1, the self-similar correlations at all time scales are persistent, i.e. increases at any time are more likely to be followed by increases over all later time scales.

3.2.2 *Winter's Exponential Smoothing*

In order to take the effects of seasonality and trend into consideration, winter's Exponential Smoothing is used to preliminarily forecast the quantity of sales. For time serial data, Winter's Exponential Smoothing is used to preprocess all the historical data and use them to predict the production demand, which will be entered into the proposed hybrid model as input variable (K4)(see Table 1).Similar to the previous researches, we assume $\alpha= 0.1$, $\beta= 0.1$ and $\gamma= 0.9$. The data generating process is assumed to be of the form

$$x_t = (a_{0,t} + a_{1,t})C_t + \varepsilon_t$$

Where C_t seasonal factor

$$a_{0,t} = \alpha\frac{x_t}{C_{t-N}} + (1-\alpha)(a_{0,t-1} + a_{1,t-1})$$

is exponentially smoothed level of the process at the end of period t

x_t actual monthly sales in period t

N number of periods in the season (N=12 months)

α_{t-1} trend for period t-1

α smoothing constant for α_0.

The season factor, C_t, is updated as follows

$$C_t = \gamma\frac{x_t}{a_{0,t}} + (1-\gamma)C_{t-N}$$

Where γ is the smoothing constant for C_t. For updating the trend component

$$\alpha_{1,t} = \phi(\alpha_{0,t} - \alpha_{0,t-1}) + (1-\phi)\alpha_{1,t-1}$$

Where Φ is the smoothing constant for α_1. Winter's forecasting model is then constructed by

$$\hat{x}_t(\alpha_{0,t} + \alpha_{1,t})C_t$$

Where $\hat{x}_t$ is the estimate in time period t.

3.3 FCBPN forecasting stage

FCBPN[7] (Fuzzy Clustering and Back-Propagation (BP) Neural Networks with adaptive learning rate) is utilized to forecast the future packaging industry sales. As shown in figure 2, FCBPN is composed of three steps: (1) utilizing Fuzzy C-Means clustering method (Used in an clusters memberships fuzzy system (**CMFS**)), the clusters membership levels of each normalized data records will be extracted; (2) After fuzzification of the inputs with signal inputs, the clusters will be fed into parallel BP networks with a learning rate adapted as the level of cluster membership of training data records.

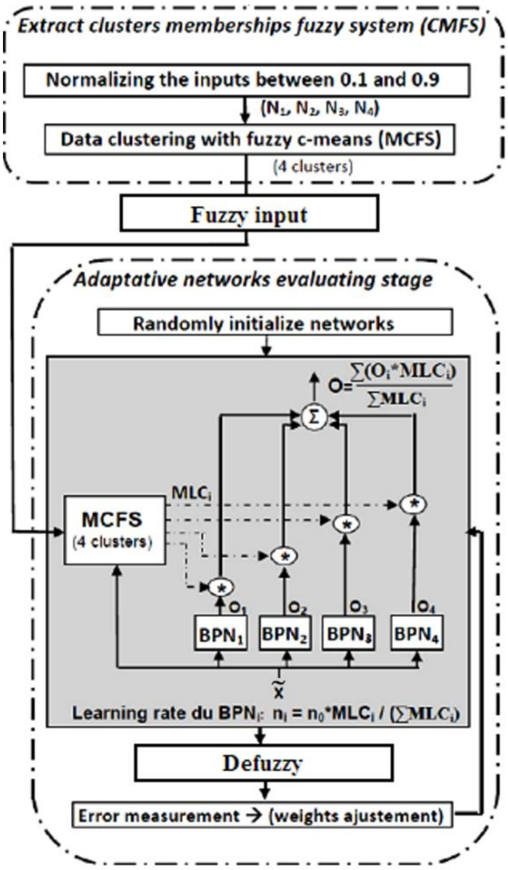

Figure 2: The architecture of FCBPN model.

3.3.1 Extract membership levels to each cluster (CMFS)

Using Fuzzy C-Means clustering method (utilized in an adapted fuzzy system (CMFS)), the clusters centers of the normalized data records will be founded, and consequently, we can extract the clusters membership levels of each normalized data records.

3.3.1.1 Data normalization

The input values (**K1, K2, K3, K4**) will be ranged in the interval [0.1, 0.9] to meet property of neural networks. The normalized equation is as follows:

$$N_i = 0.1 + 0.8 * (K_i - min(K_i))/(max(K_i) - min(K_i)). \quad (1)$$

Where $\mathbf{K_i}$ presents a key variable, $\mathbf{N_i}$ presents normalized input (see Table 1), max ($\mathbf{K_i}$) and min ($\mathbf{K_i}$) represent maximum and minimum of the key variables, respectively.

3.3.1.2 Fuzzy c-means clustering

In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster. In Fuzzy c-means (FCM) (developed by Dunn 1973 [3] and improved by Bezdek 1981 [1]), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \|x_i - c_j\|^2 \qquad ,1 \le m < \infty.$$

Where $\mathbf{u_{ij}}$ is the degree of membership of x_i in the cluster **j** , $\mathbf{x_i}$ is the i^{th} of measured data and $\mathbf{c_j}$ is the center of the $\mathbf{j^{th}}$ cluster. The algorithm is composed of the following steps :

Step 1 : Initialize randomly the degrees of membership matrix

$$U=[u_{ij}] , U^{(0)}$$

Step 2 : Calculate the centroid for each cluster $C(k)=[c_j]$ with $\boldsymbol{U(k)}$:

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

Step 3: For each point, update its coefficients of being in the clusters $\boldsymbol{(U(k), U(k+1))}$:

$$u_{ij} = \frac{1}{\sum_{i=1}^{C}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{2/(m-1)}}$$

Step 4: If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon \;, 0 < \varepsilon < 1.$ then STOP; otherwise return to step 2.

This procedure converges to a local minimum or a saddle point of $\boldsymbol{J_m}$. According to Bezdek [1], the appreciated parameter combination of two factors (m and **ε**) is **m** = 2 and **ε**= 0.5

Using fuzzy c-means, Table 2 shows that the use of four clusters is the best among all different clustering numbers.

Table 2: total distance of different clustering algorithms.

Clustering groups	fuzzy c-means total distance
Clustering 2 groups	5.8935
Clustering 3 groups	2.3822
Clustering 4 groups	1.3667

3.3.1.3 The degree of Membership levels (MLCk)

In this stage, we will use the sigmoid function (Figure 3) to improve the precision of results and to accelerate the training process of neural networks. Then, the advanced fuzzy distance between records data ($\mathbf{X_i}$) and a cluster center ($\mathbf{c_k}$) ($\mathbf{AFD_k}$) will be presented as follow:

$$AFD_k(X_i) = sigmf(\|C_k - X_i\|, [50, 0.5])$$

$$sigmf(x, [a, c]) = \frac{1}{1 + e^{-a(x-c)}}$$

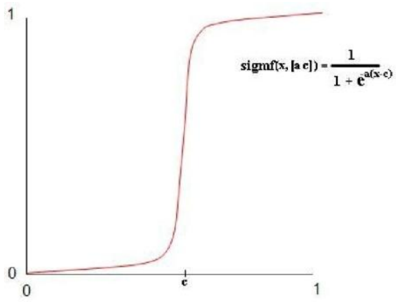

Figure 3: Sigmoid function, a = 50 and c = 0,5.

The membership levels of belonging of a record $\mathbf{X_i}$ to $\mathbf{k^{ith}}$ cluster ($\mathbf{MLC_k}$ $(\mathbf{X_i})$) is related inversely to the distance from records data $\mathbf{X_i}$ to the cluster center $\mathbf{c_k}$ ($\mathbf{AFD_k}$ $(\mathbf{X_i})$):

$$MLC_k(X_i) = \frac{1}{AFD_k(X_i)}$$

The clusters memberships' fuzzy system (CMFS) return the memberships level of belonging of data record X to each clusters:

$$CMFS(X) = (MLC_1(X), MLC_2(X), MLC_3(X), MLC_4(X))$$

Thus, we can construct a new training sample (X_i , $MLC_1(X_i)$, $MLC_2(X_i)$, $MLC_3(X_i)$, $MLC_4(X_i)$) for the adaptive neural networks evaluating (Figure **2**).

3.3.2. Adaptive neural networks evaluating stage

3.3.2.1 Input fuzzification.

Each input unit N_j, which was generated by many experts, receives input signal:

$$\tilde{\mathbf{N}}(i) = \tilde{S}(i)\mathbf{N}(i)$$
$$= (\tilde{\mathbf{N}}^1(i), \tilde{\mathbf{N}}^2(i), \tilde{\mathbf{N}}^3(i))$$
$$= (u_i * \mathbf{N}(i), \mu_i * \mathbf{N}(i), \ell_i * \mathbf{N}(i))$$

Then this signal will be broadcasted to the adaptive neural networks. $\tilde{S}(i)$ is the fuzzy membership function, which is supported by the experts, and the normalized fuzy input is :

$$\tilde{X}_{(i)} = (\tilde{N}_{i,1}, \tilde{N}_{i,2}, \tilde{N}_{i,3}, \tilde{N}_{i,4})$$

In the Adaptive neural networks evaluating stage:

(**+**) represents fuzzy addition: max

(*) represents fuzzy multiplication: min

3.3.2.2 Adaptive neural networks

The artificial neural networks (ANNs) concept is originated from the biological science (neurons in an organism). Its components are connected according to some pattern of connectivity, associated with different weights. The weight of a neural connection is updated by learning. The ANNs possess the ability to identify nonlinear patterns by learning from the data set. The back-propagation (BP) training algorithms are probably the most popular ones. The structure of BP neural networks consists of an input layer, a hidden layer, as well as an output layer. Each layer contains **I** ; **J** and **L** nodes denoted. The $\boldsymbol{w_{ij}}$ is denoted as numerical weights between input and hidden layers and so is $\boldsymbol{w_{jl}}$ between hidden and output layers as shown in Figure 4.

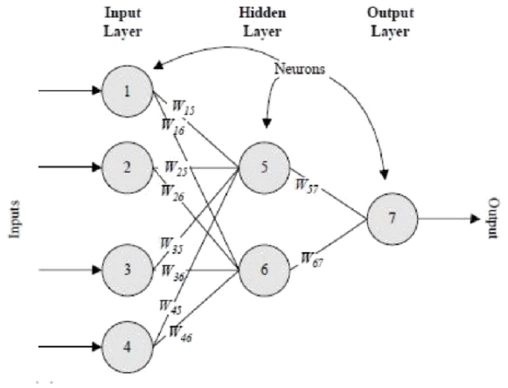

Figure 4: The structure of back-propagation neural network

In this stage, we propose an adaptive neural networks evaluating system which consists of four neural networks. Each cluster **K** is associated with the $\boldsymbol{K^{ith}}$ BP network. For each cluster, the training sample will be fed into a parallel Back Propagation networks (BPN) with a learning rate adapted according to the level of clusters membership ($\boldsymbol{MLC_k}$) of each records of training data set. The structure of the proposed system is shown in Figure **2**.

The Adaptive neural networks learning algorithm is composed of two procedures: (a) a feed forward step and (b) a back-propagation weight training step. four two separate procedures will be explained in details as follows:

Step 1- All BP networks are initialized with the same random weights.

Step 2 - Feed forward.

For each $\boldsymbol{BPN_k}$ (associate to the $\boldsymbol{K^{th}}$ cluster), we assume that each input factor in the input layer is denoted by $\boldsymbol{x_i}$. $\boldsymbol{y_j^k}$ and $\boldsymbol{o^k_l}$ represent the output in the hidden layer and the output layer, respectively. And $\boldsymbol{y_j^k}$ and $\boldsymbol{o^k_l}$ can be expressed as follows:

$$Y_j^k = f(X_j) = f(w_{oj}^k + \sum_{i=0}^{I} w_{ij}^k x_i)$$

and

$$o_l^k = f(Y_l^k) = f(w_{ol}^k + \sum_{j=1}^{J} w_{jl}^k y_j^k)$$

where the $\boldsymbol{w_{oj}^k}$ and $\boldsymbol{w_{ol}^k}$ are the bias weights for setting threshold values, $\boldsymbol{f}$ is the activation function used in both hidden and output layers and $\boldsymbol{X_j^k}$ and $\boldsymbol{Y_l^k}$ are the temporarily computing results before applying activation function $\boldsymbol{f}$. In this study, a sigmoid function (or logistic function) is selected as the activation function. Therefore, the actual outputs $\boldsymbol{y_j^k}$ and $\boldsymbol{o^k_l}$ in hidden and output layers, respectively, can also be written as :

$$y_j^k = f(X_j^k) = \frac{1}{1 + e^{-X_j^k}}$$

and

$$o_l^k = f(Y_l^k) = \frac{1}{1 + e^{-Y_l^k}}$$

The activation function f introduces the nonlinear effect to the network and maps the result of computation to a domain (0, 1).

In our case, the sigmoid function is used as the activation function.

$$f(t)=\frac{1}{1+e^{-t}} \qquad ,f'=f(1-f)$$

The globate output of the adaptive neural networks is calculated as :

$$o_l=\frac{\sum_{k=1}^{4}(MLC_k(X_j)\times o_l^k)}{\sum_{k=1}^{4}MLC_k(X_j)}$$

As shown above, the effect of the output o^k_l on the global output o_l is both strongly and positively related to the membership level (MLC_k) of data record X_i to k^{ith} cluster.

Step 3- Output defuzzification.

Defuzzify the output signals $\tilde{o}=(o_1,o_2,o_3)$ to the forecasting value:

$$o=\text{defuzzification}(\tilde{o})=\frac{1}{4}(o_1,2o_2,o_3)$$

Step 4- Back-propagation weight training. The error function is defined as:

$$E=\frac{1}{2}\sum_{l=1}^{L}e_l^2=\frac{1}{2}\sum_{l=1}^{L}(t_l-o_l)^2 \qquad -$$

Where t_k is a predefined network output (or desired output or target value) and e_k is the error in each output node. The goal is to minimize **E** so that the weight in each link is accordingly adjusted and the final output can match the desired output. The learning speed can be improved by introducing the momentum term. Usually, falls in the range [0, 1]. For the iteration n and for BPN_k (associated to k^{th} cluster), the adaptive learning rate in BPN_k and the variation of weights Δw_k can be expressed as

$$\eta_k=\frac{MLC_k(X_j)}{\sum_{k=1}^{4}MLC_k(X_j)}\times\eta$$

$$\Delta w_k(n+1)=\eta_k\times\Delta w_k(n)+\alpha\times\frac{\delta E}{\delta w_k(n)}$$

As shown above, we can conclude that the variation of the BPN_k network weights (w_{oj}^{k} and w_{ol}^{k}) are more important as long as the the membership level (MLC_k) of data record X_j to k^{th} cluster is high. If the value of membership level (MLC_k) of data record X_j to k^{ith} cluster is close to zero then the changes in BPN_k network weights are very minimal.

The configuration of the proposed BPN is established as follows:

- Number of neurons in the input layer: I =4
- Number of neurons in the output layer: L = 1
- Single hidden layer
- Number of neurons in the hidden layer: J =2
- Network-learning rule: delta rule
- Transformation function: sigmoid function
- learning rate: =0.1
- Momentum constant: = 0.02 – learning times : 20000

4. EXPERIMENT RESULTS AND ANALYSIS

4.1 Experimental setup

To perform the experiments we utilized a kind of cloud platform named SPC (Scientific Private Cloud) [2] which consists of a dedicated platform to solve embarrassingly parallel problems while taking full advantages of Cloud Computing such as resizable compute capacity to perform large amount of data analysis in order to transform raw data into meaningful information.

The SPC, utilized in this search, uses open source components and the Hadoop 2.0 computation framework, it's composed of one master acting as the resources manager and 22 nodes, each node is a virtual machine with 2.4 GHz, 2 GB of memory and 20 GB of disk space allocated for HDFS (Hadoop Distributed File System), making the total size of 440 GB, these nodes are monitored through a Node Manager service.

Table 3: the performance improvement of Delphi-FCBPN after using Scientific Private Cloud

Execution platform	Time execution
Using scientific Private Cloud	19 min 32 s
Without using Scientific Private Cloud	2 hours 9 min 47s

As shown in Table 3, the time execution of Delphi-FCBPN in Scientific Private Cloud is significantly lower.

4.2 Constructing Delphi-FCBPN-ERP System

The data test used in this study was collected from sales forecasting case study of manufactures packaging In Tangier, The target company manages its information system using ERP called OpenERP .The total number of training samples was collected from January 2001 to December 2008 while the total number of testing samples was from January 2009 to December 2009.The proposed Delphi-FCBPN-ERP system was applied as case to forecast the sales. The results are presented in Table 3.

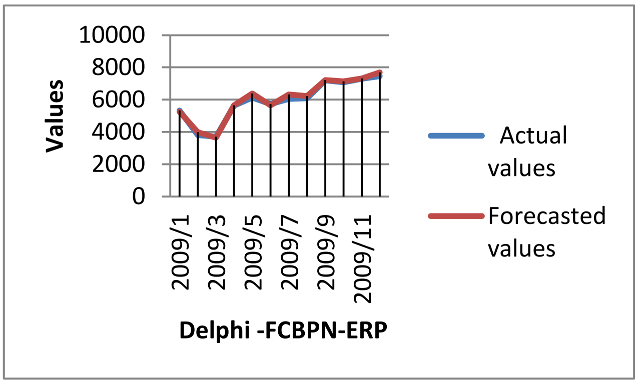

Figure 5: The MAPE of Delphi-FCBPN-ERP.

4.3 Comparisons of FCBPN model with other previous models

Experimental comparison of outputs of DELPHI-FCBPN-ERP with other methods shows that the proposed model outperforms the previous approaches. We apply two different performance measures called mean absolute percentage error (MAPE) and root mean square error (RMSE), to compare the FCBPN model with the previous methods: BPN, WES and FNN.

$$MAPE = 100 \times \frac{1}{N}\sum_{t=1}^{N}\frac{|Y_t - P_t|}{Y_t}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(Y_t - P_t)^2}$$

Where, P_t is the expected value for period t , Y_t is the actual value for period t and N is the number of periods.

Table 4: Summary MAPE and RMSE values of prediction methods DELPHI-FCBPN-ERPERP, WES, BPN and FNN.

Methods	**Precision**	
	MAPE	RMSE
DELPHI- FCBPN-ERP	2,6	169
WES	8,38	591
BPN	4,42	293
FNN	3,98	263

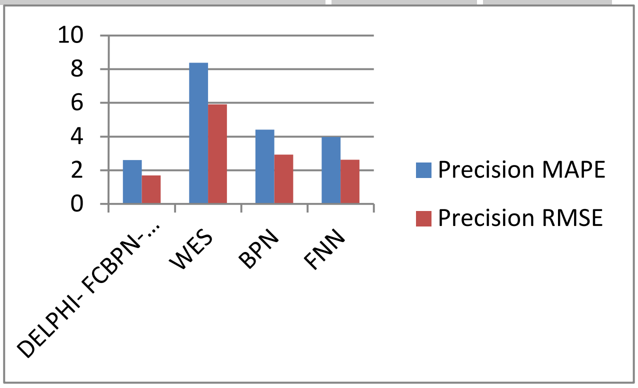

Figure 11: Summary MAPE and RMSE values of prediction methods DELPHI-FCBPN-ERPERP, WES, BPN and FNN

DELPHI-FCBPN-ERPhas made 2.6 as MAPE evaluation and 169 as RMSE evaluation. Therefore, the forecasting accuracy of FCBPN outperforms the other traditional approaches regarding MAPE and RMSE evaluations which are summarized in Table 4.

5. CONCLUSION

This search describes a hybrid system based on the Fuzzy Delphi method, fuzzy clustering and Back-propagation Neural Networks with an adaptive learning rate (FCBPN) for sales forecasting.The experimental results of the proposed approach show that the effectiveness of the DELPHI-FCBPN-ERP is superior to the traditional approaches: WES, BPN and FNN.

Compared to previous researches which tend to use the classical method of collection of key factors, the advantage of our proposed system (DELPHI-FCBPN-ERP) is that it utilizes Method Fuzzy Delphi based on the attributes existing in ERP database. Another advantage of our proposed system (DELPHI-FCBPN-ERP) is that it uses a fuzzy clustering (fuzzy, c-means clustering) which permits each data record to belong to each cluster to a certain degree, which allows the clusters to be larger which consequently increases the accuracy of forecasting system results.

We applied DELPHI-FCBPN-ERP for sales forecasting in a case study of manufacturing packaging in Tangier. The results demonstrated the effectiveness and superiority of the DELPHI-FCBPN-ERP compared to the previous approaches regarding MAPE and RMSE evaluations. Other academic researchers and industrial practitioners may find these contributions interesting.

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