Sales Budget Forecasting and Revision by Adaptive Network Fuzzy Base Inference System and Optimization Methods

Kaban Koochakpour[a], Mohammad Jafar Tarokh[b*]

[a] *Faculty of Computer and Information Technology Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

[b] *Associate Professor of IT Group, Industrial Engineering Department, K.N.Toosi University of Technology*

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Abstract

The sales proceeds are the most important factors for keeping alive profitable companies. So sales and budget sales are considered as important parameters influencing all other decision variables in an organization. Therefore, poor forecasting can lead to great loses in organization caused by inaccurate and non-comprehensive production and human resource planning. In this research a coherent solution has been proposed for forecasting sales besides refining and revising it continuously by ANFIS model with consideration of time series relations. The relevant data has been collected from the public and accessible annual financial reports being related to a famous Iranian company. Moreover, for more accuracy in forecasting, solution has been examined by Back Propagation neural Network (BPN) and Particle swarm Optimization (PSO). The comparison between prediction taken and real data shows that PSO can optimize some parts of prediction in contrast to the rest which is more coincident to the output of BPN analysis with more precise results relatively.

Keywords: Sales Forecast, ANFIS, Time Series Analysis, PSO & BPN methods.

1. Introduction

The important of sales forecasting for a firm has often been stressed [1] and is best expressed by what happens when it is absent. “Without a sales forecast, in the short term, operations can only respond retroactively, learning to lose orders, inadequate service and poorly utilized production resources. In the longer term, financial and market decision making misallocate resources so that the organizations continuing existence may be brought into question” [2]. The forecasts are used for a number of purposes in the firm, including production planning, budgeting, sales quota setting and personnel planning ([3],[4]), the factors that contribute to sound forecasting practice have long been a concern in the literature ([2],[3],[5])

The primary objective of most business enterprises is the securing of a profit and the accumulation of wealth. The basic idea in budgeting is to conserve and increase the capital of a business. Budgeting aides management in realizing its profit objective by providing a scientific technique for forecasting business operations and establishing standards [6]. Managers use the budget as a road map for allocating the company's resources. The main purpose of budgeting is aligning the company activities with the objectives. It means that should be monitoring the immediate effects of activities on others to change them

* Corresponding author. Email: mjtarokh@kntu.ac.ir

flexibly. Due to the changing conditions and the influences of many internal and external factors, decision making about the budget allocation is so important and has too much complexity. Ease and making flexible this decision making in these changing conditions of organizations is so essential. Therefore, it is important to periodically and flexibly adjust the budget and systematize this process can help to be done more accurately and reduce human faults. Structuring and systematize of this process, while grant the framework and logic to thinking and decision-making architecture for managers, with the help of fuzzy logic, provides freedom to non-precise and ambiguous data.

Efforts to balance and adjust the budget, lead to a better understanding of income, expenditure and cash flow in business. Inappropriate Budgeting in an organization can't help to any one and can't improve performance. Budget that is planned inappropriately in an organization will be ignored because it can't give staffs, reasonable criteria for comparison with actual performance. That is why it is very important to review and revise the budget periodically in accordance with the actual performance. Additionally, analysis of variance from budget during the budget revises process; help managers to determine when to adjust their operations and costs. Otherwise, the appropriate regulation of the activities that are moving in relation to each other would be impossible. Also, because of the lack of dynamism, reflection of any phenomena such as increased sales, reduced production, lack of access to raw materials, loss of market share, change and improve the cost structure and … cannot be shown by resource and budget allocation.

The successful combination of some methods, such as neural networks, fuzzy logic and evolutionary computation, developed a new method called Soft and Intelligent Computing, That these soft techniques can be used in estimation, forecasting and decision making in various context. Neuro fuzzy or Fuzzy Neural system is a hybrid system that combines the fuzzy logics ability of making decisions to the neural network's ability of learning, in high levels of complexity, to be able to present a modeling/ estimation system. Fuzzy Neural system is a neural network performing with neuro fuzzy inference system co-ordinately [7].

For sales forecasting and budget assessment is necessary to identify the relation between variables influencing this forecast. There are several methods to correlate variables with sales volume such as multiple linear regressions and computational intelligence regression is statistical method for studding and modeling the relations between variables. Artificial neural networks (ANNs) and Adaptive Network Fuzzy base Inference System (ANFIS) are two common nonlinear techniques for sale forecasting in recent years. ANFIS first proposed by [8] which is two combine of ANNs and Fuzzy Inference System (FIS). In addition, ANFIS can do training more precisely due to using fuzzy system which causes to get membership function parameters and optimize them. There are several methods for optimizations and composing them with ANFIS. Training algorithm used in this research for error reduction are PSO and BPN methods.

In this study, we proposed a different, novel way to find a suitable method to forecast sales budget of a company in Iran. For this purpose, we designed an integrated system to forecast sales budget of a company by some features about company/industry characteristics. This also presents time series historical data using Adaptive Neuro-Fuzzy Inference System. On the other hand, to achieve more accuracy, we applied the benefit from learning capabilities of Neural Network in ANFIS and PSO to optimize the prediction.

This article is divided into the following sections. The related literature of the research problem and the forecasting study are reviewed in Section 2. In Section 3, we described Techniques and Methodologies that are in relation with this study. In Section 4, we explained a modified forecast model for sales budget forecasting in a proposed framework. To validate our model, we test the proposed model with a case study in Section 5. In Section 6, we analyzed the results produced by proposed methodology. Finally, we conclude the findings along with further research in Section 7.

2. Literature Review

In this section, forecasting methods and sales forecasting are briefly reviewed. In addition, fuzzy expert system, fuzzy neural networks and time series models that are used in previous researches, are also discussed.

2.1. Forecasting and Budgeting Sales

In commercial decision making, planning and controlling are critical. Forecasting attempts to calculate and predict a future circumstance. Forecasting provides the achievable commercial information. The information is used by the manager to make the strategy decision. The manager usually utilizes the historical trend data by a statistical method or a linear programming model to perform forecasting. Some researchers attempt to identify the effective factors in sales forecasting. Generally one can use:

(1) Qualitative methods, e.g., Expert opinion (Delphi method), Consumer sentiment survey.

(2) Time series Analysis Methods, e.g., Moving average, Box Jenkins method.

(3) Causal methods, e.g., Statistical demand analysis, Economic model.

Too many efforts have been made in budget allocation area and some of them try to identify the effective factors on budget and its allocation. One did about operational budget allocation [9] or allocate operational budget to precise tasks [10] and another about marketing budget [11]. Number of them try to make an expert system, method, or numerical dynamic program to do budget allocation that only their way and method are just different [12],[13],[14],and in some of them, they different in their tools that they used. For example in [15], researcher used the combination of FAHP and ANN and [16] used ANFIS to allocate budget. Also some researches exist too that instead of focusing on method or tools that can use, focus on managerial margins and paid attention to business strategies, BSC factors, competitors, budget deviations and so on [10],[17],[18].

Sales forecasting always plays a prominent role in a decision support system. Sales forecasting in advance can help the decision maker calculate production and materials costs, even determine the sale price. This will result in a lower inventory level and achieve the objectives in just in time. Regarding most of the conventional sales forecasting methods ([19], [20], and [21]) used either factors or time series data to determine the forecast. For example [22] in order to plan the production process for complex products such as cars, proceed to sales and demand forecasting. Because sales forecasting According to the perspective of [23], [24] and [25], is considered as a realistic assessment of expected future demand [26]. Obtaining results through the above mentioned approaches is quite difficult. Therefore, various decision makers prefer using their own intuition, instead of model based approaches (i.e., time series, regression models and etc.). However, a model free approach, ANN, is applied in the area of forecasting because of its adequate performance in controlling and pattern recognition.

Although some efforts have been made to focus on budget allocation area, and some researches could improve their predictions by combination of many methods and tools but no research couldn't be found that design a systematic and integrate process to revise budget and also accompanied benefits of ANFIS, Time series trend, industry factors, company factors, expert concepts and experiences, and relations that exist between data in trends. In addition, this research use continues learning for revising on one hand, and improve learning engine in some parts by PSO and BPN and hybrid technique on the other hand. So it seems that proposed system and framework will help us to Structure the analytic budget revision process and could be a step to improve budgeting.

2.2. Sale Forecast methods

2. 2. 1. Neural Network Method

As usual For budget and sales forecasting researchers apply consulted economic call index method or statistical method, for instance in [27] sales and demands have been forecast by applying regression model with many variables, although the use of linear methods have many restrictions [28].

As well as the use of linear statistical methods some efforts have been made to apply new methods and techniques such as neural networks, in forecasting systems recently. Artificial neural network is a simulation method being in spired by brain and neural network of alive creatures. The most important advantage of ANN over the other methods is that, it doesn't need any basic models to relate inputs and outputs in forecasting. High learning power, in spite of limited informational environments, and the generalizing ability of these learning is another advantages of ANN. In general this method tries to build a linear or non-linear model of relations between independent and dependent variables according to essential relationships between data.

Another suitable method of sale forecasting is neuro fuzzy system. ANFIS combining neural network with fuzzy logic determined the parameters of fuzzy systems by using the neural network training algorithm. This hybrid system is based on the fuzzy system reflecting uncertainty. In fact the neural fuzzy systems have learning ability as well as the fuzzy performance. According to the reference [28], has been concluded that ANFIS method has the better forecasting performance than ANN in specific problems. So in this article ANFIS is applied for sales and budgets forecasting.

Takagi-sugeno used in this essay, is the most popular fuzzy model between FIS models [29]. This kind of fuzzy control system needs through knowledge of the dynamics of system under control for analytical design, despite of its efficiency and easy control of non-linear systems.

2.3. Combined Computing Techniques for Modelling Time Series

Recently many researchers apply time series model for forecasting when data is collected at specific period. The different kind of this method's applications include hydrology ([30], [31]) and auto sales [32] forecasting.

3. Methodologies and Model Setting

In this section the procedure to forecast sales budget at a company located in Iran will be discussed. Therefore, this section is divided into two main parts. The first part the selection of effective criteria at predicting sales will be expressed. In the second part, the adaptive neuro-fuzzy inference system (ANFIS) and performance and optimization algorithms that are to join on ANFIS system will be discussed.

3.1. Selection of Prediction Variable

Sale forecasting is a complex activity. It requires careful and systematic analysis of various component of internal and external environment. The main factors affecting sales forecasting are discussed below:

1- Economic conditions: it refers to level of income, stage of business cycle and standard of living.
2- Condition within the industry: the aggregate demand of a product of the industry also affects the sales –level of individual business unit.
3- Condition within organization: conditions whiten the organization refer to internal environment of the organization. It includes price policy of the organization, sales promotion schemes, promotion budget, product design and distribution and development policies.
4- Level of competition: if level of competition is high then it will adversely affect the level of sales.
5- Past sales and growth trend in sales. Previous sales levels and trends and selling expenses necessary to generate former sales volumes, Trends of the company's need to borrow (supplier, trade credit, and bank credit) to support various levels of inventory and trends in accounts receivable required to achieve previous sales volumes.
6- Government policy.
7- Amount of promotion budget.
8- Fashion and taste of consumers [33].

Once these factors are identified, they may be used to estimate the possible level of sales in a future period of operations. Applying business experience extracted from past financial statements help management and salespeople to make decisions better. Monitoring the sales volume month by month or season by season, can determine what percent of annual sales occurs in each month (seasons) on average. According to these, we could find some above factors that seem to be more effective in sales forecasting than others, Researches showed that meaningful relations exist between these factors in prior period and sales in the next period.

Table 1

Company and industry factors

Indicator	Description
Operating Income Margin	**Operating profit / Net Sales Of Company**
Inventory Turnover	**Goods Sold Cost Price/Average Inventory**
Debt Ratio	**Total liabilities / Total Assets**
Return On Assets	**Net profit / Total Assets**
Industry Share	**Net Sales Of Company / Average Sales Of Companies In The Statistical Sample**

3.2. Adaptive Neuro Fuzzy Inference Systems

ANFIS is an adaptive network of nodes and directional links with associated learning rules. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks identify and learn relationships between

Table 2

Internal and external factors

Variable	Abbreviation	Source	Test Data (2014)
Operating Income Margin	OIM	prior financial statement	0.814
Inventory Turnover	IT	prior financial statement	26.21
Debt Ratio	DR	prior financial statement	0.252
Return On Assets	ROA	prior financial statement	0.328
Employee Count	EC	company data	127
Asset	A	company data	350000
Industry Share	IS	company/Industry data	0.023
Currency	C	Industry factors	24846
Inflation rate	IR	Industry factors	182.5
Sale	Sale	company data	424786

inputs and outputs. The basic architecture of ANFIS consist five layers with different function [34].

In first layer the nodes directly transmit input forecast to the next layer. Each node function can be modeled by fuzzy membership function (MF). This MF is including: triangular, trapezoidal, bell, and Gaussian. In this paper has been used of Gaussian function (see Eq (1)).

$$\mu_i(x) = e^{\frac{-(x-c_i)^2}{2a_i}} \quad (1)$$

Where a_i and c_i are the parameters set. Gaussian MF is determined completely by c_i anda_i; c_i represents the MFs center and a_i determines the MFs width. Figure 1 plots a Gaussian MF defined by Gaussian (x; 50; 20).

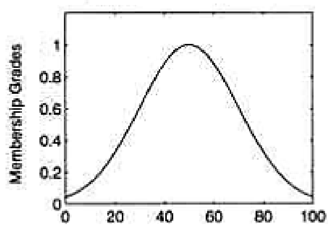

Fig. 1. Gaussian MF

In addition, the nodes in fourth layer are adaptive the consequent of the rules for two inputs is given as follow:

If x is α and y is β then $f_i = (p_i x + q_i + r_i)$ (2)

Where x is input for each node in each layer,p_i q_i and r_i are consequent parameters, α and β are linguistic terms. Finally, the last layer output data in ANFIS network is calculated as follows:

$$f = \sum_i \overline{w}_i f_i \quad (3)$$

Where $\overline{w}_i$ is the normalized firing strength that calculated in third layer [34]?

3.2.1. Learning Algorithm Based on the Model of ANFIS

Along with neural network-fuzzy, numerous of method for network training and optimization set of the rules and output parameters and presumptive that achieved from layers one and four [34]. Each of these methods is trying to improve the network performance. These improvements include the reduction of detection system error and increase the speed of the convergence system. Until now, the methods based on gradient descent and least square are provided to network training [35]. The following, a brief overview of the BPN and PSO technique which has less complexity and fast convergence.

3.2.1.1. Back propagation algorithm

The ability to create useful features distinguishes Back Propagation Neural network (BPN) from earlier, simpler methods such as perceptron-convergence procedure. Using this method for Training data, initially the error must be calculated and finally that is minimize. To minimize errors, must be modified to reduce the weight of communication networks. In fact, The BPN algorithm is used to find a local minimum of the error function. The total error in the performance in the network with a particular set of weights can be computed by comparing the actual and desired output vectors for every case. The total error is defined as:

$$E_i = \frac{1}{2}\sum_{i=1}^{p}(O_i - t_i)^2 \quad (4)$$

Where $O_i$is the desired output of the i-th unit and t_i is the actual state of an output unit. Unit i is a typical unit in the output layer.

BPN algorithm consisted of 4 steps to train network that in reference [36] the fourth step is mentioned. In this method firstly the initial network randomly weights defines and then the calculated error function. This error is used to modify the initial weights. Finally improved weight replaced in initial weight. In fact the first step of the optimization process including the expansion of the network.

So that the error will be automatically calculated (See Fig 2). Every one of the j output units of the network is connected to a node which evaluates the function$\frac{1}{2}(O_{ij} - t_{ij})^2$, where $O_{ij}$and t_{ij}denote the j-th component of the output vector O_i and of the targett_i. O_{ij} And t_{ij} denote the jth component of the output vector O_i and of the target t_i and$i = 1,2, \ldots, p$, where consisting of p ordered pairs of input and output dimensional vectors.

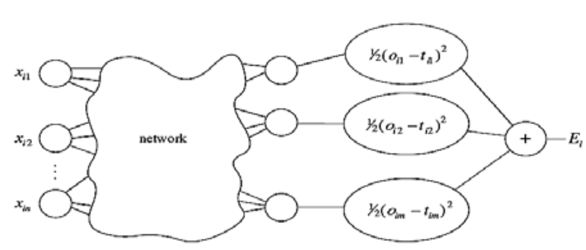

Fig. 2. Extended network for the computation of the error function [37]

3.2.1.2. Particle Swarm Optimization (PSO) Algorithms

PSO method as a powerful way to optimize could be an internal block structure that used by artificial neural networks for Training data. This method was discovered in 1995 by Kennedy [38] and since then is used a strong algorithm with a relatively simple structure. This method is an optimization method based on population and a multitude of particles. The basis of this algorithm group movement of birds, fish, etc., that indicates collective behavior itself. So that the components in the form of a component, not intelligence but the whole system of intelligent behavior.

A technique that PSO uses is a vector for moving. The motion vector to be intelligent trying every moment itself updates. To find the best moving must follow two types of motion: 1) Move to the previous experience or local best (x_{lb}) 2) Move to the pattern or global best (x_{gb}). Since full motion of particle it is impossible to x_{gb}, as well as full motion to x_{lb} particle the best answer that is x_{gb} Away, Therefore, a move that Particle Selects, movement between these two terms a din this way particle will update your location. The position of each particle is updated using its velocity vector as shown in Equation and depicted in Figure 3.

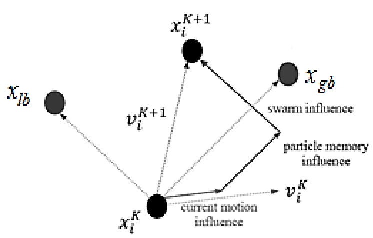

Fig. 3. Depiction of the velocity and position updates in PSO

Where in figure 3 the Current position of the particle is x_i^k and update position isx_i^{k+1}. Finally the position of the i-th particle is updated according to [39]. Position update is the last step in each iteration. The new location is given Equation 6.

$$v_i^{K+1} = wv_i^K + c_1r_1(x_{lb} - x_i^K) + c_2r_2(x_{gb} - x_i^K) \quad (5)$$

$$x_i^{K+1} = x_i^K + cv_i^{K+1} \quad (6)$$

Where, w is the inertia factor that $w \in (0.4,1.4)$, x_{lb} and x_{gb} are local best and global best and c_1 and c_2 are random variables that $c_1$and $c_2$are defined as $c_1 = r_1b_1$ and $c_2 = r_2b_2$, with r_1& $r_2 \sim U(0,1)$, and c_1 and c_2 are positive acceleration constant. Kennedy asserted that $c_1 + c_2 \leq 4$ guarantees the stability of PSO [40]. Figure 4 shows the flowchart of the proposed PSO algorithm.

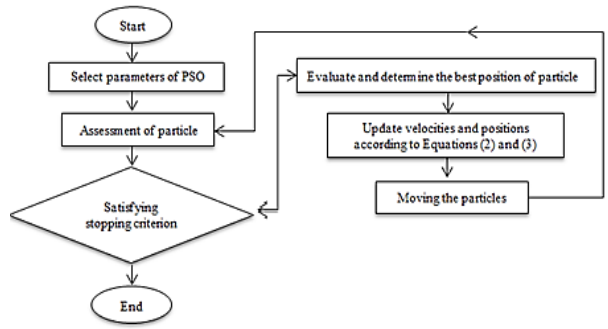

Fig. 4. Flowchart of the proposed PSO technique

3.2.2. Time Series Model

In this contribution an additive model with the following components to mimic the time series is applied. The purpose of a time series is a collection statistical data which in are collected equal and regular time intervals. Statistical methods are used to this kind of statistical data called time-series analysis. Time series analysis usually has two goals. First, understand and modeling of random mechanism which leads to the observed series and second, predicts future values of the series that according to its previous will be done.

A technique was used in this article using time-series methods to predict the future according to defined patterns liable of the past. This model works so that first, a certain number of data end of to assess forecast regardless and other data are evaluated and Training. In fact, if x_t represents the amount of data in the moment now, it can be expressed in the following equation.

$$x_t = f(x_{t-\delta_1}, x_{t-\delta_2}, \ldots, x_{t-\delta_n}) \quad (7)$$

Where δ_i is delay? In fact equation 4 expresses the amount of data in the current situation related to the values of the past. In this paper, time series analysis using ANFIS Based on PSO and BPN algorithm optimization.

4. Industrial Case Study

4.1. Proposed Framework

The process of this research can described in the proposed frame work that shown in the five steps in Figure 5. To design the budget revision system, the steps are:

Step 1:

• Collecting the main factors which have effect on budget sales.

• Completing the source data with internal and external factors and accessible data. (Some of these factors are obtained from available items in financial statements and some of them from company/industry variables which have been found in previous researches or discovered through expert's opinions.)

Step 2:

• Designing and training the first adaptive neuro fuzzy inference system (ANFIS-1).

(Because of having training data in biannually periods, training system could be done just for this periodic time.)

• Try and test improving learning engine with PSO algorithm.

Step 3:

• Designing (ANFIS-2), to predict second biannually period by using the time series analysis.

(By using ANFIS-2, prediction could be done without any date about effective factors. Total sales forecasting will be achieved by aggregating the results of ANFIS-1 and ANFIS-2.)

Step 4:

• calculate the ratios of every season sales to total sales with seasonal sales data in various years

• Designing ANFIS-3 by using time series of ratios, to predict the next period.

• Obtaining the sales forecasting of all seasons as a result.

• One part of prediction system will be realized and sales forecasting can be more accurate, after happening each season.

Step 5:

• Gathering the realized data of last two seasons

• Returning to the first step and go through the previous steps with new data to calculate sale forecasting and its revision of next year.

As seen, the budget revision is done 4 times which can cause budgeting decisions adapt to criteria and circumstances with more flexibility.

4.2. Data Collection

This case study provides two data components. The first component is Company data, and the second component is industry data. We collected the company data from the databases with the annual financial reports that the companies mail and distribute to investors. Therefore, we selected only public, accessible, and verifiable financial data that were in that reports. We had to provide sufficient historical data as much as possible, to conduct reliable time-series analysis and neuro fuzzy learning.

Therefore, we use the yearly and seasonal data of the years 2008 to 2013. The sales figures of these data are shown in Figures 6 and the seasonal pattern of these time series is clearly recognizable in the figures 7. Also the values given by seasonal factors and input data included internal and external factors of the company from 2008 to 2013, are shown in tables 3 and 4, respectively.

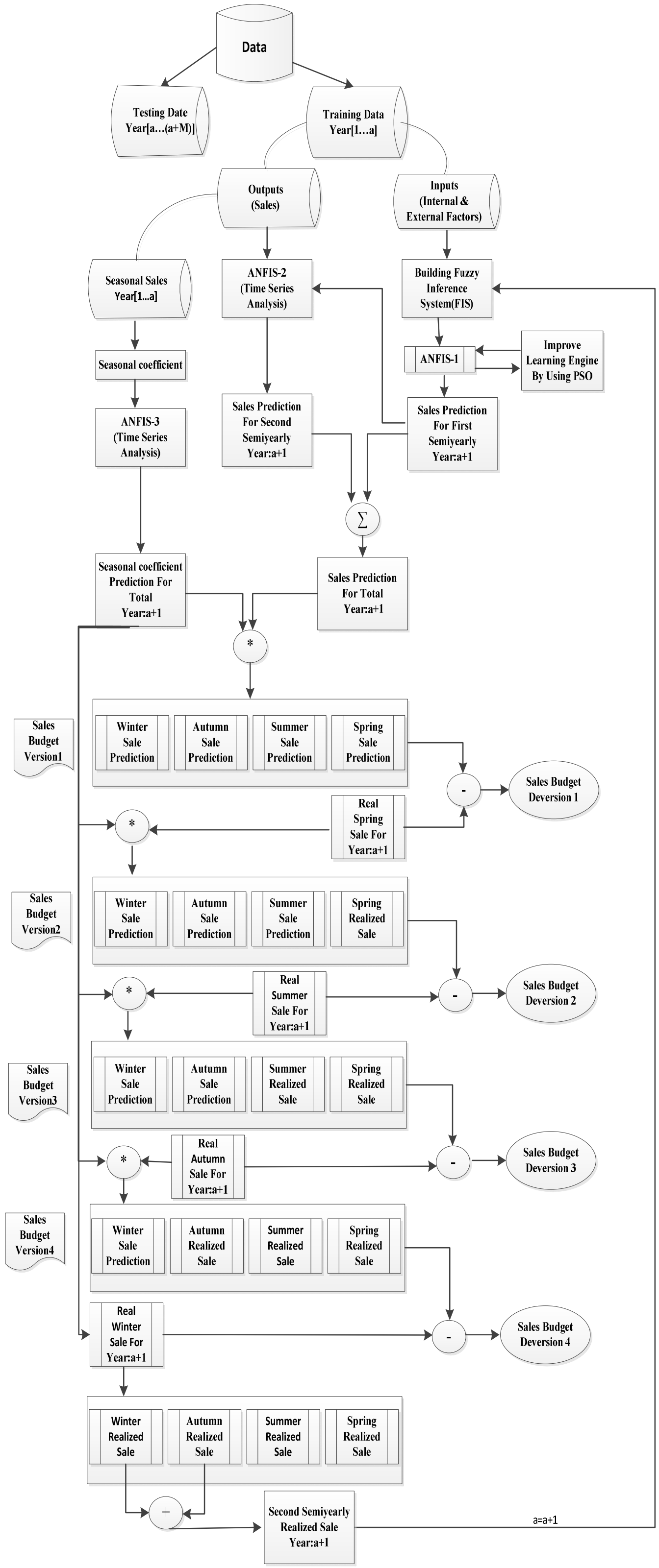

Fig. 5. The proposed Frame work

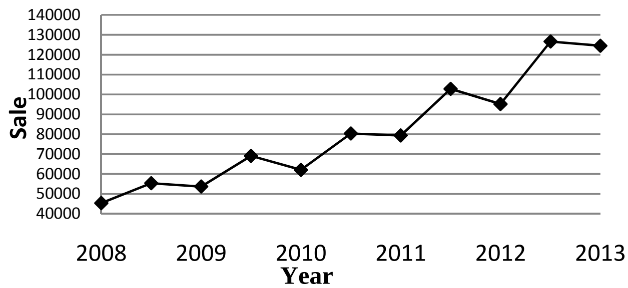

Fig. 6. The value of sales from 2008 to 2013-Six month of year data

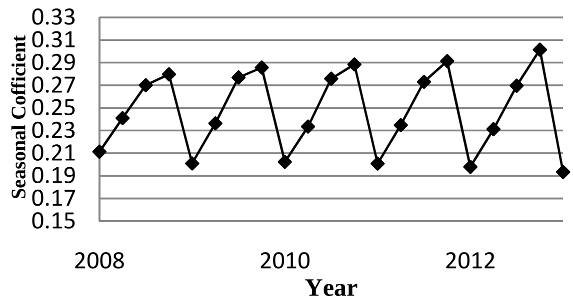

Fig. 7. Seasonal data from 2008 to 2013

Table 3

Data (inputs and outputs)

Sale	**45358**	**55385**	**56710**	**67077**	**62086**	**80385**	**84481**	**97689**	**95157**	**126660**	**124526**	**164913**
Industry Share	0.16	0.16	0.02	0.02	0.19	0.19	0.33	0.33	0.47	0.47	0.52	0.52
Asset	80000	120000	120000	160000	160000	200000	200000	250000	250000	250000	250000	350000
Return On Assets	0.127	0.235	0.126	0.239	0.126	0.237	0.148	0.263	0.0585	0.317	0.111	0.328
Debt Ratio	0.242	0.242	0.242	0.242	0.241	0.241	0.284	0.306	0.422	0.303	0.252	0.252
Inventory Turnover	360.62	444.5	63.69	55.91	63.65	69.65	154.8	46.9	69.88	21.78	26.54	26.21
Operating	0.408	0.682	0.408	0.793	0.407	0.366	0.896	0.459	0.462	0.824	0.392	0.814
Inflation rate	63.3	68.9	71.8	74.6	78.6	85.95	95.8	104.2	118.4	142.7	169.25	182.5
Currency	9260	9844	9260	9947	10307	10373	10625	11201	12260	12260	17630	24846
Employee Count	40	40	62	62	60	60	171	171	135	135	127	127
Year	**2008**	**2008**	**2009**	**2009**	**2010**	**2010**	**2011**	**2011**	**2012**	**2012**	**2013**	**2013**

Table 4

Seasonal Ratio from 2008 to 2013

	2008	**2009**	**2010**	**2011**	**2012**	**2013**
Spring of the Year	0.211251	0.20097	0.2023	0.200807	0.19783	0.193326
Summer of the Year	0.24109	0.236455	0.23348	0.234797	0.231159	0.236907
Fall of the Year	0.270143	0.276859	0.275769	0.273053	0.269538	0.26981
Winter of the Year	0.279622	0.285717	0.288431	0.288431	0.301474	0.299958

5. Results

5.1. Biannually Modelling

In this section the output of ANFIS-1 has been trained with both BPN and PSO methods. The left graphs below prepare the comparison between real data and the trained output of ANFIS-1 and the right ones illustrate the percentage error.

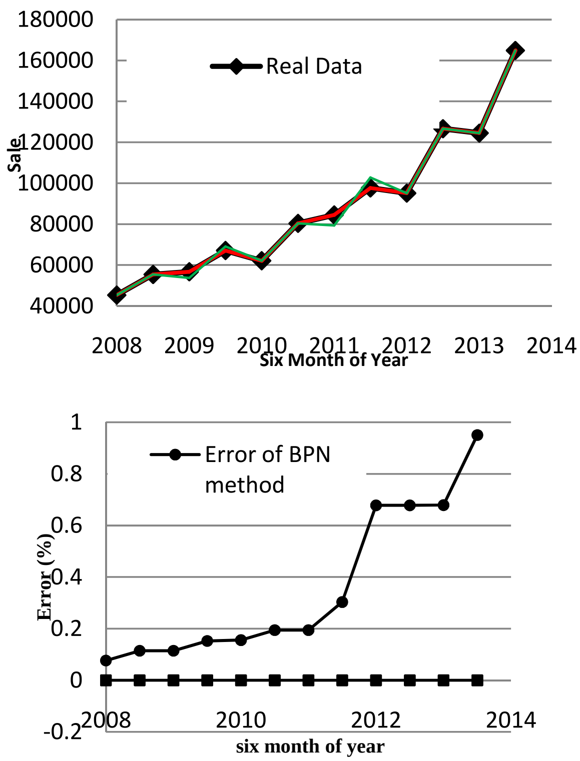

Fig. 8. Biannually modeling a) Training data with BPN & PSO methods b) Percentage error

These outputs show when we have effective factors as inputs, forecasting system trained by PSO method has better and more accurate results than by BPN method.

Three common indices such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE), is used as performance evaluation criteria.

Let xi, i=1... T, be the original values after the elimination of special effects and z_i, i=1... T, the estimated values. Then, the error function considered for testing data, is represented by the following formulas:

$$E_{MAPE} = \frac{1}{T}\sum_{i=1}^{T}\frac{|x_i - z_i|}{x_i} \tag{8}$$

Table 5

The comparison of two different optimized results for sale prediction with ANFIS-1

	Training Data			Testing Data	
Optimization Method	**MSE**	**RMSE**	**MAPE (%)**	**Sale Prediction**	**MAPE**
BPN	**654,360**	**808.925**	**0.5714**	**163,330**	**3.7205**
PSO	**0**	**0**	**2.0551e-4**	**164,990**	**2.7482**

5.2. Seasonal Modelling by Time Series

In this section the output of ANFIS-2 has been trained with both BPN and PSO methods. The left graphs below prepare the comparison between real data and the trained output of ANFIS-2 and the right ones illustrate the percentage error.

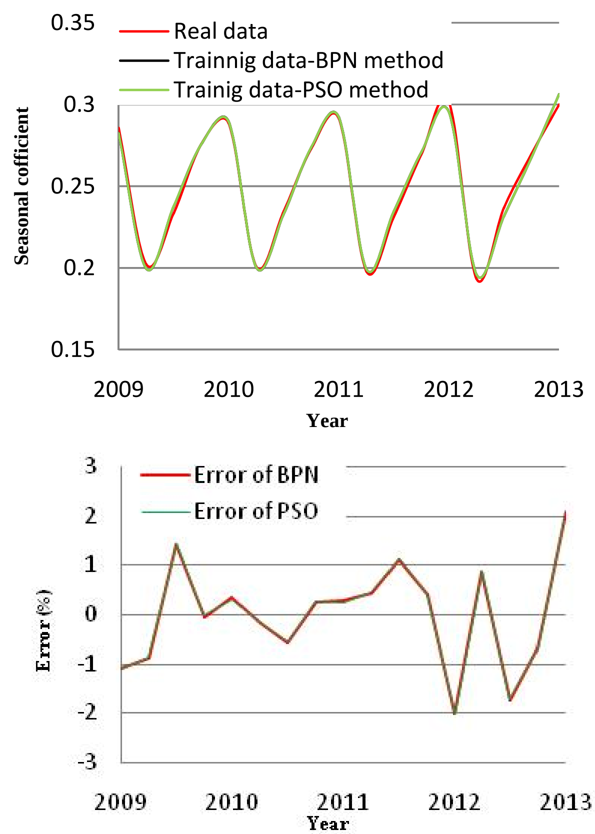

Fig. 9. Seasonal modelling a) Training with BPN & PSO b) Percentage of error

These outputs show that, trained forecasting system, when we are using time series data as inputs, is ambiguous and is not clear.

Table 6

The comparing results of different optimization methods for seasonal coefficient of prediction with time series method

		Training Data			TestingData		
Optimization Method		MSE	RMSE	MAPE (%)	Seasonal Cofficent Prediction	MAPE (%)	MSE
Spring	BPN	3.981e-6	0.002	0.8975	0.1912	1.242	5.5e-6
	PSO	3.995e-6	0.0021	0.8980	0.1913	1.260	
Summer	BPN	1.478e-5	0.0038	1.5473	0.2375	2.3959	3.398e-5
	PSO	1.481e-5	0.0038	1.5478	0.2376	2.3803	
Fall	BPN	1.633e-6	0.0013	0.3910	0.2659	1.5094	1.659e-5
	PSO	1.630e-6	0.0013	0.3911	0.2658	1.4883	
Winter	BPN	1.766e-5	0.0042	1.1747	0.3051	2.4319	5.075e-5
	PSO	1.771e-5	0.0042	1.1686	0.3050	2.3607	

5.3. Biannually Modelling by Time series

In this section the output of ANFIS-3 has been trained with both BPN and PSO methods. The left graphs below prepare the comparison between real data and the trained output of ANFIS-3 and the right ones illustrate the percentage error.

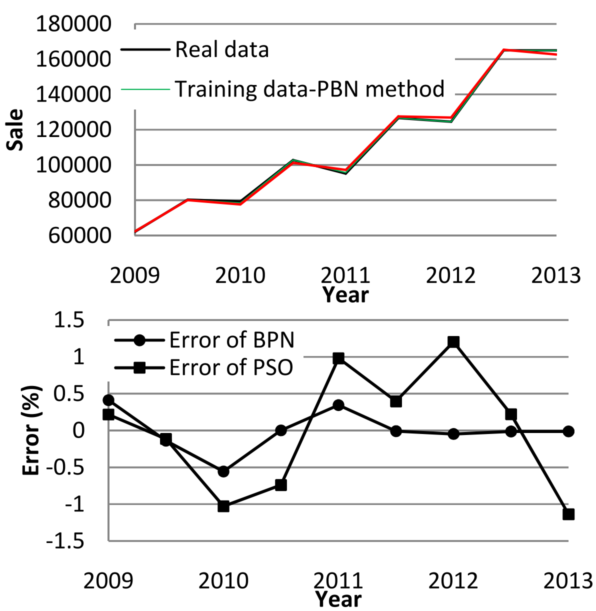

Fig. 10. Second Biannually Modeling a) Training with BPN & PSO b) Percentage of error

These outputs show that, trained forecasting system by BPN method, when we are using time series data as inputs, has better and more accurate results than by PSO method.

Table 7

The comparing results of different optimization methods for second six-month prediction using time series method

	Training Data			Testing Data	
Optimization Method	MSE	RMSE	MAPE (%)	Second Six Month Prediction	MAPE(%)
BPN	1.8739e5	432.89	0.3591	214,530	3.7298
PSO	1.683e6	1297.2	1.0342	213,970	3.9822

Considering the fact that we face high test errors although we start from low training errors, one can assume that the training set was too small for this specific problem and the model is over fitted. Especially, data points which are not in close proximity to the training set are hard to predict correctly.

It seems that, we need more data to train a system by time series inputs.

5.4. Forecast Testing

For testing the results, Sale forecasting for each season in 2014 is provided. As seen below, the table illustrates the forecast and error of both models.

Table 8

Sale prediction for each season using BP and PSO optimization methods

	Training Data			Testing Data	
Optimization Method	MSE	RMSE	MAPE (%)	Second six month prediction	MAPE(%)
BPN	1.8739e5	432.89	0.3591	214,530	3.7298
PSO	1.683e6	1297.2	1.0342	213,970	3.9822

Table 9 indicates the revising process based on one realized data. Realized spring sales are replaced with its prediction, and revise all other seasons accordingly and this process repeats for summer too.

Table 9

The comparison between the results of PSO and BPN methods in all steps of proposed frame work

	The actual amount of spring	The actual amount of summer	Optimization method	The amount of sales of the first semi-yearly	Forecast for second semi-yearly	Forecast seasonal coefficient		MAPEE (%)
Seasonally Revised Prediction With Real Data Of Spring Sales	74,148	-	BPN	164,270	260,850	Spring	-	-
						Summer	0.2377	2.2861
						fall	0.2658	1.4339
						Winter	0.3051	2.4143
			PSO	163,760	259,110	Spring	-	-
						Summer	0.2378	2.2654
						fall	0.2659	1.4578
						Winter	0.3051	2.4039
Seasonally Revised Prediction With Real Of Spring and Summer Sales	74,148	95,491	BPN	169,640	266,560	Spring	-	-
						Summer	-	-
						fall	0.2665	1.2226
						Winter	0.3052	2.3909
			PSO	169,640	264,300	Spring	-	-
						Summer	-	-
						fall	0.2665	1.2490
						Winter	0.3051	2.3838

5. Conclusion

A budget sale is the factor which influences all other decision variables in an organization. It is obvious that reliable forecast can increase the overall performance of organization and the effectiveness of all decisions will be depending on the validity and accuracy of the forecast.

For this reason, sale budgeting and sales budget revision is the main strategic activities in decision making process. The purpose of this paper is expressed an integrated system to forecast sales budget of a company by some features about company/industry characteristics. This also presents time series historical data using Adaptive Neuro-Fuzzy Inference System.

To achieve more accuracy, we applied the benefit from learning capabilities of Neural Network in ANFIS and PSO. the comparison between optimized prediction by PSO and BPN and real data indicates that each method can optimize some part of prediction better than other parts so , we could have improve forecast accuracy more if we combined both methods according to their abilities of optimization.

By the way, there are still some ideas that lack of time and sufficient data, caused to prevent them in this research. Combination of mentioned methods and improving performance of those methods which were using in this research can extend in future studies.

Furthermore, entering the result of sale forecasting to another fuzzy inference system for getting the ideal data from it and comparing the real data and ideal data with each other can be taken into consideration in future works as practical solution of decision makers.

References

[1] S. Steven Makridakis, C. Wheelwright, R. J. Hyndman. (1998). Forecasting: Methods and Applications. Third edition, John Wiley and Sons.

[2] R. Fildes, R. Hastings, (1994). The organization and improvement of market forecasting. Journal of the Operational Research Society, 45, 1–16.

[3] J. Mentzer, K. Kahn, (1995). Forecasting technique familiarity, satisfaction. Usage and application. Journal of Forecasting, 14(5), 465–476.

[4] H. R. White, (1986). In Sales Forecasting: Timesaving and Profit-Making Strategies that Work. London, UK: Scott, Foresman and Company.

[5] D. J. Dalrymple (1975). Sales forecasting methods and accuracy. Business Horizons, 18, 69–73.

[6] H. Charles Walker, C. Marine Corps (1956). The George Washangton University, Budgetary Administration and Control Facilitates Intelligent Management.

[7] R. Ata, Y. Kocyigit, (2010). An adaptive neuro-fuzzy inference system approach for prediction of tip speed ratio in wind turbines. Expert Systems with Applications, 37 (7): 5454-5460.

[8] J. S. R. Jang (1993). ANFIS: Adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man, Cybernetics, 23, 665–685.

[9] P. Promís, Developing a databased budget allocation strategy: The University of Arizona Library experience. Collect Build, 15(3), 1996, pp.5–9.

[10] D. Kannan, A. Jafarian, H. Alibabaei Khamene, L. Olfat, (2013). Competitive performance improvement by operational budget allocation using ANFIS and fuzzy quality function deployment: a case study, Springer-Verlag London, 68, pp.849–862.

[11] MK. Baidya, P. Basu, (2011). Allocation of budget on marketing efforts: an econometric approach in India. Asia Pac J Mark Logist, 23(4), pp.501–512.

[12] PD. Berger, NN. Bechwati, (2001). The allocation of promotion budget to maximize customer equity. Omega, 29(1), pp.49–61.

[13] QS. Jia, (2012). Efficient computing budget allocation for simulation based policy improvement. IEEE, New York, pp. 920–925.

[14] JM. Eckhause, SA. Gabriel, DR. Hughes, (2012). An integer programming approach for evaluating R&D funding decisions with optimal budget allocations engineering management. IEEE Transactions, 59(4), PP. 1–13.

[15] YC. Tang, (2009). An approach to budget allocation for an aerospace company fuzzy analytic hierarchy process and artificial neural network. Neurocomputing, 72(16–18), pp.3477–3489.

[16] S. Moayer, PA. Bahri, (2009). Hybrid intelligent scenario generator for business strategic planning by using ANFIS. Expert Syst Appl, 36(4), pp.7729–7737.

[17] J. Tobias, S. Sven, (2014). The appropriateness of tight budget control in public sector organizations facing budget turbulence. Elsevier, Management Accounting Research, 25(4), pp.271–283.

[18] OH. Fjeldstad, S. Kirk Jensen, F. Miguel Paulo, (2014). Poor revenue forecasting: A major challenge for sound fiscal policy in Angola. CMI, 4(1).

[19] W. Charles, Jr. Chase (1993). Ways to improve sales forecasts. The Journal of Business Forecasting Methods & Systems, 12(3), Fall, pp. 15-17.

[20] M.M. Florance, M.S. Sawicz, (1993). Positioning sales forecasting for better results. Journal of Business Forecasting, 12, pp. 27-28.

[21] G.G. Meyer (1993). Marketing research and sales forecasting at schlegel corporation. Journal of Business Forecasting, 12, pp. 22-23.

[22] A. Sa-ngasoongsonga, S.T.S. Bukkapatnama, J. Kimb Iyerc, S. Parameshwaran, R.P. Suresh, (2012). Multi-step sales forecasting in automotive industry based on structural relationship identification. International Journal of Production Economics, 140(2), pp. 875–887.

[23] C.-W. Chu, G.P. Zhang, (2003). A comparative study of linear and nonlinear models for aggregate retail sales forecasting, International Journal of Production Economics, 86, pp. 217–231.

[24] P. Danese, M. Kalchschmidt, (2011). The role of the forecasting process in improving forecast accuracy and operational performance. International Journal of Production Economics, 131, pp.204–214.

[25] J.T. Luxhøj, J.O. Riis, B. Stensballe, (1996). A hybrid econometric neural network modeling approach for sales forecasting. International Journal of Production Economics, 43, pp. 175–192.

[26] J.T. Mentzer, M.A. Moon, (2005). Sales forecasting management: A demand management approach. 2 ed. Sage Publication, Inc, Thousand Oaks, California.

[27] R. L. Carlson, M. M. Umble (1980). Statistical demand functions for automobiles and their use for forecasting in an energy crisis. The Journal of Business, 53, 193–204.

[28] W. Fu-Kwun, C. Ku-Kuang, T. Chih-Wei (2011). Using adaptive network-based fuzzy inference system to forecast automobile sales. Expert Systems with Applications, 38, 10587–10593.

[29] T. Takagi, M. Sugeno, (1985). Fuzzy identification of systems and its applications to modeling and control. IEEE Transactions on Systems, Man, Cybernetics, 15, 116–132.

[30] G. Atsalakis, C. Minoudaki, (2007). Daily irrigation water demand prediction using adaptive neuro-fuzzy inference system (ANFIS). In Proceedings of international conference on energy, environment, ecosystems and sustainable development.

[31] P. C. Nayak, K. P. Sudheer, D. M. Rangan, K. S. Ramasastri, (2004). A neuro-fuzzy computing technique for

modeling hydrological time series. Journal of Hydrology, 291, 52–66.

[32] B. Brühl, M. Hülsmann1, D. Borscheid, C.M. Friedrich, D. Reith, (2009). A Sales Forecast Model for the German Automobile Market Based on Time Series Analysis and Data Mining Methods. ICDM Springer, LNAI 5633, pp. 146–160.

[33] M. Trehun, R. Trhun, (2007). Advertising and Sales Management. p325.

[34] J.K. Jeon, M.S. Rahman, (2008). Fuzzy Neural Network Models for Geotechnical Problems, Department of Civil Engineering, North Carolina State University, Raleigh, NC.

[35] J.-S.R. Jang, (1993). ANFIS: Adaptive-Network- Based Fuzzy Inference System. IEEE Trans. Sys., Man and Cybernetics, Vol. 23, No. 3.

[36] Yu-Ch. Tang, (2009). An approach to budget allocation for an aerospace company-Fuzzy analytic hierarchy process and artificial neural network. Neurocomputing, 72, 3477–3489

[37] R. Rojas, (1996). The Back propagation Algorithm. Neural Networks, Springer-Verlag, Berlin.

[38] J. Kennedy, R.C. Eberhart, (2001). Swarm Intelligence. Morgan Kaufmann Publishers, San Francisco.

[39] D. P. Rini, S. M. Shamsuddin, S. S. Yuhaniz, (2011). Particle Swarm Optimization: Technique, System and Challenges. International Journal of Computer Applications (0975 – 8887) Volume 14– No.1.

[40] J. Kennedy, (1998) the behavior of particle swarm in VW, N saravan, D Waagen (eds), proceeding of 7th international conference on evolutionary programming, pp581-589.

[41] G. Evers, (2009). An Automatic Regrouping Mechanism to Deal with Stagnation in Particle Swarm Optimization (MASTER'S THESIS). The University of Texas-Pan American, Department of Electrical Engineering.

[42] M.R. Bonyadi, Z. Michalewicz, (2014). A locally convergent rotationally invariant particle swarm optimization algorithm. Swarm intelligence 8 (3): 159–198.