Time Series Forecasting: A Hybrid Neuro-Fuzzy-Particle Swarm Optimization Model

Muneer Abdullah Saeed Hazaa Al-Mekhlafy, PhD
Associate Professorof
Faculty of Computer Sciences and Information Systems
Thamar University

Muneef Abdulkarim Farea Ahmed
M.S degree in Science of Computer(Undergraduate)
Study in Thamar University
Teach for Taiz University

Mohamed Ghaleb Yosuef
M.S degree in Computer Since
University Since Malaysia(USM), Malaysia

ABSTRACT

Forecasting is very important for planning and decision-making in all fields to forecast the conditions and cases surrounding the problem under study before making any decision[21]. Hence, many forecasting methods have been developed to produce accurate forecasting values, reduce the degree of randomness, the changes that affect the time series, and non-linearity of data. In this proposed research,A Hybrid model (Neuro-Fuzzy-PSO) to forecast Time series. The proposed Hybrid model in the first stage after data initialization generate fuzzy inference system(FIS) by NEURO-FUZZY, which use grid partition method, Fuzzy C-Mean (FCM), and subtractive clustering.In the second stage trains the model NEURO-FUZZY by back propagation method, Hybrid method, and PSO method. The Revenue Tax data taken from the Republic Yemen during the period 2000-2014 as a data of time series to achieve, ministry of Finance. The performance of the proposed forecasting system is evaluated using common statistical standard measures such as Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and The linear repression. Also, the forecasting results obtained are compared with all models used. Experimental results showed that the hybrid model Neuro-Fuzzy-PSO of forecast reduces the degree of randomness, the changes that affect the time series, and non-linearity of data. The results for real data sets under consideration clearly prove that the hybrid model (generation by subtractive method and PSO training) is able to outperform each components model used separately in terms of increasing the forecasting accuracy and decreasing the overall forecasting errors.

Keywords

Neuro-Fuzzy, PSO Algorithm, Subtractive Clustering

1. INTRODUCTION

Time Series Forecasting: A Hybrid Neuro-Fuzzy-Particle Swarm Optimization Model (Neuro-Fuzzy-PSO) hybridization results in a hybrid intelligent system that synergizes these three techniques by combining the human-like reasoning style of fuzzy systems and connectionist structure of neural networks(ANN) with Particle Swarm Optimization Algorithm(PSO). Neuro-fuzzy hybridization is widely termed as fuzzy neural network(FNN or Neuro-Fuzzy system NFS) in the literature. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of Neuro-Fuzzy systems is that they are universal approximates with the ability to solicit interpretable IF-THEN rules. The strength of Neuro-Fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. The Neuro-Fuzzy in fuzzy modeling research field is divided into two areas: linguistic fuzzy modeling that is focuses on interpretability, mainly the Mamdani model; and precise ,fuzzy modeling that is focuses on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model. The main objective of the present research is to develop a new forecasting time-series system based on hybrid model between Fuzzy logic, ANN and PSO (Neuro-Fuzzy-PSO) models. To achieve the main objective, a number of sub-objective have been identified as follows:

(1) To reduce rule count in neuro-fuzzy model by generating FIS by used Subtractive Clustering better than Grid Partition or Fuzzy C-Mean Clustering
(2) To train Neuro-Fuzzy model by more than one way (Back-Propagation, Hybrid and PSO Algorithm).
(3) To improve forecasting time series, use NEURO-FUZZY-PSO(SC) model.

2. RELATED WORK

Many have contributed to research in the Neuro-Fuzzy-PSO models such as Forecasting,which is a process the behavior of a particular phenomenon in the past is forecasted in order to know what can happen for it now and in the future time[23],Forecasting is known as planning, setting assumption [6], [11] that depends on to developing the assumptions about future conditions, forecasting the output power of solar systems [22] is an important aid to effective and efficient planning. Including [12][20][1][8][16][7][14][19] [9] Economic and financial,forecasting uses PSO for reducing count of rules .mor than which use G.P method or FCM-mean method for generation FIS.The PSO technique IN the NF-PSO-SC ues improved Training models and use S.C method for generation FIS.We gets results mor than methods (G.P or FCM compar BY S.C) and PSO compare B.P or Hybrid in training models.

3. MEASURING ACCURACY OF FORECASTING MODELS

The forecasting error is the difference between the actual value and the forecasting value of the corresponding period [11, 9, 13] Equation 1.

$$E_i = Y_i - F_i \tag{1}$$

where E_i is the forecast error at period i, Y_i is the actual value at period i, and F_i is the forecast for period i. In the proposed forecasting system, the flowing measures are used to find out:

3.1 Mean Absolute Error (MAE)

: Mean Absolute Error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by [11, 9, 13] equation 2:-

$$MAE = \frac{1}{n\sum_{i=1}^{n}|y_i - f_i|} = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{2}$$

As the name suggests, the mean absolute error is an average of the absolute errors where y_i is the prediction and f_i the true value.

3.2 Mean Absolute Percentage Error (MAPE)

: The Mean Absolute Percentage Error (MAPE), also known as Mean Absolute Percentage Deviation (MAPD), is a measure of prediction accuracy of a forecasting method in statistics, for example in trend estimation. It usually expresses accuracy as a percentage, and is defined by the formula[11, 9, 13] :-

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - f_i}{y_i}\right| \tag{3}$$

where
y_i is the actual value f_i is the forecasting value.

3.3 Mean Squared Error (MSE)

:
In statistics, the Mean Squared Error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss.
If $\top y$ is a vector of n predictions, and y is the vector of observed values corresponding to the inputs to the function which generated the predictions, then the MSE of the predictor can be estimated by [11, 9, 13] :-

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

3.4 Root Mean Square Error (RMSE)

:
The RMSE is identified as follows[11, 9, 13] :-

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

3.5 The linear repression

:
This method is that the demand occurs because of one or more variables, and calls on the application of the variable name by the Dependent Variable or the factors that cause the request to launch the Independent variables. The following equation is used to describe the relationship between two other regions independent and the other [11]:

$$Y = A + B_x \tag{6}$$

Fixed A and B in the way in Least Squares Method. The link R is calculated through the following equation[5, 9, 13] : r^2 (Coefficient of Determination)

$$r^2 = \frac{\sum(y_i - \top y_i) - \sum(y_i - \top y_i)^2}{\sum(y_i - \top y_i)} \tag{7}$$

The relationship type is determined through the link the label, wherever the same point is that the relationship is credible, and if the signal is the negative that the relationship is reverse. In the interpretation of the value of the linear linked to the data of the sample data, there are no constitutional rules but are subject to the prosperization process which is based on the study area. The corporate factor is usually referee in the following table 1

Table 1. Independent and the value of the link coefficient variables

Value	Descraption
$\lvert 0.25\rvert > r >= \lvert 0.0\rvert$	No relationship
$\lvert 0.50\rvert > r >= \lvert 0.25\rvert$	weak
$\lvert 0.75\rvert > r >= \lvert 0.50\rvert$	Middle
$\lvert 0.90\rvert > r >= \lvert 0.75\rvert$	strong
$1 > r > 0.90$	strong too

4. METHODS AND PROCEDURES OF RESEARCH

the following methods and procedures are used (see figure 1).In the proposed forecasting system,

(1) **Data collection:**The data used for the revenues are taken from the Ministry of finance in f Yemen during the period 2002-2014, which is count 156 monthly,The data set is divided into two parts, one is 85% used for training, and other is used 15% for testing
(2) **Data analysis and preprocessing**: The time series data summarized and displayed in statistical methods such as tables and graphs in order to find out all the details related to this data using the Excel.
(3) **Implementation:** the proposed forecasting system is implemented using Matlab.

(4) **Performance evaluation:** the performance of the proposed forecasting system is evaluated using the forecasting accuracy measures like MAE, MSE,RMSE, and MAPE, and the obtained results and compared with each model used and with other related systems. The study is a descriptive and analytic study depending on multiple sources:
   (a) A documentary study of input and output finances and references used in the process of gathering the required information as a study of time series using hybrid model $(Neuro - Fuzzy - PSO)$ by the following:
      i. Constructing an NEURO-FUZZY that's to generation fuzzy inference system(FIS) using:
         A. grid partition method(GP) 2(a).
         B. FCM clustering(FCM) 2(b).
         C. subtractive clustering(SC) 2(c).
      ii. Train NEURO-FUZZY model by:
         A. back propagation method(BP).
         B. Hybrid method(H).
         C. PSO method.
      iii. Constructing an $NEURO - FUZZY - PSO$ that's capable of forecasting the future finances using the programming language MATLAB.
      iv. Checking $(validation)$ DATA to prevent over fitting of the training data set.
      Over fitting can be detected when the checking error (difference between output & target)
      v. starts increasing while the training error is still decreasing.

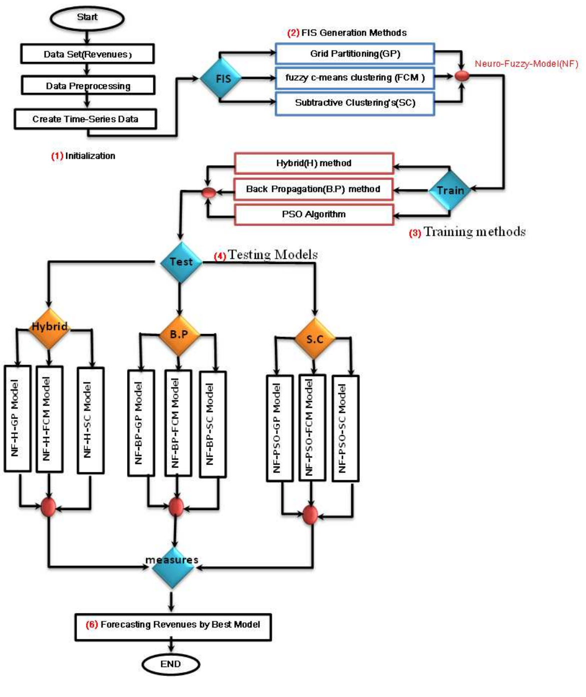

Fig. 1. Flowchart showing the flow of the methodology

5. THE PROPOSED FORECASTING DATA SET

5.1 Data Preprocessing

As the range of data values is very large, the data has been normalized Normalization transforms measures of 4: Variables Training PSO for Neuro-Fuzzy magnitude (counts or weights) into measures of intensity. It is the process of creating the shifted and scaled versions of statistics; this is done because the normalized values eliminate the effects of certain gross.The equation Scalling 8,9 is used in this research,Which is Data Actual and Scaling of Revenues Tax in Yemen 2002-2014,shown in Table 2,3

$$Scalling\,(A) = N_{min} + \frac{(A - O_{min})\,(N_{max} - N_{min})}{(O_{max} - O_{min})} \quad (8)$$

$$Normal\,(A) = O_{min} + \frac{(A - N_{min})\,(O_{max} - O_{min})}{(N_{max} - N_{min})} \quad (9)$$

Table 4. Variables Training PSO for Neuro-Fuzzy

Varible	Descrapation	value
nVar	Number of Decision Variables	48
VarSize	Size of Decision Variables Matrix	[1 nVar]
VarMin	Lower Bound of Variables	-30
VarMax	Upper Bound of Variables	30
MaxIt	Maximum Number of Iterations	500
nPop	Population Size (Swarm Size)	30
W	Inertia Weight	1
Wdamp	Inertia Weight Damping Ratio	0.95
C_1	Personal Learning Coefficient	1.46
C_2	Global Learning Coefficient	1.46
VelMax	Maximum Velocity Limits	=0.1*(VarMax-VarMin);-5.4
VelMin	Minimum Velocity Limits	=-0.1*(VarMax-VarMin);5.4

5.2 FIS Generation Method

(FIS Generation by Subtractive Clustering's(SC)) find cluster centers with subtractive clustering which Generates by algorithm :$[C, S] = subclust(X, radii, xBounds, options)$ estimates the cluster centers in a set of data by using the subtractive clustering method [10, 3].The function returns the cluster centers in the matrix C. Each row of C contains the position of a cluster center. The returned S vector contains the sigma values that specify the range of influence of a cluster center in each of the data dimensions. All cluster centers share the same set of sigma values[2, 15, 4].
The subtractive clustering method assumes each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the density of surrounding data points. Compare the number of rules in different FIS formations grid partition (GP) , FCM (Fuzzy C-mean)AND Subtractive-Cluster(SC) was as scheduled and the results were aspired as the schedule has been turned out that the subtractive word Cluster has been able to reduce the number of RULES and MF and there are a parameters shown in Table 5 ,in which there are numbers of rules in fis with grid partition , FCM AND subtractive cluster .

5.3 The algorithm does the following

(1) Selects the data point with the highest potential to be the first cluster center.

Table 2. Data Actual and Scaling of Revenues Tax in Yemen 2000-2014(Actual)

year/m	1	2	3	4	5	6	7	8	9	10	11	12
2002	11301.09	11563.26	8108.73	13274.29	14866.01	10362.78	18851.76	6632.72	8184.2	17177.16	6294.32	11370.08
2003	12523.91	11379.45	16218.49	11780.62	8852.2	14804.07	12137.5	6454.69	13502.58	14433.78	18229.42	12600.37
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2013	46992.29	46647.47	49861.18	55197.3	45672.61	43090.61	54050.3	33389.69	50664.46	44988.17	55943.21	47279.18
2014	49341.91	49051.59	55284.23	55027.16	44636.24	48565.14	53361.07	35225.78	53197.69	47070.98	62060.37	49643.14

Table 3. Data Actual and Scaling of Revenues Tax in Yemen 2000-2014(Scaling)

year/m	1	2	3	4	5	6	7	8	9	10	11	12
2002	0.1718253	0.1755863	0.1260288	0.2001322	0.2229664	0.1583646	0.2801446	0.1048546	0.1271115	0.2561214	0.1	0.172815
2003	0.1893674	0.1729495	0.2423687	0.1787045	0.1366944	0.2220779	0.1838241	0.1023006	0.2034071	0.2167658	0.2712166	0.1904643
.	.	.	.	.	.	.	.	.	.	.	.	.
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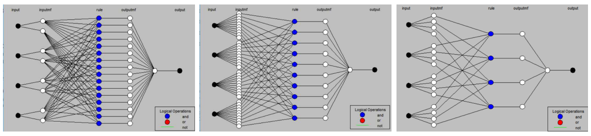
2013	0.6838387	0.678892	0.7249947	0.8015448	0.664907	0.6278666	0.7850904	0.4887006	0.7365184	0.6550883	0.8122454	0.6879543
2014	0.7175455	0.7133807	0.802792	0.7991041	0.6500396	0.7064023	0.7752029	0.5150405	0.7728591	0.6849676	0.9	0.7218669



(a) GP. (b) FCM. (c) SC.

Fig. 2. The FIS structure

Table 5. Numbers of rules in FIS.

Method Name	Numbers of Rules
grid partition	32 2(a)
FCM	10 2(b)
subtractive	3 2(c)

(2) Removes all data points in the vicinity of the first cluster center (as determined by radii), in order to determine the next data cluster and its center location.

(3) Iterates on this process until all of the data is within radii of a cluster center $[C, S] = subclust(X, 0.55)$.

(4) This command sets the minimum number of arguments needed to use this function. A range of influence of 0.55 has been specified for all data dimensions

5.4 Training Models

At this stage, all the proposed models are trained using 85% specific training data in order to obtain the best weights so that the model can achieve the best predictions and the training process is as follows: Get the values whites of FIS, which is Parameters Membership Function of Inputs and output,the variables: select variables that need the algorithm and the problem are as follows in Table 4

5.4.1 *Generate of the first generation*

(1) It is a generation statement that is the first of the Particle, which consists of the Position array: which size equal the P_0 vector size. it is generated Random values and are initialization P_1.

(a) Vector Velocity: which equal to the size of P_0. The speed of the particle is expected to be made modified, which is $zero$.

(b) Best local: is better saved on the local at one session and Vector best Global: which is better than the squad at all session

(2) Calculate the Vector Cost:((the value of the Cost of Particle) The value of the $MAPE$ error is saved in the Neuro-Fuzzy network after the training and evaluation.

(a) Replace network Neuro-Fuzzy parameters with a valve p vector.

(b) Train for the Neuro-fuzzy model on all the Input Data Training, Target data Train

(c) Calculate the measurements error: Mean Absolute Percentage Error (MAPE)

(d) Store the $MAPE$ value in the Particle. Cost variable for the same Particle item

(e) Repeate step with the rest of the path of the population.

(f) The best Local vector values takes the same as the vector particle (position and cost)

(g) best global vector values taken the best value in the vector best local (position and cost)

(h) The velocity vector value is zero initialization (position)

5.4.2 *Stage of the repetition*

(1) Reparation: The number of duplicates that must be tried iteration = 1000 each time each is generated by the new Population squad as follows[17, 18]:

(2) Update Velocity: $Vi+1 = w * V_i + c_1 * r_1 * P - particle(i) \cdot Position) + c_2 * rand(VarSize) * (BestSol \cdot Position - particle(i) \cdot Position)$

(3) Update Position: $particle(i).Position = particle(i).Position + particle(i).Velocity$

(4) Calculate the value of the Particle. Cost as a step 2

(5) Store the best local in the iteration calculate the value of the particle. Best according to the equation

(6) Store the best global in all iteration calculate of the Global. Best value according to the equation

(7) Repeats step until the right to be precisely or the end of the number of iterations.:

(8) After the training process, the Neuro-Fuzzy network parameters are replaced by the best value step 2a

5.4.2.1 Forecasting using x models Model with Train Data. Statistical results can be summarized by measurements(MSE, RMSE, MAPE, RMAPE) with table6 that Shows Error measurements of Train Data for Revenues by all models

Table 6. Shown Error of Train Data for Revenues by x models

Hybrid Models	MSE	RMSE	MAE	MAPE
NF-H-GP	1877077	1370	2710.91	0.0773
NF-H-FCM	3539676	1881	2476.497	0.0766
NF-H-SC	27336033	5228	3887.589	0.1618
NF-BP-GP	285448716	16895	13644.02	0.5934
NF-BP-FCM	274224607	16560	14071.146	0.628
NF-BP-SC	258783681	16087	14116.934	0.6228
NF-PSO-GP	28604705	5348	4128.49	0.1805
NF-PSO-FCM	13357496	3655	3130.894	0.1342
NF-PSO-SC	13191335	3632	3147.57	0.1275

5.5 Testing Models

At this stage, all proposed models are tested using the 15% specified test data as follows:nine models are use Training and Testing :NF-H-GP,NF-H-FCM,NF-H-SC,NF-BP-GP,NF-BP-FCM,NF-BP-SC,NF-PSO-GP,NF-PSO-FCM,and NF-PSO-SC Model 7below.

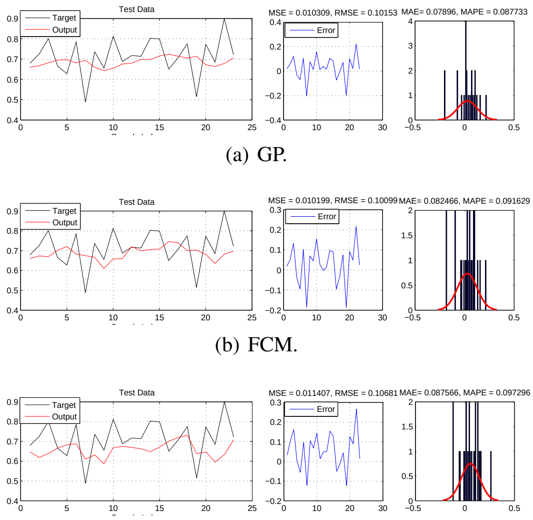
6. RESULTS AND ANALYSIS

Comparison the tested results of the hybrid model using different FIS generating methods as training data is trained after generation FIS in one way of the following ways (shown in Table 8 and figure 2:Testing test data of NF-Y-X models output and the corresponding targets was carried out.
Demonstrates the correlation of experimental and Neuro-Fuzzy-PSO forecasted values for fuel consumption.
It shows a good fit of NF-PSO-SC forecasted values to the actual measured data with higher values of R than the others forecasting model. Statistical results can be summarized by measurements

Table 8. Numbers of rules in fis with grid partition , FCM AND subtractive cluster

Method Name	Numbers of Rules
grid partition	32 fig.2(a)
FCM	10 fig.2(b)
subtractive	3 fig.2(c)

MSE, RMSE, MAPE,and RMAPE with table9 Shown Error measurements of Data for Revenues by NF-PSO as they appear Figures 3



(a) GP.

(b) FCM.

(c) SC.

Fig. 3. Output and Error of Test Data for Revenues by Neuro-Fuzzy-PSO

6.0.1 Linear Regression. the value of linear Regression(r) in figure **??** and relationship type and degree by Neuro-Fuzzy-PSO model
also A regression analysis between the Figure 4 Regression plots for training, testing and all data of Neuro-Fuzzy- PSO model output and the corresponding targets was carried out. 4 demonstrates the correlation of experimental and Neuro-Fuzzy- PSO forecasted values for fuel consumption. It shows a good fit of Neuro-Fuzzy-PSO forecasted values to the actual measured data with higher values of R than the others forecasting model

7. COMPARATIVE STUDY

To show the effectiveness or ineffectiveness of these constructed models, comparative analysis with individual model were performed. The MAE, MSE, RMSE and MAPE are selected to be the forecasting accuracy measures. Revenues data for the period from 01/2002 up to 12/2014 and cancer patient's data for the period (01/01/2015 to 01/12/2016) are used in this research. Table **??** gives the forecasting results for the revenues dataset. Results show that applying Neuro-Fuzzy-PSO model alone can improve the forecasting accuracy over the Neuro-Fuzzy-Forward model or Neuro-Fuzzy-back propagation model captures all of the revenues in the data. The results of the hybrid model show that by combining three technical methods together, the overall forecasting errors can be significantly reduced. More precisely, the NF-PSO-SC=0.024243 hybrid model output forms all other models with the lowest forecasting errors as indicated by the results.

8. FORECASTING USING NF-PSO-SC MODEL

9. CONCLUSION

Time series forecasting is an active research area and the accuracy of time series forecasting is fundamental to many decision processes. In this rsearch, the time series forecasting system is proposed. The hybrid model collects more than one technique where the Fuzzy logic is used to its ability to control decision-making and use of neural networks for their learning. and mortar in the

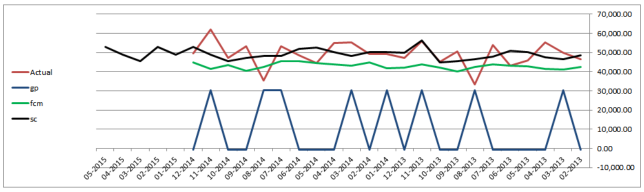


Fig. 5. Forecasting by Neuro-Fuzzy-PSO model

Table 10. Forecasting data by Neuro-Fuzzy-PSO model

month	In1	In2	In3	In4	In5	Out put	Target
Feb-13	40087.78	36010.83	48124.82	40778.58	42527.57	40248.59	42220.57
Mar-13	36010.83	48124.82	40778.58	42527.57	42220.57	38506.18	45081.72
Apr-13	48124.82	40778.58	42527.57	42220.57	45081.72	39734.65	49832.45
May-13	40778.58	42527.57	42220.57	45081.72	49832.45	41441.96	41352.66
Jun-13	42527.57	42220.57	45081.72	49832.45	41352.66	42459.98	39053.92
Jul-13	42220.57	45081.72	49832.45	41352.66	39053.92	42784.95	48811.29
Aug-13	45081.72	49832.45	41352.66	39053.92	48811.29	37951.71	30417.23
Sep-13	49832.45	41352.66	39053.92	48811.29	30417.23	39268.53	45796.89
Oct-13	41352.66	39053.92	48811.29	30417.23	45796.89	36535.09	40743.31
Nov-13	39053.92	48811.29	30417.23	45796.89	40743.31	41585.89	50496.53
Dec-13	48811.29	30417.23	45796.89	40743.31	50496.53	41955.39	42782.98
Jan-14	30417.23	45796.89	40743.31	50496.53	42782.98	41627.64	44619.42
Feb-14	45796.89	40743.31	50496.53	42782.98	44619.42	41214.5	44360.96
Mar-14	40743.31	50496.53	42782.98	44619.42	44360.96	40329.57	49909.85
Apr-14	50496.53	42782.98	44619.42	44360.96	49909.85	41738.91	49680.98
May-14	42782.98	44619.42	44360.96	49909.85	49680.98	43600.82	40429.98
Jun-14	44619.42	44360.96	49909.85	49680.98	40429.98	44730.78	43927.87
Jul-14	44360.96	49909.85	49680.98	40429.98	43927.87	45465.78	48197.66
Aug-14	49909.85	49680.98	40429.98	43927.87	48197.66	39682.78	32051.89
Sep-14	49680.98	40429.98	43927.87	48197.66	32051.89	40216.03	48052.21
Oct-14	40429.98	43927.87	48197.66	32051.89	48052.21	37020.01	42597.62
Nov-14	43927.87	48197.66	32051.89	48052.21	42597.62	39422.58	55942.62
Dec-14	48197.66	32051.89	48052.21	42597.62	55942.62	44003.59	44887.61
Jan-15	32051.89	48052.21	42597.62	55942.62	44003.59	44239.24	
Feb-15	48052.21	42597.62	55942.62	44003.59	44239.24	41607.47	
Mar-15	42597.62	55942.62	44003.59	44239.24	41607.47	51142.39	
April-15	55942.62	44003.59	44239.24	41607.47	51142.39	40701.78	
May-15	44003.59	44239.24	41607.47	51142.39	40701.78	41951.48	
Jun-15	44239.24	41607.47	51142.39	40701.78	41951.48	40120.47	
Jul-15	41607.47	51142.39	40701.78	41951.48	40120.47	41505.63	
Aug-15	51142.39	40701.78	41951.48	40120.47	41505.63	38137.15	
Sep-15	40701.78	41951.48	40120.47	41505.63	38137.15	37514.05	
Oct-15	41951.48	40120.47	41505.63	38137.15	37514.05	36512.64	
Nov-15	40120.47	41505.63	38137.15	37514.05	36512.64	35273.74	
Dec-15	41505.63	38137.15	37514.05	36512.64	35273.74	34798.47	

second stage. The Grid Partition algorithms are used to create FIS and then use FCM to improve center of groups but remained the problem of the most beautiful RULES .The subtractive cluster algorithm is used to reduce the number of RUIES 8,and the NF-PSO-SC=0.024243 hybrid model output forms all other models with the lowest forecasting errors as indicated by the results. The ninth models combines the forecasts to improve the overall modeling and forecasting performance. For each model, the experimental results are given and analyzed based on common statistical standard measures such as MAE, MSE, RMSE and MAPE.

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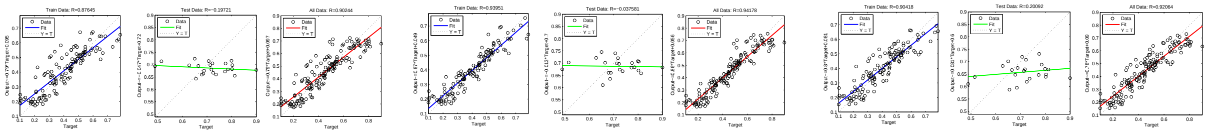
Table 7. Testing Revenues Data Using NF-Y-X MODEL

In1	In2	In3	In4	In5	Target	NF-H-GP	NF-H-FCM	NF-H-SC	NF-BP-GP	NF-BP-FCM	NF-BP-SC	NF-PSO-GP	NF-PSO-FCM	NF-PSO-SC
0.644526	0.578832	0.774029	0.655657	0.683839	0.678892	0.406974	0.595532	0.707317	0	0.186209	0.476128	0.659636	0.660159	0.647117
0.578832	0.774029	0.655657	0.683839	0.678892	0.724995	0.835178	0.635742	0.616387	0	0.67567	0.447607	0.667047	0.673421	0.619041
0.774029	0.655657	0.683839	0.678892	0.724995	0.801545	0.354416	0.564013	0.67979	0.442972	0.503257	0.479375	0.681836	0.669737	0.638835
0.655657	0.683839	0.678892	0.724995	0.801545	0.664907	0.50737	0.522734	0.707058	0.442972	0.620578	0.524201	0.694799	0.701518	0.666346
0.683839	0.678892	0.724995	0.801545	0.664907	0.627867	0.499623	0.561008	0.719571	0	0.393226	0.257861	0.697222	0.721348	0.68275
0.678892	0.724995	0.801545	0.664907	0.627867	0.78509	0.721392	0.610815	0.670924	0.442972	0.196948	0.275824	0.680678	0.683129	0.687986
0.724995	0.801545	0.664907	0.627867	0.78509	0.488701	0.682692	0.558577	0.629764	0.442972	0.189726	0.267883	0.693647	0.674775	0.610106
0.801545	0.664907	0.627867	0.78509	0.488701	0.736518	0.606968	0.685886	0.562343	0.442972	0.36869	0.463933	0.660126	0.666931	0.631325
0.664907	0.627867	0.78509	0.488701	0.736518	0.655088	0.605752	0.615651	0.646622	0.442972	0.349806	0.630408	0.643165	0.610114	0.58728
0.627867	0.78509	0.488701	0.736518	0.655088	0.812245	0.689523	0.674086	0.641265	0.442972	0.540566	0.123972	0.655011	0.658108	0.668665
0.78509	0.488701	0.736518	0.655088	0.812245	0.687954	0.484238	0.501071	0.760394	0.442972	0.336394	0.422555	0.675645	0.660182	0.674619
0.488701	0.736518	0.655088	0.812245	0.687954	0.717545	0.654091	0.600775	0.677421	0.442972	0.423127	0.257014	0.680173	0.720115	0.669338
0.736518	0.655088	0.812245	0.687954	0.717545	0.713381	0.425626	0.532487	0.732723	0.442972	0.671413	0.548831	0.698147	0.698918	0.662681
0.655088	0.812245	0.687954	0.717545	0.713381	0.802792	0.833564	0.576847	0.648843	0	0.66797	0.449526	0.697953	0.705832	0.648422
0.812245	0.687954	0.717545	0.713381	0.802792	0.799104	0.262793	0.484439	0.725789	0.442972	0.637279	0.47127	0.715497	0.70794	0.671131
0.687954	0.717545	0.713381	0.802792	0.799104	0.65004	0.475959	0.478637	0.746541	0.442972	0.259062	0.477994	0.723757	0.745446	0.701132
0.717545	0.713381	0.802792	0.799104	0.65004	0.706402	0.53841	0.540263	0.739428	0.442972	0.487159	0.32193	0.714537	0.740109	0.71934
0.713381	0.802792	0.799104	0.65004	0.706402	0.775203	0.811771	0.56031	0.669871	0.442972	0.446775	0.114305	0.704726	0.700334	0.731183
0.802792	0.799104	0.65004	0.706402	0.775203	0.51504	0.461974	0.526022	0.658726	0.442972	0.501172	0.469449	0.713698	0.702744	0.638
0.799104	0.65004	0.706402	0.775203	0.51504	0.772859	0.450148	0.649085	0.668607	0.442972	0.546967	0.160397	0.672155	0.68135	0.646592
0.65004	0.706402	0.775203	0.51504	0.772859	0.684968	0.747225	0.588284	0.644201	0.442972	0.175917	0.342032	0.663326	0.635515	0.595094
0.706402	0.775203	0.51504	0.772859	0.684968	0.9	0.52651	0.619043	0.62297	0.442972	0.385585	0.132255	0.678293	0.68262	0.633807
0.775203	0.51504	0.772859	0.684968	0.9	0.721867	0.336627	0.425261	0.807503	0.442972	0.620108	0.388134	0.70526	0.697046	0.707622

Table 9. Shown Error of Test Data for Revenues by x models

*	NF-H-GP	NF-H-FCM	NF-H-SC	NF-BP-GP	NF-BP-FCM	NF-BP-SC	NF-PSO-GP	NF-PSO-FCM	NF-PSO-SC
MSE	0.055598	0.029595	0.013272	0.156823	0.0991	0.155956	0.010309	0.010199	0.011407
RMSE	0.235791	0.172033	0.115203	0.396009	0.314801	0.394912	0.101532	0.100989	0.106805
MAE	0.190075	0.151224	0.097691	0.34811	0.271278	0.344353	0.07896	0.082466	0.087566
MAPE	0.211194	0.168027	0.108546	0.386789	0.30142	0.382614	0.087733	0.091629	0.097296
figure							3(a)	3(b)	3(c)



(a) GP. (b) FCM. (c) SC.

Fig. 4. linear regression of targets relative to outputs By Neuro-Fuzzy-PSO model