

Using newrb for analysts' equity forecasts

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Abstract: A neural network (NN), in the case of artificial neurons called artificial neural network (ANN) is an interconnected group of natural or artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. This study utilizes *newrb* technique. The function *newrb* creates and trains an RBF neural network. In this way, it examines 42 samples from 2005 to 2012. The results shows that the method demonstrate about 99% for train data and test data performance of classification rate.

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Keywords: newrb function, artificial neural network.

1. Introduction

Neural networks, as used in artificial intelligence, have traditionally been viewed as simplified models of neural processing in the brain, even though the relation between this model and brain biological architecture is debated, as it is not clear to what degree artificial neural networks mirror brain function.

Recent work has demonstrated that neural networks (NNs) represent an efficient tool for modeling a variety of geophysical transfer functions. Thanks to their non-parametric nature, regression by means of NNs has been successfully applied by different authors (Buckton and O'Mongain 1999, Keiner and Brown 1999, Gross et al. 2000, Cipollini et al. 2001) to model the relationship between satellite-received radiances and OAP concentrations. In this

paper, we investigate two different NN architectures and make a comparison of their performances. RBF networks are three-layer networks, whose output nodes form a linear combination of the basic functions (usually of the Gaussian type) computed by the hidden layer nodes. Each node provides a significant non-zero response only when the input falls within a small localized region of the input space.

This study uses different classification methods to find the best solutions and also to create the framework for predicting forecast equity. The objective of this study is to present a model in order to forecast equity from 2005 to 2012 using *newrb*.

2. Material and Methods

In the study area used 12 characteristics that is following:

Table 1. Characteristics of input data

Elements	Maximum	Minimum	Average	STDEV
Notes receivable	5253206	3885	1261087	1399529
Inventory	688701	0	120072	163515
Inventory stock and other inventory	2542277	0	636372	623930
Advance payment	2521124	39	326940	655760
Long-term assets	17363330	54030	4689123	4879249
Notes payable	5695291	16278	1478423	1763770
prepaid	3139402	3068	704671	791798
spare parts	9726510	0	1653372	2447987
Cash	1182705	900	214590	308493
Long-term liability	3001470	0	368339	759892
Short-term investments	3564611	-3868050	270927	1794244
equity	5253206	3885	1261087	1399529

The function *newrb* iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls

beneath an error goal or a maximum number of neurons has been reached. The call for this function is:

$net = newrb(P, T, GOAL, SPREAD)$

The function `newrb` takes matrices of input and target vectors, `P` and `T`, and design parameters `GOAL` and `SPREAD`, and returns the desired network.

The design method of `newrb` is similar to that of `newrbe`. The difference is that `newrb` creates neurons one at a time. At each iteration the input vector that results in lowering the network error the most, is used to create a radial basis neuron. The error of the new network is checked, and if low enough `newrb` is finished. Otherwise the next neuron is added. This procedure is repeated until the error goal is met, or the maximum number of neurons is reached.

designing a radial basis network often takes much less time than training a sigmoid/linear network, and can sometimes result in fewer neurons being used, as can be seen in the next demonstration.

Radial basis networks can be used to approximate functions. `newrb` adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal.

`net = newrb(P,T,goal,spread,MN,DF)` takes two of these arguments,

`P` *R-by-Q matrix of Q input vectors*
`T` *S-by-Q matrix of Q target class vectors*
`goal` *Mean squared error goal (default = 0.0)*
`spread` *Spread of radial basis functions (default = 1.0)*
`MN` *Maximum number of neurons (default is Q)*
`DF` *Number of neurons to add between displays (default = 25)*

3. Results

in the study used `newrb` function the show in the following:

`NEWRB, neurons = 0, MSE = 0.506321`
`NEWRB, neurons = 2, MSE = 0.0496654`
`NEWRB, neurons = 3, MSE = 0.0103193`
`NEWRB, neurons = 4, MSE = 0.00296928`
`NEWRB, neurons = 5, MSE = 0.00249247`
`NEWRB, neurons = 6, MSE = 0.0024331`
`NEWRB, neurons = 7, MSE = 0.00238815`
`NEWRB, neurons = 8, MSE = 0.00235325`
`NEWRB, neurons = 9, MSE = 0.00234853`
`NEWRB, neurons = 10, MSE = 0.00233756`
`NEWRB, neurons = 11, MSE = 0.00233661`
`NEWRB, neurons = 12, MSE = 0.00232898`
`NEWRB, neurons = 13, MSE = 0.00232898`
`NEWRB, neurons = 14, MSE = 0.00232896`
`NEWRB, neurons = 15, MSE = 0.0023241`
`NEWRB, neurons = 16, MSE = 0.0023241`
`NEWRB, neurons = 17, MSE = 0.00232412`
`NEWRB, neurons = 18, MSE = 0.00232412`
`NEWRB, neurons = 19, MSE = 0.00232415`
`NEWRB, neurons = 20, MSE = 0.00232415`
`NEWRB, neurons = 21, MSE = 0.00232418`
`NEWRB, neurons = 22, MSE = 0.00232418`

`NEWRB, neurons = 23, MSE = 0.00232405`
`NEWRB, neurons = 24, MSE = 0.00232405`
`NEWRB, neurons = 25, MSE = 0.00232406`
`NEWRB, neurons = 26, MSE = 0.00232406`
`NEWRB, neurons = 27, MSE = 0.00232407`
`NEWRB, neurons = 28, MSE = 0.00232407`
`NEWRB, neurons = 29, MSE = 0.00232407`
`NEWRB, neurons = 30, MSE = 0.00232407`
`NEWRB, neurons = 31, MSE = 0.00232407`
`NEWRB, neurons = 32, MSE = 0.00232407`
`NEWRB, neurons = 33, MSE = 0.00232407`
`NEWRB, neurons = 34, MSE = 0.00232407`
`NEWRB, neurons = 35, MSE = 0.00232407`
`NEWRB, neurons = 36, MSE = 0.00232407`
`NEWRB, neurons = 37, MSE = 0.00232408`
`NEWRB, neurons = 38, MSE = 0.00232408`
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`NEWRB, neurons = 41, MSE = 0.00232408`
`NEWRB, neurons = 42, MSE = 0.00232408`
`NEWRB, neurons = 43, MSE = 0.00232408`
`NEWRB, neurons = 44, MSE = 0.00232408`
`NEWRB, neurons = 45, MSE = 0.00232408`
`NEWRB, neurons = 46, MSE = 0.00232408`
`NEWRB, neurons = 47, MSE = 0.00232408`
`NEWRB, neurons = 48, MSE = 0.00232408`
`NEWRB, neurons = 49, MSE = 0.00232408`
`NEWRB, neurons = 50, MSE = 0.00232408`
`NEWRB, neurons = 51, MSE = 0.00232372`
`NEWRB, neurons = 52, MSE = 0.0023238`
`NEWRB, neurons = 53, MSE = 0.0023238`
`NEWRB, neurons = 54, MSE = 0.0023238`
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`NEWRB, neurons = 62, MSE = 0.00232378`
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`NEWRB, neurons = 69, MSE = 0.00232378`
`NEWRB, neurons = 70, MSE = 0.00232378`
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 NEWRB, neurons = 87, MSE = 0.00232267
 NEWRB, neurons = 88, MSE = 0.00232267
 NEWRB, neurons = 89, MSE = 0.00232267
 NEWRB, neurons = 90, MSE = 0.00232263

NEWRB, neurons = 91, MSE = 0.00232263
 NEWRB, neurons = 92, MSE = 0.00232262
 NEWRB, neurons = 93, MSE = 0.00232262
 NEWRB, neurons = 94, MSE = 0.00232261
 NEWRB, neurons = 95, MSE = 0.00232253
 NEWRB, neurons = 96, MSE = 0.00232253
 NEWRB, neurons = 97, MSE = 0.00232253
 NEWRB, neurons = 98, MSE = 0.00232253
 NEWRB, neurons = 99, MSE = 0.00232255
 NEWRB, neurons = 100, MSE = 0.00232255

The results of the research is show in Figure 1 to Figure 4.

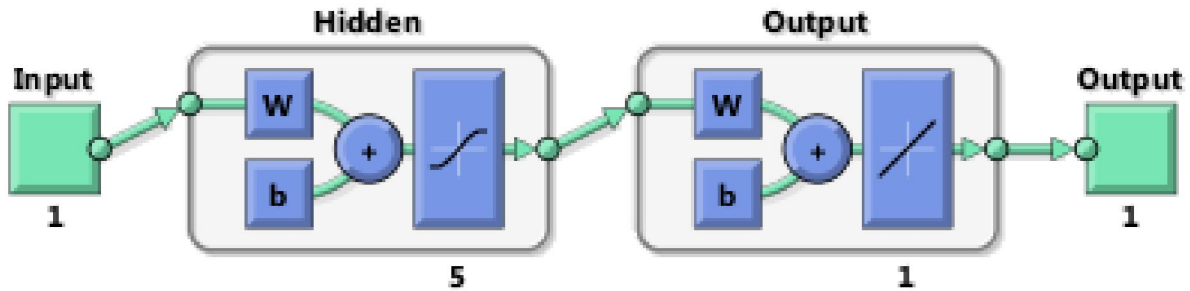


Figure 1. newrb for the research to forecast equity

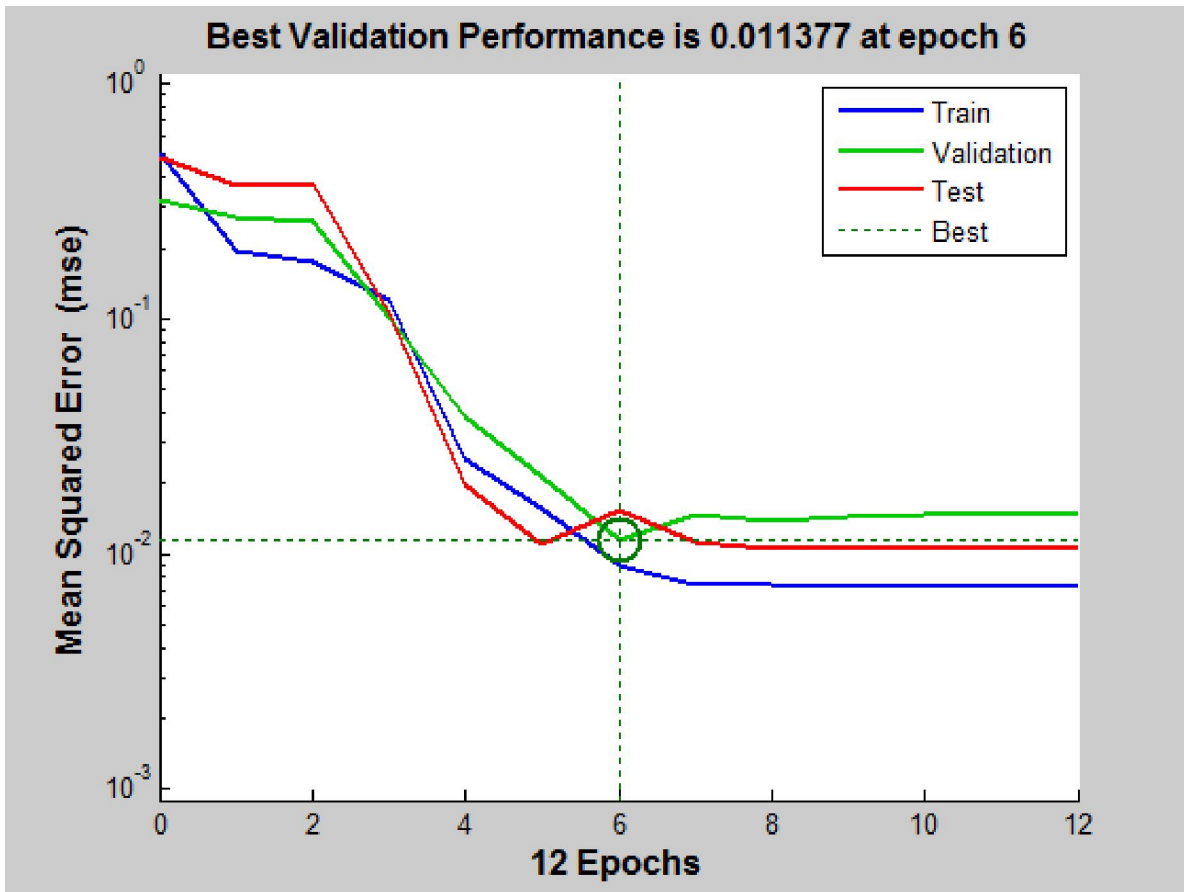


Figure 2. Best validation performance for the research to forecast equity

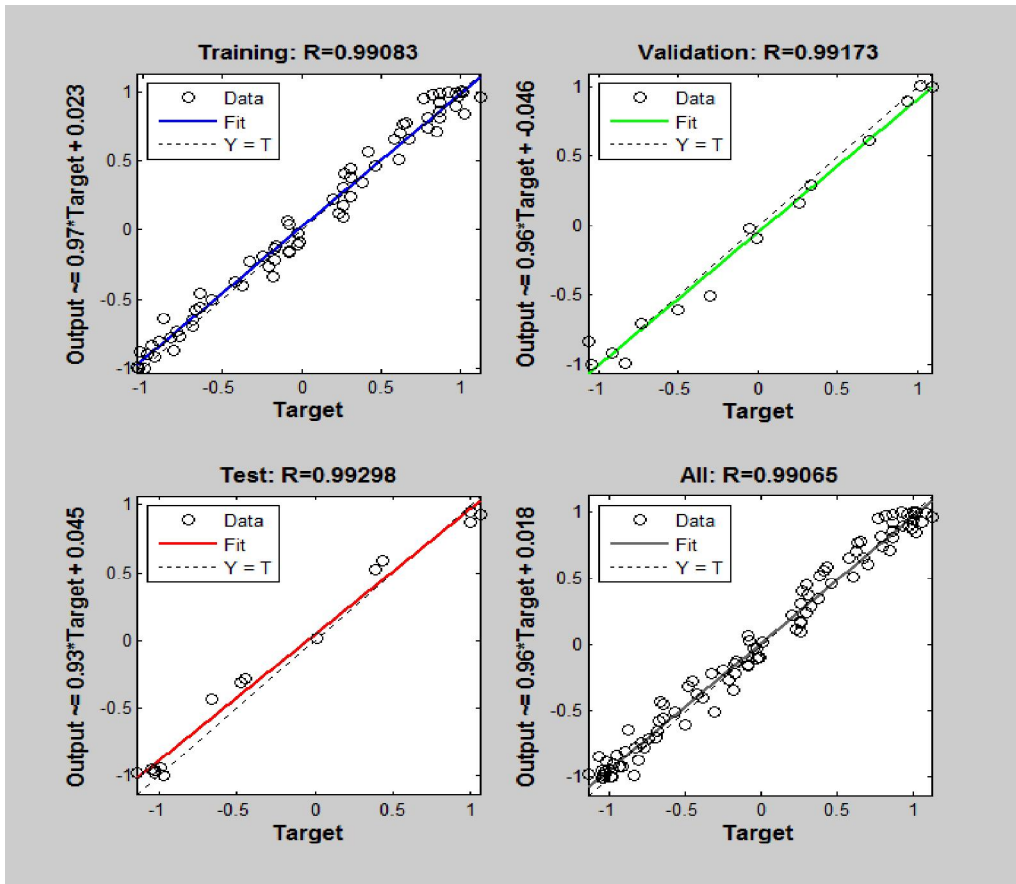


Figure 3. The results of the *newrb* method for to forecast equity

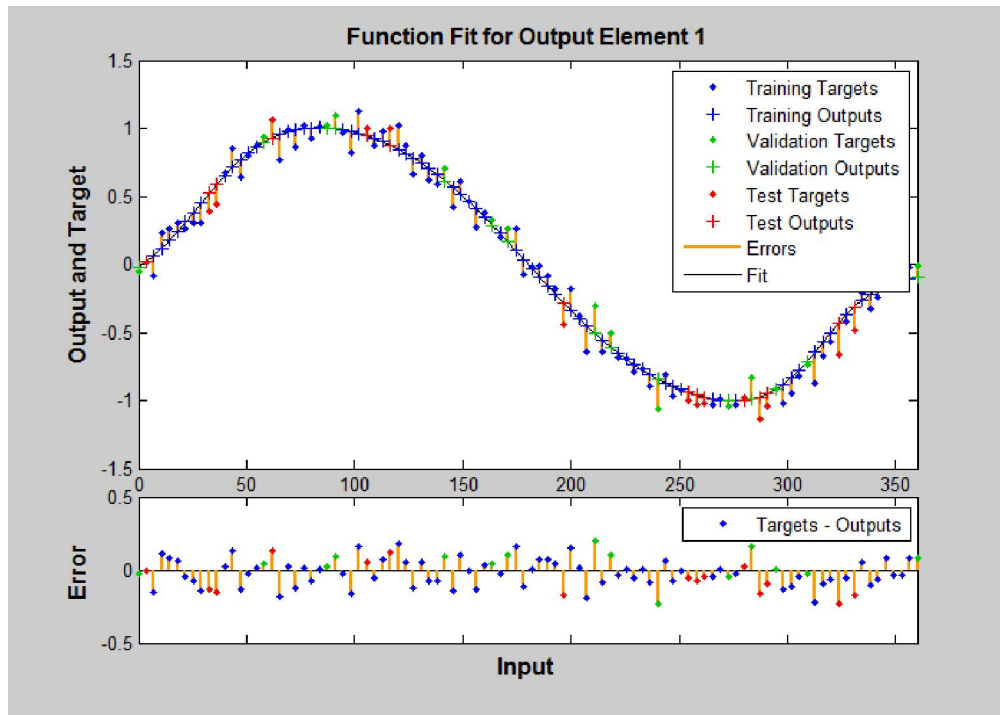


Figure 4. Function fit for outputs elements (equity)

4. Discussions

In the research were used 11 input that involve Cash, Short-Term Investments, Notes Receivable, Inventory, Spare Parts, Inventory Stock and Other Inventory, Advance Payment, Long-Term Assets, Notes Payable, Prepaid, Long-Term Liability that applied for clustering equity. For predicting forecast equity used newrb method. According to results, the method demonstrate about 99% for train data and test data performance of classification rate.

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