optimization problems. Examples of optimization problems like Traveling Salesman Problem and Satellite Broadcasting Scheduling problem have been explained. The neural network in combination with simulated annealing mechanism could solve large sized optimization problems. We have implemented the proposed method using Java for the Satellite Broadcasting Scheduling problem. Here we have used Hopfield net in combination with mean field annealing. This technique allows fast convergence and escape from local minima in search for global optima.

REFERENCES

[1] J.J. Hopfield, Neural networks and physical systems with emergent collective computational abilities, in Proc. *Nat. Acad. Sci.,* 1982, vol. 79, pp. 2554-2558.

[2] J.J. Hopfield and D.W. Tank, Neural computation of decisions in optimization problems, *Biological Cybernetics*, vol. 52, pp. 141-152, 1982.

[3] D. Kunz, Channel assignment for cellular radio using neural networks, *IEEE Trans. Veh. Tech.*, vol. 40, pp. 188-193, Feb 1991.

[4] C. Lee Giles, Routing in optical multistage interconnection networks: A neural network solution, *IEEE Journal Lightwave Tech.* Vol. 13, pp. 1111-1115, June 1995.

[5] N. Ansari, A new method to optimize the satellite broadcasting schedules, *IEEE Trans. Neural Networks*, vol. 6, pp. 470- 483, Mar. 1995.

[6] Nobuo Funabiki and Seishi Nishikawa, A binary Hopfield neural network approach for satellite broadcast scheduling problems, *IEEE Trans. Neural Networks,* vol. 8, pp. 441-444, mar. 1997.

FORMING OF THE INVESTMENT PORTFOLIO USING SELF ORGANIZING NEURAL NETWORKS

G. Stankevicius

Dept. Process Control, Kaunas University of Technology, Studentu 48-327, Kaunas, LT-3031, Lithuania, giedrius@earthling.net

ABSTRACT

The problem of comparison of different companies is facing, when looking for possible candidates for the investment portfolio. Screening of the companies, using “well-known” trading strategy parameters, is one of the ways to solve this problem. Actually, much more companies appear on the list, than the trader is willing to buy. To define the best companies or group of the best companies self-organizing (Kohonen's) neural network could be used. Using fundamental financial parameters as inputs, the output of neural network forms the different groups of companies located into a number of disjoint clusters.

Then, by the special averaging technique, the 3D map of quality of investment could be formed. Investing portfolios could be formed by simple technical analysis approach.

Non-linear ranging technique was applied as an alternative to self-organizing neural network procedure. The certain meanings of weights were given to the factors, which characterize the companies. Then, by estimation of all weights, companies were assigned to their place in the general listing.

Four different portfolios were formed as a result of these researches. The performance of these portfolios showed which of the researched techniques gave better result. The real data from USA stock markets was used for the realization of the whole idea.

1. INTRODUCTION

Due to the globalization of financial markets, expansion of the electronic trade and the growth of information about the market, the specialists of investment funds more frequently try to use artificial intelligence methods for the market analysis [1]. These methods are widely used in so-called intelligent process control and monitoring systems. Works related with the use of neural networks, obscure sets methods, fuzzy logic and expert systems for financial analysis and formation of trade decisions, receive the greatest recognition and interest in financial markets today.

The possibilities of self - organizing neural networks and ranging techniques in financial markets analysis are analyzed in this work.

2. Screening of the Companies

The number of individual investors increased dramatically in recent years with the growth of electronic trade services. The "right" choice of the "right" company is one of the biggest problems the individual investor is facing. The use of different screeners for selection of stocks is one of the ways to solve this problem. The choice of the factors and parameters, which most comprehensively characterize the analyzed companies, is the case there. The financial analysts more frequently try to combine the methods of technical and financial analysis during stock selection procedures lately. That's what the individual investors also should do.

It is accepted that price changing tendencies could be established with the use of prehistoric data of stock parameters and factors [2]. There are some of the parameters, which are used for the technical stock analysis:

1. Shares outstanding;
2. Opening price of share;
3. Closing or last bid price of share;
4. Highest price of share during the trading day;
5. Lowest price of share during the trading day;
6. Average daily trading volume;
7. The values of different stock indexes, etc.

The detailed analysis of the company activities and its financial reports is carrying out, when using fundamental stock analysis. Stock market analysts turn their attention at these parameters [3]:

1. Earning per share growth;
2. Return on assets and equity ratios;
3. Debt to assets and equity;
4. Net profit margin, etc.

To build the list of the companies for the possible investments certain meanings of mentioned parameters should be chosen. One of the possible ways to do so is to follow the recommendations of financial analysts again.

In our case the "Netscreen" screener was chosen for the screening of the companies [4]. The meanings of the parameters for the screening were chosen according the recommendations of William O'Neil [5] and Ted Allrich [3].

3. Application of Self-Organizing Neural Networks

To create portfolio from the selected stocks after the screening operation self-organizing neural networks could be applied. The major function of self-organizing networks is to automatically classify input patterns into a number of disjoint clusters. The patterns located in the same cluster have similar features. The self-organizing network is formed in terms of unsupervised learning, i.e. learning without a teacher, for instance winner-take-all competitive learning. Here we introduce the algorithm of competitive learning self-organizing networks. In a self-organizing network, a vector quantizer can be performed by adjusting weights from N input nodes to M output nodes. When the input patterns have been· presented sequentially to the network without specifying the desired output, the input patterns can be automatically classified into M clusters. The structure of self-organizing neural networks and the geometrical explanation of competitive learning are schematically illustrated in fig. 1 and 2.

The detailed learning algorithm can be summarized as follows:

Step 1: Randomly initialize small valued weights

$$W_{ij}(0),\ i=1,\ N;\ j=1,M.$$

Step 2: Present input vector:

$$xi,\ i=1,N.$$

Step 3: Calculate the distance between the input vector and the weight vector for all individual output nodes:

$$d_j = \sum_{i=1}^{N} (x_i(k) - W_{ij}(k))^2 \qquad (1)$$

Where $x_i(k)$ is the input to the node i at time k, and $W_{ij}(k)$ is the weight from input node i to output node j at time k.

Step 4: Select the most active output node j^*, or the so-called 'winner' which has the least distance, i.e.

$$d_{min}=min\{d_j, j=1,M\} \quad (2)$$

If $d_j=d_{min}$ then $j=j^*$ and $y_j^*=1$, otherwise $y_j=0$ (j is not equal j^*).

Step 5: Upgrade the weights for the 'winner' node

$$W_{ij}(k+1)=W_{ij}(k)+g(k)y_i\,(x_i-W_{ij}(k)) \quad (3)$$

Where $g\,(k)$ denotes learning rate and is defined as a time decreasing function within the range (0,1).

Step 6: Repeat by going to Step 2.

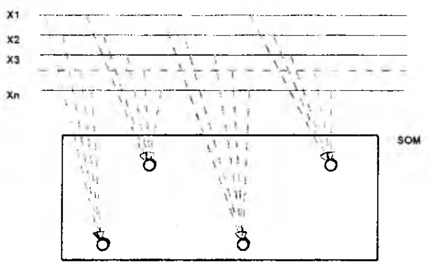

Figure 1. Topology of Kohonen self-organizing network.

From equation (2), we can see that eventually the weights are upgraded only for the winner node j^*. However, in practice, the weights can also be upgraded only for the winner node j^*, but also for all nodes in the neighborhood of the winner. The size of the neighborhood $NE_j(k)$ can be predefined and can start large and slowly decrease in size with time. The weights upgrading may follow a modified version:

$$W_{ij}(k+1)=W_{ij}(k)+g(k)(x_i-W_{ij}(k)) \quad (4)$$

for all j which are located in the neighborhood $NE_j(k)$.

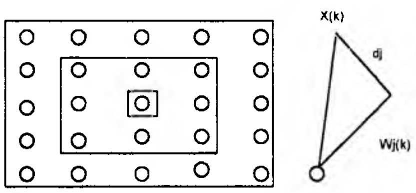

Figure 2. Geometrical illustration of competitive learning

The use of self-organizing neural networks is based on the possibilities of neural networks to find the similar companies using companies' fundamental parameters and factors during the neural network training procedure. The technical and financial data about the market's state and the company's financial state is used as the inputs for the neural network in this case. The merit there is that relations between different factors are not fixed a priori, but are identified during the training with the help of experimental data. Thus their outputs are safe from so-called "human factor", when the desirable result is obtained.

There are lots of different software packages for the realization of self-organizing networks. In our study, we used "Viscovery SOMine" software [6].

The list of the companies and their financial ratios was used as an input. Then, the clustering operation was implemented. The map with some quite clearly formed groups of the companies appeared as an output (fig. 3).

4. Ranking of the Companies

Alternative way to form the portfolio is the application of ranking procedure to the companies, which appeared on the list after the screening

Ted Allrich [3] in his book "The On-line Investor" proposed the method of ranking of the stocks of the companies. The basic concept for this procedure is to assign a value for each ratio of the stock, add up those valuations and compare that number with all others. Then it is possible to rank the stocks from the highest value to the lowest.

The most interesting there are the values used for the ranging. T. Allrich picked these values empirically i.e. by the use of his investment experience.

In this paper alternative values for the ranking procedure were proposed. The proposed values are based on nonlinear regression analysis of the relationships between different stock ratios and the stock price change during last 52 weeks. The performance of about 500 companies in the stock market was analyzed (NYSE, NASDAQ and AMEX markets). The polynomial regression of the 2nd degree was used to describe the relationship between stock ratio and stock price change. Such relationships were constructed for every stock ratio/parameter. The more complicated non-linear regression didn't improve significantly the root mean square error of estimated relationship. The values of the ratios were determined according the value of the root square error value - the smaller value of the root square error, the bigger value of the ratio.

The final values of the ratios used for the ranking procedure are shown on the tabl. 1.

The investor should pay attention at the top companies on the list after the application of ranging procedure, analyze them closely (graphs, inside data and profile) and most probably buy the stocks of these companies.

5. RESULTS

After the implementation of screening, clustering course and ranging procedures four portfolios of the shares were formed. The data set used for the screening was formed on 23rd August 1999.

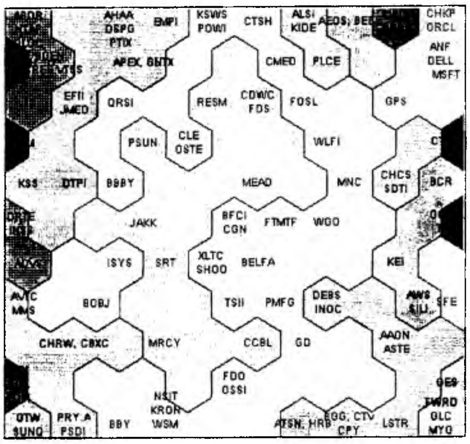

Figure 3. Clustering result

The formation of the portfolios according ranging results was quite simple. The companies, which appeared on the top of the list, were chosen for the possible investments. One of the portfolios was named "Allrich portfolio" and another one – "Alternative portfolio".

The forming of the investment portfolio according the clustering results was complicated. Despite the fact, that some groups of the stocks appeared quite clearly, it was still difficult to decide, which one should belong to the investment portfolio. There the simple technical analysis approach was used. Using the averaging technique the 3D map was drawn.

Table 1. Values of the ratios used for the ranking

Ratios and parameters	Values (Allrich's ranking)	Values (Alternative ranking)
Free cash flow per share	8	12
Price to sales ratio	8	11
Price earning ratio	10	10
Price to book ratio	7	9
Current ratio	5	8
Return on assets	6	7
Profit margin	10	6
Debt to equity ratio	5	5
Earning per share growth during 12 trailing months	9	4
Return to equity	8	3
Institutional ownership	7	2
Management ownership	8	1

There is the basic idea of the averaging technique. The mean growth (diminution) of the price for each cluster of the map should be counted. By choosing the "neighbors" of the each cluster in the map the certain area will be covered.

Then the price change for the past 12 trailing months should be counted for every company, which belongs to the covered area. Finally, the mean of these price changes should be counted. The covering area of the "neighbors" will vary depending on the chosen cluster.3D map was drawn using the results of the averaging (fig. 5).

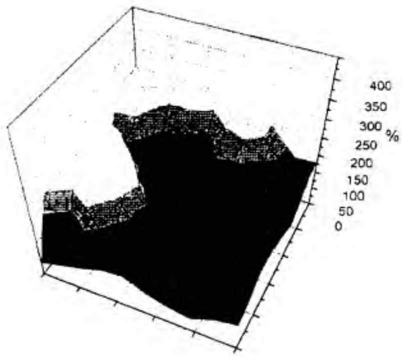

Figure 5. 3D map

Two portfolios were formed according this map (fig. 6). First portfolio consisted of the companies, which were on the peaks of the map. The growth of the share prices of these companies was the biggest during the last 12 trailing months. It was supposed, that the share prices of these companies will grow for some time and then the correction of the prices should emerge. This portfolio was called a "Winners portfolio.

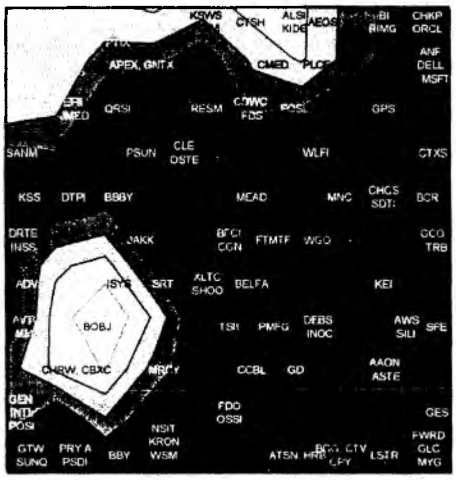

Figure 6. Map of the clustering results merged with the 3Dmap

Second portfolio consisted of the "losers". The share prices of these companies declined during the last 12 trailing months. It was supposed, that the downtrend will continue for a very short time and the share prices should go upwards shortly.

It was supposed, that 100000 USD are available for the investments of the each portfolio. This imaginary capital was divided into equal parts and the stocks were "bought". The contents of all portfolios are shown on tabl. 2.

Table 2. The contents of the portfolios

Winners portfolio	Losers portfolio	Allrich portfolio	Alternative portfolio
CTSH	GTW	BELFA	PMFG
ALSI	SUNQ	DEBS	KEI
KDE	ATSN	KEI	BELFA
AEOS	HRB	POWI	GCO
BEBE	BGG	KSWS	WGO
BOBJ	CTV	INOC	DEBS
ISYS	CPY	KDE	MNC
CHRW	PSDI	CHKP	INOC

All of the portfolios were tracked from August 1999 to November 1999. The S&P 500 index was also tracked for the comparison of the portfolios performance with the whole situation in the market.

Final research results (fig. 7) showed, that earlier assumptions about the performance of the "Winners" and "Losers" were quite incorrect. The value of the "Winners" and "Losers" portfolio declined during the first tracked month. So as the value of S&P 500 index.

Value of the" Winners" and "Losers" went upwards during the following two months "Winners" showed impressive gain during this period. The whole market was on the positive mood too. "Allrich" portfolios showed stable gains during the whole period. "Alternative" portfolio results were not so good during the first two months, but during the final month it showed some gain, mostly according the positive mood on the whole market.

6. Conclusions

The results showed that ranging techniques and self-organizing neural networks could be applied for the financial market analysis.

Self-organizing networks are a bit complicated when investor should decide which group of companies could form the portfolio. The whole preprocessing of the data for the 3D map is a time consuming job, but the results are quite impressive.

Research also showed, that screening and clustering course should be done every month. By introducing the data of the new companies to the neural network they will appear in one of the earlier formed groups. By tracking the movement of the earlier chosen companies within the map, it is possible to say, towards which direction new companies will move.

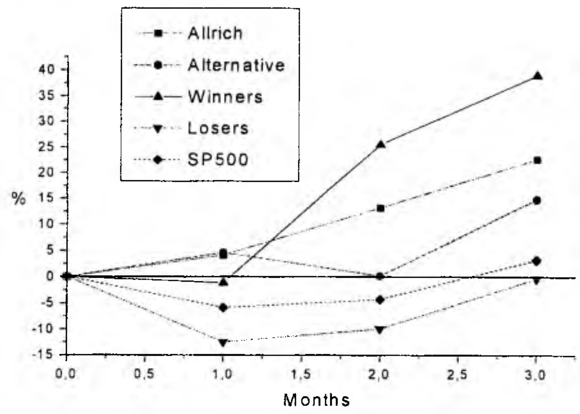

Figure 7. Performance of the portfolios during the August – November 1999 period

Ranging techniques are quite simple and easy to use. The portfolio formed using Allrich's ranging showed better results than the portfolio formed using alternative ranging parameters. Thus it is possible to come to the conclusion that pure statistical approach cannot reflect clearly the relationships between price change and different financial parameters. The stable gains of "Allrich" portfolio proved that ranging parameters were chosen correctly.

Finally, it should be noted, that further research is required for the improvement of the use of the self-organizing neural networks for the financial market analysis.

References

[1]. J. Ed. Marshall, *Conference on Computational Intelligence for Financial Engineering (CIFEr)*, 1997, 307-308, Crown Plaza Manhattan, New York.

[2]. R. Perk, *Professionelle aktienanalyse fur jedermann* (Munchen: Verlag C.H.Beck, 1990).

[3]. T. Allrich, *The on-line investor. How to find the best stocks using your computer* (New York: St. Martin's Griffin, 1995). *www.marketguide.com/mgi/*

[4]. W. J. O'Neill, *How to make money in stocks* (New York: McGraw-Hill Inc., 1995). *www.eudaptics.com*