# FUZZY LOGIC AND NEUROFUZZY SYSTEM TECHNOLOGY FOR STOCK EXCHANGE TRADING STRATEGY

**Domingo Senise de Gracia**
MSc in Artificial Intelligence
Universidad Politécnica de Madrid
Boadilla del Monte, 28660 Madrid (Spain)
domingo.senise@haitta.com

**Abstract**

This paper aims to present two distinct approaches to stock exchange trading based on fuzzy logic and neurofuzzy system technologies.

The first approach introduces an intelligent decision-making model, based on the application of Fuzzy Logic and Neurofuzzy System (NFs) technology, the name of which is **Intelligence Trading System**; it is used to capture the knowledge in technical indicators for making trading decisions such as buy, hold, and sell.

The second approach employs pattern classification methods using Artificial Neural Networks (ANNs), Fuzzy Inference Systems as well as Adaptive Neuro-Fuzzy Inference Systems. Based on the forecasted performance of certain indices, the so-called **Stock Quantity Selection Component** recommends the investor to purchase stocks, hold the current investment position, or sell stocks in possession.

KEYWORDS: fuzzy logics, neurofuzzy systems, artificial neural networks, neuro-fuzzy inference systems, fuzzy inference systems, rate of return profit, moving average convergence/divergence, relative strength index, exponential moving average

## I.- Introduction

The stock exchange market is one of the main foundations of our economic capitalist system. Throughout the last decade traders have used gradually more sophisticated technological tools for decision making in order to work efficiently, and most importantly, to generate the highest profit as possible. In fact the use of artificial intelligence has had a big influence on the forecasting and investment decision-making technologies.

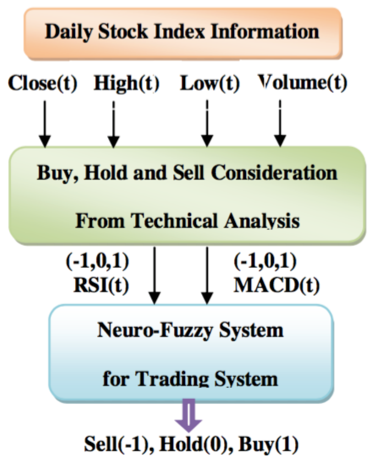
With respect to the first approach, the model put forward by the researchers is going to be focused on decision-making in stock markets, but not on forecasting in stock markets: the proposed trading strategy based on fuzzy logic captured knowledge from experts who are making decisions to buy, hold, or sell from technical analysis, as well as input from the suggested trading systems based on NFs. Moreover, optimization algorithms based on the rate of the return profit of each stock index are used to develop the NFs model. The objective of this approach is **to analyze the stock daily and to make one day forward decisions related to the purchase of stocks**.

In relation to the second approach, **it focuses on a pattern classification problem utilized within an application that could assist individual as well as institutional investors in making trading decisions**. In this approach artificial neural network (ANN) architectures, Fuzzy Inference Systems (FISs) as well as Adaptive Neuro-Fuzzy Inference Systems (ANFISs) have been considered.

## II.- State of the Art

Regarding the first approach -the decision-making model **Intelligence Trading System**, firstly we must bear in mind that both neural networks and the fuzzy system imitate human reasoning process. In fuzzy systems, relationships are represented explicitly in forms of if-then rules, and in neural networks the relations are not explicitly given but coded in designed networks and parameters.

In the first step of the realization of **Intelligence Trading System**, technical analysis techniques are used for the decision strategy recommendation. The recommendations (R) represent the relative rank of investment attraction to each stock in the interval [−1, 1]. The values −1, 0, and 1 represent recommendations: Sell, Hold and Buy, respectively[3]. After that, the recommendations are included in the input of the proposed intelligence system. The intelligence system output is the evaluating recommendation based on several decided courses of action from various techniques used by investors as shown below[1]:




Technical analysts usually use indicators to predict future buy and sell signals, such as Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), or Exponential Moving Average (EMA). Each indicator is included in the input signal for the intelligence system. E.g., MACD is a popular and simple indicator for trends. Stochastic and RSI are some simple indicators which help traders identify turning points.

To test the solution performance according to the Rate of Return Profit (RoRP), 3 scenarios were proposed with different input parameters and procedures and, as it can be noticed in the performance table below, the NFs display a greater rate of return profit than the "buy, sell and hold" model and the NN model [1]:

| Stock Index | Stock Group | Possible Profit | Profit Buy & Hold | Model 1. | | Model 2. | | Model 3. | |
|---|---|---|---|---|---|---|---|---|---|
| | | Training Days(%) | | Profits of Training Days (274 Days). % | | | | | |
| | | | | NN | NFs | NN | NFs | NN | NFs |
| BCP | Energy | 254 | 50 | 90 | 115 | 240 | 250 | 240 | 254 |
| PTT | Energy | 320 | 80 | 115 | 180 | 300 | 308 | 300 | 320 |
| SCB | Banking | 180 | 70 | 75 | 98 | 160 | 172 | 160 | 180 |
| Stock Index | Stock Group | Testing Days(%) | | Profits of Testing Days (28 Days). % | | | | | |
| | | | | NN | NFs | NN | NFs | NN | NFs |
| BCP | Energy | 4.5 | 0.8 | 1.2 | 1.4 | 3.3 | 4.1 | 4.5 | 4.3 |
| PTT | Energy | 7.1 | 1.5 | 2.5 | 3.6 | 4.5 | 5.9 | 7.1 | 6.9 |
| SCB | Banking | 3.2 | 0.5 | 1.1 | 2.1 | 2.1 | 2.5 | 3.2 | 2.9 |

Regarding the second approach -the **Stock Quantity Selection Component**, the system is based on the trading strategy "Buy low, sell high", with the percentage threshold combination of 0.8% and -0.20% of the closing value for the previous day, since it is the most profitable.

Three classifier designs of the SQSC are developed to test the model[2]:

1. First design: it has 1 classifier with 16 inputs and 16 outputs. The model inputs: the forecasted performance of the closing price of the indices. The classifier outputs: investment recommendations for the indices.

2. Second design: it has 4 classifiers, and each classifier has 4 inputs and 4 outputs. Each classifier is used to generate an investment recommendation for an index. The classifier input: the forecasted performance of the closing price of an index. The classifier output: the investment recommendation for the index.

3. Third design: it has 16 classifiers, each classifier has 4 inputs and 1 output. Each classifier is used to categorize whether or not to execute an investment. The classifier input: the same as design 2. The classifier outputs are fed into an interpretation function that generates the final investment recommendations for indices.

The data utilized in developing and testing the various classifiers are divided into: **training data** set, used to train the ANN to find the general pattern between its inputs and outputs; v**alidation data** set, used to assess the network; and **test data** set: employed to confirm the classification quality of the developed model.

The accuracy of the designs is gauged through a matrix to identify the number of true and false classifications that are generated by the models developed[2]:

$$Accuracy = \sqrt{\frac{TP * TN}{(TP + FN) * (FP + TN)}}$$

where:
TP is the true positive (1 classified as a 1); TN is the true negative (0 classified as a 0); FN is the false negative (1 classified as a 0); FP is the false positive (0 classified as a 1).

From the three designs what is the most adequate one? Number 2 since it has low complexity, high scalability., and it is not required to re-create the existing classifiers, when additional recommendations are added.

## III.- Conclusion

Both models are a remarkable progress in the stock exchange trading scenario: on the hand, the **Intelligence Trading System** means a one-step forward decision, achieving more stable results and higher profits when compared with NNs and Buy and Hold strategy [1]. On the other hand the **Stock Quantity Selection Component** implies the development of acceptable classifier architectures to guide traders in their investments[2]

Nonetheless, from my standpoint both models fails in the sense of considering the trading activity as a game-theory exercise, when actually it is more a **goal programming activity** in which the information asymmetry, the limits of our knowledge, and such an important factor as fear, can play an extremely meaningful and definite role.

## IV.- References


1. Monruthai R., Hataitep W., and M.L. Kulthon Kasemsan (2012) Intelligence Decision Trading Systems for Stock Index. In *Intelligent Information and Database Systems*, pp. 366-375.

2. Pretesh B. P. and Tshilidzi M. (2006) Neural Networks, Fuzzy Inference Systems and Adaptive-Neuro Fuzzy Inference Systems for Financial Decision Making. In *Neural Information Processing*, pp. 430-439.

3. Monruthai Radeerom, M. L. Kulthon Kasemsan (2010). Neurofuzzy Decision-Making Approach for the Next Day Portfolio Thai Stock Index Management Trading Strategies. In *Advances in Intelligent Information and Database Systems*, pp 371-381.

4. D. E. Koulouriotis (2004) Investment analysis & decision making in markets using adaptive fuzzy causal relationships. In *Operational Research*, pp. 213-233.