Application of artificial intelligence model in financial markets

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Abstract

This paper deals with the application of artificial intelligence model in financial markets. Specifically, a hybrid model based on fuzzy logic and artificial neural networks is chosen. The neuro-fuzzy model is then applied to the stock Exchange Traded Funds on the American and European stock markets. Based on four input variables and five attributes, the basis of rules is determined by neural networks. The amount of rules is then reduced by fuzzy clustering. The output is a model serving to support the decision-making for the investor whether or not to invest in the stocks of Exchange Traded Funds.

Key words

Artificial Intelligence, Fuzzy Logic, Neural Networks, ANFIS, Financial Market

JEL classification

G11, G12, C45

1 Introduction

Financial markets are an integral part of all national economies. It is actually the most important way to raise capital. For financial analysts, traders and brokers, it is a major challenge to determine the best moment to buy or sell financial instruments in order to obtain the expected return in view of the risk that investors are exposed to when spending their money. The original theories and models make use of assumptions that, while simplifying solutions, may, in practice, cause considerable problems [1]. Price forecasting is a complicated and difficult task due to the chaotic behavior and the high level of uncertainty in the prices of financial instruments on the market. The design of a highly accurate, simple and understandable prediction model [2] is of paramount importance in this area. There are numerous factors that potentially affect the prices of financial instruments that need to be considered. Each trader attempts to make his own forecasts, either subjectively, i.e. through models based on their personal feelings and experiences, or objectively using different types of indicators and indicators [3].

In addition, many important changes have been made to international finance in the last two decades. The liberalization of financial markets and the development of communication and trading tools have expanded the range of choice of financial instruments for investors. Most of the major developed countries' financial markets must now be considered highly integrated. Traditional financial market theory has also changed and the methods of financial analysis have improved significantly. The existence of non-linearities in the movement of financial markets has been emphasized in recent years by various scientists and financial analysts. With regard to both aspects, a new type of financial analysis, namely a non-linear analysis of integrated financial markets, seems necessary [4]. However, these models are considerably limited, particularly as regards seasonal and non-linear uncertainty problems. It is reasonable to assume

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that, as the price data of financial instruments is influenced by deterministic and random factors, the stock market forecast can only be successful using tools and techniques that can overcome the problem of price uncertainty, noise and non-linearity. These problems, along with other shortcomings of traditional methods, have led to a growing interest in artificial intelligence methods, including artificial neural networks, fuzzy logic or hybrid neuro-fuzzy systems.

In the article [5] the authors propose a neuro-fuzzy model using financial indicators. Traditional techniques, such as linear programming or regression modeling, often fail to predict future values, especially if the data being tested is non-linear and chaotic. This is where neural networks can play an important role in investment predictions with their learning and predicting properties. The fuzzy inference system can simulate human knowledge and address nonlinear problems and uncertainty. The proposed model has five inputs with one output, and the output is a signal of investment in a high-yield and low-risk portfolio.

A proposal for a cluster-based ANFIS model for APPLE stock price prediction is presented in [6]. The study suggests four technical indicators that serve as inputs to the neuro-fuzzy system. From the simulation results it was found that the average performance of the model is significantly better than the other methods. In the context of the gradual information forecasting mechanism, the study [7] examines the predictability of the stock market by designing and evaluating a trading system that is conceptually close to fuzzy logic based on the IF-THEN rule. More specifically, it examines the extent to which foreign and domestic stock markets return signals of varying size and direction, and subsequently help predict the performance of domestic capital markets. [8] use the hybrid ANFIS model and predict the Jakarta Composite Index, which is one of the stock indices of the Indonesian Stock Exchange. Experimental results provide a prediction accuracy of 90 %.

Another study [9] proposes a hybrid five-layer neuro-fuzzy model and a corresponding learning algorithm with application in predictive tasks of stock market time series. The key difference between classical ANFIS and the proposed model is in the fourth tier, where the multidimensional Gaussian function is used to achieve better computational performance and representational capabilities in processing highly nonlinear volatile data. Experimental results show the advantages of the described model. Similarly, article [10] deals with the construction of a stock market decision machine that can improve the accuracy of the forecast. It uses basic, psychological and technical analysis along with simulation and other methods. Prediction is made using dynamic models, fuzzy logic, neural networks, genetic algorithms and hybrid models. The proposed methodology is used to process data to obtain information on buy and sell signals about share prices on world markets.

2 Artificial Intelligence Model

Currently, linear models are widely used to predict financial time series, but these models are considerably limited especially when applied to seasonal and non-linear uncertainty problems. Therefore, nonlinear methods such as neural networks, fuzzy logic and hybrid neuro-fuzzy models attract more and more attention. [11] states that artificial intelligence outperforms statistical regression models and allows deeper analysis of large data sets.

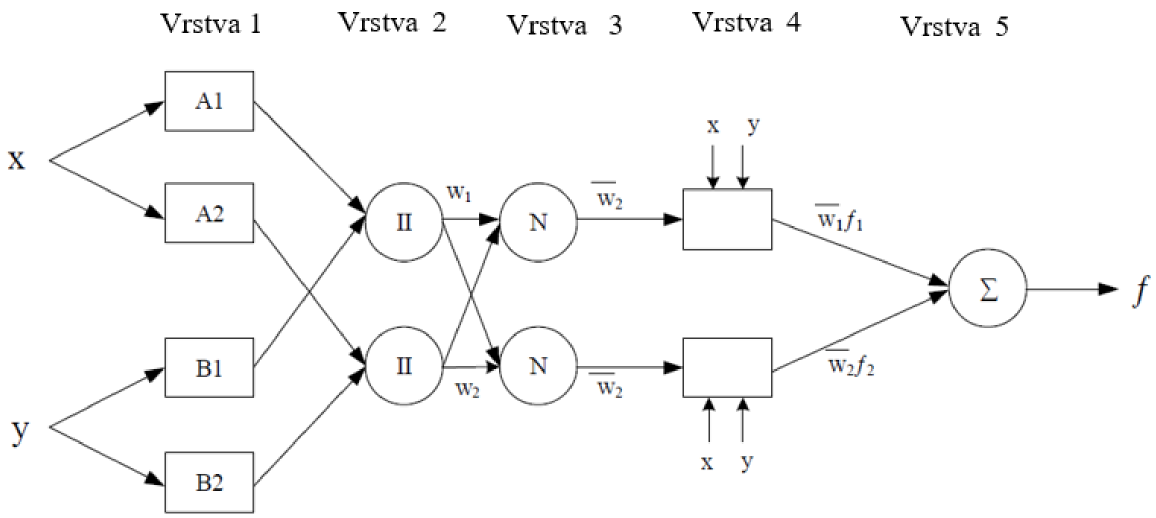
In particular, financial markets are influenced by deterministic and random factors. [10] also adds that the time series values of stock titles, commodities, currency rates, etc. are affected by complex economic and psychological phenomena that contain a high degree of chaos, hence fuzzy logic and other artificial intelligence tools are among the best currently exists for processing and evaluating information and data from the economic and financial field.

2.1 Adaptive Neuro-Fuzzy Inference System

By combining fuzzy logic with a neural network, it creates an intelligent system, commonly referred to as a neuro-fuzzy system, that effectively utilizes the quality of both of these approaches. The neuro-fuzzy system combines human logical thinking of fuzzy systems with the neural network training and interconnect structure. The most widely used neuro-fuzzy system is the adaptive neuro-fuzzy inference system (ANFIS). The adaptive neuro-fuzzy inference system is a forward neural network that uses a hybrid learning method for network learning, as reported [12].

Thanks to its design, ANFIS can benefit from both artificial intelligence techniques, but also overcome their shortcomings. Compared to ANN, the ANFIS model is more transparent to users and causes fewer errors in remembering. As a result, there are several advantages of ANFIS, including adaptive ability, nonlinear ability and rapid learning capability. Neural networks can easily learn from data. However, it is difficult to interpret the acquired knowledge as meaning associated with every neuron and every mass that is quite difficult to understand. In contrast, as described [13], fuzzy logic itself cannot learn from the data. However, fuzzy models are easy to understand because they use linguistic terms rather than numeric and IF-THEN rules structure. Language variables are defined as variables whose values are words or sentences in natural language with associated degrees of membership. The fuzzy set to which linguistic variables belong is an extension of a "sharp" set where an element can have full or no membership. However, fuzzy sets also allow for partial membership, which means that an element may partially belong to more than one set.

Figure 1: ANFIS architecture



source: [12]

The architecture of the neuro-fuzzy inference system, as described [14], contains five basic layers:

Layer 1: Input layer

The layer includes solely adaptive nodes, while each node transforms the input variable to a linguistic form by fuzzification and determines their membership function. The Gaussian curve is one of the most frequently used membership function shapes. For this reason, this fuzzy function type is used, same as in the survey by [15].

$$O_i^1 = \mu A_i(X) \tag{1}$$

Layer 2: Rule layer

This layer consists of non-adaptive nodes, with each node corresponding to one T-S fuzzy rule. The node inputs are signals from the previous layer and at input they give weight or strength of the rules whose antecedent is given by a combination of the linguistic values of the respective variables.

$$w_i = \mu A_i(X) \times \mu B_i(Y), i = 1, 2 \tag{2}$$

Layer 3: Normalization layer

The nodes in this layer are fixed. The aim of this layer is to normalize the strength of a given rule, which is a ratio of the respective rule weight and the sum of the weights of all rules.

$$\overline{w_l} = \frac{w_i}{\sum_{i=1}^{2} w_i}, i = 1, 2 \tag{3}$$

Layer 4: Defuzzification layer

It is a layer consisting of adaptive nodes connected to normalisation nodes, while the transfer function is given by the required consequent shape.

$$\overline{w_l} f_i = \overline{w_l}(m_i X + n_i Y + q_i), i = 1, 2 \tag{4}$$

Layer 5: Summation layer

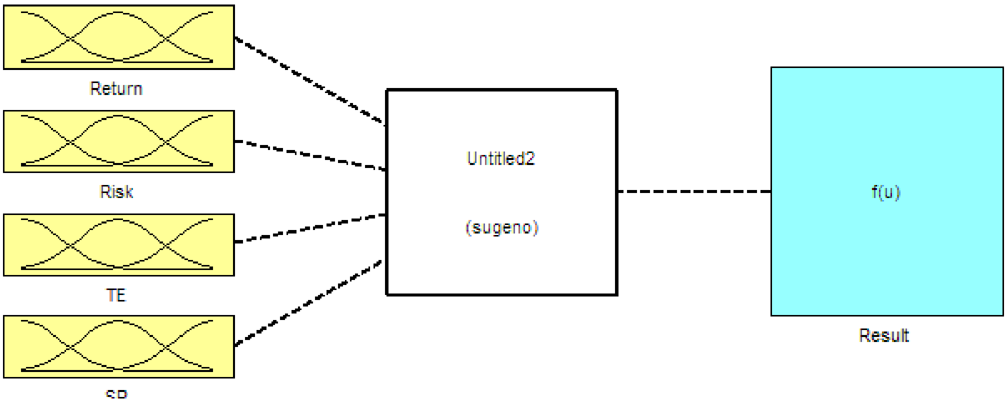
The last layer contains a single non-adaptive node that determines the overall ANFIS output based on the sum of all input signals from previous layers.

$$\sum_i \overline{w_l} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, i = 1, 2 \tag{5}$$

3 Application of the ANFIS model

To create a neuro-fuzzy model, 20 Stock Exchange Funds (ETFs) with passive management following the stock indices from two sectors: US and European, are chosen. ETFs are a suitable and cost-effective tool for investors seeking large-scale market indices, certain sectors or geographical regions, etc. The largest ETF organizer in the world is the US, which according to [16] offers 1832 ETFs and $ 3.4 trillion of managed assets.

Figure 2: FIS architecture



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Based on the above description, a fuzzy inference system is created consisting of four input variables: yield, risk, tracking error (TER), Sharpe ratio, and one output variable indicating the investor's decision to invest or not in the ETF. Feno type Sugeno is used, which is able to work with adaptive neuro-fuzzy inference system.

For each input variable it is necessary to establish an appropriate jurisdiction function. According to the selected dataset originating from the financial market, its character best fits Gaussian's function of belonging. Figure 3-6 shows the individual membership functions for the input variables. Five attributes are specified for each input variable, namely: VL - very low, L - low, M - medium, H - high, VH - very high. The output of the model is coded as follows: 0 - SELL, 0.25 - rather sale, 0.5 - hold, 0.75 - rather buy and 1 - BUY.

Figure 3: Return membership function

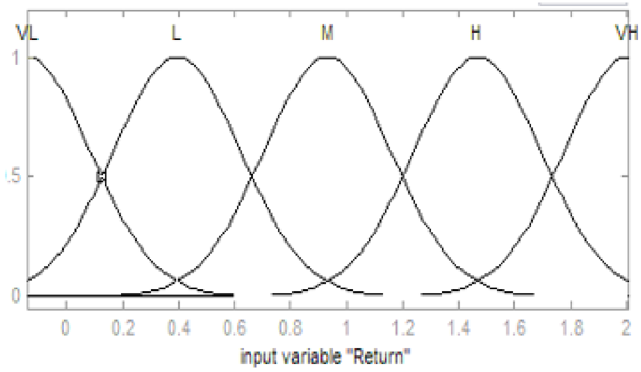

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Figure 4: Risk membership function

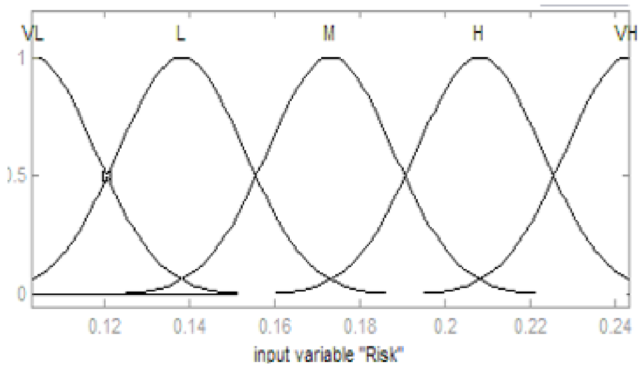

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Figure 5: TER membership function

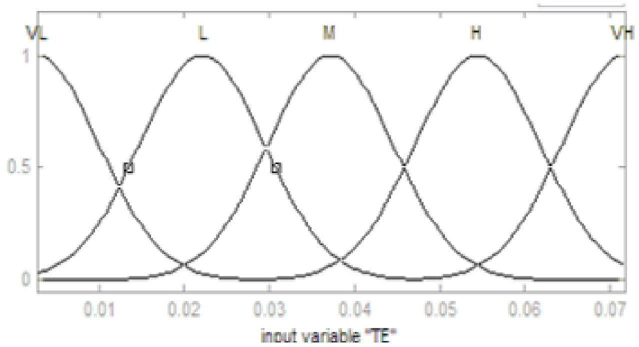

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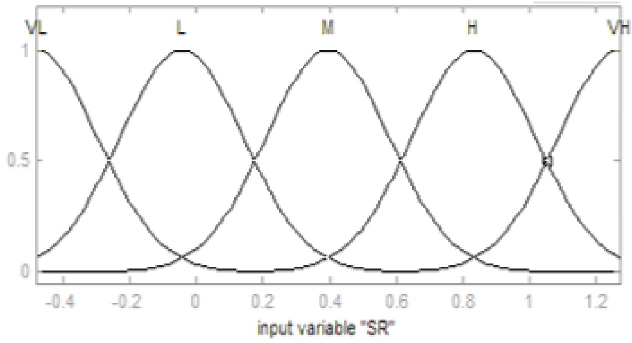
Figure 6: Sharpe ratio membership function



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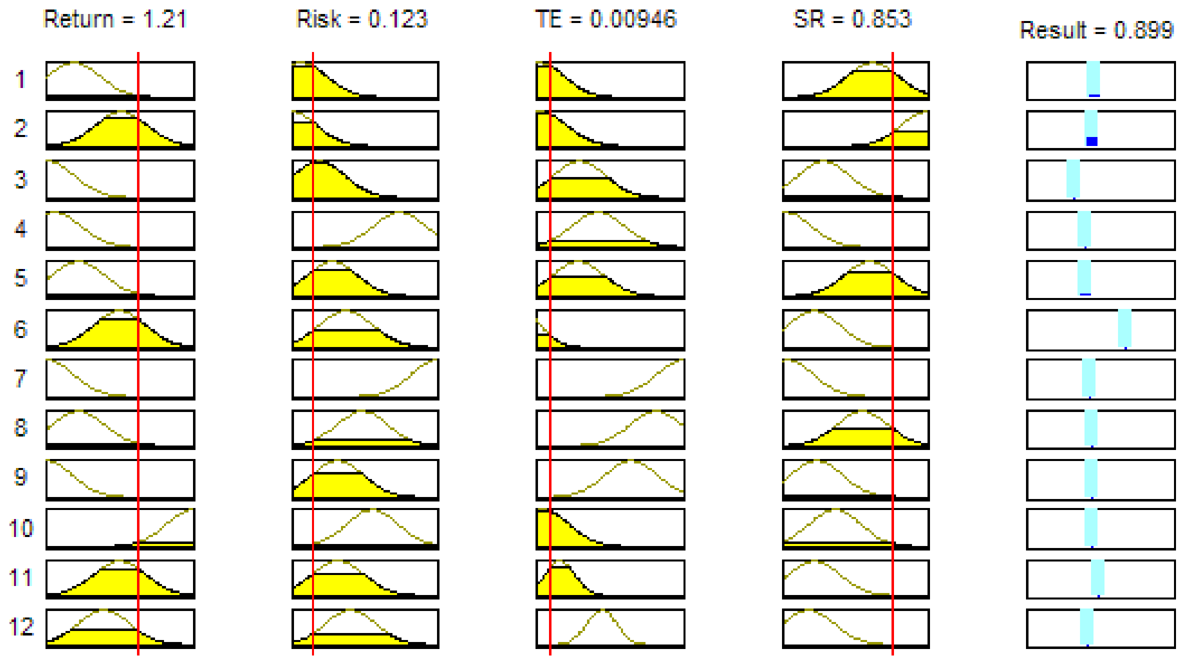
The rules necessary for the operation of the fuzzy system are either set by experts or set up using artificial neural networks. In our case, the adaptive neuro-fuzzy inference system ANFIS is used. To generate the FIS method, a gradient method is selected and the generated FIS is trained using hybrid learning.

Figure 7: Resulting rule block



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The number of rules created is equal to 5x5x5x5 = 625. However, many rules created usually reduce the model's performance. Therefore, the number of fuzzy rules created is reduced by fuzzy clustering. In the case of fuzzy clustering, each element is assigned a membership level; The membership level indicates the strength of the assignment between the element and the respective cluster. Fuzzy clustering, therefore, is the process of assigning these membership levels. One of the most common fuzzy clustering algorithms is Fuzzy C-Means (FCM). In our case, 12 fuzzy clusters are created. The resulting rule block is shown in Figure 7.

The resulting block of rules can be used to make decisions about investing in ETFs. The decision process can be interpreted according to the set parameters in Figure 7. If the return is 1.21%, the risk is 12.3%, tracking error (TER) is 0.946% and the Sharpe ratio is 0.853, then the ANFIS result is 0.899, which is very close to 1, so it is recommended to invest in of the ETF.

4 Conclusion

This paper deals with the use of artificial intelligence methods in financial markets. Specifically, a hybrid neuro-fuzzy inference system is used to support decision-making on investing in ETFs on the American and European continents. A total of four input parameters are selected, representing return, risk, tracking error, and Sharp ratio. The output of the model is a decision whether to invest in the ETF or not. Created is a model ANFIS provides rules for the fuzzy model. Due to the large number of fuzzy rules caused by the number of selected attributes of the membership function, the fuzzy clustering method is used to reduce the number of fuzzy rules and improve the model's performance.

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