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Decision-Making Process Using Neuro-Fuzzy Model for Capital Market

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Abstract

Purpose of the article The paper discusses the proposal of a neuro-fuzzy model as support in decision-making on investments in exchange traded funds (ETF) focused on the real estate sector and listed on the American exchange. The created model is based on the neuro-fuzzy inference system (ANFIS).

Methodology/methods The methods of analysis, synthesis and mathematical neuro-fuzzy modelling were used to achieve the goal. Selected financial indicators represent the fuzzy system input. Based on the Gauss membership function, the neural network generates the fuzzy rules. The model output is a signal to buy or sell the ETF stock.

Scientific aim The paper aims to create a suitable model for decision-making on investments in analyzed investment instruments based on selected financial indicators.

Findings The proposed neuro-fuzzy decision-making model consists of 4 input variables, one rule block (with 81 fuzzy rules) and one output variable (to invest or not to invest). The input variables and the output variable have three attributes (L – large, M – medium, S – small). The created ANFIS model is a suitable tool for investment decisions on buying or selling ETF stock. The model significance lies mostly in the fact it provides the expert analyst or potential investor with enough space to express and incorporate their subjective evaluation in the model.

Conclusions The paper discussed the proposal of a neuro-fuzzy model as support in decision-making on ETF investment opportunities listed on the American market. For further research, the proposed model should be extended by other significant fundamental indicators, possibly incorporate technical and psychological indicators and monitor the strength of the revised model in other capital markets as well.

Keywords: fuzzy logic, artificial neural networks, stock market, stock trading, soft computing, ETF, ANFIS

JEL Classification: G11, G12, C45

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Introduction

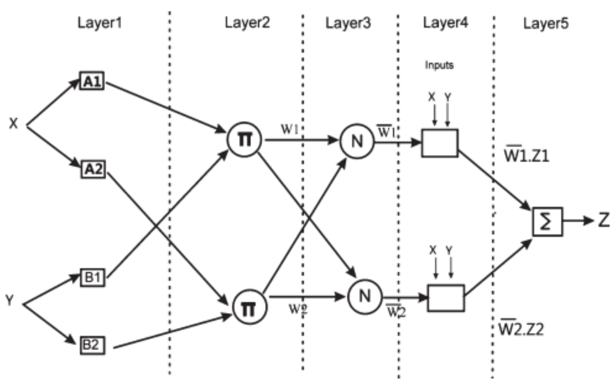
The financial industry has been increasingly dependent on advanced computer technologies, in particular due to the need to retain competitiveness in the global market. The issue of decision-making in capital market using data mining techniques is one of the most important areas in finance. This had drawn a lot of scientific attention and become the crucial research providing a more accurate forecast and decision-making process. As stated by Tung and Le (2017) and Zadeh (1978) fuzzy logic and artificial neural network are promising techniques with extensive forecast applications. More and more scientists and resarchers realize the fuzzy set theory introduced by Zadeh is a suitable instrument for mastering stock market uncertainties and ambiguities. Dostál and Kruljacová (2018) state that fuzzy logic and artificial neural network belong among soft computing methods. The guiding principle of fuzzy logic means to the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability and robustness. Artificial neural network has been widely accepted mostly for its ability to learn and reveal the relationships between non-linear variables. The artificial neural network primarily overcomes the statistical regression models and allows a deeper analysis of large data sets. The created model helps in decentralization of decision-making processes to be standardized, reproduced, and documented.

1 Theoretical Background

Since the data on investment instrument prices are affected by deterministic and random factors (Bao and Yang, 2008), a stock market forecast may be successful solely when instruments and techniques overcoming the price uncertainty and non-linearity problem are used, as mentioned by Chang et al. (2011). Wang and Wang (2015) state that fuzzy logic and neural networks are more and more frequently used in the financial markets and their prediction capability is widely acknowledged mostly thanks to their ability to detect non-linear behaviour. Jilani and Burney (2008) introduced a simple fuzzy time series forecasting method. Chang and Liu (2008) implemented a system based on Takagi-Sugeno-Kang (TSK) fuzzy rules for stock price prediction. Dostál and Kratochvíl (2011) applied fuzzy logic as decision-making support in stock markets. Similarly, Janková (2018) deals with fuzzy logic application in investment portfolio optimization as an effective tool in the upcoming digital age. Svalina et al. (2013) used the adaptive network system based on fuzzy inferences to predict the closeness of Crobex prices on the Zagreb Stock Exchange. The article by Gunasekaran and Ramaswami (2014) deals with stock portfolio optimization using the neuro-fuzzy inference system and the capital asset pricing model (CAPM). Atsalakis et al. (2016) used the neuro-fuzzy inference system for stock market predictions in turbulent times. The obtained results showed that the proposed model gives accurate stock price trend forecasts within the stock market crisis.

2 Neural Networks and Fuzzy Logic

The currently widespread data mining technique has provided a more accurate forecasting process and has attracted a lot of scientific attention. Tung and Le (2017) state that fuzzy logic and artificial neural network represent a method with a wide range of application in forecasting future stock price changes, exchange rates, commodities and other financial instruments. Fuzzy logic allows definitive conclusions to be drawn from un-clear, ambiguous or inaccurate information. Artificial neural network has been widely accepted mostly for its ability to learn and reveal the relationships between non-linear variables. The artificial neural network primarily overcomes the statistical regression models and allows a deeper analysis of large data sets.



Source: Gunasekaran and Ramaswami, 2014

Figure 1 ANFIS architecture

A hybrid neuro-fuzzy system was created by a combination of artificial neural networks and fuzzy logic. The system aims to use the advantages of both the neural networks and fuzzy logic. According to Karray and de Silva (2004), it takes the description of vagueness from fuzzy logic and the above mentioned ability to learn from the neural networks. Neuro-fuzzy systems use a neural network to avoid manual setting of various parameters and enable the system to learn them itself and possibly adapt. Negnevitsky (2002) emphasizes that ANFIS (Adaptive Neuro-Fuzzy Inference System) has become one of the widespread neuro-fuzzy systems.

Figure 1 depicts a multi-layer network, which includes an input layer, one or more hidden layers and one output layer, state Dostál (2011). Thanks to the multi-layer technology, neural networks are capable of better identification of non-linear relationships between input and output variable sets compared to other methods. As added by Fanta (1999), each neural network input corresponds to one variables. The neural network output is the task solution. Weights are key elements of the neural network, expressing the relative strength of input data or various connections transferring data between layers. Thus the weights express the relative significance of neural network input data. There is currently a number of various neural network architectures. Apart from the hidden structure model, there are systems with associative memory, double-layer structure, etc. In neural net-works, although they are mostly based on determination by examples and not predominantly on rules, there are algorithms that help determine the neural network, i.e. change the weights of the respective neurons in the calculation process.

3 Experimental Results and Analysis

The following part of the paper presents not only a selected data sample but also the required outputs. Then a model is created based on the neuro-fuzzy inference system (ANFIS). Based on the selected membership function, the neural network generates the fuzzy rules. The model output is a signal to buy or sell the ETF stock.

3.1 Data Sample

For the neuro-fuzzy model creation, 10 exchange-traded funds (ETF) in the real estate sector are selected. ETF are a suitable and cost effective instrument for investors who strive to acquire extensive market indexes, particular sectors or geographic regions, etc. The selected market is the Americal market that, according to ICI Factbook (2018), offers 1,832 ETF and 3.4 trillion dollars of managed assets and is the largest ETF organizer in the world. Table 1 shows selected ETF entering the model.

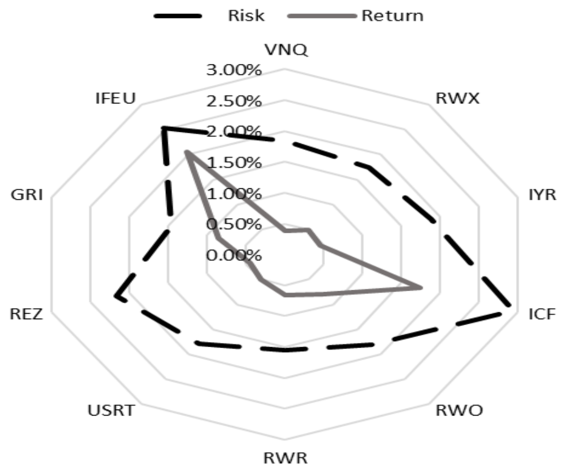
Table 1 Asset values of selected ETFs

ETF	Ticker	AUM (bil. USD)
Vanguard Real Estate ETF	VNQ	32.3
SPDR DJ Wilshire International Real Estate ETF	RWX	2.3
iShares U.S. Real Estate ETF	IYR	4.6
iShares Cohen & Steers REIT ETF	ICF	2
SPDR DJ Wilshire Global Real Estate ETF	RWO	2.3
SPDR Dow Jones REIT ETF	RWR	2.8
iShares Core U.S. REIT ETF	USRT	1.1
iShares Residential Real Estate ETF	REZ	0.4
Cohen & Steers Global Realty Majors ETF	GRI	0.054
iShares Europe Developed Real Estate ETF	IFEU	0.031

Source: Finance Yahoo, 2018

3.2 Financial Indicators

Fang et al. (2006) state that return and risk are usually the two crucial factors considered by investors in in-vestment decision-making. Gupta et al. (2008) divides return to long term and short term and his model also includes dividends. In some cases, investors may consider other factors, such as liquidity. For example, liquidity was accounted for by Arenas et al. (2001) who tested the selected unit trusts using fuzzy logic. Other authors claim that ignoring transaction costs leads to ineffective portfolios, see Li et al. (2000) or Khayamim et al. (2018). For this reason, the selected model input variables are: return, dividend, risk and total expanse ratio (TER). Figure 2 graphically depicts the values of the respective variables entering the model, except for very low TER values.



Source: Finance Yahoo, 2018

Figure 2 Return and Risk of ETFs

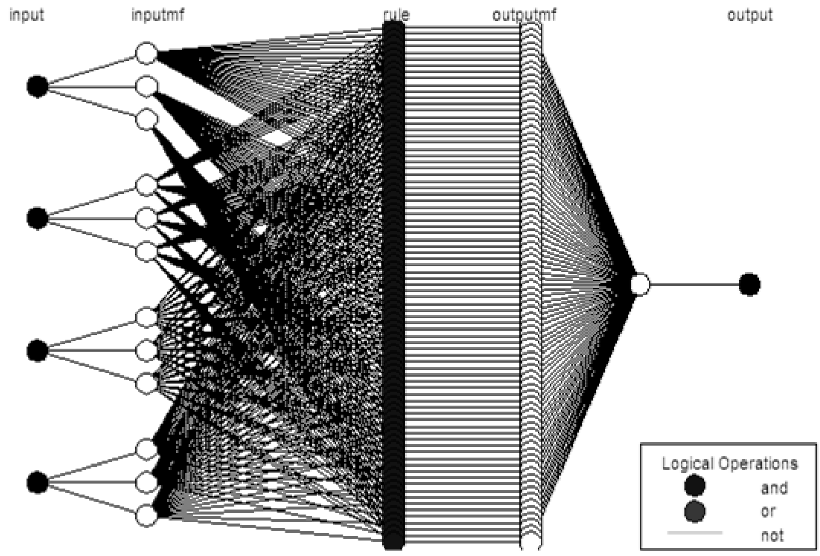
3.3 Experimental Results

Research results present an expert neuro-fuzzy model for decision-making on investments in ETF in the American stock market. First, it is necessary to determine the variables entering the model, their attributes and membership functions. The proposed neuro-fuzzy model consists of four input variables and one output variable. The inputs are represented by the following variables: return, dividend, risk and TER. There are 3 attributes of the input variables: High, Medium, Low. Gaussian membership function has been used. The output variable represents the BUY or SELL decision.

Based on the described procedure, the best fuzzy inference system (FIS) results are achieved with the following parameters:

- Generate FIS method: Grid partition.
- Train FIS optimum method: Hybrid learning.
- Gaussian membership function (gaussmf).

Gaussian membership function is selected in context to paper Talpur at al. (2017), when are compare the different membership functions. Their study shows that the Gaussian membership function is the most suitable among other selected membership function (triangular, trapezoidal, bell) when employed in ANFIS with grid partitioning method. Mayilvaganan and Naidu (2011) found that the best performance and results was obtained with using Gaussian membership function. The bell and trapezoidal membership function are poorer then Gaussian. Also, Esfahanipour and Aghamiri (2010) use Gaussian membership function in ANFIS to test the stock data.



Source: authors' research

Figure 3 ANFIS architecture

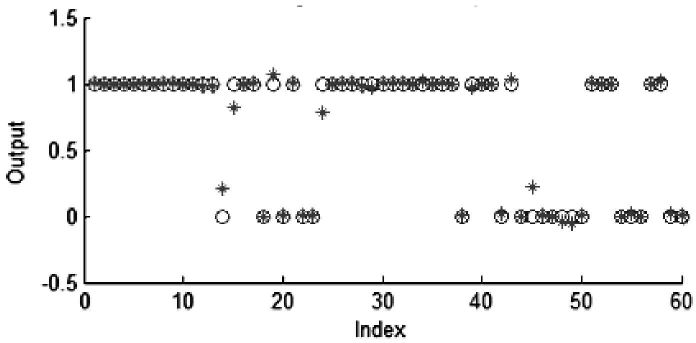
A rule block sample generated by artificial neural networks is shown in Table 2. ANFIS created a total of 81 IF-THEN rules. An example of the first rule meaning is as follows: If the return is high, risk low and overall fund costs low, the ETF is recommended for purchase. On the other hand, the last rule states: If both the return and risk are high as well as the total cost indicator, the ETF is recommended for sale.

Table 2 Examples of rule block

		IF		THEN
Return	Dividend	Risk	TER	Results
High	High	Low	Low	BUY
High	High	Low	Medium	BUY
High	High	Low	High	BUY
High	High	Medium	Low	BUY
High	High	Medium	Medium	BUY
High	High	Medium	High	BUY
High	High	High	Low	BUY
High	High	High	Medium	SELL
High	High	High	High	SELL

Source: authors' research

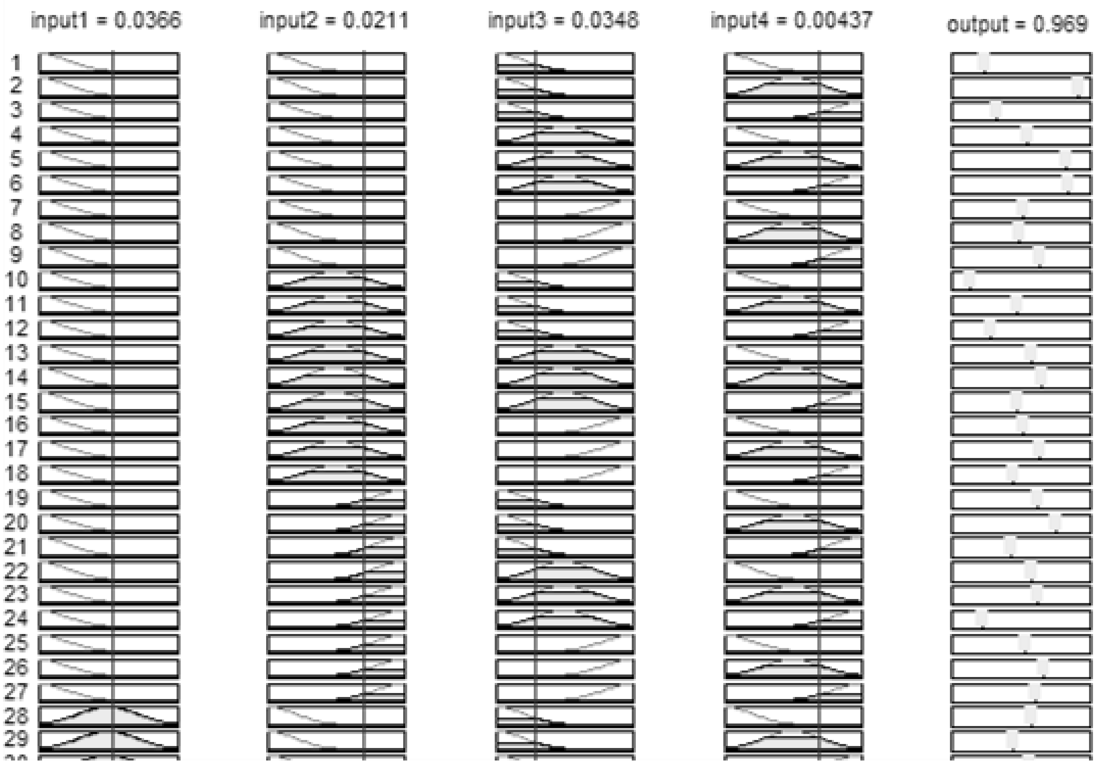
For this model, the number of training epochs is 30 and training error tolerance is set to zero. The training process stops whenever the maximum epoch number is reached or the training error goal is achieved. For splitting the data into training and testing purpose, according to literature (Sallah et al., 2018, Shrivastava and Sridharan, 2013) most researchers practiced the 70% training and 30% testing because the more data applied for the training, the more optimal and accurate results a system generates. Therefore, in this study the 70% of the dataset instances were selected for training set and the remaining 30% of the dataset instances were chosen for testing set. The error in the training process reached 0.055954. The figure 4 shows the testing of the data set which is slightly different from the one used to train the system. It is obvious that in the model learning most values were mapped to the adequate output value (1 – Buy ETF, 0 – Sell ETF).



Source: authors' research

Figure 4 Testing of the data set

Figure 5 depicts the decision-making process of ETF investments. The input variables of the created model in the case study are set as follows: risk = 3.66%, return = 2.11%, dividend = 3.48% and TER = 0.437%. Decision to invest or not to invest is 0.969, which is a value close to 1, thus based on the created neuro-fuzzy model, the recommendation is to invest in the ETF.



Source: authors' research

Figure 5 Part of table for decision making process

4 Discussion

The model includes key input variables that have been used in the long run as criteria for decision-making concerning investments not only in exchange-traded funds but also in other investment instruments. The neurofuzzy model is set for expert data, which may be further modified based on investor's requirements. If new relationships are identified, the model needs to be reviewed and verified again. As stated by Doskočil and Dostál (2017), only a verified model may be used for investment decision-making in practice. For this reason, the proposed neuro-fuzzy model may not be considered final and the only correct option.

However, Fullér (1995) notes some problems and limitations of fuzzy systems. A major issue for fuzzy control is stability, lack capabilities of learning and have no memory as stated previously, but neuro-fuzzy systems eliminate this drawback. Also, determining or tuning good membership functions are not always easy, even after extensive testing, it is difficult to say how many membership functions are really required. Verification and validation of fuzzy expert system generally requires testing with hardware in the loop. Salleh et al. (2017) mentioned that the computational cost of ANFIS is high due to complex structure and gradinent learning. This is significant bottleneck to applications with large inputs. Therefore, the more parameters in ANFIS architecture, the more is the training and computational cost. Interpretability is highly compromised, even through, the large number of rules contribute to improvement in model accuracy. More rules tend to produce better accuracy, on the other hand, it is difficult to interprete the model. Contrarily, reducing the rule-base may result in low accuracy.

Conclusion

The paper discussed the proposal of a neuro-fuzzy model as support in decision-making on ETF investment opportunities listed on the American market. For this purpose, financial indicators were used based on the analysis of previous published outputs concerning the issue of investments in financial markets. Based on the obtained results it can be stated that the proposed ANFIS model is a suitable tool for investment decision-making concerning the purchase and sale of ETF stock. The model significance lies mostly in the fact that although the neuro-fuzzy model is based on a number of quantitative data, the model provides an expert analyst with sufficient space to express and incorporate their subjective evaluation in the model. For further research, the pro-posed model should be extended by other significant fundamental indicators, possibly incorporate technical and psychological indicators and monitor the strength of the revised model in other capital markets as well.

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