Forecasting the investors behavior on the capital market in Romania: Trading strategies based on technical analysis versus Artificial Intelligence techniques

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ABSTRACT

This research aims at characterizing and modelling the investors' behaviours present on the Romanian capital market, by analyzing the behaviours proposed by the efficient markets theory and investigating the possibility of financial time series behaviour forecasting through artificial intelligence concepts and tools (artificial neural networks, fuzzy logic, neuro-fuzzy systems).

The analysis of various forecasting strategies has been conducted using data sets on a daily basis, on a time horizon of nine years, for a total of 22 companies listed on BSE and for the BET and BET-C exchange indexes; the research is differentiating the pre-crisis period and the crisis period.

Keywords: financial time series forecasting, trading strategies, artificial neural networks, fuzzy logic, neuro-fuzzy systems

1. Introduction

Modern technologies use artificial intelligence to create systems that replicate human behavior. Black-box modeling approach, characteristic of neural networks is suitable for process modeling or intelligent control systems and less applicable in decision making, while inaccurate data handling and explaining and decision reasoning in linguistic form in the context of available factors is an asset to fuzzy expert systems, but they can not automatically acquire the linguistic rules underlying the formulation of such decisions.

Neuro-fuzzy systems are structures that combine into a hybrid intelligent technology the advantages of neural networks: the ability to learn and to adapt, to those of fuzzy logic: the ability to manage specific human reasoning at the linguistic level, transparency and interpretation of patterns, handling uncertain data.

2. Literature review

The first rule of learning for artificial neural networks was introduced by Donald Hebb (1949), Frank Rosenblatt (1958) has developed advanced models that have the ability to learn, the most famous being the perceptron, Cowan (1967) has introduced the sigmoid function as an activation function, Paul Werbos (1974) has published the learning method called backpropagation (BKP). Chenoweth and Obradovic (1996) have applied artificial neural networks in finance, investigating the behavior of a system designed for predicting the stock market index S&P 500 and Terna (1998) used several neural network to simulate the behavior of investors in the capital market.

In the scientific literature many papers have been published comparing different methods of forecasting financial time series. Leung, M.T. et al. (2000) uses linear discriminant analysis, probit and logit analysis, probabilistic neural networks to determine the movement of stock market indices. Tino et al. (2001) describes a system that simulates the trading of options on FTSE and DAX, forecasting the volatility of the two indices using the delta-neutral trading strategy. Ho et al. (2002) performs a comparative study between artificial neural networks and ARIMA Box-Jenkins method for time series forecasting, using multilayer feedforward network and recurrent neural network. Phua et al. (2003) applies genetic algorithms to neural networks in order to forecast stock market development indices in Singapore. Zhang (2003) uses a hybrid technique of decomposition of a time series into linear and nonlinear form. Kamruzzaman and Sarker (2004, 2006) conduct a comparative study of ARIMA and ANN models for forecasting exchange rates, concluding in favor ANN. Santiago Maia and Carvalho (2011) combine Multi-Layer Perceptrons (MLP) neural networks with Holt method.

Fuzzy expert systems have been applied in numerous studies to address various forecasting problems (Bezdek, 1993; Bolloju, 1996; Kaneko, 1996; Shaout and Al-Shammari, 1998; Kee, 2002; Hakan et al., 2010; Wei, Chen and Ho, 2011).

Combining the learning abilities of neural networks and the fuzzy logic have emerged neuro-fuzzy approaches. Numerous studies exploit hybrid neuro-fuzzy systems, obtaining encouraging results and proposing various architectures (Gupta and Rao, 1994; Brown and Harris, 1994; Pedrycz, 1995; Buckley and Hayashi, 1995; Dash et al., 1995; Lie and Sharaf, 1995; Studer and Masulli, 1997; Padmakumari et al., 1999; Mitra and Hayashi, 2000; Kulkarni, 2001; Lee et al., 2002; Craiger et al., 2003; Kim et al., 2004; Dušan, 2004; Srinivasa et al., 2006; Sushmita and Chaudhury, 2007; Radeerom et al., 2012).

Ebrahimpour et al. (2011) predict the evolution of stock prices listed on the stock exchange in Tehran, Iran and use a mix of MLP expert systems, combining three specific neural networks methods and comparing its performance with the neuro-fuzzy networks.

3. Methodology

3.1 Trading strategies based on technical analysis

Alongside the classical approach based on the interpretation of various types of charts, the technical analysis also uses trading strategies based on the calculation of some indicators: Moving Average (MA), BIAS, Stochastic Oscillator (%K and %D lines, WMS%R indicator), RSI (Relative Strength Index), MACD (Moving Average Convergence Divergence) or even strategies based on incorporating behavioral elements within technical analysis to achieve forecasts (Behavioral Forex Trading System).

Moving Average: $MA_t = MA_{t-1} \cdot \frac{n-1}{n} + P_t \cdot \frac{1}{n} = EMA(P_t, n)$ [1] , $n = 9$

BIAS: $BIAS_t = \frac{P_t}{MA_t} - 1$

KD strategy: $RSV_t = \frac{P_t - L_n}{H_n - L_n} \cdot 100$, RSV_t(*Raw Stochastic Value* or raw K)

$$K_t = \frac{1}{3} \cdot RSV_t + \frac{2}{3} \cdot K_{t-1}$$

$$D_t = \frac{1}{3} \cdot K_t + \frac{2}{3} \cdot D_{t-1}$$

In order to define better the KD trading strategy and the representative rules we use the following notations:

$K\_D_{t-1} = K_{t-1} - D_{t-1}$, $K\_D_t = K_t - D_t$ and $Trend_t = \frac{P_t - P_{t-1}}{P_{t-1}}$.

WMS%R: $WMS\%R_t = \frac{H_n - P_t}{H_n - L_n} \cdot 100.$ [2]

The KD strategy and the WMS% R indicator are stochastic oscillators reflecting the power of the asset prices movements and can be used together to spot buying/selling signals, according to the following rules:

$R1$: If $KD > 80$ and $WMS\%R = 0$, then is a selling signal.

$R2$: If $KD < 20$ and $WMS\%R = 1$, then is a buying signal. [3]

RSI: $RSI = 100 - \frac{100}{1+RS}$, $RS = relative\ strength\ factor = \frac{EMA\ (U,n)}{EMA\ (D,n)}$

MACD: $MACD(12{,}26{,}9) = EMA(P_t, 12) - EMA(P_t, 26)$

$signal = EMA(MACD, 9)$

$h = histogram = MACD(12{,}26{,}9) - signal$

[1] The relation is derived from the exponential moving average formula (EMA, *Exponential Moving Average*): $EMA_t = EMA_{t-1} \cdot (1-\alpha) + \alpha \cdot P_t$, $\alpha = 1/N$.

[2] The momentum indicator $WMS\%R$ (Williams %R or %R) was proposed by Larry Williams in 1973.

[3] If the buy/sell signal does not change, then the output will inherit the previous value (which is equivalent to the signal "hold").

To test the technical analysis specific strategies, all the indicators presented above have been used, and the results obtained are a basis for comparison of the effectiveness of these indicators on the Romanian capital market.

Selection of strategies based on one or more of these indicators may be conducted in accordance with the relevant time horizon, with the restriction of rules that generate trading signals, with the threshold values and the number of signals determined by each model

3.2 Strategies based on artificial neural networks

The representative model of the neural network structure is defined by the following relationship: $Trend_{t+1} = f_2(w_2 \cdot f_1(w_1 \cdot x))$, where: f_1 and f_2 are the transfer functions for the hidden nodes and for the output nodes. For f_1 and f_2 transfer functions, the most used is unipolar sigmoid function (logistic), which has the following expression: $f(x) = \frac{1}{1+e^{-k \cdot x}}$, $k > 0$.

The f function is the activation function, and w_1 and w_2 are the weighting matrices of the connections between inputs and the hidden layer, the weighting matrices of the connections between the hidden layer and the output layer, respectively. The input variables vector

(K_t, D_t, KD_{t-1}, KD_t) is x.

The goal for the artificial neural network traning is to estimate the weight matrix w_1 and w_2, so that the sum of squared errors (SSE) or the mean squared error (MSE) is minimized.

Implementation of the neural network with the characteristics described above was carried out as shown in the following image:

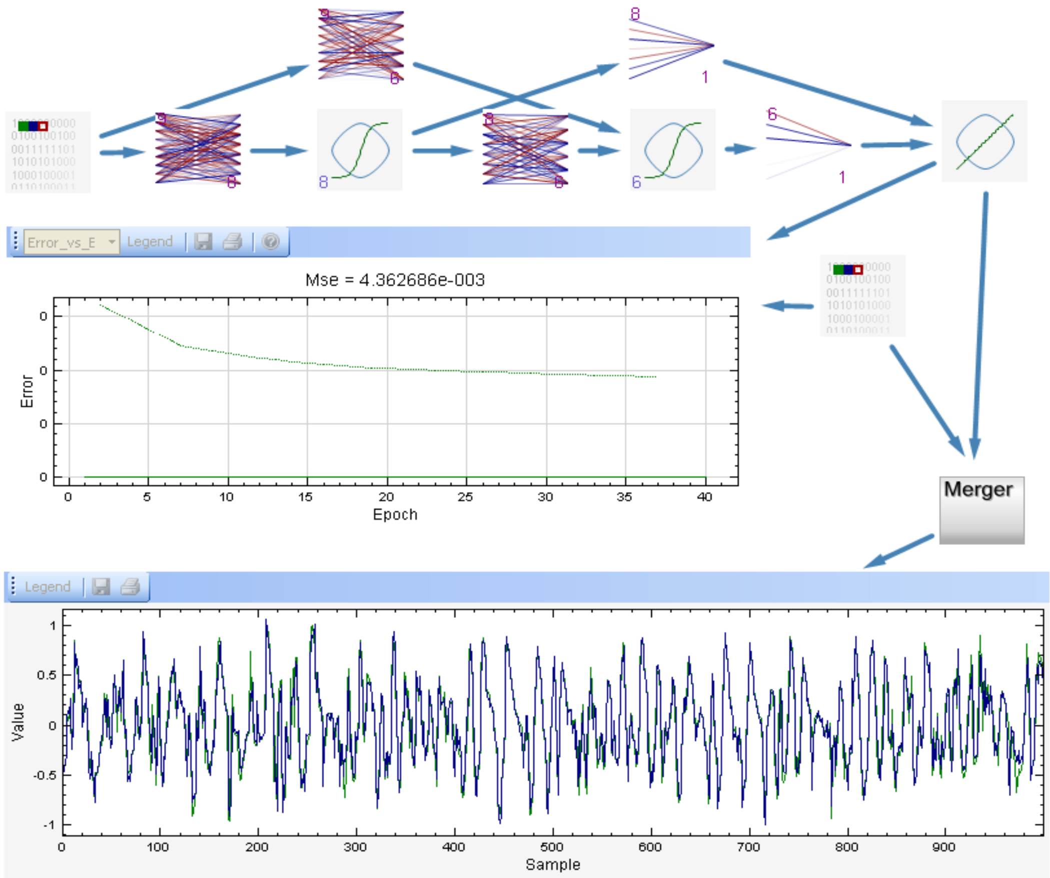


Figure 1. ***Artificial neural networks architecture***

The graphical analysis confirms the pattern stability (for 95% confidence level).

3.3 Fuzzy logic and neuro-fuzzy systems

KD trading system rules can capture short-term changes, however, are quite simple and based on the experience of human experts, with the characteristics of expert systems. Therefore we are going to change these rules of technical analysis using the fuzzy logic into a fuzzy logic system and a neuro-fuzzy hybrid system.

Building a fuzzy logic system

The fundamental idea of building a fuzzy system is to substitute the numerical values specific to neural networks (eg, "if K is greater than 80") with fuzzy logic specific linguistic terms (eg. to describe the K indicator value, we may use the quality terms "very low", "low", "medium low", "medium", "medium high", "high", "very high") to be transformed into quantitative signals belonging to the $[0,1]$ interval.

To describe the behaviour of the two trading rules as closely in a fuzzy logic system, K and D variables are needed, and the difference between the two indices at the earlier time (KD_{t-1}) and at the present time (KD_t). A set of four input variables is formed and the result is an output variable: $Trend$.

Each term is described by a membership function, $u_A(x)$, which expresses the extent to which an object x belongs to a fuzzy set A. In this context, the notations are: x - linguistic variable, A - linguistic value, u - membership degree , u_A - membership function.

The most widely used membership functions are: Z, S, λ şi π[4].

Table 1. ***Linguistic variables and values properties***

Linguistic variable			Linguistic value
Name	**Value**	**Type**	
K	$[0,100]$	input	v_low, low, medium_low, medium, medium_high, high, v_ high
D	$[0,100]$	input	v_ low, low, medium_low, medium, medium_high, high, v_ high
KD_{t-1}	$[-1,1]$	input	negative, positive
KD_t	$[-1,1]$	input	negative, positive
$Trend$	$[-1,1]$	output	strong_decrease, low_decrease, stable, low_growth, strong_growth

Following the transformation of the numerical values into linguistic terms, more sophisticated rules can be obtained, called rules of inference, described by the two parts of the conditional IF-THEN statement. System response can be quantified by means of a validity operator[5] of the IF-THEN decisional rule, represented by the minimum valid values.

The number of initial rules generated by the fuzzy logic system is determined as the product of the linguistic values numbers describing linguistic variables (for this case: 7 · 7 · 2 · 2 · 5 = 980 initial rules). Thus, it is necessary to solve two problems: removing those inference rules that are not practical and the optimal use of the remaining rules to achieve an accurate value of the trend. Neural network training method is used and to refine the membership functions and to remove the irrelevant inference rules[6].

The *purchase* signal is recognized when the forecast trend value is greater than a predetermined threshold value and the *sale* signal is notified when the forecast trend value is less than another predefined threshold value.

[4] von Altrock, C., Krause, B. şi Zimmermann, H.-J. (1992) „*Advanced fuzzy logic control technologies in automotive applications*", Fuzzy Sets and Systems, vol. 48, no. 1, pp. 41-52.

[5] Operator proposed by H.J. Zimmermann, 1978.

[6] Initially all the inference rules have equal weight, and during the neural network training process, these weights continually adjust (falling or rising), following to diminish the difference between the forecast trend and the one recorded based on actual data. During the training process, if the weight of an inference rule is less than a threshold value, then the rule is removed (Kosko, 1992). Similarly, the ANN specific training algorithm is used to adjust the membership functions, to minimize the difference between the forecasts and the actual values.

Neuro-fuzzy approach

The basic idea of a neuro-fuzzy system is to determine the parameters of a fuzzy system, using learning methods specific to a neural network.

For this, we used the FAM approach, characterized by fuzzy rules with associated weights, which allows the use of the modified backward error propagation algorithm (MBE) with fuzzy logic. This technique is useful for the generation and optimization of membership functions and the weights associated to each rule in the data set.

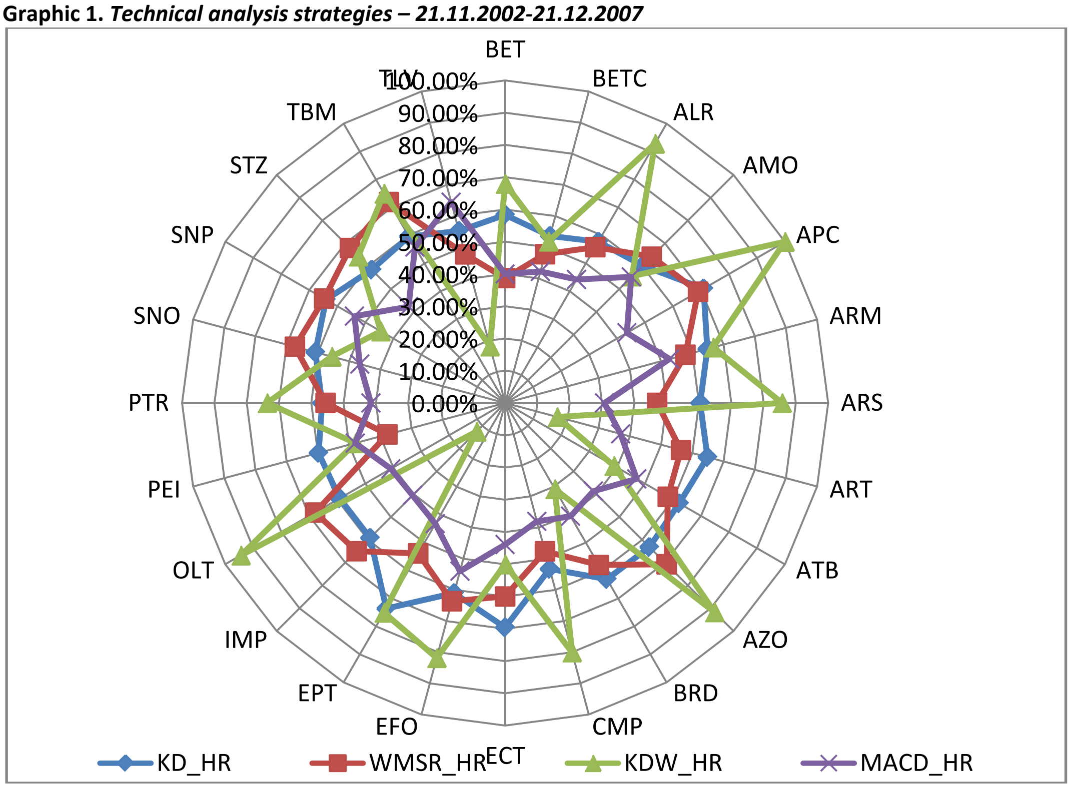
3.4 Data

The time series used for the analysis consist of the closing prices for a number of 22 companies listed on the Bucharest Stock Exchange (ALR, AMO, APC, ARM, ARS, ART, ATB, AZO, BRD, CMP, ECT, EFO, EPT, IMP, OLT, PEI, PTR, SNO, SNP, STZ, TBM, TLV), Romanian BET and BET-C stock market indices. The analysis period is between the 21.11.2002 - 14.02.2012, the data used having daily frequency. The time series were resized into two samples, considering the impact of the global financial crisis to the Romanian capital market. For each sample the data were divided into two sets: the training set (21.11.2002 - 19.12.2006, 03.01.2008 - 30.12.2010) and the testing set (03.01.2007 - 21.12.2007, 03.01.2011 - 14.02.2012).

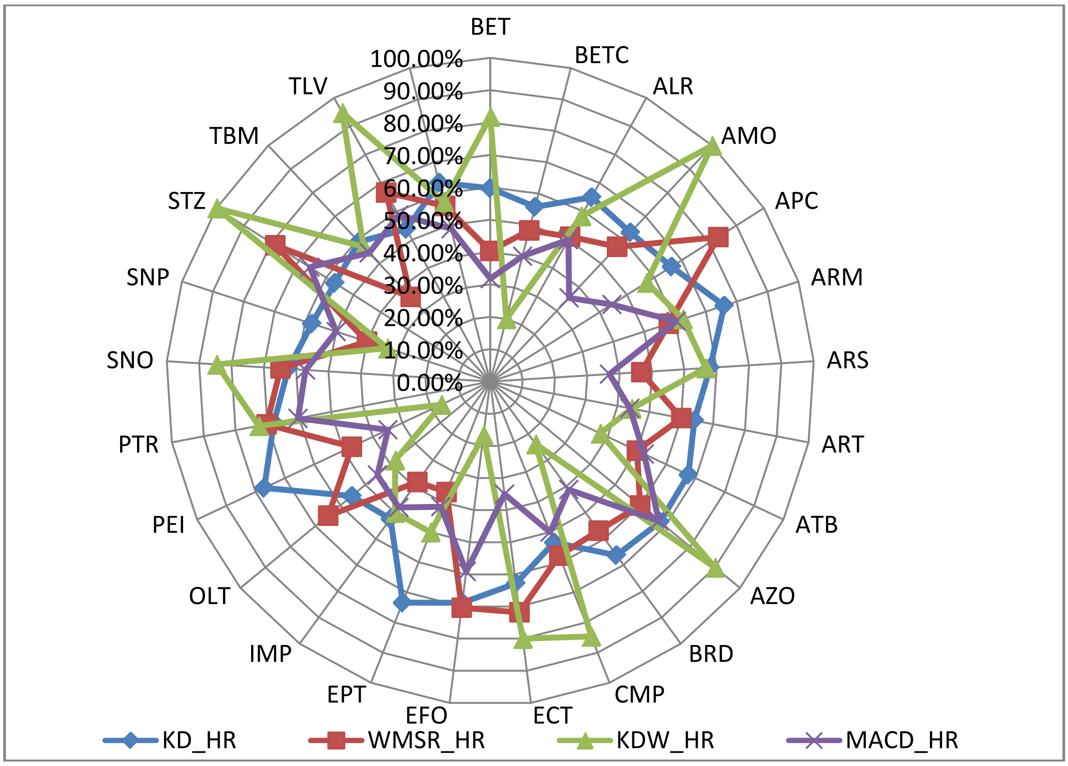
4. Results and discussion

The results obtained from testing the technical analysis indicators for the two samples (pre-crisis period, crisis period, respectively) are presented in the following graphs.

Graphic 1. ***Technical analysis strategies – 21.11.2002-21.12.2007***



Graphic 2. ***Technical analysis strategies – 03.01.2008-14.02.2012***



Source: authors' calculation

The technical analysis strategies used are highlighted; the mean HR values obtained fall within the domestic capital market background. The best HR result has been achieved for the KD strategy, and the least efficient, for the MACD strategy, for both periods analyzed. Combined KD and WMS%R strategy lead to a strong fluctuation of the results.

In this study, we implemented an MLP neural network with three layers of neurons and we applied the standard BKP technique with momentum. Through repeated tests we considered the optimal values of the training parameters: learning rate and momentum (which can take values between 0 and 1), as being 0.1 for the learning rate, and 0.7 for momentum.

Artificial neural networks constructed were trained using a total of 1003 data for the first sample, 755 data respectively for the second sample. Testing and datasets validation were performed for 249 data of the first sample and 285 data of the second.

Table 2. ***Comparative average results for statistics and performance indicators***

Model	**h**	**N**	**Hit Rate (HR)**[7]	**RMSE**[8]
ANN (the first sample)	3868	5976	0,6473	0,8598
ANN (the second sample)	4045	6840	0,5914	0,9114
Neuro-fuzzy (the first sample)	4276	5976	0,7155	0,7807
Neuro-fuzzy (the second sample)	4261	6840	0,6229	0,7885

[7] The hit rate (*HR*) is equal to the ratio of the number of correct forecasts made (*h*) and the total number of forecasts (*N*): $HR = h/N$.

[8] $RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} \varepsilon_i^{2}}$.

For the two data samples (before and during the crisis), EMA, RSI, MACD, KD and WMS%R technical analysis indicators were determined. The values obtained indicate a moderate performance of all indicators, consistent with the structure and characteristics of the Romanian capital market. The best results were obtained for the KD trading strategy (HR: 61% and 63%, respectively), the HR values being similar for all the series, in contrast with the results of the KD and WMS% R combined strategy (HR: 59%, and 57 % respectively), which showed a strong fluctuation of the HR.

As shown in the table comparing the model results analyzed, the neuro-fuzzy model achieved the best values for the performance indicators for both data samples (4276 correct forecasts from the total number of 5976 forecasts for the pre-crisis period, with a value of 71,55% for the HR and the lowest RMSE value: 0,7807; 4261 correct forecasts from the total number of 6840 forecasts, equivalent to a HR of 62,29% and RMSE: 0,7885 during the crisis). The performance of estimations made using artificial neural networks have similar results (3868 correct forecasts from the total of 5976, HR: 64,73% and RMSE: 0,8598 for the first sample; 4045 of 6840, HR: 59,14% and RMSE: 0,9114 for the second sample).

Although showed superior performance than the classical models (in previous research we obtained HR values below 53% and HR GARCH-M values below 55% for linear regression), the AI-based models may be more difficult to understand, apply and interpret, leaving open potential better options for other choices and combinations of parameters (learning rate, momentum, selection of certain algorithms, linguistic variables, membership functions, etc.).

5. Conclusion

In this research we aimed to investigate the possibility of forecasting financial time series using the comparative research of various methods, specific to the classical models and to the Artificial Intelligence-based techniques (artificial neural networks, fuzzy logic, neuro-fuzzy systems).

The same limitations can be determined, however, for the classical models; neither those offer the safety of the pattern variables correct selection. The human factor, characterized by experience, multiple trials, intuition, remains a part of the decision in both building the classical models, and the ones based on artificial intelligence.
Following the application of models and tests within this research, the potential of patterns based on the use of neural networks, fuzzy logic, neuro-fuzzy hybrid systems is highlighted, by their ability to capture and copy specific human characteristics (learning, generalization, pattern making, ratings).

What stands out for the models using artificial neural networks and neuro-fuzzy systems is their ability to be used with the tests specific to the chaos theory and fractal theory to optimize the financial time series forecasting, offering complex and multidisciplinary tools, which may explain and better shape the reality.

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