Innovative methods for improving portfolio management based on artificial intelligence instruments

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Abstract: - Financial markets represent one of the most complex environments for business and there are a lot of types of external factors which impact their dynamics. The recent financial turbulence materialized by the global financial crisis 2008-2009 and the European sovereign debt crisis (2010-2012) made serious pressure on financial markets that proved their fragility and sensitivity in a different manner. The use of different instruments used on artificial intelligence could be applied in decision making process in financial markets because they offer a unique capability of learning. The conventional theories regarding the anticipation of financial markets evolution are represented by the efficient market hypothesis (Fama, 1970) and the paradigm regarding the methods to anticipate the future performance of financial assets. The actual interest is to identify optimal strategies for portfolio management by using artificial intelligence. The basic steps of incorporating different types of artificial intelligences on the study of the future dynamic of the performance of different financial assets are the following: the analysis of the strategies used by different portfolio managers and their performances; the identification of new instruments capable to improve the strategy references; the selection/ development and testing of the new instrument; the analysis of the differential performance. Actual artificial intelligence instruments are difficult to create/develop and to use because in this paper will be presented a new concept in which the basis will be the application data transformation in order to build different sets of training artificial neural networks in order to optimize/modify in an easy way their behavior. This module for simulating the artificial neural network is improved by using genetic algorithms to select the best network regarding the predictions of the performance of financial instruments, but also the optimal timing in the process of portfolio management.

Key-Words:- financial markets, portfolio management, financial decision making process, artificial intelligence, Fama-French paradigm, neural network, system dedicated for portfolio management based on artificial intelligence (SPM-AI)

1. Introduction

The active portfolio manager should select and manage the capital market assets by using a multitude of instruments and strategies in order to obtain the performance with the restrictions of risk and liquidity. The most common strategy of selection is based on the fundamental analysis, but in this case the valuation of risk is only intuitive in the actual context of dynamics in markets. It is also important to understand how to anticipate the movements at macro/ sector level in order to select the most performance candidates.

The conventional theories regarding the anticipation of financial markets evolution are represented by the efficient market hypothesis (Fama, 1970) and the paradigm regarding the methods to anticipate the future performance of financial assets. The actual interest is to identify optimal strategies for portfolio management by using artificial intelligence. The fundamental analysis is difficult to use in prognosis but a strategy based on artificial intelligence could better anticipate future performance by using the historical data base of the financial instrument.

The interest of this paper is to present aspects regarding the use of intelligence in financial decision making process and the steps of the evolution of a system dedicated for portfolio management based on artificial intelligence (SPM-AI). Based on the prognosis offered by this instrument it is possible to adapt / change the strategy of investment according to the future trends in the markets.

The state of the art in the domain of financial decision making process demonstrate that artificial neural networks are already use with success and give a good support in the building and active management of portfolio/ financial assets (White, 1998; Yoon, Swales, 1991; Rhee, 1994; Qi, 1999).

The objective is to analyze the impact of artificial intelligence in the process of active selection of the candidate assets for portfolio. The application is direct for portfolio managers of investment funds and this support could decisively enhance the performance of the management and the attractiveness of the investment fund.

The basic steps of this attempt are: the analysis of the actual strategies use by investment funds; the identification of new instruments capable to improve the actual performance; the selection/ test of the new instrument; the comparative analysis.

The system dedicated for portfolio management based on artificial intelligence (SPM-AI) should meet the following tasks: to collect and update specific databases; to provide the necessary information for data analysis with data fusion possibilities; to apply desired data transformations and to build sets of training for the neural networks; to enable drive/ optimize networks, changing the drive parameters and save them; to allow the easy use in financial decision making process.

2. Classical models for portfolio management

2.1 The CAPM classic version

The CAPM model (Sharpe, 1961; Lintner, 1965) represents another paradigm in finance, which follows the work of Markowitz (1952) on the selection of the best portfolios from the risk-return standpoint. The CAPM model is used to estimate the performance of risky securities/portfolios, in relation to the overall market portfolio. The assumptions (investors have a Markovitz type behaviour, based on the selection of efficient portfolios Investors choose to invest in portfolios of financial assets traded on a secondary market and can take/grant loans at an interest rate called risk-free rate; investors have homogenous expectations, i.e. they estimate similarly distributed future returns; the financial instruments are divisible; there are no exchange costs; the capital markets are in equilibrium and assets are accurately measured; there is perfect competition between investors) reduce the range and efficiency of the CAPM model since all investors will have similarly efficient portfolios, i.e. the market portfolio, while the risk-return ratio expected by investors is identical for all market participants. Given the P portfolio, made up of an I asset weighting w_i and the market portfolio M, weighting $1\text{-}w_i$. Thus, the risk-return ratio of the P portfolio will be:

$$E(R_P) = w_i E(R_i) + (1 - w_i) E(R_M) \qquad (1)$$

$$\sigma_P = \sqrt{w_i^{\,2}\sigma_i^{\,2} + (1-w_i)^2\sigma_M^{\,2} + 2w_i(1-w_i)\sigma_{iM}} \qquad (2)$$

where:

$E(R_i)$ - average return of I asset $E(R_M)$ - return of the market portfolio

$\sigma_i^{\,2}$ - variance of the I asset $\sigma_M^{\,2}$ - variance of the market portfolio σ_{iM} - co-variance between the risky asset I and the market portfolio.

The CAPM equation is written:

$$E(R_i) = \beta_i (E(R_M) - r_f) + r_f \qquad (3)$$

and describes the relation between the return of a risky financial asset and the return of a completely diversified portfolio by means of the risk indicator $\frac{\sigma_{iM}}{\sigma_M^{\,2}} = \beta_i$ and the market risk premium, $E(R_M) - r_f$.

Depending on their risk aversion, investors choose a certain structure of the portfolio of risky and risk-free assets. The graph below shows the relation between the β indicator measured by CAPM and the return of an asset as defined by the Security Market Line (SML).

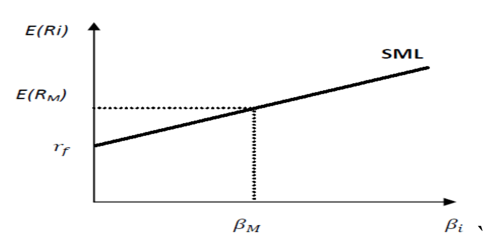

Fig. 1. The Security Market Line

If CAPM is expressed:

$$E(R_i) = \alpha_i + \beta_i E(R_M) + \varepsilon_i \qquad (4)$$

with α_i - constant describing the intercept with OY of the estimated line; β_i - the slope of the estimated line and describes the sensitivity of the I asset return to the market portfolio return; ε_i -the risk component for random events, it results:

$$\mathrm{var}(E(R_i)) = 0 + \beta_i^2 \,\mathrm{var}(E(R_M)) + \mathrm{var}(\varepsilon_i) = \beta_i^2 \sigma_M^{\,2} + \sigma_{\varepsilon_i}^{\,2} \; (5)$$

The relation (5) suggests the two types of risk: systematic (non-diversifiable), $\beta_i \ \sigma_M$ and unsystematic risk $\sigma_{\varepsilon i}$.

2.2 Extensions of the classical version of CAPM

a) The CAPM model has been extensively criticized for its unrealistic assumptions. Thus, in 1972, Fisher and Black have analysed certain portfolios uncorrelated with the market portfolio (zero co-variance, or $\beta = 0$).

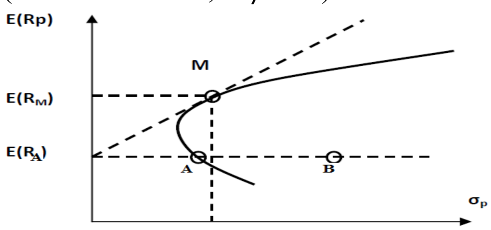

Fig.2. The fundamental security market line (without risk-free assets)

The result was an extension of the CAPM model with two factors:

$$E(R_i) = E(R_A) + \beta_i (E(R_M) - E(R_A)) . \qquad (6)$$

The limitations of this version are mainly related to the hypothesis that only short selling transactions are allowed on the market.

b) Another assumption of the CAPM model is related to the borrowing of funds at a risk free rate of interest. If there is a differential of the assets/ liabilities rate of interest, the fundamental line of the capital market can be depicted by two security market lines, i.e.:

- r_f -M1 that traces the portfolios acquired by investing (long position) in the M1 market portfolio to a certain extent and by acquiring risk-free securities
- M2-S that depicts the portfolios purchased with funds borrowed at a rate of interest R_d and by investing in the M2 market portfolio.

The slope of the line r_f -M1 is steeper than the slope of the M2-S line, thus meaning that for the same level of assumed risk, the expected return of the portfolios on M2-S is lower than if the investor had borrowed funds on the r_f .

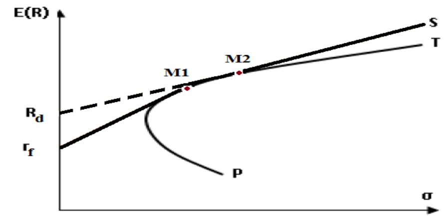

Fig.3. The fundamental capital market line

c) Another assumption of the CAPM model refers to the non-zero transaction costs. In the case when the return of the investment is corrected by the taxation:

$$E(R_i) = \frac{(P_T - P_0)\cdot(1 - t_C) + D_T(1 - t_C)}{P_0}, \qquad (7)$$

where P_T is the payoff of the asset, P_0 is the asset price, D_T is the received dividend, t_C is the taxation rate.

d) Intertemporal Capital Asset Pricing Model (ICAPM) is based on the behaviour of the selected capital, where a random number of investors act towards maximising the expected return, as they can continue to operate over time. The ICAPM version is mainly centred on the consumer-investor behaviour and the model assumptions must be intertemporal in order to be as realistic as possible. The model assumptions are as follows: all the assets have limited liability; there are no taxes or transaction costs; the capital market is in equilibrium; transactions are made continuously over time; short selling are allowed; there is a sufficient number of investors and a deep market; there is an exchange market for lending or borrowing at the same rate of interest; only local deviations in the process variables are allowed, i.e., for limited periods of time, the changes in prices or rate of return and the changes in opportunities are very small; the expected rate of return of each asset per time unit is defined by:

$$\alpha = E_t\left[\frac{P(t+h) - P(t))}{P(t)}\right] / h$$

and the variation of the rate of return per time unit is

$$\sigma^2 = E_t\left[\left(\frac{P(t+h) - P(t))}{P(t)} - \alpha h\right)^2\right] / h \cdot$$

The stochastic differential equation of the return on the asset I is:

$$\frac{dP_i}{P_i} = \alpha_i dt + \sigma_i dz_i,$$

2.3 The Fama-French paradigm (the three factor model)

Famma and French (1996) have pointed out that the return of an asset can be described by means of three factors: the market portfolio's rate of return, the size of the company and the book-to-market ratio. Thus, they define two variables related to the stock market capitalization, i.e. the book-to-market ratio – SMB (small minus big) and HML (high - minus low) and thus the relation for the return is:

$$E(R_i) - r_f = \alpha_i + \beta_M (E(R_M) - r_f) + \\ + \beta_{HML} E(R_{HML}) + \beta_{SMB} E(R_{SMB}) + \varepsilon_i \quad (8)$$

$E(R_M)$ - market portfolio rate of return; $E(R_{HML})$ - difference between the rate of return of the stocks rated as "high" and the return of the stocks rated as "low"; $E(R_{SMB})$ - the difference between the rate of return of "small" rated stocks and the rate of return of the stocks rated as "big"; ε_i - residue or the specific risk related to the company.

2.4 The APT model (Arbitrage pricing theory)

The APT model is based on the following assumptions: capital markets are in perfect competition and, therefore, there are no arbitrage opportunities; the investors' main objective is to maximise the value of the portfolio; the rate of return of an asset is a linear function of k factors:

$$R_i = E(R_i) + \beta_{1i}\delta_1 + \beta_{2i}\delta_2 + ... + \beta_{ki}\delta_k + \varepsilon_i \quad (9)$$

where R_i is the rate of return of the I asset at a specific moment, $E(R_i)$ is the expected rate of return of the asset i, β_{ki} is the sensitivity of the asset I rate of return to the changes in the risk factor k, δ_k is a set of factors influencing the rate of return of all the assets, ε_i is a random variable defining the risk of the asset i.

The systematic risk is not outlined by a single factor but by a series of several macroeconomic factors: the slope of a stock market indicator, business cycles, the oil price, and the inflation rate, the interest rate, the exchange rate, etc.

If the CAPM model described the relation between the β risk indicator and the rate of return of asset i as a line, the APT model, that has a multi-factor structure, describes the same relation as a hyper-plan.

3. Investment strategies based on artificial intelligence in active portfolio management

The most used strategies used in portfolio management are represented by: fundamental strategy, diversification strategy, options strategy (speculation, hedging), technical analysis (trend analysis, MACD, Bollinger, RSI stochastic oscilator) and strategies based on artificial intelligence.

The methods based on artificial intelligence for obtain associative relationships in the case of problems which can not be solved in a formal way are: neural computing (with the aim to create asociative relationships input-output by supervized/ nonsupervized learning); fuzzy logic (used when the input is not described accurately and it exist an uncertainty named fuziness); evolutionary computing (used in optimization in huge space of potential solutions). The advantages of nbeuronal and evolutionary computing is expressed by the use of units which function based on simple rules and the treatment of complexity is given by the parallel functioning of these simple units.

3.1 The use of Artificial Neural Networks (ANN) in financial decision making process

The main advantage is given by the capacity to adapt at the informational environment according to a certain problem via a learning process. The network represents a multitude of units interconected, characterized by simplicity. Every unit is influenced by a set of adaptive parameters and it resultsan extremely flexible system which can represent complex functions. Every unit process input signals and transfer to the conected units an output signal. Then, according to the results in the outputlayer it exists a process of modification of units in order to approach the response of the network to the real response. These systems capable to modify their structure in a learning process are usefull in the problems difficult/ impossible to formalize, and in this case, there exists only examples for solving.

The elements that define an ANN are represented by the following: an architecture (meaning the placement of the functional and the connections between them), the functioning (that defines the way the network transforms the input signals into the output signals), adapting or learning (signifying the way the parameters of the network should be modified, in order to obtain the estimated behavior of the network). Learning the way of the supervision and non-supervision will mean the modification of parameters, and/or of the structure of the network until the responses of the network will enough closer to the real ones.

The main applications of ANN are: classification and recognition; grouping and classification of data; approximation and estimation; prediction; optimization; storing and finding the information in accordance to the content; processing and analysis of signals.

The main models of ANN are represented by:

a) The model of the biological neuron – the neuron receives information by means of dendrites, and under the form of nervous pulses of electric type; if the amount of the inputs exceeds the threshold of activation, an action potential is generated, which is transmitted by means of the axon;
b) The model of the artificial neuron – functional unit that receives input signals from other units of which this is connected, it processes them and then sends the signal forwards.

The steps included within the design of an ANN are explained by: establishing the initial architecture adapted by the issue solving; choosing the learning algorithm, depending upon the network structure and the information amount that has to be processed (an algorithm for supervised learning, WTA, meaning winners take all, and the ART, meaning the adaptive resonance theory, within the self-organization networks); network training (calculation of outputs, errors and of modifying the weights, depending upon the algorithm); network validation, by checking the outputs, when values outside the training set will be introduced.

3.2. The use of Genetic Algorithms in optimizing neural networks

The Genetic Algorithms (abbreviated as GA) are used in order to evaluate a population of possible solutions, by using the biological inspiration as regards the natural selection. As a matter of fact, such evolution is a method of choosing from a lot of possibilities the most adequate solution for the given conditions.

The living bodies are formed of cells and each cell includes a set of chromosomes, which are decomposable in genes. As regards the revolutionary computing, we define the chromosome as a candidate of the problem's solution, which is coded under the form of bits (0 and 1). The genes are formed of many bits adjoining, which encrypt a candidate element at the problem's solution.

In order to choose the set of potential solutions as being the best, the GA use operations such as: selection, meaning an operation that allows chromosomes selection for reproduction; mutation, meaning that a bit is randomly changed within a chromosome; crossing, combining the characters of two individuals – parents, in order to create other two chromosomes that inherit a part of the features.

As regards the process of using the GA, the following should be mentioned: the way each solution of the quest area has a chromosome associated; the size and way of people initialization; the mechanism of parents selection; the mechanism of crossing; mechanism by which chromosomes that will survive are determined; the criteria of stopping the algorithm.

In accordance to these specifications, the following stages are processed (Koza, 1992): a codification is established; a population of chromosomes is randomly chosen; the degree of matching with the aimed solution is calculated; one repeat the set of steps, until the new population of chromosomes (a pair of chromosomes is selected from the already existing people, meaning a selection of replacement) is achieved; crossing process is carried out; a mutation operation is applied, and individuals resulted into a new population will be placed); the old people is replaced with the new one; the second step is restarted, up to reaching the stopping criteria.

4. A comparative analysis of the portfolio management for a global index in turbulent/ crisis periods

The aim of this application consists in comparing the performance of a global portfolio based on fundamental analysis and a neural network based portfolio. Training eight neural networks (for eight world indices) was carried out by using historical data (2007- 2010), in order to estimate a prognosis for the future performances at the end of the month in 2011.

The steps carried out have included: the identification, recovering and processing of data used in training, validation and prognosis; establishing the GA network based architecture; preparing the input vectors; network training; foreseeing the most profitable index and modifying the portfolio; analysis of the resulted performance by applying the two strategies.

A neural network is created and trained, as emphasized in the current paper, by using the already known data, so as to estimate the performances and to allocate the optimal index. The optimal architecture is based on a GA. The network is endowed with a hidden layer, an input layer and the output layer; the number of neurons per input/hidden layer is selected by using a GA. The output layer is endowed with just one neuron. Determining the optimal architecture of the network is carried out based on the following algorithm: the network training period is established; generating a population formed of four chromosomes, each of two genes; estimating the performance of each chromosome (with an error as less as possible); maintaining the best chromosome and modifying the rest of the population; determining the most notable chromosome, by using GA techniques (selection, mutation, crossing), at which a population complies within the evolution process; in order to select chromosomes, the method of roulette is used; a procedure of crossing into a single point is used (p=0.55).

The performance function of a chromosome trains a network endowed with a set of values, specific to an index, and from where the error between foresight and the real value of the index results. In this way, the population will evaluate, by maintaining finally the most notable chromosomes. The architecture given by the chromosome with the highest performance is maintained, and an index will be foreseen within this basis.

In order to underlie the decision of the global portfolio assignation, the network is trained in accordance to the following algorithm: creating the chromosomes population; for each index; for each month of 2011, the values of 2007-T are taken from the database; generating a population of four chromosomes (each having two genes Ni, Nh, integers generated randomly within values 1 and 20); for each chromosome, the performance function is calculated, function that is given by the network error; loading the best network; computing the index foresight and selecting the most notable index.

5. Conclusions

The aim of this paper consists in analyzing the impact of using the artificial intelligence tools within the portfolio management. Regarding from various strategies of portfolio management point of view, the neural network tools were selected in order to create an optimal global portfolio, during a turbulent and full of crisis period, where most of the investment funds suffered significant losses.

The disadvantage of using the artificial networks is represented by the output, which results within a process that cannot be either decomposed or analyzed. As regards the process training, a risk of extra-learning might take place (the network can learn quite well the vectors of training, with a single case and can lose the advantage of generalization). A solution of preventing such phenomenon is given by the moment of combining the neural algorithms with the fuzzy techniques. Another issue might be the fact that neural algorithms can stop within the process of error minimization within a local minimum. The non-linear transfer functions of the multilayer networks do not offer enough explanations concerning their output or any data consistency as regards the given answer; therefore, these would be difficult to be tested.

Future research will focus towards: using techniques of reducing the data processing times, by means of parallel computing libraries; using some variants of the back propagation algorithm implemented at the libraries level; testing some new mechanisms of weights initialization; using less volatile data (especially in disorderly periods, as those under analysis).

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