

Application of Artificial Intelligence and Data Mining Techniques to Financial Markets

Využití technik umělé inteligence a dolování dat na finančních trzích

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Abstract

The aim of artificial intelligence is to discover mechanisms of adaptation in a changing environment with utilisation of intelligence, for instance in the ability to exclude unlikely solutions. Artificial intelligence methods have extensive application in different fields such as medicine, games, transportation, or heavy industry. This paper deals with interdisciplinary issues – interconnection of artificial intelligence and finance. The paper briefly describes techniques of data mining, expert systems and agent based computation intelligence and specifies the types of tasks solved by these techniques in the context of financial tasks. It provides deeper insight into potential usage of intelligent systems on financial markets.

Keywords

artificial intelligence, data mining, financial markets, forecasting, stock exchange

Abstrakt

Cílem umělé inteligence je objevit mechanismy adaptace v měnícím se prostředí s použitím inteligence, například ve schopnosti odmítnout nepravděpodobná řešení. Metody umělé inteligence mají rozsáhlé využití v nejrůznějších oblastech jako medicína, hry, doprava a těžký průmysl. Tato práce pojednává o interdisciplinární problematice - propojení umělé inteligence a financí. Práce ve zkratce popisuje techniky dolování dat, expertní systémy a výpočetní inteligenci založenou na agentech a specifikuje typy úkolů řešené pomocí těchto technik v kontextu finančních problémů. Přináší hlubší pohled na možné využití inteligentních systémů na finančních trzích.

Klíčová slova

umělá inteligence, dolování dat, finanční trhy, prognózování, burza cenných papírů

Introduction

Current economics requires a prompt and accurate decision-making process in a constantly changing market environment. There is an increasing tendency in the usage of information technologies in the decisions of economic subjects. Traditional statistic methods are in recent times often complemented by methods of machine learning. The potential of applied machine learning rests not only in prompt and reliable performance but also in its ability to discover hidden knowledge in huge amounts of data. Decision making with artificial intelligence support can partly eliminate the bounded rationality of a decision maker to make better decision with more relevant data and information.

Artificial intelligence deals with problems of classification, prediction and optimization incorporating processes that can be called intelligent in decision making etc. where the problems cannot be simply formalised. These problems are typical also for economics and therefore there is a potential in usage of artificial intelligence techniques in this field.

The main goal of this paper is to point out the artificial intelligence techniques that can be utilised in financial application and to provide an overview of research undertaken in this field. The paper is aimed toward an economic audience unfamiliar with artificial intelligence techniques and may consider utilization of these techniques in further research.

1 Data Mining and Artificial Intelligence

Data mining is defined as the process of extracting valid, previously unknown, comprehensible, and actionable information from large databases and using it to make crucial business decisions (Simoudis, 1996). Data mining is considered as the key process of Knowledge Discovery in Databases (KDD) (Seifert, 2004). The main data mining techniques are Classification and Clustering analysis, Time-series mining, and Association rules mining (Johnson, 2011).

Data mining techniques are mostly based on statistics, as well as machine learning while the patterns may be inferred from different types of data. Methods used in data mining, such as machine learning, belong to the field of artificial intelligence.

Artificial intelligence (AI) systems are designed to adapt and learn. The first definition of AI is based on the Turing test. Alan Turing undertook a test of a machine's ability to demonstrate intelligence. It proceeds as follows: a human judge engages in a natural language conversation with one human and one machine, each of which tries to appear human. The aim of the judge is to distinguish human from machine, only on the basis of conversation (without visual or other help). When the judge cannot distinguish between human and machine, then the machine may be considered as intelligent.

The AI approach can be split into two main approaches – Symbolic (Conventional) AI and Sub symbolic AI (Computational intelligence). Conventional AI uses logic and rules to make decisions. Examples of conventional AI techniques are expert systems and Bayesian networks. It is a top-down approach. Computational Intelligence (soft computing) takes inspiration from biological mechanisms and uses a bottom-up approach. Examples of computational intelligence techniques used in economic application are neural networks, genetic algorithms, fuzzy systems etc. (Johnson, 2011).

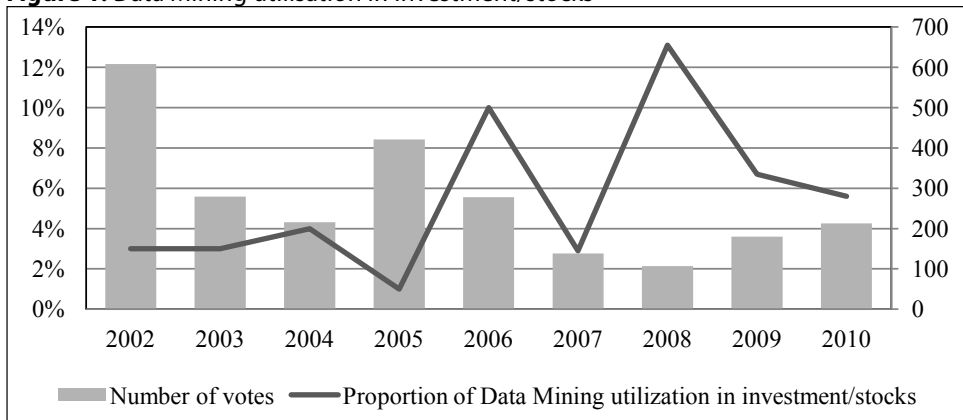
2 Application of Data mining on Financial Markets

According to a poll undertaken by KD Nuggets in 2010 (Figure 1) there was an increasing trend in utilizing data mining techniques in investment until 2008.

Recent research concerns the design of quantitative trading tools based on data mining techniques. Data mining can help to find associations between assets and create forecasting models based on wide ranges of data. Utilizing historical data; short-term exchange rates (Buryan, P., Taušek, J., 2008); interest rates (Liberopoulou, 2006); and stock prices (Shaaf, 2000) can be forecasted. Tung et al. (2003) adopted a simple trading strategy of support and confidence on 10 stock exchange indexes. Association rules have been found to be useful in stock prediction as a form of classification task.

Text mining is also a useful tool for solving the problem of stock price prediction. Schumaker and Chen (2009) applied statistical machine learning methods on financial news. The main goal of proposed technique was to learn what article terms from Yahoo Finance are going to have an impact on stock prices of companies listed in the S&P 500, how much of an impact they will have, and then make an estimate of what the stock price is going to be 20 minutes into the future. To test the effectiveness of proposed system they arbitrarily selected a group of experts and funds for comparison. Their simulated trading return was 8.50% which outperformed S&P 500 index, well known trading experts and top 4 quantitative mutual funds of 2005.

Figure 1: Data Mining utilisation in investment/stocks



Note: Number of votes depicts the absolute number of data miners participating at the poll and the percentages are relative to the number of voters

Source: KDnuggets Pool, 2010 [Online]. [s.a.]. [Cit. 2010-02-01]. Available at: <<http://www.kdnuggets.com/polls/2010/analytics-data-mining-industries-applications.html>>

Data mining tools are very interactive, easy to understand visually and require low investment cost while they enable identification of significant anomalies which require further examination. Their high potential on financial markets is proved, but utilization of data mining requires attention in data pre-processing. Apparent outliers may in fact be genuine and back-filling of missing data may be needed. It is important to prevention overfitting data and therefore useless in out-of-sample analysis (Johnson, 2011).

3 Application of Artificial Intelligence on Financial Markets

3.1 Expert (knowledge) Systems (ES)

An expert system is a computer-based system with artificial intelligence that emulates the reasoning process of a human expert within a specific domain of knowledge. Expert systems are based on explicitly formulated special knowledge obtained from experts to achieve decision on the expert level (Feigenbaum et al., 1988). The aim of an expert system is not modelling the mental processes of human experts during a decision process but achievement of high quality decision. Expert systems have to provide recommendation even when part of the required data is not available. This requires databases with multiple or alternative inferences. In addition these partial conclusions may be explained by expert system and appropriate additional question may be provided (Mařík et al., 1997).

The study by Collopy and Armstrong (1992), developed a rule base to make annual extrapolation forecasts for economic and demographic time series on M-competition data. Their rule-based expert system produced more accurate forecasts than the random walk and equal-weights combined. They performed better, particularly in long term periods for series with significant trends, low uncertainty, stability and good domain knowledge. Korczak and Lipinsky (2004) compared two real time trading systems using Stochastic Oscillators, Relative Strength Index and Ease of Movement. The first system was based on 350 trading rules and the second on 150 trading rules created by linear combination of the first system. The experiment was realized on Paris Stock Exchange and they found out that reducing the trading rules reduced the computation time without considerable influence on expertise quality.

One of the main advantages of expert systems is that they allow combination of different knowledge sources. The expert system is able to provide permanent documentation of decision making process and overview of all steps.

On the other hand in comparison to human experts the expert system must be explicitly updated and can't draw analogies from other sources to solve newly encountered problems (Liberopoulou, 2006).

3.2 Artificial Neural Networks (ANNs)

Artificial Neural Networks are composed of simple elements operating in parallel. Likened to a biological nervous system the function of ANN is determined largely by the connections between elements. With explicit knowledge about target values the network is able to "learn" by adjusting the values between connections (weights between elements). ANNs are widely used to solve problems of classification, prediction, and control (Hlaváček et al., 2005).

The main advantage in utilizing ANNs is their ability to capture nonlinearity without prior knowledge about functional relationships between variables. ANNs operate as „universal approximation systems“ with the ability to mimic almost any function dependency. They are resistant to outliers and do not require a specific distribution. In comparison to econometric models ANN give results in a shorter time period. By employing ANN the weight

and parametric system are adjustable and it is possible to work with a given degree of accuracy (Fanta, 2001).

The drawback in ANN application is the absence of a standard paradigm to design the network. For ANNs, the main disadvantage in utilization is described by the concept of the “black box”. It is difficult to identify the influence of a selected input variable upon the output (Fanta, 2001). When using ANNs a data set of sufficient length is required to prevent overfitting the network during a learning phase (Gonzalez, 2000).

Neural networks have been successfully applied to solve problems of generalization in prediction of corporate bond rating, where traditional mathematical modelling techniques performed weakly (Dutta et al., 1988); (Chaveesuk et al., 1999); (Manzoni, 2004).

Kim et al. (2009) modelled a system evaluating the current time series against the past stable time series by stationary autoregressive model via artificial neural networks. The potential of the proposed model was demonstrated on the Korean stock market.

ANNs are widely used by central banks to forecast the interest rates and the monetary policy of governments (Hlaváček et al., 2005). Utilization of ANNs is common in research regarding inflation forecasting (Haider, 2009); (Choudhary et al., 2008); (Mc Nelis, 2004); (Moshiri et al., 2000); (Nakamura, 2005); and they are mostly focused on prediction accuracy comparison with econometric models (Haider, 2009); (Hlaváček et al., 2005); (Choudhary et al., 2008); (Mc Nelis, 2004); (Moshiri et al., 2000).

Table 1 depicts the comparison between forecasting accuracy of ANN and ARIMA models using MSE on data of the U.S. GDP deflator from the first quarter of 1960 to the third quarter of 2003. The ANN models performed well relative to ARIMA models in the first two quarters on test set. While the early stopping approach was preferable for short horizon inflation forecasting, the advantage disappeared for longer horizon.

Table 1: Ratio of Neural Networks to AR Models

	Test set					Training/validation set			
	Forecast horizon (quarters)					Forecast horizon (quarters)			
	1	2	3	4		1	2	3	4
AR1	0.84	0.77	0.98	1.20		0.85	0.77	0.77	0.72
AR2	0.89	0.84	1.04	1.18		0.86	0.81	0.81	0.73
AR3	0.90	0.83	1.01	1.15		0.90	0.85	0.81	0.73
AR4	0.90	0.82	0.96	1.12		0.90	0.85	0.83	0.72
AR5	0.93	0.80	0.94	1.07		0.90	0.87	0.82	0.72
AR6	0.86	0.79	0.91	1.04		0.92	0.86	0.82	0.72
AR7	0.77	0.75	0.84	0.98		0.94	0.87	0.84	0.74
AR8	0.77	0.73	0.83	0.91		0.93	0.88	0.84	0.76

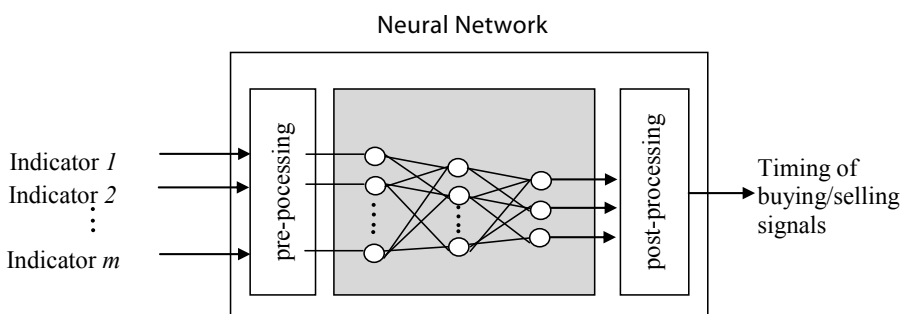
Note: Each cell shows the ratio of the Mean Square Error of the Neural Network model to the Mean Squared Error to the Auto Regression model.

Source: Nakamura, 2005.

Other research proves that neural networks perform better particularly in long term periods (Moshiri et al., 2000). Higher accuracy in long-term periods was proven also on forecasting of GDP (Tkatz et al., 1999), GNP and unemployment rate (Feinbaum et al., 1988) in comparison to nonlinear regression models. The suitability of ANNs is examined also on time series of financial markets. The researchers are mostly focused on Forex (Gabbi et al., 2000); (Chen et al., 2008); (Kiani et al., 2008); (Nagarajan et al., 2005).

Recently there has been an abundance of research attempting to forecast the price levels of international stock market indices (Egeli et al., 2003); (Gençay, R.; Stengos, T., 1998); (Safer, 2003). Extensive research is concentrated on utilizing indicators of technical analysis as input variables into ANN (Chen et al., 2008); (Mizuno et al., 1998); (Nagarajan et al., 2005); (Yao et al., 2000). The results demonstrate that indicators of technical analysis as inputs into ANN improve the forecasting accuracy although they are only statistical calculations of previous stock prices. Figure 2 depicts the process of data transformation in ANN applied on Tokyo Stock Exchange.

Figure 2: Prediction system composed of ANNs and indicators of technical analysis as inputs into network on TOPIX



Source: Mizuno et al., 1998.

Nagarajan (2005) utilized besides indicators of technical analysis also indicators of fundamental analysis (inflation, interest rates, etc.) but he did not achieve better performance in next day forecasting of USD/GPB exchange rate. Incorporating indicators of fundamental analysis had a negative impact on forecasting accuracy measured by mean error. The highest returns were achieved by forecasting direction of price movement not in specific price level.

Chen et al. (2008) set up a hybrid model containing three neural networks for short-term, midterm and long-term forecasting of TWD/USD exchange rate. For short and midterm period indicators of technical indicators were utilized (*Stochastic Oscillator, MACD, DMI, MA, Momentum, Williams Overbought/Oversold Index* and *RSI*) while for long-term period monthly data of *Price Levels, Interest Rates, Money Supply, Export/Import* and *Productivity* were used. Model based on monthly data had higher accuracy than models based on indicators of technical analysis. The hybrid model incorporating both indicators of fundamental and technical analysis achieved the best forecasting results (Table 2).

Table 2: Performance of Neural Networks with different input variables

Prediction model	Average	Standard Deviation
NN using indicators of fundamental analysis (FA) as inputs	59.58%	6.23%
NN using 15-day indicators of technical analysis (TA) as inputs	54.78%	4.26%
NN using 1-day indicators of technical analysis (TA) as inputs	49.26%	1.47%
NN using both indicators of technical and fundamental analysis	66.82%	4.21%
"random walk"	47.25%	4.97%

Source: *Chen et al., 2008.*

Research undertaken by Lam (2004) didn't validate the forecasting improvement incorporating macro economical input variables into ANN but she proved that utilization data from financial reports into input variables of proposed model exceeded the average rate of return on the market. This study demonstrates the advantage of uniting technical and fundamental analysis particularly in recession.

3.3 Genetic Algorithms

Genetic Algorithms (GAs) are a subset of Evolutionary Algorithms and are inspired by biology (Fanta, 2001). The main idea of genetic algorithms is to increase individual fitness value during the iterations of evolution process through application of genetic operators, such as mutation or crossover. It leads to evolution of individuals which meet given requirements, represented with so-called fitness function, better than their ancestors. Individuals in population are represented with chromosomes, which are often represented by binary strings but generally they may be represented by other value types. Genes, as parts of chromosomes, are related to specific characteristic of individuals.

The main advantage of GAs is that their application doesn't require any explicit knowledge about the target function. GAs are able to attain good performance within huge amount of potential data set. On the other hand it is difficult to select a sample of primary representative individuals, setting parameters and conditions of selection mechanism.

Genetic algorithms are used for solving optimization problems (for instance portfolio optimization) and problems of retrieval.

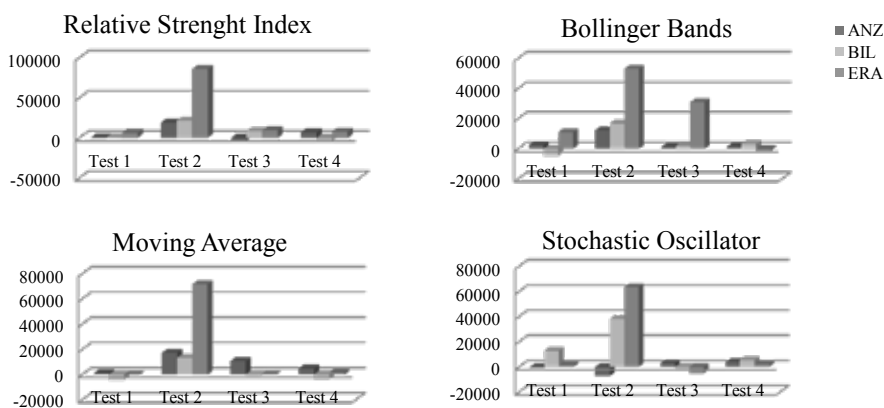
Baba et al. (2003) attempted to improve technical analysis applying intelligent systems to make decisions. They utilized 13 and 26-weeks moving averages and techniques of genetic algorithms to form a trading system on NIKKEI-225 and TOPIX. Undertaking a huge amount of computer simulation they achieved better performance using only technical analysis techniques without GAs.

De la Fuente et al. (2006) tried to optimize timing on stock market by automatized trader. They applied genetic algorithm on daily data 2004-2005 of a Spanish telecommunication firm. The decision making was based on indicators of technical analysis (RSI, MACS and Stochastic Index). The fitness function was set up on a rule that unfound data got the worst assessment. Chromosomes that occur repeatedly were evaluated as positive.

This study evidences the possibility of beating the market by application of genetic algorithms.

Ni and Zhang (2005) set up a trading system using GAs and Technical indicators. Figure 3 depicts the results of their models tested on data from 1997 to 2005 on selected indicators of technical analysis. Although their research did not affirm unambiguously higher profitability using trading strategy based on GAs than buy&hold strategy, they concluded that GAs contribute to quick identification of the limitations of strategies based on technical analysis.

Figure 3: Gaining profit/loss (in USD) using Genetic Algorithms based on indicators of technical analysis on Australian indices ANZ, BIL and ERA



Source: Ni; Zhang, 2005.

Genetic algorithms have been used for solving problems of optimization in research undertaken by Hirabayashi et al. (2009). They tried to increase the short term return of investment on Forex by trading systems using GAs. Their objective was to implement an evolutionary system able to learn nuances of trading rules from historical data and adapt to the changing market environment. The learning system is looking for buying and selling signals that combine indicators of technical analysis and their parameters with highest returns. The training set was created using hourly exchange rates of USD/JPY. They achieved a strong tendency of similar behaviour to real exchange rates using four indicators (RSI, MA, EWMA_M and Percent Difference from Moving Average) and a genetic algorithm. The proposed method distinguishes high gain in period of rapid decline of prices caused by collapse of Lehman Brothers. The research validates the ability of techniques of machine learning to gain profit in recession. They found that trend following strategies increase the probability of attaining high return in a short-term period.

Gorgulho et al. (2009) employed GAs to create a portfolio from 100 equities forming index S&P. They applied six indicators of technical analysis (MACD, Hull MA, EMA, ROC, and RSI) to set up a portfolio. They created a new portfolio at the beginning of each month and at the end of the month they closed the positions. The portfolio return was evaluated by Return of Investment. During the trading period they set up a buy&hold strategy and port-

folio based on random selection of stocks into a portfolio during the period 02/01/2005 – 02/01/2005 to compare the performance of the proposed models. The portfolio forms' highest return was achieved by GA.

GAs have been successfully applied for timing the trading position in combination with candle sticks analysis (Belford, 2006). The result of the proposed system was compared with return of agent designed to make random investment strategies.

3.4 Fuzzy Systems

Fuzzy systems are expert systems coming out from fuzzy logic. Fuzzy logic measures uncertainty from membership values in the range $\langle 0.0, 1.0 \rangle$ with 0.0 representing absolute Falseness and 1.0 representing absolute Truth. In comparison to probability theory the fuzzy logic does not assume that the sum of occurrences is equal 1. The degree of membership is not explicitly defined and fuzzy set enable work with linguistic variables like probably, maybe and enough.

The scheme of the fuzzy system consists of three steps – fuzzification, fuzzy inference and defuzzification. The whole process starts with fuzzification which is the transformation of real data to fuzzy data. Then the fuzzy logic system is used to make fuzzy inference, usually based on *IF...THEN* rules, and then the fuzzy data are transformed back to real data.

Fuzzy systems are well suited for decision making tasks characterized by uncertainty and therefore they are well suited for application in financial markets when decisions about volume of buying/selling of underlying assets are undertaken. Fuzzy systems used to be utilized in combination with other artificial intelligence techniques. For instance the genetic algorithm based on fuzzy neural networks was applied to form a database for investigating quantitative effects of different events (e.g. political events) on stock markets (Kuo et al., 2001). Romahi and Shen (2000) built an expert system based on evolutionary rules for financial forecasting. They put together fuzzy logic with inductive rules to create a system with the ability of generalization.

Neural networks based on fuzzy rules have been applied to forecast stock market returns many times in research. Ang and Quek (2006) proposed a trading system based on moving average rules which achieved higher paper return than a random trading system. Similar approach of Fuzzy Neural Network (FNN) based on trading rules utilizing fundamental data of 32 companies employed Wong et al. (1992). Kuo (1998) applied a FNN utilizing both quantitative and qualitative factors to set up a decision support system on the Taiwan stock market and achieved better results than single ANNs.

Gil-Aluje et al. (2011) proposed a new framework of portfolio management based on some topological axioms to select the titles of a portfolio. Homogeneity according to some attributes was established to extract one or several titles of each subset in order to get the desired properties. The designed system generalized previous algorithms for portfolio selection.

The main advantage of fuzzy systems is their capability to solve problems with abstention of strict boundaries, vaguely defined concepts and without strict. Every rule within a fuzzy system is easy to understand and revise (for instance *IF* the costs are high *THEN* the manufacturing process is inefficient and vice versa) (Pathak et al., 2003). The disadvantage of fuzzy systems is that they require knowledge about the problem solved.

3.5 Agent-based Computational Economics (ACE)

The economy can be described as a complex adaptive system with the capability to adapt to the external environment. The agents operating in the economy adjust their behaviour to the system without realizing this adaptation. Economic agents' are thinking about their actions and about the consequences of their actions and they adjust their behaviour with concern for these aspects. They form the notion of the system they belong to (Umpleby, 2007) and their behaviour influences the whole system.

From the notion of economy as a complex adaptive system emerges Agent-based Computational Economics (ACE). ACE is a bottom up system forming models of agents and interaction rules which lead to setting up the whole system using simulations (Bruun, 2006). Within this modelling approach the structure evolves without forcing any presumptions upon it. The resulting ACE models must be dynamically complete - the modelled economic system must be able to develop over time solely on the basis of agents' interactions without further intervention from the modeller.

ACE is based on bottom-up approach and requires specific features. Therefore financial markets are a challenging field for ACE application due to high data accessibility and clearly specified goals of agents.

Early researches of artificial agents are based on zero intelligent agents. Le Baron (2000) investigated the efficiency of zero intelligence traders on artificial foreign exchange markets and he found that budget allocation of these agents was similar to human agents. In other studies simulations with more sophisticated agents have evolved. Raberto et al. (2003) set up a model where trading strategies of agents were based on technical trading rules and fundamental values. Kendall and Su (2003) utilized agent based approach on five selected stocks from London Stock Exchange. Trading behaviour of artificial agents was based on indicators of technical analysis. This study demonstrated stable and satisfactory learning abilities of artificial traders. Different learning behaviour related to the different stock price patterns was discovered; an important finding for further research in portfolio selection. Kumar and Bhattacharya (2009) used multi agent approach for portfolio selection and they achieved higher average returns across one month, two months and three months out-of-sample period than the FTSE 100 index.

Viewing markets as very large aggregations of agents with heterogeneous beliefs and goals often reveals very different perspective on traditional theoretical thinking. The main advantage of ACE modelling is the ability of a system to create autonomous agents with more realistic capabilities – they are able to communicate, adapt to an external environment according to previous experiences, mimic, create and maintain patterns of social behaviour etc. These features are based on internal processes which are hidden from

other agent from the external environment. It leads to unpredictable and uncontrolled behaviour of the agents in relation to their external environment. ACE models increase the transparency and clarity of the modelling process and complement analytical and statistical modelling approaches.

The relative disadvantage of ACE modelling is that it requires detailed specification for agent data and methods determining structural attributes, institutional arrangements, and behavioural dispositions. If the agent interactions induce sufficiently strong positive feedbacks, small changes in initial specifications could radically affect the types of outcomes that result. (Tsfatsion, 2005). It is also difficult to get empirical evidence of results obtained by simulation.

Conclusions

Studies offers supportive evidence for suitability of use artificial intelligence methods in various economic applications according to their ability to process nonlinear relationships, ability to learn and evolve in time and also ability to make decisions at expert level.

Genetic algorithms are used for optimization problems – optimization of stock market timing and portfolio creation. When solving prediction problems, genetic algorithms are used in combination with other methods of artificial intelligence. Data mining tools can be used for creation of quantitative tools for short-time prediction of exchange and interest rates. Expert systems try to make decisions on the expert level and they are applied in analysis of securities as well as in company assessment. If we have an uncertain notion of the methods leading to a decision (what is typical for human decision makers), fuzzy systems could be the appropriate solution. Fuzzy systems are used mainly in insurance. In recent years the Agent-based Computational Economics has emerged. Current ACE concentrates on financial market modelling. The approach of Artificial Neural Networks is put into effect thanks to their ability to study the nonlinear relation between variables and their ability to work with uncertainty. They are frequently used for solving prediction problems – forecasting macroeconomic indicators and time series prediction on financial markets.

In following research we would like to focus on analysis of the dependency between fundamental and technical analysis of securities using artificial intelligence.

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