FINANCIAL MARKET FORECASTUSING ARTIFICIAL INTELLIGENCE

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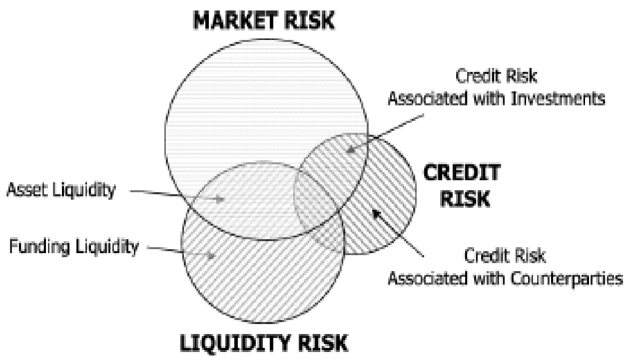
Summary

The study of financial systems requires methods of analysis and simulation with some intelligent systems for application to risk assessment and forecast infinancial market area. The most common applications of computational finance are within the area of investment banking and financial risk management, and currently employ learning methods such as Support Vector Machines, Bayesian approaches, Logistic Regression, Artificial Neural Network, Fuzzy Logic and Genetic Algorithms, Ant colony and Particle Swarm Optimization. Financial market can be considered as multi-agent systems.The research was focused on the new approach of financial market risk forecast and assessment based on Agent Modeling Paradigm. The aim of the paper is to discuss the application of artificial intelligence methods to computing the financial market risks.

Keywords: Financial Market Risk. Particle Swarm Optimization. Data Clustering.

1. Background

Relevance of problems. Financial Market is a confluence of several disparate fields such as finance and risk management, information technology, communication technology, computer science, and marketing science.Any financial institutions such as banks, leasing companies, investment and pension funds are subject oriented to making successful financial market policy. In this paper we discuss the application of intelligent methods to financial areas including forecasting, portfolio optimization, risk management, agent-based market modeling and etc.



Risk management is a critical aspect of the investment decision. Some of the main types of risks faced by investors are illustrated in Fig.1 below [1].

Market risk refers to the risk faced by an investor arising from changes in financial market prices. *Credit risk* is the risk that the counterparty to a deal fails to perform their obligations. *Liquidity risk* is the risk of negative effects on the financial result and capital of the bank caused by the bank's inability to meet all its due obligations.

Fig.1. Risk illustration

2. Financial Market as aMulti-Agent System

During recent years, the use of modern approaches in the financial and economic industries have increased substantially, providing a new perspective to the agenda of finance and economics. The study of complex financial systems, form viewpoint of financial risk management, requires methods of analysis and simulation with some complex systems methodologies for application to risk assessment and forecastingof trend in the financial market area. Prediction and forecast of financial market risks is an important issue in finance.

In this section, we will point out that multi-agent models can be seen as an alternative view on financial markets that supplements the theory of informational efficient markets [2]. Multi-Agent Systems, also called Swarms of Agents or Societies of Agents, are systems capable of achieving their goals through the interaction of constituent agents.

Probably the most important design issue of a multi-agent approach is the modeling of the agents. In the simulation, different agents are used to capture the heterogeneityof restructured markets.

Agents are self-directed objects with specific traits. Agent-based Approach is a new modeling paradigm and is one of the most exciting practical developments in modeling since the invention of Artificial Adaptive Agents models based on Artificial Intelligence methods [3]. Market performance may depend on the degree of "intelligence" or "rationality" of the agents buying and selling, which has led to computer experiments in which trading occurs between artificial agents of limited or bounded rationality, as discussed further below.

The ABMS modeling system provides the ability to the complex relations between Intelligent Agents, which generally are computer programs that are capable of accomplishing their goals under conditions of uncertainty through the interaction with other intelligent agents.

The most common applications of computational finance are within the area of investment banking and financial risk management, and currently employ learning methods such as Support Vector Machines, Bayesian approaches, Logistic Regression, Artificial Neural Network, Fuzzy Logic and Genetic Algorithms, Expert Systems and Intelligent agents, Ant colony and Particle Swarm Optimization. They are often used in combination with each other.

Agent-Based Market Modeling. The essence of Agent-based Modeling (ABM) lies in the notion of autonomous agents whose behavior evolves endogenously leading to complex, emergent, system dynamics which are not predictable from the properties of individual agents. In designing ABMs of financial markets, NC methods can be used to model the information processing and storage by agents, the process of adaptive learning by agents, or to model the trading mechanism. A key output from the ABM literature on financial markets is that it illustrates that complex market behavior can arise from the interaction of quite simple agents. Carefully constructed, ABM can help increase our understanding of market processes and can potentially provide insights for policy makers and regulators. Of course, issues of model validation are important in all ABM applications including those in financial markets.

3. Related Work

It is well established that PSO gets better results in a faster, cheaper way compared with other methods of global optimizations. In [4], the authors had effectively applied PSO to select active portfolios under a constraint on tracking error volatility. Recently Computational finance has deeply benefited from Swarm Intelligence. In [5] the authors used an interesting approach for financial classification by tapping the potential advantages of both ACO and PSO.

The authors in [6] applied PSO in the problem of single variety option pricing and compared their experimental result with standard classical Black-Scholes model. In recent years, this research has been extended to complicated economy and finance systems. It is well known that economy and financial systems are very complicated nonlinear systems containing several complex factors. It is the developmental direction of economics to utilize the nonlinear dynamics, especially the bifurcation and chaos theory to study the internal complexity of economy and finance systems.

Multi-purpose parameter estimation methods play an increasingly important role in financial as well as insurance mathematics. There are some alternative estimation methods, especially martingale estimating functions proposed in[7], leading to consistent and asymptotically normal estimators.

The control of nonlinear chaotic system and the estimation of parameters is a daunting task till date. Studies on parameter estimation for chaotic systems have been investigated recently [8,9]. The authors in [10] developed an efficient strategies based on dynamic multiswarm particle swarm optimizer having swarms of small size and proved the effectiveness by applying it on a set of shifted rotated benchmark function. Recently, the authors in [11], presented a novel Drift Particle Swarm Optimization algorithm, and applied it in estimating the unknown parameters of chaotic system. Then another modified version of PSO was demonstrated by the authors [12], in the form of a parallel multi-swarm optimization algorithm with the aim of enhancing the search ability of the generic single-swarm PSO for global optimization of very large-scale multimodal functions.

4. Proposed approach

Based on the PSO paradigm, each of particles represents a potential solution to an optimization problem, navigate through the search space. The goal of algorithm is to converge to the global (over the search space) or local (into the particular cluster) optimum of a target function [13].

Algorithm flow diagram. Assuming that the set of particles with their parameters are given initial part of algorithm proceeds as follow steps [14]:

I. Initialize:

Particle Description.Each particle has three features:

p_k^i– Position (this is the *i-th* particle at time or step *k*, notice vector notation) with the coordinates:

$$p_k^i=[x_k^i, y_k^i], \qquad i=1,2, \ldots N.$$

The particles are assumed to move within the search space iteratively. This is possible by adjusting their *position* using a proper position shift, called *velocity*(similar to search direction, used to update the position) and denoted as: v_k^i

$f(p_k^i)$ – Fitness or objective (determines which particle has the best value in the swarm and also determines the best position of each particle over time.

The swarm is defined as a set:

$$P_k = \{p_k^i\}, \qquad i=1,2, \ldots N.$$

(a) Set parameters $N, c_1, c_2, x_{min}, x_{max}, y_{min}, y_{min}$, G, μ.

where: c_1, c_2 are weighting factors, called the *cognitive* and *social* parameter, respectively.

(b) Set $k \leftarrow 0$.

Initial Swarm.

(c) Generate N particles (in 2-D space) with random locations (positions with their coordinates) and “velocities” (the steps) for each particle.

$$p_0^i= p_{min} + rand(p_{max} - p_{min}). \qquad (1)$$

where:p_{min} and p_{max} are vectors of lower and upper limit values respectively.

Evaluate the fitness of each particle and store:

• particle best ever position (particle memory b^i here is same as p_0^i).

• Best position in current swarm (influence of swarm)

Initial velocity is randomly generated.

$$v_0^i=\frac{p_{min}+rand(p_{max}-p_{min})}{\Delta t}. (2)$$

II. Clustering:

(a) Fitness function$f(p_k^i)$ evaluation for each particle in given coordinates.

(b) Election the leader (or leaders) as best position and the outsiders in the cluster (or clusters).Given a set of leaders with their positions $l_r= \{p_k^i\}$,r=1,2, …M.

(c)Clustering of swarm (part of outsider particles around of each leader) by K-Means algorithm.

K-means clustering aims to partition the *N* outsiders into *M* sets:$L = \{l_r\}$, r=1,2, …M, so as to minimize the within-cluster sumsquare:

$$\underset{L}{\operatorname{argmin}} = \sum_{l_c=1}^{M} \sum_{p_k^i \in L} \left\|p_k^i - p_k^j\right\|^2$$

III. Updating:

(a) Velocity Update:

– Provides search directions.

– Includes deterministic and probabilistic parameters.

– Combines effect of current motion, particle own memory, and swarm influence.

$$v_{k+1}^{i} = wv_{k}^{i} + c_1 rand \frac{(\mathrm{p}_k^l - p_k^i)}{\Delta t} + c_2 rand \frac{(\mathrm{p}_k^g - p_k^i)}{\Delta t} \quad (3)$$

where:

w – inertia factor;

p_k^l – local best position;

p_k^g – global best position;

wv_k^i – current motion;

$\frac{(\mathrm{p}_k^l - p_k^i)}{\Delta t}$ – particle memory influence;

$\frac{(\mathrm{p}_k^g - p_k^i)}{\Delta t}$ –swarm influence.

(b) Position Update:

Position of each particle is updated by own velocity vector.

$$p_{k+1}^{i} = p_k^i + v_{k+1}^i \Delta t \quad (4)$$

Constraints: If a particle is infeasible, last search direction (velocity) was notfeasible. Set current velocity to zero.

$$v_{k+1}^{i} = c_1 rand \frac{(\mathrm{p}_k^l - p_k^i)}{\Delta t} + c_2 rand \frac{(\mathrm{p}_k^g - p_k^i)}{\Delta t} \quad (5)$$

© Memory Update:

At each iteration, after the update and evaluation of particles, best positions are also updated. Thus, the new best position p_{k+1}^g of leader l_{k+1}^r at iteration k+1 is defined as follows:

$$l_{k+1}^r = p_{k+1}^g = [x_{k+1}^g, y_{k+1}^g], \qquad r=1,2,\ldots M. \quad (6)$$

$$\mathrm{p}_{k+1}^g = \begin{cases} p_{k+1}^i & if\ f(p_{k+1}^i) \le f(\mathrm{p}_k^g), \\ \mathrm{p}_k^g & Otherwise \end{cases} \quad (7)$$

(d) Set $k \leftarrow k+1$.

IV. Stopping Criteria

Particles convergence (and entropy, respectively) metrics, as one of the criteria, can be defined by measuring the location or dispersion around the leader and is more convenient to use in some cases.

(a) Calculate the movement of the best position of leader:

$$\partial_{k+1} = |f(\mathrm{p}_{k+1}^g) - f(\mathrm{p}_k^g)| \le \mu \quad (8)$$

where:

μ - specified tolerance.

(b) Calculate the degree (or measurement) of convergence of particles into the cluster:

$$D = \frac{1}{N}\sum_{l=1}^{N} \sqrt{|p_k^i - p_k^j|^2} \le G. \quad (9)$$

where:

p_{k+1}^c - position of convergence central point

$$\mathrm{p}_{k+1}^c = \frac{1}{Q}\sum_{l=1}^{Q} \sqrt{|\mathrm{p}_{k+1}^c - \mathrm{p}_{k+1}^i|^2}, \quad i \ne j. \quad (10)$$

(c) Calculate the current value of function:

$$S = \partial_{k+1} + D \;\Rightarrow min. \quad (11)$$

(d) Stopping criteria satisfied?
If "Yes", go to IV (e).
If "No", go to III (a).

(e) Output results.

The above logic is illustrated as a flow diagram without detailing the working of the dynamic reduction parameters. Problem independent stopping conditions based on convergence tests are difficult to define for global optimizers. Consequently, we use a conditionally fixed number of fitness evaluations or swarm iterations as a stopping criteria.

5. Conclusion

This work is motivated by the idea to computing the financial market risks, whichcan be realized by continuously collecting particles from a financial market data warehouse. Relevance of problems is particularly pointed by the assessment and forecasting of fitness function, which consists of anuncertaintyand dynamism of financial processes. We have discussed different kind of metrics to particle swarm behavior. We defined some number of metrics such as convergenceof particles or entropy, which will help us in evaluation of performance of theswarming behavior.

References:

1. Bansal A. Kauffman R.J., Mark R.M. Peters E. Financial risk and financial Risk Management Technology. Information&Management (1993), 24, 267-281 North-Holland Center for Digital Economy Research Stern School of Business Working Paper IS-93-23

2. Ellerman D. Introduction to Property Theory. The Fundamental Theorems. World Bank. 2002

3. Holland J.H. Miller J.H. Artificial Adaptive Agents in Economic Theory. *The American Economic Review.* vol. 81, 1991. 365-370 pp.

4. Thomaidis N., Angelidis T., Vassiliadis V., Dounias G. Active Portfolio Management With Cardinality Constraints. An Application Of Particle Swarm Optimization. *Intern. Jou. of Computer Applications (0975 – 8887), vol.6– No.10, Sep., 2010 New Mathematics and Natural Computation (NMNC).* WorldScientific Publishing Co. Pte. Ltd. 5(03) : 535-555

5. Marinakis Y., Marinaki M., Doumpos M., Zopounidis C. Ant colony and particle swarm optimization for financial classification problems. *Expert Systems with Applications* 36(7) : 10604-10611. 2009

6. Jha G.K, Kumar S., Prasain H. Thulasiraman P., Thulasiraman R.K. Option pricing using Particle Swarm Optimization : *Proceedings of the 2nd Canadian Conference on Computer Science and Software Engineering* : 267-272. 2009

7. Bibby B.M., Sorensen, M. Martingale estimation functions for discretely observed diffusion processes, *Bernoulli* 1*(1/2)* : 017-039. 1995

8. He Q., Wang L., Liu, B. Parameter estimation for chaotic systems by particle swarm optimization. *Chaos, Solitons and Fractals,* 34 : 654–661. 2007

9. Tang Y., Guan X. Parameter estimation for time-delay chaotic system by particle swarm optimization.*Chaos, Solutions and Fractals,* 40 : 1391–1398. 2009

10. Liang J.J., Suganthan P.N. Dynamic multi-swarm particle swarm optimizer, *Swarm Intelligence Symposium,Proceedings IEEE* : 124 – 129. 2005

11. Sun J., Zhao J., Wu X., Fang W., Cai Y., Xu W. Parameter estimation for chaotic systems with a Drift Particle Swarm Optimization method. *Physics Letters* A. 2010.

12. Fan S.K.S., Chang Ju-Ming. Dynamic multi-swarm particle swarm optimizer using parallel PC cluster systems for global optimization of large-scale multimodal functions, *Engineering Optimization* 42(5): 431 – 451. 2010

13. Venter G., Sobieski J. Particle Swarm Optimization. AIAA 2002-1235, 43rd AIAA/ASME/ ASCE/AHS/ASC Structures,Structural Dynamics, and Materials Conference, Denver, CO. 2002

14. Kervalishvili P., Meparishvili B., Meparishvili T. *New Approche of Intelligent Techniques to Financial Risk Management.* SynEnergy Forum (S.E.F.) -2 The conference for International Synergy in Energy, Environment, Tourism and Information Technology. Spetses, Greece 24-26 September.

საფინანსო ბაზრის პროგნოზირება ხელოვნური ინტელექტის გამოყენებით

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რეზიუმე

რთული საფინანსო სისტემების კვლევა საჭიროებს ანალიზისა და მოდელირების მეთოდების გამოყენებას საფინანსო ბაზრის რისკების ხარისხის შეფასებისა და პროგნოზირებისათვის. საფინანსო რისკების მართვა შეიცავს ქმედებებს გადაწყვეტილების მიღების მხარდაჭერის, მონაცემთა შეკრების, მათი ანალიტიკური და სტატისტიკური დამუშავების, აგრეთვე პროგნოზირებისათვის. ყველაზე გავრცელებულ საინვესტიციო-საბანკო საქმიანობაში ფინანსური საგამოთვლო პროცესები და საფინანსო რისკების მართვის პროცესები შეიძლება განვიხილოთ მულტიაგენტური მოდელირების საფუძველზე, სადაც ხელოვნური ინტელექტის მეთოდების გამოყენება მნიშვნელოვნად ამაღლებს ეფექტურობას. მოცემული სტატიის მიზანია ხელოვნური ინტელექტის არსებული თანამედროვე მეთოდების მიმოხილვა საფინანსო ბაზრის რისკების მართვის ეფექტური მიდგომების ანალიზისა და შემუშავებისათვის.

ПРОГНОЗИРОВАНИЕ ФИНАНСОВОГО РЫНКА С ПРИМЕНЕНИЕМ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

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Резюме

Исследование сложных финансовых систем требует применения методов анализа и моделирования для оценки степени риска и управления в сфере финансового рынка. Управление финансовыми рисками включает действия систем поддержки принятия решений, вопросов аналитической обработки, статистического анализа, прогноза, и сбора данных. Наиболее распространенные применения финансовых вычислительных процессов в области финансовой деятельности, и финансовый риск-менеджмент можно рассмотреть на основе мультиагентного моделирования. Целью данной статьи является обзор существующих современных методов искусственного интеллекта для анализа и подбора эффективных подходов по управлению финансовыми рисками рынка.