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Dynamic Physical Behavior Analysis for Financial Trading Decision Support

Introduction

The application of physics to financial and economic problems is not a new paradigm. Many principles of physics have been employed to derive various models of financial engineering, such as the widely held random walk theory of stock price fluctuation which can be simulated by the Brownian motion, and the pricing model of options which applies the heat equation to closed-form solutions. Recently, quantum mechanics has been applied in market microstructure analysis to perform simulation [1] [2]. Further, statistical physics has been employed to simulate the probability and stochastic process in economic and financial issues [3] [4]. All of these have given rise to the study of physical phenomenon in economic and financial activities, which is termed "econophysics" [5].


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This article aims to discuss the application of computational intelligence (CI) techniques in combination with classical concepts in physics in devising investment strategies. In the analysis of investment strategies, many CI techniques are employed to predict market trends, such as the neural network (NN) [8] [9], the support vector machine (SVM) [10] [14], and particle swarm optimization (PSO) techniques [11]. Other techniques such as evolutionary computing (EC) and genetic algorithm (GA) are utilized to identify the knowledge rules of trading [12] [13]. However, changes in market behavior are dynamic and time variant. Thus, using a single CI technique can occasionally be better than traditional statistic models, but the trading models may pose risks from the changing market. Recently, the hybrid model and the data mining concept, which combine multiple CI techniques into multiple stages, have emerged to improve the trading model's stability and profitability [7]. For example, fuzzy logic is employed to differentiate the parameters in the first stage, and then similarity search is used for data clustering in the second stage.

A novel perspective for analyzing the dynamic physical behavior behind historical financial data is proposed in this article, which is focused on the movement or change in the future of a time series. This perspective differs from that of "econophysics" research, which focuses on analyzing dynamic physical behavior by stochastic process, such as geometric Brownian motion. The philosophical background for adopting dynamic physical behavior analysis originates from fundamental mathematics—the Taylor series expansion.

The Taylor series of a function $f(x)$, which is infinitely differentiable in a neighborhood of a number x_0, is the power series:

$$f(x) = f(x_0) + \frac{f'(x_0)}{1!}(x - x_0) + \frac{f''(x_0)}{2!}(x - x_0)^2 + \frac{f^{(3)}(x_0)}{3!} \times (x - x_0)^3 + \ldots, \quad (1)$$

which, in a more compact form, can be written as follows:

$$f(x) = \sum_{n=0}^{\infty} \frac{f^{(n)}(x_0)}{n!}(x - x_0)^n, \quad (2)$$

where $n!$ denotes the factorial of n, and $f^{(n)}(x_0)$ denotes the nth derivative of f evaluated at point a; the zeroth derivative of f is defined to be f itself.

First-order and second-order Taylor series expansions are mostly adopted because computing high-order derivatives in the Taylor series is very complicated. The Taylor series may also be generalized to the functions of multivariables. The first-order and second-order Taylor series expansions of a multivariable function can be written respectively as

$$f(x) = f(x_0) + \sum_{i=1}^{n} \frac{\partial f(x_0)}{\partial x_i}(x - x_{i0}) \quad (3)$$

$$f(x) = f(x_0) + \sum_{i=1}^{n} \frac{\partial f(x_0)}{\partial x_i}(x - x_{i0}) + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \frac{\partial^2 f(x_0)}{\partial x_i \partial x_j} \times (x - x_{i0})(x - x_{j0}). \quad (4)$$

Assume in a financial market that the price P is the function of two variables, x and y. According to the second-order Taylor series expansion, the differential of P can be expressed as

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Inspired by the philosophy of classical physics concepts and the Taylor series, the n-order derivative—which may be represented as dynamic physical behaviors such as velocity, acceleration, momentum [6], impulse, potential energy, kinetic energy, and so on—facilitates the analysis of the difference between cause and effect in financial dynamics.

$$\Delta P = \frac{\partial P}{\partial x}\Delta x + \frac{\partial P}{\partial y}\Delta y + \frac{1}{2}\frac{\partial^2 P}{\partial^2 x}(\Delta x)^2 + \frac{1}{2}\frac{\partial^2 P}{\partial^2 y}(\Delta y)^2 + \frac{\partial^2 P}{\partial x \partial y}\Delta x \Delta y. \quad (5)$$

The financial market price expressed in Taylor series expansion has been widely used in financial engineering, such as for the derivation of the Black-Scholes option pricing model, and for measuring the sensitivity of a bond's market price to interest rate movements by its duration and convexity.

Observed form Taylor series expansion, both sides of the equation can be recognized as cause-and-effect relationships. The right side of the equation signifies the cause, which will lead to the effect expressed in the left side of equation. Any numerical variation of the cause, including the first and second derivatives, will alter the value of the effect. This phenomenon is commonly observed in dynamic physical behavior, where the first derivative is often used to illustrate the momentum, and the second derivative often pertains to the impulse. Consequently, the traditional cause-and-effect analysis by qualitative methodology can be utilized instead of the quantitative approach by introducing the classical physics concept.

The difference between cause and effect is difficult to measure owing to the absence of an absolute criterion. A feasible approach involves transferring the cause and effect into a relative magnitude. Inspired by the philosophy of classical physics concepts and the Taylor series, the n-order derivative—which may be represented as dynamic physical behaviors such as velocity, acceleration, momentum [6], impulse, potential energy, kinetic energy, and so on—facilitates the analysis of the difference between cause and effect in financial dynamics.

When applying dynamic physical behavior analysis to financial trading, the relative magnitude of physical behavior measurement is derived by differencing time series, which reflects financial market dynamics. For example, when the first differencing of price time series, specifically the first derivative or slope which can be considered as the momentum, is positive, the price series is uptrend. Additionally, when the second differencing of price time series, specifically the second derivative or convex which can be considered as the impulse, is positive as well, the price series is still uptrend and will be sustained for a longer period as compared to a series whose first derivative is positive and whose second derivative is negative. Based on these mathematical principles, capturing dynamic physical behaviors for explaining social science phenomenon is a powerful tool in building the forecasting model under a nonlinear dynamic environment.

Three applications of financial investment decision are presented in the following section to illustrate the idea and process behind dynamic physical behavior analysis.

Selected Applications

Financial Time Series Analysis

The capability to look ahead and predict future trends is vital in making financial investment decisions. Time series models are preferred forecasting models adopted for financial markets. These models can loosely be classified into two categories. One is the linear model, which includes the simple regression method and the Box-Jenkins approach, such as the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models. The other is the nonlinear model, such as the generalized autoregressive conditional heteroskedasticity (GARCH) family models, which are most commonly used in economics and finance. These typical time-series models are known as parametric models as well. They are derived from stochastic processes, employing parameters to estimate the relationship between previous data points and following data points. However, a number of restrictions must be considered when applying the parametric modeling process. For example, the time series must possess stationary or time-invariant characteristic.

Majority of financial market price series are non-stationary and time variant. The returns series exhibits a fat-tailed and leptokurtic distribution. Consequently, when applying these typical time-series models to financial time-series data, the data must be preprocessed by transformation to fulfill the stationary request. In a case involving finance, the original price series is converted to return series by differencing; however, the property of the original price series may be eliminated. Instead of typical time-series models, using CI techniques to model time series is an alternative approach. Having emerged in recent decades, this is likewise known as the non-parametric model. The advantage of using a CI-based model is that the characteristics of time series are unrestricted. The nonparametric modeling approaches are capable of dealing with high nonlinearities and complex time-series data without conversion.

The relationship between the previous data points and the following data points of the time series can be considered as the cause-and-effect relationship. It is an extremely suitable modeling by CI techniques combined with dynamic physical behavior analysis. Financial market dynamics are affected by various factors in the real world. Forecasting the following data points according to previous data points is insufficient. Referencing more information which can describe the time series' behavior can help increase the accuracy of forecasting. Therefore, a number of related time series derived from differencing time series may be adopted to determine the relationship. The first-order difference of time series can represent price velocity, and the second-order difference can represent price acceleration. According to the Taylor series expansion concept, price series is composed of price velocity and price acceleration. Consequently, using the original time series accompanied by its first- and second-order differencing time series for CI-based models is believed to create more meaning.

Further, Taylor series expansion and dynamic physical behavior can extend the longitudinal data analysis of time series to cross-section data analysis. The most typical time-series models merely consider univariate analyses. However, CI models have the capacity to proceed to multivariate analyses. The first- and second-order differencing time series are dependent on the original time series and are treated as redundant in statistics. However, simultaneously considering these dependent time series is helpful in analyzing the state-space of the time series, which is similar to the state-space model for engineering and the spatial econometrics models [14] for the social sciences. Through this, time series can be expressed in state-space or vector form for using CI techniques in advanced analysis, which is difficult to perform using typical time series models, such as cluster analysis, pattern recognition, features retrieval, temporal data mining, knowledge discovery, and so on.

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Pricing Model for Financial Engineering

A number of studies have combined statistical physics with arbitrage pricing theory to assess the value of derivative instruments and design the pricing model for evaluating derivatives in the real world. However, the model structured on statistics seeks to determine the most possible price by using the probability distribution of statistics; the real price probability distribution does not always follow the hypothesized probability distribution. Applying the widely used European option pricing model, the Black-Scholes (B-S) model, as example, it is assumed that a stock's future price has a lognormal distribution. The assumption of probability distribution is based on geometric Brownian motion, and the solution of the partial differential equation in the B-S model utilizes the heat equation of physics. However, there exist disparities between the real price and the price calculated by the option pricing model. Therefore, a number of subsequent studies adopted a new probability distribution assumption and other numerical partial differential equations in an attempt to arrive at a more accurate pricing model. Accordingly, the jump diffusion model, binomial tree model, and other more accurate pricing models were developed. However, the option price can sensitively reflect the market trend in the future. These models only assume the distribution of a stock's future price and do not forecast the market

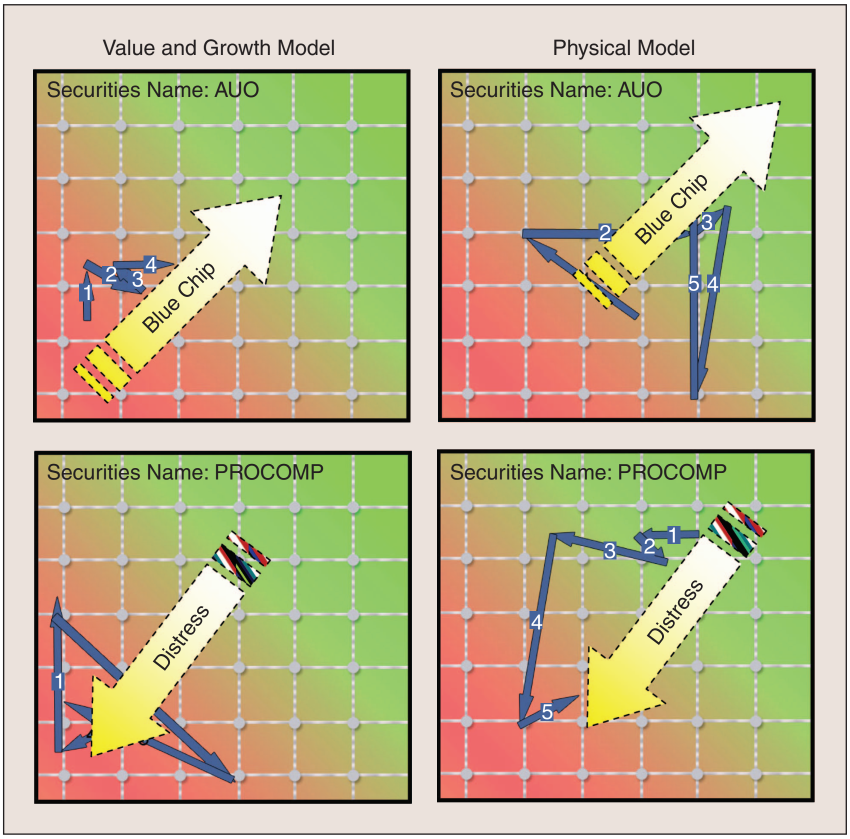

FIGURE 1 The visualized interface for cluster trajectory analysis of financial statements.

The main reason behind the use of CI techniques is to conduct qualitative analysis.

trend of a stock in the future. Thus, the option prices in the future are still difficult to forecast for making trading decisions in practice.

Neural networks possess non-linear regression capability in CI techniques, so they are tapped as methods for improving the option pricing model in a number of studies. In earlier research, the B-S model's output values were mostly utilized as the input values of the NN model [15]. However, comparing the results of the NN and B-S models, only in certain conditions would the pricing model's accuracy be superior to that of the B-S model. Further, in subsequent research, scholars learned that the estimation of implied volatility primarily influences the pricing of option. Therefore, recent studies have focused on assessing implied volatility [16] or proposing a new error correction model combined with the original B-S model [17] to improve the pricing model's accuracy or hedge efficiency [18].

Instead of directly adopting the basic theory model's original variables as input for the NN model, combining the output value of the basic theory model with the dynamic physical behavior as input can result in more advantages. The dynamic physical behavior is basically employed to describe the financial market's temporal and spatial environment, and it can be applied to evaluate implied volatility, modify the deviation of the B-S model, or improve the efficiency of hedging. For example, to correspond to price fluctuation in the real world, the original result computed by the B-S model can be combined with any other type of physical characteristic and be input into the NN model. With the exception of using the result of the B-S model as one of the input nodes, the commonly used indicators of technical analysis, such as the moving average convergence divergence (MACD) indicator comprised of a fast line, a signal line, and a histogram, can be inputted as well. These dynamic physical behaviors will undergo comparisons by computing the relationship of relative magnitude via supervised learning network. Thus, the NN model provides option price forecasting in the future, which assists the trader in estimating the differences between the B-S model price and the real market price, allowing them to devise sound trading decisions.

This approach can also be utilized in financial engineering tasks such as risk management, yield curve modeling, credit evaluation, pricing new financial instruments, and so on. The approach can provide several advantages, such as allowing the model developed from CI to retain its original traits of financial engineering theory. Further, in practical financial trading, the model can consider the market trend in the future and provide assessment references of the differentiated values between theory models and the real world.

Advanced financial engineering research focusing on volatility is a new direction for dynamic physical behavior analysis and CI techniques. When considering the delta hedge by option, using a specific number of days of historical data to estimate the applicable volatility in the future for option pricing is difficult. Using CI technique as an alternative approach, the volatility can be estimated by using data which have a similar pattern of dynamic physical behavior. In addition, even the estimation of volatility can be abandoned when the option delta hedge strategy is carried out. This is because the risk of option hedge can be directly assessed from historical data by using data mining techniques. Further, CI techniques combined with dynamic physical behavior analysis can ease the similarity search of time series.

Portfolio Management and Security Selection

The most fundamental issue of investment decisions, which is the most time consuming as well, is the formulation of a security selection decision. Whether performing tactical asset allocation or strategic asset allocation strategies, the key issue is selection of the portfolio's underlying assets. This is a common problem in practical implementation. For purposes of academic research, security selection issues are considered as the optimal portfolio problems or asset allocation problems. CI techniques have been applied to these problems, which employ fuzzy logic for portfolio optimization [19] [20], as well as GA [21] and PSO [22] in allocating assets to ensure that investment portfolios will gain the maximum profit with minimum risks. These studies often focus on the Markowitz portfolio theory and Sharpe ratio, which mainly address risks and return, or portfolio volatility according to historical market data. However, they failed to forecast the future of the market.

An investment portfolio consists of underlying assets, including securities, options, bonds, and mutual funds, to name a few. Each asset has different selecting criteria to process the allocation and management of portfolios, and to match the investment goal. As for stock investments, the growth investing strategy or value investing strategy is traditionally employed [23], considering its price-to-book (P/B), price-to-earnings (P/E), and price-to-sales (P/S) ratios. However, selecting stocks according to these indicators is difficult when aiming for stable profits in the future. Therefore, funds managers often set specific investment strategies in advance and select underlying assets based on these.

The equity long-short strategy is one of the most popular strategies that succeed regardless of whether the market also succeeds or fails. The market risk is hedged by taking both long and short equity positions. The simplest formulation equity long/short strategies are designed to buy an undervalued stock and sell an overvalued stock, and then profit from a change in the spread between two stocks. By well selection stock, the short positions are most likely to underperform the market, and the long positions are likely to outperform the short position on a relative basis. Thus, the position may still be profitable if both stocks decline insofar as the long position declines less that the short position. This type of investment strategy has been gradually improved and applied on hedge funds in recent years, reaping remarkable profits. As for distinguishing undervalued or overvalued stocks, combining CI techniques and physics concepts can result in relevant investment decisions.

The main reason behind the use of CI techniques is to conduct qualitative analysis. Stock selection employs the dividend discount model, price-earnings ratio analysis, book value per share analysis, discounted cash flow technique, capital asset pricing model (CAPM), and arbitrage pricing theory, whether by growth investment or value investment strategy. These theories and models are mostly quantitative analyses, and since stock selection criteria are based on numeric values calculated from historical data, these are unable to forecast the future trend of the selected stocks. Qualitative analysis may provide more information for stock selection, which includes the future trend for a specific time period, speed of change, duration, and so on. It likewise lends decision makers a view of the future.

The following is an example of constructing a portfolio of equity long-short strategy by the CI approach. First, two groups of underlying equities are identified—one is the undervalued stocks for the long position, and the other is the overvalued stocks for the short position. For each underlying equity, their published financial statements are respectively taken as the benchmark to measure similarity with the blue chip stocks. These may be the constituent of an index tracked by exchange traded funds (ETFs), and the distress stocks which may have experienced financial crisis. To align the two groups, clustering algorithm is employed, such as a self-organized map (SOM). After clustering, each underlying stock is clustered, and the position of the cluster to which it belongs is plotted on the cluster distribution maps, where the upper right side of the map can be considered as the cluster of undervalued stocks, and the lower left side can be considered as the cluster of overvalued stocks.

To conduct qualitative analysis of clustered individual stocks, dynamic physical behavior analysis can be used. In Figure 1, two analysis models are defined for equity selection. One is the value and growth model, in which the original financial statement data are adopted for clusters similarity measurement. The other is the physical model, in which the first- and second-order variations of financial statement data are adopted. By using either value and growth model or physical model, for each equity, the trajectory of the cluster position to which it belongs on the distribution map is sketched when continuously perform clustering in several periods. Analyzing the trajectory of clusters [24] can be interpreted as the changes in energy or can refer to the external forces which influence the future trend of the equity. If the equity is on a trajectory toward the cluster of blue chip stocks, then it may be undervalued. If it is in the opposite direction, that is, toward the cluster of distressed stocks, then it may be overvalued. Therefore, the problem of selecting portfolio stocks can be analyzed using a qualitative instead of the traditional quantitative method, providing a visualized interface to help investors build their view of future trends.

Conclusion

The methodology of combining dynamic physical analysis and CI techniques for financial investment decisions support is introduced in this paper. Similar to most social science studies, reasoning and inference are created based on the causality model. The dynamic physical behavior can help CI-based models to clearly describe the change in market trend and to recognize the implied relationship between cause and effect. This novel methodology can be applied to forecast the market dynamics for financial investment decisions instead of being limited to traditional financial models. Ultimately, this decreases the gap between financial theory and practical trading.

References

[1] M. Schaden, "Quantum finance," *Phys. A-Statist. Mech. Applicat.*, vol. 316, pp. 511–538, 2002.

[2] M. I. Loffredo, "On the statistical physics contribution to quantitative finance," *Int. J. Modern Phys. B*, vol. 18, pp. 705–713, Feb. 2004.

[3] M. Ausloos, et al., "Applications of statistical physics to economic and financial topics," *Physica A*, vol. 274, pp. 229–240, Dec. 1999.

[4] E. Jimenez and D. Moya, "Econophysics: From game theory and information theory to quantum mechanics," *Phys. A-Statist. Mech. Applicat.*, vol. 348, pp. 505–543, Mar. 2005.

[5] D. Stauffer, "Econophysics—A new area for computational statistical physics?," *Int. J. Modern Phys. C*, vol. 11, pp. 1081–1087, Sept. 2000.

[6] L. K. C. Chan, et al., "Momentum strategies," *J. Finance*, vol. 51, pp. 1681–1713, Dec. 1996.

[7] R. J. Kuo, et al., "An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network," *Fuzzy Sets Syst.*, vol. 118, pp. 21–45, Feb. 2001.

[8] P. C. Chang, et al., "Integrating a piecewise linear representation method and a neural network model for stock trading points prediction," *IEEE Trans. Syst., Man, Cybern. C*, vol. 39, pp. 80–92, Jan. 2009.

[9] E. W. Saad, et al., "Comparative study of stock trend prediction using time delay, recurrent and probabilistic neural networks," *IEEE Trans. Neural Networks*, vol. 9, pp. 1456–1470, Nov. 1998.

[10] L. J. Cao and F. E. H. Tay, "Support vector machine with adaptive parameters in financial time series forecasting," *IEEE Trans. Neural Networks*, vol. 14, pp. 1506–1518, Nov. 2003.

[11] J. Nenortaite, "A particle swarm optimization approach in the construction of decision-making model," *Inform. Technol. Control*, vol. 36, pp. 158–163, 2007.

[12] A. Ghandar, et al., "Computational intelligence for evolving trading rules," *IEEE Trans. Evol. Comput.*, vol. 13, pp. 71–86, Feb. 2009.

[13] J. Seiffertt and D. Wunsch, "Intelligence in markets: Asset pricing, mechanism design, and natural computation," *IEEE Comput. Intell. Mag.*, vol. 3, pp. 27–+, Nov. 2008.

[14] N. L. Sapankevych and R. Sankar, "Time series prediction using support vector machines: A survey," *IEEE Comput. Intell. Mag.*, vol. 4, pp. 24–38, May 2009.

[15] J. T. Yao, et al., "Option price forecasting using neural networks," *Omega-Int. J. Manage. Sci.*, vol. 28, pp. 455–466, Aug. 2000.

[16] R. Gencay and R. Gibson, "Model risk for European-style stock index options," *IEEE Trans. Neural Networks*, vol. 18, pp. 193–202, Jan. 2007.

[17] P. Lajbcygier, "Improving option pricing with the product constrained hybrid neural network," *IEEE Trans. Neural Networks*, vol. 15, pp. 465–476, Mar. 2004.

[18] H. Amilon, "A neural network versus Black-Scholes: A comparison of pricing and hedging performances," *J. Forecasting*, vol. 22, pp. 317–335, July 2003.

[19] X. X. Huang, "Mean-entropy models for fuzzy portfolio selection," *IEEE Trans. Fuzzy Syst.*, vol. 16, pp. 1096–1101, Aug. 2008.

[20] X. Li, et al., "A hybrid intelligent algorithm for portfolio selection problem with fuzzy returns," *J. Comput. Appl. Math.*, vol. 233, pp. 264–278, Nov. 2009.

[21] K. J. Oh, et al., "Portfolio algorithm based on portfolio beta using genetic algorithm," *Expert Syst. Applicat.*, vol. 30, pp. 527–534, Apr. 2006.

[22] V. A. F. Dallagnol, et al., "Portfolio management using value at risk: A comparison between genetic algorithms and particle swarm optimization," *Int. J. Intell. Syst.*, vol. 24, pp. 766–792, July 2009.

[23] L. K. C. Chan and J. Lakonishok, "Value and growth investing: Review and update," *Financial Analysts J.*, vol. 60, pp. 71–86, Jan./Feb. 2004.

[24] T. Schreck, et al., "Visual cluster analysis of trajectory data with interactive Kohonen maps," *Inform. Visual.*, vol. 8, pp. 14–29, Spring 2009.