An Introduction to Natural Computing in Finance

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Abstract. The field of Natural Computing (NC) has advanced rapidly over the past decade. One significant offshoot of this progress has been the application of NC methods in finance. This paper provides an introduction to a wide range of financial problems to which NC methods have been usefully applied. The paper also identifies open issues and suggests multiple future directions for the application of NC methods in finance.

1 Introduction

Recent years have seen the application of multiple Natural Computing (NC) algorithms (defined in this paper as computer algorithms whose design draws inspiration from phenomena in the natural world) for the purposes of financial modelling [7]. Particular features of financial markets including their dynamic and interconnected characteristics bear parallel with processes in the natural world and prima facie, this makes NC methods 'interesting' for financial modelling applications. Another feature of both natural and financial environments is the phenomenon of emergence, or the activities of multiple individual agents combining to co-evolve their own environment.

The scale of NC applications in finance is illustrated by Chen & Kuo[10] who list nearly 400 papers that had been published by 2001 on the use of evolutionary computation alone in computational economics and finance. Since then several hundred additional papers have been published illustrating the continued growth in this application area (see also [53,47,8] for additional examples of NC applications in finance). In this paper we provide a concise review of some of this work, describing the utility of NC methods within each of the following financial areas: forecasting, algorithmic trading, portfolio optimisation, risk management, derivative modelling and agent-based market modelling. As NC methods have general utility as optimisation, model induction and agent-based modelling tools, there is potential for wide application of these methods in finance.

The rest of this paper is organised as follows. Section 2 provides a concise overview of some key families of NC methods. Section 3 introduces various financial applications of NC methods and shows how these methodologies can add value in those applications. Section 4 concludes this paper, suggesting multiple avenues of future work at the intersection of finance and natural computing.

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2 Natural Computing

Natural computing (NC) algorithms can be clustered into different groups depending on the aspects of the natural world upon which they are based. The main clusters are illustrated in Fig.1 below.

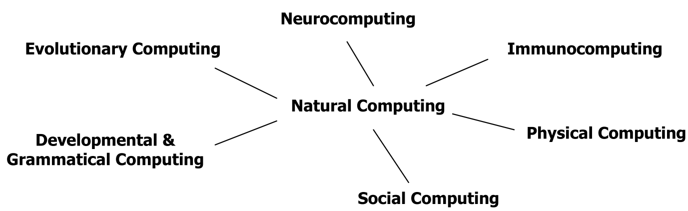

Fig. 1. An overview of the main families of Natural Computing Algorithms

Neurocomputing (or neural networks, NNs) typically draws inspiration from the workings of human brain or nervous system. NNs can be characterised by a set of neurons, the network structure describing the pattern of connectivity between neurons, and the learning approach used. The predominant neurocomputing paradigms include *multi-layer perceptrons*, *radial basis function networks*, *self-organising maps*, and *adaptive resonance theory.*

Evolutionary Computation (EC) is based upon neo-Darwinian principles of evolution. A population-based search process is used, whereby better (fitter) members of the population are selected for reproduction and modification, leading to a new population of individuals increasingly adapted to their environment. The main streams of EC are *genetic algorithms*(GA), *evolution strategies*(ES), *evolutionary programming*(EP) and *genetic programming* (GP).

Social Computing adopts a swarm metaphor and includes algorithms inspired by the flocking and schooling behaviour of birds and fish, and the behaviours observed in social insects such as ants. The characteristics of these social systems facilitate self-organisation, flexibility, robustness, and direct or indirect communication among members of the population. Examples of social computing include *ant colony*, *particle swarm* and *bacterial foraging* algorithms.

Immunocomputing encompasses a family of algorithms inspired by the complex and adaptive biological immune system of vertebrates. The natural immune system represents an intricate network of specialised chemicals, cells, tissues and organs with the ability to recognise, destroy and remember an almost unlimited number of foreign bodies, and to protect the organism from misbehaving cells.

Physical Computing draws inspiration from the physical processes of the natural world, such as simulated annealing and quantum mechanics. A claimed benefit of the quantum-inspired algorithms is that because they use a quantum representation, they can maintain a good balance between exploration and exploitation, they can also offer computational efficiencies since smaller population sizes can be used compared to typical evolutionary algorithms.

Developmental and Grammatical Computing borrows from both a developmental and a grammar metaphor. Grammatical computing adopts concepts from linguistic grammars, where generative grammars are used to construct a sentence(s) in the language specified by the grammar. This process is metaphorically similar to the developmental process in biology where 'rules' govern the production of a multi-cellular organism from a single cell. An example is *grammatical evolution* (GE), which is a grammatical variant of genetic programming.

These families of NC algorithms provide a rich set of tools for the development of quality optimisation, model induction and agent-based modelling applications, and all have seen applications in finance. Readers requiring detailed information on these algorithms are referred to [13,25].

3 Financial Applications

In this section we introduce the application of NC methods across a range of financial areas including forecasting, algorithmic trading, portfolio optimisation, risk management, derivative modelling and agent-based market modelling.

3.1 Forecasting

Financial markets are affected by a myriad of interacting economic, political and social events. The relationships between these factors are not well understood, and moreover, not stationary over time. To predict future values of macroeconomic variables, market indices, the volatility of some financial products, etc., NC methods can be applied for parameter estimation (optimisation), or more generally for model induction wherein the structure of the underlying data generation process is uncovered.

For example, GA has been used to select explanatory variables from financial statements in order to predict corporate earnings [45] and for prediction of IPO underpricing [40]. NNs have been employed for the prediction of index levels [7], take-over targets [21] and auditor qualification of financial statements [44]. GP has been used to forecast exchange rate volatility [39] and for developing investment rules [46].

Typically, studies applying NC methods for financial forecasting use measures of goodness of fit such as mean squared error, mean absolute percentage error etc. as their fitness function. The aim is to uncover or train a model which 'fits' a historic dataset well. Unsurprisingly, the choice of fitness function usually has a critical impact on the behaviour of resulting model, hence a model constructed using one fitness measure will not necessarily perform well on another.

3.2 Algorithmic Trading

Algorithmic (or automated) trading is the use of computer programs to make decisions relating to some aspect of the trading of financial instruments including the timing, price, or even the final quantity of the order. Below we illustrate some important processes of algorithmic trading where NC methods can be applied.

Trading Strategy

A trading strategy is a predefined set of rules for making trading decisions. Algorithmic trading can be applied in any trading strategy such as hedging, arbitrage, or pure speculation (including trend following). A trading rule should specify the entry, profit-taking, and stop-loss or exit strategy. NC methods can be used for rule optimisation (to find optimal parameters for a fixed rule) or rule induction (to find optimal combination of diversified rules). Early applications of EC to uncover trading rules include [6,38,3]. Markets have periods in which a rule can work, but it is hard to find evidence of rules which are successful over long time periods. Hence an adaptive trading strategy seems more plausible [20,12]. Instead of typical data drawn from the market, financial statements or macroeconomic data, [43,30] used text data drawn from either internet message boards or the financial press to find market trends and evolve trading rules. A wide range of hybrid forecasting approaches have also been employed such as the neuro-fuzzy hybrids [54], neuro-genetic hybrids, geno-fuzzy [20] and ensemble methods (combining multiple models to make a trading decision) [29].

Trade Execution

An important issue in trading financial assets is the efficient trade execution. The design of trade execution strategies seeks to balance out the cost of market impact and opportunity cost. In selecting a trade execution strategy, the investor (or the computer if the process is automated) decides the number of slices the trade will be split into, the size of each individual trade, when to submit an order, and the type of order to use (limit or market). Applications of NC for optimal trade execution have begun to emerge in recent years. For example, Lim & Coggins [33] used a GA to evolve a strategy in order to optimise trade execution performance using order book data from the Australian Stock Exchange. In their approach, the basic structure of the execution rule is determined in advance (number of trades etc.) and the task of GA is to parameterise the rule.

3.3 Portfolio Optimisation

'Optimization is the engineering part of portfolio construction', as mentioned by Fabozzi et al [18] in their recent survey for quantitative equity portfolio management: *'Most portfolio construction problems can be cast in an optimization framework, where optimization is applied to obtain the desired optimal risk-return profile'.* Multiple elements of the portfolio management process, such as asset allocation, security selection, index tracking, etc. where optimisation is crucial, are amenable to NC methodologies.

A classical approach used for portfolio optimisation is the Markowitz mean-variance model [36]. It assumes that investors wish to maximise their return (measured as mean or expected return) and minimise their risk (measured as variance or the standard deviation of their return). Real-world portfolio optimisation can present a difficult, high-dimensional, constrained optimisation problem. In this setting, heuristic approaches such as evolutionary computing methods are of particular interest because of their ability to find good solutions even if optimality is not assured. For example, *differential evolution* (DE) has been applied to the index tracking problem [35] and *evolutionary algorithm* has been used for multi-period pension fund asset allocation problem [5,41]. Practically, portfolio managers are concerned with a variety of risk and return measures, not just expected return and its variance. A variety of papers have applied Multi-Objective Evolutionary Algorithms (MOEAs, see [9] for a review of their applications in finance) to non-Markowitz risk metrics, including [34] which uses a compound risk metric. An evolutionary stochastic portfolio optimisation method is introduced in [22] and applicable to a set of structurally different risk measures. Recent work has also seen the application of coevolutionary MOEAs for portfolio optimisation [16].

3.4 Risk Management

Risk management is a critical aspect of the investment decision. Some of the main types of risks faced by investors are illustrated in Fig. 2 below.

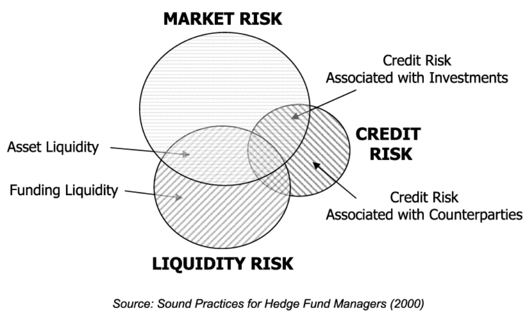

Fig. 2. Risk illustration

Market Risk Computation

Market risk refers to the risk faced by an investor arising from changes in financial market prices. Traditionally, a measure for market risk is Value-at-Risk (VaR), which measures the worst expected loss under normal market conditions over a specific time interval. The loss distribution is usually assumed to be Normal when calculating VaR. Evolutionary algorithms do not need to embed this assumption and can incorporate any preferred loss distribution type [49]. Other market risk measures such as Conditional VaR estimates and expected shortfall can be calculated using NNs [32,15].

Credit Risk Assessment

Credit risk is the risk that the counterparty to a deal fails to perform their obligations. Over the past several decades an extensive literature has amassed on modelling creditworthiness and default risk. The objective is to develop a model which will provide a metric of creditworthiness from a series of explanatory variables. As the range of NC techniques have expanded over the past twenty years, each new technique has been applied to credit scoring and corporate failure prediction. Examples include feedforward neural networks [4], self-organising maps [42,27], GAs [28,50], Ant models [51,7], GP and GE [37,7,2].

Of course, there are other types of risks which need to be quantified in practice, such as liquidity risk (arising when an institution is unable to raise cash to fund its business activities) and operational risk (arising due to poor or inadequate management control systems or due to human error). However, as yet, there is little literature concerning the application of NC methods in these areas.

3.5 Derivatives Modelling

Derivatives are contracts whose value is derived from the value of the underlying assets, such as equities, interest rates, currencies, market indices, commodities etc.. Two of the best known forms of derivative are futures and options. A future is an agreement to buy or sell goods, currency or securities on an agreed future date and for a price fixed in advance. An option is a financial instrument simply gives the holder (buyer) the right, but not the obligation, to buy or sell a specified underlying asset at a pre-agreed price on or before a given date.

The key issue for investors wishing to trade in derivatives is the determination of the fair price for the derivative. There have been two main avenues of application of NC methods in pricing financial derivatives, namely, model calibration and model induction. In model calibration, the objective is to estimate the parameters of (or 'calibrate') a theoretical pricing model. The parameters are estimated by fitting the model to the relevant returns time series. Typically the pricing model will have a complex, non-linear structure with multiple parameters, where global search heuristics such as GA can be utilised to uncover a high-quality set of parameters. Examples of using NC algorithms for model calibration include [14,19]. In model induction, NC approach such as self-organising, fuzzy neural networks or GP would have particular utility when little is known about the underlying asset pricing dynamics as both the structure and the parameters of the pricing model are estimated directly from the data, thereby extracting the pricing model implicitly. Applications of such methods include NNs [23,52,48] or GP [26,11] to recover a proxy for the price-generating model.

3.6 Agent-Based Market Modelling

The essence of Agent-based Modelling (ABM) lies in the notion of autonomous agents whose behaviour 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. One example of the use of ABM to simulate a financial market is provided by LeBaron [31]. This model simulates price generation and trading in a market made up of artificial adaptive agents.

Other applications of ABM include the simulation of a foreign exchange market [24], the modelling of artificial stock option market [17] and the modelling of an artificial payment card market [1]. A key output from the ABM literature on financial markets is that it illustrates that complex market behaviour 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.

4 The Future

Though a plethora of academic literature on NC applications in finance exists, it is notable that many papers have concerned proof of concept rather than robust, industry-strength finance applications. While NC methods offer potential in multiple finance areas, the maturing of their application requires future work focusing on complex real-world finance problems. This will require the construction of multi-disciplinary research teams with possible industrial collaborations, drawing expertise as necessary from finance, computer science, mathematics, biology, etc.. Some promising future directions for research at the nexus of natural computing and finance include:

– ***Forecasting:*** While forecasting models applying NC methods can typically be constructed to fit historical data fairly well, a common finding is that the quality of the out-of-sample forecasts diminishes over time. Hence we can expect to see increased use of more sophisticated methods for pre-processing the raw time-series inputs, and for the adaptation of the resulting models in response to changing environmental conditions. Another area of growing interest is the incorporation of information from text mining (e.g. from the financial press) into forecasting models.
– ***Algorithmic Trading:*** While many published papers have focussed on the development of simplified trading systems, successful real-world applications have often focussed on the support of specific elements of the investment process. In the medium term, we can expect to see a notable increase in the rigor of published work in this area as computer scientists form teams with finance academics and practitioners, incorporating realistic models of market microstructure. The area of trade execution has seen relatively little published application of NC methodologies, despite its real-world significance. Model induction tools such as GP offer interesting potential here, as do agent-based modelling approaches. The latter could be used to uncover robust trade execution strategies.
– ***Portfolio Optimisation:*** There has already been an extensive application of NC methods for portfolio optimisation, but a further systematic investigation is still needed, i.e., dealing with portfolio constraints for special sub-application areas, e.g., hedge fund, pension fund, insurance, etc..; improving the effectiveness and efficiency for dynamic asset allocation, optimising portolio managing strategies taking account of reasonably multiple risk measures.

- ***Risk Management:*** Recent events on the financial markets have underscored the importance of risk management, and the weakness of existing theoretical models in this area. It is interesting to note that applications of NC methods in risk management have not attracted as much attention as might be expected in the literature and this remains an open research area. For example, NC methods could be applied to model assist development of enterprise-wide risk management, improve the flexibility and efficiency for large scale multi-stage *asset liability management* (ALM) models with millions of variables and constraints.
- ***Derivatives Modelling:*** In spite of the vast array of derivatives products available, and the weakness of financial theory once we move beyond vanilla products, there have only been a relatively limited number of applications of NC for model calibration or model induction in this area. Possibilities also exist to hybridise NC methods with traditional numerical methods.
- ***Agent-based Market Modelling:*** The field of ABM is attracting significant attention with the increasing questioning of agent homogeneity which underlies classical financial economics. ABM allows us to examine the effect of differing forms of market structure on market behaviour. Doubtless, the next few years will see increased focus on this given the failures of market regulation over the of the recent financial crisis. The co-evolutionary element of markets lends itself well to NC approaches in terms of modelling of agent behaviour and strategy adaptation.

Some elements affecting above various financial areas, such as market microstructure, liquidity, etc. are also worth to be explored in future research. A practical issue arisen in applications of NC to finance is that the underlying algorithms are themselves undergoing a process of maturation. Recent years have seen extensive research in order to extend the canonical algorithms into high-dimensional problem environments (scalability), to develop the efficient algorithms for constrained optimsation, and to develop practical application of the algorithms in dynamic problem environments. Meantime, we have seen developments in computer hardware, and in our ability to implement parallel versions of NC algorithms (e.g. GPU implementations). These two strands of development are creating an ever more powerful toolbox of NC algorithms for financial modellers. In future, we await a systematic applications of these methods growing from both the natural computing and the computational finance community.

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