Available online at www.sciencedirect.com
ScienceDirect
Information Sciences xxx (2006) xxx–xxx
INFORMATION SCIENCES
AN INTERNATIONAL JOURNAL
www.elsevier.com/locate/ins

Editorial

Computationally intelligent agents in economics and finance

Abstract

This paper is an editorial guide for the second special issue on Computational Intelligence in economics and finance, which is a continuation of the special issue of *Information Sciences*, Vol. 170, No. 1. This second issue appears as a part of the outcome from the *3rd International Workshop on Computational Intelligence in Economics and Finance*, which was held in Cary, North Carolina, September 26–30, 2003. This paper offers some main highlights of this event, with a particular emphasis on some of the observed progress made in this research field, and a brief introduction to the papers included in this special issue.

Keywords: Computational intelligence; Agent-based computational economics

1. The origin and evolution

The *3rd International Workshop on Computational Intelligence in Economics and Finance* (CIEF'2003) was held in Cary, North Carolina, on September 26–30, 2003, as a part of *the Sixth Joint Conference on Information Sciences*. The attempt to explore the connections between information sciences and economics has a long history, both by information scientists and economists. However, there are very few conferences actually joining these two subject areas, and hence these two groups of people. CIEF breaks this silence. As a continuation of the special issue published in Vol. 170 (No. 1) of this journal, this issue seeks to archive the on-going event, connecting its past to the present, and pointing to the future.

The CIEF workshop is mainly composed of two young but promising research areas, namely, *Computational Intelligence* (CI) and *Agent-Based Modeling and Simulation* (ABMS). While these two areas can be treated independently, they are put together as a coherent framework in this conference because in our vision, or in a legacy of Herbert Simon, the former is actually the foundation of the latter.[1] More specifically, it is the tools from CI which help us to characterize the autonomous agents in a complex heterogeneous interacting environment [12]. Therefore, as before, the papers presented at this conference can be divided into one of these two areas, even though in some cases a strict delineation may be difficult. Having said that, we shall highlight some distinguishing features which we evidenced in the conference in light of these two main areas.

However, like many other conferences which are associated with a fast growing field, CIEF quickly notices that there is no clear-cut boundary for both of these two areas. CI, as a new quantitative approach, inevitably

[1] Both [11,15] have emphasized this foundational relationship between the two.

0020-0255/$ - see front matter © 2006 Published by Elsevier Inc.
doi:10.1016/j.ins.2006.08.001

has to be compared with other conventional approaches, such as statistics or econometrics. Therefore, in order to enhance the interaction between the traditional statistical approach and the newly-arising CI approach, CIEF also accommodates studies on econometrics. Such is also the case for agent-based computational economics (ACE). Agent-based computational modeling is not just confined to economics; in fact, it is a new platform which can demolish the long-existing ad hoc walls among all branches of the social sciences. The field known as *agent-based computational social sciences* reflects the already on-going interdisciplinary activities. To avoid the unnecessary isolation, CIEF has extended the areas of interest from agent-based computational economics and finance to management, and further to the social sciences in general.

Furthermore, within the area of economics itself, ACE with its models of software agents matches well with experimental economics and behavioral economics as models of human agents. It has recently been noticed that models of software agents and human agents should not be separate entities. A framework which can combine the study of the two will benefit economists on both sides. By acknowledging the important connection, CIEF would like to be characterized as the first economic conference on agents, and accept submissions from experimental economics and behavioral economics. This characterization also makes CIEF appealing to computer scientists who are interested in agents, specifically, social agents.[2]

Simulation, partially due to the lack of rigorousness, is still not regarded as a science by many scientists. As a simulation-based conference, CIEF cannot sidestep the respective criticisms or attacks. It is aware that, without support from theory, the acknowledgement of the contribution of ACE can be rather limited. Hence, in addition to the experimental and behavioral aspects, it is important to consolidate the ACE study with theoretical underpinnings. There are two theoretical frameworks that exist for the study of agents, which may also facilitate the work of connecting software agents and human agents. One is game theory, and the other is statistical physics, or, more precisely, econophysics. CIEF, therefore, also solicits game theorists and econophysicists to participate and contribute in bridging the gap between theory and simulation.

This roughly sketches the origin and the evolution of CIEF. Needless to say, the evolution will not stop here. To give an example, upon writing this introductory article, the preparation of CIEF'2006 is underway, and the program committee has decided to add *neural economics* as a new topic of interest. We believe that the joint study of software agents and human agents cannot be deeply grounded without the physical foundation of human behavior, i.e., the *brain*. It is hoped that in the future neuropsychologists and neural scientists will also be participating members of CIEF, to make CIEF a truly exciting interdisciplinary conference.

This introductory article is organized as follows. We first highlight some features of the work presented in the workshop. Sections 2 and 3 cover the work related to agents and to Computational Intelligence, respectively.[3] Section 4 gives a synopsis of the articles included in this issue. The concluding remarks are presented in Section 5.

2. Agents

2.1. Robert Axtell and his speech

Agent-based computational economics is one of the mainstays of the CIEF workshop series. The significance of the idea of agents and its use in economic modeling had always been well-demonstrated in the past keynote speeches of the series. This year is no exception. We have Robert Axtell, coming from the Brookings Institution, Washington, DC, as the keynote speaker. His speech "*Artificial Economies of Adaptive Agents: Positive Economics via Agent Computing*" gives a comprehensive review of how agent-based computational economics may contribute to the advances in economics. His review covers the various economic applications of agent-based computing, ranging from the theory of markets, the theory of the firm, and game theory to macroeconomics.

[2] By saying so, we admit that there are already many agent conferences, regardless of whether they are organized by social scientists or computer scientists.

[3] Basic statistics on the participants' backgrounds, research techniques, and application areas can be found in a preview of the workshop [18].

By asking what the computational complexity of economic exchange processes is,[4] he discussed the relevance of the computational complexity theory to economics, an issue which had been long neglected among economists until very recently.[5] This discussion leads us to see *agent-based computing* as a modeling strategy to avoid the computational burdens associated with solving realistic large scale general equilibrium models. Bilateral exchange as a characterization of the decentralized interactions of agents is then compared with the Walrasian mechanism on their computational efficiency (polynomial complexity vs. exponential complexity). A particularly interesting implication coming out of this comparison is that price heterogeneity improves market performance. He then went further to investigate the impact of adaptive agents (strategic agents) on the complexity of decentralized markets.

Agent-based computing can also been applied to explain many statistical features of firms, that include a Pareto distribution of firm sizes, a double exponential distribution of growth rates, a power-law distribution of the life expectancy of firms, a power-law distribution of the variance in growth rates, wages as a function of size, and constant returns to scale at a macrolevel, etc. [4].[6] In his talk, Axtell showed that heterogeneous agents who best reply locally in an economic environment of increasing returns with free agent entry and exit are sufficient to replicate the empirical features of firms.

In his last part of his speech, Axtell attempted to compare agent-based computing or multi-agent systems with certain other related fields, specifically, operations research and algorithms. He considered agent-based computing as a generalization of operations research and algorithms. It is a generalization of operation research as we now have a population of agents using operations research, which are exemplified by RoboCup and trading agent competition [63,38]. It is also a generalization of algorithms as we now have interaction as a new basis for computer sciences. He concluded this subject with a specific reference to genetic algorithms, which can also be viewed as a special case of agent-based computing when it is applied with some usual stipulations. To generalize from genetic algorithms, one can easily depart from most of the conventional stipulations and maintain the character of genetic algorithms, e.g., by using aperiodic and asynchronous updating, variable populations, local interactions, and local parameters [5].

Using the title "beyond optimization," his final message brought us back to the essence of the entire workshop, i.e., the legacy of Herbert Simon. In particular, he referred to Simon's satisficing principle, "nature may be more concerned with performance improvements than optima, and with robustness instead of equilibrium." He concluded his talk by saying that the perspective of multi-agent systems significantly alters the conventional results of mainstream, neoclassical economics.

Axtell's keynote speech is well given in an environment richly surrounded by so many presentations of agent-based computing. In the following subsections, we shall highlight some of their distinguishing features.

2.2. Experimental economics and behavioral economics

It becomes gradually clear that agent-based computational economics should be able to interact with experimental economics and behavioral economics in a more integrated framework. A series of papers at CIEF'2003 motivated the need for an integrated framework and sketched how this work can be done. First, the behavioral approach and the agent-based approach can collaboratively work together in a bi-directional manner. On the one hand, experimental and behavioral approaches can help answer some modeling issues related to agent engineering, while, on the other hand, agent-based computational finance can help test the robustness or the generality of some behavioral rules observed from psychological laboratory experiments.

Ref. [13] serves as an example of the first direction. While the essence of agent-based computing is agents, not so much has been said as to how to model or program these agents. Disputes still prevail on the issue like the simple/naive agents vs. the sophisticated/smart agents.[7] A proposed solution to this problem is to work with real human behavior, in particular, when the respective fields or an experimental study are available.

[4] More precisely, three questions are raised. First, how hard is it for the Walrasian auctioneer to determine the equilibrium price? Second, what is the complexity of decentralized (non-Walrasian) markets? Third, what is the complexity of realistic market processes?

[5] See [67,44].

[6] Also see [22] included in this special issue.

[7] See [15] for an in-depth discussion of this issue.

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

For example, there are already some empirical observations regarding gamblers' behavior; hence, one may get some ideas on how a gambling agent should be programmed in light of the empirical evidence. Chen and Chie's [13] work on the agent-based modeling of lottery markets serves as a demonstration of this idea.

Ref. [14] serves as an example of the other direction. Psychologists have been long distinct from economists in the rational assumption of human behavior. The gap between the two has, however, been narrowed in recent years, thanks to a series of celebrated works by Amos Tverskey, Daniel Kahneman, and their followers. Findings based on a series of psychological experiments concerning decision-making under risk and uncertainty are now applied to address a number of financial anomalies, which fosters the growing field currently known as behavioral finance. Chen and Liao [14], however, questioned the legitimacy of financial models directly built upon psychological experiments. Their main concern is that psychological experiments which lend support to various cognitive biases seem to focus only on independent individual behavior in a rather static environment. This setting is, therefore, distant from the financial markets, where agents are able to learn and adapt in an interactively dynamic environment. As a result, various cognitive biases observed from the psychological experiments may be corrected via learning and may not be exogenously fixed as in most behavioral financial models. Chen and Liao [14] proposed an alternative: instead of exogenously imposing a specific kind of behavioral bias, e.g., overconfidence or conservatism, on the agents, we can canvass the emergence and/or the survivorship of this behavioral bias in the highly dynamic and complex environment through computer simulations.

Second, when software agents are commonly used to replace human agents in making decisions and taking action in an era of electronic commerce, human agents and software agents can quite often be placed in a common arena and their interaction becomes more intense than ever. Questions pertaining to the consequences of this interaction, therefore, become crucial. Grossklags and Schmidt [31] pioneered such a research direction, and raised two fundamental issues which define this line of research.[8] First, will artificial agents in markets influence human behavior? Second, will the interaction between human and artificial agents have a positive or negative effect on the market's efficiency? They designed a continuous double-auction market in the style of the Iowa electronic market, and introduced software agents with a passive arbitrage seeking strategy to the market experiment with human agents. Whether or not the human agents are well informed of the presence of the software agents can have significant impacts upon market efficiency (in the form of price deviations from the fundamental price). They found that if human agents are well informed, then the presence of software agents triggers more efficient market prices when compared to the baseline treatment without software agents. Otherwise, the introduction of software agents results in lower market efficiency.[9]

2.3. Agent-based computing and market/policy design

One of the research areas in which agent-based computational economics and experimental economics are closely intertwined is the *double-auction market* (DA market), or the agent-based DA market. The agent-based market serves as a good starting point for applying agent-based simulation to market/policy design. One important application of agent-based computational models to market/policy design is the electricity market [7,47,48]. In this application area, we are convinced that agent engineering (learning schemes) plays a crucial role in simulating the consequences of various market designs.

By agent engineering, Duffy [23] categorized the agent-based models which have been developed to characterize or understand data from human subject experiments into three classes, namely, zero-intelligent (ZI) agents, reinforcement and belief learning, and evolutionary algorithms. Among the three, ZI agents are considered to be a useful benchmark or a good building block for developing more advanced agent-based models. Zero-intelligent agents are introduced by Gode and Sunder [30], which is the earliest ACE work motivated by the double-auction market experiment.[10] However, as far as market efficiency is concerned, ZI traders are not sufficient for the market to converge to the social-welfare maximization price, or the equilibrium

[8] Also, see [32].
[9] These two issues have been further pursued in the recent development of the **U-Mart** platform [63,58,38].
[10] For a survey of the later development, see [10].

price. The necessary condition, therefore, requires agents to learn. Among all learning agents studied in the agent-based DA models, the simplest one is the ZI Plus (ZIP) agents, introduced by [20].

At CIEF'2003, Wu and Bhattacharyya [70] continued this line of research and studied the boundary beyond which ZIP traders may fail the market mechanism. They introduced speculators into standard DA markets. They found that ZIP traders can no longer guarantee market efficiency when there is a large number of speculators, as compared to the number of normal traders. In some scenarios, the efficiency losses about 25% of the social welfare.[11]

The purpose in studying the agent-based double-auction market is to adequately equip ourselves to tackle the much more complex agent-based electricity market. North [50], as an invited speaker at CIEF'2003, gave a splendid review of the well-known Electricity Market Complex Adaptive System (EMCAS) developed by the Argonne National Laboratory. EMCAS is an agent-based electricity market model written using the Recursive Agent Simulation Toolkit (Repast), a special-purpose agent-based simulation tool. The research on the agent-based electricity market is motivated by the undergoing transition from centrally regulated electricity markets to decentralized markets. These transitions introduce a highly intricate web of interactions of a large number of heterogeneous companies and players, which causes the consequences of new regulatory structures largely unknown and leaves policy design in a state of high stakes.[12] Given this uncertainty, agent-based models can help construct suitable laboratories that can provide ranges of possibilities and test regulatory structures before they are actually implemented. EMCAS now serves as a basis for evaluating Illinois' deregulation of the market.

Boyle [8], also an invited speaker at CIEF'2003, presented an ambitious project on the agent-based model of the whole criminal justice system in the UK, which was funded by the Home Office in the UK. The criminal justice system in England is delivered by three diverse government bodies, the Home Office, the Department of Constitutional Affairs, and the Crown Prosecution Service. Within the criminal justice system as a whole, there must be some dependencies among the functions of the three agencies. Nonetheless, the three constituents might not have been "joined up" sufficiently well to encourage the best use of resources, and this caught the attention of the Treasury in her biennial spending review. Therefore, the purpose of this project is to build an agent-based model to help diverse operating groups engage in strategic policy making and take into account the complex interactions within the criminal justice system so as to better observe the policy impacts.

To make the model fulfill this objective, Boyle [8] introduced a new thinking regarding the agent-based model, called *the mirror function*, which is equivalent to producing a model of the whole criminal justice system in which all actors in the system acknowledge that the model was really "them". The work entailed gathering evidence of links between the behavior and actions of one person or group of people, and those of another, and through this making arguments for the best use of resources, while also reaching agreement between each group of people regarding all of this. This is essentially to do with encouraging a change in the style of working of these core government agencies. Boyle [8], therefore, demonstrates a very distinctive class of agent-based models, which integrates a vein of social work into model-building.[13]

2.4. Agent-based econometric modeling

We now have seen some progress regarding how agent-based models can be built upon laboratory experiments with human subjects, field studies, and social work, but not directly with the data themselves. This is concerned with agent-based econometric models. The complexity of the agent-based models makes their empirical estimation a daunting task, if not an impossible one. Therefore, few attempts have been made to conduct an econometric analysis of an agent-based model. However, recently, we have started to see some progress in the estimation of some relatively simple agent-based models, and CIEF'2003 also had that flavor. Ref. [46] was one of the pioneering efforts.

[11] The full paper is available in [17, Chapter IV].
[12] This can be exemplified by the extremely unsatisfactory experience of California. While, according to economic theory, deregulation and free competition will lead to increased economic efficiency expressed in higher quality services and products at lower prices, the reality of today's emerging electricity markets does not fit this straightforward economic model.
[13] At present, there are very few agent-based models of this sort. Ref. [45] is the only case known to us.

Ref. [46] can be regarded as an outcome of the new research trend that embeds the conventional discrete choice models, also known as the qualitative response models, in a social network, and examines the impact of the social interaction upon individuals' discrete choices.[14] With moderate degrees of simplifying assumptions on individuals' decision models as well as interaction mechanisms, this network-based agent-based model can be parameterized and estimated as an econometric model. This is basically what was done in [46], which estimated the interaction mechanism among young people in relation to smoking behavior by using the result of [2].[15] Its empirical results strongly support the presence of positive peer effects in smoking behavior among young people.

2.5. Agent-based social networks

Having noticed that agent-based econometric models were first successfully developed in the area of the network-based discrete choice models, we noticed that the social network plays an increasingly important role in ACE models. In fact, the network should be an essential ingredient of agent-based models, while most agent-based simulation models do not explicitly include this element. One distinguishing feature of CIEF'2003 was the demonstration of the non-trivial incorporation of networks in agent-based modeling.

Network externalities may be viewed as one of the best places to see the use of agent-based social networks. The celebrated work [37] was demonstrated in this year's CIEF in an agent-based manner. Tsuji and Kawamura [66] built an agent-based model and evaluated it by verifying the simulation results with conventional Beta and VHS systems. Frels et al. [28] enhances our understanding of the significance of network effects by creating agent-based computational simulations of such markets. Insights into the dominance of the inferior technologies are further explored within a model called Standard-Scape.

2.6. Agent-based models of games

Among many contributions of agent-based computational economics to mainstream economic theory, maybe the most important one is that it enriches our exploration of economic dynamics, in particular the learning dynamics. It makes us be aware that our established economic theory may not be robust to various learning algorithms. Because of this dependence effect, economists are able to realize the relevance of laboratory experiments, psychology, cognitive sciences and neural sciences to economics.

Two contributions at CIEF'2003 are sufficient to illustrate the significance of learning algorithms to economic theory. Both of these contributions studied *reinforcement learning* in agent-based models of games.[16] Sasaki and Flann [56] addressed the traffic-flow problem in the context of games. This issue concerns the most efficient distribution of the road space among drives, characterized by the travel time among different paths among drivers connecting the same origin with the destination being identical. The intriguing part of this issue is: can we achieve this goal in a bottom-up manner without the top-down supervision? Sasaki and Flann [56] explored the possibility by assuming that each driver learns how to choose the paths by means of reinforcement learning. Several different versions of reinforcement learning have been attempted. They differ in one key parameter, learning speed or the degree of forgetting. It has been found that the allocative efficiency of roads is not independent of this parameter. In other words, unless the learning speed is tuned correctly, there is no guarantee that drivers will necessarily coordinate their use of roads in the most efficient way, and congestion can happen all the time, a result that is not surprising at all. Since it is implausible to expect all drivers to use

[14] Other similar works can be found in [6,24]. Certainly, not all agent-based econometric models are network-based. There are a series of agent-based financial econometric models which do not explicitly refer to a network or a graph [43,33,53].

[15] Ref. [2] can be read as one of the earliest available econometric results of agent-based models. Given the profile of individual attributes and the social interaction mechanism, Ref. [2] provides an analytical solution for the equilibrium distribution of the collection of individuals' behavior. Hence, it is possible to describe the macroequilibrium from the microlevel.

[16] Before the advent of agent-based computational models, mainstream economics had two main formulations, namely, general equilibrium analysis and game theory [69]. While strategic interactions of agents were largely ignored in the former, they constitute the core of the game theory. By sharing this common feature, agent-based computational modeling, in a sense, can be regarded as an extension from the *analytical games* to *computational games*. The two essentially have the same formulation, but agent-based simulation can help game theorists ponder on the sensitivity of their analysis to various learning schemes.

the "right" version of reinforcement learning, an intelligent transportation system composed of software agents (on-line driving assistants) is proposed.[17]

By also using reinforcement learning, Feltovic [26] studied a problem which has troubled economists for a long time. The problem known as the *winner's curse* refers to the systematic overbidding behavior observed in many human-participants experiments of bilateral exchange with asymmetric information. What makes this problem even more puzzling is that this "irrational" behavior does not go away even though the experiments are repeatedly conducted: participants simply repeatedly overbid as if they were not learning. Feltovic [26] proposed a solution to this puzzle. It shows that if decision-makers learn via a specific version of reinforcement learning, their behavior typically changes *very slowly*, and persistent mistakes are likely. We previously (Section 2.2) mentioned that models of behavioral finance are largely built upon some cognitive biases of agents. These biases are persistent as if agents were not learning. However, Feltovic [26] pointed out the difference between slow learning and no learning, and showed that the persistent irrational behavior is not inconsistent with bounded rationality.[18]

In both [56,26], reinforcement learning is used to show the significant economic consequence of learning. Reinforcement learning (RL) has been considered to be one of the three major classes of agent-based models [23]. Among all of the CI tools, reinforcement learning is probably the only one originating from psychology, and it works well with some prominent psychological observations, such as *law of effect* and *power law of practice*. Unlike genetic algorithms, the RL model is relatively simple since it only has few parameters. At CIEF'2003, Prof. Nicholas Feltovich from the University of Houston gave a tutorial on this subject. He used the simple-minded RL model to point out the essential ingredient of reinforcement learning. He then showed that various degrees of smartness can be added to this simple-minded behavior by modifying the propensity updating rule. These complications involve different cognitive activities, such as forgetting (recency and extinction), association (competitive learning, local experimentation), imagination (counterfactual reasoning) [9], and expectation (reference points) [54]. The prediction power of the RL models was illustrated via the matching-pennies game [51], and its relation with the Nash equilibrium is also discussed. Finally, he gave a brief literature survey on the comparison between reinforcement learning and other alternatives, such as belief learning [29].

2.7. Agent-based macroeconomic and financial models

Macroeconomics and financial markets are the two most long-standing areas of agent-based modeling and simulation. As usual, a large number of CIEF submissions are devoted to this area. They have also contributed to the growth of this area in different respects.

Agent-based computational macroeconomics basically relaxes the assumptions of the *representative households* and the *representative firms*, and replaces them by individual households and firms, which are largely heterogeneous. With this relaxation, the *aggregation* work, conventionally performed in an analytical way, can become extremely difficult, and has to be done via simulation with intensive computation. The agent-based simulation generates observations at both the micro and macrolevel. By combining data from both levels, one can stand in a better position to inquire and examine the possible relationship between micro and macro-observations. This feature can be particularly useful when both micro and macrodata are available. Ref. [22] serves as an perfect example on this, which we shall come back to in Section 4.2.

Lin and Mao [42] provided the first agent-based version of a famous real business cycle model [41]. Real business cycle models address the issue on how the stochastic exogenous shocks can impact the business fluctuation

[17] The congestion problems can be studied in different forms. The famous *El Farol problem*, originally proposed by Arthur [3], or even the familiar *cobweb model* are other examples. It has also been shown that there is no guarantee that agents with arbitrary learning algorithms can coordinate well to avoid congestion [27]. These kinds of studies together indicate the coordination limit of the market mechanism. Beyond the limit, coordination failure, the rejection of the Hayek hypothesis, is the rule rather than an exception. The implication is that, to coordinate economic activities, the market alone is not enough, and a network, institution, or a central coordinator is indispensable.

[18] The finding of Feltovic [26] can be interestingly compared with models of *learnability* in economics [59]. Both provide us with a mathematical analysis of cognitive biases. These models point out that, under some circumstances, bounded-rational behavior and truly naive behavior may be observationally equivalent.

when both profit-maximizing firms and utility-maximizing households are homogeneous and hold rational expectations. Lin and Mao [42] extended this model by introducing bounded rationality into the model. Instead of rational expectations, firms' perceptions of the future shocks were constantly modified via learning, and their learning behavior was implemented by the standard genetic algorithm. Via simulation, it then compared the aggregate dynamics on consumption, investment, output, the real wage and the interest rate between the case of rational expectations and the case of bounded rationality.

As mentioned earlier, one feature of agent-based modeling is that it attempts to connect the micro and macrobehavior. In agent-based financial models, efforts have been made to connect the traders' strategies to price dynamics. There are a number of recent studies devoted to inferring the price dynamics from the trading strategies. In characterizing trading strategies, most earlier work only considered trading volumes or portfolios, Ref. [52] being one of the few exceptions that also took *trading time* into account. Random trading times can be important in explaining some of the stochastic properties of financial time series, such as stochastic volatility. The two-dimensional trading strategies, trading volume and trading time, are further driven by one key variable, i.e., the type of traders. The authors studied two types of traders, namely, trend traders and value traders. Using the diffusion approximation, the authors derived the aggregate price dynamics through the aggregated excess demands of traders characterized by different trading behavior.

In addition to trading time, another issue that has also received little attention in the literature of the agent-based financial markets is the *role of financial engineering*. Up to the present, financial engineering has only been studied from an individual perspective. The classes on option pricing, portfolio management and risk management only teach what each individual investor should do for his or her own benefit. Almost no study has ever asked what is the resultant aggregate dynamics when some or all investors follow the same recipes of risk management. Ref. [62] is probably the first paper in this area. It introduced risk management behavior to a fundamentalist–chartist model. In this extended model, portfolios of traders are not just determined by the mean-variance model, but further by a risk control model, known as the Value at Risk (VaR) model.[19] The authors then studied the price dynamics from such a group of risk-controlling investors. It was found that a severe mispricing behavior can occur when the degree of risk control is high. In a similar vein, the authors also discussed the role of option pricing (the Black–Scholes Model). This paper shows how financial engineering can be studied within the agent-based artificial stock market. It also makes us wonder whether individual risk management behavior may end up with an unintended consequence in terms of aggregate price inefficiency.

3. Computational intelligence

In the discussed framework, Computational Intelligence refers to a family of toolkits. Ref. [16] provides a comprehensive review of the development of Computational Intelligence with a specific reference to its economic and financial applications. The three major toolkits, namely, *fuzzy logic*, *neural networks*, and *genetic algorithms*, are nowadays familiar to a large number of economists. Many of them have started to conduct serious research with these toolkits. The number of publications using this type of research has increased at a very fast rate. The contributions of these publications can be acknowledged via one of the following four criteria, according to which we shall highlight some of the CIEF'2003 papers.

3.1. Introducing new CI tools

First, there is the application of a CI tool that has never been employed in the economic and financial domain before. Nonetheless, instead of just applying the tool blindly, the researcher also justifies the use of this tool with some economic interpretations or intuitions. A number of new CI tools were presented at CIEF'2003. We start with the *Bayesian network*.

[19] The mean used in the mean-variance model is not the historical mean, but is derived from the well-known Black–Litterman model, which generates an implied return. Since the Black–Litterman model also allows users to input their own perceived return [62], therefore, combines the implied return with the perceived returns of fundamentalists and chartists separately, and uses that combined return in the mean-variance model.

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

Computational Intelligence has been frequently criticized for its lack of a theoretical foundation, since many CI tools are inspired by some natural phenomena the embedding system of which has not been well understood. However, the *Bayesian network* (causal network), which is well grounded in Bayes' theorem, is one of the exceptions. However, compared to other CI tools, the economic or financial applications of the Bayesian network are rather rare, partially due to the fact that the Bayesian network is largely unfamiliar to economists. To enhance the exposure of the CIEF society to the Bayesian network, a tutorial was arranged and delivered by Prof. Chiu-Che Tseng from Texas A&M. An application of the *influence diagram*, a special type of Bayesian network, to the investment decision was also shown by Tseng [65]. By conducting some performance analysis with a Bayesian network and decision trees (C5.0), Tseng [65] found that both systems outperform the leading mutual fund and the market (Vanguard Index 500 and S&P 500) by a significant margin in 1997 and 2000.[20]

The *Naive Bayesian Classifier* is another tool built upon Bayes theorem. Svangard et al. [61] pioneered its application to financial text mining. Most of the current financial forecasting models developed with CI are mainly quantitative models, which rely heavily on numbers. It remains a curiosity on whether one should build forecasting models upon *words* rather than *numbers*, especially when computing with words is already not infeasible [68]. Svangard et al. [61] demonstrates an initial attempt to construct a news-based forecasting model using naive Bayesian classifiers.

3.2. Modifying existing CI tools

Second, such a contribution involves the application of a modification of an already used CI tool, and the modified version is shown to perform significantly better as opposed to the already existing versions. This modification can be performed within the existing framework, such as through the extension of the feedforward neural net to the recurrent neural net, but can also be performed by taking advantage of other CI tools, such as the development of hybrid systems.

Ref. [60] satisfies this criterion. A central problem of GP is its inefficiency in terms of manipulating constants, while it is good at generating the structure. One of the suggestions made to tackle this problem is to work with its constants separately from GP. Ref. [60] can be considered to be one specific development in this direction. By using the nonlinear optimizer engine DONLP2, it applied nonlinear programming to optimize the constants in genetic programs. This hybrid system (GP + nonlinear programming) was then applied to evolve investment policy and was found to perform better than the standard GP both in terms of the return and the program size.

Ref. [71] is another example. This work also focused on the possible improvements made to GP, but instead of constants it mainly dealt with representation, which is another important issue in genetic programming. Basically, this work was motivated by the question as to whether representation can impact the performance of GP. To answer this question, the author proposed three versions of GP, the standard one and two modified ones. The modification was made mainly to the function set, which was purported to strengthen the semantic structure of GP. In one case, it added the automatically defined functions [39], and, in the other case, it added Boolean functions. Then these versions of GP were tested on both financial and artificial time series. The interesting finding is that the modified versions of GP did not help in forecasting the financial time series (Nasdaq), while they did improve the predictions of the artificial one (the Mackey–Glass Time Series). One possible explanation for this different result is that the former is less structured than the latter [34].

3.3. Conducting thorough examination

Third, another contribution is to provide a thorough examination of the relevance of a CI tool applied in the economic and financial domain. A thorough examination can be performed using the accompanying analytical analysis, careful selection of testbeds, benchmarks, and performance criteria, as well as rigorous

[20] See also [72] in this special issue for more applications of the influence diagram.

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

statistical tests. In particular, the comparison made between the target CI tool and many other alternatives is a contribution of this kind. Unfortunately, none of the CIEF'2003 papers met this criterion.[21]

3.4. Proposing new application issues

While the above three criteria mainly focus on the tool itself, the next criterion focuses on the issue. So, fourth, we have an application of a CI tool to an interesting economic or financial issue which has never been attempted before. At CIEF'2003, we observed a series of novel applications which provided a procedural approach (a constructive approach) to enrich the foundation (fundamental elements) of economic theory, such as the cost function, utility function and bilateral bargaining strategy. These contributions show that Computational Intelligence can not only help financial engineering, but also has potential value to the core of economic theory.

The cost function is a very fundamental element in economics. Nevertheless, how to construct a practical cost function from historical data is seldom mentioned in economics textbooks. This is not surprising given that this job can be extremely complicated. Kaminsky and Douglas [36] took a leading step toward tackling this problem with computational intelligence. It applied the well-known ANFIS (adaptive network-based fuzzy inference systems) and neural networks to build a hybrid fuzzy-neural cost estimating system to predict the cost of performing component and engine tests at NASA's John C. Stennis Space Center testing facilities. This work is probably the first which evidenced the promising feature of applying Computational Intelligence to cost modeling and prediction.

The utility function, as another major element in economic analysis, is even harder to construct than the cost function. This is because cost is mainly engineering oriented and is more observable, whereas utility is a psychology- or neuron-oriented concept and is less observable. Sasaki [57] proposed a novel application of a genetic neural net to represent human agents' utility functions. Basically, it started with questionnaires on consumer's scoring on different sets of commodities, say, steaks and potatoes. The data were then used to train the genetic neural net, and the resultant net was a representation of the utility function of the respective consumer.

This work combined with the recent rise in the importance of neural economics can be considered as to be a first step toward a neuron-based foundation of the utility function. This is so because the information processing through the derived neural net can be imagined as the neural activities of the real brain when encountering a set of steaks and potatoes. This genetic neural net then serves as the value function for reinforcement learning, which is designed to direct the artificial agent to learn how to make a choice or trade. The real choice behavior or trading behavior of human agents can then be simulated by an equivalent group of artificial agents. While the work is far from mature, the idea is very creative. It shows that a society of software agents, each of which is designated by a respective human agent, can have bargaining and exchange behavior in line with consumption theory.

The determination of prices is a subject on which economists expend a lot of time and efforts. The fundamentals alone, including the cost function and utility function, are usually not sufficient to spell out a precise answer. Part of the indeterminacy comes from the strategic interactions of traders. Bargaining theory is devoted to the study of this unsettled area. However, behavior involving strategic interactions is hard to analyze analytically. Therefore, Computational Intelligence has been applied to this area to gain more information on possible outcomes. Nonetheless, most of the earlier work has neglected the importance of using time in forming bargaining strategies. In real situations, human agents frequently use time advantages to suspend a deal, and to wait for a more favorable opportunity to come later. Eiji Nawa [25] made progress by taking the time advantage explicitly into account. Following Rubinstein's [55] work on the alternating offer model, the author used finite state automata to represent bargaining strategies which regarded time as a part of them, and then applied evolutionary strategy to evolve these finite state automata. The effect of the time discount rate on the evolved bargaining behavior is discussed.

In addition to economics, CIEF'2003 also evidenced a few novel applications to finance. In finance, it has been questioned whether there is a potential gain for firms to tailor securities to the preferences of investors.

[21] An example, however, can be found in [64].

An important paper by [1] showed that, in incomplete markets, firms can reap gains from exploiting the difference in the marginal valuation of investors; therefore, it suggested that breaking cash flows up into pure securities maximizes value. From this theory, we should expect firms to issue a huge number of securities with respect to different states. However, in the real world, firms finance by issuing only one or two standard securities. Despite the existence of a few explanations for this puzzle, Noe et al. [49] tried to solve this puzzle from an evolutionary perspective. It applied genetic algorithms to conduct adaptive agent simulation. The genetic algorithm was applied to evolve the design of securities for firms, and it was also applied to evolve the bidding prices proposed by investors. The puzzle can then be answered by simulating the market via the co-evolution between these adaptive firms and investors.

Mergers and acquisitions are the hottest current issue in real-world business. The Monetary amounts involved in these activities are astronomical. Therefore, developing models to forecast corporate takeover can be valuable. Ref. [19] applies decision trees and artificial neural nets to predicting corporate takeover. While this is not the first application of CI to corporate takeovers, it is definitely among the few.

4. Article synopsis

At CIEF'2000 and CIEF'2002, we invited participants to submit their full papers after conference, and via a refereed process, we selected some of these papers for the inclusion in the special book volume and special journal issue. The five papers included in this volume are selected out of 29 submissions.[22] Based on the structure given in Sections 2 and 3, two of the five papers are contributions to agents, and the other three are contributions to the business and financial applications of Computational Intelligence. This section provides a quick overview of these five contributions.

4.1. Business and financial applications of computational intelligence

The core of the economic theory of firms is to identify the features of productivity, efficiency, competitiveness or survivability of firms, or more generally, to answer what makes some firms thrive and others decline. Using observations of firms, economic theory provides different approaches to the answer. Some are more theoretical and require rigid assumptions, while others do not. Data envelopment analysis [21] and stochastic frontier analysis [40] belong to the former, whereas self-organizing feature maps (SOFM) belong to the latter. The first article entitled "Strategic Supplier Selection in the Added-Value Perspective: A CI Approach" authored by Raquel Florez–Lopez applies the SOFM to the supplier selection problem. Given suppliers' attributes, the SOFM transfers a high-dimensional attribute space into a two-dimensional Euclidean space (map). Not only can the map inform the purchasing manager how the suppliers are distinct from or close to each other, but it also shows how far they are away from what the manager exactly wants. Thus the map helps the manager select an ideal supplier. However, the usual SOFM only deals with quantitative attributes and is not applicable to problems, such as customer satisfaction, which involve qualitative attributes. Florez–Lopez takes a fuzzy linguistic approach and employs a two-tuple fuzzy model to tackle this problem so that the SOFM can be applied to both quantitative and qualitative attributes.

The spirit of economics is the market mechanism. The market mechanism may serve as a unified principle of CI design. The second paper entitled "Self-Organizing Learning Array and its Application to Economic and Financial Problems" provides us with a manifestation of the market-based design. In this paper, the authors Zhen Zhu, Haibo He, Janusz Starzyk, and Chiu-Che Tseng, propose a network of classifiers (neurons) called SOLAR. SOLAR can be regarded as an extension of the feedforward neural net and the kernel machine (support vector machine): both the individual and the collective behavior of the classifiers in SOLAR are more sophisticated, and they are guided by an information-based self-organizing principle. With this principle, each neuron is asked to separate the input data into subspaces by maximizing the information gain. The authors can do so by choosing different neighborhoods associated with different inputs and a different separation plan (a transfer function and a threshold).

[22] Another 15 of these 29 were published in a book volume [17].

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

Since these neurons are distributed in a multi-layer feedforward architecture, neurons actually maximize information gain in a hierarchical order. It is this hierarchical structure that relates SOLAR to decision trees. The classification task is then performed by letting all these neurons "compete" with each other via the voting mechanism which is operated by a boosting algorithm. This competition design also connects SOLAR to the SOFM, while the former is a supervised learning and the latter is an unsupervised learning. The performance of SOLAR is also compared to the influence diagram, support vector machine, artificial neural net, decision tree, naive Bayesian classifier, and many other items on various testbeds.

Economists care about numbers more than other social scientists. While nothing can be more precise than numbers, it is not clear whether economists should take such preciseness seriously, in particular given the complexity and uncertainty of the surrounding system. The fuzzy number provides one possible solution to decision-makers to make sense of numbers. The fuzzy number has been introduced to economics and finance for years [35], but not much has been said about its incorporation into genetic programming. In particular, the crossover operator which is applicable to fuzzy terminals has not been attempted, and the vanilla subtree crossover, which only swaps two fuzzy terminals, may not be the most ideal way to go. Therefore, in their paper entitled "FuzzyTree Crossover for Multi-Valued Stock Valuation," the authors Pin-Chen Lin and Jiah-Shing Chen extend the conventional crossover operator so as to deal with the recombination of two fuzzy numbers, and hence establish a style of fuzzy genetic programming. The fuzzy genetic programming is then applied to the issue of stock valuation. The trapezoidal fuzzy number employed can be further connected to an investment recommendation based on the membership degree.

4.2. Agent-based computational economics

Both of the last two papers included in this issue belong to agent-based computational economics: one belongs to *agent-based computational macroeconomics*, and one belongs to *agent-based computational finance*.

Recent developments in macroeconomics have to some extent combined the theoretical work with the empirical work, known as *stylized facts replication*. Basically, the validity of a macroeconomic model is judged by its ability to replicate the stylized facts found in the empirical studies. However, most replication work done in macroeconomics is done *just at the macrolevel*. Most studies largely focused on the facts pertaining to business cycles. Few have attempted to replicate both the stylized facts of macro and microbehavior, such as the industrial sector and financial sector, simultaneously. The behavior of the constituents, or the microstructure, is largely absent in most macroeconomic models simply because of the excessive use of the homogeneity assumption. The paper entitled "Complex Dynamics and Empirical Evidence" written by Domenico Delli Gatti, coauthored with Edoardo Gaffeo, Mauro Gallegati, Gianfranco Giulioni, Alan Kirman, Antonio Palestrini and Alberto Russo, shows how agent-based macroeconomic models can effectively simultaneously replicate the stylized facts both at the microlevel and the macrolevel.

The authors propose an agent-based economic model, called the HIA (Heterogeneous Interacting Agents) model. This model is composed of a heterogeneous profit-maximizing firm which produces a homogeneous product with the same technology. The prices assigned to each firm's products are stochastic and different, but they follow the same distribution which is exogenously given. Firms can finance their investment either internally (by retained earnings) or externally (by banks). Depending on the firms' financial soundness or fragility, banks charge firms different interest rates, which in turn, creates different cost advantages and profitability for firms, and which can further impact firms' relationship with banks. The feedback dynamics determine the firms' structure of capital and scale, the banks' supply of credit, and the aggregate output. Therefore, not only can macroeconomic activities, such as output, the interest rate, and investment be observed in this model, but also the microeconomic phenomena, such as the firms' size, can be studied as well.

The last paper included in this issue is a contribution to agent-based computational finance or agent-based artificial financial markets. The typical agent-based financial models study the impact of investors' behavior upon price dynamics.[23] They also address the survival of different types of investors with respect to different kinds of trading behavior. While traders are heterogeneous in different aspects of trading

[23] See also Section 2.7.

behavior, they generally share the same risk preference (the utility function). This, therefore, leaves the role of risk preference largely unclear in this type of model. As a matter of fact, there is a long debate in the mainstream finance literature concerning whether investors' survivability depends on their risk preference. The last article entitled "Relative Risk Aversion and Wealth Dynamics," written by Shu-Heng Chen and Ya-Chi Huang, introduced agents with heterogeneous risk preference into the artificial stock market. They considered a specific class of risk preference, knows as CRRA (constant relative risk aversion). Agents' preferences for risk are characterized by the respective coefficients of risk aversion. Through agent-based simulation, it was found that risk aversion can have a significant impact upon saving behavior, which in turn affects the survivability of agents. Specifically, those who are more risk averse eventually dominate a large proportion of wealth.

5. Concluding remarks

In this paper, we have highlighted some of the progress regarding the economic and financial applications of Computational Intelligence observed at the CIEF'2003 conference. While more details regarding the above-mentioned ideas in this review can be found in the proceedings of the 7th JCIS, the book volume [17], and this special issue, the purpose of this paper is to give readers who wish to quickly grasp the issues that are current in this research field a general and well-structured picture.

Acknowledgements

We are grateful to Prof. Paul Wang, General Chair JCIS'2003 and Special Issue Editor of Information Sciences, as well as Witold Pedrycz, the editor, for their great support in publishing this special issue. We would also like to take this opportunity to express our appreciate to all the participants of CIEF'2003, who together not only produced a high-quality conference, but also contributed to significant progress in this research filed. The author is also grateful for research support in the form of Grant NSC94-2415-H-004-003.

References

[1] F. Allen, D. Gale, Optimal security design, Review of Financial Studies, vol. 1(3), Oxford University Press for Society for Financial Studies, 1988, pp. 229–263.
[2] T. Amemiya, Qualitative response models, Annals of Economics and Social Management 4 (1975) 363–372.
[3] W.B. Arthur, Inductive reasoning and bounded rationality, American Economic Association Papers and Proceedings 84 (1994) 406–411.
[4] R. Axtell, US firm sizes are zipf distributed, Science 293 (2001) 1818–1820.
[5] R. Axtell, Effect of interaction topology and activation regime in several MAS, in: S. Moss, P. Davidsson (Eds.), Multi-Agent-Based Simulation, Springer Lecture Notes in Artificial Intelligence, vol. 1976, Springer, Berlin, 2001, pp. 33–48.
[6] E. Bonabeau, Econometrics of Agent-based Models, A keynote speech given at the 2nd Lake Arrowhead Conference on Human Complex Systems, Lake Arrowhead, California, March 19–22, 2003.
[7] J. Bower, D. Bunn, Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the England and Wales electricity market, Journal of Economic Dynamics and Control 25 (2001) 561–592.
[8] S. Boyle, S. Guerin, D. Kunkle, An application of multi-agent simulation to policy appraisal in the criminal justice system, in: S.-H. Chen, L. Jain, C.-C. Tai (Eds.), Computational Economics: A Perspective from Computational Intelligence, IDEA Group Publishing, Hershey, PA, 2005, pp. 228–234.
[9] C. Camerer, T.H. Ho, Experience-weighted attraction learning in normal form games, Econometrica 67 (4) (1999) 827–874.
[10] S.-H. Chen, Toward an agent-based computational modeling of bargaining strategies in double auction markets with genetic programming, in: K.S. Leung, L.-W. Chan, H. Meng (Eds.), Intelligent Data Engineering and Automated Learning-IDEAL 2000: Data Mining, Financial Engineering, and Intelligent Agents, Lecture Notes in Computer Sciences 1983, Springer, Berlin, 2000, pp. 517–531.
[11] S.-H. Chen, An overview, in: S.-H. Chen (Ed.), Genetic Algorithms and Genetic Programming in Computational Finance, Kluwer, Dordrecht, 2002, pp. 1–26.
[12] S.-H. Chen, Computational intelligence in economics and finance: carrying on the legacy of Herbert Simon, Information Sciences 170 (1) (2005) 121–131.
[13] S.-H. Chen, B.-T. Chie, Agent-based modeling of lottery markets, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1227–1230.

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

[14] S.-H. Chen, C.-C. Liao, Behavioral finance and agent-based computational finance: toward an integrating framework, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1235–1238.
[15] S.-H. Chen, C.-C. Tai, On the selection of adaptive algorithms in ABM: a computational-equivalence approach, Computational Economics, forthcoming.
[16] S.-H. Chen, P. Wang, Computational Intelligence in Economics and Finance, Springer, Heidelberg, 2003.
[17] S.-H. Chen, L. Jain, C.-C. Tai, Computational Economics: A Perspective from Computational Intelligence, Idea Group Publishing, Hershey, PA, 2005.
[18] S.-H. Chen, C.-C. Tai, X. Yao, A preview of the third international workshop on computational intelligence in economics and finance (CIEF'2003), in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 985–987.
[19] C.-H. Chu, D. Zhu, Computational intelligence for predicting corporate takeovers: a comparison of alternative models, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1187–1190.
[20] D. Cliff, J. Bruten, Minimal-intelligence agents for bargaining behaviors in market-based environments, Technical Report No. 97-91, Hewlett Packet Lab, 1997.
[21] W.W. Cooper, L.M. Seiford, K. Tone, Introduction to Data Envelopment Analysis and Its Uses: With DEA-Solver Software and References, Springer, New York, 2005.
[22] D. Delli Gatti, E. Gaffeo, M. Gallegati, G. Giulioni, A. Kirman, A. Palestrini, A. Russo, Complex dynamics and empirical evidence, Information Sciences, this special issue.
[23] J. Duffy, Agent-based models and human-subject experiments, in: L. Tesfatsion, K.L. Judd (Eds.), Handbook of Computational Economics, vol. 2, North Holland, Amsterdam, forthcoming.
[24] E. Dugundji, L. Gulyas, Empirical estimation and multi-agent-based simulation of a discrete choice model with network interaction effects, Paper presented at The Agent 2003 Conference on Challenges in Social Simulation, University of Chicago, October 2–4, 2003.
[25] N. Eiji Nawa, Designing agents that strategically use time in negotiation situations, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1009–1012.
[26] N. Feltovic, Slow learning in the market for lemons: a note on reinforcement learning and the winner's curse, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1023–1026.
[27] D. Fogel, K. Chellapilla, P. Angeline, Evolutionary computation and economic models: sensitivity and unintended consequences, in: S.-H. Chen (Ed.), Evolutionary Computation in Economics and Finance, Springer, Heidelberg, 2002, pp. 245–269.
[28] J.K. Frels, D. Heisler, and J.A. Reggia, Standard-Scape: An Agent-Based Model of Adoption with Incomplete Information and Netwrok Externalities, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1219–1222.
[29] D. Fudenberg, D.K. Levine, The Theory of Learning in Games, MIT Press, Cambridge, MA, 1998.
[30] D. Gode, S. Sunder, Allocative efficiency of markets with zero-intelligence traders: market as a partial substitute for individual rationality, Journal of Political Economy 101 (1) (1993) 119–137.
[31] J. Grossklags, C. Schmidt, Interaction of human traders and artificial agents on double auction markets: simulations and laboratory experiments, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1269–1272.
[32] J. Grossklags, C. Schmidt, Artificial software agents on thin double auction markets: a human trader experiment, in: Proceedings of the 2003 IEEE/WIC International Conference on Intelligent Agent Technology, 2003, pp. 400–407.
[33] C. Guo, Predictability of the Shanghai stock market by an agent-based mix-game model, in: Proceedings of the 2005 International Conference on Neural Networks and Brain, IEEE Press, NJ, 2005, pp. 1651–1655.
[34] M.A. Kaboudan, A measure of time series predicitability using genetic programming applied to stock returns, Journal of Forecasting 18 (1999) 345–357.
[35] C. Kahraman, C.E. Bozdag, Fuzzy investment analysis using capital budgeting and dynamic programming techniques, in: S.-H. Chen, P. Wang (Eds.), Computational Intelligence in Economics and Finance, Springer, Heidelberg, 2003, pp. 92–127.
[36] E.J. Kaminsky, F. Douglas, A fuzzy-neural highly accurate cost estimating model (HACEM), in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1035–1039.
[37] M.L. Katz, C. Shapiro, Network externalities, competition, and compatibility, American Economic Review 75 (1985) 424–440.
[38] Y. Koyama, H. Sato, H. Matusi, Y. Nakajima, Report on UMIE 2004 and summary of U-Mart experiments based on the classification of submitted machine agents, in: T. Terano, H. Kita, T. Kaneda, K. Arai, H. Deghchi (Eds.), Agent-Based Simulation: From Modeling Methodologies to Real-World Applications, Springer Series on Agent-Based Social Systems, vol. 1, Springer, Tokyo, 2005, pp. 158–166.
[39] J. Koza, Genetic Programming II: Automatic Discovery of Reusable Programs, MIT Press, Cambridge, MA, 1994.
[40] S.C. Kumbhakar, C.A. Knox Lovell, Stochastic Frontier Analysis, Cambridge, Cambridge, 2003.
[41] F.E. Kydland, E.C. Prescott, Time to build and aggregate fluctuation, Econometrica 50 (6) (1982) 1345–1371.
[42] C.-Y., Lin, C.-S. Mao, Heterogeneous expectations and learning mechanisms in a RBC model, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 988–991.

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

[43] T. Lux, Estimation of agent-based models: the case of an asymmetric herding model, Workshop on Agent-Based Modeling for Economic Policy Design, Center for Interdisciplinary Research, University of Bielefeld, Germany, June 30–July 2, 2005.
[44] S.M. Markose, The new evolutionary computational paradigm of complex adaptive systems: challenges and prospects for economics and finance, in: S.-H. Chen (Ed.), Genetic Algorithms and Genetic Programming in Computational Finance, Kluwer, Dordrecht, 2002.
[45] G. Midgley, Systemic intervention for community involvement in complex policy, 1st International Workshop on Complexity and Policy Analysis, Cork, Ireland, June 22–24, 2005.
[46] R. Nakajima, Measuring peer effects in youth smoking behavior, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1206–1210.
[47] J. Nicolaisen, M. Smith, V. Petrov, L. Tesfatsion, Concentration and capacity effects on electricity market power, in: A. Alzala et al. (Eds.), Proceedings of the 2000 Congress on Evolutionary Computation, IEEE Society Press, NJ, 2000, pp. 1041–1047.
[48] J. Nicolaisen, V. Petrov, L. Tesfatsion, Market power and efficiency in a computational electricity market with discriminatory double-auction pricing, IEEE Transactions on Evolutionary Computation 5 (5) (2001) 504–523.
[49] T.M. Noe, J. Rebello, J. Wang, The evolution of security design, Paper presented at the 3rd International Workshop on Computational Intelligence in Economics and Finance, Cary, NC, September 26–30, 2003.
[50] M. North, Applying computational intelligence to economic policy, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1231–1234.
[51] J. Ochs, Simple games with unique mixed strategy equilibrium: an experimental study, Games and Economic Behavior 10 (1) (1995) 202–217.
[52] J.A. Primbs, M. Rathinam, Trade behavior in the modeling of asset price dynamics, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1247–1250.
[53] S. Reitz, F. Westerhoff, C. Wieland, Target zone interventions and coordination of expectations, Paper presented at The 10th International Conference on Computing in Economics and Finance, University of Amsterdam, Amsterdam, The Netherlands, July 8–10, 2004.
[54] A.E. Roth, I. Erev, Learning in extensive-form games: experimental data and simple dynamic models in the intermediate term, Games and Economic Behavior 8 (1995) 164–211.
[55] A. Rubinstein, A bargaining model with incomplete information about time preferences, Econometrica 53 (1982) 1151–1172.
[56] Y. Sasaki, N. Flann, Online optimization of traffic policy through multi-agent reinforcement learning, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1211–1214.
[57] Y. Sasaki, Utility modules: embedding real world preferences and behaviors in artificial economic agents, Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1013–1016.
[58] H. Sato, S. Kawachi, A. Namatame, The statistical properties of price fluctuations by computer agents in a U-Mart virtual future market simulator, in: T. Terano, H. Dehuchi, K. Takadama (Eds.), Meeting the Challenge of Social Problems via Agent-Based Simulation, Springer, Tokyo, 2003, pp. 67–76.
[59] S.E. Spear, Learning rational expectations under computability constraints, Econometrica 57 (4) (1989) 889–910.
[60] N. Svangard, P. Nordin, Generating investment policies for nonlinear portfolio optimization with genetic programming, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1161–1164.
[61] N. Svangard, P. Nordin, S. Lloyd, Predicting stock market reactions to financial news using naive Bayesian classifiers, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1067–1070.
[62] T. Terano, H. Takahashi, Analyzing micro-macro structures in a financial market via agent-based simulation, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1255–1258.
[63] T. Terano, Y. Shiozawa, H. Deguchi, H. Kita, H. Matsui, H. Sato, I. Ono, Y. Kakajima, U-Mart: an artificial market testbed for economics and multiagent systems, in: T. Terano, H. Dehuchi, K. Takadama (Eds.), Meeting the Challenge of Social Problems via Agent-Based Simulation, Springer, Tokyo, 2003, pp. 53–66.
[64] C.-Y. Tsao, S.-H. Chen, Statistical analysis of genetic algorithms in discovering technical trading strategies, Advances in Econometrics 17 (2004) 1–43.
[65] C.-C. Tseng, Influence diagram for investment portfolio selection, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1171–1174.
[66] M. Tsuji, H. Kawamura, A. Ohuchi, Measuring the effect of indirect network externality in VCR standardization process, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1215–1218.
[67] K. Velupillai, Computability, Complexity And Constructivity In Economic Analysis, Blackwell, Oxford, 2005.
[68] P.P. Wang, Computing With Words, Wiley-Interscience, New York, 2001.
[69] E.R. Weintraub, Microfoundations: The Compatibility of Microeconomics and Macroeconomics, Cambridge University Press, Cambridge, 1979.
[70] S. Wu, S. Bhattacharyya, Minimal intelligence agents in double auction markets with speculators, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1265–1268.
[71] C.-H. Yeh, The Influence of GP's representation in financial data mining, in: Proceedings of 7th Joint Conference on Information Sciences, 2003, pp. 1092–1095.

Please cite this article as: Computationally intelligent agents in economics and finance, Information Sciences (2006), doi:10.1016/j.ins.2006.08.001

[72] Z. Zhu, H. He, J.A. Starzyk, C. Tseng, Self-organizing learning array and its application to economic and financial problems, Information Sciences, this special issue.

Shu-Heng Chen
AI-ECON Research Center,
Department of Economics,
National Chengchi University,
Taipei 116, Taiwan
Tel./fax: +886 2 29387308.
E-mail address: chchen@nccu.edu.tw
URL: http://www.aiecon.org