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The relationship between model complexity and forecasting performance for computer intelligence optimization in finance

Adam Ghandar[a,b], Zbigniew Michalewicz[b,c,d], Ralf Zurbruegg[e,*]

[a] Schneider Electric SDO, Adelaide, SA 5000, Australia
[b] School of Computer Science, University of Adelaide, Adelaide, SA 5005, Australia
[c] Institute of Computer Science, Polish Academy of Sciences, ul. Ordona 21, 01-237 Warsaw, Poland
[d] Polish-Japanese Institute of Information Technology, ul. Koszykowa 86, 02-008 Warsaw, Poland
[e] Business School, University of Adelaide, Adelaide, SA 5005, Australia

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ABSTRACT

The objective of this paper is to show that the ability of nature-inspired optimization routines to construct complex models does not necessarily imply any improvement in performance. In fact, the reverse may be the case. We demonstrate that under the dynamic conditions found in most financial markets, complex prediction models that seem, ex-ante, to be at least as good as more simple models, can underperform in out-of-sample tests. The correct application of these optimization methods requires a knowledge of how and when these techniques will yield beneficial outcomes. We highlight the need for future research to focus on appropriate protocols and a systematic approach to model selection when computer intelligence optimization methods are being utilized, particularly within the realm of financial forecasting.

1. Introduction

Recent years have seen a growing interest in the application of computational intelligence (CI) systems and methods to a range of financial and economic applications, from facilitating automated trades to forecasting (see Bahrammirzaee, 2010). The term *computational intelligence* is generally used to represent problem-solving approaches that use nature-inspired optimization processes. Methods that involve the use of biologically-inspired algorithms have been shown to be successful in many cases where the complexity of the issue means that structural and stepwise modelling of the problem is not possible. This is particularly true when considering the use of CI methods in financial forecasting (see Atsalakis & Valavanis, 2009). At the same time, much of this technology has been developed by the computer sciences for applications in areas outside the fields of finance and economics (see Lam, Ling, & Nguyen, 2012, for a review of CI applications). The highly dynamic environment of the financial markets can require a high level of adaptability (see Kasabov, Erzegovezi, Fedrizzi, Beber, & Deng, 2000). However, there has been little research establishing protocols and systematic approaches for algorithm selection and parameter settings in financial forecasting applications. These issues are important because all CI optimization routines are stochastic searches, with the consistency of their performance inevitably being tied to the parameter settings of the search routine.

We attempt to address this gap, and, to the best of our knowledge, are the first to examine the issues sur-

* Corresponding author. Tel.: +61 8 8313 5535.
E-mail address: Ralf.Zurbrugg@adelaide.edu.au (R. Zurbruegg).

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rounding the relationship between the way in which CI optimization structures its solutions and its effect on the out-of-sample performance, within the dynamic setting of financial market forecasting. To initiate further dialogue on this subject, we examine one of the primary drivers of the overall performance in CI optimization, *model complexity*, which is a measure of the number of parameters and their corresponding relationships, as utilized within a prediction model. CI methods have a theoretical advantage in being able to handle large numbers of linear and nonlinear relationships, which can then be expressed in a range of computational formats. However, this inherent benefit may also be a cost. If relationships are time-variant, as is the case in the dynamic environment of financial markets, an increase in model complexity can result in redundant information being retained, leading to sub-optimal solutions. In fact, White's (2006) review of nonlinear forecasting highlights the fact that these types of forecasts can be computationally demanding, as well as having the potential for overfitting.[1] CI includes several techniques that can handle this, including the utilization of penalty functions that can serve as an Ockham's razor, ensuring that the benefits of complex models outweigh the costs of overfitting the data. However, the current research that focuses on the use of CI processes for financial forecasting is devoted overwhelmingly to showing how CI can 'beat' traditional methods, with little attention being paid to the process of selecting the right optimization and model representation routines.

This paper provides an example of how a CI optimization routine needs to be tailored carefully towards the underlying financial data structure that is being examined. In particular, it emphasizes that the rush to develop ever more complex CI models is not necessarily beneficial, given the dynamic environment under which financial markets operate. We hypothesize that the relationship between performance and model complexity will not necessarily be the same for underlying data structures from static and dynamic environments. We show this by first developing a comprehensive CI optimization routine whose multi-objective function is to provide a Pareto front of models that trade-off complexity for performance, then examining the performances of these models via out-of-sample tests. The performance is measured by examining the forecast errors, as well as investigating which models belong to the model confidence set (MCS), as was proposed by Hansen, Lunde, and Nason (2011). Our results illustrate that the use of a given optimization technology leads to different types of trade-offs between model complexity and performance in static (for credit card screening) and dynamic (stock selection in a portfolio) environments. For a given optimization process, we find the over-fitting problem to be more pronounced for the dynamic financial markets environment than a for static environment, with an inverted-U shaped relationship existing between an increasing model complexity and performance.

[1] Varian (2013) provides a review of recent techniques that deal with over-fitting when dealing with large data, and Clark (2004), Hansen (2009), Inoue and Kilian (2006), and Rossi and Sekhposyan (2011) are but a few examples of work examining the over-fitting problem in general regression frameworks.

We conclude the paper by highlighting how our findings point to the need for future research to switch its emphasis from demonstrating the performances of these methods, relative to standard financial and economic models, to developing protocols for building models that deal with the intricacies of the functioning of CI optimization. The application of CI methods to finance requires a richer understanding of the processes used for optimization, and the establishment of guidelines and steps for assisting future users of this technology.

The rest of the paper is structured as follows. Section 2 provides a short background on CI and its use in finance, while Section 3 discusses the CI tools and research methods that we use for analyzing the tradeoff between model complexity and performance. Section 4 provides empirical results, and Section 5 concludes with summary remarks on directions for future research.

2. Background

The increased interest in the application of computational intelligence methods to financial modelling and forecasting has come simultaneously with a corresponding dramatic rise in the automation of trading around the world. Narang (2009) estimates that over 40% of the market orders executed in 2008 were attributable to computational methods in major developed stock markets. Related to this is the interest in using CI methods to examine and develop technical trading rules. Early works by Allen and Karjalainen (1999) and Neely, Weller, and Dittmar (1997) are good examples of academic research that has investigated the use of CI methods for finding trading rules in stock and foreign exchange markets, respectively. This line of work has now expanded to the prediction of everything from bank failures to rating bonds and stock picking. Bahrammirzaee (2010) provides a comparative survey of the emergent literature, primarily in the field of computer science. The amount of research published in finance and economics journals has also increased, with Safarzyńska and Bergh (2010) providing a survey of a number of CI methods and their applications. Most of the emphasis in terms of their application to finance is still on the use of the technology to design trading rules. Recent examples of this include the studies by Gradojevic and Gençay (2013) and Hsu and Kuan (2005), who both demonstrate the advantages of using CI rules for technical trading.

The growth in the development of financial market applications for CI has also been spurred on by the technical advancement of modern computers, in that these advances have rendered CI processes practicable from a time-processing perspective (see Arenas, Romero, Mora, Castillo, & Merelo, 2012). Moreover, it could be argued that the underlying optimization methods are conducive to the solving of complex nonlinear problems that largely do not require any *a priori* assumptions about the data generating process. Relative to traditional methods, there is a substantial potential for the solving of complex problems in a dynamic environment that has not been examined fully before in the fields of economics and finance.

Given the number of CI optimization routines that there are to choose from (see Neumann & Witt, 2012, for a review