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Enhancing risk-adjusted performance of stock market intraday trading with Neuro-Fuzzy systems

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ABSTRACT

Whilst the interest of many former studies on the application of AI in finance is solely on predicting market movements, trading practitioners are predominantly concerned about risk-adjusted performance. This paper provides new insights into improving the time-varying risk-adjusted performance of trading systems controlled by Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Systems (ANFIS) or Dynamic Evolving Neuro Fuzzy Systems (DENFIS). Contrary to most former studies which focus on daily predictions, we compare these models in an intraday stock trading scenario using high-frequency data. Firstly, we propose a dynamic extension of the popular moving average rule and enhance it with a model validation methodology using heat maps to analyse favourable profitability in specific holding time and signal regions. Secondly, we study the effect of realistic constraints such as transaction costs and intraday trading hours, which many existing approaches in the literature ignore. Thirdly, unlike most former studies that only aim to minimise statistical error measures, we compare this approach with financially more relevant risk-adjusted objective functions. To this end, we also consider an innovative ANFIS ensemble architecture which on an intraday level dynamically selects between different risk-adjusted models. Our study shows that accounting for transaction costs and the use of risk-return objective functions provide better results in out-of-sample tests. Overall, the ANN model is identified as a viable model, however ANFIS shows more stable time-varying performance across multiple market regimes. Moreover, we find that combining multiple risk-adjusted objective functions using an ANFIS ensemble yields promising results.

1. Introduction

The profitability of technical trading rules is an incessant debate. By examining 30 min prices Schulmeister [33] claims that beyond the 1990s profitability of technical trading rules has possibly moved to higher frequency prices as a result of faster algorithmic trading and more efficient markets. Opposing views [23] claim that aggressive high-frequency trading (HFT) does not lead to the expected high excessive returns. In spite of this persisting contention in the high frequency space, a recent survey [24] showed that the majority of former studies still focus on daily price forecasts using lagged index data and technical trading indicators. Moreover, many former studies focus on the application of models solely to predict market movements [34] and seem to disregard the fact that investors are more interested in risk-adjusted performance rather than just price predictions themselves [6,44].

Tsai and Wang [39] and Krollner et al. [24] identified that Artificial Neural Networks (ANNs) are the dominant machine learning technique in AI based financial applications. On the downside ANNs are regarded as black boxes that cannot describe the cause and effect. Moreover, hybrid models were again found to provide better forecasts compared to ANNs used alone or traditional time series models. Following the emergence of Fuzzy Logic [45], Neural Networks and Fuzzy Inference Systems were brought together as general structures for approximating non-linear functions and dynamic processes. A popular cited technique in nonstationary and chaotic time series prediction is the Adaptive Neuro-Fuzzy Inference System (ANFIS) by Jang [19]. With a focus on dynamic learning of rules from data Kasabov and Song [22] introduced pioneering work on evolving Neuro-Fuzzy systems with the introduction of Dynamic Evolving Neural-Fuzzy Inference System (DENFIS) and its application for time-series prediction. The proposition of evolving models is to keep systems continuously adapting, and hence evolving, to address recurring and changing patterns in underlying environments. Successful application of ANFIS in trading applications by predicting stock price was demonstrated in Gradojevic [16] and Kablan and Ng [20] and many others. To our best knowledge DENFIS was not previously applied in a high-frequency setting.

Recently, Melin et al. [28] and Lei and Wan [25] identified that ANFIS ensembles (which we denote as eANFIS in this paper) provided better generalisation and a reduction in mean squared error when compared against conventional ANFIS and other

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chaotic time series models. Their ensemble integration approach was based on applying the average or weighted average methods across the regression predictions of all components of the ensemble (see also [36] who extended this by applying a fuzzy integrator approach). Despite these claims, Faulina et al. [12] showed that ensemble models involving more complex ANFIS combinations do not necessarily lead to improved performance. In this paper, we explore potential trading performance improvements in a high-frequency trading setting with the application of ANFIS ensembles and the identification of integration methods driven by risk-return objectives.

This paper provides new insights into improving the risk-adjusted performance of simple technical trading rules in an intraday stock trading scenario using high-frequency data with the application of artificial intelligence and soft computing techniques. In our experiments we use a set of stocks listed on the London Stock Exchange with a focus on a number of objectives:

1. We explore the debated profitability and an augmentation of moving average rules, particularly focusing on high-frequency data in an intraday trading scenario rather the more common day ahead predictions.
2. In contrast to common trading system designs that focus on a fixed target returns, we investigate return bands in the region between 0.1% and 0.5% which act as a threshold for unprofitable small trades.
3. We evaluate the profitability of less aggressive HFT strategies, with holding time of trading positions (PT) in the region between 10 min and 1 h, in view of stated claims of unattainable high excessive returns from more aggressive HFT strategies.
4. We consider real world intraday trading constraints like trading costs, realistic trading hours and no overnight positions, which are ignored in existing studies dealing only with daily trading frequencies.
5. We investigate the risk-adjusted performance attained from three representative milestone models in Neurocomputing, namely Artificial Neural Networks (ANNs), ANFIS and DENFIS models and also explore the effectiveness of the more sophisticated eANFIS architecture.
6. We also compare the time series of risk-adjusted performance measures obtained using different model optimisation functions such as single risk-return functions, an innovative combination of different risk-return functions via an ensemble, Root Mean Squared Error (RMSE), and Period Return and models optimised without considering transaction costs.

Our first contribution is the simple but yet effective extension of common technical trading strategies by considering a dynamic ‘portfolio’ of moving average prediction models controlled by Neuro-Fuzzy systems. This is further extended by applying dynamic rules for return bands and trade position times. In line with Tsang [40] our models try to answer questions of the following form: “*Will the price go up* (*or down*) *by r% in the next t minutes*?” An important challenge in this study is the choice of moving average window length. For example, if the price over an interval is, in general, trending up, there are also several short-term downtrends in the price data. Some of them are real trend reversal points and others are just noise. The trend identifying mechanism should not be overly sensitive to short-term fluctuations, hence applying a too short moving average, as that would result in falsely reporting a break in trend. On the other hand, choosing a too long moving average will result in late reaction to price movement. We suggest a combination of multiple moving average rules as input to the prediction models. This is further enhanced by applying a model validation methodology using heat maps to analyse favourable risk-return regions that identifies profitability in specific holding time and signal regions.

As our second major contribution we further extend our trading systems with decision rules accounting for transaction costs and trading hours. Krollner et al. [24] find that although more than 80% of the papers state that their proposed framework surpassed the benchmark model, most of them are actually ignoring trivial constraints in the real world which would bias the results (see also [2]). This introduces a risk of overestimated profitability when realistic constraints are applied.

When training and evaluating a trading system, most former studies only have very limited view of what constitutes successful investment decisions, defining on grounds of forecast accuracy and win ratios, and often choose to minimise the forecast error of the price prediction, setting this as the objective function [3,7,9,27]. However, small forecast error does not guarantee trading profits [5]. Krollner et al. [24] also identify a lack of literature studying whether AI based algorithms can enhance an investor's risk-return trade-off. While a few attempts were reported recently, mainly for other financial applications [8,10,11], the implementation of risk-adjusted performance control has to our best knowledge not been studied in a intraday high-frequency setting before (see also a recent comprehensive survey by Bahrammirzaee [4] and the references therein).

As our third contribution we explore how the high-frequency trading performance can be improved by analysing the time series of risk-adjusted performance measures. To assess their performance, we also compare our findings against results obtained from other model optimisation functions such as Root Mean Squared Error (RMSE) and models not considering transaction costs. Recent lessons such as the flash crash in 2011 suggest that not all risks are worth taking in intraday trading. Our paper aims to shed more light on the risk return profile for selected stocks traded at the London stock Exchange and explains how this information can be capitalised. We also consider an innovative combination of these risk-return functions using an ANFIS ensemble dynamic selection method, and show how it can improve the intraday trading performance of AI models. Finally, in contrast to common approaches in the literature which evaluate models using performance measures at an arbitrary single point in time (e.g. only at the end of the sample period), our goal is to provide a deeper understanding of the time-varying performance profile of the applied models.

The remainder of the paper is structured as follows. In Section 2 we first introduce the moving average signals and explain on how these can be combined to model stock returns. We then discuss our experiment and describe model components and underlying prediction and trading algorithms. Section 3 presents the data, our findings and a discussion in the light of existing literature. Section 4 concludes.

2. Method

A central theme in the technical trading approach is the ability to recognise patterns in market prices that supposedly repeat themselves and hence can be used for predictive purposes. A number of authors showed the predictive capabilities of simple trading rules in conjunction with the application of Artificial Neural Networks. For a survey, e.g. see Vanstone and Finnie [42] and Vanstone and Finnie [43], and the references therein. This body of research showed the predictive ability of simple trading rules on daily returns with the application of ANNs and contrasted the weaknesses with traditional econometric models which fail to give satisfactory forecasts for some series because of their linear