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Combining technical trading rules using particle swarm optimization

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ABSTRACT

Technical trading rules have been utilized in the stock market to make profit for more than a century. However, only using a single trading rule may not be sufficient to predict the stock price trend accurately. Although some complex trading strategies combining various classes of trading rules have been proposed in the literature, they often pick only one rule for each class, which may lose valuable information from other rules in the same class. In this paper, a complex stock trading strategy, namely performance-based reward strategy (PRS), is proposed. PRS combines the two most popular classes of technical trading rules – moving average (MA) and trading range break-out (TRB). For both MA and TRB, PRS includes various combinations of the rule parameters to produce a universe of 140 component trading rules in all. Each component rule is assigned a starting weight, and a reward/penalty mechanism based on rules' recent profit is proposed to update their weights over time. To determine the best parameter values of PRS, we employ an improved time variant particle swarm optimization (TVPSO) algorithm with the objective of maximizing the annual net profit generated by PRS. The experiments show that PRS outperforms all of the component rules in the testing period. To assess the significance of our trading results, we apply bootstrapping methodology to test three popular null models of stock return: the random walk, the AR(1) and the GARCH(1,1). The results show that PRS is not consistent with these null models and has good predictive ability.

1. Introduction

Technical trading rules are widely used in the financial markets as technical analysis tools for security trading. Typically, they predict the future price trend by analyzing historical price movements and initiate buy/sell signals accordingly. Technical trading rules have been developed for more than a century and many empirical studies including, but not limited to, Brock, Lakonishok, and LeBaron (1992), Gencay (1998), Kestner (2003), Austin, Bates, Dempster, Leemans, and Williams (2004), Hsu and Kuan (2005), Lento and Gradojevic (2007), Metghalchi, Marcucci, and Chang (2012), and Chiang, Ke, Liao, and Wang (2012), provided supporting evidence to the significant profitability of various technical trading rules. Until nowadays trading rules are commonly used by practitioners to make trading decisions in many financial markets (Menkhoff, 2010).

Instead of asking whether specific rules work, Allen and Karjalainen (1999) proposed using genetic algorithms (GA) (Holland, 1992), a class of machine learning algorithms, to discover profitable technical trading rules. The targeted rules were logical combination of many fundamental technical indicators using arithmetic operators and logical functions. Similarly, Dempster and Jones (2001) used genetic programming (GP) (Koza, 1994) which is an extension of GA to develop a trading system consisting of different technical indicators for a foreign exchange market. In their studies, a set of training data was used to find the optimal trading rules, then these rules were tested on an out-of-sample data. However, the discovered rules did not show consistent and robust profitability for the testing data even though they had significant performance for the training data. One reason may be that these studies ignored the existing profitable trading rules in the literature and the discovered rules were totally data driven.

In practice, investors may not stick to only a single rule without considering the available information generated from other technical trading rules. Pring (1991) also argued that no single trading rule can ever be expected to forecast all price trends and it is important to combine simple trading rules together to get a complex trading strategy. Hsu and Kuan (2005) first examined the profitability of three classes of complex trading strategies: learning strategies (LS), vote strategies (VS) and fractional position strategies (FPS). Their results, however, showed that these complex trading strategies did not provide significant improvement as compared with simple trading rules. The failure of these trading strategies may be because they are relatively primitive. For example, LS picked the best simple trading rule for trading decision making

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each time instead of combining all rules in an appropriate manner. For VS and FPS, both of them regarded all simple trading rules as equally important without considering their relative performances.

Unlike the above primitive combination methods, Subramanian, Ramamoorthy, Stone, and Kuipers (2006) proposed a weighted combination of technical trading rules. In their study, each rule is assigned a weight, and the strategy's signal is determined by the weighted sum of all component rules' signals. They created this combination by applying a GA to optimize the best set of weight vector. Thereafter Briza and Naval (2011) proposed a similar stock trading strategy whose weight vector was optimized by particle swarm optimization (PSO) (Kennedy & Eberhart (1995)). Both strategies were found to outperform the best component trading rules in terms of profit in the testing period. However, they only considered a commonly used rule for each class of trading rule in their studies. This may not guarantee that the trading rules under consideration always perform better than those not considered. Results from Brock et al. (1992), Sullivan, Timmermann, and White (1999) and Hsu and Kuan (2005) also support that the profitability of various rules belonging to the same type vary significantly. Therefore it is important to include various combinations of parameters for each class of rule as many as possible to get a comprehensive coverage of simple trading rules. Note that above approaches (Subramanian et al., 2006; Briza & Naval, 2011) assumed the weights of component rules were held fixed during the entire trading period. However, component rules' performances may not be stable and hence a trading strategy with a static choice of component weights may be hard to perform well consistently over time. In this regard, an objective of this work is to consider a dynamic updating scheme for component weights.

As discussed above, the optimization of complex trading strategies is to find the optimal combination of simple trading rules, or in other words the optimal set of parameter values with the goal of making profit as high as possible. As opposed to traditional function optimization problems, the evaluation functions of complex trading strategies are non-differentiable. Therefore, the classic mathematical optimization methods such as linear programming and Newton's method are not practical. In the literature, GA and PSO are the two most popular stochastic optimization algorithms used for financial forecasting purposes. For example, Allen and Karjalainen (1999) used GA to learn technical trading rules for the S& P 500 index; Esfahanipour and Mousavi (2011) generated technical trading rules for decision making in stock markets by using GP; Hsu et al. (2011) presented a new funds trading strategy which combines turbulent particle swarm optimization (TPSO) and mixed moving average techniques, and recently Sermpinis, Theofilatos, Karathanasopoulos, Georgopoulos, and Dunis (2013) introduced a hybrid of PSO and adaptive radial basis function for foreign exchange forecasting. More applications of GA and PSO in financial market prediction can be found from Dempster and Jones (2001), Briza and Naval (2011), Wong, Leung, and Guo (2012), and Kuo and Hong (2013). Compared to GA, PSO is not only easy to be implemented, but also could achieve the same performance as GA with higher computing efficiency (Lee, Lee, Chang, & Ahn, 2005; Babaoglu, Findik, & Ülker, 2010). Therefore PSO seems to be a better choice for trading rules optimization and is adopted in this work.

In this paper, we present a complex stock trading strategy called performance-based reward strategy (PRS). PRS combines two types of the most popular trading rules: moving average (MA) and trading range break-out (TRB). In all 140 trading rules are created as component rules of PRS by taking different parameter values of MA and TRB rules. All parameter values are well chosen to represent a wide coverage of the parameters for each rule class (Brock et al., 1992; Sullivan et al., 1999). Each component rule is assigned a starting weight which indicates its significance in trading decision. A reward/penalty mechanism based on component rules' performance is proposed to update all component rules' weights over time. The trading signal of PRS is determined by the weighted sum of component rules' signals and two additional signal threshold parameters. Together with component rules' starting weights and other five parameters of PRS (to be discussed later), there are altogether 145 parameters for PRS. We use an improved time variant particle swarm optimization (Ratnaweera, Halgamuge, & Watson, 2004) to optimize the best set of the 145 parameters.

To assess PRS performance in the stock market, we apply bootstrapping methodology to determine whether PRS makes profit by finding some useful information hiding in the stock market or by good fortune. Three popular null models – random walk, AR(1) and GARCH(1,1) – are used to generate a great number of bootstrapping samples. Then we compare the excess return of PRS on original stock data and the bootstrapping samples to find the evidence of strong prediction ability of PRS.

The rest of this paper is organized as follows: Section 2 gives details of the proposed complex trading strategy PRS. Section 3 briefly introduces PSO and describes how PRS is optimized with PSO. Empirical results are presented and discussed in Section 4. Section 5 accesses the significance of the trading results by bootstrapping methodology. Conclusions and future works are drawn in Section 6, and Appendix A gives details of all trading rules used in this study.

2. Performance-based reward strategy

2.1. Component trading rules

Technical trading rules have been developed for more than a century and are widely used in financial market as a technical analysis tool for stock trading. Various kinds of trading rules were proposed in past decades. As Pring (1991) argued that no single trading rule can ever be expected to predict all price trend, it is important to combine these simple rules together to get a complex trading strategy. In fact, almost all traders, investment firms and fund managers make trading decisions with the help of a trading strategy consisting of a set of technical indicators instead of a single trading rule (Pardo, 2008). In this study, we consider two types of the simplest and most popular technical trading rules in the literature – moving average (MA) and trading range break-out (TRB).

Essentially, a moving average is the mean of stock prices over a moving window of n days as follows:

$$\bar{p} = \frac{1}{n} \sum_{i=t-n+1}^{t} p_i \tag{1}$$

where t is the current trading day and p_i is the close stock price on day i. It is recalculated and updated each trading day. In MA rules, there are two averages (long-period and short-period averages) over two moving windows of m days and n days, respectively, where $m > n$. Consider a trading day t, a MA rule initiates buy (sell) signal if the short-period moving average is above (below) the long-period moving average. It is the simplest form of this rule (Brock et al., 1992) and is used in this paper.

The second technical trading rule is trading range break-out (TRB). It calculates the highest close price H and the lowest close price L over a fixed n days interval as follows:

$$\begin{aligned} H &= Max(p_{t-1}, p_{t-2}, \ldots, p_{t-n}) \\ L &= Min(p_{t-1}, p_{t-2}, \ldots, p_{t-n}) \end{aligned} \tag{2}$$

The highest and lowest price form a running channel (trading range) for each day's stock price and the trading signals are invoked by the stock price's breakout from the channel. Suppose the close