Engineering Applications of Artificial Intelligence 61 (2017) 47–56

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

A relative value trading system based on a correlation and rough set analysis for the foreign exchange futures market

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ARTICLE INFO

Keywords:
Correlation analysis
Foreign exchange futures
Relative value trading system
Rough set analysis

ABSTRACT

This paper describes the conceptual framework of a relative value (RV)-based trading system focused on the data characteristics of the foreign exchange futures market using a correlation and rough set analysis. RV trading is an investment strategy that can generate potential profits based on the RV of two securities, regardless of market direction. We select pairs with a positive correlation, negative correlation, or no correlation based on the correlation coefficients between foreign exchange futures contracts. To implement and experiment with the proposed system, trading rules are generated using a rough set analysis that employs technical indicators derived from the RVs of the pairs. The performance of the proposed trading system is analyzed using the momentum and buy-and-hold trading strategies as benchmarks. The experimental results and analyses demonstrate that the level of the correlation of the pairs must be considered when developing stable and profitable RV trading systems in a foreign exchange futures market.

1. Introduction

Capital market liberalization and globalization have led to opportunities for investment in the foreign exchange (FX) market for commercial banks, international companies, individual traders, and government organizations. Moreover, the FX market has become increasingly competitive and unstable as circulating foreign currency-denominated assets have become volatile worldwide (Chang et al., 2013). The FX market is influenced by many co-integrated, micro-economic, macro-economic, political, and even psychological factors. As a result, both modeling and forecasting the FX markets pose an important challenge because the FX market behaves like a random walk in a global economy (Ni and Yin, 2009). For several years, researchers and investors have dedicated considerable effort to developing models for forecasting the FX markets, which is one of the more important international monetary market indices (Meese and Rogoff, 1983).

Researchers have determined that classical econometric and time series models are inadequate to overcome the random walk effect because market prices move in a purely random and unpredictable manner and are partially based on unrealistic assumptions applied to traditional methods (Kilian and Taylor, 2003). To resolve this limitation, appropriate modeling and forecasting of time series data – in combination with both linear and non-linear methods – have been studied in various markets (Adhikari, 2015; Bas et al., 2015). For example, Chen et al. (2016) proposed a multi-factor time series model based on an adaptive network-based fuzzy inference system (ANFIS) for both the Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) and Hang Seng Index (HSI) forecasting. These authors selected a technical indicator using a stepwise regression method combined with ANFIS to develop their forecasting model. Bas et al. (2015) proposed a new hybrid forecasting model that combined an autoregressive model and a fuzzy time series model with their proposed model, which is evaluated using criteria such as the root mean square error (RMSE) and mean absolute percentage error (MAPE) for the TAIEX and Istanbul Stock Exchange markets. In addition, Chen et al. (2014) developed a forecasting model that integrated fuzzy time series models that based on fitting functions to forecast the TAIEX and HSI. Their model applied correlation coefficients to select prominent input variables, such as technical indicators. In general, a growing number of studies combine statistical analysis and machine learning techniques for application to the financial market domain.

Several studies have demonstrated that in an inefficient FX market, machine learning techniques outperform linear models, such as the

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http://dx.doi.org/10.1016/j.engappai.2017.02.014
Received 26 September 2016; Received in revised form 14 February 2017; Accepted 27 February 2017
0952-1976/

autoregressive moving average and random walk models (Hann and Steurer, 1996; Koskela et al., 1997; Kodogiannis and Lolis, 2002; Cao, 2003; Chen and Leung, 2004). Recently, trading system models for FX have been developed based on trading rules that generate profit using historical data. Ince and Trafalis (2006) analyzed the EUR/USD, GBP/USD, JPY/USD, and AUD/USD exchange rates using multilayer perceptron and support vector regression methods. Olson (2004) studied a moving-average crossover system with 18 currencies between 1971 and 2000 and observed profits for the early part of the sample period when assuming the normality of trading profits and ignoring interest differentials. Hirabayashi et al. (2009) introduced a forecasting optimization model based on a genetic algorithm (GA) to automatically create trading rules based on technical indicators (i.e., the moving average and relative strength index). Deng et al. (2012) developed trading rules in a GA model using technical indicators as input variables and generated a profit in simulated trading with real FX market data. However, these trading models do not consider the correlations between FX financial instruments, which are affected by the interactions between currencies, as they only considered correlations for constructing a well-diversified portfolio. This oversight is a limitation. Given that a single FX determines the system payoff, such trading systems may yield unstable profits when the correlations are ignored. Therefore, the relative value (RV) arbitrage must be an investment strategy that exploits price differentials between related financial instruments – such as stocks, futures, options, and bonds – by simultaneously buying and selling the different securities and allowing investors to potentially profit from the RV of the two securities as a result. In this study, the RV is defined as the price of security A divided by the price of security B.

In addition, a trading system based on data-driven approaches considers data characteristics. The FX market is generally acknowledged to be less efficient than the stock market due to Central Bank intervention (Neely, 2002). Engel and Hamilton (1990) proved that there is a long-term mean reverting pattern in the FX market. Chiang and Jiang (1995) found that FX returns are highly positively correlated over a short-time horizon (i.e., 12–52 weeks) and negatively correlated over a longer time horizon (i.e., 3 years). Similarly, Okunev and White (2003) find that a momentum strategy in the FX market is appropriate for obtaining profit over the short-term. Notably, a momentum strategy consists of buying currencies (winners) that have obtained high returns and selling currencies (losers) that have yielded low returns in the recent past (Serban, 2010). Thus, an FX trading system model must be built that considers the characteristics of the data among FXs based on their relative value.

This study proposes a conceptual framework for an RV-based trading system (*RVTS*) that is designed to generate profitability based on the correlation and a rough set analysis of the FX futures market. The proposed trading system employs a correlation analysis to form pairs and a rough set analysis to generate trading rules. Rough set theory has been successfully applied to the financial domain (Lee et al., 2012; Kim and Enke, 2016; Yeh et al., 2016) to identify potential information from vague and uncertain data. Moreover, no studies of trading systems based on integrating the correlation and a rough set analysis of the FX futures market were found. This approach relies on rough set theory to generate decision rules that determine buying, selling, and holding a position when RV movements and certain pair formations occur. We conduct a correlation analysis among several foreign exchange futures and select pairs with a positive correlation (POC), negative correlation (NEC), or no correlation (NOC). The *RVTS* generates trading rules using a rough set analysis with the technical indicators derived from the RV of the pairs and simulates an RV for trading. The performance of the *RVTS* is then compared to that of a simple momentum strategy and a buy-and-hold trading strategy as benchmarks. This study also utilized an ANOVA analysis to identify the performance of the *RVTS* in terms of correlation strength and the training window width for generating trading rules in a given exchange rate data period.

The remainder of this paper is organized as follows. Section 2 briefly introduces the concepts of the rough set, whereas Section 3 presents the construction procedure for the *RVTS*. Section 4 presents an empirical study that was performed to verify the performance of the *RVTS*. Finally, conclusions are presented in Section 5.

2. The basic concepts of the rough set

Rough set theory was introduced by Pawlak (1982) to address uncertain, noisy, or incomplete information in various industry domains (Wang, 2005; Shyng et al., 2007). Recently, various approaches have implemented rough sets as a data mining tool (Liao and Chen, 2014; Jiang and Chen, 2015; Zhang et al., 2015). In general, rough set theory utilizes indiscernibility relationships that allow examples to be partitioned based on the application-specific definition of an equivalence class (Chou et al., 2007). The partition follows two steps. In the first step, the data objects are classified into elementary sets, which are also referred to as indiscernible sets. In the second step, the elementary sets are inducted to generate the reducts. The rules generated from the reducts provide the most precise method of detecting the data objects and establishes the minimal subset, which includes the attributes of the data objects. The classification based on this subset is the same as that used for the universal set of attributes.

Rough set theory can assess the degree of approximation from certain data objects, and the approximation set is called the boundary set. To obtain a boundary set, the lower and upper approximations are calculated with respect to the addressed data objects. Let U be a nonempty set of objects, called the universal set, and let R be an equivalence relation to U, called the indiscernibility relation, which is based on a set of available attributes V (i.e., $R \subseteq V$). $[x]_R$ is the equivalence class of R containing object x for each $x \in U$. If X represents a subset of U, the lower and upper approximations and the boundary set of X under R are defined as follows:

$$\underline{R}X = \{x \in U \mid [x]_R \subseteq X\} \tag{1}$$

$$\overline{R}X = \{x \in U \mid [x]_R \cap X \neq \varnothing\} \tag{2}$$

$$RN_B(X) = \overline{R}X - \underline{R}X \tag{3}$$

Consider the following example for the initial classification result of the stock price in Table 1, where V is an available set of attributes of U, including "the 1st, 2nd, and 3rd indicator." Equivalent relations are designated based on the value of the attributes in R. Let $X = \{x\colon Signal(x) = Buy\}$, as shown in Table 1, and the set X is approximated by the set of conditional attributes $R = \{1\text{st } indicator, 2\text{nd } indicator, 3\text{rd } indicator\}$. x_{t-3} to x_{t-6} belong to the lower approximation of the signal set because all times with the same equivalence relation are classified as signals. However, it is impossible to classify the objects between x_{t-1} and x_{t-2} as the values of the conditional attributes are equivalent, while the decision value is different. As a result, the following approximations are obtained: $\underline{R}X = \{x_{t-3}, x_{t-4}, x_{t-5}, x_{t-6}\}$, $\overline{R}X = \{x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5}, x_{t-6}\}$, and $RN_B(X) = \{x_{t-1}, x_{t-2}\}$.

The decision rule introduced by Pawlak (2002) describes the approximations and was represented in the form "*IF condition(s),*

Table 1
Example of stock price attributes.

Time	1st indicator	2nd indicator	3rd indicator	Signal
x_{t-6}	10–20	15–30	5–20	*Buy*
x_{t-5}	10–20	15–30	5–20	*Buy*
x_{t-4}	10–20	15–30	10–30	*Buy*
x_{t-3}	10–20	15–30	10–30	*Buy*
x_{t-2}	10–20	35–45	0–15	*Buy*
x_{t-1}	10–20	35–45	0–15	*Sell*
x_t	40–60	55–65	35–45	*Sell*