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A novel evolutionary multi-objective ensemble learning approach for forecasting currency exchange rates

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Abstract: Due to the potential impact of the (currency) exchange rate risk in the financial market, forecasting exchange rate (FET) has become a hot topic in both academic and practical worlds. For many years, the various methods have been proposed and used for FET problems including the method of the artificial neural network (ANN). However, in many cases of FET, there is the limitation of using separate methods since they are not able to fully capture financial characteristics. Recently, more researchers have been beginning to pay attention to FET based on an ensemble of forecasting models (in other words, the combination of individual methods). Previous studies of ensemble methods have shown that the performance of an ensemble depends on two key elements *(1) The individual performance* and *(2) diversity degree of base learners*. The main idea behind this paper comes from these key elements, the authors use ANNs as the base method (or weak learners), and weights of these ANNs will be optimized by using the Non-Dominated Sorting Genetic Algorithms (NSGA). To assist NSGA, a number of diversity-preservation mechanisms are used to generate diverse sets of base classifiers and finally we propose to use modified Adaboost algorithms to combine the results of weak learners for overall forecasts. The results show that the proposed novel ensemble learning approach can achieve higher forecasting performance than those of individual ones.

Keywords: Currency exchange rates forecasting, ensemble learning, multi-objective evolutionary, non-dominated differential evolution.

1. INTRODUCTION

Nowadays, exchange rates play a vital role in controlling dynamics of the foreign exchange market. Economists and investors always tend to forecast the future exchange rates so that they can exploit the predictions to derive monetary values. For decades, FET has been a widely and continually studied topic in the financial field. There are a lot of computational methods being used for forecasting. These methods can be divided into 2 groups: *single (or base)* and *combination (or ensemble)* methods. Many base methods have been presented for FET, including traditional techniques (ARIMA, logistic regression, multiple regressions) and some nonlinear models (ANNs, SVM...). However, it has been indicated that individual forecasting methods still have a limited capability since each classifier has unstable results in many cases of datasets. An ensemble method is expected to reduce the variance of estimated errors and to improve the stability of overall prediction performance.

For ensemble methods, diversity and performance of members are key factors to generate a successful model. If the base methods are identical or give same results, then the ensemble brings no improvement except increasing the complexity. Further, if an ensemble member has very poor performance, the combination can't get the good result even though they are totally diverse [1]. So, the issue is how to design an ensemble of base methods that simultaneously ensure the above mentioned factors? This paper will tackle this issue.

In general, there are three approaches to generate diversity of base methods in ensemble learning [1]. One is to apply different base methods to a single dataset (e.g. using SVM, ANNs and ARIMA as base methods). Another is to