A Quantitative Analysis Decision System Based on Deep Learning and NSGA-II for FX Portfolio Prediction

Hua Shen(✉) and Xun Liang

RenMin University of China, Beijing 100872, China
sarah_h_shen@yahoo.com, xliang@ruc.edu.cn

Abstract. Forecasting foreign exchange (FX) rate and optimizing FX portfolio with the help of Artificial Intelligence has aroused wide interest among global capital market. As far as we know, this is the first paper which, from the perspective of institutional and individual investors, proposes a complete quantitative analysis decision system based on Deep Learning and NSGA-II to forecast FX rate and select FX portfolio successively. To be specific, we provide a whole procedure from data collection to FX forecasting with Stacked Autoencoders and further to optimal FX portfolio selection with NSGA-II. Furthermore, an empirical analysis has been conducted with 28 FX currency pairs, in which our algorithm has been compared with two other machine learning algorithms. Ultimately, our system provides optimized FX portfolio solutions for investors with diverse preference.

Keywords: Deep learning · Stacked autoencoders · NSGA-II

1 Introduction

Recent decades have witnessed an ascending number of governments, institutions and individuals paying much attention to foreign exchange (FX) rate prediction concerning its significant role in world economy. Increasingly, researches start to utilize machine learning methods to forecast FX rate [1]. Although there are a rising number of researchers who use the state-of-the-art deep learning methods for FX rate forecasting, few researches have been explored in providing a complete decision support for FX investments in capital market [2, 3]. Under this circumstance, we propose a practical quantitative decision analysis system based on deep learning and NSGA-II for FX rate forecasting and portfolio selecting. It involves the whole procedure of data collection—foreign exchange rate forecasting—FX portfolio selection, which is conducive to FX investment decision making from the perspective of investors. Furthermore, for the first time, we propose a FX forecasting model based on deep learning with SAE-SVR (Stacked Autoencoders and Support Vector Regression), and an FX portfolio Dual-Object optimization algorithm based on NSGA-II. The following sections will give the detailed descriptions.

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2 The Quantitative Analysis Decision System

2.1 An Overview of the Quantitative Analysis Decision System

In general, the architecture of the Quantitative Analysis Decision System for FX portfolio prediction can be illustrated as Fig. 1. Historical raw data from existing FX transaction platform (MetaTrader4 of FXCM) would be put into the system. After being preprocessed for normalization and vectorization, the vectorized time series data would be sent into the SAE-SVR model, in which a forecasted vector dataset will be produced. In order to maximize the returns and to minimum the risks at the same time, the system utilizes a FX Dual-Objective Optimization Algorithm based on NSGA-II to select portfolio from the forecasted dataset. Finally we obtain the top 6 optimal portfolio solutions from the system. In practice, investors can choose the solutions in terms of different preferences, furthermore, these solutions could be combined with various derivatives such as FX Forward, FX Future, FX Swap, Currency Swap, FX Options, etc.

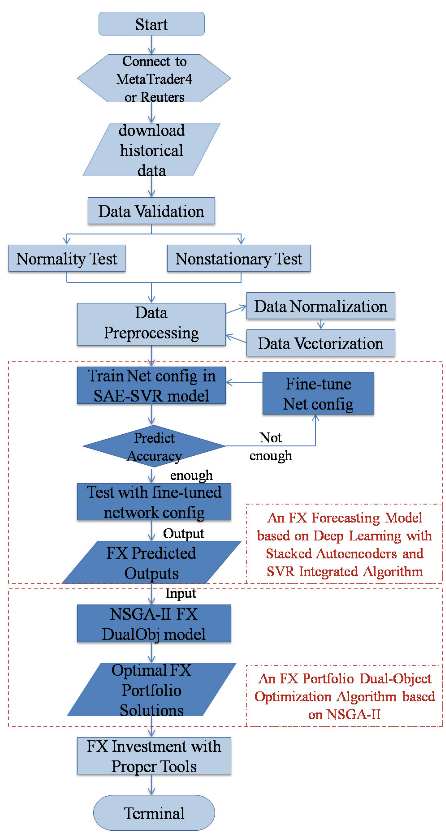


Fig. 1. The foreign exchange forecasting-portfolio quantitative decision analysis system

2.2 An FX Forecasting Model Based on SAE-SVR Algorithm

The Deep Learning forecasting model we proposed innovatively combines the merit of Stacked Autoencoders (SAE) to deeply learn features of datasets with the advantage of SVR's superior predicting capacity. The brief process is demonstrated in Fig. 2. Overall, the SAE-SVR model consists of one Input Layer, K Hidden Layers and one SVR Output Layer. Each hidden layer represents a Sparse Autoencoder, which can learn part-whole features of the dataset. The result of the K$^{\text{th}}$ feature layer will be sent into SVR model for final prediction. For more details, please refer to author's existing publication [4].

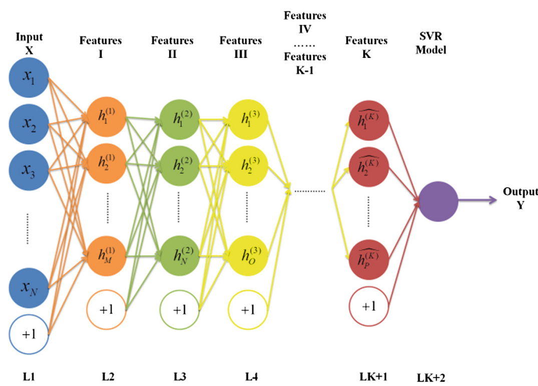


Fig. 2. Deep learning with SAE-SVR integrated algorithm structure

2.3 FX Portfolio Dual-Object Optimization Algorithm Based on NSGA-II

In order to select optimal FX portfolio solutions using results generated by the SAE-SVR model, considering diverse Multi-Objective Evolutionary Algorithms (MOEAs) [5], we take use of an improved version of Elitist Non-dominated Sorting Genetic Algorithm- NSGA-II to find the optimal solution with maximized return rate and minimized investment risk at the same time, which is in converging near the true Pareto-optimal set [6]. In this paper, concerning an FX portfolio pool with N currency pairs, we propose an FX Portfolio Dual-Object Model as below.

$$\begin{cases} \max ER(x) = \sum_{i=1}^{N} \mathrm{x}_i \mathrm{R}_i \\ \min SD(x) = \sum_{i=1}^{N} \mathrm{x}_i \mathrm{std}(\mathrm{R}_i) \end{cases} \quad (1)$$
$$s.t. \sum_{i=1}^{N} \mathrm{x}_i = 1, \mathrm{x}_i \geq 0, i = 1, 2, \ldots N$$

ra ID="Par6">Where $\mathrm{X} = (\mathrm{x}_1, x_2 \ldots, \mathrm{x}_N)$ indicates the target portfolio solution, we set $0 \leq \mathrm{x}_i \leq 1, \sum_{i=1}^{N} \mathrm{x}_i = 1$. $\mathrm{R} = (\mathrm{R}_1, \mathrm{R}_2 \ldots, \mathrm{R}_N) \in R$ indicates the return vector for all the N currency pairs. Besides, ER(x), SD(x), $\mathrm{std}(\mathrm{R}_i)$ means the Expected Return, the Investment Risk, and the Standard Deviation for a specific portfolio respectively.

Furthermore, we take use of the Elitist Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to optimize the FX Portfolio Dual-Object Model and finally obtain the optimal portfolio solutions. To be concrete, the main procedure of our FX Portfolio Dual-Object Optimization Algorithm based on NSGA-II can be illustrated in Fig. 3.

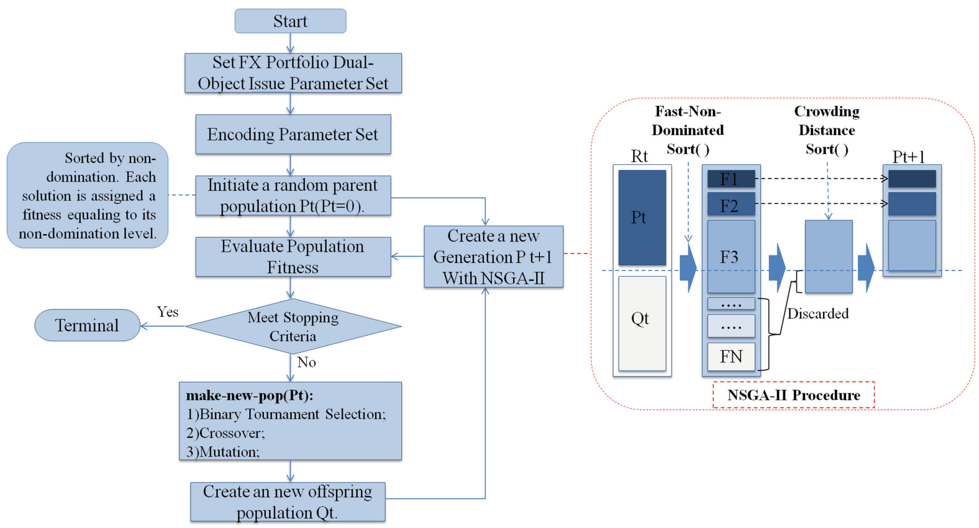


Fig. 3. The FX portfolio dual-object optimization algorithm flow chart

First of all, the parameter set should be determined according to the practical issues. Secondly, the parameter set will be encoded for the sake of following implementation. Thereafter, a random parent population P0 is created, and the population is sorted based on the non-domination. Next, the first offspring population Q_0 is created in usual GA method involving binary tournament selection, crossover and mutation operators. Then the following generations will be generated step-by-step. Table 1 gives a creation procedure description of the t^{th} generation. For NSGA-II details, readers are encouraged to refer to the original studies.

Table 1. The t^{th} generation created procedure of NSGA-II

$R_t = P_t \cup Q_t$	Combine parent and offspring population
$F = fast - non - dominated - sort(R_t)$	$F = (F_1, F_2, \ldots, F_N)$, all non-dominated fronts of R_t
$P_{t+1} = \emptyset, i = 1$ until $\lvert P_{t+1}\rvert + \lvert F_i\rvert \leq$ N	Until the parent population is filled
Crowding-distance-assignment (F_i)	Calculate crowding-distance in F_i
$P_{t+1} = P_{t+1} \cup F_i$	Include the i^{th} non-dominated front in the parent pop
i = i + 1	Check the next front for inclusion
Sort $(F_i, \prec_n)$	Sort in descending order using $\prec_n$
$P_{t+1} = P_{t+1} \cup F_i[1 : (N - \lvert P_{t+1}\rvert)]$	Choose the first (N $-$ $\lvert P_{t+1}\rvert$) elements of F_i
$Q_{t+1} = make - new - pop(P_{t+1})$	Use make-new-pop to create a new population Q_{t+1}
t = t + 1	Increment the generation counter

3 Data Processing

We collect G7 currencies (USD, GBP, EUR, JPY, AUD, CAD, CHF) from MetaTrader4, and CNY from SAFE (State Administration of Foreign Exchange) website during 5/21/2009 to 2/1/2016 with daily interval. Overall, there are 28 currency pairs and 52223 records, which are divided into 38703 as TrainingSet and 13520 as TestingSet.

Before being sent into the system, the data will be normalized between [0, 1] scale. Then we get the normalized currency pair time series $\mathrm{Z} = (\mathrm{z}_1, \ldots, \mathrm{z}_\mathrm{T})$ before being transformed into an L-lag-window multi-dimension time series vector $\mathrm{X} = [\mathrm{X}_1, \ldots, \mathrm{X}_\mathrm{M}] = (\mathrm{x}_{\mathrm{ij}})_{\mathrm{i,j=1}}^{\mathrm{L,M}}$, where $\mathrm{X}_\mathrm{i} = (\mathrm{z}_\mathrm{i}, \ldots, \mathrm{z}_{\mathrm{i+L-1}})' \in \mathrm{R}^\mathrm{L}$, $\mathrm{M} = \mathrm{T} - \mathrm{L} + 1$, and the lag-window L is an integer meeting $2 \leq \mathrm{L} \leq \mathrm{T}/2$.

The output vector is a one-dimensional time series vector $\mathrm{Y} = (\mathrm{y}_1, \ldots, \mathrm{y}_M) \in R$, where $y_n = z_{n+L}$, and y_n indicates the forecasting value of $X_n = (\mathrm{z}_n, \ldots, \mathrm{z}_{n+L-1})' \in R^L$. Thereafter, the 28 time series input and output vectors will be tested with non-linear and non-stationary attributes successively, with Augmented Dickey-Fuller for Unit Root Test to validate the non-stationary attribute and Jarque-Bera test for Normality Test to verify the nonlinear attribute respectively. Details of the data processing can also be found in [4].

4 Empirical Analysis

We benchmark our SAE-SVR model with Artificial Neural Network and Support Vector Regression. In summary, the SAE-SVR model has higher predicting accuracy with 610.92% (MSE) and 240.61% (MAE) compared with ANN and SVR. The detailed forecasting results of 28 currency pairs in comparison with ANN and SVR are illustrated in [4]. Moreover, they will act as the input of the FX Portfolio Dual-Object Optimization Algorithm in the following part after being transformed into general scale by $s_i = \mathrm{s}_{max} - \mathrm{z}_i(\mathrm{s}_{max} - \mathrm{s}_{min})$.

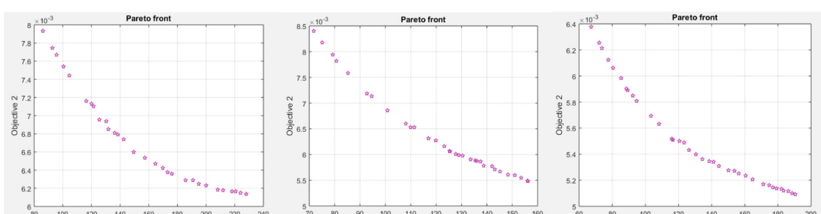
The expiration date of our dataset is 02/01/2016, therefore, we set it as benchmark date and select the data during 50 days before it to compute the return rate and standard deviation of each currency pair. Table 2 illustrates the output results.

Afterwards, the return rates and standard deviations are sent into the NSGA-II Algorithm. For the sake of more rapid computation, lower time complexity and better precision, we get rid of negative return rate currency pair before implementing NSGA-II simulation. During the empirical test, we test different generation settings of NSGA-II, and the corresponding Pareto Front diagrams are represented in Fig. 4.

It turns out the Optimization Algorithm with 150 generations obtains the highest expected return rates and lowest risks. So we select top 6 portfolio solutions based on the FX Portfolio Dual-Object Optimization Algorithm with 150 generations, the results are shown in Table 3. From the perspective of investors, risk preference investors can focus on 1–3 solutions for a higher expected return rate as well as higher risk, while risk aversion investors could focus on 4–6 solutions for a lower investment risk but also relative lower expected return rate. In summary, investors with diverse return rate and risk preferences could select a couple of solutions provided by our quantitative analysis decision system in practical FX investment.

Table 2. Return rate and standard deviation of each currency results

Currency pair	EURUSD	GBPUSD	AUDUSD	EURGBP	USDCAD	EURCAD	GBPCAD
RETURN(R)	–0.00814	–0.0056	0.001469	–0.0013	–0.00575	–0.01595	–0.01027
STD(R)	0.005413	0.004716	0.006188	0.00568	0.005477	0.009524	0.005852
Currency pair	AUDCAD	EURAUD	GBPAUD	USDJPY	EURJPY	GBPJPY	CADJPY
RETURN(R)	–0.00439	–0.00867	–0.00767	0.017073	0.009015	0.012546	0.018132
STD(R)	0.004703	0.010337	0.006284	0.006031	0.005936	0.006993	0.009869
Currency pair	AUDJPY	USDCHF	EURCHF	GBPCHF	CADCHF	AUDCHF	CHFJPY
RETURN(R)	0.016961	0.009572	–0.00091	0.001333	0.011588	0.008666	0.00939
STD(R)	0.010665	0.006277	0.002692	0.006398	0.008022	0.008963	0.005946
Currency pair	USDCNY	EURCNY	GBPCNY	CADCNY	AUDCNY	JPYCNY	CHFCNY
RETURN(R)	–0.00018	0.003119	0.006087	0.003512	0.00825	–0.00346	–0.0002
STD(R)	0.001119	0.005538	0.004578	0.004342	0.005868	0.004348	0.009266



Generation=100 Generation=150 Generation=200

Fig. 4. Pareto front diagram of the FX portfolio dual-object optimization algorithm

Table 3. Top 6 portfolio solutions of the optimization algorithm (Descending Order of ER)

NO.	USD CNY	JPY CNY	CHF CNY	USD JPY	EUR JPY	GBP JPY	CAD JPY	AUD JPY	USD CHF	GBP USD
1	0	0	0	5.15%	0.01%	0.28%	78.50%	0.52%	3.63%	3.75%
2	0	0	0	5.15%	0.01%	0.28%	78.50%	0.52%	3.63%	3.75%
3	0	0	0	6.32%	0.07%	0.28%	69.01%	0.73%	3.77%	3.59%
4	0	0	0	7.66%	0.18%	0.25%	54.07%	4.75%	3.93%	3.36%
5	0	0	0	7.82%	0.19%	0.25%	52.90%	4.68%	3.95%	3.34%
6	0	0	0	7.31%	0.21%	0.27%	49.77%	0.97%	4.05%	3.25%
NO.	GBP CHF	CAD CHF	AUD CHF	CHF JPY	EUR CNY	GBP CNY	CAD CNY	AUD CNY	ER(x)	SD(x)
1	0.87%	1.85%	0.20%	0.16%	2.23%	1.85%	0.53%	0.57%	0.016146	0.009088
2	0.87%	1.85%	0.20%	0.16%	2.23%	1.85%	0.53%	0.57%	0.016146	0.009088
3	1.26%	1.65%	0.25%	0.24%	2.26%	2.62%	7.35%	0.70%	0.014967	0.008605
4	1.87%	1.34%	0.32%	0.43%	2.37%	3.45%	15.21%	0.90%	0.013532	0.008071
5	1.92%	1.31%	0.33%	0.44%	2.37%	3.55%	16.12%	0.92%	0.013375	0.008005
6	2.08%	1.22%	0.33%	0.40%	2.32%	3.84%	23.09%	0.97%	0.012356	0.00759

5 Conclusion

In general, we innovatively propose the Quantitative Analysis Decision System based on Deep Learning and NSGA-II for FX forecasting and portfolio selection, which gives a complete procedure of FX investment. It involves FX trading platform selection—data collection—foreign exchange rate analysis—portfolio optimal selections. To be specific, the most important modules in this system consist of an FX Forecasting Model based on Deep Learning with SAE-SVR Algorithm, and a FX Portfolio Dual-Object Optimization Algorithm based on NSGA-II. Furthermore, we verify the whole procedure with 28 currency pairs from MetaTrader4 and SAFE website, and implement the empirical analysis with self-programming codes, and finally provide a list of FX investment solutions for investors with different return rate and risk preference.

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