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ARE FOREIGN EXCHANGE RATES PREDICTABLE? A SURVEY FROM ARTIFICIAL NEURAL NETWORKS PERSPECTIVE*

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This study presents a survey on the applications of artificial neural networks (ANNs) in foreign exchange rates forecasting. With their ability to discover patterns in nonlinear systems, ANNs have been widely used as a promising alternative approach to predict foreign exchange rates. In this paper, the predictability of foreign exchange rates is first investigated from neural networks perspective. We examine 45 journal articles about exchange rates prediction with ANNs between 1971 and 2004 in detail, and compare the performances of ANNs and those of other forecasting methods, finding mixed results. Subsequently, the main reasons leading to the inconsistent results are explored by literature analysis and inference. Meanwhile the study summarizes the general situations in which foreign exchange rates are predictable with ANNs in view of previous literature analysis. Finally, some implications and interesting research topics are presented as future research directions in foreign exchange rates forecasting with ANNs.

Keywords: Exchange rates forecasting, artificial neural networks, exchange rates predictability.

1. INTRODUCTION

After more than two decades of research since Meese and Rogoff's seminal work on exchange rates predictability (see Meese and Rogoff, 1983a, 1983b), the goal of exploiting forecasting models of exchange rates to beat naïve random walk forecasts remains as elusive as ever (Taylor, 1995) due to the fact that evidence supporting or refuting the exchange rate predictability seems plausible. For example, Bekaert and Hodrick (1992), Fong and Ouliaris (1995), LeBaron (1999), Levich and Thomas (1993), Liu and He (1991), McCurdy and Morgan (1988), Baillie and Bollerslev (1989), Sweeney (1986) and Soofi et al. (2006) found evidence against the martingale (random walk or pure unit-root) hypothesis for nominal or real exchange rates, indicating that exchange rates are predictable.

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While Diebold and Nason (1990), Fong, Koh and Ouliaris (1997), Hsieh (1988, 1989, 1993), McCurdy and Morgan (1987), and Meese and Rogoff (1983a, b) found little evidence contradicting the martingale (random walk or pure unit-root) hypothesis for nominal or real exchange rates, implying that predictability of foreign exchange rates is impossible. One simple and possible explanation is that traditional exchange rate forecasting models are inadequate. Due to the fact that exchange rate forecasting is of practical as well as theoretical importance, a large number of methods and techniques (including linear and nonlinear) have been introduced to beat the random walk model in foreign exchange rates forecasting. With increasing development of artificial neural networks (ANNs), researchers and investors are hoping that the mysteries of the foreign exchange market can be unraveled (with ANN models). The main reason of selecting ANNs as an exchange rate forecasting tool is that several distinguishing features of ANNs make them valuable and attractive in forecasting. First of all, in contrast to many model-based forecasting methods, ANNs are data-driven self-adaptive methods in that there are few restrictive assumptions involved in these models, for the problems under study. This unique feature is highly desirable in several financial forecasting situations, where data are generally abundant but the underlying data generating mechanism is often unknown (Qi and Zhang, 2001; Yu et al., 2006e). Secondly, ANNs can be generalized. Thirdly, ANNs are universal functional approximators (Hornik et al., 1989; White, 1990). Besides, ANNs are a class of nonlinear models (Zhang et al., 1998). Since Lapedes and Farber (1987) first proposed using multi-layer feed-forward neural networks (MLFNN) for nonlinear signal prediction, much research using ANNs have justified their use for nonlinear time series forecasting (Shin and Han, 2000; Yu et al., 2006e).

However, no one technique has been successful enough to consistently beat other methods in predicting foreign exchange rates. Therefore, it is difficult to say that ANNs uniformly perform better than other methods. Some articles show that ANNs perform well in foreign exchange rates forecasting, while others give negative conclusions. Even in the same article, conflicting results are often presented. For example, Hann and Steurer (1996) found that if monthly data are used, ANNs do not show much improvement over some of the linear models; but for weekly data, ANNs are much better than both monetary and random walk models in forecasting the exchange rate for Deutsche mark (DEM) against U.S. dollar (USD). Hence, the main purpose of this study is to investigate whether foreign exchange rates are predictable by ANNs. In concrete terms, we examine the following five issues.

(1) Why there are mixed results in the literature?
(2) In what situations foreign exchange rates are predictable by ANNs?
(3) In what situations exchange rates are unpredictable by ANNs?
(4) What are the factors that affect performance of ANNs?
(5) What can be done to improve the performance of ANNs?

Due to unique features of the ANNs, their financial applications are a research stream by themselves and these applications have been reviewed by many researchers. Typically, Wong et al. (2000) have presented a bibliography of neural network business applications between 1988 and 1998. Wong and Selvi (1998) gave a literature review and analysis of neural networks' applications in finance during the period 1990-1996. Likewise, Fadlalla and Lin (2001) presented an analysis of applications of neural networks in finance. In these three reviews, there are few neural networks' applications for foreign exchange rates. Recently, Huang et al. (2004a) provided a review of foreign exchange rates forecasting with ANNs and described several important design features of ANNs relevant to foreign exchange rates forecasting applications. Their work is, however, different from the current study, presented in this paper, because the main purposes of this paper are to investigate whether foreign exchange rates are predictable and what should be done to improve the performance of ANNs (i.e. future research topics).

In view of these stated objectives (of the study), we present a general analytical framework of the survey in Fig. 1. As can be seen from Fig. 1, our analytical process is as follows. First of all, we collect the literature about exchange rates forecasting with the ANN approach. Then some related articles are classified into three categories in terms of the conclusions of the articles: (i) ANNs perform better than other models; (ii) ANNs perform worse than other models; and (iii) ANNs give mixed results, i.e., ANNs perform better than some other methods in some situations and worse under some other situations. Subsequently, several main factors that affect the performance of the ANNs, such as prediction horizon, data frequency, train set size, network type, control strategy and training algorithm, are investigated, for each article, to further analyze the reasons behind the mixed results. Furthermore, some general situations of foreign exchange rates predictability are introduced and summarized. Finally, some future research directions for ANNs in exchange rate prediction are given.

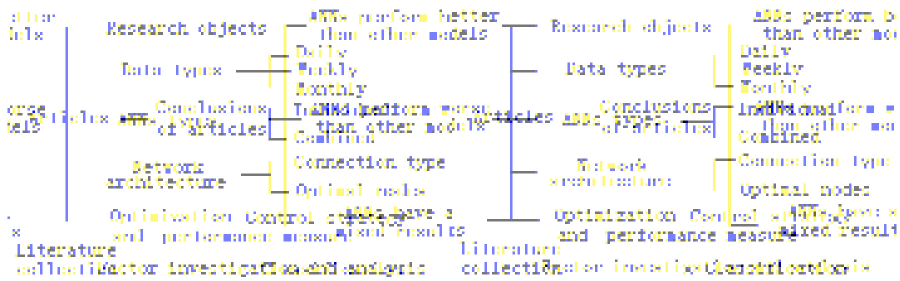

Fig. 1 A general analytical framework

The remainder of the study is organized as follows. In the next section, we explain how the articles were selected. Section 3 examines and analyzes 45 journal articles in detail and investigates the main factors that affect the performance of the ANNs. Subsequently, some implications and future research directions are presented in Section 4. Finally, Section 5 concludes this paper.

2. LITERATURE COLLECTION

Since we are interested in investigating the main factors that affect the performance of the ANNs, the criteria of literature selection for this survey is that they should have detailed discussions on the development process of neural networks for exchange rates forecasting. The literature collection was carried out in two steps. First, ten databases (Science Citation Index, Social Science Citation Index, ScienceDirect, Wiley InterScience, IEEE Xplore, JSTOR, Kluwer online, ProQuest Database, Springerlink, and Academic Search Premier) were searched with the keywords "(artificial) neural network(s) (in) exchange rates forecasting (prediction)" for the period 1971-2004. Searching the ten databases is the most important step in our literature collection process since they include more than 2000 different business-related journals. In these databases, we were able to retrieve about 300 abstracts that answered to the keywords, for the specified period.

Second, a reference search of books on neural networks and exchange rates forecasting (prediction) was conducted. We considered a total of fourteen books: Azoff (1994), Masters (1995), Beltratli et al. (1996), Gately (1996), Kacapyr (1996), Trippi and Turban (1996), Kindon (1997), Lisboa et al. (2000), Kovalerchuk and Vityaev (2000), Graf (2002), Shadbolt and Taylor (2002), Soofi and Cao (2002), Smith and Gupta (2003), and Zhang (2003a). However, the related articles in Zhang (2003) and Smith and Gupta (2003) are the same as the journal articles searched in the ten databases, while other books are about applications of ANNs to some other financial research, such as stock, interest rate and bank failure prediction. Therefore, those books are excluded in our investigations.

Thus, we investigated only the journal articles. Some of the retrieved articles did not present detailed discussions on the development process of neural networks for exchange rates forecasting. Consequently, we reviewed only 45 articles with detailed forecasting process in the survey (see Tables 2-4). Fig. 2 shows the distribution of the articles by the year of publication. Although our research covers the period 1971-2004, we find no applications about neural networks in exchange rates forecasting published earlier than 1993.

We also find that the number of articles published in 1998, 2000 and 2002 are fewer than their respective preceding and following years, i.e., articles in 1998 are fewer than those in 1997 and 1999, articles in 2000 are fewer than those in 1999 and 2001 and articles in 2002 are fewer than those in 2001 and 2003. There are several articles related to ANN and exchange rates forecasting but some articles do not satisfy the above selection criteria and, therefore, they are excluded from this survey.

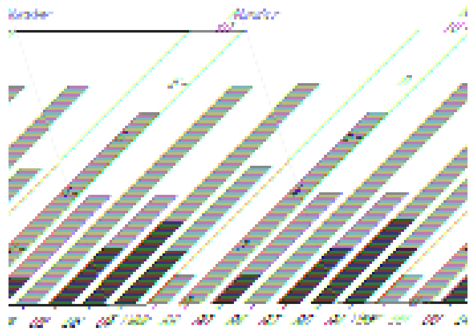

Fig. 2 Distribution of articles by year

3. RESULTS AND ANALYSIS

After literature collection, we begin analyzing the factors affecting foreign exchange rates forecasting with ANNs. In this section, a basic classification and factor summarization are first presented according to the collected literature. Then some main reasons that affect ANNs in foreign exchange rates forecasting are explored through literature analysis and inference. Finally, we summarize the situations in which foreign exchange rates are predictable with ANNs in view of literature analysis.

3.1. Basic Classification and Factors Summarization

As earlier noted, a final total of 45 articles were selected for analysis in this survey. In accordance with the general analytical framework, the articles are classified into three categories, by the forecasting performance of the ANNs, as follows:

(I) ANNs perform better than other methods;
(II) ANNs perform worse than other methods;
(III) ANNs perform better than other methods in some situations, while worse in some other situations.

Table 1 shows classification of 45 articles by prediction performance. It indicates that the ANNs are not uniformly better than other methods in all situations, even though ANNs are a class of advanced artificial intelligence (AI) technique. Even within the same article, mixed conclusions are often presented, as shown in the third category.

Table 1 Classification of 45 articles by performance

Category	Articles	Ratio (%)
I	27	60.00
II	2	4.44
III	16	35.56

To find out the reasons for the inconsistent conclusions, we decompose and investigate the factors that affect the performance of the ANNs, from the following aspects:

(a) prediction horizon, including short-term (1-3 steps), medium-term (4-8 steps) and long-term (more than 8 steps) forecasting;
(b) data frequency (daily, weekly, monthly and quarterly);
(c) training set size;
(d) network type (e.g. MLFNN, RNN, hybrid etc.);
(e) control strategy (recurrent, feedforward etc.);
(f) training algorithm;
(g) transfer function;
(h) performance measure.

Accordingly, the factors are summarized in Tables 2-4. For convenience, we give classification order of the references in terms of the above categories: articles of nos. 1-27 are in the first category, nos. 28-29 are in the second category and nos. 30-45 are in the third category.

3.2. Factor Analysis

In Tables 2-4, basic information about these articles is presented, including background information (authors, year and classification), research objects and forecasting horizon, information about the data used (data type, time range, number of training samples, number of testing samples), information about network architecture (connection type, model type, number of nodes per layer, comparable methods) and information about optimization strategies used (control strategy, training algorithm, transfer function, performance measures). In order to mine useful information and present a reasonable explanation for the issues we are concerned with, it is necessary to further investigate the factors and summarize the comparisons. It should be mentioned that some of the values shown in Tables 2-4 are not explicit in the articles and some of them are inferred from the information provided.

3.2.1. Research objects and data type

In all the examined articles, it is found that 43 applications (95.56%) are related to several internationally traded currencies, such as Canadian dollars (CAD), Australian dollars (AUD), German marks (DEM), Swiss francs (CHF), Japanese yen (JPY), and British pounds (GBP). Only two applications (Shin and Han (2000), Wu (1995)) focus on Korean wons (KRW) and Taiwanese dollars (TWD) against U.S. dollars. Some other currencies are also included in these applications, as shown in Table 2. The data type of the research objects include daily, weekly, monthly and quarterly. Of the 45 journal articles, 21 articles (46.67%) used daily data, 14 articles (31.11%) used monthly data, and 8 articles (17.78%) used weekly data, while only one article (El Shazly and El Shazly, 1999) used quarterly data and one article (Bolland and Conner, 1997) used high frequency tick data. Furthermore, of the 27 articles in category I, 11 articles used daily data, 5 articles used weekly data and 9 articles used monthly data. Besides, one article used quarterly data and another used tick data. Likewise, of the articles in category III, 9 articles used daily data and 3 articles used weekly data and 4 articles used monthly data. While in the two articles of category II, one is daily data and the other is monthly data. Therefore, it is hard to say which data type is good for predicting foreign exchange rates in terms of the analysis.

In view of the results in Table 2, several conclusions can be summarized. First of all, different pairs of currencies often lead to different forecasting results. Secondly, different data types often result in different forecasting performance, which is the same as the first conclusion. These two conclusions from Table 2 are quite evident. Thirdly, for the same research objects, different data types may generate different conclusions. For example, Parhizgari and De Boyrie (1997) showed that the ANNs perform better than some other methods for GBP, CAD, DEM and JPY, while in Qi and Wu (2003), the authors found that the ANNs were worse than other methods for the same research objects, i.e., currencies. Even within the same article, this conclusion holds good. For example, in Hann and Steurer (1996), if monthly data are used, ANNs do not show much improvement over the linear models; but for weekly data, ANNs are much better than both the monetary and random walk models in DEM/USD forecasting. Finally, even for the same data type, the same search objects may lead to conflicting conclusions. For example, with daily data, Giles et al. (2001) pointed out that the ANNs perform better than some other approaches for GBP, DEM, JPY and CHF, but Gencay (1999) found that the ANNs perform worse than other approaches for the same objects (currencies). Therefore, it is difficult to say which currencies are predictable, or unpredictable to some extent.

Therefore, different research objects and different data types often result in different forecasting performance with ANNs, according to the literature review. This is one of the main reasons leading to inconsistent results, as revealed by Hu and Tsoukalas (1999) and Medeiros et al. (2001). It is, however, hard to infer exchange rates predictability from the research objects and data types with the use of ANNs, as indicated in the analysis. For interpretation, further factor analysis about ANN itself is required.

3.2.2. Forecasting horizons

From the examined articles, it is found that different forecasting horizons often lead to different forecasting performance, and they sometimes lead to mixed results even in the same article, which is the same as different results for the same research objects. As such, different forecasting horizons are one of the reasons that affect the performance of the ANNs. As Huang et al. (2003) indicated, for forecasting horizons of 1, 3, 5 days, the ANNs perform better than the random walk, while for forecasting horizons of 10 and 30 days, the general performance of ANNs is worse than the random walk model. Thus, determining an appropriate forecasting horizon is necessary. In the literature review, Chun and Kim (2003) proposed using Lyapunov exponent to determine the most suitable predictive horizons from the information loss perspective. For the most suitable forecasting horizon, the ANNs can generate good forecasts. Generally, for short and medium term forecasting, ANNs can give effective forecasts. On the contrary, for long-term forecasting, foreign exchange rates are not predictable with the use of ANNs, according to Chun and Kim (2003). It is worth noting that we define "short-term" as "1-3 step(s)", "medium-term" as "4-8 steps", and "long-term" as "more than 8 steps". Here, "step" denotes data frequency, such as "days", "weeks", "months" or "quarters". Of the 45 journal articles, 39 articles discuss short-term forecasting, 15 articles discuss medium-term prediction and only 6 articles discuss long-term forecast of foreign exchange rates. Furthermore, of the 27 articles in category I, all the articles, except Zhang (2003b), used ANNs for short-term or medium-term forecasting, while the two articles in category II used ANNs for long-term forecasting, besides short-term and medium-term forecasting. Similarly, of the 16 articles in category III, three articles used ANNs for long-term forecasting. Thus, we can infer that long-term prediction horizons generally lead to negative or mixed forecasting results in foreign exchange rates forecasting with ANNs, according to the literature analsis.

3.2.3. Data division and training set size

In applications of ANNs to foreign exchange rates forecasting, data partition is necessary. Furthermore, the data split can have a significant impact on the results obtained (Dawson and Wilby, 1998; Maier and Dandy, 1996). In this literature review, data division is carried out in most of the articles. Although at least two data sets were used, the validation data are used as part of the training process in many instances, either by using a trial-and-error procedure to optimize model inputs and some network parameters, or by using cross-validation (CV) to verify the effectiveness of the ANNs (Hu et al. (1999) found that the CV can effectively improve the robustness of the ANNs). Generally, division of data is carried out on an arbitrary basis and the statistical properties of the respective data sets are seldom considered. In the first category of the articles we examined, three data sets (i.e. training dataset, validation dataset and testing dataset) are used and good results are obtained.

Table 2 Details of the articles reviewed (Basic information and research objects) *

Basic information and classification				Research objects and prediction horizon		Comparable methods
No	Author(s)	Year	Classification	Object(s)	Prediction horizon	Benchmark models
1	Bolland & Connor	1997	Better	USD/DEM	One step	AR, Kalman filter
2	Chen & Leung	2004	Better	(GBP, CAD, JPY)/USD	1 month	RW, MTF, GMM, BVAR, Error correction
3	Chun & Kim	2003	Better	JPY/USD	1 day	CBR, PCA, FA
4	El Shazly & El Shazly	1997	Better	(GBP, DEM, JPY)/USD	4 weeks	?
5	El Shazly & El Shazly	1999	Better	(GBP, DEM, JPY, CHF)/USD	1 quarter	GA
6	Giles et al.	2001	Better	(DEM, GBP, CAD, JPY, CHF)/USD	1-7 day(s)	RW
7	Jamal & Sundar	1997	Better	USD/DEM, USD/FRF	1 month	Regression model
8	Jasic & Wood	2003	Better	USD/(DEM,JPY,CHF,GBP)	1 day	RW, Linear model
9	Kaashock & Van Dijk	2002	Better	(GBP,NLG,FRF,DEM,JPY)/USD	1 month	ARIMA
10	Kodogiannis & Lolis	2002	Better	USD/GBP	1,4,8 day(s)	BP
11	Kumar et al.	2003	Better	CAD/USD	1 month	Regression
12	Leung et al.	2000	Better	(GBP,CAD,JPY)/USD	1 month	RW, ARIMA, MTF, MLFNN
13	Li et al.	1999	Better	USD/SGD	1 month	MLFNN
14	Nag & Mitra	2002	Better	DEM/USD, JPY/USD, USD/GBP	1 day	GARCH, ARCH, FGNN
15	Parhizgari& De Boyrie	1997	Better	(GBP,CAD,DEM,JPY,CHF)/USD	1,3,6 day(s)	RW, Locally weighted regression
16	Poddig & Rehkugler	1996	Better	USD/DEM, JPY/DEM, USD/JPY	6 month	RW, Regression, SLP
17	Qi & Zhang	2001	Better	GBP/USD	1 week	RW, AR
18	Refenes et al.	1993	Better	DEM/USD	Varied	AR, ES
19	Rivas et al.	2003	Better	GBP/USD	1 week	?
20	Shin & Han	2000	Better	KRW/USD	1 day	RW
21	Tenti	1996	Better	DEM/USD	2 days	BP
22	Vojinovic et al.	2001	Better	USD/NZD	1, 3, 5 day(s)	AR, RW

23	Walczak	2001	Better	(GBP, DEM, JPY)/USD	?	?
24	Wu	1995	Better	TWD/USD	1,6 month(s)	ARIMA
25	Yao & Tan	2000	Better	USD/(JPY,GBP,DEM,CHF.AUD)	1 week	RW
26	Yu et al.	2004	Better	USD/(DEM, GBP, JPY)	1 Month	GLAR, Single MLFNN
27	Zhang	2003	Better	GBP/USD	1,6, 12 week(s)	ARIMA, Single MLFNN
28	Qi & Wu	2003	Worse	(JPY,DEM,CAD,GBP)/USD	1,6,12 month(s)	RW, Linear regression
29	Gencay	1999	Worse	(GBP,DEM, FRF, JPY, CHF)/USD	1, 5, 10 day(s)	RW, GARCH, GARCH, KNN
30	Davis et al.	2001	Mixed	CAD/USD	1-15 day(s)	RW
31	Dempster et al.	2001	Mixed	GBP/USD	1 month	RW, Logit, RL, GA, LP, Heuristic
32	Dunis & Huang	2002	Mixed	GBP/USD, USD/JPY	1 day	GARCH, Regression
33	Franses & Van Homelen	1998	Mixed	(USD,CAD,GBP,JPY)/NLG	1 day	GARCH, Bilinear
34	Hann & Steurer	1996	Mixed	DEM/USD	4 weeks	RW, Linear model
35	Hong & Lee	2003	Mixed	(CAD, DEM, GBP, JPY, FRF)/USD	1 week	RW, AR, FC, PN
36	Hu & Tsoukalas	1999	Mixed	12 currencies of EU	1 day	MAV, GARCH, EGARCH, IGARCH
37	Hu et al.	1999	Mixed	GBP/USD	(1,6,12) month(s)	RW
38	Huang et al.	2003	Mixed	USD/GBP, USD/JPY	(1,3,5,10,30) day(s)	RW
39	Kuan & Liu	1995	Mixed	(GBP,CAD,DEM,JPY,CHF)/USD	1 day	RW
40	Lisi & Schiavo	1999	Mixed	(FRF, DEM, LIT, GBP)/USD	1 month	RW, Chaotic model
41	Medeiros et al.	2001	Mixed	14 exchange rates	1-4 month(s)	RW, AR, NCSTAR
42	Taylor	2000	Mixed	(DEM, JPY)/USD	1 day	GARCH, Line quantile regression
43	Walczak & Cerpa	1999	Mixed	(GBP, JPY, DEM)/USD	?	BP
44	Yao et al.	1997	Mixed	CHF/USD	1 day	RW
45	Zhang & Berardi	2001	Mixed	GBP/USD	1 day	KTB

[*] AR: auto-regression; ?: not specified; RW: random walk; MTF: multivariate transfer function; GMM: generalized method of moments; BVAR: Bayesian vector auto-regression; CBR: case based reasoning; RW: random walk; GARCH: generalized autoregressive conditional heteroskedasticity; BP: back-propagation; ARIMA: autoregressive integrated moving average; ES: exponential smoothing; GLAR: generalized linear auto-regression; KTB: keep-the-best.

Table 3 Details of the articles reviewed (Network architecture and data types) *

	Network type and its architecture			Data type and its specification			
No	Network type	I/O nodes	Hidden layer: nodes	Data type	Time range	Training size	Testing size
1	Hybrid RNN	?/1	1: 4	Tick data	1993:03-1995:04	?	?
2	GRNN	?/?	2: ?	Monthly	1980:01-2001:12	144	60
3	MLFNN	6/1	1:4	Daily	93:01:25-94:09:30	428	100
4	MLFNN	4/1	1: 10	Weekly	88:01:08-94:04:08	289	32
5	MLFNN+GA	5/1	?	Quarterly	1977:01-1996:04	72	8
6	SOM, RNN	?/2	5	Daily	73:09:03-87:05:18	1210-1959	750
7	MLFNN	?/?	?	Monthly	1984:01-1993:12	?	?
8	MLFNN	(6, 7)/1	1:4	Daily	86:01:02-99:11:11	2606	1010
9	MLFNN	?/?	?	Monthly	1957:01-1998:03	?	?
10	RNN, RBF, ELM, AFLS	(24,4)/(6,1)	2: (34,16), (8,18,24)	Daily	1997:12-2000:03	800	200
11	RNN	?/?	?	Monthly	1974:01-2001:11	300	35
12	GRNN	(1,2,12)/1	?	Monthly	1974:01-1995:07	129	65
13	Fuzzy NN	3/3	2: 9,27	Monthly	1990:01-1995:09	50	19
14	GANN	?/1	2: (2-16)	Daily	1992:01-1998:05	?	?
15	MLFNN	(2-18)/1	1:10	Daily	85:01:02-94:06:30	1989-2078	248-251
16	MLFNN, RNN	?/?	?	Monthly	1978:01-1994:05	143	24
17	MLFNN	(1-5)/1	1:1-5	Weekly	1976:01-1993:12	1976:01-1989:12	1990:01-1993:12
18	MLFNN	9/3	2: 12, 6	Daily	1988:01-1989:01	200	60
19	Evolved RBF	?/?	?	Weekly	79:12:31-83:12:26	?	?
20	GANN	(4,12)/1	1: (4,12)	Daily	90:01:10-97:06:25	90:01:10-95:08:15	95:08:07-97:06:25
21	RNN	18/1	1: 5	Daily	1990:01-1994:12	424	100
22	RBF	?/?	?	Daily	1997:01-2001:12	100,600,1300	?
23	MLFNN	(1,2,3,5)/?	?	Daily	73:03:01-95:06:30	73:03:01-94:12:30	95:01:01-95:06:30
24	MLFNN	8/1	1: 25	Monthly	1979:01-1992:12	162	6

25	MLFNN	(5, 6)/1	1: Varied	Weekly	84:05:18-95:07:07	1984:05-1993:10	1993:11-1995:07
26	Hybrid MLFNN	4/1	1:4	Monthly	1971:01-2003:12	360	36
27	Hybrid MLFNN	7/1	1: (5,6)	Weekly	1980:01-1993:12	?	?
28	MLFNN	?/?	?	Monthly	1973:03-1997:07	?	?
29	MLFNN	?/?	?	Daily	73:01:02-92:07:07	?	?
30	BP, MOD, RBF, LVQ, ARTMAP, GRL	1/1 (BP, RBF, GRL); 2 (LVQ ARTMAP); 4 (MOD)	2:5,2 (BP, RBF); 2: 9,4 (MOD); 1:6 (LVQ); 2: 4,5 (ARTMAP); 1: 5(GRL)	Daily	92:01:02-94:12:15	544	200
31	BP	?/?	?	Monthly	1994:01-1998:01	?	?
32	RNN &Combined	44/1	1:1 (2: 10,5)	Daily	93:12:31-00:05:09	1329	280
33	MLFNN	?/?	?	Daily	1986-1992	Three years data	One years data
34	MLFNN	?/?	?	Weekly/Monthly	86:01:27-94:10:10	368	87
35	MLFNN	?/?	?	Weekly	75:01:01-89:12:31	?	?
36	MLFNN	4/1	1:4	Daily	79:03:13-94:12:30	79:03:13-90:04:04	93:06:03-94:12:30
37	MLFNN	10/1	1: (4,8,12,16,20)	Weekly	1976:01-1993:12	?	?
38	MLFNN	(3,5,7,9)/1	1:4	Daily	97:01:01-02:09:06	2000	70
39	MLFNN, RNN	(1-6)/?	1:2-6	Daily	80:03:01-85:0128	50,100,150	1194,1144,1094
40	MLFNN	(2,6,10,20)/1	1: (1-5,7,10)	Monthly	1973:01-1995:10	175	48
41	Bayesian MLFNN	?/?	?	Monthly	1971:01-2000:07	Varied	Varied
42	QRNN	?/?	?	Daily	88:07:04-96:07:05	1014	1000
43	ART, RBF	?/?	?	?	?	?	?
44	MLFNN	6/1	1: Varied	Daily	1983:03-1995:11	Varied	Varied
45	NN ensemble	(1-5)/1	1: (2,4,8)	Daily	1976-1994	782	92

* RNN: recurrent neural network; ?: not specified; GRNN: generalized regression neural network; MLFNN: multilayer feedforward neural networks; PCA: principle component analysis; FA: factor analysis; MOD: modular, RBF: radial basis function, LVQ: learning vector quantization; ARTMAP: adaptive resonance theory map; GRL: genetic reinforcement learning; RL: reinforce learning; GA: genetic algorithm; LP: linear programming; GA: genetic algorithm; SOM: self-organizing map; PN:

polynomial; FC: functional coefficient; NCSTAR: Neuro-coefficient smooth transition autoregressive model; GANN: genetic algorithm neural networks; QRNN: quantile regression neural network; GRG: generalized reduced gradient.

Table 4 Details of the articles reviewed (Network strategy and optimization algorithm) *

	Network strategy		Network algorithm and transfer function			Performance measure
No	Model type	Control strategy	Training algorithm	Learning rate	Transfer function	Indicator
1	Hybrid	Recurrent	Estimation maximization	?	Logistic	MSE, MAD
2	Individual	Feedforward	Modified backpropagation	?	Gaussian	RMSE, U_{stat}, R^2, Profit
3	Individual	Feedforward	Backpropagation	Fixed value	Logistic	MAPE
4	Individual	Feedforward	Backpropagation	Fixed value	Logistic	TAFE, MAFE, Correct
5	Hybrid	Feedforward	Genetic algorithm (GA)	Fixed value	Logistic	TAFE, MAFE, Correct
6	Individual	Recurrent	?	?	Gaussian	Error rate
7	Individual	Feedforward	Backpropagation	Fixed value	Logistic	Percent error
8	Individual	Feedforward	Conjugate gradient	Fixed value	Logistic	RMSE, NMSE, S_{stat}, D_{stat}
9	Individual	Feedforward	Backpropagation	Fixed value	Logistic	RMSE
10	hybrid	Hybrid	Gradient descent	?	Logistic/RBF	RMSE, SDE
11	Individual	Recurrent	?	?	Hyperbolic Tangent	RMSE
12	Individual	Feedforward	?	?	Gaussian	RMSE, MAE, U_{stat}
13	Hybrid	Feedforward	Self-organized learning	?	Gaussian	MSE, MAPE, U_{stat}
14	Hybrid	Feedforward	GA	?	Hyperbolic Tangent	AAE, MAPE, MSE
15	Individual	Feedforward	Backpropagation	Fixed value	Logistic	MSE, RMSE
16	Individual	Hybrid	?	Fixed value	?	MSE, hit rate, return
17	Individual	Feedforward	Backpropagation	Fixed value	Logistic	RMSE, MAE, DA, Sign
18	Individual	Feedforward	Backpropagation	Fixed value	Squashing function	Returns
19	Hybrid	Feedforward	GA, Hill climbing	?	Radial basis function	MSE
20	Hybrid	Feedforward	GA, Hill climbing	?	?	RMSE
21	Individual	Recurrent	Backpropagation	?	Logistic	NMSE, ROE, ROC

22	Individual	Feedforward	?	?	Radial basis function	RMSE, Direction
23	Individual	Feedforward	Backpropagation	Fixed value	Logistic	Forecast accuracy
24	Individual	Feedforward	Backpropagation	Fixed value	Logistic	RMSE, MAPE, MAE
25	Individual	Feedforward	Backpropagation	Fixed value	Logistic	NMSE, D_{stat}, return
26	Hybrid	Feedforward	Levenberg-Marquardt	Fixed value	Logistic	NMSE, D_{stat}, return
27	Hybrid	Feedforward	GRG2	Fixed value	Logistic	MSE, MAD
28	Individual	Feedforward	Levenberg-Marquardt	Fixed value	Logistic	RMSE, Direction accuracy
29	Individual	Feedforward	Backpropagation	Fixed value	Logistic	MSPE, Sign
30	Individual	Hybrid	Hybrid	?	Varied	Sign
31	Individual	Feedforward	GA, RL, LP, Heuristic	Fixed value	?	Monthly returns
32	Ensemble	Recurrent	?	?	Logistic	RMSE, MAE, U, CDC
33	Individual	Feedforward	Backpropagation	Fixed value	Logistic	Directional accuracy
34	Individual	Feedforward	Backpropagation	Fixed value	Logistic	Return, hit rate, U_{stat}
35	Individual	Feedforward	Backpropagation	Fixed value	Logistic	MSPE, sign
36	Individual	Feedforward	Backpropagation	Fixed value	Logistic	RMSE
37	Individual	Feedforward	GRG2	Fixed value	Logistic	RMSE
38	Individual	Feedforward	Backpropagation	Fixed value	Logistic	RMSE
39	Individual	Hybrid	Backpropagation /Newton	Fixed value	Logistic	RMSPE, Sign
40	Individual	Feedforward	Backpropagation	Fixed value	Logistic	NMSE
41	Individual	Feedforward	Levenberg-Marquardt	?	Logistic	RMSE, MAE, MAD, Sign
42	Individual	Feedforward	Backpropagation	?	Logistic	MSE
43	Individual	Feedforward	Backpropagation	?	Logistic	Forecast accuracy
44	Individual	Feedforward	Backpropagation	Fixed value	Logistic	NMSE, Return
45	Ensemble	Feedforward	Scaled Conjugate gradient	?	Logistic	MSE, MAE

* ?: not specified; MSE: mean squared error; MAE: mean absolute error; MAD: mean absolute deviation; RMSE: root mean squared error; MSPE: mean squared prediction error; MAPE: mean absolute percentage error; TAFE: total absolute forecasting error; MAFE: mean absolute forecasting error; AAE: Average absolute error; NMSE: normalized mean squared error. The "hybrid" of the second column represents the mix of recurrent and feedforward strategy.

Similarly, training set size is also an important factor that affects the performance of ANNs. As Walczak (2001) revealed, neural networks, given an appropriate amount of historical knowledge, can predict future currency exchange rates with 60 percent accuracy while neural networks trained on a smaller or larger training set have a lower forecasting accuracy. His experimental results indicate that for financial time series, two years of training data is frequently used for producing good forecasting accuracy. Besides, Huang et al. (2004b) proposed using change-point detection method to seek training sets for neural networks in exchange rates forecasting. Of the 27 articles in category I, 22 articles use data split and have corresponding training set size, while of the two articles in category II, data division is not specified. Of the 16 articles in category III, 11 articles divide the data into at least two data sets and only 5 articles do not provide information related to data division. Thus, appropriate data division and training set size are helpful to predict foreign exchange rates accurately. That is, splitting data into three datasets and use of adequate training data can effectively predict foreign exchange rates with ANNs.

3.2.4. Network types and model types

In this survey, multi-layer feed-forward neural networks (MLFNN) were used in 30 articles (66.67%) and some other types of networks were used in the remaining articles, such as recurrent neural network (RNN), general regression neural network (GRNN), and radial basis function network (RBFN). In addition, of the 27 articles in category I, 15 articles used multi-layer feedforward neural networks with one hidden layer. This implies that multi-layer feedforward neural networks with single hidden layer and enough nodes can predict the exchange rates quite well. Besides, Hornik et al. (1989) and White (1990) found that a single hidden layer architecture with an arbitrarily large quantity of hidden nodes in the single hidden layer is capable of modeling any categorization mapping. In this sense, MLFNN is adequate for predicting foreign exchange rates.

In 14 of the examined articles, the ANN model type is hybrid or ensemble, while the others are individual. Of the 14 articles, 9 articles are in the first category. Actually, the hybridization of neural networks with other technologies, such as expert systems, fuzzy logics and genetic algorithms (GA) can improve the applicability of neural networks in addressing various types of finance problems. Although each technique has its own strengths and weaknesses, these technologies are complementary. Weakness of one technology can be overcome by the strengths of another by achieving a synergistic effect. Such an effect can create results that are more efficient and effective than the simple sum of their parts. In our survey, five of the 14 articles are integrated with genetic algorithms and two of them are combined with fuzzy logics. In addition, three of the 14 articles used an ensemble strategy for foreign exchange rates prediction and reported some promising and potential results. Furthermore, all the hybrid or ensemble models are superior to the individual models in the examined articles. This indicates that the hybridization and ensemble of neural networks is an effective way to improve the performance of exchange rates prediction.

3.2.5. Control strategy

In fact, the control strategy describes the way information flows, and a neural network uses the control strategy to learn and to improve its performance. Table 5 shows the number of articles employing different control strategies. 36 articles employed the feed-forward strategy; 5 articles employed the recurrent or feedback strategy; and 4 articles employed the hybrid strategy (as shown in Table 5). It indicates that the feed-forward strategy is the most widely used, but the recurrent and hybrid strategies are also potential candidates.

As can be seen from Table 5, 21 of the 27 articles in category I used feed-forward control strategy. It indicates that the feed-forward control strategy is suitable for foreign exchange rates forecasting with ANNs.

Table 5 The number of articles employing different control strategies

Control strategy	Category I	Category II	Category III	Sum
Feed-forward	21	2	13	36
Recurrent or Feedback	4	0	1	5
Hybrid	2	0	2	4
Sum	27	2	16	45

3.2.6. Training algorithm

In this survey, the backpropagation (BP) algorithm was used to search optimal connection weights in 23 of the 45 articles examined, as shown in Table 4. In 3 articles, Levenberg-Marquardt algorithm was used to speed up the convergence. In addition, some other algorithms, such as GA, GRG2 and conjugate gradient were also used. As is well known, BP is by far the most widely used algorithm for optimizing feedf-orward neural networks; it is based on the method of steepest descent. However, BP is prone to be trapped into a local optimum and, therefore, GA and simulated anneals (SA) can be used to improve this defect; but they are time-consuming and offer weak convergence. Therefore, Levenberg-Marquardt algorithm, GRG algorithm and conjugate gradient algorithm were developed to overcome the drawbacks. However, in our survey, both BP and other algorithms perform better than those of other models, except Gencay (1999) and Qi and Wu (2003).

It should be mentioned that the selection of optimal learning algorithm is an open problem (Walczak and Cerpa (1999)) and ANNs' design must use the constraints of the training data set for determining a learning method. If a reasonably large quantity of relatively noise-free training examples is available, then BP algorithm can provide effective forecasting results.

In the 45 articles, 24 articles (53.33%) used BP learning algorithm. Moreover, 12 articles in category I also used BP algorithm and obtained good performance. This shows that the BP algorithm is a widely used and good training algorithm for foreign exchange rates forecasting. In addition, 5 articles adopted GA algorithm, while the others utilized other training algorithms, such as LM, GRG2, conjugate gradient, and self-organized learning algorithms.

In addition, an important factor related to learning algorithms is the learning rate (i.e. step size), which actually controls the learning speed and the convergence property. In the examined 45 articles, 39 articles (86.67%) used a fixed learning rate with different values; the remainder do not specified the learning rate. Usually, a fixed learning rate does not lead to an optimal convergence rate. Therefore, deriving an optimally adaptive learning rate is very important for ANN applications (Yu et al., 2005a).

3.2.7. Transfer function

The transfer functions that are most commonly used are sigmoidal-type functions, such as logistic and hyperbolic tangent functions. However, other transfer functions may be used as long as they are differentiable. In an empirical study, Moody and Yarvin (1992) compared the performance of logistic, polynomial, rational function and Fourier series transfer functions on datasets containing varying degrees of noise and nonlinearities. They found that the non-sigmoidal-type transfer functions performed best when the data were noiseless and contained highly nonlinear relationships. While performance using the polynomial activation function was inferior to the one of the sigmoidal-type transfer functions when the data were noisy and contained mildly nonlinear relationships. Kalman and Kwasney (1992) argued that the hyperbolic tangent transfer function should be used. Another option is to use a radial basis transfer function. Generally, the same transfer function could be used in all layers. However, it is advantageous to use sigmoidal-type transfer functions in the hidden layers and linear transfer functions in the output layer when it is necessary to extrapolate beyond the range of the training data (Kaastra and Boyd, 1995).

In the examined articles, 34 articles (75.56%) used sigmoidal-type transfer function (logistic or hyperbolic tangent) in the hidden layer. Because the foreign exchange markets have the features of high noise, large volatility and complexity, it is advisable to use the sigmoidal-type transfer functions. Furthermore, of the 27 articles in category I, 18 articles used logistic or hyperbolic tangent function as their transfer function, two articles of category II and 14 of 16 articles in category III also used logistic function as the transfer function for predicting exchange rates. This implies that the sigmoidal-type transfer functions are appropriate for exchange rates prediction.

3.2.8. Performance comparison between ANNs and other models

In measurement of performance of foreign exchange rates forecasting, level measurement and directional accuracy are two important criteria. In this review, almost all the articles adopt these two performance measures.

Based on the two criteria, performance comparisons are made between the neural network approach and some other comparable methods in exchange rates forecasting. 40 of the 45 articles compared the performance of the neural networks with performance of statistical models, mainly linear, multiple regression analysis (see Table 2). In 27 of the 40 articles, the authors concluded that ANNs perform better than other models, while Gencay (1999) and Qi and Wu (2003) showed that ANNs perform worse than some other models. To some extent, this implies that the ANN approach is also a promising approach, although ANNs produce some mixed results.

3.3. General Situations of Exchange Rate Predictability with ANNs

In view of the above analysis, we can summarize when foreign exchange rates are predictable with ANNs, as shown in Table 6.

Table 6 The general situations of foreign exchange rates predictability by ANNs

Factors	General situations
Forecasting horizon	Short and medium-term
Data division	Three data sets, at least two data sets
Training set size	Appropriate size, e.g., two years data
Control strategy	Feed-forward strategy
Training algorithm	Backpropagation algorithm
Transfer function in hidden layer	Sigmoidal-type function
Transfer function in output layer	Linear function
Network type	Multi-layer feed-forward neural network

As can be seen from the analysis and Table 6, foreign exchange rates are predictable in the following situations: when forecasting horizon is short-term or medium-term, sample data must be divided into at least two data sets (i.e. training set and testing set, and validation set if necessary). These data sets must have an appropriate size individually; especially for training set, network control strategy is feed-forward strategy, training algorithm is backpropagation algorithm, transfer functions in hidden layer and in output layer are sigmoidal type functions and a linear function respectively, and network type is multi-layer feed-forward neural network (MLFNN). On the contrary, if prediction horizon is long-term, sample data can not be divided into (at least) two data sets and training set size is either too small or too large; then foreign exchange rates are not predictable with the ANN approach. It is worth noting that this is only a sufficient condition to guarantee exchange rates predictability with ANNs. Of course, this does not necessarily mean that other-types of ANNs do not forecast foreign exchange rates; or foreign exchange rates are unpredictable by other-types of ANNs.

4. IMPLICATION AND FUTURE RESEARCH TOPICS

In the last section, some general conditions are given to guarantee predictability in foreign exchange rate forecasting with ANNs. But in the process of our analysis, the implicit information also suggests some future research topics. First of all, we seldom mention data preparation, such as data collection, variable selection and data cleaning, for foreign exchange rates forecasting. Actually, data preparation should have a great impact on the success of exchange rates prediction, as discussed by Yu et al. (2006a).

Second, in almost all listed studies about foreign exchange rate prediction with ANNs, ANN models do not use optimal learning rates. In these studies, the learning rates are set to a fixed value during training. It is, however, crucial to determine a proper fixed learning rate for ANN applications. If the learning rate is too large, learning may occur quickly, but ANN may also become unstable and may even learn at all. If the learning rate is too small, it may lead to a long learning time and a slow convergence. Also, a suitable fixed learning is usually problem-depended and it varies with different neural network structures for different problem applications (Sha and Bajic, 2002; Yu et al., 2005a, 2006b, 2006c). Therefore, a suitable learning rate is important for any learning algorithm. However, in the examined 45 articles, almost all authors do not use optimal learning rates, which might be a subject for further research to improve the forecasting performance.

Third, as earlier noted, hybrid and ensemble strategies usually achieve better prediction performance than individual ANN models, implying that the hybrid and the ensemble ANNs will also be promising research topics for foreign exchange rates prediction with ANNs. In recent two years, Lai et al. (2006a, 2006b, 2006c) and Yu et al. (2005c, 2005d, 2005e, 2005f, 2005g, 2006d, 2006e, 2006f) have done some innovative work in these research topics. Interested readers can be referred to Lai et al. (2006a, 2006b, 2006c) and Yu et al. (2005c, 2005f, 2005h, 2006d, 2006e, 2006f) for more details.

Relying on the above three implications, we can extend the foreign exchange rates forecasting research with ANNs from following five aspects:

(1) Proposing an integrated data preparation scheme for neural network data analysis, including foreign exchange rates prediction. Although Yu et al. (2006) proposed an integrated data preparation framework for neural network data analysis, there is still some problems to be addressed.

(2) Deriving optimally instantaneous learning rates and adaptive momentum factors for individual neural network model in foreign exchange rates prediction. In 2002, Sha and Bajic (2002) derived out the optimal learning rate for multi-layer perceptron. Yu et al. (2005a, 2006b, 2006c, 2006e) further derived out optimal learning rates and adaptive momentum factors of the three-layer feed-forward neural networks using optimization theory and technique. In fact, if the layer adds, there is much work to be done in the future. In addition, the determination of neural network architecture is a difficult issue in foreign exchange rates forecasting. Yu et al. (2005b) proposed a double robustness analysis approach to determine neural network architecture, but the proposed approach is required to be improved. That is, the determination of neural network architecture is still an open problem that needed to be solved.

(3) Constructing hybrid neural network models for foreign exchange rates forecasting. Although many researchers, such as Zhang (2003b), Lai et al. (2006b), Yu et al. (2005c, 2005g), have done a lot of studies about foreign exchange rates forecasting, there is still much space.

(4) Combining different neural network models into an ensemble model for foreign exchange rates prediction. Using ensemble strategy to predict foreign exchange rates is a promising approach. There are many linear ensemble strategies (Lai et al., 2006d; Yu et al., 2006d, 2006e, 2006f) in the literature, but only two nonlinear ensemble strategies (Yu et al., 2005c; Lai et al., 2006c) are presented. More nonlinear ensemble strategies are waiting for exploring in the future work.

(5) Developing an intelligent decision support system (DSS) for foreign exchange rates forecasting. Lai et al. (2005) and Yu et al. (2005g, 2006f) presented some prototypes of foreign exchange rates forecasting and trading decision support system, but more practically feasible trading systems may be a promising research direction.

5. Conclusions

This study provides an analysis of verifying exchange rates predictability from the neural networks perspective. We have described the literature collection process, examined 45 articles with details about predicting exchange rates with ANNs, and reported the analytical results. In terms of factor decomposition and investigation, some situations of exchange rate predictability are summarized by literature analysis and inference. Meanwhile, we also point out several research topics that have some implications for exchange rates forecasting.

To summarize, we can have the following conclusions. First of all, within the constraints, ANNs can be used to effectively forecast foreign exchange rates, although some negative or mixed results were reported in some literature. Secondly, from the analysis of ANNs in exchange rate forecasting, we can confirm that the performance of exchange rates forecasting can be improved by adjusting some factors that affect the performance of the ANN approach. As advancements are made in AI technology and computer-based systems, there should be new opportunities to apply neural network technology for exchange rates forecasting. This would motivate academics and practitioners to collaborate in further exploration of applications of ANNs.

It is necessary to be cautious in explaining the results of this survey since the main findings are based on literature collected only from journal articles. The results, therefore, do not include all actual business applications. Although a large number of actual systems may be in use, the sponsoring companies may not wish to divulge any information on successful applications. Furthermore, we have examined only academic journal articles; conference proceedings and doctoral dissertations are excluded, as we assume that high-quality research is eventually published in journals. Also, some related journals might not have been included in this survey; they may not have been within the scope of our computer searches.

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