

PIPDYNAMICS – AN AI-BASED FOREX MARKET ANALYSIS & TRADING RECOMMENDATION SYSTEM

Mrs. M.R .Geetha

*Department of AI&DS,
DMI Engineering College,
Tamil Nadu, India 629301*

Mr. ArunManiyan

*Department of AI&DS,
DMI Engineering College,
Tamil Nadu, India 629301
maniyans07@gmail.com*

Mr. Murugan V

*Department of AI&DS,
DMI Engineering College,
Tamil Nadu, India 629301
Vmurugamm84@gmail.com*

Mr. Kajenthiran K

*Department of AI&DS,
DMI Engineering College,
Tamil Nadu, India 629301
kajenthiran8637@gmail.com*

Abstract

*In this project, an AI-driven system named **PipDynamics** is proposed to support foreign exchange (forex) market analysis and trading recommendations by using machine learning models to predict price movements from historical and live quantitative data, along with automated decision logic to assist traders in making informed trading decisions, and its effectiveness is validated through experimental evaluation.*

1. Introduction

The foreign exchange (forex) market, which has been investigated by various researchers, is a rather complicated environment. As forex is one of the world's most popular investments, it is important for business practitioners to be able to predict forex tendencies in order to support trading decisions and obtain high returns. However, many factors, such as political events, general macro-economical conditions and even traders' psychological expectations may seriously influence forex trends, which imply that forex tendency forecasting is quite difficult.

According to academic investigations, movements in financial market prices are increasingly shown not to be random. Rather, they behave in a highly nonlinear, dynamic manner [1]. The empirical evidence reveals that foreign exchange rates are not unpredictable. But it is hard for any single method to predict forex trends due to the interaction of many factors. It is therefore essential that quantitative methods and qualitative methods be integrated in any prediction. In view of the large number of assumptions in traditional statistical methods, some emerging artificial intelligent (AI) techniques – such as neural networks and expert systems – have been applied in the financial market and these have been found to have performed well [23].

Neural networks have three major advantages: nonlinearity, robustness, and adaptivity. But they also have disadvantages: lack of explanation capability, and difficulty in handling qualitative factors [4]. Which expert systems can explain market status, interpret patterns and help with investors' decision-making. A distinct feature of expert system is that it can deal with qualitative factors well. Furthermore, expert systems can be more efficient than the other methods if they use high-quality knowledge which is well-organized and formalized [5]. Therefore, the integration of the neural

network and expert system is a wise selection because they are complementary.

Under such a background, a neural network and an expert system are chosen to construct a hybrid AI system. The main motivation of this study is to construct a robust forex trading decision support system integrating the advantage of neural network and expert system. The rest of this study is organized as follows. Section 2 describes the proposed hybrid AI system in detail. In order to demonstrate the effectiveness of the proposed hybrid AI system, Section 3 presents several simulation experiments and reports the results. Section 4 concludes the study.

2. The proposed hybrid AI system

2.1 The framework of the hybrid AI system

In the forex market, many factors, such as trade situations (export and import), interest rates, the economic situation, political events and speculation affect forex price movements. Usually, some factors can be easily quantified, while others are hard to quantify but are not neglected in trading decisions. However traditional approaches can only handle any one of the two situations, so traditional methods do not meet practical needs. In order to solve this problem, a hybrid AI system is proposed here to support trading decisions in the forex market. The general framework is shown in Figure 1.

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graph LR
    A[Quantitative factors] -- Data --> B[Neural Nets]
    B -- Output results --> C[Expert System]
    D[Qualitative factors] -- "Expert experience" --> C
    C --> E[Forex Trading strategies]
    E --> F[Users]
  
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The diagram illustrates the architecture of a hybrid trading system. It starts with two input paths: 'Quantitative factors' leading to 'Neural Nets', which then produce 'Output results'; and 'Qualitative factors' leading to 'Expert experience'. Both paths converge into a central 'Expert System'. The 'Expert System' then generates 'Forex Trading strategies', which finally reach the 'Users'.

Figure 1 The framework of the hybrid AI system

As can be seen from Figure1, the hybrid AI system includes two modules. One is the neural network module that deals with quantitative factors affecting the forex price, while the other is the expert system module that deals with qualitative factors. In this hybrid AI system, the output of the neural network module is sent to the expert system module. The expert system module presents some trading strategies integrating the neural network outputs and expert experience to investors in the forex market. In the following subsections, details of two modules are described based on the conceptual framework.

2.2 Quantitative Analysis Using Machine Learning Models

In the proposed hybrid AI system, the neural network module is used to deal with the quantitative factors. In forex trading, it is vital that the trader can predict the forex tendency. Several factors which affect this, such as trade (exports and imports), interest rates, economic development (e.g., GDP), can be quantified. These factors are sent to the neural network module and the future trend in forex price can be obtained by the neural network module. The neural network's basic prediction principle is described as follows.

In this study, one of the widely used neural network models – the back-propagation neural network (BPNN) – is used. Usually, the BPNN model consists of an input layer, an output layer and one or more intervening layers, also referred to as hidden layers, as shown in Figure 2. The hidden layers can capture the nonlinear relationship between variables. Each layer consists of multiple neurons that are connected to neurons in adjacent layers. Since these networks contain many interacting nonlinear neurons in multiple layers, the networks can capture relatively complex phenomena. More details can be referred to [6].

2.3 Expert system for forex trading decisions

Expert system is another artificial intelligent tool for finance [7]. The key to an expert system is construction of knowledge base (KB). In our study, the KB is represented by rules from a knowledge engineer who collects and summarizes related knowledge and information from domain experts. Thus, the main tasks of the expert system module are to incorporate expert knowledge and neural network output, and generate some trading strategies. In this study, expert system contains the rules that can judge the forex tendency and forex trading strategies from neural network output results, and the rules generated by combining neural network outputs and expert knowledge and experience.

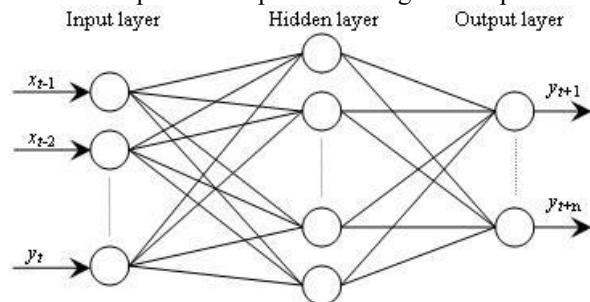


Figure 2 The topology of BPNN

2.3.1 Rules for forex trading decision support with neural net outputs. In terms of neural network outputs, three criteria are presented here and each criterion contains different trading rules in different conditions.

The first criterion is a simple price comparison judgment criterion. In general, this criterion is the simplest of all, and includes the following three rules.

Rule I: If $(\hat{x}_{t+1} - \hat{x}_t) > 0$, then the forex trend is “*upward*” and the current trading strategy is “*buy*”. Rule II: If $(\hat{x}_{t+1} - \hat{x}_t) < 0$, then the forex trend is “*downward*” and the current trading strategy is “*sell*”.

Rule III: If $(\hat{x}_{t+1} - \hat{x}_t) = 0$, then forex trend is “*unchangeable*” and the current trading strategy is “*hold and deposit*”.

The second criterion is a cost-adjusted filter judgment criterion. This rule introduces cost as adjusted bands. The objective of the band is to reduce the number of buy (sell) signals by eliminating weak signals when the predicted value and the actual value are very close. After considering transaction costs, some trades are not worth doing. Thus, this rule can help a trading system eliminate unnecessary trading and gain more profits. Usually, the trading rules can be expressed as follows.

Rule I: If $(\hat{x}_{t+1} - \hat{x}_t) > c$, then the current trading strategy is “*buy*”.

Rule II: If $(\hat{x}_{t+1} - \hat{x}_t) < c$, then the current trading strategy is “*sell*”.

Rule III: If $(\hat{x}_{t+1} - \hat{x}_t) = c$, then the current trading strategy is “*hold and deposit*”.

where c denotes transaction costs. Under this criterion, users can obtain some trading suggestions when inputting the value of the costs according to the regulations and their personal preferences.

The third criterion is a probability-based threshold judgment criterion. The trading probability based on the predicted forex price return is the basis of this trading judgment criterion. Its procedures include three steps.

Firstly, based on the predicted value \hat{x}_{t+1} that is produced by neural network module, the forex price return can also be calculated by

$$R^*_{t+1} = (\hat{x}_{t+1} - x_t) / x_t \quad (1)$$

Secondly, let the “*buy*” and “*sell*” probability of the forex price return be denoted by $B_{t+1(j)}$ and $S_{t+1(j)}$ respectively. As the forex price is a stochastic process, the probability $B_{t+1(j)}$ and $S_{t+1(j)}$ for the next day are calculated by

$$B_{t+1(j)} = P\{R_{t+1(j)} > 0\} \quad (j=1, 2, \dots, N) \quad (2)$$

$$S_{t+1(j)} = P\{R_{t+1(j)} < 0\} \quad (j=1, 2, \dots, N) \quad (3)$$

where j denotes the number of forex.

In the “*buy*” case, the basic rule is that the predicted forex price for the next day is higher than the current price, i.e. the predicted forex price return R^*_{t+1} is larger than zero ($R^*_{t+1} > 0$). In the “*sell*” case, the basic criterion is that the predicted forex price of the next day is lower than the current price, i.e. the predicted forex price return should be smaller than zero ($R^*_{t+1} < 0$).

It is worth noting that in the “*buy*” case, the forex with the largest trading probability $B_{t+1(\max)}$ is chosen from the trading probability $B_{t+1(j)}$ of all N forex candidates by

$$B_{t+1(\max)} = \max\{B_{t+1(1)}, B_{t+1(2)}, \dots, B_{t+1(N)}\} \quad (4)$$

Thirdly, the thresholds for buying and selling, Θ_B and Θ_S , are set to some certain values in advance.

Up until now, the corresponding trading judgment rules are given by:

Rule I: If $B_{t+1(\max)} \geq \Theta_B$, then the trading strategy is “*buy*”.

That is, the investor should buy if the trading probability $B_{t+1(\max)}$ exceeds a buying threshold Θ_B . Rule II: If $S_{t+1(j)} \geq \Theta_S$, then the trading strategy is “*sell*”.

In the same way, if the trading probability $S_{t+1(j)}$ of holding forex j is larger than a selling threshold Θ_S , the investor should sell.

Under this criterion, once the users or decision makers specify a certain threshold, the optimal trading strategies will be presented explicitly.

2.3.2 Rules for forex trading decision support with expert experience. In the previous subsection, the rules generated only consider neural network output from a quantitative perspective. As has been discussed above, some qualitative factors such as speculation and important events are not neglected in making forex

trading decisions. In this study, expert systems can integrate these qualitative factors into the forex trading decision by consulting domain experts. Some basic rules for forex trading with expert knowledge are summarized in Table 1.

Table 1 Some basic rules for forex trading decision with expert experience

Expected Factors	Conditions	Forex trend	Trading decision
Market demand	Increase/Decrease	Up/Down	Buy/Sell
Market supply	Increase/Decrease	Down/Up	Sell/Buy
GDP	Increase/Decrease	Up/Down	Buy/Sell
Inflation rate	Increase/Decrease	Down/Up	Sell/Buy
Interest rate	Increase/Decrease	Up/Down	Buy/Sell
Unemployment	Increase/Decrease	Down/Up	Sell/Buy
Trade surplus	Increase/Decrease	Up/Down	Buy/Sell
Political events	Yes/No	Down/Up	Sell/Buy
Rumors	Yes/No	Uncertainty	Uncertainty
Intervention	Increase/Decrease	Uncertainty	Uncertainty
Psychological	Yes/No	Uncertainty	Uncertainty

From Table 1, we can see that there are 11 basic factors related to forex price fluctuation. They can formulate 22 basic rules. Note that some uncertain factors should be determined according to the actual market situation. When several basic rules hold at the same time, the majority vote principle is used to judge the forex movement direction.

2.3.3 Rules for forex trading decisions with neural outputs and expert experience. In the previous two subsections, rules for forex trading decision are presented in terms of either quantitative factors or qualitative factors. Because the forex market is a complex environment, integrating quantitative analysis and qualitative analysis may result in a good selection. The integration rules are derived as follows.

Rule I: If the results of the quantitative analysis are the same as for the qualitative analysis, then the trading decision is adopted.

Rule II: If the results of the quantitative analysis differ from those of the qualitative analysis, then the trading decision is aborted.

All above rules are sent to the expert system's KB and they are used to support forex trading decisions for forex traders and practitioners.

2.4 The implementation of the AI system

In this hybrid AI system, the neural network is implemented by Matlab and expert system is constructed by Prolog. Generally, the factors affecting forex movement are divided into two categories: qualitative and quantitative factors. In this study, the three-layer

BPNN is used to handle the quantitative data and expert system is used to deal with the qualitative data. In the BPNN model, the size of input neuron is determined by the number of related factors, the hidden nodes is determined by trial and error, and the output node is set to one, representing the prediction value. In addition, there are 153 rules for forex trading decision in expert system.

3. Simulation study

3.1 Experiment design

The data used in this paper are daily and are obtained from Pacific Exchange Rate Service (<http://fx.sauder.ubc.ca/>), provided by Professor Werner Antweiler, University of British Columbia, Vancouver, Canada. They consist of the US dollar exchange rate against each of three currencies (EUR, GBP and JPY) with which it has been studied in this research. We take weekly data from 1 January 1993 till 31 December 2000 with a total of 521 observations as in-sample data sets (training sets), which are used to model, and take the data from 1 January 2003 to 31 December 2004 with a total of 105 observations as out-of-sample sets (testing sets), which are used to evaluate the performance of the proposed hybrid AI system based on some evaluation measurements and certain trading strategies. For space, the original data are not listed here, and detailed data can be obtained from the website.

As described previously, in order to examine the effectiveness of the proposed hybrid AI system approach for forex trading decision support, we consider three types of experiments according to trading rules presented in the Section 2.3.

In this study, the transaction cost is set to be 1% of the agreed price, the simulation is performed with an initial capital of US\$10,000 and a trading period of two years with trading twice every month at the appropriate time in order to save transaction costs. In order to compare results easily, we select the annual return rate (ARR) of investment as a general measurement.

According to the compound interest principle, the mathematical expression for the ARR is given by:

$$ARR = \frac{... \cdot \frac{\$ TR - TC - FC \cdot 12/M}{IC}^1 \cdot 1,12 \times 100 \%}{IC \cdot (\frac{fx}{fxspr})^{\odot 1}} \quad (5) \$$$

$$TR = + (fx \times IC_F) \quad (6) fx + fxspr$$

$$TC = commission + tax + others \quad (7)$$

$$FC = \frac{\$ ilocal + ispr \times IC}{12 \times 100}$$

$$\$ - iforeign - ispr \times (IC \times (fx - fxspr)); \quad (8)$$

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where TR denotes total return at the end of the trading period, IC is the initial capital at the start of the trading period, TC represents transaction costs, FC is funding costs (otherwise referred to as interest cost/gain) and M is the number of months in whole trading period. IC_L denotes one part of disinvestment of initial capital, fx denotes foreign exchange rates, $fxspr$ denotes the foreign exchange rate bid/ask spread, IC_F represents the other part of holding forex of initial capital at the end of trading period, i_{local} is the local interest rate, $i_{foreign}$ is the foreign interest rate and $ispr$ represents the interest rate bid/ask spread. Additionally, in our study, the foreign exchange rate spread is 15 basis points or 0.0015 for each buying/selling and reselling/re-buying deal, while the interest rate spread is 2 basis points or 0.02%, which represents the funding cost. It is worth noting that, for simplicity, there is no short sale or re-investing in the simulation.

3.2 Experiment results

3.2.1 Trading simulation results under the rules only considering neural outputs. According to the settings given in Section 3.1 and three trading criteria presented in Section 2.3.1, the simulation results of the trading experiment under the rules only considering neural network outputs are presented in Table 2.

Table 2 The ARR (%) for different currencies only considering neural net outputs

Trading criterion	EUR	GBP	JPY
Simple price comparison criterion	13.24	13.85	13.28
Cost-adjusted filter judgment criterion	7.61	7.94	3.70
Probability-based judgment criterion	15.02	12.40	13.15
Average ARR	11.96	11.40	10.04

From Table 2, we can find the following points. (1) Without considering the cost factor, in terms of average ARR, GBP performance is the best, followed by that for JPY and EUR; considering the cost factor, GBP performs better, while for the probability-based criterion, the EUR return rate is the highest. (2) Considering the cost factor, the ARR of the second criterion for all testing currencies are lower than those of the first criterion. (3) Generally, from an average perspective the EUR return rate is the highest, followed by that for GBP and JPY. (4) Comparing the results with those of the first two criteria, the probability-based judgment criterion seems to be the

best solution because the average return of every test currency is larger than 12 percent, considering the effect of transaction costs.

3.2.2 Simulation results under the rules only considering expert experience. In the same way, we can calculate the annual return rate for different foreign currencies under the rules in terms of expert experience. The experimental results are shown in Table 3.

Table 3 The ARR (%) for different currencies only considering expert experience

Currency	EUR	GBP	JPY
ARR	9.39	8.93	9.01

As can be seen from Table 3, when only qualitative factors are considered, EUR performs the best (the ARR is 9.39%), followed by JPY (9.01%) and GBP (8.93%). Comparing these with the previous results in Section 3.2.1, the ARR is slight low.

3.2.3 Simulation results under the rules considering quantitative and qualitative factors. In the previous subsection, simulation results are obtained in terms of either quantitative factors or qualitative factors. According to the rules presented in Section 2.3.3, both quantitative and qualitative factors are considered in order to obtain good performance. Accordingly, the experimental results are summarized in Table 4.

Table 4 The ARR (%) for different currencies considering quantitative and qualitative factors

Currency	EUR	GBP	JPY
ARR	15.13	14.57	13.52

As presented in Table 4, we can see that the average ARR for all test currencies considering both neural network outputs and expert knowledge are higher than those under the other two rules only considering partial factors, revealing that the rules considering both quantitative and qualitative factors are the best choice in making forex trading decisions. Similarly, the EUR return rate is the highest, followed by those for GBP and JPY. This implies that the EUR is a promising investment currency.

4. Conclusions

In this project, an AI-based system named **PipDynamics** is developed to support trading decisions in foreign exchange (forex) markets. The key distinction of the proposed system from existing approaches is its integration of machine learning-based quantitative analysis with automated decision logic for hybrid AI

system is a promising artificial intelligent tool for forex trading decision support.

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