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External Stimuli Predict Financial Market Behavior From the Brain Perception Perspective

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ABSTRACT The information that the brain perceives is usually consistent with a range of possible incentives. Therefore, all of our perceptual decisions are almost made in an uncertain situation. As we all know, this uncertainty affects our behavior, but how this uncertainty to modify human behavior is unclear. We attempt to establish the relationship between financial market behavior and external stimulus information. We adopt a new approach that is entirely different from the existing literature. This approach combines neuroscience and machine learning methods to explore how the brain perceives external stimulus information and ultimately influences financial market behavior. We improve the BP neural network in two aspects. Firstly, the output of the brain perception model serves as the input of the BP neural network. By this method, the number of input nodes of the BP neural network can be reduced to six, and the mental process behind the stimulus is simulated. Secondly, we optimize the parameters of the brain perception model and construct the optimal brain perception model for specific external stimuli. By comparing the performance of all models, the results show that the improved BP neural network is superior to other models. Firstly, in all two periods, trends are similar between the improved BP neural network and other models. Secondly, in all three samples, except for one result, the average prediction performance of the improved BP neural network is better than other models.

INDEX TERMS External stimulus information, financial market behavior, brain perception model, BP neural network.

I. INTRODUCTION

Economics and neuroscience have written extensively about the impact of information on behavior [1]. However, there seems to be a wide gap between the two documents. Firstly, although economists tend to focus on the impact of new information on financial market behavior, peers in the neuroscience field emphasize the relationship between external stimulus information and future behavior [1]. Secondly, although most articles in economics focus on the impact of unexpected policies on financial markets behavior, research in neuroscience usually fails to distinguish between expected and surprise information [2]. We attempt to establish a connection between economics and neuroscience [1]. Particularly, we examine an unanticipated change in the Federal Funds Rate provided by the Federal Open Market Committee affects the volatility of the currency market.

Inputs of BP neural network are historical data, lagged observations of the data series, and outputs are future value. Each input pattern consists of a fixed length moving window along times series [3]. The question of how much lag time should be included in predicting future costs. Too short or too long lag time will affect prediction capability of BP neural network. Some researchers design experiments to help select the number of input nodes, while others employ intuitive experience [4], [5].

Previous BP neural network most apply external stimulus as input, so it is challenging to learn mental activities behind stimulation [6]–[8]. We adopt a new approach that is entirely different from the existing literature. This approach combines neuroscience and machine learning methods to explore how the brain perceives external stimulus information and ultimately influences financial market behavior. The output of the brain perception model serves as the input of the BP neural network. By this method, the number of input nodes of the improved BP neural network can be reduced to six, and

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the mental process behind the stimulus is simulated. Also, we optimize the parameters of the brain perception model and construct the optimal brain perception model for specific external stimuli.

The remaining part of the paper is organized into the following sections. In section 2, we present the related work of financial forecasting, BP neural network, and neuroscience. In section 3, we made a general description of BP neural network algorithm. In Section 4, we introduce the improved BP neural network and discuss the brain perception model in detail. In Section 5, we provide data and experimental design. Particularly, we supply the results of all models and analysis and compare the improved BP neural network with other methods. Section 6 conclusions.

II. RELATED WORKS

A. FINANCIAL FORECASTING

The issue of financial market behavior prediction has attracted the attention of many researchers in recent years. The primary purpose of forecasting is to reduce decision-making risk of financial institutions, companies, and private investors. Stock prices, interest rates, prices indices, and currency exchange rates are extensive financial time series. These time series are complex, non-stationary and noisy so that they are not suitable for linear models and demanding to be measured by traditional economic models [9].

In the past decades, according to goals, nature of information, and mathematical tools propose several different forecasting methods. The first method of socio-economic forecasting mainly relies on expert judgment. Contrary to the current short-term forecast, this forecasting approach is long-term forecast based on some specific indices in real time [10]. Subsequently, classical statistical methods based on regression, correlation and spectral analysis emerge to predict financial and economic indicators [11], [12]. However, due to some limitations, these methods have not been widely utilized. Next, the time series prediction introduces adaptive techniques [13]–[15]. These methods are effective under conditions of non-stationarity, low data volume, mutations and so forth. However, these methods reduce the prediction performance due to utilizing of the linear structure. In recent years, financial forecasting applies machine learning methods based on multilayer artificial neural network [16]–[18], fuzzy logic [19], genetic algorithm (GA) [20] and genetic programming [21]. Notably, the artificial neural network has been mainly applied to predict financial market behavior such as interest rate [22], exchange rate [23], [24], stock market [3], [25], and bankruptcy [26], [27]. By reviewing the existing literature of economic forecasting, we obtain that exchange rate forecasting is an essential field of financial market forecasting. Predicting exchange rate trend is one of the most critical tasks for economic policymakers [28]. Because of the particularity of exchange rate forecasting, it is difficult to have a simple and effective forecasting method [29]. Thus, we attempt to propose a practical and low-complexity exchange rate forecasting model.

B. BP NEURAL NETWORK

As a promising prediction method, BP neural network has been widely utilized in the financial field [23], [24]. Several factors have a significant influence on the accuracy of BP neural network [3]. These factors include input variables, accessible data, and network architecture. Because each factor has its effectiveness in different situations, researchers have yet to reach a consensus in which element has more influence on the accuracy of BP neural network [3]. We mainly consider the importance of input variables on the prediction accuracy of BP neural network.

BP neural network inputs include essential inputs and technical inputs. Necessary inputs include consumer price index, foreign reserve, GDP, export and import volume, interest rates and so forth. Technical inputs include delayed time series data, moving average, relative intensity indices, and the link. Except for above two kinds of inputs, a single prediction result can also be applied as input when using BP neural network as a combined prediction instrument [4], [5].

Although some scholars believe that multivariate inputs are necessary [6], most BP neural network for exchange rate prediction take univariate input. Univariate input directly utilizes data of predicted time series, which depends on forecasting ability of time series itself. Inputs of BP neural network are historical data, lagged observations of the data series, and outputs are future value. Each input pattern consists of a fixed length moving window along times series. The question of how much lag time should be included in predicting future costs. Some researchers design experiments to help select the number of input nodes, while others employ intuitive experience [4], [5].

Ideally, there will be only a small amount of delay. If it contains a significant number of cycles, it will significantly increase the training time of BP neural network, and the algorithm is likely to fall into a local optimum. Also, if lag is less than required, the search will be limited to one subspace, which will affect the accuracy of prediction [3]. Too short or too long lag time will affect prediction capability of BP neural network. Therefore, we expect to minimize the number of input nodes.

C. NEUROSCIENCE

Social science, especially psychology, aims to understand and predict human behavior [30], [31]. Traditionally, psychologists have achieved this goal through laboratory experiments [32], [33]. However, laboratory experiments can only predict behavior in a specific environment. Recent research has shown that neuroscience can predict buying behavior, decision-making and so forth [34]. As we all know, the human does not understand why they do something consciously [35]. However, the psychological processes behind the behavior can be represented in the brain [36], [37]. We believe that current knowledge of neuroscience has reached a level that can complement the existing psychological research on behavioral prediction.

The brain perception model has a significant trend in sensory uncertainty prediction problem [38]. Decoding the accuracy of the brain perception model can be compared with traditional classification methods, which is relatively simple. This model is only applied to capture stimulus, allowing us to reconstruct stimulus from observed patterns of brain activity and compare these reconstructed stimuli with real values [39], [40]. This model is used to determine the input variables of BP neural networks. It does not require any assumptions and is entirely independent of the model.

III. BP NEURAL NETWORK ALGORITHM

A. BP PRINCIPLE

BP neural network is a multilayer feedforward neural network based on an error back propagation algorithm [7]. By applying back propagation learning algorithm to adjust weights of the different neuron, any nonlinear mapping relationship from inputs to outputs can be obtained [7]. BP neural network has distributed storing of information and processing structure and has fault tolerance. Therefore, BP neural network has robustness and the ability to handle complex problems [8].

B. BP ALGORITHM

At present, in most BP network modeling toolbox, the perform function utilizes the MSE between network output and expected output. The learning principle of BP network is to modify weight and threshold and quickly reduce the direction of performing function [8].

We apply three layers BP neural network, the input node is x_i, the hidden layer node is y_j the output node is z_l. Weight between the input node and the hidden layer node is w_{ji} and weight between the hidden layer node and the output node is v_{lj}. Where the expected value of the output node is t_l, error function between network output and expected value deviation to the output node is

$$\frac{\partial E}{\partial V_{lj}} = -\delta_l y_j, \tag{1}$$

where $\delta_l = (t_l - z_l) \cdot f'(N_l), N_l = \sum v_{lj} y_j - \theta_l, \theta_l$ is the threshold and f' is the inverse function of the transfer function. Deviation E to the hidden layer node is defined by

$$\frac{\partial E}{\partial w_{ji}} = -\delta_j' x_i, \tag{2}$$

where $\delta_j' = f'(N_j) \cdot \sum \delta_l v_{lj}, N_j = \sum w_{ji} x_i - \theta_j$ and θ_j is also a threshold.

It is the modification of the weight Δv_{lj} and Δw_{ji} are proportional to deviation reduction of the error function, weights in $k+1st$ the iteration are

$$v_{lj}(k+1) = v_{lj}(k) + \Delta v_{lj} \tag{3}$$

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji}, \tag{4}$$

where

$$\Delta v_{lj} = -\eta \cdot {}^{\partial E}/_{\partial v_{lj}} = \eta \delta_l y_j, \Delta w_{j_i} = -\eta' {}^{\partial E}/_{\partial w_{ji}} = \eta' \delta_j x_i.$$

Equally, it can obtain the modification value of the output node threshold

$$\theta_l(k+1) = \theta_l(k) + \eta \delta_l \tag{5}$$

Moreover, the hidden layer node threshold

$$\theta_j(k+1) = \theta_j(k) + \eta' \delta_j' \tag{6}$$

Here, η and η' are the learning rates [41].

Through the adjustment process of BP neural network, error function E between network outputs and expected value directly affects adjusting the result of weight and then revises the final prediction model of BP neural network

IV. IMPROVED BP NEURAL NETWORK

Several factors have a significant influence on the accuracy of BP neural network. Researchers have yet to reach a consensus in which element has more effect on the efficiency of BP neural network. We mainly consider the impact of input variables on the prediction accuracy of BP neural network. The brain perception model is applied to determine the input variables of the BP neural network. This method reduces the number of input nodes of the improved BP neural network to six. The selection of input nodes are data-driven and take full advantage of the information between sample data.

The input of BP neural network includes organic inputs and technical inputs. Few kinds of literature consider the influence of these input factors on investor mental activity, which is difficult to describe [42]. However, the brain perception model can explain how the brain perceives external stimuli.

Fig.1 is the model structure of the improved neural network.

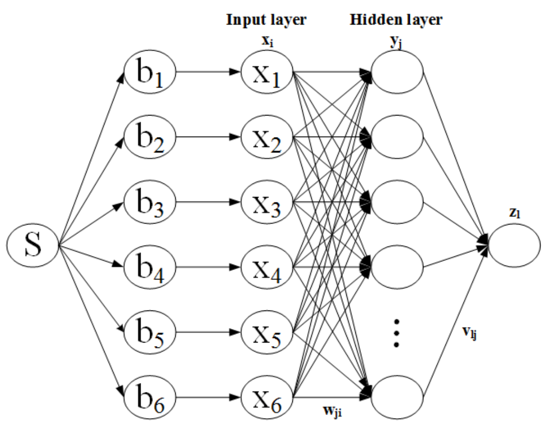

FIGURE 1. Model structure of Improved BP neural network.

A. BRAIN PERCEPTION MODEL

Brouwer and Heeger [38] propose the brain perception model, also known as the forward model. This method has a significant trend in sensory uncertainty prediction problem. This method can decode and reconstruct stimuli from spatially distributed voxel response patterns, and demonstrate fidelity of sensory knowledge.

Estimated response amplitude of voxel can be divided into training(B_1) and testing (B_2) two phases. In the first phase of training, sample data is applied to estimate weights of six channels. In the second stage, these weights are utilized to calculate channel outputs, which is related to the stimulus. Set k as the number of channels, m as the number of the voxel, and n as the number of experiments. The matrix of estimated response amplitudes (B_1, $m \times n$) is connected to the output array of open channel (C_1, $k \times n$) and weight matrix (W, $m \times k$):

$$B_1 = WC_1 \tag{7}$$

Least-squares estimate of weights is computed with linear regression:

$$\hat{W} = B_1 C_1^T (C_1 C_1^T)^{-1} \tag{8}$$

Channel responses (C_2) is related to testing data (B_2) and weights ($\hat{W}$):

$$\overset{\wedge}{C_2} = (\hat{W}^T \hat{W})\hat{W}^T B_2 \tag{9}$$

Finally, decoding stimulus by comparing channel outputs $\overset{\wedge}{C_2}$ with known channel output. We describe stimulus selectivity of each neuron as the weighted sum of six open channels, each of which has an idealized stimulus tuning-curve, such that the conversion from stimulus to channel outputs is one-to-one and reversible [39]. This process effectively reduces dimensions of data to six.

B. IMPROVED BRAIN PERCEPTION MODEL

Our decoding method starts in the early visual cortex, where voxel is selective [40], [43]–[47]. More specifically, we hypothesize that voxel i perception of stimulus s can be described as a linear weighted sum of the idealized tuning functions $f(s)$ of k neural populations [44], [45]($k = 6$)

$$B_i = \sum_{k}^{K} W_{ik} f_k(s) \tag{10}$$

Here, $f_k(s)$ is the adjustment curve of k the population as a function of stimulus s and W_{ik} is the contribution of the community k to the response of voxel i.

Population tuning curves $f(s)$ are half-wave-rectified cosine functions, raised to the second power [44].

$$f_k(s) = max(0, sin(\pi \frac{s - \varphi_k}{90}))^2 \tag{11}$$

Here, φ_k is the preferred stimulus of k the population.

GA is a valid parameter search approach. It simulates the evolution process of biology and reveals the most basic functional parameters. We apply GA to help search for optimal parameters of the brain perception model under specific external stimuli. Besides, the existence of crossover and mutation mechanism avoids local minimization problem in the search process and shortens search time [48].

V. EXPERIMENT AND RESULTS

A. SAMPLE AND DATA

To evaluate the performance of the improved BP neural network, we select the closing index of the exchange rate for the demonstration. The exchange rate is the relative change between the US dollar and other three currencies. Three currencies are Chinese Yuan, Japanese yen and Canadian dollar. We apply USD/CNY, USD/JPY, and USD/CAD to replace three exchange rates. Investing provide exchange rates.

Federal Open Market Committee provide Federal Funds Rate. The sampling period includes all Federal Funds Rate from September 27, 1982, to November 1, 2017, excluding September 17, 2017. The latter is an extreme example of a combined response by Federal Reserve, several other central banks and financial markets to the terrorist attacks of September 11, 2017.

B. EXPERIMENTAL DESIGN

We improve BP neural networks and utilize outputs of the brain perception model as inputs of the improved BP neural network. Besides, we optimize the parameters of the brain perception model to construct the optimal brain perception model for specific external stimuli. We compare the improved BP neural network with BP neural network and SVM. SVM is a promising method for its attractive characteristics and excellent generalization performance on a wide range of issues [33]. Next are the steps and details of the experiments.

Step 1. Collect data and divide it into training and testing.

Step 2. We employ GA and fitness function to seek optimal parameters of the brain perception model. Fitness function is

$$y = \min \sum_{ci=1}^{CI} RMSE \tag{12}$$

Here, ci is the rolling start and CI represents the rolling end.

We utilize Matlab (2016(a)) and apply optimal parameters to build the brain perception model. There are no rules for setting the initial point. Typically, start with the first data point and obtain the minimal RMSE after running the prediction.

Step 3. Inputs of the improved BP neural network apply outputs of the brain perception model, and we take MSE in Matlab (2016(a)) toolbox as the perform function to train the model.

Step 4. we obtain the final model. The kernel function employs Gaussian function.

Step 5. We compare the improved BP neural network and other models.

C. COMPARISON AND RESULT

For comparing the predictive accuracy of two or more methods, researchers tend to utilize k-fold cross-validation to minimize the bias associated with the random sampling of the training and holdout data samples dimensions [49], [50].

TABLE 1. 10-fold cross-validation prediction performance at (t+1) (for USD/CNY).

Fold no.	Improved BP				BP				SVM			
	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER
1	-0.758	2.213	1.441	0.274	0.112	2.002	1.700	0.361	0.267	1.892	1.484	0.344
2	-0.023	1.626	1.171	0.312	-0.334	1.841	1.408	0.342	1.117	2.230	1.659	0.485
3	-0.762	2.060	1.457	0.309	-0.445	2.154	1.775	0.372	0.156	2.223	1.583	0.389
4	-0.484	1.149	0.852	0.153	-0.458	1.534	1.155	0.203	0.145	1.557	1.124	0.225
5	0.297	1.941	1.398	0.371	0.598	2.309	1.970	0.602	1.265	2.605	2.017	0.682
6	-0.158	2.016	1.548	0.326	-0.244	1.792	1.376	0.281	0.159	2.259	1.766	0.388
7	0.477	2.018	1.649	0.479	0.644	2.215	1.906	0.552	1.030	2.240	1.692	0.544
8	0.396	1.688	1.157	0.322	0.231	1.844	1.269	0.329	0.979	2.171	1.613	0.468
9	-0.396	1.922	1.356	0.257	-0.183	2.103	1.838	0.391	0.299	1.905	1.483	0.359
10	0.008	2.247	1.625	0.432	-0.026	2.680	1.992	0.516	0.806	2.872	2.057	0.634
Mean	-0.140	1.888	1.365	0.324	-0.011	2.047	1.639	0.395	0.622	2.195	1.648	0.452

TABLE 2. 10-fold cross-validation prediction performance at (t+2) (for USD/CNY).

Fold no.	Improved BP				BP				SVM			
	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER
1	0.480	1.883	1.243	0.346	1.228	2.194	1.645	0.461	1.258	2.283	1.687	0.476
2	0.770	1.987	1.467	0.423	0.191	2.116	1.718	0.422	1.145	2.483	1.894	0.560
3	-1.274	2.311	1.821	0.276	-1.421	2.327	1.998	0.303	-0.945	2.239	1.765	0.287
4	-0.070	1.432	1.025	0.238	-0.423	1.980	1.473	0.330	0.602	2.041	1.330	0.392
5	0.329	2.017	1.518	0.477	0.169	2.112	1.749	0.526	0.982	2.428	1.896	0.614
6	-0.308	1.884	1.043	0.277	0.375	1.951	1.283	0.356	0.649	2.176	1.342	0.410
7	-0.233	1.641	1.292	0.283	-0.384	2.177	1.952	0.398	0.288	1.991	1.561	0.367
8	0.341	2.099	1.816	0.416	0.039	2.254	1.981	0.436	0.670	2.260	1.947	0.474
9	-0.174	1.722	1.278	0.305	0.005	2.479	2.038	0.546	0.661	2.271	1.703	0.541
10	-0.427	1.754	1.170	0.270	0.000	1.819	1.484	0.339	0.664	2.028	1.385	0.377
Mean	-0.057	1.873	1.367	0.331	-0.022	2.141	1.732	0.412	0.597	2.220	1.651	0.450

TABLE 3. 10-fold cross-validation prediction performance at (t+1) (for USD/JPY).

Fold no.	Improved BP				BP				SVM			
	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER
1	-3.176	12.375	9.295	0.083	-5.885	9.590	7.446	0.065	-3.347	12.312	10.461	0.092
2	-0.833	10.032	8.349	0.073	0.585	10.200	8.438	0.074	-3.411	12.799	11.044	0.095
3	2.176	16.808	13.105	0.125	0.906	11.779	10.542	0.101	-0.364	18.539	15.679	0.153
4	2.239	13.554	10.786	0.104	3.851	17.020	12.566	0.125	4.350	16.328	13.657	0.135
5	2.173	13.071	10.355	0.099	-0.702	13.016	10.627	0.099	2.802	15.756	11.791	0.117
6	-0.783	13.209	10.640	0.105	-1.586	14.550	12.085	0.116	3.707	20.475	17.488	0.175
7	-2.232	14.272	11.363	0.109	-4.142	15.399	13.840	0.131	1.630	20.439	18.083	0.174
8	1.217	14.348	11.523	0.112	2.625	11.610	8.800	0.091	3.599	17.070	13.636	0.142
9	-6.818	13.418	10.691	0.093	0.917	26.125	15.002	0.124	-0.285	15.089	11.032	0.100
10	3.337	11.614	10.259	0.102	0.435	11.661	10.422	0.099	3.146	16.341	12.734	0.129
Mean	-0.270	13.270	10.637	0.100	-0.300	14.095	10.977	0.103	1.183	16.515	13.561	0.131

TABLE 4. 10-fold cross-validation prediction performance at (t+2) (for USD/JPY).

Fold no.	Improved BP				BP				SVM			
	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER
1	1.278	11.165	9.432	0.083	-0.311	9.795	8.319	0.076	-3.136	15.817	13.276	0.118
2	-2.040	15.732	12.833	0.116	-1.840	15.231	12.895	0.116	-2.007	14.135	11.697	0.106
3	-0.890	14.659	11.358	0.102	-2.708	12.550	10.297	0.093	-3.963	17.895	15.044	0.133
4	-4.836	10.396	7.760	0.070	0.791	16.163	11.001	0.106	3.349	16.907	13.705	0.133
5	0.547	9.469	7.692	0.076	3.702	10.312	7.769	0.078	4.722	14.336	11.057	0.112
6	5.066	12.574	10.695	0.116	5.272	14.814	10.830	0.120	10.243	20.391	16.301	0.182
7	2.822	14.922	13.727	0.130	3.688	12.998	11.425	0.113	2.681	18.471	16.023	0.158
8	-1.954	12.094	9.793	0.085	-3.378	12.628	10.438	0.091	-3.449	15.534	11.999	0.105
9	0.992	10.444	8.139	0.081	5.894	13.322	10.624	0.107	1.550	15.745	12.882	0.129
10	1.968	14.873	10.925	0.110	0.154	13.267	10.122	0.100	0.795	18.982	15.445	0.150
Mean	0.295	12.633	10.235	0.097	1.126	13.108	10.372	0.100	1.078	16.821	13.743	0.133

We adopt the 10-fold cross-validation method. Literatures have shown that ten folding number seems to be optimal, which minimizes the time required for testing while reducing deviations and variances [51], [52]

Mean Absolute Error (MAE), relative Root Mean Squared Error (rRMSE), Mean Error (ME) and Prediction Error Rate (PER) are utilized to evaluate the performance of these models. Eqs. (13)-(16) provide formulas of these evaluation

TABLE 5. 10-fold cross-validation prediction performance at (t+1) (for USD/CAD).

Fold no.	Improved BP				BP				SVM			
	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER
1	-0.004	0.137	0.106	0.085	0.024	0.143	0.122	0.101	0.025	0.156	0.129	0.109
2	-0.013	0.142	0.123	0.100	-0.017	0.138	0.121	0.098	-0.031	0.150	0.124	0.100
3	-0.055	0.136	0.108	0.080	-0.048	0.132	0.111	0.083	-0.088	0.163	0.129	0.095
4	0.006	0.116	0.105	0.088	0.020	0.141	0.119	0.099	0.026	0.134	0.116	0.098
5	0.042	0.137	0.115	0.097	0.027	0.128	0.102	0.087	-0.002	0.145	0.108	0.091
6	0.013	0.127	0.109	0.091	0.026	0.132	0.114	0.097	0.009	0.142	0.123	0.103
7	0.055	0.147	0.119	0.101	0.027	0.147	0.112	0.094	0.004	0.155	0.118	0.099
8	-0.033	0.145	0.119	0.094	-0.046	0.146	0.122	0.096	-0.033	0.168	0.140	0.112
9	0.009	0.144	0.117	0.097	0.019	0.108	0.098	0.082	-0.004	0.120	0.104	0.086
10	-0.025	0.110	0.083	0.068	-0.015	0.109	0.088	0.072	0.011	0.136	0.106	0.090
Mean	-0.001	0.134	0.110	0.090	0.002	0.132	0.111	0.091	-0.008	0.147	0.120	0.098

TABLE 6. 10-fold cross-validation prediction performance at (t+2) (for USD/CAD).

Fold no.	Improved BP				BP				SVM			
	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER	ME	RMSE	MAE	PER
1	0.043	0.132	0.103	0.088	0.027	0.111	0.092	0.079	0.042	0.104	0.090	0.078
2	-0.016	0.133	0.107	0.086	-0.027	0.126	0.100	0.081	-0.054	0.122	0.106	0.084
3	0.031	0.133	0.110	0.094	0.051	0.135	0.110	0.096	0.028	0.158	0.136	0.115
4	0.015	0.154	0.131	0.111	0.026	0.198	0.165	0.141	0.032	0.192	0.165	0.142
5	-0.021	0.135	0.120	0.096	-0.017	0.135	0.119	0.096	0.001	0.158	0.127	0.105
6	-0.002	0.106	0.082	0.066	-0.013	0.110	0.085	0.068	-0.023	0.130	0.104	0.083
7	0.014	0.124	0.109	0.089	0.027	0.135	0.120	0.100	0.029	0.154	0.132	0.112
8	0.004	0.157	0.120	0.094	0.039	0.238	0.152	0.118	-0.017	0.150	0.112	0.089
9	-0.013	0.118	0.100	0.080	-0.016	0.109	0.096	0.079	-0.046	0.137	0.114	0.091
10	-0.032	0.144	0.123	0.094	-0.045	0.140	0.114	0.086	-0.067	0.165	0.128	0.096
Mean	0.002	0.134	0.110	0.090	0.005	0.144	0.115	0.094	-0.008	0.147	0.122	0.100

measures.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - T_i| \tag{13}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T_i - P_i)^2}{n}} \tag{14}$$

$$ME = \frac{\sum_{i=1}^{n}(T_i - P_i)}{n} \tag{15}$$

$$PER = \left|\frac{T_i - P_i}{T_i}\right| \tag{16}$$

where T and P represent actual and predicted values respectively.

To illustrate the effectiveness of the improved BP neural network, we compare the improved BP neural network with BP neural network and SVM. We apply one point ahead of prediction point to run the algorithm regarding the closing price of the same day as a lag period. Because changes in target rate are usually announced before closing of the currency market, exchange rate closing price generally contains new information about monetary policy for the day. Table 1 and Table 2 reveal results of USD/CNY. Table 3 and Table 4 depict similar results of USD/JPY. Table 5 and Table 6 show the results of USD/CAD. All results are calculated to three decimal places.

From Table 1 to Table 6, except for a few points, the performance of the improved BP neural network is better than BP neural network and SVM. These results verify the effectiveness of the improved BP neural network.

TABLE 7. Average prediction performance for USD/CNY.

Prediction Model	ME	RMSE	MAE	PER
Improved BP	0.099	1.881	1.366	0.328
BP	0.017	2.094	1.686	0.404
SVM	0.610	2.208	1.650	0.451

TABLE 8. Performance improvement for USD/CNY.

Models under comparison	ME	RMSE	MAE	PER
Improved BP vs. BP	-496.970%	10.196%	18.956%	18.835%
Improved BP vs. SVM	83.839%	14.813%	17.187%	27.384%

TABLE 9. Average prediction performance for USD/JPY.

Prediction Model	ME	RMSE	MAE	PER
Improved BP	0.283	12.952	10.436	0.099
BP	0.713	13.602	10.675	0.102
SVM	1.131	16.668	13.652	0.132

TABLE 10. Performance improvement for USD/JPY.

Models under comparison	ME	RMSE	MAE	PER
Improved BP vs. BP	60.379%	4.779%	2.234%	2.956%
Improved BP vs. SVM	75.011%	22.297%	23.557%	25.379%

Table 7 and Table 8 compare prediction performance of the improved BP neural network, BP neural network, and SVM of USD/CNY. Table 9 and Table 10 summarize similar results of USD/JPY. Table 11 and Table 12 provide results of USD/CAD. The results in Table 7, Table 9 and Table 11 are

TABLE 11. Average prediction performance for USD/CAD.

Prediction Model	ME	RMSE	MAE	PER
Improved BP	0.002	0.134	0.110	0.090
BP	0.004	0.138	0.113	0.093
SVM	0.008	0.147	0.121	0.099

TABLE 12. Performance improvement for USD/CAD.

Models under comparison	ME	RMSE	MAE	PER
Improved BP vs. BP	57.143%	2.899%	2.655%	2.703%
Improved BP vs. SVM	81.250%	8.844%	9.091%	9.091%

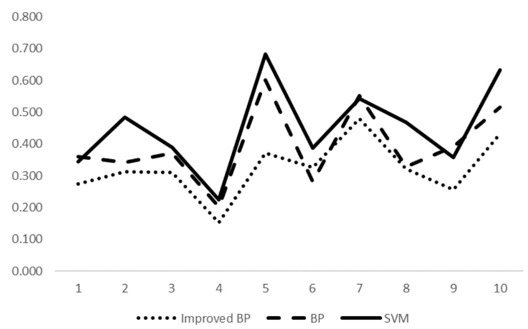

FIGURE 2. Comparison of PER at (t+1) (for USD/CNY).

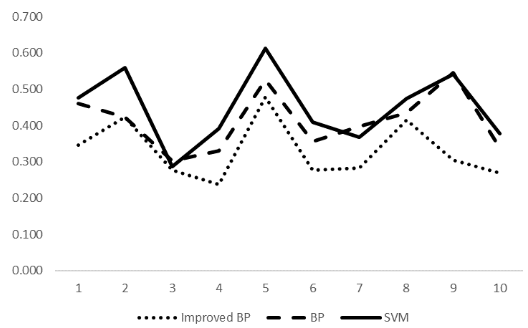

FIGURE 3. Comparison of PER at (t+2) (for USD/CNY).

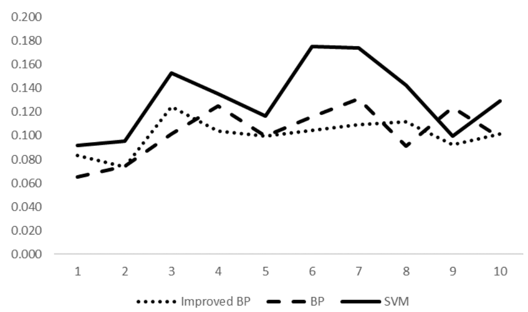

FIGURE 4. Comparison of PER at (t+1) (for USD/JPY).

based on average prediction performance, and Table 8, Table 10 and Table 12 show performance improvement.

From Figure 2 to Figure 7, we can see that the performance of the improved BP neural network is much better than the

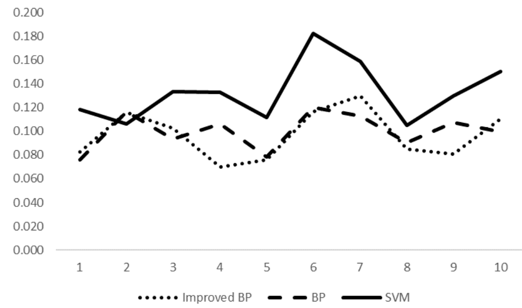

FIGURE 5. Comparison of PER at (t+2) (for USD/JPY).

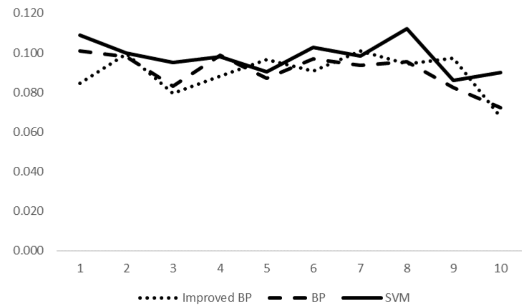

FIGURE 6. Comparison of PER at (t+1) (for USD/CAD).

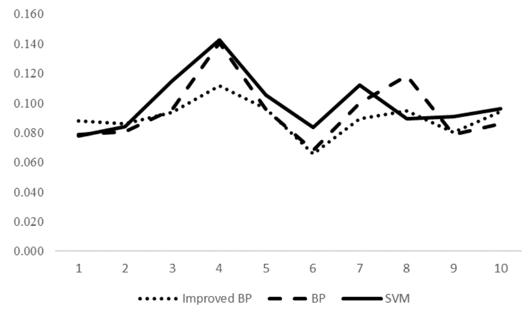

FIGURE 7. Comparison of PER at (t+2) (for USD/CAD).

other two methods. The visual representation also verifies the effectiveness of the improved BP neural network.

VI. CONCLUSION

We establish the relationship between financial market behavior and external stimulus information. We adopt a new approach that is entirely different from the existing literature. This approach combines neuroscience and machine learning methods to explore how the brain perceives external stimulus information and ultimately influences financial market behavior. We improve the BP neural network in two aspects: Firstly, the output of the brain perception model serves as the input of the BP neural network. By this method, the number of input nodes of the BP neural network can be reduced to six, and the mental process behind the stimulus is simulated. Secondly, we optimize the parameters of the brain perception model and construct the optimal brain perception model for specific external stimuli. By comparing the performance of all models, results show that the improved BP neural network is superior to other models. Firstly, in all two periods, trends are similar between the improved BP neural network and other models. Secondly, in all three samples, except for one result, the average prediction performance of the improved BP neural network is better than other models.

The application of the brain perception model provides a novel way to predict financial market behavior, and it expands the utilization field of the model. In further research, we will explore different types of dynamic and necessary information. Other issues that worth further consideration include more careful observation of the first and second moment of policy news and precise analysis of market behavior around the announcement day.

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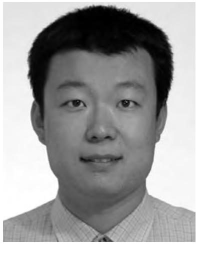

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