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Hybrid Chaotic Radial Basis Function Neural Oscillatory Network (HCRBFNON) for Financial Forecast and Trading System

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Abstract—Nowadays, financial prediction and trading are two major topics in financial engineering. With the advance of artificial intelligence (AI), the application of AI to finance has gradually became the main focus of research. In this paper, we proposed a hybrid chaotic radial basis function neural oscillatory network (HCRBFNON) based financial prediction and trading system. From the financial forecast perspective, HCRBFNON consists of three components: 1) Quantum Finance Theory to model the secondary financial market and extract the financial energy level feature, 2) Long short-term memory layer to extract the temporal financial feature, 3) Chaotic type-2 transient-fuzzy membership function based transient chaotic radial basis layer to model the highly chaotic financial timeseries. In the quantum finance hedging & trading system (QFHTS), we employ the forecasting prices from HCRBFNON and the respective nearest quantum price levels to construct the trading signals. From the experimental perspective, we compare CRBFNON with RNN, FFBPN, RBFN, SVR and RFR models to evaluate forecast performance; we also compared the trading performance of QFHTS with the moving average convergence/divergence (MACD) and moving average (MA) based trading strategies. By using 12 most popular forex products for system testing, the experimental results revealed that both the HCRBFNON and QFHTS achieve promising results in terms of forecast and trading performances.

Keywords—Financial Prediction, Financial Trading, Chaotic Neural Network, Quantum Finance, Financial Investment.

I. INTRODUCTION AND LITERATURE REVIEW

Financial investment and trading is a challenging problem attracting the interest of us over hundreds of years. With the development and evolution of the modern finance and investment theory, the contemporary investment activity usually contains two independent aspects including: 1) Financial timeseries analysis and 2) Financial trading [1]. With the advance of artificial intelligence (AI) nowadays, applying the contemporary AI tools in both financial timeseries analysis and financial trading become one of the most popular topics in both academia and finance industry.

A. Neural Network in Financial Timeseries Analysis

Traditionally, finance analysis consists of two major doctrines, they are: 1) fundamental analysis and 2) technical analysis [1]. In essence, both them can be considered as some kinds of analysis and prediction tools onto the financial markets, but from two different perspectives. In the financial time series analysis, there are two major methods being used, they are traditional statistical forecasting models such as Autoregressive Integrated Moving Average model (ARIMA), and soft computing (SC) method by integrating both computational techniques and engineering disciplines [2] such as deep learning models including neural network (NN) and support vector regressor (SVR) [3][4]. Comparing with the statistical model, due to the evolution of the computational power and data mining capability of these deep learning models, especially for the deep neural networks, become one of the most powerful models in financial engineering [1].

In terms of neural networks, various neural network models have been proposed in financial prediction problem. The artificial neural network (ANN) [5], recurrent neural network (RNN) [6] and convolutional neural network (CNN) [7] are the three most popular models in financial time series prediction, and there are many proposed variant models in different researches based on these three major types of model architecture such as Elman recurrent neural network, recurrent radial basis function neural networks [6][8].

In order to analyze and model such a complex and highly chaotic movements of financial timeseries, and inspired by Lee-Oscillator neural dynamic model with remarkable transient-chaotic property which provided a perfect solution to serve as Bifurcation Transfer Unit (BTU) to model highly chaotic and complex problems such as financial timeseries prediction [9], we proposed an effective chaotic radial basis function called transient chaotic radial basis function (TCRBF). Based on our TCRBF, we proposed a chaotic radial basis function neural oscillatory network (CRBFNON) by replacing the classical radial basis function with its chaotic counterpart.

B. Quantum Finance Theory in Financial Forecast and Trading

In order to extract the extensive features of financial timeseries data, we applied the latest research on Quantum Finance Theory (QFT) [10-12]. By modeling the market movements in the secondary financial market using quantum anharmonic oscillator (QAHO) model [10], and through the solving of Quantum Finance Schrödinger Equation (QFSE), we calculated the energy levels for the Quantum Financial Particle (QFP) in each financial market directly – the Quantum Price Level (QPL). As compared with traditional features we used in the financial prediction problems, QPL reflected the nature of the quantum dynamics of the QFPs, which cast lights on the exploration of the intrinsic characteristics of the QFPs in the financial markets. According to the QFT, QPL could be used not only for financial forecast but also for the design of trading strategy as analogue to the resistance and support lines in technical analysis [12], which could be combined with other traditional trading strategy such as trend following trading, reversal trading and breakthrough trading and so on [10].

C. Overall System Introduction

In this paper, we propose a financial intelligent forecast and trading system which compose of two major sub-systems 1) Chaotic radial basis function neural oscillatory network (CRBFNON) based financial time series forecast system, and 2) quantum finance-based hedging & trading system (QFHTS).

In the CRBFNON based financial forecast system, we adopt the latest research on Quantum Finance which provides an intrinsic method to extract the deep feature of each single financial product movement by calculating the quantum price levels (QPLs) for the financial particles [10]. In our financial forecast model, the input time series contains two parts: 1) daily 4 price variables (Open, High, Low, Close prices), 2) daily 8 nearest QPLs evaluated by solving the quantum finance Schrödinger equation (QFSE). In the neural network model of the forecasting system, it consists of two major components. Firstly, we input the raw series data into a long short-term memory (LSTM) layer to learn the temporal relationship, then the CRBFNON will take the output of the LSTM layer and forecast the next-day High and Low prices.

In the quantum finance-based trading subsystem, we utilize the QPLs as the support and resistance lines which are commonly used in the technical analysis and corresponding trading [12][13]. Based on these QPLs R/S line, by combining with our forecasting result of the CRBFNON, we predefine two “boundary region” whose breakthrough are utilized as the trading trigger of our hedging strategy.

In terms of experimental and system testing, we select the worldwide top 6 commonly traded currencies and their 12 highly traded bilateral currency pairs which are AUDCHF, AUDUSD, CADCHF, EURAUD, EURCHF, EURGBP, EURUSD, GBPAUD, GBPCAD, GBPUSD, USDCAD and USDCHF [14] for system evaluation. In addition, we separate the overall system performance evaluation into forecast and trading performance tests. In the forecast performance test, we select the recurrent neural network (RNN), simple radial basis function network (RBFN) and feedforward backpropagation neural

network (FFBPN) which are widely used deep learning models in financial prediction [5-8] as basic benchmarks. In addition, we also include two classical machine learning models which are support vector regressor (SVR) and random forest regressor (RFR) [4][15] for forecast testing. Our experimental results revealed that the HCRBFNON model outperforms than other deep learning and machine learning models in terms of both training convergence speed and prediction accuracy. In terms of financial trading system test, we compare our QFHTS with the classical Moving Averaging Convergence/Divergence based trading system (MACDTS) and Moving Average based trading system (MATS) which are commonly used in the financial industry and academia such as combining with the forecasting system to implement the integrated financial forecast and trading systems [16]. Experimental results of the trading system performance test revealed that the proposed methodology outperforms the traditional MACDTS and MATS in terms of the net profit, profit factor and expected payoffs.

II. METHODOLOGY

In our research, there are 4 major components are utilized in our hybrid chaotic radial basis function neural oscillatory network based financial forecast and trading system, which are 1) Quantum Price Level Calculation; 2) Transient Chaotic Radial Basis Function (TCRBF); 3) Hybrid Chaotic Radial Basis Function Neural Oscillatory Network (HCRBFNON); 4) Quantum Finance based Hedging & Trading System (QFHTS).

A. Quantum Price Level Calculation

In the Quantum Finance Theory (QFT) [10-12], it mainly focuses on the modeling of each financial product in the secondary financial market as quantum finance particle (QFP) and interpreted by the quantum finance anharmonic oscillator (QAHO) model. Different from the traditional harmonic oscillator model in the classical quantum mechanics and quantum field theory, financial movement is dominated by the 5 major participants and their activities in the financial market and activity, including: 1) Investor, 2) Speculator, 3) Arbitrageurs, 4) Hedger and 5) Market maker. Each of them has the contribution or damping factor on the financial movement, and influence the financial market movement in the subatomic levels. For each of the QFP, the corresponding quantum finance dynamics is governed by the Quantum Finance Schrödinger Equation (QFSE) [10], which is the combination of a harmonic term and anharmonic term (also known as “perturbation term”). By considering all the impacts caused by the market participants and their behaviors on the financial market, we could model the quantum dynamics of each QFP by the QFSE, which is given by [10]:

$$\left[\frac{-\hbar}{2m} \frac{d^2}{dr^2} + \left(\frac{\gamma\eta\delta}{2} r^2 - \frac{\gamma\eta\nu}{4} r^4 \right) \right] \psi(r) = E\psi(r) \quad (1)$$

In the QFSE, the first and the second term denote the kinetic energy (KE) term, and the potential energy (PE) term of the quantum finance market respectively. $\psi(r)$ is the wavefunction of the QFSE, which analogue to the Time-independent Schrödinger Equation in classical quantum mechanics, and E denotes the eigenvalue for that certain QFP’s dynamic, which describes the discrete quantum energy levels of the QFPs.

According to the QFT, the discrete quantum energy levels obtained from solving the QFSE, represents the quantum price levels (QPL) for that particular quantum finance particle (QFP). The QPLs are interpreted as the phased result of the QFP's movement within every trading day. If there is no outside stimulus from other QFP's interactions or breaking financial events, the QFP will remain in their temporarily stable QPL and perform chaotic oscillations, otherwise the QFP would perform energy transition among the different QPLs by absorbing or releasing the quantum energy. In other word, the QFT and the QPL calculation provides an excellent method for us to extract the intrinsic and essential property or phased results of the QFP's dynamic. More importantly, it could be directly observed from the financial markets and utilized through calculations.

From the application perspective, we utilize the QPLs in both the HCRBFNON based financial forecast and trading systems. In the HCRBFNON based financial forecast system, we use the QPLs to enhance the temporal resolution of the financial timeseries data and extract the deep features of the financial timeseries due to its intrinsic QPLs. In details, we evaluate the QPLs for each QFP and combines with the 4 OHLC (Open, High, Low, Close) price variables as daily financial price features. So, in our timeseries data, totally we have 12 features for each trading day, as illustrated in Table I.

TABLE I. INPUT COMPONENTS OF ONE TRADING DAY IN TIME SEIRES

Input Components	Input Type	No of Input	Description
Daily Open Price	Price variables	1	The open price within one trading day, considered as the ground state of the QFP in this trading day.
Daily High Price	Price variables	1	The highest price within one trading day.
Daily Low Price	Price variables	1	The lowest price within one trading day.
Daily Close Price	Price variables	1	The close price within one trading day.
4 higher QPLs	QPL	4	4 QPLs with higher value than ground state.
4 lower QPLs	QPL	4	4 QPLs with lower value than ground state.

In our quantum finance trading system, by following with the traditional technical analysis trading strategy, we consider the QPLs as the support/resistant price levels of the price movement, and the detailed trading strategy will be discussed later in this section.

B. Transient Chaotic Radial Basis Function (TCRBF)

In the conventional radial basis function network (RBFN), the dominant used radial basis function (RBF) is the gaussian function, which is given by:

$$f(x) = e^{-(x-c)^2/2\sigma^2} \quad (2)$$

Where the c represent the center of the input, and σ denotes the standard derivation of the input distribution. For the gaussian RBF, it could evaluate the different activated values according to the distance between the input and the input set.

In our HCRBFNON model, we utilize the neural dynamic model of the Lee-Oscillator [9] to construct the transient chaotic radial basis function (TCRBF), which has the similar bell-shape as the traditional gaussian function, except that it has two chaotic boundaries. With these two chaotic boundaries the activation function could be used to fit the highly chaotic and complex financial time series data preeminently.

The Lee-Oscillator model consist of 4 different functional neurons as the components: 1) Excitatory neurons (E), 2) Inhibitory neurons (I), 3) Input neurons (Ω) and 4) Output neurons (LO). The model and corresponding formula of their neural dynamics are given as followed respectively [9],

$$E(t+1) = \text{sigmoid}(e1 \cdot E(t) - e2 \cdot I(t) + S(t) - \zeta_E) \quad (3)$$

$$I(t+1) = \text{sigmoid}(i1 \cdot E(t) - i2 \cdot I(t) - \zeta_I) \quad (4)$$

$$\Omega(t+1) = \text{sigmoid}(S(t)) \quad (5)$$

$$LO(t) = [E(t) - I(t)] \cdot e^{-kS^2(t)} + \Omega(t) \quad (6)$$

Where E, I, Ω and L represented the excitatory, inhibitory, input and output neurons, $e1$, $e2$, $i1$ and $i2$ were the weights, ζ_E and ζ_I were the threshold values and $S(t)$ was the external input stimulus. By adopting the latest research on type-2 fuzzy logic, based on the chaotic type-2 transient-fuzzy membership function (CT2TFMF) [17], we successfully modeled the TCRBF whose formulation is given as follow,

$$TCRBF(x) = \begin{cases} \frac{\text{Lee-oscillator}(2x)}{2} + 0.5, & x \leq 0.5 \\ \frac{\text{Lee-oscillator}(2-2x)}{2} + 0.5, & 0.5 < x \leq 1 \end{cases} \quad (7)$$

Where the Lee-oscillator() is given by LO in (7), x corresponding to the strength of the external stimulus taking the domain with (0, 1), and the MATLAB simulation result of the construction for TCRBF is shown as follow:

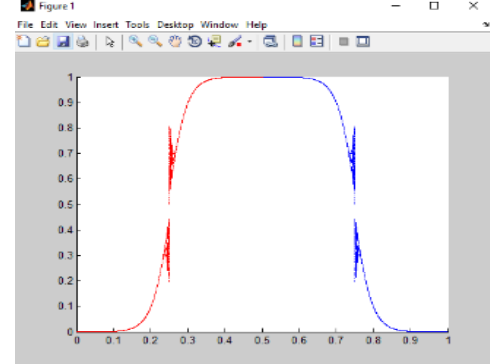


Fig. 1. Bell-shaped transient chaotic radial basis function simulation in matlab 2009

C. Hybrid Chaotic Radial Basis Function Neural Oscillatory Network (HCRBFNON)

In our research, we proposed a hybrid neural model by integrating the Long short-term memory (LSTM) neural network with our chaotic radial basis function neural network, called hybrid chaotic radial basis function neural oscillatory network model (HCRBFNON). LSTM is a variant of the recurrent neural network (RNN) by replacing the basic network neurons in RNN with the LSTM cell. LSTM cell is a combination of several non-linear combinations, intuitively, one LSTM cell is an imitation of a memory cell in human brain, which has the ability in: 1) forget; 2) input; and 3) output by maintaining two independent data flow which represents the

short-term memory and long-term memory respectively. The model for LSTM cell is given followed Graves and Olah [18][19].

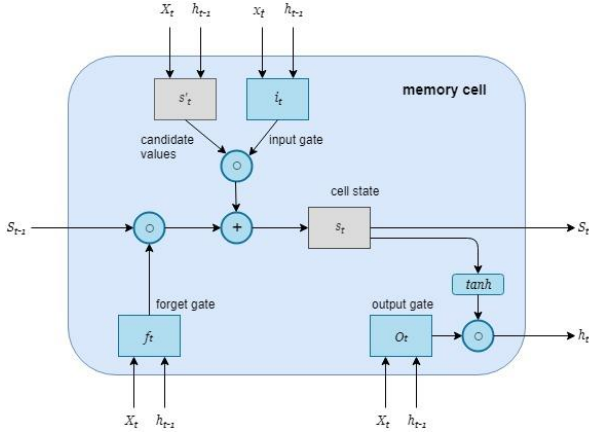


Fig. 2. Structure of the LSTM memory cell followed Graves and Olah [18][19]

The forward calculation procedure of the LSTM cell are given as follow [18]:

First, LSTM cell decides what information (long-term memory) from the previous step need to be forgotten, which is handled by the forget gate, and the equation is given:

$$f_t = \text{sigmoid}(W_{f,x}x_t + W_{f,h}h_{t-1} + b_{\text{forget}}) \quad (8)$$

Where the f_t represents the output value of the forget gate, x_t denotes the input in time step t , h_{t-1} represent the output in timestep $t-1$, b denotes bias and W is the weight for its corresponding subscript.

Second, for each LSTM cell, the input contains: 1) input value x_t in this timestep t , 2) previous cell's output h_{t-1} (short-term memory), the input gate maintains the input value by the input gate,

$$s'_t = \tanh(W_{s',x}x_t + W_{s',h}h_{t-1} + b_{s'}) \quad (9)$$

$$i_t = \text{sigmoid}(W_{i,x}x_t + W_{i,h}h_{t-1} + b_i) \quad (10)$$

Where the s'_t denotes the candidate state value in timestep t and i_t denotes the activation value of the input gates. x_t represents the input in time step t , h_{t-1} represents the output in timestep $t-1$, b is bias value and W is the weight for its corresponding subscript.

Third, the LSTM cell will calculate the state value in this timestep t by applying the following equation,

$$s_t = f_t \circ s_{t-1} + i_t \circ s'_t \quad (11)$$

Where the current state and previous state is given by s_t and s_{t-1} , and \circ is the Hadamard product.

In the last step, the output gate controls the output value of this LSTM cell by applying the following two equations:

$$o_t = \text{sigmoid}(W_{o,x}x_t + W_{o,h}h_{t-1} + b_o) \quad (12)$$

$$h_t = o_t \circ \tanh(s_t) \quad (13)$$

Where the o_t denotes the value o_t of the output gate, and h_t denotes the output value in timestep t of this LSTM cell.

There are enormous researches and experiments in LSTM has demonstrated that LSTM outperforms than simple RNN and other neural network architecture in learning the temporal relationship among the series data type [3][20]. Hence, by applying the extra LSTM layer before the chaotic radial basis function neural oscillatory network, we enable our neural network model to have the learning ability in both long-term and short-term dependency inside the input, which significantly improved our neural network model's learning ability in the potential dependence and movement pattern of the financial time series.

In the forward propagation of our neural network, the input data consist of the past 6 trading-day timeseries. As mentioned, 12 features including 8 QPLs and 4 (OHLC) price variables shown in Table I, and the output consists of next-day forecast High and Low prices. After the input to the LSTM layer, data will be fed into our CRBFNON model which consists of three layers: 1) TCRBF activation layer; 2) sigmoid layer; and 3) output layer. Specifically, we integrate another sigmoid layer inside the CRBFNON model as compared with the classical three layers of RBFN. The reason is that in the chaotic activation layer, the activation function has a certain interval of the bifurcation zone, which means the TCRBF layer usually outputs in a chaotic output range. This special feature allows the system to jump out of the local minimum and solving the deadlock problem during the training process. In general, the experimental result demonstrated that one of the effective use of the chaotic activation layer is to add an additional layer of common activation functions (sigmoid etc.) behind it, which will help our model to achieve a good tradeoff between jumping out of the local optimal solution to achieve global optimal convergence accuracy. The architecture of our HCRBFNON is shown in Fig. 3.

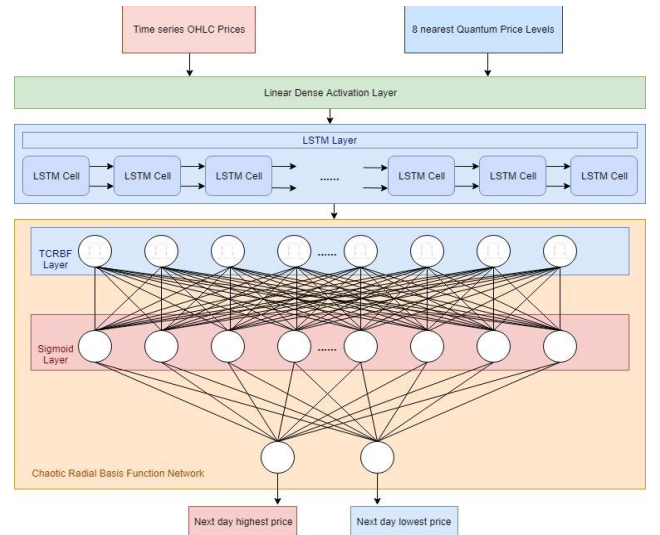


Fig. 3. Architecture of the HCRBFNON financial forecasting system

As shown in Fig. 3, TCRBF and sigmoid layer contains 20 hidden neurons, and the LSTM layer is constructed by 30 hidden LSTM cells. During the data preprocessing phase, we apply the L2 normalization method to standardize the price variables and QPLs. We adopt the traditional sliding window method to labeled the training instance: 1) we label out the first 9 days as the input and the highest and lowest price in 10th day as the labeled data; 2) we translate the fixed size (10) sliding window in a day size along the direction of the time series; 3) repeat until the end of the time series. In terms of the network training, the LSTM layer take input with 80 batch size. In addition, to decrease the impact from the stochastic gradient in TCRBF layer during the process of global minimum convergence, the state-of-art optimization method Adaptive Moment Estimation (ADAM) optimizer has been used with 500 epochs training period.

D. Quantum Finance based Hedging & Trading System

In this section, we apply the QPLs with the daily High and Low price forecast results to integrate with our single market – single product trading strategy system. The main three steps are given as followed.

Firstly, we evaluate the value of each QPL by solving the QFSE. During this process, the direct result of solving the QFSE is the normalized quantum price return (NQPR) which describe the relative relationship among the energy levels and the daily open price, treated as the ground state [10], and the relationship is shown by the followed equations:

$$HQPL_i = OpenPrice \times NQPR_i \quad (14)$$

$$LQPL_i = Open Price \div NQPR_i \quad (15)$$

where the $HQPL_i$ and $LQPL_i$ denote the i -th QPL with higher and lower value than the ground state (i.e. the daily open price). Specifically, in order to determine the QPLs that could be used in trading activity, we will evaluate those QPLs which are in the range of the forecast High and Low prices as the available QPLs.

Secondly, based on this available QPLs, we locate the QPLs closest to the forecast High and Low prices, defined as the highest and lowest critical QPLs. Based on the highest and lowest critical QPLs, we define the highest boundary region as the price interval that lower than the forecast High and higher than the highest critical QPL, and the lowest boundary region as the price interval that higher than the forecast Low price and lower than the lowest critical QPL.

Thirdly, we define the trading trigger as: 1) Once the price up crosses the highest critical QPL and enters the highest boundary region defined by the highest critical QPL and the forecast High price, we take short with the *bearish* direction. 2) Once the price down crosses the lowest critical QPL and enters the lowest boundary region defined by the lowest critical QPL and the forecast Low price, we take long with the *bullish* direction. The flow chart is given by,

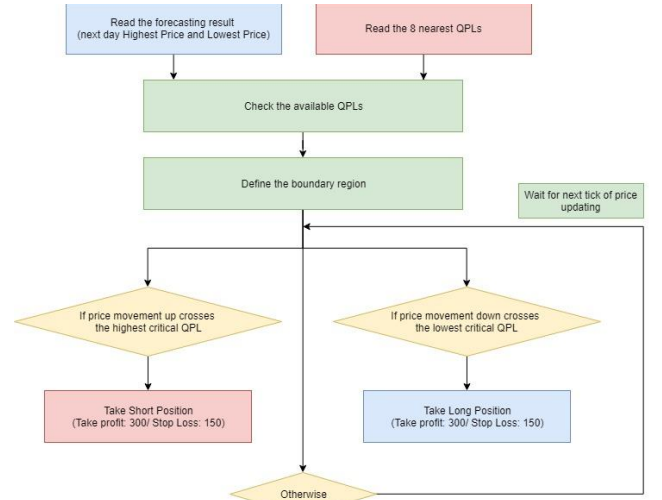


Fig. 4. Flowchart of the QFHTS financial trading system

By applying this trading strategy, once the price crosses the two critical QPLs, the single market-single product hedging will be achieved by setting long and short orders in the direction of the bullish and bearish market movement within one trading day.

III. EXPERIMENT RESULTS

In this section, we implement our HCRBFNON based quantum finance hedging & trading system by using the 6 highly traded currencies which combine into 12 different forex pairs which are: AUDCHF, AUDUSD, CADCHF, EURAUD, EURCHF, EURGBP, EURUSD, GBPAUD, GBPCAD, GBPUSD, USDCAD and USDCHF as shown in Table II.

TABLE II. DESCRIPTION ON 12 TESTING FOREX PRODUCTS

Symbol	Description	Size of Trading days
AUDCHF	Australian Dollar vs. Swiss Franc	2051
AUDUSD	Australian Dollar vs. US Dollar	2051
CADCHF	Canadian Dollar vs. Swiss Franc	2051
EURAUD	Euro vs. Australian Dollar	2051
EURCHF	Euro vs. Swiss Franc	2051
EURGBP	Euro vs. British Pound	2051
EURUSD	Euro vs. US Dollar	2047
GBPAUD	British Pound vs. Australian Dollar	1531
GBPCAD	British Pound vs. Canadian Dollar	1531
GBPUSD	British Pound vs. US Dollar	2047
USDCAD	US Dollar vs. Canadian Dollar	2047
USDCHF	US Dollar vs. Swiss Franc	2051

In order to evaluate our model in both the perspective in forecast ability and the profitability of trading strategy. We evaluate our HCRBFNON model and the QFHTS separately with different benchmark models and strategies. In terms of the forecast performance comparison, we select 5 commonly used deep learning and machine learning models which are RNN, FFBN, RBFN, SVR and RFR as benchmarks in 2048 trading days comparison, and we used the sliding window method which is commonly used in time series analysis, to separate the label data and training data. Furthermore, after labeling all the training instances, we separated them to 85% as training set and 15% as testing set respectively. Furthermore, we evaluate the forecast ability by: 1) convergence comparison in training set; and 2) prediction accuracy comparison in testing set independently. In the trading system comparison, we compare

our model with two conventional used strategies 1) Moving Averaging Convergence/Divergence based trading system (MACDTS), 2) Moving Average based trading system (MATTS) integrated in the MetaTrader 4 platform in half-year trading period. The detailed experimental information is shown in Table III.

TABLE III. TRADING SYTEM EXPERIMENT SETTING

Trading Model	Testing Interval	Trading Period	Modeling Method	Spread	Initial deposit
QFHTS	2019.02.01 - 2019.07.01	Daily	Every tick (the most precise method based on all available least timeframes)	current	10000.00 USD
MATS	2019.02.01 - 2019.07.01	Daily	Every tick (the most precise method based on all available least timeframes)	current	10000.00 USD
MACDTS	2019.02.01 - 2019.07.01	Daily	Every tick (the most precise method based on all available least timeframes)	current	10000.00 USD

From the implementation perspective, we conducted the QPL evaluation process in the MetaTrader 4 platform [21] by using the MQL4 programming language. For data pre-processing, we conducted it in the Python 3.6 with *numpy* and *pandas* packages. For model construction, we developed the HCRBFNON and its training comparison model RNN, FFBPN and RBFN with *Google Tensorflow* in version 1.31 which is commonly used for the machine learning research and development. In addition, for accuracy comparison model including Support Vector Machine Regressor and Random Forest Regressor; we constructed these models by using the *scikit learn* package in Python. For the trading system comparison, all the trading model are conducted in MetaTrader 4 platform with MQL4 programming language. All the models including HCRBFNON and its comparison model are operated in CPU cluster with Windows 10 operating system and Intel(R) Core(TM) i5-6300HQ CPU @ 2.30GHz, 2304 Mhz processor.

A. Training Convergence Comparison

In our research, we compare our HCRBFNON financial forecast model with the benchmark models in terms of average mean square error (MSE) comparison. During the system training comparison, we compare four neural network based forecasting models in which the mini-batch with 80 batch size training method was selected for the HCRBFNON and RNN model. The batch size training method was selected for the RBFN and FFBPN model. During the data preprocessing phase, all of them are applied the same continuously train-test spilt series method and L2 normalization method. The average MSE vs. training epoch diagram is shown as followed in Fig. 5.

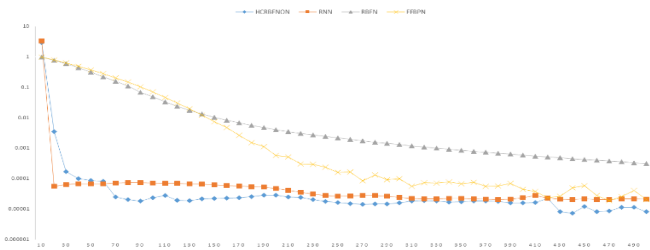


Fig. 5. 4 models' average MSE among 12 products versus 500 training epoch

Where the x-axis and y-axis represent the training epoch and average MSE among 12 forex products. Furthermore, the standard derivation MSE among 12 products for 4 neural network models comparison is shown in Fig. 6.

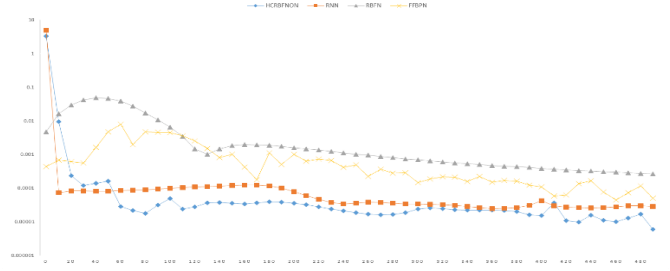


Fig. 6. 4 models' standard derivation of the MSE among 12 products versus 500 training epoch

Where the x-axis and y-axis represent the training epoch and standard derivation of the MSE among 12 forex products. Table IV shows the overall comparison table of the MSE in the 500th epoch.

TABLE IV. TRAINING CONVERGENCE MSE COMPARISON

Models	HCRBFNON	RNN	RBFN	FFBPN
AVG MSE	8.16E-06	2.07E-05	3.12E-04	2.04E-05
STDEV MSE	5.91E-06	2.88E-05	2.63E-04	5.09E-05

Where the AVG MSE and STDEV MSE represents the mean and the standard derivation of the MSE among 12 products, respectively. From the Fig. 5, Fig. 6 and Table 4, the experimental results revealed that the HCRBFNON outperforms than other THREE models during the global minimum convergence in terms of the convergence speed and the accuracy. During training convergence test of the HCRBFNON model, the result revealed that the convergence process of the HCRBFNON accompanied with obvious oscillation of average MSE. Additionally, the training oscillation positively contributed to the reduction of the average MSE and improvement of the accuracy, which demonstrated by the contribution of the TCRBF layer.

B. Daily Prediction Accuracy in Testing Set

In the testing set, we adopt the 4 trained neural network models with 2 extra machine learning models which are Support Vector Regression (SVR) and Random Forest Regression (RFR) to forecast the target price and measure the general ability in the else 15% testing set which enables the testing interval contains at least 200 actual trading days (Table V). Fig. 7 shows the 6 models' predictive MSE among 12 products in testing set.

TABLE V. PREDICTION ACCURACY MSE COMPARISON

	<i>AUDCHF</i>	<i>AUDUSD</i>	<i>CADCHF</i>	<i>EURAUD</i>	<i>EURCHF</i>	<i>EURGBP</i>
CRBFNN	4.93E-07	4.56E-07	4.71E-07	9.84E-08	1.65E-07	1.41E-07
RNN	7.84E-06	1.21E-06	3.71E-06	9.68E-07	7.68E-06	1.17E-04
RBFN	1.15E-03	1.16E-03	1.15E-03	1.15E-03	1.15E-03	1.15E-03
FFBPN	3.22E-06	1.43E-01	1.72E-02	4.33E-03	1.19E-03	1.18E-05
RFR	7.52E-04	7.59E-04	8.68E-04	1.02E-03	1.05E-03	1.02E-03
SVR	6.47E-04	6.77E-04	6.83E-04	7.60E-04	7.52E-04	7.03E-04

	<i>EURUSD</i>	<i>GBPAUD</i>	<i>GBPCAD</i>	<i>GBPUSD</i>	<i>USDCAD</i>	<i>USDCHF</i>
CRBFNN	5.00E-07	1.19E-07	3.79E-07	3.34E-07	4.56E-07	4.83E-07
RNN	3.80E-06	9.69E-06	2.51E-05	2.10E-05	3.14E-06	2.92E-06
RBFN	1.16E-03	1.57E-03	1.56E-03	1.16E-03	1.16E-03	1.15E-03
FFBPN	4.52E-03	4.77E-03	9.75E-02	1.74E-02	1.08E-03	1.67E-06
RFR	9.45E-04	1.19E-03	1.26E-03	9.14E-04	8.91E-04	1.08E-03
SVR	7.13E-04	9.08E-04	9.34E-04	7.37E-04	7.28E-04	7.57E-04

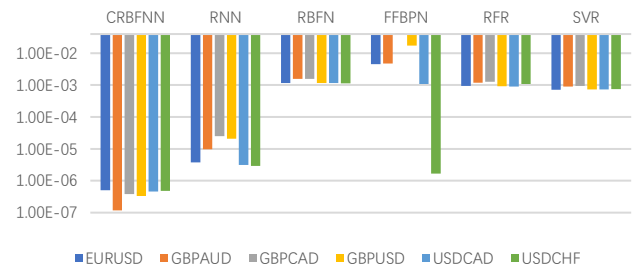
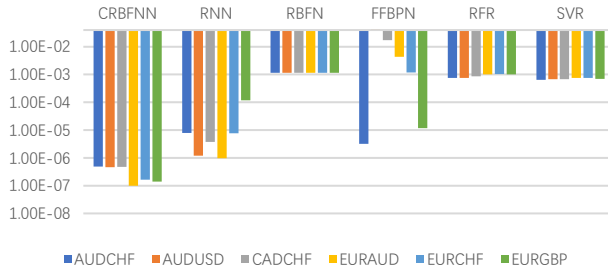


Fig. 7. 6 models' predictive MSE among 12 products in testing set.

Where the y-axis denotes the MSE displayed in logarithmic scale with base 10, x-axis denotes 6 different comparison models respects to 12 different testing products. The overall comparison in average mean square error of 12 products (AVG MSE), standard derivation mean square error of 12 products (STDEV MSE), Root Mean Square Error (RMSE), Average Outperform Rate (AOR) is given as followed, and AOR is calculated by (16) in which n denotes the number of the models,

$$AOR_i = \frac{\sum_{j=1}^n AVG\ MSE_j}{n \times AVG\ MSE_i} \quad (16)$$

TABLE VI. OVERALL ACCURACY COMPARISON IN TESTING SET

	AVG MSE	STDEV MSE	RMSE	AOR
CRBFNN	3.41E-07	1.63E-07	5.84E-04	1331862.05%
RNN	1.70E-05	3.25E-05	4.13E-03	26695.57%
RBFN	1.22E-03	1.60E-04	3.50E-02	371.58%
FFBPN	2.43E-02	4.64E-02	1.56E-01	18.71%
RFR	9.81E-04	1.57E-04	3.13E-02	463.26%
SVR	7.50E-04	8.72E-05	2.74E-02	605.87%

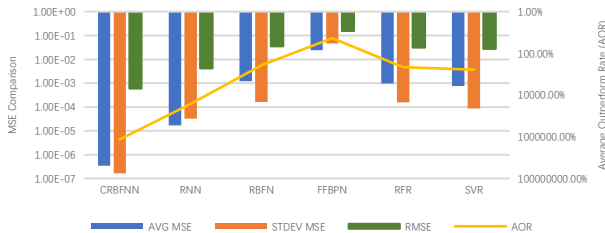


Fig. 8. 6 models' overall forecasting performance comparison.

The Table VI and Fig. 8 illustrated that the HCRBFNN outperforms than other deep learning models and machine learning models in highly chaotic, irregular and complex financial time series prediction problem by measuring the AVG MSE, STDEV MSE, RMSE and AOR indicators. In detail, the Table V shows that the HCRBFNN contains the smallest MSE in all 12 different products, and the average MSE among these 12 different products contains almost two orders of magnitude smaller by comparing with RNN.

C. Trading System Comparison

In this section, we compared the proposed QFHTS with two commonly used trading system which are Moving Average Convergence/Divergence Trading System (MACDTS) and Moving Average Trading System (MATS) constructed inside the MetaTrader 4 platform. Follow the industrial criterion, we propose the evaluation from the perspective in profitability in three common used index: 1) Net Profit (NP), the net profit in the time interval from beginning of the test to the end; 2) Profit Factor (PF), the proportion between gross profit and gross loss; and 3) Expected Payoff (EP), the mathematical expectation of the gained profit. After testing the historical data for three trading systems in half year trading day test, we selected all the profitable products for three models respectively to form the corresponding investment portfolio. Based on these three indicators, we evaluate three trading systems and their

investment portfolio, the result is illustrated in Tables VII and VIII.

TABLE VII. OVERALL TRADING PERFORMANCE COMPARISON IN INVESTMENT PORTFOLIO

	<i>AUDUSD</i>			<i>CADCHF</i>			<i>EURCHF</i>		
	NP	PF	EP	NP	PF	EP	NP	PF	EP
	1736.55	1.07	7.3	2811.24	1.14	13.85	1014.08	1.1	10.67
Strategy 1. QFHTS	<i>EURUSD</i>			<i>GBPCAD</i>			<i>USDCHF</i>		
	NP	PF	EP	NP	PF	EP	NP	PF	EP
	1755	1.16	15.13	2849.65	1.05	3.73	3633.89	1.13	12.49
Strategy 2. MACDTS	<i>AUDUSD</i>			<i>CADCHF</i>			<i>EURCHF</i>		
	NP	PF	EP	NP	PF	EP	NP	PF	EP
	64.4	1.17	0.47	21.9	1.05	0.2	3.29	1.01	0.05
	<i>EURGBP</i>			<i>EURUSD</i>			<i>GBPCAD</i>		
	NP	PF	EP	NP	PF	EP	NP	PF	EP
	115.17	1.19	0.81	266.6	2.3	2.12	169.49	1.28	0.72
	<i>GBPUSD</i>			<i>USDCAD</i>			<i>USDCHF</i>		
	NP	PF	EP	NP	PF	EP	NP	PF	EP
	156.56	1.25	0.74	291.31	2.28	1.7	82.57	1.31	0.79
Strategy 3. MATS	<i>GBPAUD</i>								
	NP	PF	EP						
	1455.25	1.51	21.09						

TABLE VIII. AVERAGE TRADING PERFORMANCE COMPARISON IN INVESTMENT PORTFOLIO

	Average Net Profit	Average Profit Factor	Average Expected Payoff	Gross Net Profit
Strategy 1. QFHTS	2300.07	1.11	10.53	13800.41
Strategy 2. MACDTS	130.14	1.43	0.84	1171.29
Strategy 3. MATS	1455.25	1.51	21.09	1455.25

As shown in Tables VII and VIII, it is clear that the QFHTS achieve promising profitability in terms of average net profit and gross net profit, with average net profit 2300.07 and gross net profit of the portfolio 13800.41. Due to the fact that QFHTS trading strategy mainly depends on the quantum hedging techniques, for one pair of hedging in different directions, profit taking is usually accompanied by a certain degree of loss, the average profit factor is around 1.1 which is close to the median 1. Furthermore, the average expected payoff shows that the QFHTS outperforms than the MACDTS. Compared with MATS, the average expected payoff of QFHTS is 10.53 against 21.09; however, the portfolio of the QFHTS contains 6 different forex product to invest, the MATS only contains one product, which shows that the QFHTS has the better tradeoff between generalization and the profitability in various forex product investment.

IV. CONCLUSION

In this paper, we proposed a hybrid chaotic radial basis function neural oscillatory network with a quantum finance based financial forecast and trading system. In our proposed system, the HCRBFNON is applied to predict the next-day High and Low prices based on the price information and QPLs of the past 9 trading-days. In the HCRBFNON system, two methods are adopted, which are 1) Long short-term memory temporal

feature extraction layer; 2) Oscillator based transient chaotic radial basis function layer. The LSTM layer is used to extract and learn the time relationship in the series data, and the TCRBF layer has been proved with promisingly result to handle highly chaotic and irregular problem such as forex markets. In the system comparison, we compare our model with 5 benchmark models which are RNN, FFBN, RBFN, SVM and RFR, and using 12 commonly traded forex pairs for performance analysis. The experimental results illustrated that the HCRBFNON outperforms than other models in terms of training convergence with average MSE among 12 products in $8.16E-06$, and testing prediction accuracy in $3.41E-07$.

By applying the forecasting results of our HCRBFNON financial forecast system, we proposed a quantum finance based hedging & trading system. In our QFHTS, based on the daily forecast High and Low prices, we evaluate the two QPLs closest to the forecast prices, defined them as the critical QPLs. When the price crosses the critical QPL, we take the position in the reverse of the crossing. Therefore, within one trading day, we placed an order for each of the two price movements direction, thus achieving a single market-single product hedging strategy. In the performance testing, the QFHTS significantly outperforms the two classical trading strategies MATS and MACDTS in terms of profitability evaluated in net profit (2300.07), profit factor (1.11) and expected payoff (10.53).

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REFERENCES

- [1] T. Guida, *Big Data and Machine Learning in Quantitative Investment*. Hoboken: Wiley, 2019.
- [2] D. Pradeepkumar and V. Ravi, "Soft computing hybrids for FOREX rate prediction: A comprehensive review," *Computers and Operations Research*, vol. 99, pp. 262-284, 2018.
- [3] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," *European Journal of Operational Research*, vol. 270, (2), pp. 654-669, 2018.
- [4] S. Huang *et al*, "Chaos-based support vector regressions for exchange rate forecasting," *Expert Systems with Applications*, vol. 37, (12), pp. 8590-8598, 2010.
- [5] M. Nakano, S. Takahashi and A. Takahashi, "Bitcoin technical trading with artificial neural network," *Physica A: Statistical Mechanics and its Applications*, vol. 510, pp. 587-609, 2018. K. Elissa, "Title of paper if known," unpublished.
- [6] J. Wang *et al*, "Financial Time Series Prediction Using Elman Recurrent Random Neural Networks," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 4742515-14, 2016.
- [7] V. Neagoe, A. Ciotea and G. Cucu, "Deep convolutional neural networks versus multilayer perceptron for financial prediction," in 2018, . DOI: 10.1109/ICComm.2018.8484751.
- [8] R. Singh and S. Srivastava, "Stock prediction using deep learning," *Multimedia Tools and Applications*, vol. 76, (18), pp. 18569-18584, 2017.
- [9] Raymond S.T. Lee. and J. N. K. Liu, James N. K., "NORN Predictor-Stock Prediction using a Neural Oscillatory-based Recurrent Network", *International Journal of Computational Intelligence and Applications* 1(4) 439-451, 2001.
- [10] Lee, Raymond S. T., *Quantum Finance - Intelligent Financial Forecast and Program Trading Systems*, Springer NATURE, Singapore, 2019 (in printing).
- [11] T. Gao and Y. Chen, "A quantum anharmonic oscillator model for the stock market," *Physica A: Statistical Mechanics and its Applications*, vol. 468, pp. 307-314, 2017.
- [12] X. Meng *et al*, "Quantum spatial-periodic harmonic model for daily price-limited stock markets," *Physica A: Statistical Mechanics and its Applications*, vol. 438, pp. 154-160, 2015.
- [13] R. A. DeFusco, *Quantitative Investment Analysis*. (2nd ed.) New York: Wiley, 2007.
- [14] Source: online <https://www.countries-ofthe-world.com/most-traded-currencies.html> (accessed on 9 July 2019)
- [15] D. Liu and Z. Li, "Gold price forecasting and related influence factors analysis based on random forest," in 2017, . DOI: 10.1007/978-981-10-1837-4_59.
- [16] S. Deng *et al*, "Hybrid Method of Multiple Kernel Learning and Genetic Algorithm for Forecasting Short-Term Foreign Exchange Rates," *Computational Economics*, vol. 45, (1), pp. 49-89, 2015;2013;.
- [17] R. S. T. Lee, "Chaotic Type-2 Transient-Fuzzy Deep Neuro-Oscillatory Network (CT2TFDNN) for Worldwide Financial Prediction," *IEEE Transactions on Fuzzy Systems*, 2019. DOI:10.1109/TFUZZ.2019.2914642
- [18] Graves A., "Generating Sequences With Recurrent Neural Networks," *Computer Science*, 2013.
- [19] Olah, Christopher: *Understanding LSTM Networks*. colah.github.io. N.p., colah.github.io., last accessed 2019/6/18, 2019.
- [20] J. Wang, W. Fang, H. Niu, "Financial Time Series Prediction Using Elman Recurrent Random Neural Networks," *Computational Intelligence and Neuroscience*, vol. 2016, pp. 4742515-14, 2016.
- [21] Online <https://www.metatrader4.com> (accessed on 9 July 2019)