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COSMOS Trader – Chaotic Neuro-oscillatory Multiagent Financial Prediction and Trading System

Abstract—**Over the years, financial engineering ranging from the study of financial signals to the modelling of financial prediction is one of the most stimulating topics for both academia and financial community. Not only because of its importance in terms of financial and commercial values, but more it vitally poses a real challenge to worldwide researchers and quants owing to its highly chaotic and almost unpredictable nature.**

This paper devises an innovative Chaotic Oscillatory Multi-agent-based Neuro-computing System (a.k.a. COSMOS) for worldwide financial prediction and intelligent trading. With the adoption of author's theoretical works on Lee-oscillator with profound transient-chaotic property, COSMOS effectively integrates chaotic neural oscillator technology into: 1) COSMOS Forecaster - Chaotic FFBP-based Time-series Supervised-learning agent for worldwide financial forecast and; 2) COSMOS Trader - Chaotic RBF-based Actor-Critic Reinforcement-learning agents for the optimization of trading strategies. COSMOS not only provides a fast reinforcement learning and forecast solution, more prominently it successfully resolves the massive data over-training and deadlock problems which usually imposed by traditional recurrent neural networks and RBF networks using classical sigmoid or gaussian-based activation functions.

From the implementation perspective, COSMOS is integrated with 2048-trading day time-series financial data and 39 major financial signals as input signals for the real-time prediction and intelligent agent trading of 129 worldwide financial products which consists of: 9 major cryptocurrencies, 84 forex, 19 major commodities and 17 worldwide financial indices. In terms of system performance, past 500-day average daily forecast performance of COSMOS attained less 1% forecast percentage errors and with promising results of 8-13% monthly average returns.

Index Terms—**financial prediction system, intelligent agent-based trading system, chaotic neural networks, actor-critic reinforcement-learning, intelligent agents.**

1. Introduction

Over the years, financial engineering ranging from various financial signals and chart patterns study to the modelling of financial prediction and trading systems is one of the most stimulating topics for both academia and financial community. Not only because of its utmost importance in terms of financial and commercial values, but more it vitally poses a real challenge to worldwide researchers and quantitative analysts (a.k.a. "quants") throughout the world.

Conventional technical analysis and chart analysis methods probe various trading signals (e.g. K-lines, MAs, Bollinger-band index, KDJ and RSI indices) and chart patterns (e.g. major reversal and trend patterns, Golden-ratio patterns, Fibonacci patterns, Elliot-wave patterns) that believe to affect the market price trends, trading patterns and individual reasonings to determine the best time to trigger the buy or sell decisions (Border, 2018; Brown, 2012; Bulkowski, 2005; Murphy, 1999) . However, these numerous trading-signals and chart-patterns are usually self-contradictory between different time-frames, let's alone with the fact that they are highly subjective to the traders' own judgment and psychological condition.

With the advance of computational capacity in the past decades, the modelling of complex financial prediction systems ranging from artificial neural networks (ANNs) (Chang et. al, 2012; Dai et. al., 2012) to fractal-based financial forecast systems (Ling, 2013) using ordinary desktop PCs and workstations is not a dream anymore.

Current research on financial prediction includes: stock prediction using Deep Neural Network (DNN) with PCA (Principal Component Analysis) by Singh & Srivastava (2017); fuzzy models by Hwang & Oh (2010); Postfix-GP (Genetic Programming) models by Dabhi & Chaudhary (2016); SVM (Support Vector Machine) and hybrid SVR (Support Vector Regression) models by Henrique et. al. (2018), Nahil & Lyhyaoui (2018) and Ouahilal et. al. (2017).

Moreover, the popularity of free and open quantitative financial system development platforms such as MetaTrader (MT) platform (MetaTrader, 2018) provides an ideal environment for worldwide researchers and quants to test their trading algorithms, strategies and financial signals with real time financial data streams which prosper the popularity of program trading, especially the HFAPT (High Frequency Algorithmic Program Trading) in the past 10 years.

From the financial market perspective, the blooming of cryptocurrency originated from bitcoin in 2009 had increased to more than 4000 cryptocurrencies in the worldwide financial market. More importantly, major international fund houses and forex trading platforms integrate 24x7 electronic trading of cryptocurrency into their forex trading platforms since 2013. Together with the flourish of HFAPT in the past 10 years, the worldwide financial markets; especially the international currency market become more volatile and unpredictable. An effective, open and reliable worldwide financial prediction, trading and advisory system is profoundly required for worldwide traders and investors (especially independent investors) than ever before.

This paper devises an innovative **C**haotic **Os**cillatory **M**ulti-agent-based Neur**o**-computing **S**ystem (a.k.a. "COSMOS") for worldwide financial prediction and intelligent trading.

With the adoption of author’s theoretical works on Lee-oscillator with profound transient-chaotic property (Lee, 2004), COSMOS effectively integrates chaotic neural oscillator technology into: 1) COSMOS Forecaster - Chaotic FFBP-based Supervised-learning agent for worldwide financial forecast and; 2) COSMOS Trader - Chaotic RBF-based Actor-Critic Reinforcement-learning agents for the optimization of trading strategies. COSMOS not only provides a fast reinforcement learning and forecast solution, more importantly it successfully resolves the massive data over-training and deadlock problems which usually imposed by traditional recurrent neural networks and RBF networks using classical sigmoid or gaussian-based activation functions.

From the implementation perspective, COSMOS is integrated with 2048-trading day time series financial data and 39 major financial signals as input signals for the real-time prediction and agent-based trading of 129 worldwide financial products which consists of: 9 major cryptocurrencies, 84 forex, 19 major commodities and 17 worldwide financial indices.

2. An Overview of Chaotic Neural Networks

Over decades, traditional Artificial Neural Networks (ANNs) using simple artificial neurons as constituting elements are refuted to be oversimplification to simulate real-world problems. For problems with complex and highly chaotic behaviors such as severe weather situations like rainstorms or wind-shear, or highly fluctuated real-time currency markets, there is strong evidence that neural network with the adoption of neural oscillators seems to be a more viable solution (Chen and Aihara, 1995; Lee 2005).

In contrast with most computational intensive neural oscillators using time-continuous-based architecture, Wang (Wang, 1991) proposed a simple but effective time-discrete-based neural oscillator so-called “Wang-oscillator”. Its bifurcation diagram provides a strong evidence to be served as a CTU (Chaotic Transfer Unit) to model complex and chaotic phenomena.

A typical Wang-oscillator consists of 3 neural elements: E, I, and W which corresponds to the Excitatory, Inhibitory and Output neurons. The neural dynamics are given by:

$$\mathrm{E(t+1)} = Sig\left[\omega_{EE} \cdot E(t) - \omega_{EI} \cdot I(t) + S_E(t) - \xi_E\right] \qquad (1)$$

$$\mathrm{I(t+1)} = Sig\left[\omega_{IE} \cdot E(t) - \omega_{II} \cdot I(t) + S_I(t) - \xi_I\right] \qquad (2)$$

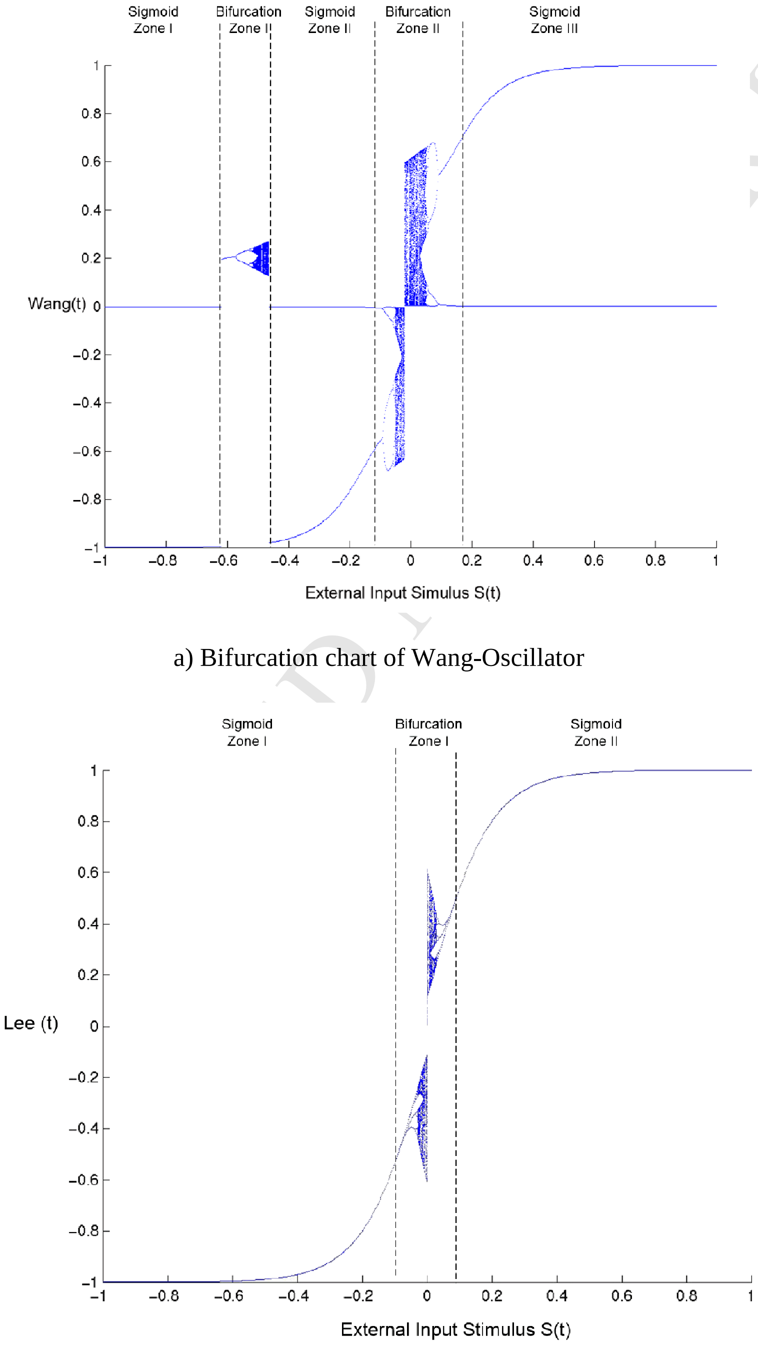
$$\mathrm{W(t)} = E(t) - I(t) \qquad (3)$$

Where S_E and S_I are the input stimulus; ω are the weights; ξ_E and ξ_I are the threshold values; the Sigmoid function Sig() is given by:

$$Sig(k) = {}^{1}\!/_{1+e^{-k}} \qquad (4)$$

Fig. 1 shows the bifurcation charts of Wang-oscillator vs. Lee-oscillator. As shown in Fig 1a, the bifurcation chart of a typical

Wang-oscillator consists of “Sigmoid” and “Bifurcation” zones. The original idea is that the “Sigmoid zone” imitates the classical sigmoid function and the “Bifurcation zone” imitates the chaotic property of complex system during the sigmoid-transition period. However, there are two intrinsic problems: 1) the existence of an extra “Bifurcation zone I” destructs the continuity of the sigmoid curve in the initial period; 2) the “Bifurcation zone II” is “too chaotic” to model the chaotic-transition region in real-world problems. A more transient progressive-growth in terms of neural dynamics is needed to be achieved.



a) Bifurcation chart of Wang-Oscillator

b) Bifurcation chart of Lee-oscillator

Fig. 1. Bifurcation charts of Wang-oscillator vs Lee-oscillator

Lee-oscillator(Leery ,2004 ;Lee, 2006a)successfully emulates the transient-chaotic progressive growth in its neural dynamics, which helps to shed light on acting as a perfect CTU to model complex and chaotic problems.

Basically, Lee-oscillator consists of 4 neural elements: E, I, Ω and L which corresponds to the Exhibitory, Inhibitory, Input and Output neurons.

$$\mathrm{E}(\mathrm{t}+1) = Sig\left[e_1 \cdot E(t) - e_2 \cdot I(t) + S(t) - \xi_E\right] \qquad (5)$$

$$\mathrm{I}(\mathrm{t}+1) = Sig\left[i_1 \cdot E(t) - i_2 \cdot I(t) - \xi_I\right] \qquad (6)$$

$$\Omega(\mathrm{t}+1) = Sig[S(t)] \qquad (7)$$

$$\mathrm{L}(\mathrm{t}) = [E(t) - I(t)] \cdot e^{-kS^2(t)} + \Omega(t) \qquad (8)$$

where e_1, e_2, i_1 and i_2 are the weights; ξ_E and ξ_I are the threshold values and S(t) is the external input stimulus.

As compared with the bifurcation chart of Wang-oscillator, the bifurcation chart of Lee-oscillator exhibits a perfect “sigmoid-like” function with chaotic property in the transition region (so called “bifurcation zone”). Such neural dynamics can be perfectly served as CTU to model complex and chaotic systems such as severe weather situation (Wong et. al, 2008), complex scene analysis (Lee and Liu, 2002) and real time financial prediction and trading agents discussed in this paper.

3. Chaotic FFBP-based Time-Series Supervised-Learning Neural Networks for Financial Prediction

3.1 Time Series Prediction using Supervised-Learning-based Artificial Neural Networks

Time series prediction, ranging from weather forecast to stock prediction have been studied for over 50 years. With the improvement of computational speed, non-linear models as such Artificial Neural Networks (ANN) have proven success to tackle with these problems. Traditional ANN such as FFBPN (Feedforward Back-Propagation Neural Network) is a typical kind of Supervised-learning (SL) neural network to tackle these problems with certain success.

However, when it comes up to massive input data such as financial prediction with over thousands time series financial data and signals as input vectors, these conventional ANNs using classical sigmoid-based activation function are usually “trapped” in local maxima (or minima) during neural network training; which not only affect the efficiency (time cost), but also the accuracy of the forecast results (Lee, 2006b).

3.2 COSMOS CSL Network – Chaotic FFBP-based SL Network for Time-series Financial Prediction

In short, COSMOS Chaotic Supervised-Learning (CSL) Network is the integration of Lee-oscillator with classical FFBPN by replacing all the neurons with Lee-oscillators. Figs 2 and 3 show the system architecture and chaotic FFBP-based time-series supervised-learning algorithm of COSMOS CSL Network for financial prediction.

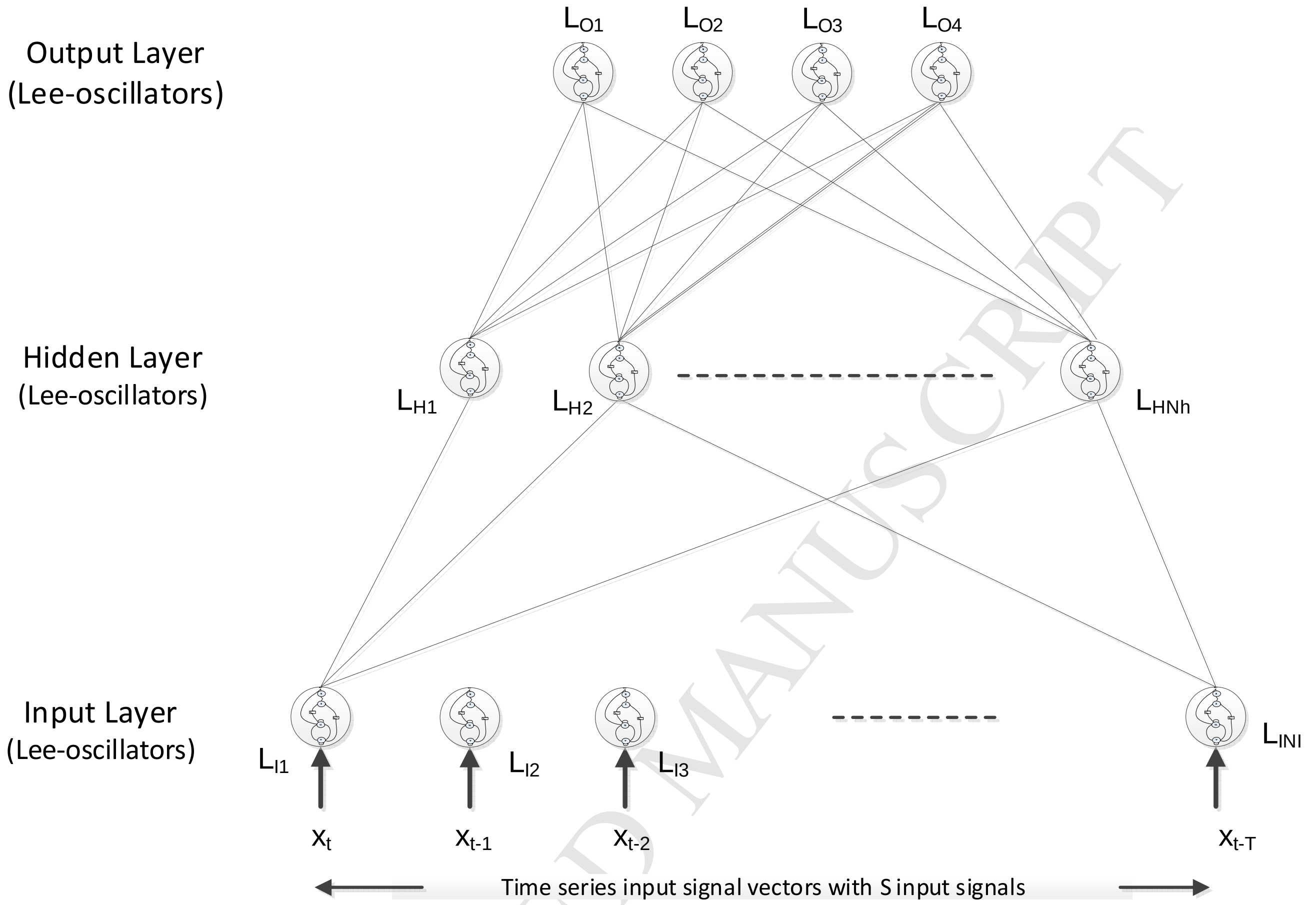


Fig. 2. System Architecture of COSMOS CSL Network for Time Series Financial Prediction

COSMOS CSL NETWORK LEARNING ALGORITHM

```
1   COSMOS CSLN Initialization Phase
    1.1 Initialization all the network weights $\omega$ by a random number generator to values between 1 and 0.
2   COSMOS CSLN Checking Stop Training Criteria
    IF MSE < Training Threshold $\delta$ (say $1\text{x}10^{-6}$) STOP,
    Else CONTINUE
3   COSMOS CSLN Forward Propagation Phase
    3.1 Evaluate the total inputs for all hidden Lee-oscillators ($L_H$)
        $\overrightarrow{L_{H\imath nput}} = \sum_{n=0}^{N_I} \overrightarrow{L_{In}}\,\overrightarrow{\omega_n}$
        Noted that $N_I = T \times S$ is the total number of input Lee-oscillators, where T is the forecast horizon and S is the dimension of the input signal vector.
    3.2 Evaluate the TCAF values of all $\overrightarrow{L_{H\imath nput}}$ vectors using chaotic Lee_operator given by equations (5) to (8)
        $\overrightarrow{L_H} = \overrightarrow{Lee_H(L_{H\imath nput})}$
    3.3 Evaluate the total input vectors all output Lee-oscillators ($L_O$)
        $\overrightarrow{L_{O\imath nput}} = \sum_{n}^{N_H} \overrightarrow{L_{Hn}}\,\overrightarrow{\omega_n}$
        Noted that $N_H$ is the total number of hidden Lee-oscillators.
    3.4 Evaluate the TCAF values of all $\overrightarrow{L_{O\imath nput}}$ vectors
        $\overrightarrow{L_O} = \overrightarrow{Lee_O(L_{O\imath nput})}$
4   COSMOS CSLN Backward Propagation Phase
    4.1 Evaluate the $\vec{\delta}_o$ (Correction Error Vector) and $\overrightarrow{\Delta\omega_{HO}}$ (weight adjustment vectors between hidden and output layer) of all $\vec{L}_o$ against the target output vectors $\vec{L}'_O$ with network learning rate $\beta$.
        $\overrightarrow{\delta_{HO}} = (\vec{L}'_O - \vec{L}_O) f'_{L_O}(\overrightarrow{L_{O\imath nput}})$
        $\overrightarrow{\Delta\omega_{HO}} = \beta\overrightarrow{\delta_{HO}}\,\overrightarrow{L_H}$
    4.2 Evaluate the $\vec{\delta}_H$ and $\overrightarrow{\Delta\omega_{IH}}$ of all $\vec{L}_H$
        $\overrightarrow{\delta_{IH}} = [\sum \overrightarrow{\delta_{HO}} \cdot \overrightarrow{\omega_{HO}}](\vec{L}'_O - \vec{L}_O) f'_{L_O}(\overrightarrow{L_{O\imath nput}})$
        $\overrightarrow{\Delta\omega_{IH}} = \beta\overrightarrow{\delta_{IH}}\,\overrightarrow{L_I}$
    4.3 Evaluate the all the weight vectors at the same time.
        $\overrightarrow{\omega(t+1)} = \overrightarrow{\omega(t)} + \overrightarrow{\Delta\omega(t)}$
5   COSMOS CSLN STEP 2 to Check for Stopping Criteria.
```

Note:

1. L_I , L_H and L_O are the Lee-oscillator in the input, hidden and output layer.
2. The four output Lee oscillators correspond to the next-day forecasts of Open, High, Low and Close.
3. ω are the network weights.
4. TCAF – Transient Chaotic Activation Function.
5. δ are the correction error vectors.

Fig. 3. COSMOS CSL Network Learning Algorithm

4. Chaotic RBF-based Actor-Critic Reinforcement-learning Networks - Optimization of Trading strategy

4.1 An Overview of Reinforcement-Learning (RL)

Different from supervised-learning model with well-defined “input/target-output” pairs to train the network, there are many situations in which input/target-output pairs do not existed. For example, in stock investment, even-though we have the best stock forecast to tell us when to set the buy/sell bid, but “How much we should invest?” and “When to close the bid?” in order to get the highest returns is a typical optimization problem without exact solution. In that case, we can make use of Reinforcement-Learning (RL) method.

Reinforcement Learning (RL) theory is originated from behavior psychology. Its main concept is to train the neural network with the adoption of feedback signals namely Reinforcement-Signal (RS). For the right behavior, the network will respond with a positive RS to “award” the RL network; while for the wrong behavior, the network will respond with a negative RS to “punish” the RL network. As we can see, RL networks don’t need well-defined input/target-output pairs, all they need to do is to search for a set of optimal weights to minimize the negative reinforcement signals.

Classical RL model such as Markov Decision Process (MDP) using stochastic-based reinforcement learning algorithms such as Q-Learning, Dynamic-Programming (DP) and TD-Learning (TDL) with certain success (Kaelbling, et. al, 1996). However, when it come up with time-series financial optimization problems with over thousands of input signals and possible trading strategies, these classical stochastic RL methods are either too computational intensive or difficult to adopt for actual implementation.

With the flourishing of recurrent neural networks in the past decades, researchers start to explore how recurrent neural networks can be applied for RL on various optimization problems (Li et. al., 2009; Liu et. al., 2005).

4.2 Discrete-Time Actor-Critic RL Model

A typical time-series RL model can be visualized as a Discrete-Time Actor-Critic RL Model (DTAC-RLM).

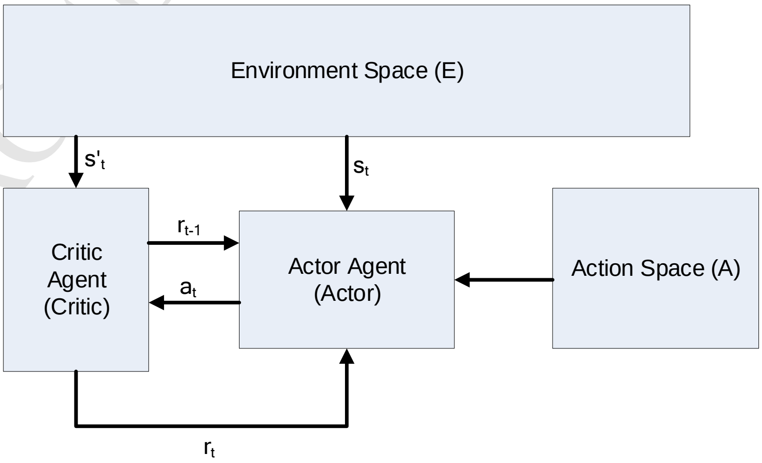


Fig. 4. Discrete-Time Actor-Critic RL Model

DTAC-RLM is a multi-agent system (Lee, 2006b) consists of four components: Environment Space (E), Action Space (A), Actor Agent (Actor) and Critic Agent (Critic). Different from its Continuous-Time AC model counterpart (such as MDP), DTAC-RLM visualizes its "world" as a collection of discrete-time-step states and actions. More vitally, all these states are related as time-series events. The role of the Actor is based on the input signals provided at current state at time t (s_t) to response with the "best" available actions (a_t); whereas the role of the Critic is to evaluate the Reinforcement Signal (RS, or "reward, r_t" in short) based on the action(s) taken by the Actor and the signals provided by the new states (s_{t+1}). Then the reward signal r_t feedbacks as input to the Actor to decide the next action **a** at time t+1.

The formulations are given by:

$$\boldsymbol{s} \in \{\boldsymbol{S}\}, \boldsymbol{a} \in \{\boldsymbol{A}\}, \boldsymbol{r} \in \{\mathbb{R}\} \quad (9)$$

$$\boldsymbol{\Pi} = \{\boldsymbol{a_t}, \boldsymbol{t} = \boldsymbol{1}..\boldsymbol{T}\} \quad (10)$$

$$\boldsymbol{V} = \sum_{t=1}^{T} \boldsymbol{r_t}(\boldsymbol{s_t}, \boldsymbol{a_t}) \quad (11)$$

$$\mathbf{V}^* = \mathbf{max}_{\boldsymbol{\Pi}} \boldsymbol{V}^{\boldsymbol{\Pi}} \quad (12)$$

As shown in the above formulation: **S** and **A** denote the State Space and Action Space; **s** and **a** denote the state and action vectors, **r** denotes the reward vector; Π denotes the action policy from time t=1 to t=T (Dimension of Policy Space); V denotes the Value Function which represents the total returns for a particular policy Π. For DRL with maxI iterations, there will be totally maxI policies Π being generated, and V^* is the optimal returns obtained by the calculation of all possible return values $\boldsymbol{V_k^{II}}$ (where k = 1 .. maxI) from these policies. So the whole optimization problem is to find the best policy Π^* via DRL in order to attain the optimal returns V^*. Next section we will explore how to adopt CRBFN (Chaotic Radial Basis Function Neural Network) for DRL.

4.3 Radial Basis Function Neural Network (RBFN) for RL

Like FFBPN, a typical multi-layer RBFN (Radial Basis Function Neural Network) also consists of: Input, Hidden and Output Layers. Although the network architectures between FFBPN and RBFN are highly similar, the network activations in RBF networks are localized RBF functions such as Gaussian functions, resulting in a much faster training rate (Markopoulos et.al., 2016).

Unlike FFBPN, input vectors in RBFN distribute the values to the hidden layer neurons uniformly, without multiplying them with weights. The neurons in the hidden layer are presented by RBF neurons using radial-basis-function such as Gaussian function as activation function, which is given by:

$$G(\mathrm{r}) = exp\left[-\frac{r}{2\sigma^2}\right] \quad (13)$$

Different from FFBPN which is only tailored for supervised learning, experimental results revealed that RBFNs can basically approximate any functions. As a result, they are usually known as "universal-approximators". In other words, RBFN can be used for both SL and RL by using RBFN to approximate the V-value function.

However, like FFBPNs, when it comes up with handling massive input data and/or highly chaotic nature such as time series financial forecast using over thousands input values and financial signals as network input vectors, RBFNs also encounter "over-training" and "deadlock" problems which hinder the further improvement of network accuracy and resulted in an expensive time costs from the computational perspective.

4.4 COSMOS CRL Network - Chaotic RBF-based Actor-Critic RL Network for the Optimization of Trading Strategy

A) System Overview

COSMOS Chaotic Reinforcement-Learning (CRL) Network integrates the Lee-oscillator technology with conventional RBFN by: 1) Replacing all the Gaussian-based radial basis functions in the hidden layer of RBFN with Lee-oscillatory RBF functions (namely "LRbf"); and 2) Replacing the output neurons with Lee-oscillator to facilitate transient-chaotic neural activations. Fig. 5 shows the LRbf() which served as the chaotic RBF activation function in COSMOS.

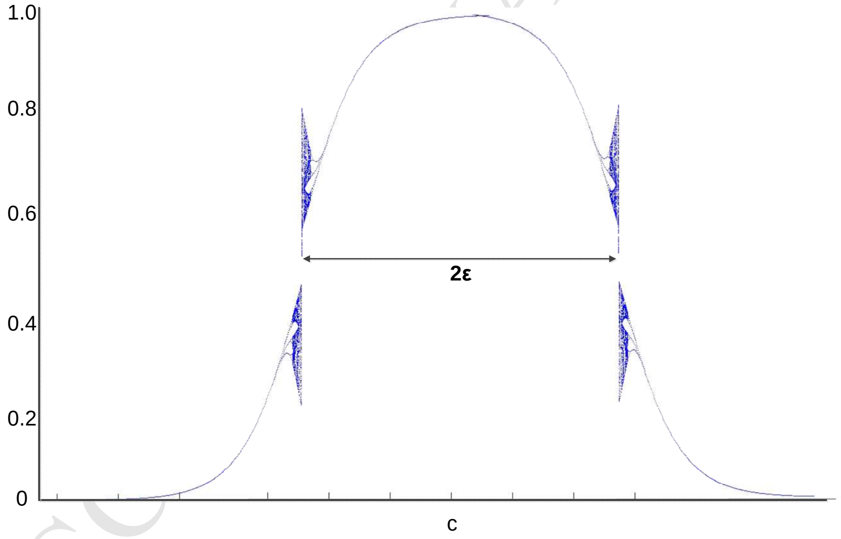


Fig. 5. Chaotic RBF Activation Function using Lee Oscillators (LRbf)

The formulation of LRbf is given by:

$$LRbf(x) = \begin{cases} L(x),\ x < c \\ L(2c - x),\ x \geq c \end{cases} \qquad (14)$$

where L(x) is the Lee-oscillator function given by equation (8) and c is the center of the LRbf().

In contrast with the Gaussian Function counterpart, the LRbf exhibits a progressive-transient-chaotic property in the two RBF activation regions which provides some sort of "controlled-hysteresis" to sort out the over-training and deadlock problems during

RL with massive input vectors.

B) COSMOS CRL Network System Architecture for the Optimization of Trading Strategy

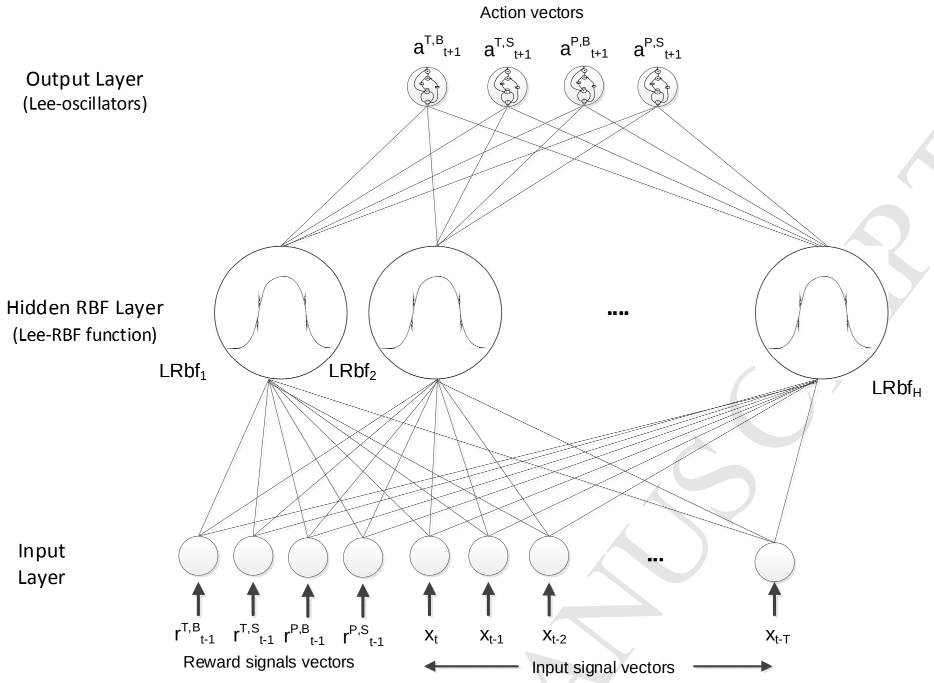


Fig. 6. COSMOS CRL Network System Architecture

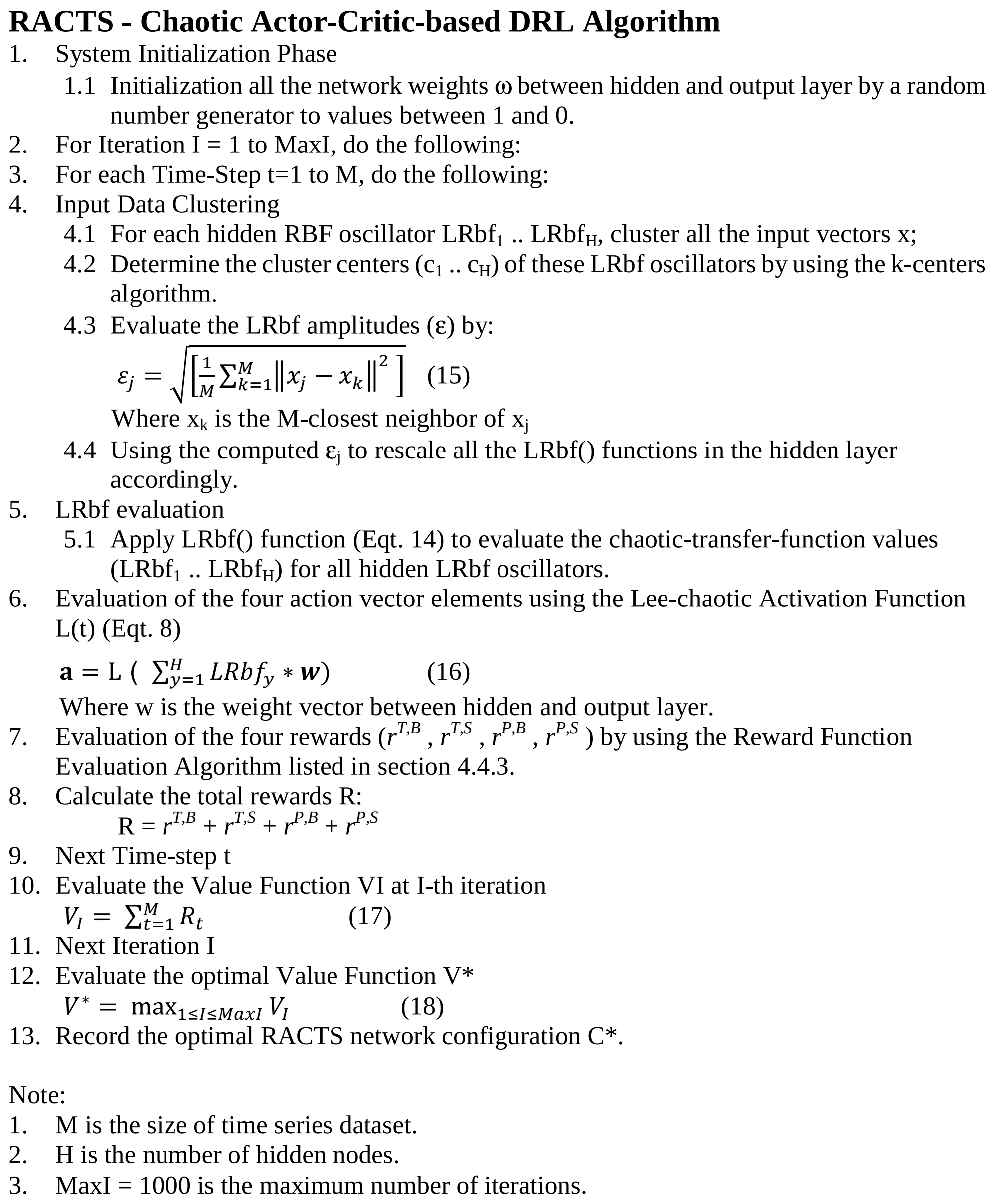
As depicted in Fig. 6, COSMOS CRL Network is a three-layer chaotic RBF-based neural network with input, hidden and output layers. To accomplish Actor-Critic-based RL, the input layer consists of two classes of input vectors: the reward signal vector **r** and input signal vector **x**. The input signal vector **x** composes of all time-series input signals with T denotes the span of the time-series. Reward signal vector **r** contains four reinforcement feedback signals which are generated by the Critic Agent in the previous time step. These four reward signals $r^{T,B}$, $r^{T,S}$, $r^{P,B}$, $r^{P,S}$ correspond to the four actions $a^{T,B}$, $a^{T,S}$, $a^{P,B}$ and $a^{P,S}$ which emulate de-facto short-term trading strategies:

1) Time-driven-Buy Strategy – Trigger Buy action $a^{T,B}$ when current price reaches forecast Low, day-end harvest;
2) Time-driven-Sell Strategy – Trigger Sell action $a^{T,S}$ when current price reaches forecast High, day-end harvest;
3) Price-driven-Buy Strategy - Trigger Buy action $a^{P,B}$ when current price reaches forecast Low, closing when reaching target price / stop-loss price;
4) Price-driven-Sell Strategy - Trigger Sell action $a^{P,S}$ when current price reaches forecast High, closing when reaching target price / stop-loss price.

The hidden layer of COSMOS CRL Network consists of H LRbf nodes which facilitates transient-chaotic RRB-based RL.

The output layer consists of the four possible actions: $a^{T,B}$, $a^{T,S}$, $a^{P,B}$ and $a^{P,S}$ as described above. Their scalar values are normalized values between 0 and 1 which represent the size (lot) of investment (“0” means “not invest”; “1” means “invest one complete lot”).

C) COSMOS CRL Network Learning Algorithm



RACTS - Chaotic Actor-Critic-based DRL Algorithm

```
1.  System Initialization Phase
    1.1 Initialization all the network weights ω between hidden and output layer by a random
        number generator to values between 1 and 0.
2.  For Iteration I = 1 to MaxI, do the following:
3.  For each Time-Step t=1 to M, do the following:
4.  Input Data Clustering
    4.1 For each hidden RBF oscillator $LRbf_1$ .. $LRbf_H$, cluster all the input vectors x;
    4.2 Determine the cluster centers ($c_1$ .. $c_H$) of these LRbf oscillators by using the k-centers
        algorithm.
    4.3 Evaluate the LRbf amplitudes (ε) by:
          $\varepsilon_j = \sqrt{\left[\frac{1}{M}\sum_{k=1}^{M}\left\|x_j - x_k\right\|^2\right]}$   (15)
        Where $x_k$ is the M-closest neighbor of $x_j$
    4.4 Using the computed $\varepsilon_j$ to rescale all the LRbf() functions in the hidden layer
        accordingly.
5.  LRbf evaluation
    5.1 Apply LRbf() function (Eqt. 14) to evaluate the chaotic-transfer-function values
        ($LRbf_1$ .. $LRbf_H$) for all hidden LRbf oscillators.
6.  Evaluation of the four action vector elements using the Lee-chaotic Activation Function
    L(t) (Eqt. 8)
      $\mathbf{a} = L\left(\sum_{y=1}^{H} LRbf_y * \boldsymbol{w}\right)$   (16)
    Where w is the weight vector between hidden and output layer.
7.  Evaluation of the four rewards ($r^{T,B}$ , $r^{T,S}$ , $r^{P,B}$ , $r^{P,S}$ ) by using the Reward Function
    Evaluation Algorithm listed in section 4.4.3.
8.  Calculate the total rewards R:
          $R = r^{T,B} + r^{T,S} + r^{P,B} + r^{P,S}$
9.  Next Time-step t
10. Evaluate the Value Function VI at I-th iteration
      $V_I = \sum_{t=1}^{M} R_t$   (17)
11. Next Iteration I
12. Evaluate the optimal Value Function V*
      $V^* = \max_{1 \le I \le MaxI} V_I$   (18)
13. Record the optimal RACTS network configuration C*.

Note:
1.  M is the size of time series dataset.
2.  H is the number of hidden nodes.
3.  MaxI = 1000 is the maximum number of iterations.
```

The overall COSMOS CRL Network learning algorithm is presented in Fig. 7.

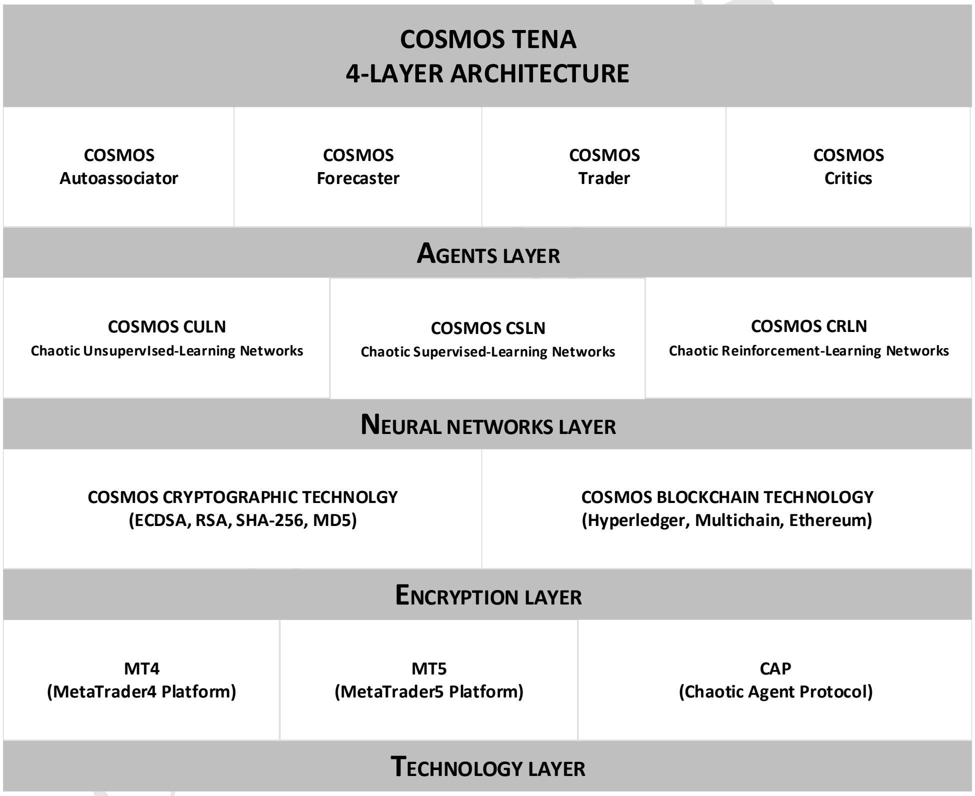
Fig. 7. COSMOS CRL Network Learning Algorithm

As shown in Fig. 7, the Lee-oscillators are adopted into the algorithm in two aspects: 1) Replacement of the Gaussian RBF with the chaotic RBF (LRbf) in the Hidden Layer; 2) Replacement of Sigmoid-based activation function with Lee-transient-chaotic activation function L in the Output Layer for the determination of the action **a**. From the neural dynamic perspective, the adoption of chaotic RBF and activation function can be considered as the emulation of the chaotic trading behaviors in the time-series events and actions. While from the financial perspective, such adoption of transient-chaotic activation and RBF can be considered as the imitation of "transient-hysteresis" behavior of the investors during real-time trading.

For the Value Function V, the physical meaning of its optimal value V* in terms of financial investment is even more profound: While $\mathbf{r}_t$ is the total returns (rewards) at time-step t which represents the Short-term returns in day-trade; its Value Function V plainly represents the Long-term returns of the whole investment policy Π; and its optimal V* directly represents the optimal Long-term returns by using the optimal COSMOS network configuration and hence the optimal policy Π*.

5. System Implementation

5.1 COSMOS – TENA 4-Layer Architecture



COSMOS TENA
4-LAYER ARCHITECTURE

COSMOS Autoassociator | COSMOS Forecaster | COSMOS Trader | COSMOS Critics

AGENTS LAYER

COSMOS CULN Chaotic UnsupervIsed-Learning Networks | COSMOS CSLN Chaotic Supervised-Learning Networks | COSMOS CRLN Chaotic Reinforcement-Learning Networks

NEURAL NETWORKS LAYER

COSMOS CRYPTOGRAPHIC TECHNOLGY (ECDSA, RSA, SHA-256, MD5) | COSMOS BLOCKCHAIN TECHNOLOGY (Hyperledger, Multichain, Ethereum)

ENCRYPTION LAYER

MT4 (MetaTrader4 Platform) | MT5 (MetaTrader5 Platform) | CAP (Chaotic Agent Protocol)

TECHNOLOGY LAYER

Fig. 8. COSMOS – TENA 4 -Layer System Architecture

From the implementation perspective, COSMOS adopts a 4-layer system implementation architecture namely "TENA" (Fig. 8). COSMOS TENA System Architecture consists of:

__T__echnology Layer – supports MT4/MT5 [1] platforms and related programming technologies such as Expert Advisors (EAs), COSMOS agent protocol (CAP).

__E__ncryption Layer – supports critical cryptographical technologies include both encryption and blockchain technologies.

__N__eural Networks Layer – supports COSMOS Chaotic Supervised-learning (CSL) Networks, COSMOS Chaotic Unsupervised-learning (CUSL) Networks and COSMOS Chaotic Reinforcement-learning (CRL) Networks.

__A__gents Layer – supports intelligent chaotic agent applications include COSMOS autoassociator, forecaster, trading and critic agents.

5.2 COSMOS System Implementation using 129 Worldwide Financial Products

From the application perspective, real-time and historical data of worldwide 129 financial products provided by Forex.com (Forex.com, 2018) (major online Forex trading platform) and AvaTrade.com (AvaTrade.com, 2018) (the biggest cryptocurrency trading platform) are adopted for COSMOS system implementation. They include: major cryptocurrencies (9), worldwide forex (84), major commodities (19), worldwide financial indices (17). Table 1 shows the list of financial products under these four categories. As shown in Table 1, owing to the short trading history of cryptocurrencies, 300 trading day records are provided by AvaTrader.com, while all other financial products consist of 2048 past trading day records for each product with data provided by Forex.com which provide sufficient training and test sets for system testing.

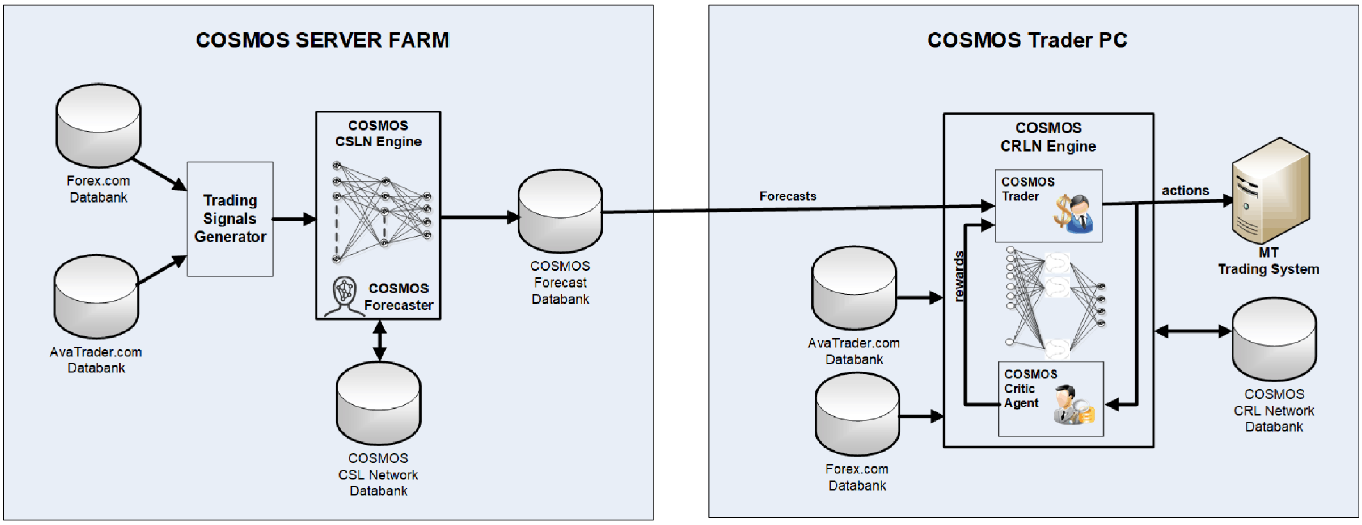


Fig. 9. System Implementation Framework of COSMOS

Table 1
List of 129 Financial Products

Product Code	Product Description	Product Code	Product Description
Cryptocurrencies (Data provided by AvaTrader.com)			
BCHUSD	BitCoin Cash vs US Dollar	EOSUSD	EOS vs US Dollar
BTCEUR	BitCoin vs Euro	ETH	Ethereum
BTCJPY	BitCoin vs JapaneseYen	LTC	Litecoin
BTCUSD	BitCoin vs US Dollar	XRP	XRP
BTGUSD	Bitcoin Gold vs US Dollar		
Financial Index (Data provided by Forex.com)			
AUS200	AUSSIE 200	N25	Netherlands 25 Index
CHINAA50	China A50 Index	NAS100	Nasdaq Index
ESP35	Spain 35 Index	SIGI	Singapore Index
ESTX50	EURO STOXX 50 Index	SPX500	SP500 Index
FRA40	CAC 40 Index	SWISS20	Switzerland 20 Index
GER30	DAX 30 Index	UK100	FTSE 100 Index
HK50	Hang Seng Index	US2000	US Small Cap 2000
IT40	Italy 40 Index	US30	Dow Jones Index
JPN225	Nikkei Index		
Commodity (Data provided by Forex.com)			
COPPER	Copper	US_OIL	WTI Crude Oil
CORN	Corn	WHEAT	Wheat
COTTON	Cotton	XAGUSD	Silver vs US Dollar
HTG_OIL	HTG Oil	XAUAUD	Gold vs Australian Dollar
PALLAD	Palladium	XAUCHF	Gold vs Swiss Franc
PLAT	Platinum	XAUEUR	Gold vs Euro
SOYBEAN	Soybean	XAUGBP	Gold vs British Pound
SUGAR	Sugar	XAUJPY	Gold vs Japanese Yen
UK_OIL	Brent Crude Oil	XAUUSD	Gold vs US Dollar
US_NATG	US Natural Gas		
Forex (Data provided by Forex.com)			
AUDCAD	Australian Dollar vs Canadian Dollar	GBPDKK	British Pound vs Danish Krone
AUDCHF	Australian Dollar vs Swiss Franc	GBPHKD	British Pound vs Hong Kong Dollar
AUDCNH	Australian Dollar vs Chinese Yuan	GBPJPY	British Pound vs Japanese Yen
AUDJPY	Australian Dollar vs Japanese Yen	GBPMXN	British Pound vs Mexican Peso
AUDNOK	Australian Dollar vs Norwegian Krone	GBPNOK	British Pound vs Norwegian Krone
AUDNZD	Australian Dollar vs New Zealand Dollar	GBPNZD	British Pound vs New Zealand Dollar
AUDPLN	Australian Dollar vs Polish Zloty	GBPPLN	British Pound vs Polish Zloty
AUDSGD	Australian Dollar vs Singapore Dollar	GBPSEK	British Pound vs Swedish Krona
AUDUSD	Australian Dollar vs US Dollar	GBPSGD	British Pound vs Singapore Dollar
CADCHF	Canadian Dollar vs Swiss Franc	GBPUSD	British Pound vs US Dollar
CADJPY	Canadian Dollar vs Japanese Yen	GBPZAR	British Pound vs South African Rand
CADNOK	Canadian Dollar vs Norwegian Krone	HKDJPY	Hong Kong Dollar vs Japanese Yen
CADPLN	Canadian Dollar vs Polish Zloty	NOKDKK	Norwegian Krone vs Danish Krone
CHFHUF	Swiss Franc vs Hungarian Forint	NOKJPY	Norwegian Krone vs Japanese Yen
CHFJPY	Swiss Franc vs Japanese Yen	NOKSEK	Norwegian Krone vs Swedish Krona
CHFNOK	Swiss Franc vs Norwegian Krone	NZDCAD	New Zealand Dollar vs Canadian Dollar
CHFPLN	Swiss Franc vs Polish Zloty	NZDCHF	New Zealand Dollar vs Swiss Franc
CNHJPY	Chinese Yuan vs Japanese Yen	NZDJPY	New Zealand Dollar vs Japanese Yen
EURAUD	EUR vs Australian Dollar	NZDUSD	New Zealand Dollar vs US Dollar
EURCAD	EUR vs Canadian Dollar	SGDHKD	Singapore Dollar vs Hong Kong Dollar
EURCHF	EUR vs Swiss Franc	SGDJPY	Singapore Dollar vs Japanese Yen
EURCNH	Euro vs Chinese Yuan	TRYJPY	Turkish Lira vs Japanese Yen
EURCZK	EUR vs Czech Koruna	USDCAD	US Dollar vs Canadian Dollar
EURDKK	EUR vs Danish Krone	USDCHF	US Dollar vs Swiss Franc
EURGBP	EUR vs British Pound	USDCNH	US Dollar vs Chinese Yuan
EURHKD	Euro vs Hong Kong Dollar	USDCZK	US Dollar vs Czech Koruna
EURHUF	EUR vs Hungarian Forint	USDDKK	US Dollar vs Danish Krone
EURJPY	EUR vs Japanese Yen	USDHKD	US Dollar vs Hong Kong Dollar
EURMXN	Euro vs Mexican Peso	USDHUF	US Dollar vs Hungarian Forint
EURNOK	EUR vs Norwegian Krone	USDILS	US Dollar vs Israeli Shekel
EURNZD	EUR vs New Zealand Dollar	USDJPY	US Dollar vs Japanese Yen
EURPLN	EUR vs Polish Zloty	USDMXN	US Dollar vs Mexican Peso
EURRON	Euro vs Romanian Leu	USDNOK	US Dollar vs Norwegian Krone
EURRUB	Euro vs Russian Ruble	USDPLN	US Dollar vs Polish Zloty
EURSEK	EUR vs Swedish Krona	USDRON	US Dollar vs Romanian Leu
EURSGD	Euro vs Singapore Dollar	USDRUB	US Dollar vs Russian Ruble
EURTRY	EUR vs Turkish Lira	USDSEK	US Dollar vs Swedish Krona
EURUSD	EUR vs US Dollar	USDSGD	US Dollar vs Singapore Dollar
EURZAR	Euro vs South African Rand	USDTHB	US Dollar vs Thai Baht
GBPAUD	British Pound vs Australian Dollar	USDTRY	US Dollar vs Turkish Lira
GBPCAD	British Pound vs Canadian Dollar	USDZAR	US Dollar vs South African Rand
GBPCHF	British Pound vs Swiss Franc	ZARJPY	South African Rand vs Japanese Yen

5.3 COSMOS - System Implementation Framework

For the ease of fully integration and automation of the COSMOS system with both real time and historical financial data provided by Forex.com and AvaTrade.com, the whole intelligent agent-based system fully integrated with MT platforms. Fig. 9 shows the System Implementation Framework of COSMOS.

The whole COSMOS system consists of two main modules: 1) COSMOS Forecaster using COSMOS CSL Network for time-series worldwide financial prediction; and 2) COSMOS Trader and Critic Agents using COSMOS CRL Network for the optimization of trading strategy.

The agent activities of these COSMOS agents are described as follows:

COSMOS Forecaster

COSMOS Forecaster is a server-side forecast agent located at the server farm of Quantum Finance Forecast Center (QFFC, 2018) using Intel i5 CPU 2.39 GHz 32MB RAM Dell Servers.

For each financial product, 2048-trading day data (except cryptocurrency which only have 300-trading day data) include: Open (O), High (H), Low (L), Close (C) and Volume (V) are automatically generated by MT4 engines of Forex.com and AvaTrader.com. Through the Trading Signal Generator, 39 most common trading signals are generated, together with the 2048-trading day data, they are fed into the forecast system for training and forecast of the next-day OPEN (O), HIGH (H), LOW (L) and CLOSE (C). The predicted forecasts of these 129 financial products are stored at the COSMOS Forecast Database for the COSMOS trading agents to access. Table 2 shows the 39 trading signals generated by Trading Signal Generator.

Table 2
List of 39 Trading Signals

Code	Signal Name	Code	Signal Name
AC	Accelerator Oscillator	Gator	Gator Oscillator
AD	Accu. and Distribution	Ichimoku	Ichimoku Kinko Hyo
ADX	Average Directional	BWMFI	Market Facilitation Index
ADXWilder	Av Dir by Welles Wilder	Momentum	Momentum
Alligator	Alligator	MFI	Money Flow Index
AMA	Adaptive MA	MA	Moving Average
AO	Awesome Oscillator	OsMA	MACD Histogram
ATR	Average True Range	MACD	MACD
BearsPower	Bears Power	OBV	On Balance Volume
Bands	Bollinger Bands	SAR	Parabolic Stop & Rev Sys.
BullsPower	Bulls Power	RSI	Relative Strength Index
CCI	Commodity Channel	RVI	Relative Vigor Index
Chaikin	Chaikin Oscillator	StdDev	Standard Deviation
Custom	Custom indicator	Stochastic	Stochastic Oscillator
DEMA	Double Exponential MA	TEMA	Triple Exp. MA
DeMarker	DeMarker	TriX	Triple Exp. MA Oscillator
Envelopes	Envelopes	WPR	Williams' Percent Range
Force	Force Index	VIDyA	Variable Index Dynamic Av.
Fractals	Fractals	Volumes	Trading Volumes
FrAMA	Fractal Adaptive MA		

COSMOS Trader

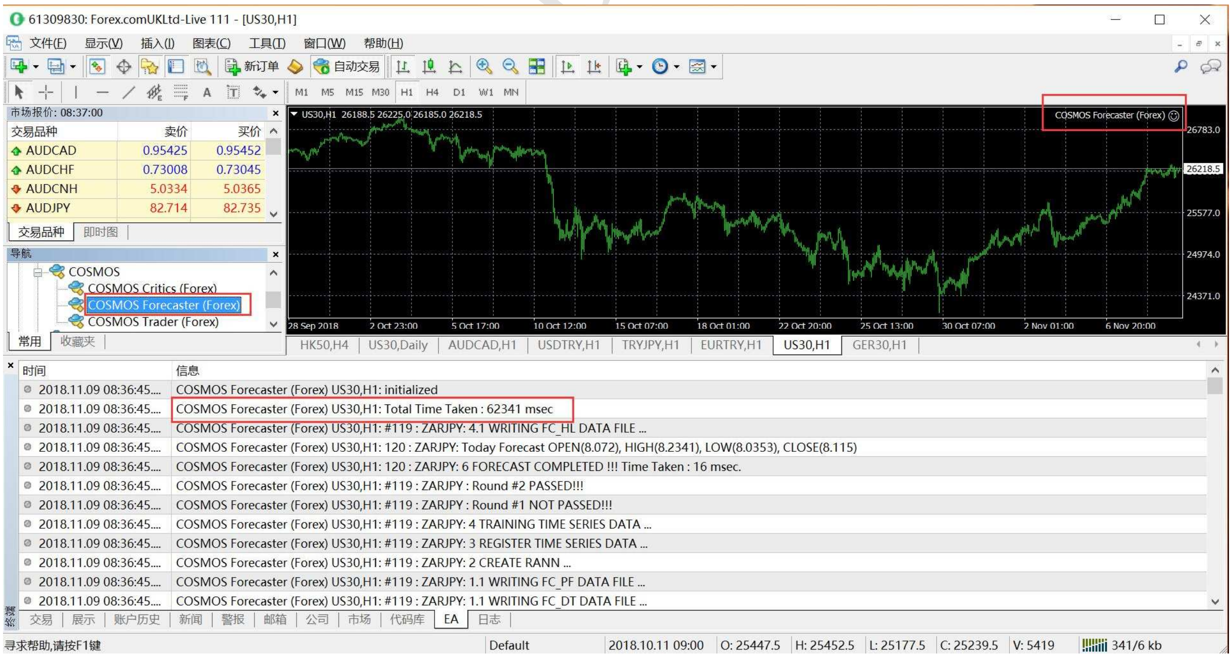
The COSMOS Trader receives inputs from three sources: 1) Input signals from the markets (stored at the Input Signal Databanks of the COSMOS Server Farm) of the current and past records; 2) Current forecasts stored at the COSMOS Forecast Database of the COSMOS Server Farm; 3) Reward signals from the previous time-step generated by COSMOS Critic Agent. By using the COSMOS CRL algorithm, it evaluates the four possible actions **a**. Updates its trading policy and keep track the market movements in order to trigger the trading actions.

COSMOS Critic Agent

COSMOS Critic Agent receives inputs from two sources: 1) Input signals from the markets of the current and past records; 2) Latest action **a** taken by the COSMOS Trader. By using the reward evaluation algorithm, COSMOS Critic Agent evaluates the latest rewards **r** of the four actions and feedbacks to COSMOS Trader as reinforcement signals for the determination of the investment actions in the next time-step.

5.4 COSMOS Daily Forecast at QFFC

Fig.10 shows a snapshot of the COMOS Forecaster for the training and forecast of 120 financial products of Forex.com on 09 Nov 2018. As shown in Fig. 10, in a typical daily forecast, the COSMOS Forecaster only takes 62341 msec (62.341 sec) to finish the training of forecast of 120 financial products. On the average, it takes 0.519 sec (less than 1 sec) to complete the network training and forecast process of a single financial product.



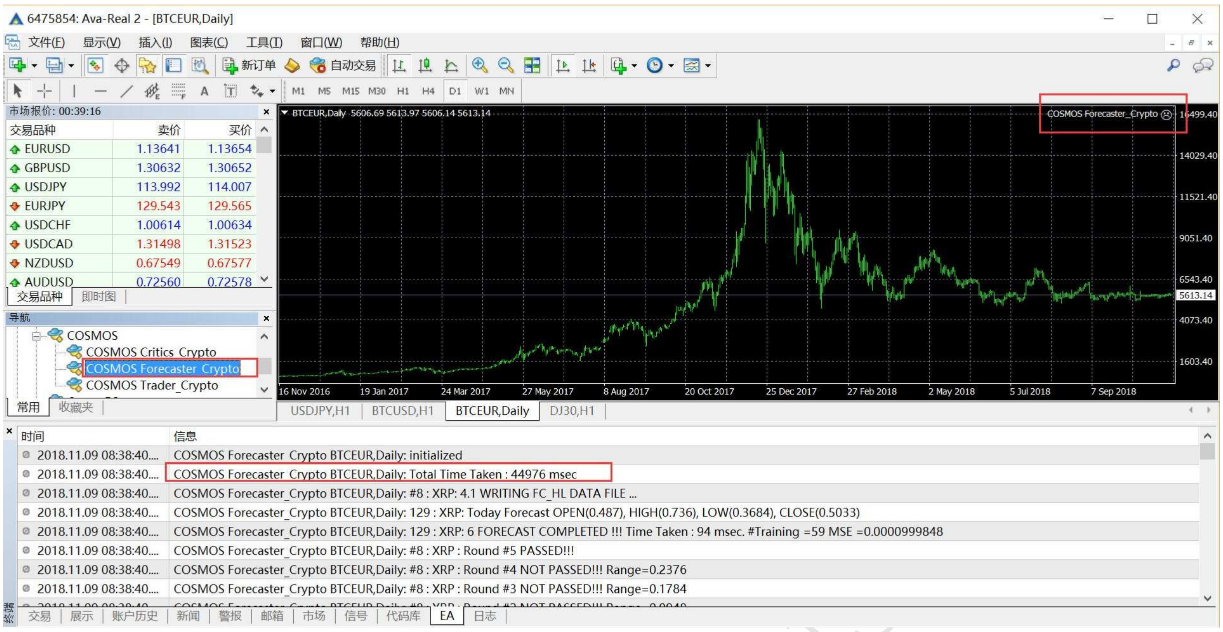
市场报价: 08:37:00

交易品种	卖价	买价
AUDCAD	0.95425	0.95452
AUDCHF	0.73008	0.73045
AUDCNH	5.0334	5.0365
AUDJPY	82.714	82.735

```
时间                    信息
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: initialized
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: Total Time Taken : 62341 msec
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY: 4.1 WRITING FC_HL DATA FILE ...
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: 120 : ZARJPY: Today Forecast OPEN(8.072), HIGH(8.2341), LOW(8.0353), CLOSE(8.115)
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: 120 : ZARJPY: 6 FORECAST COMPLETED !!! Time Taken : 16 msec.
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY : Round #2 PASSED!!!
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY : Round #1 NOT PASSED!!!
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY: 4 TRAINING TIME SERIES DATA ...
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY: 3 REGISTER TIME SERIES DATA ...
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY: 2 CREATE RANN ...
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY: 1.1 WRITING FC_PF DATA FILE ...
2018.11.09 08:36:45....  COSMOS Forecaster (Forex) US30,H1: #119 : ZARJPY: 1.1 WRITING FC_DT DATA FILE ...
```

寻求帮助,请按F1键 | Default | 2018.10.11 09:00 | O: 25447.5 | H: 25452.5 | L: 25177.5 | C: 25239.5 | V: 5419 | 341/6 kb

Fig. 10. Snapshot of COSMOS Forecaster for the training and forecast of 120 financial products for Forex.com MT4 platform on 09 NOV 2018.



交易品种	卖价	买价
EURUSD	1.13641	1.13654
GBPUSD	1.30632	1.30652
USDJPY	113.992	114.007
EURJPY	129.543	129.565
USDCHF	1.00614	1.00634
USDCAD	1.31498	1.31523
NZDUSD	0.67549	0.67577
AUDUSD	0.72560	0.72578

时间	信息
2018.11.09 08:38:40....	COSMOS Forecaster Crypto BTCEUR,Daily: initialized
2018.11.09 08:38:40....	COSMOS Forecaster Crypto BTCEUR,Daily: Total Time Taken : 44976 msec
2018.11.09 08:38:40....	COSMOS Forecaster_Crypto BTCEUR,Daily: #8 : XRP: 4.1 WRITING FC_HL DATA FILE ...
2018.11.09 08:38:40....	COSMOS Forecaster_Crypto BTCEUR,Daily: 129 : XRP: Today Forecast OPEN(0.487), HIGH(0.736), LOW(0.3684), CLOSE(0.5033)
2018.11.09 08:38:40....	COSMOS Forecaster_Crypto BTCEUR,Daily: 129 : XRP: 6 FORECAST COMPLETED !!! Time Taken : 94 msec. #Training =59 MSE =0.0000999848
2018.11.09 08:38:40....	COSMOS Forecaster_Crypto BTCEUR,Daily: #8 : XRP : Round #5 PASSED!!!
2018.11.09 08:38:40....	COSMOS Forecaster_Crypto BTCEUR,Daily: #8 : XRP : Round #4 NOT PASSED!!! Range=0.2376
2018.11.09 08:38:40....	COSMOS Forecaster_Crypto BTCEUR,Daily: #8 : XRP : Round #3 NOT PASSED!!! Range=0.1784

Fig. 11. Snapshot of COSMOS Forecaster for training and forecast of 9 major cryptocurrencies for AvaTrade.com MT4 platform on 09 NOV 2018.

Fig. 11 shows the snapshot of COSMOS Forecaster for the system training and forecast of 9 major cryptocurrencies over AvaTrade.com MT platform on the same trading day.

As shown in Fig. 11, COSMOS Forecaster takes 44976 msec (44.976 sec) to finish the training and forecast of the 9 cryptocurrencies. On the average, it takes 4.99 sec to train and forecast a single cryptocurrency.

As compared with all those 120 non-cryptocurrency products, COSMOS Forecaster takes 9.62 times of computer time to predict cryptocurrency, even though cryptocurrency only have 300-trading day records while the other 120 financial products each have 2048-trading day records for system training. It might because cryptocurrencies in general are much more chaotic and fluctuant in nature, which take more time and iterations for COSMOS Forecaster to learn the market patterns.

6. System Performance and Worldwide Evaluation

6.1 COSMOS Forecaster Performance Test

The forecast performance of COSMOS Forecaster is compared with the traditional FFBPN by applying 500 forecast simulations for each system. For the ease of comparison, four categories of worldwide 129 financial products are tested with network MSE (Mean-Square-Error) ranging from 1x10-4 to 1x10-6 respectively.

Besides traditional FFPBN, two state-of-the-art financial forecasting methods: i) SVM (Support Vector Machine) forecasting tool provided by R Project (2018), one of the most popular financial forecasting tools used in the finance industry and ii) Deep Neural Network (DNN) with PCA (Principal Component Analysis) model (Singh & Srivastava, 2017) are contrasted with COSMOS Forecaster for forecast performance comparison. Table 3 presents the COSMOS Forecast Performance Comparison Chart of these FOUR systems.

Table 3
COSMOS Forecast Performance Comparison Chart

Product	No. of	FFBPN		SVM		DNN-PCA		COSMOS Forecaster	
Category	PRD	Total STT	Av. STT	Total STT	Av. STT	Total STT	Av. STT	Total STT	Av. STT
				Case 1 (MSE = 1x10-4)					
Cryptocurrency	9	557251	61916.78	372244	41360.41	244633	27181.47	5720	635.56
Forex	84	508453	6053.01	331511	3946.56	291344	3468.38	6323	75.27
Financial Index	19	41120	2164.21	26152	1376.44	19738	1038.82	923	48.58
Commodity	17	46641	2743.59	29384	1728.46	22108	1300.46	1223	71.94
Overall	129	1153465	8941.59	759291	5885.98	577823	4479.25	14189	109.99
				Case 2 (MSE = 1x10-5)					
Cryptocurrency	9	1460000	162222.22	937320	104146.67	823440	91493.33	15121	1680.11
Forex	84	1235543	14708.85	841405	10016.72	720322	8575.26	17231	205.13
Financial Index	19	111024	5843.37	68391	3599.51	50627	2664.58	2312	121.68
Commodity	17	109142	6420.12	71925	4230.86	44967	2645.09	2640	155.29
Overall	129	2915709	22602.40	1919041	14876.29	1639356	12708.19	37304	289.18
				Case 3 (MSE = 1x10-6)					
Cryptocurrency	9	DL	-	6102255	678028.38	3601307	400145.17	57235	6359.44
Forex	84	DL	-	5477816	65212.10	4184833	49819.44	71243	848.13
Financial Index	19	577324	30385.47	373529	19659.40	318683	16772.78	6623	348.58
Commodity	17	687595	40446.76	468252	27544.25	385741	22690.64	9126	536.82
Overall	129	-	-	12421852	96293.43	8490564	65818.33	144227	1118.04

Note:
1. Results are generated by 500 simulations of each neural network system (measured in msec).
2. “Total STT” denotes the total average system training time for 500 simulations of network training.
3. “Av. STT” denotes the average system training time for a single financial product of each category.
4. “DL” denotes deadlock during system training.

Certain interesting findings are revealed in Table 3:

i) For Case I simulation using MSE 1x10-4, COSMOS Forecaster outperforms FFBPN, SVM and DNN-PCA by 81.29, 53.51 and 40.72 times respectively. Similar findings can be found in Case II simulation results. It clearly reflects the improvement of network learning rate by the adoption of chaotic neural oscillators into traditional FFBPN.

ii) Across the 3 Cases with decreasing MSE from 1x10-4(Case I), 1x10-5 (Case II) to 1x10-6 (Case III). All forecast systems can achieve the MSE in Case I and Case II. However, for the Case III simulations using MSE 1x10-6, FFBPN encounters "deadlock" problems during the network training of Cryptocurrency and Forex products; while COSMOS Forecaster can still finish the network training with promising training speeds. It clearly demonstrates the resolution of over-training and deadlock problems and sufficient improvement of system training efficiency by COSMOS Forecaster over traditional neural networks using classical sigmoid-based activation function.

iii) In terms of the system performance across different financial products, the simulation results clearly reflect that both cryptocurrency and forex are more chaotic and difficult for network training than other financial products as expected, which will be one of the future R&D directions of Quantum Finance Forecast Center.

6.2 COSMOS Trading Strategy Performance Test

In order to conduct a systematic test of COSMOS on intelligent trading, two more benchmark agents are implemented for comparison purposes: 1) Time-driven Trading Agent (TmAgent); 2) Price-driven Trading Agent (PrAgent). These two agents simulate real-world traders by using COSMOS forecasts together with simple short-term trading strategies of: 1) Day-end harvest strategy (Time-driven Strategy); or 2) Target-profit and Stop-loss strategy (Price-driven Strategy) with ratio 2:1 (i.e. target-profit = 2 x stop-loss). For the 9 cryptocurrency products, 300 trading day simulations are performed for each trading agent; while 500 trading day simulations are performed for the 120 non-cryptocurrency financial products. Table 4 summarizes the trading performance results for three trading strategies.

Table 4
COSMOS Trader Trading Strategy Performance Comparison Chart

Product	Time-Driven Strategy			Price-Driven Strategy			COSMOS Trader Strategy		
Category	BUY	SELL	Overall	BUY	SELL	Overall	BUY	SELL	Overall
Cryptocurrency	2.66%	3.17%	2.92%	3.12%	3.82%	3.47%	6.71%	9.37%	8.04%
Forex	5.52%	7.22%	6.37%	6.32%	7.76%	7.04%	12.41%	13.83%	13.12%
Financial Index	5.72%	6.11%	5.92%	5.49%	6.71%	6.10%	9.56%	10.21%	9.89%
Commodity	4.39%	6.01%	5.20%	5.12%	6.43%	5.78%	10.43%	11.88%	11.16%
Average	4.57%	5.63%	5.10%	5.01%	6.18%	5.60%	9.78%	11.32%	10.55%

Note:

1. Results (Monthly Returns %) are generated by 300 trading day simulations of the 9 Cryptocurrencies and 500 trading day simulations of the 120 non-cyptocurrency products.

Major findings can be concluded from Table 4 in three aspects:

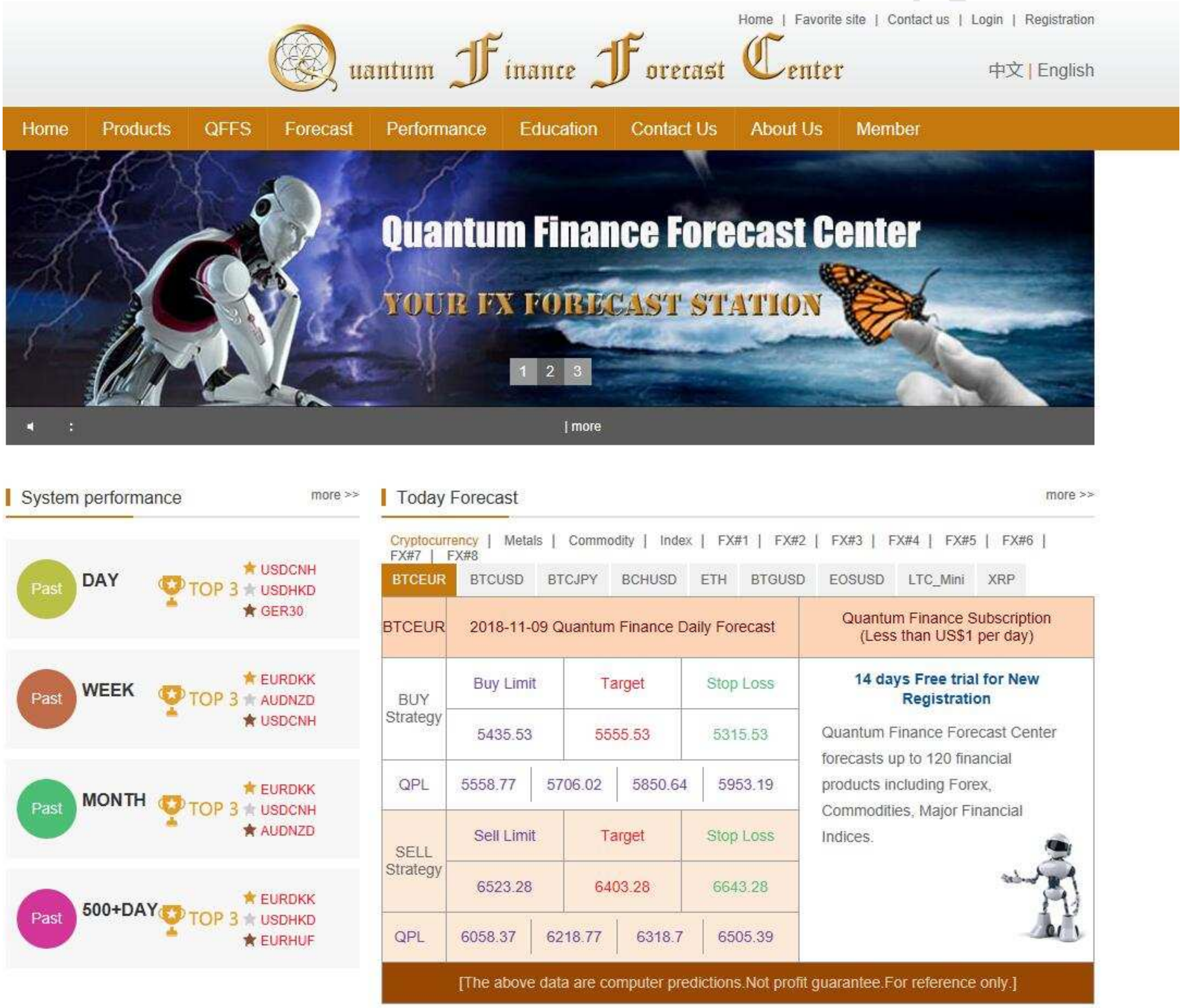
i) Across the three trading strategies, overall speaking, COSMOS Trading Strategy outperforms Time-Driven Strategy and Price-Driven Strategy by 106.86% and 88.52% respectively. It clearly reflects the effectiveness of the combined strategy in COSMOS Trader by using chaotic reinforcement-learning technique. Comparing Time-Driven Strategy with Price-Driven Strategy, it is interesting to reveal that Price-Driven Strategy are consistently outperforms its Time-Driven counterpart by around 9.73%. It can be explained by the fact that although Time-Driven Strategy is rather typical in automatic program trading for day-trade, the closing-price normally won't be the optimal price for bid-closing, as compared with the 2:1 Target-profit and Stop-loss Price-Driven Strategy which is more sensible in terms of short-term trading.

ii) Across the four different categories of financial products, the overall returns of cryptocurrency products are the worst as expected, since the forecast performance of cryptocurrency products are also the lowest as compared with other three categories. However, for Forex products, it is interesting to find out that although the forecast performance of forex products is not as good as financial indices and commodities, their overall returns outperforms these two categories and rank no. 1. As reflected by experienced traders, it might be owing to the fact that although the daily patterns of the forex products are highly chaotic, their price patterns are mostly (over 80% of time) oscillations between the predicted HIGH/LOW without trigger the stop-loss thresholds.

iii) As compared with the BUY vs. SELL strategy, it is interesting to find out that the overall returns from SELL strategy are consistently higher that its BUY strategy counterpart by around 16%. Which is quite consistent with the comments from experienced traders that automatic program trading usually favors SELL vs. BUY strategy.

6.3 COSMOS Worldwide Trading Strategy Evaluation

Quantum Finance Forecast Center (QFFC, 2018) is a non-profit making, self-funded AI-Fintech R&D and worldwide financial forecast center aims at the R&D and provision of a fair and open platform for worldwide traders and individual investors to acquire free knowledge of worldwide financial forecasts based on state-of-art AI technologies. QFFC launched the 129 financial products daily and weekly forecast services from 1 Jan 2018 for over 1000 worldwide traders and individual investors for testing and evaluations. Fig. 12 shows the official site of Quantum Finance Forecast Center.


Home | Favorite site | Contact us | Login | Registration
Quantum Finance Forecast Center
中文 | English
Home
Products
QFFS
Forecast
Performance
Education
Contact Us
About Us
Member
Quantum Finance Forecast Center
YOUR FX FORECAST STATION
1 2 3
| more
System performance
more >>
Today Forecast
more >>
Cryptocurrency | Metals | Commodity | Index | FX#1 | FX#2 | FX#3 | FX#4 | FX#5 | FX#6 | FX#7 | FX#8
BTCEUR
BTCUSD
BTCJPY
BCHUSD
ETH
BTGUSD
EOSUSD
LTC_Mini
XRP

Past DAY	TOP 3	★ USDCNH ★ USDHKD ★ GER30
Past WEEK	TOP 3	★ EURDKK ★ AUDNZD ★ USDCNH
Past MONTH	TOP 3	★ EURDKK ★ USDCNH ★ AUDNZD
Past 500+DAY	TOP 3	★ EURDKK ★ USDHKD ★ EURHUF

BTCEUR	2018-11-09 Quantum Finance Daily Forecast			
BUY Strategy	Buy Limit	Target	Stop Loss	
	5435.53	5555.53	5315.53	
QPL	5558.77	5706.02	5850.64	5953.19
SELL Strategy	Sell Limit	Target	Stop Loss	
	6523.28	6403.28	6643.28	
QPL	6058.37	6218.77	6318.7	6505.39

Quantum Finance Subscription (Less than US$1 per day)

14 days Free trial for New Registration

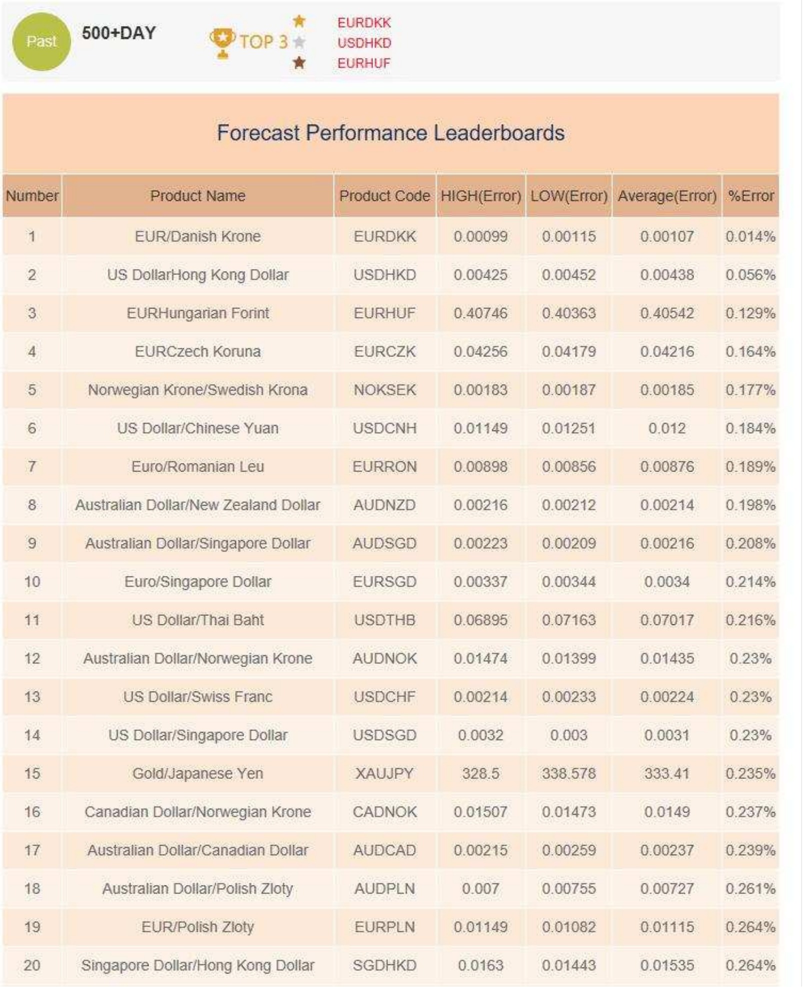
Quantum Finance Forecast Center forecasts up to 120 financial products including Forex, Commodities, Major Financial Indices.

[The above data are computer predictions.Not profit guarantee.For reference only.]

Fig. 12. The official site of Quantum Finance Forecast Center with COSMOS Daily Forecast on 09 Nov 2018

A) Past 500-Day Forecast Performance

From forecast performance and evaluation perspectives, COSMOS system evaluates the daily forecast performance of the 129 financial products in four timeframes: daily, weekly average, monthly average and past 500-day average. Fig. 13 shows the past 500-day COSMOS forecast performance ranking list of the top 20 financial products. As shown in Fig. 13, the 500-day average forecast % error of the top 20 financial products are ranging from 0.014% to 0.227% respectively, which is rather promising and significant as reflected by over 1000+ members of QFFC which consists of professional forex traders, quants and investors.



Forecast Performance Leaderboards

Number	Product Name	Product Code	HIGH(Error)	LOW(Error)	Average(Error)	%Error
1	EUR/Danish Krone	EURDKK	0.00099	0.00115	0.00107	0.014%
2	US DollarHong Kong Dollar	USDHKD	0.00425	0.00452	0.00438	0.056%
3	EURHungarian Forint	EURHUF	0.40746	0.40363	0.40542	0.129%
4	EURCzech Koruna	EURCZK	0.04256	0.04179	0.04216	0.164%
5	Norwegian Krone/Swedish Krona	NOKSEK	0.00183	0.00187	0.00185	0.177%
6	US Dollar/Chinese Yuan	USDCNH	0.01149	0.01251	0.012	0.184%
7	Euro/Romanian Leu	EURRON	0.00898	0.00856	0.00876	0.189%
8	Australian Dollar/New Zealand Dollar	AUDNZD	0.00216	0.00212	0.00214	0.198%
9	Australian Dollar/Singapore Dollar	AUDSGD	0.00223	0.00209	0.00216	0.208%
10	Euro/Singapore Dollar	EURSGD	0.00337	0.00344	0.0034	0.214%
11	US Dollar/Thai Baht	USDTHB	0.06895	0.07163	0.07017	0.216%
12	Australian Dollar/Norwegian Krone	AUDNOK	0.01474	0.01399	0.01435	0.23%
13	US Dollar/Swiss Franc	USDCHF	0.00214	0.00233	0.00224	0.23%
14	US Dollar/Singapore Dollar	USDSGD	0.0032	0.003	0.0031	0.23%
15	Gold/Japanese Yen	XAUJPY	328.5	338.578	333.41	0.235%
16	Canadian Dollar/Norwegian Krone	CADNOK	0.01507	0.01473	0.0149	0.237%
17	Australian Dollar/Canadian Dollar	AUDCAD	0.00215	0.00259	0.00237	0.239%
18	Australian Dollar/Polish Zloty	AUDPLN	0.007	0.00755	0.00727	0.261%
19	EUR/Polish Zloty	EURPLN	0.01149	0.01082	0.01115	0.264%
20	Singapore Dollar/Hong Kong Dollar	SGDHKD	0.0163	0.01443	0.01535	0.264%

Note:

1. High (Error) = Abs(HighForecast – HighActual)
2. Low (Error) = Abs(LowForecast – LowActual)
3. Average (Error) = Average(High(Error), Low(Error))
4. % Error = Average(Error) / CloseActual

Fig. 13. Past 500-Day COSMOS Forecast Performance Chart

B) Worldwide Trading Strategy Performance Evaluation

Started from 1 Jan 2018, 342 members of QFFC, which consists of professional traders and quants from major fund houses are invited to join the COSMOS system evaluation focus group for a ONE-YEAR worldwide evaluation program of COSMOS trading system as compared with their own trading strategies. They are all provided with free COSMOS daily forecasts for the 129 financial products and the two de-facto agent trading programs (i.e. the Time-Driven and Price-Driven Trading Agents). Based on the COSMOS daily forecasts, they are free to use either the de-facto trading agents or their own trading strategies to do the trading. Table 5 presents the Nine Months (1.1.2018 – 30.9.2018) trading performance comparison chart for the worldwide evaluation scheme.

Table 5
COSMOS Trader Trading Performance comparison chart

Product	FFBPN	SVM	DNN-PCA	ALL Traders	Top 15% Traders	Top 5% Traders	COSMOS
Cryptocurrency	2.03%	5.08%	5.32%	2.76%	6.54%	8.76%	7.62%
Forex	2.72%	7.91%	8.29%	5.32%	12.31%	16.71%	13.16'%
Financial Index	3.65%	7.59%	7.89%	4.24%	11.22%	15.23%	11.37%
Commodity	3.87%	9.52%	10.01%	4.12%	11.81%	16.71%	12.67%
Average	3.07%	7.53%	7.88%	4.11%	10.47%	14.35%	10.55%

For the ease of comparison, COSMOS Trader trading performance (overall 10.55%) is compared with: 1) Traditional FFBPN with day-trade algorithm (overall 3.07%); 2) SVM forecasting tool with day-trade algorithm (overall 7.53%); 2) DNN-PCA forecasting model with day-trade algorithm (overall 7.88%); 3) Overall average performance of the focus group (overall 4.11%); 4) Top 15% traders' performance (overall 10.47%); 5) Top 5% traders' performance (overall 14.35%).

As revealed from the performance analysis, it is clear that the overall trading performance of COSMOS Trader outperforms FFBPN, SVM and DNN-PCA by around 7.49%, 3.03% and 2.67% respectively (in terms of overall returns). On the other hand, as compared with professional traders, COSMOS Trader trading performance is close to a typical Top 15% trader, outperforms the average traders by over 6.44%, which is rather promising as feedbacks from the professional traders.

7. Conclusion

This paper devises an innovative chaotic oscillatory multi-agent-based neuro-computing system - COSMOS. From the implementation perspective, COSMOS is integrated with Quantum Finance Forecast Center for the provision of worldwide 129 financial product forecasts and intelligent trading systems.

In fact, for a professional trader and investor, a reliable and effective financial forecast system is only the beginning of the story. A good financial investment also needs: 1) good and effective trading and hedging strategies; 2) stable, logical and rational investment psychology.

Current research of QFFC includes: -

1）Quantum Price Level (QPL) research using quantum field theory;

2）Integration of COSMOS with fractal technology for market trends/patterns mining and prediction;

3）R&D on quantum entanglement of Quantum Finance system on severe financial event modeling and prediction;

4）Design and development of intelligent agent-based hedging and trading systems.

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