

# Chaotic Type-2 Transient-Fuzzy Deep Neuro-Oscillatory Network (CT2TFDNN) for Worldwide Financial Prediction

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**Abstract**—Over the years, financial engineering ranging from the study of financial signals to the modeling of financial prediction is one of the most exciting topics for both academia and financial community. With the flourishing AI technology in the past 20 years, various hybrid intelligent financial prediction systems with the integration of neural networks, chaos theory, fuzzy logic, and genetic algorithms have been proposed. An interval type-2 fuzzy logic system (IT2FLS) with its remarkable capability for the modeling of highly uncertain events and attributes provides a perfect tool to interpret various financial phenomena and patterns. In this paper, the author proposes a chaotic type-2 transient-fuzzy deep neuro-oscillatory network with retrograde signaling (CT2TFDNN) for worldwide financial prediction. With the extension of author's original work on Lee oscillator—a chaotic discrete-time neural oscillator with profound transient-chaotic property—CT2TFDNN provides: effective modeling of an IT2FLS with a chaotic transient-fuzzy membership function; and effective time-series network training and prediction using a chaotic deep neuro-oscillatory network with retrograde signaling. CT2TFDNN not only provides a fast chaotic fuzzy-neuro deep learning and forecast solution, but also successfully resolves the massive data overtraining and deadlock problems, which are usually imposed by traditional recurrent neural networks using classical sigmoid-based activation functions. From the implementation perspective, CT2TFDNN is integrated with 2048 trading-day time-series financial data and top-10 major financial signals as fuzzy financial signals for the real-time prediction of 129 worldwide financial products that consists of: nine major cryptocurrencies, 84 worldwide forex, 19 major commodities, and 17 worldwide financial indices.

**Index Terms**—Chaotic bifurcation transfer function, chaotic deep neuro-oscillatory network, chaotic type-2 transient-fuzzy logic (CT2TFL), financial prediction, Lee oscillator.

## NOMENCLATURE

|          |   |
|----------|---|
| ANN      | Artificial neural networks.                                       |
| CDNONRS  | Chaotic deep neuro-oscillatory network with retrograde signaling. |
| CNON     | Chaotic neuro-oscillatory networks.                               |
| CT1-FNON | Chaotic T1 fuzzy neuro-oscillatory network.                       |

Manuscript received December 27, 2018; revised March 22, 2019 and April 16, 2019; accepted April 29, 2019. Date of publication May 2, 2019; date of current version April 1, 2020. This work was supported by the Research Grant R201948 of Beijing Normal University-Hong Kong Baptist University United International College.

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Digital Object Identifier 10.1109/TFUZZ.2019.2914642

CT2TFDNN

IT2FLS  
CBTF  
CNON  
CT2TFL  
CT2TFLS  
CT2TFMF

CTU  
DNN  
EC System  
FFBPN  
FFS  
FFSCM  
FFSFEM  
FFSMM  
FFSPGM  
FFSV  
FLS  
FOU  
FSGM  
GA  
HFAPT  
IT2FLS  
IT2-FNN  
T2FLS  
LORS  
MQL  
MT4  
NGPSM  
PCA  
QAOM  
QFFS  
QPL  
RMSE  
STR  
SVM  
T2FL  
T2FMF  
TOP10-FFSSM

Chaotic T2 transient-fuzzy deep neuro-oscillatory network with retrograde signaling.  
Interval T2 fuzzy logic system.  
Chaotic bifurcation transfer function.  
Chaotic neural oscillatory network.  
Chaotic T2 transient-fuzzy logic.  
Chaotic T2 transient-fuzzy logic system.  
Chaotic T2 transient-fuzzy membership function.  
Chaotic transfer unit.  
Deep neural network.  
Evolutionary computing system.  
Feed-forward backpropagation networks.  
Fuzzy financial signals.  
FFSs crossover module.  
FFSs fitness evaluation module.  
FFSs mutation module.  
FFSs population generation module.  
FFS vector.  
Fuzzy logic system.  
Footprint of uncertainty.  
Financial signal generator module.  
Genetic algorithms.  
High-frequency algorithmic program trading.  
Interval type-2 fuzzy logic system.  
Interval type-2 fuzzy-neuro network.  
Type-2 fuzzy logic system.  
Lee oscillator with retrograde signaling.  
MetaQuotes Language.  
MetaTrader4.  
New generation population selection module.  
Principal component analysis.  
Quantum anharmonic oscillatory model.  
Quantum Finance Forecast Centre.  
Quantum price level.  
Root-mean-square error.  
State transition region.  
Support vector machine.  
Type-2 fuzzy logic.  
Type-2 fuzzy membership function.  
Top-10 fitness FFS selection module.

## I. INTRODUCTION

OVER the years, financial engineering ranging from the study of various financial signals (FSs) and chart patterns to the modeling of financial prediction 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 also more vitally poses a real challenge to worldwide researchers and quantitative analysts (*quants*) throughout the world.

Started in the 1970s, technical analysis and chart analysis methods probe various trading signals [e.g., *K* lines, moving averages (MAs), Bollinger bands (BB), and KDJ index and relative strength index (RSI)] and chart patterns (e.g., major reversal and trend patterns, Golden Ratio patterns, Fibonacci patterns, and Elliott wave patterns) that believe to affect the market price trends, trading patterns to determine the best time to trigger the *buy* or *sell* decisions [1]–[4]. Although these trading signals and chart patterns in certain extent do provide some cues on the market behaviors, however, they are usually self-contradictory between different time frames; let us alone with the fact that they are usually highly subjective to the traders' own judgment and psychological conditions.

With the advancement of computational power and capacity of computing systems in the past decades, the modeling of complex financial prediction systems ranging from time-series artificial neural networks (ANNs) [5], [6] to fractal-based financial forecast systems [7] using ordinary desktop PCs and workstations is not a dream anymore. Current research on time-series financial prediction includes: hybrid time-series neural network systems using reinforcement learning [8], deep neural network (DNN) with principal component analysis (PCA) [9], fuzzy time-series models [10]–[17], EC systems using postfix genetic programming [18], and recurrent neural networks using support vector machine (SVM) and hybrid support vector regression financial prediction models [19]–[21].

From the financial engineering perspective, the popularity of free and open quantitative financial system development platforms, such as MetaTrader (MT) platform [22] provides an ideal environment for worldwide researchers and quants to test for their trading algorithms, strategies, and FSs with real-time financial data streams, which prosper the popularity of program trading, especially the High Frequency Algorithmic Program Trading (HFAPT) in the past ten 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 notably, major international fund houses and forex trading platforms integrate  $24 \times 7$  electronic trading of cryptocurrency into their forex trading platforms since 2013. Together with the flourishing HFAPT in the past ten years, the worldwide financial markets, especially the international currency market, become more volatile and unpredictable. An effective, open, and reliable worldwide financial prediction system is profoundly required for worldwide traders and investors than ever before.

This paper proposes an innovative chaotic type-2 transient-fuzzy deep neuro-oscillatory network with retrograde signaling (CT2TFDNN) for worldwide financial time-series prediction. With the extension of author's original work on the Lee oscillator—a discrete-time neural oscillator with profound transient-chaotic property on temporal information progressing [23], [24]—together with the author's latest works on the exploration of Lee oscillator with retrograde signaling (LORS), which generalizes into eight categories of bifurcation transfer functions for deep learning, CT2TFDNN successfully integrates discrete-time chaotic neural oscillators (for chaotic neural activity modeling), chaotic deep neuro-oscillatory network with eight hidden layers of neuro-oscillators with various degree of retrograde signaling (RS) (for chaotic time-series deep learning and

prediction), and chaotic type-2 transient-fuzzy logic (CT2TFL) (for high-order uncertainty modeling of FSs) into the following: first effective modeling of type-2 fuzzy logic with chaotic type-2 transient-fuzzy membership function (CT2TFMF); and second, effective time-series network training and prediction using CD-NONRS. CT2TFDNN not only provides a fast chaotic fuzzy-neuro deep learning and forecast solution, but also successfully resolves the massive data overtraining and deadlock problems, which are usually imposed by traditional recurrent neural networks and fuzzy neural networks using IT2 fuzzy membership functions and/or hybrid neural networks using classical sigmoid-based activation functions.

From the implementation perspective, CT2TFDNN is integrated with 2048 trading-day time-series financial data and top-10 major FSs as input signals for the real-time prediction and agent-based trading of 129 worldwide financial products that consists of: nine major cryptocurrencies, 84 worldwide forex, 19 major commodities, and 17 worldwide financial indices.

The main contributions and originality of this paper include the following.

- 1) The introduction of an innovative type-2 fuzzy logic system (T2FLS), which is inspired by the author's original work on Lee oscillators [24]. Different from the contemporary research on the T2FLS, which mainly focus on the R&D of the interval type-2 fuzzy logic system (IT2FLS)—a simplified version of T2FLS due to its computational complexity—this paper proposes a CT2TFL system (CT2TFLS)—a truly IT2FLS with remarkable chaotic transient-fuzzy property to resolve the computational complexity problem.
- 2) The introduction of CT2TFDNN—an innovative fuzzy-neuro DNN that is not only the integration of two AI technologies as two separated functional modules proposed by numerous hybrid fuzzy-neuro systems—the CT2TFDNN introduced in this paper is constructed by LORS—chaotic neural oscillators invented by the author that serve as “transient-fuzzy input neurons” of the DNN and effectively converts it into CT2TFDNN system. In other words, the chaotic transient-fuzzification process is actually part of the neural model of the CT2TFDNN.
- 3) The successful resolution of the massive data overtraining and deadlock problems that are usually imposed by traditional recurrent neural networks using classical sigmoid-based activation functions.
- 4) The successful design and implementation of a real-time financial forecast system of worldwide financial products with the state-of-the-art CT2TFDNN system.

This paper is presented as follows: Section II presents the literature review on: first, type-1 and interval type-2 fuzzy logic systems (FLSs) on financial prediction; and second, chaotic neural networks (CNN), Lee oscillator, and the author's latest work on LORS. Section III presents the system framework and methodology of the CT2TFDNN for financial time-series prediction, which includes the following: first, chaotic type-2 transient-fuzzification scheme; and second, genetic algorithm (GA) based top-10 fuzzy FSs (FFSs) selection scheme and the chaotic deep neuro-oscillatory network learning algorithm. Section IV presents the system implementation of the CT2TFDNN for the real-time prediction of worldwide 129 financial products. Section V presents the performance analysis of the proposed CT2TFDNN and compares with the following five forecast systems:

- 1) traditional time-series feed-forward backpropagation networks (FFBPNs);
- 2) SVM provided by R Project (2018)—one of the most popular financial forecasting tools used in finance industry;
- 3) DNN with PCA model [9];
- 4) classical interval type-2 fuzzy-neuro network (IT2FNN);
- 5) chaotic type-1 fuzzy neuro-oscillatory network (CT1FNON).

Section VI presents the conclusion and discussion of the related work and future studies.

## II. LITERATURE REVIEW

In a typical financial prediction problem, there are two basic problems we must tackle with: first, massive and highly uncertain financial patterns and signals; and second, massive time-series data and information for system training and machine learning. An FLS [25] with its intrinsic property of handling attributes of uncertainty provides a viable solution for system modeling and data representations. This section gives a general overview of type-1 and type-2 FLSs, their systems characteristics and limitations, and the current research of the FLS in financial predictions. To tackle with highly chaotic and massive time-series data such as severe weather information and financial data, data scientists and AI researchers are now exploring the possibility of adopting chaotic neural oscillators into traditional recurrent neural networks—chaotic neuro-oscillatory networks (CNON, or chaotic neural networks, CNN in short) for chaotic time-series modeling and forecast. This section gives a general overview of a chaotic neural oscillator and the author's original work on a Lee oscillator, its neural architecture, and the latest works on LORS.

### A. Overview on Type-1 and Interval Type-2 FLSs on Financial Prediction

Like many real-world phenomena, the linguistic variables used to describe the financial markets (or market patterns), ranging from worldwide financial indices and stocks to highly volatile markets, such as worldwide forex and cryptocurrencies, are typical FLSs with high degree of uncertainty and fuzziness. For example, to describe a typical stock market (e.g., NASDAQ Index), financial professionals are usually using the fuzzy linguistic variables such as *bearish*, *bullish*, *over-buy*, or *over-sell*. More importantly, these fuzzy linguistic variables are usually coexisting and overlapping in nature. For instance, when a stock market (e.g., Dow Jones Index) appears to be *bearish* (means *short-sell*), it is also having certain degree of *over-sell* (means *rebound*, with just the opposite trading signal) at the same time. Same case happens in a *bullish* market. Besides, all these linguistic variables are *fuzzy* in the sense that the meaning of *bearish* or *bullish* are highly subjective and different for different people, even for the same person, the meanings of these linguistic variables are usually different at different times and scenarios.

In order to model these highly uncertain and fuzzy linguistic variables into computer system (such as neural networks) for system modeling, an FLS is one of the most viable solutions. A typical FLS consists of the following three main modules:

- 1) fuzzification module;
- 2) inference module; and
- 3) defuzzification module.

Fig. 1 shows a typical T1-FMF of the RSI—one of the most commonly used financial index in financial engineering.

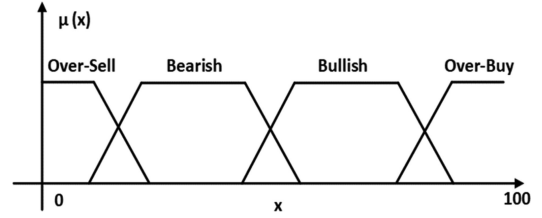


Fig. 1. Type-1 fuzzy membership function (T1-FMF) of the RSI.

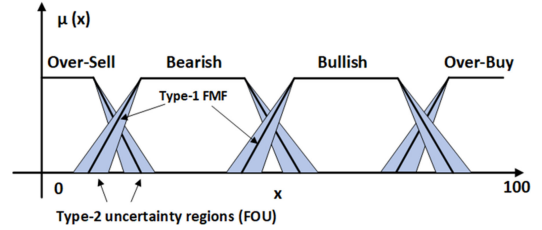


Fig. 2. Interval type-2 fuzzy membership function of the RSI.

Zadeh introduced the concept of higher order type- $n$  FLS (T $n$ -FLS), as follows [25].

**Definition 1:** A fuzzy set is of type  $n$ ,  $n = 2, 3, \dots$ , if its membership function ranges over fuzzy sets of type  $n-1$ . The membership function of a fuzzy set of type 1 ranges over the interval  $[0, 1]$ .

For example, in a typical T2FLS, the membership function of each attribute of the system itself is also a fuzzy set with fuzzy range over the interval  $[0, \dots, 1]$ . In other words, a higher order ( $n > 1$ ) T $n$ -FLS will increase the degree of uncertainty of each fuzzy variable substantially.

But it has an intrinsic problem of computational complexity. For a simple situation of a T2FLS with  $k$  fuzzy variables, each fuzzy variable has  $m$  membership functions and each membership function is quantized into  $N$  different states. The total number of possible fuzzy rules/states will be  $(N^m)^k$ , which will be an astronomical number when such method is applied to real-world financial time-series prediction problems that usually have more than 50 fuzzy attribute signals (from different financial indicators and oscillators) to consider and each attribute has four membership functions, each can span up to 100 different states, which means  $(100^4)^{50}$  possible states/fuzzy rules.

In order to solve this computational problem, IT2FLS is introduced. In a typical IT2FLS, only certain interval(s) of the T2 membership function [usually the intervals of the state transition region (STR)] are fuzzified to a second-order FMF. Fig. 2 shows a typical interval type-2 FMF (IT2-FMF) of RSI for financial engineering.

A typical interval type-2 fuzzy set (IT2-FS) denoted by  $\tilde{A}$  is formulated as follows:

$$\mu_{\tilde{A}}(x) = \int_{x \in X} \int_{u \in [\bar{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)]} 1/u \quad (1)$$

where  $\bar{\mu}_{\tilde{A}}(x)$  and  $\underline{\mu}_{\tilde{A}}(x)$  denote the upper and lower membership functions for the IT2-FS ( $\tilde{A}$ ).

As shown in Fig. 2, the IT2-FMF is characterized by the second-order FMF (the “gray areas”) in the fuzzy membership function, which are also known as footprints of uncertainty (FOU). Owing to this highly uncertainty modeling



capability of IT2FLS as compared with its T1-FLS counterpart, extensive researches have been done in the past 20 years, especially in the fields of fuzzy financial modeling and time-series predictions.

Latest works of T2FLS in financial time series modeling and predictions include: Castillo *et al.* [26]–[33] have done extensive research on IT2FLS and fuzzy-neuro systems on time-series financial predictions including the Mexican Stock Exchange and Taiwan Stock Exchange; Bhattacharya *et al.* [34]–[36] using self-adaptive IT2FLS for stock prediction; IT2FLS for chaotic time-series prediction proposed by Lee *et al.* [37] and Han *et al.* [38]; multiorder fuzzy time-series forecasting model proposed by Ye *et al.* [39] and Yolcu *et al.* [40]; compact evolutionary interval-valued fuzzy rule based system for real-time financial prediction proposed by Sanz *et al.* [41]; interval type-2 mutual subthreshold fuzzy neural inference system proposed by Sumati and Patvardhan [42] for time-series prediction and function approximation; fuzzy time-series forecast of Taiwan stock market based on two-factors second-order fuzzy-trend logical relationship groups with particle swarm optimization technique proposed by Chen and Jian [43]; IT2FLS for stock index forecast based on fuzzy logical relationship map proposed by Jiang *et al.* [44]; and type-2 neuro-fuzzy for stock price prediction based on self-constructing clustering method of fuzzy rules and particle swarm optimization technique [45].

Although IT2FLS provides a viable and computational feasible solution to model highly uncertain phenomena, the determination and formulation of FOU is still an area of interest in which the de-facto usage of triangular-shape formulation as FOU is also queried to be a bit artificial in nature, which motivates the author to search for an integrated mathematical framework to model both the interval type-2 fuzzy and type-1 fuzzy regions in IT2-FMF as a single continuous transient-fuzzy membership function.

By the extension of the author's original work on Lee oscillators [24], this paper proposes an innovative solution for the modeling of CT2TFL by using multiple composite Lee oscillators.

The motivation of introducing CT2TFL in this paper is in the following three aspects.

- 1) Typical FSs and indicators, such as RSI and MACD, coexist with multiple linguistic variables (over-buy, bearish, bullish, and over-buy), and FLS is a viable solution for technical signal modeling.
- 2) These linguistic variables themselves exist with different degrees of uncertainty and fuzziness in nature, and T2FLS is the best tool for handling such high-order degree of fuzziness.
- 3) If we can construct a chaotic neural oscillator model in which its transient-chaotic bifurcation diagram itself can directly model (simulate) a typical T2FLS with transient-fuzzy property only appears in FOU, the computational complexity problem of T2FLS will be effectively resolved.

More importantly, if such composite chaotic neural oscillators themselves are exactly the input neurons of a DNN, the type-2 fuzzification process will become the “intrinsic property” of the DNN itself, instead of “external” fuzzification process in many contemporary fuzzy-neuro systems.

In Section II-B, we discuss an overview of discrete-time neural oscillators and CNNs, and how it can be used to implement type-2 chaotic fuzzy neural network for time-series prediction. In Section III, we will explore how composite Lee oscillators

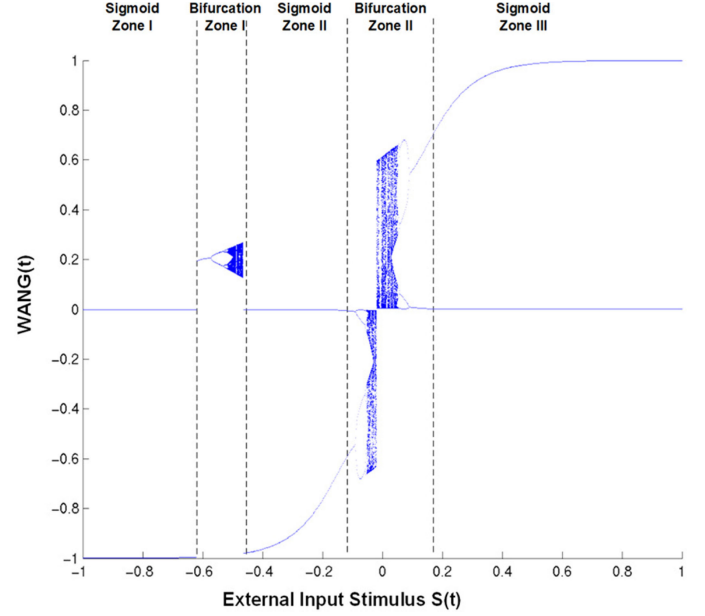


Fig. 3. Bifurcation diagram of a Wang oscillator.

can be used to model T2FMF for financial time-series financial prediction.

## B. Overview of CNNs

1) *Chaotic Neural Oscillators*: Over decades, traditional 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 phenomena like wind-shear and hurricane forecasts, 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 [46], [47].

2) *Wang Oscillators*: In contrast with computationally intensive neural oscillators using time-continuous architecture, Wang [48] proposed a simple but effective time-discrete neural oscillator, the so-called Wang oscillator. Its bifurcation diagram provides a strong evidence to be served as a chaotic transfer unit (CTU) to model complex and chaotic phenomena.

A typical Wang oscillator consists of three neural elements:  $E$ ,  $I$ , and  $Wang$  that correspond to the excitatory, inhibitory, and output neurons. The neural dynamics are given by the following [48]:

$$E(t+1) = \text{Sig}[\omega_{EE}E(t) - \omega_{EI}I(t) + S_E(t) - \xi_E] \quad (2)$$

$$I(t+1) = \text{Sig}[\omega_{IE}E(t) - \omega_{II}I(t) + S_I(t) - \xi_I] \quad (3)$$

$$Wang(t) = E(t) - I(t) \quad (4)$$

where  $S_E$  and  $S_I$  are the input stimulus,  $\omega$  are the weights,  $\xi_E$  and  $\xi_I$  are the threshold values, and the sigmoid function  $\text{Sig}()$  is given by

$$\text{Sig}(k) = \frac{1}{1 + e^{-k}}. \quad (5)$$

Fig. 3 shows the bifurcation diagram of a Wang oscillator.

As shown in Fig. 3, the bifurcation diagram of a typical Wang oscillator consists of sigmoid and bifurcation zones. The original idea is that the sigmoid zone imitates the classical sigmoid

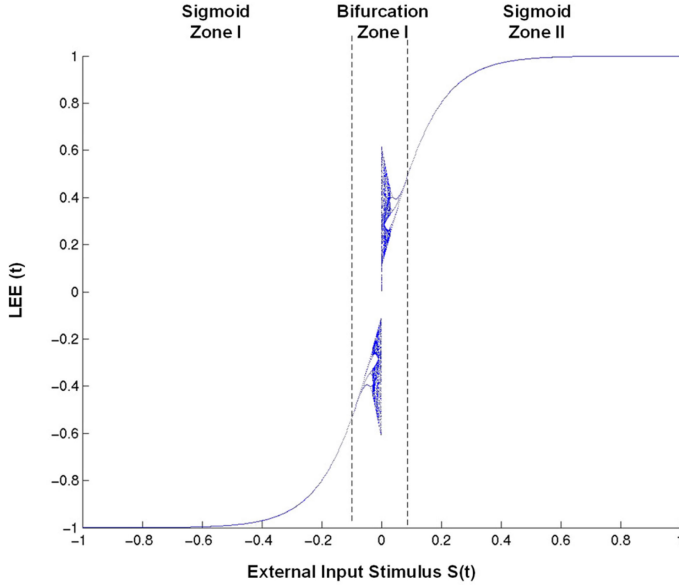


Fig. 4. Bifurcation diagram of a Lee oscillator.

function and the bifurcation zone imitates the chaotic property of complex systems during the sigmoid-transition period. However, there are the following two intrinsic problems.

- 1) The existence of an extra bifurcation zone I that destroys 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.

3) *Lee Oscillators*: A Lee oscillator [24], [49] successfully emulates the transient-chaotic progressive growth in its neural dynamics, which helps to shed new light on acting as a perfect CTU to model complex and chaotic problems. Basically, a Lee oscillator consists of four neural elements:  $E$ ,  $I$ ,  $\Omega$ , and  $Lee$  that corresponds to the excitatory, inhibitory, input, and output neurons. Fig. 4 shows the bifurcation diagram of a Lee oscillator

$$E(t+1) = \text{Sig}'[e_1 E(t) - e_2 I(t) + S(t) - \xi_E] \quad (6)$$

$$I(t+1) = \text{Sig}'[i_1 E(t) - i_2 I(t) - \xi_I] \quad (7)$$

$$\Omega(t+1) = \text{Sig}'[S(t)] \quad (8)$$

$$Lee(t) = [E(t) - I(t)] e^{-kS^2(t)} + \Omega(t) \quad (9)$$

where  $e_1$ ,  $e_2$ ,  $i_1$ , and  $i_2$  are the weights,  $\xi_E$  and  $\xi_I$  are the threshold values, and  $S(t)$  is the external input stimulus.

$\text{Sig}'(k)$  is the sigmoid function given by

$$\text{Sig}'(k) = \frac{1}{1 + e^{-sk}}. \quad (10)$$

As compared with the bifurcation diagram of a Wang oscillator, the bifurcation diagram of a 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 temporal information processing [24], progressive memory recalling [23] and complex scene analysis [50], and chaotic time-series financial prediction discussed in this paper.

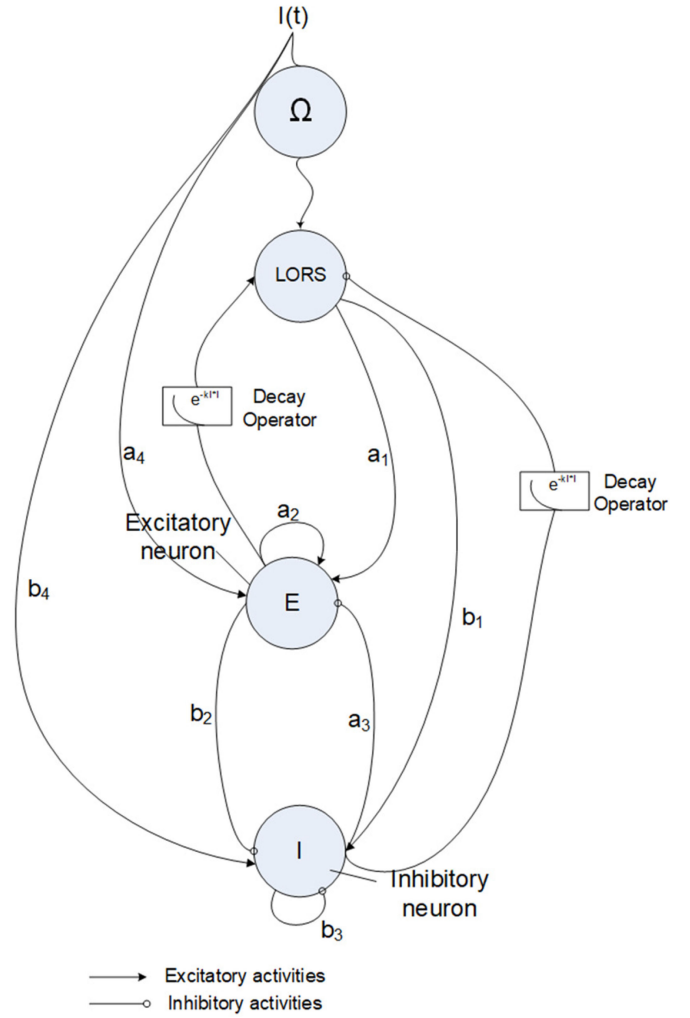


Fig. 5. Neural architecture of LORS.

4) *Lee Oscillators With Retrograde Signaling (LORS)*: Latest research in neuroscience reveals that RS in neurons plays a vital role in temporal information processing and memory recalling in human brain [51]–[54], whereas abnormal RS may lead to various types of memory disorders, such as dementia, memory loss, Alzheimer disease, and Down syndrome [55]–[58].

Inspired by RS in neurons, chaotic LORS is the extension of the author's previous works on Lee oscillators [23], [24] with the integration of retrograde feedback signals in the neural dynamics for the improvement of temporal information processing in the neural oscillatory networks. Fig. 5 shows the neural architecture of LORS.

The neural dynamics of LORS are given as follows:

$$E(t+1) = \text{Sig}'[a_1 \text{LORS}(t) + a_2 E(t) - a_3 I(t) + a_4 S(t) - \xi_E] \quad (11)$$

$$I(t+1) = \text{Sig}'[b_1 \text{LORS}(t) - b_2 E(t) - b_3 I(t) + b_4 S(t) - \xi_I] \quad (12)$$

$$\Omega(t+1) = \text{Sig}'[S(t)] \quad (13)$$

$$\text{LORS}(t) = [E(t) - I(t)] e^{-kS^2(t)} + \Omega(t) \quad (14)$$

TABLE I  
PARAMETER SETTINGS OF EIGHT MAJOR CATEGORIES OF LORS

| Parameters | Lee-oscillator with Retrograde Signaling (LORS) |         |         |         |         |         |         |         |
|------------|---|---------|---------|---------|---------|---------|---------|---------|
|            | LORS #0   | LORS #1 | LORS #2 | LORS #3 | LORS #4 | LORS #5 | LORS #6 | LORS #7 |
| $a_1$      | 0.00  | -0.50   | -0.50   | 0.50    | 0.90    | 0.90    | 5.00    | 5.00    |
| $a_2$      | 5.00  | 0.55    | 0.55    | 0.55    | 0.90    | 0.90    | 5.00    | 5.00    |
| $a_3$      | 5.00  | 0.55    | 0.55    | 0.55    | 0.90    | 0.90    | 5.00    | 5.00    |
| $a_4$      | 1.00  | 0.50    | 0.50    | 0.50    | 0.90    | 0.90    | 5.00    | 5.00    |
| $b_1$      | 0.00  | -0.50   | 0.50    | 0.50    | -0.90   | -0.90   | -1.00   | -1.00   |
| $b_2$      | -1.00   | -0.55   | -0.55   | -0.55   | -0.90   | -0.90   | -1.00   | -1.00   |
| $b_3$      | 1.00  | -0.55   | -0.55   | -0.55   | -0.90   | -0.90   | -1.00   | -1.00   |
| $b_4$      | 0.00  | 0.50    | -0.50   | -0.50   | -0.90   | -0.90   | -1.00   | -1.00   |
| $k$        | 1.00  | 1.00    | 1.00    | 1.00    | 1.00    | 1.00    | 1.00    | 1.00    |
| $\xi_E$    | 500   | 50      | 50      | 50      | 50      | 300     | 50      | 300     |
| $\xi_I$    | 0.00  | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    |
| $s$        | 0.00  | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    | 0.00    |

where  $E$ ,  $I$ ,  $\Omega$ , and LORS denote the excitatory, inhibitory, input, and output neurons of LORS, the  $a_i$  and  $b_i$  are the weights for the excitatory and inhibitory neurons,  $\xi_E$  and  $\xi_I$  are the threshold values, and  $S(t)$  is the external input stimulus.

After extensive experiments and research (during 2008–2018) on the bifurcation behaviors of LORS with different parameter settings and conditions (see Table I), we categorize LORS into eight major categories (LORS#0–LORS#7), with LORS#0 corresponds to the original Lee oscillator without retrograde signals and LORS#1 to LORS#7 correspond to different degree of bifurcations, from single to multiple bifurcation regions. Fig. 6 illustrates the bifurcation diagrams for the eight major categories of LORS.

### III. CT2TFDNN FOR WORLDWIDE FINANCIAL PREDICTION

#### A. CT2TFDNN—System Framework

The CT2TFDNN proposed in this paper is a hybrid intelligent worldwide financial prediction system with the integration of:

- 1) chaotic neural oscillators (Lee oscillators) as CT2TFDNN basic neural structure;
- 2) chaotic type-2 transient-fuzzification of the FSs for CT2TFDNN signal modeling;
- 3) GAs for the selection of top-10 significant FFSs; and
- 4) chaotic transient-fuzzy deep neuro-oscillatory networks with RS for the chaotic financial time-series deep learning and prediction.

Fig. 7 depicts the system framework of the CT2TFDNN for worldwide financial prediction.

#### B. FS Generator Module (FSGM)

In the FSGM, 39 worldwide commonly used financial indicators/oscillators are generated. They include: MA, RSI, BB, MACD, and stochastic oscillators. Table II shows the list of 39 financial trading signals generated in the proposed system.

All the daily financial time-series databanks will be used to generate these 39 trading signals that are used for type-2 transient-fuzzification process performs in the next module. Also, for the ease of fuzzification and network training, all the technical indicators/oscillators being generated in this module will be converted into technical oscillator and normalize

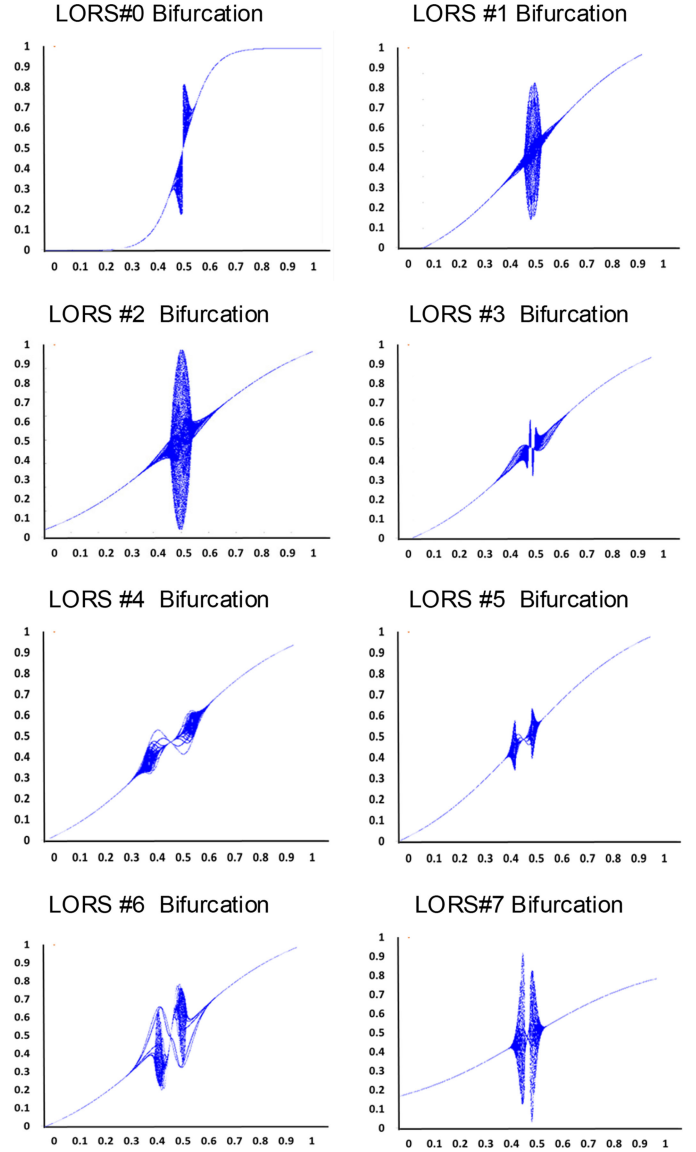


Fig. 6. Eight major categories of bifurcations in LORS.

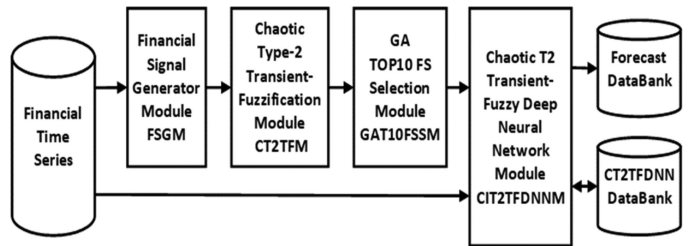


Fig. 7. System framework of CT2TFDNN for worldwide financial prediction.

with values between 0 and 1. For instance, the MA technical indicator will be converted into an MA oscillator by evaluating the signal crossing between two MA signals, such as MA5 and MA13, the two most commonly used *Fibonacci numbers* commonly used for technical signal crossing in financial engineering [1].

TABLE II  
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     |            |                            |

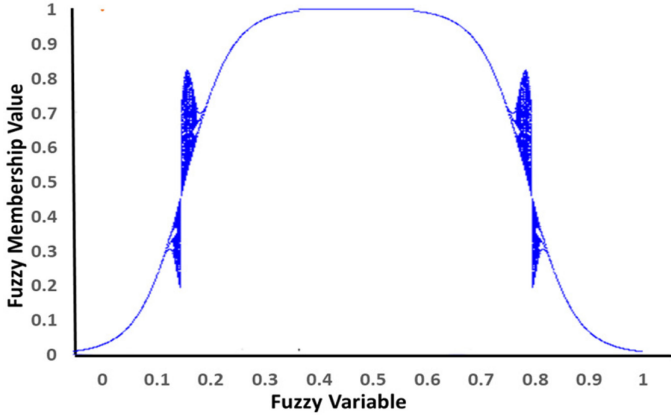


Fig. 8. Chaotic type-2 transient-fuzzy membership function (CT2TFMF).

### C. Chaotic Type-2 Transient-Fuzzification Module (CT2TFM)

1) *Chaotic Type-2 Transient-Fuzzy Membership Function (CT2TFMF)*: CT2TFMF is the modeling of interval type-2 fuzzy logic by using the author's devised time-discrete chaotic neural oscillator—LORS. The formulation of CT2TFMF (normalized) is given by

$$CT2TFMF(x, t) = \begin{cases} LORS(2x, t), & x \leq 0.5 \\ LORS(2 - 2x, t), & x > 0.5 \end{cases} \quad (15)$$

where  $x$  is the fuzzy variable value (e.g., RSI value), which corresponds to the input stimulus  $S(t)$  in the LORS formulations (11)–(14),  $t$  is the type-2 fuzzy logic index, and  $LORS(x, t)$  is the normalized LORS function given by (14). Fig. 8 shows the CT2TFMF by using LORS#0 with MATLAB simulation result of  $1000 \times 200$  time steps.

As shown in Fig. 8, the CT2TFMF generated by LORS has certain special features, which are as follows.

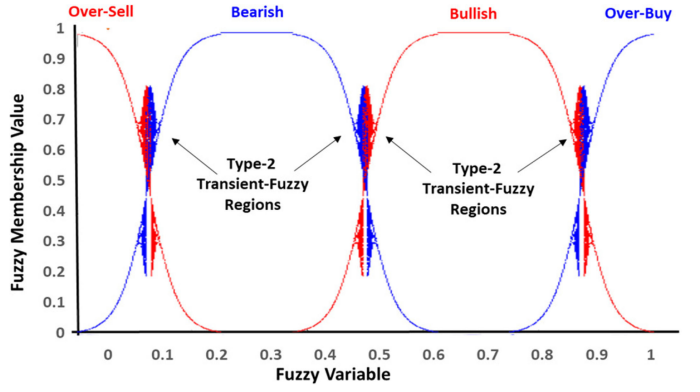


Fig. 9. Chaotic T2 composite transient-fuzzy membership functions of the RSI.

- 1) The membership function generated is a typical type-2 fuzzy membership function with remarkable *transient-fuzzy* FOU, which corresponds to the bifurcation regions of the chaotic oscillators.
- 2) The whole type-2 fuzzy membership function can be modeled and generated by a simple time-discrete chaotic neural oscillator, which can be easily implemented to model various IT2FLS.
- 3) As the neural dynamics of FOU's generated by CT2TFMF is inherited from the Lee oscillators, so it naturally converges to the two stable states at both ends while exhibiting progressive and controlled fuzziness (bifurcation in the chaos theory).
- 4) By regulating various parameters (e.g., weights of the inhibitory and excitatory neurons, the threshold values  $\xi_E$  and  $\xi_I$ , and the decay constant  $k$ ) in the Lee oscillator, the FOU's of the CT2TFMF can be adjusted and transformed to other chaotic patterns to tackle with different complex IT2FLS problems.

2) *Chaotic Type-2 Composite Transient-Fuzzy Membership Function (CT2CTFMF)*: For the ease of modeling type-2 fuzzy logic for the 39 FSs, CT2CTFMF is constructed to model the following four type-2 fuzzy financial linguistic variables: over-sell (OSell), bearish (Bear), bullish (Bull), and over-buy (OBuy).

Fig. 9 shows the MATLAB simulation of the normalized CT2CTFMF for FS RSI using four composite Lee oscillators (LORS#0) with MATLAB simulation results of  $1000 \times 200$  time steps.

The CT2CTFMF of these four linguistic variables are as follows:

$$CT2CTFMF_{OSell}(x, t) = \begin{cases} CT2TFMF(2x + 0.5, t), & x \leq 0.25 \\ 0, & x > 0.25 \end{cases} \quad (16)$$

$$CT2CTFMF_{Bear}(x, t) = \begin{cases} CT2TFMF(1.6x, t), & x \leq 0.625 \\ 0, & x > 0.625 \end{cases} \quad (17)$$

$$CT2CTFMF_{Bull}(x, t) = \begin{cases} 0, & x \leq 0.375 \\ CT2TFMF(1.6x - 0.6, t), & x > 0.375 \end{cases} \quad (18)$$



$$CT2CTFMF_{OBuy}(x, t) = \begin{cases} 0, & x \leq 0.75 \\ CT2CTFMF(2x - 1.5, t), & x > 0.75 \geq 1. \end{cases} \quad (19)$$

From the fuzzy-neuro perspective, Fig. 9 is the bifurcation diagram of the composite Lee oscillators with the superposition of four LORS#0 Lee oscillators which model the membership function CT2CTFMF of the four type-2 fuzzy variables: over-sell, bearish, bullish, and over-buy with their neural dynamics governed by (16)–(19), respectively.

As shown in the above equations, the formulations of all the type-2 fuzzy linguistic variables are continuous state functions with *transient-chaotic* (named as *transient-fuzzy* in Tn-FLS) properties within the state-transition regions, which correspond to the FOU in the T2FLS. Besides, since the CT2CTFMF is generated by a Lee oscillator, which is discrete-time chaotic oscillator, all the type-2 fuzzy states can be easily modified, implemented, and evaluated by adjusting the total number of first-order ( $x$ ) and second-order ( $t$ ) *composite transient-fuzzy membership values* (TFMVs) to fit for different requirements of granularity for any IT2FLS problems.

From the theoretical perspective, the chaotic bifurcation diagram of the composite Lee oscillators is the transient-chaotic output states of these chaotic oscillators subjected to input stimulus. In terms of type-2 fuzzy logic, the transient-fuzzy bifurcations at the “type-2 transient-fuzzy regions” shown in Fig. 9 are theoretically analogue to the interval type-2 concept in fuzzy logic. The difference is that, this chaotic transient-fuzzy membership function is not an additional or external “fuzzification engine” that usually be applied by typical IT2 FLS, but rather it is an intrinsic property of the fuzzy-neuro network itself. In other words, the type-2 fuzzification process proposed in this system is just part of the neural dynamics of the input neurons by simply replacing each of the input neuron (FS) by four LORS#0 Lee oscillators and automatically “inherited” the transient-fuzzy capability during the system training and forecast process.

3) *Chaotic T2 Transient-Fuzzification Module (CT2TFM)*: In this module, all the 39 normalized trading signals (oscillators) will undergo the chaotic interval type-2 fuzzification process by applying the CT2CTFMF described in (16)–(19). The resulted 39 (each FFS has four second-order type-2 TFMV) fuzzified FSs will enter to the GA selection module for top-10 financial fuzzy signals selection.

#### D. GA-Based Top-10 FSs Selection Module (GAT10FSSM)

GAT10FSSM is a vital process in this system to screen-out noncritical signals/data, as usually there are too many signals and time-series data appeared in many financial engineering problems. If all the related signals and time-series are used for financial prediction, it will not only slow down the whole system training and prediction process, but also, more importantly, it will cause serious system overtraining and deadlock problems by being trapped in the local maxima/minima. TOP10-FFSSM is a GA-based module to select the best (top ten) FFSs generated in the CT2TFDNN. It consists of six functional modules (see Fig. 10).

1) *FFSs Population Generation Module*: In this module, a population of 1000 FFS vectors  $FFSV(s, w)$  are generated, where  $s$  and  $w$  are the signal vectors of the 39 FFSs and their weights with values between 0 and 1. Noted that  $s$  is the composite FFS

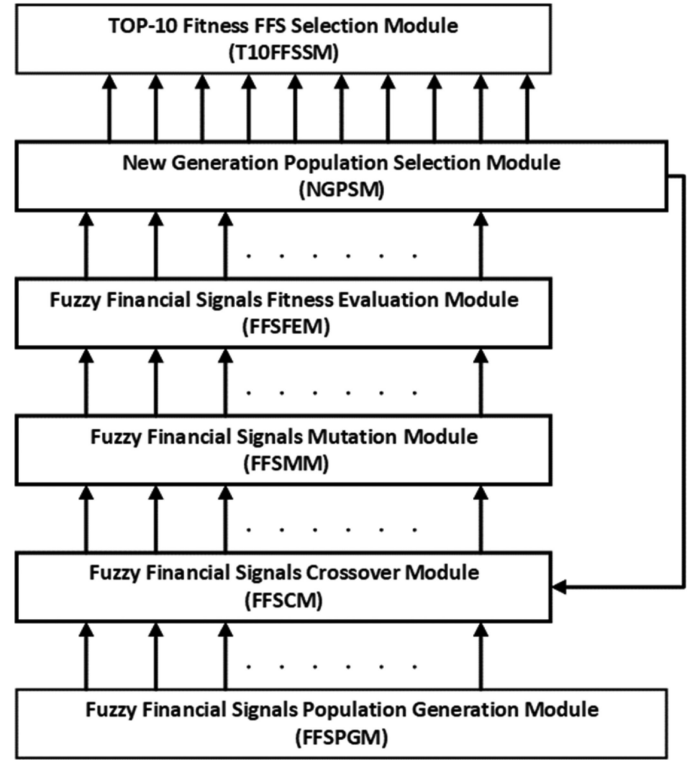


Fig. 10. GA-based top-10 fuzzy FSs selection scheme.

vectors with four dimensions correspond to the four type-2 fuzzy variables.

In the initialization stage, a random number generator is used to generate all the weights for these 1000 FFSVs. Noted that these weights are also used as the initial weights used for the CT2TFDNN for fitness evaluation. In fact, the objective of this GA-based signal selection scheme is to evaluate the best (fitness) FFSV and retrieve the top-10 FFSs with highest weights for system training and prediction in CT2TFDNN.

2) *FFSs Crossover Module*: The whole FFSCM consists of the following steps.

- Step 1*: Randomly selects two FFSVs from the population.
- Step 2*: Performs a two-point crossover operation.
- Step 3*: Two new FFSVs offspring are generated.
- Step 4*: Perform Steps 1–3 for 500 times until 1000 FFSV offspring are created.

3) *FFSs Mutation Module (FFSMM)*: In FFSMM, a 5% (i.e., 0.05) mutation rate is adopted [49].

The whole FFSMM consists of the following steps.

- Step 1*: For each of the 1000 FFSV offspring, generate a random number (between 0 and 100) for each of the 39 FFSs.
- Step 2*: If the random number generated for a particular FFS is less than 5, then the weight ( $w$ ) for that FFS will be replaced by a new random number between 0 and 1.
- Step 3*: Repeat Steps 1 and 2 until all the 1000 FFSV offspring have gone through the FFS mutation operation.

4) *FFSs Fitness Evaluation Module*: In this module, each of the 1000 FFSV offspring will be used (in turn) with the time-series financial data as input vectors for the CT2TFDNN



TABLE III  
LIST OF TOP-10 FFSs

| No | FFS Code   | Fuzzy Financial Signals       |
|----|------------|-------------------------------|
| 1  | AO         | Awesome Oscillator FFS        |
| 2  | Bands      | Bollinger Bands FFS           |
| 3  | Gator      | Gator Oscillator FFS          |
| 4  | Ichimoku   | Ichimoku Kinko Hyo FFS        |
| 5  | Momentum   | Momentum FFS                  |
| 6  | OsMA       | Moving Average Oscillator FFS |
| 7  | MACD       | MACD FFS                      |
| 8  | RSI        | Relative Strength Index FFS   |
| 9  | RVI        | Relative Vigor Index FFS      |
| 10 | Stochastic | Stochastic Oscillator FFS     |

deep training (detail training algorithm will be discussed in next section).

After 1000 iterations, the overall root-mean-square errors (RMSE) between the *target next-day close* and the *actual day-close* will be evaluated and stored as the *fitness value* (FV) for that particular FFSV offspring.

5) *New Generation Population Selection Module*: For the 1000 FFSVs of the current population and their 1000 FFSV offspring, evaluate their FVs and choose the first 1000 best FFSVs with the lowest RMSE as the members for the new generation.

6) *Top-10 Fitness FFS Selection Module*: Repeat the above-mentioned GA modules for 1000 generations. For the last generation, select the best (fit) FFSV with the highest FV (i.e., the lowest RMSE). Inspect the weights ( $w$ ) of its 39 FFSs and choose the top-10 FFSs with the highest weights as the target top-10 FFS and use these weights as the initial for the network training in the CT2TFDNN module.

Table III shows the list of top-10 FFS after 1000 generations.

As shown in Table III, it is not surprising to find out that those popular FSs such as: MACD, RSI, MA (OsMA), and stochastic signals appear in the top-10 list, mainly because these FSs are so popular that many traders and investors are using them to design their trading strategies so that are more correlated with the forecast results than other FSs.

#### E. Chaotic T2 Transient-Fuzzy Deep Neural Network Module (CT2TFDNNM)

In short, CT2TFDNN is a multilayer deep supervised-learning neural oscillatory network with the replacement of all neurons of all layers of the networks with LORS with CBTF as the activation functions. Besides, eight chaotic bifurcation hidden layers, which correspond to the eight different modes of bifurcation in LORS, are used to facilitate fat chaotic deep learning in CT2TFDNN. Figs. 11 and 12 show the system architecture and the chaotic deep-learning algorithm of CT2TFDNN for worldwide financial prediction.

As shown in Fig. 12, the input vectors of CT2TFDNN include the following:

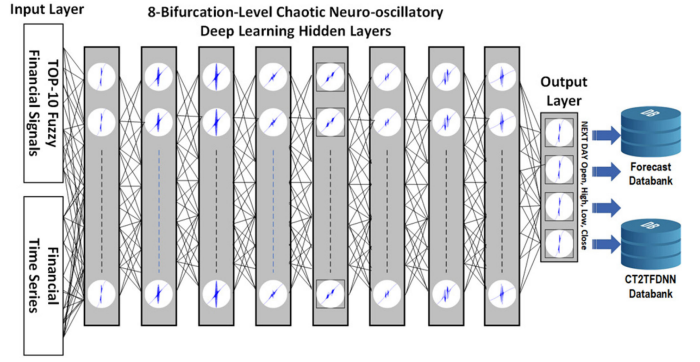


Fig. 11. System architecture of CT2TFDNNM.

#### CT2TFDNN CHAOTIC TRANSIENT-FUZZY DEEP LEARNING ALGORITHM

- 1 CT2TFDNN Initialization Phase
    - 1.1 Initialization all the network weights  $\omega$  by a random number generator to values between 1 and 0.
  - 2 CT2TFDNN Checking Stop Training Criteria
 

IF MSE < Training Threshold  $\delta$  (say  $1 \times 10^{-6}$ ) STOP,  
Else CONTINUE
  - 3 CT2TFDNN Forward Propagation Phase
    - 3.1 Evaluate the total inputs for all hidden LORS ( $L_{H0}$ )
 
$$\vec{L}_{H0input} = \sum_{n=0}^{N_i} \vec{L}_{In} \omega_n$$

Noted that  $N_i$  is the total number of input LORS.
    - 3.2 Evaluate the TCAF values of all  $\vec{L}_{H0input}$  vectors using chaotic Lee\_operator given by equations (6) to (9)
 
$$\vec{L}_{H0} = Lee_{H0}(\vec{L}_{H0input})$$
    - 3.3 Evaluate the total input vectors for hidden LORS ( $L_{H1}$ )
 
$$\vec{L}_{H1input} = \sum_n^{N_{H0}} \vec{L}_{H0} \omega_n$$

Noted that  $N_{H0}$  is the total number of hidden LORS at layer  $H0$ .
    - 3.4 Evaluate the CBTF values of all  $\vec{L}_{H1input}$  vectors
 
$$\vec{L}_{H1} = Lee_{H1}(\vec{L}_{H1input})$$
    - 3.5 Repeat the forward propagation to next layer until propagate to the output layer.
  - 4 CT2TFDNN Backward Propagation Phase
    - 4.1 Evaluate the  $\vec{\delta}_o$  (Correction Error Vector) and  $\Delta\omega_{H7O}$  (weight adjustment vectors between hidden layer 7 and output layer) of all  $\vec{L}_o$  against the target output vectors  $\vec{L}'_o$  with network learning rate  $\beta$ .
 
$$\vec{\delta}_{H0} = (\vec{L}'_o - \vec{L}_o) f'_{L_o}(\vec{L}_{Oinput})$$

$$\Delta\omega_{H7O} = \beta \vec{\delta}_{H7O} \vec{L}_{H7}$$
    - 4.2 Evaluate the  $\vec{\delta}_{H7}$  and  $\Delta\omega_{H6H7}$  of all  $\vec{L}_{H7}$ 

$$\vec{\delta}_{H6H7} = [\sum \vec{\delta}_{H7O} \cdot \omega_{H7O}] (\vec{L}'_o - \vec{L}_o) f'_{L_o}(\vec{L}_{Oinput})$$

$$\Delta\omega_{H6H7} = \beta \vec{\delta}_{H6H7} \vec{L}_{H6}$$
    - 4.3 Evaluate the all the weight vectors at the same time.
 
$$\omega_{H6H7}(t+1) = \omega_{H6H7}(t) + \Delta\omega_{H6H7}(t)$$
    - 4.4 Backward propagate to the previous hidden layer.
  - 5 CT2TFDNN STEP 2 to Check for Stopping Criteria.
- Note:
1.  $L_i, L_o, L_{H0} \dots L_{H7}$  are the Lee-oscillator in the input, output and the 8 hidden deep-learning layers.
  2. The four output Lee oscillators correspond to the next-day forecasts of Open, High, Low and Close.
  3.  $\omega$  are the network weights.
  4. CBTF – Chaotic Bifurcation Transfer Function.
  5.  $\delta$  are the correction error vectors.

Fig. 12. CT2TFDNN: chaotic transient-fuzzy deep learning algorithm.

- 1) top-10 T2 FFSs, each consists of four fuzzy attributes indicating the T2 FMV of: *over-sell (OS)*, *bearish (BR)*, *bullish (BU)*, and *over-buy (OB)*; and
- 2) time-series financial data, each set consists of the *open (O)*, *high (H)*, *low (L)*, *close (C)*, and *volume (V)* of ten trading

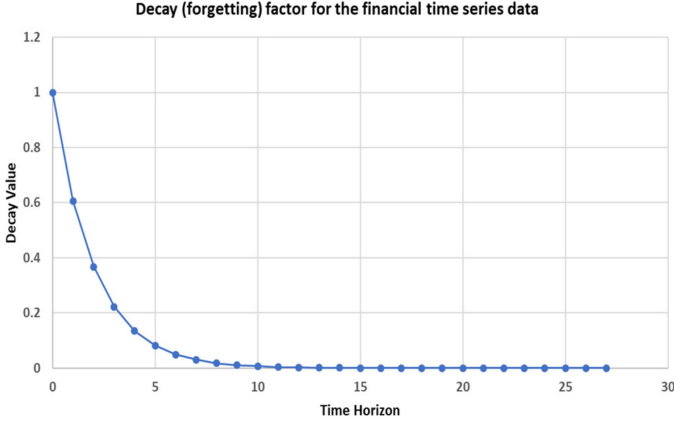


Fig. 13. Decay (forgetting) factor for the financial time-series data.

days' normalized time-series data, each is multiplied by time-step decay ("forgetting") function  $fg()$  [59] given by

$$fg(D) = e^{-kD} \quad (20)$$

where  $D$  is the time horizon (TH) for the time series and  $k = 0.5$  is the decay factor. Fig. 13 shows the decay chart for the financial time-series data [59].

As shown in Fig. 13, the decay function almost converges to 0 when TH is close to day ten. So, we set the TH for the time-series financial data to 10. As reflected from the previous works [55], the introduction of decay (forgetting) factor is vital not only because it simulates the time-series relationships of the historical data, but also it can avoid overtraining by effectively controlling the data size of the time-series input vectors and speed up the whole training process. Also, by replacing all the neurons of CT2TFDNN with Lee oscillators, the traditional FF-PBN effectively transforms into a multilayer neuro-oscillatory network with inherited transient-chaotic neuron activation properties from Lee oscillators, which not only significantly speed up the whole network training process, but also, more importantly, resolves the overtraining and deadlock problems, which commonly occur in most recurrent neural networks with massive financial time-series data. Detail system performance analysis will be discussed in Section V.

#### IV. SYSTEM IMPLEMENTATION

##### A. Quantum Finance Forecast Center (QFFC)

QFFC [60] is a nonprofit organization making AI-Fintech R&D and worldwide financial forecast center aims at the R&D and the provision of totally free and open platform for worldwide traders and individual investors to acquire free knowledge of worldwide financial forecasts based on state-of-the-art quantum finance and related AI technologies. Fig. 14 shows the system architecture of QFFC.

As shown in Fig. 14, CT2TFDNN forecaster is a server-side intelligent forecast agent located at the MT4 server farm of QFFC using Dell Precision T5820 Tower Workstation with Intel 6-Core 3.6GHz Xeon Processor. For each financial product, 2048 trading-day time series (except cryptocurrency that only has 300 trading-day data) include open (O), high (H), low (L), close (C), and volume (V), which are automatically generated by MT4 engines of Forex.com and AvaTrade.com.

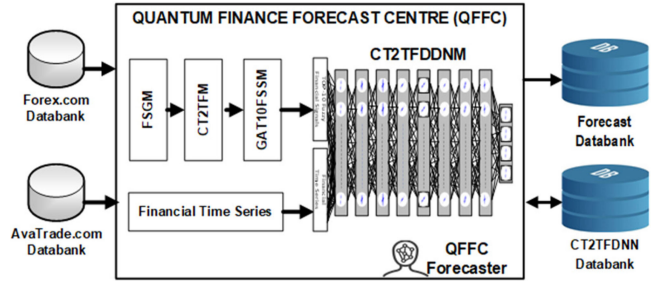


Fig. 14. System architecture of the QFFC.

Through the four functional processes discussed in Section III, the next-day forecasts of these 129 financial products are stored at the CT2TFDNN Forecast Database for the CT2TFDNN trading agents to access and release for public access.

##### B. 129 Worldwide Financial Products

With the successful cooperation with AvaTrade.com [61] (major cryptocurrency MT4 service provider) and Forex.com [62] (major Forex MT4 service provider), QFFC launched the 129 financial products' free daily and weekly forecast services from January 1, 2018 for more than 2000 worldwide traders and individual investors. They include the following:

- 1) nine major cryptocurrencies;
- 2) 84 worldwide forex;
- 3) 19 major commodities; and
- 4) 17 worldwide financial indices.

Table IV shows the list of 129 financial products under these four categories.

As shown in Table IV, owing to the short trading history of cryptocurrency, 300 trading days of historical time series are provided by AvaTrade.com, whereas all other financial products consist of 2048 trading days of historical time series for each financial product provided by Forex.com, which provide sufficient training and test sets for system implementation and performance analysis. Also, each time-series record consists of the following daily information: open (O), high (H), low (L), close (C), and volume (V).

##### C. CT2TFDNN Network Parameter Settings

Table V shows the parameter settings of CT2TFDNN for network training and forecast. As shown in Table V, ten trading-day time series are input into CT2TFDNN for network training, so in total, we have 50 input nodes (LORS#0) for time-series inputs and 100 FFS inputs with total 400 FFS input nodes (LORS#0). For each hidden layer, 400 LORS (LORS#0–LORS#7) hidden nodes are used for network training. For financial products with 2048 trading-day time-series data, 1228 (60%) time-series datasets are used for training, and 401 (20%) time-series datasets are used for network testing and validation. For cryptocurrency with only 300 trading-day time-series data, same proportion of datasets are employed for next training, testing, and validation.

##### D. System Implementation and Pilot Run

From the implementation perspective, the whole CT2TFDNN system is implemented over MT4 (MetaTrader4) platform [22]—the world's biggest online financial program trading and development platform with more than hundreds of participating

TABLE IV  
LIST OF 129 WORLDWIDE FINANCIAL PRODUCTS

| Code   | Product Description                     | Code    | Product Description                   |
|--|---|---------|---------------------------------------|
| Cryptocurrencies (Data provided by AvaTrade.com) |   |         |                                       |
| BCHUSD   | BitCoin Cash vs US Dollar               | EOSUSD  | EOS vs US Dollar                      |
| BTCEUR   | BitCoin vs Euro                         | ETH     | Ethereum                              |
| BTCJPY   | BitCoin vs Japanese Yen                 | LTC     | Litecoin                              |
| BTCUSD   | BitCoin vs US Dollar                    | XRP     | XRP                                   |
| BTGUSD   | Bitcoin Gold vs US Dollar               |         |                                       |
| Financial Index (Data provided by Forex.com)     |   |         |                                       |
| AUS200   | AUS\$ 200                               | N25     | Netherlands 25 Index                  |
| CHINA50  | 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                                | XAUUSD  | Gold vs US Dollar                     |
| SOYBEAN  | Soybean                                 | XAUGBP  | Gold vs British Pound                 |
| SUGAR  | Sugar                                   | XAUJPY  | Gold vs Japanese Yen                  |
| UK_OIL   | Brent Crude Oil                         |         |                                       |
| 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        | GBPHK   | 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       |
| CHFCHF   | 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     |
| CHNJPY   | Chinese Yuan vs Japanese Yen            | NZDJPY  | New Zealand Dollar vs Jap. Yen        |
| EURAUD   | Euro vs Australian Dollar               | NZDUSD  | New Zealand Dollar vs US Dollar       |
| EURCAD   | Euro vs Canadian Dollar                 | SGDHKD  | Singapore Dollar vs Hong Kong Dollar  |
| EURCHF   | Euro vs Swiss Franc                     | SGDJPY  | Singapore Dollar vs Japanese Yen      |
| EURCNH   | Euro vs Chinese Yuan                    | TRYJPY  | Turkish Lira vs Japanese Yen          |
| EURCZK   | Euro vs Czech Koruna                    | USDCAD  | US Dollar vs Canadian Dollar          |
| EURDKK   | Euro vs Danish Krone                    | USDCHE  | US Dollar vs Swiss Franc              |
| EURGBP   | Euro vs British Pound                   | USDCNH  | US Dollar vs Chinese Yuan             |
| EURHKD   | Euro vs Hong Kong Dollar                | USDCZK  | US Dollar vs Czech Koruna             |
| EURHUF   | Euro vs Hungarian Forint                | USDDKK  | US Dollar vs Danish Krone             |
| EURJPY   | Euro vs Japanese Yen                    | USDHKD  | US Dollar vs Hong Kong Dollar         |
| EURMXN   | Euro vs Mexican Peso                    | USDHUF  | US Dollar vs Hungarian Forint         |
| EURNOK   | Euro vs Norwegian Krone                 | USDILS  | US Dollar vs Israeli Shekel           |
| EURNZD   | Euro vs New Zealand Dollar              | USDJPY  | US Dollar vs Japanese Yen             |
| EURPLN   | Euro vs Polish Zloty                    | USDMDXN | 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   | Euro vs Swedish Krona                   | USDRON  | US Dollar vs Romanian Leu             |
| EURSGD   | Euro vs Singapore Dollar                | USD RUB | US Dollar vs Russian Ruble            |
| EURTRY   | Euro vs Turkish Lira                    | USDSEK  | US Dollar vs Swedish Krona            |
| EURUSD   | Euro vs US Dollar                       | USD SGD | 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 Jap Yen         |

TABLE V  
PARAMETER SETTINGS OF CT2FDNN

| Parameters   | Values                    |
|--|---------------------------|
| No. of trading day for network input               | 10                        |
| No. of time series LORS in input layer             | 50                        |
| No. of input Fuzzy Financial Signals (FFS)         | 100                       |
| No. of FFS LORS in input layer                     | 400                       |
| No. of LORS in each hidden layer                   | 400                       |
| No. of output LORS                                 | 4                         |
| Network training stop criteria (RMSE)              | $1 \times 10^{-6}$        |
| Deadlock criteria                                  | 10,000 epochs             |
| LORS parameter settings in input and output layers | LORS#0 settings (Table I) |
| LORS parameter settings in 8 hidden layers         | LORS#0-LORS#7 (Table I)   |

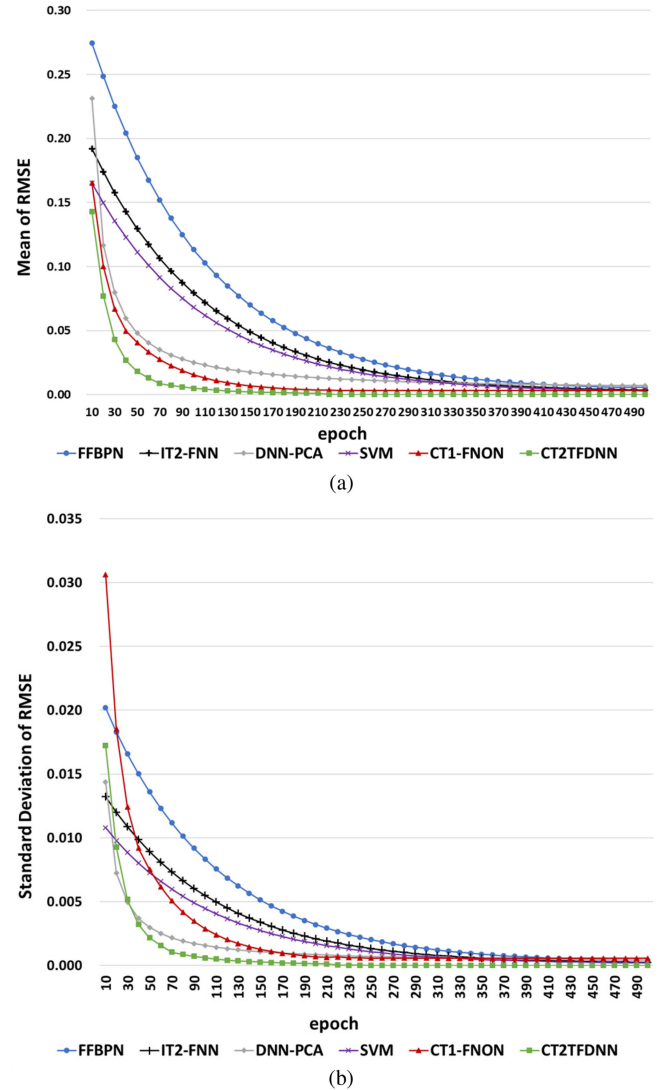


Fig. 15. System training performance (over 500 epochs) of six financial forecast models for 129 financial products. (a) Mean of RMSE. (b) Standard deviation of RMSE.



TABLE VI  
SYSTEM FORECAST SIMULATION PERFORMANCE ANALYSIS

| Product                | no. of<br>Items | FFBPN        |           | SVM          |            | DNN-PCA     |            | IT2FNN       |           | CT1FNON      |           | CT2TFDNN     |            |
|------------------------|-----------------|--------------|-----------|--------------|------------|-------------|------------|--------------|-----------|--------------|-----------|--------------|------------|
| Category               |                 | Total<br>STT | Av. STT   | Total<br>STT | Av. STT    | Total STT   | Av. STT    | Total<br>STT | Av. STT   | Total<br>STT | Av. STT   | Total<br>STT | Av.<br>STT |
| Case 1 (RMSE = 1x10-4) |                 |              |           |              |            |             |            |              |           |              |           |              |            |
| Cryptocurrency         | 9               | 557251       | 61916.78  | 372244       | 41360.41   | 244633      | 27181.47   | 305240       | 33915.56  | 5720         | 635.56    | 1023         | 113.67     |
| Forex                  | 84              | 508453       | 6053.01   | 331511       | 3946.56    | 291344      | 3468.38    | 275154       | 3275.64   | 6323         | 75.27     | 1128         | 13.43      |
| Financial Index        | 19              | 41120        | 2164.21   | 26152        | 1376.44    | 19738       | 1038.82    | 21183        | 1114.89   | 923          | 48.58     | 159          | 8.37       |
| Commodity              | 17              | 46641        | 2743.59   | 29384        | 1728.46    | 22108       | 1300.46    | 25564        | 1503.76   | 1223         | 71.94     | 231          | 13.59      |
| Overall                | 129             | 1153465      | 8941.59   | 759291       | 5885.98    | 577823      | 4479.25    | 627141       | 4861.56   | 14189        | 109.99    | 2541         | 19.70      |
| Case 2 (RMSE = 1x10-5) |                 |              |           |              |            |             |            |              |           |              |           |              |            |
| Cryptocurrency         | 9               | 1460000      | 162222.22 | 937320       | 104146.67  | 823440      | 91493.33   | 862334       | 95814.89  | 15121        | 1680.11   | 2673         | 297.00     |
| Forex                  | 84              | 1235543      | 14708.85  | 841405       | 10016.72   | 720322      | 8575.26    | 782507       | 9315.56   | 17231        | 205.13    | 2894         | 34.45      |
| Financial Index        | 19              | 111024       | 5843.37   | 68391        | 3599.51    | 50627       | 2664.58    | 62236        | 3275.58   | 2312         | 121.68    | 481          | 25.32      |
| Commodity              | 17              | 109142       | 6420.12   | 71925        | 4230.86    | 44967       | 2645.09    | 64733        | 3807.82   | 2640         | 155.29    | 551          | 32.41      |
| Overall                | 129             | 2915709      | 22602.40  | 1919041      | 14876.29   | 1639356     | 12708.19   | 1771810      | 13734.96  | 37304        | 289.18    | 6599         | 51.16      |
| Case 3 (RMSE = 1x10-6) |                 |              |           |              |            |             |            |              |           |              |           |              |            |
| Cryptocurrency         | 9               | DL           | -         | 6102255      | 678028.38  | 3601307     | 400145.17  | DL           | -         | 234663       | 26073.67  | 10324        | 1147.11    |
| Forex                  | 84              | DL           | -         | 5477816      | 65212.10   | 4184833     | 49819.44   | DL           | -         | 218661       | 2603.11   | 13234        | 157.55     |
| Financial Index        | 19              | 577324       | 30385.47  | 373529       | 19659.40   | 318683      | 16772.78   | 459441       | 24181.11  | 6623         | 348.58    | 1292         | 68.00      |
| Commodity              | 17              | 687595       | 40446.76  | 468252       | 27544.25   | 385741      | 22690.64   | 622775       | 36633.82  | 9126         | 536.82    | 1983         | 116.65     |
| Overall                | 129             | -            | -         | 12421852     | 96293.43   | 8490564     | 65818.33   | -            | -         | 469073       | 3636.22   | 26833        | 208.01     |
| Case 4 (RMSE = 1x10-7) |                 |              |           |              |            |             |            |              |           |              |           |              |            |
| Cryptocurrency         | 9               | DL           | -         | 25141291     | 2793476.73 | 14405228    | 1600580.89 | DL           | -         | 1928929      | 214325.44 | 51213        | 5690.33    |
| Forex                  | 84              | DL           | -         | 26896077     | 320191.39  | 17785540    | 211732.62  | DL           | -         | 1600598      | 19054.74  | 62256        | 741.14     |
| Financial Index        | 19              | DL           | -         | 1714498      | 90236.74   | 1446821     | 76148.46   | 2451732      | 129038.53 | 37088        | 1952.00   | 6231         | 327.95     |
| Commodity              | 17              | DL           | -         | 2088404      | 122847.29  | 1917133     | 112772.52  | 2756693      | 162158.41 | 48641        | 2861.24   | 7132         | 419.53     |
| Overall                | 129             | -            | -         | 55840269     | 432870.30  | 35554721.84 | 275618.00  | -            | -         | 3615256      | 28025.24  | 126832       | 983.19     |

Note: 1. Results are generated by 500 simulations of each financial forecast systems (measured in ms).

2. "Total STT" denotes the total average system training time for 500 simulations of system 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.

financial institutions for the provision of online program trading and development services of all common worldwide financial products.

Since January 1, 2018, QFFC has been releasing daily financial forecast using CT1FNN as pilot run, which opened testing for worldwide traders and investors.

From October 1, 2018, after finishing the system implementation of CT2TFDNN, QFFC daily worldwide financial predictions have been conducted by the CT2TFDNN system.

## V. PERFORMANCE ANALYSIS

From the system performance perspective, three types of system performance analysis are conducted:

- 1) system training performance analysis;
- 2) system forecast simulation performance analysis; and
- 3) actual daily forecast performance analysis.

In all of these performance analyses, the system performance of CT2TFDNN is compared with the following five forecast models:

- 1) traditional time-series FFBPN;
- 2) SVM forecasting tool provided by R Project—one of the most popular financial forecasting tools used in the finance industry;
- 3) DNN with PCA model [9];
- 4) classical IT2FNN; and

## 5) CT1FNN.

### A. System Training Performance Analysis

In CT2TFDNN training performance analysis, 60% of time series data of the 129 financial products are employed for system training in two aspects. Fig. 15 shows the system performances of the six forecast models over 500 epochs of network training of the 129 financial products in terms of mean and standard deviations of RMSE.

As shown in Fig. 15, two observations can be found: first, CT2TFDNN outperforms the other five models in terms of both mean and standard deviation of RMSE; and second, CT2TFDNN attains the promisingly low RMSE in 70 epochs, whereas the RMSE of other networks especially FFBPN, SVM, and IT2FNN are still "half-way" of their lowest RMSE levels.

### B. System Forecast Simulation Performance Analysis

In the system forecast simulation performance analysis, four categories of worldwide 129 financial products are tested with target RMSE of the forecast next-day closing price ranging from  $1 \times 10^{-4}$  to  $1 \times 10^{-7}$ . The test is done by applying 500 forecast simulations for each system. Table VI presents the system forecast simulation performance test of these six systems.

Certain interesting findings are revealed in Table VI, which are as follows.

- 1) For Case 1 simulation (RMSE  $1 \times 10^{-4}$ ), CT2TFDNN forecaster outperforms FFBPN (453.94 times), SVM (298.92 times), DNN-PCA (227.40 times), IT2FNN (246.81 times), and CT1FNN (5.58 times). Similar findings can be found in Case II simulation results. It clearly reflects the improvement of network learning rate achieved by the hybrid type-2 transient-fuzzy with deep chaotic neuro-oscillatory network system and GA-based top-10 FFS selection scheme.
- 2) Across the three cases with decreasing RMSE from  $1 \times 10^{-4}$  (Case 1),  $1 \times 10^{-5}$  (Case 2), and  $1 \times 10^{-6}$  (Case 3) to  $1 \times 10^{-7}$  (Case 4). All forecast systems can achieve the target RMSE in Case 1 and Case 2. However, for the Cases 3 and 4, simulations using target RMSE  $1 \times 10^{-6}$  and  $1 \times 10^{-7}$ , both FFBPN and IT2FNN (which are using sigmoid-based FFBPN for machine learning), encounter deadlock problems during the network training of cryptocurrency and forex products; whereas CT2TFDNN forecaster can still finish the network training with promising training speeds. It clearly demonstrates the resolution of overtraining and deadlock problems and improvement of system training efficiency by CT2TFDNN forecaster over traditional recurrent neural networks using classical sigmoid-based activation function.
- 3) Comparing CT2TFDNN against CT1FNN across the three cases, it is interested to reveal that CT2TFDNN outperforms its counterpart by 5.58 times (Case 1), 5.65 times (Case 2), 17.48 times (Case 3), and 28.50 times (Case 4). As shown in Table VI, the overall performance of the CT1FNN forecast system deteriorates substantially when the target RMSE is set to  $1 \times 10^{-6}$  and beyond, especially on cryptocurrency and forex forecasts, whereas CT2TFDNN still performs stable result. It clearly reflects the merits for the integration of a type-2 transient-fuzzification scheme with chaotic neural oscillator technology with RS for time-series chaotic deep learning.
- 4) 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 QFFC.

### C. Actual Daily Forecast Performance Analysis

Since October 1, 2018, CT2TFDNN has been providing the official daily forecast of these 129 financial products via the QFFC official site on every trading day at 08:00 HKT (00:00 UTC) and reporting the previous-day forecast performance. Fig. 16 shows the actual daily forecast performance chart of the six forecast models between October 1, 2018 and March 15, 2019 (120 trading days). The daily forecast percentage error (DFPE) is defined as follows:

$$\text{DFPE} = \frac{\text{Average}(\text{DFErr}(H), \text{DFErr}(L))}{\text{DClose}} \times 100\% \quad (21)$$

where  $\text{DFErr}(H)$  and  $\text{DFErr}(L)$  are the daily errors of Daily\_Forecast\_High (Low) with the Daily\_Actual\_High (Low), respectively, and  $\text{DClose}$  is the daily closing price.

As shown in Fig. 16, the 120 trading-day actual forecast performance of the six forecast models are rather consistent with

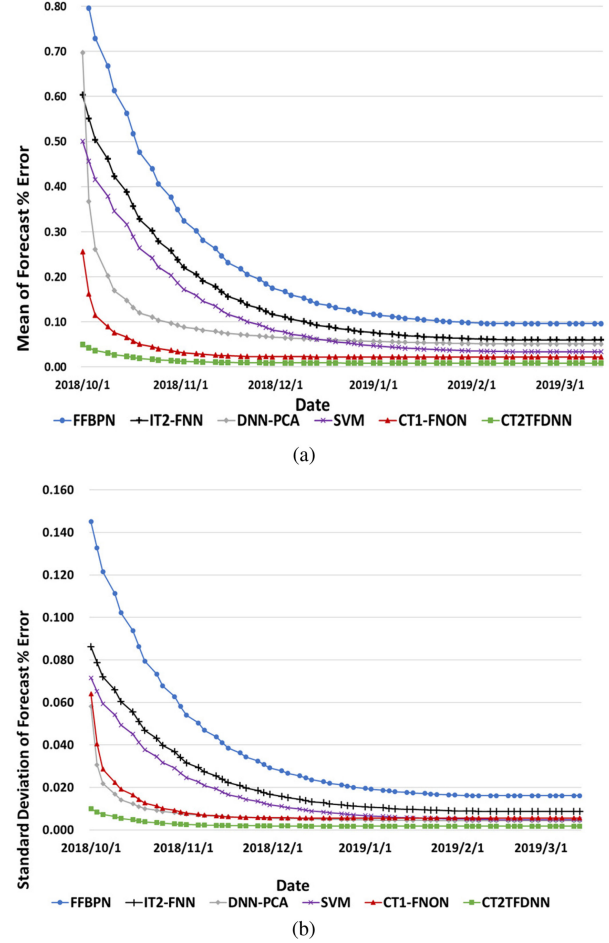


Fig. 16. Actual daily forecast performance of six financial forecast models for 129 financial products between October 1, 2018 and March 15, 2019. (a) Mean of forecast percentage error. (b) Standard deviation of forecast percentage error.

their system training results shown in previous tests, in which FFBPN performs the worst and the CT2TFDNN performs the best.

But one interesting difference is that although the ranking of their performances are the same between the system training performance and the actual forecast performance, the “overall forecast performance gaps” between these six forecast systems are more distinct in which CT2TFDNN outperforms the other five forecast model significantly and it takes less than 20 trading days to attain its stable forecast performance state, whereas other forecast systems take 40–60 trading days to attain their stable forecast performance states.

Fig. 17 shows the daily forecast performance of CT2TFDNN across the four different categories of financial products. As shown in Fig. 17, owing to different levels of chaotic behavior and disturbance between different categories of financial products, there are two interesting findings: First, the forecast performance of cryptocurrency is significantly poorer than all other categories even though their differences in training performance are not so significant. This might be due to the highly chaotic property of cryptocurrency and insufficient time-series history data. Second, the forecast performance of forex is better than its performance in system training, which is rather consistent with the observations from the professional traders using the CT2TFDNN forecast service during this period of time and also

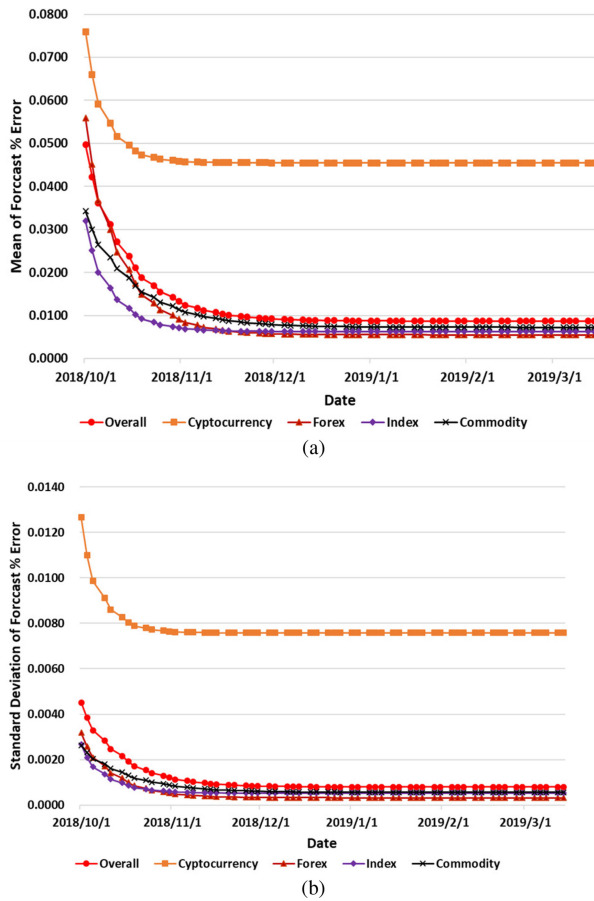


Fig. 17. Actual daily forecast performance of CT2TFDNN of four different categories of financial products between October 1, 2018 and March 15, 2019. (a) Mean of RMSE. (b) Standard deviation of RMSE.

concluded that although forex products overall are highly chaotic in nature, CT2TFDNN provides a reliable daily forecast with a relatively stable degree of accuracy.

## VI. CONCLUSION AND DISCUSSION

The dawn of big data epoch has driven us to face new challenges from overflowing data and information. This paper devises an innovative CT2TFDNN to address the overtraining and deadlock problems, which are commonly occurred during network training of massive data, such as financial, weather, and biomedical big data. For the system architecture perspective, CT2TFDNN provides an integration of the following four different innovative AI technologies:

- 1) chaotic neural oscillator for the modeling of neural dynamics;
- 2) type-2 transient-fuzzy logic for the modeling of FFSs;
- 3) GA for the selection of the best FFSs; and
- 4) deep CNN for network training and prediction.

From the implementation perspective, CT2TFDNN has been adopted for the real-time prediction of 129 worldwide financial products. In comparison with five forecast systems ranging from traditional FFBPN, SVM, DNN with PCA, and IT2FNN to CT1FNON, CT2TFDNN produces promising results in terms of system training performance and actual daily forecast performance.

The future and related works include the following.

- 1) Further research and study of CT2TFLS for the modeling, analysis, and data mining of other big data problem, such as weather, biometric, and biomedical engineering.
- 2) Further study of CT2TFDNN for the categorization of various CT2TFMF using neural RS techniques.
- 3) R&D of intelligent agent-based hedging and trading systems based on CT2TFLS.
- 4) Integration of CT2TFDNN with QPL study using QAOM for financial trend prediction and long-term investment.

## ACKNOWLEDGMENT

The author would like to thank Forex.com and Avatrade.com for the provision of historical and real-time financial data. The author also would like to thank QFFC of the United International College for the R&D supports and the provision of the channel and platform qffc.org for worldwide system testing and evaluation.

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