Wind Shear Forecasting by Chaotic Oscillatory-based Neural Networks (CONN) with Lee Oscillator (Retrograde Signalling) Model

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Abstract—**Wind shear is a conventionally unpredictable meteorological phenomenon which presents a common danger to aircraft, particularly on takeoff and landing at airports. This paper describes a method for forecasting wind shear using an advanced paradigm from computational intelligence, Chaotic Oscillatory-based Neural Networks (CONN). The method uses weather data to predict wind velocities and directions over a short time period. This approach may have a wide variety of applications but from the aviation forecast perspective, it can be used in aviation to generate wind shear alerts.**

I. INTRODUCTION

Wind shear is a conventionally unpredictable meteorological phenomenon which presents a common danger to aircraft, particularly on takeoff and landing at airports. However, even after almost thirty years of research, because of the instability of weather phenomena and complex terrain around airports, current approaches to prediction remain inaccurate [4], [22].

In this paper, we propose a Chaotic Oscillatory-based Neural Networks (CONN) approach to forecasting wind shear. There is an extensive literature on chaos and chaos theory. Deterministic chaos has described many complex behaviors of nonlinear systems, such as the fact that they are essentially periodic even though they appear random [20]. Wind shear would appear to be a good candidate for chaos theory approaches. The motion of wind is governed by a fluid mechanism. The stability of fluid flows depends on various conditions such as temperature, pressure, velocity and humidity. If one of these conditions changes even a little, a laminar flow will become turbulent [20]. In a somewhat similar way, chaotic models are sensitive to initial conditions. Small changes can produce large differences in outcomes. Further support for the view that fluid dynamics are equivalent to a kind of non-linear dynamical systems comes from the fact that the core equations for fluid dynamics are the Navier-Stroke equations, which are sets of non-linear differential equations [21]. On the other hand, common chaotic systems are usually applied in sets of differential equations coincidentally.

II. CHAOTIC NEURAL NETWORKS & LEE OSCILLATOR

A. Chaotic Neural Networks

The idea of chaotic neural networks is proposed by Aihrar, Takabe and Toyoda in Physics Letters A [2]. They stated that from a neurophysiologic point of view real neuron operations are more complex than the simple use of threshold; therefore non-linear output function is more suitable to act as the activation function of a neuron. They developed chaotic neural networks to model non-linear behavior of neurons.

B. Lee Oscillator –Previous Work

Research on neuroscience and brain science in this couple of years observed that there are various chaotic phenomena in brain functions [9] and behaviour of neurons are inactivate triggering (called as oscillation) between excitatory and inhibitory neurons [1]. From above findings, authors tried to develop and simulate neural behaviour – Chaotic Oscillatory-based Neural Network (CONN) and Lee Oscillator [13]. We believe that using a chaotic oscillator as an activation function of neural networks will provide a highly dynamic transfer than using hyperbolic tangent function. We also believe that such neural networks are able for predicting or modelling highly complexity problems in real world.

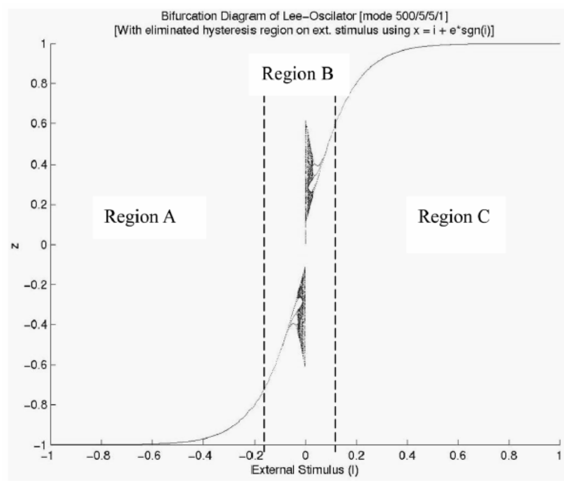

Fig. 1 Bifurcation Diagram of Lee Oscillator [13]

A Lee Oscillator consists of four neural dynamics of four constitutive neural elements: *u*, *v*, *w* and *z*. The neural dynamics of each of these constituent neurons are given by

$$u(t+1) = f[a_1 \cdot u(t) - a_2 \cdot v(t) + I(t) - \theta_u] \quad (1)$$

$$v(t+1) = f[b_1 \cdot u(t) - b_2 \cdot v(t) - \theta_v] \quad (2)$$

$$w(t+1) = f[I(t)] \quad (3)$$

$$z(t) = f[u(t) - v(t)] \cdot e^{-kI^2(t)} + w(t) \quad (4)$$

where *u(t)*, *v(t)*, *w(t)*, and *z(t)* are the state variables of the excitatory, inhibitory, input, and output neurons, respectively; *f()* is the

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hyperbolic tangent function; a_1, a_2, b_1, and b_2 are the weight parameters for these constitutive neurons; θ_u and θ_v are the thresholds for excitatory and inhibitory neurons; $I(t)$is the external input stimulus; and k is the decay constant. Fig. 1 shows the bifurcation behavior of the Lee Oscillator Model [13].

C. *Lee Oscillator (Retrograde Signalling) Model – The Implementation of Retrograde Axonal Transport Concept*

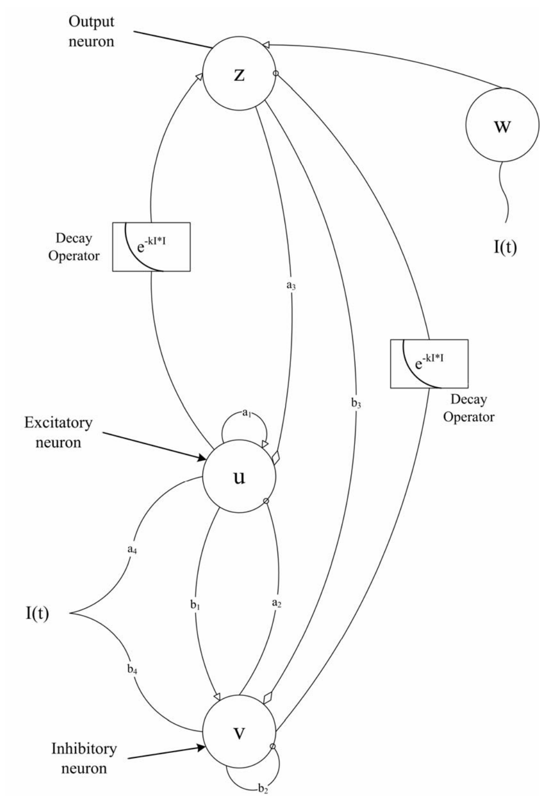

Fig. 2 Lee Oscillator (Retrograde Signalling) Model

The enhancement of the Lee Oscillator is derived from retrograde transport mechanism in axons, axonal transport (also named as axoplasmic flow) was discovered by Paul Weiss in 1948 [14]. Axons are not able to synthesize proteins; all synthesis of proteins takes places in the cell body. Receptors, signalling proteins, enzymes for synthesis of neurotransmitter must be moved to distant axon terminals or dendrites. The movement of a cell body towards terminals or dendrites is called anterograde transport. On the other hand, retrograde transport is a backward transmission mechanism. This mechanism transmits neurotrophin from axon terminals to the cell body [8], [14], [16], [17]. Neuroscientists had an important discovery in recent years, they found out the major functionality of retrograde transport is signalling. This functionality is also called Retrograde Signalling. Retrograde signals influence neuronal survival, differentiation, homeostasis and plasticity [11], [18], [23]. Latest researches on neuroscience had pointed out those neurological diseases such as Alzheimer's disease and Down's

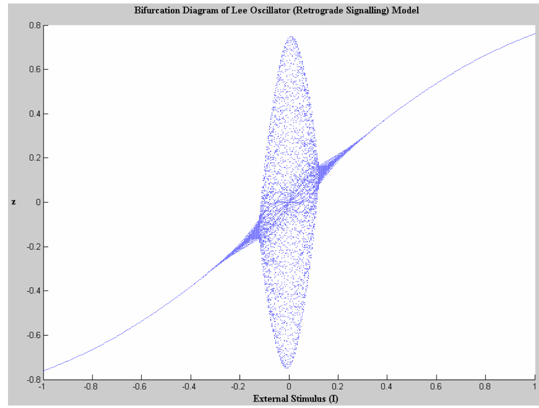

Fig. 3 Bifurcation Diagram Type A Oscillator
(Parameter Details shown in Table I)

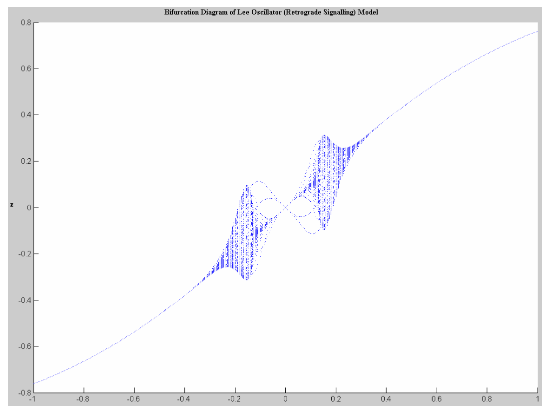

Fig. 4 Bifurcation Diagram of Type B Oscillator
(Parameter Details shown in Table I)

syndrome are significantly related to malfunction of retrograde transport mechanism [7]. Fig. 2 is a depiction of Lee Oscillator (Retrograde Signalling) Model, then Eqs 5 to 8 present the neural dynamics of this model.

$$u(t+1) = f[a_1 \cdot u(t) - a_2 \cdot v(t) + a_3 \cdot z(t) + a_4 \cdot I(t) - \theta_u] \quad (5)$$

$$v(t+1) = f[b_3 \cdot z(t) - b_1 \cdot u(t) - b_2 \cdot v(t) + b_4 \cdot I(t) - \theta_v] \quad (6)$$

$$w(t+1) = f[I(t)] \quad (7)$$

$$z(t) = f[v(t) - u(t)] \cdot e^{-kI^2(t)} + w(t) \quad (8)$$

There are three major modifications on previous work. Firstly, by implementing retrograde signalling concept, the output value of $z(t)$ is re-imported into both the excitatory neuron (Eq. 5) and the inhibitory neuron (Eq. 6) to simulate retrograde transport mechanism for generating a full chaotic region instead of two separate chaotic regions of previous work. The $z(t)$ in Eq. 6 simulates human learning usually through experiences, errors and pains. Secondly, $I(t)$ is also used in Eq. 6, it is because an incoming signals should be considered in inhibitory neurons, not only processing by excitatory neurons. Thirdly, switching *v(t) – u(t)* (Eq. 8) from *u(t) – v(t)* (Eq. 4) is a different concept against the previous work, the concept of presynaptic inhibition is implemented in this modification. Presynaptic Inhibition is a neurotransmitter release mechanism, a strong suppression of an excitatory neuron's responses before stimulus reaches synaptic terminals mediated by an inhibitory neuron [14], [17]. Lastly, new parameters a_3, a_4, b_3, b_4 were added in Eqs. 5 & 6, as every variable should have its own parameter to adjust the outcomes.

We have improved on previous work in three areas. First, the variability of chaotic state is increased because of new parameters being introduced in this model. Chaotic regions are easier to reshape and it is possible to generate either single or dual chaotic regions by tuning different parameters. Figs. 3 (Table I, Lee Oscillator (RS) Type A) and 4 (Table I, Lee Oscillator (RS) Type B) show bifurcation behaviour by using different parameter sets on Lee Oscillator (Retrograde Signalling) model, detail part of these oscillators are shown in Appendix. The values in x-axis are *I(t)* and numbers in y-axis are results of *z(t)*. Second, chaotic region is wider than previous work, so temporal information processing [13] can be more effectively. Third, to generate chaotic region in the Lee Oscillator (Retrograde Signalling) model requires just one tenth of the number of iterations of previous models, and for this reason, computation time is saved.

III. WIND SHEAR FORECASTING

A. Overview

The data were collected from Juneau Airport Winds System (JAWS), a system for Juneau International Airport (JIA) in Alaska. JIA is surrounded by mountainous terrain and often experiences strong winds from the Gulf of Alaska and the Canadian interior [3]. Planes encounter severe wind shear and turbulence while approaching and departing. JAWS was developed by Research Applications Laboratory (RAL) of the National Center for Atmospheric Research (NCAR) [6].

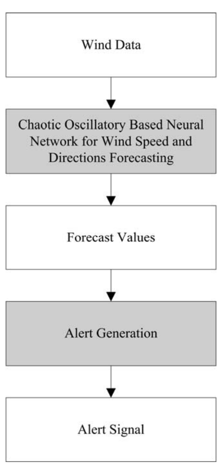

Fig. 5 Organization of Forecasting Model

The wind shear forecasting model is divided into two components – wind forecasting and alert generation, Fig. 5 shows the organization of the forecasting model. Wind forecasting predicts wind speed and direction value through a Chaotic Oscillatory-based Neural Network (CONN) by fitting in different types of weather data. Alert generation applies wind speed and direction values to calculate the speed of shear through basic trigonometry as follows:

$$a = \sqrt{b^2 + c^2 - 2bc\cos A} \tag{9}$$

where a is speed of shear in knots, b and c are predicted wind speed knot values in time t_{i-1} and t_i, and A is a vector difference between wind directions in t_{i-1} and t_i. Eq. 9 is taken from ICAO Doc 9817, Chapter 2.4 [12]. If the speed of shear is between 15 to 30 knots, wind shear alerts will be generated. Severe wind shear alerts will be given when speed of shear is over 30 knots [10].

B. Chaotic Oscillatory-based Neural Networks (CONN)

i. System Framework of CONN

Chaotic Oscillatory-based Neural Networks (CONN) is the core part of the forecasting model. The structure of CONN (Eq. 10 and Fig. 6) is similar to MLP neural networks, but the major difference between them is the activation function of each neuron. Therefore, neural networks are more plasticity through using different kind of oscillators as activation function.

$$y_k = f_{lee}\left[\sum_j w_{kj} f_{lee}\left(\sum_i v_{ji} x_i\right)\right] \tag{10}$$

x_i are input values, y_k are output values, weights connected between input layer unit i and hidden layer unit j are denoted by v_{ji}, and weights connected between hidden layer unit j and output layer unit k are designated as w_{kj}. f_{lee} are Lee Oscillators (Retrograde Signalling) models with different optimal values in system parameters. f_{lee} replace hyperbolic tangent activation function in MLP neural networks.

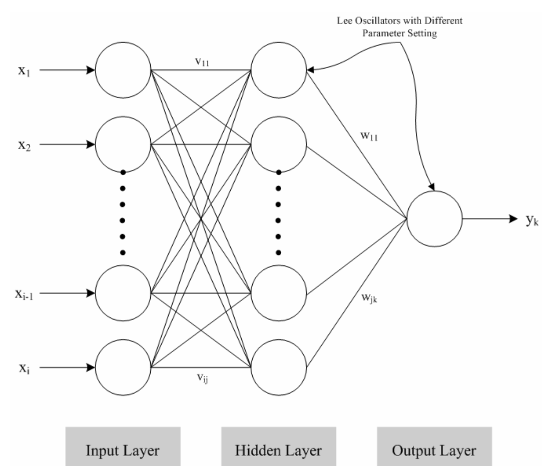

Fig. 6 System Architecture of Chaotic Oscillatory-based Neural Networks (CONN)

ii. Delta Rule for Weight Tuning in CONN

The Delta rule is part of back propagation learning algorithms in MLP neural networks. This rule calculates error gradients for each neuron and using them to adjust weighting values.

The Delta rule should be modified to cater for the CONN with different oscillators. This modification is pinpointed on chaotic regions in the oscillators so non-chaotic areas can use a normal derivative of hyperbolic tangent. In chaotic regions, a hyperbolic arc tangent is used to transform the input value in a hyperbolic tangent transfer function. The calculations are as follows:

$$d = \begin{cases} 1 - \tanh(\operatorname{atanh}(z))^2 & \text{If } \textit{value of } I \text{ is within chaotic region} \\ 1 - \tanh(I)^2 & \text{Otherwise} \end{cases} \quad (11)$$

where d is a delta value, I is an input value to the oscillator model and z is an output value from the model. The *atanh* is a hyperbolic arc tangent function and *tanh* is a hyperbolic tangent function. Figs. 7 and 8 show the plot of a derivative of type A and B oscillators, x axis represents values *atanh(z)* and y axis represents values d.

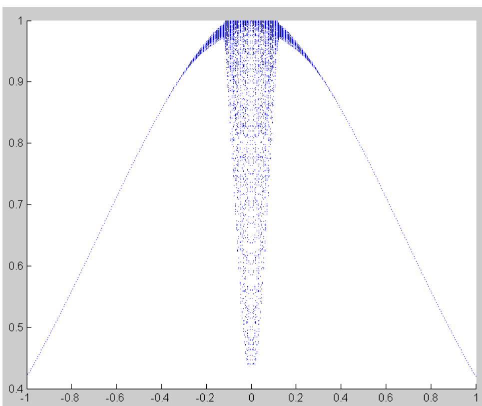

Fig. 7 Plot of Derivative of Type A Lee Oscillator (RS)

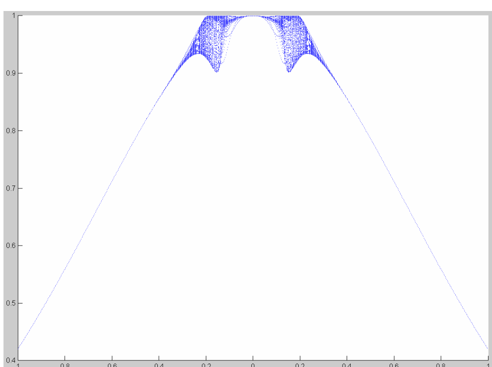

Fig. 8 Plot of Derivative of Type B Lee Oscillator (RS)

iii. Selecting System Parameters in CONN

The central nervous system (CNS) and the peripheral nervous system (PNS) are formed by different types of neurons with different functionalities, such as multipolar neurons, bipolar neurons and unipolar neurons [8]. The formation and development of neural networks can be affected by semaphorins and their receptors [14]. We tried to make use of these findings to develop chaotic neural networks in a different way. A neural network can use different oscillators in every neuron to enhance the abilities of traditional neural networks. Therefore, we built up a CONN structures for predicting Cartesian velocity component values – U (Eastward wind velocity) and V (Northward wind velocity). The structure (Fig. 9) shows four types of oscillators *A, B, C* and *D* which are equally distributed in two hidden layers, then Type *A* oscillators are placed in output layer for velocities forecasts. The parameters of these oscillators are shown in Table I and its bifurcation diagrams are shown in Appendix A1 to A4.

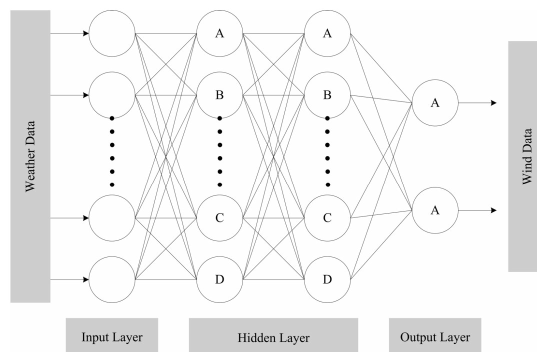

Fig. 9 Lee Oscillator (RS) Allocation in CONN for Wind Speed Forecasting

Table I
Optimal Parameter Set Used in the CONN

Parameters	Lee Oscillator (RS) Type A	B	C	D
a_1	0.6	1	0.55	1
a_2	0.6	1	0.55	1
a_3	-0.5	1	-0.5	1
a_4	0.5	1	0.5	1
b_1	-0.6	-1	-0.55	-1
b_2	-0.6	-1	-0.55	-1
b_3	-0.5	-1	0.5	-1
b_4	0.5	-1	-0.5	-1
k	50	50	50	300
θ_u	0	0	0	0
θ_v	0	0	0	0

The reason to implement such settings is intended for evaluating the plasticity of using different oscillators in neural networks. Experimental results showed that these structures perform better than just using only one type of oscillators in whole CONN. We assumed that the fluctuation power is too strong or too weak when using single parameter setting in CONN. If using in this way, the oscillation can be balanced. Further research is still ongoing to find out the characteristics of chaotic oscillators with different parameters, to counteract and complement chaotic oscillators in CONN, and to discover how best to construct and arrange chaotic oscillators to solve problems in different domains.

IV. EXPERIMENTAL RESULTS

This section compares prediction results between Chaotic Oscillatory-based Neural Networks (CONN) and ANN with hyperbolic tangent activation function. It is intended as an aid to understanding which model is more suitable for generating wind shear warnings. Wind data for testing was recorded by an anemometer located on west of runway (rw) in JIA at 19 Nov 2005, 0940hrs UTC.

A. *Performance Measurement*

i. U and V Components Forecast

Forecasting results of U – V wind speed components, and the resultant speed are shown in Fig. 10, Fig. 11, Fig. 12 respectively. They are compared with corresponding actual measurement. We found that CONN was able to track along with actual wind speed in U components quite accurately, especially on significant and rapid wind changes. Relatively speaking, ANN provided a range bound volatility.

The predicted U and V values are transformed back to wind speed and direction values respectively for Eq. 9 to calculate the speed of shear for performance measures. As mentioned before, shear speeds are used to generate a wind shear warning if the speed is between 15 knots and 30 knots and severe wind shear warning are issued if it is above 30 knots [10]. Performance measures focus on the correspondence between forecasts and observations, either on an individual or collective basis. Therefore, performance are measured using conditional probabilities such as hit rate (proportion of occurrences), false alarm rate (proportion of non occurrences that were incorrectly forecast), proportion correct (proportion in the whole sample of correct forecast of either hit or correct rejection) and false alarm ratio (proportion of forecasts of occurrence that followed by non occurrence) [15].

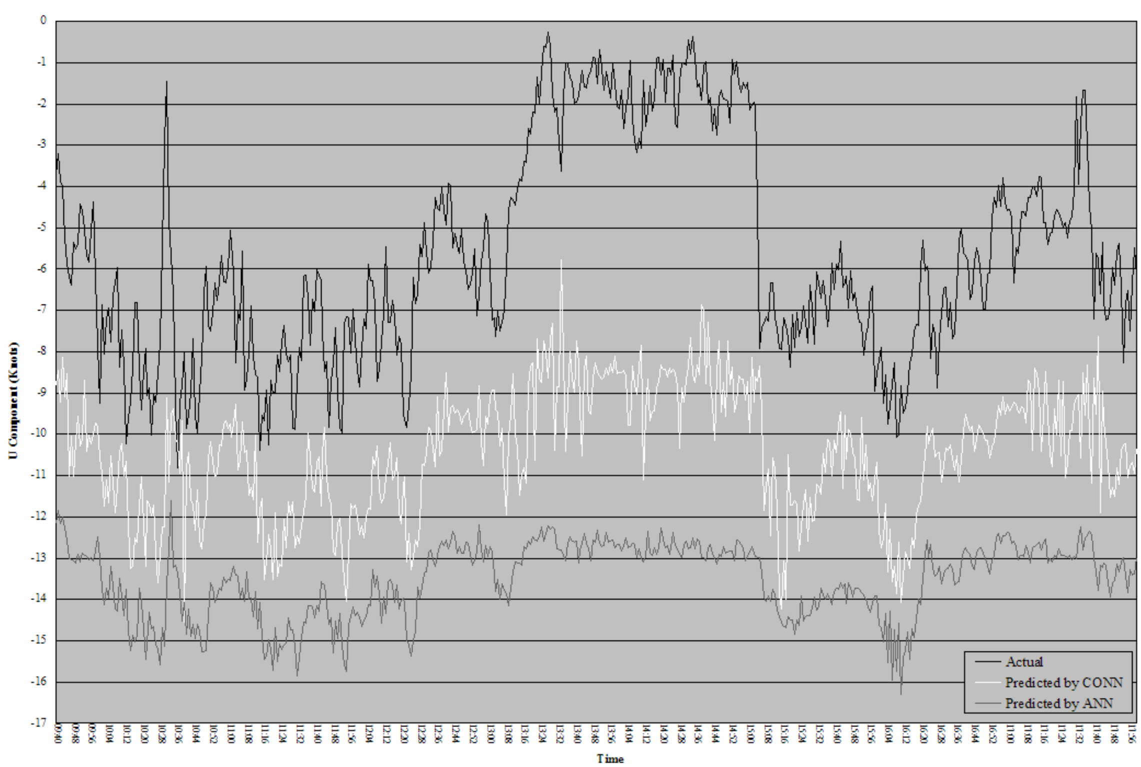

Fig. 10 U Component Forecast at 19 Nov 2005

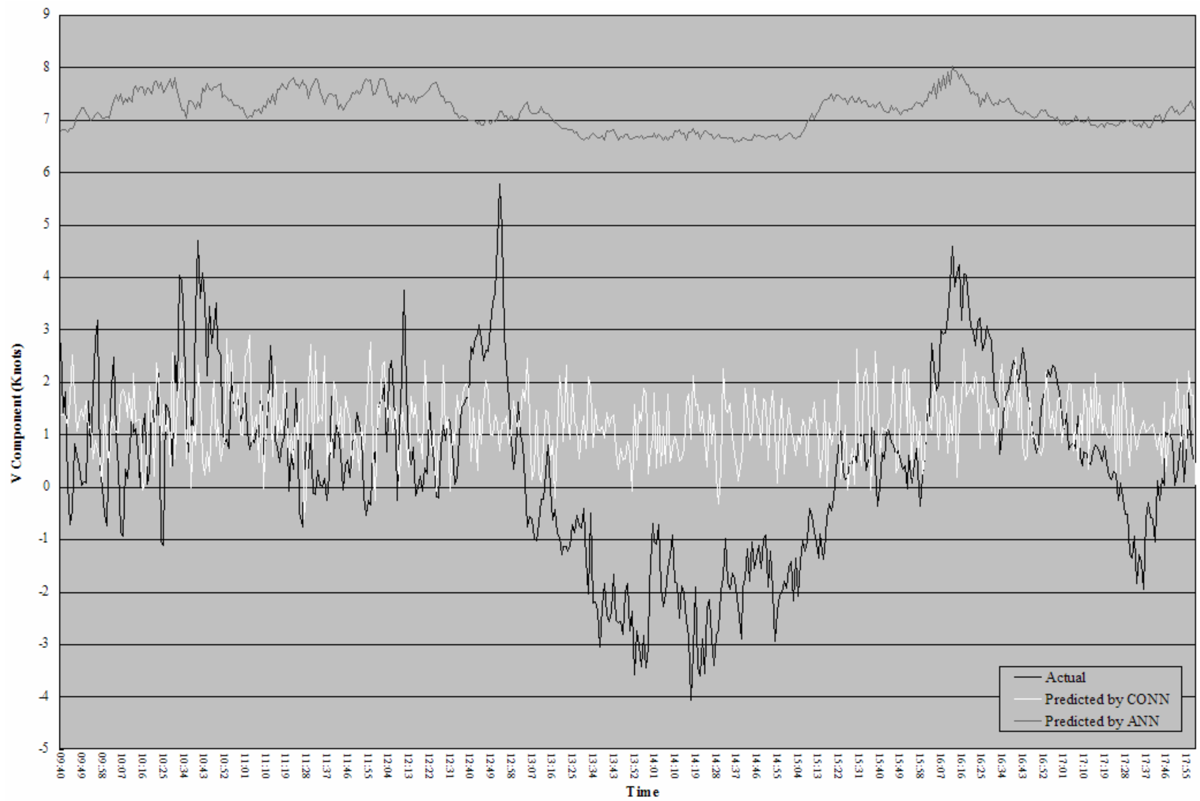

Fig. 11 V Component Forecast at 19 Nov 2005

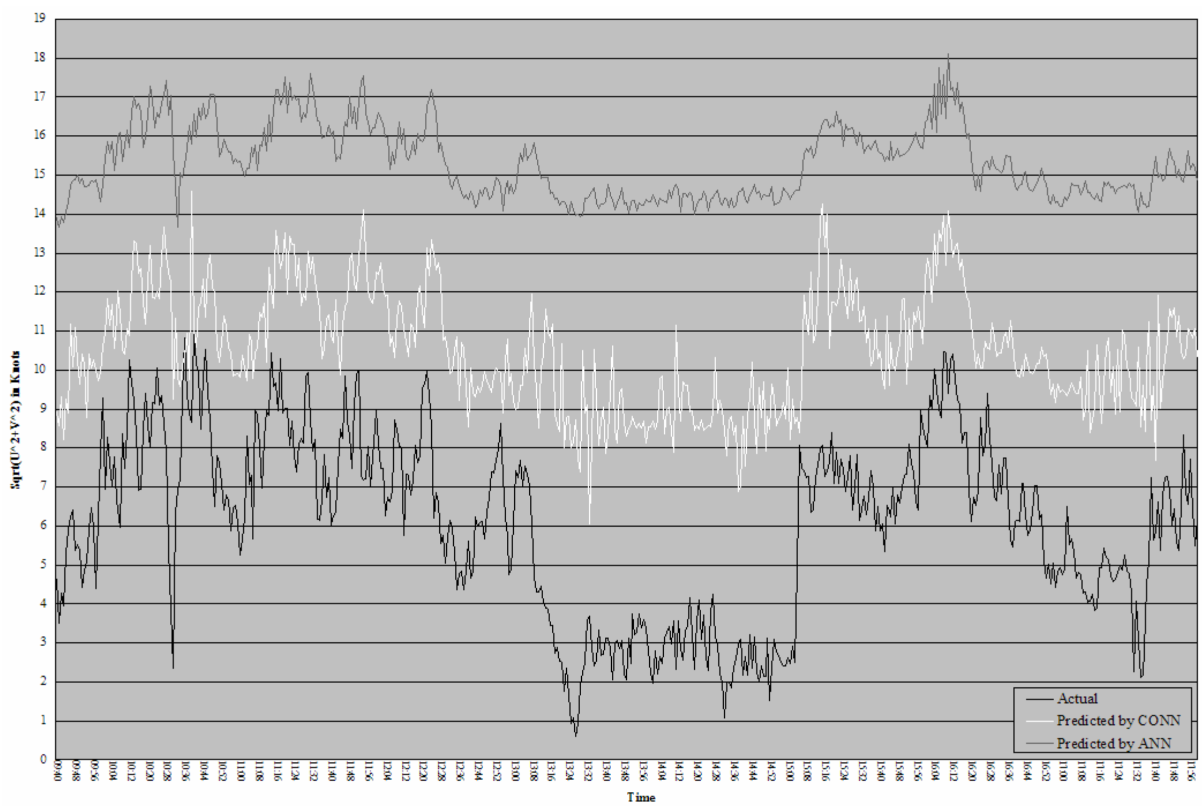

Fig. 12 U & V Resultant Forecast at 19 Nov 2005

ii. Analysis and Discussion

Table II
Performance Measures for CONN and ANN

	Wind Shear Alert	
Performance Measures	*Values for CONN*	*Values for ANN*
Hit Rate	0.7143	0.2143
False Alarm Rate	0.4770	0.0853
Proportion Correct	0.5390	0.8557
False Alarm Ratio	0.8790	0.8667

Table II shows performance measures on both methods, the hit rate of CONN is around 71.43% in wind shear warning, but ANN is 21.43%. We believe that CONN performs better in highly chaotic systems than traditional neural network models. On the other hand, the false alarm rate of CONN is also higher than ANN. This means CONN issues more false alarms than ANN. We assume that the optimal parameters of oscillators in CONN should not be in a set of constant values during the training and testing process, they should be tuned over a certain period of time, the evaluation mechanism and time duration for update require more investigation in future study.

V. CONCLUSION AND FUTURE WORK

Wind shear forecasting is a highly complex problem. It is totally different from predicting normal weather or stock market trends. This paper offers a preliminary study of a chaos-theory based approach to predicting wind speed and direction and triggering warning signals. The proposed method requires further improvement in terms of accuracy and learning. The Chaotic Oscillatory-based Neural Networks (CONN) and Lee Oscillator (Retrograde Signalling) models have the potential to handle complex problems and solve problems in other application domains, many of which are speculative, including cardiology, ecology, fluid dynamics or other types of severe weather forecasting.

Further research will focus on parameter tuning technique for each chaotic oscillator. Because different parameters could lead to different oscillation behaviors, we tried to pick different oscillation model to give better prediction results in CONN. We have already investigated the use of LIDAR wind data to generate prediction and comparing results with anemometer measurements. We believe that an accurate source can eliminate the effect of sensitivity to initial conditions. A study of how initial conditions can affect wind shear occurrences can be obtained from an ensemble weather forecast, using different initial conditions to generate all possible forecasts and improving the average forecast accuracy [19]. This is the basis of numerical weather prediction and also of wind shear forecasting.

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APPENDIX

X-axis represents *I(t)* and Y-axis are results of *z(t)* for following Bifurcation Diagrams.

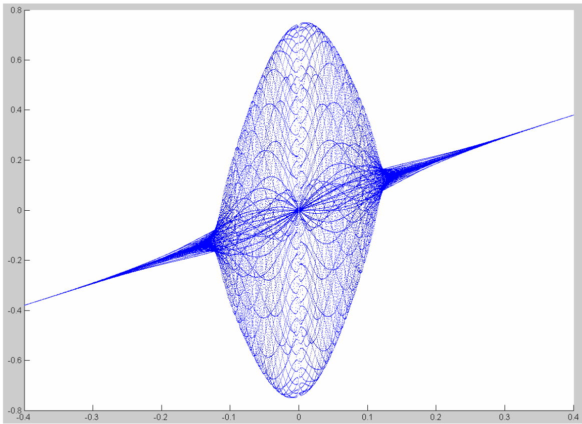

Fig. A1 Bifurcation Behavior (detailed part) of Type A Oscillator

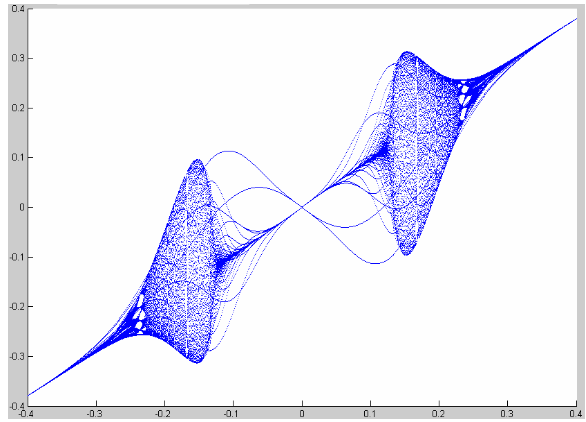

Fig. A2 Bifurcation Behavior (detailed part) of Type B Oscillator

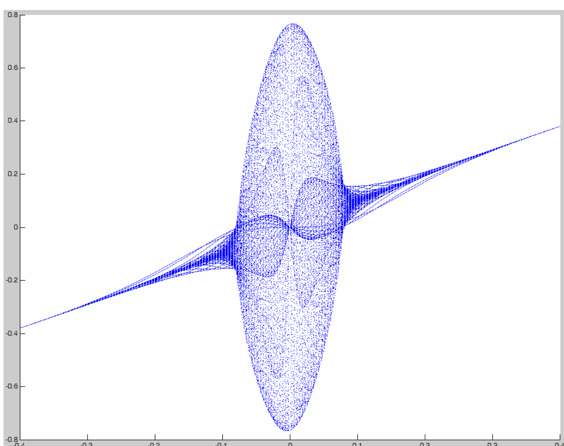

Fig. A3 Bifurcation Behavior (detailed part) of Type C Oscillator

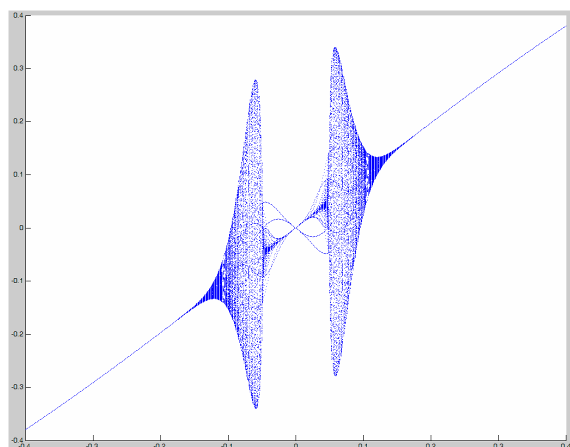

Fig. A4 Bifurcation Behavior (detailed part) of Type D Oscillator