Using LIDAR Doppler Velocity Data and Chaotic Oscillatory-based Neural Network for the Forecast of Meso-scale Wind Field

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Abstract—Current research based on various approaches including the use of numerical prediction models, statistical models and machine learning models have provided some encouraging results in the area of long-term weather forecasting. But at the level of meso-scale and even micro-scale severe weather phenomena (involving very short-term chaotic perturbations) such as turbulence and wind shear phenomena, these approaches have not been so successful. This paper focuses on the use of chaotic oscillatory-based neural networks for the study of a meso-scale weather phenomenon, namely, wind shear, a challenging and complex meteorological phenomena which has a vital impact on aviation safety. Using LIDAR data collected at the Hong Kong International Airport via the Hong Kong Observatory, we are able to forecast the Doppler velocities with reasonable accuracy and validate our prediction model. Preliminary results are promising and provide room for further research into its potential for application in aviation forecasting.

I. INTRODUCTION

Wind shear and turbulence are weather phenomena that may adversely affect aircraft operations. Wind shear refers to a change in the wind direction and speed for typically 3 to 40 seconds resulting in a sustained change in the headwind to the aircraft. A decrease in headwind will result in decreased lift and this will lead to the aircraft not rising to its planned flight path [1]. Turbulence is caused by the rapid, irregular motion of air and can cause an aircraft to bump and jolt. In cases of severe turbulence, abrupt changes in the altitude and attitude of the aircraft may result in momentary loss of control and possibly even injuries to passengers and flight crew [1].

The Hong Kong International Airport (HKIA) was built on an artificial island located north of mountainous Lantau Island, which has peaks rising to nearly 1,000 meters adjacent to valleys as low as 400 meters. North-east of HKIA there are also a number of smaller hills with peaks rising to 600 m (see Fig. 1). In this hilly, coastal environment, a wide variety of weather phenomena can cause low-level wind shear and turbulence [2]. Since the opening of HKIA in July 1998, meteorological studies have been conducted to support the safety of aircraft landing and taking off, including the detection of wind shear and turbulence.

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Since the opening of HKIA, about 1 in 500 arriving and departing flights reported significant wind shear, i.e. headwind change of 15 knots or more. Over the same period, around 1 in 2,000 flights reported significant turbulence, viz. moderate or severe turbulence. A majority of these events were reported in the spring, around March and April. [1] To improve the detection of wind shear under rain-free conditions, a Light Detection And Ranging (LIDAR) system was installed at HKIA in mid-2002. It is the first such system of its kind in the world to be used in providing weather alerts to an operational airport. The data it collects has been put to good use in detecting occurrences of wind shear with high accuracy, [3] but there has been little research into the prediction of wind shear.

II. LITERATURE REVIEW

In this paper we describe our research using accurate Doppler velocities measured by LIDAR at HKIA. Our focus is the prediction of the evolution of the wind field around the area of HKIA and wind motion along the glide path by combining the LIDAR data with Chaotic Oscillatory-based Neural Networks. Section II introduces these ideas through a literature review; Section III presents the system architecture and methodology; Section IV presents the experimental results and comparison; Section V provides our conclusion.
the original version of the Lee Oscillator and then the enhanced version to be used in this work - the Retrograde Transport Modeling.

A. Different methods of wind shear prediction

The Lincoln Laboratory of Massachusetts Institute of Technology (MIT) has proposed an algorithm for predicting types of wind shear that are caused by microbursts. It uses machine intelligence techniques to determine Terminal Doppler Weather Radar (TDWR) images in different time sequences, with detection probability of 72% and false alarm rate of 27% for the unrestricted prediction mode, i.e. when the microburst prediction algorithm is considered independent of the microburst detection algorithm [4]. This is quite a long way far from its target false alarm rate of 10% and would in any case not be suitable for use at HKIA, where most wind shear and turbulence is caused not by microbursts but by strong winds blowing across the hills over Lantau Island to the south of the airport, including winds associated with the passage of tropical cyclones and strong monsoons [1].

B. Chaotic Oscillatory-based Neural Network (CONN)

The idea of chaotic neural network was proposed by Aihara, Takabe and Toyoda in Physics Letters A [5]. They stated that real neuron operations in neurophysiology are far more complex than simple thresholds. Holding that a non-linear output function is a more suitable activator of a neuron, they developed a chaotic neural network to model the non-linear behavior of neurons.

Chaotic behavior provides a rich library of behaviors to aid computer systems. Neural networks mimic the flexibility of biological systems and offer just as wide a range of potential applications. Scientists have started using neural network architectures and learning algorithms using chaos for the storage in memory of analog patterns, for example in face recognition systems. Chaotic neural networks may be applied to prediction and control or to better understand a biological neural network, such as the role of chaos in brain activities.

The system architecture of most chaotic neural network models are based on the computational neuroscience models developed from the theoretical work of Hodgkin and Huxley [9]. These computational neuroscience models focus on spiking neural dynamic behavior. The main stream of neuroscience has focused on the behavior of the neural populations. Celebrated models include the neural oscillatory model proposed by Wilson and Cowan in 1972 [10], who described the behavior of the neurons as interactive triggering between the excitatory and inhibitory neurons. This theory has also formed the basis of many subsequent studies and models in the field of cognitive information processing [11] and on the synchronization and desynchronization behaviors of the neural oscillators. The latest applications include pattern and memory associations, scene analysis, and pattern recognition.

C. The Lee Oscillator (LeeOsc)

Research on neuroscience and brain science in recent years has discovered that there are various chaotic phenomena in brain functions [5] and behaviors of neurons are inactivated by triggering between excitatory and inhibitory neurons. Based on this, AI scientists have developed artificial neural networks such as Chaotic Oscillatory-based Neural Networks to simulate human neural behavior. One of these models is the Lee Oscillator (see Fig.2).

The 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:

\[ u(t+1) = f(a_1 \cdot u(t) - a_2 \cdot v(t) + I(t) - \theta_u) \]  
\[ v(t+1) = f(b_1 \cdot u(t) - b_2 \cdot v(t) - \theta_v) \]  
\[ w(t+1) = f[I(t)] \]  
\[ z(t) = f[u(t) - v(t)]e^{-\beta z(t)} + w(t) \]

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 hyperbolic tangent function; $a_1$, $a_2$, $b_1$ and $b_2$ are the weight parameters for these constitutive neurons; $\theta_u$ and $\theta_v$ are the thresholds for excitatory and inhibitory neurons; $I(t)$ is the external input stimulus; and $k$ is the decay constant.

Fig. 2 Model of the Lee Oscillator [7]

D. The Improved Lee-Oscillator

An improved Lee Oscillator has been developed that is modeled on the retrograde transport mechanism in axons, known as axonal transport or axoplasmic flow [9]. Retrograde transport stands in opposition to anterograde transport. Anterograde transport [7] is the phenomenon where a cell body moves towards terminals or dendrites as part of the process of supporting axons, which cannot synthesize proteins. To compensate for this, receptors, which are signaling proteins and enzymes for the synthesis of neurotransmitter must be moved to distant axon terminals or dendrites. In contrast, retrograde transport moves materials back to the soma. There are two hypotheses as to the function of this: recycling and signaling. Recycling suggests materials are returned from the terminal to the soma for degradation or
reuse. Signaling assumes that postsynaptic cells can secrete substances to be picked up by terminal through vesicles and carried back to the cell body [7].

\[
\begin{align*}
    u(t+1) &= f[a_1 u(t) - a_2 v(t) + a_3 z(t) + a_4 I(t) - \theta] \\
    v(t+1) &= f[b_1 z(t) - b_2 u(t) - b_3 v(t) + b_4 I(t) - \theta] \\
    w(t+1) &= f[I(t)] \\
    z(t) &= f[v(t) - u(t)] e^{-g^2(t)} + w(t)
\end{align*}
\]

(5) (6) (7) (8)

The Improved Lee Oscillator (Retrograde Transport) model takes into account these changes by implementing the following four changes.

1. The recycling concept of the axon’s retrograde transport is implemented by reusing the value of \(z(t)\) in both the excitatory (Eq. 5) and inhibitory neurons (Eq. 6).
2. \(I(t)\) is imported into Eq. 6. This is because incoming signals should also be considered in inhibitory neuron.
3. Switching \(v(t) - u(t)\) from \(u(t) - v(t)\) in Eq. 8. The modified approach presynaptic inhibition, a neurotransmitter releases mechanism in which the responses of an excitatory neuron are suppressed before any stimulus reaches synaptic terminals mediated by an inhibitory neuron. [8]
4. New parameters \(a_3, a_4, b_3, b_4\) were added in Eqs. 5 & 6. The rationale for this is that every variable should have its own parameter for adjusting outcomes.

Three advantages flow from these amendments to the model. First, they make it easier to reshape the chaotic region. Second, it is possible to generate dual chaotic regions generated by tuning different parameters. Finally, it requires only one-tenth of the number of rations to generate chaotic regions (see Fig. 3).

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. System architecture

Data preparation subsystem

The data preparation subsystem collects data from the output of LIDAR system. It has six to seven major functions, depending on the different predictions that it is to make. The following consider two types of prediction.

For predicting the evolution of the wind field around the area of HKIA

1. Converts the binary coded LIDAR Doppler velocity data to decimals
2. Fits the decimal Doppler velocities data to a grid map
3. Repairs the missing decimal Doppler velocity data
4. Normalizes the repaired decimal Doppler velocity data
5. Transforms the Doppler velocity data located on the same coordinates into time series
6. Splits up the time series
7. Groups the split time series of data point being predicted and the surrounding points into a training set and a testing set for the Chaotic Oscillatory Based Neural Network (Fig. 4).

For predicting wind motion along the selected glide path at HKIA

1. Converts the binary coded LIDAR Doppler velocity data to decimals
2. Picks the decimal Doppler velocities data located along the selected glide path
3. Removes the points that contain missing data
4. Sorts the Doppler velocity data into time series
5. Normalizes the sorted decimal Doppler velocity data.
6. Splits up the time series into training data set and testing data set for the Chaotic Oscillatory Based Neural Network

**Chaotic Oscillatory Based Neural Network**
The Chaotic Oscillatory Based Neural Network (CONN) is the core part of this Doppler velocity prediction system. It is made up of a Multi-Layered Perceptron (MLP) Neural Network and a LeeOsc (Retrograde Transport) with different sets of parameter settings. The MLP neural networks constructed by one or two hidden layers with seven neurons, and the transfer function of the neurons will be LeeOsc (Retrograde Transport). The following sections will introduce the training and testing of CONN and the Delta Rule for CONN.

a. Training and testing of CONN
The neural network is trained using a back propagation learning algorithm and a momentum term is used to speed convergence and avoid local minima [5]. The network is trained using two hours of Doppler velocity data. CONN will be trained around 100 times (epochs), and 30 minutes of progressive (Doppler of velocity) data is used as input to predict the output one time step ahead. The process is repeated for the following time step and so on.

b. Delta Rule for CONN
The Delta rule is part of the back propagation learning algorithm used in the MLP neural network. This rule calculates error gradients of each neuron and uses these error gradient values to adjust weighting values. The delta rule should be modified to suit different parameter settings in the LeeOsc (Retrograde Transport). This modification pinpoints chaotic regions of the LeeOsc (Retrograde Transport) so that non-chaotic areas can use a normal derivative of a hyperbolic tangent function. In chaotic region, an inverse hyperbolic tangent is used to simulate the input value in hyperbolic tangent function. In chaotic region, an inverse hyperbolic tangent is used to simulate the input value in hyperbolic tangent function. In chaotic region, an inverse hyperbolic tangent is used to simulate the input value in hyperbolic tangent function. In chaotic region, an inverse hyperbolic tangent is used to simulate the input value in hyperbolic tangent function.

\[
d = \begin{cases} 
1-\tanh(\tanh(z))^2 & \text{if } I \text{ is in chaotic region} \\
1-\tanh(I)^2 & \text{otherwise} 
\end{cases} 
\]  

(9)

The LeeOsc (Retrograde Transport) can use two different parameter settings. Neurons use both settings in hidden layer alternately and just one in the output layer.

The reason for using two parameter settings in the LeeOsc (Retrograde Transport) is that the oscillation of single setting in CONN model maybe too strong or too weak. By mixing a parameter setting with a strong oscillation and a parameter setting with a weak oscillation allows us to balance the power of the oscillation.

**Visual display program**
The visual display program allows the predicted Doppler velocities to be displayed in the form of picture rather than a list of real numbers.

**B. Methodology**
This study applies chaos theory to forecasting a meso-scale wind field by using a model that combines a Chaotic Oscillatory-based Neural Network (CONN) with a Chaotic Oscillator model. We intend to extend the forecast to the wind motion around HKIA with the use of the data measured by LIDAR System in HKIA rather than merely a single point measurement, e.g. by using a surface anemometer located near the runway. The following describes data preparation first in general and then specifically for predicting wind evolution and wind motion.

**Data Preparation**
Since local air density, local temperature variations, local effects of cloud and rain are difficult to measure [11] [please check if this is reference 11] and LIDAR can only measure the Doppler velocities, we used Doppler velocity data derived from 1-degree elevation angle scans. They are first processed with the quality control algorithm. If there was no data for a particular location in the surveillance scan data and if valid velocity data are available at the neighboring positions, we derived its velocity value through a linear interpolation of the velocities at the neighboring points.

The training and testing data set were normalized by using minimum (-1) - maximum (+1) normalization before training and testing.

**Data used to predict wind evolution of the wind field**
Each set of training data included a number of normalized Doppler velocity data of 25 points (one was the data point being predicted and others were the surrounding data points) on the grid in time series. Each time series included 5 time slots at 6 minute intervals (totaling half an hour).

**Data used to predict wind motion along a glide path**
Each set of training data referred to the glide path 07RA at a specific time. It included the Doppler velocities on a slant range, angle of elevation and azimuth. These were used to train the result of the Doppler velocities along the glide path 07RA in the upcoming three minutes. The time interval between two training sets was around 4 minutes.

**Training and testing of the CONN**
The neural network is trained with the result of subsequent intervals and it learns from the root mean square error between the predicted result and the measured value from the
LIDAR through back propagation. In the testing process, the neural network uses the experience gained in the training process to generate the forecast for the next time interval(s).

Fig. 5 shows the structure of the CONN. The input nodes of the neural network represent patterns of wind motion, while the output nodes represent the forecast of patterns of wind motion in the next time frame. There is one hidden layer and it used several neurons. The number of hidden layers and hidden neurons were chosen experimentally since there is no simple clear-cut method for determination of these parameters [12]. Characters A and B in the neurons indicate different parameter settings used with the LeeOsc (Retrograde Transport) Model as discussed in Section IIB and C. These parameters were chosen experimentally. Fig. 6a and 6b show the Bifurcation Diagrams of LeeOsc (Retrograde Transport) Model with Parameter sets A and B.

IV. EXPERIMENTAL RESULTS

Prediction wind evolution of the wind field

Wind shear and turbulence events at HKIA are associated with strong winds blowing across the hills over Lantau Island to the south of the airport. In this test of the CONN method we study the emergence of mountain wake flow (i.e. decelerated flow with possibly reversal of wind direction relative to the prevailing wind) to the southwest of HKIA on 20 July 2006. As Artificial Neural Network (ANN) require more computer time than statistical models [13] and due to the large amount of data and limitations on computing power, we carried out the training process on the CONN using data from the last two hours only.

A. Forecasting for 6 minutes

After training with the two-hour data, the neural network forecasts the future distribution of the radial velocity by using the data of the latest 30 minutes. To remove computational noise from the neural network in the individual forecasts, the system makes a total of 15 forecasts of the wind field in the next 6 minutes. The two extreme wind forecasts are removed and the remaining 13 velocity values are averaged to give the final forecast. Such 6-minute nowcasting of the wind field would be useful in the detection of rapidly changing wind phenomena such as wind shear and turbulence.

The forecast results are shown in Fig. 7. The forecast at time 10:11:59 UTC is based on the data between 09:36 and 10:06 UTC, the forecast at 10:17:54 UTC is based on the data between 09:42 and 10:12 UTC, and so on. The forecast wind field basically captures the occurrence and the northward expansion of the mountain wake to the southwest of the airport, i.e. the area of lighter wind (grey in the wind distribution diagrams) with reverse flow (green) against the prevailing easterly wind (i.e. away-from-the-LIDAR wind, brown).

B. Forecasting for 30 minutes

Again, we train the neural network using data from the last two hours. The neural network forecasts the distribution of the radial velocity by using the data of the latest 30 minutes.

To remove computational noise from the neural network in the individual forecasts, the system makes a total of 15 forecasts. The two extreme wind forecasts are removed and the remaining 13 forecasts are averaged to give the final forecast. Such short-term forecasting of the wind for the next 30 minutes would be useful in runway operations, e.g. switching of the runways for aircraft landing/departing, which requires that the direction of aircraft movement should be opposite to the low-level wind direction in order to get the lift.

The results of the neural network prediction are shown in Fig. 8. The forecast between 10:01:05 and 10:23:20 UTC is based on the data between 09:24 and 09:54 UTC. Though the reverse flow area (green) is more extensive in the forecast compared to the actual observations, the neural network could capture the trend of the occurrence and the northward
expansion of the mountain wake to the southwest of the airport.

The forecasting of 30-minute wind fields would take longer to compute because the neural network would have to be trained to establish the correlation between the wind fields in the last 30 minutes with those in the following 30 minutes.

Prediction wind motion along a glide path at HKIA

Focusing on wind motion along the glide path and the causes of wind shear at the HKIA, we chose to study a sea breeze from 28 October 2007. We chose this because, on the one hand, LIDAR works best in fine weather, yet on the other, sea breezes, which usually develop in fine weather and light wind conditions, are one of the major causes of wind shear at HKIA [1]. Further, it is easy to identify the movements of sea breezes.

Fig. 9 presents the actual LIDAR measurement of the radial wind velocity along the glide path 07RA between 28 October 2007 02:03 UTC and 02:59 UTC. The x-axis is the distance away from the end of the runway in nautical miles. The y-axis is the wind velocity in meters per second. Colored lines indicate LIDAR observations along the glide path. In Fig. 9, the sea breeze enters the glide path 07RA at 1.6 NM from the end of the runway at 02:29 UTC. Later on, the area affected by sea breeze extended to 0.8 NM away from the runway end at 02:59 UTC.

In this experiment, a training set is constructed from the data recorded between 24 October 2007, 00:00:00 (UTC) and 28 October 2007, 02:00:00 (UTC) and a testing set is constructed from the data recorded between 28 October 2007, 02:00:00 (UTC) and 28 October 2007, 03:00:00 (UTC).

After training, the neural network forecasts the future distribution of the radial velocity by using the data about the latest wind profile along the glide path. The forecast at time 02:03 UTC is based on the data 02:01 UTC, while the forecast at 02:07 UTC is based on the data 02:03 UTC, and so on.

Fig. 10 and Fig. 11 show the forecast of the wind profile along the glide path 07RA made using a traditional MLP neural network and CONN. Both can capture the occurrence and the movement of the sea breeze. However, the forecasts generated by the MLP neural network are so smooth that they fail to describe the wind profile, while the forecast from CONN seems a little bit noisy.

To remove computational noise from the neural network in the individual forecasts, we do as follows:

1. We make a total of 15 forecasts of the wind field in the following 3 minutes and take their average.
2. We make a total of 15 forecasts of the wind field in the following 3 minutes, remove two extreme wind forecasts and take the average of the remaining 13 velocity values.
3. We make a total of 15 forecasts of the wind field in the following 3 minutes and take their median.

The results of these three methods are shown in Fig. 12, 13 and 14. Apart from capturing the occurrence and the movement of the sea breeze, they are less noisy.

Table 1 shows the average of RMSE and the correlation coefficient for the actual LIDAR observation and the forecast generated by MLP neural network and CONN. The CONN with an average of 15 trials has the best performance in the correlation coefficient, with the RMSE comparable to MLP neural network.

Table 2 compares forecasting the wind field around HKIA and forecasting wind profile along a glide path at HKIA. The forecast for the glide path produces better results in both computational time and RMSE against time.

V. CONCLUSION AND FUTURE WORK

Using the LIDAR’s Doppler velocity data from Hong Kong Observatory, we have conducted research on the prediction of the meso-scale wind field. Preliminary experiments show interesting results and CONN appears to be able to capture the occurrence and evolution of mountain wake in the vicinity of the Hong Kong International Airport. Further research is needed to optimize the computational process, learning algorithm and predictive capability. Our further work will focus on the winds along the glide paths rather than the whole scanning sector of the LIDAR as a potential way to capture the major features of the wind fluctuations while minimizing the requirement for computational resources.

REFERENCES


Fig. 7: Actual LIDAR observations separated by 6-minute interval (left) and the corresponding 6-minute forecast by CONN (right)

<table>
<thead>
<tr>
<th>Time (UTC)</th>
<th>Actual LIDAR observations</th>
<th>Forecast by CONN</th>
</tr>
</thead>
<tbody>
<tr>
<td>10:11:59</td>
<td><img src="image1" alt="Actual LIDAR observation" /></td>
<td><img src="image2" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:17:54</td>
<td><img src="image3" alt="Actual LIDAR observation" /></td>
<td><img src="image4" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:23:20</td>
<td><img src="image5" alt="Actual LIDAR observation" /></td>
<td><img src="image6" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:28:48</td>
<td><img src="image7" alt="Actual LIDAR observation" /></td>
<td><img src="image8" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:34:43</td>
<td><img src="image9" alt="Actual LIDAR observation" /></td>
<td><img src="image10" alt="Forecast by CONN" /></td>
</tr>
</tbody>
</table>
Fig. 8: Actual LIDAR observations separated by 6-minute interval (left) and the corresponding 30-minute forecast by CONN (right)

<table>
<thead>
<tr>
<th>Time (UTC)</th>
<th>Actual LIDAR observations</th>
<th>Forecast by CONN</th>
</tr>
</thead>
<tbody>
<tr>
<td>10:01:05</td>
<td><img src="image1" alt="Actual LIDAR Observations" /></td>
<td><img src="image2" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:06:31</td>
<td><img src="image3" alt="Actual LIDAR Observations" /></td>
<td><img src="image4" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:11:59</td>
<td><img src="image5" alt="Actual LIDAR Observations" /></td>
<td><img src="image6" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:17:54</td>
<td><img src="image7" alt="Actual LIDAR Observations" /></td>
<td><img src="image8" alt="Forecast by CONN" /></td>
</tr>
<tr>
<td>10:23:20</td>
<td><img src="image9" alt="Actual LIDAR Observations" /></td>
<td><img src="image10" alt="Forecast by CONN" /></td>
</tr>
</tbody>
</table>
Fig. 9: Actual LIDAR observations separated by 6-minute interval (left) and the corresponding 30-minute forecast by CONN (right) [please remove the thick black curve]

Fig. 10: The forecast result made by MLP neural network along the glide path 07RA between 28 October 2007 02:03 UTC and 28 October 2007 02:59 UTC

Fig. 11: The forecast result made by CONN along the glide path 07RA between 28 October 2007 02:03 UTC and 28 October 2007 02:59 UTC

Fig. 12: The forecast result made by CONN along the glide path 07RA between 28 October 2007 02:03 UTC and 28 October 2007 02:59 UTC with taking the average of 15 trials.
FIG 13: The forecast result made by CONN along the glide path 07RA between 28 October 2007 02:03 UTC and 28 October 2007 02:59 UTC that averaged with the remaining 13 velocity values by removing the two extreme wind forecasts.

FIG 14: The forecast result made by CONN along the glide path 07RA between 28 October 2007 02:03 UTC and 28 October 2007 02:59 UTC with displaying the median of 15 trials.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>MLP Neural Network</th>
<th>CONN (Single trial)</th>
<th>CONN (Average of 15 Trials)</th>
<th>CONN (Averaged with removing the two extreme)</th>
<th>CONN (Median of 15 Trials)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.079904</td>
<td>0.103628</td>
<td>0.084404</td>
<td>0.084503</td>
<td>0.085545</td>
</tr>
<tr>
<td>Correlation coefficient</td>
<td>0.792748</td>
<td>0.684286</td>
<td>0.794531</td>
<td>0.790169</td>
<td>0.779514</td>
</tr>
</tbody>
</table>

* indicates the best performance

Table 1: The comparison of the average of RMSE and correlation coefficient between the actual Lidar observation and the forecast generated by MLP, neural network and CONN.

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Forecast of the whole area</th>
<th>Forecast along the glide path</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computational time</td>
<td>Longer</td>
<td>Shorter*</td>
</tr>
<tr>
<td>RMSE after 12 mins</td>
<td>0.09410335</td>
<td>0.065118*</td>
</tr>
<tr>
<td>RMSE after 23 mins</td>
<td>0.11079297</td>
<td>0.064375*</td>
</tr>
<tr>
<td>RMSE after 34 mins</td>
<td>0.12110289*</td>
<td>0.150031</td>
</tr>
<tr>
<td>RMSE after 51 mins</td>
<td>0.13549476</td>
<td>0.113208*</td>
</tr>
<tr>
<td>Average</td>
<td>0.11537349</td>
<td>0.098183*</td>
</tr>
</tbody>
</table>

* indicates the best performance

Table 2: The comparison between the forecasting result between the previous work and current work.