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RESEARCH ARTICLE

Ensemble forecast of tropical cyclone tracks based on deep neural networks

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Abstract A nonlinear artificial intelligence ensemble forecast model has been developed in this paper for predicting tropical cyclone (TC) tracks based on the deep neural network (DNN) by using the 24-h forecast data from the China Meteorological Administration (CMA), Japan Meteorological Agency (JMA) and Joint Typhoon Warning Center (JTWC). Data from a total of 287 TC cases over the Northwest Pacific Ocean from 2004 to 2015 were used to train and validate the DNN based ensemble forecast (DNNEF) model. The comparison of model results with Best Track data of TCs shows that the DNNEF model has a higher accuracy than any individual forecast center or the traditional ensemble forecast model. The average 24-h forecast error of 82 TCs from 2016 to 2018 is 63 km, which has been reduced by 17.1%, 16.0%, 20.3%, and 4.6%, respectively, compared with that of CMA, JMA, JTWC, and the error-estimation based ensemble method. The results indicate that the nonlinear DNNEF model has the capability of adjusting the model parameter dynamically and automatically, thus improving the accuracy and stability of TC prediction.

Keywords tropical cyclone track, deep neural network, ensemble forecast

1 Introduction

Tropical cyclones (TCs) can cause enormous damage to human lives and properties owing to severe flooding, destructive wind and coastal inundation from storm surges. The accurate forecast of TC track is essential for emergency responders to resist the influence of TCs effectively.

Traditional objective TC forecast techniques can be divided into three categories: dynamic numerical models, statistical prediction method and ensemble forecast technology. Dynamic numerical models use dynamic equations to achieve the forecast of TC tracks (Jeffries et al., 1993; Elsberry, 1995). With better understanding of TC dynamics and the development of computing powers, a variety of numerical models have been developed and widely applied for operational TC forecast such as the GRAPES (Global/Regional Assimilation and PrEdiction System) model developed at China Meteorological Administration (CMA) (e.g., Zhang and Shen, 2008), the GFS (Global Forecast System) model developed at National Centers for Environmental Prediction (NCEP) of the United States (e.g., Rappaport et al., 2009; Saha et al., 2014), the IFS (Integrated Forecasting System) model developed at the European Centre for Medium-Range Weather Forecasts (ECMWF) (e.g., Raddaway, 2012), and so on. With the application of advanced data assimilation techniques in numerical models, the accuracy of TC track prediction has been significantly improved (Elsberry, 1995; Hamill et al., 2011) and the 24-h forecast error is less than 90 km (Peng et al., 2017). However, these numerical models have different architectures, such as the representation of topography, data assimilation schemes, treatment of physics and dynamics, spatial resolutions, and initialization etc., which makes the forecast results have different deviations from the observations (Plu, 2011; Chen et al., 2013). In recent years, the improvement of TC track forecast accuracy has slowed down significantly, and some scientists believe that numerical models have reached a bottleneck (Landsea and Cangialosi, 2018).

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The statistical prediction models are usually based on the regression method, among which the Climatology and Persistance (CLIPER) model proposed by Neumann and Lawrence (1975) is considered to be the most classic one (Veigas, 1996; Knaff et al., 2007). The CLIPER model establishes the regression between the TC track and climatic persistence factors, such as the longitude and latitude of the TC center, the maximum wind speed and minimum air pressure in the past few hours. Although the demand for computing resources has reduced greatly, the forecast accuracy is usually worse than that of numerical models.

In the late 1960s and early 1970s, an ensemble forecast technology based on the initial value disturbance and mode disturbance was proposed by Epstein (1969) and Leith (1974). Since then, the technology has been widely used for predicting the tracks of TCs, wind field and sea surface temperature all over the world (Toth and Kalnay, 1997; Buizza et al., 1999; Leutbecher and Palmer, 2008; Buckingham et al., 2010; Li et al., 2019). However, this method requires a huge amount of computing resources. Later, Krishnamurti et al. (1999) and Zhi et al. (2011) proposed some kinds of multi-model ensemble method for predicting the wind field as the weighted average of the results from several independent numerical models. This method uses a weighted average formula to fit the complex relationships between different numerical model results. Yuan et al. (2017) improved the weighting method based on the error-estimation principle and developed an ensemble model for TC track forecast by using the historical forecast results from several forecast centers. The overall accuracy of the ensemble model has been increased, but the empirical parameter in this model needs to be determined first at each forecast time, which leads to some uncertainty and instability of the forecast results to some extent. In addition, the model cannot completely simulate the complex relationship between different forecast models due to its linearity.

Recently, neural networks, especially the deep neural networks (DNNs) have been applied to TC track prediction. Jin et al. (2015) and Zhu et al. (2016) used pure linear neural network (PLNN) and Bayesian neural network (BNN) to predict the 24-h TC track in the South China Sea, and the average forecast errors are 122.8 km and 125.4 km respectively. By inputting historical TC track data into a long-short-term memory (LSTM) model, Gao et al. (2018) achieved an accuracy of 105.7 km for TCs in the Northwest Pacific Ocean. Although the accuracy is not very high, these studies show that the neural networks have great potential in the fast prediction of TC tracks due to its high-speed computing performance.

The DNN is a feedforward neural network, which is inspired by the notion that a neuron's computation involves a weighted sum of the input values. The network can be viewed as consisting of numerous piecewise functions and is able to simulate complex nonlinear functions (Sze et al., 2017). It has achieved great success in applications of speech recognition, image recognition, time series prediction and other research fields (Krizhevsky et al., 2012; Deng et al., 2013; Silver et al., 2016; Esteva et al., 2017). In this study, we aim to develop a 24-h TC track forecast model by combining the ensemble technique with DNN, i.e., a DNN based ensemble model which integrates forecast results from several individual forecast centers. In this way, the nonlinear relationship between different forecast models can be learned effectively. We organize the paper as follow. Section 2 introduces the data set and methods. The results of our model will be presented and discussed in Section 3. Section 4 is the conclusions.

2 Materials and methods

2.1 Materials

The input data of the DNN based ensemble forecast (DNNEF) model are 24-h forecast results of TC tracks, i.e., the longitude or/and latitude of the TC center within the next 24 h, published every 6 h by CMA (available at CMA Tropical Cyclone Data Center website), Japan Meteorological Agency (JMA, available at Japan Meteorological Agency website) and Joint Typhoon Warning Center (JTWC, available at Naval Oceanographic Portal-Public Facing website) in the United States. The Best Track data provided by CMA (Ying et al., 2014) with a time interval of 6 h is used as the "ground truth data" for verification of the model.

Totally, we obtained 369 TC cases over the Northwest Pacific (NWP) Ocean from 2004 to 2018. Data for 287 TCs in the first 12 years are randomly divided into training and validation data sets at a ratio of 8:2, which are used for training the DNNEF model and preventing model overfitting, respectively. The remaining data between 2016 and 2018 (Fig. 1) are set as test data and used to evaluate the model performance. One can see from Fig. 1(a) that the TCs generated over the NWP Ocean travel on different paths. Some move to the west, some to the northwest, while others suddenly change their directions. As shown in Fig. 1(b), there are totally 28 abrupt turning TCs which turned more than 60° along the movement direction within 24 h according to the definition proposed by Wu et al. (2011).

2.2 Methods

A typical DNN model contains a combination of input layer, hidden layer and output layer. The hidden layer is used to simulate the complex nonlinear relationship between the input and output. According to the different input and output parameters, we designed three schemes

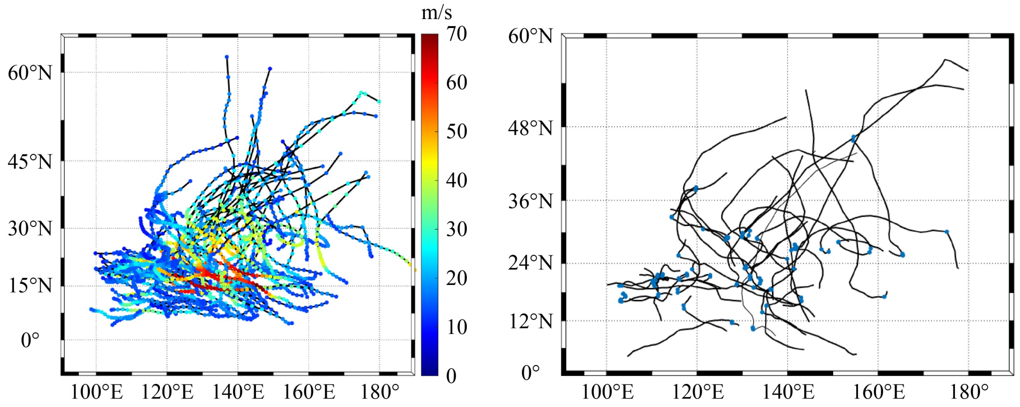

Fig. 1 (a) Tracks of TCs over the Northwest Pacific Ocean between 2016 and 2018. The colored dot represents the Saffir-Simpson TC intensity scale. (b) TCs with sudden track changes. The blue dot indicates where the TC suddenly changes its direction.

Table 1 The average 24-h TC track forecast error (km) of the DNNEF-CJJ model with different schemes between 2016 and 2018

Scheme	Input	Output	Error/km
A	Latitude Longitude	Latitude Longitude	64
B	Latitude & Longitude	Latitude Longitude	63
C	Latitude & Longitude	Latitude & Longitude	66

for TC track forecast, as shown in Table 1. Scheme A consists of two models which predict the longitude and latitude of the TC center, respectively, with the longitude or latitude information forecasted by CMA, JMA and JTWC as the model input. Scheme B also includes two models, but with both longitude and latitude forecast results from three centers as input in either the longitude or the latitude forecast model. Scheme C only contains one model, and the input of this model is the same as that in Scheme B, but the longitude and latitude are predicted at the same time.

Schemes A, B and C have the same architecture except for the different parameters in the input and output layers, which is shown in Fig. 2. Each DNNEF model consists of one input layer, two hidden layers, and one output layer. The activate function is “linear” in the output layer, and “sigmoid” in the other layers. The loss function is set as “mse.” Take the longitude forecast model in Scheme A as an example, with the 24-h forecast results of TC longitude from three forecast centers as the model input, the first hidden layer will establish 18 links between the three inputs and the six neurons. Then 24 links will be generated between the four neurons in the second hidden layer and the six neurons in the first hidden layer. Finally, four links are established between the second hidden layer and the output layer. In this way, the DNN model will learn a total of 62 parameters. As shown in Fig. 3, the model stops training when the loss of the training and validation data tends to be stable. The model with the lowest loss of the validation data is then retained as the model of the test data.

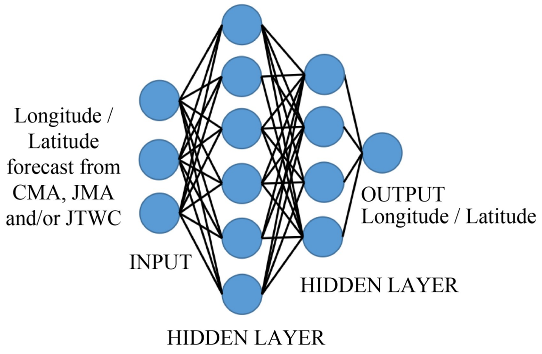

Fig. 2 Architecture of our DNNEF model for 24-h prediction of longitude or latitude of TC centers.

Since the TC track forecast results from JTWC are usually released later than CMA or JMA, we will also investigate how many models of input data are necessary for an accurate and efficient forecast in an DNNEF model by comparing the performance of our models which combines the forecast results from all the three forecast centers (DNNEF-CJJ model) and that from CMA and JMA only (DNNEF-CJ model).

3 Results and discussion

To evaluate the performance of the DNNEF model, the forecast error is presented as the distance D between the forecasted and observed TC centers, which is calculated as

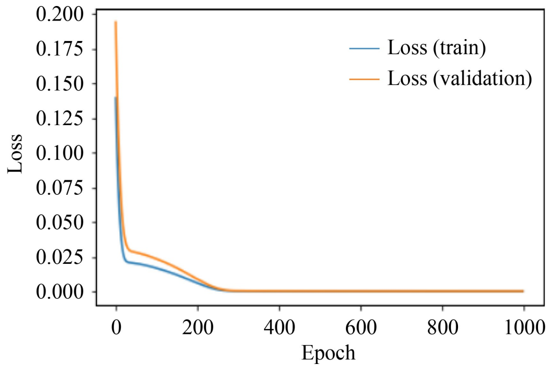

Fig. 3 Loss value in the training process.

$$D = R \times \arccos[\cos(Y_1) \times \cos(Y_2) \times \cos(X_1 - X_2) + \sin(Y_1) \times \sin(Y_2)], \tag{1}$$

where R is the radius of the earth; X_1 and Y_1 are the longitude and latitude forecasted by the model, respectively; X_2 and Y_2 are the observed longitude and latitude, respectively.

We also compared our model results with that from the error-estimation based ensemble forecast (EEF) model proposed by Yuan et al. (2017):

$$\vec{P}_i = \vec{P}_{0i} + k \times \vec{e}_i, \tag{2}$$

$$a_i = \frac{1/\left|\vec{e}_i\right|}{\sum_{i=1}^{N}(1/\left|\vec{e}_i\right|)}, \tag{3}$$

$$\vec{P}_e = \sum_{i=1}^{N} a_i \vec{P}_i, \tag{4}$$

where $\vec{P}_{0i}$ is the TC center position vector of the original forecast from the ith forecast center, including the longitude and latitude; $\vec{P}_i$ is the position vector of the corrected forecast value; k is the empirical parameter, $\vec{e}_i$ is the estimated deviation between the TC center position predicted by the ith forecast center and the real TC track; a_i is the weight coefficient of the forecast result from the ith center; N is the total number of the forecast centers; $\vec{P}_e$ is the final TC center position vector predicted by the EEF model.

Compared with Scheme A, when both latitude and longitude are input into the DNNEF model, the forecast result of Scheme B is slightly better (Table 1), indicating that the additional introduction of latitude (or longitude) into the model helps to improve the performance of the longitude (or latitude) forecast model. However, the result of Scheme C gets worse if the latitude and longitude forecast models are integrated into one model. One possible reason is that for a single latitude or longitude forecast model, we only need to adjust each model to the optimal configuration. The integration of the two models in Scheme C makes the problem more complicated and difficult to get better results based on the existing data.

As shown in Table 2 and Fig. 4, our DNN based ensemble forecast models in Scheme B have a higher accuracy than all the individual models of the forecast center or the EEF model for 24-h TC track prediction. Compared with CMA, JMA, JTWC and the EEF model, the average forecast error of the two DNNEF models both reduced by 17%, 16%, 20%, 5%, respectively. Although our DNNEF model only performs slightly better than the error-estimation based ensemble forecast model, it is more stable because there is no need to adjust the empirical parameters manually at each forecast time. In addition, the model can better simulate the complex nonlinear relationship between different numerical models.

If we compare the DNNEF-CJJ and DNNEF-CJ models, we can find that the 3-year average forecast errors of the two models are the same, although the former has additional input data from JTWC. In 2017, the accuracy of the DNNEF-CJJ model is even a little lower than the DNNEF-CJ model partly due to the relatively unstable forecast results of JTWC in this year. This indicates that the DNNEF model can produce a fairly accurate prediction of TC tracks with the combination of CMA and JMA outputs. At the same time, considering that the JTWC forecast results are generally released later than CMA and JMA, the DNNEF-CJ model may be more efficient and suitable for the operational forecast of TC tracks in the Northwest Pacific Ocean.

The forecast error of the latitude and longitude of TC center in 2016–2018 predicted by the DNN based ensemble forecast models and three forecast centers are shown in Table 3 and Fig. 5. One can see the JTWC, JMA, and CMA TC forecast data are not homogeneous. The forecast error bias changes from year to year. Take the JTWC forecast result as an example, it tends to have track error bias to the left or west of a TC track in 2016 and 2017 TC seasons. In 2018 season, this bias changes to a right or eastward bias. Although the forecast error bias of different forecast centers changes every year, both the DNNEF-CJJ and DNNEF-CJ models can well adapt to the inter-annual variation of the bias and achieve better forecast results. This indicates that the DNN based

Table 2 24-h TC track forecast error (km) of different forecast centers and models. The number in bracket denotes the accuracy improvement (%) of the DNNEF-CJ model compared with that of each forecast center or EEF method

Year	Model					
	CMA	JMA	JTWC	EEF	DNNEF-CJ	DNNEF-CJJ
2016	81	77	74	67	65	63
2017	73	75	88	65	62	65
2018	78	70	73	62	60	60
All TCs	76 (17.1%)	75 (16.0%)	79 (20.3%)	66 (4.6%)	**63**	**63**
TCs with sudden track changes	83 (14.5%)	82 (13.4%)	87 (18.4%)	73 (2.7%)	**72**	**71**

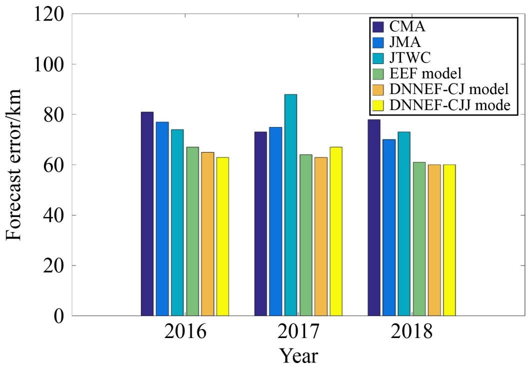

Fig. 4 24-h forecast error (km) of TC tracks in different years.

Table 3 24-h TC center latitude and longitude forecast error (°) of different forecast centers and models. Positive/negative values denote northward/southward or eastward/westward bias of the predicted TC track

Model	Year		
	2016	2017	2018
CMA(Latitude/Longitude)	−0.11/−0.02	0.03/−0.01	−0.07/−0.20
JMA(Latitude/Longitude)	0.01/−0.01	0.06/0.02	0.10/−0.06
JTWC(Latitude/Longitude)	0.09/−0.04	0.06/−0.06	0.12/0.05
DNNEF-CJJ(Latitude/Longitude)	−0.02/−0.01	0.03/−0.01	0.03/−0.04
DNNEF-CJ(Latitude/Longitude)	−0.03/−0.01	0.03/0.01	−0.03/−0.03

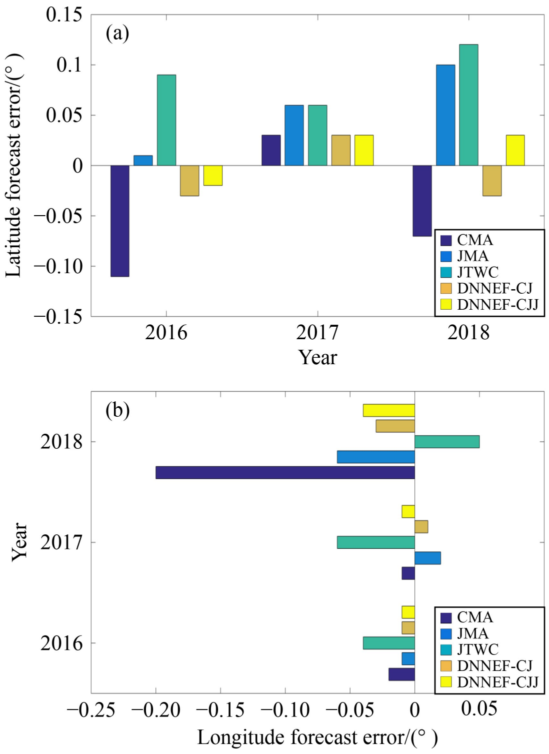

Fig. 5 24-h forecast error (°) of TC center latitude and longitude in different years.

ensemble forecast method is able to restrain the propagation of uncertainties caused by these biases to a certain extent.

We further analyzed the model performance for individual TCs. Figure 6 shows the comparison of 24-h forecast results from different models with the observations of TC Lionrock in August 2016 and Ampil in July 2018. Lionrock was generated on August 17, 2016. It became a tropical storm on August 18, intensified into TC category 5 days later, and made landfall on August 30 near Ofunato in northeastern Honshu. Ampil was formed on the evening of July 18, 2018. It made landfall in Shanghai’s Chongming Island at noon on July 22, with the intensity continuing weakened and disappeared on July 24. These two TCs caused huge economic damage to Japan and China. As shown in Fig. 6, both are steering TCs which are more difficult to forecast.

The 24-h forecast results of CMA, JMA, and JTWC are all improved greatly by the DNNEF models. For Lionrock, compared with CMA and JMA, the TC track forecast error of our DNNEF-CJ model is significantly reduced by 14% and 29%, respectively. For Lionrock, which suddenly turned its direction at (130.5°E, 23.0°N), the track forecast error of our DNNEF-CJ model is significantly reduced by 29% compared with that of JMA. As shown in Fig. 7, the accuracy of the DNN based model is higher than that of the three forecast centers in the whole life cycle of the TC and the maximum improvement in the model performance is more than 80% compared with CMA or JTWC forecasts. In general, the DNN based ensemble model is more helpful to modify the track forecast at the early and weakening stage of the TC. For Ampil, the forecast errors reduced by 22% compared with that of CMA. Also, the DNNEF models capture the movement of Ampil more accurately at its early stage, while JMA’s forecasts during this period are quite different from the observations. This indicates that the trend of the TC track predicted by the DNNEF model is more stable, thus avoiding the abnormally large error that might exist in the forecast results of different agencies at some time.

To investigate the performance of the DNN based ensemble model in forecasting the movement of TCs with sudden track changes between 2016 and 2018 (Fig. 1(b)), we carried out a statistical analysis. Take the DNN-CJ model as an example, as shown in Table 2, the 24-h track forecast accuracy is significantly improved by 14.5%, 13.4%, 18.4%, and 2.7%, respectively, compared with that of CMA, JMA, JTWC and EEF, indicating that the DNN ensemble forecast model also has the ability to accurately predict the tracks of abrupt turning TCs.

4 Conclusions

In this study, a completely objective model for predicting the 24-h TC tracks was developed based on the deep neural network. With an ensemble of the forecast results

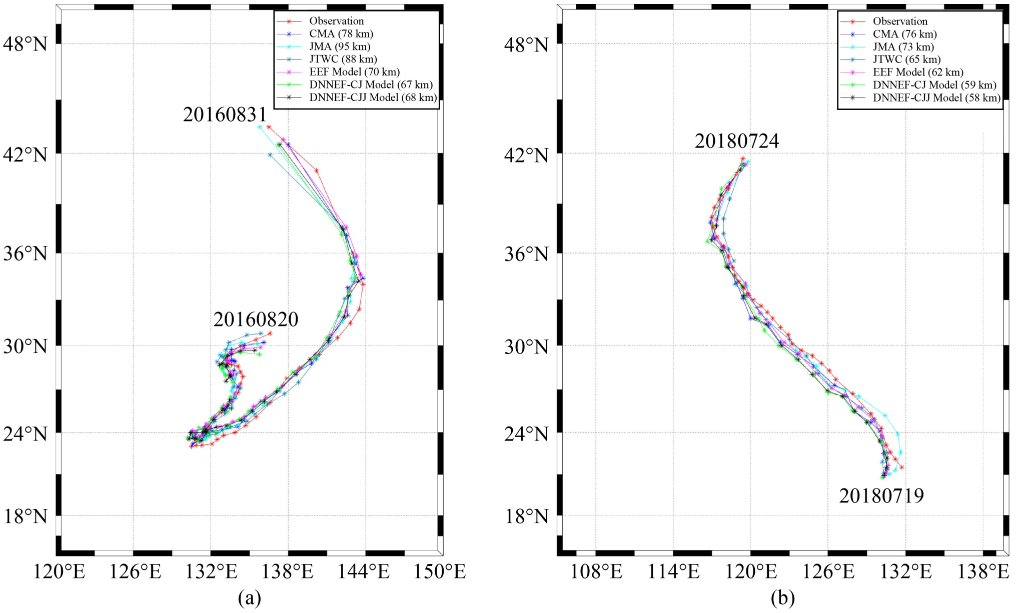

Fig. 6 Comparison of 24-h forecast results of TC tracks from different models with the observation from the Best Track data every 6 h: (a) Lionrock in August 2016, (b) Ampil in July 2018. The value in the parentheses is the forecast error in km.

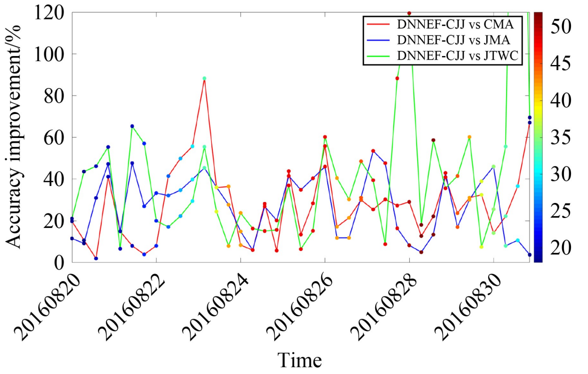

Fig. 7 Improvement (%) in accuracy of our DNNEF-CJJ model for track forecast of Lionrock with time. The colored dot on the curves represents the maximum wind speed (m/s) of Lionrock at the corresponding time with a time interval of 6 h.

from CMA, JMA and/or JTWC, the DNN based ensemble forecast model has a higher accuracy than that applied by the individual forecast centers. Both the overall forecast results of TCs between 2016 and 2018 and case studies show that the DNNEF model is more accurate and stable.

Compared with the traditional ensemble forecast model, our DNNEF model need no manual adjustment of empirical parameters. The model is able to simulate the nonlinear relationship between the forecast results from different models or forecast centers and correct the results automatically. Also, it performs slightly better in terms of model accuracy.

By inputting and outputting different parameters in the DNNEF model in three schemes, we find that the input of both longitude and latitude information helps to improve the performance of our forecast model. The average 24-h forecast error of TCs from 2016 to 2018 has been significantly reduced by 17.1%, 16.0%, and 20.3%, respectively, compared with that from the CMA, JMA and JTWC. The comparison between the DNNEF-CJ and DNNEF-CJJ models shows that the former, which combines the outputs from only two forecast centers (CMA and JMA), can predict the TC track more quickly with comparable accuracy. Therefore, the DNNEF-CJ model is more suitable for operational forecast due to simple data processing and high practicability.

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