Method Article

Comparative study on typhoon's wind speed prediction by a neural networks model and a hydrodynamical model

Tahereh Haghroosta

Physical Oceanography Researcher in Arman-Darya Inc., Tehran, Iran

A B S T R A C T

There are many models to predict natural phenomena around the world, but it is still difficult to accurately forecast the events. Many scientists, modeling professions, students, and researchers working on the tropical cyclones prediction, but they are encountered to many errors during compiling and configuring the models. Despite the increasing accuracy of weather forecasts, there is an element of uncertainty in all predictions. This paper reviews two methods used in my previous papers for predicting typhoon wind speed in the South China Sea, a dynamical model, Weather Research and Forecasting (WRF), and an Adaptive Neuro-Fuzzy Inference System (ANFIS) model. The performances of the models are calculated using statistical parameters of the root mean square error (RMSE) and Correlation Coefficient (CC), and the advantages and disadvantages of both models are represented. Regarding the statistical parameters values, the ANFIS model in comparison with the WRF model showed higher accuracy for typhoon intensity prediction because of higher CC and lower RMSE. The development of methods has represented several advanced techniques that their strengths and weaknesses have not been well-documented. In fact, a qualitative assessment and points to several ways in which the methods may be able to complement each other. The paper suggests that the scientists should improve the concepts of the models.

- Investigating two different methods and their performance in predicting typhoon intensity.
- Representing the strengths and weaknesses of both models.
- Suggesting some solutions for future researches.

Specifications Table

Subject Area:	Earth and Planetary Sciences
More specific subject area:	Air-Sea interaction
Method name:	Analyzing two different methods for predicting typhoon intensity to represent some outcomes that should be considered in future studies
Name and reference of original method	Method 1:
	Haghroosta, T., Ismail, W.R., Ghafarian, P. & Barekati, S.M. (2014), The efficiency of the Weather Research and Forecasting (WRF) model for simulating typhoons. Natural Hazards and Earth System Sciences, 14(8), 2179–2187
	Method 2:
	Haghroosta, T., & Ismail, W. R. (2015), Comparing typhoon intensity prediction with two different artificial intelligence models. Evolving Systems, 6(3), 177–185
Resource availability:	No special resource, just original methods mentioned above can be used

Method details

The South China Sea is a typhoon-prone area and the number of typhoons varies in different years. Wang [1] represented that the nature and behavior of typhoons in the South China Sea are different from those in the western North Pacific Ocean. To establish useful warning systems, typhoon intensity should be precisely predicted. Despite of improvement in typhoon intensity prediction over the last decade, the factors that control the intensity of typhoons is still poorly understood, what is still missing is a harmonization of approaches. Methodological differences among studies are recognized as significant sources of variation in quantification of typhoon characteristics' prediction.

Complicated hydrodynamical models, mathematical models, statistical models, and intelligent models predict different tropical cyclones all over the world. Different models like SCHISM, MIKE, SWAN, MMM, WRF-ARW, WRF-Chem, ROMs, COAWST, WWM-II, WWMIII, WW3 spectra, and etc were established and developed to predict different natural events or disasters. Too many studies have suggested different methods to predict typhoon wind speed, but the question is why the typhoon generation and its intensity are still not accurately predictable? Too many communities and forums are formed to discuss about compiling and configuring the models, but users have lots of problems to run the models, even with less errors (http://gradsusr.org/mailman/listinfo/gradsusr, https://sourceforge.net/projects/swanmodel/lists/swanmodel-users, and https://www.myroms.org/forum/viewtopic.php?f=1&t=4600). Although the forums and meetings are suitable for scientists' communications and knowledge improvement, they must be helpful to solve the public problem as soon as possible. Unfortunately, in such meetings there are many loops and repetitions.

Choi et al. [2] identified two major challenges in their model. The model was based on statistical regression and unlike dynamical models it could not predict individual tropical cyclones. There are some relationships between cyclone's generation and environmental conditions, but such physical consistency is not always related directly to cyclone formation. Tropical cyclones with irregular tracks showing a significant amount of uncertainty cannot be simply allocated to one defined track patterns, which may cause larger forecasting error. Their study suggested future research to resolve the limitations in the models.

An individual WRF model could simulate Phailin's track in an almost identical way to the WRF in a coupled configuration. However, the intensity (surface wind speed) in the WRF model was higher compared to the coupled model. The comparison of individual and coupled WRF model-simulated mean sea level pressure (MSLP), wind speed, and wind direction at a buoy location. The individual WRF simulated a larger pressure drop and higher wind speed compared to buoy measurements. The semidiurnal variations in MSLP, mostly caused by the radiational forcing [3], were not obtained by the model over the cyclonic region [4].

Two algorithms based on machine learning neural networks were proposed the shallow learning (S-L) and deep learning (D-L) algorithms that were used in atmospheric typhoon prediction models to provide sea surface temperature cooling (SSTC) to improve typhoon forecasts. The significance of existing SSTC in forecast models is how to accurately predict SSTC made by a typhoon that requires

information from past data and also from the future typhoon itself. The S-L algorithm combined a single layer of neurons with diverse atmospheric and oceanic factors. Such a structure could not to represent appropriately the typhoon-ocean physical interaction. In fact, any disturbances may cause unsteady changes in both pattern and strength of SSTC. In the D-L algorithm, the atmospheric and oceanic factors are assigned to a 4×5 neuron matrix in a neural network with different separated layers of neurons. Thus, it created a steady SSTC distribution, concluded largely by large-scale atmospheric factors such as winds, and small scale oceanic factors like eddy. Sensitivity experiments showed that the D-L algorithm was able to improve maximum wind intensity prediction errors by 60–70%, in comparison with its atmosphere-only model run [5].

Some parameters of typhoon such as maximum intensity and its size are still caused significant improbability. The limits in these parameters can affect on typhoon size and its intensity and are related to different parameters, such as distance to the land, SST variations and variations of large-scale circulation patterns [6]. Rappaport et al. [7], in an analysis of all tropical cyclones making landfall on the US Gulf coast, stated that during the 12 h ahead of landfall, hurricanes showed different regular patterns of development depending on their initial power 12 h before landfall. Resio et al. [8] and Levinson et al. [9] recognized similar trends in their study of pre-landfall weakening in tropical cyclones. These activities potentially represented the problems within the Gulf of Mexico that were dominated by weaker tropical cyclones. It would be expected that the weaker hurricanes indicate no enhancement in central pressure before landfall when it approaches to the coast; however, such behaviors should be warned.

Forecasting tropical cyclone intensity is improving slowly. Estimating fundamental predictability limits as well as sources of intensity error is useful. Emanuel and Zhang [10] estimated the error of growth rates in a perfect model in which is used to explore the sensitivities of tropical cyclone intensity to perturbations in the initial storm intensity and large-scale environment. These were compared to estimate made in previous studies and to intensity error growth in real-time forecasts made using the same model, in which model error also plays an important role. The authors found that error growth over approximately the first few days in the perfect model framework was dominated by errors in initial intensity, after which errors in forecasting the track and large-scale kinematic environment became more pronounced. Errors owing solely to misgauging initial intensity were particularly large for storms about to undergo rapid intensification and were systematically larger when initial intensity was underestimated compared to overestimating initial intensity by the same amount. There remains an appreciable gap between actual and realistically achievable forecast skill, which this study suggests can best be closed by improved models, better observations, and superior data assimilation techniques.

Methods and materials

The main commonly statistical indicators in the literature managing environmental evaluation models are; root mean square error (RMSE), and Coefficient of Correlation (CC) that are calculated as follows:

Root mean square error (RMSE)

The RMSE (Eq. (1)) represents some information about the short-term performance of a model by comparing equivalent values to show the real difference between the estimated value and the control data. The smaller RMSE value indicates better performance for the model.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{\left[(x_c)_i - (x_s)_i \right]^2}{n}} \tag{1}$$

which x_s and x_c are the simulated data and the control data of typhoon intensity at time step i, correspondingly, and n is for the number of data pairs. The RMSE indicates the comparison of the control data and the simulated data. The smaller RMSE values show that the simulated data are closer to the control data.

Correlation Coefficient (CC)

The CC (Eq. (2)) prepares valuable information on typhoon intensity and compares the control data and the simulated data.

$$cc = \sum_{i=1}^{n} \left[(x_c)_i - (\overline{x}_c)_i \right] \frac{\left[(x_s)_i - (\overline{x}_s)_i \right]}{\sqrt{\sum_{i=1}^{n} \left[(x_c)_i - (\overline{x}_c)_i \right]^2 \sum_{i=1}^{n} \left[(x_s)_i - (\overline{x}_s)_i \right]^2}} \tag{2}$$

which, $\overline{x}_s$ and $\overline{x}_c$ are the mean values of the simulated data and the control data of typhoon intensity at time step *i*. The CC can also measure the strength of the correlation between the simulated and control values. Higher CC value indicates better model performance.

Study area

The South China Sea is the biggest marginal sea and typhoon-prone area in the western North Pacific Ocean, expands from the equator to 23 °N latitude and from 99 to 125 °E longitude. South China Sea is bordered by countries, include of China, Vietnam, Cambodia, Thailand, Malaysia, Indonesia, Philippines, and Taiwan and these countries are most encountered with the typhoons (Fig. 1).

Two previous papers that have represented two different methods for predicting typhoon intensity are summarized herein for the aim of this research.

Summary of comparing typhoon intensity prediction with two different artificial intelligence models" by Haghroosta and Ismail [12]

The paper applied two neural network methods to predict tropical cyclone intensity in the South China Sea. The data in the study were achieved from two major sources. The first dataset is the six-hourly NCEP reanalysis of the 16 selected tropical cyclones from 1985 to 2011 in the South China Sea, in the climate prediction center (CDC). The data used in this research are latent heat flux, sensible heat flux and sea surface temperature have the grid resolution of 2.5° × 2.5° in longitude and latitude [13]. The second dataset is the typhoon characteristics from the National Oceanic and Atmospheric Administration (NOAA), the International Best Track Archive for Climate Stewardship (IBTrACS). The data includes 6-hourly tropical cyclone longitude and latitude at 00:00, 06:00, 12:00, and 18:00 UTC, during the selected cyclones [14]. The wind speed data from IBTrACS were considered as control data in the study. More details about the models' configurations are available in the study by Haghroosta and Ismail [12].

Six factors, including latitude and longitude as spatial parameters, minimum central pressure, SST, LHF, and SHF, were inserted into the ANFIS and ANN models. The models were run for 16 typhoons
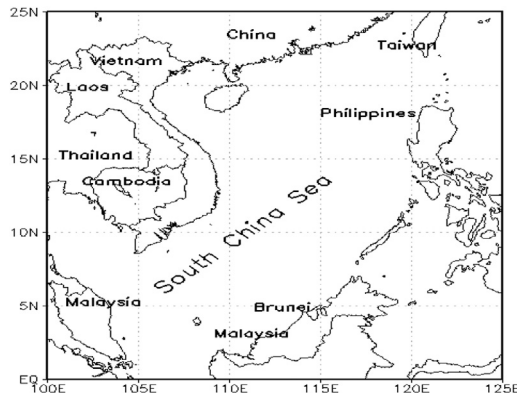

Fig. 1. Study area [11].

Table 1

Comparison of RMSE and CC values for ANN and ANFIS models with two different lags [12].

	ANN-1	ANN-2	ANFIS-1	ANFIS-2
Lag	4	8	4	8
RMSE	**6.11**	7.28	**3.78**	4.09
CC	**0.95**	0.94	**0.98**	0.98

The best experiments of statistical parameters are written in bold.

originated in or passed though the South China Sea named Irving (1985), Forrest (1992), Manny (1993), Gil (1998), TD 1121 (2001), Vamei (2001), Muifa (2004), Durian (2006), Peipah (2007), Noul (2008), TD 01W (2008), Kujira (2009), Chan-Hom (2009), Nangka (2009), Songda (2011), and Washi (2011), with two different lags.

The results confirmed the power of the Adaptive Neuro-Fuzzy Inference System based on genetic algorithm (ANFIS-GA) method with regard to an Artificial Neural Network (ANN) method. Both methods indicated a significant CC, but the root mean square error (RMSE) as a determining parameter, was 3.78 for the ANFIS-GA model, considerably lower than the value of 6.11 for the ANN model in the best experiments (Table 1). For both models, 20% of the data were used as the validation data and 80% of the data were used for training. Two different lags were also tested in both models; lag 4 in AAN-1 and ANFIS-1 and lag 8 in ANN-2 and ANFIS-2. Table 1 indicates that the variation of lags could change the solution. This finding was also stated by Sudheer et al. [15]. The study showed that the lower lag made better performance. The study also stated that the ANFIS model could make more proper predictions for typhoon intensity than the ANN model.

Summary of "The efficiency of the Weather Research and Forecasting (WRF) model for simulating typhoons" by Haghroosta et al. [16]

The study employed a hydrodynamical model to find out the best combination of physics parameterization schemes for simulating the wind speed as an important parameter of tropical cyclone intensity. Final analysis 6-hourly data sets (FNL) with a resolution of 1°, obtained from the National Centers for Environmental Prediction (NCEP), were inserted to the WRF model as initial and boundary conditions. The wind speed at the 10 m level above the earth's surface is referred to as "wind speed" all through the paper. The data used for validation of the simulated parameters were derived from the Climate Forecast System Reanalysis (CFSR) dataset that are available on the related website [17]. In fact, the outputs of the model were analyzed in comparison with the CFSR data that is referred to as control data. Many studies such as Wang et al. [18] and Saha et al. [17] show the reliability of CFSR dataset. The quality of the dataset is available in http://rda.ucar.edu/#!pub/cfsr.html.The CFSR data set with the nearest resolution (0.5° in longitude and latitude) to the WRF resolution were selected in the research. The model simulation was periodically conducted for every 4 days.

The model domain included of one nested domain and one coarse domain. The model resolution for the coarse domain was 30 km, and for the nested domain was 10 km. The data used all over the paper are from the reanalysis data set of the NCEP and the best track database of the National Oceanic and Atmospheric Administration (NOAA).

In the conducted experiments, some physics parameterization selections within the WRF model were comprehensively tested for eight different typhoons over the South China Sea; Peipah (2007), Noul (2008), TD 01W (2008), Kujira (2009), Chan-Hom (2009), Nangka (2009), Songda (2011), and Washi (2011) that passed or originated in the South China Sea. The selected typhoons happened during 1985–2011. The study outcomes were evaluated in comparison with the CFSR data set. Standard statistical measurements were applied to compare predicted and control data. In the study, they suggested different schemes and grouping physical parameters of the WRF model for predicting typhoon wind speed. Finally, the model with a combination of the Stony Brook University (microphysics), New Goddard (longwave and shortwave radiation), Eta (surface layer), 5-layer thermal diffusion (land surface), MYJ (PBL), and Tiedtke (cumulus parameterization) indicated the best

prediction of wind speed with lower amount of RMSE (7.78) with regard to the other combinations which are explained with more details in their study.

Now, in this comparative paper, the outcomes of two our earlier papers that predicted the wind speed during typhoons in the South China Sea are represented to achieve considerable and thinkable results. The potential for the WRF and ANFIS models to complement each other, in particular, may be very rewarding and should be studied further, and the methods' advantages and disadvantages are investigated in the following sections.

Results and discussion

Comparing the ANFIS and WRF models' performance

The outcomes showed that the ANFIS model based on the GA algorithm had a reasonable capability to predict typhoon intensity in the study area, but it needs too much historical data to achieve better answers. By contrast, WRF model is a complex model in terms of installation and configuration. It also requires special infrastructure to install and run. Additionally, WRF model needs high capacity computer to save the model outputs. The WRF model obtains its initial and boundary conditions from a global dataset. In addition, too many complicated calculations and interpolations occur during the pre-process, running, and post process of WRF model that can create more inaccuracies in the outcomes. The model is run based on diverse theoretical boundary conditions, which makes approximate predictions. The outputs of WRF model are also dependent on different features, such as the purpose of the model, real time versus research, type of domain and its resolution, the types of variables associated to the study objectives, how to run the model, and model run-time.

Although the ANFIS model represented higher accuracy (CC = 0.98) in typhoon intensity prediction concerning WRF model with Correlation Coefficient of 0.75 (Table 2), accessing to the former recorded data was difficult and time consuming. Even though the WRF complexity is much complimentary for predicting objective, if more stored data are not available.

Neural network model is used to execute nonlinear statistical modeling. Furthermore, the neural network model is able to prepare a pattern between inputs and outputs, statistically by learning and testing methods, and more interpolation is not necessary. The model presents several advantages, including less formal statistical training and capability of identifying complex nonlinear correlations between dependent and independent variables by various learning algorithms. The most notable disadvantage of utilizing neural network model is its "black box" nature that cannot interpret the relationship between inputs and outputs. The configuration mostly depends on the trial-and-error methods that are caused random results.

Dynamical models reflect on the physical characteristic of the atmosphere and can be developed by researchers, so they can execute well. Statistical models are also appropriate for prediction plans. In fact, choosing dynamical models at the expense of statistical models is not reasonable. This result was also found by Huth et al. [19] when they studied minimum and maximum temperature by two different climate models and five statistical models. Moreover, combining a neural network model with a numerical model can develop its performance; this consequence was also stated by De Giorgi et al. [20] who evaluated the errors in wind power prediction with an ANN model and a numerical weather prediction model. Additionally, Hsieh [21] represented that the neural networks model is a kind of adjoin data assimilation that lets it to be connected to dynamical models and is caused a new class of hybrid neural-dynamical models. Evaluations of the two models indicated that there are some

Table 2
Comparing the statistical parameters in the models.

	ANFIS	WRF
RMSE	3.78	7.78
CC	0.98	0.75

advantages and disadvantages for both models. Therefore, selecting the models is related to the problem that must be solved.

Conclusion

Tropical cyclone prediction is really vital to protect human beings and nature. Even fewer faults can cause irreparable damages. While diverse complicated models in the world have been set up and run, and they cannot exactly predict and the typhoon reliable forecasting is still a difficulty. In spite of high accuracy in weather predictions, there is an ambiguity in all forecasts. Too many conferences and meetings are held to exchange the knowledge. Moreover, too many communities and forums are formed to discuss about compiling and configuring the models, but users have lots of problems to run the models, even with less errors (http://gradsusr.org/mailman/listinfo/gradsusr and https://sourceforge.net/projects/swanmodel/lists/swanmodel-users). What should the scientists and modelers do to have successful run with least errors? The scientists and modelers should possibly disregard some models and the models should be localized based on the theoretical concepts and different real boundary conditions not hypothetical conditions for the study area. This paper suggests working on neural networks models seriously, because of repetitive characteristics of natural events like typhoons. The nature learns the intelligent models and finds better prediction than a complicated hydro-dynamical model and the hydro-dynamical model should be powered with intelligence neural networks.

Acknowledgment

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