Review of Applications of Neuro-Wavelet Techniques in Water Flows

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Abstract The flow of water over land and oceans is governed by the natural process of hydrological cycle and hence it is highly random and complex. An estimation or prediction of behavior of such flows is thus very difficult and requires continuous research with latest tools of analysis and forecasting. The methods adopted for this purpose range from earlier empirical equations and numerical methods to modern data driven techniques which follow advances in computer technology. The latter coupled with progress in neuro-science had given rise to the method of artificial neural networks (ANNs) which has been applied abundantly since late 1980s to carry out system modeling and prediction type of exercises in water resources and ocean engineering. Despite wide spread applications of ANNs issues such as non-linearity, non-homogeneity and non-stationarity of given information continue to elude high accuracy in the results and thus have prompted extension of conventional ANNs to their combination with other pre- or post-processing tools. The wavelet neural network or neuro-wavelet transform (NWT) is a recent effort in this regard to accurately model or predict different

types of parameters characterizing river or ocean processes. This paper presents a review of applications of NWT in hydrologic and Oceanic modeling.

Keywords Neuro-wavelets · Artificial neural network · Rive flow prediction · Wave prediciton

Introduction

The modeling of land based water flows encompasses the processes of rainfall, runoff, infiltration, evapo-transpiration and ground water while that of oceanic water involves the waves, tides, currents storm surges among other natural agencies. The physical processes underlying these phenomena are complex and difficult to model and further predict them accurately. The earlier attempts in this regard were in the form of analytical models, which were insufficient to reflect the real world; empirical models which were much approximate; numerical methods, which were good for large spatial coverage; and modern data-driven approaches, which have been found to be accurate when location-specific information as in engineering designs is sought for. The modern data-driven approaches generally differ from the conventional ones in that unlike the latter they do not assume any kind of fixed dependency between the input and the output set of information and thus provide immense flexibility in data fitting. Modern data-driven tools have found applications in a variety of tasks such as causal mapping, spatial mapping and temporal mapping of a given natural process. The temporal mapping typically involves a times series forecasting problem and it was conventionally addressed through stochastic models such as auto-regressive moving average (ARMA) and auto-regressive integrated moving average (ARIMA). However it

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was noticed that these models have limited capacity to capture non-stationarities and non-linearities in data series, which in turn can be better addressed through modern soft computing techniques like artificial neural network (ANN). Such techniques utilize tolerance of real world to uncertainties, imprecision, and partial truths associated with natural data to do modeling or prediction of future values.

In the basic ANN architecture (Fig. 1) the input is fed from different neurons (computational elements) of the input layer and the output is collected from different neurons of the output layer. Each neuron works identically in that it sums up weighted input, adds a bias and passes on the result through a nonlinear function, typically of sigmoid type. The layers in hidden neurons bring in system non-linearity. Before actual use the network weights and biases are fixed by optimizing them through training algorithms like the gradient decent. (Bose and Liang 1998).

Prediction of ocean parameters using ANN has been carried out by a number of researchers over last two decades (Deo and Naidu 1999; Deo et al. 2001; Arena and Puca 2004; Zamini et al. 2008; Makarynsky 2004; Mandal and Prabakaran 2006; Londhe and Panchang 2006; Browne et al. 2007; Nitsure and Londhe 2012; Barman et al. 2006; Bhaskaran et al. 2010; Deshmukh et al. 2016). Generally using a simple network architecture, namely, feed-forward or recurrent many of these authors mainly predicted waves in short and long terms based on uni-variate (wave height only) or multi-variate (wave height and wind) time series. A comprehensive review of applications of ANN to predict wave heights and periods, directional characteristics, tidal levels, sea levels, ocean wind speed, coastal currents can be seen in Jain and Deo (2006).

In the field of water resources there are abundant applications of ANN over last few decades and these typically include Sudheer et al. (2002), Sivakumar et al. (2002), Sudheer and Jain (2003), Cigizoglu (2003), Kisi (2009), Cigizoglu and Kisi (2005), Sahoo and Ray (2006),

Bhakar et al. (2006), and Moustris et al. (2011). These included estimation, forecasting and extrapolation of different hydrological variables like rainfall, runoff, reservoir inflow and stream flows.

While above works indicated the power of ANNs in general they also showed certain grey areas like long range predictions and prediction of extremes. One way to address such limitation of ANNs is to use it in association with other tools. Since recent past wavelet transform (WT) has caught attention of researchers in water related engineering for analyzing the variability, periodicity and trend in time series for subsequent use in an ANN so that non-stationary data can be conveniently analyzed in both time as well as frequency domains at the same time. Wavelet analysis is multi-resolution analysis which decomposes the original signal into several sub signals into time and frequency domains. This negates the effect of ‘autocorrelation’ in any time series which is a major cause of inefficient prediction capacity of any data driven technique (De Vos and Rientjst 2005). At this backdrop the paper reviews readily available and important applications of neuro-wavelet technique (NWT) for modeling water flows over land and sea.

The Neuro-Wavelet Technique

A Wavelet Transform (WT) is a signal processing tool with the ability of analyzing both stationary as well as non-stationary data series and to represent it in time and frequency domains with multiple resolutions, not achievable from traditional transformations of Fourier and short term Fourier Transforms (Deka and Prahlada 2012). It breaks the signal into its wavelets (wave-like functions) which are scaled and time-shifted versions of the original or mother wavelet. The scaling and wavelet functions serve as low and high pass filters, respectively. Thus effectively the signal is passed through the low and high pass filters, and sub-sampled to separate low (approximate) and high (detail) frequencies. The low frequency can be further passed through low and high passes to get more resolution in the analysis. This analysis is called as multi-resolution analysis (MRA).

Many researchers have used MRA in wavelet transforms in recent past and these include Ozger (2010), Deka and Prahlada (2012) and Abzar (2014). The wavelet transformation is classified under two heads; continuous wavelet transformation (CWT) and discrete wavelet transformation (DWT). The choice of the wavelet transformation is an important part of wavelet analysis and depends on both the signal properties and user’s requirement. The CWT is associated with redundancy or over-specification of the signal. It is computationally expensive and less amenable to statistical analysis. As against this the lack of

Fig. 1 Basic ANN architecture

redundancy in DWT and its suitability for statistical signal processing makes it a preferred choice by researchers (Addison et al. 2001). Generally the discrete wavelets are of Daubechies (db) type due to their compactness and asymmetric shape going well with to irregular and random nature of hydrological and oceanic variables. Readers are referred to Mallat (1998), Labat et al. (2000) and Alexandrinis (2013) for further details.

A Neuro-Wavelet Technique (NWT) represents a combination of ANN and DWT. The DWT analyzes the frequency of a signal with respect to time at different scales. It decomposes given time series into low (approximate) and high (detail) frequency components. The decomposition of the approximate can be carried out further to desired multiple levels in order to provide more detail and approximate components which provide a smoothly varying series. Figure 2 shows an example of a 3-level decomposition of given series X . The ANN is trained with such de-correlated series and the resulting output is retransformed back (Fig. 3).

Applications in Hydrology

One of the early works with wavelets is due to Adamowski (2008) who developed short-term flood forecasting models based on wavelet and cross-wavelet constituent components and forecasted daily stream flows with lead times of 1, 3, and 7 days.

These wavelet and cross-wavelet models were compared with ANN and simple persistence models. It was found that the wavelet based models can be used with high accuracy as a stand-alone forecasting method only for short term of 1 and 3 days into the future, provided there was no significant trend in the peaks for the same Julian day from year-to-year. The results were not accurate for longer lead time (7 days).

Fig. 2 Level multi multiple level decompositions process

Fig. 3 The neuro-wavelet scheme

In the same year, Kisi (2008) applied NWT for modeling monthly stream flows using time series of daily flows at two river stations in Turkey. The NWT was compared with the standard ANN and auto-regressive (AR) models and it was found that the WNN model was able to provide better fit to the observed data, especially over the peaks. This work gave boost to similar works by other researchers. Thus Liu et al. (2011) used a wavelet based approach for assessing timing errors in hydrologic predictions, while Kisi and Shiri (2011) applied Wavelet-Genetic Programming and Wavelet-Neuro-Fuzzy Conjunction Models for forecasting precipitation at different lead time intervals. Okkan (2012) applied NWT for monthly reservoir inflow prediction at Kemer Dam, Turkey by eliminating ineffective sub-time series through regression methods and using effective sub-time series components as new inputs to ANN. Additionally DWT was also integrated with wavelet-multiple linear regressions (WREG). The results of WNN and WREG were compared with conventional feed forward neural networks (FFNN) and multiple linear regression (REG) models. It was observed that when the data decomposed by wavelet transform was used as input the performance of FFNN and REG improved. The results indicated that WNN can be used to model the monthly series of reservoir inflows and can give good prediction performances than other methods.

Continuing with the applications Wei et al. (2013) applied a wavelet-neural network hybrid modeling

approach for estimating and predicting river monthly flows. Recently, Sang (2013) presented a review of applications of wavelet transform in hydrology and summarized the literature under six wavelet aided studies of multi-temporal scale analysis of hydrologic time series, deterministic component identification in hydrologic time series, denoising of hydrologic time series, complexity quantification of hydrologic time series, cross-correlation analysis of hydrologic time series, and general hydrologic time series simulation and forecasting.

Although efficacy of NWT was presented by some investigators issues of selecting the wavelet type, style and level of decomposition, process of filtering the dataset were required to be addressed. Khandekar and Deka (2013) applied NWT for daily River flow forecasting using 7th level decomposition and developed flow forecasting models with Daubechies (db) wavelets of order 4 (db4) and 5 (db5) for 2, 3 and 4 days into the future. For almost all lead times this model gave better and consistent results compared to conventional ANN models. It was mainly because of implementation of multi-resolution decomposed time series used as inputs. Out of ‘db4’ and ‘db5’ wavelets the latter gave slightly better results for all lead times. Model efficiency was increased with decomposition level up to 5th and 6th level of decomposition and thereafter it decreased.

Ramana et al. (2013) applied NWT for time series modeling of monthly rainfalls and compared it with standard AR and ANN models. Unlike others who dealt with uni-variate time series modeling authors resorted to multi-variate one using two antecedent values of rainfall, and minimum and maximum temperature values and this proved to be better than the ANN and AR models. Here multi-resolution analysis of wavelet effectively diagnosed the main frequency component of the signal and abstracted the local information of the time series and the improvement in results was plausible as the variation in nonlinear dynamics of temperature (which plays a predominant role in the hilly areas included in the rainfall process) was mapped effectively by wavelet based models.

Solgi et al. (2014) used NWT and compared it with adaptive neuro-fuzzy inference system (ANFIS) to predict the daily precipitation at Verayneh rain gauge station in Iran. Authors used 3 different wavelets: Haar, db4 and symlet 3 as mother wavelets and the effect of wavelet transform type on the model performance along with its prediction accuracy was analyzed. The accuracy of the hybrid model of wavelet neural network was found to be higher than that of ANFIS. The Haar wavelet was found to be superior than the fourth order db (db4) and symlet-3 and it was noticed for a particular model an optimum decomposition level can be chosen on the basis of the signal length.

The studies as above thus confirmed the gain in the accuracy by the use of NWT in hydrological predictions.

Applications in Ocean Environment

The earlier works to predict waves with NWT is due to Ozger (2010) who used wavelet in combination with fuzzy logic for significant wave height, H_s , forecasting and Deka and Prahlada (2011) who used it for improving the forecasting accuracy of H_s over lead times up to 48 h in advance at an offshore site along the west coast of India. The decomposition was done up to sixth level but authors could not improve prediction accuracy at lead time higher than 12 h. The same authors (Deka and Prahlada 2012) later repeated this work by changing the style of providing input to ANN. Only the input signals were decomposed into wavelet coefficients and not the output ones so that the ANN was exposed to large number of weights attached to many input nodes during training. The output signals were kept same as the original series without decomposition due to which its reconstruction was not required. It was observed that for lower lead times (3–12 h) a decomposition level 4 and 5 was optimum while for higher lead times higher level of 6 was needed due to increased uncertainties involved.

Some of the above works suffered from a phase lag between the given and the predicted series due to auto-correlations in neighboring values. (De Vos and Rientjst 2005; Deka and Prahlada 2012) Further, the accuracy of extreme events was hardly addressed. Similarly proper guidance to select wavelets or decomposition levels suitable for different prediction steps was also unavailable. Dixit et al. (2015a) addressed these issues in their recent work of predicting H_s at a few stations along the US coast over a lead time of 36 h. The lag removal and hence improvement in the prediction accuracy was achieved by proper choice of “db” wavelets and that of decomposition levels. Good prediction of extreme events even in hurricanes was possible in this way. Authors decomposed the given series into de-correlated approximate and detail coefficients up to 3rd level and trained two separate ANNs with their help. The outputs of networks during testing were reconstructed back using inverse DWT. The results showed that the phase lag was completely removed by the NWT model. It was found out that as the “db number” increased from 1 to 35 (db1 to db35) the number of approximate coefficients also increased and this de-correlated the series further thus removed the lag. Authors further found that for given lead time a particular type of db can work well. For example, for a 12 h ahead prediction “db14” worked well while db26 and db35 were better for 24 and 36 h (Dixit et al. 2015b; Dixit and Londhe 2016).

Fig. 4 Match of the peak of H_s observed during 200 h of passage of hurricane Katrina at station 42040 with 36-h ahead predictions made on the basis of 3rd, 5th and 7th level of decomposition. (Dixit and Londhe 2016)

In continuation of preceding work Dixit et al. (2015b) further studied the effect of different decomposition levels on the prediction accuracy. The same data series was now decomposed to 7 levels and it was found that a higher level of decomposition led to better accuracy in predicting H_s . However for the predictions over shorter intervals (6, 12 h) lower levels of decomposition were sufficient. Dixit and Londhe (2016) again confirmed necessity of going for 7-level decomposition in respect of predicting extreme events, 36 h in advance, at 4 stations in Gulf of Mexico during the passage of 5 hurricanes. Figure 4 shows how the peak of H_s observed during 200 h of passage of hurricane Katrina at station 42040 matched with the 36-h ahead predictions made on the basis of 3rd, 5th and 7th level of decomposition. It can be seen that the 7th level decomposition enabled the targeted close match.

Apart from the wave heights, tidal water levels have also been predicted with NWT efficiently as in El-Diasty and Al-Harbi (2015) in which tide gauge data at 4 stations were analyzed. Although no information on the type of wavelet used was available it was reported that the NWT worked better than the conventional sequential least-squares-based harmonic analysis method based on short data length of just 1 week.

The prowess of NWT has also been shown in the exercise of predicting sea surface temperature (SST) for operational purpose in Patil et al. (2016). In this study authors derived an error series in which each term (at each time instant) was the difference between the observed SST and the SST predicted by a numerical model. This error series was used to carry out time series forecasting using NWT and the error for a future lead time was predicted and later added to the numerical SST in order to obtain refined numerical prediction. The suggested method has the advantage that it considered physics-based as well as data-driven approaches together when making SST predictions. The study was conducted at 6 different locations in the Indian Ocean and over 3 time scales of daily, weekly, and monthly. It was also found that NWT based on the mother wavelet of “Meyer wavelet with discreet approximation”

worked more satisfactorily than other wavelets. Authors however cautioned that a large amount of experimentation with alternative network architectures and learning schemes was necessary to achieve high accuracy in results.

Conclusion

The preceding sections discussed studies reported by different investigators on applications of NWT in hydrology and ocean environment. The applications in hydrology involved short term forecasting of floods, monthly stream flows, monthly reservoir inflows, daily river flows and daily rainfall at various locations of the world.

Many investigators have proved that ANN worked better than statistical model or even ANN (Partal and Cigizoglu 2009; Deka and Prahlada 2012). Also NWT models were found to remove the phase lag in univariate time series forecasts which is highly advantageous over similar ANN or other data driven models. The NWT was successful in accurately predicting extreme events as well as predictions at high lead times.

In order that the practicing engineers find NWT reliable for routine applications many more applications of NWT in hydrologic and oceanic environment are necessary. These may include sediment transport, weather parameters like humidity, surface temperatures and pan-evaporation, various pollution indicators, wind, currents and storm surge.

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