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# Neuro-fuzzy and neural network techniques for forecasting sea level in Darwin Harbor, Australia

Sepideh Karimi [a], Ozgur Kisi [b], Jalal Shiri [a,*], Oleg Makarynskyy [c]

[a] Water Engineering Department, Faculty of Agriculture, University of Tabriz, Tabriz, Iran
[b] Civil Engineering Department, Faculty of Architecture and Engineering, Canik Basari University, Samsun, Turkey
[c] URS Australia, 17/240 Queen St., Brisbane, QLD 4000, Australia

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ABSTRACT

Accurate predictions of sea level with different forecast horizons are important for coastal and ocean engineering applications, as well as in land drainage and reclamation studies. The methodology of tidal harmonic analysis, which is generally used for obtaining a mathematical description of the tides, is data demanding requiring processing of tidal observation collected over several years. In the present study, hourly sea levels for Darwin Harbor, Australia were predicted using two different, data driven techniques, adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN). Multi linear regression (MLR) technique was used for selecting the optimal input combinations (lag times) of hourly sea level. The input combination comprises current sea level as well as five previous level values found to be optimal. For the ANFIS models, five different membership functions namely triangular, trapezoidal, generalized bell, Gaussian and two Gaussian membership function were tested and employed for predicting sea level for the next 1 h, 24 h, 48 h and 72 h. The used ANN models were trained using three different algorithms, namely, Levenberg–Marquardt, conjugate gradient and gradient descent. Predictions of optimal ANFIS and ANN models were compared with those of the optimal auto-regressive moving average (ARMA) models. The coefficient of determination, root mean square error and variance account statistics were used as comparison criteria. The obtained results indicated that triangular membership function was optimal for predictions with the ANFIS models while adaptive learning rate and Levenberg–Marquardt were most suitable for training the ANN models. Consequently, ANFIS and ANN models gave similar forecasts and performed better than the developed for the same purpose ARMA models for all the prediction intervals.


## 1. Introduction

Sea level variations are determined by ocean tides and currents, atmospheric forces (air pressure and wind), the hydrological regime of coastal rivers, and temperature and salinity of sea water (Chen et al., 2000; Douglas et al., 2000). In turn, sea level determines groundwater levels in low lying coastal areas (Meyer, 1989) and the hydrological regime of some estuaries and coastal rivers (Thain et al., 2004). Therefore an accurate estimation of sea level variations in estuaries where contributing rivers discharge into the sea, is of importance in coastal engineering, in land drainage and reclamation studies. When agricultural lands are located along rivers, estuaries, or coastal areas, the excess drainage water is disposed to rivers or the sea. Hence, the water levels at sea or river may restrict the drainage temporarily (Vries and Huyskens, 1994), which would be harmful for cultivated lands. In the downstream of the rivers that discharge into a sea or ocean, water levels are influenced by the tides. Whenever sea level reaches high values, the tide may force water back into the river and subsequently the drainage system leading to salt water intrusion, which could have severe adverse effects on water quality and adjacent soils.

Hours-to-days, short terms predictions of sea level heights in the near-shore environments are also of interest for navigation in shallow waters, for practical engineering applications concerned with protection of coastal and low-lying regions residents, as well as for the alternative energy technologies based on both sea level variation and wave energies (e.g., Herbich, 1992; Charlier and Justus, 1993).

Tides are diurnal or semi-diurnal rises and falls of water level in oceans, seas and lakes. Tides are related to the attraction forces between large celestial bodies, especially the earth, the moon and the sun. As a result of the rotation of the earth and the movement of the moon and the sun, long waves develop and travel around

* Corresponding author. Tel.: +98 4113340081.
*E-mail address:* j_shiri2005@yahoo.com (J. Shiri).

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the earth. They are altered by submarine and coastal topography, Coriolis force and other factors (Vries and Huyskens, 1994), and sometime resonate in bays and estuaries/fiords. The methodology of tidal harmonic analysis (Newton, 2003), usually employed for obtaining a mathematical description of the tides is data demanding and do not take into consideration the hydro-meteorological forces. Furthermore, tidal observations for several years need to be collected and processed in order to obtain reliable sea level estimates. Thus, obtaining accurate estimates of sea level might be problematic in locations with scarce tidal observations (Makarynska and Makarynskyy, 2008). The Admiralty method (Schureman, 1958) and the method of least squares (Kalkwijk, 1984) has also been applied for tide analysis in the past, but there are some limitations for those methods as well. For instance, to make tide predictions (spring and neap tides) with the Admiralty method, continuous hourly observations of tides over at least a 29-day period are required, while longer observation are required for eliminating wind set-up, storm surges and water level variations due to the changes of barometric pressure (Vries and Huyskens, 1994).

In the method of least squares the tidal characteristics are determined through minimizing the differences between a measured tidal signal and a basic sinusoidal function, which should describe unknown constituents (Vries and Huyskens, 1994). Although this method has capability for eliminating data gaps, these two methods are site specific; besides, if there were not enough observed data, no analysis can be performed using these techniques.

The emerging artificial intelligence (AI) techniques have capabilities for filling up the gaps in observations and for predicting future values, without long observational data (see e.g., Makarynskyy et al., 2004; Lee et al., 2007, among many others). This is advantageous in tidal analysis and sea level predictions.

In the recent years, the application of AI approaches [e.g., artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS)] in ocean and coastal related issues has become viable. Notable applications include wind evaluation (More and Deo, 2003); short wind wave (Deo and Jagdale, 2003; Makarynskyy et al., 2005) and long tidal wave parameters (Lee, 2004; Makarynskyy et al., 2004); wave predictions (e.g., Deo and Naidu, 1999; Agrawal and Deo, 2002; Makarynskyy, 2005; Makarynskyy and Makarynska, 2007), lake level forecasts (Cimen and Kisi, 2009), as well as hydrological simulations (e.g., Thirumalaiah and Deo, 2000), typhoon waves estimation (Chang and Chien, 2006) and coastal water level predictions (Huang et al., 2003).

ANNs are basically parallel information-processing systems. They represent highly simplified mathematical models of biological neural networks. An ANN is capable to learn from examples, to recognize a pattern in the data, to adapt the solutions and process information rapidly.

ANFIS is a combination of an adaptive neural network and a fuzzy inference system. It has been used in various applications and discovered to produce more accurate results compared to other conventional or soft computing techniques. Such applications include Kisi (2005) estimated daily suspended sediments using ANFIS and ANN, for which ANFIS performed better than ANN. Kazeminezhad et al. (2005) applied ANFIS for predicting wave parameters in Lake Ontario and found ANFIS superior to the coastal engineering manual (CEM) methods. Kisi (2006) investigated the ability of ANFIS technique to improve the accuracy of daily evaporation estimation. Hong and White (2009) introduced a dynamic neuro-fuzzy local modeling system for complex dynamic hydrological modeling. Shiri et al. (2011) applied ANFIS technique for short term operational sea water level forecast and found it to outperform the ANN models.

In the present study, the accuracy of ANFIS, ANN and ARMA models were compared with each other when forecasting sea level in Darwin Harbor, Australia. Various membership functions and different training algorithms were employed to, respectively find the optimal models for the ANFIS and ANN.

The parameters of the fuzzy inference system are determined by the ANN learning algorithms. Since this system is based on the fuzzy inference system, then the system should be interpretable in terms of fuzzy IF–THEN rules. ANFIS is capable of approximating any real continuous function on a compact set to any degree of accuracy (Jang et al., 1997). ANFIS identifies a set of parameters through a hybrid learning rule combining back propagation, gradient descent error digestion and ~~a~~ least squared error method. There are two approaches to fuzzy inference systems, namely, Mamdani and Assilian (1975) and Takagi and Sugeno (1985) approach. The neuro-fuzzy model used in this study implements the Sugeno's fuzzy approach. Here, ANFIS has some input variables (previously recorded sea levels) and one output, sea level at a future time step(s).

## 2. Description of the techniques

### 2.1. Artificial neural networks (ANNs)

The ANN is a computing framework patterned after the behavior of biological neural networks. The fundamental building blocks of ANNs are "nodes" comparable to neurons, and weighted connections that can be linked to synapses in biological systems. Fig. 1 illustrates such a network. Initial estimation weight values are progressively corrected during a training process, which compares predicted outputs with target (known) outputs, and back-propagates any error (from right to left in Fig. 1) to determine the appropriate weight adjustments necessary to minimize the errors. The total number of nodes in input and output layers coincides with the number of input and output variables in the data set. The ideal number of hidden layer nodes is determined through a trial and error process. More details about ANNs may be found in e.g., Haykin (1999).

### 2.2. Adaptive neuro-fuzzy inference system (ANFIS)

As a simple example, let us assume a fuzzy inference system with two input variables $x$ and $y$ and one output variable $f$. In the present paper, $x$ and $y$ might be considered as previously recorded sea levels $H_t$ and $H_{t-1,}$ while the output $f$ would represent sea level at the following time step, $H_{t+1}$. In the first-order Sugeno's

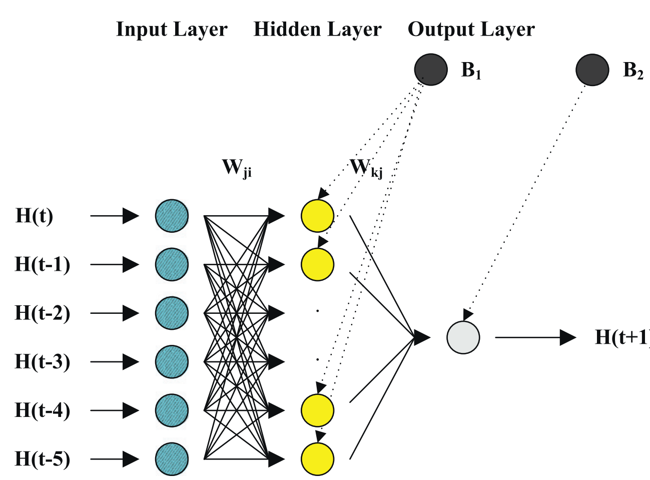


**Fig. 1.** Conventional ANN Model.