The Use of Artificial Neural Networks to Retrieve Sea-level Information from Remote Data Sources

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Abstract. The knowledge of near-shore sea-level variations is of great importance in applications such as ocean engineering and safe navigation. It also plays an essential role in the practical realisation of the height reference surface in geodesy. In the cases of gaps in tide-gauge records, estimates can be obtained by various methods of interpolation and/or extrapolation, which generally assume linearity of the data. Although plausible in many cases, this assumption does not provide accurate results because shallow-water oceanic processes, such as tides, are mostly of a non-linear nature. This paper employs artificial neural networks to supplement hourly tide-gauge records using observations from other distant tide gauges. A case study is presented using data from the SEAFRAME tide-gauge stations at Hillarys Boat Harbour, Indian Ocean, and Esperance, Southern Ocean, for the period 1992 to 2002. The neural network methodology of sea-level supplementation demonstrates reliable results, with a fairly good overall agreement between the retrieved information and actual measurements.

Keywords. Sea level, artificial neural network, simulation, validation, Western Australia

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1 Introduction

Frequently, there are gaps in sea-level records originating from failures in the measuring/recording equipment or when a tide-gauge is upgraded. Such gaps introduce difficulties and uncertainties to the stages of sea level analysis and prediction. For instance, missing data may cause the estimate of mean sea level to be biased.

There are several ways to fill such gaps. Small gaps in relatively frequent (of the order of minutes to tens of minutes) sea-level measurements can be easily fixed using linear interpolation. Missing data from both small and larger gaps can also be restored using harmonic analysis. However, the former does not account for any physics governing the sea-level variations, while the latter does not consider any hydrometeorological forcing, but only the Sun's and Moon's gravitational attractions.

Another logical way of data recovery is to use measurements from the nearest available tide-gauge. However, differences in the phase and amplitude of sea level between tide gauges (due principally to the tides) make it difficult to determine reliable relationships between stations. This holds especially for stations separated by distances from tens to hundreds kilometres.

The artificial intelligence (AI) technique of artificial neural networks (ANNs), which is a relatively new technique in the geosciences, provides reliable predictions of sea currents (Babovic 1999), wave parameters (Makarynskyy 2004a), as well as tidal (Lee et al. 2004) and sea level (Makarynskyy et al. 2004) variations. In the latter it was demonstrated that the quality of temporal extrapolation degrades with increase of the prediction interval. Therefore, this approach would only suit filling several-day gaps, while providing inferior accuracy for larger time periods.

In a number of other studies, ANNs have also been successfully employed to evaluate interrelations among wave gauges over distances from several hundred metres (Tsai et al. 2002) to ~10 km (Makarynskyy 2004b), and between water level stations located 60-600 km away from each other (Huang et al. 2003). These and many other scientific contributions exploited an ANNs' capability to determine interrelations among the elements within a complex geophysical system.

The study presented here aims to demonstrate the applicability of this AI technique to the task of sea-level information retrieval from distant tide gauges. A particular case is considered of two tide gauges in Western Australia separated by a distance of ~1000 km. The ANN technique and data used are described in the next two Sections. These are followed by a description of the results obtained, discussion and conclusions.

2 Artificial neural networks: basics

The inspiration for the development of ANNs, which started about 60 years ago, was found in the biological neural system (Fausett 1994; Haykin 1999). The basis of a neural net is the concept of neuron considered as a unit (Fig. 1). The unit takes the argument *n*, which can be formed as a sum of the weighted input *pw* and bias *b*, and by means of the transfer (activation) function *f*, typically a step function or a sigmoid function, to produce the output *a* (Fig. 1). Note that there can be many input-weight pairs to form the unique argument n_{ij} of the transfer function *f* in the *j*-th neuron (*i* is the number of input nodes, *j* is the number of neurons in the first hidden layer). Several such neurons can be combined in a layer, whereas a particular network can contain one or more interconnected layers of neurons. The pattern of these interconnections is called the architecture of the ANN.

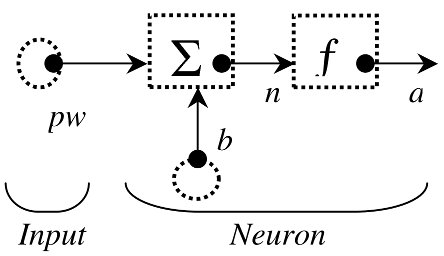

Figure 1. Architecture of a neuron with a single scalar input *pw* and a bias *b* passing through the transfer function *f* to give the output *a*

Non-linear activation functions, such as a log sigmoid or a hyperbolic tangent sigmoid, for the hidden units are needed to make the ANN capable of representing non-linear dependencies. An activation function in the output neurons should suite the distribution of the target values. Thus unbounded linear transfer function is usually used when the training data set is not scaled to some predefined range.

The method of determining the weights and biases is called learning. The learning process requires a set of patterns "input – target output". During the learning process, the weights and the biases of a network are iteratively adjusted to minimize the network performance function. This urges the entire ANN to perform in some expected way. Each presentation of a training set to a net is called an epoch.

3 Data used

The data, in the form of hourly sea-level records, were obtained from SEAFRAME (SEA-level Fine Resolution Acoustic Measuring Equipment) stations deployed at Esperance (33.87°S, 121.90°E) in the Southern Ocean, and Hillarys Boat Harbour (31.82°S, 115.73°E) in the Indian Ocean. These stations (Fig. 2) are operated and maintained by the National Tidal Centre, Australia, as part of the Australian Baseline Sea Level Monitoring Project in the Australian Greenhouse Science Program. These observations are referenced to tide gauge zero that in turn is connected to the Australian Height Datum. The period from January 1992 to December 2002 was employed for this investigation (Fig. 3). The records from both tide-gauges were divided to two data sets; one of which (January 1992-February 1999) served to train the ANNs, and the other (August 2001-December 2002) was used to [independently; i.e., it was not used to train the ANN] validate the retrieval procedure.

The period from February 1999 to August 2001 was excluded from the simulations due to a series of gaps present in the sea level registrations at Esperance. Indeed, these multiple gaps of different durations (from one day on August 13-14, 2001 to several months during March 20-August 8, 2000) were a powerful incentive for the present research. Specifically, if the proposed ANN technique is viable, then nearby tide gauges can be used to restore the missing data at Esperance.

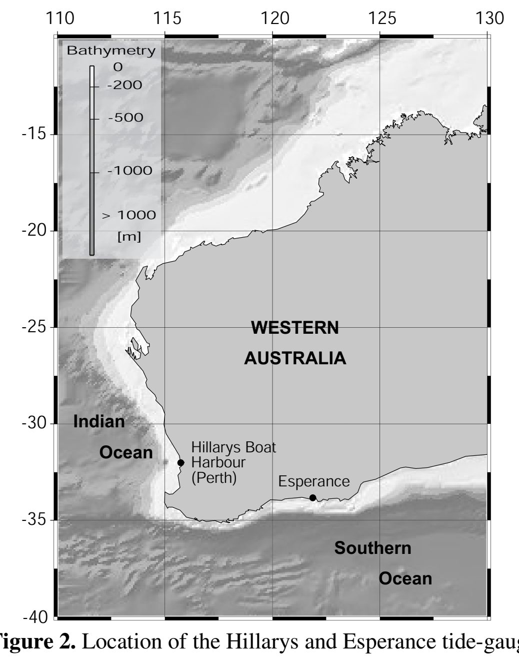

Figure 2. Location of the Hillarys and Esperance tide-gauge stations

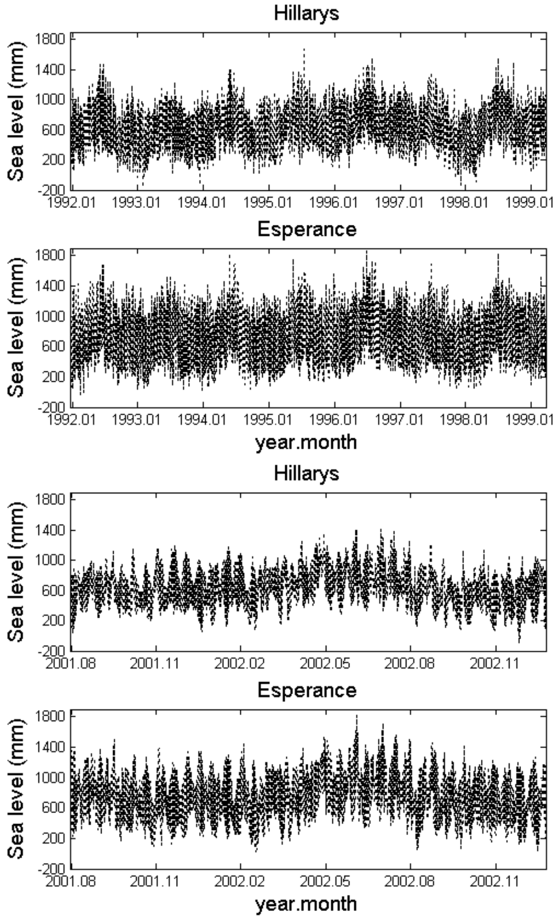

Figure 3. The ANN training (two upper panels) and validation (two lower panels) time-series from the Hillarys and Esperance tide-gauges

The Sun and Moon's gravitational attractions determine a seasonal variability of sea level observed at the tide-gauges with annual minima during the Southern Hemisphere summers and maxima in the winters. However, the non-tidal component of sea-level, which is produced by variations in atmospheric pressure, sea-water temperature, wind forcing and wave setup, can contribute up to 40-50 mm of the measured values at these locations (e.g., Anon. 1999). The range of variations is different for these two gauges: from –140 mm (December 1993) to 1680 mm (July 1995) at Hillarys, and from –30 mm (February 1992) to 1870 mm (June 1996) at Esperance.

4 Results

The feasibility of three-layer, feed-forward ANNs for the reproduction of complex-system behaviour was proved theoretically by Hornik (1993) and empirically by a number of applications (e.g., Huang et al. 2003; Lee 2004; Makarynskyy et al. 2004). Such ANNs with a non-linear, differentiable, log-sigmoid transfer function *f* in the hidden layer, and a linear transfer function in the output layer were employed in this study. This choice is also based upon the results presented in Makarynskyy et al. (2004).

The ANNs were trained with the resilient back-propagation algorithm (Hagan et al., 1996) in 200 training epochs. This learning algorithm counts on the sign of the gradient of the performance function, which for feed-forward ANNs is the average squared error between the network outputs and the target outputs. The sign is used to determine the direction of the weight update: it is increased whenever the derivative of the performance function has the same sign for two successive iterations, or decreased whenever the derivative changes sign from the previous iteration. When the derivative is zero, the update value remains unchanged.

Makarynskyy et al. (2004) demonstrate that the ANN with the number of input units *iu* equal to the number of output units *ou*, and the number of processing nodes *pu,* derived from the expression $pu=iu+ou+1$, performed well in simulations of sea-level at the Hillarys tide-gauge. Therefore, several ANNs with the same structure were tasted here. The number of neurons was also increased from 12*iu*-24*pu*-12*ou* (hereafter referred to as 12x24x12, and likewise for other architectures) to 72x145x72 in order to seek a better performance of the proposed methodology.

In one training epoch, an input-output pattern consisted of an equal number of simultaneous hourly sea-level registrations from the two tide-gauges. For example, when training the 12x25x12 network, 12 measurements from Hillarys served as the input information, while the simultaneous sea-level measurements from Esperance were introduced to the ANN as the target values.

In the simulation stage, an independent set of measurements from one tide-gauge was presented to the trained ANN, which retrieved the data for the other tide-gauge. The results obtained were then verified against the actual observations at the tide-gauge. The quality of the simulations was evaluated in terms of the correlation coefficient

$$R = \frac{\sum_{i=1}^{N} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{N} (x_i - \overline{x})^2 \sum_{i=1}^{N} (y_i - \overline{y})^2}}, \qquad (1)$$

root mean square error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - x_i)^2}{N}}, \quad (2)$$

and scatter index

$$SI = \frac{RMSE}{\bar{x}}, \quad (3)$$

where x_i is the value observed at the i-th time step, y_i is the value simulated at the same moment of time, N is the number of time steps, $\bar{x}$ is the mean value of the observations, and $\bar{y}$ is the mean value of the simulations. The statistics, averaged over the corresponding time intervals (12, 24, 36, 48, 60 and 72 hours) of retrieval, are presented in Table 1.

Table 1. Interrelations between tide-gauges at two locations

Architecture	*RMSE*	*R*	*SI*
Retrieval for Esperance			
12x25x12	141mm	0.814	0.199
24x49x24	133mm	0.838	0.187
36x73x36	130mm	0.845	0.183
48x97x48	138mm	0.831	0.193
60x121x60	140mm	0.827	0.196
72x145x72	141mm	0.825	0.198
Retrieval for Hillarys			
12x25x12	132mm	0.799	0.208
24x49x24	129mm	0.812	0.205
36x73x36	129mm	0.818	0.204
48x97x48	136mm	0.803	0.215
60x121x60	136mm	0.804	0.215
72x145x72	147mm	0.780	0.208

5 Discussion

From an analysis of the results in Table 1, it follows that all tested ANNs performed in a similar way. The range of *RMSE* variations is 11 mm and 18 mm, the *R* value changes within the limits of 0.031 and 0.019, while differences in values of the *SI* are 0.016 and 0.011, when, respectively, the records from Hillarys were used to retrieve the data for Esperance and *vice versa*. In both these cases the 36x73x36 ANN provided the highest accuracy of all the simulations trialled. The quality of the data retrieval with this ANN is illustrated in Fig. 4.

It is clear that the ANNs with simpler architectures do not include enough information to perform as well, while more complicated nets may suffer from the artefacts of over-fitting. The latter manifests itself in extracting too much information from particular training pairs and the consequent failure to generalize over unknown for the network data.

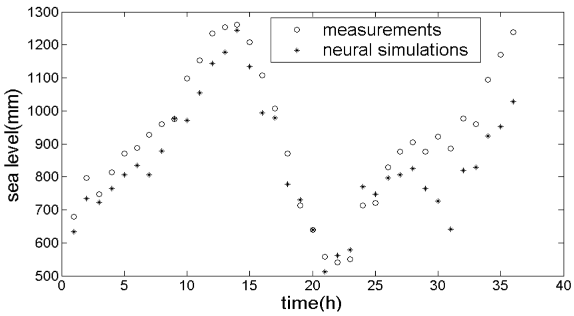

Figure 4. Randomly selected 36-hour time series of the measured and simulated sea level for Esperance

6 Conclusions

An ANN-based methodology for sea-level retrieval at remote sites was proposed and tested on observations from the Hillarys Boat Harbour and Esperance SEAFRAME tide-gauge stations deployed in the Indian and Southern Oceans, respectively. The methodology is based on the idea that, although different in phase and amplitude, sea-level variations at remote tide-gauges are related one to another, and ANNs can simulate these relations.

Three-layer, feed-forward ANNs with a non-linear differentiable log-sigmoid transfer function in the hidden layer and linear transfer function in the output layer have again proved to be useful in such research (cf. Makarynskyy et al. 2004).

Six different ANN architectures were tested when retrieving data for the both locations. Among the networks considered, the overall best performance was attained with the 36x73x36 ANN architecture. The best simulations, as evaluated versus actual sea-level observations, are characterized by the correlation coefficient of the order R=0.82-0.85, the root mean square error of about $RMSE$=130 mm (less than 7% of the range of variations) and the scatter index within the limits of SI=0.18-0.20.

The application of this validated neural methodology of sea-level retrieval could possibly be successfully generalized to other remote tide gauges in different coastal environments. For this, a necessary condition would be the availability of sufficiently long and continuous sea-level records.

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