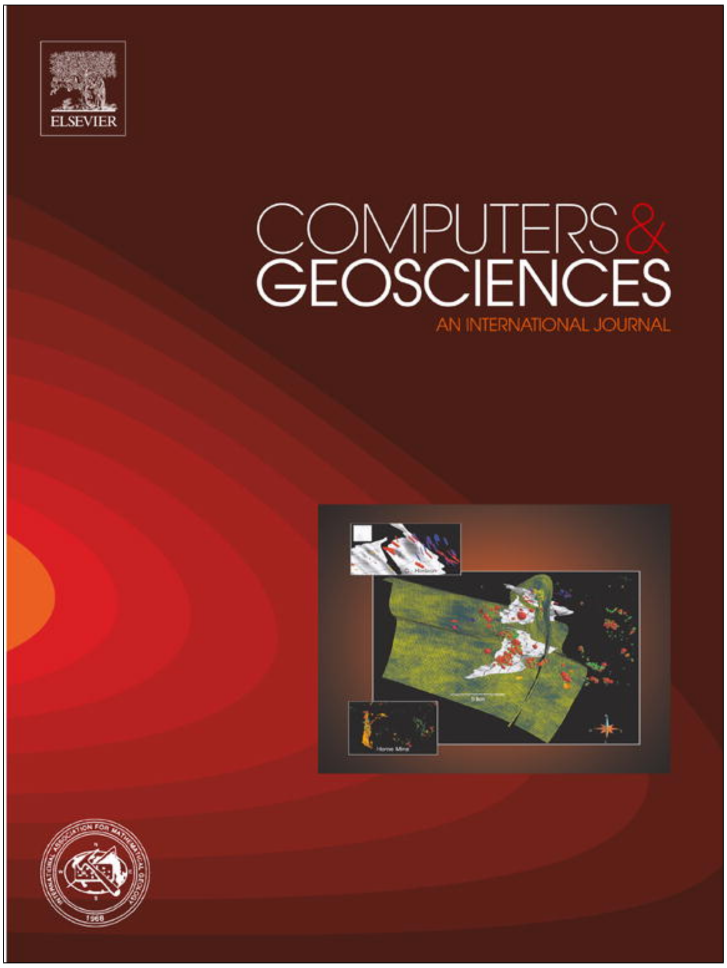
ELSEVIER
COMPUTERS & GEOSCIENCES
AN INTERNATIONAL JOURNAL

Computers & Geosciences 52 (2013) 50–59

Contents lists available at SciVerse ScienceDirect

Computers & Geosciences

journal homepage: www.elsevier.com/locate/cageo

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

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ARTICLE INFO

Article history:
Received 28 April 2012
Received in revised form
26 August 2012
Accepted 17 September 2012
Available online 22 September 2012

Keywords:
Sea-level prediction
Auto-regressive moving average
Adaptive neuro-fuzzy inference system
Artificial neural network
Darwin Harbor

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

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http://dx.doi.org/10.1016/j.cageo.2012.09.015

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

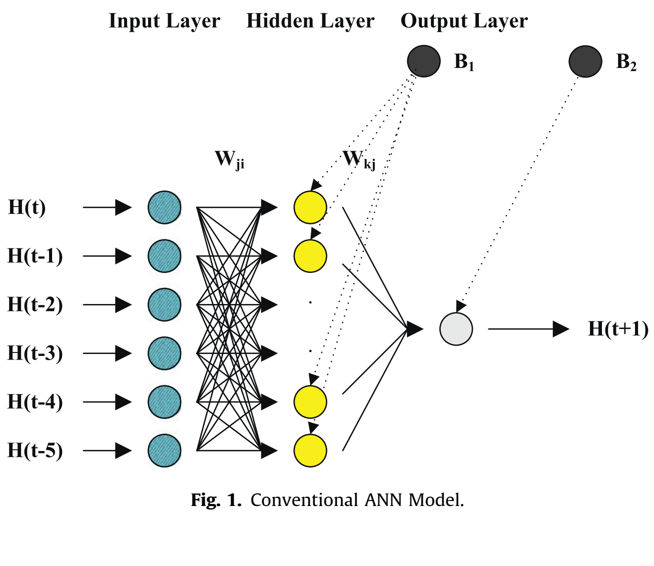

Fig. 1. Conventional ANN Model.

fuzzy model, a typical rule set with two fuzzy IF–THEN rules can be given as:

Rule 1: If x is A_1 and y is $B_{1,}$ then.

$$f_1 = p_1 x + q_1 y + r_1 \tag{1}$$

Rule 2: If x is A_2 and y is $B_{2,}$ then.

$$f_2 = p_2 x + q_2 y + r_2 \tag{2}$$

where A_1, A_2 and B_1, B_2 are the membership functions (MFs) for inputs x and y, respectively, and p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. Here the output f is the weighted average of the individual rule outputs and is itself a crisp value. Fig. 2 displays a general ANFIS architecture for a Type 3 Sugeno model.

The output of the ith node in layer l is denoted as $O_{l,i}$. Every node i in Layer 1 is an adaptive node with node $O_{l,i} = A_i(x)$, for $i=1$, 2, or $O_{l,i} = B_{i-2}(y)$, for $i=3$, 4, where x (or y) is the input to the ith node and A_i (or B_{i-2}) is a linguistic label (such as 'low' or 'high') associated with this node. The MFs for A and B are generally described by generalized bell functions (Jang, 1993), e.g.,

$$A_i(x) = \frac{1}{1+[(x-c_i)/a_i]^{2b_i}} \tag{3}$$

where $\{a_i, b_i, c_i\}$ is a set of parameters. Here, parameters a and b vary the width of the curve and the parameter c locates the center of the curve. The parameter b should be positive. As an example, a generalized bell function with a parameter set {4, 8, 12} is shown in Fig. 3. In fact, any continuous and piecewise differentiable functions, such as commonly used triangular-shaped MFs are often selected in practical tasks (Jang, 1993; Russel and Campbell, 1996). Triangular MFs were selected and used here because this MF is of linear shape and calculations of its parameters are simple.

In similarity to the hidden nodes of ANNs, there is no basic rule to determine the number of MFs, so they should be determined iteratively. However, a modeler should avoid using a large number of membership functions or parameters to save time and computational effort (Keskin et al., 2004). Parameters in this layer are called *premise parameters*. The outputs of this layer are the membership values of the premise part. Layer 2 consists of the nodes labelled Π which multiply incoming signals and send the product out. For instance,

$$O_{2,i} = w_i = A_i(x) B_i(y), \quad i=1,2. \tag{4}$$

Each node output represents the firing strength of a rule. The nodes labelled N calculate the ratio of the ith rule's firing strength to the sum of all rules' firing strengths in Layer 3,

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2}, \quad i=1,2. \tag{5}$$

The outputs of this layer are called normalized firing strengths. The nodes of the Layer 4 are adaptive with node functions

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{6}$$

where $\overline{w}_i$ is the output of Layer 3, and p_i, q_i, r_i is a set of parameters. Parameters of this layer are referred to as *consequent parameters*. The single fixed node of the Layer 5 labelled Σ computes the final output as the summation of all the incoming signals

$$O_{5,i} = \sum_{i=1} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

Thus, an adaptive network which is functionally equivalent to a Sugeno's first-order fuzzy inference system is built. More detailed information about ANFIS theory can be found in Jang (1993).

For a given input–output dataset, various Sugeno's models may be developed by using different identification methods namely grid partitioning, subtractive clustering and Gustafson–Kessel clustering methods (Jang, 1993; Jang et al., 1997). However, some recent

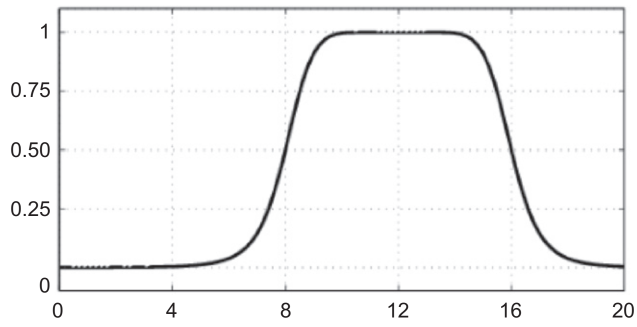

Fig. 3. Generalized bell membership function with a parameter set {4, 8, 12}.

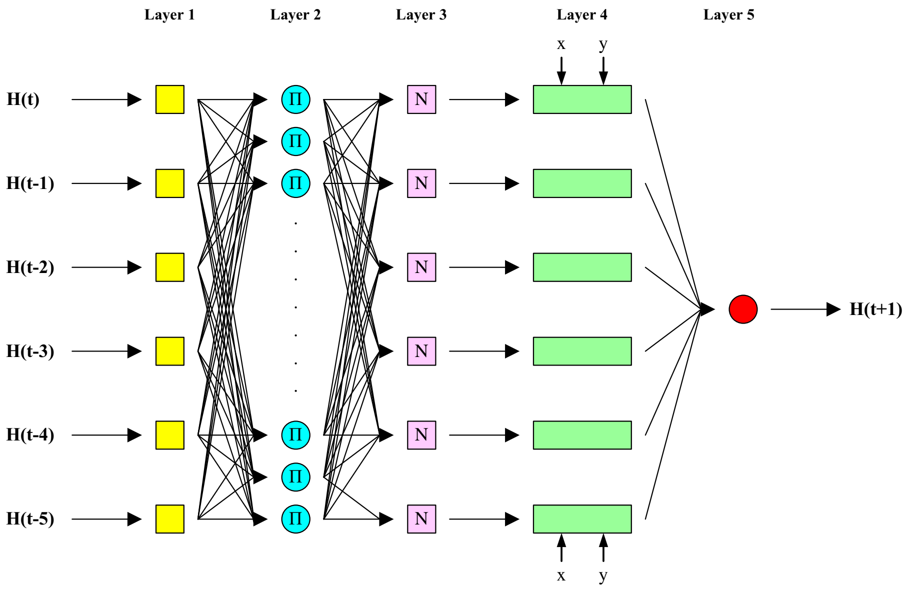

Fig. 2. ANFIS architecture.

studies (Vernieuwe et al., 2005) demonstrated that the type of identification method does not affect the results to a large degree (Vernieuwe et al., 2005). In this study, grid partitioning identification method was used for constructing the neuro-fuzzy models.

3. Materials and methods

3.1. Development of ANFIS and ANN models

According to Khatibi (2004) the modeling procedure of time series analysis consists of three major phases:

Phase 1: Reviewing the data for any possible discontinuity in both dependent and independent data set and choosing the appropriate software; dividing the data into training, validation and application blocks.
Phase 2: Implementing the time series analysis as per selected modeling application; setting the parameters of selected software and producing the results. This phase depends on the time-series analysis technique.
Phase 3: Post-processing the results in relation to training, validation and application and if applicable, carrying out some sensitivity analysis.

Consequently, the data set were divided into training, testing and validation blocks. As the first step for selecting input variables for ANN and ANFIS models, the partial auto correlation function (PACF) was constructed (see Fig. 4). Nonetheless, in order to compare the performance of soft computing techniques to traditional methods, corresponding ARMA models were developed using the same training, testing and validation data sets.

3.2. Model assessment

In any modeling circumstance, it is essential to use some performance evaluation criteria for assessing the abilities of each applied models as well as for inter-comparisons of different applied models. In the present study, three statistical indices were used for namely:

1. The coefficient of determination (R^2) defined as in Eq. (8) and ranged between 0 and 1 The higher the value of R^2, the better the performance of the model.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(H_{io}-\overline{H}_o)(H_{iM}-\overline{H}_M)}{\sqrt{\sum_{i=1}^{n}(H_{io}-\overline{H}_o)^2\sum_{i=1}^{n}(H_{iM}-\overline{H}_M)^2}}\right]^2 \tag{8}$$

where H_{io} is the recorded sea water level at the ith time step, H_{iM} is the corresponding simulated sea water level, n is number of time steps, $\overline{H}_o$ is mean of observational values and $\overline{H}_M$ is mean value of the simulations.

2. The root mean square error (RMSE) expressed as in Eq. (9) and used to describe the average magnitude of the errors between the observational values and model results. It ranges between 0 and 1 with lower values corresponding to better performance

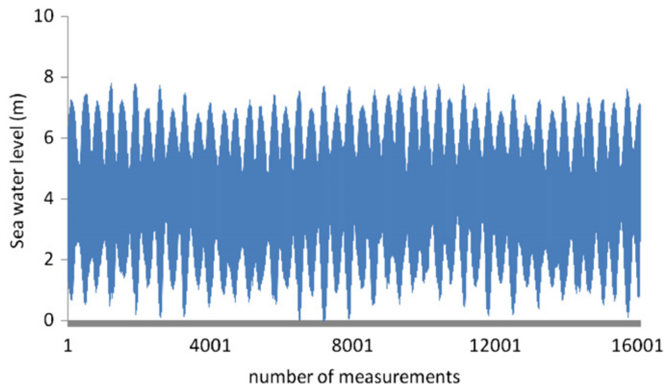

Fig. 5. Time series plot of sea level observations.

Table 1
Statistical parameters of used data sets.

	X_{mean}	X_{max}	X_{min}	S_X	C_V	C_{SX}
Training period	4.1	7.8	0.2	1.6	0.39	−0.04
Testing period	4.3	7.7	0.14	1.6	0.37	−0.03
Validation period	4.1	7.6	0.1	1.6	0.39	−0.03
Whole period	4.1	7.8	0.1	1.6	0.38	−0.04

X_{mean} X_{max}, X_{min}, S_X, C_V and C_{SX} denote the mean, maximum, minimum, standard deviation,coefficient of variation and skewness coefficient, respectively.

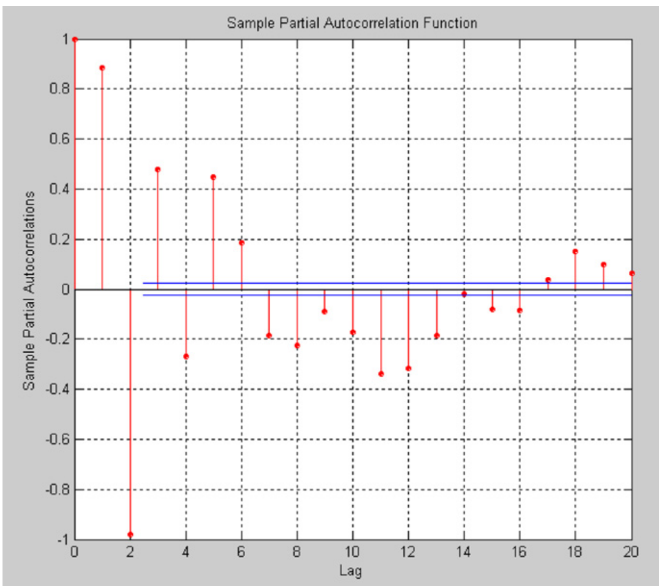

Fig. 4. Partial auto correlation function for sea level in Darwin Harbor, Australia.

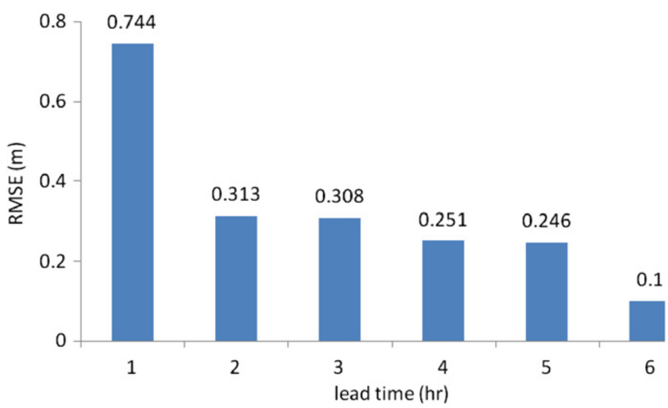

Fig. 6. RMSE values of MLR model for various lead times during test period.

Table 2
Testing and validation statistics of various ANFIS and ANN models for +1 h prediction interval (trained with optimal input combination).

	Structure	Testing			Validation		
		R^2	RMSE (m)	VAF (%)	R^2	RMSE (m)	VAF (%)
ANFIS models							
Triangular MFs (ANFIS1)	2	0.998	0.055	99.8	0.999	0.048	99.9
Trapezoidal MFs (ANFIS2)	2	0.961	0.326	96.1	0.972	0.260	97.2
Generalized bell MFs (ANFIS3)	2	0.990	0.160	99	0.995	0.111	99.4
Gaussian MFs (ANFIS4)	2	0.996	0.096	99.6	0.998	0.066	99.8
Two Gaussian MFs (ANFIS5)	2	0.971	0.283	97	0.985	0.192	98.5
ANN models							
ANN1 (trained with Levenberg–Marquardt)	(6,8,1)	0.998	0.064	99.84	0.9991	0.047	99.91
ANN2 (trained with conjugate gradient)	(6,7,1)	0.996	0.096	99.64	0.9977	0.076	99.77
ANN3 (trained with gradient descent with adaptive learning rate)	(6,7,1)	0.995	0.110	99.52	0.9970	0.087	99.70
ARMA models							
ARMA(1,0)	–	0.883	0.764	76.89	0.111	2.056	−69.72
ARMA(2,0)	–	0.989	0.369	95.20	0.725	1.760	−8.983
ARMA(3,0)	–	0.996	0.152	99.08	0.918	0.646	83.37
ARMA(4,0)	–	0.996	0.151	99.09	0.915	0.663	82.55
ARMA(1,1)	–	0.959	0.459	91.71	0.304	1.844	−35.94
ARMA(2,1)	–	0.995	0.225	98.19	0.785	1.431	27.12
ARMA(1,2)	–	0.986	0.282	96.85	0.543	1.544	4.380
ARMA(2,2)	–	0.997	0.177	98.86	0.799	1.249	43.64
ARMA(3,2)	–	0.998	0.110	99.52	0.946	0.512	89.40
ARMA(2,3)	–	0.992	0.227	98.30	0.667	1.416	34.81
ARMA(3,3)	–	0.997	0.113	99.50	0.951	0.491	90.35

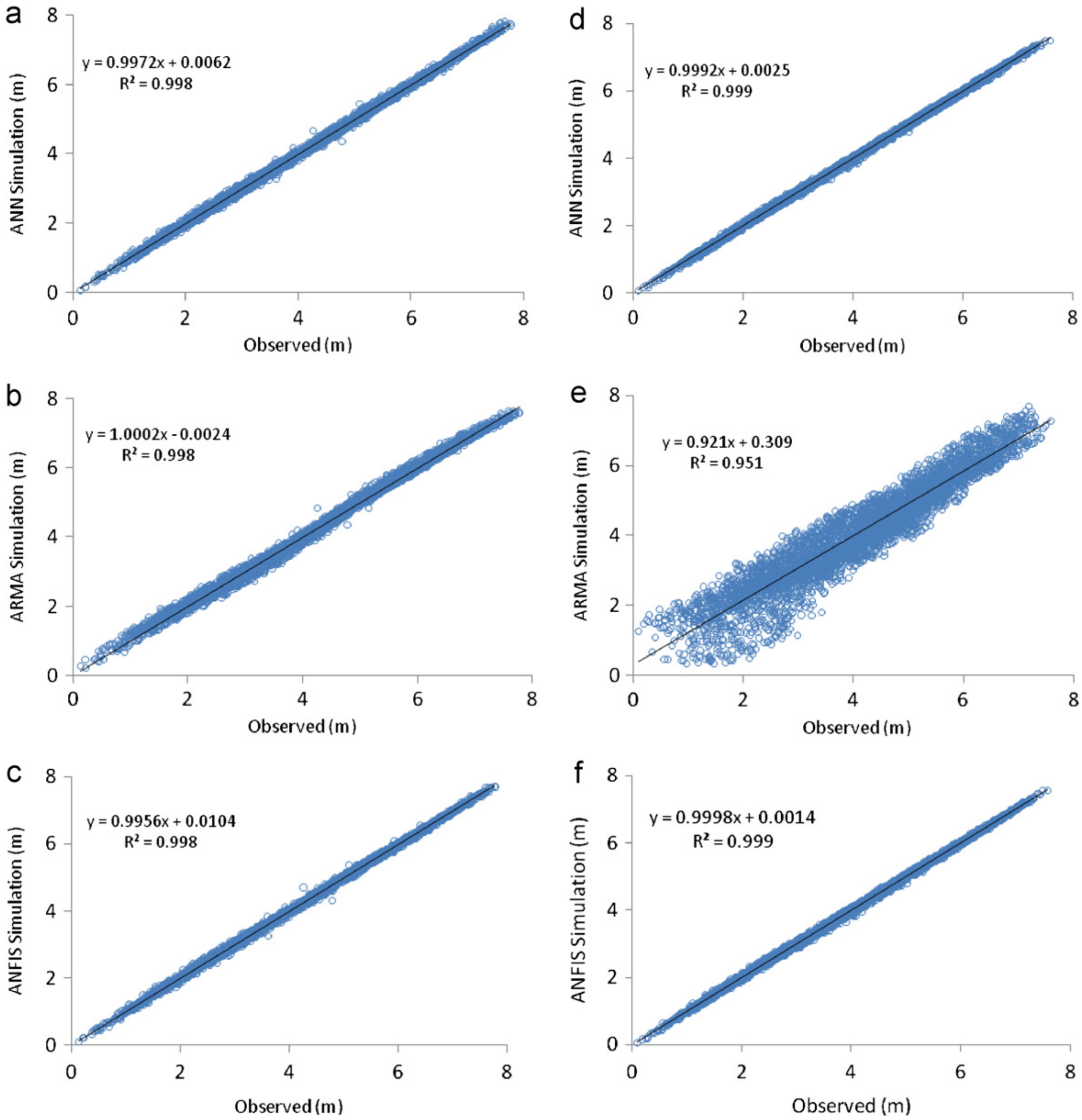

Fig. 7. Scatterplots of observed versus simulated sea levels (1 h prediction) for testing ((a)–(c)) and validation ((d)–(f)) periods.

Table 3
Performance of ANFIS, ANN and ARMA models trained with optimal input combination.

Prediction interval	Testing period			Validation period		
	R^2	RMSE (m)	VAF (%)	R^2	RMSE (m)	VAF (%)
ANFIS model						
+24 h	0.962	0.305	96.2	0.967	0.282	96.7
+48 h	0.866	0.580	86.6	0.882	0.542	88.2
+72 h	0.731	0.827	73.0	0.763	0.770	76.2
ANN model						
+24 h	0.964	0.302	96.4	0.969	0.279	96.9
+48 h	0.870	0.573	87.0	0.885	0.536	88.5
+72 h	0.742	0.809	74.1	0.800	0.760	76.9
ARMA model						
+24 h	0.925	0.747	77.9	0.931	0.732	78.4
+48 h	0.734	1.186	44.6	0.754	1.161	45.9
+72 h	0.491	1.429	20.2	0.523	1.399	21.7

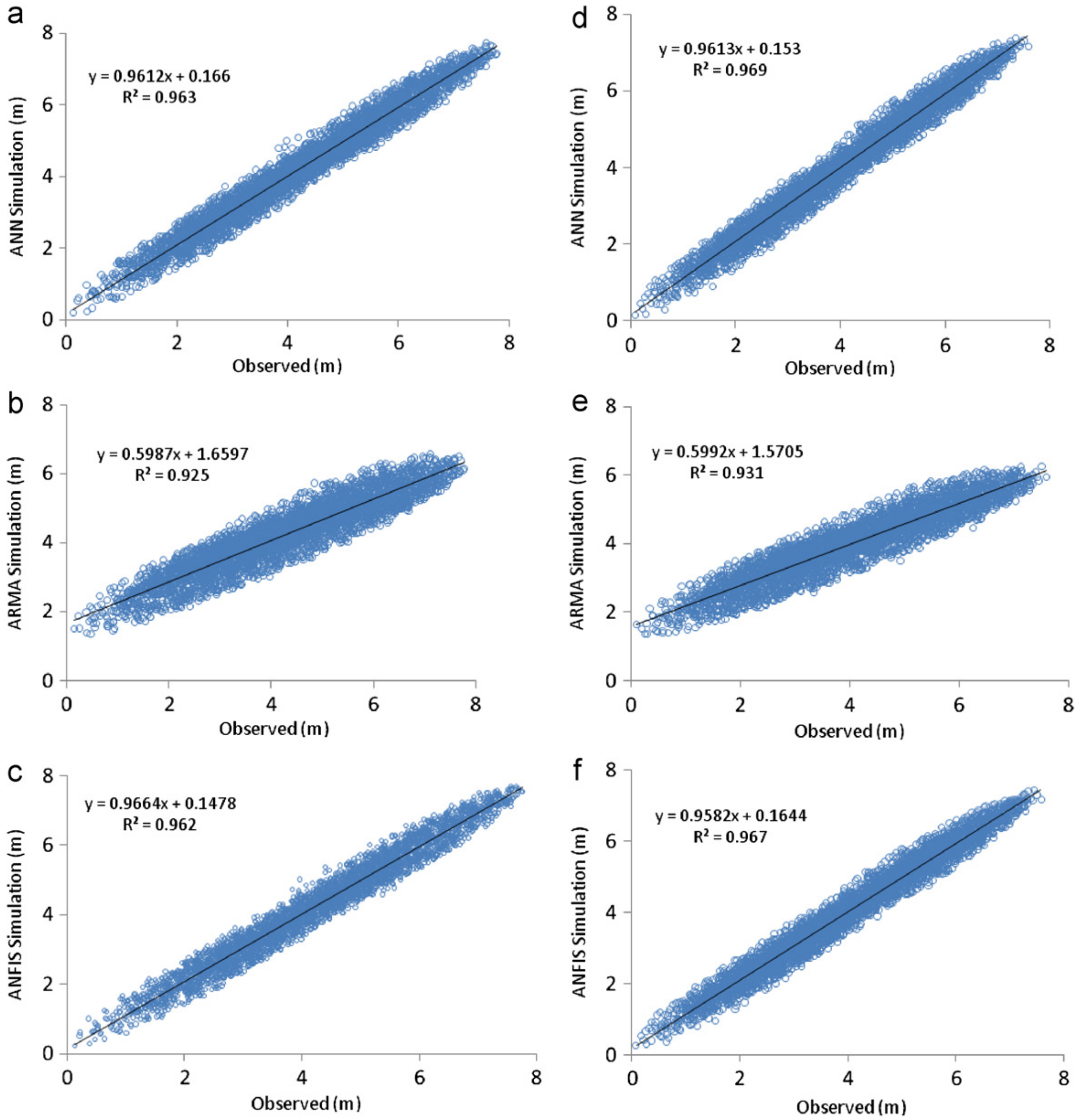

Fig. 8. Scatterplots of observed versus simulated sea level (24 h prediction interval) for testing ((a)–(c)) and validation ((d)–(f)) periods.

of the model:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_{iM}-H_{io})^2} \quad (9)$$

3. Variance accounted for (VAF) defined as in Eq. (10) and used to verify the correctness of the models. The perfect value of VAF is 100 representing the best fit of the model output to the observed values.

$$\mathrm{VAF} = \left[1-\frac{\mathrm{Var}(H_{io}-H_{iM})}{\mathrm{Var}(H_{io})}\right] \times 100 \quad (10)$$

3.2.1. Illustration of the model

Time series of hourly sea level records from the Darwin Harbor in Australia (latitude: 12.42°S, longitude: 130.89°E, altitude: 30.4 m above mean sea level) from January 01, 2007 to October 31, 2008 were used to forecast hourly sea level variations (see Fig. 5 for sea water level time series). The recorded data from 1st January 2007 to 30th November 2007 were used for training (calibrating) the applied methods while data from 30th November 2007 to 17th May 2008 were used for testing the methods. Finally, the data from 18th May 2008 to 31th October 2008 were used for validation. The statistics of the hourly sea level X during the period in question are shown in Table 1.

Multi linear regression (MLR) model was used to evaluate the degree of effect of each variable and to selectthe most effective input vectors. The following input combinations were evaluated with MLR:

(i) H_t
(ii) H_{t-1}, H_t
(iii) H_{t-2}, H_{t-1}, H_t
(iv) H_{t-3}, H_{t-2}, H_{t-1}, H_t
(v) H_{t-4}, H_{t-3}, H_{t-2}, H_{t-1}, H_t
(vi) H_{t-5}, H_{t-4}, H_{t-3}, H_{t-2}, H_{t-1}, H_t

where H_t denotes the sea level record at time t.

4. Results and discussions

It is clear from Table 1 that the data show low skewness; that is slightly leptokurtic and close to normal distribution. The difference in statistical properties of the training, testing and

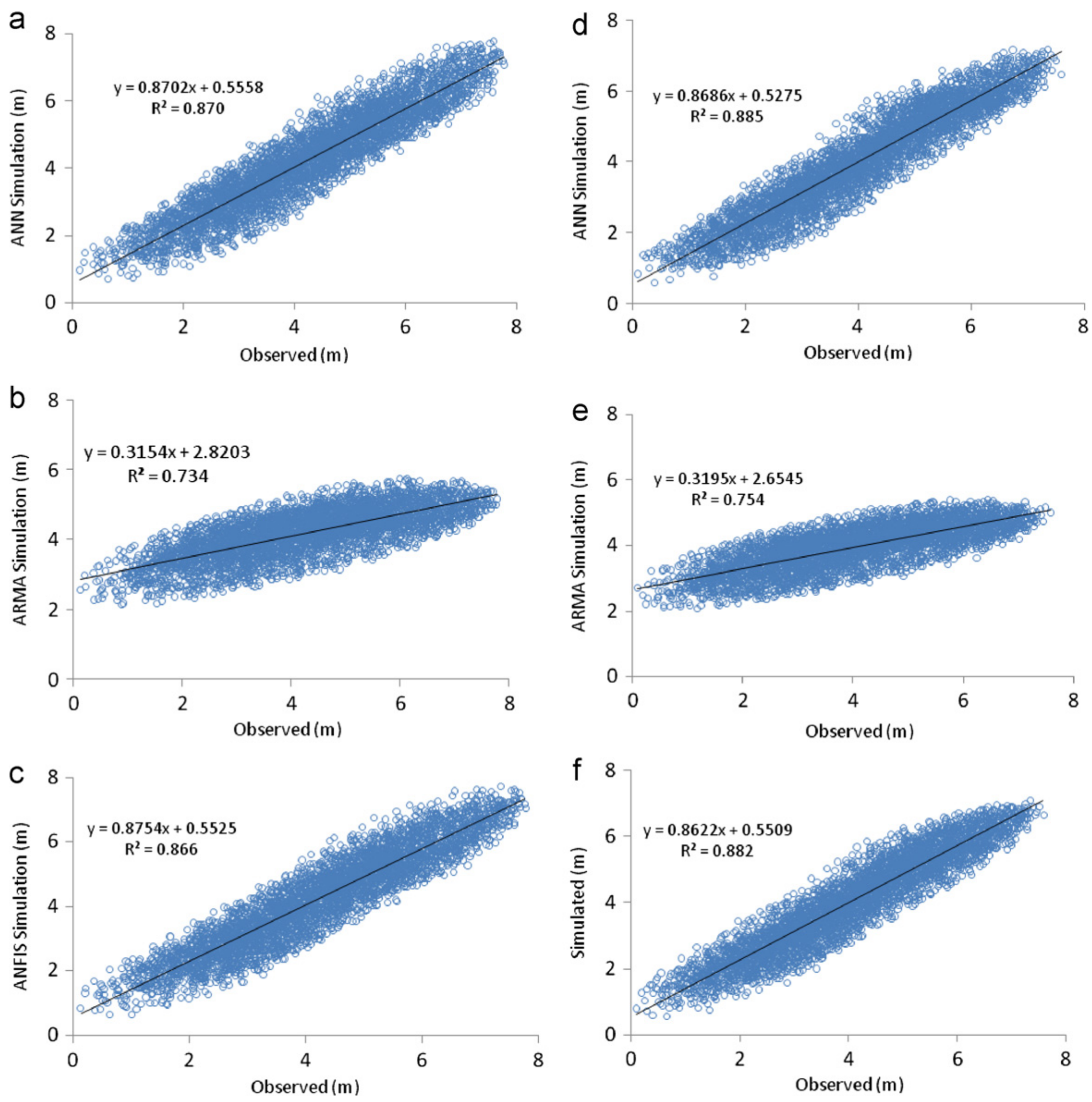

Fig. 9. Scatterplots of observed versus simulated sea levels (48 h prediction interval) for testing ((a)–(c)) and validation ((d)–(f)) periods.

validation data is infinitesimal and can be considered insignificant. Nevertheless, according to PACF, the 13 lag times have significant influence on predicting sea level for the following time step (H_{t+1}), so it seems that up to 13 sea levels are necessary for task on hands. RMSE values of MLR model for various lead times during the test period are shown in Fig. 6. Using H_t as the only input variable resulted in less accurate simulations with RMSE=0.744 m, while the input combination H_{t-5}, H_{t-4}, H_{t-3}, H_{t-2}, H_{t-1}, H_t gives the best results with RMSE=0.1 m compared to others and hence most effective for predicting 24 h, 48 h and 72 h sea level variations. Thus, the MLR application indicates that introducing sea water levels up to H_{t-5} significantly increases the modeling accuracy, while adding more variables does not noticeably affect the prediction accuracy.

4.1. Preliminary investigation on ANFIS and ANN models

Table 2 represents the ANFIS results of hourly sea water level forecasts with various membership functions for input combination (vi) for the testing and validation periods. The table clearly shows that, in terms of the VAF criterion, the ANFIS model with triangular membership function (ANFIS1 model) gives the best results. So it was employed for the subsequent modeling process. The second column of the table gives the number of MFs of each input variable in the applied ANFIS models. In the present study, introducing two MFs for each input variable was sufficient to produce good predictions.

Table 2 represents the results of the applied ANN models trained with the optimal input combination along with the number of input, hidden and output nodes and also provides the results of ARMA models for predicting a day ahead sea levels during the test and validation periods. From the table, it is clear that ARMA(3,2) performs better than, in terms of the R^2, RMSE and VAF statistics, other ARMA models in the test period with respect to.

The overall evaluation of three methods reveals that both ANFIS and ANN models give similar accuracy and generally perform better than the traditional ARMA model. Fig. 7 displays the observed and simulated sea level values produced by the optimal ANFIS, ANN and ARMA models during the testing and validation periods. The similar accuracy of the ANFIS and ANN models can be clearly seen from the figure. The ARMA model has more scattered predictions than the other models especially in the validation stage.

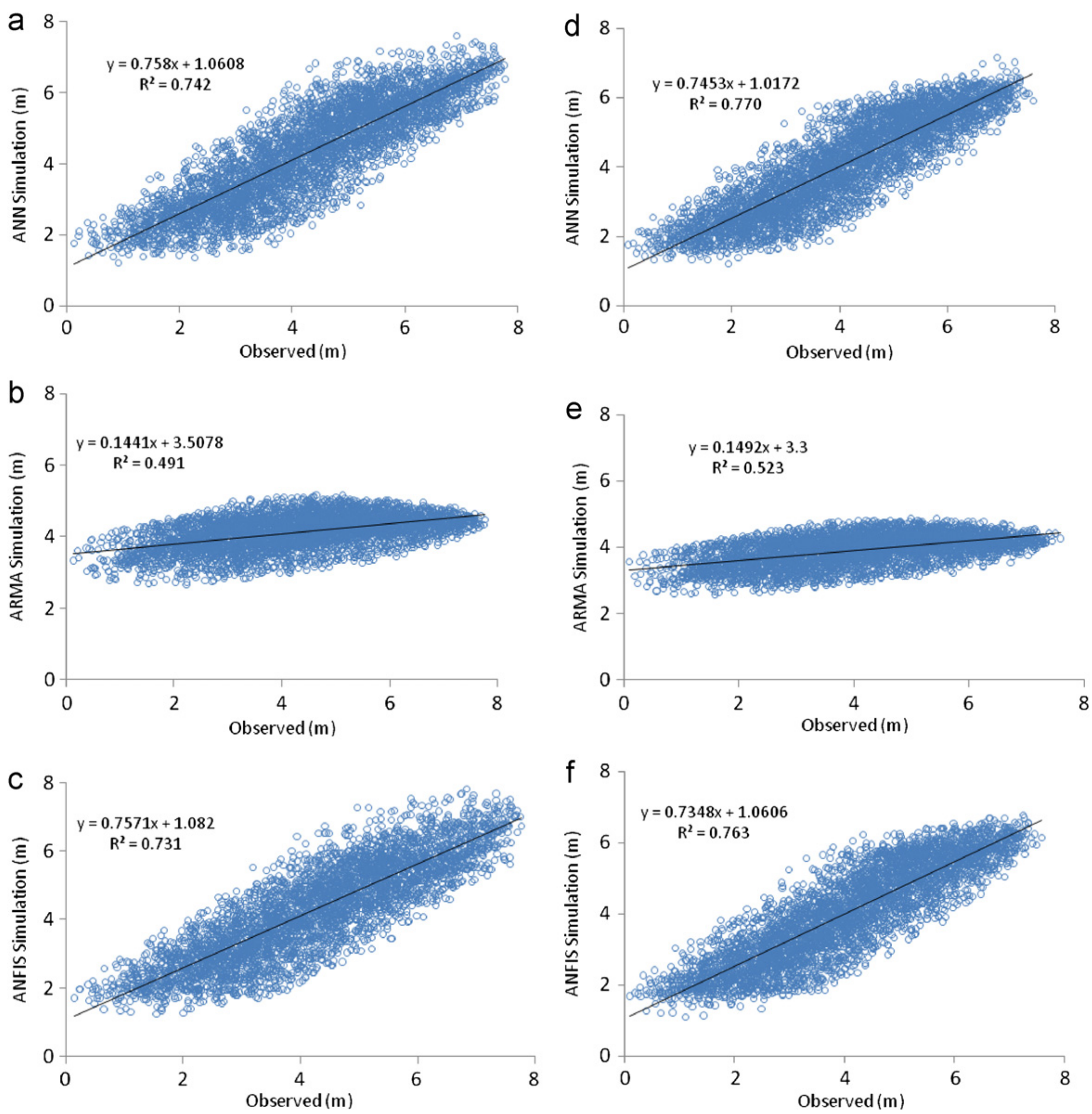

Fig. 10. Scatterplots of observed versus simulated sea levels (72 h prediction interval) for testing ((a)–(c)) and validation ((d)–(f)) periods.

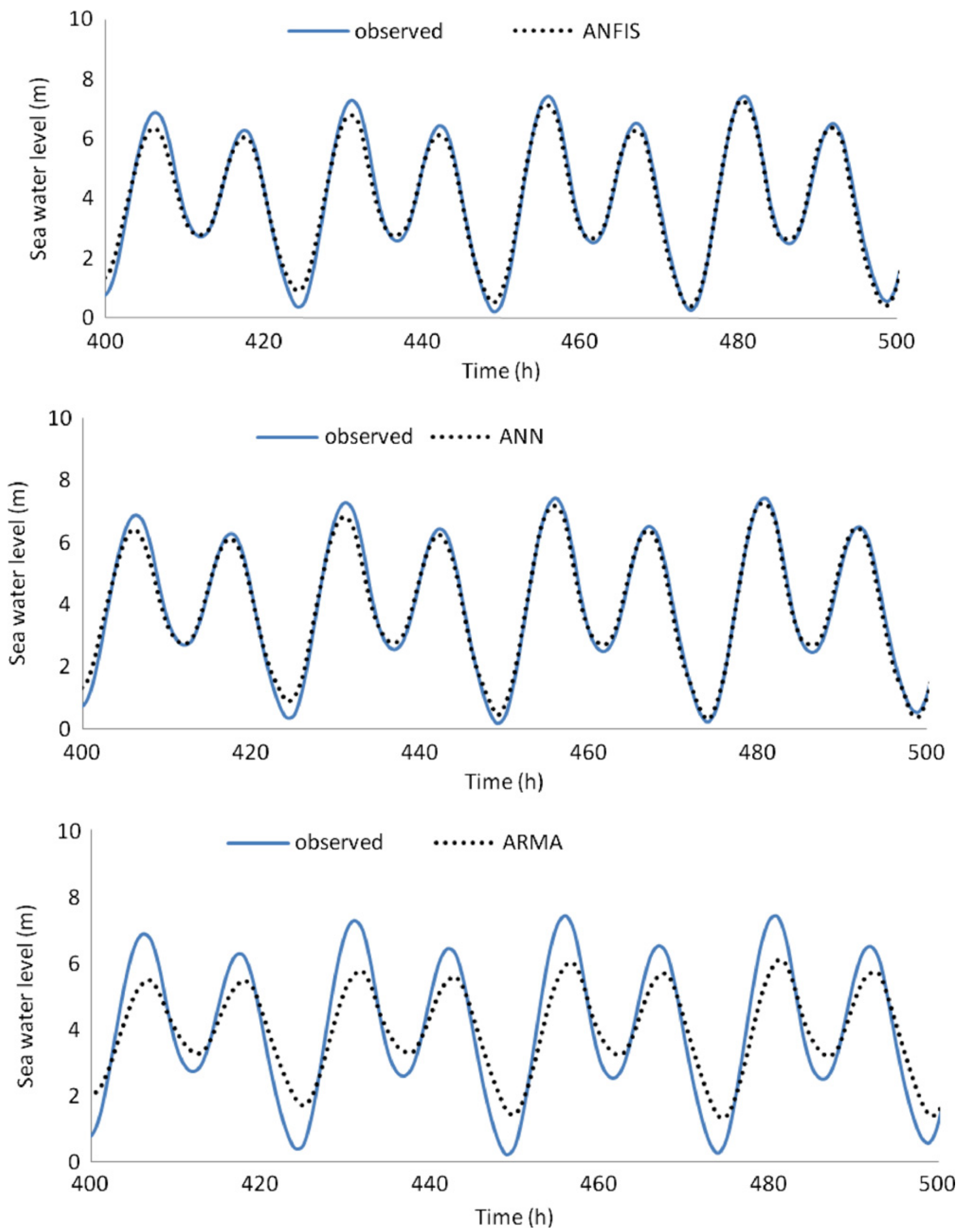

Fig. 11. Temporal variations of ANFIS, ANN and ARMA simulations for 400th and 500th hourly sea levels.

4.2. *Prediction of sea levels at longer forecast horizons*

Having selected the optimal input combination (vi), the ANFIS, ANN and ARMA models were applied to forecast sea levels 24 h, 48 h and 72 h ahead (See Table 3). The test results indicate that increasing prediction interval from 24 h to 72 h leads to a decrease in the model accuracy. The R^2 decreases from 0.962 to 0.731 for ANFIS, from 0.964 to 0.742 for ANN and from 0.925 to 0.491 for ARMA models. The RMSE increases from 0.305 to 0.827 for ANFIS, from 0.302 to 0.809 for ANN and from 0.747 to 1.429 for ARMA models. The VAF decreases from 96.2 to 73 for ANFIS, from 96.4 to 74.1 for ANN and from 77.9 to 20.2 for ARMA. The ANFIS and ANN models surpass the ARMA at all three prediction intervals.

The validation statistics also confirm that the ANFIS and ANN models surpass the ARMA at all the considered prediction intervals. Expectedly, increasing prediction intervals from 24 h to 72 h decreases the models' accuracy. Figs. 8–10 provide the scatter plots of the observed and simulated sea levels during the testing (a–c scatters) and validation (d, e, f scatters) periods. It is clear that increasing time intervals results in more scattered model estimates.

The ANFIS, ANN and ARMA predictions for the period between 400th and 500th hour sea levels (in validation period) are shown in Fig. 11. The ANFIS and ANN predictions were still well correlated with the corresponded observations, whereas the ARMA model seemed to be incapable to predict the extreme values.

5. Conclusions

In this study, the ability of ANFIS, ANN and ARMA models in forecasting sea water levels was tested. Hourly sea level observations from a Darwin Harbor tide gauge (Australia) were used for training and testing of each model using optimal input combination obtained from MLR technique. As the preliminary step, MLR technique was used for selecting the optimal input combination to be employed for predicting sea levels 1 h, 24 h, 48 h and 72 h ahead. MLR application indicated that feeding the models with sea levels up to H_{t-5} significantly increases the modeling accuracy. Various membership functions were tested for the ANFIS models; the triangular membership function was found to be optimal for the predictions. Three different training algorithms, Levenberg–Marquardt (LM), conjugate gradient and gradient descent with adaptive learning rate, were employed for the ANN models, from which Levenberg–Marquardt performed better than the others. Various ARMA models were also employed for predicting one day ahead sea levels and ARMA(3,2) model was found to be better than other ARMA models in the test period. The optimal ANFIS, ANN and ARMA models were compared against each other to estimate sea levels 1 h, 24 h, 48 h and 72 h ahead. The results demonstrated that the ANFIS and ANN models had similar forecast accuracy, and their accuracies were better than the ARMA model one.

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