Performance Evaluation for Mean Sea Level Prediction using Multivariate Adaptive Regression Spline and Artificial Neural Network*

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Abstract

Mean sea level (MSL) has been used as a vertical datum for geodetic levelling and mapping in most countries all over the world. This is because the MSL approximates the geoid and serves as a realist reference surface that could be determined mostly through tide measurements over a period of time. However, sea levels have been rising over the years due to global warming and its associated climate change which continuous to melt ice sheets around the Polar Regions. This phenomenon is likely to affect the reliability of MSL, thus it is important to determine the local MSL at regular time periods. This study assessed the performance of Artificial Neural Network (ANN) and Multivariate Adaptive Regression Spline (MARS) models in predicting the MSL. Tide gauge records from the Takoradi Harbour of Ghana were used in the study. Monthly maximum, minimum and mean tidal values were derived from the secondary data and used for both model formulation and model testing. A comparative analysis of both models showed that the ANN model performed better than the MARS model. A Root Mean Square Error (RMSE) of 0.0359 m was obtained for the ANN model, whereas 0.0555 m was obtained for the MARS model. Mean Absolute Percentage Error (MAPE) of 3.1414% was obtained for the ANN model and whereas the MARS model yielded 5.6349%. A Mean Absolute Error (MAE) for the ANN model was 0.0284 m as against 0.0446 m for the MARS model. Correlation coefficient values of 0.9720 and 0.8874 were obtained for the ANN model and the MARS model respectively. An optimum ANN structure was found to be ANN 2-11-1. Based on the outcome of this study, it is recommended that ANN model should be adopted for forecasting local mean sea level for the study area.

Keywords: Mean Sea Level, Artificial Neural Network, Multivariate Adaptive Regression Spline

1 Introduction

Mean Sea Level (MSL) refers to the average of hourly heights of the sea at one or more tide stations observed over a period of time, usually 19 years. Mean sea level varies from coast to coast due to differences in temperature, salinity, currents, density, wind, and gravitational force exerted between the earth and celestial bodies like the moon and the sun (Yakubu, 2015; Pugh, 1996). According to Lu *et al*. (2014), the MSL is practically determined by averaging the level of water at a tide station over a period of time. MSL is usually serves as a level surface to which heights are referred. Most countries have adopted the MSL as their reference surface as it is a stable surface, it practically exists and can be determined precisely usually by continuous tide gauge measurements. Another benefit is that the MSL approximates the physical shape of the earth.

The MSL is a vertical datum that is mostly used as a chart datum in marine navigation and in aviation as the standard sea level at which atmospheric pressure is measured in order to calibrate altitude and aircraft flight levels. By convention, MSL is the midpoint between the high tide (maximum tide observation) and the low tide (minimum tide observation) at a particular location (Haigh *et al*., 2010).

To determine the MSL, usually a tide station is established on stable ground that is devoid of abnormal conditions where it would be appropriate to record sea levels over time. Hence, to mark the position of the reference surface height with clarity and stability, permanent benchmarks are established and connected to the MSL by precise leveling. These benchmarks then serves as the reference control points for height measurements within a national or local framework (Lu *et al.,* 2014).

The increase in sea level as a result of global warming and its associated climate change which continuous to melt ice sheets has become a global challenge facing the international community. The threats posed to coastal areas due to the rise in sea level include: shoreline erosion and degradation; saltwater intrusion into freshwater bodies, storm surges and drainage related problems. According to Makarynskyy *et al*. (2004), predicting MSL in near-shore environment is very important for monitoring and predicting changes in fishery and marine ecosystems, protecting coastal structures and low-lying region residents against disasters. It further supports coastal construction plans in low-lying regions, and improving ocean-based energy

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technologies. MSL also plays a major role in referencing national height systems from one or more tide stations over a period of time. Therefore, adopting mathematical methods for accurate forecasting of sea level is of fundamental importance to coastal developers and planners.

Several mathematical techniques have been used in the past to predict MSL. According to Karimi *et al.* (2013), the methodology of tidal harmonic analysis which is normally used for obtaining a mathematical description of tides and sea level is data demanding and does not take into consideration the hydro-meteorological parameters. Besides, this technique for analysis of sea level is inefficient and could be replaced by non-linear techniques (Erol, 2011). 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 large amount of data required increases computation time and consumes computer memory during processing (Shetty and Dwakarish, 2013). The admiralty method and the method of least squares could also be used for obtaining description of sea level. However, they have problems similar to that of the tidal harmonic technique. In recent years, different techniques such as time series analysis, artificial neural networks (ANN), fuzzy logic, neuro-fuzzy, genetic programming and, more recently, chaos theory have been used for sea level predictions (Domenico *et al.,* 2013).

Karimi *et al.* (2013) applied the ANN and the adaptive neuro-fuzzy inference system (ANFIS) to forecast hourly sea levels in Darwin Harbour, Australia. Ghorbani *et al.* (2010), applied Genetic programming to forecast sea level variations using measurements from a single tide gauge in Hillarys Boat Harbour, Western Australia. The results of the research were compared to the set of results published by Makarynskyy *et al.* (2004) using an ANN model. The results showed that both models performed satisfactorily and could be used as alternatives to the harmonic analysis.

Filippo *et al*. (2012), used the ANN technique to forecast sea level using data obtained from Cananéia and Ilha Fiscal, Brazil. Results from the study showed that the margin of error was reduced to 12%, hence an improvement in the forecast of sea level was achieved with the ANN method.

The ANN technique has been used in recent years due to its ability to model out the non-linearity in a given set of data, work based on uncertainties, and learns from experience (Yusif-Attah, 2016). Also, ANN does not depend on the assumptions of functional model, the probability distribution or the smoothness of the underlying data (Pashova and Popova, 2011).

Similarly, the Multivariate Adaptive Regression Splines (MARS), which is a non-parametric and nonlinear regression methodology, has many advantages in modelling and prediction (Chang, 2014). MARS does not need to specify the functional form as the parametric linear regression technique, and it has greater flexibility to explore the nonlinear relationships between a response variable and explanatory variables. MARS technique like ANN does not require assumptions about the form of relationship between the independent and dependent variables (Zabihi *et al.,* 2016). MARS has been commonly applied in many scientific fields for dealing with prediction problems (Chang, 2014). Many studies have successfully applied MARS for solving different problems in engineering. Some of the areas of applications include estimating energy demand (Alreja, 2015), water pollution prediction (Kisi and Parmar, 2015), modeling of reservoir-induced earthquakes (Samui and Kim, 2012), and so on.

Since the ANN and MARS models are good prediction tools that are capable of handling data with nonlinear relationship, this study developed MARS and ANN models capable of assessing the performance of both techniques in order to select the best method for predicting MSL at the Takoradi harbour of Ghana.

2 Resources and Methods Used

2.1 Materials

Secondary data (tide gauge records) acquired from the Takoradi Harbour of Ghana was used for the study. The data spanned from January 1965 to June 1984. The maximum, minimum and mean tidal observations were determined for each month. The monthly maximum and minimum tidal observations were used as the input dataset whereas, the monthly mean tidal observations served as the output dataset. The MATLAB software was adopted for the ANN modeling and the STATISTICA software was adopted for the MARS modelling.

2.2 Artificial Neural Network

ANN is an artificial intelligence technique that is patterned to mimic the structure, operation and behaviour of biological neurons (Ziggah *et al.,* 2016). It also has the capability of exploiting the non-linear relationship between input and output variables through a learning process (Shetty and Dwakarish, 2013). The ANN can be used for modelling, prediction and pattern recognition (Yusif-Attah, 2016).

An ANN is composed of the input, hidden and output layers. Each layer is made up of several neurons and the layers are interconnected by sets of corresponding weights. The interconnections between neurons form the neural network topology (Jain *et al*., 1996; Yusif-Attah, 2016).

The ANN method uses activation functions which can be a hyperbolic tangent function, a sigmoid function or a linear function. The sigmoid function is mostly applied in transforming hidden neurons into an output (Koivo, 2008; Yusif-Attah, 2016). The sigmoid activation function used is given as shown in Equation (1):

$$g(x) = \frac{1}{1+e^{-x}} \tag{1}$$

where, x is the sum of the weighted inputs.
The activation function used is responsible for introducing non-linearity into a dataset (Ziggah *et al*, 2016). The output of the single node is given as shown in Equation (2):

$$y = \sum_{i=1}^{n} w_i x_i \tag{2}$$

where, x_i represents the inputs and w_i represents the weight.

2.2.1 Data Preparation

The original data was rearranged orderly to derive the maximum, minimum and average tide observations for each month.

2.2.2 ANN Architecture, Model Formulation and Training

The Back-propagation neural network, a supervised feed-forward neural network was employed in this project. This approach was adopted because errors determine are back-propagated for appropriate weight adjustments necessary to minimize the errors (Karimi *et al*., 2013). Supervised type of training was used due to the fact that a set of input and output datasets were presented to the network. Before the formulation of ANN model, the network was trained several times. The dataset was divided into training and testing datasets. Exactly 70% of the data was used as training, whereas, the remaining 15% was used as testing dataset. In total, 420 data points were used for training, 90 data points were used for testing and the remaining 90 data points were used for validation. The Levenberg-Marquardt training algorithm was chosen over the Bayesian regularization and the scaled conjugate gradient training algorithms. This is because this algorithm improves convergence of the solution and limits the tendencies of solution falling into local minimum (Singh *et al*., 2007; Kişi, 2007).

2.2.3 Data Normalization

Dataset to be used to develop the ANN model must be normalized between the intervals of (0, 1), (-1, 1) or other scaled criteria. The essence of data normalization is to improve convergence speed and to reduce the chances of getting stuck in the local minima (Ziggah *et al*, 2016). The function for data normalization is shown in Equation (3):

$$\overline{y_i} = \frac{(y_i - y_{\min})}{(y_{\max} - y_{\min})} \tag{3}$$

where, $\overline{y_i}$ represents the normalized data, y_i is the measured value, while $y_{\min}$ and $y_{\max}$ represent the monthly minimum and maximum tide observations respectively. The normalization process breaks down the data between the intervals of 0 and 1.

2.3 Multivariate Adaptive Regression Spline

The equation for the MARS model is expressed in Equation (4):

$$y = b_0 + \sum_{m=1}^{M} b_m B_m(x) \tag{4}$$

where y is the predicted response variable, x is the explanatory variable, b_0 is a constant term, b_m is the coefficient of the mth and M is the number of basis functions included into the model. $B_m(x)$ is the mth basis function, which can be either one single spline function or a product of two or more spline functions for different explanatory variables.

The basis function used in the MARS model is denoted in Equation (5):

$$\max(0, x-t) \text{ and } \max(0, t-x) \tag{5}$$

where, x is an explanatory variable and t is a constant corresponding to a knot location.
The MARS model is built by the Forward and Backward algorithms.

2.3.1 Forward Algorithm

In the forward algorithm, a lot of basis functions are added to the model to build Equation (3). Due to the large number of basis functions added, overfitting problems can occur during this stage (Samui and kim, 2014).

2.3.2 Backward Algorithm

In the backward stage, overfitting is prevented by deleting redundant basis functions from Equation (3). The generalized cross validation (GCV) criterion is used for the removal of excess basis functions (Samui and Kim, 2014). The generalized cross validation (GCV) criterion is basically the mean squared residual error divided by a penalty of the model complexity, which is used to measure model fit (Chang, 2014). The GCV model is denoted in Equation (6):

$$\mathrm{GCV} = \frac{\frac{1}{N}\sum_{i=1}^{N}\left[y_i - f(x_i)\right]^2}{\left[1 - \frac{C(M)}{N}\right]^2} \tag{6}$$

where, N is the number of observations and $\left[1-\frac{C(M)}{N}\right]^2$ is the penalty measure of model complexity. Also, $C(M)$ is denoted in Equation (7) as:

$$C(M) = (M+1) + d(M) \tag{7}$$

where, $C(M)$ is the number of parameters being fit and d is another penalty factor usually between 2 and 4.

2.4 Model Performance Assessment

In order to determine the accuracies of the two models used (ANN and MARS), errors between the observed and predicted sea levels were determined. The various statistical indicators were employed to determine the performance of the two models. Hence, to make an unbiased evaluation of the two models, statistical indicators such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and correlation coefficient (R) were used. Their individual mathematical languages are given by Equations (8) to (11) respectively:

$$\mathrm{RMSE} = \sqrt{\frac{\sum (A_t - F_t)^2}{n}} \tag{8}$$

where, n is the number of data points and $\sum (A_t - F_t)^2$ is the sum of squares of errors. The error refers to the difference between the actual and the predicted values.

$$\mathrm{MAPE} = \frac{100}{n} \times \sum \left|\frac{A_t - F_t}{A_t}\right| \tag{9}$$

where, A_t is the observed (actual) value, F_t is the forecasted (predicted) value and n is the number of data points. The MAPE statistic is measured in percentage.

$$\mathrm{R} = \frac{\sum_{i=1}^{n}(x-\bar{x})(y-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x-\bar{x})^2 \times \sum_{i=1}^{n}(y-\bar{y})^2}} \tag{10}$$

where, x and y are the actual and predicted mean sea level values. The variables $\bar{x}$ and $\bar{y}$ are the average values of the actual and predicted mean sea level values. For a good model, the value of R should be close to one.

$$\mathrm{MAE} = \frac{\sum |A_t - F_t|}{n} \tag{11}$$

Where $|A_t - F_t|$ is the absolute error and n is the number of data points. For a good model, the obtained MAE value should be as small as possible.

3 Results and Discussion

3.1 Results

The optimum ANN model based on the lowest mean square error (MSE) and highest correlation coefficient (R) values were determined. The input consisted of 2 neurons (monthly maximum and minimum tide observations) and a single output (monthly mean tide observation). Sample of the ANN training outcome is shown in Table 1.0.

After iterating from hidden neuron 1 to 25, ANN 2-11-1 emerged as the optimum ANN model. This is because it had the lowest MSE value and highest R value for the testing sample.

The developed MARS model consisted of a single basis function and had a generalized cross validation (GCV) error of 0.003352 at a threshold value of 0.0005. The expression of the basis function model is shown in Equation (12).

$$BF1 = \max(0, \text{monthly minimum tide observation} - 0) \qquad (12)$$

where BF1 is the basis function for the minimum tide observation variable.

The MARS equation developed for predicting Mean Sea Level is shown in Equation (13):

$$MSL = 0.7046 + 0.9930 \times BF1 \qquad (13)$$

Figs 1 and 2 shown the Prediction of MSL with the MARS and the ANN 2-11-1 models. The observed mean sea levels were plotted together with the predicted mean sea level values.

Table 1.0 Sample of ANN Training Results

ANN Model	Sample Type	MSE	R
ANN 2-1-1	TRAINING	0.00389	0.92
	VALID-ATION	0.00196	0.96
	TESTING	0.00150	0.96
ANN 2-4-1	TRAINING	0.00168	0.96
	VALID-ATION	0.00064	0.98
	TESTING	0.00132	0.97
ANN 2-11-1	TRAINING	0.00176	0.96
	VALID-ATION	0.00188	0.97
	TESTING	0.00092	0.99

Table 2.0 Performance Criteria Assessment of ANN and MARS Models

PCI	MODELS	
	ANN	MARS
RMSE	0.0359	0.0555
MAE	0.0284	0.0446
MAPE (%)	3.1414	5.6349
R	0.9720	0.8874

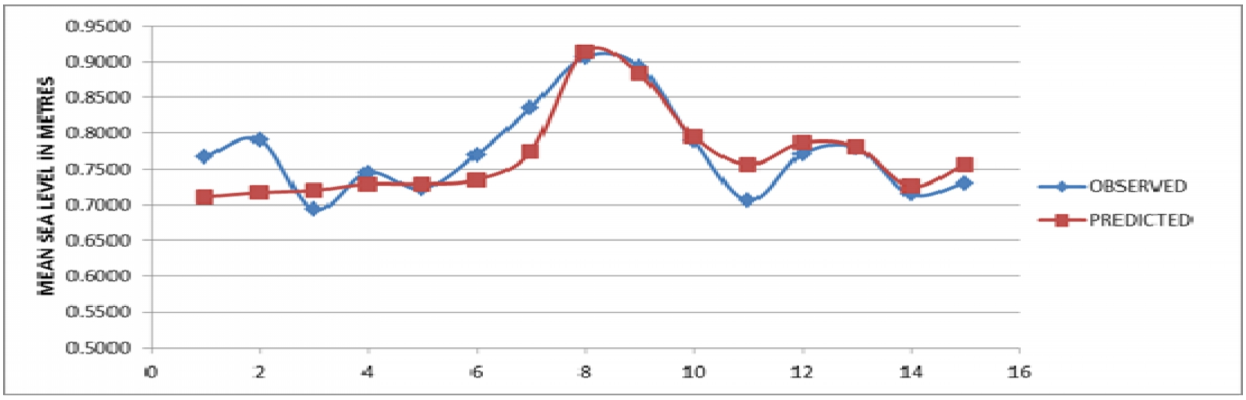

Fig 1.0 Prediction of MSL with the MARS Model

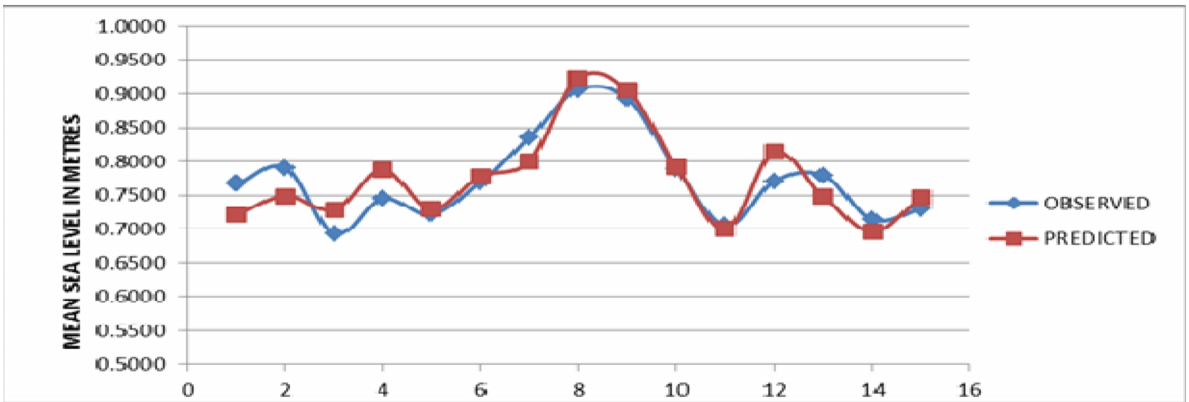

Fig 2 Prediction of MSL with the ANN 2-11-1 Model

3.2 Discussion

From Tables 1, the absolute values for the correlation coefficient (R) for the training, validation and testing results of the sample ANN models developed range from 0.92 to 0.99. Adopting existing labelling system that categorizes absolute values of R≤0.35 as low or weak correlation; 0.36 ≤R≤0.67 as moderate correlation, and 0.68 <R <1.0 as strong or high correlation (Taylor, 1990), the obtained values show strong correlation between the observed and the ANN predicted values. Again the mean standard error, which is a measure of dispersion similar to the standard deviation but functions as descriptive statistics, range from 0.00064 m to 0.00389 m. The standard error statistics represent the degree of precision with which the sample statistic represents the population parameter. The smaller the standard error, the closer the sample statistic is to the population parameter (McHugh, 2008).

The Mean Absolute Error (MAE) and Root mean squared error (RMSE) are two of the most common indicators used to measure accuracy for variables. While MAE measures the average magnitude of the errors in a set of predictions, without considering their direction, the RMSE is a quadratic scoring rule that also measures the average magnitude of the error (Willmott and Matsuura, 2005; Boye *et al.,* 2016). From Table 2.0, MAE and RMSE values for the ANN model are closer to zero compared with that of the MARS. Thus the ANN model produced more accurate results in magnitude and direction compared with that of the MARS. The Mean Absolute Percent Error (MAPE) is the most common measure of forecast error (Hyndman and Koehler, 2006).

From Table 1.0, the ANN model (ANN 2-11-1) performed better than the MARS model. The ANN model predicted MSL with less amount of the error statistics (RMSE, MAE and MAPE) as compared to the MARS model. The closer the error statistic is to zero, the better the model. For instance, the MAPE of the ANN model is 3.1414% and that of the MARS model is 5.6349%. Also, the ANN model performed better than the MARS model in terms of the MAE statistic, with ANN producing a MAE of 0.0284 m and the MARS model giving MAE value of 0.0446 m. The ANN model also gave a RMSE value of 0.0359 m and the MARS model also gave a RMSE of 0.0555 m. This indicates that the ANN model predicted MSL with higher accuracy (or less amount of error) than the MARS model.

It can be deduced from Fig 1 and Fig 2 that, the fitness of predicted MSL values compared to the observed MSL values obtained using the ANN model is better than that of the MARS model.

It can also be deduced that there is a strong correlation between the maximum and minimum tidal observations to the MSL in the case of the ANN compared to that of the MARS. Again, stronger relationship exist between the dependent variables (input) and the predicted variables (output) the correlation coefficient R is closer to 1 with the ANN model compared that of the MARS which recorded a value of 0.8874. Both ANN and MARS could be used to predict MSL depending on the accuracy requirement. Hence, tidal observations can be used for mean sea level estimation.

The MARS model could also be used as a substitute model in the absence of the ANN model since it also gives quite satisfactory results. Finally, it could be argued that the MARS model performed less satisfactorily probably due to inadequate number of input parameters and uncertainties in the dataset. It could also be deduced that the ANN model would show significance improvement in performance if other input parameters were added

4 Conclusions and Recommendations

The study has shown that both ANN and MARS models developed are capable of predicting MSL. Better accuracy and precision was obtained using the ANN model. The best performing ANN model for MSL was found to be ANN 2-11-1 which could be used for future forecasting of MSL.

It is recommended that ANN 2-11-1 be used predicting the local MSL in the study area. Other methods such as genetic programming, chaos theory, random forest algorithm and boosted trees algorithm should also be researched on and possibly used for MSL prediction. Hydro-meteorological parameters such as sea surface temperature, wind speed and direction as well as barometric pressure should be integrated with tidal observations for effective MSL prediction.

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