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SEA WATER LEVEL ESTIMATION USING SIX DIFFERENT ARTIFICIAL NEURAL NETWORKS TRAINING ALGORITHM

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Abstract

Water level estimation is important at various time intervals using the records of past time series in water resources engineering and management. For instance, sea level affects groundwater tables in low-lying coastal areas, Also hydrological regimes of some coastal rivers. Therefore, a reliable forecast of sea-level variations is required in coastal engineering and hydrologic studies. In this study, it has been tried to predict the changes in sea level by six different artificial neural networks (ANN's) training algorithms (Quasi-Newton, Conjugate Gradient, Levenberg-Marquardt, One Step Secant, Resilient back propagation and scaled conjugate gradient algorithms) and multiple linear regression (MLR) methods, three time steps, for a set of time intervals comprising 6 hour, 12 hour, 18 hour, 24 hour, 2 day time intervals using observed sea levels. The measurements from a single tide gauge at Hillarys Boat Harbor Western Australia. The results of the ANN's algorithms are compared models with respect to root mean square error (RMSE), mean absolute error (MAE), and determination coefficient (R^2). The comparison results indicate that the Levenberg-Marquardt is faster and has a better accuracy than the other training algorithms in modelling sea level. The Levenberg-Marquardt with RMSE = 0.004 m, MAE = 0.002 m and R^2 = 0.999 in test period was found to be superior in modelling sea level than the other algorithms, respectively.

Keywords: Artificial neural networks; Hillarys Boat Harbor Western Australia; Sea level modelling training algorithm

1 Introduction

Gauge readings and most recently satellite measurements tell us that over the past century, the Global Mean Sea Level (GMSL) has risen by 4 to 8 inches (10 to 20 centimeters). However, the annual rate of rise over the past 20 years has been 0.13 inches (3.2 millimeters) a year, roughly twice the average speed of the preceding 80 years (URL-2 2019). Over the past century, the burning of fossil fuels and other human and natural activities was released a lot amounts of heat-trapping gases into the atmosphere. These emissions were caused the Earth's surface temperature to rise, and the oceans absorbed about %80 of this additional heat. The reasons for the rise in sea level are closely related to global warming and are based on three main reasons; (1) Thermal expansion: The water expands when it is warm. Approximately half of the sea level increase in the last century is due to the fact that the oceans warm up and expand and take up more space. (2) Melting of glaciers: Large ice masses, such as ice sheets and glaciers, that melt the polar regions, actually melt a little each summer. Normally, snow falling in winter is enough to balance this melt. However, in recent years due to the global warming, high temperatures, the increase in the amount of melting ice in the winter due to the decrease in snowfall in the winter months, resulting in a clear melt in the glaciers and sea level increases. (3) Ice losses: The increasing temperature of the Earth causes the ice layers in the polar regions to melt rapidly. High sea temperatures lead to the melting of the ice field and eventually breaking and splitting (URL-3 2019).

A small rise in sea level has striking results in coastal areas. The progression of the sea to the inner parts leads to destructive erosion, flooding in the wetlands, pollution in the aquifer and agricultural lands as well as the destruction of habitats of bird, fish and plant species. When large storms hit the shore, the rising sea level will cause storm waves that are more severe than normal, and these waves are able to sweep away everything that comes against them. In addition, the living space of hundreds of millions of people is to become vulnerable against flooding. The rising sea level forces these people to leave their homes.

Using past records, estimating water levels at various time intervals is important in water resources engineering for the continuity and feasibility of planning. For example, the sea level affects the hydrological regime of some coastal rivers and the level of groundwater in the sub-coastal areas. Therefore, sea level changes are important for coastal engineering (Thain et al. 2004). Sea level changes; tidal currents in the oceans are related to atmospheric effects (air pressure and wind), hydrological regime of coastal rivers, temperature and salinity of sea water (Chen et al. 2000). Therefore, the sea level determines the underground water level in the coastal areas and the hydrological regime of the rivers in the coastal rivers (Thain et al. 2004). Thus, the accurate estimation of sea level changes in the downstream of the river is of great importance in coastal engineering, land drainage and land reclamation works.

Artificial Neural Networks (ANN's) is an information processing technology that is inspired by the information processing technique of the human brain. The operation of the simple biological nervous system with the ANN's is simulated. The imitated nerve cells contain neurons and these neurons connect to each other in various ways to form a network. These networks are capable of learning, memorizing and revealing the relationship between data. In other words, ANN's provide solutions to problems that normally require the natural abilities of a person to think and observe. The main reason why a person can produce solutions to the problems that require thinking and observing skills is the human brain, and therefore the ability of the human brain to experience and learning. ANN's are mathematical systems consisting of several processing units (neurons) connected in a weighted manner. A processing unit is actually an equation commonly referred to as the transfer function. This processing unit receives signals from other neurons; combines them, converts them and creates a numerical result. In general, processing units roughly correspond to real neurons and are connected to one another in a network; this structure also forms neural networks. The mathematical function, which is the main element of ANN's, is shaped by the architecture of the network. The basic structure of the function determines the size of the weights and the operation of the process elements. The behaviour of ANN's is affected by how they relate the input data to the output data, firstly the transfer functions of the neurons, how they are connected to each other, and the weights of these connections (Papik et al. 1998, Tekkanat and Saris 2015).

From hours to days, short-term estimates of sea level heights in coastal areas are important for engineering practices related to sea level changes, development of alternative energy technologies based on wave energies and protection of inhabitants in coastal areas (Herbich 1992). For this reason, the water level values of Hillary station near Perth in Western Australia were forecast. The data were tried to be estimated between January 2016 - August 2018 by using water levels at 6, 12, 18, 24 and 48 hours intervals. MANN model, different training algorithm were used. These algorithms; Quasi-Newton (QN), Conjugate Gradient (CG), Levenberg-Marquardt (LM), One Step Secant (OSS), Resilient Back Propagation (RBP) and Scaled Conjugate Gradient (SCG) algorithms. The main reason for choosing this area is that the data are accessible, continuous and regular intervals are obtained.

2 Workspace and Data

2.1 Workspace

Australia has a very different soil structure with its stony and sandy large deserts and plateaus in the west and center, and with its flats and plains surrounding the coastal series leading to a narrow slope. The coastal lakes have extensive beaches and a fertile vegetation. Most of the country is about 70% dry or arid, and a large part of the center is not suitable for settlement. 20 main desert forms 20% of the mainland. More than 1/3 of the continent is deserted due to low rainfall. Australia has fertile soils that are well watered near the coastal strip where the population is most concentrated. In all parts of Australia, a warm summer and partly warmer winter is experienced, and snowfall is quite rare in settlements or densely populated areas (URL-1 2019).

Perth (near to station) is the capital of Western Australia, Australia's richest province. One of the most isolated cities on earth, Perth is surrounded by deserts. Located at the site of the Swan River and has an impressive silhouette, there are long and wide avenues, lush parks and numerous waterways. Perth is the largest port city in Australia. With 80 km of sandy beaches and sparkling sea, it has the best beaches in Australia. The most famous of these are Cottesloe and Scarborough. It is a quiet, comfortable city away from speed and flashiness. It also has lower living expenses compared to other Australian cities and has a young and dynamic population that likes to have fun. Perth's population is 1.945.000 (2014) (URL-4 2014). Time zone, Western Standard Time "Western Standard Time Zone" (URL-1 2019).

It is a typical example of Perth Mediterranean climate with warm and dry summers and warm and rainy winters from late December to late March. The hottest month of the year is February. Rainfall usually occurs in May and September. It is very rare that even during the winter months, the temperature is below 15 °C. In the summer, the sea breeze, called the "The Frementle Doctor" reduces the temperature to 15 °C and provides a comfortable breathing for the city. The station used in the study, Hillary Harbor, located in the west of Australia, near the city of Perth, is a regular recording station (URL-1 2019). The station used in the study is located on a length of approximately 33,349 latitude, 116,626 longitude. The position of the station used in the study is shown in Figure 1.

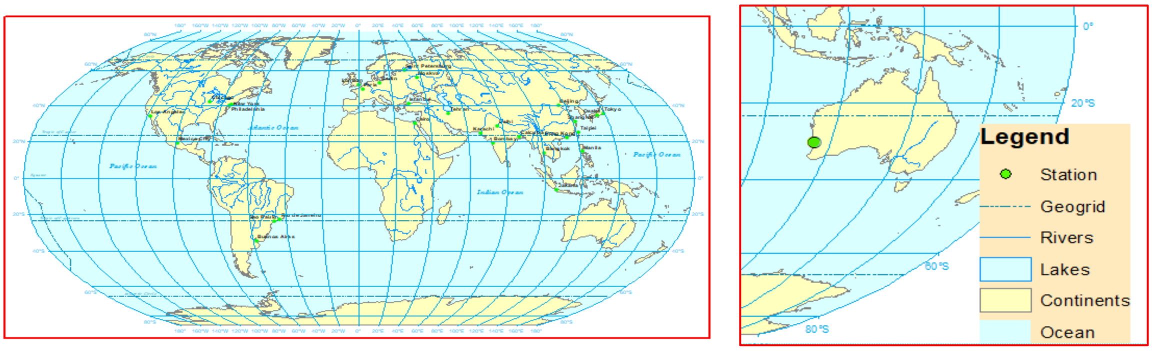

Figure 1. Station location

2.2 Data

Hillary station sea level data used in this study because is current and accessible. Data was provided with the help of "Sea Level Monitoring Station Facility" web page which was organized with the participation of many countries under the leadership of United Nations Educational, Scientific and Cultural Organization (UNESCO). The relevant web page is "http://www.ioc-sealevelmonitoring.org/station.php?code=hill". Descriptive statistical data are given in Table 1.

Table 1. Statistical information

Parameters	Data number	Maximum value (m)	Minimum value (m)	Average (m)	Standard deviation (m)	Skewness coefficient
T-6	3892	1.538	0.184	0.755	0.203	0.278
T-12	1946	1.538	0.184	0.777	0.222	0.157
T-18	1295	1.527	0.190	0.755	0.203	0.234
T-24	969	1.527	0.184	0.774	0.253	0.201
T-48	483	1.423	0.190	0.774	0.255	0.204

The expression T in the first column in Table 1 indicates the moment of measurement. The past time (hours) from this moment is designed in T-time. T-12 represent measurement before 12 hours. Or the expression T-48 represents 2 days before the measurement. There are 3892 hours water level in total. In Table 1, the maximum value is 1.538 and the minimum value is 0.184. Between the data were observed that the skewness coefficient is less than 1 and the standard deviations do not change much. These are important parameters affecting the accuracy of modeling. In addition, the number of ANN's data affects the working accuracy.

Table 2. Correlation values between data

	T-6	T-12	T-18	T-24	T-48
T-6	1				
T-12	0.0333	1			
T-18	-0.0154	-0.0083	1		
T-24	0.0384	-0.0062	-0.0154	1	
T-48	0.1842	0.0437	0.0087	0.0306	1

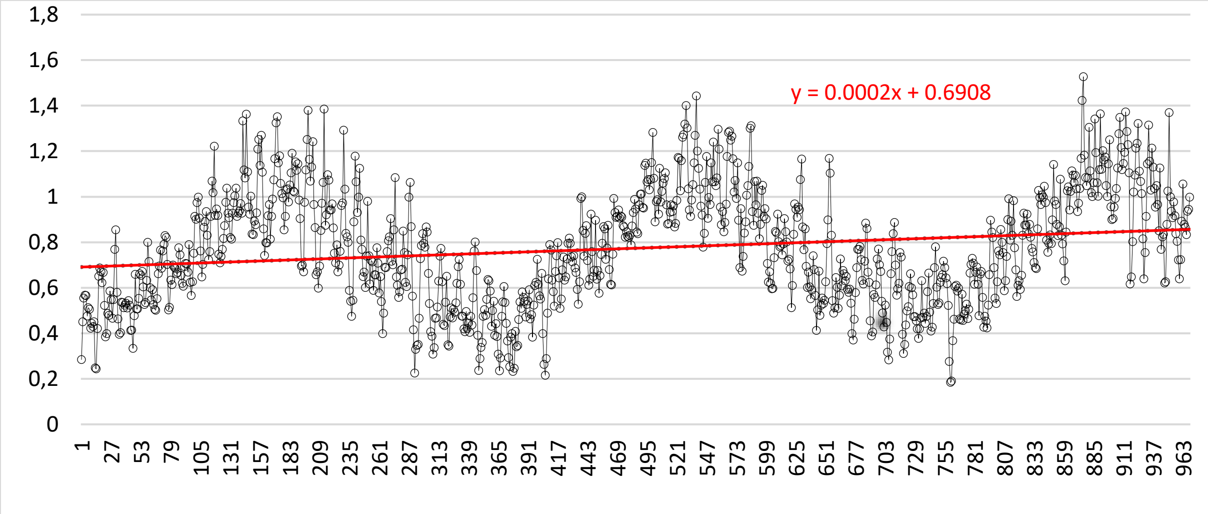

Figure 2. Daily going chart of data (T-24)

Figure 2 shows the chart of the data. A total of 19.38 cm increase was observed at the end of 969 days of sea level change. Accordingly, the annual increase is 7.3 cm. The relation of data with each other is given in Table 2.

When the table is examined, the measurements between the hours are quite independent from each other. While there was a negative relationship between the data of 18 hours and 12-6 hours, the data before 48 hours had a positive relationship with the data of 24, 18, 12 and 6 hours. It seen that the T-6 data set is associated with the T-48 (0,1842) data set than others.

3 Methods

ANN's is a system based on the principle of learning the human brain through trial and generalization. It is one of the common methods used to calculate the output of many mechanisms and systems. It is successfully used by many academics in various disciplines (finance, health, engineering, physics, geology and hydrology) (Papik et al. 1998, Tekkanat and Saris 2015, Ozcan and Sezgin 2009, Toraman 2008, Caliskan and Devran 2017). In this study, sea level estimation was made according to MANN method and 6 different training algorithms.

3.1. Multi-layered artificial neural network

Multi-layer Artificial Neural Networks (MANN) consists of an input layer, one or more hidden (intermediate) layers, and an output layer where information is input. MANN has transitions between layers called forward and backward propagation. In the forward propagation phase, the output and error value of the network are calculated. In the back-propagation phase, the inter-layer link weight values are updated to minimize the calculated error value (Arı and Berberler, 2017). The MANN model uses the backpropagation learning algorithm, which is the generalization of the least squares algorithm in linear perception. The backpropagation consists of the feedback phases in which the weights are updated by spreading backward, with the algorithm defining the forward feed to which the output of the network is determined and the resulting error is reduced. In the forward feed stage, the inputs of the training set are presented to the input layer of the network. The input layer contains neurons that receive these inputs. Therefore, the number of neurons in the input layer must be the same as the number of input values in the data set. The neurons in the input layer pass the input values directly to the hidden layer. Each neuron in the hidden layer calculates the total value by adding the threshold value to the weighted input values and processes them with an activation function and passes them to the next layer or directly to the output layer. Weights between layers are usually randomly selected at the beginning. The error value is calculated by comparing the output values of the network with the expected output values. Figure 3 shows the structure of the MANN. The multi-layer sensor model consists of an input (X_1, X_2, X_3,….., X_n), a hidden, and an output layer (Y). Each layer may also have one or more processing elements. The processor elements in the input layer act as a buffer that distributes the input signals to the processor elements in the intermediate layer. The intermediate layer processor elements use the outputs of the previous layer as inputs. With all inputs, weights are multiplied and total. This value is then passed through a transfer function and the output value of that neuron is calculated. These operations are repeated for all the processor elements on this floor. These operations are repeated for all processor elements in this layer. The processor elements in the output layer also act as intermediate layer elements and the network output values are calculated. These model is also known as feed forward ANN's as the information flow is in the forward direction (Gemici et al. 2013). Different learning algorithms are used to train the network.

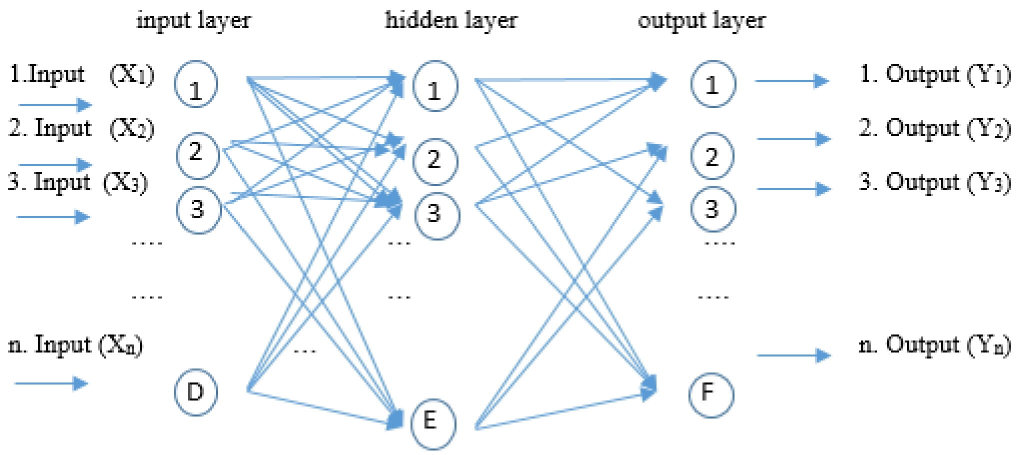

Figure 3. Model of MANN

The activation function processes the net input to the cell and determines the output that the cell will generate for that input. One of the most used activation functions in applications is the Sigmoid-type activation function (Gemici et al. 2013). The formula of the function is shown in equation (1). The most active site of the function is between 0.2 and 0.8.

$$y = F(v) = \frac{1}{1+e^{-v}} = \frac{1}{2}[\tanh(\frac{v}{2})-1] \tag{1}$$

3.2.Multi lineer regression

According to the equation "y" dependent, "x" is an independent variable, "ε" can be expressed as an error (Okkan and Mollamahmutoğlu 2010). Equations where variable number increases. Linear regression between two variables can express with equation (2).

$$y = a + bx + \varepsilon \tag{2}$$

Linear regression biger then two variables can express with equation (3).

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + ...b_nx_n + \varepsilon \tag{3}$$

These equations are called multiple linear regression equations.

4 Application

In the modelling, 5 different combinations (M_1, M_2, M_3, M_4 and M_5) and 6 different training algorithms (QN, CG, LM, OSS, RBP, SCG) have been tried and the combinations are shown in Table 3. Where T indicates's the estimated time, "T-6" means "T-48" 6 hours ago and 48 hours earlier. The algorithms used in the training phase of 5 models were compared and root mean square error (RMSE), mean absolute error (MAE) and the determination coefficient (R^2) were used as the evaluation criteria. RMSE, MAE and R^2 formulas can be expressed as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z_e - Z_o)^2} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Z_e - Z_o\right| \tag{5}$$

$$R^2 = \left(\frac{N*\left(\sum Z_o * Z_e\right) - \left(\sum Z_o\right)*\left(\sum Z_e\right)}{\sqrt{\left(N*\sum Z_o^2\right) - \left(\sum Z_o\right)^2 * \left(N*\sum Z_e^2\right) - \left(\sum Z_e\right)^2}}\right)^2 \tag{6}$$

In the equations, "Z_e" and "Z_o" show the estimated and observed elevation values and "N" represents the number of data.

Table 3. Used combinations

Model	Input Number	Input	Output
M_1	i	T-6	T
	ii	T-6, T-12	T
	iii	T-6, T-12, T-24	T
M_2	i	T-12	T
	ii	T-12, T-24	T
	iii	T-12, T-24, T-48	T
M_3	i	T-18	T
	ii	T-18, T-36	T
	iii	T-18, T-36, T-54	T
M_4	i	T-24	T
	ii	T-24, T-48	T
	iii	T-24, T-48, T-72	T
M_5	i	T-48	T
	ii	T-48,T-96	T
	iii	T-48,T-96,T-144	T

Table 3 shows the number of input cells in i, ii, iii artificial neural networks. T-6, T-12, T-24 and T-48 and others respectively show the parameters used in the inputs. T shows the output parameter.

Table 4. Number of hidden layer for each training algorithm and MLR coefficients

Models	Inputs	Methods						
		MANN						MLR
		LM	QN	CG	OSS	RBP	SCG	b_1 ; b_2 ; b_3
M_1	i	2	13	13	5	8	13	0.9311
	ii	4	16	9	10	9	8	0.1487 ; 0.8162
	iii	10	1	11	1	14	1	0.6049 ; -0.3445 ; 0,7259
	Average	**5.3**	**10.0**	**11.0**	**5.3**	**10.3**	**7.3**	
M_2	i	3	7	1	1	4	1	0.9908
	ii	1	2	11	14	10	1	0.9460 ; 0.0495
	iii	4	1	12	1	9	1	-0.4232 ; 0.9674 ; 0.4488
	Average	**2.7**	**3.3**	**8.0**	**5.3**	**7.7**	**1.0**	
M_3	i	2	4	1	5	12	1	0.9213
	ii	3	10	11	15	2	10	0.1951 ; 0.7646
	iii	3	1	1	1	10	1	0.6069 ; -0.2673 ; 0.6452
	Average	**2.7**	**5.0**	**4.3**	**7.0**	**8.0**	**4.0**	
M_4	i	2	4	4	16	5	4	0.9776
	ii	7	19	20	1	17	20	-0.0765 ; 1.0651
	iii	6	1	16	1	3	16	0.1800 ; -0.2664 ; 1.0772
	Average	**5.0**	**8.0**	**13.3**	**6.0**	**8.3**	**13.3**	
M_5	i	2	15	7	1	16	14	0.9635
	ii	4	3	2	1	6	2	0.1745 ; 0.8073
	iii	12	1	1	1	1	16	0.2014 ; 0.0130 ; 0.7713
	Average	**6.0**	**6.3**	**3.3**	**1.0**	**7.7**	**10.7**	

Table 4. The number of hidden layer used for each analysis is examined. In the analysis, the intermediate layer cell number was limited to 30. MLR coefficients are on the right in the table.

Table 5. ANN's training algorithms and MLR modeling time comparison

Hours	Inputs	Methods and Times							
		MANN							
		LM	QN	CG	OSS	RBP	SCG	Average	MLR
6 Hours	1 Input	1.614	1.296	0.918	0.717	0.307	0.515	**0.895**	0.001
	2 Input	2.177	1.253	0.802	0.815	3.316	0.457	**1.470**	0.001
	3 Input	0.398	0.447	0.139	0.531	0.364	0.34	**0.370**	0.001
	Average	**1.396**	**0.999**	**0.620**	**0.688**	**1.329**	**0.437**		**0.001**
12 Hours	1 Input	1.130	0.589	0.141	0.577	0.274	0.229	**0.490**	0.001
	2 Input	0.311	0.467	0.676	0.612	0.277	0.304	**0.441**	0.001
	3 Input	0.227	0.474	0.624	0.435	0.284	0.295	**0.390**	0.001
	Average	**0.556**	**0.510**	**0.480**	**0.541**	**0.278**	**0.276**		**0.001**
18 Hours	1 Input	0.361	0.321	0.164	0.456	0.287	0.302	**0.315**	0.001
	2 Input	1.221	0.578	0.603	0.573	0.234	0.328	**0.590**	0.001
	3 Input	0.228	0.413	0.585	0.447	0.306	0.281	**0.377**	0.001
	Average	**0.603**	**0.437**	**0.451**	**0.492**	**0.276**	**0.304**		**0.001**
24 Hours	1 Input	0.957	0.343	0.280	0.517	0.246	0.282	**0.438**	0.001
	2 Input	1.213	0.885	0.572	0.408	0.281	0.343	**0.617**	0.001
	3 Input	0.217	0.406	0.342	0.468	0.244	0.337	**0.336**	0.001
	Average	**0.796**	**0.545**	**0.398**	**0.464**	**0.257**	**0.321**		**0.001**
48 Hours	1 Input	0.581	1.152	0.228	0.398	0.271	0.271	**0.484**	0.001
	2 Input	1.005	0.471	0.217	0.430	0.430	0.243	**0.466**	0.001
	3 Input	0.225	0.393	0.337	0.451	0.451	0.275	**0.355**	0.001
	Average	**0.604**	**0.672**	**0.261**	**0.426**	**0.384**	**0.263**		**0.001**

Table 5 shows the modelling time of the methods in seconds. Generally, fastest modelling is iii models. Comparisons of the models are as follows: for iii-M_1 model QN (RMSE=0.137, MAE=0.1085, R^2=0.4167), for iii-M_2 model LM (RMSE=0.0783, MAE=0.0591, R^2=0.8268), for iii-M_3 model LM (RMSE=0.1337, MAE=0.1049, R^2=0.4313), for iii-M_4 model QN (RMSE=0.0961, MAE=0.0739, R^2=0.8057), for iii-M_5 model LM (RMSE=0.1328, MAE=0.1039, R^2=0.6347).

For MANN, different hidden layer cell numbers have been tried (Table 4) and the value of the least squared error in the test phase is based. Table 6-7 shows the test results of MANN and MLR. As can be clearly seen from the table, the MANN model of the LM algorithm using the 3rd combination input of the M_2 model is detected lower RMSE (0.0040) and MAE (0.0023) and greater R^2 (0.9999) values.

5 Results

Many studies suggest that the Earth will continue to warming up. Similarly, sea levels will continue to rise; but it is still a matter how much will increase is a matter debate. The change in sea level was investigated in this study with different ANN’s training algorithms. Training algorithms used in the study; Quasi-Newton, Conjugate Gradient, Levenberg-Marquardt, One Step Secant, Resilient Back propagation and Scaled Conjugate Gradient algorithms.

1. According to the comparison criteria, the best-performing algorithms are Levenberg-Marquardt and Scaled Conjugate Gradient. Levenberg-Marquardt algorithms have 4 best result, Scaled Conjugate Gradient algorithms have 3 the fastest results.
2. The fastest algorithm is Multiple Linear Regression.

Table 6. Hourly estimation results of modelling

Comparison (Test)	Methods	M_1 Input Data (6 Hours)				M_2 Input Data (12 Hours)				M_3 Input Data (18 Hours)			
		(i)	(ii)	(iii)	**Average**	(i)	(ii)	(iii)	**Average**	(i)	(ii)	(iii)	**Average**
RMSE	LM	0.2159	0.1872	0.0106	**0.1379**	0.1151	0.1159	0.0040	**0.0783**	0.2076	0.1876	0.0059	**0.1337**
	QN	0.2144	0.1884	0.0084	**0.1371**	0.1162	0.1160	0.0080	**0.0801**	0.2075	0.1903	0.0082	**0.1353**
	CG	0.2142	0.1902	0.2710	**0.2251**	0.1159	0.1171	0.0205	**0.0845**	0.2080	0.1882	0.0172	**0.1378**
	OSS	0.2152	0.1890	0.0240	**0.1427**	0.1158	0.1215	0.0241	**0.0871**	0.2128	0.1907	0.0228	**0.1421**
	RP	0.2142	0.1893	0.0456	**0.1497**	0.1153	0.1206	0.0350	**0.0903**	0.2132	0.1910	0.0342	**0.1461**
	SCG	0.2138	0.1894	0.0146	**0.1393**	0.1159	0.1158	0.0176	**0.0831**	0.2077	0.1947	0.0152	**0.1392**
	MLR	0.3077	0.2340	0.1776	**0.2398**	0.1213	0.1198	0.1086	**0.1166**	0.3226	0.2503	0.1971	**0.2567**
	Average	**0.2279**	**0.1954**	**0.0788**		**0.1165**	**0.1181**	**0.0311**		**0.2256**	**0.1990**	**0.0429**	
MAE	LM	0.1705	0.1512	0.0050	**0.1089**	0.0873	0.0876	0.0023	**0.0591**	0.1624	0.1491	0.0031	**0.1049**
	QN	0.1693	0.1516	0.0045	**0.1085**	0.0880	0.0876	0.0047	**0.0601**	0.1627	0.1512	0.0046	**0.1062**
	CG	0.1694	0.1528	0.2148	**0.1790**	0.0877	0.0885	0.0129	**0.0630**	0.1634	0.1499	0.0111	**0.1081**
	OSS	0.1705	0.1529	0.0131	**0.1122**	0.0876	0.0919	0.0148	**0.0648**	0.1652	0.1518	0.0137	**0.1102**
	RP	0.1692	0.1523	0.0301	**0.1172**	0.0872	0.0914	0.0211	**0.0666**	0.1667	0.1515	0.0251	**0.1144**
	SCG	0.1694	0.1521	0.0079	**0.1098**	0.0878	0.0875	0.0109	**0.0621**	0.1627	0.1562	0.0089	**0.1093**
	MLR	0.2499	0.1937	0.1420	**0.1952**	0.0919	0.0904	0.0817	**0.0880**	0.2647	0.2050	0.1566	**0.2088**
	Average	**0.1812**	**0.1581**	**0.0596**		**0.0882**	**0.0893**	**0.0212**		**0.1783**	**0.1592**	**0.0319**	
R^2	LM	0.0105	0.2429	0.9975	**0.4170**	0.7419	0.7385	0.9999	**0.8268**	0.0699	0.2246	0.9994	**0.4313**
	QN	0.0193	0.2324	0.9985	**0.4167**	0.7370	0.7383	0.9988	**0.8247**	0.0708	0.1994	0.9985	**0.4229**
	CG	0.0187	0.2173	0.3775	**0.2045**	0.7388	0.7332	0.9919	**0.8213**	0.0683	0.2161	0.9931	**0.4258**
	OSS	0.0152	0.2206	0.9887	**0.4082**	0.7392	0.7132	0.9888	**0.8137**	0.0283	0.2011	0.9880	**0.4058**
	RP	0.0199	0.2283	0.9537	**0.4007**	0.7410	0.7178	0.9765	**0.8118**	0.0316	0.2018	0.9731	**0.4022**
	SCG	0.0206	0.2226	0.9954	**0.4129**	0.7386	0.7392	0.9940	**0.8239**	0.0661	0.1612	0.9947	**0.4074**
	MLR	0.0106	0.1030	0.3315	**0.1484**	0.7324	0.7274	0.7816	**0.7471**	0.0686	0.0241	0.1771	**0.0899**
	Average	**0.0164**	**0.2096**	**0.8061**		**0.7384**	**0.7297**	**0.9616**		**0.0577**	**0.1755**	**0.8748**	

Table 7. Hourly estimation results of modelling (continues)

Comparison (Test)	Methods	M_4 Input Data (24 Hours)				M_5 Input Data (48 Hours)			
		(i)	(ii)	(iii)	**Average**	(i)	(ii)	(iii)	**Average**
RMSE	LM	0.1662	0.1161	0.0095	**0.0972**	0.2135	0.1770	0.0080	**0.1328**
	QN	0.1656	0.1127	0.0100	**0.0961**	0.2225	0.1751	0.0105	**0.1360**
	CG	0.1653	0.1114	0.0216	**0.0994**	0.2144	0.1750	0.0156	**0.1350**
	OSS	0.1701	0.1142	0.0253	**0.1032**	0.2145	0.1756	0.0312	**0.1404**
	RP	0.1658	0.1134	0.0273	**0.1021**	0.2172	0.1752	0.0797	**0.1574**
	SCG	0.1653	0.1131	0.0172	**0.0985**	0.2192	0.1749	0.0262	**0.1401**
	MLR	0.1802	0.1209	0.0000	**0.1004**	0.2401	0.1870	0.1773	**0.2015**
	Average	**0.1664**	**0.1135**	**0.0185**		**0.2202**	**0.1771**	**0.0498**	
MAE	LM	0.1300	0.0868	0.0050	**0.0740**	0.1701	0.1370	0.0048	**0.1039**
	QN	0.1290	0.0865	0.0062	**0.0739**	0.1802	0.1355	0.0069	**0.1075**
	CG	0.1284	0.0848	0.0160	**0.0764**	0.1725	0.1373	0.0100	**0.1066**
	OSS	0.1331	0.0866	0.0163	**0.0787**	0.1699	0.1367	0.0222	**0.1096**
	RP	0.1288	0.0866	0.0205	**0.0786**	0.1770	0.1349	0.0622	**0.1247**
	SCG	0.1284	0.0879	0.0124	**0.0762**	0.1783	0.1361	0.0176	**0.1107**
	MLR	0.1418	0.0932	0.0938	**0.0783**	0.1893	0.1453	0.1387	**0.1578**
	Average	**0.1313**	**0.0875**	**0.0243**		**0.1768**	**0.1375**	**0.0375**	
R^2	LM	0.5995	0.8049	0.9987	**0.8010**	0.3511	0.5538	0.9992	**0.6347**
	QN	0.6025	0.8161	0.9986	**0.8057**	0.3005	0.5630	0.9985	**0.6207**
	CG	0.6043	0.8201	0.9933	**0.8059**	0.3456	0.5641	0.9968	**0.6355**
	OSS	0.5799	0.8111	0.9909	**0.7940**	0.3450	0.5595	0.9863	**0.6303**
	RP	0.6015	0.8135	0.9894	**0.8015**	0.3302	0.5633	0.9239	**0.6058**
	SCG	0.6044	0.8152	0.9957	**0.8051**	0.3196	0.5639	0.9905	**0.6247**
	MLR	0.5773	0.7983	0.7907	**0.7221**	0.3365	0.5446	0.5785	**0.4865**
	Average	**0.5956**	**0.8113**	**0.9653**		**0.3326**	**0.5589**	**0.9248**	

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