GUJARAT TECHNOLOGICAL UNIVERSITY

PHD SYNOPSIS

PREDICTION OF SEA SURFACE TEMPERATURE USING MACHINE LEARNING TECHNIQUES

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CONTENTS:

a.	Title of the thesis and abstract	3
b.	Brief description on the state of the art of the research topic	4
c.	Definition of the Problem	7
d.	Objective and Scope of work	7
e.	Original contribution by the thesis	8
f.	Methodology of Research, Results / Comparisons	8
g.	Achievements with respect to objectives	15
h.	Conclusion	15
i.	Copies of papers published and a list of all publications arising from the thesis	16
j.	Patents (if any)	16
k.	References	16

a.Title of the Thesis and Abstract:

PREDICTION OF SEA SURFACE TEMPERATURE USING MACHINE LEARNING TECHNIQUES

Abstract:

As the seas and oceans are subject to dynamic change, the various different parameters that are associated with it also reflect these changes. These parameters are Sea Surface Temperature (SST), Sea Surface Salinity (SSS), Sea Bottom Temperature (SBT), Air Temperature at the interface, the Zonal and the Meridional winds. The air water interface is a highly active region where all kind of interactions like Heat exchange, transfer of momentum, radiation, flux distribution,temperature shift etc is a continuous process.

Readings are recorded by contact based thermometers and thermistors using Buoys and Moored Arrays and also by Satellite links. We have used one dataset that is using buoys and another that is using Satellite data. These datasets are reconstructed and available either as monthly datasets or as daily or weekly datasets. For our experimental setup, we have used both monthly and daily datasets.

This work is meant to address the issue of prediction of sea surface temperature data.We have evaluated the performance of the different data predicting algorithms for SST data. We started with single step prediction and improved our algorithms thereby achieving multistep prediction.

For monthly datasets, we started with the Auto Regressive Integrated Moving Average (ARIMA) model by Box Jenkins methodology. All ARIMA models are characterized as ARIMA (p,d,q)- where p is the Auto Regressive component, d is the number of non seasonal differences needed to achieve stationarity and q is the Partial Auto Regressive component. The time series under study should be stationary-ie a stochastic process with unconditional joint probability distribution that is time invariant. It essentially conveys that the statistic parameters like mean and variance when computed on different sections of the time series remain unchanged. For non stationary processes, it needs to be transformed using differentiation. Using the Auto Correlation Function (ACF) and the Partial Auto Correlation Function (PACF) plots of the time series under study, for as many as 40 lags, we study the same to identify the parameters associated with ARIMA models, namely p and q that gives us the best predicted values of SST.

Next, we attempted the Non linear Auto Regressive (NAR) NN model where a set of time delay elements are recognized to be the significant contributors in predicting the future values using a particular number of hidden neurons. This was done for single step prediction. Later, this is extended to multiple step prediction-weekly (7 days) & yearly (12 months).

Sea Surface Temperature Anomaly (SSTA) is recognized as the variation about 3-month running mean exceeding $\pm$ 0.5°C and lasting for 5 months in consecutive (as per the Oceanic Nino Index) as declared by National Oceanic and Atmospheric Admininstration (NOAA).In a site specific approach from La Jolla, Western Californian Coast, and using bouys, an archived dataset (1916-2015) comprising of SST, SSS and SBT is used for analysis to check the dependency of SSS and SBT on SST, one at a time using single step analysis and by detecting extreme readings.

Using a daily dataset downloaded from Pacific Marine Environmental Laboratory (PMEL), we have attempted to recognize SSTA by a modification of the NAR network using an additional input- the Air Temperature, the Zonal Winds and the Meridional Winds, one at a time and evaluating their influences over SST by means of weekly prediction, over 10 iterations predicting a timestamp of 70 days wherein the Wind data is found to have been maximally correlated to SST values, due to obvious reasons.

Using a Long Short Term Model (LSTM) deep neural network and using previous data, we have attempted single step and multistep prediction of SST values.

We have proposed a hybrid model, specifically to predict the Daily SST dataset on a weekly basis. For this hybrid model, we have explored the linear characteristics of the time series by means of the ARIMA model and the nonlinear characteristics by the NAR/LSTM model. Using Residuals obtained from ARIMA model, and feeding these to the NAR/LSTM model, a set of Residuals are predicted. Later these residuals are combined with the ARIMA predicted results, giving us the final forecasted values.

b. Brief description on the state of the art of the research topic

Consider the work by W.W. Hsieh and B. Tang [1], way back in 1997, who presented the use of Neural Network for the purpose of Prediction and Analysis of Meteorological as well as Oceanographic data along the equatorial Pacific belt, covering the regions, popularly known as

the Nino 3, Nino 3.4, Nino 4, P4 and P5, using PCA-Principal Component Analysis, CCA-Canonical Correlation Analysis and NN- Neural Networks. Parallelly, the duo along with F. Tangang [2], worked on seasonal prediction of Sea Surface Temperature Anomalies for a lead time of 9 to 12 months. They experimented with Rossby signature detection using Wind and SSTA data, separately and together, especially in the Nino 3.4 region. Again in 1998, all three proceeded to explore and chart the prediction of Sea Surface Temperature using Sea Level Pressure and Wind Stress as the dependent parameters including Nino 3.5 and P2 regions along with the previously mentioned zones for lead time as high as 15 months [3]. In 2000, the trio along with A.H. Mohanan [4] performed an investigative study of linear and non linear methods in terms of correlation coefficient and root mean square error extending the lead time to 21 months. All of them had used monthly datasets over the Pacific region during the years 1950 to 1997 and these datasets are either reconstructed from Smith's SST dataset or Reynold's SST dataset [5] or a combination of both using various preprocessing steps. An improved version of these datasets using bias correction of the historical datasets, especially for high latitude locations using sea ice concentration is also available for Researchers [6] by the same authors.

The changes observed in the Indian Ocean are linked to variations observed in the Pacific Ocean and also to the Asian Australian rainfall occurrence [7], [8]. Moreover, El Nino events are accompanied by the warming of the Indian Ocean. Utilizing the Equatorial Heat Content as one parameter and the Western Pacific Wind in combination to it, the occurrence of the El Nino and La Nina events can be forecasted to near precision and its peculiar relationship with the SST of the Indian Ocean is realized. Certain zones around the Indian Peninsula are recognized as potential locations that are linked to cause global variations.

Also K.E. Trenberth in the duration of 1990-1994 [9, 10, 11] with D.J.Shea, in 1992 and with J. W. Hurrell in 1994 have investigated the drastic changes that caused the major events of El Nino and La Nina (1976-1988). They proposed a monthly global SST climatology using data derived from Climate Analysis Center using Comprehensive Ocean-Atmosphere Dataset (COAD) linking the changes over the Pacific to the tropical variations.

And that is how the Indian Ocean Region is studied in parallel to the Pacific Ocean and many researchers have identified the existence of a Dipole at the Indian Ocean claiming to have high correlation with each other.

K C Tripathi with I M L Das and A.K. Sahai [12], in 2006, has together identified such an area in the Indian region (27S-35S, 96E-104E) that they claim to be having a high potential influence over the global climate. Using 52 years (1950-2001) of data derived from Reynold's dataset of reconstructed SST, they have used twelve neural networks, one corresponding to each month of SST Anomaly data and with the help of corresponding time series presented a comparative with linear regression models using Correlation coefficient (CC) and Root Mean Square Error (RMSE) as the prediction parameters. K.C. Tripathi [13], in 2008, along with S. Rai, A.C. Pandey & I.M.L. Das have also tried to map the occurrence of Indian Summer Monsoon with the quarterly mean SST variations with details from four locations namely Central Southern Indian Ocean (CSIO; 22S-24S, 79E-81E) , Northwest of Australia (NWA; 14S-17S, 114E-116E), Southern Indian Ocean (SIO; 40S-41S, 82E-85E), Antarctic Circumpolar Current (ACC; 38S-42S, 64E-68E) using artifical neural network.

The Indian Ocean Dipole in literature is termed to be Indian Ocean counterpart of the Pacific El Nino and La Nina. Different SSTs are reported in the eastern pole - somewhere in the south Indian Ocean and the western pole - that is in the Arabian Sea. S.B. Mohongo [14]with M.C. Deo in the year 2013, identified a coastal site (EAF; 6S-7S, 39E-40E) located on the East African shore and another site (EQT; 0-1S, 59E-60E) that is located in the Indian Ocean. Using the monthly SST data derived from HadISST datasets from January 1870 to December 2011 (142 years), they have compared the performance of NARX, FFNN, RBFN, GRNN and the ARIMAX model for predicting the SST Anomalies using monthly and seasonal approach.

In 2013, Kalpesh Patil [15] with M.C.Deo, Subimal Ghosh and M. Ravichandran have expanded this work into six different locations in the Indian Ocean vicinity. Their attempt is about Sea Surface Temperature SST value forecast using Neural Networks using 61 year data (January 1945 to December 2005) at six different locations around India over 1 to 12 months in advance. And the locations are (AS; 19N-20N, 68E), (BOB; 18N-19N, 90E), (EEIO; 1S-1N, 90E), (WEIO; 1S-1N, 65E), (SOUTHIO; 9S-11S, 95E-98E) and (THERMO; 14S-16S, 56E-58E).

In 2016, K. Patil [16] with M.C.Deo and M. Ravichandran have targeted the SST Anomaly-SSTA(Actual SST-meanSST) prediction at the above mentioned sites on daily, weekly and monthly basis using a combined approach based on Wavelet and ANN architecture.

c. Definition of the Problem

The SST data is generally available as monthly and daily datasets. The methods proposed so far address the monthly data to a good amount of precision. Moreover, anomaly detection is well documented for monthly dataset by various agencies like NOAA, National Centers for Environmental Information (NCEI) formerly known as National Climatic Data Center (NCDC) and many other research laboratories.However when it comes to daily data, the pure basic models fail to deliver appreciable results.

The water bodies are subject to variation every single day of the year. Very few researchers have attempted to predict the daily SST. It suggests identification of the linear and non linear characteristics of the SST.We found this attractive and decided to investigate if it is possible to predict the SST values on a daily scale using previous datasets only given the dynamic nature of the sea in a site specific approach.

d. Objective and scope of work

With the intention of filling the identified Research gaps, the following objectives are proposed:

- To study and understand thevariation and predictive nature of ocean parameters.
- Establish inter-relationship of the parameters with SST (SST, SSS, SBT, Zonal winds, Meridional winds, wind direction, relative humidity, air temperature etc) and their significance in oceans.
- Development/Use of machine learning based methods in prediction of SST.
- Development/Use of deep learning based methods in prediction of SST.
- Computation of SST anomalies through machine learning techniques.
- Development of hybrid models using machine learning and Deep learning based methods for prediction of daily SST.

e. Original contribution by the Thesis

The contribution made by the Thesis is listed as follows:

- We propose the forecast of Sea Surface Temperature data using various existing models and seek to achieve the same with more precision.
- We address anomaly detection in the values of SST, popularly addressed as SSTA.
- For the monthly SST datasets, the basic Auto Regressive Integrated Moving Average-ARIMA, the Nonlinear Auto Regressive – NAR NN and the Long Short Term Memory-LSTM deep neural network approach are able to provide satisfactory results.
- For the Daily SST dataset, we have addressed the inter relationship amongst various ocean parameters using the Non linear Auto Regressive network with external inputs (like Sea Surface Salinity, Sea Bottom Temperature, Air Temperature, Zonal and Meridional Winds).
- We demonstrate that the best match results for SST Daily dataset prediction can be achievedby the proposed hybrid model that explores the capabilities of ARIMA and Neural based approach including Deep Learning.

f. Methodology of Research, Results / Comparisons

- Nonlinear Auto Regression (NAR) model

In their article, in 2013, K Patil [15], along with MC Deo, S Ghosh (all from IIT Bombay) and M. Ravichandran (Indian National Center for Ocean Information Services-INCOIS, Hyderabad) had identified six potential locations that are in the vicinity of the Indian Dipole as shown in the map.Arabian Sea-AS (19N-20N, 65E), Bay of Bengal-BOB (18N-19N, 90E),East of Indian Ocean-EEIO (1S-1N, 90E),West of Indian Ocean-WEIO(1S-1N, 65E), South of Indian Ocean-SOUTHIO (9S-11S, 95E-98E), Off the African Coast-THERMO (14S-16S, 56E-58E).

Sea Surface Temperature SST value forecast using Nonlinear Autoregressive Networks 61 year data (January 1945 to December 2005) around India over 1 to 12 months in advance, only one month at a time. The time series is composed of 61 X 12 = 732 values for single step forecast.

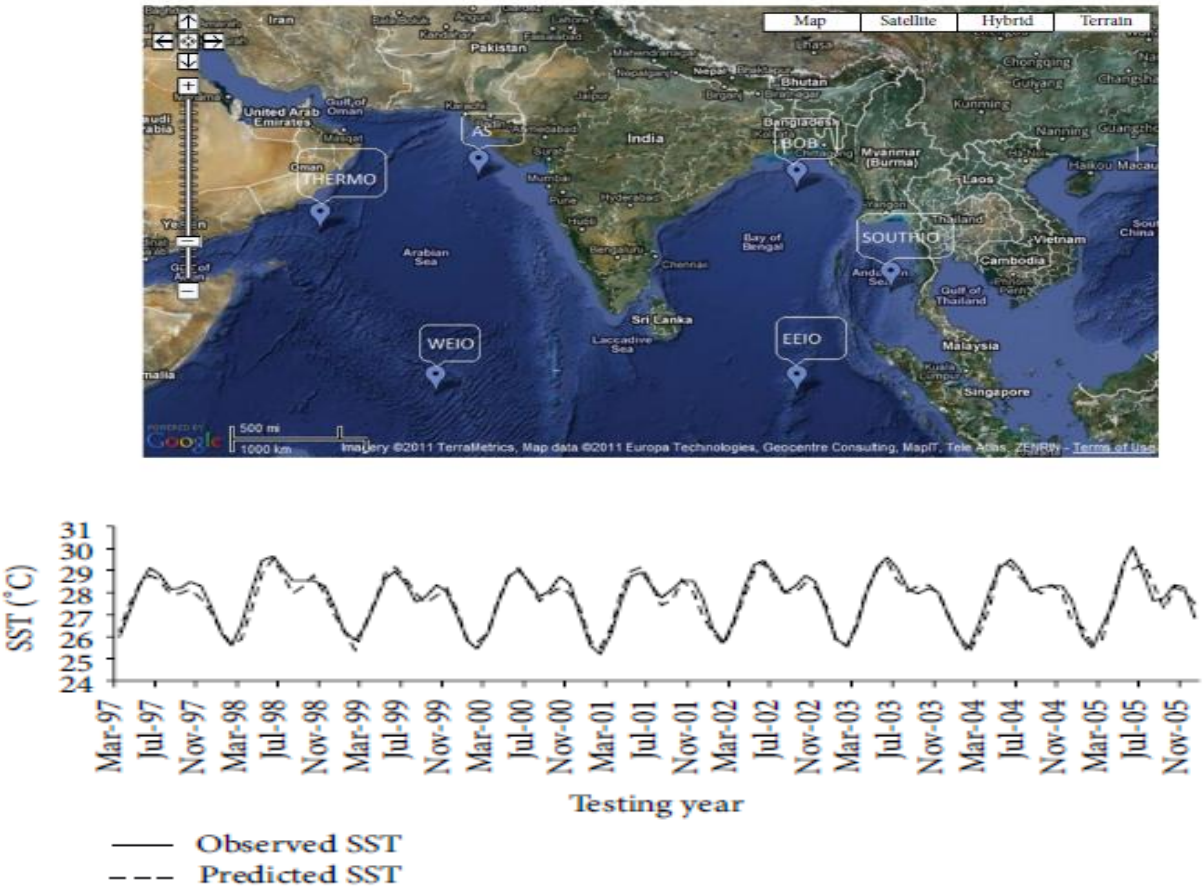

Fig.1 Resultant time series D=24 and H is not shared. [15]
Total number of time stamps is 108; Testing years 1997-2005.

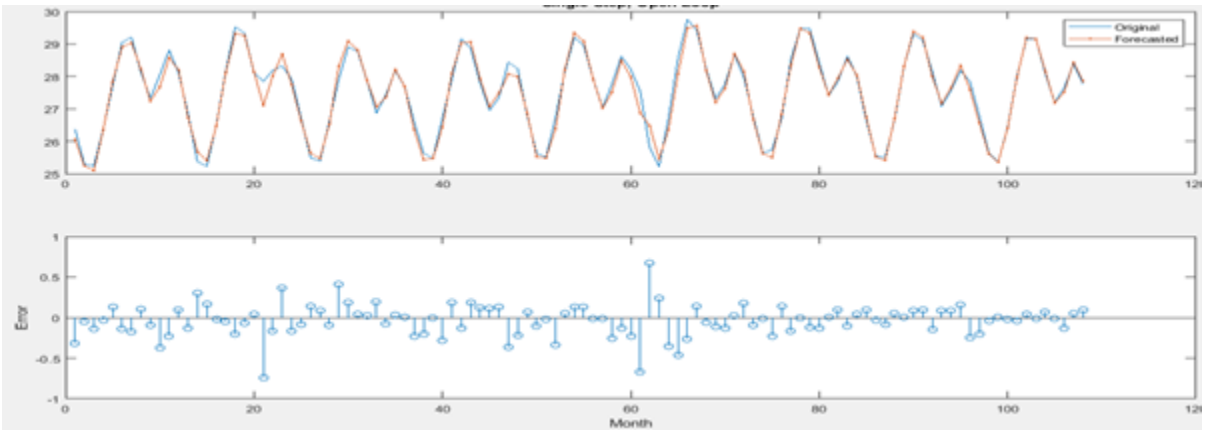

Fig. 2 The proposed model provides the following time series

In our work, we have evaluated the optimum lag values (D) and the number of hidden neurons (H) needed to achieve better results using the network shown below (Fig.3). The results using the proposed model are tabulated in Table 1 (Right)

Table 1. A comparative of the errors computed using the same experimental setup as [15]

TABLE 2: NAR network testing at site AS.

Prediction horizon in months	Testing phase CC	MAE in °C	MSE in °C^2	NSE in %
$SST_{(t+1)}$	0.99	0.15	0.04	96.90
$SST_{(t+2)}$	0.96	0.28	0.13	90.70
$SST_{(t+3)}$	0.96	0.27	0.12	91.20
$SST_{(t+4)}$	0.95	0.29	0.15	89.50
$SST_{(t+5)}$	0.95	0.28	0.14	90.10
$SST_{(t+6)}$	0.96	0.28	0.14	90.20
$SST_{(t+7)}$	0.96	0.28	0.14	90.30
$SST_{(t+8)}$	0.96	0.30	0.14	89.90
$SST_{(t+9)}$	0.96	0.28	0.13	90.10
$SST_{(t+10)}$	0.95	0.30	0.15	89.20
$SST_{(t+11)}$	0.95	0.30	0.15	89.30
$SST_{(t+12)}$	0.96	0.28	0.12	91.00

Note: $SST_{(t+i)}$: SST at *i*th time (month) ahead than the present time (month) "*t*".

Prediction horizon in months	MAE	MSE	NSE
$SST_{(t+1)}$	0.1987	0.0395	92.14
$SST_{(t+2)}$	0.1196	0.0206	98.26
$SST_{(t+3)}$	0.0801	0.0137	99.19
$SST_{(t+4)}$	0.0651	0.0104	99.14
$SST_{(t+5)}$	0.0596	0.0086	98.93
$SST_{(t+6)}$	0.0572	0.0075	99.47
$SST_{(t+7)}$	0.0509	0.0065	99.55
$SST_{(t+8)}$	0.0536	0.0063	99.77
$SST_{(t+9)}$	0.0491	0.0056	99.74
$SST_{(t+10)}$	0.0575	0.0068	99.29
$SST_{(t+11)}$	0.0569	0.0064	99.53
$SST_{(t+12)}$	0.0598	0.0066	99.78
$SST_{(t+i)}$: SST at ith time (month) ahead that the present time (month) "t"			

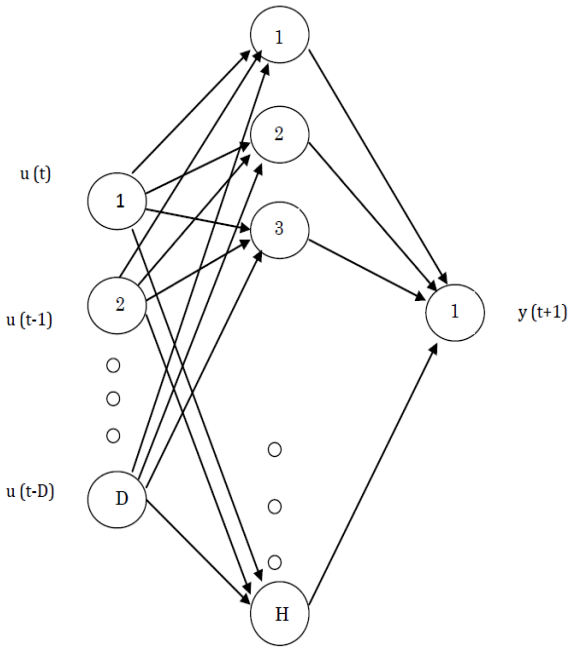

Fig. 3 The proposed NAR Network that is used for prediction with D=12 and H=18 having input u(t) and output y(t+1).

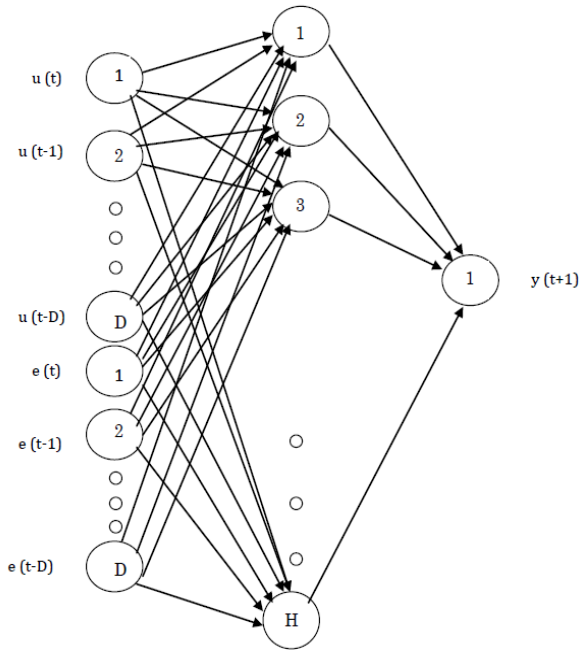

Fig. 4 The proposed NARX Network that is used for prediction with D=5 and H=5 having input u(t),output y(t+1) with exogenous input e(t).

K C Tripathi [12]in2006had proposed SST prediction at(27S-35S, 96 E-104 E) for their study.We have chosen a site (9S-11S, 95E-98E).They have opted for twelve neural networks one for each month of the year and an error comparative of the testing year is available in Table 2. We have opted for monthly multistep prediction (12 months-1st year, 24 months-2nd year and …..). Underneath their result, the results of our proposed model are shown. In [12], and in Table 2, ob is the notation for observed and o/p is for predicted output.

Table 2: ANN performance measures for test cases[12] and our proposed model results

Test cases of the years 1997,1998,1999,2000 and 2001 [12]							
Month	Var(ob)	Var(o/p)	SD (ob.)	**SD (o/p)**	**cc**	**RMSE**	Bias
Jan	0.26	0.04	0.51	**0.20**	**0.97**	**0.32**	-0.08
Feb	0.18	0.25	0.42	**0.49**	**0.95**	**0.16**	-0.14
Mar	0.09	0.05	0.30	**0.22**	**0.59**	**0.25**	0.19
Apr	0.04	0.02	0.20	**0.17**	**0.76**	**0.13**	0.22
May	0.13	0.01	0.36	**0.11**	**0.90**	**0.26**	0.18
Jun	0.06	0.04	0.26	**0.22**	**0.92**	**0.10**	0.33
Jul	0.05	0.01	0.24	**0.08**	**0.77**	**0.18**	0.09
Aug	0.02	0.03	0.14	**0.17**	**0.89**	**0.08**	0.02
Sep	0.03	0.05	0.18	**0.21**	**0.87**	**0.10**	-0.01
Oct	0.10	0.01	0.33	**0.03**	**0.69**	**0.31**	0.06
Nov	0.09	0.06	0.31	**0.25**	**0.76**	**0.20**	0.14
Dec	0.20	0.02	0.45	**0.15**	**0.99**	**0.31**	0.04

months	SD(o/p)	CC	RMSE
12- 1st year	**0.2508**	**0.97**	**0.2562**
24-2nd year	**0.2778**	**0.96**	**0.2722**
36- 3rd year	**0.2585**	**0.96**	**0.2564**
48- 4th year	**0.2571**	**0.95**	**0.2578**
60- 5th year	**0.2552**	**0.95**	**0.2571**

- Non linear Auto Regression using External input (NARX model)

Using the bottle sampling dataset obtained from Scripps Pier, La Jolla, Californian Western Coast containing the SST, the SSS and theSBTdata (from August 1916 – October 2015) we tried to predict the values of SST using previous values of SST (Fig.3) and also by taking the help of supporting SSS and SBT time series (Fig.4).

For Surface readings, the depth is upto 0.5 m and the Bottom readings are restricted to a depth of 5 m. This is achieved for step ahead prediction and a significant reduction in the error measures is observed using Optimum D and H in the NAR Network. Fig 5 shows the SST time series being predicted using previous SST values only. Observe the extreme readings being forecasted with the help of the SBT (Fig 6) and SSS (Fig. 7) respectively for the last 600 readings.

An error comparative is available in Table 3.

Table 3. A comparative of the errors computed using the experimental setup

Error Parameter	NAR	SBT as exogenous input	SSS as exogenous input
MSE	1.4315	0.3459	0.3462
NMSE	1.1964	0.5882	0.5884
RMSE	0.0912	0.0220	0.0221
NRMSE	0.0762	0.0375	0.0377

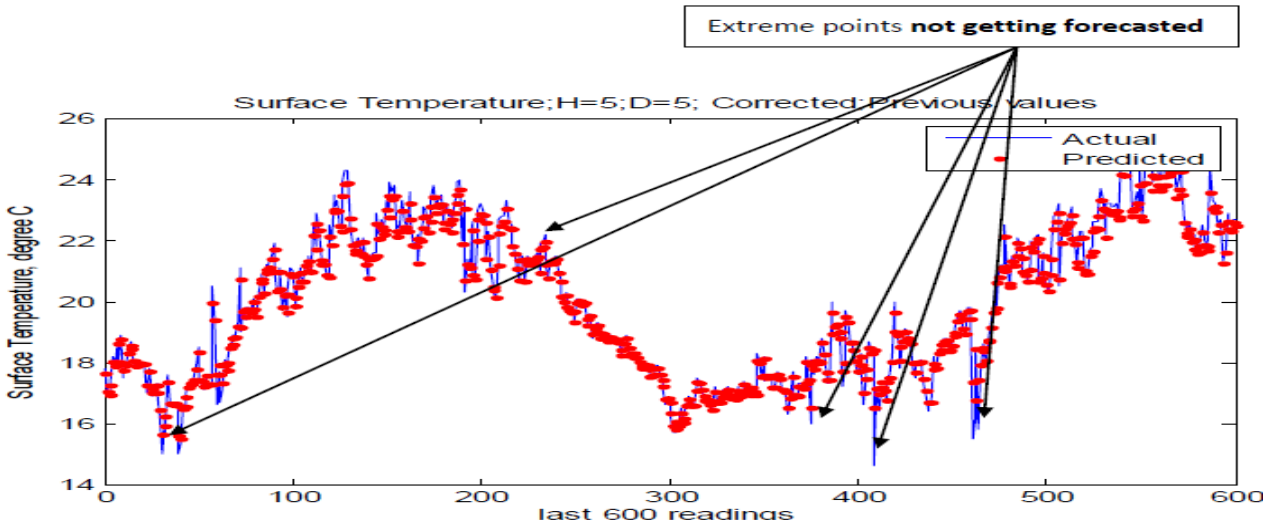

Fig. 5 Time series of the step ahead prediction using previous values of SST only

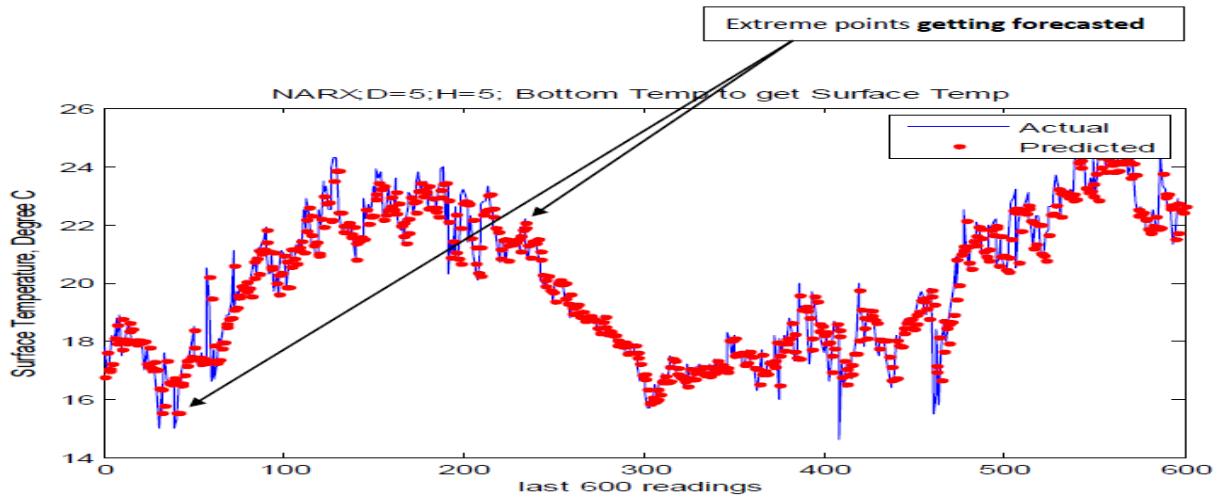

Fig. 6Step ahead time series prediction using previous values of SST and SBT

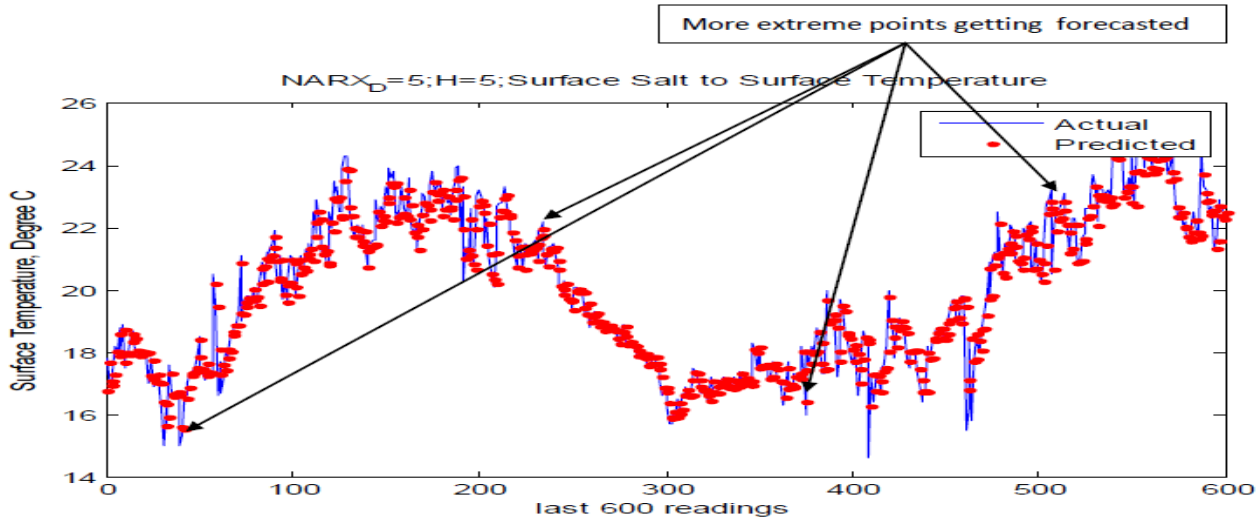

Fig. 7Step ahead time series prediction using previous values of SST and SSS

- Surface Temperature Anomaly (SSTA)

Using the ElNino daily dataset obtained from NOAA's PMEL, we attempted to predict future values on weekly basis using the previous values of SST only (Refer fig. 5). We further modified the network to include additional inputs – Air Temperature, Zonal Winds and Meridional Winds, one at a time (Refer fig 6.)that can improve the prediction values to a larger extent. At thelocation,(0N, -110E), using optimal values of H and Dusing 10 years data as a training dataset, we predicted 70 days SST values, on a weekly basis for 10 iterations.

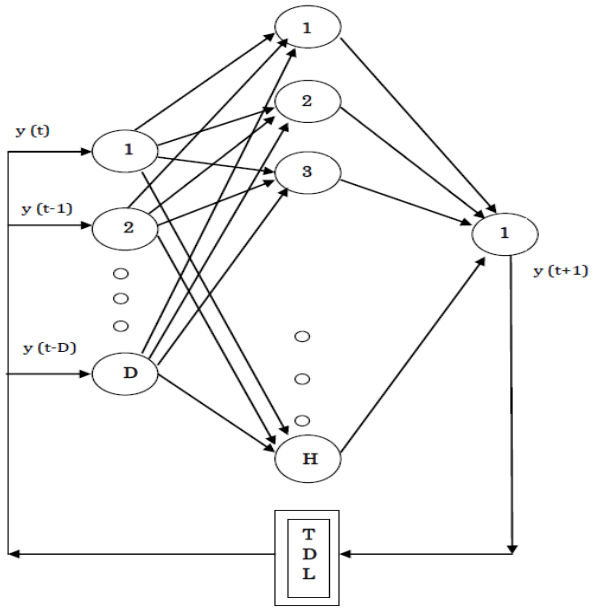

Fig.5 SST prediction using previous values of SST only

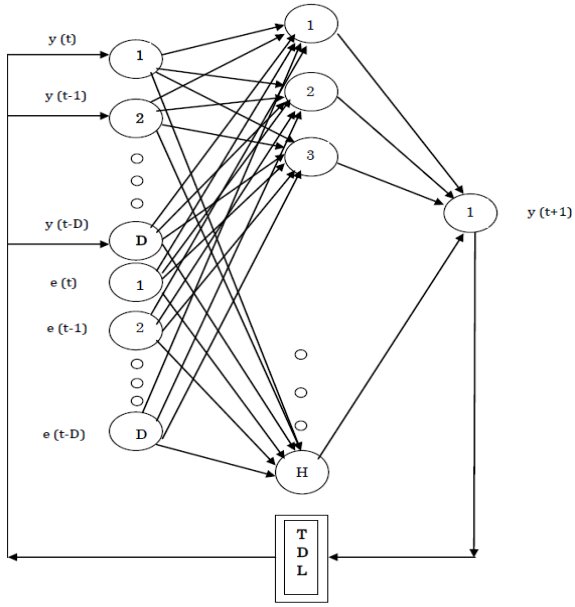

Fig.6 SST prediction using previous values of SST and (e(t) one at a time).

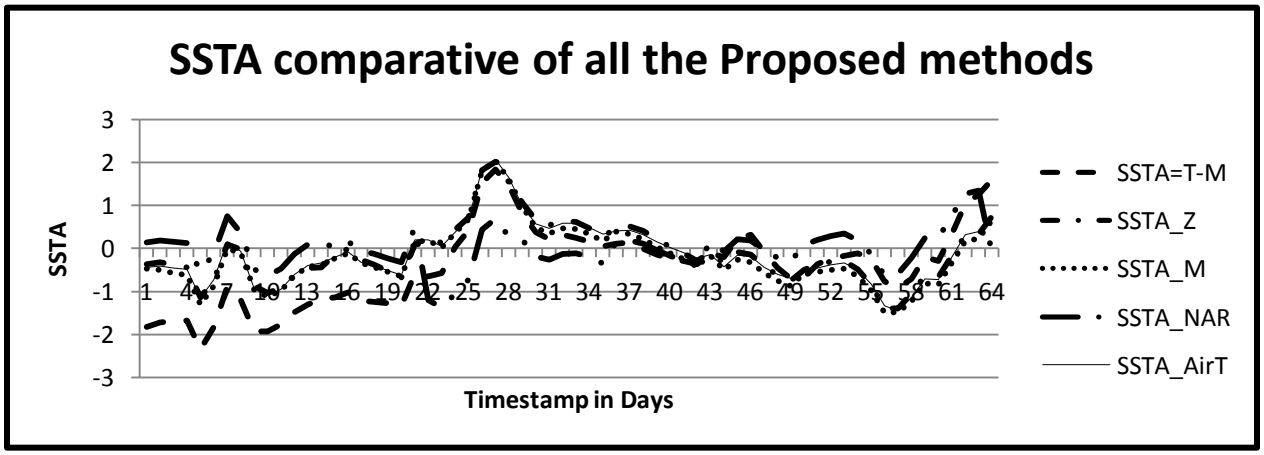

Fig.7 SSTA prediction using all the proposed techniques

The training data is from 10/05/1985 to 10/05/1995. [10 years]. The independent test dataset is from 11/05/1995 to 20/07/1995.

- LSTM

As Deep learning models are getting popular, we tried to implement the prediction of SST in multiple steps using a proposed LSTM. In all, we have utilised 5 datasets and a comparative of their error performance is tabulated as shown below in table 4:

Table 4: Error comparative of all datasets using LSTM network

Dataset	Type	Multistep	RMSE	NRMSE
Melbourne Mean Temperature	Monthly	12	1.0539	0.0631
Nottingham Castle Mean Temperature	Monthly	12	1.7858	0.1069
HadISST	Monthly	12	0.9290	0.1984
Elnino dataset	Daily	12	3.0122	1.2049
La Jolla, California, West Coast	Daily	12	1.6752	0.2043

- Hybrid

Using the ElNino daily dataset obtained from NOAA's PMEL, it is observed that for daily dataset, the above stated models, even with optimized values, are not able to predict the future values efficiently for multiple steps and hence a hybrid model is proposed for the same. G.P Zhang [17] in the year 2001, had proposed a hybrid model for standard datasets. Our proposedmodel is derived from Zhang's technique and has been tested for various combinations so as to provide the nearest match to the actual value. The results evidently show a very appreciable forecast for duration of about 200 days in advance, one week at a time.

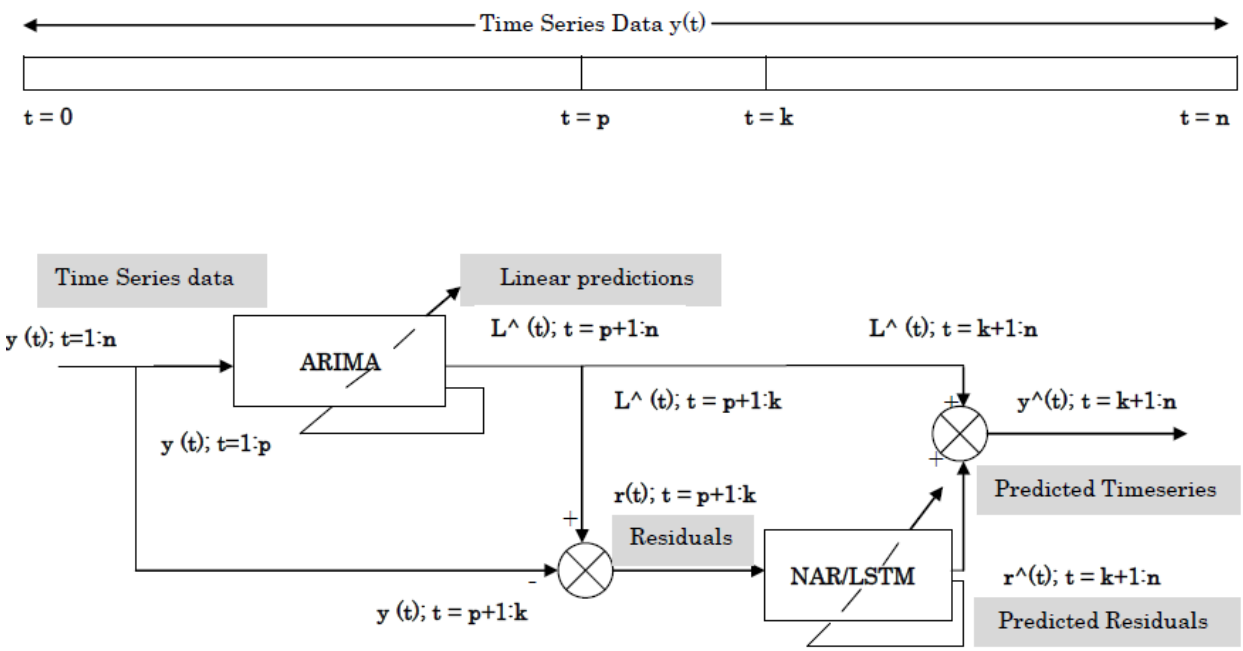

Fig.8 block diagram SST time series prediction using the proposed hybrid technique

Steps of the proposed algorithm:

1] Select a daily SST time series.

2] Here n = 10 years of SST data, p = 5 years of SST data; k = 1 year of SST data.

3] Linear predictions of the time series data is achieved by ARIMA model using last 5 years of SST data and 30 residuals are calculated.

4] A set of 1 year of residuals is fed to the NAR/LSTM network to predict 7 residuals.

5] These residual values are algebraically added to the ARIMA predicted values to give the final forecasted values.

6] Error is computed by comparing the actual and predicted values.

7] This is a sliding window algorithm. The steps are repeated again in succession.

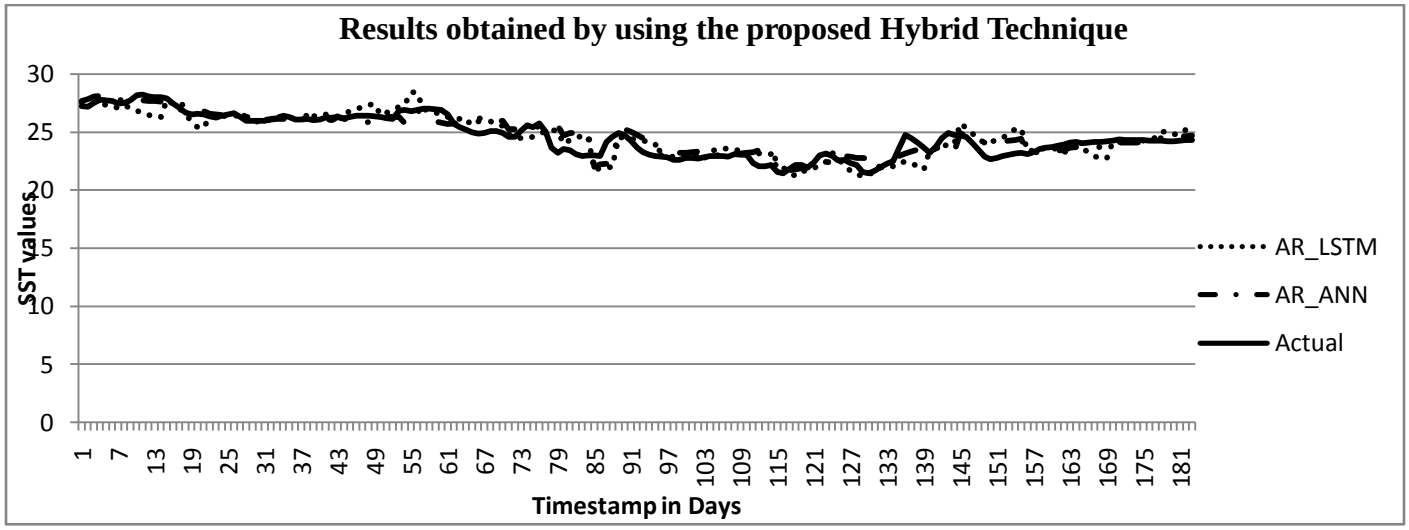

Fig.9 SST time series prediction by the proposed hybrid techniques(AR+NAR/LSTM)

g. Achievements with respect to objectives

- We have studied and understood the predictive nature of ocean parameters.
- We have established a relationship between SST-SBT and SST-SSS for the Scripps Pier, La Jolla, and Western California.
- We have developed an ARIMA, NAR, NARX, LSTM, a hybrid model to address the SST data.
- SSTA computation is accomplished for Elnino daily SST dataset using Air temperature, Zonal and Meridional Winds time series dataset.
- A hybrid model is developed to cater to daily SST data prediction.

h. Conclusion

In this work, we have tried to optimize the performance of existing algorithms. The algorithms addressed are the basic linear algorithm- the ARIMA model and the most commonly implemented nonlinear algorithm – the Neural Network model, specifically the Feed Forward Neural Network using back propagation of error. Apart from that, a Deep Neural Network algorithm, specifically the Long Short Term Model is implemented whose performance is better than the regular Neural Network.

While working with these datasets, it is observed that the monthly datasets show good performance with pure basic models even for multistep prediction. However for daily SST datasets, the error increases.

To overcome this, a hybrid model is proposed that explores the linear characteristics of the dataset using ARIMA model Box Jenkin's methodology and non linear characteristics of the NAR/LSTM model. During implementation, it was observed that some specific lengths of multistep prediction tend to offer reduced errors. A variable length of multistep prediction is tried using Residuals obtained by ARIMA prediction algorithm. These residuals when fed to the Neural Network results in some predicted residuals. Final predicted value is the algebraic summation of the ARIMA predicted value and the NAR/LSTM residuals. Evidently from fig. 9, the hybrid model provides minimum error.

i. Copies of papers published and a list of all publications arising from the thesis-

1]Geetali Saha, Narendra Chauhan, "Numerical Weather Prediction using Nonlinear Auto Regressive Network for the Manaus Region, Brazil", in *IEEEInternational Conference on Innovations in Power and Advanced Computing Technologies*, iPact2017, VIT University, Vellore, 21st-22nd April, 2017, Technically Sponsored by IEEE Madras section.

2]Geetali Saha, Narendra Chauhan, "Dependency Investigation of Sea Surface Temperature on Sea Bottom Temperature and Sea Surface Salinity", in *IEEEInternational Conference on Innovations in Power and Advanced Computing Technologies*, iPact2019, VIT University, Vellore, 22nd-23rdApril, 2019, Technically Sponsored by IEEE Madras section.

3] Geetali Saha, Narendra Chauhan "Week ahead Time series Prediction of Sea Surface Temperature using Non Linear Auto Regressive Network with and without Exogenous Inputs", Book chapter for book titled "Elements of Statistical Learning" in Springer Nature (Singapore) Book Series "Algorithms for Intelligent Systems (AIS)".

j. Patents (if any)------NA------

k. References

1] W.W. Hsieh and B. Tang, “Applying Neural Network Models to Prediction and Data Analysis in Meteorology and Oceanography”, Bulletin of the American Meteorological Society, September 1998, Vol. 79, Issue 9, pp.1855-1870.

2] F.T. Tangang, W.W. Hsieh and B. Tang, “Forecasting regional sea surface temperatures in thetropical Pacific by neural network models, with windstress and sea level pressure as predictors”, Journal Of Geophysical Research, Vol. 103, no. C4, pages 7511-7522, April 15, 1998

3] F.T.Tangang, W.W. Hsieh and B.Tang, “Forecasting the Equatorial Pacific Sea Surface Temperatures by Neural Network models” Climate Dynamics, 13(2), 135–147, 1997.

4] B. Tang, W.W. Hsieh, A. H. Monahan and F. T. Tangang “Skill Comparisons between Neural Networks and Canonical Correlation Analysis inPredicting the Equatorial Pacific Sea Surface Temperatures”**,** Bulletin of the American Meteorological Society, 2000, pg 287-293.

5] R.W. Reynolds and T. M. Smith “Improved Global Sea Surface Temperature Analyses Using Optimum Interpolation”, Journal of Climate, Volume 7, June 1994, pg 929-948.

6] T.M. Smith and R.W. Reynolds, “Improved Extended Reconstruction of SST (1854–1997)”, Journal of Climate, Volume 17, June 2004, pg 2466-2477.

7] J. S. Kug,S.I. An, F.F Jin and I.S. Kang “Preconditions for El Nino and La Nina onsets and their relation to theIndian Ocean”, Geophysical Research Letters, Vol. 32, L05706,2005

8] S. H. Yoo, S. Yang and C.H. Ho,“Variability of the Indian Ocean Sea surface temperature and itsimpacts on Asian-Australian monsoon climate”Journal Of Geophysical Research,Vol.111,6

9] K. E. Trenberth, “Recent Observed lnterdecadal Climate Changes in the Northern Hemisphere”, American Meteorological Society, Vol. 71, No. 7, July 1990, pp 983-993.

10] D. J. Shea, K. E. Trenberth, “A global monthly Sea Surface Temperature Climatology”, American Meteorological Society, Vol 5, September 1992, pp 987-1001

11] K. E. Trenberth, J.W. Hurrell, “Decadal atmosphere-ocean variations in the Pacific”, Climate Dynamics, Volume 9, 1994, pp 303-319.

12] K C Tripathi, I M L Das, A.K Sahai, " Predicatability of sea surface temperature anomalies in the Indian Ocean using Artificaial Neural Networks", Indian Journal of Geo Marine Sciences, Volume 35(3), pg 210-220, September 2006.

13] K C Tripathi, S.Rai, A.C. Pandey & I.M.L. Das, "Southern Indian Ocean SST Indices as early predictors of Indian Summer Monsoon", Indian Journal of Marine Sciences, Vol 37 (1), March 2008, pp 70-76.

14] S. B. Mohongo, M.C. Deo, "Using Artificial Neural Networks to forecast monthly and seasonal sea surface temperature anomalies in the western Indian Ocean", International Journal of Ocean and Climate Systems, Volume 4, Number 2, 2013.pg 133-150.

15] K Patil, M C Deo, S. Ghosh and M. Ravichandran, "Predicting Sea Surface Temperatures in the North Indian Ocean with Nonlinear Autoregressive Neural Networks" International Journal of Oceanography, Volume 2013, Article ID 302479, 11 pages.

16] K Patil, M C Deo and M. Ravichandran, "Prediction of Sea Surface Temperatures by combining Numerical and Neural Techniques", Journal of Atmospheric and Oceaninc Technology, Volume 33, August 2016. Pg. 1715-1726. American Meteorological Society.

17] G.P. Zhang, "Time Series forecasting using a hybrid ARIMA and neural network model", Neurocomputing, Volume 50, 2003, pg 159-175.