Regional Ocean Wave Height Prediction using Sequential Learning Neural Networks

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Abstract

Wave height prediction is a critical factor in the efficient operation of many offshore and coastal engineering activities. The classical numerical solutions to this problem, based on the wave energy-balance equation, involves complex implementation with higher computational powers. In recent years, machine learning approaches are being widely used for the prediction of wave heights. However, these approaches involve batch learning algorithms that are not well-equipped to address the demands of continuously changing data stream. In this paper, we conduct a study to predict the daily wave heights in different geographical regions using sequential learning algorithms, namely the Minimal Resource Allocation Network (MRAN) and the Growing and Pruning Radial Basis Function (GAP-RBF) network. The study is conducted using data collected from 13 stations across three geographically distinct regions, viz., the Gulf of Mexico, the Korean region and the UK region, for the period between Jan 1, 2011 and Aug 30, 2015. The data is chosen such that the study covers a wide range of geographical terrains and locations, a wide range of wind speed and wave heights. We compare the performance of MRAN and GAP-RBF with Support Vector Regression (SVR) and Extreme Learning Machine (ELM). The performance study results show that the MRAN and GAP-RBF outperform the SVR and ELM with minimal network resources, in the daily wave height prediction. They also predict the significant wave heights accurately. Performance comparison between MRAN and GAP-RBF shows that MRAN outperforms GAP-RBF with minimal architecture.

Keywords: GAP-RBF, Minimal Resource Allocation Network, Sequential learning, Prediction, Ocean wave height.

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1. Introduction

The various activities such as maritime traffic [1], shipping, fishing, recreation, coastal management for defence, port and transportation authorities, dredging industry requires accurate prediction of wave height [2], [3], [4], [5], [6], [7], [8], [9], [10]. Wave forecast helps in planning and scheduling offshore risk management activities [11], [12], [13], [14]. The offshore oil and gas industry that performs engineering tasks such as design of sea states, fatigue analysis and marine operations is also in need of future wave characteristics at open sea, in order to plan and perform efficient operations. Wave height prediction is also very important in the climate processes as they play a huge role in exchange of heat, energy, gases and particles between the oceans and atmosphere.

Wave forecasting is the process of estimating how waves evolve as changing wind fields act on the surface of ocean. Wind blowing across the surface of ocean creates a surface stress, generating most ocean waves. The process of wave generation due to wind starts with small wavelets appearing on the water surface. This increases the drag forces, which in turn allows short waves to grow. These short waves continue to grow until they finally break and their energy is dissipated. It is observed that a developing sea or storm starts with high frequencies, creating a spectrum with a peak at a relatively high frequency. A storm which has lasted for a long time is said to create a fully developed sea. After the wind has stopped, a low frequency decaying sea or swell is formed. These long waves form a wave spectrum with a low peak frequency. If the swell from one storm interacts with the waves from another storm, a wave spectrum with two peak frequencies may be observed. Thus, the process of wave generation is a complex process with many forces and modeling the process for forecasting requires to identify the various parameters influencing the energy of waves. It has been observed in [15] that the wave energy at a given location is influenced by advection, external environment and dissipation, which are represented in a spectral energy-balance equation.

The most general formulation for wave models using computer involves the spectral energy- balance equation(1) which describes the development of the surface gravity wave field in time and space,

$$\frac{\partial E(f,\theta,t)}{\partial t} = S = S_{in} + S_{nl} + S_{ds} \tag{1}$$

where $E(f,\theta,t)$ is a two dimensional wave spectrum depending on frequency f and propagation direction θ. S is the net source function that depends on S_{in}, the external wave making factors such as local wind and local current, S_{nl} the non-linear energy transfer by wave-wave interactions and S_{ds} the dissipation. i.e wave energy loss mechanism related to wave-breaking processes and interaction of waves with turbulence of the upper water layer. For further details on elements of wave modelling, one may refer to [15].

The basis of wave modeling is to solve the energy balance equation in Eq. (1). In a numerical model, energy input term S_{in} is generally expressed as the resonant interaction between waves and turbulent pressure patterns in the air [16] and the feedback between growing waves and induced turbulent pressure patterns [17]. The dissipation term S_{ds} depends on the existing energy in the waves and on the wave steepness and is formulated in the wave model as a function of wave steepness [18]. The biggest challange in wave modeling is the representation of the nonlinear term, S_{nl}. Based on the nature of this representation, there are three generations of wave models. The first generation models do not have an explicit representation for S_{nl}, the second generation models handle the S_{nl} term by parametric methods and the third generation models calculate the non-linear energy transfer by analytic and numerical approximations. Performance of the numerical wave model depends on how best the physical concepts of wave models are expressed into the numerical schemes. The details on different generations of wave models and their limitations are explained in [15]. Though the complex and unpredictable non-linear source term is approximated with considerable computation techniques in all these models, the wave height predicted by these models are neither exact nor applicable uniformly across different oceans and seas. In the last decades, several numerical wave models such as WAM [19], JONSWAP [18], SWAN[20], WIS, WAVEWATCH III [21] have been employed to predict wave heights. However, due to the complexity, mulitple input and boundary conditions, high amount of processing time and the need for very accurate local bathymetric surveys, their implementation is very difficult [22], [23], [24], [25], [26].

In recent years, there are many works in literature for wave height prediction using soft-computing methods such as machine learning, genetic algorithms, and fuzzy inference systems. As neural networks can approximate any complex nonlinear process without *a priori* knowledge of the underlying physics, they have been widely used to solve this problem [27], [28], [29], [30], [31], [32], [33], [34], [35], [36]. [37],[38], [39]. Several network topologies like resilient back propagation [27], nonlinear auto-regressive model recurrent network [30] etc, have been applied to solve this problem in these studies. Adaptive Network-bases Fuzzy Inference System (ANFIS) has been used for modeling wave parameters from data set comprising wind and wave data collected from buoy 45012 in deep water location of Lake Ontario [40], [41], [42]. However, it is seen that the performance of the ANFIS is only better for wave heights less than 1m. In [43], the performances of Support Vector Machines (SVM), Bayesian Networks (BN), artificial neural networks and ANFIS have been studied in predicting wave heights at western Laker superior in the United States of America (USA). The long-term predictions of significant wave height at Northern North sea using BN and extreme value techniques has been performed in [44]. However, the flexible nature of the BN leads to uncertainty in the three parameters namely, location, scale and shape of Generalized Extreme Value (GEV) distribution. GEV, a model of extreme value theory, has been used in combination with BN to estimate the significant wave height in [44]. Rough set theory (RST) has also been used to predict wave height in Lake superior, USA [45]. Although RST outperforms SVM, BN, ANN and ANFIS, it involves complex mathematics. The combination of numerical wave models and typical ANN has shown to increase the accuracy of the former [22], [46], [47], [48]. In distinct, the lengthy and complicated calculations of the numerical models is simplified with ANN [49].

In addition, soft-computing methods has also been effectively used for reconstruction of missing time series data from ocean buoys [50], [51]. The X-band radar images together with Support Vector Regression (SVR) is used for prediction of significant wave height in [52]. Here, the performance of SVR is compared with mulitlayer perceptron (MLP) neural network. Nevertheless, this approach requires a reliable simulation of radar images which inturn requires simulation of a realistic wave field. Moreover, using simulation results instead of real values shall be another source of error. In [53], a hybrid approach using genetic algorithm and ELM has been used for significant wave height prediction, but the correlation coefficient of predictions using this approach is fairly less. Prediction of significant wave height at 6h time-horizon has been performed using eight different ordinal and nominal classifiers and one SVR algorithm in [54]. Although several methods are available in the literature for prediction of wave heights, these methods employ batch learning algorithms with back propagation that involve complex computation. Some of these methods rely on simulation results [52], [38]. Moreover, they also require the complete data set *a priori* for the prediction of wave heights. Further, a number of network parameters need to be fixed *a priori*. However, practically, the signals from the various sensors arrive continuously and are not available *a priori*. In such cases, the batch learning and other algorithms used in these studies need to be retrained whenever a new data arrives. This increases the computational complexity of the learning algorithm. Therefore, there is a need to solve this problem with a network that can learn as the data arrives, without involving complex computations.

As sequential learning algorithms do not need re-training and are capable of learning as data arrives, we propose to solve this problem using sequential learning algorithms. As Radial Basis Function (RBF) networks are capable of representing different localized behavior, sequential learning algorithms based on RBF networks are suitable for this problem. Sequential learning algorithms for solving approximation problems include the Resource Allocation Network (RAN) [55], Resource Allocation Network using Extended Kalman Filter (RAN-EKF) [56], Minimal Resource Allocation Network (MRAN) [57], [58], [59], Growing and Pruning Radial Basis function (GAP-RBF)[60], [61] and Online Sequential Extreme Learning Machine (OS-ELM) [62]. Although RAN and RAN-EKF paved the way for the development of the later sequential learning algorithms including MRAN and GAP-RBF, these algorithms do not prune the neurons during the learning process. The OS-ELM, on the other hand, handles data chunk-by-chunk, and its input parameters are initialized randomly for each chunk, which may result in inconsistent and unreliable generalization performance [63], [64], [65]. In addition, it requires the number of neurons to be fixed *a priori*. Therefore, we consider the sequential learning GAP-RBF and MRAN that add and prune neurons in the hidden layer of a RBF network, and update the network parameters during the learning process to predict wave heights in this study. In both of these algorithms, samples are presented one-by-one and only once. In MRAN, the neurons in the hidden layer are added and pruned based on the novelty of the sample. On the other hand, GAP-RBF adds and prunes neurons based on the significance of the neurons and connects it to the learning accuracy. Thus, the network obtained by MRAN and GAP-RBF algorithms are compact and approximates the relationship between the input and targets accurately.

In this study, we consider three geographically distinct regions of prominent off-shore activity: (a) Gulf of Mexico, (b) Korean region and (c) UK region. The network is trained using data obtained between Jan 1, 2011 and Dec 31, 2014. The trained network is tested with the data between Jan 1, 2015 and Aug 30, 2015. We collect six-hourly data from 13 stations of varying terrains in these three selected regions, to predict the daily wave heights at 12AM in these stations. The atmospheric condition and wave height at 6AM, 12PM and 6PM are used as inputs to predict the wave height in these stations at 12AM everyday. It must be noted that this is a pilot study and the study can be extended to predict hourly wave heights at different locations. First, we compare the performances of MRAN and GAP-RBF with Extreme Learning Machines (ELM) and Support Vector Regression (SVR) for all the 13 stations in the three regions. Performance study results show that the sequential learning MRAN and GAP-RBF algorithms outperform the ELM and SVR with minimal network resources. Both MRAN and GAP-RBF are capable of predicting the most significant wave height accurately. Comparison between MRAN and GAP-RBF shows that MRAN outperforms GAP-RBF with minimal network resources. Next, we compare the performances of the MRAN and GAP-RBF with those of the existing results in the literature for wave height prediction, involving any of the 13 stations considered in the study. From this performance comparison, it can be observed that MRAN and GAP-RBF outperform the previous results in the literature in the stations considered.

This paper is organized as follows : Section 2 presents a detailed description of the datasets used in this paper. Section 3 describes the GAP-RBF and MRAN in detail. In section 4, performance and results of this study is presented. Finally, section 5 summarizes the conclusions from the study.

2. Materials

This section presents a brief description of the data collected from various sources. There are three different types of sources to obtain marine data [15], [66] that are taken routinely at six-hour synoptic intervals by ships, ocean buoys and land (coastal) weather stations. In addition, remote measurements of surface wind speed over global oceans using active and passive microwave sensors such as scatterometers, radiometers and radar altimeters that are installed on-board the satellites are also available. The quality of wind measurements obtained from satellite-borne sensors depends on the accuracy of the algorithms used to derive wind-related parameters from the sensor measurements and various corrections that need to be applied for atmospheric water vapour and liquid water contamination [15], [67], [68], [69]. Furthermore, the sensor response may drift in time and careful quality-control procedures should be used to monitor the obtained data [15], [70], [71], [72]. An extensive comparsions by [73], [74] indicates that measurement of significant wave height from satellite is underestimated by 13%. The data measured by a ship is not accurate as it is affected by ship's motion and location of sensors [75], [76]. However, the data obtained from moored ocean buoys are always better in quality due to the following reasons: (a) sensors location on the buoys are carefully considered to avoid atmospheric exposure problems that causes measurement errors, (b) sampling and averaging periods for the measurements are determined after accounting for buoy motion, (c) duplicate sensors are used for redundancy and each is calibrated before deployment. Hence, in this paper, we consider 6-hourly data from the buoys stationed at different terrains in the following regions, available through the respective sources:

(a) Gulf of Mexico; Source: National Oceanic and Atmospheric Administration

(http://www.ndbc.noaa.gov/)

(b) Korean region; Source: European Marine Observation and Data Network

(http://www.emodnet-physics.eu/map/)

(c) UK region; Source: Meteorological Office

(http://www.metoffice.gov.uk/public/weather/marine-observations)

These organizations operate a number of directional buoys including large 6-20 m heave/pitch/roll buoys, a smaller 3 m system operate closer to the coast and research vessels. The measurements are within the accuracy specified by the National Data Buoy Center that meets World Meteorological Organization (WMO) regulation.

Thirteen offshore stations at various terrains from the three regions are considered in this study. The details of the thirteen stations, including the latitude, longitude, and water depth obtained from the various organizations listed above, are presented in Table 1. From the table, it can be seen that the chosen locations are geographically widely distributed. Further, the water depths at these stations range from as small as a few meters to a few thousand meters below sea level.

The study is conducted for the period between Jan 1, 2011 and Aug 30, 2015. The network is trained using the data obtained between Jan 1, 2011 and Dec 31, 2014. The trained network is tested with the data between Jan 1, 2015 and Aug 30, 2015. The atmospheric condition and wave height at 6AM, 12PM and 6PM are used as inputs to predict the wave height at these stations at 12AM everyday. Although a number of parameters are available in the meteorological data for each of the selected stations, only the parameters that are vital for wave generation, namely, the latitude and longitude of the stations, wind speed [16],[17], [77], month, air to sea temperature difference [15], water depth [78], [79], atmospheric pressure [80], [81], [15] wave heights at previous 6th hour, 12th

Table 1: Details of the Selected Buoy/ Ship Stations

Region	Station Location	Latitude	Longitude	Water depth(m)	Type of Buoy / Ship	Station Id
Gulf of Mexico	Mid Gulf	25.888	-89.658	3207	3-m Discus	42001
	East of Brownsville Texas	26.091	-93.758	3125.1	3-m Discus	42002
	South of Freeport Texas	27.907	-95.353	82.2	3-m Discus	42019
	East of Galveston	29.232	-94.413	15.8	3-m Discus	42035
Korean Region	Korea Strait	34	127.5	130	3-m Discus	22103
	Tsushima Basin	37.53	130	1729	3-m Discus	22105
	Tsushima Basin	37.46	131.11	2277	3-m Discus	21229
	Yellow Sea	36.25	125.75	60	3-m Discus	22108
UK Region	Western European Basin	48.7	-12.5	2500	2.5-meter ODAS buoy	62029
	Celtic Sea	50.1	-6.1	70	Seven Stones	62107
	Celtic Sea	51.4	2	30	F3 Light Vessel	62170
	Bay of Biscay	48.5	-5.8	110	3-m Discus	62052
	English Channel	49.9	-2.9	65	Channel Lightship	62106

hour and 18th hour are used in this study. It is worth noting that the most important parameter that affects the height of waves is the wind speed [72]. The nature of wind can be categorized as calm winds, light air, breeze, gale, storm and hurricances, based on their speeds [15]. The information of storms, hurricanes and cyclones that occurred during this period in the each of these regions are collected from National Hurricane Center and WMO as listed in Table 2. Thus, the data collected for our study includes a whole range of wind

Table 2: List of Cyclones,Storms and Hurricanes (Period 2010-2014)

Region	Year	Period	Name	Type	Max.Wind Speed (Knots)
Gulf of Mexico	2011	Jul 27-30	Don	Cyclone	45
	2011	Sep 2-5	Lee	Tropical Storm	50
	2012	Aug 21-Sep 2	Issac	Cyclone	55
	2013	Aug 25-26	Fernand	Tropical Storm	50
	2013	Sep 12-17.	Ingrid	Hurricane	75
	2013	Oct 2-6	Karen	Tropical Storm	55
	2014	Sep 1-3	Dolly	Tropical Storm	45
Korean Region	2011	Jul 21-24	Nock-ten	Storm	65
	2011	Jul 27-Aug 15	Muifa	Hurricane	95
	2011	Sep 23-30	Nesat	Hurricane	78
	2012	Jul 14-20	Khanun	Storm	52
	2012	Jul 27-Aug 4	Damrey	Hurricane	70
	2012	Aug 17-Sep 1	Tembin	Hurricane	78
	2012	Sep 10-12	Sanba	Hurricane	108
	2014	Jul 2-13	Neoguri	Hurricane	100
	2014	Jul 16-26	Matmo	Hurricane	70
	2014	Sep 17-25	Fung-Wong	Strong Gale	44
	2015	Jun 25-Jul 12	Chan-Hom	Hurricane	91
	2015	Jul 29-Aug 12	Sudelor	Hurricane	113
UK Region	2011-2012	Dec 31-Jan 6.	Ulli	Hurricane	92
	2013	Oct 27-28	St.Jude	Hurricane	86
	2013	Dec 17-21	Bernd (Emily)	Hurricane	72
	2015	Jan 7-19	Elon	Hurricane	98
	2011	Sep 11-12	Katia	Hurricane	70
	2011	Nov 24-25	Xavier	Hurricane	100

speeds and hence, wave heights.

In the next section, we briefly describe the sequential learning algorithms used in our study.

3. Methods: Sequential Learning Algorithms

In this section, we briefly discuss the two sequential learning algorithms, MRAN and GAP-RBF used to estimate the wave height.

3.1. Minimal Resource Allocation Network

For any data set with L training samples, $\{(\mathbf{u}_1, \mathbf{y}_1), \cdots, (\mathbf{u}_t, \mathbf{y}_t), \cdots, (\mathbf{u}_L, \mathbf{y}_L)\}$; $\mathbf{u}_t \in \Re^m$, $\mathbf{y}_t \in \Re^n$, the regression problem is defined as approximating the functional relationship $f : \mathbf{u}_t \rightarrow \mathbf{y}_t$, as accurately as possible, enabling output prediction for new samples with better accuracy.

The Minimal Resource Allocation Network (MRAN) is a Radial Basis Function (RBF) network that approximates this functional relationship using a sequential learning algorithm. MRAN begins with zero hidden neurons, adds, prunes the neurons or updates the network parameters, as it learns. Thus, it sees each sample only once and discards them after learning. Without loss of generality, let us assume that K neurons are added after learning $t-1$ samples. For each sample, $(\mathbf{u}_t, \mathbf{y}_t)$ in the data set, the responses of the K neurons in the hidden layer are given by:

$$h_k(\mathbf{u}_t) = exp - \left(\frac{\|\mathbf{u}_t - \boldsymbol{\mu}_k\|^2}{\sigma_k^2} \right); \quad k = 1, \cdots, K \tag{2}$$

where, $\boldsymbol{\mu}_k \in \Re^m$ is the Gaussian center of the k-th hidden neuron, and $\sigma_k \in \Re$ is its width.

The output of the network has the following form:

$$\widehat{\mathbf{y}}_t = = \alpha_0 + \sum_{k=1}^{K} (\alpha_k h_k(\mathbf{u}_t)) \tag{3}$$

where α_k is the weight connecting the k-th hidden neuron to the output neuron, α_0 is the bias term and $\widehat{\mathbf{v}}_t$ is the predicted output.

The learning process of MRAN involves allocation of new hidden neurons as well as adjusting the existing network parameters. A neuron is added to the hidden layer if the following criteria are satisfied:

$$\mathbf{u}_t - \mu_{tr} > \epsilon_t \tag{4}$$

$$\mathbf{e}_t = \mathbf{y}_t - \widehat{\mathbf{y}}_t > \mathbf{e}_{min} \tag{5}$$

$$e_{rms} = \sqrt{\frac{1}{M} \sum_{i=t-(L-1)}^{t} (\mathbf{y}_i - \widehat{\mathbf{y}}_i)^2} > e'_{min} \tag{6}$$

where, $\boldsymbol{\mu}_{tr}$ is the center of the hidden neuron closest to $\mathbf{u}_t$. The parameters ϵ_t, $\mathbf{e}_{min}$ and e'_{min} are the thresholds to be selected appropriately. The threshold $\epsilon_t = max(\epsilon_{max}\gamma^t, \epsilon_{min})$, where $0 < \gamma > 1$ is a decay constant and $\mathbf{M}$ is length of sliding window. Thus, the growth criterion in MRAN (4) and (5) follows RAN [57], [59] with an additional condition (Eq. (6)) based on the RMS value of the output error over a sliding data window. This condition checks if the RMS value of the output error (e_{rms}) over a sliding window (M) is greater than a given threshold. This condition is included to ensure the transition in number of hidden units due the growing and pruning strategy is smooth. Thus, MRAN checks the novelty of the sample based on the RMS error and the distance of the sample from the existing neuron centers to add a neuron. The pruning strategy of MRAN computes the normalized hidden neuron outputs for the samples. If the normalized output of a neuron over a set of consecutive samples defined by the sliding window (M) is less than a threshold (δ), the neuron is pruned from the network.

The learning algorithm of MRAN can be summarized as:

1 For each sample $\mathbf{u}_t$, compute the network output $\widehat{\mathbf{v}}_t$.

2 If criteria (4), (5) and (6) are satisfied, add a neuron with RBF center and width to the hidden layer.

3 If the contribution of a hidden neuron for a window of consecutive samples is below a threshold, delete the neuron from the network.

4 Adjust the centers, widths and weights of the network using an Extended Kalman Filter.

5 Increase t and go to step 1.

For complete details of neuron initialization and EKF update of MRAN, one should refer to [57].

3.2. Growing And Pruning-Radial Basis Function Network

Growing and Pruning Radial Basis Function (GAP-RBF) network is similar to the MRAN, except that it uses the desired accuracy to compute the significance of a neuron. The significance of a neuron is computed as the contribution made by that neuron to the network output averaged over all the sample inputs received thus far. In addition to the add criteria in Eqs. (4), (5), the GAP-RBF uses the significance of a neuron that depends on the distribution of the inputs, to add a neuron to the network. If the significance of a neuron is greater than a desired accuracy, a neuron is added to the hidden layer. If the significance is less than the desired accuracy, the neuron is pruned. Further, the significance of a neuron is only computed based on the Euclidean distance between the current sample and the nearest neuron. If the input sample is not significant to add a neuron, the parameters of the nearest neuron is alone updated. For complete details of the GAP-RBF algorithm, one can refer to [60],[61].

In the next section, we conduct a study for wave height prediction using MRAN and GAP-RBF. The performances of MRAN and GGAP-RBF are compared against SVR and ELM.

4. Performance Study

In this section, we present the results of daily wave height prediction in all the stations shown in Table 1 in the Gulf of Mexico, the Korean region and the UK region. The root mean square error (RMSE) and the correlation coefficient (CC) are used as the performance measures to compare the performances of the various algorithms. The root mean square error represents the accuracy of prediction and is defined by

$$RMSE = \sqrt{\frac{1}{L}\sum_{i=1}^{L}\left(\mathbf{y}_i - \widehat{\mathbf{y}}_i\right)^2} \tag{7}$$

$$\tag{8}$$

The correlation coefficient measures the strength and the linear dependency of two random variables. A CC greater than 0.8 is generally described as *strong*, whereas a correlation less than 0.5 is described as *weak*. It is defined as:

$$CC = \frac{Cov\left(\mathbf{y}, \widehat{\mathbf{y}}\right)}{\sqrt{Var\left(\mathbf{y}\right) Var\left(\widehat{\mathbf{y}}\right)}} \tag{9}$$

where $Cov(,)$ and $Var()$ refer to the covariance and variance operator, respectively.

First, we present the results of the performance study in the chosen stations in the selected regions for the period Jan 1, 2014-Aug 31, 2015. For this data, the results of MRAN and GAP-RBF are compared against the batch learning ELM and SVR. Next, we compare the performances of MRAN and GAP-RBF with the results of the past studies for wave height prediction, available in the literature, at the stations considered in this study.

4.1. Performance study with state-of-the-art regression models

In this section, we present the performance study results for the wave height prediction in the stations listed in Table 1 for the period between Jan 1, 2014 and Aug 31, 2015. The total number of samples used in training and testing in each region is tabulated in Table 3.

The wave height prediction study is conducted using the sequential learning MRAN and GAP-RBF networks, in comparison with other state-of-the art predictors available in the literature, namely, the Extreme Learning Machine (ELM) and Support Vector Regression (SVR). It must be noted that although the online sequential extreme learning machine is a sequential learning algorithm, it converges to ELM when the size of the chunk is equal to the size of the training data [82]. The parameters in SVR algorithm are selected based on the guidelines available in [83], [84] and in this work the *cost*, *epsilon* and *gamma* are 1, 0.5 and 0.3 respectively. The parameters in ELM algorithm are selected based on the constructive-destructive procedure, similar to that presented in [85].

The number of hidden neurons (K), the Root Mean Square Error (RMSE) and the correlation coefficients (CC) of GAP-RBF, MRAN, ELM and SVR are presented in Table 4, where ^{a} indicates support vector in SVR. From table 4, the GAP-RBF and MRAN predicts the daily wave heights more accurately than the ELM and SVR with very fewer number of neurons. Thus, it can be inferred that the GAP-RBF and MRAN performs much better than SVR

Table 3: Size of Training and Testing Data

Region	No. of Samples	
	Training	Testing
Gulf of Mexico	4747	465
Korean Region	3195	864
UK Region	12080	1501

and ELM in predicting the daily wave heights in individual regions. Moreover, MRAN and GAP-RBF are capable of predicting the peaks in waves accurately. Comparison between MRAN and GAP-RBF shows that MRAN outperforms GAP-RBF in predicting the daily wave heights. This could be because GAP-RBF performance is linked to the distribution of the input data. Further, using the GAP-RBF and MRAN for daily wave height prediction avoids the tedious numerical integration and approximation approach of the existing numerical wave models and is also uniformly applicable across different oceans and seas.

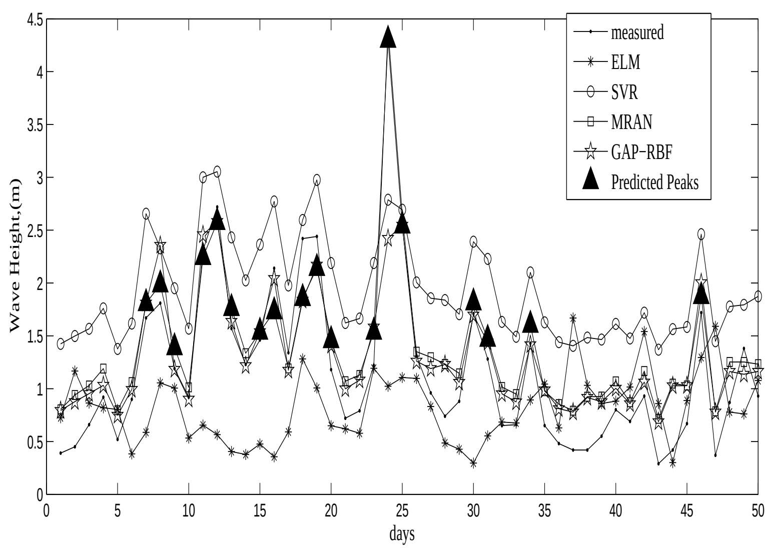

Figure 1: Predicted Wave Height for the period between Jan 1, 2015 and Aug 30, 2015 at station 42002, Gulf of Mexico

Fig. 4.1 shows the wave height predictions over a window of 50 samples, at station 42002 in the Gulf of Mexico, with the significant wave heights (represented by Δ in the plot) of about **4.4 m**. It can be seen that MRAN can predict the significant wave heights more accurately than the other networks.

Fig. 4.1 shows the wave height predictions over a window of 50 samples at Station 22108 of the Korean region, with the significant wave heights (rep-

Table 4: Performance Study Results

Region	Station	Algorithm	K	RMSE	CC
Gulf of Mexico	42001	SVR	283^a	0.5721	0.8283
		ELM	700	0.4742	0.8018
		GAP-RBF	**13**	**0.2659**	**0.9110**
		MRAN	**4**	**0.2464**	**0.9308**
	42002	SVR	283^a	0.4936	0.8646
		ELM	700	0.2243	0.8878
		GAP-RBF	**13**	**0.2135**	**0.8987**
		MRAN	**4**	**0.2014**	**0.9270**
	42019	SVR	283^a	0.6858	0.8063
		ELM	700	0.2977	0.8481
		GAP-RBF	**13**	**0.4653**	**0.8275**
		MRAN	**4**	**0.2458**	**0.8612**
	42035	SVR	283^a	0.7247	0.7914
		ELM	700	0.1878	0.9363
		GAP-RBF	**13**	**0.2153**	**0.8146**
		MRAN	**4**	**0.2082**	**0.8512**
Korean Region	22103	SVR	195^a	0.5207	0.5865
		ELM	275	0.3843	0.7867
		GAP-RBF	**13**	**0.3367**	**0.8134**
		MRAN	**3**	**0.2979**	**0.8752**
	22105	SVR	195^a	0.7037	0.6624
		ELM	275	0.6586	0.8157
		GAP-RBF	**13**	**0.6367**	**0.8277**
		MRAN	**3**	**0.4968**	**0.8755**
	21229	SVR	195^a	0.6194	0.6511
		ELM	275	0.5199	0.8426
		GAP-RBF	**13**	**0.4784**	**0.8734**
		MRAN	**3**	**0.4373**	**0.9135**
	22108	SVR	195^a	0.4082	0.7298
		ELM	275	0.3616	0.8629
		GAP-RBF	**13**	**0.3262**	**0.9050**
		MRAN	**3**	**0.2395**	**0.9376**
UK Region	62029	SVR	220^a	0.3593	0.9010
		ELM	175	0.6140	0.7755
		GAP-RBF	**12**	**0.3694**	**0.9008**
		MRAN	**5**	**0.2265**	**0.9108**
	62107	SVR	220^a	0.5552	0.8938
		ELM	175	0.6739	0.8093
		GAP-RBF	**12**	**0.6702**	**0.8880**
		MRAN	**5**	**0.3778**	**0.9067**
	62170	SVR	220^a	0.6685	0.8564
		ELM	175	0.7380	0.7505
		GAP-RBF	**12**	**0.6583**	**0.8735**
		MRAN	**5**	**0.5409**	**0.8840**
	62052	SVR	220^a	0.9203	0.7313
		ELM	175	0.8412	0.7434
		GAP-RBF	**12**	**0.7541**	**0.8296**
		MRAN	**5**	**0.7005**	**0.8521**
	62106	SVR	220^a	0.660	0.6802
		ELM	175	0.5786	0.7465
		GAP-RBF	**12**	**0.4481**	**0.7808**
		MRAN	**5**	**0.5047**	**0.7610**

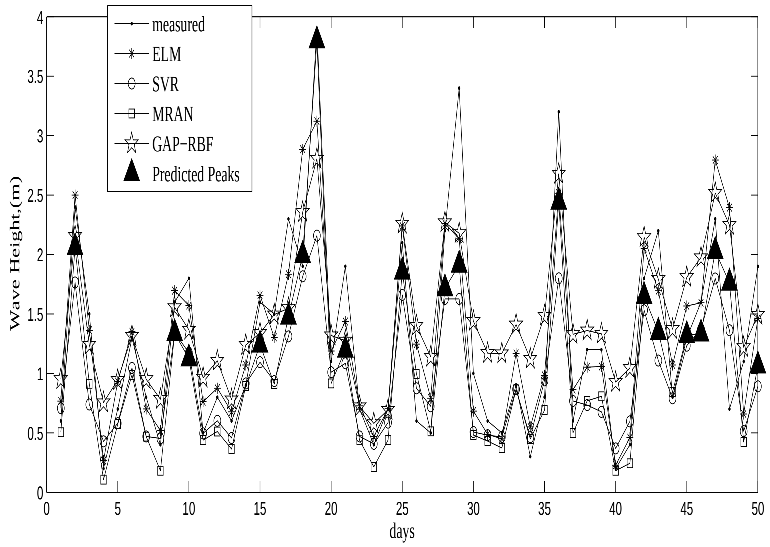

Figure 2: Predicted Wave Height for the period between Jan 1, 2015 and Aug 30, 2015 at station 22108, Korean Region

resented by Δ in the plot) of about **3.9 m**. It can be seen that MRAN can predict the significant wave heights more accurately than the other networks, although it is high.

Fig. 4.1 shows the wave height predictions over a window of 50 samples at station 62052 of the UK region, with the significant wave heights (represented by Δ in the plot) of about **4.8 m**. It can be seen that MRAN can predict the significant wave heights more accurately than the other networks, although the height is about 4.8 m.

4.2. Comparison with existing works in literature

In this section, we present the wave height prediction results of MRAN and GAP-RBF, in comparison with existing results in the literature for the stations considered in our study. Earlier, the wave height prediction performances of the second generation numerical model WISWAVE, and the third generation models, namely WAM and WAVEWATCH III, in stations 42001 and 42035 for October 1995 has been reported in [21]. In addition to these, the conventional MLP with BP algorithm (MLP-BP) was used to predict wave heights at station 42035 for Feb 2004 in [34]. As MRAN and GAP-RBF outperform the SVR and ELM in the wave height prediction as shown in Section 4.1, we compare these results only with MRAN and GAP-RBF. The results for WISWAVE, WAM and WAVEWATCH III are reproduced from [21] and that of MLP-BP is reproduced from [34].

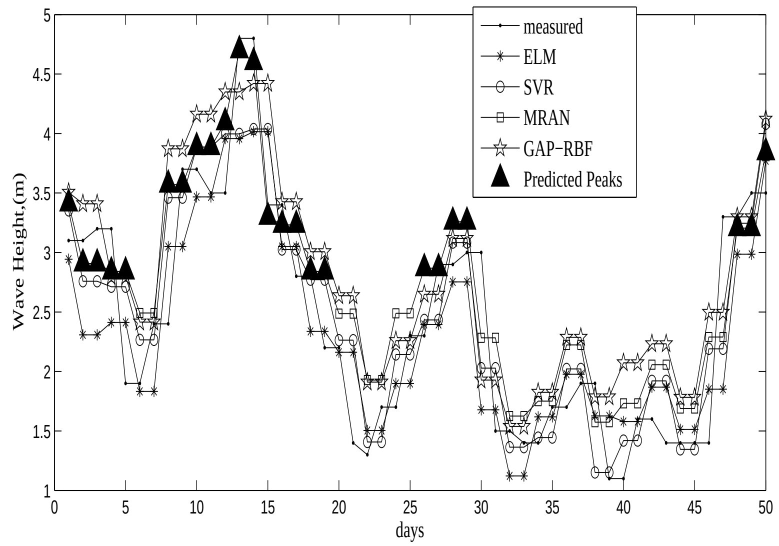

Figure 3: Predicted Wave Height for the period between Jan 1, 2015 and Aug 30, 2015 at station 62052, UK Region

The wave height prediction performances of the various models are compared using the performance measures namely RMSE and CC. The RMSE and CC of MRAN and GAP-RBF in comparison with those of the WISWAVE, WAM and WAVEWATCH III for the stations 42001 and 42035 in October 1995, is shown in Table 5. From the table, it can be observed that the performances of MRAN and GAP-RBF are almost similar to those of WISWAVE, WAM and WAVEWATCH III in predicting wave heights at station 42001 in October 1995. Moreover, it can also be observed that at station 42035, the MRAN and GAP-RBF outperform the numerical models. It must also be noted that the numerical models involve huge computational effort and requires high processing time [22]. This also limits their ability to be applicable across different oceans and seas.

The wave height prediction performances of GAP-RBF and MRAN are compared against that of the MLP-BP in station 42035 for February 2004, and the results are presented in Fig. 4.2. The RMSE of the MLP-BP, MRAN and GAP-RBF are **0.4305**, **0.2661** and **0.2808**, respectively. From the figure and the RMSE of the various algorithms, it can be seen that MRAN and GAP-RBF outperform MLP-BP in the prediction of wave heights. Moreover, it must also be noted that the MLP-BP is a batch learning algorithm that requires the complete data to be available *a priori*, and is not capable of representing the dynamically changing data stream. Thus, it requires retraining when a new data arrives.

From the results in this section, we can observe that the sequential learning algorithms namely MRAN and GAP-RBF outperform the existing methods in

Table 5: Comparison of MRAN and GAP-RBF with Numerical wave models

Station Id	Model/Algorithm	RMSE	CC
42001	WISWAVE	0.28	0.91
	WAM	0.26	0.91
	WAVEWATCH III	0.28	0.90
	MRAN	**0.2646**	**0.9128**
	GAP-RBF	**0.2801**	**0.8924**
42035	WISWAVE	0.21	0.87
	WAM	0.21	0.86
	WAVEWATCH III	0.24	0.83
	MRAN	**0.2253**	**0.8707**
	GAP-RBF	**0.2092**	**0.8939**

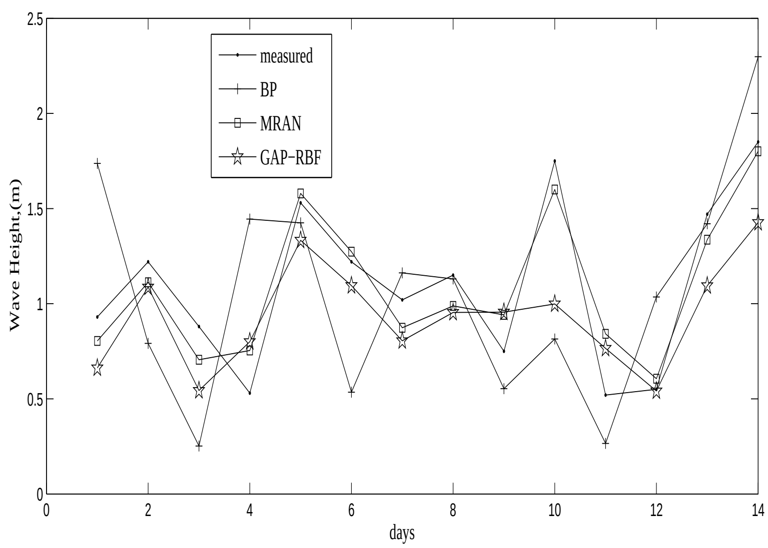

Figure 4: Predicted Wave Height for Feb 2004 at station 42035, Gulf of Mexico

literature for the problem of ocean wave height prediction.

5. Conclusion

In this paper, we study the performances of the RBF sequential learning algorithms to predict the daily wave heights at 13 different stations from three geographical locations, namely, Gulf of Mexico, Korean region and the UK region. The data is collected from the respective organizations for the period between Jan 1, 2011 and Aug 30, 2015. The past wave data and the measured atmospheric conditions obtained in these stations between Jan 1, 2011 and Dec 31, 2014 are used in training and the data in these stations between Jan 1, 2015 and Aug 30, 2015 are used in testing. The data is chosen such that the study covers a wide range of geographical terrains and locations, a wide range of wind types (ranging from light air to hurricanes), and a wide range of wave heights (ranging from a few centimeters to a few meters).

The Minimal Resource Allocation Network (MRAN) and the Growing and Pruning Radial Basis Function (GAP-RBF) networks are the sequential learning algorithms used in our study. The MRAN uses the novelty of the sample to add and prune neurons, while the GAP-RBF uses the significance of a neuron in deciding the addition/pruning criteria. The performances of MRAN and GAP-RBF are compared against those of ELM and SVR. From this study, we infer that the GAP-RBF and MRAN outperform SVR and ELM in the daily wave height prediction and in the prediction of the most significant wave height, with very less network resources. The performance of GAP-RBF is slightly lesser than the MRAN, and requires more neurons than the MRAN for the prediction. This may be because the GAP-RBF depends on the input distribution. It must be noted that this work can be easily extended to predict hourly wave heights. Moreover, the features that are critical for wave generation are selected based on the guidelines in [15] and [72]. However, there is a need for a detailed study on the effects of the individual parameters on the ocean wave heights. Therefore, ideal choice of input features for ocean wave height prediction will be a separate study topic for future work.

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