3.2 OPTIMIZATION AND PERFORMANCE OF A NEURAL NETWORK MODEL FORECASTING WATER LEVELS FOR THE CORPUS CHRISTI, TEXAS, ESTUARY

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1. Introduction

Accurate water level forecasts are of vital importance along the Texas coast as the waterways of the northern Gulf of Mexico play a critical economic role for a number of industries including shipping, oil and gas, tourism, and fisheries. The economic impact of these industries is not limited to the Gulf coast as for example more than 50% of the US tonnage reaching the US by waterways transits through the Gulf of Mexico. In the study area the Corpus Christi (CC) estuary (see Figure 1) is home to the fifth largest US port by tonnage, the Port of Corpus Christi. Astronomical forcing or tides are well tabulated; however water level changes along the Gulf coast are frequently dominated by meteorological factors whose impact is often greater than the tidal range itself (e.g. Cox et al. 2002a). The National Oceanic and Atmospheric Administration (NOAA) stated that "presently published predictions do not meet working standards" when assessing the performance of current predictions, a parameter closely related to water levels, for regular weather conditions in Aransas Pass and CC Bay, both part of the study area (NOAA 1991, NOAA 1994).

For more than ten years the Texas Coastal Ocean Observation Network (TCOON) has measured and archived water levels as well as other coastal variables that have been recorded in CC Bay and along the coast of Texas. TCOON was constructed and operated by Texas A&M University-Corpus Christi (TAMUCC) Conrad Blucher Institute (CBI) Division of Nearshore Research (DNR). The network presently consists of 42 weather platforms from Brownsville to the Louisiana border (Michaud et al. 2001). In addition to the TCOON stations, CBI-DNR manages another 18 data collection platforms. The overall network provides real-time or near real-time coastal measurements such as water levels, wind speeds and wind directions, barometric pressures as well as other variables such as dissolved oxygen, salinity and wave climates depending on the station. This abundance of archived measurements provides a unique opportunity to test data intensive modeling and forecasting techniques such as the application of Artificial Neural Networks (ANN) to forecast future water levels and improve on the presently inadequate harmonic forecasts.

A comparison between harmonic forecasts and measured water levels is illustrated in Figure 2 for one of the TCOON stations of the study area, the Naval Air Station (NAS). As can be observed, the difference between harmonic and measured water levels is frequently larger than the tidal range itself. The water anomaly or difference between measured and harmonically forecasted water levels is presented in Figure 2b. The anomaly regularly shifts from positive to negative by about half a meter during frontal passages in winter spring and fall or Julian Day (JD) 0-120 and JD 280-365. Figure 2c displays the squared wind speed or wind pseudostress for the same period. The strong and shifting winds during frontal passages are well correlated with the water anomaly and wind is generally recognized as the main non-tidal forcing driving water level changes (Garvine 1985, NOAA 1991, NOAA 1994). The agreement between harmonic and measured water levels is typically much closer during the summer months with the exception of the passage of tropical storms. In 1998 this was illustrated by tropical storm Frances, which affected water levels in CC Bay from JD 245 to JD 260. Although the focus of this model is the forecast of water levels during frontal passages, data affected by tropical storms have not been removed and the performance of the model will be assessed during the passage of tropical storms.

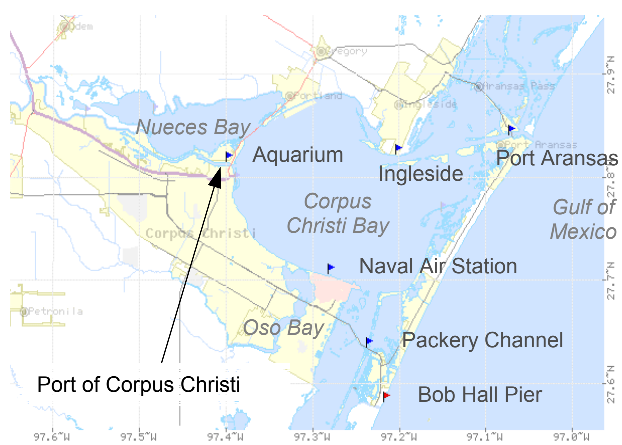

Figure 1. The Corpus Christi estuary with the location of the TCOON stations used for this study.

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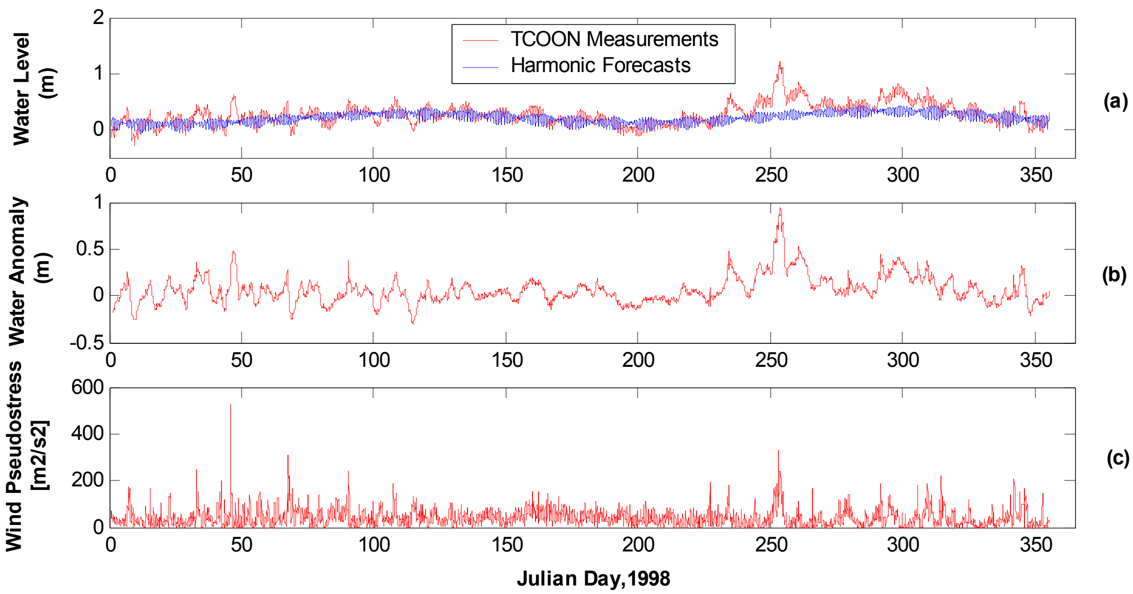

Figure 2. (a) Comparison between harmonic forecasts (blue) and measured water levels at the TCOON NAS station for 1998. (b) Water level differences between measured water levels and harmonic forecasts. (c) Measured wind pseudostress (squared wind speeds) at the TCOON NAS station for 1998.

At the present time the impact of meteorological factors is unaccounted for in water level forecasts in the Gulf of Mexico. To include weather forcing, a linear model and an ANN model were recently developed and tested for the entrance of Galveston Bay (Cox et al., 2002, Tissot et al., 2002). The linear model was based on the locally measured wind and a nine-hour lag between the wind forcing and the water level response. The input to the ANN model included east-west and north-south winds, barometric pressure, and wind and tidal forecasts. Both models were found to improve significantly short-term (3-24 hours) predictions of total water levels and the ANN was shown to outperform the linear model particularly in the five to fifteen hour range when including forecasted winds. The objective of this work is to develop and assess the performance of ANN models for the forecast of total water levels in the CC estuary for stations on the open coast and within CC Bay.

2. Site, Methodology, and Model Description

The site of this study, the CC estuary, is composed of CC Bay, Nueces Bay, and Oso Bay. It communicates with the Gulf of Mexico near Aransas Pass through the Corpus Christi Ship Channel, with the Laguna Madre at the south end of CC Bay and with Mission Bay at the north end of the bay. Other inputs to the bay include the Nueces River and the Cayo del Oso. The Corpus Christi Ship Channel runs through CC Bay from the CC port to the Gulf of Mexico at Port Aransas. The ship channel is 36 miles (58 km) long, 400 feet (122 m) wide, and 45 feet (14 m) deep. CC Bay is also traversed by the Intra Coastal Waterway (ICW), a 12 feet (3.7 m) deep and 125 feet (38.1 m) wide channel, that is used by barges to transport goods along the Gulf coast from South Texas to Florida. The average depth of the rest of CC Bay is relatively shallow at about 10 feet (3.0 m). The Bob Hall Pier (BHP) station and the Naval Air Station (NAS) will be studied extensively as representatives of an open coast and a bay location. The model will then be assessed for the other stations of the study: Port Aransas, Ingleside, Aquarium, and Packery Channel. The stations' locations are illustrated in Figure 1.

The data sets for each station consist of five yearly records from 1997 to 2001 including measured water levels and harmonic water level predictions for all stations. A description of the data sets is presented in Table 1. The table lists for the BHP and NAS stations the measurements available, the exact span of the yearly data sets, and the percent of data missing for water level and wind measurements. The abbreviations pwl, wsd, and wdr stand respectively for primary water level, wind speed, and wind direction. For the other four stations only the type of data available is mentioned, as the data sets are not extensively studied. The quality of the data sets for these other stations is similar although no wind measurements are available for the Aquarium and Packery stations. For these stations the wind measurements from the nearest station were used for the model. Other measurements collected and archived at some of the stations include barometric pressure, air and water temperature. This study will concentrate on the use of measured water levels, harmonic forecasts, measured wind speeds and wind directions as they were found in previous studies to be the dominant factors when predicting future water levels. The missing data was replaced by a linear interpolation between the closest known measurements. For a few data sets such as the 1997 and 2001 NAS the starting or end date are not January 1st or December 31st. In such cases data was removed at the beginning or the end of the year to improve the quality of the data set by removing periods during which measurements are missing or incomplete. The water level measurements in the study are all referenced to mean lower low water. The choice was made as mean lower low water levels are the measurements indicated in nautical charts and ship captains are one of the main targeted audiences for the application of this model. The harmonic forecasts included in the study are also extracted from the TCOON database. The forecasts are computed following NOAA procedures (Mostella et al., 2002) and are based on one year of observations of water levels and a set of 26 harmonic constituents.

Table 1. Summary of the data sets used in the study with available measurements, time span, and % missing data.

Station / Data Set Year	Data Set Span	Data Available	% pwl Missing	% wsd & % wdr Missing
Bob Hall Pier				
1997	1/1/97 – 12/31/97	pwl, wsd, wdr	0.66 %	5.20 %
1998	1/1/98 – 12/31/98	pwl, wsd, wdr	0.01 %	0.48%
1999	1/1/99 – 12/31/99	pwl, wsd, wdr	1.20 %	2.20 %
2000	1/1/00 – 12/31/00	pwl, wsd, wdr	0.08 %	0.24 %
2001	1/1/01 – 12/31/01	pwl, wsd, wdr	0.06 %	0.26 %
Naval Air Station				
1997	1/22/97 – 12/31/97	pwl, wsd, wdr	0.66 %	3.9 %
1998	1/1/98 – 12/31/98	pwl, wsd, wdr	0.65 %	2.30 %
1999	1/1/99 – 12/31/99	pwl, wsd, wdr	0.10 %	0.94 %
2000	1/1/00 – 12/31/00	pwl, wsd, wdr	0.01 %	0.15 %
2001	1/22/01 – 12/31/01	pwl, wsd, wdr	0.21 %	1.90 %
Aquarium	1997-2001	pwl		
Ingleside	1998-2001	pwl, wsd, wdr		
Packery	1997-2001	pwl		
Port Aransas	1997-2001	pwl, wsd, wdr		

The structure of the ANN selected to start the optimization process was based on the results obtained for previous studies conducted in and directly outside of Galveston Bay (Cox et al., 2002, Tissot et al., 2002) and at the Port Aransas station (Drikitis, 2002). These studies indicated that very simple ANNs including two layers, one output neuron and one or two neurons in the hidden layer, are optimal for the forecasting of water levels, at least under the conditions encountered along the Texas Gulf coast. Previous studies also indicated that previous wind and water level measurements and wind and tidal forecasts were the most important input. A schematic of a typical ANN model used in this study is presented in Figure 3 with a two layer ANN, 1 output neuron, two hidden neurons, and an input deck consisting of previous water level differences, previous east-west and north-south wind pseudostress, barometric pressure and wind and tidal forecasts. All inputs to the ANNs are scaled to a [–1.1,1.1] range. The optimum ANN topology and input deck are determined by varying each input parameter starting with previous water levels. Section 3 presents the optimization process for the BHP and the NAS stations. The ANN models were developed, trained, and tested within the Matlab R13 computational environment and the related Neural Network Toolbox (The MathWorks, Inc., 1998). The computers used for the study were Pentium IV PCs with CPUs ranging between 500 MHz and 1.4 GHz. All ANN models were trained using the Levenberg-Marquardt algorithm as implemented within the Matlab Neural Network Toolbox. Training times varied between a few minutes and several hours. It is important to note that although training times can be lengthy, generating water level forecasts is a sub-second process once the models are trained.

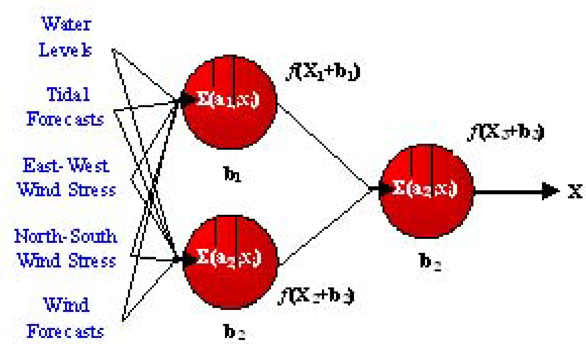

Figure 3. Typical ANN used in this study with two layers, a small number of neurons and input deck consisting of previous measurements and wind and tidal forecasts.

The performance of the models is assessed based on criteria used by NOAA for the development and implementation of operational nowcast and forecast systems (NOAA, 1999). In this study we focus on a subset of these skill assessment variables. A single forecasting error or e_i is defined as the difference between the predicted value p_i and the observed value r_i or $e_i = p_i - r_i$. The models are assessed by averaging the individual errors over the full data sets, typically one year of water level measurements. The skill assessment variables used are the following:

Average error: $E_{avg} = (1/N) \Sigma e_i$

Absolute Average Error: $|E_{avg}| = (1/N) \Sigma |e_i|$

Root Mean Square Error: $E_{rms} = ((1/N) \Sigma e_i^2)^{1/2}$

POF(X) – Positive Outlier Frequency or percentage of the forecasts X cm or more above the actual measurement.

NOF(X) – Negative Outlier Frequency or percentage of the forecasts X cm or more below the actual measurement.

MDPO(X) – Maximum Duration of Positive Outlier.

MDNO(X) – Maximum Duration of Negative Outlier.

The value defining an outlier is set at 15 cm for this study. An X=15 cm requirement limits water level errors to within +/- ½ foot and is based on NOAA's estimates of pilots' needs for under keel clearance. Additionally a skill assessment variable, the Normalized RMS Error is defined to compare model performance at different locations (Cox et al., 2002a). The root mean square of the error is divided by the root mean square of the signal to normalize the error with the variability of the signal.

Root Mean Square Signal: $R_{rms} = ((1/N)\ \Sigma\ r_i^2)^{1/2}$

Normalized RMS Error: $NE = E_{rms}/R_{rms}$

To evaluate the variability due to both the training of the models and the year-to-year differences between water level records and overall weather conditions, the models are successively trained over each yearly data set and tested on the other four data sets. The rotation between training and testing years leads to five training sets and twenty testing sets. The standard deviation of the skill variables is used to evaluate the variability of the model forecasts and predict their reliability. The standard deviation of the skill variables is however only used for general guidance during the optimization of the ANNs as the variability due to the inherent year to year changes in weather conditions is larger than the variability associated with the training of the ANN models. As an illustration the average absolute error over the testing sets for the optimum ANN making 3-hour water level predictions at BHP is 3.1 cm. The overall standard deviation when considering all testing sets is 0.3 cm. The variability of the average absolute error associated with the testing of one ANN over the four other years is also 0.3 cm. The average standard deviation when considering one year and the performance of the 4 ANNs trained on other years is 0.1 cm. While the 0.1 cm is considered as the overall criteria to determine differences between model performances, the optimization process will be sometimes based on smaller differences as this is a step-by-step process with small successive improvements leading to the final optimum model performance.

Finally the performance of the ANNs is also compared to a simple model that assumes that the water level anomaly at the time of forecast will be constant throughout the forecasting period. The model is referred to as the Constant Water Level Difference model (CWLD). This simple model works well when the water level anomaly changes slowly with time. A lag proportional to the forecasting span will however always be present when applying the CWLD model. As will be discussed in the following sections, while the ANNs systematically outperform the CWLD model the performance of this simple model is impressive for the CC estuary. The CWLD model is considered here as a benchmark but could be used as a simpler yet effective replacement to the harmonic forecasts when the necessary input to the ANN models are not available or when the implementation of ANN models is not possible.

3. Application of the Model to the Corpus Christi Estuary

The BHP station is the first location considered. The station is located on the open coast near Corpus Christi and therefore can be used to provide information to ship captains navigating the ship channel during their approach to the coast. Measurements and forecasts for this station will also be used to model in-bay locations as BHP will provide an indication of the water level dynamic in the nearby Gulf of Mexico. The model is optimized by first considering a simple 1x1 ANN with logsig and purelin neural functions and an input deck consisting of an increasing number of previous water level differences. The absolute average errors of the model are displayed in Figure 4 for forecasting times of 3, 6, 12, and 24 hours. For a 3-hour forecast the optimum performance is obtained when including the past 6 hours of water level differences. The absolute average error for this optimum configuration is 0.0314 m. As the forecasting time increases the importance of previous water levels decreases. For a 6-hour forecast the performance of a model including the past 6 hours record of previous water levels is the same as a model including the past 3 hours. Including only the past 3 hours of water level measurements is also optimum for all longer forecasting times. The improvements recorded when considering more than 1 previous water level measurements even for long forecasting times were expected as two or more previous water levels give a measure of the trend, rising or decreasing, in the water level anomaly.

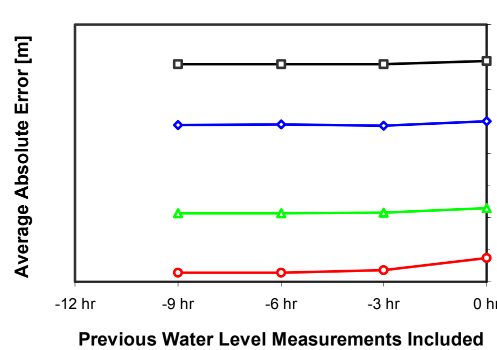

Figure 4. Changes in ANN performance for a 1x1 ANN trained with increasing numbers of previous water level differences for various forecasting times, 3-hour (red/circles), 6-hour (green/triangles), 12-hour (blue/diamonds), and 24-hour (black/squares).

The second step in the optimization process involves the inclusion of past wind measurements. The models are tested with the optimum number of previous water level differences and an increasing number of previous wind measurements. For 3-hour forecasts, including the past 6 hours of wind records leads to the best performance, an average absolute error of 3.09 cm as compared to 3.14 cm when including only past water level measurements. As discussed in section 2, while these step-by-step differences in model performances during the optimization process are often small (1.6% here) the cumulative improvements are significant. For forecasts longer than 3 hours the optimum extent of the past wind records is 3 hours, although the benefits of having the past 3 hours of wind readings as compared to only the wind reading at the time of forecast decreases as the forecasting time increases.

The final inputs considered for the BHP model are wind forecasts. In the operational model the wind forecasts will be provided through the local Corpus Christi Weather Forecasting Office (WFO) (Patrick et al., 2002, Stearns et al., 2002). A database of forecasts is presently been accumulated at CBI-DNR for a number of locations mostly along the Gulf coast but with a few locations inland and within the Gulf of Mexico. The forecasts are extracted from the National Center for Environmental Predictions (NCEP) Eta-12 model and are provided in 3-hour increments. Similarly when including the wind hindcasts into the ANN models, the wind information is provided in 3-hour increments up to and including the time of forecast. For the BHP station significant improvements are recorded for forecasting times equal or larger than 12 hours. For 24-hour forecasts the model performance as measured by the absolute average error improves from 6.4 cm to 6.0 cm or a 6 % improvement. A comparison between the performances of predictions computed with harmonic analysis, the CWLD model, ANNs without wind forecasts and ANNs with wind forecasts is presented in Figure 5.

Finally the number of neurons was increased to form a 2x1 ANN and 3x1 ANN for 6 hour, 24 hour, and 36 hour forecasts. The increase in the number of neurons in the hidden layer did not lead to significant improvements in any of the skill variables and the performance of the ANNs decreased for all cases when tested with 3 ANNs. The optimum models for the BHP station therefore consists of 1x1 ANN with the past water level difference and wind pseudo stress measurements (past 6 hours for 3-hour forecasts and past 3 hour measurements for longer forecasts) and the forecasted wind pseudostress up to the time of forecast. A comparison between water levels measured and forecasted using both harmonic and ANN modeling is presented in Figure 6. As can be observed in the figure the ANN model is capable of forecasting both negative (e.g. JD 346 to 354) and positive (JD 361 to 364) water level anomalies and improves substantially over the harmonic analysis. Figure 6 also shows a tendency of the ANN model to under predict the water anomaly as it is increasing and then over predict the water anomaly as it is decreasing. This model behavior is consistent throughout the data sets and is one of the focuses of present efforts to improve the model.

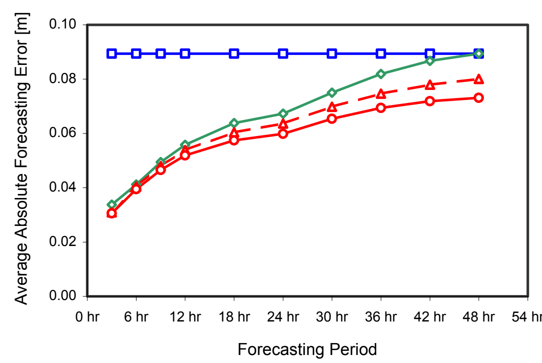

Figure 5. Models' performance for the 1997-2001 time span for harmonic forecasts (blue/squares), the constant water level difference model (green/diamonds), the ANN model without wind forecasts (red dashed/triangles) and the ANN model with wind forecasts (red/circles) for the BHP Station.

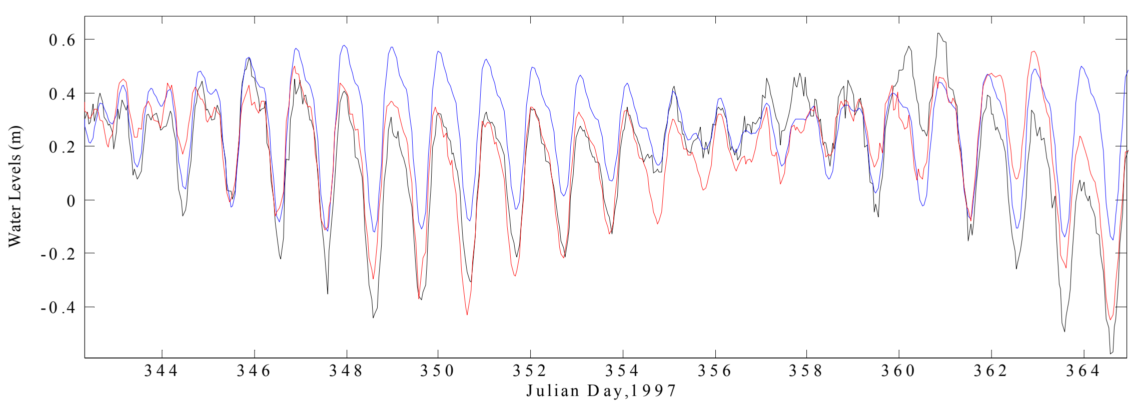

Figure 6. Comparison of water levels predicted (24 hours) and measured at the BHP station for 1997 JD 343 to 365 during the passage of cold fronts. The measured water levels are in black, the harmonic forecasts in blue and the ANN forecasts in red. The ANN forecasts are computed with an ANN trained over the 2001 data set.

The NAS is then considered as representative of the stations inside CC Bay. Similarly to the BHP station, the input decks to the ANNs are optimized by first using 1x1 ANNs and varying the number of previous water level differences from 0 (measurement at the time of forecast only) to –12 hours. For forecasting times up to 9 hours the optimum performance is reached by including the past 6 hours of water levels. The difference between models including the past 3 hours and the past 6 hours measurements is however relatively small. For forecasting times larger than 12 hours including only the past 3 hours of measurements is optimal with the exception of 24-hour forecasts. In this case the optimum performance is obtained when including the past 15 hours but when increasing the forecasting time to 30-hours the optimum performance is obtained again when including the past 3 hour measurements. As the difference is relatively small between including the past 3 hours and the past 15 hours, the input to the optimum ANN forecasting 24-hour water level is kept the same as for the other long forecasting times (past 3 hours). The difference between the 24-hour forecasts case and other cases is likely related to either daily phenomena such as the strong sea breezes in the spring and summers or possibly a small tidal signals not captured by the harmonic analysis. Previous wind pseudostress measurements are then included in the models. While previous wind records were found beneficial for BHP, this is not the case for NAS for any of the forecasting times. Furthermore wind hindcasts do not improve the performance of the ANNs for NAS. The absence of correlation between wind records, past and hindcasted, at the NAS will be discussed in section 4.

The number of neurons in the hidden layer is then varied from 1 to 5 for 9-hour, and 24-hour forecasts. Recorded improvements in the absolute average error are equal or smaller than 0.05 cm. As these differences are small (see section2), 1x1 ANNs are used again for the rest of the study. Possible improvements to NAS water level predictions are then investigated when including data from the BHP station. The BHP station gives an indication to the model as to the changes in water levels on the coast. For 24-hour and longer forecasts significant improvements are recorded when including the BHP water level and wind measurements at the time of forecast. Including BHP wind hindcasts further improves the performance of the model. Including more than the last water level and wind measurements do not lead to improvements. The significant improvements obtained when including BHP data are discussed in section 4. The results obtained with the optimum ANN with and without including BHP Data are presented in Figure 6 for each forecasting period tested.

The performance of the ANN model for NAS is illustrated in figures 8, 9 and 10. Figure 8 displays a comparison between water levels measured and predicted by the harmonic and ANN models for 1997 with an ANN model trained over the 2001 data set. The graphic illustrates the ability of the ANN model to take into account past and forecasted water levels and weather information and model the changes in water

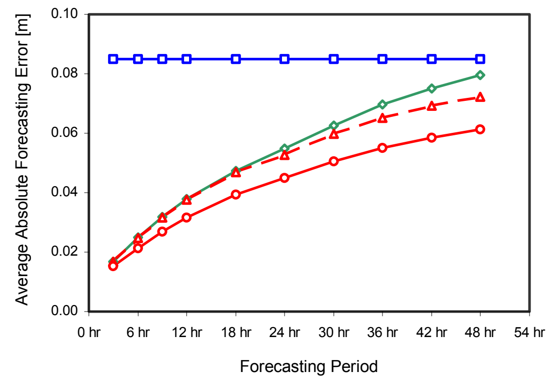

Figure 7. Models performance for the 1997-2001 time span for harmonic forecasts (blue/squares), the constant water level difference model (green/diamonds), the ANN model with only NAS data (red dashed/triangles) and the ANN model with additional BHP date (red/circles) for the Naval Air Station.

Anomaly for NAS. Figure 9 presents a detailed view of the 1997 forecasts for JD 70 to JD 130 and illustrates the capacity of the model to predict positive as well as negative water anomalies. Figure 10 illustrates the model performance for NAS during the passage of 1998 tropical storm Frances. The ANN model was trained on the 1997 Data set and the displayed results are for 12-hour forecasts. The graphic illustrates the potential of the model to give valuable indications to local emergency management personnel during the passage of small storms. It should be pointed out that real-time models will rely on forecasted winds and that they are typically not as accurate during tropical storms. However for short-term forecasts forecasted winds are not as important to the model performance and any forecasts with a reasonable margin of error would be very valuable. Further testing of the model will be necessary to determine its applicability during tropical storms.

Finally the harmonic and ANN water level forecasts are compared in Table 2 for 24-hour forecasts. The ANN model results are obtained using the optimized models for the BHP and NAS stations. The optimum ANN model obtained for NAS is used as well for the other stations as they are all located within CC Bay. The optimum 24-hour ANNs input decks for in-bay stations include the past 3 hours of water level measurements from the bay station, the last water level difference and wind measurement and the wind hindcasts up to the time of forecast from the BHP station. The improvements of the ANN model over the harmonic forecasts are substantial in all cases.

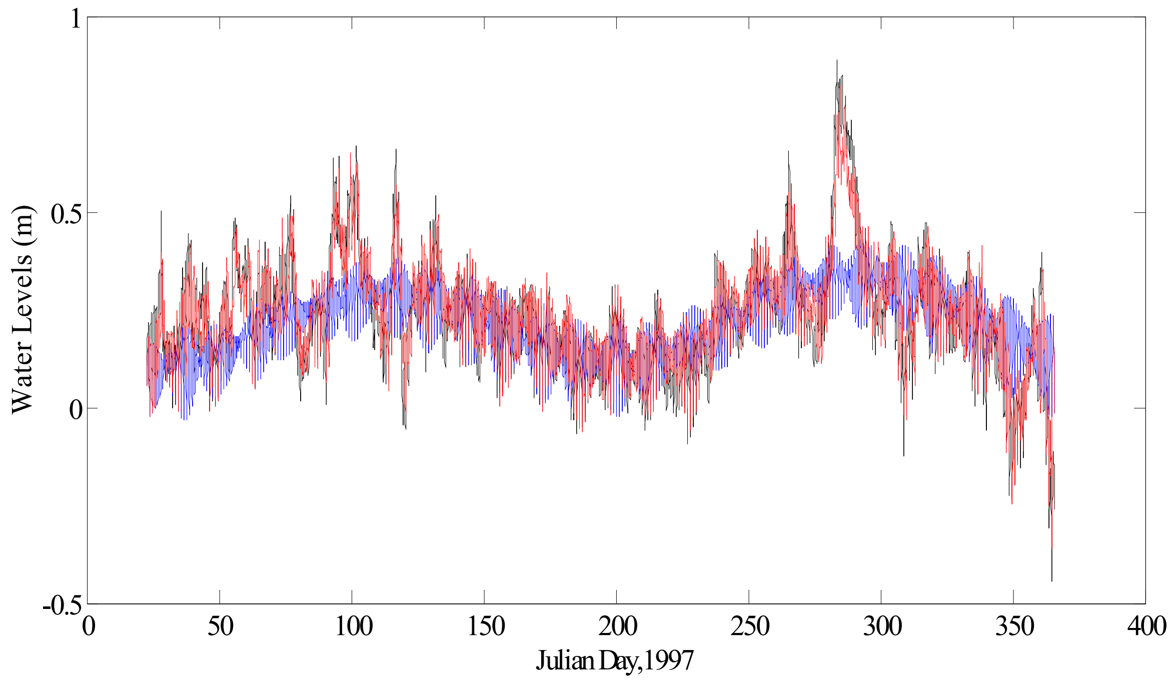

Figure 8. Comparison of 24-hour water level forecasts during 1997 for NAS. The black line represents measured water levels, the blue line harmonic forecasts and the red line ANN forecasts. The ANN model was trained on the 2001 data set with the past 3 hours of water levels at NAS and the last water level and wind readings at BHP as well as wind hindcasts at BHP.

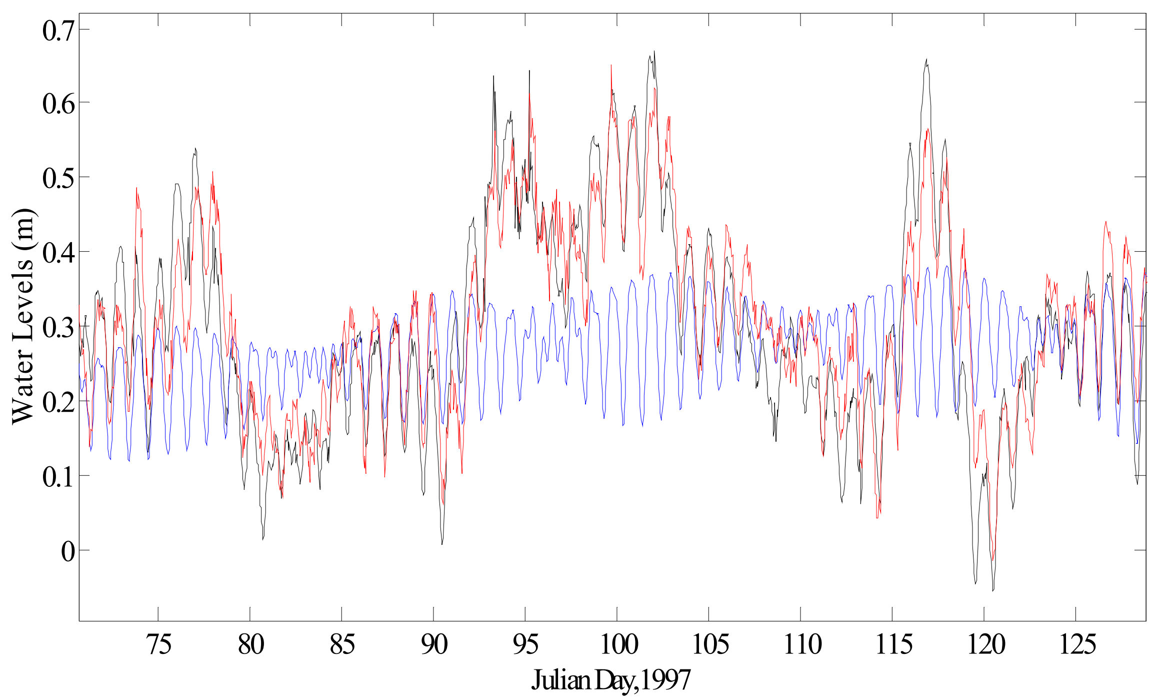

Figure 9. Detailed view of the previous figure during frontal passages. The black line represents measured water levels, the blue line harmonic forecasts and the red line ANN forecasts.

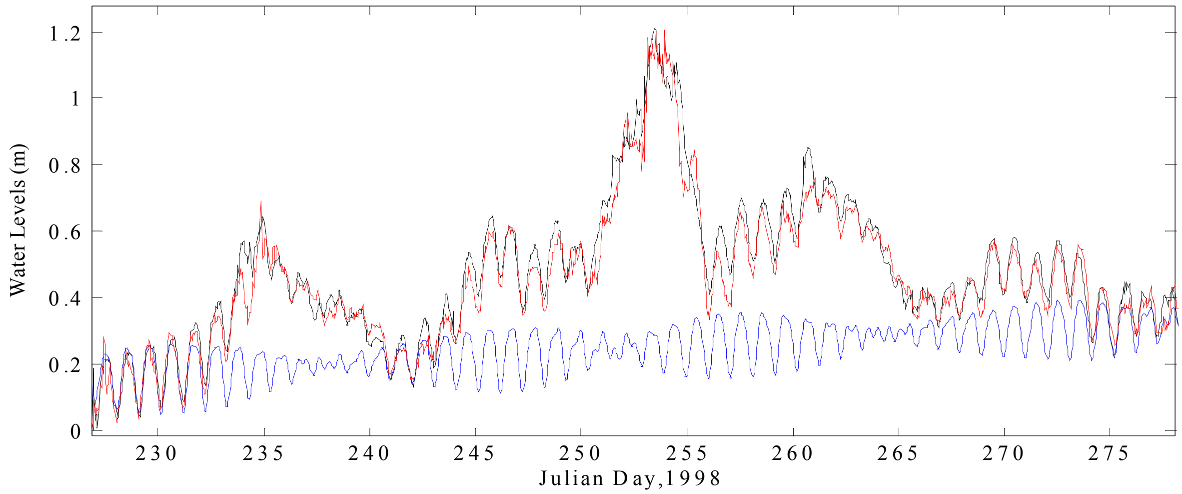

Figure 10. Performance of an ANN trained on the 1997 data set and applied to 1998 during the passage of tropical storm Frances for the NAS station – 12-hour forecasts (input to the ANN is same as for Figure 8). The black line represents measured water levels, the blue line harmonic forecasts and the red line ANN forecasts.

Table 2a. Comparison of harmonic analysis and ANN model performance for the BHP station (1997-2001).

	Tide Tables	**ANN Model**
Average error (bias)	-2.7 ± 2.9 cm	-0.4 ± 1.7 cm
Average Absolute error	8.9 ± 1.5 cm	6.0 ± 0.6 cm
Normalized RMS error	0.29 ± 0.05	0.20 ± 0.02
POF (15 cm)	4.5% ± 1.9%	2.6% ± 1.3%
NOF (15 cm)	12.8%±6.8%	3.8%±2.6%
MDPO (15 cm)	67 ± 25 hrs	24 ± 7 hrs
MDNO (15 cm)	103 ± 67 hrs	39 ± 34 hrs

Table 2b. Comparison of harmonic analysis and ANN model performance for the NAS (1997-2001).

	Tide Tables	**ANN Model**
Average error (bias)	-2.6 ± 2.4	-0.1 ± 1.1 cm
Average Absolute error	8.5 ± 1.5 cm	4.5 ± 0.4 cm
Normalized RMS error	0.40 ± 0.05	0.21 ± 0.01
POF (15 cm)	4.8% ± 1.1%	0.9%±0.4%
NOF (15 cm	11.4%±5.6%	1.3%±1.4%
MDPO (15 cm)	103 ± 31 hrs	19 ± 6 hrs
MDNO (15 cm)	205±177 hrs	29 ± 33 hrs

Table 2c. Comparison of harmonic analysis and ANN model performance for the Aquarium Station (1997-2001).

	Tide Tables	**ANN Model**
Average error (bias)	-1.8 ± 2.2 cm	-0.1 ± 0.9 cm
Average Absolute error	8.4 ± 1.2 cm	4.6 ± 0.4 cm
Normalized RMS error	0.39 ± 0.04	0.21 ± 0.02
POF (15 cm)	5.0%±1.5%	1.0% ± 0.4%
NOF (15 cm)	9.9%±5.0%	1.5% ± 1.3%
MDPO (15 cm)	99 ± 35 hrs	19 ± 5 hrs
MDNO (15 cm)	178±184 hrs	28 ± 24 hrs

Table 2d. Comparison of harmonic analysis and ANN model performance for the Ingleside Station (1998-2001).

	Tide Tables	**ANN Model**
Average error (bias)	-2.9 ± 3.2 cm	-0.3 ± 1.4 cm
Average Absolute error	8.2 ± 1.7 cm	4.5 ± 0.6 cm
Normalized RMS error	0.29 ± 0.05	0.21 ± 0.02
POF (15 cm)	3.8%±1.7%	0.8% ± 0.4%
NOF (15 cm)	10.6±7.5%	1.7% ± 2.3%
MDPO (15 cm)	86 ± 33 hrs	18 ± 6 hrs
MDNO (15 cm)	204±205 hrs	36 ± 43

Table 2e. Comparison of harmonic analysis and ANN model performance for the Packery Station (1997-2001).

	Tide Tables	**ANN Model**
Average error (bias)	-2.6 ± 2.2 cm	-0.2 ± 0.8 cm
Average Absolute error	7.6 ± 1.6 cm	3.5 ± 0.4 cm
Normalized RMS error	0.45 ± 0.07	0.21 ± 0.03
POF (15 cm)	2.6%±1.1%	0.4% ± 0.3%
NOF (15 cm)	9.6%±6.4%	1.0% ± 1.3%
MDPO (15 cm)	77 ± 41 hrs	14 ± 10 hrs
MDNO (15 cm)	201±187 hrs	30 ± 38 hrs

Table 2f. Comparison of harmonic analysis and ANN model performance for the Port Aransas Station (1997-2001).

	Tide Tables	**ANN Model**
Average error (bias)	-2.4 ± 2.6 cm	-0.2 ± 1.3 cm
Average Absolute error	8.4 ± 1.4 cm	5.2 ± 0.5 cm
Normalized RMS error	0.31 ± 0.05	0.19 ± 0.02
POF (15 cm)	4.6%±1.8%	1.8% ± 0.6%
NOF (15 cm)	11.1%±5.9%	2.2% ± 2.2%
MDPO (15 cm)	74 ± 21 hrs	23 ± 7 hrs
MDNO (15 cm)	123 ± 81 hrs	31 ± 37 hrs

4. Discussion

The ANN models described in this study offer substantial performance improvements over harmonic analysis for all the main skill variables characterizing water level predictions. The ANN models are beneficial for all locations but as can be observed in tables 2a to 2f the improvements are more important for in-bay locations than for the open coast station, BHP, or the Port Aransas station located near the entrance to the bay. This is not surprising as the accuracy of the ANN forecasts will be linked to the ability to find a relationship between available data at the time of forecasts and future water levels. As the water level dynamic in the in-bay stations is largely controlled by the Gulf of Mexico and water level changes in the Gulf take some time to influence the bay (hydraulic resistance of the ship channel linking the Gulf and the bay) the information collected at the BHP station provides information as to the sign and magnitude of the future water level changes in the bay. The further in-bay the station is located the longer the lag and the better the performance of the ANN models.

The absence of correlation between the past and future winds and the water level changes at NAS is probably due to the same dynamic. The water level changes in the bay are largely dominated by the Gulf and the in-bay set-up is likely comparatively small similarly to the case of Galveston Bay (Cox et al, 2002b). Therefore a strong correlation between in-bay processes and water level changes should not be expected. NAS wind could have provided information as to the wind climate in the Gulf but the winds in CC Bay are often different than on the coast due to topology and coastal effects. Even for in-bay processes representative in-bay wind measurements are difficult to achieve unless the measurements are obtained from a platform away from the shorelines. In-bay wind measurements are therefore generally not a good measure of the overall coastal and/or local wind climates and will often not provide valuable information. Following these observations it should be expected that BHP measurements and forecasts lead to significant performance improvements for in-bay models while local winds do not.

As wind hindcasts rather than actual archived wind forecasts are used throughout this study it is important to discuss the potential impact on the results of this study. For the real-time application of the model the wind forecasts will be extracted from the regional Eta-12 models through a collaboration with the Corpus Christi Weather Forecasting Office (Patrick et al., 2002). Forecasted and measured winds have been recently compared for three of the stations studied here, BHP, NAS and Port Aransas (Stearns et al, 2002). A systematic bias was found between forecasted and measured wind speeds and wind directions for each station as well as for other stations along the coast. Once the biases are taken into account the error is on average just a few tenths of a meter per second depending on the station with a very slowly increasing forecasting error with forecasting time. Also it was shown in previous work for a site on Galveston Island (Cox et al., 2002a) that the water level predictions are not overly sensitive to the accuracy of the wind forecasts. A database of forecasts is presently accumulated for many stations and locations along the Gulf of Mexico and the models will be shortly tested with the Eta-12 forecasts.

While the performance improvements are substantial further improvements could come from a better prediction of the onset of rapidly increasing or decreasing water level anomalies. As was mentioned in section 3, the ANN forecasts often lag the measurements during frontal passages. The main parameters allowing for the anticipation of rapid water level changes are the forecasted winds. In this study forecasted winds at BHP were used for all stations. As winds over the Gulf of Mexico rather than coastal winds likely drive the water level anomalies better results could be obtained with offshore wind measurements. Such data series are presently accumulated for an offshore platform located about 10 miles from the coast. Other strategies are considered such as having different models for the three seasons and therefore training neural networks that are inherently more sensitive to rapid water level changes during frontal passages. Finally once a large database of wind forecasts is accumulated the ANN could be trained including pure wind forecasts over specific portions of the Gulf of Mexico not related to TCOON stations. The flexibility of ANN modeling allows to easily mix many different types of inputs and is viewed as a significant advantage for the modeling of future water level changes.

As the model will be applied in real-time starting during the late spring of 2003 practical challenges should be mentioned. They include accommodating dynamically small gaps in the measured data and possible equipment malfunctions and building redundant strategies when possible to improve the reliability of the model. As the forecasts will be partially based on Eta-12 forecasts the models might have to be updated or at least tested during the regular updates to the Eta model conducted by the National Center for Environmental Predictions (NCEP). Such modifications will necessitate a continuing and close collaboration between the local ANN modelers, the staff responsible for the measurement platforms and the local weather forecasting office.

5. CONCLUSIONS

ANN models were developed and tested to predict water levels at six stations in and directly outside of the CC estuary. Consistent with models previously developed for Galveston Bay small 1x1 ANN models were found to be optimum. Increasing the number of hidden neurons did not lead to significant improvements in the performance of the models. The optimum number of previous water levels and previous wind pseudostress measurements varied depending on the span of the forecast and the station. For the open coast station, BHP, including the past six hours of measurements was found optimal for 3-hour forecasts while including only three hours of past measurements was found optimum for longer forecasts. Including previous open coast measurements improved the forecasts for in- bay stations indicating that as expected water levels inside the bay are in large part driven by water level changes in the Gulf of Mexico. The addition of wind forecasts improved the performance of all models consistent with the observation of a strong correlation between wind pseudostress and the water level anomaly. The performance of the model was measured by a variety of skill variables. ANN models provided significant improvements over harmonic forecasts for all skill variables. The improvements were often better than 50% for the absolute average error and more than a factor of 4 or 5 for skills such as POF, NOF, MDPO, and MDNO. Model performances for stations deep inside the bay were a little better than for stations at the entrance of the bay as the hydraulic resistance of the bay and ship channel provide a lag that ANN models can take advantage of. While wind hindcasts were used in this work the excellent agreement between Eta-12 forecasts and measured winds, once a consistent bias is included, should lead to similar model performances for the real-time model. A database of Eta-12 historical wind forecasts is presently accumulated to confirm the performances and applicability of the model.

Finally the use of ANN modeling methodology provided a relatively simple method to include a diversity of inputs, both geographically and physically, to water level forecasting models. We believe that ANNs represent a powerful and computationally efficient modeling technique to provide point forecasts when a large database of previous measurements is available. A prototype operational model is in development and starting during the spring of 2003 ANN water level forecasts will be published on the web and possibly other venues to provide better forecasts for mariners and other coastal users along the Texas Gulf coast.

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