Performance and Comparison of Water Level Forecasting Models for the Texas Ports and Waterways

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Abstract

The ports and waterways of the Texas Gulf Coast are of vital importance to the shipping industry as well as the overall US economy. Safe navigation, particularly underkeel clearance, within these shallow, confined waterways requires accurate water level forecasts. While tide tables are tabulated for a number of locations along the Texas Gulf coast, they do not meet National Ocean Service (NOS) standards due to meteorological forcing. This paper presents and compares alternative models to improve real-time water level forecasts, including a new model based on Artificial Neural Networks (ANN). All models include real-time measurements collected by the Texas Coastal Ocean Observation Network (TCOON) and the forecasts are published on the World Wide Web. The new ANN model is shown to improve considerably upon the tide tables and the other models tested and to meet NOS criteria for many locations for up to 48-hour forecasts. Model performances are compared for Corpus Christi Bay and Galveston Bay and present model limitations and future improvements are discussed.

Introduction

The ports and waterways of the Gulf of Mexico (GOM) play an important role in the overall US economy. For example more than 50% of the US tonnage reaching the US by waterways transit through the GOM (USACE, 2001). The Port of Houston and the Port of Corpus Christi, are located along the Texas coast and were respectively the second and sixth largest US ports by tonnage in 2001 (USACE, 2001). Because of the shallow, confined navigation channels, underkeel clearance is a major issue for the deep-draft vessels. The Corpus Christi ship channel has depths of 45 to 47 feet soon to be deepened to 50 feet (Brogan, 2001) and the Houston ship channel has depths of 40 to 45 feet (USACE, 2003). As vessel draft is steadily increasing, accurate water level forecasts are becoming increasingly important to avoid groundings and accidents. For most US ports, tide tables provide adequate water level forecasts; but for the Gulf of Mexico, meteorological factors are often more important than astronomical forcing (Cox et al, 2002a). A comparison between measured water levels and tidal forecasts is presented in Figure 1 for Morgans Point in Galveston bay, Texas.

One of the principal skill assessment statistics used by NOS to assess the operational adequacy of water level forecasts is the Central Frequency of 15 cm (CF15 for brevity). CF15 is the percentage of predictions that are within plus or minus 15 cm from the actual measurement. For NOS to consider a model operational, its CF15 must be equal or

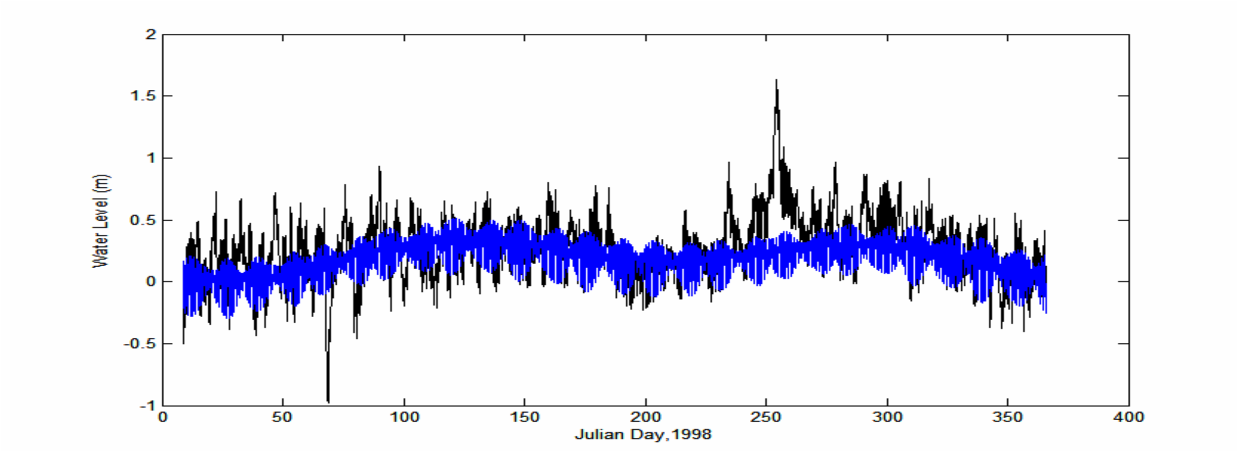

Figure 1. Comparison of measured water levels (black) and tidal forecasts (blue) for Morgans Point Station in Galveston Bay.

greater than 90%. The performance of harmonic forecasts was measured for several stations located along the entire coast of Texas for the three year span from January 2000 to December 2002 (Bowles et al., 2003). The harmonic forecasts were computed following National Oceanic and Atmospheric Administration (NOAA) procedures and using web-based software at the Division of Nearshore Research (DNR) at Texas A&M University-Corpus Christi (TAMUCC) (Mostella et al., 2002). None of the locations satisfied the criteria with the central frequencies ranging from 70% near Louisianna to 89% near the Mexican border. Central frequencies of 15 cm for the stations which are part of this study are presented in Table 1. The inadequacy of tidal forecasts in the GOM has also been recognized for a number of years by NOAA, including for regular weather conditions in Aransas Pass and Corpus Christi Bay, both part of the study area (NOAA 1991, NOAA 1994).

Extensive monitoring and communication systems provide real-time information to ship captains and other coastal users through NOAA's Physical Oceanographic Real Time System (PORTS) (http://co-ops.nos.noaa.gov/d_ports.html) for Galveston Bay and through DNR Real-Time Navigational System (RTNS) for Corpus Christi Bay. Both systems monitor water surface elevations, currents, temperature, and meteorological information. The information is conveyed to users through websites and cell phones. For the rest of the Texas coast DNR has been operating and maintaining the Texas Coastal Ocean Observation Network (TCOON) presently consisting of 42 weather platforms located from Brownsville to the Louisiana border (Michaud et al., 2001). In addition to the TCOON stations, DNR manages another 18 data collection platforms forming a dense network of platforms providing 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. Presently, harmonic forecasts are provided by the PORTS website for Galveston Bay while harmonic and persistent model forecasts are provided by the DNR website for the other sites. Efforts are underway to develop better water level forecasting systems for both Bays and the Texas coast in general. To complement PORTS, a nowcast/forecast

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Table 1. Central Frequencies of 15 cm for tidal forecasts computed over the 2000-2002 time period for the stations considered in this study.

Station	Station Description	Central Frequency
Corpus Christi Bay		
Bob Hall Pier	Gulf Station	84.2 %
Port Aransas	Ship Channel Station	83.7 %
Packery Channel	In-bay Station	85.1%
Galveston Bay		
Pleasure Pier	Gulf Station	72.8 %
Morgans Point	In-bay Station	67.3 %

system is being developed based on NOS Galveston Bay three-dimensional hydrodynamic model (Schmalz, 2001). When available, this Galveston Bay model will provide bay-wide water level forecasts and current velocity forecasts near the bay entrance. DNR is taking advantage of the abundance of real-time and archived measurements for the Texas coast to develop novel statistical and ANN based models to improve water level forecasts. In the following sections the performance of ANN water level forecasts is compared to other models for the Corpus Christi Bay and Galveston.

Methodology and Sites Description:

The goal of the training and application of an ANN model for the forecasting of water levels is to find a good set of neuron functions, weights, and biases which will link past measurements and meteorological forecasts to future water levels (Tissot et al., 2003). The advantages of using ANNs over other techniques are their ability to model non linear systems, their robustness to noisy data and their generic modeling capability. Previous studies (Tissot et al., 2003) have shown that very simple neural network structures with one hidden and one output neuron are, at present, the best choice. In the future, additional inputs to the models and more sophisticated training techniques could lead to more complex optimal ANN structures. The choice of the neural functions does not lead to significant changes in the performance of the models. In this study a logsig function is used for the hidden layer neuron while a purelin function is used for the output layer neuron (The MathWorks, 1998). Inputs to the models are composed of time series of previous water level measurements, previous wind measurements, and harmonic water level forecasts. Future models may include time series of past atmospheric pressure measurements and wind forecasts. The choice of inputs is presently the essential element determining the performance of the models (Tissot et al., 2003). Prior to being processed by the ANN models harmonic forecasts are subtracted from the overall water levels to separate the tidal and non-tidal components of the water level changes. Thus the models are using and forecasting the non-tidal component of the overall water levels. One of the important inputs to the models is wind measurements. Strong and shifting winds during frontal passages are well correlated with changes in water levels and wind is generally recognized as the main non-tidal force that drives water level changes (Garvine 1985, NOAA 1991, NOAA 1994, Cox et al., 2002b). The East-West and North-South components of the wind are squared prior to being included in the models' input in order to be directly proportional to the wind velocity stress on the water. Wind forecasts will likely be an essential element of future models, but long time series of previous wind forecasts are needed to train and test ANN models. Time series of previous meteorological forecasts are presently archived as part of a collaboration with the National Weather Service Corpus Christi Weather Forecasting Office (Patrick et al., 2002). As the differences between wind forecasts and measurements are relatively small (Stearns et al., 2002) the impact of including wind forecasts in the input can be evaluated by replacing them with future wind measurements and could lead to substantial improvements (Cox et al., 2002b). A schematic of a typical ANN model used in this study is presented in Figure 2 with a two layer ANN, one output neuron, one hidden neuron, and an input deck consisting of previous water levels, previous East-West and North-South wind velocity squared and tidal forecasts. The optimum ANN topology and input deck are determined by varying each input parameter starting with previous water levels (Tissot et al., 2003). The structure of the optimized input sets are described in the next section. 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 Matlab. 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.

The performance of the models was 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 presented in Table 2. A single forecasting error or e_i is defined as the difference between the predicted value pi 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, one year or three years of water level measurements for this study. The Central Frequency has been defined previously in the text. The other skill assessment variables used are presented in Table 2. The value defining an outlier is set at 30 cm for this study (a typical value) while the criteria for the central frequency is set at X=15 cm also a typical. This requirement limits water level errors to within 15 cm and is based on NOAA's estimates of pilots' needs for under keel clearance value.

Harmonic forecasts are computed following NOAA procedures including up to 26 tidal coefficients and using DNR web-based software (Mostella et al., 2002). As discussed previously harmonic forecasts are operationally ineffective for the Texas coast but until recently they were the only water level forecasts available and tidal forecasts are included in all other models. A persistence model forecast is computed by assuming that the difference between water level and tidal forecast at the time of the last water level measurement will remain unchanged (NOAA, 1999). The availability of real time water level measurements has allowed DNR to implement and publish this model's results on the World Wide Web. The persistence model is also a useful model as it improves considerably upon harmonic forecasts and is predictable in its shortcomings: always

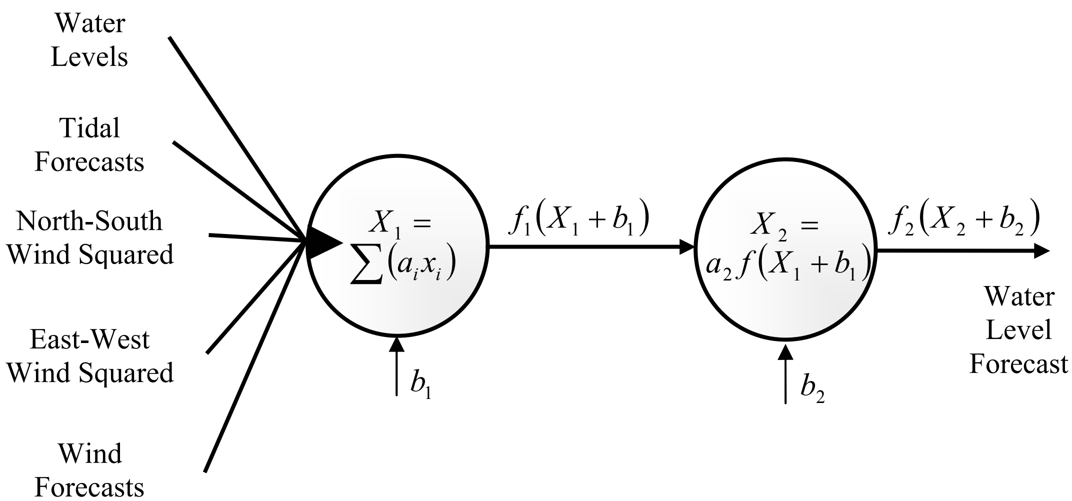

Figure 2. Structure of a typical ANN model used in this study. a_i's and b_i's are the weights and biases and f_i's are the respective neuron functions.

Table 2. Skill assessment statistics for water level forecasts.

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

lagging meteorologically driven water level changes. The linear regression based model (Sadovski et al., 2002) links previous water levels and tidal forecasts with future water levels. The regression model is a linear model and does not directly include wind information. It generally improves upon the performance of the persistence model and is very straightforward to implement.

The performance of the models were compared for several locations in both Corpus Christi Bay and Galveston Bay. The locations of the study's stations are Pleasure Pier and Morgan's point for Galveston Bay and Bob Hall Pier, Port Aransas and Packery Channel for Corpus Christi Bay. These locations are highlighted in Figure 3. Outside of the ship channels, both bays are relatively shallow with depths of about 3 m (10 feet) for Corpus Christi Bay and 2 to 3 m (7 to 9 feet) for Galveston Bay. For Corpus Christi Bay the Bob Hall Pier (BHP) station is representative of open coast conditions, Port Aransas is representative of conditions at the entrance of the ship channel and Packery Channel is representative of conditions inside the bay. For Galveston Bay, Pleasure Pier is representative of open coast conditions while Morgans Point is representative of conditions in the bay.

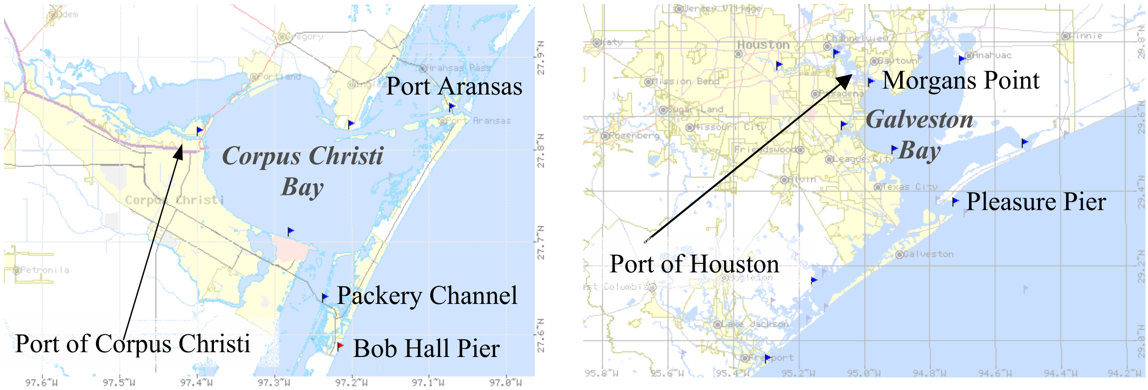

Figure 3. Corpus Christi Bay (left) and Galveston Bay (right) with the Ports of Corpus Christi and Galveston and the study's stations indicated.

Model Performance and Discussion:

The performance of the ANN model was computed and compared for the above mentioned five locations. The ANN models were trained over 1 consecutive year of data prior to January 1st 2000. The model performance was then assessed over the 3 year period from January 1st 2000 to December 31st 2002. The models were optimized by varying the types and lengths of the input time series as well as the location of the secondary input station and the training year. The variability of the model performance with training parameters was previously studied (Tissot et al., 2002, Tissot et al., 2003). The optimum training year was 1998 for all cases except for 48 hour forecasts at Pleasure Pier where the optimal model was obtained when training on the 1997 data set. Neural Networks trained over data containing the widest possible range of meteorological and water level conditions typically lead to better models. The 1998 year saw several strong frontal passages and tropical storms thus forming a good training set. Other training procedures designed to emphasize the relative importance of weather events are presently under development. The model parameters for each station are presented in Table 3.

The performances of the ANN models and comparisons with the other models studied are presented in Table 4. The results are presented for 24 hour and 48 hour forecasts. For all locations and forecasting times the ANN model improves upon all other models based on the Central Frequency criterion. For Corpus Christi Bay the ANN forecasts are all above a CF of 90% and the CFs are 10 percentage points higher than harmonic forecasts for 24 hour forecasts. These results make the ANN models operationally applicable for 24 hour forecasts. The 48 hour forecasts CFs are 96.0% for Packery Channel (see Figure 4), 89.9% for Port Aransas, and 88.2% for Bob Hall Pier. The higher in-bay performance should not be surprising as the narrow pass and shallow bay leads to a delay between water level changes in the GOM and inside the bay. ANN models can link water level changes and winds at the coastal station, Bob Hall Pier, with the future water levels inside the bay leading to the better performance. While the CFs for the coastal station and the entrance of the ship channel are slightly below the required 90% it is expected that future versions of the model will improve upon the present results and that the ANN

Table 3. ANN Model parameters for the study's stations

Station	Secondary Station	Input Time Series
Bob Hall Pier-24 hrs	Pleasure Pier	Previous water levels and winds for both stations (48 hrs)
Bob Hall Pier-48 hrs	Pleasure Pier	Previous water levels and winds from primary station (past 48 hrs)
Port Aransas-24 hrs	None	Previous water levels (48 hrs)
Port Aransas-48 hrs	None	Same as for 24 hr forecasts
Packery Ch.-24 hrs	Bob Hall Pier	Previous water levels at primary station (4 hrs) and previous water levels and winds at secondary station (24 hrs)
Packery Ch.-48 hrs	Bob Hall Pier	Same as for 24 hr forecasts
Pleasure Pier-24 hrs	none	Previous water levels and wind (48 hrs)
Pleasure Pier-48 hrs	none	Last water level and wind
Morgans Point.-24 hrs	Pleasure Pier	Previous water levels and winds at primary station (24 hrs) and previous water levels and winds at secondary station (3 hrs)
Morgans Point-48 hrs	Pleasure Pier	Last water level and wind at both stations

models will satisfy NOS criteria for 48 hour forecasts as well. ANN models also improve upon or show similar performances as compared to the other models for the other performance measurements. While the ANN models also have the best performance by a considerable margin for the two Galveston Bay stations, the CFs do not reach the operationally required 90%. It is believed that the models are input limited and that including wind forecasts will improve considerably upon the present performance. Water level changes inside Galveston Bay were shown to be mostly correlated to GOM water levels and that in-bay set-up played only a minor role in water level changes (Cox et al., 2002b). Furthermore, the water level changes at the Pleasure Pier coastal station were shown to be strongly correlated to changes in wind speeds and wind directions with an approximately 7 hour lag (Cox et al., 2002a). The addition of wind forecasts in the input to the ANN was evaluated by making artificial forecasts based on actual measurements and leads to substantial improvements in model performance (Cox et al., 2000a). A database of meteorological forecasts is presently archived based on an atmospheric model from the National Center for Environmental Predictions (NCEP) (Patrick et al., 2002). The next generation of ANN models will include not only wind forecasts at the station locations but wind forecasts at different locations in the Gulf of Mexico and along the coast. The additional flexibility for the location of the wind forecasts is believed to have the potential for substantial improvements in model performance. Other improvements presently considered include training techniques for the neural networks which are more specifically geared to improving the performance during extreme events rather than based on the average performance of the models.

Conclusions

The performance of Artificial Neural Network models forecasting water levels was evaluated for Corpus Christi Bay and Galveston Bay, homes of two of the largest US ports. The ANN models improve significantly upon the present harmonic forecasts and upon all other models tested based on a set of NOS skill assessments statistics. In particular the Central Frequencies of 15 cm are all above 90%, the NOS requirement, for 24 hour forecasts and within 2% or less of this 90 % criterion for 48 hour forecasts of Corpus Christi Bay. The ANN models also improve upon harmonic analysis and the other models considered for both bays based on other NOS criteria. The performance of the ANN model is however still not sufficient to satisfy NOS criteria for Galveston Bay. It is believed that other inputs and in particular offshore wind forecasts will bring substantial improvements to the present models. Other improvements considered include ANN training techniques specifically tailored to the problem of water level forecasts. It is believed that the next generation of ANN models will bring further improvements and have the potential to provide NOS compliant water level forecasts for forecasting times up to 48 hours for a large portion of the coast of Texas.

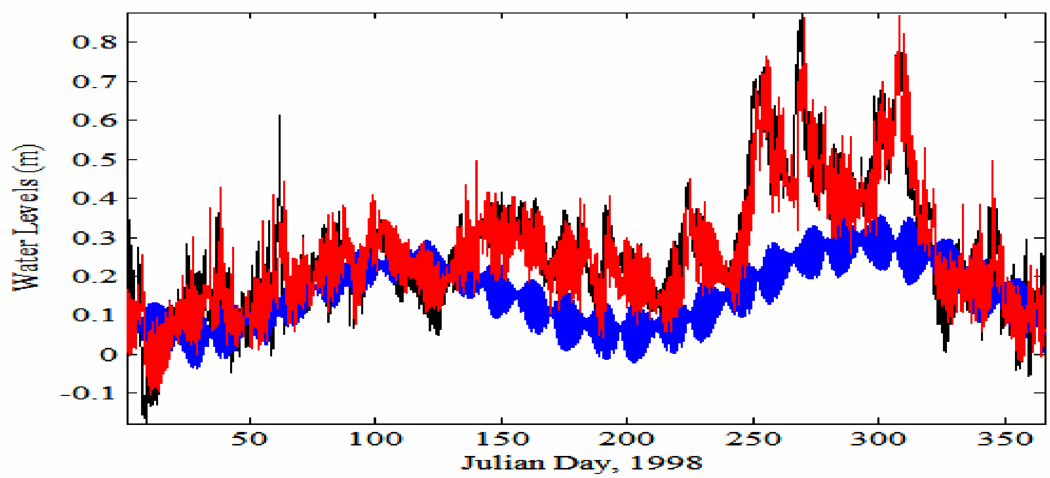

Figure 4. Comparison of measured water levels (black), tidal forecasts (blue), and 24-hour ANN forecasts (red) for the Packery Channel Station in Corpus Christi Bay.

Acknowledgements

The work presented in this paper was funded in part by grants from the National Oceanic and Atmospheric Administration Coastal Management Program (CMP) and Sea Grant. The views expressed herein are those of the authors and do not necessarily reflect the views of NOAA or any of its sub-agencies.

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Table 4. Model performances for the study's stations.

Station/Model	RMSE [m]	CF [%]	POF [%]	NOF [%]	MDPO [hrs]	MDNO [hrs]
Bob Hall Pier						
Harmonic	0.114	84.2	0.35	1.65	17	54
Persistence (24 hr)	0.086	92.0	0.45	0.17	8	8
Linear Regression (24hr)	0.224	93.2	0.33	0.17	17	16
ANN (24 hr)	0.075	94.6	0.30	0.10	8	6
Persistence (48 hr)	0.114	84.3	1.52	0.88	30	14
Linear Regression (48 hr)	0.188	76.6	0.73		23	46
ANN (48 hr)	0.102	88.2	0.90	0.57	22	16
Port Aransas						
Harmonic	0.112	83.7	0.31	1.53	19	43
Persistence (24 hr)	0.075	94.2	0.25	0.03	9	0
Linear Regression (24hr)	0.172	94.8	1.05	0.02	24	2
ANN (24 hr)	0.070	95.7	0.16	0.02	7	0
Persistence (48 hr)	0.103	87.0	1.14	0.41	20	10
Linear Regression (48 hr)	0.208	89.8	1.76	0.26	48	36
ANN (48 hr)	0.093	89.9	0.51	0.24	23	9
Packery Channel/JFK Causeway						
Harmonic	0.108	85.1	0.00	2.31	0	71
Persistence (24 hr)	0.055	97.5	0.06	0.01	5	0
Linear Regression (24hr)	0.101	97.3	0.71	0.00	24	0
ANN (24 hr)	0.044	99.2	0.00	0.00	0	0
Persistence (48 hr)	0.078	93.0	0.25	0.12	12	7
Linear Regression (48 hr)	0.124	93.3	1.11	0.16	48	22
ANN (48 hr)	0.068	96.0	0.12	0.06	5	5
Pleasure Pier						
Harmonic	0.149	72.8	1.41	3.39	28	72
Persistence (24 hr)	0.146	79.6	3.07	2.29	25	29
Linear Regression (24hr)	0.149	83.7	2.43	1.31	26	34
ANN (24 hr)	0.123	84.6	2.34	0.80	22	20
Persistence (48 hr)	0.172	71.2	4.49	3.80	39	33
Linear Regression (48 hr)	0.137	71.5	2.50	1.60	35	47
ANN (48 hr)	0.140	79.0	2.38	2.38	38	24
Morgans Point						
Harmonic	0.174	67.3	3.88	4.56	47	74
Persistence (24 hr)	0.178	71.2	5.29	4.18	31	34
Linear Regression (24hr)	0.110	55.6	2.86	1.33	18	22
ANN (24 hr)	0.142	80.4	4.13	0.68	26	12
Persistence (48 hr)	0.219	61.6	7.83	7.22	47	44
Linear Regression (48 hr)	0.173	64.5	4.74	3.02	51	65
ANN (48 hr)	0.175	71.3	6.26	1.69	59	21

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