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SUPPLEMENTAL DATA ACQUISITION TOOLS FOR MODELING ENVIRONMENTAL SYSTEMS

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Abstract

The goal of our on-going research is to develop effective and reliable tools for modeling the environmental systems of the Gulf of Mexico. For example, our on-going research into methodologies for the prediction of water levels in the shallow waters of the bays and estuaries along the Texas Gulf coast. Our modeling approaches are based on the real-time data collected by the Texas Coastal Ocean Observation Network (TCOON). TCOON is managed by the Division of Nearshore Research (DNR) in cooperation with the Department of Computing and Mathematical Sciences (CAMS) both of Texas A& M University-Corpus Christi. TCOON consists of approximately 50 data gathering stations located along the Texas Gulf coast from the Louisiana to Mexico borders.

In addition to a short description of our major data acquisition system for our research efforts, this paper presents design issues, development issues, and test results encountered in the production of two supplemental data acquisition systems as well as several of our environmental systems modeling efforts at Texas A&M University Corpus Christi.

Keywords: Data acquisition, environmental modeling, robotics.

Resumen

El objetivo de nuestra investigación es desarrollar herramientas eficaces y confiables para modelar los sistemas ambientales en el Golfo de México. Por ejemplo, nuestra investigaci
'on actual en metodologías para la predicción del nivel del agua en las aguas poco profundas de las bahías y estuarios a lo largo de la costa del Golfo de Texas. Nuestro

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enfoque de modelación está basado en datos obtenidos en tiempo real por la Red de Observación Oceánica de la Costa de Texas (TCOON, por sus siglas en inglés). TCOON es manejado por la División de Investigación de la Ribera (DNR, por sus siglas en inglés) en cooperación con el Departamento de Ciencias de la Computación y Matemáticas (CAMS), ambos de la Universidad Texas A & M en Corpus Christi. TCOON consiste en una50 estaciones para la recopilación de datos localizadas a los largo de la costa del Golfo de Texas, desde las fronteras con Luisiana y México.

Además de una corta descripción de nuestro principal sistema de adquisición de datos para nuestros esfuerzos de investigación, este artículo presenta aspectos de diseño y desarrollo, así como resultados de pruebas hechas en la producción de dos sistemas adicionales de adquisición de datos, así como varios de nuestros esfuerzos de modelación en la Universidad de Texas A& M en Corpus Christi.

Palabras clave: Adquisición de datos, modelación ambiental, robótica.

Mathematics Subject Classification: 93A30.

1 Introduction

Due to the heavy dependence on water level forecasts of trade and industry along the Gulf of Mexico coast, accuracy in these forecasts is essential, but the current standard forecasting methodologies do not provide accurate predictions for this region. Tide charts, produced by harmonic analysis and published by the National Ocean Service, are the existing standard, but these charts only show the astronomical forces acting upon the water. While this proves to be an accurate predictor for major portions of the other coasts, water level changes along the Texas Coast are strongly effected by meteorological factors [1]and thus require a modified prediction model.

2 Texas Coastal Ocean Observation Network

The Texas Coastal Ocean Observation Network (TCOON) started in 1988 serves as the major environmental data acquisition system for our modeling efforts. TCOON consists of over 50 environmental data collection platforms along the Gulf Coast, from Mexico to Louisiana (Figure1). Primary project sponsors include the Texas General Land Office, Texas Water Development Board, U.S. Army Corps of Engineers, and NOAA National Ocean Service. TCOON stations [2] measure and archive various measurements such as water levels, wind speed and direction, temperature, salinity, and barometric pressure(Figure 2). TCOON follows U.S. federal standards for the installation of its stations and has a very useful real-time, online database.

Data sampled at these stations include: precise water levels, wind speed and direction, atmospheric and water temperatures, barometric pressure, and water currents. The measurements collected at these stations are often used in legal proceedings such as littoral boundary determinations; therefore data are collected according to National Ocean Service standards. Some stations of TCOON collect parameters such as turbidity, salinity, and other water quality parameters. All data are transmitted back to A&M-CC at multiples

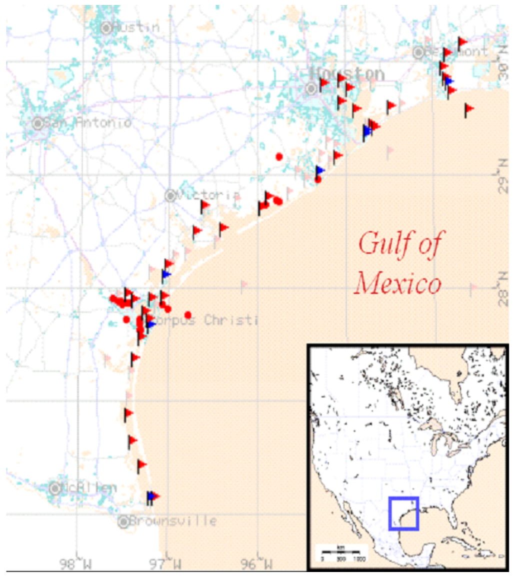

Figure 1: Map of TCOON Stations.

of six minutes via line-of-sight packet radio, cellular phone, or GOES satellite, where they are then processed and stored in a real-time, web-enabled database. TCOON has been in operation since 1988.

TCOON data are valuable for tidal datum, coastal boundaries, oil-spill response, navigation, storm preparation and response, as well as research. See Figure 3 for examples of TCOON web pages. The screen on the left depicts an illustration of graphical representations of TCOON measurements in near-real time. The screen depicted to the right contains the latest measurements taken at the selected station.

3 Supplemental data acquisition systems

3.1 Shallow draft vehicle

In shallow water areas not covered directly by TCOON stations data collection normally requires setting up sensors in several places. In addition to being redundant and time consuming, this task when performed manually has a high chance of disturbing the test area. CAMS investigators in conjunction with the Center for Coastal Studies (CCS) of A&M-CC currently collect water quality data in areas with water 3 ft. or deeper by a man-controlled boat. A number of research centers have been developing autonomous boats [3, 4, 5, 6]. These boats, however, require course planning prior to deployment. As a result, the pre-planned course is not easily changed once the boat is in the water. This paper describes a project undertaken by an interdisciplinary team of CAMS computer science, engineering technology, geographic information sciences, and mathematics professors and students along with environmental investigators at CCS to design and develop a remotely controlled boat that continuously and efficiently collects water quality in shallow water areas (6 in-3 ft), rather than using fixed position sensors to make the water quality collections.

Our boat is small in size (7ft in length and 3 ft in width), has a shallow draft, and can be easily steered to collect data in real-time. The prototype is designed to collect salinity and other environmental data and is equipped with onboard computers, water quality instruments (Hydrolab©), GPS, digital compass, a remote control receiver, and a receiver/transmitter radio (Freewave). It also has sensors to detect objects from all directions (front, sides, back, and bottom) and will eventually have the ability to intelligently maneuver around obstacles. Acquired data is transmitted wirelessly via a radio to a remote control station in real-time and data is logged to a PC for later processing.

3.2 Boat system design

Designing the boat took into consideration the following operational requirements: (a) The boat was to be remotely controlled within the operator's line of sight, (b) It was to be small and easy to transport in the back of a truck without extra towing equipment, (c) It was to be stable enough to resist waves and wind, (d) It had to have the ability to travel through areas with a draft as small as 6 inches, (e) It had to have sensors to detect objects from all directions (front, sides, back, and bottom), and (f) It had to transmit data wirelessly to a docking and control station in real-time. The following paragraphs describe the major components of the system (see Figure 4).

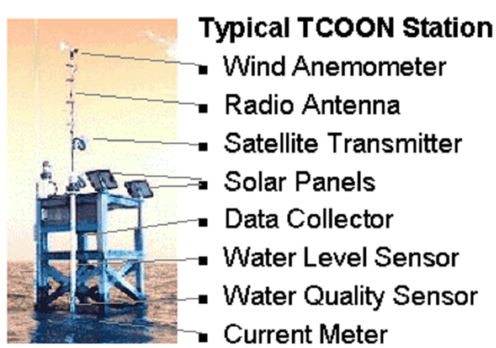

Figure 2: Example of a TCOON Station.

The boat is controlled remotely by a remote controller and a PC. The remote controller transmits data to steer the boat and select its speed. The PC is used to store and process the received data and to display the status of major systems and onboard sensors. The PC display serves as a guide to assist the operator with navigation when objects around

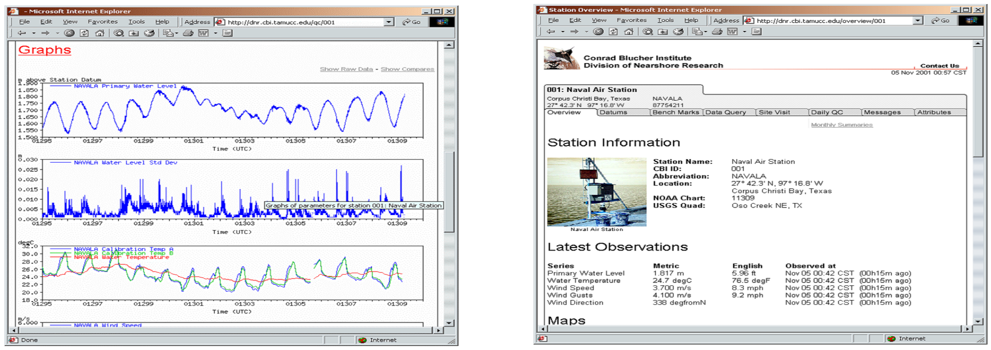

Figure 3: Typical Web pages the TCOON web-site.

or under the boat are detected. The operator is able to direct the boat to investigate areas of interest.

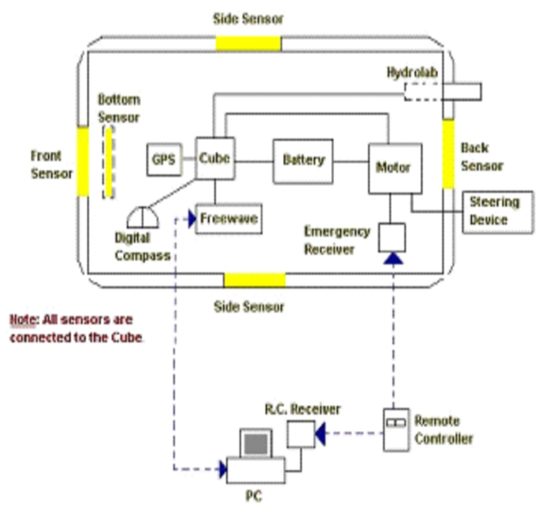

Figure 4: System diagram.

Issues considered in selecting a hull shape included onboard weight, type of power, condition of the water in which the boat is used, means of transportation to the launch site, and the desired draft [7]. Since the draft of the boat is one of the most important criteria, a flat bottom was selected. After considering a variety of hull materials, it was determined that most materials are too heavy to meet our shallow draft displacement requirement, thus, we selected polyurethane. Polyurethane has two major advantages: (1) It floats with an extremely shallow draft (see Table 1), and (2) It can be easily shaped by carving it before adding a protective coating of fiberglass. Recesses in the boat deck were carved to house the battery and the waterproof container which houses the electronic components. Total weight of the prototype is approximately 150 pounds. The transom is strengthened, in order to secure the motor, with 3/16" aluminum sheets. All pieces are configured with reusability in mind and for easy replacement of damaged parts (see Figure 5).

Boat condition	Draft at bow	Draft at transom (IN)
Empty	1	1.5
Loaded	2	3

Table 1: Boat draft characteristics.

A MotorGuide model GWT36 electric trolling motor is used to propel the boat. This motor is rated for salt water operations and can propel a boat as heavy as 1500 lb. It has hand-controlled steering and 5-speeds forward and 2-speeds reverse.

The motor was easily modified for remote control. The remote control function was accomplished via a Futaba© 6-channel FM radio. Currently only two channels are used. One channel controls the steering via a high torque servo and pushrod that connects to the shaft of the motor and the other channel controls forward and reverse speed via a remote control switch. The control switch consists of two relays that open and close according to the pulse signal of the Receiver (Rx).

Since the original equipment servo harness was made of plastic and could easily break. This was corrected by replacing the servo harness with a 12 VDC steering motor that drives a built-in worm gear in combination with an RC switch to control the direction, left or right. Additionally, the RC switch did not allow us to control variable speed. It could only provide one speed forward and one speed reverse. This problem was solved using electronic control, which would allow varying the speed in forward and reverse. The speed of the motor is simply a function of the position of the radio controller joystick [8].

Two nested boxes are used to keep water from reaching the added steering motor. The outside box prevents splashing water from reaching the motor, and the inside box is an electronic waterproof box that prevents the water that escapes from the first box from reaching the steering motor. The boxes are attached to the transom mount of the trolling motor.

Two batteries are used to power the boat and its systems: A marine battery for the motor and another small battery to operate the other onboard electronic components, including; radio, embedded PC, sensors, and GPS. The system operates at medium speed with the 98Ah marine battery for about 4.8 hrs without recharging.

The onboard control and data acquisition computer is a stack of PC/104 modules, called the "Cube," with analog-to-digital conversion capabilities and serial port interfaces. The cube acts as a central control unit and interfaces with the radio and all onboard sensors, including the GPS and digital compass. The water quality sensor is a Hydrolab© designed to be used in fresh, salt, or polluted water. This instrument measures several parameters, including temperature, pH, dissolved O2, and salinity. Our Hydrolab© model includes a pump via a tube to take the water through the process onboard. This device is useful in shallow water areas since the Hydrolab© does not have to be immersed in water [9].

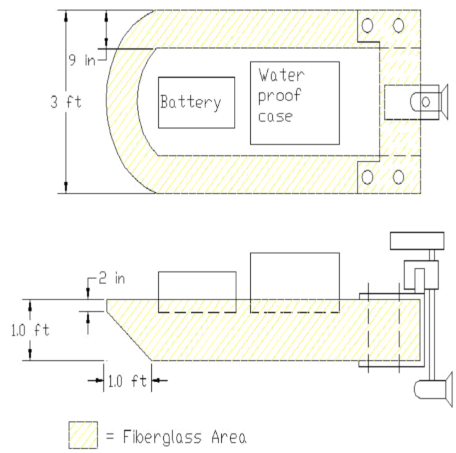

Figure 5: Boat hull dimensions.

We have developed our system on a Linux-based platform. We have written a serial task scheduler to collect data. For example, data is collected from the GPS receiver and Hydrolab at 15 second intervals and written directly to compact flash disk memory. The data is wirelessly transmitted by radio from the serial port of the Linux based platform on the boat to the laptop control computer on shore. After error checking the incoming data, the control computer processes the received data for display on a graphical user interface.

To provide the researcher/operator with navigational and current data collection information we have designed a GUI, which presents the most recently collected GPS, Hydrolab, and depth finder information. Additionally, system power constraints in terms of battery voltage and computed estimated running time are displayed on the GUI. In addition, the depth and GPS navigational data are displayed graphically in a separate window to visually aid the researcher/operator. The GUIs are written in Visual Basic and Gnuplot is used to plot the depth and navigational data in the separate window (see Figure 6).

3.3 Airborne Multi-Spectral Imaging System (AMIS)

The integration of remote sensing and geographic information systems (GIS) in environmental applications has become increasingly common in recent years. Remotely sensed, multi-spectral images of earth's surface are excellent sources for scientific information. There are many multi-spectral Satellite Remote Sensors such as the LANDSAT MSS and LANDSAT TM, but these systems offer only 30-meter spatial resolution pixels. Another limitation of satellite sensors is that their temporal resolution is based on their orbital passes.

Advances in imaging technology and sensors have made airborne remote sensing systems viable for many environmental applications that require reasonably good resolution at low cost. Digital cameras are making their mark on the market by providing high resolution images at very high rates. These images provide a higher temporal

resolution with superior spatial resolution as sources of information for various ap-

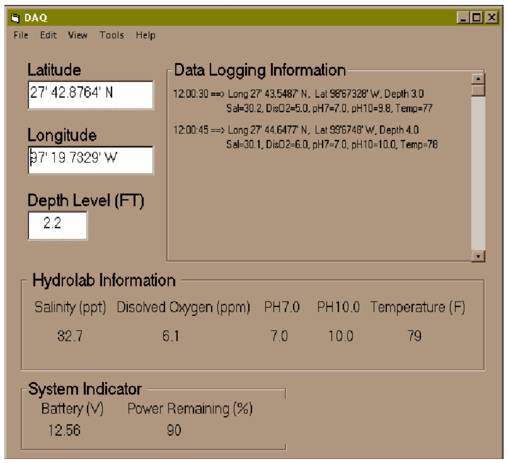

Figure 6: Graphical User Interface

Figure 7: Sea trial

plications including vegetation detection, oceanography, GIS, and environmental coastal science analysis. An examination of the spatial and spectral resolution for mapping and interpretation of flood area and land classification conducted with digital imagery is a product of GIS.

We have designed and developed an AMIS to provide us with further supplemental data for our environmental modeling efforts at A& M-CC. Our prototype AMIS consisted of one Sony DCR-PC1 MiniDV handycam. Our flight test results show that the use of high-resolution digital cameras meets the needs of the scientific staff at A& M-CC. The aerial images of the prototype system have a 20 cm resolution for a flying height of 1500 feet. Our configuration, like the airborne remote sensing system at Ohio State University or the digital camera system at the University of Calgary, requires data to be recorded and post-processed. Although this solution delays the availability of results, it produces good spatial results and provides us with higher resolution data more rapidly than satellite data, for example, 2-meter positional accuracy and 3-meter accuracy in height [10]. Recently, a small-format aerial photographic system was used in combination with lower resolution images for rectification [11]. Compared to existing scanned products, the digital frame array offers a pixel resolution of around 4.5 mm.

An LCD screen (an 8 mm Sony Digital Player) mounted on the pilot's control allows the pilot to see what the video camera is viewing. The LCD screen and the video camera were connected through an S-video cable. The images were recorded on both the digital videotape and by utilizing Pinnacle Studio DV version 7 software on a laptop with an Adaptec Inc. IEEE 1394 PCMCIA (firewire) interface card.

The camera and the GPS control software is written in Delphi 5.0. The software enables the user to display and record the video to the system hard disk. The GPS receiver is connected to the COM port of the system computer. The software reads and records the GPS coordinates and the corresponding time. The software incorporates the ActiveX controls package, which enables easy access to imaging devices connected to the computer.

In early July 2002, there was massive flooding in south Texas. On 12th July 2002, a second test flight was conducted over the Chapman Ranch located in Nueces, Kleberg, and King counties of south Texas. The purpose of the flight was to determine the quality of the system's vegetation detection as well as record the flooding of the Nueces River.

For vegetation detection, we flew over the Chapman ranch at lower altitude (3000 ft.) before capturing the Nueces River flooding at 12,500 feet. A raw small-format image is shown in Figure 8(a). Some of the images were processed and analyzed. The images were also enhanced to improve convolution, edge enhancement, and contrast utilizing a spectral pass filter. The image was rectified using existing Digital Ortho Quarter Quadrangle images from the US Geological Survey. Next, the images were enhanced to improve convolution, edge enhancement, and contrast utilizing a spectral pass filter. The next objective was to replace visual colors with a classified pattern. An unsupervised classification method was used to determine the natural breaks between the shapes, sizes and spectral signature. The objective of the development of the classified map is to (i) identify a flooded area and its boundaries, and (ii) assign land ownership to flooded area. A more involved method of reclassification was used to identify land cover types. A six-color classification was performed using spectral pattern recognition of the Jenks natural breaks as seen in Figure 8(b). This image groups similar spectral signature items for classification. Land cover is represented by the natural and artificial compositions covering the earth surface and are used to assess the flood impact.

4 Tide (water level) modeling

The goal of our on-going research is to develop effective and reliable tools for predicting water levels in the shallow waters of the Gulf of Mexico. Different schemes that we are using for the prediction of water levels include harmonic analysis, statistical models, and neural networks. Multivariate statistical based models of predictions of tides and neural network predictions are under development at the Division of Nearshore Research (DNR) of the Center for Coastal Studies in cooperation with the Department of Computing and Mathematical Sciences of Texas A& M University - Corpus Christi.

4.1 Statistical modeling

Tide charts, based on harmonic analysis, are generally the method of choice for the forecast of water levels. However there are limitations to the use of tide charts. Tide charts are mostly based on astronomical forcing or the influence on water levels of the respective motions of the earth, the moon, and the sun. There are locations around the world, including the Gulf of Mexico, where other factors such meteorological forcing often dominate tidal forcing [12] and limit significantly the application of tide charts. In such cases other models must be developed to accurately forecast water levels.

We have considered three different models for "next-hour" predictions, and two of these produced quite reliable predictions. The first of these models is a multi-regression model in which the "next-hour" prediction is based on the levels of water, speeds and directions of wind for the previous 48 hours with a step of 2 hours. This model did not produce the expected results. The coefficient of correlation for these predictions was less than 0.5.

The second approach was another multi-regression model in which two-hour predictions of water level are based on the levels of water during the previous 48 hours, using 2-hour steps. Here we now believe that information about weather (pressure, wind, temperature, etc.), used in the model previously described, is hidden in the levels of water. Since this model excluding wind parameters worked remarkably well: R squared for all TCOON stations was greater than 0.95. To make further predictions we used the previously determined levels of water. Such a step by step approach produced quite good predictions. Table 1 below presents statistical data for the differences between predicted and real levels of water for 6, 12, 18, 24, 30, 36, 42, and 48 hours [12].

The third approach was also based on linear multi-regression of the levels of water, first differences, and second differences for such levels for the previous 48 hours with the step equal to two hours. This approach produces the same quality of water level prediction as the second approach, i.e. $R^2 > 0.95$. These results are quite understandable, since in both cases we have to deal with linear combinations of previous water levels. The difference

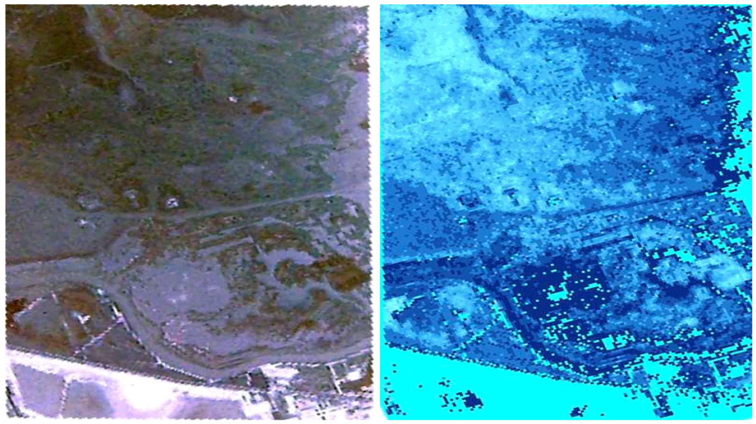

Figure 8: (a) Digital image of Nueces river flooding. (b) Classified image of flooded area river flooding.

in these two models is as follows: the third approach has between four (4) and eight (8) significant variables in a linear regression while in the second model of linear regression we use all twenty four (24) variables where these variables are the water levels for the previous 48 hours. Results of these predictions can be seen in Table 2 below.

We believe that this statistical model may also be useful as a means to fill gaps, due to equipment failure, in the observed water level data. To fill gaps in water level data, we will use the following procedure: First, we will find backward and forward linear regressions for the predicted water levels, and then we will evaluate lost data as a linear combination of forward and backward predictions with weights proportional to the distances from the edges of the gap.

4.2 Factor analysis

After analyzing different regression models we faced the following question, "Why do models with only previous water levels work much better than models with all kinds of meteorological data provided by TCOON stations?" To answer this question we applied factor analysis to the water levels over the period of 48 hours with the interval of 2 hours. The conclusion is that no more than 5 factors explain over 90% of variance for water levels for all TCOON stations. Then we compared the results of the factor analysis for shallow waters with the results of the factor analysis for deep water stations.

Analyzing the for the different TCOON stations we have discovered the following:

- In shallow coastal waters and estuaries the principal or first of the major component is not periodical, and we call this component "weather". Other main components are periodical and we call them "astronomical".

- In off-shore deep waters, the first two or three components are astronomical components, while weather is a less dominant component.

- Our conclusion is that for estuaries and shallow waters, weather is the prime factor affecting the variations of water levels, while tidal forces are the major factors affecting the variations of water levels in deep waters.
- It has been observed also, that linear regression models for different locations have different coefficients for the same variables. We think that such differences may be explained by the geography of the place where the data is collected.

4.3 Integration of regression and harmonic analysis

These conclusions assisted us in improving predictions in the shallow waters since the conclusion suggested integrating the regression approach with harmonic analysis. Namely, we use the idea that variations of water levels depend on two things: a harmonic component (which is called tides) and the weather component. Let us denote:

$$x_n = w_n - h_n,$$

where: x_n is the difference between water level w_n and the harmonically predicted water level h_n at the moment n.

Then we can apply a technique, which is similar to that used for our statistical model described above. That is, we can predict the difference between water level and harmonic level for the next hour

$$x_1 = a_0 x_0 + a_{-1} x_{-1} + \cdots + a_{-n} x_{-n}$$

and step by step

$$x_k = a_0 x_{k-1} + a_{-1} x_{k-2} + \cdots + a_{-n} x_{k-n}.$$

Now we can predict the water levels as follows:

$$pw_t = h_t + x_t.$$

This approach to predictions of water levels proved to be very effective. In table 4 below we present comparisons of this approach with other approaches, thus, we were able to evaluate the effectiveness of this symbiosis of regression and harmonic analyses.

4.4 ANN modeling and predictions

The Artificial Neural Network (ANN) modeling approach is also based in forecasting future water level differences as a function of past water level differences. Other inputs to the ANN model have also been tested. For example, past wind squared is included in the model discussed below; as it has been recognized that wind forcing is well correlated with water anomalies. Other inputs, such as barometric pressure, have been tested but models which included past water level differences, past wind measurements and wind forecasts have been shown to be optimal [13]. It has also been shown that simple neural networks with one hidden layer and one output layer have the best performance [14]. With one input neuron with a tansig function and one output neuron with a purelin function and a number of total different inputs ranging from 10 to 30 the ANN forecast of a water level n hours beyond the time of forecast can be expressed as follows:

$$x\left(t_0+n\right)=a+\left(\frac{2b}{\left(1+e^{-\left(c+\sum d_i y_i\right)}\right)}\right)-1.$$

Model	RMSE	CF	POF	NOF	MDPO	MDNO
Harmonic	0.11± 0.02	85.02± 4.12	0.21±0.19	1.90± 2.51	16±16	73±81
Pers 24 hr	0.069± 0.006	95.75± 1.19	0.24±0.231	0.023±0.029	14±19.17	0.6±1.342
LR 24 hr	0.106	97.18	0.261	0.027	9	1
NN-1 24 hr	0.0588±0.0085	97.848± 1.284	0.132± 0.114	0.104±0.232	8.5±8.7	7.6±17.1
NN-2 24 hr	0.053± 0.0079	98.563±1.284	0.124±0.115	0.08± 0.204	8.4± 8.7	6.2± 17.1
Pers 48 hr	0.101± 0.009	87.18± 2.22	0.785± 0.528	0.424± 0.255	25.4+/17.813	13.8±10.232
LR48 hr	0.122	91.05	0.466	0.409	16	19
NN-1 48hr	0.0889±0.0123	91.396±2.768	0.199± 0.158	0.57±0.937	9.6± 7.6	26.4±37.7
NN-2 48 hr	0.0779± 0.0108	94.500± 2.616	0.123±0.162	0.299±0.575	6.8±9.6	16.3± 30.7

Table 2: Comparison of 24 and 48 hours predictions by different methods, where RMSE: root mean error, CF: central frequency, % of errors within the limits of $-X$ and X. $POF/NOF(2X)$: positive/negative outlier frequency % of errors greater than X. $MDPO/MDNO(2X)$: maximum duration of positive/negative outlier; an event is two or more consecutive occurrences of an error greater than X; MDPO/MDNO is the length of the longest event.

In the expression above, the additive parameters (a, c) are identified as the model biases and the multiplicative parameters (b, d_i) are referred to as the model weights. These parameters of the ANN are defined in the process of training of neural network over the known set of data. The yi are the inputs to the model. The exponential terms in the ANN model provide a non-linear modeling capability.

The training of ANN models is different in nature as compared to the methods for our statistical model. There is typically no demonstrated method to identify a global optimum. The goal of the training process is therefore to find a suitable local optimum. To identify a good local optimum ANNs are trained over past data sets starting with a random guess of the model parameters and using the repeated comparison between the output of an ANN and an associated set of target vectors to optimize the weights of the neurons and biases of the model. All the ANNs discussed in this work were trained using the Levenberg-Marquardt back-propagation algorithm and implemented using version 4.0 of the Matlab Neural Network Toolbox and the MATLAB 6.0 Release 12 computational environment [15] running on a Pentium PC.

The performance of the ANN for the prediction of water levels was tested at the Bob Hall Pier, Texas, TCOON station. The model was trained and tested using three data sets composed of 3600 hourly measurements of water levels, wind speeds and wind directions. The data sets covered the spring seasons of 1998, 2000, and 2001 from Julian day 21 to Julian day 182. The model was successively trained on each data set and applied to the other two data sets. This procedure provided a set of six time series of predicted water levels to be used for validation. For each time series the average absolute error between predicted and measured water levels was computed.

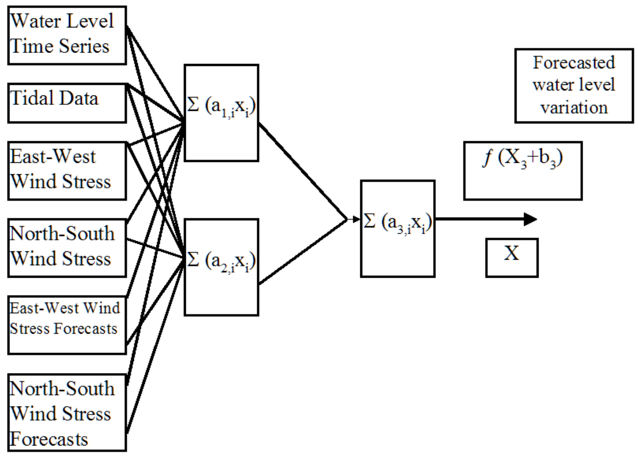

Figure 9: Schematic of the type of neutral network applied to the problem of water level.

Averages and standard deviations were then computed for the results of the six validation time series for these two parameters. The standard deviation gives an overall measure of the variability due to the differences between training sets as well as the differences resulting from the training process. The inputs to the model were selected as the previous12 hourly water level and wind measurements based on experience gathered during the modeling for other locations [16]. One model was trained without wind predictions while for the second case wind measurements were used to simulate wind forecasts. These wind forecasts consisted of future wind measurements at 3 hour intervals up to 36 hours. A database of wind forecasts is presently being constructed and models based on wind forecasts are expected to be more representative of future model performance. Figure 11 displays a comparison between a 36-hour water level hindcast, the tide tables, and TCOON measurements. As can be observed in the figure, the ANN model captures a large fraction of the water anomaly and improves significantly on the tide tables. The performance of the models with and without wind forecasts is compared with the performance of the tide tables for forecasting times ranging from 6 to 36 hours. Both ANN models improve significantly on the tide tables for forecasting times up to 24 hours. Improvements for 30-hours and 36-hours predictions are still measurable. The addition of wind forecasts improves the model performance although not significantly as compared to the improvement over the tide tables. Comparisons of ANN and Regression models may be found in Table 2.

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