Coastal Hurricane Inundation Prediction for Emergency Response Using Artificial Neural Networks

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Abstract. Emergency managers require both fast and accurate estimates of hurricane inundation to make critical decisions about evacuations, structure closures, and other emergency response activities before, during, and after events. Probability analyses require multiple simulations which, generally, cannot be performed with the physics-based models under the time constraints during emergency conditions. To obtain highly accurate results with a fast turnaround computation time a "surrogate" modeling approach is employed. This surrogate modeling approach uses an extensive database of storms and storm responses and applies "smart" pattern recognition tools such as Artificial Neural Networks (ANN) as well as interpolation techniques. The goal is to provide forecasts of hurricane inundation and waves with the accuracy of high-resolution, high-fidelity models but with very short execution time (minutes). The city of New Orleans as well as surrounding municipalities along the Gulf of Mexico coastal area encompasses the region used to demonstrate this approach. The results indicate that the developed surge prediction tool could be used to forecast both magnitude and duration to peak surge for multiple selected points in a few minutes of computational time once the storm parameters are provided. In this paper, only results of surge magnitude are presented.

Keywords: Storm Surge Prediction, surrogate modeling, neural networks, multilayer perceptron.

1 Introduction

The most severe loss of life and property damage occurred in New Orleans, Louisiana, USA which flooded as the levee system catastrophically failed; in many cases hours after the storm had moved inland. At least 1,836 people lost their lives in Hurricane Katrina and in the subsequent floods, making it the deadliest U.S. hurricane since the 1928 Okeechobee Hurricane. The storm is estimated to have been responsible for $81.2 billion (2005 U.S. dollars) in damage, making it the costliest natural disaster in U.S. history. The city of New Orleans as well as surrounding municipalities is located well within hurricane striking distances along the Gulf of Mexico and within the north central region of the Gulf that has the highest probability of a major hurricane strike.

The Corps of Engineers of US (USACE) is committed to protection of these areas and has created a Hurricane and Storm Damage Risk Reduction System (HSDRRS)

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consisting of hundreds of miles of levees, integrated with flood walls, locks, flood gates, and other water control structures. The exact timing of the storm surge to determine the gate operations during extreme weather conditions is critical to ensure the safety of populated areas and a minimal amount of flooding. The forecasting capability for surge behavior during the initial (critical) hours of approaching storms is particularly important to the decision making to support storm preparations and emergency operations. An operational storm surge water level forecast for the greater New Orleans area and coastal Louisiana has come to be realized as essential to provide critical data that can be used to potentially reduce damages, risk, and save lives.

2 A Surrogate Neural Network Storm Surge Model

Several storm surge forecasting systems have been studied by using Computational Intelligence/statistics methods ([1], [2], [3], [4], [5], [6], [7], and [8]) but this approach uses "surrogate modeling approach to simulate multiple selected surge points. Recently, a very successful interagency team effort in the United States has been formed to perform operational storm surge numerical modeling (Figure 1) in response to hurricane events in the coast of Gulf of Mexico. Application of the ASGS (ADCIRC Surge Guidance System) has demonstrated that due to the computational needs of numerical models, and real time operational requirements, mandatory compromises limit implementation aspects such as the model geometry size and region domain.

The Advanced CIRCulation model (ADCIRC) is a two-dimensional, depth-integrated, barotropic time-dependent long wave, hydrodynamic circulation model. Although the current warning system has been greatly improved through the use of a region specific efficient model geometry (SL15 Light), additional tools have the potential to more quickly and more accurately provide wind, wave height and surge levels that affect all critical coastal structures and low lying flood prone areas. The potential value of promising alternative tools should be explored. A number of significant compromises had to be made relative to the very detailed modeling and coupled wave-surge models that have been set up and validated for the region.

To avoid these significant compromises, a complimentary approach is proposed which combines the strength of both physical-driven (coupled surge and wave numerical modeling done at highly detailed, fine resolution) and data-driven methods (artificial neural networks – ANNs as well as other computational intelligence components) methods to form a predictive knowledge base to estimate the water levels including magnitude and duration to peak surge for selected locations. This approach is called surrogate modeling approach. A surrogate model is an engineering method or alternative model used when an outcome of interest cannot be easily directly measured nor quickly computed with physics-based models, so a model of the outcome is used instead. The technical tools include the well-validated full SL15 ADCIRC numerical storm surge model application (simulator), unsupervised (clustering) and supervised (prediction) ANNs. In this approach new situations (or events) can be performed with additional storm surge simulations, done offline, which can be added (retrained) to the existing knowledge base.

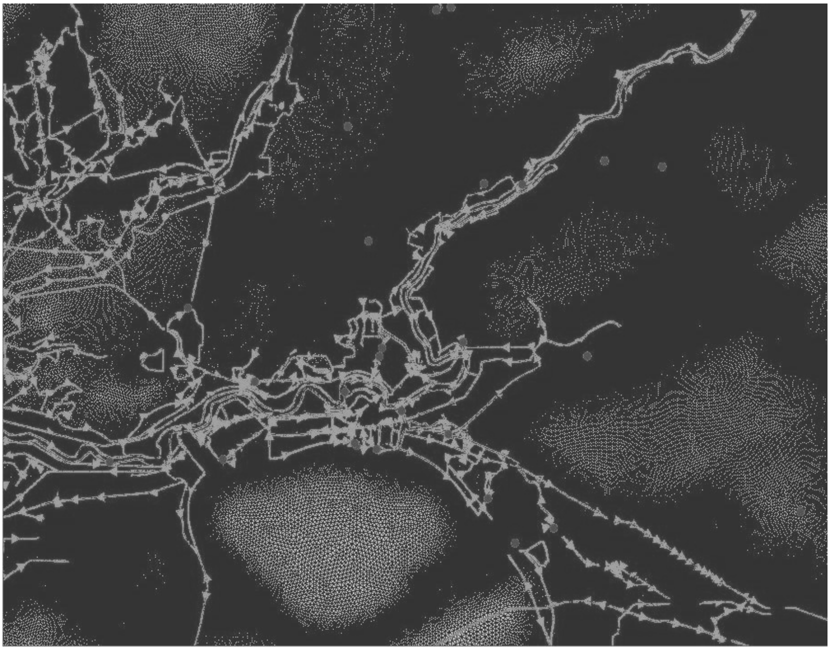

Fig. 1. A numerical storm surge model with computational mesh, levee stream (white), and selected key observed locations (gray)

3 Knowledge Base Development for a Surrogate Neural Networks Model and Basic Data Analysis

Peak surge prediction is the first goal of the ANN model. An initial form of a knowledge database is created to form a linkage between the ANNs and ADCIRC model peak surge results. The goal of this phase is primarily to estimate model peak surges at selected point locations. The main effort is to quantify the relationship between input parameters (such as track or maximum wind speed) and peak surge outputs for all selected interest points from the physics-based coupled wave-surge modeling system (ADCIRC / STWAVE), and convert to a data-driven system.

3.1 Selection of Forecasting Points

The ADCIRC model is executed with a high resolution triangular mesh containing million of nodes and elements. A small subset of nodes is selected to implement the ANN model. It is important that these nodes (points) are selected at key locations which can provide emergency decision makers with appropriate information needed to make critical time constrained decisions. Peak surge water levels, wind speeds, and wave heights are needed to know which flood gates to close/open, when to open/close gates and other structures such as which pumps (and times) to operate. Forecast point locations are selected near critical flood protection system components as well as at key gages (measured observation stations) to enable model comparison and validation. In the New Orleans area a total of 30 point locations have been selected in the south eastern Louisiana (Figure 2) some of which are used during operational forecasting efforts. It is important to select points that are spatially well distributed throughout the area of vulnerability.

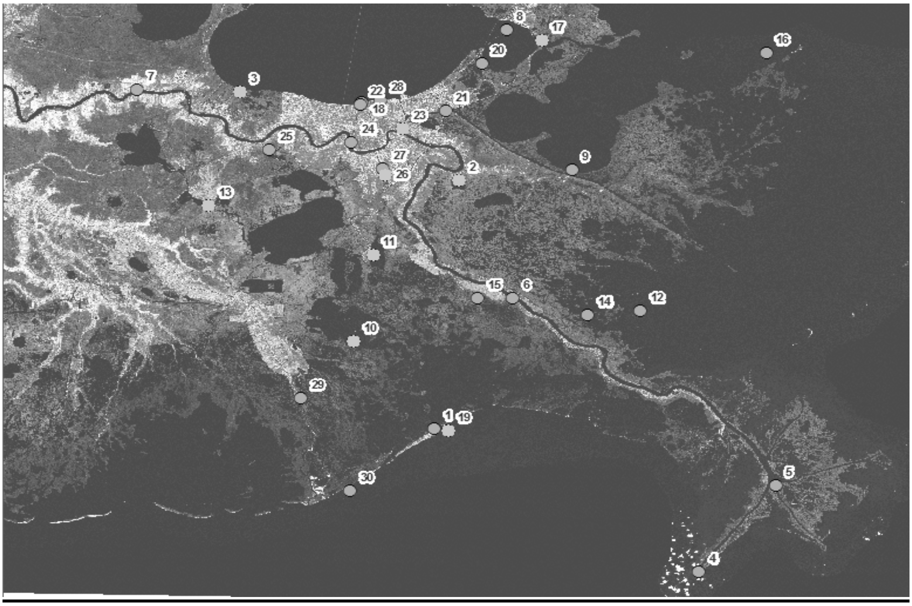

Fig. 2. 30 selected locations (gray color) as forecast points from surrogate model

3.2 Determination of Input/Output Parameters for ANNs Model

The ANN model is "trained" using selected components (parameters) of the physics-based system (in this case ADCIRC/STWAVE). The goal is to use the ANN model to predict storm response surges. In order to achieve this goal a strategy must be employed to select the key parameters from the physics-based system. An understanding of the numeric physics based model is important. This enables selection of the key "force" elements that most affect the final results. In this case the storms are the key force element. Quantitative characteristics of the key force elements must be defined to provide ANN input. An understanding and knowledge of how the physics-based system changes in force and their affects on results both spatially and temporally will enable selection of relevant ANN parameters. Key to the ANN (or any pattern recognition) method is that all parameters vary either spatially and/or temporally over the domain.

The final parameters selected for this effort are shown in Table 1. Sensitivity analyses were performed to determine these most significant parameters and the reliability for multiple point ANNs simulations. The force or input parameters can be grouped into geometric and storm related components. The geometric components are the distance between the forecast point and the storm land fall location, and the angle of storm approach relevant to the forecast point location at time of landfall. The storm force components include the central pressure at the time of landfall, the average forward velocity, the radius to maximum winds, and the maximum wind speed achieved at the forecast point location over the entire storm event. The output parameters selected for ANN model are the peak storm surge. Usually, the distance from storm landfall location, angle of storm approach, and local maximum wind speed are considered as local forcing parameters while remaining forcing parameters are regarded as global forcing parameters.

Table 1. ANNs model input and response output parameters for storm surge model

Forcing (Input) Parameters	Result (Output) Parameters
Geometry	
Distance from storm landfall location (local)	
Angle of storm approach (very minor impact – local)	Peak Storm Surge
Storm Force	
Central Pressure (global)	
Average Forward Speed (global)	
Radius to Maximum Winds (global)	
Local Maximum Wind Speed (local)	

It is noted that due to some data error involved in the system 4 simulation runs as well as 2 selected points (point 25 and 29) are eliminated. This results in 442 sets of storms and associated parameters at 28 saved points as the knowledge base for the ANNs model. The typical central pressure and over 442 storm events are shown in Figure 3. The corresponding output functions, surge height and duration, are plotted as Figure 4.

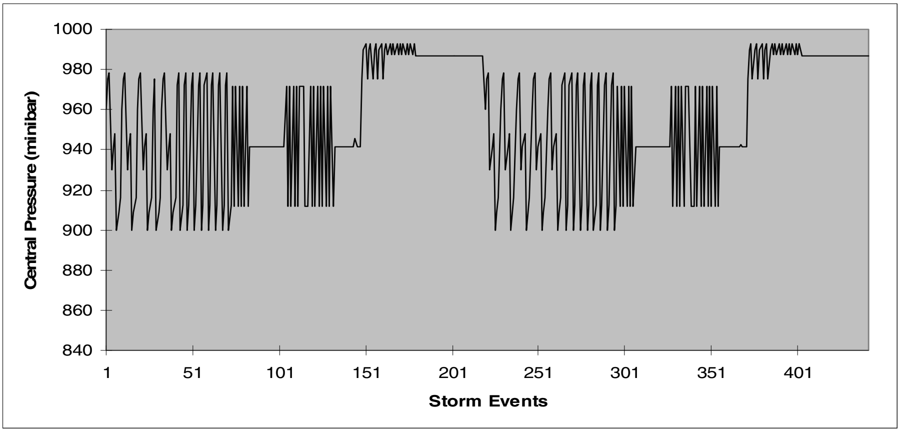

Fig. 3. Global storm parameter (central pressure- mb) for 442 ADCIRC physical model runs

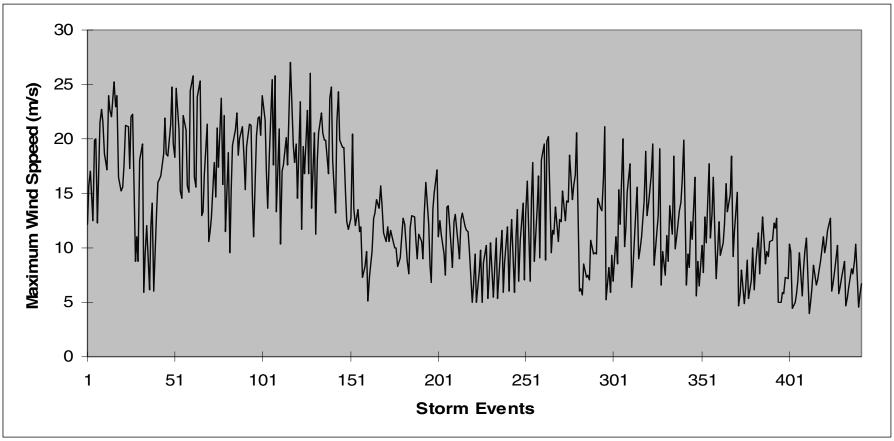

Fig. 4. Peak storm surge (ft) at gauge 3 for 442 ADCIRC model runs

3.3 Preliminary Multiple Linear System Identification and ANNs Model Design

Before dealing with a complex nonlinear system to quantify the relationship among parameters, a linear system, such as correlation coefficient analysis can be used as a preliminary analysis tool to determine the approximate functionality. Therefore, one set of correlation coefficients (maximum surge height) with six inputs and one output system are computed (Figure 5). Due to very low correlation coefficients associated with angle of storm approach for both magnitude and duration of surge; the system is reduced to five inputs/one output structure. Figure 5 shows two parameters (central pressure and distance from storm landfall location) that are negative related to corresponding surge height. This indicates an inverse physical relationship to surge for these two parameters. The local maximum wind speed is a dominate surge producing parameter.

Based on the above analysis, a nonlinear neural network model with feed forward architecture can be assumed as Figure 6. This architecture represents a system with 3 global inputs, N locations, 3 hidden nodes (one hidden layer and if 3 hidden nodes are selected), and n corresponding maximum surge magnitude and duration. The maximum hidden nodes which depend on the prevention from over-training under a set of optimal weights are adjustable. For example, if this system involves 28 prediction points, the size of the neural network is 59x3x28 with a total number of 261 weights .It should be noted that the input arrays between surge height and surge duration are somewhat different sign although the values are the same. Therefore, the system is considered as two individual response structures – one for surge height and the other for surge duration. This paper only presents the results for surge height prediction.

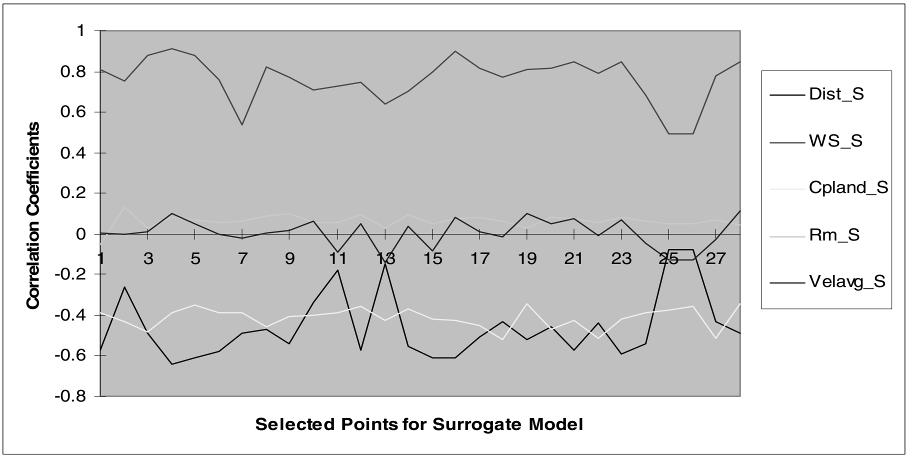

Fig. 5. 28 points correlation coefficients for storm parameters response to peak surge

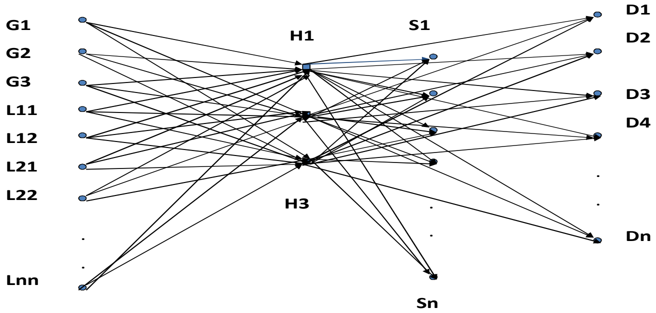

Fig. 6. A neural networks model for N selected points with 3 hidden nodes, N peak surge and N duration outputs architecture

4 Identification and Test for Surrogate Neural Networks Model

After initial model test based on general over-trained prevention, training algorithms, and training strategies using two most offshore points (point 4 and point 5), it found this surrogate model could get a satisfactory agreement with the multilayer perceptron procedure. The proposed ANNs model is further examined by its accuracy up to all 28 points. NeuroSolutions [9] is used to perform this analysis.

4.1 Optimal Point Selection for Surge Prediction

Due to the fact that strength of response from a set of locations is not equally distributed in a given domain, the accuracy of storm surge prediction using the surrogate approach will not readily provide the same results across the domain. It is important to determine the point(s) with the highest prediction accuracy. Table 2 summaries 5 different tests which extend the response points to multiple point bases.

Table 2. Optimal point selection for surge prediction

Selection Reason	Total Point Number	Selected Points	Number of Hidden Nodes	Average CC
Priority	9	2, 3, 10, 11, 13,17, 19, 23, 26	5	0.932
A Statistical Similar Group	11	1, 4, 10, 11, 13, 18, 19, 22, 26, 27, 28	4	0.913
Better Individual Response	15	3, 4, 6, 7, 8, 12, 14, 17, 18, 20, 21, 22, 23, 24, 28	3	0.934
Full Scale	28	Every points	2	0.770

Based on Table 2, nine priority points are chosen as the most critical. The considerations are dependent on key locations which can provide emergency decision makers with water levels and time series data needed for critical decisions (time to close flood gates, start pump stations, etc.), near critical flood protection system components, at key gauge locations for comparison and validation, and spatially distributed through area of vulnerability. An unsupervised ANNs (SOFM) is used to cluster four different response groups with similar statistical parameters (mean, standard deviation, skewness, maximum, and minimum). The first group involves 11 response points. The average CC is computed from each test case. The results show the optimal maximum number of points for creating a surge prediction system is between 9 and 15. The lower CC from a similar group could be those points that are widely spatial distributed. Figure 8 shows the comparison between ADCIRC model simulation and ANNs results for point 23 (9 points priority case).

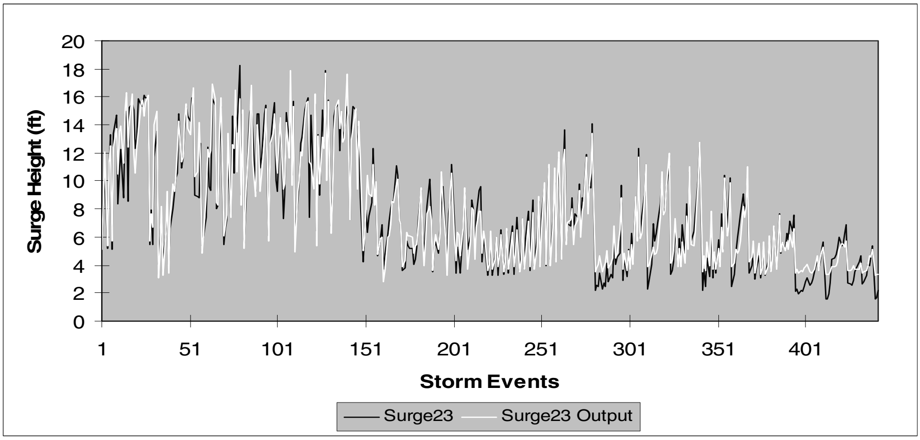

Fig. 7. Training results of station 23 for 9 priority points surge (ft) model (black color represents ANNs simulation and white color shows ADCIRC model simulation)

4.2 Surrogate Model Simulation for 9 Priority Point's Case

This 9 priority points surrogate ANNs model can be used to demonstrate the surge response (magnitude and duration) under very short period (less than few minutes) once new storm parameters are provided. Figure 9 displays the surge height of simulated 50 storm events for 9 priority points. It is note that the maximum local wind speeds as a major forcing parameter for these 50 storm events are presented in this figure as the impact contribution.

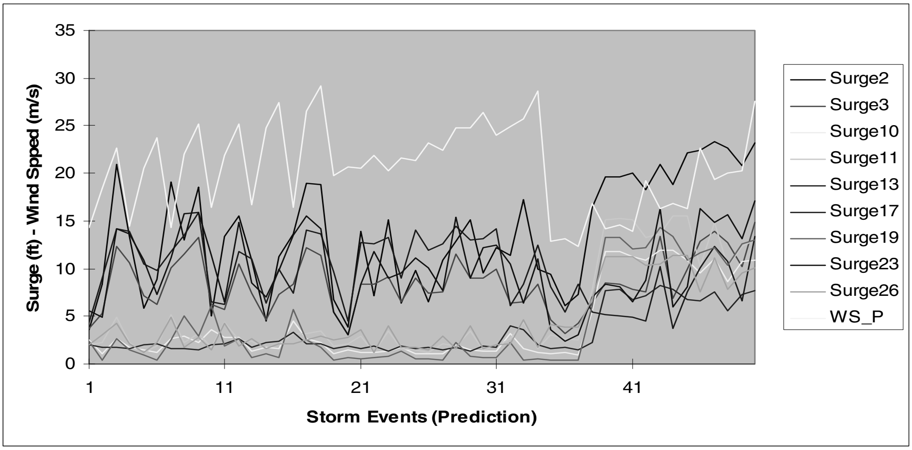

Fig. 8. 50 storm surge events prediction for 9 priority point's model with 442 events as knowledge base

5 Conclusions

This work demonstrates successfully use of ANNs to quantify the relationship between storm forcing as well geometry and response parameters (maximum surge magnitude and duration) from a knowledge base of 442 storm surge numerical model simulations. The city of New Orleans as well as surrounding municipalities along the Gulf of Mexico coastal area is used as the demonstration site. The developed "static" mode surrogate surge prediction tool can be used to predict surge response and duration to peak surge with multiple selected points within minute's turnaround time once the storm parameters are provided. This effort investigates the most significant procedures for developing an ANN model from training strategies, algorithm selection, and prevention from overtraining consideration approaches. The results indicate that the surge is the most influenced by local maximum wind. The "dynamic" operational surrogate ANN model is being developed for further practical application.

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