HURRICANE HARVEY AND FIRE DISASTER IMPACTS AND NEW TECHNOLOGIES FOR RAPID RECOVERY INTEGRATED WITH ARTIFICIAL NEURAL NETWORK

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Abstract

Disasters are very difficult to predict and are having major impact on the growing population and commercial activities. Based on the total losses and the impact it had on the largest population across many states within a period of two weeks, United States had its worst hurricane season in year 2017 with two category 4 hurricanes in the Gulf of Mexico. Hurricane Harvey ranked as category 4, made landfall on August 25, 2017 on San Jose Island east of Rockport, Texas. It moved back to the Gulf of Mexico on August 28 and moved along the Texas coast with strong wind and rain fall making it the worst destruction in the Texas History with inland flooding. Immediately after Hurricane Harvey a survey (web based (http://hurricane.egr.uh.edu/news/hurricane-harvey-survey-2017) and phone based (Hurricane HARVEY Assessment)) was undertaken by the Texas Hurricane Center for Innovative Technology (THC-IT) to determine the damages to residential structures and utilities in Texas based on zip codes. The survey had responses from over 100 most affected zip codes. Harvey survey results have identified the problems related hurricane inland flooding into homes buildings and streets, insurance issues, power failure, repairing of structural damages, debris issues and rapid recovery. Based on the analyses of the survey and also visiting some of the most affected neighborhoods several issues have been identified and quantified. FEMA had listed 24 zip codes from 8 counties which represented 4.3% of the total population of over 6.5 million in the eight counties.

The THC-IT hurricane Harvey survey results related to losses was also comparable to the FEMA data. Also factors affecting the inland flooding caused by hurricane Harvey have been identified to develop enhanced inland flooding models for built-in environment with the lessons learned on preparedness, losses, raid recovery and debris from the hurricane Harvey. In recent years there have been many fire disasters. New technologies representing real-time monitoring, drones, smart cement, flooding and fire protection and debris issues integrated with the artificial neural networks (ANN) are being investigated to be used in preparedness, minimizing losses and rapid recovery after many types of major disasters including hurricanes, fire, flooding and oil spills.

Introduction

Based on the losses, damages and affected population, hurricanes are the worst natural disaster affecting the United States. One hurricane can cause enormous economic losses, human deaths and place tremendous burden on the local, state and federal governments and insurance industry. In year 2017, United States had the worst hurricane season based on the total losses. In the Gulf of Mexico, there were three hurricanes in the year 2017 with hurricane Harvey (category 4) being the worst hurricane in the State of Texas history and hurricane Irma (category 4) being the worst hurricane in the State of Florida history. Uniqueness about this is that for the first time two hurricanes rated as category 4 happened in the Gulf of Mexico within two weeks originating from the Atlantic Ocean.

The prediction of the impact of a hurricane on economic losses is not only beneficial to the public, but it could also be used by the insurance companies as the reference to decide their policies

(Huang et al. 2001; Vipulanandan 2009 and 2018). Also it is very important to develop building codes to design appropriate building structures and also potential flooding based on these information at different locations. The government could also make regulations for buildings to include not only wind withstanding design but control indoor flooding.

Despite significant improvements in predicting, tracking and warning the public about hurricanes using number of models, there has been relatively little progress in predicting inland flooding and estimating the expected hurricane losses in the built-in environments and industrial facilities with debris accumulation. These losses can be in the form of flooding of houses, structural damages to critical infrastructures, damage to utilities, power loss and interruptions to businesses and educational activities. After hurricane Harvey, a survey was initiated by the Texas Hurricane Center for Innovative Technology (THC-IT) on August 31, 2017 to determine the preparedness, rapid recovery with damages to residential structures, transportation infrastructure and utilities in the region based on the zip codes. The responses to the survey have been very good.

(a) Hurricanes

Hurricanes are initiated as tropical storms over the moist warm waters in the Atlantic and Pacific Oceans near the equator. As the moisture evaporates it rises until enormous amounts of heated moist air are twisted high in the atmosphere. The winds begin to circle counterclockwise north of the equator or clockwise south of the equator. The relatively peaceful center of the hurricane is called the eye. Around this center, winds move at speeds between 74 and 200 miles per hour. As long as the hurricane remains over waters of 79^{o}F or warmer, it continues to pull moisture from the surface and grow in size and force. When a hurricane crosses land or cooler waters, it loses its source of power and its wind gradually slow until they are no longer of hurricane force--less than 74 miles per hour.

Hurricanes over the Atlantic often begin near Africa, drift west on the Trade Winds, and veer north as they meet the prevailing winds coming eastward across North America. Hurricanes over the Eastern Pacific begin in the warm waters off the Central American and Mexican coasts. Eastern and Central Pacific storms are called "hurricanes." Storms to the west of the International Date Line are called "typhoons."

The two NASA-GOES satellites keep their eyes on hurricanes from 22,300 miles above Earth’s surface. These satellites were built by NASA and operated by the National Oceanic and Atmospheric Administration (NOAA). It helps with the weather forecasting and warning people when and where these severe storms will hit the land. Drones are being used for pre and post monitoring.

(b) Fires

Fire disaster can be a natural and/or human made disaster. Natural fire can be in the jungles and spreads rapidly in the direction of the winds. There is need for monitoring of the jungle fire to control it to minimize the impact on the animals, birds, vegetation and also polluting the environment. Human made fire can happen on power grids, buildings, storage facilities, transportation vehicles, gas pipelines and chemical plants on land and also on offshore oil platforms and ships. Unlike hurricanes, there is very limited warning about fire disasters and it requires real-time monitoring.

Objectives

The objectives were to investigate the impact of hurricane Harvey on the Texas communities and fire disasters by analyzing the survey data and identifying the parameters that needs to be considered for predictions related to preparedness, minimize losses and rapid recovery. The specific objectives are as follows:

(a) Analyze the hurricane Harvey survey data collected to reflect the preparedness, damages, recovery and other issues and compare it to the FEMA data. Identify the important issues/factors that need to be integrated with the future predictions of hurricanes and fire disasters, losses and rapid recovery.

(b) Review the potential use of new technologies that can be adopted to support the preparedness and rapid recovery related to disasters.

(c) Review the adaptation of Artificial Intelligent (AI) and Artificial Neural Network (ANN) to support the predictions related to disasters.

In this study, the Hurricane Harvey Assessment survey prepared by the THC-IT included questions on housing, preparedness, evacuation, insurance, recovery and problems with debris. The data was collected based on the zip codes but the initial analyses are based on the overall responses by the affected communities. Also included in the study are analyses of the data provided by FEMA based on zip codes.

1. Analyses of hurricane Harvey

FEMA Data

The published data from FEMA in December 2017, top 20 zip codes have been identified for both individual assistance and house hold assistance. Combining the two assistances represented total of 24 different zip codes from 8 counties. The total population in the eight counties was 6,573,067. Total of 280,797 were listed in the FEMA application data (individual and housing), which represented 4.3% of the population (Table 1). Analyses and discussions are based on the total affected people and percentage affected based on the county population. Also counties are ranked based on the population in year 2017. The zip code with the highest number of claims was from Jefferson County (Vipulanandan et al. 2018).

Table 1. Top 20 Zip Codes Applied for Individual and Housing Assistance from FEMA

Zip Code	Number of Claims			City	County	% Population Affected
	Individual	House	Total			
77642	13,654	6,425	20,079	Port Arthur Area	Jefferson	7.8
77084	12,770	5,632	18,402	Houston-Addick/ Bear Creek Area	Harris	0.4
78382	11,333	7919	19,252	Rock Port	Aransas	75.3
77539	11,328	6,648	17,976	Dickenson	Galveston	5.4
77901	10,373	4,755	15,128	Victoria	Victoria	16.4
77662	9,782	6,840	16,622	Vidor	Orange	19.5
77630	9,686	5,151	14,837	Orange	Orange	17.4
77089	9,090	4,876	13,966	Houston-South Belt/ Ellington Area	Harris	0.3
77044	8,354	4,776	13,130	Lake Houston	Harris	0.3
77705	8,269	3,878	12,147	Beaumont	Jefferson	4.7
77090	8,141		8,141	Cypress	Harris	0.2
77449	7,951	4,026	11,977	Katy	Harris	0.3
77459	7,885	5,853	13,738	Missouri City	Fort Bend	1.8
77632	7,702	5,581	13,283	Crange/Mauriceville	Orange	15.6
77521	7,516	3803	11,319	Baytown	Harris	0.2
77088	7,468		7,468	Acres Home/Inwood Pines	Harris	0.2
77077	7,390		7,390	Briar Forest	Harris	0.2
77640	7,345	4,047	11,392	Port Arthur	Jefferson	4.4
78415	7,198	3,543	10,741	Corpus Christi	Nucess	3.0
77016	6,960		6,960	Trinity garden	Harris	0.1
77450		4,533	4,533	Cinco Ranch	Fort Bend	0.6
77479		4,251	4,251	Sugar Land /New Territory	Fort Bend	0.6
77407		4,054	4,054	Richmond	Fort Bend	0.5
77573		4,011	4,011	League City	Galveston	1.2
Total	180,195	100,602	280,797	17 Cities	8 counties	4.27

Hurricane Harvey Assessment Survey

One week after the hurricane passed through Texas, an assessment survey was initiated by the Texas Hurricane Center for Innovative Technology (THC-IT). The survey was web based (http://hurricane.egr.uh.edu/news/hurricane-harvey-survey-2017) and phone based (Hurricane HARVEY Assessment) to determine the home ownership, preparedness, damages to residential structures, power loss, recovery and debris issues in Texas based on zip codes. The survey is ongoing and responses have been received from 14 counties, over 100 zip codes and 30 cities. Also data on the cost of damages and type of government assistance received are being collected. The survey also included issues related to rapid recovery, transportation, work place/educational institutions and debris removal and are grouped into three classes (no problem, problem and major problem) for analyses. The preliminary analyses are based on the total data collected from the hurricane Harvey survey.

a. Home Ownership

Over 80% of the survey respondents owned their homes and hence the data collected will help identify the losses encountered during hurricane Harvey. Also 18% of the respondents were in rented houses and apartments. Also 0.4% of the respondents were in living in facility and others include institutional housing. The results of the survey on the types of living homes are compared in Fig. 1.

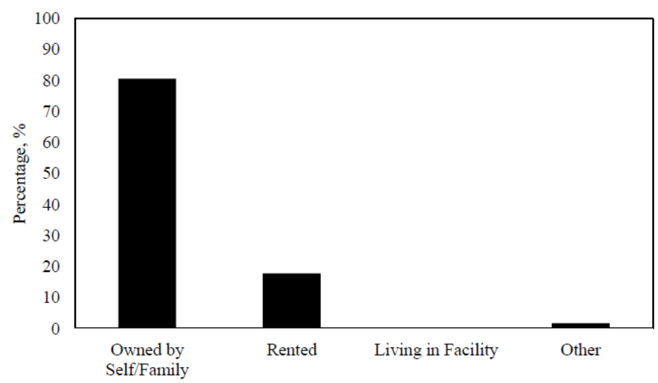

Figure 1. Percentage of Home ownership compared to rented homes and others

b. Type of Insurance

In order to have faster recovery having relevant insurances are important. During hurricane Harvey over 1 million cars were lost or damaged. Over 86% of the survey respondents had homeowners insurance indicating that some of the rented homes also had Homeowners insurance. About 37% had flood insurance and 15% had wind insurance. The results of the survey on the types of insurances are compared in Fig. 2. The trends observed will require more detailed study and educating of the communities on the benefits of having some of these insurances.

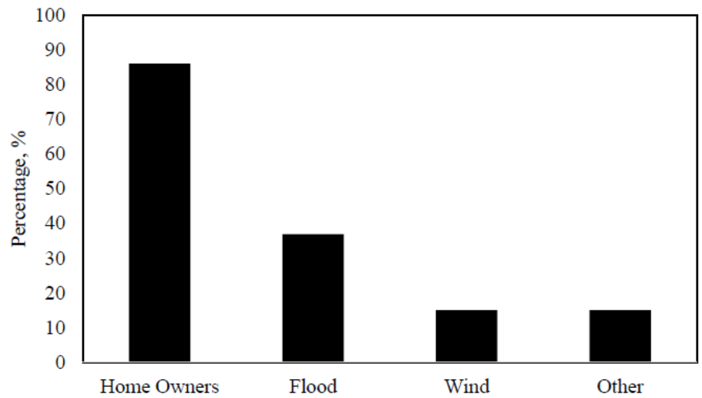

Figure 2. Percentage of Various types of insurances owned by the respondents

c. Flooding area

Inland flooding was the most damaging event during hurricane Harvey. Flooding areas are identified based on the total rain fall. During hurricane Harvey the maximum rainfall reported was about 60 inches. Based on the survey 27% of the respondents were in the 100 year flooding area and 28% were in the 500 year flooding areas. Also 16% of the respondents were in the 1000 year area. The results of the flooding area types are compared in Fig. 3. Using this data more detailed study is needed based on the rain fall and wind speed distribution, ground elevation, built-in-environment and drainage conditions to identify the worst flooded areas. Also models have to be developed to quantify the flooding.

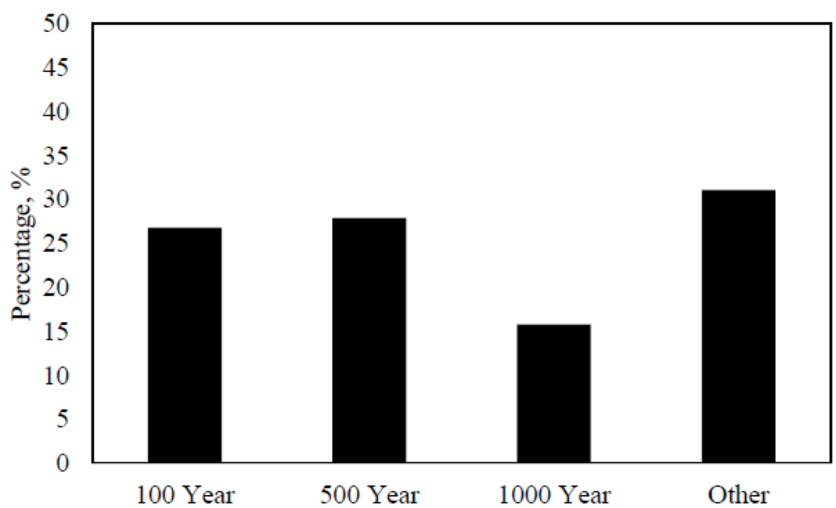

Figure 3. Percentages of respondents in different areas of flooding.

d. Evacuation

Based on the survey respond, 16% of the population was evacuated (Fig. 4). More detailed study is needed to identify the causes of evacuation. Also models have to be developed to quantify the evacuations and will help with future planning.

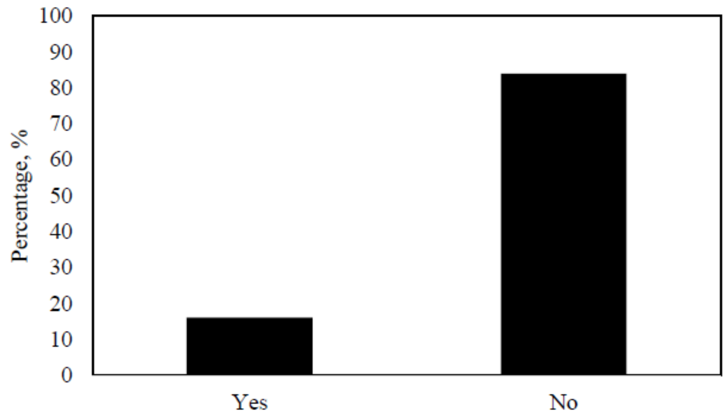

Figure 4. Percentages of respondents evacuated during hurricane Harvey.

e. Drinking Water

House drinking water system was totally damage for 4% of the respondents. Also it was partially damaged for 6.7% of the respondents (Table 2). More detailed analyses are needed to quantify these trends and identify the major causes of this problem. Since drinking water is the most essential item, methods to solve the problem must be identified.

Table 2. Summary of drinking water problems based on the survey

House Drinking Water Damage	Percentage, %
None or Minor Loss	89.3
Partly Damaged/ Usable	6.7
Totally Damaged/ Unusable	4

f. Garbage Pickup

Based on the survey, 6.6% respondents had total damage to the garbage pickup system. Also 20.3% had partial damage to the garbage pickup system (Fig. 5). More detailed analyses are needed to identify the major causes of this problem. Also garbage pickup is important to keep the neighborhood clean.

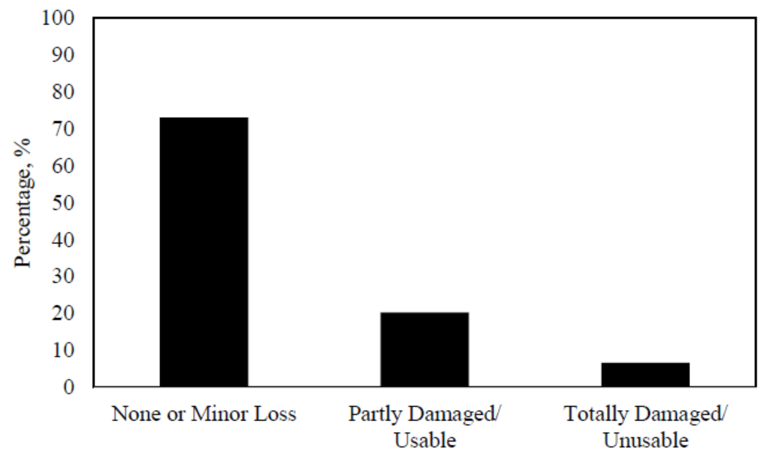

Figure 5. Garbage Pickup problem during hurricane Harvey.

g. Power Loss

Based on the survey, 6.5% had total power failure and 7.5% partial power failure (Fig. 6). More detailed analyses are needed to quantify these trends and to identify the major causes of this problem since power failure will have impact on many activates including rapid recovery.

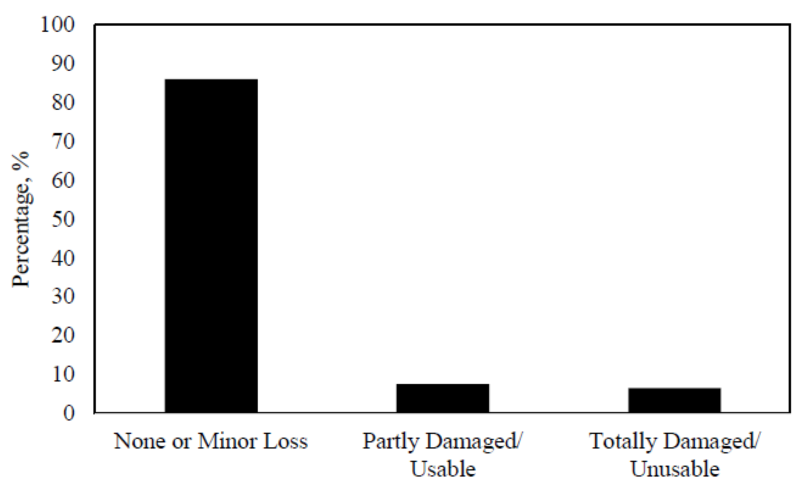

Figure 6. Power failure problem during hurricane Harvey.

h. Structural Damage

Based on the survey, 4.9% had total damage and 6.7% partial damage to the houses (Table 3). More detailed analyses are needed to quantify these trends and identify the major causes of this problem and will be compared to the data provided by FEMA. The highest housing assistance request was from Rockport, the location of the hurricane Harvey landfall.

Table 3. Summary of structural damages to houses

House Structural Damage	Percentage, %
None or Minor Loss	88.8
Partly Damaged/ Usable	6.7
Totally Damaged/ Unusable	4.9

i. Total Loss

Based on the survey, 5.4% of the respondents had over $100,000 in total loss and the total applications received by FEMA were 4.23%, the numbers are comparable (Table 4). More detailed analyses are needed to quantify these trends and identify the major losses and the causes (wind, flooding, others).

Table 4. Distribution of the total loss

Total Loss	Percentage, %
<$1000	84.2
<$10,000	4.6
<$100,000	5.8
>$100,000	5.4

j. Debris

Debris was caused by flood waters carrying various types of waste materials and fallen trees. Also flooding of houses resulted in large volumes of debris in various neighborhoods. Removal of debris was a major problem after hurricane Harvey and the survey data also indicates that over 50% of the respondents had debris removal problem (> 7 days) (Table 5). More detailed analyses are needed to quantify these trends and identify the major causes (wind, flooding, others).

Table 5. Debris Removal Days and Percentage

Number of Days	% Percentage
1 Day	21.5
< 7 days	28.2
>7 days	37.3
Others	12.9

2. Important Issues

There is an urgent need for better quantification of inland flooding and potential damages to houses and other infrastructures. This is important for preparedness and rapid recovery. Inland flooding due hurricane is totally different from rain fall flooding currently used 1D and 2D models. Current models also do not take into account the built in environment, wind effects and floating debris. Hence 3D inland flooding model have to be developed taking into account all the important variable.

3. Other Models

In order to quantify the inland flooding (FL), losses (L), debris (DB) and damages (DM), models will be developed taking into account variables such as total rainfall (R), maximum rate of rain fall (r) wind speed (V), ground elevation (E), distance from the coast (D), area of the zip code (A), number of bayous and rivers (C), built-in-environment (B), Tree Distribution (T) and population (P). As need the damaged models developed after hurricane IKE (DM-THC) will be used and/or modified for future hurricane applications (Vipulanandan et al. 2009).

$$FL, L, DB \& DM = f(R, r, V, E, D, A, C, B, T, P) \quad (1)$$

4. New Technologies

(a) **Real-Time Monitoring**: Recent advances in sensor technology and communication have catalyzed progress in remote monitoring capabilities. Monitoring is only effective if the collected information can be stored and interpreted real-time. These advances have led to improved statistical and mechanistic modeling in monitoring.

(b) **Drones:** The earliest recorded use of an unmanned aerial vehicle (UAV) for warfighting occurred on July 1849. Since then technology has evolved to make very efficient light weight aircrafts with cameras for monitoring before and after disasters.

(c) **Smart Cement**: Highly sensing smart cement has been recently developed for real-time monitoring (Vipulanandan et al. 2017-2018). Smart cement is a chemo-thermo-piezoresisitive cement and a 3D sensor that could detect gas leaks, seismic activities, loadings and fire (Vipulanandan et al. 2019)

(d) **Flooding Protection**: There is an urgent need to developing simple and innovative methods to protect houses and streets from flooding. The flooding is greatly affected by the rate of run-off of the rain water which has to be controlled.

5. Artificial Neural Network (ANN) for Artificial Intelligent (AI)

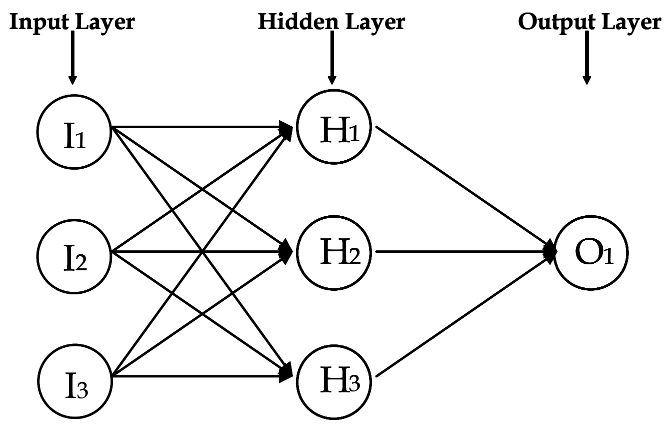

Figure 7. Artificial Intelligent (AI) with Integrated Artificial Neural Networks (ANN)

An artificial neural network is a mathematical or computatioanl model which is based on, at some level, brain like learning; as opposed to traditional computing which is based on programming. The model consists of interconnected groups of artificial neurons, which simulate the structure of the brain to store and use experience, and processes information using a connectionist approach. Artificial neural network is an adaptive system which trains itself (changes its structure) during the learning phase based on the information flowing through the network.

The researchers who have studied neural networks aimed to model the fundamental cell of the living brain: neuron. The recognized US pioneers who first introduced the concept of artificial neural network were neurophysiologist Warren McCulloch and the logician Walter Pitts in 1943. They developed a simple model of variable resistors and summing amplifiers that represent the variable synaptic connections or weights which link neurons together and the operation of the neuron body, respectively. The popularity of neural network increased in 1962 with the introduction of ‘perceptron’ by Frank Rosenblatt who used the term to refer to a system which recognized images using the McCulloch and Pitts model (Alexander 1990).

Hurricane Predictions

Five coastal states (including west side of Florida) along Gulf of Mexico (GOM) have had the largest number of hurricane landfalls in the history of the United States. From 1851 to 2017, representing 168 years, there have been 175 hurricane landfalls in the five coastal states. During this period the east coast had 90 hurricane landfalls compared to only 7 along the west coast of the U.S. It must be noted that there were also hurricanes without landfall but affecting the coastal states.

By analyzing the data from NOAA for all the five GOM states, the hurricane frequency has been parametrically modeled using the Poisson distribution (Texas Hurricane Center for Innovative Technology Website: http://hurricane.egr.uh.edu) as follows:

$$f(h)=\exp(-\lambda)*\lambda^{\wedge}h/h!; \qquad (h=0,1,2,\ldots), \qquad (2)$$

where, h is the number of hurricane per year, λ is the expected number of hurricanes during a year.

Table 6. Actual and Predicted Frequency of Hurricanes

Number of Hurricanes in a year (h)	Count	Hurricane Frequency (Real date)	Predicted Hurricane Frequency (Poisson distribution)
0	59	59.00%	58.29%
1	36	36.00%	31.46%
2	5	5.00%	8.49%
Total	100	100.00%	98.24%

Hence based on 100 data from NOAA for one-year cycle, the parameter λ for Texas was 0.54 (Table 6) (Liu and Vipulanandan, 2009). Interpreting the data, especially the λ value showed that Texas can expect one hurricane every two years.

The prediction models were developed for one-year cycle, two-year cycle to up to 10 year cycle. For ten years from 2009 to 2018 there was one hurricane in Texas. Hence using the 10-year cycle, it predicts 77% possibility of hurricane in year 2019 (Fig. 8) compared to 30% possibility of hurricane based on 1-year cycle. For Gulf of Mexico, using the 10-year cycle, it predicts 91% possibility of hurricane in year 2019 (Fig. 8) compared to 66% possibility of hurricane based on 1-year cycle (http://hurricanes.egr.uh).

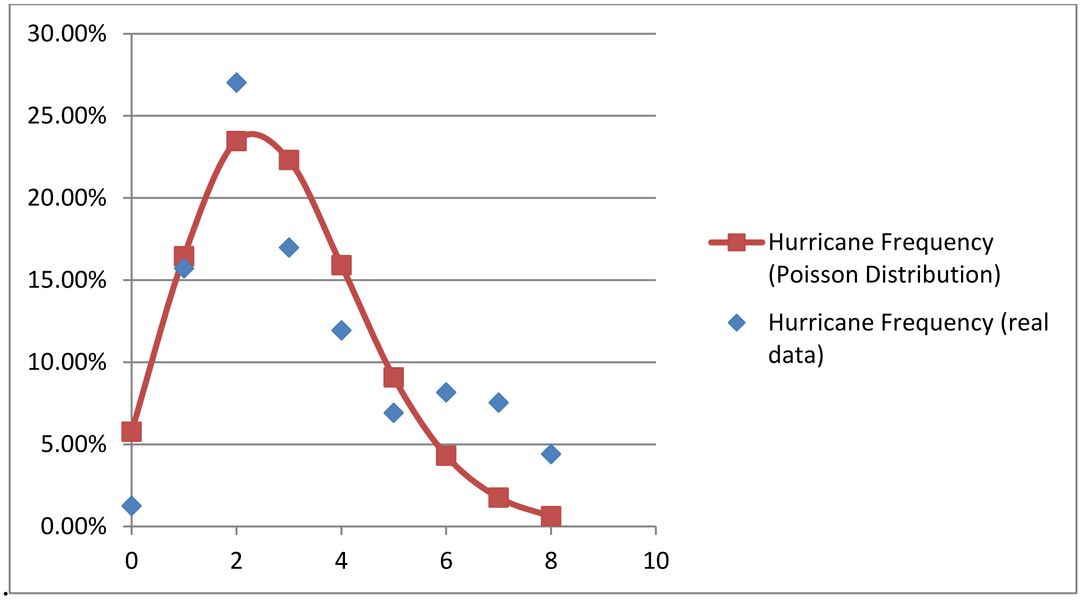

Figure 8. Probability distribution for 10-year cycle hurricanes in Texas

6. Lessons Learned

Based on the experiences from the worst hurricane in the State of Texas history and fire disasters the lessons learned are as follows:

a. Better prediction models are need for hurricane path after landfall with the intensity, rainfall and size of the hurricane. Also models are needed for fire disaster predictions.
b. Inland flooding has to be minimized and need better predictions for urban built in environments.
c. Real-time monitoring is critical for minimizing urban area fires and losses due to hurricanes
d. Educate the communities regarding preparedness, minimize losses and rapid recovery.
e. Minimize the drinking water infrastructure damages. Build redundancy in in power grids to minimize losses.
f. Improve debris removal and minimize the delay.
g. Consider adopting new technologies for real-time monitoring using drones, smart cement, flood protection, debris removal.
h. Evaluate the adaptation of Artificial Intelligent and Artificial Neural Network for predictions related to preparedness, losses and rapid recovery.

CONCLUSIONS

Based on the data collected from the Hurricane Harvey survey, FEMA report and NOAA data and evaluating new technologies following conclusions are advanced:

(1) Frequency of hurricanes reaching the Gulf of Mexico coast can be represented by the Poisson's distribution. Gulf coast has had 173 hurricanes in the past 167 years.

(2) Year 2017 was a historic year in the U.S. history where there was two category 4 hurricanes in two weeks in the Gulf of Mexico. Hurricane Harvey was the worst hurrincen the State of Texas history.

(3) Hurricane Harvey survey indicated varying degree of structural and utility damages. Several factors other than just the rainfall caused the damages.

(4) Damage models (DM-THC) developed after hurricane IKE will be modified to predict the structural, power and utility damages, debris issues due to a hurricane Harvey. Hurricane Harvey survey data will be used with the FEMA data to support the analyses.

(5) New technologies must be adopted with appropriate artificial intelligent and artificial neural network related to prediction about preparedness, losses, debris and rapid recovery.

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