EFFECTS OF LOSS ASSESSMENT AND MITIGATION OF BUILDINGS DUE TO CLIMATE CHANGE(HURRICANE)

Dhruti S Gowda
Dept.of Electronics and Communications
BNM Institute Of Technology
Bengaluru, India
dhruti.sreedhar@gmail.com

Joshitha Lakshminarayana
Dept.of Electronics and Communications
BNM Institute Of Technology
Bengaluru, India
joshithal1082@gmail.com

Vimalesh J
Dept.of Electronics and Communications
BNM Institute Of Technology
Bengaluru, India
vimaleshjyothish31@gmail.com

Kunal R
Dept.of Electronics and Communications
BNM Institute Of Technology
Bengaluru, India
kunalramesh123@gmail.com

Champa P.N.
Assistant Professor, Dept. of EEE
BNM Institute Of Technology
Bengaluru, India
champa.pn@gmail.com

***Abstract: Taking into account several climatescenarios, this research proposes a stochastic methodology for assessing hurricane risk for residential structures in hurricane-prone areas. Three mitigation measures are assessed as part of the framework, which also assesses the impact of climate change variability on wind hazard and induced losses. According to the study, hurricane intensity and frequency variations cause uneven annual losses, and using the wrong probability density function could understate the damage caused by hurricanes. Economic losses and human mortality are anticipated to rise disproportionately in hurricane-prone locations as coastal populations rise as a result of migration and urbanization. Developing appropriate and effective risk mitigation techniques requires an accurate assessment of hurricane-induced damage.Index Terms*—NPK Sensor, Soil Fertility, Mositure, Arduino, IoT**

I. INTRODUCTION

A large rise in their induced risk is anticipated as a result of the changing climate. So it is essential to accurately quantify hurricane-related losses in a changing environment in order to help create the most effective prevention measures. In order to estimate the damages caused by hurricanes to residential buildings situated in hurricane-prone areas, a stochastic framework for hurricane risk assessment that accounts for various climate scenarios is created in this study. The simulations of the future climate models are based on two global climate models and relate to the worst-case scenario SSP5-8.5. The consequences of the wind danger and its induced losses are quantitatively assessed in relation to the variability of climate change models. By comparing the associated losses experienced under various climate change scenarios, three mitigation solutions are assessed, each with varying levels of structural mitigation. The anticipated annual losses with the consideration of various mitigation techniques are found to shift unevenly from one location to another due to the variance of hurricane intensity and frequency over the coastal areas. Additionally, if the wrong probability density function is chosen to estimate the wind distribution, the loss caused by hurricanes may be underestimated. This is mostly because the wrong probability density function will not be able to effectively capture the upper tail ends of the wind distribution. Both economic losses and human mortality are anticipated to rise disproportionately in hurricane-prone areas due to the growing coastal population brought on by coastward migration and urbanization, as well as potential climate change effects on storm severity and frequency.Because storm intensities, durations, and frequency are shifting, coastal areas will disproportionately bear the brunt of the damage and losses caused by hurricanes. In order to design appropriate and effective risk mitigation methods, it is crucial to estimate the hurricane-induced damage and loss in the impacted areas in light of the changing climate.

Few studies have been dedicated to simulating climate change, although many have been proposed to assess the response/damage of light-frame wooden buildings subjected to wind loads in current climate. Studies have also examined the effects of climate change on hurricane dangers such wind, rain, and storm surge. Studies have also examined the effects of climate change on hurricane dangers such wind, rain, and storm surge.

Based on a series of synthetic hurricanes that reflect the effects of climate change through SST, Wang and Rosowsky []

assessed the regional loss in South Carolina.

As can be inferred, the majority of research papers are exclusively concentrated on a certain hurricane-prone region and they primarily analyze the effects of climate change through SST, which may not be correct because other environmental characteristics, known to significantly affect the storm intensity, are not taken into account.

In order to evaluate the losses of residential buildings situated in hurricane-prone areas, a stochastic hurricane risk framework is created in this study.

The average yearly losses are calculated for each location, and the effects of the varying climate change models on the wind danger and its associated losses are quantitatively assessed..

II. HURRICANE RIK AND FRAME WORK

A. Loosing Assessment for residual buildings

By representing the intensity measures vector X = [xh1, xh2, …]T corresponding tohurricane-induced hazards H = [h1, h2…] with the joint distribution function (PDF) fX(xh1, xh2, …) of X, one can evaluate the hurricane- induced loss for a residential building in terms of the total residential average annual loss (AALr) as **[ ]:** AALr = V × ∫ ∫ ∫ … ∫ L(X) × fX(xh1, xh2,…)dxh1dxh2… (1) where L(X) correspondsto the loss function of the residential building.

As a result, the intensity measure vector, X, is reduced to a scalar, v, which is the highest wind speed that can be computed using the discussed hurricane danger models and synthetic hurricane tracks.

When a joint PDF distribution, which can be quickly and effectively produced from the suggested GKDE technique, is used, multivariate loss functions can also be included without harming the generality of the proposed framework.

However, the Monte Carlo method is preferred in this framework since its extension to higher-dimensional integration, which is needed for multivariate loss function estimation, is straightforward and efficient.

B. Synthesic hurricane track

synthetic hurricane tracks in light of climate change In this work, synthetic storms are produced using the statistical-dynamical hurricane track model created by Snaiki and Wu [] under both the present and projected climates.

The statistical-dynamical model combines the statistical (based on data) and dynamical (based on physics-based equations) approaches, in contrast to other frameworks that exclusively rely on data to construct purely statistical models (not necessarily suitable for the modeling of future climate scenarios).

The hurricane genesis module, which gives the basic conditions (such as the location and storm parameters) of the storm, is where the development of the synthetic tracks begins.

Following this process, synthetic hurricanes covering a period of 10,000 years were produced for both the "observed climate" and the "future climate." simulated using the Earth3P-HR and CMCC-CM2-VHR4 global climate models, respectively. **[33].**

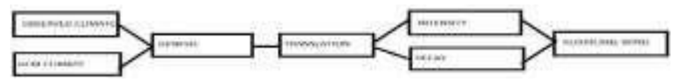

Fig. 1. Hurricane Track Methodology

C. Hurricane wind

The hurricane boundary-layer wind field is simulated in this study using an analytical wind model [].

The gradient wind and boundary-layer wind are the two terms that the analytical model in use breaks down the wind into.

D. Probability distribution using GKDE

Point estimates, such as moments, given by the estimated PDF are equal to the point estimates received from the data. This is achieved by using the Gaussian distribution, copulas, and gPC to fit a particular distribution or a family of distributions to the data. In this work, the PDF of the intensity measure was roughly estimated using a Gaussian kernel density estimation.

f x 1 K(X — Xi), where n is the total number of samples in the dataset and Xi is the ith sample of the intensity measures, is the formula for a general kernel density estimation (KDE) of the PDF of a random vector X. Based on engineering judgment and due tothe Gaussian kernel function's straightforward implementation and reliable performance, it was chosen for this study.

Fig.2. Geographical location of the selected cities

1. Case study

1.1 Picking a location

The suggested framework was tested on three homes in three coastal cities: Galveston, Texas (Fig. 2), Miami, Florida (25.79 latitude, 80.13 longitude), and Atlantic City, New Jersey (39.39 latitude, 74.49 longitude). Without losing the generality of the methods stated, it was assumed that the residence was worth $250,000.

1.2 Tracks and intensity measurements for hurricanes

CMCC-CM2-VHR4 (future climate 1) and EC-Earth3PHR (future climate 2) are two global climate models that were used to generate the current database of synthetic hurricane tracks, which is based on the Best Track Archive for Climate Stewardship (IBTrACS).

Fig.3 displays the data obtained for Atlantic City in the form of histograms based on the three chosen climatic scenarios, including (a) the current climate, (b) future climate 1, and (c) future climate 2.

The upper tail comparison leads to the conclusion that climate change will result in an increase in the frequency of strong winds.

Fig.4.One could draw the conclusion that, in contrast to Miami, Galveston will suffer more frequent and powerful wind speeds under future climate scenario 1.

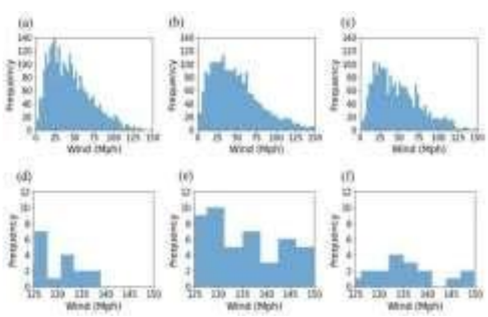

Fig. 3. Histogram shows the yearly maximum wind speed at the Atlantic City site for the three future climates shown in (a), (b), and (c), as well as the zoomed data corresponding to the upper tails for (d), (e), and (f) future climates.

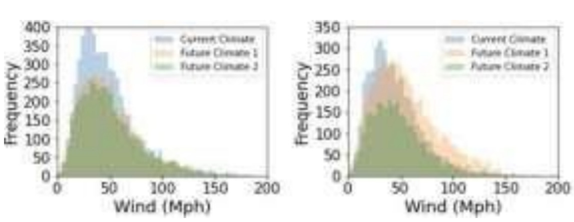

Fig. 4.Miami (left) and Galveston (right) yearly maximum wind speed histograms for the three chosen climatic scenarios.

1.3. Estimation of probabilitydistribution function

This study uses the Gaussian kernel density function (KDE) to determine the PDF of the yearly maximum wind speed. For the best fit, a cross-validation analysis identified a smoothing parameter h of 2.1. Under the current climatic scenario, the normalized histogram is placed on model wind data for three cities: Atlantic City, Miami, and Galveston. Particularly at tail ends where data concentration is minimal, the Gaussian KDE effectively captures data variance.

Loss estimate is considerably impacted since the KDE captures the upper tail ends of the distribution significantly better than the Weibull distribution. The Gaussian KDE captures higher order central moments more correctly than the Weibull distribution, according to the first four central moments estimated using model wind data, Weibull, and the Gaussian KDE.

It can be seen that there is a significant reduction in error when the moments are computed using the Gaussian KDE by comparing the absolute error (%) between estimated moments derived using the fitted PDF and their corresponding values from the generated data..

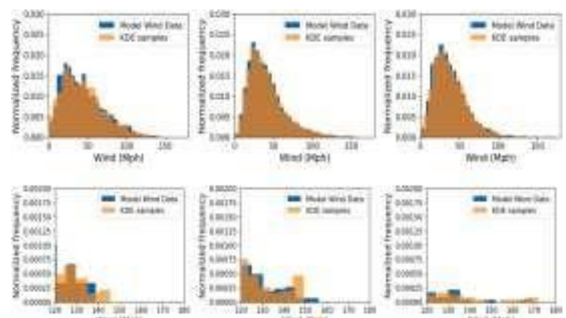

Fig. 5. Using the current climate scenario, KDE samples are placed on model wind data (top) and their associated zoome (bottom) for the wind speed distribution in Atlantic City (left), Miami (center), and Galveston..

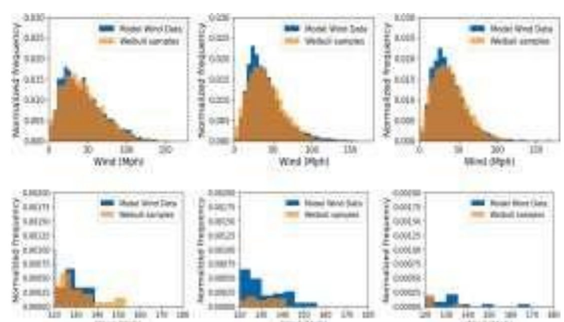

Fig. 6. Using the current climate scenario, Weibull samples were superimposed on model wind data (top) and their corresponding zoomed plot (bottom) for the wind speed distribution at Atlantic City, Miami, and Galveston.

Through increased understanding, sophisticated modeling, and in-depth statistical analysis, inherent uncertainties, which are divided into aleatoric and epistemic categories, can be eliminated. Epistemic uncertainty in the factors governing wind dispersion can be incorporated into Monte Carlo simulation. However, the ability to anticipate is constrained by knowledge gaps and high computing costs.

1.1 Residential loss assessment

A one-story, single-family woodframe house falling under the first group is not protected by any mitigation measures. The home is assumed to have a gable roof with 6d roof sheathing nails and a toe-nailed roof to wall connection. The roof is better on the second type of buildings, which have some mitigation. This is accomplished by putting in wind resistance roof shingles, which are thought to be 20% more resistant than the old house's standard shingles. Additionally, 8d nails are used, which now form a 6"/6" pattern connecting the roof to the deck. In the third case, a completely mitigated home has improved its roof as before and added a second layer of water resistance by employing a waterproof seal..

Fig.7. Estimated loss using the KDE distribution for three

cities under the current, future climate 1, and future climate 2 scenarios, with various mitigation techniques Type 0 has no mitigation (a). type 1-intermediate mitigation and type 2-high-level mitigation, respectively..

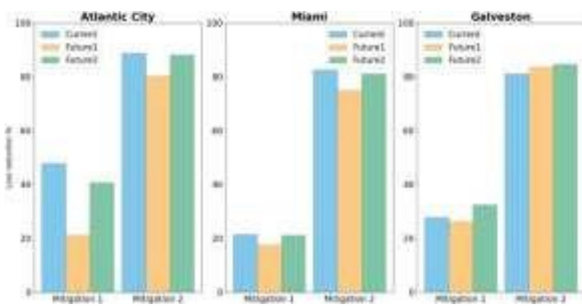

Fig.8. KDE distribution was used to estimate loss reduction for three cities under the current, future climate 1 and future climate 2 climatic scenarios.

Examples of this include global warming scenarios, model resolution, and the different parameterizations that were selected.

Due to the limited number of GCM simulations, it is unfortunately challenging to exactly quantify such uncertainties and determine the level of confidence in the forecast values.

In order to evaluate how the employed PDF, which estimates the wind speed distribution, affects the losses, the results of the Weibull distribution are shown in Fig. 8. By contrasting Figs. 8 and 10, it is clear that the selected PDF considerably affects the simulation results. For instance, KDE's loss at the unadjusted building in Miami under the present circumstances is $3907 dollars.

Fig. 8. Using the Weibull distribution and a variety of mitigating techniques, estimated loss for three cities under the current, future climate 1, and future climate 2 scenarios Type 0 has no mitigation (a). type 1-intermediate mitigation and type 2-high-level mitigation, respectively.

I I I .CONCLUSION

This research created an advanced stochastic hurricane risk framework to model the destruction of residential buildings as a result of hurricanes in hurricane-prone areas and systematized possible mitigating options under shifting climate scenarios. Two global climate models, CMCC-CM2-VHR4 and EC-Earth3P-HR, constitute the foundation of the future climate scenarios, which cover the years 2020–2050. The 1990–2020 period covered by the current climate scenario is based on the IBTrACS database. The worst-case emission scenario (SSP5-8.5) is considered in both future climate models. The constraints of the traditional parametric models are then removed by fusing the artificial tracks with a physics-based wind model. It was found that for three coastal cities—Atlantic City, Miami, and Galveston—the GKDE correctly predicted wind hazard probability.

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