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# MACHINE LEARNING ALGORITHMS FOR PERFORMANCE-BASED TORNADO ENGINEERING IN THE MATLAB® COMPUTING ENVIRONMENT

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## ABSTRACT

- Average annual insured losses from severe convective storms (includes ***tornadoes***) in the United States amount to ***11.23 billions dollars*** (adjusted for 2016).
- Despite significant strides made in improving investigations of tornadic wind actions on the built environment, the ***stochastic, non-stationary numerical analysis*** is still hampered by its ***heavy computational demand***.
- The predictive capabilities of ***machine learning algorithms*** in the field of ***performance-based tornado engineering*** can further enable ***smarter, more risk-informed decisions*** in prone environments.

## OVERVIEW OF RESPONSE SIMULATION PROCEDURE

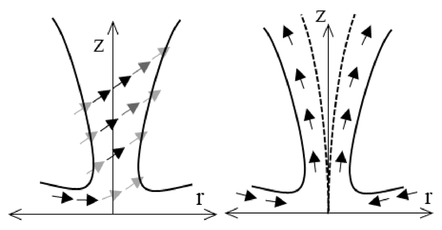
**Start**

**Dynamical System Module**
Develop differential equations of motion

**Vertical Structure**

$$\ddot{\varepsilon}_x + (R_x)\dot{\varepsilon}_x + (S_x)\dot{\varepsilon}_y + (\omega_{0,x}^2)\varepsilon_x = F_x$$
$$\ddot{\varepsilon}_y + (R_y)\dot{\varepsilon}_y + (S_y)\dot{\varepsilon}_x + (\omega_{0,y}^2)\varepsilon_y = F_y$$

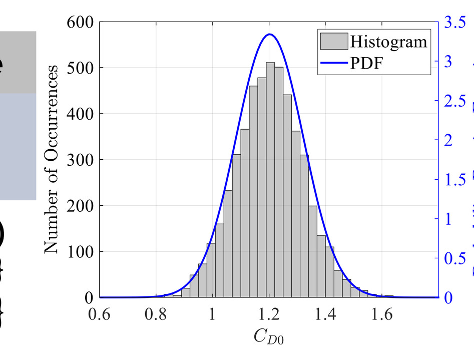
**Wind Loading Module**
Synthetic generation of wind field



**Wavelet-Galerkin Module**
Transformation into the wavelet domain

**WG approach (matrix notation)**

$$[\mathbf{A_{11}}]\boldsymbol{\eta}_{\mathbf{x(k)}} + [\mathbf{A_{12}}]\boldsymbol{\eta}_{\mathbf{y(k)}} = \{\mathbf{F_x}\}$$
$$[\mathbf{A_{12}}]\boldsymbol{\eta}_{\mathbf{x(k)}} + [\mathbf{A_{22}}]\boldsymbol{\eta}_{\mathbf{y(k)}} = \{\mathbf{F_y}\}$$



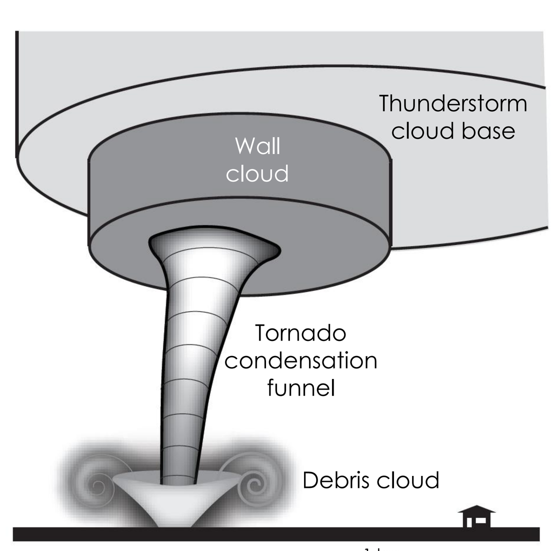

**Approximated time history of randomized structural response**

Repeat as needed for Monte-Carlo generation of training data

## INTRODUCTION

### Tornado

- Microscale columns of violently **rotating** and **ascending** air
- Highly **complex** and **non-stationary** wind field
  - Kuo-Wen, Fujita, Modified Rankine, Burgers-Rott, Baker
- Initial touchdown location
- Average radius 100 m
- Tangential velocities between 18 and 140 m/s

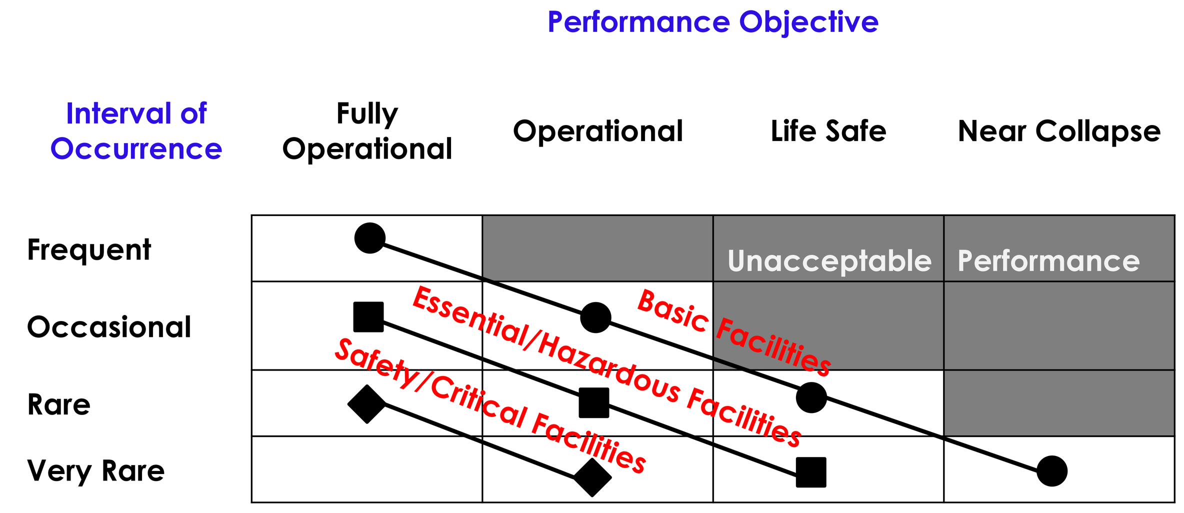



*(Left) Schematic of formation of tornado funnel cloud from thunderstorm. (Source: Stull, R., 2016, "Practical Meteorology: An Algebra-based Survey of Atmospheric Science")*

*(Right) Tornado touching down in Laramie, Wyoming, USA. (Source: Amateur photograph from Time magazine)*

### Performance-based Tornado Engineering

- Engineering demand parameter (e.g. structural displacement)
- **Performance objectives** (i.e. thresholds or limit states)
- Aleatory and epistemic sources of **uncertainty**




SEAOC Vision 2000 performance objectives for seismic design.

## OVERVIEW OF MACHINE-LEARNING ENABLED RISK AND DAMAGE ASSESSMENT

**Fragility Module**
Approximate fragility functions

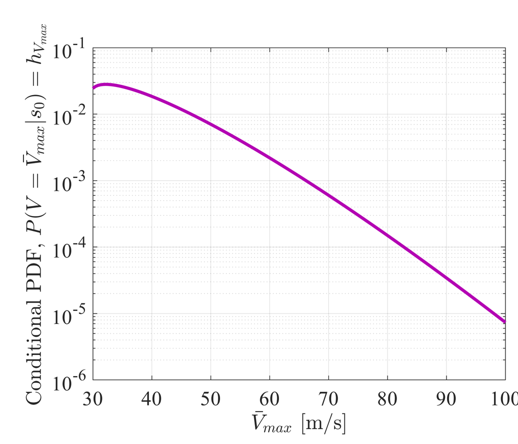
**Limit State**

$$T_C = 183\ \text{m} \times \frac{1}{400}$$
$$T_P = 35\ \text{m} \times \frac{1}{10}$$

**Complementary Cumulative Distribution Function**

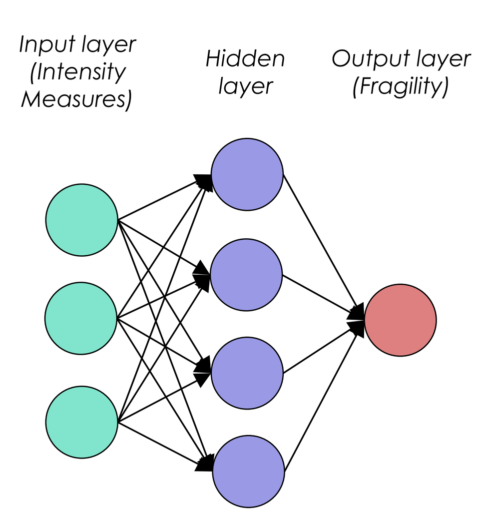
$$F_T(IM) = P[q^{max} > T_i | IM]$$

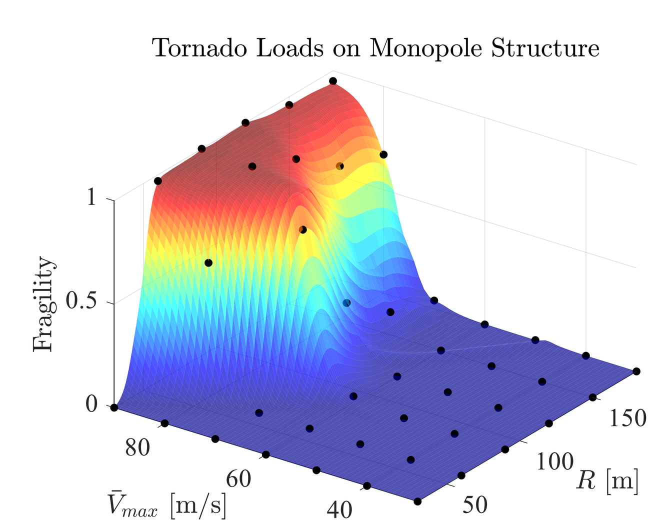
**Hazard Module**
Develop hazard curves




*Hazard curve for maximum mean tangential velocity of tornado.*

**Machine-learning Module**
**Smart Predictions**
Model fragility functions
Predict hazard occurrences
Low up-front computational costs



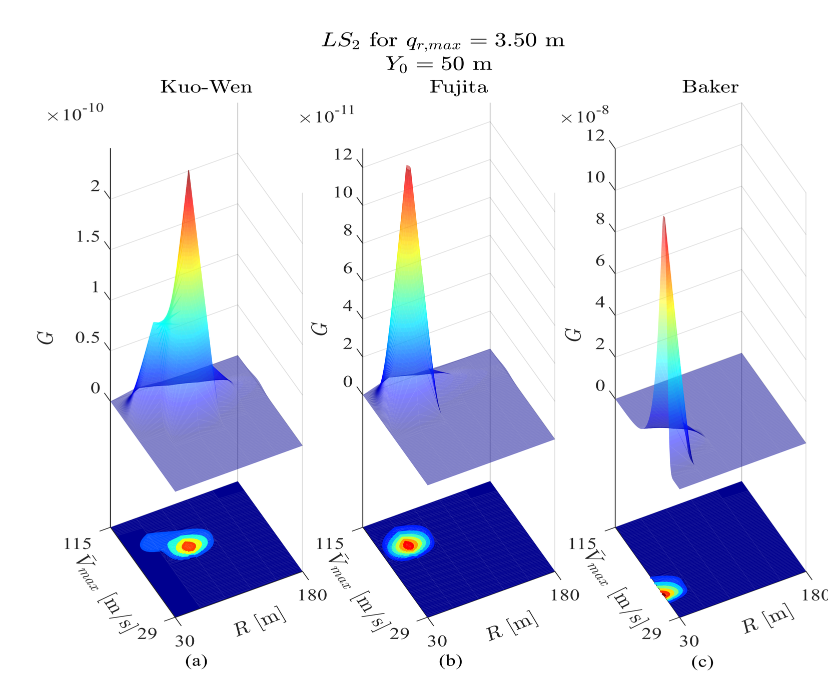




*(Left) Schematic of example feedforward neural network.*

*(Right) Neural network fitting of a fragility surface. Dots represent MC sample data points (R, tornado vortex radius, $V_{max}$ max. mean tangential wind speed).*

**Risk Assessment Module**
Calculate probability of performance/failure

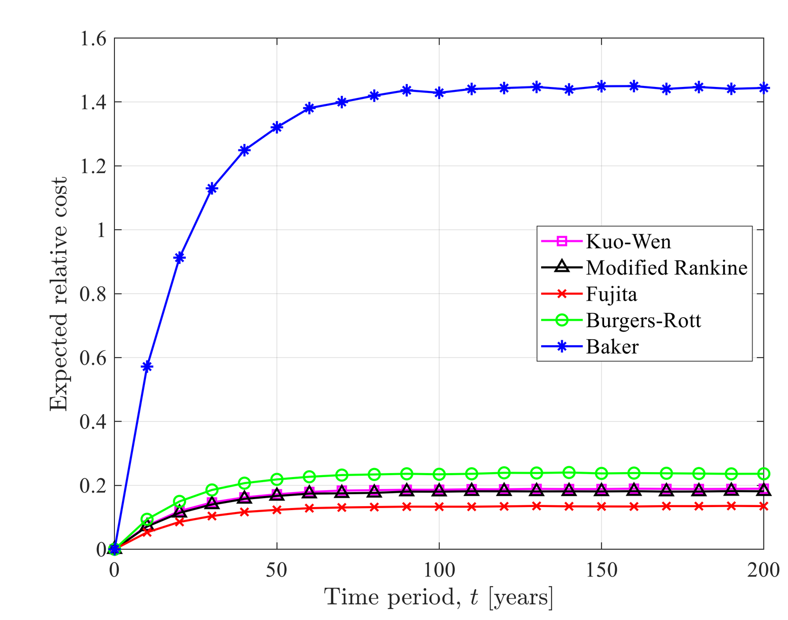
$$P_f = \int_{x=0}^{x=\infty} F_T(IM)\,h(IM)\,\mathrm{d}IM$$




Integrand probability for three tornado models.

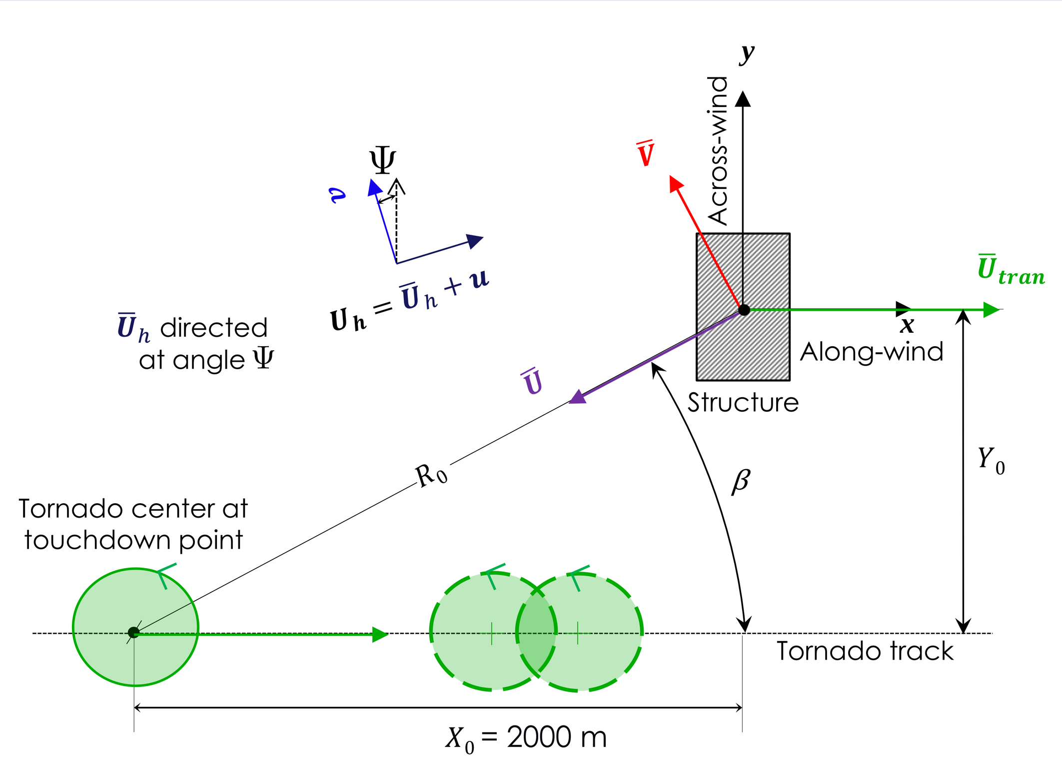
**Cost Module**
Evaluate life-cycle costs for maintenance or repair

$$\boldsymbol{E}\left[\frac{C(t) - C_0}{C_0}\right] = \boldsymbol{E}\left[\sum_{i=1}^{N(t)} \sum_{j=1}^{k} \epsilon_j e^{-\lambda t_i} P_j\right]$$

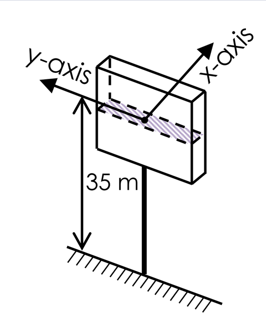



Relative cost curves for tornado loading on monopole structure.

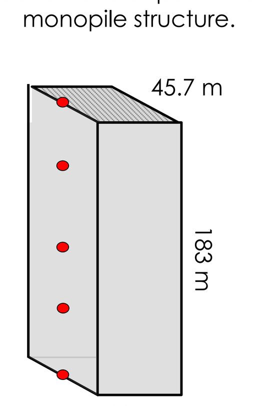
## WIND FIELD SIMULATION



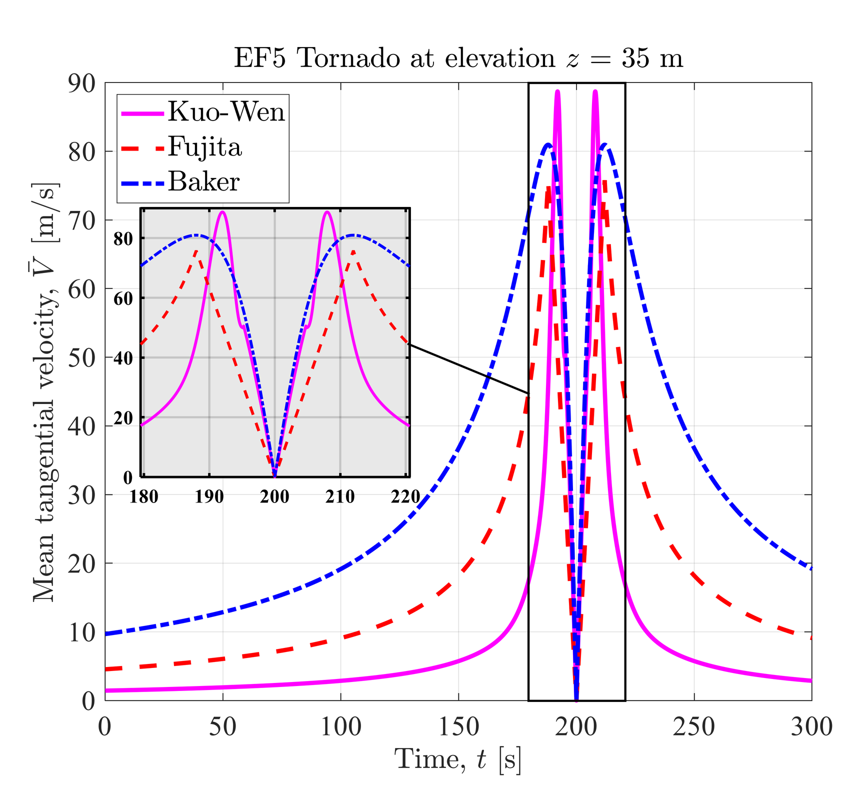

Schematic of fluid-structure system




Schematic of point-like monopile structure.




Schematic of reduced-order model of tall building.




Mean tangential velocity using three tornado models.

## RESEARCH HIGHLIGHTS

- Tornadic loading on vertical structures is a significant factor in risk assessment
- Advancements in numerical methods to analyze non-stationary, complex wind fields are hampered by their computational demand
- Machine-learning algorithms can be utilized to predict damages and risks within the performance-based tornado engineering framework
- Numerical models can be updated as additional information on the loads and the structure arrive.

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