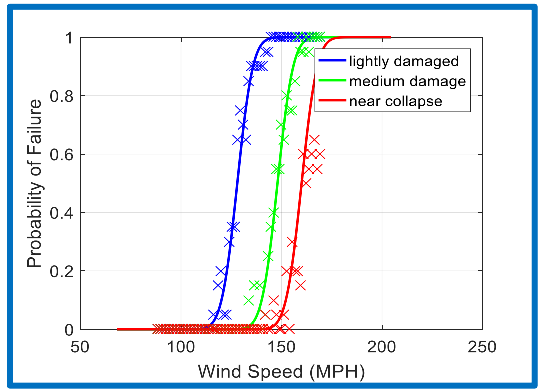
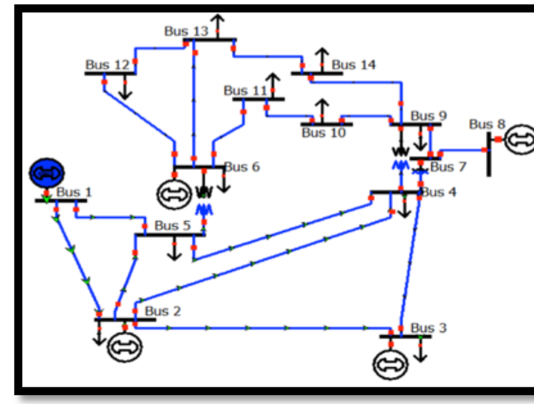
MACHINE LEARNING ASSISTED PREVENTIVE STOCHASTIC UNIT COMMITMENT

Hurricane Forecasting Module



Power Component Failure Estimation



Power System Preventive Operation

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The Use of Weather Forecast in Power Systems Operation

- Weather forecast is used for:
  - Load forecast
  - Renewable energy forecast (solar and wind)
- Extreme weather:
  - System operators have access to weather forecast
  - Some ISOs have meteorologists onsite
  - The forecast is not systematically used to adjust operation
  - **Most adjustments are made through engineering judgment**

Impacts of Extreme Weather

- Extreme weather
  - Windstorms: Hurricanes, Tornados
  - Ice storms and snow storms
- Impacts:
  - Load: load forecast models capture the impacts on load
  - Generation: the impacts are often minimal
  - **T&D systems: T&D failures**

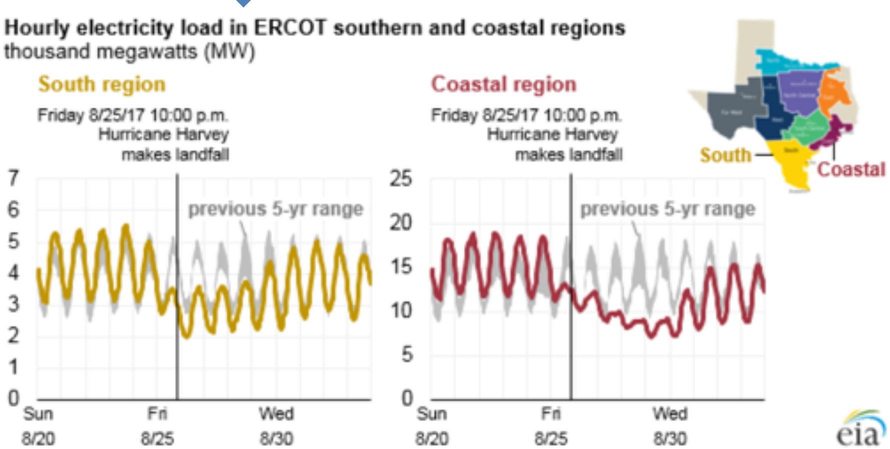
Example: Hurricane

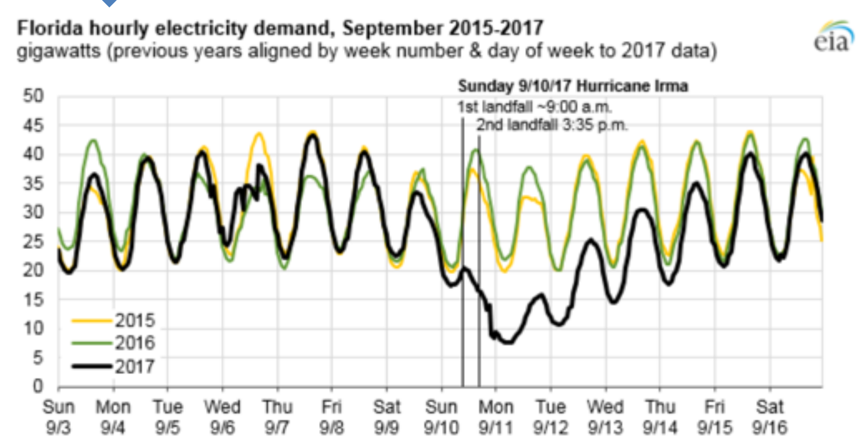
• **Damage level:** Low • **Main cause:** Flooding • **Wind**: Rarely an issue	• **Damage level:** High • **Main cause:** Wind force • **Flooding**: May aggravate the situation	• **Damage level:** High • **Main cause:** Wind force • **Flooding**: May aggravate the situation

Power Outage Statistics

- Hurricane season of 2017:

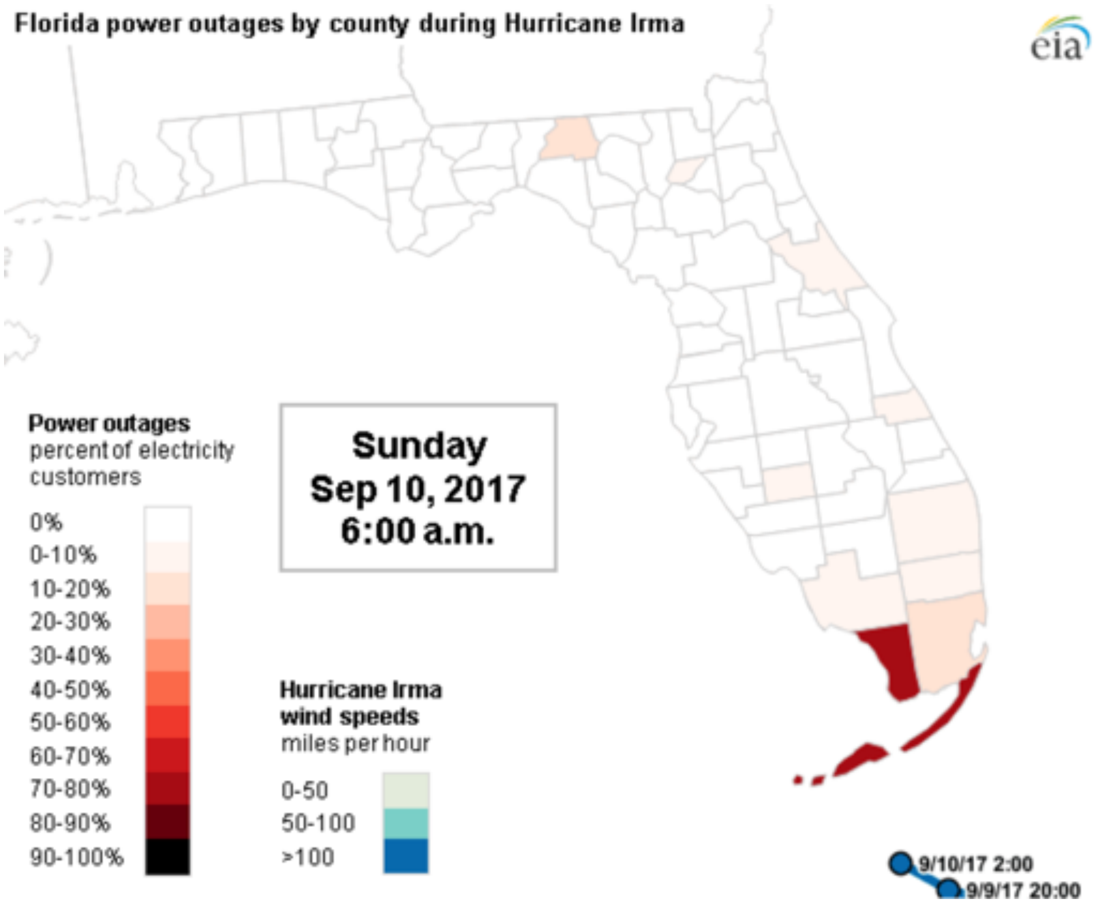
Harvey	Irma	Maria
August	September	September
• 300,000 customer outages in Texas	• 6 Million customer outages in FL (59%) • ~1 Million customer outages in GA (22%)	• 100% customer outage in PR





Why Focus on Transmission?

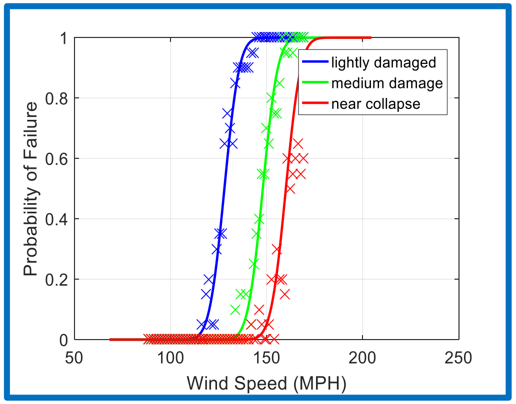
- Power outage in the areas, not in the hurricane track, is due to transmission-level damage.
- Such outages may be manageable, through weather-aware preventive operation.
- Transmission line outages in the past:
  - Harvey: 97 lines (>139 kV)
  - Sandy: 218 lines (>115 kV)



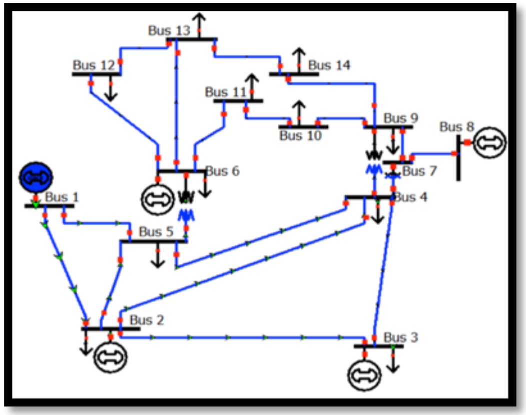
Preventive Operation

- Systematic integration of weather forecast data in power system operation
  - Conversion of weather data into useful information for operation: **component damage probability**

Weather Forecast Module



Power Component Failure Estimation

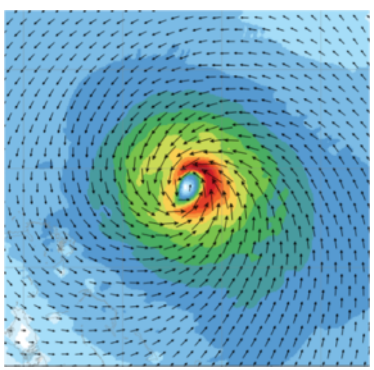


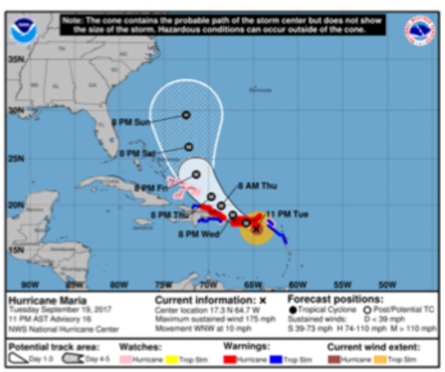
Preventive Power System Operation

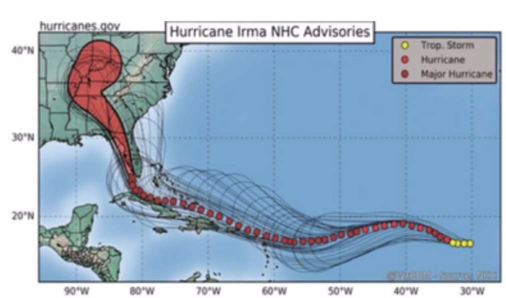
Uncertainty Propagation

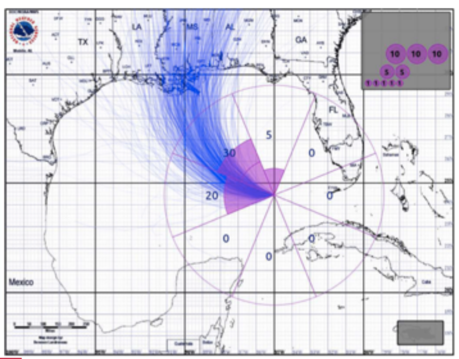
Weather Forecasting (Atmospheric Sciences)

- High-resolution wind field modeling
  - 1 Km horizontal
- Hurricane track and movement speed estimation
- Ensemble forecasting
  - Multiple tracks with different probabilities
- Forecast at different time scales
  - 5-day ahead, 48-hr ahead, day-ahead, hour-ahead



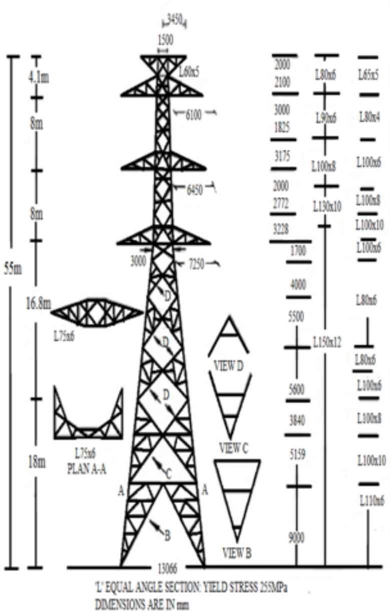




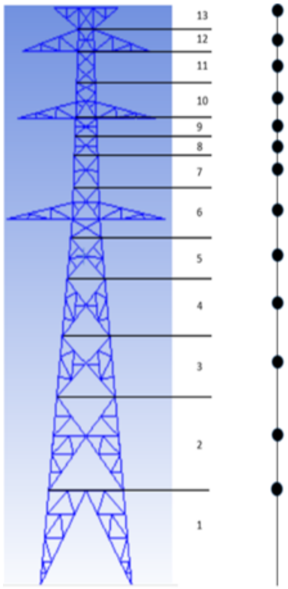


Transmission Failure Estimation

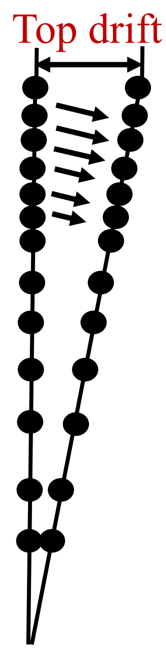
Structural Drawings



Finite Element Modeling

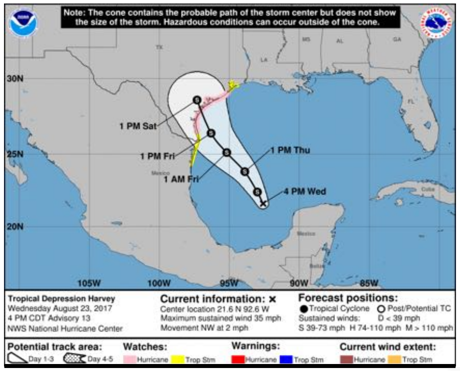


Stability under Dynamic Wind Loading

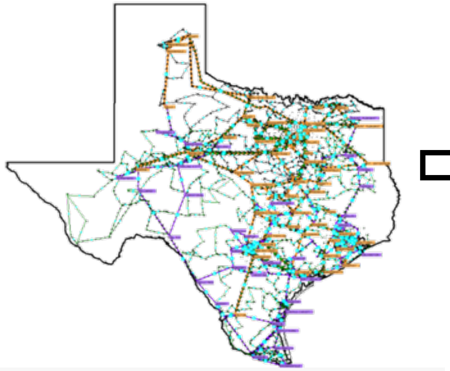


Transmission Failure Estimation cnt'd

Transmission line outage is estimated based on tower failure likelihood.



Hurricane Harvey Path



Texas System

$$P[FL,k] = 1 - P[SL,k]$$

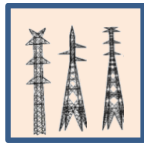
$$= 1 - \prod_{m=1}^{NT} F_{R,m}(V_m)$$

$P_m = F_{R,m}(V_m)$: m^{th} individual transmission line's failure probability

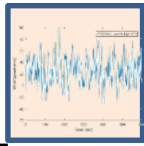
$P[SL,k]$: k^{th} transmission line's survival probability

NT: number of the tower

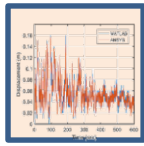
V_m: Wind Speed at the m^{th} tower



Transmission Tower Modeling



Wind Speed and Load Simulation

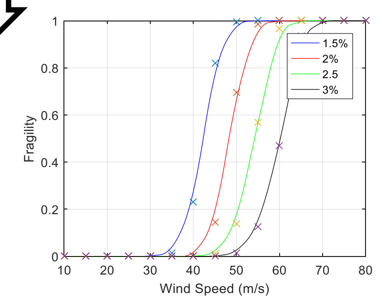


Dynamic Response of Transmission Tower Finite Element Model and Lumped Mass Model

Monte-Carlo Simulation to generate wind speed and set the limit state of transmission tower

$$F_R = P[l > LS | V_{10} = V]$$

- $l > LS$: Top drift of the transmission tower exceed the limit
- V : 10m/s-70m/s



Fragility Curve

Preventive Stochastic Unit Commitment

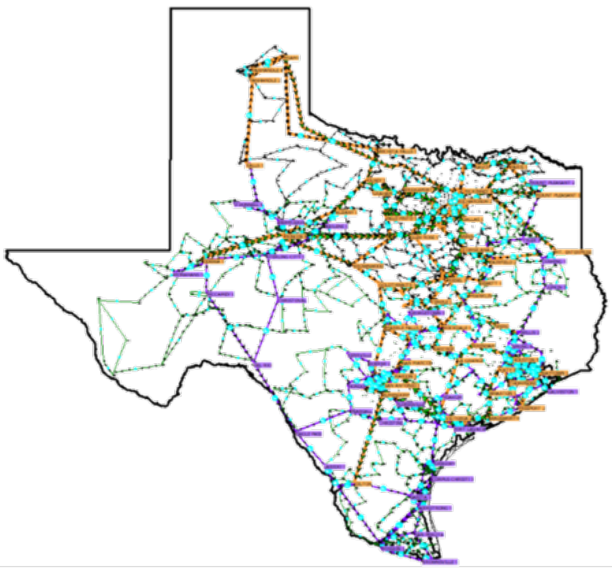
- Principles:
  - The estimated line outages are explicitly modeled, through scenarios
  - The objective function minimizes the expected cost, including penalty for power outage
- Solution: reduced power outages
- Challenges:
  - Multiple line outage modeling
  - Uncertainty management
  - Computational tractability

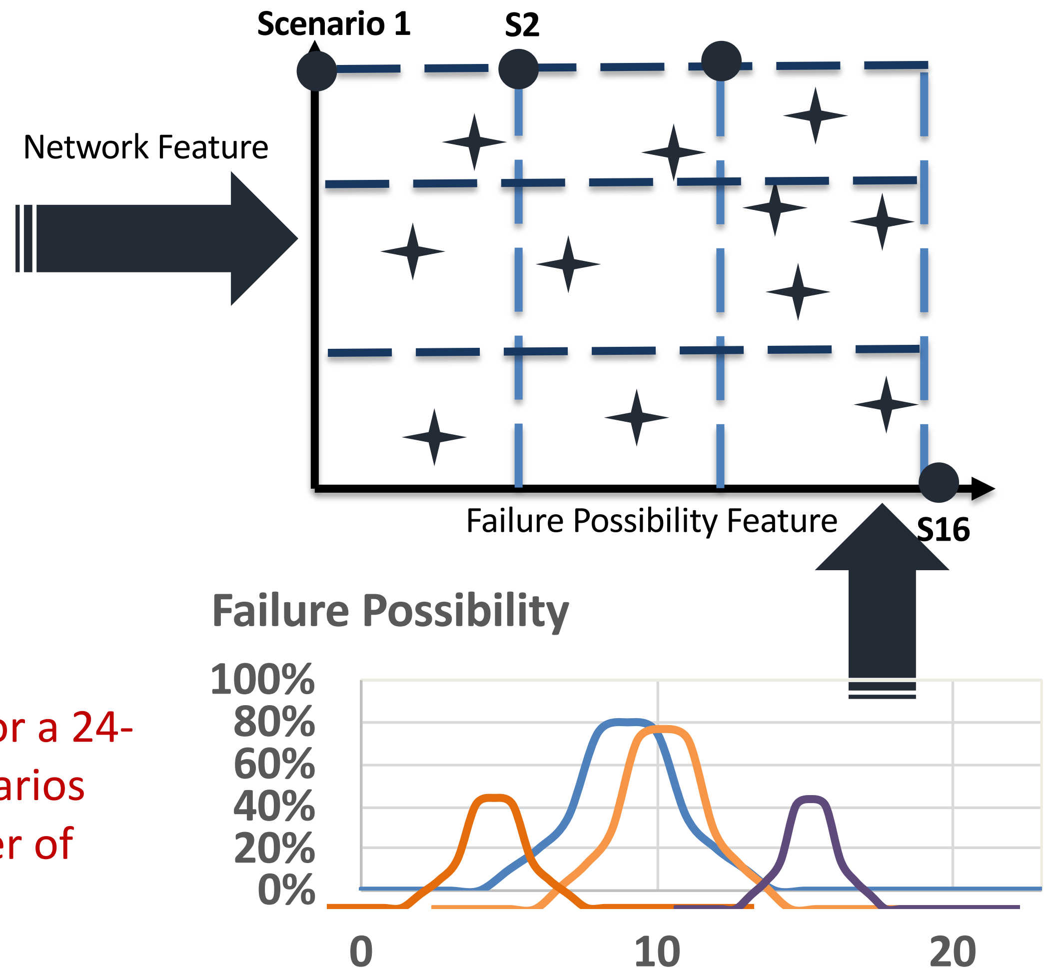
Multiple Outage Handling

- Shift factors are used in UC for flow modeling
- Shift factors change as the topology of the network changes
- Single line outages can be modeled by Line Outage Distribution Factors (LODF)
- LODFs are not valid for multiple line outages
- We use flow canceling transactions or generalized LODFs

F. Mohammadi and M. Sahraei-Ardakani, "Tractable Stochastic Unit Commitment for Large Systems during Predictable Hazards," *IEEE Access,* forthcoming, 2020

Uncertainty Management: Scenario Selection



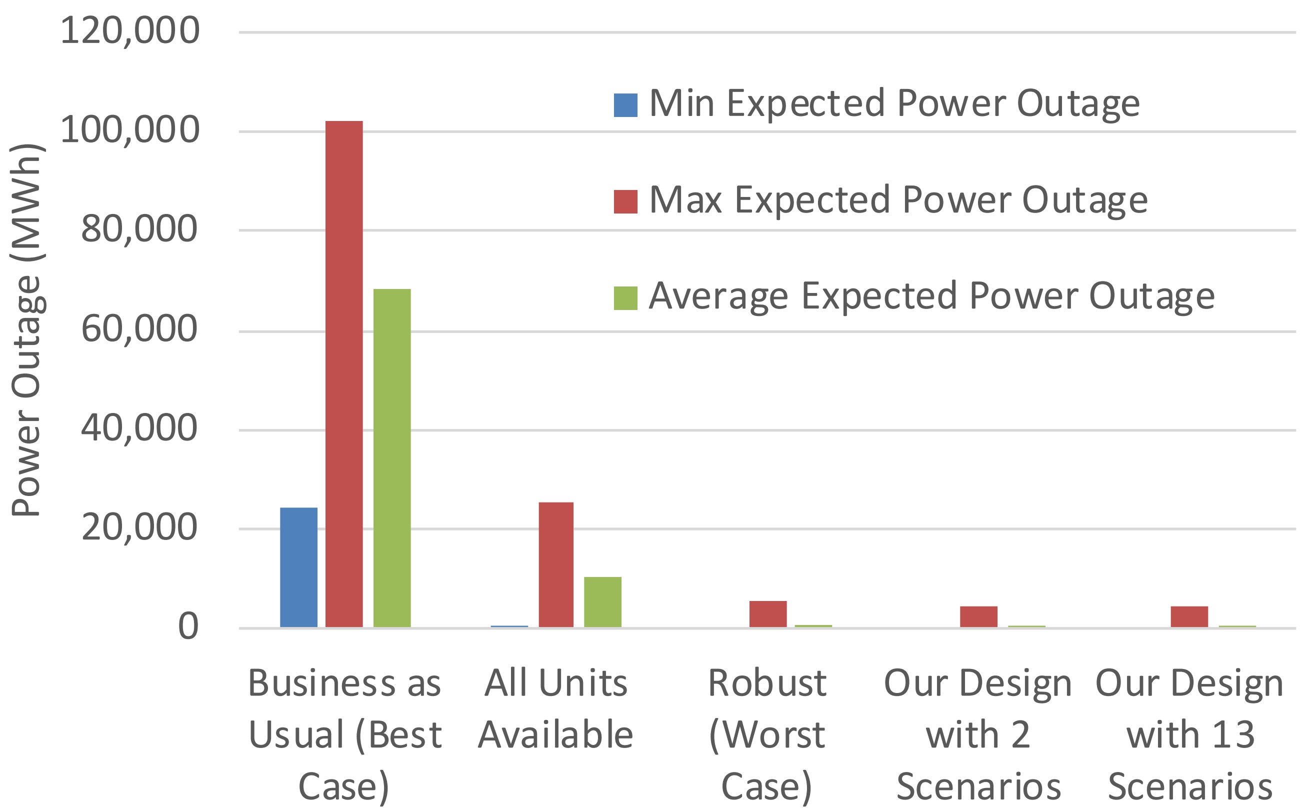


Large uncertainty set:

With only 36 lines affected, for a 24-hour UC, the number of scenarios can be larger than the number of atoms in earth!

F. Mohammadi and M. Sahraei-Ardakani, “Multidimensional Scenario Selection for Power Systems with Stochastic Failures,” *IEEE Transactions on Power Systems,* early access, 2020.

Simulation Results: Hurricane Harvey–Texas 2000 Bus System

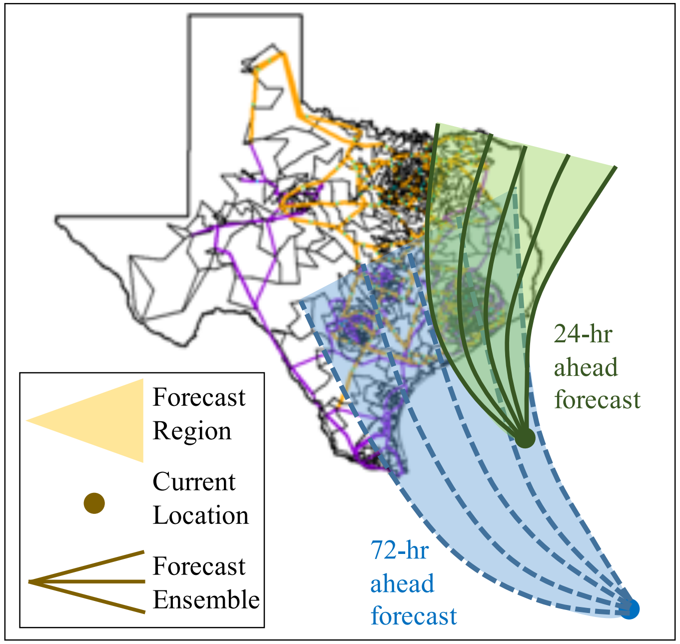


Computational Time:

~4 hours with 7 scenarios

Can machine learning be used to improve the solver?

- Improvement:
  - Solution quality (more scenarios)
  - Solution time (faster solve)
- Training data:
  - Earlier forecasts
    - Larger uncertainty range
    - More time to solve

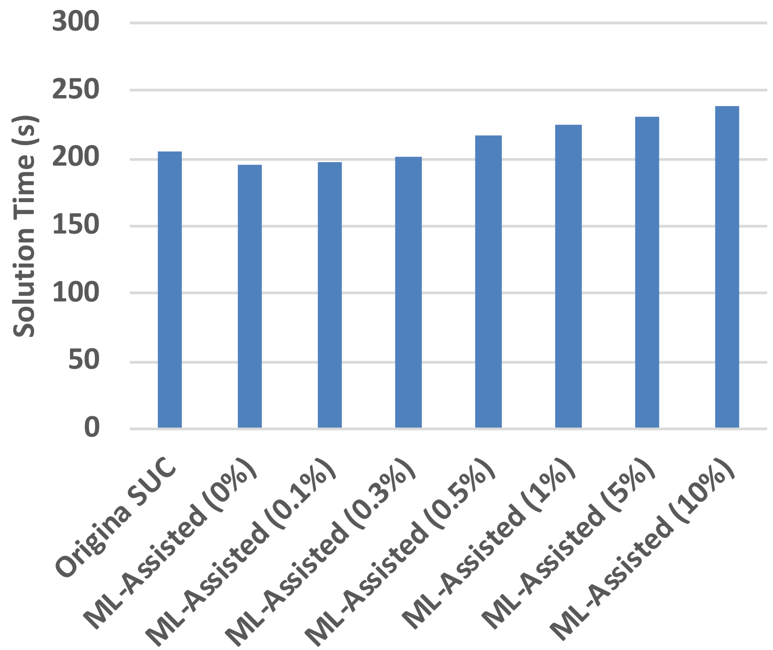


What to learn?

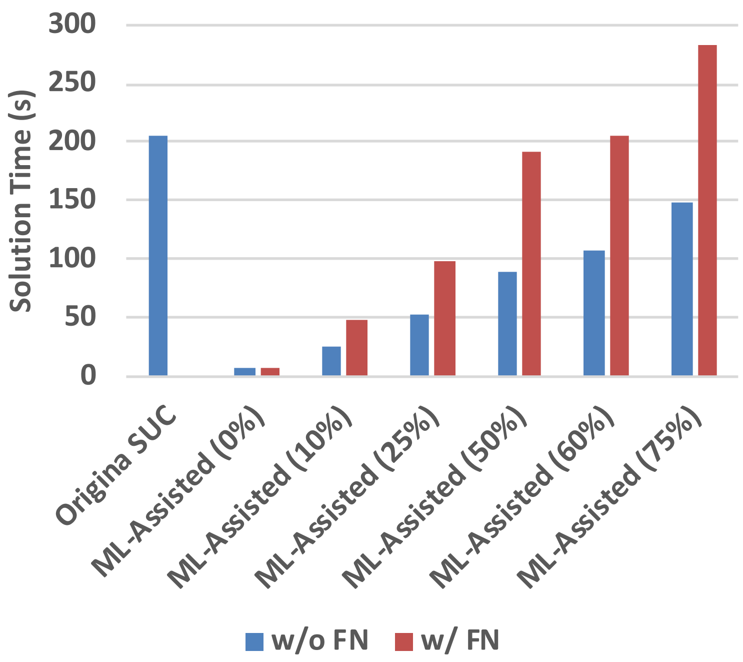
- Candidates:
  - Solution: commitment variables
  - Congested lines (model parameter)
    - Consistent with industry practices in normal operation
- Analysis:
  - The model is very sensitive to commitment estimation errors
  - Although commitment variables can be learned rather accurately, the computational time does not improve significantly
  - Learning congested lines has a significant impact, and the model is not sensitive to errors

Sensitivity Results

Learning Commitment Variables

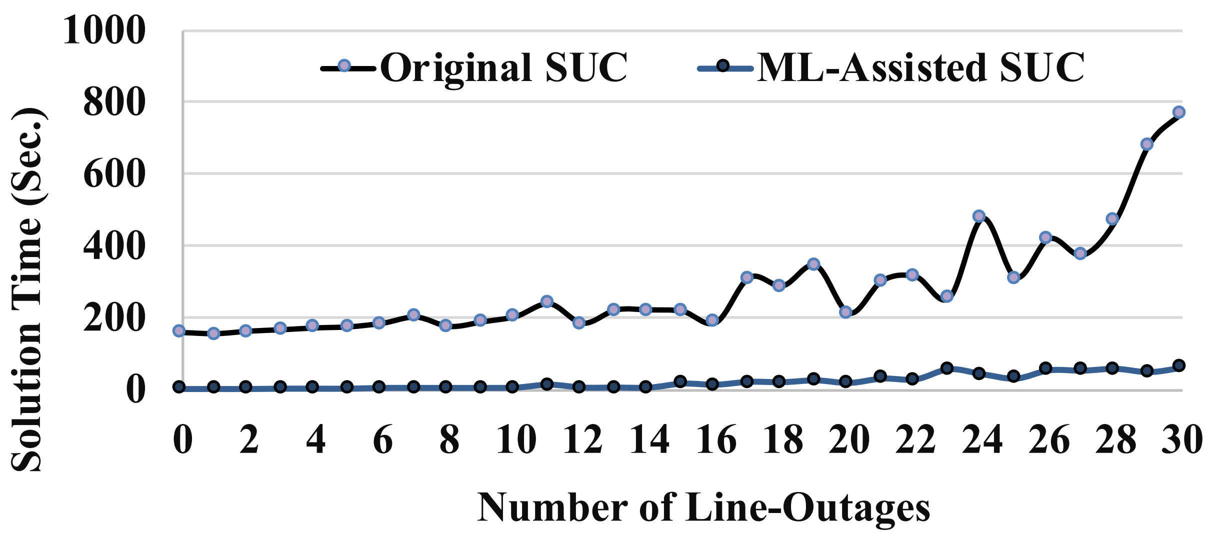


Learning Congested Lines



- Learning to identify the congested lines seems to be very effective
- This is consistent with industry practices

Results on South Carolina 500—Bus System



- Machine learning can be used effectively to identify congested lines, using early hurricane forecasts.
- The model is not too sensitive to estimation errors.
- False negatives can be removed to improve the model: overestimate congestion.
- The solution time is significantly reduced with the help of machine learning.
- This would allow for quality improvements such as modeling more scenarios.

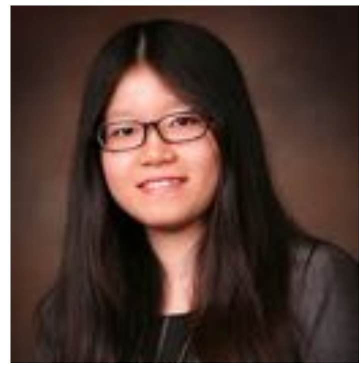
Conclusions

- Predictable weather-related natural hazards are the cause of about half of the blackouts in the US.
- Weather forecast data can be used to estimate component damage likelihood.
- Component damage estimations can be used to guide preventive operation.
- Appropriate integration of weather forecast data within power system operation can enhance system reliability.
- Machine learning can be effectively used to enhance computational tractability and model quality.
- Estimating the congested lines seems to be an appropriate way of using machine learning.
- Early hurricane forecasts can be used for model training.

Acknowledgement

Our Research Team

Principal Investigators

Atmospheric Sciences	Civil Engineering	Electrical Engineering
		
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References and Further Reading

- F. Mohammadi and M. Sahraei-Ardakani, "Tractable Stochastic Unit Commitment for Large Systems during Predictable Hazards," *IEEE Access*, forthcoming, 2020.
- J. Xue, X. Li, F. Mohammadi, M. Sahraei-Ardakani, Z. Pu, and G. Ou, "Impact of Transmission Tower-Line Interaction to the Bulk Power System during Hurricane," *Reliability Engineering and System Safety*, forthcoming, 2020.
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- Y. Sang, J. Xue, M. Sahraei-Ardakani, and G. Ou, "An Integrated Preventive Operation Framework for Power Systems During Hurricanes," *IEEE Systems Journal*, in press, 2019.
- P. A. Ruiz, E. Goldis, A. M. Rudkevich, M. C. Caramanis, C. R. Philbrick, and J. M. Foster, "Security-Constrained Transmission Topology Control MILP Formulation Using Sensitivity Factors," *IEEE Trans. Power Syst.*, vol. 32, no. 2, pp. 1597–1605, 2017.

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Thank You!