

# Modeling & Analytical Tools

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# **Probabilistic Wildfire Threat Model for Electric Systems**

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### BASIC PURPOSE OF THE PROBABILISTIC WILDFIRE THREAT MODEL (Model based on the Monte Carlo Technique)

- Provide stakeholders the ability to assess the risk posed by wildfires to regional or local electric infrastructure.
  - Given a high-level description of the scenario, evaluate the possible occurrence of wildfire in the region of interest .
  - Generate fragility curves (damage functions) for use to determine damage levels of electric assets given the fire intensity and/or wildfire zone perimeters/coverage.
  - Generate a list of possible at-risk electric assets that will serve as input to the probabilistic grid simulator (Enhanced *EPfast*).
  - Assess impacts (using EPfast) of the de-energization of the affected electric assets on the overall grid performance in a probabilistic fashion using the Monte Carlo technique. Measure impacts in terms of expected load loss, power flow re-routing, and economic dispatch cost (production cost).



### **MODELING APPROACH AND ARCHITECTURE**



### MODEL INPUTS: ELECTRIC INFRASRUCTURE, FRAGILITY CURVES, AND FIRE PROBABILITY HEAT MAPS

### FIRE IGNITION PROBABILITY HEAT MAPS

- UCLA Merced Index
- KBDI Drought indices
- FDI Fire Danger Index

### FRAGILITY CURVES

- probabilistic damage function
- binary damage function

### ELECTRIC INFRASTRUCTURE LAYER

- regional
- local

### HISTORICAL WILDFIRE PROGRESSION MAPS

- empirical wildfire patterns
- empirical wildfire intensities.



# MODEL OUTPUT: FIVE PROBABILISTIC GRAPHS



### MW loss frequency distribution graph





MW Lost versus Iteration Scatter Plo

Iterations Average StdDev+1 StdDev-

MW loss probability distribution curve









# MODEL OUTPUT: SEVEN RELIABILITY INDICES

- Allow comparison of system performance before and during event of wildfire.
- Expected load loss can be used to assess cost of unserved energy.

### **Reliability Indices**

ltem No.	Reliability Index	System 1 (A)	System 2 (B)	Ratio (B/A)
1	Expected Ave Load Loss (MW)	284	1,365	5
2	Expected Ave load loss as % of total sys load (%)	7%	34%	5
3	Probability of Exceeding System 1's Expected Ave load loss (%)	22%	90%	4
4	Probability of zero load loss (%)	70%	2%	0
5	Probability of losing 50% or more of total sys load	5%	24%	5
б	Expected Maximum Load Loss (MW)	2,941	3,470	1
7	Expect Max Load Loss as percent of total system load (%)	74%	87%	1





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# MODEL OUTPUT: DATA SHEET

- Contains list of the 2,000 cases simulated by the model
- Each case has an assigned seed number to allow for recovery/extraction of specific cases of interest.
- Extracted case can be studies in more detail.

				One Std Dev	One Std Dev										
	Iteration No.	Seed No.	MW Lost	Ave MW Lost above Ave	below		Seed No.	MWLost	Prob (%)			MW Lost	Frequency	Prob (%)	Cum prob (%)
esults	1	103586939	0	294.497658 907.0614111	-318.066095	Results Sorted	1712451782	2946.68	0.0005		Histogram	0	1372	0.686	0.68
eration	2	932398030	0	294.497658 907.0614111	-318.066095	Seed	1763485122	2737.22	0.001		MWLost	100	83	0.0415	0.727
eed	3	1900141615	0	294.497658 907.0614111	-318.066095	MWLost	949737376	2737.22	0.0015		Count	200	109	0.0545	0.78
IWLost	4	2043924542	0	294.497658 907.0614111	-318.066095	Pct	2021788353	2732.36	0.002		Pct	300	9	0.0045	0.786
	5	2025573606	0	294.497658 907.0614111	-318.066095	MWLost	1885994360	2732.36	0.0025		Cum. Pct	400	48	0.024	0.810
	6	674893329	0	294.497658 907.0614111	-318.066095		1798058629	2732.36	0.003			500	6	0.003	0.813
	7	962333120	0	294.497658 907.0614111	-318.066095		1629893394	2732.36	0.0035			600	13	0.0065	0.8
	8	584126828	0	294.497658 907.0614111	-318.066095		1440570268	2732.36	0.004			700	39	0.0195	0.839
	9	277669617	0	294.497658 907.0614111	-318.066095		1278569991	2732.36	0.0045			800	24	0.012	0.851
	10	1443737864	0	294.497658 907.0614111	-318.066095		1096897933	2732.36	0.005			900	15	0.0075	0.85
	11	1010655695	0	294.497658 907.0614111	-318.066095		1064922500	2732.36	0.0055			1000	50	0.025	0.88
	12	2113933863	0	294.497658 907.0614111	-318.066095		1035255858	2732.36	0.006			1100	29	0.0145	0.898
	13	804752883	0	294.497658 907.0614111	-318.066095		936849797	2732.36	0.0065			1200	21	0.0105	0.90
	14	1447432733	0	294.497658 907.0614111	-318.066095		890732729	2732.36	0.007			1300	15	0.0075	0.916
	15	533079150	0	294.497658 907.0614111	-318.066095		854738358	2732.36	0.0075			1400	10	0.005	0.921
	16	2033714755	0	294.497658 907.0614111	-318.066095		792815818	2732.36	0.008			1500	14	0.007	0.928
	17	147779121	0	294.497658 907.0614111	-318.066095		649590858	2732.36	0.0085			1600	7	0.0035	0.93
	18	1784708591	0	294.497658 907.0614111	-318.066095		601207988	2732.36	0.009			1700	24	0.012	0.94
	19	354433635	0	294.497658 907.0614111	-318.066095		590085885	2732.36	0.0095			1800	12	0.006	0.9
	20	1316836703	0	294.497658 907.0614111	-318.066095		368021599	2732.36	0.01			1900	11	0.0055	0.955
	21	1135220496	0	294.497658 907.0614111	-318.066095		352224629	2732.36	0.0105			2000	0	0	0.955
	22	808166901	0	294.497658 907.0614111	-318.066095		222899915	2732.36	0.011			2100	42	0.021	0.976
	23	489314026	0	294.497658 907.0614111	-318.066095		91748033	2732.36	0.0115			2200	3	0.0015	0.97
	24	462891880	0	294.497658 907.0614111	-318.066095		407102577	2609.246	0.012			2300	14	0.007	0.98
	25	1484647301	0	294.497658 907.0614111	-318.066095		1836843710	2527	0.0125			2400	4	0.002	0.98
	26	2138807462	0	294.497658 907.0614111	-318.066095		147011166	2498.64	0.013			2500	2	0.001	0.98
	27	1642791599	0	294.497658 907.0614111	-318.066095		402969883	2392.42	0.0135			2600	1	0.0005	0.988
	28	2336276	0	294.497658 907.0614111	-318.066095		569626507	2379	0.014			2700	22	0.011	0.999
	29	64097873	0	294.497658 907.0614111	-318.066095		88747366	2371.7	0.0145			2800	0	0	0.999
	30	1178691392	0	294.497658 907.0614111	-318.066095		894334533	2362.378	0.015		7	2900	1	0.0005	
	31	454283407	533.654	294.497658 907.0614111	-318.066095		1667081354	2343.32	0.0155			3000	0	0	
	32	1144339388	0	294.497658 907.0614111	-318.066095		1665847718	2343.32	0.016	up to 2	,0000				
	33	789347885	0	294.497658 907.0614111	-318.066095	up to 2,0000	1413942817	2343.32	0.0165						
	34	1160570963	0	294.497658 907.0614111	-318.066095		1243654187	2343.32	0.017						
	35	6022978	0	294.497658 907.0614111	-318.066095		1230712111	2343.32	0.0175						
	36	741828302	0	294.497658 907.0614111	-318.066095		1156152924	2343.32	0.018						
	27	489022542	0	294 497658 907 0614111	-218 066095		1075209199	22/12 22	0.0195						





### SUMMARY AND CONCLUSIONS

### A. The Probabilistic Threat Model can Potentially have following capabilities:

- > assess risk in terms MW loss from a variety of curves and tables.
- > compare system performance pre-event and during event via reliability indices.
- indicate alternate routing paths if there is no load loss by extracting no-load loss cases of interest from out of 2,000 simulated cases.
- > quantify increase in production cost due to re-routing or changes in generation dispatch.

### **B. Areas Needing Further Research or Effort:**

- > collection or development of fire probability heat maps for more regions of interest.
- development of wildfire fragility curves for electric assets.
- use of high-speed computers for increased Monte Carlo iterations and for analysis of broader regions of interest in finer geographic resolutions.





### **Probabilistic Wildfire Threat Model for Electric Systems**

**Edgar Portante, Steve Folga, Mark Petri - Argonne National Laboratory** 



# Wildfire Risk Modeling

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Apr 22, 2021

# **Capability Summary**

### **Objectives:**

- Better understand the contributing factors of wildfire caused by power delivery
- Better understand the dynamics of wildfire trend
- Predict wildfire incidents and outages

### Capabilities:

• Wildfire and outage analytical tools with statistical methods, stochastic process models, and machine learning

### **Potential Users:**

- Utilities (electricity, water, etc.) that do not own dedicated wildfire and outage tools
- Research community
- Policy makers, stakeholders, community developers, etc



# **Contributing Factors: Wildfire Ignitions by Power Systems**

• Three factors required for a wildfire ignition by power system infrastructure



### **Fire Danger Indices**

Fire danger indices provide an estimation of the **wildfire risk**. We have developed the capability to determine the following commonly-used indices for a range of time scales, from near **real-time** to a week, to seasonal outlook, to the longer-term projection over the next decades at high spatial (4km and 12km) resolutions.

- a) KBDI (Keetch-Byram Drought Index) [3,4]
  - Applied by U.S. Forest Service (USFS), Texas Forest Service, U.S. Army
- **b) FPI** (Fire Potential Index) [5,6]
  - Applied by USFS, United States Geological Survey (USGS)
  - Proprietary versions of FPI are being used by power utilities (e.g., PG&E, SCE)
- c) **CFWI** (Canadian Fire Weather Index) [6,7]
  - Applied by the Canadian Forest Service and variations have been adopted by Australia, France, and Croatia.
- d) A machine-learning fire danger model is being developed

[3] Keetch J. J. and Byram G. M. (1968). A Drought Index for Forest Fire Control SE-38 U.S.D.A. For. Serv. Res. Pap

[4] Brown, E.K., J. Wang, and Yan Feng. 2021. U.S. wildfire potential: a historical view and future projection using high-resolution climate data. Environmental Research Letters.
 [5] Burgan R.E., Klaver R. W., and Klarer J.M. (1998). Fuel models and fire potential from satellite and surface observations. International Journal of Wildland Fire, 8(3), 159 – 170
 [6] Yu, G., J Wang, Y. Feng, E. Brown, and D. Wright. 2021. The performance of fire danger indices and its utility in predicting future wildfire danger over the conterminous United States. To be submitted

[7]Turner, J.A. and Lawson, B.D. (1978). Weather in the Canadian Forest Fire Danger Rating System. A user guide to national standards and practices. Environment Canada, Pacific Forest Research Centre, Victoria, BC



# Methodologies

Statistics Analysis														
<ul> <li>Ordered logistic regression</li> </ul>														
<ul> <li>Association rules</li> </ul>														
<ul> <li>Decision tree</li> </ul>														
Lat Creat														
• Hot Spot														
<ul> <li>Emergent hot spot analysis</li> </ul>														
Stochastic Process														
<ul> <li>Spatial-temporal point process</li> </ul>														
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### Data Sets

### **Data Selection**

- PG&E, SCE, and SDG&E's Fire Incident Data 2014 2019<sub>4</sub> ~ ٠
- NLDAS Primary Forcing Data (Hourly) < potential evaporation, pressure, specific humidity,
- USGS Fire Forecast<sub>6</sub>
   fire potential index (FPI) and large fire probability (LFP)
- LandFire Existing Vegetation Type (EVT) and Height (EVH)7
- Environmental Protection Agency<sub>8</sub> Level III ecoregion and Level IV ecoregion
- CPUC Fire Threat Map<sub>9</sub> Tier 2 Elevated and Tier 3 Extreme
- California Public Utilities Commission (CPUC), available at https://www.cpuc.ca.gov/wildfires/ 4.
- NASA Land Data Assimilation System (NLDAS), available at https://ldas.gsfc.nasa.gov/nldas/v2/forcing 5.
- United States Geological Survey (USGS), available at https://firedanger.cr.usgs.gov/apps/staticmaps 6.
- LandFire (LF), available at https://www.landfire.gov/version\_comparison.php
- Environmental Protection Agency (EPA), available at https://www.epa.gov/eco-research/level-iii-and-iv-ecoregions-continental-united-states 8.
- 9. California Public Utilities Commission (CPUC), available at https://ia.cpuc.ca.gov/firemap/

- contact from object, date, equipment failure,
  - size (categorical), geographic location, time, and
    - temperature,
    - total precipitation,
    - relative humidity,

- utility name,
- voltage,
- among other variables

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- wind U component,
- wind V component, and
- wind speed.

- fuel class name, physiognomy, physiognomic order,
- physiognomic class, and
- physiognomic subclass.

material of origin,

outage,



# **Statistical Analysis**

Ordered Logistic Regression • Not statistically **Statistically Statistically** Model significant significant significant 6 Features 9 Features 8 Features Weather: Weather: Weather: potential evaporation potential evaporation potential evaporation pressure pressure pressure specific humidity specific humidity specific humidity temperature temperature temperature total precipitation total precipitation total precipitation wind speed wind speed wind speed Fire forecast: Fire forecast: fire potential index fire potential index NDVI Relative greenness large fire probability large fire probability Fuel Model Map FPI Live and dead fuel Vegetation: physiognomy **Statistically significant** 10-h dead fuel moisture Tmax, RH features

Results may be further improved by including power delivery information, e.g., power flow.

### **Fire Size**

- Decrease Risk
- Developed-Low Intensity
- Developed-Medium Intensity
- Developed-High Intensity
- Developed-Roads

#### Increase Risk

- Exotic Herbaceous
- Exotic Tree-shrub
- Grassland

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# **Statistical Analysis**

- Association rules
  - Identifies frequently occurring patterns on a dataset.
  - Makes predictions from subsets of co-occurring past events.

#### 9 Features

#### Weather:

- potential evaporation
- pressure
- specific humidity
- temperature
- total precipitation
- wind speed

#### Fire forecast:

- fire potential index
- large fire probability

#### Vegetation:

physiognomy

Examples of identified association rules	Fire Size S	Support	Confidence	Count
Developed-Roads	< 3 meters	7%	24%	160
No precipitation, Wind speed [2.47,4.59)	< 0.25 Acres	23%	54%	511
No precipitation, Temperature [14.8,21.7)	< 0.25 Acres	19%	55%	426
No precipitation, FPI [52.6,72)	< 0.25 Acres	17%	57%	375
No Precipitation, LFP [27.8,37]	< 10 Acres	8%	24%	187
FPI [72,99]	< 10 Acres	7%	24%	171



#### Definition

Support: How often a given rule appears in the data set.

Confidence: The amount of times a given rule appears, turns out to be true.

Count: Number of times the rule appears in the data set.





# **Statistical Analysis**



# **Emergent Hot Spot Analysis**

Emergent Hot Spot Analysis of PG&E, SCE, and SDGE's 2014-2019 Fire Incident Reports



Identifies trends in the clustering of point densities (counts) in a space-time cube.



New hot spots / cold spots – location that have never had an increasing / decreasing trend before



Sporadic hot spots / cold spots – location that is on and off an increasing / decreasing trend



Oscillating hot spots / cold spots – location that shows an increasing / decreasing trend in the last time a decreasing / increasing trend a time before.





# **Spatial-Temporal Point Process Modeling**

#### **Spatial-temporal point process** (STPP) model:

0.0065

0.0060 0.0055

ê <sup>0.0050</sup>

λ(*t*, *k*) 0.0040

0.0035 0.0030 0.0025

Winter

- Models the conditional intensity, i.e., the probability of an event occurring at time and location given history.
- It captures spatial-temporal correlation among events.
- Leverages available features (e.g., FPI, weather variables)
- Probabilistic generative model from which fire events can be simulated.

#### 2014 – 2019 Fire Incidents By EcoRegion Lvl 4

#### Cascades

- Central Basin and Range
- Central California Foothills and Coastal Mountains
- Central California Valley
- Coast Range
- Eastern Cascades Slopes and Foothills
- Klamath Mountains/California High North Coast Range
- Mojave Basin and Range
- Sierra Nevada



# **Power Outage Analysis and Prediction**



- Collected from public websites since 2018
- At city/county/zip code resolution
- Refresh every 3-15 minutes
- Weather record/forecast data
  - From NOAA
  - 100+ fields, including wind, temperature,...
  - 3-km resolution
  - Refresh every 15 minutes
- Studied regions
  - Massachusetts
  - Georgia (Georgia Power)
  - North & South Carolinas (Duke)





### Motivation: Multiple dimensions of grid resilience

- Grids in different regions are vulnerable to different weather variables.
- Figures show how the outages develop with regard to accumulated wind force.
- The jumps in blue lines indicate when largescale outages occur. The earlier the jump occurs, the less accumulated impacts the grid can absorb.
- The three figures on the right suggests that, among MA, GA, and NC&SC,
- GA grid can withstand more accumulated wind force. However, once



# Methodology

- A spatial-temporal model: consider both outage evolvement in time and interactions among geographic locations
- Assumptions
  - # outages at a location: a multivariate non-homogeneous Poisson process
  - Outages at a location results from the combination of:
    - (A) direct weather <u>cumulative</u> impacts cumulative: weather in the past d days matters; recent weather plays a bigger role

$$v_{i,t,m} = \sum_{\tau=t-d+1}^{t} x_{i,\tau,m} \exp\{-\omega_m(t-\tau)\}$$

- (B) neighboring outages (e.g., fault propagation, cascading outages)
- The outage **rate** at location *i* in time *t* is:

$$\lambda_{it} = \gamma_i \mu(\boldsymbol{v}_{it}; \varphi) + \sum_{t' < t} \sum_{(i,j) \in \mathcal{E}} g(i, j, t, t')$$
Direct cumulative Indirect impacts from

Direct cumulative weather impacts

Indirect impacts from neighboring outages





### **Results: outage prediction**



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### **Results: outage propagations**

- The learned spatial parameters indicate that the outages at a certain number of "critical" locations are likely to "cause" outages at other locations (see figures below).
- □ The causality might be: outage propagations, relative locations in grid topology or terrain, etc.
- It might suggest that, improving the resilience at these "critical" locations might further reduce the outages at other locations.



The map shows the spatial propagation of power outages among geographical locations during extreme weather.

- An edge between two locations indicates the power outages occurred in one location (light red) are resulted by the other (dark red).
   Edge width and color depth represent the number of customer power outages at the target attributed to the source.
- The size of dots represents the total number of customers of the corresponding geographical location.



# **Results: resilience characterization**

- Our model quantifies the classic resilience curve
  - Service degradation stage:
    - Grid can absorb weather impacts up to a certain level
  - Service recovery stage
    - Outage numbers will reduce as system restoration starts

Resilience curve	Our model
Grid capability in absorbing weather impacts	<ul> <li>Use accumulative weather force as inputs</li> <li>Parameters modeling weather force accumulation length</li> <li>Stochastic model characteristics</li> </ul>
Service restoration stage	<ul> <li>Two types of parameters control the decay rate of outages, which are essentially the service restoration rate.</li> </ul>





### **Results: Resilience Enhancement Suggestions**

By adjusting model parameters, we can reduce the outage numbers produced by the model. Does this suggest some strategies for enhancing system resilience?



Reduce interdependence among locations: reduce negative impacts from neighboring locations, which, in reality, might mean hardening the electric connection between two locations. Figures on the left suggest that, for NC&SC, reducing locational interdependent among just few locations can achieve significant reduction on outages; but the benefits diminish quickly. For GA to achieve a similar level of outage reduction, we need to reduce interdependence among a large number of locations and by a large amount.

**Reduce vulnerability at a location:** change parameter values at a location that reflect its capability of absorbing weather impacts. The red graphs indicate that, by just enhancing the few top vulnerable locations in NC&SC, the outages can be significantly reduced. However, this is not the case for MA and GA. These experiments suggest that, for different regions, there are different resilience enhancement strategies that work best for each region.



# **Argonne's Wildfire Team**

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# **Operations and Planning for Wildfire Risk Mitigation**

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Apr 22, 2021

# **Contributing Factors: Wildfire Ignitions by Power Systems**

• Three factors required for a wildfire ignition by power system infrastructure



# **Capability Summary**

### **Objective:**

- Incorporate wildfire risk understanding in power systems operations and planning to
  - mitigate risks of causing fires and
  - reduce interruptions of service

### Capabilities:

- Operation Stage
  - Topology control/re-routing power to avoid high-fire-risk areas
  - Demand response to reduce loads
- Planning Stage
  - Transmission expansion planning considering long-term wildfire threat
  - Networked microgrids to reduce outages during power shutoff
- Disaster Response
  - Grid services restoration after fires or other disasters

### **Potential Users:**

Utilities, research communities





### **Optimal Public Safety Power Shutoff**

Wildfire Mitigation Via Optimal Transmission De-Energizing

- **Decision-Support Wildfire Mitigation Tool** 
  - Assist in optimally dispatching PSPS
  - Input: Wildfire risk associated with each transmission line
  - <u>Output:</u> Set of lines and buses to de-energize to reduce the probability of a power-systemsignited wildfire while minimizing load shedding
  - Developed novel anti-islanding scheme, method to enforce N-1 security


# **Demand Response for Resilience**

- Integrate demand response into restoration and emergent energy management
  - Further extend island operation duration
  - Applicable for buildings and residential homes
  - Powered by two-level management framework
- Real-time building-level management is verified
  - Facility for Low Energy eXperiments (FLEXLAB) at LBNL
  - Stone edge farm microgrid in Sonoma, California



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Tested at FLEXLAB and Stone edge farm microgrid

# **Grid Design and System Hardening**

### Stochastic Expansion and Switching Planning for PSPS [6]

- Transmission and generation expansion (TGEP)
- Optimal power flow (OPF)
- Transmission line hardening: targeted undergrounding
- Transmission line switching
- Weather station information
- Index: KBDI
- Satellite vegetation images

Cost/Benefit Analysis					
Planning budget	Hardening budget	Transmission lines*			
(US\$ million)	(US\$ million)	(km)	Percentage		
600	0	169	37 %		
600	38	118	26 %		
600	76	68	15 %		
600	127	0	0 %		
400	0	169	37 %		
400	38	118	26 %		
400	76	68	15 %		
400	127	0	0 %		

High-fire-threat identified locations: Mexico's most wildfire affected regions



- Optimization model
  - Large-scale MILO model
  - Stochastic approach
  - High performance computer (HPC)





\*Powered transmission lines with wildfire ignition risk after line switching

[6] D.A. Zuniga Vazquez, F. Qiu, N. Fan, K. Sharp, D. Zhao, T. Hong, Stochastic Expansion and Switching Planning for Public Safety Power Shutoffs, to be submitted to IEEE Transaction on Power Systems, Apr 2021.

# **Planning Stage - Grid Design and System Hardening**

### Grid Topology Improvements to Mitigate or Reduce Public Safety Power Shutoff (PSPS) Events

#### Pacific Gas and Electric (PG&E) [4]:

- 6 temporary microgrids (3 via pre-installed interconnection hubs) for PSPS events
- 62 substations operationally ready to leverage temporary generation during PSPS events

PG&E Targets	2021	2022
Temporary Distribution Microgrid	5 additional microgrids	7 additional microgrids
Substation Distribution Microgrid	8 microgrids	8 microgrids

#### Southern California Edison (SCE) [5]:

- In early 2020, a Request for Proposal (RFP) was issued unsuccessfully for six microgrid. Further research/analysis is required.
- Over the next three years (2021-2023) SCE aims for the substantial completion of a microgrid site.



#### Key innovation:

- Dynamic (networked) microgrids when disconnected from main grid
- · Use mobile generator to supply local demand
- Co-optimized repair truck routing for distribution system restoration
- Optimized vegetation management for fire ignition risk reduction





[4] Pacific Gas and Electric Company (PG&E), 2021 Wildfire Mitigation Plan Report
 [5] Southern California Edison (SCE), 2021 Wildfire Mitigation Plan Update.

# **Networked Microgrids**

- Networked Microgrids
  - Physically-connected for exchanging power;
  - Functionally-networked for coordination;
- Significantly extend island operation duration
- Successfully demonstrated
  - Bronzeville-IIT "microgrid cluster"
- ANL is leading the efforts to demonstrate on IIT campus with multiple building microgrids





https://www.comed.com/News/Pages/NewsReleases/2018\_02\_28.aspx

# **Networked Microgrids w/ Dynamic Boundary**

### Static Microgrids vs. Dynamic Microgrids

 A distribution grid can be automatically divided into several autonomous microgrids surrounding local energy resources in response to power outages in the system. The configuration of these microgrids can be changed dynamically

Static MGs	Dynamic MGs
Static electric boundaries and connection point with external system	Dynamic electric boundaries and dynamic point of interconnection with external system
Energy resources are managed in a static group	Energy resources need to be grouped dynamically
Operates as a single entity	Coordination operation is required





Regrouped

DG

(R)

Dynamic MG #2

Dynamic MG #1 (R)-



# **Distribution Restoration**

- Integrated restoration framework developed by ANL
  - Solar + Storage
  - Mobile storage
  - Crew dispatch
- Address practical issues (e.g., cold load pick-up, switching sequence, large-scale, repair and maintenance)
- Powered by comprehensive modeling and optimization techniques



Integrate flexible operational concepts (e.g., DER, microgrid, mobile storage) with practical constraints (e.g., CLPU, switching, repair)



# **Argonne's Wildfire Team**

#### Grid Program Lead:

Mark Petri

#### Energy Systems (ES) Division:

Feng Qiu, Dongbo Zhao, Tianqi Hong, Rui Yao, Alinson Xavier, Shijia Zhao, Alyssa Kody, Daniel Zuniga, Bo Chen, Shijia Zhao,

Manager, Advanced Grid Modeling, Optimization and Analytics Principal Energy Systems Scientist Energy System Scientist Energy Systems Scientist Computational Scientist Postdoctoral Appointee Argonne Scholar Co-Op Technical – PhD Energy System Scientist Research Staff





## Acknowledgement

Most of these works are supported by

Argonne Laboratory Directed Research and Development (LDRD), Advanced Grid Modeling (AGM) under DOE Office of Electricity, Solar Energy Technology Office (SETO) under DOE EERE, Advanced Research Projects Agency–Energy (ARPA-e),

Grid Modernization Lab Consortium (GMLC)



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> **Feng Qiu,** Manager, Advanced Grid Modeling, Optimization, and Analytics, Argonne National Laboratory

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# Geospatial Analysis Tool Kit for Regional Climate Datasets (GATOR)

James Kuiper • Environmental Science Division

April 22, 2021

# What does GATOR do?

- GATOR\* computes climate statistics from Argonne climate modeling results, and outputs mapping layers
- Input data are daily values for: •
  - Heat index,
- Temperature (maximum and minimum),
- Precipitation, Wind chill,
- Relative humidity, • Wind speed, and
- Solar radiance,
- Keetch-Byram Drought Index (KBDI)

spanning three 10-year periods:

- Historical (1995 2004)
- Mid-century (2045 2054), and
- End-of-century (2085 2094)

for North America at a 12km resolution

 The GATOR data repository was recently updated to include KBDI data, and the code was updated to include it (GATOR-FIRE)

\*Kuiper, James, Veerabhadra Kotamarthi, Andrew Orr and Jiali Wang. Geospatial Analysis Tool Kit for Regional Climate Datasets (GATOR) An Open-source Tool to Compute Climate Statistic GIS Layers from Argonne Climate Modeling Results. Argonne National Laboratory, ANL/EVS-18/3, August, 2017.



# What is the Keetch-Byram Drought Index (KBDI)?

- KBDI\* is an index used to describe wildfire potential
- Calculated using daily maximum temperature, daily precipitation, and annual accumulated precipitation
- Values range from 0 (low wildfire potential) to 800 (extreme drought and unpredictable wildfire behavior)
- Used by the U.S. Forest Service, Texas Forest Service, U.S. Army, and Canadian Forest Service for fire management and planning

\*Keetch, J. J.; Byram, G. M. A Drought Index for Forest Fire Control SE-38. U.S.D.A. Forest Service Research Paper 1968.



Spruce beetle damage in Oregon Source: USFS, https://www.flickr.com/photos/

151887236 @N05/36317722686/in/album-72157687935138872/





# What is the Keetch-Byram Drought Index (KBDI)?

- Computed KDBI for most of North America from observed historical data, and modeled historical and projected future data<sup>1,2</sup>
- KBDI performs best in regions less sensitive to wind effects, and with sufficient fuel on the ground
- Many other wildfire risk indices exist for different regions/environments, and Argonne will be adding more of them

<sup>1</sup>Brown, E.K., J. Wang, and Yan Feng. 2020. U.S. wildfire potential: a historical view and future projection using high-resolution climate data. Environmental Research Letters. 16 034060.

<sup>2</sup>Wang, J., and V. R. Kotamarthi, 2015: High-resolution dynamically downscaled projections of precipitation in the mid and late 21st century over North America. *Earth's Future*, 3, 268-288, doi:10.1002/2015EF000304.







# Example KBDI statistics computed by GATOR-FIRE

- KBDI from observed historical data
  - Monthly, and annual average KBDI
  - 95<sup>th</sup> percentile (value 95% of values are below)
- KDBI from climate model results
  - 95<sup>th</sup> percentile for historical period
  - Number of days over 95<sup>th</sup> percentile for mid-century, and end-of-century periods
- At right, 95<sup>th</sup> percentile KBDI for 2002 from climate model results →



## **Example KBDI statistics computed by GATOR-FIRE**



## **Example KBDI statistics computed by GATOR-FIRE**



## **KBDI** statistics are being added to the Energy Zones Mapping Tool

- Publicly available web-based mapping tool
- Large geospatial data library (>330 layers)
  - Energy infrastructure
  - Energy resource
  - Siting factors relevant to energy analysis
  - Reference/background
- Suitability modeling and analysis for:
  - Power generation (37 power plant models)
  - Energy corridor paths (3 corridor models)
- KBDI statistics (to be added in near future):
  - Data downloadable
  - Visualize wildfire risk with any mapping layer
  - Include wildfire risk as a siting factor when modeling suitability of potential projects



# **Research staff and funding**

- Original climate modeling
  - Jiali Wang, Atmospheric and Earth Scientist
  - Rao Kotamarthi, Chief Scientist, Atmospheric Science and Climate Department Head
  - Funded by Strategic Environmental Research and Development Program (SERDP), and DoD
- Raw KBDI computations funded by DOE Science Undergraduate Laboratory Internship (SULI) Program
  - Emily Brown, Argonne SULI Intern, now at Berkeley University
  - Yan Feng, Principal Atmospheric and Climate Scientist
  - Jiali Wang
- GATOR and GATOR-FIRE
  - Jim Kuiper, Principal Geospatial Engineer
  - Funded by SERDP
- Energy Zones Mapping Tool (EZMT)
  - Jim Kuiper, EZMT Technical Coordinator, and many others
  - Funded by the U.S. Department of Energy, Office of Electricity



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**Geospatial Analysis Tool Kit for Regional Climate Datasets (GATOR)** 

James Kuiper • Argonne National Laboratory • jkuiper@anl.gov



# National Preparedness Analytics Center · Modeling and Analytic Tools

Iain Hyde, Deputy Director, National Preparedness Analytics Center, Decision and Infrastructure Sciences Division

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April 22, 2021

## **OUR CAPABILITIES AND STAFF EXPERTISE** Fielding a Multi-disciplinary Team of Subject Matter Experts

## **Our Capabilities**

- Decision science
- Modeling and simulation
- Geospatial analysis and data visualization
- Resilience analysis
- Preparedness
- Hazard mitigation
- Response
- Recovery
- Social and behavior systems
- Infrastructure sciences

### **Our People**

- Emergency Managers
- Geospatial analysts
- Engineers
- Economists
- Social scientists
- Urban planners
- Public policy experts
- Operations researchers
- Intelligence analysts





# **CURRENT ANALYTIC TOOLS AND RESOURCES**







# **RESILIENCE ANALYSIS AND PLANNING TOOL (RAPT)**



### www.fema.gov/rapt







# VISUALIZE AND ANALYZE DATA ABOUT YOUR COMMUNITY



People and Community (22 indicator layers)



**Infrastructure** (21 infrastructure layers)



### Hazards/Risk

Estimated annualized frequency, historic, real-time hazard layers



- RAPT allows users to stack multiple data layers to identify and address different areas of concern.
- Data available at the county or census tract level.







# **RAPT: HAZARD AND RISK LAYERS**

- Historic Tornado and • Hurricanes
- National Flood Hazard Zones
- **Real-Time Weather** • Watches and Warnings

Cold wave	Lightning	
Drought	Riverine Flooding	
Earthquake	Strong Wind	
Hail	Tornado	
Heatwave	Wildfire	
Hurricane	Winter Weather	
Ice Storm		

•



# RAPT: ADDRESSING WILDFIRE RISK

### LAYER COMBINATION – Santa Clara, CA

Hazard/Risk:

Wildfire (frequency event days/year); Incident Analysis Tool enables users to draw projected fire path.

### Infrastructure:

Hospitals inside and outside potentially affected area.

Census Tract: % of population age over 65.



### **DECISION SUPPORT EXAMPLES**

- Priority hospital/nursing homes for evacuation support.
- Hospital locations outside of impact zone to re-direct patients.
- Planning and operations support to help evacuate people with disabilities.



# COVID-19 MISSION ASSIGNMENT: RECOVERY DATA AND ASSESSMENT

- Provide data analytics support to 20+ federal agencies involved in COVID-19 recovery efforts.
- A key objective has been to collect and analyze data to identify near real-time socio-economic impacts.
- Analyses can provide insight into communities impacted by other types disasters.
  - Products used to support impact assessments from Western wildfires and Gulf Coast hurricanes during 2020.
- 2021 Focus: providing analytic resources to state, local, tribal, and territorial jurisdictions.



County GDP Impacts as of October 2020



County GDP Impacts as of January 2021



# PUBLICLY AVAILABLE COVID IMPACT ASSESSMENT RESOURCES

- On May 10<sup>th</sup>, Argonne will publicly release a series of indices and other analytic resources to support ongoing COVID recovery decision making.
- Users will be able to find these resources at www.anl.gov.
- Forthcoming products include:
  - County Economic Impact Index: Measures the estimated monthly change in county GDP since the onset of the COVID-19.
  - State and Local Government Revenue Vulnerability Indices: Measures the estimated monthly change in state and local government revenue since the onset of COVID-19.
  - Housing Stability Index: Measures the near real-time change in housing stability for renters and owners since the onset of COVID-19.
  - Internet Access Index: Measures household access to highspeed internet based on the availability of broadband from Internet Service Providers, household subscription rates, and access to internet-enabled devices.







# **ONGOING RESEARCH AND DEVELOPMENT**



**ENERGY** Argonne National Laboratory is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC.



# ELECTRICITY SUBSECTOR RISK CHARACTERIZATION

DOE's Infrastructure Security and Energy Restoration (ISER) Division asked ANL to model the risks to the electric system posed by six (6) natural hazards. The analysis leverages ANL's advanced climate and electric power flow models to determine the risk, extent, and duration of outages.

- ANL will estimate the exceedance probability of electric outages of a certain magnitude caused by wildfires, hurricanes, earthquakes, tornados, ice storms, and severe thunderstorms
  - Historical data will be supplemented by data from ANL's advanced climate models, including a novel hurricane model designed to simulate offshore storm formation, storm paths, and landfall.
  - ANL will examine risks under both current conditions and RCP 4.5 & 8.5 scenarios.
- Hazard scenarios will be run through ANL's EPfast and EGRIP electric system models to assess impacts to the electric system.
- ANL will report estimates for demand loss (MW), unserved energy (MWh), customers affected (#), equipment damage (\$), and restoration time (hours).





# **RAPID ASSESSMENT OF IMPACTS AND NEEDS** MODEL

Goal: Provide rapid, high-confidence, quantitative assessments of impacts from disasters to infrastructure, housing, and the economy.

- New laboratory-directed research initiative.
- Planned Approach:
  - Phase 1 (2021)
    - Develop an event generation and characteristics methodology for hurricanes, including trajectory, intensity, duration
    - Overlay event characteristics with existing infrastructure and population data.
    - Incorporate methodology to model estimated economic impacts to the affected region.
  - Phase 2 (2022)

    - Develop methodology to produce downscaled, sub-county impact estimates.
      Incorporate high-resolution climate change data.
      Develop event generation and characteristics methodology for additional hazards, including riverine flooding and wildfire.
- Intended use cases:
  - Support critical decision-making during response and recovery. Inform long-term mitigation and resilience investments.







### THANK YOU

Iain Hyde • Argonne National Laboratory • ihyde@anl.gov



### **SUMMIT: Standard Unified Modeling, Mapping,** and Integration Toolkit Sandia National Laboratories is a **Overview and Wildfire Applications** International Inc., for the U.S.

Russell Gayle, Sandia National Laboratories

multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell Department of Energy's National Nuclear Security Administration under contract DE-NA0003525. SAND2021-4741 PE

4/22/2021

# **SUMMIT: Problem Statement**

### **Objective:**

Provide USG (FEMA, CWMD, CISA, etc.) a **scalable M&S platform** to efficiently produce data for multiple scenarios or archive, share, and reuse any data utilized in plan creation for future planning, comparative analysis or during emergency response operations.

### **Current Gaps**

- Integration: Currently disparate systems prohibits complex, cascading analysis, sharing, and collaboration
- **Uncertainty:** Planning only done for single scenarios and response does not typically convey uncertainty
- **Reuse:** Data from planning not archived and used during response or subsequent planning



#### **Desired Outcome**

- Enhanced national preparedness (THIRA) through robust multi-scenario planning capability
- Dramatically shorten the time to respond to disaster requests for informations



## **Modeling and Simulation Situational Awareness**





## **SUMMIT for Planning**


## **The SUMMIT Process**



### SUMMIT Engagement: California Exercise and Simulation Center (2016)

- Highlights and Impacts:
  - Supported "Decisions Matter" exercise series
  - Sacramento MetroFire awarded \$50K by State Homeland Security Grant Program (SHSGP) to develop SUMMIT templates for CA
  - New business model for sustainment: state/regions invests
  - CESC team is a strong SUMMIT advocate
- Risks:
  - DHS license for technology transfer still pending
  - Need to implement new business model (pay-per-use, certifications, etc.) to sustain SUMMIT
- Outlook for the future...
  - Harden 3 templates (Cl<sub>2</sub> Tanker, **Wildfire**, crude oil?)
    - For single runs and batch analysis
    - Work supported in part by SHSGP (Jan-Sep 2016)
  - Create exercise guides for the use of each template
  - Seek additional CA support for sustainment (SacOES, CalFire)









## Wildfire Scenario Template: Overview



## Wildfire Scenario Template: Model Selection



## Wildfire Scenario Template: Fire Configuration

#### Set weather conditions



## Wildfire Scenario Template: Infrastructure Configuration



## Wildfire Scenario Template: Wildfire Results



### Wildfire Scenario Template: Affected Infrastructure Results





## **Thank You!**

Any Questions?



## Web-Based Geospatial Analytics Application Frameworks and Demos

Leo Bynum, R&D S&E, Computer Science, Sandia National Laboratories Phone: (505) 284-3702

E-mail: lbynum@sandia.gov

Apr 22, 2021



# Using and Valuing Ecosystem / Physical Science and Earth Observations in Wildfire Management Decisions

R. Bernknopf and O. Olofinsao UNM, C. Broadbent BYU – Idaho, V. Tidwell Sandia National Laboratories, D. Goodrich USDA, T. Smith UPenn emeritus, C. F. Casey, USGS, B. Peterson USGS, J. Cain NMSU Collaborators

USGS: Fort Collins Science Center, National Land Imaging Program, National Geologic Mapping Program, Northwest Science Center – Corvallis, U.S. Forest Service: Pacific Southwest Region and Geotechnical Applications Center



Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc. for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

April 22, 2021

# Assessing wildfire risk management tradeoffs on public lands and in nearby communities

- Why: Measure wildfire benefits and risks
- What: Create analytical tool for benefits vs. risks
- How: Apply Bayesian network (probabilistic causal model)
  - Utilize remote sensing: Landsat and MTBS transitions
  - Estimate probability of habitat suitability: spotted owl and black bear
  - Forecast post fire impact of natural hazards
    - Debris flows and floods
    - Short and long run impacts to water quality from erosion and sedimentation
  - Estimate exceedance probabilities of critical resources losses
  - Estimate economic benefits of forest mitigation or adaptation activities



# Study region, California spotted owl habitat, and probability of habitat suitability



## Impacts of the Rim fire on CA spotted owl habitat

MTBS\_CLASS
Background
Unburned to Low
Low Severity
Moderate Severity
High Severity
Increased Greenness
Missing Data



Forest Resource Distribution and Redistribution

Two measures to risk analysis:

- 1. Economic inequality measurement of the distribution of economic benefits
- 2. Biological inequality measurement of the distribution of habitat suitability
- 3. Impact of redistribution



# Analysis: Cost effectiveness of a hypothetical prescribed burn program



Ranked CA spotted owl grid cells identified for prescribed burns

	Cost	Owl Benefit
16 protected cells	\$ 1,547,208.00	\$ 1,127,992.00

Wildfire creates uniform habitat for spotted owls:

- + in economic value
- in ecological habitat suitability

Wildfire impacts on economic value for black bear habitat are currently inestimable: + positive externality impact from owl habitat protection on black bear habitat?

## Legends: land use, infrastructure and post fire expected sediment yield in the Rim fire impacted region

#### ✓ FSTopo\_Culture\_PT

- <all other values> FCSUBTYPE
- Cave/Mine Tunnel Entrance/Adit
- Cemetery or Grave
- Cliff Dwelling
- Corral ٠
- Lighthouse/Beacon
- Lighthouse/Beacon w/ Cont Sta
- Located or Landmark Object
- Mineshaft
- Pit
- Power Substation
- Prospect ۰
- Quarry or Open Pit Mine
- Ruins/Archaeologic Site
- Sewage Disp/Water Filter
- Tanks/Tower Small
- Well/Drill Hole Exclude Water
- Windmill or Wind Generator

- FSTopo Culture LN
- <all other values> **ECSUBTYPE**
- Athletic Field or Track
- **Baseball or Softball Diamond**
- Boardwalk
- Boat or Seaplane Ramp
- Breakwater
- Cemetery
- Coke Ovens
- Corral/Feedlot/Stockvard
- Fence
- Pipeline- Gas/Oil Aboveground
- Pipeline- Gas/Oil Underground
- Pipeline- Submerged
- Power Substation\Pumping Static
- Power Transmission Line
- Race Track/Way
- Ruins/Archaeologic Site (outline)
- Ski Lift/Cableway/Conveyor
- Telephone or Telegraph Line
- Wall

- □ ✓ streams Discr Rim Sediment Yield (tons)
  - 0.00 0.19
  - -0.19 0.83
  - -0.83 4.74
  - -4.74 17.27

  - 21.67 31.32
  - 31.32 41.63 41.63 - 65.18

-0.08 - 0.50

0.50 - 6.76

6.76 - 10.83

10.83 - 28.55

28.55 - 30.48

30.48 - 66.91

66.91 - 173.23

173.23 - 255.65

255.65 - 492.18

- 65.18 138.04
- Park-City, Small County, Mobile H ⊡ 🗹 swat2005\_Discr\_Rim Sediment Yield (t/ac)
- Pipeline Elevated



Debris flow could impact powerhouse and transmission lines

Holm Powerhouse San Francisco Water, Power and Sewer SF Public Utilities Commission

## **Integrated Model: Mitigation vs. Adaptation**

- Resource tradeoffs
  - Natural resources
  - Engineered infrastructure
  - Decision making priorities subject to budget/time constraints
- Mitigation: Pre-fire treatments
  - Bear and owl habitat
  - Natural / cultural resources
- Adaptation: Post-fire treatments
  - Infrastructure impacts (Kineros2/AGWA)
  - Community resilience
- Value of information
  - Remote sensing
  - Updated science (e.g., burn severity maps using LANDFIRE)





## **Thank You**

Richard Bernknopf <u>rbern@unm.edu</u> Vince Tidwell <u>vctidwe@sandia.gov</u> Craig Broadbent <u>broadbentcr@byui.edu</u>



## Grid Resilience and Intelligence Platform PI: Alyona Ivanova Teyber aivanova@slac.stanford.edu

## **GRIP** Overview

- $\checkmark\,$  Using machine learning and data-driven approaches to
  - Anticipate extreme events;
  - **Absorb** using controls for DERs and flexible resources;
  - **Recover** by managing DERs in the case of limited communication to reduce recovery time.
- $\checkmark$  High level impacts
  - Developed a platform and metrics that capture the resilience of grid assets
  - Anticipate multi-time scale grid vulnerabilities, for example:
    - Trigger asset replacement on multi-month scale
    - Help mitigate the need for PSPS events on multi-week scale by minimizing the customer interruptions
    - Better control of day-of events
  - IT/OT system integration
    - Reduce impacts of cyber events in the event of communication loss
  - Sophisticated User Interface



## Wildfire prevention with GRIP

#### Anticipation

- Pole Failure Modeling
- Vegetation line contact analysis using GIS data
- PSPS analytics

#### Absorption

- Fault Isolation
- Virtual Islanding Formation
- Power Balancing

#### Recovery

- Fast Anomaly Detection using ML
- ML image recognition for poles
- Transmission blackstart











## Anticipation

#### Vulnerability metric

- Captures the impact of wind pressure on face of pole and proximity of vegetation on the overhead lines
- Defines a pole vulnerability metric
- Models the electrical fault propagation and pole restoration
- Uses weather data to drive the model
- Uses 3m GIS data to capture vegetation proximity to lines
- Supports arbitrary vulnerability simulations
- Accounts for pole degradation
- Capable of large equipment and model library import
- Integrates with CYME

#### PSPS analytics

- Determines the optimal power-shut off for short term decisions in wildfire prevention
- Objective: maximize amount of power while minimizing risk of fire ignition
- Selective de-energization of system components



Data provided by California Forest

## **Absorption - fire use-case**

- Motivation: avoid loss of power to downstream portions of the grid
- Allows utilities to better understand the transition to a system where distribution circuits can continue to serve load post loss of bulk grid
- Algorithm identifies the fault and reconfigures the system into "virtual islands" while balancing maximum amount of load using local DERs
- Uses the slack bus, DERs and flexible loads, such as water heaters and HVACs to maintain maximum load







## Absorption

- Motivation: avoid loss of power to downstream portions of the grid
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## Absorption

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## Absorption

- Large-scale test and validation:
  - Vermont Electric Co-op distribution feeder
  - Deployed 150 water heaters with Ο controls
  - Results showed the unserved energy Ο reduction from 100% to 10% using GRIP





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## Recovery

- Anomaly Detection using ML
  - Detects equipment failure and non-technical losses from meter data streams
  - Achieves near perfect identification of theft and hardware failures from same meter test/training data
- Fast anomaly detection
  - Detects equipment failure (residential, transformer) from meter data streams
  - Sub-hour train/test performance to enable real-time detection
- ML image recognition for poles
  - Neural networks for image recognition from video data
- Transmission black start
  - Sequences to de-energize generators and opening/closing switches to restore power in transmission network
  - Visualization of the sequence using power flow









## **Deployment and Integration with Utility Tools**

- OpenFIDO Open Framework for Integrated Data Operations
  - Integrates data converters to re-format model compatible with GRIP
    - CYME converter
    - Equipment libraries
  - $\circ$  Supports on-premise and cloud deployment
- HiPAS GridLAB-D High Performance Agent-based Solver
  - Power flow solver for simulation and modeling of electrical networks
- NRECA OMF.coop
  - Analytics hosted on the platform with users from over 176 utilities, vendors, and universities
- California IOU Deployment in progress
- 150 field deployed thermostatically controlled devices with GRIP absorption algorithm

## SLACE NATIONAL ACCELERATOR LABORATORY

## Thank you

We invite you to collaborate and participate in testing our tools.

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SLAC NATIONAL ACCELERATOR LABORATORY



**U.S. DEPARTMENT OF** NER **OFFICE OF** ELECTRICIT

## **Grid Resilience and Intelligence Platform**

Alyona Teyber on behalf of SLAC National Accelerator Laboratory

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### **Thank You**

**Our Next Webinar:** 

Modeling & Analytical Tools | Post Fire Analysis

April 29, 2-4 PM ET

https://www.energy.gov/oe/wildfire-mitigation-webinar-series

Want to Connect? Contact Stewart Cedres at stewart.cedres@hq.doe.gov