Distribution system outage management after extreme weather events

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- Topic III: Distribution System Repair and Restoration
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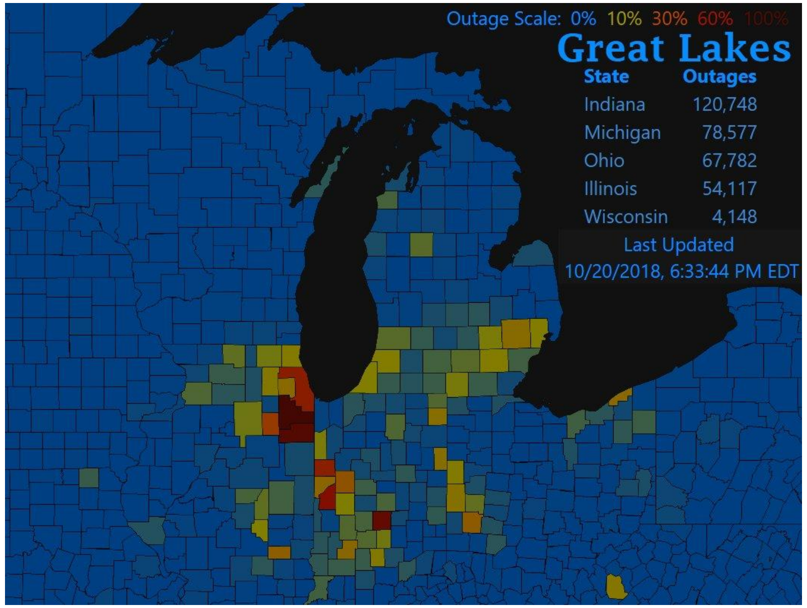
Motivation

- Severe power outages caused by extreme weather events
  - Hurricane Irene (2011): 6.69 million customers
  - Hurricane Sandy (2012): : 8.66 million customers
  - Hurricane Irma (2017): 15 million customers
  - Cost of weather-related outages: $25 to $70 billion annually in U.S.
- Current restoration practices used by utilities
  - Rely on customer calls for outage detection
  - Lack of situational awareness
  - Experience-based crew scheduling
  - Recovery operation and crew scheduling are separated
  - DERs and automatic switches are not fully utilitzed
  - Inefficient and sub optimal

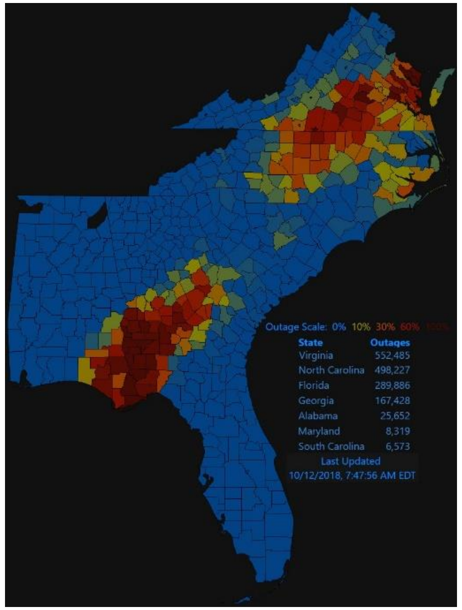
Extreme Weather and The Grid

- Extreme weather events constantly threaten and damage the electrical system
- Overhead distribution systems are vulnerable to severe weather events such as hurricanes, wind, rain, lightning, ice, freezing rain, and snow
- Recent years have seen an increase of weather events and outages

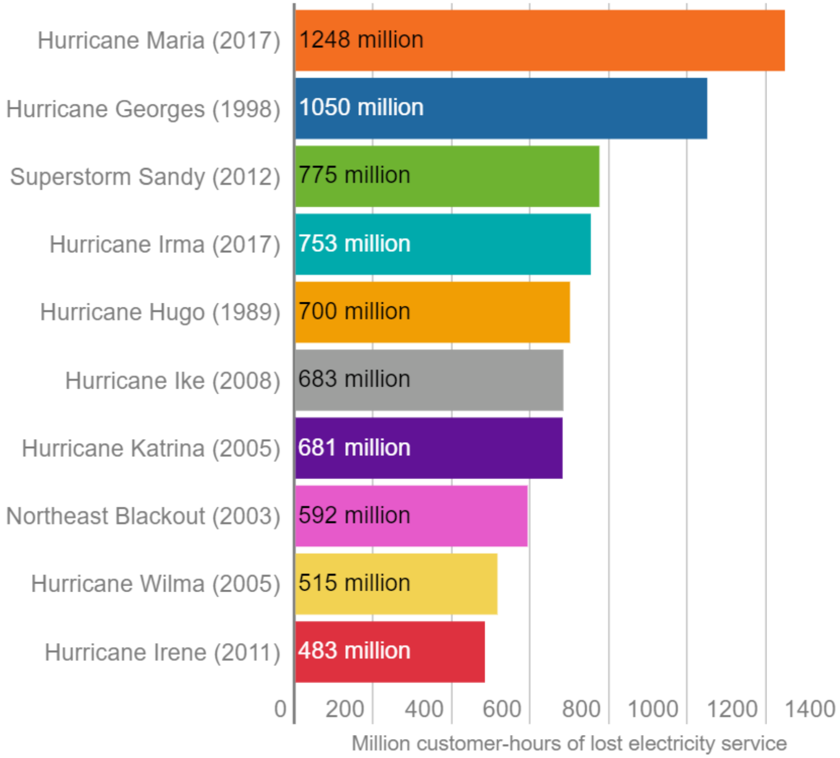
320k customers were without power due to high winds and thunderstorms.



Over 1.54 Million power outages from Hurricane Michael.

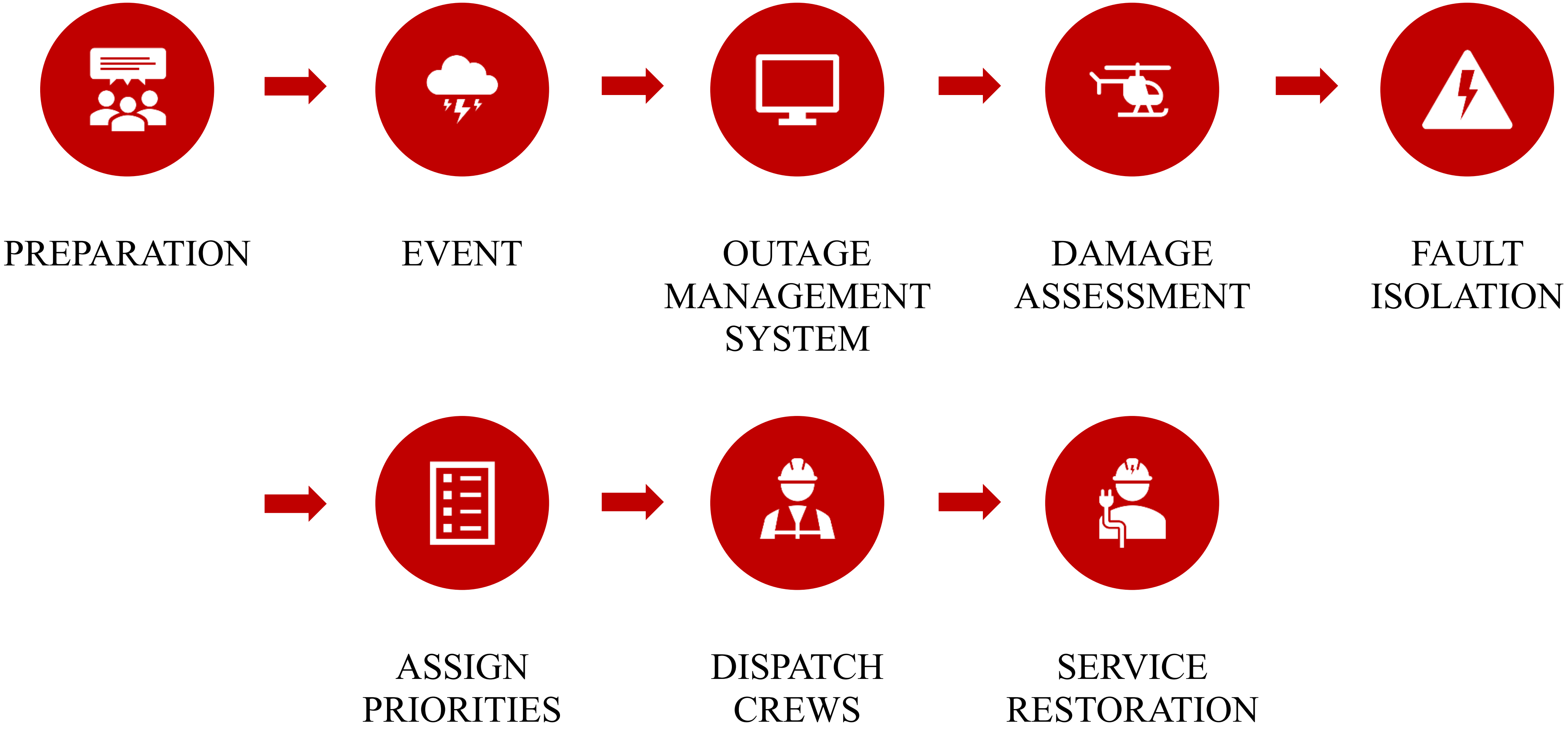


Source: accuweather.com



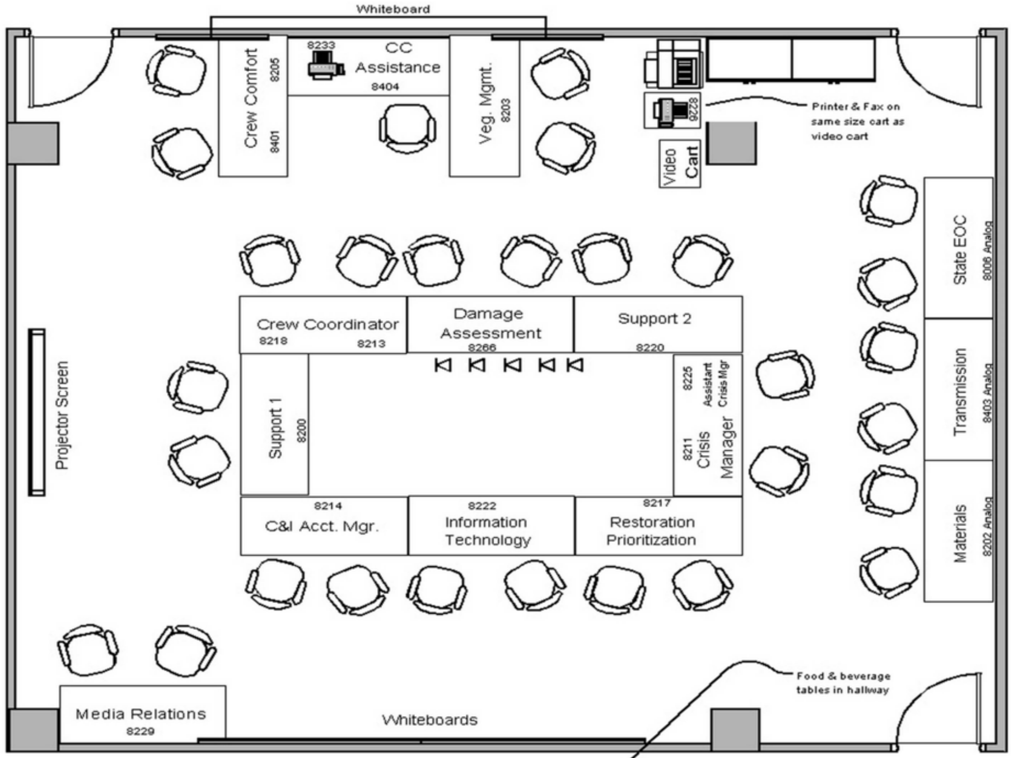
Source: https://poweroutage.us/

Utility Practices (1/2)



Utility Practices (2/2)

- Preparation
  - Crews and staff on alert
  - Request assistance
  - Pre-storm allocation of crews and resources
- Outage Management System
  - Data from customer calls, SCADA, AMI, etc are collected
  - Determines the likely location of the trouble
- Damage assessment process
  - Damage assessors navigate to the outage locations
  - Record damage data
  - Estimate repair times
- Prioritizing restoration activities
  - Hazards → critical customers (e.g., hospitals) → prioritize by number of customers
- Crew Scheduling
  - Schedule in sequence of priority



Crisis Center – Westar Energy

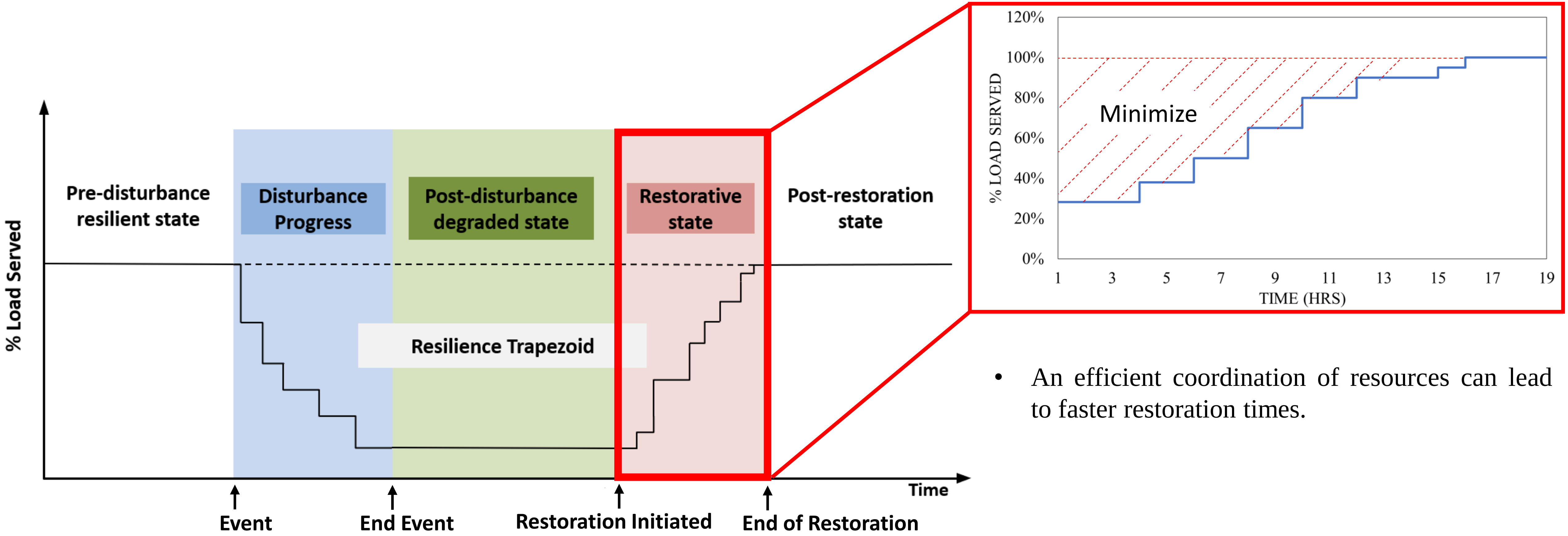
Resilient Distribution System (1/2)

- **Resilience:** The ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions
- Develop tools, methods, and algorithms to design a resilient power distribution system

- Planning
  - Hardening infrastructure
  - Optimal locations of DERs and switches
  - Pre-storm preparation
  - Resource allocation

- Disaster response
  - Fault isolation and service restoration
  - Damage assessment and repair time estimation
  - Co-optimization of crew scheduling and network operation

Resilient Distribution System (2/2)



- An efficient coordination of resources can lead to faster restoration times.

Problem Statement (1/2)

What is missing?

- A preparation strategy before repair and restoration to ensure a fast response
- Estimating the repair time efficiently
- A co-optimization method that jointly optimizes crew routing and distribution system operation
- Modeling the connectivity status of different types of solar PV systems
- Modeling fault isolation and tree/obstacle removal before repairing damages

Problem Statement (2/2)

Objectives:

1. Proactive response: develop a mathematical model to pre-stage and prepare human resources and equipment before extreme weather events
2. Use machine learning to predict repair times of damaged components
3. Design solution algorithms and develop mathematical models to co-optimize repair scheduling and recovery operation of distribution systems
4. Develop models for coordinating interconnected microgrids

Outage scenario generation

- Weather forecast
- Fragility model

Pre-storm planning

- Choose staging locations
- Mobilize available crews and request assistance if necessary
- Obtain and allocate resources and equipment

Post-storm repair and restoration

- Estimate the repair time
- Coordinate tree and line crews
- Manage Equipment
- Isolate damaged components
- Operate the distribution system

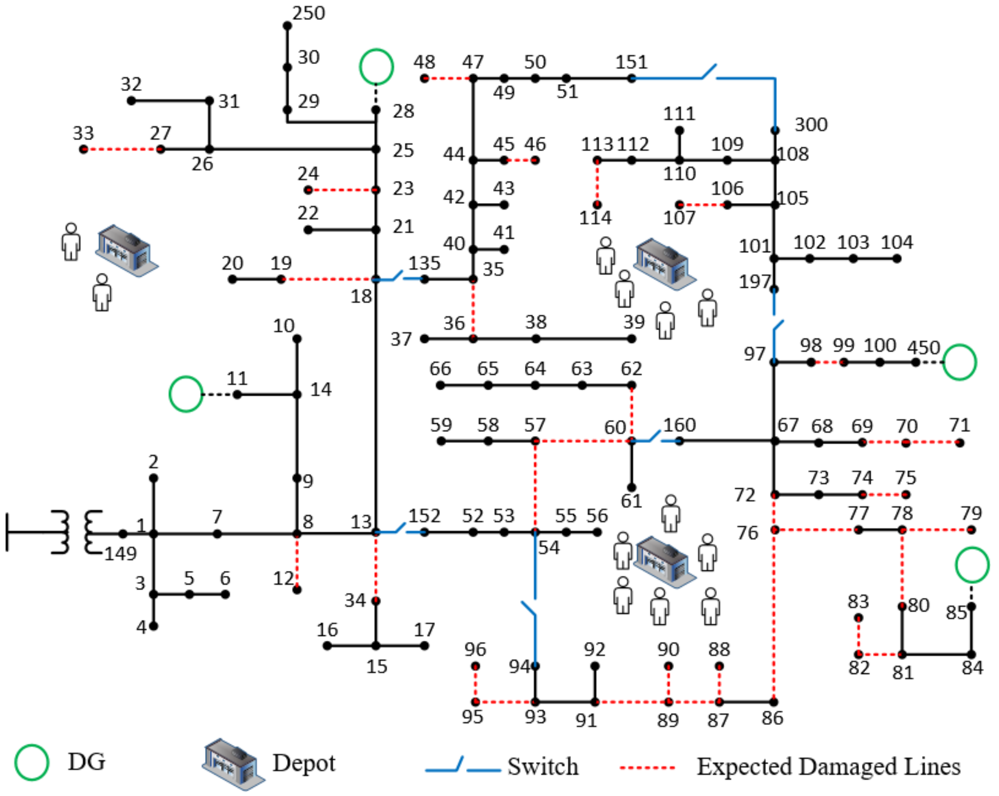
Research Achievement

- A two-stage stochastic mixed integer linear program (SMIP) is developed to acquire and pre-stage crews and equipment before an extreme event
- Effectively used Deep Learning to predict repair times of damaged components
- A novel mixed integer linear program (MILP) for jointly optimizing the repair crew routing and distribution network operation is developed. The model can improve utilities' response to extreme events. Our research group is the first to develop a single mathematical model for co-optimizing crew routing and power restoration
- A mathematical formulation is developed for fault isolation and service restoration. Isolation has been neglected in existing distribution system restoration studies that use mathematical programming
- Development of efficient algorithms for solving the co-optimization problem
- 4 journal and 6 conference papers have been published, and 2 journal papers are under review

Disaster Preparation

Pre-Disaster Resource Allocation

- To achieve a faster and more organized emergency response, utilities can devise a plan beforehand to ensure a proactive response
- The first step is to forecast the event and predict its impact
  - Historical data
  - Fragility model and weather forecast
  - Estimate the number of equipment required
  - Estimate the repair times
- Pre-event preparation:
  - Select staging areas (depots)
  - Order equipment
  - Request external crews
  - Allocate the equipment and crews to the depots



Review – Disaster Preparation

- Pre-disaster planning enables efficient post-disaster recovery by ensuring there are enough equipment and crews to quickly conduct the repairs
- Utilities must provide water, food, and shelter and communicate differences in work practices to visiting crews
- Few studies focused on disaster preparation in the context of power system and its infrastructure
- The previous work approached the preparation stage by dividing the electric network into different areas, with each area having a specific demand, which neglects the individual components within each area and the distances between these components and the depots

Ref.	Application	Method
Mete 2010	Identify the amount of medical supplies and storage location for the supplies	SMIP
Verma 2015	Select facility location for storing emergency supplies before a disaster	SMIP
Rodriguez-Espindola 2018	Select the location of emergency facilities and allocate relief resources	MILP
Ni 2018	Select the location of emergency facilities and allocate relief resources	Robust Optimization
Wang 2004	Find optimal number of depots and their locations around the power network	MILP
Coffrin 2011	Determine the number of resources to stockpile before a disaster n order to repair the power network	SMIP

Review – Stochastic Programming

- Mathematical program in which some of the data are not known with certainty
  - Decision variables
  - Objective function
  - Constraints
- Two-stage Stochastic Program
  - ✓ Given: A large number of potential scenarios
  - Stage I: Make some advance decisions (plan ahead)
  - ✓ Observe the actual input scenario
  - Stage II: Take recourse actions in response to the realization of the random variables and the first stage decisions

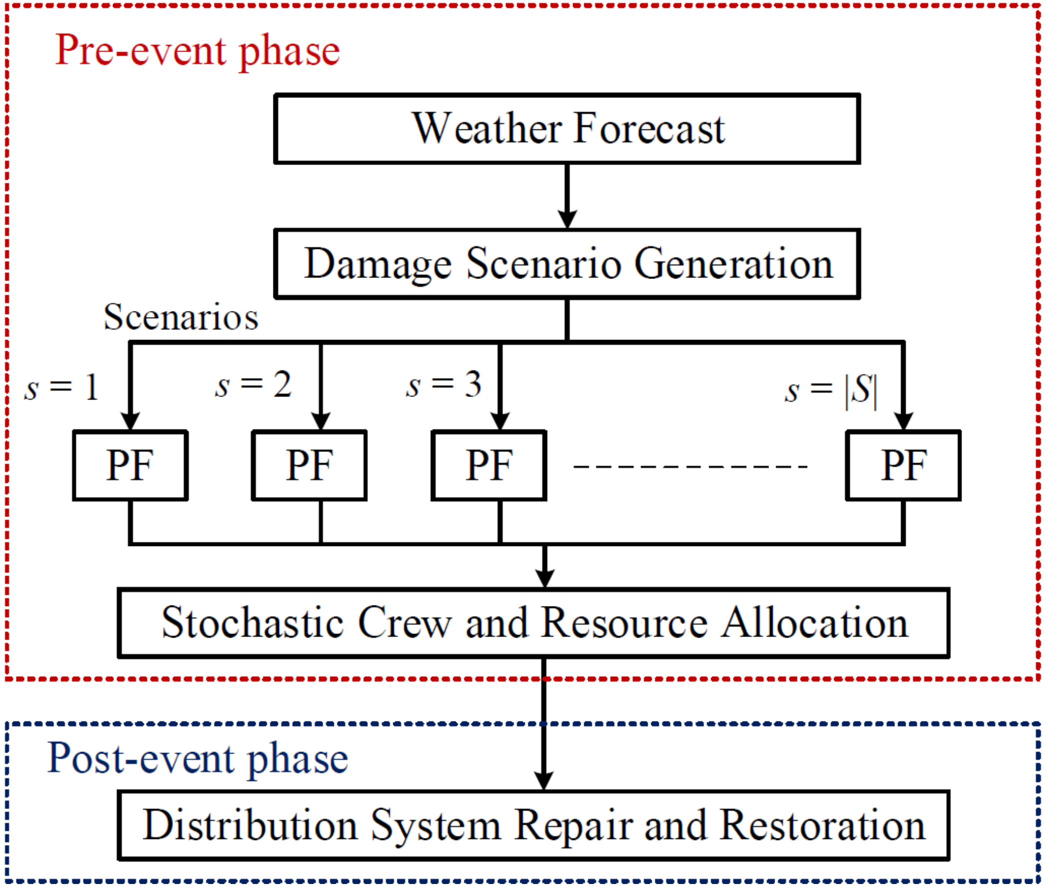
Objectvie: $\min c^T x + \frac{1}{N}\sum_{s=1}^{N} Q(x, \xi_s)$

Subject to $A\,x = b$

$x \geq 0$

Framework

1. The forecasted weather and fragility models of the components are used to generate damage scenarios
2. For each scenario, we solve a power flow (PF) problem to identify critical components that must be repaired to restore service for high-priority customers
3. The stochastic crew and resource allocation problem (SCRAP) model is then solved to select depot locations and allocate the crews and equipment
4. After the event, the distribution system repair and restoration problem (DSRRP) model can be solved to schedule the repairs and operate the network

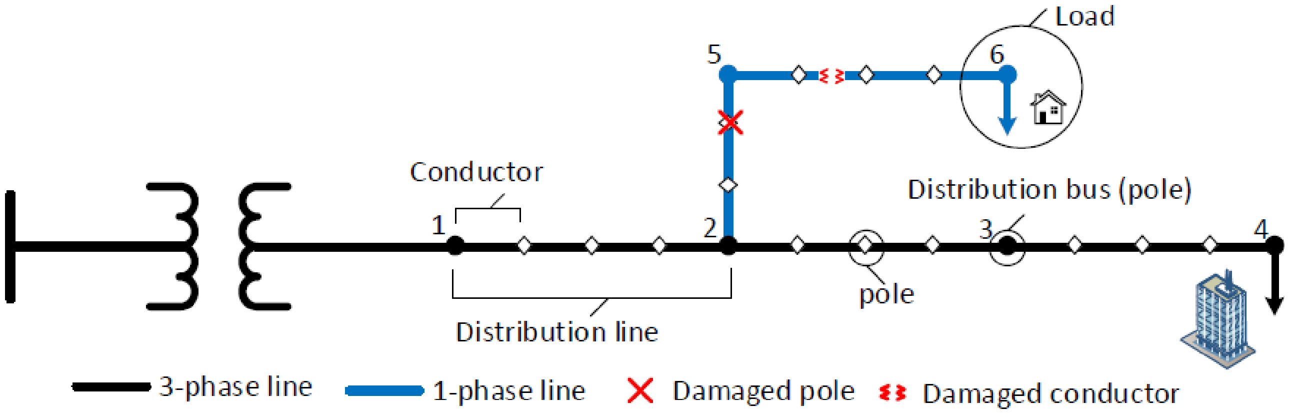


Scenario Generation (1/2)

- Generate wind speeds according to forecasted data
  - Example: Hurricane category 3 - lognormal distribution with μ = 4.638 and σ = 0.039 (Javanbakht 2018)
  - Use hurricane decay model to calculate the maximum wind speed on the area (Kaplan 1995)
- Use fragility models to (Ouyang 2014):
  - Calculate the probability of failure of each pole: $p_z^{pole}(w) = \min\{a\, e^{b\, w}, 1\}$
  - Calculate probability of failure of each conductor
    - Probability of wind induced damage: $p_l^{wind}(w) = \min\left\{\frac{wind\ loading}{conductor\ endurance}, 1\right\}$
    - Probability of damage due to fallen trees $p_l^{tree}(w)$ (Canham 2001)
- Using Bernoulli distribution to find the damage state of each pole and conductor in every scenario
  - Bernoulli(p) = 1 (damaged) with probability p, and 0 (functional) with probability 1-p

Scenario Generation (2/2)

- Calculate required equipment
- Types of equipment:
  - Type 1: Poles for 3-phase lines
  - Type 2: Poles for 1- and 2-phase lines
  - Type 3: 3-phase transformers
  - Type 4: 1-phase transformers
  - Type 5: Conductors
- Estimate the repair times
  - Each damaged distribution pole: normal distribution (5,2.5)
  - Each damaged distribution conductor: normal distribution (4,2)
- Identify critical components
  - Solve a MILP to identify minimum number of lines to repair
  - Status of the line: u_k
  - Status of the load: y_i
  - Set of damaged lines for each scenario ($\Omega_{DL(s)}$)
  - Set of critical loads (Ω_{CD})



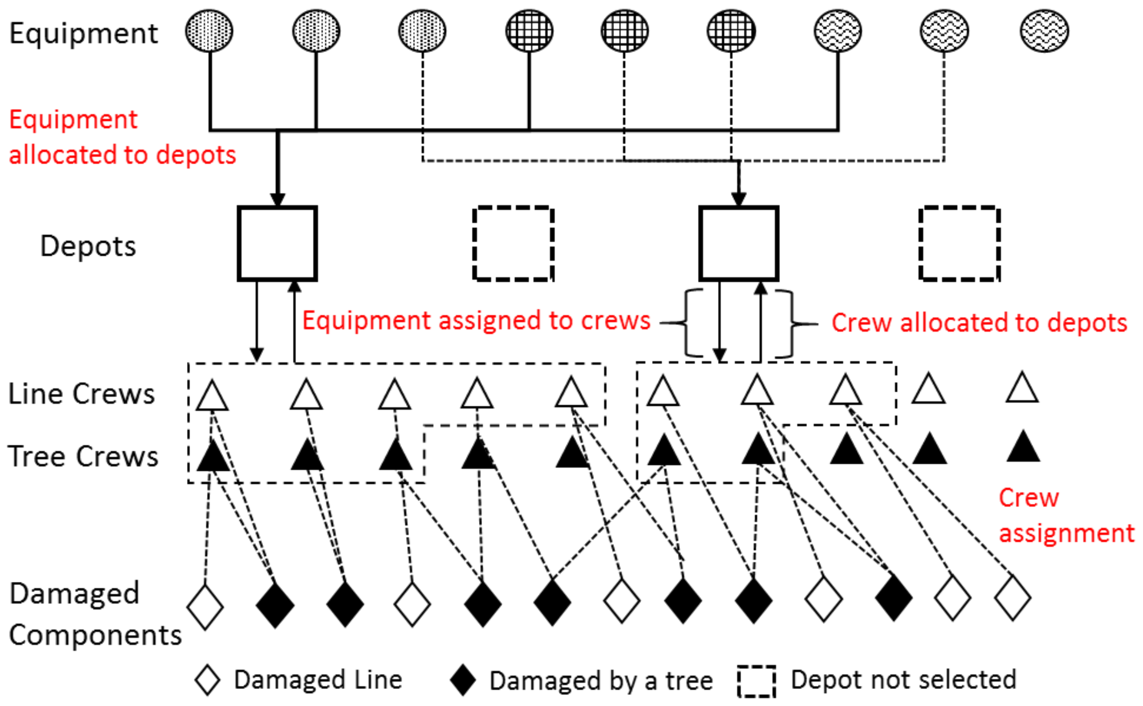
$$\min \sum_{k \in \Omega_{DL}(s)} u_k$$

$$\text{subject to } \; y_i = 1, \forall i \in \Omega_{CD}$$

$$\text{subject to power operation constraints}$$

SCRAP Model - Summary

- Uncertainty
  - Damage to the grid
  - Equipment required
  - Repair times
- Objective:
  - Minimize preparation costs and penalty over unmet demand and late repairs
- First-stage constraints
  - Depot selection
  - Crew and equipment allocation
- Second-stage constraints
  - Assign crews to damaged components
  - Working hours
  - Assign equipment to crews



Objective

- First-stage objective: minimize the costs of equipment transportation, ordering equipment and external crews, and staging depots

$$\min \sum_{\forall d,e,\tau} \mathcal{P}^{TE}_{d,e,\tau} E_{d,e,\tau} + \sum_{\forall d,\tau} \mathcal{P}^{EI}_{\tau} EI_{d,\tau} + \sum_{\forall d} \left(\mathcal{P}^{EC}(LI_d + \mathcal{T}I_d) + \mathcal{P}^{D}_{d} \nu_d\right)$$

- Second-stage objective:
  - Minimize the costs associated with the crews. The costs of crews include labor, food, and accommodation
  - Minimize penalty costs of unmet equipment demand and time it takes to repair all components

$$\min \sum_{\forall s} \Pr(\mathrm{s}) \Big(\sum_{\forall c} \mathcal{P}^{H}_{c} H_{c,s} + \sum_{\forall d,\tau} \mathcal{P}^{LF}_{\tau} \mathcal{E}_{d,\tau,s} + \mathcal{P}^{R}(\mathcal{L}^{T}_{s} + \mathcal{L}^{L}_{s})\Big)$$

First-Stage Constraints

- The number of selected depots is limited to v^{max}
- Each depot, if selected, can contain a limited amount of equipment
- Limit the number of crews in the depots

$$1 \leq \sum_{\forall d} \nu_d \leq \nu^{max}$$

$$0 \leq \sum_{\forall \tau} \mathcal{C}^R_\tau E^D_{d,\tau} \leq \mathcal{C}^E_d \nu_d, \forall d$$

$$0 \leq \sum_{\forall c} \delta_{d,c} \leq \mathcal{C}^H_d \nu_d, \forall d$$

- Determine the number of equipment/line crews/ tree crews at each depot
  - Resources in depot d = resources initially in d + resources transferred to d + newly resources - resources transferred to other depots

$$E^D_{d,\tau} = E^0_{d,\tau} + \sum_{\forall e, e \neq d} E_{e,d,\tau} - \sum_{\forall e, e \neq d} E_{d,e,\tau} + EI_{d,\tau}, \forall d, \tau$$

$$\sum_{\forall c \in C^L} \delta_{d,c} = L^0_d + \sum_{\forall e, e \neq d} L_{e,d} - \sum_{\forall e, e \neq d} L_{d,e} + LI_d, \forall d$$

$$\sum_{\forall c \in C^T} \delta_{d,c} = \mathcal{T}^0_d + \sum_{\forall e, e \neq d} \mathcal{T}_{e,d} - \sum_{\forall e, e \neq d} \mathcal{T}_{d,e} + \mathcal{T}I_d, \forall d$$

- Internal crews must be in one of the depots
- External crews can be either located in one depot, or not used

$$\sum_{\forall d} \delta_{d,c} = 1, \forall c \in IC$$

$$\sum_{\forall d} \delta_{d,c} \leq 1, \forall c \notin IC$$

Symmetry-Breaking Constraints

- The presented problem allow a large number of feasible symmetric solutions with equal objective value
- We add symmetry breaking constraints to keep at least one solution and remove all other symmetric solutions
- Example:

$$\delta_{d,c} = \begin{pmatrix}1100\\0000\\0011\end{pmatrix} \equiv \begin{pmatrix}1010\\0000\\0101\end{pmatrix} \equiv \begin{pmatrix}0101\\0000\\1010\end{pmatrix} \equiv \begin{array}{cc} \text{Crew} & \\ \begin{pmatrix}0011\\0000\\1100\end{pmatrix} & \text{Depot} \end{array}$$

- Allocate the crew with the lowest index first
- Allocate the crews starting from the depots with the lowest index and skip depots that are not staged
- Apply constraints for both line and tree crews

$$\sum_{\forall d} \delta_{d,c+1} \geq \sum_{\forall d} \delta_{d,c}, \forall c \in C^L, c < |C^L|$$

$$\sum_{\forall d} (|\Omega_P| - d)\delta_{d,c+1} \geq \sum_{\forall d} (|\Omega_P| - d)\delta_{d,c}, \forall c \in C^L, c < |C^L|$$

$$\sum_{\forall d} \delta_{d,c+1} \geq \sum_{\forall d} \delta_{d,c}, \forall c \in C^T, c < |C^T|$$

$$\sum_{\forall d} (|\Omega_P| - d)\delta_{d,c+1} \geq \sum_{\forall d} (|\Omega_P| - d)\delta_{d,c}, \forall c \in C^T, c < |C^T|$$

Second-Stage Constraints (1/2)

- The second-stage constraints are dependent on the realization of the uncertainty
- Crew assignment
  - Each damaged component is assigned to a crew
  - Only crews that are present are used
  - Crews are assigned to damaged components within a reasonable distance from their locations

- Working hours
  - Equals the sum of the estimated repair times of the assigned components
  - Time when last component is repaired = largest working hour

$$\sum_{\forall c \in C^L} A^L_{k,c,s} = \mathcal{U}^L_{k,s}, \forall k, s$$

$$\sum_{\forall c \in C^T} A^T_{k,c,s} = \mathcal{U}^T_{k,s}, \forall k, s$$

$$\sum_{\forall k} A^L_{k,c,s} \leq M \sum_{\forall d} \delta_{d,c}, \forall c \in C^L, s$$

$$\sum_{\forall k} A^T_{k,c,s} \leq M \sum_{\forall d} \delta_{d,c}, \forall c \in C^T, s$$

$$\bar{D} \geq D_{d,k}(\delta_{d,c} + A^L_{k,c,s} - 1), \forall d, k, c \in C^L, s$$

$$\bar{D} \geq D_{d,k}(\delta_{d,c} + A^T_{k,c,s} - 1), \forall d, k, c \in C^T, s$$

$$H_{c,s} = \sum_{\forall k} (ET^L_{k,s} A^L_{k,c,s}), \forall c \in C^L, s$$

$$H_{c,s} = \sum_{\forall k} (ET^T_{k,s} A^T_{k,c,s}), \forall c \in C^T, s$$

$$\mathcal{L}^L_s \geq H_{c,s}, \forall c \in C^L, s$$

$$\mathcal{L}^T_s \geq H_{c,s}, \forall c \in C^T, s$$

Second-Stage Constraints (2/2)

- The number of equipment available must be enough for repairing all critical lines before the extreme event occurs
- The total equipment that the utility have must be equal or greater than the required equipment to repair the damaged components
- $\mathcal{E}_{d,\tau,s}$ identifies the additional number of equipment (unmet equipment demand) that must be ordered in each scenario to finish the repairs
- Each crew can obtain equipment from the depot they are positioned at
- The number of resources the crew have should be enough to repair the assigned damaged components

$$\sum_{\forall d} E^D_{d,\tau} \geq \sum_{\forall k \in \Omega_{CL}(s)} \mathcal{R}_{k,\tau,s}, \forall \tau, s$$

$$\sum_{\forall d} (E^D_{d,\tau} + \mathcal{E}_{d,\tau,s}) \geq \sum_{\forall k} \mathcal{R}_{k,\tau,s}, \forall \tau, s$$

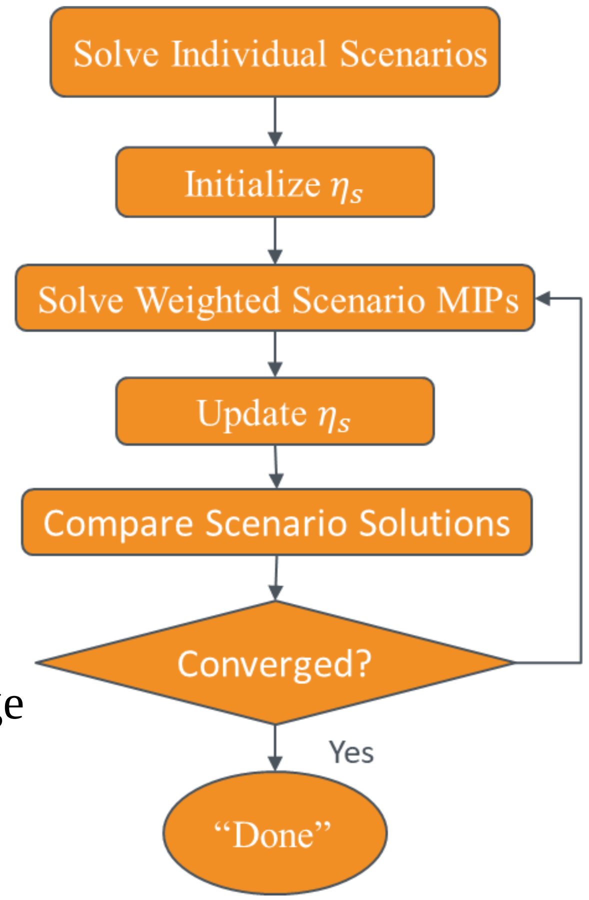
$$\sum_{\forall \tau} E^C_{c,d,\tau,s} \leq M\delta_{d,c}, \forall d, c \in C^L, s$$

$$\sum_{\forall c \in C^L} E^C_{c,d,\tau,s} \leq E^D_{d,\tau} + \mathcal{E}_{d,\tau,s}, \forall d, \tau, s$$

$$\sum_{\forall d} E^C_{c,d,\tau,s} \geq \sum_{\forall k} A^L_{k,c,s} \mathcal{R}_{k,\tau,s}, \forall c \in C^L, \tau, s$$

Solution Algorithm

- Progressive hedging makes a scenario-decomposition and then obtains a solution by penalizing the scenario-problems
- Solve each scenario independently and update penalty term until convergence
- Algorithm:
  1. Solve each scenario without penalty terms
  2. Find the average first-stage solution $\bar{x} = \sum_{\forall s} \Pr(s)\, x_s$
  3. Calculate penalty factor $\eta_s = \rho(x_s - \bar{x}_s)$
  4. Augment the penalty factor to the stochastic model and solve
  5. If $\sum_{\forall s} \Pr(s)\, ||x_s - \bar{x}_s|| > \epsilon$ go to 2
- The algorithm terminates once all first-stage decisions x_s converge to a common $\bar{x}$
- The PH algorithm may experience slow convergence
- A detailed analysis of PH showed that individual first-stage variables frequently converge to specific values across all scenario subproblems [32].
- We fix some of the first-stage variables (depot selection and crew allocation) if they converge to the same values after some number of iterations.
  - 5 iterations for depots
  - 20 iterations for crews



Test Case

- Modified IEEE 123-bus distribution feeder
- The network is modified by including:
  - 3 × dispatchable DGs
  - 18 × new switches
  - 5 × PVs
  - 2 × BESSs.
- 100 damage scenarios are generated
- Reduced to 30 using GAMS's SCENRED2 tool
- 5 potential depots
- Maximum of 10 line crews
- Maximum of 10 Tree crews
- Depot 1 has: 5 line crews, 3 tree crews, 25 poles (10 for 3-phase lines and 15 for 1- and 2-phase lines), 4 km of conductor, 8 single-phase transformers, and 3 three-phase transformers

SIMULATION DATA FOR SCRAP ON THE IEEE 123-BUS FEEDER

Parameter	Value
Depot supply capacity (unit)	$\mathcal{C}_d^E$ = {600,400,400,250,250}
Depot crew capacity (crew)	$\mathcal{C}_d^H$ = {8,7,7,5,5}
Capacity required (unit)	$\mathcal{C}_\tau^R$ ={10,8,5,4,6}
Staging areas costs ($)	$\mathcal{P}_d^D$ = {0,170K,170K,90K,90K}
Equipment costs ($/unit*)	$\mathcal{P}_\tau^{EI}$ = {2K,1.2K,2.5K,1.2K,3.3K}
Hourly cost ($/crew)	Line crew: 225, Tree crew: 120
Transportation costs ($/tkm)	0.098
Contracting costs	$4285/crew

*For the conductor, 1km = 1 unit.

Results (1/2)

- SCRAP is compared with deterministic allocation (DA) and a robust stochastic optimization method (RSO)
- The staging sites and the number of crews are found to be the same for all methods
- The deterministic solution is biased towards a single scenario and did not consider some of the extreme cases
- RSO favors a solution that would perform better with worst-case scenarios, which can lead to over-preparation and over-investment

Pre-event Preparation Results

		SCRAP		DA		RSO	
Staged Depots		1	4	1	4	1	4
Line Crews		6	4	6	4	6	4
Tree Crews		2	1	2	1	2	1
Equipmant	1	10	6	10	0	15	8
	2	16	13	13	6	26	15
	3	3	0	3	0	3	0
	4	6	2	7	1	6	3
	5	3.8 km	2 km	2.5 km	1.5 km	5 km	3 km
Costs		$146,766		$117,443		$183,371	

Results (2/2)

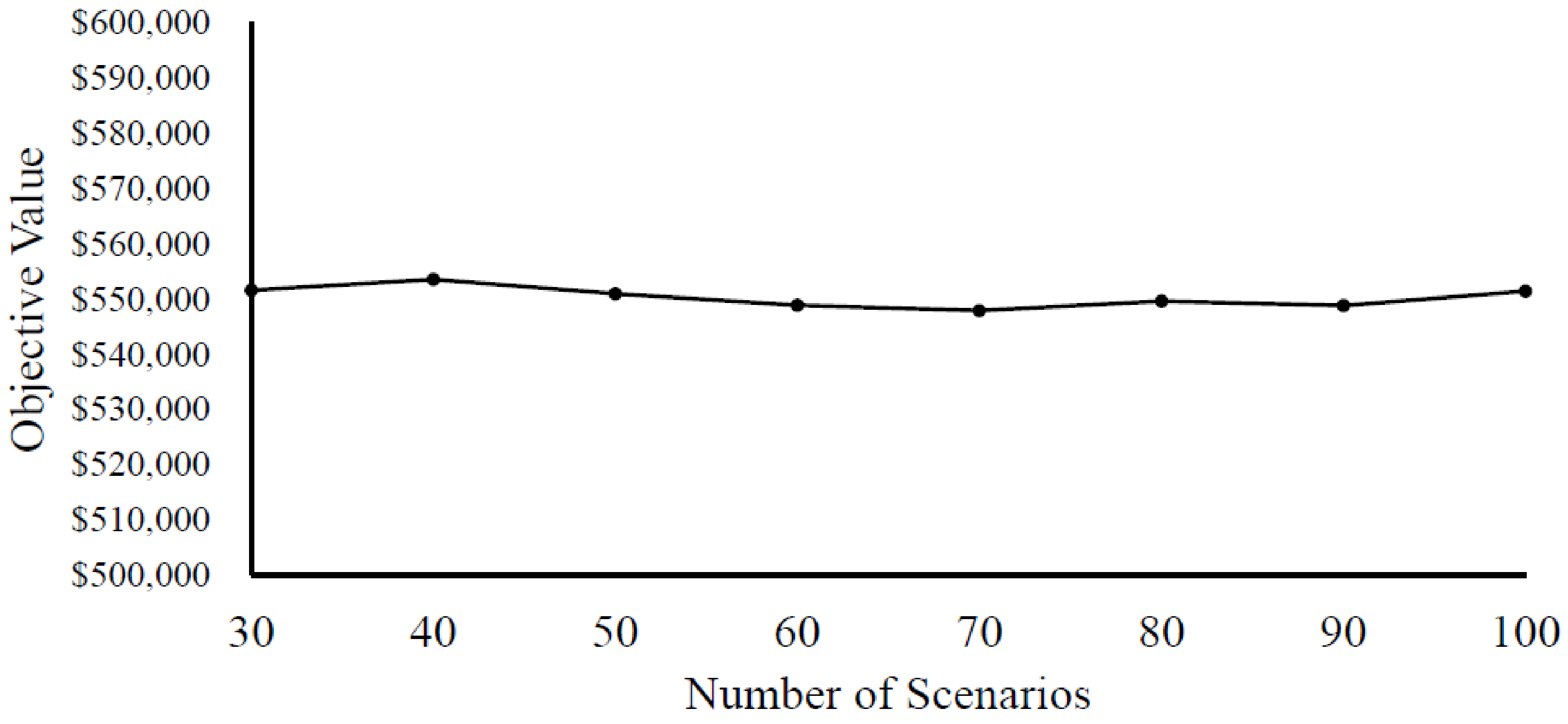
- SCRAP is solved using the extensive form (EF) and PH
- The performance is evaluated by comparing the solutions with the wait-and-see (WS) solution and calculating the expected value of perfect information (EVPI)
- ED is the expected value of the deterministic solution
- The difference between PH and ED is $163,017, which is around 80% of the difference between ED and WS
- This indicates that the stochastic model leads to a better preparation strategy by acquiring and positioning enough equipment
- PH achieved a solution only 0.36% less than EF with a considerably lower computation time
- RSO achieved a solution that outperforms the deterministic one, however, the EVPI for RSO is $95,513 and $38,415 for SCRAP-PH

PERFORMANCE OF THE STOCHASTIC PROGRAM

Method	Objective Value	Computation Time	EVPI
WS	$513,170	N/A	N/A
SCRAP-EF	$549,554	300 min	$36,384
SCRAP-PH	$551,585	106 min	$38,415
RSO	$608,683	335 min	$95,513
ED	$714,602	2 min	$201,432

Stability Analysis

- We test the sensitivity of the solution to the number of scenarios (Kaut 2007)
- If the variation of the objective value is limited, then the solution is stable



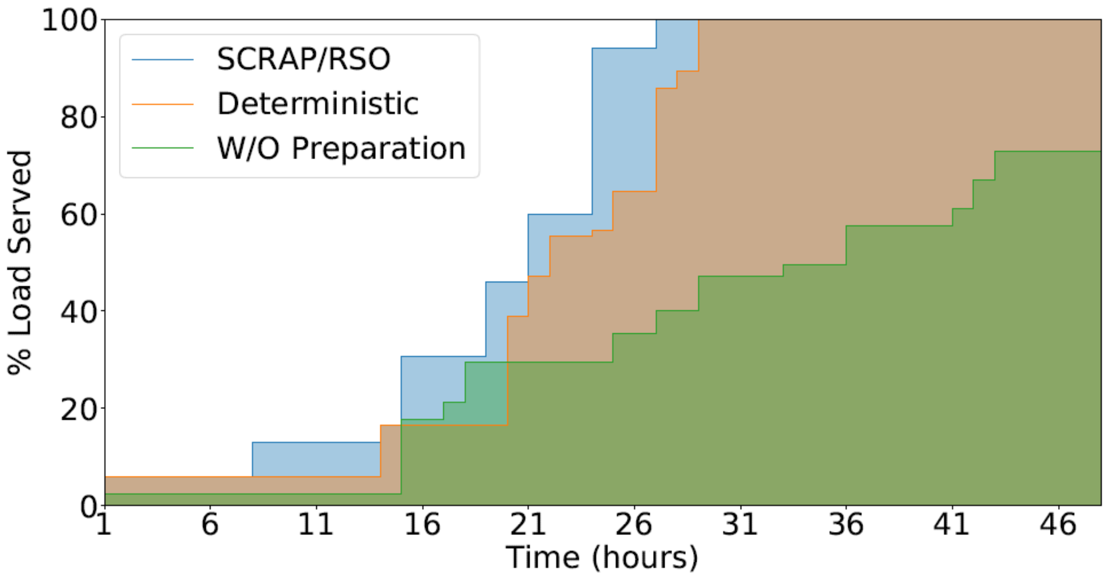
Restoration Phase

- To assess the devised preparation plan, we solve the repair and restoration problem with and without preparation
- A new random damage scenario is generated on the IEEE 123-bus system
- In the generated scenario, 13 three-phase poles, 18 single-phase poles, 2 single-phase transformers, and 4343.4 meter of conductor are damaged

REPAIR AND RESTORATION PERFORMANCE AFTER THE EVENT

Preparation	Equipment	Load served (kWh)
SCRAP	{+3,+11,+3,+6,+0.32 km}	80,136 kWh
RSO	{+10,+23,+3,+7,+3.7 km}	80,136 kWh
DA	{-3,+1,+3,+6,-0.34 km}	77,448 kWh
W/O Preparation	{-3,-3,+3,+6,-0.34 km}	46,667 kWh

"-": shortage; "+": surplus; the load served is for the first 48 hours
Equipment: {Poles for 3-phase lines, Poles for single-phase lines, 3-phase transformers, single-phase transformers, conductor}



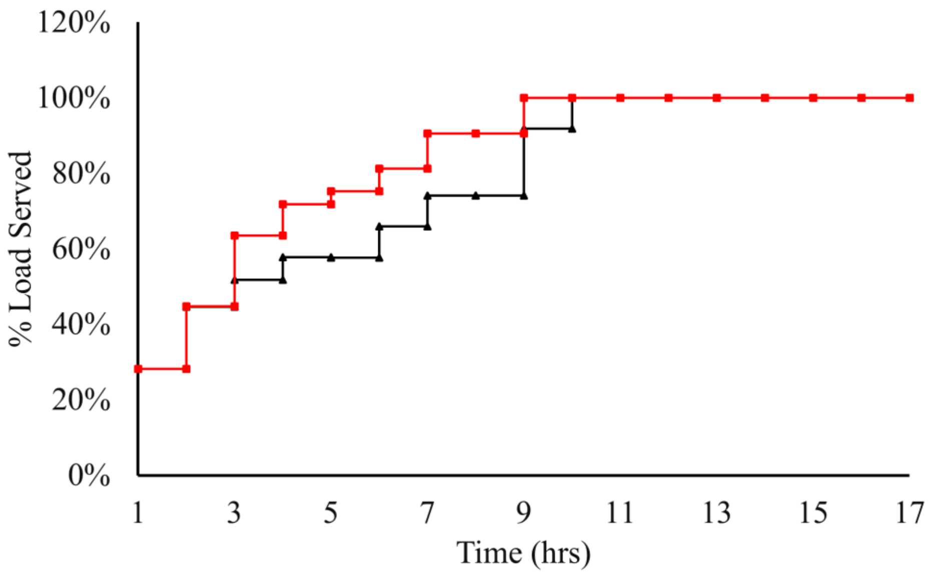
Conclusions

- A two-stage stochastic mathematical model is developed to select staging locations, and allocate crews and equipment
- SCRAP is able to consider the variability of the extreme event outcome compared to the deterministic solution
- Solving the two-stage stochastic problem is more beneficial than solving a deterministic problem
- Robust optimization may lead to over-preparation
- By using an effective preparation procedure, we can ensure that enough equipment is present for repairing the damaged components in the network and facilitate a faster restoration process

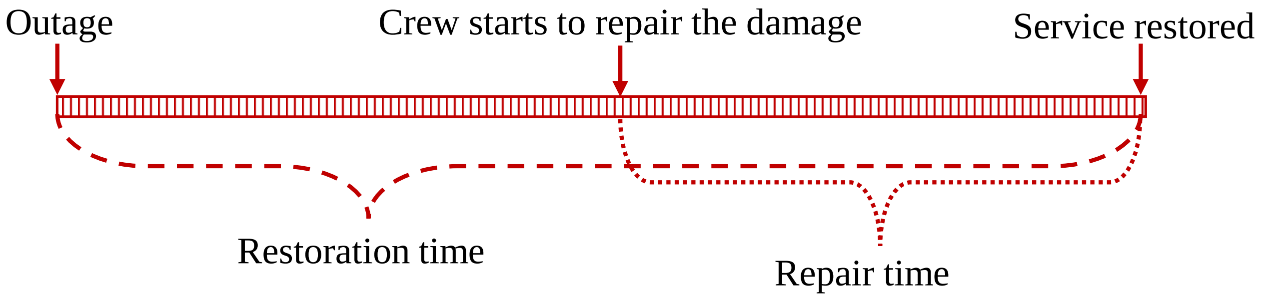
Repair Time Prediction

Objectives

- Estimate the repair time
  - An efficient repair schedule can be obtained if the estimated time is close to the actual time required by the crews
  - A better schedule can lead to a faster disaster response
- Estimate the restoration time
  - Provide customers with estimated restoration times
  - What is the difference between restoration and repair times?

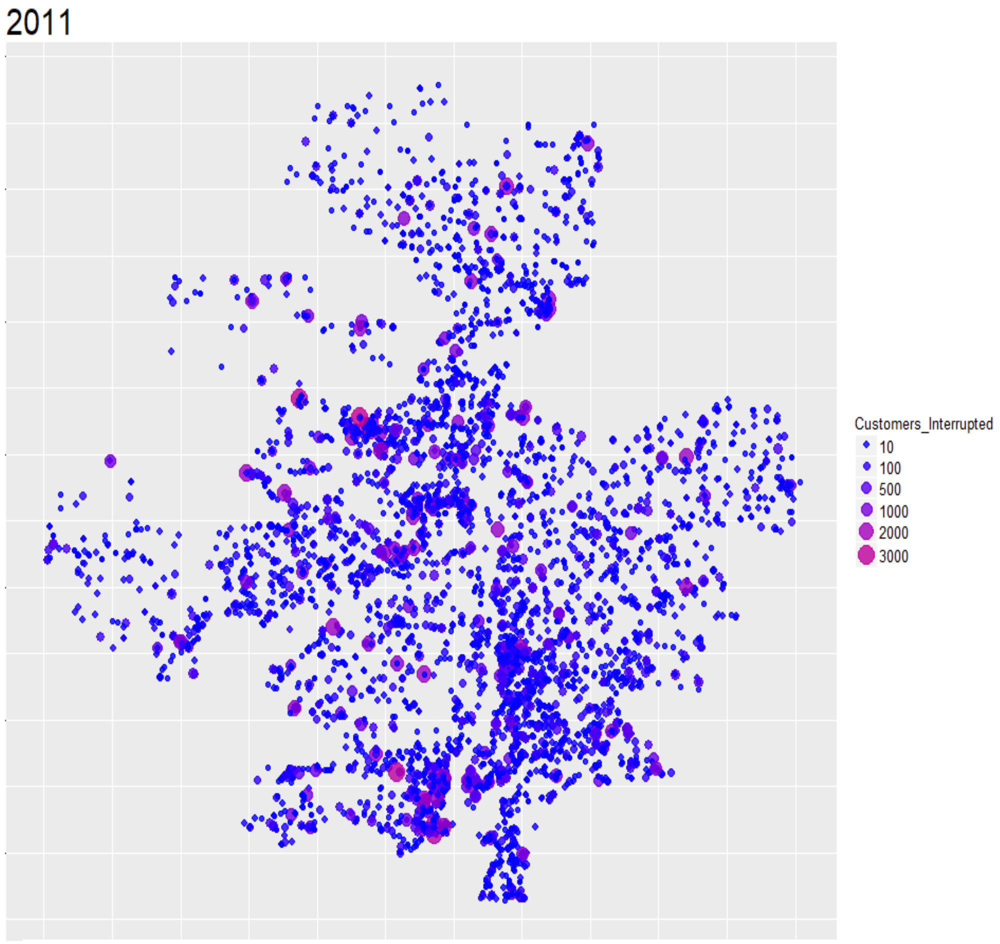


Two different repair schedules



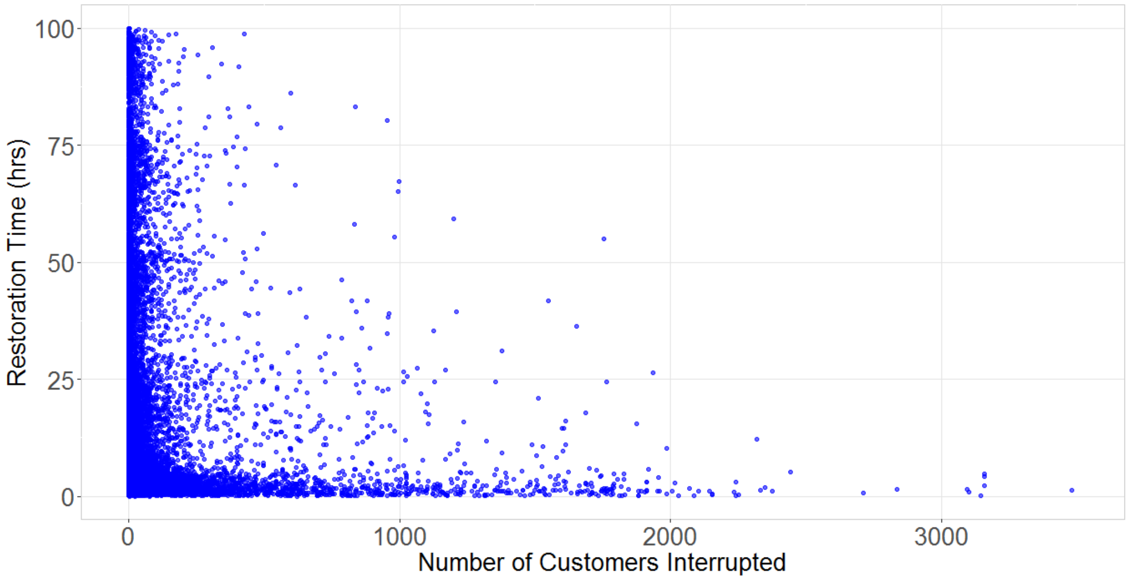
Outage Data Overview

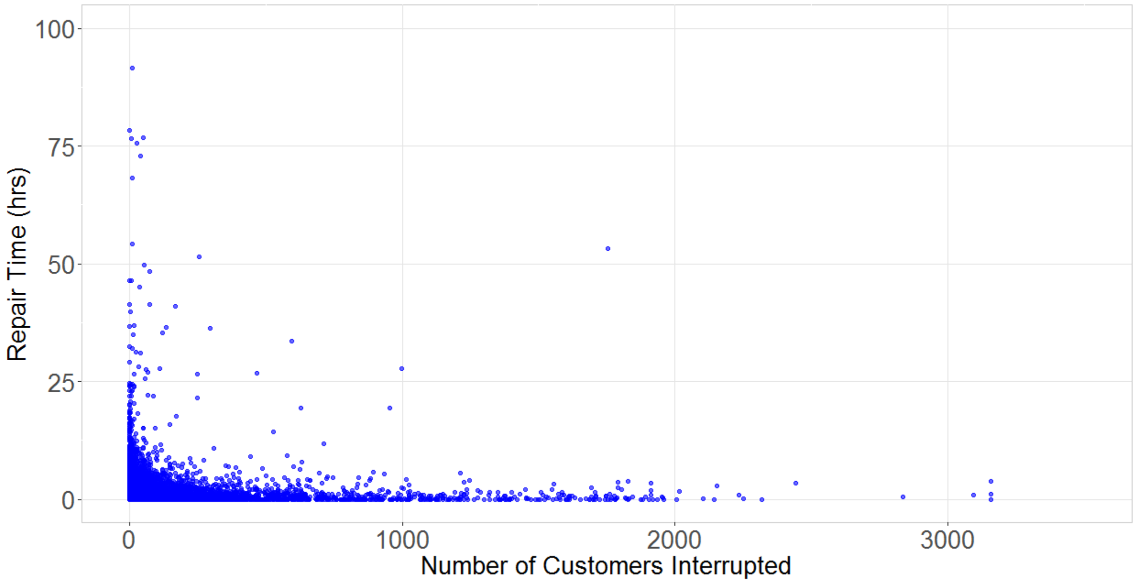
- Outages from 2011-2016
- 32,291 power outages
- 253 circuits
- 2 hurricanes and several storm events
- Data provides
    - Repair time
    - Restoration time
    - Customers interrupted
    - Location
    - Cause
- Weather events are collected from National Oceanic and Atmospheric Administration (NOAA)



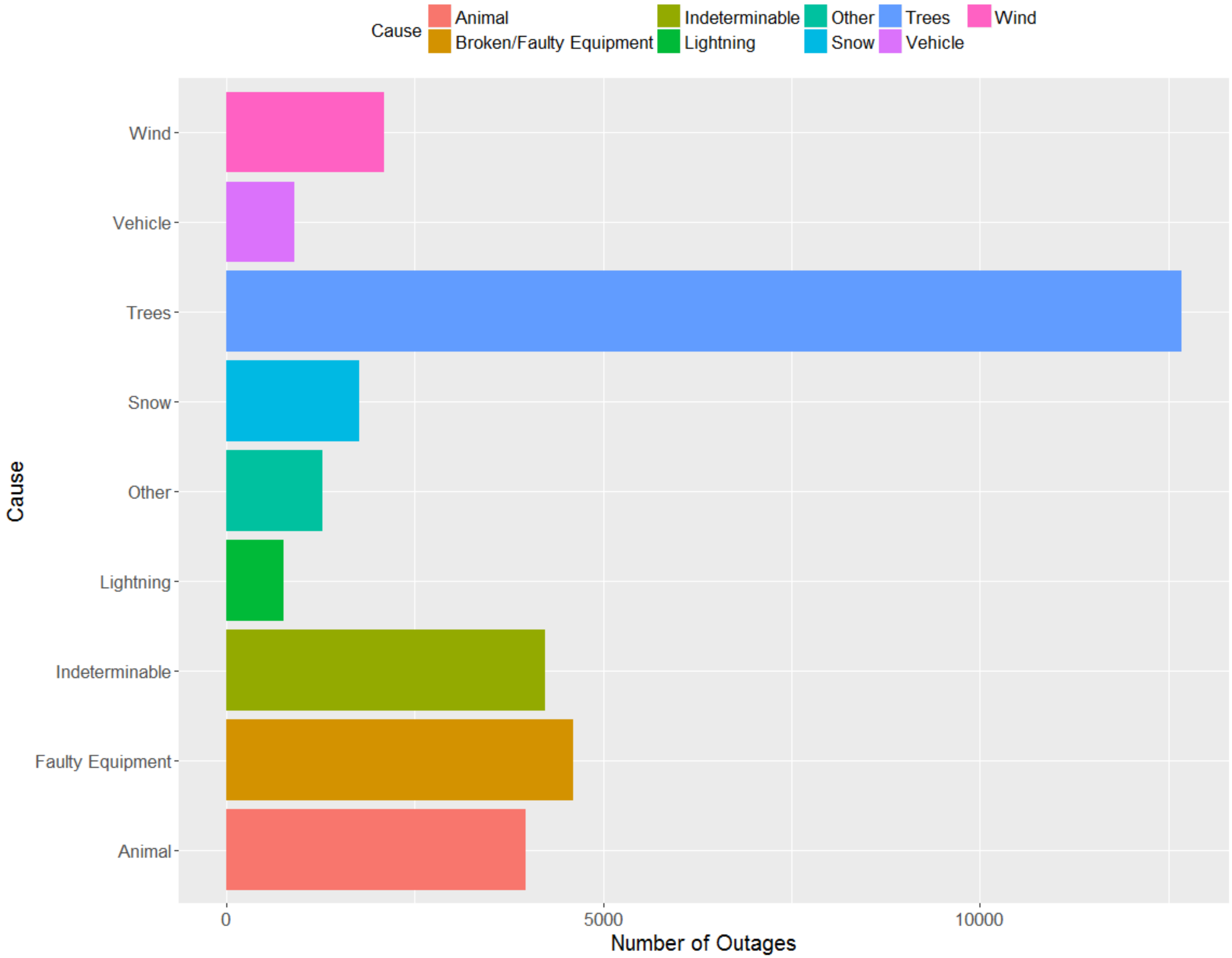
Outage Data Overview (Cont.)

- Besides the causes and weather events, the number of customers interrupted has a significant impact on restoration and repair time
- With a larger number of affected customers, both the restoration and repair times tend to be shorter



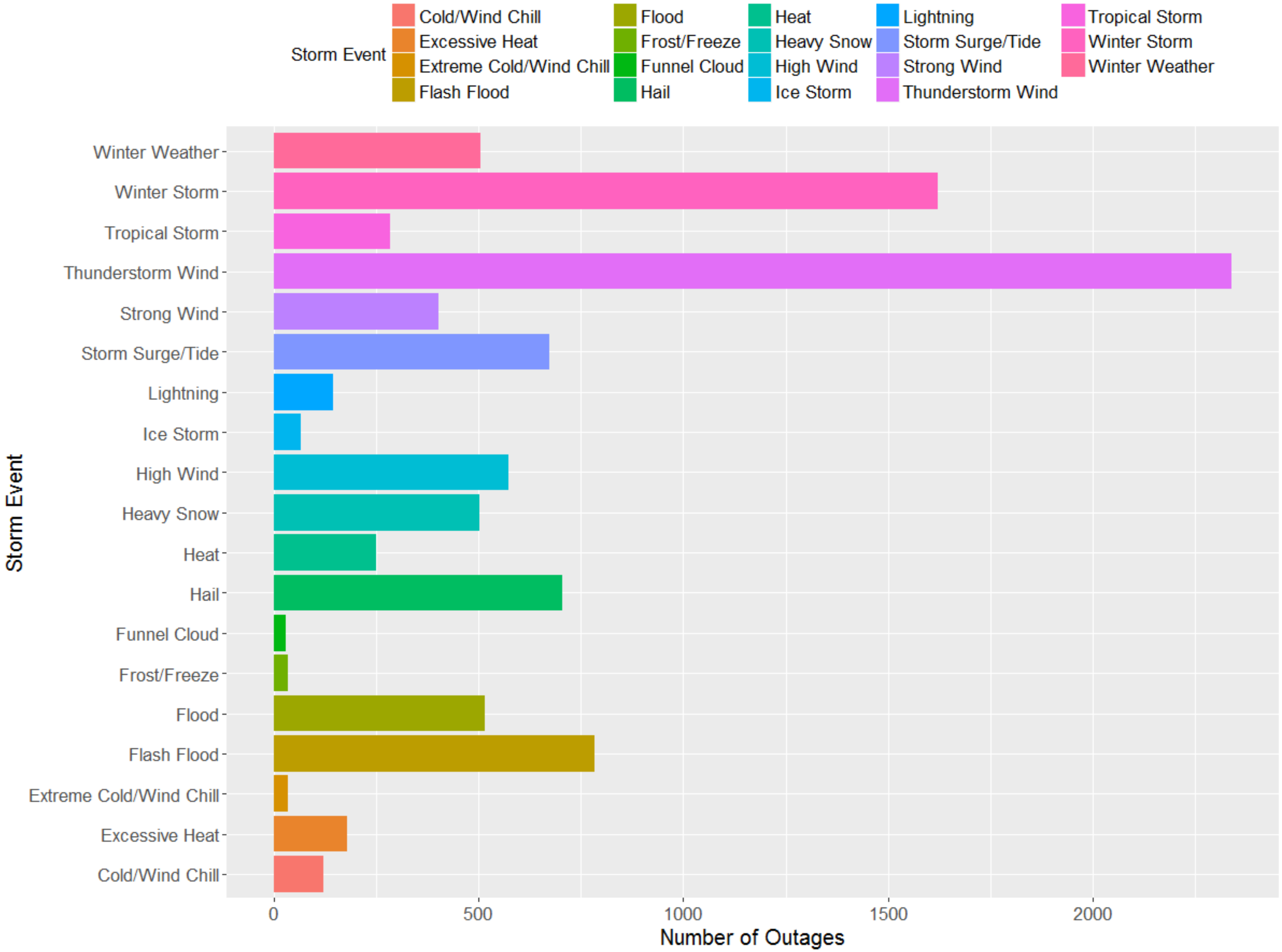


Outage Causes



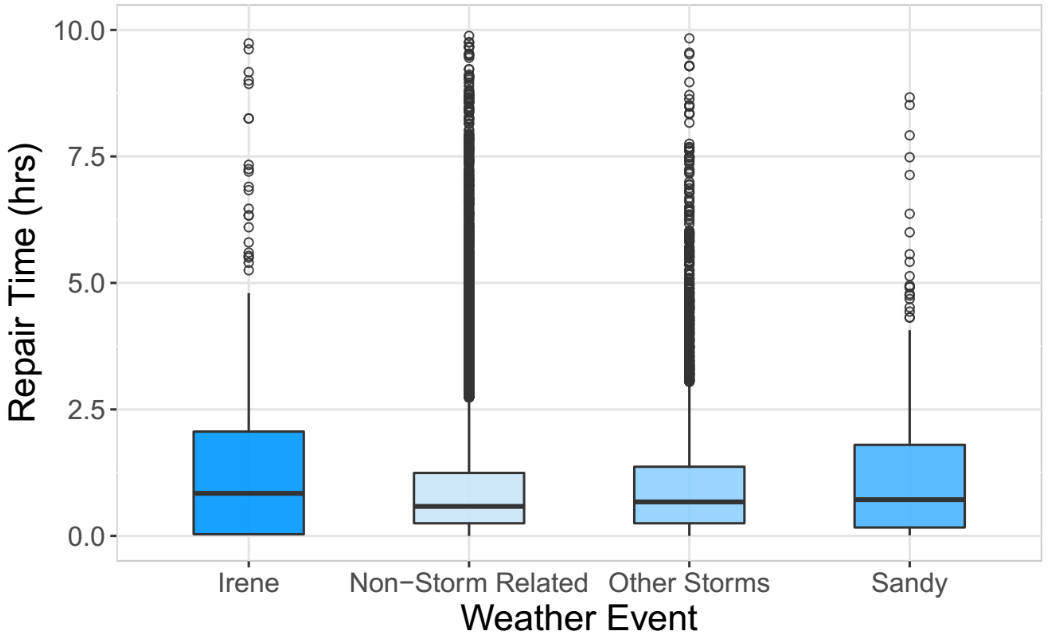
Cause	Restoration Time (hrs)		Repair Time (hrs)	
	mean	standard deviation	mean	standard deviation
Animal	1.79	1.76	0.41	0.63
Broken/Faulty Equipment	4.43	5.07	1.58	2.38
Indeterminable	3.32	4.22	0.67	1.29
Lightning	5.26	5.46	0.82	2.04
Other	3.41	13.11	1.46	13.26
Snow	37.37	29.04	0.89	4.87
Trees	10.48	17.59	0.97	2.07
Vehicle	2.82	2.50	1.91	6.11
Wind	25.65	24.73	0.84	3.78

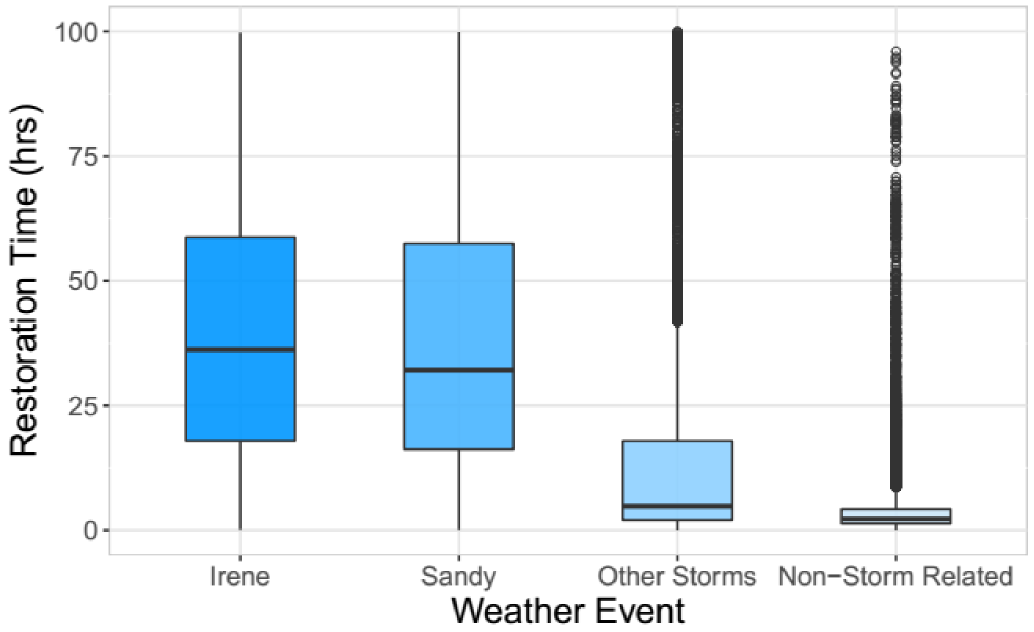
Outages and Weather Events



Weather Event	Restoration Time (hrs)		Repair Time (hrs)	
	mean	standard deviation	mean	standard deviation
Cold/Wind Chill	2.73	1.79	1.09	1.39
Excessive Heat	6.80	5.84	1.25	1.32
Extreme Cold/Wind Chill	2.73	2.07	1.74	2.31
Flash Flood	26.07	28.68	0.76	3.07
Flood	30.55	25.63	0.91	4.46
Frost/Freeze	2.07	1.55	0.67	1.14
Funnel Cloud	9.23	6.58	0.82	0.77
Hail	8.14	7.60	0.95	1.65
Heat	3.65	2.96	1.18	1.45
Heavy Snow	32.34	27.75	0.59	2.21
High Wind	26.46	26.35	0.78	4.34
Ice Storm	50.29	18.89	1.22	4.34
Lightning	4.57	4.07	1.12	1.35
Storm Surge/Tide	38.03	28.45	1.03	5.19
Strong Wind	6.08	6.26	1.41	2.37
Thunderstorm Wind	7.39	7.15	1.02	1.89
Tropical Storm	35.50	22.37	1.73	5.52
Winter Storm	37.55	29.83	0.79	4.63
Winter Weather	4.47	5.12	1.17	1.42

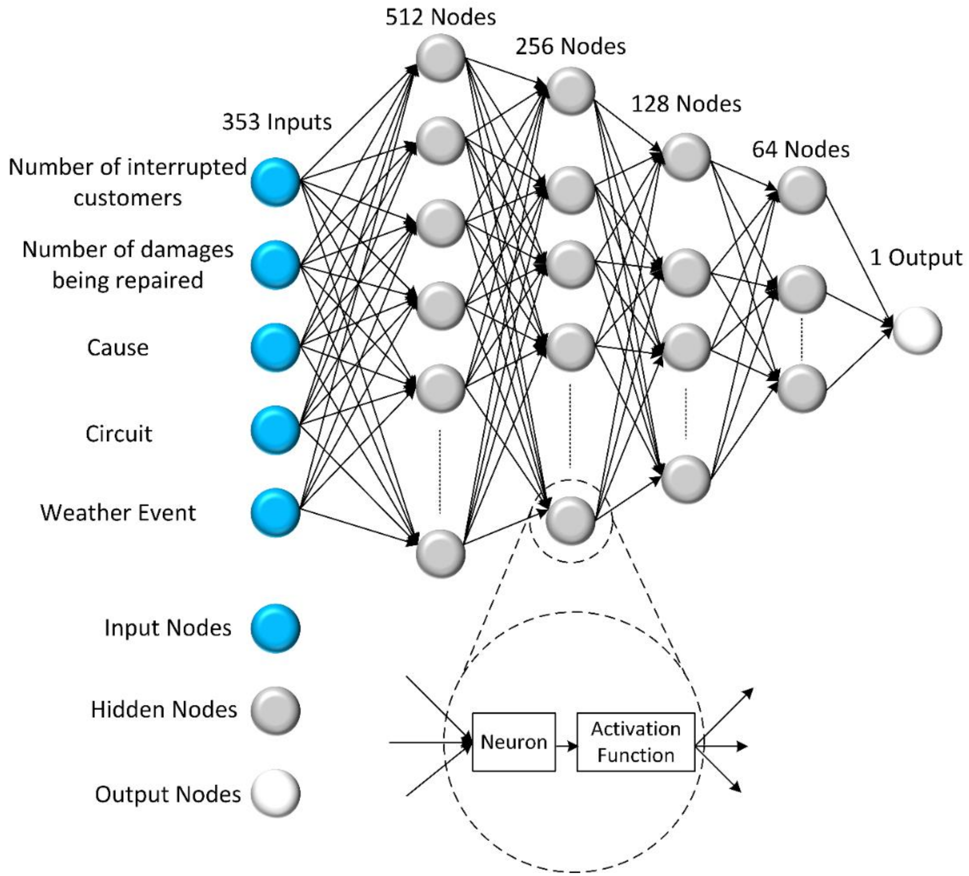
Outages and Weather Events (Cont.)





Deep Neural Network

- In the prediction model for both repair and restoration times, we consider 353 inputs, where 2 are continuous and 351 are categorical (binary)
- Continuous inputs:
    - Number of customers interrupted
    - Number of damages to repair
- Categorical inputs:
    - Cause of outage
    - Circuit number
- Weather events (e.g., flash flood, hail, heavy snow, rain, storm surge/tide, etc)



Deep Neural Network (Cont.)

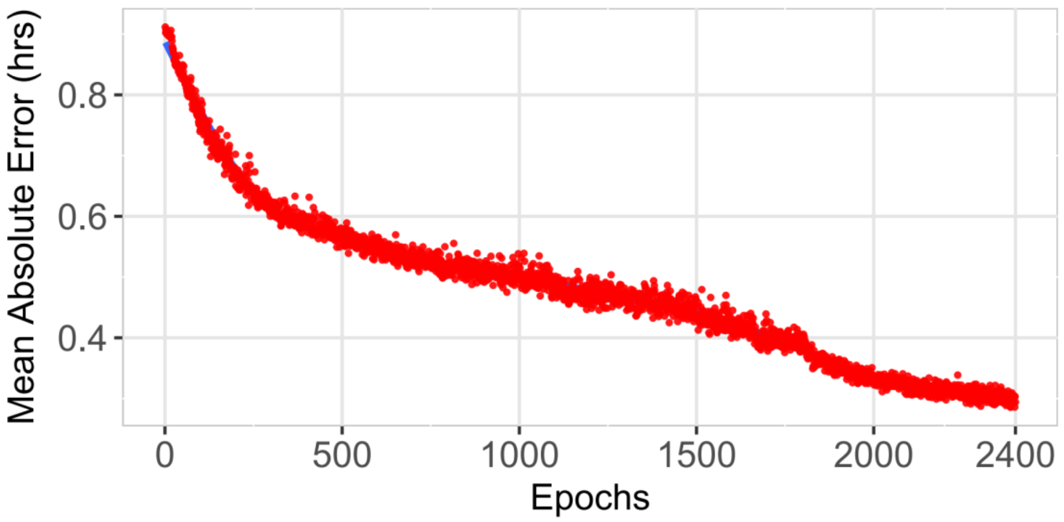
- R with Keras and Tensorflow packages is used to model the DNN
- DNN has 4 hidden layers: 512, 256, 128, and 64 nodes
- Dropout regularization technique for reducing overfitting
- Activation function: Rectified Linear Unit (Relu)
- Optimizer: Adam optimization algorithm
- The cost function used in the proposed model is the mean absolute error

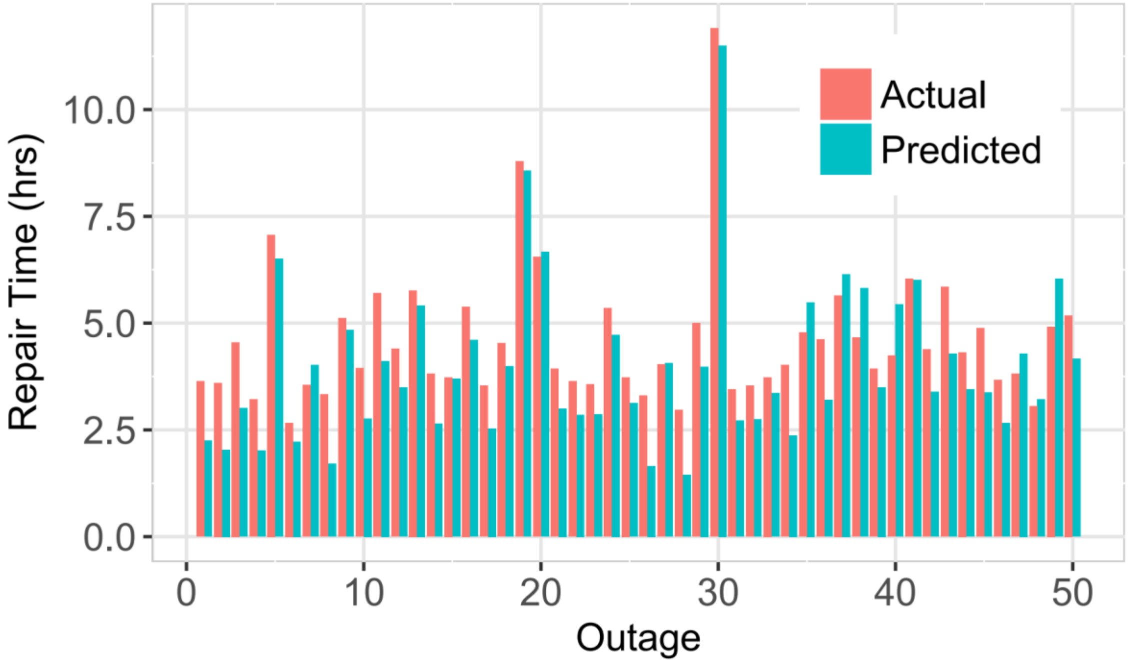
	DNN-Restoration Time	DNN-Repair Time
Cost Function	MAE	MAE
Optimizer	Adam	Adam
Training Samples	26332	22791
Epochs	4000	2400
Batch Size	50	50
Total Iterations	2108000	1094400

Layer	Nodes	Activation	Trainable Parameters	Dropout Rate
Input	353	N/A	N/A	N/A
Hidden	512	Relu	181248	20%
Hidden	256	Relu	131328	20%
Hidden	128	Relu	32896	N/A
Hidden	64	Relu	8256	N/A
Output	1	Relu	65	N/A

Repair Time Prediction

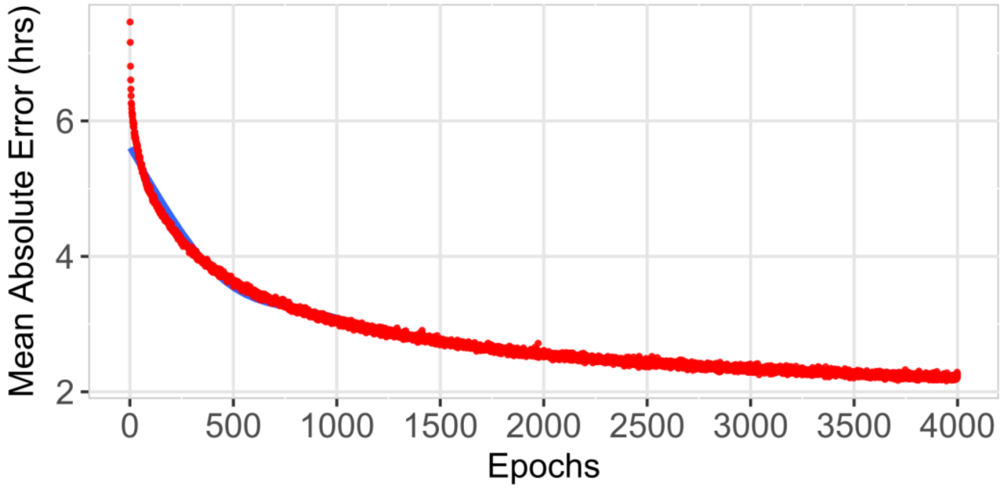
- Outages from 2011-2015 used as training data
- Outages on 2016 used as testing data
- 80% of the predicted repair time is within 30 minutes of the actual time
- 5% of the predicted repair time is 120 minutes longer the actual time

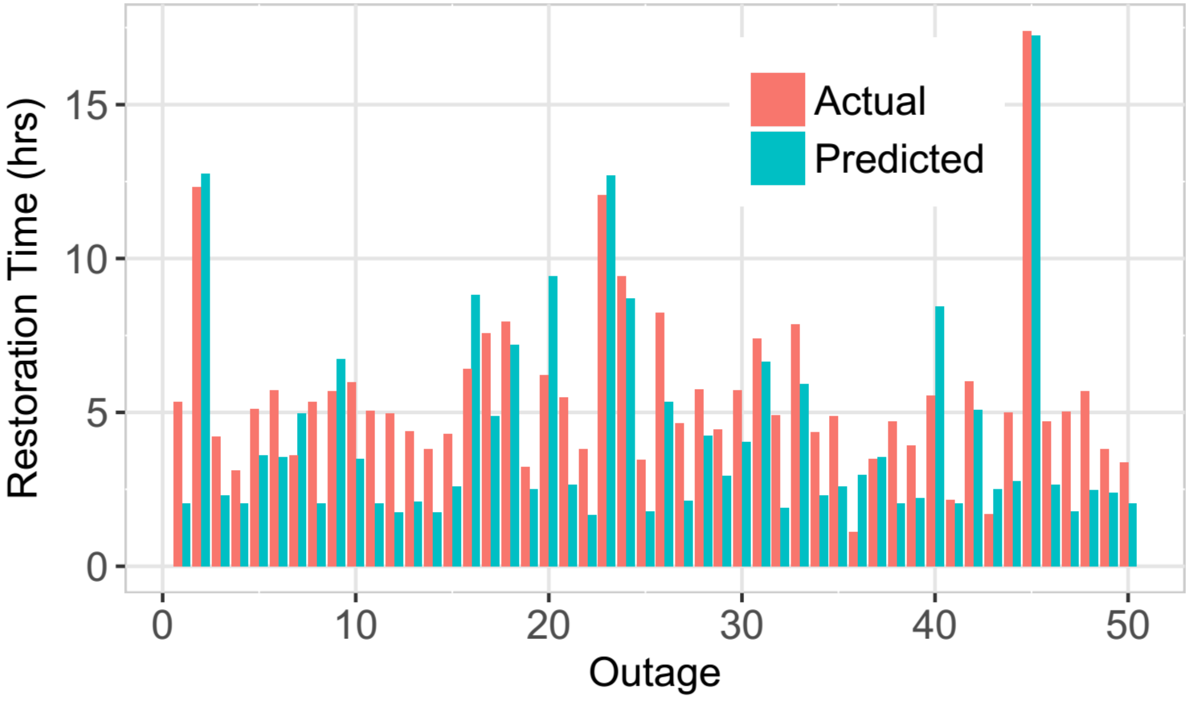




Restoration Time Prediction

- Outages from 2011-2015 used as training data
- Outages on 2016 used as testing data
- 27% of the predicted restoration times are within 30 minutes from the actual time
- 72% of the predicted restoration times are within 120 minutes from the actual time





Results Summary

- The predictive model for the repair time outperforms the restoration time
- The MAE in both the training and testing set is around 2 hours for the restoration time model, which is about 90 minutes higher than the repair time DNN model

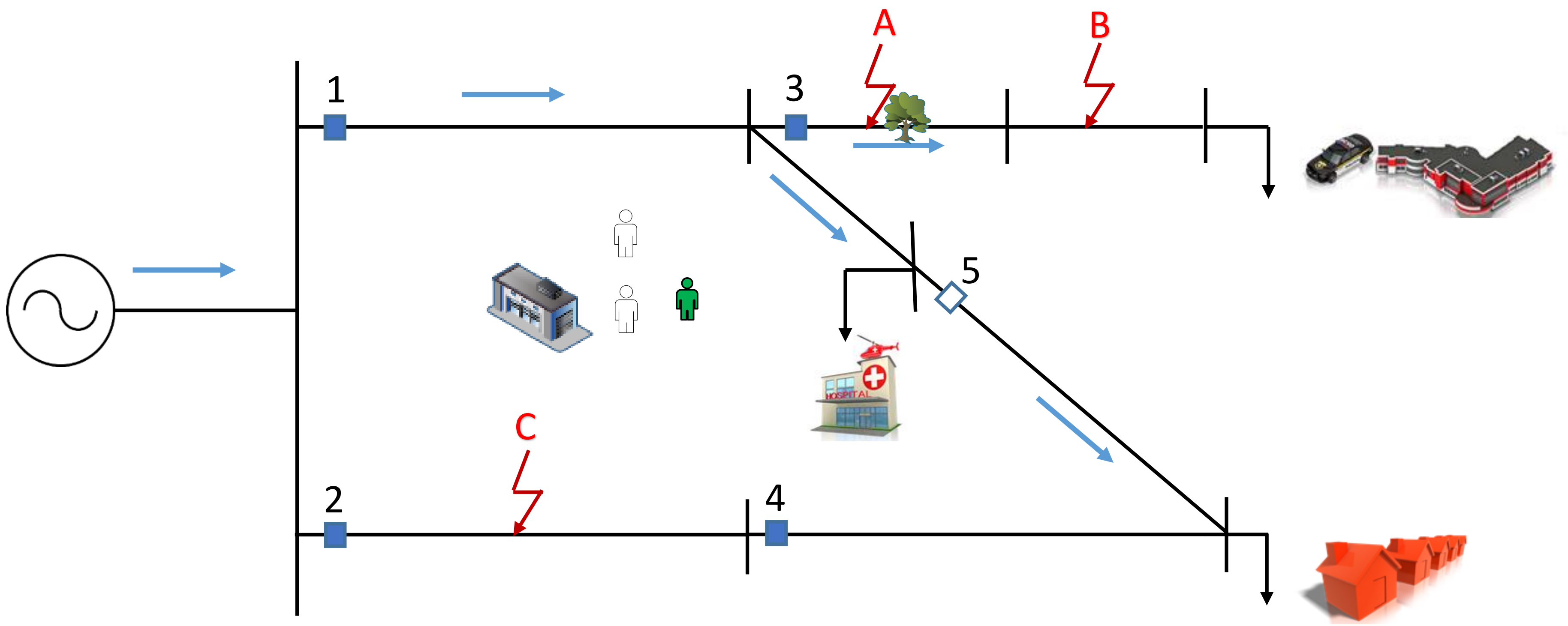
| Predicted - Actual |	Percentages of Prediction	
	Restoration Time	Repair Time
Less than 30 min	27%	80%
Between 30 and 60 min	22%	11%
Between 60 and 90 min	15%	4%
Between 90 and 120 min	8%	1%
Between 120 and 150 min	6%	2%
Greater than 150 min	22%	2%
Mean Absolute Error	1.98 hrs	18.03 min

Conclusion

- We can conclude that predicting the repair time is easier than predicting the restoration time. This result is not surprising because of the high variability of the restoration time. In addition, the restoration time includes another uncertain variable, which is the travel time of the repair crews
- Machine learning can be used to improve situational awareness by predicting the repair time
- After predicting the repair times, the utility can schedule the crews more efficiently
- Once the repair time and the crew schedule is obtained, a more reliable estimation of the restoration time can be obtained

Distribution System Repair and Restoration

Problem Overview



Closed switch Open switch

Problem Statement

Challenges

- Distribution systems are becoming more complex with new devices. DERs and automatic switches can greatly accelerate restoration if being operated effectively
- Managing crews, equipment, and the operation of the network is a demanding task. After an extreme event, a sudden influx of crews can overwhelm operators and storm planners
- The recovery operation problem and repair scheduling are interdependent
- Currently, crews are scheduled based on a priority list. If the priorities are not well defined, the schedule will be inefficient

Improvements

- Development of advanced optimization methods to jointly optimize the recovery operation and logistic problems. An optimization process can help the operator in making critical and more informed decisions after outages
- Design solution algorithms for the co-optimization problem to obtain a quick and efficient solution

Distribution System Restoration

- **Reconfiguration**: optimal reconfiguration of the distribution network with the objective of maximizing the served loads
- **Reconfiguration and DG dispatch**: optimal reconfiguration of the distribution network and DER operation
- **Networked Microgrids**: optimal operation of interconnected individual microgrids with defined boundaries
- **Microgrid formation**: optimal operation of microgrids with dynamic boundaries
- **Repair Scheduling**: repair scheduling of distribution systems' assets without considering network operations

Method	Model/Algorithm			
	MILP	Stochastic/Robust	Agent-based	Heuristic
Reconfiguration	Butler 2018	Lee 2015	Solanki 2007	Kumar 2008
Reconfiguration+DGs	López 2018	Chen 2016	Zidan 2012	Drayer 2018
Networked Microgrids	Wang 2016	Wang 2015	Zhao 2018	Hu 2017
Microgrid Formation	Chen 2016	Sharma 2018	Sharma 2015	Kumar 2014
Repair Scheduling	Golla 2017	Xu 2007		Johns 1994

MILP: Mixed integer linear Program

Review: Repair and Restoration (1/3)

❖MILP for **transmission** system repair and restoration (Arab 2015)

Assumptions

- Neglect travel time
- Crews are immediately present at the damaged components
- No specific crew assignments

Model

- Transmission system operation
- Repair schedule

Limited by number of crews

Repair time

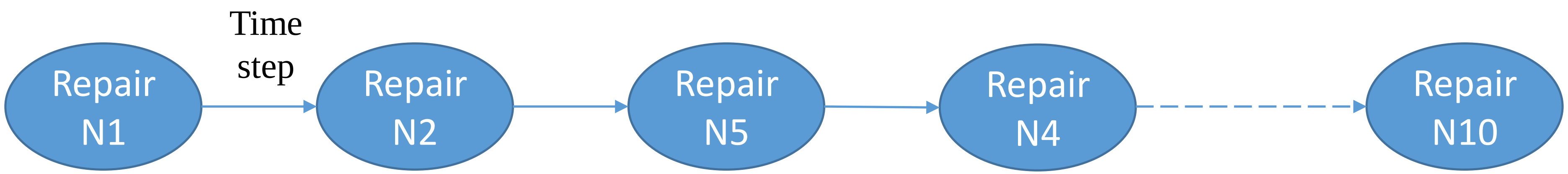
	Repair status						
Line 1	1	1	1	0	0	0	0
Line 2	1	1	1	1	0	0	0
Line 3	0	0	0	1	1	0	0
Line 4	0	0	0	0	1	1	0

	Operation status						
Line 1	0	0	0	1	1	1	1
Line 2	0	0	0	0	1	1	1
Line 3	0	0	0	0	0	1	1
Line 4	0	0	0	0	0	0	1

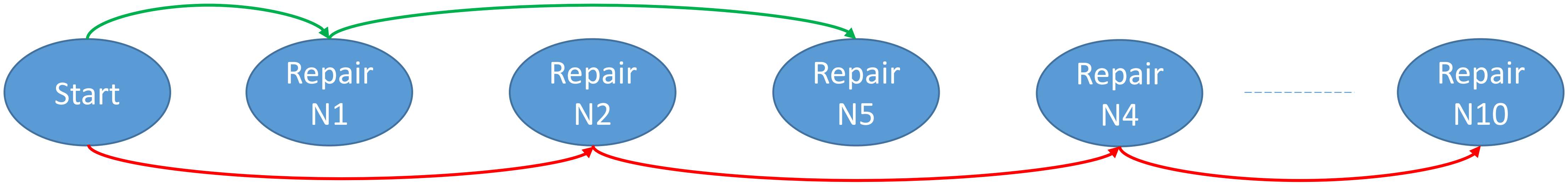
Review: Repair and Restoration (2/3)

- ❖ A project by Los Alamos National Lab and National ICT Australia (NICTA), Australian National University
- ❖ 2-Step approach for **transmission** systems (Pascal Van Hentenryck and Carlton Coffrin 2015):

1. Restoration Ordering Problem: assume only one component can be repaired at each time step
   - ❖ Solved using MILP

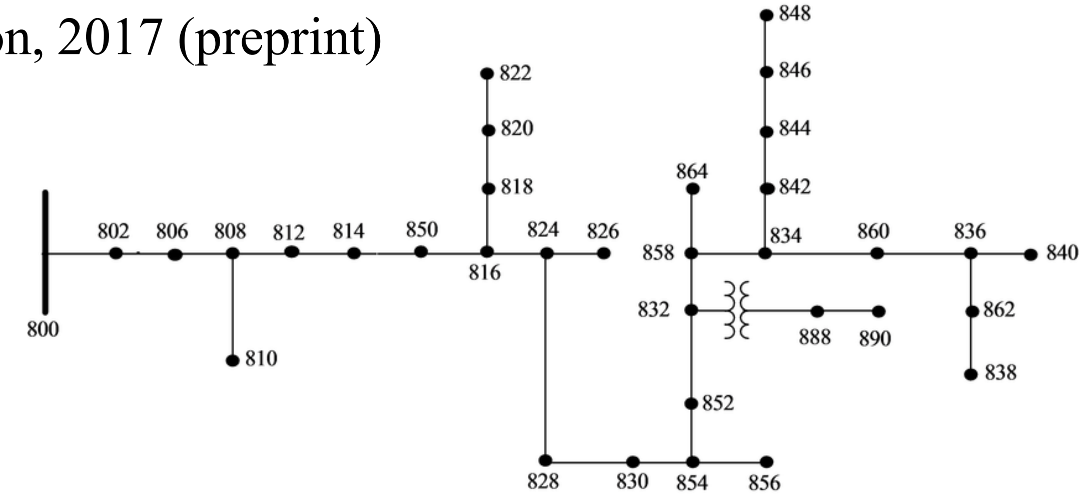


2. Routing: solve a routing problem with precedence constraints
   - ❖ Solved using Constraint Programming
   - ❖ Precedence constraint



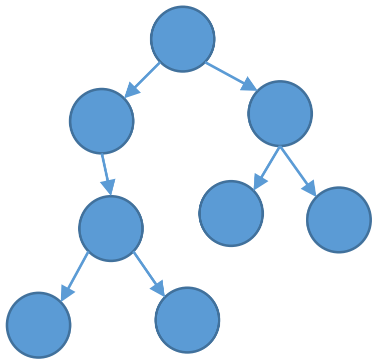
Review: Repair and Restoration (3/3)

❖Yushi Tan and Daniel S. Kirschen , University of Washington, 2017 (preprint)



- **Assumptions**
  - Network is radial without switches
  - Power only from substation
  - Travel time is neglected
  - Power operation constraints are neglected
- **Method**
  - Solve scheduling problem (LP) to minimize the total weighted completion time under with “outtree” precedence constraint

    → obtain priority list
  - Whenever a crew is free, select among the remaining candidate lines the one with the highest priority



Method 1: Deterministic MILP

Distribution system repair and restoration problem (DSRRP)

Objective

- Minimize cost of shedding loads and switching operation

load shedding cost switching cost $\gamma = 1$ if switch k operates

$$\min \sum_{\forall t} \Big(\sum_{\forall \varphi} \sum_{\forall i} (1 - y_{i,t}) \rho_i^D P_{i,\varphi,t}^D + \rho^{SW} \sum_{k \in \Omega_{SW}} \gamma_{k,t} \Big)$$

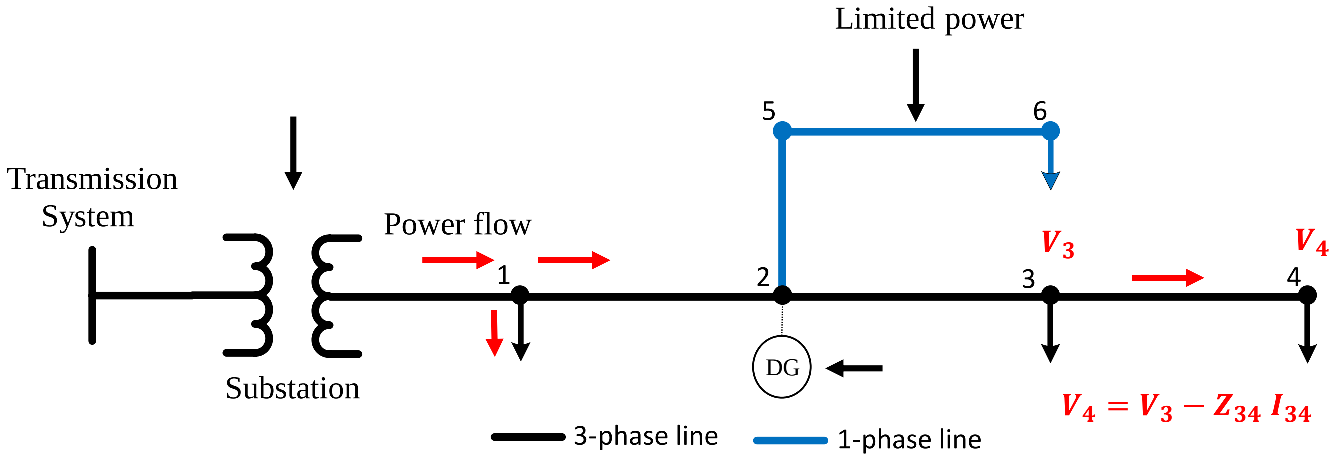
status of the load load on bus i, phase φ, and time t

Constraints

- Distribution system operations
  - ➢ Power flow
  - ➢ Voltage constraints
  - ➢ Reconfiguration and fault isolation constraints
  - ➢ PV systems
  - ➢ Battery storage
- Crew routing
  - ➢ Path-flow constraints
  - ➢ Start/end location
  - ➢ A damaged line is repaired by one crew
  - ➢ Arrival (repair start) time
  - ➢ Tree removal before line repair
  - ➢ Equipment constraints

Distribution System

1. Generator/substation power limits
2. Line limits
3. Node balance
4. Kirchhoff voltage law (Gan 2014)
   - Losses are neglected



$$0 \leq P_{i,\varphi,t}^{G} \leq P_i^{G max} \;, \forall i,\varphi,t$$

$$0 \leq Q_{i,\varphi,t}^{G} \leq Q_i^{G max} \;, \forall i,\varphi,t$$

$$-u_{k,t} p_{k,\varphi} P_k^{K max} \leq P_{k,\varphi,t}^{K} \leq u_{k,t} p_{k,\varphi} P_k^{K max} \;, \forall k,\varphi,t$$

$$-u_{k,t} p_{k,\varphi} Q_k^{K max} \leq Q_{k,\varphi,t}^{K} \leq u_{k,t} p_{k,\varphi} Q_k^{K max} \;, \forall k,\varphi,t$$

$\boldsymbol{p}_k$: for line k with phases a, c, $\boldsymbol{p}_k = [1,0,1]$

status of the line: $u = 0 \rightarrow$ line is damaged or open

$$\sum_{\forall k \in K(.,i)} P_{k,\varphi,t}^{K} + P_{i,\varphi,t}^{G} + P_{i,\varphi,t}^{PV} + P_{i,\varphi,t}^{dch} = \sum_{\forall k \in K(i,.)} P_{k,\varphi,t}^{K} + P_{i,\varphi,t}^{L} + P_{i,\varphi,t}^{ch}, \forall i,\varphi,t$$

$$\sum_{\forall k \in K(.,i)} Q_{k,\varphi,t}^{K} + Q_{i,\varphi,t}^{G} + Q_{i,\varphi,t}^{PV} + Q_{i,\varphi,t}^{ES} + u_{i,t}^{C} Q_{i,\varphi}^{C} = \sum_{\forall k \in K(i,.)} Q_{k,\varphi,t}^{K} + Q_{i,\varphi,t}^{L}, \forall i,\varphi,t$$

$$\boldsymbol{U}_{j,t} - \boldsymbol{U}_{i,t} + \bar{\boldsymbol{Z}}_k \boldsymbol{S}_k^* + \bar{\boldsymbol{Z}}_k^* \boldsymbol{S}_k \leq (2 - u_{k,t} - \boldsymbol{p}_k) M, \forall k,t$$

$$\boldsymbol{U}_{j,t} - \boldsymbol{U}_{i,t} + \bar{\boldsymbol{Z}}_k \boldsymbol{S}_k^* + \bar{\boldsymbol{Z}}_k^* \boldsymbol{S}_k \geq -(2 - u_{k,t} - \boldsymbol{p}_k) M, \forall k,t$$

$U = V^2$

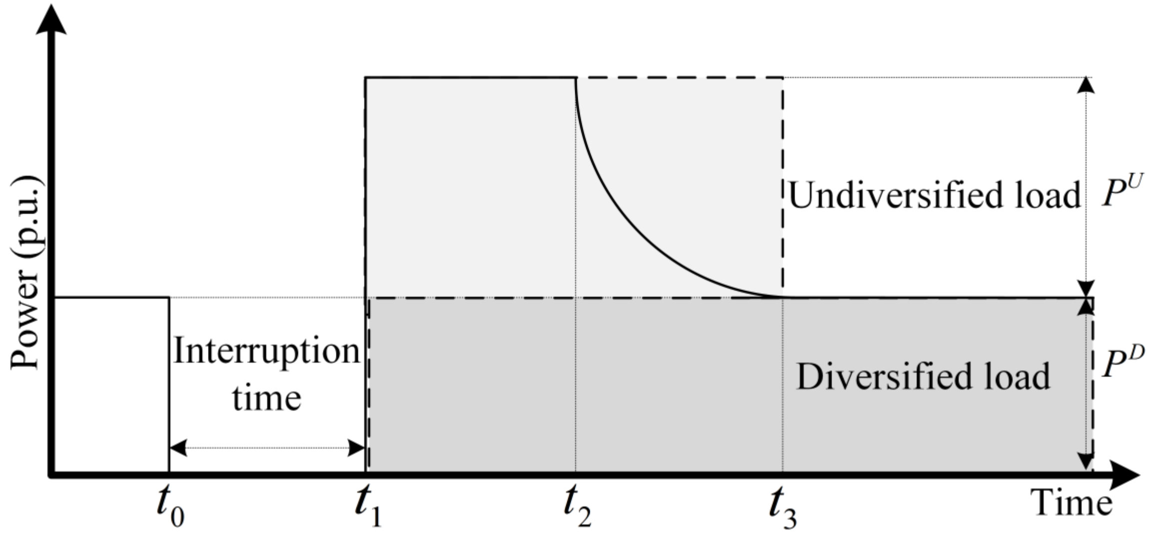
Cold-Load Pickup

- Cold load pickup (CLPU) is the well-known problem defined as excessive inrush current drawn by loads when the distribution circuits are re-energized after extended outages
- The typical behaviour of CLPU can be represented using a delayed exponentially decaying function
- We use two blocks to provide a conservative approach and guarantee the supply-load balance (Liu, PSERC 2009)

$$P^L_{i,\varphi,t} = y_{i,t}P^D_{i,\varphi,t} + (y_{i,t} - y_{i,\max(t-\lambda,0)})P^U_{i,\varphi,t}, \ \forall i,\varphi,t$$

$$Q^L_{i,\varphi,t} = y_{i,t}Q^D_{i,\varphi,t} + (y_{i,t} - y_{i,\max(t-\lambda,0)})Q^U_{i,\varphi,t}, \ \forall i,\varphi,t$$

- λ: number of time steps required for the load to return to normal condition
- If a load goes from a de-energized state y = 0, to an energized state y =1, it will go back to normal condition after λ



Fault Isolation and Reconfiguration

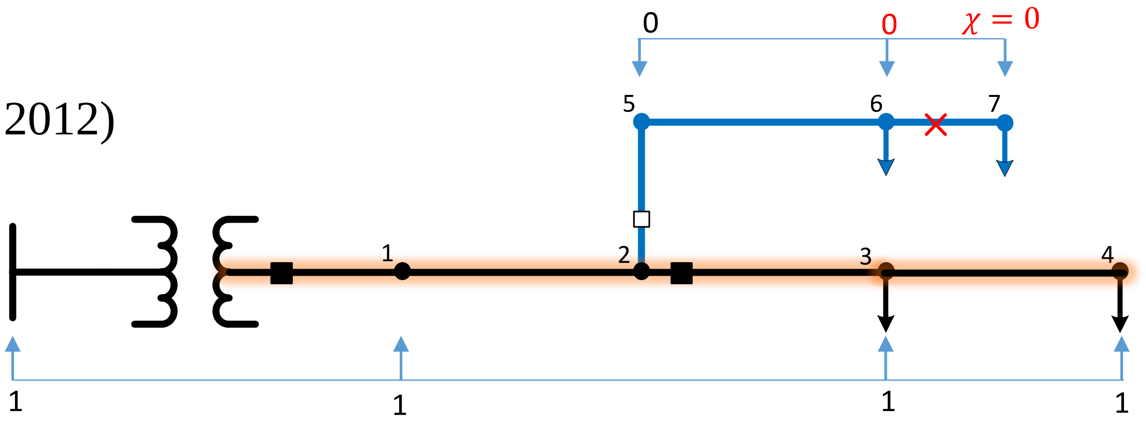
- Fault Isolation
  - Force the voltage to be zero on damaged lines
    - Voltage should be between 0.95 and 1.05 p.u. for energized buses
  - The voltage propagates through KVL until a switch stops the propagation
- Radiality constraints (for radial networks)
  - Find the loops in the network (offline process) (Borghetti 2012)
  - At least one switch must be open in the loop
- Count switching operations
  - $u_{k,t} = 0 \;\&\; u_{k,t-1} = 1 \rightarrow \gamma_{k,t} = 1$
  - $u_{k,t} = 1 \;\&\; u_{k,t-1} = 0 \rightarrow \gamma_{k,t} = 1$

$$2u_{k,t} \geq \mathcal{X}_{i,t} + \mathcal{X}_{j,t}, \forall k \in \Omega_{DK}, t$$

$$\mathcal{X}_{i,t} U_{min} \leq \boldsymbol{U}_{i,t} \leq \mathcal{X}_{i,t} U_{max}\ ,\ \forall i, t$$

$$\mathcal{X}_{i,t} \geq y_{i,t}, \forall i, t$$

$$u_{k,t} = 1, \forall k \notin \{\Omega_{SW} \cup \Omega_{DK}\}, t$$



χ: outage status of bus
$\Omega_{K(l)}$: set of lines in loop l
Ω_{DK}: set of damaged lines

$$\gamma_{k,t} \geq u_{k,t} - u_{k,t-1}, \forall k \in \Omega_{SW}, t$$

$$\gamma_{k,t} \geq u_{k,t-1} - u_{k,t}, \forall k \in \Omega_{SW}, t$$

$$\sum_{k \in \Omega_{K(l)}} u_{k,t} \leq |\Omega_{K(l)}| - 1, \forall l, t$$

Voltage Regulator

- Voltage regulator with variable tap setting
- Voltage on the secondary side = a × voltage on the primary
- $a = [1 + 0.00625 \times Tap] \ \rightarrow U_j = [1 + 0.00625 \times Tap]^2 \ U_i$
- Tap = -16, -15, …., 16
- Size(Tap) = 33
- Define variable $\boldsymbol{\tau} \in \{0,1\}^{33}$
- $\boldsymbol{r} = a^2 = [0.8100, 0.8213, \ldots, 1.2100]$
- Nonlinear constraints

$$U_j = U_i \times \sum_{k=1}^{33} r_k \, \tau_k$$
$$\sum_{k=1}^{33} \tau_k = 1$$

- Linear constraints

$$U^{min}(1 - \tau_k) + r_k U_i \leq U_j \leq \ r_k U_i + U^{max}(1 - \tau_k), \forall VR, k \in \{1..33\}$$

- Simplified

$$0.81 \ U_i \leq U_j \leq 1.21 \ U_i$$

PV and Battery Systems

Types of PV systems considered:

- On-grid (grid-tied) system (Ω_{PV}^{G})
- Hybrid on/off-grid → PV with battery (Ω_{PV}^{H})
- PV + battery with grid forming capabilities (Ω_{PV}^{C})

PV power constraints: Active and reactive power constraints

Solar irradiance

Power rating

$$P_{i,\varphi,t}^{PV} = \frac{Ir_{i,t}}{(1000W/m^2)} \overline{P}_i^{PV}, \forall i \in \Omega_{PV} \backslash \Omega_{PV}^{G}, \varphi, t$$

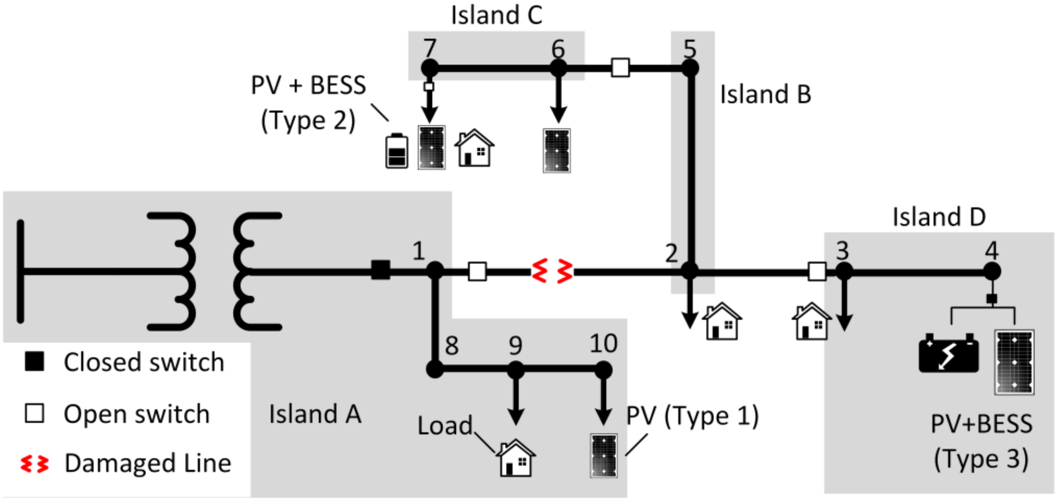
$$P_{i,\varphi,t}^{PV} = \mathcal{X}_{i,t} \frac{Ir_{i,t}}{(1000W/m^2)} \overline{P}_i^{PV}, \forall i \in \Omega_{PV}^{G}, \varphi, t$$

$$|Q_{i,\varphi,t}^{PV}| \leq \sqrt{(S_i^{PV})^2 - (\hat{P}_{i,t}^{PV})^2}, \forall i \in \Omega_{PV} \backslash \Omega_{PV}^{G}, \varphi, t$$

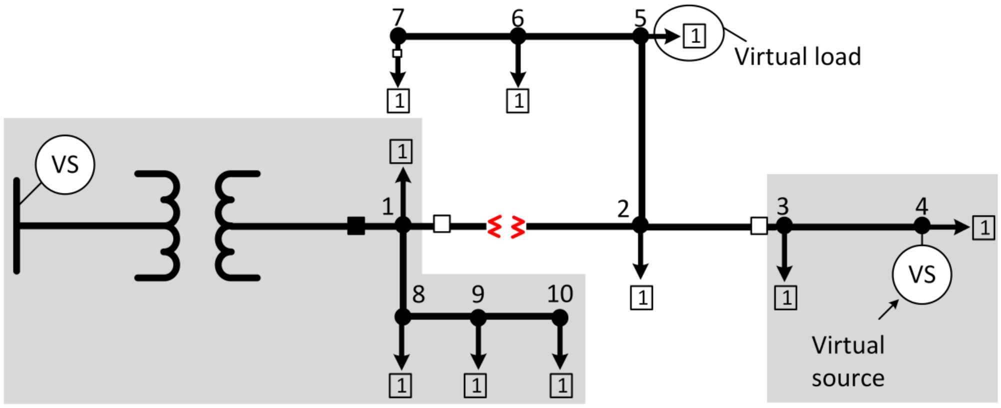
$$|Q_{i,\varphi,t}^{PV}| \leq \mathcal{X}_{i,t} \sqrt{(S_i^{PV})^2 - (\hat{P}_{i,t}^{PV})^2}, \forall i \in \Omega_{PV}^{G}, \varphi, t$$

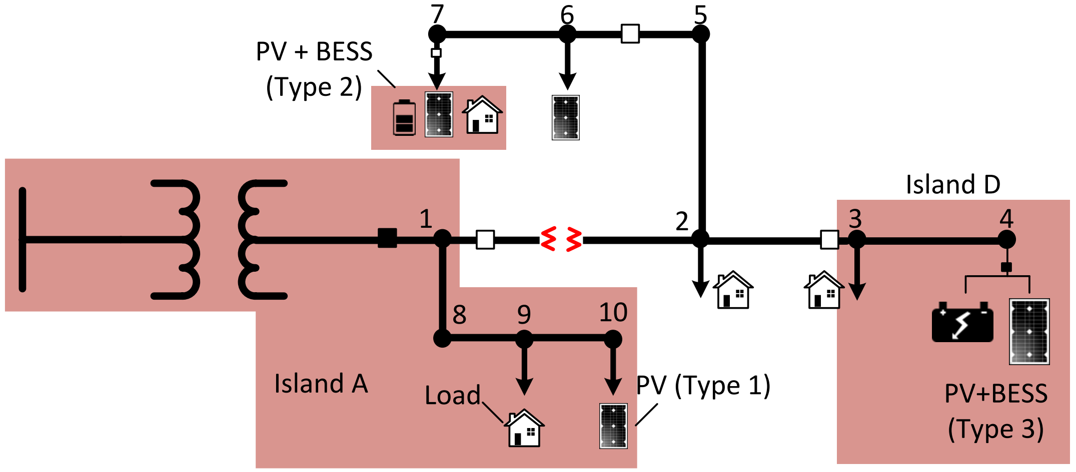
where $$\hat{P}_{i,t}^{PV} = \frac{Ir_{i,t}}{(1000W/m^2)} \overline{P}_i^{PV}$$

PV System Connectivity



Virtual Network





$$v_{i,t}^{S} + \sum_{k \in K(.,i)} v_{k,t}^{f} = \mathcal{X}_{i,t} + \sum_{k \in K(i,.)} v_{k,t}^{f}, \forall i, t$$

$$\sum_{\forall t} v_{i,t}^{S} = 0, \forall i \in \Omega_B \backslash \{\Omega_{PV}^{C} \cup \Omega_G \cup \Omega_{Sub}\}$$

$$-u_{k,t} M \leq v_{k,t}^{f} \leq u_{k,t} M, \forall k \in \Omega_K, t$$

$$\mathcal{X}_{i,t} \geq y_{i,t}, \forall i \in \Omega_B \backslash \{\Omega_G \cup \Omega_{PV}^{C} \cup \Omega_{PV}^{H}\}, t$$

Battery Energy Storage Systems

- Battery energy storage constraints (for mobile and fixed storage)
  1. Charging and discharging limits
  2. State of energy

1
$$0 \leq P_{i,\varphi,t}^{ch} \leq u_{i,t}^{ES} \overline{P}_i^{ch}, \ \forall i \in \Omega_{ES}, \varphi, t$$
$$0 \leq P_{i,\varphi,t}^{dch} \leq (1 - u_{i,t}^{ES}) \overline{P}_i^{dch}, \forall i \in \Omega_{ES}, \varphi, t$$

2
$$E_{i,t}^S = E_{i,t-1}^S + \Delta t(\eta_c \sum_{\forall \varphi} P_{i,\varphi,t}^{ch} - \frac{\sum_{\forall \varphi} P_{i,\varphi,t}^{dch}}{\eta_d}), \forall i \in \Omega_{ES}, t$$
$$\underline{E}_i^S \leq E_{i,t}^S \leq \overline{E}_i^S, \forall i \in \Omega_{ES}, t$$

Crew Routing (1/2)

Vehicle routing problem (VRP)

1. Starting and ending locations
2. Path-flow constraint
3. A damaged component is visited only once by a line crew and a tree crew (if required)

$$\sum_{\forall m \in N} x_{\phi_c^0, m, c} = 1, \forall c$$

$$\sum_{\forall m \in N} x_{m, \phi_c^1, c} = 1, \forall c$$

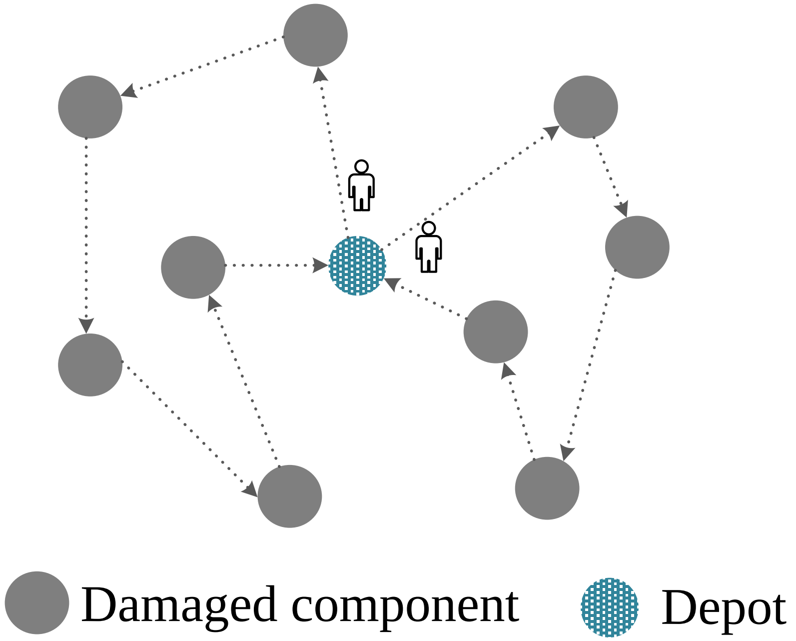
$$\sum_{\forall n \in N \backslash \{m\}} x_{m,n,c} - \sum_{\forall n \in N \backslash \{m\}} x_{n,m,c} = 0, \forall c, m \in N \backslash \{\phi_c^0, \phi_c^1\}$$

$$\sum_{\forall c \in C^L} \sum_{\forall m \in N \backslash \{n\}} x_{m,n,c} = 1, \forall n \in \Omega_{DK}$$

$$\sum_{\forall c \in C^T} \sum_{\forall m \in N \backslash \{n\}} x_{m,n,c} = 1, \forall n \in \Omega_{DT}$$

x: binary var equals 1 if crew travels the path
$\phi^{0/1}$: start/return location time
N: set of nodes
Ω_{DT}: set of lines damaged by trees
$C^{L/T}$: set of line/tree crews

Valid route



Crew Routing (2/2)

1. Calculate arrival time
   $Arrival_n = Arrival_m + Travel_{mn} + Repair_m$
2. Tree crews must finish before the line crews start repairing
3. Set arrival time = 0 (empty) if a crew does not visit a component

4. Crews must have enough equipment to repair the components
5. Each crew has a capacity
6. Equipment are used/picked up as the crews travel between components
   Equipment on hand = equipment at previous location – equipment used
7. The equipment is taken from the depot/warehouse

α: arrival time
T: repair time
tr: travel time
Res^C: number of resources a crew takes from a depot
Res^D: number of resources in the depot
Cap^r: capacity required to carry an equipment
Cap^C: capacity of the crew
E: number of resources a crew has at location
R: required resources to repair a damaged component

1
$$\alpha_{m,c} + \mathcal{T}_{m,c} + tr_{m,n} - (1 - x_{m,n,c})\, M \leq \alpha_{n,c} \quad \forall m \in N \backslash \{\phi_c^1\}, n \in N \backslash \{\phi_c^0, m\}, c$$

2
$$\sum_{c \in C^L} \alpha_{m,c} \geq \sum_{c \in C^T} \alpha_{m,c} + \mathcal{T}_{m,c} \sum_{\forall n \in N} x_{m,n,c}, \forall m \in \Omega_{DT}$$

3
$$0 \leq \alpha_{m,c} \leq M \sum_{n \in N} x_{n,m,c}, \ \forall m \in N \backslash \{\phi_c^0, \phi_c^1\}, c$$

4
$$\sum_{\forall n \in N} x_{n,m,c} \mathcal{R}_{m,r} \leq E_{c,m,r}, \forall m, r, c \in C^L$$

5
$$\sum_{\forall r} Cap_r^R E_{c,m,r} \leq Cap_c^C, \forall m, c \in C^L$$

6
$$-M(1 - x_{m,n,c}) \leq E_{c,m,r} - \mathcal{R}_{m,r} - E_{c,n,r} \leq M(1 - x_{m,n,c}),$$
$$\forall m \in N \backslash \{\phi_c^1\}, n \in N \backslash \{\phi_c^0, m\}, c \in C^L, r$$
$$-M(1 - x_{w,n,c}) \leq E_{c,w,r} + Res_{c,w,r}^C - E_{c,n,r} \leq M(1 - x_{w,n,c}),$$
$$\forall w, n \in N \backslash \{\phi_c^0, \phi_c^1, w\}, c \in C^L, r$$
$$-M(1 - x_{\phi_c^0,n,c}) \leq Res_{c,\phi_c^0,r}^C - E_{c,n,r} \leq M(1 - x_{\phi_c^0,n,c}), \forall n \in N \backslash \{\phi_c^0\}, c \in C^L, r$$

7
$$Res_{w,r}^D \geq \sum_{\forall c \in C^L, \phi_c^0 = w} Res_{c,\phi_c^0,r}^C + \sum_{\forall c \in C^L} Res_{c,w,r}^C, \forall w, r$$

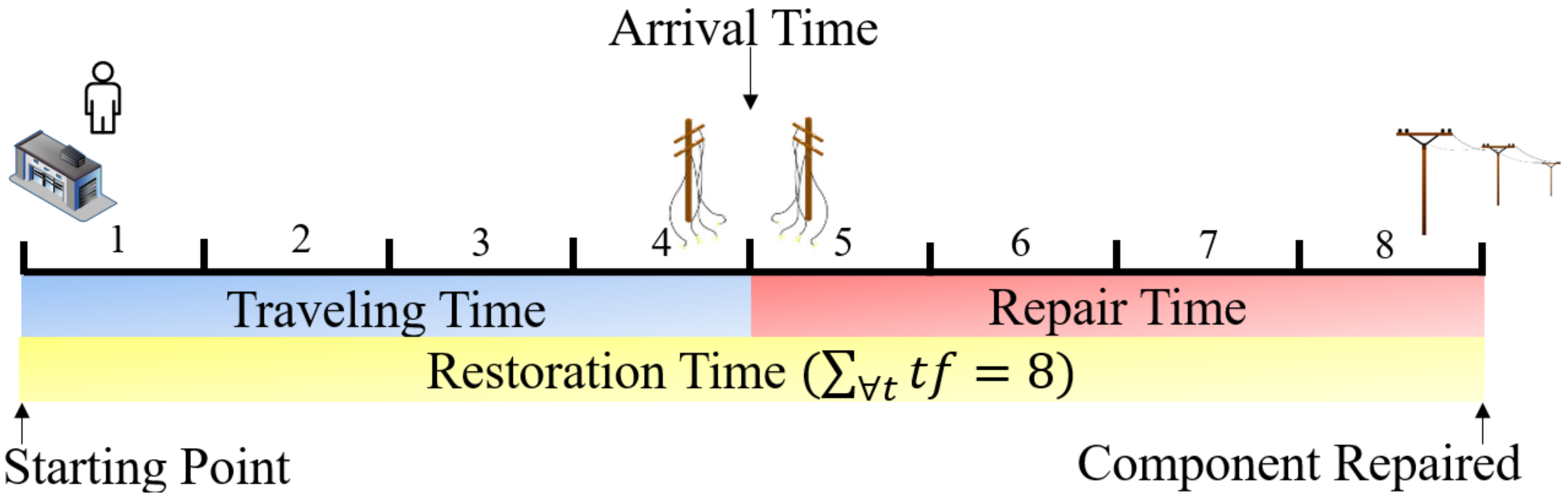
Connecting Operation and Routing

- When can we operate the component?
  1. Define binary variable f which equals 1 once the line is repaired
  2. Calculate the restoration time (Arrival time + Repair time)
  3. Set the status of the line ($u_{k,t}$) to 1 once the line is repaired

$$\sum_{\forall t} f_{m,t} = 1\ ,\ \forall m \in \Omega_D$$

$$\sum_{\forall t} t f_{m,t} \geq \sum_{\forall c} (\alpha_{m,c} + \mathcal{T}_{m,c} \sum_{\forall n \in N} x_{m,n,c}), \forall m \in \Omega_D$$

$$u_{m,t} = \sum_{\tau=1}^{t} f_{m,\tau}\ ,\ \forall m \in \Omega_{DL}, t$$



Challenges

- VRP is NP-hard, obtaining the optimal solution for large cases is very challenging
- VRP is commonly solved using heuristic methods
- Combining VRP with distribution system operation highly increases the complexity
- Large number of damages:

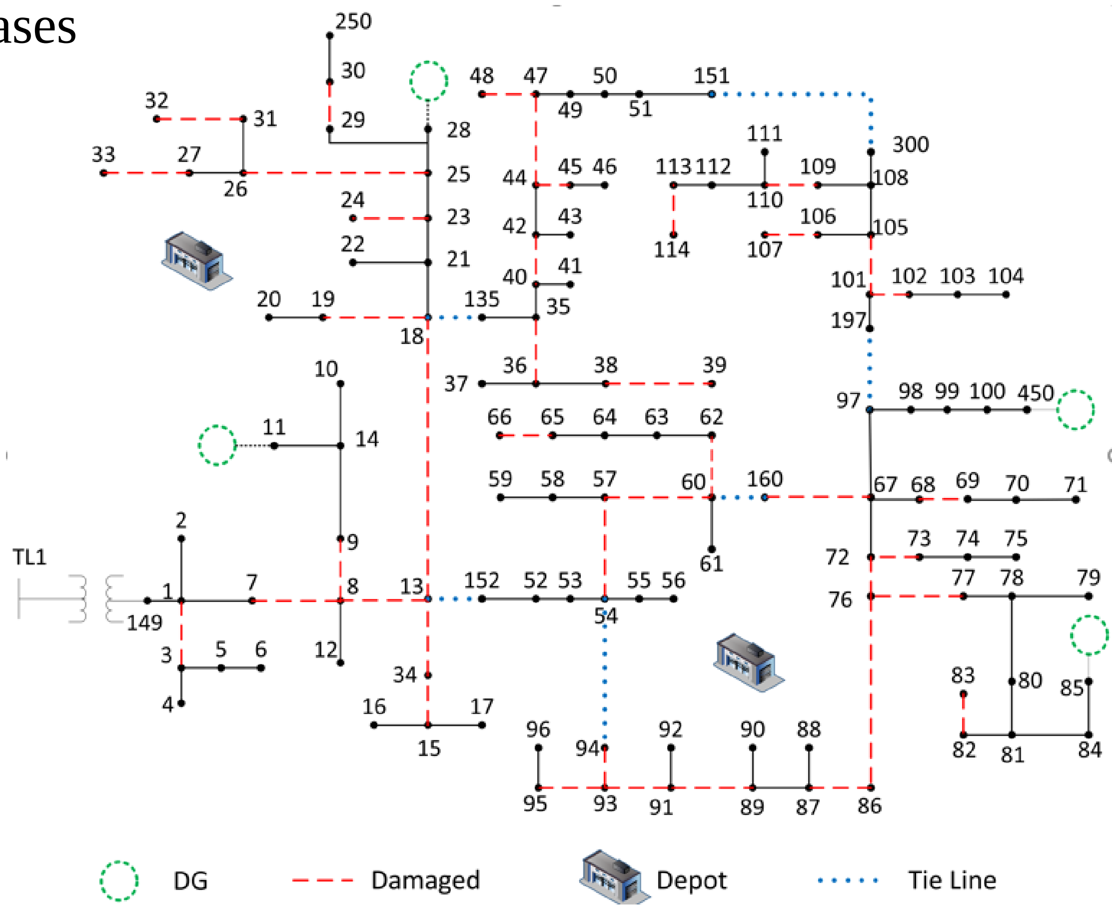
  → Routing becomes extremely difficult

  E.g. 30 damaged components and 10 crews:

  $$x_{m,n,c} \rightarrow 30 \times 30 \times 10 =$$

  → 9000 integer variables for routing only

- Computation time is critical!



Proposed Solution Algorithms

- Direct method
  - Use commercial solvers (e.g., CPLEX, GUROBI) to solve the mathematical model
- Priority-based
- Cluster-based (C-DSRRP)
- Assignment-based (A-DSRRP)
- A-DSRRP → Neighborhood Search

Priority-based

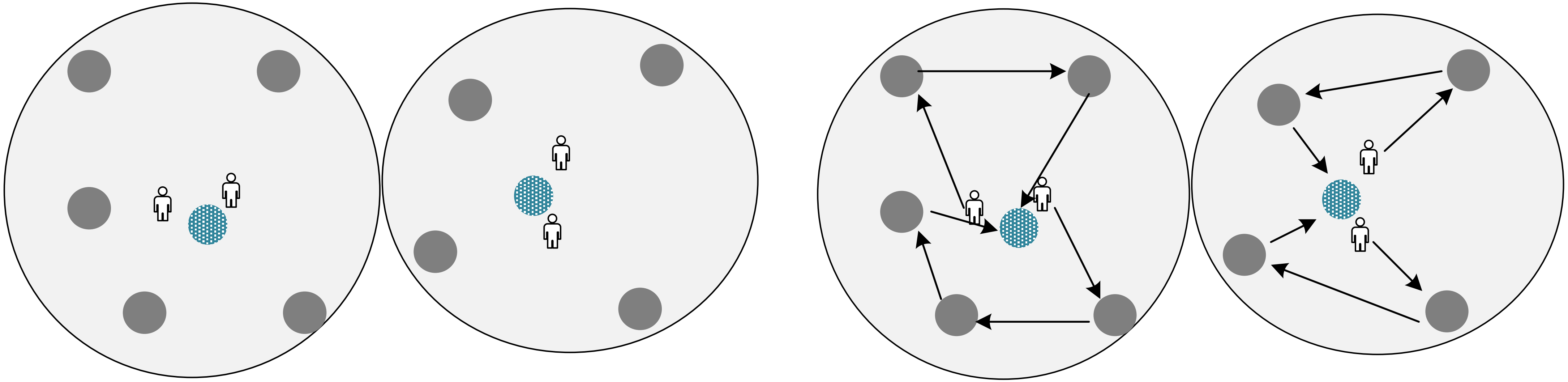
- The goal of this method is to mimic the approach used in practice
- Define the priority of the lines
    1. Repair lines connected to high-priority customers — Weight factor $W_1 = 10$
    2. Repair 3-phase lines — Weight factor $W_2 = 5$
    3. Repair single phase lines and individual customers — Weight factor $W_3 = 1$
- Identify the lines that must be repaired to restore high-priority customers
    - min{(lines to repair)| s.t. operation constraints, high-priority customers must be served}
- Solve the crew routing problem
    - $\min\{(\sum_{\forall p} \sum_{k \in L_p} \sum_{c \in C^L} W_p\, \alpha_{c,k})|$ s.t. routing constraints$\}$

L_p:set of lines to repair with priority p

Cluster-based

- Cluster the damaged components to depots
  - min {(distance between depots and components)| s.t. resource constraint}
- C-DSRRP
  - Solve DSRRP with the crews routed based on the clusters

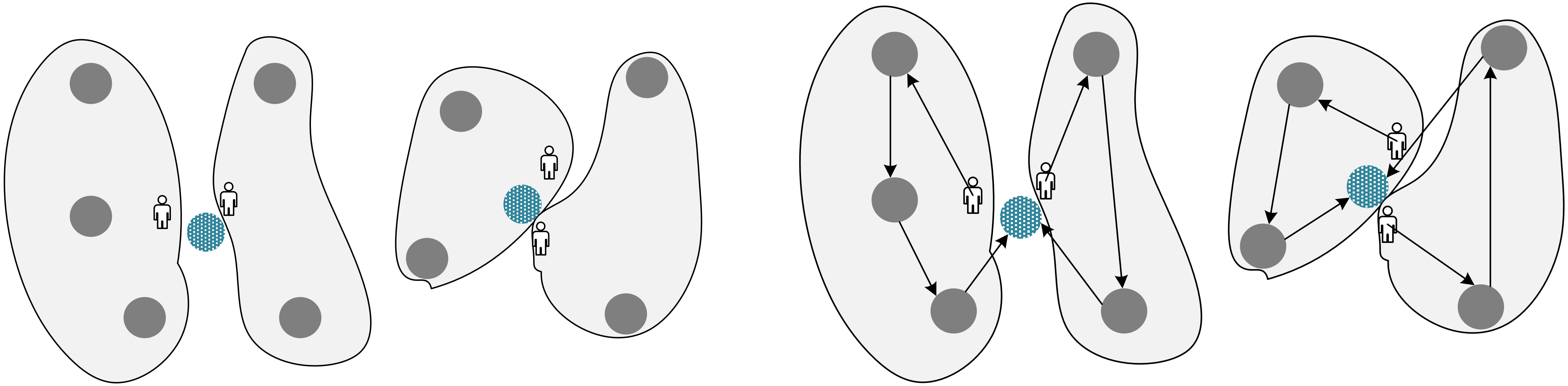
➢VRP problem → Multi-VRP subproblems



Assignment-based

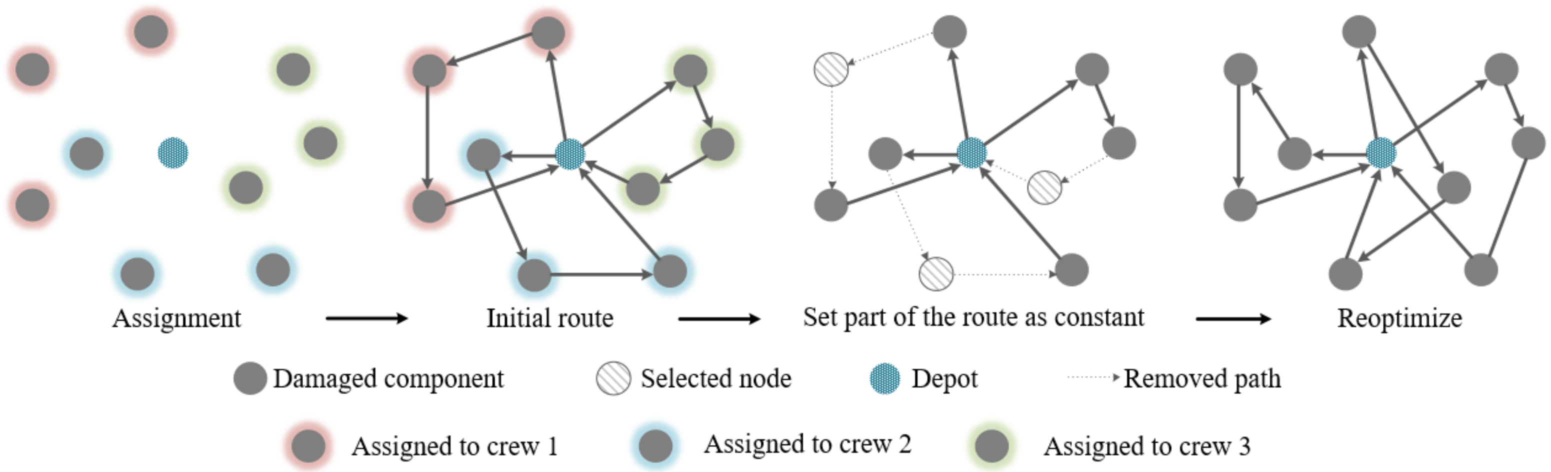
- Assign the damaged components to crews
  - min {(distances between components that are assigned to the crews)| s.t. resource constraint and assignment constraints}
- A-DSRRP
  - Solve DSRRP with the crews routed based on the assignments

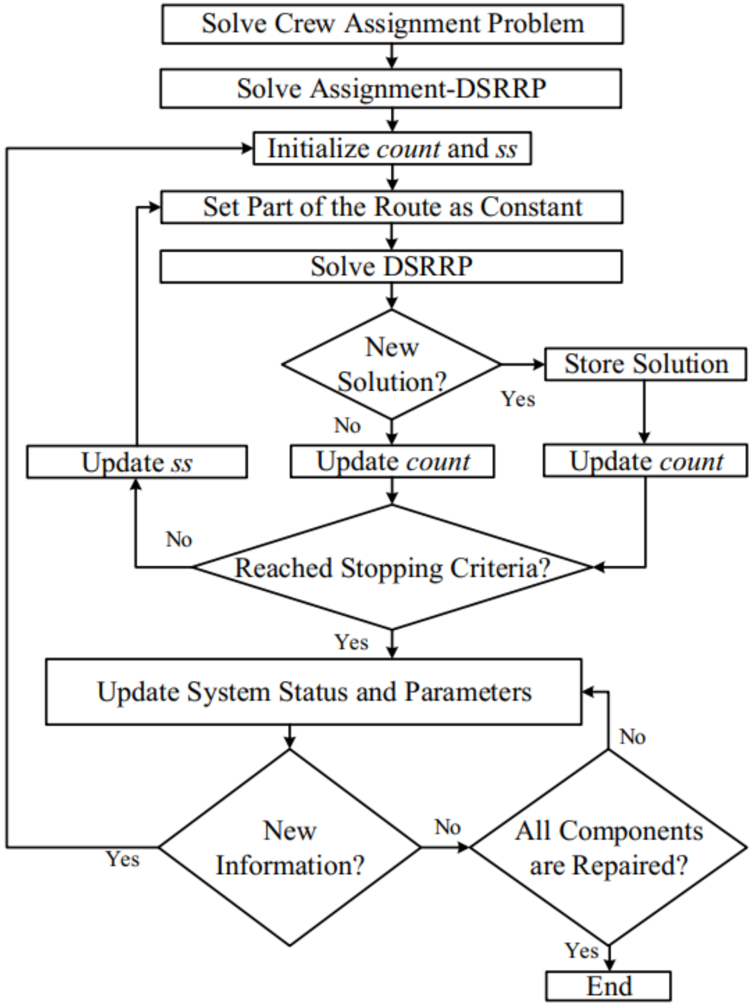
➢VRP problem → Multi-TSP subproblems



Reoptimization (A-DSRRP → Large Neighborhood Search)

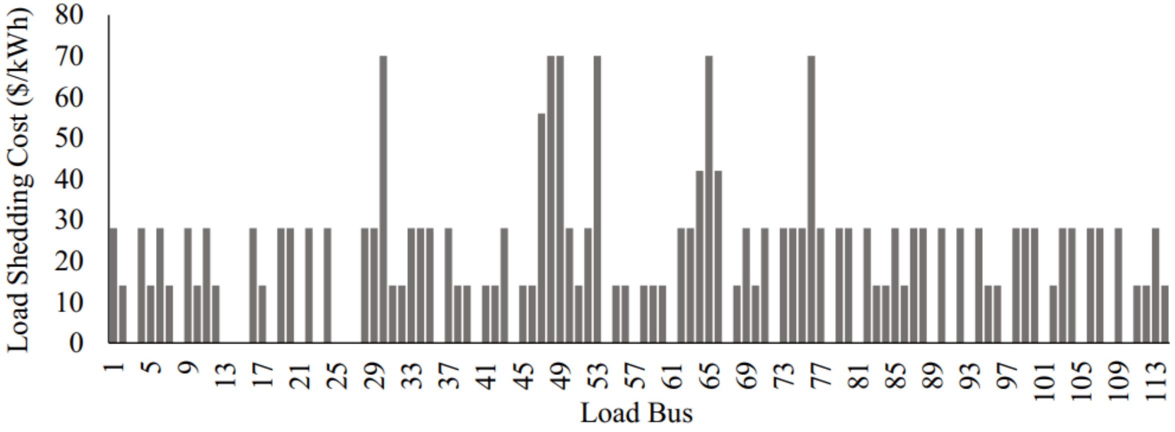
1. Select *ss* nodes (damaged components)
2. Remove part of the route connected to the selected components
3. Set rest of the route to be constant
4. Solve the optimization problem DSRRP (with *warm start* and limit 120 s)
5. Repeat until we reach the stopping criteria (increase *ss* after *count* iterations without change)
6. Update the route once new information is obtained

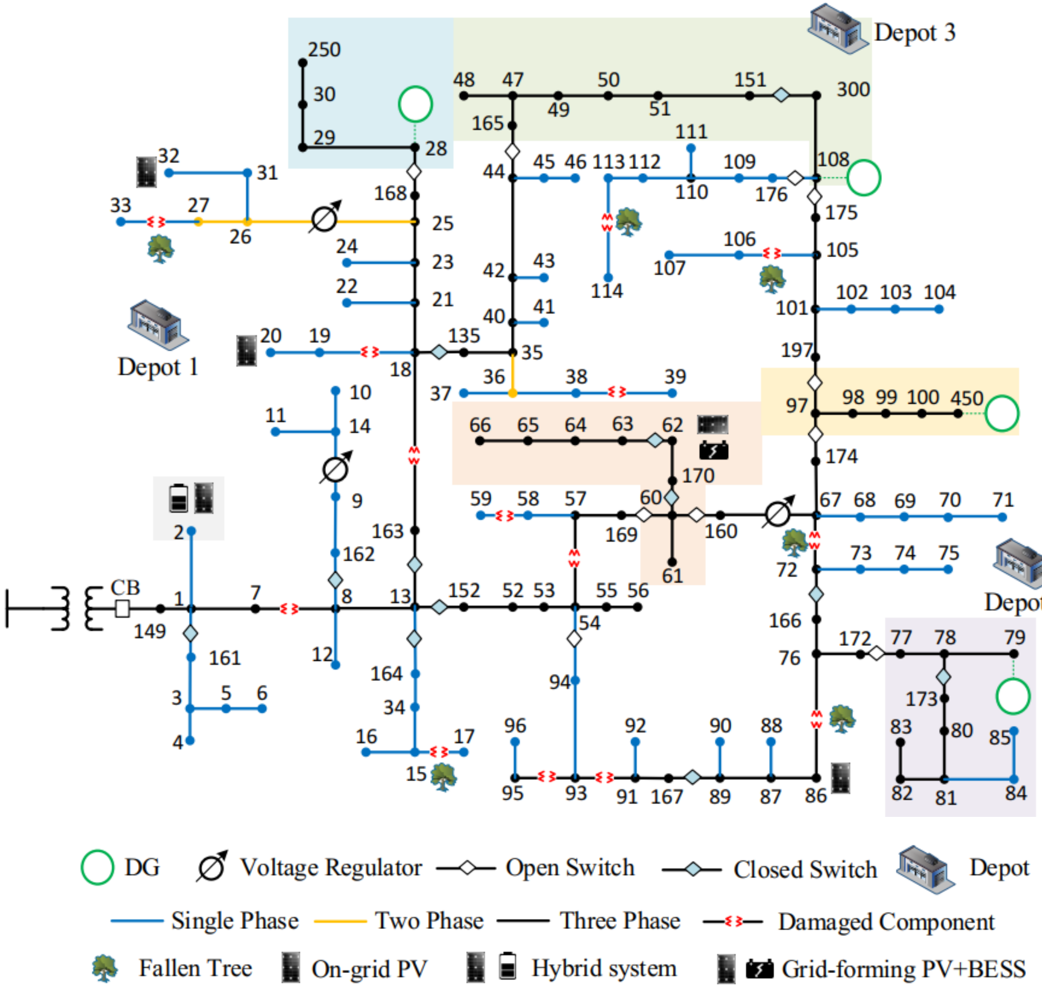




Test Case

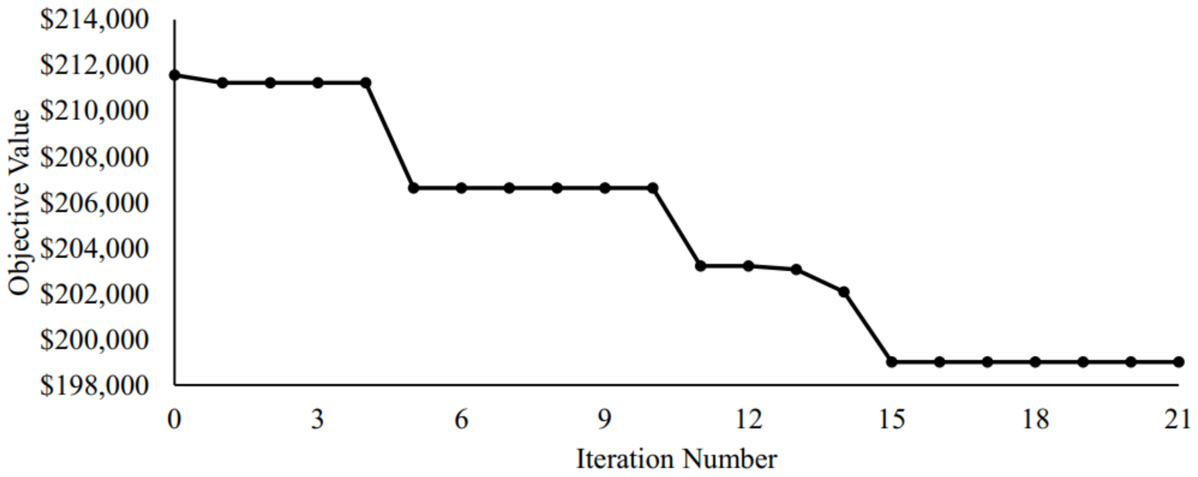
- Modified IEEE 123-bus distribution feeder.
- 9 controllable DGs (e.g., diesel generators) and 23 switches
- 3 depots, 6 line crews, and 4 tree crews.
- 14 damaged lines
- 1 hour time-step
- The model and algorithm are implemented in AMPL, with CPLEX solver

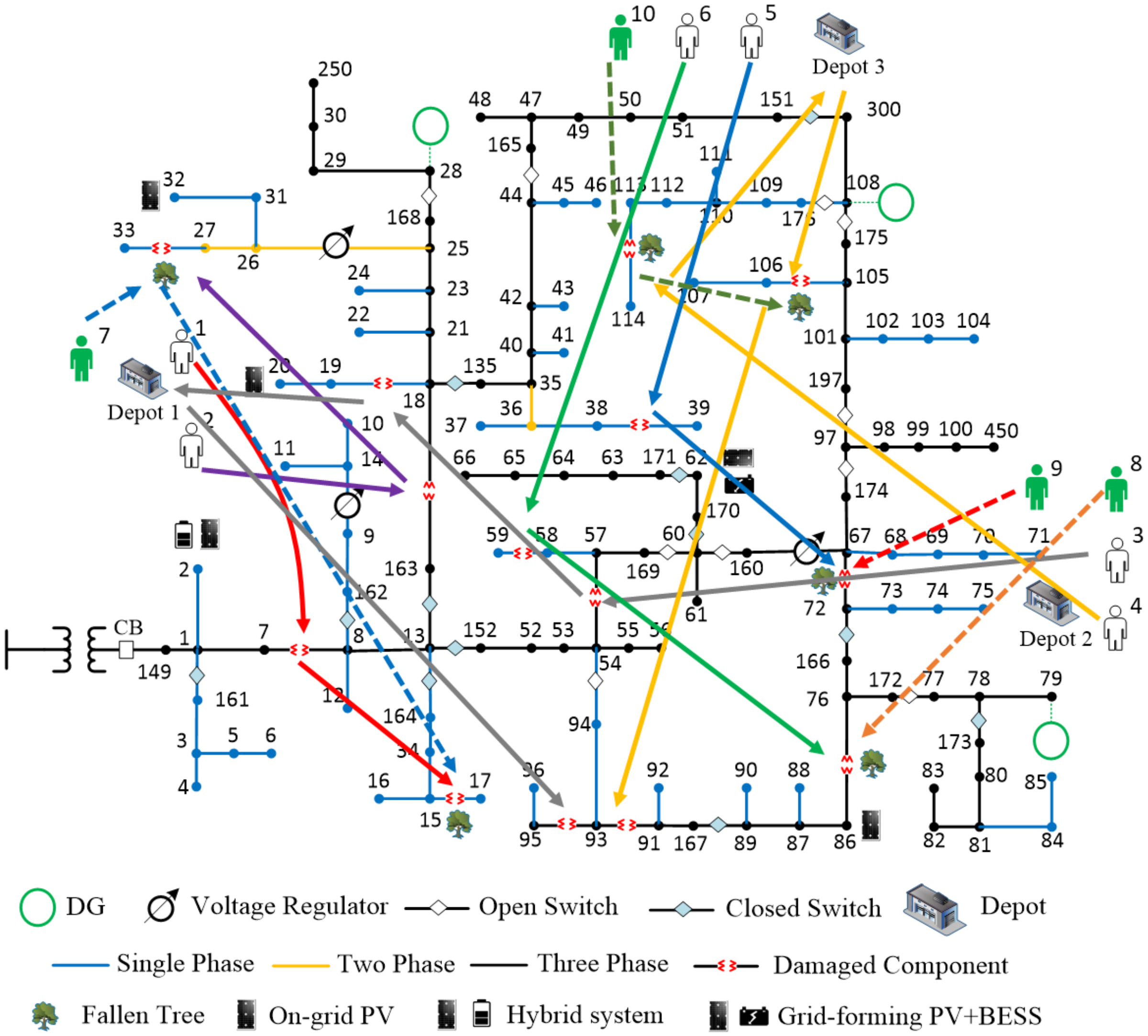




Results: Reoptimization

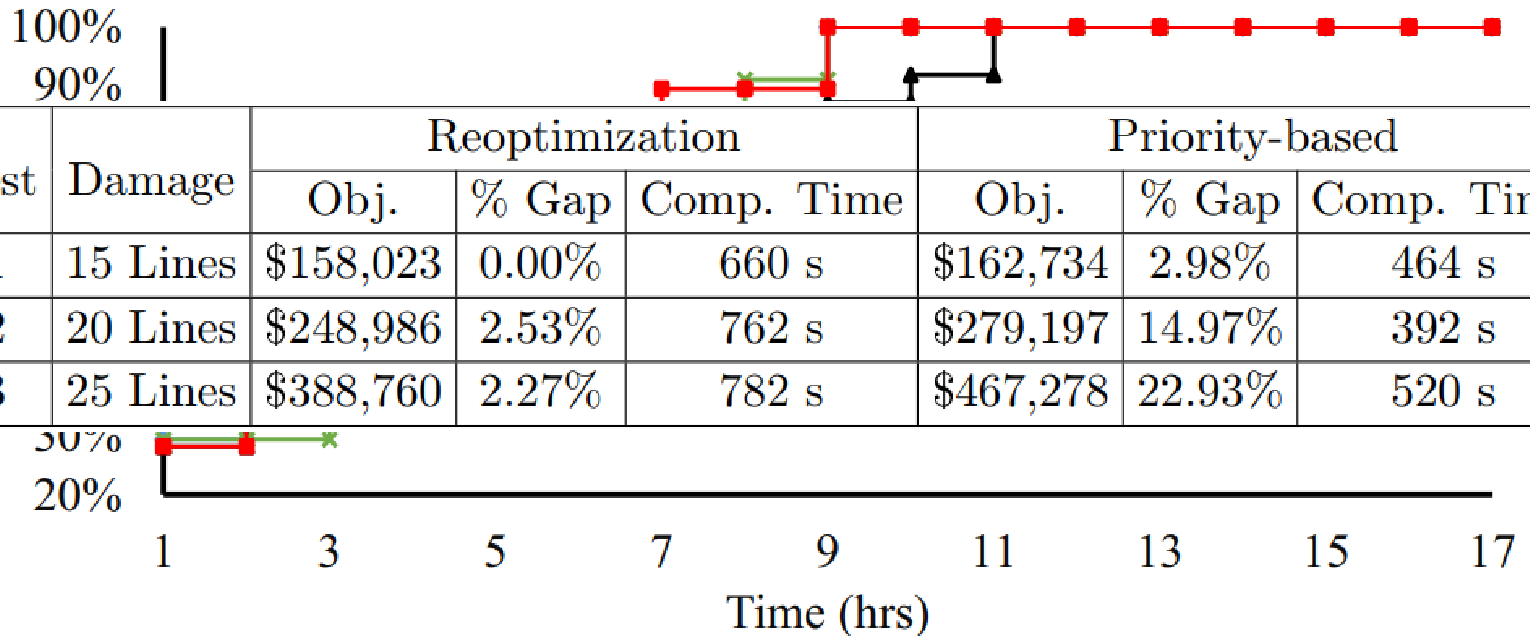
- Objective value: $199,210
- Iterations: 21
- Computation time: 694 seconds





Results: Solution Comparison

- Optimal solution is obtained by using the Reoptimization solution to warm-start CPLEX and solve the complete method



Test	Damage	Reoptimization			Priority-based		
		Obj.	% Gap	Comp. Time	Obj.	% Gap	Comp. Time
1	15 Lines	\$158,023	0.00%	660 s	\$162,734	2.98%	464 s
2	20 Lines	\$248,986	2.53%	762 s	\$279,197	14.97%	392 s
3	25 Lines	\$388,760	2.27%	782 s	\$467,278	22.93%	520 s

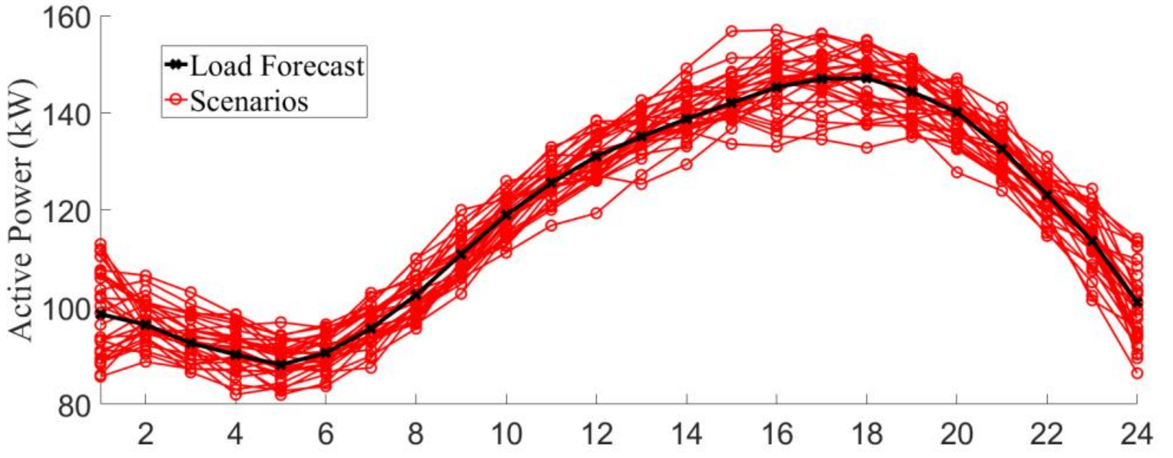
Method 2: Two-Stage Stochastic MILP

- Uncertainty
  - Repair time
  - Demand
  - Solar irradiance
- Objective

  Minimize cost of shedding loads and switching operation
- First-stage constraints
  - Dispatch repair crews
  - Equipment constraints
- Second-stage constraints
  - Distribution system operation
  - Arrival time constraints
  - Connect crews routing and power operation

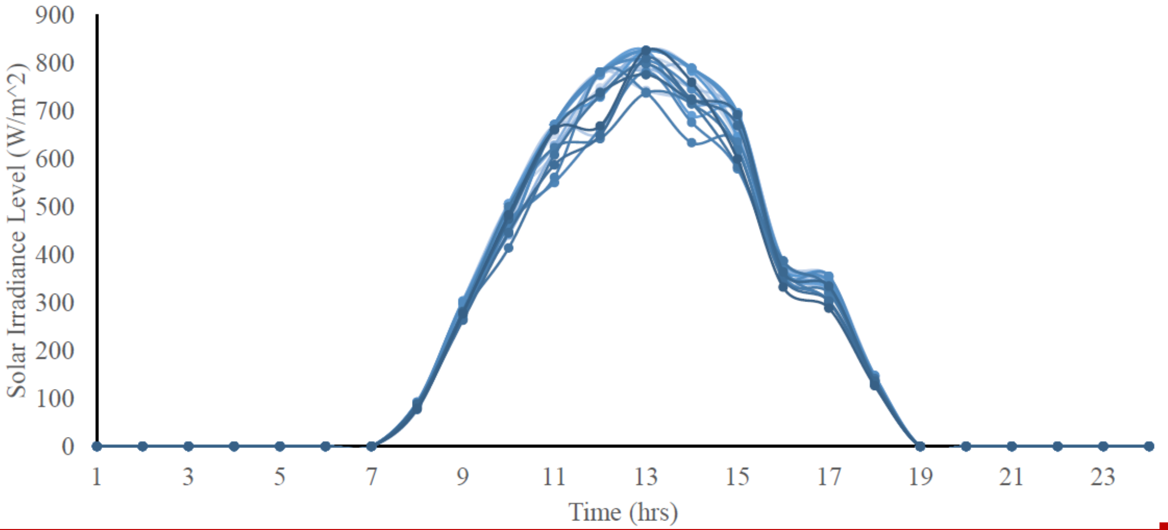
Uncertainty

- Repair time: lognormal distribution (Zhu 2012)
- Demand: truncated normal forecast error distribution (Lu 2013)
- Solar irradiance: cloud coverage level and normal distribution (Torquato 2014)



Repair time

Damage	Scenario 1	Scenario 2	Scenario 3	…	Scenario *S*
Line 1	2.71	3.61	1.97	…	3.11
Line 2	4.01	2.36	3.85	…	5.11
Line 3	1.24	3.21	1.06	…	4.62
Line 4	1.5	1.87	2.88	…	3.45
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
Line *D*	1.68	1.84	4.69	…	2.46



Algorithm

- Use assignment-based approach
- Subproblem I:
  - Assign the damaged components to the crews
  - Consider uncertainty of the repair times
  - Solve using the extensive-form
- Subproblem II
  - Solve stochastic DSRRP with the crews dispatched to the assigned damaged components
  - Use Progressive Hedging to solve the stochastic DSRRP model

Stochastic vs Deterministic

- Decomposed stochastic DSRRP (DS-DSRRP)
- Static-Reoptimization: routing solution is not updated
- Dynamic-Reoptimization: routing solution is updated once the actual repair time is known
- Dynamic approach achieved the best solutions

The objective value for the IEEE 123-bus system (14 damaged lines) with constant routing solutions and different scenario realizations

Case	DS-DSRRP (PH)		Static-Reoptimization		Dynamic-Reoptimization		Optimal
	$F(x^S, \xi_{case})$	% Gap	$F(x^R, \xi_{case})$	% Gap	$F(x^D, \xi_{case})$	% Gap	
1	\$256,104.7	10.84%	\$241,661.9	4.59%	\$232,728.8	0.72%	\$231,065.4
2	\$248,671.7	6.98%	\$299,586.4	28.88%	\$245,558.6	5.64%	\$232,447.7
3	\$269,505.5	6.85%	\$291,036.7	15.38%	\$259,189.3	2.76%	\$252,235.3
4	\$251,256.7	13.27%	\$268,590.5	21.08%	\$236,415.2	6.58%	\$221,828.2
5	\$240,549.3	15.22%	\$246,431.5	18.04%	\$221,790.7	6.24%	\$208,772.2

Conclusions

- Co-optimizing repair and recovery operation leads to better results compared to solving the two problems separately
- Efficient repair schedule along with DGs and controllable switches can limit the outage size and recue the restoration time
- Fault isolation must be modeled in order to obtain an applicable solution
- Advanced solution algorithms are required for solving the co-optimization problem due to its complexity
- It is important to consider the uncertainty of the repair times. However, methods such as stochastic programming may require large computation times
- A dynamic approach where the deterministic solution is periodically updated can achieve better solutions

Networked Microgrids

Introduction

- Microgrids (MGs) are localized group of electricity generators and loads that are connected to the distribution grid but can be disconnected from the main grid and maintain operation
- The microgrids may not always be networked, but become networked after closing normally open switches, which may be associated with an outage or physical damage to the distribution grid
- There is a need to develop a method for coordinating the microgrids after outages to maximize the amount of loads to be served

Mathematical Formulation

Uncertainty: load and solar power

Objectives: maximize the served load

First-stage constraints :

- Switching operation
- Microgrids power exchange constraints
    - A linear decision-making function is developed to model the coordinated power exchange among MGs
    - The linear decision-making process is represented by a type 1 special ordered set (SOS1)
    - SOS1 is a set that contains non-negative variables, of which only one can take a strictly positive value, all others are zeros

Second-stage constraints: Power operation constraints

$$\Delta_{n,t} = \sum_{\forall i \in I_n^{\mathrm{MG}}} (P_i^{\mathrm{DGmax}} + P_{i,t}^{\mathrm{dch}} + P_{i,t}^{\mathrm{PV_F}} - P_{i,t}^{\mathrm{ch}}) - \sum_{\forall i \in I_n^{\mathrm{MG}}} \left(y_{i,t} P_{i,t}^{\mathrm{F}} + P_{i,t}^{\mathrm{CL}}\right), \quad \forall n, t, s$$

$$-D_n^{\max} \delta_{n,t}^A - \epsilon \delta_{n,t}^B + (P_n^{\mathrm{th}} + \varepsilon) \delta_{n,t}^C \leq \Delta_{n,t}, \quad \forall n, t, s$$

$$\Delta_{n,t} \leq -\epsilon \delta_{n,t}^A + (P_n^{\mathrm{th}} + \epsilon) \delta_{n,t}^B + P_n^{\max} \delta_{n,t}^C, \quad \forall n, t, s$$

$$\delta_{n,t}^A + \delta_{n,t}^B + \delta_{n,t}^C = 1, \quad \forall n, t$$

$$\mu_{n,t} = \delta_{n,t}^A + \delta_{n,t}^C, \quad \forall n, t$$

$$u_{k,t} \leq \mu_{n,t}, \quad \forall k \in \mathrm{MD}, \forall t$$

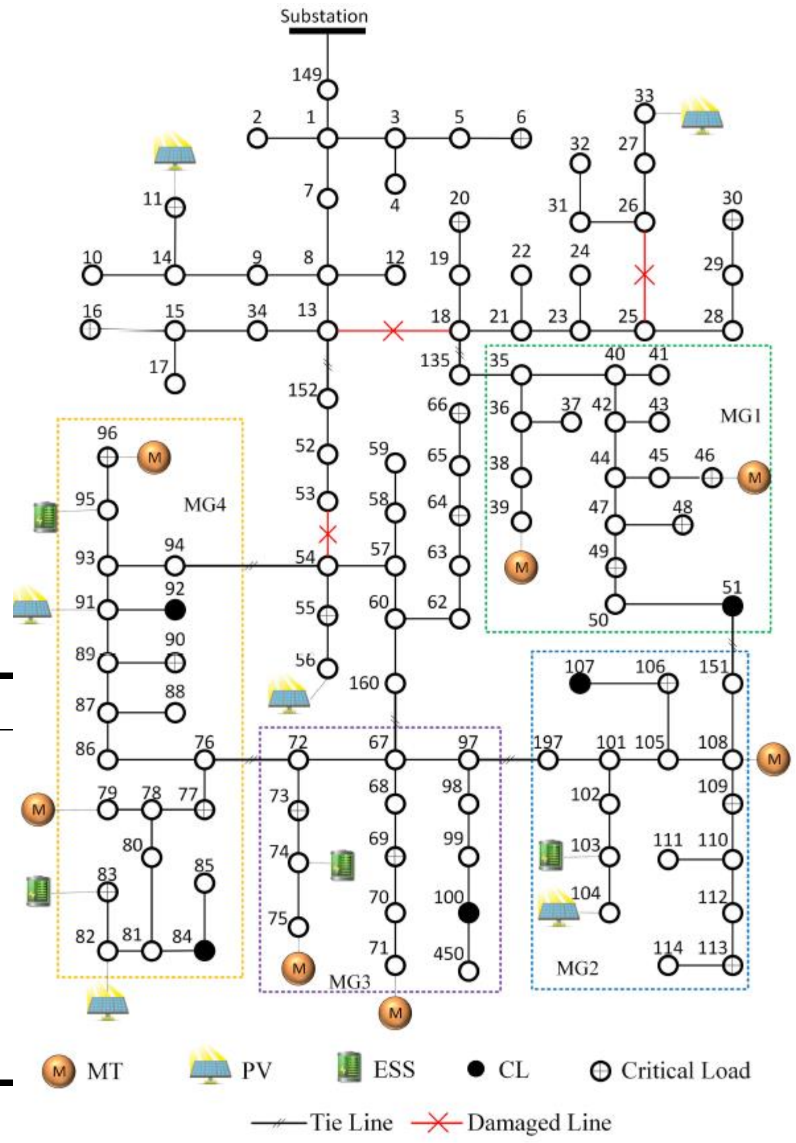
$$2u_{k,t} \leq \mu_{n,t} + \mu_{m,t}, \quad \forall k \in ML, \forall t$$

Simulation Results (1/2)

- The problem is modeled as a two-stage stochastic mixed-integer linear programming problem
- The proposed method has been examined on a modified IEEE 123-bus distribution system
- A centralized method and a decentralized method are compared
- In the decentralized method, each microgrid decides on whether to connect to the grid or not on its own

		Centralised approach
objective		18845.21
solution time		324.43 s
load shed (bus number)	MG 1	38, 45
	MG 2	111
	MG 3	68, 70
	MG 4	86
	DN	19, 31, 32, 60

DN: demand not served; Objective: weighted-kWh



Simulation Results (2/2)

- The results show that the interactions among MGs play an important role in facilitating the system restoration
- The centralized approach emphasizes the cooperation of the MGs and the distribution to obtain a better overall result
- The results confirm that the proposed networked MG-aided approach can improve the service restoration capability of a distribution grid

Research Conclusions

- Extreme weather-induced outages have very different characteristics than regular outages
- Effective preparation procedures can ensure that enough equipment is present for repairing the damaged components in the network and facilitate a faster restoration process
- Machine learning can be used to improve situational awareness and ensure efficient repair scheduling by predicting the repair times
- A MILP and SMIP formulations are proposed to solve the joint optimization of damage repair and recovery operation
- Co-optimizing repair and recovery operation leads to better results compared to solving the two problems separately
- Sectionalizing a distribution grid into multiple microgrids in emergency and coordinating them could enhance the system resilience

Publications

Journal Papers

1. A. Arif, Z. Wang, C. Chen, B. Chen, “, A stochastic multi-commodity logistic model for disaster preparation in distribution systems,” *IEEE Trans. Smart Grid*, Under Review.
2. A. Arif, Z. Wang, J. Wang, and C. Chen, “Repair and resource scheduling in unbalanced distribution systems using neighborhood search,” *IEEE Trans. Smart Grid*, Under Review.
3. A. Arif, S. Ma, Z. Wang, J. Wang, S. M. Ryan and C. Chen, “Optimizing service restoration in distribution systems with uncertain repair time and demand,” *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6828-6838, Nov. 2018.
4. A. Arif, Z. Wang, J. Wang, B. Mather, H. Bashualdo, and D. Zhao, “Load modeling - a review,” *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 5986-5999, Nov. 2018.
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6. A. Arif and Z. Wang, “Networked microgrids for service restoration in resilient distribution systems,” *IET Gener. Transm. Distrib.*, vol. 11, no. 14, pp. 3612-3619, Sep. 2017.

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1. S. Ma, S. Li, Z. Wang, A. Arif, K. Ma., “A novel MILP formulation for fault isolation and network reconfiguration in active distribution systems,” *IEEE PES General Meeting*, Portland, OR, 2018, pp. 1-5.
2. A. Arif, Z. Wang, “Distribution network outage data analysis and repair time prediction using deep learning,” *IEEE Int Conf. Probabilistic Methods Appl. Power Syst.*, Boise, ID, 2018, pp. 1-6.
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4. A. Arif, S. Ma, Z. Wang, “Online decomposed optimal outage management after natural disasters,” *IEEE PES General Meeting*, Chicago, IL, 2017, pp. 1-5.
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6. A. Arif and Z. Wang, “Service restoration in resilient power distribution systems with networked microgrid,” *IEEE PES General Meeting*, Boston, MA, 2016, pp. 1-5.

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