Real Time Outage Detection from Utility Big Data

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Aclara Technologies
Research and Advanced Product Development

Overview

- About Aclara
- Fault Detection & Localization Product
- Example Detections

Who We Serve

Serving 780+
Utilities - 40 of the largest in 24 countries

27 Million AMI and 71 Million Meter
endpoints with billion+ readings per day

99%
Customer Loyalty

Comprehensive Solutions
Suite

6 Million Customers
Actively Engaged

Who We Serve

Aclara's Continued Expansion

Meters

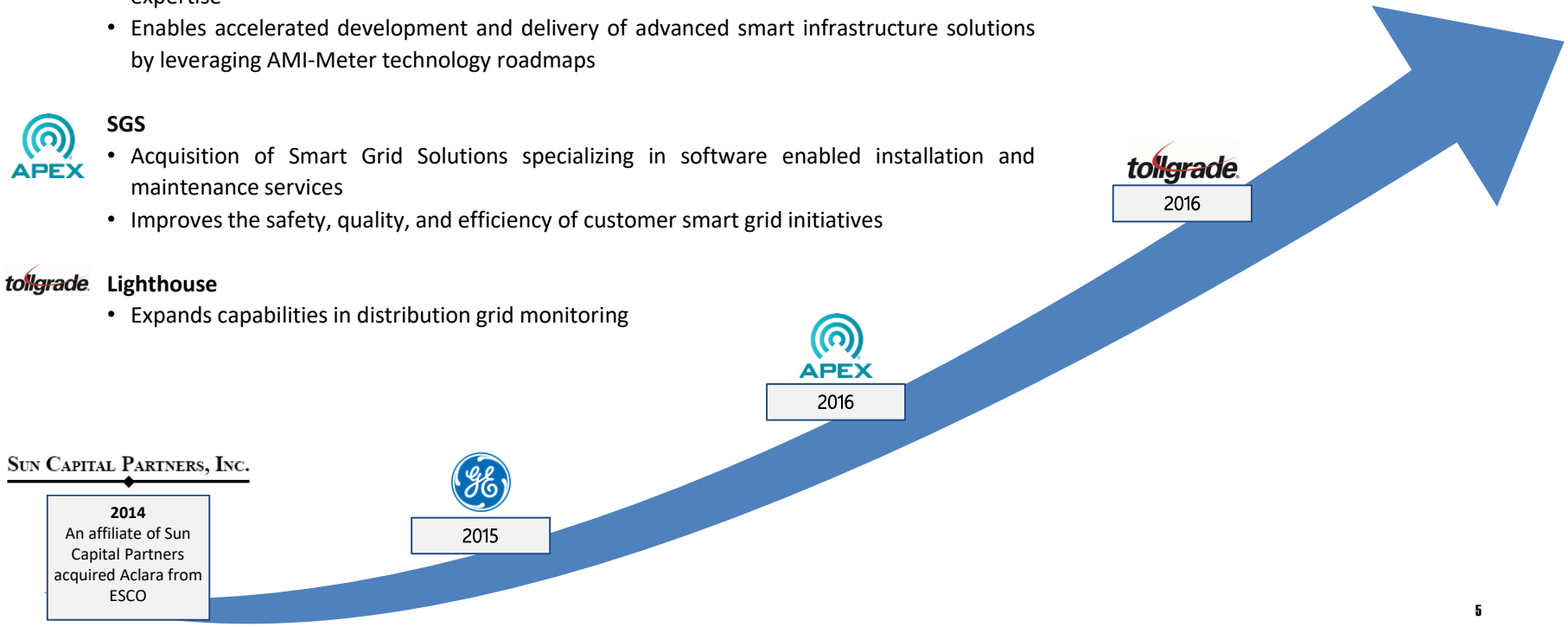
- The acquisition of GE Meters combines Aclara's industry leading AMI technology with GE Meters' 130 years of operating experience, technology development and commercial expertise
- Enables accelerated development and delivery of advanced smart infrastructure solutions by leveraging AMI-Meter technology roadmaps

SGS

- Acquisition of Smart Grid Solutions specializing in software enabled installation and maintenance services
- Improves the safety, quality, and efficiency of customer smart grid initiatives

Lighthouse

- Expands capabilities in distribution grid monitoring



Electric Utility Experience

ComEd

- 4.1 million meters
- 11.4K square miles of coverage
- Satellite manufacturing facility in Chicago, IL will generate local production

Florida Power & Light

- 5 million meters
- 1 million load control devices (2GW)
- 20+ years of partnership

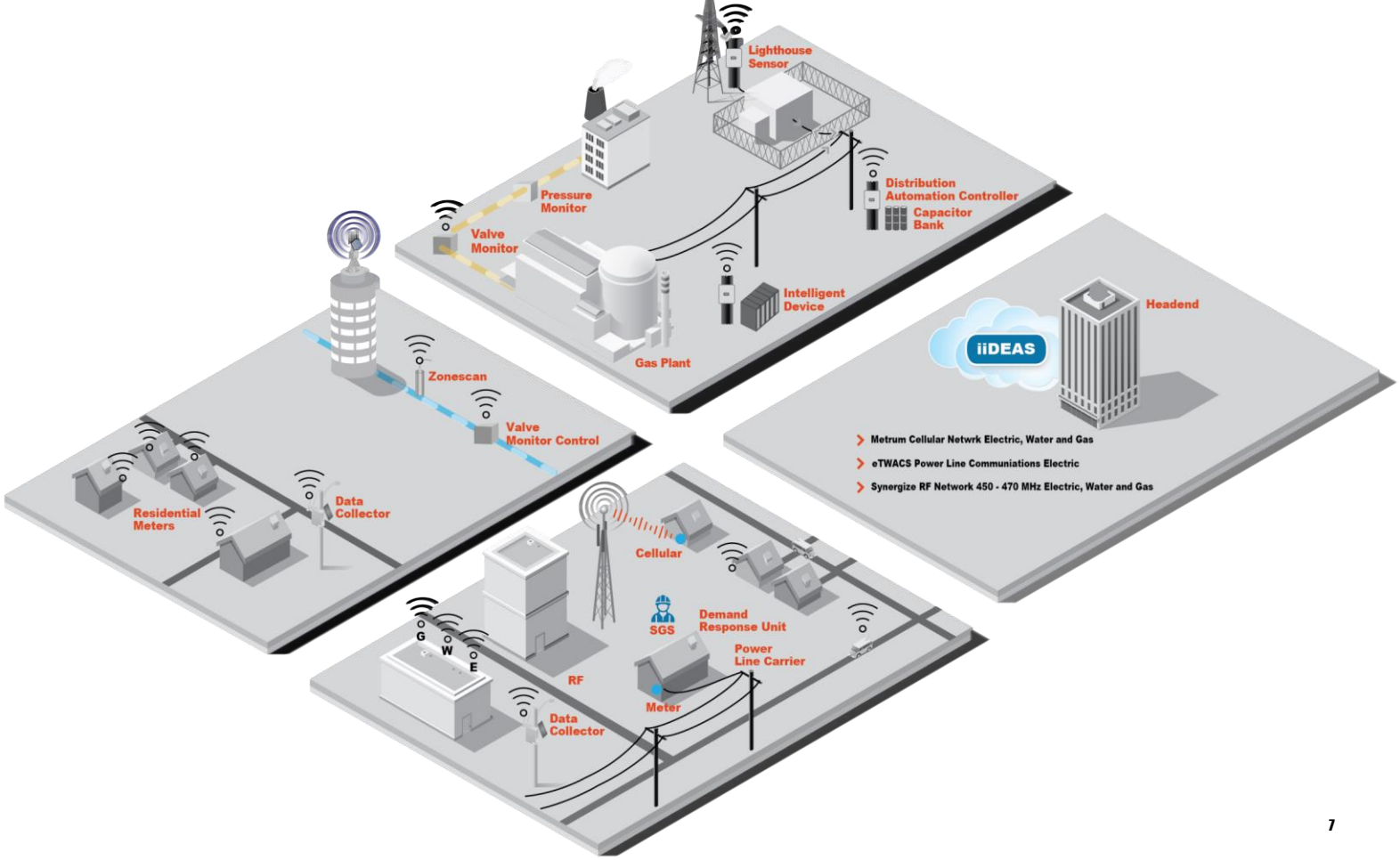
Scottish Power

- Renewable management and load monitoring
- Accelerating Renewable Connection (ARC) IFI Project

Puerto Rico Electric Power Authority

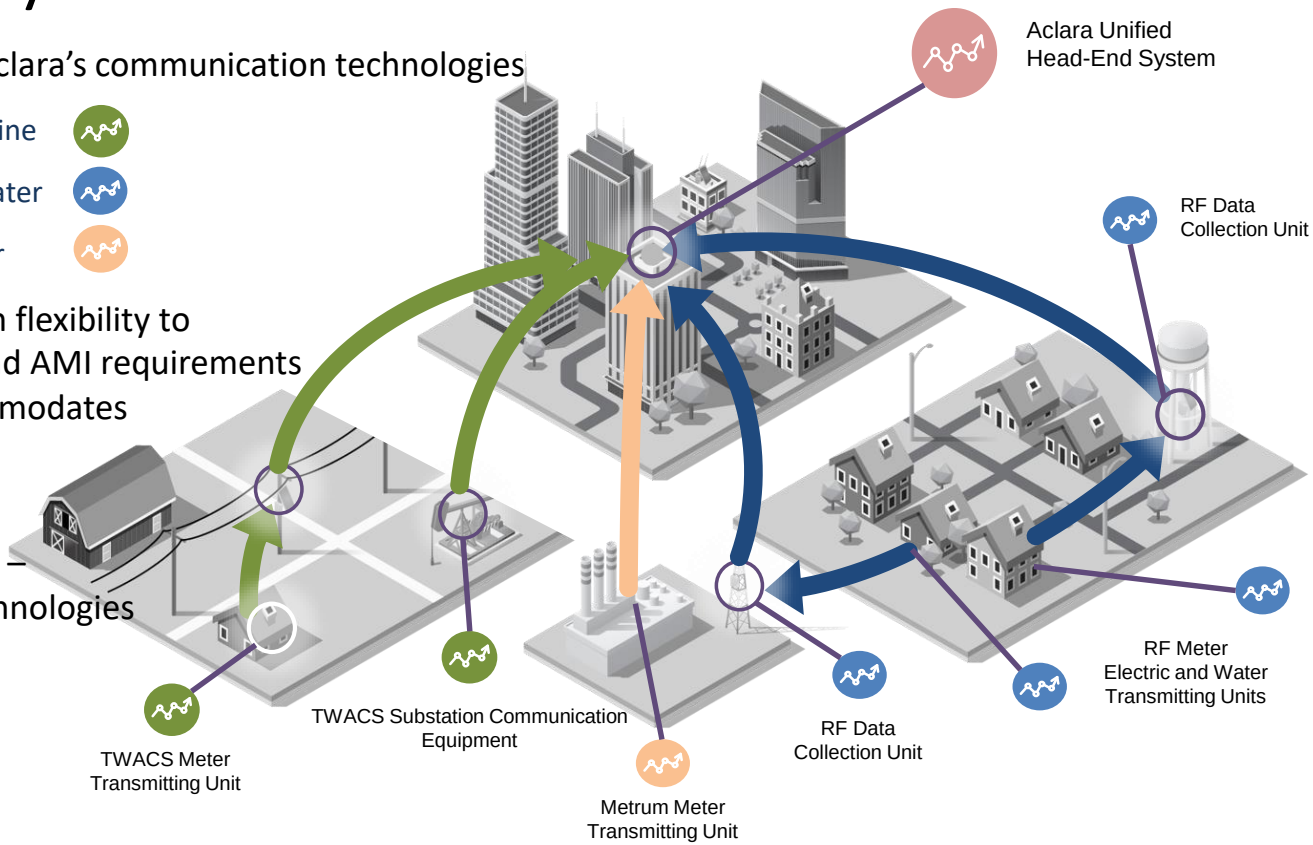
- 1.5 million endpoints
- Business partner for more than 15 years

Aclara Solutions Portfolio



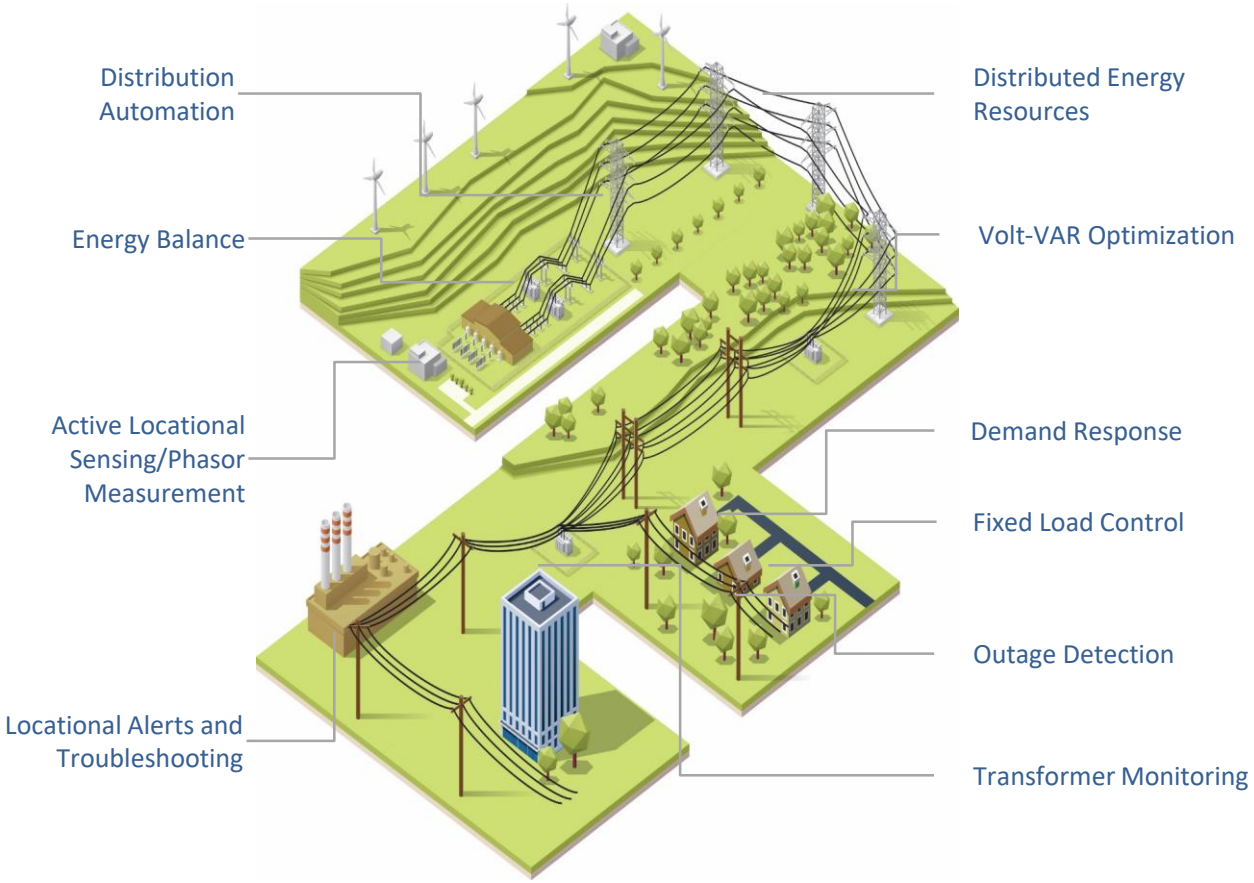
AMI - Unified System

- Head-end unifies Aclara's communication technologies
  - TWACS Power Line
  - RF – Electric/Water
  - Metrum Cellular
- Providing maximum flexibility to meet Smart Grid and AMI requirements
- Migratable - accommodates evolution of AMI technology use
- Optimize a solution – the best-suited technologies for the application



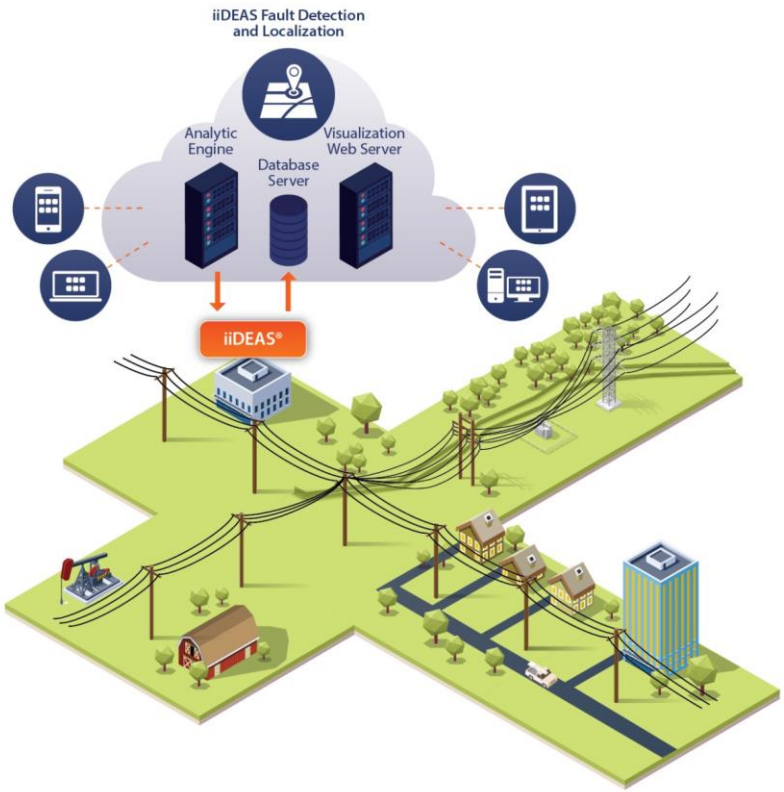
AMI

Electric Smart Infrastructure



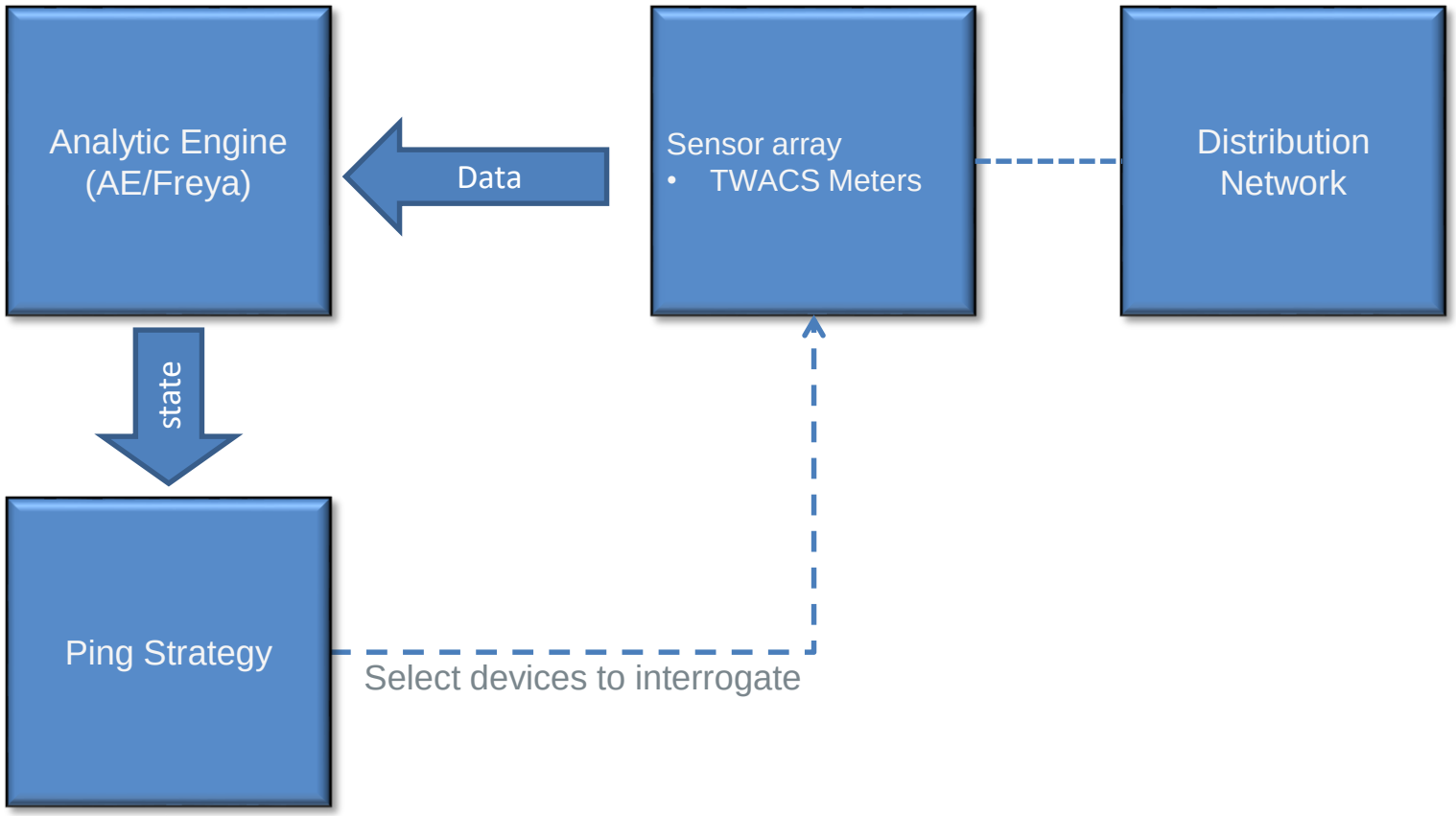
Fault Detection and Localization

"Automatically display outages, determine fault locations and verify restorations in record time"



AMI

Algorithm Architecture



Network state

Sensor data are collected on nodes and edges

$$\mathbf{X} \equiv \{x(v)\,\forall v \in V\}$$
$$\mathbf{\Theta} \equiv \{\theta(e)\,\forall e \in E\}\,.$$

$$\theta : E \to \{0,1\}$$
$$\theta(e) \mapsto \begin{cases} 0 & \text{edge } e \text{ is faulted} \\ 1 & \text{edge } e \text{ is not faulted.} \end{cases}$$
$$x : V \to \{0,1\}$$
$$x(v) \mapsto \begin{cases} 0 & \text{node } v \text{ is not powered} \\ 1 & \text{node } v \text{ is powered} \end{cases}$$

Sensor data

We are given data

$$\mathbf{D} = \{d(v) : v \in V\} \cup \{d(e) : e \in E\}$$

which are independent measurements made at some or all nodes or edges. The data must satisfy

$$p(\mathbf{D}|\mathbf{X}, \mathbf{\Theta}) = \prod_{e \in E} p(d(e)|\theta(e)) \prod_{v \in V} p(d(v)|x(v)).$$

Problem statement

Calculate the MMSE estimates:

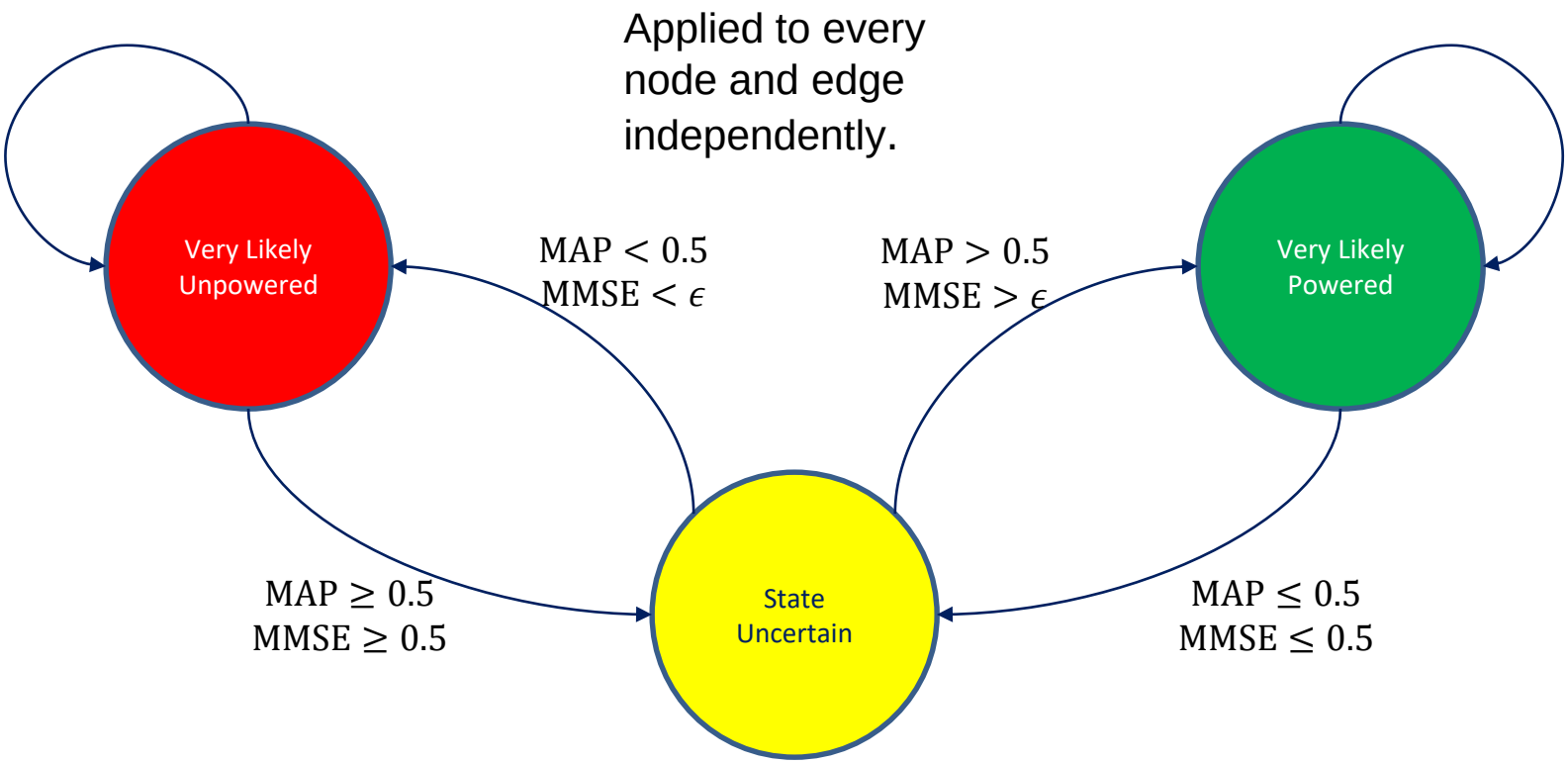
$$\hat{x}(v) = \sum_{x(v)} x(v) p(x(v)|\mathbf{D}) = p(x(v) = 1|\mathbf{D})$$

$$\hat{\theta}(e) = \sum_{\theta(e)} \theta(e) p(\theta(e)|\mathbf{D}) = p(\theta(e) = 1|\mathbf{D})$$

and the MAP estimate:

$$\left(\hat{\mathbf{X}}, \hat{\mathbf{\Theta}}\right) = \arg\max_{\mathbf{X}, \mathbf{\Theta}} p(\mathbf{X}, \mathbf{\Theta}|\mathbf{D}).$$

Node/Edge Displayed State



TWACS communications/TNS

	AMI	Link-level ping	Fast poll
Inbound length	10-20 bytes	3 bytes	1 bytes
Duration	~10 sec	1.5 seconds	0.5 seconds
Probability of responding when powered (P_D)	Moderate	High	Not as high as you might think!
Probability of responding when unpowered (P_{FA})	Virtually Zero	Very low	Not as low as you might think!

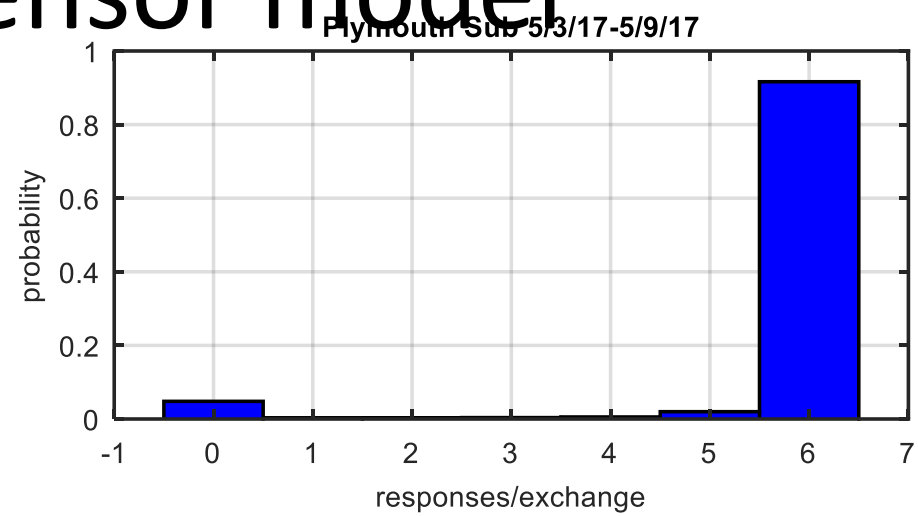
Successful transactions	Unsuccessful transactions
$\phi = ln\left(\frac{P_D}{P_{FA}}\right)$	$\phi = ln\left(\frac{1 - P_D}{1 - P_{FA}}\right)$

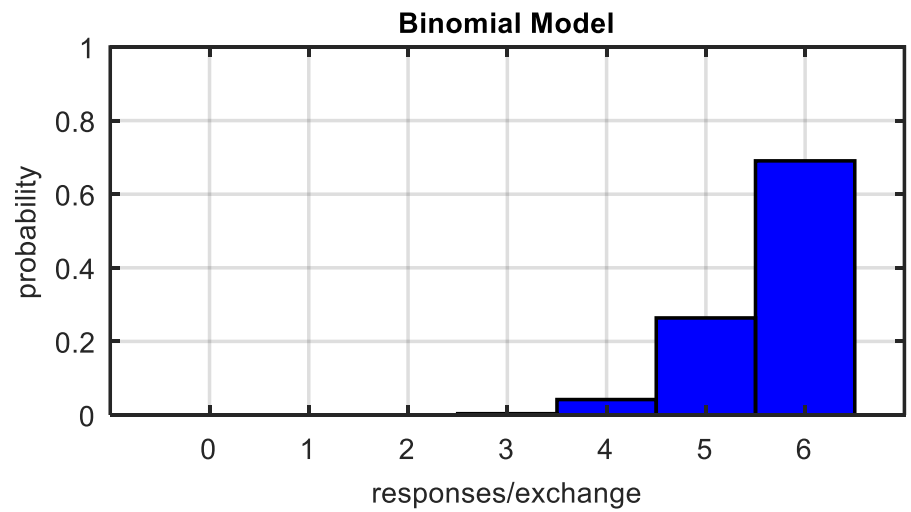
Naïve sensor model

$$p(d(v) = 0|x(v) = 0) = 1 - P_{FA}$$
$$p(d(v) = 1|x(v) = 0) = P_{FA}$$
$$p(d(v) = 0|x(v) = 1) = 1 - P_D$$
$$p(d(v) = 1|x(v) = 1) = P_D$$

$$\implies \sum_{n=1}^{N} d(v_n)|(x(v_n) = 1) \sim B(n, P_D)$$

Exchanges	72052
P_{FA}	N/A
P_D	0.94





Less naïve sensor model

Transactions within a single exchange are jointly distributed:

$$
\begin{aligned}
P(d(v_1),\ldots,d(v_N)|x(v_1),\ldots,x(v_N)) =& P(d(v_1),\ldots,d(v_N)|x(v_1),\ldots,x(v_N),y=1)P_y + \\
& P(d(v_1),\ldots,d(v_N)|x(v_1),\ldots,x(v_N),y=0)(1-P_y) \\
&= P_y \prod_{n=1}^{N} p(d(v_n)|x(v_n),y=1) + (1-P_y)\prod_{n=1}^{N} p(d(v_n)|x(v_n),y=0)
\end{aligned}
$$

if y=0

	d(v)=0	d(v)=1
x(v)=0	$1-P_{FA}$	P_{FA}
x(v)=1	$1-P_D$	P_D

if y=1

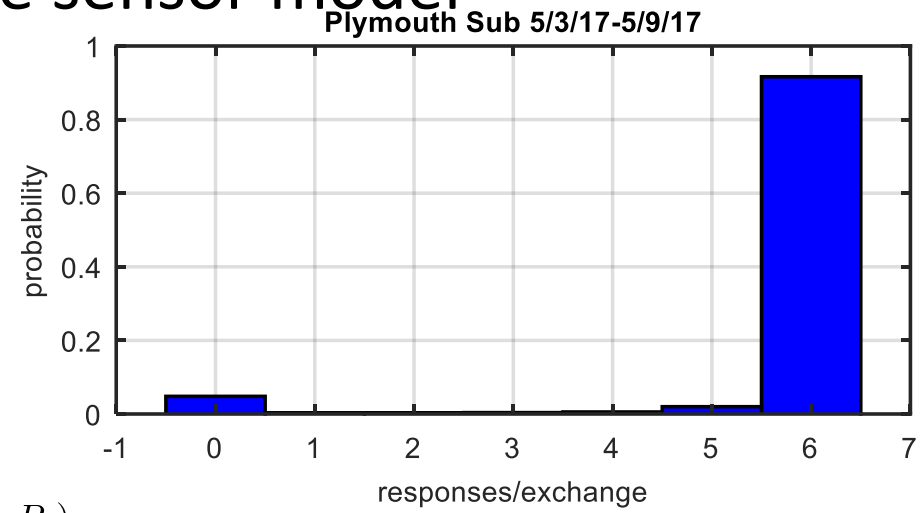
	d(v)=0	d(v)=1
x(v)=0	$1-P_{FA}$	P_{FA}
x(v)=1	$1-P_e$	P_e

Less naïve sensor model

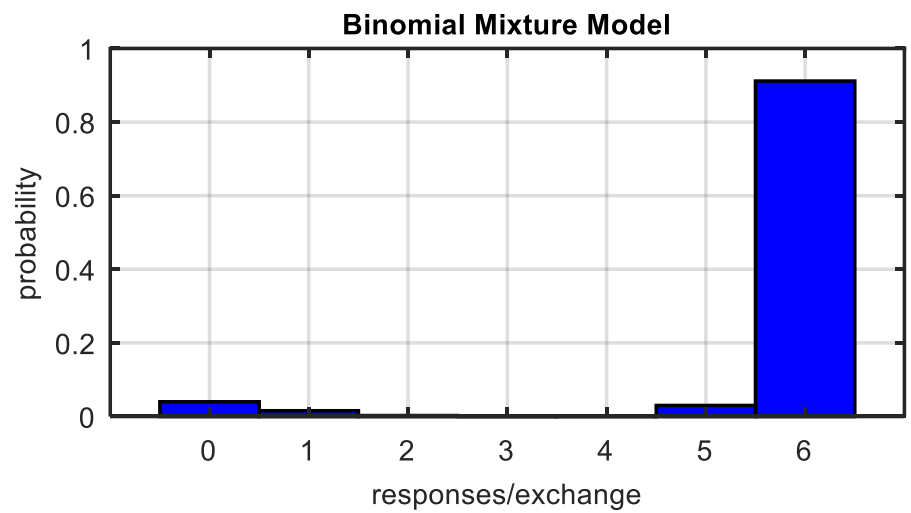
Successful transactions in an exchange:

$$D \equiv \sum_{n=1}^{N} d(v_n)|(x(v_n) = 1)$$

$$\implies D \sim P_y B(n, P_D) + (1 - P_y) B(n, P_e)$$



Exchanges	72052
P_{FA}	N/A
P_D	0.99
P_Y	0.058
P_e	0.061



Dynamic networks

Problem: The network state is not constant. We must redefine the network state variables and data as functions of time:

$$
\begin{aligned}
x &: V \times \mathbb{R} \mapsto S_x \\
\theta &: E \times \mathbb{R} \mapsto S_\theta \\
\mathbf{X}(t) &= \{x(v,t) : v \in V\} \\
\mathbf{\Theta}(t) &= \{\theta(e,t) : e \in E\} \\
\mathbf{\Gamma}(t) &\equiv \mathbf{X}(t), \mathbf{\Theta}(t) \\
D(t) &= \{d(v,t) : v \in V\} \cup \{d(e,t) : e \in E\}
\end{aligned}
$$

The problem now is to estimate

$$p(\mathbf{\Gamma}(t_N), \ldots, \mathbf{\Gamma}(t_1) | D(t_N), \ldots, D(t_1))$$

Hidden Markov models

One approach is to model the state as a Markov random process:

$$p(\mathbf{\Gamma}(t_N)|\mathbf{\Gamma}(t_{N-1}),\ldots,\mathbf{\Gamma}(t_1)) = p(\mathbf{\Gamma}(t_N)|\mathbf{\Gamma}(t_{N-1}))$$

Then,

$$\begin{aligned}
p(\mathbf{\Gamma}(t_N),\ldots,\mathbf{\Gamma}(t_1)|D(t_N),\ldots,D(t_1)) &\propto p(D(t_N),\ldots,D(t_1)|\mathbf{\Gamma}(t_N),\ldots,\mathbf{\Gamma}(t_1)) \\
&\quad \times p(\mathbf{\Gamma}(t_N),\ldots,\mathbf{\Gamma}(t_1)) \\
&= p(\mathbf{\Gamma}(t_1)) \prod_{n=1}^{N} p(D(t_n)|\mathbf{\Gamma}(t_n))p(\mathbf{\Gamma}(t_n)|\mathbf{\Gamma}(t_{n-1}) \\
&= p(\mathbf{X}(t_1),\mathbf{\Theta}(t_1)) \prod_{n} p(\mathbf{X}(t_n),\mathbf{\Theta}(t_n)|\mathbf{X}(t_{n-1},\mathbf{\Theta}(t_{n-1})) \\
&\quad \times \prod_{e\in E}\prod_{v\in V} p(d(e,t_n)|\theta(e,t_n))p(d(v,t_n)|x(v,t_n))
\end{aligned}$$

Hidden Markov models

The network state term can be factored

$$p(\mathbf{X}(t_n), \mathbf{\Theta}(t_n)|\mathbf{X}(t_{n-1}), \mathbf{\Theta}(t_{n-1})) = p(\mathbf{X}(t_n)|\mathbf{\Theta}(t_n), \mathbf{X}(t_{n-1}), \mathbf{\Theta}(t_{n-1}))p(\mathbf{\Theta}(t_n)|\mathbf{X}(t_{n-1}), \mathbf{\Theta}(t_{n-1})).$$

For fault detection it is true that

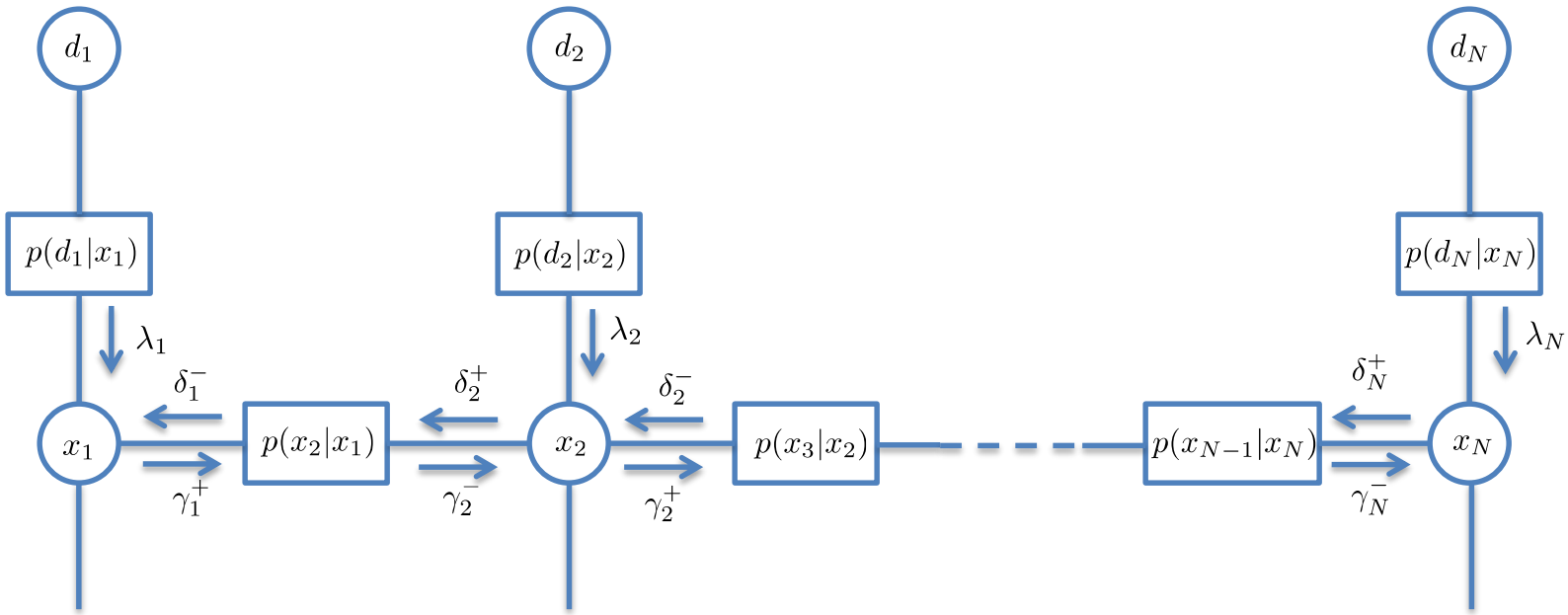
$$\mathbf{X}(t) = f(\mathbf{\Theta}(t)).$$

Therefore, for fault detection

$$p(\mathbf{X}(t_n), \mathbf{\Theta}(t_n)|\mathbf{X}(t_{n-1}), \mathbf{\Theta}(t_{n-1})) = p(\mathbf{X}(t_n)|\mathbf{\Theta}(t_n))p(\mathbf{\Theta}(t_n)|\mathbf{\Theta}(t_{n-1})).$$

Thus having dynamic states introduces a new term to the factor graph.

Example: Single-variable state



Ping strategy

Henceforth, we will use the complete network state vector

$$\mathbf{\Gamma} \equiv \{\mathbf{X}, \mathbf{\Theta}\}.$$

Find a subset of nodes, $V^O \subset V$, such that

$$H(\mathbf{\Gamma}|d(v)\forall v \in V^O)$$

is minimized.

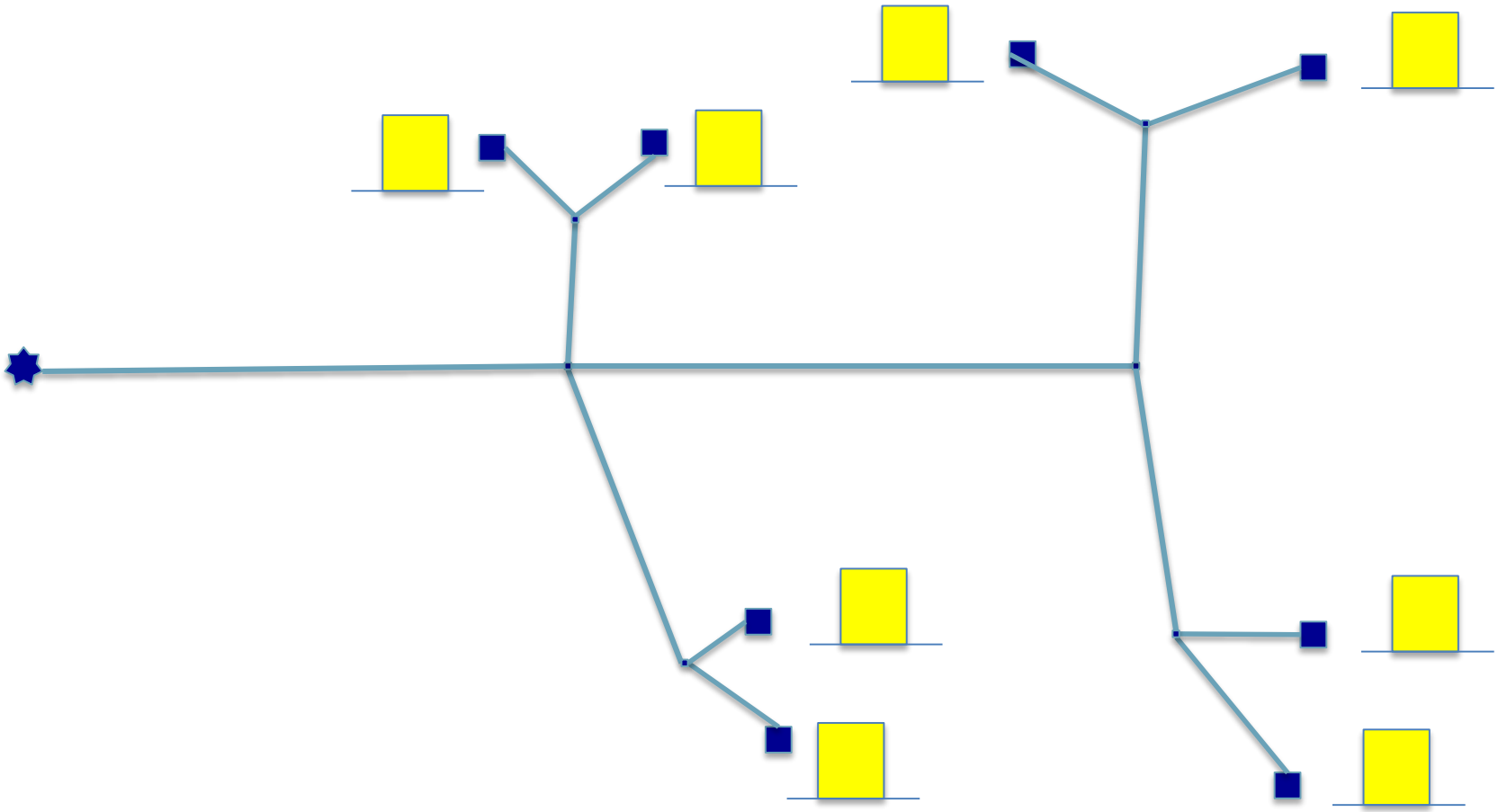
$$H(\mathbf{\Gamma}|d(v)\forall v \in V^O) = H(\mathbf{\Gamma}) - I(\mathbf{\Gamma}; d(v)\forall v \in V^O)$$

Equivalently, find $V^O \subset V$ such that

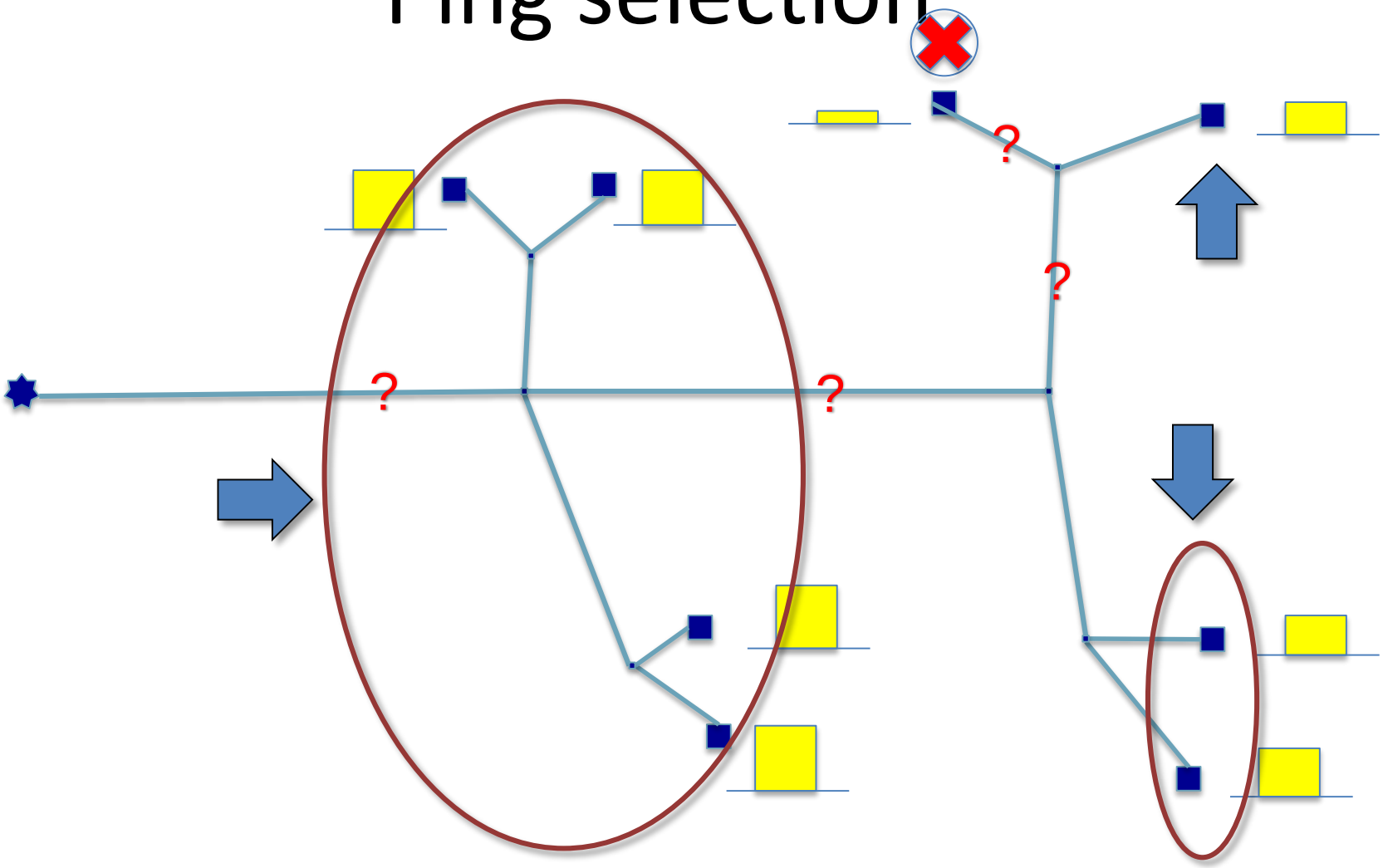
$$I(\mathbf{\Gamma}; d(v)\forall v \in V^O)$$

is maximized.

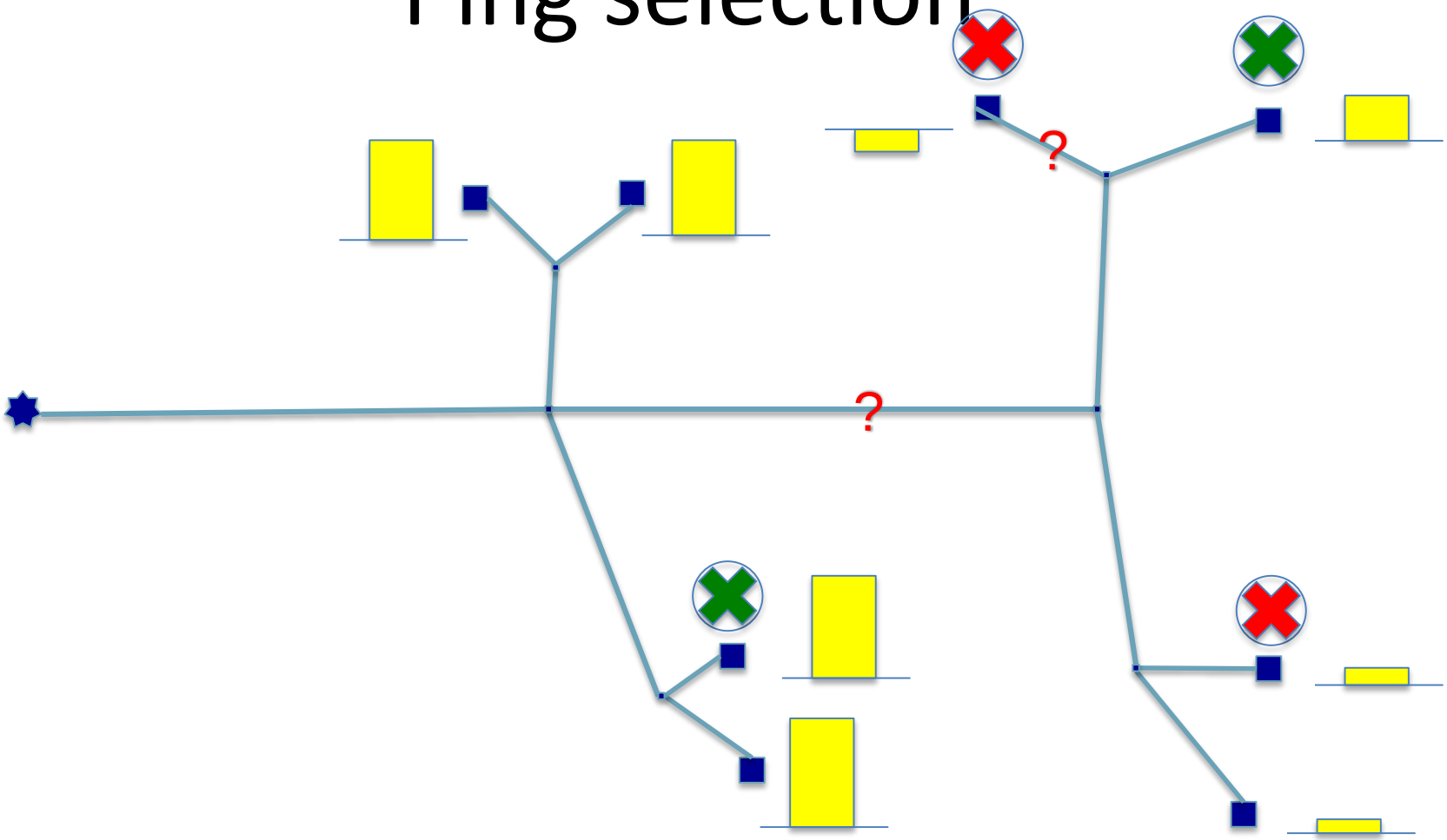
Ping selection



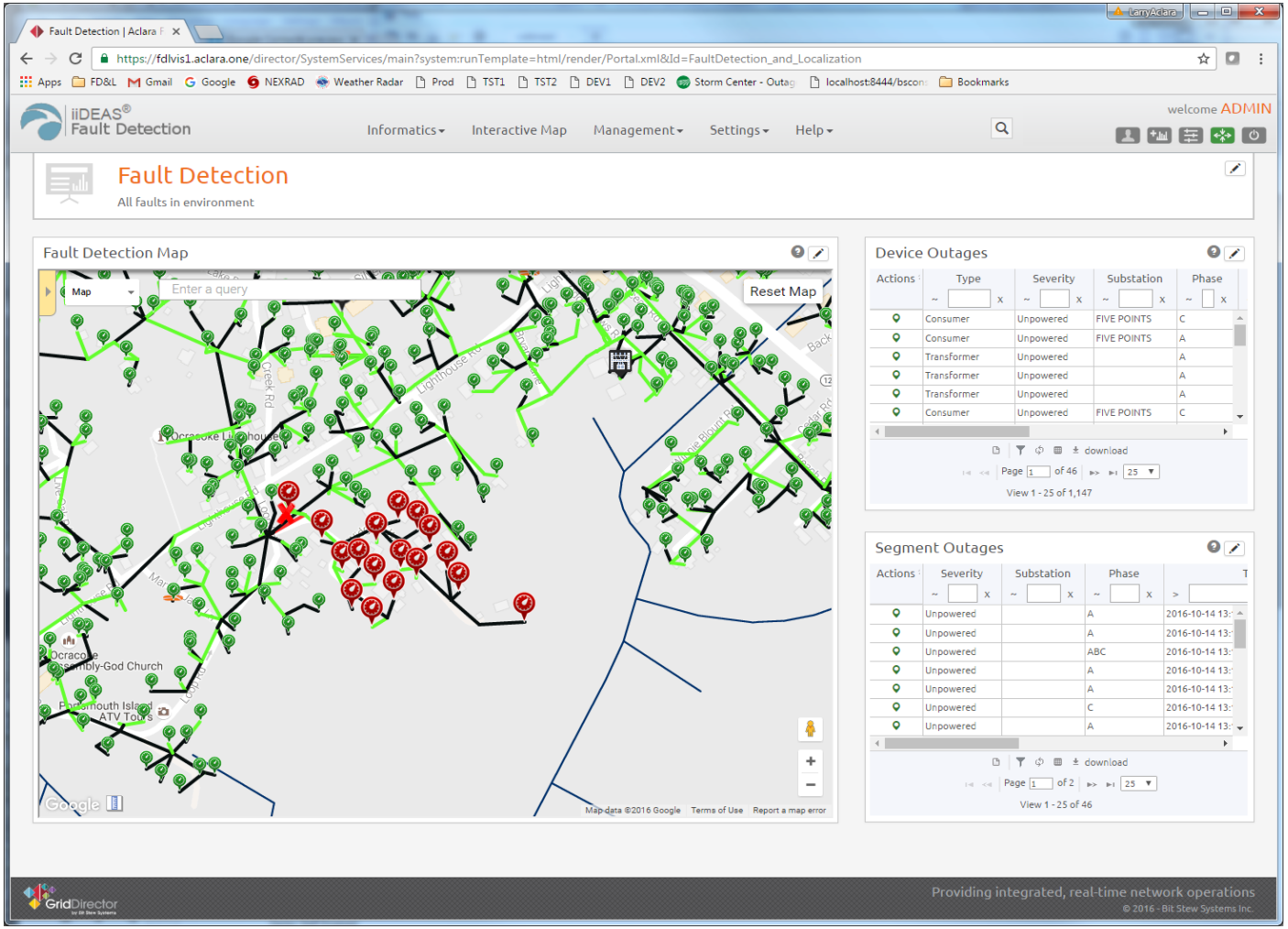
Ping selection



Ping selection



Example 1: Overnight detection



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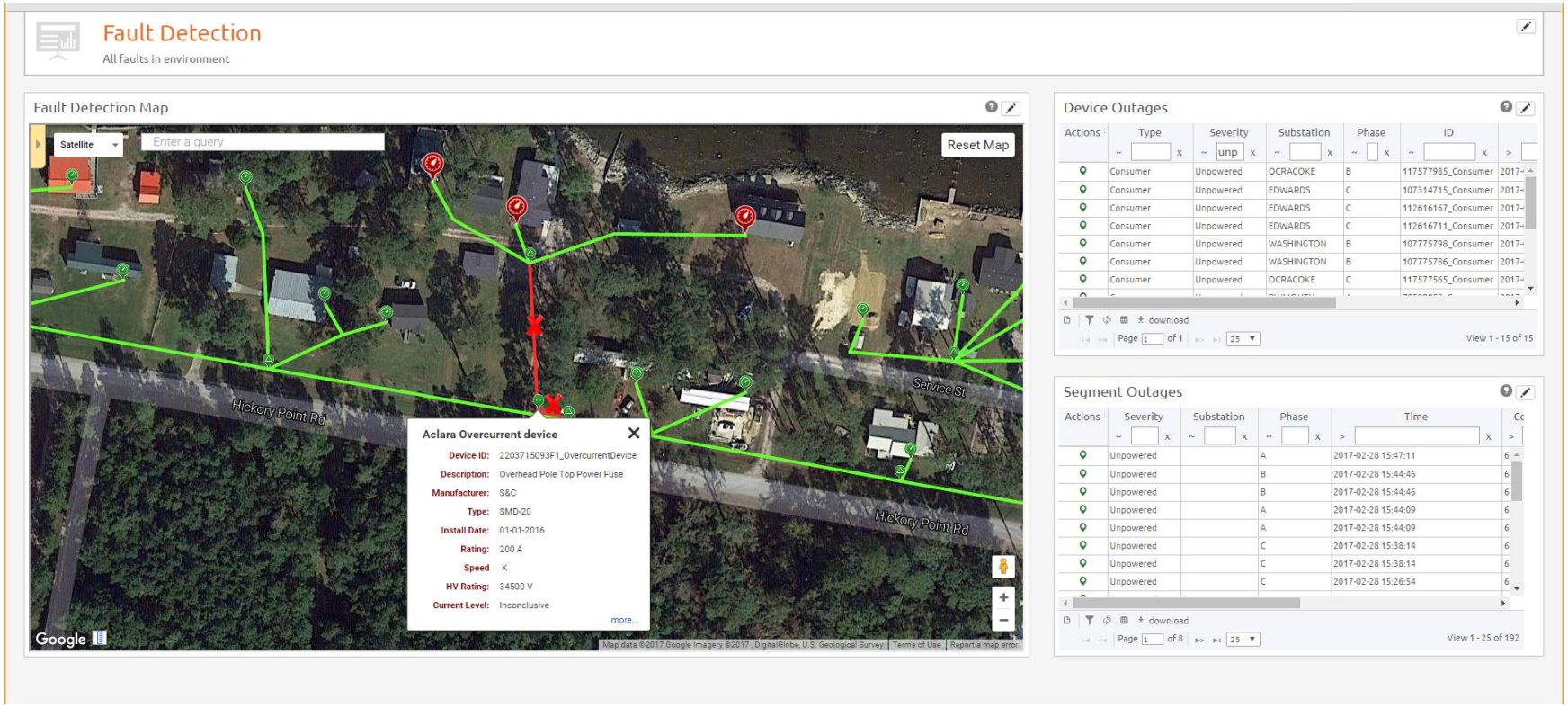
Example 2: Vacation home outage



Closing Remarks

- Product launch later this year
- Presently running 24/7 at two co-ops
- Over ten more awaiting product launch