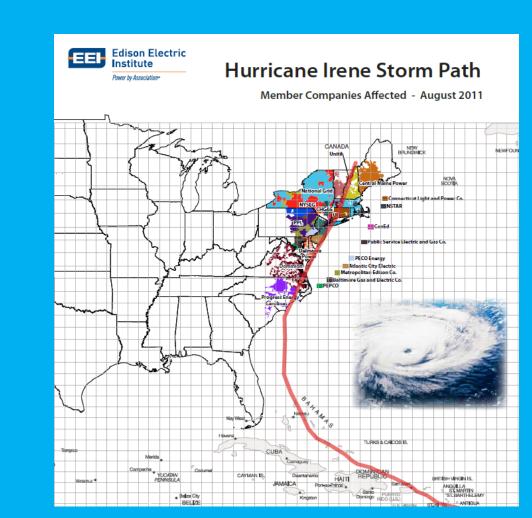
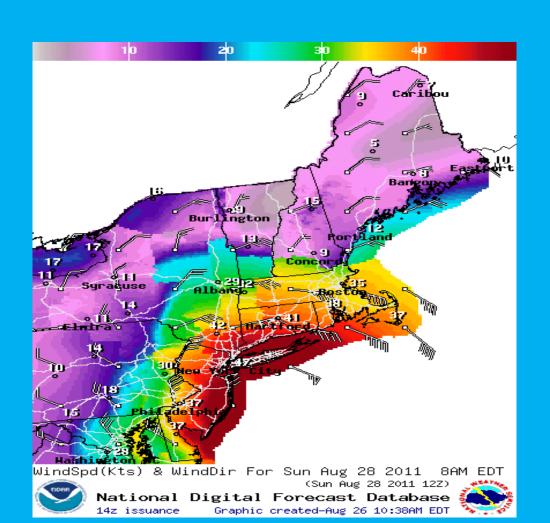
# Weathering the Storm: Using Predictive Analytics to Minimize Utility Outages





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# **Abstract**

In order to meet ever-increasing customer service expectations, electric utilities must continuously improve the reliability of their electric distribution systems. Over the last decade, utilities have invested in digital technologies that give them near-real time readings on the health of their electric grid. This data is incredibly useful during major storm outages, but the flood of data pouring in from transformers and meters can quickly overwhelm even the most seasoned Distribution Engineer. Without analytical technologies, engineers cannot respond quickly enough to prevent additional outages and improve restoration times.

Distribution Optimization for storm management equips utility engineers and dispatchers to predict which assets will be affected by storms while optimizing the placement of crews, thus decreasing outage restoration times. Combining geospatial visualization with predictive analytics, the predictive enterprise utility can shorten outages from weather events and identify weak points in the electrical distribution system thus preventing future outages.

#### Introduction

The days immediately preceding a storm are a critical decision period for electric utility distribution company. The actions a company takes with respect to monitoring weather forecasts for an upcoming storm, predicting damage from that event according to its Emergency Response Plans (ERPs), and obtaining joint service agreements to obtain work crews will determine how well a utility can respond to customer outages when a storm hits. Then, a utility meets its second critical obstacle of determining the best method to restore power to its customers given safety, crew, and system constraints.

# Preparing for the Storm

- Traditional analytics and advanced visual analytics
   Utility visualizes Predicted assets impacted
   Based on given storm forecast path
- Detect system grid weaknesses real-time
   Holistic damage assessment
- Combine historical and projected systemPredict damage using reliability analysis.



Figure 1. Current Method (Source: ESRI Storm Archives)

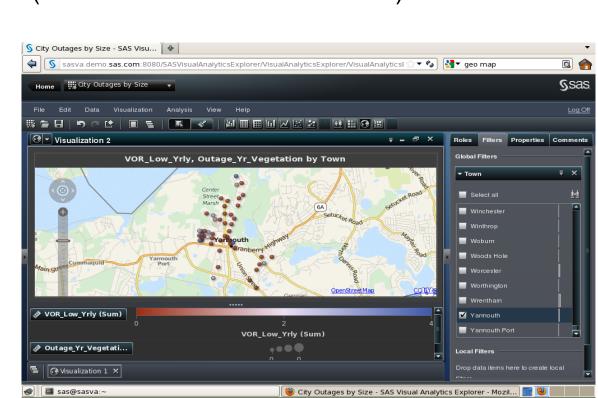
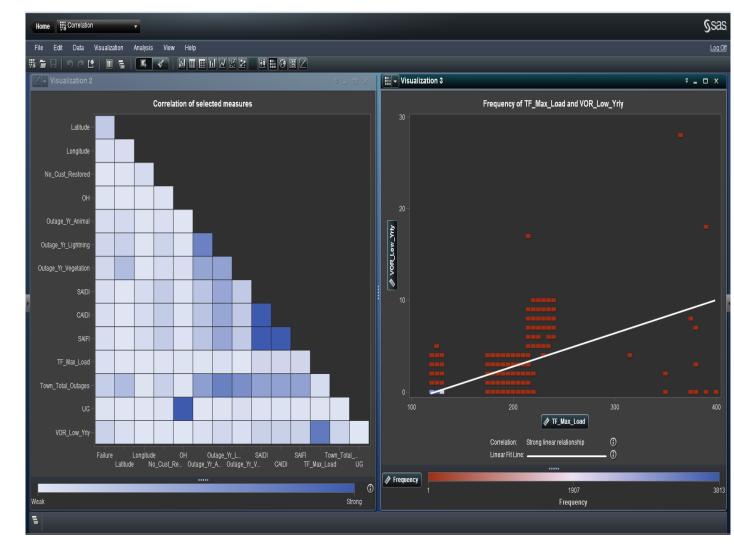


Figure 2. Advanced Method (Source: SAS® Visual Analytics)



**Figure 3.** Correlate Variables to for Outage Model (Source: SAS® Visual Analytics)

Modeling Asset Failure

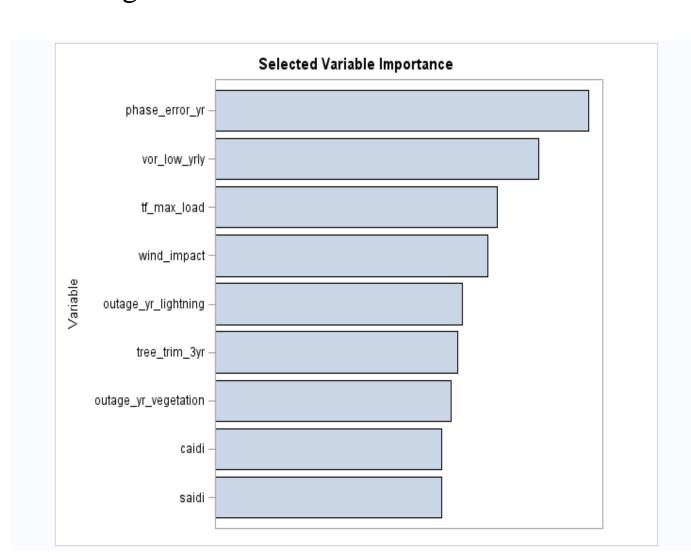
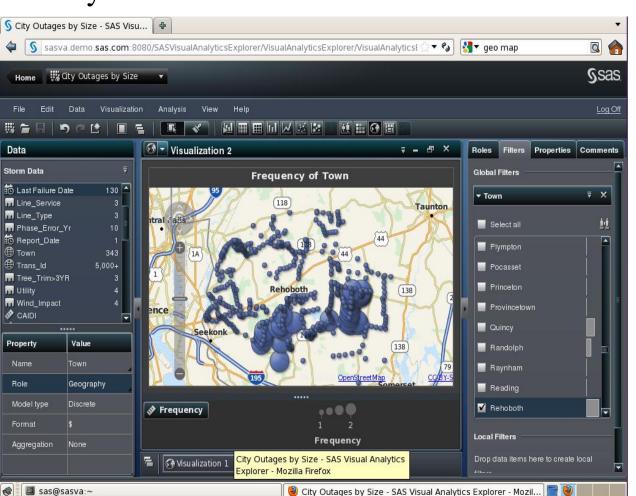


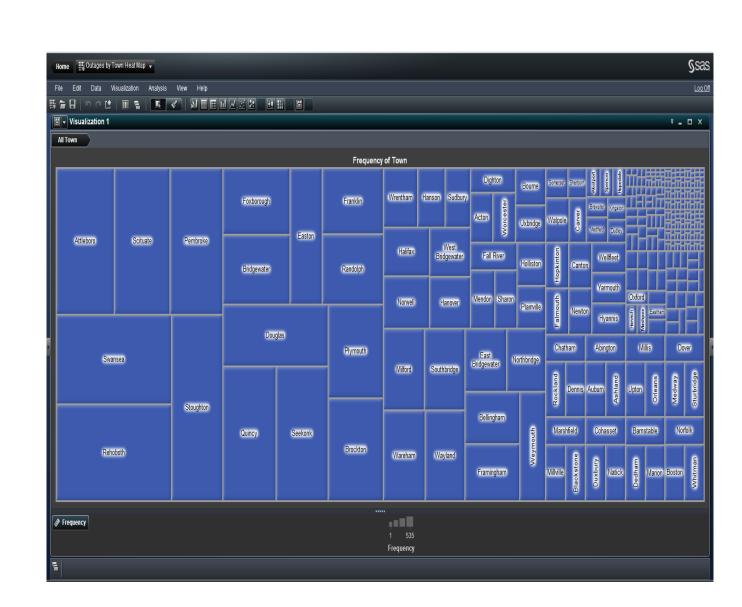
Figure 4 Advanced Modeling To Predict Outages (Source: SAS® Enterprise Guide)

# **During the Storm**

Integrating data from social media, a utility can better pinpoint outages in real-time from sources such as Twitter and can incorporate this information into real time forecasting including optimization analytics. In Figure 5, real-time outage information is viewable in an analytical format.



**Figure 5.** Hurricane Irene Outages by City – 9/1/2011 Real-time outage information leads to greater communications with customers and regulators. (Source: SAS® Visual Analytics)



**Figure 6.** With millions of outages, a distribution engineer can tell at a glance where the majority of outages are located. (Source: SAS® Visual Analytics)

# **After the Storm**

- Dbjective: Restore the most customers while the work crews are covering the least distance given skill set, labor, and vehicle constraints
- ➤ In this poster, we will examine the optimal method for restoring power using an enhancement to an optimization technique known as Capacitated Vehicle Routing Problem using SAS® OR.
  - > STEP ONE: TRAVEL TIME CALCULATION FOR MODEL PREPARATION

TIM	1E ▼				
<b>5</b> 5	Filter and Sort	Query Builder	Data - Describ	e 🕶 Graph 🕶 Anal	yze 🕶   Export 🕶
	→ TCrew1  →	→ TCrew2	→ TCrew3	₁ TCrew4	¹ TCrew5
1	0	0	0	0	0
2	1.1241357337	1.2238171506	1.1947545386	1.2999892675	1.2998266593
3	2.4245825478	2.5362124227	2.5725075433	2.5760524007	2.5790852151
4	3.8091098647	3.8872295845	3.9502705434	3.986986096	3.9731091129
5	5.2588843627	5.1536752928	5.3554162876	5.4175884187	5.4463654994
6	6.5599837037	6.6363251881	6.8962434052	6.8761271472	6.7663538671
7	7.9150542003	8.1343529879	8.3003893671	8.2281248557	8.2835437897
8	9.2881638619	9.4723181197	9.850282193	9.5648219921	9.8307602777
9	10.80503156	11.072307778	11.261118602	11.171472737	11.461229388
10	12.252119786	12.553719183	12.748217746	12.807027917	13.118050987
11	13.875195898	14.263629829	14.40385985	14.305424817	14.799408466
12	15.638760288	15.963353778	15.762052575	15.612079271	14.824594994
13	15.66065641	15.998163537	15.839348822	15.647107812	14.824594994
14	24	24	24	24	24

**Figure 7**. Time Calculation using PROC Geodist (Source: SAS® Enterprise Guide)

> STEP TWO: MODIFY MIXED INTEGER
LINEAR PROGRAMMING (MILP)
FRAMEWORK FOR CUSTOMER
RESTORATION CONSTRAINTS

<b>1</b>	v	13	day	13	time	CustRestored_i	UnderGround_i	13	хi	13	yi	13	хj	1	yj
		1		1	0	0	0		-71.41684055		42.276705465		-71.43160343		42.272926
		1		1	1.1241357337	9	0		-71.43160343		42.272926714		-71.42980099		42.271942
		1		1	2.4245825478	9	0		-71.42980099		42.271942296		-71.43362045		42.273720
		1		1	3.8091098647	9	0		-71.43362045		42.273720588		-71.42778397		42.272863
		1		1	5.2588843627	9	0		-71.42778397		42.272863203		-71.42598152		42.273752
		1		1	6.5599837037	8	0		-71.42598152		42.273752342		-71.41460896		42.282801
		1		1	7.9150542003	8	0		-71.41460896		42.282801797		-71.40542507		42.289373
		1		1	9.2881638619	8	0		-71.40542507		42.289373744		-71.40091896		42.291310
		1		1	10.80503156	9	1		-71.40091896		42.291310273		-71.41151905		42.29797
		1		1	12.252119786	8	0		-71.41151905		42.29797656		-71.41345024		42.297913
		1		1	13.875195898	9	0		-71.41345024		42.297913075		-71.41070366		42.278070
		1		1	15.638760288	9	0		-71.41070366		42.278070841		-71.41684055		42.276705
		1		2	24	0	0		-71.41684055		42.276705465		-71.42915726		42.277975
		1		2	25.761806884	9	0		-71.42915726		42.277975583		-71.44237518		42.27168
		1		2	27.384890349	8	0		-71.44237518		42.27168825		-71.44061565		42.272672
		1		2	29.066408546	8	0		-71.44061565		42.272672672		-71.43301964		42.287976
		1		2	30.825598386	8	0		-71.43301964		42.287976865		-71.42885685		42.294802
		1		2	32.52179117	8	0		-71.42885685		42.294802226		-71.41791344		42.297627
		1		2	34.028415804	7	0		-71.41791344		42.297627391		-71.43035889		42.289437
		1		2	35.600147361	7	0		-71.43035889		42.289437237		-71.43439293		42.299976
		1		2	37.448191734	8	1		-71.43439293		42.299976309		-71.44387722		42.270545
		1		2	39.596567017	9	1		-71.44387722		42.270545031		-71.41684055		42.276705
		1		3	48	0	0		-71.41684055		42.276705465		-71.43121719		42.280579
		1		3	49.514114056	6	0		-71.43121719		42.280579244		-71.42503738		42.286167
		1		3	51.014031406	6	0		-71.42503738		42.286167227		-71.42422199		42.274482
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		1		3	54.923255282	8	1		-71.39744282		42.272037563		-71.39993191		42.28026
		1		3	56.641657795	6	1		-71.39993191		42.28026173		-71.42864227		42.276356
		1		3	58.133693696	4	0		-71.42864227		42.276356178		-71.41383648		42.277340
		1		3	59.709447593	4	0	0	-71.41383648		42.277340527		-71.41671181		42.27794
		····÷·····		·····										·	

Figure 8. Vehicle and Skillset Calculations (Source: SAS® OR and SAS® IML)

> STEP THREE: MILP SOLVER TO CREATE
OPTIMAL SOLUTIONS VERSUS
STANDARD UTILITY ROUTING

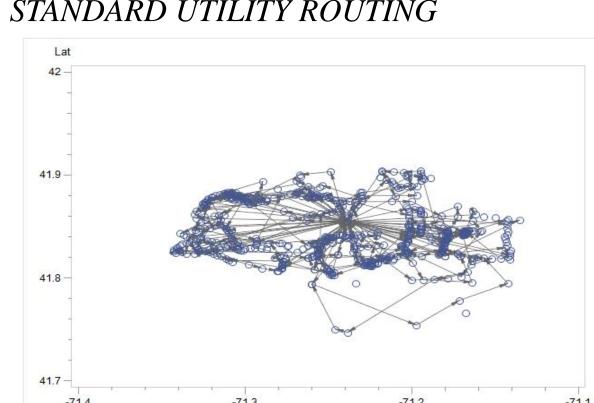


Figure 9. Dynamic crew scheduling
Sample Town: Fall River Massachusetts outages from Hurricane Irene 2017

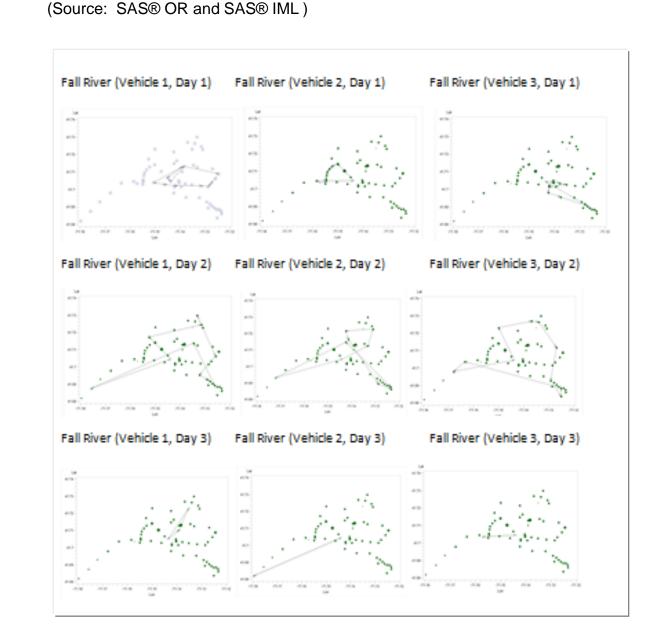


Figure 10. Dynamic crew scheduling (Source: SAS® OR and SAS® IML)

### Conclusions

#### BEFORE THE STORM RESULTS

- Predictive and visual analytics play a key role in pinpointing transformer outages in a proactive versus reactive manner.
- The methods used in this paper such as storm transformer outage prediction combined with geospatial modeling helps a utility better plan for assistance, materials, and potential storm impact.
- While the accuracy results in this simulated dataset were higher than should be expected at 98% over existing techniques, additional studies with real storm data could be beneficial for all.
- This could lead to timelier outage restoration, improved system reliability, and better communications with governmental and regulatory bodies.

#### **AFTER THE STORM RESULTS**

- Results from the Constrained Customer Restoration Optimization varied in this simulated dataset from no change to a 22% improvement in outage restoration time for optimized routes from non-optimized routes.
- On average, towns were able to have customers restored 13.8% faster than the present heuristic restoration technique.
- Variables contributing to the greatest gains include dynamic crew scheduling capability, distances between outages, number of underground outages, with crew and vehicle capabilities playing a role as well.

#### References

- Massachusetts Government information from the Department of Public Utilities, Storm Orders regarding Hurricane Irene. Available at <a href="http://www.mass.gov/eea/grants-and-tech-assistance/guidance-technical-assistance/agencies-and-divisions/dpu/storm-orders.html">http://www.mass.gov/eea/grants-and-tech-assistance/agencies-and-divisions/dpu/storm-orders.html</a>
- "S.P. Anbuudayasankar, Amrita University, K. Ganesh, K. Mohandas, Amrita University, "Mixed Integer Linear Programming for Vehicle Routing Problem with Simultaneous Delivery and Pick-Up with Maximum Route-Length", International Journal of Applied Management and Technology, Vol. 6, Number 1

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