**Electric Utility Storm Restoration – Crew Work Allocation Optimization**

by

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Submitted to the MIT Sloan School of Management and the Institute for Data, Systems, and Society in partial fulfillment of the requirements for the degrees of

**Master of Business Administration**
and
**Master of Science in Engineering Systems**

In conjunction with the Leaders for Global Operations Program at the
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## Abstract

Storms damage Atlantic Electric's electric distribution network, resulting in power outages and expensive repairs. After severe storms Atlantic Electric hires external contractor crews to perform the majority of the restoration work. This project focuses on increasing the effectiveness of contractor crews by: 1) improving work flow processes that can result in restoration delays; 2) staging contractor crews at operations bases that are close to damage; and 3) optimizing the work allocation to contractor crews so that customers have their power restored sooner.

An optimization model used by Atlantic Electric to pre-stage their crews is modified and improved so that it can suggest locations for staging crews throughout a restoration effort. The model compares well to actual storm assignments in previous storms, normally preempting Atlantic Electric's decision by one day. This suggests that Atlantic Electric's experts and storm managers are already operating efficiently, but that the model can help them reach their decisions faster since it incorporates all data instantaneously and objectively. The use of the model will also provide a valuable justification to the state regulators, who monitor storm responses, for crew movements and postings.

Next, an optimization model is developed to improve the assignment of individual repair jobs to crews. Currently the process is performed manually and can vary from base to base. Decision makers must balance multiple factors, such as the number of crews available, location of damage points, the severity of the damage, and the number and type of customers without power. Under enormous pressure in a hectic environment, it can be difficult to analyze and weigh all these factors. Additionally, due to the infrequent nature of these large events, some personnel have limited first-hand experience in these situations, while others are extremely experienced and skilled. The model captures and codifies the methodology of Atlantic Electric's storm experts and provides a quick, consistent tool for assigning work efficiently. Finally, we suggest several process improvements to the contractor work flow.

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## Contents

## List of Figures

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## List of Tables

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# 1. Introduction to storm response at Atlantic Electric[1]

Severe weather causes damage to Atlantic Electric's electric distribution network, resulting in prolonged power outages and expensive repairs. Large storms can cause hundreds of thousands of customers to be without power and cost tens of millions of dollars. This is disruptive to Atlantic Electric's customers and draws scrutiny from states' regulators who are increasingly critical of utilities' operational decisions following storms. This thesis aims to reduce Atlantic Electric's restoration time and costs following a storm.

This project follows a previous collaboration between Atlantic Electric and the Massachusetts Institute of Technology. In 2013 the two developed a prediction model [13] that uses weather forecasts as an input and calculates the expected damage to Atlantic Electric's network. Atlantic Electric then uses this predicted damage information to optimize the pre-staging of repair crews to bases where the most amount of damage is expected.

This model is a useful tool for storm preparation; however, once a storm has hit and damage to the network is known, Atlantic Electric continues to use traditional methods to assign crews to field locations and allocate work to the crews. This project tries to increase the efficiency of the work assignment process and optimize the geographic assignment of crews throughout a restoration effort.

## *1.2 Overview of storm operations*

Atlantic Electric is a large, investor-owned utility with operations throughout the world. This paper will focus on Atlantic Electric's US electric operations, where they have several million electric customers.

Extreme weather such as hurricanes, lighting storms, and blizzards wreak havoc on utilities' electricity transmission and distribution infrastructure. High winds or heavy icing

[1] The name of the utility being studied has been changed to Atlantic Electric

can knock trees into overhead lines, cause poles to snap, or break lines. This type of damage will disrupt power to customers until the physical assets can be repaired or replaced. Large storms result in a huge number of customer outages, sometimes leaving customers without power for days or weeks. To understand the potential damage points in the electricity network it is helpful to have a basic understanding of the power system, as represented below in Figure 1-1.

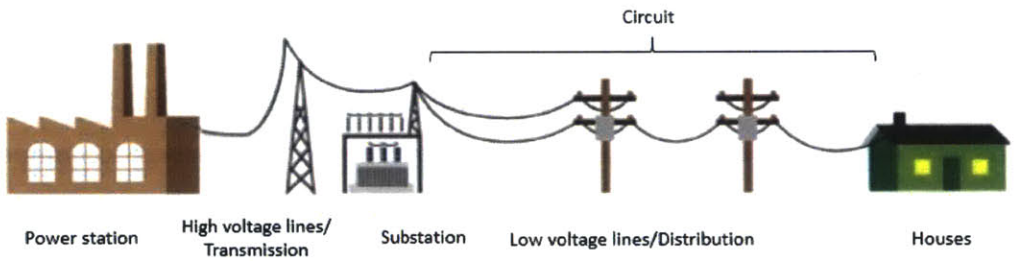



Figure 1-1: High-level representation of the electric transmission and distribution network

In general, electricity is generated at a power station and travels along high voltage transmission lines to a substation. At the substation the voltage is stepped down to a lower voltage and then enters the distribution network. Finally, the voltage is lowered via transformers located on utility poles, before being connected to a customer.

Storm damage can occur at any point in this chain. If a transmission line or a substation is affected a large number of customers will likely be out of power since one substation can feed many thousands of customers. As a result, utilities strive to repair these assets immediately. Fortunately, since transmission lines and substations are sturdy and are generally well protected from trees, storm damage is less likely. The distribution network, on the other hand, is often severely damaged, and it is this network whose repair takes the longest and is the costliest.

To support the restoration effort Atlantic Electric utilizes the Incident Command System. A state incident commander oversees operations at various branches throughout the state. Under the individual branch directors are the various restoration groups. Damage

Assessment patrols and catalogues damage immediately following a storm; Wires Down makes safe potentially dangerous wires that have been knocked to the ground; Transmission and Substation groups repair their respective areas; Overhead Line is responsible for addressing distribution damage; the Forestry group supports the repair efforts by removing fallen trees from lines. Of these groups it is Overhead Line that performs the bulk of the restoration work and is the costliest.

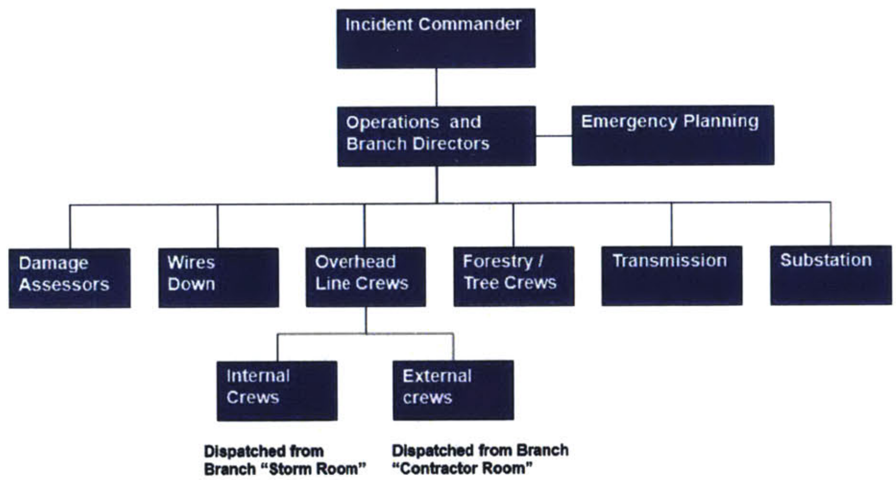



Figure 1-2: Atlantic Electric storm organization structure

When damage is extensive, Atlantic Electric does not have enough internal overhead crews to perform all the repairs in a reasonable amount of time and so they hire external crews. These external crews come from three sources:

- third-party crews who work closely with Atlantic Electric during regular, non-storm days performing construction work. These are often referred to as "contractors of choice".
- external contractors from third party vendors that do not regularly work with Atlantic Electric. These are known as "foreign" contractors.
- repair crews from other utilities who are loaned to Atlantic Electric to help with the restoration work. These are known as "mutual assistance" crews.

Repair crews, both internal and external, are stationed at Atlantic Electric facilities, known as platforms, for the duration of the storm. These platforms are the home-base for crews until restoration is complete or until they are re-assigned to other platforms. Crews repair damage that occurs in locations associated with their platforms.

The various stages of storm operations are outline below.

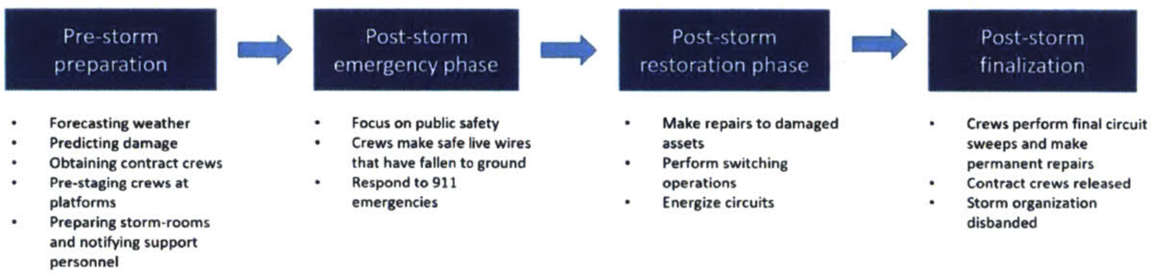



Figure 1-3: Storm restoration steps

### *1.2.1 Assigning crews to platforms*

Atlantic Electric tries to predict the impact of an approaching storm and pre-stages crews at platforms throughout their service area where the most damage is likely to occur. Whipple [13] and Monsch [10] developed a damage prediction model and optimization tool for pre-staging crews that is now used by Atlantic Electric.

Once the storm has hit, Atlantic Electric can more accurately assess damage to its network and reallocate crews to the worst affected areas. Customer outages, which are predicted by the company's Outage Management System (OMS), are used to provide some indication of where the most damage is. Smart devices and sensors provide further information on specific assets, particularly in substations. Damage assessors are also deployed to patrol certain areas, noting the type of damage along circuits. This information is used to direct the restoration effort and to calculate estimates of repair times.

Branch directors and the incident commander use all this information to move and re-deploy crews as needed. It is common for crews to move several times during a storm restoration as areas are repaired or more damage develops.

### *1.2.2 Assigning work to crews at the platform level*

Atlantic Electric utilizes different approaches for assigning work to internal and external crews. Internal crews are familiar with Atlantic Electric's network and are dispatched through a dedicated storm room where they are assigned jobs one at a time. They are often performing smaller repairs and have a key role during the 'emergency phase' of the restoration. This is a stage immediately after a storm has hit when most internal crews respond to 911 emergency calls and reports of fallen power-lines on the ground that pose an immediate public safety risk.

Contract crews, in contrast, are usually assigned work in bulk via structured work packets. The large number of contractor crews utilized in major events, and their lack of local knowledge, make it inefficient to assign them work individually. Instead contractors work in groups of four or five crews overseen by one Atlantic Electric Supervisor who is known as a Restoration Crew Supervisor (RCS). Normally an RCS will be assigned a specific circuit to work and the storm room will prepare a work packet with a list of repair jobs along the circuit. The RCS will then distribute the work among his or her crews.

## *1.3. Literature Review*

Successful storm management is critical to electric utilities and the problem has been studied extensively. Lubkeman et. al [8] provides a thorough description of the various stages of storm restoration and suggests ways in which accurate outage prediction and damage assessment can be used to guide crew placement and minimize restoration times. The authors highlight the value of having an outage management system linked with other data systems to provide guidance during restoration efforts.

Many articles have focused on network design and the most efficient switching operations to perform during a storm. Mendes et al. [9] considers the use of a genetic algorithm for improving switching operations, while Wu et al. [14] discusses a hybrid genetic algorithm that also takes into account crew scheduling.

Other papers address the issue of crew scheduling and crew placement. Yao et al. [16] develops a tactical model for staging repair crews for power failures. The model considers two phases: pre-staging crews and then dispatching them once faults occur. A penalty factor is applied if repair crews cannot reach repair sites within a desired time period and the model attempts to minimize this penalty. A weighting for penalties is applied based on the severity of the outage. Guhua et al. [5] develops approximation algorithms for two versions of the crew assignment problem. The first version aims at maximizing the number of high priority customers recovered in a single day by using a budgeted problem. The second version minimizes the time taken to recover the whole network. Weintraub et al. [12] also considers the importance of customer types when scheduling repair crews. They develop a composite heuristic for assigning repair vehicles for an electric utility in Chile. The heuristic minimizes the out-of-service time of customers, where customers of different priorities are assigned different weights. These weights are determined by a calibration performed by the utility. Another method for prioritizing repair is discussed in Wu et al. [15]. Wu proposes a fuzzy rule-based system to assist dispatchers dealing with large-scale power outages. The proposed fuzzy membership functions include the types of customers, estimated time to repair an outage, and the number of resources needed in total. It is shown how this system can be integrated into a utility's outage management system.

While fuzzy logic is one way of dealing with the inherent uncertainty involved in storm restorations, other articles try to approach the problem using stochastic or robust techniques. Herroelen and Leuus [6] provide a good review of the various techniques available for project scheduling under uncertainty and their research potential. Keller and Bayraksn [7] formulate a two-stage stochastic integer program to determine an optimal schedule for jobs requiring multiple classes of resources under uncertain processing times. Balwani [1] used this approach and showed that a stochastic optimization can reduce overtime repairs at a gas utility. Whipple [13] developed a robust optimization to pre-stage crews before a storm. His robust model used Bertismas-Sim [3] uncertainty sets to take into account the inherent uncertainty in repair time.

Many of these papers, and others, are discussed in Perrier et al. [11]. The article conducts a comprehensive survey of optimization models and solution methodologies for emergency response in electric distribution systems. These problems include the restoration of service, the sequencing of switching operations, the routing of repair vehicles, the scheduling of repair crews, and the assignment of crews to repair sites.

## *1.4 Thesis outline and contribution*

This thesis begins by exploring Atlantic Electric's current work allocation process, mapping key work flow processes and identifying critical stages, bottlenecks, and inefficiencies. First hand observations, employee interviews, repair crew surveys, and historical storm logs form the basis of this study.

Chapter 3 goes on to describe the optimization model used by Atlantic Electric for pre-staging crews in advance of a storm and explores ways to adjust this model so that it can inform crew movements after a storm has struck. The resulting model is run using data from actual storms and compared to actual crew stagings; the results suggest that the model will provide a useful tool to Atlantic Electric and help them make decisions faster. The issue of data uncertainty is addressed and a robust optimization model is considered. Investigations and a simulation suggest that a robust model leads to inefficient outcomes in this case.

Chapter 4 looks at how repair work is assigned to individual crews at the platform level. A heuristic, capturing the best practices of Atlantic Electric's storm experts is developed. Then several optimization models, capable of allocating work efficiently among different crew types, are proposed.

Finally, Chapter 5 discusses potential improvements to the models and further work.

Contribution of thesis

As a result of the analysis in Chapter 2, changes to the way contract crews are managed and provided with work instructions are suggested. These proposals have been adopted by Atlantic Electric and will be trialed during the next major storm. Atlantic Electric's work allocation process can continue to be improved and eventually an electronic remote dispatch system should be introduced. This would reduce the chance of communication-related delays and at the same time provide an effective way of recording crew utilization.

The models developed in Chapters 3 and 4 extend the trend of Atlantic Electric using data to make decisions instead of relying on human intuition and experience alone. Chapter 3 adapts an existing crew-allocation model and uses it to inform crew-staging decisions over the course of a storm restoration; this should increase the utilization and effectiveness of contract crews, hastening restoration and reducing costs. Chapter 4 captures and codifies the knowledge of experienced storm managers in a simple algorithm. The algorithm reduces a complex, variable, and time-sensitive decision making task to a quick, repeatable, understandable process.

# 2. Process Redesign - contractor work allocation

This Chapter reviews the contract work allocation process in detail and identifies issues that have historically resulted in work delays. Recent changes to Atlantic Electric's systems are then discussed, and it is shown how they can be integrated into the work allocation process to reduce delays.

## *2.1 Detailed description of historical state*

Contractors represent the largest cost of restoration after a major storm as they perform a large portion of the restoration work. As noted in Section 1.2.2, they receive their work instructions through an Atlantic Electric Supervisor, known as an RCS (Restoration Crew Supervisor) who collects a work packet from the platform storm room. Historically the development of these work packets and the distribution of the packets to RCSs has been a time consuming process. A simplified flow diagram of the contractor work assignment process is shown below.

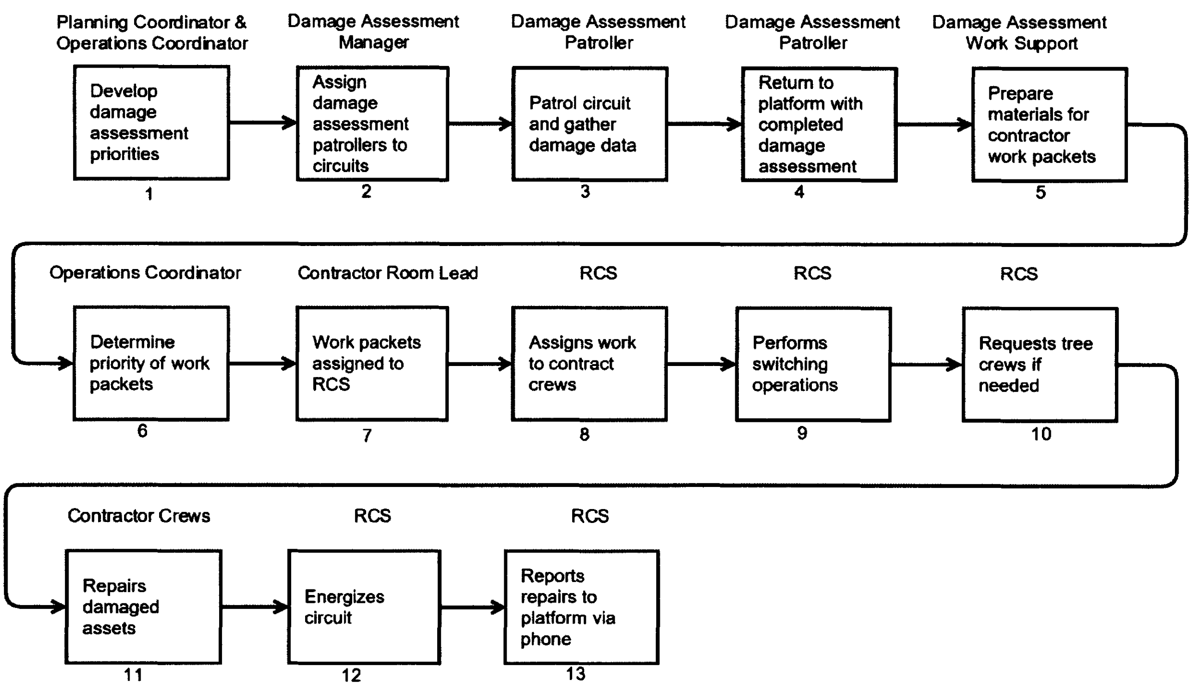



Figure 2-1: Contractor work flow

For clarity the process steps involved are shown by category type, Data Gathering, Job Assignment, and Repair, in Table 2-1.

Table 2-1: Contractor work flow steps

| Data Gathering | Job Assignment | Repair |
|---|---|---|
| 1. Review outage management system and determine which circuits to assess for damage<br>2. Assign damage assessors to circuits<br>3. Patrol circuits and assess damage<br>4. Return damage assessment information to platform | 5. Prepare materials for contractor work packet<br>6. Determine priority of work packets<br>7. Assign work packets to Restoration Crew Supervisor (RCS) | 8. Assign work to contractor crews<br>9. Perform switching operations if needed<br>10. Request tree crews if needed<br>11. Physically repair assets<br>12. Energize circuit<br>13. Report repairs to platform |

A series of in depth interviews with Atlantic Electric employees directly involved with restoration work suggest that there are several steps in the process that have historically been causes of delay. These findings were confirmed by surveys of dozens of Restoration Crew Supervisors who identified similar issues.

## *2.2 Opportunities for improvement*

Step 4

Damage assessors would patrol circuits and manually note damage points on circuit maps. The maps would then be physically returned to the local platform where the damage data would be collated manually. This was a time consuming process and made storm planning more difficult.

Step 5

Work packets have traditionally been compiled by the Damage Assessment Work Support team. Work packets could only be assembled once Damage Assessors had returned from the field, which postponed assigning work and developing estimates of restoration times.

Step 6

The Operations Coordinator must balance a number of factors to determine the most important circuits to repair first. This process can be time consuming and is performed slightly differently across different bases. A detailed description of this prioritization process, and tools developed to simplify and standardize it, is provided in Section 4.1.

Step 7

The head of the Contractor Room assigns work packets to the RCS based on the number of contractor crews that are working with the RCS and the expected workload of that packet. It can be difficult to determine the estimated work-loads and so sometimes too many or too few crews are assigned to a given work packet.

Step 8

An RCS will generally be supervising five contractor crews during a storm, but if he or she is a senior RCS, that person may have even more. To improve the work process and increase the situational awareness of the contractor crews, RCSs like to distribute marked-up circuit maps to the crews they oversee. Sometimes RCSs do not receive as many map copies as they would like and this can increase the communication required between the RCS and crews, reducing their efficiency.

Steps 9

Depending on ground conditions RCSs may be able to restore power to customers sooner by performing switching operations. To perform a switch a RCS needs approval from the central control center. Delays can occur if they do not have the contact number of the control center readily available.

Step 10

The forestry department generally dispatches tree crews to sites where there is known tree damage and they work in tandem with restoration crews. Occasionally RCSs need to request extra tree crews. Delays can occur if the RCS does have the contact number of the forestry dispatch group readily available.

Step 13

After a circuit has been energized it is important that RCSs report this so that the OMS can be updated. Delays can occur if they do not have the contact number of the control center readily available.

## *2.3 Suggested changes to process*

New tools recently introduced by Atlantic Electric can help mitigate or avoid the delays identified above, but they had yet to be fully integrated into the contractor work flow process. With effort from the Emergency Planning department at Atlantic Electric the process has been changed slightly and the benefits of these new tools can now be realized.

Technological improvements have allowed the recording of damage assessment on electronic tablets, making damage information available immediately. This means that storm rooms no longer need to wait for damage assessors to return from the field to develop a sense of damage levels and prepare work packets for contractor crews; they can prepare all this information as the data is gathered. The switch from paper recording of damage assessment to electronic has also freed up support personnel who were previously needed to prepare information packages for damage assessment patrollers. Now these personnel can be used to help prepare work packages for the contractor work packages. The Emergency Planning department has created a new role in the storm organization for this, 'Contractor Room Support.'

The electronic damage capture system presents data in a simple, visual format, which can greatly aid storm workers in developing quick situational awareness. Damage type and location are overlaid on electronic circuit maps, providing an immediate overview of important damage areas. Providing these summary damage maps in work packets for RCSs allows the RCS to quickly understand the infrastructure needing repair and helps them determine field priorities.

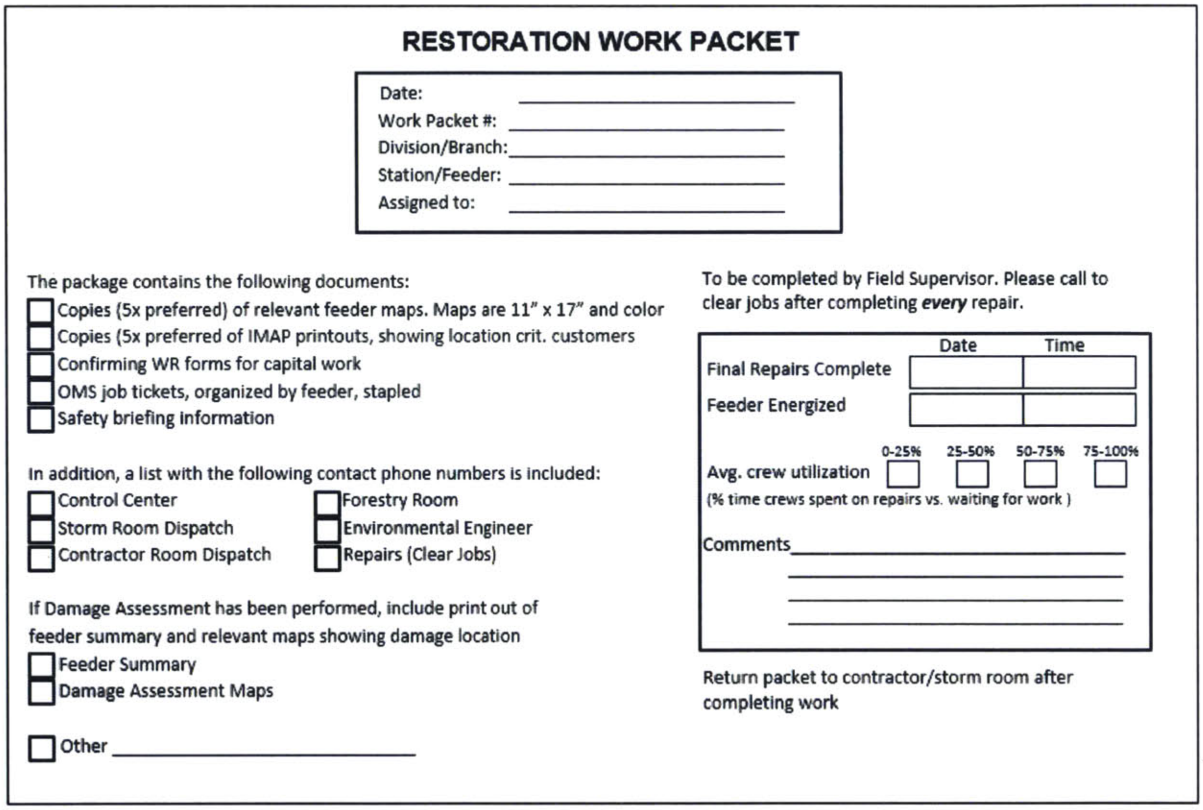
A new work packet

Previously, work instructions were provided to RCSs in a damage assessment (DA) patrol envelope. Damage assessors would receive circuit maps in an envelope, mark-up the face of the envelope with a summary of the damage they observed, and return it to their base where other materials would be added to the envelope. The envelope was then considered a contractor work packet and assigned to an RCS. This made sense since it provided RCSs with a useful overview of damage on their circuit.

However, there were no clear instructions on what other materials should be included in the packet. Depending on the work practices of the storm platform and available resources RCSs might receive different documents. Issues associated with the work packets included:

- Limited circuit maps, multiple copies of which are needed to distribute work to crews
- Absence of contact phone numbers, which are needed for coordination of restoration efforts in the field
- Absence of outage information printed from the OMS

Now that a damage data summary is provided by the electronic system there is no need for contractor work packets to be provided in the old damage patrol envelopes. Instead a new work packet envelope can be used. A new envelope has been developed with simple instructions and a checklist on the front, ensuring completion and consistency in the process between different Atlantic Electric platforms.



**RESTORATION WORK PACKET**

Date: ____________
Work Packet #: ____________
Division/Branch: ____________
Station/Feeder: ____________
Assigned to: ____________

The package contains the following documents:

- ☐ Copies (5x preferred) of relevant feeder maps. Maps are 11" x 17" and color
- ☐ Copies (5x preferred of IMAP printouts, showing location crit. customers
- ☐ Confirming WR forms for capital work
- ☐ OMS job tickets, organized by feeder, stapled
- ☐ Safety briefing information

In addition, a list with the following contact phone numbers is included:

- ☐ Control Center
- ☐ Storm Room Dispatch
- ☐ Contractor Room Dispatch
- ☐ Forestry Room
- ☐ Environmental Engineer
- ☐ Repairs (Clear Jobs)

If Damage Assessment has been performed, include print out of feeder summary and relevant maps showing damage location

- ☐ Feeder Summary
- ☐ Damage Assessment Maps

☐ Other ____________

To be completed by Field Supervisor. Please call to clear jobs after completing ***every*** repair.

| | Date | Time |
|---|---|---|
| Final Repairs Complete | | |
| Feeder Energized | | |

Avg. crew utilization ☐ 0-25% ☐ 25-50% ☐ 50-75% ☐ 75-100%
(% time crews spent on repairs vs. waiting for work )

Comments ____________

Return packet to contractor/storm room after completing work

Figure 2-2: New contractor work packet template

A summary of the proposed changes to the process is provided in Table 2-2 below

Table 2-2: Summary of suggested work flow improvements

| Step | Problem | Solution |
|---|---|---|
| **4** | Delay returning DA data to platform | Electronic capture of DA |
| **5** | Delay receiving DA data from the field. Limited DA work support. | Electronic capture of DA. Created new contractor work support role |
| **6** | Prioritize circuits for repair quickly and consistently | New tools developed in Section 4.1 |
| **7** | Contractor crew lead must estimate repair workload circuit | New tools developed in Section 4.1 |
| **8** | Delegation from RCS to contractor crews difficult | More feeder maps to be provided in work packet |
| **9, 10, 13** | Delays searching for contact phone numbers | New work packet with checklist of contact numbers |

The Emergency Planning department at Atlantic Electric helps prepare for emergency situations, including storms, by ensuring that the emergency organization is well staffed, providing training sessions, and developing protocols and best practices that support the field's restoration effort. As part of this effort the department has distributed the new work packets to field locations and has developed a new "Contractor Work Support" role. In conjunction with operations staff they have trained relevant members of the storm organization in the new tools and processes (particularly the electronic Damage Assessment) and these processes will be used during the next major restoration. At the time of publishing this thesis Atlantic Electric had not yet experienced a major storm where it could implement the developed tools.

## *2.4 Measuring performance and continuous improvement*

In addition to the tasks described above in 2.3, the Emergency Planning department performs after-action reviews following storms. This involves analyzing the performance of different groups within the storm organization during a restoration and cataloging potential process improvements. These changes are then discussed with the operations staff and they work together to implement these changes.

Due to the infrequency of major storms where large numbers contractors are utilized after-action reviews have often not specifically addressed the issues surrounding contractor utilization. To remedy this, a standardized survey that will be completed by all RCSs following a storm was developed. This survey will provide Atlantic Electric and the Emergency Planning department with relevant feedback about contractor utilization and suggestions for opportunities to further improve the process. This measurement system will help track the performance of contractors over time and give guidance to where changes could be made. Eventually, as is discussed in Section 5.1, it is envisioned that a much more accurate measurement of utilization will be captured through the use of remote job-assignment tools.

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# 3. Crew staging optimization model

This chapter introduces an existing optimization model that is used by Atlantic Electric for pre-staging crews. Improvements to this model are presented, and it is shown how the model can be adapted to inform crew movements and stagings after a storm has occurred. The outputs of this new model are compared to historical crew movements and are shown to pre-empt actual crew staging decisions by an average of one day. The concept of robust optimization is then discussed and a robust optimization formula is shown to be unnecessary in this case.

## *3.1 Description of predictive model optimization*

As mentioned previously, Atlantic Electric uses a damage prediction tool and an optimization model to help guide its crew pre-staging decisions. Atlantic Electric developed these tools in conjunction with MIT and the model is presented in Whipple's 2014 thesis [13]. The model is used in advance of a storm hitting and it helps Atlantic Electric station its crews at platforms where they are best suited to repair damage in the fastest possible time. The formulation and full notation is shown below.

The input to the model is the number of predicted repair jobs ($j$) resulting from the storm; this is the output of the prediction model. These jobs ($j$) are assigned to a platform ($k$) through the binary variable $X_{jk}$. Each job ($j$) has a total repair time that is influenced by the type of damage and the travel time from the platform ($k$). The total repair time to complete job $j$ from platform $k$ is represented by $\gamma_{jk}$. The time taken for a platform to complete all its work is thus given by the sum $X_{jk} * \gamma_{jk}$, for all $j$. Crews are then assigned to platforms in proportion to the amount of work the platform has.

The objective is to minimize the state-wide completion time, which is denoted by $C$. The function achieves this by minimizing the sum of all the platforms repair times, $C_k$.

Table 3-1: Pre-staging Formulation Variable Notation

| | Notation | Description |
|---|---|---|
| Decisions | $X_{jk}$ | Job $j$ assigned to platform $k$ |
| | $C_k$ | Platform $k$ workload |
| | $C_k^*$ | Number of crews assigned to platform $k$ |
| | $C$ | Objective value indicating total system repair time |
| Data | $\gamma_{jk}$ | Time required to do job $j$ from platform $k$ |
| | $M_k$ | Crew capacity of platform $k$ |
| | $C^*$ | Total number of crews available |

Objective: Minimize $C$, subject to the following constraints

$$\sum_k C_k \le C \qquad (3.1)$$

$$\sum_j \gamma_{jk} X_{jk} \le C_k \qquad \forall k \qquad (3.2)$$

$$\sum_k X_{jk} = 1 \qquad \forall j \qquad (3.3)$$

$$C_k^* \le M_k \qquad \forall k \qquad (3.4)$$

The number of crews staged at each platform is:

$$C_k^* = \frac{C_k}{C} C^* \qquad (3.5)\ *$$

Constraint (3.1) ensures that the sum of the platform repair times, $C_k$, is less than or equal to the state-wide completion time, C. Constraint (3.2) sets that the repair time for every platform $C_k$, as equal or greater than the time needed to complete every individual job ($X_{jk}$ * $\gamma_{jk}$), and constraint (3.3) assigns every job to a platform. Finally, constraint (3.4) ensures that the crew capacity of the platform is not exceeded.

## *3.2 Allocating crews to platforms following a storm*

This optimization model uses the predicted number of outages from the storm as its input. However, often weather forecasts are inaccurate and so actual outages can differ from the predicted outages substantially. By extending the model so that it can be used once a storm has hit, using actual outages that have occurred, we can provide real-time guidance on crew stagings and recommend crew movements throughout a restoration effort. We also suggest several other improvements to the model that take advantage of recent changes to Atlantic Electric's damage assessment collection methods.

### *3.2.1 Selecting the nominal repair time*

The value $\gamma_{jk}$ represents the time taken to repair an individual job from a given platform and its accuracy is critical to the model. At the time the predictive model was developed Atlantic Electric only had historical information about **outage durations,** not actual **repair times.** An outage can be caused by a combination of issues (eg. something simple like strong winds, or something more serious, like several poles being broken due to fallen trees) and this leads to variable repair times.

In 2013, when the model was being developed ,Atlantic Electric had limited historical data on storm damage, since prior to recently all damage data was recorded manually in local branches. There are excellent records of outages, however, and as a proxy for repair time the difference between when a particular device lost power (open-time) and when it was re-energized (closed-time) was used. During a storm a particular outage may be repaired but the circuit not energized for a number of reasons:

- A circuit will not be re-energized if other crews are repairing damage that a given device feeds.
- Only qualified Atlantic Electric employees can re-energize a circuit, so even though a contracted crew may make the repairs, the system will not turn on until a Atlantic Electric employee re-energizes the circuit, thus affecting the open-time

This means that the restoration time is not a good proxy for repair time during a storm.

Excluding storm outages from the historical data set yields the following restoration profile.

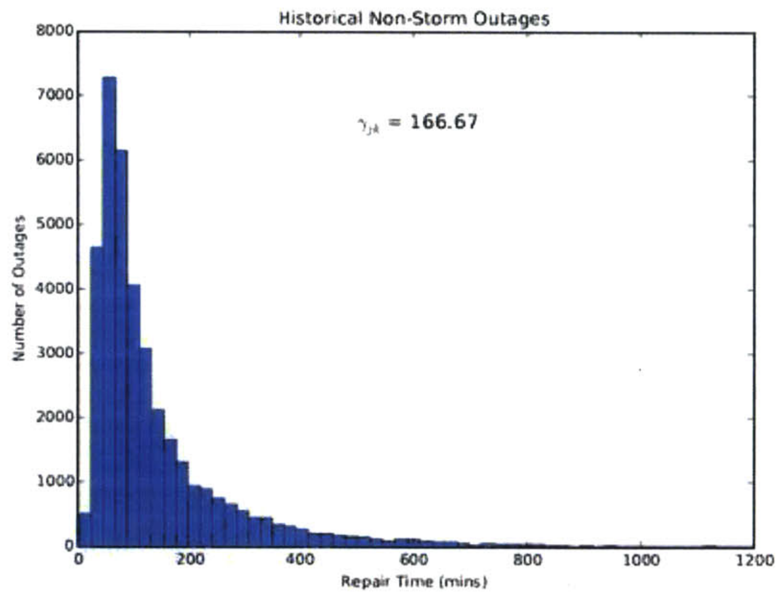


Figure 3-1: Historical non-storm outage histogram

From these data we see that the average outage duration is 166.7 minutes. Hence a nominal repair time of $\gamma_{jk} = 166.7$ was selected as a base for the original pre-staging model.

However, by using non-storm outage times we drastically under-state the average repair time of an outage during a storm because:

- During a storm each individual outage is more likely to be caused by multiple damage points.
- Each individual damage point is likely to take longer to repair during a storm due to environmental conditions.

Using the new damage data that have been captured electronically since 2013, however, we can calculate a more realistic nominal repair time for each outage. The new electronic damage assessment database provides us with records of the type of damage seen along patrolled circuits following a storm.

Atlantic Electric experts have calculated an expected repair time for a given damage type during storm conditions. These figures have been developed over many years of field reviews and analysis. With these figures, and the actual damage types seen after a storm, we can more accurately estimate the repair time of each storm outage. Using data from a previous storm (represented as Storm D in Tables 3-3 and 3-4) we cross-referenced damage points that were noted by a damage assessor with the outages reported by the Outage Management System and calculated a nominal repair time of 10.5 hrs per outage. This is a substantial increase on the previously used figure of 2.8 hrs. As more storms occur and Atlantic Electric collects more damage data this figure will be further refined. Specific storm types (eg. a hurricane vs. a winter storm) will probably have their own nominal repair time since they tend to cause different types of damage. It should be noted that the nominal repair time is an estimate only; repair times for an individual outage can vary dramatically based a variety of factors specific to each storm event.

### *3.2.2 Incorporating damage information*

While the newly calculated nominal repair time increases the accuracy of the model, we can improve it further by directly using damage data, when it is available. Damage assessors patrol circuits immediately following a storm and they upload all noted damage to a central database using mobile devices. For areas that have been patrolled, damage information can be fed directly into the model to provide even more accurate workload estimates than the nominal figure.

These data allow us to increase the resolution of the model considerably. Instead of relying only on outage data and nominal repair times to predict job duration, we can gather detailed damage information about each point. This model can be run periodically throughout a restoration effort and as more damage assessment is recorded its accuracy will increase.

### *3.2.3 Comparing nominal repair times*

We can compare the impact of using the different nominal repair times and incorporating damage data by analyzing the model outputs using outages from an actual storm. During a 2013 winter storm Atlantic Electric recorded damage data from some field locations (since the number of damage assessors is limited it is normal practice for utilities to prioritize some areas for damage patrol over others). For outages in areas where damage assessment was recorded the model estimates a repair time based on the actual damage seen. For other areas the model uses a nominal repair time. The model was run with a nominal repair time 2.8 hrs (which was the nominal repair time used in the pre-staging model) and 10.5 hrs per outage (which is the newly calculated nominal time). The results are shown below.

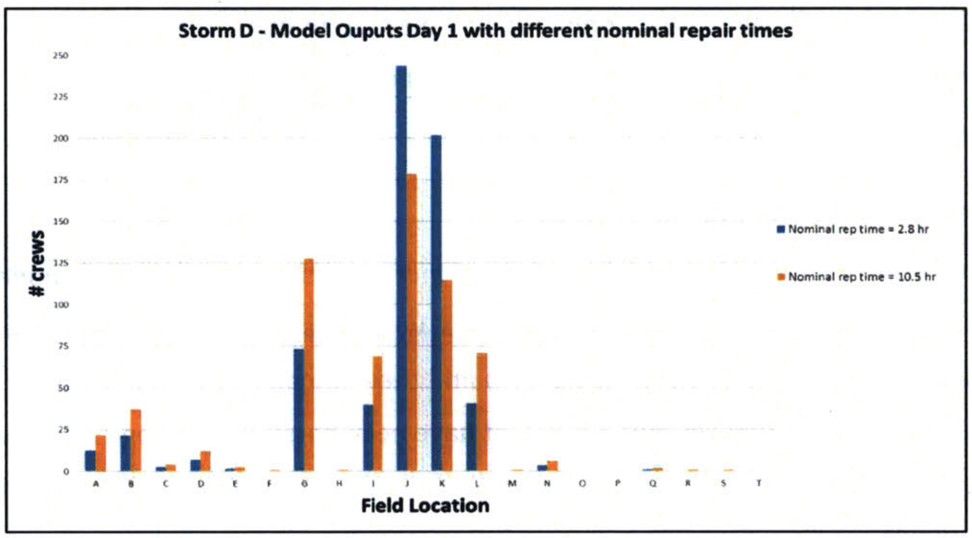


Figure 3-2: Model outputs with nominal repair time of 2.8 hr v 10.5 hr

The model takes all outages that were recorded in the Outage Management System and calculates a repair time based on either the nominal repair time or the damage data, plus travel time from the platform. Areas where damage assessment was recorded (in this case some of the areas around Field Locations J and K) have an average of 10 hrs repair time per outage. This is significantly higher than the 2.8 hrs nominal repair time, so when 2.8 hrs is used as the nominal repair times the model assigns more crews to Locations J and K (shown in blue in Figure 3-2). When a nominal repair time of 10.5 hrs is used the assignment of crews is more dispersed (shown in orange in Figure 3-2).

### *3.3 Model output compared to historical crew locations*

Using data from previous storms we can run the model with historical outage data and compare it to where crews were actually staged. By looking across different days of the storm we can get a sense of how reasonable the model outputs are.

A good measure of how close the model results are to the actual crew allocations used is the difference between the crew numbers assigned to each location on a given day. Some sample results from the second day of the restoration effort following a summer hurricane are shown below in Figure 3-3. Different field locations are shown on the X-axis and the number of crews assigned to each location is shown on the Y-axis. The orange bars show where crews were actually staged and working and the blue bars shows what the model recommended. At first glance it appears that the model differs significantly from where crews were actually staged. This would suggest that either the Atlantic Electric storm managers are not allocating crews efficiently, or that the model is excluding some critical information and is not providing reasonable results. However, if we follow the restoration effort into the future and compare the model recommendations on day $t$ to where crews were actually staged on day $t+1$, we see that the delta falls significantly. This is shown clearly in figure 3-4.

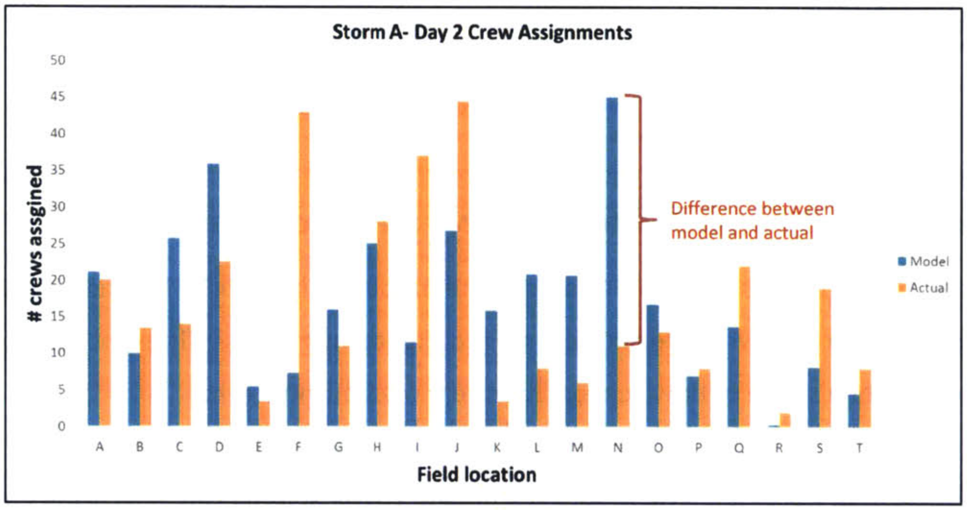


Figure 3-3: Crew locations - model suggestions vs actual allocations

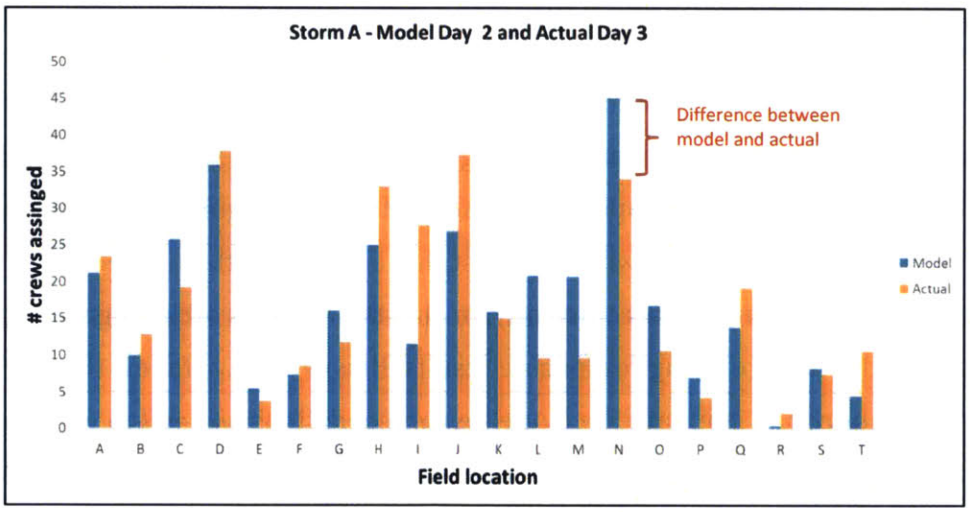


Figure 3-4: Crew locations - model suggestions vs actual allocations, shifted 1 day

We can calculate this delta between model recommendations and actual crews stagings for recent major storms and find a similar result, a summary of which is shown in Table 3-2. The model outputs seem to be preceding crew stagings by between 0.5 to 1.5 days on average. This suggests that the Atlantic Electric managers are doing an excellent job allocating crews to work in regions that have the most outages and damage; however, it takes time for storm managers to absorb and process this information and decide to re-stage. The model is able to draw from all Atlantic Electric databases and suggest an instantaneous recommendation for crew stagings. This suggests that it will be a useful guide for mangers and help them make their decisions sooner.

Table 3-2: Difference between model and actual allocations

| Storm | Day 1 Δ | Day 2 Δ | Day 3 Δ | Day 4 Δ | Total |
|---|---|---|---|---|---|
| **Storm A** | 317 | 222 | 149 | 213 | **901** |
| **Storm B** | 235 | 239 | 253 | 398 | **1125** |
| **Storm C** | 107 | 114 | 124 | 190 | **535** |
| **Storm D** | 343 | 383 | 234 | 284 | **960 (excl. Day 4)** |

Table 3-3: Difference between model and actual allocations, shifted

| Storm | Day 1 Shifted Δ | Day 2 Shifted Δ | Day 3 Shifted Δ | Day 4 Shifted Δ | Total |
|---|---|---|---|---|---|
| **Storm A** | 192 | 113 | 123 | 132 | **560** |
| **Storm B** | 111 | 277 | 239 | 246 | **873** |
| **Storm C** | 113 | 94 | 122 | 123 | **452** |
| **Storm D** | 162 | 292 | 131 | NA | **585** |

Since the total number of crews mobilized varies for each storm it is also useful to look at this information in terms of the percentage of crews actively working each day.

Table 3-4: Percentage difference between model and actual allocations

| Storm | Day 1 Δ | Day 2 Δ | Day 3 Δ | Day 4 Δ | Average |
|---|---|---|---|---|---|
| **Storm A** | 83% | 58% | 39% | 56% | **59%** |
| **Storm B** | 51% | 50% | 47% | 57% | **51%** |
| **Storm C** | 53% | 39% | 38% | 56% | **47%** |
| **Storm D** | 80% | 51% | 32% | 42% | **54% (excl. Day 4)** |

Table 3-5: Percentage difference between model and actual allocations, shifted

| Storm | Day 1 Shifted Δ | Day 2 Shifted Δ | Day 3 Shifted Δ | Day 4 Shifted Δ | Avg. |
|---|---|---|---|---|---|
| **Storm A** | 50% | 30% | 32% | 35% | **37%** |
| **Storm B** | 24% | 58% | 45% | 35% | **40%** |
| **Storm C** | 56% | 32% | 38% | 36% | **41%** |
| **Storm D** | 38% | 39% | 18% | NA | **32%** |

## 3.4 Optimization under uncertainty

Even with the integration of more accurate and granular damage assessment data, the exact repair time of every job cannot be known perfectly. Repair times can still vary significantly based on the location of the asset, road conditions, weather, and crew experience, among other things.

To account for this uncertainty, Monsch [10] and Whipple [13] developed a robust variation of the previous formulation. In it they propose that the repair time $\gamma_{jk}$ can fall across a range of possible values. This range can be represented in terms of a nominal repair time, $\bar{\gamma_{jk}}$, and a spread factor, $\hat{\gamma_{jk}}$, which is the half-width value representing half the total spread of possible repair times; this is drawn from the distribution in Figure 3-1. To capture the uncertainty in repair times they assume that some proportion of the repair times $\gamma_{jk}$ will be set to the worst possible repair time. This "worst-case" repair time is equal to the nominal time $\bar{\gamma_{jk}}$ + the half-width $\hat{\gamma_{jk}}$. A factor Γ is introduced such that:

$$\sum_j \frac{|\gamma_{jk} - \bar{\gamma_{jk}}|}{\hat{\gamma_{jk}}} \leq \Gamma \tag{3.6}$$

This factor Γ is ultimately a parameter that specifies the number of values that assume the extreme values ( $\bar{\gamma_{jk}} + \hat{\gamma_{jk}}$, $\bar{\gamma_{jk}} - \hat{\gamma_{jk}}$ ). Larger values of Γ will produce more robust solutions but hinder the resulting objective values [13]. The final formulation is shown below.

$$\sum_j \bar{\gamma_{jk}} X_{jk} + r_{jk}^{+} + r_{jk}^{-} + \Gamma R_k \leq C_k \qquad \forall\, k \tag{3.7}$$

$$R_k + r_{jk}^{+} \geq \hat{\gamma_{jk}}\, X_{jk} \qquad \forall\, j,k \tag{3.8}$$

$$R_k + r_{jk}^{-} \geq -\hat{\gamma_{jk}}\, X_{jk} \qquad \forall\, j,k \tag{3.9}$$

$$R_k, r_{jk}^{+}, r_{jk}^{-} \geq 0 \qquad \forall\, j,k \tag{3.10}$$

$$\sum_k X_{jk} \geq 1 \tag{3.11}$$

$$\sum_k C_k \leq C \qquad (3.12)$$

$$C_k^* \leq M_k \qquad \forall\, k \qquad (3.13)$$

Again, we interpret the number of crews assigned to each platform as the following:

$$C_k^* = \frac{C_k}{C} C^* \qquad (3.14)$$

This is similar to the previous, non-robust formulation. Equation (3.12) ensures the earliest state-wide completion time, (3.13) ensures that platform capacities are not exceeded and (3.11) ensures that all jobs are completed. (3.7) determines the amount of work assigned to each platform, *k*. (3.8), (3.9), and (3.10) are all equations that control for the level of uncertainty in the repair time.

The robust formulation ensures that our solutions are always valid despite the variation in potential workload values, $\gamma_{jk}$. While this is true, we need to understand how variations in $\gamma_{jk}$ affect our model and what an 'invalid' result really means. Ben-Tal and Nemirovski [2] note that the advantage of a robust optimization is that "in real-world applications.... one cannot ignore the possibility that a small uncertainty in the data can make the usual optimal solution completely meaningless from a practical viewpoint." Let us consider the real-world applications of our model and understand the practical implications of an uncertain workload $\gamma_{jk}$.

The formulation minimizes the state-wide completion time by assigning jobs to different platforms – this is the $X_{jk}$. Now, when solving the problem using nominal repair times the model will always produce some allocation of jobs to platforms and recommend the number of crews that should be assigned to each platform. This solution is always feasible from a practical perspective (ie. we will always have some allocation of crews to platforms.) If, as is almost certain, the actual repair times deviate from the nominal repair time used, what is the consequence? Recall that the only constraint using the unknown workload values, $\gamma_{jk}$, is the following:

$$\sum_{j} \gamma_{jk} X_{jk} \leq C_k \qquad \forall k \qquad (3.2)$$

If the actual repair times are higher than the nominal, then this constraint will be violated because the given $X_{jk}$ allocation will result in a platform workload greater than $C_k$. This will make our solution 'invalid' in a technical sense. But in a practical sense, the original solution provided a set of crew allocations that can still occur in the field, the only consequence is that it may now be less than optimal. More crews will have been assigned to some bases that have less repair work than originally predicted, and fewer crews will have been assigned to some bases that have more repair work than predicted. This will increase traveling times and drive up the state-wide completion time.

The robust formulation tries to account for the variability in workloads and ensure that regardless of what the actual workload values are, the constraint (3.2) is not violated. As noted in [3], when we use a robust formulation we are implicitly accepting a reduction in the objective value as tradeoff to ensure that our solution is 'valid' when dealing with the variability. The value of $\Gamma$ is what sets this tradeoff. Larger $\Gamma$ values will produce more robust formulations, but hinder the resulting objective.

Is this tradeoff worth it? In [10] and [13] Whipple and Monsch used historical outage data to select the value of $\Gamma$ for the model. We can use the same outage profile to create storm simulations and compare the performance of the original non-robust formulation and the robust formulation. Using the location of outages from an actual storm we randomly select the repair time for each outage from the historical outages profile and develop a set of $\gamma_{jk}$. Using this $\gamma_{jk}$ we can run our original optimization formulation. This represents having perfect knowledge of the repair time of each outage and so it provides the optimal allocation of crews and the lowest possible state-wide completion time. We can then run the optimization using nominal repair times, and using the robust formulation, and compare the assigned crew locations. Finally, using the $\gamma_{jk}$ selected from our distribution we can calculate and compare state-wide completion times.

This simulation was performed 30 times using actual outages from three storms that impacted Atlantic Electric. As shown below, the "robust" formulation results in significantly worse outcomes.

Table 3-6: Comparison of robust vs. non-robust model results

| Storm | Average deviation from optimal using non-robust formulation | Average deviation from ideal using robust formulation |
|---|---|---|
| **Storm A** | 1.0% | 15.4% |
| **Storm B** | 0.9% | 9.8% |
| **Storm C** | 5.0% | 23.5% |

The robust formulation tends to deal with the uncertainty by clumping crews together in central locations so that they can be dispatched from there as necessary. We can see this clearly when we look at the model recommendations for Storm A. The x-axis shows different repair bases and the y-axis the number of crews assigned to those bases. The robust formulation concentrates all repair crews into only five bases across the state.

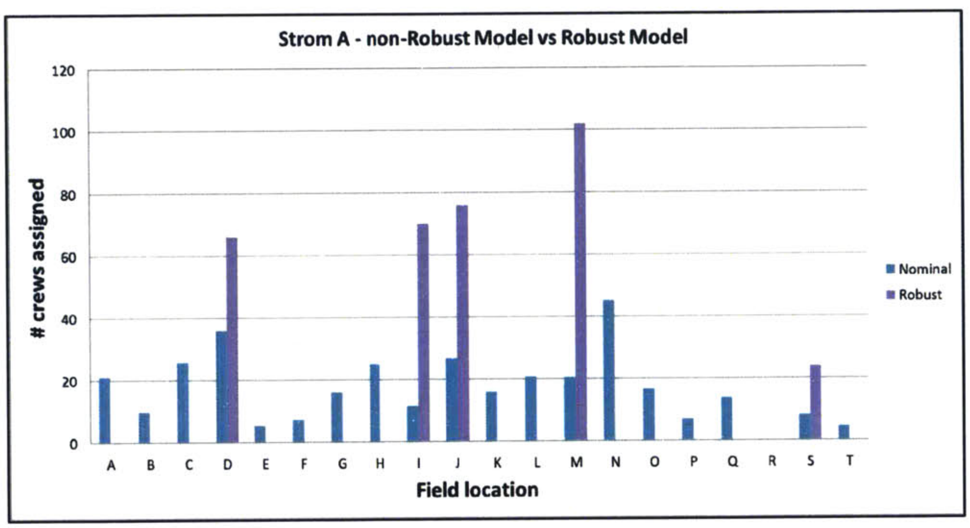


Figure 3-5: Comparison of non-robust vs robust model outputs

Even if we lower the Γ from the selected value (15.81) to 1 the total restoration time is still longer than if we had just used the non-robust formulation with the nominal repair time. In this case there is no real value in using a robust optimization. As noted by Gorissen et al. [4], robust optimizations are most applicable when dealing with "hard" constraints ie., constraint violation cannot be allowed for any realization of the data. The constraints in the relaxed formulation above are clearly not "hard". In this application the non-robust formulation is preferable.

# 4. Allocating work at the platform level

Once crews have been assigned to a platform they receive their work instructions for the day. As described in Section 2.1, the work allocation process can be complex and time consuming. Following a severe storm there will be more damage than can be repaired in one day, so storm managers must prioritize repairing certain areas over others. Managers endeavor to quickly assign the most important circuits to their crews and to ensure that the crews have an appropriate amount of work for the day. In the following section we discuss an algorithm to help them do this. An equivalent optimization model is discussed, and modifications to the model that make it applicable to multiple crew types are presented.

## *4.1 A heuristic approach for work allocation*

Atlantic Electric's experts balance a variety of different factors when deciding which electric circuits to prioritize and operations coordinators must make these decisions in very high pressure, time sensitive environments with imperfect and constantly changing information. A tool to help them make this decision would release an enormous burden from operations personnel and free them to focus on other aspects of the restoration. As well, it takes many storms to develop the expertise to make work assignment decisions well. With the frequency of severe storms being only one to two every year it takes years to develop the required experience. Furthermore, the institutional knowledge tends to rest with a handful of extremely experienced managers. As they retire, some of the storm skills may be lost and so a model that captures this knowledge will become more useful.

The restoration order of electric distribution circuits (which are prioritized after transmission lines and substations) is determined by a variety of different factors:

- Number of customers on the feeders
- The number and type of critical facilities located on feeders (which can be represented by a feeder "priority score")
- Location of crews
- Type and severity of damage

- Requests from municipalities or other agencies, such as police or fire department emergencies

Atlantic Electric has no prescribed directions for determining the order of distribution circuit restoration and work assignments since conditions in the field can change rapidly. Rather than having operators boxed in by a set of rules, Atlantic Electric prefers to let its operations coordinators make decisions in real-time as the situation warrants. While this desire for flexibility is understandable, it can be difficult for Atlantic Electric storm managers to gather all the necessary information and interpret it, especially in a hectic working environment when decisions need to be made quickly.

In general, managers assign crews to circuits in a method that they feel maximizes the impact the repair crews will have over the course of day. 'Impact' can be measured by the number and type of customers whose power is restored. As noted earlier, certain critical customers are considered more important than others and this is captured in their 'priority score'. For instance, a hospital will have a very high score compared to a residential customer. After interviews with numerous Atlantic Electric storm experts the following heuristic was developed as a best practice for work assignments.

1) Stack-rank distribution circuits in order of importance to repair.
    - This is done by summing the priority score of the customers on the circuit that are out of power.

2) Crews are assigned to work that feeder until:
    a) Enough crews are assigned to repair the circuit that day
        - To do this, managers must estimate the travel time from the base to the feeder, the number of damage points, and expected repair times.
    b) Circuit crew capacity has been reached
        - This capacity is often known from experience, since managers have close knowledge of the geographies where they work, but it can also be estimated

from the length of the circuit, the number of poles it has, and the number of customers served.

c) No more crews are available to be assigned.

3) Repeat this process with the next most important feeder

The application of this heuristic in a simple algorithm, with automatic links to all of Atlantic Electric's electronic databases, provides a clear output that shows the most important circuits to repair and the number of crews that should be sent to repair them. It automates and codifies a currently time-consuming process and helps storm managers make assignment decisions faster. A sample output from the developed algorithm is shown below.

Feeder assignments run for platform XXXX @ 2015-12-06 15:12:34.882000

| Priority | Feeder | Projected crew hours needed | Recommended # of crews | Estimated hours of tree crew work | DA has been performed |
|---|---|---|---|---|---|
| 1 | XX-XXXXXX | 38.0 | 2 | 10.0 | Yes |
| 2 | XX-XXXXXX | 61.0 | 4 | 2.0 | Yes |
| 3 | XX-XXXXXX | 41.0 | 3 | 8.0 | No |
| 4 | XX-XXXXXX | 71.0 | 4 | 6.0 | Yes |
| 5 | XX-XXXXXX | 17.0 | 1 | 6.0 | No |
| 6 | XX-XXXXXX | 31.5 | 2 | 1.0 | No |
| 7 | XX-XXXXXX | 192.0 | 12 | 40.0 | Yes |
| 8 | XX-XXXXXX | 8.0 | 1 | 0.0 | No |
| 9 | XX-XXXXXX | 42.5 | 3 | 5.0 | No |
| 10 | XX-XXXXXX | 159.0 | 10 | 8.0 | Yes |
| 11 | XX-XXXXXX | 106.0 | 7 | 4.0 | Yes |
| 12 | XX-XXXXXX | 54.0 | 3 | 2.0 | No |
| 13 | XX-XXXXXX | 46.0 | 3 | 2.0 | No |
| 14 | XX-XXXXXX | 59.5 | 4 | 7.0 | No |
| 15 | XX-XXXXXX | 85.0 | 5 | 6.0 | No |
| 16 | XX-XXXXXX | 117.0 | 7 | 10.0 | Yes |
| 27 | XX-XXXXXX | 45.5 | 3 | 3.0 | No |

Figure 4-1: Example output of the Feeder Assignment Algorithm

## *4.2 Converting the heuristic to an optimization model*

As noted in Section 1.2, different types of contractor crews may be utilized during a storm. These contractors may work from the same platform, but they often have different areas of expertise. "Contractors of choice" are familiar with Atlantic Electric's electric network and protocols and can thus be expected to work very efficiently. "Foreign" contractors are accustomed to storm restoration work, but may take more time to develop familiarity with the area where they are working. "Mutual Assistance" crews, that are loaned to Atlantic

Electric from other utilities, often have their own corporate policies that can delay the restoration. One company, for instance, prefers that its crews work only on grounded and isolated power lines, which is different to Atlantic Electric's policy of working on energized power lines.

The simple algorithm developed above struggles to take into account these differences in crew efficiencies. To capture these additional variables, an optimization model was developed. The following model is equivalent to the heuristic algorithm for one crew type.

Table 4-1: Feeder Assignment with One Crew Type - Variable Notation

| | Notation | Description |
|---|---|---|
| Decision | $X_{if}$ | Crew *i* assigned to feeder *f* |
| Data | $\gamma_f$ | Time required to repair feeder *f* |
| | $\rho_f$ | Weighted Priority score of feeder *f* |
| | $M_f$ | Crew capacity of feeder *f* |
| | $C^*$ | Total number of crews available |
| | $H_c$ | Crew working hours in a day |

Objective: Maximize S, where S equals the total feeder score repaired in a day

$$S = \sum_{i,f} \mathrm{H_c} \frac{\rho_f X_{if}}{\gamma_f} \tag{4.1}$$

Constraints:

$$\sum_{f} X_{if} = 1 \qquad \forall\, i \tag{4.2}$$

$$\sum_{i} X_{if} \leq M_f \qquad \forall\, f \tag{4.3}$$

$$\sum_{i} \mathrm{H_c} X_{if} \leq \gamma_f \qquad \forall\, f \tag{4.4}$$

$X_{if}$ is a binary decision variable representing if a given crew $i$ is assigned to feeder $f$. $\gamma_f$ is the total repair time for the circuit, calculated automatically from damage assessment and outage data. The model maximizes the amount of circuit "score" restored to power in one day by assigning crews to the most important feeders, up until the feeder is assigned enough crews or until the feeder capacity $M_f$ is reached. This provides results equivalent to the simple algorithm in 4.1.

## *4.3 Optimization with multiple crew types*

### *4.3.1 Different crew types with different "effective" hours in a day*

A simple way of capturing the difference in the ability of the various contractor types is to assume that different crews have different "effective" hours in a day. Thus in computing the amount of circuit score restored in a day we could assume that although all contractors will work for 16 hours per day, only contractors of choice will work effectively for the full 16 hours. Due to their lower efficiencies, foreign contractors will only effectively work 14 hours, and mutual assistance 12 hours. These figures are used for discussion only and are not representative of the actual effective work hours for the different contractor types.

We now have a new set of variables and a new formulation, as shown below. The decision variable is $X_{fc}$, which is the number of crew of contractor type $c$ that are assigned to feeder $f$. In practice only one type of contractor is assigned to a given circuit. This is done to ensure a clear work scope and to simplify communication. This requirement is captured in the formulation by the inclusion of a dummy variable $Y$ and a new set of constraints. The dummy variable, $Y_{fc}$, is binary for every feeder $f$ and contractor type $c$. For every feeder the sum of $Y_{fc}$ for all contractor types must be equal to 1, ensuring that only 1 contractor type is assigned.

Table 4-2: Feeder Assignment with Multiple Crew Types and Different "Effective Hours"

| | Notation | Description |
|---|---|---|
| Decision | $X_{fc}$ | Number of crews of type *c* assigned to feeder *f* |
| | $Y_{fc}$ | Dummy binary variable |
| Data | $\gamma_f$ | Time required to repair feeder *f* |
| | $\rho_f$ | Priority score of feeder *f* |
| | $M_f$ | Crew capacity of feeder *f* |
| | $C_c$ | Total number of crews available of crew type *c* |
| | $H_c$ | Effective crew working hours in a day for crew type *c* |

Objective: Maximize S, where S equals the total feeder score repaired in a day

$$S = \sum_f \sum_c H_c \frac{\rho_f X_{fc}}{\gamma_f} \qquad (4.4)$$

Constraints:

$$\sum_f X_{fc} = C_c \qquad \forall\, c \qquad (4.5)$$

$$\sum_c X_{fc} \leq M_f \qquad \forall\, f \qquad (4.6)$$

$$\sum_c H_c X_{fc} \leq \gamma_f \qquad \forall\, f \qquad (4.7)$$

$$\sum_c Y_{fc} = 1 \qquad \forall\, f \qquad (4.8)$$

$$Y_{fc} \geq \frac{X_{fc}}{M_f} \qquad \forall\, f, c \qquad (4.9)$$

Constraint (4.5) ensures that all crews are assigned to a feeder, (4.6) that no feeder capacities are exceeded, and (4.7) ensures that no more crews are assigned to a feeder than are needed to repair it. Constraint (4.8) and (4.9) utilize a binary dummy variable, $Y_{fc}$ to ensure that only one crew type is assigned to a circuit.

### *4.3.2 Different crew types with different repair capabilities*

A more precise way of capturing the different skill sets of contractor types is to look at each type's actual capability. By estimating how long a given contractor will take to repair a nominal outage or a specific damage type we can develop a better crew allocation than by simply assuming different crews have fewer productive hours in day. Using this more detailed approach, we no longer use the variable $H_c$, and instead we calculate the time taken to repair a feeder using a given contractor type, represented by $\gamma_{fc}$. All other variables are the same.

Table 4-3: Feeder Assignment with Multiple Crew Types - Variable Notation

| | Notation | Description |
|---|---|---|
| Decision | $X_{fc}$ | Number of crews of type *c* assigned to feeder *f* |
| | $Y_{fc}$ | Dummy binary variable |
| Data | $\gamma_{fc}$ | Time required to repair feeder *f* by crew type *c* |
| | $\rho_f$ | Priority score of feeder *f* |
| | $M_f$ | Crew capacity of feeder *f* |
| | $C_c$ | Total number of crews available of crew type *c* |

Objective: Maximize S, where S equals the total feeder score repaired in a day

$$S = \sum_{f,c} \frac{\rho_f X_{fc}}{\gamma_{fc}} \tag{4.10}$$

Constraints:

$$\sum_{f} X_{fc} = C_c \qquad \forall\, c \qquad (4.11)$$

$$\sum_{c} X_{fc} \leq M_f \qquad \forall\, f \qquad (4.12)$$

$$\sum_{c} X_{fc} \leq \gamma_{fc} \qquad \forall\, f \qquad (4.13)$$

$$\sum_{c} Y_{fc} = 1 \qquad \forall\, f \qquad (4.14)$$

$$Y_{fc} \geq \frac{X_{fc}}{M_f} \qquad \forall\, f, c \qquad (4.15)$$

Although at present Atlantic Electric does not keep detailed records of crew efficiencies, as electronic recording of job repair times and crew efficiencies is captured, this capability will be added to the model, improving its accuracy.

# 5. Future Work and Conclusions

## *5.1 Contractor work flow improvements*

A great improvement to Atlantic Electric's work assignment process would be the use of remote-dispatch devices for assigning work to crews. Currently internal crews receive work instructions via a call-center dispatch model, where office personnel assess repair jobs based on the Outage Management System and call up repair crews individually. This is time-consuming and labor-intensive. Contractor crews are generally assigned work in packets, as described in Chapter 2. Providing dispatch through electronic devices such as phones or tablets would offer several advantages over the current models:

- Fewer delays while preparing materials for job assignments
- Reduced travel time to collect or deliver job assignments
- Precise tracking of crew locations
- Better updates of outage and restoration status

Several of the process steps in Figure 2-1 would be eliminated and consequently the opportunity for delays would be reduced.

In addition to improving the work assignment process directly, the use of electronic devices would capture information that could improve the models developed in Chapter 4. Data could be collected on the efficiency of different contractor crew types (contractors of choice, foreign, mutual assistance) and this information could be fed into the model and used to assign work packets to different crews more efficiently.

## *5.2 Improvements to optimization models*

As noted above, improved information about the efficiency of different crew types, which are used as inputs for the models developed in Chapter 4, would improve the models considerably. Improved data about repair times for different damage types would also increase the accuracy of the crew-staging model presented in Chapter 3. As more damage data are recorded electronically after storms, Atlantic Electric will be able to refine the estimate of the nominal repair time, $\gamma$, used in the models. Most likely different storm types will have different nominal repair times (eg. damage resulting from a snow storm is likely to be different to that caused by a hurricane) and the model can be modified before it is run to reflect these differences.

Ad-hoc requests by municipalities and emergency departments are a critical input into operations coordinators' circuit prioritization decisions. These needs are usually communicated verbally and they are not captured in any central system or database. Consequently, it is impossible for the model presented in Chapter 4 to take these requests into account. This decreases the applicability of the model and means that the work assignment process is still semi-manual. If Atlantic Electric developed a system of recording these requests electronically then the model would be able to take them into account and its results would be even more relevant.

## *5.3 Decision tool to release contractors*

Contractor labor is Atlantic Electric's most expensive restoration cost after a major storm. This thesis has examined ways to improve the utilization of contractor crews while they are working, but it has not considered when to release the contractor crews from service. Atlantic Electric often holds a reserve of contractor crews out of prudence once power has been restored to a majority of customers. They do this to mitigate the real risk of A) additional unplanned work and B) potential errors in the system that tracks customer power restoration. This strategy holds some reserve capacity if it is needed, but it can also result in low utilization if it is not. While nothing can be done about A, there is great potential to reduce the necessary additional capacity if B is addressed. A tool that could objectively assess the need for contractor crews and suggest an early release would save Atlantic Electric money and provide justification to state regulators for the decision.

## *5.4 Conclusions*

Damage from weather and subsequent power outages are unavoidable and utilities must rely on proper planning and operational execution after the event to ensure that assets are repaired in a quick, cost-effective manner.

The models and work-flow improvements outlined in this paper provide a data driven approach to improve Atlantic Electric's ability to respond to storm damage. As regulator and customer demands increase, response plans built on data-driven models present a strong case to regulators to justify the operational response of utilities. These models also allow for a more seamless transfer of knowledge, which is crucial given that utilities currently require subject matter experts to make decisions based on their unique experience and intuition. The knowledge transfer of these subject matter experts is a long process that requires new employees to obtain years of experience. The models presented here still require knowledge from critical employees but do not require years of training and experience to run.

The tools presented in this thesis were developed in only one of Atlantic Electric's electric service areas; however, the broad applicability of such data-driven models mean that similar approaches can be used to improve operations to Atlantic Electric's other electric service areas. The models would also have value for Atlantic Electric's gas operations, which also face emergency repairs at multiple locations with crews staged at different service areas.

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