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Improving Grid Resilience through Informed Decision-making (IGRID)

Laurie Burnham, Kevin Stamber, Susan Stevens-Adams, Robert Jeffers, Steven Verzi, Meghan Galiardi, Michael Haass and Katherine Cauthen

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Abstract

The transformation of the distribution grid from a centralized to decentralized architecture, with bi-directional power and data flows, is made possible by a surge in network intelligence and grid automation. While changes are largely beneficial, the interface between grid operator and automated technologies is not well understood, nor are the benefits and risks of automation. Quantifying and understanding the latter is an important facet of grid resilience that needs to be fully investigated.

The work described in this document represents the first empirical study aimed at identifying and mitigating the vulnerabilities posed by automation for a grid that for the foreseeable future will remain a human-in-the-loop critical infrastructure. Our scenario-based methodology enabled us to conduct a series of experimental studies to identify causal relationships between grid-operator performance and automated technologies and to collect measurements of human performance as a function of automation. Our findings, though preliminary, suggest there are predictive patterns in the interplay between human operators and automation, patterns that can inform the rollout of distribution automation and the hiring and training of operators, and contribute in multiple and significant ways to the field of grid resilience.

ACKNOWLEDGMENTS

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We would similarly like to acknowledge the support we received from Oracle for this project and to specifically thank Brad Williams and Scott McBeth, who recognized the pioneering and important nature of our research and made possible our collaboration. We also thank the Oracle team that supported, and were vital to, the design and execution of our experimental work: Brett Doehr, Bryan Groll, Todd Hesemann, Lincoln McCabe and Andy Urtusuastegui.

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NOMENCLATURE

ARRA	American Recovery and Reinvestment Act
CMI	Customer minutes interrupted
DMS	Distribution management system
DOE	Department of Energy
FC	Field crew
FLISR	Fault location, isolation and service restoration
GMP	Green Mountain Power
GO	Grid operator
IGRID	Improving Grid Resilience through Informed Decision-making
LDRD	Laboratory-directed research and development
NMS	Network management system
SCADA	Supervisory control and data acquisition
SME	Subject matter expert
SNL	Sandia National Laboratories
WBS	Work breakdown structure

1. INTRODUCTION

The nation's electric grid, which the National Academy of Engineering calls the greatest engineering achievement of the 20th Century [1] has always been "smart" to a degree. Ever since Thomas Edison unveiled the Pearl Street electric system in 1882, devices have communicated voltage information to the grid operator and meters have measured kilowatt-hours so a utility could charge for usage. But a range of grid events (e.g., the 1965 blackout [2] and the blackout of August 2003 [3], which darkened some 50 million homes and businesses and cost billions of dollars), and regulatory policy (e.g., the Public Utilities Regulatory Policies Act of 1978 [4], the Energy Policy Act of 1992 [5], the Energy Policy Act of 2005 [6], and various state regulatory actions) proved to be the catalyst for what may be the greatest engineering feat of the 21st Century [7]: the nation's so-called "smart grid." Spearheaded by the US Department of Energy (DOE), with funding provided by the American Recovery and Reinvestment Act of 2009 [8], the modernization of the electric grid represents a technological leap forward, a concerted effort by utilities and the government alike to enhance the safety and reliability of the nation's top critical infrastructure, while also enabling 21st Century capabilities, such as the integration of renewable resources and more efficient load control.

Much of this transformation is directed at the distribution grid, which is transitioning from a centralized to a decentralized architecture, with bi-directional power and data flows, and is made possible by a surge in network intelligence and grid automation. While these advanced technologies lower operational costs, add restoration capabilities and enable the integration of renewables, they are also changing the way human operators view and run the grid, resulting in potential vulnerabilities that are not well understood.

The work described in this document, a three-year Sandia-funded Laboratory Directed Research and Development (LDRD) project titled "Improving Grid Resilience through Informed Decision-Making," or IGRID, represents the first empirical study aimed at identifying and mitigating the vulnerabilities posed by automation for a grid that for the foreseeable future will remain a human-in-the-loop critical infrastructure. As such, the research described herein is both pioneering and preliminary, providing a foundation for what we believe will become a burgeoning field of inquiry.

1.1. Human-in-the-Loop Critical Infrastructure

Our nation's rise to prominence as one of the world's most productive and innovative economies reflects broad access in the US to abundant, reliable and cheap energy. Today, it is our electric power system that almost singularly drives our digital economy and elevates our health, safety and overall standard of living. Without a functioning electric grid, every critical infrastructure in the U.S.—from banking to water to telecommunications—would fail and our economy would falter.

But as our dependence on the grid grows, so do the threats, both natural and manufactured, levied against it. Weather-related and other natural disasters, which cause the bulk of power outages, are projected to increase in intensity and frequency, with a hotter, moister atmosphere primed to trigger disasters [9]. And studies by the National Security Agency and others show that malware directed at the grid continues to evolve and grow [10]. As a consequence, the distribution grid faces an increasing risk of disruptions and the prospect of prolonged electrical outages [11].

Understanding how a system operator maintains situational awareness and makes critical decisions in response to complex unplanned events, such as a major hurricane or cyber attack, is an essential aspect of grid resilience that, to date, has been largely overlooked for the distribution grid. Yet multiple studies show the majority of major industrial, military and aviation accidents, including the failure of the Fukishima nuclear plant in 2013 and the crash of the Air France jet in 2014, are attributed to human error and to the loss of situational awareness [12] [13]. Today, situational awareness has become a key element of human-reliability research for domains that involve complex and challenging environments [14] but to date, research specific to the distribution grid, has been lacking.

But there is another facet of resilience, apart from unplanned events, that is the focus of increasing concern: the growth in automation across industrial and commercial domains. Particularly concerning is the lack of domain-specific data for the distribution grid. Despite the billions of dollars invested nationwide in grid automation, the work described in this report is the first to look at how automation impacts decision-making during high stress, unplanned outage events. Unknown, for example, is how much—and under what conditions—automation can diminish an operator's situational awareness and impact an operator's ability to interpret data and make appropriate decisions. Also unknown is how the balance between human and artificial intelligence might be optimized in order to achieve greater operational efficiency, reliability and overall grid resilience.

For this research project, we looked specifically at the dynamic interplay between distribution operators and advanced distribution automation. On the one hand, the increase in automation offers the prospect of greater efficiency, which can translate into reduced outage times; on the other, the increase raises the specter that operators can become mentally detached from the grid and lose awareness of its actual state, also known as being "out-of-the-loop"[15]. The consequences of being out-of-the-loop, as was shown for the blackout of 2003 [16] are that operators mentally detach, believing the machine is in control, and become less aware of aberrant data and alarms and therefore react slowly to dangerous situations [17].

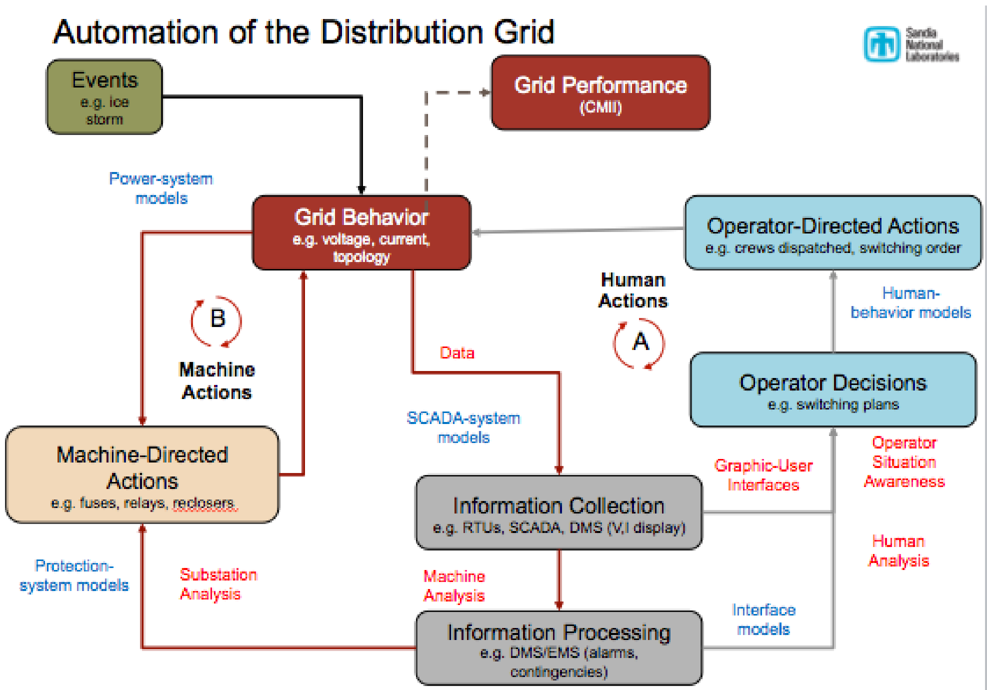

Figure 1. Information flow for a "smart" distribution grid.
Operator actions are reflected on the right, machine-directed actions on the left. As automation increases, the balance will shift to the left but may diminish the operator's situational awareness.

1.2. Collaborative Pilot Study in Vermont

The experimental phase of this project, and virtually all our data gathering, was conducted in Vermont, where the Sandia team partnered with Green Mountain Power (GMP), the state's largest electric utility and owner of more than 70 percent of its service territory, and also Oracle, a vendor of advanced distribution management software. The advantages to conducting this research in Vermont were twofold: 1) we could collect and analyze data, including high-resolution SCADA data, from a utility that had recently upgraded its network and was actively deploying advanced automation technologies; and 2) we could leverage Sandia's history of research collaborations in Vermont [18], extending back to 2008, to gain unprecedented access to the company's control rooms and operators.

In 2010, Vermont was awarded energy stimulus funds administered by the US Department of Energy (DOE) back through the American Recovery and Reinvestment Act (ARRA). The resulting so-called eEnergy Vermont $138 million smart grid project[1] funded the installation of smart meters on 85 percent of Vermont homes and the rollout of network sensors, distributed automation equipment and communications technologies statewide (both at the transmission and distribution levels), making Vermont the first state in the nation to have a statewide smart grid (not utility or region based.) Working together, Vermont's 20 utilities coordinated the upgrade of

[1] ARRA provided 50 percent, or $69M, of the total project costs.

the state's electric infrastructure to roll out a communications system that relays information about usage, voltage, existing or potential outages, and equipment performance to the control center and also sends commands from the operator back to the network. As part of this modernization effort, approximately 95 percent of all substations were equipped with supervisory control and data acquisition (SCADA) systems, with the expectation that the SCADA data would give operators' significantly more visibility into grid operations, allowing them to anticipate, mitigate and respond more quickly to emergent problems [19].

Key to the success of this project was Sandia's ability to forge essential partnerships. On the electric-utility side, Sandia worked with GMP, a utility committed to grid modernization, including distributed energy resources, system awareness and control. On the control-systems side, Sandia developed a relationship with Oracle, whose Network Management System © (NMS) software can support automated outage restoration including Fault Location, Isolation, and Service Restoration (FLISR) actions.

The three-way partnership between Sandia, GMP and Oracle, was designed so that each party could contribute expertise in specific areas, while aiming for objectives beneficial to each party and to the group as a whole. GMP wanted to 1) have confidence that advanced technologies (i.e., automation) would perform as expected (i.e., enhance grid performance) prior to their deployment; 2) better understand the overall return-on-investment for automation; and 3) obtain data that could lead to improved operator training and effectiveness. Oracle wanted to 1) receive quality feedback on their NMS software; and 2) quantify the benefits of automation, measured in customer minutes interrupted (CMI.) Sandia interests were in advancing resilience of the distribution grid and doing so by collecting data from system operators in a realistic, grid-simulated setting.

2. RESEARCH OBJECTIVES

Sandia's overarching research objective for the IGRID project was to bring focus to—and compile and analyze data on—an unrecognized but critical facet of grid resilience: the performance of the distribution-grid operator who is ultimately responsible for the safe and reliable flow of electricity to the end user. In designing our research plan, we set forth the following goals:

- To identify causal relationships between automation and grid operator performance;
- To develop measures of human performance as a function of automation; and
- To instantiate the impact of 1) and 2) on grid performance through the development of a cause-effect model

We wanted to demonstrate the linkages among automation, operator expertise and system restoration, as reflected in grid-performance metrics, in order to quantify under what circumstances automation helps or hinders outage restoration and by how much; and to collect data that would ultimately advance the rollout of advanced distribution automation. We anticipated that a set of carefully controlled experiments would increase utilities' willingness to invest in automation by demonstrating the relation between automation and outage metrics and also provide useful information on the strategic deployment of automation. In addition, we anticipated that our work would produce interesting observations regarding the human-machine interface and how it might be improved both from a design perspective and from a training perspective.

It is nonetheless important to note that the research described in this report is preliminary and involves data and system operators from one utility in Vermont. That said, we believe that the vulnerabilities and challenges we have identified exist at other utilities, several of which have described the roll-out of automation as an unresolved human-factors challenge. In short, we believe our research opens the window on an area of considerable operational uncertainty and concern for distribution utilities across the US.

3. TECHNICAL APPROACH

With little evidence in the research literature that the human dimension of grid resilience has received much attention, we developed a multi-faceted approach to IGRID that included the following elements:

- Development of a methodology for measuring levels of automation and depicting the dynamic interplay between automation and operator;
- Baseline human factors research to identify the tasks and critical decisions required of operators and to define operator expertise;
- Selective review of GMP historic data, including SCADA data, outage logs and operator logs to identify which combination of variables or sets of conditions result in the highest outage metrics (see the Appendix);
- Simulator study to measure operator interactions with automation
- Game-theoretic modeling effort to study automation-operator interactions under multiple outage parameters.

Because automation is a broad catch-term and applicable to multiple devices and processes[2], we focused our research efforts on one automated technology: the smart re-closer, which is a new fault-protection device being installed by utilities across the US, including GMP. These automated re-closers can operate independently of the operator, opening and closing in response to voltage drops and other transient fault conditions. When supported by advanced DMS software, they can operate completely automatically to isolate faults and reroute power flow to reduce the number of customers affected by an outage. Even when they are not operating in a fully automated manner, control room operators can operate these devices remotely to achieve fault isolation and service restoration functions.

Such devices are considered integral to grid modernization, moving the grid closer to a self-healing network by restoring power to the greatest number of customers in the shortest period of time. They can also be operated in multiple modes: as manual switches, without advanced capability; with operator oversight (the operator must agree to the restoration plan offered by the DMS; and as fully independent/automated devices that communicate directly with SCADA to reroute power.

Because they are so central to advanced grid functionality and have the multiple capabilities described above, the re-closers were the ideal technology for investigating the impact of automation on operator performance. With GMP as a partner, providing access to its control rooms and operators, and with Oracle providing access to its Network Management © (NMS) system and its FLISR-enabled NMS training simulator, Sandia created a technical approach rooted in empirical and observational research, one that allowed us to investigate operator decision-making and performance during grid restoration, with and without automation.

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[2] Automation for the electric grid is defined as "automatically controlled operation by mechanical or electric devices that optimize the flow of electricity and data to enable a fully controllable, interconnected and flexible distribution system."

3.1. Measuring Grid Automation

To fully understand the dynamic interplay between the operator and automated grid technologies, we needed a repeatable method for observing, measuring and documenting the level of automation. Our methodology, which reflects work described elsewhere in this report and is fully documented in Haass et al (XX), is based on an inventory of operator-to-system interfaces and a set of data, including historic SCADA data, identifying the nature and frequency of actions executed by humans and machines in near real-time (*see Table 1*).

Table 1. Example SCADA log keyword matrix.
Table entries where the SCADA logs did not include sufficient information to calculate the level of automation are marked as not applicable (N/A).

	Information Acquisition	Information Analysis	Decision Selection	Action Implementation
Machine				
Automated Action	RTU no on/off line	low limit exceeded	N/A	device change of state [OPEN, OFF]
Result of operator commanded action	N/A	N/A	N/A	control succeeded [OPEN, CLOSED, TAG]
Operator	N/A	N/A	N/A	
Command machine action	N/A	operator control, note added	N/A	Operator control [OPEN, CLOSED, TAG]

Armed with that data, we created a visual display showing the system's automation dynamics for a specific interval of time. It should be noted that the data could also be incorporated into real-time visualization systems already present in control rooms.

We found that when the level of automation approaches zero, system operations require more effort from system operators. One can therefore infer that when low levels of automation are routinely associated with certain subsystems or operator actions that investing in more automation may reduce operator workload or improve efficiency. Conversely, when levels of automation are routinely high, system operators may be vulnerable to distraction or complacency, both of which can result in decreased situation awareness. As repeatedly demonstrated for other domains [6], it is at these times that system performance is most vulnerable to automation failures.

Figure 3, for example, depicts the levels of automation for a 31-day period during which a strong snowstorm entered Vermont (day 9), causing widespread damage and power interruptions. This event, and efforts by operators and field crews to restore power, is apparent in the level of automation. After a stable period of highly automated operation from day 4 to day 9, the level of automation oscillates frequently between low and high automation, as automated systems perform fault isolation functions and human operators respond to alarms and work to restore service.

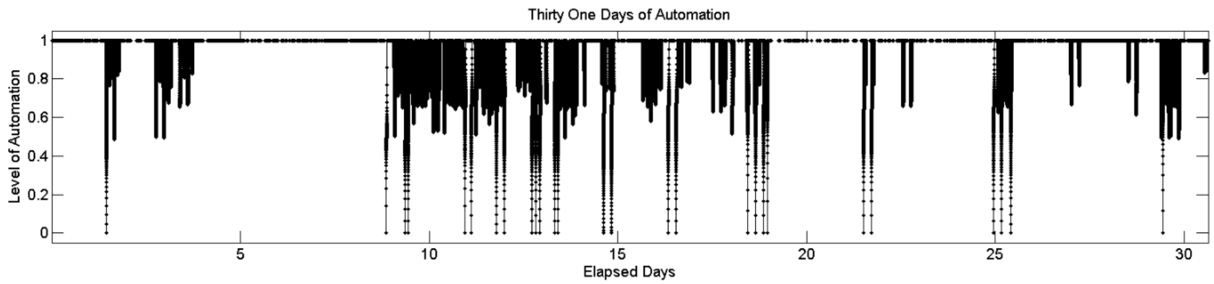

Figure 2. Variance in levels of automation vary during 31-day periods of operation.

A more detailed example of a single power outage is shown in Figure 5. Here the level of automation can be seen from the time the first device failed at approximately 23.5 hours to the time of service restoration at approximately 25.75 hours. The event began with a failure at re-closer R2, which caused the upstream breaker, R1, to open automatically. Later, at approximately 24.75 hours and 25.5 hours, operators performed two remote switching operations as part of their restoration efforts. Both switching operations began in fully manual mode and transitioned to fully automated processes, triggered by computerized actions, such as voltage alarms, that responded to the grid's new operating configuration.

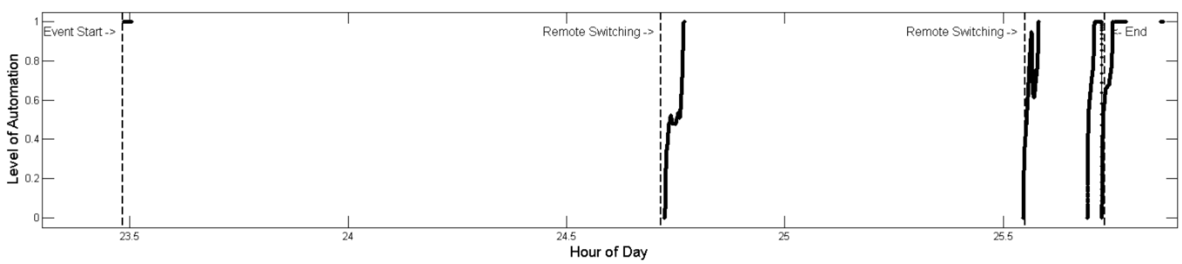

Figure 3. Level of automation from device failure to completed service restoration.

The IGRID method makes it possible to measure and track the changing level of automation as a critical infrastructure moves through its natural system dynamics and provides a detailed view of the factors that affect overall system performance, including operator workload and weaknesses or gaps in system automation. We found, for example, that when the level of automation approaches zero, system operations require more effort from system operators. One can therefore infer that when low levels of automation are routinely associated with certain subsystems or operator actions that investing in more automation may reduce operator workload or improve efficiency. Conversely, when levels of automation are routinely high, system operators may be vulnerable to distraction or complacency, both of which can result in decreased situation awareness. As repeatedly demonstrated for other domains [6], it is at these times that system performance is most vulnerable to automation failures.

We believe this method can guide infrastructure investment decisions by highlighting subsystems or operating conditions where increased automation is needed and also guide the design of the human-computer interface to ensure operator remains mentally engaged during highly automated periods so his/her situational awareness is maintained. The method is also adaptable: the moment-by-moment details can be analyzed for specific time periods (for example, weekly, or monthly), during critical events (such as storms or system upgrades), or for specific subsystems.

3.2. Situational Awareness Among Distribution Grid Operators

As a parallel effort to our automation work, we began gathering baseline information on operator tasks, responsibilities and skill sets in order to build a foundation of knowledge related to situational awareness and critical-thinking skills. (The full scope of this work is described in Stevens-Adams, et al, 2015.) Granted access by GMP to their two control rooms and 14 operators, we were able to observe the operators' work routines and, by applying human-factors methodologies to interviews with the operators, we were able to collect information specific to switching, a central activity for every distribution operator. Switching, as the name implies, refers to the opening and closing of switches (also known as breakers) to isolate faults and reroute power. Most so-called switching is planned and orchestrated under controlled conditions to allow for maintenance of the electrical network. In contrast, unplanned switching is required when there are unexpected grid outages (e.g., trees falling on lines during stormy weather, animals chewing through lines, cars running into poles, etc.) and necessary for power restoration. We learned that unplanned switching can place high cognitive demands on an operator, depending on the type, location and timing of the outage, requiring the operator to pinpoint the fault location, evaluate options to re-route power and coordinate with the field crews so the break can be repaired and the flow of power restored.

While conducting our observational studies, we also gathered data on background noise during an outage, including the frequency of audible alarms, ringing phones and number of customers (including the police) pressuring the utility for a restoration times. Given the heightened activity, unplanned switching tasks are often stressful and potentially overwhelming, requiring rapid, critical decision-making and a high level of cognitive effort. By the end of our *in situ* observational study we were able to construct a task diagram[3] that lays out the demands and skills required for a simple but unplanned grid-restoration event (see Figure XX), a diagram that set the stage for our upcoming experimental work.

[3] To construct the task diagram, we relied on a widely accepted human-factors methodology call applied cognitive task analysis.

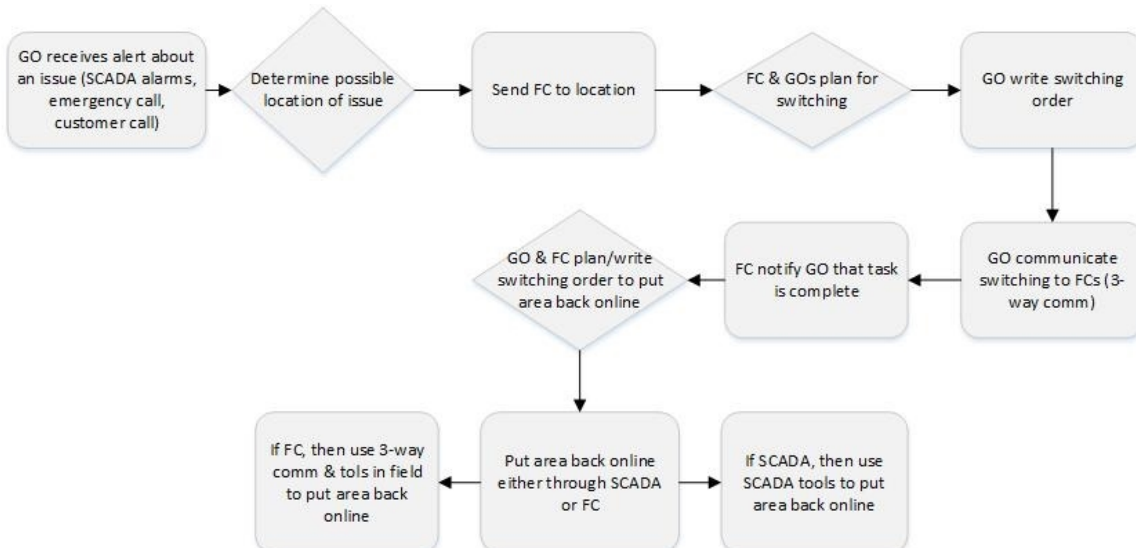

Figure 4. Task diagram of unplanned switching.

In Figure 4, the diamond shapes indicate tasks in which the grid operator (GO) had to make a critical decision; mostly involved with switching. The diagram highlights the importance of operator communication with the field crew (FC) and interaction with SCADA interfaces and tools. Using the widely accepted critical decision method XX, we also constructed a critical cue inventory, to list the multitude of cues and sources of information an operator tracks during grid restoration.

Table 2. Critical cue inventory of unplanned switching.

Cue category	Description
Alarm (visual, auditory)	On computer via Supervisory Control And Data Acquisition (SCADA) • Intrusion • Communication • Nuisance • Normal • Emergency situations Printer Control board
Phone ringing (visual, auditory)	Customer calls Field crew calls Management
Weather (visual, auditory)	Hot or cold Sunny/clear Wind Snow/wintry conditions
Control board (visual)	Visual of current outages/problems Means to see entire footprint Assists in determining number of affected customers Assists in determining how to reroute power, plan switching
Security cameras (visual)	Monitoring authorized and unauthorized access to buildings Monitoring hydrostations
Weather channel/news stations/meteorology sites (visual, auditory)	Monitoring wind patterns Monitoring storm developments
Radio (auditory)	Field crew calls
Co-workers (visual, auditory)	Communication between operators
Email (visual, auditory)	Requests from field crew Communication with upper management Communication with engineering department
Time of day (visual, auditory)	Field crews scheduled during day Customer usage greatest 6a-10p Assists in predicting load

Finally, we created the timeline for a specific outage event, asking GMP operators to choose an incident that 1) they could remember in a fair amount of detail; 2) was a recent occurrence and/or especially memorable; and 3) was supported by SCADA data (see Figure 5).

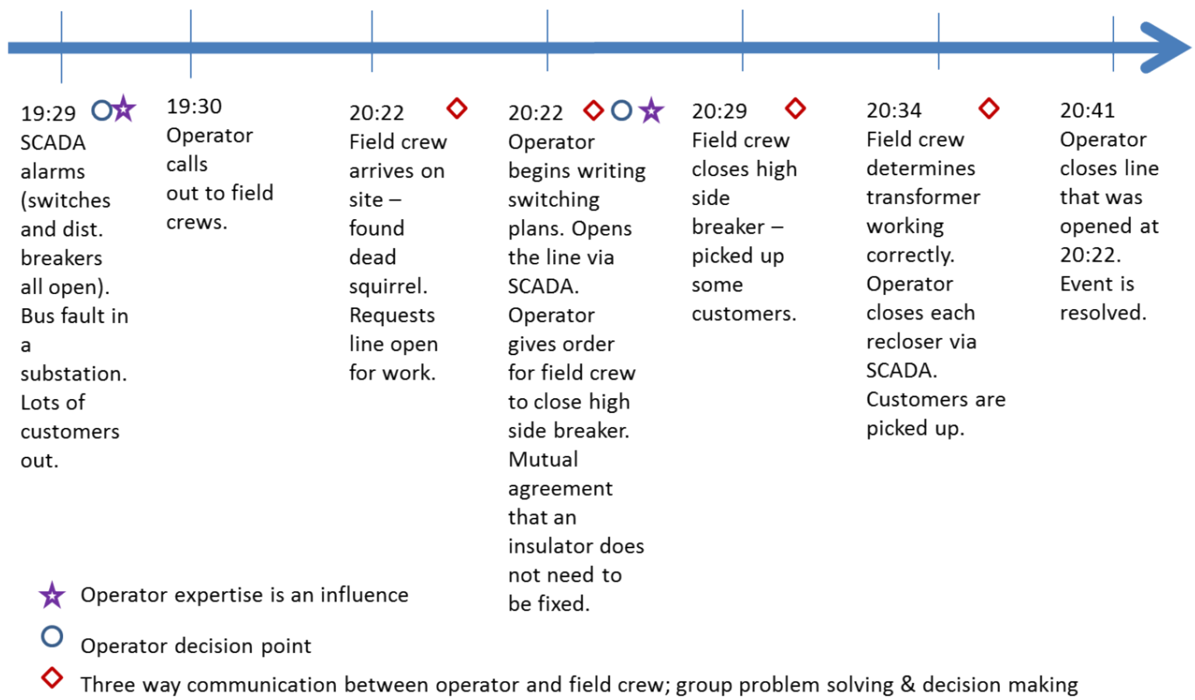

Figure 5. Timeline of unplanned switching incident.

What we found of significance was that the operator and field crews share situational awareness throughout the restoration process, each depending on the other from fault detection to full service restoration. Whereas operators have a view of the entire network, including customer load and operating parameters, and know the location of switches and other rerouting devices, they only have an abstract, or white-tower, view of an outage. In contrast, the field crew interacts physically with the grid, acting as a forensic team to identify the precise location and cause of a fault. With the proliferation of FLISR-enabled switches, the relationship between the operator and the field crew will substantially shift. At a minimum, we believe that operators will have to develop a new mental model of grid restoration and will also have to both trust, and know when not to trust, automation.

3.3. Defining Operator Expertise

One challenge of grid modernization is that most of today's control-room operators were trained in an analog environment and have skills that reflect a combination of field experience and control room confidence, but these skills do not align with digital architecture of the 21st Century grid. Yet expertise in the control room has never been well defined, either for analog or digital operations. With utilities increasingly investing in automation, the domain is long overdue for a sweeping look at expertise; it is important to understand how operator performance, combined with changes in automation may, or may not impact the grid. It is also important to understand expertise in order to optimize the design of the human-machine interface and roll-out of advanced grid visualization software. Although limited in scope, this is the first study of its kind to characterize expertise in the distribution control room; see Stevens-Adams, 2016 [23.]

We conducted our research by individually interviewing 13 control room operators, three managers, and one human resources executive at GMP, either in a conference room or the control room. We conducted the control-room interviews during a ‘quiet’ time so as not to impact the operator’s job performance and asked questions pertaining to the importance of experience in the control room, the traits that distinguish experts from non- experts and what attributes an expert in the control room possesses. We also asked the operators to assess the expertise of their colleagues. In addition, we asked operators to explain how they currently execute switching operations and how that approach might change as the grid becomes more automated.

We found the operators’ experience varied, ranging from a so-called apprentice, with just two months on the job, to a First-Class (1C), or expert, operator, with more than 37 years at GMP. Operators are promoted from Second-Class (2C) to 1C based on their ability to handle complex tasks and to complete them under decreasing amounts of supervision. Operators that reach the 1C level are expected to work independently.

Based on the responses we obtained, we determined that an ‘expert’ operator typically has 7-9 years of control-room experience and also possesses certain traits, such as the ability to remain calm, cool, and collected under pressure. He or she is also adaptable, can effectively multi-task, can synthesize large amounts of data quickly and efficiently navigate the operating system and has had exposure to many types of events. Although our findings are based on one distribution utility, we believe (based on informal interviews at multiple other utilities), they are representative of the domain and provide a solid baseline against which to consider expertise in the face of increasing automation.

3.4. The IGRID Experimental Approach

We began the experimental phase of the IGRID project in 2016, building on our previous cognitive research to lay out a technical approach that would produce quantitative data on the benefits of automation. Because GMP gave us access to their operators and Oracle gave us access to their Network Management System© (NMS) software, we had an exceptional opportunity to collect data under simulated, but close-to-realistic, conditions. We decided to develop a set of outage scenarios for the portion of the GMP grid already identified as a test bed for the rollout of FLISR technology, including the feeders where the automated re-closers[4] (Vipers©) will be installed, and to recruit GMP operators serving as test subjects.

[4] These re-closers are accompanied by advanced, automated switchgear that, with support from the Oracle NMS, can automatically generate and execute restoration plans.

Oracle agreed to upload a model of the GMP grid into their NMS, a time-consuming and complicated process involving the export of GMP's GIS data to Oracle, along with assets and electrical values and an impedance model. In addition, the NMS had to be configured to incorporate GMP's power-engineering software into FLISR and ensure FLISR-enabled SCADA capabilities. GMP agreed to support that effort, making its engineering and IT staff available to assist in the data transfer.

Working in parallel, Sandia, GMP and Oracle designed a scenario-based set of experiments. The objective was to create scenarios that would enable us to measure and better understand operator response to simulated outages that varied in both their degree of complexity and level of automation support, and to track operator performance by both restoration times and by Customer Minutes Interrupted (CMI), which is the sum of all customer interruption durations and a key performance metric for the distribution grid. We hypothesized that changes in automation would be reflected in the shape and size of outage histograms (*see Figure XX)*, allowing us to quantify how operator-automation balance affects these metrics.

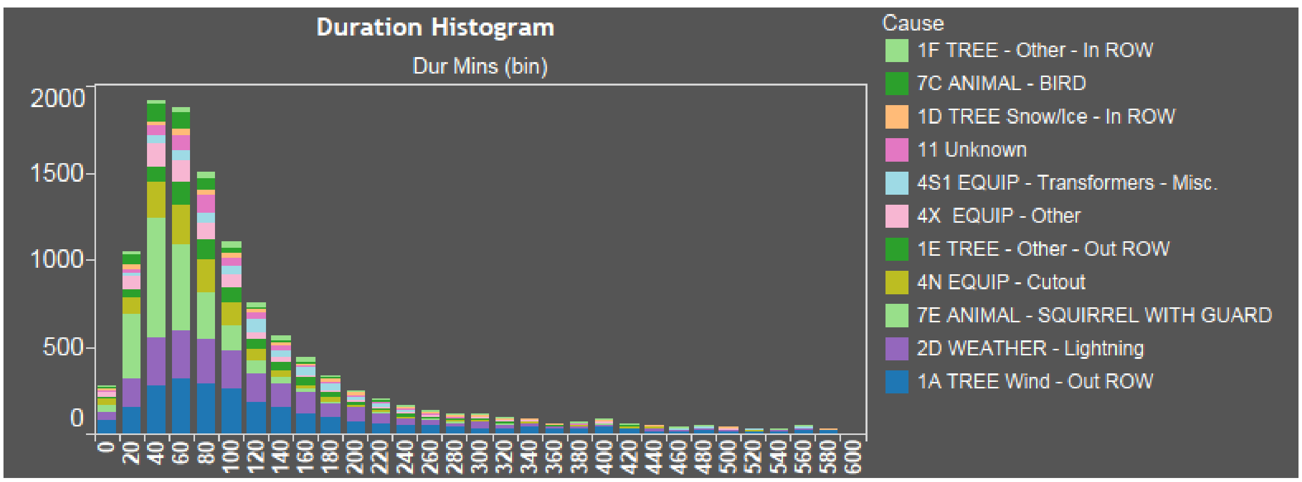

Figure 6. Sandia visualization of outages experienced by one utility over the course of several months, binning number of outages by duration (x-axis) and frequency (y-axis). Each color represents a different cause.

3.4.1. Scenario-Based Methodology

The scenarios we created range in complexity from simple to intricate, sorted into pairs based on multiple variables, such as the number of outages, anticipated number of operator switching actions, number of customers out of power, etc. (see Figure XX.) Within each pair, one scenario is designed to be executed in manual mode; the other scenario is FLISR-enabled and will automatically generate a switching plan that the operator can choose to accept to reject.

We designed each scenario as realistically as possible, reviewing historical outage data for this portion of the GMP network to identify potential causes of disruptions and to ensure the verisimilitude of the complexity associated with each disruption. In the end, we developed five detailed scenarios, all of which were vetted and refined by former GMP operators to clarify interactions, and make the scenario process as close as possible to an actual disruption, including alarms, phone calls from external parties, and other elements beyond the NMS interface. We also inserted scripts meant to mimic interactions with field crews and others, such as the state police. To further add realism, we recruited a subject matter expert (SME), a highly experienced former GMP operator, to write the scripts and to serve as the voice of the field crews (or other callers), reading from the scripts in the scenario. Overall, the scenarios provided a likely path, as determined by our SME, for operators to follow, serving therefore as a *de facto* baseline of operator performance, though (as we shall see) the scenario script does not prevent actions beyond the expected path from being pursued.

As we developed the scenarios, we also created a detailed work breakdown structure (WBS) so we could capture the interchanges between the operator and external parties, including the originator and receiver of the communication or action, the means of communication or action, and the content of the communication or action. The WBS was beneficial in three ways:

- First, in error correction of the scenarios (e.g., identifying inconsistencies in switching or identification of assets used in the scenario);
- Second, in identifying the elements of each scenario that should be timed (e.g., the time from receipt of an alarm to awareness of its cause and subsequent dispatch of the field crew) during the course of the experiment; and
- Third, identifying elements of each scenario for which timing would be neither operator-response dependent nor predictable (e.g., the time for a repair crew to reach a location once dispatched, the time for a repair crew to exact a repair once provided a switching plan).

The latter category was valuable in scenario execution within the experiment, as it created opportunities for acceleration of the scenario far beyond real timing, allowing for more scenarios to be explored (and for more data to be gathered) in a shorter period of time. Elements for which timing was deemed to be important, were often grouped. Grouping occurred because the sequencing of individual tasks within the sequence could vary. Grouping also occurred to make certain that the method of data capture (discussed later in this document) was consistent at the beginning and end of the sequence.

We also used the work breakdown structure to define the difficulty of the scenario based on the number of steps needed to return the system to a state in which all customers have power (note that this does not mean full system restoration). Automation represented whether the scenario included guidance within the NMS on a preferred path for use of FLISR-enabled controls within the NMS, or no guidance from the NMS.

3.4.2 Execution of the Experiment

Because GMP has not yet implemented NMS in its control operations, we needed to put our test subjects through NMS training, sufficient to establish an acceptable degree of proficiency. Oracle supported this effort by conducting training sessions at GMP and offering follow-up phone support. We also asked two GMP operators to participate in a pilot test to ensure, prior to the experiment, that our approach was technically and logistically sound and that our analytic framework allowed for effective data capture and analysis. Unfortunately, our pilot testers—having been through the scenarios— could not participate in the experiment, thus shrinking our subject pool, but the testing proved invaluable: we identified multiple problems, including software issues, that needed to be fixed in advance of the experiment.

We ran the experiments from June 28-July 1, 2016, during which time we tested a total of six GMP operators, or almost 75 percent of the available GMP operator pool (not counting the pilot testers.) Before each scenario was activated in the NMS, our SME briefed the operator on prevailing conditions, including weather, time-of-year, and crew availability, that could influence his decision-making. He also instructed the operator to restore the outages they encountered as safely and efficiently as possible. Although a simulator is not equivalent to a real-time environment, each operator was encouraged to treat the simulated scenarios as real events and to take into consideration all the factors that would normally influence their decision-making with respect to outage restoration.

We conducted the experiments in a private room at GMP, one operator at a time to minimize distractions and ensure privacy. The Sandia human-factors expert oversaw the experiments, ensuring their consistency and was supported in her data collection by a GMP employee and also by the SME, who interacted directly with the test subjects by playing the role of the field crew, making phone calls to the operator, etc. They captured data on the timing of particular actions (both human – human and human – machine interactions) using several methods: stopwatch for human-to-human interactions; screen capture software for general interactions with the NMS software environment; and NMS timing data for actions recorded by the NMS in the scenario. They also recorded times where appropriate, identified inconsistencies with the planned scenario actions, and corrected the path of the scenario when diversions occurred. Additionally, each operator was interviewed at the end of the experiment and asked to review the decisions he made during each of the scenarios and to assist the observers in clarifying the operator's decision-making process.

It is important to note that the participation of our test subjects was strictly voluntary per the requirements of Sandia's Human Studies Board[5]. We also made it clear to all that participants could withdraw from the study at any time, without penalty, and that their identities and results would forever remain confidential.

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[5] The experimental plan proposed by the IGRID team was thoroughly vetted by Sandia's HSN to ensure that the rights, including privacy, of all participants were protected and that no one would be coerced or pressured in any way to participate.

FLISR Enabled	Season	Time of Day	Outage Events	Substations involved	Circuits Involved	Operator Swtiching Actions	Other Operator Actions	Outage Duration	Customers Out	Operator Stress Level	Cause
No	Early Spring	Afternoon	4	3	4	17	9	1:23	2,325	1.3	Multiple
Yes	Late Spring	Afternoon	4	4	9	20	13	0:53	24,950	1.8	Multiple
No	Early Spring	am-early pm	4	3	6	20	17	3:01		1.85	Multiple
Yes	Summer	Afternoon	1	1	1	30	5	4:10	795	1.8	Car pole
No	Summer	Evening	1	1	1	10	4	4:28	602	1.5	Tree
Yes	Summer	Afternoon	1	1	2	9	4	0:57	1402	2.2	Transformer

Figure 7. Sample spreadsheet of outage scenarios.
The scenarios are sorted into pairs based on overall complexity, with one scenario in each pair FLISR-enabled.

3.4.3. Preliminary Results

Sandia created an analytic framework to document operator actions, restoration times per outage and per scenario and link the latter to CMI, sorted by both operator and scenario.
Data analysis from the experiments is ongoing. Nonetheless, some observations can be made based on the data collection effort that are helpful to outlining future activities.

1. Expertise, Speed, and Accuracy
Researchers proposed that experienced operators, defined in other research as part of this overall effort (Stevens-Adams & Hannigan, 2016), would perform tasks faster and with greater accuracy than non-experts. In the collected data, the most experienced operator was slowest at completing the tasks. Post-exercise interviews did not clarify whether this was due to the operator being measured and deliberate in his actions, or due to a lack of proficiency and confidence with the system on which the operator had recently been trained. Table 3 outlines the level of expertise as defined in this study for each participant, and also their level of familiarity with the portion of the GMP system used in the scenarios.

Table 3. Participants' levels of expertise and system familiarity for the IGRID experiment.

	P1	P2	P3	P4	P5	P6
Operator Expertise	High	Low	High	Low	High	Low
System Familiarity	Low	Low	High	Low	Low	Low

2. Situational Awareness and Critical Thinking
Researchers postulated that operator situational awareness would decline both as the scenarios became more complex and as the NMS provided FLISR solutions. The experimental data collected suggests this may be the case for the use of the NMS system. Given the instructions

provided, to “restore the outages they encountered as safely and efficiently as possible,” many operators appeared to be racing to achieve a solution as fast as possible. This strongly implies reduced situational awareness in decision-making on the part of the operators.
Observed behavior of operators also revealed that some operators take actions outside of the expert-suggested path to restoration. Some operators opened and closed switches in the system to try and identify the location of disruptions within the scenarios. When this happened, the simulated system responded as the real-world system would, avoiding actions that might lead to cascading outages through system protection devices. The guarantee that these protective devices will work every time in reality, or that switches and protective devices subject to action on a more frequent than design basis planned will protect both utility equipment as well as consumer equipment and utility- and consumer-owned distributed generation resources from further consequence is a question for operations planners. These findings lead directly into the next finding.

3. Consistency of Action
Within the experiments, the sequence of procedures expected from each of the operators was inconsistent at best, likely reflecting different perceptions of the system and the way an operator should interact with it and with other elements of the operational team (e.g., field crews). These actions, combined with some of those identified above, suggest that steps to create a more rigorous and consistent training procedure for the way operators interact with control systems and field crews, may be of value.

4. Trust in Automation
Post-experiment interviews with operators suggest that automation provides value, and is seen as the future of grid operations. But most suggested in these interviews that trust in automation would be an issue. That was seen in the actions taken in the FLISR-driven scenarios. In most cases, the FLISR solution was seen, but not acted on; rather, the operator used it as a guide for a manual operation. This behavior may change with time, but it suggests that confidence in the products of the automated system will evolve rather than be in place to begin. It also suggests an opportunity for…

5. Adequate Sample Size
Working with GMP on this effort was wonderfully productive in terms of developing a sound experimental design and testing procedure, including our scenario-based methodology, but the small size of the utility, and the number of operators, both experienced and non-experienced, meant that the data collected has limited value from a statistical analysis perspective. Identifying a utility with the proper number of operators to satisfy basic statistical limitations on collected data is an area for future examination, though trying to identify such utilities may lead beyond smaller distribution-focused entities like GMP.

6. Errors in Experiment Execution
As with other experiments, this one was not without technical flaws. But the flaws seen in this case proved to be illustrative, revealing an interesting interaction between the NMS and the operator. In reviewing the data, for example, we saw that in one case, the NMS for the scenario in question had provided an erroneous FLISR option, associated with one of the other scenarios, with switching at a location completely unrelated to the outage posed. The operator chose to

follow the erroneous FLISR option, trusting the automated input provided. It took the operator several minutes to notice the difference, correct the system changes made following the FLISR option, and begin analyzing the system to restore based on the system fault.
This raises natural questions regarding the accuracy of information received by the operator via the NMS, of the underlying confidence and surety required by the operator in this information, and the potential for malicious actors or error in code deployment to lead to such errors, which have the potential to create disruptive events. This is a growing concern with the expansion of distributed generation assets connected to distribution utility systems, and of the need for these combined systems to operate without concern for erroneous reporting of this type.

3.4.4. Analysis

We presented each of the five trials (scenarios) to the six participants in random order. The finalized list of scenarios is included in Table 4. Two scenarios were run with FLISR automation turned off, while three were run with it on. The target difficulty encapsulates the total number and complexity of tasks required of the operator if the scenario were run to full recovery completion, as in a full check of loads and voltage measurements and release of the field crew.. However, because the scenarios were only run to full restoration (all customers online) instead of full recovery (all customers online and system returned to normal topology), the difficulty and recovery time should not be used to judge the results herein.

Table 4. Final scenarios

	Target Difficulty	Target Full Recovery Time	Number of Events	Ideal Switching Operations	FLISR automation?
Scenario 1	MED	0hr38’	2	4	YES
Scenario 3	HIGH	1hr34’	1	3	NO
Scenario 4	MED	5hr30’	1	8	YES
Scenario 5	LOW	1hr22’	1	5	YES
Scenario 6	LOW	0hr26’	1	7	NO

In three individual trials, data was not accepted as valid, either because the experiment administrator mistakenly ended the session before all customers were online, or because the administrator did not adequately follow the scenario’s script:

a) Participant 1, scenario 1: Administrator did not adequately follow scenario script.
b) Participant 1, scenario 6: FLISR generated an incorrect solution, FLISR was intended to be inactive in this scenario.
c) Participant 4, scenario 3: Administrator ended session before all customers were online.

With this data removed, Figure 8 illustrates the time to full restoration for each scenario across all participants. Restoration times for scenario 4 were longest on average, and scenario 4 had the largest variance across participants. We also noted that many of the participants disagreed with a particular piece of the FLISR solution in scenario 4. Also in scenario 4, some participants did to not use the remote control options for all possible switches, but instead chose to dispatch crews for manual switching in these cases.

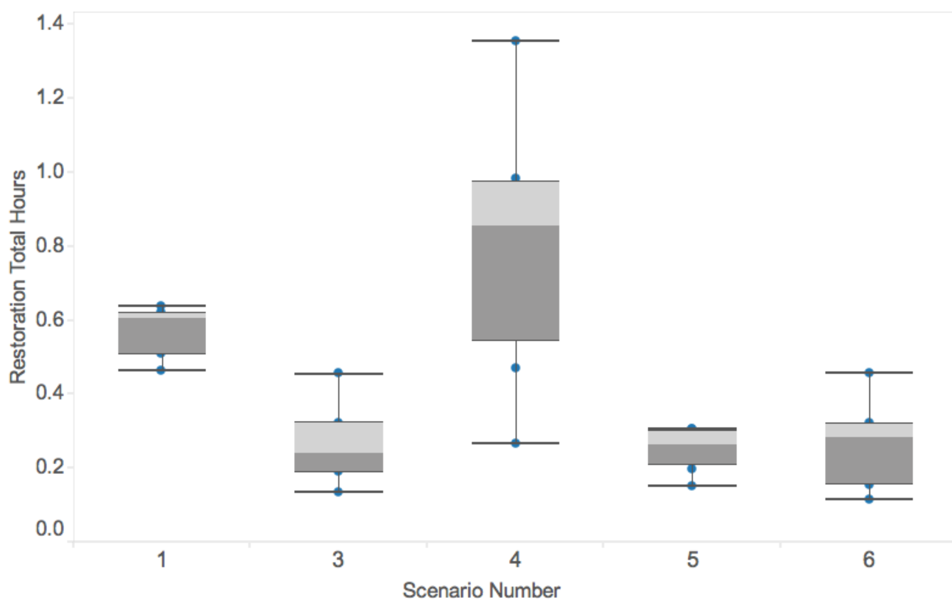


Figure 8. Box and whisker plot of restoration time.
Restoration times for each scenario in the experiment are shown for all participants.

There are similarities in some of the distributions, namely between scenarios 3 and 6, which are the two scenarios that lacked FLISR capability and also between FLISR-enabled scenarios 1 and 5, although scenario 5 has a lower median restoration time. Judging simply from these distributions, there is no strong indication that adding FLISR automation improves overall restoration times.

Figure 9 illustrates the variation in restoration times among participants across all scenarios. It is apparent that participants 1 and 2 are consistently faster across all scenarios than the other participants, having both a lower variance and lower median restoration time. For participant 1, however, we had to discard two trials because of the experimental errors noted above. Interestingly, participants 3, 4, and 5 have similar median restoration times, but widely varying distributions.

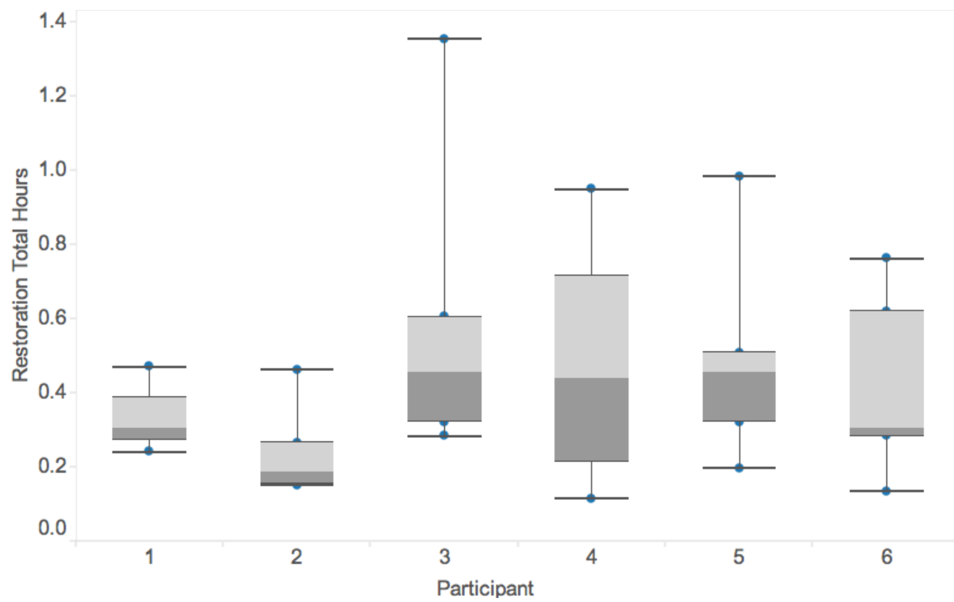


Figure 9. Box and whisker plot of restoration times for each participant for each scenario.

Figure 9 depicts how each participant performed compared to the mean restoration time for each scenario. Negative deviations indicate faster performance than the scenario mean. Whereas participant 2 was the only participant consistently faster across all scenarios, participant 3 was the only participant consistently slower across all scenarios. Notably, participant 3 was also the only expert across both operator and system knowledge categories, while participant 2 was a novice in both of these categories.

Purely based on observation, participant 3 was slowest to navigate the NMS interface but participants 1, 2, 5, and 6 also struggled at times with the NMS. Participant 4 had a noticeably heightened grasp of the NMS interface by comparison, but at times acted so quickly that mistakes were made, or cues from the experiment administrator had to be skipped.

Judging from this information, there is a slight suggestion that expertise may lead to *longer* restoration times, but this is not statistically significant. Anecdotally, participant 3 was much more deliberate in actions and made very sure that every FLISR suggestion was well-understood. Some of participant 3's lag may be attributed to the lack of familiarity with the NMS interface but much of it may be attributed to a more cautious approach that is reflective of expertise. We should also note that the fastest participant (2), who was a novice, was confused at some points by NMS interface and had to slow down.

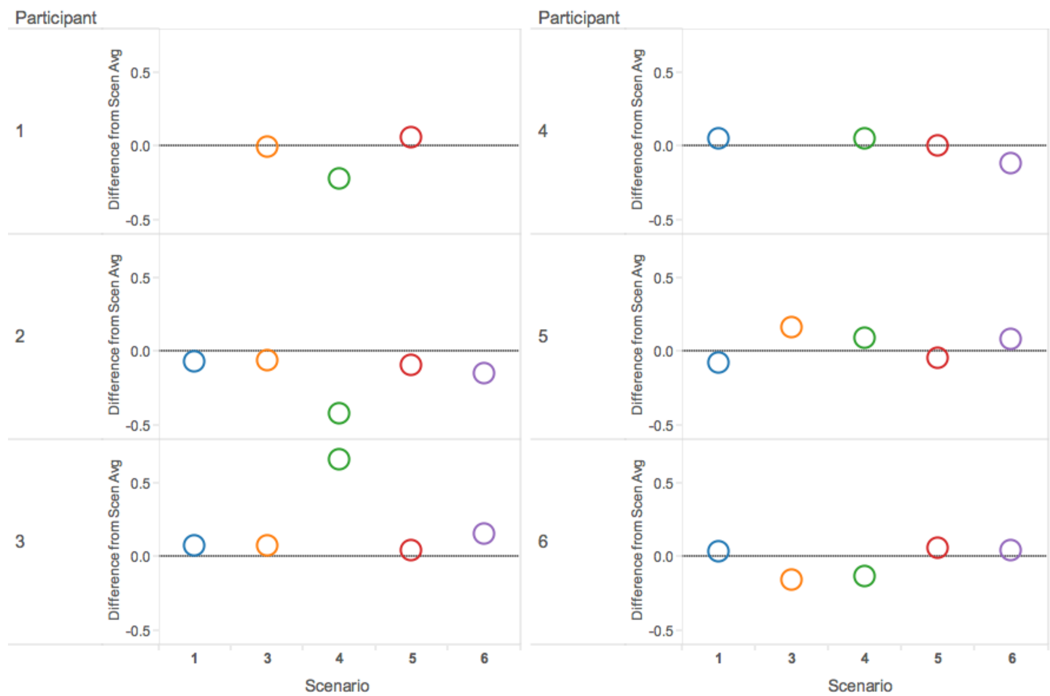


Figure 10. Deviation from scenario mean restoration time for each participant.

While time to full restoration is a helpful and accessible statistic to measure participant performance, the performance of the grid (and by association, the utility) depends on both the magnitude of customer outages and their duration. For that reason, we chose CMI as the more appropriate measure of grid performance for this study. Faced with data complexities, we calculated CMI for only one of the scenarios, but believe with additional effort, we can calculate it for the remaining scenarios. We also generated a timeline depicting customers out for scenario 4 (Figure 7) showing the range in operator contributions to CMI.

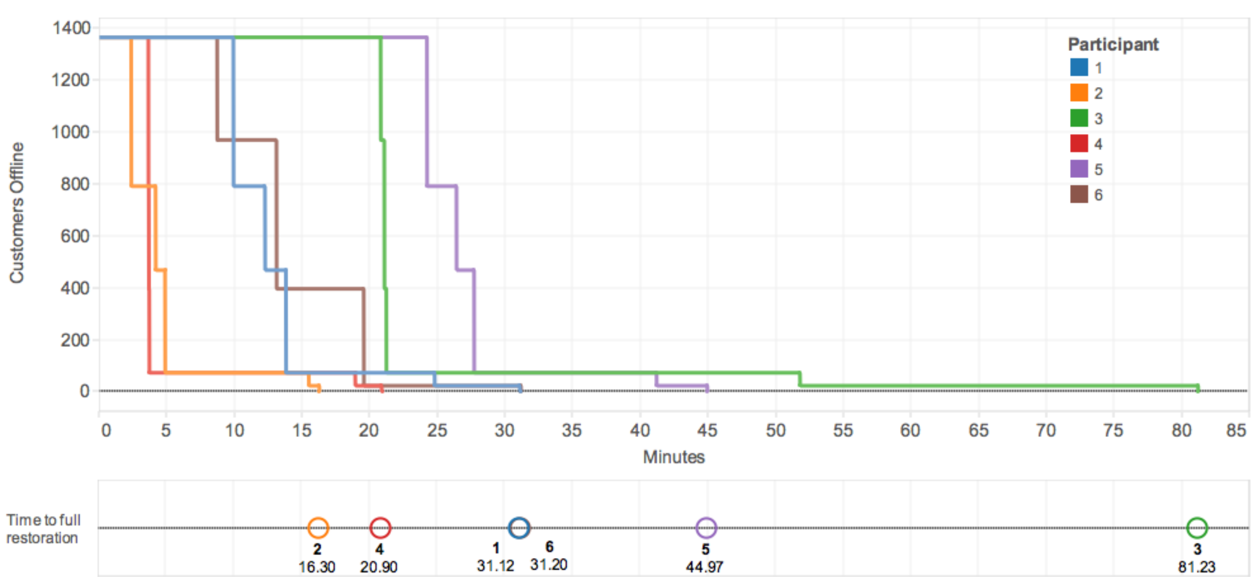


Figure 11. Timeline of customers offline across all participants for scenario 4.

Figure 7 provides excellent insight into the impact of operator performance on grid reliability and resilience. Participants 1 and 6 had nearly identical restoration times for scenario 4, yet their paths to restoration (blue and brown lines in Figure 7) are very different. Participant 1 reroutes power via remote control of SCADA-enabled reclosers more quickly than participant 6. Participant 6, on the other hand, communicates with field crews in between each decision to pick up a block of customers, leading to the more stepwise restoration timeline. Note also that participants 3 and 4 (green and red lines) both have very steep transitions to a low number of customers offline, indicating that they performed three automated switching sequences in extremely fast order. We believe this behavior is indicative of trust in the NMS FLISR automated solution. It takes participant 3 much longer to arrive at the FLISR solution than participant 4 – perhaps because of their relative levels of familiarity and comfort with the NMS interface.

Figure 8 illustrates the potential for strong difference between CMI and total restoration time for scenario 4. Even though participant 3 had the longest restoration time, participant 5 is the one who had the highest CMI measure. Other than this discrepancy, however, longer restoration times are associated with higher CMI.

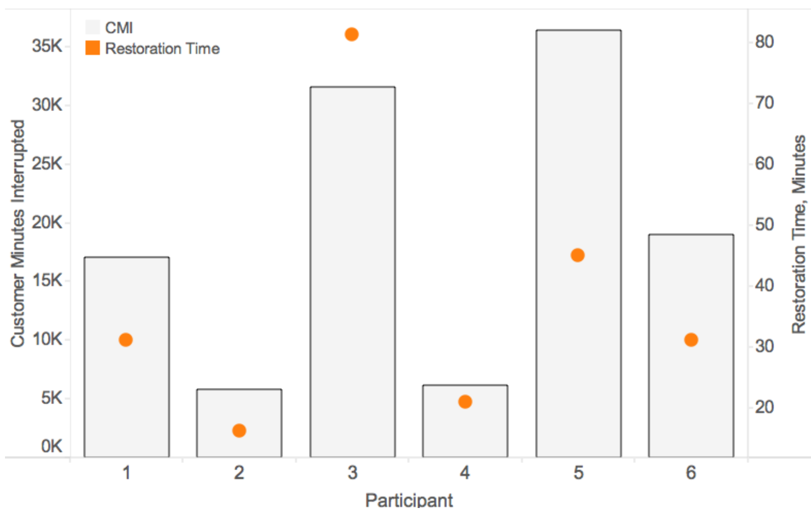


Figure 12. CMI and restoration times for scenario 4 for all participants.

3.5. Game-Theoretic Modeling

To add an important theoretical underpinning to the IGRID project, we conducted a game-theoretic modeling effort. Our aim was to develop an attacker-defender model in parallel with IGRID's experimental work (described above) to further illuminate the interactions between operator and automation. Our work builds on a game-theoretic model developed by Jones et.al. [11] with two players in the game: an attacker who attempts to gain control of a resource and a defender who tries to prevent access.

While many models for automated power grids have focused on Fault Location, Isolation and System Recovery (FLISR) algorithms, few consider the interaction between operator and automation. Our goal is not to determine the optimal FLISR algorithm, but to assume that the FLISR algorithm is a black box that the operator works with. In taking this approach, our objectives were to 1) demonstrate that the relationship between the operator and automation is worth studying and 2) identify when automation improves grid performance versus when automation is a risk and the operator needs to operate the grid in manual mode.

3.5.1. Representation of the Power Grid

We represent the power grid as a mathematical graph where is the set of vertices in graph and is the set of all edges in the graph where an edge connects any two vertices. To translate a power grid to a mathematical graph, we first described the edges as switches, which can be opened and closed, but are also directional based on whether the switch allows for unidirectional or bi-directional power flow. We also tracked the type of switch (manual/automated) and the current status of each switch (open/closed) and defined the vertices of the graph as customers on the line connecting the switches, with their number weighted by the number of customers on that line.

Our conceptual approach is depicted in Figure X, which is a graphic representation of a power grid. The edges are represented by lines where dashed/solid edges represent the open/closed property while grey/black represent the automated/non-automated property. Circles represent the vertices with their respective weights. Any vertex with a weight of 0 is a feeder and vertices are colored based on the power line they are located on. Any fault that occurs on the grid or any flipping of switches by the operator will change properties of the edges.

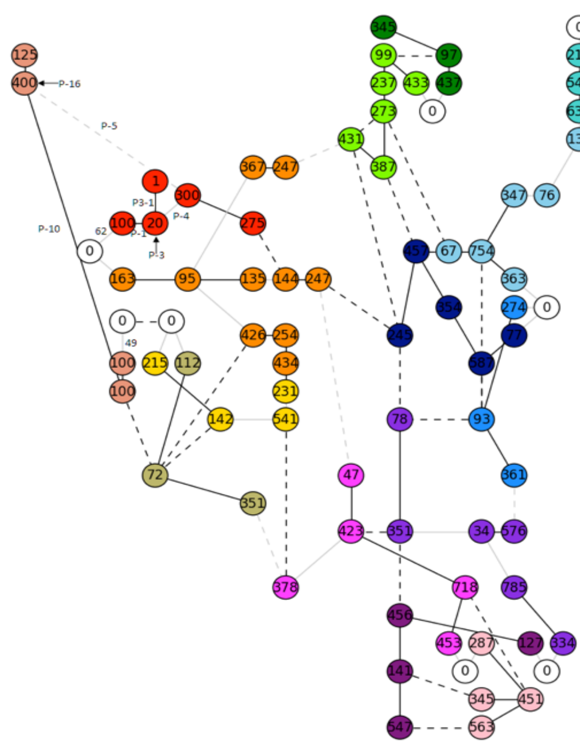


Figure 13. Mathematical graph representation of a power grid.

3.5.2. Attacker-Defender Moves

The game-theoretic model consists of two players, the attacker and the defender who take turns flipping switches in the power grid. The attacker does not have rationality or a goal but is an undefined phenomenon, such as weather or equipment failure, that causes an outage. The attacker is tracked, however, by two parameters: the number of attacks and the time at which each attack occurs.

In contrast, the defender is the grid operator whose goal is to restore power to the grid with minimal cost defined by a selected metric, which could be speed or safety or both.) Once an attack occurs, if the system is automated, a FLISR generated solution will be available to the operator. The operator has the choice of whether to blindly follow the FLISR generated solution or to create his own solution. If the operator chooses to create his own solution, he must choose which switches to flip and when based on how he wants to isolate the fault and what customers he wants to restore first. A priori, it may not be obvious why the operator would not follow the FLISR generated solution or why an operator would choose to wait before flipping switches, a topic for further investigation.

3.5.3. Parameters and Metrics

Every action in the restoration process takes a certain amount of time to perform before the next action can be performed. These times depend on the automation (i.e. it is faster to flip an automated switch as opposed to a manual switch) and operator expertise (i.e. a highly skilled operator may be faster at deciding which switches to flip than a lesser-skilled operator). For now we have the following set of parameters, although ideally they would come from a distribution of data obtained from the IGRID experiments.)

Parameter	Description
Flip time	The amount of time it takes for a single switch to be flipped. Depends on automated/non-automated
Approve FLISR	The amount of time it takes for an operator to approve a FLISR solution. This may vary depending on the skill level of the operator
Decision Time	The amount of time it takes for an operator to decide which switches to flip (for non-FLISR solutions). This may vary depending on the skill level of the operator.

We chose CMI as our reliability metric because it aligns with the key metric for our experimental work. : Customer Minutes Interrupted (CMI).

3.5.5. Examples

We present two examples of operator-autumation interaction based on one of the IGRID scenarios but modified to demonstrate important factors in the interaction between operator and automation. The times to complete different actions are demonstrative and do not reflect real world data. The assumptions made are:

Parameter	Value
Flip time	Automated switch – 1 minute Manual switch – 5 minutes
Approve FLISR	1 minute
Decision Time	Operator with high skill level – 2 minutes Operator with low skill level – 5 minutes

3.5.5.1. Example 1 – The Automation Fails

In this example, we look at two options:
1) the operator accepts the FLISR-generated solution and lets the switches operate automatically;
2) The automated switches fail and cannot be flipped automatically so the operator chooses to not follow the FLISR generated solution.

We outline three restoration process for the above options below. This example shows that the operator reduced CMI by opting to *not* follow the FLISR generated solution because he could get more customers up sooner by manually flipping switches. This example demonstrates the importance of the operator not solely relying on the FLISR generated solution.

1. Fully automated
This is the ideal case where the switches are not damaged, allowing the operator to follow the FLISR solution. For this solution, we are assigning an arbitrary time of 73 minutes for the fault to be physically repaired by a crew, which we will use as a constant in the subsequent cases.

Time	Action	Customers Out
1:05 PM	Outage starts and recloser 62 opens	696
1:11 PM	Fault located somewhere between P-3 and GE plant	696
1:12 PM	Isolate: Operator opens switch at P-4 (automated)	696
1:13 PM	Restore: Operator closes switch at P-5 (automated)	121
1:42 PM	Fault located between P3-1 and GE plant	121
1:47 PM	Isolate: Operator opens switch at P3-1 (not automated)	121
1:48 PM	Restore: Operator closes switch at P-4 (automated)	1
3:01 PM	Fault is repaired	1
3:04 PM	Operator recloses swith at P3-1 (automated), closes recloser 62 (automated), and opens switch at P-5 (automated),	0
CMI =	9879	

2. Automation fails and operator blindly follows FLISR generated solution

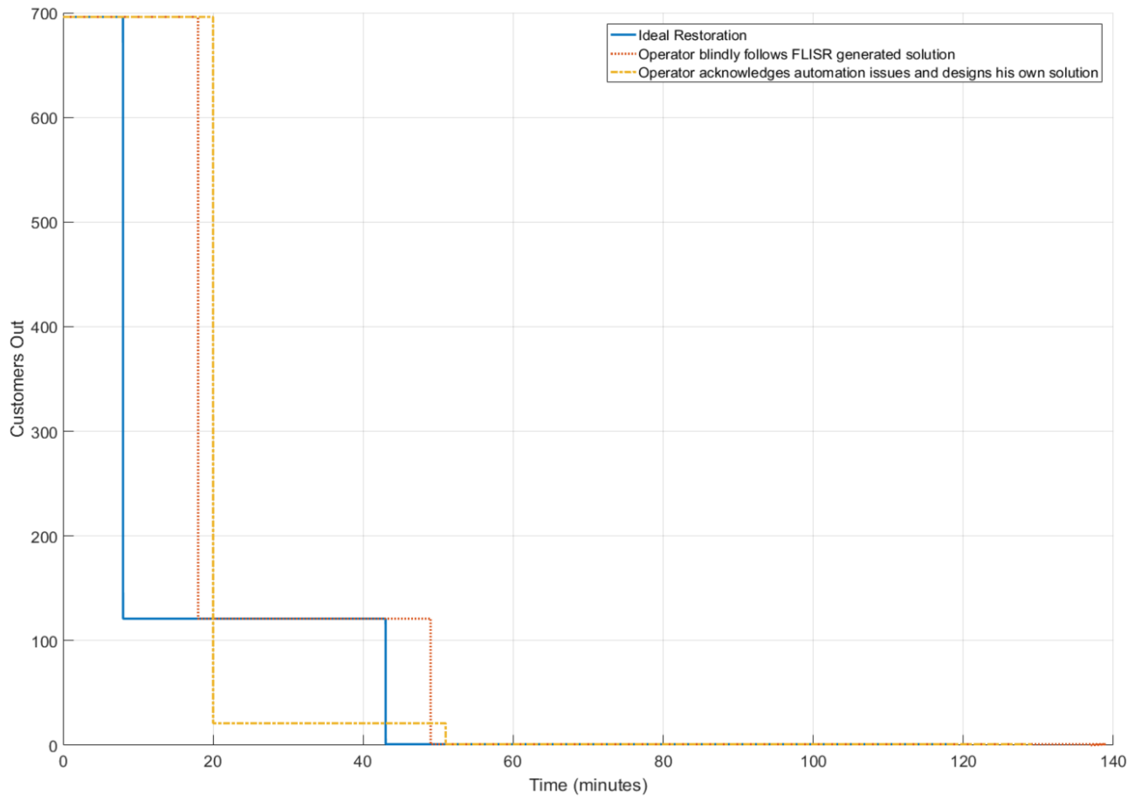
In this case, the operator accepts the FLISR generated solution without hesitation (same steps as in Section 1), but needs to flip switches manually so the restoration process takes longer.

Time	Action	Customers Out
1:05 PM	Outage starts and recloser 62 opens	696
1:11 PM	Fault located somewhere between P-3 and GE plant	696
1:17 PM	Isolate: Operator opens switch at P-4 (non-automated)	696
1:23 PM	Restore: Operator closes switch at P-5 (non-automated)	121
1:42 PM	Fault located between P3-1 and GE plant	121
1:48 PM	Isolate: Operator opens switch at P3-1 (non-automated)	121
1:54 PM	Restore: Operator closes switch at P-4 (non-automated)	1
3:07 PM	Fault is repaired	1
3:22 PM	Operator recloses switch at P3-1 (non-automated), closes recloser 62 (non-automated) and opens switch at P-5 (non-automated)	0
CMI =	16367	

3. Automation fails but operator's skill level is high

In this case, the operator acknowledges he cannot take advantage of automatic switching and therefore does not follow the FLIS- generated solution. Instead, he/she designs his/her own restoration process, with reducing CMI being a priority.

Time	Action	Customers Out
1:05 PM	Outage starts and recloser 62 opens	696
1:11 PM	Fault located somewhere between P-3 and GE plant	696
1:18 PM	Isolate: Operator opens switch at P-4 (non-automated) and opens switch at P-1 (non-automated) in parallel	696
1:25 PM	Restore: Operator closes switch at P-5 (non-automated) and closes recloser 62 (non-automated) in parallel	21
1:42 PM	Fault located between P3-1 and GE plant	21
1:49 PM	Isolate: Operator opens switch at P3-1 (non-automated)	21
1:56 PM	Restore: Operator closes switch at P-1 (non-automated)	1
3:09 PM	Fault is repaired	1
3:14 PM	Operator closes switch at P3-1 (non-automated), closes switch at P-4 (non-automated) and opens switch at P-5 (non-automated) in parallel	0
CMI =	14649	



Example where some automated switches fail. The optimal solution where the automated switches are working is compared to two solutions where all switches must be flipped manually; one where the operator blindly follows the FLISR generated solution and one where the operator designs his own solution.

Figure 14. In this model, the operator outperforms the FLISR-generated solution.

3.5.5.2. Example 2 – Waiting to implement strategy

In this example, we assume a bad storm has created multiple faults. We outline the recovery times for two cases: 1) the operator readily accepts the FLISR generated solution; or 2) the operator acknowledges the storm is bad and waits to begin the recovery process until he has more information about both faults. A review of the literature suggests that FLISR solutions cannot handle multiple faults at once but deal sequentially with each fault. [26, 27]

We therefore explore two options: one, where the operator addresses the first fault, restoring power using the FLISR-generated solution, and then addresses the second fault using the FLISR-generated solution for that fault but without any coordination or overlap between the two events. In this example, the FLISR solution has devastating consequences because it reroutes power for the first fault onto the line where the second fault occurs. In the second case, however, the operator waits for the storm to subside before starting the recovery process and enacts a very different restoration strategy. This example demonstrates that when critical thinking skills are important, such as recognizing the storm was severe and waiting to implement grid restoration, an operator can outperform FLISR. This example also demonstrates that in almost every circumstance, it behooves an operator to consider the broader picture before blindly accepting a FLISR solution.

1. Operator does not wait

In this case, the operator quickly accepts the FLISR solution for the first fault and when the rerouting is completed, he quickly accepts the FLISR solution for the second fault. Again, we assume a constant repair time of 73 minutes for the first fault and but reduce that time to 60 minutes for the second fault because the field crew is already dispatched.

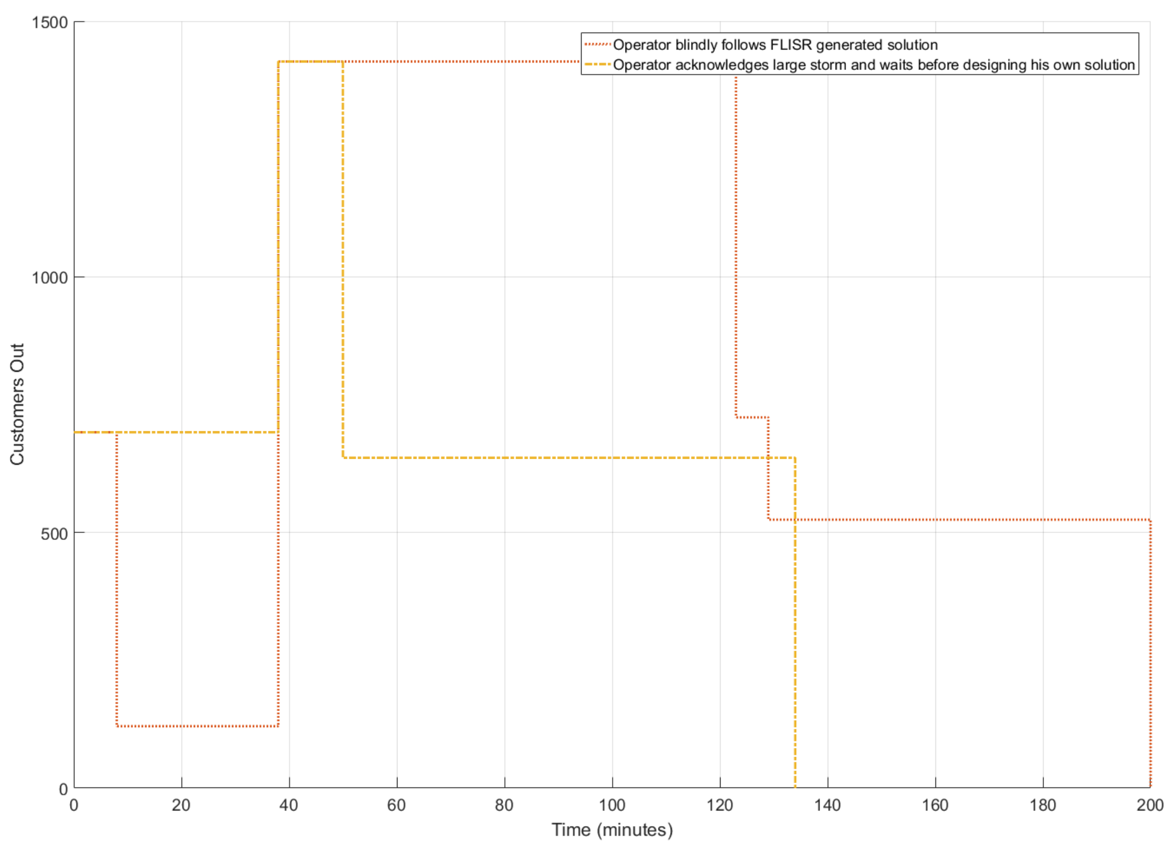
Time	Action	Customers Out
1:05 PM	Outage starts and recloser 62 opens	696
1:11 PM	Fault located somewhere between P-3 and GE plant	696
1:12 PM	Isolate: Operator opens switch at P-4 (automated)	696
1:13 PM	Restore: Operator closes switch at P-5 (automated)	121
1:42 PM	Fault located between P3-1 and GE plant	121
1:43 PM	Second outage and recloser 49 opens	1421
1:44 PM	Second fault located at P-16	
1:47 PM	Isolate: Operator opens switch at P3-1 (not automated)	1421
1:48 PM	Restore: Operator closes switch at P-4 (automated)	1421
3:01 PM	Fault is repaired	1421
3:08 PM	Operator recloses swith at P3-1 (non-automated), closes recloser 62 (automated), and opens switch at P-5 (automated)	725
3:13 PM	Isolate: Operator opens switch at P-10 (non-automated)	725
3:14 PM	Restore: Operator closes switch at P-1 (non-automated)	525
4:14 PM	Fault is repaired	525
4:25 PM	Operator recloses swith at P-10 (non-automated), closes recloser 49 (automated), and opens switch at P-1 (non-automated)	0
CMI =	167345	

2. Operator waits

In this case, the operator observes the storm is strong and, based on experience, anticipates multiple faults. He therefore decides to wait until the storm has passed, which takes 40 minutes. Able to dispatch two crews, he can manage the two outages in parallel because they are on different feeders.

Time	Action	Customers Out
1:05 PM	Outage starts and recloser 62 opens	696
1:11 PM	Fault located somewhere between P-3 and GE plant	696
1:42 PM	Fault located between P3-1 and GE plant	696
1:43 PM	Second outage and recloser 49 opens	1421
1:44 PM	Second fault located at P-16	1421
1:45 PM	Done waiting out storm	1421
1:50 PM	Isolate: Operator opens switch at P3-1 (not automated) and P-10 (non-automated) in parallel	1421
1:55 PM	Restore: Operator closes switch at P-2 (non-automated) and P-1 (non-automated) in parallel	646
3:08 PM	Fault is repaired	646
3:19 PM	Operator recloses swith at P3-1 (non-automated), closes recloser 62 (automated), opens switch at P-2 (non-automated) and then in parallel recloses swith at P-10 (non-automated), closes recloser 49 (automated), and opens switch at P-1 (non-automated)	0
CMI =	97764	

Overall, the goal of designing this game-theoretic model was to study the interactions between operators of the power grid and automation and to help pinpoint when automation helps and when it hinders grid restoration. Automation is fairly new in the recovery process of the power grid, and little work has been done to study how automation should be integrated into the current recovery process. This work does not provide an analytical solution but the model demonstrates the outcomes that can be expected from the examples we provided. The model also lends itself to a Monte Carlo approach, where based on some probability distribution, we could select switches to flip for the recovery process. By running these simulations many times, we can quantify the average CMI for a given set of fault characteristics or calculate an upper bound for the CMI, information that provides a useful context and set of parameters for operators to consider when making restoration decisions.



Example where a severe storm causes multiple faults. Two solutions are compared; one where the operator blindly follows the FLISR generated solution (eventhough FLISR cannot deal with multiple faults) and one where the operator waits until the storm has passed and then designs his own solution.

Figure 15. Differences between an operator who waits and one who accepts FLISR. The operator who waits before implementing a restoration plan still outperforms the FLISR solution because the latter requires sequential restoration whereas the operator can, in theory, restore multiple outages in parallel.

4. CONCLUSIONS

1. Our analysis of GMP's historic data suggest that both level of operator expertise and and the state of the grid are indicators of whether automation is a benefit or a detriment to grid restoration. Experts consistently improve when you give them automation; novices improve but only during non-peak activity periods. During peak periods, their performance goes down.

2. Our experimental work indicates there are predictive patterns in the interplay between human operators and automation, namely that operator-machine interactions become less predictable as outage complexity increases and that under stressful conditions, i.e., complex, unplanned and unpredictable outages, the human operating in manual mode always outperforms the automation.

3. Our experimental work, admittedly based on a small sample size, also indicates that operators' level of expertise, which determines autonomy in the control room, is inversely correlated with performance when automation is present. The more senior/expert operators appear to be more distrustful of automation and therefore slower to restore the grid.

4. Our experiment also suggests the rollout of automated switching, that will profoundly affect how the operator interacts with the grid, but more work needs to be done to understand the opportunities and vulnerabilities in this space.

5. Our game-theoretic modeling can benefit utilities by allowing operators to practice and investigate different ways for working with automation in a simulated environment.

6. Our methodology for measuring automation reveals key patterns in operator-automation interactions that can inform resource optimization.

6. Overall, our research brings a predictive element to grid operations, enabling utilities to match automation to the state of the grid, and/or level of operator that in turn suggests improved system control and resilience.

Moreover, although our research is still in the nascent stage, we now have an effective —and extensible—platform for expanding our research on the operator-automation interface and collecting more data on such important topics as situational awareness, decision-making, expertise, proficiency, trust, etc. Our methodology also allows us to investigate a broad range of other challenges facing the grid-operator interface, including cyber intrusion, extreme weather, blue-sky events and the rapid increase in intermittent renewables.

We are also confident that our research has myriad practical applications, examples of which are listed here:

- Offers a way to look at grid behavior as a function of operator behavior, which can lead to better system planning and improved grid performance metrics
- Provides a scientific basis for operator training, which is needed to reduce vulnerabilities and maintain/increase operator performance
- Supports the development of more effective human-machine interfaces and real-time decision-support tools

- Provides data to justify a utility's investment in automation and support the roll-out of distribution automation [28]
- Can inform, and be integrated with, other grid resilience efforts

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APPENDIX

Analysis of Historical GMP Outage Data

Kate Cauthen, 6132

9/7/16

Background

The goal of this analysis is to determine which factors contribute to customer hours out (CHO) during a power outage. Each observation in this dataset is one outage event that occurred somewhere in the portion of the electrical grid owned and operated by Green Mountain Power in Vermont. For each observation there is information about the time and date of the outage, the cause of the outage according to the operator, where the outage occurred (which feeder), whether it occurred during a major storm, whether the affected feeder was automated, and the level of expertise of the operators. This analysis seeks to determine how each of these factors affects CHO in conjunction with one another. To do so, two analyses are performed:

1) descriptive statistics are computed to identify which specific sets of conditions are observed to result in the greatest CHO on average, and
2) a statistical model is fit to determine how factors interact with one another to affect CHO on average, in a more general sense.

Methods

Factors and Data

Data were collected on 14,776 outages between August 1st, 2014 and October 19th, 2015. The time and date information were used to calculate time of day, day of week, and season. Time of day is a binary factor where 0 = peak hours (9:00 AM – 8:00 PM) and 1 = off-peak hours. Day of week is a binary factor where 0 = weekday (Monday – Friday) and 1 = weekend. Season is divided into three categories: 0 = winter (December - February), 1 = summer (June - August), and 2 = off-season. The operators coded the cause of the outage event as one of 55 categories. These were binned into more general causes. The resulting bins are shown in Table 1 along with frequency and percent of total outages. The operators also flagged outage events that occurred during a major storm, resulting in a binary factor where 0 = no major storm and 1 = major storm. Feeders were identified that have an automation component, and outages occurring on these feeders were considered 1 = Automated, and outages on all other feeders were considered 0 = Not Automated. Unfortunately it is unknown whether or not the automation feature was implemented on a given feeder during an outage event. Feeders were also categorized as being either 0 = urban or 1 = rural, based upon location of the feeder with respect to cities in Vermont. In general, feeders within the city of Rutland were considered urban, and all others were considered rural. Appendix A shows the automation and urban/rural designations for each feeder ID.

Finally, Sandia obtained the operator schedule for the year of 2015 (starting January 11th, 2015) as well as designations of "expert" versus "non-expert" for each operator. A level of expertise was assigned to each outage event observed during this time frame. An outage event could either have 0 = no coverage by an expert (no experts on shift for any part of outage), 1 = partial expert coverage (at least one expert for some but not all of the outage event), 2 = full expert coverage (at least one expert on shift for entire duration of outage), or NA for outage events that took place before January 11th, 2015.

Table 1. Frequency Table for Cause

Cause	Frequency	Percent of Total
Unexpected Grounding	**2731**	**18.48**
ANIMAL - RACCOON	14	0.094748
ANIMAL - BIRD	201	1.360314
ANIMAL - SQUIRREL WITH GUARD	919	6.219545
ANIMAL - SQUIRREL WITHOUT GUARD	391	2.646183
ANIMAL - OTHER	37	0.250406
EQUIP - Surge/Lightning Arrester	57	0.385761
EQUIP - Cutout	394	2.666486
EQUIP - Capacitor	1	0.006768
EQUIP - Regulators	8	0.054142
EQUIP - Line Recloser/Breakers	21	0.142122
EQUIP - Transformers - Broken Bushing	14	0.094748
EQUIP - Insulator	93	0.629399
EQUIP - Services and Serv Drops (Inc. Secondary)	199	1.346779
EQUIP - URD Secondary Cable (Only GMP Owned)	49	0.331619
EQUIP - URD Primary Cable	51	0.345154
ACCDNT - Car	239	1.617488
EQUIP - URD Failure Misc.	43	0.291012
Unexpected Line Open	**1742**	**11.79**
ACCDNT - Logger Landowner Tree	82	0.554954
ANIMAL - BEAVERS DROPPING TREES ONTO LINES	8	0.054142
ERROR - Tree Trimmer	9	0.06091
TREE - Other - Out ROW	179	1.211424
TREE - Other - In ROW	740	5.008121
TREE - Other - Limb	552	3.735788
Planned Outage	167	1.130211
ACCDNT - Muni Request	5	0.033839
Line Open Failure	**262**	**1.77**
EQUIP - Wire Splices Primary Compression or Automatic	37	0.250406
EQUIP - Compression Type Connector	83	0.561722

EQUIP - Bolt Type Connector	67	0.453438
EQUIP - Wire Break (Primary Only and not Trees)	75	0.50758
Preventable Foreseeable	**7635**	**51.67**
EQUIP - Transformers - Overload	69	0.466973
EQUIP - Transformers - Improper or No Voltage	52	0.351922
EQUIP - Transformers - Leaking Transformer	4	0.027071
EQUIP - MTC (Midpoint Terminating Cabinet)	6	0.040606
WEATHER - Flooding	6	0.040606
WEATHER - Lightning	488	3.302653
WEATHER - Snow Load/Wire Slap	1050	7.106118
WEATHER - Other	131	0.886573
TREE Snow/Ice - Out ROW	996	6.740661
TREE Snow/Ice - In ROW	1157	7.830265
TREE Wind - In ROW	2224	15.05143
TREE Wind - Out ROW	1341	9.075528
ACCDNT - Fire	78	0.527883
GMP - Planned Non Emergency	33	0.223335
Error	**46**	**0.31**
ERROR - Field Worker	1	0.006768
GMP - Emergency	45	0.304548
Supplier	**67**	**0.45**
SUPPLIER - National Grid	30	0.203032
SUPPLIER - Other	37	0.250406
Other	**2293**	**15.52**
OTHER	15	0.101516
Unknown	1373	9.292095
EQUIP - Transformers - Misc.	350	2.368706
EQUIP - Other	305	2.064158
GMP - Other	113	0.764754
ACCDNT - Other	106	0.71738
ERROR - Other	26	0.175961
(*blank*)	5	0.033839

Statistical Approach

Descriptive Statistics

A factor is a variable that is discrete and typically has non-numeric values. Each factor has at least two possible values, which are called levels. For example, the Time of Day factor has two levels: peak and off-peak. Treatments are combinations of levels of all factors. For example, one treatment in this data set would be: cause = LineOpenFailure, Time of Day = peak, Day of Week = Weekday, Season = Winter, Urban/Rural = Rural, Automation = Not-Automated, Major Storm

= No, and Expertise = Partial. In order to determine which sets of specific conditions contribute to the largest values of CHO on average, we calculated descriptive statistics on treatments. All treatments were identified, and the average CHO was calculated for all observations in each treatment. The treatments were ordered by mean CHO in order to identify those conditions under which CHO is observed to be highest, on average.

ANOVA Model

The purpose of the statistical model is to identify statistically significant factors (categorical) that are associated with the response of interest, CHO (continuous). Typically, an ANOVA would be the most appropriate data analysis method, however, in this case a standard ANOVA model could not be used. An ANOVA compares the means of groups defined by various factors to one another. The ANOVA model requires various assumptions to be met in order for the statistical tests regarding the mean comparisons to be valid. Perhaps the most important of these assumptions, homogeneity of variance, was not met. Many response variable transformations were attempted to remedy the heterogeneity of variance, including an optimized power transformation, but none were successful.

Instead, other non-parametric approaches were explored in order to circumvent the problem of heterogeneity of variance. The Aligned Rank Transform (ART) was ultimately selected since it is non-parametric, is able to model multiple factors simultaneously, and can include interaction terms (Wobbrock et al, 2011). There are two main steps to calculating the ART. The first step in the ART procedure is to align the response for each effect (main and interaction). This alignment step works by estimating marginal means and removing their effects on the response for all but one (the one for which the response is aligned). The second step in the ART procedure is to rank the responses for each aligned version of the data. This concludes the ART procedure, and we are left with an aligned, ranked version of CHO for each effect (main and interaction).

Next, an ANOVA was performed on the ART data. When using the ART data in an ANOVA, all effects (main and interaction) should be included in the model, but only the hypothesis test that corresponds to the effect for which the response is aligned is accurate. This means that to fit a model with multiple effects, the model must be fit once for each effect (but including all effects in the model), where the response is CHO aligned and ranked for the given effect. If variable selection is desired, then the highest order effect with the greatest p-value is removed and all models are refit. This process is repeated until only statistically significant effects remain.

In the case of this dataset, the design is not fully factorial. That is, not all combinations of factor levels occur in the dataset. As a result, the packages that are currently available in R for ART could not be used. Thus we implemented ART and used it to accommodate the complex outage data. The ART procedure described in Wobbrock et al. was followed for these calculations, and the code was implemented in R.

Only two-way and three-way interactions were considered in the model. Conceivably, since there are eight factors an eight-way interaction is possible. However, very high order interactions are increasingly difficult to interpret, so we limited our scope to three-way interactions. Furthermore, since there are not observations for all possible three-way interactions, only those interactions for which there are data were included in the model. This resulted in 18 possible three-way interactions. A three-way interaction has three two-way interactions associated with it that it accounts for. For our analysis, we also included the two two-way interactions that were not associated with one of the 18 three-way interactions.

Although the ART procedure allows for the fitting of a multi-factor model with interaction terms and accurate hypothesis tests regarding these terms, one limitation is that post hoc comparisons cannot be made for interaction effects. Instead, we give interaction plots and describe the patterns observed. Unfortunately, we are not able to test these relationships statistically.

Results

Exploratory Data Analysis

Table 2 shows the range, mean, and standard deviation for three response variables: customers affected, duration of outage (in hours), and CHO. Additionally, Figures 1-8 that follow plot the densities of the eight factors for all three response variables. Although the analysis focuses on CHO, this summary table and the figures may serve as references to distinguish between outage events with higher CHO caused by greater number of customers as opposed to those caused by a longer duration.

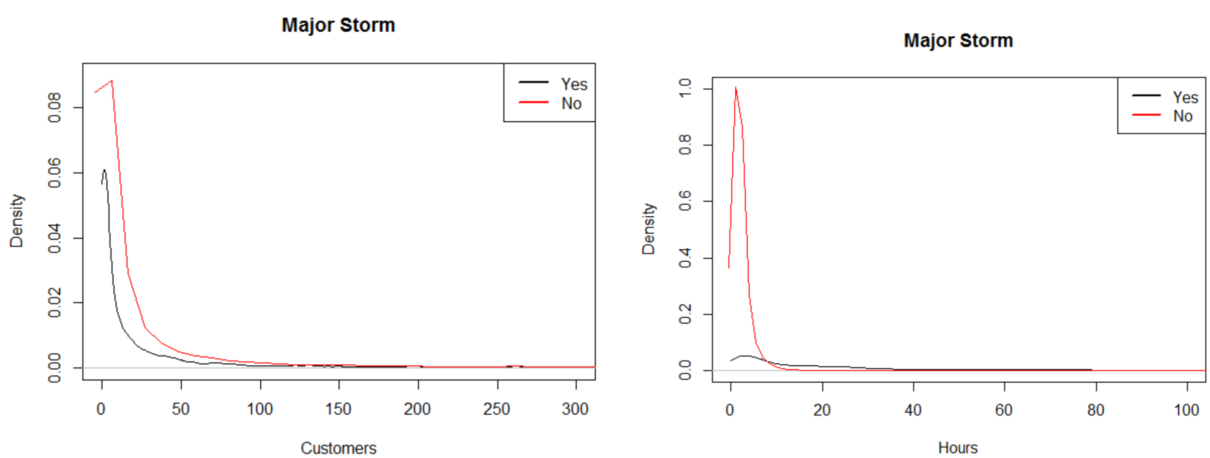
Table 2. Descriptive statistics for response variables, broken down by factor

Predictor		Output	Range	Mean	Standard Deviation
Major Storm	Yes	Hours	0.0908 - 139.7	18.41	21.74
		Customers	0 - 1,949	46.28	157.44
		CHO	0 - 71,790	672.8	3,008.97
	No	Hours	0.0844 - 739.9	2.411	11.78
		Customers	0 - 5,428	45.62	186.3
		CHO	0 - 29,520	97.14	553.2
Cause	Unexpected Grounding	Hours	0.124 - 22.86	1.727	1.4
		Customers	0 - 2,102	27	143.49
		CHO	0 - 9,663	53.33	395.53
	Unexpected Line Open	Hours	0.0864 - 739.9	6.27	41.77
		Customers	0 - 3,407	62.67	228.96
		CHO	0 - 29,520	174.5	1,181.48
	Line Open Failure	Hours	0.0878 - 5.974	1.835	1.32
		Customers	0 - 1,790	134.2	361
		CHO	0 - 1,671	158.9	373.16
	Preventable Foreseeable	Hours	0.0869 - 133.2	7.911	15.27
		Customers	0 - 5,428	52.19	196.31
		CHO	0 - 71,790	312.2	1,911.26
	Error	Hours	0.119 - 11.38	1.525	1.89
		Customers	0 - 1,703	264.6	430
		CHO	0 - 1,038	186.4	263.21
	Supplier	Hours	0.0847 -	3.805	5.05

			31.37		
		Customers	0 - 2,641	383.7	519.49
		CHO	0 - 4,872	778.1	1,040.59
	Other	Hours	0.0844 - 139.7	4.482	10.07
		Customers	0 - 2,640	34.8	140.45
		CHO	0 - 63,300	158.6	1,130.28
Time of Day	Peak	Hours	0.0844 - 739.9	5.705	17.77
		Customers	0 - 3,723	43.96	180
		CHO	0 - 71,790	209.4	1,451.35
	Off-peak	Hours	0.0864 - 133.2	5.875	12.38
		Customers	0 - 5,428	48.51	181.54
		CHO	0 - 66,630	231.4	1,529.64
Season	Summer	Hours	0.0878 - 34.11	2.209	2.07
		Customers	0 - 3,407	46.04	192.91
		CHO	0 - 17,920	106.5	603.93
	Winter	Hours	0.0908 - 139.7	13.83	19.83
		Customers	0 - 2,640	48.3	173.58
		CHO	0 - 71,790	516.3	2,571.81
	Off	Hours	0.0844 - 739.9	2.393	13.98
		Customers	0 - 5,428	44.27	180.67
		CHO	0 - 29,520	87.01	491.76
Day of Week	Weekday	Hours	0.084 - 671	6.399	16.38
		Customers	0 - 5,428	47.15	184.79
		CHO	0 - 71,790	249.5	1,660.03
	Weekend	Hours	0.0878 - 739.9	3.639	13.73
		Customers	0 - 3,407	41.02	165.54
		CHO	0 - 17,920	111.1	535.81
Automation	Auto	Hours	0.162 - 77.95	3.542	8
		Customers	0 - 1,217	36.61	144.83
		CHO	0 - 1,787	75.03	232.26
	Not-Auto	Hours	0.0844 - 739.9	5.826	15.99
		Customers	0 - 5,428	45.98	181.38
		CHO	0 - 71,790	221.5	1,499.86

Urban/Rural	Urban	Hours	0.0878 - 739.9	7.086	33.24
		Customers	0 - 1,232	37.3	111.57
		CHO	0 - 8,217	147.3	563.88
	Rural	Hours	0.0844 - 671	5.722	14.79
		Customers	0 - 5,428	46.08	182.74
		CHO	0 - 71,790	220.8	1,506.91
Expertise	None	Hours	0.099 - 9.387	1.677	1.08
		Customers	0 - 3,407	53.33	217.2
		CHO	0 - 5,063	90.76	398.66
	Partial	Hours	0.211 - 739.9	5.169	33.15
		Customers	0 - 2,641	42.87	172.71
		CHO	0 - 17,920	155.6	765.22
	Full	Hours	0.084 - 10.81	1.835	1.32
		Customers	0 - 5,428	47.51	202.82
		CHO	0 - 8,052	75.68	355.8
	NA	Hours	0.0908 - 139.7	9.279	16.66
		Customers	0 - 2,498	44.08	158.46
		CHO	0 - 71,790	350.1	2,059.84

Figure 1. Density of customers, hours, and CHO for levels of Major Storm



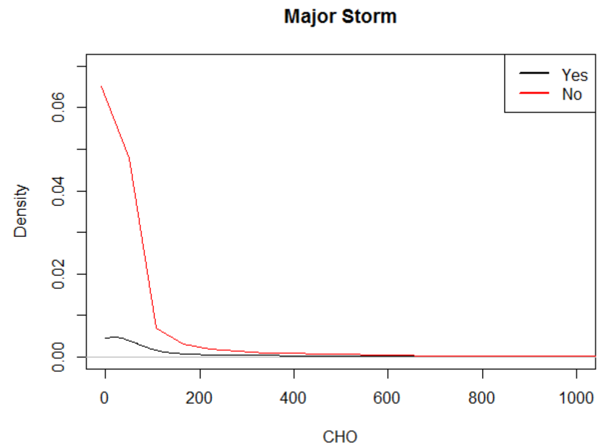


Figure 2. Density of customers, hours, and CHO for levels of Cause

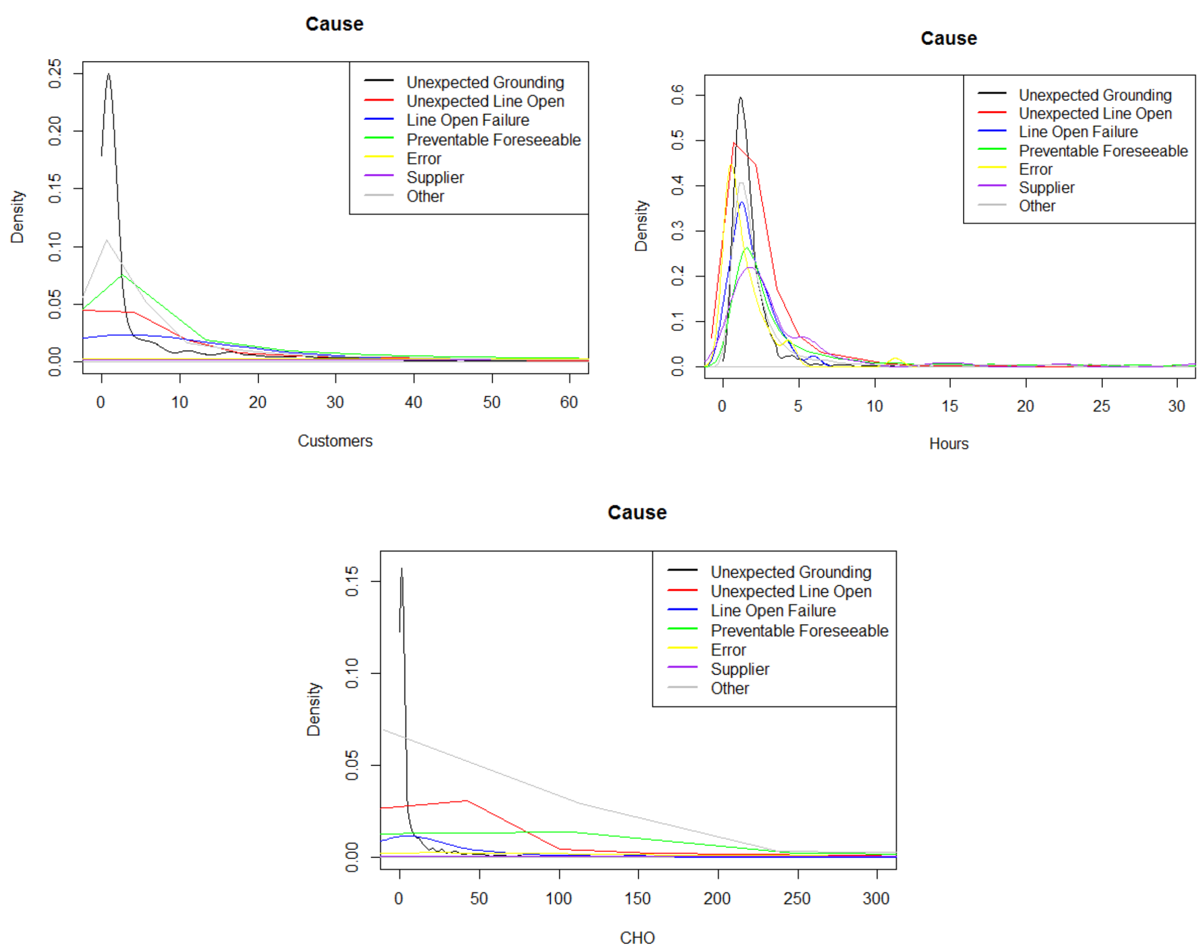


Figure 3. Density of customers, hours, and CHO for levels of Time of Day

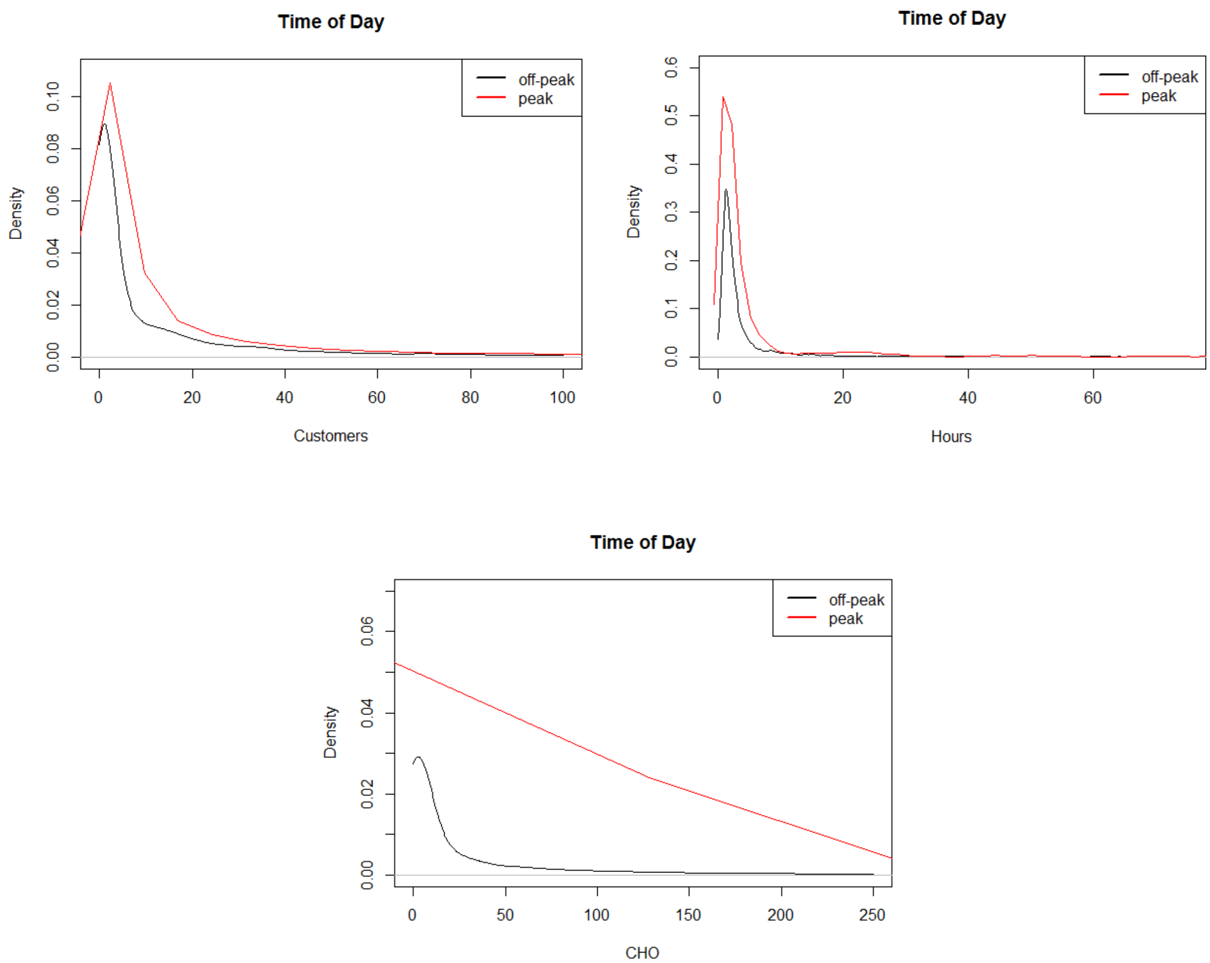


Figure 4. Density of customers, hours, and CHO for levels of Season

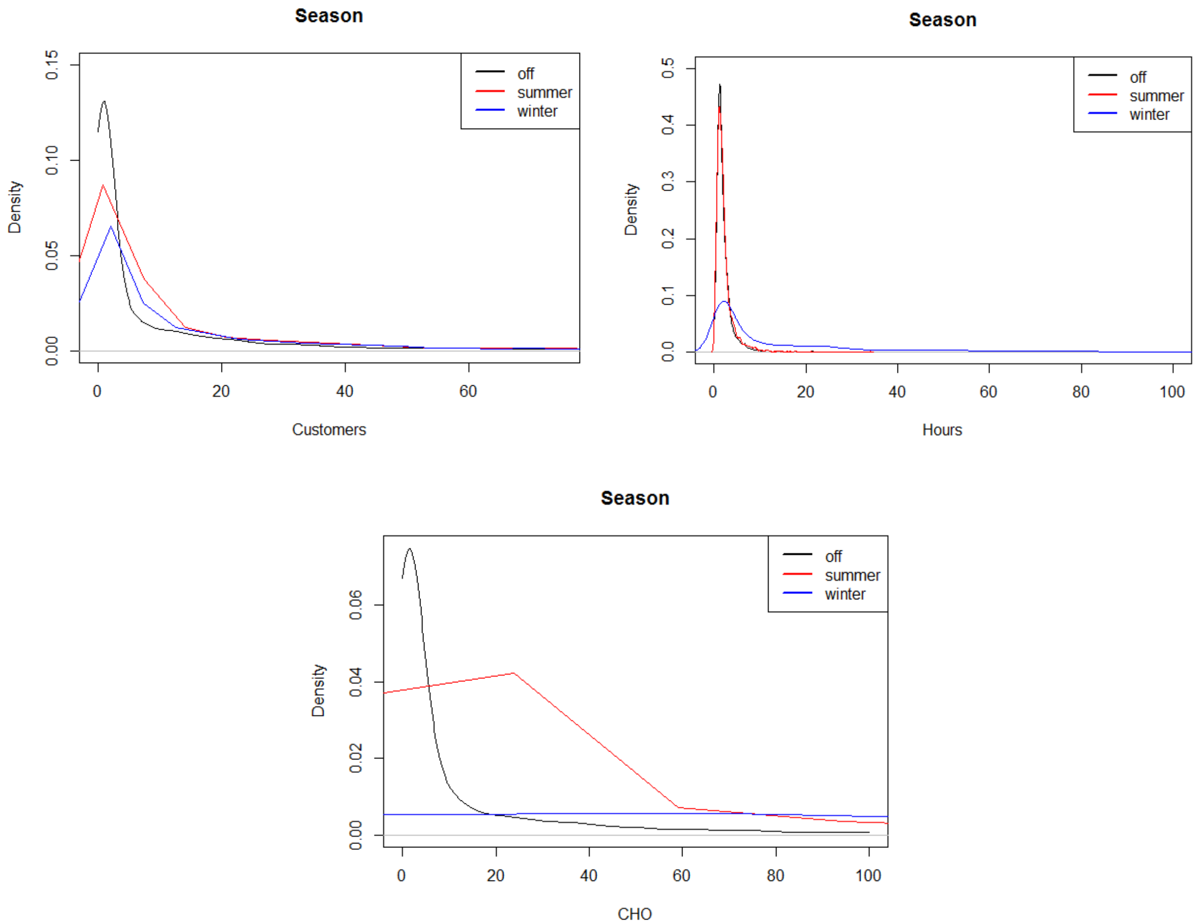


Figure 5. Density of customers, hours, and CHO for levels of Day of Week

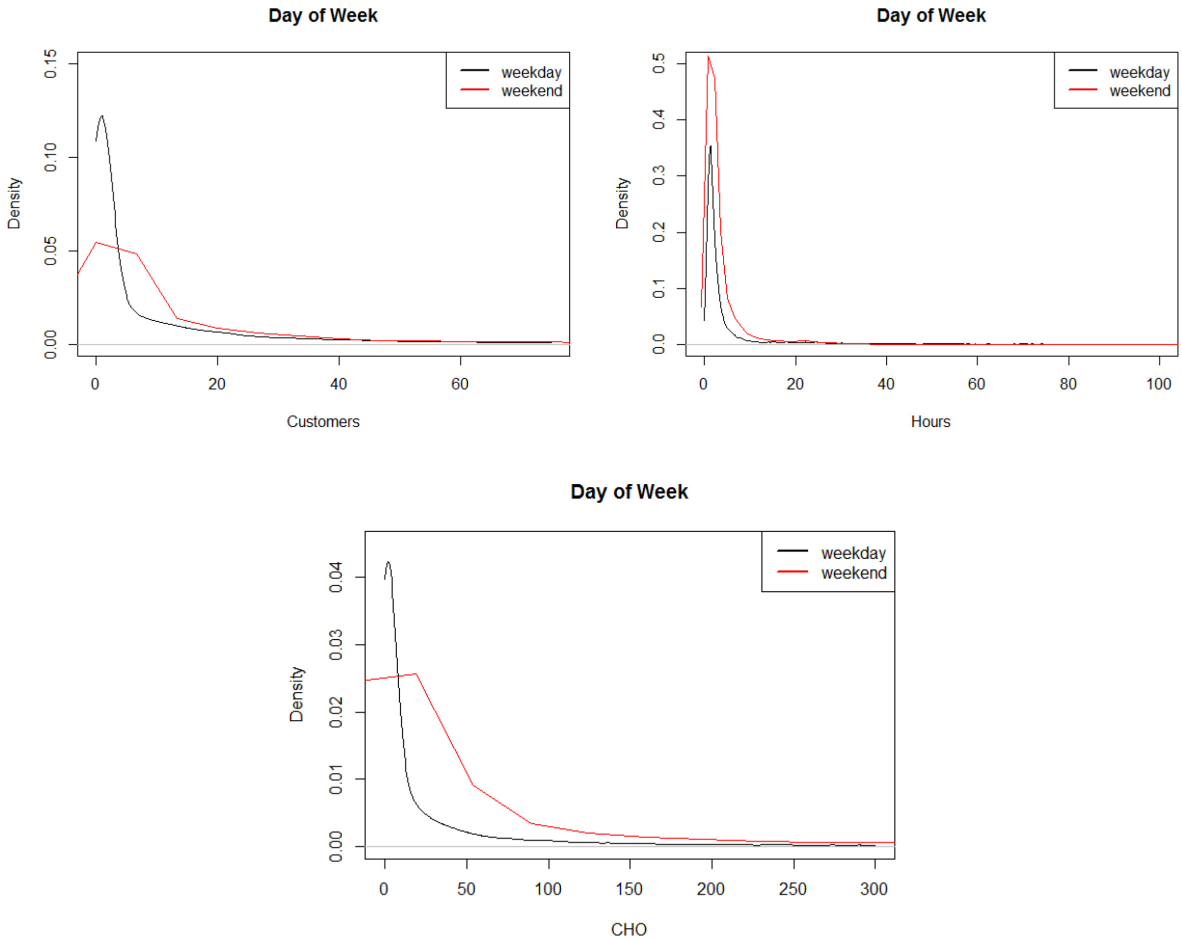


Figure 6. Density of customers, hours, and CHO for levels of Automation

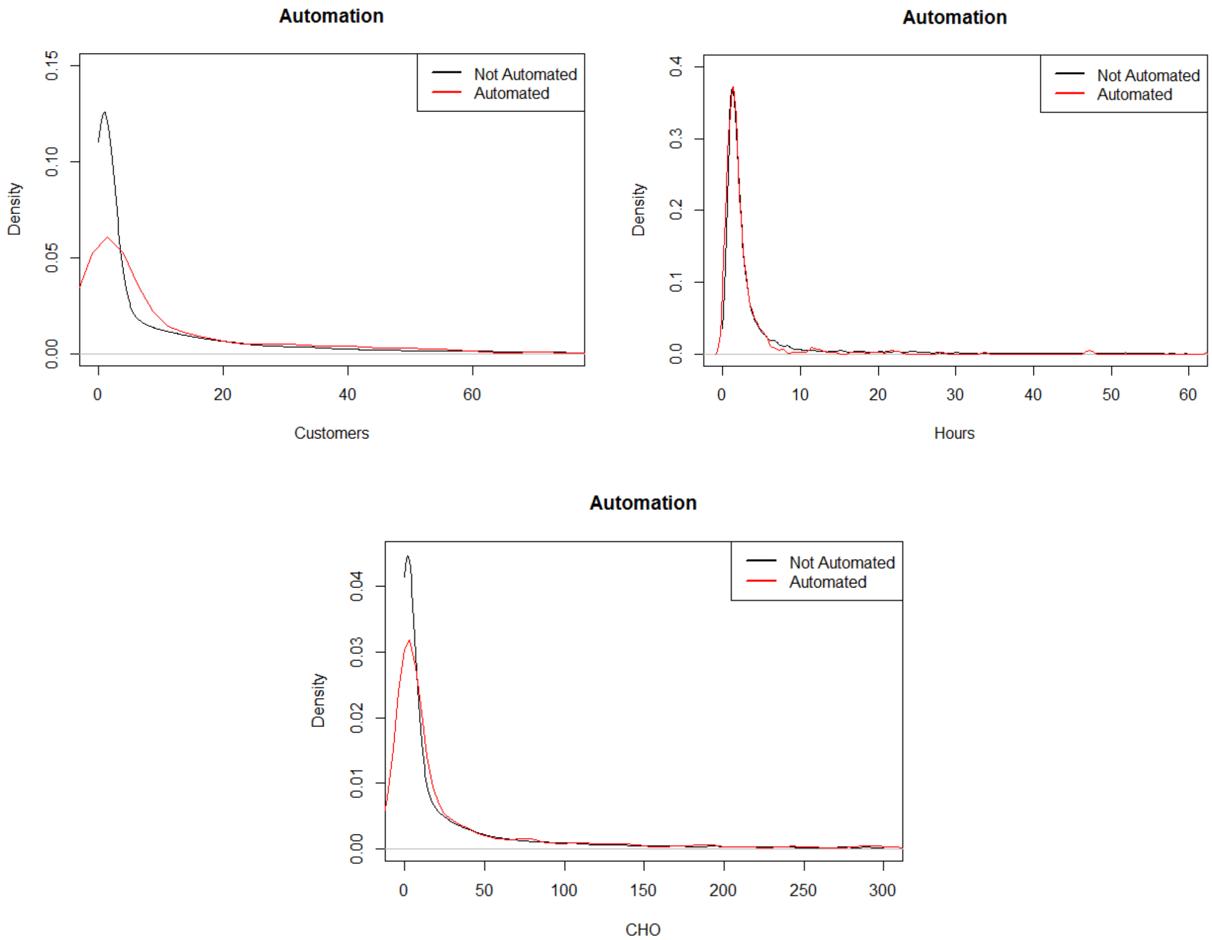
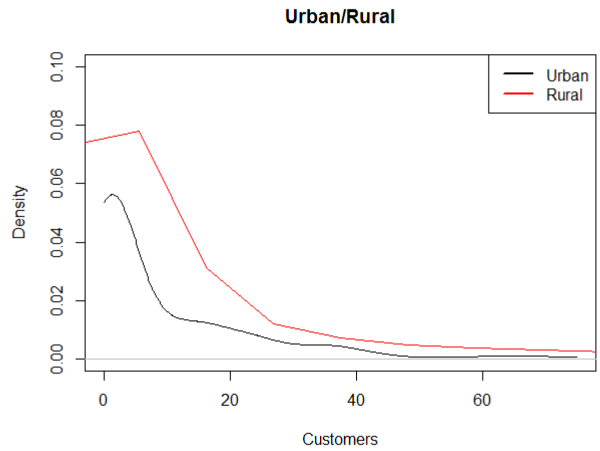
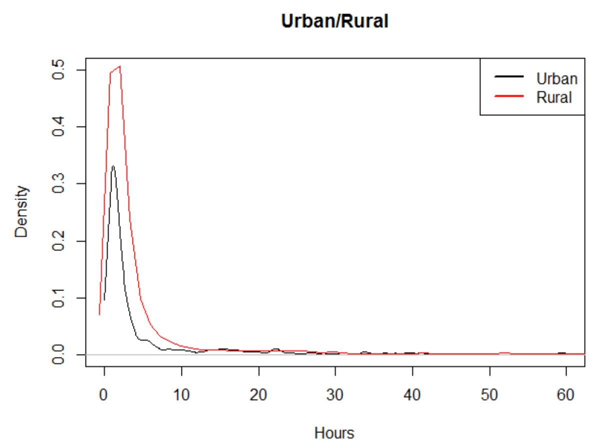


Figure 7. Density of customers, hours, and CHO for levels of Urban/Rural


Urban/Rural
Urban
Rural
Density
0.00
0.02
0.04
0.06
0.08
0.10
0
20
40
60
Customers


Urban/Rural
Urban
Rural
Density
0.0
0.1
0.2
0.3
0.4
0.5
0
10
20
30
40
50
60
Hours

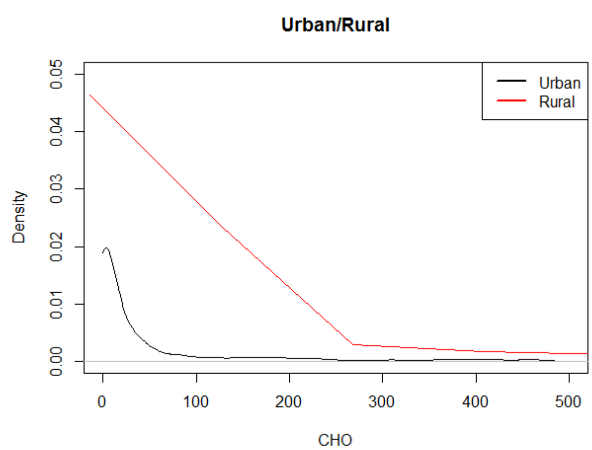
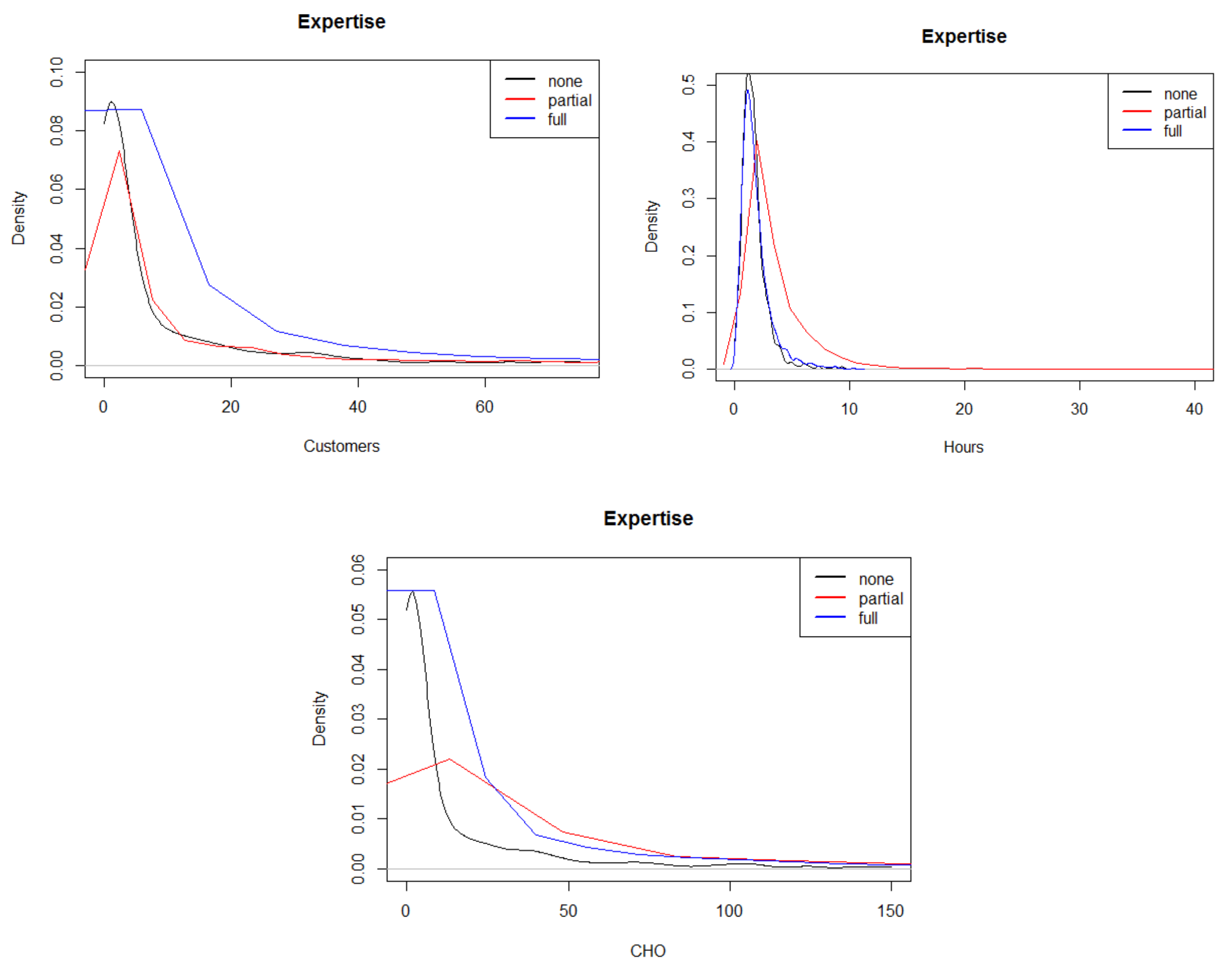

Urban/Rural
Urban
Rural
Density
0.00
0.01
0.02
0.03
0.04
0.05
0
100
200
300
400
500
CHO

Figure 8. Density of customers, hours, and CHO for levels of Expertise



When performing an ANOVA, including an ANOVA on ART data, the purpose is to determine if there is a statistically significant difference between group means. A boxplot can be useful in approximating whether or not there is a difference between group means. Figures 9-16 are boxplots of CHO for each factor. In each figure, the first subfigure includes all data points, and the second subfigure is zoomed in to see the group medians more clearly. The horizontal black line in each box represents the median, and the lower and upper limits of the box represent the 25th and 75th percentiles of the data. The problem of heterogeneity of variance is made obvious by observing the percentiles. For a given figure, boxes that have a large difference in height indicate heterogeneity of variance.

Figure 9. Boxplot of CHO for levels of Major Storm

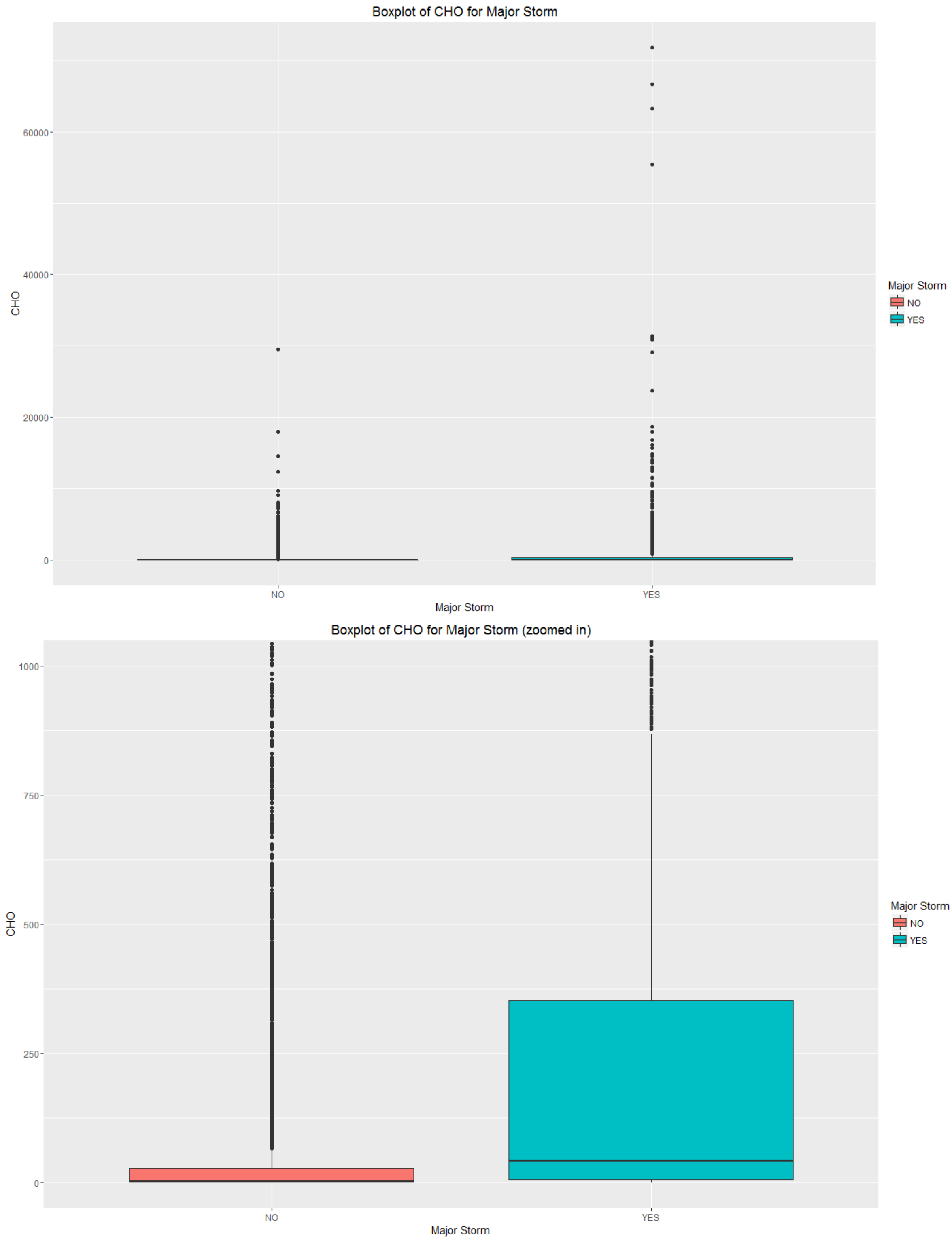


Figure 10. Boxplot of CHO for levels of Cause

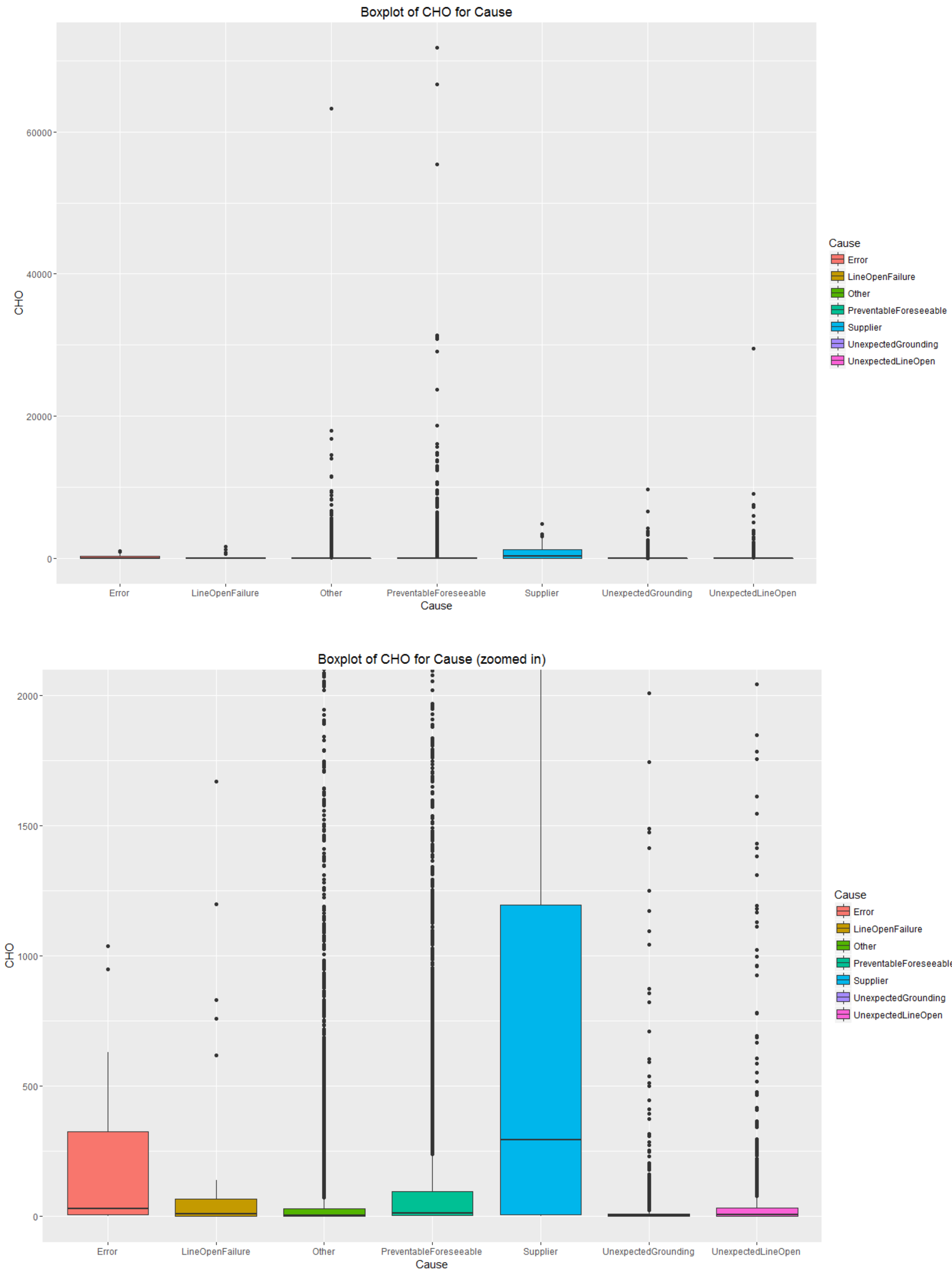


Figure 11. Boxplot of CHO for levels of Time of Day

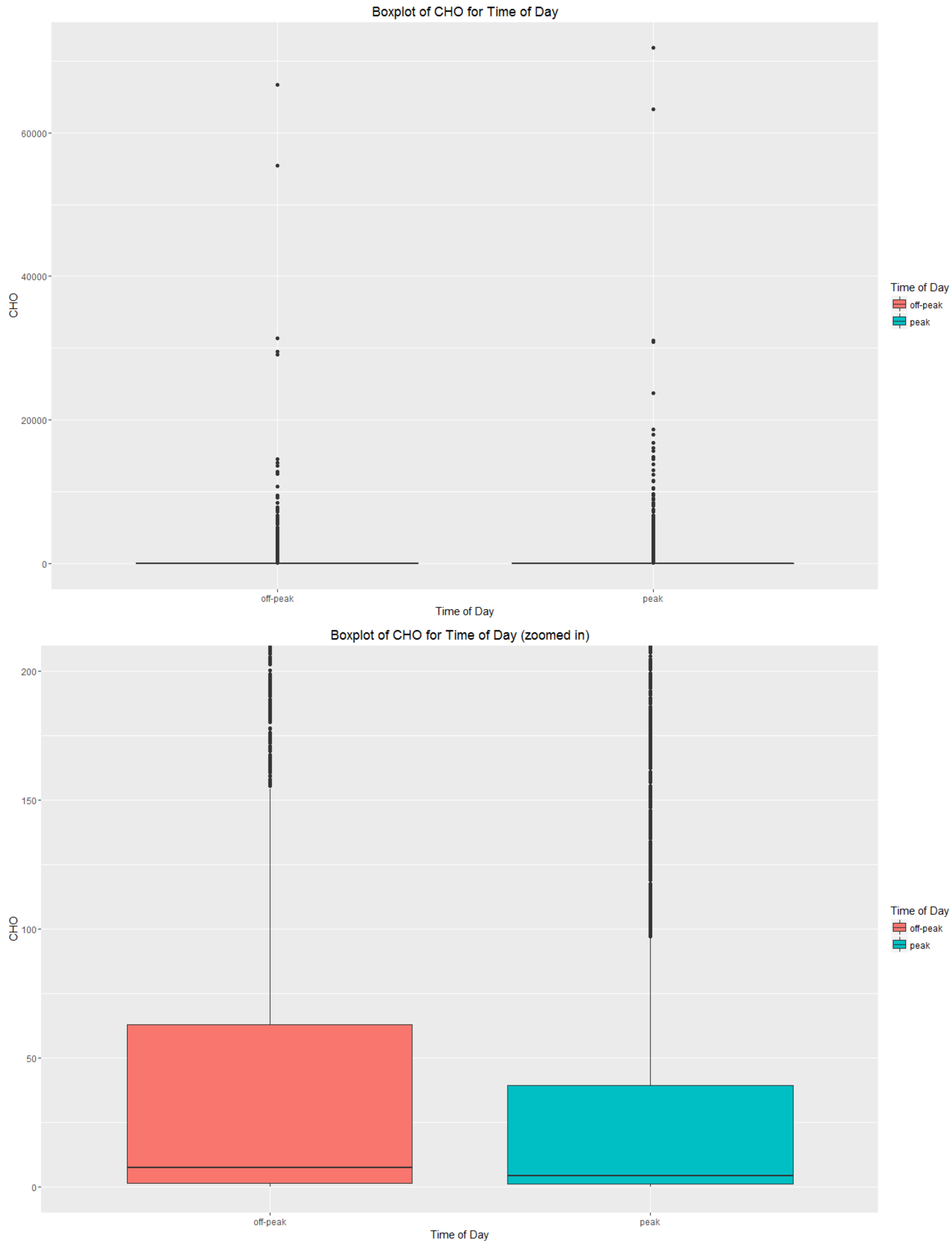


Figure 12. Boxplot of CHO for levels of Season

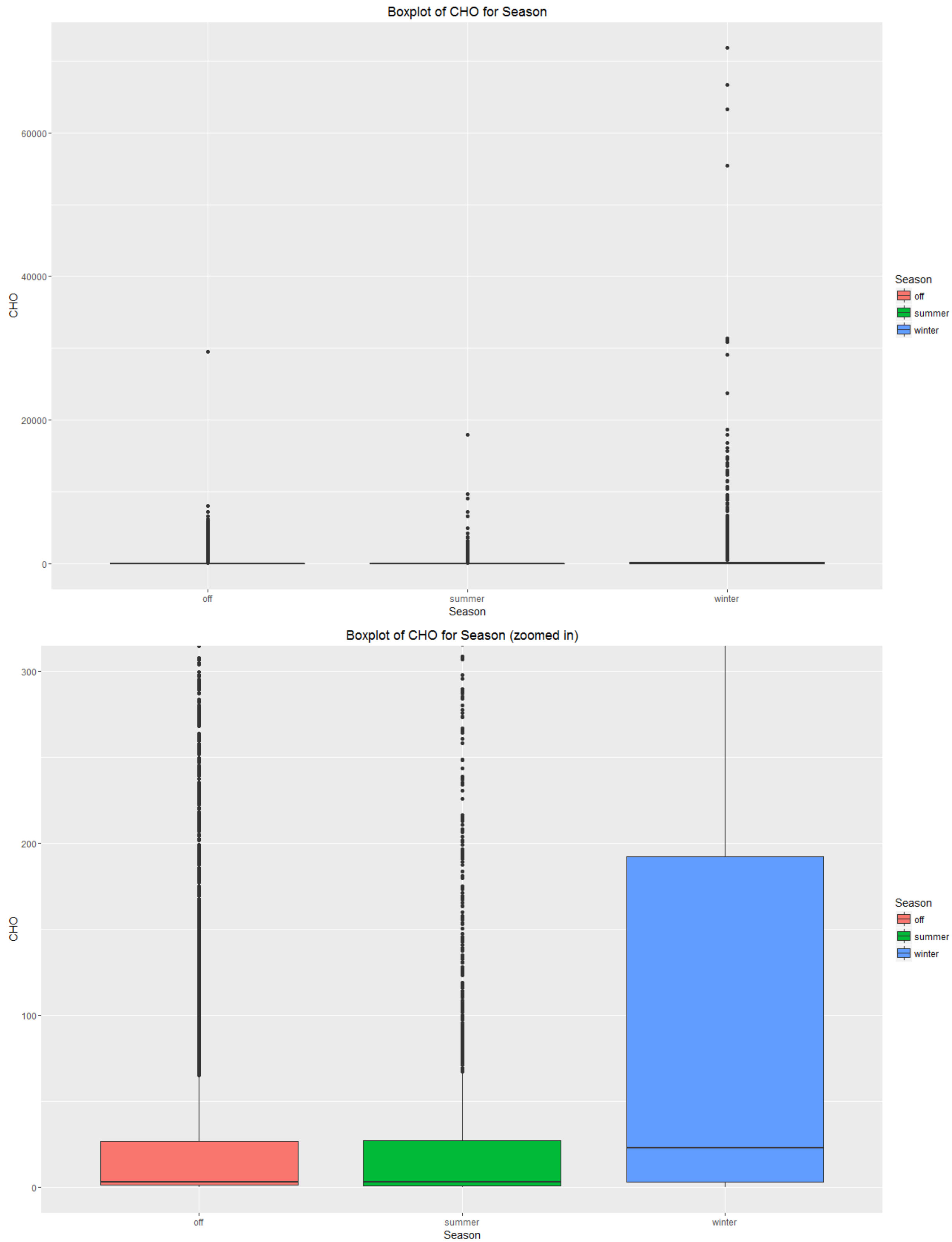


Figure 13. Boxplot of CHO for levels of Day of Week

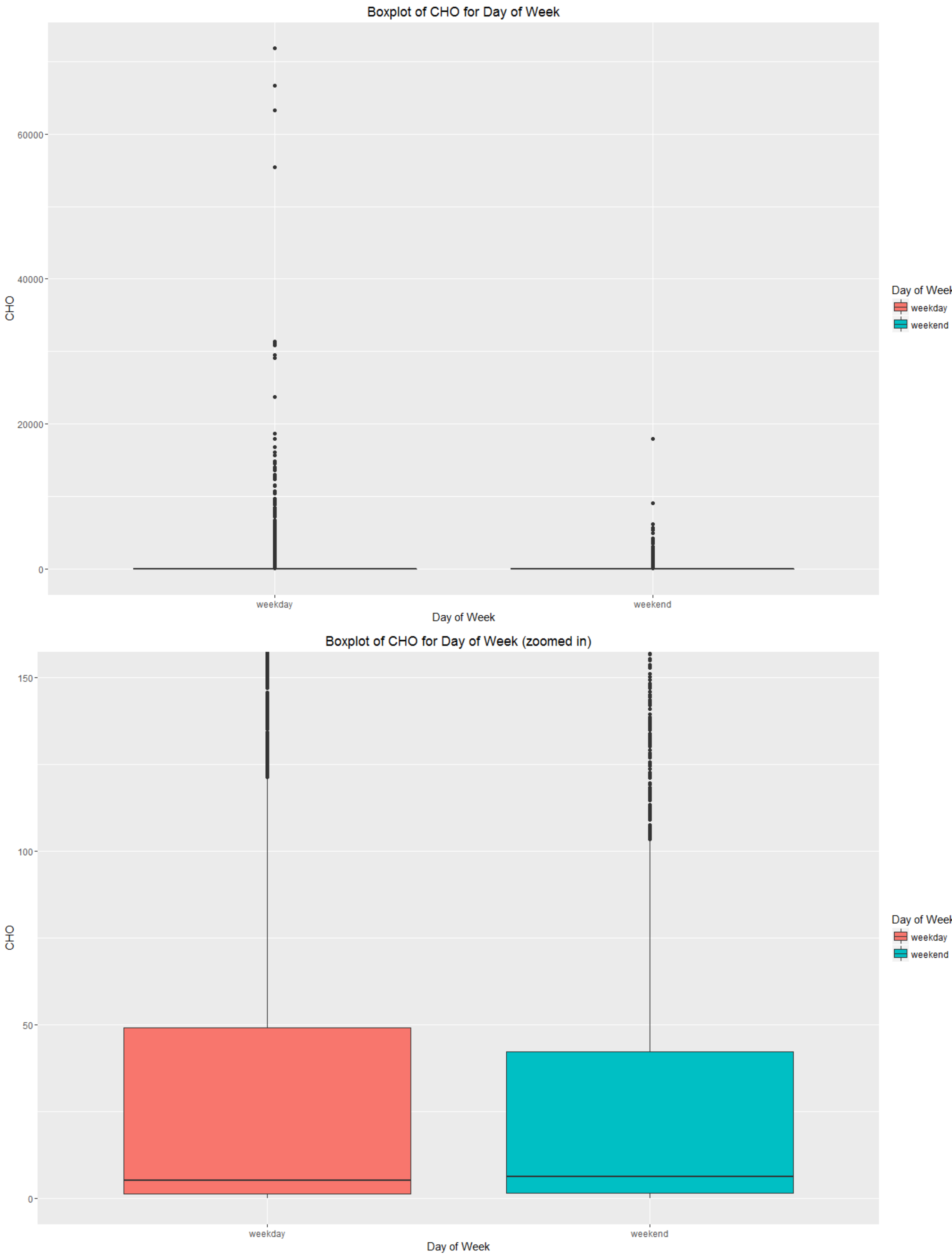


Figure 14. Boxplot of CHO for levels of Automation

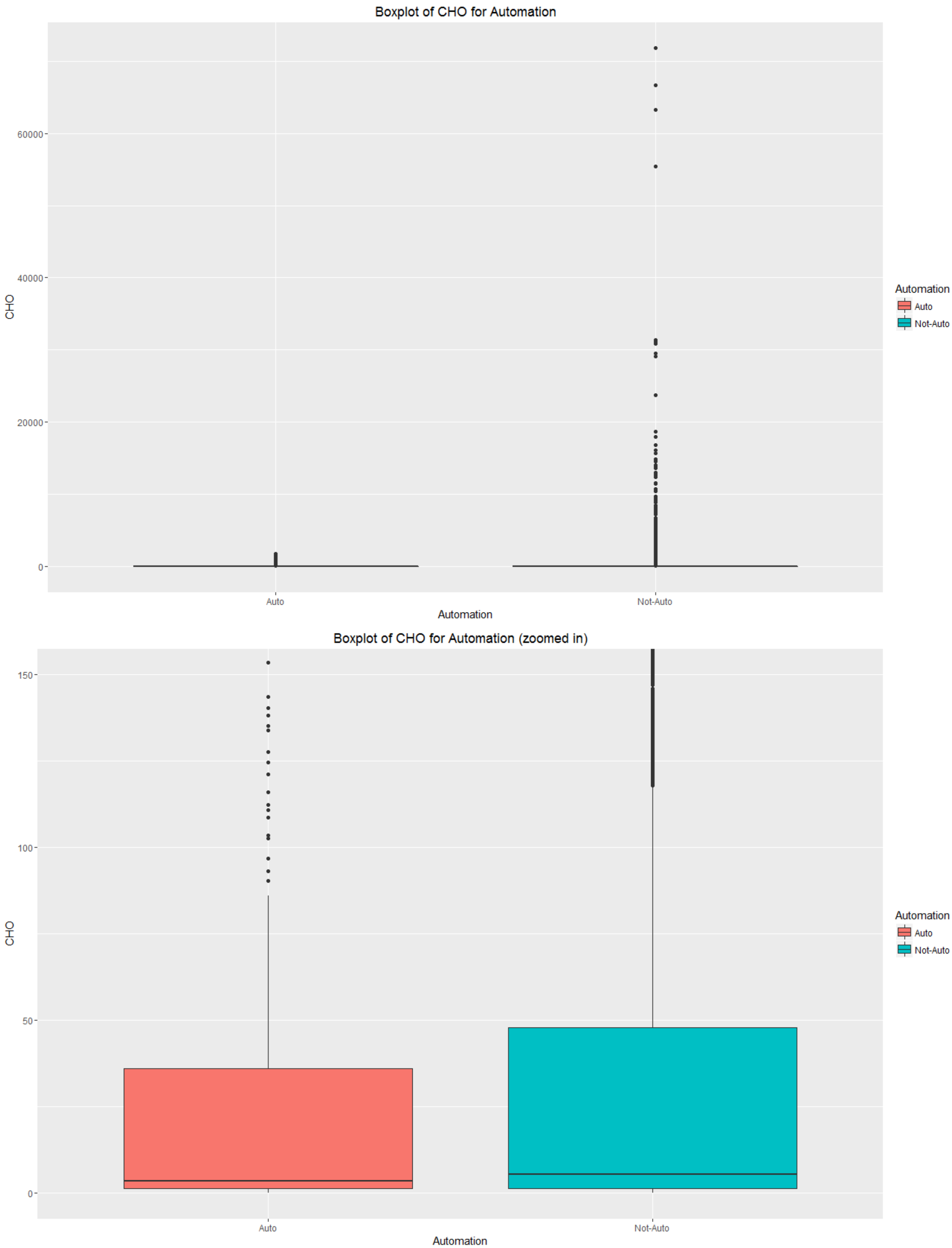
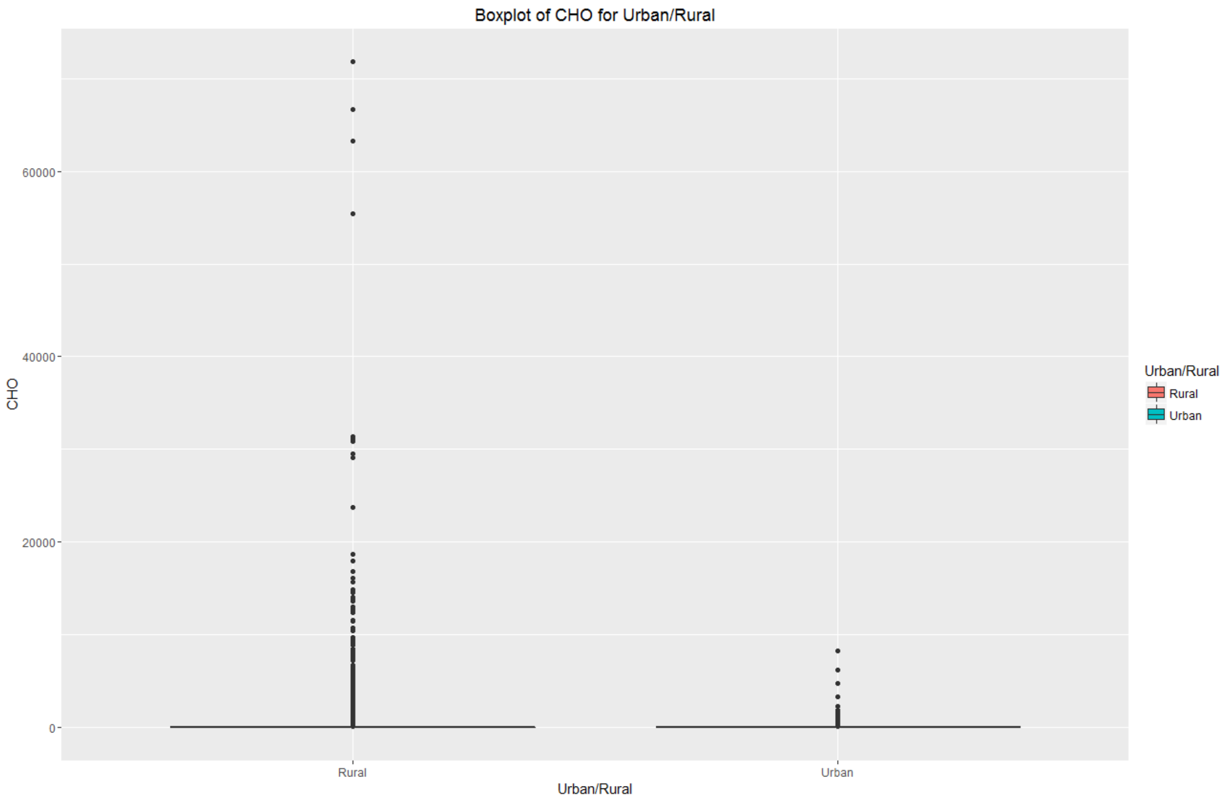


Figure 15. Boxplot of CHO for levels of Urban/Rural


Boxplot of CHO for Urban/Rural
CHO
60000
40000
20000
0
Rural
Urban
Urban/Rural
Urban/Rural
Rural
Urban

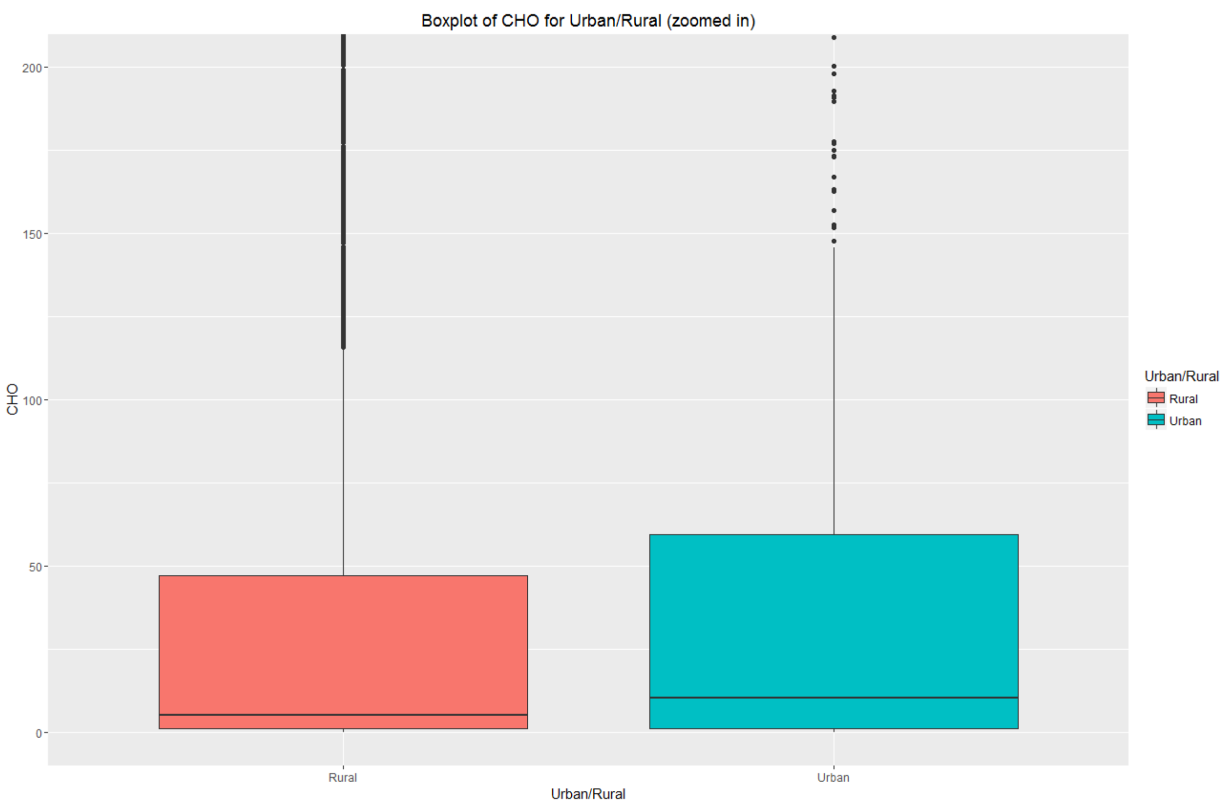
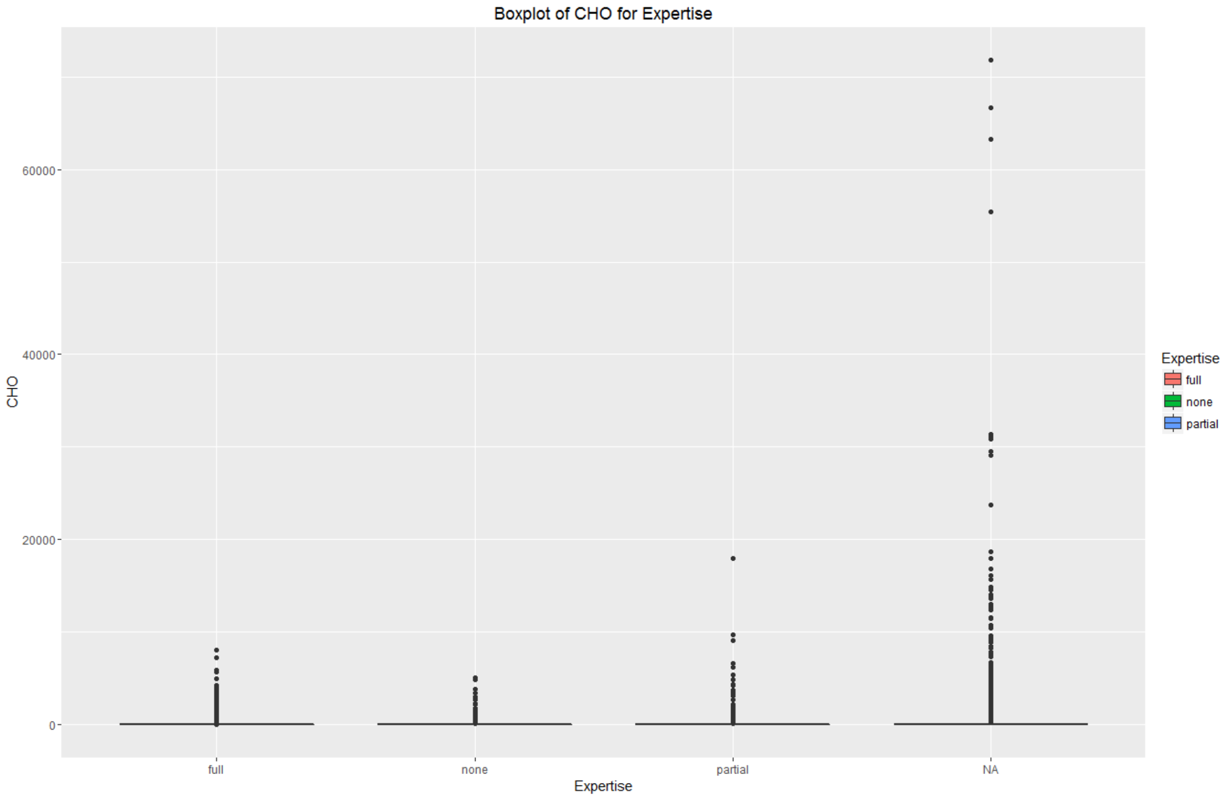
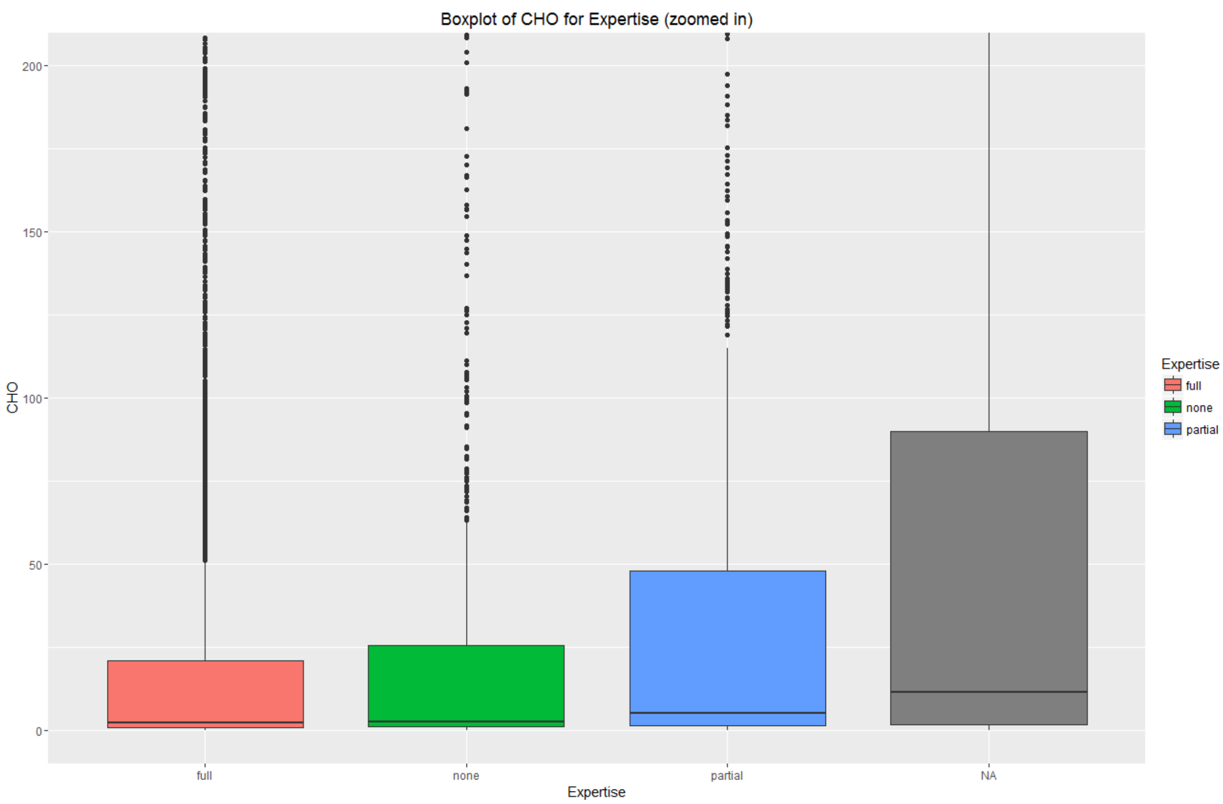

Boxplot of CHO for Urban/Rural (zoomed in)
CHO
200
150
100
50
0
Rural
Urban
Urban/Rural
Urban/Rural
Rural
Urban

Figure 16. Boxplot of CHO for levels of Expertise





Descriptive Statistics

The mean CHO was calculated for each treatment in the data. There were a total of 428 treatments that were observed in the data. (Note that based on the levels of each factor, there are 2688 total possible treatments in theory, but many of these were not observed in the data set). The results for the treatments with the top ten values of mean CHO are displayed in Table 3. The complete table can be found in Appendix B. It is important to note that this table gives only the observed ranking and mean CHO; it does not test for statistically significant differences between the treatments.

Table 3. Treatments with the top ten greatest observed mean CHO

Cause	Time of Day	Season	Urban/Rural	Automation	Major Storm	Expertise	Day of Week	Mean_CHO
Supplier	off-peak	off	Rural	Not-Auto	NO	partial	weekday	4125.605
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	NO	none	weekday	2531.543
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	partial	weekend	1834.663
Other	peak	summer	Rural	Not-Auto	NO	partial	weekend	1797.53
PreventableForeseeable	off-peak	summer	Urban	Not-Auto	NO	partial	weekend	1685.658
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	full	weekend	1631.592
Other	off-peak	winter	Urban	Not-Auto	YES	no info	weekend	1577.687
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	YES	no info	weekday	1284.5
Supplier	off-peak	winter	Rural	Auto	YES	no info	weekday	1209.878
Supplier	off-peak	off	Rural	Not-Auto	NO	no info	weekday	1034.34

Inferential Data Analysis

We fit an ANOVA model to the ART data that included all eighteen three-way interactions and two two-way interactions. We performed backwards variable selection by removing the least significant effects, one at a time, until only statistically significant effects remained in the model. The results of the final model are given in Table 4. Fifteen of the three-way interactions were statistically significant, and both of the two-way interactions were statistically significant.

Table 4. *F*-tests for each effect in the final model

Term	SS (Type III)	df	*F*	*p*
Cause*Time*Season	5.8816e+08	12	4.3411	6.152e-07 ***
Time*Season*Urban/Rural	4.3174e+08	2	17.3441	2.995e-08 ***
Time*Season*Day of Week	2.7450e+09	2	110.5799	< 2.2e-16 ***
Time*Major Storm*Urban/Rural	1.2564e+08	1	10.0969	0.0014883*
Time*Major Storm*Day of Week	8.2222e+07	1	6.6305	0.0100342 *
Time*Urban/Rural*Expertise	5.6980e+0	3	15.2462	6.670e-10 **

	8			*
Time*Expertise*Automation	2.3266e+08	3	6.2275	0.0003197 ***
Time*Expertise*Day of Week	2.5948e+09	3	70.2457	< 2.2e-16 ***
Time*Automation*Day of Week	1.4018e+08	1	11.2628	0.0007928 ***
Season*Urban/Rural*Day of Week	1.4657e+08	2	5.8846	0.0027886 **
Season*Automation*Day of Week	2.5767e+08	2	10.4147	3.021e-05 ***
Major Storm*Urban/Rural*Day of Week	4.9220e+08	1	39.6846	3.070e-10 ***
Major Storm*Automation*Day of Week	3.5126e+08	1	28.4432	9.792e-08 ***
Urban/Rural*Expertise*Day of Week	2.1828e+08	3	5.8476	0.0005490 ***
Expertise*Automation*Day of Week	1.3154e+09	3	35.3594	< 2.2e-16 ***
Cause*Expertise	3.9726e+10	18	225.3765	< 2.2e-16 ***
Cause*Day of Week	2.5676e+10	6	379.0228	< 2.2e-16 ***

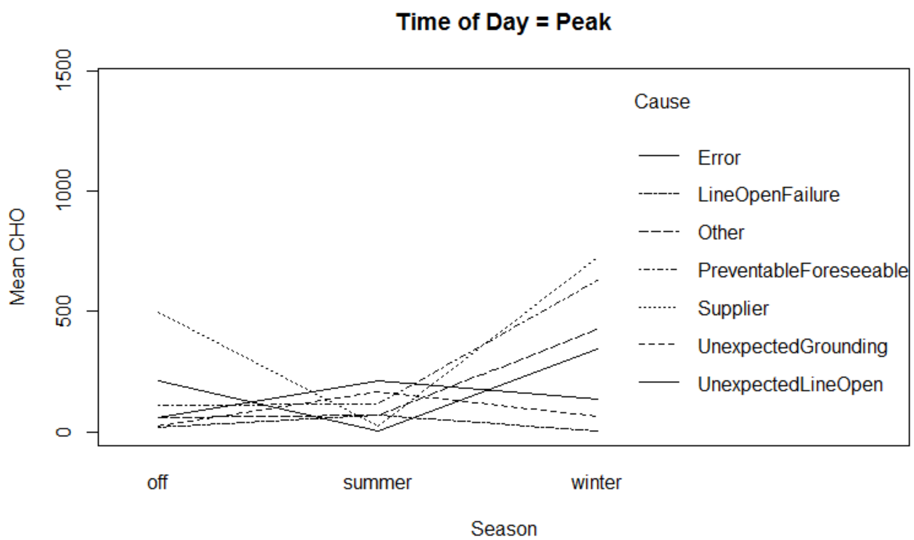
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

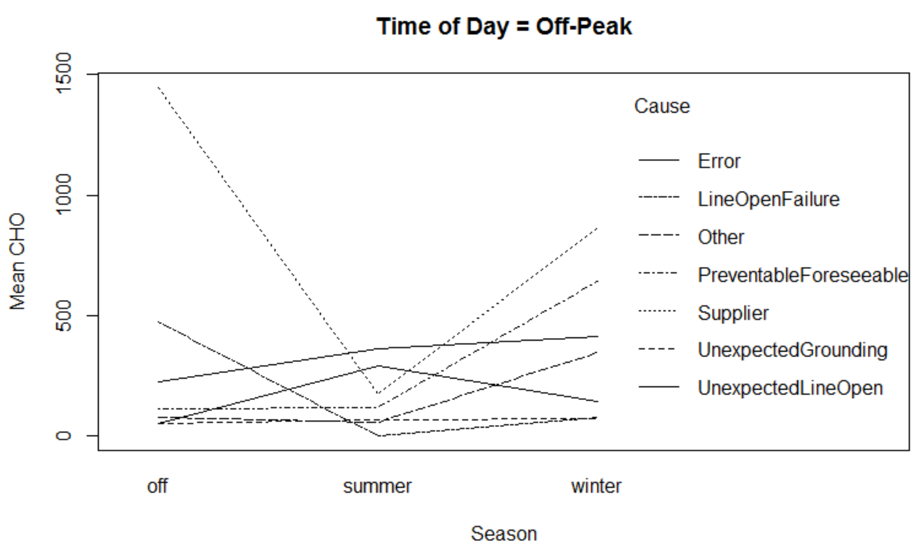
Unfortunately, using the ART it is not possible to test for contrasts above the main effect level. Instead, for each significant term an interaction plot will be displayed (Figures 17 – 33). A qualitative description of general patterns and the most obvious effects will be given, some with accompanying mean CHO values in hours. Again, these contrasts have not been tested for statistical significance.

*Cause*Time*Season*

When an outage is caused by the supplier during the off-season, mean CHO is higher (1444) for off-peak hours compared to peak hours (495). When an outage is caused by an error, during the peak hours it has the greatest mean CHO in the winter and the off-season, and during the off-peak hours it has the greatest mean CHO in the summer. When an outage is caused by a LineOpenFailure during peak hours, the mean CHO is nearly constant throughout the year (~30). However if it occurs during off-peak hours during the off-season then mean CHO is much greater (473).

Figure 17. Interaction plot of CHO for Time of Day, Cause, and Season

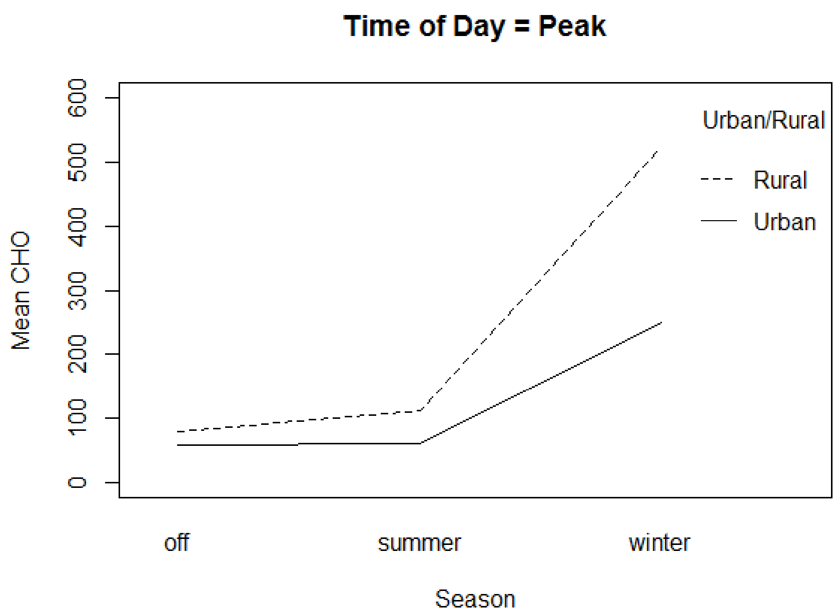


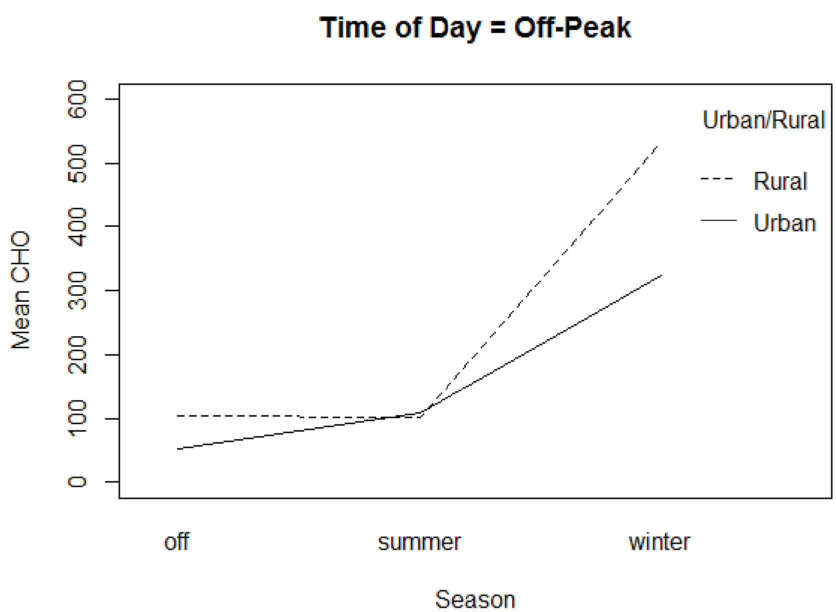


*Time*Season*Urban/Rural*

When the outage takes place in an urban setting during peak hours, mean CHO is similar in the off-season and summer months (~60) and greater in the winter (250). However, if the outage occurs during off-peak hours it is higher in the summer (108) and higher yet in the winter (324). In general, rural outages and those that take place in the winter have higher mean CHO.

Figure 18. Interaction plot of CHO for Time of Day, Urban/Rural, and Season

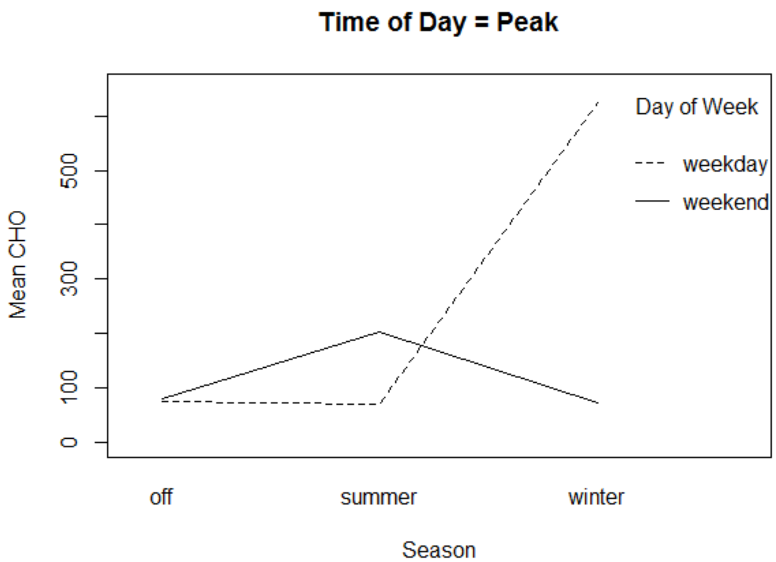


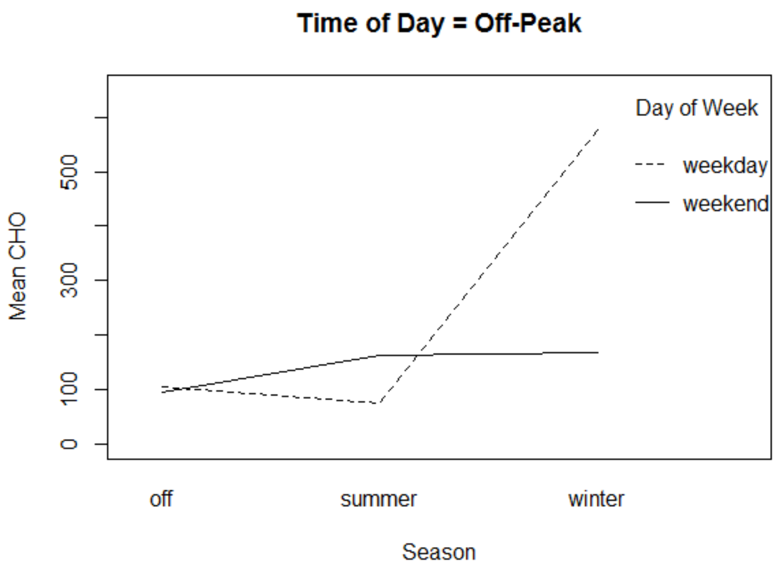


*Time*Season*Day of Week*

If an outage occurs on the weekend during the off-season, mean CHO is about the same for peak and off-peak outages (~90). Compared to the off-season, a weekend outage in the winter results in a higher mean CHO during off-peak hours and a lower mean CHO during peak hours. Compared to the off-season, a weekend outage in the summer results in higher mean CHO during both peak (202) and non-peak hours (162). In general, weekday outages in the off-season and summer have lower mean CHO compared to weekend outages, but the opposite is true during the winter.

Figure 19. Interaction plot of CHO for Time of Day, Day of Week, and Season

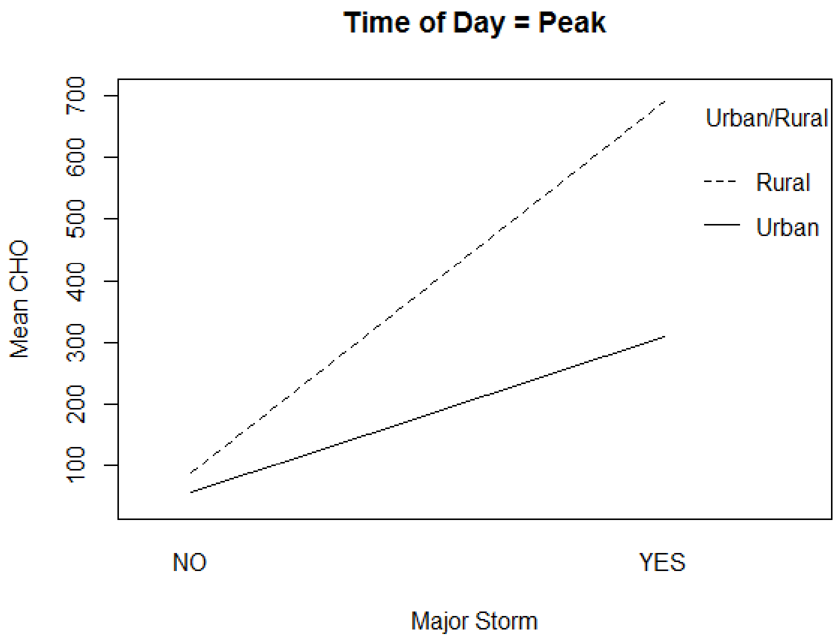


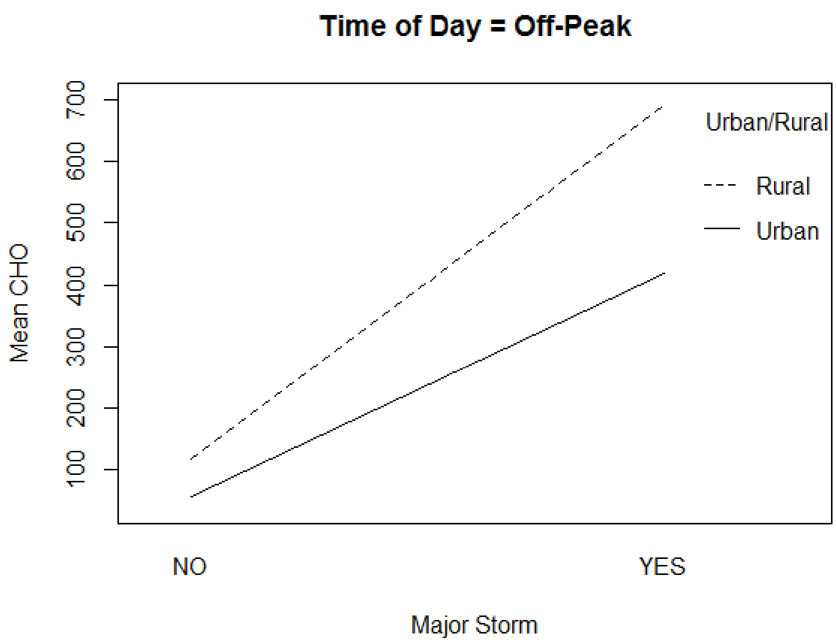


*Time*Major Storm*Urban/Rural*

For outages during a major storm in an urban area, mean CHO is higher during non-peak (417) versus peak hours (309). In general, outages in rural areas have greater mean CHO than those in urban areas, especially during a major storm.

Figure 20. Interaction plot of CHO for Time of Day, Urban/Rural, and Major Storm

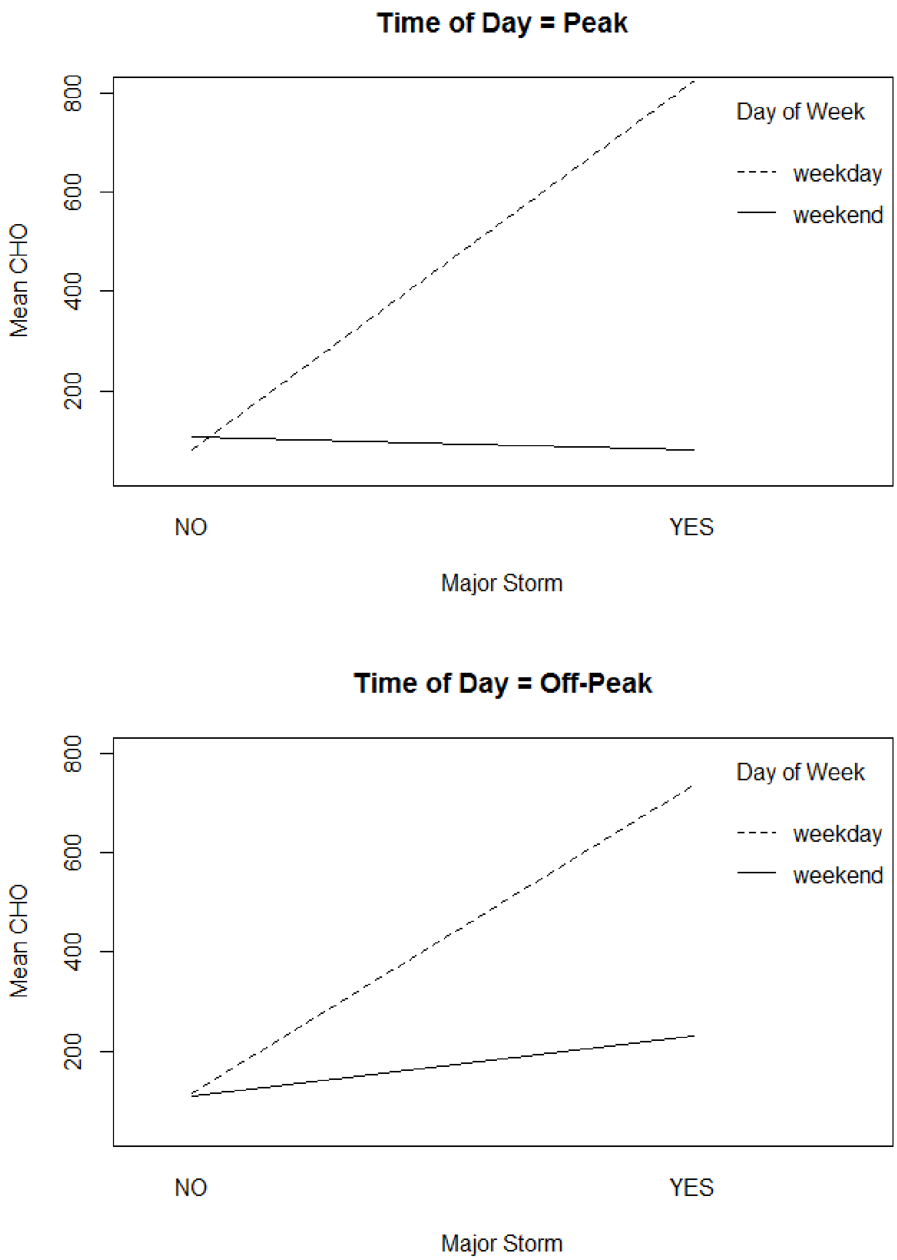




*Time*Major Storm*Day of Week*

A weekday, major storm outage has lower mean CHO during peak (823) hours than during off-peak hours (736). A weekend outage during peak hours results in about the same mean CHO, whether or not it occurred during a major storm. On the other hand, a weekend outage during off-peak hours has greater mean CHO during a major storm (232) compared to when there is no major storm (110). In general, mean CHO is about the same when it's not a major storm for all days of the week and times of day, but it is much greater on weekdays during a major storm for both peak and off-peak times.

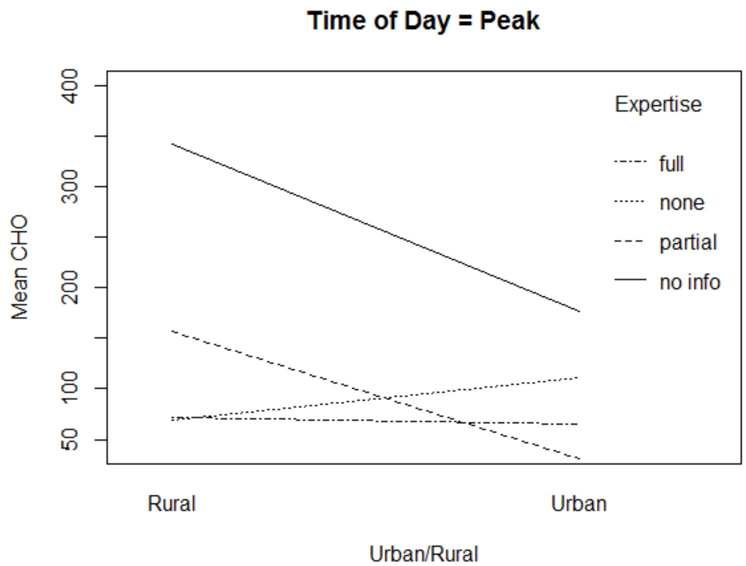
Figure 21. Interaction plot of CHO for Time of Day, Day of Week, and Major Storm

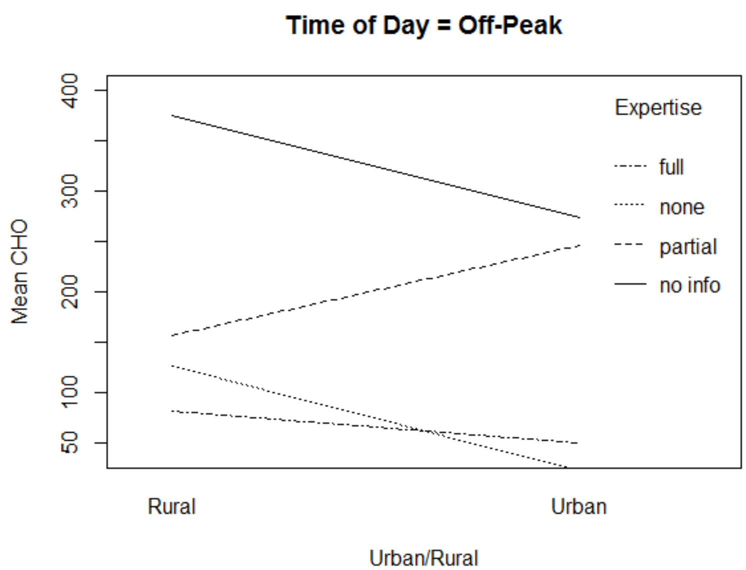


*Time*Urban/Rural*Expertise*

When an outage occurs with only non-experts in the room for the entire outage in a rural area, mean CHO is greater during off-peak (126) hours compared to peak hours (69); and when it occurs in an urban area mean CHO is greater during peak hours (111) compared to non-peak hours (22). When an outage occurs with partial coverage by an expert, mean CHO is about the same for rural outages in both peak and off-peak times (157). However, with partial coverage by an expert for an urban outage, mean CHO is greater during off-peak times (246) than peak times (31). In general, when an outage is fully covered by an expert, mean CHO is about the same for urban and rural outages in both the peak and off-peak times.

Figure 22. Interaction plot of CHO for Time of Day, Expertise, and Urban/Rural

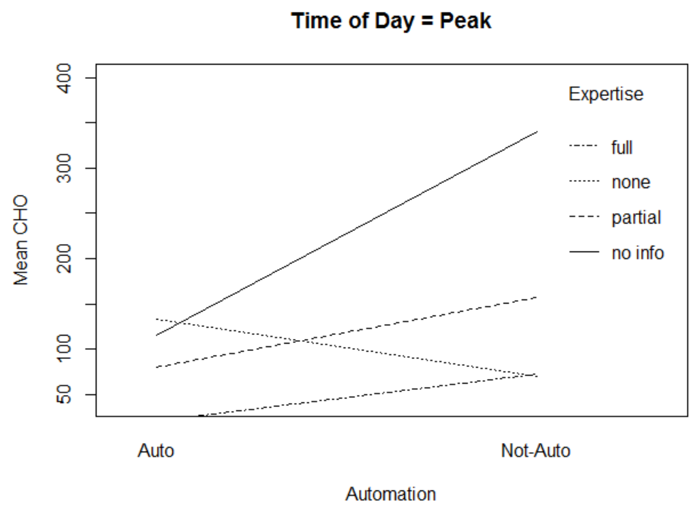


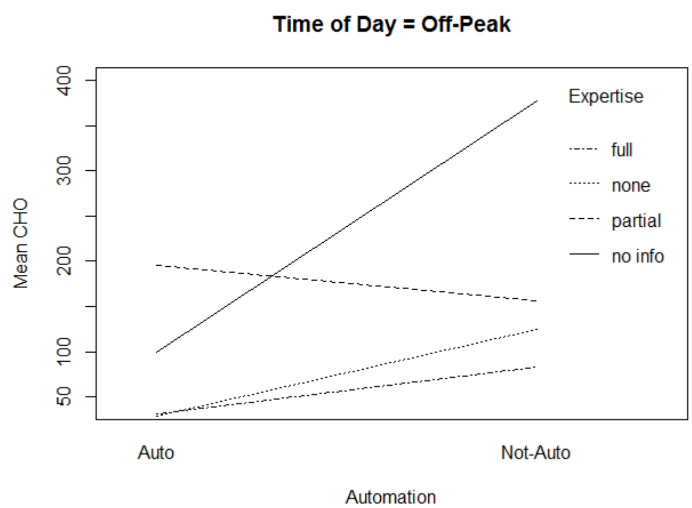


*Time*Expertise*Automation*

When an outage occurs during peak hours and it is partially covered by an expert, if the feeder is not automated the outage events have greater mean CHO (157) compared to when the feeder is automated (80). However, when a partially covered outage occurs during off-peak hours, if the feeder is not automated the outage events have smaller mean CHO (156) compared to when the feeder is automated (196). When the outage is not covered at all by an expert, the pattern is reversed. In this case if the outage occurs during peak hours, outages on automated feeders have greater mean CHO (133) compared to those on non-automated feeders (70). When the outage occurs during off-peak hours, outages on automated feeders have smaller mean CHO (29) compared to those on non-automated feeders (125). In general, outages that are fully covered by an expert operator have the lowest mean CHO, and those outages have greater mean CHO when they occur on the non-automated feeders. This pattern appears to hold across all hours of the day.

Figure 23. Interaction plot of CHO for Time of Day, Expertise, and Automation

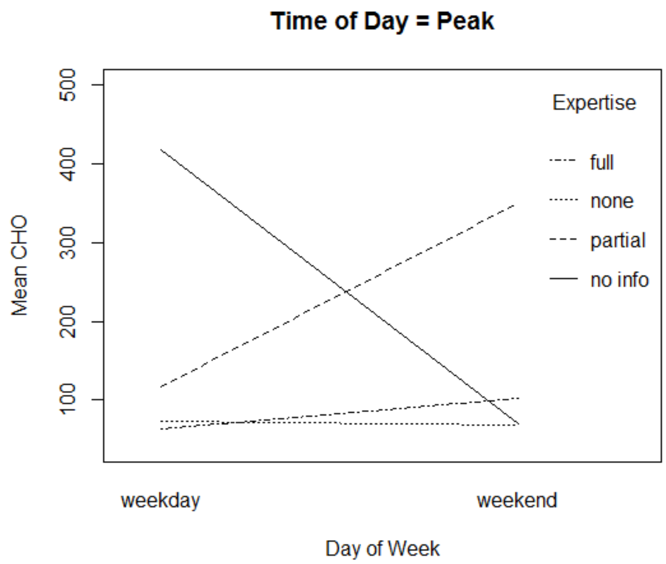


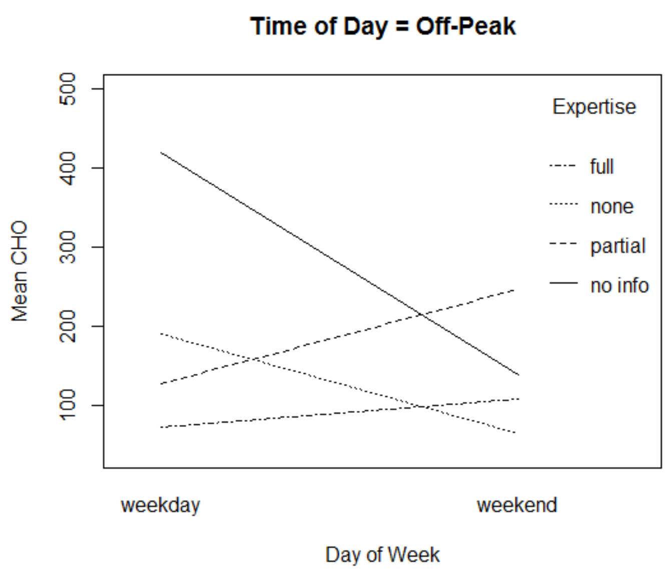


*Time*Expertise*Day of Week*

For outages that are partially covered by an expert, mean CHO on weekdays is about the same in the peak and off-peak hours (~123), however, on weekends it is greater during peak hours (349) than off-peak hours (247). For outages that are not covered at all by an expert operator, outages occurring during peak hours result in mean CHO that is about the same on all days of the week (~71); however, outages during off-peak hours result in mean CHO that is greater on a weekday (190) compared to the weekend (65). In general, when an outage is fully covered by an expert operator mean CHO is slightly lower on weekdays (~67) versus weekends (~105), regardless of time of day.

Figure 24. Interaction plot of CHO for Time of Day, Expertise, and Day of Week

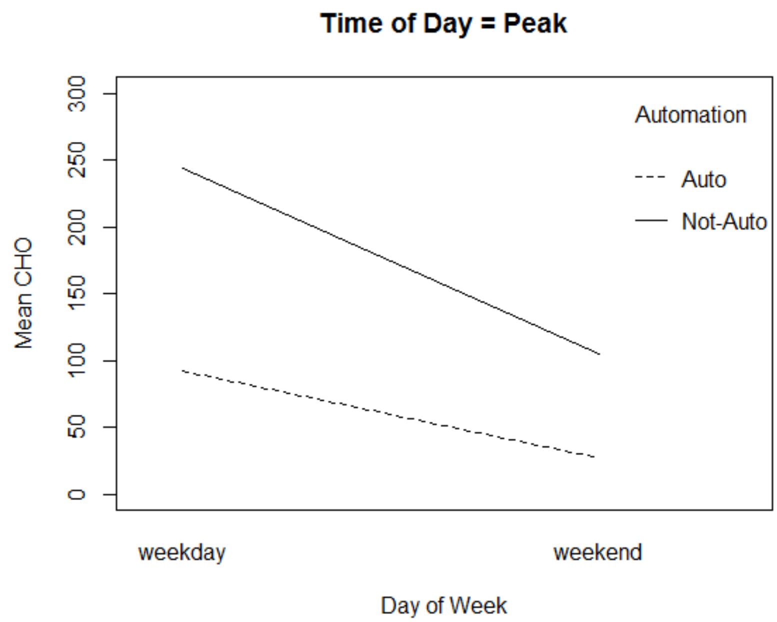


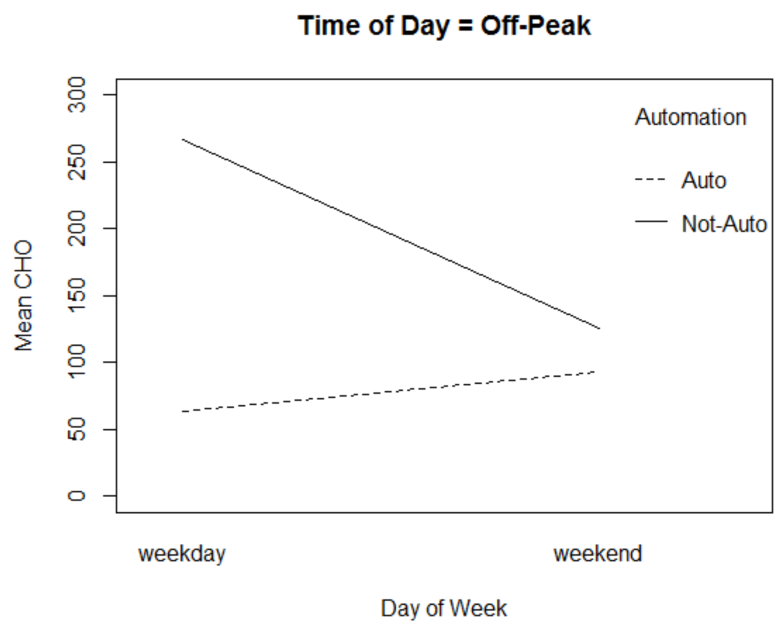


*Time*Automation*Day of Week*

When an outage occurs on an automated feeder on a weekday, mean CHO is higher during peak hours (92) versus off-peak hours (63). However, outages on automated feeders on weekends result in greater mean CHO during off-peak (92) as opposed to peak hours (27). In general, outages on non-automated feeders have higher mean CHO on weekdays (~255) as opposed to weekends (~115), regardless of time of day.

Figure 25. Interaction plot of CHO for Time of Day, Automation, and Day of Week

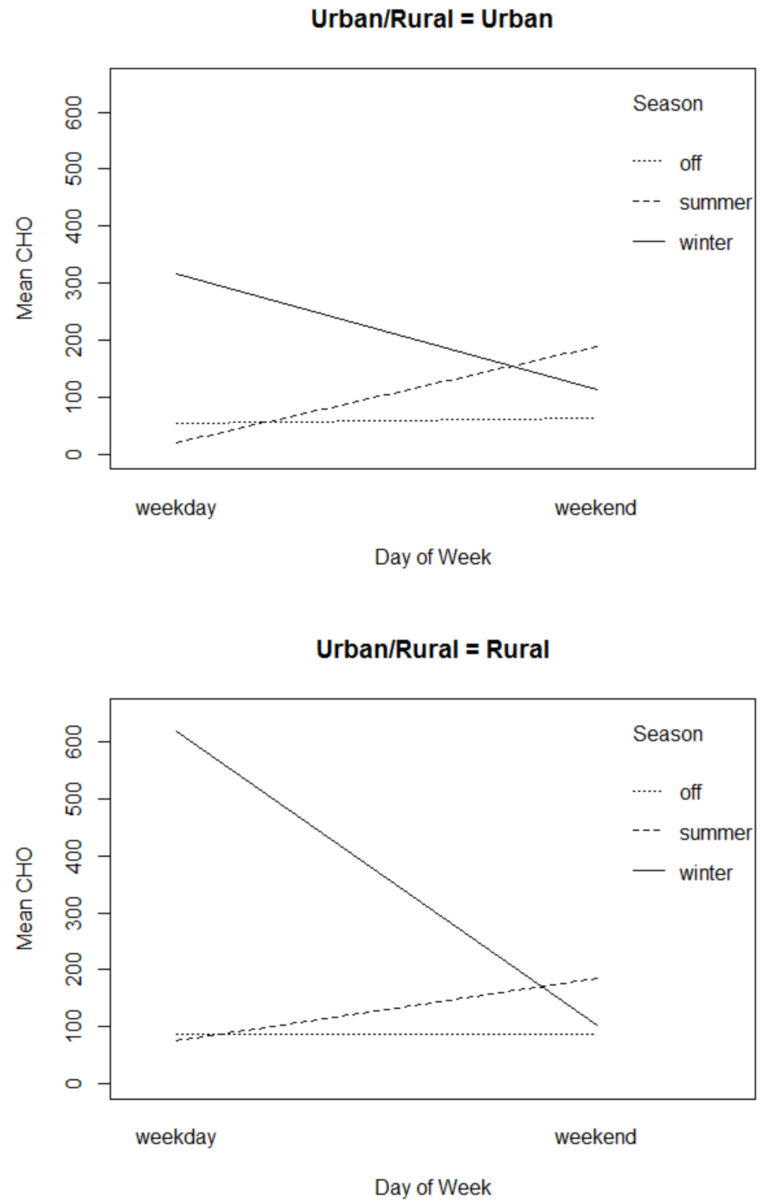




*Season*Urban/Rural*Day of Week*

Outages that occur in the winter on a weekend result in about the same mean CHO for both urban and rural settings (~108), but winter weekday outages have greater mean CHO in rural settings (618) compared to urban settings (317). In general, outages that occur during the off-season have about the same mean CHO (~73), regardless of the day of the week or urban vs. rural. In general, outages that occur during the summer tend to have mean CHO that is greater on the weekend (~187) compared to the weekday (~48), regardless of urban versus rural outages.

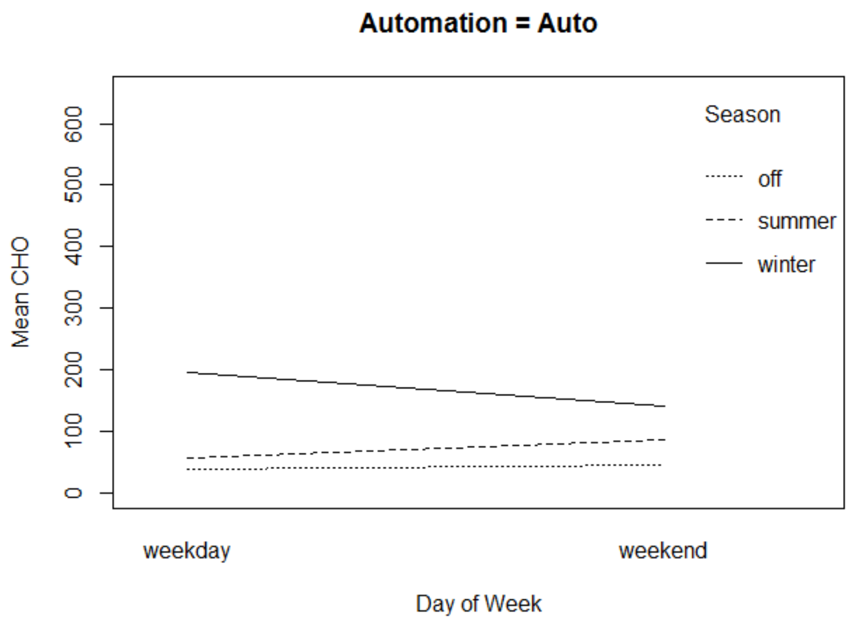
Figure 26. Interaction plot of CHO for Urban/Rural, Season, and Day of Week

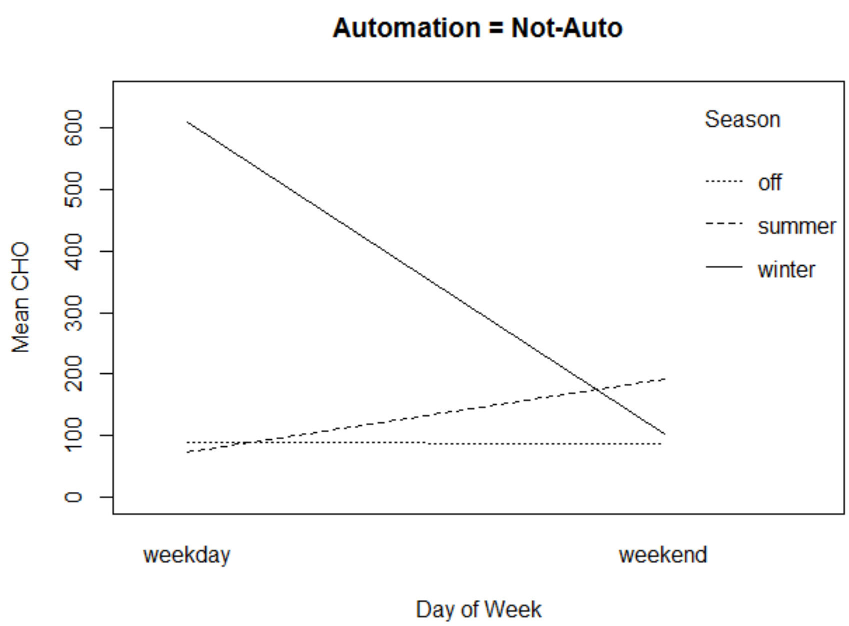


*Season*Automation*Day of Week*

For weekday winter outages on non-automated feeders mean CHO is greater (610) than those on the weekend (103). For weekday winter outages on automated feeders mean CHO is also greater (195) compared to those on the weekend (141). In general, summer and off-season outages result in mean CHO that is about the same in on weekdays for both automated and non-automated feeders (~64), but on non-automated feeders with weekend summer outages mean CHO is greater (190).

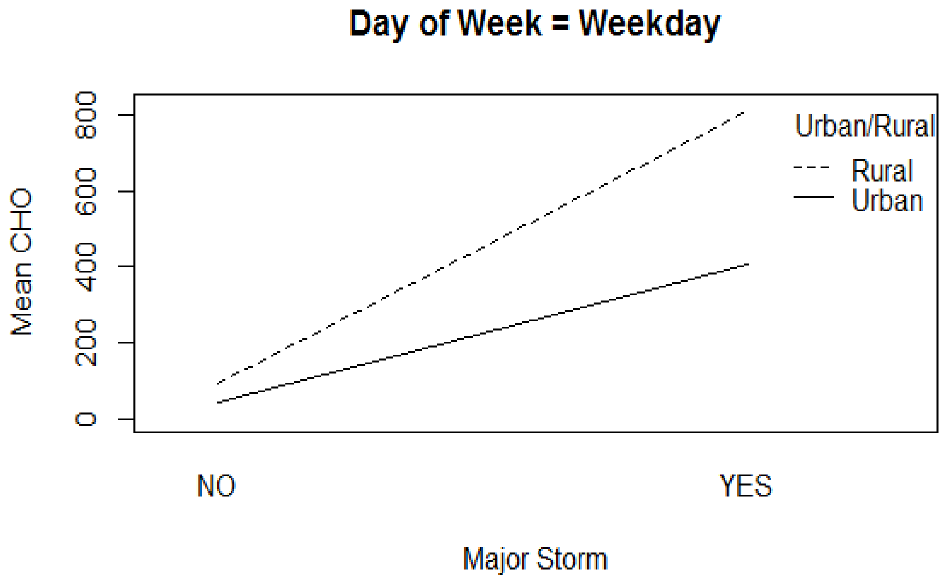
Figure 27. Interaction plot of CHO for Automation, Season, and Day of Week

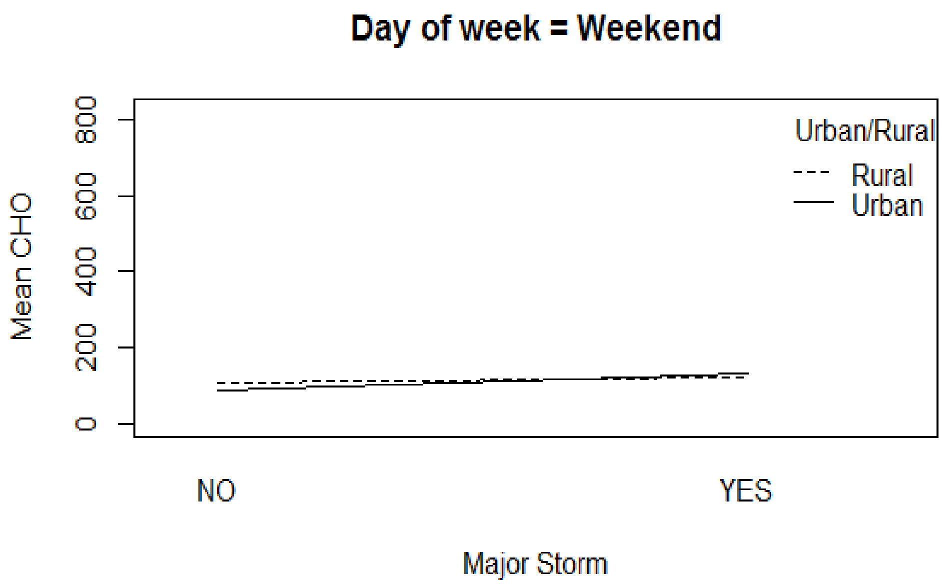




*Major Storm*Urban/Rural*Day of Week*
Outages in urban areas are lowest in mean CHO when a major storm is not involved on a weekday (43), and mean CHO is higher for weekend outages (88). If a major storm is involved in an urban area, mean CHO is higher on weekdays (407) versus weekends (131). In general, outages in rural areas result in about the same mean CHO any day of the week if a major storm is not involved (~103), but if a major storm is involved in a rural outage then mean CHO is higher for weekdays only (807).

Figure 28. Interaction plot of CHO for Day of Week, Urban/Rural, and Major Storm

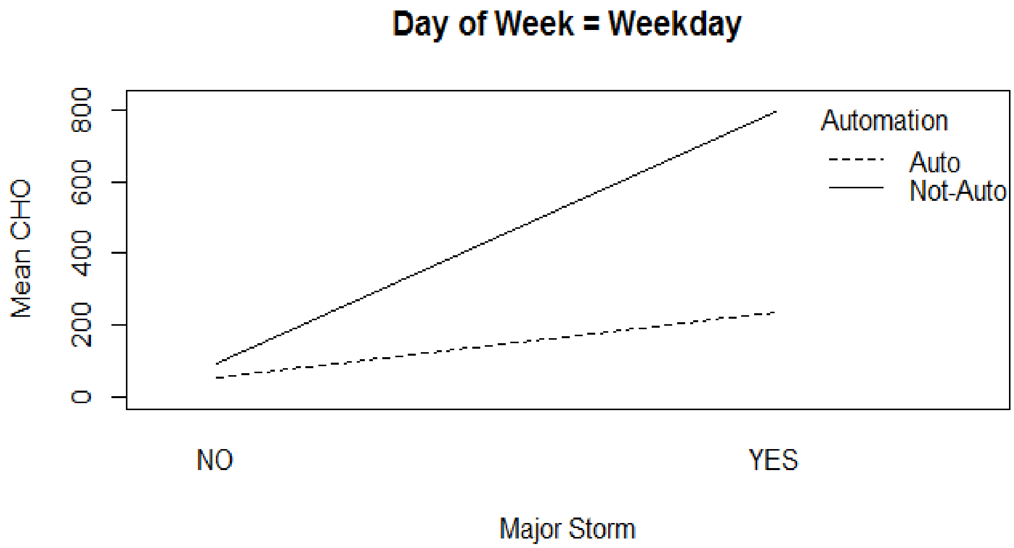


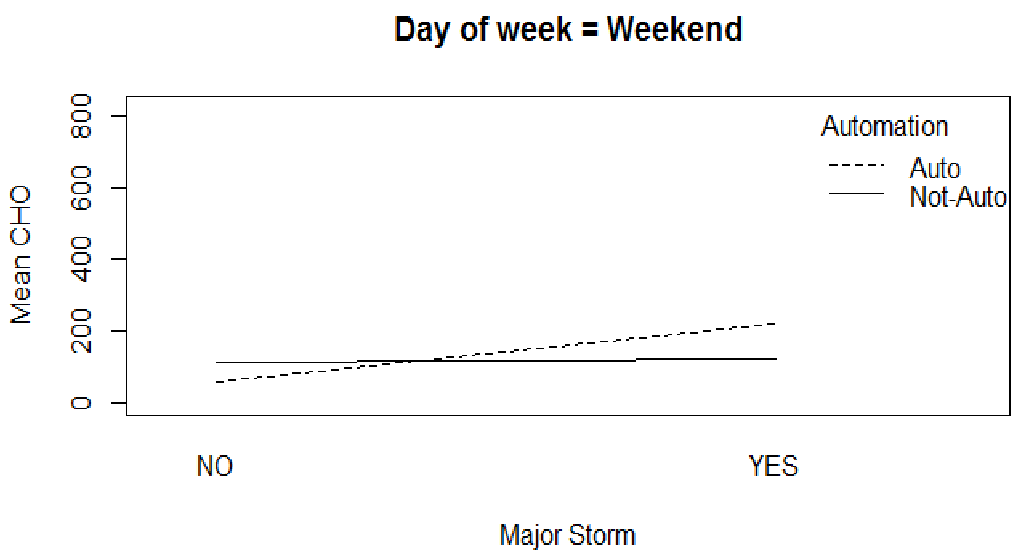


*Major Storm*Automation*Day of Week*

In general, outages on non-automated feeders when a major storm is not involved result in mean CHO that is about the same on weekdays and weekends (~102), but if a major storm is involved then mean CHO is greater on weekdays (794) versus weekends (123) for non-automated feeders. In general, mean CHO for outages on feeders that are automated is the same on weekdays and weekends, but is higher if the outage occurs in a major storm (~227) as opposed to not (~56).

Figure 29. Interaction plot of CHO for Day of Week, Automation, and Major Storm

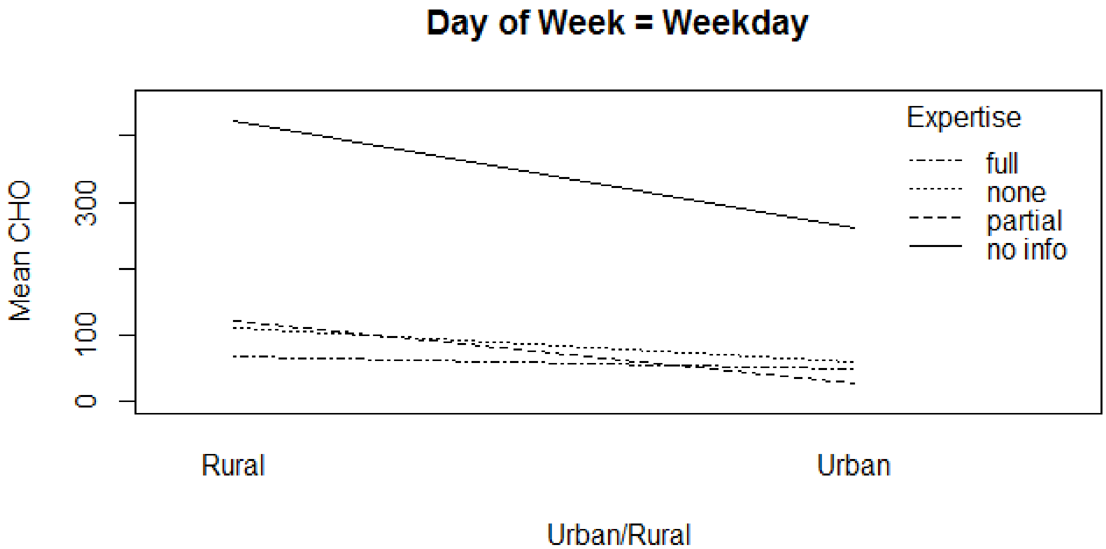


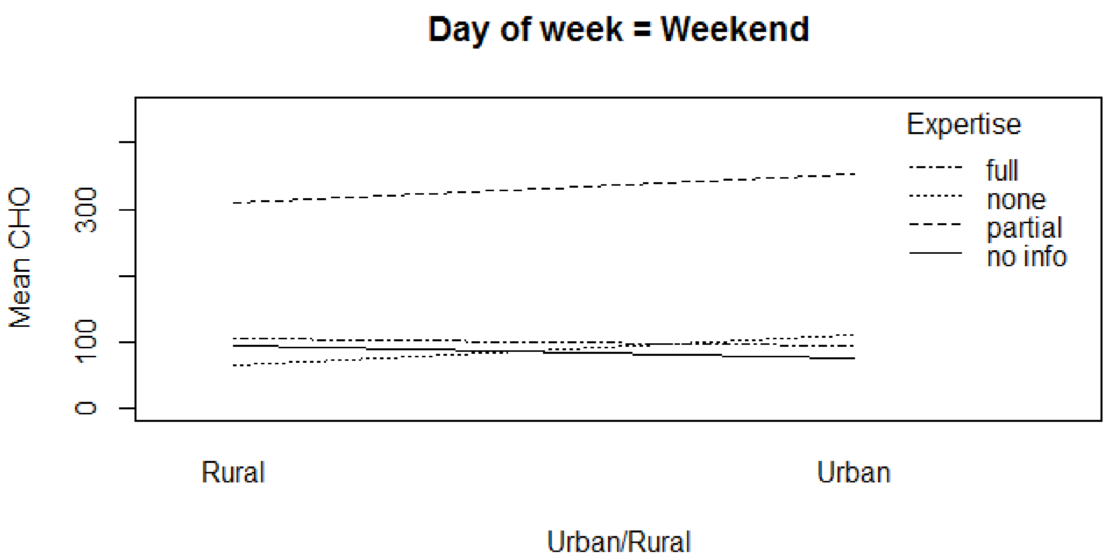


*Urban/Rural*Expertise*Day of Week*

When an outage is partially covered by an expert operator, on a weekday, mean CHO is higher for rural (122) versus urban outages (28). However, when an outage is partially covered by an expert operator, on a weekend, mean CHO is higher for urban (352) versus rural outages (310). In general, outages where there are either no expert operators or full coverage by an expert operator result in mean CHO that is about the same (~82), regardless of day of week or urban versus rural settings.

Figure 30. Interaction plot of CHO for Day of Week, Expertise, and Urban/Rural

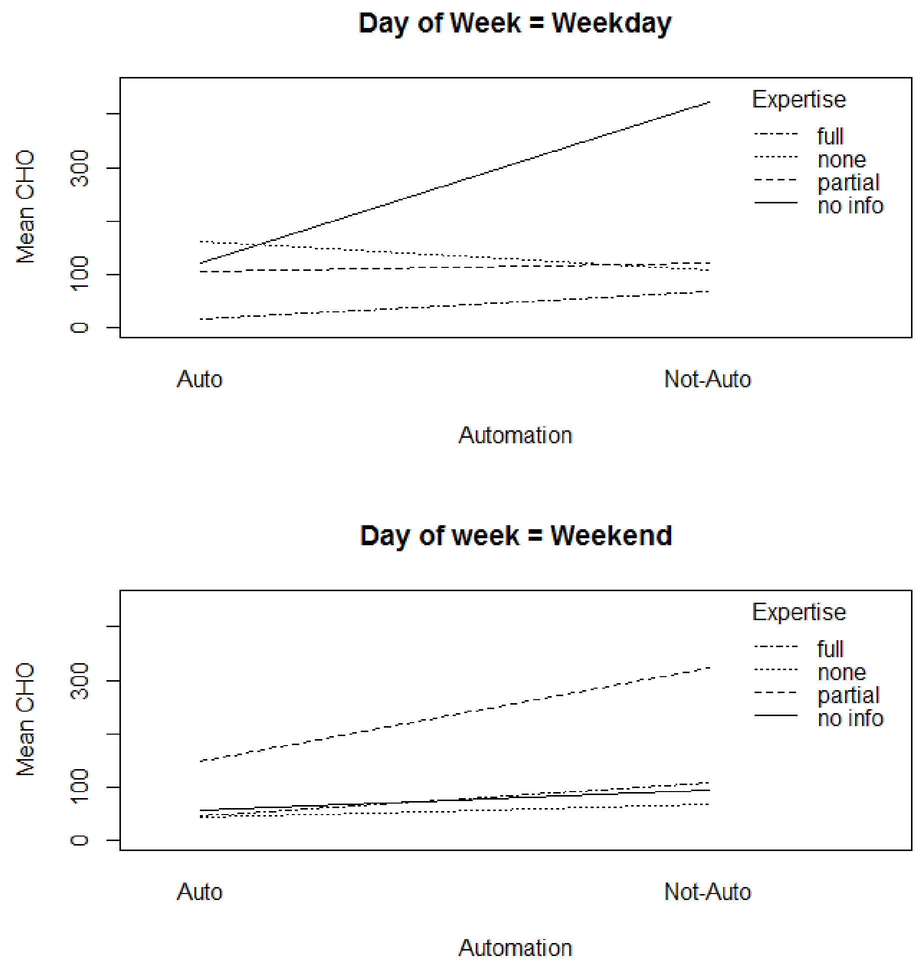




*Expertise*Automation*Day of Week*

When an outage is partially covered by an expert, if the outage occurs on a weekday then mean CHO is about the same for automated and non-automated feeders (~112). However, if a partially covered outage occurs on the weekend, then mean CHO is greater for non-automated feeders (323) versus automated feeders (147). When an outage is not covered by an expert operator at all, weekday outages result in mean CHO that is higher for automated feeders (162) versus non-automated feeders (108). However, when there is no expert coverage on weekend outages, mean CHO is about the same for feeders regardless of automation (~56). In general, when an outage is fully covered by an expert operator, mean CHO is slightly higher for non-automated feeders (~88) versus automated feeders (~32), regardless of the day of the week.

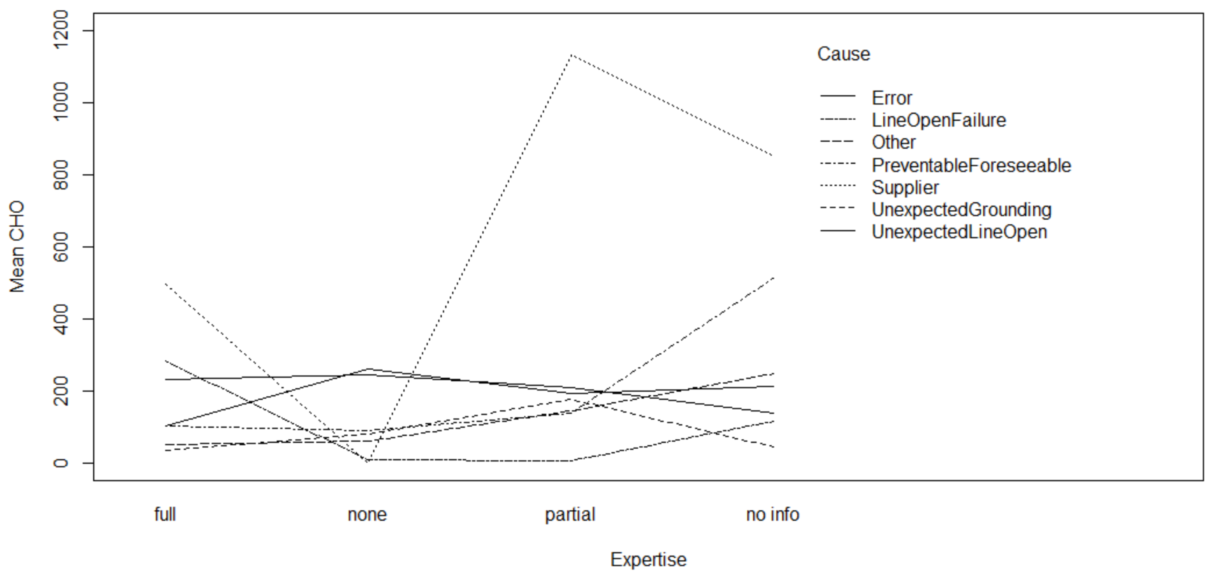
Figure 31. Interaction plot of CHO for Day of Week, Expertise, and Automation



*Cause*Expertise*

Outages with full coverage by an expert operator result in mean CHO that is highest for Supplier (498), followed by LineOpenFailure and Error (~259), followed by the other causes (~118). Outages that are partially covered by an expert and are caused by the Supplier result in the highest mean CHO compared to all other combinations of cause and expertise (1133). In general, outages with no or partial expert operator coverage that are caused by UnexpectedLineOpen and Error tend to have higher mean CHO (~228) than those caused by LineOpenFailure, Other, PreventableForeseeable, and UnexpectedGrounding with the same expertise (~88).

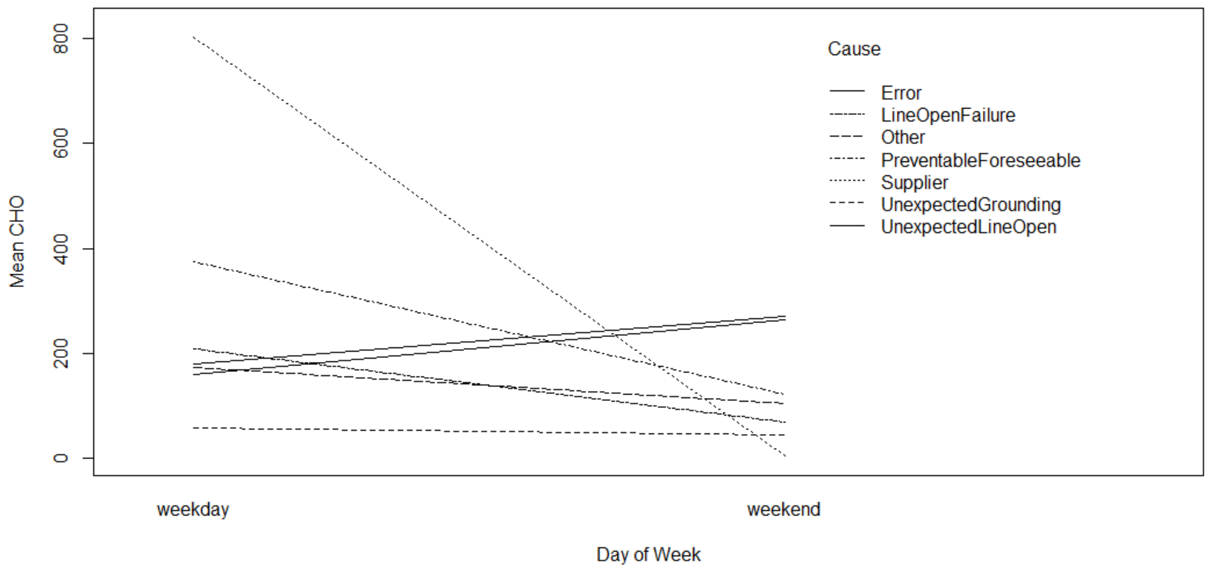
Figure 32. Interaction plot of CHO for Cause and Expertise



*Cause*Day of Week*

Mean CHO is highest for weekday outages cause by Supplier (802) compared to all other combinations of day of week and cause. In general, mean CHO is higher on weekdays compared to weekends for outages caused by LineOpenFailure, Other, PreventableForeseeable, and Supplier, and mean CHO is nearly identical and is higher on weekends (~267) compared to weekdays (~168) for UnexpectedLineOpen and Error. In general, when an outage is caused by an UnexpectedGrounding, mean CHO is lowest, regardless of day of week (~51).

Figure 33. Interaction plot of CHO for Cause and Day of Week



Conclusion

The goal of this analysis was to investigate the relationship between eight predictive factors and CHO. We started with the full model, which included all possible three-way interaction effects, and we performed backward selection to reduce the model until it contained only statistically significant effects. An aligned rank transform was used to accommodate the violation of the ANOVA's assumption of constant variance. Since this procedure was used, contrasts could not be tested for the interaction terms in the model. All eight factors were statistically significant, and all factors were involved in interaction terms. This means that the effect of one factor on CHO cannot be described without placing it in the context of other factors. For each effect, interaction plots were displayed and a description was given.

References

Wobbrock J, Findlater L, Gergle D, Higgins J. The aligned rank transform for nonparametric factorial analyses using only ANOVA procedures. Proceedings of the ACM Conference on Human Factors in Computing Systems. Vancouver, British Columbia (May 7-12, 2011). New York: ACM Press, pp.143 – 146.

Appendix A

Feeder ID	Urban/Rural	Automated/Not Automated
71G1	Rural	Not Automated
78G2	Rural	Not Automated
71G3	Rural	Not Automated

34G1	Rural	Not Automated
PS-G43	Rural	Not Automated
SJ-G63	Rural	Not Automated
LO-G26	Rural	Not Automated
BA-G71	Rural	Not Automated
QU-G16	Rural	Not Automated
EM-G76	Rural	Not Automated
39G1	Rural	Not Automated
RA-G22	Rural	Not Automated
H2-G60	Rural	Not Automated
CF-G16	Rural	Not Automated
PO-G27	Rural	Not Automated
32G7	Rural	Not Automated
70G4	Rural	Not Automated
	Rural	Not Automated
CV-G64	Rural	Not Automated
TH-G16	Rural	Not Automated
81G1	Rural	Not Automated
RC-G51	Rural	Not Automated
M-G27	Rural	Not Automated
BF-G62	Rural	Not Automated
63J2	Rural	Not Automated
PN-G46	Rural	Not Automated
EN-G26	Rural	Not Automated
HR-G37	Rural	Not Automated
HR-G38	Rural	Not Automated
WY-G81	Rural	Not Automated
19G4	Rural	Not Automated
SM-G62	Rural	Not Automated
BAY-G4	Rural	Not Automated
LJ-G13	Rural	Not Automated
CA-G37	Rural	Not Automated
44G1	Rural	Not Automated
9G2	Rural	Not Automated
EB-Y38	Rural	Not Automated
WK-G81	Rural	Not Automated
46Y1	Rural	Not Automated
56G2	Rural	Not Automated
63G4	Rural	Not Automated
83G1	Rural	Not Automated
37G7	Rural	Not Automated
28G2	Rural	Not Automated

BE-G29	Rural	Not Automated
CH-G11	Rural	Not Automated
WR-G24	Rural	Not Automated
14G2	Rural	Not Automated
PO-G7	Rural	Not Automated
EJ-G7	Rural	Not Automated
SR-G72	Urban	Not Automated
LJ-G12	Rural	Not Automated
DO-G22	Rural	Automated
PA-G20	Rural	Not Automated
53G3	Rural	Not Automated
WY-G80	Rural	Not Automated
WM-G92	Rural	Not Automated
BR-G70	Rural	Not Automated
VR-G57	Rural	Not Automated
EL-G40	Rural	Not Automated
EL-G41	Rural	Not Automated
19G7	Rural	Not Automated
15L19	Rural	Not Automated
BV-G44	Rural	Not Automated
SP-J1	Rural	Not Automated
BS-G32	Rural	Not Automated
BAY-G3	Rural	Not Automated
MH-G13	Rural	Not Automated
H7-G7	Rural	Not Automated
39G3	Rural	Not Automated
39G2	Rural	Not Automated
FH-J26	Rural	Not Automated
33Y3	Rural	Not Automated
UH-G21	Rural	Not Automated
60J1	Rural	Not Automated
27G5	Rural	Not Automated
SA-G23	Rural	Not Automated
83G2	Rural	Not Automated
WO-G92	Rural	Not Automated
GM-G62	Rural	Not Automated
BL-G24	Rural	Not Automated
57G1	Rural	Not Automated
MC-G13	Rural	Not Automated
45G1	Rural	Not Automated
MI-G36	Rural	Not Automated
GT-G47	Urban	Not Automated

SB-G93	Rural	Not Automated
UH-G23	Rural	Not Automated
85G2	Rural	Not Automated
56G1-1	Rural	Not Automated
14G1	Rural	Not Automated
RO-G62	Rural	Not Automated
60J2	Rural	Not Automated
WK-G82	Rural	Not Automated
90G1	Rural	Not Automated
EA-G52	Rural	Not Automated
53G2	Rural	Not Automated
BR-G71	Rural	Not Automated
56G1	Rural	Not Automated
BAY-G6	Rural	Not Automated
RI-G68	Rural	Not Automated
28G1	Rural	Not Automated
47G1	Rural	Not Automated
PA-G21	Rural	Not Automated
74G1	Rural	Not Automated
CV-G65	Rural	Not Automated
EM-G75	Rural	Not Automated
WK-G83	Rural	Not Automated
33G2	Rural	Not Automated
WI-G11	Rural	Not Automated
SS-G36	Rural	Not Automated
ME-G12	Urban	Not Automated
62J1	Rural	Not Automated
53G1	Rural	Not Automated
GI-G71	Rural	Not Automated
SD-G10	Rural	Not Automated
NR-G33	Urban	Not Automated
81G2	Rural	Not Automated
BE-G28	Rural	Not Automated
TA-G12	Rural	Not Automated
51G2	Rural	Not Automated
3G3	Rural	Not Automated
NB-G72	Rural	Not Automated
WI-G31	Rural	Not Automated
36G2	Rural	Not Automated
19G5	Rural	Not Automated
67G3	Rural	Not Automated
44G2	Rural	Not Automated

74G2	Rural	Not Automated
69K1	Rural	Not Automated
BR-G58	Rural	Not Automated
AP-G11	Rural	Not Automated
3321	Rural	Not Automated
MS-G50	Rural	Automated
SH-G35	Rural	Not Automated
16G1	Rural	Not Automated
9G4	Rural	Not Automated
WM-G91	Rural	Not Automated
NS-G63	Rural	Not Automated
NR-G34	Urban	Not Automated
48G1	Rural	Not Automated
CS-G34	Rural	Not Automated
SN-G40	Rural	Automated
CH-G10	Rural	Not Automated
48G2	Rural	Not Automated
SF-G20	Rural	Not Automated
67G2	Rural	Not Automated
MS-G51	Rural	Automated
BAY-G5	Rural	Not Automated
RA-G23	Rural	Not Automated
69K2	Rural	Not Automated
61G3	Rural	Not Automated
BF-G63	Rural	Not Automated
DM-G6	Rural	Not Automated
H6-G66	Rural	Not Automated
SB-G91	Rural	Not Automated
MC-G14	Rural	Automated
WF-G23	Rural	Not Automated
ST-G45	Rural	Not Automated
BA-G72	Rural	Not Automated
ME-Y86	Rural	Not Automated
BV-G43	Rural	Not Automated
FA-G6	Rural	Not Automated
SO-G33	Rural	Not Automated
SK-G60	Rural	Not Automated
65J1	Rural	Not Automated
M-G24	Rural	Not Automated
ER-G51	Urban	Not Automated
LO-G27	Rural	Not Automated
HY-G24	Rural	Not Automated

32G4	Rural	Not Automated
63G1	Rural	Not Automated
BU-G47	Rural	Not Automated
78G1	Rural	Not Automated
61G1	Rural	Not Automated
43G2	Rural	Not Automated
37G8	Rural	Not Automated
47G2	Rural	Not Automated
M-G23	Rural	Not Automated
NA-G26	Rural	Not Automated
72G1	Rural	Not Automated
NE-G16	Rural	Not Automated
PM-G14	Rural	Not Automated
GT-G49	Urban	Not Automated
NB-G73	Rural	Not Automated
3G1	Rural	Not Automated
40G7	Rural	Not Automated
NT-G53	Rural	Not Automated
PN-G45	Rural	Not Automated
ER-G53	Urban	Not Automated
SK-G59	Rural	Not Automated
AP-G10	Rural	Not Automated
43G3	Rural	Not Automated
40G6	Rural	Not Automated
PS-G42	Rural	Not Automated
FH-J28	Rural	Not Automated
78G4	Rural	Not Automated
90G4	Rural	Not Automated
ER-G52	Urban	Not Automated
27G7	Rural	Not Automated
SR-G71	Urban	Not Automated
NT-G52	Rural	Not Automated
RI-G66	Rural	Not Automated
BEL-G1	Rural	Not Automated
27G6	Rural	Not Automated
PM-G16	Rural	Not Automated
OV-G7	Rural	Not Automated
MC-G12	Rural	Not Automated
M-G26	Rural	Not Automated
PO-J31	Rural	Not Automated
FA-G4	Rural	Not Automated
19G3	Rural	Not Automated

34G2	Rural	Not Automated
LS-G62	Rural	Automated
38G1	Rural	Not Automated
38G3	Rural	Not Automated
JE-G57	Rural	Not Automated
19G6	Rural	Not Automated
VR-G58	Rural	Not Automated
LA-G61	Urban	Not Automated
SNO-G96	Rural	Not Automated
NW-G12	Rural	Not Automated
78G3	Rural	Not Automated
63J3	Rural	Not Automated
36Y5	Rural	Not Automated
41G1	Rural	Not Automated
SB-G94	Rural	Not Automated
NIM-G1	Rural	Not Automated
SS-G37	Rural	Not Automated
SL-W1	Rural	Not Automated
LA-G62	Urban	Not Automated
GI-G70	Rural	Not Automated
66J1	Rural	Not Automated
90G5	Rural	Not Automated
90G2	Rural	Not Automated
90G3	Rural	Not Automated
6Y2	Rural	Not Automated
37J5	Rural	Not Automated
SO-G32	Rural	Not Automated
71G2	Rural	Not Automated
HY-G25	Rural	Not Automated
67G1	Rural	Not Automated
SR-G73	Urban	Not Automated
BS-G124	Rural	Not Automated
WO-G91	Rural	Not Automated
73G1	Rural	Not Automated
BS-G31	Rural	Not Automated
26H1	Rural	Not Automated
BS-G123	Rural	Not Automated
GMP-G77	Rural	Not Automated
SB-G92	Rural	Not Automated
22J1	Rural	Not Automated
LS-G61	Rural	Automated
H3-G3	Rural	Not Automated

SR-G70	Urban	Not Automated
BU-G48	Rural	Not Automated
PS-G41	Rural	Not Automated
RD-G33	Rural	Not Automated
38G2	Rural	Not Automated
SO-G34	Rural	Not Automated
SO-G35	Rural	Not Automated
BL-G25	Rural	Not Automated
61G2	Rural	Not Automated
33Y4	Rural	Not Automated
51G1	Rural	Not Automated
EA-G51	Rural	Not Automated
NE-G17	Rural	Not Automated
PM-G15	Rural	Not Automated
2H2	Rural	Not Automated
32G8	Rural	Not Automated
NA-G27	Rural	Not Automated
3G2	Rural	Not Automated
9G3	Rural	Not Automated
SNO-G97	Rural	Not Automated
43G4	Rural	Not Automated
37J6	Rural	Not Automated
37H1	Rural	Not Automated
37H3	Rural	Not Automated
GT-G48	Urban	Not Automated
BEL-2	Rural	Not Automated
16G2	Rural	Not Automated
36G1	Rural	Not Automated
DQ-1	Rural	Not Automated
ro-g62	Rural	Not Automated
SJ-G64	Rural	Not Automated
3312	Rural	Not Automated
MI-G37	Rural	Not Automated
PM-G17	Rural	Not Automated
QU-G17	Rural	Not Automated
73G5	Rural	Not Automated
H3-J77	Rural	Not Automated

Appendix B

Cause	Time of Day	Season	Urban/Rural	Automation	Major Storm	Expertise	Day of Week	Mean_CHO
Supplier	off-peak	off	Rural	Not-Auto	NO	partial	weekday	4125.605
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	NO	none	weekday	2531.543
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	partial	weekend	1834.663
Other	peak	summer	Rural	Not-Auto	NO	partial	weekend	1797.53
PreventableForeseeable	off-peak	summer	Urban	Not-Auto	NO	partial	weekend	1685.658
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	full	weekend	1631.592
Other	off-peak	winter	Urban	Not-Auto	YES	no info	weekend	1577.687
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	YES	no info	weekday	1284.5
Supplier	off-peak	winter	Rural	Auto	YES	no info	weekday	1209.878
Supplier	off-peak	off	Rural	Not-Auto	NO	no info	weekday	1034.34
Supplier	off-peak	off	Rural	Not-Auto	NO	full	weekday	1027.929
UnexpectedLineOpen	peak	winter	Rural	Auto	NO	no info	weekday	957.1308
Supplier	off-peak	winter	Rural	Not-Auto	YES	no info	weekday	956.5701
PreventableForeseeable	peak	winter	Rural	Not-Auto	YES	no info	weekday	951.1976
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	none	weekend	937.9616
Supplier	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	922.415
Supplier	peak	winter	Rural	Not-Auto	YES	no info	weekday	906.8622
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	YES	no info	weekday	865.0546
UnexpectedGrounding	peak	summer	Rural	Not-Auto	NO	partial	weekday	842.1084
UnexpectedGrounding	peak	winter	Rural	Not-Auto	YES	no info	weekday	821.7163
Other	peak	winter	Rural	Not-Auto	YES	no info	weekday	734.0392
LineOpenFailure	off-peak	off	Rural	Not-Auto	NO	full	weekday	727.7639
UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	none	weekend	692.4377
PreventableForeseeable	peak	winter	Rural	Auto	YES	no info	weekday	654.2357
Supplier	peak	off	Rural	Not-Auto	NO	partial	weekday	631.0327
Error	peak	off	Rural	Not-Auto	NO	no info	weekend	628.9111
PreventableForeseeable	peak	summer	Rural	Auto	NO	partial	weekday	589.1912
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	575.2895
PreventableForeseeable	off-peak	winter	Urban	Not-Auto	YES	no info	weekday	557.4849
Other	off-peak	winter	Rural	Not-Auto	YES	no info	weekday	543.1412
Supplier	peak	off	Rural	Not-Auto	NO	no info	weekday	540.5442
Other	off-peak	off	Rural	Not-Auto	NO	partial	weekend	530.804
UnexpectedLineOpen	off-peak	off	Urban	Not-Auto	NO	full	weekday	480.2535
Other	peak	winter	Urban	Not-Auto	YES	no info	weekday	473.863
Error	peak	winter	Rural	Not-Auto	NO	full	weekday	455.6255
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	none	weeken	412.665

							d	
LineOpenFailure	off-peak	off	Rural	Not-Auto	NO	no info	weeken d	411.4471
PreventableForeseeable	peak	winter	Urban	Not-Auto	YES	no info	weekday	397.754
Supplier	peak	off	Rural	Not-Auto	NO	full	weekday	395.7897
Other	off-peak	winter	Rural	Not-Auto	YES	no info	weeken d	383.8389
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	full	weekday	364.4961
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	YES	no info	weekday	364.403
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	no info	weekday	363.3859
Error	peak	winter	Rural	Not-Auto	NO	no info	weekday	360.7967
PreventableForeseeable	peak	off	Rural	Auto	NO	none	weekday	358.0657
Other	off-peak	winter	Urban	Not-Auto	YES	no info	weekday	349.5182
UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	none	weekday	346.8153
Other	off-peak	summer	Rural	Not-Auto	NO	partial	weeken d	342.9846
Other	peak	off	Rural	Not-Auto	NO	partial	weeken d	333.6644
PreventableForeseeable	peak	summer	Urban	Not-Auto	NO	full	weeken d	313.0744
Error	peak	winter	Rural	Not-Auto	NO	partial	weekday	310.3732
Supplier	off-peak	winter	Rural	Not-Auto	NO	partial	weekday	293.6267
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	293.214
Other	off-peak	off	Rural	Auto	NO	partial	weeken d	292.687
Error	off-peak	summer	Rural	Not-Auto	NO	full	weekday	290.3003
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	none	weekday	288.5926
Other	off-peak	winter	Rural	Auto	YES	no info	weeken d	286.337
UnexpectedGrounding	off-peak	summer	Rural	Not-Auto	NO	none	weekday	283.633
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	YES	no info	weekday	282.8834
Error	peak	off	Rural	Not-Auto	NO	none	weekday	276.2625
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	partial	weeken d	252.0442
Other	off-peak	winter	Rural	Not-Auto	NO	partial	weekday	246.8772
Error	peak	off	Rural	Not-Auto	NO	full	weekday	246.4137
PreventableForeseeable	off-peak	summer	Rural	Not-Auto	NO	partial	weeken d	246.0683
Error	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	245.6755
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	partial	weeken d	244.431
Other	off-peak	off	Rural	Not-Auto	NO	none	weekday	244.0457
Other	peak	winter	Rural	Auto	YES	no info	weekday	227.3818
Error	peak	off	Rural	Not-Auto	NO	full	weeken d	223.5383
Error	off-peak	off	Rural	Not-Auto	NO	none	weeken d	215.8292
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	full	weekday	204.614
Other	off-peak	off	Rural	Auto	NO	partial	weekday	195.1954

PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	no info	weeken d	193.9513
PreventableForeseeable	off-peak	summer	Rural	Auto	NO	partial	weeken d	192.6292
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	none	weekday	189.2395
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	no info	weekday	186.4388
PreventableForeseeable	off-peak	off	Urban	Not-Auto	NO	full	weeken d	185.4543
PreventableForeseeable	peak	summer	Rural	Not-Auto	NO	full	weeken d	179.0681
Other	peak	winter	Rural	Not-Auto	NO	partial	weekday	178.9473
PreventableForeseeable	off-peak	summer	Rural	Not-Auto	NO	full	weeken d	178.6758
PreventableForeseeable	off-peak	winter	Urban	Not-Auto	YES	no info	weeken d	177.8726
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	YES	no info	weeken d	177.3136
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	none	weekday	175.9941
Supplier	off-peak	summer	Rural	Not-Auto	NO	full	weekday	175.4772
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	no info	weeken d	173.0822
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	no info	weeken d	172.0679
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	no info	weekday	166.4925
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	partial	weekday	162.6567
Other	peak	winter	Rural	Auto	NO	no info	weekday	159.5046
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	full	weekday	153.0016
Other	off-peak	winter	Rural	Auto	YES	no info	weekday	146.4396
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	full	weeken d	145.797
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	no info	weeken d	141.9221
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	partial	weekday	139.9519
PreventableForeseeable	off-peak	summer	Rural	Auto	NO	full	weeken d	138.9897
PreventableForeseeable	off-peak	off	Rural	Auto	NO	no info	weeken d	136.7383
PreventableForeseeable	peak	summer	Rural	Not-Auto	NO	partial	weekday	136.6439
Other	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	136.1776
PreventableForeseeable	off-peak	summer	Urban	Not-Auto	NO	full	weekday	135.4244
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	partial	weeken d	127.6986
LineOpenFailure	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	127.4713
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	partial	weekday	126.7273
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	partial	weekday	126.1428
PreventableForeseeable	off-peak	summer	Rural	Not-Auto	NO	partial	weekday	126.1398
PreventableForeseeable	peak	summer	Rural	Not-Auto	NO	partial	weeken d	125.704
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	none	weeken d	125.1492
Other	peak	winter	Rural	Auto	YES	no info	weeken	123.7735

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UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	no info	weekday	123.2315
Other	off-peak	winter	Rural	Not-Auto	NO	full	weekday	121.6156
Other	peak	winter	Rural	Not-Auto	NO	no info	weekend	120.9368
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	full	weekend	116.6161
PreventableForeseeable	off-peak	off	Rural	Auto	NO	no info	weekday	116.5582
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	none	weekday	115.0698
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	no info	weekday	113.664
UnexpectedLineOpen	peak	summer	Rural	Auto	NO	none	weekend	111.7114
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	full	weekday	110.2024
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	partial	weekday	106.8783
PreventableForeseeable	off-peak	summer	Urban	Not-Auto	NO	full	weekend	106.6903
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	YES	no info	weekend	104.2167
Other	off-peak	off	Urban	Not-Auto	NO	no info	weekday	100.4276
UnexpectedLineOpen	off-peak	summer	Urban	Not-Auto	NO	full	weekday	99.84
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	full	weekend	99.54037
Other	off-peak	off	Rural	Not-Auto	NO	partial	weekday	99.09455
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	none	weekday	96.87111
Other	off-peak	off	Rural	Auto	NO	no info	weekday	96.80018
Other	off-peak	off	Rural	Not-Auto	NO	no info	weekend	93.04107
Other	peak	off	Urban	Not-Auto	NO	full	weekday	92.77371
Other	off-peak	winter	Rural	Not-Auto	NO	partial	weekend	92.75444
Other	peak	winter	Rural	Not-Auto	YES	no info	weekend	90.57617
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	NO	no info	weekend	84.76063
PreventableForeseeable	off-peak	off	Urban	Not-Auto	NO	full	weekday	84.19694
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	full	weekday	83.97012
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	full	weekend	83.82596
Other	off-peak	off	Rural	Not-Auto	NO	full	weekend	83.08708
Other	off-peak	off	Rural	Not-Auto	NO	none	weekend	83.05699
PreventableForeseeable	peak	winter	Rural	Not-Auto	YES	no info	weekend	80.34699
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	none	weekend	80.02511
Other	peak	winter	Rural	Not-Auto	NO	no info	weekday	79.25006
UnexpectedLineOpen	off-peak	summer	Urban	Not-Auto	NO	none	weekday	78.885
PreventableForeseeable	off-peak	winter	Rural	Auto	YES	no info	weekday	78.57111
PreventableForeseeable	off-peak	winter	Rural	Auto	NO	no info	weekday	77.74556

Other	peak	winter	Rural	Not-Auto	NO	full	weekday	77.72379
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	no info	weeken d	76.80637
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	partial	weeken d	76.46417
UnexpectedGrounding	off-peak	off	Rural	Auto	NO	full	weeken d	76.10667
UnexpectedLineOpen	off-peak	off	Rural	Not-Auto	NO	full	weekday	75.81074
Other	peak	off	Rural	Not-Auto	NO	no info	weekday	75.30832
UnexpectedLineOpen	off-peak	off	Urban	Not-Auto	NO	no info	weekday	72.45708
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	no info	weekday	71.75074
LineOpenFailure	peak	off	Rural	Not-Auto	NO	no info	weekday	69.86681
LineOpenFailure	peak	summer	Rural	Not-Auto	NO	full	weekday	69.37444
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	full	weekday	68.82722
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	no info	weekday	68.447
Other	off-peak	summer	Rural	Not-Auto	NO	none	weekday	66.73132
UnexpectedLineOpen	peak	winter	Urban	Not-Auto	NO	no info	weekday	66.55583
UnexpectedGrounding	peak	summer	Rural	Not-Auto	NO	partial	weeken d	65.514
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	partial	weeken d	65.46222
UnexpectedLineOpen	peak	off	Rural	Auto	NO	full	weekday	65.41565
Other	peak	winter	Rural	Not-Auto	NO	full	weeken d	65.29865
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	full	weeken d	65.01417
UnexpectedGrounding	off-peak	summer	Rural	Not-Auto	NO	full	weekday	64.29122
Other	off-peak	off	Urban	Not-Auto	NO	no info	weeken d	63.67963
Other	off-peak	off	Rural	Not-Auto	NO	no info	weekday	63.65787
Other	peak	summer	Rural	Not-Auto	NO	full	weeken d	63.46895
PreventableForeseeable	peak	off	Rural	Not-Auto	NO	none	weeken d	62.45199
UnexpectedLineOpen	peak	off	Rural	Auto	NO	partial	weekday	62.0425
PreventableForeseeable	peak	summer	Rural	Not-Auto	NO	full	weekday	61.86364
UnexpectedLineOpen	off-peak	winter	Urban	Not-Auto	YES	no info	weekday	61.53667
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	full	weeken d	61.49186
Other	peak	off	Rural	Not-Auto	NO	no info	weeken d	61.4499
Other	peak	summer	Rural	Not-Auto	NO	none	weekday	60.66659
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	no info	weeken d	60.31042
Other	peak	off	Rural	Not-Auto	NO	partial	weekday	57.05853
Other	off-peak	off	Rural	Not-Auto	NO	full	weekday	57.01548
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	none	weeken d	56.76625
Other	peak	winter	Urban	Not-Auto	NO	full	weekday	56.74465
PreventableForeseeable	off-peak	summer	Rural	Not-Auto	NO	full	weekday	56.48609

Other	off-peak	summer	Rural	Not-Auto	NO	full	weekday	55.41411
UnexpectedGrounding	off-peak	summer	Rural	Not-Auto	NO	full	weeken d	55.34762
Other	off-peak	off	Rural	Auto	NO	none	weeken d	51.55315
PreventableForeseeable	off-peak	summer	Rural	Not-Auto	NO	none	weeken d	50.55789
UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	no info	weekday	50.38401
Other	peak	off	Rural	Not-Auto	NO	full	weeken d	50.13088
PreventableForeseeable	peak	summer	Rural	Not-Auto	NO	none	weekday	49.81412
Other	off-peak	winter	Urban	Not-Auto	NO	none	weekday	49.62222
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	none	weeken d	48.02083
Other	peak	winter	Urban	Not-Auto	YES	no info	weeken d	47.98574
UnexpectedGrounding	off-peak	off	Rural	Auto	NO	no info	weeken d	47.88
Other	peak	off	Rural	Not-Auto	NO	full	weekday	45.93757
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	none	weekday	45.32832
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	partial	weekday	44.66346
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	full	weeken d	43.25606
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	none	weeken d	43.09676
Error	off-peak	off	Rural	Not-Auto	NO	no info	weekday	42.9202
Other	off-peak	summer	Rural	Not-Auto	NO	partial	weekday	42.72128
UnexpectedGrounding	peak	summer	Rural	Not-Auto	NO	full	weekday	42.70417
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	full	weekday	42.62923
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	none	weekday	42.55576
Supplier	peak	summer	Rural	Not-Auto	NO	full	weekday	42.3125
Other	peak	off	Rural	Not-Auto	NO	none	weeken d	41.47861
PreventableForeseeable	peak	off	Rural	Auto	NO	full	weeken d	39.40375
PreventableForeseeable	peak	summer	Rural	Auto	NO	full	weeken d	38.32028
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	partial	weekday	38.10154
UnexpectedLineOpen	peak	winter	Urban	Not-Auto	YES	no info	weekday	37.79144
LineOpenFailure	off-peak	winter	Rural	Not-Auto	NO	no info	weeken d	37.66917
Other	peak	summer	Rural	Not-Auto	NO	partial	weekday	37.31969
Other	off-peak	winter	Rural	Auto	NO	no info	weekday	37.15
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	none	weekday	36.56631
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	partial	weeken d	36.55296
Other	off-peak	summer	Rural	Not-Auto	NO	none	weeken d	35.78822
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	full	weekday	35.39722
PreventableForeseeable	off-peak	off	Rural	Not-Auto	NO	none	weeken d	35.31619

Other	peak	off	Urban	Not-Auto	NO	none	weeken d	35.06118
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	partial	weekday	34.55972
UnexpectedLineOpen	peak	off	Rural	Not-Auto	NO	full	weeken d	33.73781
Other	peak	off	Rural	Auto	NO	full	weekday	33.39691
Other	off-peak	summer	Urban	Not-Auto	NO	full	weekday	33.10315
UnexpectedLineOpen	off-peak	off	Rural	Auto	NO	no info	weekday	32.69704
PreventableForeseeable	peak	winter	Urban	Not-Auto	NO	full	weekday	32.545
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	no info	weeken d	32.52699
Other	peak	off	Urban	Not-Auto	NO	no info	weeken d	32.42208
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	partial	weekday	32.03761
Other	peak	off	Rural	Auto	NO	none	weeken d	31.83597
Other	off-peak	summer	Rural	Auto	NO	full	weekday	31.81167
PreventableForeseeable	off-peak	winter	Rural	Not-Auto	NO	partial	weekday	31.58294
PreventableForeseeable	off-peak	winter	Urban	Not-Auto	NO	no info	weeken d	31.46611
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	none	weeken d	31.41748
Other	off-peak	winter	Rural	Not-Auto	NO	no info	weeken d	30.59338
UnexpectedGrounding	off-peak	summer	Rural	Not-Auto	NO	partial	weekday	29.40611
UnexpectedGrounding	off-peak	summer	Rural	Not-Auto	NO	none	weeken d	29.16382
PreventableForeseeable	off-peak	winter	Urban	Not-Auto	NO	full	weekday	28.4162
PreventableForeseeable	off-peak	off	Rural	Auto	NO	none	weeken d	27.96111
UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	full	weeken d	27.68194
Other	off-peak	winter	Urban	Not-Auto	NO	full	weekday	26.84278
PreventableForeseeable	off-peak	winter	Urban	Not-Auto	NO	partial	weekday	26.61556
LineOpenFailure	peak	off	Rural	Not-Auto	NO	full	weekday	26.16701
PreventableForeseeable	peak	winter	Urban	Not-Auto	NO	no info	weeken d	25.81833
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	no info	weeken d	25.78106
UnexpectedGrounding	off-peak	summer	Rural	Not-Auto	NO	partial	weeken d	24.94458
PreventableForeseeable	peak	summer	Rural	Auto	NO	partial	weeken d	24.61965
PreventableForeseeable	off-peak	summer	Rural	Not-Auto	NO	none	weekday	24.39823
PreventableForeseeable	peak	summer	Rural	Not-Auto	NO	none	weeken d	24.30854
UnexpectedGrounding	peak	summer	Rural	Not-Auto	NO	none	weeken d	23.73576
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	no info	weeken d	23.49181
PreventableForeseeable	off-peak	off	Rural	Auto	NO	full	weeken d	22.92174

PreventableForeseeable	peak	winter	Rural	Auto	NO	no info	weekday	22.84657
Supplier	off-peak	winter	Urban	Not-Auto	YES	no info	weekday	22.34528
UnexpectedGrounding	off-peak	off	Urban	Not-Auto	NO	full	weekday	22.18367
UnexpectedGrounding	off-peak	winter	Urban	Not-Auto	NO	full	weekday	21.24889
Other	peak	summer	Rural	Not-Auto	NO	full	weekday	20.45508
UnexpectedGrounding	off-peak	summer	Rural	Auto	NO	full	weekend	20.42
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	YES	no info	weekend	20.29815
Other	peak	winter	Rural	Not-Auto	NO	none	weekday	20.14833
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	full	weekday	20.13138
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	NO	no info	weekend	19.96672
UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	partial	weekday	19.92507
Other	off-peak	winter	Rural	Auto	NO	no info	weekend	19.58
Other	peak	off	Urban	Not-Auto	NO	none	weekday	19.53306
Other	peak	summer	Rural	Not-Auto	NO	none	weekend	18.70677
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	NO	partial	weekday	17.80361
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	full	weekend	17.6902
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	no info	weekend	17.33101
PreventableForeseeable	off-peak	off	Rural	Auto	NO	none	weekday	17.32
UnexpectedLineOpen	peak	summer	Urban	Not-Auto	NO	full	weekday	17.1025
Other	peak	off	Rural	Auto	NO	no info	weekday	17.08932
Other	off-peak	off	Urban	Not-Auto	NO	none	weekend	16.70481
PreventableForeseeable	off-peak	summer	Rural	Auto	NO	full	weekday	16.56676
Other	off-peak	summer	Rural	Not-Auto	NO	full	weekend	16.49299
PreventableForeseeable	peak	winter	Rural	Not-Auto	NO	none	weekday	16.47578
UnexpectedGrounding	peak	winter	Urban	Not-Auto	YES	no info	weekday	16.39
Other	off-peak	winter	Rural	Auto	NO	full	weekday	16.19222
UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	no info	weekend	15.70654
PreventableForeseeable	peak	winter	Urban	Not-Auto	YES	no info	weekend	15.62905
Other	peak	off	Rural	Auto	NO	full	weekend	15.57094
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	full	weekday	15.12227
Other	off-peak	off	Rural	Auto	NO	full	weekday	14.98086
Other	off-peak	off	Urban	Not-Auto	NO	none	weekday	14.91083
Other	peak	off	Urban	Not-Auto	NO	no info	weekday	14.90536
UnexpectedGrounding	peak	summer	Rural	Not-Auto	NO	full	weekend	14.88266
Other	off-peak	off	Urban	Not-Auto	NO	full	weekday	14.86847
Other	off-peak	winter	Rural	Not-Auto	NO	full	weekend	14.08208

Supplier	peak	winter	Urban	Not-Auto	YES	no info	weekday	13.96139
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	NO	no info	weekday	13.90036
Other	peak	off	Rural	Not-Auto	NO	none	weekday	13.17609
UnexpectedGrounding	off-peak	off	Urban	Not-Auto	NO	none	weekend	13.17028
Other	off-peak	summer	Rural	Auto	NO	partial	weekend	13.145
UnexpectedLineOpen	peak	winter	Urban	Not-Auto	NO	full	weekday	12.90611
Other	off-peak	winter	Rural	Not-Auto	NO	none	weekday	12.86139
Other	off-peak	off	Rural	Auto	NO	no info	weekend	12.70593
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	NO	no info	weekday	12.54061
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	none	weekday	12.07741
Other	peak	summer	Rural	Auto	NO	full	weekday	11.80722
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	no info	weekday	11.72339
UnexpectedGrounding	off-peak	off	Rural	Auto	NO	no info	weekday	11.59407
Other	peak	off	Urban	Not-Auto	NO	partial	weekday	11.48747
PreventableForeseeable	off-peak	off	Rural	Auto	NO	full	weekday	11.47048
Error	peak	off	Rural	Not-Auto	NO	no info	weekday	11.42731
Error	peak	winter	Rural	Not-Auto	NO	no info	weekend	11.38444
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	no info	weekday	11.22072
Other	off-peak	summer	Rural	Auto	NO	full	weekend	11.16597
PreventableForeseeable	off-peak	winter	Urban	Not-Auto	NO	no info	weekday	10.94042
LineOpenFailure	peak	off	Rural	Not-Auto	NO	none	weekend	10.92597
UnexpectedGrounding	off-peak	summer	Urban	Not-Auto	NO	full	weekend	10.87556
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	partial	weekday	9.388484
LineOpenFailure	peak	off	Rural	Not-Auto	NO	partial	weekday	9.360556
UnexpectedLineOpen	peak	off	Rural	Auto	NO	full	weekend	9.2625
LineOpenFailure	off-peak	winter	Rural	Not-Auto	NO	full	weekday	9.107778
UnexpectedLineOpen	off-peak	summer	Rural	Not-Auto	NO	partial	weekend	9.099306
Other	off-peak	winter	Urban	Not-Auto	NO	no info	weekday	8.975139
LineOpenFailure	off-peak	off	Rural	Not-Auto	NO	none	weekend	8.745
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	full	weekend	8.525328
Other	peak	summer	Rural	Auto	NO	partial	weekday	8.414889
Error	peak	off	Rural	Not-Auto	NO	partial	weekday	8.376667
LineOpenFailure	peak	off	Rural	Not-Auto	NO	none	weekday	8.354306
Other	peak	summer	Urban	Not-Auto	NO	none	weekend	8.208611
Other	peak	winter	Urban	Not-Auto	NO	no info	weekday	8.205357
UnexpectedLineOpen	peak	summer	Rural	Auto	NO	full	weekday	8
UnexpectedGrounding	peak	off	Rural	Auto	NO	no info	weekday	7.562986

UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	full	weekday	7.525397
UnexpectedGrounding	peak	winter	Urban	Not-Auto	NO	no info	weekday	7.4275
UnexpectedGrounding	off-peak	off	Urban	Not-Auto	NO	no info	weekday	6.910417
PreventableForeseeable	off-peak	off	Urban	Not-Auto	NO	no info	weekday	6.796528
Other	peak	off	Rural	Auto	NO	no info	weeken d	6.643889
UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	full	weeken d	6.588056
UnexpectedLineOpen	off-peak	off	Urban	Not-Auto	NO	no info	weeken d	6.565
UnexpectedLineOpen	off-peak	summer	Rural	Auto	NO	full	weekday	6.524444
Other	peak	summer	Urban	Not-Auto	NO	full	weekday	6.4675
UnexpectedGrounding	off-peak	summer	Urban	Not-Auto	NO	full	weekday	6.427153
Other	peak	summer	Urban	Not-Auto	NO	partial	weekday	6.083278
UnexpectedGrounding	off-peak	off	Urban	Not-Auto	NO	full	weeken d	5.897167
UnexpectedGrounding	off-peak	off	Rural	Not-Auto	NO	partial	weeken d	5.838924
Other	off-peak	summer	Urban	Not-Auto	NO	none	weekday	5.506667
UnexpectedGrounding	peak	summer	Rural	Auto	NO	full	weekday	5.456667
UnexpectedLineOpen	peak	summer	Urban	Not-Auto	NO	partial	weeken d	5.206111
PreventableForeseeable	peak	off	Rural	Auto	NO	partial	weekday	5.022056
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	YES	no info	weeken d	4.808611
Error	off-peak	off	Rural	Not-Auto	NO	full	weekday	4.748333
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	NO	partial	weekday	4.584722
PreventableForeseeable	peak	off	Rural	Auto	NO	full	weekday	4.439722
UnexpectedGrounding	peak	summer	Urban	Not-Auto	NO	full	weeken d	4.215833
Other	peak	winter	Rural	Not-Auto	NO	partial	weeken d	4.208681
Other	peak	winter	Rural	Not-Auto	NO	none	weeken d	4.207685
UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	full	weekday	4.034815
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	none	weekday	3.850972
UnexpectedLineOpen	off-peak	winter	Rural	Not-Auto	NO	full	weekday	3.785722
LineOpenFailure	peak	off	Rural	Not-Auto	NO	partial	weeken d	3.720139
UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	partial	weeken d	3.564722
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	no info	weekday	3.487778
UnexpectedLineOpen	peak	summer	Rural	Auto	NO	partial	weekday	3.441667
UnexpectedLineOpen	peak	summer	Rural	Not-Auto	NO	none	weekday	3.406944
UnexpectedGrounding	peak	summer	Rural	Not-Auto	NO	none	weekday	3.353389
Supplier	peak	summer	Rural	Not-Auto	NO	full	weeken d	3.336111
Other	off-peak	off	Rural	Auto	NO	full	weeken d	3.293434
UnexpectedGrounding	off-peak	off	Urban	Not-Auto	NO	no info	weeken	3.238889

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Error	peak	summer	Rural	Not-Auto	NO	full	weekday	3.182778
UnexpectedLineOpen	peak	off	Rural	Auto	NO	partial	weeken d	3.087778
Other	off-peak	off	Rural	Auto	NO	none	weekday	3.0625
Other	peak	summer	Urban	Not-Auto	NO	full	weeken d	3.051597
LineOpenFailure	off-peak	off	Rural	Not-Auto	NO	none	weekday	3
UnexpectedGrounding	off-peak	summer	Rural	Auto	NO	full	weekday	2.994405
Other	off-peak	off	Urban	Not-Auto	NO	full	weeken d	2.9
Supplier	peak	off	Rural	Not-Auto	NO	no info	weeken d	2.8825
LineOpenFailure	off-peak	summer	Rural	Not-Auto	NO	full	weekday	2.765
Error	off-peak	winter	Rural	Auto	NO	no info	weekday	2.72537
PreventableForeseeable	peak	off	Rural	Auto	NO	no info	weeken d	2.676111
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	NO	none	weeken d	2.629167
UnexpectedGrounding	peak	off	Rural	Not-Auto	NO	partial	weeken d	2.548457
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	NO	full	weeken d	2.401111
UnexpectedLineOpen	off-peak	winter	Urban	Not-Auto	NO	no info	weekday	2.222222
UnexpectedGrounding	peak	off	Rural	Auto	NO	none	weeken d	2.168889
Other	peak	winter	Rural	Auto	NO	no info	weeken d	2.126111
UnexpectedLineOpen	peak	off	Rural	Auto	NO	no info	weekday	2.030139
UnexpectedGrounding	peak	winter	Rural	Not-Auto	YES	no info	weeken d	1.863889
UnexpectedLineOpen	off-peak	off	Rural	Auto	NO	no info	weeken d	1.7625
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	NO	partial	weeken d	1.72
PreventableForeseeable	off-peak	off	Urban	Not-Auto	NO	none	weekday	1.705833
UnexpectedGrounding	off-peak	winter	Rural	Not-Auto	NO	full	weekday	1.699848
Other	peak	summer	Urban	Not-Auto	NO	none	weekday	1.69
UnexpectedLineOpen	off-peak	winter	Rural	Auto	NO	no info	weekday	1.688056
Other	off-peak	off	Urban	Not-Auto	NO	partial	weekday	1.687292
UnexpectedLineOpen	peak	off	Rural	Auto	NO	none	weekday	1.673333
PreventableForeseeable	peak	off	Urban	Not-Auto	NO	full	weeken d	1.594444
Other	off-peak	summer	Urban	Not-Auto	NO	full	weeken d	1.570556
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	none	weeken d	1.541736
UnexpectedGrounding	peak	winter	Rural	Not-Auto	NO	none	weeken d	1.49713
PreventableForeseeable	peak	off	Rural	Auto	NO	no info	weekday	1.450926
UnexpectedLineOpen	off-peak	off	Urban	Not-Auto	NO	full	weeken d	1.447917

UnexpectedLineOpen	off-peak	off	Rural	Auto	NO	partial	weekday	1.437778
Other	peak	off	Urban	Not-Auto	NO	partial	weeken d	1.328056
Other	peak	winter	Urban	Not-Auto	NO	partial	weekday	1.301944
LineOpenFailure	peak	winter	Urban	Not-Auto	NO	no info	weekday	1.295833
UnexpectedLineOpen	peak	summer	Rural	Auto	NO	full	weeken d	1.260833
Other	peak	summer	Rural	Auto	NO	none	weeken d	1.240556
Other	peak	off	Urban	Not-Auto	NO	full	weeken d	1.22463
UnexpectedGrounding	off-peak	off	Rural	Auto	NO	full	weekday	1.156019
UnexpectedGrounding	off-peak	summer	Rural	Auto	NO	partial	weekday	1.145556
UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	no info	weeken d	1.091667
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	NO	full	weekday	1.070463
PreventableForeseeable	peak	winter	Urban	Not-Auto	NO	no info	weekday	1.064722
UnexpectedGrounding	peak	off	Rural	Auto	NO	full	weekday	1.015722
UnexpectedLineOpen	off-peak	off	Rural	Auto	NO	full	weekday	0.984722
UnexpectedLineOpen	peak	winter	Urban	Not-Auto	NO	no info	weeken d	0.965
Other	peak	off	Rural	Auto	NO	partial	weeken d	0.691667
Other	off-peak	winter	Urban	Not-Auto	NO	no info	weeken d	0.689444
UnexpectedLineOpen	peak	winter	Rural	Not-Auto	NO	no info	weeken d	0.66746
UnexpectedGrounding	peak	off	Rural	Auto	NO	no info	weeken d	0.654722
UnexpectedGrounding	peak	summer	Urban	Not-Auto	NO	full	weekday	0.554778
Other	peak	off	Rural	Auto	NO	none	weekday	0.53375
PreventableForeseeable	peak	summer	Rural	Auto	NO	full	weekday	0.488194
UnexpectedGrounding	peak	off	Urban	Not-Auto	NO	full	weekday	0.438125
Supplier	peak	winter	Rural	Not-Auto	NO	full	weekday	0.408611
Other	peak	winter	Rural	Auto	NO	full	weekday	0.253333
LineOpenFailure	off-peak	summer	Rural	Not-Auto	NO	full	weeken d	0.207037
PreventableForeseeable	peak	summer	Urban	Not-Auto	NO	full	weekday	0.183056
Supplier	peak	summer	Rural	Not-Auto	NO	none	weekday	0
Other	peak	off	Rural	Auto	NO	partial	weekday	0
Supplier	peak	summer	Rural	Not-Auto	NO	partial	weekday	0
PreventableForeseeable	off-peak	off	Urban	Not-Auto	NO	partial	weekday	0
UnexpectedLineOpen	peak	off	Urban	Not-Auto	NO	partial	weekday	0
PreventableForeseeable	peak	summer	Urban	Not-Auto	NO	partial	weekday	0
LineOpenFailure	off-peak	off	Rural	Not-Auto	NO	no info	weekday	0
UnexpectedGrounding	off-peak	winter	Urban	Not-Auto	YES	no info	weekday	0
UnexpectedGrounding	off-peak	off	Rural	Auto	NO	none	weeken d	0
LineOpenFailure	peak	off	Urban	Not-Auto	NO	none	weeken	0

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