Pacific Gas and Electric Company

EPIC Final Report

Program	***Electric Program Investment Charge (EPIC)***
Project	***EPIC 2.10 – Emergency Preparedness Modeling***
Reference Name	***EPIC 2.10 – Restoration Work Plan***
Department	*Distribution Operations*
Project Sponsor Business Lead	Evermary Hickey Greg Molnar
Contact Info	EPIC_Info@pge.com
Date Version Type	February 22, 2019 *Final Report*

Table of Contents

List of Figures

List of Tables

Table of Acronyms

PG&E	Pacific Gas & Electric Company
ARAD	Analytics Rapid Application Development
AWS	Amazon Web Services
ARCOS	Automated Call-Out System
Athena	Amazon's Interactive Data Query Service
CAIDI	Customer Average Interruption Duration Index
CEC	California Energy Commission
CPUC	California Public Utility Commission
CSV	Comma Separated Values
DASH	Dynamic Automated Seismic Hazard (Earthquake Damage Model)
DMS	Distribution Management System
DOC	Decision Optimization Center: IBM's optimization platform
EI	Enterprise Integration – refers to an organization and the technologies which it uses
EOC	Emergency Operations Center
EP&R	Emergency Preparedness and Response business unit within PG&E
EPIC	Electric Program Investment Charge
ETOR	Estimated Time of Restoration
EV	Electric Vehicles
GIS	Geographic Information System
GHG	Greenhouse Gas
GRC	General Rate Case
ICS	Incident Command System
ICT	Information and Security Assets
ILIS	Integrated Logging and Information System
JDBC	Java Database Connectivity
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MLE	Maximum Likelihood Estimate
RWP	Restoration Work Plan
SAIDI	System Average Interruption Duration Index
SAP	Enterprise Software System
SCE	Southern California Edison
SDG&E	San Diego Gas and Electric
SOPP	Storm Outage Prediction Project
TD&D	Technology Demonstration and Deployment
UDN	Utility Data Network
UI	User Interface

1 Executive Summary

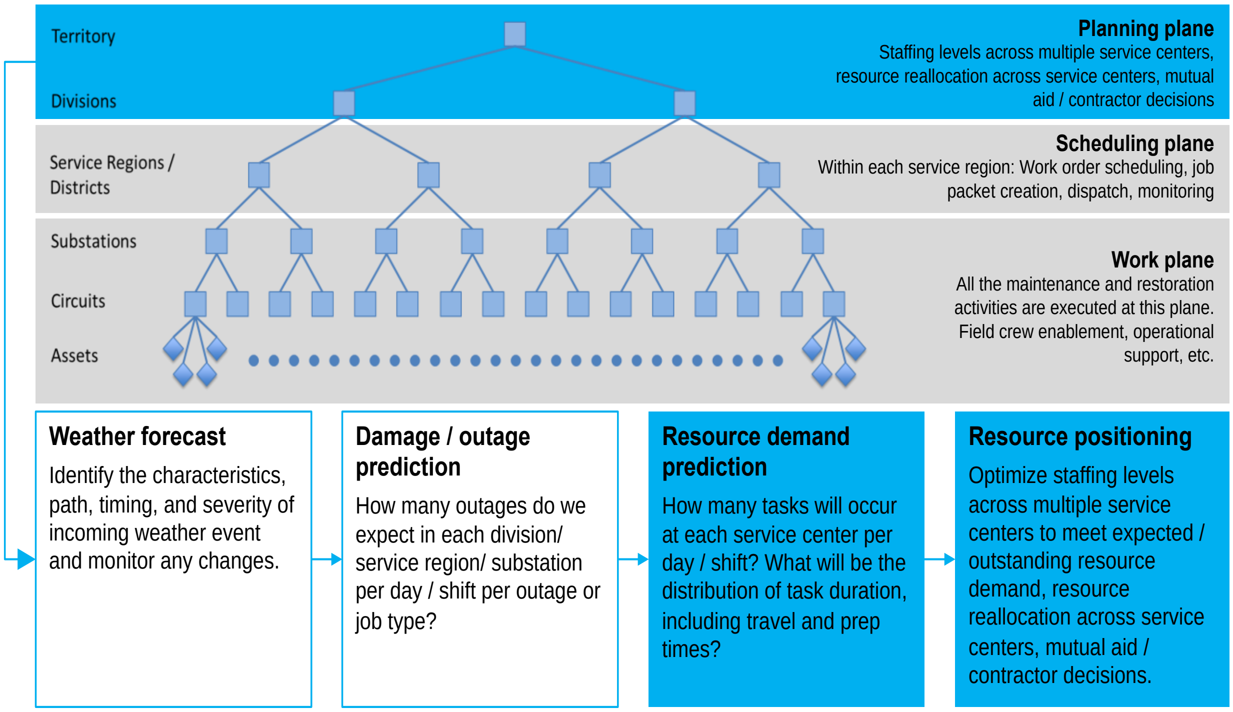
This report summarizes the project objectives, technical results and lessons learned for Electric Program Investment Charge (EPIC) Project 2.10 – Emergency Preparedness Modeling as reported in the EPIC Annual Report, also referred to as EPIC 2.10 – Restoration Work Plan.

1.1 Project Motivation

Planning and optimal resource management during an emergency is a complicated task as it requires the balancing of multiple constraints including time, resources, and costs, while interpreting uncertain data around crew movement, crew types, crew availability, asset damage, weather patterns and predicted damage. The overall workload is compounded by the fact that these constraints will change throughout the execution of the response, and the priorities from the incident commanders and planning chiefs will vary between operation periods.

Pacific Gas & Electric Company's (PG&E) current approach toward restoration strategy development is like many other utilities' as it involves multiple spreadsheets and leverages seasoned utility experts to come up with approaches towards crew allocations. The current process requires a planner to utilize a spreadsheet to compute resources for 19 divisions over five days, with productive rates and other assumptions that cannot be immediately verified. This act of balancing constraints can take an hour or more each time a planning horizon is determined by the incident commander and can be skewed according to the methodology implemented by the planner and potential typographical and clerical errors. There is no way to immediately understand the impact of a strategic resource allocation without many hours of work. Figure 1 below frames the challenge that utilities face during the planning phase of an emergency. As this illustrates, overall planning involves activities in three planes — the Planning, Scheduling and Work Planes.

Figure 1 - Framing the Planning Challenge



The potential to apply current predictive analytics using big data and artificial intelligence with Machine Learning (ML) algorithms are keys to providing more certainty in understanding work demand, resource requirements, and positioning of resources. Additionally, these advanced technologies not only make critical information more visible to key decision makers at the right time, but also provide consistency and transparency to the development and revision of restoration plans.

1.2 Project Objectives

The following were the key project objectives:

- Incorporate natural hazard damage model information into one integrated algorithm/tool, to provide the ability to quickly estimate the impacts of natural hazards on PG&E facilities
- Proactively model the impacts of potential hazards to understand system vulnerabilities and restoration resource requirements which helps to prepare for these hazards.
- Utilize artificial intelligence and statistical methods to model productive rates and automatically allocate crews and develop restoration plans.

1.3 Project Effort and Accomplishments

PG&E initiated this EPIC 2.10 project to develop and demonstrate a decision support system, called the Restoration Work Plan (RWP), that would recommend restoration strategies for PG&E electric assets after a disruptive event. This tool addresses storm events for the initial demonstration, and incorporates data from natural hazard damage models, staffing and resource locations, outage management systems, and financial models. It provides analytical recommendations and scenarios for enhanced decision making within the Emergency Operations Center (EOC) and ultimately can help achieve a more cost effective and faster response and restoration. This decision support system provides the ability to prepare for these hazards by proactively modeling the impacts of potential hazards to understand system vulnerabilities and restoration resource requirements. As such, the RWP developed under this EPIC project successfully demonstrates:

1. The ability to aggregate equipment damage estimates (via damage models, outage information systems, and damage assessments), hours to repair, and optimal work resources. This innovative approach enhances PG&E's ability to understand impacts of these natural hazards (for example, number of outages, damage types, customers without power, potential length of outages) to improve resource allocation, prioritization decisions, and ultimately to develop a more accurate Estimated Time for Restoration (ETOR).
2. The ability to recommend positioning of resources (including contractors and mutual aids) needed for the restoration, as well as intra-territory movement of these resources as they handle multiple outages.
3. A flexible user interface that enables advance planners to generate ML-based trained statistics and run multiple what-if scenario analyses with the ability to overwrite certain assumptions such as resource productivity time and conversion rates.
4. A dashboard and associated visualization functionalities that enable decision makers to review and approve proposed restoration plans.

To achieve the above, the project team developed the following models that are the core components of and enable this decision support system:

- A ML performance model to predict accurate work demand (ML Scoring) and resource performance (ML Training) which:
    - Leverages PG&E data resources and analytical techniques
    - Learns from successive incidents to improve predicted rates

- An optimization model that provides resource positioning recommendations that are:
    - Fast and transparent resource deployment plans
    - More cost effective and efficient resource allocation and movement

The optimization model is based on a Mixed Integer Linear Programming (MILP)-based method for resource planning which computes the optimal shift-level resource staffing plan while:

1) considering multiple stochastic damage scenarios
2) employing an aggregated demand model for faster resource position planning
3) minimizing the work needing to be performed, but not completed, during a work period
4) allowing for the reassignment of resources between service centers and,
5) respecting deployment policies for resources that belong to different organizations

The following presented challenges in the solution development and design process:

- Neither precise damages, nor the individual crew's availability for work are known at the time of the planning activity. This makes the creation of work schedules (allocation of crew to individual tasks) for specific crews nearly impossible. This challenge was addressed by developing the ML Training and Scoring Models.
- Due to the variability of weather conditions, having a high degree of certainty for a single damage scenario is very unlikely and therefore a stochastic optimization approach for crew planning had to be adopted. This optimization method solves for the best solution overall that accounts for the range of possible outcomes.

The team tested the RWP system by validating its generated work demand, resources performance and resource positioning, using historical data for specific storms that occurred from 2014 through 2017. The team validated the RWP output by performing the following:

1) Comparison of the performance statistics (productivity rate, outage type distribution and task transition from Troublemen to Crews) generated using the ML and the ones observed for historical events
2) Comparison of the RWP recommended work plans (resource allocation and movement) and the actual historical data from the Distribution Management System (DMS)
3) Review of RWP recommended work plans by seasoned utility experts

The development team incorporated the results from the testing to create outputs that more closely matched the format that utility experts had used for planning during prior events. This helped the team to identify the essential information required for utility employees to execute their work, and better understand how to fit the algorithm within the planning process. As a result, the time required to install the program on a local machine was reduced to under an hour, and planners are now able to produce viable plans in less than five minutes with minimal amounts of training.

1.4 Key Recommendation

Continue the adoption of this work forecasting system with additional software development projects and integration with key damage models that address emerging natural hazards for utilities, such as wildfires and public safety power shutoffs. Leadership within operations should promote the prototype's usage so the development team can receive user feedback and improve the recommendations that the system provides. In support of this request, funding to perform this work has been outlined in Chapter 15 of the PG&E General Rate Case (GRC), titled "Restoration Work Plan."

1.5 Conclusion

This project met its objectives through the successful development and demonstration of a decision support system that recommends restoration strategies for PG&E electric assets after a disruptive event occurs. This system can quickly estimate the impacts of natural hazards on PG&E facilities to enable faster response and restoration, provide the ability to prepare for these hazards by proactively modeling the impacts of potential hazards, understand system vulnerabilities and restoration resource requirements, and more efficiently allocate resources.

This project demonstrated the potential to apply predictive analytics using big data and artificial intelligence with ML algorithms to improve the certainty in understanding work demand and resource requirements as well as the positioning of resources, which results in a safer environment, improved reliability and transparency, and promote the efficient use of customer funds. In addition, applying these advanced technologies not only makes critical information more visible to key decision makers at the right time, but also provides consistency and transparency to the development and revision of restoration plans.

In addition to the GRC request, PG&E will continue to improve the system by leveraging it further in a field demonstration setting, in parallel with the existing process, for the upcoming storm season and benchmarking its output with actual damages as well as actual crew allocation and positioning. Moreover, while the current version of RWP focuses on storm events, the system's framework allows for an expansion to other hazards that PG&E deems significant in the future.

The value proposition that can be realized by this tool can be applied to many other utilities throughout the country for their needs and constraints. For example, the Hurricane Sandy response impact would have been better understood if a framework and tool like the RWP had been in place. The findings in this project related to how work was characterized and how mathematical methods determine resource allocation. This will give utilities an opportunity to replace their daily scheduling tools with components of the RWP's engine that will automatically direct crew movements and project needs.

2 Introduction

This report documents the EPIC 2.10 – Emergency Preparedness Modeling project achievements, highlights key learnings from the project that have industry-wide value, and identifies future opportunities for PG&E to leverage this project.

The California Public Utilities Commission (CPUC) passed two decisions that established the basis for this demonstration program. The CPUC initially issued Decision (D.) 11-12-035, *Decision Establishing Interim Research, Development and Demonstrations and Renewables Program Funding Level*[1], which established the Electric Program Investment Charge (EPIC) on December 15, 2011. Subsequently, on May 24, 2012, the CPUC issued D.12-05-037, *Phase 2 Decision Establishing Purposes and Governance for Electric Program Investment Charge and Establishing Funding Collections for 2013-2020*[2], which authorized funding in the areas of applied research and development, technology demonstration and deployment (TD&D), and market facilitation. In this later decision, CPUC defined TD&D as "the installation and operation of pre-commercial technologies or strategies at a scale sufficiently large and in conditions sufficiently reflective of anticipated actual operating environments to enable appraisal of the operational and performance characteristics and the financial risks associated with a given technology."[3]

The decision also required the EPIC Program Administrators[4] to submit Triennial Investment Plans to cover three-year funding cycles for 2012-2014, 2015-2017, and 2018-2020. On November 1, 2012, in A.12-11-003, PG&E filed its first triennial Electric Program Investment Charge (EPIC) Application with the CPUC, requesting $49,328,000 including funding for 26 Technology Demonstration and Deployment Projects. On November 14, 2013, in D.13-11-025, the CPUC approved PG&E's EPIC plan, including $49,328,000 for this program category. On May 1, 2014, PG&E filed its second triennial investment plan for the period of 2015-2017 in the EPIC 2 Application (A.14-05-003). CPUC approved this plan in D.15-04-020 on April 15, 2015, including $51,080,200 for 31 TD&D projects.[5]

Pursuant to PG&E's approved 2015-2017 EPIC triennial plan, PG&E initiated, planned, and implemented the following project: EPIC 2.10 – Emergency Preparedness Modeling project. Through the annual reporting process, PG&E kept CPUC staff and stakeholder informed on the progress of the project. The following is PG&E's final report on this project.

---

1 http://docs.cpuc.ca.gov/PublishedDocs/WORD_PDF/FINAL_DECISION/156050.PDF.

2 http://docs.cpuc.ca.gov/PublishedDocs/WORD_PDF/FINAL_DECISION/167664.PDF.

3 Decision 12-05-037 pg. 37.

4 PG&E, San Diego Gas & Electric (SDG&E), Southern California Edison (SCE), and the California Energy Commission (CEC).

5 In the EPIC 2 Plan Application (A.14-05-003), PG&E originally proposed 30 projects. Per CPUC D.15-04-020 to include an assessment of the use and impact of EV energy flow capabilities, Project 2.03 was split into two projects, resulting in a total of 31 projects.

3 Project Summary

3.1 Issue Addressed

Achieving optimal resource management during an emergency event is critical to PG&E. Incident Commanders must make decisions to ensure personnel and public safety is maintained, customer service needs are appropriately balanced with restoration costs, and risk and uncertainty inherent in emergency events is accounted for and reflected in restoration plans. Resource management during an emergency is a complicated task that requires an analyst to balance multiple constraints including time, resources, and costs, while interpreting uncertain data around crew movement and availability, asset damage, and predicted damage. The overall workload is compounded by the fact that these constraints will change throughout the execution of the response, and the priorities from the incident commanders and planning chiefs will vary between operation periods. There is no way to immediately understand the impact of a strategic resource allocation without many hours of work, and most of the uncertainty in the resource projections is not visible to the key decision makers. In addition, plans are adjusted based on planners' subjective experiences, which may vary from event to event, leading to inconsistency.

3.2 Project Objective

The objective of the project was to develop and demonstrate a decision support system that recommends restoration strategies for PG&E electric assets following a disruptive event. To accomplish this, the following high level key business requirements were implemented:

- Incorporate natural hazard damage model information into one integrated algorithm/tool, to provide the ability to quickly estimate the impacts of natural hazards on PG&E facilities.
- Provide the ability to prepare for these hazards by proactively modeling the impacts of potential hazards, to understand system vulnerabilities and restoration resource requirements.
- Utilize artificial intelligence and statistical methods to model productive metrics and automatically develop restoration plans.

3.3 Scope of Work and Project Tasks

EPIC 2.10 aimed to incorporate natural hazard damage model information into one integrated tool, which has the potential to provide the ability to quickly estimate the impacts of natural hazards, such as a major winter storm, on PG&E facilities, status of resources, and to perform analysis to provide recommendations to enable faster response and restoration.

The project scope included the development of the following components:

- **Damage Prediction Data and Validation:** Collecting and validating data from storm damage prediction models (PG&E's Storm Outage Prediction Project [SOPP]) and Dynamic Automated Seismic Hazard (DASH) earthquake damage prediction model into the restoration work plan to increase data granularity to the device level and customer level. Accuracy of damage prediction is the most critical factor in being adequately prepared for restoration, hence this provides valuable context on level of certainty for decision-making.
- **Resource performance model:** A ML-based model of crew performance that considers static and dynamic factors that influence the performance of crews to aid in restoration work planning.

- **Resource positioning model:** Given a set of scenarios for damage/outage with associated probabilities, a stochastic optimization model that produces an initial positioning of the crews and/or equipment across divisions.
- **Mid-event optimization modeling:** Built on predictive resource positioning optimization to develop models capable of consuming real time data collected from PG&E systems during an event and combining it with predictive modeling results to create an integrated restoration plan with the best information as it becomes available.
- **Time-variance modeling:** Analyzing different methods and available data, for modeling time-dependent variables (resource shift timing, damage timing, environmental conditions, and time-based optimization criteria such as ETOR[6]) to develop an optimization model capable of consuming and producing hourly data to have improved specificity on resource timing and events that occur within a 24-hour period.
- **Real-Time Data Integration and Repositor**y: Collecting data at near real-time intervals from enterprise source systems (DMS, Integrated Logging and Information System [ILIS], Enterprise Software System [SAP][7], SOPP, DASH, Automated Call-Out System [ARCOS], and Weather). Moving this data to a repository that is used to feed the models.
- **Cloud Solution:** Migrating the developed prototype to a cloud-based solution to enable consistency across emergency centers and stakeholders and enhance system stability under emergency situations. While the prototype would still serve as a backup for situations without an Internet connection, the cloud solution would service the primary use cases.
- **Enhanced User Interface:** Building relevant dashboards and user interfaces that align with predefined use cases as established in the Incident Command System (ICS) and any related EOC and/or Emergency Center process.

3.3.1 Tasks and Milestones

Following are the three major milestones and related tasks that comprised this project:

- **Milestone 1 – Develop a Resource Performance and Positioning Model/Application (RWP Prototype)**
  The main objective of this milestone was to develop a prototype solution and validate the performance of the model. For this purpose, a stand-alone application including Resource Performance and Resource Positioning models and a simple User Interface (UI) is developed. The RWP prototype is primarily focused on storm events.
  - **Task 1 – Project Design:** This task started with a high-level design and architecture of the application and business requirements definition. Then the detailed design was developed for each model including the Resource Performance and Resource Positioning models and the UI.
  - **Task 2 – Resource Performance Model:** This task developed a ML-based Performance model to predict accurate work demand, resource performance, and outage type distribution.

---

6 While ETOR is calculated for each RWP work plan generated, the time-based optimization feature was not developed as part of the EPIC project scope but is planned and included in the roadmap for future implementation.

7 Integration of SAP data is included in the project roadmap for future implementation.

  - **Task 3 – Resource Positioning Model:** This task developed an optimization model that provides resource positioning recommendations. The solution includes fast and transparent resource deployment plans and suggests more cost effective and efficient resource allocation and movement across the impacted territory.
  - **Task 4 – Model Validation:** This task tested the application with multiple incidents to validate the performance of the models.
  - **Task 5 – User Interface Build:** This task developed a simple UI and integrated the models to have an integrated application for use on stand-alone laptops.

  Deliverable: An **i**ntegrated application on stand-alone laptop, including files for data inputs

- **Milestone 2 – Implement a Minimum Viable RWP Product**
  - **Task 1 – Requirement Definition:** This task defined the architecture and functional requirements of the RWP.
  - **Task 2 – Migration to Cloud-Based Solution:** This task migrated the prototype produced in Milestone 1 to a cloud-based solution to enable consistency across emergency centers and stakeholders, and to evaluate system stability under emergency situations.
  - **Task 3 – Data Repository Integration:** This task connected the Real-Time Data Repository to the prototype and cloud solution with seamless data connections that avoid the need for user intervention.
  - **Task 4 – Enhanced User Interface:** The task built relevant dashboards and user interfaces that align with predefined use cases as established in the ICS and any related EOC and/or Emergency Center process.

  Deliverable: A comprehensive and automated application deployed on cloud environment

- **Milestone 3 – Field Demonstration**

  The field demonstration, which runs in parallel mode with existing planning processes, consists of using the newly developed RWP decision support system during EOC activations. All stakeholders involved, for example, advance planners, planning and intelligence resources, incident commanders, have been trained on the RWP with a focus on specific features/functions that are relevant and required for them to perform their duties. As an example, the advance planners were trained to perform what-if analysis to generate alternative work plans to be reviewed by decision makers. During the field demonstration, the following RWP related activities were performed:
  - Running RWP to generate a recommended work plan (in parallel to existing process)
  - Collecting and storing all outputs generated by the RWP for benchmarking purposes
  - Capturing any issues/defects/improvements and prioritizing accordingly
  - Resolving any show stopper issues that would prevent the field demonstration from moving forward

  Deliverable: A set of RWP outputs (work plan recommendations) benchmarked against actual results, and a detailed list of requirements that need to be incorporated into the production release.

4 Project Activities, Results, and Findings

4.1 Resource Performance and Positioning Application

The following sections describe the Resource Performance and Position Application including the following areas: Project Design, Architecture, Data Flow, Requirements, Model Design and Optimization.

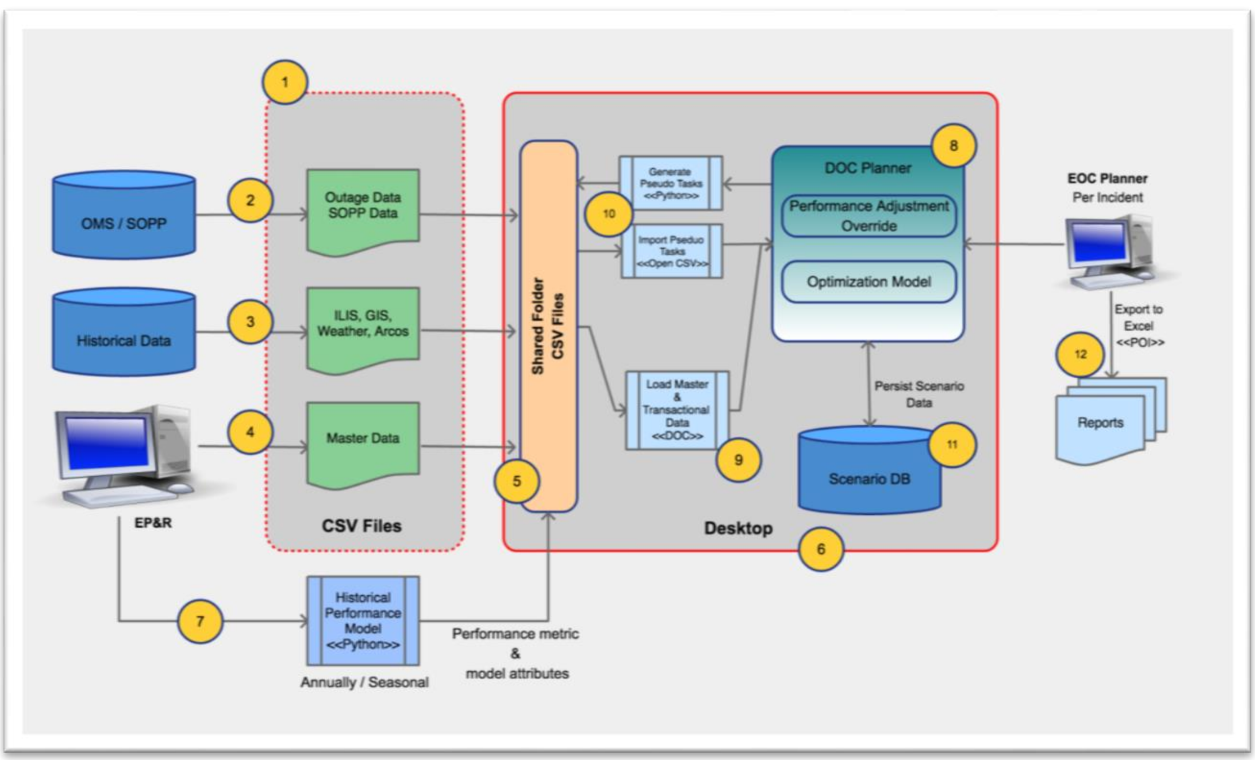
4.1.1 Project Design

The first step in developing the Resource Performance and Positioning application was to define the business requirements and prepare a high-level architecture of the application as well as detailed design of the models. The preliminary design was focused on developing and testing the models with a manual data injection process and simple user interface leveraging capabilities of a third-party software. As the project moved from prototype into the “Minimum Viable Product” stage, as defined later in this document, a data automation process and more advanced graphical user interface was designed and developed. A summary of the design process is provided in this section.

4.1.1.1 Architecture Design

Figure 4 below depicts the preliminary logical architecture of the standalone RWP solution:

Figure 2 - RWP Prototype Architecture



The main components of the architecture are input data, ML-Based Performance model, Optimizer, output reports and a shared folder. The primary user of the application is the EOC Planner.

Input data: below are the inputs to the application (Items 2, 3 & 4 in Figure 3):

- Outage and storm event data from PG&E's Outage Management System and SOPP
- Historical data including Weather, Geographic Information System, Integrated Logging and Information System (ILIS)[8] and ARCOS[9]
- Master Data including location details, crew details, crew capacity information etc. This data is created manually by the Emergency Preparedness & Response (EP&R) team.

The input data is in Comma Separated Value (CSV) format. The data is pre-processed and dropped into a shared folder (shown as Item 1 on Figure 3). The shared-folder is accessible by both the creator of the CSV files and the Decision Optimization Center (DOC) Planner application installed on a computer (desktop or laptop). This folder can be a directory in the desktop file system or on a file server within the PG&E network. This preliminary data injection process was improved and automated as explained in Section 4.2.

Shared Folder: The raw data files that are created are placed in a folder that is accessible by both the creator of the CSV files and the DOC Planner[10] application installed on a computer (desktop or laptop). This folder could be a directory in the desktop file system or on a file server within the PG&E network.

Machine Learning-Based Performance Model: the ML blocks (Items 7 & 9 on Figure 3) include:

- **Training Model**: This ML component will be run annually or seasonally (as determined by the EP&R team) to generate the underlying performance statistics. The model generates the productivity metrics and outage-distribution profiles for each division. The execution of this training model will be performed manually by EP&R team.
- **Scoring Model**: This model uses the output of the Training Model to generate pseudo tasks based on the real time input data from SOPP. The tasks include resource type, arrival time and performance metrics such as travel time and work time. Also, users have the option of overriding the default model characteristics such as productive rates and damage conversion factors and provide it as an additional input to the scoring model.

DOC Planner: Only leveraged in the preliminary design to quickly test the models and includes a basic UI and planner to manage scenarios and user inputs, as well as the optimization engine to perform resource positioning. The DOC allows a planner to manage scenarios used to generate optimized schedules and run "what if" scenarios. The DOC Planner application also allows the planner to export scenario results back to an Excel format. Scenarios are used to perform stochastic optimization.

Physical Architecture

The project also defined the preliminary physical architecture requirement for the stand-alone environment as summarized below:

---

[8] PG&E's ILIS models the actual electric switching operations reported during the circuit restoration process (which is useful for determining accurate customer outage minutes for calculating System Average Interruption Duration Index and Customer Average Interruption Duration Index).

[9] ARCOS is used to automatically call out crews in response to electric and gas emergencies.

[10] DOC is an application provided by a vendor to enable an interface between components of the prototype including the ML Model, Resource Optimization, Scenario Database, and the user interface.

Desktop/Laptop

1. Memory: Minimum 32 gigabytes (GB)
2. Processor: At least 4 cores at 2.80 gigahertz (i.e. i7 Intel Processor)
3. Disk Space: At least 500GB
4. Operating System: Windows 7 64 Bit

4.1.1.2 Data Flow Summary

The figure below outlines the data flow between the source systems and the end application. The ML Training Model consumes the outage and event historical data from 2014 to 2017. The raw historical data extracted from the source systems are made available in a shared folder in the standalone environment (for example, a laptop) in the form of CSV files. The raw data files are transformed through a data transformation pre-process to prepare the data for ingestion by the ML Performance Model. The transformed data is saved back to the shared folder in the form of CSV files. The ML Training Model then consumes the transformed CSV files and then produces an output JavaScript Object Notation (JSON)[11] file. This output JSON data file, also referred to as a "Trained Data" file, represents productivity and outage-distribution statistics that were "learned" from the historical data.

The Trained Data file which consists of the productivity metrics and outage-distribution statistics for each division is then ingested by the "ML Scoring Model" and used to generate the necessary "pseudo-tasks" for each division that correspond to the divisional outage forecasts.
The ML Training Model is made available in the form of Python scripts that can be executed from the command line by the EP&R team member.

[11] A JSON file is a file that stores simple data structures and objects in JavaScript Object Notation (JSON) format, which is a standard data interchange format. It is primarily used for transmitting data between a web application and a server.

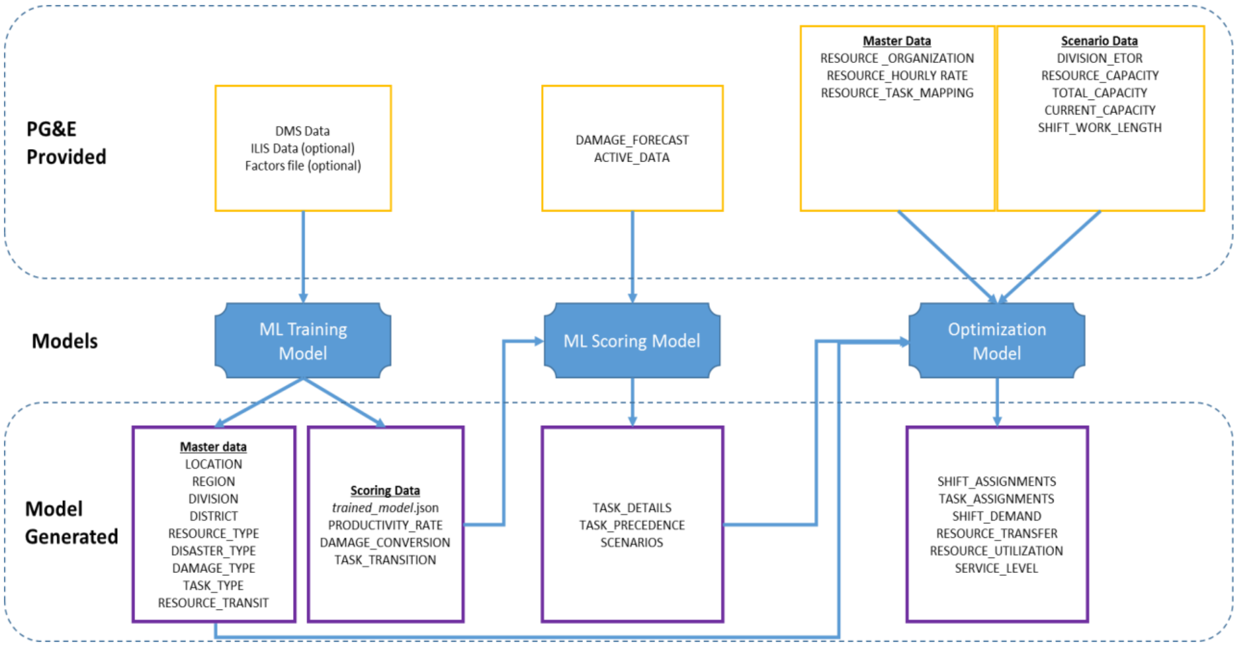


Figure 3 - RWP Prototype Data Flow

For pre-event planning, the latest outage forecast, and current resource capacity may be extracted from the PG&E systems by EP&R team and is made available in the form of CSV files in a shared folder available in the standalone environment. The precise CSV templates are provided in the shared folder. In addition, a few additional master data files are consumed by the DOC application as well. The ML Training model generates the master data files based on the historical data.

4.1.1.3 Requirements

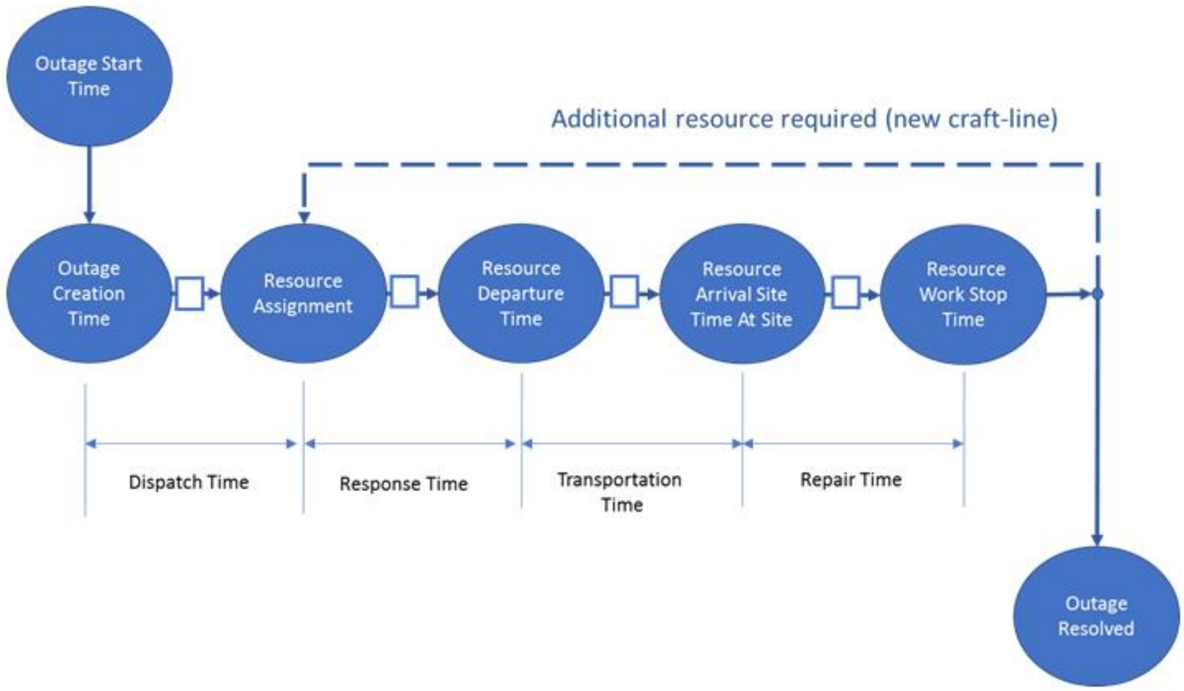
Machine Learning Performance Model: The ML Performance Model covers the following requirements:

Table 1 - Performance Model Requirement

#	Description
ML 1	Modeling performance metrics by division, using various static and dynamic factors
ML 2	Integration with Resource Optimization Model
ML 3	Retraining framework – ability for model to learn from new data
ML 4	Active Data processing – ability to ingest outage data and estimate the associated resource demand

ML1- Modeling Performance Metrics: To calculate the performance metrics, a simplified restoration process flow model shown in Figure 4 is used. This model does not capture the full complexity of the emergency restoration process. However, this model serves as a base to build from, while also being consistent with the data records available.

Figure 4 - State Diagram of Typical Restoration Process



The restoration process has many states. The different states and their corresponding time points are:

1. Outage start time – time when the outage first begins
2. Outage creation time – time when the outage record is created
3. Resource assignment – time when the resource assignment occurs
4. Resource departure time – time when the resource journey to outage location begins
5. Resource arrival at site – time when the resource arrives at the outage location
6. Resource work stop time – time when the resource stops work at the outage location
7. Outage resolved – time when the outage is completely resolved

For complex jobs, it is possible there will be multiple resources assignments because the first resource does not resolve the outage. This corresponds to multiple tasks needed to resolve the outage and is triggered by a resource reaching its "work stop time" and requesting another resource.

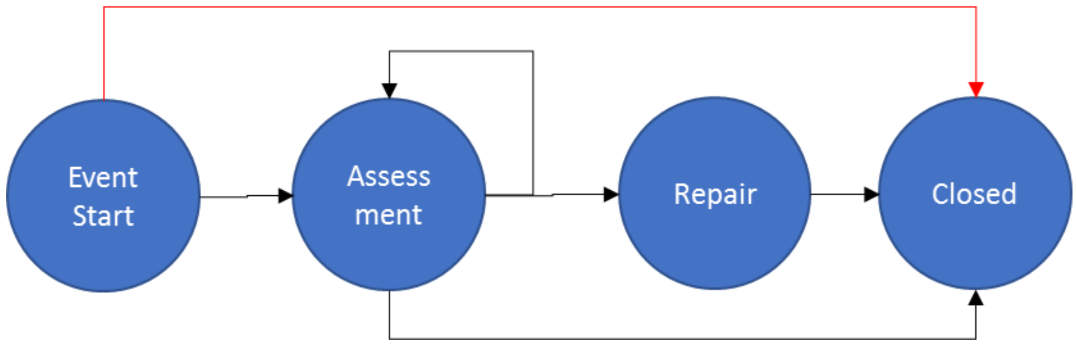
ML2- Integration with the Resource Optimization Model: Given a forecasted outage prediction, the model uses the historical information to derive the distribution of the most likely combination of different outage types. However, if the forecast provides the outage type distribution already, the model overrides the Training Model and use the forecast data.

ML3- Retraining Framework: A key requirement for this modeling effort is to ensure the model can learn from new data over time, as additional outage data is observed and added to the historical record. Given the known target output (i.e. resource performance rates) and data input (i.e. outage data) a supervised learning framework is used for the ML component.

ML4- Active Data Modeling: Active data modelling is associated with mid-event planning. Active data estimation leverages the ML scoring model for this process. The active data has two types of tasks:

assessment and repair. The state transition diagram for the active data is shown in Figure 5**Error! Reference source not found.**:

Figure 5 - Active Data State Diagram



Resource Positioning Optimization Model: The Resource Positioning Optimization Model covers the following requirements:

Table 2 – Resource Positioning Model Requirements

#	DESCRIPTION
OPT 1	User-Adjustable Planning Parameters
OPT 2	User-Adjustable Performance Parameters
OPT 3	Stochastic optimization model to position resources based on demand
OPT 4	Key Performance Indicator (KPI) Model Outputs
OPT 5	Dynamic ability to incorporate new “carves”
OPT 6	Hourly resource allocation modeling

OPT1- User-Adjustable Planning Parameters: Parameters such as Resource Availability, Target Estimated Time of Restoration,[12] and Planning Horizon may vary across different incidents and time.

OPT2- User-Adjustable Performance Parameters: The planner may change the performance model parameter, i.e. outage type, productive metrics, resource transfer time and movement.

OPT3- Stochastic Optimization Model to Position Resources Based on Demand: Due to uncertainty in damage prediction, the optimization model includes a stochastic optimization feature. This feature requires different outage prediction scenarios, each with a discrete probability of occurring. The model weighs each scenario and its probability to produce one optimal plan.

12 The ETOR Target is included in the project roadmap for future implementation.

OPT4- KPI Model Outputs: The model's objective is to minimize the unmet demand over the planning horizon while minimizing the resource transfer across different divisions. The KPIs are defined as below:

- Service Level: the % of work-demand serviced
  - The % of outages resolved at the end of each day
  - Service level is broken into assessment and repair tasks for each division.
- Resource utilization (by type)
  - Aggregate time spent on work
  - Total person-hours (productive + unproductive)
- Labor Cost Estimate – to be calculated in DOC

OPT5- Dynamic Ability to Incorporate New "Carves": During major events, it may be desirable to split existing divisions into smaller subdivisions or "carves" for a more concentrated restoration plan.

OPT6- Hourly resource allocation modeling: For Hourly Resource Modelling, the optimization model assumes demand arrives at hourly granularity.

4.1.2 Machine Learning-Based Performance Model

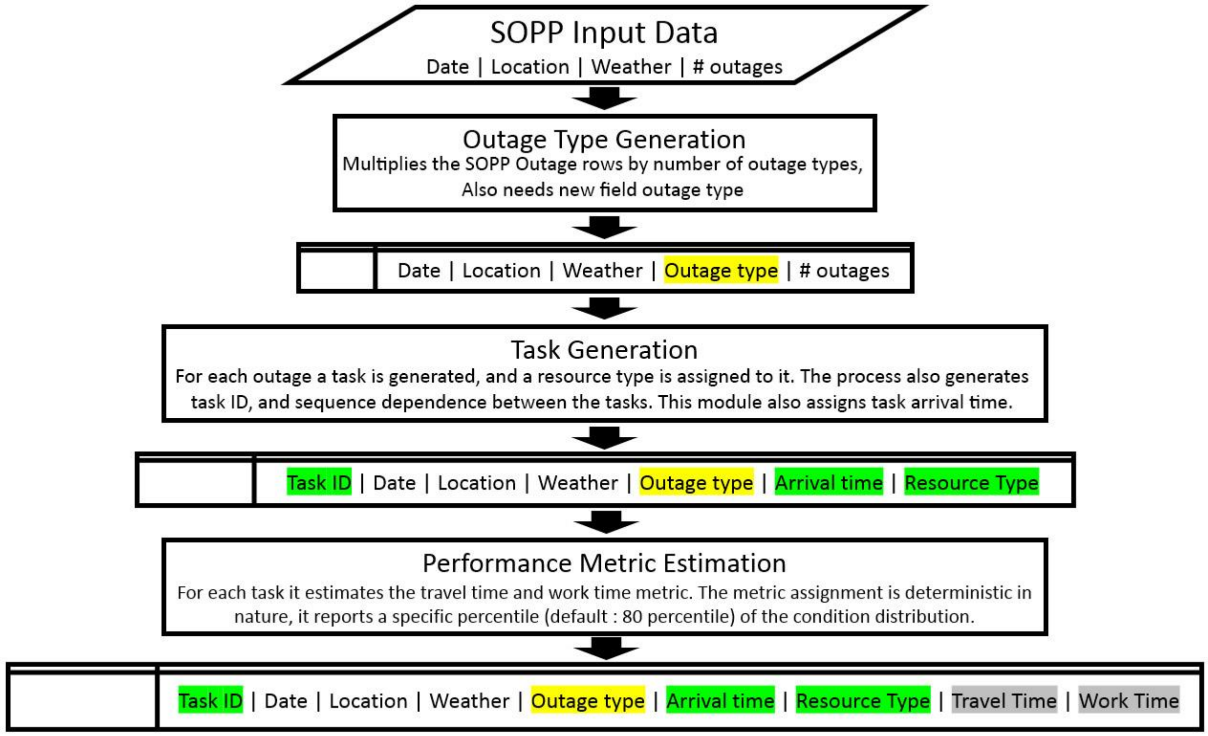
This model takes in the outage forecast data from damage model databases such as SOPP (for storm) and DASH (for earthquake), then applies a series of deterministic algorithms to produce a detailed task list. The different algorithmic steps involved in the processes are: 1) outage type generation, 2) task generation, 3) performance metric estimation (i.e. response, travel, and work times).

The order of each algorithmic execution is strictly sequential in nature. Each step introduces a new field in the estimated output, which is essential for the subsequent step to carry forward the estimation process. The process for storm events (with SOPP as the input) is shown in Figure 6 below. The input includes Date, Location, Weather, and number of predicted outages.

- **Outage Type Generation**: This step introduces a new field in the data: outage type – highlighted in yellow in Figure 6 (This can also be inherited directly from SOPP as well).
- **Task Generation**: Outage type is a necessary input field in the task generation algorithm, which then introduces additional fields for task identification (ID), resource type and arrival time to the SOPP prediction – highlighted in green in Figure 6.
- **Performance Metric Estimation**: Finally, the performance estimation algorithm adds fields for travel time and work time fields – highlighted in gray in Figure 6.

Statistical modeling and historical data is used to estimate models for the above processes (Training Model). Once the modules are developed, the integrated model including three steps can be used to generate tasks in a deterministic way based on forecasted incident input data, or real time data during the events (Scoring Model). More details on development of each of the processes are provided in the next sections.

Figure 6 - Machine Learning Based Performance Model Process



4.1.2.1 Outage Type Generation

The input to the module is an aggregated outage forecast by division, by day. The model estimates the outage type (i.e. Transformer, Jumper, Line Recloser, Switch, CB, and Fuse). The input can be modified easily to accommodate a SOPP forecast that includes job type distribution as well.

For $\boldsymbol{M}$ different types of outages, SOPP forecast predicts $\boldsymbol{O}$ as the total number of outages. The other attributes associated with the SOPP forecasts are location (ℓ), weather condition (ω), and time of the year (τ); (τ) is easily extracted from the date value. The outage type generation algorithm reads a tuple containing (time of the year (τ), location (ℓ), weather condition (ω), number of predicted outages ($\boldsymbol{O}$)), and generates counts of different outage types ($o_1, o_2, \dots\ o_M$), such that $\sum_{i=1}^{M} o_i = O$. This step is repeated across all the SOPP input rows, with one extra column added to suggest the type of outage.

Training Model

Multivariate Gaussian distribution[13] is used to represent the distribution of outage types. A Multivariable Gaussian Distribution is identified by two parameters: mean vector (μ) and covariance

[13] In probability theory, the normal (or Gaussian or Gauss or Laplace–Gauss) distribution is a very common continuous probability distribution. Normal distributions are important in statistics and are often used in the natural and social sciences to represent real-valued random variables whose distributions are not known. Multivariate normal (or Gaussian) distribution is a generalization of the one-dimensional normal distribution to higher dimensions.

matrix (Σ). The main purpose of the training model is to find the two parameters and represent the model as:

$$\mathbf{P}(O|\ell,\tau,\omega) \sim \boldsymbol{N}(\mu,\Sigma|\ell,\tau,\omega)$$

Where $\mathbf{P}$ is the outage type distribution and $\boldsymbol{N}$ is a multivariable Gaussian distribution where ℓ, τ, and ω are variables and μ, Σ are distribution parameters. Parameter estimation is performed using historically available data and a hierarchical modeling strategy.

4.1.2.2 Task Generation

This module uses the outage type generated in the previous step and other input data from SOPP and generates tasks. The tasks include task IDs, assigned resource type (i.e., T-Man for assessment and/or Crew for repair), and assigned arrival time. For each outage type, there may be multiple resources assigned to fix the outage, which influences the resource demand across the system. Resource assignment is referred to as a task.

To model the multiple resource assignment components, a Markov chain[14] is used. A Markov Chain is a mathematical system that contains states and probabilities of a state transition, which approximates a stochastic process that has discrete phases or states. Within the context of the restoration process, these discrete phases are split between restoration and assessment phases, with specific resources required to address each of these tasks. After defining the appropriate probabilities for the state transitions, Markov Chains programmed for each of the divisions create the total task workload based upon the projected outages provided by the damage models.

Training Model
To estimate the state transition matrix for the Markov Chain, historical outage data from the DMS, such as outage details and timestamps associated with each task, is used. Since the weather condition, location, and type of outage influence the task assignment process, each outage type is categorized hierarchically into multiple subgroups. Each subgroup in the transition matrix is learned separately.

4.1.2.3 Performance Metric Estimation

This module is used to estimate performance metrics for each task. Performance metrics focus primarily on two target metrics: travel time and the repair time; however, response time is included as well. These metrics are calculated from the 2014-2017 outage data. Several factors are considered in modeling the variability of performance metrics, including weather condition, location, time of the year, resource type, and damage type.

---

[14] In probability theory and related fields, a Markov process, named after the Russian mathematician Andrey Markov, is a stochastic process that satisfies the Markov property (sometimes characterized as "memorylessness"). Roughly speaking, a process satisfies the Markov property if one can make predictions for the future of the process based solely on its present state just as well as one could know the process's full history, hence independently from such history; i.e., conditional on the present state of the system, its future and past states are independent. A Markov chain is a type of Markov process that has either discrete state space or discrete index set.

First the model analyzes the effect of each factor on the target metric. This analysis is data driven and flexible in nature. The three main steps involved in the process are listed below:

1. Ranking factors by their influence. The top ranked factor has maximum influence on the target metric.
    a. Both travel time and work time for T-Man and Crews are very distinct in nature, therefore, resource type is the top ranked factor in both models.
    b. Location influences the travel time metric but does not play significant role in the repair time.
    c. Repair time is a function of outage type, while travel time is not affected by outage type.
2. Partitioning data hierarchically in the same order of ranked factors.
    a. The hierarchical partitioning ensures a large sample set at the top level, and the sample size drops exponentially with sub-partitioning.
    b. The variability in the data at top level partitions is higher; with partitioning, there is a reduction in the variability (i.e. standard deviation). The reduction in variability is significantly higher with the top level and with subsequent partitioning the degree of variability reduction is less. This is due to the rank order partitioning of the dataset.
3. At every partition level, the statistics are calculated using Maximum Likelihood Estimates (MLE). If the estimates are within a 95% confidence level, it accepts the derived statistics; otherwise it uses a Bayesian approach[15] to estimate the refined statistics.
    a. At top level partitions, due to availability of large sample sets the MLE yields the sufficient statistics.
    b. Bayesian method uses maximum a priori estimation for the parameters.
    c. The prior distribution of the parameters is obtained from the data set at immediate parent partitions.

Training Model

Based on the historical input data, the base parametric statistics are identified for each target metric. The travel time metric shows close resemblance to Lognormal[16] distribution and the work time metric is best explained by Gamma[17] distribution. The parametric nature of the distribution is imposed on the sub-partitions as well to normalize the effect of data imbalance. For every partition, first parameters are estimated using MLE statistics, where the MLE analysis assumes respective parametric form of the target metric. Once parameters are estimated, the confidence interval is calculated. If the estimated parameter falls outside a 95% confidence interval, Bayesian parameter estimation is performed.

---

15 Bayesian inference is a method of statistical inference in which Bayes' theorem is used to update the probability for a hypothesis as more evidence or information becomes available. Bayesian inference is an important technique in statistics, and especially in mathematical statistics.

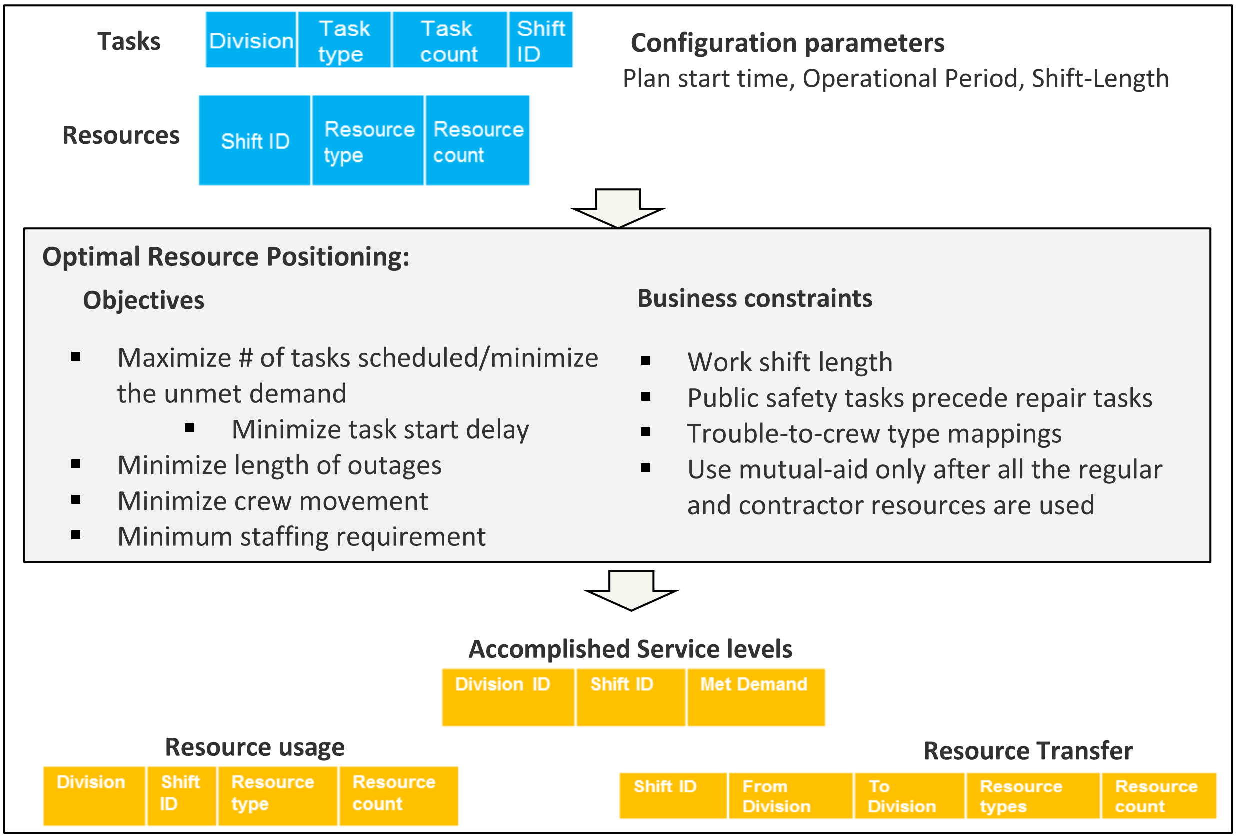
16 A gamma distribution is a two-parameter family of continuous probability distributions.

17 A log-normal (or lognormal) distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed.

4.1.3 Resource Positioning Optimization Model

The resource positioning model is developed to recommend number of resources and a resource deployment strategy to perform the tasks identified in the Performance Model. The model optimizes staffing level across service centers in PG&E territory to meet expected resource demand efficiently. The model identifies the optimal staffing levels by shift and location, resource movement plan and need for mutual assistance. The optimization framework developed has the following characteristics and is shown in Figure 7 below.

Figure 7 – Resource Positioning Optimization Framework



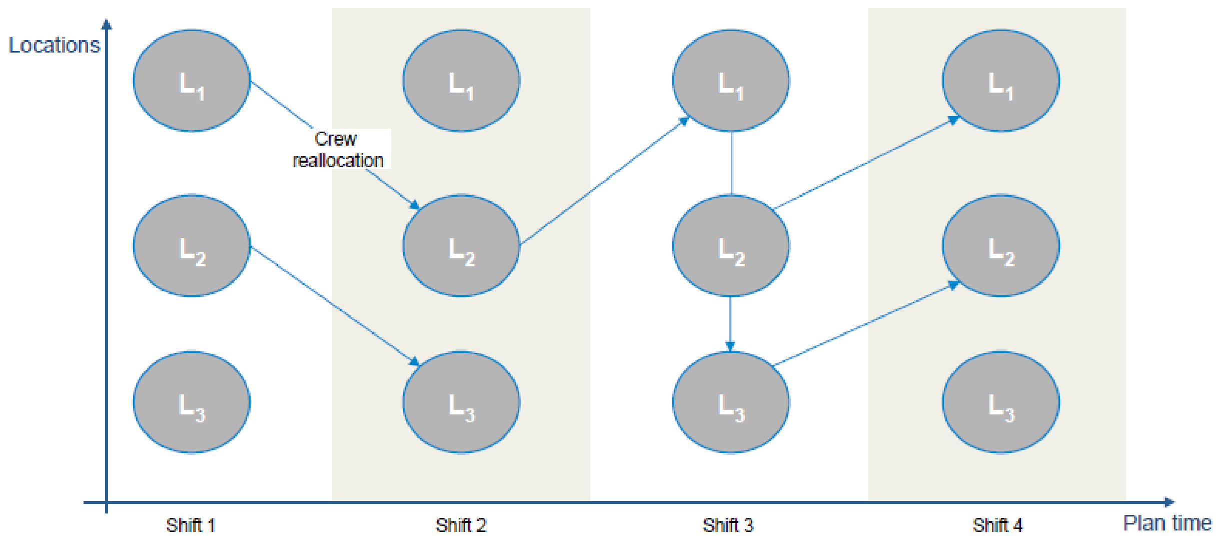
- The model inputs include the tasks and available resources.
- The constraints include staff shift length, mapping the resources (Crew vs T-Man), and use internal resource first, then contractors and then mutual aids.
- The objective is to maximize the work completed, minimize outage duration, and minimize resource movement. In addition, the optimization seeks to minimize the unmet demand at each location and minimize the resource utilization.
- The optimization results in the number of resources that should be used and the locations, the resource allocation and transfers, and the number of contractors and mutual aids (if any).

In addition to the above, to account for the uncertain damage scenarios from natural disasters, the below methods are applied:

- **Aggregated demand model for faster resource position planning**:

- The resource positioning method aggregates the work from multiple tasks with same type in each shift at a location as the aggregate shift demand and allocates resources to meet as much demand as possible. The method is formulated as a novel multi-commodity flow network to find the resource prepositioning at each node in real time. Below is a graphical representation of an example of such a flow network used for optimization, with three locations and three shifts over the planning horizon.

Figure 8 - Resource allocation network model



- There are two commodities that flow over the network.
  1. Resource flow: Resources of different types are moved between different nodes of the network.
  2. Demand flow: Demand at each node that belongs to the tasks arriving in that shift is to be met by the resources at that node. If there are not sufficient resources, the demand from a node gets added to the demand in the following shift.

- **Spatio-temporal stochastic outage scenarios**:
  - The system considers a set of possible outage scenarios (each outage scenario being a set of tasks) along with the occurrence probability of each scenario and performs stochastic optimization. The resource positioning plan output by the stochastic optimization method may not be the best suitable plan meeting individual input scenarios, but is a balanced plan meeting the demand with respect to these multiple possible outage scenarios.
- **Restoration order among buckets of demand with priorities**:
  - The method partitions the demand in each shift into buckets with different priorities, and the order of resolving these different buckets of demand is configurable (a demand bucket may represent predicted demand or realized demand).
- **Deployment policies for resources that belong to different organizations**:
  - The method considers the possible different organizational associations of the resources (for example, internal, contractor, or mutual aid), and the deployment priorities for resources that belong to these different resource organizations are

respected by associating low cost with more desired resources deployment options over less desired resource deployment options.

A Mixed Integer Linear Program is used to solve the optimization problem to include both integer variables such as a resource count and continuous variables such as unmet demand.

4.2 Implement a Minimum Viable RWP Product

Once the models were developed and tested using the RWP prototype, the team then focused on creating the Minimum Viable Product which includes a data automation process and more advanced graphical user interface, especially to display and manipulate the dashboard work plan.

4.2.1 Requirement Definition

The architecture and design decisions for the RWP were guided by the following principles:

- **Reuse process, data, and Information and Security Assets (ICT) assets whenever appropriate**: The project reuses process, data and ICT assets from related projects as appropriate, to accelerate delivery of the business capability and reduce cost. The project uses the project's key learnings to build process and data assets that are re-usable for future electric operations use cases.
- **Enable applications for reuse and portability as services**: RWP architecture is designed as a platform to facilitate future application developments. The architecture is modular and service oriented. Data from various sources are aggregated to reduce point-to-point integration.
- **Enable advanced machine learning, optimization, advanced analytics functions for future phases of the project**: RWP architecture is designed as a platform, to facilitate future ML, optimization, and advanced analytics functions. These features are necessary to improve the optimization algorithms developed in Milestone 1 and eventually help PG&E to find the most suitable RWP solution.
- **Agnostic Data Repository to serve multiple applications**: RWP architecture design is agnostic and should support multiple Restoration Work Plan solutions rather than focusing on any specific solution. The business team can select the appropriate data for the RWP optimization module from the data repository to serve their needs.
- **Scalable to serve future needs**: RWP architecture is designed as a data repository; any new data sources can be added dynamically without impacting the existing application. A data module or schema change also should not impact the existing RWP applications.
- **Design and test solutions to satisfy non-functional requirements**: The design should ensure that non-functional requirements (all technical and architectural requirements) are addressed for a normal production workload as well as for emergency conditions.
- **Design solutions to make use of infrastructure common services**: The architectural design looks for opportunities to reduce infrastructure duplication and cost, as well as reducing system and data access complexity for the end user, so that distribution operations can focus on problem identification and resolution.
- **Aim at Path to Production**: The current EPIC 2.10 is a demonstration project, so the path to production is an important consideration during system design. The goal is to move the solution to a production environment when it is proven to be mature and stable so that it may begin to provide the identified potential business value.

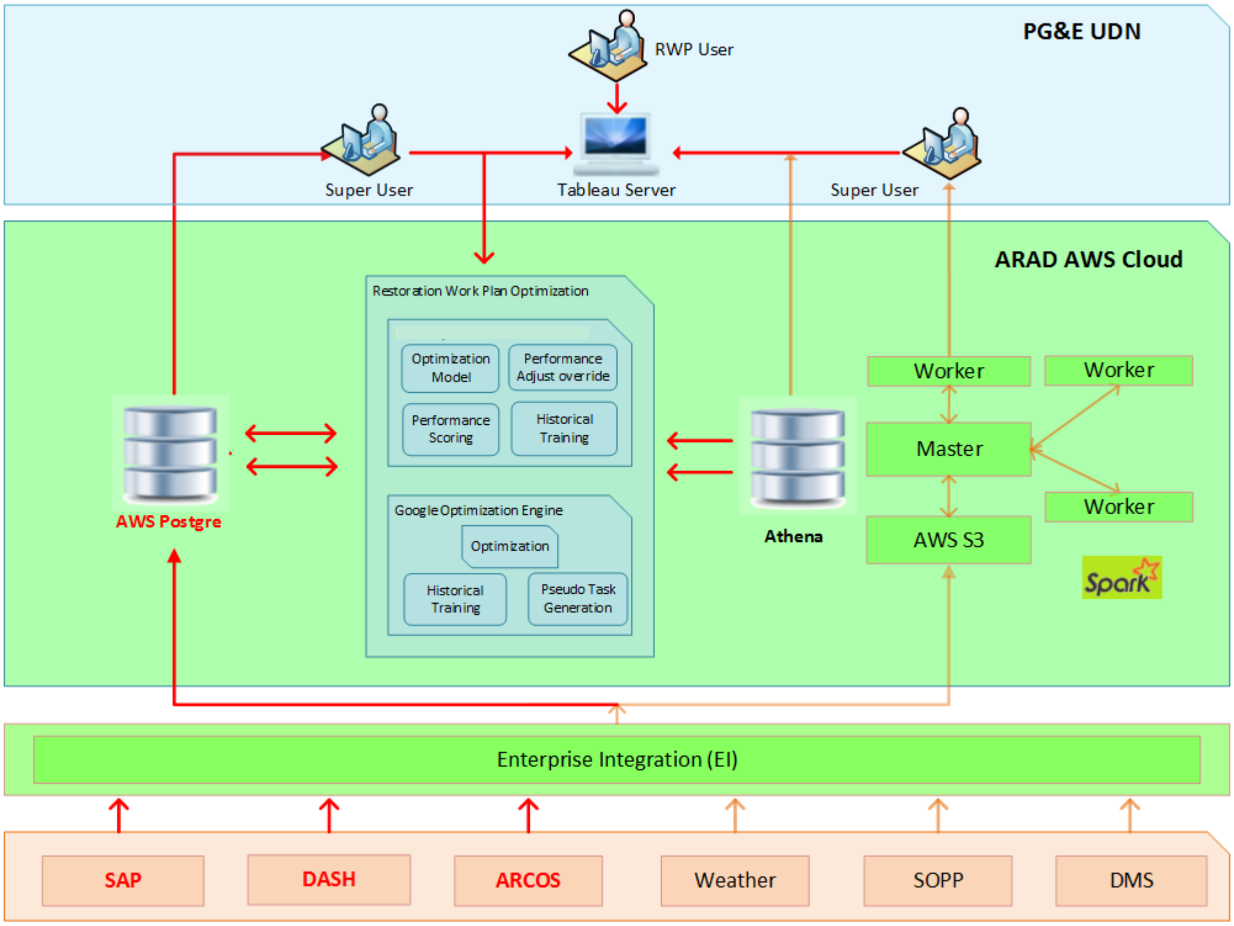
Considering the above principles, the below decisions were made:

- **Optimization Solution**: In Milestone 1 development, a vendor optimization engine was selected, implemented, and tested. For this phase, the goal was to investigate different optimization options. The team conducted analysis on multiple optimization solutions, including functionality and the risk analysis, and selected an open source engine (Google OR Tool).
- **Optimization Solution Hosting:** The Optimization Solution in Milestone 1 was hosted on a standalone Laptop and only limited users could access and create restoration work plans locally. In this phase of architectural design, the Optimization Solution is hosted in the Amazon Web Services (AWS) Cloud. All users with proper authentication and authorization can access the different optimization solutions, work with different scenarios and create work plans.
- **Data Repository Hosting:** This milestone scope included historical and real time data integration, seamless data connections that avoided the need for user intervention, access for multiple concurrent applications and users, and storage of work plan results for different scenarios. The cloud-based data repository selected i.e. Analytics Rapid Application Development (ARAD) AWS, is also able to interface with different optimization solutions and host the solution in a more durable, easy to access environment.
- **Environment (TEST/QA):** EPIC 2.10 is a demonstration project and therefore only TEST and Quality Assurance environments were provisioned. Due to the project nature, scope and data volume, a multi-node distributed cluster system with high availability was not considered in the demonstration stage. Instead, a standalone system was developed.
- **Data Integration via Enterprise Integration (EI):** It is feasible to access the raw data sources directly, retrieving data and storing data in the RWP data repository. However, from a system stability/reliability perspective, the preferred approach was to use the EI to transfer data into the RWP repository. In the repository implementation, EI integration is utilized to retrieve data from data sources and store into the data repository.
- **Coexistence of two AWS Data Repositories until the end of the demonstration**: The project incorporates the ARAD AWS and ARAD PostgreSQL data repositories. The ARAD AWS Data Repository was retained until the end of the project which allowed the team to test innovative solutions such as the Google Optimization Engine.

4.2.2 Architecture Design

RWP solution contains multiple components such as data repository, optimization engine, reporting dashboards, and cloud servers. The diagram below shows the high level architectural design for the RWP Product:

Figure 9 – RWP Product Architecture[18]



Description of components: The components of the architecture are categorized based upon the following solution scope and shown in the table below.

Table 3 – RWP Product Components

Solution Scope	Solution Components
ML/optimization algorithm for RWP generation	• Create training models based on historical data • Create outage scores (tasks and performance metrics) based on training statistics results and outage forecast data • Google optimization engine to create optimized work plan based on ML/Scoring and real time outage information from different data sources
ARAD AWS Real time data repository	• ARAD AWS RWP Data Repository (AWS S3 for data storage, and Amazon's Interactive Data Query Service (Athena) Database for data query) ○ Store real time data from different data sources

[18] SAP functionality shown in the Figure is planned for implementation in the future.

Solution Scope	Solution Components
	• ARAD RWP Data Repository (Postgres) o Collect and store Real Time and Historical data from various data sources o Store RWP work plans and system configurations o Provide RWP data to Tableau server for reporting and presentation
Advanced Analytic Framework	• Apache Spark.[19] Customized application developed using Spark platform • Provide Java Database Connectivity interface to external application • Provide Spark SQL for user to access data on demand • Provide Spark framework for advanced analytics, ML, and result optimization
Data Sources	• DMS: outage data, UPTR data, Crew Activity Data • SOPP: outage scenario data, weather forecast data • SAP:[20] outage notification data • ARCOS: Crew resource assignment information • DASH: Earthquake information
Integration	• EI: Provides access to different data sources and routes raw data to the data repository.
Tableau Server	• Platform for RWP data/results reporting and presentation

Description of different user types:
Below is a description of different user types and associated access scope/rights

- **Administrators**: Responsible for system maintenance, enhancements, developing new features, and ensuring system quality and performance of all components and their integrations. Administrator Users can be granted administrator privileges to one or all the modules in the RWP/Resource Modeling Tool, the RWP/Data Repository and its interfaces, and/or the RWP/Tableau environment as appropriate and necessary for the administration and maintenance of the solution.
- **Super users**: Have access to the RWP/Resource Modeling Application. Super users are expected to be Advance Planners and other specialist business users within the Emergency Preparedness & Response group. Super Users also require full Publisher access to the RWP/Tableau environment, as they are responsible for publishing the resource work plans and comparisons to the RWP/Tableau Site to be accessed by Business Users.
- **Business users (RWP users)**: Interacting with the Tableau work space, viewing information, evaluating with different scenarios, and creating restoration work plans.

---

19 Apache Spark is an open-source distributed general-purpose cluster-computing framework. It is used as a unified analytics engine for large-scale data processing.

20 Implementation of SAP functionality is included in scope and planned for implementation in the future.

4.2.3 Migration to Cloud-Based Solution

The ML-Based Performance model and the Resource positioning were migrated to the AWS cloud solution. The prototype would still serve as a backup for situations without an Internet connection. The cloud solution is connected to the real-time data repository and PGE Utility Data Network. The results from resource positioning are sent to Tableau Server for user review. Super users may change the configuration of the models through user interface.

4.2.4 Data Repository Integration

RWP Data Repository collects data from multiple data sources, stores data in the data lake, and provides data to different applications or interfaces. These data sources include:

- DMS (Outages and Crew Information)
- SOPP (Outage scenario and weather forecast information)
- SAP[21] (Outage Notification Information)
- ARCOS (Crew/T-man Information)
- DASH (Earthquake information)

Data collections are updated as below:

- Data sampling time: Some of the data are real time snapshots of the systems, for example, DMS outage data, and ARCOS crew activity status.
- Historical Data Storage: Real time system snapshot data is stored in the data repository for research, scenario creation purposes.
- Data updates: Certain data sources are only updated a few times per day, for example, SOPP scenario data and weather data, or DASH data. The data is collected and stored into data repository only if the data get updated, otherwise, no action is taken.

Data Automation:
The data automation process for different components of the model is shown in Figure 10 below:

The ML Training Module needs to be executed annually or semi-annually to generate the productivity rates and outage type distribution profiles for each division. Since this module is always executed offline, the historical data is provided to the RWP team upon request; there is no data automation requirement for this module. However, the current limitation of the Training Module requires some preprocessing of DMS data to generate corresponding performance metrics.

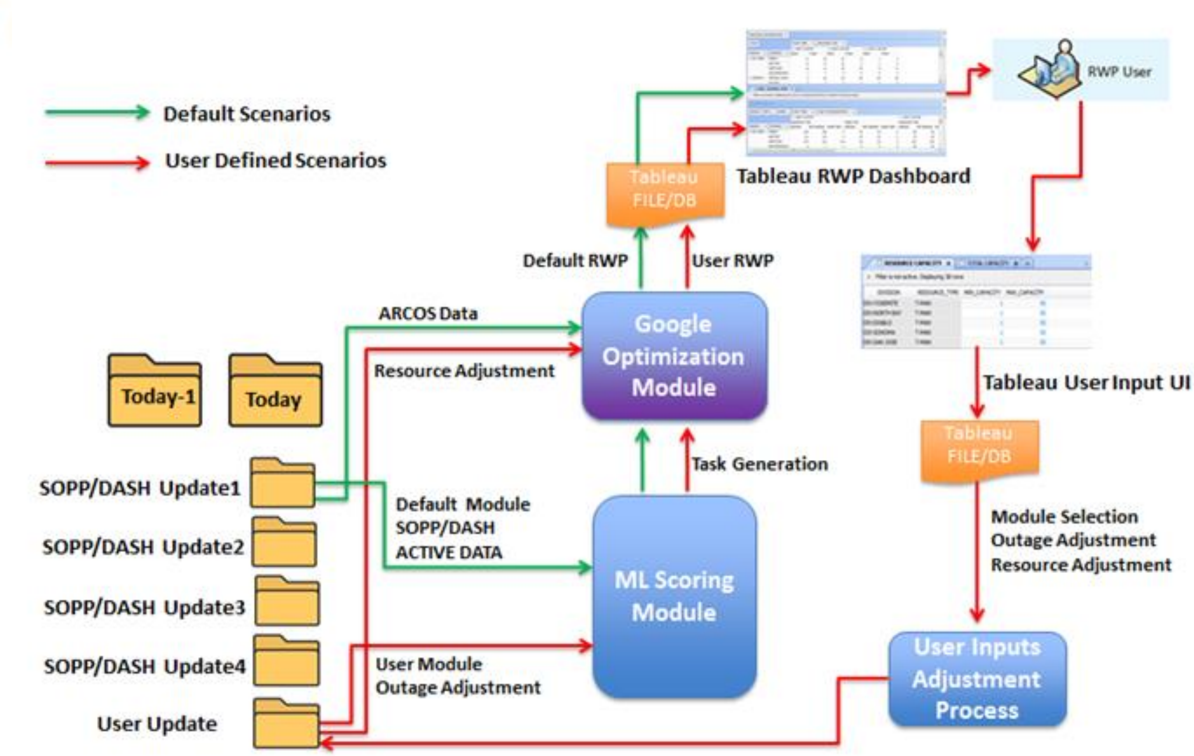
The ML Scoring Module is executed automatically when the planner selects the associated item on the user interface. This module takes Outage Forecast data from various event forecast systems (SOPP, DASH, etc.) as well as the Active Outage data from DMS, then uses the corresponding JSON model to generate Resource Demand in terms of Task.

---

21 Implementation of SAP functionality is included in scope and planned for implementation in the future.

The optimization model for resource positioning consumes the required data file for ML Scoring. The Google Optimization Module provides the ability to automate the process. The process is shown in Figure 10.

Figure 10 – Resource Positioning Data Automation Process



For Default RWP:

- The ML Scoring Module is executed when there is an SOPP/DASH update which triggers the RWP Process
- Default Model and SOPP/DASH/ACTIVE Data file in Update folder serves as input into ML Scoring Module automatically by automation scripts
- The Task generated serves as input into Google Optimization Module
- The ARCOS Resource Data serves as input into Google Optimization Module
- The Google Optimization Module generates the default Work Plan
- The default Work Plan will be loaded into Tableau Database

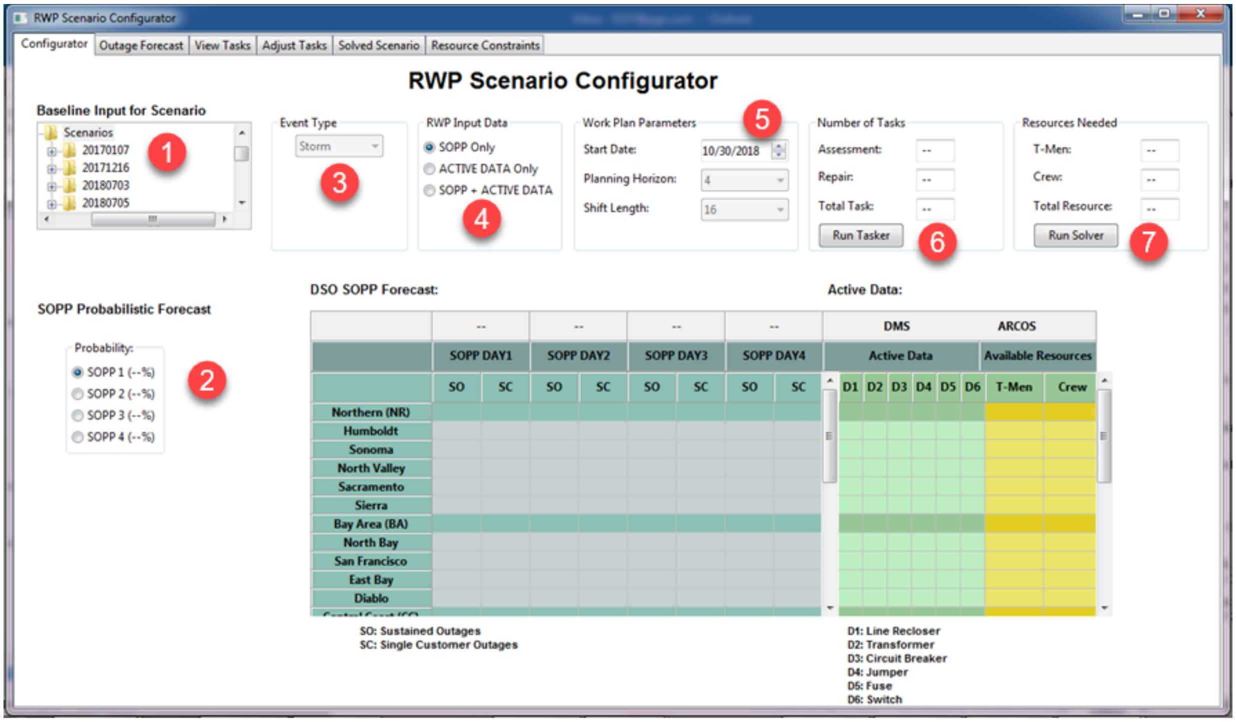
4.2.5 User Interface

The main screen of the RWP Tool is shown in Figure 11. Users select a baseline scenario that feeds into the ML component, identify the type of data inputs (forecast and/active data), as well as adjust certain parameters as described below. These selections and input enable the system to perform and run two key functions:

1. Through the “Run Tasker”: Compute/generate distribution of outage types, performance metrics and T-men and Crew tasks required

2. Through the "Run Solver": Identify resource demand needed and optimize allocation and movement of the personnel throughout the impacted divisions

Figure 11 - RWP Configuration Tool: main screen

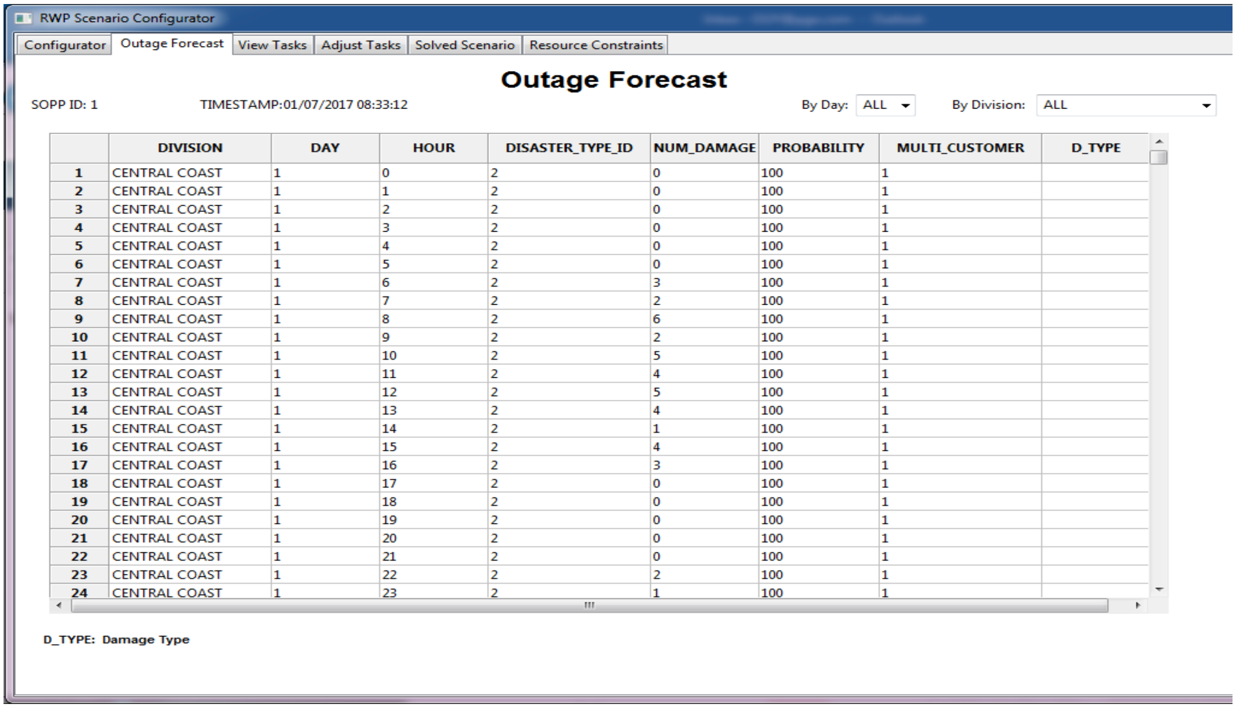


The model inputs that can be configured by the user include (input numbers are shown on Figure 12):

1. User selects the source data for the SOPP (Sustained Outage Prediction) Forecast.
2. User selects the SOPP Forecast Scenario as each SOPP file provides four probabilistic scenarios associated with a certain confidence level. The lower the %, the more outages are forecasted.
3. User selects the Event Type (currently only Storm category 2 is available).
4. User selects if the data input should be SOPP Only, ACTIVE DATA only, or SOPP + ACTIVE DATA.
5. User selects the start date and Operational Period. The Operational Period is how many hours the T-Men and Crew are working in a shift. The Planning Horizon is set for 4 days.
6. User selects Run Tasker to generate the tasks to be completed in the 4-day planning horizon.
7. User selects Run Solver to generate the number of resources needed to complete tasks as well as allocation and movement of these resources across the impacted territory.

Figure 12 below shows the SOPP model in detail. It can be filtered by day and/or division.

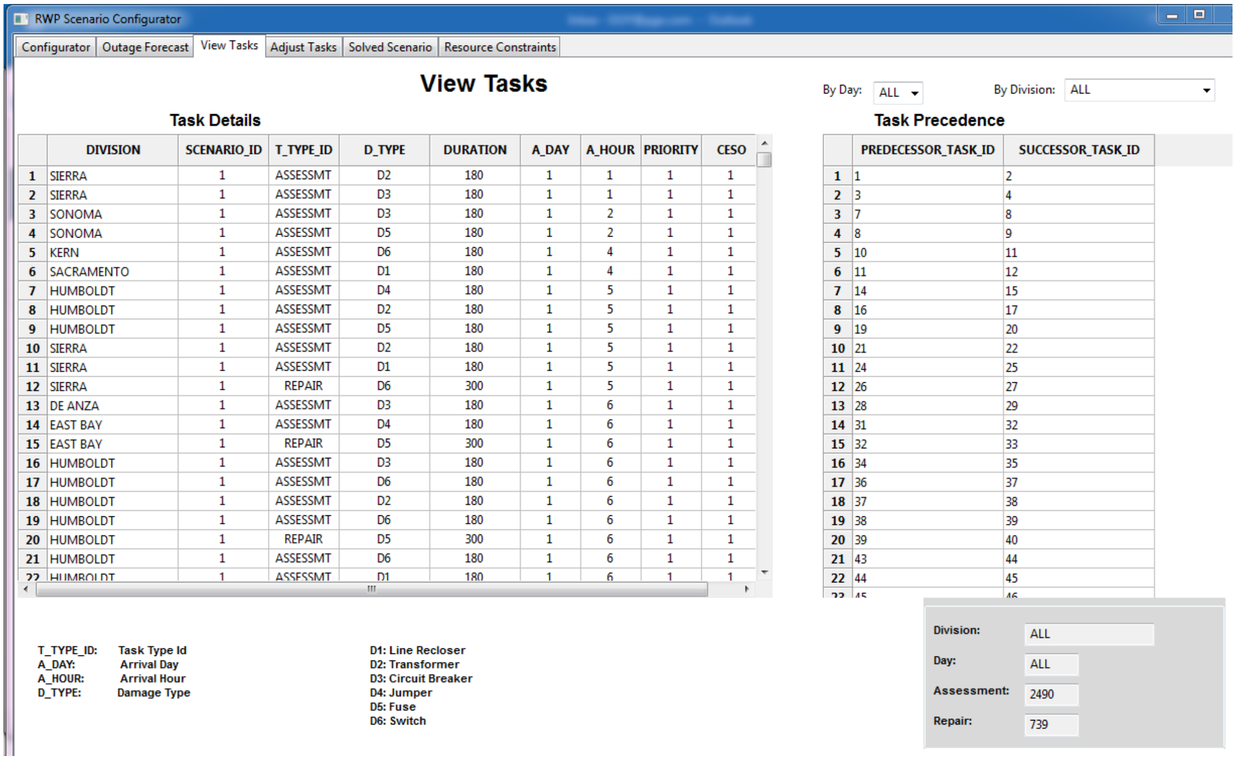
Figure 12 – RWP Configuration Tool: Outage Forecast Screen



	DIVISION	DAY	HOUR	DISASTER_TYPE_ID	NUM_DAMAGE	PROBABILITY	MULTI_CUSTOMER	D_TYPE
1	CENTRAL COAST	1	0	2	0	100	1	
2	CENTRAL COAST	1	1	2	0	100	1	
3	CENTRAL COAST	1	2	2	0	100	1	
4	CENTRAL COAST	1	3	2	0	100	1	
5	CENTRAL COAST	1	4	2	0	100	1	
6	CENTRAL COAST	1	5	2	0	100	1	
7	CENTRAL COAST	1	6	2	3	100	1	
8	CENTRAL COAST	1	7	2	2	100	1	
9	CENTRAL COAST	1	8	2	6	100	1	
10	CENTRAL COAST	1	9	2	2	100	1	
11	CENTRAL COAST	1	10	2	5	100	1	
12	CENTRAL COAST	1	11	2	4	100	1	
13	CENTRAL COAST	1	12	2	5	100	1	
14	CENTRAL COAST	1	13	2	4	100	1	
15	CENTRAL COAST	1	14	2	1	100	1	
16	CENTRAL COAST	1	15	2	4	100	1	
17	CENTRAL COAST	1	16	2	3	100	1	
18	CENTRAL COAST	1	17	2	0	100	1	
19	CENTRAL COAST	1	18	2	0	100	1	
20	CENTRAL COAST	1	19	2	0	100	1	
21	CENTRAL COAST	1	20	2	0	100	1	
22	CENTRAL COAST	1	21	2	0	100	1	
23	CENTRAL COAST	1	22	2	2	100	1	
24	CENTRAL COAST	1	23	2	1	100	1	

As shown in Figure 13, View Tasks is generated after the user clicks "Run Tasker" from the RWP Scenarios Configurator screen. This screen details all the information pertaining to tasks, their duration, predecessors/successors, damage type, etc. A total tally of tasks appears in the gray box in the lower right-hand corner.

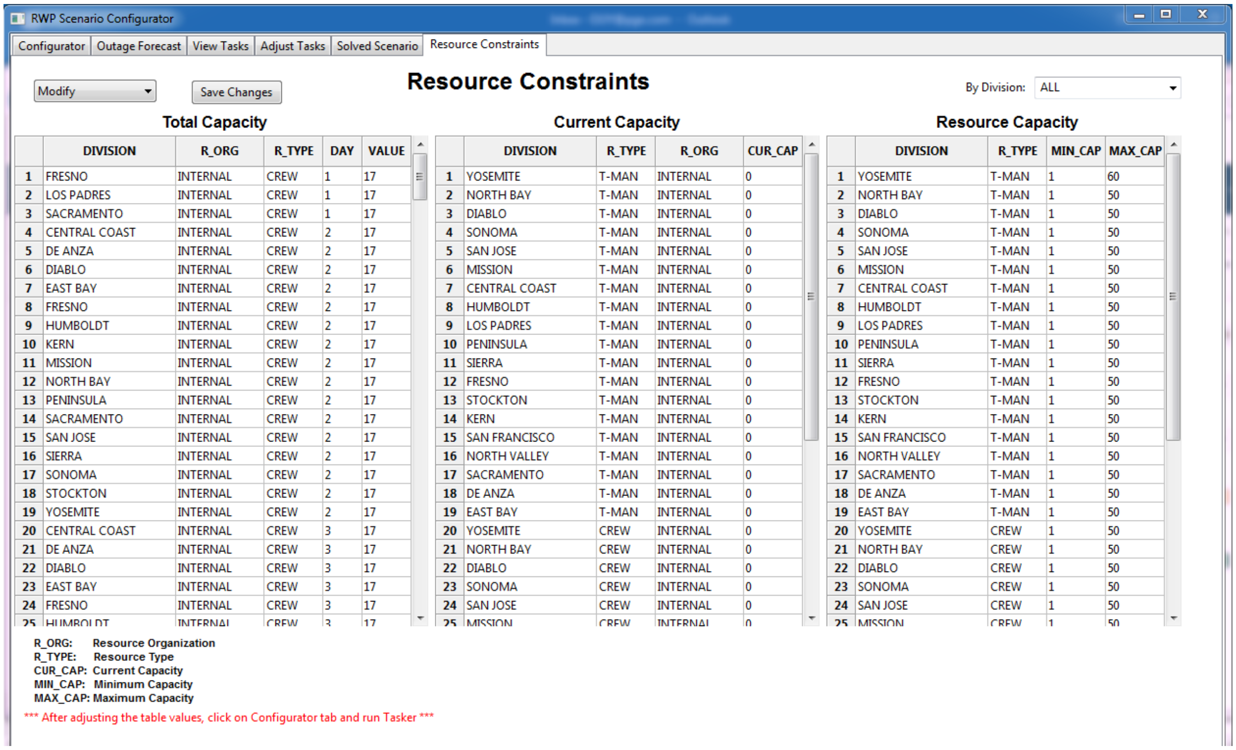
Figure 13 - RWP Configuration Tool: View Tasks Screen



Tasks can be adjusted by an advanced user who wants to modify the basic assumptions of productivity rate, task transitions, and damage distributions.

Figure 14 shows Resource Constraints screen. This screen is for the advanced user who wants to modify the basic assumptions of total capacity, current capacity, and/or resource capacity.

Figure 14 - RWP Configuration Tool: Resource Constraints Screen



RWP Scenario Configurator

Configurator | Outage Forecast | View Tasks | Adjust Tasks | Solved Scenario | Resource Constraints

Modify | Save Changes

Resource Constraints

By Division: ALL

Total Capacity

	DIVISION	R_ORG	R_TYPE	DAY	VALUE
1	FRESNO	INTERNAL	CREW	1	17
2	LOS PADRES	INTERNAL	CREW	1	17
3	SACRAMENTO	INTERNAL	CREW	1	17
4	CENTRAL COAST	INTERNAL	CREW	2	17
5	DE ANZA	INTERNAL	CREW	2	17
6	DIABLO	INTERNAL	CREW	2	17
7	EAST BAY	INTERNAL	CREW	2	17
8	FRESNO	INTERNAL	CREW	2	17
9	HUMBOLDT	INTERNAL	CREW	2	17
10	KERN	INTERNAL	CREW	2	17
11	MISSION	INTERNAL	CREW	2	17
12	NORTH BAY	INTERNAL	CREW	2	17
13	PENINSULA	INTERNAL	CREW	2	17
14	SACRAMENTO	INTERNAL	CREW	2	17
15	SAN JOSE	INTERNAL	CREW	2	17
16	SIERRA	INTERNAL	CREW	2	17
17	SONOMA	INTERNAL	CREW	2	17
18	STOCKTON	INTERNAL	CREW	2	17
19	YOSEMITE	INTERNAL	CREW	2	17
20	CENTRAL COAST	INTERNAL	CREW	3	17
21	DE ANZA	INTERNAL	CREW	3	17
22	DIABLO	INTERNAL	CREW	3	17
23	EAST BAY	INTERNAL	CREW	3	17
24	FRESNO	INTERNAL	CREW	3	17
25	HUMBOLDT	INTERNAL	CREW	3	17

Current Capacity

	DIVISION	R_TYPE	R_ORG	CUR_CAP
1	YOSEMITE	T-MAN	INTERNAL	0
2	NORTH BAY	T-MAN	INTERNAL	0
3	DIABLO	T-MAN	INTERNAL	0
4	SONOMA	T-MAN	INTERNAL	0
5	SAN JOSE	T-MAN	INTERNAL	0
6	MISSION	T-MAN	INTERNAL	0
7	CENTRAL COAST	T-MAN	INTERNAL	0
8	HUMBOLDT	T-MAN	INTERNAL	0
9	LOS PADRES	T-MAN	INTERNAL	0
10	PENINSULA	T-MAN	INTERNAL	0
11	SIERRA	T-MAN	INTERNAL	0
12	FRESNO	T-MAN	INTERNAL	0
13	STOCKTON	T-MAN	INTERNAL	0
14	KERN	T-MAN	INTERNAL	0
15	SAN FRANCISCO	T-MAN	INTERNAL	0
16	NORTH VALLEY	T-MAN	INTERNAL	0
17	SACRAMENTO	T-MAN	INTERNAL	0
18	DE ANZA	T-MAN	INTERNAL	0
19	EAST BAY	T-MAN	INTERNAL	0
20	YOSEMITE	CREW	INTERNAL	0
21	NORTH BAY	CREW	INTERNAL	0
22	DIABLO	CREW	INTERNAL	0
23	SONOMA	CREW	INTERNAL	0
24	SAN JOSE	CREW	INTERNAL	0
25	MISSION	CREW	INTERNAL	0

Resource Capacity

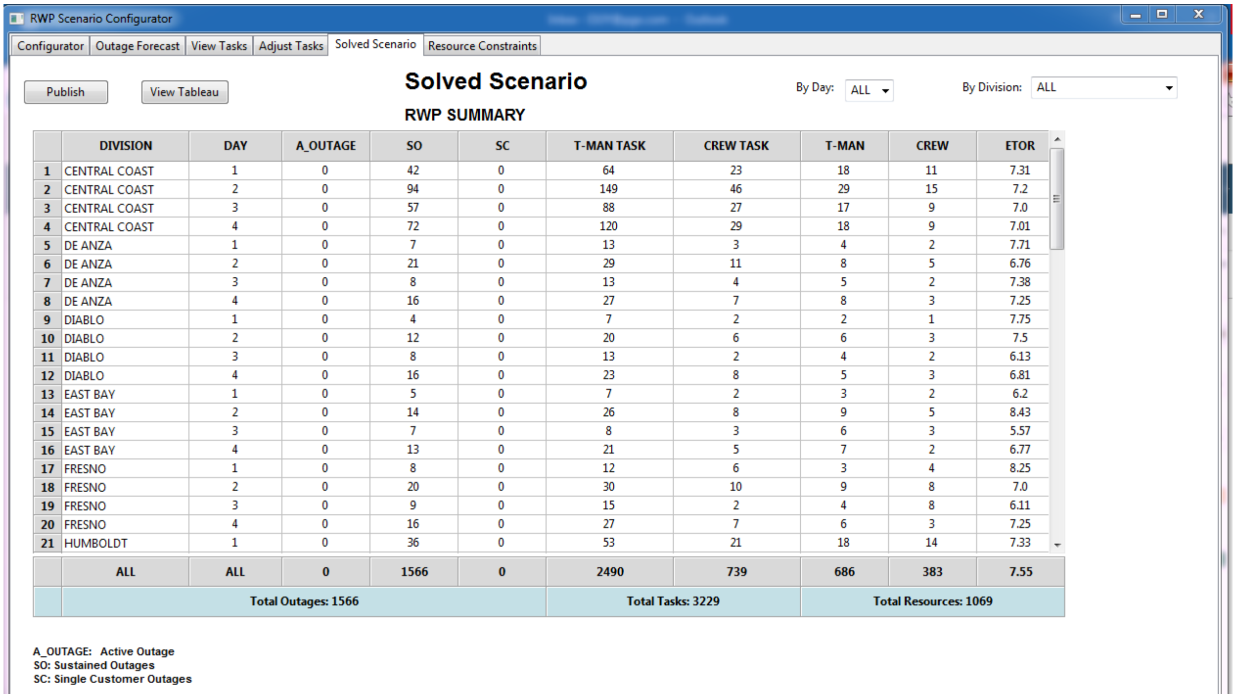
	DIVISION	R_TYPE	MIN_CAP	MAX_CAP
1	YOSEMITE	T-MAN	1	60
2	NORTH BAY	T-MAN	1	50
3	DIABLO	T-MAN	1	50
4	SONOMA	T-MAN	1	50
5	SAN JOSE	T-MAN	1	50
6	MISSION	T-MAN	1	50
7	CENTRAL COAST	T-MAN	1	50
8	HUMBOLDT	T-MAN	1	50
9	LOS PADRES	T-MAN	1	50
10	PENINSULA	T-MAN	1	50
11	SIERRA	T-MAN	1	50
12	FRESNO	T-MAN	1	50
13	STOCKTON	T-MAN	1	50
14	KERN	T-MAN	1	50
15	SAN FRANCISCO	T-MAN	1	50
16	NORTH VALLEY	T-MAN	1	50
17	SACRAMENTO	T-MAN	1	50
18	DE ANZA	T-MAN	1	50
19	EAST BAY	T-MAN	1	50
20	YOSEMITE	CREW	1	50
21	NORTH BAY	CREW	1	50
22	DIABLO	CREW	1	50
23	SONOMA	CREW	1	50
24	SAN JOSE	CREW	1	50
25	MISSION	CREW	1	50

R_ORG: Resource Organization
R_TYPE: Resource Type
CUR_CAP: Current Capacity
MIN_CAP: Minimum Capacity
MAX_CAP: Maximum Capacity

*** After adjusting the table values, click on Configurator tab and run Tasker ***

As shown in Figure 15, Solved Scenarios is generated after the user clicks "Run Solver" from the main screen. This screen details all information pertaining to the resource requirements and allocation of these resources across the divisions. Total outages, tasks, and resources are listed in Figure 15 in light blue. All information from the Configurator Tool can now be "Published". The information is pushed to a Tableau Dashboard where users can create and compare several different restoration work plans.

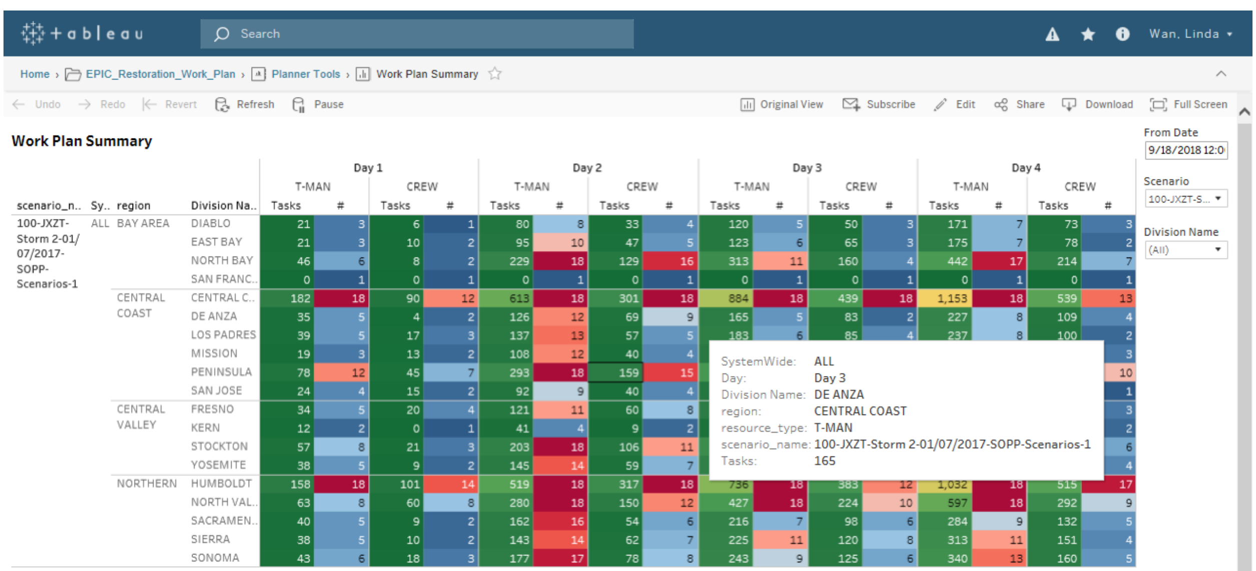
Figure 15 – RWP Configuration Tool: Solved Scenarios Screen



	DIVISION	DAY	A_OUTAGE	SO	SC	T-MAN TASK	CREW TASK	T-MAN	CREW	ETOR
1	CENTRAL COAST	1	0	42	0	64	23	18	11	7.31
2	CENTRAL COAST	2	0	94	0	149	46	29	15	7.2
3	CENTRAL COAST	3	0	57	0	88	27	17	9	7.0
4	CENTRAL COAST	4	0	72	0	120	29	18	9	7.01
5	DE ANZA	1	0	7	0	13	3	4	2	7.71
6	DE ANZA	2	0	21	0	29	11	8	5	6.76
7	DE ANZA	3	0	8	0	13	4	5	2	7.38
8	DE ANZA	4	0	16	0	27	7	8	3	7.25
9	DIABLO	1	0	4	0	7	2	2	1	7.75
10	DIABLO	2	0	12	0	20	6	6	3	7.5
11	DIABLO	3	0	8	0	13	2	4	2	6.13
12	DIABLO	4	0	16	0	23	8	5	3	6.81
13	EAST BAY	1	0	5	0	7	2	3	2	6.2
14	EAST BAY	2	0	14	0	26	8	9	5	8.43
15	EAST BAY	3	0	7	0	8	3	6	3	5.57
16	EAST BAY	4	0	13	0	21	5	7	2	6.77
17	FRESNO	1	0	8	0	12	6	3	4	8.25
18	FRESNO	2	0	20	0	30	10	9	8	7.0
19	FRESNO	3	0	9	0	15	2	4	8	6.11
20	FRESNO	4	0	16	0	27	7	6	3	7.25
21	HUMBOLDT	1	0	36	0	53	21	18	14	7.33
	ALL	ALL	0	1566	0	2490	739	686	383	7.55
	Total Outages: 1566					Total Tasks: 3229		Total Resources: 1069		

The RWP restoration strategy output is pushed to a web Tableau dashboard. This dashboard contains all scenarios that have been executed in the RWP configuration tool and can be shared across users within the company

Figure 16 – RWP Configuration Tool: Work Plan Summary Screen



4.3 Field Demonstration

The field demonstration process involved running the RWP in parallel with existing planning processes and tools whenever the EOC was activated.

During the demonstration in the field, the newly developed RWP decision support system is used in parallel mode during EOC activations by stakeholders who are involved in EOC activities including, for example, advance planners, planning and intelligence resources, incident commanders, etc. These individuals have been trained on the RWP with a focus on specific feature/functions that are relevant and required for them to perform their function. As an example, the advance planners were trained to perform what-if analysis to generate alternative work plans to be reviewed by decision makers. During the field demonstration, the following RWP related activities are being performed:

- Run RWP to generate a recommended work plan (in parallel to existing process)
- Collect and store all outputs generated by the RWP for benchmarking purpose
- Capture any issues/defect/improvements and prioritize accordingly
- Resolve any show stopper issues that would prevent the field demonstration to keep moving forward

PG&E will continue to fine tune the RWP system by leveraging it further in field demonstration setting. The Field Demonstrations will produce a full set of RWP outputs (work plan recommendations) that will be used to benchmark RWP outputs against actual results. Those benchmark results along with other learnings during the demonstration will lead to the development of a list of improvements that need to be addressed before RWP is considered operational, and a list of RWP functional enhancements to consider to further improve the system over time.

4.4 Challenges

The project encountered the following challenges:

- **Internal IT Scope and Support:** The PG&E IT role in the project was initially de-scoped due to IT capacity constraints. Although the IT work was added back in, having an internal PG&E IT project team working with the vendor and involved from the outset may have helped prototype solution fit in better to PG&E architecture standards and reduced the need for additional vendor support.
- **Business Disruptions:** 2017 was a record year for EOC activations and major emergencies which affected the availability of many key business stakeholders, SMEs, and project team members.
- **Model Complexity:** The numerous processing steps and the computational complexity added to the time required to diagnose and remedy any errors present within the code. For these models to be properly validated by field operations experts, additional work was required to visualize the intermediate outputs in an intelligible format.
- **Integration Dependency:** Increasing data granularity to hourly timing added additional requirements for hourly data that make the system difficult to use without automated integration. This limited the ability to fully test and use the vendor application prior to completion of the integration work needed to provide the necessary data.
- **Large Project Team in Multiple Locations:** The project team faced communication challenges since they were working on complex technical topics, with a large off-site vendor team who were spread out in multiple locations. Other projects facing similar challenges might consider

investing in a dedicated resource for business analysis, technical documentation, and testing in addition to the development and project management team.

- **Validation Challenges:** The project team faced several challenges while performing the business validation of RWP:
    - The Restoration Work Plans generated by the tool are speculative since they are forward-looking estimates, and their accuracy is linked to the accuracy of other forecasts, for example, weather forecast accuracy.
    - The complex interrelated factors contributing to the outage scenarios and their optimized solutions (calculated down to the hour) are too many and too dynamic to reproduce their predictions manually, or to isolate the cause of every variance between planned & actual resource deployment after the fact.
    - The unique methods used by the application have no direct comparator in the company or in the industry. No “like for like” measure exists, and the current business methods in use at PG&E today have not themselves been formally analyzed or tested.

4.5 Results and Observations

User Interface and Usability:
The planners in the EOC had the opportunity to use the RWP prototype during some minor weather events during the 2018-2019 Winter Storm Season. Since the EOC planner position is a voluntary and rotational position, many of these planners who were part of the trial were new to the position and did not have extensive experience with the older planning process and Excel models/tools. This allowed for the planners to look at the RWP prototype with fresh pair of eyes and provide unbiased opinions about the installation process, operating environment, and the visualization of information.

Since the RWP was designed as a prototype, the package that was installed as part of the demonstration was not a self-contained package and required multiple steps to bring the planner’s laptop into the appropriate environment, which will not be the case once the RWP is adopted for production. However, after the necessary steps were performed, the user environments and available data were consistent between each of the planners’ individual installations, allowing for collaboration between planner shifts.

The biggest improvement over the Excel model was the ease of use when generating a new plan. The typical working time to generate a new plan was approximately 2 hours for an advanced user of the old system, while even a novice user could create a viable plan within 5 minutes using the new system. The planner who used the system during the trial was impressed with the minimal amount of training required to operate the new tool, and instead had extreme difficulty using the older Excel model without extensive training.

While the new user interface replicated many of the screens that existed in the older Excel model to help with the familiarity of look and feel, it also added the ability to export data to a visualization suite. This decoupled the data from the originating platform and allowed the planners to customize their reports to support the Resource Unit and other requesting parties.

Model Results:
To validate the results of the RWP, two past weather events are used to run the Performance Scoring and Optimization modules on and assess the outputs as follows:

Table 4 – Validation Approach Details

Task Description	**Purpose**
Compare Epic 2.10 solver recommended work plan with that of the existing Excel-based restoration planning tool currently in use	Identify specific impacts of the different methods and levels of detail in each tool
Compare resource recommendations of EPIC 2.10 RWP and current Excel-based tool to as-deployed data from DMS (adjusted to remove SOPP forecast accuracy as a factor)	Assess variances between the work plans generated by the various RWP tools and the actual resources deployed
Compare EPIC2.10 RWP Performance Scoring Parameters Productive Time (decomposed to travel time & repair time) and Damage Type Distribution to actual travel times, repair times, and outage types by division from SAP and/or DMS	Evaluate the historically derived Performance Scoring assumptions of the EPIC 2.10 RWP solution against specific events and understand divergence
Survey business users for “gut-check” of EPIC 2.10 RWP resource recommendations and overall favorability toward the tool	Elicit feedback to improve trust, usability, and adoption of the solution

5 Value Proposition

The purpose of EPIC funding is to support investments in technology demonstration and deployment projects that benefit the electricity customers of PG&E, SDG&E, and SCE. EPIC 2.10 resulted in a system that can quickly estimate the impacts of natural hazards on PG&E facilities to enable faster response and restoration, provide the ability to prepare for these hazards by proactively modeling the impacts of potential hazards, understand system vulnerabilities and restoration resource requirements, and more efficiently allocate resources.

As discussed in the following sections the project has demonstrated meeting the Primary Principles of improving customer reliability, lowering costs and increasing safety. The project has also demonstrated meeting the Secondary Principles by providing better information regarding restoration times, reducing Greenhouse Gas (GHG), and efficiently using ratepayer funds.

5.1 Primary Principles

The primary principles of EPIC are to invest in technologies and approaches that provide benefits to electric ratepayers by promoting greater reliability, lower costs, and increased safety. This EPIC project contributes to these primary principles in the following ways:

- Reliability: EPIC 2.10 improves reliability through:
    a. Reduced restoration times leading to a more reliable electrical service: Accurate resource allocation recommendations in advance of an event will ensure that logistics will provide the right amount of support, while mutual aid or contractors can be activated and transported to the optimal locations. These decisions require lead time, so timely analysis or forecasts will eliminate any delays associated with acquisition or decisions that need to be made due to a faulty analysis.
    b. Enhance reliability using real-time information: The EOC would have the ability to explore restoration strategies using real-time information to enhance reliability of the electric and gas systems. The project would enable PG&E to better quantify, in real-time, the impacts of events and the impacts of different restoration activities taken on power outages and costs.
    c. This project has the potential to achieve reliability benefits by increasing PG&E's ability to model natural hazards and outage restorations. The tool can be agnostic to type of emergency (earthquake, flood, fire, tsunami, major storm, etc.). Benefits are multiplied because the tool has the potential to handle any type of major catastrophic event, and scale accordingly to the importance of the event.
- Affordability: The project reduces cost by optimizing restoration operations and thus provides more efficient use and allocation of resources.
- Safety: Increased safety and/or enhanced environmental sustainability:

a. This application will allow resources to more rapidly respond to public safety incidents. Deploying the appropriate amount of resources to an event will allow safety personnel to rapidly address hazards like a downed wire or leaning pole.

5.2 Secondary Principles

EPIC also has a set of complementary secondary principles. This EPIC project contributes to the following three secondary principles: societal benefits, GHG emissions reduction, and efficient use of ratepayer funds.

- Societal benefits: Better understanding and communication of event restoration. The EOC would be able to provide clearer answers to estimate time of restoration, and answers to both PG&E emergency responders and the public.
- GHG emissions reduction: GHG emissions reductions (metric tons of carbon dioxide equivalent (MMTCO2e)) by reducing total crew movements.
- Efficient use of ratepayer funds: Optimal use of restoration resources to better balance restoration times versus total expenditures.

5.3 Accomplishments and Recommendations

5.4 Key Accomplishments

The following summarize the key accomplishments of the project over its duration:

1. The ability for aggregation of equipment damage estimates (via damage models, outage information systems, and damage assessments), hours to repair, and optimal work resources. This innovative approach enhances PG&E's ability to understand impacts of these natural hazards (for example, number of outages, damage types, customers without power, potential length of outages) to improve resource allocation, prioritization decisions, and ultimately a more accurate ETOR.
2. The ability to recommend positioning of resources (including contractors and mutual aids) needed for the restoration, as well as intra territory movement of these resources as they handle multiple outages.
3. A user interface that enables advance planners to generate ML based trained statistics and run multiple what-if scenarios analysis with the ability to overwrite certain assumptions such as resource productivity time and conversion rates.
4. A dashboard and associated visualization functionalities that enable decision makers to review and approve proposed restoration plans.
5. An automated data integration that pulls forecasted and active data into RWP.

5.5 Key Recommendations

The availability of advanced technology such as artificial intelligence/ML and predictive analytics not only enables operational efficiency and cost savings, but also significantly improves safety, reliability, transparency, and efficient use of Rate-payer Monies. Thus, utilities should embrace this type of advance technology for the purpose of emergency operations as is the case on this project and in other parts of the value chain when appropriate.

In this case PG&E had identified potential pain-points and opportunities for improving its emergency restoration process given the weather seasonality and broad service area coverage. When embarking on such an initiative there are several factors/key points that utilities should consider and plan for:

- Leveraging MILP Method
  - Solves resource scheduling that works at the level of number of resources of each type available at any point in time
- Including two categories of Input
  - Scenario independent inputs (resource specific)
    - Operational constraints
    - Maximum number of continuous working hours for resources
    - Travel times
    - Appropriate matching of resource type to each task
    - Capacity constraints, or flow conservation constraints
  - Scenario specific inputs (task/demand specific)
- Incorporating Critical System Variables
  - Planning horizon
  - Locations of the service territory
  - Current resource positioning at various locations
  - Maximum possible resource at distinct locations
  - Location and task specific expected time of restoration
- Establishing Clear Resource Deployment Policies
  - Number of resources to deploy computed by the optimization model
  - Model allows the user specified resource category
    - Task specific
    - Organization specific
- Incorporating Unmet Demand Minimization
  - Unmet demand constraint implicitly resolves task prioritization
  - Solution of multi commodity network flow is computationally less expensive compared to detailed scheduling, and can be solved in real time
  - Low computational cost allows end user to change business constraint, and rerun the model multiple time to decide the best deployment policy
- Establishing Clear Objective function
  - Minimize unmet demand + resource deployment cost
  - Unmet demand incurs higher penalty compared to resource deployment cost

5.6 Technology Transfer Plan

5.6.1 Investor-Owned Utilities' Technology Transfer Plans

A primary benefit of the EPIC Program is the technology and knowledge sharing that occurs both internally within PG&E, across the other Investor-Owned Utilities (IOU), the CEC, and the industry. To facilitate this knowledge sharing, PG&E is sharing and will continue to share the results of this project in industry workshops and through public reports published on the PG&E website. Specifically, below is information sharing forums where the results and lessons learned from this EPIC project were presented:

- EPIC Symposium, Sacramento, California, 2016
- IEEE PES General Meeting, Portland, Oregon, Aug 2018

PG&E plans on continuing to share the results and lessons learned from this EPIC project in the future as well.

5.6.2 Adaptability to Other Utilities and Industry

While each utility may operate differently in how they coordinate their response to events in their territory, the RWP findings and outcomes could be leveraged by others within the Utility industry. Listed below are RWP outcomes that are potentially applicable to other utilities:

- The ML algorithms or other advanced inferential techniques that provide recommendations in stochastic or uncertain environments
- The network optimization recommendations based upon division staffing crew movements, and other constraints such as resource capacity.
- Models and underlying algorithms: Following are the type of models and underlying algorithms that can be leveraged by other utilities and below are some specific as to what could be leveraged:
    1. **Aggregated demand model for faster resource position planning**
    A Method/Model that allows aggregation of the work from multiple tasks with same type in each shift at a location as the aggregate shift demand and allocates resources to meet as much demand as possible. The method is formulated as a novel multi-commodity flow network to find the resource positioning at each node in real time.
    2. **Spatio-temporal stochastic outage scenarios**
    A Method/Model that yields the ability to consider a set of possible outage scenarios (each outage scenario being a set of tasks) along with the occurrence probability of each scenario and performs stochastic optimization. The resource positioning plan output by the stochastic optimization method may not be the best suitable plan meeting individual input scenarios, but is a balanced plan meeting the demand with respect to these multiple possible outage scenarios.
    3. **Restoration order among buckets of demand with priorities**
    A Method/Model to partition the demand in each shift into buckets with different priorities, and the order of resolving these different buckets of demand (a demand bucket may represent predicted demand or actual demand).
    4. **Deployment policies for resources that belong to different organizations**
    A Method/Model that considers the possible different organizational associations of the resources (for example, internal, contractor, or mutual aid), and the deployment priorities for resources that belong to these different resource organizations are respected by associating low cost with more desired resources deployment options over less desired resource deployment options.

5.7 Data Access

Upon request, PG&E would provide access to data collected that is consistent with the CPUC's data access requirements for EPIC data and results.

6 Metrics

The following metrics were identified for this project and included in PG&E's EPIC Annual Report as potential metrics to measure project benefits at full scale.[22] Given the demonstration nature of this EPIC project, these metrics are forward looking.

Table 5 - Project Benefit Metrics

D.13-11-025, Attachment 4. List of Proposed Metrics and Potential Areas of Measurement (as applicable to a specific project or investment area)	Reference
3. Economic benefits	
a. Maintain / Reduce operations and maintenance costs	Section 5.1
4. Environmental benefits	
a. GHG emissions reductions (MMTCO2e)	Section 5.2
5. Safety, Power Quality, and Reliability (Equipment, Electricity System)	
a. Outage number, frequency, and duration reductions	Section 5.1
c. Forecast accuracy improvement	Section 5.1
d. Public safety improvement and hazard exposure reduction	Section 5.1
e. Utility worker safety improvement and hazard exposure reduction	Section 5.1

[22] 2015 PG&E EPIC Annual Report. Feb 29, 2016. http://www.pge.com/includes/docs/pdfs/about/environment/epic/EPICAnnualReportAttachmentA.pdf.

7 Conclusion

The EPIC 2.10 project met its objectives through the successful development and demonstration of a decision support system that successfully recommends restoration strategies for PG&E electric assets after a disruptive event occurs. To accomplish this, the following high level key business requirements were achieved:

- Incorporate natural hazard damage model information into one integrated algorithm/tool, to provide the ability to quickly estimate the impacts of natural hazards on PG&E facilities.
- Provide the ability to prepare for these hazards by proactively modeling the impacts of potential hazards, to understand system vulnerabilities and restoration resource requirements.
- Utilize artificial intelligence and statistical methods to model productive metrics and automatically allocate crews and develop restoration plans.

This project demonstrated the potential to apply predictive analytics using big data and artificial intelligence with ML algorithms to improve the certainty in understanding work demand and resource requirements as well as the positioning of resources, which results in a safer environment, improved reliability and transparency, and promote the efficient use of customer revenue. In addition, applying these advanced technologies not only makes critical information more visible to key decision makers at the right time, but also provides consistency and transparency to the development and revision of restoration plans.

PG&E will continue to fine tune the RWP system by leveraging it further in a field demonstration setting, in parallel with the existing process, for the upcoming storm season and benchmarking its output with actual damages as well as actual crew allocation and positioning. This allows further validation of RWP and fine tuning of the tool as needed. Moreover, while the current version of RWP focuses on storm events, the team may plan for the integration of other events in the future to continue to scale the solution.

In addition, the value that can be realized by this tool can be applied to many other utilities throughout the country for their needs and constraints. The findings in this project related to how work was characterized and how mathematical methods determine resource allocation. This will give utilities an opportunity to replace their daily scheduling tools with components of the RWP's engine that will automatically direct crew movements and project needs.