GRIP Absorption Final Report

A report submitted as part of the
Grid Resilience and Intelligence Platform (GRIP)
project led by
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Executive Summary

Given the wide range of risks posed by anthropomorphic climate change, associated extreme weather events, and the vulnerability of power infrastructure to attack, there is an acute need to design energy infrastructure systems to be increasingly resilient to both natural events and intentional attacks. This report summarizes results from research and development work focused on making power distribution systems more resilient to extreme disturbances, such as ice storms and forest fires. The work described in this report was led by Packetized Energy and is one component of a research and development initiative led by the SLAC National Accelerator Laboratory known as GRIP: The Grid Resilience and Intelligence Platform.

The specific aim of this report is to describe the "Absorption" element of the GRIP platform. The overall goal of Absorption is to enable distribution networks to gracefully "absorb" disturbances through automatic reconfiguration of feeders into microgrids, each of which operates with local resources to serve as much load as possible. To do so, we use two key technological innovations. First, Virtual Islanding technology enables a distribution circuit to be automatically reconfigured into self-managing microgrids. Second, we adapted Packetized Energy Management to the specific problem of using distributed energy resources within the automatically formed islands to maintain the balance between supply and demand, while serving as much load as possible.

The results clearly show that Virtual Islanding has the potential to dramatically increase resilience in distribution circuits. In one illustrative 'fire' case, the use of absorption reduced the unserved energy from a one-day outage from nearly 100% to only 20%.

Forward

This report reviews the core technology, and then describes results from the three key elements of the research: (Chapter 2) Virtual Islanding and its integration into the GRIP platform, (Chapter 3) field demonstration of the Packetized Energy Management power balancing technology, (Chapter 4) machine learning methods applied to the problem of estimating the 'virtual energy storage' state of water heaters that are participating in a Virtual Island. Chapter 5 reviews our conclusions from this work.

Chapter 1

Introduction

The goal of the absorption component of the GRIP project is to enhance distribution system resilience by enabling distribution circuits to gracefully 'absorb' extreme events so that power distribution systems can provide electricity customers with as much energy service as possible, even when portions of the network have been damaged. In conventional distribution circuit operations, if there is damage to any portion of the circuit all downstream electric service is lost. The GRIP Absorption platform allows electric utilities to better understand how they can transition to a system in which distribution circuits can continue to serve load, even after either the bulk grid or portions of a distribution circuit (or both) are damaged by extreme events.

The GRIP Absorption system involves three phases:

1. **Fault Isolation**. In this phase, faults (broadly defined) are isolated and the circuit is prepared for reconfiguration. There are a wide array of commercially available technology for fault isolation [1]. As a result, this project does not focus on the the implementation details of fault isolation, but rather provides models the key outcome: the ability to isolate faults and prepare for network reconfiguration.

2. **Island Formation**. In the second phase, the distribution circuit is reconfigured into "virtual islands" to serve as much (potentially value-weighted) load as possible, while leaving as much margin as possible to serve additional load if the bulk grid outage persists over an extended period of time.

3. **Power Balancing**. During this phase, demand-side resources within the distribution network are managed in order to keep supply and demand balanced. This phase makes use of Packetized Energy's Nimble software platform and the underlying Packetized Energy Management algorithms, which together enable devices to regulate their power demand based on both local need-for-energy and grid conditions.

1.1 Review of Packetized Energy Management

Packetized Energy Management (PEM) [2, 3, 4] is a distributed energy resource (DER) coordination technology previously developed at the University of Vermont with funding

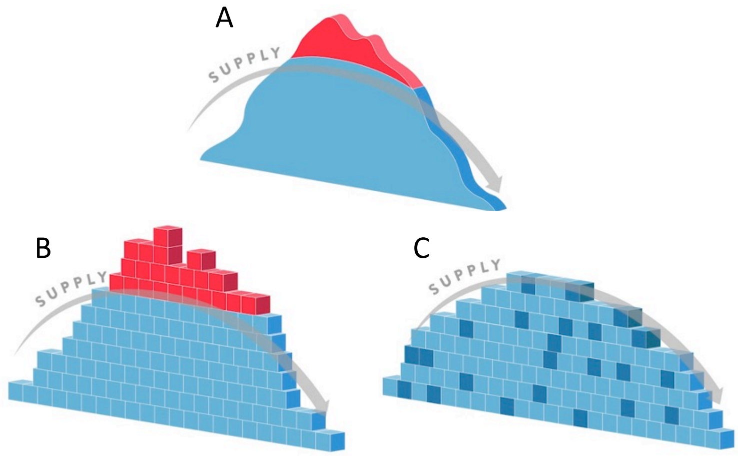


Figure 1.1: Illustration of packetization and randomization applied to reducing excess peak load. **A**: Initial load profile. **B**: Packetization. **C**: Randomization process moves the energy packets in time.

from the ARPA-E NODES program[1]. PEM enables a fleet of DERs to match demand with variable supply signals (such as renewable resource availability, market signals, or an indication of imbalance in a microgrid) through packetization and randomization (see Fig. 1.1). More specifically, a DER controller (e.g., for a water heater, HVAC system, EV charger, distributed battery) periodically wakes up, measures the local need for stored energy, and then probabilistically requests a packet of energy from a server. A packet may be defined in different ways for different DERs; for the case of an electric resistance water heater, we generally define a packet as 5-minute of consumption at the rated power (typically around 4.5kW). The probability of packet requests increases with the device's need for energy or state of charge.

Packetized devices coordinate their actions by interacting with a PVB server, which accepts or rejects packet requests. When the PVB server gets a request from a device, it compares the total power consumption of the fleet with a pre-defined set point and accepts or rejects the request based on this comparison. The server is essentially device agnostic, in that it does not keep track of the state or location of individual devices. Instead the server focuses on managing the fleet as a single virtual battery.

At scale, when there are thousands of devices coordinated with these core algorithms, the aggregated resource (the PVB) can act like a fully dispatchable energy storage resource. Figure 1.2 shows the application of PEM to the problem of coordinating several thousand water heaters simulated in the University of Vermont's cyber-physical testbed [5].

[1] ARPA-E Network Optimized Distributed Energy Systems (NODES) program web site: `https://arpa-e.energy.gov/technologies/programs/nodes`

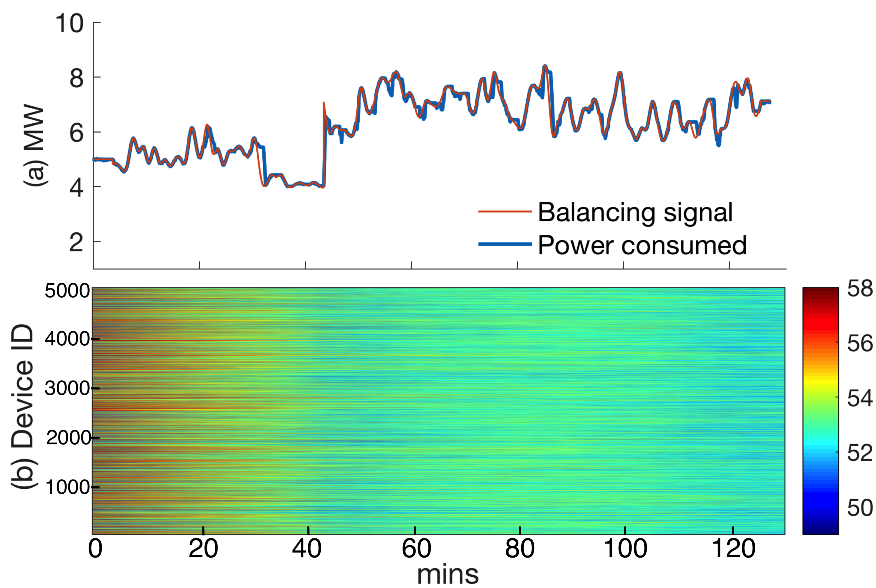


Figure 1.2: (a) Packetized virtual battery, simulated in the cyber-physical testbed, tracking a balancing signal representing variable wind or solar availability, (b) Temperature profile of water heaters over time.

Chapter 2

Virtual Islanding

This chapter reviews the design of the Absorption module within the GRIP platform, along with the underlying algorithms. Section 2.1 reviews the architecture of the software. Section 2.3 describes the test cases that we developed for preliminary testing and validation of the platform. Section 2.5 describes results from simulation tests implemented on the platform. Section 2.6 describes the methods used to simulate Packetized Energy Management within the GRIP platform. Finally, Section 2.7 describes the validation results for a large-scale circuit model from our utility partner, Vermont Electric Coop and Section 2.8 outlines our conclusions.

2.1 GRIP Absorption design

The absorption process responds to faults in the distribution circuit by segmenting the network into "virtual islands" or micro-grids, using switching devices, and then by optimally managing the devices in the resulting islands. The distribution circuit must have a sufficient number of circuit switching devices (circuit breakers, reclosers or remotely-operable disconnect switches) to enable fault isolation and distribution circuit reconfiguration. For a typical distribution feeder, virtual islanding will work best if there is a sufficient number of switching devices to separate the circuit into sections (supernodes) with 50-500 customers within each supernode.

The GRIP absorption code (see Fig. 2.1) and the virtual islanding algorithm assume that all lines adjacent to “supernodes" are switchable links in the network and that there is a “supernode list" object in the model with a ‘node group’ attribute listing all supernode names in the circuit. While this isn’t necessarily the case for all distribution circuits, it is the case that reduced models can be built from any distribution circuit to fit this model. Additionally, Absorption requires that all assets in the circuit be assigned to their supernode through a “supernode name" attribute for virtual islanding and island management. The original test circuits were build specifically for this module, described in section 2.3, and a real-world circuit model, for Hinesburg, Vermont was edited to work in the GRIP absorption platform, presented in section 2.7.

A more detailed description of the absorption module code is shown in Figure 2.2.

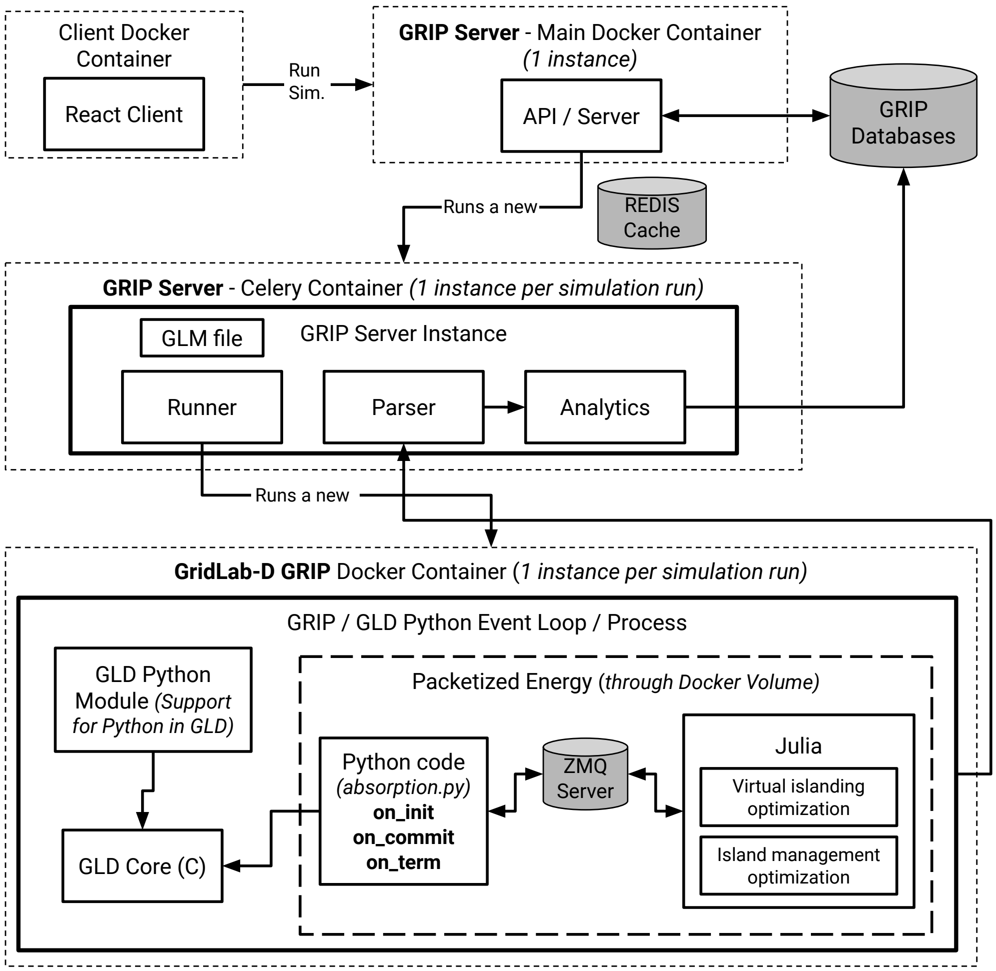


Figure 2.1: GRIP Absorption module software design schematic

2.2 The Virtual Island Identification Problem

Once a fault has been identified in a circuit and the distribution circuit, it is necessary to isolate the damaged portion of the circuit and reconfigure the circuit into 'Virtual Islands' that can be operated as independent microgrids.

The Virtual Island Identification Problem (VIIP) takes information about the configuration of the network and returns a set of switching operations that will divide the network into islands that can serve as much of the load as possible, while leaving as much margin as possible for future load increases. This section describes this problem in detail.

Decision variables in VIIP

$P_{g,n}[k]$ is the total power generation at node n (may be from multiple sources) during time step, k.

$\Delta P_{g,n}[k]$ is a change in power generation at node n during time step, k.

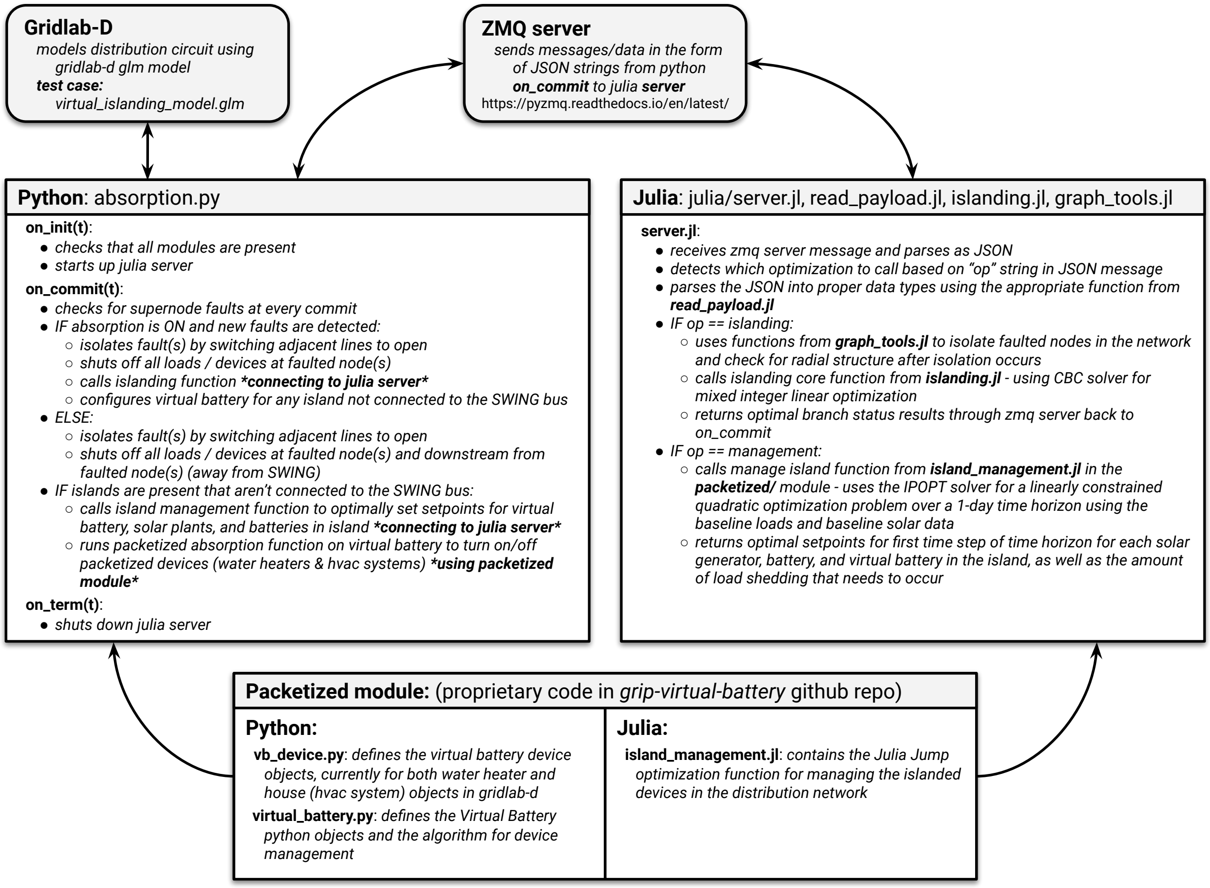


Figure 2.2: Absorption implementation - code structure

$P_{b,n}[k]$ is battery (or virtual battery) charging power at node n (may be negative) during time step, k.

$\Delta P_{b,n}[k]$ is a change in charging power during time step, k.

$\Delta P_{d,n}[k]$ represents a change in load at node n (positive values indicate increasing load) during time step, k

$P_{ft,m}[k]$ is the power traveling from bus f to bus t over link m during time step, k

$\Delta P_{ft,m}[k]$ is a change in power traveling from bus f to bus t over link m during time step, k

u_m is the binary status of branch m (ON/CLOSED=1, OFF/OPEN=0)

R is a measure of loadability margin for the system as a whole.

Input parameters

The following input data are required to run the VIIP algorithm

The network topology

$\Delta t[k]$ is the amount of time (hours) of day versus night

$CF_g[k]$ is the capacity factor multiplier for generator g during time step k (always 1.0 for all non-solar generators)

$P_{d,n}[k]$ is the total load currently being served at node n

$\overline{P_{g,n}}$ The maximum amount of power generation at each node n

$\overline{P_{b,n}}, \overline{E_{b,n}}$ The power and energy capacity of batteries located at each node n.

Other notation

K is the number of time steps, with index k, representing day and night time levels of solar availability

N is the set of all nodes, with cardinality $|N|$ and index n

M is the set of all branches, with cardinality $|M|$ and index m

M_n is the set of branches connected to node n

B is the set of all batteries, with cardinality $|B|$ and index b

G is the set of all generators, with cardinality $|G|$ and index g

F_i represents the state variables for the "from" end of branch i

T_i represents the state variables for the "to" end of branch i

$P_{ft}(\cdot)$ is a function that returns the power flowing out from a node over a branch, given the state variables for that branch.

$x[0]$ is the value of x at time zero (before switching begins)

V_d is the relative value of a particular load d

C_R is the relative value of the reserves

C_B is the relative value of the battery state-of-charge.

Objectives

The GRIP Absorption/virtual islanding algorithm will operate with five primary objectives.

The first (and primary) objective is to minimize the value-weighted amount of unserved load. The second objective is to ensure that we maintain as much reserve as possible to account for future load increases. The third objective is to maximize the batteries state-of-charge at the final time step The fourth and fifth objectives, which are less critical, but useful for arriving at reasonable solutions, are to minimize the number of switching events and the total number of loads that are "on" for reserves accounting.

Mathematically, these objectives can be written as follows:

$$\text{Maximize} \quad \sum_{d \in D} \sum_{k \in K} V_d P_d[k] \tag{2.1}$$

$$\text{Maximize} \quad C_R R \tag{2.2}$$

$$\text{Maximize} \quad C_B \sum_{b \in B} E_b[K] \tag{2.3}$$

$$\text{Minimize} \quad \sum_{m \in M} |u_m[1] - u_m[0]| \tag{2.4}$$

$$\text{Minimize} \quad \sum_{d \in D} u_d \tag{2.5}$$

where Objective 2.1 is to maximize the value (V_d) weighted total load, Objective 2.3 is to maximize the value (C_R) weighted final battery energy E_b, Obj. 2.2 is the maximize the total reserves, which comes from both the total reserves at individual nodes and the worst-case reserves at an island, R, Obj. 2.4 is to minimize the total number of switching events, and Obj. 2.5 is to minimize the number of loads that are turned on for the sake of reserves accounting. This objective ensures that we will have at most one reserve load node per virtual island, since no additional value is gained by switching on additional nodes.

Since the VIIP uses a single objective optimization solver (COIN-OR's Cbc or the commercial Gurobi solver), we integrate the objectives using a simple linear combination shown below:

$$\text{Maximize} \quad \sum_{k \in K} \sum_{d \in D} V_d P_d[k] + C_R R + C_B \sum_{b \in B} E_b[K] - \sum_{m \in M} |u_m[1] - u_m[0]| - \sum_{d \in D} u_d \tag{2.6}$$

Constraints

The following are the constraints used in the VIIP model. Equation 2.7 ensures that power supply and demand balance. Equation 2.8 ensures that power supply and demand balance, after having factored in the reserves. Equations 2.9 and 2.10 limit power the line flows to be zero if a switch on the link is open, or to be within limits if the switch is closed (or non-existant). Equation 2.11 limits power generation to be within limits and Eq. 2.11 limits power generation to be within limits for the reserves case. Equations 2.13 and 2.14 limit the load to be within limits in the base case and in the reserves case. Equations 2.15 and 2.16 limit the battery power to be within limits for both cases. Equations 2.17 and 2.18 limit the battery energy state to be within limits in the base case and in the reserves case. Equations

2.19 and 2.20 calculate the battery energy state of one time step, dependent on the previous time step energy and power values in the base case and in the reserves case. Equation 2.21 ensures that after all switching operations are complete, the distribution network remains radial. Equation 2.22 ensures that R (the reserves variable) is less than or equal to the amount of surplus in the virtual island with the smallest amount of reserves. Equation 2.23 and 2.24 ensure that the binary state variables are indeed binary.

$$
\begin{aligned}
\text{s.t.} \quad & P_{g,n}[k] - P_{d,n}[k] - P_{b,n}[k] = \sum_{m \in M_n} P_{ft,m}[k], && \forall n \in N, \forall k \in K && (2.7)\\
& (P_{g,n}[k] + \Delta P_{g,n}[k]) - (P_{d,n}[k] + \Delta P_{d,n}[k]) - (P_{b,n}[k] \\
& \qquad + \Delta P_{b,n}[k]) = \sum_{m \in M_n} (P_{ft,m}[k] + \Delta P_{ft,m}[k]), && \forall n \in N, \forall k \in K && (2.8)\\
& -\overline{P_{ft,m}} * u_m \leq P_{ft,m}[k] \leq \overline{P_{ft,m}} * u_m, && \forall k \in K && (2.9)\\
& -\overline{P_{ft,m}} * u_m \leq P_{ft,m}[k] + \Delta P_{ft,m}[k] \leq \overline{P_{ft,m}} * u_m, && \forall k \in K && (2.10)\\
& 0 \leq P_{g,i}[k] \leq \overline{P_{g,i}} * CF_g[k], && \forall i \in G, \forall k \in K && (2.11)\\
& 0 \leq (P_{g,i}[k] + \Delta P_{g,i}[k]) \leq \overline{P_{g,i}} * CF_g[k], && \forall i \in G, \forall k \in K && (2.12)\\
& 0 \leq P_{d,i}[k] \leq P_{d,i}[0], && \forall i \in D, \forall k \in K && (2.13)\\
& 0 \leq \Delta P_{d,i}[k], && \forall i \in D, \forall k \in K && (2.14)\\
& -\overline{P_{b,i}} \leq P_{b,i}[k] \leq \overline{P_{b,i}}, && \forall i \in B, \forall k \in K && (2.15)\\
& -\overline{P_{b,i}} \leq P_{b,i}[k] + \Delta P_{b,i}[k] \leq \overline{P_{b,i}}, && \forall i \in B, \forall k \in K && (2.16)\\
& 0 \leq E_{b,i}[k] \leq \overline{E_{b,i}}, && \forall i \in B, \forall k \in K && (2.17)\\
& 0 \leq E_{b,i}[k] + \Delta E_{b,i}[k] \leq \overline{E_{b,i}}, && \forall i \in B, \forall k \in K && (2.18)\\
& E_{b,i}[k+1] = E_{b,i}[k] + P_{b,i}[k+1] * \Delta t[k+1], && \forall i \in B, \forall k \in K && (2.19)\\
& \Delta E_{b,i}[k+1] = \Delta E_{b,i}[k] \\
& \qquad + (P_{b,i}[k+1] + \Delta P_{b,i}[k+1]) * \Delta t[k+1], && \forall i \in B, \forall k \in K && (2.20)\\
& \sum_{m \in L_l} u_m \leq |L_l| - 1, && \forall l \in \text{LOOPS} && (2.21)\\
& R \leq \Delta P_{d,n}[k] - M u_d, && \forall n \in N, \forall k \in K && (2.22)\\
& u_{d,i} \in \{0,1\}, && \forall i \in D && (2.23)\\
& u_{m,j} \in \{0,1\}, && \forall j \in M && (2.24)
\end{aligned}
$$

Identifying loops

One of the key requirements for solving VIIP is to know the location of loops within the distribution network (see Eq. 2.21). In order to autonomously identify loops in the network, we use the following, relatively simple algorithm:

1. Begin at a randomly selected node in the circuit, and include this node in the set of visited nodes. Call this node, node s, and the set of all visited nodes V.

2. Randomly choose one of node s's neighbors (uniform distribution). Call this node node i. Add i to the set of visited nodes, V.

3. Identify the neighbors of node i: N_i. If all of the nodes in N_i have been previously visited, quit (end point found). If there are only two nodes in V randomly select one of the nodes in N_i that are not in V, call this node i, add it to V and repeat. If there are more than two nodes in V and the only node in N_i that is not in V is s, then quit (loop of length three or more nodes has been found; repeat from step 1). If there are more than two nodes in V and s is not in N_i, then advanced to a randomly chosen node in N_i that is not in V and repeat this step.

2.3 Virtual Islanding GRIP Test Cases

In order to validate the Virtual Islanding algorithms, two different test systems were developed: a small 11-node distribution system that was used for preliminary validation and a larger test case based on real data from our utility partner, Vermont Electric Coop. This section describes the first of these two test cases, and validation results that illustrate the application of the Virtual Islanding module in Sec. 2.2 to this 11-node test case.

The 11-node test case (see top panel of Fig. 2.3 includes two substation nodes and three feeders, each of which includes both distributed Solar PV generation and grid-scale storage. In addition, we assume that there are many 'packetized' water heaters and HVAC systems that can contribute to network balancing.

For the purpose of validation, we developed two illustrative resilience scenarios, one (Case 1: Fire) representing fire damage to a distribution network and the other (Case 2:Ice) representing ice damage.

Case 1: Fire: Wildfires causes failure in the bulk grid & distribution network faults

In the first test case for our virtual islanding model, we utilize weather data from Los Angeles, CA and model the date October 15, 2020.

In this test case, the scenario involves wildfires taking out the bulk grid as well as one other node ("supernode") in the distribution circuit where a solar plant is located. Figure 2.3 (a)-(c) shows the fault locations, the results during the "baseline", where the absorption module is turned off, and the results when absorption is turned on. The resulting virtual island is shown by the dashed line in Fig 2.3(c).

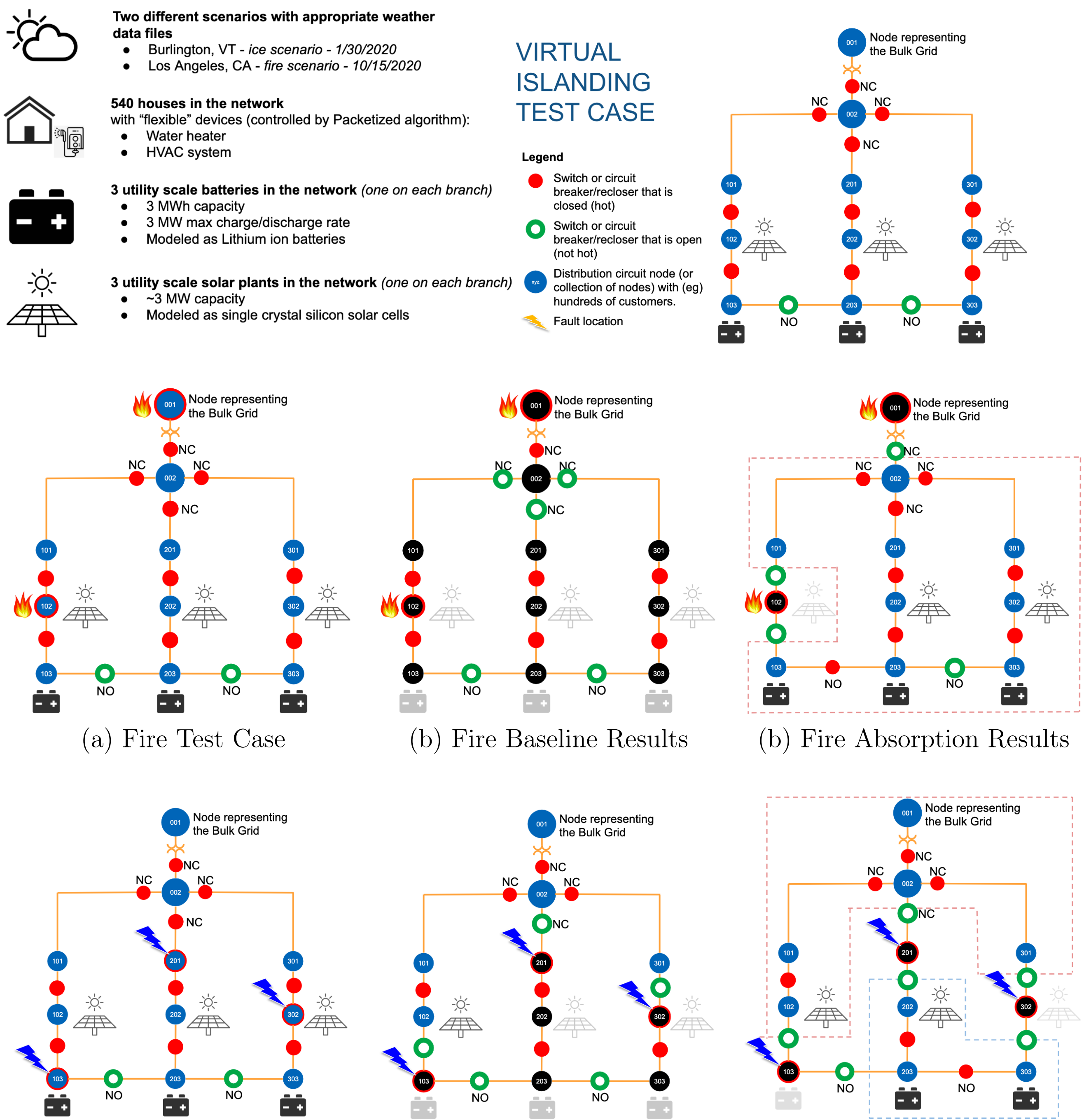
Case 2: Ice: An ice storm causes multiple distribution network faults

In the second test case for our virtual islanding model, we utilize weather data from Burlington, VT and model the date January 30, 2020.

In this test case, the scenario involves an ice storm that takes out three nodes ("supernodes") in the distribution circuit, one with a utility scale battery and one with a solar plant. Figure 2.3 (d)-(f) shows the fault locations, the results during the "baseline", where the absorption module is turned off, and the results when absorption is turned on. The resulting virtual islands are shown by the dashed line in Fig 2.3(f), but only the one in blue is an isolated island no longer supported by the bulk grid.

After initial testing, this test case was imported into the actual GRIP software and simulated within GRIP and the islanding code was re-run. Figure 2.5 shows images from the GRIP UI with the same resulting islands from the two test cases, while Figure 2.4 shows the resulting network structure with the absorption module (virtual islanding) not implemented. Clearly, the algorithms operate as intended within GRIP.

Once the virtual islands are formed, the absorption module then continually manages the loads, batteries, and generation available in each island throughout the rest of the simulation, which also includes the implementation of PET virtual battery management of flexible load devices such as water heaters and HVAC systems. This island management involves a linear optimization to minimize unserved energy over the time horizon of the full simulation and is formulated in the next section.



(a) Fire Test Case (b) Fire Baseline Results (b) Fire Absorption Results

(d) Ice Test Case (e) Ice Baseline Results (f) Ice Absorption Results

Figure 2.3: Absorption test case network model, scenarios, and virtual island results

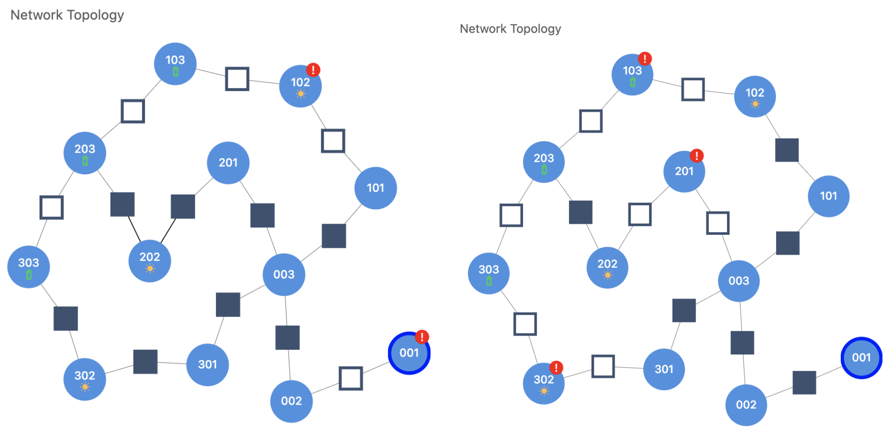


Figure 2.4: GRIP UI network visualizations of simple fault isolation (absorption module turned off) for 2 test cases, fire-scenario (left) and ice-scenario (right)

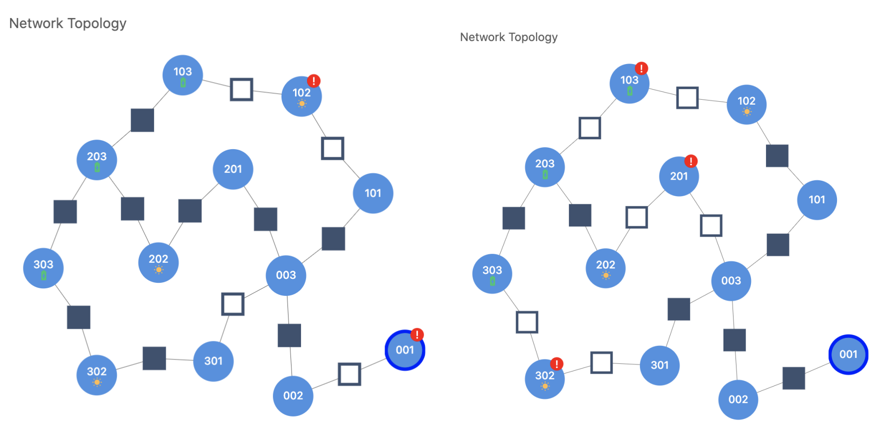


Figure 2.5: GRIP UI network visualizations of virtual island networks for 2 test cases, fire-scenario (left) and ice-scenario (right)

2.4 Island Management Optimization

Once virtual islands have been formed, it is then necessary to manage the distributed resources within those islands to maintain the balance between supply and demand. There are two key elements to making this successful. The first is an 'Island Management Optimization' (IMO) tool that centrally optimizes the assets within the island, including the aggregated group of smaller, Packetized DERs. And then, a Packetized Virtual Battery server, manages the smaller DERs as a group, based on signals from the IMO.

The Island Management Optimization takes information about the current state of larger DERs (or aggregated Packetized Virtual Batteries) in an islanded subsection of the distribution circuit, or micro-grid and the "baseline" or business-as-usual time-series data for that island, and returns the setpoints for the DERs or DER groups for the next time step. This controller is formulated as a receding horizon control (RHC) optimization problem, which is described in detail below.

Decision variables in IMO

$P_s[k]$ is the total power generation at solar plant s during time step, k.

$P_g[k]$ is the total power generation at non-solar generator[1] g during time step, k.

$P_b[k]$ is battery charging power (may be negative) for battery b during time step, k.

$P_{vb}[k]$ is virtual battery setpoint (maximum load that the flexible devices should demand) during time step, k.

$D_{\text{shed}}[k]$ represents the load shedding that should be implemented during time step, k

$E_b[k]$ energy state of battery b during time step, k.

$E_{vb}[k]$ energy state of the virtual battery during time step, k.

$c[k]$ is a measure of customer comfort, which serves as the lower bound of the virtual battery state-of-charge E_{vb} for each time step k. When negative, the flexible devices are below the range where customer comfort is being met.

Input parameters

The following input data are required to run the IMO algorithm

The island that is being managed.

k_0 is the starting time step at which the optimization is called.

t_{inc} is the time step size in minutes that the IMO will be called on (assuming that the returned setpoints will be stable over this time period).

[1]Note that for our test case there were no non-solar generators in the distribution circuit other than the SWING bus and the battery objects. Some code would need to be added to 'absorption.py' to gather the data from GLD for non-solar generator objects.

$D_f[k], D_{nf}[k]$ The baseline 24-hour time-series vector of flexible and non-flexible loads for the island.

$\overline{P_s}[k]$ The baseline 24-hour time-series vector of available solar generation for each solar plant in the island.

$\overline{P_g}$ The max power output of generator g.

$\overline{P_b}$ The max power output of battery b.

$\overline{E_b}$ The max energy capacity of battery b.

$E_b[k_0]$ The current energy state of battery b at initial time step k_0.

$\overline{P_{vb}[k]}$ The max power output of the virtual battery (estimated at $2 * D_f$).

$\overline{E_{vb}}$ The max energy capacity of the virtual battery (as a function of the number of flexible devices in the island).

$E_{vb}[k_0]$ The current energy state of the virtual battery at initial time step k_0 (calculated based on the temperature of all devices in the virtual battery).

Other notation

K is the number of time steps, with index k.

B is the set of all batteries, with cardinality $|B|$ and index b

S is the set of all solar generators, with cardinality $|S|$ and index s

G is the set of all generators, with cardinality $|G|$ and index g

Δt is the difference between each time step in hours (t_{inc} converted from minutes to hours).

Objectives

The GRIP Absorption/island management algorithm will operate with four primary objectives.

The first (and primary) objective is to minimize the value-weighted amount of total unserved (shed) non-flexible energy. The second objective is to ensure that we maintain as much battery energy at the end of the time horizon as possible. The second objective is to maximize the virtual battery energy at the end of the time horizon. The fourth objective is to maximize the value-weighted level of customer comfort over the entire time horizon.

Mathematically, these objectives can be written as follows:

$$\text{Minimize} \quad \sum_{k \in K} V_d D_{\text{shed}}[k] * \Delta t \tag{2.25}$$

$$\text{Maximize} \quad \sum_{b \in B} E_b[K] \tag{2.26}$$

$$\text{Maximize} \quad E_{vb}[K] \tag{2.27}$$

$$\text{Maximize} \quad \sum_{k \in K} c[k] \tag{2.28}$$

where Objective 2.25 is to minimize the value (V_d) weighted total unserved non-flexible energy resulting from load shedding, Objective 2.26 is to maximize the final battery energy E_b for all batteries in the island, Obj. 2.27 is the maximize the final battery energy state of the virtual battery, Obj. 2.28 is to maximize the customer comfort variable c, which serves as the lower bound on the virtual battery energy state, over the entire time horizon.

Since the IMO uses a single objective optimization solver (COIN-OR's Cbc), we integrate the objectives using a simple linear combination shown below:

$$\text{Minimize} \quad \sum_{k \in K} V_d D_{\text{shed}}[k] * \Delta t - \sum_{b \in B} E_b[K+1] - E_{vb}[K+1] - \sum_{k \in K} c[k] \tag{2.29}$$

Constraints

The following are the constraints used in the IMO model.

$$\begin{aligned}
\text{s.t.} \quad & \sum_g P_g[k] + \sum_s P_s[k] = \sum_b P_b[k] + P_{vb}[k] \\
& \qquad + D_{nf}[k] - D_{\text{shed}}[k], && \forall k \in K && (2.30) \\
& 0 \leq P_s[k] \leq \overline{P_s[k]}, && \forall s \in S, \forall k \in K && (2.31) \\
& 0 \leq P_g[k] \leq \overline{P_g}, && \forall g \in G, \forall k \in K && (2.32) \\
& -\overline{P_b} \leq P_b[k] \leq \overline{P_b} && \forall b \in B, \forall k \in K && (2.33) \\
& 0 \leq P_{vb}[k] \leq \overline{P_{vb}[k]} && \forall k \in K && (2.34) \\
& 0 \leq D_{\text{shed}}[k] \leq D_{nf}[k] && \forall k \in K && (2.35) \\
& 0 \leq E_b[k] \leq \overline{E_b} && \forall b \in B, \forall k \in K && (2.36) \\
& E_b[1] = E_b[k_0] && \forall b \in B && (2.37) \\
& E_b[k+1] = E_b[k] + P_b[k] * \Delta t && \forall b \in B, \forall k \in K+1 && (2.38) \\
& c[k] <= 0 && \forall k \in K+1 && (2.39) \\
& 0 + c[k] \leq E_{vb}[k] \leq \overline{E_{vb}} && \forall k \in K && (2.40) \\
& E_{vb}[1] = E_{vb}[k_0] && && (2.41) \\
& E_{vb}[k+1] = \gamma E_{vb}[k] + P_{vb}[k] * \Delta t - D_f[k] * \Delta t && \forall k \in K+1 && (2.42)
\end{aligned}$$

Equation 2.30 ensures that power supply and demand balance over the entire time horizon. Equations 2.31 and 2.32 limit power the output for the solar and non-solar generators.

Equation 2.33 limits batteries power to be within limits and Eq. 2.34 limits the setpoint for the virtual battery to be within a reasonable range for the flexible devices. Equation 2.35 limits the load shedding to be within the range of non-flexible load from the baseline timeseries. Equations 2.36 and 2.40 limit the energy state to be within limits for the batteries and virtual battery. Equations 2.37, 2.38, 2.41, and 2.42 model the batteries and virtual batteries energy state over the time horizon.

The output of the optimization is a time-series of setpoint values and the resulting state-of-charge of the batteries and virtual battery over the entire time horizon of 24-hours. Figure 2.6 shows this output for the optimization of the initial time step of the simulation for both the "fire" and "ice" test cases.

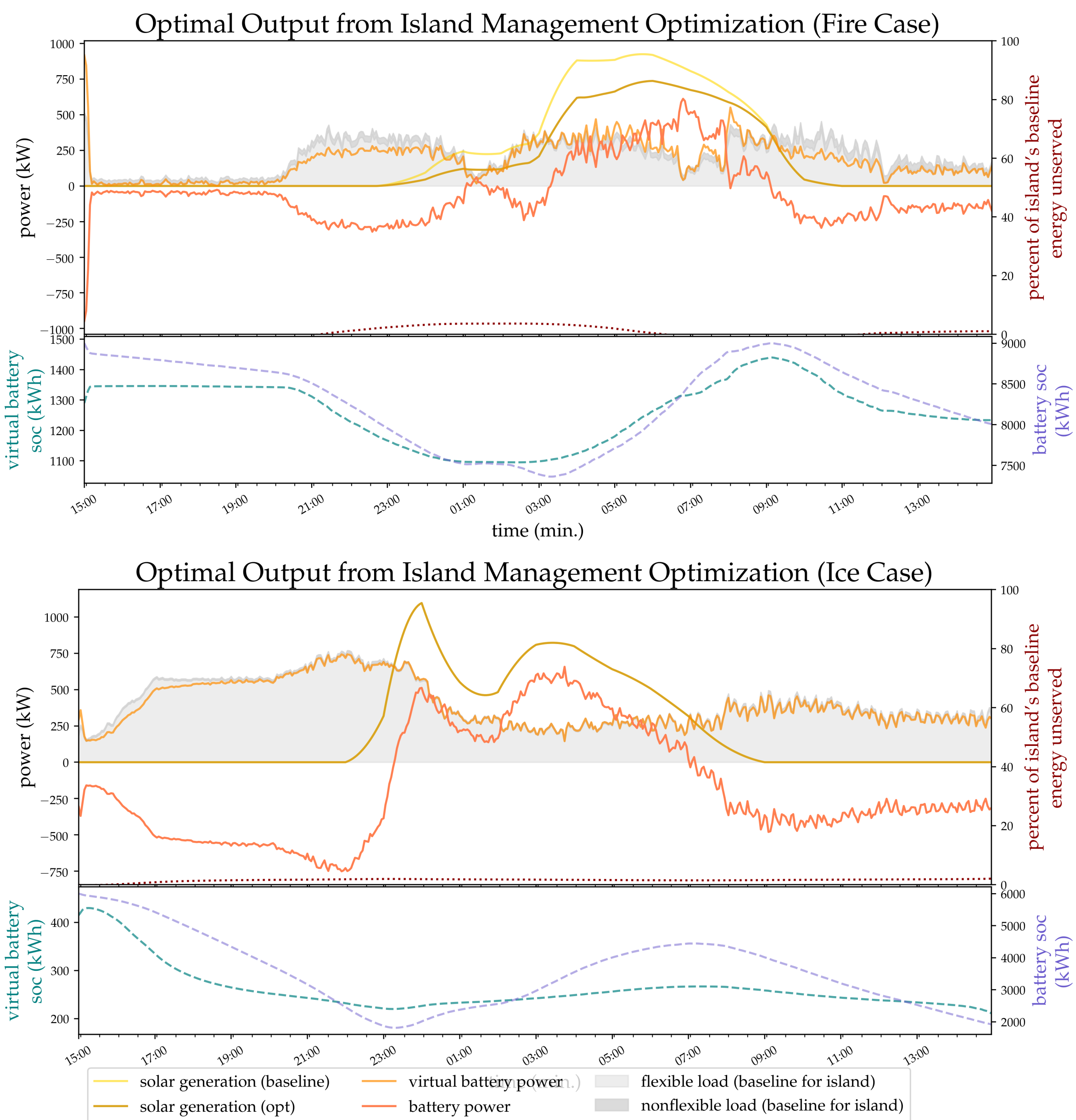


Figure 2.6: Island management optimization output at k_0 for absorption test cases

Model Output and Power Balance Check

The IMO model finds the optimal solution for all decision variables over the entire 24-hour time horizon, but returns only the setpoint values for the next time step, $k_0 + t_{\text{inc}}$, to python to be implemented in the GLD simulation. The solar and generator power output values are set first, followed by the load shedding. If the optimization returns a non-zero value for load shedding, first a check is done to make sure the flexible load is also zero, and if not the load shed value is subtracted from the virtual battery setpoint so that the flexible load is always shed first. If the setpoint of the virtual battery is zero and more load must be shed a certain number of randomly selected houses in the island are shut off, estimated by the average non-flexible baseline load per house.

After the virtual battery setpoint is updated from the IMO result, the packetized virtual battery algorithm is run, turning the flexible devices on and off according to their state-of-charge or temperature. The total load from all flexible devices in the virtual battery might not always equal the setpoint, so after this algorithm is finished, a final check is done on the power balance and any discrepancy is adjusted and balanced with the batteries power.

2.5 GRIP UI Results for Full Absorption Test Cases

Figures 2.7-2.12 show each GRIP absorption test simulation output for the timeseries data and network configuration. Figures 2.7 and 2.10 show the baseline model runs, with no faults implemented in the network and a business-as-usual simulation run. Figures 2.8 and 2.11 show the output for the faulted models, as described in section 2.3, with the absorption module turned on and virtual islanding and island management implemented. Finally, Figures 2.9 and 2.12 show the results for the same fire and ice fault scenarios, but with the absorption module turned off. In these cases, simple fault isolation is implemented and any nodes that are no longer connected to the main swing bus are shut off completely.

For the fire scenario (Figures 2.7-2.9) we see that due to weather, there is a lower flexible load profile throughout the day for the baseline fire case, versus the ice case. Since the main swing bus is faulted in this scenario, the no-absorption simulation leads to a complete blackout in the network, with 100% energy unserved, as shown in Figure 2.9. When the absorption module is on and virtual islanding is implemented, the unserved energy drops to around 12%, which almost completely due to the one faulted node (102) that is completely shut off and accounts for around 11% of the total energy served in the circuit. It order to serve the energy without the swing bus, the island management optimization utilizes the batteries in the morning and evening and recharges them with the solar assets in the middle of the day.

The ice scenario, with the UI output shown in Figures 2.10-2.12, there is a higher flexible load demand due to the hvac systems need to be on for heating. Since 3 out of the 9 supernodes that have houses attached are faulted, around a third of the energy is not served, while the virtual island continues to serve loads in the three nodes that get disconnected from the bulk grid using the one solar plant and two batteries in it. When the absorption module is off, only 3 out of 9 nodes remain connected to the main swing node and so the unserved energy spikes to around 70%, as seen in Figure 2.12.

Case 1 Results: Wildfires causes failure in the bulk grid & distribution network faults

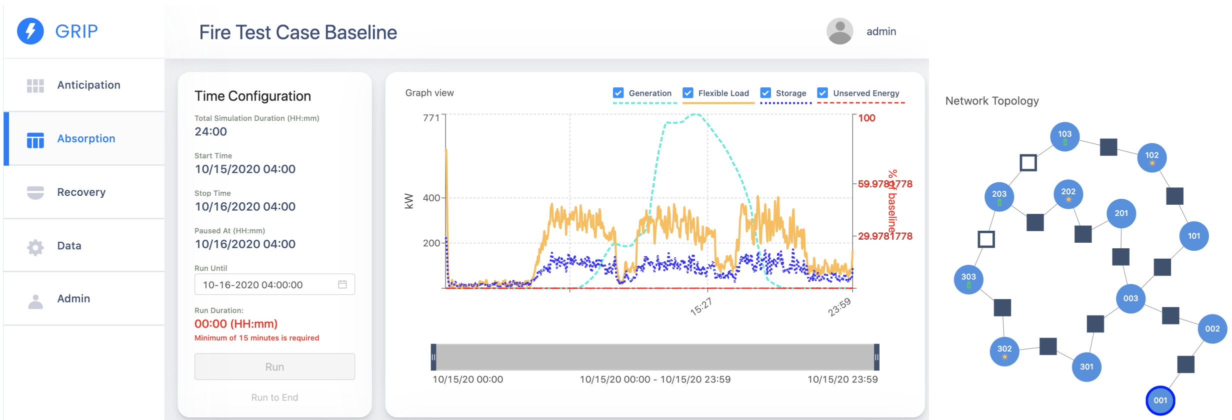


Figure 2.7: GRIP UI screenshot of fire test case - baseline run

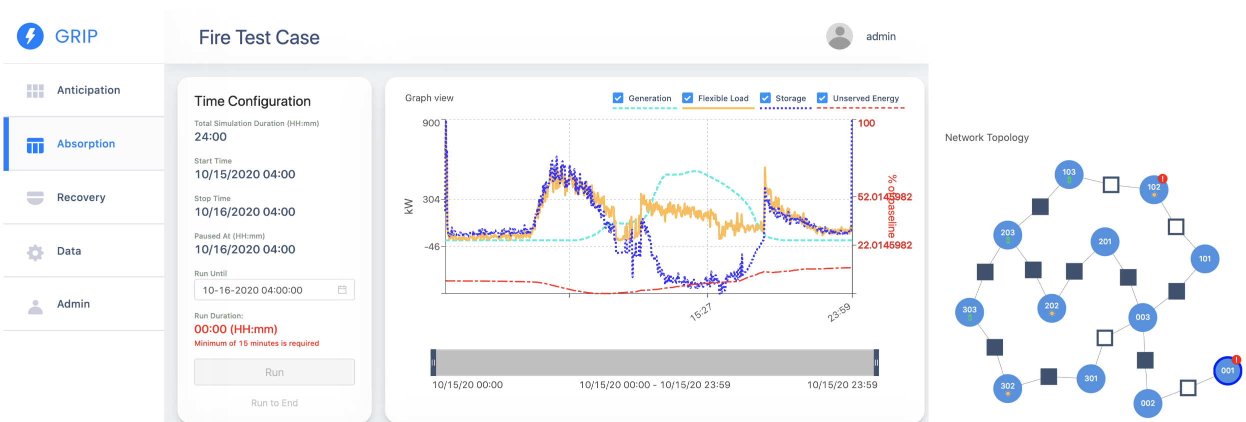


Figure 2.8: GRIP UI screenshot of fire test case - Absorption run

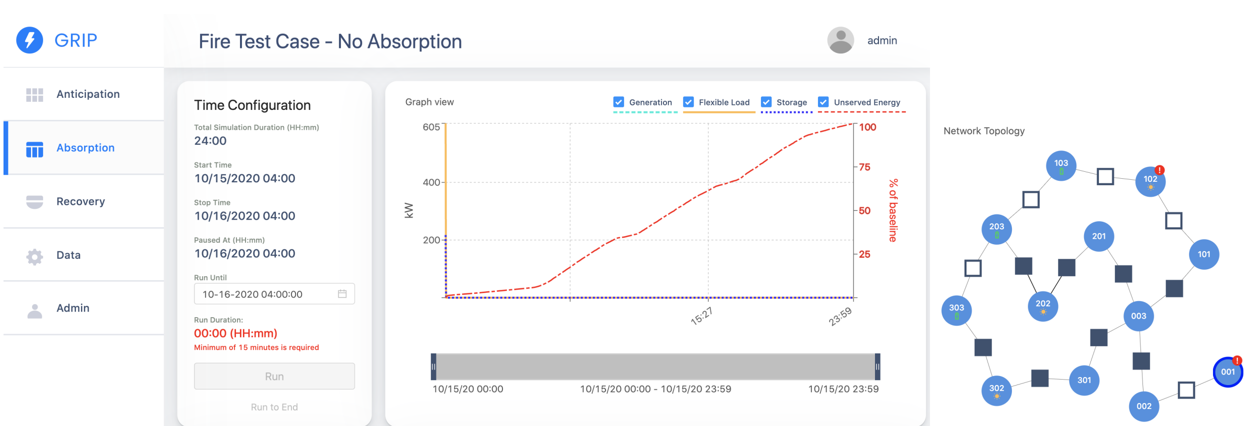


Figure 2.9: GRIP UI screenshot of fire test case - Absorption-off run

Case 2 Results: An ice storm causes multiple distribution network faults

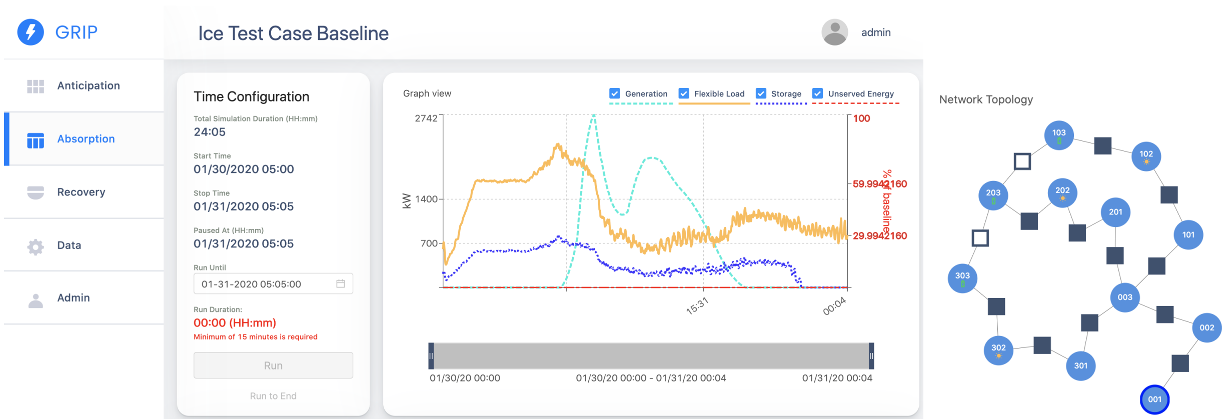


Figure 2.10: GRIP UI screenshot of ice test case - baseline run

Figure 2.11: GRIP UI screenshot of ice test case - Absorption run

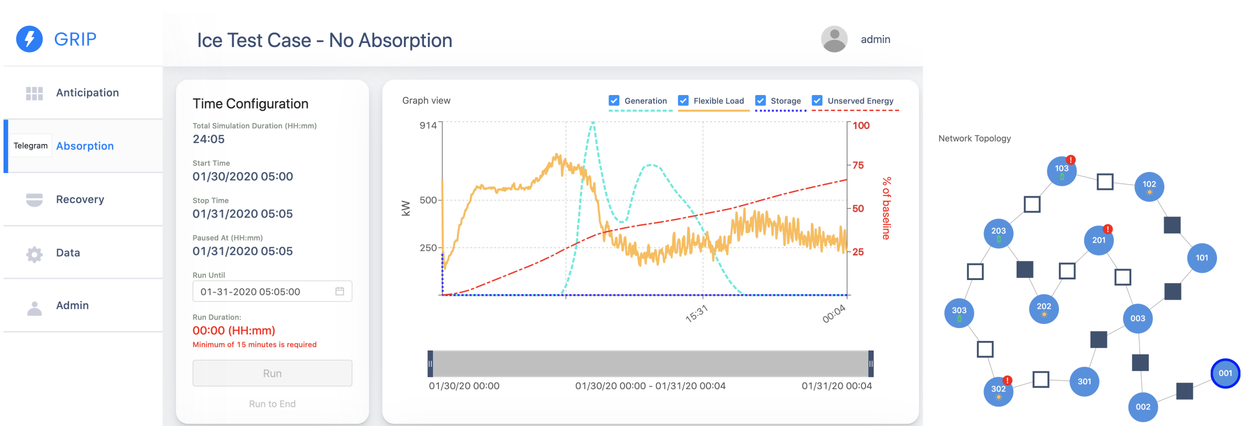


Figure 2.12: GRIP UI screenshot of ice test case - Absorption-off run

2.6 Flexible Load Management

The GRIP absorption module emulates the behavior of a fleet of devices that are coordinated to maintain the balance between supply and demand through Packetized Energy Management (PEM). PEM takes fleets of distributed energy devices at the edge of the grid and turns them into flexible energy resources, or virtual batteries. In GRIP this technology is simulated through the management of GridLab-D water heater and heating and cooling (HVAC) objects, which have their own temperature and load models. To further test the virtual battery simulated in GRIP and the water heater models, we ran a few simulations, outputting the water heater load, hot water demand, and tank temperature variables over the simulation time. In one of the simulations we implemented a simple peak reduction objective, with a morning peak and evening peak, where the virtual battery setpoint was set to 0 during these periods of time.

Figure 2.13 shows the baseline timeseries for a single water heater in the model and Figure 2.14 shows the same output for the GRIP virtual islanding fire fault case. Figure 2.15 shows the same timeseries for the same water heater during the peak reduction simulation, with peaks implemented between 6am and 10am and between 8pm and 11pm.

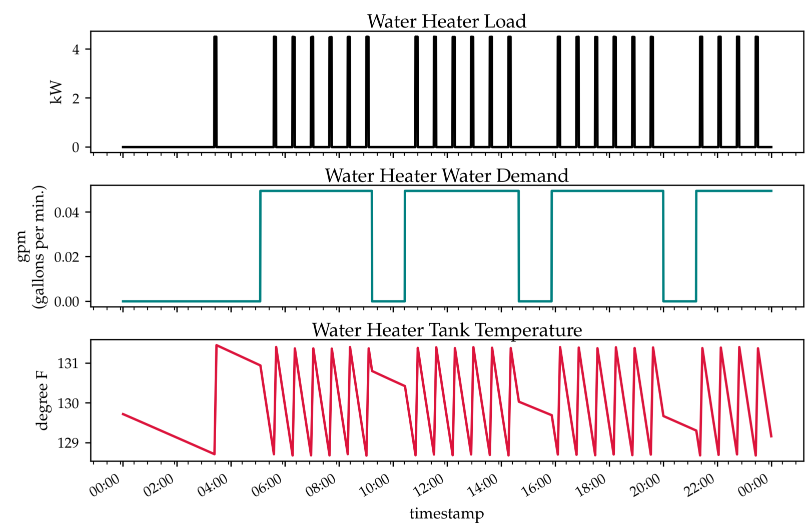


Figure 2.13: Water heater business-as-usual power, water demand, and temperature output from GRIP baseline simulation

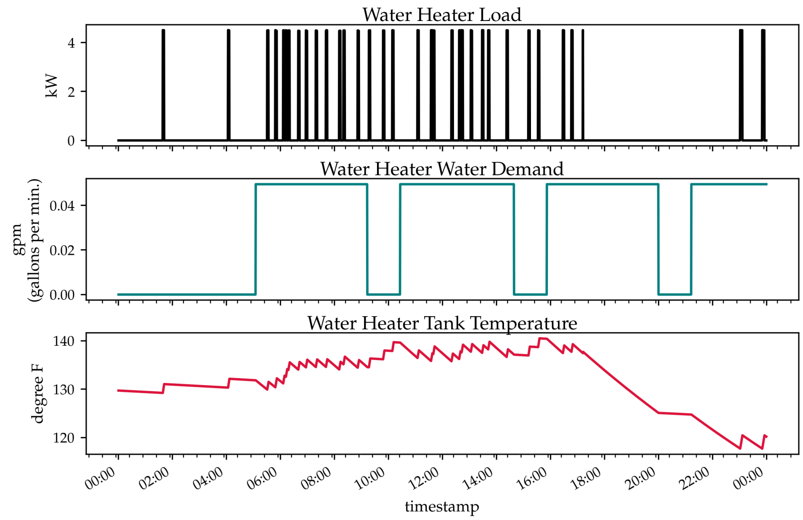


Figure 2.14: Water heater PET-managed power, water demand, and temperature output from GRIP Absorption simulation

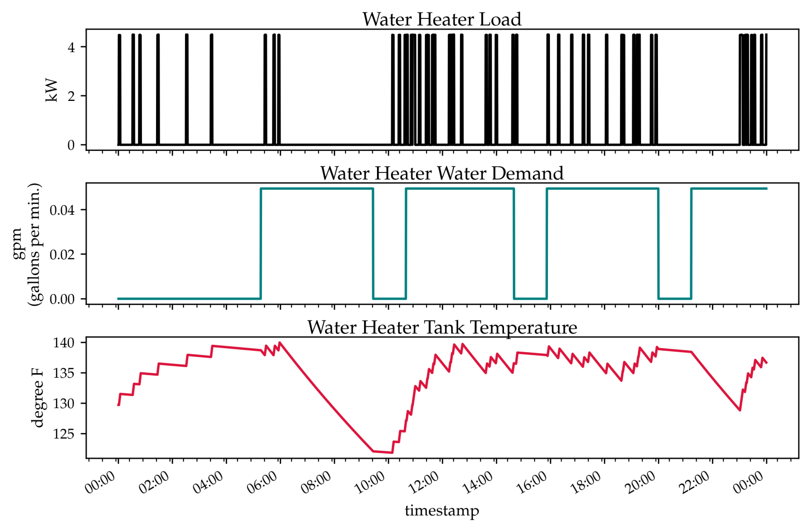


Figure 2.15: Water heater PET-managed power, water demand, and temperature output from "Peak Reduction" simulation (peak hours defined between 6-10AM and 8-11PM)

2.7 Validation with a large-scale circuit model

Here we present results from the simulation of Absorption using a real-world simulation model. The data for this circuit comes from a distribution system in Hinesburg, VT in Vermont Electric Coop's territory.

The first step in this validtion process was to develop a GridLab-D model of the full Hinesburg circuit and then validate the power flow model of this circuit by validating with our utility partner that the results aligned with their internal models. Figure 2.16) shows this circuit with link width representing power flows and Fig. 2.17 shows the same network with node colors indicating the node voltages.

Next, we built a reduced format model that could be imported into GRIP. This reduced model (illustrated in Figs. 2.18 and 2.19) was developed by dividing the circuit into sections that were separated by switching elements, and then defining each group as a "supernode" in the reduced model.

Finally, we developed a 'large ice' scenario for this full system (3 faulted nodes), and simulated this large ice scenario with the GRIP code. Without Absorption, this set of three faults would have left the entire circuit without power for 1 full day (the assumed time to repair). This represents 100% unserved energy. With Absorption on (see Fig. 2.21), we were able to reduce the unserved energy to only 10%.

2.8 Conclusions

The results from this GRIP software demonstration clearly demonstrate that the Virtual Islanding/Absorption concept can dramatically increase distribution system resilience. More specifically, the Absorption algorithm was able to reduce the unserved energy in the Hinesburg test case from 100% of the baseline energy served to 10%.

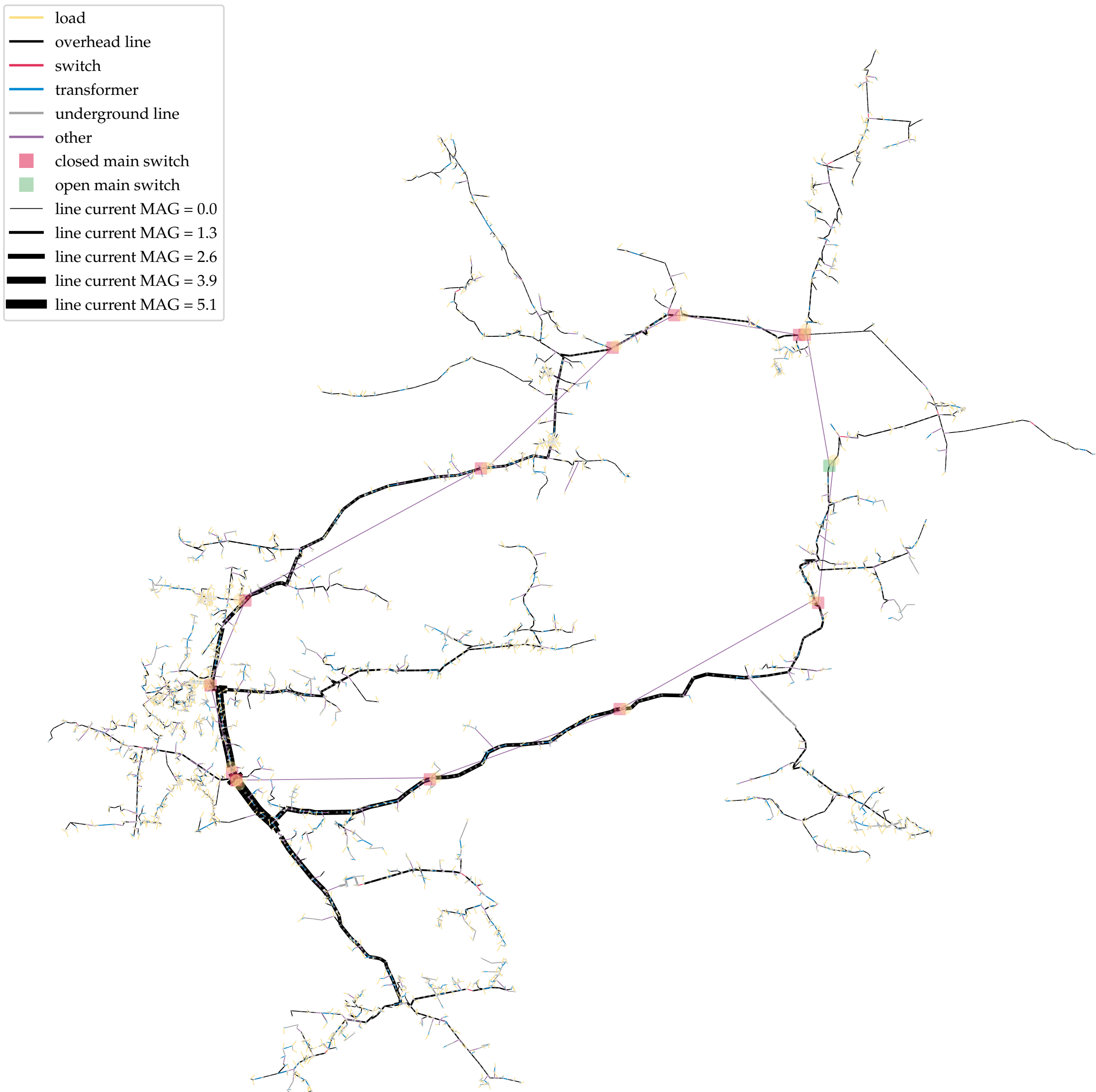


Figure 2.16: Hinesburg circuit plotted with edge width relative to GridLab-D modeled line currents and with edges colored by asset or GLD object type. Main switches for absorption / virtual islanding algorithm are denoted by large squares (red are initially closed, green are initially open).

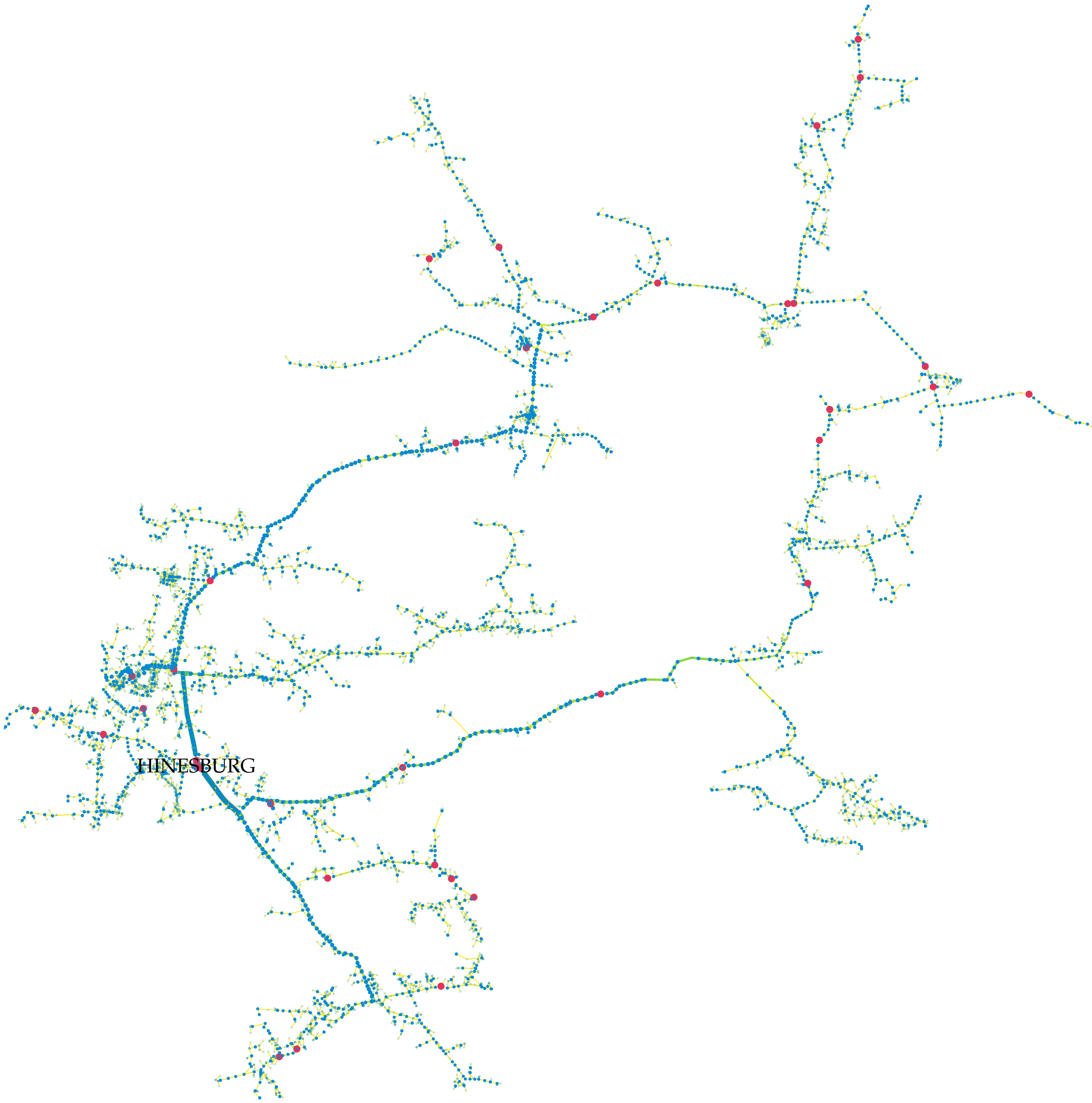


Figure 2.17: Hinesburg circuit plotted with node size relative to GridLab-D modeled voltages and edge width and color relative to GridLab-D modeled line currents (larger red nodes are switches and their size is not relative to the voltages at those locations).

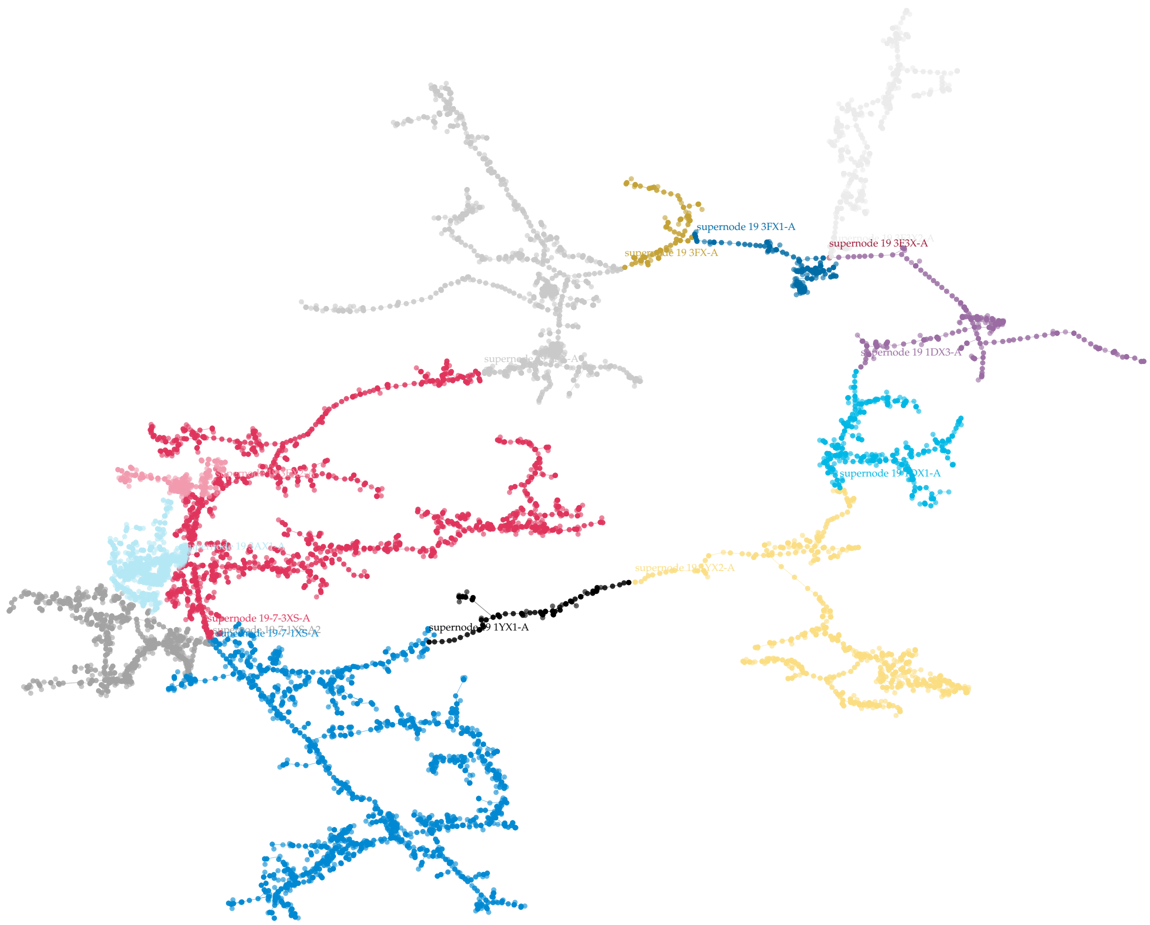


Figure 2.18: Hinesburg circuit plotted with possible islands shown in different colors.

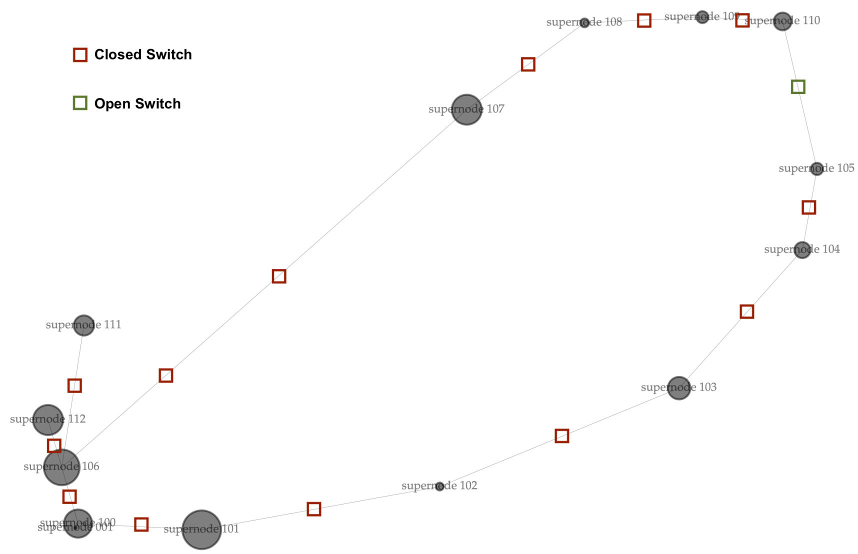


Figure 2.19: Reduced model of Hinesburg circuit with possible islands grouped into "supernodes" connected by switches, where the substation is located at "supernode_001". Supernode sizes are scaled based on number of houses connected.

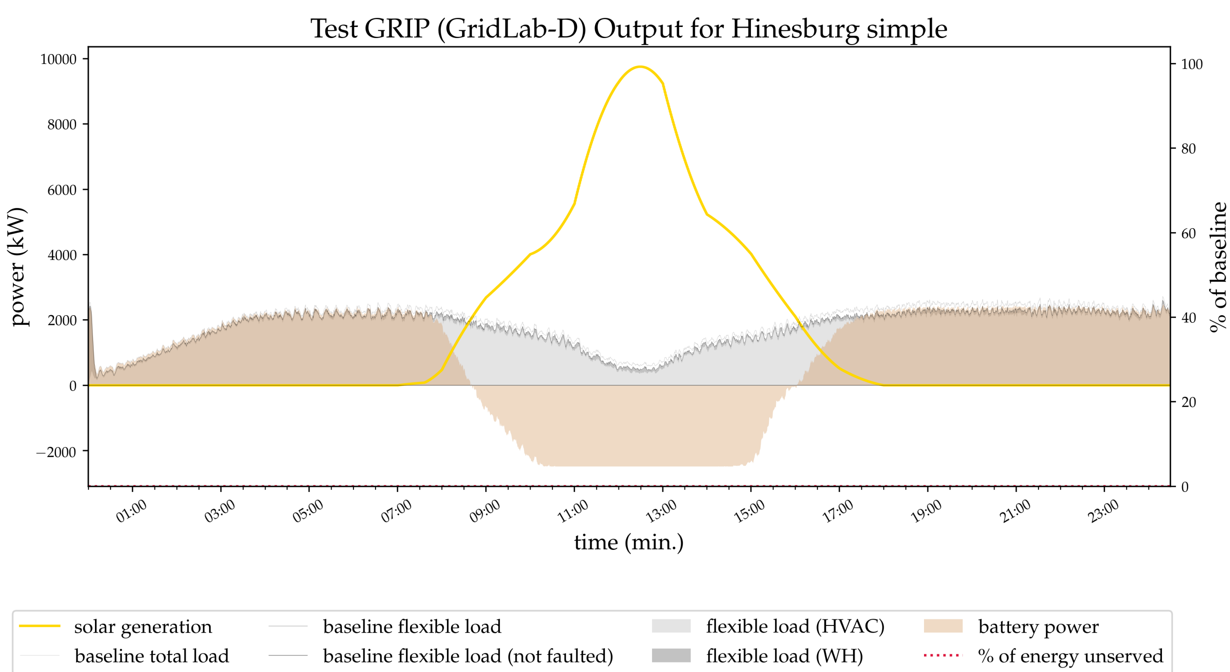


Figure 2.20: Timeseries output from GridLab-D for the reduced Hinesburg circuit (baseline).

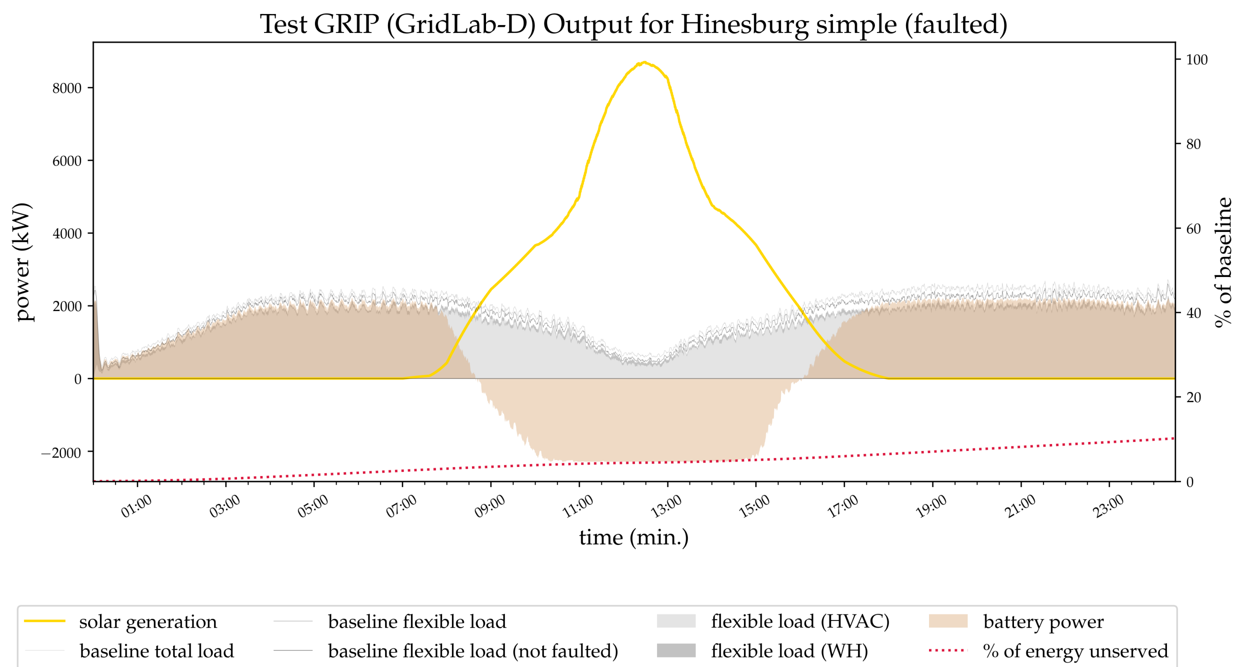


Figure 2.21: Timeseries output from GridLab-D for the reduced Hinesburg circuit with three supernodes faulted and GRIP absorption algorithms implemented.

Chapter 3

Field Demonstration

Independent of whether microgrids are pre-planned, as is typical in industry today, or autonomously formed, as presented in this report, microgrids must be designed so that when they are operating in “islanded” mode that resources actively balance between supply and demand. If the power produced is not precisely equal to the power consumed within a microgrid, then instability and collapse can result. To prevent this, microgrids are typically built with resources that can actively balance supply and demand, such as fast ramping natural gas turbines, or grid-scale energy storage systems. This chapter presents results demonstrating that when well coordinated, groups of behind-the-meter devices can contribute to this power balancing function. These results suggest that the overall cost of designing resilient, virtual islanding distribution circuits can be reduced by supplementing conventional energy storage with flexible demand-side resources, such as connected water heaters, HVAC systems and EV charging stations.

The results presented in this chapter come from the deployment of over 150 smart grid edge devices in partnership with Vermont Electric Coop. In this demonstration, we use the Packetized Energy Management algorithm to enable devices to actively balance supply and demand, while simultaneously maintaining quality of service limits for participating customers.

3.1 Customer recruitment

To implement this demonstration, we deployed approximately 150 water heater control devices, one behind-the-meter battery system, and several EV charging stations all of which are controlled through Packetized Energy’s (PEs) Nimble software platform. These devices were deployed primarily in partnership with Vermont Electric Coop (VEC).

To complete this deployment we first developed and implemented a customer recruitment plan. Key goals for this plan were the following:

- Deploy distributed energy resource (DER) control devices, such as the Mello, in ways that are easy and fun for end users, rapidly scalable for the deployment team, and cost effective.

- Identify important metrics for evaluating deployment methods, such as scalability,

Figure 3.1: Front (left) and back (right) of postcard mailed to all VEC customers in the towns of Hinesburg and Huntington, VT.

cost, participation, customer feedback, and installer feedback.

- Discuss ways of collecting data on those metrics and leaving opportunities for future deployment research.
- Result in the deployment of at least 150 grid edge, residential or small commercial controllable devices that can contribute to the validation goals of the GRIP project.

The following sections describe our original deployment plan, which included six elements: Outreach, Enrollment, Installation, Installer recruitment and follow-up survey.

3.1.1 Outreach

Broad outreach from VEC and PE team members was used to recruit residential end users interested in retrofitting Mello devices on to electric water heaters. The messaging included information about bill credits and opportunities to be entered into drawings for cash prizes. PE and VEC tested the efficacy of outreach mechanisms including:

- broad email campaigns to all customers,
- targeted postcard mailings (Figure 3.1)
- provision of literature about the Mello smart thermostat and the program at relevant events such as VEC's annual member meeting,
- social media postings
- a "refer-a-friend" campaign. The "Refer-a-friend" campaign will provide a $10 bill credit to VEC members each time a successful installation occurs in the home of a friend or neighbor who mentioned their name during signup.

Figure 3.2: An example promotional Facebook post by Vermont Electric Cooperative promoting the Packetized Energy project.

Messaging primarily came from the VEC, as VEC is a trusted name for most customers in the region. The team supplemented this deployment with media spots on local television and in local newspapers, as well as social media campaigns on the VEC Facebook page (Figure 3.2) and on town-specific list service known as "Front Porch Forum".

Installer "finders fees" and stocked-truck installations on new water heaters The team also experimented with offering water heater installers an incentive to carry the Mello on their trucks and include it in the installation of new water heaters. We expected this to be a cost-effective way to reduce customer acquisition costs and costs to installers. However, we found it somewhat difficult to motivate installers to install the device with small incentives.

3.1.2 Enrollment

Once VEC members heard of the program, they were directed to complete an online enrollment survey maintained by VEC on the VEC website to qualify them as VEC members within the appropriate service area and meeting the program requirements of an electric resistance water heater and continuous WiFi at their location. VEC then provided the information of qualified members submitted on the survey to Packetized Energy.

Once Packetized Energy received this information, within a day or two, we contacted each enrollee to positively qualify them for the program and set up an installation appointment to install the Mello smart thermostat (or other device) at their location.

Those who enrolled through a contractor during a water heater replacement will be directed to enter their information into an online form at the time of installation.

3.1.3 Installation

Packetized Energy contracted with licensed and insured installers to complete the installation of the Mello smart thermostat on the members' water heaters. At this service call, the installer will connect the Mello to the members' WiFi system and provides them a manual and information on how to connect to the Mello app. During the installation process, Packetized Energy will be available to provide support and troubleshooting to the installer and the members. In total, the project resulted in the installation and participation of nearly 150 DERs, including water heaters, EV charging stations and

3.1.4 Follow up survey

During the course of the project we conducted several short satisfaction surveys. These surveys revealed over 90% overall satisfaction with the program.

3.1.5 Recruitment results

In total, we were able to deploy approximately 130 water heater control devices, several EV charging stations and one small battery system. These DERs were used in the field demonstration described below.

Overall, we found that email and postcard recruitment methods were most effective, but no method was able to achieve the level of effectiveness that we had originally hoped for. More research and program development is needed to truly achieve a scalable DER deployment system.

3.2 Devices deployed

Together this project resulted in the deployment of nearly 130 Mello devices (Figure 3.3), several EV charging stations and 1 battery system with VEC. In order to reach the 150 devices required for this project, we included several additional devices from neighboring utilities including Green Mountain Power (GMP) and Burlington Electric Department (BED). At the time of the demonstration, GMP had 84 Mello devices deployed, and Burlington Electric had 75. The results in this report show performance from 150 devices that were spread across these projects.

For each of the water heaters using the Mello device for controls, Mello monitors that local water temperature and sends periodic requests to the Nimble cloud to consume a "packet" of energy. The Nimble server monitor's grid conditions (which, in the virtual islanding case, is a signal from the island manager based on the availability of solar power and/or storage resources to meet demand) and replies to the devices with a 'yes' or 'no' based on those grid conditions. Through this process many DERs can be managed to actively balance supply and demand for either bulk grid services, or for local grid services.

For EV charging stations, we used the Webasto TurboDX Level 2 charging station. For batteries, we installed an array of 6 of their 1.2 kWh AC battery systems at one of VEC's facilities.

Figure 3.3: The Mello Smart Thermostat for Water Heaters is a smart device that was used in this project to transform water heaters into energy storage resources.

For our GRIP Absorption field demonstration, we aggregated together a total of 150 devices and used these to demonstrate the power balancing functionality.

3.3 Demonstration results

To test this ability to balance supply and demand, we generated a fairly severe "square wave" signal that was used as the input power balancing objective/tracking signal for the fleet of devices. We then allowed the devices to track with this signal to the best of their ability (subject to the natural randomness in device behavior, usage and the core algorithms).

The results, shown in Figure 3.4 are quite good, with about 5% tracking error. Based on extensive simulations with this technology, we have found that this tracking error can be reduced to around 1% for large fleets of 1000 or more devices.

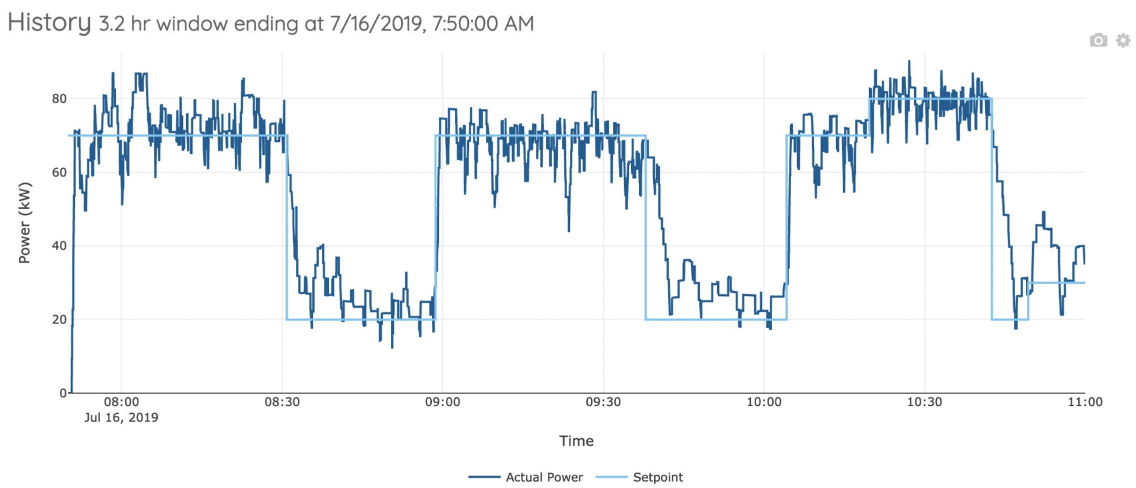


Figure 3.4: GRIP Absorption field demonstration results. This plot shows the target grid balancing signal (light blue) and the actual power usage (dark blue) for about 150 smart water heaters in Vermont.

Chapter 4

Learning DER parameters

This section outlines results from the application of machine learning tools to estimate the state of a connected hot water heater. The “state-of-charge" or percent of stored thermal energy available in a hot water heater is primarily determined by the average temperature of the column of water in the tank. Since the water enters the tank at the inlet, usually at the bottom of the tank, cold and exits the tank at the top, there is often a temperature gradient in the water heater tank. This temperature gradient and the fact that there are usually only two thermistors attached to the tank makes the task of estimating average temperature more challenging than one might expect.

In this project, machine learning tools have been utilized to predict or estimate this average water temperature in time using real-world data. The Packetized team instrumented one of our lab water heaters with many more thermistors to get thermal readings all along the water column, allowing a much more accurate estimate of the average temperature of the entire tank. The ‘Keras’ model was trained using the more accurate estimated average temperature, the upper and lower thermistor readings that are usually available, and the power consumption from the water heater. An example of this timeseries data is shown in Figure 4.1.

The input data for model testing then consists of the two usual tank temperature readings, one upper and one lower reading, and the power data.

As shown in Figure 4.2 the resulting predictive model was able to accurately predict the water heater state of charge.

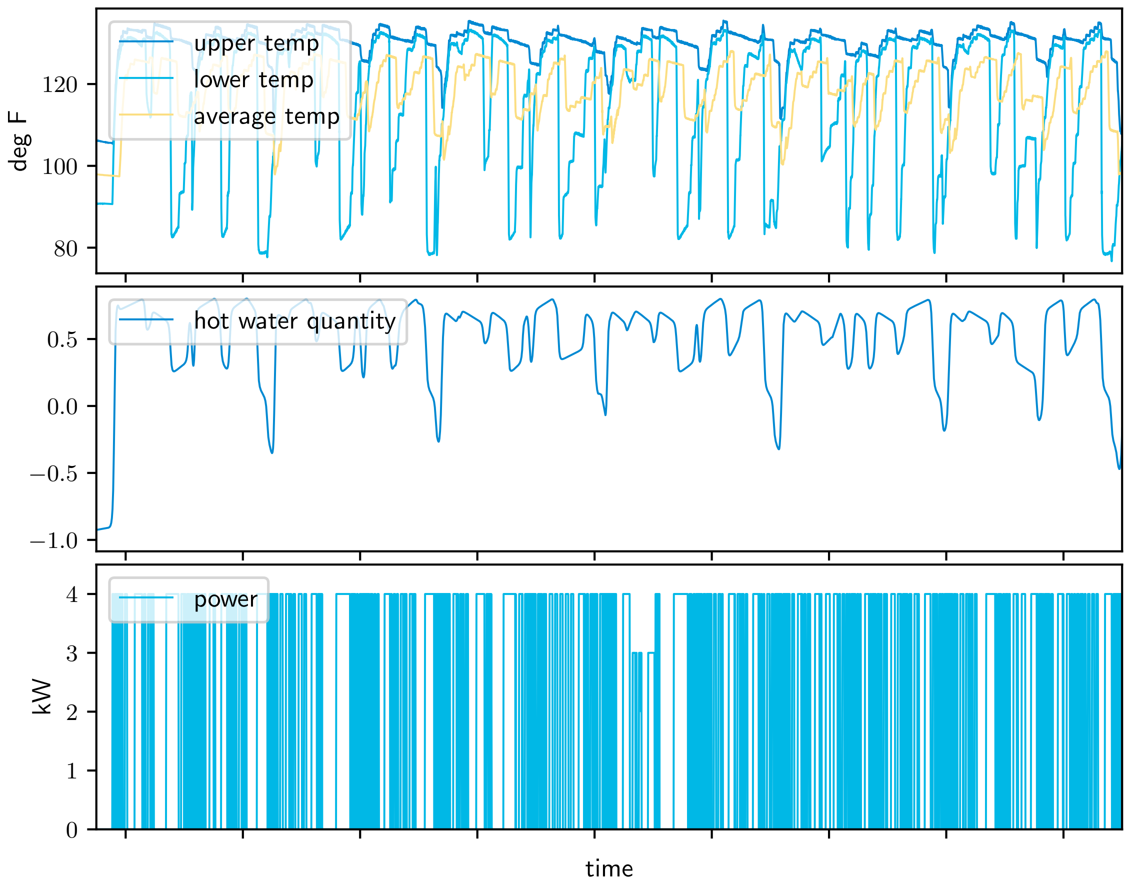


Figure 4.1: Example data for training ML model

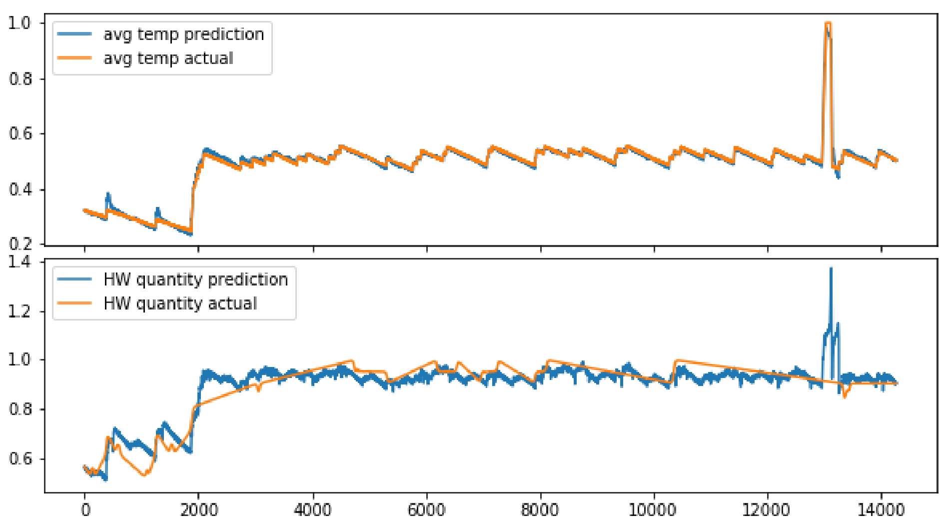


Figure 4.2: ML Model Prediction

Chapter 5

Conclusions

The GRIP Absorption method is a new approach to increasing the resilience of distribution circuits. The method combines together an extension of “Fault Location, Isolation and Service Restoration” known as Virtual Islanding, with the Packetized Energy Management algorithms for DER coordination. The validation results, which use both a small test case and a real-world three-phase distribution circuit, described in this report deomonstrate that GRIP Absoption, when combined with large amounts of distributed energy resources such as solar PV, energy storage, and smart controllers for HVAC and water heating, is able to dramatically reduce the unserved energy that result from extreme events, such as fires and ice storms.

Future work will more thoroughly evaluate the Virtual Islanding method by applying a sampling method to our test cases to more clearly estimate the statistical reduction in unserved energy that could result from Absorption, given a distribution network model and a probabilistic model for extreme weather events or attacks. This statistical verification could then be used to build an overall business case for the application of Absorption in the field and the testing of the concepts for increasing real-world distribution circuits that are subject to attacks and natural failures.

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