APPLICATION AND PARAMETER SENSITIVITIES OF A STATE-SPACE COLD LOAD PICKUP MODEL FOR A SYNTHETIC RESTORATION TEST CASE

A Thesis

by

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ABSTRACT

The electric grid is the backbone of modern society, providing an essential service that powers our homes, businesses, and industries. These intricate networks of power generation, transmission, and distribution work tirelessly to deliver reliable and uninterrupted electrical energy to meet the ever-growing demands of our technologically advanced world. Over the past three decades, extreme weather events such as hurricanes, floods, and droughts have historically increased in frequency. In power systems, these events can lead to service disruptions due to damage to equipment or failures in the network, resulting in outages or blackouts. While it is impossible to prepare for every scenario, understanding and modeling the characteristics of the grid under the influence of these events can help reduce downtime. High impact events, such as natural disasters and cyber-attacks, are known to cause outages lasting anywhere from minutes to several days, affecting the electric grid's infrastructure and delaying restoration efforts. It takes power to generate power; this is particularly important after a blackout. For a restoration to be successful following partial or total system outages, a restoration plan must be organized, put into action, and tested as required by reliability organizations. Restoring load after a prolonged interruption—generally referred to as cold load pickup—requires additional power which can exceed equipment's rating and restricts grid operators from simultaneously re-energizing the affected area. Demand after an outage is typically leads to cold load conditions. The additional power needed is caused by thermostatically controlled loads (TCL) which commonly have a temperature set by the end-user and is referred to as cold load; the naming is due to the equipment being "cold" or offline for a prolonged period. When energizing cold load takes place, this procedure is generally described as cold load pickup (CLPU). Modeling cold load is highly complex and dependent on various factors such as load type, cause of outage, duration, and weather conditions. This thesis focuses on applying an end-use load model to investigate cold load demand after a blackout. By using a state-space model, independent load characteristics present when interruption occurs can be captured for unpredictable outages based on system status and historical demand under normal conditions. Through the use of a load

accumulation state variable, excess demand is determined based on outage duration where local limitations can be set by utilities to fine tune actions to optimize restoration. Characteristic parameters were determined through sensitivity studies based on data from recorded blackstart events. By applying the proposed model to a restoration test case, we can determine the effects energizing cold load have on the system to assess grid operator's flexibility during blackstart restorations. A synthetic case is constructed with restoration performed for a baseline study as well as the study where cold load is considered. The model proposed is applied to demonstrate the considerations needed when formulating restoration procedures that meet federal regulatory organization requirements. The model is applied in this paper for integration into synthetic grids for blackout studies. Initial results remain consistent with prior work and available data, and show the effects of some of the factors affecting demand. With the ability to provide accurate load predictions, cold load data can be integrated into synthetic grids to simulate blackout restorations that reflect impacts of outages on the grid.

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1. INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

The electric grid is the backbone of modern society, providing an essential service that powers our homes, businesses, and industries. These intricate networks of power generation, transmission, and distribution work tirelessly to deliver reliable and uninterrupted electrical energy to meet the ever-growing demands of our technologically advanced world. The electric grid, comprising of interconnected power systems, forms a complex network of infrastructure that spans vast distances, serving millions of customers.

The electric grid can be categorized into three different system types: generation, transmission and distribution. Bulk power systems are large electric systems comprised of generation and transmission networks; the remaining portion is the distribution system which operates at a lower voltage. In the United States, they are organized into three major interconnections: the Eastern Interconnection, the Western Interconnection, and the Electric Reliability Council of Texas (ERCOT). Within each of these interconnections are smaller, local networks with multiple pathways for power to flow from generation to load centers to minimize loss of service in case of local failures. These large sections of the grid operate to enable seamless flow of electricity across the multiple smaller areas within each region. To ensure reliable and secure operation of these interconnections, various reliability organizations and entities play critical roles in overseeing and coordinating power system activities. The North American Electric Reliability Corporation (NERC) is a non-profit international regulatory authority that oversees all interconnected power systems in North America, including Canada and parts of Mexico.

The Eastern Interconnection covers a vast area spanning the eastern part of the United States and Canada. It encompasses numerous utilities, transmission operators, and balancing authorities working together to ensure the reliable transmission of electricity across the interconnected grid.

Similarly, the Western Interconnection spans the western part of the United States and extends

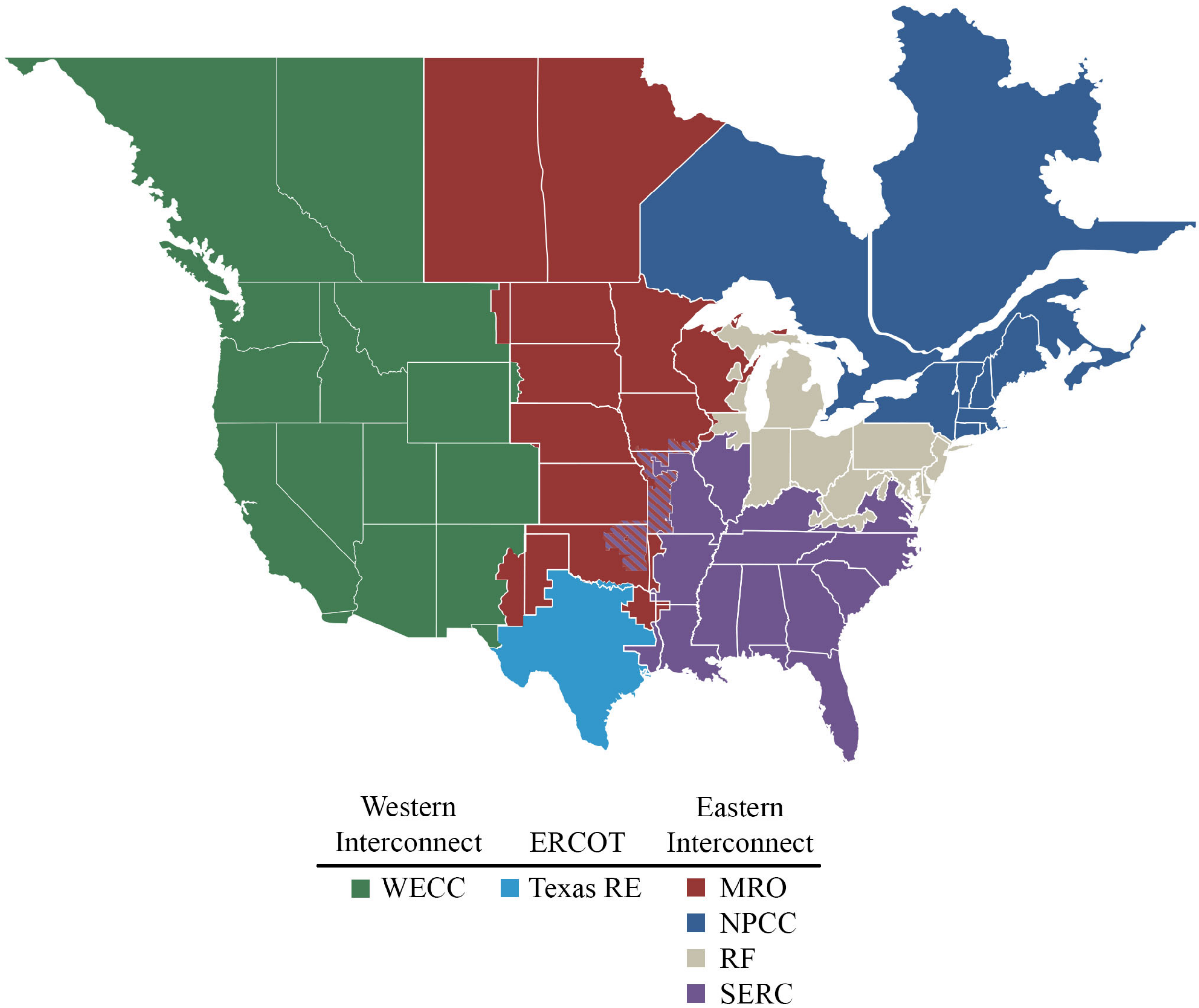

Figure 1.1: The three major interconnects in the U.S. Modified from [1].

into Canada and parts of Mexico. It consists of multiple utilities, transmission operators, and balancing authorities working in coordination to maintain grid reliability. The Western Electricity Coordinating Council (WECC) serves as the reliability organization for this interconnection, responsible for promoting the reliability and effective operation of the Western Interconnection's power system. WECC develops and enforces reliability standards, facilitates system planning, and coordinates emergency preparedness and response efforts across its vast jurisdiction.

In contrast to the Eastern and Western Interconnections, ERCOT operates as an independent grid entity in the state of Texas. ERCOT is responsible for managing the flow of electric power to more than 25 million customers, covering approximately 90% of the load in Texas. As the reliability coordinator for its region, ERCOT oversees the reliable operation of the electric grid within its jurisdiction. It coordinates the real-time balancing of electricity supply and demand, manages transmission constraints, and implements emergency procedures to ensure grid reliability and stability.

The intricate web of interconnections, reliability organizations, utilities, transmission operators, and balancing authorities exemplifies the complexity of the U.S. power grid. The collaboration and coordination among these entities are essential to maintain a resilient and reliable supply of electricity across the nation. Maintaining and operating this complex network comes with several challenges, some of which require preparation and planning for uncertain events.

One of the main goals of an electric power system is to economically and reliably maintain a balance between generation and demand, responding to disturbances with minimal casualties. Even with redundancy and careful planning, high impact low frequency (HILF) events, such as natural disasters, equipment failures, operator errors, and cyber-attacks can and have caused outages lasting anywhere from minutes to days [4]. One example is the February 13-17, 2021 winter storm (unofficially named Uri) was an extreme weather event that affected the United States, Canada, and Northern Mexico and forced utility companies in Texas' interconnect to conduct controlled outages in order to prevent a complete collapse on the grid [5]. Aside from Texas having a significantly higher peak demand due to extended low temperatures, the winter storm also affected oil wells, wind turbines, and generators, limiting the amount of resources readily available for dispatch [6].

In North America, NERC oversees transmission and reliability coordinators and works with stakeholders to develop standards for proficient power systems operation. NERC requires all system operators to have restoration planning and testing in preparation for unpredictable high impact events [7] so that when counter measures fail, the grid can return to normal operation. Regardless of the severity and length of an outage, service restoration must consider abnormal system conditions that extend from small disturbances to extreme cases of a full system outage. For residential areas with high concentrations of thermostatically controlled end-use loads (TCL), service restoration can result in higher demand after outages as short as 10 minutes [4]. For blackstart studies, TCLs are one of the main contributors to cold load, which come in the form of water heaters, electric furnaces, air conditioning units, etc. These types of loads have on-off cycles that normally operate diversely, or independently to maintain a range set by the end-user [8] and make up the majority of residential demand [9]. Determining factors affecting higher demand after extreme events can help formulate accurate models for extreme events [10].

The contribution of this thesis is on implementing a cold load model to a blackstart scenario, following methodology in [11], to explore the impact of power system restoration for cold load pick-up—increasing the number of test cases available for blackstart scenarios will help expand ongoing studies in power system restoration. A test system that behaves identical to its realistic counterpart, with the use of a cold load pick-up model, can help grid operators identify and determine some of the obstacles present during restoration.

2. BACKGROUND*

2.1 The Impact of Weather in Power Systems

Over the past three decades, extreme weather events such as hurricanes, floods, and droughts have historically increased in frequency. The severity of these events can be categorized into five levels: small impact, moderate, sesrious, major, and extreme. In power systems, these events can lead to service disruptions due to damage to equipment or failures in the network, resulting in outages or blackouts. The classification is based on factors such as the number of customers affected, as well as the duration and frequency of the blackout. In the United States, the financial impact of weather-related blackouts varies between $20-$55 billion annually [12]. Table 2.1 shows a list of the most recent blackouts in North America.

Table 2.1: Significant blackouts in North America in the 21st century. Adapted from [3].

Date	Country/Region	Outage Cause	Affected People (Millions)	Duration
February 2021	USA	Loss of generation due to cold weather	4.5	4 days
December 2018	Canada	High winds (up to 100km/h)	0.6	4 h
September 2017	USA	Hurricanes Irma and Maria	6.7	10 days
March 2017	USA	High winds (up to 100km/h)	1	9 days
October 2012	USA	Hurricane Sandy	8	8 days
September 2011	USA	Cascading failure caused by loss of 500 kV line and subsequent operator error	2.7	12 h
August 2003	USA, Canada	Series of faults by tree falls on power lines in combination with human error	55	4 days

While blackouts don't occur often, the societal and economic impact validate the investment of both financial resources and time in preparing for system restoration after such events.

2.2 Modeling The Electric Grid

In the early stages of power systems analysis, modeling primarily relied on analytical methods, which involved manual calculations and the use of physical modeling boards known as AC network analyzers [13]. One of the earliest computer simulation tools available was the Electro-Magnetic Transient Program (EMTP) [14], which utilized numerical methods to solve transient network analysis problems. This initial software tool allowed the research community to expand simulation capabilities to other areas by creating mathematical representations of the grid that computers could solve [15, 16].

As computer technology advanced and limitations in simulation software, such as memory capacity or processor capabilities, were overcome, more complex models became possible, leading to improved digital representations of the electric grid.

Simultaneously, the electric grid itself has evolved in response to the needs of society and newly available technologies. With both the grid and readily available technologies continually changing and improving, power system tools must keep pace with these changes. Synthetic test cases have emerged as a tool for comparing different algorithms and techniques in power system studies. To protect the sensitive information of actual electric grids, the research community has created fictitious models that statistically behave like realistic systems without exposing any critical details.

Ongoing contributions have made test cases more accessible to the public, enabling investigations into various aspects of power systems. Notable work has provided validation metrics, strategies, and sensitivity analysis for large synthetic cases, which are publicly available for use by the research community [17, 18, 19].

To examine the impact of cold load, a base case from [11] was utilized for the work presented in this thesis. This approach allows for exploring the effects of power system restoration during cold load pick-up, which is a condition that arises when power is restored after prolonged outages. Previous studies on blackstart scenarios have used existing test systems [20], modified versions [21], or large cases [22] for validation, while some studies have implemented their work on actual grids

[23]. Despite significant progress in addressing challenges related to blackstart scenarios, there is still a need for public test systems. Authors in [11] have developed strategies to construct public test cases for blackstart studies, as well as a synthetic case that can be used for benchmarking.

By using a realistic test system and incorporating a cold load pick-up model, grid operators can identify and assess uncertainties that occur during abnormal states of the grid caused by extreme events. The remainder of this section will breakdown multiple areas of models and tools as they relate to blackstart.

2.3 Load Modeling

In transmission studies, load behavior is difficult to represent accurately due to the large number and types of loads present on the grid at any given time. It is common for large cases to contain over 7000 buses. Including factors such as temperature and seasonality, the model increases in complexity. One of the main challenges of accurately modeling load behavior is due to the large number and types of loads present on the grid at any given time. Load modeling is widely known and been studied extensively [24, 25, 18, 26]. Load models generally fit into two categories: component-based or measurement-based and can be static or dynamic depending on the type of study. Component, or physical based models consider the physical behavior of loads to construct mathematical formulas based on these patterns. Measurement-based models make use of multiple data-sets obtained from measuring equipment to build a model based on the data-set. Measurement-based models tend to have higher accuracy but may not perform as well outside the area where the data originated. For blackstart studies, the majority of demand comes from end-user residential loads susceptible to weather conditions. Therefore, using a measurement-based model cannot be easily applied to multiple locations [24], which makes physical models adequate for studying CLPU characteristics [4].

During the February 2021 storm in Texas, customers faced power outages that varied in duration, ranging from short periods to multiple days without electricity. Although load curtailment measures helped mitigate the severity of this event, outrages resulting in cold load conditions could not be avoided entirely. Figure 2.1 shows the storm's impact extended beyond ERCOT to neighbouring interconnects which ultimately affected the majority of the state. Cold load conditions have been extensively studied in literature for several decades [27]. However, due to the limited availability of real-world data resulting from the low probability of complete system blackouts, modeling cold-load conditions remains a challenging problem to investigate.

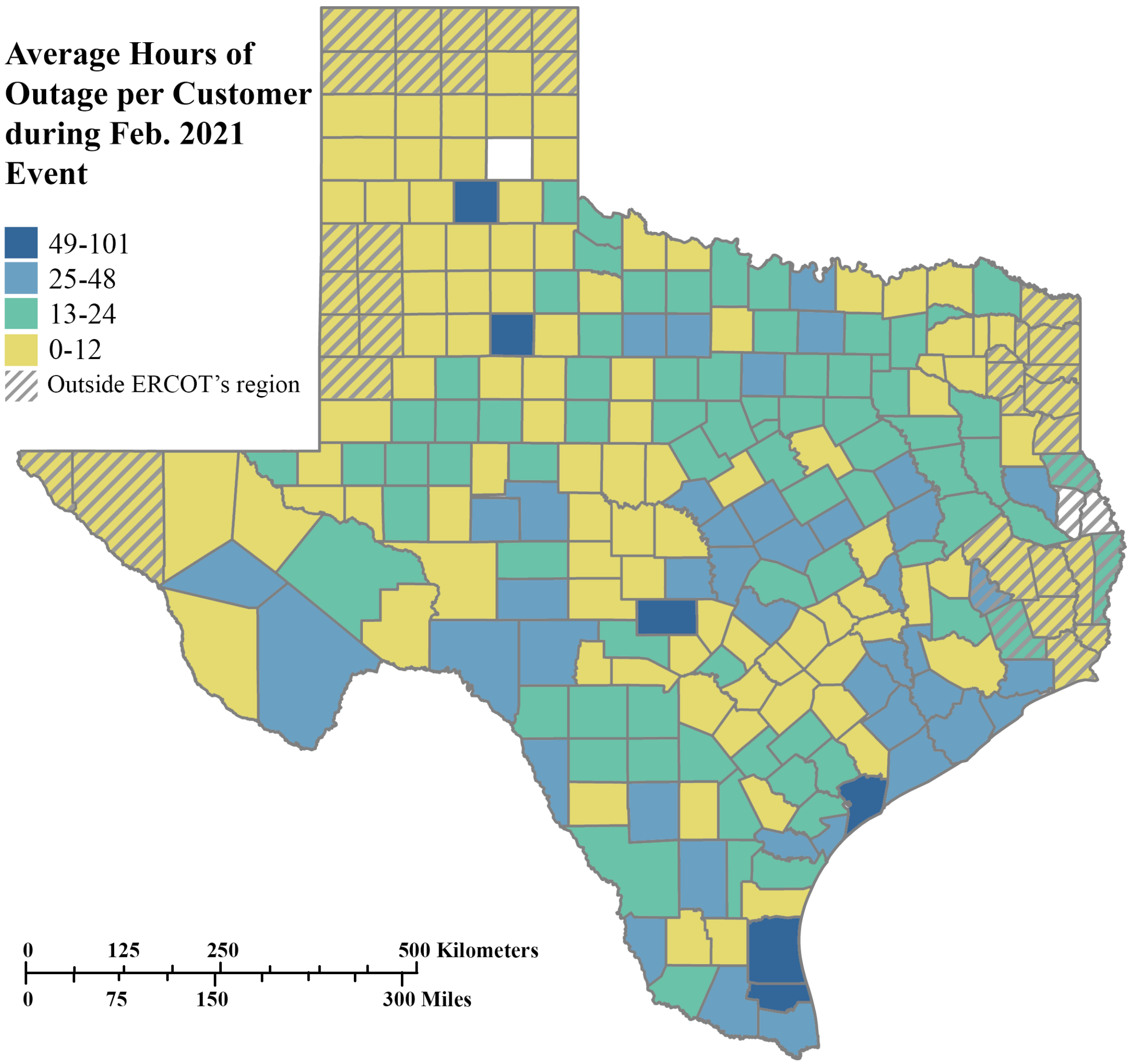

Figure 2.1: Outages during winter storm Uri in Texas; adapted from [2].

2.4 Cold Load Models

Early studies on the effects of cold load began with a physical-based model of heating components caused by a cold weather outage [28]. This fundamental study describes space areas as heating zones and estimates an aggregate power flowing into multiple households in a residential sector. The principle behind this model is behind the temperature decrease inside a home affected by an outage, changing the duty cycle of heating equipment. The analytical expression describes the continued energized behavior of loads within a network and identifies the key components to accurately represent the increased demand. The purpose of the study was to focus on the perspective of a utility company operating the grid with load under this condition. Applying an accurate model to predict network conditions helps utility companies reduce restoration time [11].

The entire process of cold load pickup can be described in four phases which consist of in-rush current, motor starting, motor running, and an enduring phase, with each phase taking place in different time-frames [29]. While the enduring phase is the main focus of this paper, we review the first three phases below. During restoration, inrush, or cold load current, is one of the main factors that initially affect load when energized. Depending on the type of load being picked up, the current's magnitude can reach up to 15 times normal values; this effect is only present for a short amount of time but can cause delays in restoration [30]. The effects of inrush currents would be studied by transient stability analysis with a model such as [31], but transient stability models do not cover the CLPU enduring phase dominated by TCLs. Table I shows the characteristics of in-rush currents when energizing loads which come into effect the moment cold load is energized.

Load variation during CLPU starts the moment a feeder is energized and can last for several hours, depending on the severity of factors leading to the outage. Three of the four CLPU phases occur within the first 3-5 seconds and are common in transient stability studies. The work presented focuses on developing a static load model for the last phase of the load under CLPU characteristics which take effect in the range of minutes to hours.

Table 2.2: In-rush Current Effects.

Type of load	in-rush current (multiple of normal value)	time-frame
Incandescent lighting and small motors	10	miliseconds
End-user controlled (TCL's)	10-15	half a second
Large Motors	5-6	seconds
Endurance Phase	3-5	seconds to minutes

2.4.1 Previous Work

The exponential decay model closely matches previously recorded CLPU events and can be used to describe load behavior more accurately by the use of a general model [32] and is used in [29] to determine voltage levels. The formulation is described as follows:

$$S(t) = \begin{cases} S_N, & \text{if } t \leq T_B \\ 0, & \text{if } T_B < t \leq T_R \\ S_{CLPU}, & \text{if } T_R < t \leq T_N \\ S_D & \text{if } t > T_N \end{cases} \tag{2.1}$$

Where: $S_D = S_N + (S_{CLPU} - S_N) \cdot e^{-\alpha(t-T_N)}$

S_D is exponentially decaying load, S_N is normal load should there be no outage, S_{CLPU} is peak load under CLPU, T_B is time of blackout, T_R is restoration time, T_N is time load begins to normalize, and α is the rate of decay of the load.

The delayed exponential model accurately matches demand by identifying a peak CLPU magnitude, a duration of the peak, followed by an exponential decay as shown in Figure 2.2. The work proposed focuses on the fourth CLPU phase and built a simple expression for quantifying the peak and duration of CLPU demand.

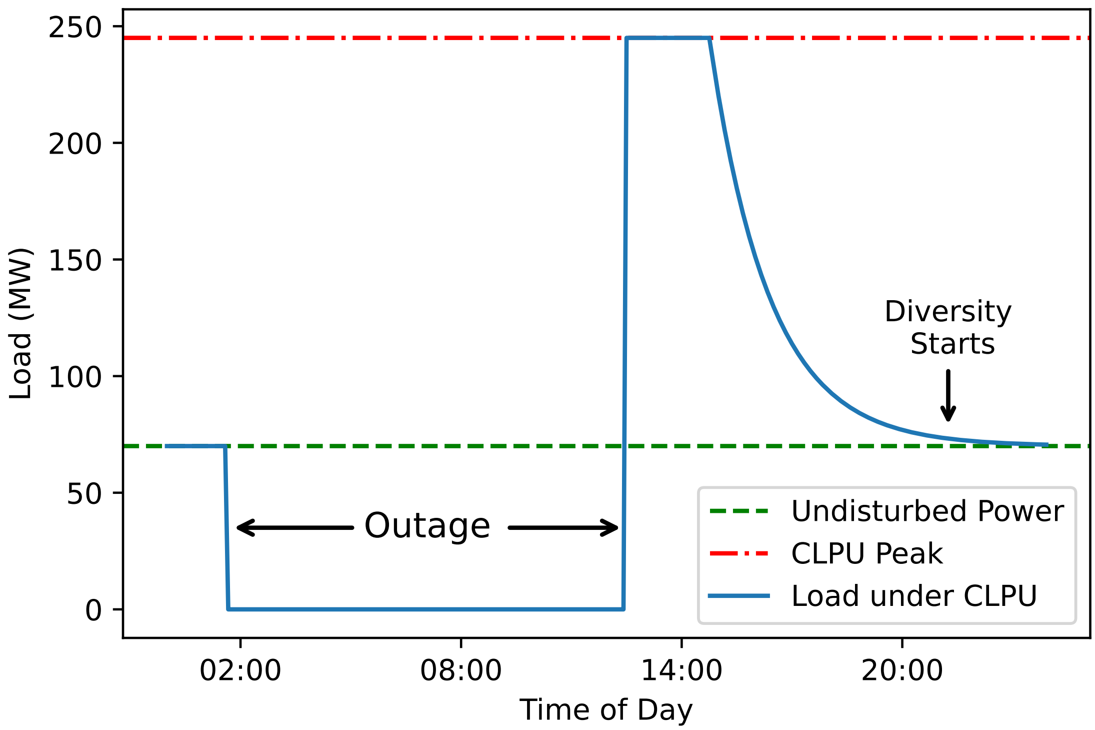

Figure 2.2: CLPU Model as Delayed Exponent.

2.4.2 Measurement-based Modeling

Substantial improvements in the grid have increased data fidelity with the addition of smart meter measuring equipment. Measurement data was used in [8] to build a model focusing on predicting residential demand of cold load. The model is composed of two layers which are at the feeder level and at the end-user level. At the feeder level, the ratio of cold load to normal (diversified) load was found using a least squares support vector machine auto-regression model. A stochastic technique is used for the second layer to determine end-user behavior and loss in diversity. The method proposed was able to accurately estimate cold load for the data-set the model was trained on with only requiring access to historical CLPU data which is easily accessible to utility companies. However, with limited CLPU data available, results could not be fully verified. Another concern is the requirement for this method to be updated with any changes made to the power distribution system.

2.4.3 Voltage Drop Modeling

Load flow analysis allows planners to see power and voltages being handled by electrical components to determine which equipment best provides reliable service at the lowest cost. Using the formulation in (3.7) [28], voltage drop calculations were included in [29] to determine levels at which equipment's life or performance would be affected. Taking into account commonly used step-wise restoration procedures, algorithms were used to determine component selection for system planners in order to mitigate CLPU effects; a similar approach was used to determine choosing a transformer's size. A case study was conducted but the case used did not represent an actual network on the grid.

2.4.4 Multi-State Models

Load models generally do not differentiate end-use loads but instead make use of a simplified model when representing demand. By combining a ZIP and physical-based load models, the authors in [33] formulate an end-use load model that consists of multiple states corresponding to different operational state and energy consumption. Each state uses a zip and/or a physical model with transitions to account for outside factors, such as heating from the sun, to determine the demand in a household. These states operate within defined set points and change depending on the temperature inside a home falling below or above their perspective set point. Different case studies were conducted to highlight the comparisons between existing end-use models and the proposed multi-state model. The model currently requires solving coupled differential equations during simulations in order to determine load behavior. CLPU magnitude and duration were estimated in [4] using this multi-state to account for end-use residential behavior.

2.5 Restoration

The objective of power system restoration is to restore power after an outage in the shortest amount of time possible—in the case of a full system outage, this process is known as blackstart. While outages generally occur in small sections of the grid and are not prolonged, blackouts are unpredictable, rare events where a wide-spread outage occurs on the system. There are three stages that take place for during blackstart: planning for restart and integration, actions taken to maintain critical loads online, and system restoration [34]. The process must be performed optimally while considering contingencies for the degraded system. This time-critical process depends on network topology, resources available, and state of the grid. Given the nature of blackouts, preparing for unpredictable factors such as unserviceable areas or damaged equipment, restoration plans may only serve as a guide to grid operators for recovery procedures [35]. In addition to operating the grid in a degraded state, the majority of the recovery process is performed off-line due to inter-dependent communication and monitoring systems, such as SCADA, not having back-up power sources. The first phase begins with analyzing the grid's condition to determine a course of action; this may involve sending technicians to areas where equipment is damaged or no information is known. Authors in [22] investigate how to improve restoration at a large-scale level by simultaneously optimizing management of repair technicians and DERs present in the grid. Other studies make use of a *resource management technique* [23] to optimize the recovery and energizing phases to account for unpredictable factors and utilize resources accordingly.

In the re-energizing phase generators are brought back online, an initial framework of the system is energized, and load restoration is started. For loss of power in smaller sections of the grid or a small number of generators tripping offline, power can be supplied from adjacent units or unaffected areas. However, for cases of a full system outage, the majority of offline generators will require external power to start up, increasing the restoration procedure's complexity. Only a small number of generators are capable of self-starting—these units are referred to as black start units (BSUs). Maintaining and selecting BSUs varies for different grid operators but is a standard, periodic procedure needed to account for regular changes or upgrades to infrastructure. ERCOT, Texas' reliability coordinator, awards biennial contracts for BSUs based on performance metrics to produce 14–18 units for the state's interconnect [36]. Notable efforts to reduce costs and improve allocating BSUs have been made in [37] and [23]. One of the main challenges in the re-energizing phase is optimizing the order of actions and network configuration that minimizes downtime given the high number of unpredictable scenarios and limited resources.

Once an adequate starting point is identified and generators are online, load restoration begins. Certain loads are considered *critical* and are given precedence for restoration. When loss of power results in life-threatening conditions, data corruption, or system crashes, these key operations must be prioritized during the re-energizing phase; examples of critical loads are hospitals, sewage plants, and airports. A restoration planning technique proposed in [38] was used to restore critical loads while accounting for uncertainties with repair time activities affecting the recovery phase. Prolonged outages will affect load behavior in the system, lead to higher demand than forecasted, and potentially exceed equipment ratings which restrict a simultaneous restoration of the grid [cite: vdrop?]. The starting condition of loads that are out of service for too long can change from a hot-start to a cold-start, leading to the effect of cold load pick-up. These loads are comprised of devices such as space heating and cooling, water pumps, fridges, and are referred to as thermostatically controlled loads (TCL). After losing power for lengthened periods, temperatures from climate-controlled areas will have fallen outside user-set thresholds, leading to TCLs becoming increasingly concentrated and uniform; this behavior can overload the transmission and distribution equipment. Cold load pickup is the additional power required when reenergizing cold load. Even with an optimal starting point, the effects of cold load restrict operators from restoring load simultaneously.

Since demand will be very high when reenergizing, restoration is normally conducted by dividing feeders into different sections, or *islands* with a respective BSU at the center. Considerations and strategies involving islanding techniques were discussed in [39] and [40] as well as the use of renewable energy sources that are continuously being added to the grid's infrastructure. As already discussed, TCLs that have on-off cycles and would otherwise operate diversely, or independently, will now turn on together when energized; this characteristic in electric loads is the largest contributor to cold load pick-up [40] and makes up the majority of residential demand [9]. With limited data and the rarity of blackouts, investigating the factors and developing methods that accurately describe cold load remains a challenge in power system studies.

Incrementing the number of open test systems will help fill the limited availability of synthetic cases to improve ongoing studies in power system restoration. This paper proposes constructing a case to assess the applicability of a cold load pick-up model [41] in order to benchmark restoration techniques while accounting for load behaviour present after extreme events where the entire system has lost load diversity. Preliminary results illustrate the additional resources needed when accounting for increased demand due to cold load conditions present in the entire area prior to returning the grid to normal conditions.

3. METHODOLOGY*

The focus of this study is to investigate the impact of cold load behavior on the grid during restoration after a full system outage. All methods discussed make use of publicly available data to ensure that properties such as network topology, equipment rating and types, and load profiles behave similar to the real grid. This section describes the test case properties, load modeling, how the cold load model was applied, and the restoration procedure.

3.1 Synthetic Test Case

Authors in [26] have proposed a general procedure for constructing synthetic test systems that behaves like the real grid representative of its area. A summary of the process is given in 3.1.

Table 3.1: Constructing Test Systems

Parameter	Description
Devices	Generators, substations, or loads, are simulated using mathematical models.
Operating condition	A condition corresponding to a specific event is determined based on the study in question.
System Variables	Inputs are selected based on initial conditions and set to match known values or an expected outcome.
Simulation software	Used to compute results for analysis.
Validation	Performed using available data of the actual system.

The synthetic case in [11] was constructed from an existing case with the goal of accurately representing the restoration process and level of control from grid operators; this case matches the geographic footprint of Illinois and did not need any further adjustments.

Notable characteristics of the case are as follow:

- To better represent the electric grid from a system operator's perspective, loads are made out of smaller blocks of 20MW or less which correspond to typical values in distribution feeders.
- Units selected as BSUs for the test case should be geographically dispersed and close to densely populated areas.
- Generators operate in 3 states depending on whether they are offline, starting up, or fully operational.
- Transmission lines, generators, and loads can freely change status as necessary.
- With the exception of BSUs, the rest of the system is deenergized.

The use of this test case allows an initial assessment on the cold load pickup model and highlights the differences when restoration considers cold load for blackstart studies; results are discussed with details in

3.2 Accumulating Load Model

In this section, characteristic equations and parameters are formulated for the state-space model. Three key parameters that contribute to cold load peaks are used to characterize restoration demand. The first is outage duration which mainly affects load decay rate. The second is unique to households on the network that affect the maximum demand needed to return load to normal conditions and the rate of increment towards this value. The third is the magnitude of undiversified demand to diversified demand which sets a peak value for load aggregated at the feeder level.

A state-space model is used to characterize the key parameters affecting load. State space models describe a dependence between the latent state variable and an observed input or measurement which can be continuous or discrete; this technique allows observing the inherent load behavior responses to blackouts separately. A similar approach was used in [33] to accurately predict load demand and was later modified in [4] for CLPU modeling.

Figure 3.1 shows a block diagram for the state-space model. U_t is a binary representation of network status and X_t is the state variable which accounts for load accumulation or decay. The outputs are expected CLPU demand Z_{t+1}, and total accumulated load X_{t+1}; the accumulated load from the previous state is used when updating a value for the next time step.

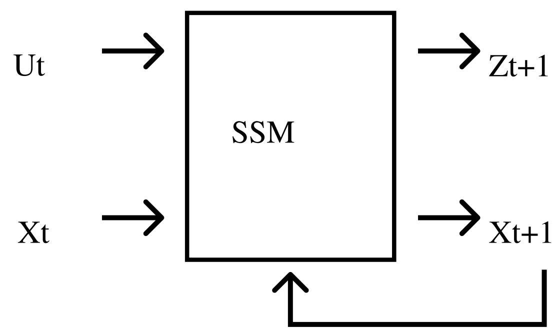

Figure 3.1: State-space model for accumulating load.

From (2.1), a general expression describing exponentially decaying behavior is formulated. A relationship between outage duration and increased demand was also observed in [42]:

$$Z(t) = A \cdot e^{-at} \tag{3.1}$$

$$\frac{dZ}{dt} = -a \cdot A \cdot e^{-at} \tag{3.2}$$

To account for total load accumulation, a state variable is constructed from 3.2. The model takes as input $P(t)$, the load demand under normal conditions:

$$X_t = X_0 + P(t) \tag{3.3}$$

3.3 State-Space Model

In order to capture the increasing and decreasing effects, (3.3) is modified to account for load increasing and decreasing behaviors. Coefficients a_0 and a_2 account for the rates of increase and decrease respectively. Load increment uses a linear model and load decay uses an exponential decay:

$$\frac{dX}{dt} = a_0 \cdot P(t) \tag{3.4}$$

When load accumulation decreases:

$$\frac{dX}{dt} = -a_2 \cdot X \tag{3.5}$$

Rewriting state variable for increasing behavior results in:

$$X_{t+1} = X_t \cdot a_0 \cdot P_N(t) \tag{3.6}$$

and decreasing behavior:

$$X_{t+1} = X_t - a_2 \cdot X_t \tag{3.7}$$

Total CLPU demand is a sum of accumulated and normal load:

$$P_{CLPU} = P(t) + a_1 \cdot X \tag{3.8}$$

Where coefficient a_1 accounts for historical load patterns in a home during winter. In [8], recorded outage data revealed that while CLPU peak can reach values double of normal conditions, restoration demand may be lower than historical peaks in some cases.

3.3.1 Load Model

A state space algorithm was used to represent cold load conditions. The model's general process is shown in 3.2. To estimate the power required during cold load enrgization, a state-space model [41] is implemented to represent cold load conditions in TCLs. This model incorporates the use of an accumulated load state variable that increases or decreases based on network status, adjusting as necessary.

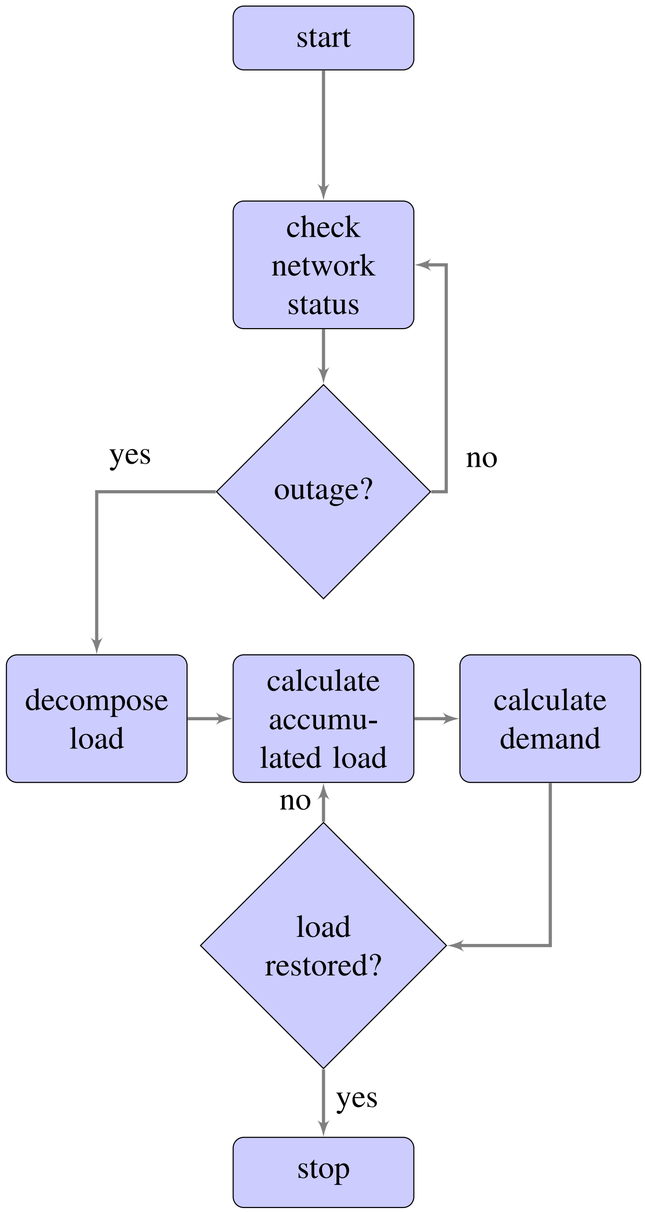

Figure 3.2: Cold load algorithm.

Since each load type has its own unique characteristics, only residential loads were considered for this study. Approximately 20% of residential electric loads contribute to TCLs [ref: eia]. Therefore, the CLPU model must consider the electric devices affected under cold-load conditions.

Extensive efforts have been made by NREL and research partners to develop synthetic load data that realistically represents residential and commercial consumers [43]. This detailed model captures individual consumption from multiple components, making it compatible with the state-space model used.

Since the cold load pickup model only accounts for active power, a constant power factor is assumed for determining reactive power. While load modeling alone is a complex topic worthy of its own study, this paper utilizes data from [43] to decompose load and account for cold load conditions while retaining common characteristics observed in electric loads under any condition.

Load was decomposed into two categories based on component: TCL and non-TCL devices. Non-TCL loads, such as lighting, remain unaffected by outages and continue to behave as they did prior to the outage. TCL loads can have multiple operating states which can increase operating time, consumption, or both. To preserve load profiles in households, all load data was normalized using peak-load values during normal operation for a single household representative of the area. The cold load model is applied to TCLs and combined with other load types to determine the total consumption. Subsequently, this value is normalized as well. A ratio of cold load to normal demand is used to represent the percentage demand relative to the peak load for a distribution feeder. This approach facilitates scaling and implementation of demand for multiple scenarios, where loads can be grouped based on similar characteristics, as is the case with residential loads.

It is important to note that even during a normal day with no interruptions, electric demand is dependent on weather conditions, time of day, and season. Shown in 3.3 is demand during winter storm Uri for the coast region of Texas, one of the eight weather zones ERCOT oversees. As temperature fluctuations occur, demand increases or decreases accordingly. One key difference is the large drop in demand during February 13^{th}, which is when load shedding started; despite the deliberate reduction in load, electric demand remained consistent in response to temperature changes. Cold load condition has been studied extensively in literature, dating back to several decades [27].

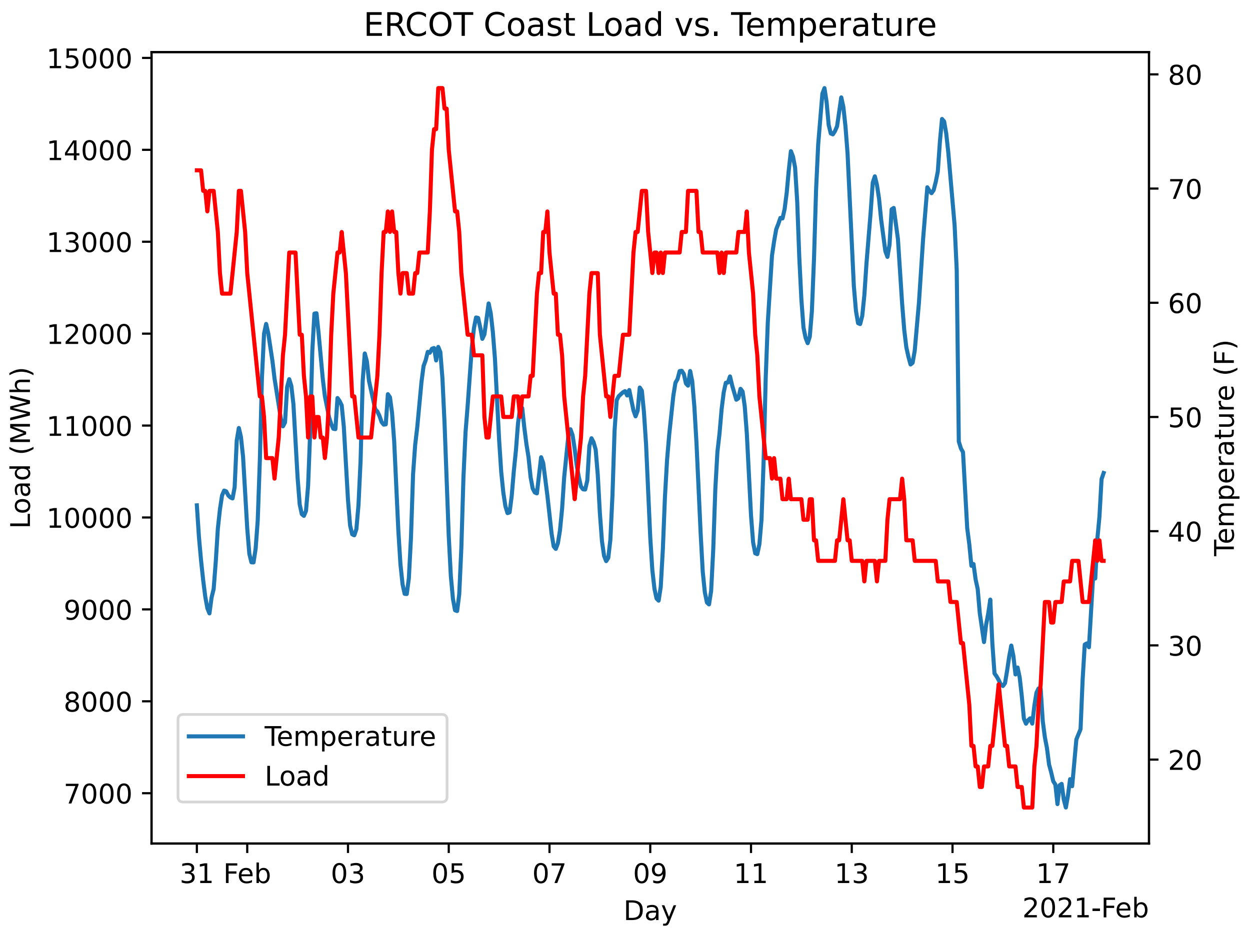

Figure 3.3: Electric demand during winter storm Uri.

3.3.2 Restoration Scenario

As described in [ref: background], When external power sources are unavailable, restoration utilizes BSUs located at specific points within the grid to form islands, serving as starting points and providing auxiliary support for critical loads and to initiate generators.

To establish a general baseline for time, an initial assumption made is BSUs are fully started, allowing restoration to begin. Furthermore, the applied cold load pickup model assumes that restoration transients have settled and focuses on power flow studies of 15-minute time steps.

Restoration procedures typically follow multiple steps or milestones while optimizing for metrics such as time, cost, and equipment limitations. A restoration technique is adapted from [11] which aims to minimize the cost of load outages during power system restoration. This algorithm consists of three stages: graph decomposition, target selection, and action selection; 3.4 describes the algorithm's general process. Simulation begins with BSUs starting the restoration process with a selected network path defined based on resources available. Load is picked up based on its active and reactive power depending on available generator capacity; critical loads and generators are selected first. Generators will behave according to their operating states: offline, cranking, and fully cranked. While cranking, generators act as a motor that consumes power until fully cranked. Fully cranked units operate under normal conditions based on their physical capabilities. Limits on transitions are set by generator capacities.

The restoration algorithm finds BSUs, creates islands at the bus of the selected units, finds optimal paths to start reenergizing devices, and chooses actions depending on resources present. A graph decomposition technique is used to form network islands. Paths between a generation source and a deenergized generating unit are known as cranking paths. These cranking paths are determined through a breadth first search algorithm where lower line susceptance is the preferred path. During early restoration stages the grid is very fragile and voltage regulation is a main concern. Actions account for a utility operator's response based on information available during the reenergizing phase; choices typically consists of picking up load, cranking up a generator, switching a line on or off, or synchronizing islands. In addition to performing a restoration with the cold load model, a second scenario is conducted without the model for comparison.

In the graph decomposition stage, the network graph is divided into islands using breadth-first searches rooted at BSUs. The goal is to ensure that each bus is connected to the nearest black-start unit in terms of electrical closeness measured by branch susceptance. This decomposition creates a spanning forest with the BSU at its center, where minimal line capacitance is required for energization.

In the target selection stage, restoration targets (loads and generators) are listed and prioritized based on their importance. Critical loads have the highest priority, followed by generators and remaining loads. The priority ordering takes into account required power to energize the target,

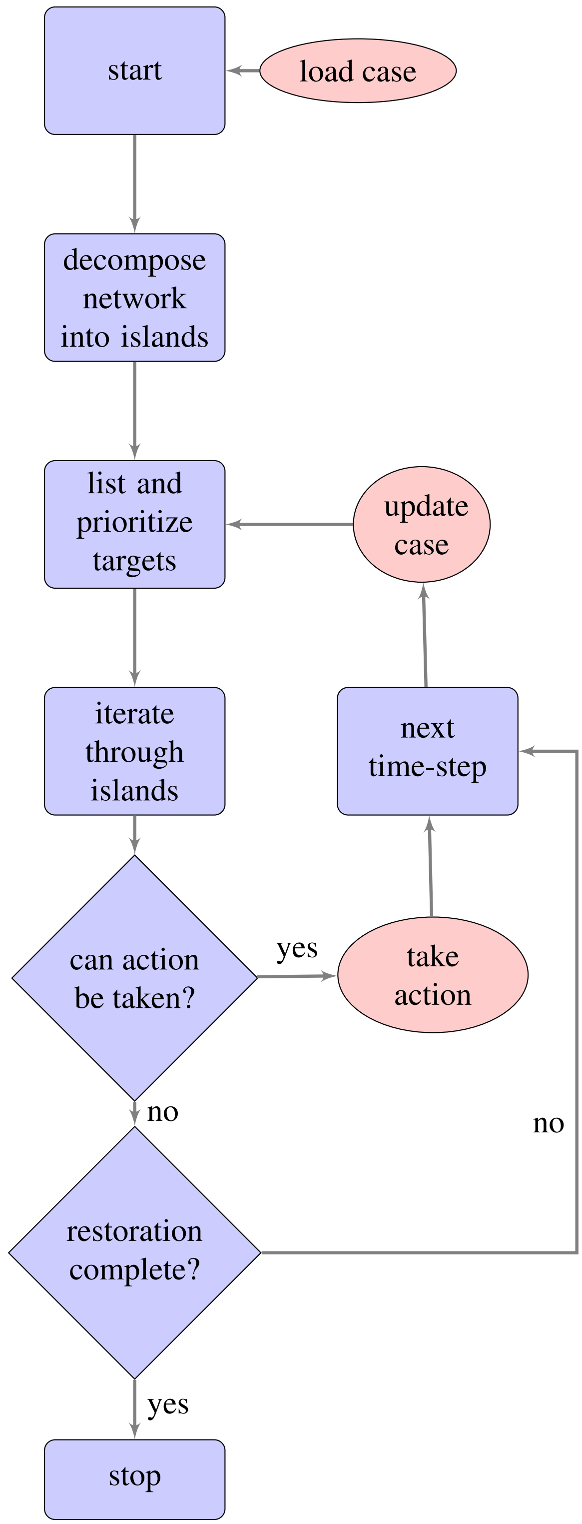

Figure 3.4: Restoration algorithm.

including cranking power for generators, as well as the reactive power generated by the lines along the energizing path.

The action selection stage involves solving the full power flow solution iteratively to choose restoration actions. Each island is given the opportunity to take an action based on the prioritized targets. If load is picked up, the cold load demand is calculated. The cold load algorithm is applied to each load at the bus prior to solving power flow. If an island cannot take an action, the next island is given the opportunity. The chosen actions are based on the availability of reserve generation and reactive power reserves.

During early restoration stages the grid is very fragile and voltage regulation is a main concern. Actions account for a utility operator's response based on available information: choices typically consist of picking up load, cranking up a generator, or switching a line on or off. The goal is to determine the impact of including cold load for restoration scenarios and provide a more realistic load behavior to study the effectiveness of different restoration strategies.

3.4 Study Results

The first study was conducted to determine the model's response and adjust parameters as needed. The second study was a restoration scenario where the cold load model was applied in a synthetic test case as discussed in methodology.

3.4.1 Load Model

The methods from studies in [42] and [44] consider identifying these parameters using load measurement data collected from rotating interruptions. Generally, accurate load models met the following criteria from findings in [44]:

- For a short outage, load should not be affected and diversity should start within minutes.
- After a longer outage, load diversity can take multiple hours to restore.
- For more severe cases where outages lasted a day or more, load diversity takes over 12 hours to be reestablished.

The first case study for the proposed model was conducted against recorded outage data in [4] to determine values for load rate increment and decay. The outage lasted approximately 3 hours in which load diversification took 40 minutes with a peak CLPU ratio of 1.49. Using the relationship between outage duration and peak demand in (3.4), a value for a_0, the rate of load increase, was calculated to meet the criteria in [44]. Figure 3.5 shows the effects for different a values. The y-axis is the ratio of undiversified demand and diversified load (normal conditions) and the x-axis is minutes after outage.

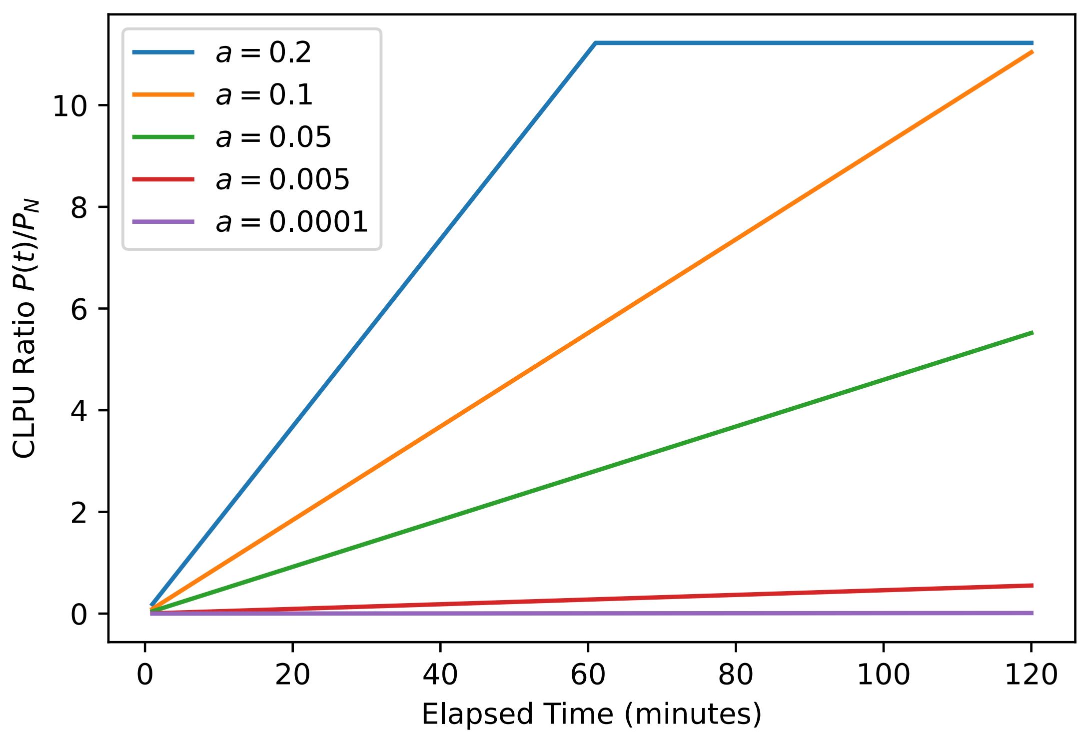

Figure 3.5: Effects of Rate of Increase.

As discussed in [44], ratio of undiversified to diversified load ranges from less than 1.0 to greater than 2.0, with values lower than 1 indicating that outages do not cause constraints. Extensive test case studies in [4] revealed that outage effects on load were lower during spring with simulation results showing an increase on CLPU peak values of 1.33 as the only response to an outage. In all cases studied this parameter followed the general load response behavior to an outage.

Case 2 looks at the effects of multiple values of a_2, load rate decay. As with case 1, a value for a was calculated from the exponential decay relationship in (3.5) and data in [4]. It is important to note that demand also depends on other factors such as temperature and equipment ratings. Authors in [45] used a similar technique to show the effects of weather and substation ratings to determine peak demand magnitudes and also concluded that load decay rate is not constant. Simulation results agree with the findings in [45] on the tendency for piece-wise CLPU model in [46] to predict a longer diversification period. Figure 3.6 shows results. As an indicator, the dashed line shows the start time for normal conditions. Given that the diversification period increases with outage duration, an inverse relationship between decay rates and outage duration can be observed.

3.4.2 System Parameters

Multiple limitations were included in the model to match physical characteristics of end-use loads. Based on [47], at time of restoration CLPU peak will reach a maximum value of 2.5 which will not be exceeded. The assumption is that restoration will not be performed in a single step due to physical constraints in the grid. A limit is set for peak CLPU demand to meet this criterion:

$$P_{max} \leq 2.5 \cdot P_N \tag{3.9}$$

Similarly, the state variable will reach a point in which load will not increase further regardless of the outage time. The state variable accounts for the extra demand needed to increase the temperature in a household. To determine an initial maximum value, residential data from Pecan Street was used to find the peak demand from end-use load profiles of 18 homes in Austin during winter peak:

$$X_t \leq P_{peak} \tag{3.10}$$

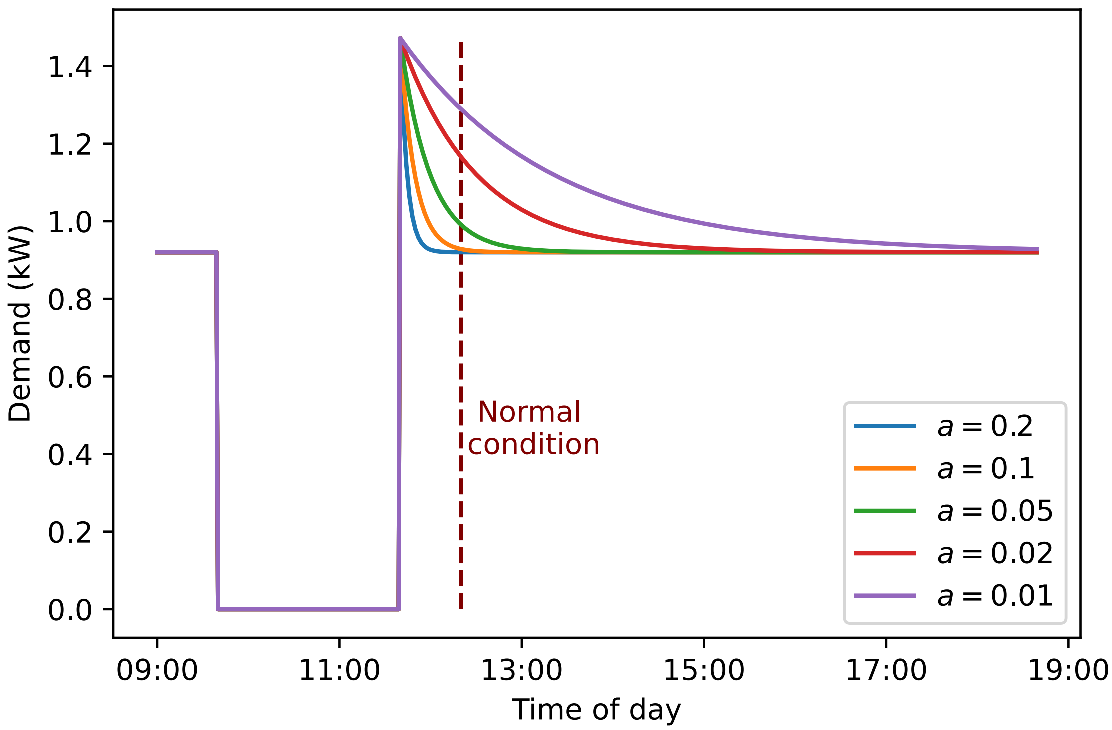

Figure 3.6: Load Rate Decay Effects.

The model calculates end-use demand to be aggregated at a feeder level. Determining which values best fit the model depends on factors unique to the types of load on each network. An assumption made is that load characteristics, such as rate of decay, are identical from one household to the next. Settings for model parameters can be specified by utility companies to accommodate the characteristics of load profiles to their respective area of service [28].

3.4.3 Outage Effects

In the last case multiple blackout duration periods were selected to observe the resulting effects. With all parameters specified in 3.4.2, results were validated with work performed and measurement data in [45]. Figure 3.7 shows results for the different outage periods where maximum physical load value was reached for all cases where outage lasted 4 hours or more, as expected. The inconsistency shown is with the 30 minutes outage which has a CLPU ratio of 1.0. Further improvements to the model will include temperature parameters to better fit load behavior as well as correctly determine peak demand for outages of shorter duration.

CLPU peak duration and diversification duration agreed with results in [45]. Load diversification increased with outage duration, with the period increasing drastically for outages past 8 hours. For a known comparison, load pattern can take more than 12 hours to return to normal conditions for outages of such lengths. Load diversity start time increased in each instance where outage duration also increased, agreeing with [8], [44]. Table 3.2 summarizes simulation results:

Table 3.2: Simulation Results for Outage Duration

Outage Duration (hours)	CLPU Peak Duration (hours)	Diversification Time (hours)	CLPU Ratio
0.5	0	0.27	1.0
4	0.03	1	2.5
8	0.3	1.9	2.5
12	3.37	12.8	2.5
24	5.28	14.7	2.5
36	5.81	15.2	2.5

3.4.4 Restoration

The objective in this paper is to determine model parameter values that are consistent with known load behavior from literature and industry data. The methods from studies in [42] and [44] consider identifying these parameters using load measurement data collected from rotating interruptions. Generally, accurate load models met the following criteria from findings in [44]:

- For a short outage, load should not be affected and diversity should start within minutes.
- After a longer outage, load diversity can take multiple hours to restore.
- For more severe cases where outages lasted a day or more, load diversity takes over 12 hours to be reestablished.

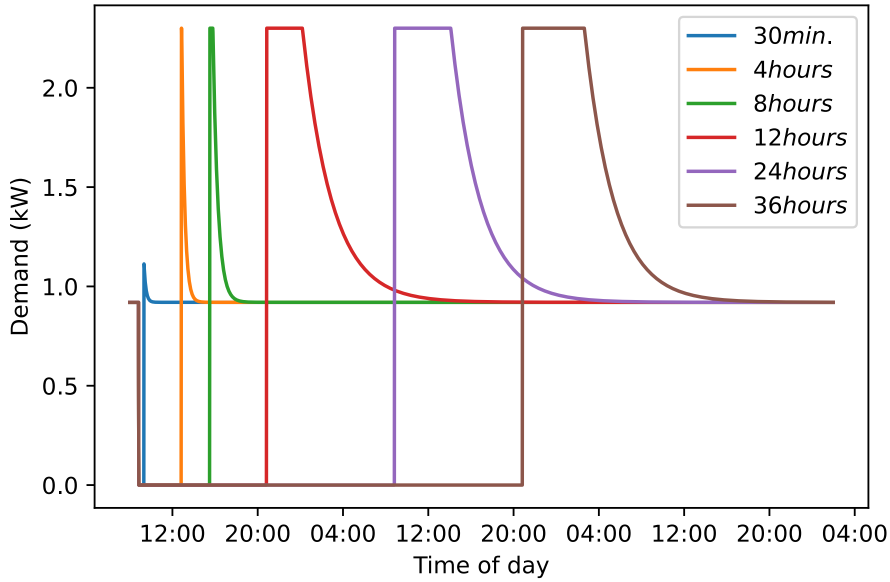

Figure 3.7: Outage Duration Effects.

3.4.5 Restoration Under Cold-load

Results provided are for the severe case of an outage lasting 12 hours. 3.8 shows loads restored over time where a prolonged restoration period is observed—this is nearly two hours longer compared to not considering cold load pickup.

Blackstart is a highly intricate process due to the fact that no amount of planning can prepare operators for every scenario possible. The operation of most extensive power plants, be it coal, gas, or nuclear-powered, requires a significant amount of electricity. While this may appear contradictory, it should be noted that the configurations and equipment differs across different plants. By accounting for cold load pickup, grid operators can anticipate and plan for the temporary, abnormal state of the grid after an outage. This enables them to allocate appropriate resources, such as generators and transformers, to handle the this additional demand effectively. Additionally, utilities can communicate with customers to provide guidance to common procedures that help reduce the impact of cold load.

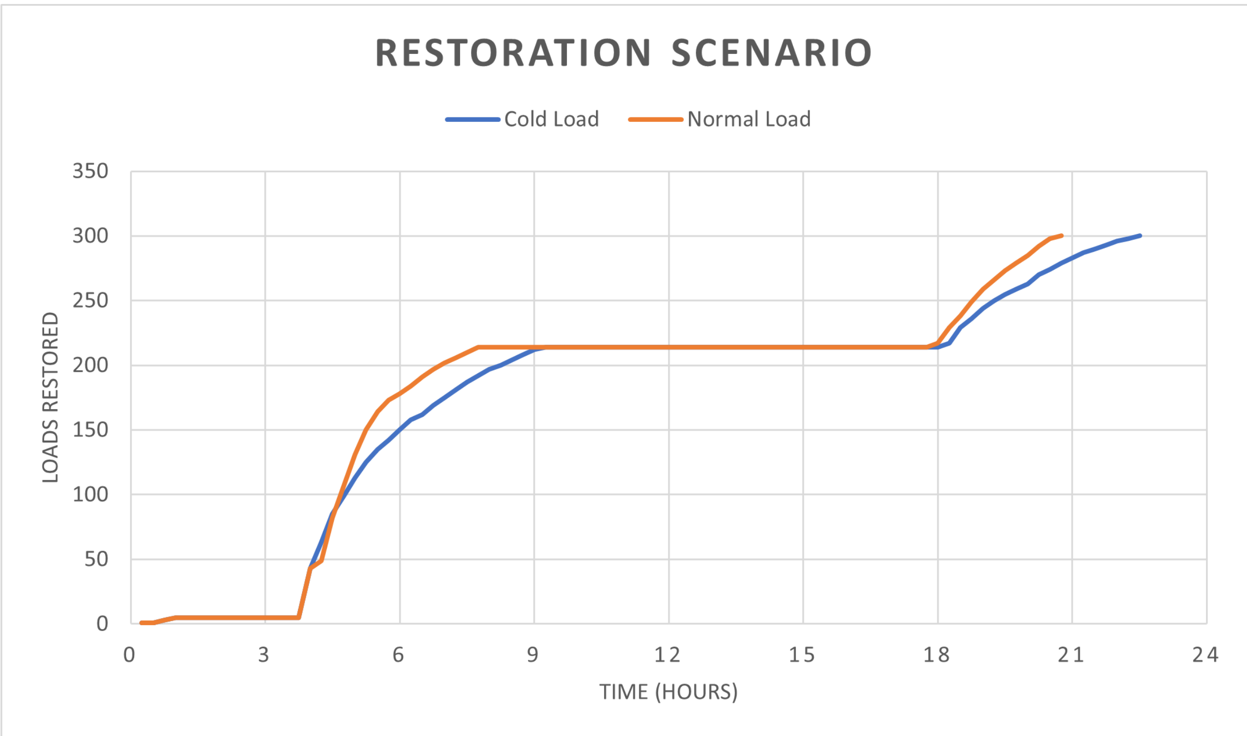

Figure 3.8: Number of loads restored over time.

4. SUMMARY AND CONCLUSIONS*

4.1 Conclusion and Future Work

The baseline of an end-use cold load pickup model is introduced in the work presented. The proposed state-space model is capable of determining CLPU through the use of an accumulated load state variable that increases or decreases based on system status. Characteristic model parameters and their effects are identified and tested against previous studies and resulted in similar responses to an outage. This model was constructed to be integrated into large synthetic grids with the long-term objective of providing future studies for blackstart simulations. There are still several areas to further explore to improve the model's accuracy. As mentioned in prior work, weather conditions as well as time of day highly influence cold load behavior. Further considerations, specifically for weather, would be required to expand onto the existing model and include the relationship between demand and ambient temperature; this would likely apply for both hot and cold weather as an independent state. Making use of a small sample of residential households served as a starting point to determine a localized peak demand. The second consideration will need to account for load composition using a technique to formulate end-use behavior more adequately as is typically described in a bottom-up load model. Since CLPU is highly dependent on several factors such as type of load, increasing details in the model can only further represent accurately the effects of prolonged outages as well as make distinctions between end-users and expected demand. The third consideration will be to simulate results on a synthetic case to study restoration scenarios and begin preparation on studying the effects of CLPU during power system transients caused by utility switching operations during restoration.

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