

The Impact of Large-scale Dynamic Load Modeling on the U.S. Eastern Interconnection

A Thesis Presented for the

Master of Science

Degree

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To my husband, Shane
and my parents, Edith and Pete.

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Abstract

The aim of this thesis is to introduce widespread dynamic load models to the United States Eastern Interconnection 2030 power grid model to help improve its accuracy and capabilities. Currently, all loads in the system are represented by static load models that are unable to capture load phenomenon associated with induction motors. Chapter 1 will provide a general introduction to load modeling by discussing popular static and dynamic load models available. This chapter will also introduce the simulation test case used in Chapter 2 to Chapter 4. In Chapter 2, the complex load model parameters are developed and applied to 28,500 loads in the Eastern Interconnection model and the impact to frequency response is discussed. Buses with large differences in frequency nadir when static or dynamic load models are applied to the system and a bus with a representative response are presented for reference. Snapshots from a movie illustrate the frequency map distribution for the Eastern Interconnection. Chapter 3 is a sensitivity study of the complex load model for certain parameters. The induction motor, constant power, discharge lighting, and static load components of the complex load model are studied. The study metrics are the frequency nadir, settling frequency, and rate of change of frequency for the system average response and a single bus. Chapter 4 validates the developed model for real events recorded by the

FNET/Grideye system. The accuracy of the dynamic load model is compared to the current static load model. Chapter 5 discusses the process to develop load models for a utility in the Eastern Interconnection using a bottom-up approach. The developed models are studied for several cases and validated.

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Chapter 1

Introduction

1.1 Literature Review

Powerful simulation software such as PSSE has been in use for decades. With improvements in computing power over this time-frame, accurate generator models have been implemented to study the frequency response in the United States (US) Eastern Interconnection (EI) for events caused by the loss of generation [1]. Load modeling has also been a subject of interest in the electric power industry. Representing load by overly pessimistic or optimistic models can have detrimental effects to grid stability and economic concerns. For example, a load model that cannot capture inter-area oscillations could produce false confidence in the results of the simulation. Meanwhile, a load model that is too conservative can cause utilities to invest in unnecessary improvements in the grid. Thus, it is imperative to treat load modeling equally as important as generator modeling. However, there exist far more loads than generators in terms of quantity and variety; Load

also constantly changes throughout the day and season, which all add to the complexity of modeling.

Unlike the western U.S. grid, which has developed and implemented a composite load model throughout their system to capture the dynamic behavior for several types of induction motors and static loads, the EI Multi-Regional Modeling Working Group (MMWG) 2030 grid model does not currently use any dynamic load models. Static load models, which are modeled by algebraic equations, are the prevalent choice in steady state and dynamic studies throughout the worldwide electric power industry. According to [2], within the Americas, static load models are used by 56% of the industry for dynamic studies. The EI MMWG model approximates load behavior for dynamic simulations with a constant current and constant impedance static load model (PIQZ). However, static load models have been proven ineffective at capturing both wide- and local-area grid phenomena, which can deteriorate confidence in the grid model. Several findings were summarized in [3] related to load modeling and the impact to small-signal and voltage stability studies. It was found that a quadratic, voltage dependent load model can overstate the damping of inter-area oscillations while, in general, static load models could not capture the behavior of motor-driven loads. These are important characteristics to consider when observing the impact of dynamic load models on the frequency response of the grid due to generation trip events.

Induction motors are among the most common and therefore most important loads in the modern power system that need to be properly characterized. For instance, [4] highlights the fact that induction motors may decelerate following a line fault and cause bus voltage to remain depressed for several cycles after a fault is cleared. This phenomenon is commonly known as fault-induced delayed voltage recovery (FIDVR) events, which occur in areas with

high penetration of air conditioning (AC) load. Single-phase AC load can stall due to low bus voltage but remain connected to the grid before its thermal protection trips the unit offline, thus causing local voltage sags [5]. During low bus voltage, induction motors will draw excessive amounts of reactive power, which cannot be modeled properly using static load models [6]. Induction motor inertia is another important factor affecting the frequency response of the system [4]. To accurately account for induction motor, dynamic load models, whose present state is a function of not only current grid conditions but also the loads' previous state, must be implemented. Induction motor models do exist strictly for capturing this behavior however, for large-scale grid models where detailed knowledge of the load is unknown, a general model should be used. For this reason, composite load models, which capture the behavior of several types of loads, are best suited.

In 2016, the Electric Power Research Institute (EPRI) developed a tool to implement component-based load modeling for utility planners in EI using the composite load (CMLD) model structure [7]. CMLD requires around 130 parameters, which presents a challenge for large-scale load modeling in terms of software limitations. Although most CMLD parameters can be set to a standard value, debugging the simulation in cases of non-convergence can be difficult and time-consuming. A simpler dynamic model can be found in the complex load (CLOD) model, which requires fewer computational resources. Thus far, most of the research regarding the CLOD model has looked at either local issues or small systems [8], [9]. The study in [8] applies the CLOD structure to improve the modeling accuracy for industrial type electricity consumers, where there exists a large presence of induction motors. The researchers in [9] investigated two methods to estimate CLOD parameters from phasor measurements for a 37-bus system. In relation to frequency response studies, [10] showed

that induction motors in the CMLD model have a detrimental impact to frequency response in the Cyprus system. However, the Cyprus system is relatively small compared to the EI. Currently, no research has shown the impact to frequency response of a large-scale system due to dynamic, composite load modeling such as CLOD. The remainder of this chapter will discuss several load models in further detail and briefly summarize the system model to be used throughout this thesis.

1.2 Load Models

Load models can be classified as static or dynamic and within these classifications are several models that have been extensively used throughout the literature; this thesis will focus on the most popular load load models as well as the built-in load models for PSSE.

1.2.1 Static Load Models

Load models that vary with the system parameters but are independent of time are considered static. All static load models can be derived from the exponential load model shown in (1.1) and (1.2).

$$P = P_o \left(\frac{V}{V_o} \right)^a \left(\frac{F}{F_o} \right)^b \quad (1.1)$$

$$Q = Q_o \left(\frac{V}{V_o} \right)^c \left(\frac{F}{F_o} \right)^d \quad (1.2)$$

Where the real and reactive power are a function of nominal power, P_o and Q_o , nominal voltage, V_o , and nominal frequency, F_o . The exponents a , b , c , and d represent the dependence of the load on voltage or frequency. The frequency dependence of the load is often neglected in many studies since voltage deviations have a larger impact on the load and occur more frequently [11]. If the exponential load model is expanded to include three terms and the exponents are fixed to 0, 1, or 2, then the model is considered a “ZIP” load. This is shown in (1.3) and (1.4). The ZIP model gets its name from the ability to represent constant impedance (Z), constant current (I), and constant power (P) load, noted by the exponent values of 2, 1, or 0, respectively.

$$P = P_o \left[c_1 \left(\frac{V}{V_o} \right)^2 + c_2 \left(\frac{V}{V_o} \right)^1 + c_3 \left(\frac{V}{V_o} \right)^0 \right] \quad (1.3)$$

$$Q = Q_o \left[c_1 \left(\frac{V}{V_o} \right)^2 + c_2 \left(\frac{V}{V_o} \right)^1 + c_3 \left(\frac{V}{V_o} \right)^0 \right] \quad (1.4)$$

The coefficients c_1 , c_2 , and c_3 are the composition of each load type and whose values sum to 100 percent. For example, $c_1 = 0.2$, $c_2 = 0.3$, and $c_3 = 0.5$ would represent a load with 20 percent Z, 30 percent I, and 50 percent P. Because the ZIP model is based on the physical behavior of the load, its interpretation is straightforward therefore adding to its popularity as the load model of choice for the worldwide power industry [2].

Power flow solutions typically use a conservative estimation of the load by assuming a 100 percent constant P load. A simplified example to illustrate this conservative assumption is given in Figure 1.1. If the load is represented in three distinct ways, constant Z, constant I, or constant P, then the per-unit consumption can be seen throughout a range of per-unit voltage.

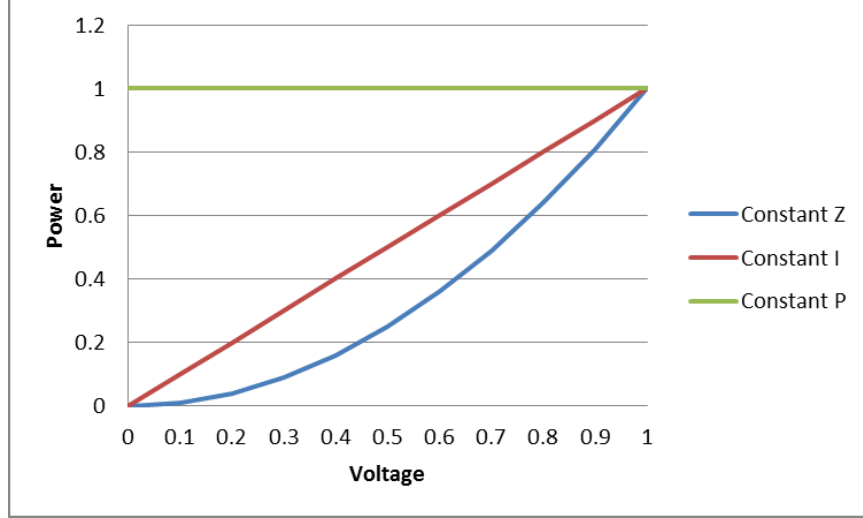


Figure 1.1: Load consumption with Z, I, or P load

Constant P load will exacerbate any disturbance that causes local bus voltage deviations by unrelentingly consuming electricity whereas constant Z load will reduce consumption by a magnitude order of two as voltage decreases, thus making it a very optimistic load model. One thing to note, this example assumes ideal load equations given by the ZIP model. In reality, constant P load will not consume 100 percent power at zero voltage, as this violates circuit laws. To overcome this reality, grid software, such as PSSE, will linearly reduce constant P load between zero volts to a voltage threshold (default of $V = 0.7$ pu).

Due to the severity of a constant P load estimate, it is not as reasonable to use during dynamic simulations. PSSE has a built-in function to convert the constant P load used in power flow analysis to a constant I model for real power load and constant Z, or admittance (Y), model for reactive power load. This is known as the PIQZ load model, which was mentioned in the introduction of this chapter. The PIQZ is the standard load model used in dynamic simulations of the MMWG grid.

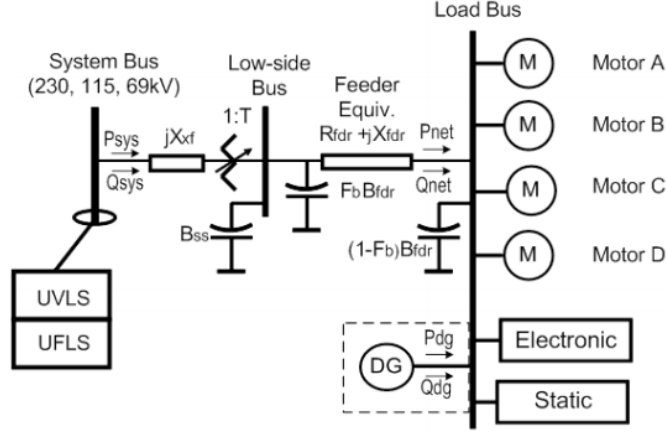


Figure 1.2: CMLD model diagram [Source: NERC]

1.2.2 Dynamic Load Models

Dynamic simulations are used to conduct transient studies of the power grid where the behavior over time is the main concern. Several dynamic load models that include induction motor models are available in PSSE such as an induction motor-only (CIM5) model, the composite load (CMLD) model, and the complex load (CLOD) model. CMLD requires approximately 130 parameters to model four induction motor of single- and three-phase types, power electronic loads, and other static loads. Its model diagram is shown in Figure 1.2. The use of CMLD is intended for highly detailed studies where motor parameters and behavior are known or can be obtained through available data. The motor D component is the only single-phase motor model and captures the behavior of AC load. Motors A, B, and C represent three-phase induction motors with various inertia and torque characteristics. The most recent model version also includes a component for small, distributed generation. CMLD also has built-in protection and load shedding schemes therefore not requiring external protection devices.

CIM5 also requires substantial knowledge of the induction motor for setting the model parameters. Additionally, it cannot represent other load types such as static load including power electronic loads. To overcome this feature would require the use of a secondary model – a static load model – and would add complexity to large-scale load modeling. Thus, this model is not explored in this thesis.

CLOD can model a composition of various load types, similarly to CMLD, but only requires eight parameters. This is achieved by internally using typical manufacturer data for induction motor models and thus cannot be modified by the user. The diagram for CLOD is shown in Figure 1.3. The CLOD dynamic model requires five parameters for the proportion of large motors, small motors, discharge lighting, transformer saturation, and constant MVA load and three additional parameters for the distribution line impedance and the voltage exponent of the remaining real power load. The proportion of the remaining load is determined internally as the sum of all other components subtracted from 100 percent. The use of CLOD is ideal when detailed information of the load is not available but dynamic behavior of induction motor load is desired.

One of the challenges for dynamic simulation of the EI MMWG grid is the software limitation. The EI is modeled in PSSE and there is limited space in the general-purpose array for algebraic variables (VARs). Most dynamic models, regardless if for a generator or load, use VARs to hold the calculated values from internal equations. The CMLD model available in PSSE requires around 140 VARs per model applied, which would limit the total number of load models that can be implemented throughout the system. CLOD uses 28 VARs per model, far less than CMLD. This means a larger quantity of the standard PIQZ models within the EI MMWG model can be converted to CLOD rather than CMLD. For

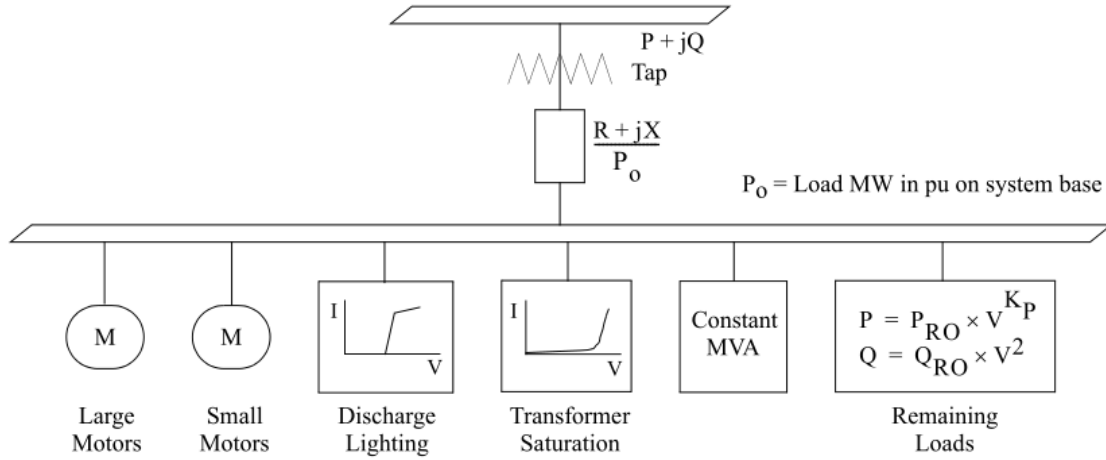


Figure 1.3: CLOD model diagram [Source: Siemens PTI]

this fact, this thesis will focus primarily on the implementation of CLOD for large-scale load modeling.

1.2.3 Parameter Estimation

Load models require accurate parameters to realistically model and predict system disturbances. The challenge of obtaining accurate parameters for a large-scale system is in the ability to represent a wide variety of load characteristics across a large geographic region. Composite and complex load models make this step easier by incorporating several types of load components but the proportion of each component is still unknown. To determine load parameters, several factors must be considered such as weather, customer type, time-of-day, etc. [12], [13]. These factors all have a role in the types of loads being used and the intensity. Some general examples: hot days will require cooling load; few people will cook at 3:00 am; an office building has far more computers than a house. Because of the human factor

affecting load consumption, the load model parameters are, at best, an estimate and never constant. Load model parameters can be estimated by using available customer data and load surveys; this is known as a bottom-up approach or component-based approach. The load parameters can also be estimated through real event data by curve fitting the model, which is known as a top-down approach or measurement-based approach.

The measurement-based approach tunes the most sensitive parameters of the load model to a system event through optimization algorithms that minimize the error of the model to the real data measurements. This approach tends to produce the most accurate response of the model to the real event however, the parameters tend to lack generalizability and thus the process must be repeated for each event [14]. To tune the parameters successfully, it is crucial to understand the sensitivity of each parameter and any inter-dependencies. The study in [15] found that multiple solutions can exist for measurement-based load modeling using CMLD and even some solutions could be considered unreasonable. Another study by the same researchers in [9] found that CLOD also suffers from non-deterministic solutions. These challenges are difficult to overcome and require additional information that may not always be available. For instance, one of the ways to overcome inter-dependencies of parameters is to only permit the parameter to deviate within a set range of expected values, which requires knowledge of the parameter either through historical data measurements or data from component-based modeling.

Lack of measurement data would require the use of the component-based approach. Customer data can be utilized such as end-use load surveys that provide a detailed load composition for individual customers. Other forms of data are customer class information and their approximate load by feeder. Since component-based load modeling is rooted in the

physical behavior of devices, the ZIP model is a popular choice to implement this strategy. Of course, any load model can use this method as long as the rules-of-association are established that can link the physical device to a parameter. This method, based on assumptions and engineering judgment, will produce a general model which naturally may have lower accuracy to specific events but on average may capture the overall behavior of the load. The study by EPRI in [7] created a tool for CMLD parameter estimation using utility distribution data to develop local models either at the area, zone, or bus level, depending on the detail of the information available.

1.3 Eastern Interconnection Power System Model

The EI MMWG 2030 model has around 70,000 buses and roughly 38,500 loads and is modeled in power system simulation software, PSSE. Simulations in Chapter 2 through Chapter 4 will be conducted using the EI MMWG 2030 model. For these simulations, the test case will be modeled after the largest generation trip event occurring within the EI, which was a 4.5 GW loss of generation [16]. No attempt is made to replicate the order or the length of the event only the size of the generation loss. The study system in Chapter 5 is the EI MMWG 2017 Summer Peak model. The simulated events are modeled after three-phase faults occurring at various locations in the Dominion Energy territory.

1.4 Thesis Organization

Chapter Two will discuss the methodology and challenges of implementing dynamic load models throughout a wide-area to improve the EI MMWG 2030 model. An average load model is built based on utility data collected for several areas within the EI. Results compare the frequency deviation of the base case load model and the developed dynamic load model at several buses which have been identified as having either a large difference between nadir or a typical response. The average system response is also shown.

Chapter Three presents the results of the CLOD sensitivity analysis conducted for several parameters of the load model with respect to frequency. A range of load model parameters were identified from the utility data collected that was used to build the load model in Chapter Two. The results compare the sensitivity of induction motors, constant power load, discharge lighting load, and other static load with respect to frequency nadir, rate of change of frequency, and settling frequency.

Chapter Four validates the improved EI MMWG model response to real system events captured by the FNET/Grideye system. Using event data for a loss of generation occurring within North Carolina and Virginia region in 2013, the frequency of transmission-level buses are compared to nearby distribution-level buses. The error of the dynamic load model and static load model are compared over the time-frame.

Chapter Five presents a local-area, highly-detailed load modeling study conducted for Dominion Energy. The data required to improve the accuracy of the load model using a bottom-up approach are presented and analyzed. This data includes customer composition, end-use load consumption, location information, weather and climate information, and

specific large-scale load information. The load model is improved for both the CLOD and CMLD dynamic models and the results are analyzed using three-phase fault cases.

Chapter 2

Implementing Complex Load Model in the Eastern Interconnection

2.1 Motivation

Large-scale data verification of dynamic generator models has been studied and improved for EI in [1]. However, literature is currently lacking in studying the impact to frequency response from dynamic load models in the large-scale Eastern Interconnection. This chapter will attempt to bridge the knowledge gap.

2.2 Load Model Placement

One of the challenges to implementing wide-scale, dynamic load models is the limitation of algebraic variables (VARs) in the software. PSSE version 33 working memory can allocate space for up to one million VARs. A more recent version of the software was tested but did

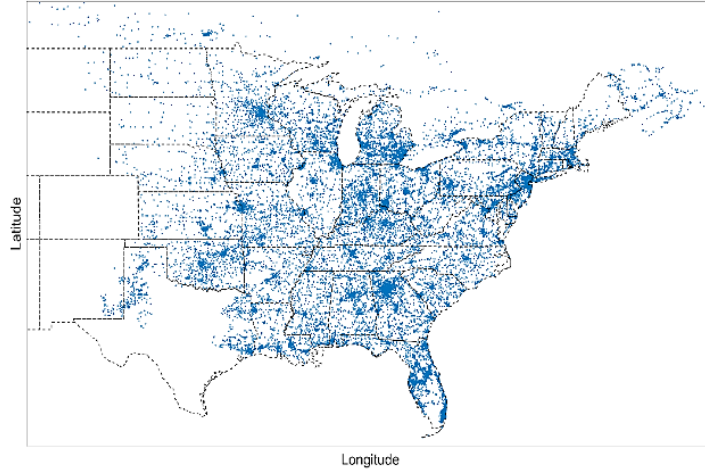


Figure 2.1: Dynamic load locations

not provide additional memory space. For each CLOD model applied, 28 VARs are required. Since the EI MMWG model has about 36,500 positive loads, it would require far more VARs than the software is capable of handling in order to model every load as CLOD. This estimate does not include the VARs required for generator-associated models, which is roughly 20,000. At most, 35,000 CLOD models can be applied while being within the software constraints. However, another consideration is numerical stability of the simulation. Small loads and loads with poor power factor may have an adverse effect to the quality of the results if they are applied dynamic load models [17]. Increasing the system complexity to model small loads will also increase the simulation time. To save resources, CLOD is applied to roughly 25,000 of the largest, positive loads (the size of the smallest load modeled is around 2 MW). This accounts for 565 GW of load – roughly 95 percent of the positive system load. The remaining load not modeled by CLOD will be kept as PIQZ load. The location of the applied dynamic load models is seen in Figure 2.1.

2.3 Parameter Development

Although there are software limitations for large-scale load model implementation, there are also challenges with estimating load model parameters. As mentioned previously, two general methods can be used to determine the values of the parameters: component-based or measurement-based. A measurement-based approach would be time consuming on this scale of a system since parameters need to be tuned at several locations throughout the system and would yield several load models for the tuned areas. The lack of generalizability of the method implies that several events must be used to tune the model and then an average of the load models could be used for studies that are more general. It is also unclear how many locations would be needed to tune the model, thus a sensitivity study on the locations would be necessary. Because of the challenges of measurement-based parameter estimation, a component-based approach is more reasonable for a wide-area study of dynamic load modeling. The US Energy Information Administration (EIA), which is a government organization dedicated to analyzing the US energy needs, has available end-use load consumption data for residential, commercial, and industrial consumers of electricity. However, without knowing the breakdown of the consumer classes (i.e. the percentage of each consumer aggregated to a given substation), it is difficult to estimate the impact of each consumer on the grid. Instead, several entities within the US have published their component-based CLOD parameters, which are listed in Table 2.1. The average of Table 2.1 will be henceforth noted as ‘typical’ CLOD parameters.

Table 2.1: EI entities' CLOD parameters

Entity	Large Motor (%)	Small Motor (%)	Discharge Lighting (%)	Transformer Excitation Current (%)	Constant Power (%)	Remaining Load (%)	K_p of Remaining Load
MISO Vectren	23.65	61.75	0	2.16	11.34	1.1	1
MISO ATC	17.55	44.225	18.6	1	4.425	14.2	1.5
NEISO ME	12.09	42.62	11.86	0	15.95	17.48	2
NEISO NH	11.97	42.19	12.78	0	15.74	17.32	2
NEISO VT	11.22	45.61	12.15	0	15.13	15.90	2
NEISO WEST MA	13.19	48.27	10.20	0	14.43	13.91	2
NEISO EAST MA	12.27	47.58	11.59	0	15.82	12.75	2
NEISO RI	13.07	47.58	10.89	0	14.12	14.34	2
NEISO CT	11.77	45.43	12.11	0	17.60	13.08	2
NERC	15	45	20	0	6	14	1.25
Average	14	47	12	0	13	14	2

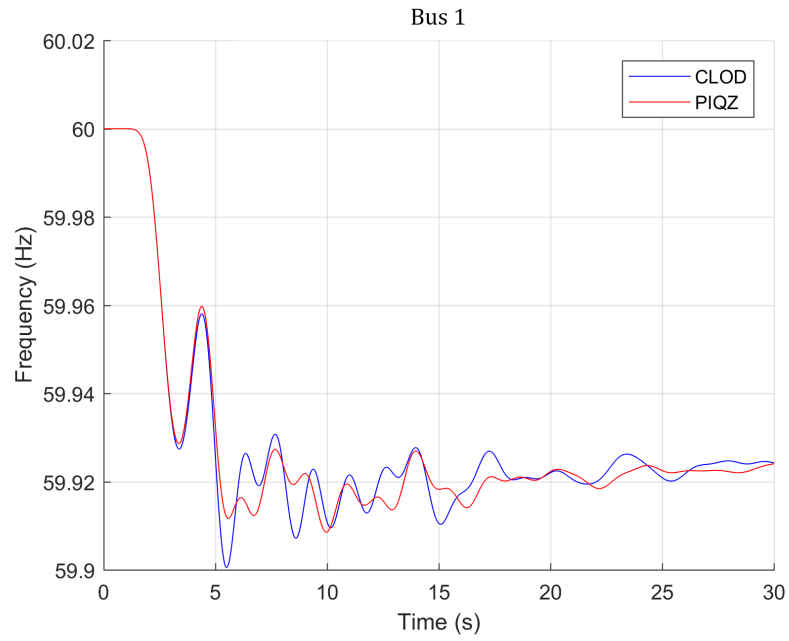
2.4 Results and Analysis

2.4.1 Buses with Large Nadir Discrepancy

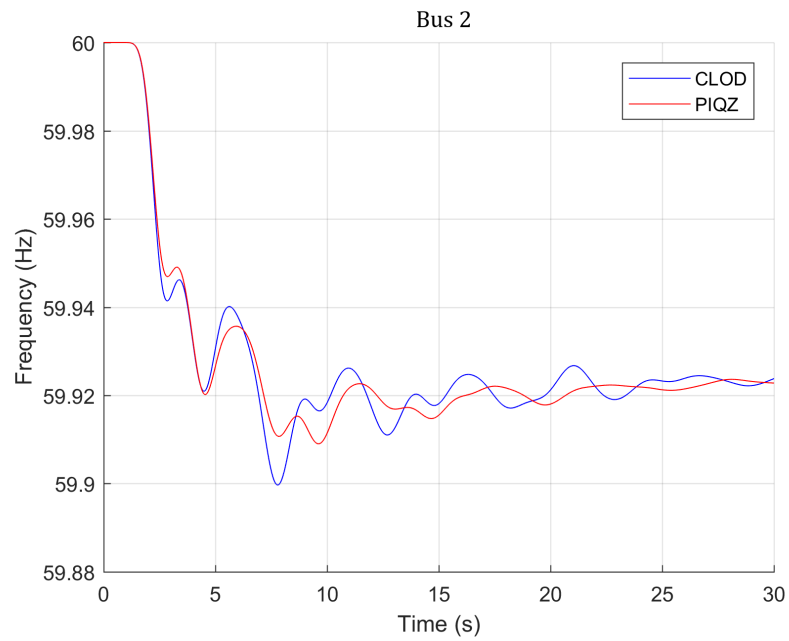
A dynamic simulation comparing the frequency of buses at the 500 kV level and above for the PIQZ model and CLOD model are shown in the following figures. Figure 2.2 shows two buses with a large difference in frequency nadir between the two load models. These buses are located towards the border of the EI grid (upstate New York and Michigan), which experience severe oscillations. The impact of CLOD on frequency response shows a more severe frequency nadir as well as reduced damping of inter-area oscillations. Additionally, implementing CLOD was found to increase simulation time up to 4.6 times than a simulation with only the standard PIQZ load model. The increase in simulation time is expected due to the additional complexity of the CLOD model.

2.4.2 Typical Response and System Average Frequency

A more typical case for comparison is shown in Figure 2.3a, which shows less difference between the load models at the nadir but further reinforces that the impact of CLOD is reduced oscillation damping. Lastly, a system average frequency plot is shown in Figure 2.3b. In all bus frequencies shown, it is apparent that a dynamic load model exhibits worse frequency oscillations; this is attributed to induction motor inertia [18] – [20].

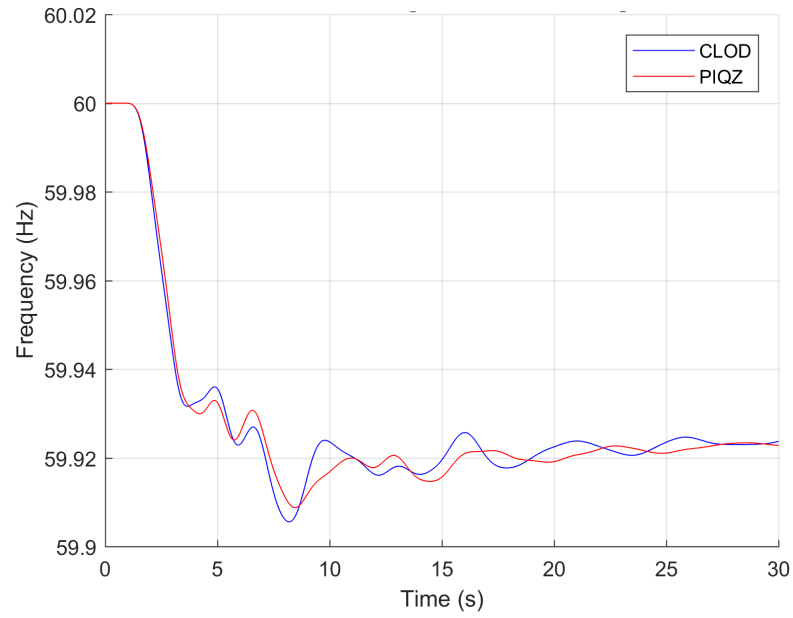


(a) Bus 1

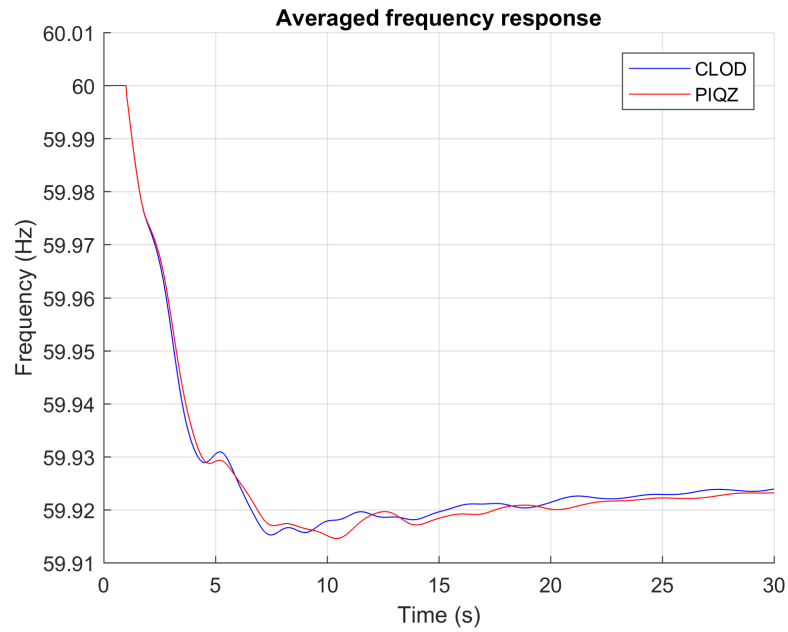


(b) Bus 2

Figure 2.2: Buses with largest variance of frequency nadir



(a) Bus with typical frequency response



(b) Average system frequency response

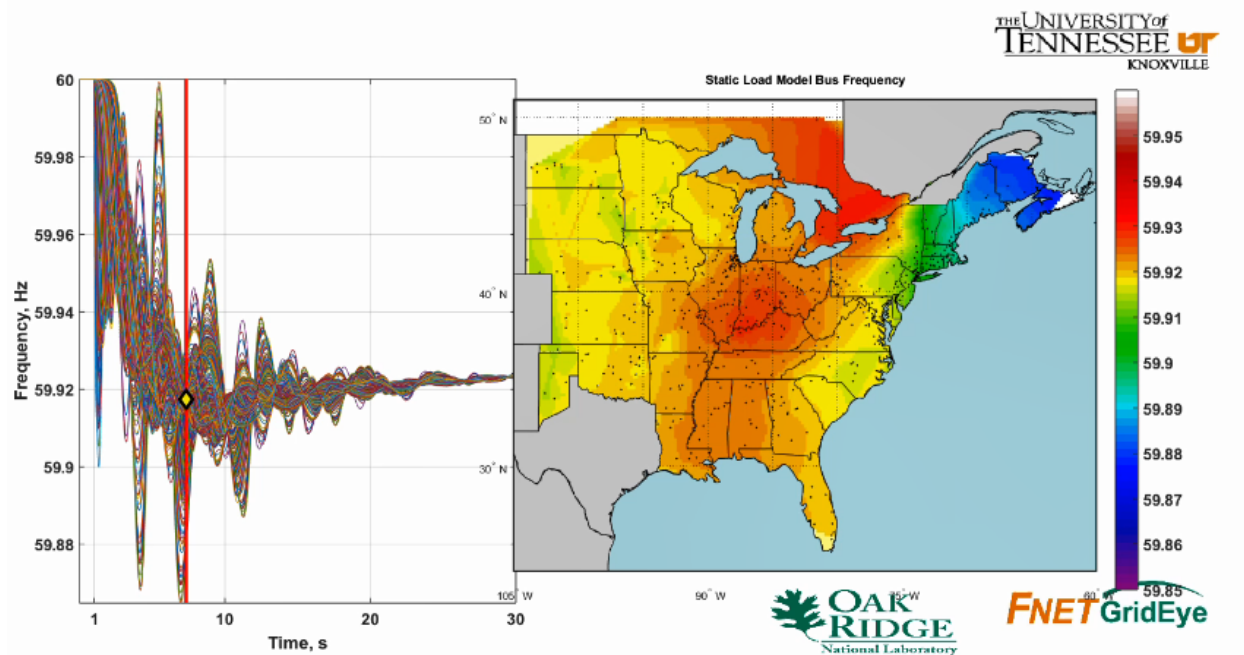
Figure 2.3: Frequency response of typical bus and average system

2.4.3 Interconnection-Wide Frequency Deviations

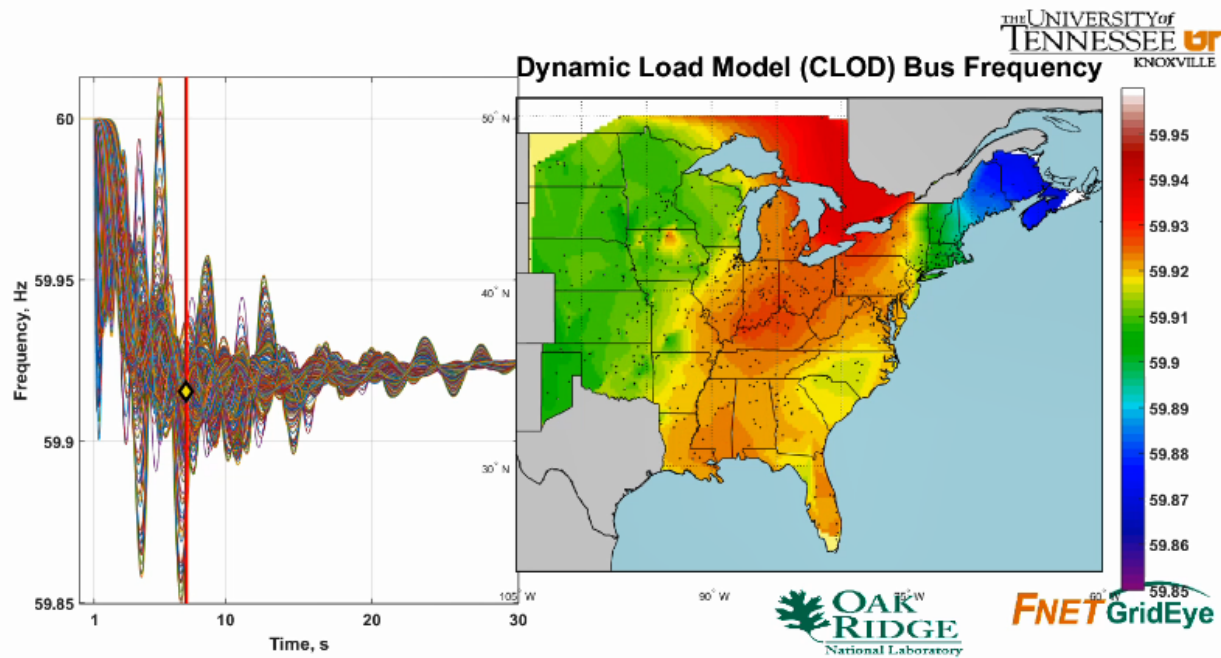
A movie was created to observe the entire grid frequency deviation when implementing the load models. Snapshots at seven seconds, ten seconds, and eighteen seconds are shown in Figure 2.4, Figure 2.5, and Figure 2.6, respectively. These snapshots were taken to highlight the main differences observed throughout the movie. Prior to seven seconds, during the initial frequency decline, the load models show little to no difference in grid frequency. At seven seconds, a significant difference in frequency in the western portion of the EI is seen in CLOD than PIQZ indicating that the system frequency becomes less stable. At ten seconds, once again the frequency in the western portion differs from the eastern portion in CLOD during an opposing oscillation swing. At eighteen seconds, it can be seen that the PIQZ model has begun to settle from the disturbance and frequency becomes more uniform throughout the grid. However, the frequency with CLOD implemented is still experiencing frequency oscillations at this time.

2.5 Conclusion

The typical CLOD dynamic model developed can help to improve load model assumptions for large-scale grids as well as proof of the feasibility to model dynamic load at this scale. The model can also help to anticipate frequency response impacts more rigorously for better dynamic stability of the grid. The increase in complexity of the software grid does negatively affect simulation time since dynamic load requires a smaller time step although it can be argued that the benefits outweigh the cost.

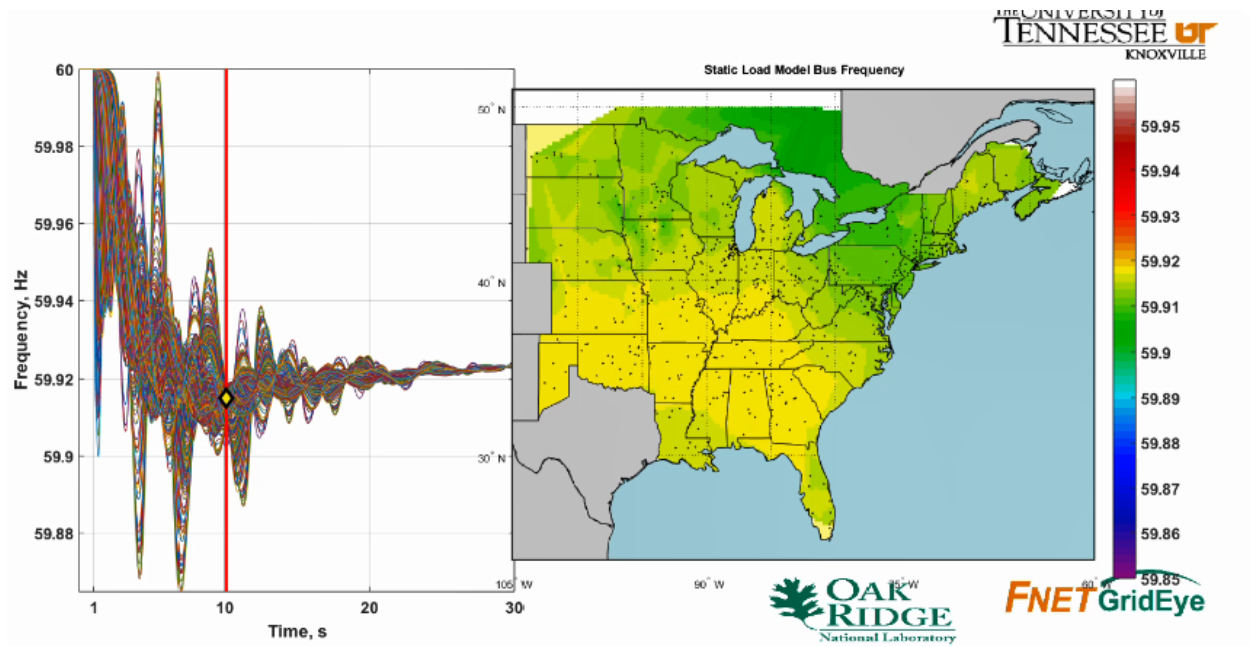


(a) Static load model

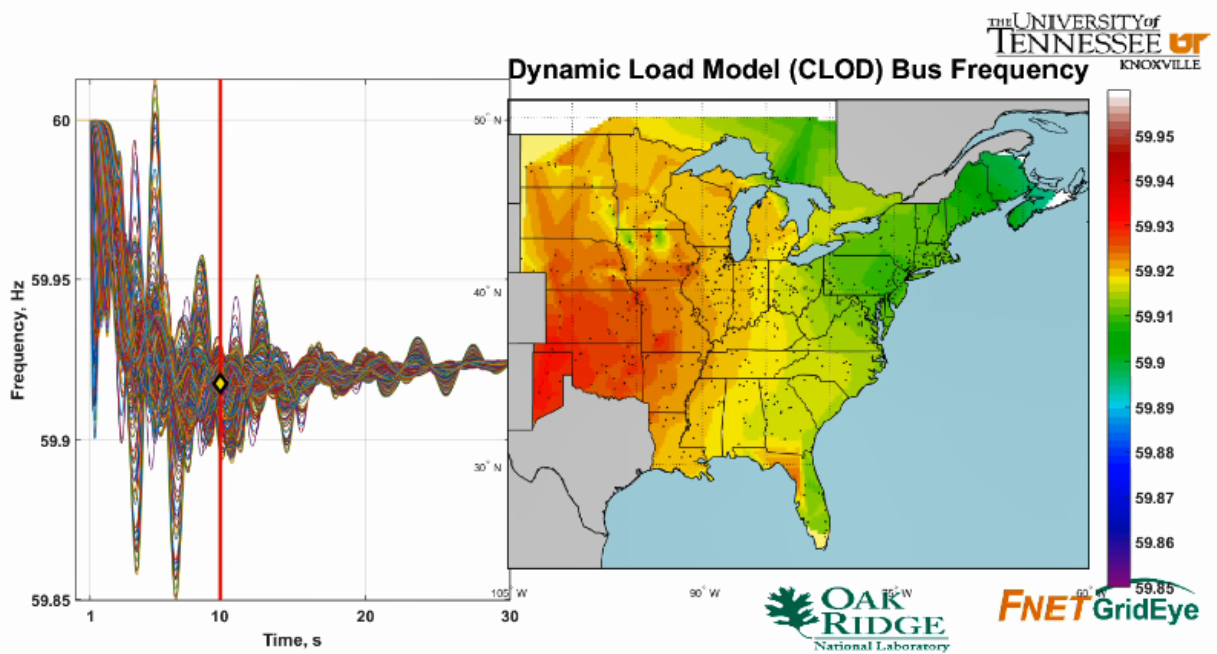


(b) Dynamic load model

Figure 2.4: Grid frequency at 7 seconds

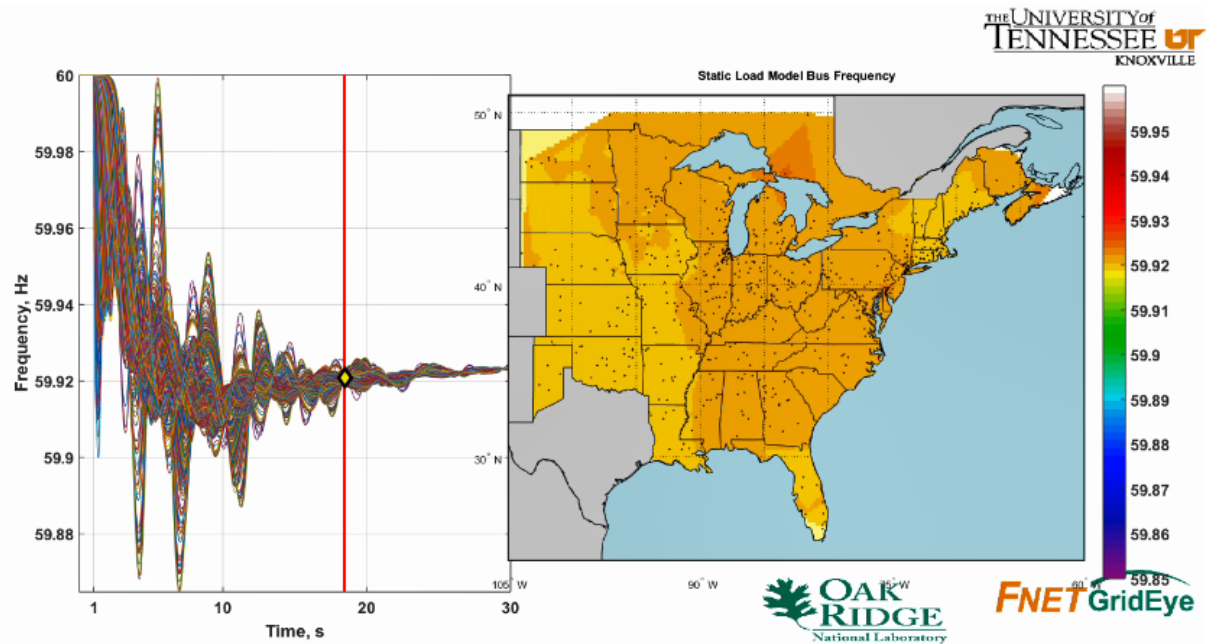


(a) Static load model

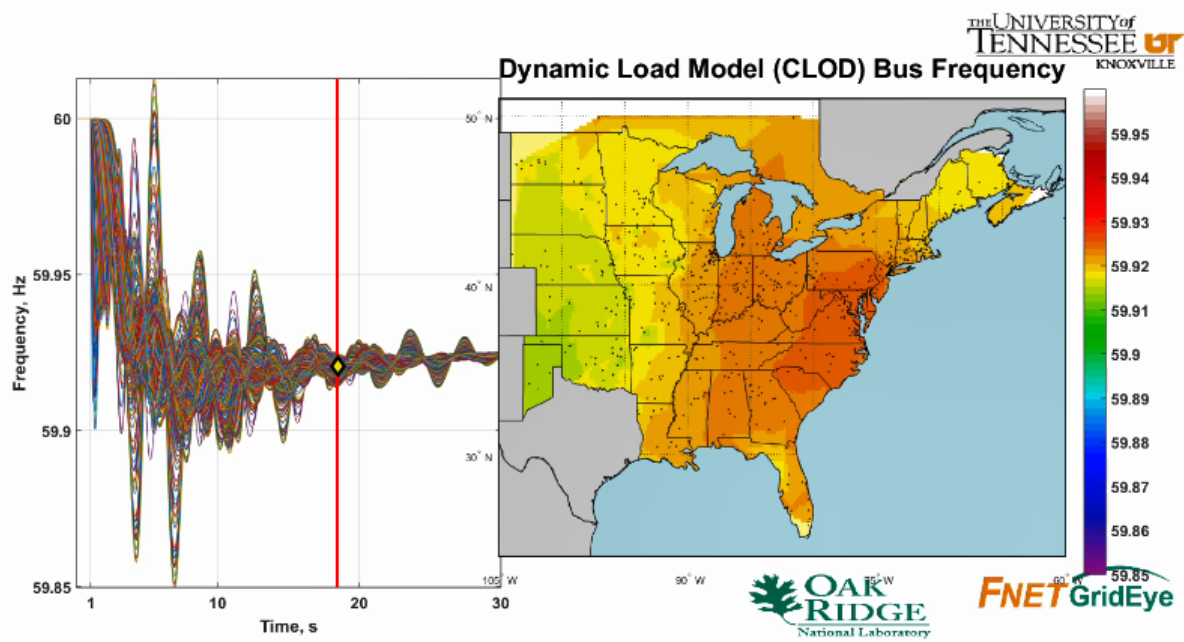


(b) Dynamic load model

Figure 2.5: Grid frequency at 10 seconds



(a) Static load model



(b) Dynamic load model

Figure 2.6: Grid frequency at 18 seconds

This chapter highlights the impact dynamic load models pose to frequency stability through reduced oscillation damping and in some local areas, decrease in frequency nadir. These issues come to the forefront during extreme conditions on the grid such as during summer time, when the grid is operating at or near maximum capacity with larger amounts of cooling load or during restoration when the grid is more fragile than usual. A better understanding of load behavior can help to anticipate critical areas that may need infrastructure improvements to damp frequency oscillations.

Chapter 3

Sensitivity Analysis of The Complex Load Model

3.1 Methodology

A sensitivity analysis provides an understanding of the model's behavior when its parameters are varied from a base value to extremes. Several metrics are used to quantify the impact of CLOD to frequency response such as frequency nadir, settling frequency, and rate of change of frequency (ROCOF). To perform the study, crucial components of the load model are selected to be varied, one-by-one, to an extreme value while all other components remain at their base value. This process is not designed to study the interactions between two or more parameters but rather is used to identify the impact of a singular component. Horizontal bar charts are used to display the results of the sensitivity analysis since it can capture all relevant information such as the base value and both extreme values for every component studied.

3.1.1 Evaluation Metrics

The frequency nadir is calculated as the minimum frequency during the simulation. The settling frequency is the frequency twenty-nine seconds after the generation trip. The ROCOF is calculated as shown in Equation (3.1).

$$ROCOF = \frac{f_{t=1} - f_{t=2.5}}{1.5} \quad (3.1)$$

Where the frequency at one second minus the frequency at 2.5 seconds divided by the total time between the data points is the rate of change of frequency. Typically, the ROCOF is calculated over a range of 0.5 seconds however, large swings were present in some local buses that affected the calculation of the ROCOF and in order to continue using the starting frequency from when the generation trip occurs, a longer duration of 1.5 seconds is used.

3.1.2 Parameter Variance

The parameters to be studied are large motor (LM), small motor (SM), discharge lighting (DL), constant power (CP), and the voltage exponent of the remaining load, Kp. Transformer saturation and distribution line impedance are not studied since very limited data is available for their values and these are highly dependent on the distribution system. Ideally, each studied parameter varies by ten percent (for maximum and minimum) of the typical value and KP will vary from two to zero, to account for common, exponential static load models (i.e. ZIP). However, due to numerical issues, some components are unable to be varied to the intended maximum value. Kp exhibited simulation errors when set to zero but exhibited no errors when set to 0.5, which was chosen as its maximum value. For SM, LM, and CP,

Table 3.1: CLOD sensitivity values

Component Value	Large Motor (%)	Small Motor (%)	Discharge Lighting (%)	Constant Power (%)	K_p of Remaining Load
Maximum	23	56	22	22	0.5
Base	14	47	12	13	2
Minimum	4	37	2	3	2

the maximum value was reduced by one percent. Table 3.1 shows the values used for all ten simulations. The base values are the same as the typical CLOD model developed previously.

3.2 Results and Analysis

Figure 3.1, Figure 3.2, and Figure 3.3 show the results from the sensitivity analysis of the frequency response for the system average and a single bus. The sensitivity results deviate from the base, which is denoted by the black, vertical line for the three frequency response metrics. The results shown in Figure 3.1 indicate that LM, SM, and CP loads are the most detrimental components to frequency nadir on a local and system average basis. When K_p is varied to 0.5, the impact is also significant although less than CP loads.

The settling frequency results shown in Figure 3.2a indicate that parameters at their maximum values exhibit an improvement over their minimum value counterpart. However, the results are inconclusive in Figure 3.2b since most minimum and maximum values show improvement over the base case. This results is due to minor oscillations that exist at the end

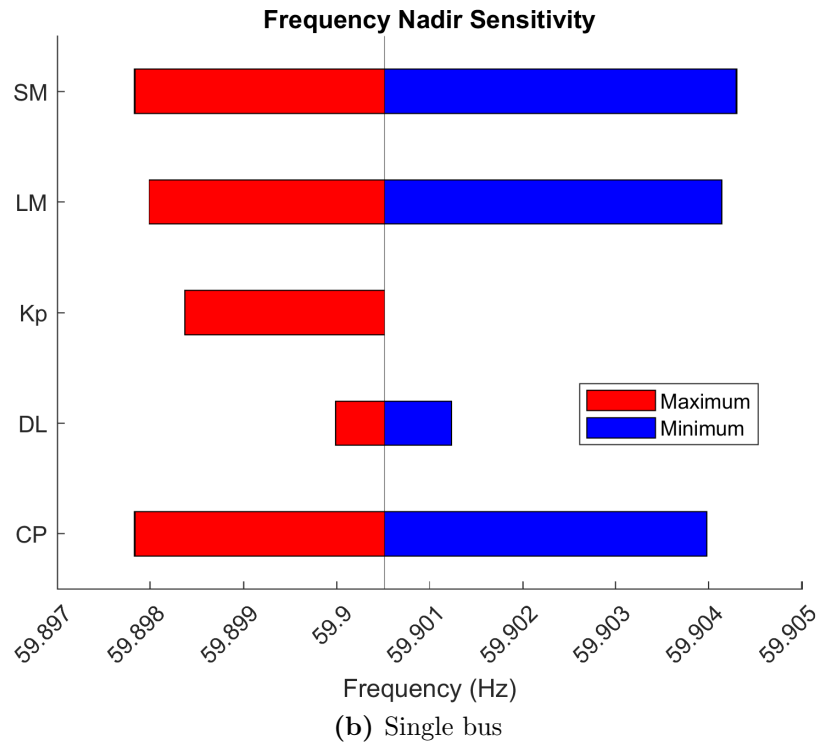
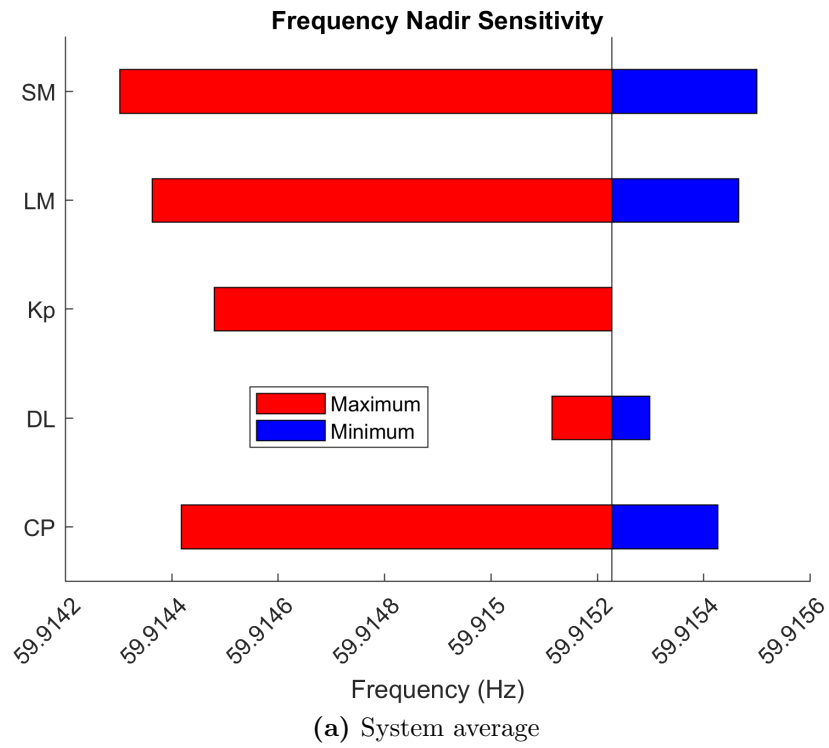


Figure 3.1: Frequency nadir sensitivity

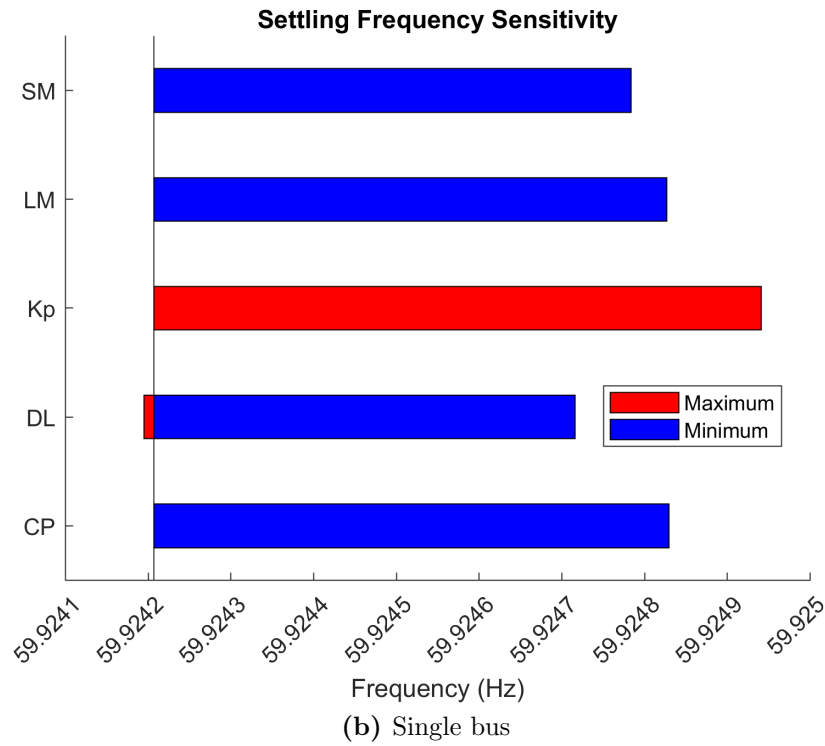
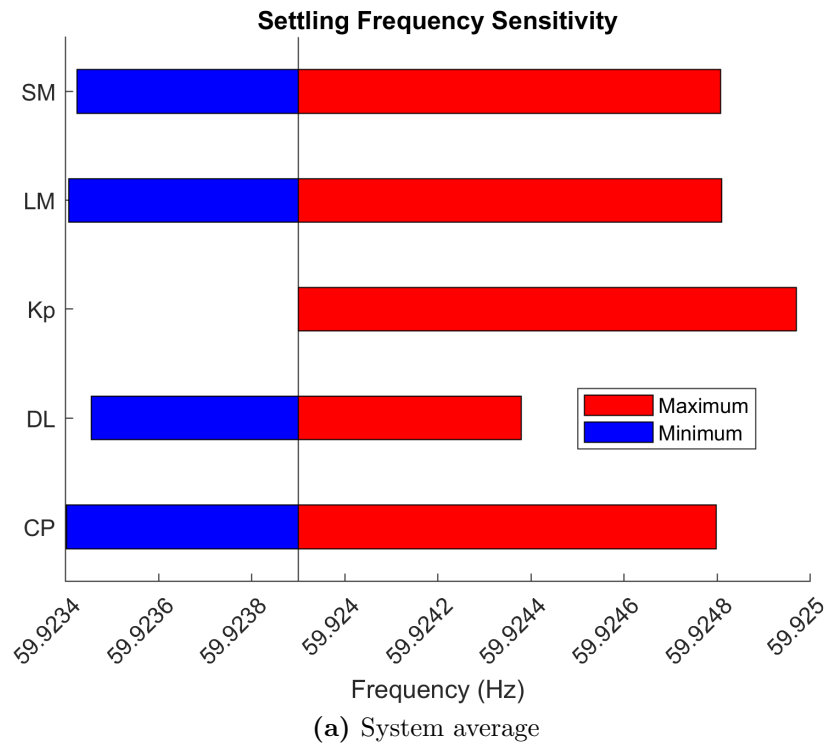
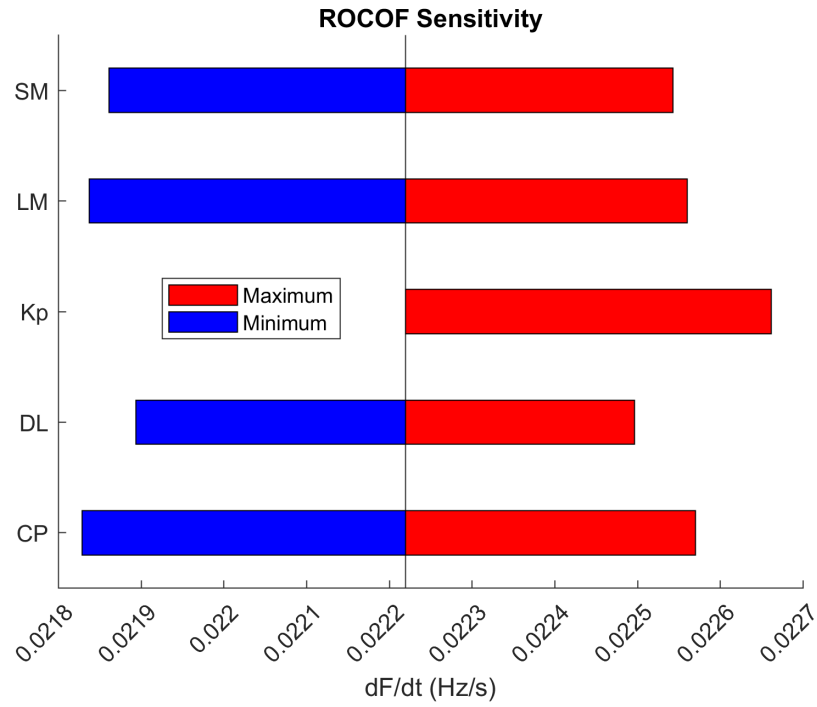
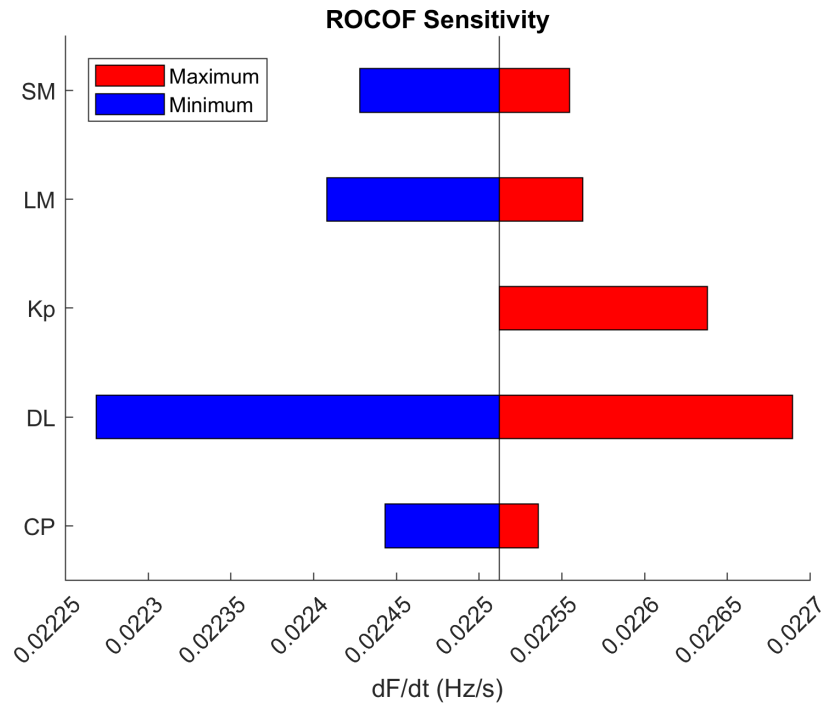


Figure 3.2: Settling frequency sensitivity



(a) System average



(b) Single bus

Figure 3.3: Rate of change of frequency sensitivity

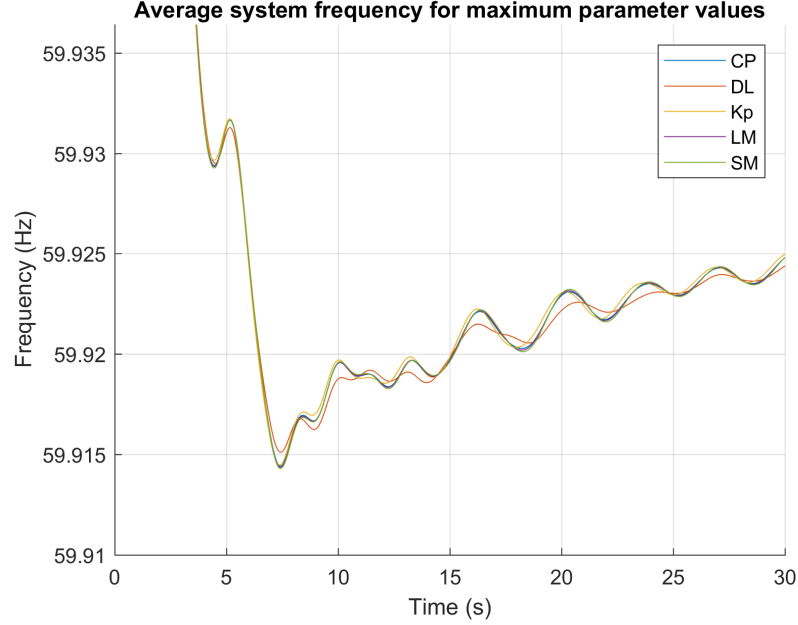


Figure 3.4: System average frequency response for maximum values

of the simulation. The oscillations can be seen in Figure 3.4, where DL exhibits the smallest oscillation amplitude while other parameters oscillate with a larger amplitude. Lastly, the ROCOF sensitivity in Figure 3.3a shows that Kp at maximum has the largest impact while LM and CP at their minimum have the smallest impact. As the ROCOF increases, the severity of the impact also increases since there is less system inertia. Figure 3.3b shows that DL has both the largest and smallest impact to ROCOF at this particular bus. Overall, it appears that some static loads (i.e. DL, Kp) have the most adverse effect on local bus ROCOF while induction motors only have a minor impact.

The real load portion of DL is voltage dependent by order of one and the reactive load is highly voltage dependent by order of 4.5. When DL is decreased by ten percent, the remaining load is automatically increased by the same amount due to the internal calculation of the CLOD model. This means that the real load portion of DL is now converted from

a constant current load to a constant impedance load and thus the voltage dependence is increased. At the same time, the voltage dependence of the reactive load portion will be reduced from 4.5 to two. This change will cause the reactive portion of the load to consume a larger quantity of reactive power for local bus voltage sags, which can contribute to a faster frequency decline [21]. This interaction between DL and Kp is an important example that illustrates the interactions between the CLOD model parameters and is a reason why the sensitivity analysis comparisons are not straightforward. For instance, increasing SM by ten percent results in a lower frequency nadir by about one millihertz while decreasing SM by ten percent results in higher nadir by about 0.3 millihertz. This nonlinearity is due to the model parameter interactions with Kp.

3.3 Conclusion

This chapter studies the sensitivity of several CLOD components to various frequency response metrics. Two cases were observed: the system average frequency and a single bus. Overall, it has been identified that no single load type contributes to a decay across all metrics. Instead, only certain parameters impact certain metrics. An important highlight from this chapter is the convergence issue encountered when setting maximum parameter values. Because of the large-scale system, unforeseen conflicts between the dynamic load model and the rest of the system poses a challenge to provide a stable model under a variety of extreme system conditions. Lastly, interactions between load components of CLOD pose some difficulty to make a uniform comparison between the parameters.

Chapter 4

Model Validation Using the FNET/Grideye Monitoring Network

4.1 Methodology

To evaluate and validate the accuracy of the developed load model, real frequency measurements are taken throughout the EI. Two load model scenarios are compared, assuming a hundred percent PIQZ or ninety-five percent CLOD with five percent PIQZ. The measurements are taken from the FNET/Grideye system, which is a vast network of frequency disturbance recorders (FDRs) that take accurate frequency, voltage, and phase angle measurements at a hundred and twenty volts wall outlets at ten samples per second [22], [23]. The event location is estimated by triangulation using the time difference of arrival of the disturbance among several FDRs. It is important to note that these measurements are from the low voltage, distribution network thus, there are some discrepancies when comparing to the high voltage, transmission network simulations from PSSE.

4.2 Event A

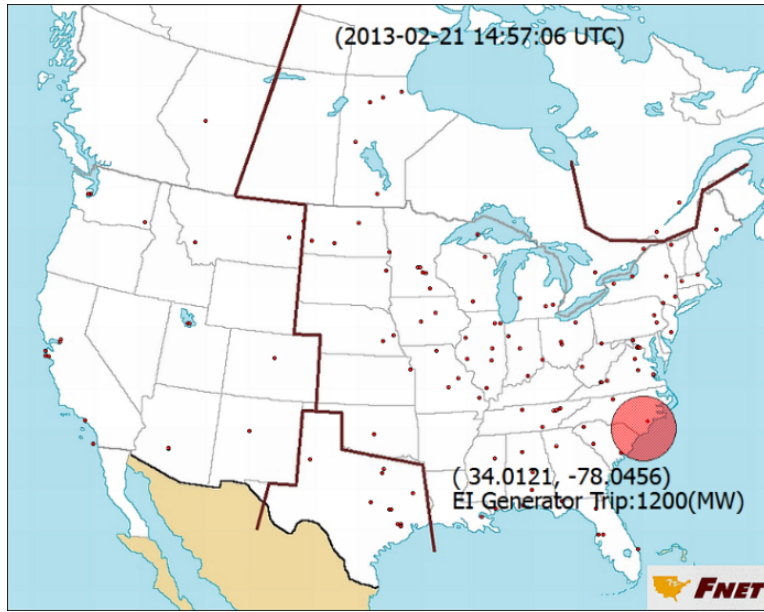
One of the largest events captured by the FNET/Grideye system was a generation trip of about 1,200 megawatts occurring on February 22, 2013 located near North Carolina. Figure 4.1a shows the estimated location and Figure 4.1b shows the recorded frequency during the event. The units that first detected this event were located in Hampstead, NC; Charleston, SC; Aiken, SC; Newport News, VA; Richmond, VA; and Blacksburg, VA. This event caused the EI frequency decline from about sixty hertz to 59.96 hertz.

4.2.1 Results and Analysis

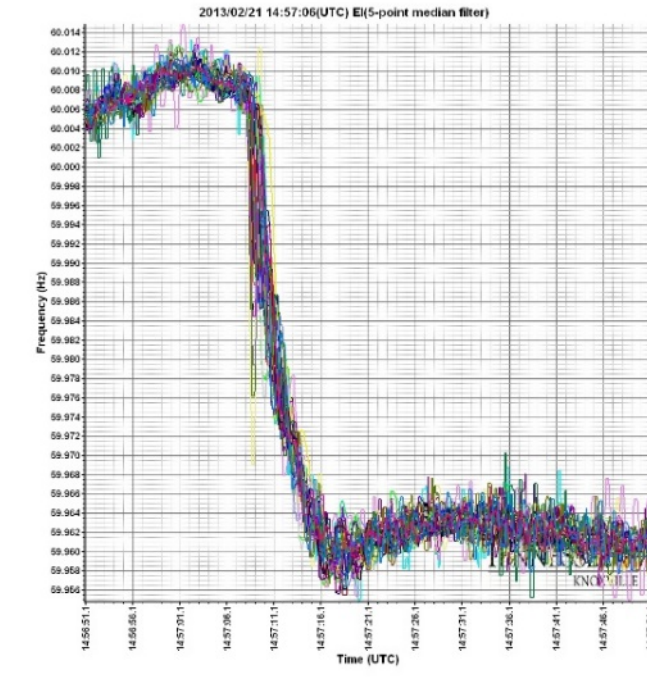
Figure 4.2a compares the measured data from FDRs (green line) to PIQZ model (red) and CLOD model (blue) and in Figure 4.2b is the corresponding frequency error for both models. The typical values of CLOD is used since model tuning was not performed. The results show that CLOD has lower error than PIQZ during the initial frequency decline but a larger error around the settling frequency. This is mainly attributed to the fact that the measured frequency begins to rise after fifteen seconds and thus, PIQZ, which had a higher settling frequency, becomes more accurate. Additional figures for Event A can be located in Appendix A.

4.3 Event B

A second generation trip event, also roughly 1,200 megawatts in size, was recorded around the Maryland-Virginia border on May 28, 2013. The event information is shown in Figure 4.3. The event was first captured by FDRs in Richmond, VA; Newport News, VA; Frederick,



(a) Estimated event location



(b) Event frequency

Figure 4.1: North Carolina generation trip captured by FNET/Grideye using FDR

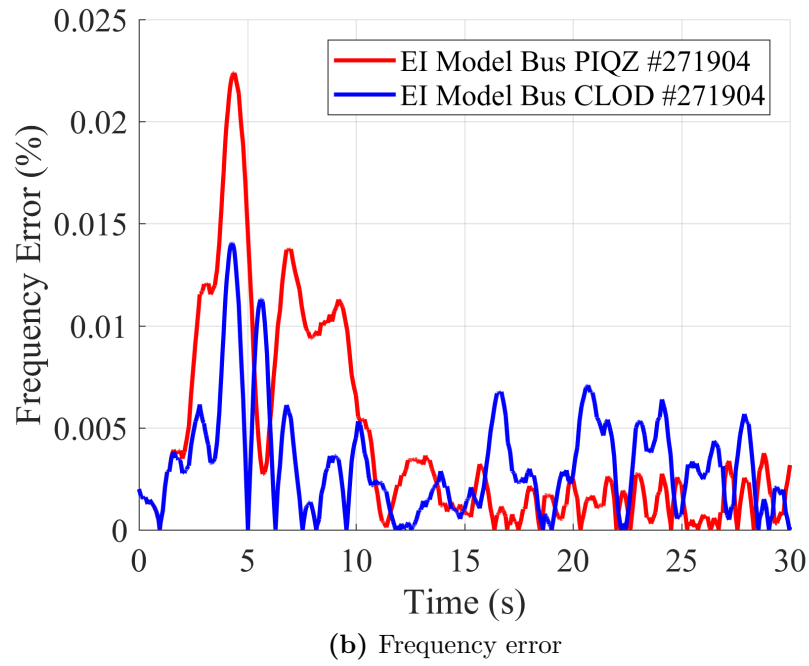
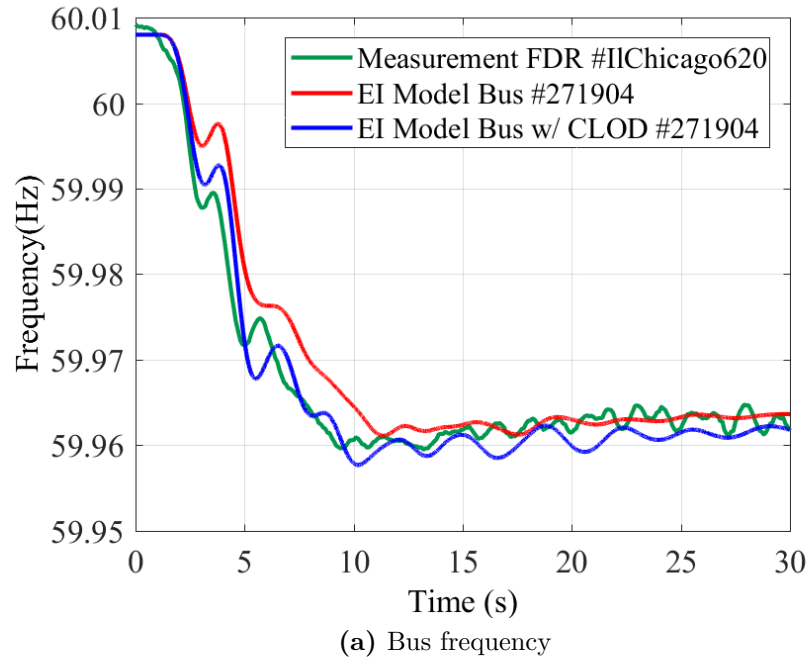


Figure 4.2: Chicago, IL measured data vs. load models

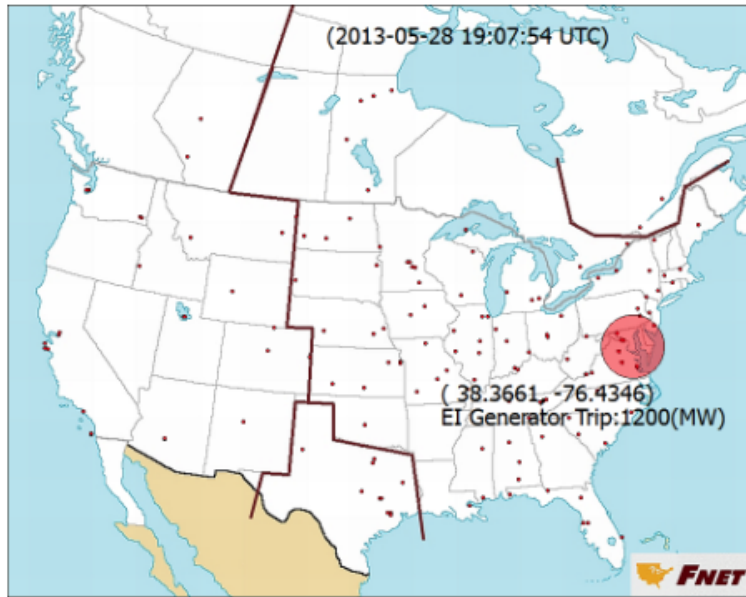
MD; Hampstead, NC; and Blacksburg, VA. The frequency declined from 60.01 hertz to 59.96 hertz. Once again, the load models for PIQZ and CLOD were compared to the frequency measurements.

4.3.1 Results and Analysis

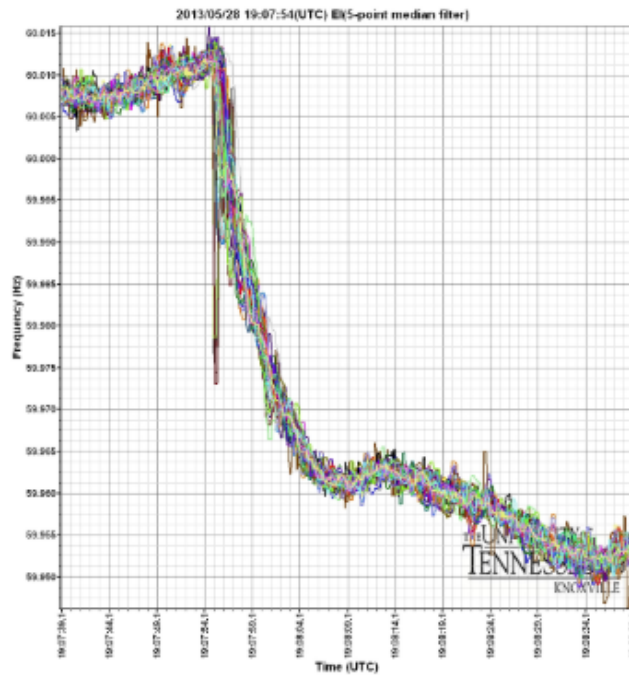
The results in Figure 4.4a and Figure 4.4b show that CLOD has overall improved accuracy from the PIQZ load model. Specifically, CLOD can capture the decline in frequency and settling frequency better than PIQZ. The error difference between CLOD and PIQZ is smaller during the last fifteen seconds of the simulation due to their settling frequencies approaching. Additional figures for Event B can be located in Appendix A.

4.4 Conclusion

This chapter compared the frequency response of the CLOD dynamic load model and the PIQZ static load model to grid-measured frequency data from FDRs. The results from Event A show that CLOD can capture a steep ROCOF but tends to over-estimate the settling frequency and settles lower than PIQZ. The results of Event B show that overall, CLOD performed better than PIQZ at estimating the frequency deviation. Considering both cases, CLOD has better overall accuracy at capturing the real frequency response.



(a) Estimated event location



(b) Event frequency

Figure 4.3: Virginia generation trip captured by FNET/Grideye using FDR

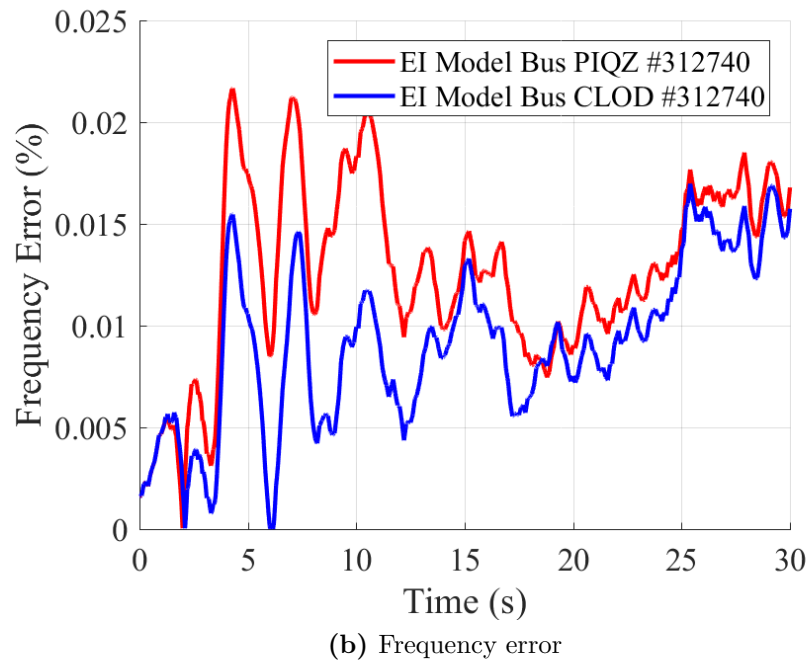
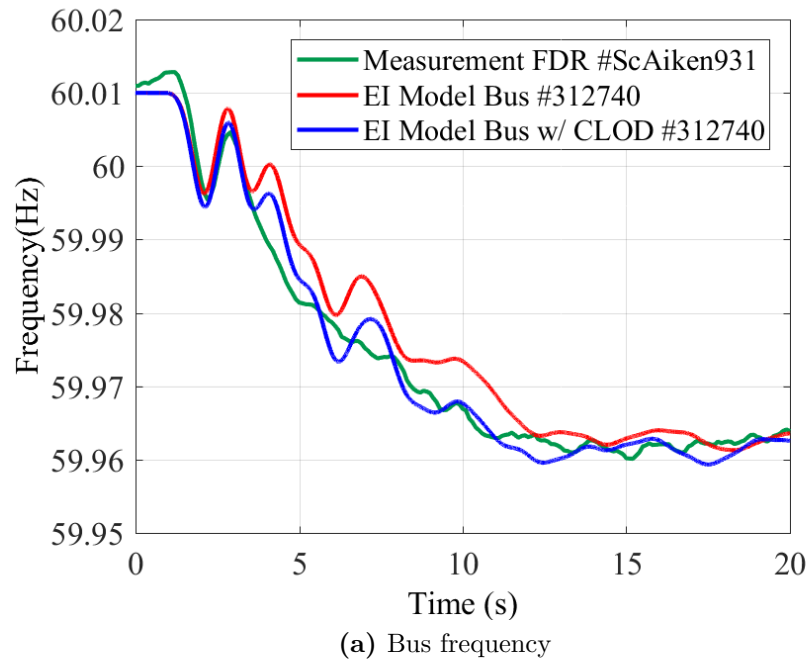


Figure 4.4: Aiken, SC measured data vs. load models

Chapter 5

Dominion Energy Load Modeling

5.1 Motivation

Dominion Energy (DE) is an investor-owned utility serving the greater area of Virginia and parts of North Carolina. Like all utilities, DE must comply with reliability standards from the North American Electric Reliability Corporation (NERC), a regulating authority for the United States grid. NERC reliability standard TPL-004-1 requires utilities to implement dynamic load models. The models must include induction motor behavior during peak summer conditions. With the efforts DE has already made with developing their load models, this chapter will serve as a process to methodically improve the load model assumptions. This is achieved by basing assumptions on several data sources from internal and external parties such as the customer composition on a feeder-basis, the end-use load for each customer, and climate region for the utility area.

5.2 Data Sources

5.2.1 Load Aggregation and Modeling

Millions of diverse loads are connected to the distribution system and to model all system load would be impractical. Instead, the load is aggregated at the substation and modeled as a larger block of loads in PSSE. Due to the aggregation, it is a simple process to apply a dynamic model to a load bus but difficulties arise when determining which dynamic load model to use and then gathering the necessary data to parametrize the load accurately. Several load models can represent induction motor behavior such as CLOD, CMLD, and CIM5. A detailed explanation of the load models can be found in 1.2.2. The first two models can represent a composition of loads at a bus while the latter represents induction motor only. Although CLOD suffers from model inaccuracies [14], it only requires eight parameters making it a typical starting model for representing dynamic load. However, because of similarities in the structure of CLOD and CMLD, both will be investigated in this chapter.

5.2.2 Customer Composition

To establish accurate load modeling, it is fundamental to gather the necessary load data from various resources. The customer composition data generally comes from distribution planners and lists several energy consumer sectors. Customer composition typically refers to residential, commercial, or industrial (RCI) consumers of electricity. However, DE elects to breakdown these consumers further into specific end-users such as resale, federal, municipal, etc. For this method, the additional consumers were accumulated into one of the RCI

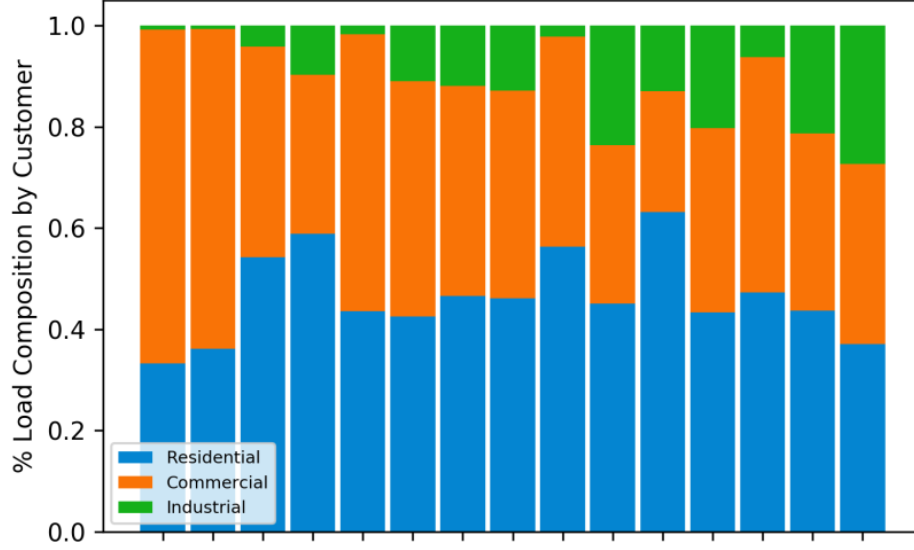


Figure 5.1: Average load zone composition

consumers to simplify the data and keep with the typical convention. The composition, which is given by feeder, will correspond to a PSSE bus and load zone. Once the bus is known, an average customer composition for each load zone in the territory can be determined. Applying a single load model to the entire DE area is too general but having a load model specific to each bus may provide unnecessary detail. Alternatively, by knowing the average customer composition by load zone, applying a single load model to each zone is manageable; unique characteristics of the load zone is preserved but not exaggerated. The composition by load zone is shown Figure 5.1.

Additional research is introduced in Appendix B as a new method to calculate the customer composition without the need for collecting and aggregating customer load surveys. In this new method, daily load curves from substation transformers are used to cluster the feeders using a soft-clustering technique known as fuzzy-clustering.

5.2.3 End-Use Load Consumption

Another fundamental data source is end-use load consumption, which gives a detailed account of how consumers use energy and to what extent. This is crucial information to quantify the impact of commonly used, individual loads (e.g. air conditioning) have on the grid that can be used to estimate load model parameters from a bottom-up approach. Some utilities may elect to conduct a customer load survey that provides detailed load usage specific to their service area but this is a time consuming process. In lieu of this data, the Energy Information Administration (EIA) collects annual electricity consumption for RCI sectors every four years by census or climate region. The most recent Residential Energy Consumption Survey (RECS) is from 2015, the Commercial Building Energy Consumption Survey (CBECS) is from 2012, and the Manufacturing Energy Consumption Survey (MECS) is from 2014. The survey data includes information for several loads associated with space heating but because these loads are not typically used during summer, they were removed from the analysis. Using the CLOD model, for residential consumers, small motor is considered the aggregate of air conditioning, air handlers for cooling, ceiling fans, dehumidifiers, clothes washers and dryers, refrigerators, freezers, dishwashers, pool pumps, and hot tub pumps. This yields 51.4 percent of the load on an annual basis as small motor. All TVs and related is modeled as constant power and comprises 8.9 percent of the annual load. Lighting is a direct conversion to the discharge lighting load component and constitutes 14.25 percent of the load consumption. The remaining load will be modeled as constant impedance in lieu of a more accurate model. A similar process is followed for assigning a load model composition for commercial and industrial consumers. The CLOD composition

of RCI consumers is shown in Figure 5.2, Figure 5.3, and Figure 5.4, respectively. Figure 5.2a, Figure 5.3a, and Figure 5.4a shows the survey load data while Figure 5.2b, Figure 5.3b, and Figure 5.4b shows the approximate CLOD composition for the corresponding customers.

5.2.4 Weather and Climate Impact on Load Consumption

One of the factors that affects load consumption in commercial and residential consumers is weather. Cooling load is highly dependent on outdoor temperature and will reach high penetration levels during the summer season. Because of this, it is appropriate to view the load consumption of residential and commercial consumers through the lens of climate region data, provided in the EIA data. However, industrial load is not filtered by climate region and thus, the census region is used. This does not present much concern for comparing the data since industrial load is more robust to weather changes [24]. Although using climate region data can account for some variations of load use due to weather, this is an average across a large geographic region of the U.S. The service area of DE traverses several geographic topologies from coastal to mountainous that have implications on the regions' weather. To reduce further modeling inaccuracies, these topologies are considered in the weather analysis.

To account for temperature change during summer for the three regions, cooling degree-days (CDD), which is a measure of how many degrees the average temperature of a day varies above a comfortable, base temperature (sixty-five Fahrenheit), is used to approximate variations in the cooling load. To account for the geographical regions, several locations with CDD historic data are needed. The National Oceanic and Atmospheric Administration (NOAA) has CDD data for four cities (Lynchburg, Roanoke, Norfolk, and Richmond) within

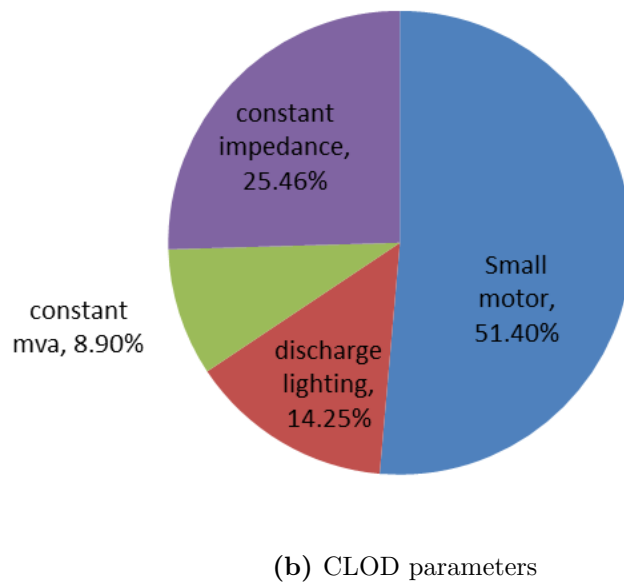
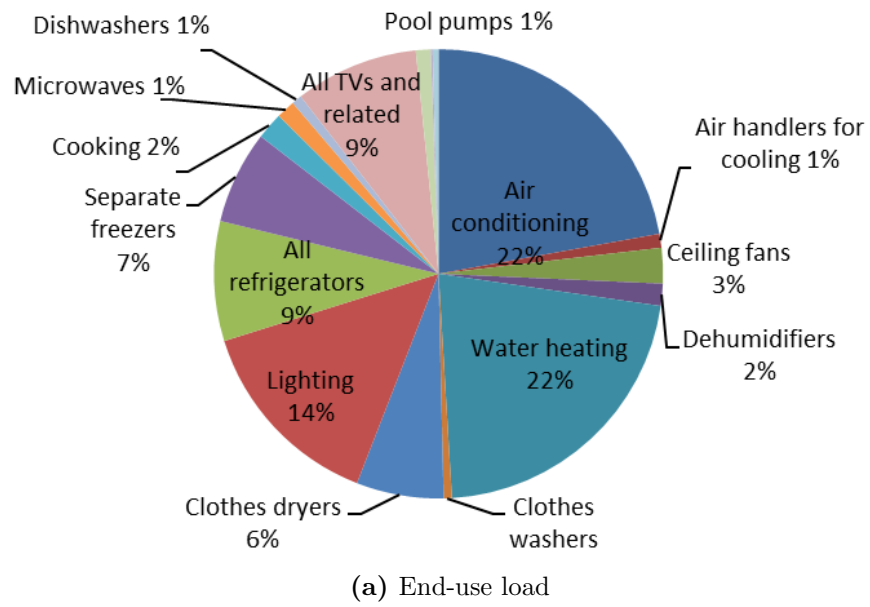
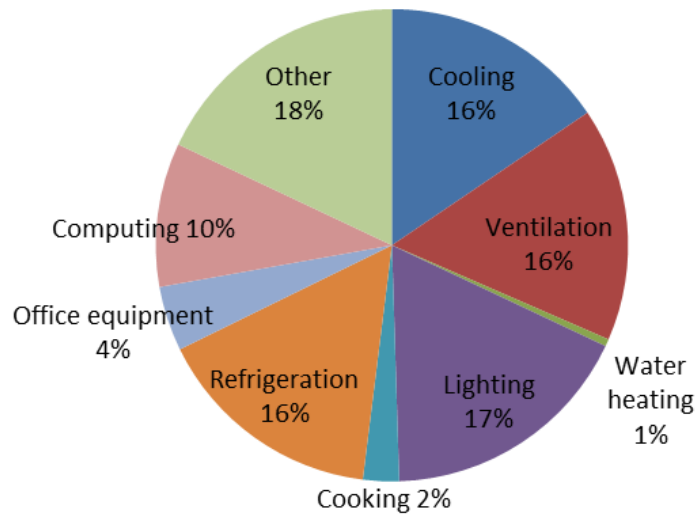
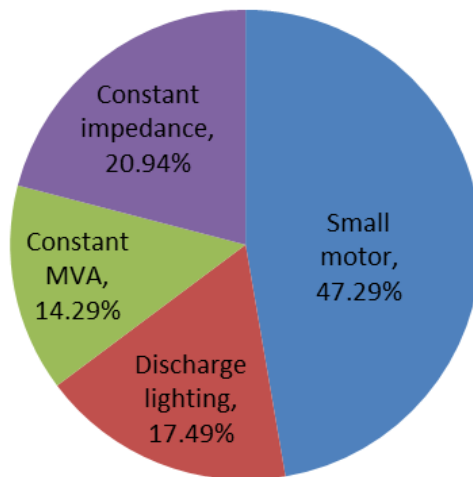


Figure 5.2: 2015 annual residential end-use breakdown for mixed-humid climate



(a) End-use load



(b) CLOD parameters

Figure 5.3: 2012 annual commercial end-use breakdown for mixed-humid climate

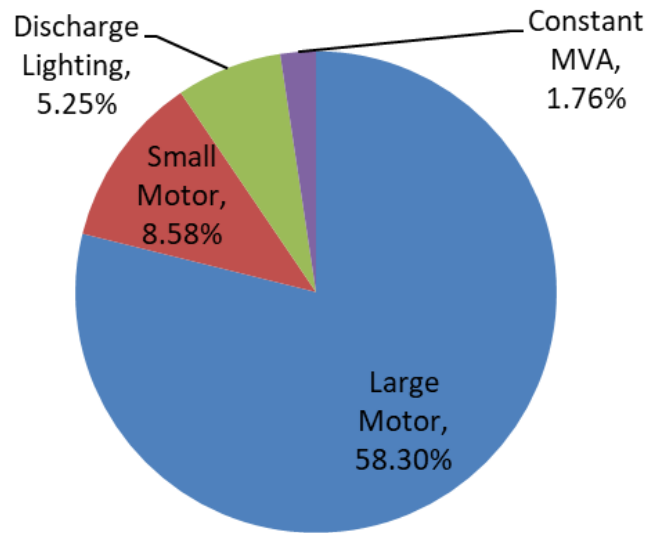
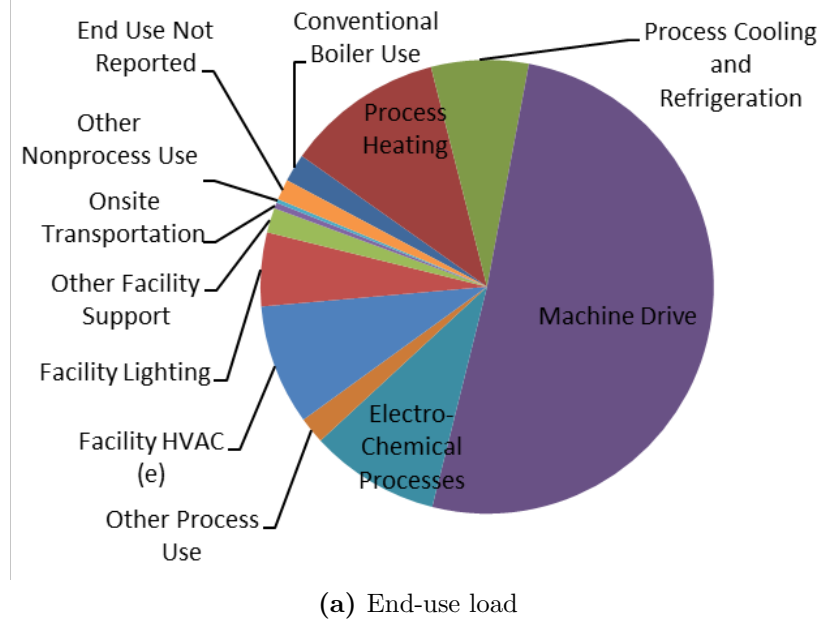


Figure 5.4: 2014 annual industrial end-use breakdown for south census region

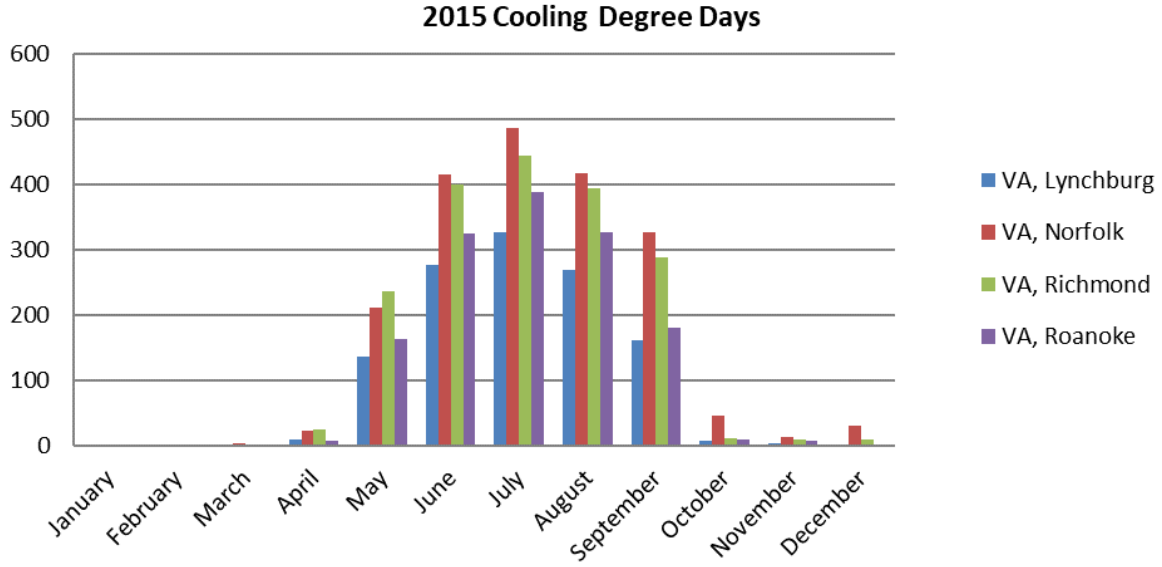


Figure 5.5: Annual cooling degree days of four Virginia cities

and surrounding the DE service area. The annual CDD for the 2015 is shown in Figure 5.5. The highest number of CDDs occurs for the months of June to August.

The calibration is done by dividing the annual cooling load in the residential and commercial sector by the respective year's annual CDD per city. This yields the consumption of cooling load per degree-day per city that is then multiplied by the total CDD during summer of 2017 per city. The remaining end-use load will be considered evenly distributed among all twelve months in a year. The calibration process is detailed in Equation 5.1 and Equation 5.2.

$$CoolLd_c = CoolLd_S \times \frac{\sum_{summer} CDD_{c,summer}}{CDD_{c,annual}} \quad (5.1)$$

Where the summer cooling load for each city, $c = Roanoke, Richmond, Lynchburg, Norfolk$ is related to the annual cooling load of the survey, $S = RECS, CBECS$, by a ratio of the CDD of the summer months, $summer = June, July, August$ for each city, and the annual

total CDD of the region.

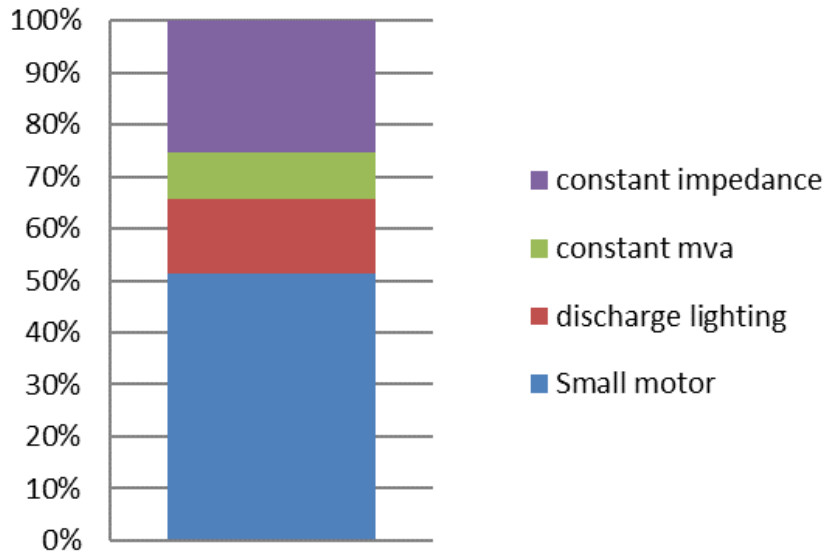
$$OtherLd_c = \sum_{m=1}^3 OtherLd_{S,m} \quad (5.2)$$

Where the remaining load during summer is the sum of the monthly non-cooling load for any three months, m of the survey, S . It is assumed that non-cooling load will not vary throughout the year.

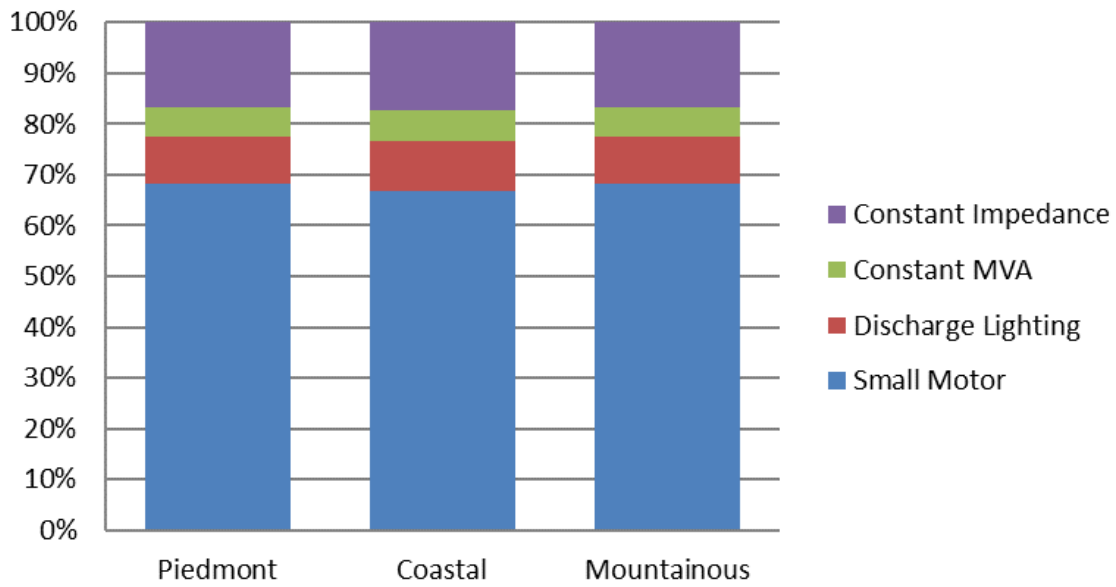
Lastly, the results of the climate and weather calibration impact to the CLOD model parameters are shown in Figure 5.6 and Figure 5.7 for residential and commercial consumers, respectively. It can be seen that climate and weather has an impact to the overall penetration of cooling load but variations within the region are minimal. Thus as a best practice, it is beneficial to model load within the season of interest but depending on the geographic size, further calibration may not be necessary.

5.2.5 Data Center Load

In the past decade, a larger need for data storage has become apparent as more people store and create data online. Data center growth has exploded to meet this need and utilities must now deal with these large, block loads on their system. Because of the sizable demand they require, data centers are typically fed through dedicated circuits. Data centers are unique loads on the system since they are predominantly power electronic loads and have a constant power demand throughout the year. Their dynamic behavior also varies significantly from other common load types (i.e. RCI) because of their strict requirements for a steady input source. If any significant disturbance occurs on the grid, they will disconnect and transfer to an uninterruptible power supply, thus reducing the system load drastically in a short period.

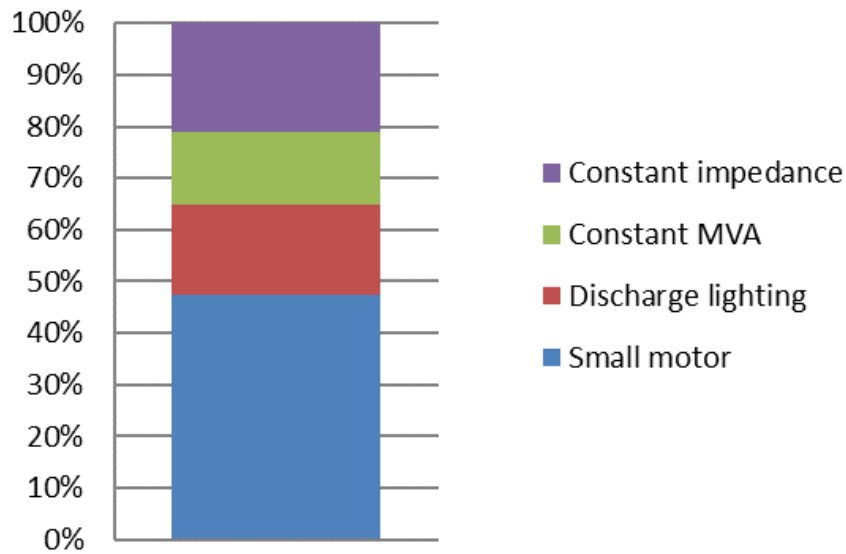


(a) Residential annual model

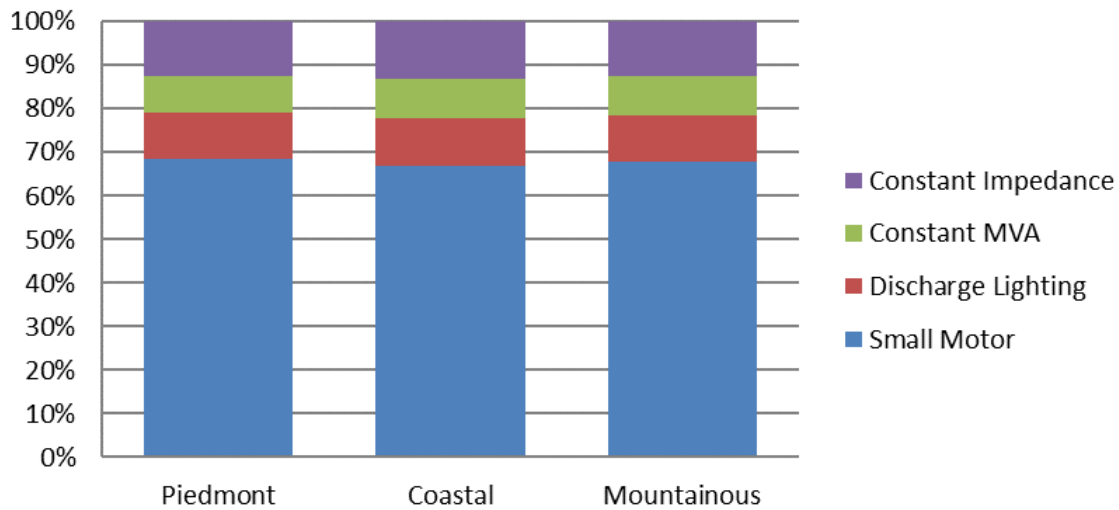


(b) Residential summer model

Figure 5.6: Residential CLOD parameters affected by weather



(a) Commercial annual model



(b) Commercial summer model

Figure 5.7: Commercial CLOD parameters affected by weather

Table 5.1: Data center CLOD parameters

Large Motor (%)	Small Motor (%)	Discharge Lighting (%)	Constant Power (%)	Remaining Load (%)	K_p of Remaining Load
0	15	0	80	5	2

These characteristics make it difficult to include in the RCI composition and need to be modeled explicitly. Although detailed data could not be obtained for a large sample of data center energy usage, an approximate consumption is listed in Table 5.1.

To model data centers, knowledge of the location of the data center in relation to the grid as well as the approximate consumption is needed. By disaggregating the data center load from the already modeled PSSE load, the appropriate dynamic model can be applied depending if it is a data center load or a general load.

5.3 Dynamic Load Models Developed

By considering consumer composition, consumer end-use load consumption, weather, and data centers, CLOD model parameter assumptions can be improved. The legacy model for CLOD, shown in Figure 5.8a, was previously used to model the entire DE system. With the additional data sources considered, the updated load models per load zone and for data center loads are shown in Figure 5.8b. It can be seen that the amount of large motor penetration varies across each load zone depending on the presence of industrial consumers. The impact of this primarily reduces the penetration of small motor and the total motor

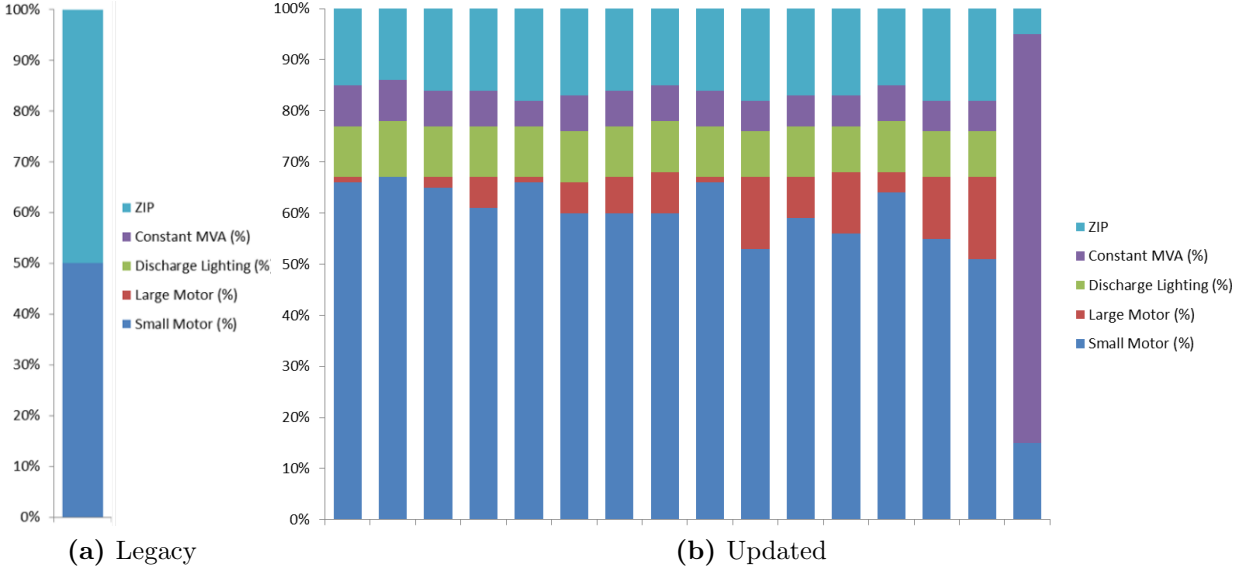


Figure 5.8: CLOD model parameters

percentage remains mostly unchanged throughout the territory. Vice-versa, the other load components maintain a constant penetration level. The data center specific load model is also apparent.

Although the data presented in this chapter focuses on model parameters for CLOD, the parameters for CMLD can also be improved by considering the recommended parameters from NERC and then adjusting the composition of the four induction motors and power electronic components. The result is shown in Figure 5.9, where the legacy model assumptions are applied to the entire DE territory and the updated model is on a load zone basis. The data center load was neglected for CMLD due to lack of detailed data about the types of motors present, which is required for CMLD.

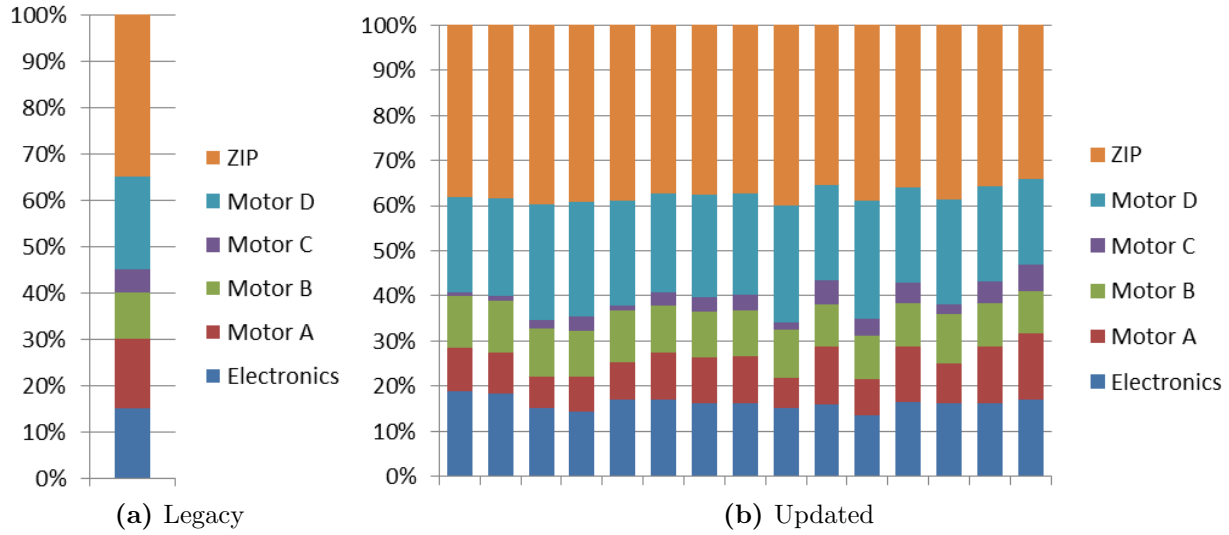


Figure 5.9: CMLD model parameters

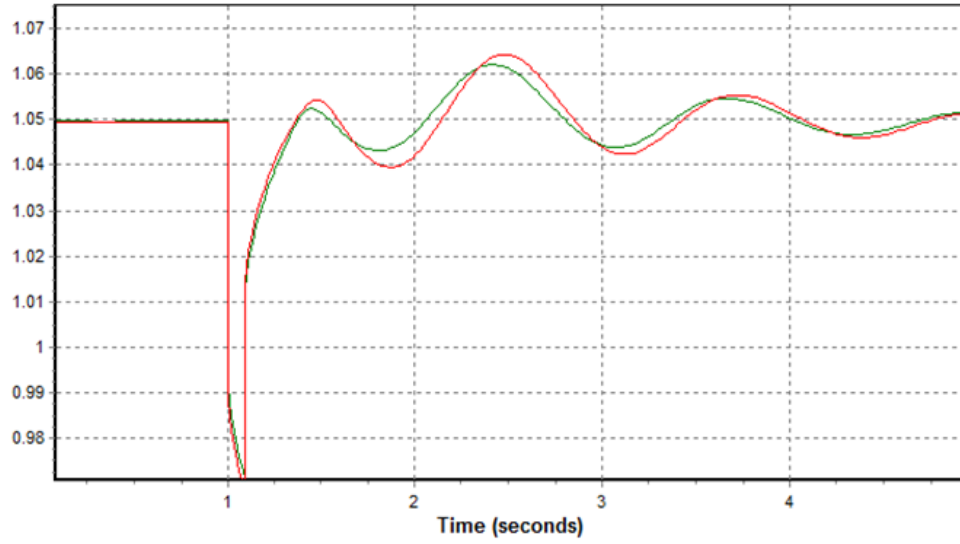
5.4 Case Studies Using Developed Models

Several studies were performed using the developed load models and some of the results are presented in this section. Unlike the majority of this thesis, these studies focus on voltage stability using dynamic load models.

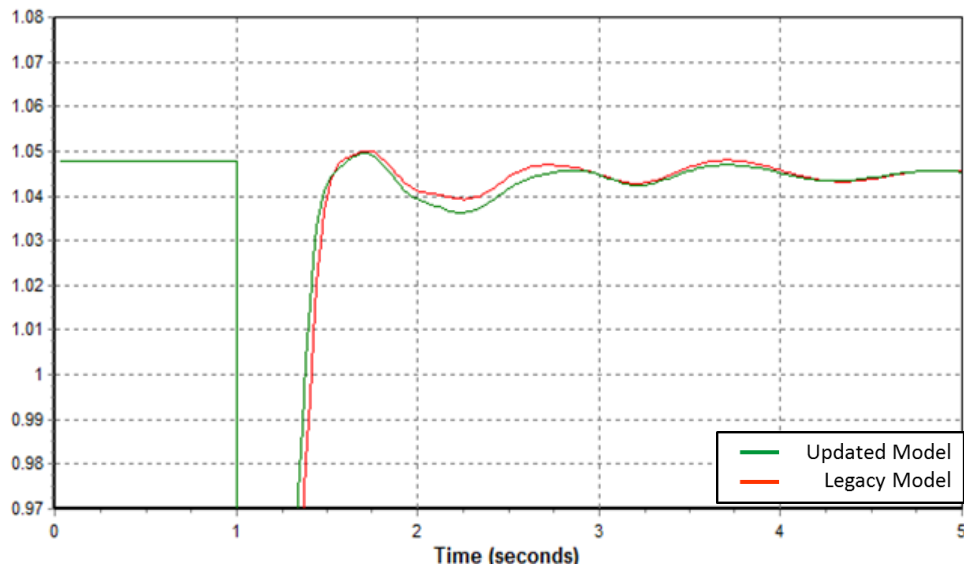
5.4.1 Simulated Fault Case

CLOD

With a three-phase, five hundred kilovolt fault simulated in PSSE, the results comparing the legacy and updated CLOD model are shown in Figure 5.10. The results show that although the modeling assumptions have been improved, only minor differences exist in the voltage recovery time. The updated model exhibits reduced oscillation amplitude.



(a) Bus voltage far from fault



(b) Bus voltage near to fault

Figure 5.10: CLOD model comparisons for three-phase fault

CMLD

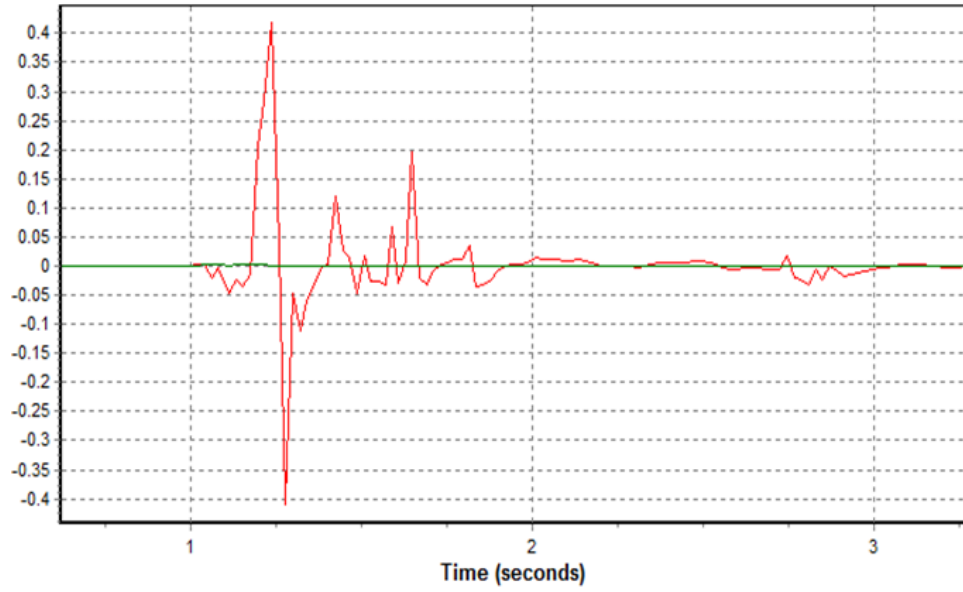
The legacy CMLD model previously developed used slightly modified NERC recommended parameters. For a specific fault case, the model was unstable and collapsed during simulation. To investigate this further, the CMLD composition was modified using information regarding the DE system similarly to the CLOD shown previously. The two models are compared in Figure 5.11 for a three-phase fault. The results show that the updated model is more stable and gives reasonable results.

5.4.2 Fault Sensitivity Study of CLOD

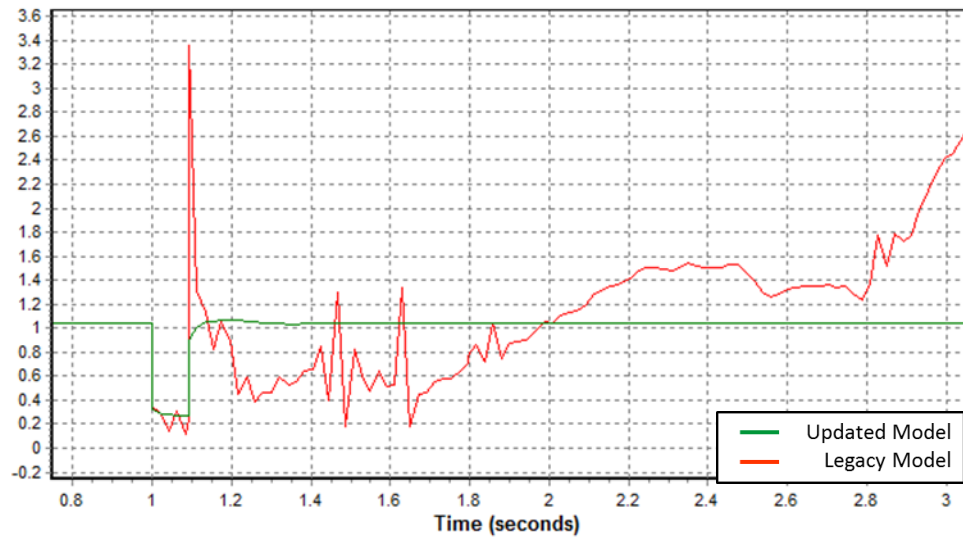
To characterize the response of the CLOD model, a sensitivity study of its large motor and small motor is carried out with respect to three-phase faults. For this study, all load components were assumed to be zero percent, except for the motor being studied. The CLOD model was applied to the entire DE area.

Small Motor

The small motor sensitivity ranged from thirty percent to eighty percent and the results are shown in Figure 5.12. The results show that the small motor model is stable throughout the entire range of parameter inputs. With increasing small motor percentage, there is a non-linear delay for the voltage recovery. This is due to the stalling of small motors caused by local low voltage. As the motor stalls, power consumption will increase and further depress the voltage until the motors disconnect.

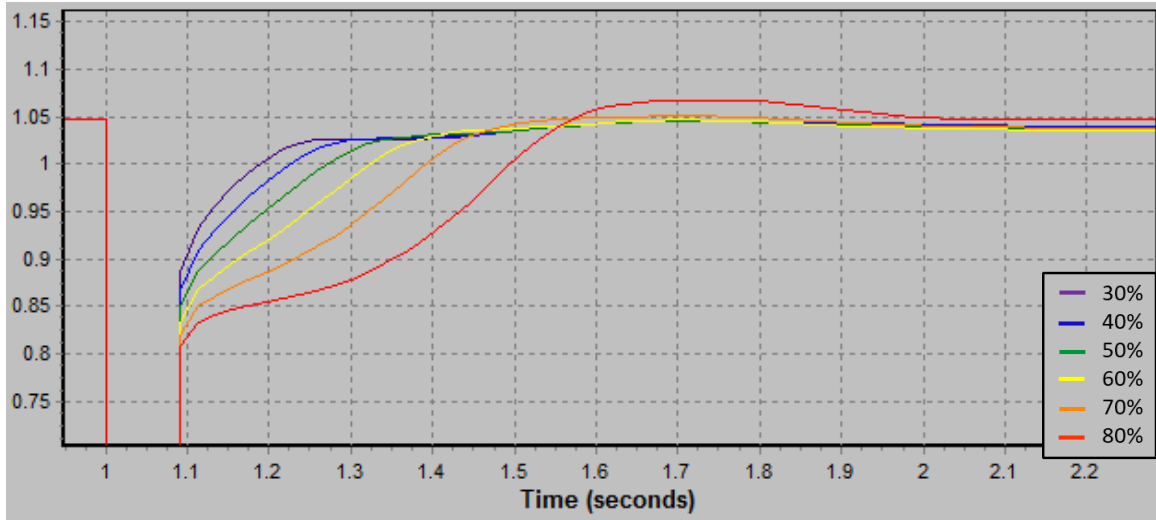


(a) Bus voltage far from fault

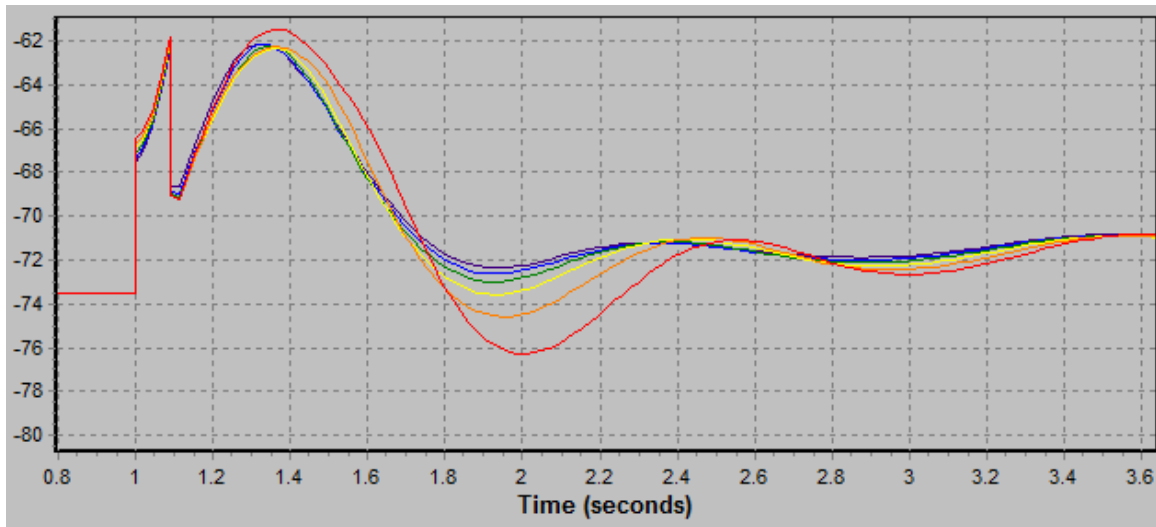


(b) Bus voltage near to fault

Figure 5.11: CMLD model comparisons for three-phase fault



(a) Bus voltage



(b) Bus angle

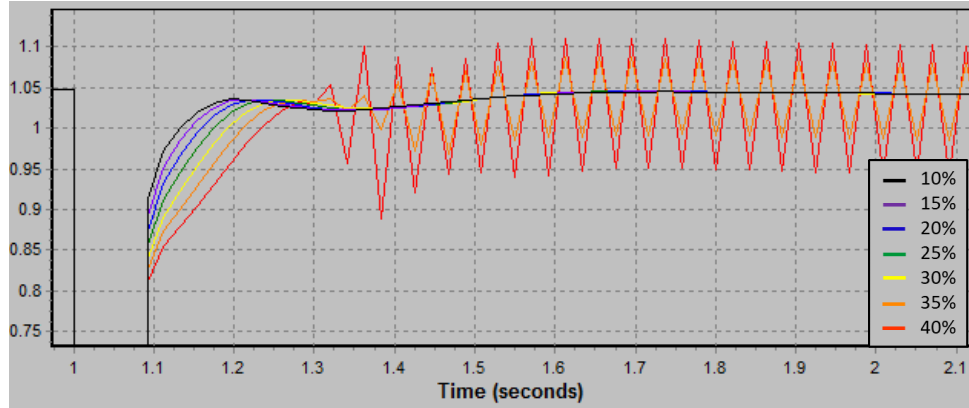
Figure 5.12: Small motor sensitivity study for three-phase fault

Large Motor

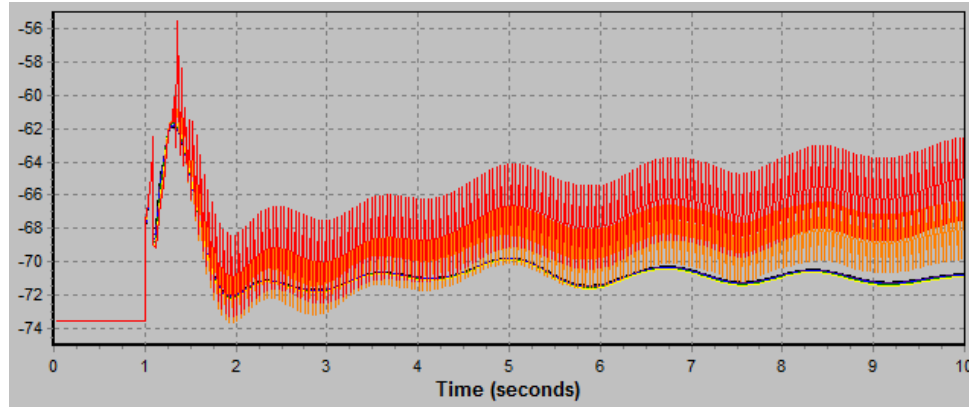
The large motor composition was varied from ten percent to forty percent. Results in Figure 5.13 show that large motor penetration above thirty percent becomes unstable. The instability was caused by a small generator (see Figure 5.13c) located several buses and branches away from the fault was out of step due to absorbing maximum reactive power at its location. For comparison, the rotor angles of two stable machines close to the fault location are shown.

5.4.3 Validated Fault Case

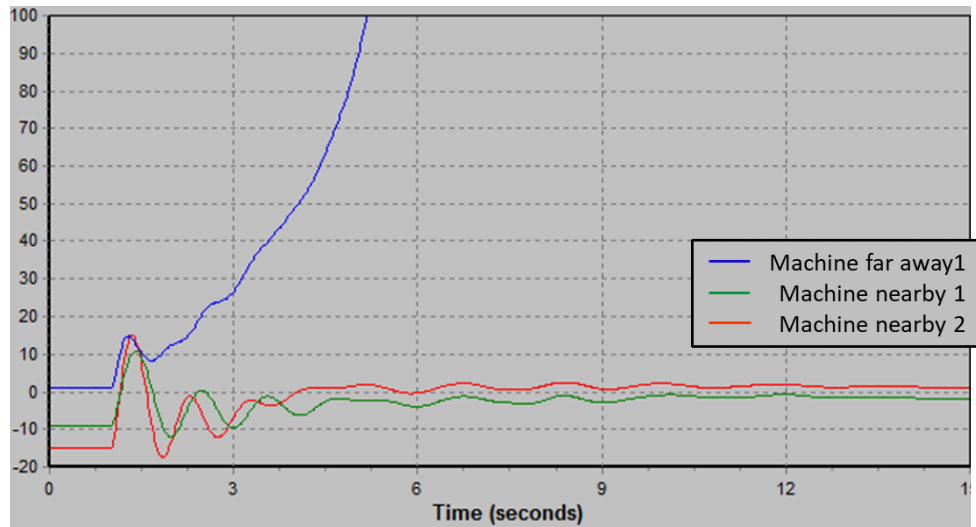
Any developed model must be validated against real-system events to ensure there is a reasonable response from the model. Because the model for CLOD incorporated summer 2017 data and because PSSE can only study three-phase faults, there were limited real-system events that matched this description. The results of validating with such an event are shown in Figure 5.14. The real data from the fault recorder shows a slower decay in the bus voltage that is not captured using PSSE for any of the models since applied faults are an instantaneous switch off. Because of the simulation behavior, the load models cannot accurately capture overall shape during the fault. However, the CMLD model provides the best results to capture the point at which voltage recovery begins although it overshoots the settling voltage. CLOD overall predicts the response more accurately although has a voltage bias of about 0.05 per-unit higher than the real event after recovery.



(a) Bus voltage



(b) Bus angle



(c) Machine rotor angles for large motor at thirty-five percent penetration

Figure 5.13: Large motor sensitivity study for three-phase fault

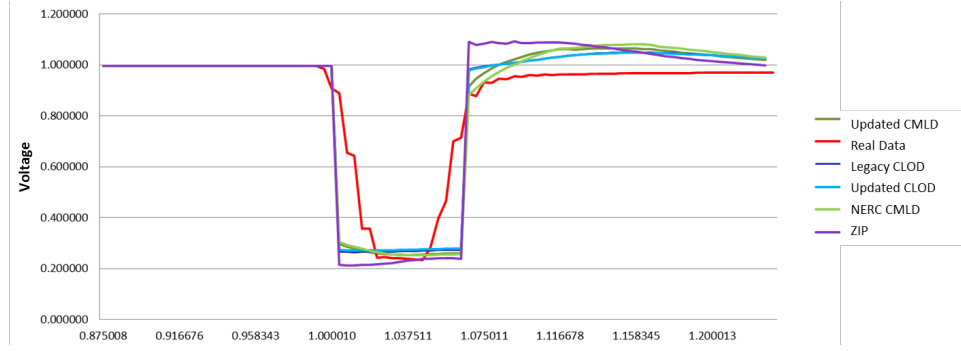


Figure 5.14: Model validation with three-phase fault measurements

5.5 Conclusion

This chapter discussed the efforts made to improve load model assumptions within the Dominion Energy territory of EI by considering available data resources. Overall, the load models can improve the systems response to three-phase faults as was seen in the validation section of this chapter. However, applying dynamic load models increases the complexity of the system and may yield numerical errors in simulation that must be fixed by the engineer.

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Appendices

A Model Validation Frequency and Error Plots In Support of Chapter 4

A.1 Event A

The following figures are from Event A studied in Chapter 4: a generation trip nearby to North Carolina, USA.

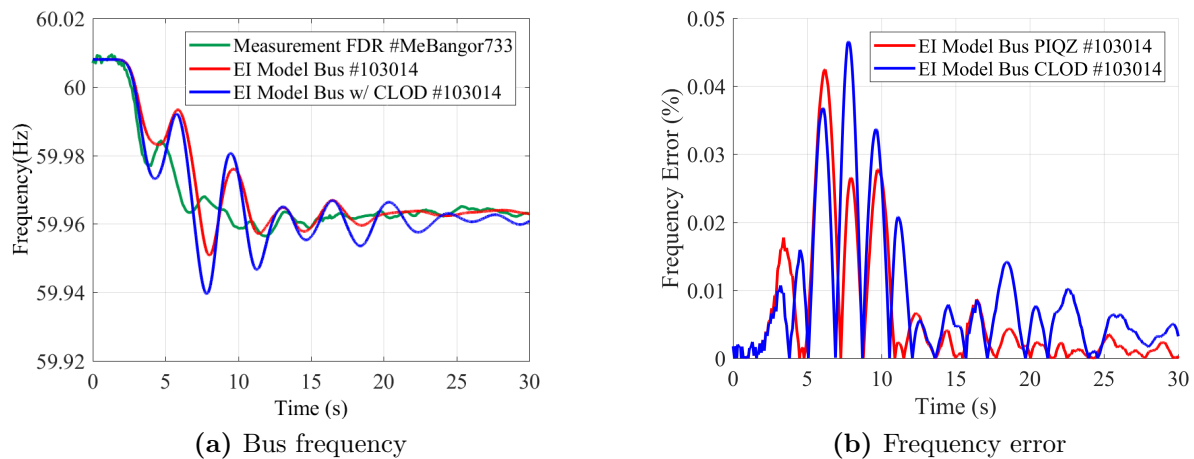


Figure A.1: Bangor, ME measured data vs. load models

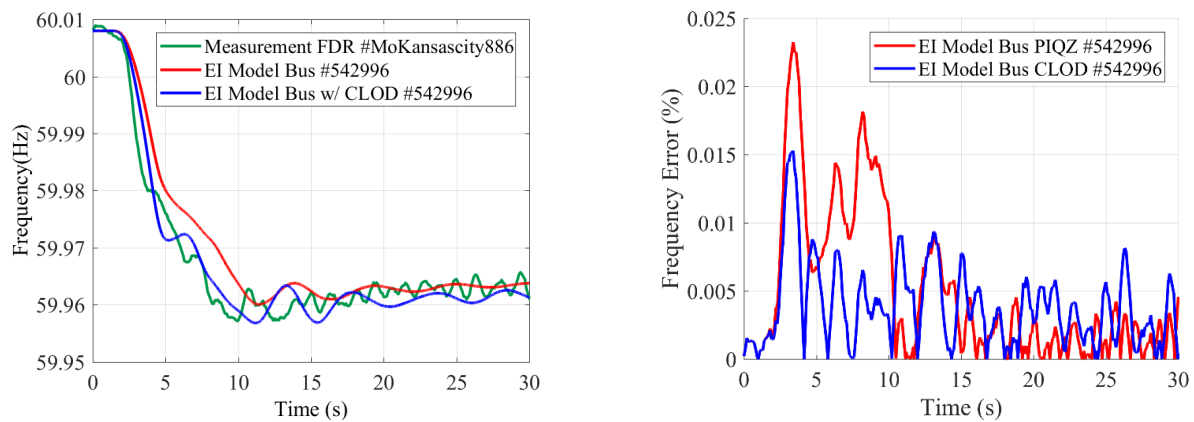


Figure A.2: Kansas City, MO measured data vs. load models

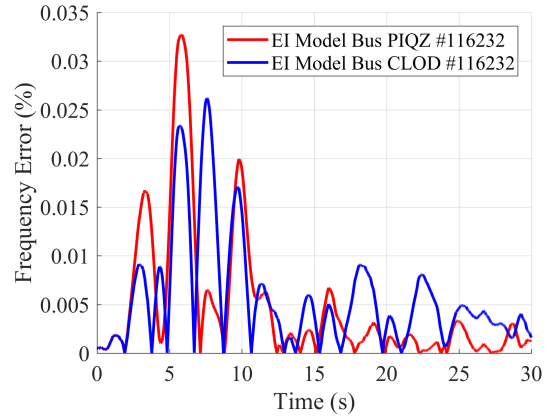
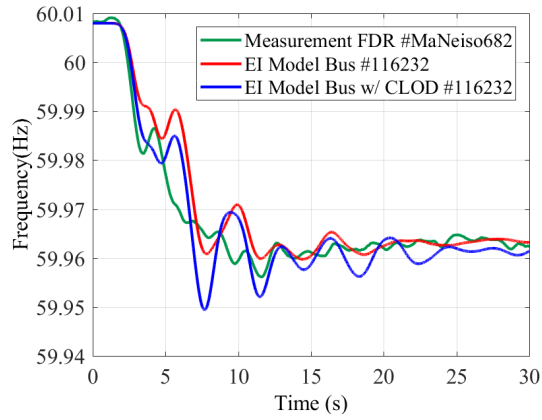


Figure A.3: NEISO (MA) measured data vs. load models

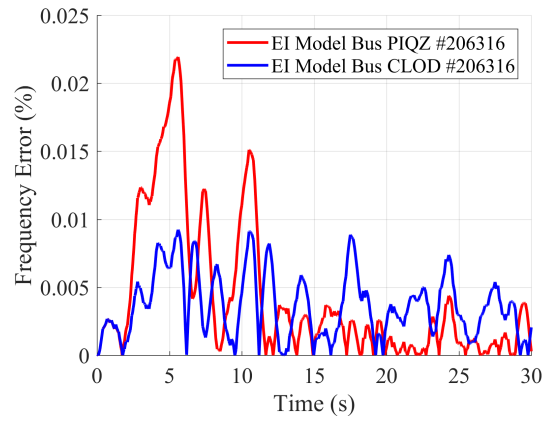
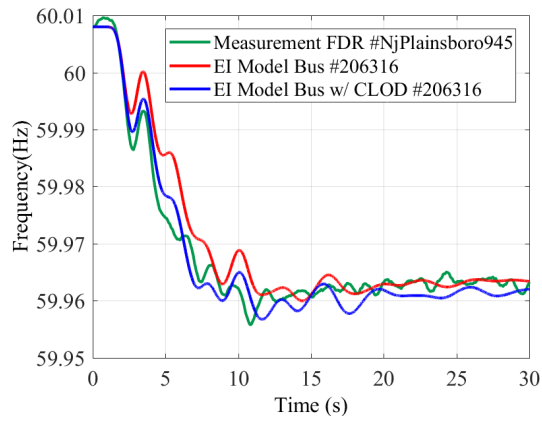
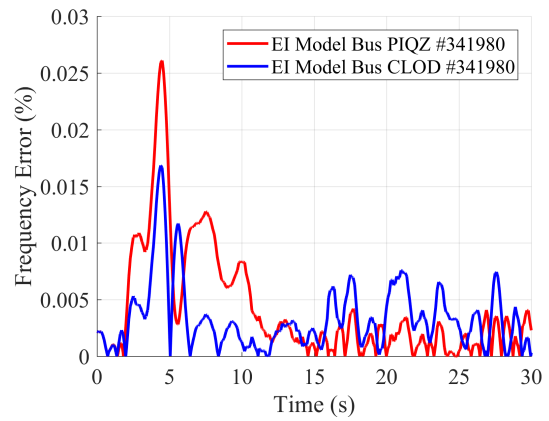
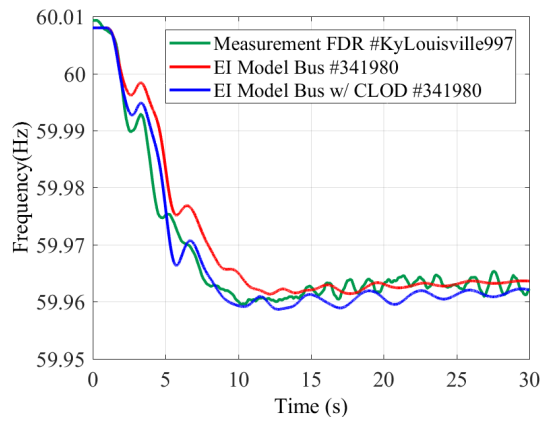


Figure A.4: Plainsboro, NJ measured data vs. load models



(a) Bus frequency

(b) Frequency error

Figure A.5: Louisville, KY measured data vs. load models

A.2 Event B

The following figures are from Event B studied in Chapter 4: a generation trip nearby to the Maryland-Virginia Border.

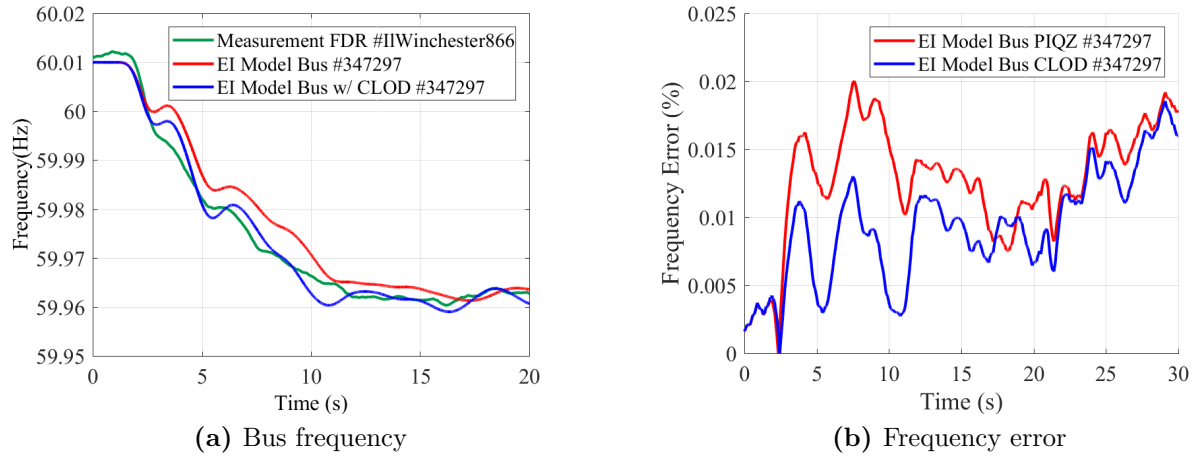


Figure A.6: Winchester, IL measured data vs. load models

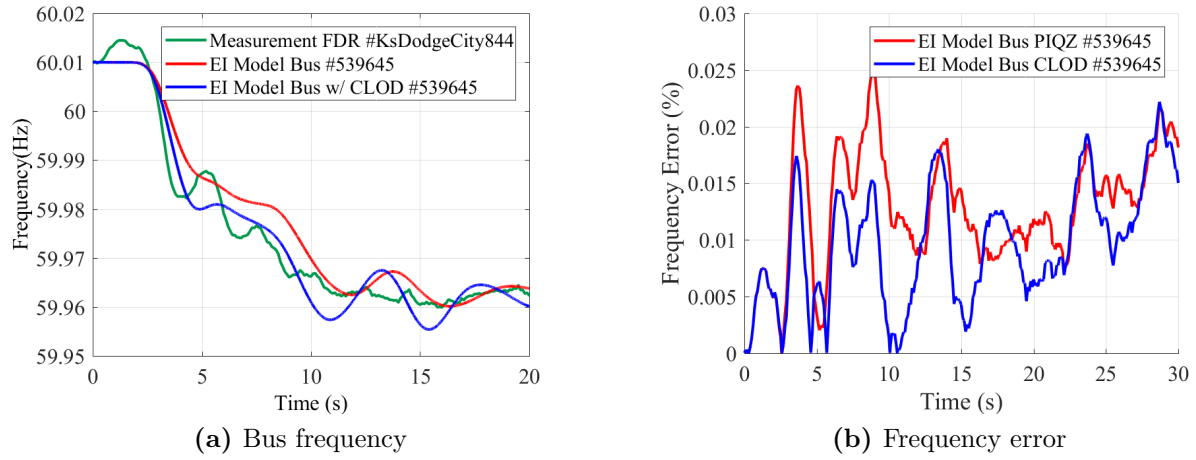
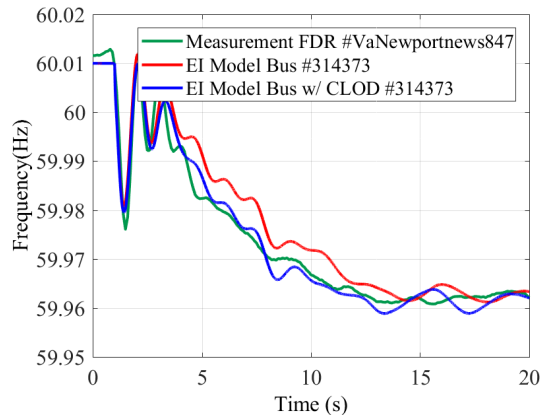
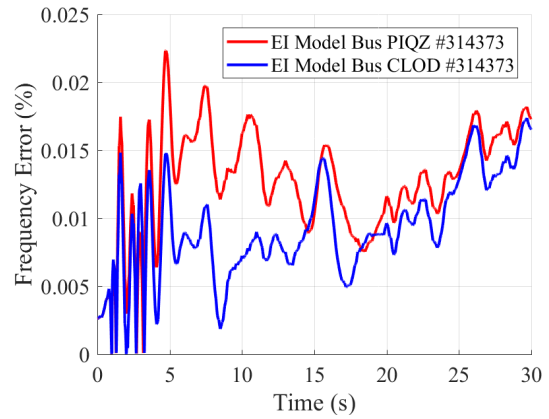


Figure A.7: Dodge City, KS measured data vs. load models

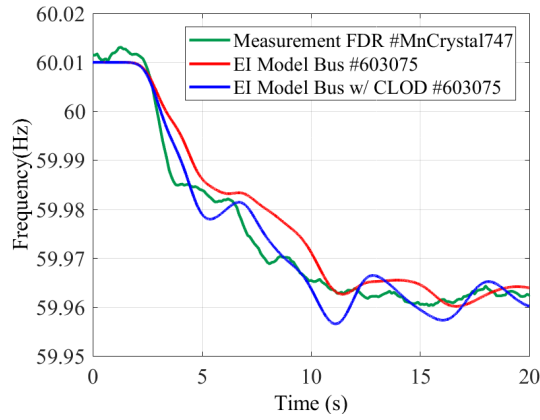


(a) Bus frequency

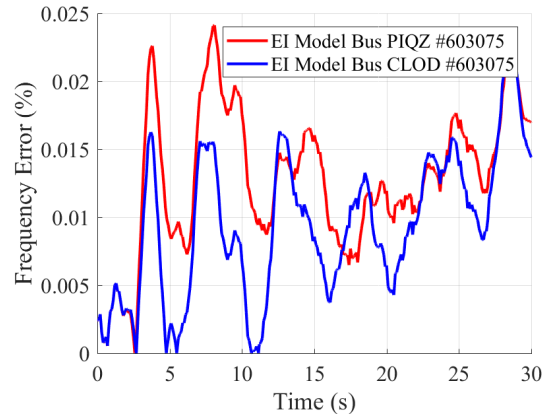


(b) Frequency error

Figure A.8: Newport News, VA measured data vs. load models

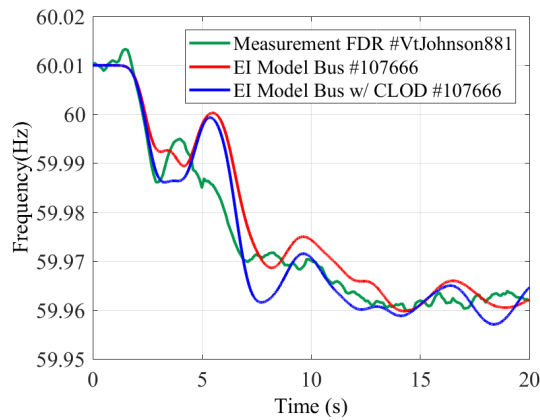


(a) Bus frequency

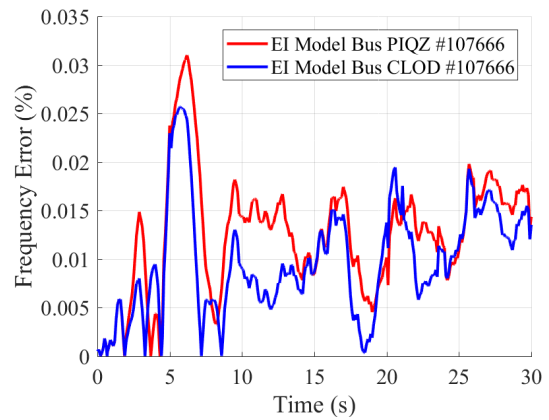


(b) Frequency error

Figure A.9: Crystal, MN measured data vs. load models



(a) Bus frequency



(b) Frequency error

Figure A.10: Johnson, VT measured data vs. load models

B Direct Estimation of Customer Composition

In Dominion Energy (DE), customer composition on a feeder-basis is estimated by engineers reviewing load surveys and customer data. This process is time consuming and introduces the possibility of human error occurring. The customer composition data obtained through this method, which was used in Chapter 5, did not cover the entire DE territory and thus, was incomplete. However, with the availability of various measurement devices, a more direct method can be used to determine the customer composition of a feeder. Load data measurements from transformers can be utilized to perform customer clustering based on the hourly shape. The measurement devices are located at transformers in all substations thus covering the entire DE footprint. Typically, customers are divided into one of three classes: residential, commercial, or industrial. Multiple types of consumers and in varying proportions may be supplied power from a single feeder. Therefore, the load measurements from substation transformers will be a mixture of each of the classes. In some cases, the mixture may be heavily dependent on a single consumer type or it may be an even distribution among all consumer types. Because of this, clustering a feeder by a single type is not accurate. If three clusters are considered, one for each customer type, then a fuzzy clustering method, also known as soft-clustering, can be used to assign a membership value that describes the relation of the load curve to every cluster. Thus, the membership values will be considered the feeder composition.

B.1 Fuzzy Clustering Algorithm

The fuzzy c-means clustering algorithm has several steps to minimize the error due to clustering the data, initializing and updating membership values, and calculating cluster centers. The objective function to minimize is,

$$\min \left\{ \sum_{i=1}^N \sum_{j=1}^c w_{ij}^m \|\mathbf{x}_i - \mathbf{c}_j\|^2 \right\} \quad (\text{B.1})$$

where w_{ij} is the membership value of the data point $\mathbf{x}_i$ as it belongs to cluster $\mathbf{c}_j$. m is the parameter that determines the fuzziness of the clusters and whose value is chosen as 2. The membership values are updated by,

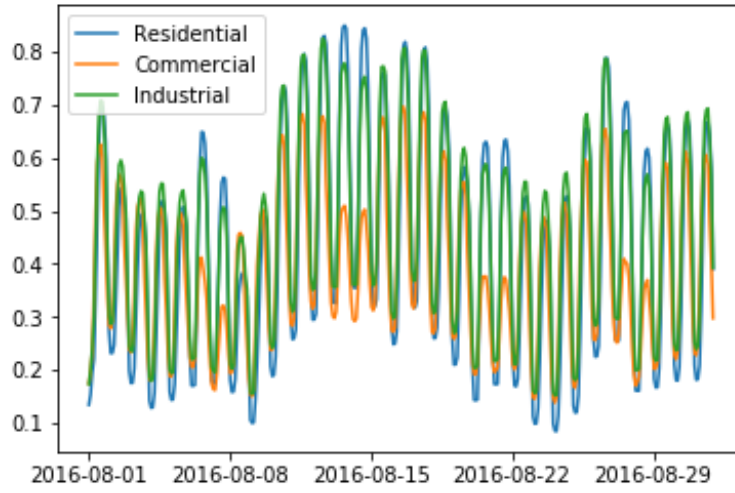
$$w_{ij} = \frac{1}{\sum_{k=1}^c \left(\frac{\|\mathbf{x}_i - \mathbf{c}_j\|}{\|\mathbf{x}_i - \mathbf{c}_k\|} \right)^{\frac{2}{m-1}}} \quad (\text{B.2})$$

for each cluster c_j . Lastly, the cluster center c_j is computed by,

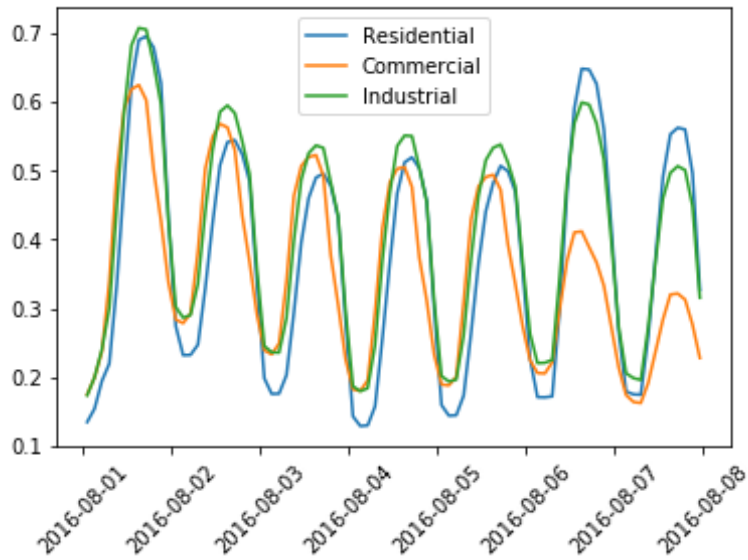
$$c_j = \frac{\sum_{i=1}^N w_{ij}^m x_i}{\sum_{i=1}^N w_{ij}^m} \quad (\text{B.3})$$

B.2 Results

The results in Figure B.1 are supervised fuzzy clustering. The algorithm is supplied several known feeder compositions that were of a single customer type and the remaining feeders are estimated using fuzzy clustering. The results in Figure B.2 are unsupervised clustering. The data is from August 2016, which is considered to be part of the summer peak.

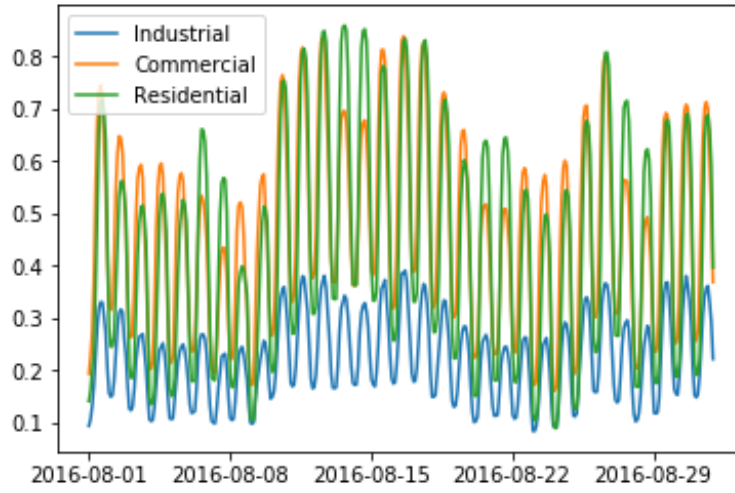


(a) August 2016

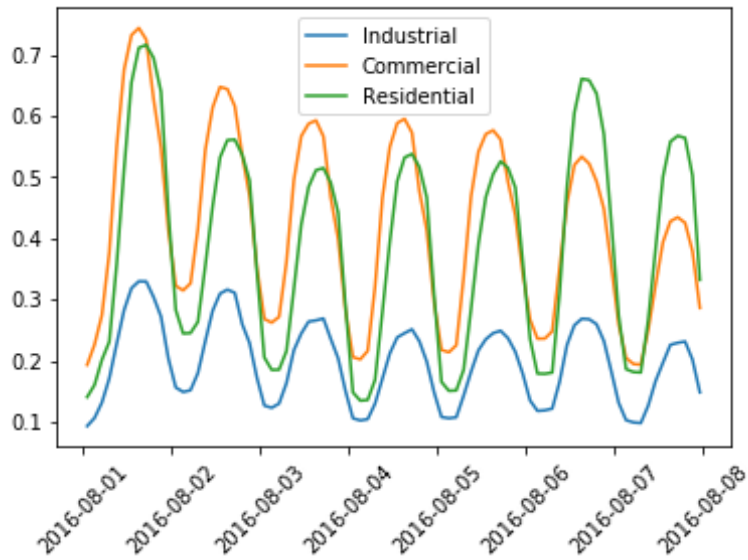


(b) Week 1 of August 2016

Figure B.1: Supervised clustering results



(a) August 2016



(b) Week 1 of August 2016

Figure B.2: Unsupervised clustering results

Vita

Melanie Bennett studied at The Florida State University in the FAMU-FSU College of Engineering where she was an undergraduate researcher with Dr. Chris S. Edrington. She graduated with her Bachelor of Science in Electrical Engineering with *magna cum laude* distinction in May of 2017. She then became a graduate student researcher at The University of Tennessee, Knoxville in the Tickle College of Engineering with Dr. Yilu Liu. While a graduate student, Melanie interned with Dominion Energy in the Transmission Operations Engineering group as well as the Transmission Planning group. Melanie graduated with a Master of Science in Electrical Engineering with a concentration in power systems in August 2019.