

Data-Driven Situation Awareness for Power System Frequency Dynamics

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ABSTRACT

As the penetration of renewable energy increases, system inertia decreases, causing changes in system frequency dynamics. The power industry desires situation awareness of power system frequency dynamics to ensure secure and economic operation and control. Moreover, FNET/GridEye has abundant measured data from power systems, making it possible to conduct data-driven situation awareness studies on power system frequency dynamics. This doctoral dissertation proposes several contributions: (a) Two accurate generator trip event MW estimation methods are proposed, in which one is based on long window RoCoF and another is based on multi-Beta values; (b) Two real-time system inertia estimation approaches are developed using ambient frequency fluctuation and pump turn-off events, along with techniques for improving RoCoF calculation in event-based inertia estimation; (c) An adaptive PV reserve estimation algorithm is established to provide PV reserve while saving energy for PV resources; (d) A practical load composition estimation tool is built for the industry to easily obtain essential load model parameters. Although conducting research using actual data from power systems for practical application is challenging and complicated, the proposed data-driven situation awareness methods in this doctoral dissertation solve practical problems and offer clear theoretical explanations for the industry. These methods address one of the key challenges for operating a high-renewable power grid and pave the way for the U.S. carbon-free power sector by 2035.

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CHAPTER 1 INTRODUCTION

1.1 Background and Motivation

As the integration of renewable energy sources within power systems continues to grow, the dynamic characteristics of system frequency are gradually changing. Without precise estimation tools to account for these changes in frequency dynamics, decision-makers may face unintended consequences, including economic inefficiencies or potential security risks. Consequently, enhancing situational awareness of power system frequency dynamics is important. This research aims to address several pressing and practical challenges related to situational awareness in power system frequency dynamics. By solving these issues, this work will contribute to overcoming key challenges in operating high-renewable power grids and lay the foundation for achieving a carbon-free power system in the United States by 2035.

In response to industry requirements and the availability of measured data, this dissertation investigates several challenging problems of situational awareness for power system frequency dynamics, including: (a) accurate estimation of generator trip event MW; (b) real-time estimation of system inertia; (c) adaptive photovoltaic (PV) reserve estimation; and (d) practical load composition estimation. These research areas are specifically designed to address the current needs within the power system industry and provide practical solutions that enhance situational awareness in the context of power system frequency dynamics.

1.1.1 Motivation for Accurate Generator Trip Event MW Estimation

Large generator trips pose significant risks to frequency stability within power systems. Prompt and precise event MW estimation can enable operators to assess risks more effectively, allowing them to make well-informed decisions that mitigate the impact of instability. FNET/GridEye provides an extensive dataset for estimating event MW; however, its current single-Beta method demonstrates a substantial median absolute error rate (i.e., 26%). Both FNET/GridEye and NERC have expressed a desire for improvements in accuracy, highlighting the need for more effective estimation methodologies to enhance frequency stability and overall system resilience.

1.1.2 Motivation for Real-Time System Inertia Estimation

Increasing renewables reduces system inertia. Insufficient inertia can lead to frequency stability issues following generator events. To maintain system frequency stability, operators require precise real-time inertia data for critical operational tasks, such as configuring MW reserve and adjusting control parameters. By closely monitoring real-time inertia, operators can mitigate the risks associated with low inertia and minimize the resulting impacts. Current practical methods for estimating inertia rely on aggregating the inertia of all online traditional generators. However, this approach overlooks the contributions from inverter-based renewable (IBR) resources, load variations, and behind-the-meter generators, among others. Consequently, obtaining accurate real-time inertia estimates is crucial for the industry to maintain system stability and reliability in the face of increasing renewable energy penetration.

1.1.3 Motivation for Adaptive PV Reserve Estimation

Reducing inertia from increasing renewable easily results in frequency stability issues. Fast PV control can provide reserve resources to support frequency response after major events. Systems under various conditions may need different reserve resources. Excessive reserve results in economic waste. Insufficient reserve results in stability issues. Thus, an adaptive PV reserve estimation is beneficial for the power system with high PV penetration, especially for the 2035 carbon-free power grid.

1.1.4 Motivation for Practical Load Composition Estimation

The dynamic load model plays a crucial role in determining accurate load characteristics, which in turn can influence the system's frequency response. Obtaining precise load composition is essential for effective dynamic load modeling; however, it is often challenging to acquire such information. Dominion Energy seeks to gain insight into the load composition within its territory, but the available data is limited to partial load composition for specific load feeders obtained through surveys. Consequently, a practical load composition estimation method is necessary to address this issue.

1.2 Contributions

1.2.1 Contributions to Accurate Generator Trip Event MW Estimation

Two enhanced MW estimation methods have been proposed to increase accuracy:

(a) Improved MW estimation employing long-window RoCoF to mitigate the effects of noise, oscillation, and wave propagation. First, the governor correction factor theory is introduced, taking into account the influence of the governor and damping. The proposed governor correction factor is both concise and practical. Second, the long-window RoCoF-

based estimation, incorporating the governor correction factor, enhances the EI MW estimation accuracy, reducing the error rate to 10% (compared to the original method's 26% error rate).

(b) Improved MW estimation using multi-Beta to consider governor deadband. Firstly, the theory of multi Beta is proposed to consider the impact of governor deadbands. The improved MW equation is simple and clear to use in practice. Secondly, two-Beta based MW estimation for EI system improved accuracy to 16% error rate (compared to the original method's 26% error rate).

1.2.2 Contributions to Real-Time System Inertia Estimation

Two novel inertia estimation methods are proposed according to different application scenarios:

(a) Pump turn-off event based inertia estimation for WECC system. This method takes advantage of the constant event MW and local measurement patterns from pump turn-off event to estimate inertia. To achieve high accuracy, an event detection trigger is designed, which has proven to be effective. The proposed inertia estimation method for WECC based on pump turn-off achieves a satisfactory accuracy of 7.7% error rate.

(b) Ambient frequency data based inertia estimation for Hawaii island. The method derives a physical equation with clear physical principles to estimate system inertia using the ambient frequency data. The proposed method is validated using the KIUC simulation data and the HECO field data, achieving error rates of around 2% and 7%, respectively. The physical equation-based method offers a reliable and accurate approach to estimate inertia in Hawaiian power systems.

1.2.3 Contributions to Adaptive PV Reserve Estimation

An intelligent PV reserve estimation technique that combines the power of neural networks with the bisection method is proposed. To validate the efficacy of the proposed method, the larger ERCOT PSS/E model and CURENT HTB are used as test cases. Remarkably, the proposed approach achieves reserve savings of 50% and 30% for these two cases, respectively, demonstrating its effectiveness in optimizing reserve allocation.

1.2.4 Contributions to Practical Load Composition Estimation

A smart machine learning-based method is proposed for estimating the load composition using readily available load profiles. The proposed method involves detailed preprocessing of raw load data and feature extraction. Validation of the proposed method indicates satisfactory performance with an average absolute error of approximately 10% using the actual Dominion Energy data. Overall, the method provides an effective approach for estimating load composition and has the potential to improve the efficiency of load modeling.

1.3 Dissertation Structure

This dissertation is structured as follows: Chapter 2 offers a comprehensive review of existing research and relevant literature. In Chapter 3, two precise generator trip event MW estimation methods are provided, which are based on long window RoCoF and multi-Beta values. Chapter 4 presents two real-time system inertia estimation approaches that utilize ambient frequency data and pump turn-off events. Chapter 5 introduces an adaptive PV reserve estimation algorithm. In Chapter 6, a practical load composition estimation tool is developed. Finally, Chapter 7 summarizes the findings and concludes.

CHAPTER 2 LITERATURE REVIEW

2.1 Real-Time Inertia Estimation in Power System

Real-time inertia estimation is crucial for power systems, as it offers valuable information regarding frequency response to counteract power disturbances. While existing literature explores various inertia estimation methods, these approaches possess certain drawbacks that limit their practical applications. For instance, conventional methods often rely on large step-change disturbances, such as unscheduled generation trips or sudden load increases [1]-[17]. However, these events are not always present, impeding real-time inertia monitoring.

In this section, I provide a comprehensive summary of the primary inertia estimation techniques. I compare the input data, investment requirements, performance, key drawbacks, and practical examples of several methods, including dispatch-based, event-driven, probing signal, and ambient signal approaches. Additionally, I discuss other promising techniques that have only been validated through simulation. Ultimately, the analysis reveals that inertia estimation methods remain an active area of research, with no single method surpassing the others in every aspect.

2.1.1 *Typical Practical Inertia Estimation Methods*

Several practical methods for inertia estimation in power systems have been identified, including: (a) dispatch-based online generator inertia summation; (b) event-driven methods; (c) probing signal-based methods; and (d) ambient signal-based methods. A comprehensive comparison of these techniques, including their input data requirements,

investment costs, performance, primary drawbacks, and practical examples, is provided in Table 2.1 [18].

- (a) The dispatch-based online generator inertia summation: The dispatch-based online generator inertia summation method involves directly summing the online inertia of each generator by taking into account their online status and known inertia. In 2017, ERCOT developed an online network-model-driven inertia calculation system based on this approach [19]. The system continuously tracks the online/offline status of all units, and those with output over 5MW are considered online. The inertia contribution of each online unit is computed as its inertia constant (in seconds) multiplied by the corresponding MVA base as provided in the unit's Resource Asset Registration Form (RARF). The sum of all these contributions gives the system inertia. Nordic TSOs in Europe have also adopted a similar method to monitor real-time system inertia [20]. To validate the accuracy of this inertia monitoring technique, tests were conducted to measure the impact of disturbances, such as the tripping of an HVDC link, which causes a frequency change that can be used to calculate the system's inertia. However, no reliable method for calculating inertia has been established. This method has a limitation of overlooking the inertia contribution from loads, IBRs, and other behind-meter inertia.

Table 2.1. Comparisons of practical inertia estimation methods.

Methods	Input data					Investment		Performance		Main drawbacks	Practical examples
	EMS	Known Unit inertia	PMU frequency	PMU active power	Event information	New monitor	Modulator	Includes load, IBR, and other behind-the-meter inertia	Results impacted by FFR and load damping		
Dispatch-based online generator inertia summation	√	√	×	×	×	×	×	~	×	IBR and load inertia may miss	EI, WECC, ERCOT, FINEGRID
Event-driven	×	×	√	×	√	×	×	√	√	not real-time	~
Probing signal	×	×	√	×	×	√	√	√	√	Invasive disturbance	National Grid(UK), TEPCO(Japan)
Ambient signal	×	×	√	√	×	√	×	√	√	Inaccurate ambient power signal	National Grid(UK), TEPCO(Japan), Landsnet(Iceland)

(b) The event-driven-RoCoF method: In this method, the event RoCoF is used together with the confirmed event power change to estimate the inertia [1]-[17]. The event is usually a large MW step-change disturbance, such as the unscheduled generation trips or sudden load increase. However, because these events do not exist all the time, this method cannot achieve real-time inertia monitoring. The event-driven method is usually based on offline analysis, due to the requirement of confirmed event information. A flow chart of the event-RoCoF-based inertia estimation is shown in Figure 2.1.

(c) Probing signal based method: The Probing signal based method involves injecting probing power disturbance into the power system and then capturing the resulting frequency signal to estimate inertia. UK company, Reactive Technologies, uses this method to detect system inertia, which they call GridMetrix [21]. A probing pulse signal is generated by an ultracapacitor, and the following instantaneous frequency movement is measured by 'XMU'. Based on the known pulse signal and measured frequency change, the system inertia can be estimated with high accuracy [22]. National Grid ESO in the UK, Japan's Tokyo Electric Power Company (TEPCO), Italy, New Zealand, and Australia have demonstrated the effectiveness of this technology. In TEPCO, modulator equipment for inertia estimation was operated, adjusted, and tested for one month from January to February 2019, with the largest error between actual and estimated system inertia reported at 9.5% [23]. A flow chart illustrating the inertia detection process from Reactive Technologies is presented in Figure 2.2.

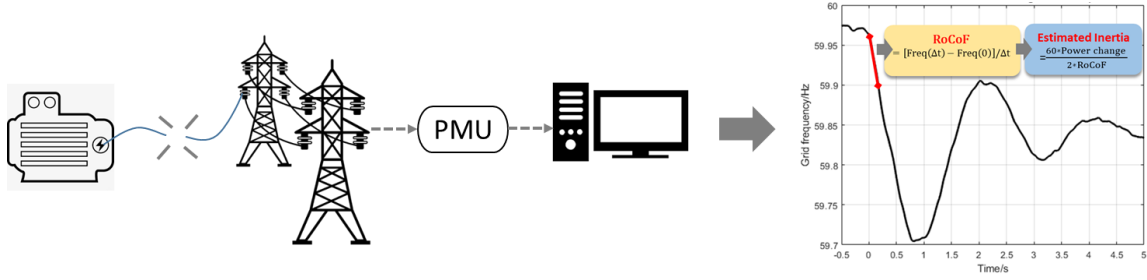


Figure 2.1. Process for estimation inertia based on event RoCoF.

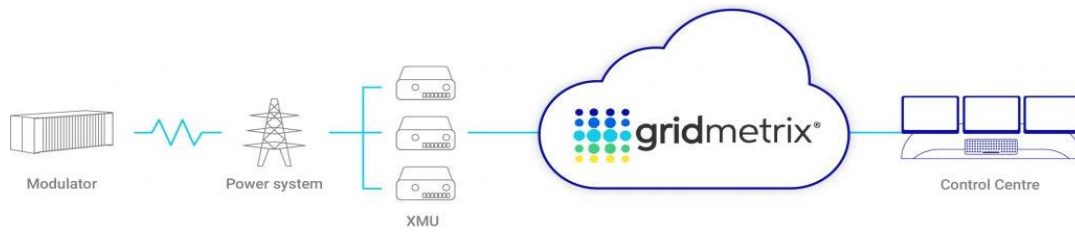


Figure 2.2. Process of the inertia estimation from Reactive Technologies.

(d) Ambient signal based method: The Ambient signal based method involves identifying regional inertia using frequency ambient signals and ambient power measurements from boundary PMUs that continuously capture power disturbances from other regions [24]-[27]. GE has developed an effective inertia metering approach for power grids that can be divided into several areas [24]. The inertia of each area is estimated separately by utilizing the boundary PMUs to determine the net boundary power exchange for each area [24]. The frequency of each area is measured by inner frequency meters [24], and the area RoCoF can be calculated. Using the area RoCoF and net boundary power change, the effective area inertia can be estimated with high accuracy [26]. Additionally, machine learning can be used with information from generation and demand predictors to forecast future inertia [26]. National Grid ESO is currently testing the accuracy of GE's approach to inertia estimation. A flow chart demonstrating the GE inertia metering process is presented in Figure 2.3.

The accuracy of inertia estimation is crucial for its practical application. However, not much information regarding the accuracy of existing practical examples has been reported. Determining the true inertia value in a real power system is also challenging, making it difficult to calculate accuracy. In practice, researchers may use the method they consider the most accurate as the background truth source for validation. Information on the accuracy of practical examples from the references can be found in Table 2.2.

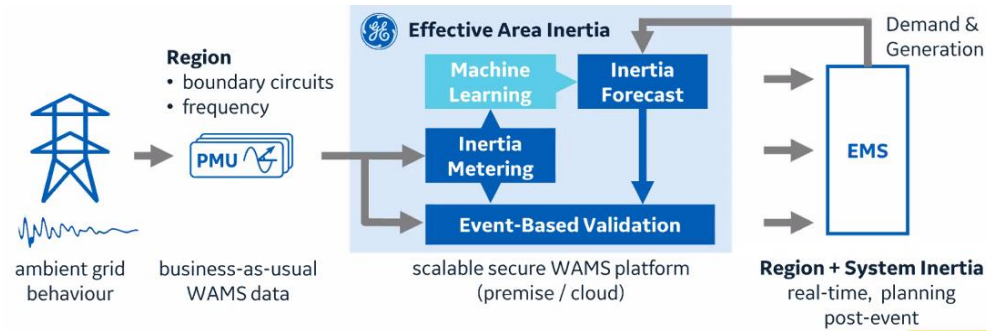


Figure 2.3. Process of the inertia metering from GE.

Table 2.2. Accuracy of several practical examples of online inertia estimation.

Method	Application	Validation
Dispatch-based online generator inertia summation	ERCOT [19], FINEGRID [20]	High accuracy for the inertia from traditional rotating synchronous generator. May not capture the inertia from behind-meter resources. [19]
Probing signal	UK Company: Reactive technologies [21]-[23]	The largest error 9.5% is reported by TEPCO [23]
Ambient signal	GE: Effective Inertia Metering [24]-[27]	Still under test [27]

2.1.2 Promising Theoretical Inertia Estimation Approaches from Research Literature

In addition to the practical examples discussed above, there is also insightful and theoretical research on real-time inertia estimation. Table 2.3 provides a summary of existing references on real-time inertia estimation. Additionally, Table 2.4 compares the validation and accuracy of various methods.

- (a) The oscillation-information-based method is presented in [28]-[30]. This method assumes that ambient excitation follows a stationary Gaussian process, allowing for the derivation of a relation equation between oscillation information and area inertia. The oscillation information, including frequency and damping, is extracted from phase angle data. Based on the derived equations, the inertia of oscillated units can be estimated.
- (b) The unit-information-based method presented in [31] uses a method similar to the status tracking approach, but with additional information and the adoption of a stochastic process as the inertia model. The method uses more information, such as real-time total demand, output of each type of energy source, and output of RESs, allowing for the consideration of the inertia contribution from both load and RESs. A stochastic model is employed to establish the relationship between inertia and all other measurements, which is then used to estimate inertia.

Table 2.3. Research summary of real-time inertia estimation.

Method		Data requirements	Drawbacks	References
Oscillation-information based method		Real-time frequency data, oscillation area of each mode	Inter-area oscillation may not exist all the time	[28]-[30]
Unit-information-based method		Realtime total demand; production per type of energy source, production from RESs, inertia constant for each type of the energy source	Need permission to get the data	[31]
Multi-factor AI-based method		Real-time frequency data, temperature, load profile	Unclear mechanism	[32], [33]
Modeling-based method	Transfer function	Real-time frequency data, active power of the disturbance	Need the active power data of the input disturbance	[34], [35]
	Subspace State Space System			[36]
	ARMAX			[37], [38]
	Discrete-time linear system			[39]
	Dynamic regressor and mixing			[40]

Table 2.4. Accuracy of the existing methods of real-time inertia estimation.

Method		References	Validation system	Accuracy
Oscillation-information based method		[28]-[30]	Simulated IEEE 39 bus system	5.98% relative error rate [29]
			Real single-generator infinite bus system	15.2% relative error rate [29]
Unit-information-based method		[31]	An islanded system connected via 400 kV undersea cable	Maximum error rate 8% mean error rate 2.5% [31]
Multi-factor AI-based method		[32], [33]	WECC system	Maximum error rate is less than 8.7% [32]
Dynamic Identification method	Transfer function	[34], [35]	Simulated 8-generator 36-bus system	Absolute error rate is 2.3% [35]
			Real physical system consists of one generator	The absolute error rate is 3.56% [35]
	Subspace State Space System	[36]	Simulated IEEE 39-bus system.	Relative error is 3.49% [36]
	ARMAX	[37], [38]	Simulated two-area test system	The maximum error is 9.79%, and the average error is 4.63%[38]
	Discrete-time linear system	[39]	Simulated IEEE-14-bus power system	The maximum error is found as 9.8% [39]
	Dynamic regressor and mixing	[40]	European ENTSO-E system	The estimation error is below 15% [40]

- (c) The multi-factor AI-based method was proposed by the UTK team [32], [33]. This approach uses historical inertia in conjunction with several inertia-related factors, including noise amplitude, load level, and temperature, to train a machine learning tool. To reduce the dimensionality of the multi-FDR and high-resolution data, the Minimum Volume Enclosing Ellipsoid (MVEE) method is utilized to represent the noise amplitude by employing the ellipsoid characteristics. Furthermore, the trained machine learning tool can be utilized to estimate real-time online inertia. This method is offline validated using WECC data and achieves a satisfactory level of accuracy.
- (d) The modeling-based method builds the frequency response model initially and then extracts inertia from this model. The method involves measuring the frequency and generator output power or assuming it to be standard noise. Using power disturbance inputs and frequency output, a frequency response model is obtained. The inertia can then be estimated from this model. Several system models are present in existing references, including: the transfer function model [34], [35], subspace state-space system model [36], ARMAX model [37], [38], discrete-time linear system model [39], and dynamic regressor and mixing model [40].

2.2 Accurate Generator Trip Event MW Estimation in Power System

Due to unexpected factors, unscheduled generator trip events can occur in power system. The power system must maintain power balance to ensure frequency stability. Therefore, unscheduled generator trips can be considered the "earthquake" of the power system, and their magnitude needs to be estimated rapidly for appropriate operations. Generator trips can cause frequency instability, which is of particular concern for future power systems with high penetration renewable generation, as it reduces the system's

inertia. To improve the frequency response after generator trips, operations such as adaptive load shedding may require accurate event magnitude in a short time. Fast and accurate magnitude estimation of generator trips plays a critical role in the power system. This section first summarizes several typical event size estimation methods in practice and research. Secondly, the generator trip event and its monitoring by FNET/GridEye are introduced. Thirdly, the first typical MW estimation method (i.e., settling-frequency based method) is detailed. Finally, the second typical MW estimation method (i.e., RoCoF based method) is also summarized in detail.

2.2.1 Typical Practical Event MW Size Estimation Methods

This section introduces typical MW size estimation methods for generator trip events, and, and Table 2.5 presents a summary of existing references on MW estimation for generator trips. To better demonstrate the performance of the estimation methods, Table 2.6 provides the validation results of these methods.

2.2.2 Generator Trip Event and Monitoring by FNET/GridEye

In power systems, unplanned generation loss events often occur due to various reasons, including human error, extreme weather, cyber attacks, and equipment failure. Some events occur from larger power plants with very high working outputs, and their sudden cessation can adversely impact power system frequency stability.

Table 2.7 presents the largest events identified in U.S. interconnections from 2003 to 2013, which are typically considered the standard event size for researching frequency stability of these grids under a larger event [50].

Table 2.5. Typical methods for MW estimation.

Method	Physical mechanism	Data used	Drawbacks	References
RoCoF based method	Inertia response	Around 0.5s frequency data after the event	Easily impact by oscillation and wave propagation	[41]-[47]
Settling-frequency based method	Governor response	Around 10-15s frequency data after the event in EI	1. Ignore the impact of deadband 2. Too long time to get the estimation results	[48], [49]

Table 2.6. Accuracy of the existing methods for generator MW size estimation.

Method	References	Validation system	Accuracy
RoCoF based method	[41]-[47]	Simulated simple 3-machine test system	Max error 0.91% is found from [42]
		Simulated IEEE 39-bus test network	Max error 2% is found from [42]
Settling-frequency based method	[48], [49]	Eastern Interconnection (EI) power system	Root Mean Square Error is 244.5MW [49]
		Western Electricity Coordinating Council (WECC) power system	Root Mean Square Error is 297.5MW [49]

Table 2.7. Largest Events in Several U.S. Interconnections from 2003 to 2013.

Interconnection	Eastern	Western	ERCOT	HQ
MW loss	4500	2740	2750	1700

Quickly obtaining the accurate event size after unplanned generation loss occurs is desired, as it provides operators with more time to take precise action to reduce the impact of this generation loss. The GridEye system at ORNL is a unique monitoring network that provides independent observations of the entire North American electrical grid continuously and in real-time [51].

GridEye captures system status, including frequency, voltage, and phase angle, after a major disturbance incident. It also collects wide frequency data from FDRs, system inertia data, and historical event recordings. An FDR is depicted in Figure 2.4, and more than 100 FDRs were deployed in the EI system, as shown in the deployment map in Figure 2.5. Based on frequency measurements, FNET/GridEye builds an online system to detect generator trip events. The frequency measurements of historical generation loss events are illustrated in movies, which can be found in [52].

2.2.3 MW Estimation Based on Beta Value and Settling Frequency

The settling-frequency-based method utilizes the governor response mechanism to estimate event size. Governor control is biased, as frequency cannot be controlled back to its pre-event value. When frequency settles down, there is a frequency deviation Δf between the initial frequency and the settling frequency. The mechanical power change ΔP_{mech} from the governor response can then be calculated as $-K\Delta f$, where K is the droop gain of the governor. After the frequency settles down following the event, frequency differential becomes zero (i.e., $df/dt = 0$). Based on the frequency response, the MW estimation formula can be expressed as follows:

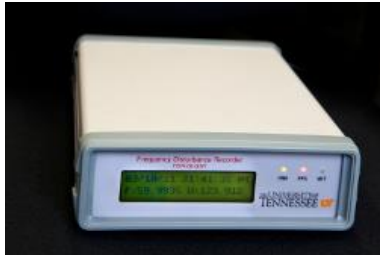


Figure 2.4. Frequency disturbance recorders from FNET/GridEye.



Figure 2.5. Deployment of frequency disturbance recorders in the United States.

$$\Delta P = K\Delta f + D\Delta f = (K + D)\Delta f = \beta\Delta f \quad 2.1$$

where β is the Beta value, which equals $K + D$ and includes the droop gain and the load damping.

In practice, using the measured frequency, frequency deviation Δf can be obtained, as shown in Figure 2.6. The beginning frequency is the average of the frequency from $t(-8)$ to $t(-1)$, and the settling frequency is the average frequency from $t(10)$ to $t(15)$ [53]. Based on Equation 2.1 and historical Beta value β , the MW value of the event can be estimated.

The settling-frequency-based method has a simple mechanism and is, therefore, commonly used as the estimation method in practice, such as in the FNET/GridEye system. However, it has been observed that random background noises, originating from random load changes and other random operations in the power system that cause random frequency changes, have an impact on estimation accuracy. These random background noises exist at all times, including during the event.

2.2.4 MW Estimation Based on Event RoCoF

After an unscheduled generation trip event, a sudden power imbalance occurs in the system leading to a significant Rate of Change of Frequency (RoCoF) resulting from the inertia response. Despite the potentially large RoCoF in the immediate response after the event, the frequency deviation Δf is very small and can effectively be considered as zero due to the limited duration after the disturbance. As a result, both the governor response and frequency damping, which are reliant on Δf , have an insignificant increase in machine power ΔP_{mech} and the damping power $D\Delta f$, so MW estimation based on RoCoF becomes:

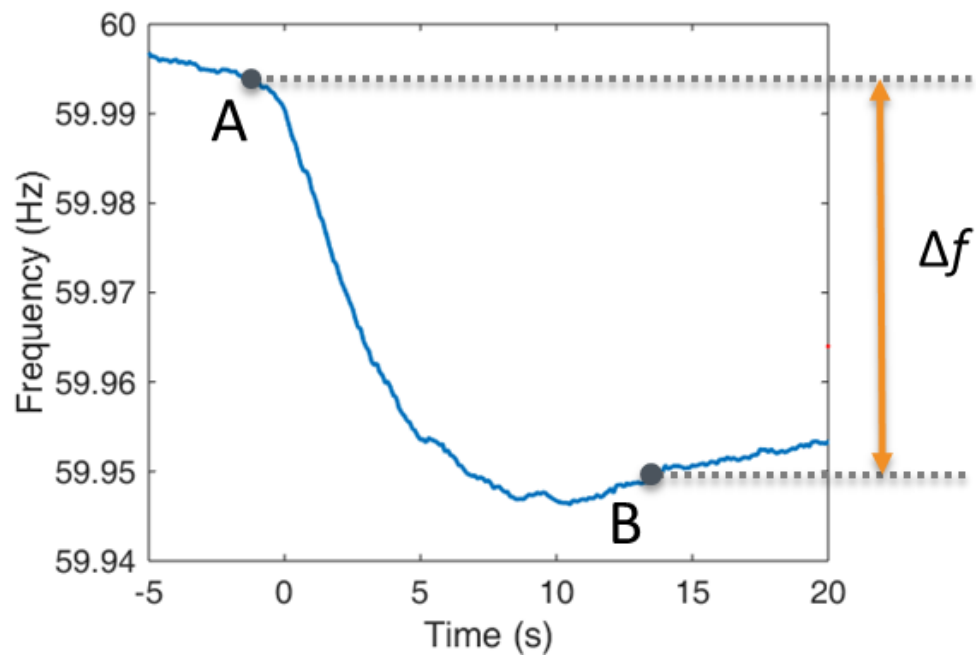


Figure 2.6. Measured frequency deviation for a generator trip event.

$$2H \cdot RoCoF = \Delta P \quad 2.2$$

where RoCoF is the rate of the change of frequency. The NERC standard, which is widely used, employs a 0.5-second time window for calculating RoCoF using frequency data. Specifically, RoCoF is determined by taking the difference between the frequency at 0.5 seconds after the event and the frequency at the time of the event, and dividing it by the time between these data points [54]. This can be expressed mathematically as:

$$RoCoF = d\Delta f/dt = [\Delta f(0.5) - \Delta f(0)]/0.5 \quad 2.3$$

where the frequency after 0.5 seconds of event happens minus the frequency when the event happens divided by the total time between the data points is the rate of change of frequency.

Further, the MW loss value ΔP from the generator trip can be estimated by:

$$\Delta P = 2H \cdot RoCoF \quad 2.4$$

Theoretically, Equation 2.4 can be employed to estimate the MW value ΔP . However, factors such as oscillations and wave propagation typically affect the accuracy of RoCoF calculations, subsequently impacting the estimation of MW values.

Oscillations are commonly observed in power systems. Figure 2.7 displays the measured frequency values for an event that occurred within the WECC. It is evident that oscillations are present. Figure 2.8 illustrates the extracted oscillation, which represents the frequency of individual FDRs subtracted from the average system frequency.

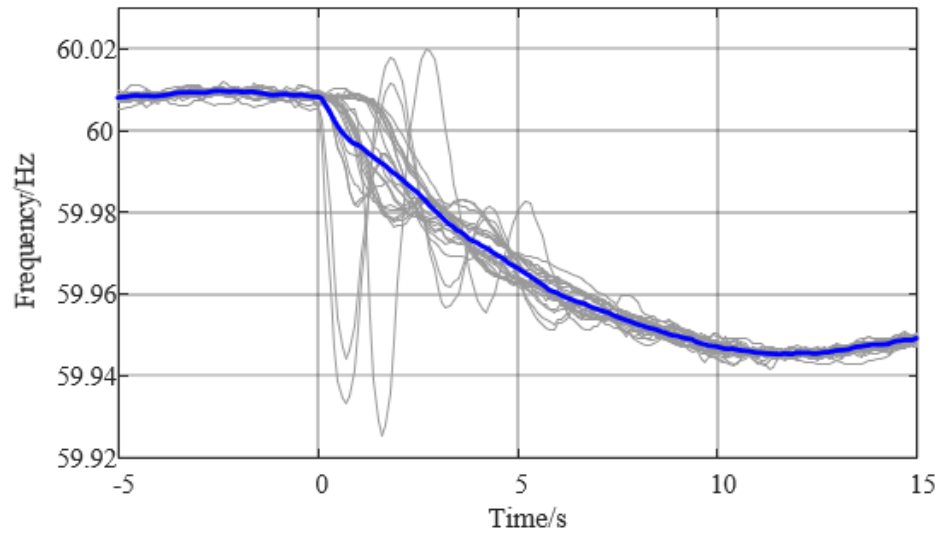


Figure 2.7. Frequency response after an event in WECC.

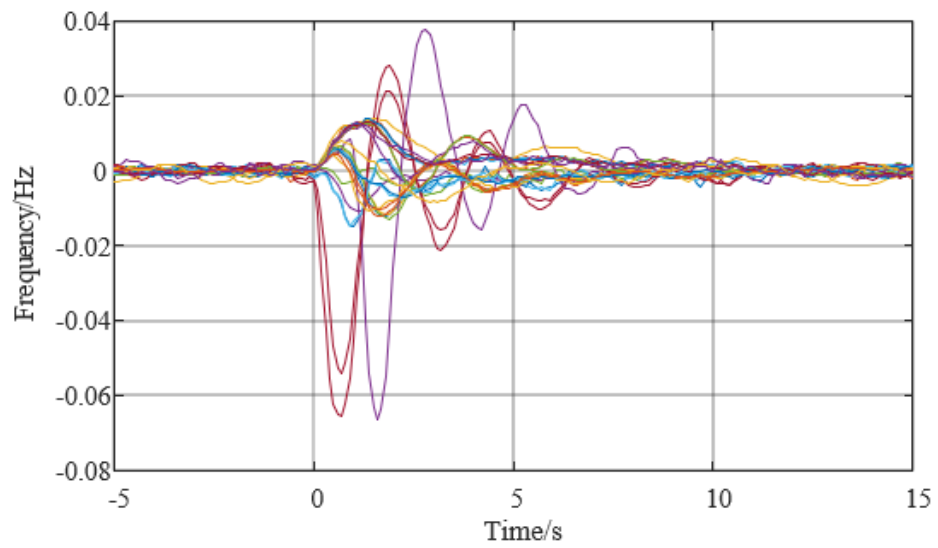


Figure 2.8. Frequency oscillation component in the system after the event.

Following an MW loss event in large-scale power grids, the frequency change requires time to propagate throughout the entire system, resulting in geographically divergent frequencies [55]-[57]. Figure 2.9 depicts the frequency wave propagation during an event. The blue lines represent the FDRs that initially detect the event, while the green lines display the event frequency response after 1 second. FNET/GridEye monitors the wave propagation and uploads related videos to YouTube, which can be accessed in [58].

2.3 Adaptive Reserve Estimation for Fast PV Control in Power System

2.3.1 System Frequency Response with Increasing PV Penetration

The United States has increasing solar resources [59]. The SunShot Initiative, spearheaded by the U.S. Department of Energy, envisions solar PV contributing to 14% of the nation's total electricity production by 2030, and 27% by 2050 [60]. With the ongoing growth in solar PV deployment, researchers have been examining the impact of increased renewable generation on power system stability, particularly for inverter-based sources such as solar PV and certain wind turbines. Without appropriate control, inverter-based sources could simply replace conventional generators with turbine governors and rotating masses, which would negatively affect the system's frequency response. Preliminary studies in U.S. power grids have indicated that overall frequency response could significantly deteriorate with increased renewable penetration [61]-[63].

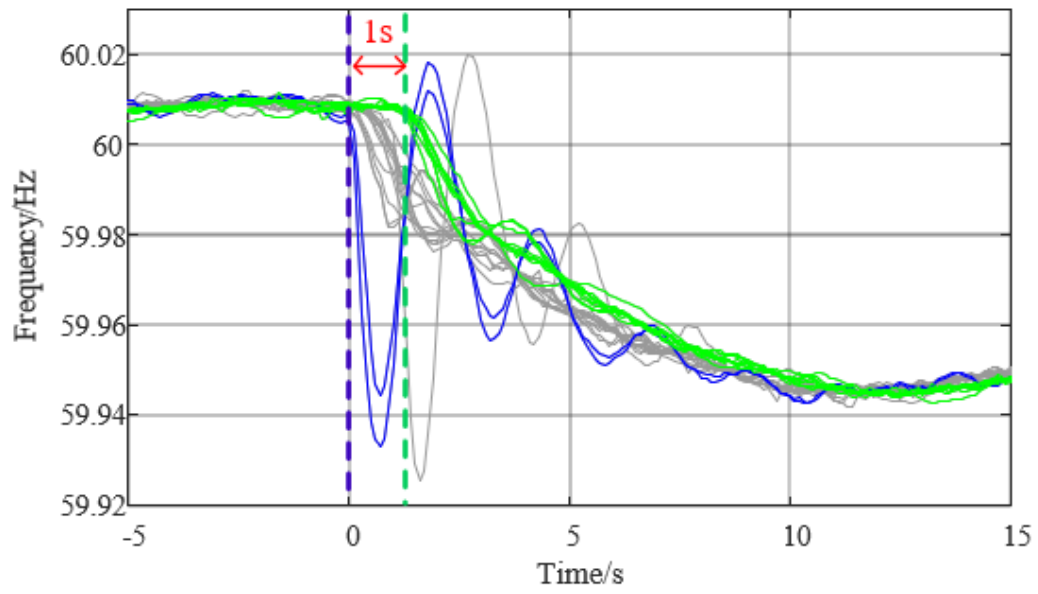


Figure 2.9. Wave propagation in power system after the event.

Similarly, research has shown that insufficient inertia can adversely impact frequency regulation in the South Australian power grid, which has a high penetration of renewable generation [64]. In [65], the Irish power grid faces challenges operating at a 50% wind generation penetration due to reduced inertia. Simulation studies in the U.S., as discussed in [66], expose the vulnerabilities of the WECC system caused by extremely high wind penetrations and explore potential mitigating strategies.

2.3.2 PV Fast Frequency Control to Support Frequency Stability

Upon reviewing system studies across various power grids with increasing PV and wind penetrations, the North American Electric Reliability Corporation (NERC) has concluded that supplementary control strategies and resources are necessary to meet primary frequency control demand as renewable penetration rises [67]. Consequently, the frequency-watt function [68], which is analogous to governors in conventional generators, has become a standard requirement in North American power grids. Furthermore, research in [69]-[75] demonstrates that synthetic inertia control of inverters, designed to emulate the inertia response of synchronous generators, aids in regulating the system's frequency response. However, no regulations or requirements currently govern the synthetic inertia control of inverters. The majority of PV inverters in operation employ a grid-following mode, wherein the inverter controls the output current magnitude and angle [76]. Another control mode is the grid-forming mode, in which inverters regulate output voltage and frequency.

2.3.3 *Frequency Reserve from PV Fast Controls*

Although inverter-based resources generally possess the capability to reserve power for frequency response [77], inverters are controlled to output the maximum available power based on Maximum Power Point Tracking (MPPT) to capitalize on the lower marginal cost of PV generation compared to conventional sources, such as gas or coal. However, as the penetration of renewables like PV increases, there may be insufficient primary frequency response resources during an under-frequency event, such as loss of generation, if no real power reserve is available in the PV inverters. While power reserve control strategies are easily implemented at the inverter level [78], and frequency-watt curves have been examined on a system level [68], a research gap exists in determining and scheduling PV real power reserves. Although other grid resources, such as energy storage systems and supercapacitors, can be employed to enhance primary frequency response [79]-[81], these options necessitate additional planning, design, and investment. If real power reserves are inadequate, particularly in high penetration scenarios, the system risks experiencing lower frequency nadirs during severe contingencies, potentially leading to under-frequency tripping of loads and/or inverters. Conversely, PV real power reserve implies lost generation with low marginal costs. Consequently, it is of significant importance and economic value from a frequency response perspective to develop a model that dispatches PV real power reserves according to system requirements and conditions.

2.4 Practical Load Composition Estimation in Power System

2.4.1 Significance of Load Models in Power System Research

Power system software, such as PSS/E, has been utilized for several decades to examine load flow and dynamic stability. As computing power has advanced, more accurate and detailed generator models have been developed to analyze frequency response in the U.S. Eastern Interconnection (EI) for events stemming from the loss of generation [82]. One of the crucial components affecting system dynamics is the load. Typically, load models are static and do not account for frequency dependence, but recent research has started to investigate the influence of loads on grid stability and model accuracy. For instance, a load model that fails to capture inter-area oscillations might lead to overconfidence, while a conservative load model could prompt utilities to invest in unnecessary grid improvements. Therefore, it is essential to treat load modeling with the same importance as generator modeling to reduce costs for transmission planners and detect potential grid stability issues. However, the sheer number and variety of loads, coupled with their non-constant nature, significantly increase the complexity of modeling.

The Western Electricity Coordinating Council has developed and implemented a composite load model for the Western U.S. grid, which accounts for the dynamic behavior of various induction motors and static loads. However, the current EI Multi-Regional Modeling Working Group (MMWG) 2030 grid model does not incorporate a dynamic load model. Instead, it relies on static load models—algebraic equations representing voltage-dependent loads—which are widely used in both steady-state and dynamic studies across

the global electric power industry [83]. In fact, 56% of the electric industry in the Americas (including North and South America) employs static load models.

The EI MMWG load model approximates real power using a constant current model and reactive power through a constant impedance model (PIQZ). Recent research, however, has underscored the limitations of static load models in capturing both wide-area and local grid phenomena, leading to diminished confidence in the grid model. Several findings, as summarized in [84], address the relationship between load modeling and its impact on small-signal and voltage stability studies. It has been discovered that a quadratic, voltage-dependent load model can overestimate the damping of inter-area oscillations, while static load models generally fail to represent the behavior of motor-driven loads accurately. These factors are crucial when evaluating the influence of dynamic load models on the frequency response of the grid.

Induction motors are found in almost every setting in the modern power system and have unique characteristics. Reference [85] highlights 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 [86]. During low bus voltage, induction motors will draw excessive amounts of reactive power and cannot be replicated using static load models [87]. Induction motor inertia is another important factor affecting the frequency oscillation amplitude of the system. To

account for induction motors, dynamic load models must be implemented, whose present state is a function of current grid conditions and the loads' previous state. Several induction motor models already exist but some may not be suitable for large-scale implementation since detailed knowledge of the load is unknown. For this reason, composite load models, which capture the behavior of several types of loads including induction motors, are best suited.

In 2016, the Electric Power Research Institute (EPRI) introduced a tool for utility planners in the EI to implement component-based load modeling using the composite load (CMLD) model structure [88]. However, the CMLD model necessitates approximately 130 parameters, which poses a challenge for interconnection-level load modeling due to software limitations. Debugging simulations in cases of non-convergence can be cumbersome and time-intensive, even though most CMLD parameters can be assigned typical values. Alternatively, the complex load (CLOD) model can also represent a composition of loads but is simpler to implement and requires fewer parameters.

To date, most research on the CLOD model has focused on local issues or small systems [89], [90]. The study in [89] utilized the CLOD structure to enhance modeling accuracy for industrial building electrical equipment, where large induction motors are present. Researchers in [90] explored two methods for estimating CLOD parameters from phasor measurements in a 39-bus system. Reference [91] demonstrates the influence of induction motors in the CMLD model on the frequency response within the Cyprus system, which is relatively small compared to the EI. At present, no research has investigated the impact of

dynamic, composite load modeling, such as the CLOD model, on the frequency response of large-scale systems.

2.4.2 Typical Load Models and Composition Estimation

Load models that depend on system parameters but are not influenced by time are deemed static and can be derived from the exponential load model presented in Equation 2.5.

$$S = S_0 \left(\frac{V}{V_0} \right)^a \left(\frac{F}{F_0} \right)^b \quad 2.5$$

Here, S represents the complex load. The dependency on voltage or frequency deviations can be adjusted by the exponents a and b. The most common static load model, known as the 'ZIP' model, is shown in Equation 2.6. Note that the frequency term is omitted:

$$S = S_0 \left[c_1 \left(\frac{V}{V_0} \right)^2 + c_2 \left(\frac{V}{V_0} \right)^1 + c_3 \left(\frac{V}{V_0} \right)^0 \right] \quad 2.6$$

where coefficients c represent the composition of each load type, and their values sum to 100%. The terms correspond to constant impedance (Z), constant current (I), and constant power (P) models, respectively. Power flow studies employ a conservative estimation of the load by assuming a 100% constant P load, as this model results in the most severe response to voltage fluctuations due to its persistent initial load consumption. To adhere to Ohm's law at lower voltages, power system software implements a voltage breakpoint, beyond which the constant P equations are no longer valid. Since the constant P load model produces a severe response, it is not suitable for dynamic simulations. PSS/E includes 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 a constant Z or admittance (Y) model for reactive power load. This conversion results in the PIQZ load model, which is the standard for dynamic simulations of the MMWG model.

To enhance the reliability of the EI MMWG model, a dynamic CLOD model is incorporated. The CLOD model can represent a composition of various load types, including induction motors and multiple static loads, while requiring only eight parameters. This is accomplished by utilizing typical manufacturer data for induction motor models internally, which cannot be altered by the user. The CLOD model's diagram is depicted in Figure 2.10. The CLOD dynamic model necessitates five parameters to account for the proportion of large motors, small motors, discharge lighting, transformer saturation, and constant MVA load. Additionally, it requires three more parameters for the distribution line impedance and the voltage exponent of the remaining real power load. The proportion of the residual load is internally determined by subtracting the sum of all other components from 100%. The CLOD model is an ideal choice when detailed information about the load is unavailable, but the dynamic behavior of the induction motor load is of interest.

Load models necessitate precise parameters to effectively model and forecast system disturbance response while remaining general enough to represent a broad range of load characteristics across geographic regions. Composite and complex load models simplify this process by incorporating multiple types of load components. However, the proportion of each component and regional variations remain uncertain. To determine load parameters, various factors must be taken into account, such as weather, customer type, time-of-day, season, and more [92], [93].

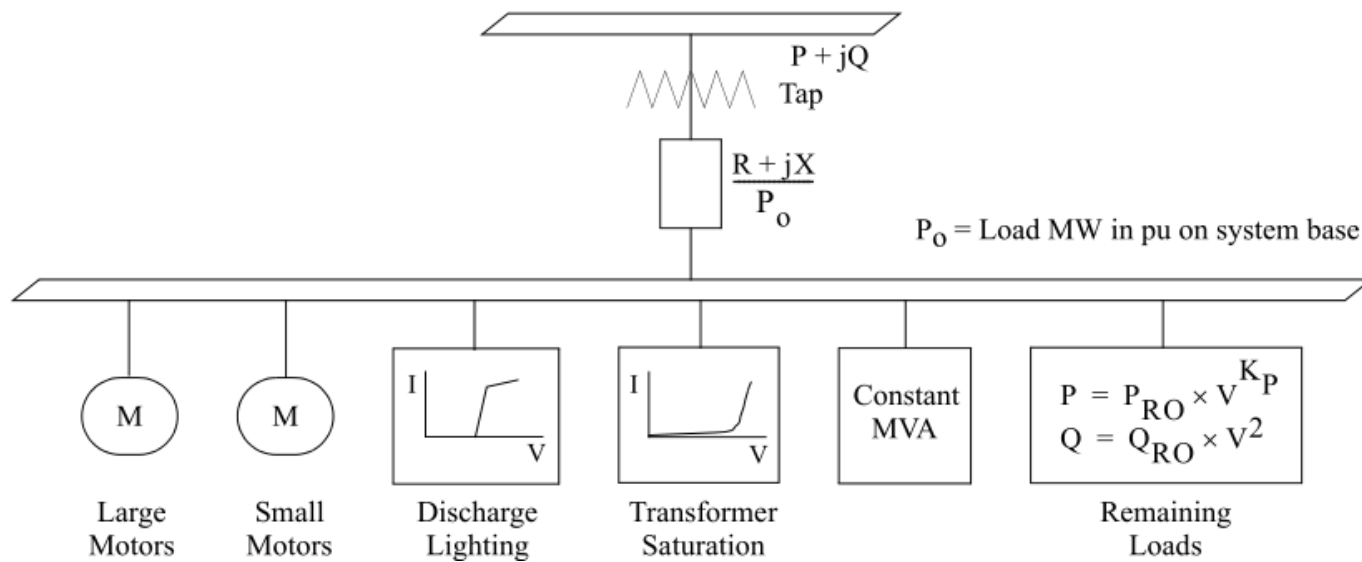


Figure 2.10. CLOD Load Model.

Load model parameters can be estimated using available customer data and load surveys, known as a bottom-up or component-based approach. Alternatively, they can be estimated through real event data by fitting the model to the data, referred to as a top-down or measurement-based approach. The measurement-based approach fine-tunes the most sensitive parameters of the load model to an event using optimization algorithms, minimizing the model's error relative to real data. Although this approach generally results in the most accurate response of the model to the actual event, the parameters may lack generalizability, necessitating repetition for each event [94]. To successfully tune the parameters, it is essential to understand the sensitivity of each parameter and any interdependencies. The study in [95] discovered that CLOD experiences non-deterministic solutions. To address this issue, users can limit parameter ranges, but this demands knowledge of the parameter through historical data or component-based modeling data. Insufficient measurement data would require employing the component-based approach.

Customer data, such as end-use load surveys that offer detailed load composition for individual customers, can be utilized. Other helpful data sources include customer class information and their approximate load by feeder. Rules-of-association are then established to connect the physical device with the corresponding load model component. This method relies on assumptions and engineering judgment and yields a general model. While the model may exhibit lower accuracy for specific events, it may improve the overall load behavior on average.

CHAPTER 3 ACCURATE ESTIMATION OF GENERATOR TRIP EVENT MW

Due to unforeseen factors, unscheduled generator trip events can occur, resulting in frequency drops. Power systems must maintain a power balance to ensure frequency stability, but generator trips can cause frequency instability. This phenomenon is particularly significant for future power systems with high renewable generation penetration, which leads to a reduction in the system's inertia [96].

The RoCoF-based method leverages the inertia response process to estimate the event size. To minimize the impact of governor response, the time window for frequency measurement used to calculate RoCoF is typically kept small. However, oscillation and wave propagation significantly affect RoCoF when based on a short window for frequency measurement. Therefore, this chapter proposes an improved method employing a long-window RoCoF to reduce the impact of noise, oscillation, and wave propagation.

The Beta value method is founded on the governor response, specifically utilizing the character of bias in governor control. As the governor response stabilizes, a frequency deviation occurs between the settling frequency and the initial frequency. Consequently, a relatively longer time is needed to obtain the settling frequency. In EI, this duration is set at approximately 10 seconds. Due to the governor's deadband, the settling frequency deviation may differ even under the same event size but with varying initial frequencies.

In this chapter, an improved multi-Beta method is proposed to account for the impact of the deadband. The Beta values both within and outside the deadband are presented.

3.1 Improved MW Estimation Based on Long-Window Rate of Change of Frequency (RoCoF)

In this section, we propose an accurate and efficient method for estimating the event size of a generator trip in a larger power system using a longer window Rate of Change of Frequency (RoCoF). Existing estimation techniques using short-window RoCoF are susceptible to oscillations, wave propagation, and background noise that commonly occur in power systems. In contrast, the proposed method based on a long-window RoCoF is robust to such disturbances. However, the governor response and load damping can affect the RoCoF value, and hence, a governor correction factor, denoted as k , is presented to address this issue. A detailed theoretical derivation of the physical meaning of k is also provided. The event size can be estimated online using a simple equation, $\Delta P = k \cdot H \cdot RoCoF$, where k can be obtained from historical data. The proposed method is validated on the U.S. WECC and EI systems, which demonstrates its advantage over traditional methods based on a single Beta-value. Specifically, the proposed method reduces the median absolute error rate from 26% to 10% in EI and reduces the estimation time from 10s to 3s after the event. Despite the challenges associated with accurately estimating event size in a large system, the proposed method offers high accuracy, rapid estimation, and a simple mechanism that is practical and beneficial for the industry.

3.1.1 System Frequency Response Model During Generator Trip Event

The system frequency response model is a commonly used approach to analyze system frequency. This model assumes that the system frequency is uniform throughout the power system and that all generator swing equations are aggregated together.

Figure 3.1 illustrates the framework of this model, where the blue block represents the inertia response of the entire system, and the orange blocks depict the governors connected to each generator.

In the event of a disturbance ΔP causing a power imbalance, the system frequency response due to inertia can be expressed as follows [47], [97]:

$$2Hd\Delta f/dt = \Delta P_{mech} + \Delta P - D\Delta f \quad 3.1$$

where Δf denotes the system frequency deviation between the system frequency f after the event and the system base frequency f_0 when event happens; H denotes the equivalent system inertia, which equals the sum of system inertia values of all generators in the system; ΔP is the sudden event size, which could be a generator loss or load shedding; D denotes the equivalent damping coefficient, which equals to the sum of damping values of all generators in the system; $D\Delta f$ is the total increased damping power after the generation loss event. ΔP_{mech} is the total increased mechanical power from the governor response after the generation loss event.

In addition to the system's inertia response, large-scale power systems like those in EI and WECC contain a multitude of governors. Figure 3.2 depicts a typical governor, specifically the IEEE standard model.

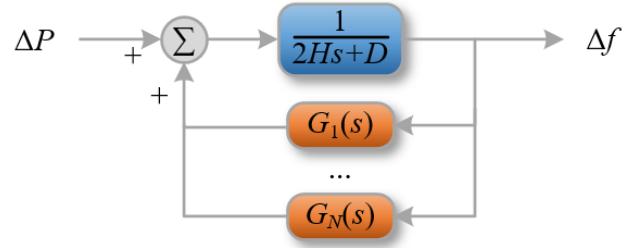


Figure 3.1. System frequency response model.

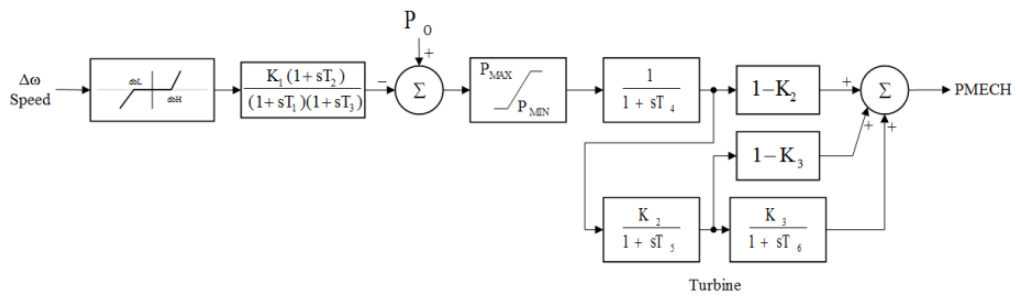


Figure 3.2. IEEE standard model of governor.

3.1.2 Theory of Governor Correction Factor and its Application in Generation Trip MW Estimation

To accurately estimate the MW size using the frequency deviation several seconds after the event, both the inertia response and governor response must be taken into account. In this study, similar to the traditional Beta method, we assume that the governor response has a linear characteristic.

Figure 3.1 shows both inertia response and governor response model after the generation trip event. Clearly, frequency response process is linear. Thus, at time Δt after the event, the total increased mechanical power from the governor response at a certain time ΔP_{mech} has a linear relation with the event size ΔP , which can be expressed as

$$\Delta P_{mech}(\Delta t) = k(t) \Delta P \quad 3.2$$

where ΔP is the event size; $\Delta P_{mech}(\Delta t)$ is the total mechanical power change at time Δt after the event; $k(t)$ is the linear coefficient at Δt , which changes with the time Δt .

To help clarify Equation 3.2, sample cases are simulated in an 18-bus test system using PSS/E. Figure 3.3 displays the total increased mechanical power after a MW loss event. As seen in the figure, the mechanical power increase from the governor is larger at a certain time if the MW loss amount is greater. Furthermore, Figure 3.4 illustrates the mechanical power at 3s under different event sizes, indicating a linear relationship between the total increased mechanical power and event amount.

Substituting Equation 3.2 into Equation 3.1 yields

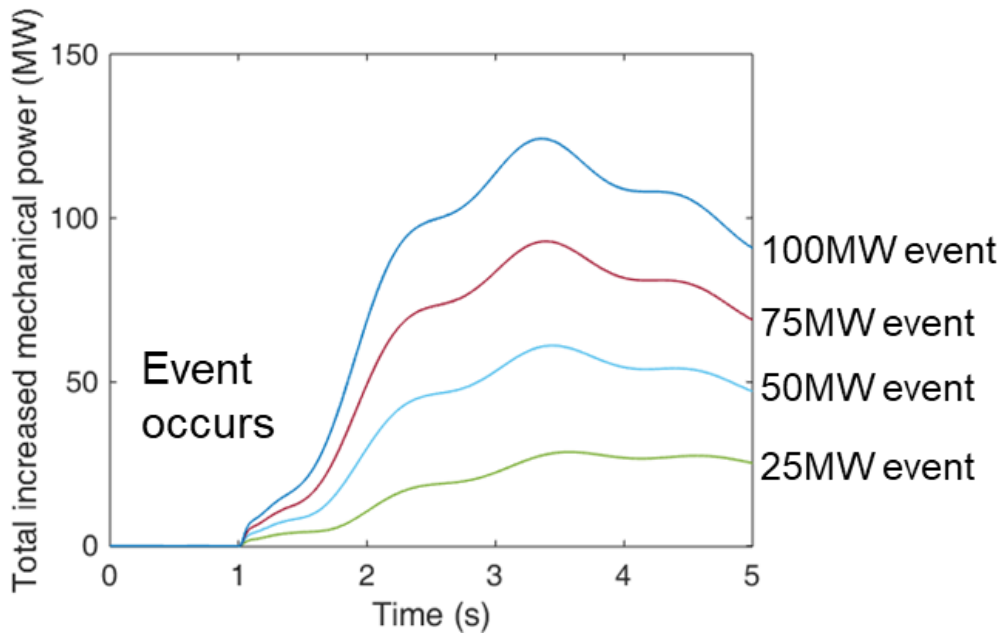


Figure 3.3. Total mechanical power change under different event sizes.

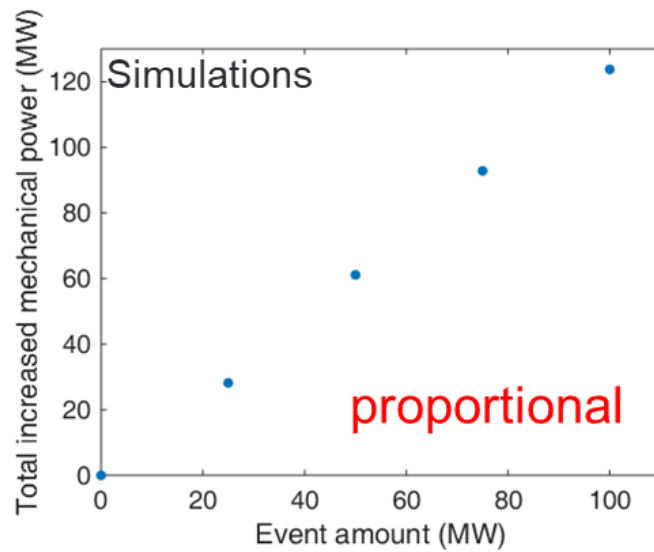


Figure 3.4. Relationship between event size and total mechanical power change at 3s after the event.

$$2Hd\Delta f/dt = -k(t)\Delta P + \Delta P - D\Delta f \quad 3.3$$

For simplicity, we assume that the damping power is much smaller than the governor power $k(t)\Delta P$ and the MW drop in this section. In the later sections, we will introduce the impact of damping in detail. As a result, Equation 3.3 simplifies to:

$$2Hd\Delta f/dt = [1 - k(t)] \cdot \Delta P \quad 3.4$$

It is important to note that the $k(t)$ is independent of the loss amount ΔP at a certain time, but it changes with time.

In Equation 3.4, let s denote t , and then the integral of Equation 3.4 over the time interval $[0, \Delta t]$ is derived as follows:

$$2H \cdot [\Delta f(\Delta t) - \Delta f(0)] = [\Delta t - \int_0^{\Delta t} k(s) ds] \cdot \Delta P \quad 3.5$$

where $\Delta f(0) = 0$;

Rearranging Equation 3.5 yields:

$$\Delta P = \frac{1}{1 - \int_0^{\Delta t} k(s) ds / \Delta t} \cdot 2H \cdot \frac{\Delta f(\Delta t) - \Delta f(0)}{\Delta t} \quad 3.6$$

where $\frac{1}{1 - \int_0^{\Delta t} k(s) ds / \Delta t}$ is a constant when Δt is selected; $\frac{\Delta f(\Delta t) - \Delta f(0)}{\Delta t}$ is the calculated event RoCoF.

It is worth noting that this event RoCoF can be calculated based on a relative larger time after the event, such as 3-5s, because of considering the governor response. Typical, NERC suggests the event RoCoF to be based on a very short window, ignoring the governor

response, but this can result in a significant impact from noise, oscillation, and wave propagation.

Furthermore, Equation 3.6 can be used in the MW estimation equation as

$$\Delta P = S \cdot 2H \cdot RoCoF \quad 3.7$$

where $S = \frac{1}{1 - \int_0^{\Delta t} k(s) ds / \Delta t}$, which is defined as a governor correction factor. $RoCoF = \frac{\Delta f(\Delta t) - \Delta f(0)}{\Delta t}$ is the rate of change of the frequency, which can be calculated based on a relatively larger Δt .

It is evident that after including the governor response, the MW estimation Equation 3.7 has the governor correction factor S compared to the traditional MW equation $\Delta P = 2H \cdot RoCoF$. Due to the impact of the governor response, part of the MW loss is compensated by the governor power. As a result, the calculated RoCoF over a long window is smaller than the actual event RoCoF over a short window, as shown in Figure 3.5. Because $k(t)$ is always a positive value, S is always greater than 1, and the calculated RoCoF using a long window is smaller than the event RoCoF using a small window.

Using Equation 3.6, the MW value can be estimated based on the measured inertia and event RoCoF. However, the governor correction factor S must first be determined using historical data (i.e., event MW value, event RoCoF, and inertia data near the event) through regression methods. Then, along with the regression governor correction factor, measured event RoCoF, and inertia data, Equation 3.6 can be used to estimate the MW value. It is worth noting that since $S = \frac{1}{1 - \int_0^{\Delta t} k(s) ds / \Delta t}$, the governor correction factor is related to Δt and $k(s)$, and therefore the regression must be recalculated each time Δt and $k(s)$ change.

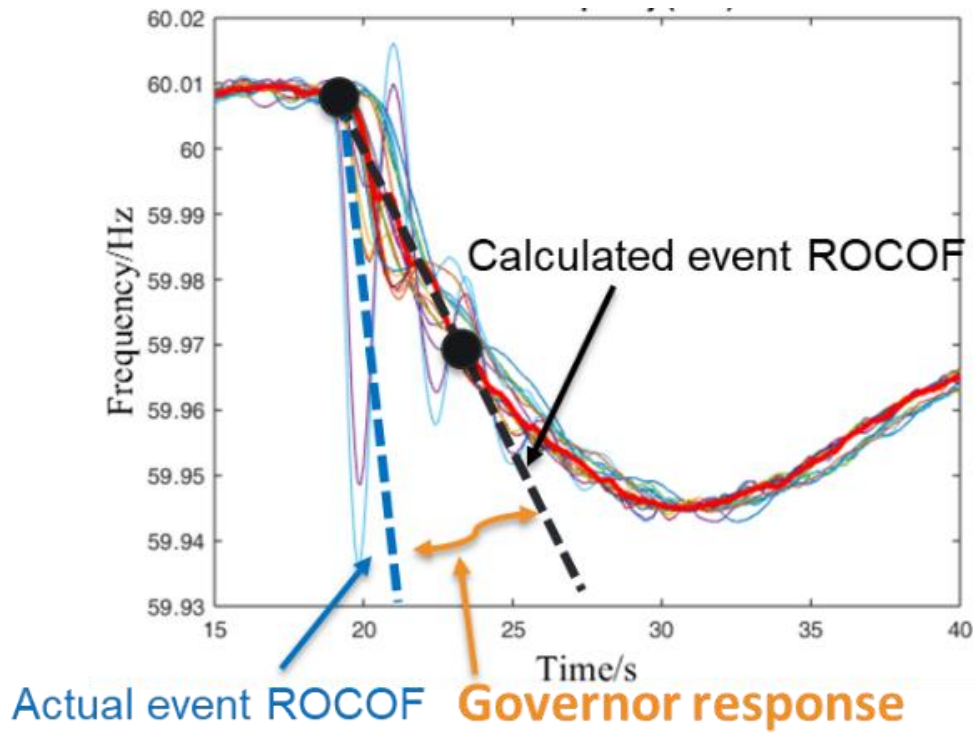


Figure 3.5. Impact of governor response on RoCoF over a long window.

Specifically, every time Δt changes, the governor correction factor S should be recalculated using regression for the best setting for MW estimation with Equation 3.6. $k(s)$ primarily describes the relationship between the increased mechanical power and MW loss, which is considered a fixed characteristic in a particular grid.

3.1.3 Impact of Damping Power on MW Estimation

Each power grid has unique characteristics, including frequency damping which cannot be disregarded in certain grids due to its significant magnitude. The damping power is intricately linked to the system load level, particularly in large-scale power systems where the system's inertia is linearly correlated with the load level. However, determining the total equivalent damping coefficient is challenging. To address this, it is assumed that in larger interconnections, the damping coefficient is proportional to the system's total inertia. This can be expressed as follows:

$$D = CH \quad 3.8$$

where C denotes the proportional factor between total inertia and damping coefficient of the whole system. It should be emphasized that C may vary across different grids.

Further, using Equation 3.8 in Equation 3.3, one obtains:

$$2Hd\Delta f/dt = -CH\Delta f + [1 - k(t)] \cdot \Delta P \quad 3.9$$

To deduce an explicit solution for Equation 3.9, both sides are multiplied by $\exp(Ct/2)$, and then one obtains

$$\begin{aligned}
& \exp(Ct/2) \cdot 2Hd\Delta f/dt \\
& = -\exp(Ct/2) \cdot CH\Delta f + \exp(Ct/2) \cdot [1 - k(t)] \cdot \Delta P
\end{aligned} \tag{3.10}$$

By calculus, Equation 3.10 can be expressed as

$$2H \cdot \frac{d[\exp(Ct/2) \cdot \Delta f]}{dt} = \exp(Ct/2) \cdot [1 - k(t)] \cdot \Delta P \tag{3.11}$$

Let s denote t in Equation 3.11, and then the integral of Equation 3.11 over the time interval $[0, \Delta t]$ is deduced as follows:

$$\begin{aligned}
& 2H \cdot [\exp(C\Delta t/2) \cdot \Delta f(\Delta t) - \exp(0) \cdot \Delta f(0)] \\
& = \int_0^{\Delta t} \exp(Cs/2)[1 - k(s)] ds \cdot \Delta P
\end{aligned} \tag{3.12}$$

where $\Delta f(0) = 0$;

Further, one obtains

$$\Delta P = \frac{\exp(C\Delta t/2)}{\int_0^{\Delta t} \exp(Cs/2)[1 - k(s)] ds/\Delta t} \cdot 2H \cdot \frac{\Delta f(\Delta t) - \Delta f(0)}{\Delta t} \tag{3.13}$$

Finally, the MW estimation equation considering the damping can be reorganized as

$$\Delta P = S \cdot 2H \cdot RoCoF \tag{3.14}$$

where $S = \frac{\exp(C\Delta t/2)}{\int_0^{\Delta t} \exp(Cs/2)[1 - k(s)] ds/\Delta t}$. $RoCoF = \frac{\Delta f(\Delta t) - \Delta f(0)}{\Delta t}$ is the rate of change of the frequency, which can be calculated based on a relatively larger Δt .

Governor correction factor in Equation 3.14 is a function of Δt , C , and $k(s)$. The regression should be redone once Δt , C , and $k(s)$ change. C and $k(s)$ are assumed to be

relative constant in a larger-scale system, so just Δt should be taken care of when using different RoCoF windows.

As mentioned previously, the governor correction factor is difficult to measure, so the regression method should be used with the historical data to get the governor correction factor in Equation 3.14. Thus, it can be found that MW estimation Equation 3.14 is the same as Equation 3.7 when estimating MW value, even if the damping is further considered.

3.1.4 Validation of the Proposed Method

The proposed MW estimation method using Equation 3.14 is validated using historical event data from NERC. The validation process involves several steps, as follows:

Step 1: Measure the real-time frequency by FNET/GridEye system.

Step 2: Detect the generator trip event.

Step 3: Determine the accurate event time.

Step 4: Extract the event RoCoF for the MW estimation.

Step 5: Estimate the MW trip value using Equation 3.14.

FNET/GridEye's existing MW estimation method is based on the Beta value method, which is further used to compare the proposed method.

The deviation rate of the estimated value from the confirmed event MW value from NERC for each case is described using the absolute error rate (AER), as follows:

$$AER = \frac{|Estimated\ value - Confirmed\ Value|}{Confirmed\ Value} \quad 3.15$$

FNET/GridEye has a wide frequency measurement system to detect generator events in the United States. An online generator trip event trigger system has been developed that can detect generator trip events when the frequency experiences an obvious drop, resulting in a real-time absolute RoCoF increase that exceeds the set threshold. Once the event is detected, it is recorded, and the MW estimation program is triggered to estimate the MW value. In the MW estimation program, an additional function is used to obtain the event time, improving the estimation accuracy. Figure 3.6 shows the process of the event trigger.

NERC keeps monitoring the inertia for EI. The process of calculating inertia is to track the status of generator and sum the inertia of all online generators every 15 minutes.

Historical event data from FNET/GridEye and inertia data from NERC are used to validate the proposed method for generator trip events that occurred between 2016 and 2019. The measured frequency is preprocessed using a median filter to obtain a reliable system frequency for the whole system. This is necessary because some FDRs may have bad data, such as frequency spikes, or may lose data due to poor internet connections. Therefore, the median value of all FDRs' frequencies is calculated as the median frequency at a certain time, which is then used to estimate the MW value, as shown in Figure 3.7.

For validation, the proposed method is used to estimate the MW values for historical events in EI, and the results are compared with the NERC background truth event MW. Figure 3.8 and Figure 3.9 show the median and average absolute error rates of MW estimation by the proposed method under different RoCoF window sizes, respectively.

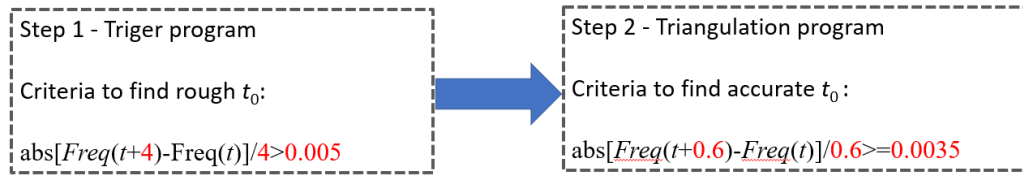


Figure 3.6. Event trigger process for detecting generator trip events.

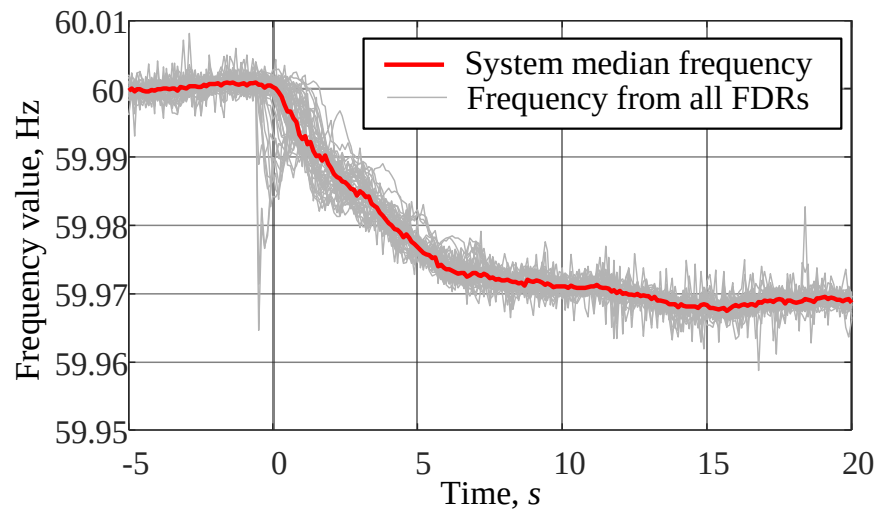


Figure 3.7. Median frequency to avoid frequency spikes, oscillations, and data loss.

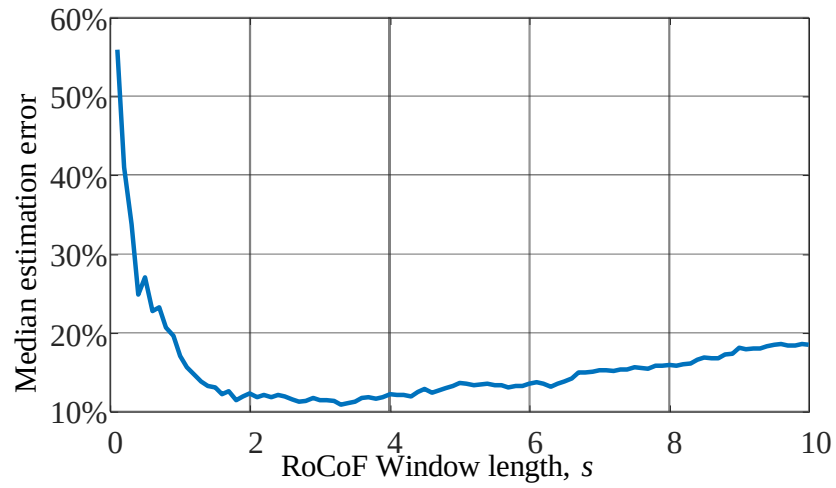


Figure 3.8. Median absolute error rate of EI MW estimation using the proposed method.

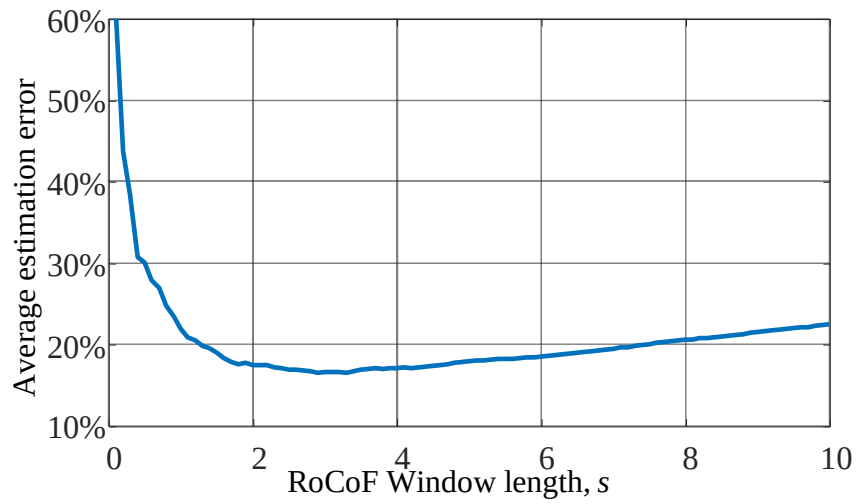


Figure 3.9. Average absolute error rate of EI MW estimation using the proposed method.

It is evident that the estimation error is lowest when using a RoCoF window size of around 3 seconds. Compared to the traditional single Beta-value based method, the proposed method significantly improves the median absolute error of estimation from 26% to around 10% in EI, achieving a substantial improvement.

3.2 Improved MW Estimation Based on Multi-Beta to Include Impact of Governor Deadband

Although the long-window RoCoF method in the previous section can significantly improve MW estimation accuracy, it requires real-time inertia data, limiting the application of the proposed method. To overcome this limitation, an improved method using multi-Beta based MW estimation is proposed in this section. The traditional Beta-based method is influenced by deadband, so the improved method considers the impact of deadband by using multiple Beta values. Currently, the existing single Beta-based method used in FNET/GridEye's estimation has a median absolute error rate of 26% for the EI system in 2017. NERC desires to reduce the accuracy of MW estimation for the EI system. After testing, the improved method using multi-Beta achieves a median error rate of 16% for the EI system in 2017. This section's main contributions include:

(a) The governor deadband is identified as one of the major reasons for the low accuracy of the single-Beta method;

(b) To improve MW estimation accuracy, the proposed method uses two Beta values, one for Beta within the deadband and another for Beta outside of the deadband, considering the usual $\pm 36\text{mHz}$ deadband in U.S. interconnections. The validation using historical events shows that the proposed method significantly improves the accuracy of MW estimation;

(c) The trend of Beta values from 2013 to 2018 is calculated using regression, which provides a more comprehensive understanding of the system governor resource change compared to the single Beta method, which does not consider deadband.

3.2.1 Impact of Governor Deadband on Single-Beta Based MW Estimation

The existing MW estimation in FNET/GridEye is based on a single Beta method, which fails to account for the impact of deadband. The effect of deadband can vary based on different beginning frequencies and MW sizes. To illustrate this, Figure 3.10 shows the single Beta estimated MW values and the background truth MW values for EI in 2018 under different beginning frequencies. It is evident that more red points (higher beginning frequency) are above the line $y = x$, indicating overestimation from the single Beta estimation. More blue points (lower beginning frequency) are below the line $y = x$, indicating underestimation of the single Beta estimation.

The color of a point indicates the initial frequency of an event, which determines the magnitude of the frequency deviation as it passes through the dead band. Typically, there are fewer governor resources available within the dead band, resulting in a lower Beta value compared to outside the dead band. If a significant portion of the frequency drop occurs within the dead band, the resulting frequency drop will be larger due to the lower Beta value. Consequently, this will lead to an overestimation of the MW value. The impact of the dead band on the estimation process is illustrated in Figure 3.11.

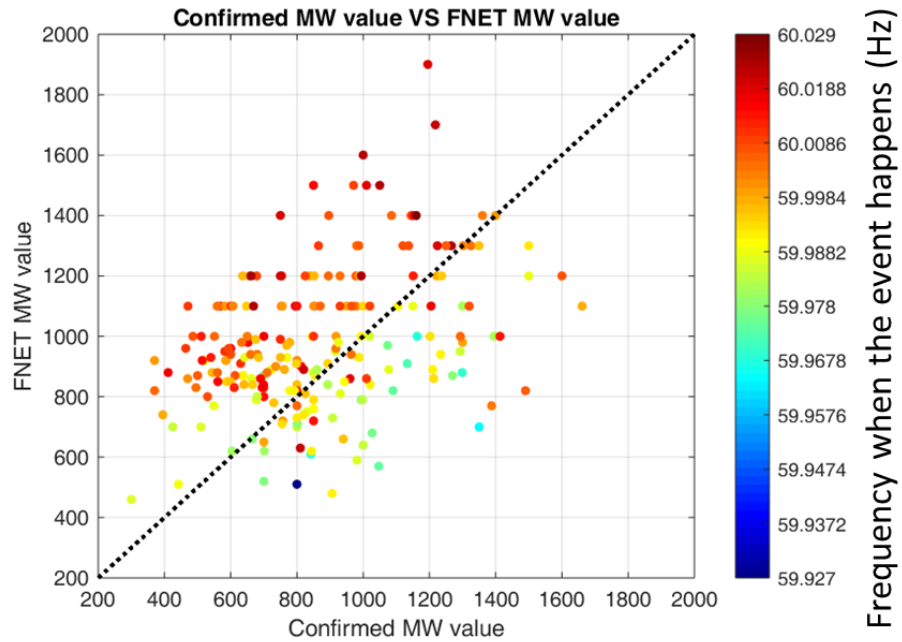


Figure 3.10. Comparison between single-Beta estimation MW and background truth

MW under different beginning frequencies for EI system in 2018.

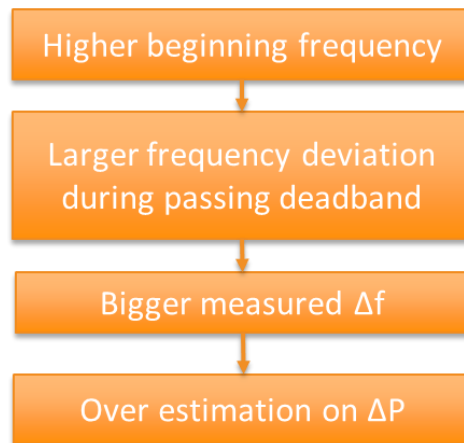


Figure 3.11. Impact of deadband on single Beta-based MW estimation.

3.2.2 Two-Beta Based MW Estimation Considering the Impact of Deadband

To address the impact of the deadband on MW estimation accuracy, the two-Beta method is employed, with a deadband range of $\pm 36\text{mHz}$ typically used for most interconnections. The measured frequency deviation, Δf , is partitioned into two components, $\Delta f_{\text{within_deadband}}$ and $\Delta f_{\text{out_deadband}}$ based on the deadband boundary $60\text{Hz} \pm 36\text{mHz}$. Using historical events, regression analysis is conducted to obtain two-Beta values ($\beta_{\text{within_deadband}}$ and $\beta_{\text{out_deadband}}$). The MW value is then calculated using the regression Beta values and the measured Δf values, as illustrated in the estimation equation in Figure 3.12. This approach improves the accuracy of MW estimation in the presence of deadband.

To verify the effectiveness of the two-Beta method, the estimation accuracy was evaluated for confirmed events in EI from 2013 to 2019. As shown in Figure 3.13, the annual average absolute error rate, median absolute error rate, and median variance were calculated. Compared to the existing single-Beta-based estimation approach, the two-Beta-based method yielded improvements in all three yearly accuracy indices. Notably, the new method resulted in a 10% reduction in the average absolute error rate from 26% of the traditional single-Beta method.

3.2.3 Trend of Beta Values Within and Outside of Deadband in EI

NERC seeks to monitor changes in governor resources, which can be achieved using the proposed two-Beta method to track trends in Beta values within and outside the deadband.

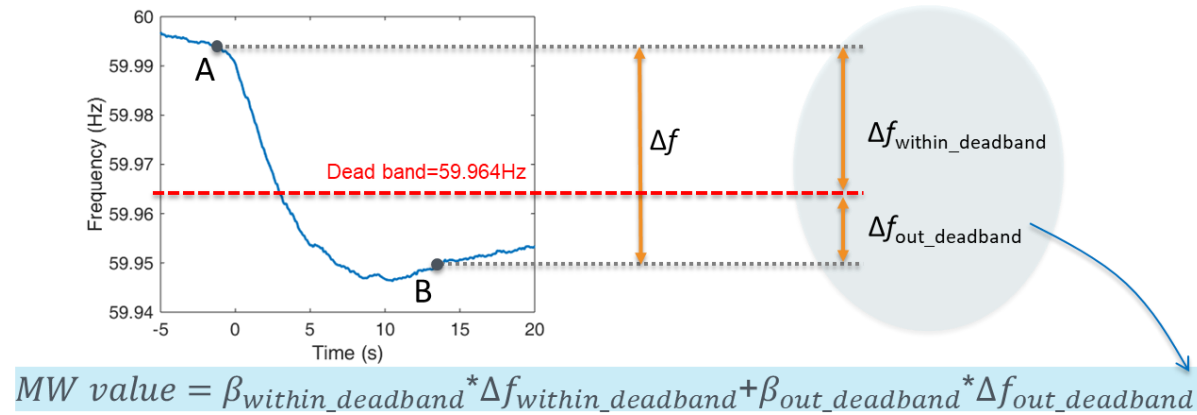


Figure 3.12. MW estimation using two Beta values to consider deadband effects.

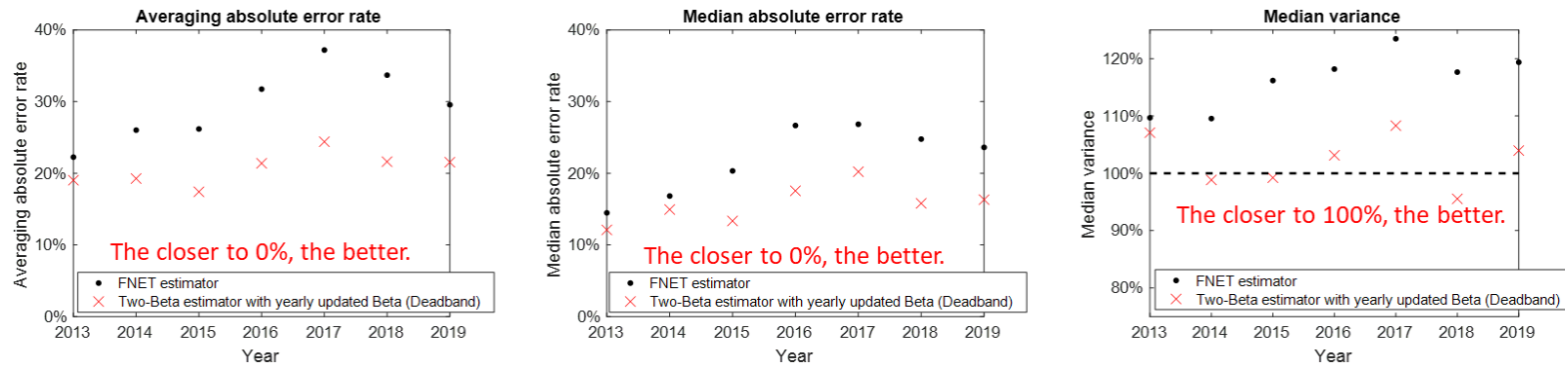


Figure 3.13. Performance of proposed two-Beta MW estimation for EI events from 2013-2019.

Historical events were used to calculate Beta values (within and outside the deadband) for the EI system from 2013 to 2018, as shown in Figure 3.14. The Beta value within the deadband (blue crosses) remained relatively stable from 2013 to 2018, hovering around 20,000 MW/Hz. In contrast, the Beta value outside the deadband (red crosses) exhibited a clear increase from 2015 to 2016. Specifically, the Beta value outside the deadband was around 31,000 MW/Hz from 2013 to 2015 and increased to around 34,500 MW/Hz from 2016 to 2018. One possible explanation for this increase is that generators with a deadband much larger than $\pm 36\text{mHz}$ were reconfigured with a smaller deadband size from 2016 onwards, as confirmed by a NERC industry advisory distributed on February 5th, 2015 [98].

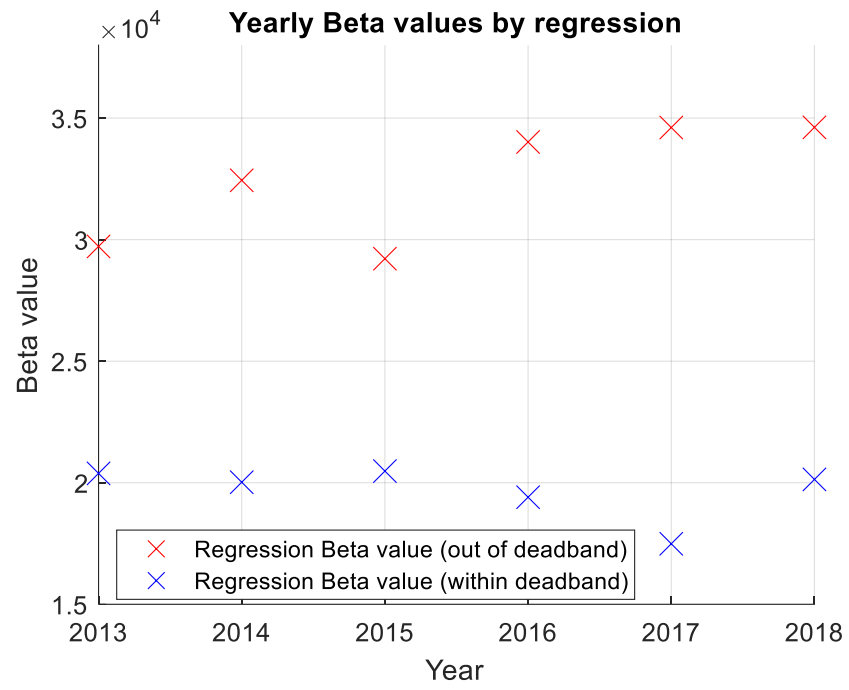


Figure 3.14. Trend of Beta values within and outside deadband from 2013 to 2018.

CHAPTER 4 REAL-TIME SYSTEM

INERTIA ESTIMATION

Monitoring the system inertia is crucial for ensuring stable operation of the power grid, particularly in high renewable grids where many resources contribute to the effective inertia. However, accurately estimating inertia poses a significant challenge due to the complexities involved, including missing synthetic and load inertia. The most commonly used approach for inertia estimation involves only considering mechanical inertia by summing up the individual inertia values of dispatched generators. To address these accuracy concerns, this chapter proposes two new practical methods for inertia estimation. The first method utilizes ambient frequency data for estimating Hawaii island's inertia, while the second leverages pump turn-off events to estimate inertia for WECC. These new methods represent important steps towards addressing a key challenge in operating high-renewable power grids and will help pave the way for the development of a carbon-free power sector in the United States by 2035.

The ambient-frequency-data-based inertia estimation method is proposed and implemented in the context of Hawaii's islands. A physical equation is derived to provide clear physical principles for estimating system inertia. The physical equation-based inertia estimation method is validated using both KIUC simulation data and HECO field data, achieving approximately 2% and 7% error rates, respectively. These results indicate that the proposed inertia estimation methods have satisfactory performance. Additionally, the

median filter window size and magnitude calculation window size are adjusted to optimize performance.

4.1 Ambient-frequency-data-based Real-time Inertia Estimation for Hawaii Island Power Grid

In this research, I aimed to develop an inertia estimation method with a clearer mechanism that would be easier to implement on Hawaii islands. To achieve this goal, we developed an inertia estimation approach using physical equations and validated it using KIUC simulation data and HECO field data.

The power grid experiences ambient power noise disturbances due to changes in real-time load and generation, which cause ambient frequency fluctuations. System inertia plays a crucial role in these ambient frequency fluctuations resulting from ambient power noise disturbances. After theoretical derivation, I found that the ambient frequency fluctuation magnitude is proportional to the inverse of the system inertia and the magnitude of the ambient power noise.

Figure 4.1 illustrates proposed ambient-frequency-based physical equation method. The method begins with high-resolution frequency signal collection using FNET frequency monitors on Maui island. After signal filtering and feature extraction, the ambient frequency fluctuation feature is obtained. To facilitate practical implementation, challenge of obtaining the ambient power noise magnitude is addressed by using system total load information, as grid typically experiences greater ambient power noise during high load conditions. For real-time inertia estimation algorithm, historical ambient frequency signal features, load data, and inertia are used to fit the physical equation.

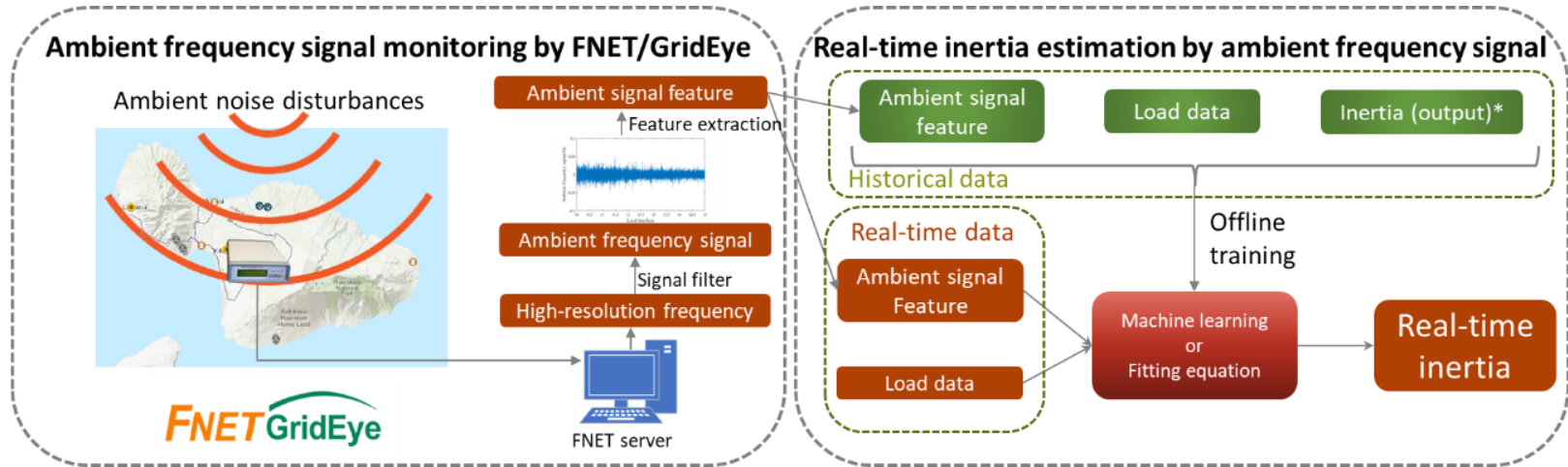


Figure 4.1. Process of the proposed physical equation method using ambient-frequency-fluctuation for inertia estimation.

In the real-time application, ambient frequency fluctuation magnitude and load data are used into the fitted physical equation to obtain the real-time inertia.

4.1.1 Physical Equation for Ambient-frequency-based Inertia Estimation

When ambient power noise is present, it can cause ambient frequency fluctuations in frequency due to the system's inertia response. The relationship among the system inertia H , ambient power source P_{noise} , and ambient frequency fluctuation f_{noise} can be described using the power system swing equation.

$$H \frac{df_{noise}}{dt} = P_{noise} \quad 4.1$$

To avoid the differential calculation for $\frac{df_{noise}}{dt}$ in the practical calculation, Equation 4.1 can be integrated on both sides, resulting in the following equation:

$$H f_{noise} = \int P_{noise} \quad 4.2$$

Using the noise magnitude calculation, such as max-min, standard deviation, or interquartile range, one further can obtain

$$H * A(f_{noise}) = A(\int P_{noise}) \quad 4.3$$

The Interquartile Range (IQR) is a preferred measure for data noise, as it effectively filters out outliers and mitigates the impact of extreme values. Defined as the difference between the upper and lower quartiles, the IQR represents the region in which the central 50% of the data lies. Specifically, the lower quartile aligns with the 25th percentile, while

the upper quartile corresponds to the 75th percentile, providing a robust and reliable measure for understanding data distribution.

Upon rearranging Equation 4.3 by shifting the term $A(f_{noise})$ to the right side, the resulting equation demonstrates that the inertia is equivalent to the product of the ambient power source noise's integral magnitude and the reciprocal of the ambient frequency fluctuation magnitude.

$$H = A(\int P_{noise}) \frac{1}{A(f_{noise})} \quad 4.4$$

In practical applications, measuring every power noise source from loads using a Phasor Measurement Unit (PMU) is challenging. Therefore, the total system load level is employed to approximate the integral magnitude of the power source noise, denoted as $A(\int P_{noise}) \approx a * load \Delta f$. Consequently, a pragmatic estimation equation that incorporates both ambient conditions and system load can be expressed as follows:

$$H = \frac{a * load}{A(f_{noise})} \quad 4.5$$

Based on the aforementioned derivation, the system inertia can be estimated by considering both the system load level and the ambient frequency fluctuation magnitude. The total system load and measured frequency data serve as inputs for this inertia estimation method. The proposed estimation process consists of three primary steps:

(a) Feature Extraction: The ambient frequency fluctuation magnitude is extracted from the collected frequency data;

(b) Equation Model Fitting: The extracted ambient signal features are combined with the system load and historical inertia data to fit Equation 4.5, which aims to establish the quantitative relationship between the input features and system inertia;

(c) Real-time Application: The fitted physical equation, derived from the previous step, is subsequently applied to estimate system inertia in real-time, utilizing both the ambient frequency fluctuation and system load data.

4.1.2 Validation of Ambient-frequency-data-based Real-time Inertia Estimation Using KIUC Simulation Data

The proposed physical equation method is initially validated using KIUC simulation data. By employing the PSS/E model from KIUC, a dataset of ambient frequency data is generated under various magnitudes of random power signals (represented by Gaussian white noises) and inertia. These random power signals are injected into all loads. The simulation time step is set to 0.0083 seconds, resulting in simulated ambient frequency data of $1/0.0083\text{s} = 120\text{Hz}$, which matches the FNET/GridEye UGA measurement resolution.

For validation of the inertia estimation, ten-fold cross-validation is employed to obtain a reliable accuracy value. 90% of the data are utilized to train the model, while the remaining 10% serve as validation data. Figure 4.2 illustrates the comparison between the estimated inertia and the benchmark inertia. The mean absolute error rate between the estimated and benchmark inertia is approximately 2%, indicating that the physical equation method for inertia estimation demonstrates satisfactory accuracy. Additionally, it is worth noting that the system inertia level is proportional to the inverse of the ambient frequency fluctuation magnitude when the power white noise magnitude remains constant.

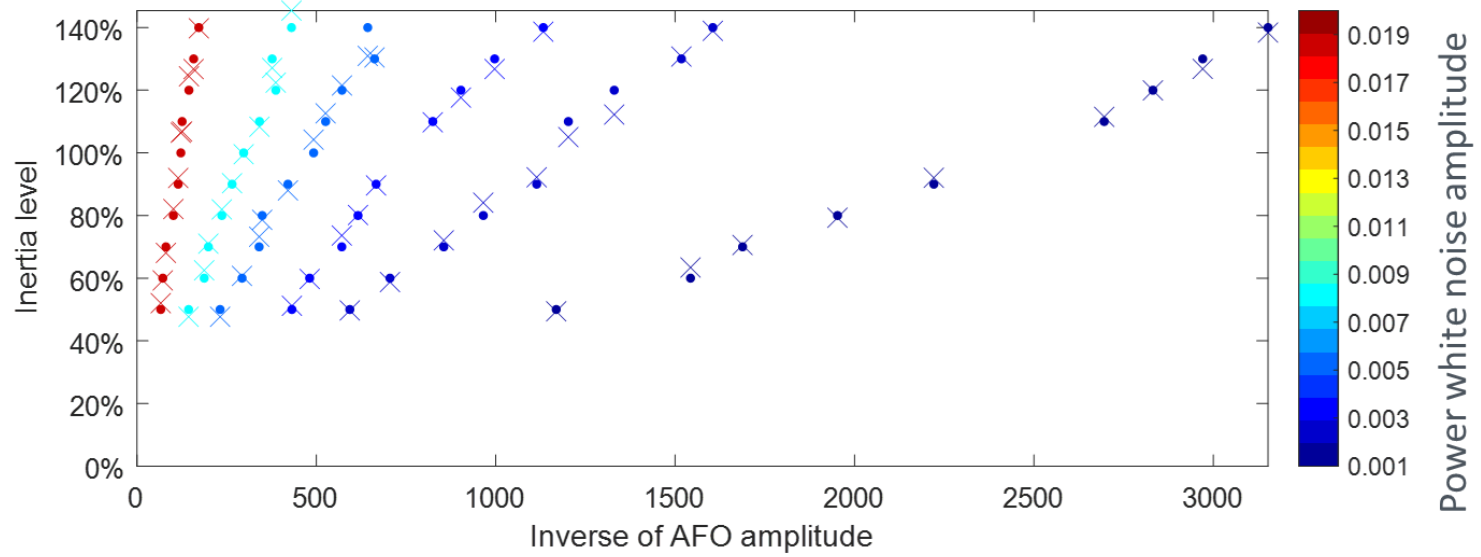


Figure 4.2. Comparison of estimated and benchmark inertia using KIUC simulation data.

4.1.3 Validation of Ambien-frequency-data-based Real-time Inertia Estimation Using HECO Grid Field Data

Since the physical equation method demonstrates promising performance with the Maui simulation data, the proposed method is further validated using HECO field data.

Two segments of HECO field data are utilized to train and validate the inertia estimation method separately: training data spans from 08/24/2021 to 09/06/2021, while validation data covers 09/28/2021 to 10/18/2021. Field data comprises system inertia and load data, with HECO grid frequency data measured by FNET/GridEye UGA units. The physical equation is fitted using regression analysis on the training data. By inputting the ambient frequency data and system load from the validation data into the fitted equation model, the real-time inertia from 09/28/2021 to 10/18/2021 is estimated (depicted by the yellow line in Figure 4.3). In comparison to the benchmark inertia (blue line), the estimated inertia exhibits a mean absolute error rate of approximately 7%, confirming the accuracy of the proposed estimation method. Moreover, since load information is highly correlated with system inertia, an equation model utilizing only the load level (i.e., $\text{Inertia} = a \cdot \text{load}$) is fitted and subsequently used to estimate the system inertia, with its estimated inertia curve displayed as an orange line in Figure 4.3. Notably, the training data is one month earlier than the testing data, which closely resembles the real-world application conditions (i.e., historical data for training precedes real-time data). These validation results further substantiate the feasibility of the proposed inertia estimation method in practical scenarios.

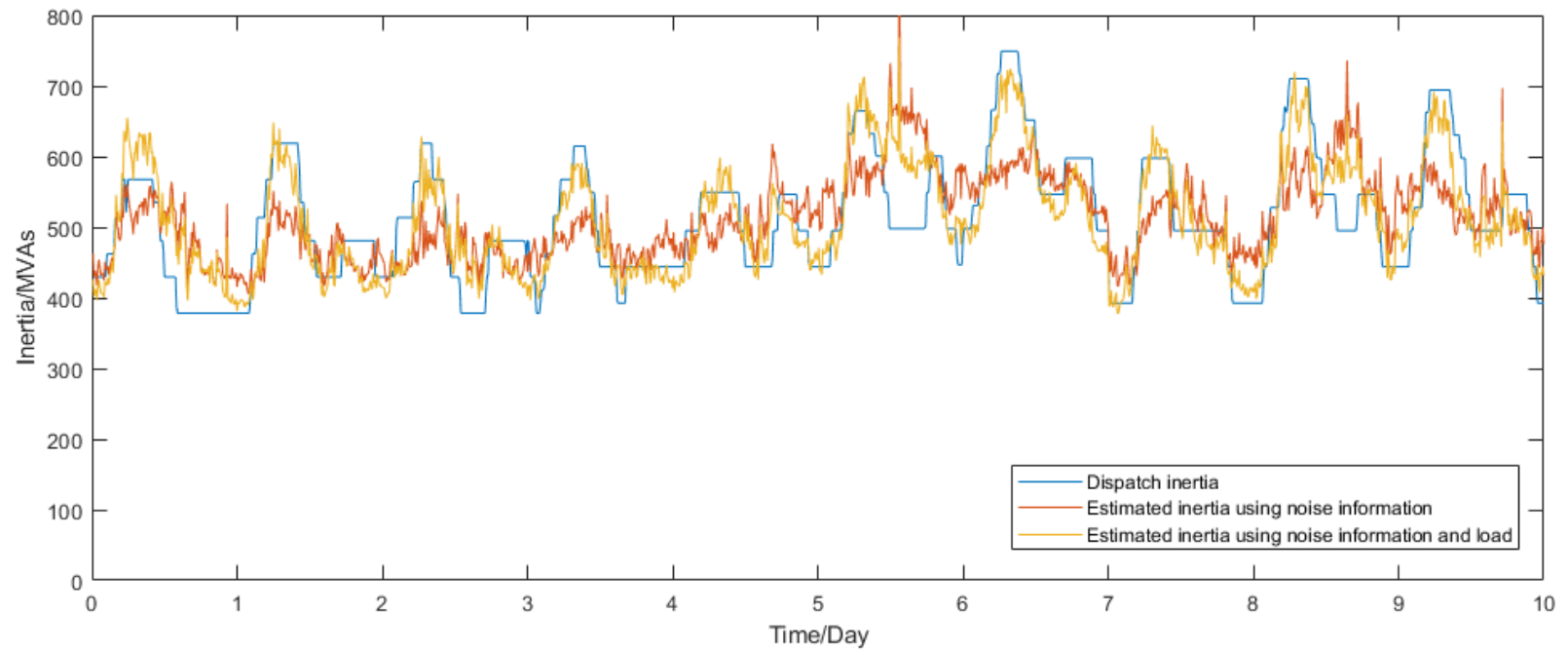


Figure 4.3. Comparison of estimated and benchmark inertia using HECO field data.

4.1.4 Improvement of Ambient-frequency-data-based Real-time Inertia Estimation for HECO Grid

In this section, the proposed method undergoes further fine-tuning to optimize performance.

First, the proposed method is compared with neural networks and random forests to determine if the equation method has captured sufficient patterns from the data. Since the physical equation is initially fitted using historical data and subsequently validated, the same process is applied to both neural networks and random forests. The average absolute error rates of the three methods are presented in Table 4.1. The proposed physical equation method achieves performance comparable to that of neural networks and random forests, thereby capturing the principal patterns within the data. Although the neural network exhibits a slightly lower error rate, it lacks the physical mechanisms inherent in the equation method.

Second, the window size employed to extract the ambient frequency fluctuation from the raw frequency data is adjusted to enhance accuracy. A moving median window is applied to the raw frequency data to capture the slow trend of the frequency data. Subsequently, the ambient frequency fluctuation data is extracted by detrending the raw data from the slow trend, as illustrated in Figure 4.4. Figure 4.5 presents the average absolute error rates of the equation method, neural network, and random forest under various median filter window sizes. A median filter window size of approximately 15 seconds yields the best performance for Maui Island. Thus, the median filter window size acts as a critical parameter using ambient frequency data for inertia estimation.

Table 4.1. Comparison of method accuracy for ambient-frequency-data-based inertia estimation.

Methods	Average absolute error rate
Fitting physical equation	7.76%
Neural network	7.37%
Random forest	7.96%

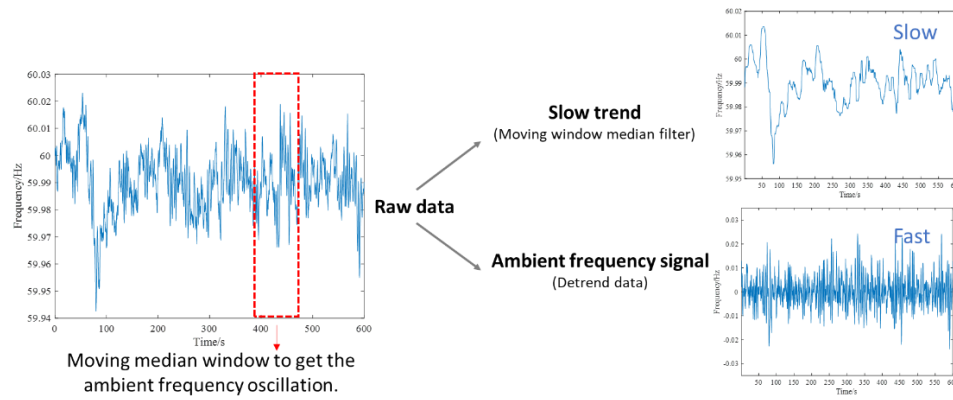


Figure 4.4. Median filter window for extracting ambient frequency data.

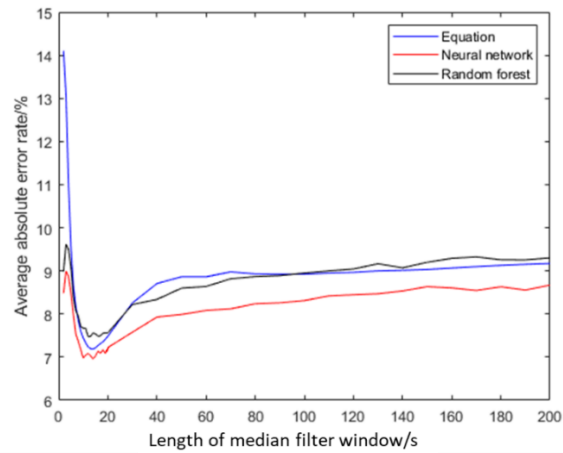


Figure 4.5. Error rate of the equation method, neural network, and random forest under different median filter window sizes.

Third, the window length used to extract the magnitude value from the ambient signal is adjusted to further enhance accuracy. When applying a moving window to the extracted ambient frequency fluctuation data, the max-min, standard deviation, or interquartile range are computed as the magnitude, as depicted in Figure 4.6.

Figure 4.7(a) displays the average absolute error rates of the equation method, neural network, and random forest under various magnitude calculation window sizes. It is evident that a longer magnitude calculation window corresponds to a smaller error rate. However, it should be noted that a larger magnitude calculation window could lead to a longer delay in inertia estimation, as illustrated in Figure 4.7(b). Consequently, when applying an ambient-based method, setting the magnitude calculation window size involves striking a balance between accuracy and estimation delay.

4.1.5 Discussion on the Ambient-frequency-data Based Inertia Estimation Method Under Deadband

While the proposed ambient-frequency-data-based method demonstrates promising performance, it is important to note that the estimated inertia may not accurately capture the synthetic inertia from inverter-based resources (IBR) with fast frequency control with deadband settings. Statistical analysis of measured frequency data from the HECO grid on a randomly selected day reveals that 96.43% of frequency values lie within $\pm 36\text{mHz}$ (a typical deadband setting) around 60Hz, as depicted in Figure 4.8. Since IBR fast frequency control with deadband does not impact frequency response when the frequency remains within the deadband, the estimated inertia based on ambient frequency data may primarily focus on the traditional generator inertia and load inertia.

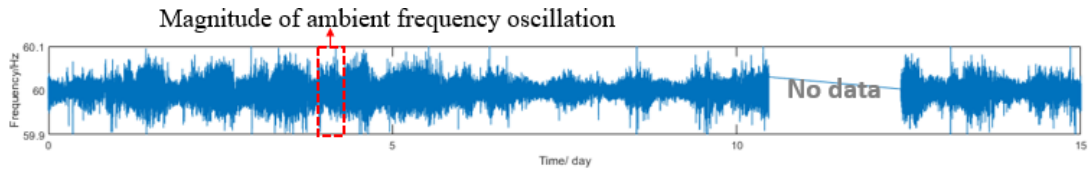
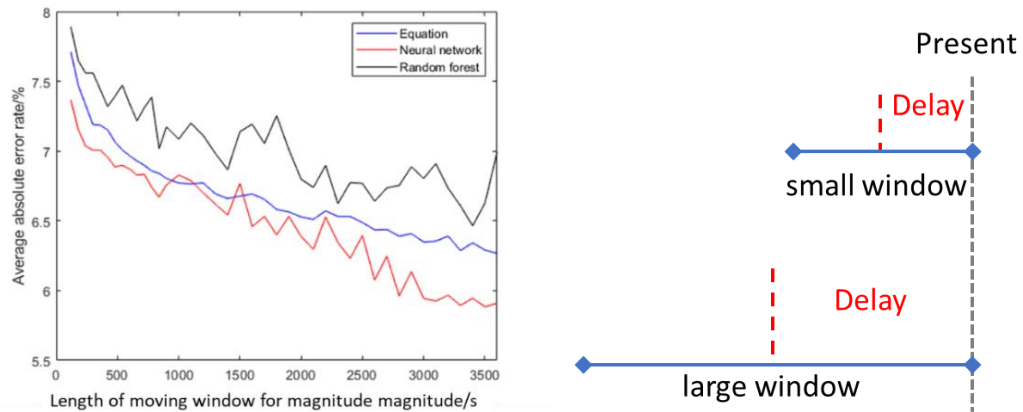


Figure 4.6. Moving window for calculating ambient frequency fluctuation magnitude.



(a) Estimation error rates

(b) Estimation delay

Figure 4.7. Error rates and delay for the equation method, neural network, and random forest under different fluctuation calculation magnitude window sizes.

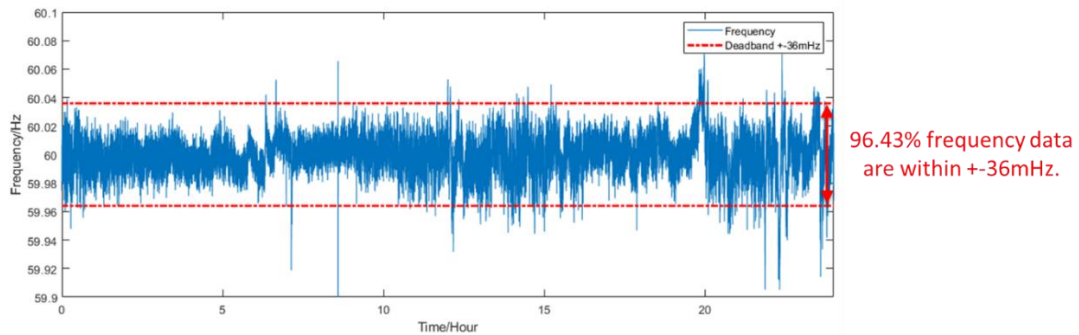


Figure 4.8. One-day frequency measurement from UGA on Maui island.

4.2 Pump Turn-off Signature Based Inertia Estimation for WECC

In this section, a novel inertia estimation method utilizing pump turn-off signatures is proposed and applied in the WECC. Since most pump storage units exhibit consistent switching patterns accompanied by a fixed amount of instantaneous power change when pumps are tripped, they serve as ideal resources for effective inertia monitoring in high-renewable power grids.

4.2.1 Pump Storage Switching Event Analysis

Before researching inertia estimation using pump hydro operation signatures, it is important to first analyze real pump events to gain a better understanding. With access to PMU data from a power grid operator, the PMU power data of one of the largest pump storage plants in the United States was obtained and analyzed. The available PMU data, recorded at 60 points per second from June 2019, includes three-phase voltage phasor, three-phase current phasor, frequency (which needs to be calculated), and power (which also needs to be calculated).

Typically, pump storage plants have four types of switching events: generator turn-off, generator turn-on, pump turn-off, and pump turn-on, as illustrated in Figure 4.9. After exploring the PMU power data for each of these events from the pump storage plant (as shown in Figure 4.10), it was determined that the pump turn-off event is the most promising for estimating inertia due to the existence of a step power change. For RoCoF-based inertia estimation to be successful, a clear power step change is required following the event. However, pump turn-on, generator turn-off, and generator turn-on events do not exhibit a clear power step change.

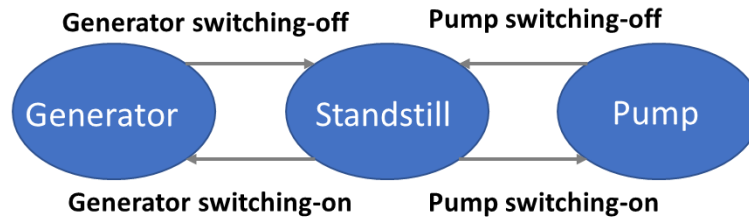
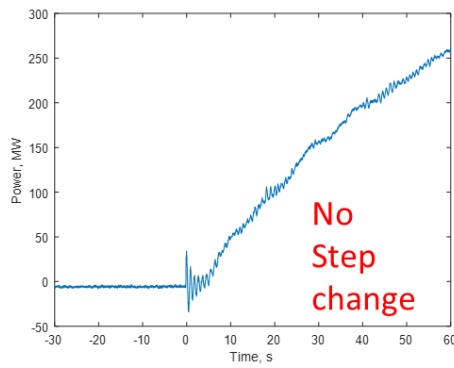
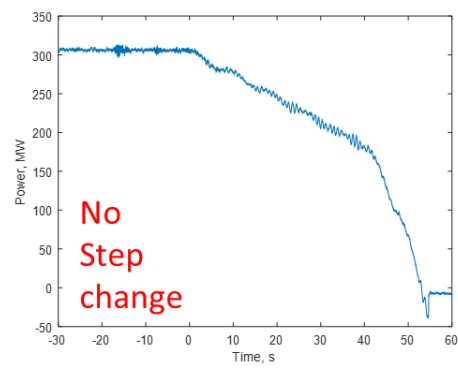


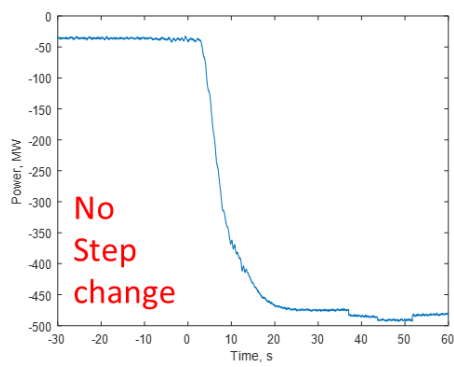
Figure 4.9. Four types of events occur in pump storage plants.



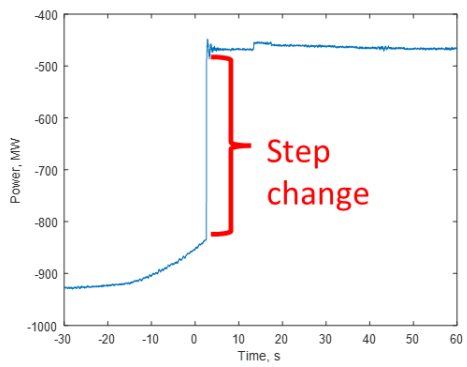
(a) Generator turn-on



(b) Generator turn-off



(c) Pump turn-on

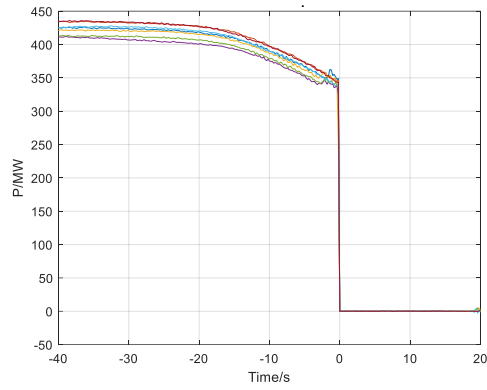


(d) Pump turn-off

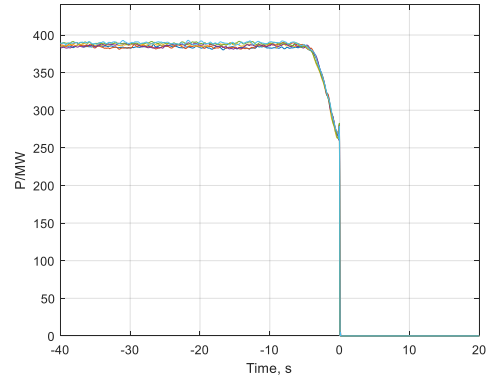
Figure 4.10. PMU power of four types of events from a pump storage plant.

To gain a better understanding of the pump turn-off operation, it is important to examine the physical process of the MW change that occurs during the pump turn-off. Figure 4.11 displays the PMU MW values of pump turn-off from two pump storage plants. It is clear that all pump turn-off events exhibit a MW ramp down, followed by a sudden trip that remains constant. The physical process of the pump turn-off event further confirms this MW change phenomenon. When a pump unit receives a turn-off command, it reduces power by closing the hydro gate, resulting in a gradual MW ramp down. As the gate opening level or active power is reduced to a threshold value, the breaker is switched off, resulting in a sudden MW step change. Therefore, both the MW data and the physical process of the pump turn-off event demonstrate the same behavior, providing a better understanding of the pump turn-off operation.

Additionally, the PMU data collected from the pump storage plant was used to examine the MW values of pump turn-off. Figure 4.12 depicts a histogram of the MW values of pump turn-off recorded by a pump storage plant in 2021. It is apparent that the pump storage plant consistently maintains MW values when the pump is turned off. The maximum, minimum, and absolute average deviation ratios from the mean MW are 5.12%, -3.84%, and 1.36%, respectively. This consistency in MW values provides a significant advantage when using the pump turn-off event to estimate inertia since the average MW value of these events can be utilized for the inertia estimation without requiring real-time confirmation of MW.



(a) Pump storage plant A



(b) Pump storage plant B

Figure 4.11. Observed MW ramp down and step change from confirmed pump turn-off.

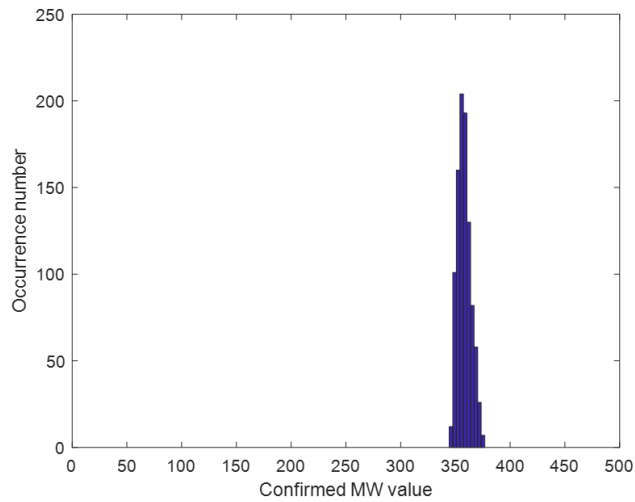


Figure 4.12. MW distribution for Pump turn-off events in a real pump storage plant.

Despite the relatively constant MW values depicted in Figure 4.12, there is still some minor variation from the average value. To investigate the seasonal pattern of this slight MW variation, Figure 4.13 illustrates the monthly maximum, mean, and minimum values of pump turn-off MW recorded by the researched pump storage plant in 2021. It is evident that the pump turn-off MW exhibits little variation across different months, indicating the absence of any significant seasonal pattern.

To increase the number of estimated inertia points, it is essential to consider a greater number of pump turn-off events. To that end, the occurrence of pump turn-off events from one pump storage plant was counted for each day of 2021, based on the trigger using PMU data collected from a real pump storage plant, as illustrated in Figure 4.14. The average number of pump turn-off events per day recorded by the researched pump storage plant was 3.6, with a maximum of 12 events observed in a single day.

As the estimated inertia points obtained from pump turn-off events are not continuous, it is better that the estimated inertia values can reflect the lowest system inertia of each day to ensure frequency stability. Upon comparing the times of lowest inertia with pump turn-off times, it was discovered that the pump-based inertia estimation can provide inertia points that are close to the lowest inertia point of each day. The operation pattern of pump turn-off events from the researched pump storage plant is depicted in Figure 4.15(a). Additionally, Figure 4.15(b) illustrates two typical load curves observed during the winter and summer seasons for the power grid in which the researched pump is located. The pump turn-off events typically occur when load ramps up around 3 AM to 6 AM. Figure 4.15(c) shows daily lowest inertia times of power grid typically occur around 1 AM to 5 AM.

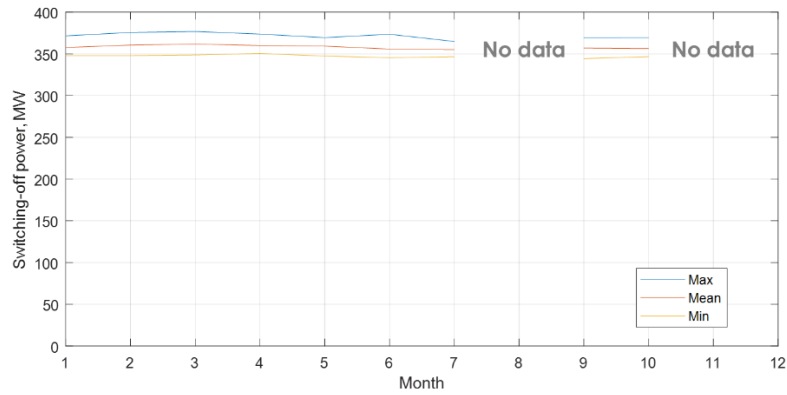


Figure 4.13. Monthly maximum, mean, and minimum MW values for Bath County pump trip events.

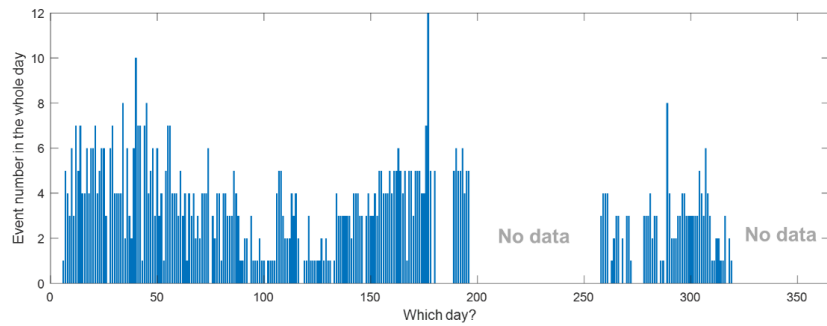
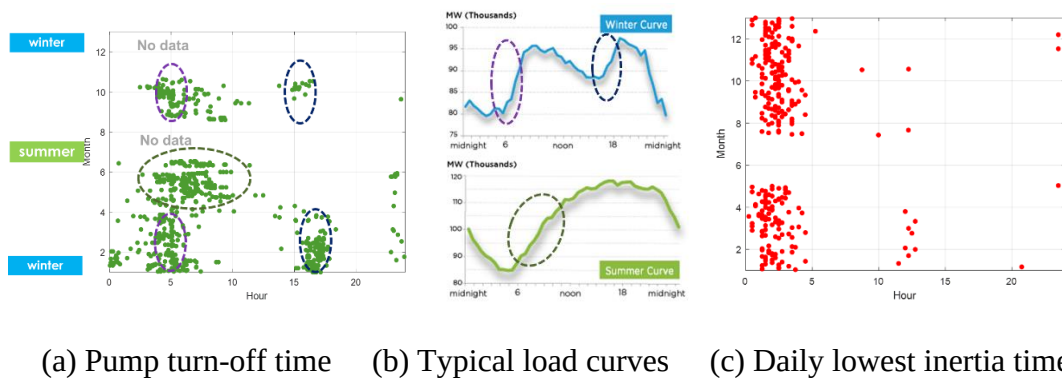


Figure 4.14. Daily occurrence of pump turn-off events from a pump storage plant.



(a) Pump turn-off time (b) Typical load curves (c) Daily lowest inertia time

Figure 4.15. Comparison between daily Bath County pump turn-off time and lowest inertia time.

4.2.2 WECC Pump Storage Plant Selection and Frequency Monitor Deployment for WECC Inertia Estimation

In this research, the Helms Pump storage plant was selected for the implementation of the pump-based inertia estimation in a U.S. grid. This selection was made after careful consideration of several factors, including: (a) the availability of accurate WECC inertia data from NERC, which can serve as the benchmark for validating the proposed pump-based inertia estimation; (b) the Helms pump storage plant has the largest unit capacity in WECC, which provides more accurate inertia estimation due to the higher signal-to-noise ratio (SNR) on the frequency signal; and (c) the Helms pump storage plant has the most detected turn-off events based on the FNET/GridEye database in 2019, providing more estimated inertia points.

To identify the most suitable pumped storage plants for inertia estimation, the unit number and capacity of U.S. pump storage plants were obtained from the EIA, and those with capacities greater than 300MW are presented in Table 4.2. Pumped storage plants with larger unit capacities are better suited for inertia estimation since they generate higher-magnitude pump turn-off events, resulting in corresponding frequency responses with high SNRs, even considering background frequency noises. Among the largest unit capacities in the U.S., the Bath County (EI), Raccoon Mountain (EI), and Helms (WECC) pumped storage stations were identified. Additionally, the EROCT grid does not have any operational pump storage plants.

Table 4.2. Pumped storage plants with unit capacities larger than 300MW.

Pump storage plants	Region	Unit capacity (MW)	Number of units
Bath County	EI	477	6
Raccoon Mountain	EI	428.4	4
Helms Pumped Storage	WECC	351	3
Ludington	EI	329.8	6
Bad Creek	EI	324	4
Bear Swamp	EI	300	2

The number of pump turn-off events is also a crucial factor in the inertia estimation from a specific pump storage plant. Pump storage plants that have more pump turn-off events can provide more inertia estimation values using the pump-based method. To determine the occurrence of pump turn-off events in 2019, the FNET/GridEye triangulation system was utilized, and the results are shown in Table 4.3 for Bath County, Raccoon Mountain, and Helms pump storage plants. As per the results, Helms pump storage plant had the highest number of pump turn-off events in the FNET/GridEye database in 2019.

NERC collects the inertia of each interconnection in the U.S. based on the dispatch data, which serves as the background truth for validating the estimated inertia. However, due to the large number of generators in the Eastern interconnection, data loss is common, leading to inaccurate inertia values. Additionally, NERC has confirmed that the accuracy of WECC inertia is better than that of EI inertia. Therefore, the Helms pump located in WECC is a better option for the proposed inertia estimation as more accurate background truth inertia can provide more trustworthy validation.

To accurately detect the pump turn-off events of the Helms pump, grid frequency monitors such as UGA-POW and FDR were deployed near the substation that connects the Helms pump storage plant via 230kV transmission lines, as illustrated in Figure 4.16.

The measurement signals and the resolution of FDR and UGA-POW are shown in Table 4.4 and Table 4.5, respectively. The UGA-POW is POW data measurable and can provide the frequency with higher resolution. After the successful deployment, 1440 points/second point-on-wave voltage and 120 points/second frequency near Helms pump storage plant allow accurate event trigger design and RoCoF calculation for the inertia estimation.

Table 4.3. Occurrence of pump turn-off events in FNET/GridEye database in 2019.

Name of pump storage station	Region	Occurrence
Bath County	EI	114
Raccoon Mountain	EI	88
Helms Pumped Storage	WECC	306

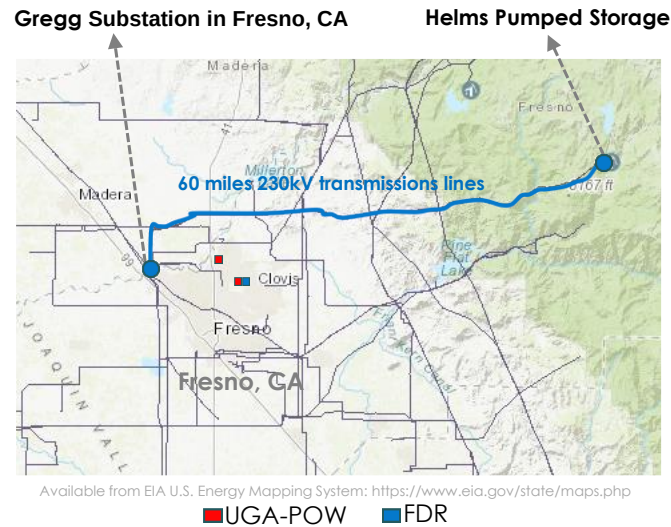


Figure 4.16. Grid frequency monitors deployed near Helms pump storage plant.

Table 4.4. FDR measurement signals and their resolutions.

Measured Signal	Resolution (points/second)
Frequency	10
Voltage	10
Angle	10

Table 4.5. UGA-POW measurement signals and their resolutions.

Measured Signal	Resolution (points/second)
Phase data (POW voltage)	1440
Frequency	120
Voltage	10
Angle	10

To ensure that UGA-POW had adequate internet resources, a 5G WIFI extender was utilized to enhance the internet connection, as depicted in Figure 4.17. Additionally, the deployed UGA-POW was relocated near a window on the top level to receive a better GPS signal, thereby improving the data quality. Typically, the UGA-POW data completeness was over 99%. However, data loss from UGA-POW still occurred at times, which may be attributed to the heavy usage of the home internet by the hosts.

The measured data obtained from the Helms FDR and UGA-POW were successfully streamed to the FNET/GridEye server and can be accessed through the FNET/GridEye Frequency Display website (<https://fnetpublic.utk.edu>), as depicted in Figure 4.18. Following two weeks of testing, it was determined that the FDR data completeness rate was approximately 99.98%, which met the application requirements for event detections, as illustrated in Figure 4.19.

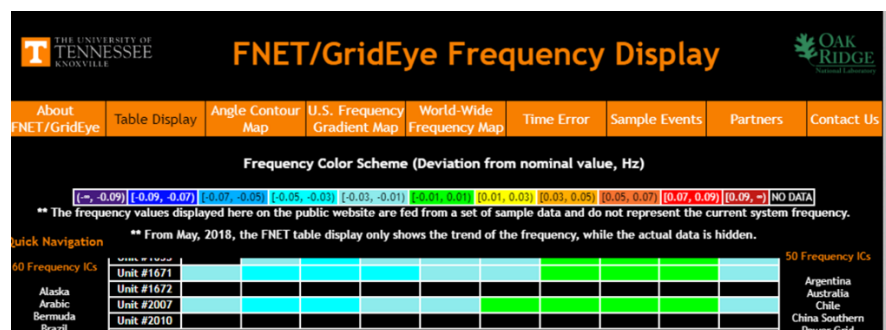
4.2.3 Trigger Design for Helms Pump Turn-off Event Detection

A trigger was designed to detect Helms pump turn-off events, which utilized three primary features of the pump trip event: local frequency spike, local voltage step change, and frequency point A-C deviation. The designed trigger was successful in detecting confirmed pump turn-off events for both Bath County and Raccoon Mountain, in addition to identifying 55 events of Helms pump turn-off over 18 days.

The local frequency spike and local voltage step change were observed from the pump turn-off events at three pump storage plants, namely Bath County, Raccoon Mountain, and Helms.



Figure 4.17. Improved internet quality with 5G WIFI.



Unit #1671, Unit #2007, and Unit #2010 are the deployed monitors near Helms

Figure 4.18. Data demonstration on FNET/GridEye website for monitors deployed near Helms pump storage plant.

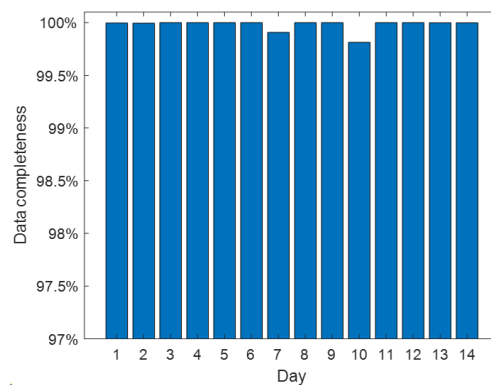


Figure 4.19. Data completeness from the deployed FDR near Helms pump storage plant.

These local features could be common across all pump plants during a pump turn-off event. Examples of the local frequency spike and local voltage step change after Helms pump turn-off event are illustrated in Figure 4.20.

Further analysis has shown that the local frequency spike and local voltage step change are unique to the local units and cannot be captured by distant units. This ensures that the detected events from units in a specific area can be attributed to specific pump storage plants. For instance, the local frequency spike and local voltage step of a confirmed pump turn-off event at Bath County are illustrated in Figure 4.21. The FDR located in Roanoke, which is closer to the substation connected to Bath County pump storage, was able to capture the frequency spike and voltage step, while the FDR in Blacksburg (the distant unit from Bath County) did not. These promising results greatly increase confidence in the accurate trigger design.

Further, it is found that it is not enough only to use the above-mentioned local features, because some pure voltage change events can also result in these features. Thus, the MW event features are also necessary for the detection trigger design, so the largest frequency deviation (frequency point A-C deviation) is further considered in the trigger, as shown in Figure 4.22.

The process of the designed trigger is shown in Figure 4.23. The raw data from the monitors in a moving window are first preprocessed. Then, the voltage step is extracted based on the voltage data. Based on the frequency data, RoCoF using 0.1s window is calculated for the spike detection, and frequency point A-C deviation is calculated as the largest frequency deviation.

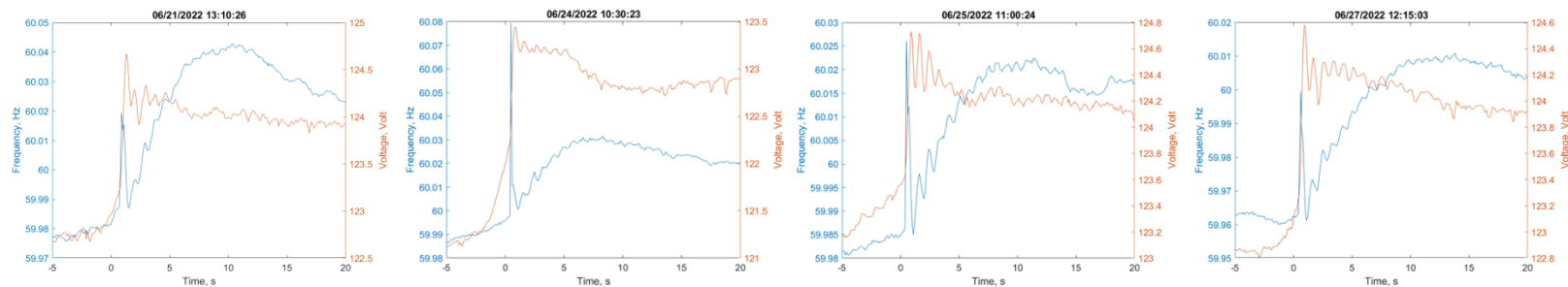
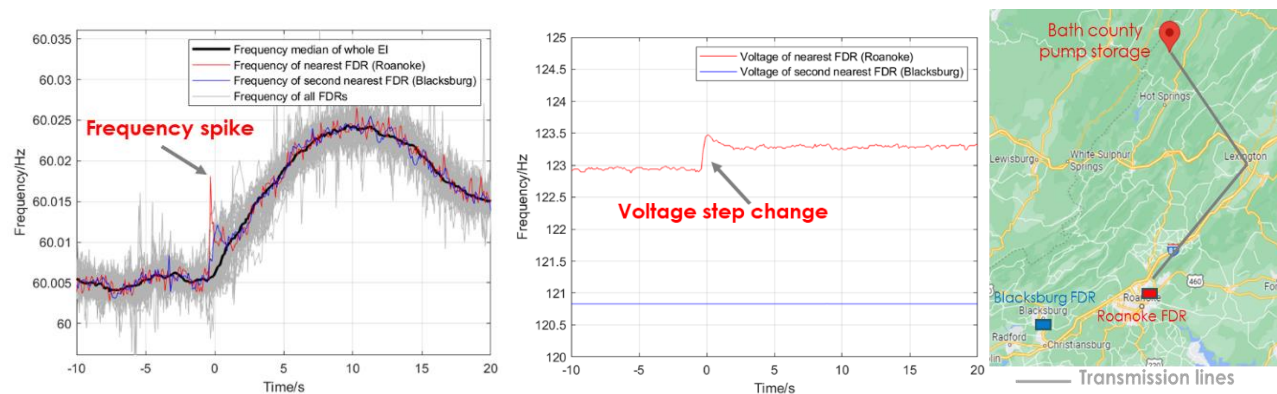


Figure 4.20. Local frequency spike and voltage step change from four Helms pump turn-off events detected by the deployed grid frequency monitor.



(a) Local frequency spike (b) Local voltage step change (c) Bath County pump storage plant and the nearby units.

Figure 4.21. Frequency spike and voltage step change during pump turn-off event are unique to the nearby unit.

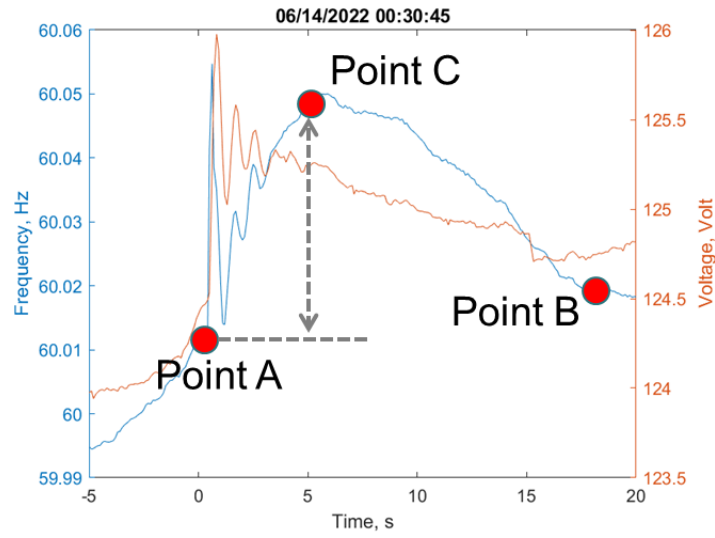


Figure 4.22. Event detection using frequency point A-C deviation to reduce false detections.

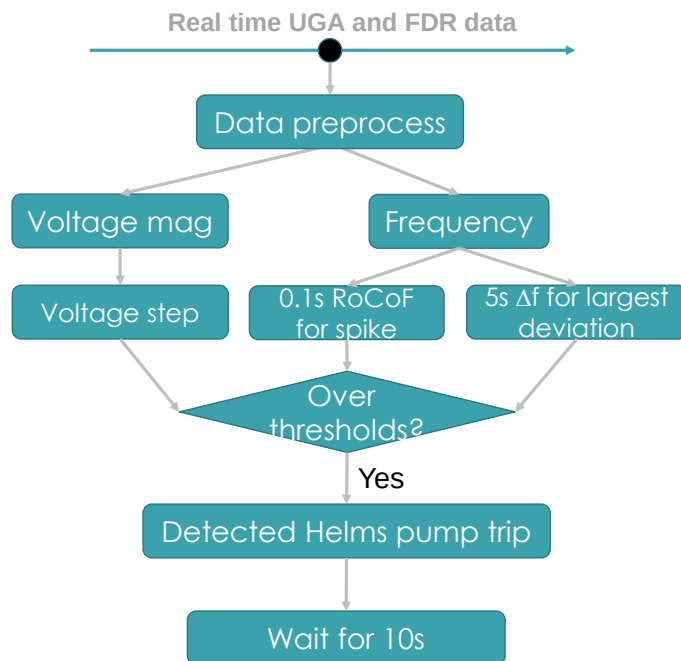


Figure 4.23. Flowchart for designed trigger for Helms pump turn-off detection.

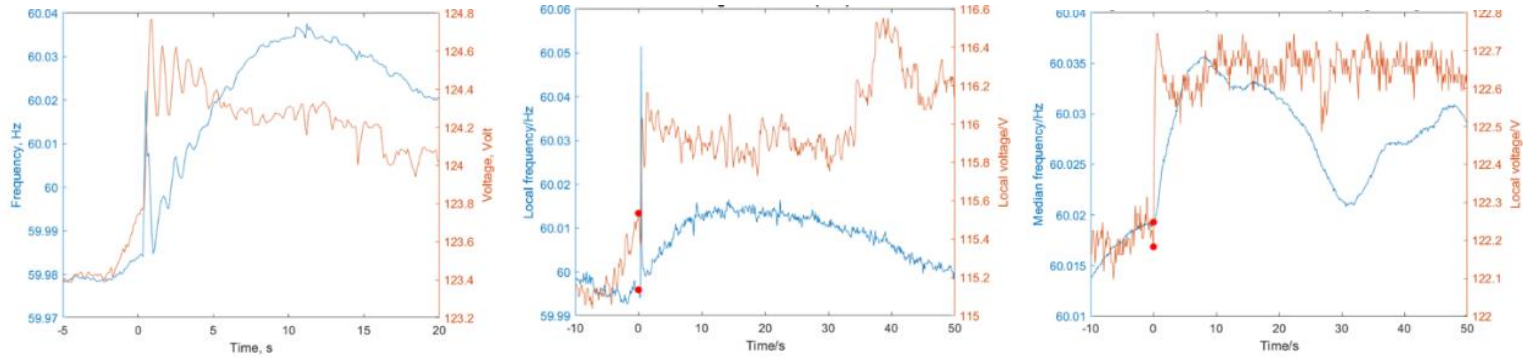
Then, these calculated values will be compared with threshold values. The threshold values are preset based on the historical real pump trip events. If voltage step, 0.1s RoCoF, and frequency point A-C deviation are larger than the preset thresholds, the trigger will record event time and send data to the inertia estimation algorithm. Pump units in the same plant are usually not turned off too close on time, so the trigger will wait for 10s and then detect for the following time.

Based on the designed pump turn-off trigger, pump turn-off events from Helms, Raccoon Mountain, and Bath County pump storage plants are successfully detected, as shown in Figure 4.24.

4.2.4 Designed Trigger Performance Test and Its Improvement Using Confirmed Pump Turn-off Events

Using the pump output power from measurements, we can get the confirmed pump operation time and then verify the developed trigger. A step detection method is developed to get the precise pump turn-off event time from a pump storage plant with 3 pump units. The measured MW power and the detected event time are shown in Figure 4.25.

Using the developed trigger, there were a total of 54 pump turn-off events detected in the testing period, as shown in Figure 4.26. Compared with the confirmed events from measurements, 53 events were confirmed to be genuine. However, there was one detection that was missed, resulting in a missing rate of 1.89% ($=1/54$) in the confirmed events. The trigger also produced two false alarms, which means that out of the total 54 events detected, only 52 were genuine. This gives the detection accuracy of the trigger 96.29%.



(a) Helms (b) Raccoon Mountain (c) Bath County

Figure 4.24. Detected pump turn-off events for three U.S. pump storage plants.

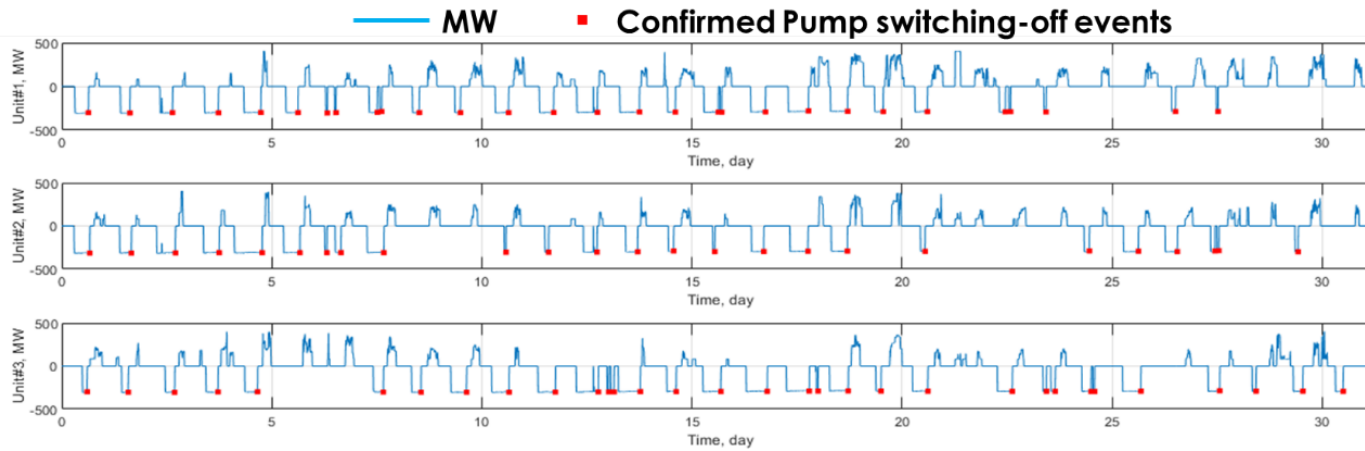


Figure 4.25. Output power and detected pump turn-off events from a U.S. pump storage plant.

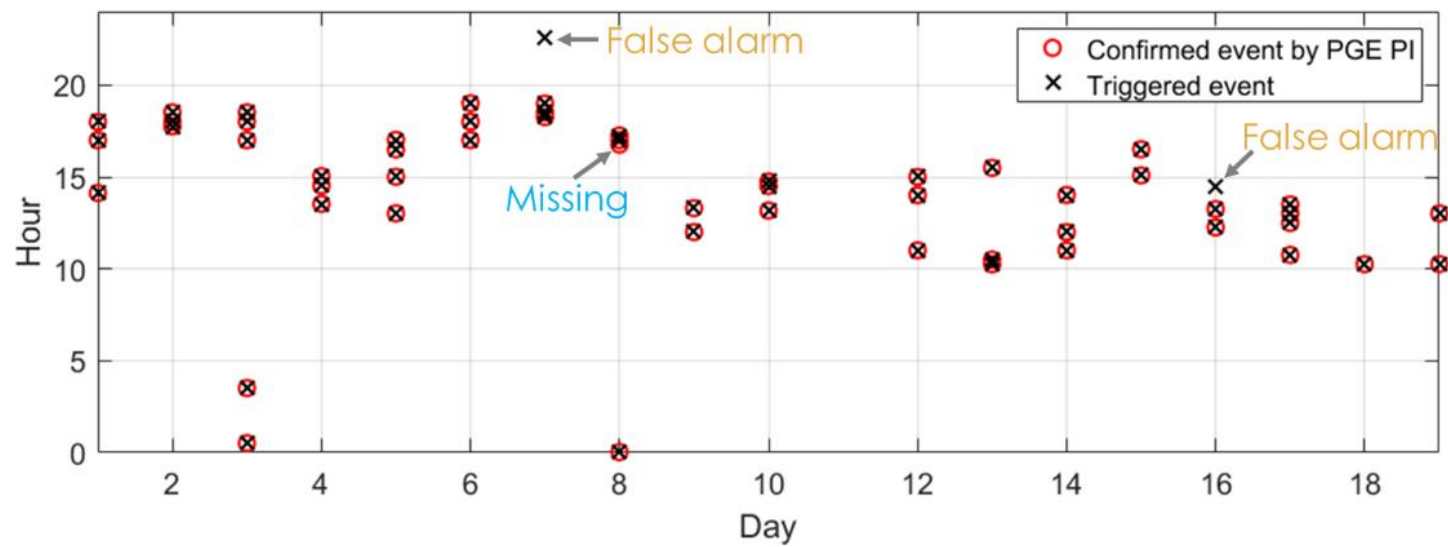


Figure 4.26. Test of designed trigger detection using confirmed events from measurements.

The reason for missing detection is found as the data missing from the monitor. As shown in Figure 4.27. The event occurred during a period when there was no monitor data available, which led to its undetected status. This highlights a potential limitation of the single monitoring system, which relies on data from one monitor to detect events. To address this limitation, a solution of multi-monitor-based detection has been proposed. With this approach, instead of relying on data from a single monitor, the system would use data from multiple local monitors to detect events. Once any of the three local monitors detects an event, the multi-monitor-based trigger will record it. The multi-monitor-based detection approach could significantly improve the sensitivity and reliability of the monitoring system. By using data from multiple monitors, it would be less likely for events to be missed due to missing data or other limitations of a single monitor. The use of multiple monitors could also provide redundancy and increase the robustness of the system.

During the testing period, the monitoring system produced false alarms due to an oscillation case with large frequency and voltage deviation, as shown in Figure 4.28. This highlights a potential limitation of the monitoring system, which may produce false alarms in situations where there are oscillation conditions. To address this limitation, a solution of a two-step trigger has been proposed to filter out these false alarms. The two-step trigger involves two stages of detection, where the first stage fast detects the events using robust and fast rules, and the second stage uses more refined criteria to filter out false alarms that have passed the first stage.

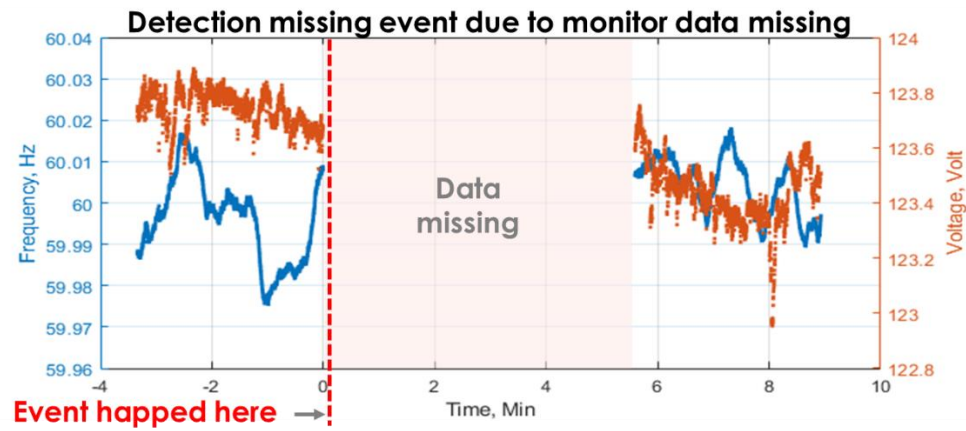


Figure 4.27. Detection missing due to missing monitor data.

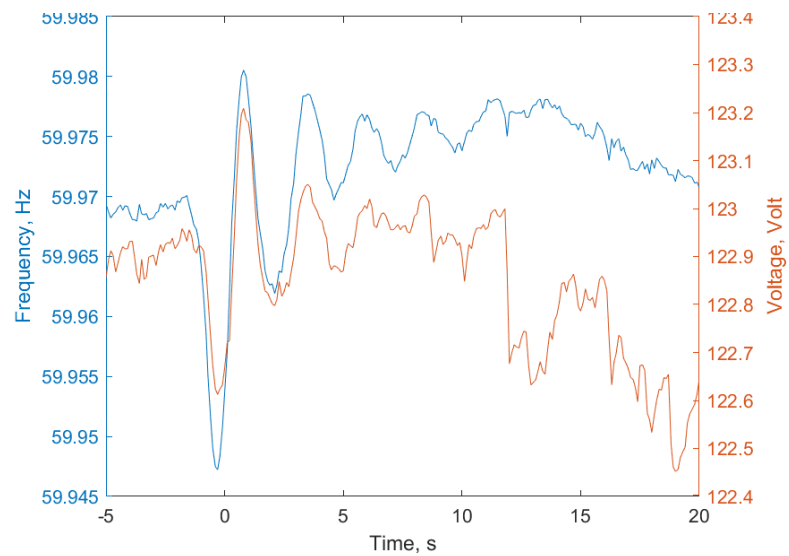


Figure 4.28. False alarm case due to oscillation.

To address this limitation, a solution of a two-step trigger has been proposed to filter out this false alarm, as shown in Figure 4.29. The two-step trigger involves two stages of detection, where the first stage filters out events that do not meet certain criteria, and the second stage uses more stringent criteria to confirm events that have passed the first stage. Using the improved trigger, the testing results show its detection accuracy can be 100% with no false alarms in the testing period.

4.2.5 WECC Inertia Estimation and Validation

Based on detected pump turn-off events from Helms pump storage plants, WECC inertia can be estimated using the pump turn-off MW and measured RoCoF. An example of the inertia estimation process is shown in Figure 4.30.

With the confirmed MW values of historical Helms pump storage turn-off events, the MW step changes are analyzed and found to be relatively constant, as shown in Figure 4.31. The average of MW step changes is around 310MW. The maximum and minimum are around 7% of the average MW values. Relatively constant MW value from Helms pumps storage plant allows the accurate inertia estimation for WECC just using the average MW value 310MW, which avoids real-time MW confirmation requirement.

To validate the accuracy of the pump turn-off based inertia estimation, 42 confirmed pump turn-off cases from Helms (2015.12~2019.10) are used to estimate WECC inertia, whose process is similar to Figure 4.30. MW step change uses the 310MW, which is the average MW of historical cases. RoCoF is calculated using FNET/GridEye historical data. Based on the MW and RoCoF values, WECC inertia for each case can be estimated by

$$Inertia = \frac{MW}{RoCoF/60} / 2.$$

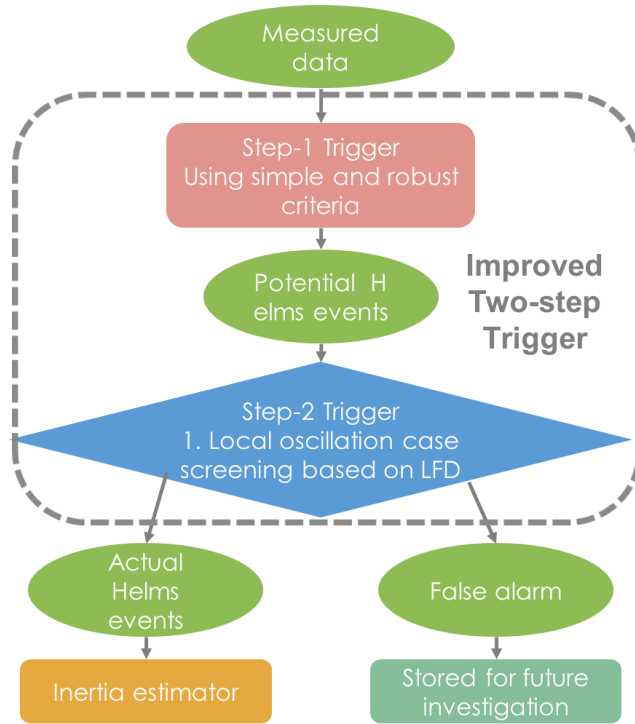


Figure 4.29. Improved two-step detection trigger design.

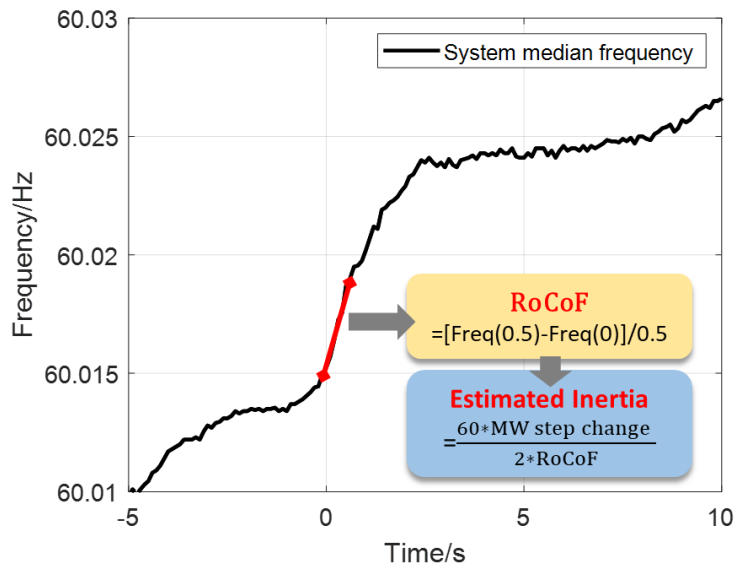


Figure 4.30. Inertia estimation based on pump turn-off event.

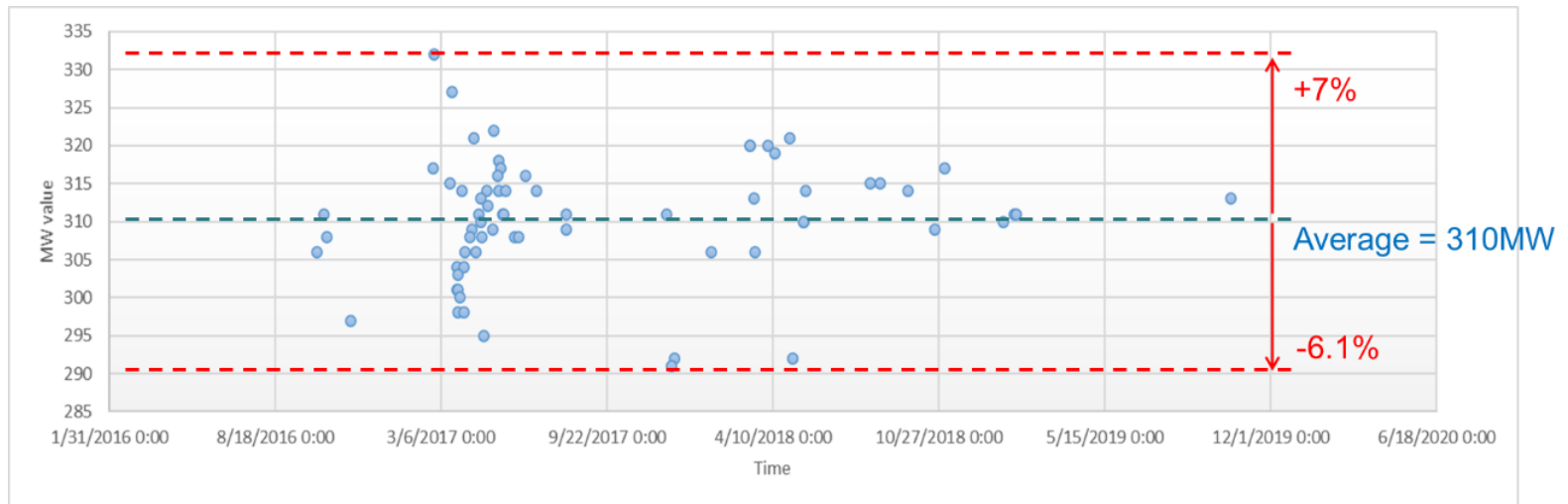


Figure 4.31. Confirmed MW values of historical Helms pump turn-off events.

Compared with NERC background truth inertia, the accuracy of the estimated inertia is calculated. Considering different RoCoF window sizes can impact the calculation of RoCoF and thus impact the inertia accuracy, the error rates of inertia estimation under different RoCoF window sizes are calculated and shown in Table 4.6. Clearly, 0.3s RoCoF window size offers the best performance of inertia estimation with 9.9% average absolute error rate.

4.3 RoCoF Calculation Techniques

As the essential part of effective inertia estimation, this task will develop the algorithm for accurate RoCoF calculation considering factors such as system oscillations, electromechanical wave propagations, random frequency fluctuations, and measurement noises. Even though this work originated from the inertia estimation using pump turn-off events, inertia estimation using MW step change events including the generator trip will benefit from this work.

4.3.1 Impact of Wave Propagation on RoCoF from Helms Pump Turn-off Event

The long transmission distance and large scale of the power grid often result in wave propagation in the frequency response after a sudden MW change event. This phenomenon leads to deeper frequency drops in nearby monitors compared to those located further away. As a result, wave propagation is often a concern when calculating the rate of change of frequency (RoCoF). To obtain accurate RoCoF readings, it is essential to determine whether wave propagation is present. If so, selecting monitors that are uniformly distributed geographically is a better strategy.

Table 4.6. Inertia estimation error rates under different RoCoF window sizes.

Error index	RoCoF window size								
	0.1s	0.2s	0.3s	0.4s	0.5s	1s	2s	3s	4s
Median absolute error rate	28.1%	8.9%	8.25%	8.3%	13.22%	29.8%	52.8%	68.9%	82.7%
Average absolute error rate	28.7%	10.6%	9.9%	10.8%	13.6%	28.6%	52.3%	68.3%	80.2%
Max absolute error rate	55.0%	26.8%	26.1%	33.2%	35.8%	56.7%	84.2%	103.7%	109.63%

In the inertia estimation using Helms pump turn-off events, based on FNET measurements, it has been observed that wave propagation had a weak impact on the rate of change of frequency (RoCoF) calculation during the Helms event. Despite resulting in frequency differences at different locations after the event, there was no significant difference in the median frequency and RoCoF values between nearby (Red) and far-away (Blue) monitors, as shown in Figure 4.32 and Figure 4.33. This finding confirms the weak impact of wave propagation on RoCoF. Thus, the median frequency from all monitors is used to calculate the RoCoF in this case.

4.3.2 Impact of Point-on-wave Voltage Ambient Noise on RoCoF and its Reduction

The frequency measurement is based on the measured point-on-wave voltage, but ambient noise on this voltage can have a significant impact on the measured frequency, as demonstrated in Figure 4.34 and Figure 4.35. This ambient POW voltage noise can distort frequency data, leading to errors in RoCoF calculations. Simulation results indicate that when subjected to noise levels of up to 60 dB, the maximum RoCoF error rate for a typical RoCoF calculation from a Helms pump turn-off event is around 40%, as shown in Table 4.7. This highlights the importance of incorporating a POW-noise-proof feature in RoCoF calculations.

To address the random nature of point-on-wave noises, multi-unit frequency measurements, and long-window RoCoF are utilized to suppress such noises. Simulation analysis reveals that using the median frequency data from 22 units for 5-second window RoCoF calculation results in an error rate of only 1.56% for a typical RoCoF calculation from a Helms pump turn-off event, as demonstrated in Table 4.8.

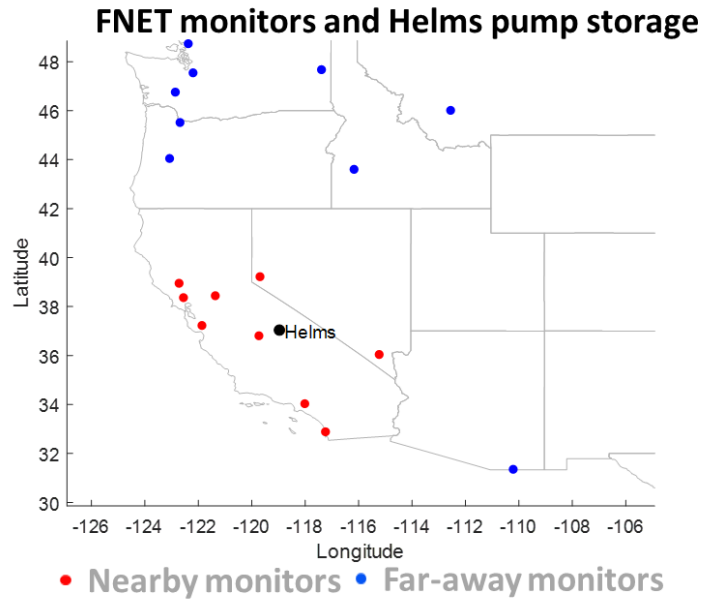


Figure 4.32. Two groups of monitors for frequency response comparison.

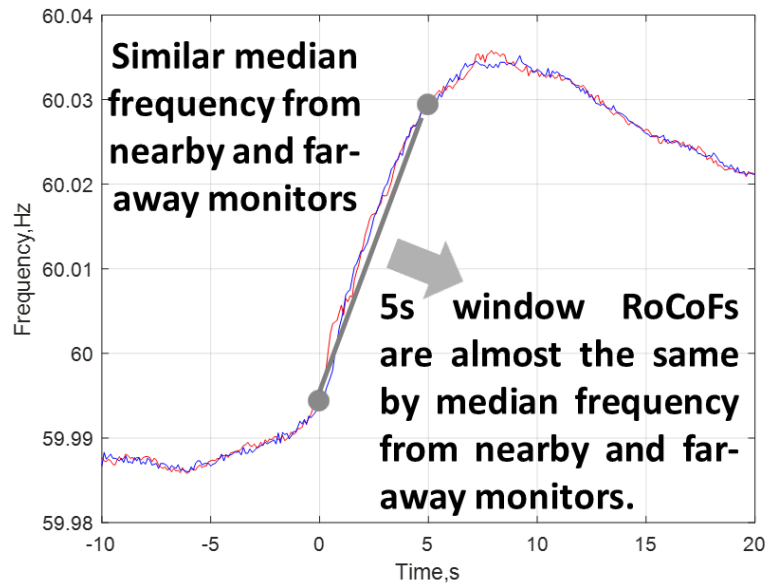


Figure 4.33. Similar WECC frequency response from nearby and faraway monitors after a Helms Pump turn-off event.

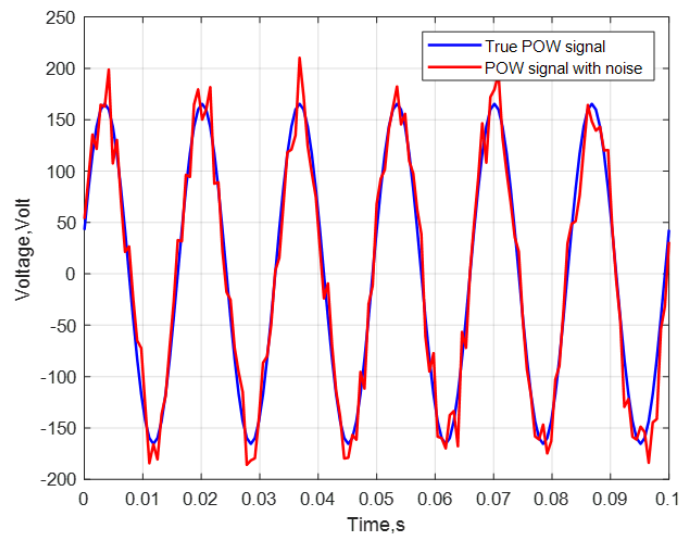


Figure 4.34. Example of point-on-wave voltage with ambient noise from measurements.

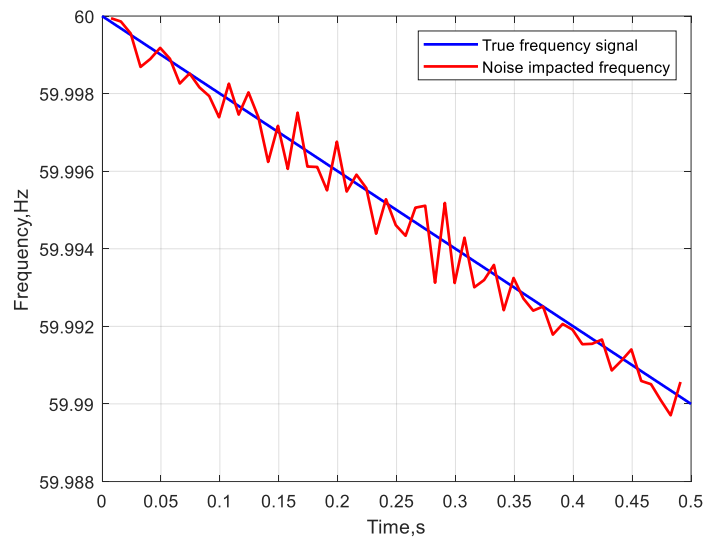


Figure 4.35. Example of POW noise-impacted frequency.

Table 4.7. Simulated maximum RoCoF error under different noise levels.

Noise level	Max RoCoF error
60 dB	~40%
65 dB	~27%
70 dB	~15%
75 dB	~6.3%

Table 4.8. RoCoF calculation errors under long window and multi-unit median measurement.

Noise level	0.5s RoCoF window using single unit data	5s RoCoF window using single unit data	0.5s RoCoF window using multi-unit data	5s RoCoF window using multi-unit data
60 dB	~40%	~4%	~15.6%	~1.56%
65 dB	~27%	~2.7%	~10.4%	~1.04%
70 dB	~15%	~1.5%	~8.4%	~0.84%
75 dB	~6.3%	~0.63%	~2.98%	~0.298%

This improvement highlights the satisfying performance of RoCoF calculation when utilizing multi-unit frequency measurements and a long RoCoF window, providing an effective noise-proof feature for RoCoF calculation.

4.3.3 Impact of Random Frequency Fluctuation on RoCoF and its Reduction

Due to random MW changes from load and generation, the system frequency always experiences random frequency fluctuations, as illustrated in Figure 4.36.

During an event, these random frequency fluctuations may affect the event's rate of change of frequency (RoCoF) by introducing pre-event RoCoF. An example of background frequency fluctuation bringing pre-event RoCoF is shown in Figure 4.37. In this case, due to the change in background frequency fluctuation, there is a pre-event RoCoF of 5.4mHz/s. The RoCoF after the event is 13.8mHz/s, resulting in a net event RoCoF of approximately 8.4mHz/s. When estimating inertia, if the traditional method only uses the post-fault RoCoF of 13.8mHz/s as the event RoCoF, there could be an error ($\approx 5.4/13.8=39.13\%$) due to the pre-event RoCoF.

To obtain an accurate event RoCoF and eliminate the influence of random frequency fluctuations, the net event RoCoF is defined as the post-event RoCoF minus the pre-event RoCoF, as illustrated in Figure 4.38. This approach provides the actual event RoCoF by removing the impact of random frequency fluctuations.

To evaluate the effectiveness of the improved RoCoF, simulations were performed using both a 23-bus system and the EI MMWG model. These simulations were designed to generate events that are similar to the measured event. An example of the simulation case is presented in Figure 4.39.

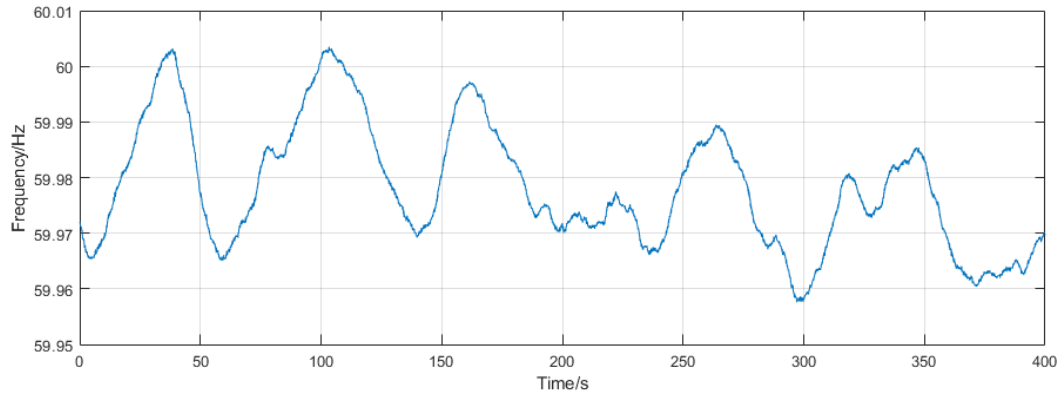


Figure 4.36. Background frequency change from random MW change.

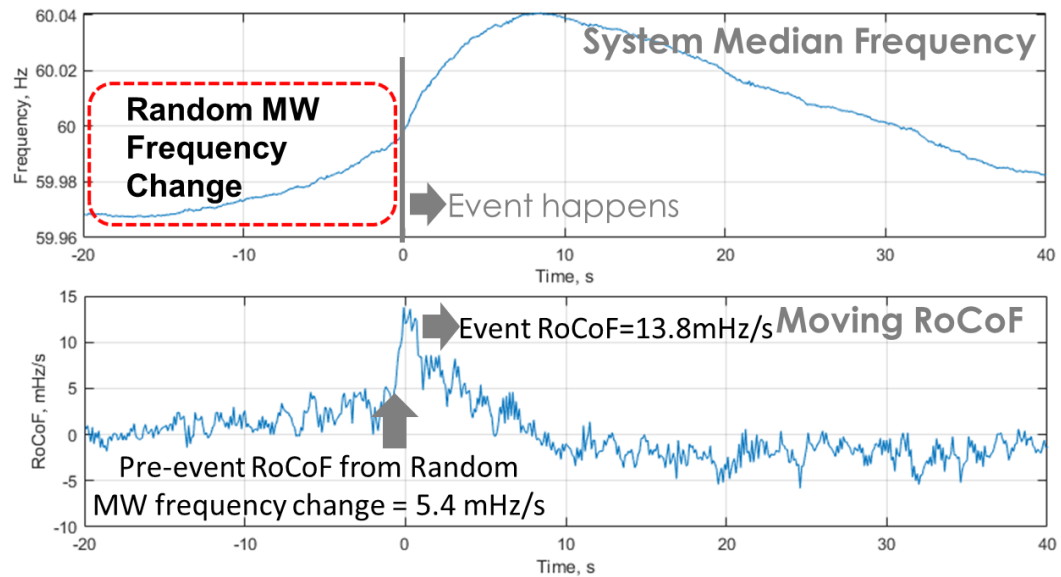


Figure 4.37. Example of event RoCoF impacted by the random frequency fluctuation.

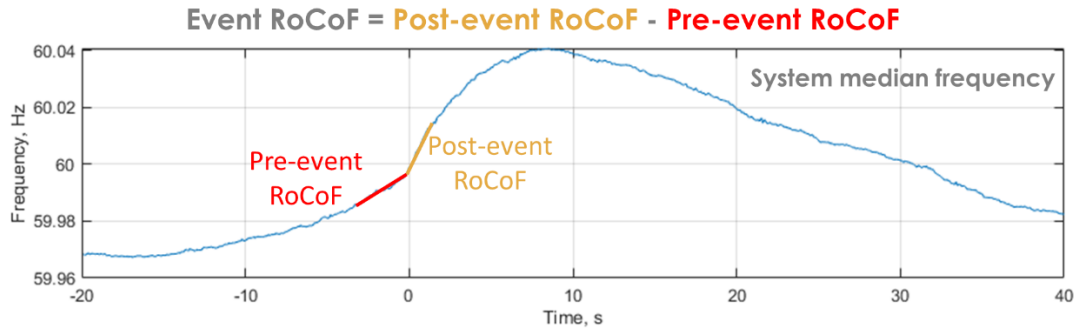


Figure 4.38. Improved event RoCoF by eliminating impact from pre-event RoCoF due to random frequency change.

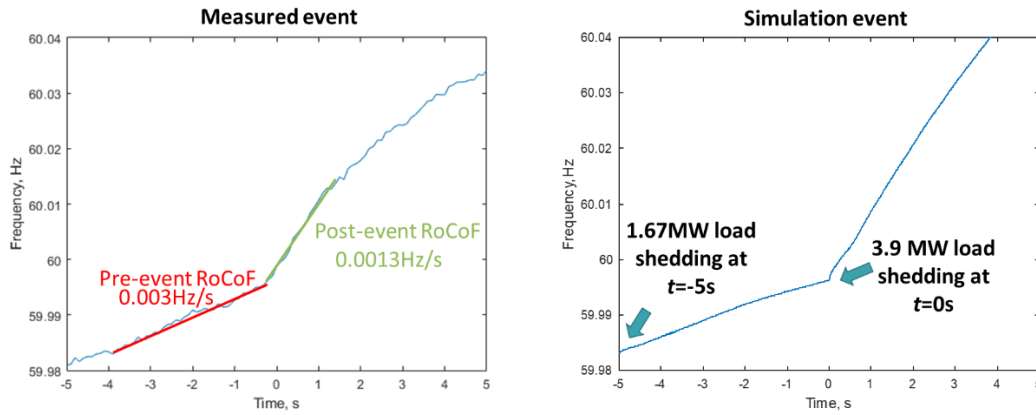


Figure 4.39. Simulation generating similar events with both pre-event RoCoF and post-event RoCoF.

In the 23-bus system, 420 cases were generated with varying downward pre-event RoCoF and post-event RoCoF, as shown in Figure 4.40. When compared to the background truth RoCoF, the proposed RoCoF calculation method improved the accuracy of RoCoF measurements, as shown in Figure 4.41. The mean absolute error rate was reduced from 45% to 4%.

In addition to testing the proposed RoCoF calculation method in the 23-bus system with varying upward pre-event RoCoF and post-event RoCoF, cases with varying upward pre-event RoCoF were also evaluated. Another 420 cases were generated with upward pre-event RoCoF and shown in Figure 4.42, and simulation results showed that the proposed method improved RoCoF accuracy, as shown in Figure 4.43. The mean absolute error rate was reduced from 27.5% to 5%.

To evaluate the effectiveness of the improved RoCoF in a larger system, the EI MMWG model with over 30,000 buses was used for testing. A total of 66 cases were generated with varying downward pre-event RoCoF and post-event RoCoF, as illustrated in Figure 4.44. The proposed RoCoF calculation method improved the accuracy of RoCoF measurements when compared to the background truth RoCoF, as shown in Figure 4.45. The mean absolute error rate was reduced from 65% to 5%. Apart from testing the proposed RoCoF calculation method in the EI MMWG model with varying upward pre-event RoCoF and post-event RoCoF, additional cases were evaluated with varying upward pre-event RoCoF. An additional 66 cases were generated with upward pre-event RoCoF and presented in Figure 4.46. Simulation results demonstrated that the proposed method improved RoCoF accuracy, as shown in Figure 4.47. Mean absolute error rate was reduced from 16% to 3%.

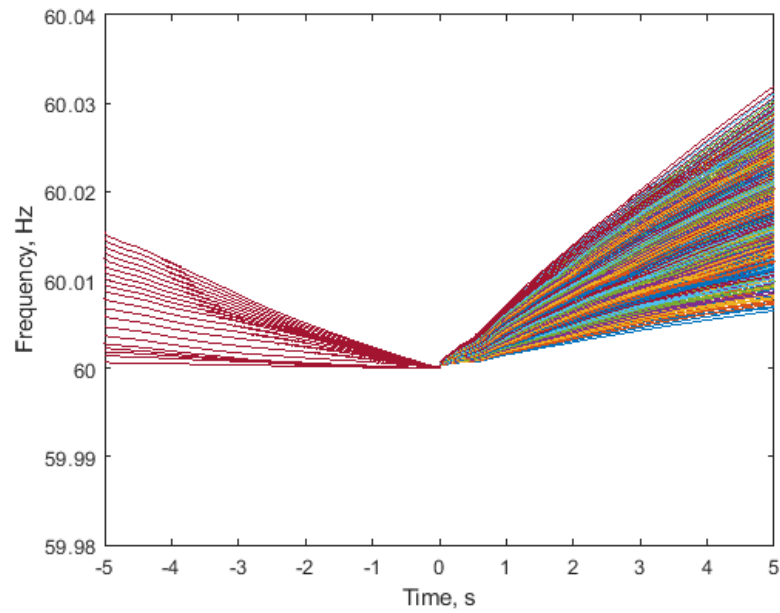


Figure 4.40. 420 generated cases with different downward pre-event and post-event RoCoF from 23-bus system.

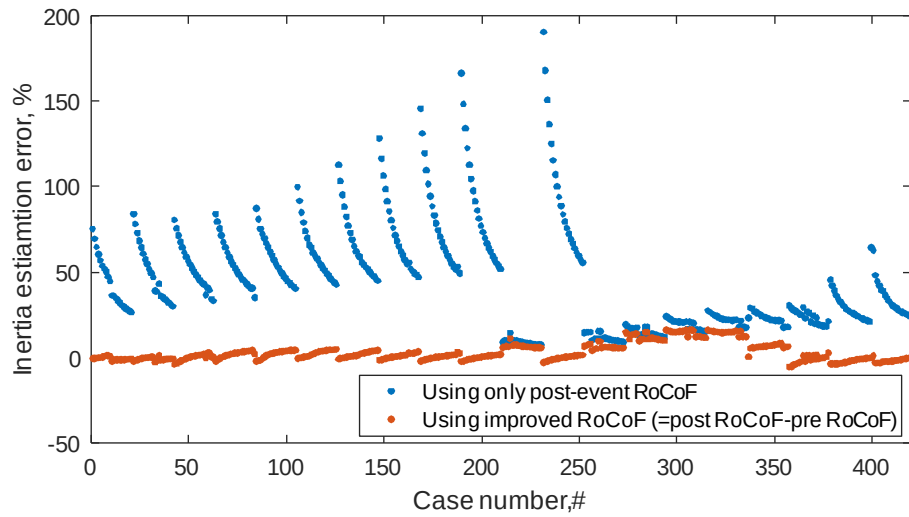


Figure 4.41. Inertia estimation error comparison for 420 generated cases with downward pre-event RoCoF from 23-bus system.

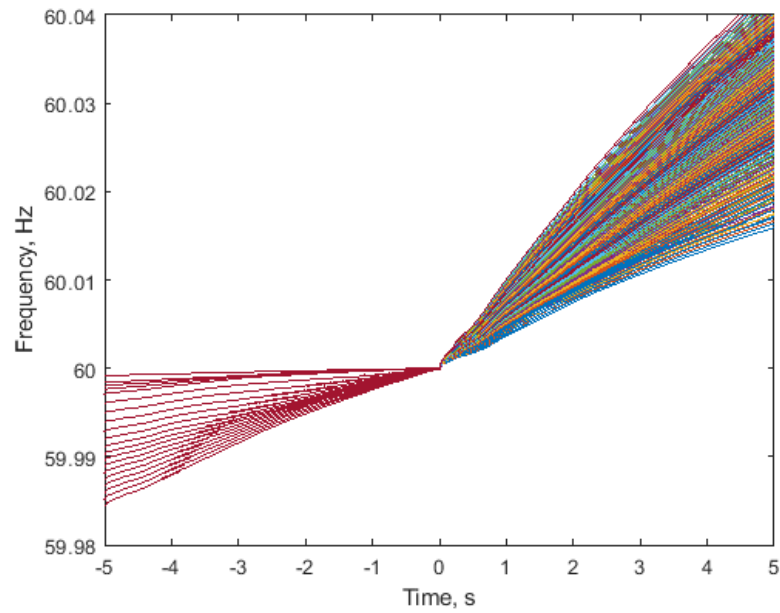


Figure 4.42. 420 generated cases with different upward pre-event and post-event RoCoF from 23-bus system.

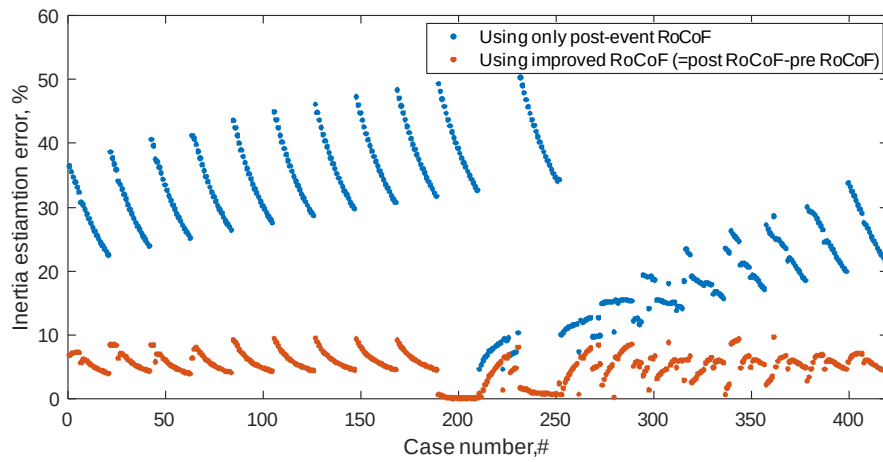


Figure 4.43. Inertia estimation error comparison for 420 generated cases with upward pre-event RoCoF from 23-bus system.

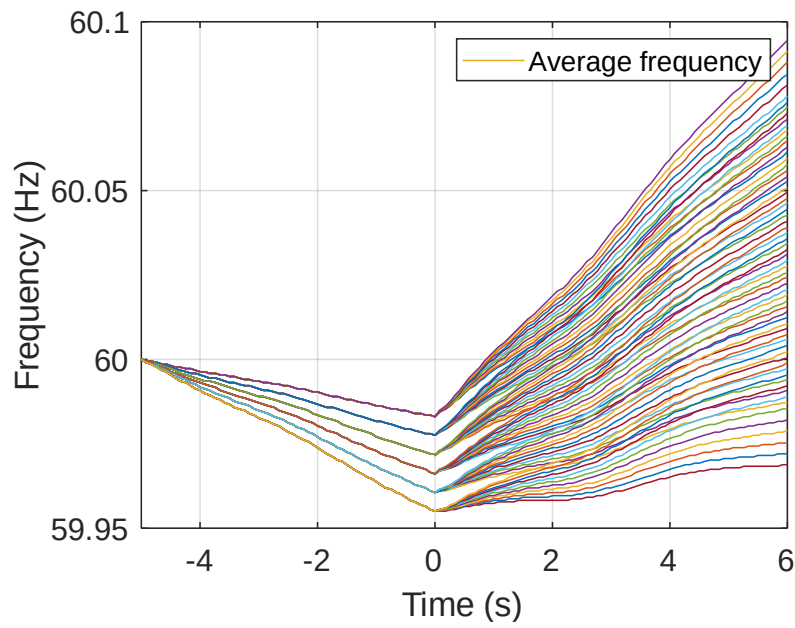


Figure 4.44. 66 generated cases with different downward pre-event and post-event RoCoF from EI MMWG model.

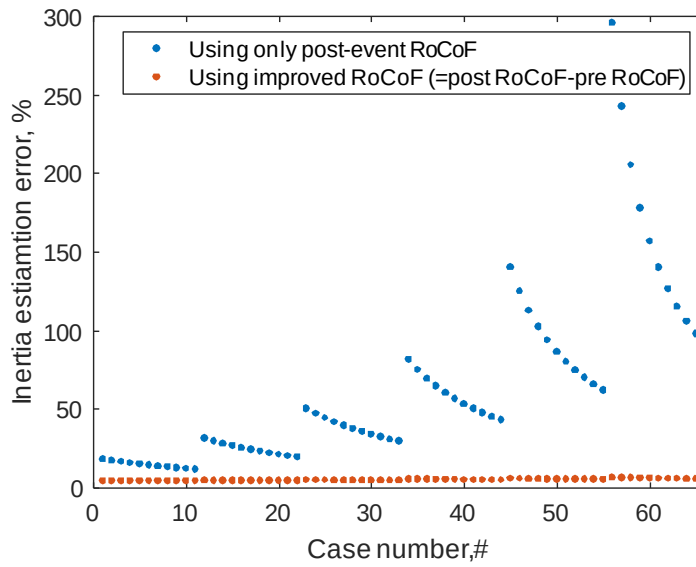


Figure 4.45. Inertia estimation error comparison for 66 generated cases with downward pre-event RoCoF from EI MMWG model.

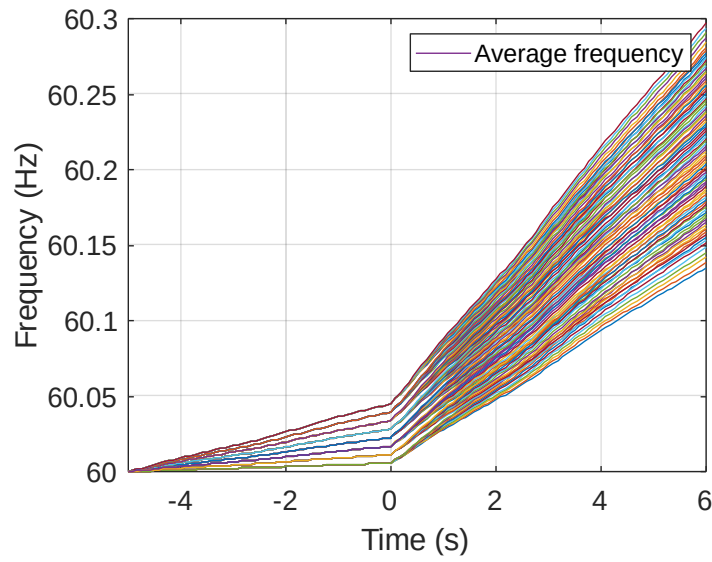


Figure 4.46. 66 generated cases with different upward pre-event and post-event RoCoF from EI MMWG model.

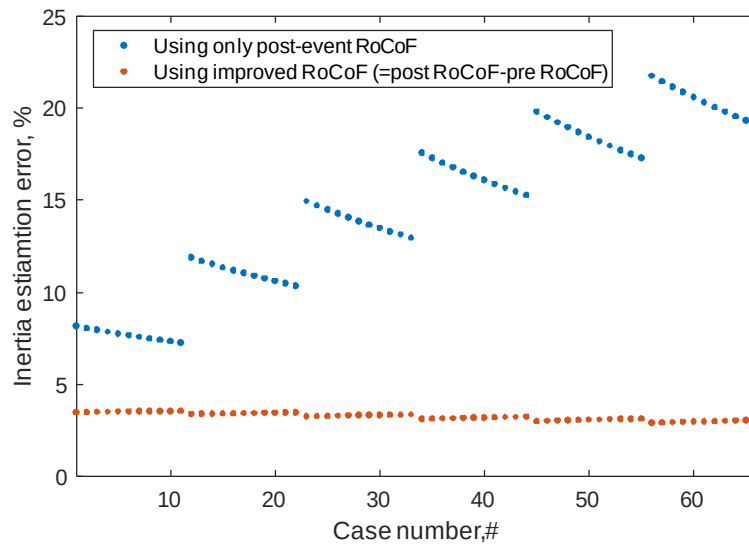


Figure 4.47. Inertia estimation error comparison for 66 generated cases with upward pre-event RoCoF from EI MMWG model.

CHAPTER 5 ADAPTIVE PV RESERVE ESTIMATION

In this chapter, a smart approach was designed to address the practical problem of PV reserve estimation for frequency stability. The proposed approach provides adaptive reserve estimation for PV fast frequency control to support frequency stability after a critical fault. Due to the variable inertia in the power system, as well as other parameters, it is economical to adjust the headroom requirement accordingly, especially in power systems with high-penetration of PV in the future. If the headroom remains fixed throughout the day, it could result in waste in some high-inertia scenarios.

Given the non-linear relationship between PV headroom reserve, PV control parameters, and the system condition, an adaptive approach is required to determine the optimal PV headroom reserve. The machine learning-based smart frequency control utilizes available system information to adjust the PV headroom and ensure frequency stability. The overall framework of the machine learning-based smart adaptive PV reserve estimation is depicted in Figure 5.1. The proposed approach is first validated by the modified ERCOT system, and then tested using CURENT HTB.

5.1 Headroom Reserve Resource from Fast PV Control

To enhance the frequency nadir above under-frequency load shedding thresholds, PV is designed with the ability to provide fast headroom support. Following an event, when the frequency drops to the preset threshold, PV rapidly increases the output MW based on the droop setting until it reaches the preset MW limit (i.e., normal output MW + headroom), as illustrated in Figure 5.2.

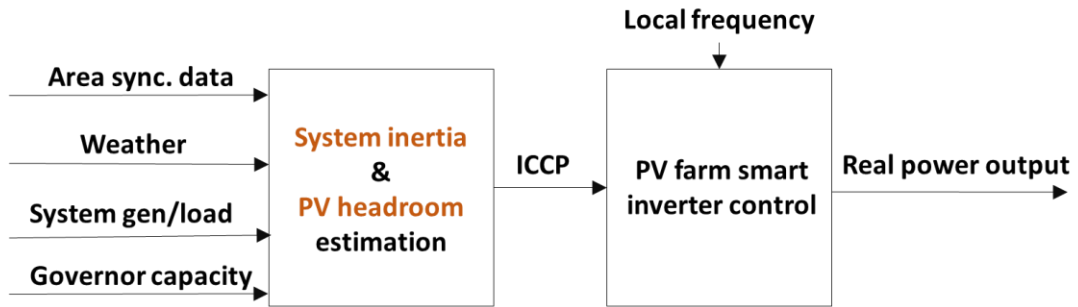


Figure 5.1. Machine learning based PV frequency control.

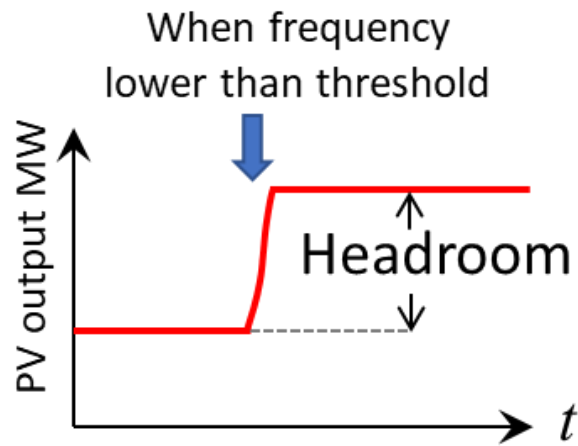


Figure 5.2. PV headroom kicking in when frequency falls below a threshold.

5.2 Impact Factors on Frequency Nadir in Frequency Stability

Since the control target under critical contingency is the system frequency nadir, this section focuses on researching the impact factors that influence system frequency nadir. By taking into account these factors, the smart PV frequency control approach can comprehensively consider all variables that may affect the system frequency nadir. The impact factors are analyzed and summarized as system inertia, governor capacity, PV headroom, and PV frequency control parameters. To better illustrate the relationship between these factors and justify the data input for the machine learning-based control approach, a correlation analysis is first conducted.

5.2.1 Impact of System Inertia on Frequency Nadir

Figure 5.3 displays the correlation between system inertia and the frequency nadir after a critical contingency (2.75 GW generation loss) for the ERCOT system. In each curve, only the inertia is modified, while the other parameters remain constant. The different curves represent various system conditions, including governor capacities, control parameters, and PV headroom. As demonstrated, increased system inertia leads to a better frequency nadir.

5.2.2 Impact of Governor Capacities on Frequency Nadir

In addition to the inertia response, the governor response also plays a crucial role. Figure 5.4 depicts the frequency nadir for different governor capacities (i.e., the total capacity of generators equipped with governors that roughly describes the overall governor resource). The various curves indicate different PV headroom reserves, control parameters, and system inertia levels. The frequency nadir increases as the governor capacities increase.

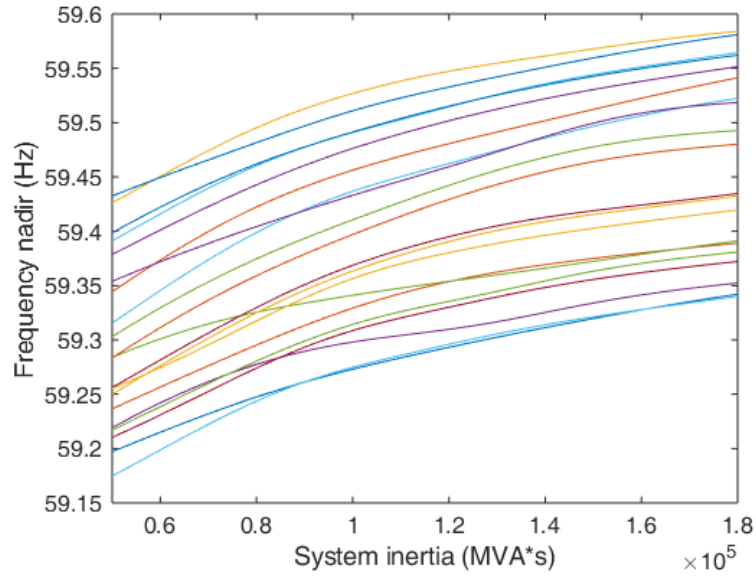


Figure 5.3. Frequency nadir under different system inertia levels (different color lines represent different system conditions and PV control settings).

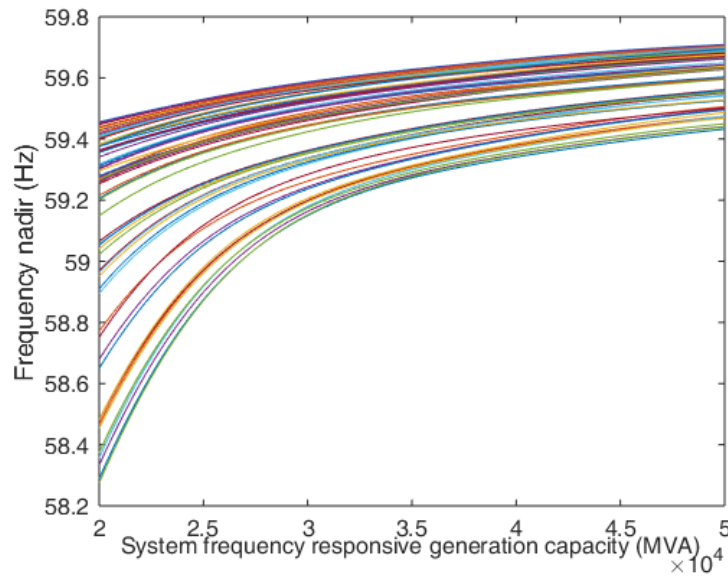


Figure 5.4. Frequency nadir under different governor capacities (different color lines represent different system inertia and PV control settings).

5.2.3 Impact of PV Control Settings on Frequency Nadir

The PV headroom and control parameters are other factors that impact the frequency nadir. A larger PV headroom corresponds to higher frequency support, which can improve the frequency nadir. The PV control gain also influences the frequency nadir, as it determines the response speed of PV farms to frequency deviation. Figure 5.5 demonstrates the relationship between PV headroom, control gain, and frequency nadir. The graph shows that when the PV headroom is small, the change in control gain has a minimal impact on the frequency nadir. However, as the PV headroom increases, the system requires a larger control gain to better utilize the PV headroom and improve the system frequency.

Figure 5.5 suggests that a larger control gain is preferable to fully utilize the available PV headroom and improve the system frequency nadir. A larger control gain results in a smaller PV headroom requirement and more headroom savings for a specified frequency response requirement. Nevertheless, it is crucial to avoid excessively large control gains as it could lead to oscillations, as demonstrated in Figure 5.6.

The time constant in the low-pass filter of the control loop is another control parameter that impacts the performance of the smart frequency control. Figure 5.7 demonstrates that a smaller time constant will enhance the performance of the smart frequency control, as the inverter will respond to faster frequency changes. However, if the time constant is excessively small, it will become overly sensitive to the high-frequency variations in the frequency signal, resulting in oscillations. For the ERCOT study case, a time constant of 20ms is selected based on actual parameter settings in the GE smart inverter product.

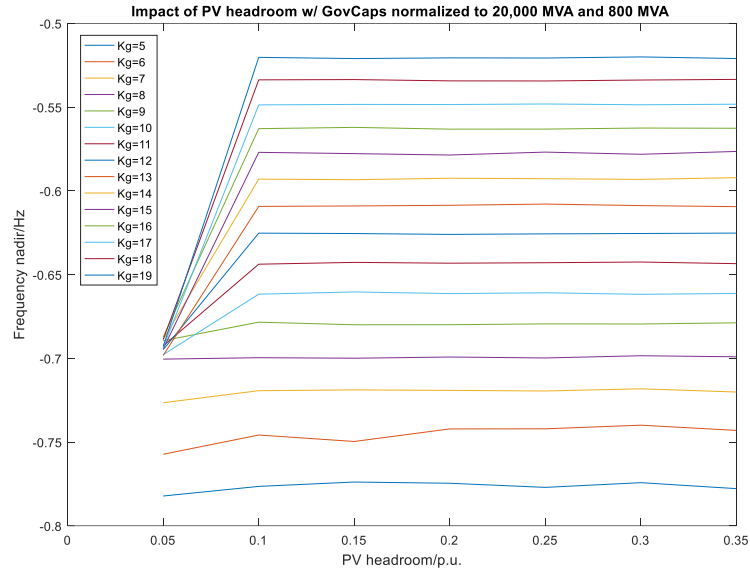


Figure 5.5. Correlation between PV headroom, control parameters, and frequency response.

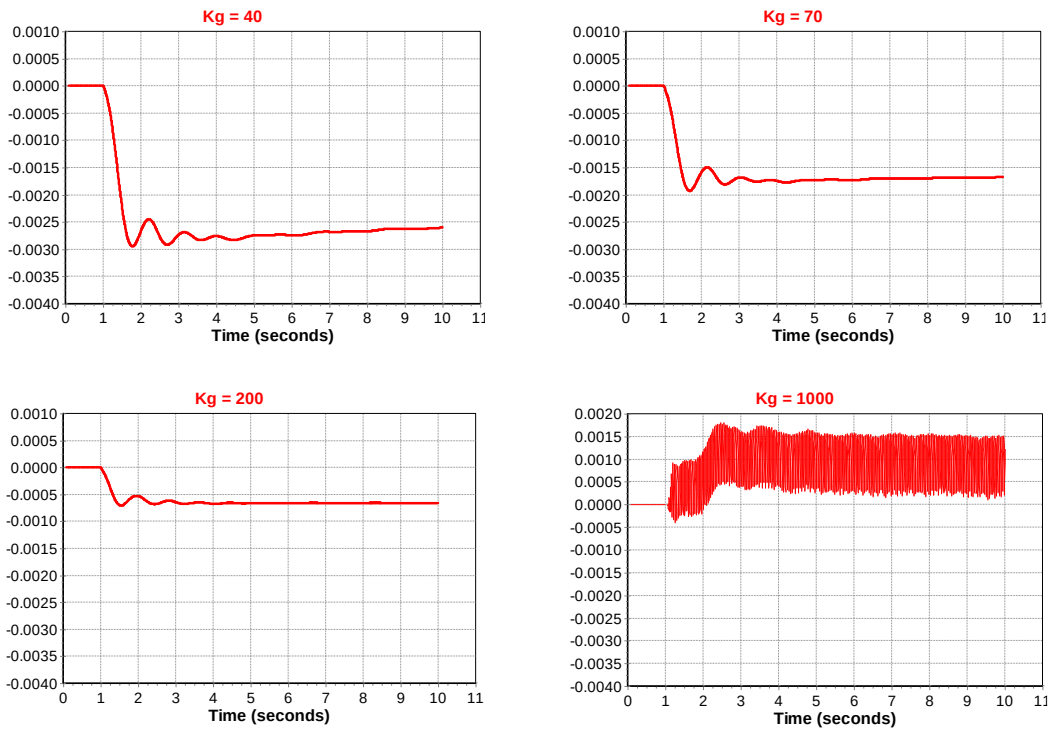


Figure 5.6. Instances of forced oscillations under large control gains.

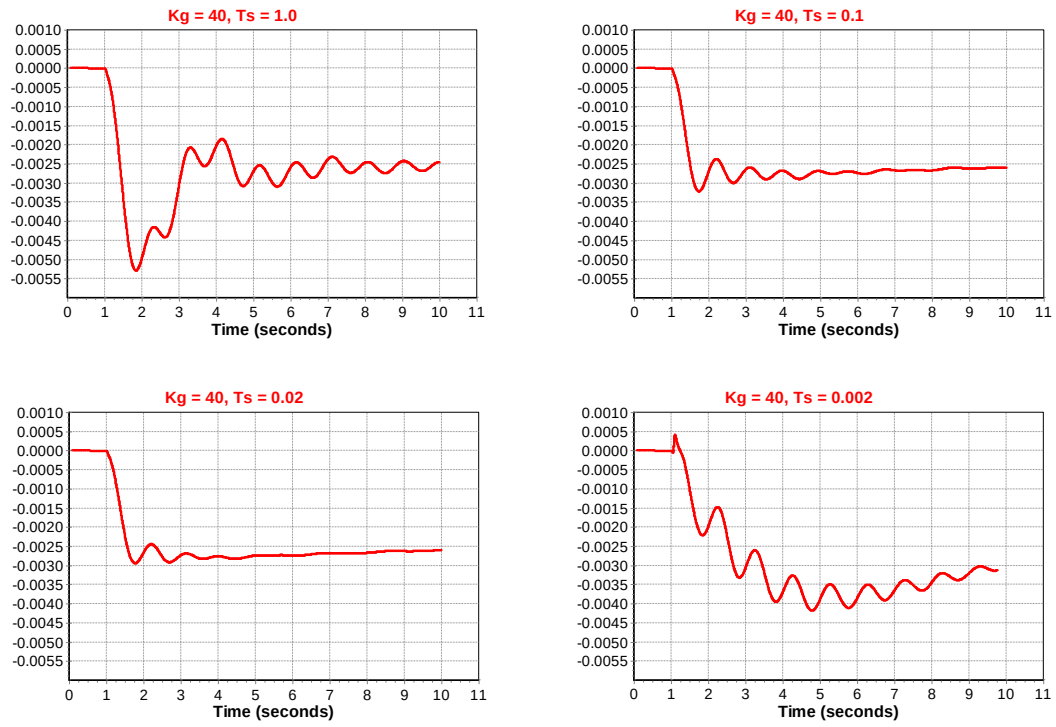


Figure 5.7. Impact of the time constant in the smart frequency control on system frequency response.

5.3 Machine Learning Based Smart PV Reserve Estimation for Frequency Stability

With the PV fast control for frequency stability, it has become important to determine the necessary headroom resource from PV to ensure sufficient frequency stability under various system conditions. To this end, a machine learning-based method has been proposed to estimate the required PV headroom while taking into account the PV parameter and system conditions. Since the total PV headroom has been estimated using the machine learning tool, a distribution method for each PV plant is further proposed based on real-time power system condition information. The overall process is outlined in Figure 5.8, and is detailed as follows:

- (a) A training dataset for machine learning is generated by PSS/E simulation under varying system conditions.
- (b) A smart method that uses machine learning and binary search method is employed to estimate the required PV headroom for the system.
- (c) The PV headroom is then distributed to multiple PV farms via the ICCP protocol every few minutes.
- (d) The PV plants execute the assigned PV headroom to ensure system frequency reliability. If a PV power plant cannot offer the assigned headroom, its PV headroom requirement will be relocated to other PVs to maintain real-time frequency stability.

5.3.1 Design of Machine Learning Based Smart PV Reserve Method

The training dataset for the machine learning model is generated through PSS/E batch simulation. To accurately estimate the PV headroom requirement for frequency stability, frequency nadir is considered as the key indicator.

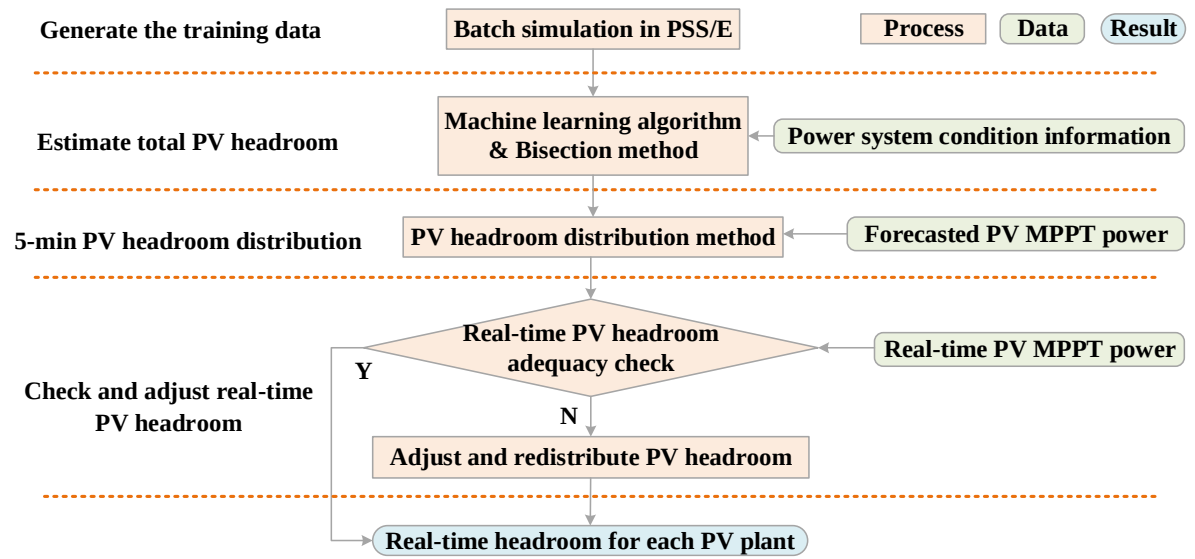


Figure 5.8. Machine learning based smart PV inertia control.

During the simulation, the governor capacity, PV headroom, and system inertia are varied to generate different system conditions. The system frequency response curves are then observed to calculate the frequency nadir under each configuration. Once sufficient simulations are performed, the dataset is created with frequency nadir as output labels and PV headroom, governor information, and system inertia as input features for the machine learning model. The machine learning tool is trained to learn the relationship between frequency nadir and PV headroom, governor information, and system inertia. The trained machine learning model is then utilized to estimate the system frequency nadir based on the system condition and PV headroom, as shown in Figure 5.9.

In this approach, a neural network is used as the machine learning model, due to its mature theories and wide range of applications. The neural network is trained using the created training dataset, allowing it to capture the complex relationship between frequency nadir and PV headroom, governor information, and system inertia as input features.

As shown in Figure 5.10, the trained neural network can estimate the frequency nadir given the PV headroom, governor information, and system inertia as input features. The histogram in Figure 5.11 displays the errors between the predicted frequency nadir and the actual testing data. It is clear that the maximum error between the predicted and simulated frequency nadir is small enough, indicating that the trained machine learning algorithm is reliable. The model's average prediction error is only a few millihertz.

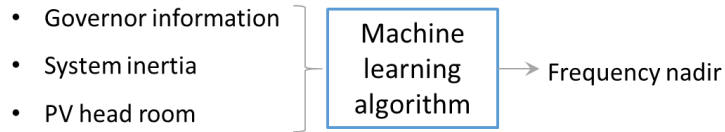


Figure 5.9. Inputs and outputs of the machine learning algorithm.

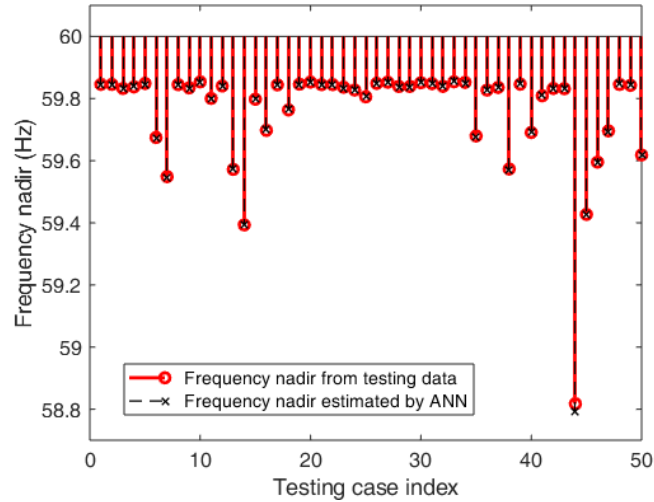


Figure 5.10. Comparison between estimated frequency nadir and background truth from simulation.

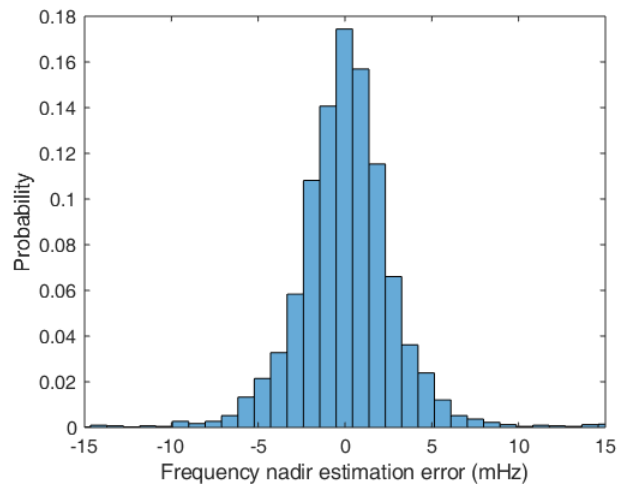


Figure 5.11. Histogram of the error distribution for the frequency nadir estimation.

Usually, there is a specific requirement for the frequency nadir in a power system to ensure frequency stability, such as maintaining all frequencies above 59.5Hz. Therefore, the required frequency nadir is determined in advance, and a smart approach is used to obtain the necessary PV headroom under real-time system conditions. This approach combines a trained neural network with bisection, as shown in Figure 5.12.

The estimated PV headroom is compared with the simulated required PV headroom for 50 testing samples in Figure 5.13, and the PV headroom estimation errors are shown in Figure 5.14. It is evident that the PV headroom estimation errors are within 0.003 p.u., which is relatively small and meets the application requirement. Thus, the proposed approach is highly accurate in estimating the required PV headroom for a specific frequency nadir.

5.3.2 PV Headroom Distribution

Two methods for 5-min PV headroom distribution are proposed in this section, taking into account the impact of headroom distribution on PV plant generation and its effect on system dispatch. Before the distribution, the forecasted PV MPPT (Maximum Power Point Tracking) power is estimated in 5-minute intervals to determine the PV generation. The two proposed methods are:

(a) Economic-dispatch-based PV headroom distribution: In this method, the headroom distribution is considered in an economic dispatch to achieve the best economic plan. The headroom of each PV plant is considered as a variable in economic dispatch, which minimizes the system cost while ensuring system constraints are satisfied. This approach ensures that the PV resources are optimally utilized in the 5-minute timescale.

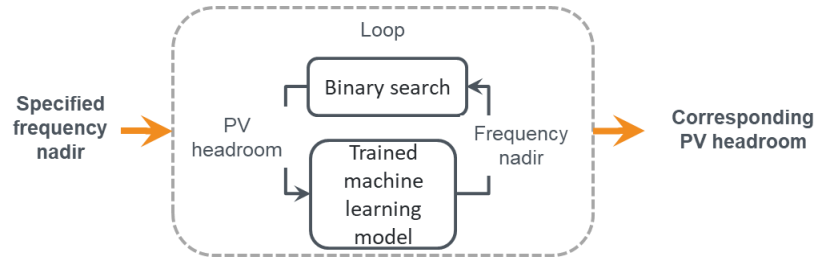


Figure 5.12. Steps to obtain the total PV headroom.

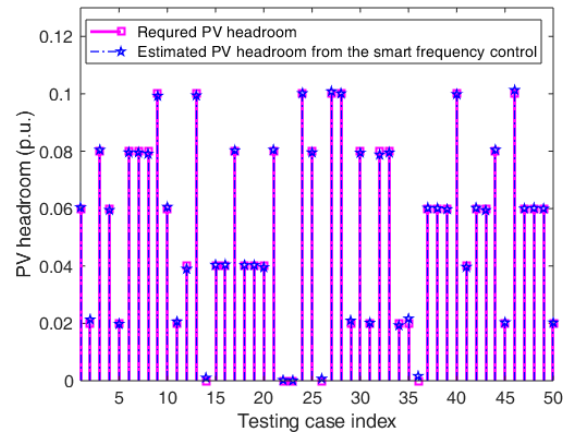


Figure 5.13. Comparison of PV headroom requirement from smart frequency nadir.

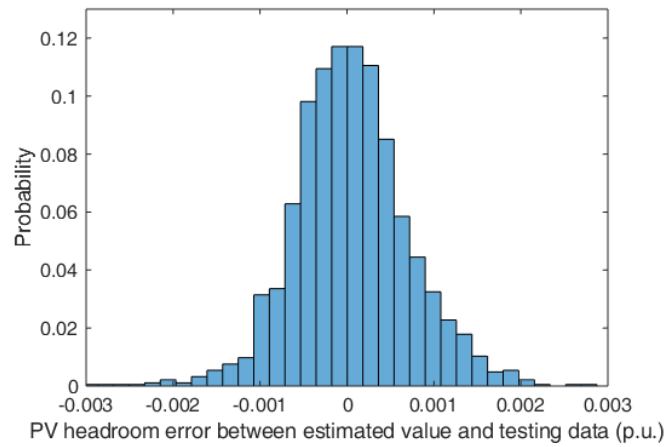


Figure 5.14. Histogram of the error between the estimated PV headroom and the actual headroom of all testing samples.

(b) Equal-proportion-based PV headroom distribution: In this method, each PV plant provides an equal percentage of headroom based on its forecasted MPPT power. Since there is no primary frequency response market in current power grids, equal proportion headroom allocation distributes the headroom cost to each PV plant in the system. This approach is fair for each PV plant when network congestion is not considered. After PV headroom is assigned for a specific plant, PV headroom power is reserved from the forecasted MPPT power for each PV power plant.

In this study, the equal-proportion-based PV headroom distribution method is selected. Since there is currently no established reward policy for PV headroom, it is considered fair for each PV farm to provide PV headroom in proportion to its MPPT output to support the system frequency.

However, due to uncertainties in PV forecasting, real-time MPPT power may fall below the assigned headroom in some cases. To address this issue, it is assumed that both real-time PV output and headroom reserve information are transmitted to the control centers, allowing the control center to verify whether the current PV headroom is sufficient to maintain frequency stability. If some PV plants are unable to provide the assigned headroom reserve in real time due to cloud shadows, the corresponding headroom will be reassigned to other PV plants. Additionally, the reduced generation of PV power plants can be compensated by fast power plants such as gas generators or hydro pump storage generators. The process of these actions is illustrated in Figure 5.15.

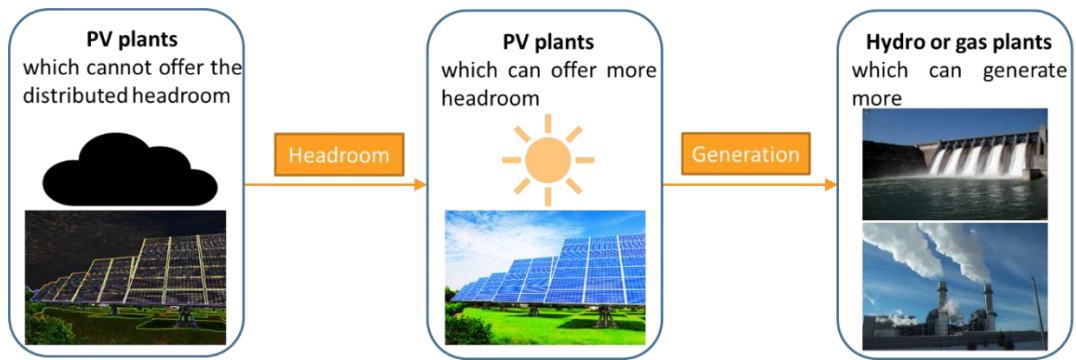


Figure 5.15. Actions when some PV plants cannot provide the assigned headroom.

5.4 ERCOT One-day Validation

This section presents the validation of the proposed PV headroom estimation method using 24-hour ERCOT scenarios. The fixed hourly headroom is used as a baseline to calculate the total headroom savings.

5.4.1 *Design of 24 Hourly Scenarios with Varying PV Penetration*

24-hour scenarios of the ERCOT system under varying PV penetration are designed to evaluate the proposed PV headroom estimation method. System inertia, the capacity of generator resources, PV control parameters, and the frequency nadir limit can impact the necessary PV headroom. For this study, the PV control parameters and UFLS threshold are assumed to remain constant throughout the scenarios. The ERCOT system inertia with high PV penetration is created by using historical inertia and PV data, and the synthetic inertia is shown in Figure 5.16.

To evaluate the performance of the proposed smart PV headroom estimation method, one-day scenarios in the future spring season under high PV penetration are selected. The hourly changes in system inertia and total PV MPPT power are shown in Figure 5.17.

In these created ERCOT system scenarios, it is designed that all generation resources, except steam turbines of combined cycle generation resources, have a governor droop characteristic. Therefore, the varying governor capacity is considered in the designed scenarios. The governor resource is assumed to be correlated with the capacity of generators with governors. In this study, the capacity of the generator with governor is further assumed to be proportional to the inertia since generators with governor usually have inertia, because the ERCOT system is a larger system.

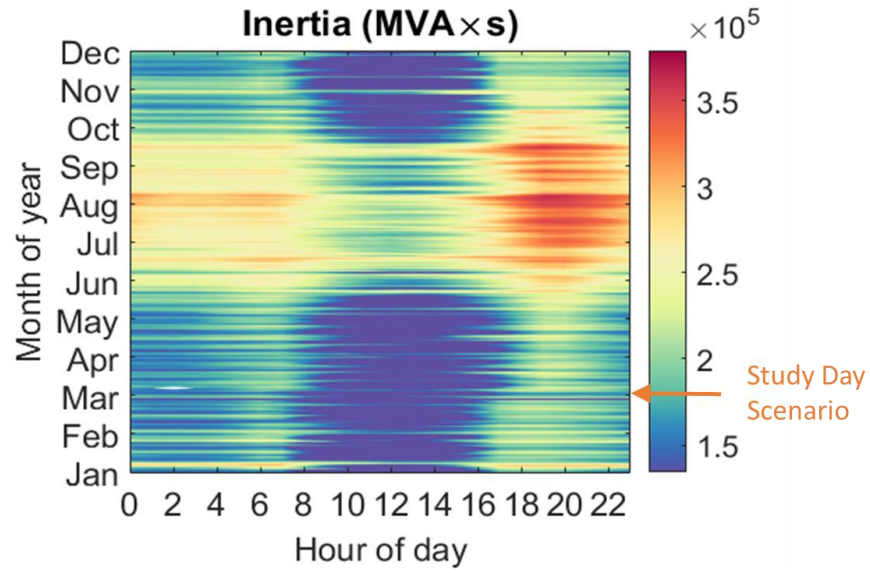


Figure 5.16. Change in system inertia in the ERCOT system with high PV penetration.

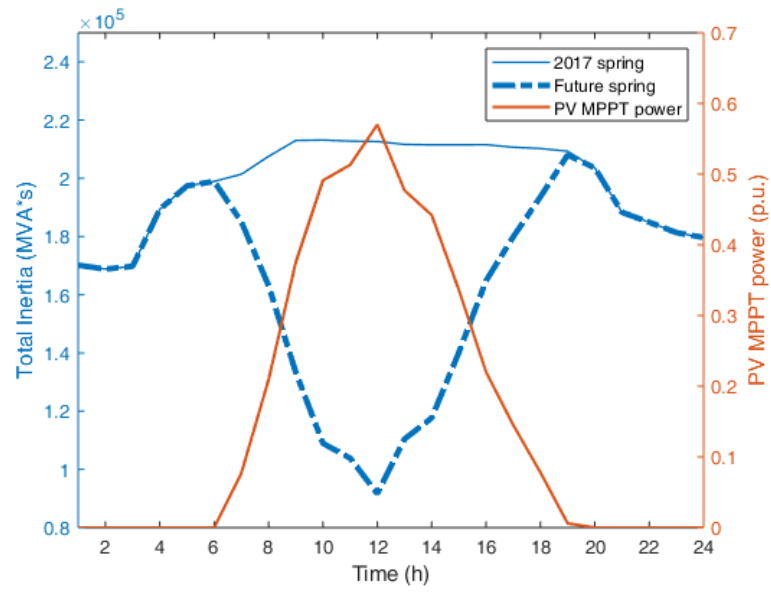


Figure 5.17. Inertia change of ERCOT system on a future spring day with high PV penetration.

In the created scenarios, it is assumed that the peak scenario has 50% PV, and the maximum capacity of governor resource is calculated as 51,540 MVA, which is around 50% of the total generation capacity at the peak load period. The change in the capacities of governor resources during the selected spring day is shown in Figure 5.18.

5.4.2 Evaluation of Frequency Stability with Smart Frequency Control

In this section, the designed scenarios for a future spring day are used to validate the proposed smart PV headroom estimation. Using the estimated PV headroom reserve, the frequency stability performance is evaluated in PSS/E simulation by checking if the frequency nadir is above the required frequency nadir limit of 59.5Hz. The droop control gain is set to 40, the time constant is set to 0.02s, and the dynamic simulation time step is set to 0.005s, based on practical experience. Table 5.1 provides a summary of the simulation parameters.

Based on the hourly scenarios created, the smart PV headroom estimation tool was used to estimate the necessary PV headroom for each hour, as illustrated in Figure 5.19. It can be observed that the maximum required PV headroom occurs when the PV MPPT power reaches its peak, due to the reduced system inertia and smaller capacity of governor resources resulting from higher PV penetration.

The estimated PV headrooms are used to evaluate the frequency stability of the created scenarios. During the dynamic simulation of each scenario, the PV headroom estimated by the smart frequency control method is distributed to each PV power plant. In the simulation of each scenario, at 1s, a generation trip of 2,752 MW event is applied to the system.

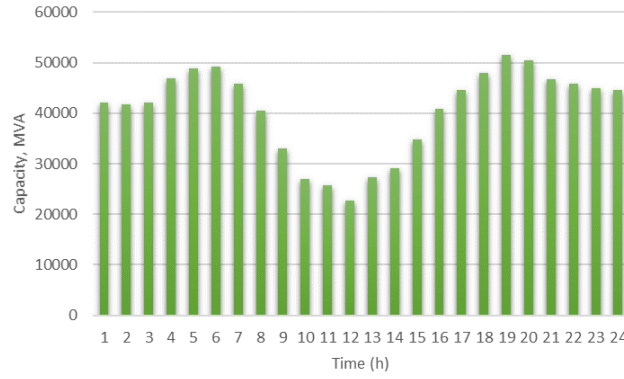


Figure 5.18. Change in system frequency responsive generation capacity during a future spring day in ERCOT system with high PV penetration.

Table 5.1. Simulation parameters setting to validate the proposed smart PV headroom estimation.

Parameter	Value
Frequency nadir limit	59.5 Hz
Droop control gain	40
Time constant	0.02s
The update time of PV control	0.015s
Time step of the dynamic simulation	0.005s

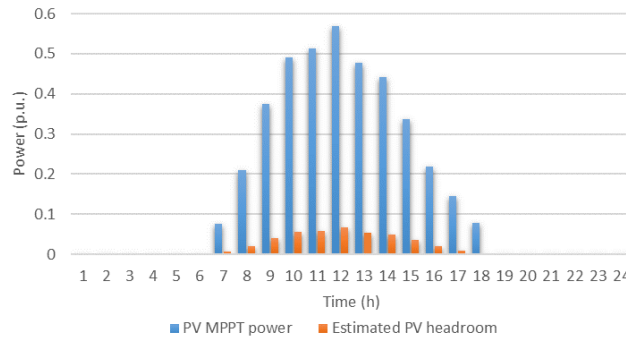


Figure 5.19. Estimated PV headroom by the proposed smart PV headroom estimation tool.

Then, the frequency curves of the scenarios from 7 AM to 6 PM are shown in Figure 5.20 since there is PV generation within this time interval. After the generation trip, the frequency values in all scenarios begin to decrease, and all the frequency nadirs with the smart frequency control headroom support are almost around 59.5Hz. However, the frequency nadirs without any headroom support are much lower than 59.5Hz in some scenarios. It is evident that the smart frequency control achieves satisfactory performance since all frequency nadir points are above 59.5Hz.

5.4.3 Calculation of PV Headroom Savings

In this section, a comparison between the proposed smart PV headroom control and fixed PV headroom control is presented to calculate the PV headroom savings. In the fixed PV headroom control, the PV headroom requirement is set to a fixed value that is large enough to ensure system frequency stability for all scenarios. The grey bars in Figure 5.21 represent the headroom of the fixed PV headroom control. However, due to the changing system conditions, the fixed PV headroom control will result in non-necessary PV headroom most of the time, which leads to the waste of PV energy. In the created one-day scenarios, the total PV headroom using smart frequency control is 0.419 p.u.*hour, whereas it is 0.809 p.u.*hour for the fixed PV headroom control. It can be observed that the total PV headroom saving is around 50% in these one-day scenarios, indicating the effectiveness of the proposed smart PV headroom control approach.

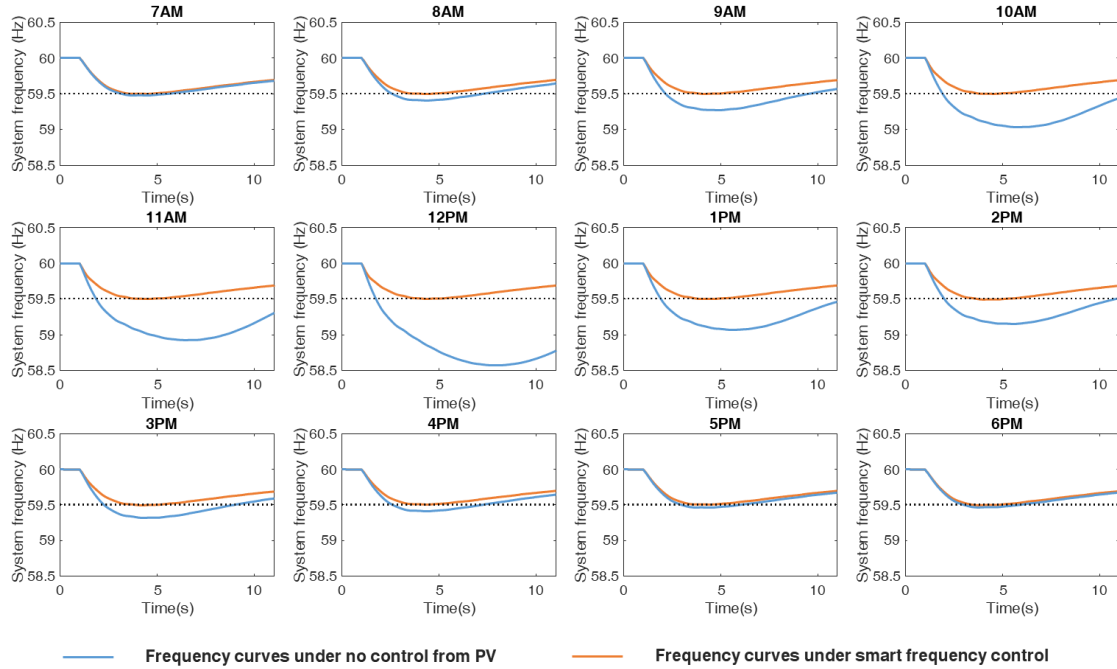


Figure 5.20. Frequency curves of scenarios from 7 AM to 6 PM.

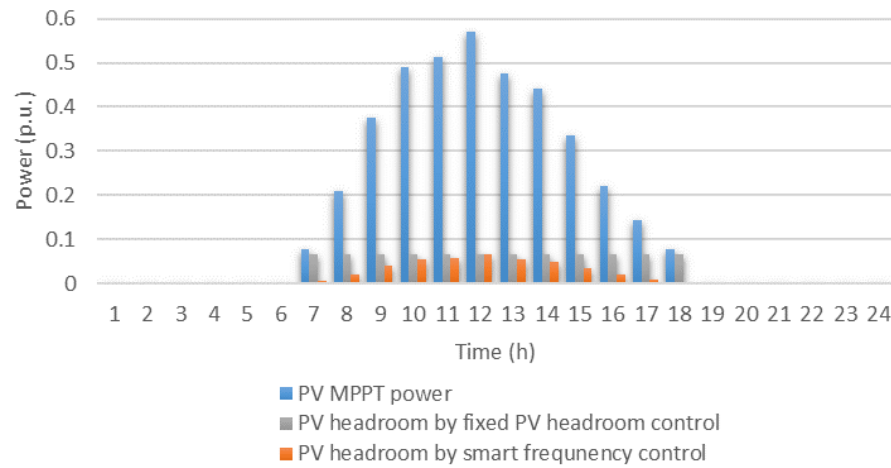


Figure 5.21. PV headroom values from the smart PV headroom control and fixed PV headroom control.

Using the PV headroom settings determined by the smart PV headroom control and fixed PV headroom control, the frequency curves after the critical event in 24 scenarios are also depicted in Figure 5.22. It is apparent that all frequency nadir points are above 59.5Hz. However, when the fixed PV headroom control is employed, the frequency nadir points are significantly higher than 59.5Hz in some scenarios, which may be unnecessary for ensuring frequency stability.

5.5 CURENT Hardware Testbed

In this section, the UTK CURENT Hardware Testbed (HTB) was utilized to test the proposed smart frequency control and verify its effectiveness in a real power system environment. The main objective was to demonstrate that the proposed smart PV headroom estimation could save PV headroom reserve compared to fixed-headroom control, for the same frequency nadir requirement. The following three main steps were performed:

(a) A training dataset was generated for the smart PV estimation tool, with various headroom and system inertia settings for the CURENT HTB test system. After a contingency was added to the test system, the frequency nadir was recorded as a training output feature for the smart PV estimation tool.

(b) The machine learning algorithm in the smart frequency control was trained to learn the frequency response patterns under varying system conditions.

(c) The effectiveness of the smart frequency control was verified in the test system under different real-time hourly scenarios. The PV headroom requirements for each scenario were estimated by the smart frequency control, and by using the estimated PV headroom requirement in the hardware system, the frequency nadir was checked after the same contingency in each hourly scenario.

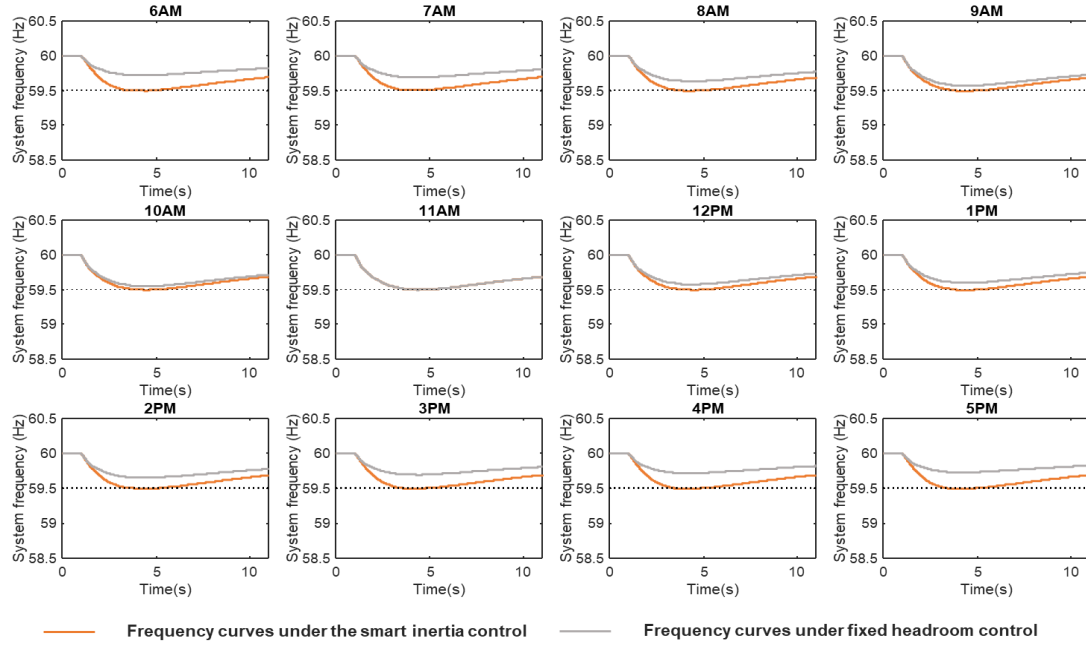


Figure 5.22. System frequency response comparisons of smart frequency control and fixed headroom control.

5.5.1 Introduction to CURENT Hardware Testbed

At the University of Tennessee, the CURENT HTB is equipped with a reconfigurable structure that can simulate a large-scale power system using multiple modular and reprogrammable converters, as depicted in Figure 5.23(a). High-resolution PMU data is measured using FDR (Frequency Disturbance Recorder), a synchrophasor measurement device, which is illustrated in Figure Figure 5.23(b). In the visualization and control room, operators issue commands and record measurements for the HTB, as shown in Figure 5.23(c).

To evaluate the PV headroom savings and the performance of smart PV inertia control in a real environment, a two-area test power system was constructed in the CURENT HTB. This system consists of two 200MW synchronous generators, a 400MW PV plant, and a 365MW load, as shown in Figure 5.24. To test the frequency response of the system, the contingency was set to an 80 MW step increase in load L1, simulating a generation loss contingency in a real power system.

The measured frequency data from CURENT HTB may contain some background noise, which could challenge the performance of the smart frequency control. These noises are usually present in the high-frequency band, as shown in Figure 5.25. To address this issue and obtain accurate frequency measurements, a low-pass filter is also used in the smart frequency control.

5.5.2 Tests in HTB to Generate Dataset for Smart Frequency Control

The training dataset for the machine learning algorithm in the smart frequency control was generated using CURENT HTB. The process consisted of the following steps:



(a) Hardware room (partial) (b) FDRs (c) Visualization and control room

Figure 5.23. CURENT hardware testbed.

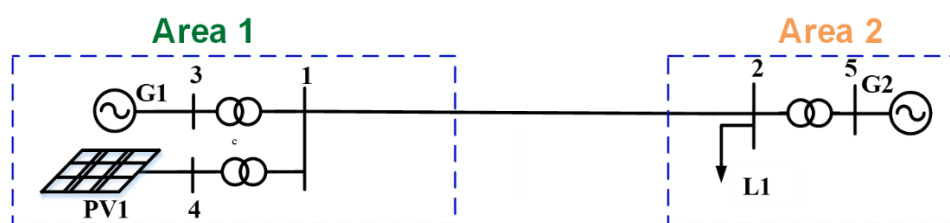


Figure 5.24. Test system in CURENT HTB.

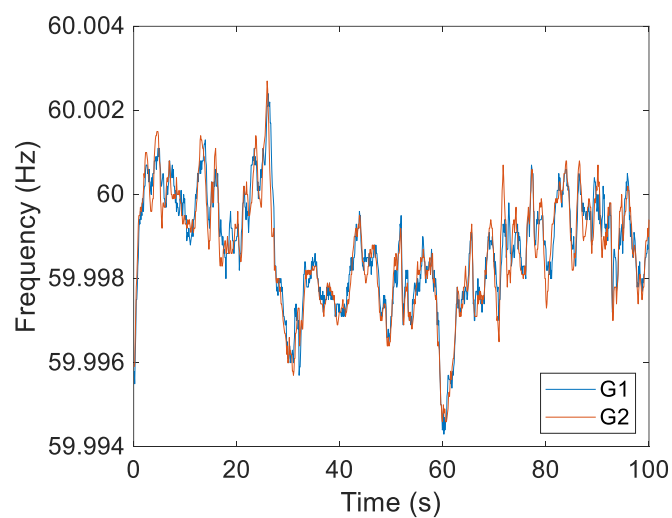


Figure 5.25. Background noise of the frequency on the hardware system.

(a) Changing the PV penetration level: The PV penetration level was varied from 0% to 80% with a step of 20%, which resulted in changes in system inertia from 2600 MVAs to 520 MVAs.

(b) Changing the PV headroom: The PV headroom was set from 0MW to 90MW with a step of 10MW.

(c) Adding the contingency: An 80MW load step change was added to simulate a generation trip in a large system.

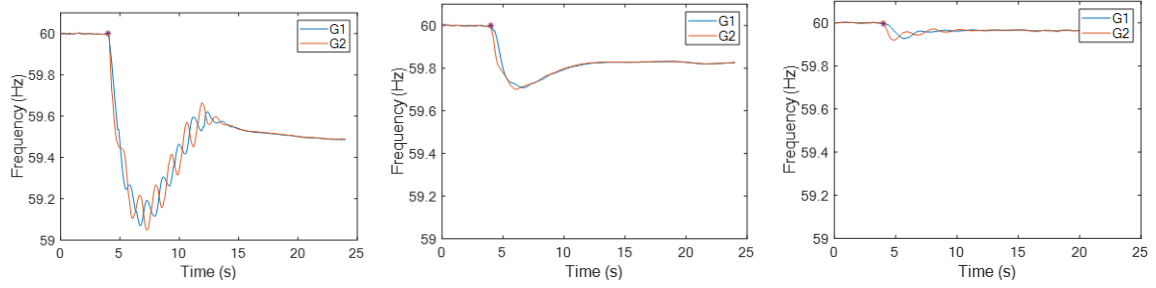
(d) Recording frequency curves: The frequency nadir of G1 and G2 was recorded from the frequency curves.

After conducting a hardware test on the CURENT HTB, frequency curves were generated and recorded for 50 test scenarios. Figure 5.26 shows frequency curves for three example test scenarios.

In this research, the frequency nadir is defined as the minimum mean frequency of two generators. The frequency nadirs for the 50 test scenarios were then determined and are represented by the blue dots shown in Figure 5.27.

5.5.3 Training of Machine Learning Algorithm for Smart Frequency Control

In this study, a machine learning algorithm was trained to recognize frequency response patterns in the test system during contingency using a feed-forward neural network. The input features were system inertia and PV headroom, while the output feature was the system frequency nadir. 40 samples were used for training, and 10 samples were used for testing the machine learning algorithm.



(a) Inertia 2.6s, headroom 0MW (b) Inertia 5.2s, headroom 30MW (c) Inertia 13s, headroom 70MW

Figure 5.26. Frequency curves of three typical test cases.

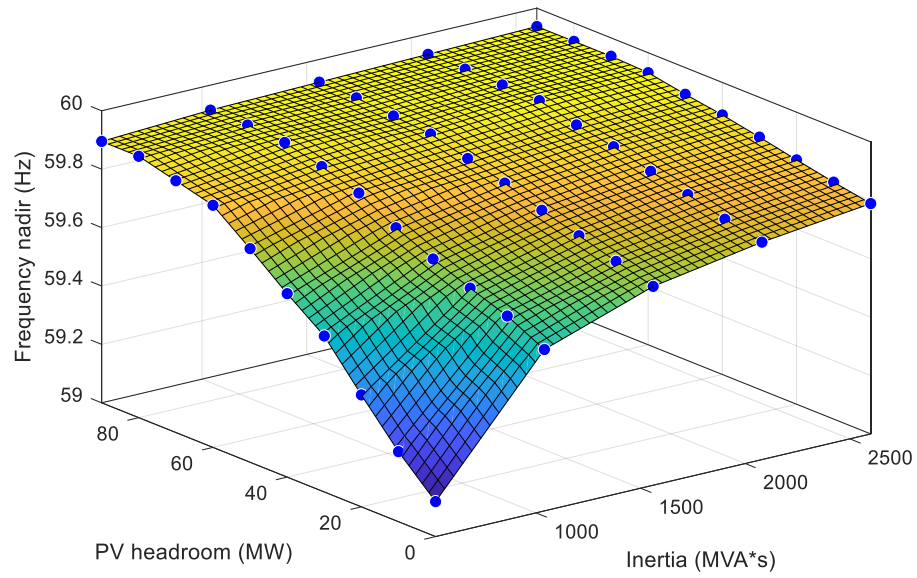


Figure 5.27. Frequency nadir of all test cases under different PV headroom and system inertia.

To ensure a fair validation of the machine learning algorithm, a 5-fold cross-validation approach was employed. The 50 samples were randomly divided into five folds with 10 samples in each fold. Then, four folds of data were used for training the algorithm, and the remaining one fold was used for testing. This process was repeated until all data were tested. Figure 5.28 shows the frequency nadir estimated based on the trained machine learning algorithm. The blue crosses represent the estimated frequency nadir of the training data, while the blue stems indicate the actual frequency nadir of the training data. The red crosses represent the estimated frequency nadir of the testing data, and the red stems indicate the true frequency nadir of the testing data. Clearly, the estimated frequency nadir matches well with the true frequency nadir for both the training and testing data.

5.5.4 Real-time PV Headroom Estimation for HTB Test System

The trained machine learning algorithm was utilized in the smart frequency control system to determine the required PV headroom needed to achieve a specified frequency nadir target using the bisection method. This is demonstrated in Figure 5.29.

The real-time PV headroom estimation in the control system requires the real-time inertia information of the test system and the specified frequency nadir target as inputs. It then outputs the real-time PV headroom requirement setpoint, as illustrated in Figure 5.30.

To evaluate the smart frequency control, multi hourly scenarios were created for the test system using typical hourly profiles of load demand and PV output in the WECC system. The base values for load demand and PV output were scaled to suit the test system. Figure 5.31 depicts the hourly scenarios designed for the test system during future summer and winter days with instantaneous 80% PV penetration.

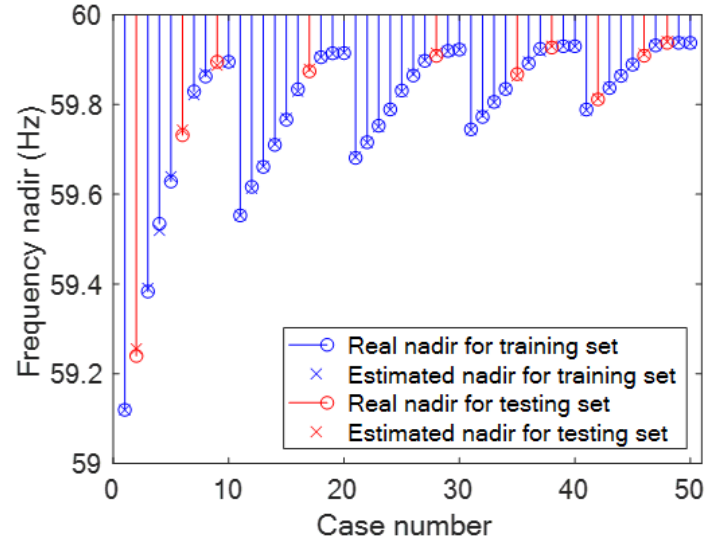


Figure 5.28. Frequency nadir estimation for the training and testing data when one-fold data is selected to test.

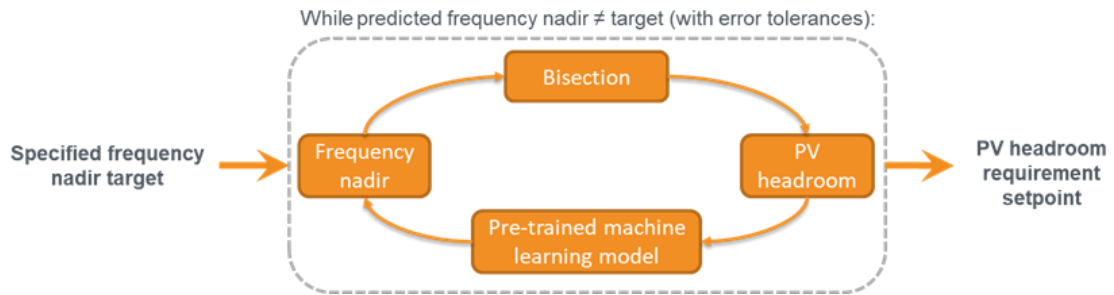


Figure 5.29. PV headroom estimation strategy in the smart frequency control.

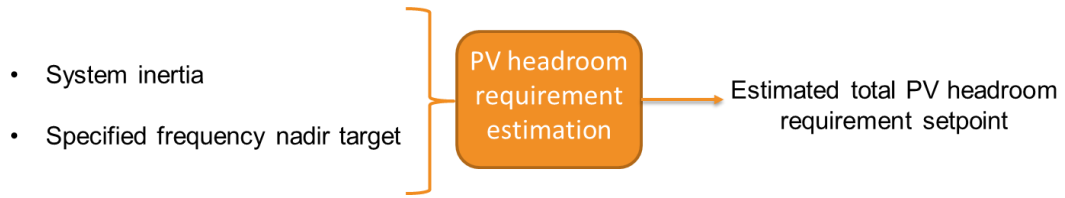


Figure 5.30. Input and output information of PV headroom estimation in smart frequency control.

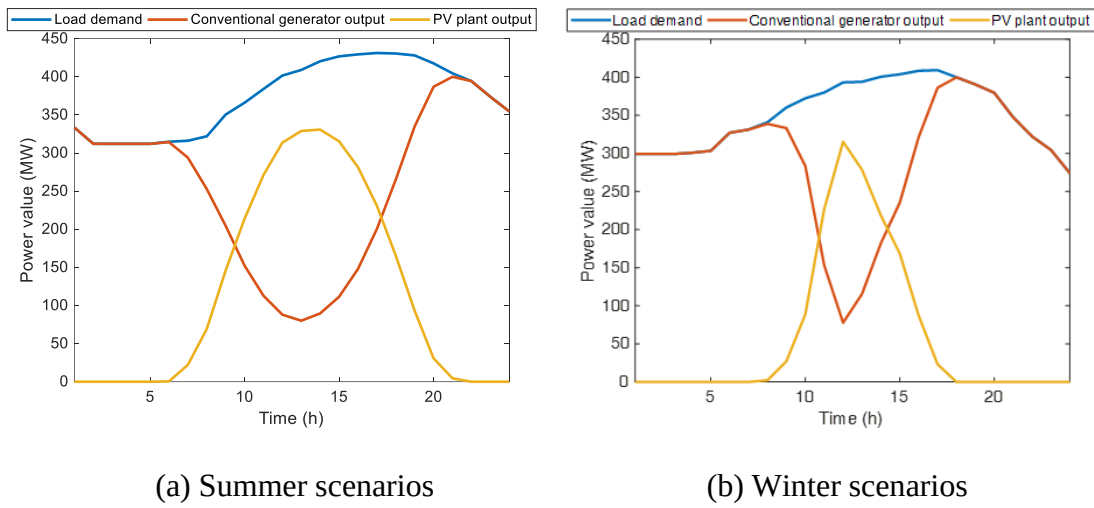
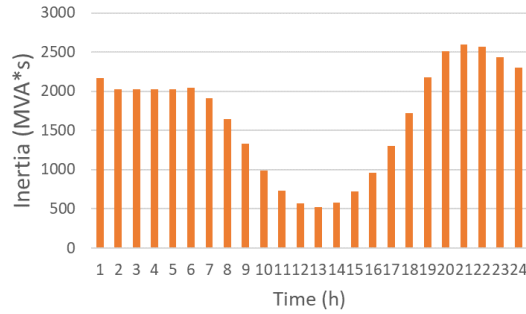


Figure 5.31. Hourly scenarios of the test system in the future summer and winter days with instantaneous 80% PV penetration.

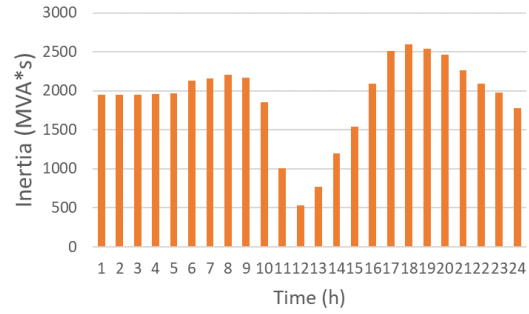
To simulate hourly inertia variations in an actual large power system, the system inertia of the HTB test system was assumed to be proportional to the output of conventional generators. In a real power system, changes in conventional generator outputs impact the working status of the generators, which in turn causes the total system inertia to change. Figure 5.32 illustrates the inertia values for the designed scenarios on two typical days in HTB test system.

In this test system, a frequency nadir limit of 59.8 Hz was set for maintaining frequency stability. Figure 5.33 displays the real-time estimated PV headroom requirement values for the hourly scenarios on two typical days, obtained through the smart frequency control system.

To evaluate the performance of the proposed smart headroom estimation, the same contingency was used in each hourly scenario. When the smart frequency control detected a frequency drop below the preset threshold, it increased the PV output until the estimated PV headroom value was reached. The system frequency nadirs were then tested with and without the smart frequency control on the two typical days, as depicted in Figure 5.34. The results indicate that the proposed smart frequency control was effective in maintaining the frequency nadir above 59.8Hz, meeting the requirement for frequency stability.

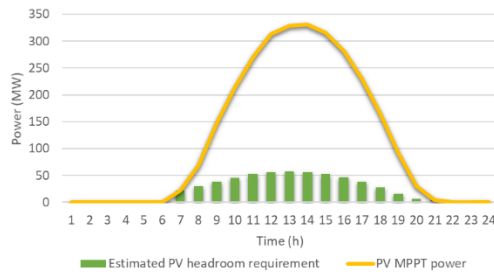


(a) Summer scenarios

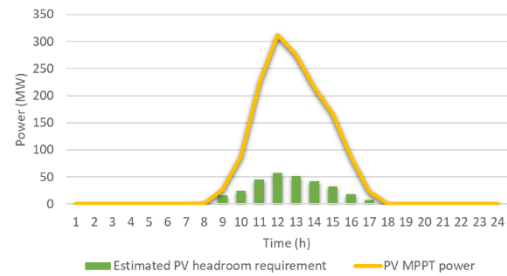


(b) Winter scenarios

Figure 5.32. Inertia variation of the summer and winter scenarios.

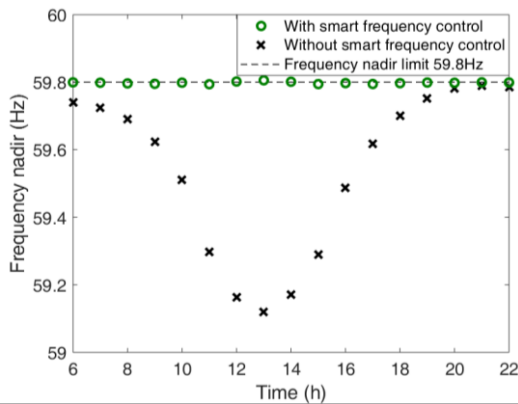


(a) Summer scenarios

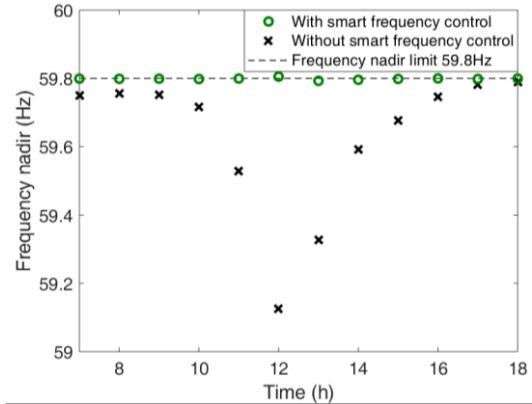


(b) Winter scenarios

Figure 5.33. Estimated PV headroom for HTB test system using proposed smart headroom estimation.



(a) Summer scenarios

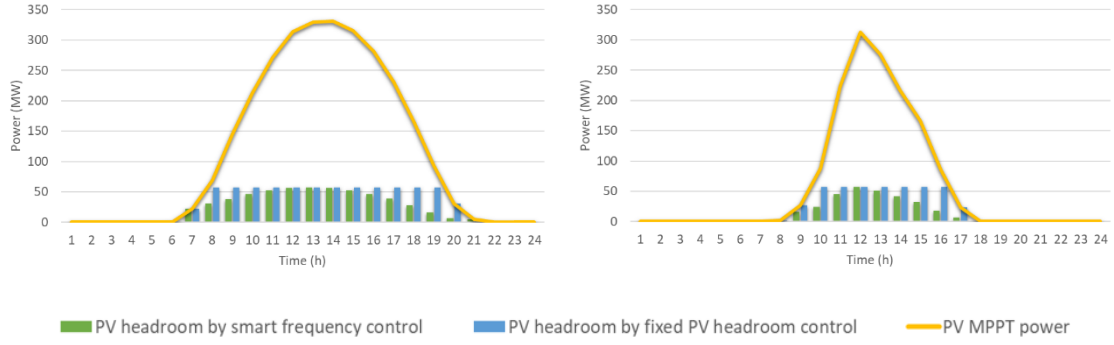


(b) Winter scenarios

Figure 5.34. Frequency nadir of the test system with and without smart frequency control.

Additionally, the economic benefits of the smart frequency control were demonstrated through calculations of PV headroom savings. The fixed PV headroom control was used as the benchmark, where the PV headroom was set to the maximum value from the smart frequency control over a single day, ensuring that each scenario had sufficient headroom. In Figure 5.35, the blue bars represent the PV headroom obtained from the fixed headroom control, while the green bars represent the PV headroom obtained from the smart frequency control. On average, the proposed smart frequency control achieved 30% headroom savings in typical summer and winter scenarios, compared to the fixed headroom frequency control.

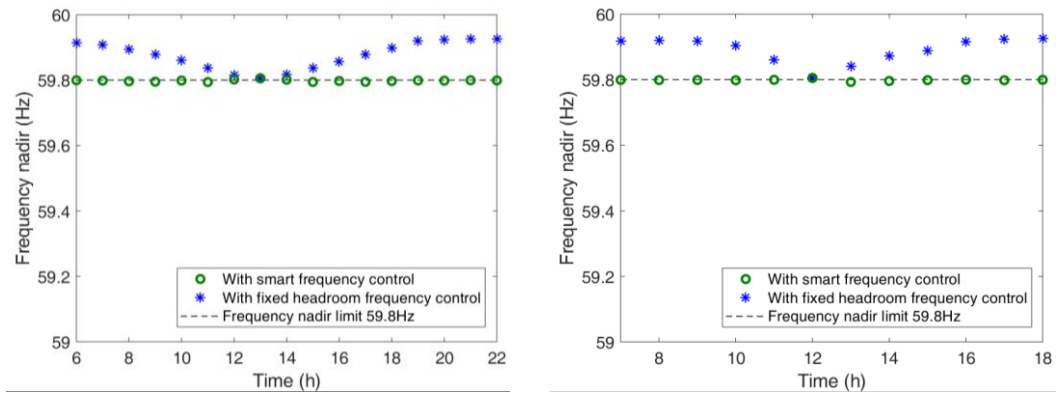
The frequency curves for scenarios under the smart frequency control and fixed PV headroom control were tested and displayed in Figure 5.36. The results indicate that all frequency nadir points are around 59.8Hz under the smart frequency control. However, when the fixed PV headroom control is used, some frequency nadir points are much higher than 59.8Hz, resulting in redundant PV headroom.



(a) Summer scenarios

(b) Winter scenarios

Figure 5.35. PV headroom estimation from smart frequency control and fixed PV headroom control.



(a) Summer scenarios

(b) Winter scenarios

Figure 5.36. Frequency nadir of the test system with smart frequency control and the fixed PV headroom control.

CHAPTER 6 PRACTICAL LOAD COMPOSITION ESTIMATION

As accurate load composition is crucial for load models, a machine learning-based method is proposed to obtain precise load composition information for Dominion Energy. Dominion Energy aims to use load profile data to acquire load composition for additional feeders, and hence, provided load composition for parts of feeders from measurements and statistics. Loads with distinct compositions exhibit different features in their load profiles. Based on these features, machine learning is used to estimate load composition using the load profile information as input. Ultimately, the load compositions for around 1900 feeders in Dominion Energy's service area are estimated, which can be used to build more accurate load models for the company. Despite the complex relationship between load composition and load profile, the final results are promising, with an average absolute estimation error of 12%, 7.3%, and 10% for commercial, industrial, and residential loads, respectively. Figure 6.1 depicts a flowchart of this work.

6.1 Data from Dominion Energy and Preprocessing

6.1.1 Dominion Energy Load Composition Data

Dominion Energy has load composition for some parts of loads, but it does not cover all feeders in the company's service area. Additionally, there is no composition information available for smaller loads, and some feeders with larger loads also lack composition information.

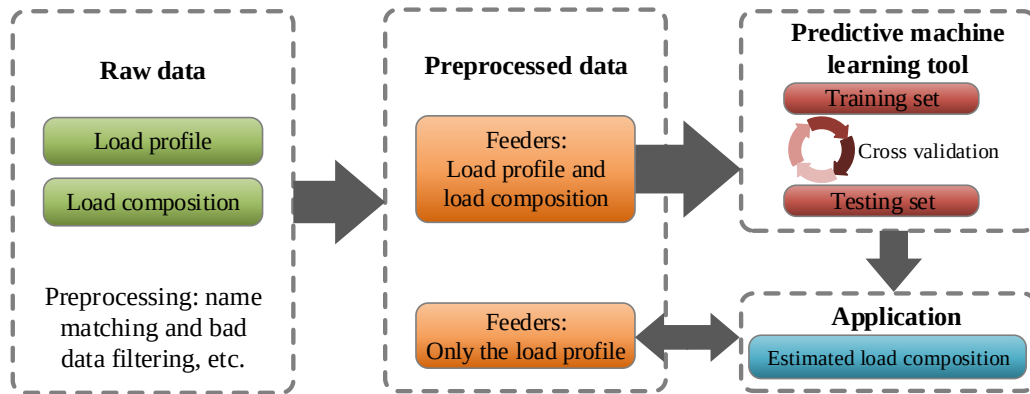


Figure 6.1. Flowchart of the developed load composition estimation tool using load profile.

Table 6.1 displays the spreadsheet from Dominion Energy, which contains load composition for loads from some feeders during the 2017 summer peak. The compositions comprise ten different load types, including commercial (C), federal (F), industrial (I), municipal (M), county (N), street lights (P), residential (R), resale (S), traffic signals (T), and commonwealth (V).

Dominion Energy measures feeder load data in its distribution networks by recording and storing the three-phase currents in the PI server. Figure 6.2 illustrates the three-phase currents of one load during the 2017 summer peak.

Before training the machine learning tool, the raw load profile data and composition information undergo preprocessing.

6.1.2 *Filtering of Bad Date*

The raw load profiles from the PI server contain some bad data, including four main types shown in Figure 6.3: spike issues, missing data issues, shifting data issues, and incomplete phase issues. Due to sufficient training data, load profiles with bad data are excluded from the training process.

6.1.3 *Name Matching*

Substation names link load profile data and load composition information. However, the load profile data and known load composition data sources use different naming conventions: load profile data uses abbreviations, while the known load composition data uses full names of substations. To align the two datasets, load profile data names are manually corrected to match those of the load composition data, which is time-consuming.

Table 6.1. Load composition information for parts of feeders.

Feeder	Load composition									
	C	F	I	M	N	P	R	S	T	V
Feeder #1	54.97%	0.82%	0.00%	2.79%	0.00%	0.00%	35.14%	0.00%	0.00%	6.28%
Feeder #2	32.83%	0.12%	0.00%	24.45%	0.00%	0.00%	41.56%	0.00%	0.00%	1.04%
Feeder #3	54.57%	0.00%	0.00%	17.55%	0.33%	0.00%	27.47%	0.00%	0.01%	0.06%
Feeder #4	52.85%	0.06%	0.00%	0.81%	0.00%	0.00%	46.22%	0.00%	0.01%	0.05%
...	...	...	...	...	...	...	...	...	...	...

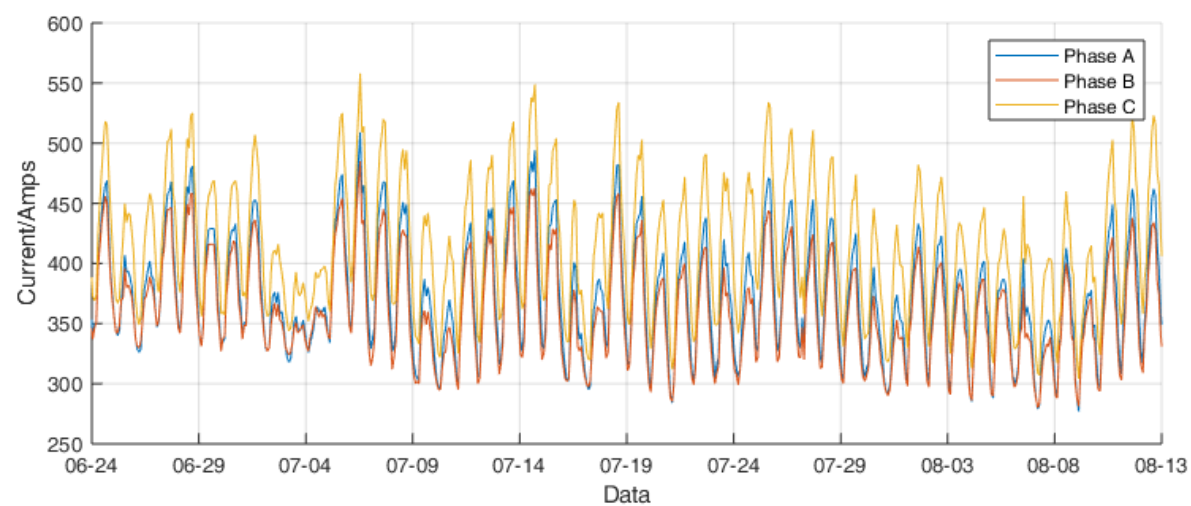
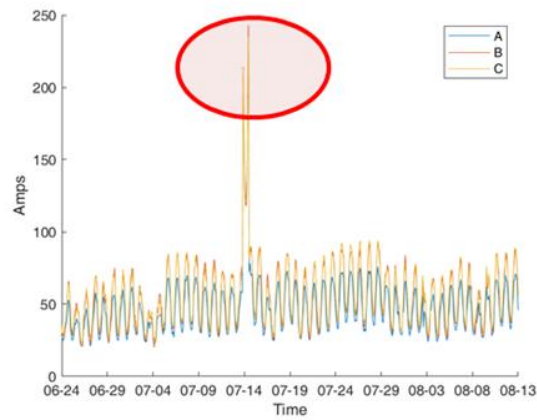
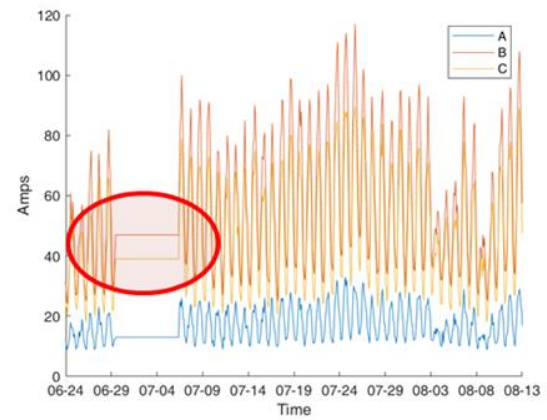


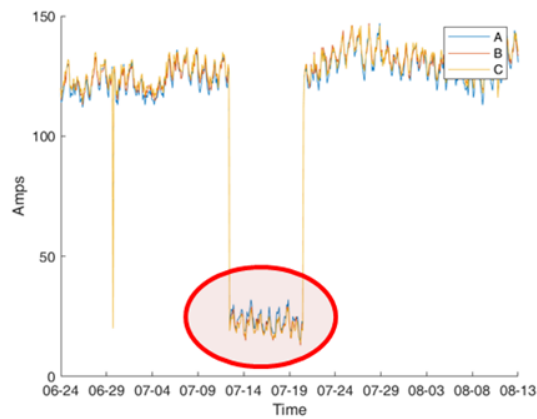
Figure 6.2. Three-phase currents of one load.



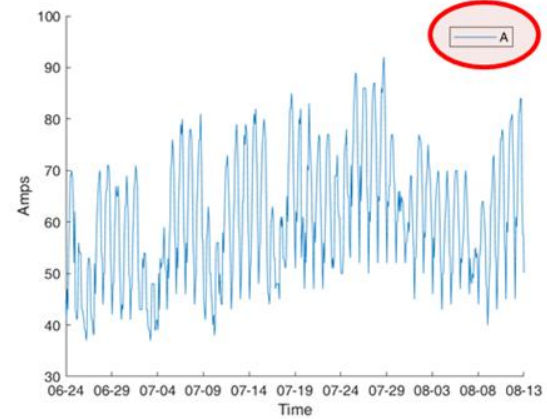
(a) Spike issue



(b) Data missing issue



(c) Data shifting issue



(d) Incomplete phase issue (only 1 or 2 phase data)

Figure 6.3. Bad data in load profiles.

6.1.4 Combination of Load Composition

The raw load composition data from Dominion Energy consists of ten load types. However, for the CLOD model, the raw load compositions are grouped into three types: commercial, residential, and industrial, as shown in Table 6.2.

6.1.5 Normalization of Load Profile

Loads with the same composition may differ in size, thus necessitating normalization of the raw load profile data. The normalization process is as follows:

$$\text{New current sequecne} = \frac{\text{Old current sequecne}}{\text{Mean value of old current sequecne}} \quad 6.1$$

6.2 Load Profile Feature Extraction

The load profiles serve as inputs for the machine learning model. However, during the 2017 summer peak, the load profile for each feeder contains only 672 data points for a single phase, which is too high for machine learning due to limited training data sets. To overcome this, key features are extracted from the inputs to reduce the dimensions.

6.2.1 Averaging One-Day Load Profile

Loads with different compositions may exhibit distinct load profile shapes. Some power consumers may have similar power-consuming behavior every day, making the averaging one-day load profile a useful feature that avoids duplicated patterns of data and maintains low data dimensions.

Table 6.2. Load types in the composition data.

Previous types	New types
Commercial	Commercial
Federal	
Municipal	
County	
Street Lights	
Traffic Signals	
Commonwealth	
Industrial	Industrial
Resale	
Residential	Residential

Figure 6.4 shows three different typical averaging one-day load profiles, each exhibiting a different shape such as flat, one-peak, or multi-peak. Moreover, peak hour can also vary among different loads with peak shapes. The averaging process involves computing the average of three-phase values.

6.2.2 *Difference in Load Demand Between Workdays and Weekends*

Selecting the average one-day load profile as a feature may lead to loss of information on different days. Some power consumers may have different power-consuming patterns on workdays and weekends, with lower (or higher) power demands during weekends compared to workdays, while others may have similar power demands throughout the week. Figure 6.5 illustrates one-day averaging load profiles for two loads over a week, where red lines indicate weekends and blue lines indicate workdays. As shown, the load in Figure 6.5(a) exhibits obvious load demand differences between workdays and weekends, while no apparent differences are evident for the load in Figure 6.5(b). To account for these load differences, the load demand ratio between workdays and weekends is selected as an additional feature.

6.2.3 *Imbalance Among Three Phases*

In some feeders, the load demands among three phases are noticeably imbalanced. Figure 6.6(a) displays a load with evident phase imbalances, while Figure 6.6(b) shows a load without such imbalances. To capture this imbalance pattern, the standard deviation among the three phases is selected as an additional feature.

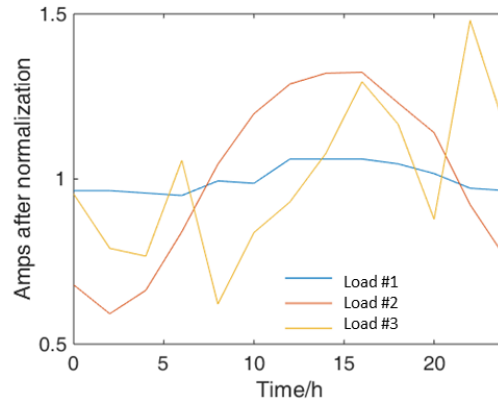
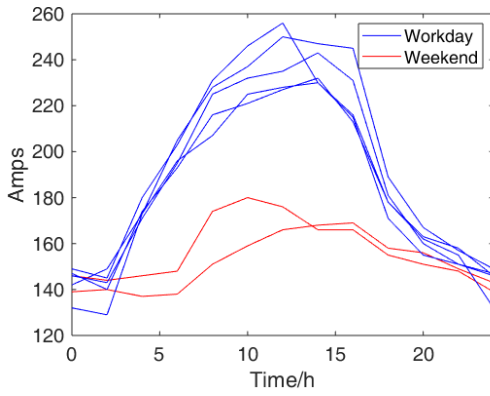
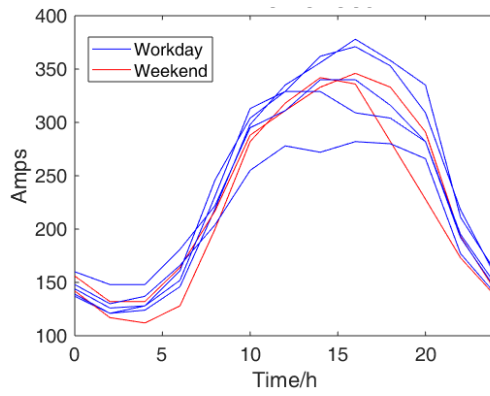


Figure 6.4. Averaging one-day load profiles of three typical loads.

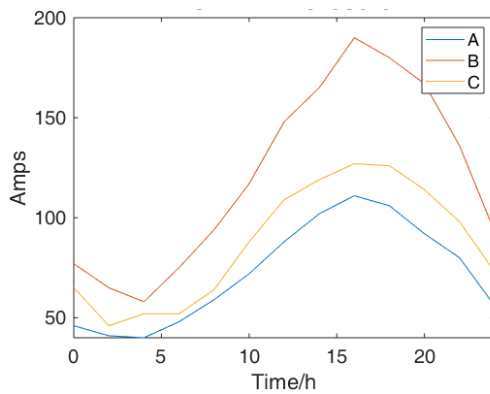


(a) Load with obvious difference

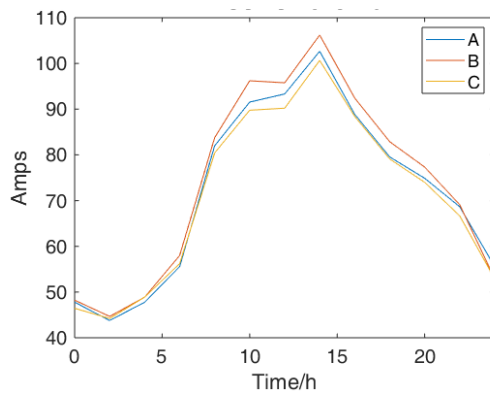


(b) Load without obvious difference

Figure 6.5. Load demand difference between workdays and weekends.



(a) Load with obvious imbalance



(b) Load without obvious imbalance

Figure 6.6. Load demand imbalance among three phases.

The input features extracted for machine learning include: 1) the averaging one-day load profile (12 data points), 2) the one-day ratio of load profile between weekends and workdays (12 data points), and 3) the one-day standard deviation among three phases (12 data points). Figure 6.7 depicts the extracted input features for three different loads. By using this approach, the input dimension of raw load profiles is reduced from 672 to 36.

6.3 Machine-Learning-Based Load Composition Estimation and its Verification

The machine learning tool takes the extracted features as inputs and produces load compositions in percentage as outputs, as depicted in Figure 6.8.

A multi-layer neural network is used as the initial machine learning tool, with a framework shown in Figure 6.9. The network consists of two hidden layers with 50 neurons each. Given that the outputs are percentage values within [0, 1], the LOGSIG function is employed as the activation function in the output layer.

In some cases, the percentage values produced by the machine learning tool do not satisfy the equality constraint that the sum of the three percentage values should be 1. To address this, the Lagrange multiplier is employed to correct the output estimation, as depicted in Figure 6.10. The theoretically best-corrected estimations by the Lagrange multiplier can be solved as the following equation:

$$\begin{cases} x^* = x + (1 - x + y + z)/3 \\ y^* = y + (1 - x + y + z)/3 \\ z^* = z + (1 - x + y + z)/3 \end{cases} \quad 6.2$$

where x , y , and z are the estimations from the machine learning, and x^* , y^* , and z^* are the corrected estimations.

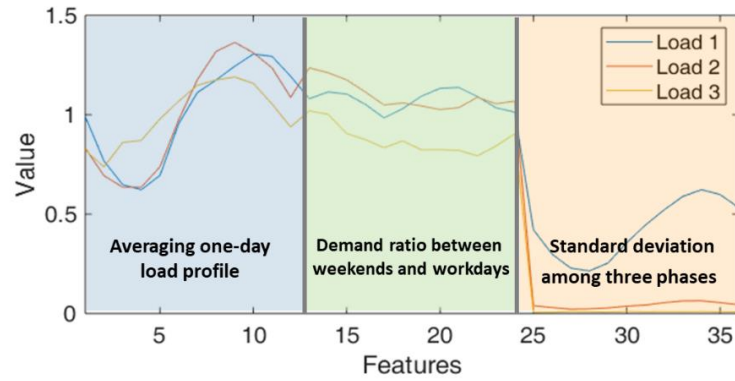


Figure 6.7. Input feature extraction for machine learning.

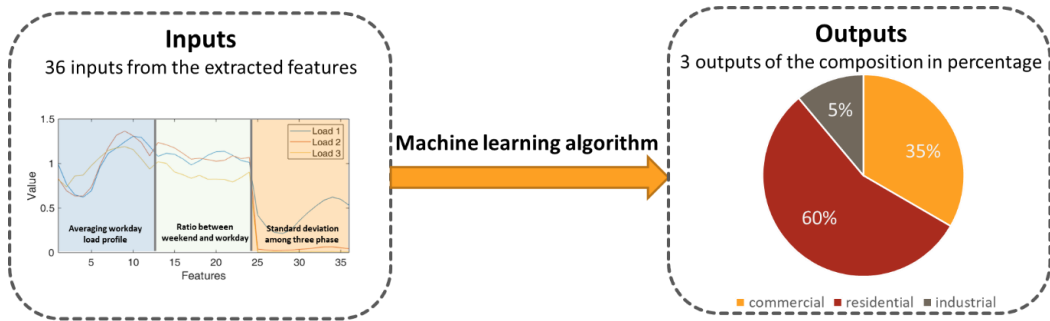


Figure 6.8. Inputs and outputs of the machine learning.

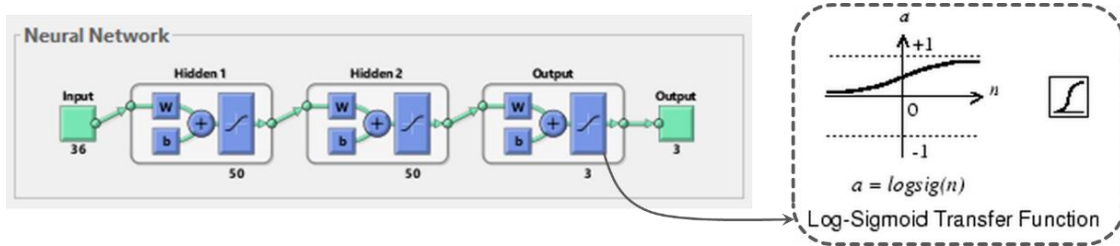


Figure 6.9. Framework of multi-layer neural network used in this study.



Figure 6.10. Estimation correction with the equality constraint.

To further validate the machine learning tool, 10-fold cross-validation is employed. The goal of cross-validation is to prevent issues like selection bias from the training data and to gain insight into how the model will perform on an independent dataset. The dataset, consisting of around 1100 cases, is randomly divided into ten folds. One fold is reserved as the testing set while the remaining data is used for training the machine learning tool. This process is repeated ten times, with each fold serving as the testing set once. The averaging error of all ten iterations is calculated as the final error, which helps avoid selection bias. Figure 6.11 illustrates the 10-fold cross-validation process.

Figure 6.12 displays the histogram of errors for all data in the testing set. The majority of testing cases have errors within the range of $[-20\%, 20\%]$. Moreover, the median absolute error is 8.5%, indicating that half of the testing cases have absolute errors less than 8.5%. The average absolute error, on the other hand, is approximately 11.9%.

To illustrate the errors more vividly, Figure 6.13 compares the original and estimated composition values. Half of the testing cases exhibit errors within 8.5%, as shown in Figure 6.13 (a). Although some cases have larger errors, such as 35%, the dominant load type is still estimated correctly, as depicted in Figure 6.13 (b).

The relationship between load composition and load profile is complex, but the proposed machine-learning-based method has demonstrated promising performance based on the above results. With the trained machine learning tool, Dominion Energy can estimate the load composition information for feeders without recorded composition information using easily obtainable load profile data.

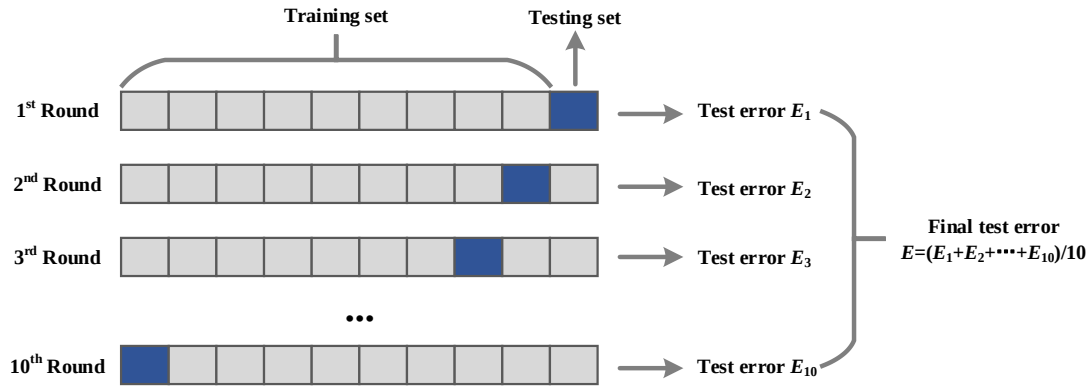


Figure 6.11. Ten-fold cross-validation.

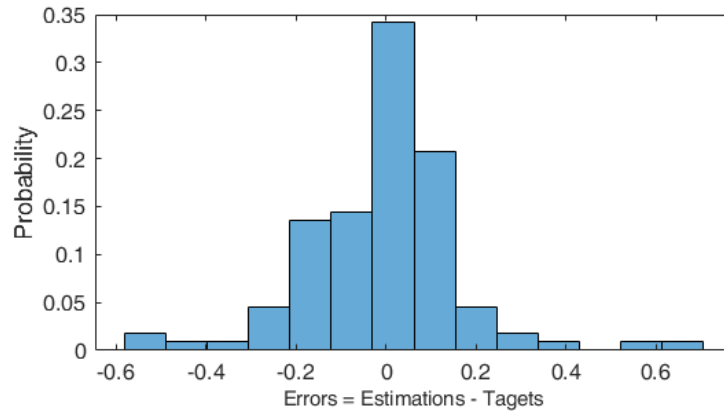


Figure 6.12. Histogram of errors for all data in testing sets.

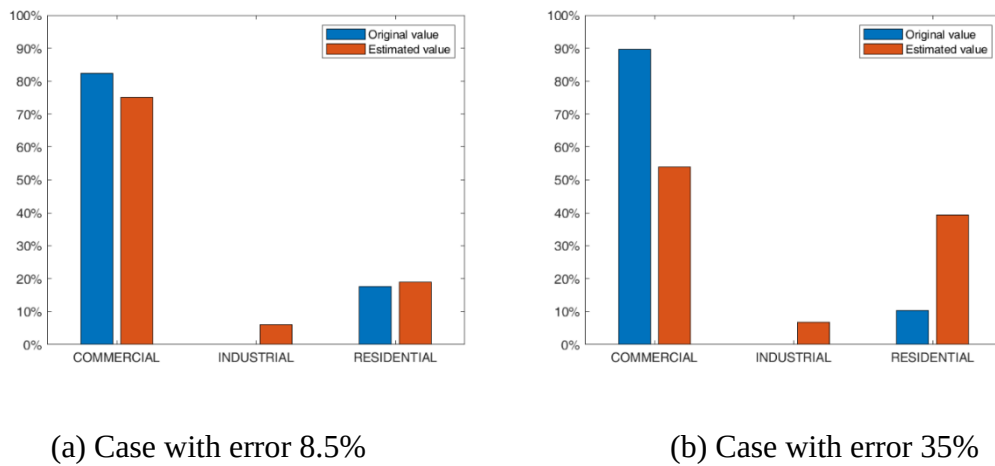


Figure 6.13. Comparisons of estimation value.

6.4 Comparisons Analysis to Improve the Estimation Accuracy

The previous section used a simple neural network, and therefore several comparisons are performed to assess the improvements made by the machine learning tool.

6.4.1 Different Combinations of Input Features

This study focuses on three main extracted features: ① one-day averaging workday load profile, ② one-day load profile ratio between weekend and workday, and ③ one-day standard deviation among the three phases. It is possible that some of these features may not be necessary for training, which could further reduce the input data. Therefore, machine learning tools are tested under different combinations of these features, and their performances are displayed in Figure 6.14. It is evident that the error is significantly reduced when using feature ②, compared to using only feature ①. Feature ③ appears to offer only minor assistance in estimation.

6.4.2 Different Length of Time Window

The raw load profile data comprises multi-week data. However, only one week of data is required to extract the load profile features. Since there is data repeatability among different weeks, it is unnecessary to use all of the data when extracting features from the raw load profile. To determine the optimal time window length for extracting input features, the length of the time window varied from one week to five weeks in 2016 and 2017, as depicted in Figure 6.15. Figure 6.16 shows the performances of the machine learning tool under different lengths of the time window in 2016 and 2017. It is apparent that the length of the time window has only a minor impact on the estimation accuracy. Thus, at least one whole week of data is necessary and sufficient for the estimation.

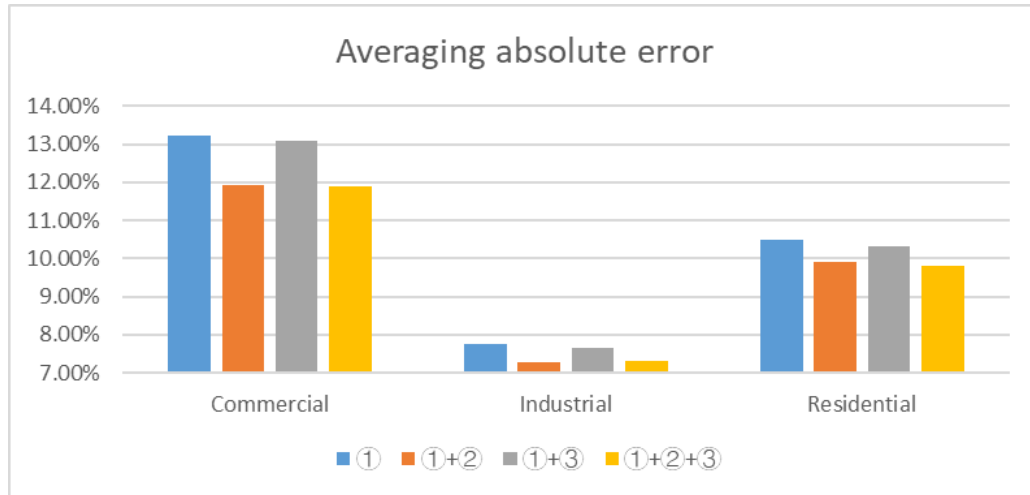


Figure 6.14. Estimation errors under different combinations of the input feature.

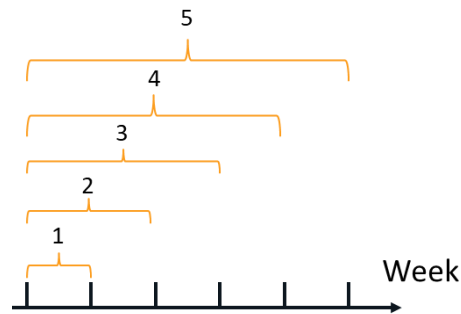


Figure 6.15. Illustration of time window length for input feature extraction.

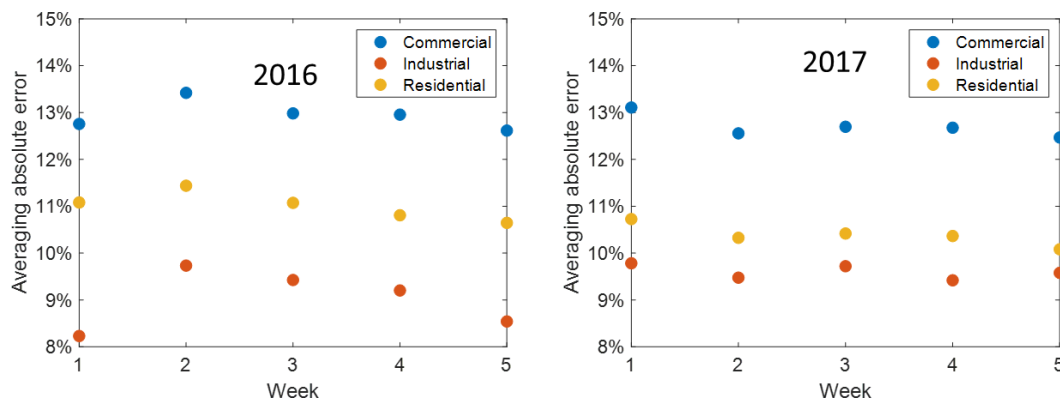


Figure 6.16. Errors under different time window lengths for input feature extraction.

6.4.3 Different Time Windows for Input Feature Extraction

To find the best time for training the machine learning tool in 2016 and 2017, the time window is moved, as depicted in Figure 6.17. The performances of the machine learning tool under different time windows in 2016 and 2017 are displayed in Figure 6.18. It is evident that changing the time window does not significantly improve the accuracy, indicating that the load profile patterns are stable for this research. Thus, it is recommended to select training period with less bad data, as it can provide more training data.

6.4.4 Different Number of Neurons for Neural Network

When using a neural network as the machine learning tool, the number of neurons must be tested to assess the accuracy improvement and time consumption. The performances and time consumption of the neural network under different neuron numbers are presented in Figure 6.19. With the increasing neuron number, there is no obvious improvement in the accuracy after the neuron number is 10, while the training time increases significantly.

6.4.5 Different Machine Learning Tools

Since different machine learning tools may have distinct characteristics, four typical regression machine learning tools, namely, the neural network, random forest, boost tree, and support vector machine, are compared using the same data set. The performance of these tools is presented in Figure 6.20. The neural network, random forest, and boost tree have almost the same performance, while the support vector machine has the least error in this study. Finally, the minimum average absolute estimation error for commercial load, industrial load, and residential are 12%, 7.3%, and 10%, respectively.



Figure 6.17. Illustration of the moving time window for input feature extraction.

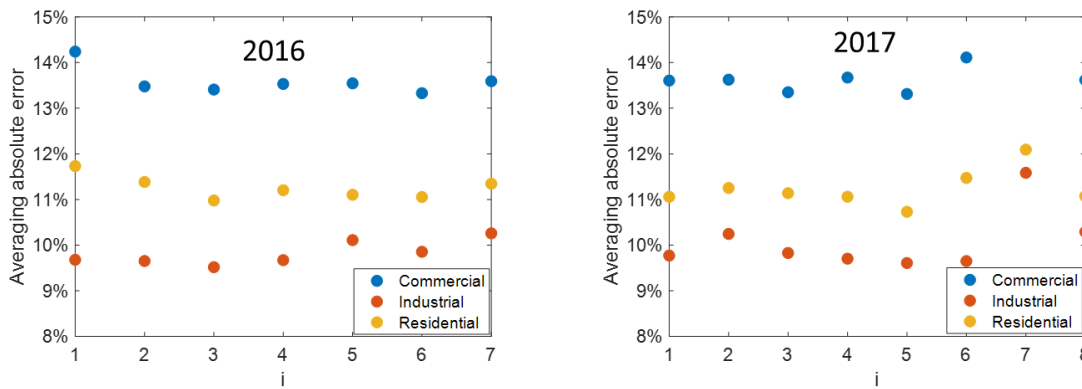


Figure 6.18. Estimation errors under different moving time windows for input feature extraction.

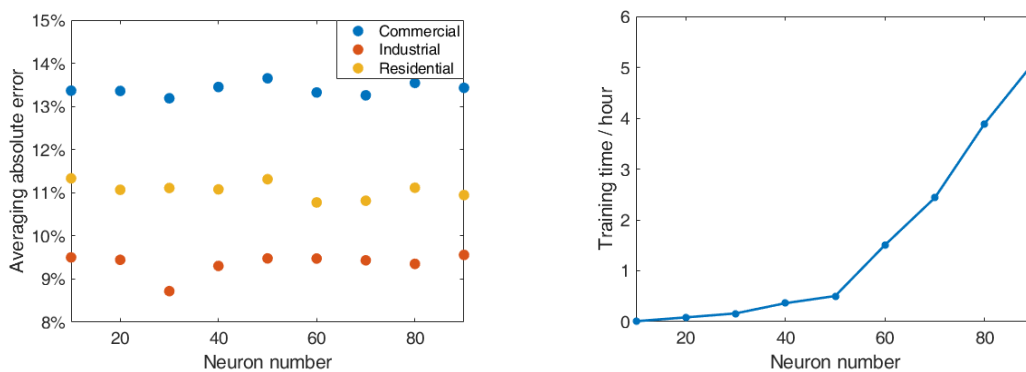


Figure 6.19. Estimation errors and consuming time of the neural network under different neuron numbers.

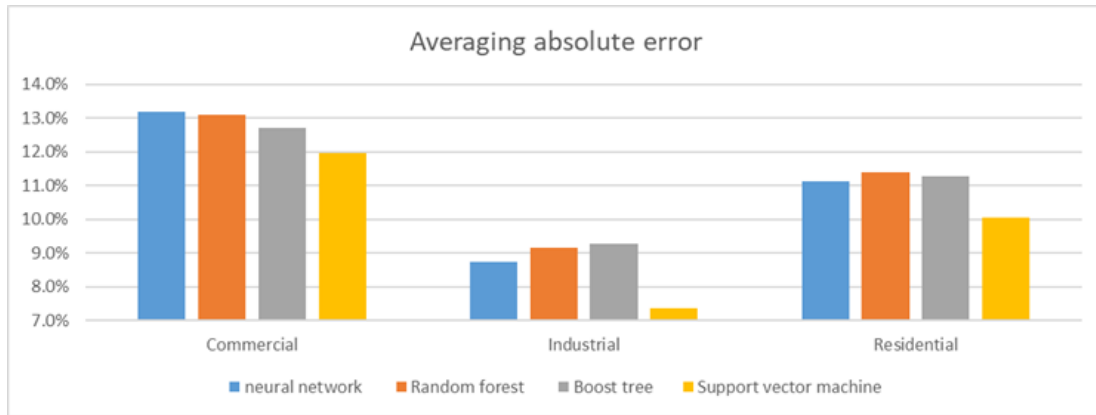


Figure 6.20. Averaging absolute error for several machine learning methods.

CHAPTER 7 CONCLUSIONS

With the growing use of renewable energy sources in power systems, there is a need for improved situation awareness of power system frequency dynamics in the power industry. To address this, this doctoral dissertation presents several solutions to situation awareness problems related to power system frequency dynamics. The main contributions of this research can be summarized as follows:

(a) Two MW estimation methods are proposed for higher accuracy, including using long-window RoCoF to reduce the impact of noise, oscillation, and wave propagation and multi-Beta to consider governor deadband. These methods improved the EI MW estimation accuracy to a 10% error rate and 16% error rate, respectively.

(b) Two novel methods for inertia estimation are proposed for different application scenarios. The first method is based on pump turn-off events and proposed for the WECC system inertia estimation, achieving a satisfactory accuracy with a 7.7% error rate. The second method is based on ambient frequency oscillations and utilizes physical equation method. This method is used in Hawaii Islands and achieves an error rate of around 2% and 7% using KIUC simulation data and HECO field data, respectively. Additionally, several techniques are provided for RoCoF calculation to improve event-based inertia estimation, mitigating the impact of wave propagation, ambient POW noise, and random frequency fluctuations.

(c) A smart PV reserve estimation method is designed using neural network and bisection method, achieving headroom saving of 50% and 30% using larger ERCOT PSS/E model and CURENT HTB, respectively.

(d) A smart machine learning-based method is proposed for load composition estimation using the easy-to-obtain load profile. The research provides detailed process on raw load data preprocessing and feature extractions. The validation shows that the proposed method has satisfactory performance, with an average absolute error of around 10%.

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