Discerning Real-World Data Center Load Behavior and the Need for Long Term Data Analysis

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***Abstract*— This paper analyzes unforeseen power swings emerging from a substation of a data center load. Because the measured response was noticed after a local line outage, at first glance, it mimicked a stability issue. However, analyzing the synchrophasor data over extended periods reveals underlying behavior akin to load cycling and not system stability issues. The difficulties in characterizing oscillatory behavior pose new challenges and underline the need for longer term analysis tools and techniques as data center loads continue to be integrated into Dominion Energy's grid.**

***Index Terms*-- data center, forced oscillation, spectral analysis**

I. Introduction

The proliferation of data centers, accelerated by artificial intelligence (AI) and high-performance computing demands, presents unprecedented challenges to power system reliability, stability, and planning. Research indicates that data center electricity demand could increase by 165% by 2030, with AI applications driving much of this growth. These facilities introduce unique operational characteristics that fundamentally differ from traditional electrical loads, creating new categories of grid reliability risks [1]. Unlike conventional loads [2], data centers may exhibit highly variable and unpredictable power consumption patterns. Large-scale GPU clusters can produce power fluctuations of hundreds of megawatts within seconds. Training AI models involves alternation between power-intensive computation phases and less demanding communication phases, creating rapid load swings that challenge grid balancing [3]. Data centers interface with the grid primarily through power electronic converters, which exhibit fundamentally different dynamic behaviors from conventional electromechanical loads [4]. Many data centers use UPS systems to protect equipment from power disturbances. However, when voltage or timing thresholds are seen from the data centers, they can disconnect the UPS and transfer to long-term back-up diesel generators. To the power system, this looks like a load loss, but because there is still electrical connectivity to the power system, it is actually a voluntary load transfer. A July 2024 incident in Northern Virginia demonstrated this risk when a routine transmission fault triggered 1,500 MW of data center load to suddenly disconnect across 25-30 substations, highlighting the unpredictable nature of data center grid responses [5].

A major challenge in addressing data center power system impacts is the lack of accurate dynamic simulation models and means to precisely characterize "normal" data center operation. Conventional power system models assume stable, predictable load patterns, but data centers can exhibit rapid, irregular power fluctuations driven by AI workload cycles. Current models do not capture the complex interactions among workload scheduling, power electronics, and grid dynamics, leaving grid operators unable to reliably assess stability or plan mitigations. While there are efforts on developing and testing models to study different data center behaviors, the best current recourse is to utilize measurements and data analytics tools to systematically analyze data center behavior and differentiate normal operations from potential grid risks. Moreover, once these models are standardized, data center facilities can change their operating modes over time which further illustrates the importance of developing strong measurement-centered workflows for analyzing behavior.

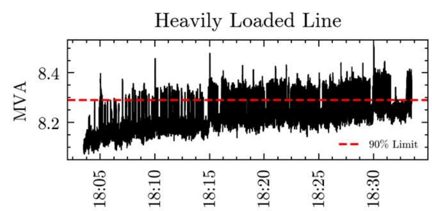

Figure 1. Line D-C MVA Swings

To illustrate a specific case, Fig. 1 shows the MVA flow on a transmission line taken in July 2025 from a 230 kV data center rich region in Dominion Energy's territory. The response was observed following a local line outage, which was believed to induce 10–15 MW power swings and trigger 90% overloading alarms. The goal of the present work is to systematically investigate this behavior using synchrophasor data, and to discern between data center load behavior and actual "swings" (oscillations) involving unstable dynamics.

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This paper is organized as follows, Section II gives an overview of the test system as well as the initiating event and Section III provides a data driven investigation of the case, while Section IV provides conclusions and future work.

II. System Overview

Fig. 2 shows a subsystem of Dominion's grid where measurements were obtained (see Fig. 1), consisting of four 230 kV substations (C, S, H, P) and a 500 kV substation (D), with no local generation. The data center at substation H is rated as 100 MW. The region is supplied via transmission paths C–D and through P, as shown in Fig. 2. A line outage of the line at P resulted in a radial network fed solely by Line C–D, which intermittently triggered a 90% thermal overloading alarm due to the SCADA sampling rates (Fig. 1). Operator analysis indicates a direct link between the outage and the perceived "swings", consistent with previous observations involving controller instability under weak grid conditions [4]. Synchrophasor data from digital fault recorders at substations C, D, S, and H provide data sampled at 4800 Hz, filtered and downsampled to 960 Hz, with synchrophasor estimates reported at 60 Hz. For long-term analysis, the data is further downsampled to 30 Hz and used in this study.

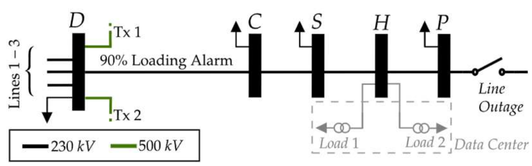


Figure 2. Study Subsystem

III. Discerning Data Center Load Characteristics

A. Spectral Characterization and Nature

Given the periodic nature of the observed power swings (Fig. 1), spectral analysis [6] was performed contrasting pre- and post-outage period active (P) power spectrum on the heavily loaded C–D line (Fig. 3). The outage produced new dominant spectral peaks at 0.40 Hz and its harmonics, pointing to slow dynamics.

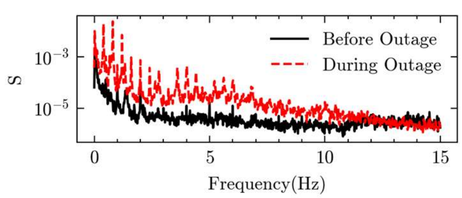


Figure 3. Spectrum of Active Power Flow on Line C-D

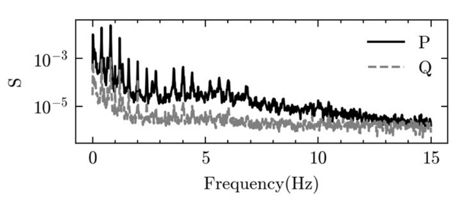


Figure 4. P vs Q Spectrum

To characterize the oscillatory behavior, which often involves volt-var dynamics in Dominion Energy's system [7] [4] [8] active (P) and reactive (Q) power spectra were compared over a 10-minute interval coinciding with the outage. This revealed a predominantly active power (P) response, which informs the choice of signals for subsequent localization as discussed below, utilizing this data window.

B. Localization

Mode shapes for active power flow on subsystem transmission lines were computed [9] at the identified fundamental and harmonic frequencies in Fig. 6. Analyzing multiple harmonics aids in drawing robust conclusions [10], [11] given the nonsinusoidal nature of the response. Substation H's Load 2 exhibited significant participation in the observed response, with notable contributions at the second and third harmonic frequencies. Conversely, Load 1 demonstrated no participation despite typically sharing the data center load equally with Load 2. Historical data presented in Fig. 5 reveal a temporary load transfer from Load 1 to Load 2 during July, the analysis window, which accounts for Load 1's absence from the observed response.

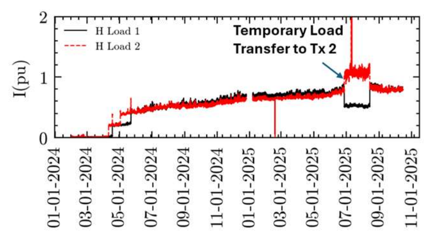
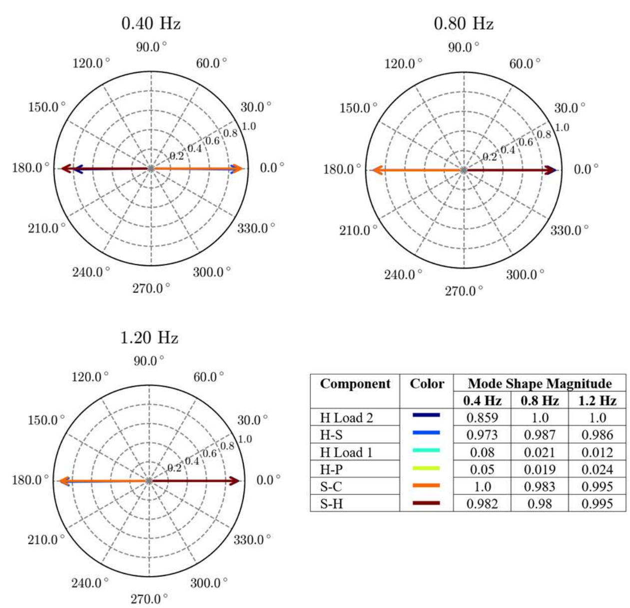


Figure 5. Substation H Load Currents



Component	Color	Mode Shape Magnitude		
		0.4 Hz	0.8 Hz	1.2 Hz
H Load 2		0.859	1.0	1.0
H-S		0.973	0.987	0.986
H Load 1		0.08	0.021	0.012
H-P		0.05	0.019	0.024
S-C		1.0	0.983	0.995
S-H		0.982	0.98	0.995

Figure 6. Mode Shape of First Three Harmonics of Response in Active Power Flow During Outage Period

Due to the radial and compact nature of this subsystem, it is difficult to determine whether Load 2 at H behaves as a source or a sink using only relative active power participation. This ambiguity is evident in Fig. 6, where line C–S, which supplies this area, exhibits a similarly high participation. Hence, input-output analysis is performed, treating active power (P) as the input (cause) to the system (converter interfaced assets are current controlled) and voltage magnitude (V) and angle (θ) as outputs (effect), with phase relationships in the frequency domain providing insight into source insight [12]. Voltage is prioritized over angle due to clock errors [13] affecting phase angle spectra. Causal contribution of load 2 at H is confirmed by comparing voltage-power cross-spectral density $S_{VP}(f)$ [6] between inflow on line C–S and power injection at load 2 at relevant frequencies (Fig. 7).A large magnitude and positive acute angle indicates causality and proves that data center H load 2 is the source.

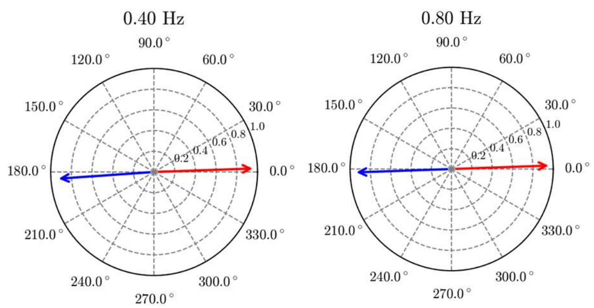


Figure 7. Cross Spectral Density S_{VP} at First Two Harmonics at Data Center H Injection (red) and Line C-S (blue)

C. Did the Line Outage Trigger the Response ?

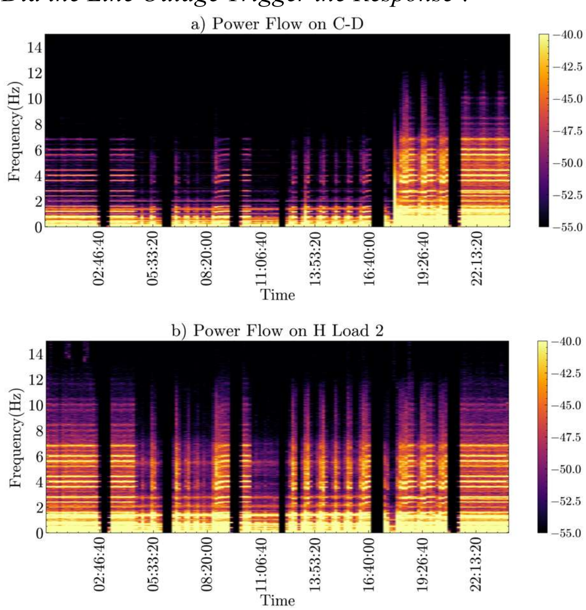


Figure 8. Outage Day Spectrograms for a) C-D Power Flow and b) Data Center Load

Since the data center load was identified as the source of the 0.40 Hz dynamics, the next step was to examine if the line outage and system weakening caused the swings as a result of instability. Twenty-four-hour spectrograms of active power at the data center load and the heavily loaded C–D line were analyzed (Fig. 8). The outage occurred around 18:05, evident from a marked change in the C–D line's power spectrum (Fig. 8 a)). However, similar spectral components were present before the outage, with the event primarily amplifying these existing features. In contrast, load 2 at substation H showed no outage-related spectral changes (Fig. 8 b)) and had consistent patterns reflecting normal periodic duty cycles rather than instability. Moreover, the load dynamics were temporarily suppressed just before the outage (due to internal behavior changes), creating the false impression that the outage triggered the oscillations (Fig. 3). In summary, the "swings" were mere load duty cycle and not a system instability, as the outage of the line from substation P redirected the flow onto the C–D line. This underscores the necessity of analyzing extended data periods rather than isolated snapshots.

D. Impact on Local Synchronous Machines

Since the data center–induced power swings do not indicate instability, the next step is to assess how the system absorbs this forced input and whether it adversely affects nearby synchronous machines, which is the major concern with large load cycling [2], [14]. Given the response is neither purely sinusoidal nor perfectly periodic (see Fig. 1), mode definitions are extended beyond sinusoids. Proper Orthogonal Decomposition (POD) [15] is employed to decompose the data into orthogonal modes, quantifying each machine's active power response via mode shapes obtained through singular value decomposition (SVD) of the data matrix in the mode relevant to the observed response, i.e. given collections of signals $\{x_m(t),\ m = 1,2 \dots M\}$ are decomposed in the form $x_m(t) = \sum_i U_{mi} V_i(t)$ where U_{mi} gives the participation of i^{th} POD mode $V_i(t)$ in m^{th} signal $x_m(t)$ – a mode shape like quantity.

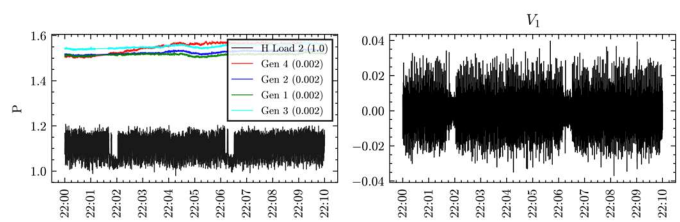


Figure 9. P at nearest plant and load 2 (left) Dominant POD Mode (right)

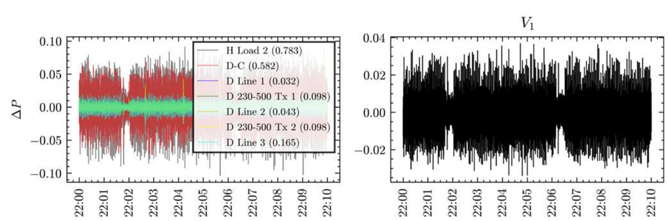


Figure 10. P Flows on Substation D Lines (left) Dominant POD Mode (right)

Using the same outage-period data window, active power (P) at the source (load 2 at H) and the electrically nearest 230 kV generation plant (700 MW capacity, four identical CT units) were analyzed. The data was preprocessed by first differencing to remove slow trends while preserving weakly periodic forcing components. Fig. 9 shows the dominant first POD (V_1) mode, which captures the data center response exclusively, with no participation (small component of U_1) from the four generation

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units, indicating no relevant impact on those units. To further explain, the same POD mode shape was examined on flows to substation D (500/230 kV), a key node linking load dynamics to the rest of the grid, including the 4 generation units analyzed above. Substation D includes two 500/230 transformers and three 230 kV lines besides the C–D line (see Fig 2.). Most of the data center load response is carried on C–D due to the radial configuration, but it is distributed among multiple transformers and lines at substation D as seen in POD mode shape U_1 in Fig. 10. As a result, only a small fraction of the 10–15 MW load cycle reaches any single part of the system, rendering the influence on the nearest generation units insignificant.

E. Coarse Grained Spectral Analysis of Historical Data

Having characterized, localized, and analyzed the impact of the data center load duty cycle using a single data window from the outage period, it is essential to evaluate whether this window is representative of the data center's broader behavior. To comprehensively characterize load dynamics, analysis must encompass all operational conditions, starting from the data center's energization. In this case, this translates to approximately one year of PMU data. However, processing such a large dataset at 30 Hz resolution is computationally prohibitive. Notably, the fundamental frequency of the load behavior is around 0.4 Hz, suggesting that focusing on the low-frequency band below 1 Hz suffices to capture most dynamics.

Predictive Grid [16], the time series data platform deployed at Dominion Energy, stores multi-resolution versions of the original synchrophasor time series. The spectral content of coarser resolution data resembles simple moving average and downsampling operations [17], enabling analysis on reduced-resolution datasets without significant distortion of relevant spectral information in low ranges. Given that these data center loads are converter interfaced, the current magnitude signal is an effective proxy for observing load dynamics.

Fig. 11 presents the current magnitude spectrogram for load 2 since its commissioning in June 2024. Multiple distinct dynamic behaviors are observed, alternating over the year, each persisting for several days at a minimum. To investigate these patterns further, Fig. 12 shows selected 24-hour spectrograms of the combined total power load (load 1 and load 2) corresponding to notable behaviors in Fig. 11

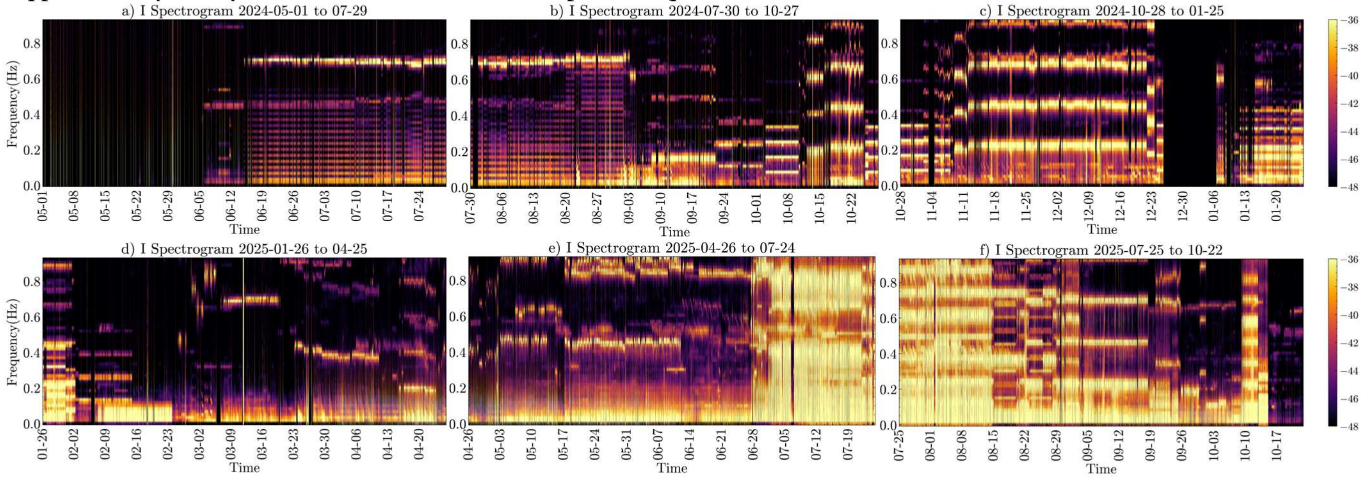

Figure 11. Long Term Historical Data Analysis for Data Center Load 2 - Current Magnitude Spectrogram

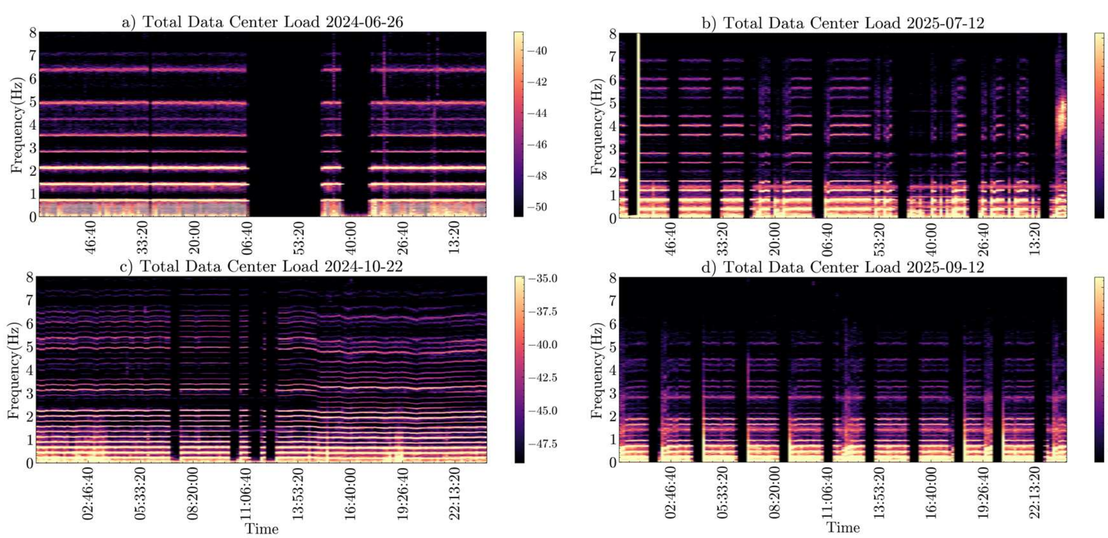

Figure 12. Data Center Total Load Spectrogram for Selected Days

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Between mid-June and early September 2024 (Fig. 11 a–b and Fig. 12 a), a relatively faster dynamic mode predominates, featuring a 0.7 Hz fundamental frequency coupled with slow dynamics concentrated below 1 Hz. This behavior was never observed thereafter. Meanwhile, the 0.4 Hz fundamental mode previously analyzed (Fig. 11 d–f and Fig. 12 b) emerged nearly a year after energization, suggesting it may represent a transient phase rather than a persistent state. The most common load behavior across the observation period has a 0.2 Hz fundamental frequency (Fig. 11 c, f and Fig. 12 c, d). Interestingly, earlier occurrences of this mode (December 2024) exhibit continuously varying spectral peaks, while later manifestations in 2025 appear stationary, raising questions about whether these arise from the same underlying dynamics. While discussions with data center customers are valuable for understanding behavior, they are not scalable. Therefore, measurement-based analyses are needed to provide more efficient insights and support future engagements with concrete data. These findings challenge the conventional view that data center loads behave as standard cyclical loads with deterministic duty cycles. Instead, the load dynamics are non-stationary and exhibit multiple distinct modes over time, complicating the definition of "normal behavior" for baselining.

IV. Conclusions and Future Work

This paper presented a data-driven analysis of an event involving perceived 0.4 Hz power swings in a data center rich region in Dominion Energy's grid. The "swings" were immediately preceded by a local transmission line outage. Initial interpretations of snapshot data suggested stability-related oscillations; however, extended synchrophasor data revealed that the swings corresponded to the data center's own load duty cycle. The outage merely redirected and concentrated this dynamic response onto a single transmission line, creating the appearance of instability-induced oscillations, and the highly meshed network upstream dispersed it into negligible portions such that the nearest generators saw no impact. Standard RMS energy detectors would likely misclassify this event as instability due to the significant energy increase in the 0-8 Hz band following the line outage. However, long-term spectral analysis clarifies that this is a persistent load duty cycle rather than an undamped mode, preventing false positives associated with RMS-based detection.

To explore the generalizability of these observations, long-term analysis reveals that data center loads switch among multiple distinct modes rather than following predictable duty cycles. These non-stationary dynamics challenge conventional baselining and raise critical questions regarding the need for location-specific frequency-domain constraints to prevent exciting nearby generator modes. Consequently, adaptive modeling frameworks and multi-resolution spectral analysis of extended non-event data are essential to track these evolving behaviors, as diligent analysis is impossible with snapshot-based methods alone.

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