The Impact of Large Datacenter Load Uncertainties on Power Grid Reliability

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***Abstract*—The growing integration of large-scale datacenters introduces new sources of stochastic, unconventional electrical demand, posing emerging challenges to power system reliability. Despite significant advances in load uncertainty modeling and reliability assessment under various contingencies, the incorporation of datacenter–induced workload uncertainties into power system studies remains limited. This gap underscores the need for integrated frameworks that couple power grid reliability analysis with the stochastic behavior of digital infrastructures. This paper presents a probabilistic modeling framework for characterizing datacenter workload uncertainties using a two-state Gaussian Mixture Model (GMM) that represents idle and busy operational modes of IT equipment. The proposed approach captures the temporal variability of datacenter loads and their probabilistic impact on grid performance under contingency conditions. The framework is validated through multiple simulation scenarios that combine stochastic workload fluctuations with grid disturbances. The results demonstrate the suitability of the method for assessing, quantifying and mitigating the adverse impacts of datacenter dynamics on system reliability, providing a scalable foundation for uncertainty-aware grid monitoring and planning.**

***Index Terms*—Gaussian mixture model, grid operation, large datacenters, load modeling, reliability, stochastic workload modeling, uncertainty quantification**

I. Introduction

Modern datacenters pose significant challenges to power system operation due to highly uncertain, rapidly varying demand profiles. Unlike conventional loads, datacenter demand, driven by computational workloads, cooling requirements, and operational strategies, can lead to abrupt fluctuations in power consumption, as shown in [1], [2]. In some cases, entire facilities disconnect from the grid by transferring to on-site battery storage or backup generation, resulting in sudden load loss. Such discontinuities strain power systems, as conventional generators are often unable to ramp up/down fast enough to offset the resulting imbalances,thereby increasing the risk of power outages, power quality issues, reliability concerns; these risks are documented in recent technical, industry, and regulatory reports [3]–[5]. Furthermore, by 2030, global datacenter electricity consumption is projected to grow substantially. Baseline forecasts indicate an increase from 286 TWh in 2016 to approximately 321 TWh in 2030, while scenarios consider demand expanding to as high as 752 TWh, representing about 2.13% of worldwide electricity use [6]. This study focuses on modeling datacenter–induced uncertainties and developing a robust framework for reliability monitoring in modern power grids under these uncertainties. Modeling load uncertainties in power systems remains a challenging task due to the complexity of load and the high computational cost of the tools used to model them [7], [8]. Traditional approaches to uncertainty modeling have primarily focused on aggregated loads or renewable resources. For instance, in [9] an analytical method to model load uncertainties is proposed by estimating the mean and variance of aggregated consumption from different customer classes. The method is simple, transparent, and applicable to state estimation, probabilistic load flow, and optimal meter placement. However, limited handling of small customer populations and the simplification of customer heterogeneity limit its accuracy, while it does not capture the highly dynamic uncertainties introduced by modern datacenters. Authors in [10] represent load forecast errors as random variables following normal distributions with variance proportional to forecasted demand, combined with scenario generation and reduction to evaluate spinning reserve requirements. Other works have employed sparse grid stochastic collocation methods to approximate the impact of uncertain parameters in static load models, thereby reducing computational complexity compared to Monte Carlo simulations [11]. Similarly, probabilistic collocation techniques have been applied to quantify uncertainty in load models for dynamic stability, considering both static constant impedance-current-power structures and composite models that combine static components with induction motor dynamics [12], [13]. While these studies provide valuable insights into the propagation of parametric load uncertainties, they largely neglect the distinct characteristics of datacenters. A more recent contribution explicitly addresses this gap by modeling the stochastic workload-driven demand of multiple datacenters in the electricity market. Through a cloud federation framework, workload migration is optimized across geographically distributed facilities to mitigate forecast errors, highlighting the importance of uncertainty management at the intersection of market economics and physical grid operations [14].

To model load uncertainties in datacenters, authors in [15] establish a quantitative model of datacenter load regulation by integrating information technology workload dynamics, cooling flexibility, and demand response mechanisms. They demonstrate that coupling geographic load balancing, batch workload scheduling, and thermal storage with thermal inertia maximizes load regulation capacity. However, the framework is deterministic and does not account for stochastic uncertainties in datacenters, limiting its application to resilience-oriented or uncertainty-driven studies. Power system resilience is defined as the capability of the grid to withstand distur-

979-8-3315-8138-1

bances, restore functionality promptly after adverse events, and adjust effectively to new risks and evolving operating conditions [16]–[18]. A review in [19] provides a comprehensive examination of power grid resilience, focusing mainly on the impacts of extreme weather. However, the uncertainties from modern heavy or datacenter loads are not considered. A key limitation across the reviewed metrics is the absence of standardized indices that fully capture all resilience dimensions, particularly anticipatory and adaptive capacities. Additionally, there exists the challenge of limited data for rare but high-impact events.

Although datacenter energy consumption modeling has been extensively reviewed in [20], the integration of datacenter–induced stochastic load variations into power system analyses, especially under contingency conditions, remains limited. The interaction between workload uncertainty and grid performance is still insufficiently explored, underscoring the need for a unified framework that links datacenter behavior with power system reliability assessment. To address this gap, this study develops a comprehensive AC power flow framework that integrates stochastic datacenter load models with grid reliability assessment. This framework uniquely addresses how datacenter workload uncertainties propagate through AC power flow constraints to impact system reliability metrics under various contingency scenarios.

II. Stochastic Modeling of Datacenter Workload Uncertainties

Figure 1 presents the proposed framework for modeling datacenter workload uncertainties and analyzing their impact on power grid reliability. The framework first incorporates datacenter loads with stochastic profiles to generate time-series operational data. A two-state stochastic model represents the workload dynamics of datacenter servers, capturing transitions between *idle* and *busy* states. For each realization, an AC power flow is executed to obtain real-time system responses, from which reliability metrics are computed. The framework enables near–real-time monitoring and quantitative assessment of grid performance under stochastic load variations. The detailed modeling and simulation process is summarized in Algorithm 1.

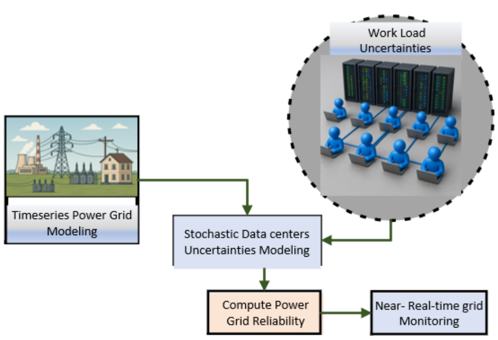

Fig. 1: Proposed framework for assessing grid reliability under datacenter workload uncertainties.

A. Stochastic Datacenter Load Modeling via Two-State Gaussian Mixture Model

Datacenter (DC) workloads exhibit inherent stochasticity arising from fluctuating user demand, dynamic resource allocation, and heterogeneous application profiles. We model the total power consumption of a datacenter at bus i at time t, denoted $P^i_{\text{DC}}(t)$ (MW), as a two-state lognormal mixture process that captures aggregate facility-level uncertainty while enabling realistic power demand time series generation. The IT equipment power $P^i_{\text{IT}}(t)$ (MW) is driven by a latent regime variable $z_t \in \{0, 1\}$ representing idle and busy states, evolving as a first-order Markov chain with persistence probabilities $\pi_{00} = \Pr(z_t = 0 \mid z_{t-1} = 0)$ and $\pi_{11} = \Pr(z_t = 1 \mid z_{t-1} = 1)$. Consequently, the marginal distribution of $P^i_{\text{IT}}(t)$ is well approximated by a two-component lognormal mixture induced by the idle/busy latent regimes [21]:

$$f(P_{\text{IT}}) = \pi_0\, \mathcal{LN}\big(P_{\text{IT}} \mid \mu'_0, \sigma_0^2\big) + \pi_1\, \mathcal{LN}\big(P_{\text{IT}} \mid \mu'_1, \sigma_1^2\big) \quad (1)$$

With $\pi_0 + \pi_1 = 1$ and ordered means $\mu_0 < \mu_1$ ensuring state identifiability. Conditioned on state z_t, instantaneous IT power is lognormally distributed, $Y_t \sim \mathcal{LN}(\mu'_{z_t}, \sigma^2_{z_t})$. Temporal correlation is imposed using exponential smoothing: $P^i_{\text{IT}}(t) = (1-\alpha)P^i_{\text{IT}}(t-1) + \alpha Y_t$, where $\alpha \in (0, 1)$ controls the degree of short-term variability. The smoothing parameter is calibrated from the lag-1 autocorrelation ϕ of the synthetic traces, with $\alpha = 1 - \max(\min(\phi, 0.999), 0)$.

For each Monte Carlo scenario $s \in \{1, \dots, S\}$, facility parameters $\theta_s = (P^s_{\text{idle}}, P^s_{\text{peak}}, \text{PUE}^s)$ are sampled subject to the separation constraint $P^s_{\text{peak}} - P^s_{\text{idle}} \geq \Delta P_{\min}$ to ensure meaningful bimodality. Synthetic IT power trajectories are generated for calibrating the Gaussian mixture model (GMM). Assuming that IT demand follows a utilization-based power model, the IT power at time t is given by [21]:

$$\hat{P}_{\text{IT}}(t) = \lambda\big[P_{\text{idle}} + \Delta P\, u(t)\big] \quad (2)$$

where λ is a facility-level scaling factor, $\Delta P = P_{\text{peak}} - P_{\text{idle}}$ denotes the operating power range, and $u(t) \in [0, 1]$ represents an autoregressive utilization process with persistence coefficient β. The GMM parameters $(\pi_k, \mu_k, \sigma_k^2)$ for $k \in \{0, 1\}$ are estimated using the expectation–maximization algorithm. To ensure positivity and capture skewness, each component is modeled as lognormal, with parameters obtained from the coefficient of variation $\text{CV}_k = \sigma_k/\mu_k$ through the standard transformations,

$$\sigma_k^2 = \ln\big(1 + \text{CV}_k^2\big)\,, \qquad \mu'_k = \ln(\mu_k) - \frac{\sigma_k^2}{2}. \quad (3)$$

Markov transition probabilities are obtained from the empirical state sequence as $\pi_{00} = n_{00}/(n_{00} + n_{01})$ and $\pi_{11} = n_{11}/(n_{11} + n_{10})$, where n_{ij} counts observed transitions $i \to j$. Finally, the total datacenter demand is estimated using scenario-specific PUE, yielding $P^i_{\text{DC}}(t) = \text{PUE}^s\, P^i_{\text{IT}}(t)$, where $\text{PUE}^s \in [\text{PUE}_{\min}, \text{PUE}_{\max}]$. Traditional loads at buses

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$j \in \mathcal{L}_{\mathrm{TL}}$ are deterministic, denoted by $P_{\mathrm{TL}}^{j}(t)$ (MW), and the total system demand at each time step is defined as:

$$D(t) = \sum_{i \in \mathcal{L}_{\mathrm{DC}}} P_{\mathrm{DC}}^{i}(t) + \sum_{j \in \mathcal{L}_{\mathrm{TL}}} P_{\mathrm{TL}}^{j}(t). \tag{4}$$

B. Grid Reliability Assessment

Grid reliability is defined as the ability of the power systems to continuously deliver adequate, secure, and stable electricity to consumers while maintaining acceptable operating conditions during both normal operation and disturbances. We assess reliability using a two-stage AC power flow (PF) procedure (Algorithm 1). For each Monte Carlo scenario s and contingency $c \in \mathcal{C}$, the post-contingency network is simulated over T time steps while enforcing operational constraints including voltage limits, thermal ratings, and generator capability curves.

A reserve margin r is applied to in-service generation, defining available post-contingency capacity as $G_{\text{avail}}^{c} = (1 - r)G_{\text{remaining}}^{c}$. Let ℓ index all load buses with scheduled demand $P_{\text{sched}}^{\ell}(t)$ aggregating datacenter and traditional loads. In Stage 1, (PF_1), the external grid is placed out of service and the largest internal generator serves as the slack bus. If PF_1 converges, the served load at each bus is extracted from the solution as $P_{\text{served}}^{(1),\ell}(t)$, yielding demand not served $\mathrm{DNS}(t) = \max\big(0, \sum_\ell P_{\text{sched}}^{\ell}(t) - \sum_\ell P_{\text{served}}^{(1),\ell}(t)\big)$.

If PF_1 fails to converge, Stage 2 applies emergency load shedding, enables external grid support, and solves PF_2. When PF_2 converges, $\mathrm{DNS}(t) = \max\big(0, \sum_\ell P_{\text{sched}}^{\ell}(t) - \sum_\ell P_{\text{served}}^{(2),\ell}(t)\big)$; otherwise, complete supply interruption is recorded as $\mathrm{DNS}(t) = \sum_\ell P_{\text{sched}}^{\ell}(t)$.

Loss of load probability for scenario s is computed as $\mathrm{LOLP}_s = \frac{1}{T}\sum_{t=1}^{T}(\mathrm{DNS}(t) > 0)$, and the ensemble average is $\overline{\mathrm{LOLP}} = \frac{1}{S}\sum_{s=1}^{S}\mathrm{LOLP}_s$.

Algorithm 1 Grid Reliability Considering DataCenter Load Uncertainty

Require: Datacenter parameters (P_i, P_p, PUE), reserve r, contingencies $\mathcal{C}$, time steps T, scenarios S

for $s = 1$ to S **do**
  Sample θ_s; fit GMM $\rightarrow (\pi_{00}, \pi_{11}, \alpha)$
  Draw $c \in \mathcal{C}$; set $G_{\text{av}}^{c} = (1-r)G_{\text{rem}}^{c}$
  for $t = 1$ to T **do**
    Generate $P_{\mathrm{DC}}^{i}(t)$; form $D(t) = \sum P_{\mathrm{DC}}^{i} + \sum P_{\mathrm{TL}}^{j}$
    Solve AC-PF_1 (ext_grid OFF)
    if converged **then**
      $\mathrm{DNS}(t) = \sum P_{\text{sched}} - \sum P_{\text{served}}^{(1)}$
    else
      $\Delta P = D(t) - G_{\text{av}}^{c}$; Load shed
      Solve AC-PF_2 (ext_grid ON)
      $\mathrm{DNS}(t) = \begin{cases} \sum P_{\text{after}} - \sum P_{\text{served}}^{(2)} & \text{if converged} \\ \sum P_{\text{after}} & \text{otherwise} \end{cases}$
    end if
  end for
  $\mathrm{LOLP}_s = \frac{1}{T}\sum_{t=1}^{T}(\mathrm{DNS}(t) > 0)$
end for
$\overline{\mathrm{LOLP}} = S^{-1}\sum_s \mathrm{LOLP}_s$

III. Case Studies

The effectiveness and robustness of the datacenter uncertainty modeling approach are validated using the modified 30-bus system [22]. Originally, this system contained unclassified loads. In this study, the loads are categorized into two groups: (1) traditional loads (representing residential and commercial consumers) and (2) datacenter loads. All case studies as described in Table I satisfy the $N-1$ contingency criterion.

TABLE I
Details of Contingencies and Case Studies

Case Study	**Description**
Case 1 (CS1)	PUE variability only; datacenter IT load treated as deterministic; no contingencies
Case 2 (CS2)	Stochastic datacenter IT load; fixed minimum PUE equal to one; no contingencies
Case 3 (CS3)	Joint uncertainty in datacenter IT load and PUE; no contingencies
Case 4 (CS4)	Joint uncertainty in datacenter IT load and PUE; N−2 transmission-line contingencies
Case 5 (CS5)	Joint uncertainty in datacenter IT load and PUE; N−2 generator contingencies

A. Datacenter Load Distributions

The probability density functions of datacenter demand across the case studies are generated using the multi-scenario framework in Algorithm 1 to quantify the impact of stochastic workload variability on grid reliability. Datacenter parameters, including idle power, peak power, number of servers, and PUE, are randomly sampled to produce 24-hour demand trajectories, and more than 3,000 scenarios are simulated.

Figure 2 illustrates workload-driven datacenter demand distributions with pronounced asymmetry, capturing both typical operating conditions and rare high-demand excursions that are critical for adequacy assessment. Moving from fixed-efficiency assumptions to joint uncertainty in IT demand and infrastructure overhead broadens the distribution and shifts probability mass toward higher demand, highlighting the importance of modeling multiplicative interactions between workload and PUE. Under $N-2$ contingencies, the distribution changes further, reflecting the interaction between post-contingency network constraints and distributed datacenter demand.

B. Performance Analysis

Figure 3 identifies a critical PUE threshold for power grid reliability. For PUE < 1.5, LOLP remains low under base conditions but increases substantially under N–2 contingencies. In contrast, datacenters with PUE ≥ 1.6 reduce reliability across all operating conditions, indicating that infrastructure inefficiency becomes the dominant driver of reliability risk.

To further analyze the effects of datacenter uncertainties during grid contingencies, Fig. 4 highlights a clear progression of reliability risk as data-center demand uncertainty and grid contingencies are introduced. The baseline case maintains

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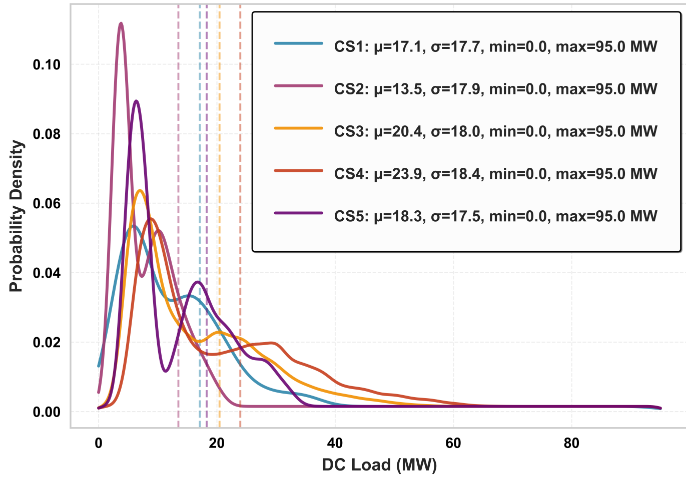

Fig. 2: Probability density function of total datacenter power consumption under various case studies.

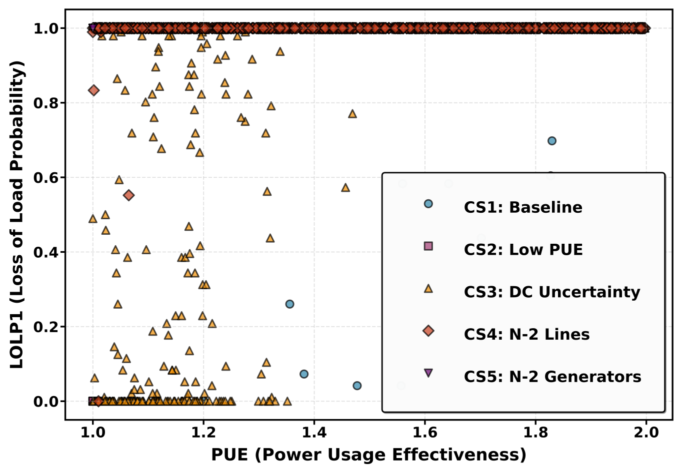

Fig. 3: Impact of datacenter PUE on grid reliability across multiple contingencies

intermediate reliability, whereas the low PUE configuration drives LOLP toward zero, indicating that improved facility efficiency reduces the effective electrical demand imposed on the grid and improves grid reliability. When stochastic datacenter workload uncertainty is incorporated, the mean LOLP increases markedly, showing that variability in IT demand increases the probability of higher loading on the grid under non-contingency conditions. Under N–2 line outages and N–2 generator outages, LOLP approaches unity, indicating a higher likelihood of loss-of-load events and reduced grid reliability.

II summarizes the loss-of-load probability across scenarios for each case study. The results show that loss of probability after first power flow (LOLP_1) decreases to near zero under low PUE datacenter operation, but increases sharply when PUE variability and workload uncertainty are introduced, and becomes dominated by N–2 contingencies.

As demonstrated in Tables III and IV, workload variability has a weak association with grid reliability, while higher PUE is associated with increased LOLP_1, indicating that facility efficiency is a more influential factor in reliability trends.

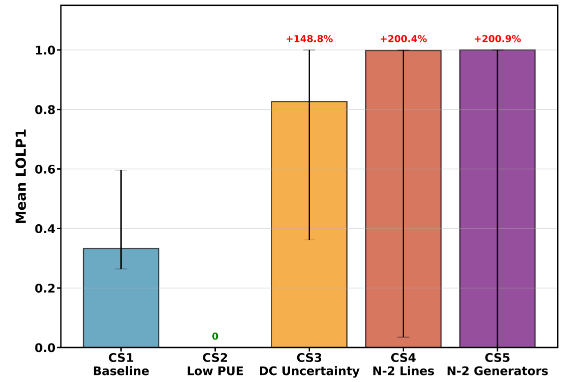

Fig. 4: A comparison of datacenter uncertainties across various case studies

TABLE II
GRID RELIABILITY STATISTICS BY CASE STUDY

Case	$\overline{\text{LOLP}_1}$	σ_{LOLP_1}
CS1	0.33	0.28
CS2	0.00	0.00
CS3	0.83	0.36
CS4	1.00	0.04
CS5	1.00	0.00

TABLE III
PEARSON CORRELATION MATRIX OF RELIABILITY DRIVERS

	Workload Var.	Peak/Idle	PUE	LOLP_1	DNS (MWh)
Workload Var.	1.00	0.13	0.02	0.03	0.09
Peak/Idle	0.13	1.00	-0.01	-0.27	-0.10
PUE	0.02	-0.01	1.00	0.41	0.31
LOLP_1	0.03	-0.27	0.41	1.00	0.64
DNS (MWh)	0.09	-0.10	0.31	0.64	1.00

TABLE IV
SPEARMAN CORRELATION MATRIX OF RELIABILITY DRIVERS

	Workload Var.	Peak/Idle	PUE	LOLP_1	DNS (MWh)
Workload Var.	1.00	0.16	0.01	0.02	0.06
Peak/Idle	0.16	1.00	-0.00	-0.42	-0.17
PUE	0.01	-0.00	1.00	0.45	0.36
LOLP_1	0.02	-0.42	0.45	1.00	0.62
DNS (MWh)	0.06	-0.17	0.36	0.62	1.00

IV. CONCLUSION

This study develops a stochastic modeling framework to represent datacenter power consumption uncertainties using a two-state Gaussian Mixture Model that captures idle and busy operating regimes and their transitions. The resulting time-varying IT demand trajectories, combined with facility overhead through the PUE, provide a tractable yet realistic representation of aggregate datacenter electrical demand suitable for power grid reliability assessment. Integrating these stochastic loads into an AC power flow-based reliability evaluation quantifies power grid reliability through LOLP and DNS under both normal and stressed conditions.

The case studies demonstrate that reliability outcomes are impacted by datacenter efficiency as well as grid stressors.

979-8-3315-8138-1

Low datacenter PUE reduces LOLP, and regardless of workload variability, it does not adversely impact grid reliability in the absence of contingencies. The inclusion of joint workload uncertainty and PUE variability increases the likelihood of reducing power grid reliability. Under $N-2$ line and generator contingencies, reliability deterioration is dominated by transmission line outages and reduced generation capacity, driving LOLP toward the high-risk region. Correlation analyses further corroborate these trends: LOLP exhibits a consistent positive association with PUE and a strong association with unserved load, while workload variability shows comparatively weak association, indicating that efficiency-driven demand scaling and deliverability limitations are potential primary drivers of reduced power grid reliability

The proposed framework quantifies the interactions between stochastic datacenter workloads and power system reliability, supporting more informed planning and operational decisions for grids with increasing digital infrastructure demand. Future work will generalize the proposed framework to larger-scale test systems and grid topologies, and incorporate a broader spectrum of datacenter load behaviors and operational profiles while accounting for renewable generation uncertainty and its interaction with system reliability.

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