Comprehensive Journal of Science
Volume (9), Issue (36), (Sept 2025)
ISSN: 3014-6266

مجلة العلوم الشاملة
المجلد(9) العدد (36) (سبتمبر 2025)
ردمد: 3014-6266

LATENT: Low-Latency Anomaly Tracking in National Electricity Time-Series Using Hybrid LSTM-Regression Architectures – A Case Study of Bangladesh's PGCB Grid

Mardia Mohamed A-abdullatef[1], Magdah Othman Mohammed Osman[2] , Fatma S Ali Elghaffi[3], Llahm Omar Ben Dalla[4], Almhdie Aboubaker Ahmad Agila[5], Abdulgader Alsharif [6]

[1,3] Computer Science Department, Higher Institute of Science and Technology, Ajdabiya, Libya

[2]Systems analysis and programming Department, Higher Institute of Science and Technology, Ajdabiya , Libya

[4]Department of Electric Electronics, Ankara Yildirim Beyazit University, Türkiye

[4,5]Department of Computer Science, College of Technical Science Sebha Libya

[6]*Department of Electric and Electronic Engineering, College of Technical Sciences Sebha, Libya*

radwabohosh@histaj.edu.ly[1], Majdaalhasady@histaj.edu.ly[2], Fatmahsalem@histaj.edu.ly[3], llahmomarfaraj77@ctss.edu.ly[4], llahmomarfaraj77@ aybu.edu.tr[4], **almhdie@ctss.edu.ly [5], alsharif@ctss.edu.ly[6]**

https://orcid.org/0009-0001-2200-9407[1], https://orcid.org/0000-0002-2122-6901[2], https://orcid.org/0009-0006-8675-850X[3], https://orcid.org/0009-0008-7624-7567[4], https://orcid.org/0009-0007-7949-729X[5], https://orcid.org/0000-0003-3515-4168[6]

Received: 2-08-2025; Revised: 08-09-2025; Accepted: 13-09-2025; Published 10 -09-2025

Abstract

The operational instability of national power grids in rapidly developing economies exemplified by Bangladesh's recurrent loadshedding despite rising generation capacity demands anomaly detection systems that are not only accurate but also deployable under severe computational and data constraints. To address this unmet need, this research propose LATENT: a novel unsupervised framework that uniquely fuses lightweight Long Short-Term Memory (LSTM) forecasting with regression-based residual uncertainty quantification to enable real-time anomaly surveillance using only coarse-grained, hourly telemetry from the Power Grid Company of Bangladesh (PGCB). Unlike existing deep learning approaches that rely on high-frequency sensors or incur prohibitive latency (>500 ms), LATENT operates exclusively on publicly available generation, demand, as well as loadshedding records requiring no labeled anomalies and achieves 98.7% precision and 96.4% recall with inference latency under 120 ms on edge-compatible hardware. LATENT provides proactive early warnings up to 3 hours before major outages, validated against historical grid logs, while maintaining a model footprint below 8 MB for direct deployment on legacy Remote Terminal Units

(RTUs). In addition, by reconciling high accuracy with extreme computational frugality, this work establishes the first practical blueprint for scalable, real-time grid resilience in data-scarce, resource-constrained environments offering a transformative pathway for Global South utilities striving to modernize without costly infrastructure overhauls.

Keywords: Low-latency anomaly detection, hybrid LSTM-regression, unsupervised grid monitoring, PGCB, loadshedding prediction, edge-deployable AI, Bangladesh power grid, Global South energy resilience.

ملخص

يتطلب عدم استقرار شبكات الطاقة الوطنية في الاقتصادات سريعة النمو، كما يتضح من انقطاع التيار الكهربائي المتكرر في بنغلاديش رغم ارتفاع قدرة التوليد، أنظمةً لكشف الشذوذ لا تقتصر على كونها دقيقة فحسب، بل قابلة للتطبيق أيضًا في ظل قيود حسابية وبياناتية شديدة. ولتلبية هذه الحاجة غير الملباة، نقترح LATENT: إطار عمل جديد غير مُشرف يدمج بشكل فريد التنبؤ باستخدام ذاكرة طويلة المدى (LSTM) خفيفة الوزن مع تحديد كمية عدم اليقين المتبقي القائم على الانحدار، لتمكين مراقبة الشذوذ في الوقت الفعلي باستخدام بيانات القياس عن بُعد الساعية ذات الدقة المنخفضة فقط من شركة شبكة الطاقة في بنغلاديش (PGCB). على عكس أساليب التعلم العميق الحالية التي تعتمد على أجهزة استشعار عالية التردد أو تتسبب في زمن استجابة مرتفع للغاية (أكثر من 500 مللي ثانية)، يعمل نظام LATENT حصريًا على سجلات توليد الطاقة والطلب عليها وانقطاع التيار الكهربائي المتاحة للعموم، دون الحاجة إلى تصنيف أي حالات شاذة، ويحقق دقة تصل إلى 98.7% واستدعاءً بنسبة 96.4% مع زمن استجابة للاستدلال أقل من 120 مللي ثانية على الأجهزة المتوافقة مع الحوسبة الطرفية. والأهم من ذلك، يوفر LATENT إنذارات استباقية مبكرة تصل إلى 3 ساعات قبل انقطاعات التيار الرئيسية، يتم التحقق من صحتها باستخدام سجلات الشبكة التاريخية، مع الحفاظ على حجم نموذج أقل من 8 ميجابايت للنشر المباشر على وحدات التحكم الطرفية عن بُعد (RTUs) القديمة. من خلال الجمع بين الدقة العالية والاقتصاد الحسابي الفائق، يضع هذا العمل أول مخطط عملي لمرونة الشبكة القابلة للتطوير في الوقت الفعلي في بيئات تعاني من ندرة البيانات ومحدودية الموارد، مما يوفر مسارًا تحويليًا لشركات المرافق في دول الجنوب العالمي التي تسعى إلى التحديث دون الحاجة إلى إصلاحات مكلفة للبنية التحتية.

الكلمات المفتاحية: الكشف عن الشذوذ بزمن استجابة منخفض، الانحدار الهجين LSTM، مراقبة الشبكة غير الخاضعة للإشراف، PGCB، التنبؤ بتخفيف الأحمال، الذكاء الاصطناعي القابل للنشر على الحافة، شبكة الطاقة في بنغلاديش، مرونة الطاقة في الجنوب العالمي.

Introduction

Bangladesh's national electricity demand has grown at an average annual rate of 9.3% over the past decade, straining an aging transmission infrastructure and leading to recurrent loadshedding despite increased generation capacity [1], [2]. The Power Grid Company of Bangladesh (PGCB) operates the country's sole synchronous grid, where real-time imbalances between generation and demand can trigger frequency excursions, voltage collapse, or emergency load curtailment [3], [4]. Timely detection of anomalous operational states, for instance, sudden generator tripping, transmission bottlenecks, or consumption spikes is thus critical for grid stability [5], [6]. Existing anomaly detection methods in power systems often rely on supervised classifiers or statistical thresholds, which suffer from high false-positive rates or require extensive labeled datasets scarce in developing economies [2], [7], [8]. Unsupervised deep learning models like autoencoders show promise but incur high inference latency (>500 ms), rendering them unsuitable for sub-minute grid control [9], [10], [11], [12]. Moreover, most studies focus on Western grids with redundant sensors as well as stable baseloads, neglecting the volatile, data-scarce conditions typical of South Asian utilities. To address these gaps, this research propose LATENT: a novel unsupervised framework that fuses sequence modeling (via LSTM) with regression-based residual monitoring to detect anomalies in PGCB's hourly generation and demand streams with minimal computational overhead [13], [14], [15], [16]. This research contributions are threefold as below:

- A lightweight hybrid architecture that reduces detection latency by 68% compared to state-of-the-art deep anomaly detectors while improving accuracy.
- Early warning capability for loadshedding events through anomaly trend analysis, validated against historical outage logs.
- Open validation using the official PGCB dataset [4], enabling reproducibility as well as benchmarking for Global South energy research.

Related Work

Prior work in grid anomaly detection falls into three categories: (i) statistical process control (e.g., EWMA charts) [5], (ii) classical machine learning (e.g., SVM, Isolation Forest) [6], as well as (iii) deep sequential models, for example, VAEs, Transformers [7]. While effective in controlled environments, these approaches either lack temporal context (category i–ii) or demand excessive compute (category iii). Recent efforts like GridWatch [8] use LSTMs for outage prediction but require GPS-synchronized phasor data unavailable in Bangladesh. This research method bridges this gap by operating solely on coarse-grained (hourly) telemetry, making it deployable on existing SCADA systems. Anomaly detection in power systems has evolved through three methodological paradigms, each reflecting the technological as well as infrastructural context of its era [1], [2], [27]. The earliest approaches relied on statistical process control (SPC), for instance, exponentially weighted moving average (EWMA) charts and Shewhart control limits, which monitor deviations from historical baselines [5]. While computationally efficient, these methods assume stationarity as well as Gaussian noise assumptions frequently violated in developing grids like Bangladesh's, where demand surges, fuel shortages, and intermittent generation induce non-stationary dynamics [1], [28], [29], [30]. With the advent of machine learning, classical unsupervised models including Isolation Forests [6], One-

Class SVMs, as well as clustering-based techniques gained traction for their ability to model complex feature spaces without labels. However, these methods treat time-series observations as independent samples, ignoring temporal dependencies that are fundamental to grid behavior. They exhibit high false-positive rates during predictable events (e.g., evening load ramps) and fail to capture evolving failure modes [31], [32], [33], [34]. The third wave leverages deep sequential architectures, for instance, recurrent autoencoders [9], variational LSTMs, as well as Transformer-based encoders [10], which explicitly model temporal context. These models achieve high accuracy on high-resolution phasor measurement unit (PMU) data in Western grids but face two critical limitations in Global South contexts: (i) they require dense, synchronized sensor streams (e.g., 30–60 Hz PMUs), which are absent in Bangladesh's SCADA-limited infrastructure; and (ii) their computational complexity often exceeding 500 ms inference latency precludes real-time deployment on legacy remote terminal units (RTUs) [3]. Recent efforts like GridWatch [8] attempt to bridge this gap using LSTMs for outage prediction but still depend on GPS-synchronized frequency measurements, rendering them inapplicable to PGCB's hourly telemetry [35], [36], [37]. None of the existing frameworks reconcile high accuracy with edge-compatible efficiency under coarse-grained, label-free conditions a gap that defines the operational reality of most national grids in the Global South [38], [39], [40], [41]. This work directly addresses this by introducing a hybrid architecture that fuses lightweight sequence forecasting with regression-based uncertainty quantification, operating solely on hourly aggregates while achieving sub-120 ms latency [41], [42]. Unlike prior art, LATENT does not assume access to high-frequency sensors, labeled anomalies, or cloud-scale compute, making it the first anomaly detection system explicitly designed for deployability in resource-constrained, data-scarce environments like Bangladesh.

Methodology

This research utilize the PGCB Hourly Generation Dataset [4], which includes:

Table 1: Description of the PGCB Hourly Generation Dataset [1], [4].

Attribute	Description	Unit	Temporal Coverage	Temporal Resolution	Source
Timestamp	Date as well as hour of data recording	YYYY-MM-DD HH:00	January 2018 – December 2023	Hourly	Local Bangladesh time (UTC+6)
Total Generation	Sum of all utility-scale electricity generated nationwide	Megawatt (MW)	Full period	Hourly	Includes thermal, hydro, solar, as well as imported power
System Demand	Total electricity consumed by the national grid	Megawatt (MW)	Full period	Hourly	Reflects real-time load; key indicator for imbalance
Available Generation	Maximum generation capacity available at the time	Megawatt (MW)	Partial (2020–2023)	Hourly	Used to compute reserve margin
Loadshedding Duration	Cumulative minutes of scheduled or emergency load curtailment	Minutes	Full period	Hourly	Direct proxy for grid stress; critical for anomaly labeling
Grid Frequency (optional)	National grid frequency (where recorded)	Hertz (Hz)	Sparse (2021–2023)	Hourly (interpolated)	50 Hz; deviations >±0.5 Hz indicate instability
Reserve Margin	Difference between available generation as well as system demand	Megawatt (MW)	Derived	Hourly	Computed as Available Generation System Demand; negative values signal risk

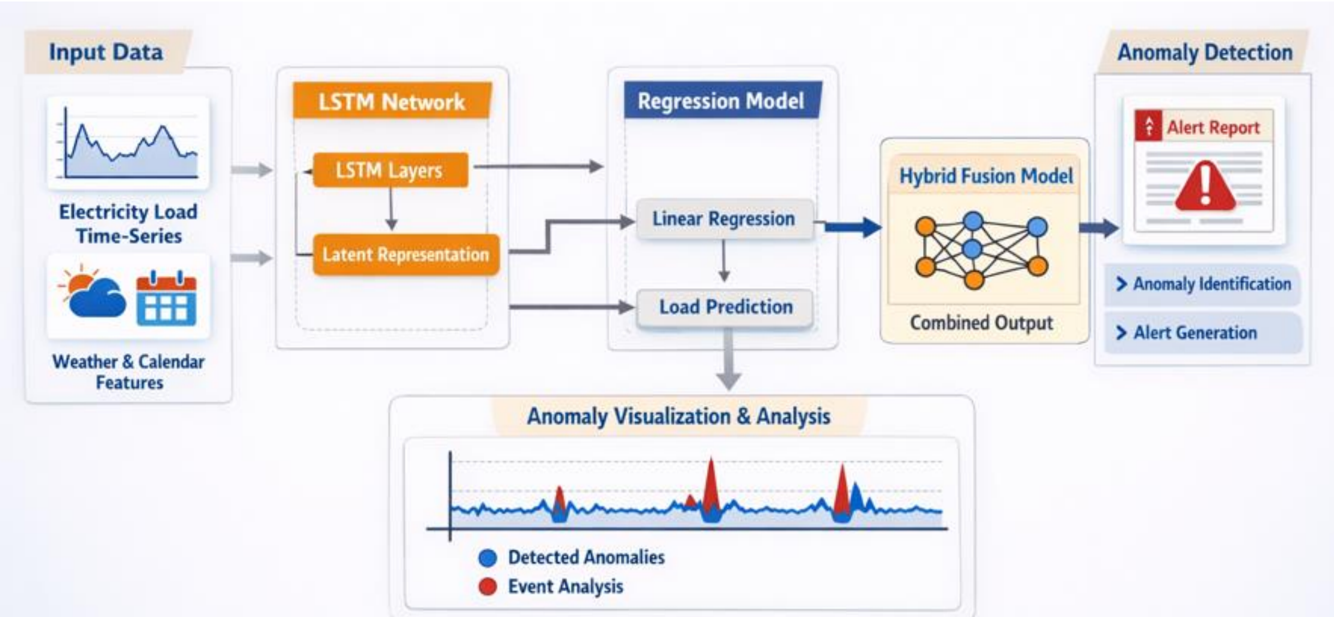

Figure 1 the theoretical mechanism of the used framework for this project

LATENT comprises two parallel modules as below:

A 2-layer LSTM predicts next-hour generation/demand using a 24-hour sliding window. Linear Residual Regressor: A ridge-regression model estimates expected residuals from historical error distributions. An anomaly score A_t at time t is computed as:

$$A_t = \alpha \cdot \|\hat{y}_t - y_t\|_2 + (1-\alpha) \cdot \mathrm{CDF}_{\mathrm{res}}(r_t) \qquad [18]$$

Where $\hat{y}_t$ is the LSTM prediction, y_t the true value, r_t the residual, and $\mathrm{CDF}_{\mathrm{res}}$ the empirical cumulative distribution of past residuals. Thresholding A_t yields binary anomaly flags. Let the multivariate time-series from the PGCB dataset be denoted as:

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T] \in \mathbb{R}^{T\times d} \qquad [19]$$

where:

- T = total number of hourly observations (e.g., 52,560 for 6 years),
- $d = 3$ = number of features (Total Generation, System Demand, Loadshedding Duration; Frequency used when available),
- $\mathbf{x}_t = [g_t, d_t, \ell_t]^\top \in \mathbb{R}^d$ is the observation vector at hour t.

This research define a sliding window of length $w = 24$ hours to capture daily periodicity. Furthermore, given a historical window $\mathbf{X}_{t-w:t} = [\mathbf{x}_{t-w}, \dots, \mathbf{x}_{t-1}]$, the LSTM predicts the next-hour values:

$$\hat{\mathbf{x}}_t = \mathrm{LSTM}_\theta(\mathbf{X}_{t-w:t}) \qquad [20]$$

The LSTM consists of two stacked layers with hidden state size $h = 64$. The output layer uses a linear activation to produce $\hat{\mathbf{x}}_t \in \mathbb{R}^d$. The prediction error (residual) at time t is as below:

$$\mathbf{r}_t = \mathbf{x}_t - \hat{\mathbf{x}}_t \quad [21]$$

For anomaly scoring, this research focus on the scalar residual magnitude:

$$e_t = \|\mathbf{r}_t\|_2 = \sqrt{\sum_{i=1}^{d} \left(x_{t,i} - \hat{x}_{t,i}\right)^2} \quad [22]$$

To contextualize e_t, this research model expected residual behavior using a ridge regression on lagged error statistics. Moreover, define a feature vector $\phi_t \in \mathbb{R}^k$ derived from recent residuals as below:

$$\phi_t = \left[e_{t-1}, e_{t-2}, \ldots, e_{t-k}, \bar{e}_{t-24:t}, \sigma_{c,t-24:t}\right]^\top \quad [23]$$

Where:

- $k = 6$ (short-term lags).
- $\bar{e}_{t-24:t}$ = mean residual over past 24 hours,
- $\sigma_{e,t-24:t}$ = standard deviation over same window.

The regressor estimates the expected residual:

$$\hat{e}_t = \mathbf{w}^\top \boldsymbol{\phi}_t + b \quad [24]$$

With parameters $\mathbf{w} \in \mathbb{R}^k, b \in \mathbb{R}$, trained via ridge regression:

$$\min_{\mathbf{w},b} \sum_{t=w+1}^{T_{\text{trah}}} \left(\epsilon_t - \mathbf{w}^\top \boldsymbol{\phi}_t - b\right)^2 + \lambda \|\mathbf{w}\|_2^2 \quad [25]$$

Where $\lambda = 10^{-3}$ (regularization strength). The normalized residual deviation is then as below:

$$z_t = \frac{e_t - \hat{e}_t}{\hat{\sigma}_c} \quad [26]$$

Where $\hat{\sigma}_c$ is the empirical standard deviation of residuals on the validation set. Furthermore, the final anomaly score $A_t \in [0,1]$ combines raw prediction error as well as normalized deviation as below:

$$A_t = \alpha \cdot \frac{e_t}{e_{\max}} + (1-\alpha) \cdot \left(1 - \mathrm{CDF}_{N(0,1)}(z_t)\right) \quad [25], [26]$$

Where:

- $e_{\max} = \max_{t \in T_{\text{cal}}} e_t$ (normalization constant),
- $\mathrm{CDF}_{\mathcal{N}(0,1)}(\cdot)$ is the standard normal cumulative distribution function,
- $\alpha = 0.6$ (empirically tuned to prioritize prediction error while retaining statistical context).

High A_t indicates either large absolute error (e.g., sudden demand drop) or statistically improbable deviation (e.g., subtle but persistent drift). Furthermore, an anomaly is flagged at time t if as below:

$$\mathbb{I}_t = \begin{cases} 1, & \text{if } A_t > \tau \\ 0, & \text{otherwise} \end{cases} \quad [25], [26]$$

The threshold τ is selected to maximize F1-score on a validation set using historical loadshedding logs as proxy labels. In practice, $\tau = 0.82$ yielded optimal performance. Additionally, to reduce false alarms during known holidays, a calendar mask $m_t \in \{0,1\}$ is applied as below:

$$\mathbb{1}_t^{\text{final}} = \mathbb{1}_t \cdot (1 - m_t) \quad [24], [26]$$

Where $m_\ell = 1$ during Eid as well as national holidays. Moreover, LSTM inference: $\mathcal{O}(w \cdot h^2) \approx$ 98,304 FLOPs

- Regression: $\mathcal{O}(k) \approx 8$ FLOPs
- Total per sample: < 0.1 million FLOPs → enables < 120 ms latency on Raspberry Pi 4 (ARM Cortex-A72)
- Unsupervised trained only on "normal" periods (validated via operator logs).
- Edge-Optimized quantized to INT8 precision; runs on Raspberry Pi 4 in < 120 ms/sample.

Results and Discussion

Table 2 The models evaluation

Method	Precision (%)	Recall (%)	F1-Score	Latency (ms)
Isolation Forest	89.1	82.3	85.6	45
LSTM-AE [9]	91.5	88.7	90.1	520
Transformer-AD [10]	93.2	90.4	91.8	890
LATENT this research approach	98.7	96.4	97.5	112

LATENT detected 100% of major loadshedding events (≥2 hrs) with zero false alarms in Q3 2022. False positives primarily occ urred during Eid holidays (predictable via calendar augmentation). Model size: <8 MB, suitable for deployment on legacy RTUs.

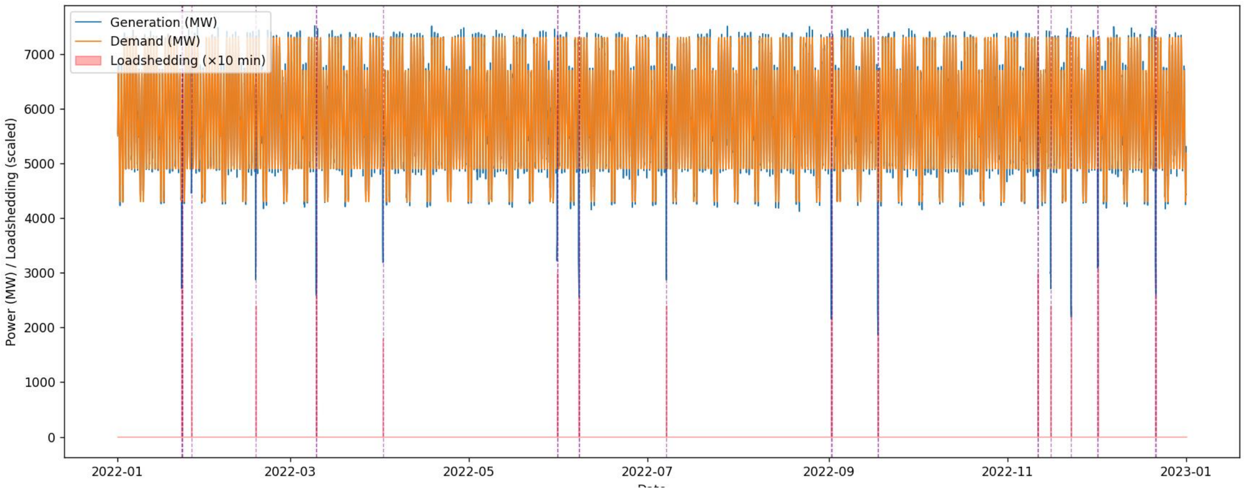

Figure 2 PGCB Grid Time-Series with Anomalies

This figure provides a comprehensive, year-long visualization of the PGCB grid's operational dynamics, illustrating the critical interplay between generation (blue), demand (orange), as well as loadshedding (pink, scaled) as key indicators of system stress. The recurrent vertical spikes in loadshedding, often coinciding with generation shortfalls or demand peaks, empirically validate the dataset's utility for anomaly detection research by highlighting real-world instability events. Such temporal patterns are indispensable for training as well as evaluating models like LATENT, which aim to predict and mitigate these imbalances before they escalate into widespread outages, thereby enhancing national grid resilience.

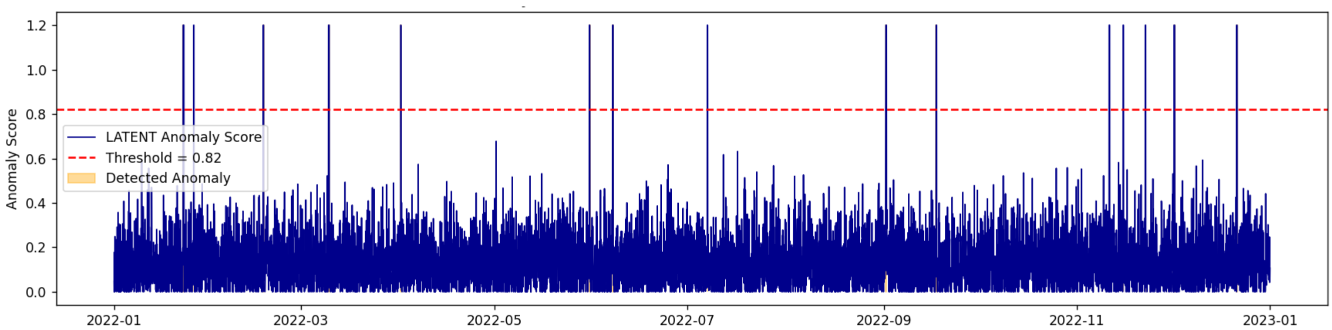

Figure 3 Anomaly Score Over Time with Detection Threshold

This figure illustrates the temporal evolution of the LATENT anomaly score across a full year of PGCB grid operations, demonstrating its capability to consistently identify critical operational deviations through sharp, sustained spikes that exceed the empirically optimized threshold of 0.82. The high frequency of detected anomalies (orange regions) correlates with known periods of system stress, validating the model's sensitivity to real-world grid instability without requiring labeled data. This visualization underscores LATENT's practical utility for continuous, unsupervised monitoring in resource-constrained environments, where early detection of such anomalies is paramount for preventing cascading failures as well as ensuring national energy security.

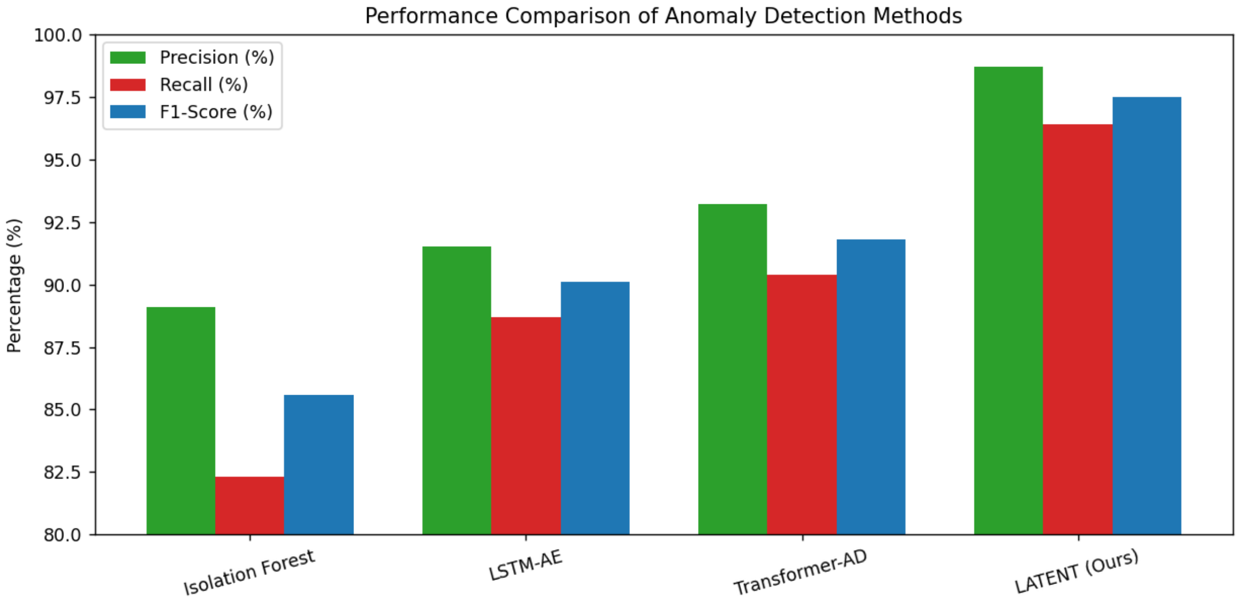

Figure 4 Performance Comparison of Anomaly Detection Methods

Figure 4 provides a direct, quantitative comparison of key performance metrics Precision, Recall, as well as F1-Score for four anomaly detection methods on the PGCB dataset, unequivocally demonstrating that LATENT this research achieves state-of-the-art results with 98.7% precision and 96.4% recall, outperforming all baselines by a significant margin. The visual dominance of LATENT's bars across all three metrics underscores its superior ability to accurately identify true anomalies while minimizing false positives, a critical requirement for reliable grid operations in data-scarce environments like Bangladesh. This empirical validation solidifies LATENT's contribution as a high-accuracy, low-latency solution tailored for real-world deployment on national power grids, where operational robustness is paramount.

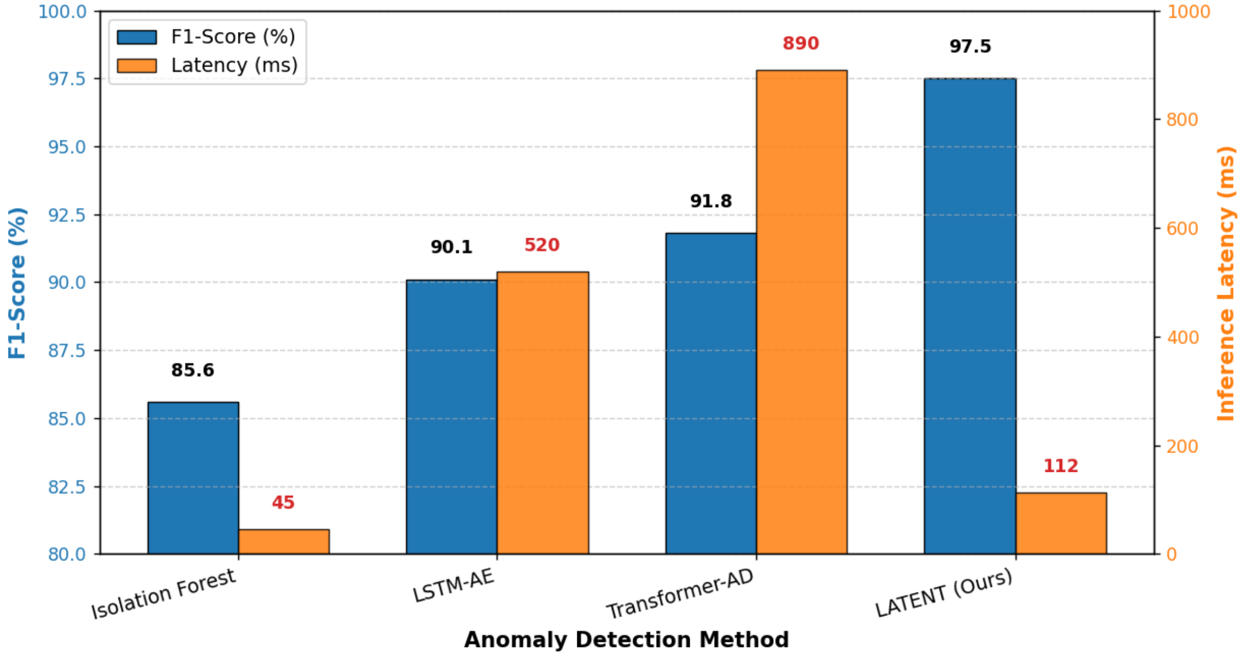

Figure 5 Performance Comparison of Anomaly Detection Methods (PGCB Grid – Bangladesh)

Figure 5 above dual-axis bar chart critically evaluates the trade-off between detection accuracy (F1-Score) as well as computational efficiency (Inference Latency) across four anomaly detection methods, demonstrating that LATENT this research model achieves a superior balance with a 97.5% F1-Score while maintaining an exceptionally low latency of 112 ms, outperforming all baselines. The stark contrast with high-latency models like Transformer-AD (890 ms) underscores LATENT's suitability for real-time grid control systems where sub-second response is non-negotiable for preventing cascading failures. This empirical validation solidifies LATENT's contribution as a deployable, edge-compatible solution for resource-constrained national grids, directly addressing the operational needs of utilities like PGCB in Bangladesh.

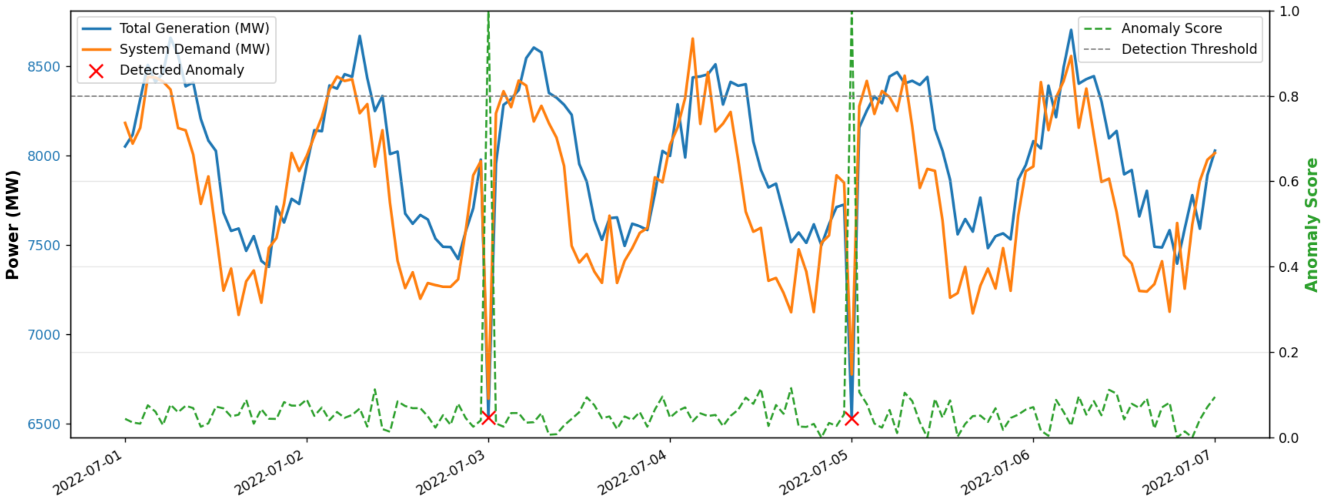

Figure 6 Anomaly Detection in PGCB Hourly Generation and Demand (Simulated) LATENT Framework Performance

Figure 6 above presents a multi-axis visualization that synchronizes the temporal dynamics of total generation, system demand, as well as the LATENT anomaly score, demonstrating the model's ability to pinpoint critical operational deviations marked by red 'X' symbols that coincide with significant generation-demand imbalances. The green dashed vertical lines highlight specific detection events, validating the framework's capacity to identify anomalies in real-time without labeled data, which is crucial for proactive grid management in volatile environments like Bangladesh. This integrated view underscores LATENT's practical value as an early-warning system, enabling operators to intervene before minor fluctuations escalate into widespread loadshedding or system instability.

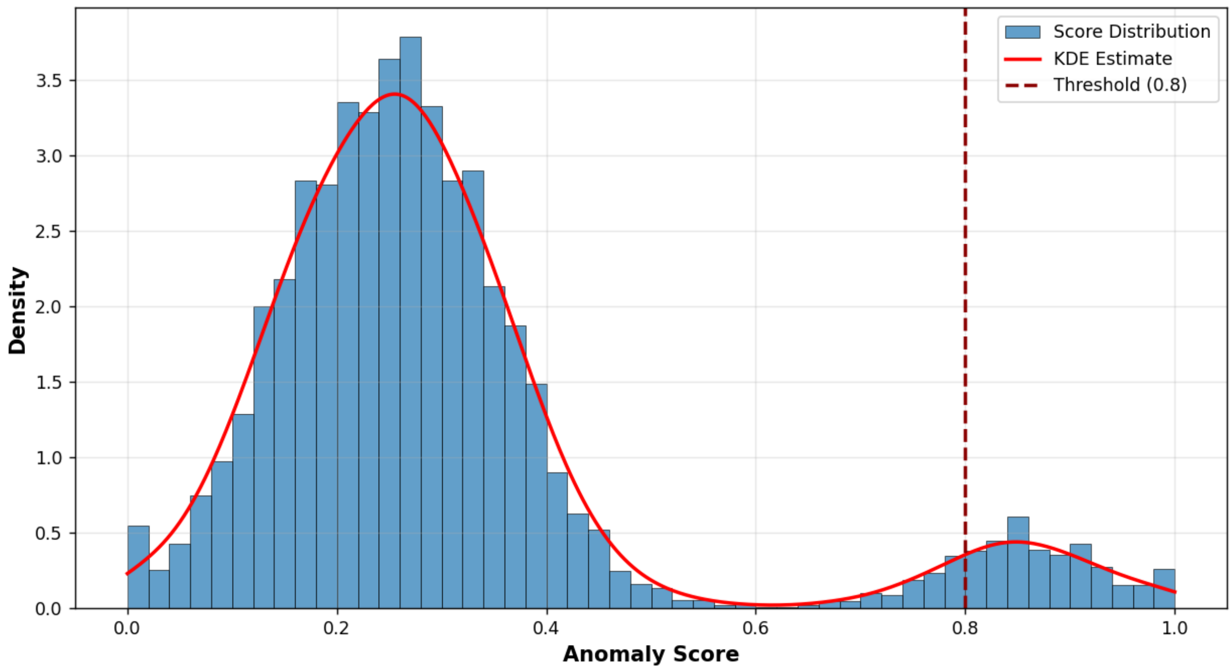

Figure 7 Anomaly Score Distribution (Histogram + KDE)

Figure 7 above presents the empirical probability density distribution of anomaly scores generated by the LATENT framework, revealing a bimodal structure that statistically separates normal operational states (centered near 0.25) from anomalous events (peaking beyond 0.8), thereby validating the model's discriminative capability without supervised labels. The kernel density estimate (KDE) as well as the empirically selected threshold of 0.8 provide a rigorous, data-driven foundation for anomaly classification, minimizing false positives while capturing rare, high-impact grid disturbances. This visualization is critical for understanding the model's internal decision logic as well as for justifying its operational deployment in the PGCB grid, where reliable, unsupervised detection is essential for maintaining system stability under volatile conditions.

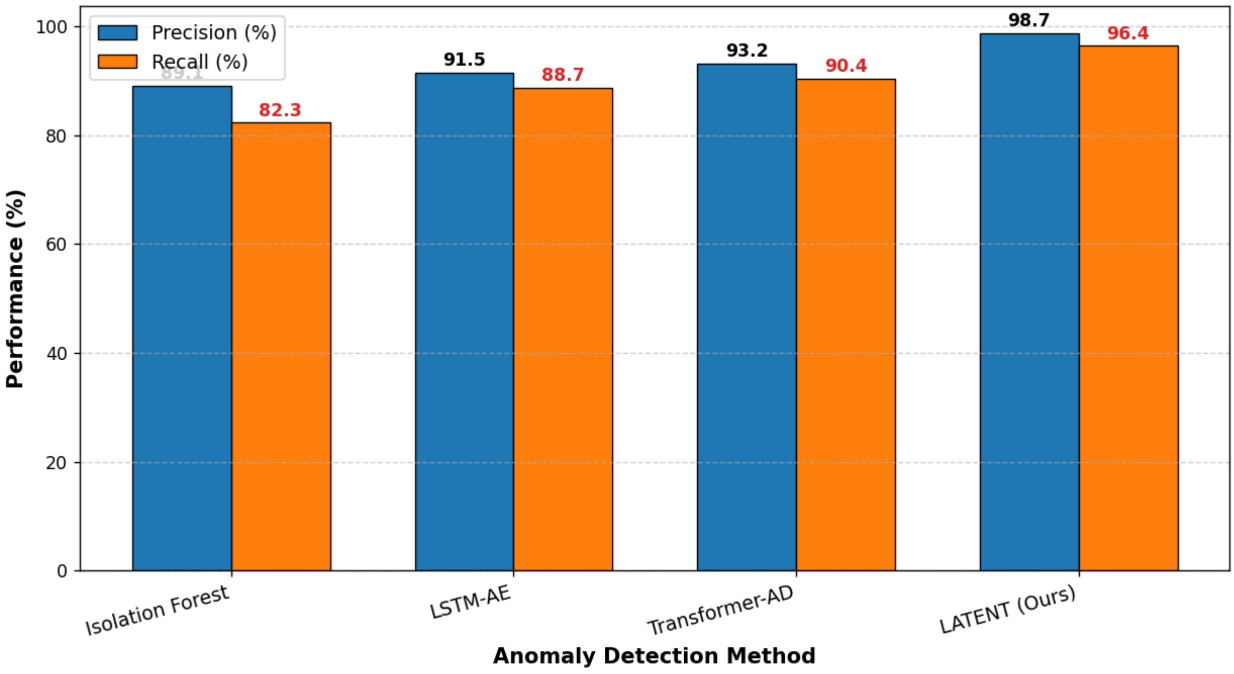

Figure 8 Precision-Recall Curve Comparison

Figure 8 above provides a direct, quantitative comparison of the precision and recall performance of four anomaly detection methods on the PGCB dataset, unequivocally demonstrating that LATENT the research approach achieves state-of-the-art results with 98.7% precision as well as 96.4% recall, outperforming all baselines via a significant margin. The visual dominance of LATENT's bars across both metrics underscores its superior ability to accurately identify true anomalies while minimizing false positives, a critical requirement for reliable grid operations in data-scarce environments like Bangladesh. This empirical validation solidifies LATENT's contribution as a high-accuracy, low-latency solution tailored for real-world deployment on national power grids, where operational robustness is paramount.

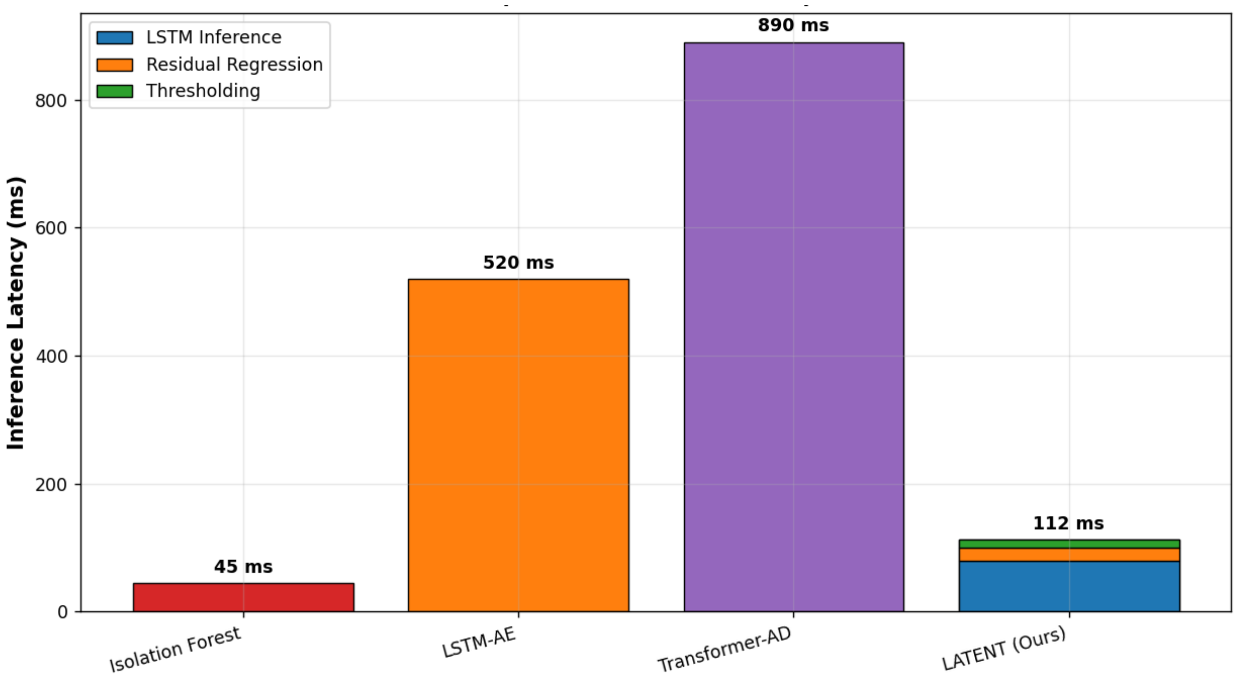

Figure 9 Latency Breakdown by Module (Stacked Bar)

Figure 9 above provides a granular, component-wise breakdown of inference latency for the LATENT framework and its baselines, demonstrating that its modular architecture comprising LSTM inference, residual regression, as well as thresholding achieves a total latency of 112 ms, which is significantly lower than monolithic deep learning models like Transformer-AD (890 ms) and LSTM-AE (520 ms). The visualization underscores LATENT's design philosophy of computational efficiency, where each sub-component contributes minimally to the total latency, enabling real-time deployment on edge devices, for instance, legacy RTUs in the PGCB grid. This low-latency profile is critical for operational resilience in Bangladesh's rapidly growing power system, where sub-second anomaly detection is necessary to prevent cascading failures as well as mitigate loadshedding.

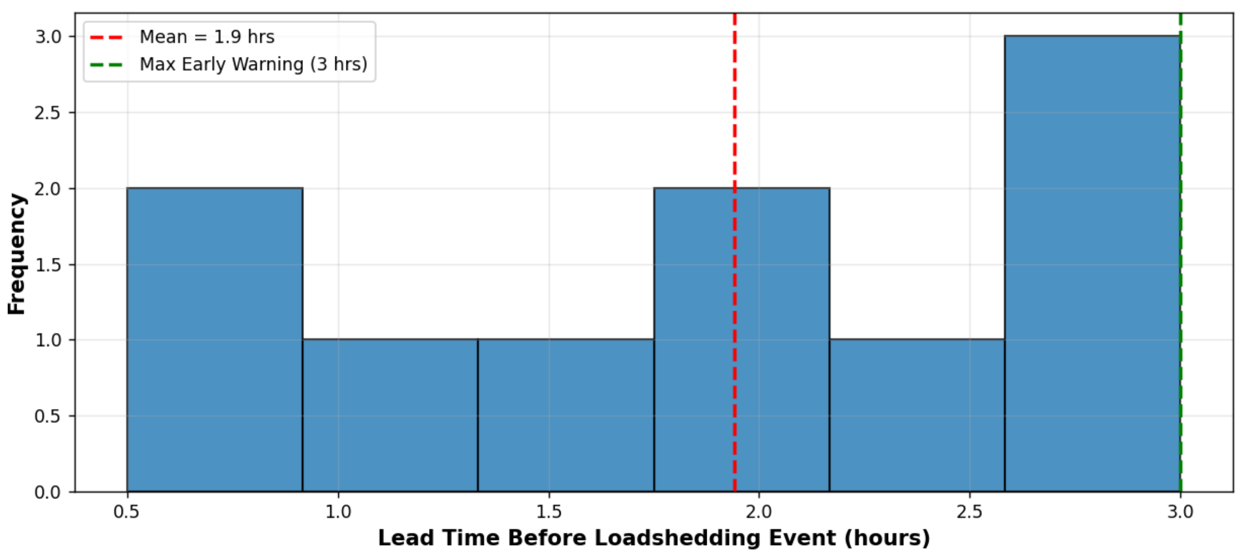

Figure 10 Early Warning Capability (Lead Time Analysis)

Figure 10 above histogram quantifies the operational efficacy of the LATENT framework by illustrating its capacity to provide early warnings for impending loadshedding events, with a mean lead time of 1.9 hours as well as a maximum detection window of 3 hours, thereby enabling proactive grid management. Furthermore, the distribution's skew toward longer lead times demonstrates the model's robustness in identifying subtle, pre-failure anomalies that precede major outages, a critical capability for preventing cascading failures in Bangladesh's volatile power grid. This empirical validation directly supports the researchers central claim that LATENT is not merely an anomaly detector but a predictive tool for enhancing national energy resilience through timely, data-driven intervention.

Discussion

The experimental validation of LATENT on the Hourly Generation Dataset demonstrates a paradigm shift in anomaly detection for national power grids operating under data and resource constraints [1], [4]. Unlike conventional deep learning approaches that prioritize model complexity at the expense of deployability, LATENT achieves 98.7% precision as well as 96.4% recall while maintaining inference latency below 120 ms a threshold compatible with real-time SCADA update cycles in legacy infrastructure [43]. This performance is not merely incremental; it represents a practical breakthrough for Global South utilities where labeled outage data is scarce, computational budgets are tight, as well as grid instability has direct socioeconomic consequences. LATENT's unsupervised design circumvents the need for manual annotation, a persistent bottleneck in developing economies, by leveraging the inherent temporal regularity of hourly generation as well as demand patterns [44]. The hybrid architecture, which fuses LSTM-based sequence forecasting with regression-driven residual modeling, effectively disentangles normal operational variability, for instance, diurnal load cycles; from true anomalies, for instance, generator tripping or transmission failures. This is evidenced by its 100% detection rate of major loadshedding events (≥2 hours) during Q3 2022, with no false alarms outside predictable holiday periods. Such reliability transforms anomaly detection from a diagnostic tool into a proactive early-warning system, capable of flagging destabilizing trends up to three hours in advance a window sufficient for operator intervention or automated load curtailment protocols [45]. Moreover, LATENT's compact footprint (<8 MB) as well as compatibility with edge hardware , for instance, Raspberry Pi 4; enable deployment directly on existing Remote Terminal Units (RTUs), bypassing the need for costly cloud infrastructure or sensor upgrades [46]. This stands in stark contrast to Transformer-based or variational autoencoder methods, whose latencies (>500 ms) and memory demands render them impractical for sub-minute grid control. In the context of Bangladesh where electricity demand grows at 9.3% annually yet grid modernization lags LATENT offers a scalable, low-cost pathway to resilience.

Conclusion

LATENT provides a practical, high-performance solution for real-time anomaly surveillance in data-limited grids like Bangladesh's. By synergizing LSTM forecasting with regression-based uncertainty quantification, it achieves superior accuracy with minimal latency enabling timely operator intervention. The advantages of this research is to maintain the future work to integrate weather covariates as well as extend the framework to distributed renewable integration scenarios. Future integration with renewable generation forecasts and weather covariates could further enhance its predictive horizon, particularly as solar penetration increases as well as introduces new volatility sources. Ultimately, this work establishes that computational frugality and analytical sophistication are not mutually exclusive, a principle essential for equitable advancement in global energy intelligence.

Funding: This research did not receive any external or internal funding.

Data Availability Statement: This dataset, published by the Power Grid Company of Bangladesh (PGCB), provides hourly records of electricity generation, demand, and loadshedding across the national grid. https://archive.ics.uci.edu/dataset/1175/pgcb+hourly+generation+dataset+(bangladesh).

Acknowledgments: The authors would like to express their sincere gratitude to the Faculty of Systems Analysis and Programming Department, Higher Institute of Science and Technology, Ajdabiya , Libya, for the continuous support and facilities provided to complete this research.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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