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Multi-Dimensional Urban Energy Stress Dynamics in Bangladesh: A Composite MD-UESI Framework for Structural Regime and Persistence Analysis in Bangladesh (2005–2024)

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Multi-Dimensional Urban Energy Stress Dynamics in Bangladesh: A Composite MD-UESI Framework for Structural Regime and Persistence Analysis in Bangladesh (2005–2024).

Abstract

Rapid urbanization and increasing electricity demand have intensified structural pressure on electricity systems in developing countries. However, previous studies have mainly focused on electricity supply and demand balance, while limited attention has been given to multidimensional structural stress within the energy system. This study develops a Multi-Dimensional Urban Energy Stress Index (MD-UESI) to evaluate the structural evolution of Bangladesh's electricity system during 2005–2024. The index integrates three dimensions of stress: supply stress, capacity stress, and network stress. Annual electricity sector data were collected from successive Bangladesh Bureau of Statistics (BBS) Yearbooks and analyzed using normalization, composite index construction, temporal trend analysis, structural break analysis, stress persistence analysis, regression diagnostics, binary classification, and stochastic scenario-based projection. The results show that supply stress declined sharply from 0.443 in 2006–07 to near-zero levels during 2016–2022 due to rapid generation expansion, while capacity stress gradually decreased from 1.000 to 0.611, indicating improved reserve margins. In contrast, network stress increased steadily from 0.078 to 0.133, reflecting rising infrastructure pressure. The composite MD-UESI identifies three structural phases: chronic high stress (2005–2011), stabilization (2012–2020), and renewed stress escalation after 2022. Structural break and persistence analyses confirm that system stabilization was significant but remained vulnerable to external shocks and infrastructure limitations. Diagnostic models further indicate weak temporal persistence and moderate predictive performance, suggesting that stress dynamics are shaped more by structural changes and disruptions than by simple temporal continuity. The study provides an integrated framework for evaluating multidimensional electricity stress and offers important implications for resilient urban energy planning in rapidly developing economies.

Keywords: Urban energy stress; MD-UESI; electricity system resilience; structural vulnerability; Bangladesh; infrastructure pressure; energy transition; regime shift analysis.

1.Introduction

Rapid urbanization and economic growth have exerted significant pressure on electricity systems globally, particularly in developing economies where infrastructure expansion often lags behind increasing demand. Here, the stress of the electricity system is defined as the state where the system operates close to or beyond its operational limits under the effects of these combined pressures. During the past decades, the world has observed a steady increase in electricity consumption due to industrialization, growing urban populations and technological progress(IEA, 2022). At the same time, many countries continue to experience supply constraints, system inefficiencies, and reliability challenges, especially in rapidly urbanizing regions(Shahbaz et al., 2014; Waite et al., 2017). Previous global research has largely focused on electricity demand forecasting, generation adequacy, and energy consumption trends, providing important insights into system performance(Klyuev et al., 2022; Ngamije & Adeniyi, 2024) and planning needs(Li, 2018). However, these studies often treat electricity systems as static supply–demand balances rather than dynamic systems under structural pressure, limiting the ability to capture underlying vulnerabilities(Santamouris et al., 2015). As a result, there remains a need for approaches that assess electricity systems as integrated socio-technical systems subject to multiple interacting stresses(Yildiz et al., 2017).

This challenge has been further sharpened by the increasing importance of the urban energy sector. Today, cities are the largest electricity consumption centers. They constitute a significant proportion of the world's energy demand due to the concentration of economic activity, population and infrastructure needs(UN-Habitat, 2020). So urban electric power systems are under increasing pressure from rising peak demand, infrastructure congestion, and climate-related stresses, such as extreme temperatures.(IEA, 2022; Santamouris et al., 2015). These pressures are particularly critical in developing countries, where rapid urban expansion often outpaces investments in transmission and distribution infrastructure(Waite et al., 2017). Consequently, electricity system stress is no longer limited to supply shortages but includes broader issues such as network congestion, reliability instability, and infrastructure strain(Li, 2018). Understanding these multidimensional pressures is essential for designing resilient and sustainable urban energy systems.

The Bangladeshi power sector has been transformed rapidly over the last two decades, as a result of strong economic growth and increasing electrification coverage. National demand for electricity has grown considerably, reflecting expansion in industrial activity, urbanization and better access to electricity services.(BPDB, 2023). Previous studies on Bangladesh's energy sector have primarily focused on demand growth(Khan et al., 2015), capacity expansion, and energy policy challenges(N. Hasan et al., 2023). While these studies provide valuable insights into supply adequacy and sectoral development, they often overlook the structural dynamics of electricity system stress, particularly the interaction between generation capacity, operational loading, and infrastructure constraints. This study contributes to the literature by developing a composite, multi-dimensional framework to assess electricity system stress over time, offering a more comprehensive understanding of structural vulnerability in the context of a rapidly developing economy.

The relationship between electricity, economic growth and structural transformation is well established at both the global and national levels. Electricity supply is important for industrial productivity, urban development and overall economic performance(Shahbaz et al., 2014). In Bangladesh, large investments in power generation have resulted in large increases in installed and derated capacity, which has led to improvements in supply adequacy and electrification coverage(BPDB, 2023). Nevertheless, despite these successes, there are still challenges of distribution inefficiencies, transmission bottlenecks and occasional supply disruptions. System losses, infrastructure constraints and uneven network expansion continue to hinder electricity delivery and reliability, reports indicate(World Bank, 2021) These issues suggest that while capacity expansion has improved generation-side performance, it has not fully resolved system-wide vulnerabilities, particularly at the distribution level.

From a structural perspective, the electricity system stress should be viewed as a dynamic rather than static process. The focus of previous research has been mainly on demand forecasting and supply adequacy, and less attention has been paid to the temporal evolution of stress in different system components. In Bangladesh, the move from chronic shortages to improved supply conditions has not eradicated vulnerability, but has changed its character throughout the system. The emerging pressures of network congestion, infrastructure strain and external shocks highlight the limitations of capacity-led planning approaches. To address this gap, this study proposes a multi-dimensional methodology to construct a composite index integrating supply, capacity and network stresses, and analyzes their temporal evolution, structural changes and persistence dynamics. This approach enables a more comprehensive diagnosis of electricity system stress beyond conventional single-indicator analysis and provides insight into how different components interact over time. Such a framework is essential for distinguishing between temporary improvements and genuine structural transformation in electricity systems.

In response, this study aims to develop and apply a Multi-Dimensional Urban Energy Stress Index (MD-UESI) to evaluate the structural dynamics of Bangladesh's electricity system over time. The specific objectives are threefold: (i) to construct a composite index integrating supply stress, capacity stress, and network stress; (ii) to analyze temporal trends, growth dynamics, and structural breaks in electricity system stress; and (iii) to assess persistence, regime shifts, and predictive relationships using diagnostic modeling approaches. By achieving these objectives, the study provides a comprehensive assessment of whether capacity expansion has led to sustained reductions in system stress or merely shifted vulnerability across different components. The findings offer important insights for policymakers and planners seeking to develop more resilient and integrated urban energy systems in Bangladesh and other rapidly developing economies.

2.Method & Concept

2.1 Conceptual Framework: Urban Energy Stress as Structural System Pressure

Electricity systems in rapidly developing economies operate under multiple interacting pressures(IEA, 2022) arising from demand growth, infrastructure constraints, and environmental variability, which together shape system performance beyond simple supply adequacy(Waite et al., 2017). Conventional planning approaches typically rely on indicators such as installed capacity, generation output, or demand forecasts to evaluate system performance(Khan et al., 2015; Li, 2018). While these metrics capture system scale and operational trends, they do not adequately reflect whether the system is operating under structural strain or approaching critical limits(Santamouris et al., 2015). Recent studies emphasize the need to conceptualize energy systems as dynamic socio-technical systems subject to interacting stresses rather than isolated supply–demand balances(Dall-Orsoletta et al., 2022),

In this research, urban energy stress is defined as a structural condition where the electricity system is operated at or beyond its functional limits under the co-action of three key pressures, including inadequacy of supply, pressure of capacity loading and strain of the network. Supply inadequacy is the inability to meet forecast demand. Capacity stress measures operational loading against effective generation capacity. Network stress is infrastructure congestion associated with increasing electricity throughput. Together, these dimensions represent observed and latent system vulnerabilities. The inclusion of these components gives rise to the interpretation of stress as a cumulative system pressure, rather than a single indicator of scarcity. To operationalize this framework, a composite indicator following the Multi-Dimensional Urban Energy Stress Index (MD-UESI) is developed, enabling a holistic assessment of structural electricity system stress over time(Alex Nutkiewicz et al., 2018; Landi et al., 2025).

2.2 Data Collection and Study Period

This study utilizes national-level electricity sector data compiled from the Bangladesh Bureau of Statistics (BBS) Yearbooks(BBS, 2024), which integrate official records from the Bangladesh Power Development Board(BPDB, 2023) and related agencies. Although the Yearbooks were published between 2010 and 2024, they include retrospective data, allowing construction of a consistent time series covering 2005–06 to 2023–24. This period captures a critical phase of rapid capacity expansion, increasing electrification, and rising urban demand in Bangladesh, making it particularly suitable for analyzing structural system dynamics in a developing country context(World Bank, 2021).

Bangladesh provides a relevant case for examining urban energy stress due to its rapid demand growth, expanding infrastructure, and ongoing transition from supply shortages to system-level constraints(Hossain, 2023). These properties make it a representative scenario for studying structural system pressure in developing countries, broadening the scope of the suggested methodology.

The dataset includes installed capacity, present (derated) capacity, maximum forecasted demand, maximum demand served, energy not served, total electricity consumption, and distribution line length. These variables correspond directly to the three stress aspects (supply, capacity, and network), ensuring compliance with the MD-UESI framework. The use of annual national data allows for investigation of long-term structural trends rather than short-term operational variations.

2.3 Construction of the Multi-Dimensional Urban Energy Stress Index (MD-UESI)

2.3.1 Rationale for Multi-Dimensional Measurement

Electricity system stress is inherently multi-dimensional and cannot be adequately represented by a single indicator(Tianbo Han et al., 2022), as modern energy systems operate through interconnected technical and infrastructural components(IEA, 2022). Traditional metrics such as energy not served, installed capacity, or total generation capture only partial aspects of system performance and often fail to reflect the underlying structural condition of the system(M. Tillmanns et al., 2026). For instance, high capacity utilization may suggest latent fragility even in the absence of perceived shortages, whereas unmet demand indicates immediate supply deficiency but does not reveal if the system is operating near technical limits. In a similar vein, fast increases in electricity usage in relation to network expansion may be a sign of infrastructure congestion without causing an immediate interruption to service.

Recent literature emphasizes that electricity systems should be analyzed as socio-technical system(Rohracher, 2018), where multiple pressures interact simultaneously to shape system reliability and resilience(Waite et al., 2017; Yildiz et al., 2017). In such systems, supply adequacy, operational loads, and infrastructure capacity are all interconnected, and stress may transfer across these dimensions rather than evaporate. As a result, relying on a single indicator may lead to incomplete or incorrect judgments about system vulnerability.

To address this limitation, a multi-dimensional approach is adopted to integrate supply inadequacy, capacity loading pressure, and network strain into a unified analytical framework. Composite index methods are widely used to combine heterogeneous indicators(Rofiq Nur Rizal et al., 2024), into a single measure while preserving their individual contributions(OECD, 2008). By creating independent components for each stress dimension and aggregating them, this study views electricity system stress as a structural issue rather than a transitory imbalance. This technique allows for a more thorough examination of whether capacity growth improves systemic vulnerability or redistributes stress across different components.

2.3.2 Stress Components and Operational Definitions

Supply stress (S_t) is defined as the proportion of unmet demand relative to forecasted demand, capturing the extent of direct supply inadequacy. This measure is used because it reflects realized shortages in relation to expected system requirements, making it comparable across time and system scale(Shahbaz et al., 2014). It is calculated as:

$$S_t = \frac{\text{Energy Not Served}_t}{\text{Maximum Forecasted Demand}_t} \quad (1)$$

Where, $S_t$represents supply stress in year *t*, *Energy Not Served* denotes unmet electricity demand during peak periods, and *Maximum Forecasted Demand* represents expected demand requirements(BPDB, 2023).

Capacity stress (C_t) is defined as the ratio of maximum demand served to present (derated) capacity, representing operational loading pressure within the generation system. This measure is used to capture how close the system operates to its effective capacity limits, reflecting reserve margin conditions and system flexibility(IEA, 2022). It is calculated as:

$$C_t = \frac{\text{Maximum Demand Served}_t}{\text{Present (Derated) Capacity}_t} \quad (2)$$

Where, $C_t$denotes capacity stress in year *t*, *Maximum Demand Served* represents actual peak demand met, and *Present (Derated) Capacity* accounts for effective generation capacity after operational constraint.

Network stress (N_t) is defined as electricity consumption per unit of distribution network length, representing infrastructure strain within the distribution system. This proxy is used due to the absence of consistent system loss data and captures the intensity of electricity flow relative to network expansion(World Bank, 2021). It is calculated as:

$$N_t = \frac{\text{Total Electricity Consumption}_t}{\text{Distribution Line Length}_t} \quad (3)$$

Where, $N_t$represents network stress in year *t*, *Total Electricity Consumption* reflects overall electricity usage, and *Distribution Line Length* indicates the physical extent of the distribution network(Rüde et al., 2014).

2.3.3 Normalization and Composite Index Construction

The three stress components; supply stress, capacity stress, and network stress are measured in different units and exhibit varying numerical ranges. Direct aggregation of these raw values would result to disproportionate influence of variables with higher magnitudes, potentially biasing the composite measure. To ensure comparability and balanced contribution across dimensions, each component is normalized using min–max scaling(Kim et al., 2025), a widely used approach in composite indicator construction(OECD, 2008).

For each stress component $X_{i,t}$, normalization is performed as:

$$Z_{i,t} = \frac{X_{i,t} - \min(X_i)}{\max(X_i) - \min(X_i)} \quad (4)$$

where $Z_{i,t}$represents the normalized value of component *i* in year *t*, scaled between 0 and 1. This transformation preserves the relative temporal variation of each variable while placing all components on a common scale, enabling meaningful comparison and aggregation.

Following normalization, the composite Multi-Dimensional Urban Energy Stress Index (MD-UESI) is constructed as the arithmetic mean of the three normalized components:

$$MD\text{-}UESI_t = \frac{Z_{S,t} + Z_{C,t} + Z_{N,t}}{3} \quad (5)$$

Equal weighting is adopted to maintain transparency and avoid subjective bias in assigning importance to individual stress dimensions(Ezell et al., 2021). Since supply inadequacy, capacity pressure, and network strain represent complementary aspects of structural vulnerability, equal contribution ensures conceptual neutrality(OECD, 2008). To assess robustness, alternative weighting schemes, including principal component analysis (PCA), are tested. The resulting MD-UESI ranges from 0 (lowest observed stress) to 1 (highest observed stress), allowing consistent temporal comparison across the study period.

2.4 Temporal Analysis of Stress Dynamics

Following index construction, the temporal evolution of MD-UESI is examined to identify long-term trends and structural changes in electricity system stress. Temporal analysis is essential because infrastructure development and policy impacts emerge gradually(Ziemba & Zair, 2023) and require longitudinal assessment to distinguish structural change from short-term variability(Mbasso et al., 2025).

Trend analysis is used to determine whether stress levels diminish, steady, or increase over time. Furthermore, annual growth rates of individual components are estimated to detect shifts in the underlying causes of system stress and establish whether improvements in one dimension are counterbalanced by increases in another.

System stability is further investigated by volatility analysis using the standard deviation of MD-UESI over sub-periods. Higher variability indicates fragile system dynamics, while lower variability suggests greater stability(K. N. Hasan et al., 2019). Together, these analyses provide a foundation for assessing whether capacity expansion has reduced structural stress or redistributed it across system components.

2.5 Structural Break Analysis

To assess whether capacity expansion resulted in structural transformation rather than gradual adjustment, the MD-UESI series is analyzed across three regimes: pre-expansion, stabilization, and recent shock period. These regimes are defined based on observed shifts in index behavior and major policy and infrastructure changes(Alejandro Lavopa & Adam Szirmai, 2018). Structural break analysis helps determine whether changes in stress represent sustained transformation or temporary variation(Hasdemir et al., 2025).

For each regime, key statistics are estimated(Bahman Zohuri et al., 2022; Long et al., 2024; Seifoddini et al., 2026), including the mean stress level:

$$\bar{MD} = \frac{1}{n}\sum_{t=1}^{n} M\,D_t \quad (6)$$

the linear trend slope:

$$MD_t = \alpha + \beta t + \epsilon_t \tag{7}$$

and model fit (coefficient of determination):

$$R^2 = 1 - \frac{\sum(MD_t - \widehat{MD}_t)^2}{\sum(MD_t - \bar{MD})^2} \tag{8}$$

These measures allow comparison of stress levels, trends, and consistency across regimes, providing evidence of structural shifts in electricity system dynamics.

2.6 Stress Persistence and Structural Lock-In

Even when average stress levels decline, vulnerability may remain structurally embedded rather than fully resolved. To capture this dynamic, stress persistence is evaluated by identifying consecutive years in which MD-UESI exceeds its historical median. The median is used as a robust threshold because it reflects the central tendency of the system while minimizing the influence of extreme values, making it suitable for distinguishing sustained stress conditions from temporary fluctuations(Diaz-Ramos et al., 2021) .

A Stress Persistence Index (SPI) is defined as:

$$SPI = \text{Number of consecutive years where } MD\text{-}UESI_t > \text{Median}(MD\text{-}UESI)$$

Long persistence periods indicate that stress is not episodic but structurally sustained, suggesting the presence of lock-in effects where infrastructure expansion does not fully eliminate system vulnerability(Shadkam et al., 2016). This condition is particularly relevant for interpreting results, as persistent stress above the median implies that improvements observed in trend analysis may reflect temporary relief rather than fundamental structural change. Therefore, SPI provides a complementary measure to trend and regime analysis by identifying whether reductions in stress translate into durable system resilience or remain confined within a structurally constrained regime.

2.7 Statistical Diagnostic Modeling

2.7.1 Lag-Based Diagnostic Modeling

To examine whether prior system conditions influence current electricity stress, lag-based regression models(Senatro Di Leo et al., 2020) are estimated using one-year lagged values of the component stresses. The composite stress index (MD-UESI) at time *t* is modeled as a function of supply stress, capacity stress, and network stress from the previous year:

$$MD_t = \alpha + \beta_1 S_{t-1} + \beta_2 C_{t-1} + \beta_3 N_{t-1} + \epsilon_t \tag{9}$$

This specification avoids circularity by predicting current stress from past conditions rather than contemporaneous variables. Lagged relationships are commonly used in infrastructure and energy studies to capture delayed system responses.

In addition, an autoregressive model(Paolella, 2018) of order one (AR(1)) is estimated:

$$MD_t = \alpha + \beta MD_{t-1} + \epsilon_t \quad (10)$$

The error term $\epsilon_t$represents unobserved influences such as policy changes, fuel supply disruptions, and climatic variability, which may cause deviations from the expected trend. Its direction and magnitude are not fixed, as shocks can either increase or decrease system stress depending on external conditions. This stochastic component allows the model to capture real-world uncertainty and short-term fluctuations beyond structural relationships. The AR model further assesses temporal persistence, indicating whether current stress levels depend strongly on their past values, consistent with standard applications in energy system analysis.

2.7.2 Binary Classification of Stress Regimes

MD-UESI values are categorized into two stress states to distinguish between relatively stable and structurally strained system conditions. The threshold is defined as:

1. High stress: MD-UESI ≥ 0.40
2. Low stress: MD-UESI < 0.40

The threshold value of 0.40 is selected based on the distribution of the normalized index, where values above this level indicate that multiple stress components simultaneously contribute to elevated system pressure rather than isolated or moderate conditions(T. Mede & Shawish, 2025). This cutoff therefore represents a transition point from moderate to structurally significant stress within the composite framework.

A probabilistic classification model based on lagged stress components is used to estimate the likelihood of entering a high-stress state(Lima et al., 2024). Model performance is evaluated using a confusion matrix and overall accuracy metrics. Such classification approaches are commonly applied to identify regime transitions and nonlinear system behavior in energy system analysis.

2.7.3 Scenario-Based Projection

Future trajectories of urban energy stress are explored using complementary deterministic and stochastic approaches to capture both structural dynamics and uncertainty(Esnil et al., 2024). First, a deterministic projection is derived from the estimated autoregressive relationship:

$$MD_t = \alpha + \beta MD_{t-1} \quad (11)$$

This formulation represents the expected evolution of MD-UESI under unchanged structural conditions, assuming that past system dynamics persist over time.

Second, a stochastic simulation is implemented to incorporate uncertainty by introducing random disturbances into the autoregressive framework following ***Eq.10***

where $\epsilon_t \sim N(0, \sigma^2)$, with variance σ^2estimated from the historical MD-UESI series. The assumption of normally distributed disturbances captures unobserved shocks such as demand variability, fuel constraints, and operational disruptions, while maintaining statistical

tractability(Kim, S., & Hur, 2020). Calibrating variance from observed data ensures that simulated fluctuations remain consistent with empirical system behavior.

These projections are not intended as precise forecasts but as scenario-based representations of potential future stress trajectories under baseline conditions. Such approaches are widely applied in energy system analysis where uncertainty and external shocks limit the reliability of deterministic forecasting.

2.8 Structural Framework of the Methodology

Fig. 1. shows the methodological steps followed for this study so that the concept and overall procedure can be easily understandable.

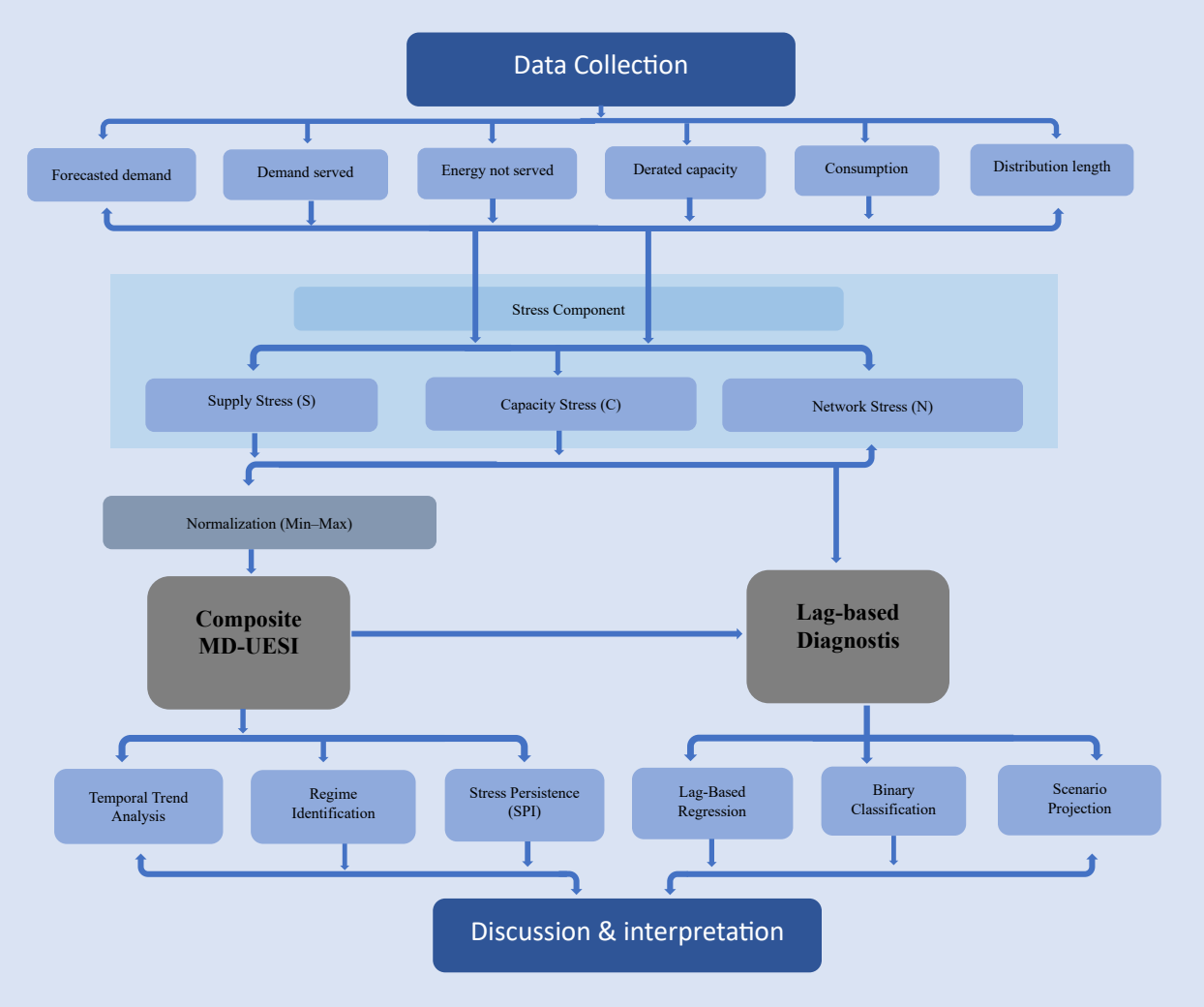


Fig. 1. Methodological workflow.

3. Results

3.1 Evolution of Multi-Dimensional Urban Energy Stress.

3.1.1 Evolution of Stress Components (Supply, Capacity, and Network)

Using ***Eq. 1. 2. 3.***, the temporal patterns of supply, capacity, and network stress indicate a clear structural transition in Bangladesh's electricity system over the study period (***Table 1***).

Supply stress shows a sharp shift from chronic inadequacy to near-elimination, followed by renewed pressure. It peaked at 0.443 in 2006–07 and remained elevated through 2011–12, then declined to ≤0.005 during 2016–17 to 2021–22, indicating effective reduction of shortages. However, it resurged to 0.223 in 2022–23 and remained elevated at 0.126 in 2023–24, evidencing renewed vulnerability.

Capacity stress declines steadily from full loading (≈1.000 in 2005–08) to 0.611 in 2023–24. After 2009–10 (0.874), it stabilizes around 0.74–0.77 (2010–15) and then decreases to 0.640–0.682 (2019–22), indicating improved reserve margins and reduced operational pressure.

Network stress increases persistently from 0.078 (2005–06) to 0.127 (2015–16), moderates slightly during 2016–20 (0.125–0.110), and rises again to its highest level of 0.133 in 2023–24. This pattern reflects growing throughput pressure relative to network expansion.

The system transitions from generation-constrained stress to infrastructure-driven pressure: reductions in supply and capacity stress are offset by rising network stress, while the post-2022 resurgence in supply stress indicates incomplete structural stabilization.

Table 1. Annual Values of Supply, Capacity, and Network Stress (2005–2024).

YEAR	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15
Supply Stress (S)	0.443	0.199	0.225	0.283	0.281	0.219	0.128	0.056	0.020
Capacity Stress (C)	1.000	1.000	0.806	0.874	0.737	0.748	0.754	0.769	0.715
Network Stress (N)	0.078	0.084	0.092	0.092	0.097	0.107	0.113	0.120	0.122
YEAR	**2015-16**	**2016-17**	**2017-18**	**2018-19**	**2019-20**	**2020-21**	**2021-22**	**2022-23**	**2023-24**
Supply Stress (S)	0.013	0.004	0.003	0.004	0.004	0.005	0.005	0.223	0.126
Capacity Stress (C)	0.768	0.742	0.711	0.699	0.640	0.648	0.682	0.647	0.611
Network Stress (N)	0.127	0.125	0.121	0.116	0.110	0.117	0.122	0.123	0.133

3.1.2 Composite MD-UESI Dynamics

The composite MD-UESI captures from normalization using ***Eq.4*** the integrated evolution of electricity system stress by combining supply, capacity, and network pressures (**Fig. 2.**). In the early phase (2005–06 to 2007–08), the index remains high, peaking at 0.667 in 2006–07, the maximum observed value, and declining slightly to 0.519 in 2007–08. This indicates a system operating under substantial structural pressure.

Between 2008–09 and 2013–14, MD-UESI shows a gradual decline, fluctuating within a narrow range (0.419–0.454). This period reflects the initial adjustment phase, where improvements in supply conditions begin to reduce overall stress, although variations indicate incomplete stabilization.

A more consistent decline is observed from 2014–15 onward. The index drops to 0.365 in 2014–15 and continues downward, reaching the minimum value of 0.218 in 2019–20. This represents the lowest stress level during the study period. Although the index rises moderately in 2020–21 (0.268) and 2021–22 (0.329), it remains below earlier levels, indicating relatively stable system conditions.

This pattern changes in 2022–23, when MD-UESI increases sharply to 0.472, followed by a slight decline to 0.427 in 2023–24. Despite this reduction, the index remains significantly higher than the minimum observed during 2018–2020, indicating a shift away from previously low stress conditions.

Following ***Eq. 5.***, the MD-UESI series shows three phases: high stress in the early years (2005–2011), gradual decline and stabilization (2012–2020), and a recent increase (2021–2024). These results indicate that while overall stress declined over time, recent values suggest a partial reversal of earlier improvements.

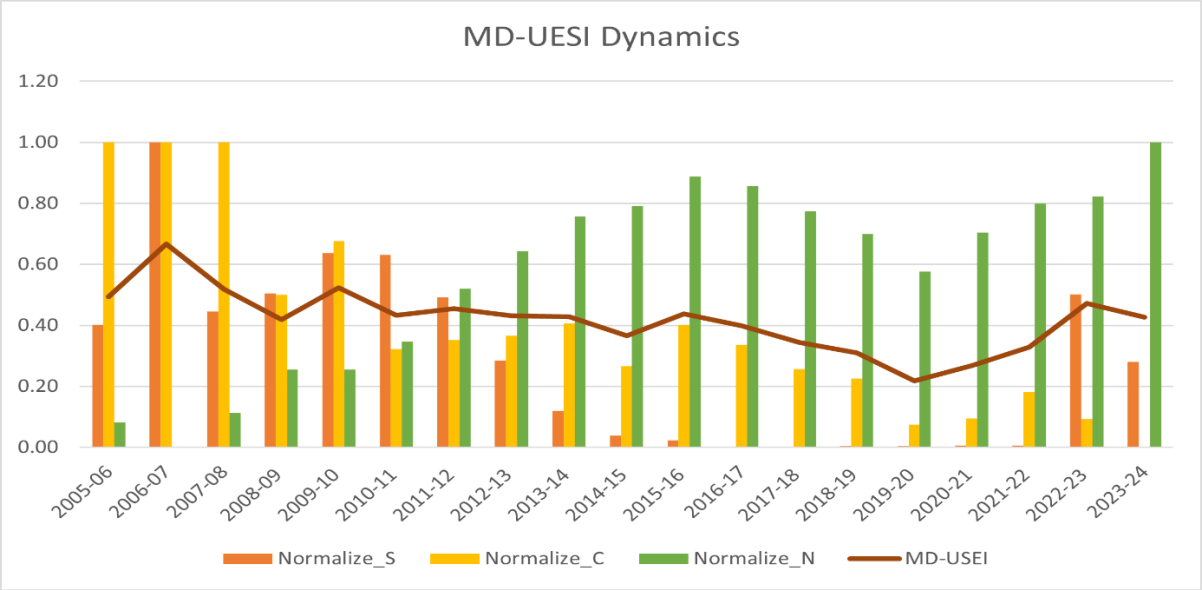


Fig. 2. Composite MD-UESI Dynamics (2005–2024).

3.2 Structural Implications for Growth, Regime Shifts, and Temporal Analysis

3.2.1 Growth Dynamics of Stress Components

The annual growth rates of supply, capacity, and network stress reveal distinct dynamic patterns that complement the level-based analysis and highlight structural adjustments in the system (***Fig. 3.***).

Supply stress exhibits the highest volatility. It increases sharply in 2006–07 (+147%), followed by a strong contraction in 2007–08 (−55%) and continued fluctuations in the early years. Between 2012–13 and 2016–17, sustained negative growth (−41% to −72%) reflects rapid improvement in supply adequacy. The sharp increase in 2022–23 (≈+4100%) is primarily due to a near-zero base in preceding years (≤0.005), meaning that a moderate absolute rise to 0.223 translates into a large percentage change. This represents a genuine system shock rather than a statistical anomaly. Although growth declined in 2023–24 (−43%), supply stress remained above pre-shock levels.

Capacity stress shows comparatively stable dynamics with a gradual downward trend. It declines notably in 2008–09 (−19%) and 2009–10 (−8%), followed by relatively small fluctuations within ±7%. Continued reductions through 2019–20 (−8%) and modest changes in recent years indicate steady improvement in reserve margins without abrupt shifts.

Network stress follows a persistent upward growth pattern. After a minor decline in 2006–07 (−5%), it increases consistently during 2007–08 to 2015–16 (typically +4% to +10%), indicating rising infrastructure pressure. A short period of decline occurs between 2016–17 and 2019–20 (−3% to −6%), but growth resumes after 2020–21 (+6% to +8%), reaching peak pressure by 2023–24.

Supply stress is characterized by episodic volatility, capacity stress by gradual structural improvement, and network stress by sustained upward pressure. These dynamics indicate that while generation-side conditions improved, infrastructure constraints continue to intensify, and system vulnerability remains sensitive to external shocks.



Fig. 3. Annual growth rate of supply stress (2006–2024). The spike in 2022–23 reflects a structural disruption in energy adequacy.

3.2.2 Structural Break and Regime Shift Analysis

To evaluate whether the electricity system experienced structural transformation rather than gradual adjustment, the MD-UESI series was examined across three regimes: pre-stabilization (2005–06 to 2013–14), stabilization (2014–15 to 2021–22), and shock reconfiguration (2022–23 to 2023–24).

Following ***Fig. 4.***, Regime I exhibits the highest average stress level, with a mean MD-UESI of 0.486. The estimated trend slope is moderately negative ($\beta = -0.0181$), while the coefficient of determination remains relatively low ($R^2 = 0.397$), indicating limited trend consistency during the early period. This phase is characterized by persistently elevated stress values and relatively unstable adjustment dynamics.

A substantial shift is observed in Regime II, where the mean MD-UESI declines to 0.334, representing a reduction of approximately 31% compared to Regime I. The trend slope becomes slightly steeper ($\beta = -0.0200$), and the explanatory fit improves ($R^2 = 0.488$), indicating a more consistent downward trajectory. Compared with the earlier regime, stress values during this period remain comparatively lower and less volatile.

Regime III shows a renewed increase in stress conditions, with the mean MD-UESI rising to 0.450, approaching the average level observed during Regime I. Although the estimated slope appears strongly negative ($\beta = -0.0453$), this result is not statistically meaningful because the regime contains only two observations. Similarly, the R^2 value of 1.000 is mechanical and reflects insufficient sample size rather than explanatory strength.

The regime-based comparison identifies clear shifts in average stress level and trend behavior across the three periods following by ***Eq. 6. 7. 8***.

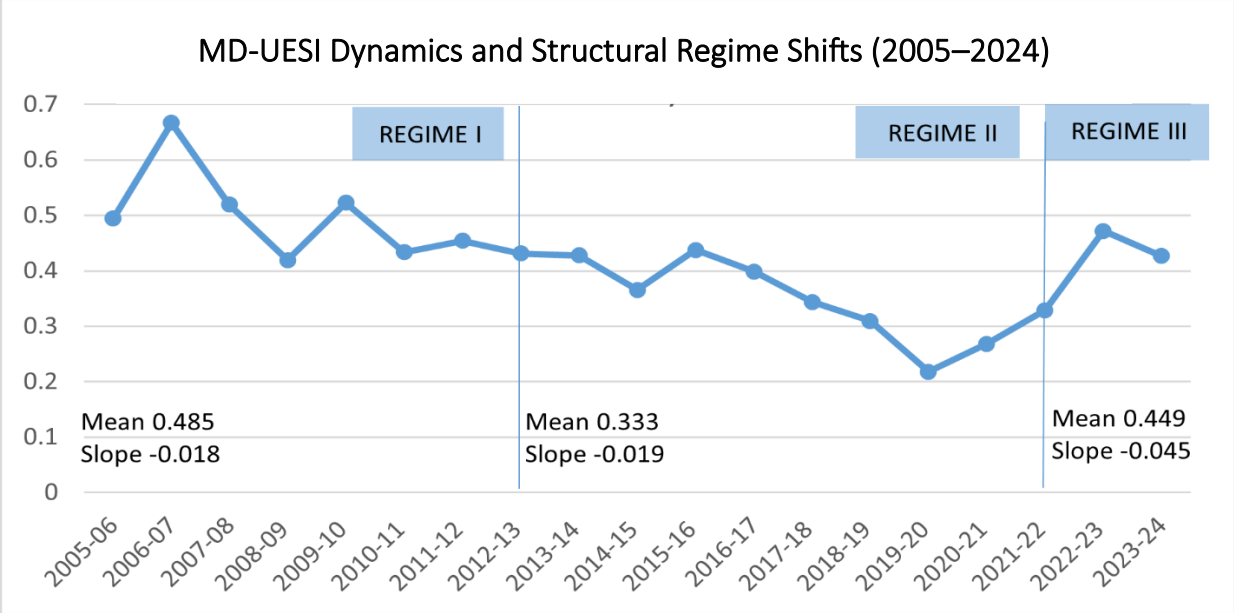


Fig. 4. Structural Regime Shifts of Composite MD-UESI Dynamics (2005–2024).

3.2.3 Stress Persistence and Vulnerability Reconfiguration

Stress persistence analysis derived from ***Fig. 4.*** and summarized in ***Table 2.*** identifies distinct phases of sustained stress behavior in the MD-UESI series. During the early period (2005–06 to 2013–14), MD-UESI remained consistently above the 0.40 threshold, indicating prolonged high-stress conditions. A transition occurs after 2014–15, with the index declining below 0.40 and remaining within the low-stress range for five consecutive years between 2017–18 and 2021–22.

During this period, MD-UESI decreased from 0.344 in 2017–18 to the minimum observed value of 0.218 in 2019–20, before moderately increasing to 0.268 in 2020–21 and 0.329 in 2021–22.

The persistence phase ended in 2022–23, when MD-UESI increased sharply to 0.472, followed by a slight decline to 0.427 in 2023–24. This shift marks the re-emergence of stress conditions after the longest continuous low-stress episode observed during the study period.

Across regimes, reductions in composite stress were primarily associated with declining supply and capacity pressure, while network stress remained comparatively elevated during the later period.

Table 2. Stress Persistence Episodes Based on MD-UESI Dynamics.

Phase	Years	Duration	Condition
High-stress persistence	2005–2014	10 years	MD-UESI > 0.40
Low-stress persistence	2017–2021	5 years	MD-UESI < 0.40
Re-escalation phase	2022–2024	2 years	MD-UESI rising

3.2.4 Temporal Analysis of Stress Dynamics

Based on the descriptive statistics presented in ***Table 3***, supply stress exhibits the highest temporal variability among all components, with a standard deviation of 0.1298 and a coefficient of variation (CV) of 1.018. The CV exceeding 1 indicates that fluctuations in supply stress are larger than its mean value (0.127), reflecting substantial year-to-year instability relative to other stress dimensions.

Table 3. Descriptive Statistics of Stress Components and MD-UESI.

Component	Mean	Std. Deviation	Coefficient of Variation
Supply Stress (S)	0.127	0.1298	1.018
Capacity Stress (C)	0.765	0.1212	0.158
Network Stress (N)	0.109	0.0167	0.153
MD-UESI	0.417	0.1014	0.243

Capacity stress shows comparatively lower variability, with a standard deviation of 0.1212 and a CV of 0.158 around a mean value of 0.765. Although the absolute variation is similar to supply stress, its relative variability remains substantially lower due to the consistently higher capacity stress level across the study period.

Network stress records the lowest dispersion, with a standard deviation of 0.0167 and a CV of 0.153, indicating relatively stable short-term variation despite gradual long-term increases. The composite MD-UESI shows moderate variability, with a standard deviation of 0.1014 and a CV of 0.243 around a mean of 0.417, positioning overall system stress between the highly volatile supply dimension and the comparatively stable capacity and network components.

3.3 Statistical Diagnostic Modeling

3.3.1 Lag-Based Predictive Model (Regression)

To evaluate temporal persistence in urban energy stress, an autoregressive regression model was estimated using lagged MD-UESI (MD_{t-1})as the predictor of current MD-UESI (MD_t). The estimated model is (***Eq. 9.***):

$$MD_t = 0.323 + 0.239MD_{t-1}$$

The regression coefficient for lagged stress is positive ($\beta = 0.239$), indicating that higher stress in the previous year is associated with higher current stress. However, the explanatory strength of the model remains limited, with an R^2value of 0.108, meaning that approximately 10.8% of the variation in current MD-UESI is explained by its lagged value (Figure 5).

The scatter distribution further shows substantial dispersion around the fitted regression line. Several observations with similar lagged values correspond to notably different current stress levels, particularly during the transition and shock periods. For example, despite moderate lagged values during 2021–22 ($MD_{t-1} = 0.329$), the index increased sharply to 0.472 in 2022–23.

The intercept value ($\alpha = 0.323$)indicates the presence of a baseline stress level within the system independent of temporal carry-over effects.

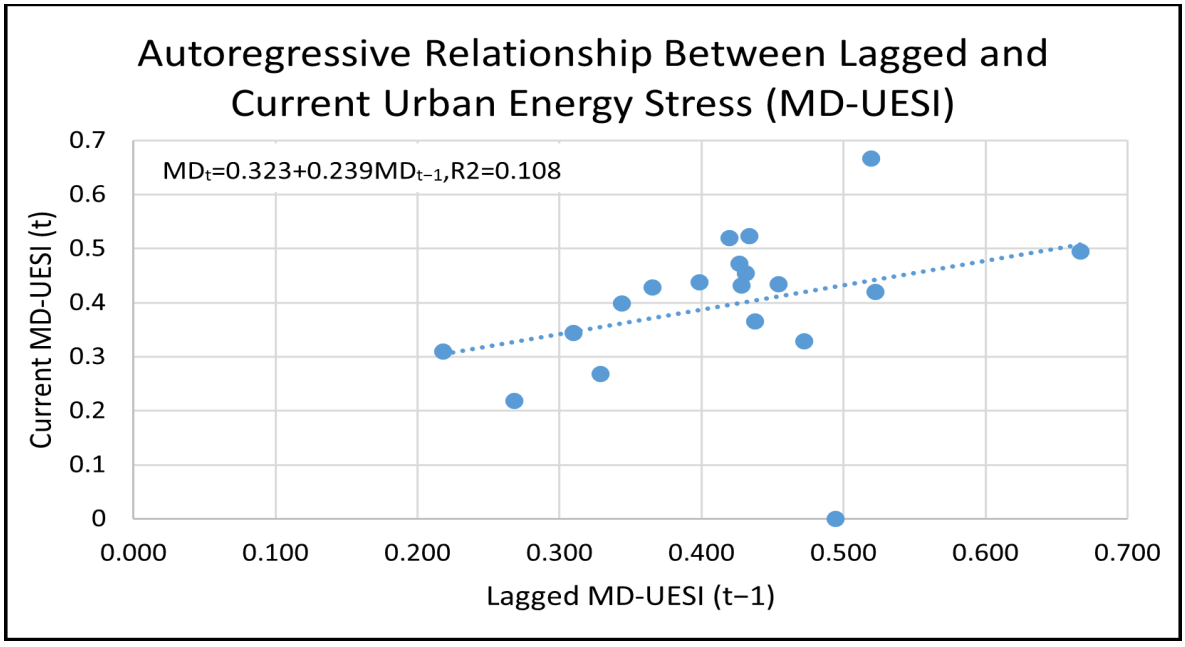


Figure 5. Autoregressive Relationship Between Lagged and Current Urban Energy Stress (MD-UESI).

3.3.2 Binary Stress Classification Model and Performance Evaluation

The binary stress classification model was evaluated using a confusion matrix and predictive accuracy metrics (***Table 4***). Based on the threshold condition ($MD\text{-}UESI \geq 0.40$), the model correctly identified 3 high-stress years as true positives (TP) and 7 low-stress years as true negatives (TN). No false positives (FP = 0) were observed, indicating that the model did not incorrectly classify any low-stress year as high stress. However, 9 high-stress years were classified as low stress (FN = 9), showing limited sensitivity in detecting elevated stress conditions. Overall classification accuracy reached 52.63%, indicating moderate predictive performance with stronger identification of low-stress conditions than high-stress episodes.

Table 4. Confusion Matrix of the Binary Stress Classification Model.

	Predicted High	**Predicted Low**
Actual High	3 (TP)	9 (FN)
Actual Low	0 (FP)	7 (TN)

Denoted by: TP (true positive), FN (false negative), FP (false positive), TN (true negative)

In the other side, ***Figure 6*** compares observed and predicted stress regimes over the 2005–2024 period. Observed stress states show prolonged high-stress conditions during the early years and renewed stress in 2022–24, whereas predicted regimes identify only a limited number of high-stress episodes, mainly during 2006–09. From 2010 onward, most years were classified as low stress despite several observed high-stress conditions. The visual comparison highlights the divergence between observed and predicted stress regimes, particularly during transitional and shock periods.

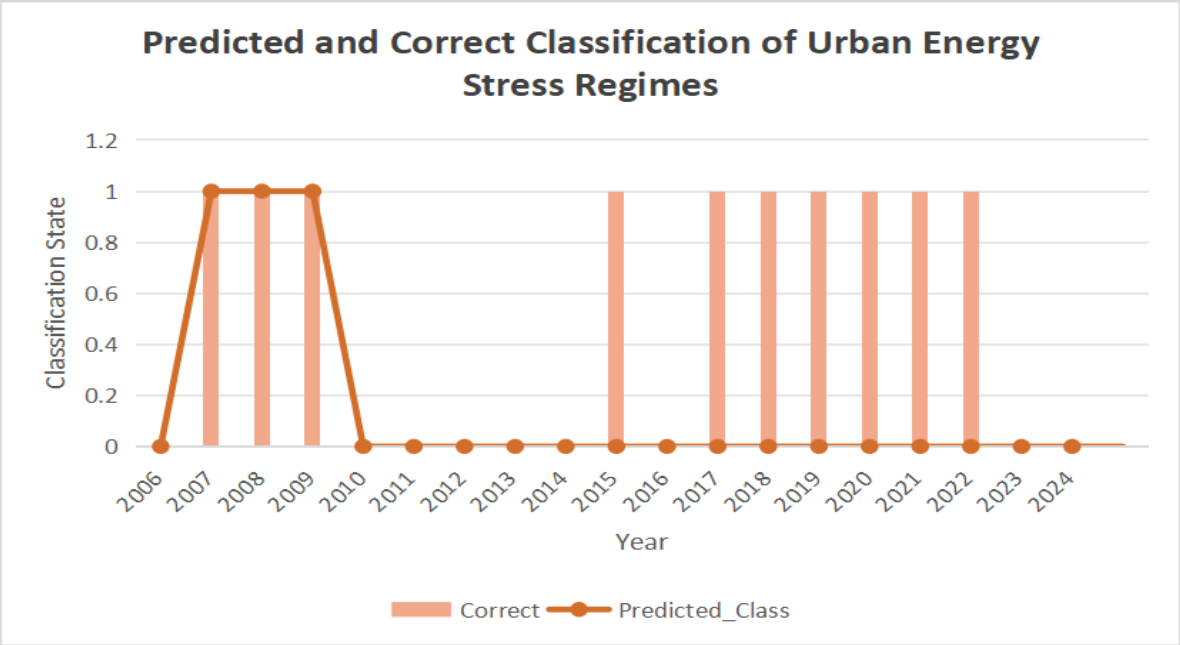


Figure 6. Observed and Predicted Urban Energy Stress Regimes (2005–2024).

3.3.3 Scenario-Based Projection of Future Urban Energy Stress

Future MD-UESI trajectories were explored using a stochastic baseline projection (***Eq. 10.***) integrating the autoregressive relationship with random disturbances derived from the historical standard deviation ($\sigma \approx 0.10$)(***Figure 7***). Unlike the deterministic autoregressive model, the stochastic simulation produces fluctuating future stress values, allowing temporal variability and uncertainty to persist throughout the projection period.

The projected series indicates substantial year-to-year variation between 2024–25 and 2033–34. The lowest projected stress value occurs in 2027–28 ($MD\text{-}UESI = 0.136$), while the highest value is observed in 2030–31 ($MD\text{-}UESI = 0.574$). Intermediate fluctuations are also evident, including moderate increases in 2024–25 (0.257), 2028–29 (0.358), and 2029–30 (0.385), followed by a sharp escalation after 2030.

Compared to the relatively smooth decline observed in the deterministic autoregressive model, the stochastic projection exhibits continuous deviation around the long-term trend line, indicating that future stress conditions may remain dynamically unstable under baseline system conditions. The projected variability remains within the approximate historical stress range observed during 2005–2024, suggesting continuity of structural uncertainty in the electricity system.

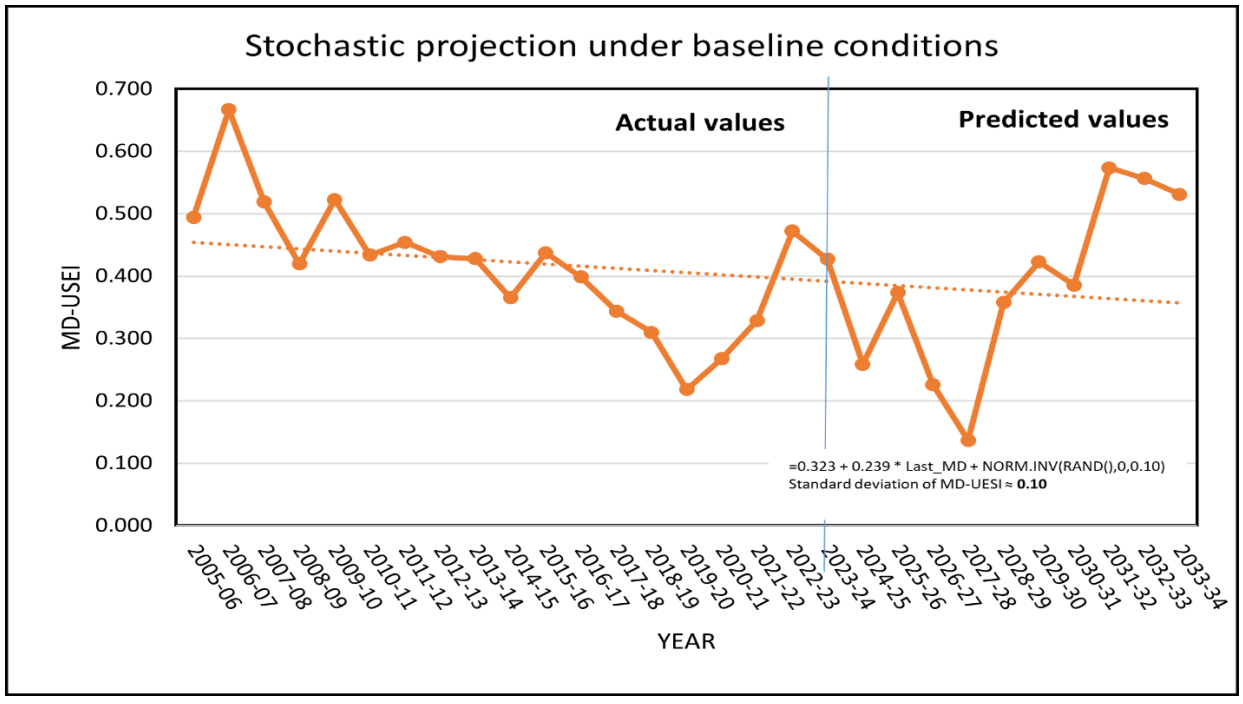


Figure 7. Stochastic Projection of Future MD-UESI Under Baseline Conditions (2024–2034).

3.4 Stress Persistence and Structural Lock-In

Stress persistence was evaluated using the Stress Persistence Index (SPI), calculated from consecutive years where MD-UESI exceeded the historical median threshold (0.428). ***Figure 8*** shows the temporal distribution of persistence intensity across the study period.

The SPI values indicate that the strongest persistence phase occurred during 2009–10 to 2012–13, where stress remained continuously above the threshold for four consecutive years ($SPI = 4$), representing the highest persistence level observed in the series. Another sustained high-stress phase occurred during 2005–06 to 2007–08, reaching a maximum SPI value of 3. In contrast, several isolated years such as 2008–09, 2015–16, and 2022–23 recorded only single-year persistence episodes ($SPI = 1$).

The lowest SPI value ($SPI = 0$)dominates the post-2013 period, particularly between 2013–14 and 2021–22, indicating prolonged interruption of consecutive high-stress conditions. During this interval, MD-UESI remained consistently below the median threshold.

Overall, the SPI distribution demonstrates a clear reduction in persistent high-stress clustering after the early study period, with later years characterized mainly by non-persistent or isolated stress episodes.

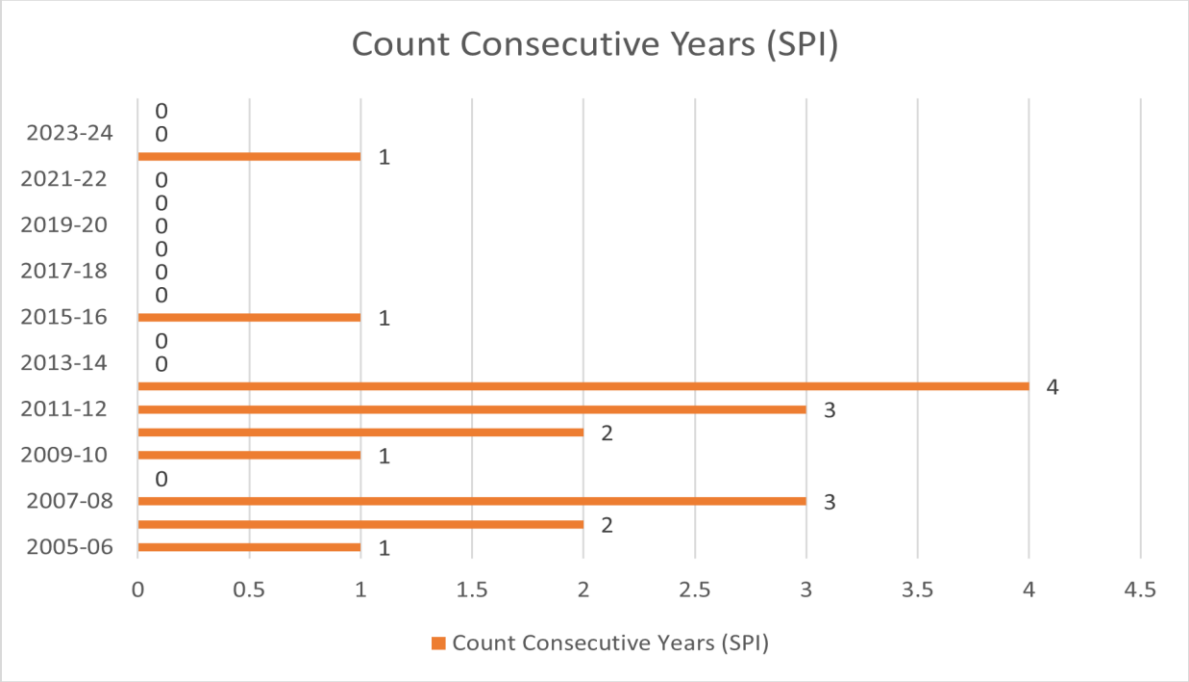


Figure 8. Stress Persistence Phases Based on the Stress Persistence Index (SPI).

4. Discussion

The results indicate that Bangladesh's electricity system experienced a major structural transformation during the study period. Supply stress declined sharply from 0.443 in 2006–07 to near-zero levels during 2016–2022, while capacity stress decreased from 1.000 during 2005–08 to 0.611 in 2023–24 (***Table 1.***). These improvements correspond with rapid generation expansion, rental power integration, increased installed capacity, and national electrification programs implemented after the 2010 Power Sector Master Plan(Chowdhury et al., 2025). However, network stress increased steadily from 0.078 to 0.133, indicating that distribution infrastructure expansion did not fully match rising electricity consumption. This imbalance explains why temporal analysis identified supply stress as the dominant source of instability, while network stress accumulated gradually as a long-term structural pressure (***Table 3.***).

The composite MD-UESI revealed three major phases in the evolution of Bangladesh's urban electricity system: chronic high stress (2005–2011), stabilization and structural improvement (2012–2020), and renewed stress escalation (2021–2024) (***Figure 3.***). The decline in composite stress after 2014 reflects the effectiveness of generation-side expansion, whereas the recent increase indicates that structural vulnerability has not been fully eliminated.

Growth dynamics further clarify the regime transitions observed in the system (***Figure 2.***). The persistent negative growth of supply stress after 2012 reflects rapid expansion of generation capacity and improved reserve margins. This contributed directly to the stabilization transition around 2014–15, when MD-UESI entered a prolonged low-stress phase. Between 2017 and 2021, the index remained below 0.40 for five consecutive years, indicating comparatively stable operating conditions (***Table 6.***). In contrast, high-stress persistence dominated the 2005–2014 period, when supply shortages and capacity limitations remained structurally embedded. The sharp growth shock in 2022–23 was likely associated with global fuel price volatility, LNG import constraints, and post-pandemic energy market disruptions, which reintroduced supply inadequacy despite earlier stabilization(Jian Xu et al., 2022). This abrupt reversal contributed to the second regime shift identified in the structural break analysis.

The lag-based regression and classification models provide additional insight into the dynamic behavior of urban energy stress (***Figure 5.***). The weak autoregressive relationship ((R^2 = 0.108)) suggests that current stress conditions are not determined primarily by previous-year stress levels, but rather by structural interventions and external shocks. Similarly, the binary classification model identified low-stress years more effectively than high-stress years because the stabilization period after 2014 produced relatively consistent low-stress conditions. In contrast, high-stress episodes were more episodic and irregular. The scenario-based stochastic projection further demonstrates the importance of historical standard deviation in representing uncertainty within future stress trajectories (**Figure 7.**). The projected fluctuations indicate that stress instability may persist under unchanged structural conditions.

The SPI analysis confirms that high-stress conditions were strongly clustered during the early years of the electricity transition, particularly between 2005–2014 (***Figure 8.***). The reduction of consecutive high-stress episodes after 2014 indicates that large-scale capacity expansion

contributed to measurable structural stabilization. Nevertheless, the re-emergence of stress after 2022 demonstrates that stabilization remains vulnerable to infrastructure limitations and external disruptions. Collectively, the findings show that electricity stress in Bangladesh has shifted from generation inadequacy toward broader infrastructure and system-management challenges. This transition suggests that capacity-led expansion alone is insufficient for long-term urban energy resilience unless accompanied by synchronized investment in transmission efficiency(M. Hasan, 2026), distribution modernization, and adaptive system management(Chowdhury et al., 2025). At the national level, this study provides an integrated framework for evaluating multidimensional electricity stress beyond traditional adequacy measures. Future research may extend this framework using district-level datasets, climate-sensitive demand variables, smart-grid indicators, and higher-frequency operational data to better capture localized and short-term stress dynamics.

5. Conclusion

The evolution of stress components demonstrates that Bangladesh's electricity system experienced substantial structural change during 2005–2024. Supply stress declined sharply from chronic shortage conditions to near-zero levels after 2016, while capacity stress gradually decreased with improved reserve margins. In contrast, network stress increased steadily over time. The composite MD-UESI confirms a transition from severe multidimensional stress toward a relatively stabilized phase before renewed stress escalation after 2022. These findings indicate that electricity system improvement was uneven across infrastructure dimensions. The results also demonstrate that generation expansion alone cannot fully represent overall system resilience. The MD-UESI framework therefore provides a more integrated perspective for evaluating structural electricity stress in rapidly urbanizing economies. Overall, the findings indicate that generation-side expansion substantially improved electricity system performance but did not fully eliminate systemic vulnerability.

The structural break and persistence analyses further reveal that the electricity system evolved through three distinct phases: chronic high stress, stabilization, and renewed reconfiguration. Stress persistence remained dominant during 2005–2014, whereas the 2017–2021 period represented the longest continuous low-stress phase. However, the abrupt increase in stress after 2022 indicates that stabilization remained conditionally vulnerable to external disruptions and infrastructure pressure. The regime analysis highlights that structural transitions occurred gradually rather than instantaneously. Persistence results further confirm that system stabilization was measurable but not permanently secured. These findings emphasize the importance of balanced investment across generation, transmission, and distribution systems for long-term urban energy resilience.

The diagnostic models provide additional evidence regarding the dynamic behavior of urban energy stress. The weak autoregressive relationship and moderate classification accuracy indicate that stress conditions are influenced more by structural interventions and external shocks than by simple temporal persistence. Similarly, the SPI analysis confirms that persistent high-stress clustering weakened substantially after large-scale capacity expansion. The stochastic projection further suggests that future stress conditions may remain unstable under unchanged structural conditions. This highlights the continuing uncertainty embedded within the electricity system

despite previous improvements. The study also demonstrates the usefulness of combining composite indices, persistence diagnostics, and scenario-based analysis within a single framework. Two limitations should be acknowledged. First, the study relies on annual national-level data, which may not fully capture seasonal or regional variations in electricity stress. Second, the absence of long-term network efficiency and outage-frequency datasets limited direct measurement of distribution performance. Despite these limitations, the study develops a comprehensive multidimensional framework for evaluating electricity system stress and provides important insight into the evolving structural dynamics of Bangladesh's urban energy system.

As a non-native English researcher, QuillBot was used solely for grammar enhancement and sentence structure polishing during manuscript preparation. All scientific interpretations, analyses, and conclusions presented in this study are entirely the author's own work.

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