CPD Working Paper 158

Forecasting Annual Peak Electricity Demand in Bangladesh

A Non-Stationary GEV Approach

Atikuzzaman Shazeed
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CENTRE FOR POLICY DIALOGUE

FORECASTING ANNUAL PEAK ELECTRICITY DEMAND IN BANGLADESH

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The present paper titled ***Forecasting Annual Peak Electricity Demand in Bangladesh: A Non-Stationary GEV Approach*** has been authored by Mr Atikuzzaman Shazeed, Research Associate, CPD (shazeed@cpd.org.bd); Mr Abrar Ahammed Bhuiyan, Research Associate, CPD (abrar@cpd.org.bd); and Dr Khondaker Golam Moazzem, Research Director, CPD (moazzem@cpd.org.bd).

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Abstract

Accurate peak demand forecasting is critical for power planning as underestimation leads to blackouts and load shedding, while overestimation results in stranded capital and inflated tariffs. Yet common approaches, deterministic extrapolation, machine learning, and time-series models, are ill-suited to small, non-stationary, data-constrained settings typical of developing economies. This paper develops a non-stationary Generalized Extreme Value (GEV) framework for forecasting annual peak electricity demand, in which the location parameter evolves linearly with time to capture systematic trends in extremes. To address the well-documented instability of shape-parameter estimation in small samples, we adopt a hybrid two-step strategy: the shape parameter is estimated via L-moments for robustness, while trend and scale parameters are estimated via maximum likelihood. Projection uncertainty is quantified through non-parametric bootstrap resampling. Applied to 31 years of annual peak demand data from Bangladesh, the model identifies a statistically significant upward trend and generates T-year return level projections through 2050, with bootstrap-derived 95 per cent confidence intervals. The resulting central estimates are substantially lower than existing official projections, which rely on deterministic extrapolation without uncertainty bounds. This study offers the first application of non-stationary extreme value theory to long-run electricity demand planning, providing a statistically defensible, transferable, and uncertainty-aware methodology for capacity planning in small-sample, data-constrained developing-country contexts.

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Acronyms

ADF	Augmented Dickey-Fuller (test)
AIC	Akaike Information Criterion
BPDB	Bangladesh Power Development Board
CDF	Cumulative Distribution Function
DF-GLS	Dickey-Fuller Generalized Least Squares (test)
EVT	Extreme Value Theory
FFT	Fast Fourier Transform
GDP	Gross Domestic Product
GEV	Generalized Extreme Value (distribution)
GRU	Gated Recurrent Unit
GW	Gigawatt
IEPMP	Integrated Energy and Power Master Plan
KPSS	Kwiatkowski-Phillips-Schmidt-Shin (test)
LSTM	Long Short-Term Memory (network)
MAPE	Mean Absolute Percentage Error
MLE	Maximum Likelihood Estimation
MW	Megawatt
QQ	Quantile-Quantile
VECM	Vector Error Correction Model

1 INTRODUCTION

For planning optimal level of future generation, transmission infrastructure, and reserve margin, having a robust long-term forecast of electricity demand is essential as it helps mitigating the risks associated with underinvestment and excess capacity. Overestimation of future demand can lead to excessive investment and underutilised infrastructure. On the contrary, underestimation results in a system that cannot keep up with the demand, causing power cuts and blackouts (Prosper O. Ugbehe, 2025). Besides, because of fast changes in the power systems in terms of increasing electrification and renewable energy integration, uncertainty has risen greatly about future electricity demand and power system planning (Zhou et al., 2026). Therefore, the forecasting approaches that account for uncertainty have increasingly gained importance for ensuing robust and cost-effective planning for the power systems (Haugen et al., 2023; Wang et al., 2023).

While most of the existing forecasting approaches are good at predicting the average level of electricity demand, they provide limited information about the occurrence and magnitude of rare demand extremes (Jacob et al., 2020). However, long-term system planning is constrained by the expected future annual peak demand rather than average consumption (Hu et al., 2026). The peak demand determines the generation capacity, transmission capability, and reserve margin required to maintain the stability of the system. As such, forecasting frameworks that model probabilistic behaviour of extreme demand events need to be applied.

For studying long-term peak electricity demand, Bangladesh emerged as a timely case. Over the past decades, the country has experienced sustained economic growth (Beyer & Wacker, 2024). At the same time, rapid urbanisation, industrial expansion and improvement in the access of electricity took place (Mahbub, 2024; Panday, 2020; Rahman et al., 2021), increasing continuous pressure on the electricity demand and generation capacity (Akter et al., 2024). Furthermore, it is also targeting ambitious objectives in terms of energy transition which also poses uncertainty resulting from technological shifts and changing electricity consumption patterns (Moazzem & Shazeed, 2025; Lindberg et al., 2019). Therefore, in such circumstances, the need for long-term forecasting becomes indispensable.

Despite progress made in predicting electricity demand, there are some inherent weaknesses (Dai et al., 2021). Current forecasting models, which include statistical, econometric and machine learning models, have been developed to predict either the average or expected electricity demand rather than modeling the stochastic nature of rare annual peaks of electricity demand (Dai et al., 2026; Jacob et al., 2020). Moreover, many of these models make assumptions about stationarity of the data or they require huge amounts of high-frequency data (Haggag et al., 2026; Kuster et al., 2017; Yu & Tang, 2025) and thus become inapplicable in predicting the annual peak electricity demand because of data scarcity and the frequent occurrence of structural change in the system under consideration (Azeem et al., 2022).

Extreme Value Theory (EVT) provides a statistical model for predicting rare events through direct characterisation of the tail behaviour of a distribution (Coles, 2001). Generalized Extreme Value (GEV) distribution can be used for modelling rare annual peaks of electricity demand and deriving return levels from this distribution (Maheshwari et al., 2019). In addition, the non-stationary GEV distribution can incorporate evolving demand patterns into the model through time (Kyojo et al., 2024; Panagoulia et al., 2026). The EVT has been widely used in hydrology, financial risk management and climate science (Jayaweera et al., 2025; Lin et al., 2024). To the best of our knowledge, no existing literature uses non-stationary GEV distribution to predict annual peaks of electricity demand in Bangladesh.

This study seeks to address this gap by developing a non-stationary GEV model based on annual peak electricity demand data for Bangladesh spanning the period 1995–2025. A hybrid estimation strategy, combining L-moments and maximum likelihood estimation, is employed to enhance the reliability of parameter estimation under limited sample size, while bootstrap confidence intervals are used to quantify the associated forecast uncertainty. By generating probabilistic return-level forecasts, the proposed framework provides a risk-informed basis for long-term generation planning and complements conventional electricity demand forecasting methods.

2. LITERATURE REVIEW

2.1 Electricity Demand Forecasting Approaches

Various statistical, econometric and machine learning approaches have been applied to the studies of electricity demand (Ghalehkhondabi et al., 2017). The choice of a particular method relies on the data nature, availability, and forecasting period. For the ability to capture structural relationships between electricity demand and economics variables, and interpretability, traditional time-series and econometric models are employed (Khuntia et al., 2016). Moreover, because of their ability to capture complex non-linear relationships and reduce forecasting errors, machine learning models have recently emerged as a popular method (Ghalehkhondabi et al., 2017) .

Recent studies in the context of Bangladesh have applied machine learning techniques including Long Short-Term Memory (LSTM) networks and FB-Prophet models to short- and medium-term electricity demand. Islam et al. (2025), using such models with weather and macroeconomic variables to forecast electricity demand, found improved predictive accuracy over short forecasting horizons. However, these models are not directly applicable to long-term annual peak demand forecasting (Hyndman & Fan, 2010). Similarly, multivariate error-correction models such as VECM have been applied to forecast long run national energy demand for Bangladesh (Quaiyyum & Moazzem, 2024). Annual peak electricity demand, however, is a series of block maxima rather than continuous stochastic process. Therefore, its statistical properties differ fundamentally from those assumed by conventional time-series models (Li & Jones, 2020; Wilson & Zachary, 2019).

Overall, existing forecasting approaches have substantially improved electricity demand prediction across different forecasting horizons. However, most studies continue to focus on estimating expected electricity demand rather than explicitly modelling the probabilistic behaviour of annual peak demand, which is of primary importance for long-term generation and transmission planning (Hyndman & Fan, 2010; Wilson & Zachary, 2019).

2.2 Applications of Extreme Value Theory in Electricity Demand Forecasting

Although Extreme Value Theory (EVT) has been widely applied in disciplines such as hydrology, finance, and climate science, its application to electricity demand forecasting remains relatively limited. Existing studies nevertheless demonstrate that EVT provides a robust framework for modelling annual peak electricity demand and supporting long-term infrastructure planning. Hor et al. (2008) were among the first to apply the block maxima approach to long-term electricity load forecasting under climate non-stationarity, showing that EVT-based models effectively characterise the tail behaviour of electricity demand. Subsequently, Li & Jones (2020) proposed a non-stationary Generalized Extreme Value (GEV) framework for modelling annual maximum substation electricity demand and highlighted the limited use of EVT in electricity demand forecasting despite its suitability for utility planning. Sigauke & Chikobvu (2012) extended this line of work to a developing-country setting, applying a non-stationary peaks-over-threshold approach to model daily peak electricity demand in South Africa using temperature as a time-varying covariate.

Collectively, these studies suggest that EVT is both theoretically sound and practically useful for modelling electricity demand extremes. However, compared with conventional statistical, econometric, and machine learning approaches, empirical applications of EVT remain relatively scarce and have largely focused on developed countries. Consequently, evidence on the use of non-stationary EVT models for long-term annual peak electricity demand forecasting in developing countries remains limited, motivating further research in this area.

2.3 Research Gap

The existing literature highlights several important gaps. First, the majority of electricity demand forecasting studies focus on estimating expected or average electricity demand rather than modelling the probabilistic behaviour of annual peak demand. Second, although EVT has demonstrated considerable potential for analysing electricity demand extremes, its application remains relatively limited compared with conventional forecasting approaches and has been concentrated primarily in developed-country settings. Third, existing forecasting studies in Bangladesh have focused predominantly on short- and medium-term operational forecasting, with little attention devoted to long-term annual peak demand as an extreme value process.

To the best of our knowledge, no previous study has employed a non-stationary GEV framework to forecast annual peak electricity demand in Bangladesh. Addressing this gap, the present study develops a non-stationary GEV model using annual peak electricity demand observations from 1995 to 2025. By explicitly modelling the evolution of demand extremes and quantifying uncertainty through return-level estimation, the proposed framework complements conventional forecasting approaches and provides a probabilistic basis for long-term generation planning and infrastructure investment.

3. DATA AND METHODOLOGY

3.1 Data

The data utilised in this study comprises annual peak demand of Bangladesh in MW from 1995 to 2025. The data was collected from Bangladesh Power Development Board (BPDB) through official administrative procedures.

The variable of interest, the total annual peak demand, is constructed as a sum of (i) the maximum served load and (ii) the corresponding load shedding observed at the time of the annual system peak each year. This adjustment is necessary because recorded peak demand in Bangladesh often reflects supply constraints rather than true underlying demand. By incorporating load shedding, the series better approximates the total annual peak demand.

Table 1: Summary Statistics of Annual Peak Electricity Demand (1995–2025)

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Annual Peak Demand (MW)	31	7709.71	5365.49	1970.00	17200.00

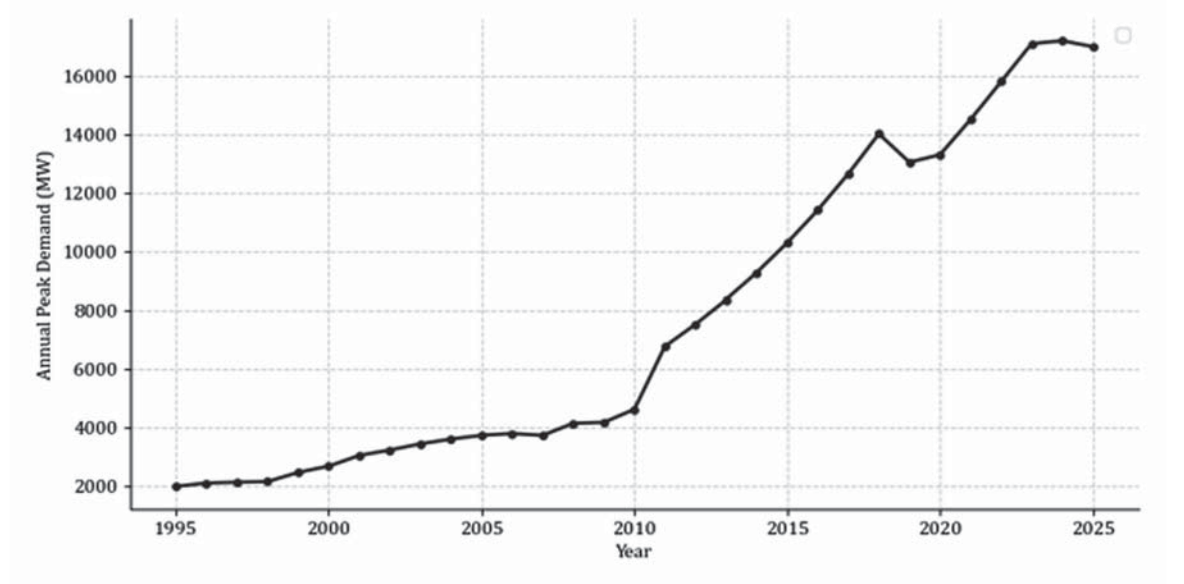
Source: Authors' estimation.

Table 1 shows summary statistics of annual peak electricity demand in Bangladesh. The annual peak demand increased from 1,970 MW to 17,200 MW over the last 31 years.

3.2 Preliminary Data Analysis

Figure 1 depicts historical annual peak demand of Bangladesh since 1995. It followed a strong upward trend over the last three decades, and the growth accelerated after 2010. The highest annual peak demand of 17,200 MW was observed in 2024.

Figure 1: Historical Annual Peak Electricity Demand in Bangladesh (1995–2025)



Source: Authors' illustration.

Table 2 shows the unit root test annual peak demand. The Augmented Dickey–Fuller and DF-GLS tests fail to reject the null hypothesis of a unit root at the 1%, 5%, and 10% significance levels. In contrast, the KPSS test rejects the null hypothesis of stationarity. These results consistently indicate that the series, annual peak demand, is non-stationary.

Table 2: Unit Root and Stationary Test Results

Test	Constant	Constant and Trend
ADF	1.7433	-1.7435
DF-GLS	-0.7189	-1.3322
KPSS	0.8266***	0.2070**

Source: Authors' estimation.

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.3 Model Selection

Machine learning and deep learning models, including Long Short-Term Memory (LSTM)networks, Gated Recurrent Units (GRUs), and related architectures, have demonstrated strong performance in short-and medium-term forecasting tasks where dense, high-frequency data are available. However, such models are highly data-dependent: deep learning models usually need more than 50,000 training examples and records of several years at high frequency to be able to find meaningful patterns without overfitting (Soham Navale, 2025). The Bangladesh annual peak demand data consists of 31 values from 1995 to 2025. In order to build a machine learning model based on this data, one would necessarily create an over-parameterised model with high in-sample fit but low out-of-sample predictive power, which is well known to happen in limited data cases (Abdul Wahab, 2020).

Spectral analysis using the Fast Fourier Transform (FFT) is designed to decompose a time series into its constituent frequency components, making it appropriate for identifying cyclical and seasonal patterns in dense, regularly sampled signals such as hourly or daily electricity load data (Scargle, 1982). Annual peak demand is recorded once per year, yielding a series with no sub-annual periodicity to decompose.

Applying FFT to 31 annual observations would produce a periodogram with insufficient resolution to identify any reliable cyclical structure, as the Nyquist frequency for annual data limits detectable cycles to periods of two years or longer. Moreover, FFT assumes stationarity, an assumption that unit root tests on Bangladesh's peak demand series reject, further rendering spectral decomposition inappropriate.

The Vector Error Correction Model (VECM) is a multivariate time series tool designed to model long-run equilibrium relationships among cointegrated I(1) variables. With only 31 annual observations, there is insufficient data to identify the lag structure and error correction parameters with statistical reliability, a degrees-of-freedom problem well-recognised in the VECM literature (Lütkepohl, 2005). Treating the annual peak as though it were generated by a VECM-type data-generating process is therefore a category error (Niko Hauzenberger, 2020).

As a result of the shortcomings associated with conventional forecasting methods and the features inherent to the dataset at hand, the model to forecast annual peak electricity demand employs the non-stationary Generalized Extreme Value (GEV) distribution. This framework provides a statistically appropriate basis for modelling extremes and estimating probabilistic return levels for long-term capacity planning.

3.4 Modelling Framework and Estimation Strategy

The annual peak electricity demand of Bangladesh is modeled using the GEV distribution. The cumulative distribution function (CDF) of GEV distributions is:

$$F(x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, \quad \text{for } 1+\xi\frac{x-\mu}{\sigma} > 0$$

where μ_t is the location parameter, σ>0 is the scale parameter, and ξ is the shape parameter representing tail behaviour.

3.5 Non-stationary Specification

Extreme Value Theory can be implemented using either stationary or non-stationary GEV models, depending on the characteristics of the underlying process (El Adlouni, 2007). Given the observed non-stationarity in annual peak demand data, a non-stationary GEV model is adopted in which the location parameter evolves over time:

$$\mu_t = \beta_0 + \beta_1 t$$

where t denotes a time index normalised relative to the beginning of the sample. The scale and shape parameters are held constant.

3.6 Estimation Strategy

Maximum Likelihood Estimation (MLE)

Parameter estimation for the GEV distribution is typically carried out using Maximum Likelihood Estimation (MLE) or L-moments, and the choice has important implications for small-sample performance. MLE possesses well-known asymptotic efficiency properties, and its extension to non-stationary GEV models is straightforward since the likelihood function directly accommodates time-varying parameters (El Adlouni, 2007). However, in small samples, MLE estimates of the GEV shape parameter ξ are notoriously unreliable and can produce implausibly extreme tail behaviour, a problem documented extensively in the hydrological literature (Martins & Stedinger, 2000).

Let x_t denote the observed annual peak demand in year t=1,2,...,T. The parameters of the non-stationary GEV model are estimated using Maximum Likelihood Estimation (MLE). The log-likelihood function is given by:

$$l\,(\beta_0, \beta_1, \sigma, \xi) = -\sum_{t=1}^{T} \left[\log \sigma + (1 + \frac{1}{\xi}) \log (1 + \xi \frac{x_t - \mu_t}{\sigma}) + (1 + \xi \frac{x_t - \mu_t}{\sigma})^{-1/\xi}\right]$$

subject to the constraint:

$$1 + \xi \frac{x_t - \mu_t}{\sigma} > 0 \quad \forall t$$

Although MLE is widely used for non-stationary block maxima (El Adlouni et al., 2007), for small sample, the shape parameter, ξ, estimated through MLE are often unreliable and lead to unstable tail behaviour (Martins & Stedinger, 2000).

L-Moment Estimation and Two-Step Estimation Approach

To address the instability of shape parameter, an alternative estimate of the shape parameter is obtained using L-moments. L-moments are less sensitive to sampling variability and provide more robust estimates of distributional characteristics in small samples (Shin et al., 2025). L-moments offer computational simplicity, greater robustness, and lower estimation variance in small and moderate samples (J. R. M. Hosking, 1997). One study extended this result to a generalised L-moment estimation framework for both stationary and non-stationary GEV models, confirming that the L-moment estimator is more efficient and robust for small samples than MLE (Shin Y. S., 2025). With 31 annual observations, the Bangladesh peak demand series falls squarely within the regime where L-moment estimation offers substantial advantages for tail characterisation. Let the L-moment estimate of the shape parameter be denoted as:

$$\xi = \hat{\xi}_{LM}$$

The critical limitation of L-moments, however, is that they were developed under the assumption of stationarity and cannot accommodate a time-varying location parameter, making them unsuitable as a standalone estimation strategy for non-stationary models (Shin, 2025).

To reconcile these limitations, a two-step estimation approach estimation strategy is adopted. The shape parameter ξ is fixed at its L-moment estimate $\hat{\xi}_{LM}$, while the remaining parameters β_0, β_1, and σ are estimated via maximum likelihood within the non-stationary GEV framework. This approach combines the robustness of L-moment estimation for tail characterisation with the flexibility of likelihood-based methods for capturing non-stationarity. The resulting log-likelihood function becomes:

$$l\,(\beta_0, \beta_1, \sigma \mid \hat{\xi}_{LM}) = \sum_{t=1}^{T} \log f(x_t \mid \mu_t, \sigma, \hat{\xi}_{LM})$$

where $f(\cdot)$ denotes the GEV density function and $\mu_t = \beta_0 + \beta_1 t$.

3.7 Return Level Estimation and Uncertainty Analysis

The T-year return level represents the threshold expected to be exceeded, on average, once every T years, and provides a direct and interpretable basis for capacity planning decisions. This approach has been applied widely in hydrology for flood design (Fernandes, 2010), instructional engineering for extreme wind loads (Alessio Torrielli, 2013), and in the electricity sector for long-term substation planning (Li, 2020). Probabilistic forecasting of peak electricity demand enables improved risk management and betterinformed investment decisions under demand uncertainty and is advocated as superior to deterministic point forecasts for capacity planning purposes (Mcsharry, 2005).

The T-year return level is defined as:

$$z_T^{(b)} = \mu_t^{(b)} + \frac{\sigma^{(b)}}{\xi^{(b)}}\left[\left(-\log\left(1-\frac{1}{T}\right)\right)^{-\xi^{(b)}} - 1\right]$$

where μ_t, σ, and ξ are the GEV location, scale, and shape parameters. Return levels are computed for 10, 20, and 50-year horizons up to 2050.

Uncertainty quantification is an indispensable complement to return level estimation, particularly for small samples where parameter uncertainty is non-trivial. For non-stationary GEV models, confidence intervals derived from asymptotic MLE theory are known to be unreliable (Sahoo, 2022). Non-parametric bootstrap resampling has emerged as the preferred alternative, providing empirically grounded confidence intervals that reflect the true sampling distribution without relying on asymptotic approximations (Sahoo, 2022) (Wehner MF, 2024).

Uncertainty is assessed using a non-parametric bootstrap with B=10,000 replications. For each bootstrap sample b, the return level is:

$$z_T^{(b)} = \mu_t^{(b)} + \frac{\sigma^{(b)}}{\xi^{(b)}}\left[\left(-\log\left(1-\frac{1}{T}\right)\right)^{-\xi^{(b)}} - 1\right]$$

The 95% confidence interval is constructed using the percentile method:

$$CI_{95\%} = \left[z_T^{(0.025)},\ z_T^{(0.975)}\right]$$

where $z_T^{(0.025)}$ and $z_T^{(0.975)}$ are the 2.5th and 97.5th percentiles of the bootstrap distribution.

4. RESULTS AND DISCUSSION

4.1 GEV Model Estimation Results

Table 3 represents the parameters of the two-stage GEV model. The location parameter is modeled as a linear function of time. Therefore, the estimated intercept β_0 is –767.7 MW, while the trend coefficient β_1 is 525.5 MW. A positive β_1 indicates a clear presence of upward trend in the annual peak electricity demand. The result suggests that, on average, the peak demand has been increasing by 525 MW per year during the estimation period.

Table 3: Parameter Estimates of GEV model

Parameters	Estimated Value	Description
β_0	-767.7 MW	Intercept (MLE)
β_1	525.5 MW	Trend Coefficient (MLE)
σ	1575.3 MW	Scale parameter (MLE)
$\hat{\xi}_{LM}$	-0.067	Shape Parameter (L-moments)

Source: Authors' estimation.

The scale parameter σ is estimated at 1575.3 MW, which reflects the spread or variability of peak demand around the trend. The shape parameter estimated using maximum likelihood is ξ ˆ_"MLE" =-0.574, while the L-moment estimate is $\hat{\xi}_{LM}$ =-0.067. The MLE estimate suggests a much tighter upper bound on extreme electricity demand compared to the L-moment estimate. This makes the use of L-moments apropos, reducing the risk of overestimating tail truncation due to MLE sensitivity.

4.2 Model Diagnostics and Selection

Model performance was evaluated using information criteria, graphical diagnostics, and resampling-based stability checks. The Akaike Information Criterion (AIC) indicates a slightly better fit for the full MLE-based specification (Model 1), with AIC = 269.82 compared to 274.30 for MLE with L-moment Shape Parameter (Model 2). The difference (ΔAIC ≈ 4.5) suggests moderate but not decisive support for Model 1.

Quantile–quantile (QQ) plots were used to assess distributional fit. In figure 4 in the appendix, the QQ plot for Model 1 shows a close alignment of empirical and theoretical quantiles across most of the distribution, indicating a good overall fit. The QQ plot for Model 2 exhibits greater dispersion, particularly in the upper quantiles, suggesting a comparatively weaker fit. Thus, in terms of in-sample fit, Model 1 performs better.

However, important differences emerge in the estimated shape parameter. The MLE-based model produces a strongly negative estimate (ξ ≈ -0.574), implying a tight upper bound on extreme electricity demand. In contrast, the L-moment-based model yields a shape parameter close to zero (ξ ≈ -0.067), indicating a much weaker upper bound and a tail behaviour closer to the Gumbel case. This difference has substantial implications for the characterisation of extreme demand.

Further concerns arise from bootstrap diagnostics. Resampling under the Model 1 resulted in highly unstable estimates for the return levels, with simulated extreme demand values spanning implausibly wide ranges. This indicates sensitivity of the maximum likelihood estimates, particularly the shape parameter, to sampling variability. In contrast, Model 2 exhibited stable behaviour under bootstrap resampling and produced more plausible ranges of extreme demand.

Taken together, the results highlight a trade-off between statistical fit and tail reliability. While Model 1 provides a better in-sample fit according to AIC and QQ diagnostics, it implies an overly restrictive tail and exhibits instability under resampling. Model 2, although slightly inferior in terms of fit, offers a more stable and credible representation of extreme demand. Given that the primary objective of the study is to characterise tail behaviour, Model 2 is preferred.

4.3 Return Level and Uncertainty Projections

Based on the fitted GEV distribution, different probability-based future scenarios (return level) of annual peak electricity demand have been estimated. Besides, for each of these return levels a 95 per cent confidence interval has been calculated utilising bootstrap method.

4.3.1 Return Level Estimates/ Probabilistic Demand Projections

Table 4 shows the projected peak annual electricity demand for year 2030, 2035, 2040, 2045, and 2050 for 2-, 5-, 10- and 25-year return levels, equivalent to exceedance probabilities of 50 per cent, 20 per cent, 10 per cent, and 4 per cent respectively.

Across all return periods, projections exhibit a consistent upward trajectory driven by the positive location trend of the non-stationary GEV model. In 2030, there is 10 per cent probability (10-year return level) that extreme demand can surpass 20,838 MW and a very low, 4 per cent probability (25-year return level), to exceed 22, 035 MW. In 2050, the 25-year return level is 32,567 MW. That is, there is 96 per cent probability that the annual peak demand will remain below this value. Table 5 in the appendix return level for each year from 2026 to 2050.

Table 4: Return Level Projections (MW) for the Year 2030, 2035, 2040, 2045, and 2050

Year	2-Year Return Level	5-Year Return Level	10-Year Return Level	25-Year Return Level
2030	18219 (16962–19632)	19834 (18409–21391)	20838 (19249–22554)	22035 (20226–24002)
2035	20852 (19332–22514)	22467 (20805–24262)	23471 (21653–25394)	24668 (22673–26829)
2040	23485 (21678–25402)	25100 (23157–27142)	26103 (24050–28251)	27301 (25089–29678)
2045	26118 (24026–28330)	27733 (25521–30025)	28736 (26420–31138)	29934 (27479–32494)
2050	28751 (26358–31216)	30366 (27884–32930)	31369 (28778–34023)	32567 (29854–35361)

Source: Authors' estimation.

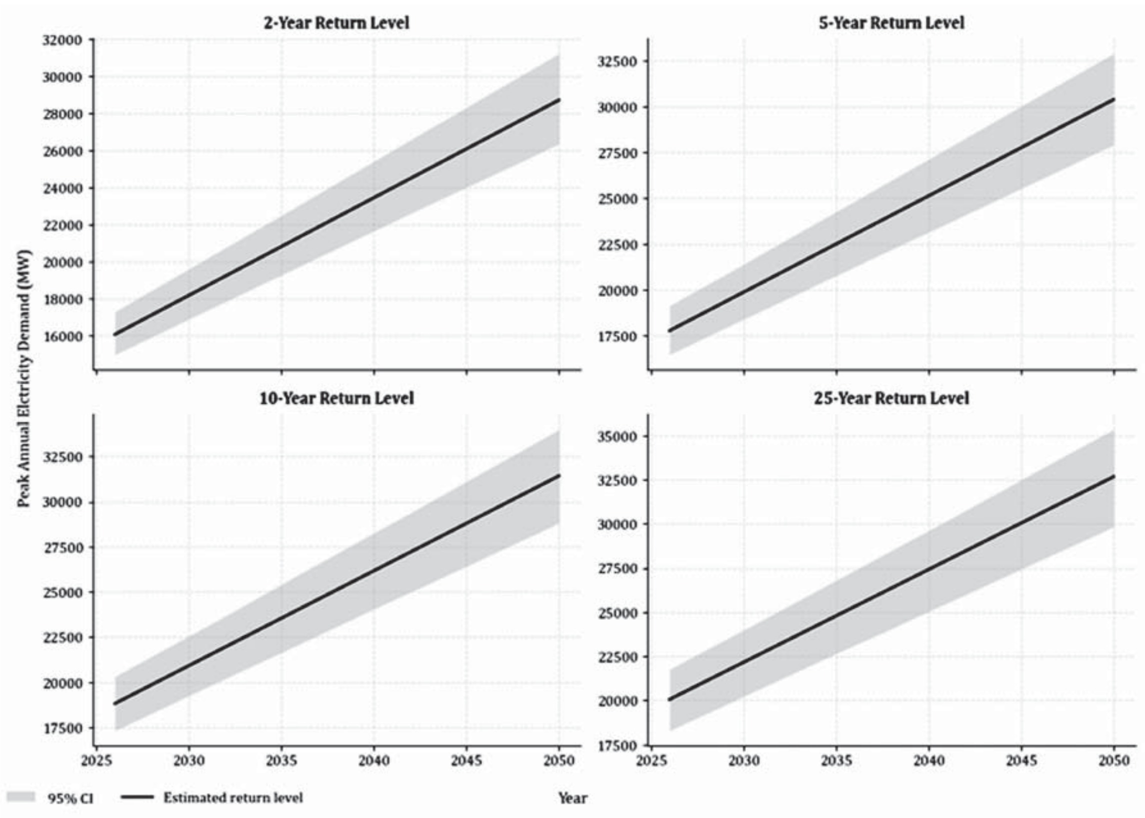
Note: 2-, 5-, 10-, and 25-year return levels are associated with 50%, 20%, 10%, and 4% probability level. The values are in MW and the values in the parenthesis represents 95% confidence interval.

4.3.2 Uncertainty Analysis

Figure 2 illustrates the projected return levels alongside its 95 per cent confidence interval from 2026 to 2050. The shaded band represents the range within which the true return level is expected to fall with 95 per cent probability, constructed via 5,000 bootstrap resampling iterations.

The confidence band widens progressively as the projection horizon extends, reflecting the increasing uncertainty in projected values. In 2030, the 25-year return level is estimated at 22,035 MW with a 95 per cent confidence interval of 20,226–24,002 MW, a width of approximately 3,776 MW. By 2050, this widens to 32,567 MW (29,854–35,361 MW), a width of 5,507 MW. Despite this widening, the interval remains well-behaved.

Figure 2: Projected Annual Peak Electricity Demand in Bangladesh Across 2-, 5-, 10-, and 25-Year Return Levels with 95% Confidence Intervals (2026–2050)



Source: Authors' illustration.

5. CONCLUSION

This paper presents the first attempt to employ non-stationary extreme value theory for annual peak electricity demand forecasting in Bangladesh. By using annual peak electricity demand data for 31 years ranging from 1995 to 2025, it is found that the non-stationary GEV distribution with a time varying location parameter gives a return level of 22,035 MW after 25 years from now and 32,567 MW after 50 years from now, which are much lower than 70.5 GW in IEPMP 2023. These results provide a statistically grounded basis for long-term generation and grid planning under uncertainty.

The primary limitation is the short observation window. While the hybrid strategy mitigates small-sample sensitivity, the widening confidence band over the projection horizon reflects genuine statistical uncertainty that cannot be resolved with 31 observations. The assumed linear trend in the location parameter may also not persist if the structural drivers of demand growth shift nonlinearly. Future work could incorporate economic covariates into the GEV location parameter and, as longer series become available, extend the framework to peaks over threshold formulations.

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APPENDIX

Table 5: Forecasted Peak Electricity Demand for Each Return Level (2026-2050)

Year	2-Year Return Level	5-Year Return Level	10-Year Return Level	25-Year Return Level
2026	16113 (15036–17328)	17728 (16451–19108)	18731 (17314–20295)	19929 (18263–21765)
2027	16639 (15524–17900)	18254 (16945–19680)	19258 (17790–20858)	20455 (18756–22319)
2028	17166 (15999–18482)	18781 (17431–20255)	19784 (18266–21429)	20982 (19253–22876)
2029	17692 (16485–19058)	19308 (17922–20821)	20311 (18755–21993)	21508 (19745–23433)
2030	18219 (16962–19632)	19834 (18409–21391)	20838 (19249–22554)	22035 (20226–24002)
2031	18746 (17448–20213)	20361 (18892–21954)	21364 (19733–23144)	22562 (20704–24569)
2032	19272 (17923–20787)	20887 (19362–22519)	21891 (20214–23711)	23088 (21196–25138)
2033	19799 (18393–21366)	21414 (19844–23094)	22417 (20701–24281)	23615 (21695–25707)
2034	20325 (18866–21940)	21940 (20329–23676)	22944 (21179–24842)	24141 (22183–26255)
2035	20852 (19332–22514)	22467 (20805–24262)	23471 (21653–25394)	24668 (22673–26829)
2036	21379 (19803–23082)	22994 (21280–24842)	23997 (22131–25971)	25194 (23149–27388)
2037	21905 (20267–23668)	23520 (21748–25420)	24524 (22609–26531)	25721 (23640–27959)
2038	22432 (20736–24246)	24047 (22228–25987)	25050 (23092–27112)	26248 (24124–28533)
2039	22958 (21199–24832)	24573 (22690–26566)	25577 (23573–27681)	26774 (24606–29103)
2040	23485 (21678–25402)	25100 (23157–27142)	26103 (24050–28251)	27301 (25089–29678)
2041	24012 (22141–25979)	25627 (23631–27722)	26630 (24524–28829)	27827 (25572–30244)
2042	24538 (22604–26567)	26153 (24113–28304)	27157 (24999–29413)	28354 (26054–30808)
2043	25065 (23076–27156)	26680 (24582–28870)	27683 (25474–29989)	28881 (26534–31368)
2044	25591 (23548–27746)	27206 (25055–29449)	28210 (25947–30566)	29407 (27010–31926)
2045	26118 (24026–28330)	27733 (25521–30025)	28736 (26420–31138)	29934 (27479–32494)
2046	26644 (24500–28904)	28260 (25990–30610)	29263 (26890–31716)	30460 (27959–33064)

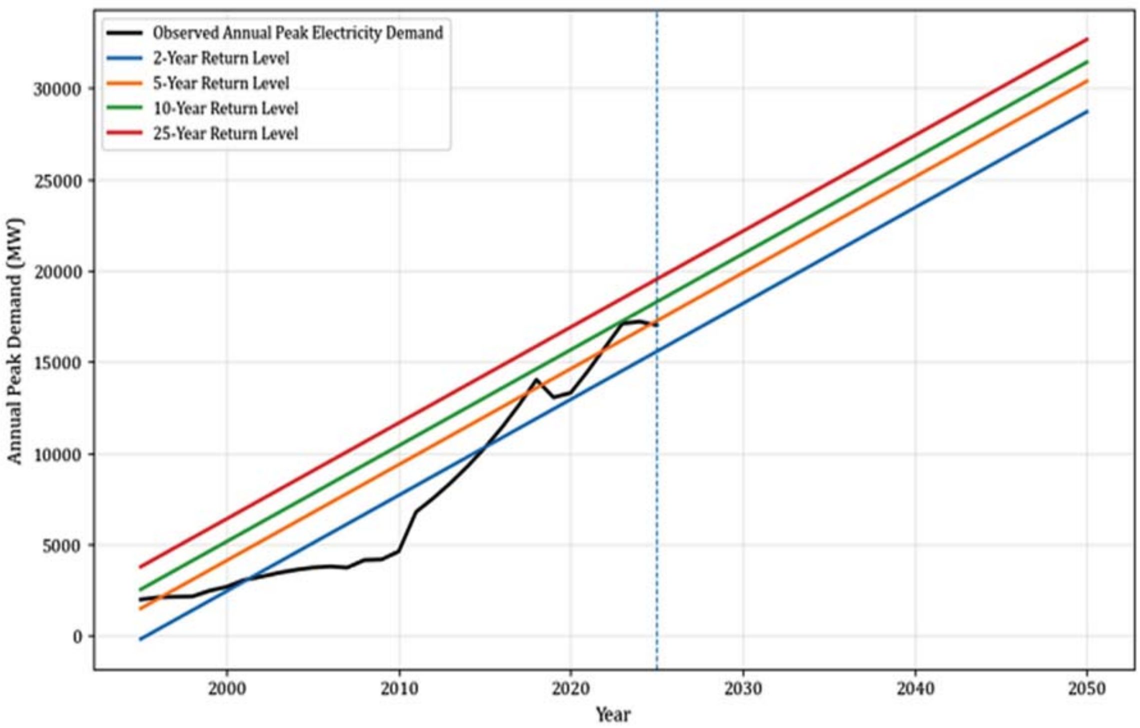
(Table 5 contd.)

(Table 5 contd.)

Year	2-Year Return Level	5-Year Return Level	10-Year Return Level	25-Year Return Level
2047	27171 (24963–29480)	28786 (26462–31179)	29790 (27342–32292)	30987 (28431–33632)
2048	27698 (25428–30063)	29313 (26948–31761)	30316 (27825–32870)	31514 (28909–34199)
2049	28224 (25892–30642)	29839 (27423–32346)	30843 (28296–33443)	32040 (29387–34776)
2050	28751 (26358–31216)	30366 (27884–32930)	31369 (28778–34023)	32567 (29854–35361)

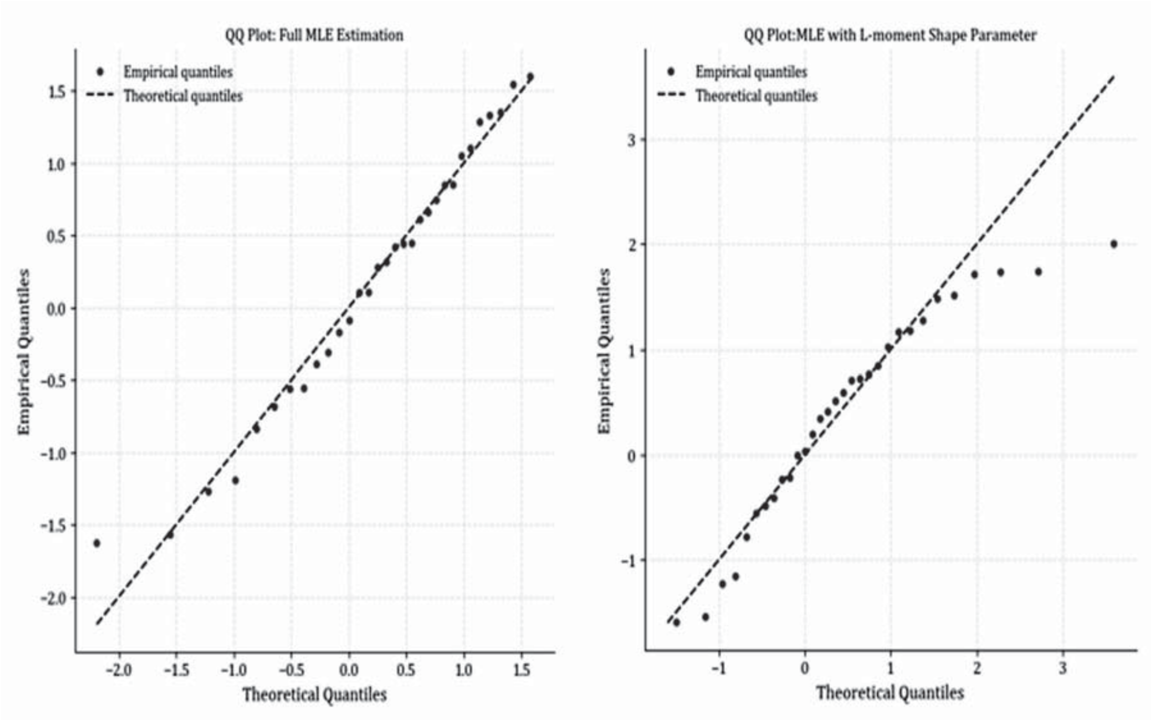
Source: Authors' estimation.

Figure 3: Observed Annual Peak Electricity Demand and Non-Stationary GEV Return Level Projections for Bangladesh (1995–2050)



Source: Authors' illustration.

Figure 4: GEV Model Goodness-of-Fit (Q-Q Plot)



Source: Authors' illustration.

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