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Research Article

Electricity Demand Forecasting in Libya under Structural Disruptions: An Ensemble Approach with Recovery and Volatility Indicators

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ABSTRACT

Accurate electricity-demand forecasting is essential for generation planning, network investment, maintenance scheduling, and demand-side management. Libya presents a structurally unstable forecasting environment in which long-run growth is interrupted by sharp contractions, rebounds, infrastructure constraints, and political disruption. This study analyzes annual national electricity demand for 2000–2024 using Ember data processed by Our World in Data and evaluates eight transparent forecasting models through expanding-window rolling-origin validation. The naive, Theta, and drift models achieved the strongest out-of-sample performance, whereas unrestricted linear-trend and grey models substantially over-predicted demand. An equal-weight ensemble of the three best models forecasts recorded demand of 37.0 TWh in 2030 and 39.0 TWh in 2035, with a 95% residual-bootstrap interval of 32.5–43.2 TWh in 2035. Historical demand reached 37.99 TWh in 2013, while the 2024 value was 34.59 TWh, equivalent to 91.1% of the historical peak. Per-capita demand recovered to 77.8% of its maximum. The study contributes a reproducible, disruption-aware small-sample framework that integrates model competition, forecast combination, uncertainty intervals, and recovery and volatility indicators. The forecast represents recorded or served demand; latent demand remains outside the empirical scope because public annual data do not contain outages, load shedding, peak deficits, or unserved energy.

1. INTRODUCTION

Electricity-demand forecasts guide generation expansion, transmission and distribution investment, fuel procurement, maintenance planning, and operational security. Forecast errors are asymmetric: persistent over-forecasting can lock capital into underutilized assets, whereas under-forecasting intensifies capacity shortages, load shedding, and service deterioration. Forecasting practice therefore distinguishes horizon, data frequency, geographical aggregation, and point versus probabilistic output [1–5].

Libya is not a conventional trend-forecasting case. Public annual data show rapid expansion before 2011, a severe contraction in 2011, a rebound and historical maximum in 2013, further contractions in 2016 and 2020, and incomplete recovery thereafter. Recent Libya-focused research documents persistent supply instability, limited operational capacity, and a substantial gap between peak demand and available generation [6]. These structural changes make in-sample fit an unreliable basis for long-term model selection.

Electricity demand in the Ember and Our World in Data series is calculated from generation adjusted for net imports and exports [7], [8]. This internationally comparable measure represents recorded national demand. In a system affected by outages and load shedding, recorded demand can be supply-constrained; consequently, the dependent variable in this study is served demand rather than latent demand.

1.1 Research Problem

Libya-focused forecasting studies cover national peak load, local control areas, annual demand, meteorological regression, fuzzy systems, artificial neural networks, ARIMA families, XGBoost, and LSTM models [9–18]. Their results are valuable, but direct comparison is limited by different frequencies, horizons, geographical scopes, validation designs, and accuracy measures. A reproducible national benchmark based on identical rolling forecast origins, multiple parsimonious models, uncertainty intervals, and disruption-sensitive indicators has not been established.

1.2 Research Questions

1. How did Libya's recorded electricity demand change across expansion, disruption, and partial-recovery regimes?

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2. Which transparent forecasting models achieve the strongest rolling-origin accuracy for the annual national series?
3. Does an ensemble of robust benchmark models provide a more stable long-term baseline than a single model?
4. Which recovery, volatility, and uncertainty indicators improve the planning value of the demand forecast?
5. How does the distinction between recorded demand and latent demand affect interpretation of the results?

1.3 Study Contributions

The study makes five contributions:

1. It constructs a reproducible national annual electricity-demand series for Libya for 2000–2024.
2. It compares statistical, trend, grey, and benchmark methods through identical expanding-window forecast origins.
3. It produces an equal-weight ensemble forecast with 80% and 95% residual-bootstrap intervals for 2025–2035.
4. It calculates demand recovery, per-capita recovery, growth volatility, and forecast-uncertainty indicators.
5. It separates served-demand forecasting from latent-demand estimation in a load-shedding environment.

2. LITERATURE REVIEW

2.1 Forecast Horizons and Data Requirements

Electricity forecasting is divided into very-short-term, short-term, medium-term, and long-term applications. High-frequency operational forecasts use hourly or sub-hourly load, weather, calendar effects, and recent lags. Medium-term forecasts support maintenance and resource planning, while long-term forecasts support capacity expansion and policy design. Long-term models typically combine annual demand with demographic, economic, technological, and policy variables [1–5]. Model complexity must remain consistent with sample size and temporal resolution.

The forecasting literature has expanded from regression, exponential smoothing, and ARIMA to machine-learning, deep-learning, hybrid, ensemble, and probabilistic methods. No method dominates across all applications. Forecast horizon, aggregation, data quality, non-stationarity, explanatory variables, and validation design determine performance [1–5]. Table I summarizes the principal method families and their suitability for the 25-observation Libyan annual series.

TABLE I. SUMMARY OF ELECTRICITY-DEMAND FORECASTING METHODS

Method family	Typical models	Main inputs	Strengths	Limitations	Suitability for this study
Benchmark methods	Naive, drift, moving average	Target series only	Transparent; difficult to beat in volatile data; essential performance benchmark	Limited structural explanation	High — essential performance baselines
Regression / econometric	Linear, log-linear, dynamic regression	Demand plus GDP, population, prices, weather, policy variables	Interpretable drivers and elasticities; supports scenarios	Sensitive to multicollinearity, structural breaks, and future regressor assumptions	Medium — constrained by missing final-year GDP data and future-regressor assumptions
Exponential smoothing	SES, Holt, damped Holt, ETS	Target series; optional seasonality	Robust, parsimonious, effective for level/trend data	Can extrapolate obsolete trends; annual data contain no seasonality	High — particularly damped trend
ARIMA family	ARIMA, SARIMA, ARIMAX	Historical demand; seasonal and exogenous variables when available	Well-established diagnostics; handles autocorrelation and differencing	Parameter uncertainty with small samples; linear structure	Medium to high — restricted orders evaluated by rolling validation
Theta / decomposition	Theta, optimized Theta	Target series	Strong benchmark performance; combines long- and short-run components	Limited causal interpretation	High — suitable for short annual series
Grey forecasting	GM(1,1) and variants	Small positive samples	Designed for limited information; simple implementation	Can impose excessive exponential growth and perform poorly under shocks	Medium/low — included as a data-scarcity comparator
Machine learning	SVR, random forest, XGBoost	Large feature matrix, lags, weather, calendar, macro variables	Captures nonlinearities and interactions	Overfitting risk; time-dependence must be handled carefully	Low for the 25-point annual series; suitable for future monthly or hourly GECOL data
Deep learning	ANN, LSTM, GRU, CNN, TCN, transformers	Large high-frequency datasets with exogenous features	Learns complex nonlinear temporal patterns	Data- and computation-intensive; limited interpretability	Unsuitable for the current annual dataset
Hybrid / ensemble	ARIMA–LSTM, statistical–ML, forecast combinations	Outputs from multiple models; possibly exogenous variables	Reduces model-selection risk; can improve robustness	Needs disciplined validation and combination rules	High for simple combinations; complex hybrids require richer data

Probabilistic forecasting	Quantiles, density forecasts, bootstrap, conformal methods	Point models plus residual or distributional information	Communicates uncertainty and planning risk	Intervals can be unstable with very small samples	Medium — residual-bootstrap intervals are feasible, but sampling uncertainty is high

Sources: [1]– [5].

2.2 Methodological Basis

Three principles define the methodology. First, model complexity is constrained by the information content of the annual series. Second, expanding-window out-of-sample validation determines model selection. Third, forecast uncertainty is reported with the point forecast. The model set therefore combines naive and drift benchmarks, damped Holt smoothing, restricted ARIMA, the Theta method, linear and structural trends, and GM(1,1). Forecast accuracy is evaluated with MAE, RMSE, sMAPE, and MASE.

3. LIBYA-FOCUSED ELECTRICITY AND ENERGY LITERATURE

3.1 Electricity-Forecasting Studies

The Libyan forecasting literature has progressed from stochastic time-series and simple regression models to fuzzy systems, ANN, ANFIS, ARIMA families, XGBoost, and LSTM [9–18]. Recent studies also forecast generation deficits and load shedding, which reflects the operational realities of the Libyan grid. Most studies, however, remain regional, use selected years, or evaluate models under different validation structures. Table II demonstrates that the present study addresses a distinct national, annual, long-term forecasting problem.

TABLE II. LIBYA-FOCUSED ELECTRICITY-FORECASTING STUDIES

Ref.	Scope / horizon	Data and variables	Method(s)	Reported result	Relevance to this study
[9]	North Benghazi electricity stations; medium-term load forecasting	Actual electricity-load and supply-deficit records obtained from GECOL's Benghazi Regional Control Center	Comparison of several machine-learning regression algorithms	Extra Trees Regressor achieved the best reported load-prediction performance	Provides recent evidence of machine-learning forecasting using operational Libyan data
[10]	National grid; long-term peak load	GECOL/National Control Center data; population and historical peak load	Simple linear regression in MATLAB	Forecast peak load through 2025; reported high fit and validation against actual data	Single functional form; vulnerable to post-2013 structural change
[11]	Libyan network; short-term	Peak load plus temperature, humidity, and wind speed from GECOL and weather sources	Multi-parameter regression	Small deviation between actual and predicted load	Limited reporting of reproducible validation and benchmark comparison
[12]	Benghazi; short-term residential load forecasting	Private household electricity-consumption data and survey-derived consumer-behaviour information	CNN-LSTM and LSTM models evaluated using MSE, MAE, and R^2	Consumer-behaviour integration significantly improved CNN-LSTM forecasting accuracy	Demonstrates the value of behavioural explanatory variables and deep learning in Libya.
[13]	Benghazi; medium-term	Benghazi electricity-load time series	ANN-based time-series approach	Demonstrated ANN applicability to Benghazi load forecasting	Local rather than national scope; limited cross-model and uncertainty analysis
[14]	Libyan grid; short-term peak load	Temperature, humidity, wind speed, previous load	Multiple regression and trend techniques	Good correlation between meteorological factors and electricity use	Uses selected periods; does not address long-run national structural regimes
[15]	Libyan power network; short-term	Temperature, humidity, previous-day peak load	Fuzzy-logic model in MATLAB/Simulink	Reported error range of approximately +3.67% to −3.75%	No comparison with strong statistical and ML benchmarks
[16]	Benghazi; demand and load shedding	Benghazi demand/load-shedding series	ARIMA models	Forecasting intended to improve load-shedding management	City-level scope; not a national long-term planning model
[17]	North Benghazi; load, generation and deficit	Daily 2019 and 2023 data plus temperature and humidity	ARIMA, SARIMA, ARIMAX, SES, XGBoost and LSTM	LSTM reported the lowest errors across target variables	Two selected years; preprocessing choices and generalization need wider-period testing
[18]	Western Libyan grid; short-term	Hourly 2023 GECOL load and meteorological variables	ANN and ANFIS	ANFIS average error 0.50% versus ANN 8.37%	Single-year regional dataset; no national annual benchmark or uncertainty interval

3.2 Electricity Planning and Renewable-Energy Decision Support

Libyan electricity planning has also been examined through multi-criteria decision analysis. Previous studies evaluated power-generation technologies using grey theory, AHP, and linguistic-neutrosophic CODAS [19–21]. Subsequent research addressed solar-park siting, wind-farm siting, solar-farm location, and strategies for overcoming renewable-energy barriers in Libya [22–25]. Additional African studies developed integrated decision-support frameworks for photovoltaic development and wind-energy deployment [26], [27]. These publications establish a strong decision-support foundation for interpreting the capacity, technology, and renewable-energy implications of electricity-demand forecasts.

The forecasting and decision-support streams have remained largely separate. This study connects them by producing a validated national demand baseline and translating the forecast into recovery, volatility, and uncertainty indicators that support generation and renewable-energy planning.

4. DATA AND INDICATOR CONSTRUCTION

4.1 Data Source and Definition

The dataset contains annual observations for Libya from 2000 to 2024, Table III. Electricity demand in terawatt-hours is obtained from Ember's Yearly Electricity Data and processed by Our World in Data [7], [8]. The indicator is defined as electricity generation plus net imports. Supporting variables include population, GDP where available, electricity generation, net imports, and electricity demand per capita.

Recent Libya-focused research provides an external sector context by documenting operational capacity shortages, supply instability, and the planning implications of electricity-demand growth [6]. The public annual series is suitable for reproducible national comparison, while its served-demand definition is retained throughout the analysis.

TABLE III. DATASET AND CORE INDICATOR SUMMARY

Indicator	Value / definition	Interpretation
Coverage	2000–2024; 25 annual observations	Suitable for parsimonious long-term models; insufficient for deep learning
Demand in 2000	15.50 TWh	Starting level of the analysis period
Demand in 2010	32.48 TWh	Pre-2011 expansion; 2000–2010 CAGR = 7.68%
Historical peak	37.99 TWh in 2013	Highest recorded annual demand in the dataset
Demand in 2024	34.59 TWh	91.1% of the 2013 historical peak
Per-capita demand in 2024	4,686 kWh/person	77.8% of the historical per-capita maximum
Long-run CAGR	3.40% for 2000–2024	Average growth is strongly affected by pre-2011 expansion
Post-peak CAGR	−0.85% for 2013–2024	Recorded demand did not regain its 2013 maximum
Observed-demand definition	Generation + net imports	Should not be interpreted as latent demand under load shedding

4.2 Supporting Indicators

The analysis reports a compact indicator set in addition to the TWh forecast. Annual growth identifies expansion and contraction; rolling growth volatility measures instability; aggregate and per-capita recovery ratios quantify the distance from historical maxima; and forecast-interval width communicates planning uncertainty. Table IV shows the historical and planning indicators.

TABLE IV. HISTORICAL AND PLANNING INDICATORS

Indicator	Formula / construction	Planning meaning
Annual demand growth	(Demand_t / Demand_{t−1} − 1) × 100	Identifies expansion, contraction, and rebound years
Growth volatility	Rolling standard deviation of annual growth	Measures instability in the demand trajectory
Demand recovery ratio	Current demand / historical maximum demand	Shows whether the recorded system has recovered its previous scale
Per-capita recovery ratio	Current per-capita demand / historical maximum per-capita demand	Separates demand recovery from population growth
Forecast uncertainty width	Upper forecast interval − lower forecast interval	Communicates planning risk and model/data limitations
Per-capita recovery gap	1 - (2024 per-capita demand / historical per-capita maximum)	22.2% below the historical maximum; indicates incomplete recovery beyond population growth

5. HISTORICAL ELECTRICITY-DEMAND ANALYSIS

Figure 1 identifies three regimes. Recorded demand increased from 15.50 TWh in 2000 to 32.48 TWh in 2010, equivalent to a compound annual growth rate of 7.68%. It fell by 20.1% in 2011, rebounded by 32.3% in 2012, and reached a historical maximum of 37.99 TWh in 2013. The subsequent period was characterized by stagnation and repeated contractions. Demand in 2024 was 34.59 TWh, approximately 9% below the 2013 maximum.

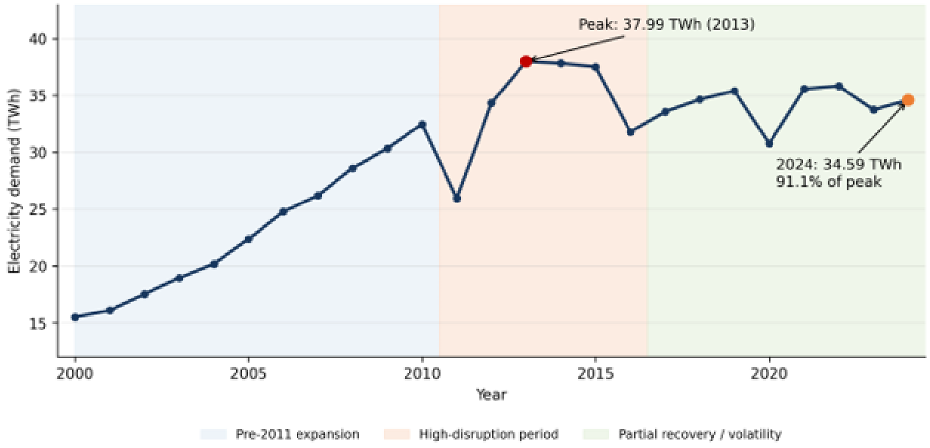

Fig. 1. Historical electricity demand in Libya, 2000–2024.

The regime pattern rejects unrestricted trend extrapolation. Models dominated by pre-2011 growth overstate the post-2013 trajectory, while models based only on the latest stagnant period understate potential recovery. The empirical comparison therefore relies on rolling-origin accuracy across multiple plausible model structures. Fig. 2 shows annual electricity-demand growth and five-year rolling volatility.

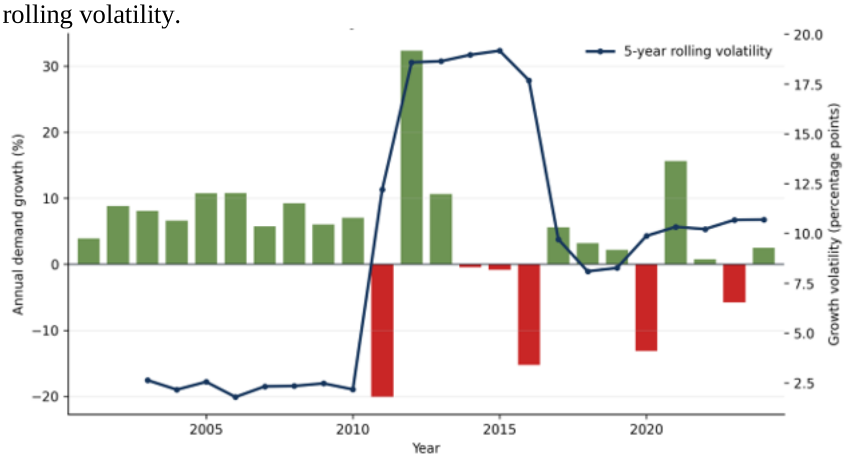

Fig. 2. Annual electricity-demand growth and five-year rolling volatility.

Annual growth averaged approximately 7.7% during 2001–2010. The average for 2014–2024 was approximately −0.5%, but this value conceals large contractions and rebounds. Five-year rolling growth volatility reached approximately 10.7 percentage points for 2020–2024, confirming that the series does not follow a smooth deterministic trend.

Per-capita demand peaked at approximately 6,026 kWh per person in 2013 and declined to 4,686 kWh per person in 2024, as shown in Fig. 3. The 2024 value equals 77.8% of the historical per-capita maximum, a weaker recovery than the aggregate-demand ratio because population continued to increase. Per-capita recovery therefore reveals incomplete restoration of electricity use beyond demographic growth.

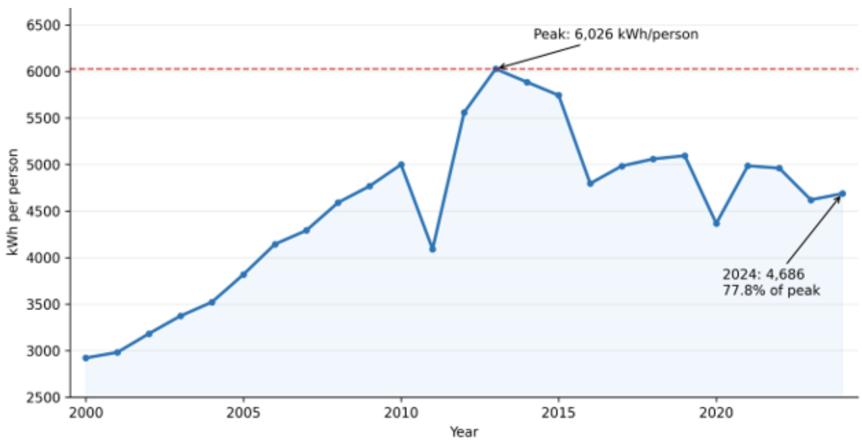

Fig. 3. Electricity demand per capita in Libya, 2000–2024.

Figure 4 show illustrates the core historical and forecast indicators.

Fig. 4. Core historical and forecast indicators.

6. FORECASTING METHODOLOGY AND RESULTS

6.1 Model Set

Eight models were evaluated: naive, drift, linear trend, damped Holt exponential smoothing, Theta, restricted ARIMA, GM(1,1), and a robust structural-trend specification. The naive model reproduces the most recent observation; the drift model extrapolates average historical change; Holt and Theta estimate evolving level and trend, with the Theta specification following the decomposition approach in [28]; ARIMA models autocorrelation after differencing; GM(1,1) represents a data-scarcity comparator; and the structural trend limits the influence of extreme observations. High-capacity machine-learning and deep-learning models were excluded because 25 annual observations do not support credible training and validation.

All models were fitted only to information available at each forecast origin. Hyperparameter choices were restricted to parsimonious structures, and the final ensemble was formed after the rolling-origin comparison rather than after in-sample optimization.

6.2 Rolling-Origin Validation

Forecast accuracy was assessed with an expanding-window rolling-origin design. The first evaluation used observations through 2013 to forecast 2014. The estimation window was expanded by one observation for each subsequent one-step-ahead forecast through 2024, producing eleven genuinely out-of-sample forecasts per model.

The comparison uses root mean squared error (RMSE), mean absolute error (MAE), symmetric mean absolute percentage error (sMAPE), and mean absolute scaled error (MASE). MASE expresses error relative to a naive scale and remains well defined when percentage errors are unstable [29]. Lower values indicate stronger performance. Table V reports rolling-origin forecast accuracy for 2014–2024, while Fig. 5 compares the corresponding RMSE values.

TABLE V. ROLLING-ORIGIN FORECAST ACCURACY FOR 2014–2024

Model	MAE (TWh)	RMSE (TWh)	sMAPE (%)	MASE
Naive	2.04	2.82	6.02	0.75
Theta	1.98	2.91	5.72	0.72
Drift	2.32	3.27	6.63	0.85
Holt damped	2.72	3.65	7.66	0.99
ARIMA	2.83	4.04	7.97	1.03
Structural trend	3.07	4.07	8.44	1.12
Linear trend	5.17	5.76	14.03	1.89
GM(1,1)	5.98	6.53	16.02	2.19

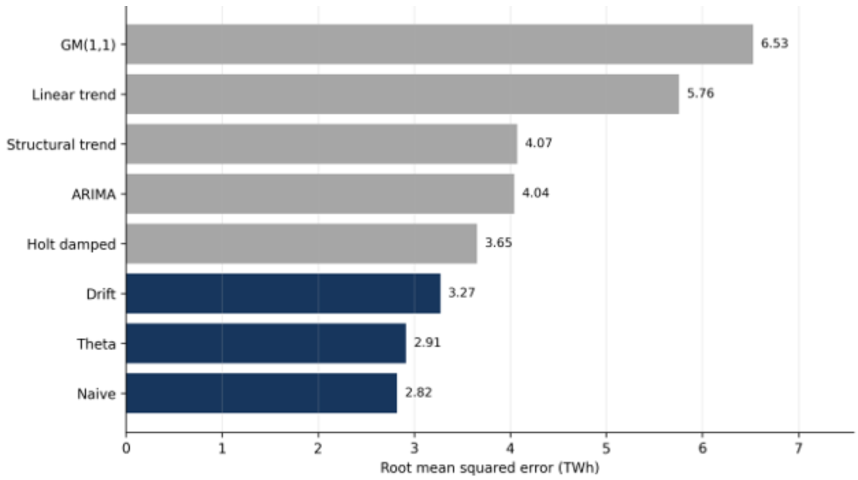

Fig. 5. Rolling-origin RMSE comparison, 2014–2024.

The naive model achieved the lowest RMSE at 2.82 TWh, followed by Theta at 2.91 TWh and drift at 3.27 TWh. Damped Holt and ARIMA produced intermediate errors. The unrestricted linear trend and GM(1,1) substantially over-predicted

demand after the structural contractions. The result confirms that transparent benchmarks outperform strongly trending specifications in this short and unstable series.
The final forecast is the equal-weight average of the naive, Theta, and drift models. Equal weighting limits estimation risk because only eleven validation forecasts are available. Forecast intervals are obtained by resampling the ensemble's rolling-origin residuals and adding the sampled errors to the point forecast.

6.3 Ensemble Forecast for 2025–2035

The ensemble forecasts recorded national electricity demand of 35.0 TWh in 2025, 37.0 TWh in 2030, and 39.0 TWh in 2035, as shown in Fig. 6. The implied annual growth rate from the 2024 observation to 2035 is approximately 1.1%. This trajectory is lower than a continuation of the pre-2011 trend because rolling-origin validation penalizes models that extrapolate rapid historical growth across later structural disruptions.

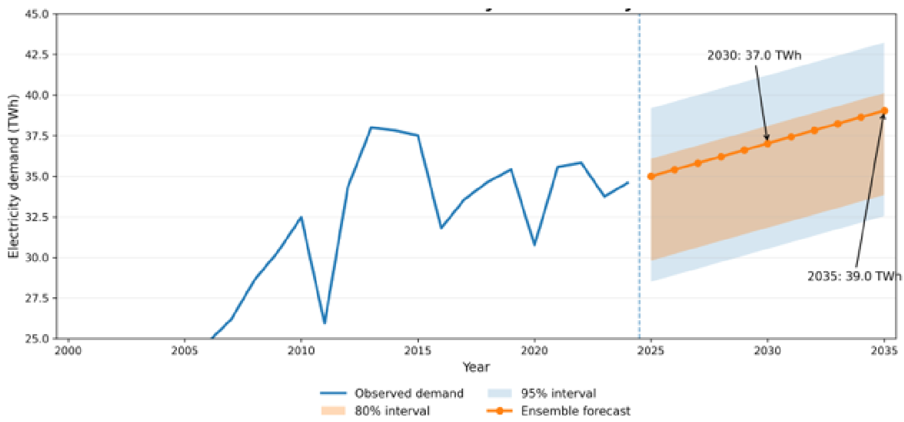

Fig. 6. Ensemble forecast with 80% and 95% uncertainty intervals.

The 95% residual-bootstrap interval for 2035 is 32.5–43.2 TWh (Table VI). The interval quantifies model error observed during rolling-origin evaluation; it does not include separate scenarios for tariff reform, industrial expansion, new generation, electrification, climate-driven cooling demand, or the release of suppressed load.

TABLE VI. ENSEMBLE FORECAST AND UNCERTAINTY INTERVALS

Year	Ensemble forecast (TWh)	80% interval	95% interval
2025	35.00	29.81–36.08	28.51–39.19
2026	35.40	30.21–36.48	28.91–39.59
2027	35.81	30.62–36.89	29.31–40.00
2028	36.21	31.02–37.29	29.72–40.40
2029	36.61	31.43–37.69	30.12–40.81
2030	37.02	31.83–38.10	30.53–41.21
2031	37.42	32.23–38.50	30.93–41.61
2032	37.83	32.64–38.91	31.34–42.02
2033	38.23	33.04–39.31	31.74–42.42
2034	38.63	33.45–39.72	32.14–42.83
2035	39.04	33.85–40.12	32.55–43.23

7. DISCUSSION AND POLICY IMPLICATIONS

Fig. 7 presents the disruption-aware electricity forecasting framework for Libya. The framework begins with the integration of annual electricity demand, population, GDP, generation, and import data, followed by historical diagnostics to identify growth regimes, structural disruptions, and recovery patterns. Several forecasting models are then compared through rolling-origin validation using common accuracy measures, and the best-performing models are combined in an ensemble. The final outputs include future demand estimates, uncertainty intervals, and recovery and volatility indicators to support electricity planning under unstable operating conditions.

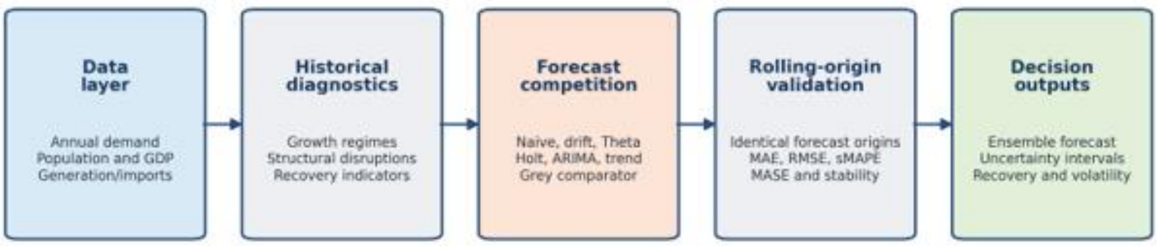

Fig. 7. Disruption-aware electricity forecasting framework.

7.1 Main Findings

Libya's annual electricity-demand series is governed by regime change and supply-system disruption rather than a stable growth law. The strongest models respond cautiously to recent observations, while the weakest models continue to extrapolate the rapid pre-2011 expansion. This explains the superior performance of naive and Theta benchmarks relative to linear trend and GM(1,1), consistent with wider evidence that model complexity does not guarantee forecast accuracy in short, noisy series [1–5].

7.2 Contribution to Knowledge

1. The study provides the first reproducible national benchmark in the reviewed Libyan literature that evaluates multiple annual-demand models over identical rolling origins.
2. Structural-regime diagnostics are incorporated directly into model interpretation rather than treating disruption years as ordinary noise.
3. The ensemble reduces dependence on a single specification and is selected exclusively from out-of-sample evidence.
4. Uncertainty intervals accompany the point forecast and expose the range relevant to long-term planning.
5. Aggregate recovery, per-capita recovery, and growth volatility connect forecasting output with electricity-sector decision support.
6. The served-demand and latent-demand distinction prevents supply-constrained observations from being interpreted as unconstrained consumption.

These elements integrate the forecasting literature [9–18] with the Libyan electricity-planning and renewable-energy decision-support stream [19–27].

7.3 Planning Implications

The 2030 and 2035 values define a conservative served-demand baseline for generation planning. The aggregate recovery ratio of 91.1% shows that the national series is close to its historical maximum, whereas the per-capita recovery ratio of 77.8% reveals substantially weaker recovery at the resident level. The combination of slow baseline growth and high recent volatility supports staged capacity decisions, explicit uncertainty allowances, and regular forecast revision. The forecast is not a substitute for short-term operational models. Benghazi and Western-grid studies use local high-frequency data to forecast hourly or daily load, generation, deficits, and load shedding [13], [16–18]. The national annual model serves capacity, investment, and policy decisions rather than unit commitment or day-ahead operation.

The 2035 baseline represents recorded demand conditional on historical system dynamics. It does not represent the electricity that the Libyan economy would consume under uninterrupted supply. Latent demand requires operational observations of outages, curtailed load, peak deficits, and energy not served. The demand forecast also provides an input to technology and renewable-energy planning. The Libyan studies in [19–25] evaluate generation technologies, solar and wind locations, and renewable-energy strategies; the forecast supplies the demand scale against which those alternatives can be assessed.

8. LIMITATIONS

The analysis is bounded by the 25-observation annual sample. Model rankings and residual-bootstrap intervals therefore contain material sampling uncertainty, even with rolling-origin validation and parsimonious specifications. The dependent variable is calculated from generation and net imports. It can understate unconstrained demand when available generation or network capacity limits supply. The results consequently describe served demand.

Macroeconomic regression was not used in the final ensemble because GDP is highly volatile and unavailable for the final years of the working dataset. The forecast also excludes tariffs, cooling-degree indicators, industrial projects, energy-efficiency changes, and technology adoption. The uncertainty intervals reproduce historical one-step forecast errors but do not constitute a complete scenario distribution for policy, infrastructure, or geopolitical change.

Ember periodically revises historical electricity data. Revisions to the source series alter the fitted models and forecast values but do not change the validation framework. These limitations define the forecast as a transparent national baseline rather than a full power-system adequacy assessment.

9. CONCLUSION

This study develops a disruption-aware long-term forecast of Libya's recorded national electricity demand. Expanding-window evaluation shows that simple benchmarks outperform unrestricted trend and grey models in the short, structurally unstable annual series. The equal-weight naive-Theta-drift ensemble forecasts 37.0 TWh in 2030 and 39.0 TWh in 2035, with a 2035 95% interval of 32.5–43.2 TWh.

The combined forecasting and indicator framework provides more decision value than a single point estimate. Demand recovery, per-capita recovery, growth volatility, and uncertainty width show that aggregate demand has nearly regained its historical maximum while electricity use per resident remains substantially below its peak. The results establish a reproducible baseline for generation and renewable-energy planning and preserve the essential distinction between served demand and latent demand.

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Conflicts of Interest:

The authors declare that there are no conflicts of interest to report.

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Authorship Contribution Statement

I.B.: Conceptualization, methodology, data curation, formal analysis, validation, and manuscript preparation.

G.D.: Writing – review and editing, formal analysis, and visualization.

Data Availability

The annual electricity-demand data are publicly available from Ember and Our World in Data [7], [8].

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