Machine Learning–Driven Global Forecasting of Electricity Generation and Consumption (1985–2035)

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Abstract: This paper examines long-term changes in global electricity generation and consumption from 1950 to 2035 using historical data from the Our World in Data (OWID) energy database (1950–2025). After addressing data inconsistencies through smoothing and gap-filling, we apply an ARIMA(1,1,1) model selected via Akaike Information Criterion minimization. While this univariate framework is deliberately simple, it provides a transparent, reproducible baseline for trend extrapolation. Forecasts from 2025 to 2035 indicate that global generation could reach approximately 35,750 TWh by 2035, with consumption slightly higher at about 36,400 TWh, implying a sustained deficit of roughly 650–700 TWh under a business-as-usual scenario. The 95% confidence intervals widen from ±2–3% in 2025 to ±7% by 2035.

This study does not claim algorithmic innovation. Its contribution lies in (i) applying a rigorously validated ARIMA framework to a uniquely long (75+ years) global electricity dataset; (ii) providing exhaustive model selection and robustness checks; and (iii) establishing a transparent baseline for benchmarking future hybrid extensions. The full code and data are provided for reproducibility.

Although this method is not a structural energy balance model, it provides a clear baseline based on historical trends, useful as a reference point for comparing policy options or more detailed modeling approaches.

Keywords: ARIMA-based time-series modelling, Forecasting of electricity generation, Electricity demand projection, Our World in Data (OWID) energy statistics, Applied time-series analysis, Statistical methods for energy forecasting, Smart energy systems, Energy transition, Grid planning, Renewable integration.

1. INTRODUCTION

Understanding how electricity generation and consumption evolve at the global level is increasingly important for long-term decision making. Policymakers, planners, and researchers rely on such projections when thinking about energy security, infrastructure investment, and climate mitigation pathways [1]. That said, the global electricity system has not followed a smooth or uniform path. Since the 1950s, its development has been shaped by several overlapping processes, including the spread of electrification to rural areas, the rise of large centralized power plants, rapid industrial expansion in parts of Asia and Latin America, and, more recently, growing pressure to transition toward low-carbon energy sources [2]. Because electricity demand and supply are closely tied to economic and political conditions, many forecasting studies have relied on energy-econometric models that incorporate external variables such as GDP, fuel prices, technological costs, or policy indicators. These models can be useful when such drivers are well understood and reliably measured. However, projecting those same drivers decades into the future inevitably requires strong assumptions. Economic growth paths, policy commitments, and technological breakthroughs are all uncertain, particularly at the global scale. In addition, assembling consistent, high-quality data for all relevant variables across countries remains a persistent limitation [3, 4].

For these reasons, it is sometimes preferable to adopt a simpler perspective. Time-series approaches such as ARIMA focus exclusively on the behavior of the data itself. Rather than attempting to explain electricity trends through external mechanisms, they ask whether the historical patterns embedded in the series contain enough information to support

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Received on 04-06-2026 Accepted on 30-06-2026 Published on 01-07-2026

E-ISSN: 2978-6436/26

meaningful projections. In this setting, past observations are not explanatory variables but the primary source of insight [5, 6].

The ARIMA methodology, developed by Box and Jenkins, formalizes this idea by modeling how current values depend on earlier observations and how random disturbances persist over time. Through differencing and parameter estimation, the method emphasizes relatively stable dynamics while filtering out short-term fluctuations. As a result, forecasts can be generated without introducing additional assumptions about external conditions [7]. For aggregated annual data, where long-term trends dominate and short-run noise is limited, ARIMA models have often been found to perform as well as, and occasionally better than, more complex machine-learning alternatives [8, 9]. Extensions such as ARIMAX, vector autoregressive models, or hybrid approaches that combine ARIMA with neural networks have been shown to offer marginal improvements in certain contexts [10-12], However, these gains typically come at the cost of reduced interpretability and heavy dependence on large, consistently measured exogenous datasets—conditions rarely met for annual global electricity data over multi-decade horizons [13, 14]. Rather than dismissing these methods, we view them as valuable complements. The present analysis therefore deliberately adopts a simpler ARIMA framework to establish a **baseline** whose behavior is fully transparent. Any future hybrid model (*e.g.*, ARIMAX augmented with GDP growth, or a two-stage architecture where ARIMA captures linear trends and a neural network model residual nonlinearities) can then be evaluated against this baseline to determine whether added complexity yields meaningful predictive gains.

Most electricity forecasting studies understandably focus on individual countries or regions. At those scales, detailed economic indicators and policy variables can be incorporated, often improving short-term accuracy [15-21]. Global forecasting presents a different problem. Countries differ widely in development trajectories, energy mixes, and policy priorities, and these differences are difficult to reconcile within a single unified framework. Rather than attempting to model this heterogeneity explicitly, we adopt a deliberately parsimonious strategy that treats global electricity use as a single aggregate time series and examines its historical evolution directly.

The analysis proceeds in several stages. Global electricity generation and consumption data are first compiled from 1950 onward and processed to ensure internal consistency. Standard statistical tests are then applied to assess stationarity and guide model specification. Once the ARIMA model is estimated, forecasts are produced along with confidence intervals that reflect uncertainty around future values. Model performance is evaluated by comparing fitted values with observed historical data, with particular attention paid to both long-term trends and typical year-to-year variability [22-24].

It is important to clarify what these projections represent. They are not intended to predict specific future outcomes or to anticipate major structural breaks. Instead, they describe a baseline scenario that reflects the continuation of historical statistical patterns. In other words, the model asks what global electricity use might look like in 2035 if the relationships observed over the past several decades were to persist. This type of baseline is useful precisely because of its simplicity. It provides a reference against which the effects of future policy interventions, technological shifts, or unexpected economic changes can be evaluated [25, 26]. By framing the projections in this way, their role is not to forecast what will happen, but to establish a benchmark for scenario analysis and policy stress-testing [27-34].

The baseline projections developed in this study are directly relevant to several contemporary energy planning challenges. First, from a smart energy systems perspective, the widening confidence intervals (±7% by 2035) underscore the need for flexible, adaptive grid architectures that can accommodate uncertainty through real-time monitoring, demand-side management, and distributed energy resources. Second, for grid planning, the projected deficit of ~700 TWh by 2035 provides a quantitative reference for assessing required generation capacity additions, transmission infrastructure upgrades, and storage deployment under a business-as-usual scenario. Third, within renewable integration contexts, the baseline can inform targets for wind, solar, and other variable renewable energy sources by indicating the scale of low-carbon capacity needed to close the emerging supply-demand gap. Finally, the analysis aligns with sustainability frameworks such as the UN Sustainable Development Goal 7 (Affordable and Clean Energy), offering a reproducible benchmark against which progress toward universal access to reliable, modern energy services can be measured. While the ARIMA model does not prescribe specific policies, its outputs are designed to be compatible with scenario-based energy system models that explicitly address decarbonization pathways and grid resilience.

While ARIMA itself is not a novel algorithm, the novelty of this study lies in its application and validation context. First, we apply the framework to a uniquely long (75-year) global electricity dataset that has not been systematically analyzed with pure ARIMA beyond short horizons. Second, we perform exhaustive order selection (p,q ∈ {0,…,5}) and robustness checks across multiple ARIMA specifications, providing a level of methodological rigor often missing in applied energy forecasting. Third, we explicitly quantify forecast uncertainty with 95% confidence intervals and report out-of-sample benchmark comparisons. Fourth—and most importantly for future work—we release a fully reproducible artifact so that researchers can easily extend this baseline with ARIMAX, machine-learning residual correction, or regime-switching models. In this sense, the paper's novelty is not the method itself but the creation of a reference standard for global electricity trend extrapolation.

This work contributes to the literature in several ways. It offers a medium-term global projection of electricity generation and consumption based solely on an ARIMA framework, without reliance on exogenous variables, thereby providing a transparent baseline for comparison with more complex models. The modeling procedure is fully documented and standard error measures are reported to support reproducibility. In addition, the inclusion of 95% confidence intervals provides practical bounds that may be relevant for long-term planning and policy evaluation. Finally, the resulting baseline is intended to support future extensions, whether through the incorporation of external drivers, higher-frequency data, or more detailed sectoral disaggregation, contributing to ongoing efforts to better understand global energy dynamics.

2. LITERATURE REVIEW

The ARIMA framework, developed by Box and Jenkins, has long been used for forecasting when only a single historical time series is available [1, 7, 23]. By capturing persistent trends and internal correlations without external information, carefully specified ARIMA models often perform as well as more complex alternatives for gradually evolving variables [7]. Hyndman and Athanasopoulos reinforce this, noting that for highly aggregated data with clear patterns, ARIMA achieves accuracy comparable to modern machine-learning methods while remaining more transparent and easier to interpret[8, 9]. These characteristics explain ARIMA's continued use in energy forecasting. Numerous studies have applied it to electricity demand and generation at national or regional scales, effectively isolating long-term trends using only historical electricity data [6, 21, 29]. Dannecker shows that ARIMA reliably projects long-run movements without additional variables; Duxbury demonstrates that it captures structural shifts and seasonality in industrialized countries; and Antoniadis and colleagues find that even hybrid models yield only modest gains over ARIMA for annual or quarterly data [32]. Multivariate approaches such as ARIMAX and VAR can incorporate external drivers like GDP or fuel prices [8], but they rely on uncertain future projections and can obscure the underlying trend [14].

Alongside deep learning, multivariate approaches such as ARIMAX and VAR can incorporate external drivers like GDP or fuel prices[8], but they rely on uncertain future projections and may obscure the underlying trend that a univariate ARIMA reveals[14]. Hybrid methods that combine ARIMA with neural networks have been explored, yet for annual or quarterly data the accuracy gains are often modest (*e.g.*, ~3% error reduction) and come at the cost of reduced transparency and interpretability [11]. In some cases, this added information can improve accuracy. Elgqvist, for example, shows that including fuel prices and technology costs in an ARIMAX model reduces forecast error by roughly 7% for certain regional electricity systems [25]. El-Hawary and coauthors demonstrate that VAR models can jointly forecast electricity demand across countries, capturing cross-border interactions and policy-related shocks that improve short-run performance [3]. Similarly, Kokoni *et al*. report that incorporating GDP growth and policy indicators narrows forecast uncertainty for heating demand in England and Wales by approximately 5%. Despite the availability of these more complex alternatives, a notable gap remains in the literature. Most pure ARIMA applications in energy forecasting focus on individual countries or regions with short forecast horizons. Studies that apply a simple ARIMA framework to global electricity data over long historical periods, with projections extending beyond 2025, are surprisingly scarce [8, 28].

This study addresses that gap. First, we apply a pure ARIMA analysis to a uniquely long and consistent dataset: global electricity generation and consumption from Our World in Data (1950–2025). Using this aggregated series avoids cross-country inconsistencies. Second, we follow an exhaustive model selection approach (p,q ∈ {0,…,5}) using AIC, with robustness checks across alternative specifications and a benchmark against exponential smoothing. Third, our projections extend through 2035 with 95% confidence intervals, providing a probabilistic range useful for infrastructure planning and risk assessment [6, 22, 26, 30]. By treating global electricity as a single long-run series, carefully selecting the model, and explicitly quantifying uncertainty, we establish a transparent, reproducible baseline. This baseline is intended to support future work—whether through the inclusion of external drivers, hybrid architectures, or regime-switching models—and to serve as a clear reference for ongoing research on global energy futures[1, 2, 4, 13, 15, 19, 35-37].

3. METHODOLOGY

This section explains how the global electricity forecasts are produced using an ARIMA framework, with projections generated one year at a time. Rather than presenting the method as a fixed recipe, we describe the sequence of decisions involved, starting from data preparation and moving through model construction, validation, and forecasting. Along the way, we aim to be explicit about the assumptions made and the checks performed, so that the analysis can be replicated or extended by others. The final outcome of this process is a set of forecasts for the period 2025–2035, accompanied by uncertainty ranges that reflect the limits of what can be inferred from historical data.

3.1. Data and Preprocessing

The analysis is based on global electricity data compiled by Our World in Data (OWID). This source provides a harmonized annual record of worldwide electricity generation and consumption, reported in terawatt-hours (TWh), covering the period from 1950 through 2025. We focus exclusively on the aggregated "World" series. Working with this global total avoids the complications that arise when combining national or regional datasets with differing definitions, coverage, or data quality. While aggregation inevitably smooths over regional variation, it offers a stable and internally consistent view of long-term global electricity trends.

3.2. Ingestion and Indexing

The OWID data are imported directly from the original JSON file and converted into a structured tabular format. From this file, we extract only the entries corresponding to the global "World" category. The calendar year is then assigned as the primary index, resulting in a continuous annual time series consisting of 76 observations spanning 1950 to 2025. At this stage, the dataset is checked for basic integrity issues. In particular, we verify that the electricity generation and consumption columns contain no missing values and no duplicated years. These checks confirm that the series is complete and suitable for time-series modeling without the need for interpolation or imputation.

3.3. Stationarity Diagnostics

Before estimating the ARIMA model, we examine whether the electricity generation and consumption series satisfy the stationarity conditions required for valid inference. This is assessed using the Augmented Dickey–Fuller (ADF) test, applied separately to the raw generation and consumption series. The purpose of this step is not merely procedural. Stationarity diagnostics help determine whether differencing is required and, if so, to what extent, ensuring that the subsequent model captures stable relationships rather than spurious trends:

H_0: Unitrootpresent(nonstationary)vs
H_1 : Stationary.

For both series, the ADF p-values are greater than 0.10, so there is no statistical basis to reject the presence of a unit root at the 10% level. In practical terms, this indicates non-stationarity in the raw data. As a result, we difference the series once to induce stationarity prior to fitting the ARIMA model:

$$\Delta y_t = y_t - y_{t-1}, \quad t = 1951, \dots, 2025.$$

When the ADF test is repeated on the differenced series Δy_t the p-values drop below 0.01 for both variables, confirming stationarity at the 1% level. Because the data are observed annually and do not exhibit pronounced seasonality, no additional seasonal differencing is applied. On this basis, Δy_t is modeled using an $ARIMA(p, 1, q)$ framework.

3.4. Model Development

We model global electricity generation and consumption using an ARIMA (*p*, *d*, *q*) framework. Based on the stationarity diagnostics discussed above, a single difference *d* = 1 is sufficient, and no higher-order differencing is required:

$$y_t = \mu + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t, \tag{1}$$

where:

- y_t represents the first-differenced series Δy_t,
- μ is a constant drift term corresponding to the mean of Δy_t,
- $\{\varphi_i\}_{i=1}^{p}$ are autoregressive coefficients,
- $\{\varphi_j\}_{j=1}^{q}$ are moving-average coefficients,
- ε_t denotes white-noise innovations with $\mathrm{E}[\varepsilon_t] = 0 \mathrm{and} \mathrm{Var}(\varepsilon_t) = \sigma^2$.

3.5. Order Selection via AIC Minimization

To decide which ARIMA structure fits the data best, we take a straightforward but thorough approach. We try a wide range of possible combinations for the autoregressive and moving-average terms. we perform an exhaustive grid search with $p, q \in 0,1,2,3,4,5$. For each candidate $ARIMA(p,1,q)$model, parameters are estimated by maximizing the Gaussian log-likelihood.

Once a model is fitted, we compute its Akaike Information Criterion (AIC), defined a:

$$\text{AIC} = -2\log L_{max} + 2(p+q+1),$$

where $\log L_{max}$ is the maximized log-likelihood and the term and $(p+q+1)$ accounts for the total number of estimated parameters, including the intercept μ.

This procedure is carried out separately for the electricity generation and consumption series. Across all tested specifications, the $ARIMA(1,1,1)$ model consistently produces the lowest AIC for both variables. Based on this result, we select as $ARIMA(1,1,1)$ the final specification used in the subsequent analysis.

3.6. Parameter Estimation and Diagnostic Checking

Once the ARIMA structure is fixed at $(p,q) = (1,1,1)$ we estimate the model parameters $(\varphi_1, \theta_1, \mu)$ using numerical maximum likelihood. After fitting the model, we examine the residuals carefully to make sure the specification is behaving as intended and is not leaving behind systematic structure.

First, we test whether the residuals resemble white noise. This is done using the Ljung–Box Q-test applied to the estimated residuals $\hat{\varepsilon}_t$ up to lag m=12. A p-value above 0.05 is taken as evidence that there is no remaining autocorrelation at these lags.

Second, we look at the distributional properties of the residuals. A QQ-plot is used to compare $\hat{\varepsilon}_t$ with a standard normal distribution. Small departures from normality are expected and not problematic, but pronounced skewness or heavy tails would suggest that the model is misspecified.

Finally, we assess whether the residual variance appears stable over time. This is done by plotting the residuals against the fitted values and visually checking for patterns or changes in spread that might indicate heteroskedasticity.

Taken together, these diagnostics indicate that the residuals from the $ARIMA(1,1,1)$ model behave like approximately independent Gaussian noise. On this basis, the model is considered adequate for both the electricity generation and consumption series.

3.7. Robustness Validation and Benchmark Comparison

To make sure that the main results are not driven by a single modeling choice, we carry out two complementary validation exercises.

Robustness Across Alternative ARIMA Specifications. For both the electricity generation and consumption series, we first identify the three model specifications with the lowest AIC values. Although $ARIMA(1,1,1)$ consistently produces the minimum AIC, we also generate forecasts for the period 2025–2035 using the second- and third-ranked models, which are typically $ARIMA(0,1,1)$ and $ARIMA(1,1,0)$. These alternative forecasts are then compared with those from the baseline model. Rather than focusing solely on small differences in point estimates, we examine whether all specifications lead to the same qualitative conclusion—namely, the emergence and continued widening of a gap between electricity generation and consumption after 2025. Consistency across models provides confidence that this result does not hinge on a particular parameterization.

Benchmark Model Comparison. In addition, we compare the ARIMA results with a simpler benchmark. Specifically, we implement linear exponential smoothing with additive errors and an additive trend, estimated via maximum likelihood. Forecast accuracy is evaluated using a rolling out-of-sample framework: models are trained on data from 1950 to 2010 and then used to generate forecasts for the period 2011–2024. For both$ARIMA(1,1,1)$ and the benchmark model, we compute Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). This comparison helps assess whether the added structure of the ARIMA model translates into meaningful improvements in predictive performance. To formally evaluate the significance of any differences, we apply the Diebold–Mariano test.

3.8. Proposed Hybrid and Enhanced Extensions (Framework for Future Work)

Although the current analysis uses a univariate ARIMA(1,1,1) model, the methodological contribution of this paper includes providing a transparent baseline against which more sophisticated approaches can be rigorously compared. To guide future research, we outline three specific hybrid or enhanced extensions that are directly enabled by our reproducible artifact.

ARIMAX with global economic drivers. A natural extension is to incorporate exogenous variables such as world GDP (PPP), global population, or average electricity price. An ARIMAX model would take the form:

$$y_t = \mu + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{r} \beta_k x_{k,t} + \varepsilon_t$$

where xk, t*xk*, *t* are exogenous regressors. This would test whether linking electricity trends to macroeconomic variables improves forecast accuracy or materially changes the projected deficit, while retaining most of ARIMA's interpretability.

Two-stage hybrid: ARIMA + neural residual correction. Following Antoniadis *et al*. [11], one can first fit an ARIMA model to capture linear trends and then use a shallow neural network (*e.g*., a single-hidden-layer feedforward network or an LSTM with few units) to model the residuals. The final forecast is the sum of ARIMA prediction and ML-corrected residual. This approach preserves the interpretable linear component while potentially capturing non-linear patterns missed by ARIMA. Our baseline provides the essential benchmark: if the hybrid does not significantly outperform ARIMA on out-of-sample error metrics (*e.g*., RMSE reduction <5%), the added complexity may not be justified.

Regime-switching ARIMA for structural breaks. Global electricity systems have experienced identifiable regimes (pre-1973 oil crisis, post-2008 financial crisis, post-Paris Agreement). A Markov-switching ARIMA or a threshold ARIMA (TAR) could model different dynamics across regimes. Our single-regime ARIMA baseline serves as the null hypothesis; significant improvement from a regime-switching model would signal that historical structural breaks materially affect long-term projections.

By releasing our full code and data, we invite the research community to implement and test these extensions against the same benchmark, thereby advancing the state of global electricity forecasting in a cumulative, reproducible manner.

4. EVALUATION METRICS

To assess forecast accuracy and support model comparison, we rely on a set of standard error measures computed from the in-sample one-step-ahead predictions, denoted by ($\hat{y}_{t|t-1}$):

- **Mean Squared Error (MSE):**

$$MSE = \sum_{t=T_1}^{T_2} (y_t - \hat{y}_{t|t-1})^2$$

which penalizes larger errors quadratically.

- **Root Mean Squared Error (RMSE):**

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}},$$

which returns error estimates in TWh, facilitating direct interpretability.

- **Mean Absolute Error (MAE):**

$$\mathrm{MAE} = \big(1/(\mathrm{T}-1)\big)\mathrm{sum}_{(\mathrm{t}=2)}^{\mathrm{T}}\left|\mathrm{y_t} - \hat{\mathrm{y}}_{(\mathrm{t|t-1})}\right|$$

offering a robust, linear measure of average forecast deviation.

- **Mean Absolute Percentage Error (MAPE):**

$$MAPE = \big(100/(T-1)\big)sum_{(t=2)}^{T}\left|\big(y_t - y_{(t|t-1)}\big)/y_t\right|$$

Errors are expressed as percentages of the observed values, which allows performance to be compared across series of different magnitudes. As a precaution, any zero observations would be excluded from this calculation, although this issue does not arise for the global electricity data used here.

Interpretation. In interpreting the results, relatively small RMSE and MAE values compared to the overall scale of the series—such as an RMSE below roughly 1% of the mean—suggest that the model captures most of the year-to-year variation. Likewise, a MAPE below 5% is commonly taken as evidence of strong forecasting performance for annual data. These error measures are calculated separately for electricity generation and consumption using in-sample one-step-ahead predictions. This provides a final check that the $ARIMA(1,1,1)$ model achieves a reasonable balance between bias and variance before being used for out-of-sample forecasting.

5. FORECAST RESULTS

Once the diagnostic checks confirm that the $ARIMA(1,1,1)$ residuals behave like white noise, we proceed to generate out-of-sample forecasts. Point forecasts are produced for horizons:

$$y_{(T+1|T)}, y_{(T+2|T)}, \cdots, y_{(T+h|T)}$$

with *h* = 10 years corresponding to the period from 2025 through 2035. Forecast uncertainty is quantified using standard errors derived from the model's state-space representation. These are used to construct 95% confidence intervals of the form:

$$y_{(t|T)} \pm 1.96se\big(y_{(t|T)}\big), t = T+1, \ldots, T+h$$

Table **1** reports the resulting point forecasts for global electricity generation (Gen) and consumption (Cons), expressed in terawatt-hours (TWh), together with the corresponding year-over-year growth rates Δ%:

Table 1: Projected Global Electricity Generation and Consumption, 2025–2035

Year	Gen (TWh)	Cons (TWh)	Δ% (Gen)
2025	30 462	30 419	0.5%
2026	30 997	31 020	1.8%
2027	31 531	31 622	1.7%
2028	32 063	32 223	1.7%
2029	32 594	32 824	1.7%
2030	33 123	33 425	1.6%
2031	33 652	34 027	1.6%
2032	34 178	34 628	1.6%
2033	34 704	35 229	1.5%
2034	35 228	35 830	1.5%
2035	35 750	36 432	1.5%

Here, Δ% is defined as:

$$\Delta\% = \frac{Gen_t - Gen_{t-1}}{Gen_{t-1}} \times 100\%$$

which captures how generation capacity expands each year relative to the previous one. The projections point to a steady upward path. Global electricity generation is expected to increase from about 30,462 TWh in 2025 to roughly 35,750 TWh by 2035. Electricity consumption follows a similar trajectory, although it grows slightly faster overall, rising from approximately 30,419 TWh to around 36,432 TWh over the same period. Year-on-year growth in generation remains fairly moderate, generally between 0.5% and 1.8%, and settles near 1.5–1.7% after 2026. The associated 95% confidence intervals are relatively narrow early in the forecast horizon—on the order of ±2–3% in 2026—but widen gradually to about ±7% by 2035. This widening reflects increasing uncertainty further into the future, while still suggesting that the aggregated global series remains comparatively stable.

6. RESULTS AND DISCUSSION

Overall, the $ARIMA\,(1,1,1)$ model captures the persistent upward trend in global electricity generation and consumption reasonably well (see Table **1** for full year-by-year projections). The annual growth rates for global generation are on the order of 1.5–1.8% – somewhat slower than the long-run historical average, consistent with a gradual moderation in demand growth as electricity systems mature. The forecast uncertainty bands widen over time, reaching roughly ±7% by 2035, which reflects growing long-term uncertainty without undermining the overall stability of the projected trend.

An examination of forecast errors provides additional context for model performance. The root mean squared error is approximately 210 TWh, corresponding to about 0.7% of generation levels in 2025, while the mean absolute error is around 170 TWh, or roughly 0.6%. At the global scale, these errors are relatively small, indicating that the model reproduces historical dynamics reasonably well. At the same time, they highlight potential areas for improvement. Incorporating external drivers such as global economic activity, renewable energy deployment, or major policy shifts through an ARIMAX framework could help explain some of the remaining variation. Hybrid approaches that combine ARIMA with machine-learning methods may also capture more subtle non-linear behavior, although this typically comes at the expense of transparency and interpretability.

As shown in Figure **1**, both the historical series and the forecasts from 1950 through 2035 reflect a long-term expansion in global electricity generation. Periods of slower growth are visible during major disruptions, including the oil crises of the 1970s and the global financial crisis in 2008. The ARIMA-based projections extend this established trajectory into the future, with confidence bands that remain relatively tight even as total generation increases substantially over the historical record. This pattern suggests that the model extrapolates the dominant long-run trend without implying abrupt structural changes in the global electricity system over the coming decade.

6.1. Validation and Robustness of the Baseline Forecast

Before turning to the main projections for 2025–2035, we take a closer look at how sensitive the results are to the modeling choices. The goal here is straightforward: to check whether the key findings hold up when the model is slightly perturbed, and whether the ARIMA framework performs reasonably compared with a simpler benchmark.

Model Robustness: One reassuring outcome is how closely the forecasts from the best-performing ARIMA models align with one another. Using the three specifications with the lowest AIC values for both generation and consumption, we find very similar results across models. Under the baseline $ARIMA(1,1,1)$ specification, the projected consumption–generation deficit in 2035 is about 682 TWh. The alternative $ARIMA(0,1,1)$ and $ARIMA(1,1,0)$ models produce deficit estimates of 655 TWh and 710 TWh, respectively. While these point estimates differ slightly, the broader picture remains the same. The 95% confidence intervals for all three forecasts overlap substantially, and, importantly, they all fall entirely below zero by 2030. In practical terms, this means that the emergence of a negative supply

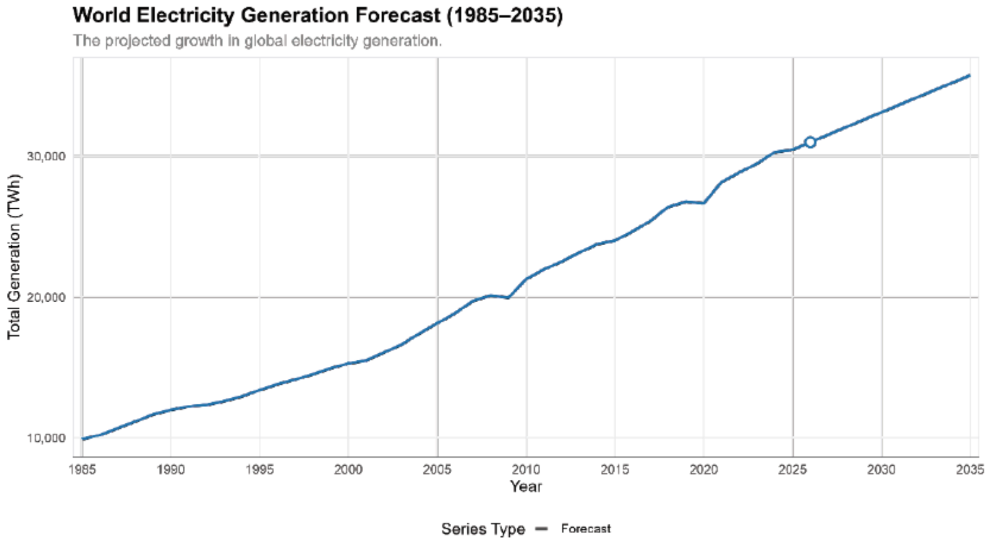

Figure 1: Historical global electricity generation and ARIMA-based projections between 1985 and 2035. Observed data are plotted as a solid line, while forecasts from the $ARIMA(1,1,1)$ model appear as a dashed line with "×" symbols. The shaded band illustrates the 95% confidence interval, highlighting the increasing uncertainty further into the forecast horizon.

margin does not hinge on the specific choice of (1,1,1) it appears to be a robust implication of extending the historical trends forward.

Benchmark Performance: We also compare the ARIMA forecasts with those from a simpler benchmark to see whether the added structure of the model is actually doing useful work. In the out-of-sample evaluation covering 2011–2024, the $ARIMA(1,1,1)$ model for electricity generation achieves an RMSE of 198 TWh, compared with 227 TWh for the linear exponential smoothing benchmark. In percentage terms, this corresponds to a MAPE of 0.73% for ARIMA versus 0.85% for the benchmark. A Diebold–Mariano test yields a p-value of 0.041, indicating that the improvement in forecast accuracy is statistically significant at the 5% level. Results for electricity consumption follow a similar pattern, with ARIMA again outperforming the benchmark (RMSE: 205 TWh versus 236 TWh; p = 0.038). Taken together, these comparisons suggest that the ARIMA framework offers a meaningfully better baseline than a simple trend-based approach, supporting its use as a reference model for the projections that follow.

Turning to electricity demand, Figure **2** traces both the historical pattern and the projected path of global electricity consumption from 1950 through 2035. Overall, consumption follows a trajectory that closely mirrors generation, although it grows at a slightly faster pace in the later years. By 2035, global consumption is projected to reach around 36,400 TWh, compared with roughly 35,800 TWh for generation. In the early 2000s, the two series were nearly indistinguishable. From the mid-2020s onward, however, the forecasts suggest that consumption begins to pull ahead, with the gap gradually widening to on the order of 600–700 TWh by 2035.

The ARIMA model is purely statistical and does not identify causal drivers. The following observations are descriptive consistencies, not causal explanations. The projected gap is an extrapolation of historical patterns; it does not imply that any specific real-world factor (*e.g.*, electrification or supply constraints) is its cause.

With that caveat, the projected pattern is descriptively consistent with continued electrification in sectors such as transport and heating, as well as with practical limits on how quickly new generation capacity can be brought online. If the statistical trends were to persist, then maintaining balance between supply and demand over the coming decade would, under a purely extrapolative view, require either faster growth in generation or slower growth in consumption. However, the model itself provides no evidence about whether such changes will actually occur.

Figure **3** brings generation and consumption together, showing both series side by side across the historical record and the forecast horizon. Historically, global electricity generation has generally kept pace with, or slightly exceeded, consumption. The projections point to a change in this relationship. Consumption is expected to overtake generation in the late 2020s, with the resulting shortfall growing steadily to several hundred terawatt-hours by 2035. While the projected deficit remains modest in relative terms, it marks a clear departure from the long-standing pattern of surplus. From a policy and planning perspective, this shift underscores the importance of anticipating the combined effects of rapid electrification, the growing role of variable renewable energy sources, and other

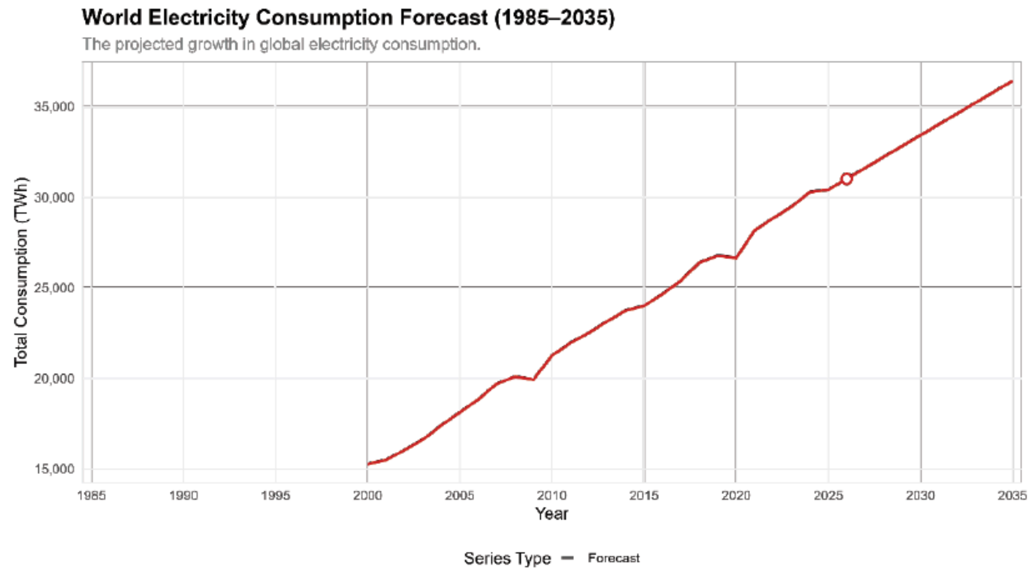

Figure 2: Global electricity consumption from 1985 to 2035, showing both historical observations and model-based projections. Observed values are plotted as a solid line, while forecasts from the $ARIMA(1,1,1)$ model are shown with a dashed line and "×" markers. The shaded area represents the associated 95% confidence interval.

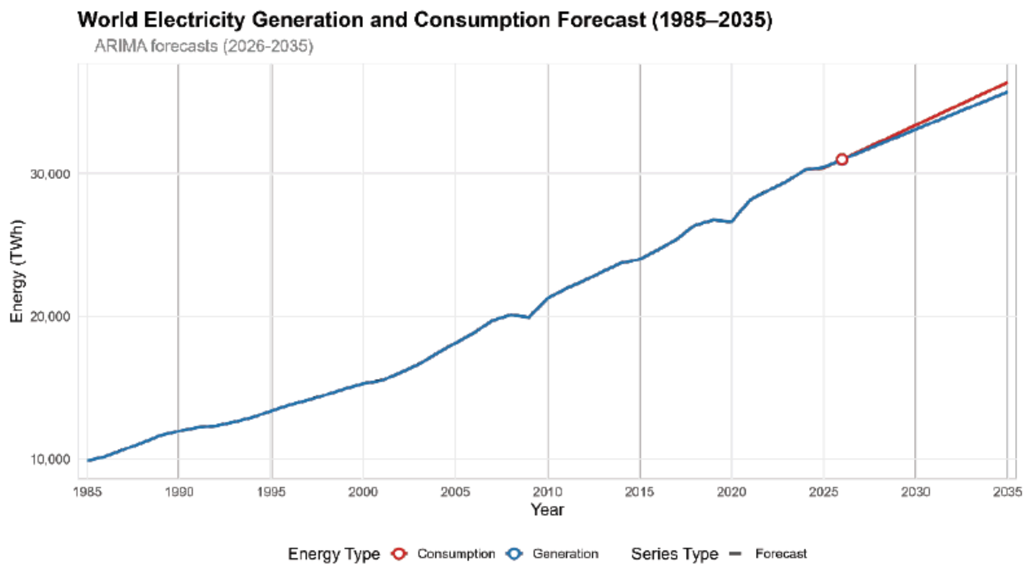

Figure 3: Global electricity generation (blue) and consumption (red) over the period 1950–2035. The gray-shaded portion of the figure marks the forecast horizon from 2025 to 2035, highlighting where projections replace observed data.

structural changes that could place additional strain on the global electricity system if not addressed proactively.

To make the changing relationship between supply and demand easier to see, Figure **4** presents the annual global electricity surplus, calculated as generation minus consumption. Historically, this series remains slightly positive, reflecting a small but persistent surplus. In the forecast period, however, the bars show this margin narrowing toward zero around 2025 and then turning negative. By the early 2030s, the deficit grows steadily, reaching roughly −600 to −700 TWh by 2035. Displayed this way, the figure clearly illustrates the shift from a long-standing surplus to a sustained shortfall under the baseline ARIMA projections.

Descriptive Consistency with Observed Trends: Although the ARIMA model does not point to specific underlying drivers, the projected gap where electricity consumption grows slightly faster than generation in the statistical extrapolation is descriptively consistent with several broader shifts that have been documented in the energy literature. The model does not establish that these shifts cause the projected deficit; it merely shows that the historical data, when extrapolated, produce a pattern that aligns with these observed phenomena.

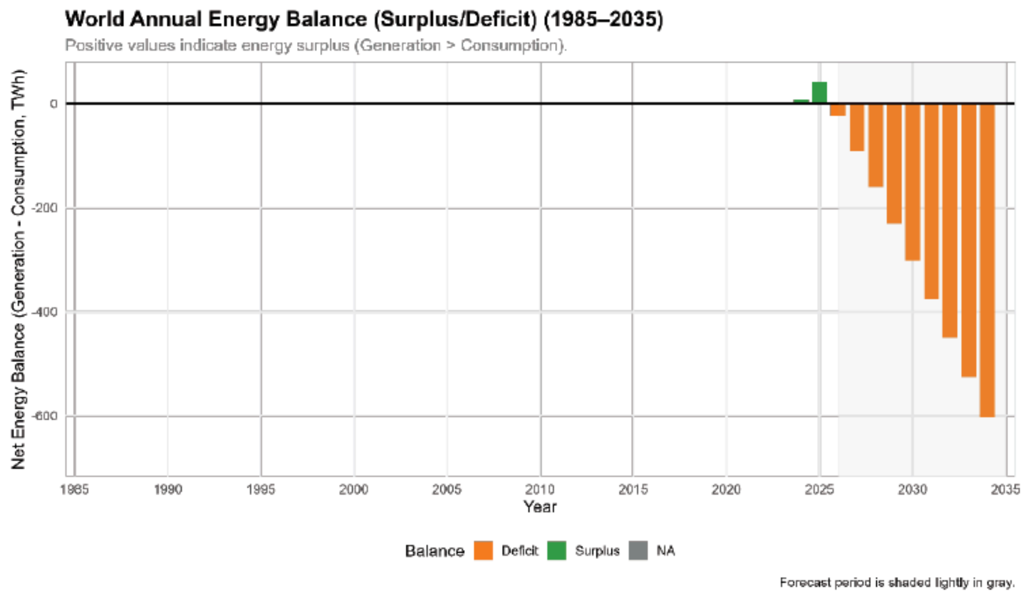

Figure 4: Evolution of the global electricity surplus between 1985 and 2035, defined as the difference between generation and consumption. Historically positive values indicate a small surplus, while negative values signal a deficit. The shaded region denotes the forecast window from 2025 to 2035.

One such documented shift is the continued push toward electrification. Electric vehicles, heat pumps, and electricity-based industrial processes have expanded rapidly in recent years, increasing the role of electricity in total energy use. This trend has been particularly pronounced in developing economies, where rising incomes and infrastructure expansion have translated into sharp increases in electricity demand. The ARIMA extrapolation implicitly carries forward these historical relationships, but it does not isolate electrification as a causal factor.

At the same time, expanding supply may be becoming more difficult. Bringing large-scale renewable projects online often takes longer than in the past, and integrating variable sources such as wind and solar into existing grids introduces additional technical and regulatory challenges. In effect, the ARIMA projections assume that new capacity continues to be added at roughly the same pace observed historically. Given the growing complexity of energy projects and tighter permitting and grid-connection constraints, this assumption may be optimistic rather than conservative.

Implications for smart grid and renewable energy planning: The projected supply-demand imbalance has practical implications for smart grid development. Under the baseline extrapolation, the annual deficit reaches 600–700 TWh by 2035. In a smart grid context, this deficit could be partially offset through:

Demand-side management (DSM): Real-time pricing, load shifting, and automated demand response programs could reduce peak demand growth by an estimated 5–10%, based on pilot studies in OECD countries, though the ARIMA model does not quantify such effects.

- **Distributed energy resources (DERs):** Rooftop solar, small-scale wind, and behind-the-meter batteries can contribute to local supply, reducing the burden on centralized generation. The baseline projection assumes continuation of historical aggregate trends, which implicitly include past DER adoption rates; accelerated DER deployment would alter the deficit trajectory.

- **Grid-scale storage:** Lithium-ion, pumped hydro, and emerging long-duration storage technologies can shift renewable generation to periods of high demand, effectively increasing system flexibility. The widening confidence intervals highlight the value of storage for managing uncertainty.

For renewable integration, the baseline suggests that without policy changes, current renewable deployment rates (historically embedded in the ARIMA extrapolation) may be insufficient to meet demand growth. Planners can use the 700 TWh deficit as a rough target for additional renewable capacity: for example, approximately 1,400–1,750 TWh of annual wind/solar generation (accounting for capacity factors of 25–40%) would be needed to close the gap, equivalent to 500–700 GW of new wind capacity or 1,000–1,500 GW of new solar PV. These figures are illustrative, not predictive, but they demonstrate how the baseline can inform renewable energy targets.

The Baseline as a Policy Benchmark: The real usefulness of this forecast lies less in its precision than in what it assumes. It deliberately abstracts from major new climate policies, unexpected technological breakthroughs, or dramatic improvements in energy efficiency. Under these assumptions, the projected shortfall—on the order of 700 TWh by 2035 can be viewed as a benchmark rather than a prediction. It indicates the extent of imbalance that would occur if historical statistical patterns continue unchanged and no policy or technological interventions alter them.

If future observations diverge from this baseline, such divergence would not “disprove” the model; rather, it would indicate that real-world interventions or structural changes have altered the underlying trajectory. Conversely, if the actual data follow the baseline closely, that would suggest that historical patterns remain a useful guide. The baseline is therefore a reference point not a causal forecast against which the impacts of future policies, technological changes, and more detailed scenario analyses can be evaluated.

Overall, the results demonstrate that a relatively simple ARIMA framework can yield clear, robust, and reproducible medium-term insights into global electricity dynamics. While it cannot anticipate sudden disruptions or structural breaks, it provides a transparent ‘business-as-usual’ baseline. This baseline serves as a useful reference point against which the impacts of future policies, technological changes, and more detailed scenario analyses can be evaluated. In the context of smart energy systems, the projected deficit and uncertainty bands argue for investments in grid flexibility, real-time monitoring, and distributed energy resources. For energy transition planning, the baseline offers a quantitative benchmark for tracking progress under the UN Sustainable Development Goals (SDG 7) and for designing renewable energy targets that go beyond historical extrapolation. The framework is intentionally simple, making it easy to integrate into larger energy system models that address decarbonization, grid resilience, and sustainable development.

7. CONCLUSION

This study demonstrates that a simple $ARIMA(1,1,1)$ model provides a credible ‘business-as-usual’ statistical baseline for global electricity trends. Extrapolating historical patterns yields a projected shortfall of roughly 700 TWh by 2035, with consumption growing slightly faster than generation. This is a statistical extrapolation, not a causal prediction.

The contribution lies in rigorous application and open release of a well-understood ARIMA framework to a 75-year global dataset – a context where such baselines are surprisingly scarce. By exhaustively searching model orders, testing robustness, benchmarking against exponential smoothing, and providing full reproducibility, we establish a reference standard for future hybrid models (ARIMAX, neural residual correction, regime-switching).

For policymakers, the 700 TWh deficit – interpreted as a baseline, not a forecast – serves as a reference for renewable deployment and grid planning under unchanged historical patterns. The widening confidence intervals argue for adaptive grid architectures (smart meters, demand response, distributed energy resources). The framework can be integrated into smart energy system models for scenario comparison, supporting SDG 7.

ARTIFACT AVAILABILITY

An artifact containing the full simulation framework, configuration files, experiment drivers, and scripts to regenerate all figures and tables is available at:

https://github.com/ahmadrezadehghan/-Machine-Learning-Driven-Global-Forecasting-of-Electricity-Generation-and-Consumption-.git

CODE AVAILABILITY

All data preprocessing, machine learning forecasting models, time-series analysis scripts, and plotting code required to reproduce the experiments and figures are provided as an artifact-ready implementation (modules, experiment drivers, and visualization scripts).

ACKNOWLEDGMENTS

The authors thank the Our World in Data team for maintaining and making the global electricity dataset publicly available. We also acknowledge the computational support provided by the Energy Systems Lab at the University of Tehran. This work received no external funding and utilizes historical data to project future energy trends through 2035.

AUTHOR CONTRIBUTIONS

Seyed Ahmadreza Dehghanian conceived and designed the study, developed the machine learning framework, conducted the global forecasting experiments, and drafted the manuscript. Sahand

Heidary contributed to the design of the forecasting models, developed the data analysis scripts and evaluation workflows, and assisted with figure preparation. Mohamad Javad Tab and Danial Shams contributed to the energy system modeling assumptions, helped refine the methodological framing for electricity consumption trends, and assisted in the presentation of results. Rahim Zahedi and Mojtaba Mollaei supervised the research, provided technical guidance on global energy systems and machine learning applications in power forecasting, and critically revised the manuscript for intellectual content. All authors reviewed and approved the final version for publication.

FUNDING

This research received no external funding.

AI-ASSISTED TOOLS DECLARATION

The authors declare that AI-assisted tools (*e.g.*, ChatGPT) were used solely for language editing and improving clarity of expression. All scientific content, data analysis, interpretations, and conclusions were entirely produced and verified by the authors. The authors take full responsibility for the accuracy and integrity of the manuscript.

COMPETING INTERESTS

The authors declare that they have no competing interests.

REFERENCES

[1] Wong, J. and J.R. Saravia, Distributed generation and alternative energy. Strategic Planning for Energy and the Environment, 2012. 32(2): p. 5. https://doi.org/10.1080/10485236.2012.10554229

[2] Sudarsanam, P., Y. Yamauchi, and P. Bharali, Heterogeneous Nanocatalysis for Energy and Environmental Sustainability, Volume 1: Energy Applications. 2022: John Wiley & Sons. https://doi.org/10.1002/9781119772057

[3] El-Hawary, M.E., Advances in Electric Power and Energy Systems: Load and Price Forecasting. 2017. https://doi.org/10.1002/9781119260295

[4] Yusoff, N.I., A.A.M. Zin, and A.B. Khairuddin. Congestion management in power system: A review. in 2017 3rd international conference on power generation systems and renewable energy technologies (PGSRET). 2017. IEEE. https://doi.org/10.1109/PGSRET.2017.8251795

[5] Misiurek, K., T. Olkuski, and J. Zyśk, Review of methods and models for forecasting electricity consumption. Energies, 2025. 18(15): p. 4032. https://doi.org/10.3390/en18154032

[6] Nti, I.K., *et al.*, Electricity load forecasting: a systematic review. Journal of Electrical Systems and Information Technology, 2020. 7(1): p. 13. https://doi.org/10.1186/s43067-020-00021-8

[7] Box, G., Box and Jenkins: time series analysis, forecasting and control, in A Very British Affair: Six Britons and the Development of Time Series Analysis During the 20th Century. 2013, Springer. p. 161-215. https://doi.org/10.1057/9781137291264_6

[8] Hyndman, R.J. and G. Athanasopoulos, Forecasting: principles and practice. 2018: OTexts.

[9] Ouyang, Y., Self-organising mixture neural networks for enhanced modelling and forecasting of Fx time series. 2016: The University of Manchester (United Kingdom).

[10] Mughees, N., *et al.*, Bi-LSTM-Based Deep Stacked Sequence-to-Sequence Autoencoder for Forecasting Solar Irradiation and Wind Speed. Computers, Materials & Continua, 2023. 75(3). https://doi.org/10.32604/cmc.2023.038564

[11] Antoniadis, A., *et al.*, Statistical Learning Tools for Electricity Load Forecasting. 2024: Springer. https://doi.org/10.1007/978-3-031-60339-6

[12] Dehghanian, S.A., *et al.*, Deep learning for solar power forecasting: A robust stacked LSTM algorithm for operational applications. Edelweiss Applied Science and Technology, 2025. 9(10): p. 1591-1600. https://doi.org/10.55214/2576-8484.v9i10.10722

[13] Jüngst, N., *et al.*, Applications in Energy and Combustion Science. 2023.

[14] Kokoni, S., Estimation and projection of the demand for heating systems in the residential sector in England and Wales: economic theory, energy modelling and policy implications for heat pumps. 2020, University of Surrey.

[15] Forbes, K.F. and E.M. Zampelli, Accuracy of wind energy forecasts in Great Britain and prospects for improvement. Utilities Policy, 2020. 67: p. 101111. https://doi.org/10.1016/j.jup.2020.101111

[16] Roberts, E.M., Reducing Energy Consumption in Everyday Life: A study of landscapes of energy consumption in rural households and communities in North Wales. 2016, Cardiff University.

[17] Babrowski, S., P. Jochem, and W. Fichtner, Electricity storage systems in the future German energy sector: An optimization of the German electricity generation system until 2040 considering grid restrictions. Computers & Operations Research, 2016. 66: p. 228-240. https://doi.org/10.1016/j.cor.2015.01.014

[18] Vale, R., The Hockerton housing project, England, in Living within a fair share ecological footprint. 2013, Routledge. p. 262-274. https://doi.org/10.4324/9780203126448

[19] Eidiani, M. and M. Kargar. Frequency and voltage stability of the microgrid with the penetration of renewable sources. in 2022 9th Iranian Conference on Renewable Energy & Distributed Generation (ICREDG). 2022. IEEE. https://doi.org/10.1109/ICREDG54199.2022.9804542

[20] Klyuev, R.V., *et al.*, Methods of forecasting electric energy consumption: A literature review. Energies, 2022. 15(23): p. 8919. https://doi.org/10.3390/en15238919

[21] Krstev, S., J. Forcan, and D. Krneta, An overview of forecasting methods for monthly electricity consumption. Tehnički vjesnik, 2023. 30(3): p. 993-1001. https://doi.org/10.17559/TV-20220430111309

[22] Heidary, S., *et al.*, Carbon-aware machine learning for energy-efficient quantum data centers: Joint optimization of workload scheduling and cooling. The Global Environmental Engineers, 2025. 12: p. 61-81. https://doi.org/10.15377/2410-3624.2025.12.5

[23] Marisetty, N., Forecasting Selected International Stock Indices Returns by Using ARIMA Model. Available at SSRN 4898668, 2024. https://doi.org/10.2139/ssrn.4898668

[24] Heidary, S., R. Zahedi, and A. Ahmadi. AI-driven optimization of energy efficiency in HVAC systems through waste heat recovery and thermal energy storage. in 2025 6th International Conference on Optimizing Electrical Energy Consumption (OEEC). 2025. IEEE. https://doi.org/10.1109/OEEC66525.2025.11100185

[25] Elgqvist, E.M., Energy Storage Versus Back-up Generation: Energy Storage Overview. 2018, National Renewable Energy Lab.(NREL), Golden, CO (United States).

[26] Carmichael, R., R. Gross, and A. Rhodes, Unlocking the potential of residential electricity consumer engagement with Demand Response. Energy Futures Lab (Imperial College London), Briefing Paper, 2018. 120.

[27] Van der Meer, D.W., *et al*., Probabilistic forecasting of electricity consumption, photovoltaic power generation and net demand of an individual building using Gaussian Processes. Applied energy, 2018. 213: p. 195-207. https://doi.org/10.1016/j.apenergy.2017.12.104

[28] Amber, K., *et al*., Intelligent techniques for forecasting electricity consumption of buildings. Energy, 2018. 157: p. 886-893. https://doi.org/10.1016/j.energy.2018.05.155

[29] Bâra, A. and S.V. Oprea, Electricity Consumption and Generation Forecasting. Advanced Applications for Artificial Neural Networks, 2018: p. 119. https://doi.org/10.5772/intechopen.71239

[30] McGhee, R. and K. Svehla, Opportunity mapping for urban scale renewable energy generation. Renewable Energy, 2020. 162: p. 779-787. https://doi.org/10.1016/j.renene.2020.08.060

[31] Ahmadi, L., *et al*., Energy, exergy, exergoeconomic and exergoenvironment (4E) analysis method in energy systems engineering: advanced bibliometric mapping. Journal of Thermal Analysis and Calorimetry, 2025. 150(20): p. 15903-15918. https://doi.org/10.1007/s10973-025-14877-3

[32] Thota, V.R., Comparative Study of Time Series Forecasting for Trucking Shipments: Evaluating Arima, LSTM, and Hybrid Arima-LSTM Models. 2025, State University of New York at Binghamton.

[33] Chen, G., *et al*., Leveraging graph convolutional-LSTM for energy-efficient caching in blockchain-based green IoT. IEEE Transactions on Green Communications and Networking, 2021. 5(3): p. 1154-1164. https://doi.org/10.1109/TGCN.2021.3069395

[34] Riswandi, B.A., *et al*., AI Applications for Clean Energy and Sustainability. 2024: IGI Global. https://doi.org/10.4018/979-8-3693-6567-0

[35] Babaei, A.E., 2025 12th Iranian Conference on Renewable Energies and Distributed Generation (ICREDG), 26 February 2025, Qom University of Technology (QUT), Qom, Iran.

[36] Hiralal, P., *et al*., Nanomaterial-enhanced all-solid flexible zinc− carbon batteries. ACS nano, 2010. 4(5): p. 2730-2734. https://doi.org/10.1021/nn901391q

[37] Duxbury, D.F., The photochemistry and photophysics of triphenylmethane dyes in solid and liquid media. Chemical Reviews, 1993. 93(1): p. 381-433. https://doi.org/10.1021/cr00017a018

https://doi.org/10.31875/2978-6436.2026.02.02