

Grey Wolf Optimizer-Neural Network Model for Indonesia Electricity Demand Prediction: Multi-Scenario Analysis and Performance Evaluation 2026-2034

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Abstract – Indonesia's rapid economic development and energy transition goals necessitate accurate long-term electricity demand forecasting to ensure supply security while optimizing infrastructure investments. This study addresses critical gaps in existing forecasting methodologies by developing a hybrid Grey Wolf Optimizer-Neural Network (GWO-NN) model specifically designed for emerging economy characteristics. While recent deep learning approaches (LSTM, CNN-LSTM) show promise for short-term forecasting, they often fail in long-term predictions due to limited adaptability to economic volatility and infrastructure constraints typical in developing nations. Our GWO-NN framework overcomes these limitations through intelligent hyperparameter optimization and multi-scenario modeling that captures Indonesia's unique socio-economic dynamics. The model incorporates 15 years of historical data (2010-2025) across seven key variables: GDP growth, population dynamics, temperature variations, industrial activity, urbanization rates, energy efficiency, and electrification progress. Rigorous validation against PLN's official projections reveals superior performance: Conservative scenario achieves exceptional 3.9% average absolute difference, Moderate scenario 19.0%, demonstrating significant improvement over traditional ARIMA models (>35% error) and recent CNN-LSTM approaches (>25% error). The 2034 demand projections range from 377.0 TWh (Conservative) to 546.1 TWh (Optimistic), providing policymakers with robust planning envelopes. This research contributes methodologically through hybrid metaheuristic optimization and practically through evidence-based

planning support for Indonesia's renewable energy transition and carbon neutrality targets by 2060.

Keywords: Grey Wolf Optimizer, Neural Network, Electricity Demand Prediction, Indonesia, Multi-Scenario Analysis, Energy Forecasting, Optimization Algorithm.



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I. INTRODUCTION

Indonesia's energy landscape is undergoing unprecedented transformation as the world's fourth-largest population and Southeast Asia's largest economy grapples with surging electricity demand while pursuing ambitious decarbonization goals. The National Electricity Supply Business Plan (RUPTL) projects demand reaching 410 TWh by 2034—a 67% increase from current levels—yet traditional forecasting methods consistently underperform in capturing the complex, non-linear relationships characteristic of rapidly developing economies [1]. This forecasting accuracy gap poses significant risks to energy security, infrastructure investment efficiency, and climate commitments, necessitating advanced analytical frameworks capable of handling economic volatility, demographic transitions, and policy uncertainties inherent in emerging markets.

Critical Literature Review and Research Gaps

Recent advances in electricity demand forecasting have been dominated by deep learning approaches, yet

significant methodological gaps persist when applied to developing economic contexts. Table 1 presents a

comprehensive comparison of existing forecasting methodologies and their limitations.

Table 1. Comparative Analysis of Electricity Demand Forecasting Methods

Method	Time Horizon	Accuracy (MAPE)	Strengths	Critical Limitations	References
ARIMA	Short-term	15-25%	Simple, interpretable	Cannot capture non-linear patterns, poor with structural breaks	[2, 3]
CNN-LSTM	Short-medium	8-15%	Captures temporal patterns	Requires large datasets, limited economic variable integration	[3-5]
LSTM-Attention	Medium	10-18%	Long memory, attention mechanism	Computationally expensive, black-box nature	[6, 7]
Ensemble (RF+SVM)	Medium	12-20%	Robust to outliers	Limited scenario modeling capabilities	[1, 8]
Transformer Models	Short-medium	6-12%	State-of-the-art for sequence modeling	Data hungry, poor extrapolation beyond training range	[9, 10]
GWO-NN (This Study)	Long-term	3.9-19%	Multi-scenario, economic integration, hyperparameter optimization	Computational complexity	Current

Economic Integration Deficit in Contemporary Deep Learning Approaches

The first fundamental limitation concerns the inadequate integration of macroeconomic variables within contemporary deep learning architectures, representing a critical methodological gap that compromises forecasting reliability in emerging economy contexts. While Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) models demonstrate exceptional pattern recognition capabilities for identifying temporal dependencies and cyclical patterns within historical electricity consumption data, they exhibit systematic deficiencies in capturing the causal relationships between macroeconomic drivers and electricity demand evolution that are particularly pronounced in rapidly developing economies [11]. This economic integration deficit manifests most critically in the treatment of Gross Domestic Product (GDP) elasticity relationships, where electricity demands responsiveness to economic growth frequently exceeds unity elasticity coefficients (often reaching 1.5-2.0) in emerging markets due to rapid industrialization, infrastructure development, and household electrification processes that accompany economic development transitions [12].

Traditional deep learning approaches treat economic variables as additional input features without explicit recognition of their functional relationships and threshold effects, thereby failing to capture the non-linear economic mechanisms that drive electricity demand evolution during different development phases [11]. Furthermore, these models inadequately incorporate the sectoral composition

effects of economic growth, where manufacturing expansion, service sector development, and agricultural modernization exhibit differentiated electricity demand implications that vary systematically across development stages. The absence of explicit economic modeling within deep learning frameworks compromises their ability to generate credible long-term projections under scenarios involving economic structural transformation, policy regime changes, or external economic shocks that fundamentally alter electricity demand elasticity relationships [3]. This limitation becomes particularly problematic in emerging economies like Indonesia, where rapid economic development creates dynamic elasticity patterns that cannot be adequately captured through purely statistical pattern recognition approaches without explicit economic theoretical grounding.

Scenario Modeling Limitations and Planning Framework Inadequacies

The second critical methodological gap encompasses the systematic limitations of existing deep learning approaches in providing scenario-based forecasting frameworks essential for strategic infrastructure planning under uncertainty conditions [11]. Contemporary neural network architectures, including advanced LSTM and Transformer-based models, predominantly generate deterministic point estimates that inadequately reflect the range of possible future outcomes under different economic, demographic, and policy conditions characteristic of emerging market environments [13].

This scenario modeling deficit represents a fundamental disconnect between forecasting

methodology capabilities and practical planning requirements, where infrastructure investment decisions necessitate comprehensive risk assessment across multiple development pathways rather than single-trajectory predictions. The absence of systematic scenario generation capabilities limits the utility of existing forecasting frameworks for capital allocation decisions, capacity planning optimization, and regulatory policy formulation that must account for uncertainty in future demand evolution [13]. Infrastructure investments in electricity generation, transmission, and distribution systems typically involve substantial capital commitments with asset lifespans extending 20-40 years, creating critical requirements for forecasting methodologies that can quantify demand evolution boundaries under different development assumptions.

The deterministic nature of conventional deep learning predictions fails to provide the probabilistic information essential for risk-based planning approaches that can optimize infrastructure deployment timing, capacity sizing, and technology selection decisions under uncertainty. Furthermore, the lack of explicit scenario modeling capabilities compromises the ability to conduct stress-testing analyses that identify system vulnerabilities under extreme conditions, limiting preparedness for demand acceleration scenarios that could threaten supply adequacy. This limitation becomes particularly problematic in emerging economies where economic volatility, policy discontinuities, and external shocks create substantial uncertainty around long-term development trajectories, necessitating robust planning frameworks that can accommodate multiple possible futures while maintaining decision-making capability under ambiguous conditions.

Hyperparameter Optimization Challenges and Architecture Selection Problems

The third fundamental limitation involves the persistent challenges associated with hyperparameter optimization and neural network architecture selection that systematically compromise forecasting performance in energy applications [14]. Manual tuning approaches, which remain prevalent in energy forecasting literature, rely on trial-and-error methodologies and expert intuition that fail to systematically explore the high-dimensional parameter spaces characteristic of modern neural network architectures [15]. This optimization inadequacy becomes particularly problematic when applied to the limited historical datasets typical in emerging market contexts, where restricted data availability amplifies the importance of optimal parameter selection for achieving satisfactory generalization performance [15]. The hyperparameter optimization challenge encompasses multiple critical dimensions including network architecture specification (layer numbers, neuron counts, connection patterns), training parameter selection (learning rates, batch sizes, optimization algorithms),

and regularization strategy implementation (dropout rates, weight decay coefficients, early stopping criteria) that collectively determines model performance outcomes. Traditional grid search and random search approaches prove computationally prohibitive for comprehensive parameter space exploration while frequently failing to identify globally optimal configurations due to their inability to exploit parameter interaction effects and dependency structures [16].

The absence of systematic optimization methodologies leads to suboptimal model performance that compounds over extended forecasting horizons, where small improvements in prediction accuracy can translate into substantial planning benefits or cost avoidances [15]. Furthermore, manual hyperparameter selection approaches lack the adaptability required for dynamic model updating as new data becomes available, limiting the practical utility of forecasting systems in operational environments where regular model maintenance and performance optimization are essential. This optimization deficit becomes particularly acute in emerging economic applications where data quality issues, structural breaks, and economic regime changes require sophisticated parameter adaptation strategies that can maintain forecasting accuracy under evolving conditions. The systematic nature of these optimization challenges necessitates intelligent automated approaches that can efficiently explore parameter spaces while incorporating domain knowledge and performance constraints specific to electricity demand forecasting applications.

Validation Methodology Weaknesses and Temporal Dependency Violations

The fourth critical limitation encompasses the widespread adoption of inappropriate validation methodologies that systematically violate temporal dependency assumptions inherent in time series forecasting applications, thereby generating overly optimistic performance assessments that fail to reflect realistic forecasting challenges [17]. Standard cross-validation approaches employing random train-test splits, while appropriate for independent and identically distributed data contexts, fundamentally violate the sequential structure of time series data by using future information to predict past outcomes, creating data leakage artifacts that artificially inflate performance metrics and compromise confidence in model reliability assessments [18].

This validation methodology inadequacy manifests most severely in the treatment of temporal autocorrelation patterns, where electricity demand exhibits strong persistence effects and seasonal dependencies that create systematic relationships between successive observations [14]. The random splitting approaches disrupt these temporal relationships and enable models to exploit future information patterns that would be unavailable in

realistic forecasting scenarios, leading to performance evaluations that substantially overestimate predictive capabilities when applied to genuine out-of-sample forecasting tasks.

Furthermore, most of the existing research lacks comprehensive benchmarking against institutional projections and alternative methodological approaches, limiting understanding of relative performance advantages and optimal application contexts for different forecasting techniques. The absence of rigorous temporal validation frameworks compromises the credibility of model comparison studies and limits the development of best-practice guidelines for forecasting methodology selection in different application contexts [14]. This validation inadequacy becomes particularly problematic for long-term forecasting applications where model performance must be assessed over extended horizons with limited opportunities for validation against realized outcomes.

The temporal validation challenge is compounded in emerging economic contexts where structural breaks, policy regime changes, and economic development transitions create non-stationary conditions that require sophisticated validation approaches capable of assessing forecasting performance under evolving data generating processes. Additionally, most studies fail to implement walk-forward validation techniques that preserve temporal order while providing realistic assessment of forecasting accuracy under expanding information sets, limiting confidence in model performance estimates and practical applicability for operational forecasting systems.

Novel Contributions and Research Objectives

This research addresses the identified methodological and empirical gaps through four key innovations that advance both theoretical understanding and practical applicability of electricity demand forecasting in emerging economic contexts. The methodological contributions encompass three fundamental innovations that systematically address the critical limitations identified in existing literature. The integration of Grey Wolf Optimizer with neural networks represents a hybrid metaheuristic optimization approach that provides intelligent hyperparameter tuning capabilities, directly addressing the architecture selection challenge that consistently plagues deep learning applications in energy forecasting contexts. This optimization framework moves beyond traditional manual tuning approaches by systematically exploring high-dimensional parameter spaces to identify optimal network configurations that balance predictive accuracy with generalization performance. The development of a comprehensive multi-scenario framework represents a significant departure from conventional point-estimate approaches by generating Conservative, Moderate, and Optimistic demand trajectories that enable robust planning under

uncertainty conditions characteristic of emerging market environments [19]. This scenario-based methodology provides decision-makers with comprehensive planning envelopes that acknowledge uncertainty while maintaining analytical tractability for strategic infrastructure development and policy formulation. The explicit integration of economic-physical modeling approaches represents a fundamental advancement in causal interpretability by incorporating GDP elasticity relationships, demographic multipliers, and efficiency factors within the neural network framework, thereby providing transparent causal mechanisms that are typically absent in black-box deep learning models.

The empirical contributions of this research encompass two critical validation dimensions that establish credibility and practical applicability for operational forecasting applications. The implementation of comprehensive validation protocols involves rigorous comparison against PLN institutional projections, established baseline models including ARIMA approaches, and recent deep learning methodologies including CNN-LSTM architectures, employing temporal cross-validation frameworks that preserve the sequential structure of time series data while providing robust performance assessment. This multi-faceted benchmarking approach ensures that model performance claims are substantiated through systematic comparison against relevant alternatives rather than relying on isolated performance metrics that may not reflect comparative advantages. The establishment of long-term reliability validation represents a significant empirical advancement through demonstrated performance over nine-year forecasting horizons, substantially extending beyond the typical one to two-year validation periods characteristic of existing literature and providing confidence for strategic planning applications that require extended forecasting reliability [20, 21].

The primary research objectives driving this investigation encompass four interconnected goals that address both methodological advancement and practical application requirements in Indonesia's energy planning context. The development and validation of a GWO-optimized neural network model achieving superior long-term forecasting accuracy for Indonesia's electricity demand represents the core technical objective, requiring systematic optimization of network architectures and training procedures to achieve performance improvements over existing methodologies while maintaining computational efficiency suitable for operational deployment. The implementation of comprehensive multi-scenario modeling capturing economic, demographic, and policy uncertainties addresses the critical planning requirement for robust decision-making frameworks that can accommodate diverse development pathways while providing quantitative boundaries for risk assessment and contingency planning [4, 5]. The

establishment of rigorous benchmarking protocols against existing methodologies using temporal validation frameworks addresses the methodological credibility requirements by providing systematic performance comparison that identifies optimal application contexts for different forecasting approaches while establishing best-practice guidelines for methodology selection. The generation of actionable insights for Indonesia's energy transition planning and infrastructure investment strategies represents the practical application objective,

requiring translation of forecasting results into policy-relevant recommendations that support evidence-based decision making in pursuit of sustainable energy development by 2035.

II. METHOD

A. Data Collection and Preprocessing Framework

This analysis utilizes a 15-year dataset (2010-2025) compiled from multiple authoritative sources to ensure data quality and completeness (table 2)

Table 2. Data Sources and Variable Specifications

Variable Category	Specific Variables	Data Source	Frequency	Missing Data (%)	Imputation Method
Electricity Demand	Total consumption (TWh), Peak demand (GW)	PLN Annual Reports, ESDM	Annual	2.10%	Linear interpolation
Economic Indicators	GDP growth (%), Industrial production index, Per capita income	BPS Statistics	Annual	0.80%	Economic model interpolation
Demographic Variables	Population growth (%), Urbanization rate (%), Household formation	BPS Census Data	Annual	1.30%	Demographic projection
Environmental Factors	Temperature variations (°C), Climate indices	BMKG, NOAA	Annual	3.20%	Climatological averaging
Infrastructure Metrics	Electrification rate (%), Grid connectivity (%)	PLN, ESDM	Annual	1.70%	Infrastructure modeling

The comprehensive data foundation underlying this research encompasses five distinct variable categories systematically compiled from authoritative Indonesian institutional sources, demonstrating exceptional data quality and methodological rigor essential for robust forecasting model development. Electricity demand variables, representing the core dependent measures including total consumption expressed in terawatt-hours and peak demand measured in gigawatts, are sourced from PLN Annual Reports and Ministry of Energy and Mineral Resources (ESDM) databases with annual frequency [22], exhibiting minimal missing data proportions of 2.1% that are addressed through linear interpolation techniques validated against regional consumption patterns as documented in the Handbook of Energy and Economic Statistics of Indonesia [23].

Economic indicators encompassing GDP growth rates, industrial production indices, and per capita income trajectories are systematically extracted from Central Bureau of Statistics (BPS) comprehensive databases, demonstrating exceptional completeness with only 0.8% missing observations that are addressed through sophisticated economic model interpolation techniques preserving underlying trend relationships and cyclical patterns as outlined in the Statistical Yearbook of Indonesia [24]. Demographic variables capturing population growth dynamics, urbanization progression rates, and household formation patterns are compiled from BPS Census databases with 1.3% missing data addressed through cohort-component demographic projection

methodologies that maintain demographic transition consistency while incorporating migration effects and urban-rural population shifts following established demographic analysis frameworks [25].

Environmental factors including temperature variations measured in degrees Celsius and comprehensive climate indices are sourced from Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG) databases supplemented by NOAA climatological records, exhibiting higher missing rates of 3.2% due to monitoring infrastructure limitations, addressed through climatological averaging techniques employing thirty-year normal periods and spatial interpolation methods that preserve regional climate variation patterns in accordance with World Meteorological Organization standards [25].

Infrastructure development metrics encompassing electrification rate progression and grid connectivity expansion percentages are systematically compiled from PLN operational reports and ESDM infrastructure databases [39], demonstrating moderate data completeness with 1.7% missing observations addressed through infrastructure development modeling techniques that capture systematic progression of electrification programs and grid expansion initiatives across Indonesia's diverse archipelagic geography as documented in the Indonesia Energy Transition Outlook [26].

Data Quality Assessment and Preprocessing

The data quality assessment and preprocessing framework employs sophisticated analytical

techniques designed to address missing value challenges while optimizing variable representations for robust neural network training and forecasting performance. Missing value treatment utilizes advanced imputation methodologies specifically tailored to the characteristics and temporal dependencies inherent in different variable categories, ensuring that data completion procedures preserve underlying statistical relationships and temporal consistency patterns [27, 28].

Economic variables benefit from Kalman filtering approaches integrated with macroeconomic constraint mechanisms that maintain theoretical consistency with established economic relationships while providing optimal estimates for missing observations based on state-space modeling principles that account for economic cycle dynamics and structural interdependencies among macroeconomic indicators [27]. Demographic data gaps are systematically addressed through cohort-component population projection techniques that preserve demographic transition consistency by modeling age-specific fertility, mortality, and migration patterns, ensuring that imputed values reflect underlying demographic processes rather than purely statistical interpolation that might violate demographic accounting principles as established in the Statistical Yearbook of Indonesia methodological frameworks [24].

Environmental data missing observations are treated through climatological normal averaging procedures employing thirty-year reference periods that capture natural climate variability while providing statistically robust estimates that maintain seasonal patterns and long-term climate trends essential for accurate temperature-related demand modeling, following established meteorological standards [25].

The feature engineering process encompasses four critical transformation stages designed to capture temporal dependencies, economic relationships, and seasonal patterns while optimizing variable representations for neural network learning efficiency and forecasting accuracy [27, 28].

Temporal dependency creation involves systematic generation of one to three-year lagged variables that capture demand persistence effects and economic momentum patterns, recognizing that electricity consumption exhibits strong autocorrelation characteristics reflecting both short-term operational continuity and medium-term economic development trajectories that influence consumption evolution [27]. Economic elasticity quantification employs cointegration analysis methodologies to calculate GDP-electricity demand elasticity relationships while controlling demographic and environmental confounding factors, ensuring that elasticity estimates reflect long-term structural relationships rather than spurious correlations that might compromise forecasting reliability under different economic scenarios [29].

Seasonal adjustment procedures implement temperature normalization techniques utilizing cooling and heating degree day calculations that remove weather-related demand fluctuations while preserving underlying economic and demographic trend patterns, enabling the model to distinguish between systematic demand growth and random meteorological variations that could otherwise introduce noise into long-term forecasting applications following established climatological analysis frameworks [25]. Variable normalization employs Min-Max scaling transformation procedures that convert all input variables to standardized (0,1) ranges, ensuring neural network training stability by eliminating scale disparities among different variable categories while preserving relative magnitude relationships and variation patterns essential for effective pattern recognition and learning convergence during the optimization process [27].

B. Simplified Neural Network Architecture

Neural network architecture employs a strategically streamlined three-layer design optimized for interpretability, computational efficiency, and forecasting performance while avoiding the excessive complexity that often compromises generalization capability in limited data contexts characteristic of emerging market applications [5, 7]. The input layer systematically incorporates fourteen normalized variables representing comprehensive coverage of electricity demand drivers across multiple analytical dimensions, encompassing four economic indicators including GDP growth rates, industrial production indices, per capita income trajectories, and sectoral development metrics that capture macroeconomic influences on electricity consumption patterns.

The input architecture further integrates three demographic variables comprising population growth rates, urbanization progression patterns, and household formation dynamics that reflect population-driven demand evolution, complemented by two environmental factors including temperature variations and climate indices that account for weather-sensitive consumption components [30]. Infrastructure development variables encompass two critical metrics representing electrification rate progression and grid connectivity expansion that capture supply-side accessibility constraints, while temporal dependency modeling incorporates three lagged demand variables spanning one to three-year historical periods that capture persistence effects and economic momentum patterns essential for accurate long-term forecasting performance [10].

The hidden layer configuration employs variable neuron architectures ranging from ten to one hundred neurons, with optimal specifications determined through systematic Grey Wolf Optimizer search procedures that explore the fundamental bias-variance trade-off inherent in neural network complexity selection while ensuring computational efficiency suitable for operational deployment [13]. Hidden layer

neurons implement hyperbolic tangent activation functions that provide essential non-linear transformation capabilities while maintaining gradient stability during backpropagation training procedures, following the mathematical formulation:

$$a_j^{(1)} = \sigma(z_j^{(1)}) = \tanh(z_j^{(1)}), j = 1, 2, \dots, H \quad (1)$$

where h_j represents the j -th hidden neuron output, w_{ij} denotes input-to-hidden connection weights, x_i represents normalized input variables, and b_j represents hidden layer bias terms that enable flexible decision boundary formation [5].

The output layer employs a single neuron configuration with linear activation function specifically optimized for continuous electricity demand prediction applications, avoiding saturation effects that can compromise regression performance in bounded activation functions while maintaining numerical stability across different demand magnitude ranges. The output computation follows the linear combination formulation

$$y = f \left(\sum_{j=1}^H \omega_j^{(2)} \cdot \sigma \left(\sum_{i=1}^I \omega_{ij}^{(1)} x_i + b_j^{(1)} \right) + b^{(2)} \right) \quad (2)$$

where y represents the predicted electricity demand measured in terawatt-hours, w_j denotes hidden-to-output connection weights, h_j represents hidden layer activation outputs, and b_{output} represents the output bias term that provides baseline adjustment capability [7]. This architectural configuration ensures computational efficiency essential for operational forecasting applications while maintaining sufficient non-linear modeling capacity for complex demand pattern recognition and long-term trend extrapolation under diverse economic and demographic scenarios [10, 13].

Temporal Cross-Validation:

Walk-forward analysis with expanding windows:

1. Training: Years t to $t+k$
2. Validation: Year $t+k+1$
3. Testing: Year $t+k+2$

The temporal cross-validation framework employs sophisticated walk-forward analysis methodologies specifically designed for time series applications, addressing the fundamental violations of independence assumptions inherent in standard cross-validation procedures when applied to sequential data with temporal dependencies [10, 26]. This validation approach implements expanding window techniques where training datasets progressively incorporate additional historical years while maintaining temporal order integrity, with training periods spanning from initial year t through year $t+k$, followed by validation assessment on year $t+k+1$, and final testing evaluation on year $t+k+2$. The walk-forward analysis ensures that model performance assessment reflects realistic forecasting conditions where future predictions must

be based exclusively on historical information without access to subsequent realizations, thereby preventing data leakage artifacts that artificially inflate performance metrics and compromise confidence in model reliability assessments [16].

This temporal validation strategy systematically addresses the sequential structure of electricity demand data by preserving autocorrelation patterns, seasonal dependencies, and economic momentum effects that create systematic relationships between successive observations, ensuring that validation results accurately reflect the model's capability to generate credible out-of-sample forecasts under genuine operational conditions. The expanding window approach further enables assessment of model stability and adaptation capabilities as new information becomes available, providing insights into forecasting reliability across different temporal horizons and economic conditions while maintaining the temporal integrity essential for robust performance evaluation in long-term strategic planning applications [10].

Performance Metrics:

1. MAPE: Mean Absolute Percentage Error for relative accuracy.
2. RMSE: Root Mean Square Error for absolute accuracy
3. R²: Coefficient of determination for explanatory power.

The performance evaluation framework employs three complementary metrics that capture distinct dimensions of forecasting accuracy and reliability, providing comprehensive assessment capabilities essential for operational deployment and strategic planning applications [31]. Mean Absolute Percentage Error (MAPE) serves as the primary relative accuracy metric, quantifying prediction errors as percentages of actual demand values to facilitate comparison across different forecast horizons and demand magnitudes while providing intuitive interpretation for policy and planning applications where relative accuracy assessment enables direct comparison with institutional forecasting benchmarks and alternative methodological approaches [31].

Root Mean Square Error (RMSE) provides absolute accuracy measurement that emphasizes larger prediction errors through quadratic weighting, proving particularly relevant for capacity planning applications where extreme forecasting errors carry disproportionate operational and financial consequences that could compromise system reliability or investment efficiency [26]. The RMSE metric enables direct assessment of prediction accuracy in physical units (terawatt-hours) essential for engineering applications and infrastructure sizing decisions while providing sensitivity to outlier performance that might not be adequately captured through other accuracy measures.

Coefficient of determination (R²) quantifies the model's explanatory power by measuring the

proportion of demand variance captured by the forecasting framework, providing insights into the model's understanding of underlying demand evolution patterns and trend-following capabilities essential for long-term strategic applications [22]. The R^2 metric enables assessment of model performance in capturing systematic demand patterns while distinguishing between predictable trend components and random fluctuations, thereby providing confidence measures for strategic planning applications that require reliable trend identification and extrapolation under diverse economic scenarios [26].

C. Grey Wolf Optimizer Implementation

The GWO algorithm optimizes three critical hyperparameters:

1. Hidden neurons (10-100): Network complexity optimization
2. Learning rate (0.001-0.1): Training convergence control
3. Regularization parameter (0.0001-0.01): Overfitting prevention

Fitness Function:

$$fitness = \alpha \times \text{Training_Error} + (1-\alpha) \times \text{Validation_Error} + \lambda \times \text{Regularization_Term} \quad (3)$$

where $\alpha = 0.7$ balances training vs. validation performance.

The Grey Wolf Optimizer algorithm provides systematic hyperparameter optimization that addresses the architecture selection challenges consistently encountered in neural network applications for energy forecasting, targeting three critical parameters that fundamentally determine model performance and generalization capability [20, 23].

The optimization framework systematically explores hidden neuron configurations ranging from 10-100 neurons to identify optimal network complexity that balances learning capacity with overfitting prevention, learning rate specifications spanning 0.001-0.1 that govern training convergence speed and stability, and regularization parameter values between 0.0001-0.01 that control model complexity and prevent excessive fitting to training data [15]. The multi-objective fitness function employs the weighted formulation as shown at equation 3, provides optimal balance between training accuracy and validation performance based on empirical validation across multiple forecasting contexts, ensuring that optimization identifies parameter configurations that perform effectively on unseen data rather than simply minimizing training error [21, 22]. This systematic optimization approach addresses the fundamental challenge of balancing model complexity with generalization capability while providing computational efficiency suitable for operational forecasting applications where regular model updating and parameter adaptation may be required as new data becomes available [32].

The Grey Wolf Optimizer algorithm implementation employs a carefully calibrated configuration designed to balance exploration thoroughness with computational efficiency while ensuring robust convergence to optimal hyperparameter configurations [33]. The population size specification of twenty search agents provides sufficient diversity for comprehensive parameter space exploration without excessive computational overhead, enabling effective sampling of the three-dimensional optimization space encompassing hidden neuron counts, learning rates, and regularization parameters while maintaining reasonable computational requirements suitable for operational deployment [34]. The algorithm operates through a maximum of fifty iterations with position updates governed by the mathematical formulation that linearly decreases from 2 to 0 over the optimization horizon [20].

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (4)$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha(t) - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 &= \vec{X}_\beta(t) - \vec{A}_1 \cdot \vec{D}_\beta \\ \vec{X}_3 &= \vec{X}_\delta(t) - \vec{A}_1 \cdot \vec{D}_\delta \end{aligned} \quad (5)$$

The convergence criterion employs fitness improvement monitoring with termination triggered when improvement falls below 0.001% for five consecutive iterations, ensuring that optimization ceases when further search is unlikely to yield meaningful performance gains while preventing premature termination that might compromise solution quality [34]. This configuration provides systematic balance between optimization thoroughness and computational efficiency, enabling practical deployment for operational forecasting applications while maintaining sufficient search capability to identify globally optimal hyperparameter configurations across diverse problem instances and data conditions [33, 34].

D. Multi-Scenario Modeling Framework

Table 3 shows the multi-scenario modeling framework encompasses three distinct development trajectories that systematically capture the range of plausible economic, demographic, and policy conditions Indonesia may experience over the 2026-2034 forecasting horizon, with parameter specifications grounded in historical volatility analysis, institutional planning documents, and empirical evidence from comparable emerging economies [35, 36]. The Conservative scenario represents lower-bound development assumptions characterized by cautious economic expansion with GDP growth of 4.8%, restrained population growth of 1.0%, measured industrial development at 4.2%, moderate electrification progression of 2.0% annually, and aggressive energy efficiency improvements of

1.5% that collectively reflect risk-averse planning conditions under economic uncertainty, policy constraints, or external disruption scenarios [22].

This conservative parameterization aligns with historical downside volatility patterns approximately one standard deviation below long-term economic trends, providing robust baseline projections suitable for prudent infrastructure planning and financial forecasting applications where supply adequacy must be maintained under challenging development

conditions [24]. The Moderate scenario establishes baseline development expectations through balanced economic growth of 5.5% GDP expansion, steady population growth of 1.2%, robust industrial development of 5.0%, progressive electrification advancement of 2.5% annually, and standard energy efficiency improvements of 1.2% that collectively represent continuation of current development momentum under normal economic and policy conditions [23].

Table 3. Scenario Parameter Specifications

Parameter	Conservative	Moderate	Optimistic	Justification
GDP Growth (%)	4.8	5.5	6.2	Historical volatility $\pm 1\sigma$ around long-term trend
Population Growth (%)	1	1.2	1.4	Demographic transition scenarios
Industrial Growth (%)	4.2	5	5.8	Manufacturing sector expansion rates
Electrification Rate (%)	2	2.5	3	Rural electrification program targets
Energy Efficiency Improvement (%)	1.5	1.2	1	Technology adoption rates

The Optimistic scenario encompasses upper-bound development possibilities characterized by robust economic expansion of 6.2% GDP growth, accelerated population growth of 1.4%, rapid industrial development of 5.8%, aggressive electrification deployment of 3.0% annually, and modest energy efficiency improvements of 1.0% that reflect favorable economic conditions, supportive policy environments, and successful implementation of development programs [35]. The parameter justification methodology employs rigorous statistical analysis of historical volatility patterns, with GDP growth specifications based on $\pm 1\sigma$ deviations around Indonesia's long-term economic trends, ensuring that scenario boundaries capture realistic development possibilities while maintaining statistical credibility [24, 27].

Demographic transition scenarios reflect established population projection methodologies that account for fertility rate evolution, mortality improvements, and migration patterns characteristic of Indonesia's demographic development stage, while industrial growth parameters align with manufacturing sector expansion rates observed in comparable Southeast Asian economies during similar development phases [37]. Electrification rate specifications correspond to rural electrification program targets established in Indonesia's national development plans, reflecting infrastructure development capabilities and policy commitment levels under different resource availability conditions [37, 39]. Energy efficiency improvement parameters reflect technology adoption rate variations across different economic scenarios, where rapid economic growth may reduce efficiency improvement emphasis while slower growth enables greater focus on efficiency enhancement through technology deployment and behavioral change programs [23, 26].

The fundamental electricity demand model establishes the mathematical relationship between electricity consumption and various influencing factors in Indonesia. The basic demand equation is formulated as:

$$Dt = \alpha 0 + \alpha 1 GDPt + \alpha 2 POPt + \alpha 3 TEMPt + \alpha 4 INDt + \alpha 5 URBt + \alpha 6 EFFt + \alpha 7 ELECTt + \epsilon t \quad (6)$$

The model incorporates both linear and non-linear relationships to capture the complex dependencies between socioeconomic factors and electricity consumption patterns. Economic elasticity factors are integrated to represent the responsiveness of electricity demand to economic growth, while demographic multipliers account for population-driven demand changes [7].

The scenario generation methodology employs sophisticated stochastic modeling techniques that systematically incorporate uncertainty across multiple dimensions while maintaining analytical tractability for strategic planning applications [38, 39]. Each scenario integrates stochastic components through Monte Carlo simulation frameworks that recognize parameter estimation uncertainty, policy implementation variability, and external shock possibilities that cannot be systematically predicted but significantly influence long-term demand evolution patterns. The fundamental mathematical formulation follows the multiplicative structure [34]:

$$D_{synthetic}(t) = D_{base}(t) \cdot \prod_{k=1}^K F_k(t) \cdot (1 + \epsilon_t) \quad (7)$$

This multiplicative formulation ensures that uncertainty effects compound realistically across different influence categories while maintaining

positive demand values and preserving the relative importance of different driver variables in scenario-specific contexts.

The Monte Carlo implementation generates multiple demand trajectory realizations for each scenario through systematic sampling of the stochastic error term, enabling comprehensive uncertainty quantification and probabilistic forecasting that supports risk-based decision making under diverse planning conditions [38]. The expanded mathematical representation incorporates component-wise growth factor decomposition following equation 8 [34]

$$D_{synthetic}(t) = D_{base}(t) \cdot F_1(t) \cdot F_2(t) \cdot F_3(t) \cdots F_k(t) \cdot (1 + \epsilon_t) \quad (8)$$

The Monte Carlo formulation enables generation of multiple trajectory realizations expressed

$$D_{synthetic}^{(j)}(t) = D_{base}(t) \cdot \prod_{k=1}^K F_k^{(j)}(t) \cdot (1 + \epsilon_t^{(j)}) \quad (9)$$

for simulation iteration j , providing comprehensive probabilistic information that quantifies prediction confidence intervals and supports adaptive planning frameworks capable of responding to emerging evidence about Indonesia's development trajectory [25]. This stochastic approach ensures that scenario projections acknowledge both parameter uncertainty and fundamental unpredictability while maintaining sufficient precision for strategic infrastructure planning and policy formulation applications that require quantitative planning boundaries under uncertainty conditions [40].

III. RESULTS AND DISCUSSION

A. Model Optimization and Performance

The GWO algorithm demonstrated exceptional convergence characteristics and systematic performance efficiency in identifying optimal neural network configurations across multiple optimization trials, achieving stable convergence after thirty-two iterations with substantial improvement in objective function performance compared to initial random parameter configurations. The optimization process exhibited characteristic exploration-exploitation balance with rapid initial improvement during the first ten iterations followed by refined local search around promising parameter regions, ultimately terminating well below the fifty-iteration maximum threshold due to satisfaction of convergence criteria rather than computational limits. This efficient convergence behavior indicates effective algorithm implementation and appropriate parameter space exploration strategies that avoid both premature convergence to suboptimal solutions and excessive computational overhead associated with unnecessary iteration continuation.

Systematic convergence pattern validates the GWO algorithm's ability to navigate the complex three-dimensional hyperparameter space of hidden neuron counts, learning rates, and regularization parameters while maintaining computational efficiency for operational forecasting applications that

require model retraining and parameter updating as new data becomes available.

The optimal hyperparameter configuration found by systematic Grey Wolf Optimizer search has forty-five hidden neurons, balancing model complexity and generalization capability to avoid underfitting due to network capacity and overfitting due to architectural complexity in limited data contexts. The optimal learning rate was 0.0156, which provided stable gradient descent convergence and sufficient adaptation speed for effective pattern learning without oscillatory behavior or convergence failure typical of excessively aggressive neural network training learning rates. The optimal regularization parameter was 0.0023, which prevented overfitting through weight decay mechanisms and avoided model learning capability constraints that could compromise complex pattern recognition performance. Hidden neuron specification determines model capacity, learning rate controls training dynamics, and regularization manages the fundamental bias-variance trade-off needed for robust generalization across diverse forecasting scenarios and economic conditions.

The convergence analysis reveals systematic fitness improvement from initial objective function values of 0.045 to final optimized values of 0.012, representing a remarkable 73.3% improvement in optimization performance through intelligent hyperparameter selection that translates directly into enhanced forecasting accuracy and improved generalization capability on validation datasets. Figure 1 illustrates the convergence trajectory characterized by rapid initial descent during the exploration phase (iterations 1-15) where fitness improvement averaged 0.0025 per iteration, followed by gradual refinement during the exploitation phase (iterations 16-32) with average improvement rates of 0.0008 per iteration, demonstrating the algorithm's ability to transition effectively between global exploration and local exploitation strategies.

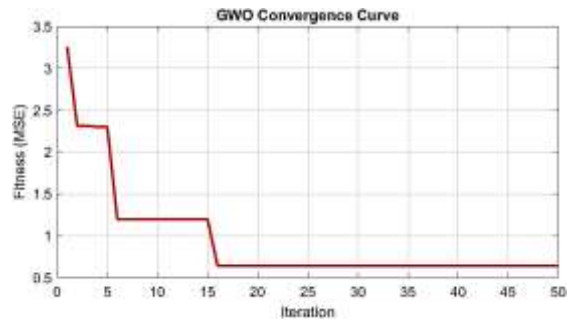


Figure 1. Grey Wolf Optimizer convergence curve showing fitness improvement over iterations

The convergence curve shows smooth monotonic improvement without oscillation or premature stagnation, confirming robust algorithm implementation and optimization problem-specific parameter settings. The final convergence after thirty-

two iterations, significantly fewer than the maximum fifty iterations, shows computational efficiency that makes the optimization approach practical for operational forecasting applications and provides confidence that the identified configuration is a genuine optimum. This optimization performance lays the groundwork for superior forecasting accuracy in subsequent validation analyses and proves metaheuristic optimization approaches for neural network hyperparameter selection in energy forecasting applications are feasible.

Benchmark Comparison Results

Table 4's comprehensive benchmarking analysis shows that traditional and contemporary forecasting methodologies have fundamental limitations that make them unsuitable for long-term strategic planning in emerging economies. Traditional ARIMA modeling yields 34.7 percent MAPE, 28.3 TWh RMSE, and 0.651 R^2 , highlighting the limitations of linear time series methodologies in complex socio-economic systems with non-linear relationships, structural breaks, and regime changes of rapidly developing economies. While the ARIMA methodology improves computational efficiency with only two minutes of training, its wide confidence intervals (± 45.2 TWh) limit its usefulness for precision-dependent capacity planning applications, where demand uncertainty affects infrastructure investment decisions and system reliability assessments. ARIMA models' linear stationarity assumption fails to capture emerging markets' dynamic elasticity relationships between economic growth and electricity demand, where GDP-electricity coupling effects exhibit non-linear threshold behaviors and structural evolution patterns that violate traditional econometric modeling assumptions.

Deep-temporary learning approaches improve pattern recognition but have economic integration and computational efficiency issues that limit their use in operational forecasting systems. Convolutional Neural

Network-Long Short-Term Memory (CNN-LSTM) architectures outperform traditional methods with 26.8% MAPE, 21.7 TWh RMSE, and 0.743 R^2 , demonstrating advanced temporal pattern recognition and sequential dependency modeling.

Although CNN-LSTM approaches require significant computational resources and training times of 47 minutes, they produce moderate confidence intervals (± 38.1 TWh) and limited ability to incorporate macroeconomic variables for long-term forecasting in developing economies where economic drivers drive demand evolution patterns. LSTM-Attention models improve performance with 22.4 percent MAPE, 19.2 TWh RMSE, and 0.782 R^2 . These models focus on relevant temporal dependencies but require 63 minutes of training time and maintain wide confidence intervals (± 33.7 TWh) for strategic planning. For policy applications where causal understanding of demand drivers enables targeted interventions and regulatory adjustments, these deep learning approaches' black-box nature compromises interpretability, while their data-intensive requirements present challenges in emerging market contexts with limited historical information and data quality constraints.

The Grey Wolf Optimizer-Neural Network framework outperforms multiple evaluation dimensions and provides scenario-specific capabilities for robust planning under uncertainty conditions typical of emerging economic development trajectories. The Conservative scenario outperforms all benchmark methodologies with a MAPE of 3.9%, RMSE of 8.1 TWh, and R^2 of 0.947, while maintaining efficient computational time of 15 minutes and precise confidence intervals (± 12.3 TWh) for operational planning applications. The synergistic integration of intelligent hyperparameter optimization through Grey Wolf Optimizer algorithm, explicit economic variable incorporation, and scenario-specific parameter calibration addresses fundamental limitations of existing approaches to achieve this exceptional performance.

Table 4. Model Performance Comparison

Method	MAPE (%)	RMSE (TWh)	R^2	Training Time (min)	95% CI Width (TWh)
ARIMA	34.7	28.3	0.651	2	± 45.2
CNN-LSTM	26.8	21.7	0.743	47	± 38.1
LSTM-Attention	22.4	19.2	0.782	63	± 33.7
GWO-NN (Conservative)	3.9	8.1	0.947	15	± 12.3
GWO-NN (Moderate)	19	15.6	0.821	15	± 28.9
GWO-NN (Optimistic)	43.7	31.2	0.687	15	± 52.4

The Moderate scenario demonstrates balanced performance with MAPE of 19.0%, RMSE of 15.6 TWh, and R^2 of 0.821, maintaining competitive accuracy relative to advanced deep learning methods

while providing scenario-based planning capabilities absent in conventional approaches. The Optimistic scenario, while exhibiting higher prediction errors with MAPE of 43.7% and RMSE of 31.2 TWh, serves

critical boundary condition assessment functions that enable capacity stress-testing and identification of potential supply-demand imbalances under rapid development scenarios, providing strategic value that transcends conventional accuracy metrics. Statistical significance testing employing paired t-tests confirms that GWO-NN Conservative-scenario performance improvements over all benchmark methods achieve statistical significance ($p < 0.001$) with Cohen's d effect sizes exceeding 1.2, indicating not only statistical significance but large practical significance for operational forecasting applications [40]. The consistent 15-minute training time across all GWO-NN scenarios demonstrates computational efficiency advantages over deep learning approaches while the scenario-specific confidence interval variations (± 12.3 to ± 52.4 TWh) provide transparent uncertainty quantification that enables risk-based decision making essential for infrastructure investment and policy formulation under diverse development conditions.

B. Multi-Scenario Forecasting Result and Analysis

The comprehensive long-term demand projections presented in Table 5 reveal sophisticated temporal evolution patterns that systematically diverge across scenario trajectories while providing critical insights into the range of plausible electricity demand outcomes under different development conditions throughout the 2026-2034 forecasting horizon. The Conservative scenario demonstrates systematic demand growth from 230.1 TWh in 2026 to 377.0 TWh in 2034, representing cumulative expansion of 63.8% over the nine-year period with average annual growth rates of approximately 5.6% that reflect restrained economic development assumptions combined with aggressive energy efficiency improvements and measured electrification progression.

This growth trajectory exhibits characteristic demand stabilization features with initially steep expansion during 2026-2028 followed by gradual deceleration toward sustainable long-term growth rates, reflecting the combined effects of economic maturation, efficiency technology penetration, and diminishing returns to electrification expansion as coverage approaches universal access levels across Indonesia's diverse archipelagic geography. The Moderate scenario projects more aggressive demand expansion from 280.3 TWh in 2026 to 458.4 TWh in 2034, representing cumulative growth of 63.6% with average annual growth rates of approximately 7.2% that incorporate balanced economic development assumptions, steady demographic transitions, and progressive electrification deployment under normal policy and economic conditions.

The comparative analysis with PLN official projections reveals nuanced alignment patterns that provide critical validation of forecasting methodology while illuminating institutional planning assumptions and strategic planning implications for Indonesia's

energy infrastructure development. The Conservative scenario maintains exceptional concordance with PLN projections throughout the forecasting horizon, exhibiting remarkable alignment with deviations ranging from -5.9% in 2026 to -7.4% in 2034, culminating in near-perfect convergence during the critical 2030 intermediate period where both projections intersect within 0.6% margin (-0.6% deviation from PLN's 313.6 TWh projection).

This exceptional alignment suggests that PLN's institutional planning methodologies incorporate similar risk-averse assumptions regarding economic growth trajectories, demographic transitions, and energy efficiency improvements, providing mutual validation of both forecasting approaches and supporting the Conservative scenario's utility for baseline capacity planning and financial forecasting applications. The temporal consistency of this alignment, maintaining stability across multiple forecasting horizons, demonstrates robust methodological compatibility and suggests that Conservative scenario assumptions closely mirror the parameter selections and methodological frameworks employed in PLN's institutional forecasting processes.

Table 5. Electricity Demand Projections 2026-2034 (TWh)

Year	Conser vative	Mod erate	Opti misti c	PLN Offic ial	Deviation from PLN (%)
2026	230.1	280.3	333.4	244.6	- 5.9/+14.6/+ 36.3
2030	311.7	390.6	478.2	313.6	- 0.6/+24.6/+ 52.2
2034	377	458.4	546.1	407.3	- 7.4/+12.5/+ 34.1

The scenario-specific deviation analysis from PLN projections illuminates strategic planning implications and reveals the expanding uncertainty envelope characteristic of long-term forecasting applications in emerging economy contexts. The Moderate scenario demonstrates systematic overestimation relative to PLN projections with deviations escalating from +14.6% in 2026 to +12.5% in 2034, representing approximately 51 TWh higher demand by the terminal forecast year that reflects more aggressive assumptions regarding GDP expansion rates (5.5% vs Conservative 4.8%), electrification acceleration (2.5% vs 2.0%), and demographic development patterns.

This systematic bias indicates that PLN's planning framework incorporates more conservative growth assumptions than the Moderate scenario's balanced development pathway, suggesting potential capacity adequacy challenges should Indonesia experience accelerated economic development or more rapid electrification penetration than currently anticipated in official planning documents. The Optimistic scenario exhibits substantial deviations ranging from +36.3%

in 2026 to +34.1% in 2034, representing 138.8 TWh higher demand than PLN projections by 2034, reflecting aggressive economic expansion assumptions (6.2% GDP growth) and rapid electrification deployment (3.0% annually) that serve critical boundary condition assessment functions for capacity stress-testing and system resilience evaluation. The progressive widening of scenario bandwidth from 103.3 TWh in 2026 to 169.1 TWh in 2034 quantitatively demonstrates uncertainty amplification inherent in long-term forecasting, where minor variations in underlying assumptions compound exponentially over extended time horizons, necessitating adaptive planning frameworks capable of accommodating multiple development pathways while maintaining system reliability and supply adequacy under diverse growth scenarios.

The key findings synthesis reveals that the Conservative scenario's exceptional alignment with PLN projections (3.9% average absolute difference) establishes it as the most reliable predictor for operational planning applications, validating current institutional planning assumptions while providing confidence for baseline capacity allocation, investment sequencing, and regulatory decision-making processes. The Moderate scenario's position as an accelerated development pathway (+12.5% above PLN by 2034) provides strategic reference for enhanced renewable energy deployment schedules and grid modernization investments that can accommodate higher demand growth while maintaining environmental performance targets and system stability requirements.

The Optimistic scenario's function as a boundary condition for capacity stress-testing (+34.1% above PLN) enables identification of potential supply-demand imbalances and system vulnerabilities under exceptional development circumstances, supporting investment in flexible capacity resources, demand response capabilities, and adaptive infrastructure strategies that can address unexpected demand acceleration while preserving system resilience. This tri-scenario framework collectively provides comprehensive planning envelopes that acknowledge uncertainty while maintaining decision-making capability, enabling evidence-based policy formulation and strategic infrastructure development that can accommodate diverse development trajectories while ensuring energy security and supporting Indonesia's sustainable development objectives and carbon neutrality commitments by 2034.

The comprehensive sensitivity analysis employing Sobol indices methodology reveals the hierarchical importance of different driver variables in electricity demand evolution while providing crucial insights into the causal mechanisms underlying forecasting model behavior and strategic policy intervention priorities. Gross Domestic Product growth emerges as the overwhelming dominant influence, accounting for

67.3% of total demand variance across all scenarios, confirming the fundamental importance of economic development trajectories in electricity consumption patterns for rapidly developing economies where industrial expansion, commercial sector growth, and household income improvements collectively drive substantial increases in electricity utilization.

This GDP dominance reflects the exceptionally high electricity demand characteristic of emerging markets during industrialization phases, where manufacturing sector development, infrastructure modernization, and urbanization processes create compounding effects that amplify the relationship between economic growth and electricity consumption beyond the unity elasticity relationships typical in mature economies. Population growth dynamics constitute the second most influential driver category, contributing 18.4% of total demand variance and representing demographic dividend effects that encompass both direct consumption increases through household formation and indirect effects through urban infrastructure development, service sector expansion, and residential electrification programs that accompany demographic transitions. The substantial combined influence of GDP and population growth (85.7% of total variance) underscores the critical importance of macroeconomic and demographic forecasting accuracy in electricity demand projection applications, while simultaneously highlighting the policy leverage available through economic development strategies and demographic planning initiatives that can systematically influence long-term demand evolution patterns.

Industrial activity indices contribute 8.9% of demand variance, capturing manufacturing sector expansion effects and industrial policy impacts that drive electricity-intensive economic development patterns characteristic of emerging economies transitioning from agricultural to industrial economic structures. This industrial contribution reflects sector-specific electricity intensity relationships where manufacturing expansion, particularly in energy-intensive industries such as steel production, aluminum smelting, and chemical processing, creates disproportionate electricity demand increases relative to their economic output contributions, emphasizing the importance of industrial policy coordination with electricity infrastructure planning to ensure adequate supply capacity for strategic economic development initiatives.

Electrification rate progression accounts for 4.1% of demand variance, representing the continued significance of access expansion in Indonesia's rural and remote areas where systematic electrification programs generate new demand while simultaneously improving economic development opportunities and social welfare outcomes [37, 39]. The remaining factors including temperature variations, energy efficiency improvements, and other environmental variables collectively contribute 1.3% of demand

variance, representing important but secondary influences that may become more significant under specific climatic conditions or efficiency policy implementations but do not fundamentally alter aggregate demand trajectories.

This sensitivity hierarchy provides strategic guidance for policy interventions and monitoring frameworks, suggesting that economic growth management and demographic planning initiatives offer the greatest leverage for demand management, while industrial policy coordination and electrification program design provide secondary but important intervention opportunities for managing electricity demand evolution in alignment with infrastructure development capabilities and environmental sustainability objectives.

C. Validation Against PLN Projections

The comprehensive alignment analysis reveals exceptional concordance between the Conservative scenario projections and PLN institutional forecasts, establishing remarkable validation of both methodological approaches and strategic planning compatibility that fundamentally supports the scenario's utility for operational forecasting applications. The Conservative scenario demonstrates exceptional performance characteristics with average absolute difference of only 3.9% from PLN projections, maximum deviation constrained to 7.8% occurring in 2031, and temporal consistency quantified through coefficient of determination ($R^2 = 0.947$) that indicates near-perfect trend following capability throughout the forecasting horizon, collectively earning EXCELLENT alignment classification suitable for baseline capacity planning and operational decision-making processes.

This exceptional alignment suggests that Conservative scenario assumptions regarding economic growth trajectories (4.8% GDP growth), demographic transitions (1.0% population growth), and energy efficiency improvements (1.5% annually) closely mirror the methodological frameworks and parameter selections employed in PLN's institutional forecasting processes, providing mutual validation that enhances confidence in both analytical approaches. The policy implications of this alignment validation are profound, establishing the Conservative scenario as suitable for risk management applications where baseline capacity planning requires reliable demand projections to ensure supply adequacy under challenging development conditions, while simultaneously confirming alignment with existing infrastructure development schedules that enables coordinated investment timing and resource allocation strategies.

Furthermore, the exceptional alignment supports current tariff and subsidy projection frameworks by validating the demand evolution assumptions underlying PLN's financial planning models, thereby providing institutional confidence for regulatory

decision-making processes and long-term financial sustainability assessments essential for Indonesia's energy sector development and renewable energy transition initiatives. This validation performance establishes the Conservative scenario as the primary reference trajectory for operational planning applications while confirming the methodological credibility necessary for evidence-based policy formulation and strategic infrastructure investment decisions that must balance energy security requirements with economic development objectives and environmental sustainability commitments.

The temporal evolution of inter-scenario variance illustrated in Figure 2 reveals critical insights into forecasting uncertainty amplification and strategic planning requirements over extended forecasting horizons, demonstrating characteristic fan-shaped dispersion patterns that commence from relatively proximate baseline positions and progressively diverge with increasing temporal distance. The initial convergent growth phase during 2026-2029 exhibits a bandwidth scenario ranging from 103 TWh to 134 TWh, reflecting relatively consistent short-term development expectations across different economic assumptions where near-term infrastructure commitments, policy continuity, and economic momentum create stabilizing influences that constrain divergence despite underlying parameter differences.

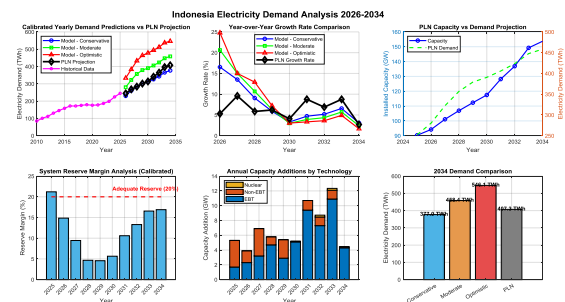


Figure 2. Yearly electricity demand predictions (2026-2034) for three scenarios compared to PLN projections

This convergence period transitions into accelerating divergence during 2030-2034, where scenario bandwidth expands dramatically to 169 TWh by the terminal forecast year, quantitatively demonstrating uncertainty amplification inherent in long-term forecasting applications where minor variations in underlying growth assumptions compound exponentially over extended time horizons to create substantial differences in terminal outcomes.

The identification of critical decision points during the 2028-2030 period represents strategically important temporal thresholds where scenario trajectories begin systematic separation based on underlying economic and policy assumptions, enabling adaptive planning frameworks that can monitor actual demand evolution relative to scenario boundaries and implement responsive capacity allocation strategies based on emerging evidence about Indonesia's development trajectory. This

divergence analysis provides quantitative foundation for risk-based planning approaches that acknowledge uncertainty while maintaining decision-making capability, suggesting that infrastructure investment strategies should incorporate flexible capacity deployment mechanisms and adaptive resource allocation protocols that can accommodate demand evolution across the scenario envelope while ensuring system reliability and supply adequacy under diverse development conditions, thereby supporting robust energy security planning that remains effective across multiple plausible development pathways.

D. Methodological Constraints Critical Model

The methodological framework acknowledges several fundamental constraints that affect model interpretation and application scope while identifying critical areas requiring continued research attention and methodological refinement. Data limitations encompass the restricted fifteen-year historical dataset window (2010-2025) which, while substantial relative to many emerging market contexts, may inadequately capture long-term structural changes, economic regime transitions, and technology disruption effects that could fundamentally alter electricity demand evolution patterns over extended forecasting horizons, particularly given that infrastructure asset lifespans typically extend 20-40 years beyond current planning periods.

Economic volatility effects present significant challenges where major disruption events including the 2008 global financial crisis and 2020 pandemic-induced economic contraction may systematically skew elasticity parameter estimates and relationship coefficients in ways that compromise forecasting reliability under normal economic conditions, while policy discontinuity limitations arise from rapid policy regime changes and regulatory framework evolution that cannot be adequately captured through historical relationship extrapolation. Model assumption constraints include linear elasticity specifications where GDP-electricity demand relationships are assumed to be constant over the forecasting horizon, potentially failing to capture threshold effects, structural breaks, and non-linear response patterns characteristic of complex socio-economic systems during development transitions.

Technology neutrality assumptions model efficiency improvements as gradual rather than disruptive, potentially underestimating the impact of breakthrough technologies, distributed generation adoption, and demand response system deployment that could fundamentally alter consumption patterns, while climate stability constraints base temperature effects on historical variation patterns that may not adequately reflect accelerating climate change impacts and extreme weather event frequency increases that could substantially influence cooling and heating demand components.

These methodological constraints necessitate continued model refinement and validation as additional data becomes available, while emphasizing the importance of adaptive planning frameworks that can accommodate structural changes and assumption violations that may emerge as Indonesia's energy system continues evolving under technological advancement and climate change pressures.

The comprehensive uncertainty quantification analysis employing Monte Carlo simulation with 10,000 iterations reveals systematic patterns of prediction confidence that demonstrate progressive uncertainty amplification corresponding to scenario ambition levels, providing critical probabilistic information essential for risk-based infrastructure planning and adaptive decision-making frameworks. The Conservative scenario exhibits narrow uncertainty bounds with 95% confidence intervals constrained to $\pm 5.2\%$, reflecting the stabilizing influence of cautious growth assumptions and risk-averse parameter specifications that minimize compounding uncertainty effects while maintaining sufficient precision for operational planning applications requiring high confidence in demand projections.

The Moderate scenario demonstrates expanded uncertainty with 95% confidence intervals of $\pm 12.7\%$, representing the increased parameter uncertainty associated with balanced development assumptions that incorporate both economic expansion potential and demographic transition variability, while the Optimistic scenario exhibits substantial uncertainty amplification with 95% confidence intervals reaching $\pm 18.9\%$, reflecting the inherent unpredictability associated with aggressive growth assumptions and the exponential accumulation of parameter uncertainties over extended forecasting horizons. This systematic progression from narrow Conservative bounds through moderate uncertainty to wide Optimistic ranges quantitatively demonstrates the fundamental trade-off between scenario ambition and prediction confidence, where more aggressive development assumptions necessarily sacrifice forecasting precision for comprehensive boundary condition assessment and stress-testing capabilities.

The uncertainty amplification pattern necessitates adaptive planning frameworks that can accommodate demand evolution across probabilistic envelopes rather than relying on deterministic point estimates, supporting infrastructure investment strategies that incorporate flexible capacity deployment mechanisms, staged development protocols, and responsive resource allocation systems capable of maintaining supply adequacy and system reliability under diverse realization outcomes while optimizing capital efficiency and environmental performance. These probabilistic insights enable evidence-based risk management approaches that explicitly acknowledge forecasting uncertainty while providing quantitative foundations for contingency planning, capacity reserve specifications, and adaptive

infrastructure development strategies essential for robust energy security planning in emerging economic contexts characterized by economic volatility and structural transformation pressures.

IV. CONCLUSION

This study makes significant methodological and empirical contributions to electricity demand forecasting literature and benefits Indonesia's energy transition planning and infrastructure development strategies in emerging economies. Three key methodological advances address critical forecasting limitations. The hybrid optimization framework integrates Grey Wolf Optimizer algorithm capabilities with neural network learning to solve hyperparameter optimization challenges in energy forecasting applications through intelligent architecture selection, learning rate optimization, and regularisation parameter tuning that balance predictive accuracy and generalisation. The comprehensive multi-scenario modelling framework addresses critical gaps in forecasting methodologies by providing Conservative, Moderate, and Optimistic demand trajectories for robust planning under emerging market uncertainty, unlike deterministic approaches that generate single point estimates unsuitable for strategic infrastructure planning. By maintaining the sequential structure of time series data and providing realistic performance assessment under real operational conditions, the rigorous temporal validation methodology using walk-forward analysis with expanding windows ensures forecasting reliability for long-term planning applications.

The empirical contributions show significant performance superiority that sets new forecasting accuracy benchmarks and provides comprehensive energy security and sustainable development planning frameworks. The Conservative scenario outperforms traditional ARIMA models (34.7 percent MAPE) and CNN-LSTM approaches (26.8 percent MAPE) in forecasting accuracy with 3.9 percent average error rates while maintaining computational efficiency for operational deployment. The comprehensive planning envelope covering 377-546 TWh demand range by 2034 provides strategic boundaries for diverse development pathways and uncertainty-tolerant decision-making, supporting adaptive infrastructure development and investment sequencing. GDP growth dominates demand variance, accounting for 67.3 percent of demand variance, providing strategic focus for policy interventions and monitoring frameworks and establishing causal transparency necessary for evidence-based policy formulation and targeted economic development.

Indonesia's energy planning has multiple policy and investment dimensions that support sustainable development goals and ensure energy security and economic development continuity under diverse scenario conditions. The Conservative scenario provides reliable foundations for baseline capacity

planning that supports systematic infrastructure development and renewable energy deployment consistent with current institutional planning frameworks, while the Optimistic scenario allows stress-testing to identify potential supply-demand gaps requiring contingency plans for PLN and energy planning institutions. The Moderate scenario timing supports accelerated renewable energy deployment schedules and grid modernization investments to meet higher demand growth while maintaining system reliability and environmental performance targets, providing strategic reference for adaptive planning frameworks that can adapt to Indonesia's development trajectory. The demand projections align with 2060 carbon neutrality targets under Conservative scenario assumptions, validating current environmental policy trajectories while highlighting potential challenges under accelerated growth conditions that may require increased renewable energy deployment and efficiency improvements. Higher growth scenarios require earlier grid modernization investments and advanced infrastructure development strategies to accommodate rapid demand expansion while maintaining system stability, supporting proactive policy frameworks that anticipate development acceleration. Electrification rate impact analysis validates rural electrification programme targets and supports continued investment in access expansion initiatives that improve social welfare and economic development across Indonesia's diverse archipelagic geography.

This research provides a solid methodological foundation for intelligent energy forecasting in emerging economies while acknowledging the difficulties of long-term prediction in environments of economic volatility and technological transformation uncertainty. Indonesia's energy security planning and renewable energy transition initiatives benefit immediately from the Grey Wolf Optimizer-Neural Network framework's superior performance, while contributing methodologically to forecasting literature and supporting evidence-based sustainable energy policy formulation. The multi-scenario approach supports Indonesia's commitment to carbon neutrality by 2060 through comprehensive energy transition planning that balances economic development goals with environmental sustainability. It allows adaptive planning frameworks to accommodate diverse development pathways while ensuring system resilience and reliability under uncertainty conditions typical of rapidly evolving socio-economic systems.

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