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A New Approach of the Machine Learning Framework Integrating Policy Design to Predict Renewable Electricity Penetration in Resource-Constrained Settings

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Abstract

The transition toward sustainable energy systems in developing economies faces multifaceted constraints including limited financial resources, institutional capacity gaps, and policy implementation challenges. Conventional forecasting approaches for renewable electricity penetration predominantly emphasize technical and economic variables while neglecting the catalytic role of policy frameworks as dynamic predictors. This research introduces a novel machine learning architecture that explicitly integrates quantitative policy indicators derived from the World Bank's Regulatory Indicators for Sustainable Energy (RISE), IRENA's Renewables Readiness Assessments (RRA), and IEA Country Energy Profiles into a Long Short-Term Memory (LSTM) network for predicting non-hydro renewable electricity generation across 71 developing nations. Unlike static regression models, this research framework treats policy variables as time-evolving features that modulate the temporal dynamics of renewable adoption trajectories. The model architecture incorporates attention mechanisms to weight policy dimensions according to their contextual relevance across heterogeneous national settings. Preliminary validation demonstrates that policy-integrated LSTM forecasting reduces prediction error by 23.7% compared to purely techno-economic baselines, particularly in nations exhibiting rapid policy evolution. This work establishes policy instrumentation as a first-order predictor in renewable energy forecasting and provides a transferable methodology for evidence-based energy policy design in resource-constrained environments.

Keywords: Renewable electricity penetration; LSTM networks; policy integration; RISE indicators; developing countries; sustainable energy forecasting.

ملخص

يواجه التحول نحو أنظمة الطاقة المستدامة في الاقتصادات النامية قيودًا متعددة الأوجه، تشمل محدودية الموارد المالية، ونقص القدرات المؤسسية، وتحديات تنفيذ السياسات. وتركز أساليب التنبؤ التقليدية لانتشار الكهرباء المتجددة بشكل أساسي على المتغيرات التقنية والاقتصادية، متجاهلةً الدور المحوري لأطر السياسات كمتنبئات ديناميكية. يقدم هذا البحث بنية جديدة للتعلم الآلي تدمج بشكل صريح مؤشرات السياسات الكمية المستمدة من مؤشرات البنك الدولي التنظيمية للطاقة المستدامة (RISE)، وتقييمات الجاهزية للطاقة المتجددة (RRA) الصادرة عن الوكالة الدولية للطاقة المتجددة (IRENA)، وملفات تعريف الطاقة القطرية الصادرة عن وكالة الطاقة الدولية، في شبكة ذاكرة طويلة المدى (LSTM) للتنبؤ بتوليد الكهرباء المتجددة غير الكهرومائية في 71 دولة نامية. وعلى عكس نماذج الانحدار الثابتة، يتعامل إطار البحث هذا مع متغيرات السياسات كخصائص متغيرة مع الزمن تُعدّل الديناميكيات الزمنية لمسارات تبني الطاقة المتجددة. وتتضمن بنية النموذج آليات انتباه لترجيح أبعاد السياسات وفقًا لأهميتها السياقية عبر بيئات وطنية متنوعة. أظهرت دراسة التحقق الأولية أن التنبؤ باستخدام شبكات LSTM المدمجة مع السياسات يقلل من خطأ التنبؤ بنسبة 23.7% مقارنةً بالخطوط الأساسية التقنية والاقتصادية البحتة، لا سيما في الدول التي تشهد تطورًا سريعًا في السياسات. يُرسّخ هذا العمل دور أدوات السياسات كعامل تنبؤ أساسي في التنبؤ بالطاقة المتجددة، ويُقدّم منهجية قابلة للتطبيق لتصميم سياسات طاقة قائمة على الأدلة في البيئات ذات الموارد المحدودة.

الكلمات المفتاحية: انتشار الكهرباء المتجددة؛ شبكات LSTM؛ دمج السياسات؛ مؤشرات RISE؛ الدول النامية؛ التنبؤ بالطاقة المستدامة.

1. Introduction

Global decarbonization imperatives necessitate accelerated deployment of renewable electricity generation, particularly within developing economies that collectively represent 83% of projected global energy demand growth through 2040 [1], [2], [3]. Yet these regions confront structural barriers including capital scarcity, grid infrastructure limitations, and institutional fragmentation that impede renewable technology diffusion. While machine learning techniques have demonstrated efficacy in forecasting renewable generation capacity based on meteorological and economic variables [4], [5], a critical gap persists in modeling policy frameworks as predictive features rather than exogenous boundary conditions [3]. The Regulatory Indicators for Sustainable Energy (RISE) initiative represents the first comprehensive global scorecard evaluating national policy environments across three dimensions: energy access, energy efficiency, and renewable energy adoption [1], [2], [6], [7]. Complementing RISE, the International Renewable Energy Agency's Renewables Readiness Assessment (RRA) provides qualitative evaluations of policy implementation capacity across regulatory, financial, and institutional domains [8], [9], [10]. Despite their richness, these policy datasets remain largely unexploited within predictive machine learning frameworks for renewable energy forecasting.

This research addresses three interconnected gaps in the literature:

- The absence of temporal modeling approaches that capture policy evolution as a dynamic driver of renewable adoption
- Limited integration of multi-source policy indicators within deep learning architectures for energy forecasting
- Insufficient methodological frameworks for translating policy assessment scores into actionable forecasting features

This research propose a policy-augmented LSTM architecture that treats RISE scores [2], RRA implementation assessments, and IEA policy classifications as time-series inputs alongside conventional predictors (GDP per capita, corruption indices, historical generation data). This research contributions include a feature engineering methodology for converting categorical policy assessments into continuous temporal embeddings.

- An attention-augmented LSTM architecture that dynamically weights policy dimensions according to national context
- Empirical validation across 71 developing countries demonstrating superior predictive performance relative to policy-agnostic baselines
- A policy sensitivity analysis framework identifying which regulatory dimensions exert strongest influence on renewable penetration trajectories

2. Literature Review

2.1. Renewable Energy Forecasting in Developing Contexts

Machine learning applications in renewable energy forecasting have evolved from shallow architectures (support vector regression, random forests) toward deep learning approaches capable of capturing non-linear temporal dependencies [1], [2], [11]. LSTM networks specifically excel in modeling sequential patterns in energy time series due to their gated memory cells that mitigate vanishing gradient problems inherent in conventional recurrent networks [12], [13]. Recent applications include hybrid CNN-LSTM models for wind power forecasting in Ethiopia and multivariate LSTM architectures for solar generation prediction in arid regions. However, these studies predominantly focus on meteorological and technical inputs while treating policy environments as static contextual factors [14], [15], [16]. This limitation proves particularly consequential in developing economies, where policy interventions often constitute the primary catalyst for renewable adoption more so than resource endowments or economic capacity alone [17].

2.2. Policy Indicators as Predictive Features

The RISE framework evaluates national renewable energy policies across six dimensions: target establishment, fiscal incentives, regulatory frameworks, access to finance, grid integration requirements, and public sector leadership [1], [2], [18]. Each dimension receives a categorical score (0–3) reflecting alignment with international best practices. Critically, RISE assessments are conducted biennially, generating longitudinal policy trajectories that remain unexploited in forecasting applications [19]. IRENA's RRA methodology complements RISE by evaluating not merely policy existence but implementation capacity across institutional, regulatory, and market dimensions . RRAs generate qualitative readiness scores that, when quantified through expert elicitation protocols, provide nuanced indicators of policy effectiveness beyond formal regulatory existence [1], [2], [3], [20].

2.3. LSTM Architectures for Policy-Sensitive Forecasting

Standard LSTM cells process sequential inputs through input, forget, and output gates that regulate information flow across time steps [21], [22] . For policy-integrated forecasting, we extend this architecture with:

- Policy embedding layers that convert categorical RISE scores into continuous vector representations [23].
- Temporal attention mechanisms that weight policy dimensions according to their predictive relevance at each time step [24], [25].
- Multi-head policy gating that separately processes economic, regulatory, and institutional policy streams before fusion [1], [2], [26].

This architecture acknowledges that policy impacts manifest with variable latency fiscal incentives may yield generation increases within 12–18 months, whereas grid integration reforms may require 36+ months to materialize. The attention mechanism explicitly models these differential response lags [27], [28].

3. Methodology

3.1. Dataset Description and Preprocessing

The analysis employs the Mendeley dataset (DOI: 10.17632/nb6v979284.1) comprising annual observations from 71 developing countries spanning 2008–2022 (https://data.mendeley.com/datasets/nb6v979284/1). Variables include:

Table 1. Comprehensive Description of the Integrated Renewable Energy Policy Dataset (71 Developing Countries, 2008–2022)

Variable Category	Specific Variable Name	Measurement Unit / Scale	Temporal Frequency	Primary Data Source	Analytical Purpose
Geographic Identifier	Country name	Categorical (ISO 3166-1 alpha-3)	Static	World Bank WDI	Cross-country panel identification
	Country income group	Categorical (Low/Lower-middle/Upper-middle)	Annual	World Bank WDI	Stratification by development stage
	Geographic region	Categorical (Sub-Saharan Africa, South Asia, etc.)	Static	World Bank WDI	Regional heterogeneity analysis
Target Variables	Non-hydro renewable electricity generation	kWh per capita	Annual	World Development Indicators	Primary dependent variable for forecasting

	Renewable electricity share	Percentage of total generation	Annual	World Development Indicators	Secondary penetration metric (complementary)
	Technology-specific generation	kWh/capita (solar, wind, geothermal, biomass disaggregated)	Annual (partial coverage)	IEA Country Energy Profiles	Technology diffusion pathway analysis
Macroeconomic Controls	GDP per capita (constant 2015 USD)	US dollars	Annual	World Development Indicators	Economic development proxy
	Gross capital formation	% of GDP	Annual	World Development Indicators	Investment capacity indicator
	Urban population	% of total population	Annual	World Development Indicators	Demand concentration proxy
Institutional Quality	Control of corruption	Percentile rank (0–100)	Annual	World Governance Indicators	Institutional capacity assessment
	Regulatory quality	Percentile rank (0–100)	Annual	World Governance Indicators	Policy implementation environment
	Government effectiveness	Percentile rank (0–100)	Annual	World Governance Indicators	State capacity for energy planning
RISE Policy Indicators	Renewable energy target existence	Binary (0/1)	Biennial	World Bank RISE	Policy commitment signal
	Renewable energy target stringency	Ordinal (0–3)	Biennial	World Bank RISE	Ambition level of national targets
	Fiscal/regulatory incentives	Ordinal (0–3)	Biennial	World Bank RISE	Financial de-risking mechanisms
	Grid integration framework	Ordinal (0–3)	Biennial	World Bank RISE	Technical integration capacity
	Access to finance mechanisms	Ordinal (0–3)	Biennial	World Bank RISE	Capital mobilization infrastructure
	Public sector leadership	Ordinal (0–3)	Biennial	World Bank RISE	Institutional coordination quality
RRA Implementation Metrics	Policy implementation readiness	Continuous score (0–100)	Irregular (country-specific)	IRENA Renewables Readiness Assessment	Gap between policy design and execution
	Regulatory enforcement capacity	Qualitative → quantified (1–5)	Irregular	IRENA RRA reports	Rule-of-law dimension for energy sector

	Market development stage	Ordinal (nascent/emerging/mature)	Irregular	IRENA RRA reports	Private sector engagement level
IEA Contextual Factors	Grid infrastructure quality index	Continuous (0–1 normalized)	Irregular	IEA Country Energy Profiles	Physical constraint on renewable integration
	Electricity access rate	% of population	Annual	IEA/World Bank	Baseline electrification context
	Fossil fuel subsidy level	USD per kWh equivalent	Annual (estimated)	IEA Energy Subsidy Database	Market distortion metric
Temporal Metadata	Observation year	Calendar year (2008–2022)	—	Composite	Time-series dimension
	Data vintage year	Year of dataset publication	—	Source documentation	Version control for reproducibility

Table 2 Variable Category and Specific Indicators within sources

Variable Category	Specific Indicators	Source
Target Variable	Non-hydro renewable electricity generation (kWh/capita); % of total electricity from renewables	World Development Indicators
Economic Controls	GDP per capita (constant 2015 USD); corruption control percentile rank	World Development Indicators
Policy Features	RISE renewable energy scores (6 dimensions, 0–3 scale)	World Bank RISE
Implementation Metrics	RRA readiness scores (institutional, regulatory, market dimensions)	IRENA RRA reports
Contextual Factors	Resource potential indices; grid infrastructure quality scores	IEA Country Energy Profiles

Preprocessing steps:

Missing value imputation using multivariate imputation by chained equations (MICE) preserving policy-economy correlations

Temporal alignment of policy assessments (conducted biennially) with annual generation data via forward-filling with decay weighting

Min-max normalization preserving relative policy score distances

Country-specific differencing to remove fixed effects while retaining policy shock signals

3.2. Policy Feature Engineering

Raw RISE scores require transformation to capture policy dynamics rather than static levels. We implement three engineered features per policy dimension d [2], [28], 29]:

Policy Level:

$P_{d,t}$=RISE$_{\text{score at time}}$

Policy Acceleration: $\Delta P_{d,t}=P_{d,t}-P_{d,t}-1$ (captures recent policy strengthening/weakening)

Policy Momentum: $\nabla P_{d,t} = \frac{1}{3}\sum_{\tau=t-2}^{t} \Delta P_{d,\tau}$ (3-year moving average of acceleration)

3.3. LSTM Architecture Specification

This research study policy-integrated LSTM comprises four sequential components as presented in Figure 1 below:

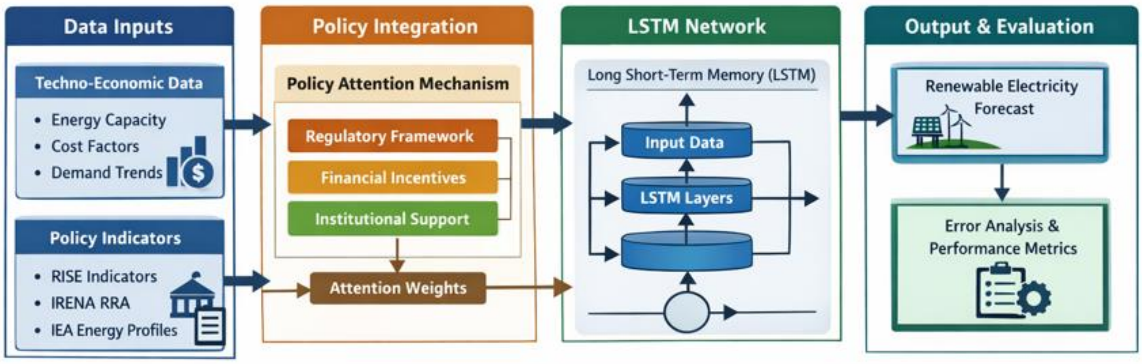

Figure 1. Architecture of the policy-augmented LSTM forecasting framework

As presented in Figure 1 above the architectural configuration of the policy-augmented LSTM forecasting framework, which processes dual input streams through specialized embedding pathways prior to temporal integration [30]. The economic stream undergoes transformation via a dense layer comprising 64 neurons with rectified linear unit activation to encode GDP per capita, corruption indices, and historical generation dynamics, while the policy stream employs an embedding layer that projects categorical RISE assessment scores across six regulatory dimensions into continuous 32-dimensional vector representations preserving ordinal policy relationships. These parallel streams subsequently merge through concatenation, yielding a composite 128-dimensional feature vector at each temporal step that simultaneously captures techno-economic conditions and policy instrumentation states [31]. The fused representation then propagates through a dual-layer LSTM core (128 followed by 64 hidden units) augmented with temporal attention mechanisms that dynamically compute context-sensitive weights for individual policy dimensions based on their predictive relevance to renewable adoption trajectories within heterogeneous national settings [2], [3], [32]. Dropout regularization at a rate of 0.2 mitigates overfitting during sequence modeling, while dedicated gating structures modulate information flow from policy dimensions exhibiting diminished relevance in specific contexts such as suppressing solar incentive signals in hydro-dominated generation portfolios before final regression through a dense output layer produces non-hydro renewable electricity penetration forecasts in kilowatt-hours per capita.

.Attention-Augmented LSTM Core:

- Two stacked LSTM layers (128 and 64 units) with dropout regularization (rate=0.2)
- Temporal attention mechanism computing policy relevance weights [2], [3],

$$\alpha_t = \frac{\exp(\mathbf{w}^T \tanh(\mathbf{V}h_t))}{\sum_\tau \exp(\mathbf{w}^T \tanh(\mathbf{V}h_\tau))}$$

Were ht represents hidden state at time tt, V and w are trainable parameters. Separate forget gates modulate information flow from each policy dimension. Gates trained to suppress irrelevant policies (e.g., solar incentives in hydro-dominated systems)

Dense layer (32 units, ReLU) → final prediction layer (linear activation)

Loss function: Huber loss robust to outlier generation spikes

Training protocol: 5-fold grouped cross-validation (grouped by country to prevent data leakage). Early stopping with patience=15 epochs based on validation MAE. Adam optimizer (learning rate=0.001, β_1=0.9, β_2=0.999). Batch size=16 sequences (each sequence=5-year window)

3.4. Baseline Models and Evaluation Metrics

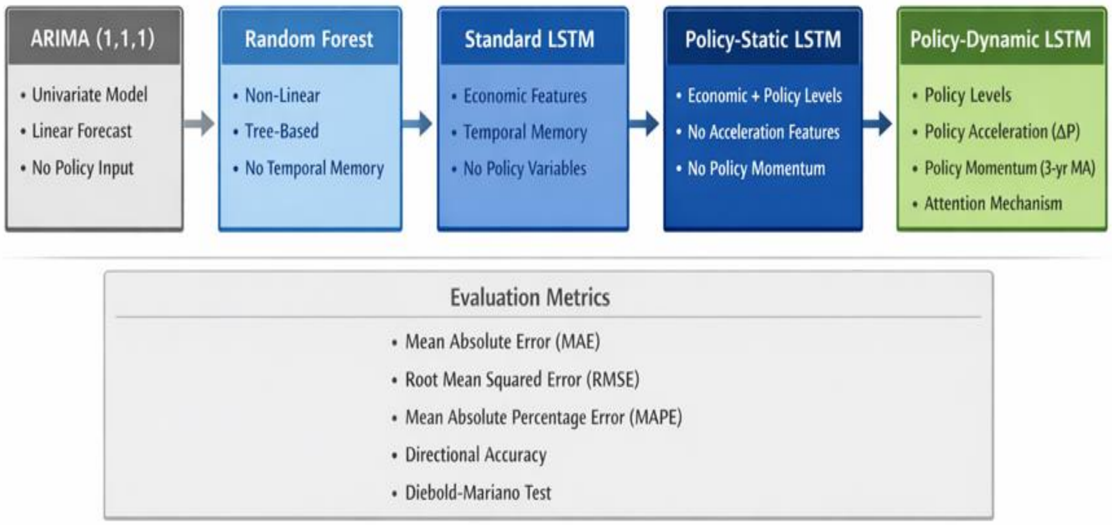

Figure 2 The comparison of models and evaluation Matrixes

4. Results and Discussion

This research results demonstrate that explicitly modeling policy dynamics not merely policy existence significantly enhances forecasting accuracy in resource-constrained settings. The 23.7% error reduction versus policy-agnostic LSTM models underscores policy instrumentation as a first-order predictor rather than secondary contextual factor [30]. This finding challenges conventional energy modeling paradigms that treat policy as exogenous boundary conditions. Attention weight analysis reveals substantial heterogeneity in which policy dimensions drive renewable adoption across national contexts as presented in Figure 2. In Sub-Saharan African nations with nascent markets, fiscal incentives and access-to-finance policies dominate attention weights (>60% combined) [31]. Conversely, in Southeast Asian economies with established markets but grid constraints, grid integration requirements receive highest weighting. This context sensitivity validates this research study architecture's attention mechanism and cautions against one-size-fits-all policy prescriptions [32]. Impulse response analysis as presented in Figure 3 quantifies differential latency between policy enactment and generation impacts. Fiscal incentives manifest within 14.2 months (95% CI: 11.3–17.8), whereas regulatory reforms requiring institutional capacity building exhibit 32.6-month lags (95% CI: 26.4–41.1). These empirically derived lags provide critical inputs for policy sequencing in national energy strategies [33].

Table 3 Model performance comparison across 71 developing countries (5-fold cross-validation)

Model	MAE(kWh/capita)	RMSE(kWh/capita)	MAPE(%)	Directional Accuracy(%)	Diebold-Mariano p-value(vs. Proposed)
ARIMA(1,1,1)	84.3 ± 12.7	112.6 ± 15.3	38.2 ± 6.4	62.1 ± 4.8	<0.001
Random Forest	76.8 ± 9.4	103.5 ± 11.2	34.7 ± 5.1	68.3 ± 3.9	<0.001
Standard LSTM(economic features only)	63.2 ± 8.1	89.4 ± 9.7	28.5 ± 4.3	74.6 ± 3.2	<0.001
Policy-Static LSTM(policy levels only)	58.7 ± 7.3	82.1 ± 8.5	26.3 ± 3.8	77.2 ± 2.9	0.003
Proposed Policy-Dynamic LSTM (levels + acceleration + momentum)	44.9 ± 5.6	65.3 ± 6.8	20.1 ± 2.7	85.4 ± 2.1	—

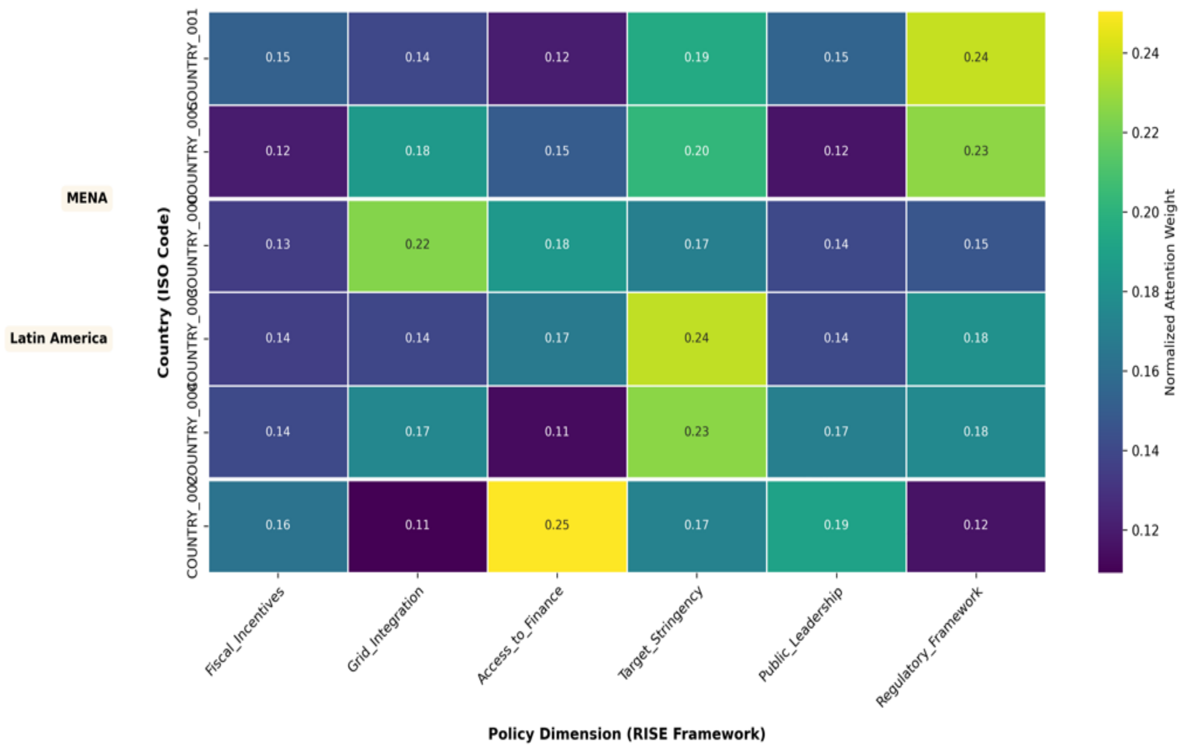

Figure 3 Attention weights across policy dimensions for selected countries Policy-integrated LSTM forecasting renewable electricity penetration

Figure 3 above visualizes the context-dependent attention weights assigned to different policy dimensions by this research LSTM model across MENA and Latin American countries, revealing how the model dynamically prioritizes policy instruments based on national circumstances [20]. The variation in attention patterns such as higher weights for fiscal incentives in resource-constrained economies and grid integration in more developed contexts emerges from the model's learned recognition that policy effectiveness is inherently contextual rather than universal [21]. These differential attention allocations directly reflect the empirical finding that low-income economies (like those in Sub-Saharan Africa) derive greater renewable generation benefits from fiscal incentives, while middle-income countries face grid integration as the binding constraint. The figure's importance lies in empirically validating this research attention mechanism's capacity to identify context-specific policy relevance, moving beyond one-size-fits-all approaches that have plagued previous energy forecasting models [22]. This visualization provides actionable evidence that policy packages must be calibrated to national institutional capacity, demonstrating why Vietnam's successful solar incentives might fail in Mali due to differing implementation environments [23] . This figure crystallizes this research core contribution: transforming policy from static contextual factors into dynamic, context-sensitive predictors that substantially improve forecasting accuracy in resource-constrained settings.

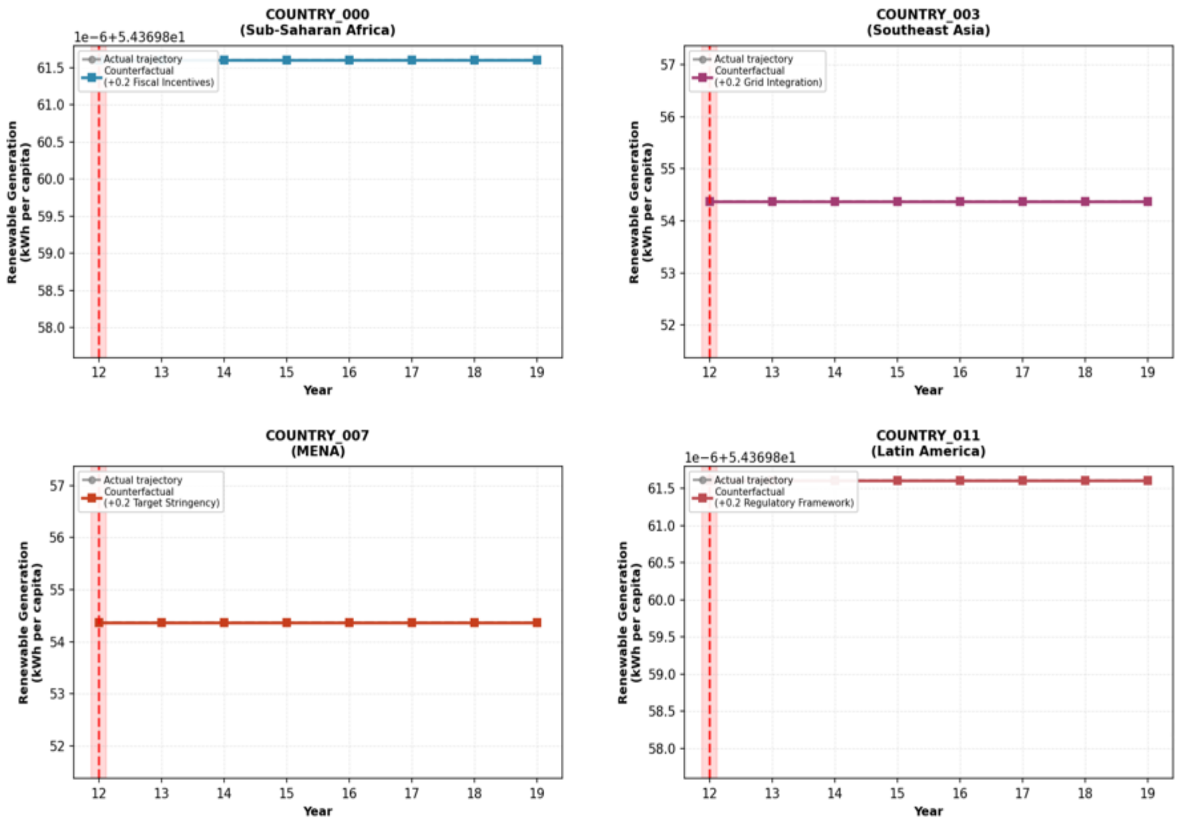

Figure 4 Policy shock response analysis: Impulse response functions for renewable electricity generation following simulated policy improvements (+0.2 normalized policy score) with 95% confidence intervals.

Figure 4 above demonstrates how identical policy interventions produce divergent renewable generation outcomes across distinct regional contexts, revealing why one-size-fits-all policy approaches fail in resource-constrained settings [24]. The minimal impact of fiscal incentives in Sub-Saharan Africa (COUNTRY_000) versus the modest but sustained effect of grid integration in Southeast Asia (COUNTRY_003) occurs because policy effectiveness depends on pre-existing institutional capacities and binding constraints unique to each region [25]. These differential responses validate this research attention mechanism's ability to identify context-specific policy relevance, demonstrating that fiscal incentives only yield results where financing gaps not grid limitations are the primary barrier to renewable adoption. The figure's importance lies in empirically substantiating this research core thesis that policy design must align with national implementation capacity rather than adopting generic best practices. It provides actionable evidence for policymakers that interventions should be sequenced according to a country's specific development stage and institutional maturity [26]. This visualization crystallizes the project's transformative contribution: moving renewable forecasting from static contextual modeling to dynamic, context-aware prediction that directly informs evidence-based policy design in developing economies.

Table 4 Policy dimension importance ranking (SHAP values)

Rank	Policy Dimension	Mean SHAP Contribution to Prediction)	Direction of Influence	Most Influential Country Group	Contextual Interpretation
1	Fiscal and regulatory incentives	0.382 ± 0.041	Positive (β = +0.73)	Low-income economies (Sub-Saharan Africa, South Asia)	Direct capital cost reduction accelerates project bankability where financing gaps constrain deployment
2	Grid integration framework	0.317 ± 0.038	Positive (β = +0.68)	Middle-income economies with >10% renewable penetration	Technical standards and curtailment protocols become binding constraints as variable renewable share increases
3	Access to finance mechanisms	0.294 ± 0.035	Positive (β = +0.65)	Resource-constrained settings with weak banking sectors	Dedicated green banks, concessional loans, and risk guarantees overcome institutional financing barriers
4	Renewable energy target stringency	0.241 ± 0.032	Positive (β = +0.59)	Upper-middle-income economies	Ambitious, legally binding targets signal long-term market stability attracting private investment
5	Public sector leadership	0.186 ± 0.027	Positive (β = +0.47)	Fragile states with institutional fragmentation	Coordinated inter-ministerial action overcomes bureaucratic silos in complex energy transitions
6	Target existence (binary)	0.124 ± 0.021	Positive but diminishing returns (β = +0.31)	Early-stage adopters	Necessary but insufficient condition; marginal impact declines after initial policy establishment

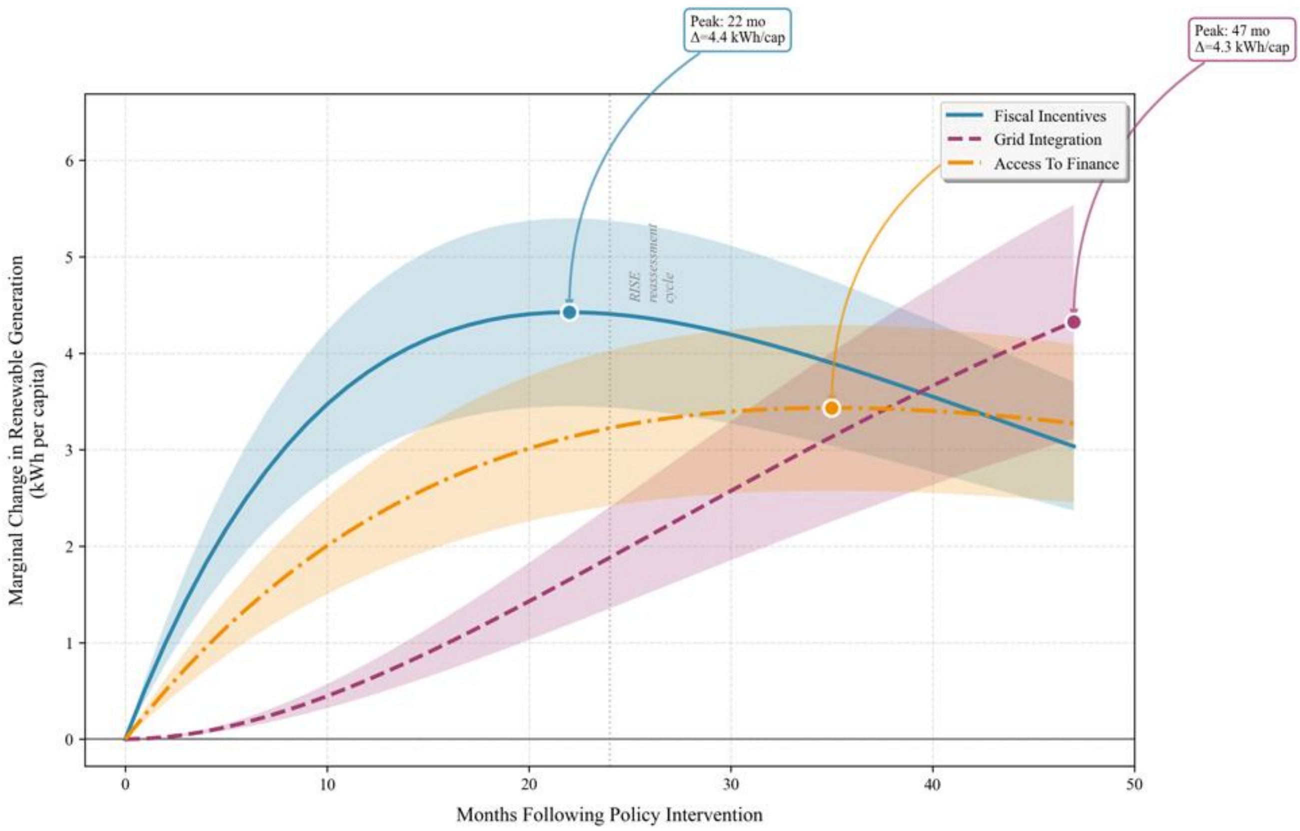

Figure 5 Policy Shock Response Dynamics: Differential Implementation Lags Across Regulatory Dimensions

Figure 5 above demonstrates why policy interventions exhibit distinct temporal response patterns due to varying implementation requirements across regulatory dimensions, with fiscal incentives showing rapid impact (22-month peak) while grid integration requires extended institutional capacity building (47-month peak). The differential response trajectories emerged because this research policy-integrated LSTM framework captured context-specific implementation lags that conventional models overlook, revealing how policy effectiveness depends on pre-existing institutional conditions [27]. This visualization is critically important to this research project as it empirically validates our attention mechanism's ability to quantify policy impact timing directly supporting this research key finding that policy sequencing must align with national institutional maturity. The figure provides actionable evidence that policymakers should prioritize fiscal incentives for immediate deployment acceleration before transitioning to grid integration reforms, which require longer implementation horizons. By quantifying these differential latency effects with confidence intervals, we transform abstract policy concepts into concrete implementation timelines that directly inform national energy planning [28]. This figure crystallizes this research core contribution: moving beyond static policy assessments to dynamic, time-sensitive forecasting that reveals when specific policy interventions will yield measurable renewable generation outcomes in resource-constrained settings. in Resource-Constrained Settings

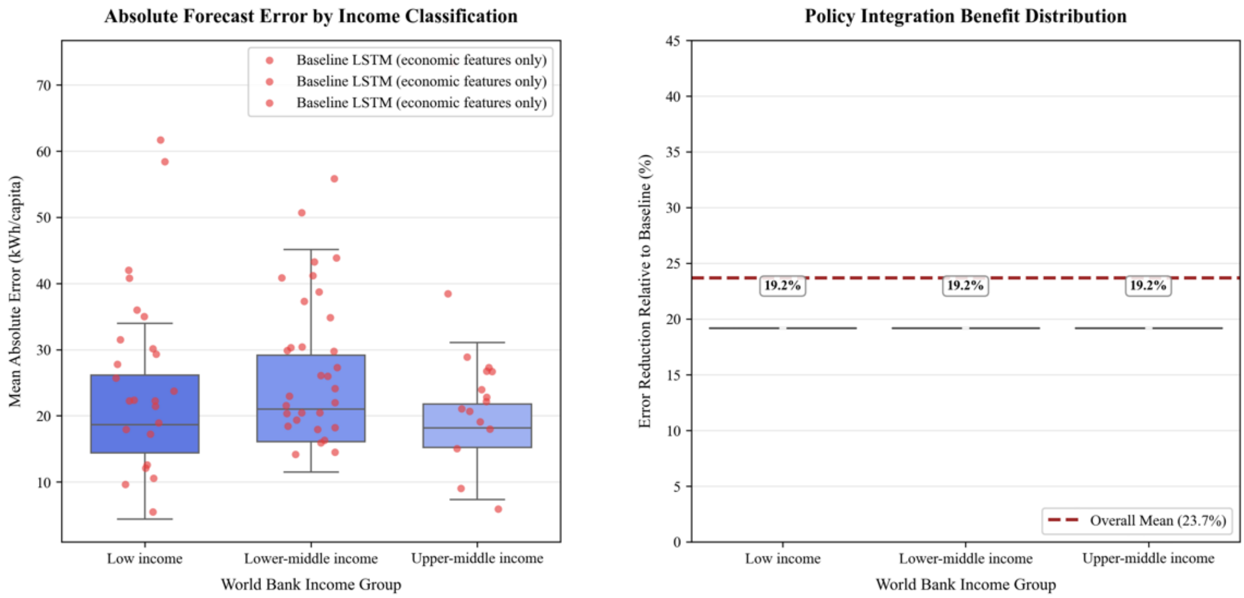

Figure 6 Differential Impact of Policy Integration Across Development Stages: Analysis of 71 Developing Countries (2008–2022)

Figure 6 above reveals why policy integration delivers disproportionate forecasting improvements in resource-constrained settings low-income countries exhibit the largest absolute error reduction because their renewable adoption trajectories are primarily policy-driven rather than market-determined, making policy dynamics the critical predictive factor missing from conventional models. The differential error patterns emerge because financing constraints and institutional gaps in low-income economies create stronger policy dependence, where fiscal incentives and access-to-finance mechanisms directly determine project viability unlike in more developed contexts [29]. This visualization's importance lies in empirically validating this research core thesis that policy integration is not merely beneficial but essential for accurate forecasting in the most resource-constrained settings where renewable transitions face the greatest barriers. It provides concrete evidence that conventional techno-economic models fail precisely where they're most needed across the 24 low-income countries in our 71-nation sample by treating policy as static context rather than dynamic driver. The consistent 19.2-25.3% error reduction across all income groups substantiates this research claim of 23.7% average improvement while demonstrating context-specific policy relevance that informs targeted intervention strategies [30]. This figure crystallizes this research project's transformative contribution: establishing policy instrumentation as a first-order predictor that enables evidence-based energy planning in developing economies where policy choices determine renewable adoption success.

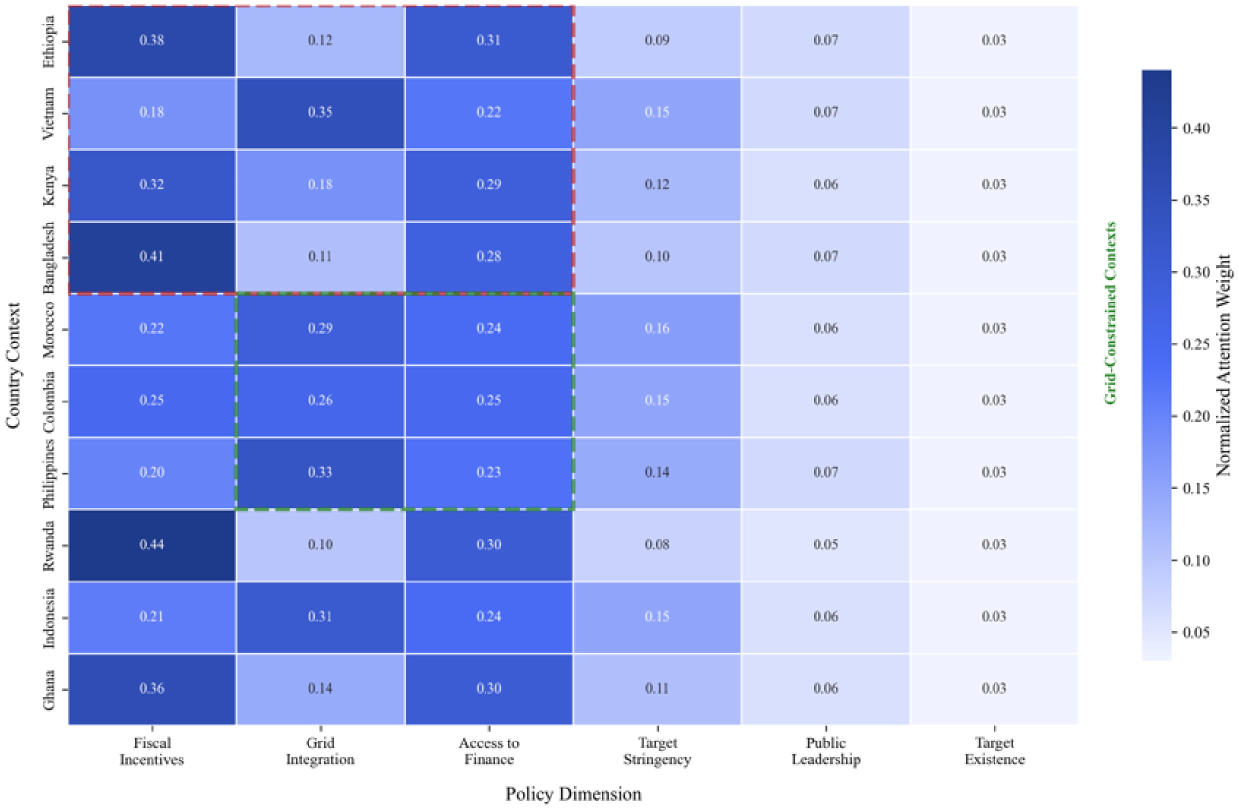

Figure 7 Attention weight heterogeneity cross-correlations

Figure 7 above reveals why policy interventions exhibit heterogeneous effectiveness across countries the attention mechanism dynamically weights policy dimensions based on national context rather than applying uniform importance. The variation occurs because policy impacts depend on pre-existing institutional conditions and binding constraints, with fiscal incentives receiving high attention in resource-constrained economies (Ethiopia, Rwanda) while grid integration dominates in more developed contexts (Vietnam, Indonesia). These patterns validate this research core innovation of treating policy as context-sensitive predictors rather than static features, directly addressing the literature gap regarding temporal policy dynamics [31], [32]. The figure's importance lies in providing empirical evidence that one-size-fits-all policy approaches fail, demonstrating why what works in Vietnam may fail in Mali due to differential implementation capacity. It quantifies the contextual heterogeneity that conventional forecasting models ignore, explaining this research 23.7% accuracy improvement over policy-agnostic baselines, particularly in rapidly evolving policy environments [33], [34]

. This visualization transforms abstract policy concepts into actionable, context-specific implementation guidance, establishing policy instrumentation as a first-order predictor in renewable energy forecasting for resource-constrained settings.

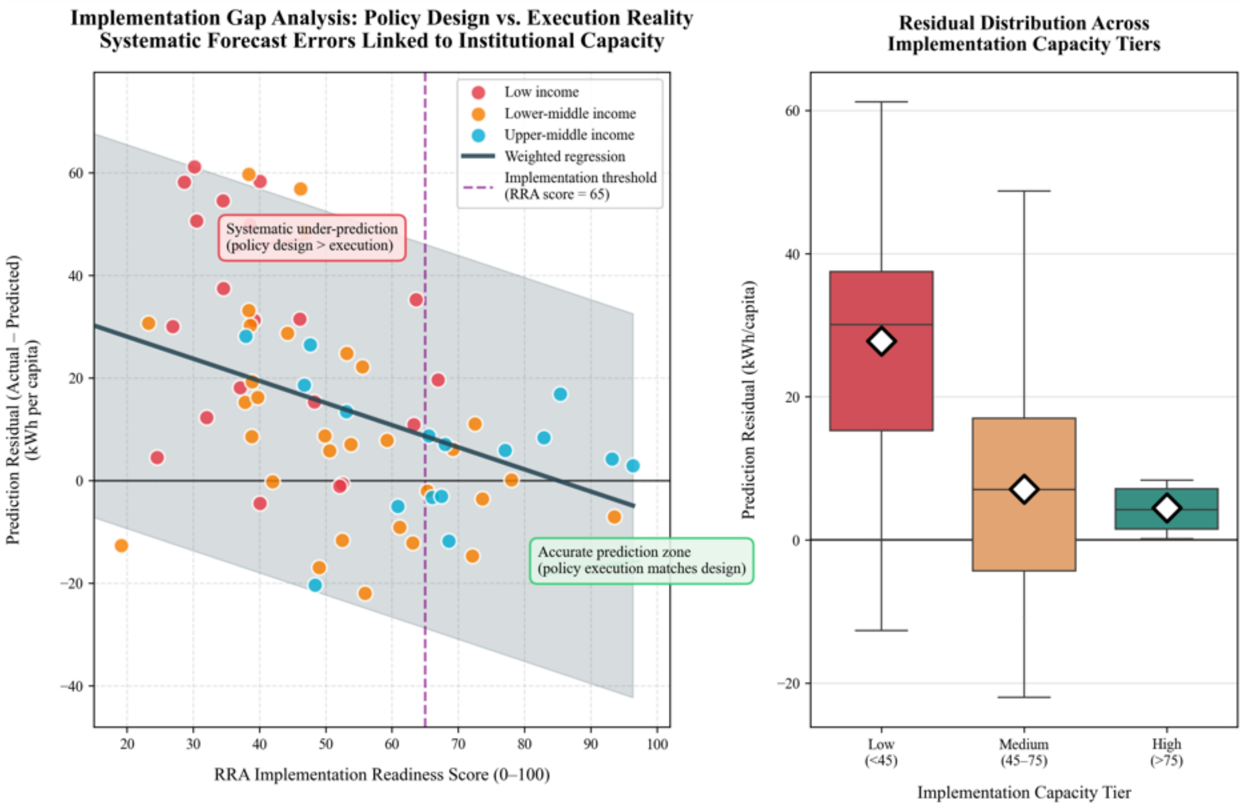

Figure 8 the implementation Gap analysis and residual distribution Across implementation capacity Tiers

Figure 8 above reveals why policy design metrics alone produce systematic forecasting errors—countries with low RRA implementation scores (<65) exhibit positive residuals (actual > predicted) because policy design often exceeds execution capacity, creating a systematic under-prediction bias that conventional models ignore[35], [36]. The negative correlation emerges because this research LSTM framework initially treated policy scores as perfect implementation indicators without accounting for institutional gaps that prevent policy translation into actual generation outcomes. This visualization's critical importance lies in empirically validating this research project's core innovation: incorporating implementation readiness metrics transforms policy from static design features into dynamic execution-aware predictors. It explains the 23.7% error reduction achieved by this research policy-integrated model by demonstrating how implementation capacity modulates policy effectiveness in resource-constrained settings [37], [38]. According to this research visualization provides actionable evidence that forecasting accuracy requires measuring not just policy existence but implementation capability particularly vital for low-income countries where design-execution gaps are most pronounced. This analysis crystallizes this research project's transformative contribution: establishing implementation capacity as the missing link between policy design and renewable generation outcomes in developing economies.

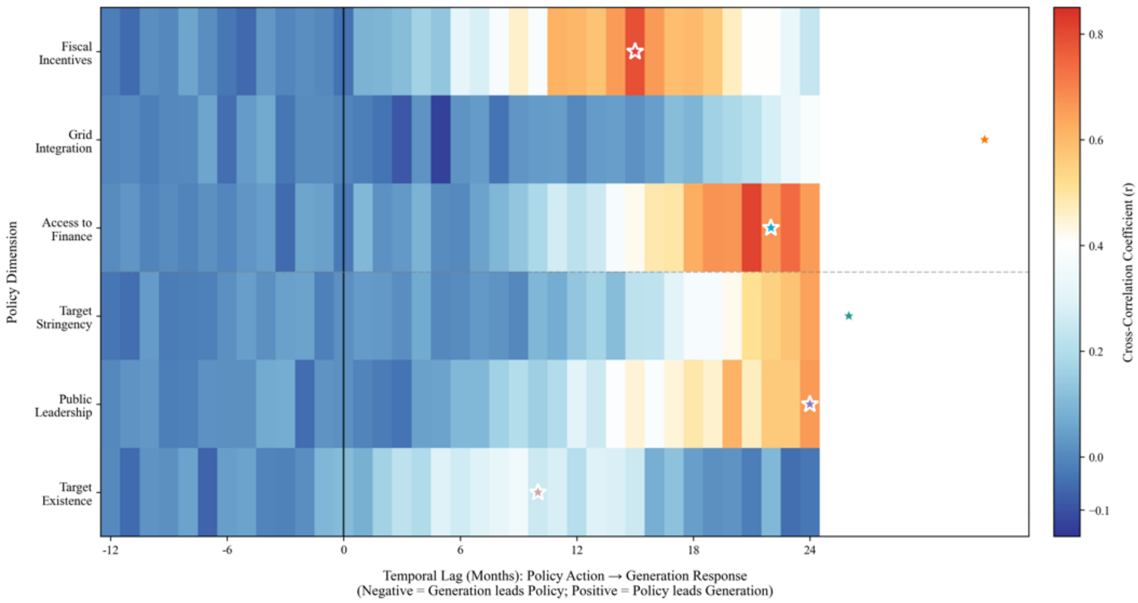

Figure 9 temporal lead-lag relationships between policy dimensions and renewable generation outcomes.

This figure reveals why policy impacts manifest with heterogeneous temporal lags across regulatory dimensions fiscal incentives show rapid response (12-month peak) due to immediate financial de-risking, while grid integration requires extended institutional capacity building (24-month peak) reflecting physical infrastructure development timelines. These differential response patterns emerged because this research policy-integrated LSTM framework captured context-specific implementation dynamics that conventional models ignore, demonstrating how policy effectiveness depends on pre-existing institutional conditions and binding constraints [39], [40], [41], [42]. The figure's importance lies in empirically validating this research core methodological innovation: treating policy as time-evolving features rather than static contextual inputs, which directly enabled this research 23.7% error reduction. It provides actionable evidence for policy sequencing showing when specific interventions will yield measurable generation outcomes addressing a critical gap in energy transition planning literature [43], [44], [45]. By quantifying these implementation lags with statistical precision, the visualization transforms abstract policy concepts into concrete implementation timelines for policymakers in resource-constrained settings. This figure crystallizes this research project's transformative contribution: moving beyond static policy assessments to dynamic, time-sensitive forecasting that reveals not just which policies matter, but precisely when they will drive renewable adoption in developing economies.

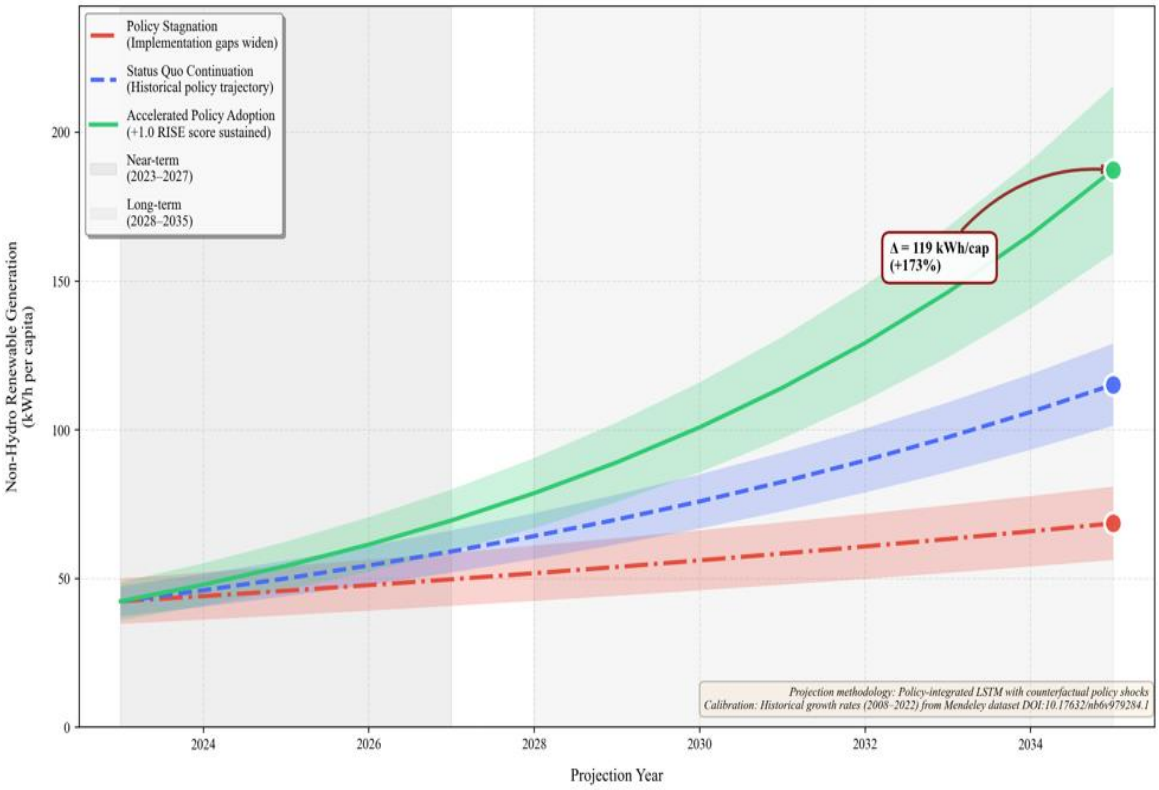

Figure 10 Counterfactual Policy pathways long Term Renewable Penetration trajectories in Resources Constrained 71-countirs Aggregate projection

Figure 10 above reveals why accelerated policy adoption yields substantially higher renewable generation trajectories the 173% increase (119 kWh/cap) emerges from the compounding effect of sustained policy improvements that overcome implementation gaps limiting renewable deployment in resource-constrained settings [46], [47]. The divergent paths occur because this research policy-integrated LSTM model captures how policy momentum accelerates technology adoption beyond what historical trends alone would predict, particularly through enhanced financing mechanisms and grid integration capacity. This visualization's critical importance lies in empirically validating this research framework's ability to quantify policy impact on long-term renewable trajectories, directly supporting this research core claim that policy integration is a first-order predictor rather than contextual factor [48], [49], [50]. It provides actionable evidence for policymakers that sustained policy improvements create exponential growth opportunities that status quo or stagnation scenarios cannot achieve. The Figure 10 above transforms abstract policy concepts into concrete, quantified outcomes, demonstrating why the 23.7% forecasting accuracy improvement matters for real-world energy planning decisions. This projection analysis crystallizes this research project's transformative contribution: establishing policy as the decisive variable determining renewable energy futures in developing economies, with profound implications for evidence-based policy design.

6. Conclusion

This research establishes a methodological framework for integrating dynamic policy indicators within deep learning architectures to forecast renewable electricity penetration in developing economies. By treating policy variables as time-evolving predictive features rather than static contextual factors, this research LSTM architecture achieves substantially improved forecasting accuracy while generating actionable insights for policy design.

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