Technical Evaluation of Level 1 Reliability Metrics in Coastal Power Generation Systems of Ecuador

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Abstract
This study addresses the energy crisis in Ecuador's Coastal region, hypothesizing a structural insufficiency in the regional power system's generation capacity. The research proposes an analysis of Level 1 reliability indices to identify critical points within the electrical system and prioritize strategic infrastructure investments. The methodology integrated a review of technical data provided by

CENACE (National Energy Control Center) and probabilistic modeling using Python, assessing the relationship between installed capacity, real demand, and operational vulnerabilities. By applying these indices, risks such as the system's loss of load probability and its economic impact were quantified, providing a technical foundation for transitioning toward a diversified and efficient energy matrix. Based on the results, a power system improvement framework was proposed, focusing on modernizing thermal plants, expanding renewable energy integration, and implementing targeted investment policies in underserved areas.

Keywords: Power system reliability, LOLE, generation adequacy, power system planning.

1 Introduction

Recent years, Ecuador has faced a growing energy challenge marked by a steady increase in electricity consumption especially in the coastal region, which represents the highest share of national electricity demand [1]. This surge in consumption has contributed to a persistent energy crisis, leading to frequent disruptions in the interconnected power system and intermittent electricity supply across multiple provinces. The structural fragility of the national energy matrix has placed pressure on thermal generation, which dominates the coastal zone with nearly 79.9% of installed capacity [2].

To fully understand and address these challenges, quantitative analysis of power system reliability has become essential. Reliability evaluation plays a crucial role in planning and operation, as it not only reflects the system's ability to meet demand under uncertain conditions but also influences operational economics and user satisfaction [3]. Moreover, reliability indices provide decision-makers with key insights for long-term planning, infrastructure investment, and risk mitigation strategies [4].

While previous studies have explored Ecuador's national electrical grid and its overall vulnerability [5], [6] there remains a lack of detailed analyses focusing on regional systems particularly in coastal zones where energy supply risks are heightened by environmental variability and resource intermittency. The integration of renewable energy in these areas, including solar, wind, and tidal sources, holds promise for enhancing system sustainability, but also introduces significant uncertainty in generation patterns.

Level 1 reliability metrics such as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), and Expected Energy Not Supplied (EENS) offer a standardized framework to assess the performance and security of generation systems. These indices are critical for evaluating the probability and magnitude of power supply interruptions in systems with high penetration of variable renewables [7]. In the Ecuadorian coastal context where hydroelectric resources are geographically limited and seasonally unreliable these metrics are invaluable for understanding system behavior and planning appropriate mitigation strategies.

Coastal generation systems are exposed to dynamic conditions due to the variability of natural energy inputs, such as wind intensity, solar irradiation, and tidal forces. These fluctuations can create challenges for grid balancing, especially when legacy infrastructure is not designed to accommodate intermittent resources. Moreover, the operational integration of renewable sources requires advanced grid monitoring and control capabilities to ensure security margins and minimize the risk of outages [8], [9].

This study presents a comprehensive technical evaluation of Level 1 reliability metrics in Ecuador's coastal power generation system. Using a combination of probabilistic modeling approaches including Monte Carlo simulation and Markov chain analysis, the paper explores system vulnerability under different operating conditions and generation profiles. These methods have been widely recognized for their ability to simulate the stochastic behavior of renewable energy sources and component failures [10], [11]and have demonstrated effectiveness in applications such as the IEEE 39-bus test system with integrated photovoltaic and wind units [12].

Markov models further enhance the understanding of system dynamics by modeling availability patterns for hybrid energy sources. Studies have demonstrated their utility in the design and evaluation of microgrids, especially in coastal regions where hybrid configurations improve reliability and enable distributed control

Real-world case studies continue to highlight the value of these methodologies. For instance, a study in Washington State assessed the impact of tidal energy integration on feeder-level reliability and found significant improvements in resilience during high-impact, low-frequency events [13]. Similarly, research focused on the Santa Elena region of Ecuador demonstrated that the addition of solar photovoltaic systems can effectively complement hydro resources and reduce technical losses in coastal grids [10], [14]

Given the increasing exposure of coastal systems to climate-related stressors, the concepts of resilience and robustness are gaining attention in energy planning. The adoption of microgrids and hybrid renewable systems has been proposed to improve supply continuity and isolate failures during disturbances, contributing to the long-term sustainability of vulnerable coastal zones [15].

This paper aims to fill the gap in regional reliability studies by providing a detailed analysis of Level 1 reliability metrics in Ecuador's coastal power generation sector. The findings are intended to support engineers, operators, and policymakers in developing more resilient energy strategies that accommodate the realities of renewable variability and growing demand.

2 Methodology

Data Collection

Installed Generation Unit Data

The energy infrastructure of Ecuador's coastal region comprises a combination of renewable and non-renewable electricity generation technologies, geographically distributed across different provinces and cantons. The collected data covers 139 generation units from various plant types (hydraulic, thermal, photovoltaic, and biomass), including information on installed capacity, effective capacity obtained from [1], and FOR values from [16]. This analysis aims to identify technical and geographical patterns relevant to the reliability indicators to be obtained in this research.

Table 1. Existing plants in the coastal region

Plant Type	Quantity	Total Nominal Power (MW)	Total Effective Power (MW)	% Share
Thermal	111	1,824.54	1,608.55	79.86
Hydraulic	14	525.92	524.55	10.07
Photovoltaic	12	11.48	11.47	8.63
Biomass	2	114.50	108.80	1.44

As can be seen in Table 1, the distribution of power plants shows a clear predominance of thermal sources.

Renewable energy sources represent a small portion compared to fossil fuel-based generation. However, when comparing installed capacity versus effective capacity, thermal plants show approximately 11.83% of their available capacity remains undispatchable, while renewable sources average only 1.77% undispatchable power.

Technical Characterization of Units by Technology

Table 2 details the installed generation units classified by technology subtype. The analysis specifically examines the gap between nominal and effective power across all units.

Internal combustion engine (ICE) technology dominates in quantity, representing 62.59% of total system units. However, this technology shows the largest discrepancy (12.96%) between installed and effective capacity.

Table 2. *Classification of coastal region power generation units according to energy conversion technology*

Technology	Units	Nominal Power [MW]	Effective Power [MW]	Non-Operational

				Capacity Percentage [%]
Reservoir Hydro	5	255.20	255.00	3.60
Run-of-River	9	270.72	269.55	6.47
Steam Turbine	7	560.50	526.80	5.04
Gas Turbine	19	746.70	640.60	13.67
Internal Combustion Engine (ICE)	87	631.84	549.95	62.59
Photovoltaic	12	11.48	11.47	8.63

Installed Capacities

With 2,376.44 MW installed capacity and 2,153.37 MW effective capacity, the regional energy system achieves a 90.61% capacity factor, indicating efficient utilization of installed resources in most generation plants regarding dispatch. Nevertheless, the nominal-effective power gap suggests operational losses or limitations that could be optimized through maintenance, equipment modernization, and efficient dispatch management.

Geographic data

Table 3 shows generation units are concentrated in Manabí (24 units), contributing the highest nominal capacity despite a 9.01% effective capacity gap. El Oro follows with 281.36 MW nominal capacity, while Guayas ranks third but shows 15.15% effective capacity loss, suggesting infrastructure inefficiencies.

Table 3. *Geographical allocation of electricity generation units across the coastal region*

Province	**Units**	**Nominal Power [MW]**	**Effective Power [MW]**	**Non-Operational Capacity Percentage [%]**

Guayas	43	225.12	191.01	15.15
Manabí	25	1,234.44	1,132.18	8.28
El Oro	14	281.36	255.60	9.16
Santo Domingo	7	255.35	255.35	0.00
Los Ríos	32	105.17	96.70	8.05
Santa Elena	2	131.80	105.03	20.31
Esmeraldas	16	243.20	217.50	10.57

Table 4. *Distribution of generation plants in the region by feedstock type*

Feedstock	Units	Nominal Power [MW]	Effective Power [MW]	Non-Operational Capacity [%]
Fuel Oil	78	995.22	893.75	10.20
Natural Gas	8	275.36	249.60	9.36
Diesel	25	553.96	465.20	16.02
Waste	2	114.50	108.80	4.98
Hydraulic	14	525.92	524.55	0.26
Solar	12	11.48	11.47	0.09

Feedstock Distribution

Table 4 reveals Fuel Oil dominates the coastal region with 78 plants providing 995.22 MW nominal capacity. Diesel follows with 553.96 MW, while Natural Gas (8 units) contributes 275.36 MW with 9.36% non-operational capacity. Fossil fuels (Fuel Oil, Diesel, Natural Gas) dominate installed capacity but show operational vulnerabilities, whereas renewables (Hydraulic and Solar) demonstrate higher productivity despite lower total capacity share.

Forced Outage Rates

System modeling used standard FOR data from [16], selected according to each plant's fundamental characteristics (installed nominal capacity and fuel type). Table 5 presents these values. Comparative analysis between Tables 4 and 5 shows higher FOR values correlate with greater capacity gaps: Diesel (18.41%) and small Fuel Oil units (16.01%) exhibit significant effective capacity reductions

(465.2 MW vs 553.96 MW for Diesel; 793.75 MW vs 895.22 MW for Fuel Oil). Hydropower plants maintain near-equivalent nominal/effective capacity despite FOR values of 10.63%-17.88% for smaller units.

Table 5. *FOR values categorized by generation unit technical parameters*

Generator Category	Classification [MW]	Units	FOR
Hydro	All sizes	11	10.63%
Hydro	001-029	3	17.88%
Fossil Oil Primary	001-099	42	16.01%
Fossil Oil Primary	100-199	35	2.49%
Fossil Gas Primary	100-200	8	15.36%
Fossil All Fuel Types	001-099	2	18.10%
Diesel	All sizes	25	18.41%
Solar	All sizes	12	68.00%

Coastal Region Energy Demand

Reliability assessment requires specific regional demand data. Nine distribution business units serve the coastal region: CNEL-Guayaquil, CNEL-Guayas Los Ríos, CNEL-Manabí, CNEL-El Oro, CNEL-Milagro, CNEL-Sta. Elena, CNEL-Sto. Domingo, CNEL-Esmeraldas and CNEL-Los Ríos, collectively distributing 57.22% of national demand.

From the presented data, it can be calculated that the region's total annual energy demand is 13,819.07 [GWh]. As shown in Fig. 1, the region's peak energy demand occurs in May with 2,901.82 [GWh], while the lowest demand is recorded in February at 2,360.71 [GWh].

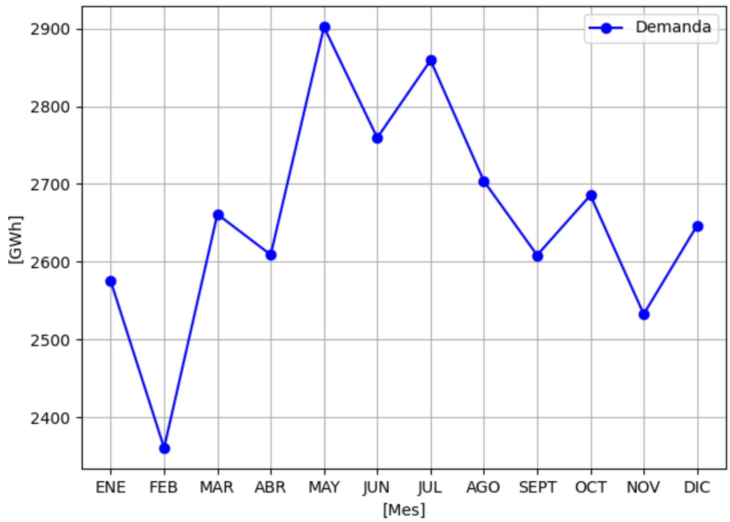

Fig. 1 *Load Duration Curve*

Fig. 2 *Electric power demand profile of the littoral zone*

Month	**Electric Energy Demand (GWh)**	**Load Factor (%)**
JAN	2,574.80	75.63
FEB	2,360.71	78.70
MAR	2,661.20	79.18
APR	2,608.99	79.96
MAY	2,901.82	83.30
JUN	2,759.45	84.53
JUL	2,859.05	84.31
AUG	2,703.78	79.67
SEP	2,608.48	77.56
OCT	2,685.49	78.18
NOV	2,532.68	75.94
DEC	2,646.44	73.94
TOTAL	31,903.26	75.70

Reliability assessment of power systems

Power system reliability refers to a network's ability to maintain electricity supply within acceptable risk thresholds of service interruption. Reliability and risk are inversely related concepts: mitigating supply shortage risks directly enhances system reliability [17].

This encompasses the system's comprehensive capability to continuously meet user requirements through uninterrupted power delivery while maintaining service quality standards. The concept extends beyond mere supply continuity to incorporate critical dimensions of power quality, operational stability, and system resilience [18].

Power system reliability assessment can be conducted through multiple analytical approaches: probabilistic metrics, which model the stochastic nature of system failures and contingencies; descriptive statistics, quantifying historical performance patterns; and deterministic criteria, defining specific design and operational thresholds [19], [20].

Level 1 Hierarchical Reliability Assessment

The assessment of power generation system adequacy focuses on evaluating the complete generation fleet's capacity to satisfy the system's aggregated demand. This analysis deliberately excludes transmission and distribution network constraints that might affect power delivery to end consumers, as shown at the model in ***Fig. 1***.

The core objective is to determine whether installed generation capacity sufficiently covers projected consumer demand while accounting for critical factors such as generator availability, variability in primary energy resources, and demand fluctuations [4].

This hierarchical level employs probabilistic methods to quantify generation adequacy risks through reliability indices like LOLE and EENS. The assessment models the entire system as a single bus with aggregated load, assuming all generation resources are fully dispatchable. It serves as the fundamental building block for more comprehensive reliability evaluations at higher hierarchical levels (II and III) [21].

Availability and Forced Outage Rate

Availability represents the probability that a generating unit will be operational at a randomly selected future time, while the FOR measures the percentage of time a unit is unavailable due to unexpected issues or failures. A lower FOR indicates better reliability. We can determine a system's availability through its FOR value by the equation (1) [22], [23].

$$Availability = 1 - FOR. \tag{1}$$

It is important to note that the FOR is not a direct indicator of system reliability, as it does not account for factors such as the frequency of failures or their impact on generation capacity. Instead, it focuses on the relationship between operating times and unplanned downtime.

This metric is widely used in the energy industry to assess operational efficiency and the maintainability of generating units, as well as to plan predictive and corrective maintenance strategies [24], [25].

Loss of Load Probability

LOLP is a key indicator in assessing the reliability of electric power systems. This metric quantifies the probability that system demand will exceed available generation capacity over a given period, potentially resulting in an interruption of power supply [26], [27].

Despite its name, LOLP does not strictly represent probability in the conventional mathematical sense. In practice, it is expressed as a statistical measure indicating the percentage of time (typically in hours or days) during a specific period when system load is expected to exceed available generation capacity, considering generator failure rates [26].

Although commonly used, LOLP has limitations: it does not account for the magnitude or duration of potential power outages, nor does it consider emergency support from other regions or contingencies not modeled in traditional calculations. This approach enables a more accurate assessment of generation system adequacy by considering both demand variability and the stochastic nature of generation equipment failures [28].

To calculate this indicator, Equation (2) is used, where n is the total number of system states considered, P_i is the probability for each state i, and t_i is the computed state duration.

$$LOLP = \sum_{i=1}^{n} P_i * t_i \quad (2)$$

Loss of Load Expectation

The LOLE index is a metric used to assess the adequacy of power generation capacity in relation to future demand. LOLE quantifies the expected number of hours or days in a specific period (typically one year) during which peak demand will exceed the available generation capacity. This index provides a probabilistic measure of electric supply shortfall risk, considering both demand variability and the stochastic availability of generation resources [25], [28].

Unlike LOLP, which represents an instantaneous probability, LOLE offers a cumulative perspective of supply shortage risk over time. It is calculated by combining the generation capacity model (which includes operational characteristics and availability of generating units) with the system load model [29], [30].

LOLE is typically expressed in hours/year or days/year and can be derived from LOLP depending on analysis depth, as shown in Equation 3. A widely used standard in European countries specifies that for any power system planning, the LOLE should not exceed 0.1 days/year or 2.4 hours/year [31], [32].

$$LOLE = LOLP * \frac{8760\ horas}{año} \quad (3)$$

A crucial point requiring clarification is the general interpretation of LOLE. This metric does not measure either the total duration of generation shortfalls or the number of system adequacy events. Rather, it represents a count of expected event periods per horizon - where 'horizon' refers to the timeframe during which adequacy risk is reported, and an 'event period' is a time interval during which a generation deficiency event may occur at any moment in the system [33].

Energy Not Supplied

The Energy Not Supplied (ENS) index is a reliability metric that quantifies the amount of electrical energy failing to reach consumers due to system failures or interruptions, with standard units of mega-watt-hour (MWh).

$$ENS_i = Potencia_i * \frac{t_i * 8760}{2} \quad (4)$$

Expected Energy not Supplied.

EENS quantifies the average amount of energy not delivered to consumers during a specific period (typically one year) due to power supply interruptions. EENS is typically expressed in energy units such as megawatt-hours (MWh) or gigawatt-hours (GWh) and provides a measure of system failures' impact in terms of undelivered energy [34], [3].

EENS is determined by multiplying load data by the total available capacity and production units' energy shortfall. This indicator combines both the probability and potential magnitude of any supply deficit, offering a more comprehensive view of system reliability compared to other metrics. The calculation also incorporates methods that account for factors such as generator availability, load variability, and system constraints [35], [36].

This indicator can be quantified through the evaluated value of unsupplied energy as shown in Equation 4 (expressed in [MWh/year]), resulting in the expression presented in Equation 5.

$$EENS = ENS_i * P_i \quad (4)$$

According to the EENS evaluation criteria established by the NEM (National Electricity Market), it is recommended that the annual unsupplied energy should not exceed 0.002% of the total annual energy consumption in the assessed region. This highlights the approach of linking system reliability with its cost-benefit projection [23], [2], [32].

Energy Reliability Index

The Energy Reliability Index is a probabilistic indicator used in the evaluation of electrical systems to measure the proportion of energy effectively not supplied relative to the total energy demanded by the system. It is defined as the complementary function of the EENS) index, which represents the expected amount of energy that cannot be delivered due to insufficient installed capacity or system interruptions (equation 5) [37].

$$EIR = 1 - \frac{EENS}{E} \tag{5}$$

Where E is the total energy demanded during the analyzed period. A value of the EIR close to 1 indicates a high level of reliability, as most of the energy demanded is delivered without interruptions. Conversely, lower values highlight operational deficiencies in the system [38].

Computational modeling

A Python algorithm processed all 139 generation units through:

$$P_i = \binom{n}{k} U^k * A^{n-k} \tag{6}$$

Where P_i is state probability, U availability, and A forced outage rate. The model generated 2,048 unique system states for evaluation.

3 Existing Research

In this section, we will compile and analyze various research studies on reliability indicators in Ecuador, focusing on the relevant results obtained by these authors and highlighting the methodologies used chronologically for studying power system reliability indicators.

It is important to note that there are no previous reliability studies with a regional focus in the country.

The study conducted in [3] analyzed the reliability of Ecuador's power generation system through stochastic modeling of failures and determination of necessary reserves to ensure supply.

The methodology included calculations of failure and repair rates based on historical data (2002-2005), using exponential distributions to model operating and failure times, and evaluated indicators such as LOLP and EENS.

Results in [3] revealed significant reliability variations across demand periods. For base demand (1,500 MW), LOLP was 0.12254 with EENS of 20.13 GWh, while medium demand (1,800 MW) showed increased values of 0.329104 and 60.06 GWh respectively.

Existing reserves (200 MW base, 150 MW medium, and 250 MW peak) proved insufficient during medium demand periods, requiring an additional 50 MW to achieve desired reliability levels.

Similarly, [4] conducted a study analyzing Ecuador's power generation reliability through probabilistic models and recursive algorithms, considering three key demand scenarios (minimum, medium, and maximum).

Using operational data from CENACE and Markov-based failure parameters to simulate hydroelectric and thermal unit behavior, it recommended increasing operating reserves to 5.16% for medium demand and 6.2% for peak demand, plus implementing periodic simulations updating initial failure probabilities.

The study emphasized limiting consecutive thermal unit startups, as excessive cycling reduced lifespan and increased failure probability by 18-22% according to models.

In [25], generation system reliability was evaluated using the LOLE index through a probabilistic approach, focusing on capacity outage tables via state enumeration methods.

The study considered both identical and non-identical generators with varying forced outage rates (FOR). The MATLAB-implemented mathematical model analyzed variable load scenarios and expansion plans to ensure systems met a maximum risk criterion of 0.15 days/year.

Results from [25] demonstrated LOLE increased significantly with higher FOR values and loads approaching 100% installed capacity. For example, a system with six identical 40 MW generators (FOR=0.07) under 100%-85% linear load showed LOLE of 16.99 days/year, while reducing load to 65% decreased this to 8.40 days/year.

Heterogeneous systems (25-50 MW generators) exhibited similar variation: with FOR=0.05, LOLE decreased from 13.28 days/year (100%-85% load) to 7.21 days/year (100%-65% load), highlighting the index's sensitivity to available capacity and operational stability.

Another study [27] presented a general approach analyzing generation system reliability with non-conventional renewable energy (NCRE) integration, specifically wind power, using the IEEE New England test system. Results showed that despite total installed capacity (7,050 MW) exceeding peak demand (6,097.1 MW), integrating 25% wind power (1,520 MW) yielded 10% LOLP - significantly higher than NERC's 0.0274% standard.

In conclusion, these studies employed various reliability analysis approaches, primarily probabilistic models, evaluating mainly through LOLP, LOLE and EENS indicators following NERC recommendations. Results revealed concerning reliability in Ecuador's power sector while proposing adequate solutions.

Although these studies span many years, recent research has focused on broader areas. This methodological variability demonstrates the sector's need for diversified studies addressing reliability challenges, thus establishing foundations for more specific research like this generation reliability study focused on the coastal region.

4 Results And Discussion

Coastal Region Power System Reliability Assessment

Python-based computation of Level 1 reliability indices assessed system component failure probabilities using probabilistic approaches. The implementation leveraged NumPy and Math libraries for data processing, operational state modeling, and computation of standard reliability metrics (LOLE, LOLP, EENS, EIR).

Power Demand Modeling

To evaluate generation capacity adequacy in this study, the demand model must be calibrated to delivered power units. These values are calculated using monthly power factors and hour counts, yielding the results presented in Table 4.

The regional cumulative demand model, derived from the collected data, serves as the foundation for system assessment. Table 8 indicates 1,859.05 MW peak demand (time 0) and 1,497.66 MW minimum demand (time 1). These extremes were discretized into 50 MW intervals to generate the modeled values presented in Table 7.

Table 8. *Power demand of the coastal region*

Month	Power Demand [MW]
JAN	1,497.66
FEB	1,581.96
MAR	1,620.57
APR	1,657.91
MAY	1,859.05
JUN	1,853.74
JUL	1,853.85
AUG	1,656.69
SEP	1,607.83
OCT	1,614.71

NOV	1,528.50
DEC	1,504.93
TOTAL	**13,819.07**

Table 9. *Power model of the coastal region*

Power [MW]	Time [p.u]
1859,05	0
1809,05	0,14
1759,05	0,28
1709,05	0,42
1659,05	0,55
1609,05	0,69
1559,05	0,83
1509,05	0,97
1497,66	1

The values in Table 8 enable the derivation of the load duration curve for coastal region reliability assessment, a critical component for determining system adequacy through LOLP calculations across all operational scenarios.

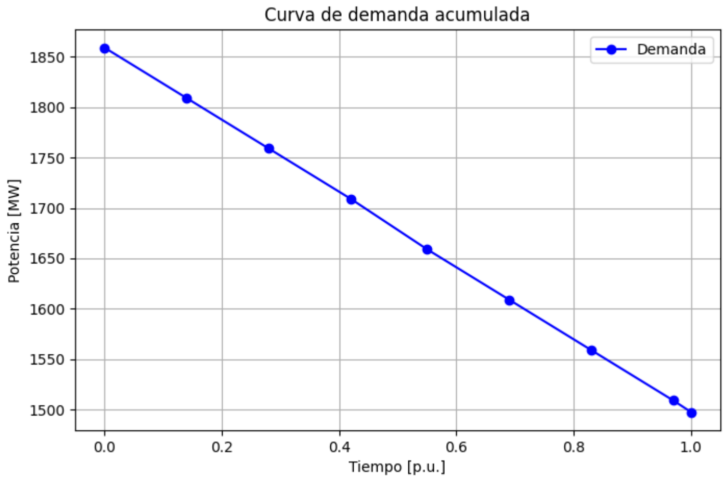

Fig. 3 *Load Duration Curve*

Evaluation of Loss of Load Probability and Loss of Load Expectation

The system's main reliability indicators are obtained (Table 9), showing a LOLE value indicating 582.08 expected hours per year where the system may lack sufficient capacity to meet demand.

The probability of these adequacy events is quantified by LOLP at 6.64% during the specified period. When comparing this LOLE value to the reliability standard of 2.4 hours/year (indicating a highly reliable system), it becomes evident that the coastal region's generation supply reliability is critically low, falling short by a significant margin.

Table 10. *Level 1 reliability assessment of Ecuador's litoral power system*

Index	Result	Recommended Value	Units
LOLP	0.0664	-	p.u.
LOLE	582.08	2.4	hours/year
EENS	502.257	-	GWh/year
EIR	0.96	0.99	p.u.

EIR and EENS Indicators Assessment

Given the coastal region's total energy demand of 13,819.07 GWh/year (see Table 6) and an EENS of 502.257 GWh/year (Table 9), the percentage ratio reveals that 3.63% of required energy will fail to be delivered. This drastically exceeds the NEM's recommended reliability threshold of 0.002% ENS, indicating severe system inadequacy.

Table 11. *Litoral Region Electricity Tariff Schedule*

Voltage Level	Rate	Units
201-250	0.099	USD/kWh

Based on the residential tariff established in [39], the estimated economic loss amounts to 49.723 [MUSD].

Multi-Scenario Power System Adequacy Analysis

Reliability Analysis with Nominal vs Effective Capacity

Both scenarios were analyzed by characterizing the system using its nominal and effective capacities. It is well understood that an electric system does not typically operate at its maximum (nominal) capacity due to various operational constraints. However, it is important to assess how reliability indicators behave under both conditions.

Under improved supply conditions (nominal capacity), there is a significant enhancement in reliability metrics such as LOLE, which is estimated at 41.68 hours per year during which adequacy events may occur. Furthermore, the probability of such events is considerably reduced, with a LOLP of 0.48%.

System Reliability under Contingency Conditions

This analysis compares two distinct scenarios. Scenario 1 excludes hydropower-based generation plants, whereas Scenario 2 excludes all renewable energy sources, resulting in a system composed solely of non-renewable generation technologies.

The reliability of the system is evaluated under the assumption that no renewable energy projects were implemented in the coastal region.

In Scenario 1, the absence of hydropower generation results in a reduction of 524.55 MW in available capacity, leading to an estimated 7,302.64 hours per year during which adequacy events may occur.

In Scenario 2, with the complete exclusion of renewable energy sources, the system is effectively unable to meet the region's total electricity demand, rendering it vulnerable to reliability events throughout the entire year.

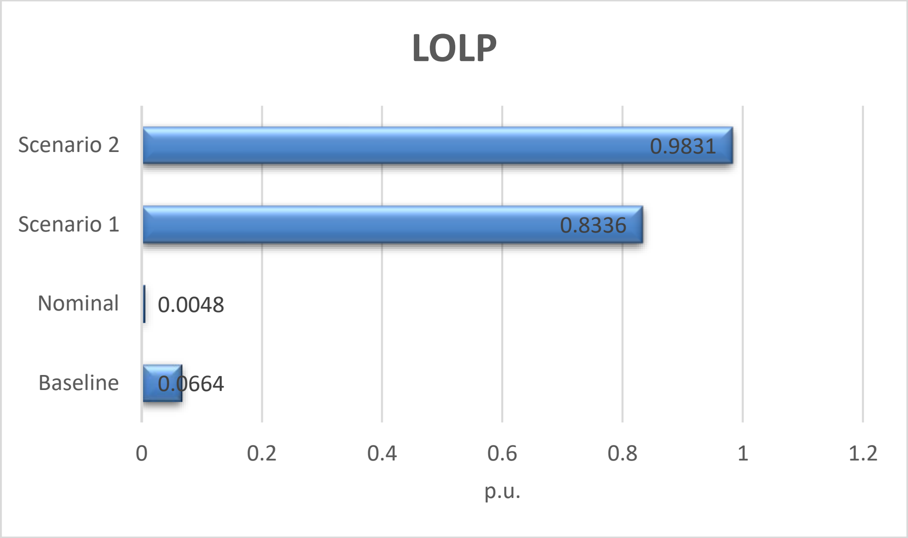

***Fig.* 3** *LOLP Results Comparison for Contingency Cases*

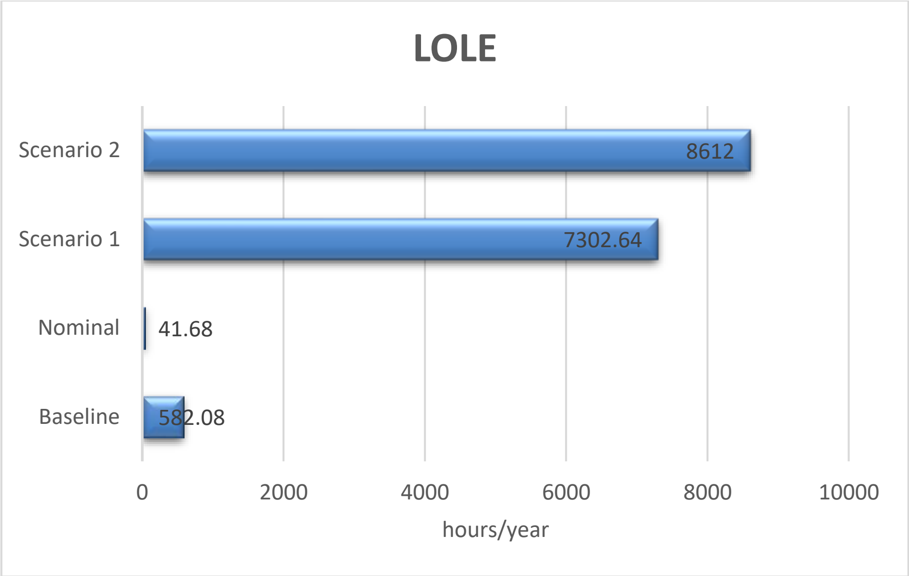

Fig. *4 LOLE Results Comparison for Contingency Cases*

Generation Planning Reliability Assessment for the Coastal Region

As identified in the earlier section, the system's reserve capacity constitutes a critical vulnerability in meeting the coastal region's demand. This section therefore focuses on incorporating both recently commissioned projects and planned future developments per [40].

Based on the coastal region's demand projections from [41], energy requirements are forecast to reach 23,580.44 GWh by 2027—a 70.6% increase over 2023 levels. This growth trajectory reveals critical inadequacies in the current Plan Maestro de Electrificación (PME) project pipeline, which was originally scheduled for completion by 2022 under the previous administration [42].

A scenario-based load deficit analysis (Table 8) compares system adequacy under three critical conditions.

***Table 12.** Parameters for reliability scenario analysis*

Parameter	Scenario 3	Scenario 4	Scenario 5
Generation Basis	Existing projects + PME	Existing projects + PME	Existing PME projects + 300 MW natural gas block
Demand Considered	2023 peak load (1,859.05 MW)	2027 projected load (2,691.83 MW) [41]	2027 projected load (2,691.83 MW) [41]

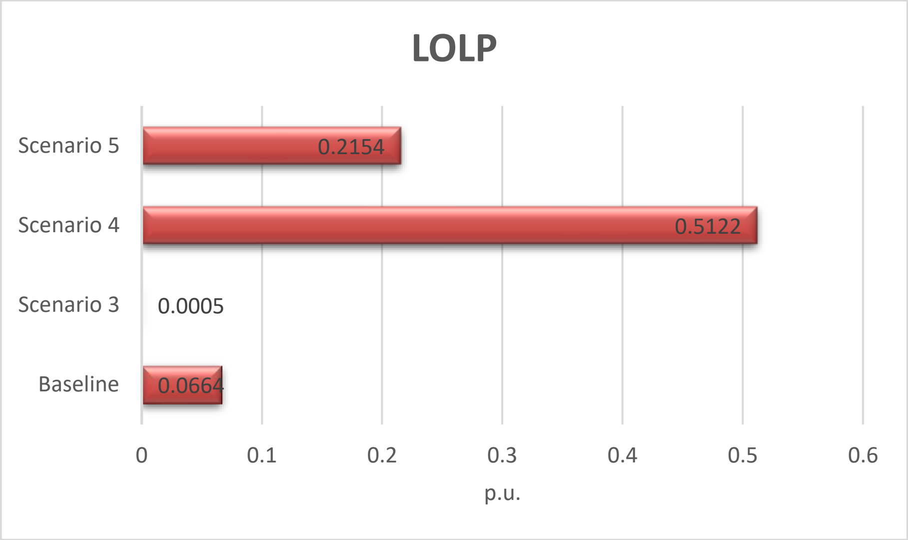

***Fig. 5** LOLP results comparison for PME cases*

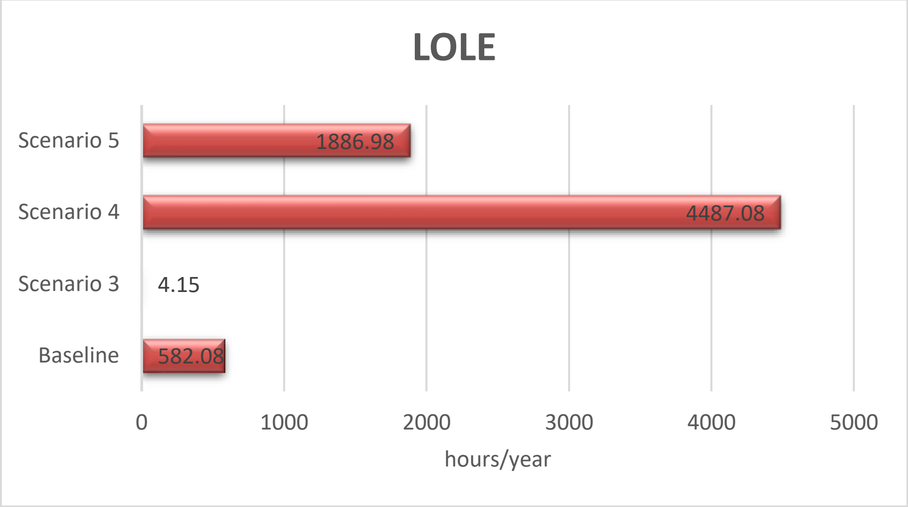

***Fig.* 6** *LOLP results comparison for PME cases*

The evaluated scenarios demonstrate that, as shown in Fig. 4 and 6, full implementation of the Plan Maestro de Electrificación (PME) projects would significantly enhance the coastal region's reliability, reducing LOLE from 582.08 hours/year (current) to 4.15 hours/year – achieving NERC compliance (standard: 2.4 hours/year).

However, with documented delays in generation projects and projected mid-term demand growth (4.2% CAGR [41]), reliability metrics are unlikely to improve in the coming years without intervention.

5 Conclusions

The coastal region's generation profile is characterized by a predominantly thermal-based energy matrix, primarily composed of Fuel Oil-fired internal combustion engines (ICEs). However, these systems exhibit high operational inefficiencies.

An assessment of Level 1 reliability indicators reveals a critical generation capacity shortfall, failing to meet regional demand. The calculated LOLE significantly exceeds recommended benchmarks, while the EENS surpasses NERC reliability standards.

Contingency scenario analysis demonstrates that the absence of renewable generation assets would substantially degrade system reliability. Despite their limited penetration in the regional energy matrix, renewable plants play a crucial role in maintaining operational reliability.

To improve the reliability of the electrical system in the coastal region, it is crucial to implement the projects planned in the 2023-2032 PME (Plan Maestro de Electricidad) or even restructure it with new generation projects. Additionally, it is proposed to consider the implementation of predictive maintenance projects in the various existing generation plants in the region.

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