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Operational Performance of ATRIA ENERGIA S.A.C.'s Micro-Hydroelectric Plant: Daily Generation Analysis

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***Abstract*—This study presents a detailed analysis of the operational performance of ATRIA ENERGIA S.A.C.'s Purmacana micro-hydroelectric plant, based on 165 days of daily generation records from June 1, 2024, to May 31, 2025, with January 2025 excluded due to data unavailability. The 1.8 MW facility, located in Supe district, Barranca province, Lima department, Peru, demonstrates highly variable operational characteristics with pronounced seasonal fluctuations. Daily energy production ranged from 0.10 MWh to 14.90 MWh, averaging 6.07 MWh with a standard deviation of 3.67 MWh (coefficient of variation: 60.5%). The plant achieved an actual capacity factor of 14.1%, substantially lower than the theoretical 71.3%. Monthly analysis revealed peak performance during October–November (19.7%–24.6% capacity factor) and minimum performance during February–April, with capacity factors of 7.3%, 6.4%, and 6.5%, respectively, reflecting coastal Peru's hydrological patterns. Performance distribution analysis showed that 62.4% of operations fell within normal parameters ($\mu \pm \sigma$), 17.6% exceeded high-performance thresholds, and 20.0% experienced low-performance conditions; notably, 29 high-performance days contributed 34.2% of total energy. The projected annual generation of 2.22 GWh—extrapolated from 165 operational days—falls significantly below the expected 9 GWh, representing only 24.7% of theoretical output; whether this gap reflects structural hydrological constraints, extended maintenance, or data collection limitations could not be conclusively determined and requires dedicated investigation. These findings provide critical insights for renewable energy planning and performance validation in Peru's coastal region, particularly for facilities operating under the RER framework.**

***Keywords*—Micro-hydroelectric Plant, Operational Performance, Capacity Factor, Seasonal Variability, Renewable Energy.**

I. Introduction

Peru's renewable energy sector has experienced significant growth under the *Renewable Energy Resources* (RER) framework [1], with micro-hydroelectric plants playing a crucial role in the country's diversified energy matrix [2]. The Purmacana micro-hydroelectric plant, owned and operated by ATRIA ENERGIA S.A.C., represents a typical small-scale hydroelectric facility contributing to Peru's renewable energy targets [3]. Located in the Supe district of Barranca province, Lima department, this 1.8 MW facility commenced commercial operations on July 1, 2011, under a 20-year RER contract extending until June 30, 2031 [4].

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Small-scale hydroelectric plants are particularly important for Peru's energy security [5], providing clean electricity while supporting rural development and environmental sustainability goals [6]. The coastal region of Peru, where the Purmacana plant operates, presents unique hydrological challenges compared to highland facilities [7], with seasonal variations in water availability significantly impacting generation patterns [8]. Understanding the operational characteristics of such facilities is essential for optimizing performance [9], predicting generation behavior, and informing policy decisions regarding renewable energy development [10].

The reported operational parameters of the Purmacana plant indicate an annual generation capacity of approximately 9 GWh with a capacity factor of 71.3% [11], suggesting highly efficient and consistent operation. However, empirical analysis of actual operational data is crucial for validating these projections [12] and identifying potential areas for performance improvement [13]. This study addresses the gap between theoretical capacity and actual performance by analyzing daily generation records over a complete annual cycle, providing insights into the plant's operational characteristics, seasonal variations, and performance consistency [14]. The significance of this research extends beyond the individual facility, offering valuable data for stakeholders involved in renewable energy planning, investment decisions, and policy formulation within Peru's hydroelectric sector.

This paper is organized as follows: Section II outlines the theoretical framework, covering installed capacity, capacity factor, seasonal variability, statistical performance classification, and hydrological management. Section III describes the methodology, including data collection, statistical validation, and performance classification. Section IV presents results on operational metrics, seasonal patterns, and performance distribution. Section V discusses optimization opportunities and implications for renewable energy planning. Section VI concludes with key findings and recommendations for improving micro-hydroelectric efficiency under the RER framework.

II. Theoretical Framework

A. Installed Capacity and Energy Conversion Factors

In a micro-hydroelectric plant, the *installed capacity* $P_{\text{installed}}$ (MW) establishes the theoretical upper limit of generation, determined by the nominal power of the turbines and generators under design operating conditions [15]. This value represents the maximum continuous electrical output that the facility can produce if operating at full load for the entire time period considered. The conversion of hydraulic energy into electrical energy depends on the overall system efficiency, which includes losses in mechanical transmission, hydraulic conveyance, and electrical transformation [16]. Understanding the installed capacity is fundamental, as it serves as the baseline for calculating performance indicators such as the *capacity factor* and for evaluating the operational potential under varying hydrological conditions. In (1), $E_{\text{max,day}}$ (MWh) denotes the maximum energy the plant could generate in a full day of operation at nominal capacity, $P_{\text{installed}}$ (MW) is the installed capacity, and 24 (h) represents the total number of hours in one day [17].

$$E_{\text{max,day}} = P_{\text{installed}} \times 24 \quad [\text{MWh}] \tag{1}$$

B. Capacity Factor as an Efficiency Indicator

The *capacity factor* (CF) is a widely recognized performance metric that evaluates the efficiency of plant operation over a given time period [18]. It expresses the ratio between the energy actually generated and the maximum possible generation if the plant operated at its installed capacity continuously. This indicator integrates the influence of water resource availability, equipment reliability, scheduled and unscheduled maintenance, and operational strategies adopted by plant operators. Higher capacity factors indicate more efficient utilization of the installed capacity, while lower values suggest constraints or inefficiencies in operation. CF is particularly relevant for comparing plants across different locations and hydrological regimes. In (2), E_{actual} (MWh) denotes the total energy generated during the evaluated period, $P_{\text{installed}}$ (MW) represents the rated installed capacity of the plant, and T (h) is the total number of hours in the considered time period [19].

$$CF = \frac{E_{\text{actual}}}{P_{\text{installed}} \times T} \times 100\% \tag{2}$$

C. Seasonal Variability in Hydroelectric Plants

In coastal regions such as Supe, water availability is strongly influenced by seasonal precipitation patterns and river flow fluctuations [20]. This results in generation peaks during high-flow months, often associated with the wet season, and significant drops during the dry season when inflows diminish. Hydrological modeling and historical flow data enable operators to anticipate these changes and adjust operations accordingly [21]. Seasonal generation can be estimated by incorporating the average monthly flow Q_m (m^3/s), the net hydraulic head H (m), the overall turbine–generator efficiency η_{total} (–), the density of water ρ (kg/m^3), the gravitational acceleration g (m/s^2), and the total operational time in the month t_m (h). In (3), E_m (MWh) represents the total monthly energy generation [22].

$$E_m = \eta_{\text{total}} \cdot \rho \cdot g \cdot Q_m \cdot H \cdot t_m \tag{3}$$

D. Statistical Analysis of Daily Production

To characterize operational behavior and identify performance trends, statistical analysis is applied to daily generation data. Metrics such as the mean μ (MWh), standard deviation σ (MWh), median, quartiles, and percentiles provide a detailed description of central tendency and variability. Performance classification is frequently based on thresholds defined by μ and one standard deviation σ, allowing operations to be categorized into high, normal, and low production days [23]. In (4), E_d (MWh) denotes the daily energy generation, μ (MWh) is the mean daily generation over the analysis period, and σ (MWh) is the corresponding standard deviation. This approach supports the identification of periods of exceptional or deficient performance, which may be linked to hydrological anomalies, equipment malfunctions, or maintenance activities [24].

$$\text{Category} = \begin{cases} \text{High}, & E_d > \mu + \sigma \\ \text{Normal}, & \mu - \sigma \leq E_d \leq \mu + \sigma \\ \text{Low}, & E_d < \mu - \sigma \end{cases} \tag{4}$$

E. Hydrological Influence and Water Resource Management

Hydroelectric generation is directly conditioned by the available water flow and its temporal variability throughout the year [25]. In micro-hydroelectric plants, optimal water resource management involves regulating the water intake to maximize production during high-flow periods, while conserving and strategically using stored water or minimum flows during low-flow seasons [26]. This balance ensures sustained generation and minimizes operational downtime. Performance modeling considers the instantaneous relationship between flow $Q(t)$ (m^3/s), net head $H(t)$ (m), and overall efficiency $\eta(t)$ (–), offering valuable insight into the dynamic nature of plant output and enabling predictive control strategies. In (5), $P(t)$ (MW) represents the instantaneous electrical power output, ρ (kg/m^3) is the density of water, and g (m/s^2) is the gravitational acceleration [27].

$$P(t) = \eta(t) \cdot \rho \cdot g \cdot Q(t) \cdot H(t) \tag{5}$$

III. Methodology

This study adopts a longitudinal quantitative approach [28] to evaluate the operational performance of the Purmacana micro-hydroelectric plant operated by ATRIA ENERGIA S.A.C., using 165 daily energy generation records collected between June 1, 2024 and May 31, 2025 [29]. January 2025 was excluded from the analysis due to complete data unavailability, resulting in an effective observation period of eleven months.

The technical characterization, electrical configuration, powerhouse infrastructure, and main generation components are presented in an integrated manner in Table I and Fig. 1–4 [30]. Data quality was ensured through a structured validation protocol, including completeness verification, range validation based on the plant's installed capacity ($0 \leq E_d \leq 43.2\,\text{MWh}$), outlier detection using the interquartile range method with no records excluded after validation, and temporal consistency checks to identify anomalous fluctuations.

Descriptive statistical analysis was conducted to characterize the central tendency, dispersion, and distribution of daily energy production using the mean, median, standard deviation, quartiles, percentiles, and the coefficient of variation [31]. Operational efficiency was assessed through capacity factor calculations [32], employing the plant's gross installed capacity of 1.8 MW as reference.

It should be noted that the reported theoretical capacity factor of 71.3% was derived using the plant's net capacity of approximately 1.44 MW, which corresponds to 57.1% expressed on a gross capacity basis, i.e.,

$$\mathrm{CF} = \frac{9{,}000\ \mathrm{MWh}}{1.441\ \mathrm{MW} \times 8{,}760\ \mathrm{h}} \approx 71.3\%$$

This distinction is maintained throughout the analysis to ensure methodological consistency. Daily operational performance was classified using statistical thresholds defined by the mean (μ) and standard deviation (σ) [33], allowing categorization into high, normal, and low production levels. Monthly aggregation and seasonal analysis were applied to identify temporal trends and hydrological variability characteristic of Peru's coastal region. Annual generation was projected by scaling total recorded energy (1,002.04 MWh) proportionally from 165 days to 365 days, yielding an estimated 2.22 GWh.

TABLE I
TECHNICAL DATA OF THE PURMACANA MICRO-HYDROPOWER PLANT OPERATED BY ATRIA ENERGIA S.A.C.

PLANT DATA	
Installed Capacity	1.8 MW
Plant Type	Run-of-river
Net Head – Gross Head	100–105 m
Water Resource	Pativilca River
TURBINE DATA (G1)	
Turbine Type	Francis
Nominal Flow Rate	2.2 m^3/s
GENERATOR DATA (G1)	
Rated Power	2.0 MW
Generation Voltage	2.3 kV
Power Factor	0.8
TRANSFORMER DATA (T1)	
Rated Power	2.8 MVA
Transformation Ratio	2.3/20 kV

Fig. 1. Purmacana Micro-Hydroelectric Plant Location

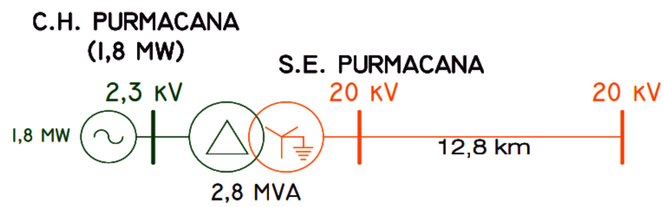

Fig. 2. Single-Line Diagram – Purmacana Micro-Hydropower Plant

Fig. 3. Powerhouse - Purmacana Micro-Hydropower Plant

IV. RESULTS

A. Overall Operational Performance

The comprehensive statistical analysis of daily energy production, presented in Table II, reveals significant variability in operational performance, with the coefficient of variation reaching 60.5%. The wide range between minimum and maximum production (14.90 MWh) indicates substantial operational fluctuations. The median value of 5.30 MWh, which is lower than the mean of 6.07 MWh, suggests a right-skewed distribution, with occasional high-production days influencing the average. The interquartile range (IQR) of 6.07 MWh demonstrates considerable dispersion in operational performance, highlighting the plant's sensitivity to external factors affecting generation capacity.

The efficiency metrics and capacity utilization data com-

Fig. 4. The Turbine and the Electric Generator

TABLE II
DESCRIPTIVE STATISTICS OF DAILY ENERGY PRODUCTION

Parameter	Value	Unit
Total Energy Production	1,002.04	MWh
Mean Daily Production	6.07	MWh
Standard Deviation	3.67	MWh
Minimum Daily Production	0.10	MWh
Maximum Daily Production	14.90	MWh
Median Daily Production	5.30	MWh
Q1 (25th Percentile)	2.90	MWh
Q3 (75th Percentile)	8.95	MWh

piled in Table III demonstrate that the overall capacity factor of 14.1% significantly underperforms the reported 71.3%, indicating substantial deviations between theoretical and actual performance. The peak daily efficiency of 34.5% reflects the plant's potential under optimal conditions, whereas the minimum efficiency of 0.2% highlights operational challenges during low-water periods. The projected annual generation of 2.22 GWh falls considerably short of the expected 9 GWh, suggesting either data collection limitations or significant operational constraints requiring further investigation. The average daily utilization of 14.1% confirms the substantial gap between installed capacity and actual operational performance.

B. Temporal and Seasonal Analysis

The monthly performance breakdown detailed in Table IV demonstrates pronounced seasonal variations, with peak performance during October and November, achieving capacity factors of 19.7% and 24.6%, respectively. The lowest performance period occurs between February and April, with capacity factors dropping to the 6.4–7.3% range. This seasonal pattern aligns with Peru's coastal hydrological cycles, where water availability decreases significantly during the summer

TABLE III
CAPACITY FACTOR AND EFFICIENCY METRICS

Metric	Value	Unit
Overall Capacity Factor	14.1	%
Maximum Theoretical Daily	43.2	MWh
Peak Daily Efficiency	34.5	%
Minimum Daily Efficiency	0.2	%
Projected Annual Generation	2.22	GWh
Average Daily Utilization	14.1	%

months. November represents the optimal operational period, with the highest average daily production of 10.65 MWh, while March shows the lowest performance, with a daily average of 2.77 MWh. January 2025 shows shutdown.

TABLE IV
MONTHLY PERFORMANCE ANALYSIS

Month	Total Energy (MWh)	Average Daily (MWh)	Capacity Factor (%)	Days
2024–06	85.3	4.49	10.4	19
2024–07	103.7	5.76	13.3	18
2024–08	85.5	6.58	15.2	13
2024–09	118.1	6.95	16.1	17
2024–10	161.5	8.50	19.7	19
2024–11	138.4	10.65	24.6	13
2024–12	98.9	8.99	20.8	11
2025–01	Shutdown			0
2025–02	47.2	3.14	7.3	15
2025–03	41.5	2.77	6.4	15
2025–04	25.4	2.82	6.5	9
2025–05	96.7	6.05	14.0	16

The temporal evolution of daily production, illustrated in Fig. 5. The linear regression over the 165 days shows a slope of -0.0070 MWh/day ($R^2 = 0.0083$, $p = 0.245$), which is not statistically significant, confirming that the observed variability is seasonal rather than secular in nature. The absolute maximum of 14.90 MWh occurred on $07/11/2024$, while the minimum of 0.10 MWh was recorded on $08/03/2025$, yielding a peak-to-minimum ratio of $149:1$. The average inter-day volatility was 3.14 MWh, with 18.9% of consecutive pairs exhibiting jumps greater than 5 MWh, evidencing high short-term hydrological sensitivity. The maximum gap between records reached 63 days, corresponding to January 2025.

The comparative analysis of monthly averages and capacity factors, presented in Fig. 6. The ratio between the peak month (November: 10.65 MWh/day, $CF = 24.6\%$) and the minimum month (March: 2.77 MWh/day, $CF = 6.4\%$) is $3.84\times$, with an absolute amplitude of 7.88 MWh. The intra-month coefficient of variation ranges from 23.5% in December—the most stable operating month—to 76.3% in March, which

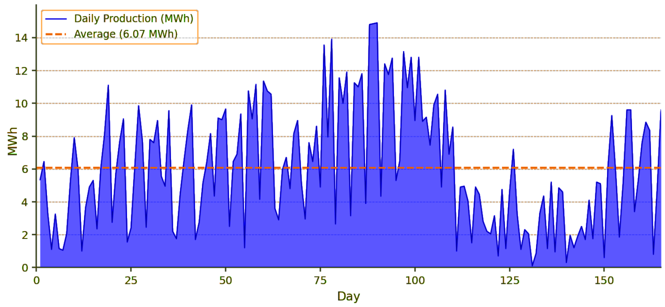

Fig. 5. Daily Energy Production Time Series

combines minimum production with maximum operational irregularity. December exhibits the lowest standard deviation (2.12 MWh), whereas November, being the month with the highest generation, simultaneously records the largest absolute dispersion (4.12 MWh), reflecting the intrinsic variability of hydrological conditions under high water availability.

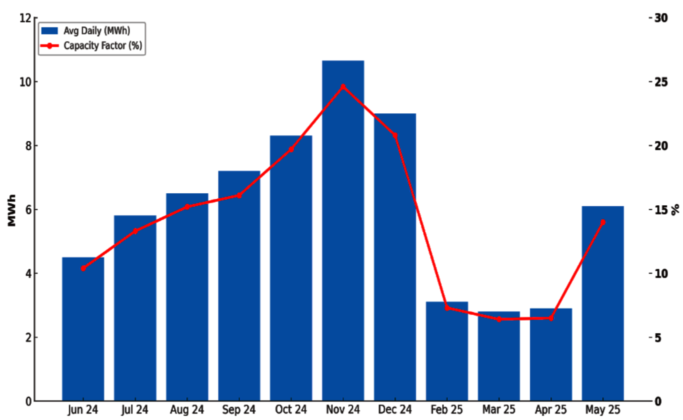

Fig. 6. Monthly Average Production and Capacity Factor

The seasonal comparative assessment shown in Fig. 7 demonstrates significant variations in operational characteristics across different periods. The one-way ANOVA that yields $F = 14.55$ ($p < 0.001$) and the Kruskal–Wallis test yields $H = 31.56$ ($p < 0.001$), confirming highly significant seasonal differences. Autumn (Sep–Nov, $n = 49$) leads with 8.53 MWh/day, differing significantly from all other seasons (Mann–Whitney, $p \leq 0.002$). Winter and summer do not differ from each other ($p = 0.874$), nor do spring and summer ($p = 0.104$), indicating that outside autumn the plant operates within a statistically homogeneous performance range. Paradoxically, spring, with the lowest mean production (4.09 MWh/day), exhibits the lowest IQR (3.70 MWh), making it the most predictable operating season.

C. *Performance Distribution Characteristics*

The categorized performance analysis summarized in Table V reveals that the majority of operational days (62.4%) fall within normal performance parameters, defined as the range $\mu \pm \sigma$ (2.40–9.75 MWh). High-performance days, representing 17.6% of operations, typically occur during favor-

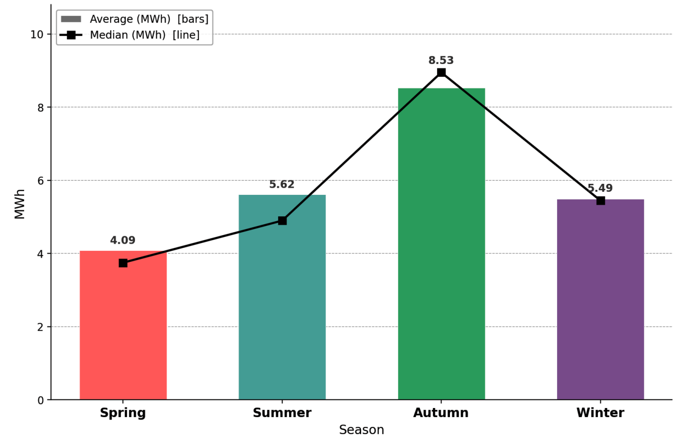

Fig. 7. Seasonal Performance Comparison

able hydrological conditions and exceed 9.75 MWh of daily production, while low-performance days account for 20.0% of the operational period with production below 2.40 MWh. This distribution suggests relatively stable operations with predictable performance variations. The higher proportion of low-performance days compared to high-performance days indicates operational challenges during adverse hydrological conditions that may benefit from technical interventions or operational optimization strategies.

TABLE V
PERFORMANCE DISTRIBUTION ANALYSIS

Performance Category	**Days**	**Percentage**	**Energy Range (MWh)**
High Performance ($> \mu + \sigma$)	29	17.6%	>9.74
Normal Performance ($\mu \pm \sigma$)	103	62.4%	2.40 – 9.74
Low Performance ($< \mu - \sigma$)	33	20.0%	<2.40

The frequency distribution analysis displayed in Fig. 8 reveals that the modal class is 4–5 MWh (21 days, 12.7%), followed by 1–2 MWh (19 days, 11.5%), yielding a distribution with three identifiable local maxima in the ranges 1–2, 4–5, and 9–10 MWh, the latter with 15 days (9.1%), associated with high-generation autumn days. The negative kurtosis (-0.76) confirms a platykurtic distribution, with positive skewness (skewness $= +0.38$). Quantitatively, high-performance days (> 9.76 MWh) represent only 17.6% of the days but account for 34.2% of the total energy (342.75 MWh), whereas low-performance days (< 2.39 MWh), comprising 20.0% of the days, contribute only 4.6% (46.25 MWh), underscoring the disproportionate energy impact of high-generation days.

V. DISCUSSION

A. *Operational Performance Analysis*

The observed capacity factor of 14.1% represents a significant deviation from the reported theoretical value of 71.3%,

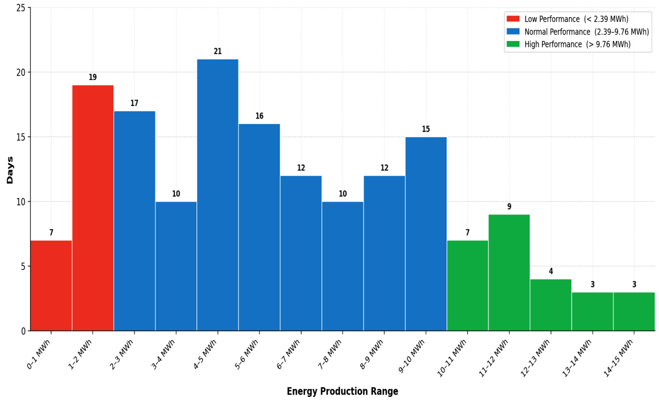

Fig. 8. Performance Distribution Histogram

indicating substantial performance gaps requiring investigation. As noted in Section III, however, the referenced figure of 71.3% was computed against the plant's net capacity of approximately 1.44 MW; expressed on a gross installed capacity basis of 1.8 MW, the theoretical benchmark reduces to 57.1%, narrowing the observed gap by 14.2 percentage points — though the deviation remains substantial and warrants further analysis. This disparity may result from several factors, including data collection limitations, maintenance periods, or operational constraints not reflected in theoretical projections. The high coefficient of variation (60.5%) demonstrates considerable operational instability, suggesting that external factors significantly influence daily production. The performance distribution analysis reveals that while 62.4% of operations fall within normal parameters, the 20.0% of low-performance days indicate systemic challenges that may benefit from technical interventions or operational optimization strategies.

B. Seasonal Variability and Hydrological Impact

Monthly performance analysis confirms strong seasonal dependencies, with peak operations during October–November and minimum performance during February–April. This pattern aligns with Peru's coastal hydrological cycles, where precipitation and river flows peak during winter months and reach minimum levels during summer. The 18.2 percentage point variation in capacity factor between peak and minimum months demonstrates significant hydrological sensitivity. Understanding these patterns is crucial for operational planning, maintenance scheduling, and revenue forecasting. The pronounced seasonal amplitude suggests potential for improved water resource management or storage systems to moderate production variability.

C. Performance Optimization Opportunities

Five concrete optimizations emerge directly from the dataset. First, scheduling major maintenance in January is justified by the observed complete shutdown and December's lowest variability (CV = 23.5%), preserving the high-performance autumn window. Second, the empirically derived threshold of 2.40 MWh/day ($\mu - \sigma$) and inter-day volatility data support SCADA alert configuration. Third, autonomous instrumentation during February–April would resolve the dominant ambiguity between hydrological and operational causes of low performance. Fourth, correlating the 165 daily records with ANA hydrometric data would diagnose whether the CF gap (14.1% vs. 71.3%) requires hydraulic or electromechanical intervention. Fifth, enforcing zero scheduled maintenance during October–November is critical, given that 29 high-performance days alone contributed 34.2% of total recorded generation.

D. Implications for Renewable Energy Planning

These findings have important implications for renewable energy planning in Peru's coastal regions. The significant deviation between theoretical and actual performance highlights the importance of empirical data in project evaluation and investment decisions. The seasonal variability patterns provide valuable insights for grid integration planning and complementary renewable energy deployment. Understanding micro-hydroelectric performance characteristics enables more accurate forecasting and better integration with other renewable sources. The study demonstrates the need for comprehensive performance monitoring and data-driven operational optimization in Peru's expanding renewable energy sector.

VI. Conclusion

This study analyzed 165 operational days of ATRIA ENERGIA S.A.C.'s Purmacana micro-hydroelectric plant, covering June 2024 to May 2025 with January excluded due to data unavailability. The overall capacity factor of 14.1% falls critically short of the reported theoretical value of 71.3%—equivalent to 57.1% when expressed on a gross installed capacity basis of 1.8 MW—and the projected annual generation of 2.22 GWh represents only 24.7% of the expected 9 GWh. Whether this gap reflects structural hydrological constraints or data collection limitations could not be conclusively determined and constitutes the primary question for subsequent research. Seasonal variability is pronounced, with monthly capacity factors ranging from 6.4% in March to 24.6% in November, confirmed by statistically significant ANOVA results ($F = 14.55$, $p < 0.001$). A critical asymmetry was identified: 29 high-performance days (17.6%) contributed 34.2% of total energy, while 33 low-performance days (20.0%) contributed only 4.6%, underscoring the disproportionate operational value of the autumn hydrological window. Five evidence-based recommendations are proposed: scheduling major maintenance in January, implementing SCADA alert thresholds at the empirically derived 2.40 MWh/day boundary, deploying autonomous instrumentation during February–April, correlating generation records with ANA hydrometric data, and enforcing a zero-maintenance policy during October–November. These findings reinforce the critical importance of empirical validation over theoretical projections for facilities operating under Peru's RER framework.

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